The Computation of Inflectional Morphology

by

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B.A., Harvard University (1988)

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Abstract

In this paper I examine a fundamental question in the study of language: Are linguistic forms learned in and retrieved from associative memory or are they produced by a symbol-processing system? According to the tenets of associative memory, linguistic forms have distributed representations whose interconnections are strengthened during each computation over those connections. According to the tenets of symbol-processing, linguistic forms are symbolic representations manipulated by distinct rules and principles. To distinguish between these two theories I have turned to a simple linguistic system: English inflectional morphology, the grammar of words underlying transformations such as past tense formation: *spring-sprang*, *talk-talked*. Past tense formation lends itself particularly well to the task of distinguishing between the two theories because of the existence of ***regular*** and ***irregular*** forms. Regular forms (*walk-walked*) are formed completely predictably by a symbol-manipulating-like system concatenating the stem (*walk*) and the suffix (*/ed/*) to form the past (*walked*). Irregular forms, on the other hand, show a range of predictability, from the completely suppletive *go-went* to the partial similarity of *sing-sang, spring-sprang, string-strung, bring-brought.*

While the predictability of the regulars is characteristic of symbol-manipulating systems, the partial similarity of irregulars is characteristic of associative memory. Thus the question that I have attempted to answer is: How are regulars and irregular computed? Are they both produced by a symbol-manipulating rule (the All-Rules model)? Are they both learned and retrieved from associative memory (the All-Associative model)? Or are indeed regulars rule-produced while irregulars are associatively computed (the Hybrid model)? In this paper I have presented evidence in support of the Hybrid Model. Moreover, I have developed a more detailed model of the learning and computation of irregulars in associative memory as well as of the interaction between irregulars and regulars.

To test the hypothesized models I first acquired three types of empirical measure of the computational success (representation strength) of past tense forms: acceptability ratings, production likelihood, and reaction time. Second, I developed two variables which I expected to predict the empirical measures of past tense representation strength *if* the pasts were associatively computed according to my model. The first predictor variable was an estimate of the frequency of each past tense form: the more often we compute *sprang* as the past tense of *spring*, the easier that computation should subsequently be. The second predictor variable was an estimate of the contribution of similar-sounding forms: computing *sang* as the past of *sing* should facilitate subsequent computation of *sprang* as the past tense of

spring if the two stem-past pairs share phonological mappings (e.g., *ing-ang*).

Using this approach, evidence from the predictiveness of the past tense frequency and similarity variables on the past tense representation strength variables suggested the following computational system for English past tense forms: Irregulars (*spring-sprang, dive-dove*) are learned and computed in an associative memory which can be described as a function approximation system learning and computing stem-past phonological feature mappings. The representations of both stems (*spring*) and pasts (*sprang*) are distributed over their phonological forms. Mappings are learned between stem phonological features (e.g., the *i* of *spring*) and past phonological features (e.g., the *a* of *sprang*). Each presentation of a given stem-past feature mapping (e.g., *i-a*) will strengthen that mapping, thus facilitating subsequent computation over that mapping. Thus each time *sprang* is interpreted or produced as the past tense of *spring*, the *i-a* mapping is strengthened, *facilitating* subsequent interpretation or production of *sprang* as the past tense of *spring*. Similarly, since *sing-sang* shares the the *i-a* mapping with *spring-sprang*, each computation of *sing-sang* will also strengthen the *i-a* mapping, thus also facilitating subsequent computation of *sprang*. However, if a given input feature such as *i* is mapped to a *different* output (such as *o*) other mappings from that input will be weakened. Thus presentation of *bring-brought* should strengthen the *i-o* mapping at the expense of the *i-a* mapping, resulting in subsequently *hindered* computations of *sprang*. This weakening follows from the principles of function approximation whereby the strengthening of one output from a given input should weaken other outputs from that input.

Regulars (*walk-walked*) are produced by a distinct symbol-processing system. However, the production of regulars is inhibited by associative memory: The more successfully a set of outputs are computed by the associative system from a given input, the more the operation of the rule system will be *blocked*. Thus the production by the rule system of *over-regulars* such as *spring-springed* is blocked by the successful associative computation of *sprang* from *spring*. However, not all regulars are rule-produced. The more similar a regular is to the stems of irregulars, the more likely it is that that regular will be associatively learned alongside the irregulars. For example, *dive-dived* and *glide-glided* should have a relatively high probability of being associatively learned because their stems are quite similar to the stems of irregulars (*dive-dove, ride-rode*). This should follow from the principle that the function approximation system should learn any stem-past mapping if the stem's features have already been learned in a mapping.

These findings suggest that both the associative memory and symbol-processing theories of computation are correct and that language is modular: the computation of linguistic forms such as English past tense takes place in *both* associative memory *and* a distinct symbol-processing-like system, and these two subsystems interact in a variety of ways.

Thesis Supervisor: Steven Pinker
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Part I

Introduction, Background and Approach

Chapter 1

Introduction

When biologists tackled the problem of explaining molecular genetics in the 1950s, they chose to investigate a simple organism, *E. Coli.* Its simplicity allowed them to understand it more quickly and more thoroughly than a complex multicellular organism. Furthermore, many of their findings have proven generalizable to more complex organisms such as ourselves. This is but one example of how studying a simple system can help us to understand a complex system.

I and others in the same research group (Steven Pinker, Alan Prince, Marie Coppola, Michelle Hollander, John Kim, Gary Marcus, Annie Senghas, Fei Xu) have taken a similar approach in the investigation of language. The system we have chosen to explore is morphology, the grammar of words. For example, morphological changes underlie the relations between *mouse, mice* and *mouser*, and novel forms such as *mouseness* or *mousable.* Morphology shows promise of being an ideal linguistic system to study for the same two reasons that *E. Coli* lent itself so well to the task. First, it is apparently far simpler than the grammar of sentences, and therefore can be more quickly and more thoroughly investigated. Second, it seems likely that many morphological findings will prove generalizable to other linguistic systems.

Although the investigation of all morphology is the ultimate goal of our research program, we have found that by focusing on a particular subset of morphology we have been able to shed light on those issues most of interest to us. This subset is inflectional morphology, the transformation of words which are grammatically related and share the same linguistic category. For example, the inflectional morphology of verbs is responsible for the relations between stem (*walk*) and past (*walked*), and with other verbal forms (*walks, walking*).

English inflectional morphology provides us with a very important distinction: there are two types of inflectional forms — regulars and irregulars. The vast majority of English verbs and nouns take **regular** inflectional morphological forms (*walk-walked, rat-rats*) following a rule-like process of concatenation of the stem (*walk, rat*) with an affix (*/ed/, /s/*). However, there are number of words that take **irregular** inflectional forms (*sing-sang, mouse-mice*), whose phonological shape is not predictable by a simple rule. For example, in English about 180 verbs take an irregular past tense. Because regular and irregular forms apparently share so many characteristics (they can be matched on their meanings, sentence positions or frequencies in the language), it is relatively straightforward to hold these shared characteristics constant, thereby convincingly constrasting those characteristics which differ.

In this paper I will focus on two issues related to the regular-irregular distinction, and propose a model integrating the two issues. First, I will investigate the *theory of computation* that best explains inflectional morphology. I will show that entirely different types of computational systems are involved in computing irregular and regular forms, and I will propose a relatively detailed mechanism for the computation of irregulars. Second, will will examine the interaction between irregular and regular forms. I will propose that the same mechanisms involved in the computation of irregulars is responsible for many of the interactions between irregulars and regulars.

1.1 Computation

1.1.1 Two Theories of Computation

Two classes of theories compete for the explanation of the computation and representation of linguistic forms: symbol processing theories and theories of associationism.

Symbol Processing

Since the 1950s *symbol processing* has maintained a position of primacy as an explanatory theory of the computation of not only language, but of other domains of cognition as well. According to the symbol processing framework, linguistic forms are symbolic representations that are manipulated by rules and principles. These rules apply completely predictably in an all or none fashion to a set of symbolic inputs which must meet certain necessary and sufficient conditions. The rules in turn generate symbolic outputs. Furthermore, symbol-processing theories of the mind usually assume that the existence of distinct and structured rules and principles is due to innately specified structures in the mind. [1]

The rules, principles and representations of modern linguistics are built on a foundation of

[1] Despite this assumption of innateness, there is no logical necessity for symbol-processing systems to be innately specified. However, it is consistent with the general tenor of specialization in both the mind and brain.

symbol-processing. For example, the theory has been called upon to explain that apparently uniquely human ability to produce and comprehend an infinite number of sentences: linguistic rules can manipulate not only symbols that represent existing forms, such as words in the lexicon, but also completely novel symbols, such as those created by rules themselves. The theory has also, not surprisingly, been invoked to explain inflectional morphology. English regular past tense forms seem to be consistent with all the characteristics of symbolic systems. Thus the computation of regular pasts could be achieved with a single morphological rule which concatenated the */ed/* morpheme to a verb stem (e.g., *walk* + */ed/* → *walked*)

Regulars are entirely predictable in at least three ways. First, the stem-past alternation (*walk-walked*) is entirely predictable, consisting of the addition of the */ed/* suffix to the stem. [2] Second, a regular past tense can be formed by the application of the rule to an entirely predictable set of inputs — any input that meets certain necessary and sufficient conditions: it is a verb stem which does not take an irregular past. [3] Thus new verbs will be regularized (*fax-faxed*), and both adults and children will easily form a regular past for an entirely novel verb (*rick-ricked*) (Berko, 1958). Third, the application of the regular rule seems to apply entirely predictably — in an all-or-none fashion to its stem inputs. Thus there seems to be no gradedness of regular pasts with respect to their stems: the degree of goodness of a regular past is entirely predictable from the goodness of its stem and the rule.

Associationism and Connectionism

However, an alternative account of cognitive computation has long been on the table. Although it has taken many forms since its putative conception by Aristotle (see Mandler and Mandler, 1964), *associationism* as a theory of mind maintains several general principles (Locke, 1690; Hume, 1739; Hartley, 1749 — in Mandler and Mandler, 1964). According to the theory, the mind is a relatively homogeneous structure consisting of networks of interconnected units. Learning consists of the emergence of these connections (associations) between co-occuring units: the more frequent their co-occurence, the stronger their associations. Co-occurence can result from contiguity in space or time, similarity, and perhaps in other situations. The representational system is atomistic, with units representing whole entities such as words, ideas, or concepts. Mental computation consists of somehow using previously learned associations, often by the method of activation spreading through the network (e.g., Quillian, 1967), to think, to recall, or even to form generalizations by analogy.

[2] There are three pronunciations of the */ed/* morpheme — [t] (*walked*), [d] (*jogged*), and [ɨd] (*patted*) — but they represent a predictable phonological alternation that occurs elsewhere in English (see Zwicky, 1975 and Pinker and Prince, 1988).

[3] If a verb takes an irregular past, the potential regular is blocked (*drive-drove/*drived*). See immediately below and section 1.2 for more on blocking.

This associationist framework slowly developed from the British empiricists (e.g., Locke and Hume) through William James (1890) to the semantic nets of the 1960s and 1970s, beginning with the work of Ross Quillian (1967). There were three problems with most of these associative models: there were no well-specified learning algorithms, no well-specified mechanisms for computation, and the atomistic ("localist") representational system was problematic in a variety of ways. All three problems were addressed by a new field whose foundation was laid by McCulloch and Pitts' *A logical calculus of the ideas immanent in nervous activity* (1943). This field, which goes by many names (connectionism, parallel distributed processing, neural computation), has advanced enormously in the half-century since that seminal paper. With inspiration from various fields, including traditional associationism, neuroscience and statistical mechanics, it has made great strides in the solution to many problems, including the three stated above.

Although there have been a phenomenal range of connectionist systems proposed, most of them adhere to a basic framework. Several aspects of this framework conform to the principles of traditional associationism: the mind is usually thought to consist of a homogeneous structure of interconnected units; learning consists of the emergence of these connections between co-occuring units; and the more frequent their co-occurence, the stronger their connections (often called *weights*). But here the basic similarities end, for all three of the fundamental problems of associationism described above were quite successfully addressed. First, the type of threshold functions described by McCulloch and Pitts (1943) were shown to be capable of *universal computation* (see Minsky, 1967). Second, *learning algorithms* were developed, providing a way to change the strength of connections (e.g., Rosenblatt, 1962). Third, *distributed representations* were developed, in which a single entity such as word, idea or concept is broken down into features spread out over many units (Hebb, 1949; Lashley, 1950; Winograd and Cowan, 1963).

One of the greatest sources of excitement about connectionist systems is their ability to *generalize*. After being *trained* on a number of examples of a given relationship (that is, after learning), a network can often induce a complete relationship. For example, a network can often approximate a function (appropriately called *function approximation*) when it is trained on a number of examples of input-output pairs from that function. In this sort of system the network can generalize what it has learned to novel inputs, thereby producing novel outputs consistent with the function it induced from the previously presented pairs. Because the distributed representational system results in similar representations being computed over the same units, novel inputs will often produce outputs similar to the outputs of those trained input items most similar to the novel inputs. It is just these capabilities which might be sufficient to learn and compute a variety of cognitive functions, especially those which appear to display characteristics such as gradedness and the lack of any necessary or sufficient features for inclusion in the function, such as the type of concept studied by Rosch (Rosch and Mervis, 1975). These networks could also apply to linguistic functions such as inflectional morphology. For example, a network might be trained on stem-past input-output pairs, allowing generalization of one or more inflectional relationships to other forms. Such a network might nicely capture various partially predictive similarity effects of irregulars as a result of the shared units in its distributed representations.

Symbol Processing versus Associationism

These two theories of computation are not mutually exclusive. If the mind is not completely homogeneous, both types of computation could be taking place in different cognitive systems. These two computational systems could interact in a variety of ways. For example, rule-produced forms could subsequently be stored in associative memory, from which they could thereafter be retrieved. Alternatively, the two computational systems could be responsible for different types of computations. This latter possibility is in fact what I will be claiming in this paper: specifically, that irregular inflectional forms (*drive-drove, sing-sang*) are associatively represented, while regular forms (*walk-walked*) are symbolically rule-generated anew during each computation.

1.1.2 Models of Inflectional Morphology

Given that irregulars and/or regulars could be rule-produced or associatively represented, there are three possible models: both irregulars and regulars are rule-produced ("All-Rules Model"); both are associatively represented ("All-Associative Model"); or irregulars are associatively represented, while regulars are rule-produced ("Hybrid Model"). [4] In addition, the traditional model (Chomsky and Halle, 1968; Halle and Mohanan, 1985) is one in which irregulars are stored in *rote memory*, with each form in its own distinct slot, while regulars are rule-produced.

Rote-Rule

In rote-rule models (Chomsky and Halle, 1968; Halle and Mohanan, 1985), irregulars are stored in rote memory's distinct slots, while regulars are rule-produced. These models capture very nicely the symbol-processing predictability of regulars. They also capture several characteristics of irregulars. First, irregulars' unpredictability is consistent with their independent storage. Second, this independent storage is also consistent with the finding that irregularly inflected forms show *word frequency effects* — the more frequently an irregular form occurs in the input (is heard or read), the more successfully it is retrieved

[4] It is implausible that regulars are computed associatively while irregulars are computed by a symbol processing system because regulars are more predictable (and therefore more rule-like) than irregulars.

from its memory slot (Chomsky and Halle, 1968; Halle and Mohanan, 1985). [5] Third, the hypothesis of rote-stored irregulars is consistent with the finding by Bybee and Slobin (1982) that when adults make vowel-change errors in the production of either irregulars or regulars, the form is usually (80% of vowel-change errors) an existing irregular past-tense from a different word rather than a novel one or a regular past tense from a different word (e.g., *set-sat* instead of, for example, *set-sot*).

However, rote-rule models are also somewhat problematic. First, a mechanism must be proposed for how children learn to distinguish between irregulars and regulars, as they must in this model. Second, childrens' acquisition of irregulars and regulars must be explained because there are no well-specified learning mechanisms for rules, and even possibly for rote memory items (although see Pinker, 1984).

Rote models are also inconsistent with at least two characteristics of irregulars, both of which reveal some degree of predictability among verb forms. First, most irregulars share most of their phonological form between stem and past. For example, in the pair *spring-sprang* only one phoneme is changed, while four are retained. This **stem-past similarity** is unexpected in a rote model of irregulars because stems and pasts are independently stored. Second, there is some degree of predictability in the type of stem-past *alternation* that an irregular verb undergoes. Thus at least eleven verbs with an *i* in their stems take the *i-a* stem-past transformation: *ring-rang, drink-drank, swim-swam, begin-began, sit-sat, spit-spat*, and so on. The effect of this **alternation similarity** is *clusters* of irregulars in which a set of stem-past alternations are more similar to each other than to the alternations of other verbs. However, alternation similarity is unexpected in a rote model because verb stems and verb pasts are all stored independently of each other. [6]

All-Rules

The types of predictable similarity in irregulars that rote-rule models fail at are attempted to be explained by *All-Rules* models. In this class of models (Chomsky and Halle, 1968; Hoard and Sloat, 1973; Halle and Mohanan, 1985) both regular and irregular inflected forms are created by the application of morphological or phonological symbol-manipulating rules. While regulars are subject to the kind of suffixation rule desribed above, the irregulars are created by the application of phonological "minor rules". For example, the Lowering Ablaut rule, which is responsible for the *sing-sang* transformation, specifies that *i* changes to *a*.

[5] One problem with rote memory models is their lack of well-specified computational learning mechanisms. This creates problems both for the learning of irregulars as well as their frequency effects.

[6] In fact, stem-past and alternation similarity are both consistent with the rote model if we assume a historical explanation in which there were originally morphophonemic rules responsible for the alternations (such rules are still proposed by Halle and Mohanan (1985) and others to explain current irregular stem-past alternations. See the next section for more on this theory. Nonetheless, various other evidence contradicts the rote model of irregulars, including stem-stem similarity, other existing evidence which we discuss in the next chapter, and my findings which we present in this paper.

These models are appealing for several reasons. First, they offer a unified computational theory covering both regulars and irregulars. Second, this unification removes the learning problem the child faces in a dual system such as the rote-rule model, in which he or she would have to decide if a form is regular or irregular. Third, the symbolic nature of regulars is evidently nicely captured. Fourth All-Rules models are consistent with irregular stem-past similarity: The minor rules should produce stem-past similarity because they only apply to those segments of the stem which undergo *systematic* change, which in the case of irregulars is usually only one or two segments in the word. Thus the Lowering Ablaut only modifies one phoneme (*i-a*), leaving the rest of the verb intact. Fifth, alternation similarity is nicely explained by morphophonemic symbolic rules: this kind of consistency is exactly what a rule should produce.

However, All-Rules models are also problematic in several ways. First, the lack of well-specified algorithms for rule-learning poses difficulties for the acquisition of both regular and irregular inflected forms. Second, the word frequency effects found for irregulars is inconsistent with their on-line production by symbol-processing rules. Third, Bybee and Slobin's (1982) finding that adults almost always produce existing irregular past-tense forms rather than novel ones when they make vowel-change errors is inconsistent with rule-produced forms: if the pasts are not stored, why should they be so favored, particularly if the change to the produced past is not one which any other verb undergoes (e.g., *seat-sat, search-sought, shun-shone*). Fourth, irregular stem-past similarity is actually not entirely predictive: it ranges from retention of the entire stem (*hit-hit, wed-wed*) to the stem except for the vowel (*sing-sang, bite-bit*) or final consonant (*make-made, have-had*), to the stem except for the vowel and the addition of a final consonant (*creep-crept, sell-sold*), to none of the stem, in suppletive forms (*go-went*). This *partially* predictive similarity is difficult to explain with symbolic rules. Fifth, alternation similarity among irregulars is also only partially predictive, as can be seen in irregulars which do not follow the same alternation despite the fact that they contain an *i* in their stems: *hit-hit, rid-rid, spill-spilt, build-built, bring-brought, think-thought, cling-clung, stick-stuck, win-won.* Any symbolic rule conditioned only on *i* would produce the wrong results; for it to produce the correct results its conditions must be of a complexity so great that the unifying appeal of rules is drastically reduced.

There are two other types of partially predictive similarity in irregulars that also pose difficulties for rule-produced irregulars. First, in at least some irregular clusters there is some degree of similarity between the non-alternating (primarily consonantal) segments of the different irregular verbs. This **stem-stem similarity** is particularly interesting because it entails characteristic but non-defining features — different subsects of verbs within each cluster show similarity for different segments in different amounts. Thus Bybee and Moder (1983) found upon examination of the *i-a* alternation cluster that many of its verbs share non-vowel phonemes: eight out of eleven begin with an *s*, and many (but not all) have a velar and/or nasal consonant as their last or second to last phoneme (e.g., *sing,* *drink*). Symbolic rules cannot account for such stem-stem similarity within clusters: Because symbol-manipulation rules apply to inputs which meet necessary and sufficient conditions, a rule-based system should not have such characteristic but non-defining features.

Second, among some verbs similarity exists between the past forms even when their stems are quite dissimilar from each other. This **past-past similarity** can be seen in clusters such as verbs ending in *ought* (*bring-bought, buy-bought, catch-caught, fight-fought, seek-sought, teach-tought, think-thought*), in verbs whose irregulars pasts take a əʊ (*rise-rose, write-wrote, ride-rode, drive-drove, shine-shone, wake-woke, choose-chose, tell-told, speak-spoke, steal-stole, weave-wove*), or in those whose pasts take a ʌ (*cling-clung, stick-stuck, dig-dug, win-won, stink-stunk, hang-hung, sneak-snuck*). Such past-past similarity is unexpected in rule systems because the rule produces the same output (ʌ) for dissimilar inputs, and different outputs for similar inputs (e.g., *seek-sought, speak-spoke* and *sneak-snuck*).

The rote-rule model is also inconsistent with stem-stem and past-past similarity because of its independent storage of all verb forms.

All-Associative: Single Net Model

Many of the problems of rote-rule and All-Rules models have been addressed with single net All-Associative models. In this type of model both regulars and irregulars are learned, represented and computed in a *single function approximation connectionist net* — which computes stem-past transformations from distributed phonological forms. [7] For example, a distributed representation of the phonological form of *sing* is presented as the input, and it computes a distributed represention of the form *sang* as its output by spreading activation over all the connections between the input and output units. These stem-past functions are learned by adjusting the connection weights upon presentation of stem-past pairs. [8]

All-Associative models are particularly interesting because they have been built as actual simulation models based on the connectionist framework, first by Rumelhart and McClelland (1986), and subsequently by Plunkett and Marchman (1990; 1991), Egedi and Sproat (1991; see also Sproat, 1992), MacWhinney and Leinbach (1991), Hare and Elman (1992), Cotrell and Plunkett (19xx), and Seidenberg and Daugherty (1992). These models are particularly interesting because they usually make the strong assumption that there is little or no structure in the network to aid in the distinction between regular and irregular transformations. In other words, they conform to the traditional associationist assumption of the

[7] All models that have actually been built for simulation are single-net models — probably both because of the traditional assumption of the homogeneity of associationist systems and because single-net systems have been much more widely studied and are simpler to implement than modular multi-net modules (e.g., Jacobs, Jordan and Barto, 1991).

[8] All connectionist simulation models built so far have used supervised learning techniques. All but one (Cotrell and Plunkett, 19xx), is a feed-forward (non-recursive) net. Nets based on unsupervised learning, in which stem and past would not need to be presented together, have not yet been investigated.

mind as a relatively homogeneous entity.

All-Associative models offer several advantages. First, like All-Rules models, All-Associative models offer the beauty of a unified computational approach. Second, this unity not only confers an Occam's Razor elegance, but also simplifies the learning task, since the child would not have to distinguish between regulars and irregulars, as he or she would in dual system models like the rote-rule model. Third, in connectionist models learning' and computation can be theoretically well-specified and can actually be simulated.

Several characteristics — particularly the partially predictive similarity effects — of irregulars are elegantly addressed by these models. First, connectionist models can learn idiosyncratic irregulars, including the utterly unpredictable suppletive forms. Second, irregulars' word frequency effects are consistent with connectionist learning principles. Third, All-Associative models are consistent with Bybee and Slobin's (1982) finding that when adults make vowel-change errors they tend to produce real irregular past-tense forms rather than novel ones — because the connections for existing irregular pasts would be tend to be stronger than those for computing a novel past. Fourth and fifth, partial stem-stem and past-past similarities fall out from the nature of these networks. Because the input and output representations are distributed, the representations of similar sounding inputs share many of the same units, and analogously for the outputs. [9] Sixth, partial alternation similarity is expected because the mapping between distributed inputs and outputs involves all those features they have in common. Thus those input-output connections between features shared by many often-presented forms will be better learned than those connections between features sharing few rarely-presented forms.

While connectionist models are consistent with the unpredictability and partial predictability of irregulars, they are also consistent with the complete predictability of regulars. Such models are able to capture the full range of regularity, from the true regulars (*walked*) to the clustered *irregulars* (e.g., the *i-a* cluster) to completely suppletive irregulars such as *go-went*. This capability derives from the ability of nets to generalize more or less or not at all.

The regulars should nonetheless show several of the same kinds of connectionist characteristics that are found in irregulars; the apparent lack of these characteristics in regulars is problematic for All-Associative Models. First, although regulars would be expected to show word frequency effects, there is no evidence of such effects ([various references]). Second, if regulars were learned in the same net as irregulars, we would expect that regular pasts be wrongly selected just as irregular pasts were in Bybee and Slobin's (1982) task. But this did not occur: all (but one) of these errors involved the selection of irregular pasts.

[9] However, the particular associative or connectionist architecture will crucially determine if both stem-stem and past-past similarity or just one of them is expected. In Chapter 3 below I address this issue by introducing a model (the Stem-Past model) which makes this distinction.

Third, the partially predictive similarity effects of irregulars might also be expected for regulars, since they are represented in the same network as the irregulars. But the regulars seem to be completely predictable, with no obvious partial similarity among them. Even if the network has been able to learn the regulars extremely well by approximating their suffixation functions [10] highly successfully, one would still expect gradedness for regulars phonologically close to irregulars. I investigate this prediction in this paper.

In addition to these difficulties with regulars, there are two more general problems with All-Associative models. First, stem-past similarity (in either irregulars or regulars) is not expected. Pinker and Prince (1988, 1991) point out that connectionist systems can learn arbitrary input-output mappings — not only the sort of mappings that are actually found English inflectional morphology, but also those which exist in no language at all, such as string reversal (which, if applied to the stem *feed*, would produce *deef*). Because the transformation does not favour retention of input features, one might expect that they would be lost or mixed up in the output form, thereby resulting in input-output pairs which are quite dissimilar.

Second, distributed nets with purely phonological representations lack the means to distinguish similar-sounding stems which take different pasts. For example, they cannot differentiate homophones such as *ring-rang/wring-wrung* or *meet-met/mete-meted*. Similarly, forms derived from a different lexical category (*high-sticked*) or with meanings differing from the meaning of the irregular verb (*hang-hung/hanged*) cannot be distinguished. [11]

Hybrid Model

In Hybrid models regulars and irregulars are processed by different types of computational systems: While regulars are rule-produced by a symbol-processing system, irregulars are learned and computed in associative memory.

Hybrid models are motivated by the associative characteristics of irregulars and the symbolic characteristics of regulars. On the one hand, the irregulars' associative representations are consistent with the same traits that favor irregulars' associative representation in the single-net All-Associative models: their idiosyncratic nature, word frequency effects, real-word effects as described in Bybee and Slobin (1982), and especially their stem-stem, past-past and alternation partial similarities. On the other hand Hybrid models' symbol-processing regular rule elegantly captures all the symbolic qualities of regulars, and avoids falsely predicting that regulars share the same word frequency and partial similarity characteristics of irregulars.

[10] I have used "function*s*" in the plural here bcecause there would have to be three different types of suffixation learned, corresponding to the three allomorphs [t], [d], and [ɨd].

[11] It is possible to add units corresponding semantic or lexical category information to the net (see for example MacWhinney and Leinbach, 1991). See Chapter 2.

However, these models are also potentially problematic in several ways. First, there must be a learning mechanism to allow the child to distinguish between regulars and irregulars. Second, as with all models that rely on symbolic rules, the specification of a learning mechanism for the regular rule might be difficult (though see Pinker, 1984).

Furthermore, the associative component of Hybrid models suffers from two of the same possible problems that strike All-Associative models. First, stem-past similarity for irregulars is not necessarily expected because of connectionist systems' ability to learn arbitrary mappings. Second, if the associative net is based on phonological representations alone, it will fail to distinguish *rang-rang* from *wring-wring*, and will incorrectly irregularize denominals such as *high-stick*.

In this paper I will argue for the Hybrid model. Further, I will propose a specific model for the associative irregulars. I describe the model below, in section 1.1.2, and discuss existing evidence for it in chapter 2, my theoretical and experimental approaches to showing support for it in chapters 3, 4 and 5, and my own results support it in the subsequent chapters. In the next section I will address the two shortcomings related to associative irregulars: *irregular stem-past similarity* and the *homophony and root problems.*

Irregular stem-past similarity The problem of stem-past similarity can be addressed in at least two ways. First, one can abandon basic phonologically distributed associative models in favor of one in which stem-past similarity is more evidently expected. This approach has been carried out in different ways by Pinker and Prince (1991) and Ling and Marinov (1993). However, I will follow the second approach, arguing for the plausibility of stem-past similarity for basic phonologically distributed associative models of the the sort proposed by All-Associative theories of inflection.

The ability of connectionist nets to learn arbitrary mappings does not necessarily imply that stem-past mappings will look arbitrary in the contemporary language; there could be other factors which constrain these mappings such that they retain the stem-past similarity. Consider the following possible story. Many of the verbs which are currently irregular undergo alternations (such as the Lowering Ablaut rule) which at one time historically were far more predictable and pervasive in the language. This stem-past similarity thus dates back to a time when current "irregulars" were actually quite regular, and hence their similarity would not be unexpected in the language at that point in time. Since the Hybrid model acknowledges the existence of regular inflectional rules, these early "irregulars" could in fact have been computed by a symbol-processing rule of the sort proposed by Halle and Mohanan (1985). Over time these verbs somehow came to be represented in a purely associative representation. Since these associative representations were based on the predictive constraints of the previous rule-based system, they should at first continue to display these same constraints: While one such constraint must have been alternation similarity, another one was clearly stem-past similarity. Once in place, this stem-past similarity had no force against it, but a very strong one keeping it in place. This positive force was, and still is, alternation similarity, which (along with stem-stem and possibly past-past similarity) would maintain the existence of clusters of irregulars. Since verbs in each cluster undergo similar stem-past alternations, the clusters would tend to prevent any individual verbs from escaping it (in fact, we know they even attract new verbs, such as *cost-cost*), and hence from taking another past. In other words, another past would be more difficult to learn. If a form does escape the cluster, it should tend to become regular because the regular system does not have to be learned either (since the rule is already learned). Finally, the entire entire cluster could drift; but this is also seems unlikely (because of stabilization factors akin to the reasons why gene pools remain stale [expand on this...]). [12] Thus stem-past similarity is not clear evidence against purely associative systems.

The homophony and root problems Pinker and Prince (1988) point out that a purely phonological associative net such as Rumelhart and McClelland's (1986) cannot distinguish between homophonous stems which take different pasts, such as *ring-rang* and *wring-wrung.* In addition to this problem of **homophony**, such models are not able to correctly regularize forms such as *ring-ringed* ("ringed the city") or *Julia Childs* — words whose "roots" are not associated with the features (such as verb part-of-speech) normally associated with the root of a verb with an irregular past. These two problems can be treated as two symptoms of the same problem — a problem for which two solutions have been proposed.

<u>Lexical Entries:</u> The first solution crucially requires the existence of *lexical items* which are independent of their phonological content (Williams, 1981; Pinker, 1990; Pinker and Prince, 1991). These lexical items allow distinctions not only between *ring* and *wrung*, but also between *ring-rang* and *ring-ringed*, and *child-children* and *Julia Child-Julia Childs.* According to these theories such distinctions are made on the basis word *roots* and *heads.* The root of a word is a lexicalized form constituting part or all of the word, together with a variety of features such as a lexical category (e.g., Noun or Verb), subcategory information (e.g., transitive or intransitive), and both semantic and phonological representations. According to the approach taken by Pinker (1990), "a word takes an irregular form only if it has an irregular root as its head," and "irregular roots, since they are stored in the lexicon, encode not only the general morphological feature [past] or [plural], but the word-specific variety of pastness or plurality." The *head* of a word shares various features, such as the lexical category and referent, with that word, and for English words is usually the rightmost morpheme. Furthermore, these features percolate upwards in the tree structures representing complex words. This is the same principle defined in syntax, in which a phrase inherits only those features belonging to its head word. For example, *the boys who eat snails* is a

[12] the ing-ung verbs, which started with ing-ang, seem to be dragged to an already-existing cluster: the ing-ung cluster used to be past participles.

third person plural noun refering to boys, because its head is the word *boys*, which contain those features.

On this view, since irregularity is part of the root, and only the root features percolate up to the head of the word, then only if the head of a word is an irregular root will the word be irregular: If the features cannot percolate up then the irregularity cannot apply. Thus in cases of denominalization (*ring-ringed*), the word's root is a noun, which clearly does not have an irregular verb's past tense (*rang*) associated with it; hence the past tense cannot be *rang*, and the default regular takes over. Similarly, *Julia Child* or *walkman* have roots which are not associated with irregular plurals, so their plurals cannot be irregular. This notion of roots and heads also provides a solution to the homophony problem: since *wring* has a different root than *ring*, and each root is associated with a different word-specific irregular form, inflectional confusion between the two forms is eliminated.

While this lexicalized solution of roots and heads conforms very nicely with linguistic theory, it is also problematic: If we are still wedded to an associative net to explain irregulars, the lexical and associative approaches must be combined. However, these two approaches might indeed be quite difficult to merge, and in fact to date there has been no explicitely descriptive model, let alone any simulation model, which has attempted this.

Additional Units: The second solution to the homophony and root problems consists of adding other types of units to the existing associative net. The root problem could possibly be solved by adding semantic units, possibly in addition to units specifying lexical category — thus distinguishing $ring_{\mathrm{V}}$ from $ring_{\mathrm{N}}$. Such semantic units should also distinguish *ring* from *wring*, thus solving the homophony problem.

There are several advantages inherent in this approach. First, it offers a unified associative approach. Second, this type of solution has been successfully implemented in actual simulation models. For example, Machwinney and Leinbach (1991) added semantic nodes to a feedforward network based on phonological representations, and successfully trained it to distinguish among *wring-wrung*, *ring-rang* and *ring-ringed*. Third, Bybee and Slobin (1982) found in a high-speed past tense generation task with adults that not only did most (80%) of the vowel-change errors result in real irregular past-tense forms of other verbs (e.g,. *seat-sat, set-sat, search-sought*), but of these real irregular past-tense forms, 83% were past forms that were semantically related to the actual stem presented to the subject (e.g., *set-sat* instead of *set-set*). This finding supports a model in which the semantic as well as phonological characteristics of a verb stem affect the computation of its past tense. [13]

[13] While the high percentage (80%) of existing past tense forms produced as vowel change errors might seem to support a model of lexicalized past tense forms, it also supports a purely associative model: Existing past tense forms would naturally be the easier to compute than nonce past tense forms because the former should be better learned from the presentation of these actual past tense forms. Furthermore, fully 100% of the vowel change errors, including the nonce forms (e.g., *glow-glew, heapt-hept, snooze-snoze*) were phonologically related to the stem — which supports a model which is primarily phonological, and not necessarily lexicalized.

An Associative Model of Irregulars: The Stem-Past Model In this paper I will argue for a particular associative model of irregulars, which I call the Stem-Past model. This model is purely associative, with no lexical entries. While it does not attempt to solve the root or homophony problems in that it does not explicitely addresses the issue of semantic or other types of units, it is designed with the assumption that the kind of solely associative solutions described above for these two problems would apply.

The stem-past model is designed to conform to the characteristics of many function approximation models — including various connectionist systems. It assumes that past-tense learning is function approximation in that the mapping from stems to pasts is a function which is being learned from the presentation of input-output pairs. [14]

In the stem-past model both stems (*blow*) and pasts (*blew*) have distributed representations of their phonology. Stems are represented over one set of units and pasts over another. The stem-past (*blow-blew*) mapping is learned over connections between the two sets of units. The connections over which a given stem-past pair (*blow-blew*) is computed are strengthened when the mapping between the pair members is computed. This should produce word frequency effects: the more often the past tense form is presented, the stronger the connections between stem and past, and thus the more successful the computation in future trials. Because both the stem and past representations are phonologically distributed, a pair (*throw-threw*) which shares phonological material with *both* the stem *and* past of a given pair (*blow-blew*) will also strengthen the connections over which the stem-past mapping of the given pair (*blow-blew*) is computed, thus also increasing the comptutational success of the given pair. It is crucial to note that this *similarity effect* is strongest when the stems are most similar, since in function approximation systems the range of a function over a particular area of the domain should be maximally affected by input-output pairs over that domain.

Such positive contributions of one pair (*throw-threw*) to the computational success of another pair (*blow-blew*) should be highest when *both* stems and pasts are maximally similar. In fact, the *past tense frequency* (which I will sometimes refer to as *Pf*) effects we expect to find for the computation of a given pair (*blow-blew*) is simply the result of the special case when the similarity between the contributing pair and the given pair is at its maximum. If the similarity between the contributing stem and the given stem (*blow*) is held constant, but the similarity between the contributing past and the given past (*blew*) decreases, the contribution of this past to the given past should also decrease — because less phonological material is shared. Thus *ring-rang* should contribute more than *wring-wrung* to *sing-sang*.

As the similarity between the pasts decreases even more, I expect the contribution to decrease even more — to the point where there should be no contribution at all. If the

[14]This paper does not address the important question of how this learning takes place, particularly given that children surely do not hear stem-past pairs, but rather pasts alone.

similarity decreases *beyond* even this point, then the "contribution" should turn from positive to negative, hindering the computation of the given pair. For example, *think-thought* should actually *hinder* the computational success of *drink-drank.* I expect this hindrance because in many function approximation systems, dissimilar outputs (*thought, drank*) with similar inputs (*think, drink*) make learning each input-output pair more difficult. Similarly, the more dissimilar the outputs *relative to* the inputs, the more the outputs should hinder each other.

1.2 Blocking

All irregular-regular interactions seem to be based on one phenomenon, which I call *blocking*: if a verb takes an irregular past (*blew*) it will not take a regular past (*blowed*). A fair number of theories have attempted to explain this and related phenomena: The Principle of Contrast (Clark, 1987; Clark, 1990), the Unique Entry Principle (Pinker, 1984), the Blocking Principle (Aronoff, 1976), and the Elsewhere Condition (Kiparsky, 1982). All of these theories explain blocking as the prohibition of a predictable form by the existence of a less predictable form. For example, *blew* is a relatively unpredictable past tense, and its existence as a past form blocks out the more general regular past *blowed.* Similarly, the existence of *cook*, referring to the person who cooks, blocks out *cooker*, which is formed by the more general suffixation of the verb with an /er/ to refer to the person who carries out the action described by the verb.

None of these theories proposes an explicit computational account of blocking. I will propose such a theory — in fact, I have already proposed such a theory, in section 1.1.2, above. According to the theory of Associative Blocking, the blocking of a past form (*blowed*) results from the decrease in its computational success from the learning of *Alternative Past Tense* forms (*blew, grew, threw*) with similar stems. Thus the blocking of a given past (*blowed*) is a function of the type and token frequency and dissimilarity of other pasts, as well as the similarity of their stems. Blocking is thus nothing more than one case of the normal function approximation that also results in positive similarity effects.

In computational rather than learning terms, the blocking of a given past is a function of the computational success of all alternative forms from the given stem. Because the computational success of alternative forms increases with the type and token frequency of those forms, blocking is an inverse function of the type and toke frequency of all alternative forms. For example, the more we hear *blew*, the more successfully it will be computed, and thus the less successfully *blowed* will be computed. Similarly, the more we hear *drink-drank*, the more successful its computation, and thus the less successful the computation of *think-thought.*

We must be careful, however, about the distinction between blocked forms which are normally associatively computed (*thought*) and those that I hypothesize to be rule-produced (*blowed*). In the former case blocking can be described as competition among outputs, in the framework of function approximation. However, if rule-produced forms such as *blowed* are not computed in the same net (ie, in associative memory) as their competing forms (e.g., *blew*), how are they blocked? To explain blocking for these forms I hypthesize some kind of link between the associative system (in which the alternative forms are computed) and the rule system. Blocking of the rule system will occur if alternative forms are successfully computed; the more successfully they are computed, the more the rule will be blocked from applying to the stem.

1.2.1 Apparent Exceptions to Blocking

There are at least two types of apparent exceptions to blocking. I will show how each of these three apparent exceptions actually conforms to the Stem-Past Model and the theory of Associative Blocking. First, children sometimes *over-regularize* by producing a regular past for a verb which adults give an irregular past (e.g., *blow-blowed*) (for a review, see Marcus et. al., 1992). Second, some verbs, commonly called *doublets*, take *both* an irregular and the regular form (*dive-dove/dived*).

Over-regularization

According to the theory of Associative Blocking, over-regularization (*blowed*) should occur when the alternative irregular past tense (*blew*) has not been learned well enough to be successfully computed itself or to completely block out the alternative form (*blowed*). Thus over-regularization is not an exception to blocking, but is rather incomplete blocking. We might expect over-regularization to occur in children because they have heard fewer irregular pasts than adults, and therefore the irregulars will be less successfully computed than in adults. Similarly, we might expect over-regularization to occur in adults under adverse performance conditions wherein the irregular form may not be successfully computed in associative memory; in such circumstances blocking should also be incomplete.

Doublets

According to my theory doublets (*dive-dove/dived*) should exist under two circumstances — which are actually two cases of the Associative Blocking theory. First, if an irregular past *slew* is of extremely low frequency, it will not be very successfully computed, nor will it be very successful at blocking the regular form (*slayed*). In such cases a speaker will often fail to compute the irregular successfully, and will resort to the rule-produced regular, which is not very highly blocked. These doublets are thus essentially over-regulars with very weak blocking.

Second, if the speaker actually hears both forms (*dove, dived*) in his or her input, both will be learned in associative memory. The regular will be computed and learned in the memory because its stem is (maximally) similar (i.e., identical) to the stem of irregulars. However, blocking will still take place, just as it does between any two or more forms computed and learned in the memory which have similar inputs and dissimilar outputs (e.g., *drink-drank* and *think-thought*). Furthermore, just as in such cases of competing pairs of irregular pasts (*drank, thought*), the blocking should be bi-directional: the irregular (*dove*) should block the regular (*dived*) *and* vice-versa.

Attracted Regulars

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Just as doublet regulars (*dived*) are computed and learned alongside irregulars in associative memory, so should regulars whose stems are slightly less similar to the stem of irregulars. These *attracted regulars* such as *glide-glided* or *flow-flowed*, whose stems are similar to the stems of irregulars (*ride-rode, hide-hid* or *blow-blew, throw-threw*, respectively), should be learned and computed in associative memory alongside these irregulars. Furthermore, an attracted regular whose stem is highly similar to the stems of many irregulars should be learned in associative memory with higher probability than an attracted regular whose stem is less similar to the stems of fewer irregulars. Once learned in the memory, its computational success in the memory will be lower with more dissimilar irregular pasts — because those irregular pasts will *block* the associative computation of the attracted regular.

[15] Regulars whose stems are *not* phonologically close to the stems of irregulars I call *True Regulars*.

Chapter 2

Existing Evidence

In this chapter I present existing evidence from word frequency and similarity effects in support of the Hybrid Model — showing that irregulars are associatively computed while regulars are rule-produced. I will discuss evidence both from my own judgments and other experiments. I will discuss all evidence in the context of the notion of computational success: That the degree of computational success of associative past forms will correlate with their word frequencies and similarity to other forms, while rule-produced pasts vary with measures of stem strength or stem frequency, but not with past frequency or similarity, as long as stem strength or stem frequency is held constant. Computational success should be able to be captured in at least three ways: judgments of the naturalness of forms (how good a form sounds), the success at producing forms (how many errors does one make), and the reaction time at producing or recognizing forms.

2.1 Regulars and Irregulars

2.1.1 Word Frequency

Naturalness

There are several ways to demonstrate word frequency effects on the naturalness of inflected forms. One straightforward approach, which I follow experimentally in this paper, is to elicit acceptability ratings from subjects for inflected forms and then determine whether their word frequencies predict their ratings: the higher the frequency, the better the rating (holding stem strength or frequency constant).

Another approach, which is easier to examine informally, is to compare the goodness of the stem and past forms of the same verb. If a past form is memorized, and that form's frequency differs from that of its stem, the goodness of the two should differ. Verbs with stems of higher frequency than their pasts should have better-sounding stems than pasts. Verbs with stems of lower frequency than their pasts should have worse-sounding stems than pasts. But if an inflected form is rule-generated, past frequency should not be a good predictor of past goodness. Rather the past should be about as good as the stem. [1]

Irregular pasts can sound odder and more stilted than their stems. But regulars do not seem to show this characteristic. This contrast is apparent in two classes of verbs.

First, we can see the effect in verbs whose stem frequencies are much higher than their past frequencies. For example, both the irregular verb *forgo-forwent* and the regular verb *ascertain-ascertained* have stem and past frequencies [2] of 45 and 0; yet while *forwent* sounds awkward, *ascertained* sounds fine. The following examples further illustrate this phenomenon.

(1). Irregulars

(a) Every day I *forgo* the pleasure of her company. (freq = 45)

(b) (?) Every day I *forwent* the pleasure of her company. (freq = 0)

(c) I *thrive* on chocolate and spaghetti. (freq = 66)

(d) (?) I *throve* on chocolate and spaghetti. (freq = 0)

(e) I will *slay* him the second he sets foot in my house. (freq = 11)

(f) (?) I *slew* him the second he set foot in my house. (freq = 0)

(g) I will *tread* the path with trepidation. (freq = 24)

(h) (?) I *trod* the path with trepidation. (freq = 5)

(i) I will *plead* with him not to go bungee jumping. (freq = 315)

(j) (?) I *pled* with him not to go bungee jumping. (freq = 0)

(k) The dragon will *rend* him limb from limb. (freq = 1)

(l) (?) The dragon *rent* him limb from limb. (freq = 6) [3]

(2). Regulars

[1] The rule may add a computational cost, which should make the past form sound worse, but this cost will be constant across all verbs.

[2] All relative frequency counts, unless otherwise specified, refer to the Associated Press counts. See chapter 4 for details.

[3] This count of 6 for *rent* as the past tense of *rend*) seems clearly inflated – I suspect it reflects the occasional no-change error in forming the past tense for the verb *rent*. This view is supported by Francis and Kučera frequency counts of 1 and 0 for *rend* and *rent*, respectively.

(a) I can easily *ascertain* the validity of that statement. (freq = 45)

(b) I easily *ascertained* the validity of that statement. (freq = 0)

(c) Those unreachable peaches *tantalize* me unmercifully. (freq = 2)

(d) Those unreachable peaches *tantalized* me unmercifully. (freq = 0)

(e) I am sure you can *cope* with the situation. (freq = 413)

(f) She *coped* quite well with the situation. (freq = 0) [4]

(g) He will *afford* as the opportunity to go. (freq = 1063)

(h) He *afforded* us the opportunity to go. (freq = 24)

(i) She will *stint* no effort to get it done. (freq = 1)

(j) She *stinted* no effort to get it done. (freq = 0)

The second class of verbs are those which have a different and rarer meaning (from their more common usages which are associated with irregular pasts), such as in idiomatic or slang usage, in which the stem form seems to be used more commonly than the past form. Because we have no frequency counts in which meaning is distinguished, we have had to rely on our judgments for the relative frequencies of stem and past. The following irregular and regular verbs demonstrate this contrast.

(3). Irregulars (slang or idiomatic usage)

(a) I really *dig* the Doors, man.

(b) (?) Back in the 60's, your mother and I *dug* the Doors, son.

(c) If Capone *sings* to the cops, we'll kill him.

(d) (?) I heard that Capone *sang* to the cops, so we gotta kill him.

(e) Let's *split* right after the conference.

(f) (?) We *split* right after the conference.

(g) Sheila's new dress really *becomes* her.

(h) (?) But her old dress *became* her even more.

(i) I don't know how she *bears* it.

(j) (?) I don't know how she *bore* it.

[4]This 0 frequency is surprisingly low. In fact, the form "coped" has a frequency count in Associated Press of 16, but as a *noun* — a fact which should reinforce our wariness of the accuracy of the Associated Press frequency database. As explained in chapter 4, this accuracy arises from the fact that the counts were created by a stochastic part-of-speech analyzer only, and were never gone over by hand.

(k) I don't know how she *stands* him.

(l) (?) I don't know how she *stood* him.

(m) I'll *hold* for a couple of minutes, but then I'll hang up.

(n) (??) I *held* for a couple of minutes, but then I hung up.

(o) Alfred will *shine* his shoes tomorrow.

(p) (?) Alfred *shone* his shoes yesterday.

(4). Irregulars (slang or idiomatic usage) (continued)

(a) This story is really gonna *bend* her mind.

(b) (?) When I told this story, it really *bent* her mind.

(c) He should just *bite* the bullet, and get it over with.

(d) (?) He just *bit* the bullet, and got it over with.

(e) Let's *break* after the next talk.

(f) (??) We *broke* after that horrible talk.

(g) You'll *break* wind after eating those beans.

(h) (?) She *broke* wind after eating those beans.

(i) You will *drive* me up the wall with your constant sneezing!

(j) (?) He *drove* me up the wall with his constant sneezing.

(k) He's getting antsy, so I'm sure he'll *fly* the coop pretty soon.

(l) (?) After sitting tight for three days, he *flew* the coop.

(m) I think that idea will *fly* quite well.

(n) (???) That idea *flew* quite badly.

(o) Hemophelia *runs* in several European royal families.

(p) (?) Hemophelia *ran* in Tsar Nicholas's family.

(q) This phenomenon *falls* out of the theory.

(r) (?) It was clear that the phenomenon *fell* out of the theory.

(s) That *goes* without saying.

(t) (?) I thought that *went* without saying.

(u) *Go* for it.

(v) (?) We *went* for it.

(w) Let's *get* it on.

(x) (?) We *got* it on.

(y) Oh, the way she *grinds* her hips when she dances!

(z) (?) Oh, the way she *ground* her hips when she danced!

(5). Irregulars (idiomatic usage) (continued)

(a) Do you guys *shoot* the shit every time you get together?

(b) (??) Last night we *shot* the shit.

(6). Regulars (slang or idiomatic usage)

(a) I'm really *counting* on you, Bill.

(b) I really *counted* on him, but he didn't come through.

(c) She doesn't *suffer* fools gladly

(d) She never *suffered* fools gladly

(e) Do you guys *chew* the fat every time you get together?

(f) Last night we *chewed* the fat.

This class also applies to **nouns** which have a rarer meaning in which the singular (stem) form seems to be used more commonly than the plural (inflected) form.

(7). Irregulars

(a) The *foot* of this mountain is covered with forests.

(b) (?) The *feet* of these mountains are covered with forests.

(c) The *foot* of this page is well designed.

(d) (?) The *feet* of these pages are well designed.

(e) The Macintosh came with a *mouse.*

(f) (?) The Macintoshes came with *mice.*

(g) Jack is not trustworthy; he's a real *louse.*

(h) (?) Jack and Jim are not trustworthy; they are real *lice.*

(8). Regulars

(a) The *base* of this mountain is covered with forests.

(b) The *bases* of these mountains are covered with forests.

(c) The *head* of this page is well designed.

(d) The *heads* of these pages are well designed.

(e) Jack is not trustworthy; he's a real *worm.*

(f) Jack and Jim are not trustworthy; they are real *worms.*

If the stem and past are stored separately, then if the past is **more** frequent than the stem it should be **better** than the stem. Thus we should find examples of better-sounding pasts than stems in the same two kinds of situations described above: First, in which the past frequency is higher than the stem frequency; second, in which the verb has a rare meaning which seems to be used more in the past than stem forms.

(9). Irregulars

(a) They *wrought* destruction everywhere they went. (freq = 7)

(b) They will **work/*wreak* destruction everywhere they go. [5]

(c) When the ship *hove* into sight, we all cheered with joy.

(d) (?) When the ship *heaves* into sight, we will be able to relax.

(e) I think he *bought* it during the shoot-out.

(f) (?) Do you think he'll *buy* it during the shootout?

(g) It was Sue who *broke* the story.

(h) (?) Do you think Sue will *break* the story?

(i) I *stole* a glance in her direction.

(j) (?) I'll *steal* a glance in her direction.

(k) He has *flown* the coop. (Irregular past participle)

(l) (?) If you don't key an eye on him, he'll *fly* the coop.

(m) I think he *did* her in.

(n) (?) I think he'll *do* her in.

(10). Regulars

(a) I *sobbed* uncontrollably when I saw him. (freq = 64)

[5]It is not clear that the past form *wrought* has any stem form with the same meaning. *Wrought* is an old past form for *work*, and is still considered to be an alternative past, as used in the previous sentence. However, it seems quite clear that most contemporary speakers would not consider *work* to be the present tense of *wrought*. Some might consider *wreak* to be its stem, but my guess is most people would simply not be able to identify any stem for *wrought*.

(b) I'm sure that I'll *sob* uncontrollably when I see him. (freq = 0)

(c) We *pelted* him with rocks when we saw him. (freq = 98)

(d) We shall *pelt* him with rocks when we see him. (freq = 2)

Production Likelihood

I define production likelihood to be the ratio of linguistic forms produced divided by attempts at producing those forms. As described below and in chapter 4, there are a variety of way of acquiring this information and calculating the ratio. Production likelihood can be taken to reflect computational success if one views the latter to be a probabilistic phenomenon, wherein the successful computation of a linguistic form is one which has a high probability of computing that form.

If inflectional forms are represented associatively, their production success should correlate with word frequency. Thus the Hybrid model predicts that irregular past tense forms with high word frequencies and cluster strengths should be produced more readily, with fewer errors than low frequency irregulars; but regulars should not show this distinction (as long as stem strength or frequency are held constant) [6] Evidence that irregularly inflected forms are stored, while regularly inflected forms are not, has emerged both from analyses of spontaneous speech and from experiments, with both adults and children.

Adults Errors occurring naturally in spontaneous speech have been analyzed by Stemberger and MacWhinney (1988). From a corpus of 7220 errors, 91 no-marking errors (production of the stem form in lieu of the inflected form) on intended past tense and past participle forms were identified. Irregular and regular verbs were separated, and each group was divided into verbs with either low or high frequency inflected forms. The authors found that the number of errors on irregular low-frequency verbs was significantly greater than chance ($\chi^2(1) = 23.90$, $p < .0005$). They also found that the number of errors on regular low-frequency verbs was greater than expected, but this result was not significant ($\chi^2(1) = 2.03$, $p < .10$). These results support the storage of irregulars, though they leave the question of regulars open.

There are at least two problems with this study, however. First (and acknowledged by the

[6] In fact, rule-produced forms should not even show stem strength or stem frequency effects if the errors are no-change errors (that is, if the subject produces the stem form in lieu of the regular past — *walk-walk* instead *walk-walked*). This is because the firing of the rule should be independent of stem access, which has already been achieved successfully, as evidenced by the production of the no-change form. However, it also expect to find a correlation between stem strength or frequency and production likelihood for rule-produced forms *if* we hypothesize some processing theory wherein the more computation takes place for one process, the less is available for other processes; thus low frequency stems would require more computation for their retrieval, leaving less available for the rule, which would then misfire more often than with a high frequency stem.

authors as a flaw in the study) any difference in error rates between low and high frequency regulars might be difficult to detect because of their highly successful production, resulting in a possible floor effect: errors on the regulars occurred far less often than on the irregulars. Second, stem frequencies were not controlled for. Because there is positive correlation in frequency between different inflections of the same verb, verbs with low frequency past forms tend to have low frequency stem forms. If access to the stem form is necessary for past production, more errors should result from those verbs with low frequency stems. This is particularly worrisome for the regular verbs, in which the difference between low and high frequency errors was slight, and thus could be due only to stem frequency differences.

Thus Stemberger and MacWhinney's findings based on naturally occurring errors are suggestive of the hybrid model, but flaws in the study leave the issue open.

In the same paper, Stemberger and MacWhinney also investigated word frequency effects on errors occurring during a high speed past tense generation task. Subjects were given twenty *regular* verbs, one at a time on a computer screen in the frame *was* ________*ing*, with instructions to read each one silently and then produce the past form out loud as quickly as possible. All twenty regular verb stems ended in /t/ or /d/. Ten of the verbs were low-frequency and ten high-frequency. They found that there were significantly more errors on the low-frequency than on the high-frequency verbs, over subjects. This result seems to support a model in which *regular* past tense forms are stored, contrary to the hybrid model.

However, there are at least two problems with the study. First, it is not clear that they controlled for stem frequency. They do not even specify if their high- and low-frequency verbs were selected according to past or stem frequencies. Assuming that they correctly selected them based on past frequency, they do not claim to have controlled for stem frequency. But if the low-frequency verbs had lower stem frequencies than the high-frequency verbs, we would expect production of their pasts to be slower even if they were rule-produced. The second problem with the study is the authors' selection of verbs whose stems ended in /t/ or /d/. These were chosen "since such verbs have fairly high error rates" (page 106). However, verbs such as these whose stems sound like the stems of irregulars may be computed alongside those similar-sounding irregulars in associative memory (see Chapter 1). If this is true we would expect these regulars to show word frequency effects, while other regulars could be rule-produced.

Children In an study of spontaneous speech from pre-school children, Kuczaj (1977) showed that chronological age is a better predictor of success in producing irregulars than is MLU, which has been claimed to reflect the ability to formulate rules (Brown, 1973). Since chronological age should be correlated with the number of irregular forms heard, this evidence is strongly suggests that children show word frequency effects for irregulars, thus supporting the view that they are stored in memory.

Reaction Time

It is reasonable to assume that within a given computational system (e.g., associative memory), those forms which are more successfully computed as measured by naturalness or production likelihood should also be computed more quickly. Thus the *time* it takes to compute a form can be taken as another measure of computational success.

There are at least two ways of using reaction time to measure the computational success of an inflected form: First, as the recognition time of a presented inflected form, as tested by a lexical decision or past tense decision task. Second, as the generation time of an inflected form from a presented stem form. In addition, reaction time can be used in priming experiments to distinguish between rule-produced and associatively represented inflected forms, as I describe below.

Recognition Time There have been no experiments that I know of investigating the frequency effects of regular and irregular inflectional forms by measuring their recognition times.

Generation Time Prasada, Pinker and Snyder (1990) found that when adult subjects are presented with verb stems on a computer screen, and they have to produce the past form as quickly and accurately as possible, they take significantly more time (16-29 msec) for irregular verbs with low past tense frequencies, than for those with high past tense frequencies (holding stem frequency constant). However, production times for regulars does not differ significantly between high and low frequency past tense forms, holding stem frequency constant.

Priming When people are presented with a word, they are quicker at deciding whether or not it is a word if they have recently seen that word. This *priming* is thought to depend on the fact that stored words are activated when they are accessed, and that later access is thus facilitated by this previous activation ([references]). If inflected forms are computed by the application of a rule to the stem, then inflected forms should prime their stems as much as the stems prime themselves. However, if inflected forms are stored distinctly from their stems, then they should prime their stems significantly less than their stems prime themselves.

In fact, regular past tense forms prime their stems no less than stems prime themselves (181 versus 166 msec reduction), while irregular past tense forms prime their stems significantly less than their stems prime themselves (39 versus 99 msec reduction) (Stanners et. al., 1979;

Kempley and Morton, 1982). Because phonological and orthographic overlap between the members of regular and irregular pairs was controlled for, these artifacts could not be responsible for the results.

2.1.2 Similarity

If inflected forms are computed associatively, similarity effects should be apparent in their computational success as measured by goodness of form, productions success and reaction time: The more neighbours a form has, the more similar those neighbors are to the form, and the more frequent they are, the more successfully the form should be computed. However, these factors should have no effect on rule-produced forms. Therefore the hybrid model predicts that irregular pasts should show similarity effects, while regular pasts should not.

Naturalness

There have been no experiments that I know of investigating similarity effects of inflectional forms by measuring their naturalness.

Production Likelihood

Adults Bybee and Moder (1983) presented subjects with both real and novel verbs in sentence contexts which required past tenses: *Sam likes to ... Yesterday he ....* Their verb stems varied in phonological proximity to the prototypical pattern which they defined for the *i*-$\wedge$ (*string-strung*) group of irregular verbs: *sCCV*[velar nasal]. They found a continuous effect of similarity as a function of proximity to the prototype. The closer a (real or novel) verb stem to the prototype, the more likely it was to be inflected to the $\wedge$ form. Thus *spling* is more likely to go to *splung* than *vin* is to *vun*. They took this semi-productivity as evidence that irregular verbs are organized into family resemblance categories in lexical memory of the same sort that Rosch (1978) has described for concepts.

Stemberger and MacWhinney (1988) presented subjects with regular verb stems that resembled irregular pasts (e.g., *spank*, resembling *drank, sank* and *stank*) and with regular verbs stems that did not, and asked them to produce the past tense form as quickly as possible. They found that there were significantly more no-marking errors (*spank-spank*) on stems that resembled irregular pasts than on stems which did not. Furthermore, the average number of phonemes shared between the stem (*spank*) and its irregular past tense neighbours correlated with the number of no-marking errors for the stems.

Reaction Time

There have been no experiments that I know of investigating similarity effects of regular and irregular inflectional forms by measuring their reaction times.

2.2 Over-regularizations

According to the Hybrid model and the theory of Associative Blocking, over-regularizations (*blow-blowed*) are rule produced, but are blocked by their analogous associative irregular pasts (*blow-blew*, as well as by similar-sounding irregulars (*throw-threw, grow-grew*). Thus over-regularizations should show *blocking* word frequency effects (*blew* blocks *blowed*) as well as (possibly) blocking similarity effects (e.g., *threw, grew* block *blowed*). However, over-regularizations should not show similarity effects from other regulars (e.g., *flowed, mowed* should not support *blowed*).

2.2.1 Word Frequency

Naturalness

There have been no experiments that I know of investigating the frequency effects of irregular inflectional forms (*blew*) on the blocking of over-regulars (*blowed*) by measuring their naturalness or acceptability ratings.

Production Likelihood

Adults Bybee and Slobin (1982) carried out a past tense generation task in which subjects were given 90 irregular and 270 regular verbs, read out loud by the experimenter one at a time, with instructions to produce the past tense form of each verb as fast as possible. The authors did not report any frequency effect analyses for the regular verbs. For the irregular verbs they reported frequency analyses for different irregular classes, such as the no-change class, but not for all irregulars together. They found significant correlations between past tense frequencies (Francis and Kučera) and *overregularization* error rates for two irregular classes and near-significant correlations for another class. Correlation were not attempted for two classes because they contained too few tested verbs. Thus three out of six classes showed word frequency effects.

Children If irregulars are stored in memory, children should be more prone to errors on irregulars than adults: they have not heard the irregular inflected forms very often because they are still young, and so their memory traces are weak, and therefore the irregular pasts are less likely to be successfully computed. This should also result in weaker blocking of over-regulars, which should be computed without any problems because the rule has already been learned.

Indeed, Bybee and Slobin (1982) found in both preschoolers and 3rd graders that less frequent irregulars were over-regularized more often than more frequent irregulars. Similarly, Marcus et. al. (1992) found the same effect with 19 out of 19 children.

Reaction Time

There have been no experiments that I know of investigating word frequency effects of irregular pasts blocking over-regulars by measuring reaction times for over-regulars.

2.2.2 Similarity

Naturalness

There have been no experiments that I know of investigating similarity effects of irregular pasts blocking over-regulars, or of surrounding regulars supporting over-regulars, as measured by the naturalness of over-regulars.

Production Likelihood

Adults There have been no experiments that I know of investigating similarity effects of irregulars pasts blocking over-regulars, or of surrounding regulars supporting over-regulars, as measured by the production likelihood of over-regulars in adults.

Children I have found (reported in Marcus et. al.) that irregulars with more irregular neighbours are over-regularized less than those with fewer neighbours. In other words, the number of irregulars surrounding a given irregular (*blew*) seems to block its potential over-regular (*blowed*). However, the tendency to produce over-regulars is *not* predicted by the number of *regular* neighbours (*flowed, rowed*) of a given over-regular (*blowed*). This supports both the Hybrid model and Associative Blocking because attracted regulars such as *flowed* and *rowed* should have a much lower probability of being stored than irregulars: That is, while irregular pasts *must* be learned and computed in associative memory, the probability of attracted regulars such as *flowed* or *rowed* being associatively computed is correlated with the number and similarity of irregular stems (*blow, grow).* Thus there should be little or no support of an over-regular from its surrounding attracted regulars.

Reaction Time

There have been no experiments that I know of investigating the similarity effects of irregular pasts blocking over-regulars, or of surrounding regulars supporting over-regulars, as measured by the reaction time of over-regulars.

2.3 Doublets

There have been no experiments that I know of investigating either word frequency or similarity effects of either blocking or support of either the irregular pasts (*dive-dove*) or the regular pasts (*dive-dived*) of doublets, by any measure at all.

2.4 Attracted Regulars

There have been no experiments that I know of investigating either word frequency or similarity effects of either blocking or support of either the regular pasts (*glide-glided*) or over-irregular pasts (*glide-glid/glode*) of attracted regulars, by any measure at all.

2.5 Nonce Forms

2.5.1 Similarity

Naturalness

Prasada and Pinker (1993) investigated similarity effects for regular and irregular novel forms. They asked subjects to rate the naturalness of pasts of novel stems which varied in phonological proximity (either close, medium or far) from hypothesized prototypes. Half the verbs were selected to vary from irregular prototypes (e.g., *spling-splung, ning-nung, nist-nust*), while the other half varied from regular prototypes (e.g., *gloke-gloked, ploag-ploaged, ploamph-ploamphed*). Furthermore, the regulars at medium and far distances from their prototypes were selected so as to be far from all English verbs – hence the strange-sounding *ploamph.* [7] They found that as novel irregulars increased in proximity to the irregular prototype, they increased in their naturalness as well, but novel regulars did not increase in goodness with proximity to the regular prototype. They claimed that these

[7] This study also tested the production of pasts from novel stems. The same set of verbs was used, with analogous results. This part of the study is also discussed briefly below.

results suggest that irregulars "are stored and generalised in a memory system containing a level of representation in which the phonological properties of words are superimposed, fostering graded generalisation by similarity." For regulars, on the other hand, "although the experiments do not rule out the possibility that there are associative-memory effects on generalisations of regular morphology, they provide no evidence for such effects."

However, there were several problems with the Prasada and Pinker study. First, the need to select verb stems which were phonologically illegal appeared to result in strange effects. Second, the spelling of many verbs was different from the spelling of their prototypes. For example, the irregular pair *froe-froo* is spelled quite differently from the irregular verbs it was meant to approximate, such as *throw-threw*. Analogously, the regular pair *smeej-smej* contains word-final sequences (*eej, ej*) which are found in no English words. [8] While these anomalous spellings were selected to avoid orthographic similarity effects, they may have introduced orthographic interference effects instead. These interference effects could have weakened the irregular similarity effects and hidden regular similarity effects. Third, the prototypes were defined in a relatively arbitrary manner. Both the regular and irregular prototypes were selected according to the number of verbs of that class that rhymed with them. But it is far from clear that the number of rhyming stems in a class defines a prototype. Fourth, assuming that the prototype representation was correct, similarity effects are not necessarily present only in the context of a prototype representation. Even if there are no prototype effects for regulars, there could be similarity effects from non-prototypical representations. Fifth, the comparison between the irregulars and the regulars was not exactly analogous. The irregulars were selected to vary in phonological proximity from the putative prototype, but were all phonologically legal. The regulars, however, were selected according to two criteria: The forms in the group closest to the hypothetical prototype were selected according to the number of regular verb stems they rhymed with; but the two groups of verb stems further from the prototype were selected according to how closely they matched rules of English phonology.

Production Likelihood

Prasada and Pinker (1993) found similar results in a task in which subjects were asked to produce (in an untimed situation) the best past tense for the same nonce verbs presented in the judgment task described above. And as in the judgment task, they found that as novel irregulars increased in proximity to the irregular prototype, they increased in their likelyhood of being produced as well, but novel regulars did not increase in their likelyhood of production with proximity to the regular prototype.

[8] This pattern is absent among English words in word-final position in both the A.P. and Francis and Kučera word counts.

Reaction Time

There have been no experiments that I know of investigating similarity effects of the support of nonce true regular pasts (*plam-plammed*), or of either the blocking or support of nonce attracted regular pasts (*strink-strinked*) or nonce irregular pasts (*strink-strunk*), by any measure of reaction time.

Chapter 3

Experimental Measures and Methods

In this paper I am attempting to elucidate the mechanisms involved in computing past forms — such as true irregular pasts (*blew*), true regular pasts (*walked*), or over-regulars (*blowed*). In particular, I am examining the explanatory power of three basic theories for each class of past forms: associative and rule theories of computation, and a theory of associative computational blocking.

I have followed a two-pronged approach to testing these three theories. First, I acquired empirical measures of the underlying dependent variable of the computational success of past forms. The three measures of acceptability rating, production likelihood and production time are treated as different measures of the same dependent variable Past Tense Success. In section 3.1 below I examine these three different measures.

Second, I acquired both empirical and estimated measures of those factors which each of the theories expects to be predictive of the dependent variable Past Tense Success. There are three such predictor variables, one of which is an empirical measure (Stem Strength) (see section 3.2), while the other two (past frequency and past tense cluster strength) are the outputs of functions whose purpose is to estimate the contribution of past tense frequency (see section 4.1) and past tense cluster strength (see section 4.2) to the computational success of a past form. In this chapter I address the issues and experimental methods of the two empirical measures (Stem Strength and Past Tense Success), while in the next chapter I address the issues and methods of the estimated measures (past tense frequency and past tense cluster strength).

3.1 Past Tense Success (Ps)

In order to understand the mechanisms involved in computing linguistic forms, one can acquire empirical measures of these forms' computational success. The degree of computational success or failure reflected in these measures can be used to elucidate the mechanisms involved in the forms' computation. For example, a linguist's grammaticality judgment for a sentence is often taken to be a reflection of the success of that sentence's computation; thus a sentence may sound bad because a certain binding cannot be computed, according to a particular syntactic theory.

In this paper I have acquired three measures of computational success for past tense forms: acceptability ratings, production likelihood, and production time. I have acquired three rather than one measure based on the argument of converging evidence: The chance of a Type I or Type II error resulting from particularities of one measure would be greater than that from relying on several measures.

3.1.1 Past Tense Acceptability Ratings

Acceptability ratings (or judgments or ratings of naturalness or grammaticality) of linguistic forms have been widely used as measures of computational success. Traditionally, they have been adopted by linguists in syntactic studies of sentences, where they are often treated as reflections of the degree of success of the computation of the surface representation of sentences. Similarly, I treat acceptability ratings of past forms as reflections of the degree of success of the computation of their representations. Just as in syntactic studies, I use the variance in these acceptability ratings across different linguistic forms to explain their computational mechanisms.

The acceptability or naturalness of linguistic forms can be captured in two ways. Theoretical linguistics has adopted an approach in which only the author of the paper and perhaps a few other linguists or trained native speakers provide grammaticality judgments. This approach has been motivated by the claim that every speaker has his or her own dialect; therefore every speaker's linguistic knowledge is different, and so one person's jusdgments are are less noisy than those acquired from many people. An additional motivation for the expert judgment approach is that many of the complex grammatical structures being investigated are extremely difficult for non-linguists to give judgments for. The second approach for capturing the acceptability of linguistic forms is by testing large numbers of naive subjects. The main advantage of this multi-subject approach is that it can capture subtle effects and distinctions about which a single speaker would not have reliable judgments. As long as all subjects are extracted from a pool with a relatively homogeneous dialect, the increased signal from the large pool of subjects should outweigh any noise introduced from heterogeneity of dialect.

In chapter 2 I presented sentences which contained forms to which I gave my own judgments. In this paper I will explore in depth the computational implications of these judgments by acquiring acceptability ratings for forms in sentences from large numbers of subjects. I elicited these judgments in three separate experiments: The All-Verbs study, the Doublets study, and the All-Classes study, each described in the current chapter.

3.1.2 Past Tense Production Likelihood

I define production likelihood to be the ratio of linguistic forms produced over attempts at producing those forms. Production likelihood can be taken to reflect computational success if one views the latter to be a probabilistic phenomenon, wherein the successful computation of a linguistic form is one which has a high probability of computing that form.

There are several ways to acquire measures of production likelihood. First, one can examine spontaneous speech, and calculate production likelihood of a given form as the ratio described above. However, there can be practical difficulties in calculating the denominator of the ratio, which represents the attempts at producing the forms. First of all, the speech context is sometimes missing, as is the case with some databases of speech errors. Even with the speech context (e.g., from speech transcripts), it can be extremely difficult or impossible to identify attempts at producing a form. Furthermore, because such searches often have to be done by human scanning rather than computerized search, the tediousness and expense of such an effort often precludes it. Instead of calculating the denominator, one can approximate the ratio by simply calculating the numerator — the number of instances of a particular form that were uttered. If one can identify all or many of the possible forms for a given attempt, one can calculate production likelihood as the following ratio: The number of instances of a particular form divided by the total number of instances for all forms for a given attempt. For example, the production likelihood of irregular past forms (*sang*) can be calculated as the ratio of the number of instances of *sang* over the total number of instances of *sang* and *singed*, which one might hypothesize to be the two most common forms produced as the past of *sing*.

In the second type of measure of production likelihood the experimenter gives subjects a particular context, and ask them to produce what they think is an appropriate form for that context. For example, in this paper I describe an experiment in which I gave subjects both sentences in the past context and verbs, and asked them to produce appropriate past forms of those verbs. In this type of production likelihood measure the denominator of the ratio is fixed, being equal to the number of subjects who are given the context sentences. The numerator is simply the number of subjects who produced the given form for which the ratio is being calculated. For example, in this paper I present results from such an experiment:

In the Past Production task of the All-Classes study 40 subjects produced past forms for sentences in past contexts. Of those 40 subjects 35 of them produced *wrung* as the past tense of *wring*; the ratio is thus 35/40 = 87.5%. Similarly, the ratio for *drive-drove* was 39/40.

This second example epitomizes a major problem with this type of production likelihood measure: Because production is an all-or-nothing phenomenon, computations which are highly successful will tend to produce ceiling effects. Thus testing the production likelihood of existing past tense forms such as *drove* or *wrung* may not be very revealing because such verbs will have production likelihood rates at or near ceiling, and thus there will be almost no variation among them. Since it is this variation which I use to reveal the underlying computational mechanisms, such results are not always very useful. However, in some situations there should be more variance because the computation of each form should be less successful. For example, doublet verbs such as *knit* tend to result in more balanced ratios between the two possible forms *knit* (14/40) and *knitted* (26/40). Similarly, nonce verbs such as *strink* usually elicit a variety of responses over subjects, including *strunk* (17/40), *strank* (14/40), and *strinked* (5/40).

The third type of measure of production likelihood attempts to alleviate the major problems of both the spontaneous speech and normal elicited production methods. Like the normal elicited production method, in this approach subjects are given appropriate contexts and asked to produce a form for that context; thus the denominator of the ratio is known. However, the subject is put in a situation in which his or her performance is degraded. [1] This degraded performance is normally induced by asking the subject to respond as quickly (and accurately) as possible. Such time constraints often result in less successful computations, thus diminishing the problem of ceiling effects. In this paper I present results from one such experiment — the Reaction Time study, in which 40 subjects were presented with verb stems (*blow*) on a computer screen, and were instructed to produce the appropriate past form as fast and as accurately as possible. I calculated the production likelihood ratio for a given past form as the number of subjects who produced that past form over the total number of subjects who made no recording or measurement errors (e.g., false starts) for that verb. For example, the production likelihood of *blew* is 35/40, and of *blowed* is 5/40 —

[1] A related approach is to test subjects whom I hypothesize to have inherent processing problems. For example, if irregular pasts forms are simply memorized, while regular pasts are rule-produced, people with disadvantaged memory systems but intact rule systems should have more problems with the production of irregulars than of regulars. Furthermore, when they are not able to access an irregular past, they should often resort to rule-production — that is, over-regularization. There are several populations of people who might be subject to these kinds of errors. First, I might expect such errors in children — if they have already learned the add-/ed/ rule, but are still not old enough to have been exposed to enough irregular pasts for them to avoid such errors to the extent that adults do. Indeed, children do over-regularize (Marcus et. al., 1992). Second, we might expect such errors in people with memory impairments such as those caused by Alzheimer's disease or simply old age. Indeed I have found this to be true for both elderly subjects and those with Alzheimer's disease (Ullman, Hickok and Pinker, 1992; Ullman, 1992; Ullman et. al., 1993).

all 40 subjects were counted because none of them made recording or measurement errors for the verb *blow.*

3.1.3 Past Tense Production Time

I define past production time to be any timed measure of the computation of past forms. The production time of a past form can be taken to reflect the computational success of a form if I view the latter as being correlated with the time it takes to computed a form.

As I have seen in chapter 2, past production time can be measured in several ways. First, it can be measured as the recognition time of a presented form, as tested by lexical decision or past tense decision. In this approach the subject could be presented with a past form and would judge as quickly as possible if it is a word, or perhaps if it is an acceptable or correct past tense tense (perhaps of a previously shown verb stem). To perform such tasks the subject I would expect the subject to have to compute the form before deciding, based on its success of computation, whether it is an acceptable past tense form or not. If computational success is indeed reflected by computational time, the production time measures from such a task should reflect computational success.

Second, past production time can be measured as the generation time of a past form. In this approach the subject is presented with a *stem form*, and has been instructed to generate an appropriate or the correct past form as quickly and accurately as possible. To generate the past form the subject has to compute it, and thus the generation time should be a reflection of computational success. In this paper I present results from such an experiment — the Reaction Time study, in which subjects are presented with verb stems (e.g., *blow*) on a computer screen, and must generate their correct past form as quickly and accurately as possible.

3.2 Stem Strength (Ss)

If a past form is produced by a symbol manipulating rule, the representational strength of the stem should be the best predictor of its computational success. [2] That is, most of the variance in the computational success of past forms should be accounted for by the representational strength of the stem. This falls out from the theory of symbol manipulation, which claims that a rule should apply equivalently to all input symbols, no matter what their content. Thus the rule should add a constant computational cost, while its inputs, which are not necessarily symbolically computed, could vary in their computational

[2] In this version of the paper I do not examine results from the prediction of Past Tense Success by Stem Strength.

costs. Because the phonological forms of verb stems (*walk, balk*) are essentially idiosyncratic with respect to their meanings, they must be stored, and therefore their representational strengths should vary with factors such as word frequency. For example, since *walk* is more frequency than *balk*, the representational strength of *walk* should be greater than that of *balk*, and therefore the computational successes of their rule-produced pasts (*walked* and *balked* should be proportionately different.

The representational strength of verb stems can be measured in many of the same ways that I measure the computational success of past forms. In this paper I use both acceptability ratings and production time. I selected these two measures mainly because I wanted to use the same empirical measures for both stem and past forms in any given statistical analysis. Because each measure might differ with respect to accuracy or to information being captured in addition to computational success, it might be problematic to use one type of stem measure (e.g., acceptability ratings) in an analysis with another type of past measure (e.g., production time). I did not use production likelihood as a measure of stem strength for two reasons: There was no obvious equivalent for stems of the untimed past production task (in the All-Classes study); and for the Reaction Time study stem production likelihood turned out not to be a valid measure because of ceiling effects — subjects produced almost all stem forms correctly (apart from technical errors such as false starts). Therefore in analyses with production likelihood I used other measures of stem strength: stem acceptability ratings acquired from the same subjects who produced past forms in the untimed past production task of the All-Classes study; and production time (from different subjects) in the past production task from the Reaction Time study.

Unfortunately, I expect Stem Strength to predict Past Tense Success under *both* the rule and associative theories, and therefore it cannot be used to distinguish the two theories. Under the rule theory, as I describe above, Stem Strength should predict Past Tense Success because the latter should be computed by the application of a rule with constant computational cost to the varying Stem Strength. Under the associative theory, there are at least two ways in which Stem Strength can predict Past Tense Success: First, because Stem Strength is correlated with Stem Frequency, and Stem Frequencyis correlated with Past Tense Frequency, which predicts Past Tense Success (Stem Frequency and Past Tense Frequency are correlated because the more we tend to use the past form, the more we tend to use the stem and other forms); second, because if the stem and past forms are associatively linked, there could be some sort of "leakage" between stem and past — each time we hear the stem, activation extends to the past as well, and the stem-past connections are strengthened.

Because I expect Stem Strength to predict Past Tense Success under both the rule and associative theories, I will *not* actually present results demonstrating the predictiveness of Stem Strength on Past Tense Successin the results chapters. However, I will discuss both in this chapter and in chapter 5 (the analyses chapter) the expected outcome of Stem Strength as a predictor on Past Tense Success.

The reader might wonder why I are using Stem Strength instead of Stem Frequency as the the predictor of Past Tense Success under the rule theory. There are four reasons for this choice. The first reason is theoretical. Because a symbol-processing rule applies to the entire symbol in its input, the add-/ed/ rule should apply to the entire verb stem. Furthermore, the rule should add a constant computational cost because it applies equally, irrespective of the strength of its input, and so it is solely this input strength which should determine the strength of the rule's output. Thus the representation strength of a rule-produced past form should be predicted solely by the representation strength of the stem form — whose value should be better estimated by the direct experimental measurement Stem Strength (acceptability ratings or production time) than by Stem Frequency, which is only one possible factor in the strength of the stem. In addition, stem strength could also be affected by other factors which I have not investigated, such as a "stem cluster strength".

Second, it is unclear which frequencies to include in the value of Stem Frequency. According to the rule theory the frequencies of all rule-produced forms, in addition to the stem form itself, should contribute to the strength of the stem: If a form occurring in a speaker's input (through hearing or reading) is successfully parsed into its stem plus the suffix, this occurrence of the stem should strengthen the stem representation. Since all rule-produced forms should be parsed in this way, the frequencies of all rule-produced forms should be summed to form Stem Frequency. However, such wide inclusion causes a problem — I have to eliminate Past Tense Frequency, even if it is expected to be rule formed, because I am using Past Tense Frequencyas a distinct predictor, and want to avoid confounding it with Stem Strength. However, by eliminating Past Tense Frequency I could lose a substantial part of the predictive power of Stem Frequency, especially for verbs such as *ram*, whose past frequency is higher than the frequencies of all their other forms combined — the Associated Press frequency of *rammed* is 111, while the combined frequency of *ram, rams* and *ramming* is 42.

The third reason is statistical — the problem of *multicolinearity* (see Hayes, 1988, page 654). Stem Frequency and Past Tense Frequency tend to be extremely highly correlated because the more I use a verb in one inflection, the more I use it in other inflections. But when two independent variables used in a partial correlation are highly correlated, the residual of the non-partialed independent variable becomes very unstable — because so much of it is removed by the partialed variable, small differences (i.e., noise) can change the pattern of its residual dramatically. Since Stem Strengthis less well correlated with Past Tense Frequency(because Stem Frequencyis only one possible factor predicting it), it does not succumb to this problem of instability.

The fourth reason for using Stem Strength rather than Stem Frequency is an empirical one: I have found that Stem Strength consistently predicts the past strength of hypothesized rule-produced forms better than does Stem Frequency.

3.3 Methods: Summary

I have acquired six experimental measures of computational success of past forms: three measures of past naturalness, two of past production success, and one of past production time. Three of these six measures were also acquired for verb stems: two of stem naturalness and one of stem production time.

These six measures were acquired over a total of four experiments: the All-Verbs study, the Doublet study, the All-Classes study, and the Reaction Time study. The All-Verbs study measured acceptability ratings of stems and both irregular and regular pasts in sentence contexts for 288 monomorphemic verbs: 104 true irregular verbs (*wring-wrung/wringed*), 48 true regular verbs [3] (*walk-walked*), 25 doublets (*dive-dove/dived*), and 111 attracted regulars (*glide-glid/glided*). The Doublet study measured acceptability ratings of irregular and regular pasts in sentence contexts of 29 monomorphemic doublet verbs (*dive-dove/dived*). The All-Classes study measured the past production likelihood rate as well as acceptability ratings of stems and both irregular and regular pasts, all in sentence contexts, for a total of 120 monomorphemic verbs: 20 true irregulars (*wring-wrung/wringed*), 20 true regulars *walk-walk/walked*), 20 doublets (*dive-dove/dived*), 20 attracted regulars (*glide-glid/glided*), 20 nonce irregulars (*strink-strunk/strinked*), and 20 nonce regulars (*plam-plam/plammed*). The Reaction Time study measured production likelihood and production time for the past generation and stem reading of isolated verb stems for 171 monomorphemic verbs: 97 true irregulars (*wring*), 40 true regulars (*walk*), and 36 attracted regulars (*glide*).

3.4 The All-Verbs Study: Past Tense and Stem Judgments

The irregular and regular pasts as well as the stems of 288 verbs were presented in appropriate sentence contexts. Each verb form was judged on a 7-point scale by 32 subjects. The 288 verbs consisted of 104 true irregulars (*wring-wrung/wringed*), 48 true regulars (*walk-walked*), 25 doublets (*dive-dove/dived*), and 111 attracted regulars (*glide-glid/glided*).

3.4.1 Verbs

In addition to the 288 monomorphemic verbs that I tested and analysed, the questionnaires contained another 184 verbs which I will not discuss in this paper. Thus there were a total

[3] True regulars are defined to be those whose stems are not similar to the stems of irregular verbs.

of 472 verbs tested in the questionnaires. These 184 verbs were treated separately from the 288 analysed verbs for nine reasons, as described in the following footnote. [4]

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[4]

First, there were 120 prefixed or other multimorphemic verbs (these 106 verbs do not include the 3 past forms *forbid-forbid/forbad/forbade* or the possible denominal *sublet*. The treatment of these 4 is discussed in subsequent paragraphs.) — 61 irregulars or doublets (*forgo-forwent/forgoed, interweave-interwove/interweaved*), 18 true regulars (*devour-devoured, overlook-overlooked*), and 41 attracted regulars (*accost-accost/accosted, decide-decid/decided*). I treat multimorphemic irregulars separately for both theoretical and empirical reasons. First, such prefixed forms might themselves be formed by a rule which combines prefix with root, and hence would not be stored in their entirety in associative memory. In addition, I hypothesize that the role of blocking is different in multimorphemic than in monomorphemic irregulars. Specifically, I predict that even if the entire prefixed irregular past (*forwent*) is stored, blocking of the potential regular past (*forgoed*) takes place at the root level, with *went* blocking *goed* as well as *forgoed*. This prediction is based partly on the empirical observation that both the irregular and regular pasts of such prefixed forms are often questionable or unacceptable (*forgo-(?)forwent/(?)forgoed*) — a situation which would arise if the infrequent *forwent* derived its computational success from its word frequency, while *forgoed* was blocked by the highly frequent *went*.

Second, there were 4 past forms which can take the role of auxiliary or modal: *be-was, be-were, have-had*, and *do-did*. I treated these forms separately because my focus was on past forms, not auxiliaries and modals, and I wanted to eliminate any possibility that either the frequency counts of these forms or my experimental measures of their computational success were in fact picking up information about the computation of the auxiliary forms.

Third, there were 11 irregular past forms belonging to a total of 5 verbs with more than one irregular past, as determined by my own dialect, by Pinker and Prince (1988), or by Francis and Kučera or Associated Press frequency counts greater than 0 for more than one of the irregular past forms: *spit-spit/spat, bid-bid/bade, forbid-forbid/forbad/forbade, drink-drank/drunk, stink-stank/stunk*, and I treated these forms separately because I suspected they might be involved in inter-irregular blocking, in which one irregular past (*spat*) blocks another (*spit*).

Fourth, there were 18 verbs which I judged to be possible denominals, de-adjectivals, or of onomatopoeic origin: 8 true regulars (*nap-napped, rap-rapped, snap-snapped, sound-sounded, brace-braced, place-placed, hash-hashed, lash-lashed*), and 10 attracted regulars (*sublet-sublet/subletted, blast-blast/blasted, trust-trust/trusted, hoot-hot/hooted, toot-tot/tooted, heap-heapt/heaped, clink-clank/clinked, scratch-scrought/scratched, jeer-jerd/jeered, grin-gran/grinned*). These forms were treated separately because such derived forms have been shown to be inflected differently from ordinary non-derived verbs (Kim, Pinker, Prince and Prasada, 1991). Specifically, such derived forms are usually regularly inflected even if they have maximal phonological similarity to irregular verbs ("The army **rang/ringed* the city"). Thus it was particularly important for us eliminate any derived attracted regulars from my analyses — because such forms should not be associatively represented like other attracted regulars.

Fifth, there were 4 verbs whose stem or past forms seemed to us to be easily confoundable with another word: the true regular *found-founded* (the stem *found* can be confounded with the irregular past *found*), the attracted regular *wend-went* (the past *went* can be confounded with the irregular past *go-went*, *rend-rent* (the past can be confounded with the noun *rent*, and the irregular *lie-lay/lied* (the regularized past *lied* can be confounded with the existing regular past of the distinct regular verb *lie-lied*). These verbs were eliminated because the computational success of their past forms might involve these confoundable words. In addition, the frequency counts of my tested forms are falsely inflated from the actual frequencies of the confoundable words.

Sixth, there were 5 verbs whose irregular pasts are marginally acceptable: *learn-learnt/learned, spell-spelt/spelled, smell-smelt/smelled, spoil-spoilt/spoiled*, and *cleave-cleft/cleaved*. (I had originally classed the first 4 as irregulars and *cleave* as a attracted regular.) The first four are acceptable in British English, and all five seem to be more acceptable as past participles than as past tenses. I treated these verbs separately because it is not clear to which class they belong. They are not true irregulars because their regular past forms are acceptable. They are not clearly doublets because their irregular past forms are only marginally acceptable. And they are not clearly attracted regulars precisely because their irregular pasts are not impossible.

True Irregulars

The 104 true irregulars were chosen according to lists of irregulars in Pinker and Prince (1988), Quirk et. al. (1985), Mencken (1936), Curme (1935), and my own dialect. These true irregulars included no doublet verbs — that is, no verbs for which the regular past was acceptable were included. For each verb I elicited ratings for its irregular past (*wring-wrung*), its over-regular past (*wring-wringed*), and its stem (*wring*).

True Regulars

The 48 true regulars were chosen from the Francis and Kučera and Associated Press frequency count lists. I attempted to select them such that their past frequencies varied from very low to very high counts. For each verb I elicited ratings for its regular past (*walk-walked*) and its stem (*walk*). There were no ratings elicited for any possible or imaginary irregular or no-change past.

As described in chapter 1, my definition of a true regular is a regular verb whose stem is not phonologically similar to the stem of any irregular verb. I attempted to meet this criterion by choosing regular verbs whose final consonant cluster was not shared with any irregular stem. For example, because neither /sk/ nor /sh/ exist as a final consonant cluster among irregular stems, I chose a fair number of non-rhyming regulars ("True Regulars") ending in these consonants. Similarly, I avoided true regulars with a final /t/ or /d/ because the stems of many irregulars end in these two phonemes. I also attempted to choose true regulars whose vowel is not present in any irregular stems.

Seventh, there were 5 verbs which were not originally classed as doublets, but whose low irregular ratings and high regular ratings demonstrated their doublethood: *smite-smote/smited*, *weave-wove/weaved*, *wake-woke/waked*, *fit-fit/fitted*, *speed-sped/speeded*, I analyzed these five verbs as neither doublets nor true irregulars.

Eighth, there were 11 verbs whose stems end in either /t/ or /d/, and hence are neither obvious true regulars nor obvious attracted regulars: *chat-chatted*, *pat-patted*, *boast-boasted*, *coast-coasted*, *doubt-doubted*, *flout-flouted*, *pout-pouted*, *shout-shouted*, *laud-lauded*, *bound-bounded*, and *pound-pounded*. I treated these verbs separately because they are neither clearly similar enough to the stems of irregular verbs for them to be analysed as attracted regulars, not clearly far enough for them to analysed as true regulars.

Ninth, there were 6 verbs with accidental errors in their presentation or apparent errors in their frequency counts. One of these (the irregular *spread-spreadded*) was misspelled in the presentation of its over-regular past form. Four others were accidentally presented in strange-sounding sentences: the irregular *shed-shed/shedded*, the attracted regular *bide-bode/bided*, and the true regulars *jibe-jibed*, *cow-cowed*. Finally, the remaining form (*wind-wound/winded*) is orthographically identical in its over-regular form (*winded*) to an existing denominal regular (the verb based on the noun *wind*), and thus has a probable over-inflated frequency count for that form.

Doublets

The 25 doublet verbs were chosen according to my own dialect and Appendix A in Pinker and Prince (1988). For each verb I elicited ratings for its irregular past (*dive-dove*), its regular past (*dive-dived*), and its stem (*dive*).

Attracted Regulars

The 111 attracted regulars were chosen from the Francis and Kučera and Associated Press frequency count lists. I attempted to select them such that their past frequencies varied from very low to very high counts. For each verb I elicited ratings for its regular past (*glide-glided*) its over-irregular past (*glide-glid*) and its stem (*glide*).

As described in chapter 1, my definition of a attracted regular is a regular verb whose stem is phonologically similar to the stem of one or more irregular verbs, with an emphasis on the rhyme portion of the stem. I attempted to meet this criterion by choosing regular verbs whose stems shared some or all of the following rhyme segments with the stems of one or more irregulars: vowel, final consonant, and final consonant cluster. Full rhyming stems were preferred. In cases where the selected attracted regular could take more than one imaginable over-irregular (eg, *glide* could irregularize to *glode*, on analogy to *ride-rode*, or *glid*, on analogy to *slide-slid*), I chose the over-irregular which I judged to be more acceptable.

3.4.2 Presentation

All verb forms were presented to subjects in sentences. All sentences — both past and stem sentences — were written in the *completive* aspect (also called the perfective aspect), in which the verb is used in an action or manner which has a definite beginning and end. [5] Although I did not have a theoretical preference for completive over non-completive, I wanted to hold aspect constant because it has been claimed (Bolinger, 1980) that the naturalness of a verb form in different aspects can be affected by its phonology. Specifically, forms with higher vowels or diphthongs may be more natural sounding when used in a non-completive rather than a completive aspect, and forms with lower or shorter vowles may be more natural sounding when used in a completive rather than a non-completive aspect. Because many verbs whose stems have higher or longer vowels are transformed to lower or shorter vowels in their irregular forms (*dream-dreamt*) while the same verb would remain high in the regular form (*dream-dreamed*), it is important to hold aspect constant.

[5] Non-completive aspect, on the other hand, connotes a long action without a definite beginning or end. The same verb can often be used in both completive and non-completive aspects. For example, in the sentence "George *dove* into the water", *dove* is completive, while in the sentence "George *dove* for many hours", *dove* is used in a non-completive aspect.

Past Sentences

For all verbs other than true regulars, both an irregular and a regular past form was presented. For example, subjects rated both *blow-blew* and *blow-blowed*, and both *glide-glided* and *glide-glid.* These regular and irregular pasts were presented in different sentences to a given subject. Other than the constraint of completive aspect, no attempt was made to relate the content of the two sentences for a given verb.

Thus for all verbs other than true regulars, there were twice as many sentences as verbs: 208 sentences for irregular verbs (2 sentences each for 104 verbs), 48 sentences for true regular verbs (only 1 sentence for each of 48 verbs), 50 sentences for doublet verbs (2 sentences each for 25 verbs), and 222 sentences for attracted regular verbs (2 sentences each for 111 verbs), for a grand total of 528 past sentences. [6] The true regular verbs were only presented one, in their regular past form, because no irregular past is plausible for them.

Randomization To control for the possible influence of presentation order and sentence context influences, I created four large questionnaires which differed with respect to each verb's combination of past form (irregular or regular) with its two sentences, as well as with respect to the order of these sentences. For each verb's sentence pair, one sentence preceded the other in two of the questionnaires, while in the other two the sentence order was reversed. Within the two questionnaires having the same sentence order, the verb order varied — in one questionnaire the irregular past was presented in the first sentence and the regular past in the second sentence, while in the other questionnaire this verb order was reversed. Within these sentence and verb order constraints the position of each sentence with its verb form was random — that is, the absolute position of each sentence in the questionnaire was random within the constraint that it lie either before or after its sister sentence. Within each questionnaire half of the verbs had their irregular past form presented first and half had their regular form presented first.

More specifically, I randomly assigned two positions to each verb out of the total of 528 sentences positions. Then for each of the four questionnaire versions I assigned each verb's sentence/verb form combinations to the two positions in the manner described above. For example, if the 79th and 235th sentence positions in the questionnaire had randomly been assigned to the verb *sing*, then the four questionnaires would have the following sentences and verb forms:

Questionnaire I:

79: George *sang* "Mary Had a Little Lamb" in the shower this morning.

235: I *singed* my favorite song to my child last night.

[6] Past judgments were also elicited for the remaining 184 verbs not analysed in this experiment, giving a grand total of 856 past sentences in each questionnaire.

Questionnaire II:

79: George *singed* “Mary Had a Little Lamb” in the shower this morning.

235: I *sang* my favorite song to my child last night.

Questionnaire III:

79: I *sang* my favorite song to my child last night.

235: George *singed* “Mary Had a Little Lamb” in the shower this morning.

Questionnaire IV:

79: I *singed* my favorite song to my child last night.

235: George *sang* “Mary Had a Little Lamb” in the shower this morning.

Format The past form which the subject was asked to rate was printed in italics in its sentence. Below each sentence was a scale from 1 to 7, with 1 labelled “worst” and 7 “best”. For all past tense sentences the stem form was printed above the sentence in italics. This was necessary because the subjects were being asked to judge the naturalness of the past form as a past of a given verb. This was particularly important for the invented and hence unfamiliar over-irregulars of the attracted regulars, such as *glide-glid*, as well as for verbs whose pronunciation was clarified by its stem — such as *sing-singed*, whose over-regular past could be pronounced like the past tense of *singe*.
A typical past sentence looked like this:

walk

John and Ralph *walked* to the store.

1 2 3 4 5 6 7

worst best

Because the over-irregular pasts of some attracted regulars did not have an obvious pronunciation, immediately after such forms their pronunciation was indicated with a common rhyming word. For example, such a sentence might look like this: Mishimoto *concealt*[pronounce-like-“belt”]) his dagger under his kimono.

Stem Sentences

Stem naturalness judgments were also elicited for all 288 verbs. [7] All stems were presented in sentences in the present tense in any person other than third person singular (in order to avoid any overt inflectional morphological suffixes). I made no attempt to make the stem sentence of each verb similar in content to that verb's past sentences. The stem sentences were not always in the completive aspect. [8] The order of their presentation was randomized. Each verb stem was presented in a format almost identical to the format in which the pasts were presented, with the verb in the sentence being italicized, and a scale from 1 ("worst") to 7 ("best") laid out below the sentence. For example, one of the sentences looked like this:
walk

People often *drop* things when they have oily hands.

1 2 3 4 5 6 7

worst best

3.4.3 Subjects and Questionnaires

Each of the 4 full questionnaires contained 816 sentences: 528 past sentences and 288 stem sentences. [9] Because this was far too many sentences for a single subject to judge in a single sitting, I broke up each large questionnaire into four smaller sub-questionnaires, giving a total of 16 versions of sub-questionnaire. To ensure that in my analyses my comparisons of different forms of the same verb (stem, irregular and regular past) were not confounded with subject differences, each of these sub-questionnaires were entirely self contained in that each contained all sentences for a given verb; that is, no verb had sentences in different sub-questionnaires.

Because I wanted 32 subjects for each verb, I had 32 full-length questionnaires — 8 instances for each of the 4 versions of the full-length questionnaire. But because each full questionnaire was broken down into 4 sub-questionnaires, there were a full 128 instances of sub-questionnaire filled out — 8 instances for each of the 16 versions of the sub-questionnaire. Because each sub-questionnaire was answered separately by each subject, I effectively had 128 subjects. in fact, the number of actual subjects was slightly less, since a fair number of subjects filled out more than one sub-questionnaire: there were 99 subjects, of whom

[7] Stem judgments were also elicited for the remaining 184 verbs not analysed in this experiment. Thus a total of 472 stem judgments were elicited in as many sentences.

[8] There were two reasons for which I did not insist on a completive aspect for each stem sentence. First, I do not hypothesize that the naturalness of stem forms is affected by completive versus non-completive aspect. Second, sentences in the completive aspect sound awkward in the present tense for many of the verbs I tested.

[9] In addition to which there were the 328 past sentences and 184 stem sentences from the unanalysed verbs, for a grand total of 1328 sentences.

78 filled out 1 sub-questionnaire, 17 filled out 2 sub-questionnaires, 2 filled out 3 sub-questionnaires, 1 filled out 4 sub-questionnaires, 0 filled out 5 sub-questionnaires, and 1 filled out 6 sub-questionnaires. Subjects who filled out more than one sub-questionnaire were never given the same sub-questionnaire, and were given sub-questionnaires from the same full questionnaire in most cases. In addition, they were not given analogous sub-questionnaires from different full questionnaires — these sub-questionnaires contained the same verbs in different sentences and orders. [10]

All the subjects were MIT undergraduates (for the most part freshmen) who were native U.S. or Canadian speakers of English. [11]

3.4.4 Instructions

Each sub-questionnaire was split into two parts, which were filled out in order in their entirety by every subject filling in that sub-questionnaire: the first part contained the past tense sentences and the second part the stem sentences. Each part was preceded by instructions.

In the past tense section (Part I), I asked the subjects to give judgements based on the naturalness of the past form printed in italics in each sentence. I gave examples of how it would look, and stressed that I were not asking for judgements about the real-world plausibility of the sentences, but rather about the naturalness of the past form in the sentence: "Is the verb in a form that 'sounds' right to you and that you would naturally use in your own speech?" I also asked the subjects to use the entire scale between 1 and 7. I stressed that "it is important to remember that I are looking for your *intuitions* and gut feelings], and *not* what you believe the correct form to be according to what the dictionary says or what your teachers have told you. ... It is extremely important to judge all past forms according to their **sound, not their spelling**". The last sentences in the instructions were: "Please fill out the questionnaire **in order**, so do **not go back to sentences you have already done. Remember, there are no 'right' or 'wrong' answers.**"

The instructions to the stem section (Part II) were almost identical to those of Part I, except much shorter, and asking the subject to judge the naturalness of the **present tense** forms of verbs, rather than past tense forms.

[10]The 2 exceptions to this constraint were mistakes on my part: the subject who filled out 4 sub-questionnaires took version 3.4 (full questionnaire 3, sub-questionnaire 4) and 4.4; and the subject who filled out 6 sub-questionnaires took versions 3.2 and 4.2 as well as 3.4 and 4.4. However, in this second case there was a several week lag between the sub-questionnaires containing the same verbs.

[11]Native U.S. or Canadian speakers of English were defined in the instructions as someone who "grew up in either of these two countries and whose first and *subsequently primary language* was and has been the English spoken in either of these two countries. To put it another way, it is your mother tongue."

3.4.5 Mean Acceptability Ratings

Most of the analyses, including the basic computation and blocking analyses, were carried out on mean acceptability ratings. For each verb form I averaged the acceptability ratings over all subjects to whom that verb form had been presented. For past forms which were presented in two sentences (all but the true regulars), I averaged over the ratings of the forms in both sentences.

3.5 The Doublet Study: Past Tense Judgments

32 adult native English speakers were asked to rate the naturalness of both the regular and irregular past forms of 29 monomorphemic doublet verbs (e.g., *dive-dove/dived*), presented in appropriate sentence contexts.

3.5.1 Verbs

I selected the 29 monomorphemic doublet verbs on the basis of the acceptability of both their irregular and regular past forms. Decisions of past form acceptability were based on my dialect as well as on the list of verbs in Appendix A of Pinker and Prince (1988).

These 29 doublet verbs consisted of two types of verbs. First, there were 8 bisemous verbs — verbs whose irregular and regular pasts are associated with different meanings (*hang-hung/hanged*). I selected these verbs and their meanings on the basis of my own dialect and several other sources (Pinker and Prince, 1988; Mencken, 1936; Quirk et. al., 1985). I treated each of these bisemous verbs as two verbs, one for each meaning. Accordingly, I elicited ratings for both the irregular and regular pasts of the bisemous verbs in sentences for each meaning. However, in the basic computation and blocking analyses we averaged the ratings across both meanings for a given past form, treating them as one verb. [12] Second, I selected 21 other doublet verbs — which were presented in their irregular and regular past forms associated with only one meaning.

In addition to these 29 doublet verbs, I presented subjects with a total of 30 other verbs of four types. Thus subjects judged irregular and regular pasts of a total of 59 verbs. I did not include these other verbs in any of the analyses described in this paper.

First, there were 5 multimorphemic irregulars (*alight, beget, bespeak, forbear, forswear*), which were excluded from my main analyses because I hypothesize that their past com-

[12] I treated them as one verb instead of two for my word frequency and cluster strength based analyses because the Francis and Kučera and Associated Press frequency counts do not distinguish between the different meanings, and hence confound them.

putation and blocking mechanisms are different from those of monomorphemic verbs. See page 52 for a more detailed explanation.

Second, there were 5 verbs whose irregular pasts we judged to be only marginally acceptable in my dialect. Four of these verbs have irregular pasts that seem to be acceptable in British English: *learn-learnt/learned*, *spell-spelt/spelled*, *smell-smelt/smelled*, and *spoil-spoilt/spoiled*. Of these four verbs, *spoil* was presented as a bisemous verb, with one meaning associated with food spoiling and the other with coddling or pampering a person. The remaining verb (*rend-rent/rended*) has an irregular past which is easily confounded with the noun *rent*. All 5 of these forms were treated separately because they are not obviously doublets — since doublets must have an acceptable irregular past.

Third, there were 4 verbs for which more than one irregular past was possible according to my dialect and other sources (e.g., Mencken, 1936, Quirk et. al., 1985) (*forbid, bid, spit, stink*). Although according to these sources only *forbid* had three only *forbid* has three possible irregular pasts (*forbid-forbid/forbad/forbade*), while *bid* and *spit* have only two, for the sake of presentation symmetry I presented three irregular pasts for *bid* and *spit* as well — even though the third irregular pasts seem to be implausible forms (*bid-bid/bad/bade, spit-spit/spat/spate*). For *stink* I presented only irregular form (*stank*) in addition to the regular *stinked*. I treated 4 verbs separately because I suspected they might be involved in inter-irregular blocking, in which one irregular past (*spat*) blocks another (*spit*).

Third, there were 3 verbs for which I presented more than one irregular form in addition to the regular form (*spit, bid, forbid*). Although according to all my own dialect and other sources (e.g., Mencken, 1936, Quirk et. al., 1985), only *forbid* has three possible irregular pasts (*forbid-forbid/forbad/forbade*), while the other two verbs have only two, for the sake of presentation symmetry I presented three irregular pasts for the other two verbs as well — even though the third irregular past seem to be an implausible form (*bid-bid/bad/bade, spit-spit/spat/spate*). I treated these differently because I suspected they might be involved in inter-irregular blocking, in which one irregular past (*spat*) blocks another (*spit*).

Fourth, there were 16 control verbs — 4 types of control verbs with 4 actual verbs for each type: 4 true irregular verbs, for which a regular past is not acceptable (*come-came, write-wrote, say-said, blow-blew*); the over-regular forms of the same 4 true irregulars (*come-comed, write-writed, say-sayed, blow-blowed*); 4 true regulars (*walk-walked, type-typed, rob-robbed, move-moved*); and 4 over-irregular pasts of attracted regulars (*succumb-succame, tide-tode, collide-collode, blind-blound*). I had two motivations for presenting these control verbs. First, I wanted to present very good and very bad past forms to clearly set the endpoints of the 7-point rating scale — the true regulars and irregulars on the one hand, and the over-regulars on the other should have accomplished this. Second, by introducing truly bad and good forms, I hoped to prevent subjects from automatically giving all past forms a medium rating.

3.5.2 Presentation

Subjects rated both the regular and irregular past forms of each of the 37 doublets. Each doublet past form (e.g., the irregular past *dove*) was presented in two separate sentences, one of which was in the completive aspect, the other in the non-completive aspect. Each subject thus rated each irregular form in two sentences (one completive, one non-completive), and each regular form in two sentences (one completive, one non-completive). Thus the 21 non-bisemous analysed verbs were presented in a total of 84 sentences (21 verbs * 2 past forms * 2 aspects). Because the 9 analysed bisemous verbs were treated as distinct verbs for their two meanings, they were presented in a total of 64 sentences (8 verbs * 2 meanings * 2 past forms * 2 aspects). Thus each subject rated past forms in a total of 148 sentences (84 non-bisemous + 64 bisemous verbs) for the analysed verbs. [13]

Every subject was thus presented with both regular and irregular forms of each verb in both completive and non-completive contexts. However, there were 16 different versions of questionnaires which varied with respect to the order of sentence and past form presentation, as well as with respect to the combination of past forms with sentences. Specifically, half the subjects got the irregular form of each verb in one completive sentence and the regular form in the other completive sentence, while the other half of the subjects got them the other way around. For example, half the subjects saw the sentences in (11), while the other half saw those in (12).

(11). (a) On the day of his inauguration, Reagan *dreamt* that an evil communist punched him.

(b) Last night I *dreamed* that I hit a home run.

(12). (a) On the day of his inauguration, Reagan *dreamed* that an evil communist punched him.

(b) Last night I *dreamt* that I hit a home run.

Simlarly, half the subjects got the irregular form of each verb in one non-completive sentence and the regular form in the other non-completive sentence, while the other half of the subjects got them the other way around. For example, half the subjects saw the sentences in (13), while the other half saw those in (14).

[13] In addition to these 148 sentences for the analysed verbs, there were 88 sentences for the unanalysed verbs: 8 each for 4 verbs (the bisemous *spoil* and the multiple-irregular past forms *forbid*, *bid* and *spit*, whose 4 tested past forms were each tested on 2 sentences); 4 each for 10 verbs (the prefixed forms *alight*, *beget*, *bespeak*, *forbear* and *forswear*, the marginal irregulars *learn*, *spell*, *smell*, and both *stink* and *rend*); and 1 each for 16 verbs (the 16 control verbs). Thus subjects rated a grand total of 236 (148 + 88) sentences.

(13). (d) For years and years Roger *dreamt* stories of love and peace.

(e) Idly I *dreamed*, and as I lay dreaming, I saw her face again and again.

(14). (d) For years and years Roger *dreamed* stories of love and peace.

(e) Idly I *dreamt*, and as I lay dreaming, I saw her face again and again.

Four combinations of sentences were created by pairing each of the two completive sentences ((11) and (12)) with each of the two non-completive sentences ((13) and (14)) for every verb: (11) with (13), (11) with (14), (12) with (13), and (12) with (14).

Finally, for each of these 4 combinations there were 4 different questionnaires, for a grand total of 16 questionnaires. The order of the 2 completive and 2 non-completive sentences differed in each of the 4 different questionnaires of each combination, as shown in the following table. Within these constraints, the absolute position of each sentence within the sub-questionnaire was random.

Order			
(a)	(a)	(b)	(b)
(b)	(b)	(a)	(a)
(c)	(d)	(c)	(d)
(d)	(c)	(d)	(c)

3.5.3 Subjects

Acceptability ratings were elicited from 32 native English speakers, all of whom were undergraduates at M.I.T. Since there were 16 different versions of the questionnaire, two subjects completed each version.

3.5.4 Instructions

I asked subjects to give judgments on the "naturalness of verb forms. ... I are not asking for judgements about the real-world plausibility of the sentences, but rather about the naturalness of the verb form within that sentence. Namely, is the verb in a form that 'sounds' right to you and that you would naturally use in your own speech? There are no right or wrong answers; I are asking for a 'gut feeling' type of response." I gave two examples, and indications as to how we would rate them. I asked the subject to use the entire rating scale from 1 to 7. The last sentences in the instructions were: "Please fill out the questionnaire *in order*, so do *not go back to sentences you have already done.* Remember, there are no 'right' or 'wrong' answers."

3.5.5 Mean Ratings

For the basic computational and blocking analyses described in the results chapters, mean ratings for each past form were calculated as the average of all ratings for that form over all sentences: over the completive and non-completive sentences for the 21 non-bisemous verbs, and over the two meanings as well as the two aspects for the 8 bisemous verbs. Those analyses for which the means were not collapsed across aspect or meaning are described in chapter 6. Because no stem ratings were acquired in this experiment, the stem ratings in Doublet Study analyses were taken from the All-Verbs study.

3.6 The All-Classes Study: Past Tense Production Likelihood and Past Tense and Stem Judgments

40 adult native English speakers were first asked to produce past forms in sentence contexts and then to rate the naturalness, also in sentence contexts, of both regular and irregular past forms as well as stem forms of a total of 120 monomorphemic verbs of six classes: 20 true irregulars (*come-came/comed*), 20 true regulars (*walk-walk/walked*), [14] 20 doublets (*dive-dove/dived*), 20 attracted regulars (*glide-glid/glided*), 20 nonce irregulars (*strink-strunk/strinked*), 20 nonce regulars (*plam-plam/plammed*).

3.6.1 Verbs

The verbs of each class were selected on the basis of nine criteria. [15] First, within each verb class, I selected half lower frequency verbs and half higher frequency verbs. Second, within each verb class, I selected half lower cluster strength verbs, and half higher cluster strength verbs. Third, within each verb class, I attempted to select verbs that covered a range of

[14] For all classes other than true regulars, past judgments were elicited for both irregular and regular past forms. For the true regulars, past judgments were elicited for the regular past (*walked*) and the no-change past (*walk*).

[15] The All-Classes study was designed for three purposes. First, to confirm the findings on true irregulars, true regulars, doublets, and attracted regulars from the All-Verbs and Doublet studies; second, to test normal adults on irregular and regular nonce forms. and third, to test various brain-damaged populations (such as agrammatic and anomic aphasics, and subjects with Alzheimer's disease, Parkinson's disease, Huntington's disease, Specific Language Impairment, and Williams syndrome) on all six types of verbs. It is this third purpose which led us to constrain the verbs and sentences with such stringency with respect to pronunciation and spelling, since many of these brain-damaged subjects may have difficulty in reading and have reduced processing abilities.

cluster types — that is, verbs with different rhymes, vowels and final consonants. Fourth, within each verb class, I attempted to select at least one verb from the **same** cluster among both the low and high frequency verbs.

Fifth, I avoided any verbs which can also play the role of auxiliary or modal — because I wanted to ensure that forms were computed as past tenses, and not as auxiliaries or modals. Sixth, I avoided any verbs which I judged to be possible denominals, de-adjectivals or of onomatopoeic origin — because such derived forms have been shown to be computed differently from inflected forms (Kim et. al., 1991). Seventh, I attempted to avoid too much similarity between any of the forms presented and other existing words. Thus I avoided attracted regulars like *rend*, whose irregularized past *rent* already exists as another word. Similarly, nonce forms like *flam* or *shar* were rejected as being too similar to *flame* or *share*, respectively.

Eighth, I attempted to avoid any ambiguous pronunciations for any of the forms presented (stems, irregular pasts or regular pasts). Thus I avoided forms like *blow*, which could rhyme with either *flow* or *allow*, or the nonce form *tound*, which could rhyme with *wound* or *ground*. Similarly, I avoided nonce forms like *spling*, whose regular pasts *splinged* could be pronounced to rhyme with *hinged*. I also avoided forms such as *palk*, which might be incorrectly pronounced with the "l" sound, rather than attracted with *walk*. Ninth, all nonce forms had legal English spellings. Thus forms such as *krog* and *krive* were eliminated in favor of ones such as *crog* and *crive*.

True Irregulars

I selected the true irregulars from the list of true irregulars in the All-Verbs study — only those verbs whose **results** in the All-Verbs study demonstrated them to be non-doublets according to the criterion that the mean ratings of their over-regular pasts were less than 3.5. The value of 3.5 was selected for two reasons. First, it is slightly less than the mean rating value of 4 from the All-Verbs study, and thus the over-regulars are on the "bad" side of the scale, and therefore not doublets. Second, the cutoff of 3.5 conformed very well with my own judgments — true irregulars below and doublets above.

Half the true irregulars were verbs of low irregular past frequency, and half of high. In addition, half of them had low irregular cluster strength, and half had high. The low and high frequency verbs were split evenly among the low and high irregular cluster strength verbs: 5 verbs with low frequency and low cluster strength, 5 verbs with low frequency and high cluster strength, 5 verbs with high frequency and low cluster strength, and 5 verbs with high frequency and high cluster strength.

True Regulars

I selected the true regulars from the list of true regulars in the All-Verbs study. Half the true regulars were verbs of low regular past frequency, and half of high. In addition, half of them had low regular cluster strength, and half had high. The low and high frequency verbs were split evenly among the low and high regular cluster strength verbs: 5 verbs with low frequency and low cluster strength, 5 verbs with low frequency and high cluster strength, 5 verbs with high frequency and low cluster strength, and 5 verbs with high frequency and high cluster strength.

Doublets

I selected the doublet verbs from the list of doublets in the All-Verbs study. All of the doublets met the criterion (described above) of having regular pasts (e.g. *dived*) with mean ratings from the All-Verbs study greater than 3.5. The doublet verbs were not selected according to any word frequency or cluster strength criteria. However, I attempted to select the doublet verbs from as many different clusters and rhymes as possible.

Attracted Regulars

I selected the attracted regulars from the list of attracted regulars in the All-Verbs study. Half the attracted regulars were verbs of low regular past frequency, and half of high. In addition, half of them had low **irregular** cluster strength, and half had high. The low and high frequency verbs were split evenly among the low and high regular cluster strength verbs: 5 verbs with low frequency and low cluster strength, 5 verbs with low frequency and high cluster strength, 5 verbs with high frequency and low cluster strength, and 5 verbs with high frequency and high cluster strength.

Nonce Irregulars

[16]

Half the nonce irregulars were verbs of low **irregular cluster strength**, and half of high. In addition, half of them had low **regular cluster strength**, and half had high. The low and high irregular cluster strength verbs were split evenly among the low and high regular cluster strength verbs: 5 verbs with low irregular cluster strength and low regular cluster strength, 5 verbs with low irregular cluster strength and high regular cluster strength, 5

[16] In this paper I do *not* present results from analyses of nonce forms — simply from a lack of time on my part.

verbs with high irregular cluster strength and low regular cluster strength, and 5 verbs with high irregular cluster strength and high regular cluster strength.

Nonce Regulars

[17]

Half the nonce regulars were verbs of low regular cluster strength, and half of high.

3.6.2 Presentation

All 40 subjects completed 3 tasks in the following order: a past production task, a past judgment task, and a stem judgment task. Each task tested all 120 verbs. All subjects received the same pseudo-randomized version of each task — for each task, the order was randomized and then gone over by hand to ensure that similar-sounding forms were not too close to each other. [18]

The verbs in all three tasks were presented in the context of sentences. For a given verb the sentences for all three tasks were almost identical. [19] For example, for the verb *dig*:

(15). **Production** Every day I *dig* a hole.

Just like every day, yesterday I __________ a hole.

Past Judgment Every day I *dig* a hole.

Just like every day, yesterday I *dug* a hole.

Stem Judgment Every day I *dig* a hole.

All sentences were written to conform to 5 criteria. First, every stem sentence — the sentence preceding the past sentence in the past production and past judgment tasks, and

[17]In this paper I do *not* present results from analyses of nonce forms — simply from a lack of time on my part.

[18]I gave all the subjects a single version of the questionnaire for three reasons, all of which were motivated by the fact that subjects from several brain-damaged populations were also taking the experiment. First, I wanted to avoid similar-sounding forms (e.g., forms from the same cluster, such as *strink* and *frink*) from lying close to each other in the questionnaire — in order to minimize inter-item bias effects, including problems of perseveration which are quite common among several of the tested brain-damaged populations. To successfully separate such similar sounding forms I had to go over the randomized list by hand, which made it impractical to generate a new randomized list for each subject. Second, given that the number of subjects for any one population was likely to be very small, I were unable to have a predetermined balanced ordered — because we could not know beforehand if I would be able to test enough subjects to have even so much as one subject for every ordered version of the questionnaire. Third, I wanted the same order for each subject to facilitate detection of an order effect — such as habituating and therefore improving on the regular past tense pattern.

[19]The purpose of having the same sentence in all three tasks was again primarily for the brain-damaged populations. By using similar sentences I attempted to hold constant any interference from the sentence meanings.

the only sentence in the stem judgment task task — began with "Every day I" before the verb. [20]

Second, all past sentences — in both the past production and past judgment tasks — began with "Just like every day" before the verb position. [21]

Third, all post-verbal arguments were two words long. Furthermore, none of these words were inflected forms, and I attempted to select them to be both common and of few syllables. [22]

Fourth, the first word in each post-verbal two word argument never began with a dental (t, d, θ – as in *thin*, ð – as in *that*), and most began with a vowel. Specifically, of these first post-verbal words, 111 began with a vowel, 4 with a *w*, 3 with an *f*, 1 with an *h* and 1 with an *m*. [23]

Fifth, the two word argument for nonce verbs was selected with an attempt to avoid the possibility of conjuring up a meaning for the nonce form from an existing verb. For example, I avoided any argument that might conjure up the verb *drop* for the nonce verb *brop*; thus I rejected sentences such as "Every day I *brop* a penny." [24]

Production Task

In the production task subjects were presented with the 120 verbs in pseudo-randomized order, and were asked to write down the the word that most naturally filled in the blank in sentence pairs such as:

(16). Every day I *dig* a hole.

Just like every day, yesterday I ____________ a hole.

Past Judgment Task

In the past judgment task subjects were presented with 240 sentence pairs. Two sentence pairs were presented for every verb — one with its regular past, and one with an irregular past. In the case of true regulars the irregular past was the no-change form (*walk-walk*).

[20] The motivation for this consistency was to facilitate the task and avoid distraction for the brain-damaged subjects.

[21] The motivation for the repetition of "Just like every day" was to facilitate the task for brain-damaged subjects. After extensive piloting with brain-damaged subjects I found that this phrase made the past production task far easier than beginning the sentence with "Yesterday", or some other initial support such as "As usual, yesterday...".

[22] All post-verbal arguments were short and two words long for two reasons: consistency among verbs, and a short argument to avoid distracting the brain-damaged subjects.

[23] Because subjects from some brain-damaged populations have articulatory problems (e.g., Parkinson's disease and Huntington's disease patients), I wanted to maximize my chances of hearing their uttered endings, however faint or difficult to understand they were. Words beginning with a dental or some other consonants similar to the *t* or *d* at the end of regular verbs made this task harder, and vowels or related phonemes made this task easier.

[24] This was to minimize the chance of such confusion errors in the brain-damaged subjects.

Subjects were asked to give a rating between 1 and 10 for the verb form in the second sentence **as a past tense** of the verb in the first sentence of each sentence pair. A range of 1 to 10 (rather than the more common but smaller 1 to 7) was used because I wanted subjects to use as large a range as possible for both the existing and nonce forms. A smaller range (e.g., 1 to 7) would increase the chance that subjects would use very few values at the low range for nonce forms at at the high range for existing forms. In the instructions subjects were given examples of very good (*go-went*), very bad (*do-doed*), "in-between" (*shed-shedded*), and nonce (*spling-splung*) past forms. They were instructed to ignore the meaning of the verb in the sentence, and rather to base the judgment on how good a past tense it was of the verb in the first sentence. They were also strongly encouraged to use the entire scale when making their judgments.

The irregular and regular past forms of the same verb were in pseudo-random order with respect to each other: After two positions in the questionnaire were randomly selected for each verb (one for the irregular sentence pair, one for the regular sentence pair), I went over the questionnaire to assign new positions for any sentence pairs whose past form was too similar to the past form of a nearby sentence — for past forms form the same verb (*come* and *camed*) or for similar sounding stems or past forms (*strink-strunk* and *frink-frunk*).
Here is one sentence pair from the experiment:

(17). Every day I **come** into town.

Just like every day, yesterday I **came** into town. 1 2 3 4 5 6 7 8 9 10

Every day I **come** into town.

Just like every day, yesterday I **comed** into town. 1 2 3 4 5 6 7 8 9 10

Stem Judgment Task

In the stem judgment task subjects were presented with 120 verbs, in the same stem sentences in which they appeared in the other two tasks, in pseudo-randomized order, and were asked to judge how good or bad the word "sounds" on a 1 to 10 scale. In the instructions subjects were given examples of forms (in sentence contexts) which I suggested should get a high rating (*walk*) and a somewhat lower rating (*hew*). They were also given an example of a nonce form (*spling*, for which I suggested most people would give a relatively low rating. For all three examples they were instructed not to base their judgment on meaning. They were strongly encouraged to use the entire scale when making their judgments.
Here is one stem sentence from the experiment:

(18). Every day I **wink** at them. 1 2 3 4 5 6 7 8 9 10

3.6.3 Subjects

All 40 subjects were M.I.T. undergraduates and native English speakers. In the initial instructions, preceding the first task, subjects were asked to proceed with the experiment only if their first language was English — if "you spoke only English with your parents and at school when you were growing up."

3.6.4 Past Tense Production Likelihood Rates and Mean Ratings

From the production task I calculated past production likelihood rates: the percentage of trials of a given stem for which a particular past was successfully produced. This measure was applied to all past forms — the commonly acceptable irregular (*came, dove*) or regular (*walked, glided*) pasts, alternate pasts for these verbs (*comed, dived* and *walk, glid*), as well as the various pasts of nonce stems (*strink-strunk, strink-strinked, plam-plam, plam-plammed*). For all these past forms the past production likelihood rate of a given form was calculated as the percentage of subjects who produced that given form. For example, if 38 subjects wrote down *wrung* tense of *wring*, the past production likelihood rate of *wrung* would be calculated as $95\% = (38/40) * 100$. If the remaining two subjects wrote down *wringed* as the past form of *wring*, then the past production success rate of *wringed* would be calculated as $5\% = (2/40) * 100$. Similarly, if 30 subjects wrote down *strunk* as the past for *strink*, the past production likelihood rate of *strunk* would be calculated as $75\% = (30/40) * 100$.

From the past and stem judgment tasks I calculated mean ratings. The mean rating value for each past or stem form was calculated as the mean of all subjects' ratings for that form. Because there is no equivalent measure of stem for past production success, any All-Classes study analyses using Stem Strength as a variable used stem judgment ratings from the All-Classes study as well.

3.7 Experiment 4: The Reaction Time Study: Past Tense and Stem Production Likelihood and Time

40 adult native English speakers were asked to respond as quickly and accurately as possible to isolated verb stems (*walk*) presented briefly on a computer screen. In the past generation task they produced the past form of that stem, while in the stem naming task they read the stem out loud. There were a total of 171 monomorphemic verbs, of which 97 were true irregulars, 39 were true regulars, and 35 were attracted regulars.

3.7.1 Verbs

The 171 verbs in this study [25] were extracted from the 288 verbs in the All-Verbs study (163 of the 171) and the 120 verbs in the All-Classes study (8 of the 171). [26] The verbs in each subset were selected so as to cover a wide range of past form word frequencies.

3.7.2 Presentation, Procedure and Instructions

Both the past generation and stem reading experiments were run on an IBM/PC which had been modified to record the reaction time of responses. In both experiments, each subject was tested individually for a period of about fifteen minutes. Subjects were seated in front of the monitor and microphone, with their heads resting on a chin-rest. They were given written instructions which were also explained to them orally. They were directed to look at a fixation row (indicated by a row of asterisks), which appeared at the center of the screen. The fixation row remained on the screen for 250 milliseconds. The screen then remained blank during 300 milliseconds, after which point a verb stem appeared and remained on-screen for 200 milliseconds. The verb stem was then immediately replaced by a mask (########).

In the stem reading experiment, subjects were instructed to say the verb stem aloud. In the past generation experiment, subjects were instructed to say the verb's past tense form aloud. In both cases, they were asked to utter the form "as quickly as possible, while responding as accurately as possible." In addition, immediately before the experiment began, the experimenter emphasized the following: "Please remember to respond as quickly as possible while responding accurately, and try to speak loudly and clearly **without any false starts or extraneous sounds like *um*, *uh* or clearing your throat.**"

In both experiments the mask remained on the screen until the subject uttered the form. The screen then remained blank for about two seconds before the next trial began. Reaction time (latency) was measured as the time between the presentation of the verb and the utterance of the verb form, as detected by a voice-triggered microphone hooked up to the IBM/PC computer. If system was triggered by any noise other than the expected response (the stem or the appropriate past, in the respective experiments), this was noted for later

[25] Not counting the 12 practice verbs, the total number of verbs in the study was 180. However, I had mistakenly included 7 verbs ending in *t* or *d* in the list of true regulars. I eliminated these verbs from my analyses. In addition, I eliminated 2 verbs which subjects visually confused with other words. Specifically, subjects often had a hard time with the true regular *maim* and the attracted regular *gleam*, both of which were sometimes confused with similar words ending in "n" rather than "m": in the stem reading task 9 of 40 subjects produced "main" rather than "maim", and 12 of 40 produced "glean" instead of "gleam". After these 2 verbs in addition to the 7 ending in *t* or *d* were eliminated, I were left with the 171 verbs on which analyses were performed.

[26] The 8 verbs taken from the All-Classes study were: the 2 true regulars *rob*, *stir*; and the 6 attracted regulars *writhe*, *sneeze*, *squeak*, *fend*, *squeeze*, *trim*.

use in analysis. Each experiment was recorded on audio tape, allowing us to check any unclear responses.

The 180 verbs were randomized separately for each subject, who was first presented with 12 practice trials.

3.7.3 Subjects

There were 40 subjects for both the past generation and stem reading tasks.

3.7.4 Mean Reaction Times and Production Likelihood Rates

The mean reaction time for both stems and past forms was calculated by averaging the reaction times for a given form across all subjects' correct responses. If a subject had made an error his or her reaction time for that form was not included in the calculation of its mean. [27]

The production likelihood rate for both stem and past forms was calculated as the percentage of subjects who successfully produced a given form. For example, if 34 subjects successfully produced *wrung* as the past tense of *wring* (while the other 6 subjects made errors), the past production success rate was calculated as 85% = (34/40) * 100. Similarly, if 38 subjects successfully read the stem *wring* out loud in the stem reading task, the stem production likelihood rate was calculated as 95% = (38/40) * 100.

The concept of production likelihood rate was also applied to forms produced as errors: the production likelihood of such a form was calculated as the percentage of subjects *of those who made an error on that item* who produced the given form. For example, of the 6 subjects who were *not* successful at producing *wrung*, what percentage of the produced *wringed*? If 4 of those 6 subjects produced *wringed*, then the past production likelihood rate of *wringed* was calculated as 67% = (4/6) * 100.

[27] Errors included false starts (the microphone was triggered by a noise prior to a correct response); subject's failure to activate the voice trigger; subject's failure to see or identify the word; mispronunciations or incorrect forms in lieu of the expected forms. For the past generation task, these incorrect forms included over-regulars (*bite-bited*), over-irregulars (*wink-wunk*), past participles (*take-taken*), or simply the wrong word (*flee-flew*). For the stem reading task incorrect forms usually entailed simply uttering the wrong word (e.g., *flight* instead of *fight*).

Chapter 4

Estimated Measures

I developed two estimated measures as predictor variables of the dependent variable Past Tense Success: past tense frequency and past tense cluster strength.

4.1 Past Tense Frequency (Pf)

If a past tense form is computed in associative memory, the frequency of that form *interpreted as the past tense of the its stem* should predict the past's computational success. This falls out of theories of associationism, which claims that the connections over which a form is computed are strengthened with each presentation of that form. In addition, if I view associatively computed pasts as being stored in lexical memory, they should show some of the same characteristics of uninflected forms in lexical memory — and one of these forms' most salient characteristics is their word frequency effects.

4.1.1 Frequency Counts

According to the theory of associationism, the word frequency measure which should best predict the computational success of a past form for a given subject is some function of the actual number of times the subject has heard or seen the form. Since such exact counts are highly infeasible to acquire, I have resorted to a now common approach — to use word counts from a corpus of written language. The assumption in using such as corpus is that the *relative* frequency of each word in the corpus approximates the relative frequency of each word in the written and spoken input of the tested subjects. I attempted to meet this assumption by following two criteria in selecting the corpora.

First, I attempted to select *large* corpora — for two reasons. A large corpus decreases the chance of floor effects — that rare words would all have 0 frequency counts, even if in the language they have different relative counts. In addition, since it is axiomatic in statistics that the standard error of any estimate of a population parameter decreases as sample sizes increase, and in this case larger corpora correspond to larger sample sizes, I expect to obtain more accurate estimates of population frequency (the true relative frequency of words in the language) with large corpora.

Second, I attempted to select corpora whose words were likely to be accurate reflections of those words the subjects I tested would read and hear. This is especially important because my corpora are written texts, while it seems likely that most people's language input is largely from spoken sources.

In attempting to satisfy these two criteria, I selected frequency counts from two corpora. First, I used the Francis and Kučera frequency counts, which are derived from 1 million words of text from several sources which were selected to cover a range of topics, thus attempting to satisfy the second criterion. In addition, the Francis and Kučera counts are widely used in the psycholinguistic literature, thus helping validate their use. Second, I used the Associated Press frequency counts. These were extracted from a 44 million word corpus of Associated Press news wires from February through December of 1988. Although these news wires evidently covered a huge range of topics, there was clearly a bias towards some words more than others (e.g., "Reagan" has a count of 28533, versus 428 for "Clinton").

Both frequency counts distinguished different parts of speech. Thus *talked* used as a past tense was counted separately from *talked* used as a past participle. In the Francis and Kučera counts these part of speech distinctions were made in a first pass by a stochastic part of speech analyzer — a computer program that uses n-gram probabilities to distinguish different parts of speech; and in a second pass by raw human effort, checking all the automatically generated counts by hand. In the Associated Press counts these part of speech distinctions were made exclusively by a stochastic part-of-speech analyzer developed by Ken Church of Bell Labs.

I used both frequency counts because they two have different advantages. The Francis and Kučera counts are more widely used and trusted, are based on a variety of text sources, and are distinguished by part of speech with great accuracy. However, the texts on which they are based contain a relatively small number of words. The Associated Press counts, while based on an extremely large corpus, have the disadvantages of being quite unknown in the psycholinguistics literature, of being biased towards certain words, and of not being checked by hand.

I found that the two frequency counts were highly correlated. For a random sample of 100 verb stems, the results of a simple correlation between the two counts for those words were

$r = .95$, $p < .001$. [1] Furthermore, as I show in each of the results chapters, the correlations between the two counts for each class of verb stem or past forms were very high.

In some cases I have used only one frequency count; in such cases I relied on the Associated Press count. For example, the cluster strength values (see below) were calculated from Associated Press counts. Similarly, in the results chapters the graphs displayed for each analysis show word frequency and cluster strength values derived from Associated Press counts. In such cases I chose Associated Press rather than Francis and Kučera for one reason: I found that Associated Press derived word frequency or cluster strength values made better predictors than those derived from Francis and Kučera. This superiority of Associated Press is not surprising, given its enormous sample size and its heterogeneity of topics.

4.1.2 Transformations

Past Tense Frequency is a predictor of Past Tense Success because associative theories expect frequency to strengthen the connections over which the form is computed. However, it is not at all clear that the increase in computational success from an increase in word frequency is the identity function of the raw relative frequency counts drawn from corpora. In fact, evidence from three sources suggests that these raw frequency counts should be transformed according to some *non-linear function*.

First, work from learning theory suggests that non-linear functions such as the logarithm of item frequency, negative exponentials like the capacitor function $(1 - \frac{1}{\exp(\alpha * \text{Item Frequency})})$ and hyperbolics are appropriate. Second, work in psycholinguistics and other areas of psychology has shown empirically that these types of non-linear functions are the best transformation functions of word frequency counts for predicting empirical measures such as lexical decision and naming times (Whaley, 1978). Third, my own empirical findings for the experiments reported in this paper show that non-linear transformations such as the logarithm or the capacitor function are dramatically superior to the raw counts in predicting the Past Tense Success of forms such as irregular pasts (*blew*), which both the Hybrid and All-Associative Models hypothesize to be associatively learned and represented.

The Log Transformation

In the statistical analyses that I describe in the results chapters I have used one transformation: the natural log of the raw frequency counts. This log transform was carried not only on past frequencies, but also on stem frequencies, whenever those were used in analyses.

[1] These 100 verb stems were randomly extracted from among the first 1000 alphabetically ordered verbs in the vdb database (see section 4.2.3 below).

To get around the problem of log(0) being undefined I added 1.1 to the original frequency counts before applying the log to them; I added 1.1 rather than 1 to be consistent with the log tranformation function for cluster strength (see below).

4.2 Past Tense Cluster Strength (Pc)

If a past form is associatively computed on a distributed representation, its computational success should be predicted by some function of the similarity, type frequency and token frequency of other past forms. This is because similar distributed representations should be computed over many of the same units, and so the connections strengthened during the learning of one past form should increase the computational success of similar past forms. Thus an associative memory trained on stem-past pairs of verbs such as *throw-threw* and *grow-grew* should be more successful at computing *blow-blew*: The more frequently *throw-threw* and *grow-grew* were presented, the stronger the connections over which they were learned, and the more successfully they will be computed; because *blow-blew* should be learned and computed over many of these same connections, its computation should become more successful as well.

If one can build a function to capture the contribution to the computational success of a given stem-past pair (*blow-blew*) from the type and token frequencies and similarities of all other stem-past pairs, then one can use the output of this function as a predictor of the computational success of that given stem-past pair (*blow-blew*). I have defined this to be the *cluster strength function* and its output for a given stem-past pair to be the *cluster strength* of that pair.

To test whether irregular pasts (*blow-blew, dive-dove, glide-glid, strink-strunk*) are computed in an associative memory (as claimed by both Hybrid Models and All-Associative Models), I calculated their *irregular cluster strength* — the cluster strength based on only other irregular verbs. If irregular pasts are indeed associatively computed, their irregular cluster strengths should correlate with their Past Tense Success. To test whether true regular pasts (*walked*) are computed in an associative memory (as claimed by All-Associative Models), I calculated their *regular cluster strength* — based on only other regular verbs. If regular pasts are indeed associatively computed, their regular cluster strengths should correlate with their Past Tense Success.

According to my theory, in addition to irregular pasts, certain regular pasts are also computed in the same associative memory as irregulars. Specifically, regulars whose stems are phonologically similar to the stems of irregulars are computed in the same associative memory as those irregulars. Thus doublet regulars (*dive-dived*) and attracted regulars (*glide-glided*) are associatively computed alongside irregulars. Because the theory predicts that only regular pasts whose stems are close to the stems of irregulars are associatively computed, relatively few such regulars will be stored in the memory, and therefore I do not expect to find much support from other regulars for a given regular in the memory. In other words, I do not expect to find that the regular cluster strength of associatively computed regulars (*dived, glided*) predicts their past computational success.

On the other hand, I *do* expect these regulars to be predicted by their *irregular* cluster strengths — that is, the number of irregular neighbours of a given associatively computed regular past should affect its computational success. These associative regulars are learned in the memory because their stems are similar to the stems of irregulars, so the more irregular stems they are close to, the more likely they are to be stored. However, the nature of these neighbouring irregulars' effects on the computation of the regular pasts is not necessarily the same as the nature of the effects of the same neighbouring irregulars on an irregular past. Given that the stems of an irregular and a regular are similar, if their pasts are also similar, the regular should be more easily computed (because its stem-past function is shared with the irregular's); but if their pasts are not similar, the regular should be computed with greater difficulty — according to my Associative Computational Theory of Blocking, which claims that the blocking of a given past form (e.g., *glide-glided*) is an inverse function of all the possible alternative forms (*ride-rode, hide-hid*) for that past's stem.

Thus only irregulars whose stems are close to the stem of a given regular past (*glided*) affect that regular past's computation; if the irregular pasts are close to the regular past, they increase the computational success of that regular, while if they are far from it, they decrease its computational success. Since most irregular pasts (*rode, hid*) will probably be phonologically quite far from regular pasts (*glided*), they will tend to decrease the computational success of the regular pasts. However, whether a given regular past (*glided*) is helped or hurt by its neighbours makes no difference to the hypothesized predictiveness of the irregular cluster strength. Regular pasts which are hurt more than helped simply have negative irregular cluster strength values, while those that are helped more than hurt have positive irregular cluster strength values. But over all verbs, the irregular cluster strength should still predict the computational success of regular pasts.

This notion of cluster strength being some combination of support and hindrance applies not only to these associative regulars, but also to all other forms computed in the memory. Thus irregulars such as *drink-drank* should be helped by *swim-swam* or *ring-rang*, and even by *swing-swung* or *dig-dug*, but not by *think-thought* or *bring-brought*. The final irregular cluster strength value of *drink-drank* will depend on the support or hindrance from all of these other verbs whose stems are similar to the stem *drink*.

Similarly, regular cluster strength is also calculated as a combination of support and hindrance. For example, if the All-Associative theory is correct, all regular pasts should be computed in a memory alongside other regulars. Thus the computational success of *glided* should be a function of the support of close forms (e.g., *cited*), and the hindrance of more distant forms (e.g., *jived*.

I have calculated irregular cluster strength for all past classes whose stems are in the phonological area of the stems of irregular pasts. Thus I have calculated irregular cluster strength for all past classes other than true regulars and nonce true regulars, both of which are defined as having stems distant from the stems of irregulars. I have calculated regular cluster strength for every past class — because there is no phonological area which I know to have an absence of the stems of verbs with regular pasts.

When calculating either irregular and regular cluster strength calculations I only included verbs with monomorphemic stems because this precludes having to worry about the possible rule generation of multimorphemic stems.

In this paper I examine what I call the Stem-Past Model of the hypothesized associative memory, which I now describe.

4.2.1 Stem-Past Cluster Strength

The Stem-Past cluster strength of a given past form (*blew*) is a function of the type and token frequency and past similarity of verbs whose stems are similar to the stem belonging to the given past form. The irregular Stem-Past cluster strength of a past form is calculated over only irregular verbs (e.g., *throw-threw, grow-grew*) whose stems are similar to the stem of the given past, while the regular Stem-Past cluster strength of a past form is calculated over only regular verbs (*flow-flowed, row-rowed*) whose stems are similar to the stem of the given past.

Specifically, the Stem-Past cluster strength function of a given stem-past pair A was calculated as follows. For every other stem-past pair B (for only irregular pasts if calculating irregular cluster strength, or for only regular pasts if calculating regular cluster strength) do the following.

First, if similarity(stem(A),stem(B)) < (C1 * similarity(stem(A),stem(A)), then do not include B's contribution to A's cluster strength — because their stems are not similar enough. [2] The inequality tests if the similarity of the two verb stems is less than some percentage (indicated by the constant C1) of the similarity of A with itself. As I describe below, the similarity of a form with itself will increase with its length (because there are more phonemes in common in the same positions), and thus calculating a minimum similarity as a percentage of its reflexive similarity (rather than as an absolute number) makes sense. I chose C1 to be .25 as the best fit of those constants that I tried out.

My motivation for only including verbs with similar stems is that the cluster strength is

[2]See section 4.2.2 below for a description of my similarity metric and calculation.

approximating function approximation systems, and in these systems the learning of a range from a particular domain of the function tends to take place from examples in that domain. In other words, the output of the function in the region of a given value in the input can be most easily be modified by training from input-output where the input is similar to the input in question.

Once I have constrained the selection of B to a verb whose stems are similar to the stem of A, I then want to capture the notion that the support of B to the cluster strength of A (that is, to the computational success of A) is increases with the similarity of the the pasts of A and B *compared to* the similarity of their stems. Specifically, the less similar the pasts *relative to the stems*, the less B should increase to the cluster strength of A. If the past of B is equally similar with the past of A as are their stems, then B should contribute highly to A. [3] I capture this notion by calculating the following ratio: similarity(past(A),past(B))/similarity(stem(A),stem(B)).

This ratio also captures the notion that any hindrance of B to the cluster strength of A is a function of the *dissimilarity* of the pasts of A and B compared to the similarity of the stems of A and B. Because my similarity function produces negative values for dissimilar forms, the more dissimilar the two pasts compared to the similarity of the stems, the more B will hinder A, decreasing its computational success. Thus the ration captures the notion of a continuity of both support and hindrance for cluster strength.

My motivation for this continuity arises from the fact that in many function approximation systems, the more different the outputs for very similar inputs, the harder those outputs are to learn — specifically, *more* difficult to learn than if each input-output pair were learned independently. In a connectionist system this is reflected in the tendency for there to be competition between learning of the two or more different outputs, when their inputs are similar.

The ratio thus produces negative values for verb pairs whose past similarities are negative. However, it would be somewhat arbitrary to use the similarity functions calculation of similarity (positive values) versus dissimilarity (negative values) as the basis of support versus hindrance of B to the computation of A. In fact, it would not be surprising if B hindered A even if they were quite similar — if the similarity of their pasts was much less than the similarity of their stems.

To capture this notion I subtracted a constant (C2) from the value of the ratio. When the value of the ratio is smaller than C2, the result of the subtraction is negative, which

[3] Verb pairs whose pasts are *more* similar than their stems are extremely rare once the criterion of similar stems has been applied. The x-ought class may contain a few such cases, depending on the stem similarity criterion: *think-thought* and *bring-brought*; *teach-taught* and *catch-caught*. While there is no theoretical motivation for such cases to result in contributions from B *greater* than when the ratio of past similarity to stem similarity is 1, these cases are so rare as to make them probably unimportant in the overall cluster calculation for those few verbs they might apply to, let alone to all verbs.

corresponds to a hindrance of A. When the value of the ratio is larger than C2, the result of the subtraction is positive, which corresponds to support of A.

I chose .5 to be the value of the constant. Although the selection of this exact value was somewhat arbitrary, it was driven by three motivations. First, I wanted to select a number between 0 and 1: less than 1 because the (normal) maximum value of the ratio is 1; and greater than 0 because I did not want dissimilar pasts to result in support, but rather similar pasts to result in hindrance. Once the constant was narrowed down to between 0 and 1, I wanted to select a value which reflected the point at which shared phonological features should outweight different features. A reasonable point is halfway, or .5, where by definition the divergence in similarity between the pasts is twice that of the stems – in other words, half the similarity of the stems is lost in the pasts. The third reason for which I selected .5 was empirical: .5 proved to be a value which resulted in cluster strength values which predicted the Past Tense Success of those past types which I had *a priori* hypothesized to be predicted by them.

The negative contribution or competition from alternative outputs is the essence of the associative blocking theory, which claims that the computational success of a past form, whether it is computed associatively or by a rule itself, is an inverse function of the associative computation of its alternatives. As described in chapter 1, one version of this theory also takes an even more specific view blocking: If a verb stem is similar to the verb stems of pairs that have already been learned in the memory, the computation of the past in question will be attempted. This computation within the memory may or may not succeed, depending on whether the ouptut in question was learned sufficiently well – which in turn is a function of such factors as the frequency of that form, the positive contribution of related forms, and the hindrance of forms with similar stems but different pasts. Thus forms with high frequency or many similar past neighbours will be tend to be successfully computed, while those with low or zero frequency and/or many competing past neighbours will tend to be less successfully computed. If the computation takes place in the rule system, as with over-regulars (*blowed*), the output of the rule system will be blocked by the computational success of the alternative forms computed by the associative memory. For example, if *blow-blowed* is being processed, *blow* will automatically be processed by the associative memory because it is (in this case maximally) similar to an input already learned in the memory. However, the probability of *blowed* being successfully computed in the memory is very low because of the high probability/success of its alternate *blew*, as well as because of the small number of regulars such as *flow-flowed*. The high success/probability of *blew* will not only decrease the success of *blowed* being computed in the memory, but will also block the output of *blowed* from the rule system.

As described above, the positive or negative contribution among stem-past pairs should only take place if the stems are similar. This is the motivation for only calculating cluster strength for verbs (B) whose stems are at least minimally similar to the stem of A. However, even with this cutoff there should be differences in the contribution among pairs whose stems are more or less similar to the stem of the given verb A: the closer the stem of B is to A, the greater the weight of the (negative or positive) contribution. For this reason I multiply the value calculated above by the similarity between the stems of A and B (which is always positive because of the cut-off requiring minimum similarity): (((similarity(past(A),past(B))/similarity(stem(A),stem(B))) - 0.5) * similarity(stem(A),stem(B)).

This value, which measures the potential contribution of B, is multiplied by the frequency of the past of B — in order to capture the frequency effect: The more frequently a form or forms are presented to an associative system or a connectionist net, the stronger the connections on which they are computed. However, this frequency value is not the raw frequency count, but rather the log of the frequency count, with 1.1 added to the frequency count before the log is applied. The log is taken for learning-theoretic reasons. I added 1.1 to the raw frequency count first, before taking the log, under the following reasoning: I wanted to include the contribution of all verbs, even if their relative frequency count was 0; if their similarity was very high they would be expected to have an effect on the computation of A, even if they were very rare. Since all verbs included in the calculation of cluster strength were real verbs, with real pasts, I wanted to include the contribution even of very rare verbs — which should have a substantial contribution if they are highly similar. Thus I added 1.1 to the raw frequency counts to give raw frequencies of 0 some contribution (log (0+1.1) = .095), and to give frequencies of 1 even more contribution (log (1+1.1) = .74). Adding this constant simply offset the log, but maintained its shape.

Finally, I divided this cluster strength value by the (log transformed) past frequency of the verb. For example, I divided the above cluster strength value for *sing-sang* by the log transformed past frequency of *sang*. For over-regulars (*blow-blowed*) or over-irregulars (*glide-glid*) I divided the cluster strength by the alternative past frequency (of *blew* or *glided*, respectively). For doublets I divided the cluster strength by the product of the past frequency and the alternative past frequency (e.g., the frequencies of *dove* and *dived*). My motivation for these divisions was based on the learning of individual forms versus patterns. Word frequency effects have proven to be much more important than cluster effects. Furthermore, I would expect that the better learned a stem-past pair is, the less cluster strength should contribute to it: If *sing-sang* is very high frequency, and thus the pattern is almost perfectly learned, irregular neigbours such as *spring-sprang* or *sink-sank* should not contribute very much to the computation of *sang*.

Finally, I summed all such frequency weighted contributions for all verbs B which met the stem similarity criterion.

4.2.2 Calculating Similarity

The similarity between any two verb forms (two pasts or two stems) was calculated the same way. The calculation was based on the approach of the Contrast Model, as proposed by Amos Tversky (Tversky, 1977). On this view, the similarity between two forms is a function of the sum of the features the two forms have in common, minus some function of those features they do not have in common. Thus two forms can be similar (their similarity value is positive), neutral (their similarity value is 0), or dissimilar (their similarity value is negative).

To calculate the similarity between two verb forms, I applied the contrast model twice — once in computing the similarity between phonemes, and then, using these phoneme similarities, in computing the final similarities between the two verb forms.

At the phoneme level I computed similarity values for all pairs of English phonemes, using a variant of the distinctive features described in Sound Patterns of English (Chomsky and Halle, 1968) as the comparison features. I weighted the contribution of unshared features more heavily than shared features, with weights of 4 and 1, respectively. [4] This weighting of features conforms to Tversky's definition of the weights for both the shared (θ) and unshared (α and β) features as free parameters: $S(a,b) = \theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A)$. My motivation for this weighting was my own intuition that unshared distinctive features seem to weaken the similarity between two phonemes more than shared features help it.

Furthermore, because the first few unshared features seem to contribute much more to weakening similarity than further unshared features, I took the log of these unshared features. Thus if there is one unshared feature it will weaken the similarity more than a second one will if there are two. Finally, I also applied to log function to the shared features – largely to have a consistent equation, but also partly because shared features seem to follow a log pattern as well (holding unshared features constant): a single shared feature adds a lot to strengthen similarity, a second one is somewhat weaker, and so on.

Once I had calculated the similarities between all English phonemes, I used this information to calculate the similarities between word forms. For a given pair of word forms A and B, similarity was calculated according to the principles of dynamic programming. I used dynamic programming to find the best fit between the two words, where all phoneme pairs between the two words were compared, and the path of maximal similarity (the path with the largest sum of similarity values) was chosen. Thus the similarity values from the phonemes were used in the word comparisons. Where more than one phoneme had to be "squished" onto a single phoneme on the other word, a cost (negative value) was incurred.

[4] I selected all constants based on a combination of theoretical motivations and empirical results — that is, those constants which resulted in similarity values which most closely approximated my own similarity judgments over a range of word pairs. However, a variety of other constants produced the same pattern of results as those described in the results chapters of this paper.

This cost was equal to the maximum similarity between two phonemes (ie, the total number of distinctive features, which equaled 20).

In addition, I weighted both the phoneme comparison and the "squish cost" according to the phonemes' position in their words. If both phonemes were in the rhyme portion of the last syllable of their respective words they weight was increased from 1 to 4. In other words, the rhyme portion of the last syllable was weighted 4 times more than all earlier segments of the word.

Finally, to avoid certain mismatches between syllables, I created an extra cost for squishing phonemes across syllables. More specifically, if the word had two syllables, the ending rhyme onset incurred this extra cost if it was squished onto any phoneme in the first syllable of the other word. This weighting simply doubled the (already weighted by 4) weight by 2. Note that because all my words were monomorphemic, the purpose of this extra cost was to prevent the /Id/ allomorph (as in patted, padded) from being matched to the rhyme of the syllable in the verb stem.

4.2.3 Method

All cluster strength values were calculated automatically by a program I wrote in C on Sun stations. This program simply followed the various algorithms described above. The set of all "other" verbs B was extracted from a database (the "vdb database") of 5350 verbs which I constructed from a variety of sources. For each of the 5350 verbs, the database contains various information for each of the following inflections of the verb: stem (*dive*), s-form (*dives*), ing-form (*diving*), ed-form (*dived*), irregular past tense form (*dove*), and irregular past participle form (*leapt, taken, driven*). For each of these inflections (for each verb), the database contains the following information: various spellings (ordered from most to least important), various pronunciations (ordered from most to least important) in various formats (syllabified and non-syllabified, with and without stress indicated), frequency counts (Francis and Kučera, Associated Press, and a British count named COBUILD), and various other information (such as the number of syllables in that pronunciation of the form).

To calculate the cluster strength of a given stem-past pair A, my program applied the algorithm to all verbs which met the basic criteria: monomorphemic in all cases, with one or more irregular pasts for irregular cluster strength, and with a regular past for regular cluster strength.

Because the spelling and pronunciation information was extracted from the Dutch *Celex* database, which used British spellings and pronunciations, the "primary" pronunciation was always British. Although the coding of many of these pronunciations did not differ at all from the probable General American pronunciations of most of our subjects, there were some obvious differences (e.g., words ending in "r"). In the calculation of cluster strength, these differences were equivalent in the introduction of noise — they resulted in similarity calculations that were occasionally somewhat inaccurate, thus introducing inaccuracy into the cluster strength values. If the cluster strength values predict Past Tense Success despite this noise, this noise only strengthens ther validity.

4.2.4 Cluster Strength Versus Connectionism

The reader might ask why I calculated cluster strength rather than building a connectionist net and training it on the same verb forms which contributed to cluster strength. There were two reasons for following the route of cluster strength rather than that of connectionism.

First and foremost, I wanted to capture certain basic principles of function approximation and systems that learn and generalize, rather than commit myself to connectionism, let alone a particular connectionist approach (e.g., feedforward versus feedback networks), learning algorithm, or input and output representations. Second, I wanted to apply the best from different areas: Tversky's similarity function, dynamic programming for calculating similarity between sequences of items (i.e., the sequences of phonemes in words), SPE's distinctive features for phonemes, and of course the general principles of function approximation which I followed. The combination of these approaches would be simply undoable in a connectionist system.

Chapter 5

Statistical Analyses

In this paper I use the argument of converging evidence to support my theories. This has led me to capture three measures of computational success (acceptability ratings, production likelihood, and production time), some acquired experimentally more than once (acceptability ratings three times, production likelihood twice, and production time once) for each class of past forms. The argument of converging evidence has also led me to test my theories by applying a number of statistical analyses to each experimental acquisition (e.g., the All-Classes study) of each measure (e.g., acceptability ratings) of each class of pasts forms (e.g., true irregular pasts such as *blew*). For example, to test the theory that true irregular pasts are associatively computed, I applied a number of analyses to each experimental acquisition of each measure of true irregular pasts.

To distinguish between the associative and symbolic rule theories of computation for a particular class of past forms (such as true irregular pasts or true regular pasts), I carried out 6 classes of analyses whose purpose was to test the predictive power on Past Tense Success of the two associative predictors (Past Tense Frequency and Past Tense Cluster Strength) versus the rule predictor (Stem Strength): 1 class of simple correlations, 4 classes of partial correlations, and 1 difference test (a t-test). To test the existence of blocking I carried out 5 types of analysis to test the negative relationship between Altern. Past Tense Success and Past Tense Success: simple correlations and 4 types of partial correlations. To test the theory of associative computational blocking, I carried out 6 classes of fundamental analyses to test the predictive power of Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength on Past Tense Success: simple correlations and 5 classes of partial correlations.

All the analyses testing a single predictor variable's (e.g., Past Tense Frequency) predictive power for a given theory (e.g., Associative Theory) for a particular class of past forms (e.g., true irregulars) from a particular experimental measure (e.g., the All-Verbs study) are displayed in a single Analysis Table. There are six types of Analysis Table, each associated with one of the six predictor variables — three for for the three predictor variables testing theories of computation (Stem Strength, Past Tense Frequency, Past Tense Cluster Strength), and three for the three predictor variables testing the blocking theory (Altern. Past Tense Success, Altern. Past Tense Frequency, Altern. Past Tense Cluster Strength). See the example Table 5.1 below.

Apart from the particular analyses in each row, which vary over the six Analysis Tables, all of these tables have the same format. Each table is displayed on a single page. Its title indicates the particular predictor variable (e.g., Past Tense Frequency), the dependent variable (e.g., Past Tense Successas measured by Acceptability Ratings on a scale from 1 to 7), the verb class (e.g., True Irregulars), the experiment (e.g., All-Verbs Study) and the theory or theories being tested (e.g., the Rule and Associative Theories). The main body of the table under the title section consists of six cells, each associated with one of the six classes of analyses described above.

In each analysis cell a variety of information is displayed (see the example Table 5.1 below) . First, a title describing the analysis (e.g., simple correlation); below the title, the predictions according to the theory or theories being tested (e.g., Rule Theory: no prediction; Associative Theory: significant with r in the positive direction); below the predictions, the value of the statistic, with its degrees of freedom, its significance level (p value), and an indication as to whether it was significant in the predicted direction (e.g., "+"). On the right side of these analysis results is a graph representing the analysis. For simple correlations the graph is a scatterplot between the predictor variable (e.g., Past Tense Frequency) and Past Tense Success. For partial correlations the graph is a scatterplot between the two residuals. In both types of scatterplot the least mean squares fit line is displayed. For difference tests (t-tests,) the graph contains a pair of box plots, one for each Past Tense Success variable.

In some analysis rows there is more than one actual analysis, each based on a different manifestation of the predictor variable. For analyses involving word frequency (Past Tense Frequency or Altern. Past Tense Frequency), there are at least 2 actual analyses — based on the two frequency counts Francis and Kučera and Associated Press. For analyses involving cluster strength (Past Tense Cluster Strength or Altern. Past Tense Cluster Strength), there are also at least 2 actual analyses — based on the two cluster strength functions (Past and Stem-Past). When such multiple manifestation predictor variables are used together in a single type of analysis, the number of actual analyses grows geometrically. For example, the partial correlation $r_{PsPf.SsPc}$ (correlation between Past Tense Success (Ps) and Past Tense Frequency (Pf), holding Stem Strength (Ss) and Past Tense Cluster Strength (Pc) constant) has 4 actual analyses (2 word frequency * 2 cluster strength) displayed in its row.

In such cases with more than one actual analysis in a row, the graph shows the data from only one of these actual analyses. For analyses involving Past Tense Frequency I have always selected a graph from an analysis using the Associated Press frequency counts because Associated Press has proven to be a better predictor of stored forms than Francis and Kučera. footnoteAnalyses based on the Associated Prss word frequency count are better than those based on the Francis and Kučera count probably because the corpus from which the Associated Press count is derived is so much larger (44 million words) than the corpus from which the Francis and Kučera count is derived (1 million words). For analyses involving Past Tense Cluster Strength, I have always displaye a graph from an analysis using the Stem-Past cluster strength function rather than the Past cluster strength function — because it has proven to be a better predictor of those past forms which I hypothesize to be associatively computed and because I have hypothesized that it is a more faithful model of the underlying associative structure in humans.

To facilitate the interpretation of the plethora of data in each table, at the bottom of the table are analysis summary values indicating the overall predictive success of the table's predictor variable, as interpreted by the theory or theories being tested. The analysis summary value for each theory (the two associative computation theories, the rule computation theory, or the blocking theory) is calculated as the ratio (and percentage) of all analyses which meet the predictions of that theory. Where a theory claims that a predictor variable should be predictive in a given analysis, the numerator of the ratio is incremented for that analysis if its statistic (r, t, etc.) has the predicted sign *and* it is significant at or below the .05 level (i.e., $p <= .05$). Where a theory claims that a predictor variable should not be predictive in a given analysis, the numerator of the ratio is incremented for a given analysis if the statistic does not have the predicted sign *or* it is not significant at or below the .05 level. For example, in the example Table 5.1, the predictive power of Past Tense Frequencyunder the Stem-Past Associative Theory is 100% because all 8 of the relevant analyses in the table were significant at the .05 level in the expected (positive) direction. For some analyses there is no strong claim for a theory about the predictive power of the predictor variable. For example, according to the rule theory, the predictive power of Past Tense Frequency is uncertain unless Stem Strength is held constant. For analyses in which Stem Strength is not held constant (e.g, the first analysis cell in example Table 5.1), there is thus no prediction for the rule theory.

These unified displays of multiple analyses that I have described are highly consistent with the argument of converging evidence. If all or most of a range of analyses confirm a hypothesis, the chance of a Type I error — that the null hypothesis has been falsely rejected — is dramatically minimized. For example, if Past Tense Frequency truly does not predict true irregular pasts (*blew*), then chances are slim that all or most of the analyses testing the predictive power of Past Tense Frequency would be significant.

Furthermore, a general *lack* of confirmation of a theory over many analyses minimizes the chance of a Type II error — that I failed to find significant result when the theory is in fact true. For example, if there is an agreement among many analyses that Past Tense Frequency does not predict Past Tense Success for true regulars, this decreases the probability that true regulars are truly associatively computed.

I do not expect or even want the reader to examine every actual analysis in every analysis-row of a given Analysis Table. The argument of converging evidence should lead him or her to look for a more general pattern of of predictive power (or pattern of differences between past forms) or lack thereof. It is precisely to draw attention away from the kind of noise that might distract the reader and lead him or her as well as me astray, that I carried out so many analyses on so many frequency counts, cluster strength functions, and measures of of computational success acquired by so many experiments. Focusing my own and the readers' attention on the big picture was also the motivation for creating the parallel structure among the Analysis Tables, as well as for displaying the analysis summary values at the bottom of each table.

5.1 Theory of Computation

To distinguish between the associative and rule theories of computation I have carried out analyses which reveal the power of each theory's predictive variables on Past Tense Success. I use these revealed effects to distinguish between the two theories for a particular class of verb pasts such as true irregular pasts (*blow-blew*). According to the associative theories, Past Tense Frequency and Past Tense Cluster Strength should be predictive; the predictiveness of Stem Strength is uncertain. According to the rule theory, Stem Strength should be predictive, while Past Tense Frequency and Past Tense Cluster Strength should not be. For example, if Stem Strength is predictive of true regulars, while Past Tense Frequency and Past Tense Cluster Strength are not, I interpret this as support for the true regulars' rule-production and against their associative computation.

According to the rule theory, Stem Strength should be the best predictor of Past Tense Success because Past Tense Success is formed by the application of a rule to the representation of the stem. The strength of this stem representation can be measured indirectly as Stem Strength — by acceptability judgments, production likelihood or production time. Because the rule should add a constant amount of computation penalty to the process, irrespective of the strength of the stem representation, Stem Strength as a measure of stem representation strength should be a very good predictor of Past Tense Success.

The rule theory does not expect Past Tense Cluster Strength to predict Past Tense Success at all because the number and similarity of past forms to a given past form should not influence Stem Strength. However, in addition to the possibility that rule-generated forms are stored after their production, [1] there are two ways in which Past Tense Frequency could predict Past Tense Success. First, this could occur through the correlation between Past Tense Frequency and Stem Strength — which is expected because Past Tense Frequency correlates with Stem Frequency (because the frequency of use of stem and past inflections of a given verb are correlated), and Stem Frequency predicts Stem Strength (because Stem Strength is stored). Second, Past Tense Frequency could predict Past Tense Success because Past Tense Frequency is one component in the true value of Stem Frequency, which affects Stem Strength: Under the rule theory, when one hears a rule-processed past form one parses it as stem plus suffix. Thus such past forms contribute to the frequency of the stem, contributing to the strength of the stem representation. For both these reasons Past Tense Frequency should be held constant in analyses testing the predictive power of Stem Strength on Past Tense Success.

According to the associative theories, Past Tense Frequency and Past Tense Cluster Strength should be the best predictors of Past Tense Success because they strengthen the associative connections involved in the computation of Past Tense Success. Stem Strength should not be a particularly good predictor of Past Tense Success under the associative theory because there is no way in which Stem Strength could affect Past Tense Success directly. However, there are three *indirect* ways that Stem Strength could predict Past Tense Success; these warrant Stem Strength being held constant in analyses testing for the predictive power of Past Tense Frequency or Past Tense Cluster Strength. First, Stem Strength could predict Past Tense Success through the correlations between Stem Strength and Stem Frequency, between Stem Frequency and Past Tense Frequency, and between Past Tense Frequency and Past Tense Success, as described above. Second, if the stem and past representations are intimately linked through connections, as in most associative or connectionist models proposed (including mine), there could be some "leakage" from the stem representation to the past representation: Each time the stem representation is strengthened, this strengthening could "leak" into connected representations — one of which is the past representation. Conversely, each time the past representation is strengthened (e.g., by hearing the word or a past form in its cluster), so its stem representation could be too. Third, if past associative forms are accessed through their stems, the stronger the stem representation, the more easily it should be accessed, and thus the more easily the past form should be computed.

[2]

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[1] It could be that rule-produced forms are stored after their production, in which case they could be retrieved rather than rule-produced in the future. If this occurred I might find word frequency effects.

[2] If I compare the predictive power of Stem Strength versus Past Tense Frequency or Past Tense Cluster Strength, am I not comparing apples and oranges? After all, Stem Strength is an empirical measure of computational success, while Past Tense Frequency and Past Tense Cluster Strength are the outputs of scaling or modeling functions. It thus might be claimed that it is not surprising if Stem Strength is a better predictor of Past Tense Success, since both are experimental measures of the same thing (e.g., acceptability ratings); and therefore if Stem Strength is better than Past Tense Frequency or Past Tense Cluster Strength

5.1.1 Types of Analyses

I apply three kinds of analysis: First, simple correlations between each independent variable (Stem Strength, Past Tense Frequency, Past Tense Cluster Strength) and Past Tense Success. Second and third, two sorts of statistical analyses in which I test the predictive power of one independent variable while holding the effects of other independent variables constant. In the second kind of analysis, I perform partial correlations between the predictor variable (e.g., Past Tense Frequency) and Past Tense Success, while holding one or more independent variables constant (e.g., Stem Strengthand Past Tense Cluster Strength). In the third kind of analysis, I select pairs of verbs (within a given class of pasts) which match on the values of one independent variable (e.g., Stem Strength), but differ on the values of another (e.g., Past Tense Frequency) in that one member of each pair has a low (Past Tense Frequency) value, while the other has a high (Past Tense Frequency) value — and then perform a t-test between the Past Tense Success values of the low (Past Tense Frequency) and high (Past Tense Frequency) verbs.

Simple Correlations

If a class of verbs is rule-produced, I expect their Past Tense Success's to correlate well with Stem Strength, less well with Past Tense Frequency, and not at all with Past Tense Cluster Strength. If a class of verbs is associatively computed, I expect their Past Tense Success's to correlate well with Past Tense Frequency and Past Tense Cluster Strength, and perhaps less well with Stem Strength.

Partial Correlations

The partial correlation allows me to hold the effect of one or more independent variables constant. For example, to determine the relationship between Past Tense Frequency and Past Tense Success, while holding Stem Strength and Past Tense Cluster Strength constant,

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at predicting Past Tense Success, this is only a reflection of this experimental similarity, rather than of an underlying rule theory of computation.

While the logic of this claim may be correct, the dissociation that I will reveal between different verb classes (e.g., true regulars and true irregulars) will demonstrate that despite this similarity of measures, certain past classes (e.g., true irregular pasts) are better predicted by Past Tense Frequency and Past Tense Cluster Strength, while others (e.g., true regular pasts) are better predicted by Stem Strength. This demonstration that Stem Strength is not necessarily a better predictor of Past Tense Frequency is reinforced by the fact that these findings meet my *a priori* predictions with respect to particular past classes.

Furthermore, if the apples and oranges claim is made in defense of single-net models, the implication is that Stem Strength must be correlated with Past Tense Frequency, Past Tense Cluster Strength or other predictors which one *does* expect to find for associatively represented forms — otherwise, why would Stem Strength predict Past Tense Success, even if they are similar experimental measures? While I readily agree to a correlation between Stem Strength and Past Tense Frequency (via Stem Frequency, as described above), if when Past Tense Frequency is held constant Stem Strength is not predictive of Past Tense Success, the apples and oranges claim can be thrown into the rotten-fruit basket.

in a partial correlation I can remove all linear influences of Stem Strength and Past Tense Cluster Strength on the predictor and dependent variables, whose linear correlation with each other can then be determined. Thus I have an index of the linear relationship between Past Tense Frequency and Past Tense Success, with all linear influences eliminated from other independent variables.

Partial correlations can be particularly revealing because they hold the linear effects of the selected independent variables (e.g., Stem Strength and Past Tense Cluster Strength) constant for *both* the predictor variable (e.g., Past Tense Frequency) *and* the dependent variable Past Tense Success. Removing these linear effects from the predictor variable ensures that any indirect linear relationship between the partialed out independent variables and the dependent variable through the predictor variable will be eliminated, leaving only the effect of the predictor variable itself. For example, I want to eliminate all linear influences between Stem Strength and Past Tense Frequency (which could occur because of the correlations between Stem Strength and Stem Frequency and between Stem Frequency and Past Tense Frequency) so that any correlation between Past Tense Frequency and Past Tense Success is solely due to Past Tense Frequency's predictive abilities.

Removing linear effects from the dependent variable (Past Tense Success) is just as important. I am interested to what extent the predictor variable accounts for the variation in Past Tense Success. To determine this I want to eliminate the variation in Past Tense Success due to other independent variables. This is exactly what a partial correlation will do. For example, I want to eliminate the variation in Past Tense Success due to Stem Strength to determine how much Past Tense Frequency accounts for the remaining variation — i.e., the residual from predicting Past Tense Success from Stem Strength.

It is important to remember that only **linear** influences are removed or detected in partial linear correlations (just as in a simple correlation). Thus non-linear relations might escape detection by such correlations. However, I have attempted to overcome this problem by trying to select word frequency scaling functions and cluster strength functions whose output is linearly related to my three measures of computational success of both stem (Stem Strength) and past (Past Tense Success) — acceptability ratings, production likelihood, and production time.

I performed 4 classes of partial correlations, each holding different independent variables constant. First, I held the two other computation independent variables constant. For example, in testing the predictive power of Past Tense Frequency on Past Tense Success , I held Stem Strength and Past Tense Cluster Strength constant in the partial correlation $r_{P_sPf.StemStrengthPc}$. Second and third, I held any potential blocking independent variables constant — Altern. Past Tense Success, Altern. Past Tense Frequency, and Altern. Past Tense Cluster Strength. In the second analysis I held Altern. Past Tense Success constant, while in the third analysis I held Altern. Past Tense Frequency and Altern. Past

Tense Cluster Strength constant. The purpose of these two analyses was to partial out any possible effects of these blocking variables on either the predictor variable (e.g., Past Tense Frequency) or on the dependent variable Past Tense Success. This is extremely important for past classes such as over-regulars or doublet irregulars or regulars, which I hypothesize to be blocked by their alternative forms (Altern. Past Tense Success, Altern. Past Tense Frequency, and Altern. Past Tense Cluster Strength). The fourth class of partial correlation holds all computation and blocking variables constant: the two other computation independent variables (e.g., Stem Strength and Past Tense Cluster Strength) and the two variables hypothesized to be involved in associative blocking (Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength).

One independent variable matched, the other differing

Perhaps the most conceptually straightforward way to hold the influence of one independent variable (e.g., Stem Strength) constant is to select verb pairs such that they are matched on that variable. These verb pairs can also be selected such that another independent variable (e.g., Past Tense Frequency) differs between the verbs in that it has a low value for one verb and a high value for the other. With a differences test such as a *t*-test, one can then check the hypothesis that the high and low verbs differ with respect to the dependent variable Past Tense Success. If they do differ, this implies that the differing independent variable (Past Tense Frequency) predicts Past Tense Success — even with the influence of the matched variable (Stem Strength) held constant. If they do not differ, this implies that the differing variable does not predict Past Tense Success while the matched one is being held constant.

For a given verb class I selected verb pairs in three different ways for three different analyses: First, to match on Past Tense Frequency, but to differ on Stem Strength; second, to match on Stem Strength, but to differ on Past Tense Frequency; third, to match on Past Tense Frequency, but to differ on Past Tense Cluster Strength. There is no need to select verbs with matched Past Tense Frequency but differing Past Tense Cluster Strength, or vice versa, because they should have the same predictive power — both should predict Past Tense Success if it is associatively computed, but neither should predict Past Tense Success if it is rule-produced.

After I selected verb pairs according to these criteria I performed a matched pairs *t*-test between the Past Tense Success values of the low value verbs and the high value verbs. For example, once the true irregulars from the All-Verbs study were paired according to matched Stem Strength values and differing Past Tense Frequency values, a *t*-test was run testing the hypothesis that the Past Tense Success values of the low-Past Tense Frequency verbs were significantly different from the Past Tense Success values of the high-Past Tense Success verbs.

Selection method Perhaps the most crucial step in this analysis is choosing the verb pairs. Here I describe my selection method. For each experimental measure (e.g., All-Verbs' acceptability ratings) of each verb class (e.g., true irregulars) I selected pairs of verbs according to the following four step algorithm. This selection was carried out automatically by a program I wrote in *C*. For the sake of simplicity, in this description I assume that Stem Strength is being matched, while Past Tense Frequency differs.

My first goal was to select verbs with matching (Stem Strength) values. For all possible verb pairs in the data set ($(n * (n - 1))/2$ verb pairs), I selected those verbs whose (Stem Strength) values differed by at most an amount equal to 5 percent of the larger of the two (Stem Strength) values.

My second goal was pick those verb pairs with differing (Past Tense Frequency) values. To do this I selected those pairs from step 1 whose (Stem Strength) and (Past Tense Frequency) values went in opposite directions: Given verbs A and B of a pair, if $Ss(A) > Ss(B)$, then I selected the pair only if $Pf(A) < Pf(B)$; and conversely, if $Ss(A) < Ss(B)$, then $Pf(A) > Pf(B)$. This step was extremely conservative, going beyond picking pairs with matched (Stem Strength) and differing (Past Tense Frequency) values — it ensured that if indeed there proved to be a significant difference between the Past Tense Success values of the high and low (Past Tense Frequency) verbs, it was not due to an analogous difference between the (Stem Strength) values.

At this point in the process each verb could belong to more than one pair. However, because no such verb duplication could occur in the statistical analysis, I wanted to select the best pair for each verb. This was the purpose of steps three and four. In the third step I calculated, for each pair, a ratio reflecting the distance between the (Past Tense Frequency) values while taking account of the similarity between the (Stem Strength) values: the ratio of the absolute value of the difference between (Past Tense Frequency) values to the absolute value of the difference between the (Stem Strength) values. Thus the further apart the (Past Tense Frequency) values and the closer the (Stem Strength) values, the larger the ratio. In the fourth and final step I sorted the verb pairs based on the value of this ratio, and selected the instance of each verb with the largest ratio value. [3] Thus each verb was represented only once in the final list of pairs. [4]

[3]This algorithm only selects locally optimal pairs. It does not find the best overall solution, as defined by the sum of the ratio values of all final pairs. This is because the algorithm does not backtrack, rather sticking with its first choice for a pair of a given verb.

[4]However, no every verb is guaranteed to occur in this list of pairs: for example, if a particular verb's (Stem Strength) value is close to the (Stem Strength) value of no other verb, it will not occur in any pair.

5.1.2 Layout, Display and Predictions

The computation analyses I have described above will be applied separately to each experimental measure of each past type of each past class. For example, they will be applied to the true irregulars as measured by acceptability ratings in the All-Verbs study, to the over-regulars (of true irregulars) as measured by acceptability ratings in the All-Verbs study, to the true regulars as measured by production time in the Reaction Time study, and so on.

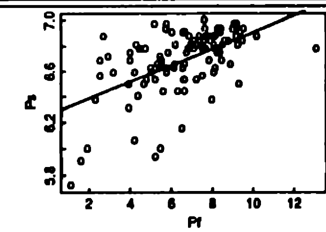
Predictiveness of Past Tense Frequency(*blew*)
on Past Tense Success(*blew*) as accept. ratings (1-7)
under Rule and Associative Theories for True Irregulars from All-Verbs Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

\+ $r(102) = 0.49$ $p < 0.001$ (F.K.)

\+ $r(102) = 0.54$ $p < 0.001$ (A.P.) ⟶

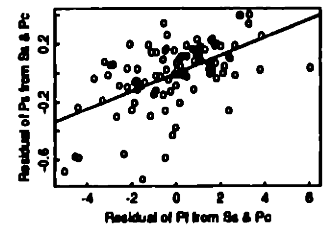


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

\+ $r(100) = 0.53$ $p < 0.001$ (F.K., Stem-Past)

\+ $r(100) = 0.56$ $p < 0.001$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

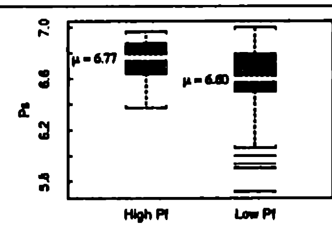
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

\+ $t(51) = 2.47$ $p = 0.017$ (F.K.)

\+ $t(51) = 3.86$ $p < 0.001$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 4/4 (100%)
Predictive power of Past Tense Frequency under Rule Theory = 0/4 (0%)

Table 5.1: All-Verbs Study: acceptability ratings for true irregulars

For each such past type and experimental measure the analyses will be displayed in separate Analysis Tables for each of the three predictor variables Stem Strength, Past Tense Frequency and Past Tense Cluster Strength. Table 5.1 shows a sample Analysis Table. Each Analysis Table has a cell for each of the 6 types of analysis. Each cell contains the results from each analysis, the predicted outcome for the analysis according to the theory or theories being tested, and a graphical display of the analysis (see page 85 for a more detailed description, and Table 5.1 for an example).

Graphs displaying simple correlations show a scatterplot of the two variables, while those displaying partial correlations show a scatterplot of the two residuals. The scatterplots of both simple correlations and partial correlations have least mean squares fit lines drawn in them. For the t-test, the accompanying graph displays two box plots, one for each variable. The left box plot represents the high-value variable, while the right box plot represents the low-value variable. [5] For example, with matched Stem Strength's and differing Past Tense Frequency's, the the box plot representing Past Tense Success values for verbs with high Past Tense Frequency's is on the left, while the box plot representing Past Tense Success values for verbs with low Past Tense Frequency's is on the right.

Table 5.2 is a combination of the three Stem Strength, Past Tense Frequency and Past Tense Cluster Strength predictor variable Analysis Tables: the first column represents the Stem Strength Analysis Table, the second column the Past Tense Frequency Analysis Table, and the third column the Past Tense Cluster Strength Analysis Table.

The predictions of Past Tense Success for each analysis type, according to the rule and associative theories, are layed out in Table 5.2. The prediction (Predictive, Not Predictive, Likely Not Predictive, No Prediction) for each theory for a given analysis makes a claim about the statistically significant predictive ability of the predictor variable of that column in that analysis. The direction ($+$, $-$) indicates the possible directions of the prediction. These directions depend on the nature of Stem Strengthand Past Tense Success: the direction is usually positive because most measures (acceptability ratings and production likelihood) produce higher values for more successfully computed stems or pasts; but the measure of production time (as acquired by stem reading time or past generation time) produces values which *decrease* as computational success increases, thereby producing statistics for many analyses which produced positive statistics for the other two measures.

I now explain these predictions in the order of the three columns which represent the three predictors Stem Strength, Past Tense Frequency and Past Tense Cluster Strength.

Stem Strength: According to the rule theory Stem Strength should predict Past Tense Suc-

[5] Each box plot shows various information: the horizontal line in the box is located at the mean; the height of the entire box is equal to the interquartile distance, which is the difference between the first and third quartiles; the whiskers (the dotted lines extending from the top and bottom of the box) extend to the extreme values of the variable's values or a distance 1.5 times the interquartile distance, whichever is less; points outside the whiskers are denoted by short horizontal lines.

Analysis Tables for Stem Strength, Past Tense Frequencyand Past Tense Cluster Strength

With Predictions for Rule and Associative Theories

Stem Strength	Past Tense Frequency	Past Tense Cluster Strength
$r_{S_sP_s}$ Rule: Predictive $(+,-)$ Asso: No Prediction	$r_{P_fP_s}$ Rule: No Prediction Asso: Predictive $(+,-)$	$r_{P_cP_s}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$
$r_{P_sS_s.P_fP_c}$	$r_{P_sP_f.S_sP_c}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$	$r_{P_sP_c.S_sP_f}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$
$r_{P_sS_s.P_s'}$ Rule: Predictive $(+,-)$ Asso: Likely Not Predictive	$r_{P_sP_f.P_s'}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$	$r_{P_sP_c.P_s'}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$
$r_{P_sS_s.P_f'P_c'}$ Rule: Predictive $(+,-)$ Asso: No Prediction	$r_{P_sP_f.P_f'P_c'}$ Rule: No Prediction Asso: Predictive $(+,-)$	$r_{P_sP_c.P_f'P_c'}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$
$r_{P_sS_s.P_fP_cP_f'P_c'}$ Rule: Predictive $(+,-)$ Asso: Likely Not Predictive	$r_{P_sP_f.S_sP_cP_f'P_c'}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$	$r_{P_sS_s.P_fP_cP_f'P_c'}$ Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$
match Pf, diff Ss Rule: Predictive $(+,-)$ Asso: Likely Not Predictive	*match Ss, diff Pf* Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$	*match Ss, diff Pc* Rule: Not Predictive (not+,not−) Asso: Predictive $(+,-)$

Table 5.2: Analysis Tables for Stem Strength, Past Tense Frequency and Past Tense Cluster Strength with predictions for the rule and associative theories

cess no matter which other independent variables are held constant. According to the associative theory, however, the predictive power of Stem Strength is uncertain: as described on page 88, while Stem Strength should *not* be an excellent predictor of Past Tense Success because they are not intimately connected, there are three looser connections which could result in a successful prediction. One of these connections occurs *through* Past Tense Frequency: Stem Strength is correlated with Stem Frequency, which is correlated with Past Tense Frequency, which is correlated with Past Tense Success under the associative theory. Thus this path of influence should be eliminated if Past Tense Frequency is held constant — and therefore those analyses holding Past Tense Frequency constant are likely to be not preditive. However, because the other two possible pathways of influence are not eliminated, these analyses could still be predictive. On the other hand, those analyses in which Past Tense Frequency is *not* held constant have completely uncertain predictions — though all three looser connections between Stem Strength and Past Tense Success are present, the lack of a direct connection decreases the likelyhood of Stem Strength successfully predicting Past Tense Success.

Past Tense Frequency: According to my associative theories Past Tense Frequency should predict Past Tense Successno matter which other independent variables are held constant. According to the rule theory, however, Past Tense Frequency should not predict Past Tense Success when Stem Strength is held constant — because the only two ways in which Past Tense Frequency can predict Past Tense Success are through Stem Strength (see page 88). Therefore the rule theory expects Past Tense Frequency predictor analyses in which Stem Strength is held constant to be not predictive. However, if Stem Strength is *not* held constant, the outcome according to the rule theory is uncertain because Past Tense Frequency could predict Past Tense Success through Stem Strength.

Past Tense Cluster Strength: According to the associative theory Past Tense Cluster Strength should predict Past Tense Successno matter which other independent variables are held constant — this effect should be especially strong for past forms which have lower or zero past frequencies, such as infrequent irregular pasts or nonce irregular pasts. However, according to the rule theory Past Tense Cluster Strength should *never* predict Past Tense Success, no matter which other independent variables are or are not held constant. Because Past Tense Cluster Strength should in no way be related to Stem Strength, it should not matter whether or not Stem Strength is held constant.

The predictions in each cell shown in Table 5.2 will not be displayed in the actual Analysis Tables in the results chapters. However, at the base of each Analysis Table there will be displayed two analysis summary values — one for the Stem-Past associative theory and one for the rule theory. Each of these values summarizes the results from all analyses in that Analysis Table — according to the predictions of the theory with which the value is associated. The analysis summary value for each theory is calculated as the ratio (and percentage) of all analyses which meet the predictions of that theory (as shown out in Table 5.2). Only strong predictions (Predictive, Not Predictive) are counted; weak predictions (Likely Not Predictive, No Prediction) are not counted in either the numerator or denominator of the ratio. Where a theory claims that a predictor variable should be predictive in a given analysis, the numerator of the ratio is incremented for that analysis if its statistic (r, t, etc.) has the predicted sign *and* it is significant at or below the .05 level (i.e., $p <= .05$). Where a theory claims that a predictor variable should not be predictive in a given analysis, the numerator of the ratio is incremented for a given analysis if the statistic does not have the predicted sign *or* it is not significant at or below the .05 level.

5.2 Blocking

There are two sorts of analyses related to blocking. First, those that show that blocking exists between one type of past form (Past Tense Success) and an alternative past form (Altern. Past Tense Success). These analyses test the hypothesis that there is a inverse relationship between Altern. Past Tense Success and Past Tense Success — the higher the value of one, the lower the value of the other. For example, to investigate whether over-regulars (*blowed*) are being blocked by their corresponding irregulars (*blew*), I examine the inverse relationship between them.

The second type of analysis related to blocking examines the mechanisms of blocking by testing the Associative Computational Blocking theory. This theory claims that the blocking of a past form whose value is measured by Past Tense Success is an inverse function of the associative predictors Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength — because blocking is a function of the representational strength of the alternative past form as measured by Altern. Past Tense Success; it is this associatively computed alternative form which blocks the past form being measured by Past Tense Success. For example, to test whether over-regulars (*blowed*) are being blocked by the associative computational strength of their corresponding irregular pasts (*blew*), I test for an inverse relationship between the over-regulars (*blowed*) and Altern. Past Tense Frequency (e.g., frequency of *blew*) or Altern. Past Tense Cluster Strength (a function of the frequency of *threw* and *grew*) of over-regulars.

5.2.1 Types of Analyses

To reveal whether blocking is taking place between one type of past form (Past Tense Success) and an alternative form (Altern. Past Tense Success), I apply simple correlations as well as partial correlations in which one or more other independent variables (Stem Strength, Past Tense Frequency, Past Tense Cluster Strength) are held constant. If there is blocking going on there should be statistically significant negative correlations in all cases — even when Stem Strength, Past Tense Frequency or Past Tense Cluster Strength are held constant because according to my theory the computation or representation of the associatively computed alternative form Altern. Past Tense Success blocks the past form Past Tense Success irrespective of the mechanisms involved in the computation of Past Tense Success.

To reveal the computational mechanisms underlying blocking I apply the exact same set of analyses that I applied to reveal whether blocking is taking place, but with either Altern. Past Tense Frequency or Altern. Past Tense Cluster Strength instead of Altern. Past Tense Success. Because the blocking theory claims that the blocking of a past form Past Tense Success is an inverse function of the computational success of associatively computed alternative forms, any factors contributing to the success of these alternatives should correlate negatively with Past Tense Success. Therefore if I find blocking between Altern. Past Tense Success and Past Tense Success *and* if Altern. Past Tense Success is associatively computed, then Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength should correlate negatively with Past Tense Success.

In both the analyses revealing blocking and those testing the predictive influence of Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength, there are partial correlations in which Stem Strength, Past Tense Frequency, and Past Tense Cluster Strength are held constant. There three reasons for which want to hold Stem Strength, Past Tense Frequency and Past Tense Cluster Strength constant. First, the blocking theory claims that blocking is independent from the effects of these three variables on Past Tense Success. therefore even one or more of these variables are factored out, blocking will still occur — that is, Altern. Past Tense Success, Altern. Past Tense Frequency or Altern. Past Tense Cluster Strength will still predict Past Tense Success. Second, when I remove the variation Stem Strength, Past Tense Frequency and Past Tense Cluster Strength account for, I will be able to detect the amount of variation accounted for by Altern. Past Tense Success, Altern. Past Tense Frequency or Altern. Past Tense Cluster Strength. Third, I also want to eliminate any effects of Stem Strength, Past Tense Frequency, and Past Tense Cluster Strength on Altern. Past Tense Success, Altern. Past Tense Frequency, and Altern. Past Tense Cluster Strength to ensure that the former does not account for any of the latter's ability to predict Past Tense Success.

Indeed, there are at least two possible paths of influence from Stem Strength, Past Tense Frequency and Past Tense Cluster Strength to Altern. Past Tense Success, Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength. First, since Altern. Past Tense Success is an associative alternative past of the same verb from which Past Tense Success is produced, Stem Strength could influence Altern. Past Tense Success in one or more of the three ways in which Stem Strength can influence an associative past (see page 88).

Second, Stem Strength could be correlated with Altern. Past Tense Frequency because of the underlying correlations between Stem Strength and Altern. Stem Frequency(which is the same thing as Stem Frequency), and Altern. Stem Frequency and Altern. Stem Frequency and Altern. Past Tense Frequency.

In addition to the partial correlations in which the Stem Strength, Past Tense Frequency and Past Tense Cluster Strength are held constant, there is a partial correlation in which either Altern. Past Tense Cluster Strength or Altern. Past Tense Frequency are held constant. In the last row of each Altern. Past Tense Frequency Blocking Analysis Table I perform the partial correlation $r_{PsPf'.Pc'}$, while in the last row of each Altern. Past Tense Cluster Strength Blocking Analysis Table I perform the partial correlation $r_{PsPc'.Pf'}$. The purpose of these analyses is to reveal the relative predictive power of Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength.

5.2.2 Layout, Display and Predictions

The computation analyses I have described above will be applied separately to each experimental measure of each verb class. For example, they will applied to over-regularizations (of true irregulars) as measured by acceptability ratings in the All-Verbs study; to over-irregularizations (*glide-glid*) as measured by production likelihood in the All-Classes study, and so on.

For each such past type and experimental measure the analyses will be displayed in separate Analysis Tables for each of the three predictor variables Altern. Past Tense Success, Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength. Each Blocking Analysis Table has a row for each of the 6 types of analysis. The results and graphs for each analysis are displayed in exactly the same manner as in the Computation Analysis Tables: The results from each analysis are towards the left side of each row. Towards the right side of each row is a graph representing the analysis. For simple correlations (e.g., $r_{Pf'Ps}$) the analysis result contains the r and p values, while the accompanying graph is a scatterplot between the independent variable (Altern. Past Tense Frequency) and the dependent variable Past Tense Success. For partial correlations the analysis result contains the r and p values, while the accompanying graph is a scatterplot of the two residuals. The scatterplots of both simple correlations and partial correlations have least mean squares fit lines drawn in them.

Just as in the Computation Analysis Tables, each analysis type in a given row of the Blocking Analysis table consists of more than one actual analysis — because there are more than one word frequency scaling or cluster strength functions and more than one frequency count. Because there is only one graph per analysis type (per row), in rows with several actual analyses the data from only one analysis is displayed in the graph. For analyses involving Past Tense Frequency I have selected those analyses using the Associated Press counts, and

Analysis Tables for Altern. Past Tense Success Altern. Past Tense Frequencyand Altern. Past Tense Cluster Strength With predictions for associative blocking		
Altern. Past Tense Success	Altern. Past Tense Frequency	Altern. Past Tense Cluster Strength
$r_{Ps'Ps}$ Predictive $(-)$	$r_{Pf'Ps}$ Predictive $(-,+)$	$r_{Pc'Ps}$ Predictive $(+,-)$
$r_{PsPs'.Ss}$ Predictive $(-)$	$r_{PsPf'.Ss}$ Predictive $(-,+)$	$r_{PsPc'.Ss}$ Predictive $(+,-)$
$r_{PsPs'.Pf}$ Predictive $(-)$	$r_{PsPf'.Pf}$ Predictive $(-,+)$	$r_{PsPc'.Pf}$ Predictive $(+,-)$
$r_{PsPs'.PfPc}$ Predictive $(-)$	$r_{PsPf'.PfPc}$ Predictive $(-,+)$	$r_{PsPc'.PfPc}$ Predictive $(+,-)$
$r_{PsPs'.SsPfPc}$ Predictive $(-)$	$r_{PsPf'.SsPfPc}$ Predictive $(-,+)$	$r_{PsPc'.SsPfPc}$ Predictive $(+,-)$
NA Predictive $(-)$	$r_{PsPf'.Pc'}$ Predictive $(-,+)$	$r_{PsPc'.Pf'}$ Predictive $(+,-)$

Table 5.3: Analysis Tables for Altern. Past Tense Success, Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength

for analyses involving Past Tense Cluster Strength, I have selected those analyses using the complex cluster strength function rather than the simple cluster strength function. [6]

Table 5.3 is a combination of the three Altern. Past Tense Success, Altern. Past Tense Frequency and Altern. Past Tense Cluster Strength independent variable Analysis Tables: the first column represents the Altern. Past Tense Success Analysis Table, the second column the Altern. Past Tense Frequency Analysis Table, and the third column the Altern. Past Tense Cluster Strength Analysis Table. The prediction in each cell makes a claim about the statistically significant predicitive ability of the predictor variable of that column in that analysis. The predictions in each cell shown in Table 5.3 will not be displayed in the actual Analysis Tables in the results chapters. However, at the base of each Analysis Table there will be displayed two analysis summary values — one for the rule theory, the other for the associative theory. Each of these values summarizes the results from all analyses in that Analysis Table according to the predictions of the blocking theory. The analysis summary value for each theory is calculated as the ratio (and percentage) of all analyses which meet the predictions of the blocking theory (as shown out in Table 5.3). The numerator of the ratio is incremented for a given analysis if its statistic (r, t, etc.) has the predicted sign *and* it is significant at or below the .05 level (i.e., $p <= .05$).

[6] See page 86 for an explanation of my choice of Associated Press over Francis and Kučera, and complex over simple cluster strengths.

Part II

Results and Discussion

Chapter 6

True Regulars and True Irregulars

6.1 The Predictiveness of Past Tense Frequency (Pf) (*blew, walked*)

6.1.1 True Irregulars (*blew*)

If irregular pasts (*blew*) are associatively retrieved from their stems (*blow*), the more frequent the past tense form (*blew*), the more successfully it should be retrieved. That is, Past Tense Frequency (Pf) should predict Past Tense Success(Ps). In this case the second and last cells of the Display Tables should show analyses revealing the significance of these predictions, with Stem Strength held constant.

However, if irregular pasts are produced by a symbol-processing system, there should be no such past tense frequency effects. In this case the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Stem Strength held constant.

Predictiveness of Past Tense Frequency(*blew*)

on Past Tense Success(*blew*) as accept. ratings (1-7)

under Rule and Associative Theories for True Irregulars from All-Verbs Study

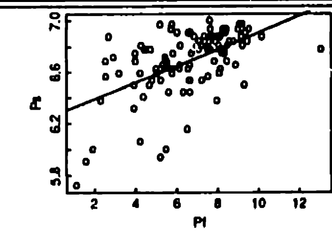
---

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

+ $r(102) = 0.49$ $p < 0.001$ (F.K.)

+ $r(102) = 0.54$ $p < 0.001$ (A.P.) ⟶



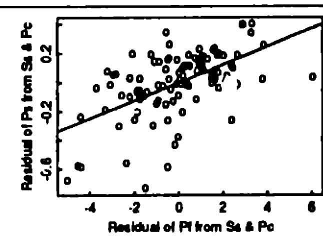
---

partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

+ $r(100) = 0.53$ $p < 0.001$ (F.K., Stem-Past)

+ $r(100) = 0.56$ $p < 0.001$ (A.P., Stem-Past) ⟶



---

partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

---

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

---

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

NA

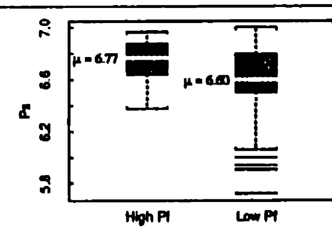
---

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

+ $t(51) = 2.47$ $p = 0.017$ (F.K.)

+ $t(51) = 3.86$ $p < 0.001$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 4/4 (100%)

Predictive power of Past Tense Frequency under Rule Theory = 0/4 (0%)

Table 6.1: All-Verbs Study: acceptability ratings for true irregulars

Predictiveness of Past Tense Frequency(*blew*)

on Past Tense Success(*blew*) as accept. ratings (1-10)

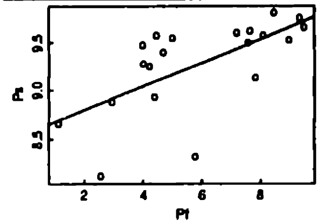
under Rule and Associative Theories for True Irregulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

+ $r(18) = 0.73$ $p < 0.001$ (F.K.)

+ $r(18) = 0.65$ $p = 0.002$ (A.P.) ⟶

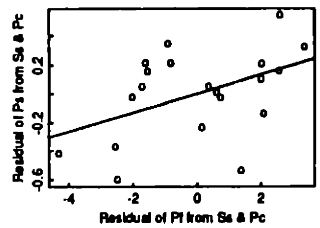


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

+ $r(16) = 0.52$ $p = 0.026$ (F.K., Stem-Past)

not+ $r(16) = 0.46$ $p = 0.056$ (A.P., Stem-Past) ⟶



partialing out *Ps′*: $r_{PsPf.Ps'}$

NA

partialing out *Pf′*, *Pc′*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf′*, *Pc′*: $r_{PsPf.SsPcPf'Pc'}$

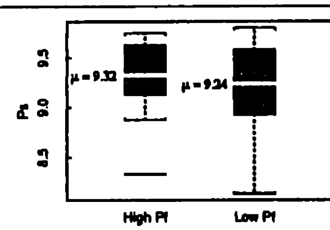
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.76$ $p = 0.112$ (F.K.)

not+ $t(9) = 0.51$ $p = 0.624$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 1/4 (25%)

Predictive power of Past Tense Frequency under Rule Theory = 3/4 (75%)

Table 6.2: All-Classes Study: acceptability ratings for true irregulars

Predictiveness of Past Tense Frequency(*blew*)

on Past Tense Success(*blew*) as prod. like. (% subjs)

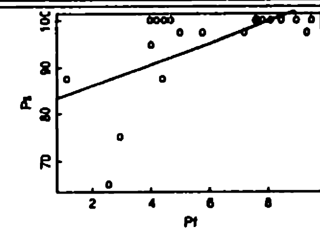
under Rule and Associative Theories for True Irregulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

+ $r(18) = 0.56$ $p = 0.010$ (F.K.)

+ $r(18) = 0.60$ $p = 0.005$ (A.P.) ⟶

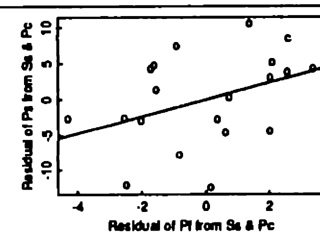


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(16) = 0.22$ $p = 0.386$ (F.K., Stem-Past)

not+ $r(16) = 0.39$ $p = 0.112$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

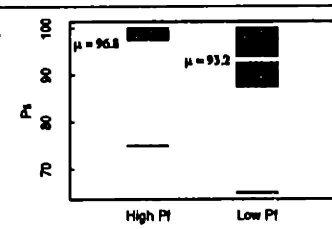
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.95$ $p = 0.084$ (F.K.)

not+ $t(9) = 0.88$ $p = 0.402$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)

Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

Table 6.3: All-Classes Study: production likelihood for true irregulars

Predictiveness of Past Tense Frequency(*blew*)

on Past Tense Success(*blew*) as prod. like. (% subjs)

under Rule and Associative Theories for True Irregulars from Reaction Time Study

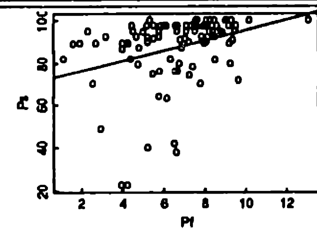
---

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

\+ $r(94) = 0.37$ $p < 0.001$ (F.K.)

\+ $r(94) = 0.31$ $p = 0.002$ (A.P.) $\longrightarrow$



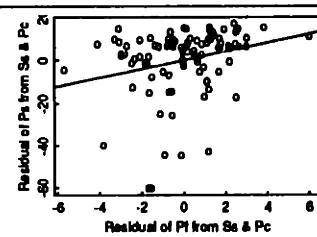
---

partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

\+ $r(92) = 0.31$ $p = 0.002$ (F.K., Stem-Past)

\+ $r(92) = 0.25$ $p = 0.016$ (A.P., Stem-Past) $\longrightarrow$



---

partialing out *Ps′*: $r_{PsPf.Ps'}$

NA

---

partialing out *Pf′*, *Pc′*: $r_{PsPf.Pf'Pc'}$

NA

---

partialing out *Ss*, *Pc*, *Pf′*, *Pc′*: $r_{PsPf.SsPcPf'Pc'}$

NA

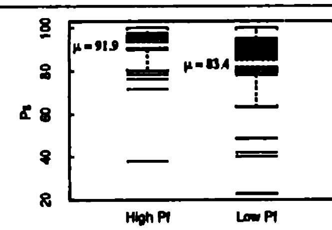
---

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(47) = 1.66$ $p = 0.104$ (F.K.)

\+ $t(47) = 2.52$ $p = 0.015$ (A.P.) $\longrightarrow$



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 3/4 (75%)

Predictive power of Past Tense Frequency under Rule Theory = 1/4 (25%)

Table 6.4: Reaction Time Study: production likelihood for true irregulars

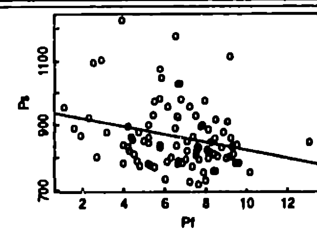
Predictiveness of Past Tense Frequency(*blew*)
on Past Tense Success(*blew*) as generation time (ms)
under Rule and Associative Theories for True Irregulars from Reaction Time Study

by a simple correlation: r_{PfPs}

R:none A: – (prediction)

– $r(94) = -0.31$ $p = 0.002$ (F.K.)

– $r(94) = -0.26$ $p = 0.010$ (A.P.) ⟶

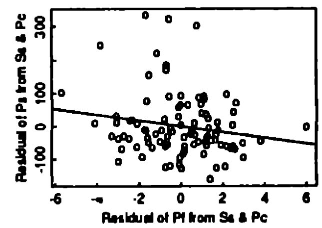


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not– A: – (prediction)

– $r(92) = -0.21$ $p = 0.038$ (F.K., Stem-Past)

not– $r(92) = -0.18$ $p = 0.086$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

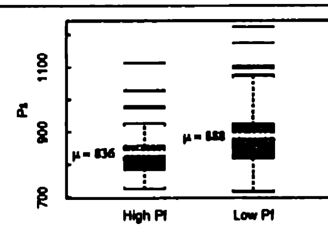
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*),
given similar *Ss* values for each *Ps* pair

R:not– A: – (prediction)

– $t(47) = -2.82$ $p = 0.007$ (F.K.)

– $t(47) = -2.71$ $p = 0.009$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 3/4 (75%)
Predictive power of Past Tense Frequency under Rule Theory = 1/4 (25%)

Table 6.5: Reaction Time Study: production time for true irregulars

6.1.2 True Regulars (*walked*)

If regular pasts (*walked*) are associatively retrieved from their stems (*walk*), the more frequent the past tense form (*walked*), the more successfully it should be retrieved. That is, Past Tense Frequency should predict Past Tense Success. In this case the second and last cells of the Display Tables should show analyses revealing the significance of these predictions, with Stem Strength held constant.

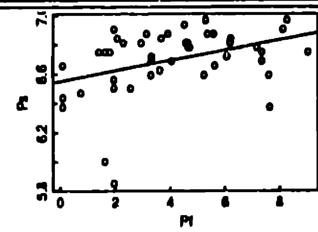
However, if regular pasts are produced by a symbol-processing system, there should be no such past tense frequency effects. In this case the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Stem Strength held constant.

Predictiveness of Past Tense Frequency(*walked*)
on Past Tense Success(*walked*) as accept. ratings (1-7)
under Rule and Associative Theories for True Regulars from All-Verbs Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

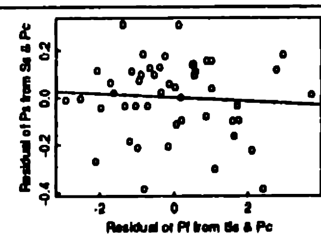
not+ $r(46) = 0.16$ $p = 0.274$ (F.K.)
\+ $r(46) = 0.37$ $p = 0.009$ (A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(44) = -0.22$ $p = 0.144$ (F.K., Stem-Past)
not+ $r(44) = -0.07$ $p = 0.625$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

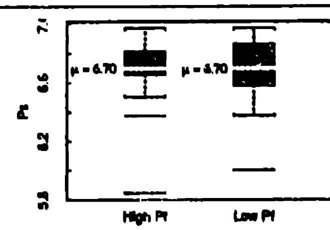
partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(23) = 1.31$ $p = 0.205$ (F.K.)
not+ $t(23) = 0.08$ $p = 0.938$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

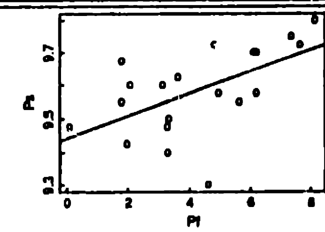
Table 6.6: All-Verbs Study: acceptability ratings for true regulars

Predictiveness of Past Tense Frequency(*walked*)
on Past Tense Success(*walked*) as accept. ratings (1-10)
under Rule and Associative Theories for True Regulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

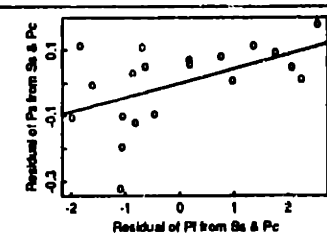
+	$r(18) = 0.50$	$p = 0.026$	(F.K.)
+	$r(18) = 0.57$	$p = 0.009$	(A.P.) ⟶



partialing out Ss, Pc: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+	$r(16) = 0.38$	$p = 0.123$	(F.K., Stem-Past)
+	$r(16) = 0.51$	$p = 0.032$	(A.P., Stem-Past) ⟶



partialing out Ps': $r_{PsPf.Ps'}$

NA

partialing out Pf', Pc': $r_{PsPf.Pf'Pc'}$

NA

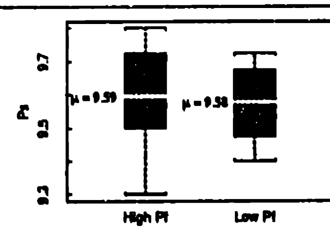
partialing out Ss, Pc, Pf', Pc': $r_{PsPf.SsPcPf'Pc'}$

NA

by a t-test comparing (Ps with high-Pf) with (Ps with low-Pf),
given similar Ss values for each Ps pair

R:not+ A: + (prediction)

not+	$t(9) = 0.68$	$p = 0.513$	(F.K.)
not+	$t(9) = 0.44$	$p = 0.669$	(A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 1/4 (25%)
Predictive power of Past Tense Frequency under Rule Theory = 3/4 (75%)

Table 6.7: All-Classes Study: acceptability ratings for true regulars

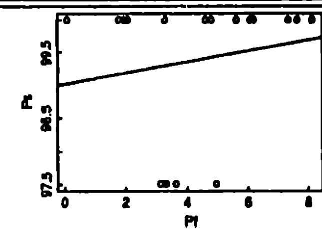
Predictiveness of Past Tense Frequency(*walked*)
on Past Tense Success(*walked*) as prod. like. (% subjs)
under Rule and Associative Theories for True Regulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

not+ $r(18) = 0.38$ $p = 0.096$ (F.K.)

not+ $r(18) = 0.17$ $p = 0.477$ (A.P.) ⟶

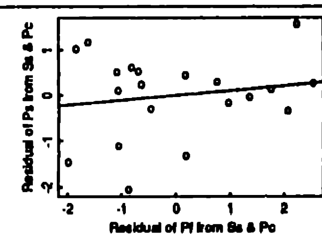


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(16) = 0.29$ $p = 0.247$ (F.K., Stem-Past)

not+ $r(16) = 0.17$ $p = 0.508$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

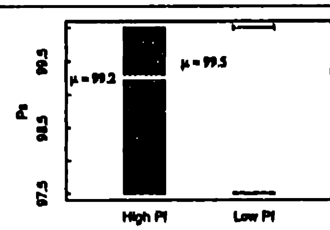
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 0.56$ $p = 0.591$ (F.K.)

not+ $t(9) = -0.43$ $p = 0.678$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

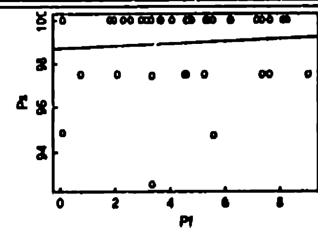
Table 6.8: All-Classes Study: production likelihood for true regulars

Predictiveness of Past Tense Frequency(*walked*)
on Past Tense Success(*walked*) as prod. like. (% subjs)
under Rule and Associative Theories for True Regulars from Reaction Time Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

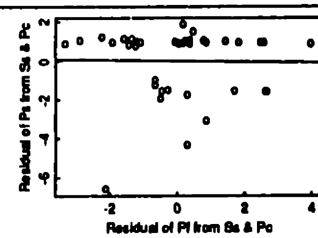
not+ $r(37) = 0.12$ $p = 0.456$ (F.K.)
not+ $r(37) = 0.08$ $p = 0.647$ (A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(35) = 0.02$ $p = 0.909$ (F.K., Stem-Past)
not+ $r(35) = -0.02$ $p = 0.910$ (A.P., Stem-Past) ⟶



partialing out *Ps′*: $r_{PsPf.Ps'}$

NA

partialing out *Pf′*, *Pc′*: $r_{PsPf.Pf'Pc'}$

NA

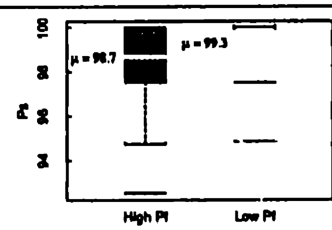
partialing out *Ss*, *Pc*, *Pf′*, *Pc′*: $r_{PsPf.SsPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(18) = -0.22$ $p = 0.828$ (F.K.)
not+ $t(18) = -1.00$ $p = 0.329$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

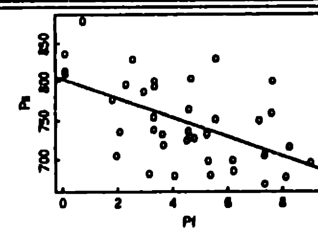
Table 6.9: Reaction Time Study: production likelihood for true regulars

Predictiveness of Past Tense Frequency(*walked*)
on Past Tense Success(*walked*) as generation time (ms)
under Rule and Associative Theories for True Regulars from Reaction Time Study

by a simple correlation: r_{PfPs}

R:none A: – (prediction)

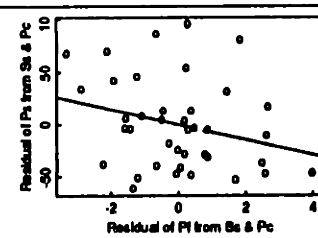
–	$r(37) = -0.46$	$p = 0.003$	(F.K.)
–	$r(37) = -0.55$	$p < 0.001$	(A.P.) $\longrightarrow$



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not– A: – (prediction)

not–	$r(35) = -0.17$	$p = 0.307$	(F.K., Stem-Past)
not–	$r(35) = -0.28$	$p = 0.099$	(A.P., Stem-Past) $\longrightarrow$



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

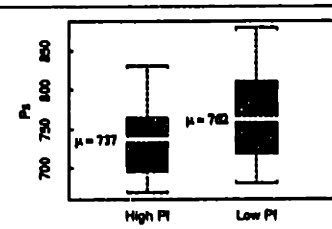
partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not– A: – (prediction)

not–	$t(18) = -0.55$	$p = 0.590$	(F.K.)
not–	$t(18) = -1.54$	$p = 0.141$	(A.P.) $\longrightarrow$



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

Table 6.10: Reaction Time Study: production time for true regulars

6.1.3 Discussion

The results showed that Past Tense Frequency predicts Past Tense Success for true irregulars, while for true regulars Past Tense Frequency predicts Past Tense Success extremely weakly, if at all.

Acceptability Ratings from All-Verbs Study:

For true irregulars I found that Past Tense Frequency was an extremely strong predictor of Past Tense Success for acceptability ratings from the All-Verbs study (Table 6.1). All four analyses in which Stem Strength were held constant were highly significant with the statistic (t or r for the t-tests or partial correlations, respectively) in the expected direction.

For true regulars Past Tense Frequency did not predict Past Tense Success at all (Table 6.6): all four analyses in which Stem Strength was held constant were non significant. Furthermore, both the correlation coefficients were in the *opposite* direction (negative) from that expected if Past Tense Frequency were indeed predictive.

Before concluding that this difference in predictiveness between true irregulars and true regulars is due to differences in their computational systems, we must first examine two alternative explanations: the difference could be caused by a smaller verb sample size for true regulars (48 verbs for true regulars versus 105 for true irregulars), or by a smaller Past Tense Frequency range for true regulars (maximum of 9.04 versus maximum of 13.07 after applying the log transform to the Associated Press frequency counts). To test the predictive power of Past Tense Frequency for true irregulars under *both* of these conditions, I randomly selected 48 true irregulars whose pasts were less frequent than 9.04, and applied the same analyses as before. I found that in these circumstances Past Tense Frequency is also a strong predictor, even if slightly less strong than with the full data set: although both partial correlations holding Stem Strength and Stem-Past Past Tense Cluster Strength were statistically significant in the expected direction, the two t-tests were not significant, even though their t-values were in the expected direction.

Acceptability Ratings from All-Classes Study:

For true irregulars I found that Past Tense Frequency was a moderately good predictor of Past Tense Success for acceptability ratings from the All-Classes study (Table 6.2). Both partial correlations holding Stem Strength and Stem-Past Past Tense Cluster Strength constant were significant (Francis and Kučera: r=.52, p=.026) or borderline significant (Associated Press: r=.46, p=.056) in the expected direction. In addition, one of the t-tests holding Stem Strength constant was close to significance (p=.11). [1]

It is also noteworthy that the two significant or borderline significant partial correlations

[1] I will treat all p values close to .1 as borderline significant because I make strong predictions about the direction of the statistic, and thus could justify using one-tailed analyses.

and the near-significant t-test are all based on Francis and Kučera frequencies. This led me to examine the Associated Press data set; I found on examination of the graphs (in particular, the box-plot, where the reader can see the outlier), that one verb stands out as an outlier: *split-split.* Compared to the Francis and Kučera frequencies, it seems to have an inflated count for the past form *split.* Since the Associated Press frequencies have a more biased origin than the Francis and Kučera frequencies, it is possible that the past form of *split* has a high count because of a somewhat anomalous news usage. When I ran the same analyses after eliminating *split*, I found that both partial correlations with the Associated Press frequencies were highly significant in the expected direction, while its t-test was now similar to that of the Francis and Kučera based t-test.

For true regulars Past Tense Frequency is a somewhat weaker predictor (Table 6.7). All four analyses were in the expected direction. One of the two partial correlations holding Stem Strength and Stem-Past Past Tense Cluster Strength constant was significant (r=.51, p=.032), while the other was not too far from significance (r=.38, p=.123). Crucially, however, neither of the t-tests even approaches significance (unlike the true irregulars). Furthermore, as the reader can see on the box-plot, there are no obvious outliers whose inflated or deflated frequencies could be causing the lack of significance for either the partial correlations or the t-tests.

Production Likelihood from All-Classes Study:

Analyses from untimed and unpressured production likelihood measures, as here in the All-Classes study, must be interpreted with great care because of strong ceiling effects: For existing stems and pasts such as true irregulars and true regulars, most if not all subjects will tend to produce the correct past form. Therefore there is often not enough variance for a valid analysis. This is patently obvious for the true regulars in the All-Classes study. Of the 20 true regular verbs presented to the 40 subjects, all subjects produced the correct pasts of 15 verbs, while the remaining 5 verbs garnered incorrect pasts from only 1 subject each. As a result, I will not interpret the analyses carried out on production likelihood from the All-Classes task for true regulars (Table 6.8).

While the true irregulars for this task suffer from a similar problem, it is not quite as bad (Table 6.3). Of the 20 true irregulars verbs, only 11 resulted in all correct responses. Thus, although we must interpret the results with caution, we might glean some information from analyses of this data. These analyses show that Past Tense Frequency is a weak predictor of Past Tense Success: The statistics of the two partial correlations and two t-tests are all in the expected direction; of these four analyses one partial correlation (r=.39, p=.112) and one t-test (r=1.95, p=.084) approached significance.

Production Likelihood from Reaction Time Study:

The timed reaction time task is more pressured than the All-Classes production task, and therefore there should be more errors. However, while there are clearly enough errors for true irregulars to warrant interpreting their analyses, this is still not the case for true regulars (see Table 6.9): of the 39 true regular verbs, 27 had no errors and 9 had one error, leaving only 3 verbs with more than 1 error. Thus I will not interpret any of the analyses for true regulars.

True irregular pasts, on the other hand, show very strong evidence of being predicted by Past Tense Frequency (Table 6.4): Both of the partial correlations were significant and in the expected direction, as is one of the two t-tests, with the other t-test approaching significance in the expected direction.

Production Time from Reaction Time Study:

True irregulars show a very strong effect of Past Tense Frequency for the production time measure from the Reaction Time study (Table 6.5): All six analyses (the four analyses shown in the Analysis Table in addition to two partial correlations holding only Stem Strength, and not Past Tense Cluster Strength, constant) were in the expected direction; five of them were significant, while one was borderline significant. Crucially, the two t-tests were both *highly* significant and in the expected direction (Associated Press: t=-2.71, p=.009; Francis and Kučera: t=-2.82, p=.0071), as were the two partial correlations holding only Stem Strength constant (Associated Press: r=-.20, p=.05; Francis and Kučera:-.26, p=.011), and one of the two partial correlations holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant (Francis and Kučera:r=-.21, p=.038), while the other one was borderline significant (Francis and Kučera:r=-.18, p=.086).

True regulars showed a much weaker effect of Past Tense Frequency. Although all six analyses were in the expected direction, only one of the six was significant (the partial correlation with Associated Press Past Tense Frequency predictor, holding only Stem Strength constant: r=-.37, p=.02). The Francis and Kučera predicting partial correlation holding only Stem Strength constant had r=-.25, p=.13, while the two partial correlations holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant were as follows: Associated Press: r=-.28, p=.099; Francis and Kučera: r=-.17, p=.307. Crucially the two t-tests were also non-significant — Associated Press: t=-1.54, p=.14; Francis and Kučera: t=-.55, p=.59).

As with the All-Verbs study, one could argue that the difference in effects between true irregulars and true regulars is due to the larger sample size or greater frequency range of the true irregulars. To test this hypothesis I selected from the true irregular verbs a random subset of the same sample size as the true regulars (39 verbs) with the same frequency range (less than 9.04 by the Associated Press frequency after the log transform). The same 6 analyses yielded slightly weaker but still strong results: All six of the analyses were in the expected direction, and two of the partial correlations and one of the t-tests were highly significant.

6.2 The Predictiveness of Past Tense Cluster Strength(Pc)

6.2.1 True Irregulars (*threw, grew*)

If irregular pasts (*blew*) are associatively retrieved from their stems (*blow*), the presentation of other irregular pasts (*throw-threw*) whose stem-past mappings are shared with those of *blow-blew* should facilitate the latter's computation. That is, irregular cluster strength (*threw, grew*) should predict Past Tense Success (*blew*). In this case the second and last cells of the Display Tables should show analyses revealing the significance of these predictions, with Past Tense Frequency (*blew*) or Stem Strength (*blow*) held constant.

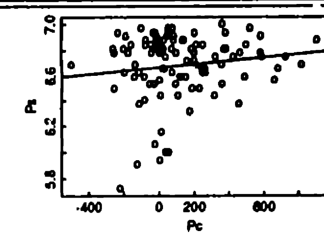
However, if irregular pasts are produced by a symbol-processing system, there should be no such irregular cluster strength effects. In this case the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Past Tense Frequency or Stem Strength held constant.

Predictiveness of Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blew*) as accept. ratings (1-7)
under Rule and Associative Theories for True Irregulars from All-Verbs Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

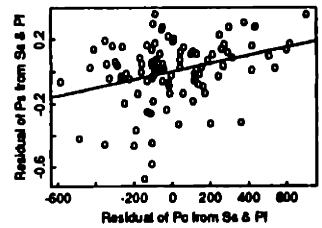
not+ $r(102) = 0.10$ $p = 0.316$ (F.K., Stem-Past)
not+ $r(102) = 0.13$ $p = 0.180$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

\+ $r(100) = 0.35$ $p < 0.001$ (F.K., Stem-Past)
\+ $r(100) = 0.31$ $p = 0.001$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

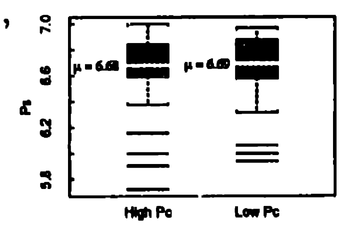
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(51) = 0.90$ $p = 0.370$ (F.K., Stem-Past)
not+ $t(51) = -0.21$ $p = 0.833$ (A.P., Stem-Past) ⟶

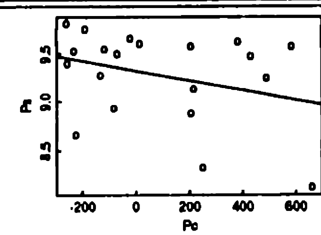


Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 2/4 (50%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 2/4 (50%)

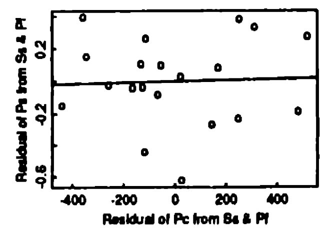
Table 6.11: All-Verbs Study: acceptability ratings for true irregulars

Predictiveness of Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blew*) as accept. ratings (1-10)
under Rule and Associative Theories for True Irregulars from All-Classes Study

by a simple correlation: r_{PcPs}
R:not+ A: + (prediction)
not+ $r(18) = -0.49$ $p = 0.027$ (F.K., Stem-Past)
not+ $r(18) = -0.33$ $p = 0.160$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$
R:not+ A: + (prediction)
not+ $r(16) = -0.06$ $p = 0.811$ (F.K., Stem-Past)
not+ $r(16) = 0.04$ $p = 0.875$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

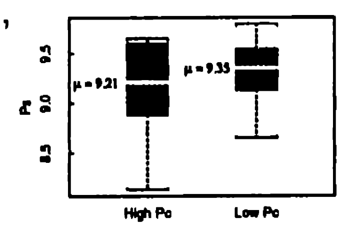
partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair
R:not+ A: + (prediction)
not+ $t(9) = -2.01$ $p = 0.075$ (F.K., Stem-Past)
not+ $t(9) = -0.69$ $p = 0.506$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 6.12: All-Classes Study: acceptability ratings for true irregulars

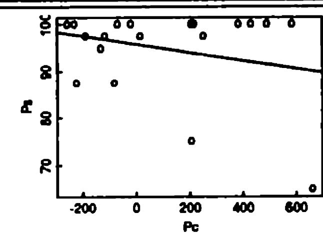
Predictiveness of Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blew*) as prod. like. (% subjs)
under Rule and Associative Theories for True Irregulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = -0.47$ $p = 0.034$ (F.K., Stem-Past)

not+ $r(18) = -0.27$ $p = 0.254$ (A.P., Stem-Past) ⟶

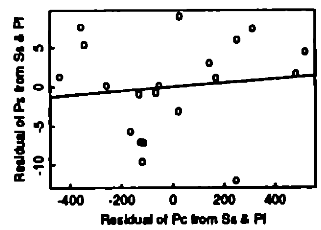


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(16) = -0.09$ $p = 0.714$ (F.K., Stem-Past)

not+ $r(16) = 0.11$ $p = 0.653$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

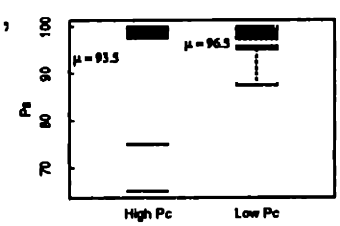
NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = -0.70$ $p = 0.502$ (F.K., Stem-Past)

not+ $t(9) = -0.78$ $p = 0.454$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

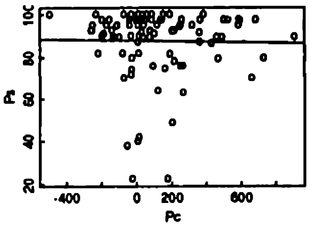
Table 6.13: All-Classes Study: production likelihood for true irregulars

Predictiveness of Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blew*) as prod. like. (% subjs)
under Rule and Associative Theories for True Irregulars from Reaction Time Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

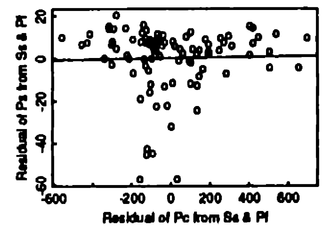
not+ $r(94) = -0.07$ $p = 0.482$ (F.K., Stem-Past)
not+ $r(94) = -0.02$ $p = 0.843$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(92) = 0.02$ $p = 0.843$ (F.K., Stem-Past)
not+ $r(92) = 0.02$ $p = 0.837$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

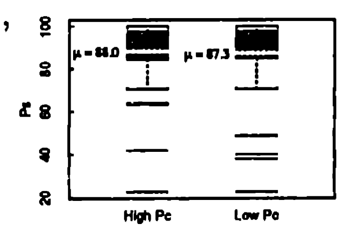
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

\+ $t(47) = 2.42$ $p = 0.020$ (F.K., Stem-Past)
not+ $t(47) = 0.23$ $p = 0.821$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 1/4 (25%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 3/4 (75%)

Table 6.14: Reaction Time Study: production likelihood for true irregulars

Predictiveness of Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blew*) as generation time (ms)
under Rule and Associative Theories for True Irregulars from Reaction Time Study

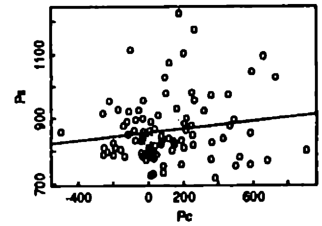
---

by a simple correlation: r_{PcPs}

R:not– A: – (prediction)

not– $r(94) = 0.21$ $p = 0.042$ (F.K., Stem-Past)

not– $r(94) = 0.15$ $p = 0.143$ (A.P., Stem-Past) ⟶



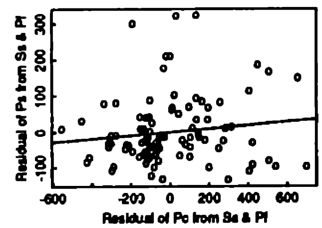
---

partialing out *Ss, Pf*: $r_{PsPc.SsPf}$

R:not– A: – (prediction)

not– $r(92) = 0.15$ $p = 0.156$ (F.K., Stem-Past)

not– $r(92) = 0.12$ $p = 0.231$ (A.P., Stem-Past) ⟶



---

partialing out *Ps′*: $r_{PsPc.Ps'}$

NA

---

partialing out *Pf′, Pc′*: $r_{PsPc.Pf'Pc'}$

NA

---

partialing out *Ss, Pf, Pf′, Pc′*: $r_{PsSs.PfPcPf'Pc'}$

NA

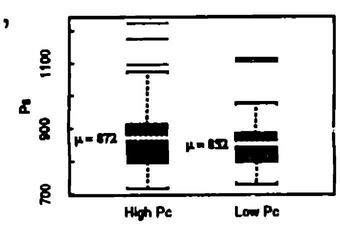
---

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not– A: – (prediction)

not– $t(47) = -0.60$ $p = 0.548$ (F.K., Stem-Past)

not– $t(47) = 0.99$ $p = 0.330$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 6.15: Reaction Time Study: production time for true irregulars

6.2.2 True Regulars (*balked, stalked*)

If regular pasts (*walked*) are associatively retrieved from their stems (*walk*), the presentation of other regular pasts (*balk-balked*) whose stem-past mappings are shared with those of *walk-walked* should facilitate the latter's computation. That is, regular cluster strength (*balked, stalked*) should predict Past Tense Success (*walked*). In this case the second and last cells of the Display Tables should show analyses revealing the significance of these predictions, with Past Tense Frequency (*walked*) or Stem Strength (*walk*) held constant.

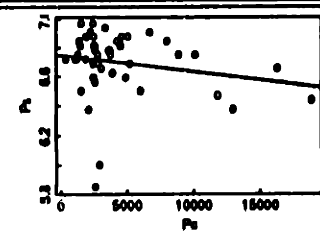
However, if regular pasts are produced by a symbol-processing system, there should be no such regular cluster strength effects. In this case the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Past Tense Frequency or Stem Strength held constant.

Predictiveness of Past Tense Cluster Strength(*balked, stalked*)
on Past Tense Success(*walked*) as accept. ratings (1-7)
under Rule and Associative Theories for True Regulars from All-Verbs Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

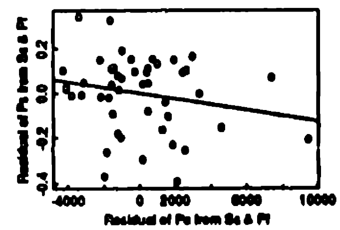
not+ $r(46) = -0.01$ $p = 0.941$ (F.K., Stem-Past)
not+ $r(46) = -0.20$ $p = 0.169$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(44) = -0.13$ $p = 0.373$ (F.K., Stem-Past)
not+ $r(44) = -0.21$ $p = 0.153$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

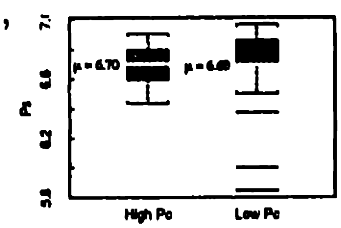
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(23) = 0.75$ $p = 0.462$ (F.K., Stem-Past)
not+ $t(23) = 0.10$ $p = 0.919$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

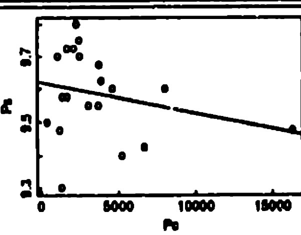
Table 6.16: All-Verbs Study: acceptability ratings for true regulars

Predictiveness of Past Tense Cluster Strength(*balked, stalked*)
on Past Tense Success(*walked*) as accept. ratings (1-10)
under Rule and Associative Theories for True Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

<ins>R:not+ A: + (prediction)</ins>

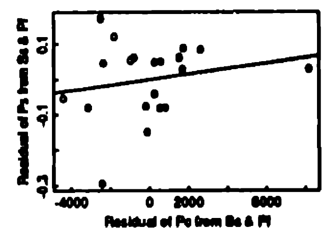
not+ $r(18) = -0.26$ $p = 0.272$ (F.K., Stem-Past)
not+ $r(18) = -0.25$ $p = 0.287$ (A.P., Stem-Past) ⟶



partialing out Ss, Pf: $r_{PsPc.SsPf}$

<ins>R:not+ A: + (prediction)</ins>

not+ $r(16) = -0.05$ $p = 0.843$ (F.K., Stem-Past)
not+ $r(16) = 0.19$ $p = 0.442$ (A.P., Stem-Past) ⟶



partialing out Ps': $r_{PsPc.Ps'}$

NA

partialing out Pf', Pc': $r_{PsPc.Pf'Pc'}$

NA

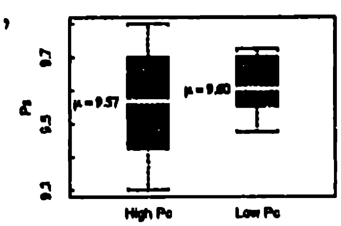
partialing out Ss, Pf, Pf', Pc': $r_{PsSs.PfPcPf'Pc'}$

NA

by a t-test comparing (Ps with high-Pc) with (Ps with low-Pc), given similar Pf values for each Ps pair

<ins>R:not+ A: + (prediction)</ins>

not+ $t(9) = 0.25$ $p = 0.812$ (F.K., Stem-Past)
not+ $t(9) = -0.71$ $p = 0.497$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 6.17: All-Classes Study: acceptability ratings for true regulars

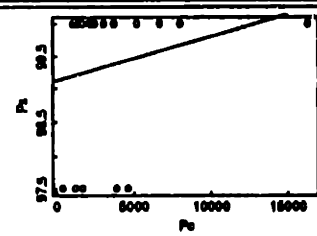
Predictiveness of Past Tense Cluster Strength(*balked, stalked*)
on Past Tense Success(*walked*) as prod. like. (% subjs)
under Rule and Associative Theories for True Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = 0.01$ $p = 0.982$ (F.K., Stem-Past)

not+ $r(18) = 0.22$ $p = 0.353$ (A.P., Stem-Past) ⟶

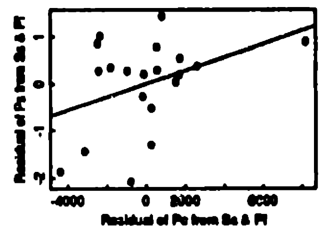


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(16) = 0.21$ $p = 0.395$ (F.K., Stem-Past)

not+ $r(16) = 0.39$ $p = 0.111$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

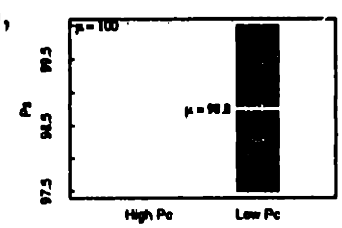
NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = -0.43$ $p = 0.678$ (F.K., Stem-Past)

\+ $t(9) = 3.00$ $p = 0.015$ (A.P., Stem-Past) ⟶



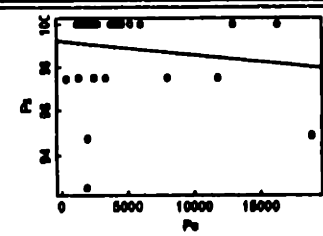
Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 1/4 (25%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 3/4 (75%)

Table 6.18: All-Classes Study: production likelihood for true regulars

Predictiveness of Past Tense Cluster Strength(*balked, stalked*)
on Past Tense Success(*walked*) as prod. like. (% subjs)
under Rule and Associative Theories for True Regulars from Reaction Time Study

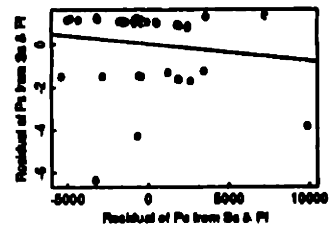
by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)
not+ $r(37) = -0.23$ $p = 0.150$ (F.K., Stem-Past)
not+ $r(37) = -0.15$ $p = 0.367$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)
not+ $r(35) = -0.20$ $p = 0.228$ (F.K., Stem-Past)
not+ $r(35) = -0.13$ $p = 0.433$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

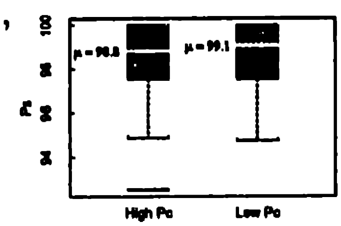
NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)
not+ $t(18) = -0.23$ $p = 0.823$ (F.K., Stem-Past)
not+ $t(18) = -0.44$ $p = 0.668$ (A.P., Stem-Past) ⟶



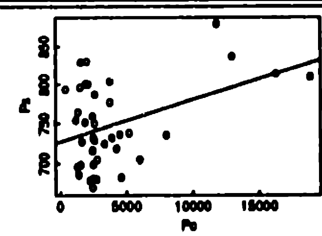
Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 6.19: Reaction Time Study: production likelihood for true regulars

Predictiveness of Past Tense Cluster Strength(*balked, stalked*)
on Past Tense Success(*walked*) as generation time (ms)
under Rule and Associative Theories for True Regulars from Reaction Time Study

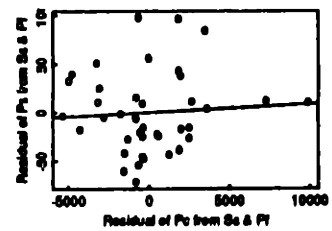
by a simple correlation: r_{PcPs}

R:not– A: – (prediction)
not– $r(37) = 0.34$ $p = 0.037$ (F.K., Stem-Past)
not– $r(37) = 0.42$ $p = 0.008$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not– A: – (prediction)
not– $r(35) = 0.12$ $p = 0.478$ (F.K., Stem-Past)
not– $r(35) = 0.07$ $p = 0.695$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

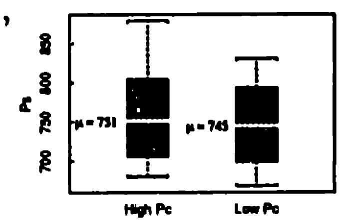
NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not– A: – (prediction)
not– $t(18) = 1.01$ $p = 0.328$ (F.K., Stem-Past)
not– $t(18) = 0.45$ $p = 0.655$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 6.20: Reaction Time Study: production time for true regulars

6.2.3 Discussion

The results show that Stem-Pair Past Tense Cluster Strength weakly predicts Past Tense Success for true irregulars, while for true regulars Stem-Pair Past Tense Cluster Strength does not predict Past Tense Success at all.

Before I look at individual analyses, I will address a problem that complicates my cluster strength analyses. Because I have divided the original cluster strength by past or alternative past word frequency (see Chapter 3), those verbs with high past or alternative past frequency counts will tend to have final cluster strength values close to zero. Moreover, for associatively represented forms, past frequency is a much better predictor than cluster strength — as we can see throughout my results for all verb categories. Thus there will be a clump of points with high Past Tense Success values around zero cluster strength. For rule-produced forms this should also occur because Past Tense Frequency is correlated with Stem Frequency, so rule-produced forms with high Past Tense Frequency values will also cluster around zero cluster strength with high Past Tense Success values.

This clump is problematic for correlations and partial correlations, since the least mean squares fit line will be pulled towards such a clump. This can result in either false negative or false positive results: false negative results can emerge if the clump pulls the line away from an otherwise valid pattern; false positive results can emerge if the clump is so strong that it anchors one end of the line, leaving the other end free to be pulled near any random points at the diagonal end of the clump.

Therefore when I analyse cluster strength effects, I must be aware of this clump, and attempt to avoid such false negative and false positive results. I will use a variety of techniques to do this. First, I will analyse all points to one side of the clump. This makes sense in many instances because the vast majority of cluster strength values in any given analysis are either negative or positive, but not both. This probably comes about because when the cluster strength is the same type as the past form (either irregular or regular), most forms will be supported by clusters, but when the cluster strength is of the oppositive type as the past form (either irregular or regular), most forms will be hindered by the cluster. By performing analyses only to one side of the clump, even though the clumping problem will probably still exist in principle (because in general there should be more points closer to zero cluster strength) the problem should be lessened: the further away the cutoff, the less the clumping problem; on the other hand, the further away the cutoff, the fewer points there will be, and thus the less chance of finding an existing pattern (ie, the more chance of a false negative). Since a larger cutoff will thus both help and hurt the chance of finding an existing pattern, I can choose a cutoff relatively safely without the danger of being biased.

Second, I will analyse all points either above or below the clump, depending on the Past Tense Success measure (below the clump for acceptability ratings and production likelihood, and above the clump for reaction time, and vice versa for all three for blocked forms). As with the previous approach, the further the cutoff, the less effect of the clump but the fewer the points. This approach has an advantage over the previous one: it includes points on both sides of zero (if in fact there are points on both sides). This this is important because it deals with the possible objection I describe below.

Third, I will use non-correlation analyses: specifically, the matched-difference t-tests described in chapter 5, holding Past Tense Frequency (or Altern. Past Tense Frequency, for blocked past forms) constant as the matched form. The main problem with this approach is that we can only hold one variable constant, while in fact we often want to hold more than one constant.

Someone might claim that in fact there will be a natural clumping around zero cluster strength even without the division by Past Tense Frequency or Altern. Past Tense Frequency. In addition to this clumping, it could be claimed that most past forms tend to have better than worse Past Tense Success values (and vice versa for blocked forms). If these two claims are true, then it could be argued with the additional fact that for a given cluster strength type most cluster strength values will be either positive or negative (see above), then the correlations that I will show exist for true irregulars (and certain other past classes) simply emerge from the half-normal distribution which results from these three factors: most forms have high Past Tense Success values, are normally distributed around zero cluster strength, with only one tail of the distribution.

However, my retort to such a claim is as follows: The first claim, that there is a natural clumping around zero cluster strength before dividing by past frequency, is simply false. For true regulars, in fact regular cluster strength ranges from 1717 to 25124 for the All-Verbs study, *before* dividing the cluster strength by past frequency; while after dividing by past frequency, we find a clumping towards zero. For true irregulars, the first claim seems to be more or less true. Crucially however, for them the third claim is false: before dividing by past frequency, irregular cluster strength ranges from -4710 to 5633. In addition, while the first technique I describe above (analysing the points to one side) might not avoid this problem if it exists, the other two techniques (analysing the points above or below, and performing a t-test) should avoid the problem.

Below I present the results from Stem-Past cluster strength effects for both true irregulars and true regulars for acceptability ratings from the All-Verbs study, production success from the Reaction Time study, and production time from the Reaction Time study. I do not report clustering analyses from the two All-Classes measures (ratings and production likelihood) because the small number of verbs tested (20) precludes meaningful results for either irregulars or regulars.

Acceptability Ratings from All-Verbs Study:

For true irregulars Past Tense Cluster Strength is good predictor of Past Tense Success

(Table 6.11). While neither of the two t-tests are significant, all 4 partial correlations are highly significant for two-tailed tests, with r in the expected direction (two partial correlations holding Past Tense Frequency (Associated Press or Francis and Kučera) and Stem Strength constant; and two partial correlations holding those variables constant *in addition to holding Altern. Past Tense Cluster Strength constant* — that is, the regular cluster strength of the surrounding attracted regulars). [2]

If I only include verbs with irregular cluster strength greater than 100 (i.e., apply the cutoff principle), I get similar results: All six analyses are in the expected direction. Moreover, the two t-tests now approach significance. Two of the partial correlations are still highly significant, while the other two approach significance.

If I only include verbs with past acceptability ratings less than 6.8, I get similar results: All six analyses are in the expected direction. Although neither t-test is significant, all four partial correlations are highly significant.

For true regulars Past Tense Cluster Strength does not predict Past Tense Success at all. Both t-tests and both partial correlations are not significant, In fact, the signs of the correlation coefficients of the two correlations are *negative*, while I expect a positive sign if Past Tense Cluster Strength does predict Past Tense Success.

The regular cluster strength of true regulars for the All-Verbs study ranges from 396 to 18913. When I included only verbs with regular cluster strength values greater than 500, I got similar results: none of the four analyses are significant, and the correlation coefficients of the two partial correlations had negative signs, when in fact I expected positive ones.

When I included only verbs with acceptability ratings less than 6.8, I also got similar results. None of the 4 analyses were significant, and the two correlations were still negative.

<u>Production Likelihood from Reaction Time Study:</u>

Production likelihood suffers from the problem of ceiling effects: As I describe above, most true regulars were produced correctly by all subjects. Therefore it does not make sense to interpret analyses for production likelihood for true regulars from this study. (However, if we do look at the analyses, we see that none of them are significant; furthermore, like the partial correlations for true regulars from the All-Verbs study, the correlation coefficients are in the opposite direction (negative) from what we would expect if Stem-Past Past Tense Cluster Strength were indeed predicting Past Tense Success.) Although true irregulars also suffer from this ceiling effect problem, there is enough variance to warrant interpreting the analyses. Furthermore, this interpretation shows that in fact for true irregulars Past Tense Cluster Strength is a relatively good predictor of Past Tense Success.

If we analyse the complete set of true irregular verbs tested in the experiment, we find a

[2]The partial correlations holding Altern. Past Tense Cluster Strength in addition to Past Tense Frequency and Stem Strength constant are not reported in the Analysis Tables.

very weak effect of Past Tense Cluster Strength: only one of the two t-tests is significant, and none of the four partial correlations is significant, although all six analyses are in the expected direction.

Because the production likelihood ceiling effect is nothing more than an aggravated "clumping" problem, we can apply the same anti-clumping techniques as above. First, when I only included verbs with irregular cluster strength greater than 100, I got a stronger effect: All six analyses were in the expected direction. While the two t-tests were not significant, two of the partial correlations were significant, while the other two approached significance.

Similarly, when I only included verbs with production likelihood values less than 80, I got a *stronger* effect: All six analyses were in the expected direction. All four partial correlations were highly significant, as were the two t-tests for one-tailed analyses.

Production Time from Reaction Time Study:

Past Tense Cluster Strength was a relatively weak predictor of Past Tense Success as production time for true irregulars (Table 6.15). When all data points were analysed together, I got no effect at all: none of the six analyses were significant. While the above-elimination technique (cutoff at the mean production time value of 682) resulted in no significant analyses whatsoever, the side-elimination anti-clumping technique (cutoff at irregular cluster strength of 100) revealed the predictive power of Past Tense Cluster Strength: All four analyses are in the expected direction. Two of the partial correlations were significant, while one t-test was approaching significance (p=.074), as were the other two of the partial correlations (p=.060 and p=.066).

Past Tense Cluster Strength is not predictive at all of Past Tense Success as production time for true regulars (Table 6.20). When all data points are analysed together, there was no effect at all: none of the 4 analyses were significant (even for a one-tailed interpretation); furthermore, all 4 were in the opposite direction than expected (positive rather than negative). When I selected only those verbs with regular cluster strength above 500 (the range of regular cluster strength for this experiment was 396 to 18913), I got similar results: None of the 4 analyses were significant, and all 4 were in the opposite direction than expected. Similarly, when I selected only those verbs with reaction times above the mean (above 749 milliseconds), none of the 4 analyses were significant, and all 4 were in the opposite direction than expected.

Chapter 7

Over-Regulars (blowed)

7.1 The Predictiveness of Alternative Past Tense Success (Psa) (*blew*)

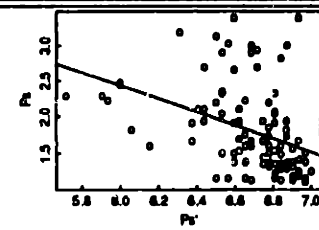
If over-regulars (*blowed*) are blocked by the associative computation of their corresponding irregulars (*blew*), then the more successful the computation of the irregular (*blew*), the more the over-regular (*blowed*) will be blocked. Thus we expect a negative correlation between the computational success of over-regulars (*blowed*) and their alternative forms, their corresponding irregulars (*blew*). If this is the case the first and second cells of the Display Tables should show analyses revealing this negative correlation.

Predictiveness of Altern. Past Tense Success(*blew*) as accept. ratings (1-7)
on Past Tense Success(*blowed*) as accept. ratings (1-7)
under Blocking Theory for Over-Regulars from All-Verbs Study

by a simple correlation: $r_{P_s'P_s}$

B: – (prediction)

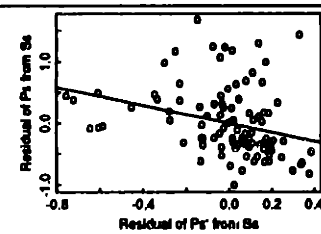
– $r(102) = -0.39$ $p < 0.001$



partialing out *Ss*: $r_{P_sP_s'.S_s}$

B: – (prediction)

– $r(101) = -0.30$ $p = 0.002$



partialing out *Pf*: $r_{P_sP_s'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{P_sP_s'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s'.S_sPfPc}$

NA

NA

Evidence for Blocking under Stem-Past Assoc Theory = 2/2 (100%)

Table 7.1: All-Verbs Study: acceptability ratings for over-regulars

Predictiveness of Altern. Past Tense Success(*blew*) as accept. ratings (1-10)

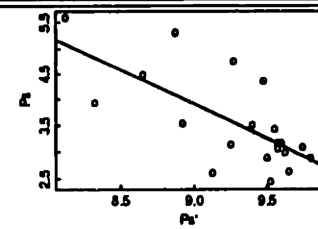
on Past Tense Success(*blowed*) as accept. ratings (1-10)

under Blocking Theory for Over-Regulars from All-Classes Study

by a simple correlation: $r_{Ps'Ps}$

B: – (prediction)

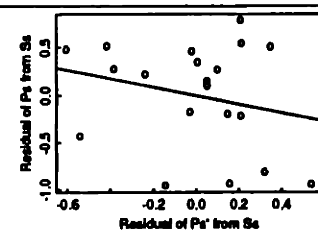
– $r(18) = -0.70$ $p < 0.001$



partialing out *Ss*: $r_{PsPs'.Ss}$

B: – (prediction)

not– $r(17) = -0.24$ $p = 0.313$



partialing out *Pf*: $r_{PsPs'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPs'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPs'.SsPfPc}$

NA

NA

Evidence for Blocking under Stem-Past Assoc Theory = 1/2 (50%)

Table 7.2: All-Classes Study: acceptability ratings for over-regulars

Predictiveness of Altern. Past Tense Success(*blew*) as prod. like. (% subjs)

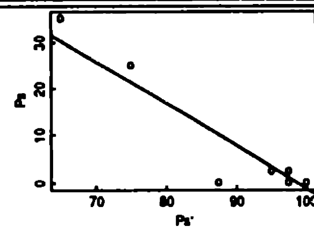
on Past Tense Success(*blowed*) as prod. like. (% subjs)

under Blocking Theory for Over-Regulars from All-Classes Study

by a simple correlation: $r_{Ps'Ps}$

B: – (prediction)

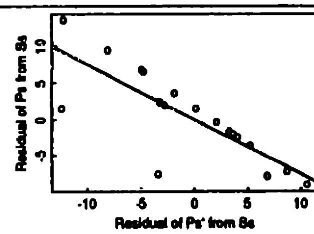
– $r(18) = -0.92$ $p < 0.001$



partialing out *Ss*: $r_{PsPs'.Ss}$

B: – (prediction)

– $r(17) = -0.81$ $p < 0.001$



partialing out *Pf*: $r_{PsPs'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPs'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPs'.SsPfPc}$

NA

NA

Evidence for Blocking under Stem-Past Assoc Theory = 2/2 (100%)

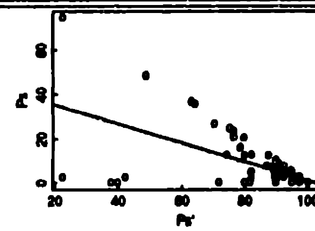
Table 7.3: All-Classes Study: production likelihood for over-regulars

Predictiveness of Altern. Past Tense Success(*blew*) as prod. like. (% subjs)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Blocking Theory for Over-Regulars from Reaction Time Study

by a simple correlation: $r_{P_s'P_s}$

B: – (prediction)

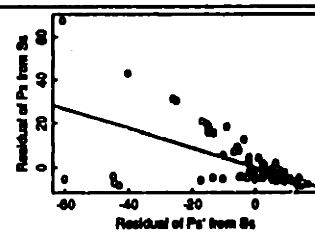
– $r(94) = -0.61$ $p < 0.001$



partialing out *Ss*: $r_{P_sP_s'.S_s}$

B: – (prediction)

– $r(93) = -0.61$ $p < 0.001$



partialing out *Pf*: $r_{P_sP_s'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{P_sP_s'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s'.S_sPfPc}$

NA

NA

Evidence for Blocking under Stem-Past Assoc Theory = 2/2 (100%)

Table 7.4: Reaction Time Study: production likelihood for over-regulars

There is a strong blocking relationship between over-regulars and their respective irregulars. That is, there is a strong negative correlation between the Past Tense Success of over-regulars (*blowed*) and their Altern. Past Tense Success values from irregulars (*blew*). As can be seen in tables 7.1 and 7.2 there is a strong negative correlation between Past Tense Success and Altern. Past Tense Success for acceptability ratings. Tables 7.3 and 7.4 reveal even stronger negative correlations for production success measures, although these analyses must be interpreted with caution because the over-regular success rate will very nearly be the complement of the irregular success rate — as both are calculated as the percentage of subjects producing those forms.

7.2 The Predictiveness of Alternative Past Tense Frequency (Pfa) (*blew*)

If over-regulars (*blowed*) are blocked by the associative computation of their corresponding irregulars (*blew*), then the more frequent the alternative past, the irregular (*blew*), the more successful its computation, and the more the over-regular (*blowed*) will be blocked. Thus we expect a negative correlation between the past tense frequency of irregulars (*blew*) and the computation success of their corresponding over-regulars (*blowed*). If this is the case the first, second and third cells of the Display Tables should show analyses revealing this negative correlation.

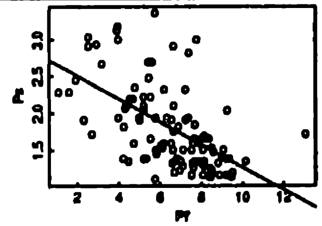
Predictiveness of Altern. Past Tense Frequency(*blew*)
on Past Tense Success(*blowed*) as accept. ratings (1-7)
under Blocking Theory for Over-Regulars from All-Verbs Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(102) = -0.55$ $p < 0.001$ (F.K.)

– $r(102) = -0.55$ $p < 0.001$ (A.P.) ⟶

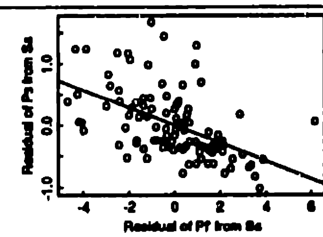


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(101) = -0.52$ $p < 0.001$ (F.K.)

– $r(101) = -0.52$ $p < 0.001$ (A.P.) ⟶



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

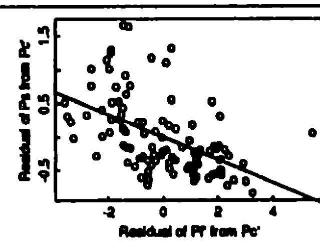
NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(101) = -0.51$ $p < 0.001$ (F.K., Stem-Past)

– $r(101) = -0.52$ $p < 0.001$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 6/6 (100%)

Table 7.5: All-Verbs Study: acceptability ratings for over-regulars

Predictiveness of Altern. Past Tense Frequency(*blew*)

on Past Tense Success(*blowed*) as accept. ratings (1-10)

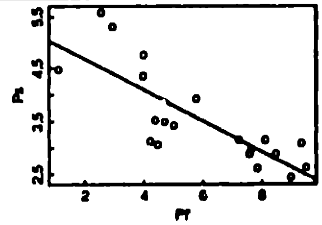
under Blocking Theory for Over-Regulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(18) = -0.75$ $p < 0.001$ (F.K.)

– $r(18) = -0.80$ $p < 0.001$ (A.P.) ⟶

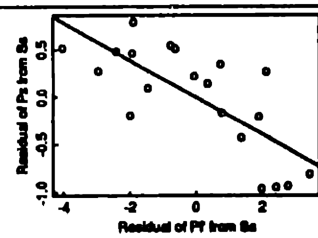


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(17) = -0.57$ $p = 0.011$ (F.K.)

– $r(17) = -0.75$ $p < 0.001$ (A.P.) ⟶



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

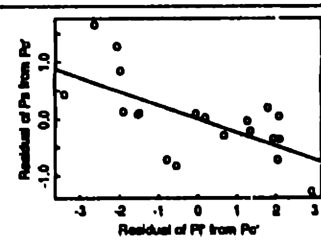
NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(17) = -0.58$ $p = 0.009$ (F.K., Stem-Past)

– $r(17) = -0.66$ $p = 0.002$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 6/6 (100%)

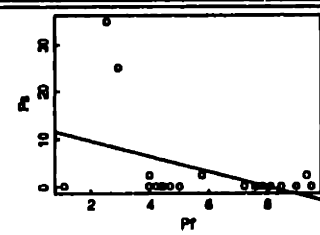
Table 7.6: All-Classes Study: acceptability ratings for over-regulars

Predictiveness of Altern. Past Tense Frequency(*blew*)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Blocking Theory for Over-Regulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

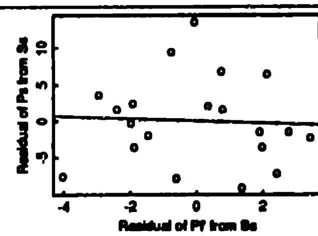
– $r(18) = -0.46$ $p = 0.041$ (F.K.)
not– $r(18) = -0.43$ $p = 0.061$ (A.P.) ⟶



partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

not– $r(17) = -0.01$ $p = 0.962$ (F.K.)
not– $r(17) = -0.05$ $p = 0.830$ (A.P.) ⟶



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

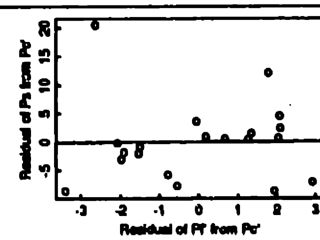
partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

not– $r(17) = 0.06$ $p = 0.821$ (F.K., Stem-Past)
not– $r(17) = 0.01$ $p = 0.978$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 1/6 (17%)

Table 7.7: All-Classes Study: production likelihood for over-regulars

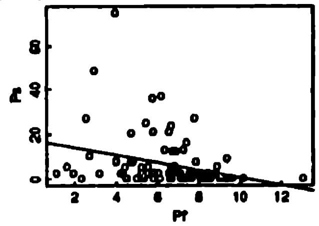
Predictiveness of Altern. Past Tense Frequency(*blew*)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Blocking Theory for Over-Regulars from Reaction Time Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(94) = -0.39$ $p < 0.001$ (F.K.)

– $r(94) = -0.31$ $p = 0.002$ (A.P.) ⟶

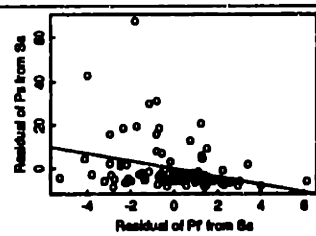


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(93) = -0.38$ $p < 0.001$ (F.K.)

– $r(93) = -0.30$ $p = 0.003$ (A.P.) ⟶



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

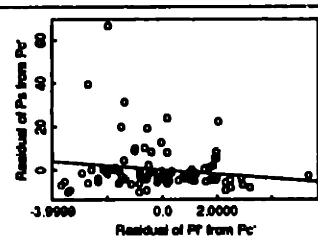
NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(93) = -0.24$ $p = 0.020$ (F.K., Stem-Past)

not– $r(93) = -0.16$ $p = 0.131$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 5/6 (83%)

Table 7.8: Reaction Time Study: production likelihood for over-regulars

7.2.1 Discussion

Altern. Past Tense Frequency (frequency of irregular pasts such as *blew*) strongly predicts Past Tense Success (*blowed*). That is, there is a strong negative correlation between the Past Tense Success of over-regulars (*blowed*) and the past frequencies of their corresponding irregulars (*blew*). This negative correlation can be seen clearly in the Analysis Tables for acceptability ratings from the All-Verbs study, acceptability ratings from the All-Classes study, production likelihood from the All-Classes study, and production likelihood from the Reaction Time study.

7.3 The Predictiveness of Altern. Past Tense Cluster Strength (Pca) (*threw, grew*)

If over-regulars (*blowed*) are blocked by the associative computation of alternative irregular pasts from the same stem, then the more easily the more irregulars (*threw, grew*) are computed, the more the over-regular (*blowed*) will be blocked. Thus we expect a positive correlation between the irregular cluster strength (*threw, grew*) of the over-regular (*blowed*) and the computational success of the over-regular: the more negative the irregular cluster strength, the worse the computational success of the over-regular. If this is the case the first, second and third cells of the Display Tables should show analyses revealing this positive correlation.

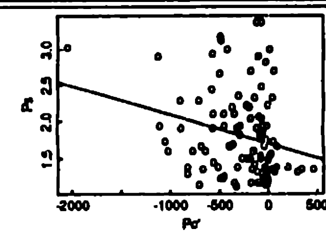
Predictiveness of Altern. Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blowed*) as accept. ratings (1-7)
under Blocking Theory for Over-Regulars from All-Verbs Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(102) = -0.26$ $p = 0.008$ (F.K., Stem-Past)

not+ $r(102) = -0.24$ $p = 0.013$ (A.P., Stem-Past) $\longrightarrow$

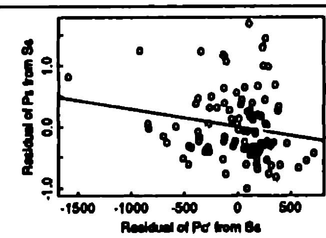


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(101) = -0.20$ $p = 0.039$ (F.K., Stem-Past)

not+ $r(101) = -0.18$ $p = 0.063$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf, Pc*: $r_{PsPc'.PfPc}$

NA

partialing out *Ss, Pf, Pc*: $r_{PsPc'.SsPfPc}$

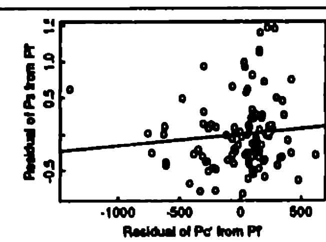
NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(101) = 0.07$ $p = 0.485$ (F.K., Stem-Past)

not+ $r(101) = 0.10$ $p = 0.327$ (A.P., Stem-Past) $\longrightarrow$



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 7.9: All-Verbs Study: acceptability ratings for over-regulars

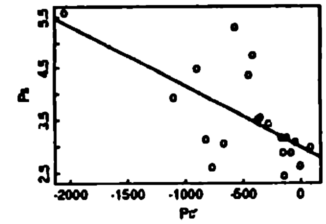
Predictiveness of Altern. Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blowed*) as accept. ratings (1-10)
under Blocking Theory for Over-Regulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(18) = -0.61$ $p = 0.004$ (F.K., Stem-Past)

not+ $r(18) = -0.64$ $p = 0.002$ (A.P., Stem-Past) ⟶

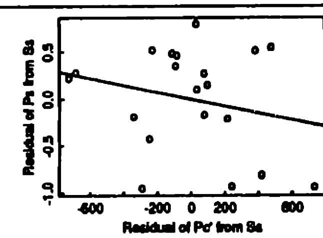


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(17) = -0.14$ $p = 0.559$ (F.K., Stem-Past)

not+ $r(17) = -0.25$ $p = 0.311$ (A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

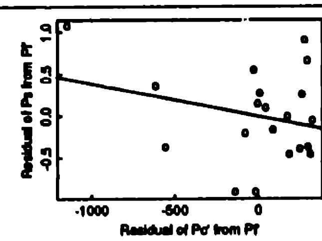
NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(17) = -0.22$ $p = 0.355$ (F.K., Stem-Past)

not+ $r(17) = -0.27$ $p = 0.263$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 7.10: All-Classes Study: acceptability ratings for over-regulars

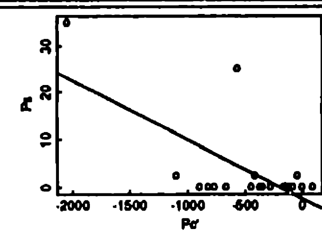
Predictiveness of Altern. Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Blocking Theory for Over-Regulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(18) = -0.74$ $p < 0.001$ (F.K., Stem-Past)

not+ $r(18) = -0.66$ $p = 0.001$ (A.P., Stem-Past) ⟶

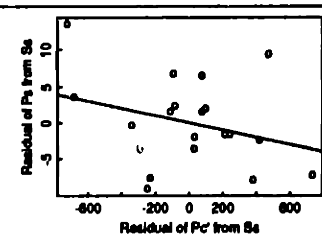


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(17) = -0.45$ $p = 0.054$ (F.K., Stem-Past)

not+ $r(17) = -0.31$ $p = 0.197$ (A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

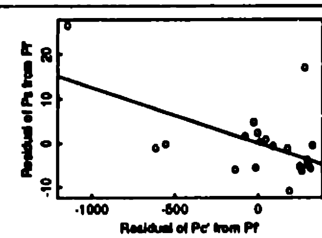
NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(17) = -0.65$ $p = 0.003$ (F.K., Stem-Past)

not+ $r(17) = -0.56$ $p = 0.012$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 7.11: All-Classes Study: production likelihood for over-regulars

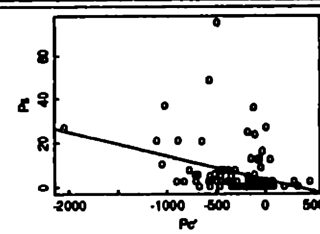
Predictiveness of Altern. Past Tense Cluster Strength(*threw, grew*)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Blocking Theory for Over-Regulars from Reaction Time Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(94) = -0.37$ $p < 0.001$ (F.K., Stem-Past)

not+ $r(94) = -0.33$ $p < 0.001$ (A.P., Stem-Past) ⟶

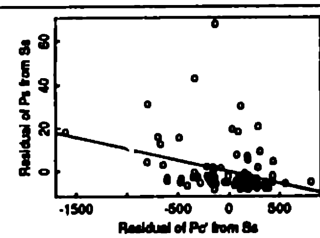


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(93) = -0.36$ $p < 0.001$ (F.K., Stem-Past)

not+ $r(93) = -0.32$ $p = 0.001$ (A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

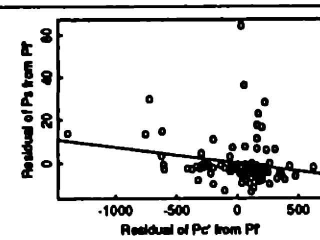
NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(93) = -0.21$ $p = 0.038$ (F.K., Stem-Past)

not+ $r(93) = -0.20$ $p = 0.048$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 7.12: Reaction Time Study: production likelihood for over-regulars

7.3.1 Discussion

Altern. Past Tense Cluster Strength (*threw, grew*) is a very weak predictor of Past Tense Success for over-regulars.

<u>Acceptability Ratings from All-Verbs Study:</u>

While none of the 4 analyses (2 t-tests with matched irregular past frequencies and differing irregular cluster strength, and two partial correlations holding Stem Strength and irregular past frequency constant — each for both Associated Press and Francis and Kučera frequency counts) [1] were significant, one of them approached significance, and all 4 analyses were in the expected direction — Francis and Kučera t-test: t=1.75, p=0.087; Associated Press t-test: t=1.01, p=0.318; Francis and Kučera partial correlation: r=.10, p=0.302; Associated Press partial correlation: r=.13, p=0.184. When I included only those verbs with irregular cluster strength less than -100, the 4 analyses were still in the expected direction, and now one of the t-tests was significant. Furthermore and importantly, when I removed *slitted* and *grinded*, which the production likelihood of over-regulars from the All-Classes study showed were doublets (see immediately below), both partial correlations were significant in the expected direction (r=.20, p=.049 and r=.20, p=.047), and the two t-tests approached significance.

<u>Acceptability Ratings from All-Classes Study:</u>

None of the 4 analyses were significant — either with the full 20 verbs or without *slitted* or *grinded*.

<u>Production Likelihood from All-Classes Study:</u>

The floor effect is too severe to analyse these verbs: 15 of the 20 verbs had no subjects overregularize them, while 3 more had only one subject overregularize it. Furthermore, for the other two verbs (*slit-slitted, grind-grinded*) a relatively large number of subjects overregularized them: 14 out of 40 produced *slitted*, while 10 out of 40 produced *grinded*. Because this is an untimed task, these subjects clearly believe these are the correct forms, which calls into question the validity of treating these verbs as over-regulars rather than doublets.

<u>Production Likelihood from All-Classes and Reaction Time Studies:</u>

The analyses for these two measures produced statistics lying in the *opposite* direction than expected (negative rather than positive). I suspect that this is a floor effect — 65 out of the 96 verbs had over-regularization rates of 5% or less. Furthermore, examination of the scatterplots of residuals in which irregular past frequency is held constant reveals what appears to be a *positive* relationship between irregular cluster strength and over-regularization rate, as expected. This relationship seemed hidden by the attraction of the least squares fit line

[1] None of these four analyses are reported in the Analysis Tables.

by the clump centered around zero. However, because the floor effect is so bad, the clump will be closer to the floor than for acceptabilility ratings (c.f. Table 7.9). In other words, the clumping problem is aggravated by the floor effect. To avoid the clumping problem I relied on the same anti-clumping solution I had used previously: applying the analyses above a cutoff. In fact, when I applied the analyses to those points only above 20 percent success (this was the only cutoff tried, which I chose to be just above the clump, based on the points in the scatterplot), I found that *the significant negative statistics had been eliminated*: the two t-tests were not even approaching significance (one was still negative, the other positive), while the two partial correlations holding Stem Strength and irregular past frequency constant were now **positive**, either significant or approaching significant under one-tailed tests (r=.59, p=.046; r=.58, p=.052).

7.4 The Predictiveness of Past Tense Cluster Strength (Pc) (*flowed, rowed*)

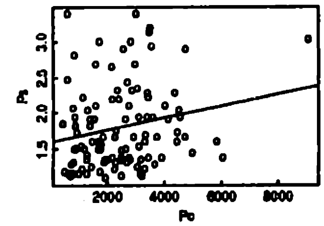
If over-regulars (*blowed*) are learned in associative memory, the frequency and similarity of their regular neighbours (*flowed, rowed*) should correlate with the computational success of the over-regulars. We would expect a positive correlation between the regular cluster strength (*flowed, rowed*) of the over-regular (*blowed*) and the computational success of that over-regular. If this is the case the first, third, fourth and sixth cells of the Display Tables should show analyses revealing this positive correlation.

However, if over-regulars are rule-produced, the frequency and similarity of their regular neighbours should not correlate at all with the computational success of the over-regulars. If this is the case the first, third, fourth and sixth cells of the Display Tables should show analyses revealing no positive correlation.

Predictiveness of Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blowed*) as accept. ratings (1-7)
under Rule and Associative Theories for Over-Regulars from All-Verbs Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)
+ $r(102) = 0.25$ $p = 0.010$ (F.K., Stem-Past)
+ $r(102) = 0.20$ $p = 0.040$ (A.P., Stem-Past) ⟶

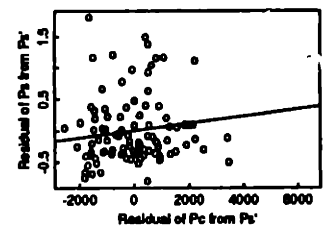


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

NA

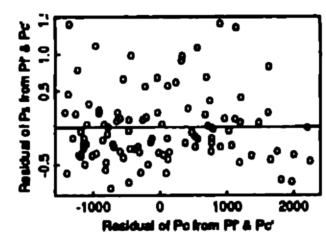
partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)
+ $r(101) = 0.22$ $p = 0.027$ (F.K., Stem-Past)
not+ $r(101) = 0.15$ $p = 0.136$ (A.P., Stem-Past) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)
not+ $r(100) = -0.06$ $p = 0.525$ (F.K., Stem-Past)
not+ $r(100) = 0.01$ $p = 0.959$ (A.P., Stem-Past) ⟶

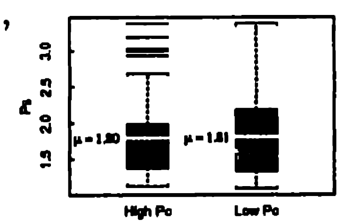


partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)
not+ $t(51) = -0.75$ $p = 0.459$ (F.K., Stem-Past)
not+ $t(51) = -0.10$ $p = 0.924$ (A.P., Stem-Past) ⟶



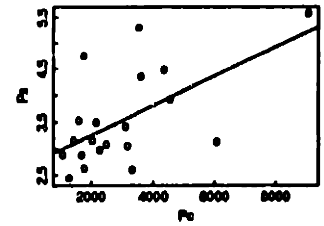
Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 1/6 (17%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 5/6 (83%)

Table 7.13: All-Verbs Study: acceptability ratings for over-regulars

Predictiveness of Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blowed*) as accept. ratings (1-10)
under Rule and Associative Theories for Over-Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

<u>R:not+ A: + (prediction)</u>
+ $r(18) = 0.58$ $p = 0.007$ (F.K., Stem-Past)
+ $r(18) = 0.59$ $p = 0.006$ (A.P., Stem-Past) ⟶

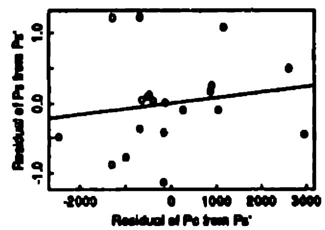


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

NA

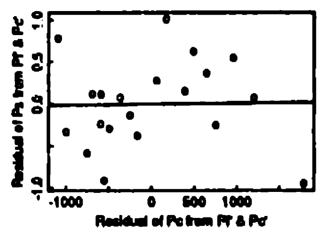
partialing out *Ps'*: $r_{PsPc.Ps'}$

<u>R:not+ A: + (prediction)</u>
not+ $r(17) = 0.12$ $p = 0.617$ (F.K., Stem-Past)
not+ $r(17) = 0.16$ $p = 0.512$ (A.P., Stem-Past) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

<u>R:not+ A: + (prediction)</u>
not+ $r(16) = -0.07$ $p = 0.783$ (F.K., Stem-Past)
not+ $r(16) = 0.02$ $p = 0.947$ (A.P., Stem-Past) ⟶

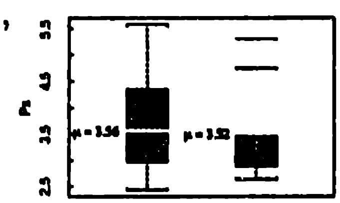


partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

<u>R:not+ A: + (prediction)</u>
not+ $t(9) = -0.48$ $p = 0.641$ (F.K., Stem-Past)
not+ $t(9) = 0.14$ $p = 0.894$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/6 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 6/6 (100%)

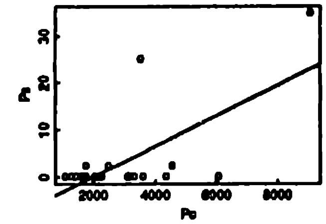
Table 7.14: All-Classes Study: acceptability ratings for over-regulars

Predictiveness of Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Rule and Associative Theories for Over-Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

$+$ $r(18) = 0.74$ $p < 0.001$ (F.K., Stem-Past)
$+$ $r(18) = 0.66$ $p = 0.001$ (A.P., Stem-Past) $\longrightarrow$



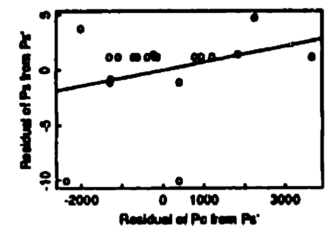
partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

NA

partialing out *Ps′*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

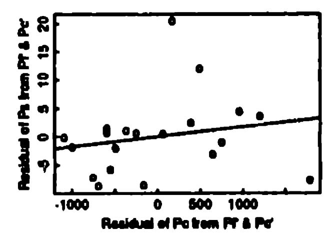
not+ $r(17) = 0.36$ $p = 0.128$ (F.K., Stem-Past)
not+ $r(17) = 0.28$ $p = 0.237$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Pf′*, *Pc′*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(16) = 0.15$ $p = 0.553$ (F.K., Stem-Past)
not+ $r(16) = 0.19$ $p = 0.447$ (A.P., Stem-Past) $\longrightarrow$



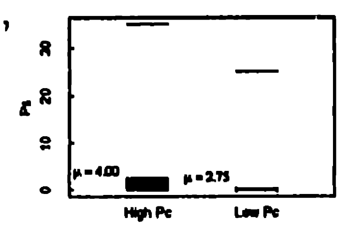
partialing out *Ss*, *Pf*, *Pf′*, *Pc′*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 0.28$ $p = 0.789$ (F.K., Stem-Past)
not+ $t(9) = 0.28$ $p = 0.789$ (A.P., Stem-Past) $\longrightarrow$



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/6 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 6/6 (100%)

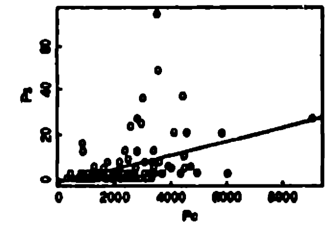
Table 7.15: All-Classes Study: production likelihood for over-regulars

Predictiveness of Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blowed*) as prod. like. (% subjs)
under Rule and Associative Theories for Over-Regulars from Reaction Time Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

+ $r(94) = 0.42$ $p < 0.001$ (F.K., Stem-Past)
+ $r(94) = 0.38$ $p < 0.001$ (A.P., Stem-Past) ⟶



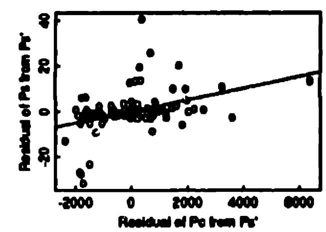
partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

NA

partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

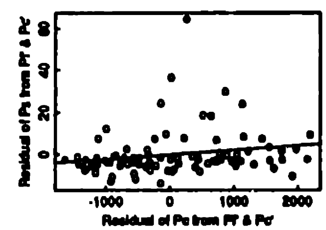
+ $r(93) = 0.39$ $p < 0.001$ (F.K., Stem-Past)
+ $r(93) = 0.40$ $p < 0.001$ (A.P., Stem-Past) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(92) = 0.15$ $p = 0.140$ (F.K., Stem-Past)
not+ $r(92) = 0.20$ $p = 0.054$ (A.P., Stem-Past) ⟶



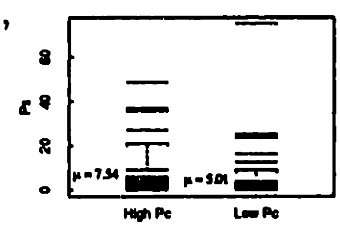
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(47) = 0.85$ $p = 0.399$ (F.K., Stem-Past)
not+ $t(47) = 1.74$ $p = 0.089$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 2/6 (33%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/6 (67%)

Table 7.16: Reaction Time Study: production likelihood for over-regulars

7.5 Discussion

There is no evidence that regular cluster strength (*rowed, flowed*) supports over-regulars (*blowed*). In fact, there is a *negative* relationship between regular cluster strength and over-regular Past Tense Success, when I expect none, and the All-Associative model should expect a positive correlation. I do not yet have an explanation for this unexpected relationship (However, I get the similar results for regular cluster strength for attracted regulars, where I briefly explore possible explanations — see Attracted Regulars Results chapter).

Acceptability Ratings from the All-Verbs Study:

The statistics of the four analyses (two t-tests with matched past irregular frequency and differing regular cluster strength, and two partial correlations with both irregular past frequency and Stem Strength held constant) were all in the opposite direction than expected (negative rather than positive) if there were cluster effects, and none were statistically significant: Francis and Kučera t-test: t=-.75, p=0.459; Associated Press t-test: t=-.097, p=0.924; Francis and Kučera partial correlation: r=-.14, p=0.169; Associated Press partial correlation: r=-.11, p=0.264. However, upon removal of *slitted* and *grinded*, which the production likelihood measure of the All-Classes study showed were doublets, one of the partial correlations reached two-tailed significance (r=-.25, p=.023), while the other reached one-tailed significance (r=-.17, p=.092).

Acceptability Ratings from the All-Classes Study:

None of the analyses were significant; moreover, three of the four had statistics in the opposite direction than expected.

Production Likelihood from the All-Classes Study:

The floor effect was too severe to warrant analyses (see above).

Production Likelihood from the Reaction Time Study:

As with the blocking effects from irregular cluster strength, all 4 analyses were in the opposite direction from the analyses from the rating study — with the two partial correlations being significant for two-tailed tests. That is, where I expected no regular cluster effects, these analyses seem to suggest that they exist. However, as I described above regarding the irregular cluster effects for production likelihood from the Reaction Time study, I believe this is due to a floor effect. In fact, when I analyse only those verbs with production success above 20% (the same cutoff as I chose to analyse irregular cluster effects — see above), the direction of one t-test *switched* to a negative direction, as did the two partial correlations, which were moreover now *significant* for two-tailed tests, consistent with my results from the other studies that there is no regular cluster strength support.

7.6 Blocking of True Irregulars (*blew*)

7.6.1 The Predictiveness of Altern. Past Tense Cluster Strength(Pca) (*flowed, rowed*)

If irregulars (*blew*) are learned in associative memory, and if regulars whose stems are similar to the stems of irregulars (*flowed, rowed*) also have a certain probability of being learned in associative memory, we should find weak neighborhood effects of these regulars on the irregulars. In this case we would expect a positive correlation between the regular cluster strength (*flowed, rowed*) of the irregular (*blew*) and the computational success of the irregular. If this is the case the first five cells of the Display Tables should show analyses revealing this positive correlation.

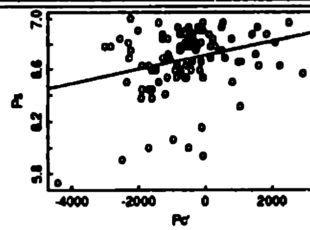
However, if irregulars are rule-produced, or if no regulars are associatively learned and computed, the frequency and similarity of their regular neighbours should not correlate at all with the computational success of the irregulars. If this is the case the first five cells of the Display Tables should show analyses revealing no postive correlation.

Predictiveness of Altern. Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blew*) as accept. ratings (1-7)
under Blocking Theory for True Irregulars from All-Verbs Study

by a simple correlation: $r_{Pc'P_s}$

B: + (prediction)

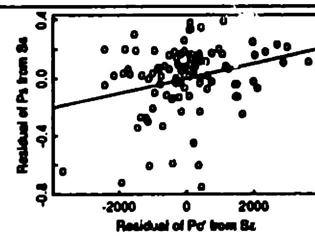
+	$r(102) = 0.21$	$p = 0.030$	(F.K., Stem-Past)
+	$r(102) = 0.27$	$p = 0.005$	(A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{P_sPc'.S_s}$

B: + (prediction)

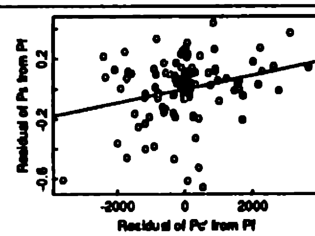
+	$r(101) = 0.22$	$p = 0.027$	(F.K., Stem-Past)
+	$r(101) = 0.27$	$p = 0.005$	(A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{P_sPc'.Pf}$

B: + (prediction)

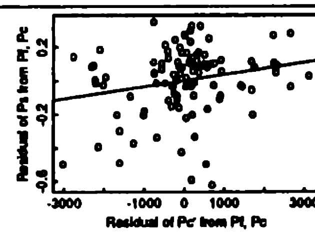
+	$r(101) = 0.22$	$p = 0.026$	(F.K., Stem-Past)
+	$r(101) = 0.26$	$p = 0.007$	(A.P., Stem-Past) ⟶



partialing out *Pf*, *Pc*: $r_{P_sPc'.PfPc}$

B: + (prediction)

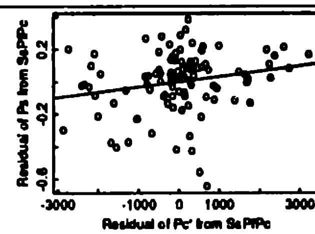
not+	$r(100) = 0.15$	$p = 0.125$	(F.K., Stem-Past)
+	$r(100) = 0.21$	$p = 0.036$	(A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pc*: $r_{P_sPc'.S_sPfPc}$

B: + (prediction)

not+	$r(99) = 0.15$	$p = 0.133$	(F.K., Stem-Past)
+	$r(99) = 0.20$	$p = 0.040$	(A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{P_sPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/10 (80%)

Table 7.17: All-Verbs Study: acceptability ratings for true irregulars

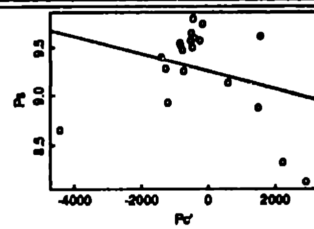
Predictiveness of Altern. Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blew*) as accept. ratings (1-10)
under Blocking Theory for True Irregulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(18) = -0.43$ $p = 0.060$ (F.K., Stem-Past)

not+ $r(18) = -0.30$ $p = 0.201$ (A.P., Stem-Past) ⟶

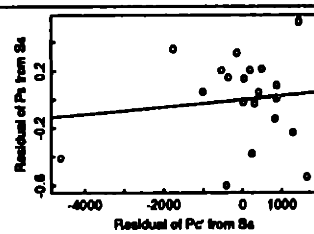


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(17) = -0.02$ $p = 0.940$ (F.K., Stem-Past)

not+ $r(17) = 0.12$ $p = 0.632$ (A.P., Stem-Past) ⟶

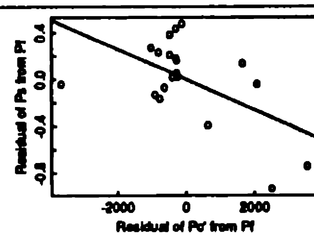


partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

not+ $r(17) = -0.53$ $p = 0.019$ (F.K., Stem-Past)

not+ $r(17) = -0.55$ $p = 0.015$ (A.P., Stem-Past) ⟶

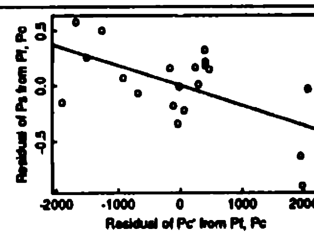


partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

not+ $r(16) = -0.52$ $p = 0.027$ (F.K., Stem-Past)

not+ $r(16) = -0.58$ $p = 0.012$ (A.P., Stem-Past) ⟶

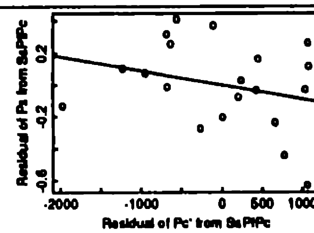


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

not+ $r(15) = -0.32$ $p = 0.213$ (F.K., Stem-Past)

not+ $r(15) = -0.28$ $p = 0.274$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 0/10 (0%)

Table 7.18: All-Classes Study: acceptability ratings for true irregulars

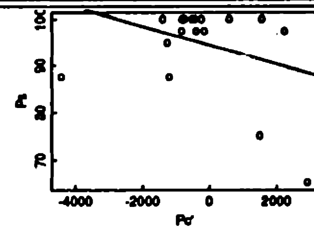
Predictiveness of Altern. Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blew*) as prod. like. (% subjs)
under Blocking Theory for True Irregulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(18) = -0.45$ $p = 0.047$ (F.K., Stem-Past)

not+ $r(18) = -0.33$ $p = 0.153$ (A.P., Stem-Past) ⟶

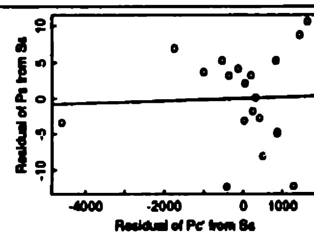


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(17) = -0.08$ $p = 0.734$ (F.K., Stem-Past)

not+ $r(17) = 0.03$ $p = 0.894$ (A.P., Stem-Past) ⟶

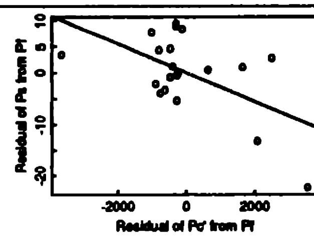


partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

not+ $r(17) = -0.48$ $p = 0.036$ (F.K., Stem-Past)

not+ $r(17) = -0.55$ $p = 0.014$ (A.P., Stem-Past) ⟶.

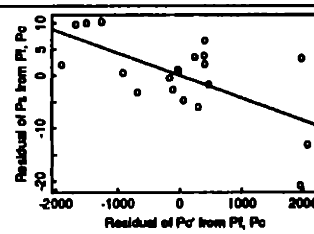


partialing out *Pf, Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

not+ $r(16) = -0.41$ $p = 0.091$ (F.K., Stem-Past)

not+ $r(16) = -0.64$ $p = 0.004$ (A.P., Stem-Past) ⟶

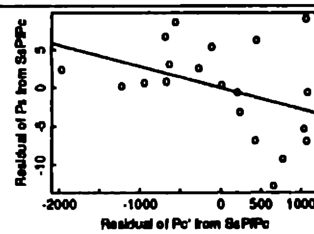


partialing out *Ss, Pf, Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

not+ $r(15) = -0.17$ $p = 0.519$ (F.K., Stem-Past)

not+ $r(15) = -0.40$ $p = 0.107$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 0/10 (0%)

Table 7.19: All-Classes Study: production likelihood for true irregulars

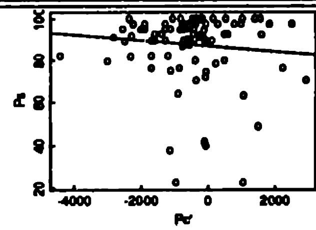
Predictiveness of Altern. Past Tense Cluster Strength(*flowed, rowed*)
on Past Tense Success(*blew*) as prod. like. (% subjs)
under Blocking Theory for True Irregulars from Reaction Time Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(94) = -0.10$ $p = 0.324$ (F.K., Stem-Past)

not+ $r(94) = -0.10$ $p = 0.313$ (A.P., Stem-Past) ⟶

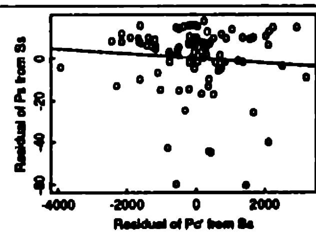


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(93) = -0.06$ $p = 0.537$ (F.K., Stem-Past)

not+ $r(93) = -0.08$ $p = 0.433$ (A.P., Stem-Past) ⟶

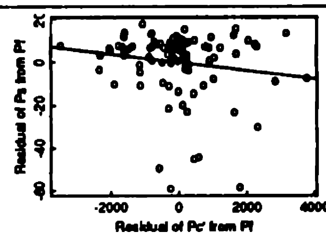


partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

not+ $r(93) = -0.14$ $p = 0.181$ (F.K., Stem-Past)

not+ $r(93) = -0.15$ $p = 0.140$ (A.P., Stem-Past) ⟶

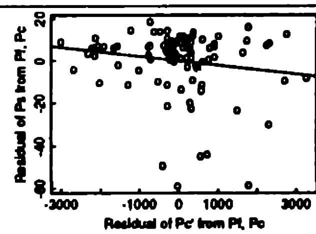


partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

not+ $r(92) = -0.15$ $p = 0.148$ (F.K., Stem-Past)

not+ $r(92) = -0.16$ $p = 0.115$ (A.P., Stem-Past) ⟶

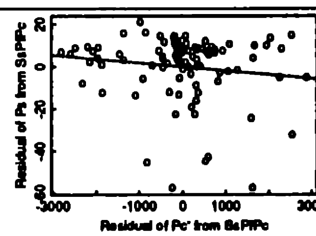


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

not+ $r(91) = -0.12$ $p = 0.243$ (F.K., Stem-Past)

not+ $r(91) = -0.14$ $p = 0.176$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 0/10 (0%)

Table 7.20: Reaction Time Study: production likelihood for true irregulars

Predictiveness of Altern. Past Tense Cluster Strength(*flowed, rowed*)

on Past Tense Success(*blew*) as generation time (ms)

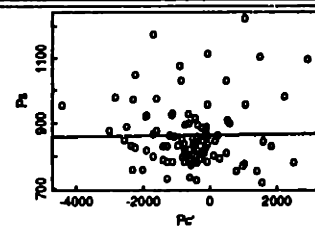
under Blocking Theory for True Irregulars from Reaction Time Study

by a simple correlation: $r_{Pc'Ps}$

B: – (prediction)

not– $r(94) = 0.04$ $p = 0.730$ (F.K., Stem-Past)

not– $r(94) = 0.01$ $p = 0.912$ (A.P., Stem-Past) ⟶

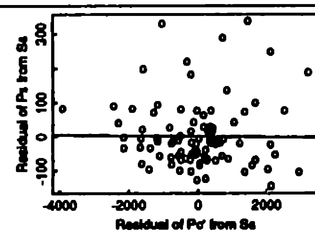


partialing out *Ss*: $r_{PsPc'.Ss}$

B: – (prediction)

not– $r(93) = 0.00$ $p = 0.997$ (F.K., Stem-Past)

not– $r(93) = -0.01$ $p = 0.915$ (A.P., Stem-Past) ⟶

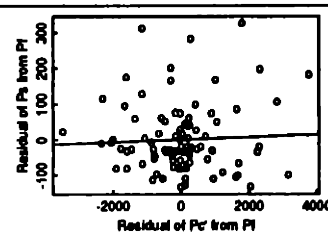


partialing out *Pf*: $r_{PsPc'.Pf}$

B: – (prediction)

not– $r(93) = 0.06$ $p = 0.560$ (F.K., Stem-Past)

not– $r(93) = 0.05$ $p = 0.656$ (A.P., Stem-Past) ⟶

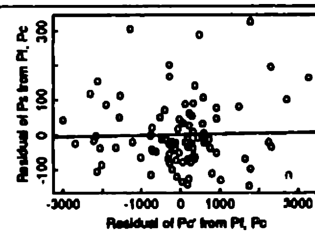


partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

B: – (prediction)

not– $r(92) = 0.03$ $p = 0.782$ (F.K., Stem-Past)

not– $r(92) = 0.02$ $p = 0.830$ (A.P., Stem-Past) ⟶

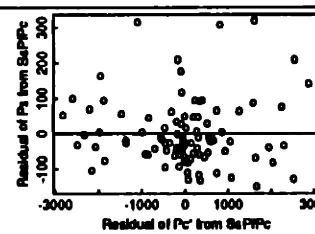


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

B: – (prediction)

not– $r(91) = 0.00$ $p = 0.978$ (F.K., Stem-Past)

not– $r(91) = 0.00$ $p = 0.974$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 0/10 (0%)

Table 7.21: Reaction Time Study: production time for true irregulars

7.6.2 Discussion

There is some evidence that the attracted regulars (*rowed, flowed*) surrounding true irregulars may have very weak blocking (or supporting) effects on those irregulars.

Acceptability Ratings from All-Verbs Study:

True irregulars are moderately blocked by their surrounding attracted regulars: Altern. Past Tense Cluster Strength is a moderately good predictor of Past Tense Success for true irregulars. One of the two t-tests is significant in the expected direction, as are three of the four partial correlations. Interestingly, the two partial correlations with irregular cluster strength held constant are much weaker than the two without it held constant: one of the former two is not significant, while the p value of the other is much higher (.04) than without irregular cluster strength held constant (.007). Given that the correlation between the irregular and regular cluster strengths is not very high (r=.22, p=0.02), this reduction is unlikely to be due to a problem of multicollinearity. Rather it suggests that regular cluster strength derived from surrounding attracted regulars is not very strong — as I would expect, given that the probability of attracted regulars being learned in associative memory is correlated with their stems' proximity to existing irregulars in the memory.

None of the analyses from the other four experimental measures (acceptability ratings from the All-Classes study, production success from the All-Classes and Reaction Time studies, and production time from the Reaction Time study) approached significance; moreover, most of them were in the *opposite* direction than expected if regular cluster strength did indeed predict true irregulars.

Chapter 8

Doublets (dive-dove/dived)

8.1 The Predictiveness of Past Tense Frequency(Pf)

8.1.1 Doublet Regulars (*dived*)

If doublet regular pasts (*dived*) are associatively learned and computed, the more frequent those pasts, the more successfully they should be computed. That is, Past Tense Frequency (*dived*) should predict Past Tense Success (*dived*). In this case the second through sixth cells of the Display Tables should show analyses revealing the significance of these predictions, with Stem Strength (*dive*), Past Tense Frequency (*dived*), Altern. Past Tense Frequency (*dove*), or various other variables held constant.

However, if doublet regular pasts are produced by a symbol-processing system, there should be no such past tense frequency effects. In this case the second through sixth cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Stem Strength or other variables held constant.

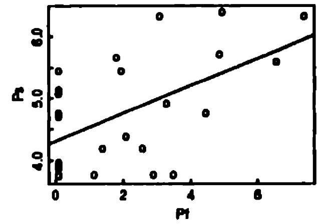
Predictiveness of Past Tense Frequency(*dived*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Regulars from All-Verbs Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

+ $r(23) = 0.49$ $p = 0.013$ (F.K.)

+ $r(23) = 0.56$ $p = 0.004$ (A.P.) ⟶

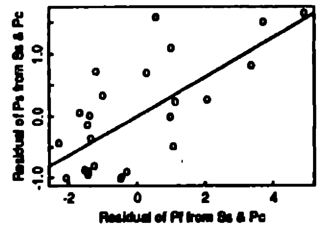


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

+ $r(21) = 0.56$ $p = 0.005$ (F.K., Stem-Past)

+ $r(21) = 0.69$ $p < 0.001$ (A.P., Stem-Past) ⟶

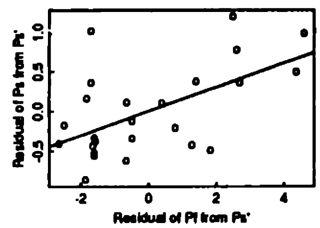


partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

+ $r(22) = 0.47$ $p = 0.019$ (F.K.)

+ $r(22) = 0.56$ $p = 0.004$ (A.P.) ⟶

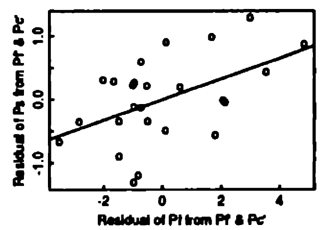


partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

+ $r(21) = 0.46$ $p = 0.028$ (F.K., Stem-Past)

+ $r(21) = 0.50$ $p = 0.015$ (A.P., Stem-Past) ⟶

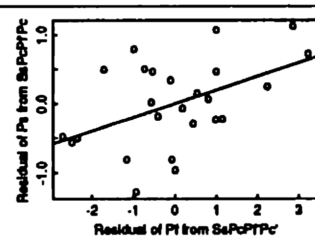


partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

+ $r(19) = 0.43$ $p = 0.050$ (F.K., Stem-Past)

+ $r(19) = 0.48$ $p = 0.029$ (A.P., Stem-Past) ⟶

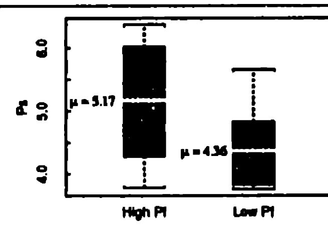


by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(11) = 1.95$ $p = 0.077$ (F.K.)

+ $t(11) = 2.24$ $p = 0.046$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 9/10 (90%)
Predictive power of Past Tense Frequency under Rule Theory = 1/6 (17%)

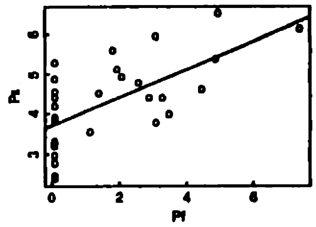
Table 8.1: All-Verbs Study: acceptability ratings for doublet regulars

Predictiveness of Past Tense Frequency(*dived*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Regulars from Doublets Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

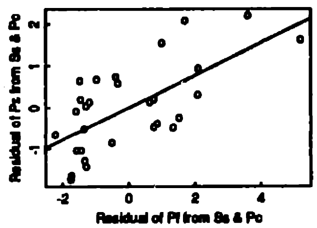
+	$r(27) = 0.55$	$p = 0.002$	(F.K.)
+	$r(27) = 0.65$	$p < 0.001$	(A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

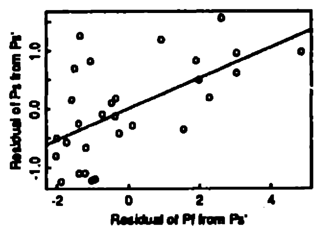
+	$r(25) = 0.60$	$p < 0.001$	(F.K., Stem-Past)
+	$r(25) = 0.67$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

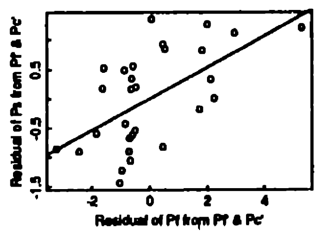
+	$r(26) = 0.55$	$p = 0.003$	(F.K.)
+	$r(26) = 0.60$	$p < 0.001$	(A.P.) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

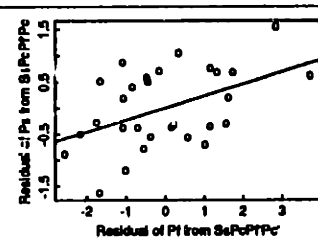
+	$r(25) = 0.53$	$p = 0.004$	(F.K., Stem-Past)
+	$r(25) = 0.58$	$p = 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

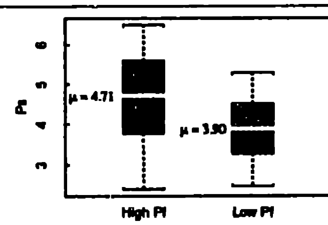
+	$r(23) = 0.47$	$p = 0.018$	(F.K., Stem-Past)
+	$r(23) = 0.46$	$p = 0.020$	(A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

+	$t(13) = 2.32$	$p = 0.037$	(F.K.)
not+	$t(13) = 1.90$	$p = 0.080$	(A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 9/10 (90%)
Predictive power of Past Tense Frequency under Rule Theory = 1/6 (17%)

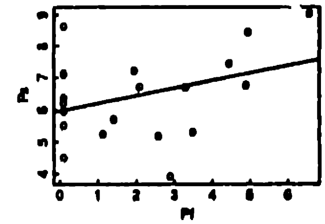
Table 8.2: Doublets Study: acceptability ratings for doublet regulars

Predictiveness of Past Tense Frequency(*dived*)
on Past Tense Success(*dived*) as accept. ratings (1-10)
under Rule and Associative Theories for Doublet Regulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

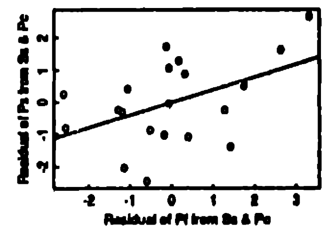
not+ $r(18) = 0.29$ $p = 0.211$ (F.K.)
not+ $r(18) = 0.35$ $p = 0.126$ (A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

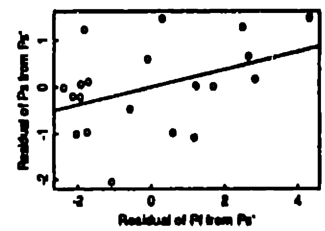
not+ $r(16) = 0.37$ $p = 0.129$ (F.K., Stem-Past)
not+ $r(16) = 0.46$ $p = 0.054$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

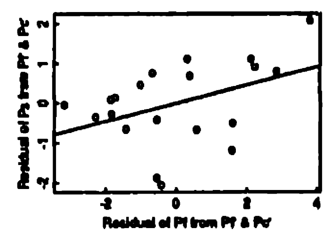
not+ $r(17) = 0.40$ $p = 0.086$ (F.K.)
not+ $r(17) = 0.41$ $p = 0.082$ (A.P.) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

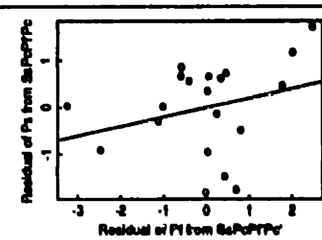
not+ $r(16) = 0.29$ $p = 0.246$ (F.K., Stem-Past)
not+ $r(16) = 0.42$ $p = 0.085$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

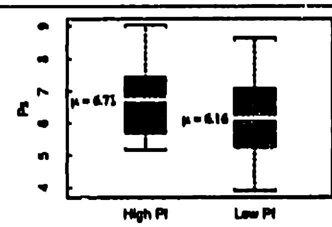
not+ $r(14) = 0.29$ $p = 0.275$ (F.K., Stem-Past)
not+ $r(14) = 0.28$ $p = 0.293$ (A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.99$ $p = 0.077$ (F.K.)
not+ $t(9) = 0.90$ $p = 0.391$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 6/6 (100%)

Table 8.3: All-Classes Study: acceptability ratings for doublet regulars

Predictiveness of Past Tense Frequency(*dived*)

on Past Tense Success(*dived*) as prod. like. (% subjs)

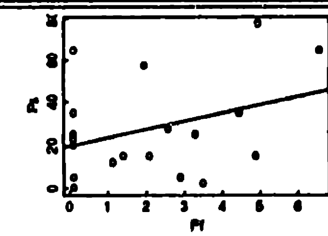
under Rule and Associative Theories for Doublet Regulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

not+ $r(18) = 0.14$ $p = 0.556$ (F.K.)

not+ $r(18) = 0.35$ $p = 0.134$ (A.P.) ⟶

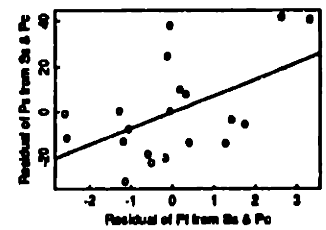


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(16) = 0.27$ $p = 0.277$ (F.K., Stem-Past)

\+ $r(16) = 0.52$ $p = 0.027$ (A.P., Stem-Past) ⟶

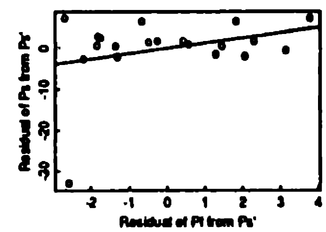


partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

not+ $r(17) = 0.19$ $p = 0.425$ (F.K.)

not+ $r(17) = 0.30$ $p = 0.205$ (A.P.) ⟶

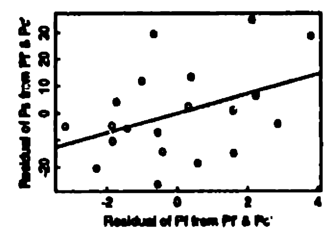


partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

not+ $r(16) = 0.10$ $p = 0.706$ (F.K., Stem-Past)

not+ $r(16) = 0.40$ $p = 0.096$ (A.P., Stem-Past) ⟶

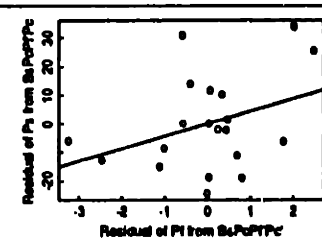


partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

not+ $r(14) = 0.19$ $p = 0.481$ (F.K., Stem-Past)

not+ $r(14) = 0.36$ $p = 0.171$ (A.P., Stem-Past) ⟶

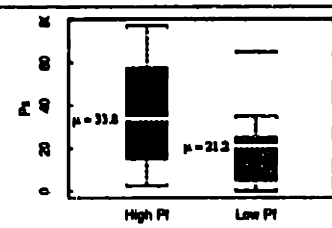


by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.18$ $p = 0.270$ (F.K.)

not+ $t(9) = 1.38$ $p = 0.200$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 1/10 (10%)

Predictive power of Past Tense Frequency under Rule Theory = 5/6 (83%)

Table 8.4: All-Classes Study: production likelihood for doublet regulars

8.1.2 Doublet Irregulars (*dove*)

If doublet irregular pasts (*dove*) are associatively learned and computed, the more frequent those pasts, the more successfully they should be computed. That is, Past Tense Frequency (*dove*) should predict Past Tense Success (*dove*). In this case the second through sixth cells of the Display Tables should show analyses revealing the significance of these predictions, with Stem Strength (*dive*), Past Tense Frequency (*dove*), Altern. Past Tense Frequency (*dived*), or various other variables held constant.

However, if doublet irregular pasts are produced by a symbol-processing system, there should be no such past tense frequency effects. In this case the second through sixth cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Stem Strength or other variables held constant.

Predictiveness of Past Tense Frequency(*dove*)

on Past Tense Success(*dove*) as accept. ratings (1-7)

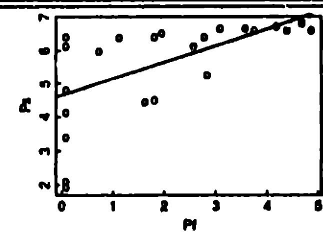
under Rule and Associative Theories for Doublet Irregulars from All-Verbs Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

+ $r(23) = 0.49$ $p = 0.014$ (F.K.)

+ $r(23) = 0.59$ $p = 0.002$ (A.P.) ⟶

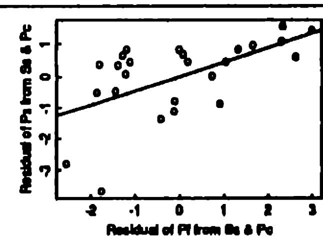


partialing out Ss, Pc: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

+ $r(21) = 0.48$ $p = 0.020$ (F.K., Stem-Past)

+ $r(21) = 0.57$ $p = 0.004$ (A.P., Stem-Past) ⟶

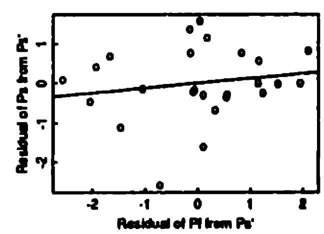


partialing out Ps': $r_{PsPf.Ps'}$

R:none A: + (prediction)

not+ $r(22) = 0.00$ $p = 1.000$ (F.K.)

not+ $r(22) = 0.16$ $p = 0.458$ (A.P.) ⟶

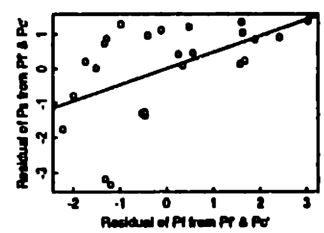


partialing out Pf', Pc': $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

+ $r(21) = 0.45$ $p = 0.032$ (F.K., Stem-Past)

+ $r(21) = 0.52$ $p = 0.012$ (A.P., Stem-Past) ⟶

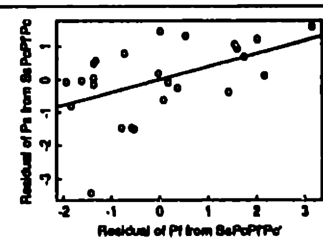


partialing out Ss, Pc, Pf', Pc': $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

+ $r(19) = 0.45$ $p = 0.040$ (F.K., Stem-Past)

+ $r(19) = 0.49$ $p = 0.023$ (A.P., Stem-Past) ⟶

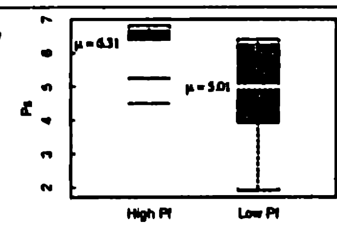


by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(11) = 0.97$ $p = 0.352$ (F.K.)

+ $t(11) = 2.87$ $p = 0.015$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 7/10 (70%)

Predictive power of Past Tense Frequency under Rule Theory = 1/6 (17%)

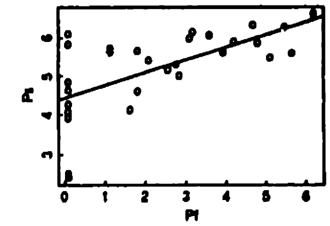
Table 8.5: All-Verbs Study: acceptability ratings for doublet irregulars

Predictiveness of Past Tense Frequency(*dove*)
on Past Tense Success(*dove*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Irregulars from Doublets Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

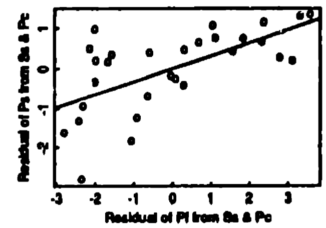
+	$r(27) = 0.56$	$p = 0.002$	(F.K.)
+	$r(27) = 0.64$	$p < 0.001$	(A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

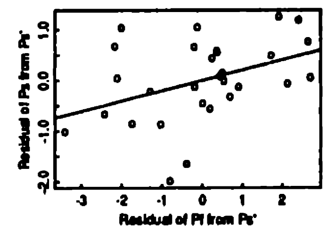
+	$r(25) = 0.56$	$p = 0.003$	(F.K., Stem-Past)
+	$r(25) = 0.63$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

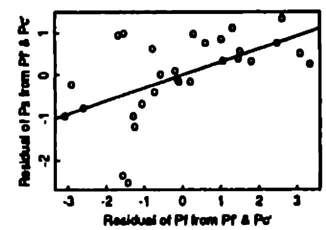
not+	$r(26) = 0.31$	$p = 0.113$	(F.K.)
+	$r(26) = 0.40$	$p = 0.034$	(A.P.) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

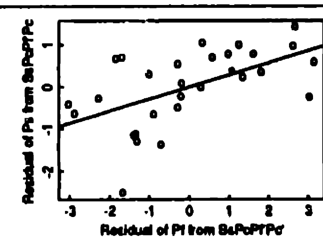
+	$r(25) = 0.52$	$p = 0.005$	(F.K., Stem-Past)
+	$r(25) = 0.56$	$p = 0.002$	(A.P., Stem-Past) ⟶



partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

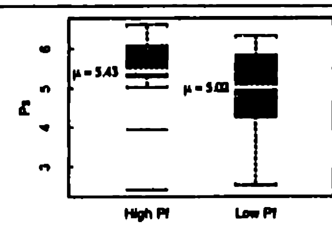
+	$r(23) = 0.53$	$p = 0.007$	(F.K., Stem-Past)
+	$r(23) = 0.56$	$p = 0.004$	(A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+	$t(13) = 2.10$	$p = 0.056$	(F.K.)
not+	$t(13) = 1.11$	$p = 0.287$	(A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 7/10 (70%)
Predictive power of Past Tense Frequency under Rule Theory = 2/6 (33%)

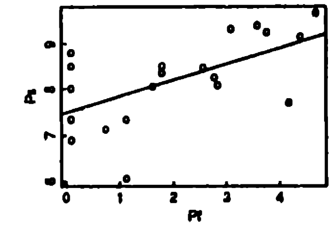
Table 8.6: Doublets Study: acceptability ratings for doublet irregulars

Predictiveness of Past Tense Frequency(*dove*)
on Past Tense Success(*dove*) as accept. ratings (1-10)
under Rule and Associative Theories for Doublet Irregulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

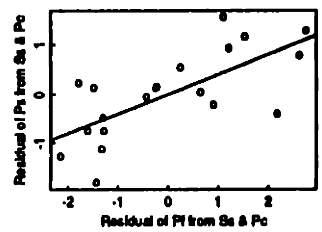
\+ $r(18) = 0.50$ $p = 0.025$ (F.K.)
\+ $r(18) = 0.60$ $p = 0.005$ (A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

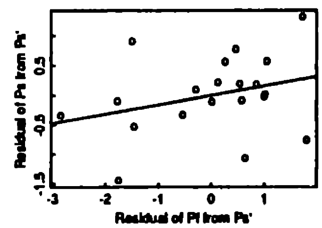
\+ $r(16) = 0.55$ $p = 0.017$ (F.K., Stem-Past)
\+ $r(16) = 0.70$ $p = 0.001$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

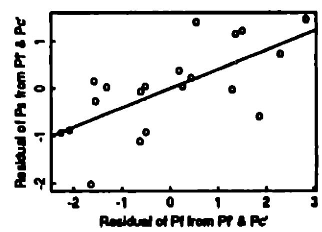
not+ $r(17) = 0.15$ $p = 0.528$ (F.K.)
not+ $r(17) = 0.30$ $p = 0.206$ (A.P.) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

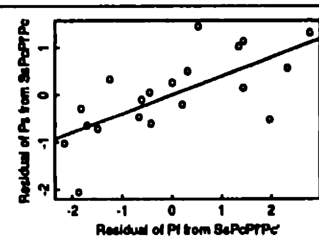
\+ $r(16) = 0.53$ $p = 0.024$ (F.K., Stem-Past)
\+ $r(16) = 0.67$ $p = 0.002$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

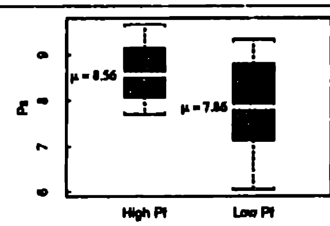
\+ $r(14) = 0.56$ $p = 0.025$ (F.K., Stem-Past)
\+ $r(14) = 0.69$ $p = 0.003$ (A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.01$ $p = 0.339$ (F.K.)
not+ $t(9) = 1.63$ $p = 0.138$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 6/10 (60%)
Predictive power of Past Tense Frequency under Rule Theory = 2/6 (33%)

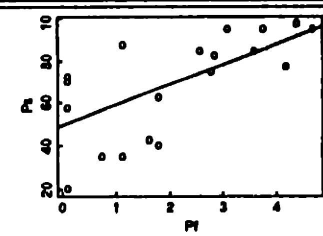
Table 8.7: All-Classes Study: acceptability ratings for doublet irregulars

Predictiveness of Past Tense Frequency(*dove*)
on Past Tense Success(*dove*) as prod. like. (% subjs)
under Rule and Associative Theories for Doublet Irregulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

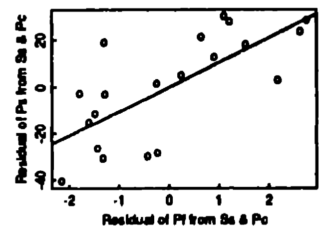
+	$r(18) = 0.64$	$p = 0.002$	(F.K.)
+	$r(18) = 0.65$	$p = 0.002$	(A.P.) ⟶



partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

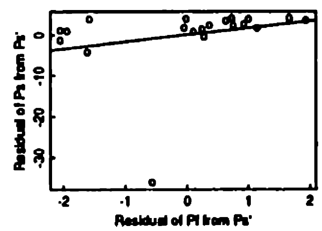
+	$r(16) = 0.68$	$p = 0.002$	(F.K., Stem-Past)
+	$r(16) = 0.72$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

R:none A: + (prediction)

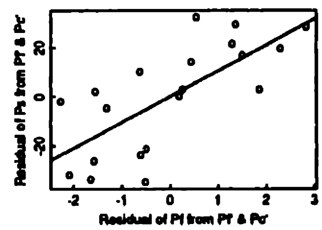
not+	$r(17) = 0.39$	$p = 0.097$	(F.K.)
not+	$r(17) = 0.24$	$p = 0.317$	(A.P.) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

R:none A: + (prediction)

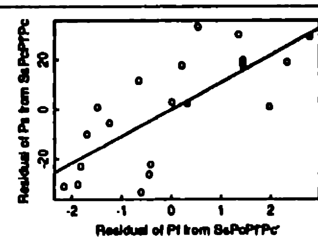
+	$r(16) = 0.73$	$p < 0.001$	(F.K., Stem-Past)
+	$r(16) = 0.72$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

R:not+ A: + (prediction)

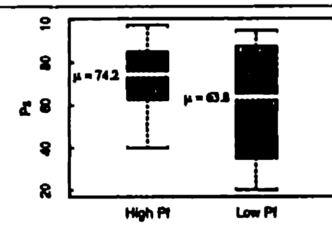
+	$r(14) = 0.76$	$p < 0.001$	(F.K., Stem-Past)
+	$r(14) = 0.74$	$p < 0.001$	(A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+	$t(9) = 1.39$	$p = 0.199$	(F.K.)
not+	$t(9) = 0.90$	$p = 0.390$	(A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 6/10 (60%)
Predictive power of Past Tense Frequency under Rule Theory = 2/6 (33%)

Table 8.8: All-Classes Study: production likelihood for doublet irregulars

8.1.3 Discussion

Past Tense Frequency is a strong predictor of Past Tense Success for doublet regulars (*dive-dived*), and even stronger for doublet irregulars (*dive-dove*).

Almost every analysis was significant in the expected direction over the four studies for which Past Tense Success was measured for doublet irregulars (*dove*): acceptability ratings from the All-Verbs study, acceptability ratings from the Doublets study, acceptability ratings from the All-Classes study, and production likelihood from the All-Classes study.

For doublet regulars (*dived*) the effect was slightly weaker but still very strong: 10 out of 12 analyses were significant for both the Past and Stem-Past associative theories for both the All-Verbs and Doublet studies' acceptability ratings, while the remaining 2 analyses in each case were in the expected direction in every case, and approaching significance (p=.06) in one case. The acceptability ratings and production likelihood measures from the All-Classes study were somewhat weaker: While 47 out of the 48 analyses were in the expected direction, only one was significant in a two-tailed test, and 5 more were significant by a one-tailed criterion.

It is tempting to use this difference between doublet irregulars and regulars as evidence for the Hybrid Model: According to my theory, regular pasts should only be computed in the irregular associative memory if they have been learned — which in turn is a function of both their stems' proximity to the stems of irregulars as well as the word frequency and regular cluster strength of this and other nearby doublet or attracted regulars (whose probability of being learned is, in turn, a function of the same factors). Thus "over-regular" doublet regulars such as perhaps *slay-slayed*, whose irregular *and* regular pasts are of very low frequencies (the Francis and Kučera and Associated Press frequencies of both are 0), have a very low probability of being computed (either within a subject or across subjects) within the memory, and thus have a high probability of being computed by the rule system. Thus the weaker predictive power of Past Tense Frequency for doublet regulars than for doublet irregulars could be used as evidence for the Hybrid Model.

However, before we can conclude that this theoretical distinction is responsible for the statistical difference between the two past classes, we must look at at least one other alternative explanation — that there is a floor effect for doublet regulars which is reducing the analyses statistical significance levels: specifically, that there are more zero-frequency pasts for regular than irregular doublet pasts. Fortunately for the Hybrid Model, this does not seem to be the case. If we redo the analyses after removing the zero-frequency regular pasts, we still do not reach statistical significance for production success from the All-Classes study, although we do reach it for acceptability ratings from the All-Classes study. Furthermore, it is not even clear whether it is justifiable to remove the zero-frequency pasts: it is these very pasts which are most likely the "over-regular" doublet regulars, while the higher frequency ones are more likely to be learned and computed in the memory.

8.2 The Predictiveness of Past Tense Cluster Strength(Pc)

8.2.1 Doublet Regulars (*jived, thrived*)

If doublet regular pasts (*dived*) are associatively learned, the presentation of other regular pasts (*jived, thrived*) whose stem-past mappings are shared with those of *dive-dived* should facilitate the latter's computation. That is, regular cluster strength (*jived, thrived*) should predict Past Tense Success (*dived*). In this case the second through sixth cells of the Display Tables should show analyses revealing the significance of these predictions, with Past Tense Frequency (*blew*), Stem Strength (*blow*), or other variables held constant.

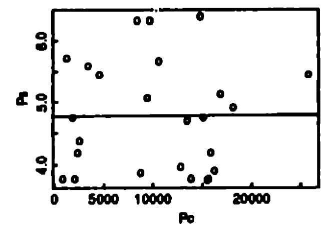
However, we expect this prediction only if doublet regulars are completely associatively learned, just as irregulars; but if regulars are only associatively learned if their stems are similar to the stems of irregulars, it is unlikely that enough regulars would be associatively learned to result in regular cluster strength effects. Similarly, if doublet regulars are completely rule-produced, there should be no regular cluster effects. In these cases the second through sixth cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions.

Predictiveness of Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Regulars from All-Verbs Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

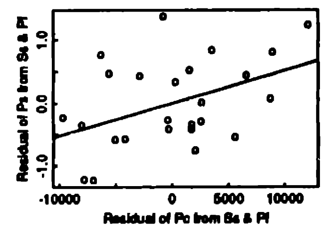
not+ $r(23) = -0.02$ $p = 0.917$ (F.K., Stem-Past)
not+ $r(23) = 0.01$ $p = 0.973$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

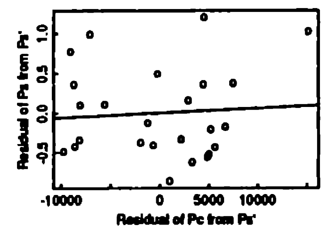
not+ $r(21) = 0.31$ $p = 0.150$ (F.K., Stem-Past)
\+ $r(21) = 0.43$ $p = 0.039$ (A.P., Stem-Past) ⟶



partialing out *Ps′*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

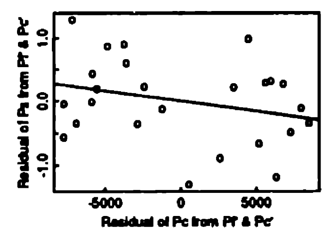
not+ $r(22) = 0.15$ $p = 0.493$ (F.K., Stem-Past)
not+ $r(22) = 0.07$ $p = 0.752$ (A.P., Stem-Past) ⟶



partialing out *Pf′*, *Pc′*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

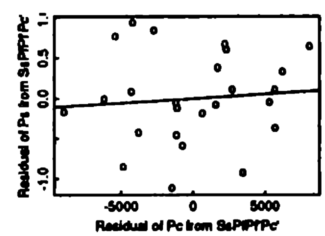
not+ $r(21) = -0.22$ $p = 0.313$ (F.K., Stem-Past)
not+ $r(21) = -0.28$ $p = 0.191$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pf′*, *Pc′*: $r_{PsSs.PfPcPf'Pc'}$

R:not+ A: + (prediction)

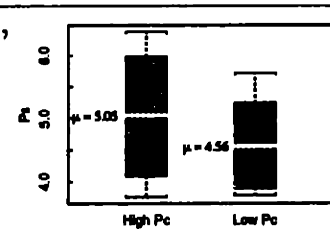
not+ $r(19) = 0.08$ $p = 0.716$ (F.K., Stem-Past)
not+ $r(19) = 0.09$ $p = 0.697$ (A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(11) = 1.33$ $p = 0.212$ (F.K., Stem-Past)
not+ $t(11) = 1.28$ $p = 0.226$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 1/10 (10%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 9/10 (90%)

Table 8.9: All-Verbs Study: acceptability ratings for doublet regulars

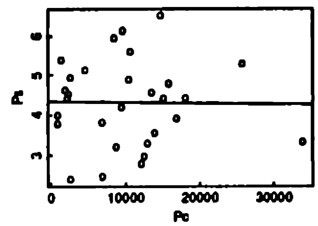
Predictiveness of Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Regulars from Doublets Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(27) = 0.04$ $p = 0.833$ (F.K., Stem-Past)

not+ $r(27) = -0.01$ $p = 0.941$ (A.P., Stem-Past) ⟶

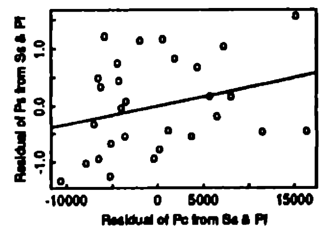


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(25) = 0.32$ $p = 0.102$ (F.K., Stem-Past)

not+ $r(25) = 0.28$ $p = 0.151$ (A.P., Stem-Past) ⟶

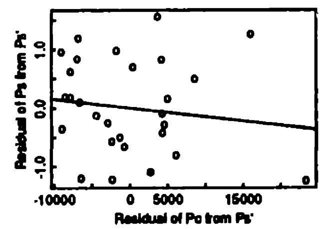


partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

not+ $r(26) = -0.06$ $p = 0.774$ (F.K., Stem-Past)

not+ $r(26) = -0.14$ $p = 0.490$ (A.P., Stem-Past) ⟶

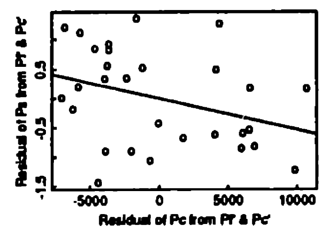


partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(25) = -0.23$ $p = 0.238$ (F.K., Stem-Past)

not+ $r(25) = -0.35$ $p = 0.076$ (A.P., Stem-Past) ⟶

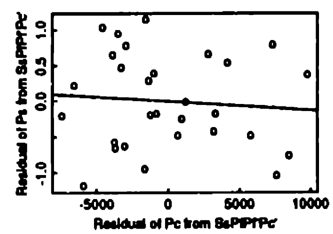


partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

R:not+ A: + (prediction)

not+ $r(23) = 0.08$ $p = 0.689$ (F.K., Stem-Past)

not+ $r(23) = -0.09$ $p = 0.673$ (A.P., Stem-Past) ⟶

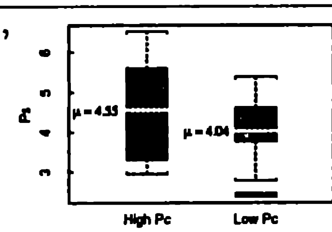


by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(13) = -0.64$ $p = 0.534$ (F.K., Stem-Past)

not+ $t(13) = 1.59$ $p = 0.136$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 10/10 (100%)

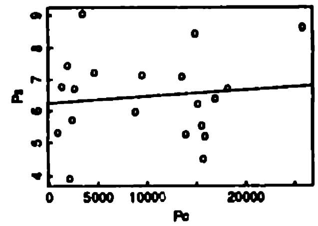
Table 8.10: Doublets Study: acceptability ratings for doublet regulars

Predictiveness of Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dived*) as accept. ratings (1-10)
under Rule and Associative Theories for Doublet Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

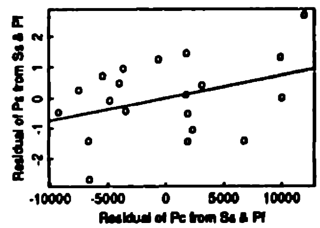
not+ $r(18) = 0.17$ $p = 0.486$ (F.K., Stem-Past)
not+ $r(18) = 0.11$ $p = 0.639$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

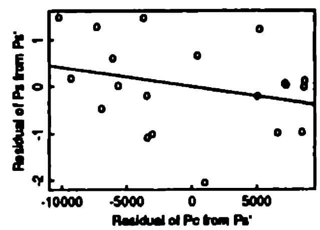
not+ $r(16) = 0.34$ $p = 0.170$ (F.K., Stem-Past)
not+ $r(16) = 0.37$ $p = 0.133$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

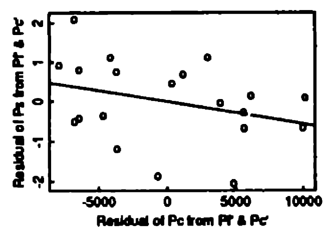
not+ $r(17) = -0.35$ $p = 0.144$ (F.K., Stem-Past)
not+ $r(17) = -0.29$ $p = 0.234$ (A.P., Stem-Past) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

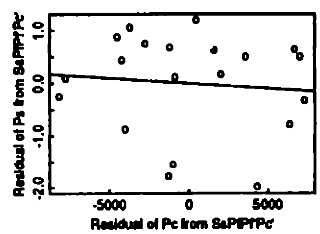
not+ $r(16) = -0.04$ $p = 0.889$ (F.K., Stem-Past)
not+ $r(16) = -0.32$ $p = 0.200$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

R:not+ A: + (prediction)

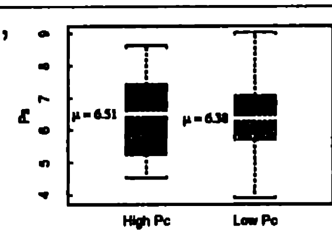
not+ $r(14) = 0.12$ $p = 0.646$ (F.K., Stem-Past)
not+ $r(14) = -0.10$ $p = 0.715$ (A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.77$ $p = 0.111$ (F.K., Stem-Past)
not+ $t(9) = 0.27$ $p = 0.795$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 10/10 (100%)

Table 8.11: All-Classes Study: acceptability ratings for doublet regulars

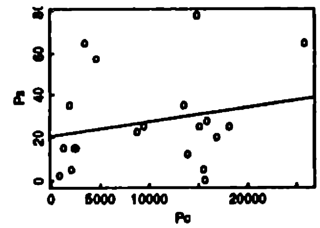
Predictiveness of Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dived*) as prod. like. (% subjs)
under Rule and Associative Theories for Doublet Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = 0.35$ $p = 0.125$ (F.K., Stem-Past)

not+ $r(18) = 0.22$ $p = 0.354$ (A.P., Stem-Past) ⟶

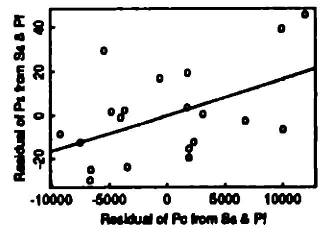


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(16) = 0.47$ $p = 0.051$ (F.K., Stem-Past)

\+ $r(16) = 0.49$ $p = 0.037$ (A.P., Stem-Past) ⟶

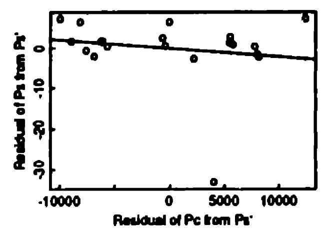


partialing out *Ps′*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

not+ $r(17) = -0.02$ $p = 0.921$ (F.K., Stem-Past)

not+ $r(17) = -0.18$ $p = 0.471$ (A.P., Stem-Past) ⟶

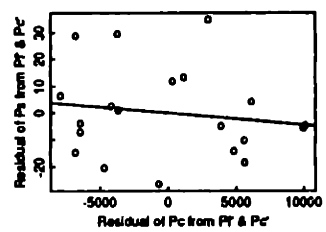


partialing out *Pf′*, *Pc′*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(16) = 0.25$ $p = 0.324$ (F.K., Stem-Past)

not+ $r(16) = -0.16$ $p = 0.537$ (A.P., Stem-Past) ⟶

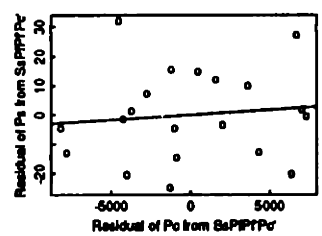


partialing out *Ss*, *Pf*, *Pf′*, *Pc′*: $r_{PsSs.PfPcPf'Pc'}$

R:not+ A: + (prediction)

not+ $r(14) = 0.34$ $p = 0.202$ (F.K., Stem-Past)

not+ $r(14) = 0.11$ $p = 0.693$ (A.P., Stem-Past) ⟶

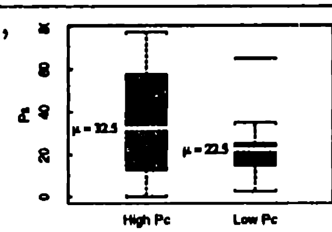


by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

\+ $t(9) = 2.59$ $p = 0.029$ (F.K., Stem-Past)

not+ $t(9) = 1.11$ $p = 0.295$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 2/10 (20%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 8/10 (80%)

Table 8.12: All-Classes Study: production likelihood for doublet regulars

8.2.2 Doublet Irregulars (*drove, rode*)

If doublet irregular pasts (*dove*) are associatively retrieved from their stems (*dive*), the presentation of other irregular pasts (*drive-drove*) whose stem-past mappings are shared with those of *dive-dove* should facilitate the latter's computation. That is, irregular cluster strength (*drove, rode*) should predict Past Tense Success (*dove*). In this case the second through sixth cells of the Display Tables should show analyses revealing the significance of these predictions, with Past Tense Frequency (*dove*), Stem Strength (*dive*), or other variables held constant.

However, if doublet irregular pasts are produced by a symbol-processing system, there should be no such irregular cluster strength effects. In this case the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions.

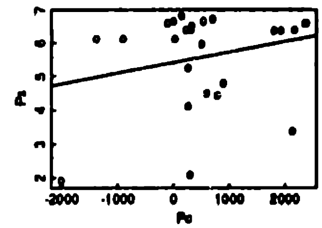
Predictiveness of Past Tense Cluster Strength(*drove, rode*)
on Past Tense Success(*dove*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Irregulars from All-Verbs Study

---

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(23) = 0.19$ $p = 0.364$ (F.K., Stem-Past)
not+ $r(23) = 0.25$ $p = 0.231$ (A.P., Stem-Past) ⟶



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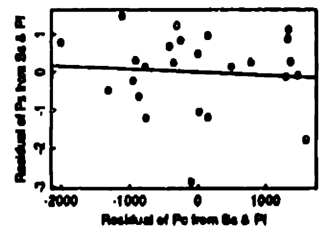
partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(21) = -0.03$ $p = 0.907$ (F.K., Stem-Past)
not+ $r(21) = -0.08$ $p = 0.730$ (A.P., Stem-Past) ⟶



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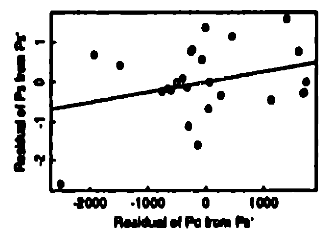
partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

not+ $r(22) = 0.31$ $p = 0.136$ (F.K., Stem-Past)
not+ $r(22) = 0.31$ $p = 0.143$ (A.P., Stem-Past) ⟶

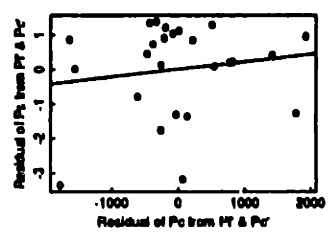


---

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(21) = 0.13$ $p = 0.544$ (F.K., Stem-Past)
not+ $r(21) = 0.15$ $p = 0.495$ (A.P., Stem-Past) ⟶



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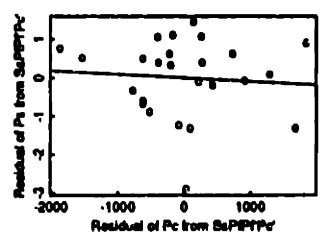
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

R:not+ A: + (prediction)

not+ $r(19) = -0.04$ $p = 0.873$ (F.K., Stem-Past)
not+ $r(19) = -0.08$ $p = 0.730$ (A.P., Stem-Past) ⟶

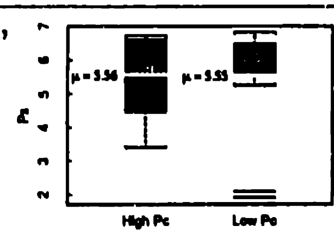


---

by a t-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(11) = -1.11$ $p = 0.293$ (F.K., Stem-Past)
not+ $t(11) = 0.02$ $p = 0.983$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 10/10 (100%)

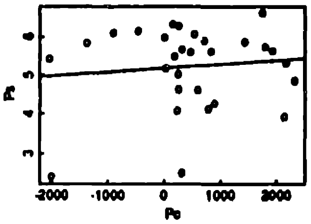
Table 8.13: All-Verbs Study: acceptability ratings for doublet irregulars

Predictiveness of Past Tense Cluster Strength(*drove, rode*)
on Past Tense Success(*dove*) as accept. ratings (1-7)
under Rule and Associative Theories for Doublet Irregulars from Doublets Study

by a simple correlation: $r_{P_cP_s}$

R:not+ A: + (prediction)

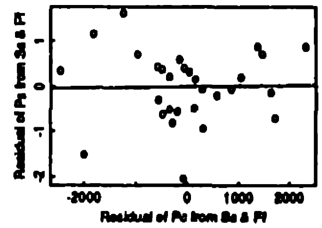
not+ $r(27) = 0.07$ $p = 0.722$ (F.K., Stem-Past)
not+ $r(27) = 0.11$ $p = 0.569$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{P_sP_c.S_sP_f}$

R:not+ A: + (prediction)

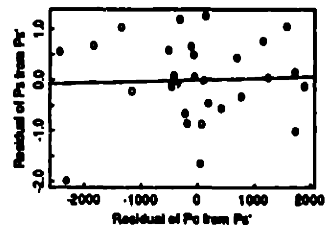
not+ $r(25) = 0.04$ $p = 0.828$ (F.K., Stem-Past)
not+ $r(25) = 0.02$ $p = 0.921$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{P_sP_c.P_s'}$

R:not+ A: + (prediction)

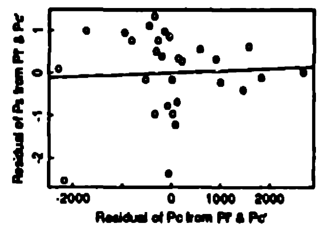
not+ $r(26) = 0.06$ $p = 0.758$ (F.K., Stem-Past)
not+ $r(26) = 0.04$ $p = 0.825$ (A.P., Stem-Past) ⟶



partialing out *Pf'*, *Pc'*: $r_{P_sP_c.P_f'P_c'}$

R:not+ A: + (prediction)

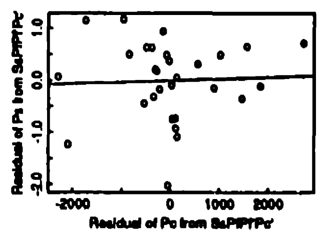
not+ $r(25) = 0.02$ $p = 0.938$ (F.K., Stem-Past)
not+ $r(25) = 0.05$ $p = 0.797$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{P_sS_s.P_fP_cP_f'P_c'}$

R:not+ A: + (prediction)

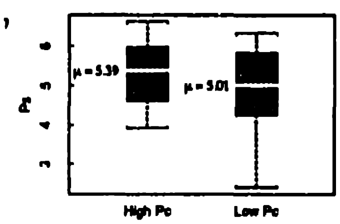
not+ $r(23) = 0.04$ $p = 0.861$ (F.K., Stem-Past)
not+ $r(23) = 0.04$ $p = 0.832$ (A.P., Stem-Past) ⟶



by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(13) = 0.29$ $p = 0.777$ (F.K., Stem-Past)
not+ $t(13) = 1.28$ $p = 0.222$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 10/10 (100%)

Table 8.14: Doublets Study: acceptability ratings for doublet irregulars

Predictiveness of Past Tense Cluster Strength(*drove, rode*)

on Past Tense Success(*dove*) as accept. ratings (1-10)

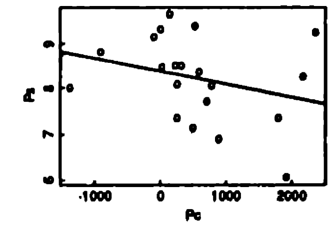
under Rule and Associative Theories for Doublet Irregulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = -0.31$ $p = 0.177$ (F.K., Stem-Past)

not+ $r(18) = -0.29$ $p = 0.214$ (A.P., Stem-Past) ⟶

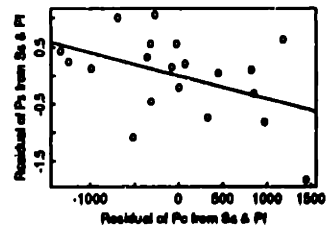


partialing out Ss, Pf: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(16) = -0.32$ $p = 0.197$ (F.K., Stem-Past)

not+ $r(16) = -0.44$ $p = 0.067$ (A.P., Stem-Past) ⟶

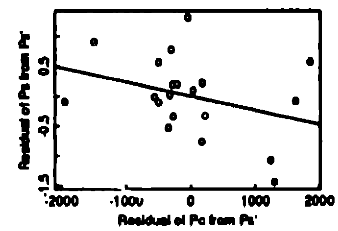


partialing out Ps': $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

not+ $r(17) = -0.26$ $p = 0.288$ (F.K., Stem-Past)

not+ $r(17) = -0.34$ $p = 0.158$ (A.P., Stem-Past) ⟶

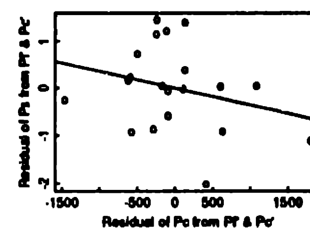


partialing out Pf', Pc': $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(16) = -0.25$ $p = 0.316$ (F.K., Stem-Past)

not+ $r(16) = -0.27$ $p = 0.273$ (A.P., Stem-Past) ⟶

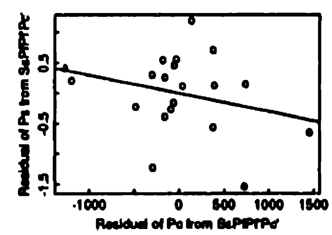


partialing out Ss, Pf, Pf', Pc': $r_{PsSs.PfPcPf'Pc'}$

R:not+ A: + (prediction)

not+ $r(14) = -0.23$ $p = 0.388$ (F.K., Stem-Past)

not+ $r(14) = -0.28$ $p = 0.288$ (A.P., Stem-Past) ⟶

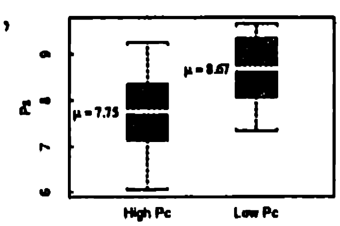


by a t-test comparing (Ps with high-Pc) with (Ps with low-Pc), given similar Pf values for each Ps pair

R:not+ A: + (prediction)

not+ $t(9) = 0.23$ $p = 0.823$ (F.K., Stem-Past)

not+ $t(9) = -2.93$ $p = 0.017$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 10/10 (100%)

Table 8.15: All-Classes Study: acceptability ratings for doublet irregulars

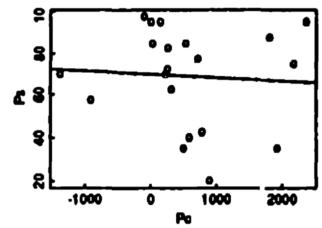
Predictiveness of Past Tense Cluster Strength(*drove, rode*)
on Past Tense Success(*dove*) as prod. like. (% subjs)
under Rule and Associative Theories for Doublet Irregulars from All-Classes Study

by a simple correlation: $r_{P_cP_s}$

R:not+ A: + (prediction)

not+ $r(18) = -0.17$ $p = 0.487$ (F.K., Stem-Past)

not+ $r(18) = -0.07$ $p = 0.777$ (A.P., Stem-Past) ⟶

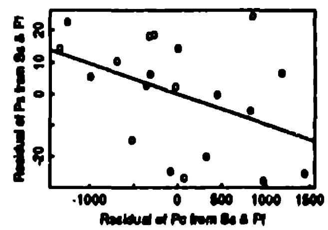


partialing out *Ss*, *Pf*: $r_{P_sP_c.S_sP_f}$

R:not+ A: + (prediction)

not+ $r(16) = -0.39$ $p = 0.108$ (F.K., Stem-Past)

not+ $r(16) = -0.43$ $p = 0.073$ (A.P., Stem-Past) ⟶

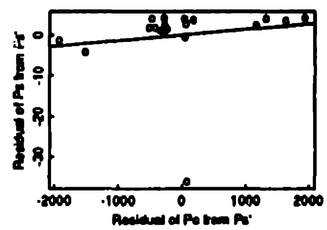


partialing out *Ps'*: $r_{P_sP_c.P_s'}$

R:not+ A: + (prediction)

not+ $r(17) = 0.22$ $p = 0.377$ (F.K., Stem-Past)

not+ $r(17) = 0.15$ $p = 0.552$ (A.P., Stem-Past) ⟶

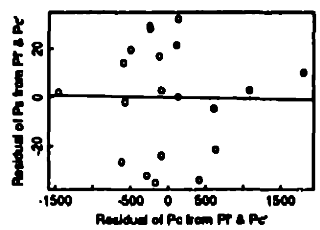


partialing out *Pf'*, *Pc'*: $r_{P_sP_c.P_f'P_c'}$

R:not+ A: + (prediction)

not+ $r(16) = 0.00$ $p = 0.992$ (F.K., Stem-Past)

not+ $r(16) = -0.02$ $p = 0.948$ (A.P., Stem-Past) ⟶

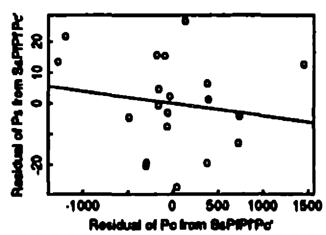


partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{P_sS_s.P_fP_cP_f'P_c'}$

R:not+ A: + (prediction)

not+ $r(14) = -0.23$ $p = 0.394$ (F.K., Stem-Past)

not+ $r(14) = -0.17$ $p = 0.538$ (A.P., Stem-Past) ⟶

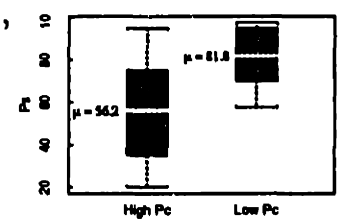


by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 0.00$ $p = 1.000$ (F.K., Stem-Past)

not+ $t(9) = -3.51$ $p = 0.007$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/10 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 10/10 (100%)

Table 8.16: All-Classes Study: production likelihood for doublet irregulars

8.2.3 Discussion

There is no evidence for cluster support (Past Tense Cluster Strength) for either doublet irregulars (*dove*) or doublet regulars (*dived*): that is, neither does irregular cluster cluster strength support (or hinder) doublet irregulars, nor does regular cluster cluster strength support (or hinder) doublet regulars.

It is not clear why there are are no cluster effects for either past class. I offer two possible explanations here. First, because both word frequency effects *and* blocking from *both the irregular and regular past directions* (see below) are so strong, cluster effects, which are quite weak in general (e.g., for true irregulars) in comparison, could be overwhelmed, so that they would be very difficult to detect. Second, because cluster effects are so weak, the small number of verbs could be insufficient to reveal such effects. With the two reasons combined, it is not all that surprising that I found no cluster effects.

One approach that might reveal such effects for irregular pasts (*dove*) would be to combine doublet irregulars with true irregulars in one data set (for a given experiment and measure, such as All-Classes production likelihood), and perform analyses on this larger data set. Similarly, one might combine doublet regulars (*dived*) with attracted regulars to form a larger data set, since I hypothesize that both of these types of regular pasts can have a relatively high probability of being learned and computed in the associative memory alongside irregulars. I will consider performing these analyses in the future.

8.3 Blocking of Doublet Regulars (*dived*): The Predictiveness of Altern. Past Tense Success (*dove*)

If doublet regulars (*dived*) are blocked in associative memory by their corresponding irregulars (*dove*), there should be a negative relationship between the two: the more successfully the irregular past (*dove*) is computed, the less successfully the regular past (*dived*) should be computed. Thus we should expect a negative relationship between Past Tense Success of doublet regulars (*dived*) and their Altern. Past Tense Success (of doublet irregulars: *dove*). That is, the first through fifth of the cells in the Analysis Tables should show significant negative correlations between Past Tense Success and Altern. Past Tense Success.

Predictiveness of Altern. Past Tense Success(*dove*) as accept. ratings (1-7)

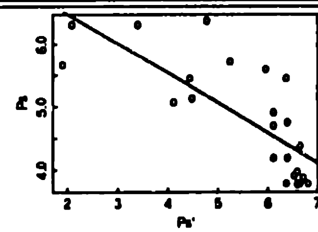
on Past Tense Success(*dived*) as accept. ratings (1-7)

under Blocking Theory for Doublet Regulars from All-Verbs Study

by a simple correlation: $r_{P_s' P_s}$

B: – (prediction)

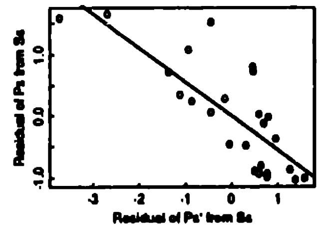
– $r(23) = -0.77$ $p < 0.001$



partialing out Ss: $r_{P_sP_s'.S_s}$

B: – (prediction)

– $r(22) = -0.79$ $p < 0.001$

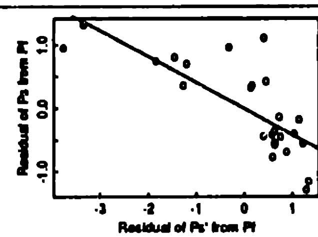


partialing out Pf: $r_{P_sP_s'.Pf}$

B: – (prediction)

– $r(22) = -0.76$ $p < 0.001$ (F.K.)

– $r(22) = -0.77$ $p < 0.001$ (A.P.) ⟶

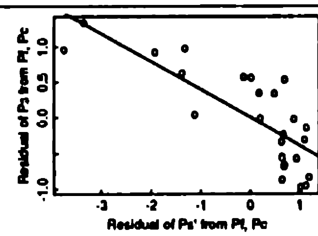


partialing out Pf, Pc: $r_{P_sP_s'.PfPc}$

B: – (prediction)

– $r(21) = -0.80$ $p < 0.001$ (F.K., Stem-Past)

– $r(21) = -0.79$ $p < 0.001$ (A.P., Stem-Past) ⟶

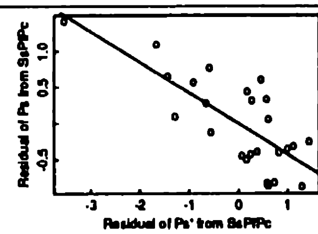


partialing out Ss, Pf, Pc: $r_{P_sP_s'.SsPfPc}$

B: – (prediction)

– $r(20) = -0.80$ $p < 0.001$ (F.K., Stem-Past)

– $r(20) = -0.76$ $p < 0.001$ (A.P., Stem-Past) ⟶



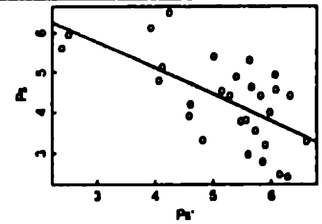
NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

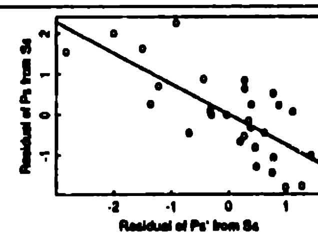
Table 8.17: All-Verbs Study: acceptability ratings for doublet regulars

Predictiveness of Altern. Past Tense Success(*dove*) as accept. ratings (1-7)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Blocking Theory for Doublet Regulars from Doublets Study

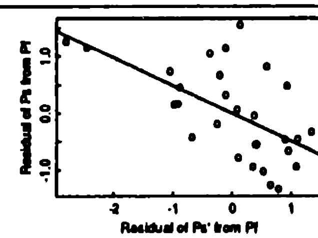
by a simple correlation: $r_{P_s{}'P_s}$
B: – (prediction)
– $r(27) = -0.65$ $p < 0.001$



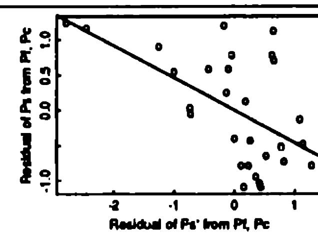
partialing out Ss: $r_{P_sP_s{}'.S_s}$
B: – (prediction)
– $r(26) = -0.73$ $p < 0.001$



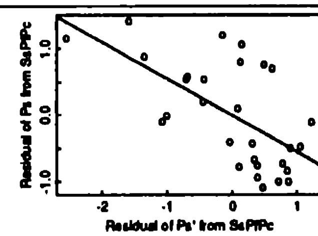
partialing out Pf: $r_{P_sP_s{}'.Pf}$
B: – (prediction)
– $r(26) = -0.64$ $p < 0.001$ (F.K.)
– $r(26) = -0.59$ $p < 0.001$ (A.P.) ⟶



partialing out Pf, Pc: $r_{P_sP_s{}'.PfPc}$
B: – (prediction)
– $r(25) = -0.61$ $p < 0.001$ (F.K., Stem-Past)
– $r(25) = -0.56$ $p = 0.002$ (A.P., Stem-Past) ⟶



partialing out Ss, Pf, Pc: $r_{P_sP_s{}'.SsPfPc}$
B: – (prediction)
– $r(24) = -0.70$ $p < 0.001$ (F.K., Stem-Past)
– $r(24) = -0.62$ $p < 0.001$ (A.P., Stem-Past) ⟶



NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

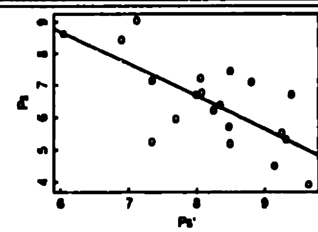
Table 8.18: Doublets Study: acceptability ratings for doublet regulars

Predictiveness of Altern. Past Tense Success(*dove*) as accept. ratings (1-10)
on Past Tense Success(*dived*) as accept. ratings (1-10)
under Blocking Theory for Doublet Regulars from All-Classes Study

by a simple correlation: $r_{P_s{}'P_s}$

B: – (prediction)

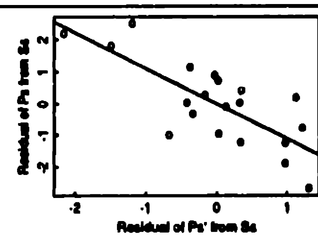
– $r(18) = -0.71$ $p < 0.001$



partialing out *Ss*: $r_{P_sP_s{}'.S_s}$

B: – (prediction)

– $r(17) = -0.76$ $p < 0.001$

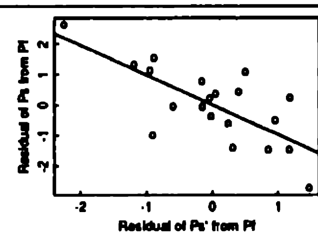


partialing out *Pf*: $r_{P_sP_s{}'.Pf}$

B: – (prediction)

– $r(17) = -0.74$ $p < 0.001$ (F.K.)

– $r(17) = -0.73$ $p < 0.001$ (A.P.) ⟶

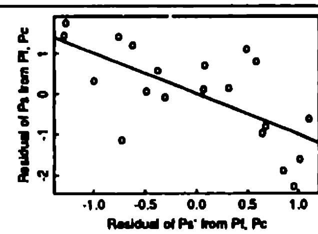


partialing out *Pf*, *Pc*: $r_{P_sP_s{}'.PfPc}$

B: – (prediction)

– $r(16) = -0.71$ $p < 0.001$ (F.K., Stem-Past)

– $r(16) = -0.68$ $p = 0.002$ (A.P., Stem-Past) ⟶

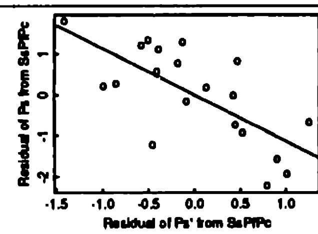


partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s{}'.SsPfPc}$

B: – (prediction)

– $r(15) = -0.74$ $p < 0.001$ (F.K., Stem-Past)

– $r(15) = -0.70$ $p = 0.002$ (A.P., Stem-Past) ⟶



NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

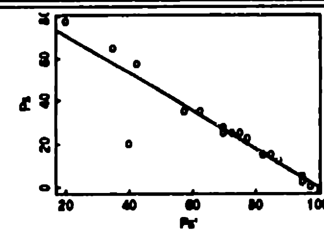
Table 8.19: All-Classes Study: acceptability ratings for doublet regulars

Predictiveness of Altern. Past Tense Success(*dove*) as prod. like. (% subjs)
on Past Tense Success(*dived*) as prod. like. (% subjs)
under Blocking Theory for Doublet Regulars from All-Classes Study

by a simple correlation: $r_{P_s{}' P_s}$

B: – (prediction)

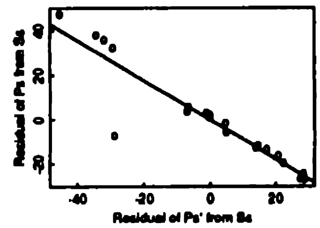
– $r(18) = -0.93$ $p < 0.001$



partialing out *Ss*: $r_{P_sP_s{}'.S_s}$

B: – (prediction)

– $r(17) = -0.93$ $p < 0.001$

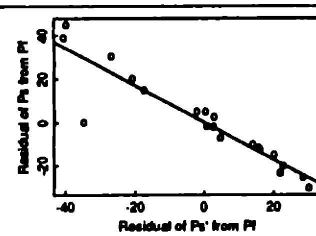


partialing out *Pf*: $r_{P_sP_s{}'.Pf}$

B: – (prediction)

– $r(17) = -0.93$ $p < 0.001$ (F.K.)

– $r(17) = -0.92$ $p < 0.001$ (A.P.) ⟶

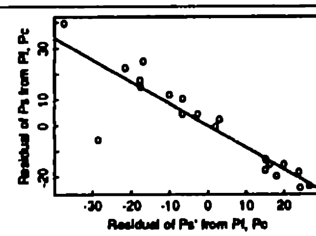


partialing out *Pf*, *Pc*: $r_{P_sP_s{}'.PfPc}$

B: – (prediction)

– $r(16) = -0.91$ $p < 0.001$ (F.K., Stem-Past)

– $r(16) = -0.90$ $p < 0.001$ (A.P., Stem-Past) ⟶

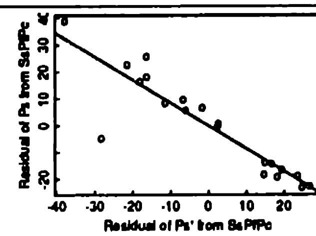


partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s{}'.S_sPfPc}$

B: – (prediction)

– $r(15) = -0.91$ $p < 0.001$ (F.K., Stem-Past)

– $r(15) = -0.90$ $p < 0.001$ (A.P., Stem-Past) ⟶



NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

Table 8.20: All-Classes Study: production likelihood for doublet regulars

8.3.1 Discussion

There is an extremely strong blocking relationship between doublet irregulars (*dove*) and doublet regulars (*dived*): ***Every single*** analysis for all four experimental measures is highly significant (p ¡ .001) in the expected direction (a negative relation between the two past classes). Note, however, that the production success measure (from the All-Classes study) must be interpreted with caution, since the production likelihood of doublet regulars will naturally be close to the complement of doublet irregulars.

Given that both forms show evidence of being associatively computed (from their past frequency effects), this seems to be strong support for my blocking theory. However, there are at least three alternative explanations which we must first examine.

First of all, the negative relationship could be a reflection of the real world relative frequencies of these verbs' irregular and regular past forms. That is, perhaps for some other reason, which I have not considered, the distribution of past frequencies is such that the higher the frequency of one past form, the lower the other. If this is true, then we should find a similar negative correlation between the relative frequencies of the irregular pasts and the regular pasts. However, such a negative correlation simply does not exist: r = -0.1185 p = 0.6620 (for the verbs in the Doublet study).

The second alternative explanation for the negative correlation is that it might be an averaging artifact across the 32 subjects. That is, in no subject does blocking actually take place, so there is no negative correlation for any given subject, but when the irregular and regular goodnesses are averaged over all subjects, a negative correlation emerges. However, when the correlation between irregular past goodness and regular past goodness was carried out on all 32 subjects from the Doublet study: 30 of the 32 subjects had negative correlations. The two positive correlations were not significant. Of the 30 negative correlations, the significance (p) of 23 was less than 0.1, 21 was less than 0.05, 19 was less than 0.01, 18 was less than 0.001, and 14 was less than 0.0001.

The third alternative explanation for the negative correlation is that it might be due to a response bias or demand characteristics. That is, perhaps each subject, after correctly judging the first form of each he or she came across, judged the second form only as a response to the first - either at an unconscious level or perhaps even as a result of guessing what the experimenter is looking for. Thus if the first was form was given a good judgement, the second would be given a bad judgement only as a result of this bias, and therefore the negative correlation would have nothing at all to do with blocking. To test for this possibility, I performed the following stringent analysis for the Doublet study: I extracted the first presentation of each verb, whether in its irregular or regular form, from each subject's answers as ordered in the questionnaire. Thus for the 32 subjects I extracted 16 judgements of irregular pasts for each verb, and 16 judgements of regular pasts for each verb.

Thus the irregular (*dove*) and regular (*dived*) pasts are being judged by *different* subjects, thus eliminating the possibility of a response bias. I then averaged these 16 judgements for irregular pasts for each verb, and similarly for the regular pasts. The result clearly shows that the negative correlation is clearly not due to a response bias: r=-0.6749 p ¡ 0.001.

8.4 The Predictiveness of Altern. Past Tense Frequency(Pfa)

8.4.1 Doublet Regulars (*dived* blocked by *dove*)

If doublet regulars (*dived*) are blocked in associative memory by their corresponding irregulars (*dove*), there should be a negative relationship between the frequency of Altern. Past Tense Success (that is, Altern. Past Tense Frequency, or the past frequency of *dove*) and the computational success of doublet regulars (*dived*): the more frequent the irregular past (*dove*), the less successfully the regular past (*dived*) should be computed. Thus we should expect a negative relationship between Past Tense Success of doublet regulars (*dived*) and the past tense frequency of their corresponding doublet irregulars (*dove*). That is, all six cells in the Analysis Tables should show significant negative correlations between Past Tense Success and Altern. Past Tense Success.

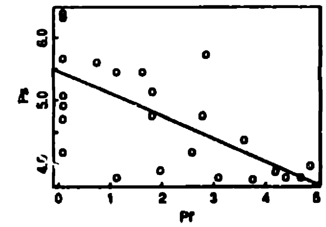
Predictiveness of Altern. Past Tense Frequency(*dove*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Blocking Theory for Doublet Regulars from All-Verbs Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(23) = -0.64$ $p < 0.001$ (F.K.)

– $r(23) = -0.67$ $p < 0.001$ (A.P.) ⟶

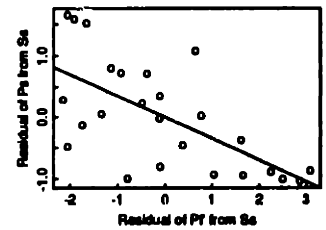


partialing out Ss: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(22) = -0.63$ $p = 0.001$ (F.K.)

– $r(22) = -0.65$ $p < 0.001$ (A.P.) ⟶

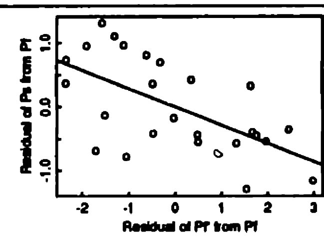


partialing out Pf: $r_{PsPf'.Pf}$

B: – (prediction)

– $r(22) = -0.62$ $p = 0.001$ (F.K.)

– $r(22) = -0.61$ $p = 0.002$ (A.P.) ⟶

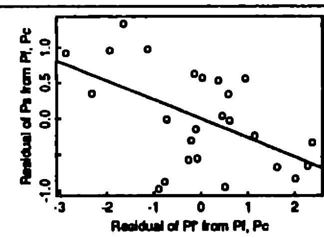


partialing out Pf, Pc: $r_{PsPf'.PfPc}$

B: – (prediction)

– $r(21) = -0.58$ $p = 0.003$ (F.K., Stem-Past)

– $r(21) = -0.53$ $p = 0.010$ (A.P., Stem-Past) ⟶

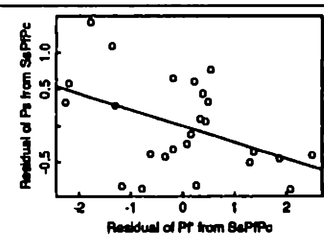


partialing out Ss, Pf, Pc: $r_{PsPf'.SsPfPc}$

B: – (prediction)

– $r(20) = -0.56$ $p = 0.007$ (F.K., Stem-Past)

– $r(20) = -0.45$ $p = 0.038$ (A.P., Stem-Past) ⟶

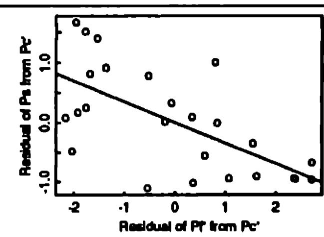


partialing out Pc': $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(22) = -0.64$ $p < 0.001$ (F.K., Stem-Past)

– $r(22) = -0.66$ $p < 0.001$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 12/12 (100%)

Table 8.21: All-Verbs Study: acceptability ratings for doublet regulars

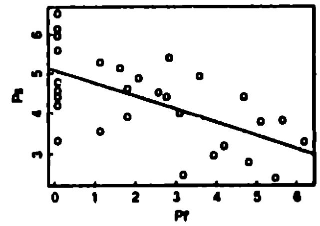
Predictiveness of Altern. Past Tense Frequency(*dove*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Blocking Theory for Doublet Regulars from Doublets Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(27) = -0.56$ $p = 0.002$ (F.K.)

– $r(27) = -0.61$ $p < 0.001$ (A.P.) ⟶

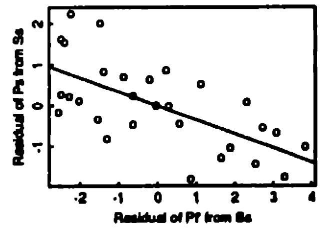


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(26) = -0.59$ $p < 0.001$ (F.K.)

– $r(26) = -0.66$ $p < 0.001$ (A.P.) ⟶

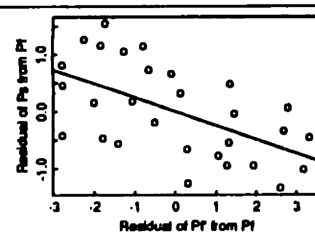


partialing out *Pf*: $r_{PsPf'.Pf}$

B: – (prediction)

– $r(26) = -0.54$ $p = 0.003$ (F.K.)

– $r(26) = -0.57$ $p = 0.001$ (A.P.) ⟶

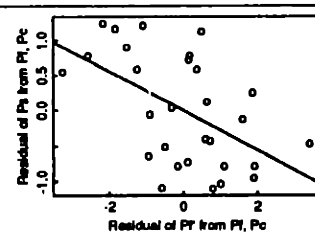


partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

B: – (prediction)

– $r(25) = -0.47$ $p = 0.014$ (F.K., Stem-Past)

– $r(25) = -0.53$ $p = 0.004$ (A.P., Stem-Past) ⟶

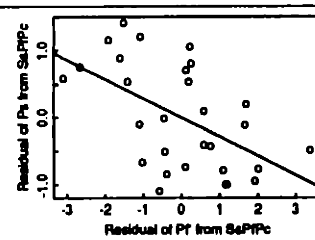


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

B: – (prediction)

– $r(24) = -0.49$ $p = 0.012$ (F.K., Stem-Past)

– $r(24) = -0.54$ $p = 0.004$ (A.P., Stem-Past) ⟶

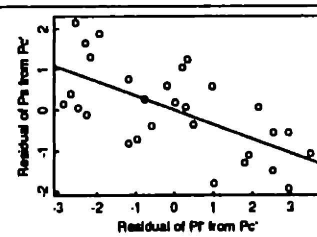


partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(26) = -0.59$ $p < 0.001$ (F.K., Stem-Past)

– $r(26) = -0.64$ $p < 0.001$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 12/12 (100%)

Table 8.22: Doublets Study: acceptability ratings for doublet regulars

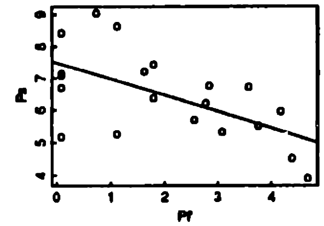
Predictiveness of Altern. Past Tense Frequency(*dove*)
on Past Tense Success(*dived*) as accept. ratings (1-10)
under Blocking Theory for Doublet Regulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(18) = -0.58$ $p = 0.007$ (F.K.)

– $r(18) = -0.60$ $p = 0.005$ (A.P.) ⟶

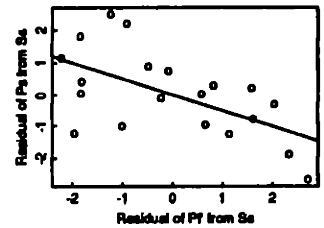


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(17) = -0.58$ $p = 0.010$ (F.K.)

– $r(17) = -0.60$ $p = 0.007$ (A.P.) ⟶

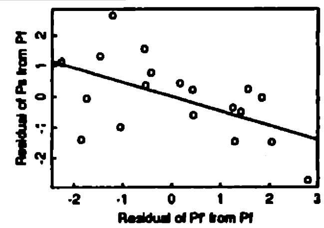


partialing out *Pf*: $r_{PsPf'.Pf}$

B: – (prediction)

– $r(17) = -0.58$ $p = 0.010$ (F.K.)

– $r(17) = -0.58$ $p = 0.010$ (A.P.) ⟶

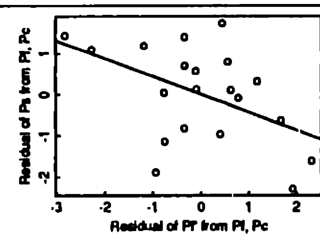


partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

B: – (prediction)

– $r(16) = -0.51$ $p = 0.031$ (F.K., Stem-Past)

– $r(16) = -0.4$[illegible] $p = 0.042$ (A.P., Stem-Past) ⟶

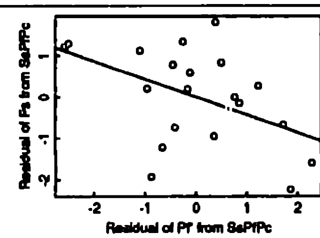


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

B: – (prediction)

– $r(15) = -0.51$ $p = 0.037$ (F.K., Stem-Past)

not– $r(15) = -0.48$ $p = 0.052$ (A.P., Stem-Past) ⟶

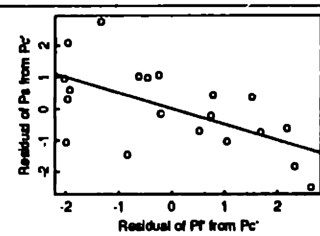


partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(17) = -0.58$ $p = 0.009$ (F.K., Stem-Past)

– $r(17) = -0.61$ $p = 0.006$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 11/12 (92%)

Table 8.23: All-Classes Study: acceptability ratings for doublet regulars

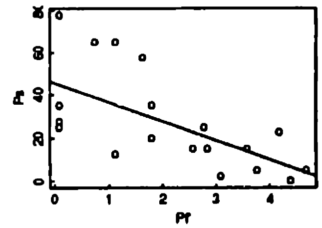
Predictiveness of Altern. Past Tense Frequency(*dove*)
on Past Tense Success(*dived*) as prod. like. (% subjs)
under Blocking Theory for Doublet Regulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(18) = -0.56$ $p = 0.010$ (F.K.)

– $r(18) = -0.63$ $p = 0.003$ (A.P.) ⟶

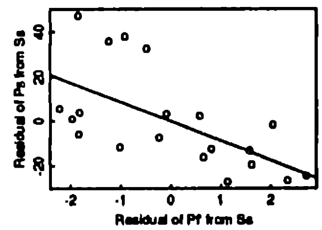


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(17) = -0.56$ $p = 0.013$ (F.K.)

– $r(17) = -0.62$ $p = 0.004$ (A.P.) ⟶

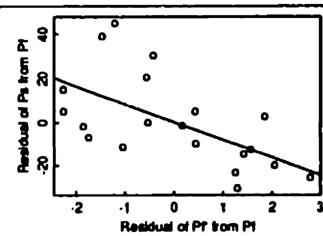


partialing out *Pf*: $r_{PsPf'.Pf}$

B: – (prediction)

– $r(17) = -0.56$ $p = 0.014$ (F.K.)

– $r(17) = -0.60$ $p = 0.006$ (A.P.) ⟶

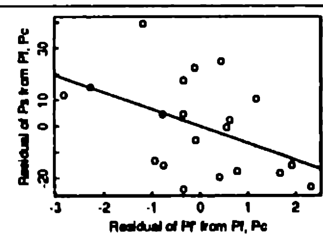


partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

B: – (prediction)

not– $r(16) = -0.45$ $p = 0.064$ (F.K., Stem-Past)

not– $r(16) = -0.46$ $p = 0.055$ (A.P., Stem-Past) ⟶

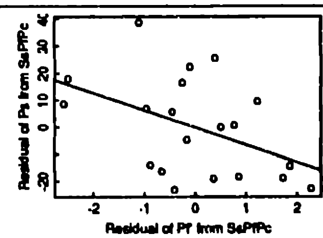


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

B: – (prediction)

not– $r(15) = -0.45$ $p = 0.073$ (F.K., Stem-Past)

not– $r(15) = -0.46$ $p = 0.066$ (A.P., Stem-Past) ⟶

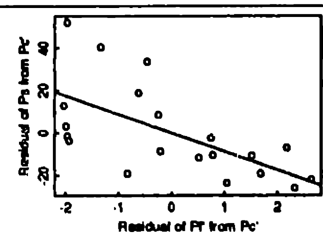


partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(17) = -0.56$ $p = 0.012$ (F.K., Stem-Past)

– $r(17) = -0.63$ $p = 0.004$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 8/12 (67%)

Table 8.24: All-Classes Study: production likelihood for doublet regulars

8.4.2 Doublet Irregulars (*dove* blocked by *dived*)

If doublet irregulars (*dove*) are blocked in associative memory by associatively learned doublet regulars (*dived*), there should be a negative relationship between the frequency of Altern. Past Tense Success (that is, Altern. Past Tense Frequency, or the past frequency of *dived*) and the computational success of doublet irregulars (*dove*): the more frequent the doublet regular past (*dived*), the less successfully the doublet irregular past (*dove*) should be computed. Thus we should expect a negative relationship between Past Tense Success of doublet irregulars (*dove*) and the past tense frequency of their corresponding doublet regulars (*dived*). That is, all six cells in the Analysis Tables should show significant negative correlations between Past Tense Success and Altern. Past Tense Success.

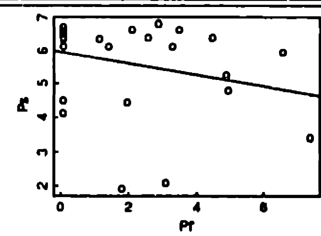
Predictiveness of Altern. Past Tense Frequency(*dived*)
on Past Tense Success(*dove*) as accept. ratings (1-7)
under Blocking Theory for Doublet Irregulars from All-Verbs Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

not– $r(23) = -0.25$ $p = 0.224$ (F.K.)

not– $r(23) = -0.27$ $p = 0.192$ (A.P.) ⟶

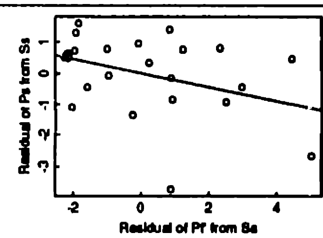


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

not– $r(22) = -0.27$ $p = 0.195$ (F.K.)

not– $r(22) = -0.39$ $p = 0.057$ (A.P.) ⟶

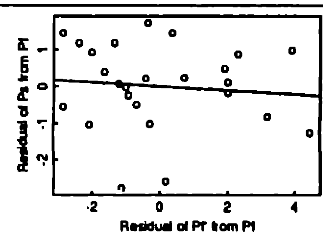


partialing out *Pf*: $r_{PsPf'.Pf}$

B: – (prediction)

not– $r(22) = -0.17$ $p = 0.426$ (F.K.)

not– $r(22) = -0.09$ $p = 0.661$ (A.P.) ⟶

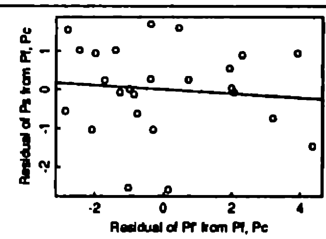


partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

B: – (prediction)

not– $r(21) = -0.16$ $p = 0.462$ (F.K., Stem-Past)

not– $r(21) = -0.10$ $p = 0.660$ (A.P., Stem-Past) ⟶

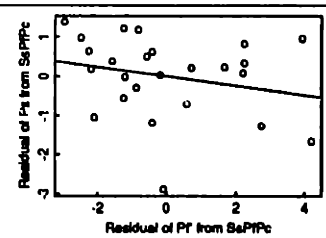


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

B: – (prediction)

not– $r(20) = -0.20$ $p = 0.371$ (F.K., Stem-Past)

not– $r(20) = -0.24$ $p = 0.283$ (A.P., Stem-Past) ⟶

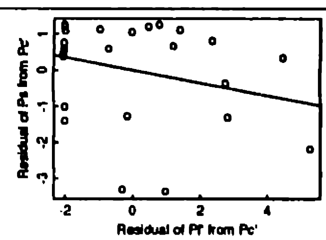


partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

not– $r(22) = -0.26$ $p = 0.223$ (F.K., Stem-Past)

not– $r(22) = -0.28$ $p = 0.191$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.25: All-Verbs Study: acceptability ratings for doublet irregulars

Predictiveness of Altern. Past Tense Frequency(*dived*)

on Past Tense Success(*dove*) as accept. ratings (1-7)

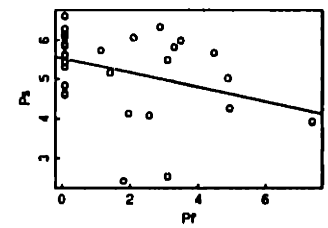
under Blocking Theory for Doublet Irregulars from Doublets Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

not– $r(27) = -0.23$ $p = 0.231$ (F.K.)

not– $r(27) = -0.34$ $p = 0.070$ (A.P.) ⟶

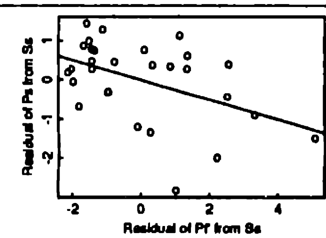


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

not– $r(26) = -0.29$ $p = 0.140$ (F.K.)

– $r(26) = -0.46$ $p = 0.013$ (A.P.) ⟶

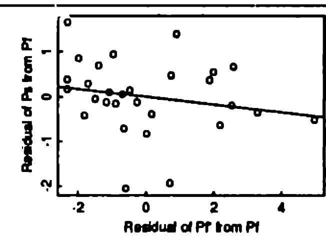


partialing out *Pf*: $r_{PsPf'.Pf}$

B: – (prediction)

not– $r(26) = -0.13$ $p = 0.512$ (F.K.)

not– $r(26) = -0.20$ $p = 0.307$ (A.P.) ⟶

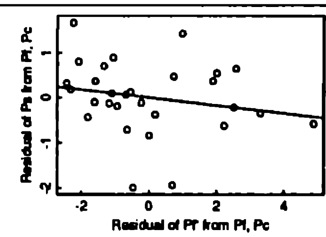


partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

B: – (prediction)

not– $r(25) = -0.12$ $p = 0.548$ (F.K., Stem-Past)

not– $r(25) = -0.20$ $p = 0.313$ (A.P., Stem-Past) ⟶

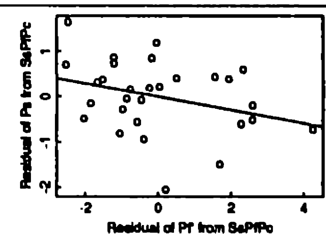


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

B: – (prediction)

not– $r(24) = -0.18$ $p = 0.370$ (F.K., Stem-Past)

not– $r(24) = -0.32$ $p = 0.113$ (A.P., Stem-Past) ⟶

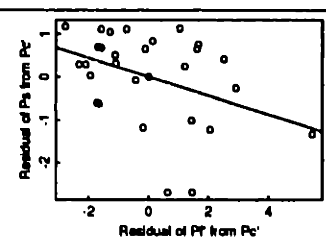


partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

not– $r(26) = -0.25$ $p = 0.208$ (F.K., Stem-Past)

– $r(26) = -0.40$ $p = 0.037$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 2/12 (17%)

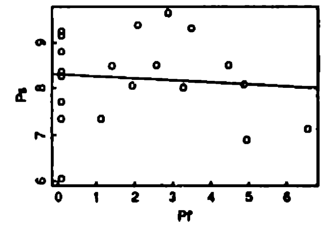
Table 8.26: Doublets Study: acceptability ratings for doublet irregulars

Predictiveness of Altern. Past Tense Frequency(*dived*)
on Past Tense Success(*dove*) as accept. ratings (1-10)
under Blocking Theory for Doublet Irregulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

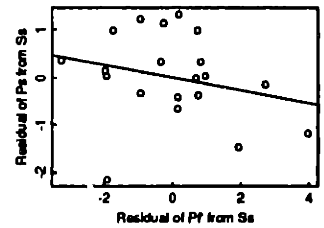
not– $r(18) = -0.01$ $p = 0.961$ (F.K.)
not– $r(18) = -0.09$ $p = 0.691$ (A.P.) $\longrightarrow$



partialing out Ss: $r_{PsPf'.Ss}$

B: – (prediction)

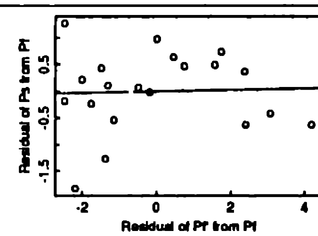
not– $r(17) = -0.14$ $p = 0.569$ (F.K.)
not– $r(17) = -0.25$ $p = 0.298$ (A.P.) $\longrightarrow$



partialing out Pf: $r_{PsPf'.Pf}$

B: – (prediction)

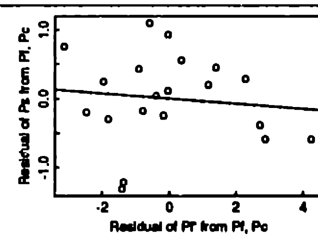
not– $r(17) = 0.04$ $p = 0.856$ (F.K.)
not– $r(17) = 0.04$ $p = 0.884$ (A.P.) $\longrightarrow$



partialing out Pf, Pc: $r_{PsPf'.PfPc}$

B: – (prediction)

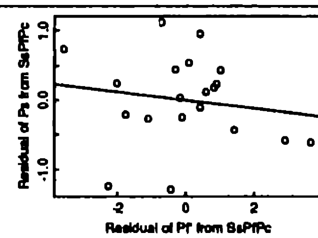
not– $r(16) = 0.01$ $p = 0.981$ (F.K., Stem-Past)
not– $r(16) = -0.12$ $p = 0.649$ (A.P., Stem-Past) $\longrightarrow$



partialing out Ss, Pf, Pc: $r_{PsPf'.SsPfPc}$

B: – (prediction)

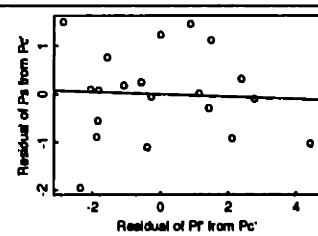
not– $r(15) = -0.07$ $p = 0.791$ (F.K., Stem-Past)
not– $r(15) = -0.16$ $p = 0.542$ (A.P., Stem-Past) $\longrightarrow$



partialing out Pc': $r_{PsPf'.Pc'}$

B: – (prediction)

not– $r(17) = 0.05$ $p = 0.845$ (F.K., Stem-Past)
not– $r(17) = -0.05$ $p = 0.826$ (A.P., Stem-Past) $\longrightarrow$



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.27: All-Classes Study: acceptability ratings for doublet irregulars

Predictiveness of Altern. Past Tense Frequency(*dived*)

on Past Tense Success(*dove*) as prod. like. (% subjs)

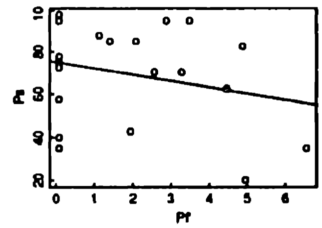
under Blocking Theory for Doublet Irregulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

not– $r(18) = -0.07$ $p = 0.761$ (F.K.)

not– $r(18) = -0.26$ $p = 0.277$ (A.P.) ⟶

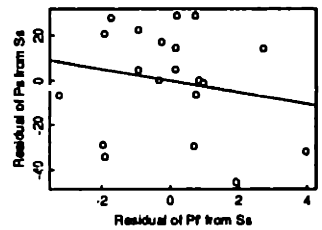


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

not– $r(17) = 0.02$ $p = 0.944$ (F.K.)

not– $r(17) = -0.19$ $p = 0.424$ (A.P.) ⟶

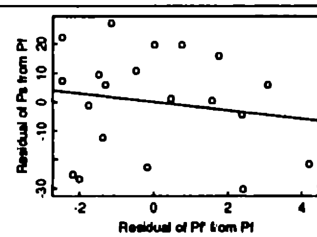


partialing out *Pf*: $r_{PsPf'.Pf}$

B: – (prediction)

not– $r(17) = -0.01$ $p = 0.965$ (F.K.)

not– $r(17) = -0.16$ $p = 0.505$ (A.P.) ⟶

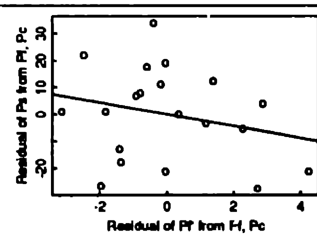


partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

B: – (prediction)

not– $r(16) = -0.04$ $p = 0.879$ (F.K., Stem-Past)

not– $r(16) = -0.25$ $p = 0.324$ (A.P., Stem-Past) ⟶

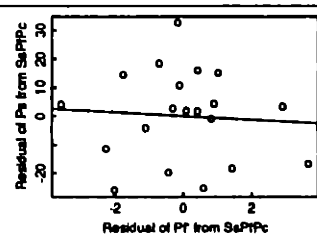


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

B: – (prediction)

not– $r(15) = 0.17$ $p = 0.524$ (F.K., Stem-Past)

not– $r(15) = -0.07$ $p = 0.787$ (A.P., Stem-Past) ⟶

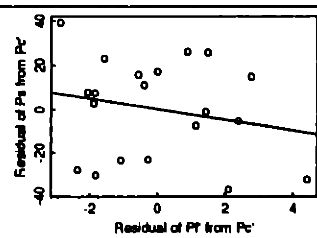


partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

not– $r(17) = 0.04$ $p = 0.874$ (F.K., Stem-Past)

not– $r(17) = -0.21$ $p = 0.377$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.28: All-Classes Study: production likelihood for doublet irregulars

8.4.3 Discussion

Doublet regular pasts (*dived*) are strongly blocked by their alternative irregular past frequency (*dove*), while doublet irregular pasts (*dove*) are weakly blocked by their alternative regular past frequency (*dived*).

For blocking of regular pasts by irregular past frequency, of the 48 analyses over the four experimental measures, all but 3 are significant in the expected direction (negative correlations). The 3 remaining analyses are also in the expected direction and approaching significance (they are significant under one-tailed tests).

On the other hand, for blocking of irregular pasts by regular past frequency, 37 out of the 48 analyses are in the expected direction (negative correlations). Of these 37 analyses, 3 are significant for two-tailed tests, and 3 more for one-tailed tests.

Just as with the non-blocking word frequency effects, this contrast between strong blocking by irregular pasts and very weak blocking by regular pasts supports my theory — since regular pasts should have a lower probability of being stored, they should also be less effective blockers. However, in an All-Associative model they should both be stored in the memory, and thus be equally effective at blocking the alternative form.

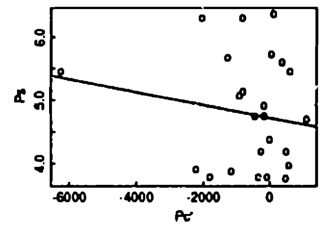
8.5 The Predictiveness of Altern. Past Tense Cluster Strength(Pca)

8.5.1 Doublet Regulars (*dived*): Irregular Cluster Strength (*drove, rode*)

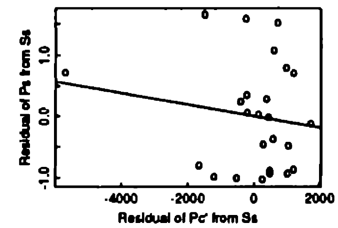
If doublet regulars (*dived*) are associatively computed, their computational success should be affected by their irregular neighbours (*drove, rode*). The higher the irregular cluster strength (the less the irregulars block *dived*, and perhaps even the more they support *dived*), the more successfully the doublet regulars (*dived*) should be computed. That is, there should be a positive correlation between irregular cluster strength (*drove, rode*) and past tense success (*dived*). In this case all six cells in the Analysis Tables should show these predictions.

Predictiveness of Altern. Past Tense Cluster Strength(*drove, rode*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Blocking Theory for Doublet Regulars from All-Verbs Study

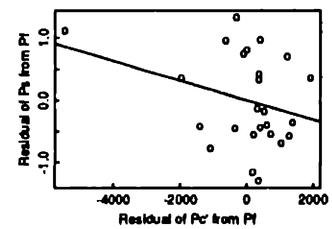
by a simple correlation: $r_{Pc'Ps}$
B: + (prediction)
not+ $r(23) = -0.01$ $p = 0.973$ (F.K., Stem-Past)
not+ $r(23) = -0.16$ $p = 0.432$ (A.P., Stem-Past) ⟶



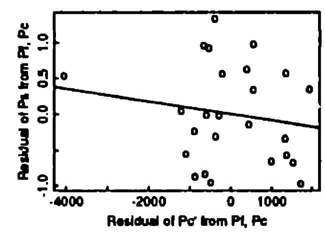
partialing out *Ss*: $r_{PsPc'.Ss}$
B: + (prediction)
not+ $r(22) = 0.00$ $p = 0.982$ (F.K., Stem-Past)
not+ $r(22) = -0.16$ $p = 0.459$ (A.P., Stem-Past) ⟶



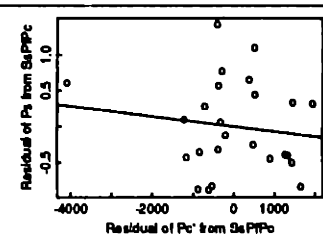
partialing out *Pf*: $r_{PsPc'.Pf}$
B: + (prediction)
not+ $r(22) = -0.03$ $p = 0.874$ (F.K., Stem-Past)
not+ $r(22) = -0.30$ $p = 0.147$ (A.P., Stem-Past) ⟶



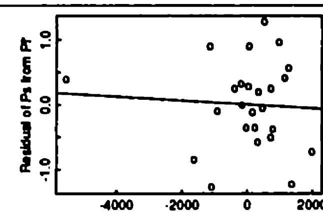
partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$
B: + (prediction)
not+ $r(21) = 0.06$ $p = 0.794$ (F.K., Stem-Past)
not+ $r(21) = -0.17$ $p = 0.451$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$
B: + (prediction)
not+ $r(20) = 0.08$ $p = 0.712$ (F.K., Stem-Past)
not+ $r(20) = -0.14$ $p = 0.530$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$
B: + (prediction)
not+ $r(22) = 0.09$ $p = 0.663$ (F.K., Stem-Past)
not+ $r(22) = -0.07$ $p = 0.758$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

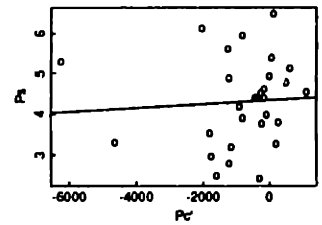
Table 8.29: All-Verbs Study: acceptability ratings for doublet regulars

Predictiveness of Altern. Past Tense Cluster Strength(*drove, rode*)
on Past Tense Success(*dived*) as accept. ratings (1-7)
under Blocking Theory for Doublet Regulars from Doublets Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

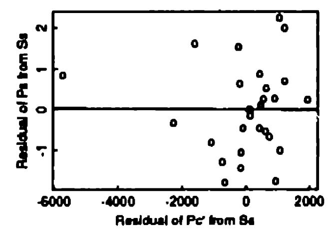
not+ $r(27) = 0.11$ $p = 0.560$ (F.K., Stem-Past)
not+ $r(27) = 0.07$ $p = 0.732$ (A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

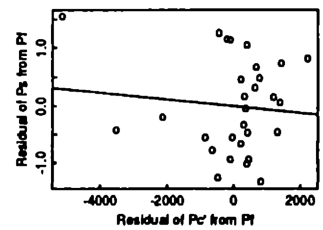
not+ $r(26) = 0.06$ $p = 0.759$ (F.K., Stem-Past)
not+ $r(26) = 0.00$ $p = 0.981$ (A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

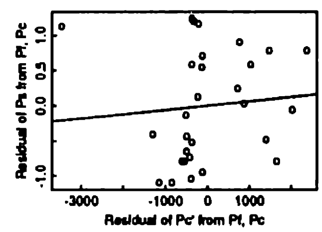
not+ $r(26) = 0.12$ $p = 0.558$ (F.K., Stem-Past)
not+ $r(26) = -0.10$ $p = 0.597$ (A.P., Stem-Past) ⟶



partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

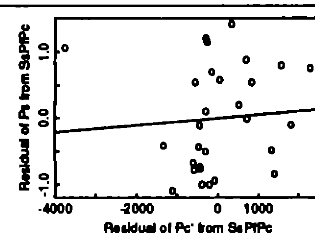
not+ $r(25) = 0.32$ $p = 0.101$ (F.K., Stem-Past)
not+ $r(25) = 0.09$ $p = 0.665$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

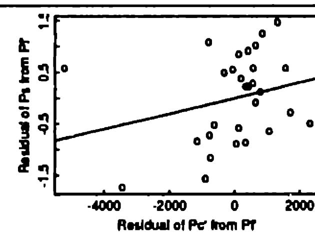
not+ $r(24) = 0.29$ $p = 0.147$ (F.K., Stem-Past)
not+ $r(24) = 0.08$ $p = 0.704$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(26) = 0.25$ $p = 0.200$ (F.K., Stem-Past)
not+ $r(26) = 0.26$ $p = 0.183$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.30: Doublets Study: acceptability ratings for doublet regulars

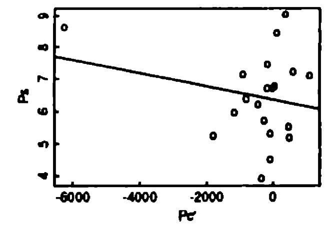
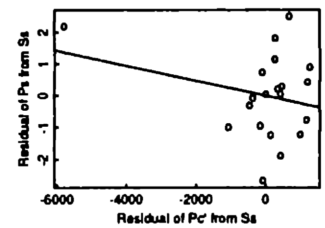
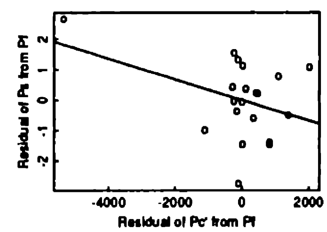
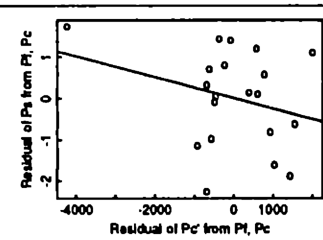
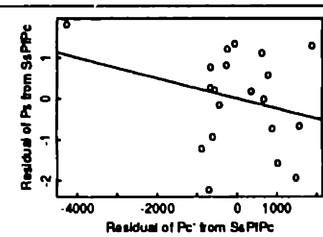
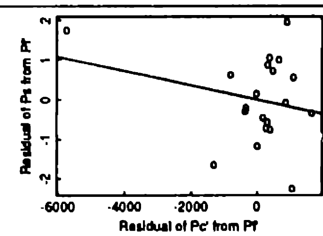
Predictiveness of Altern. Past Tense Cluster Strength(*drove, rode*) on Past Tense Success(*dived*) as accept. ratings (1-10) under Blocking Theory for Doublet Regulars from All-Classes Study	
by a simple correlation: $r_{Pc'Ps}$ B: + (prediction) not+ $r(18) = 0.01$ $p = 0.969$ (F.K., Stem-Past) not+ $r(18) = -0.23$ $p = 0.327$ (A.P., Stem-Past) ⟶	
partialing out *Ss*: $r_{PsPc'.Ss}$ B: + (prediction) not+ $r(17) = -0.01$ $p = 0.970$ (F.K., Stem-Past) not+ $r(17) = -0.27$ $p = 0.272$ (A.P., Stem-Past) ⟶	
partialing out *Pf*: $r_{PsPc'.Pf}$ B: + (prediction) not+ $r(17) = -0.03$ $p = 0.892$ (F.K., Stem-Past) not+ $r(17) = -0.39$ $p = 0.100$ (A.P., Stem-Past) ⟶	
partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$ B: + (prediction) not+ $r(16) = 0.09$ $p = 0.725$ (F.K., Stem-Past) not+ $r(16) = -0.29$ $p = 0.251$ (A.P., Stem-Past) ⟶	
partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$ B: + (prediction) not+ $r(15) = 0.09$ $p = 0.732$ (F.K., Stem-Past) not+ $r(15) = -0.28$ $p = 0.271$ (A.P., Stem-Past) ⟶	
partialing out *Pf'*: $r_{PsPc'.Pf'}$ B: + (prediction) not+ $r(17) = 0.03$ $p = 0.916$ (F.K., Stem-Past) not+ $r(17) = -0.25$ $p = 0.294$ (A.P., Stem-Past) ⟶	
Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)	

Table 8.31: All-Classes Study: acceptability ratings for doublet regulars

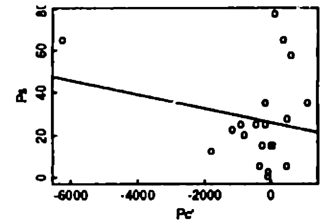
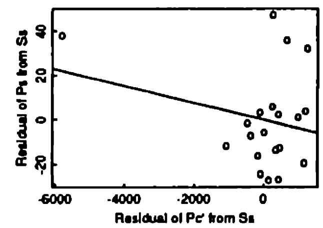
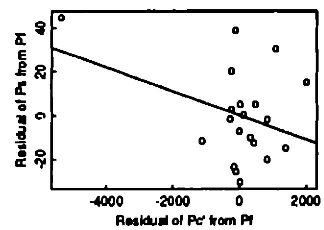
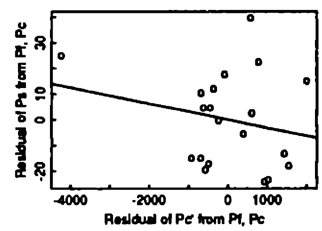
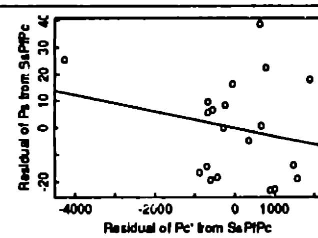
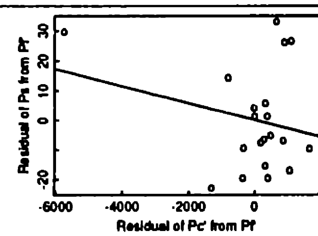
Predictiveness of Altern. Past Tense Cluster Strength(*drove, rode*) on Past Tense Success(*dived*) as prod. like. (% subjs) under Blocking Theory for Doublet Regulars from All-Classes Study	
by a simple correlation: $r_{Pc'Ps}$ B: + (prediction) not+ $r(18) = 0.03$ $p = 0.893$ (F.K., Stem-Past) not+ $r(18) = -0.22$ $p = 0.347$ (A.P., Stem-Past) ⟶	
partialing out *Ss*: $r_{PsPc'.Ss}$ B: + (prediction) not+ $r(17) = 0.01$ $p = 0.957$ (F.K., Stem-Past) not+ $r(17) = -0.26$ $p = 0.287$ (A.P., Stem-Past) ⟶	
partialing out *Pf*: $r_{PsPc'.Pf}$ B: + (prediction) not+ $r(17) = 0.01$ $p = 0.959$ (F.K., Stem-Past) not+ $r(17) = -0.37$ $p = 0.115$ (A.P., Stem-Past) ⟶	
partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$ B: + (prediction) not+ $r(16) = 0.20$ $p = 0.426$ (F.K., Stem-Past) not+ $r(16) = -0.22$ $p = 0.371$ (A.P., Stem-Past) ⟶	
partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$ B: + (prediction) not+ $r(15) = 0.19$ $p = 0.455$ (F.K., Stem-Past) not+ $r(15) = -0.22$ $p = 0.393$ (A.P., Stem-Past) ⟶	
partialing out *Pf'*: $r_{PsPc'.Pf'}$ B: + (prediction) not+ $r(17) = 0.05$ $p = 0.830$ (F.K., Stem-Past) not+ $r(17) = -0.25$ $p = 0.308$ (A.P., Stem-Past) ⟶	
Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)	

Table 8.32: All-Classes Study: production likelihood for doublet regulars

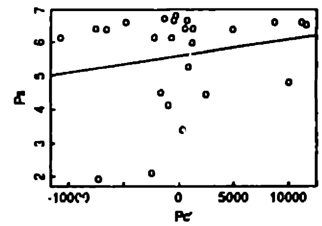
8.5.2 Doublet Irregulars: Regular Cluster Strength (*jived, thrived*)

If doublet irregulars (*dove*) are associatively computed, *and* doublet regulars are also completely associatively learned and computed, the computational success of the doublet irregulars (*dove*) should be affected by their regular neighbours (*drove, rode*). The higher the irregular cluster strength (the less the regulars block *dove*, and perhaps even the more they support *dove*), the more successfully the doublet irregulars (*dove*) should be computed. That is, there should be a positive correlation between regular cluster strength (*jived, thrived*) and past tense success (*dived*). In this case all six cells in the Analysis Tables should show these predictions.

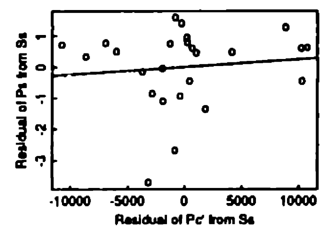
However, if doublet regulars (*dived*) are only associatively learned if their stems are similar to the stems of irregulars, there will probably be so few associatively learned regulars that there should be no regular cluster strength effects, and all six cells should show this *lack* of predictions.

Predictiveness of Altern. Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dove*) as accept. ratings (1-7)
under Blocking Theory for Doublet Irregulars from All-Verbs Study

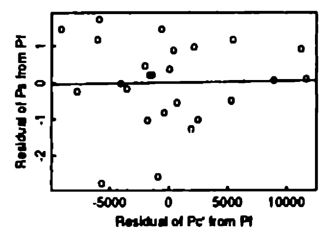
by a simple correlation: $r_{Pc'Ps}$
B: + (prediction)
not+ $r(23) = 0.09$ $p = 0.653$ (F.K., Stem-Past)
not+ $r(23) = 0.20$ $p = 0.343$ (A.P., Stem-Past) ⟶



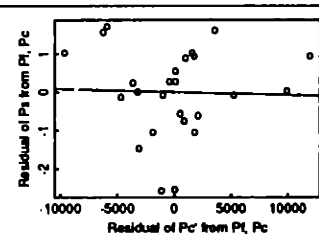
partialing out *Ss*: $r_{PsPc'.Ss}$
B: + (prediction)
not+ $r(22) = 0.02$ $p = 0.918$ (F.K., Stem-Past)
not+ $r(22) = 0.11$ $p = 0.608$ (A.P., Stem-Past) ⟶



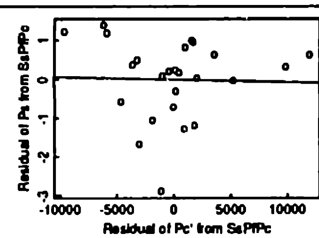
partialing out *Pf*: $r_{PsPc'.Pf}$
B: + (prediction)
not+ $r(22) = 0.03$ $p = 0.888$ (F.K., Stem-Past)
not+ $r(22) = 0.02$ $p = 0.927$ (A.P., Stem-Past) ⟶



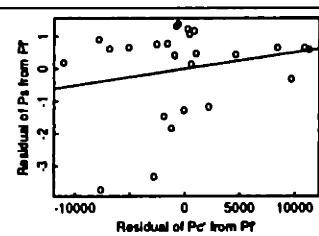
partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$
B: + (prediction)
not+ $r(21) = -0.02$ $p = 0.916$ (F.K., Stem-Past)
not+ $r(21) = -0.03$ $p = 0.885$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$
B: + (prediction)
not+ $r(20) = -0.03$ $p = 0.878$ (F.K., Stem-Past)
not+ $r(20) = -0.03$ $p = 0.891$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$
B: + (prediction)
not+ $r(22) = 0.11$ $p = 0.606$ (F.K., Stem-Past)
not+ $r(22) = 0.21$ $p = 0.332$ (A.P., Stem-Past) ⟶



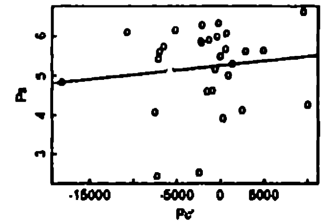
Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.33: All-Verbs Study: acceptability ratings for doublet irregulars

Predictiveness of Altern. Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dove*) as accept. ratings (1-7)
under Blocking Theory for Doublet Irregulars from Doublets Study

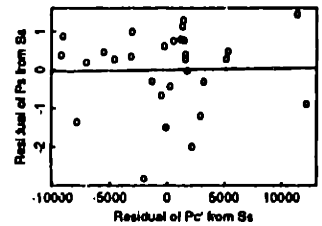
by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)
not+ $r(27) = 0.04$ $p = 0.833$ (F.K., Stem-Past)
not+ $r(27) = 0.12$ $p = 0.524$ (A.P., Stem-Past) ⟶



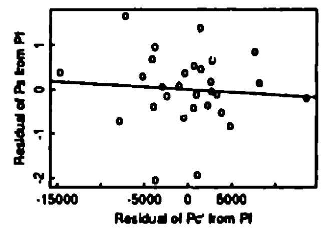
partialing out Ss: $r_{PsPc'.Ss}$

B: + (prediction)
not+ $r(26) = -0.05$ $p = 0.812$ (F.K., Stem-Past)
not+ $r(26) = 0.02$ $p = 0.915$ (A.P., Stem-Past) ⟶



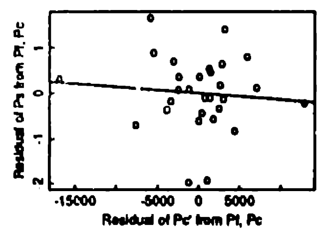
partialing out Pf: $r_{PsPc'.Pf}$

B: + (prediction)
not+ $r(26) = -0.02$ $p = 0.928$ (F.K., Stem-Past)
not+ $r(26) = -0.08$ $p = 0.687$ (A.P., Stem-Past) ⟶



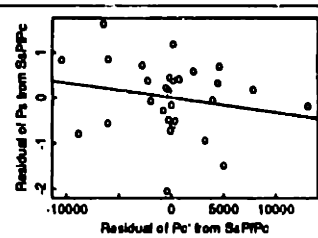
partialing out Pf, Pc: $r_{PsPc'.PfPc}$

B: + (prediction)
not+ $r(25) = -0.04$ $p = 0.831$ (F.K., Stem-Past)
not+ $r(25) = -0.09$ $p = 0.651$ (A.P., Stem-Past) ⟶



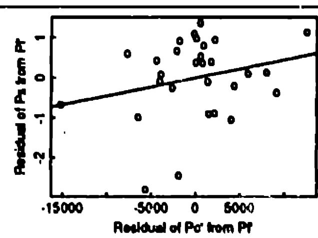
partialing out Ss, Pf, Pc: $r_{PsPc'.SsPfPc}$

B: + (prediction)
not+ $r(24) = -0.12$ $p = 0.545$ (F.K., Stem-Past)
not+ $r(24) = -0.20$ $p = 0.329$ (A.P., Stem-Past) ⟶



partialing out Pf': $r_{PsPc'.Pf'}$

B: + (prediction)
not+ $r(26) = 0.10$ $p = 0.619$ (F.K., Stem-Past)
not+ $r(26) = 0.25$ $p = 0.208$ (A.P., Stem-Past) ⟶

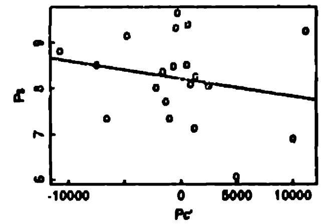


Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

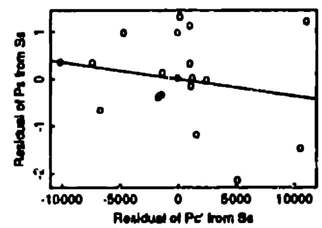
Table 8.34: Doublets Study: acceptability ratings for doublet irregulars

Predictiveness of Altern. Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dove*) as accept. ratings (1-10)
under Blocking Theory for Doublet Irregulars from All-Classes Study

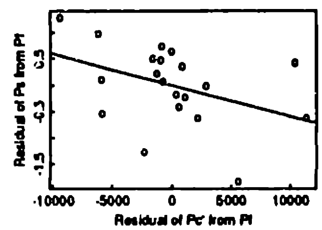
by a simple correlation: $r_{Pc'Ps}$
B: + (prediction)
not+ $r(18) = -0.22$ $p = 0.351$ (F.K., Stem-Past)
not+ $r(18) = -0.21$ $p = 0.368$ (A.P., Stem-Past) ⟶



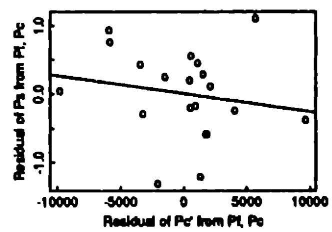
partialing out *Ss*: $r_{PsPc'.Ss}$
B: + (prediction)
not+ $r(17) = -0.22$ $p = 0.365$ (F.K., Stem-Past)
not+ $r(17) = -0.20$ $p = 0.404$ (A.P., Stem-Past) ⟶



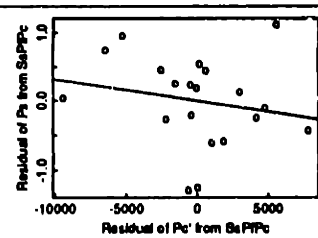
partialing out *Pf*: $r_{PsPc'.Pf}$
B: + (prediction)
not+ $r(17) = -0.27$ $p = 0.261$ (F.K., Stem-Past)
not+ $r(17) = -0.40$ $p = 0.086$ (A.P., Stem-Past) ⟶



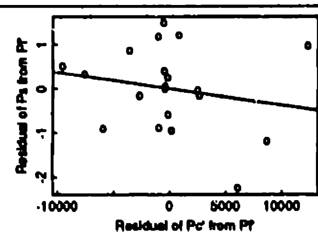
partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$
B: + (prediction)
not+ $r(16) = -0.14$ $p = 0.582$ (F.K., Stem-Past)
not+ $r(16) = -0.18$ $p = 0.485$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$
B: + (prediction)
not+ $r(15) = -0.17$ $p = 0.523$ (F.K., Stem-Past)
not+ $r(15) = -0.20$ $p = 0.437$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$
B: + (prediction)
not+ $r(17) = -0.22$ $p = 0.355$ (F.K., Stem-Past)
not+ $r(17) = -0.20$ $p = 0.416$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.35: All-Classes Study: acceptability ratings for doublet irregulars

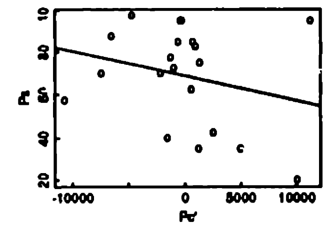
Predictiveness of Altern. Past Tense Cluster Strength(*jived, thrived*)
on Past Tense Success(*dove*) as prod. like. (% subjs)
under Blocking Theory for Doublet Irregulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(18) = -0.41$ $p = 0.069$ (F.K., Stem-Past)

not+ $r(18) = -0.26$ $p = 0.277$ (A.P., Stem-Past) ⟶

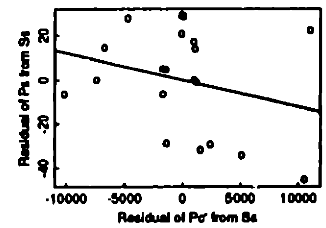


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(17) = -0.43$ $p = 0.069$ (F.K., Stem-Past)

not+ $r(17) = -0.27$ $p = 0.260$ (A.P., Stem-Past) ⟶

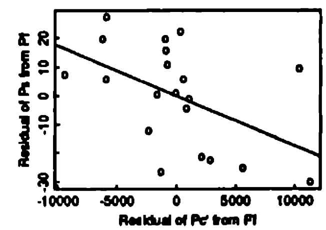


partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

not+ $r(17) = -0.57$ $p = 0.012$ (F.K., Stem-Past)

not+ $r(17) = -0.50$ $p = 0.030$ (A.P., Stem-Past) ⟶

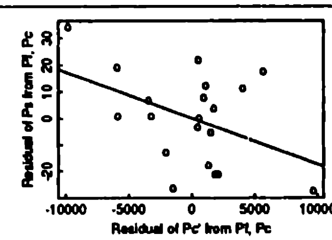


partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

not+ $r(16) = -0.52$ $p = 0.027$ (F.K., Stem-Past)

not+ $r(16) = -0.44$ $p = 0.071$ (A.P., Stem-Past) ⟶

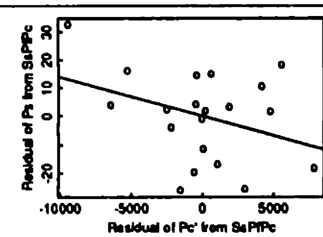


partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

not+ $r(15) = -0.50$ $p = 0.043$ (F.K., Stem-Past)

not+ $r(15) = -0.36$ $p = 0.159$ (A.P., Stem-Past) ⟶

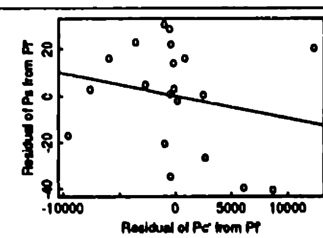


partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(17) = -0.41$ $p = 0.081$ (F.K., Stem-Past)

not+ $r(17) = -0.22$ $p = 0.376$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/12 (0%)

Table 8.36: All-Classes Study: production likelihood for doublet irregulars

8.5.3 Discussion

There is no strong evidence for blocking from irregular cluster strength to doublet regulars or from from regular cluster strength to doublet irregulars. This lack of an obvious effect could be explained by the same two reasons given above for a lack of supporting cluster effects for either past class.

However, there is a possibility that irregular cluster strength does in fact block doublet regulars: upon examination of the graphs, one can see a single outlier pulling the correlation line in a negative direction, when in fact the pattern of points looks consistent with a positive correlation — for all four data sets. I eliminated this single outlier (*knitted*) for one data set (All-Classes production likelihood) and indeed got a strong *positive* correlation. This should be looked into further, as it is highly consistent with my theory.

Chapter 9

Attracted Regulars (glided)

9.1 Attracted Regulars: The Predictiveness of Past Tense Frequency(*glided*)

If attracted regular pasts (*glided*) are associatively learned, the more frequent the past tense form (*glided*), the more successfully it should be computed. That is, Past Tense Frequency should predict Past Tense Success. In this case the second and last cells of the Display Tables should show analyses revealing the significance of these predictions, with Stem Strength held constant.

However, if attracted regular pasts are produced by a symbol-processing system, there should be no such past tense frequency effects. In this case the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions, with Stem Strength held constant.

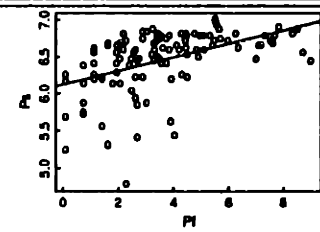
Predictiveness of Past Tense Frequency(*glided*)
on Past Tense Success(*glided*) as accept. ratings (1-7)
under Rule and Associative Theories for Attracted Regulars from All-Verbs Study

---

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

+ $r(109) = 0.46$ $p < 0.001$ (F.K.)
+ $r(109) = 0.48$ $p < 0.001$ (A.P.) $\longrightarrow$

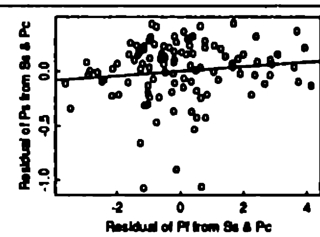


---

partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(107) = 0.06$ $p = 0.519$ (F.K., Stem-Past)
not+ $r(107) = 0.12$ $p = 0.208$ (A.P., Stem-Past) $\longrightarrow$



---

partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

---

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

---

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

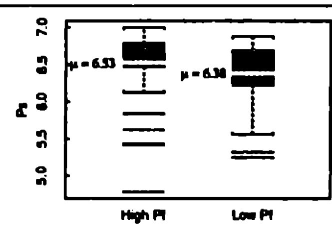
NA

---

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(54) = 1.67$ $p = 0.101$ (F.K.)
+ $t(54) = 2.56$ $p = 0.013$ (A.P.) $\longrightarrow$



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 1/4 (25%)
Predictive power of Past Tense Frequency under Rule Theory = 3/4 (75%)

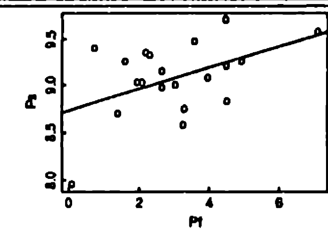
Table 9.1: All-Verbs Study: acceptability ratings for attracted regulars

Predictiveness of Past Tense Frequency(*glided*)
on Past Tense Success(*glided*) as accept. ratings (1-10)
under Rule and Associative Theories for Attracted Regulars from All-Classes Study

by a simple correlation: $r_{P_fP_s}$

R:none A: + (prediction)

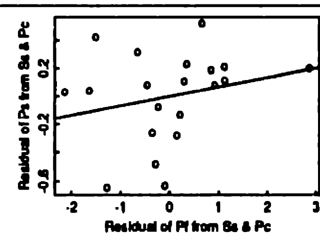
+ $r(18) = 0.45$ $p = 0.044$ (F.K.)
+ $r(18) = 0.47$ $p = 0.036$ (A.P.) $\longrightarrow$



partialing out *Ss*, *Pc*: $r_{P_sP_f.S_sP_c}$

R:not+ A: + (prediction)

not+ $r(16) = 0.29$ $p = 0.239$ (F.K., Stem-Past)
not+ $r(16) = 0.24$ $p = 0.337$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Ps'*: $r_{P_sP_f.P_s'}$

NA

partialing out *Pf'*, *Pc'*: $r_{P_sP_f.P_f'P_c'}$

NA

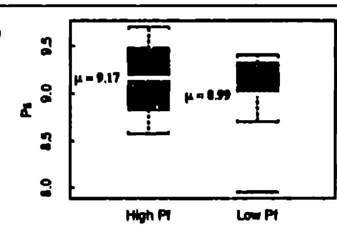
partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{P_sP_f.S_sP_cP_f'P_c'}$

NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*),
given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.92$ $p = 0.087$ (F.K.)
not+ $t(9) = 1.53$ $p = 0.161$ (A.P.) $\longrightarrow$



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

Table 9.2: All-Classes Study: acceptability ratings for attracted regulars

Predictiveness of Past Tense Frequency(*glided*)

on Past Tense Success(*glided*) as prod. like. (% subjs)

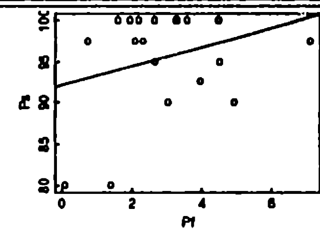
under Rule and Associative Theories for Attracted Regulars from All-Classes Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

not+ $r(18) = 0.26$ $p = 0.278$ (F.K.)

not+ $r(18) = 0.30$ $p = 0.197$ (A.P.) $\longrightarrow$

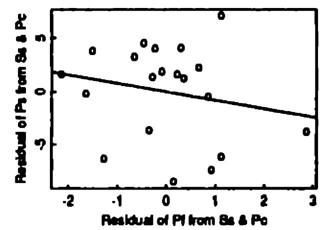


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(16) = -0.18$ $p = 0.484$ (F.K., Stem-Past)

not+ $r(16) = -0.21$ $p = 0.407$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

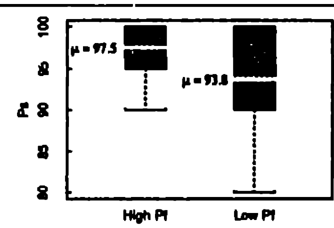
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 0.87$ $p = 0.409$ (F.K.)

not+ $t(9) = 1.31$ $p = 0.224$ (A.P.) $\longrightarrow$



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

Table 9.3: All-Classes Study: production likelihood for attracted regulars

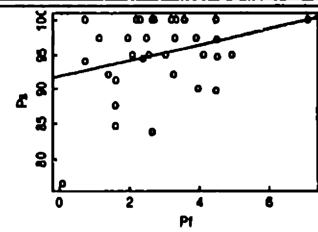
Predictiveness of Past Tense Frequency(*glided*)
on Past Tense Success(*glided*) as prod. like. (% subjs)
under Rule and Associative Theories for Attracted Regulars from Reaction Time Study

by a simple correlation: r_{PfPs}

R:none A: + (prediction)

not+ $r(33) = 0.02$ $p = 0.920$ (F.K.)

not+ $r(33) = 0.30$ $p = 0.079$ (A.P.) ⟶

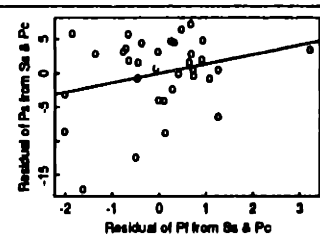


partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not+ A: + (prediction)

not+ $r(31) = 0.00$ $p = 0.985$ (F.K., Stem-Past)

not+ $r(31) = 0.27$ $p = 0.136$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

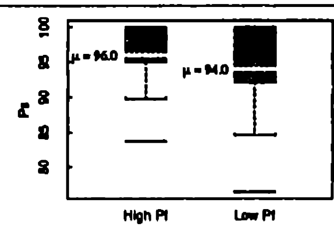
NA

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(16) = 0.52$ $p = 0.609$ (F.K.)

not+ $t(16) = 0.90$ $p = 0.384$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Frequency under Rule Theory = 4/4 (100%)

Table 9.4: Reaction Time Study: production likelihood for attracted regulars

Predictiveness of Past Tense Frequency(*glided*)

on Past Tense Success(*glided*) as generation time (ms)

under Rule and Associative Theories for Attracted Regulars from Reaction Time Study

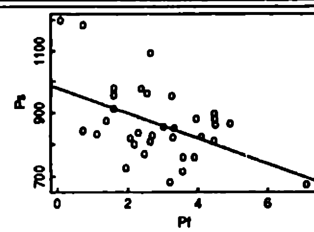
---

by a simple correlation: r_{PfPs}

R:none A: – (prediction)

not– $r(33) = -0.24$ $p = 0.158$ (F.K.)

– $r(33) = -0.48$ $p = 0.003$ (A.P.) ⟶



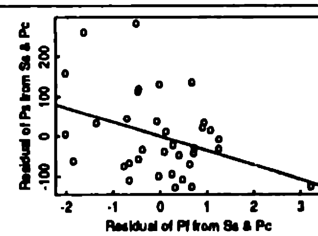
---

partialing out *Ss*, *Pc*: $r_{PsPf.SsPc}$

R:not– A: – (prediction)

not– $r(31) = -0.15$ $p = 0.402$ (F.K., Stem-Past)

– $r(31) = -0.37$ $p = 0.034$ (A.P., Stem-Past) ⟶



---

partialing out *Ps'*: $r_{PsPf.Ps'}$

NA

---

partialing out *Pf'*, *Pc'*: $r_{PsPf.Pf'Pc'}$

NA

---

partialing out *Ss*, *Pc*, *Pf'*, *Pc'*: $r_{PsPf.SsPcPf'Pc'}$

NA

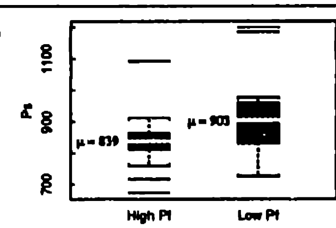
---

by a *t*-test comparing (*Ps* with high-*Pf*) with (*Ps* with low-*Pf*), given similar *Ss* values for each *Ps* pair

R:not– A: – (prediction)

not– $t(16) = -1.09$ $p = 0.291$ (F.K.)

not– $t(16) = -1.55$ $p = 0.141$ (A.P.) ⟶



Predictive power of Past Tense Frequency under Stem-Past Assoc Theory = 1/4 (25%)

Predictive power of Past Tense Frequency under Rule Theory = 3/4 (75%)

Table 9.5: Reaction Time Study: production time for attracted regulars

9.1.1 Discussion

Attracted regulars are moderately well predicted by their past frequencies. For acceptability ratings from the All-Verbs study, all 6 analyses were in the expected direction; 3 of them were significant, and one approaching significance — Francis and Kučera t-test: t=1.67, p=0.101; Associated Press t-test: t=2.56, p=0.013; Francis and Kučera partial correlation holding Stem Strength constant: r=.26, p=0.006; Associated Press partial correlation holding Stem Strength constant: r=.32, p¡0.001; Francis and Kučera partial correlation holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant: r=.06, p=0.52; Associated Press partial correlation holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant: r=.12, p=0.21. Crucially, the two stringent t-tests were significant (one for a two-tailed test — t=3.49, p¡.001, and the other for a one-tailed test). I suspected that the two non-significant analyses, which were both partial correlations holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant, were not significant due the clumping problem of cluster strength. This suspicion is supported by the fact that all four analyses in which Stem-Past Past Tense Cluster Strength was not held constant were significant.

Similarly, for the acceptability ratings from the All-Classes study, in which only 1 out of the 6 analyses was significant for two-tailed test, and another 2 for one-tailed tests: Francis and Kučera t-test: t=1.92, p=0.087; Associated Press t-test: t=1.53, p=0.161; Francis and Kučera partial correlation holding Stem Strength constant: r=.41, p=0.078; Associated Press partial correlation holding Stem Strength constant: r=.50, p=0.03; Francis and Kučera partial correlation holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant: r=.29, p=0.240; Associated Press partial correlation holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant: r=.24, p=0.337.

Analyses of the production likelihood measures from the All-Classes study were all in the expected direction (except for the two partial correlations holding both Stem Strength and Past Tense Cluster Strength constant — but when only Stem Strength was held constant, the were both in the expected direction).

Similarly, none of the analyses of the production likelihood measures from the reaction time study were significant, though they were all in the expected direction (except for one partial correlation with both Stem Strength and Past Tense Cluster Strength held constant; and when only Stem Strength was held constant, even though the direction of r was negative when I expected positive, it was wildly non significant: r=-.006, p=.973).

Finally, for the generation time measure from the Reaction Time study, all 6 analyses were in the expected direction, and 2 of them were significant (for two-tailed tests) in the expected direction: Francis and Kučera t-test: t=-1.09, p=0.291; Associated Press t-test: t=-1.55, p=0.141; Francis and Kučera partial correlation holding Stem Strength constant: r=-.21, p=0.242; Associated Press partial correlation holding Stem Strength constant: r=-.49, p=0.003; Francis and Kučera partial correlation holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant: r=-.15, p=0.402; Associated Press partial correlation holding both Stem Strength and Stem-Past Past Tense Cluster Strength constant: r=-.37, p=0.034.

9.2 Attracted Regulars: The Predictiveness of Past Tense Cluster Strength(*chided, cited*)

If attracted regular pasts (*glided*) are associatively learned, the presentation of other regular pasts (*chided, cited*) whose stem-past mappings are shared with those of *glide-glided* should facilitate the latter's computation. That is, regular cluster strength (*chided, cited*) should predict Past Tense Success (*glided*). In this case the second and last cells of the Display Tables should show analyses revealing the significance of these predictions, with Past Tense Frequency (*blew*), Stem Strength (*blow*), or other variables held constant.

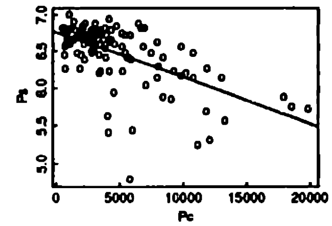
However, we expect this prediction only if attracted regulars are completely associatively learned, just like irregulars; but if regulars are only associatively learned if their stems are similar to the stems of irregulars, it is unlikely that enough regulars would be associatively learned to result in regular cluster strength effects. Similarly, if attracted regulars are completely rule-produced, there should be no regular cluster effects. In these cases the second and last cells of the Display Tables should show analyses revealing the *lack* of significance of these predictions.

Predictiveness of Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glided*) as accept. ratings (1-7)
under Rule and Associative Theories for Attracted Regulars from All-Verbs Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

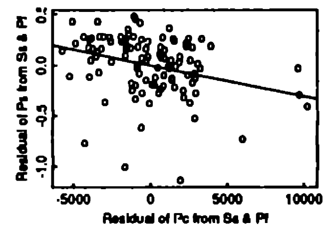
not+ $r(109) = -0.56$ $p < 0.001$ (F.K., Stem-Past)
not+ $r(109) = -0.59$ $p < 0.001$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(107) = -0.29$ $p = 0.002$ (F.K., Stem-Past)
not+ $r(107) = -0.30$ $p = 0.001$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

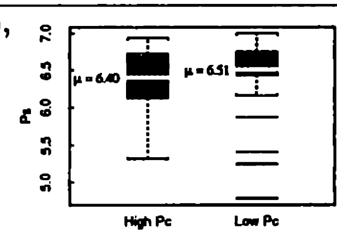
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(54) = -0.37$ $p = 0.716$ (F.K., Stem-Past)
not+ $t(54) = -1.60$ $p = 0.116$ (A.P., Stem-Past) $\longrightarrow$



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

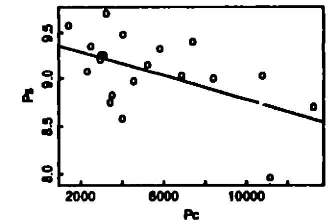
Table 9.6: All-Verbs Study: acceptability ratings for attracted regulars

Predictiveness of Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glided*) as accept. ratings (1-10)
under Rule and Associative Theories for Attracted Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

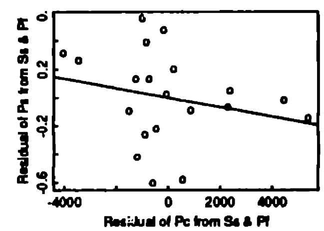
not+ $r(18) = -0.34$ $p = 0.142$ (F.K., Stem-Past)
not+ $r(18) = -0.53$ $p = 0.016$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(16) = -0.02$ $p = 0.942$ (F.K., Stem-Past)
not+ $r(16) = -0.24$ $p = 0.343$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

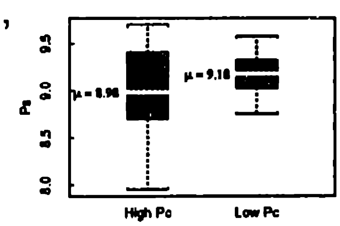
partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = -1.04$ $p = 0.326$ (F.K., Stem-Past)
not+ $t(9) = -1.21$ $p = 0.256$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 9.7: All-Classes Study: acceptability ratings for attracted regulars

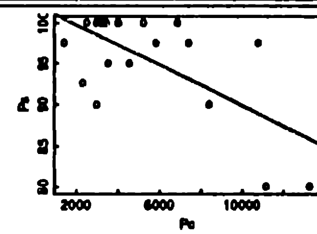
Predictiveness of Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glided*) as prod. like. (% subjs)
under Rule and Associative Theories for Attracted Regulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = -0.44$ $p = 0.051$ (F.K., Stem-Past)

not+ $r(18) = -0.65$ $p = 0.002$ (A.P., Stem-Past) ⟶

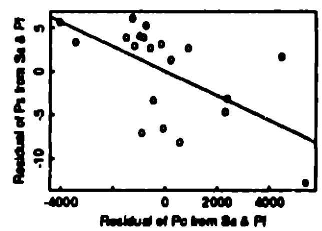


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not+ A: + (prediction)

not+ $r(16) = -0.41$ $p = 0.088$ (F.K., Stem-Past)

not+ $r(16) = -0.59$ $p = 0.010$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

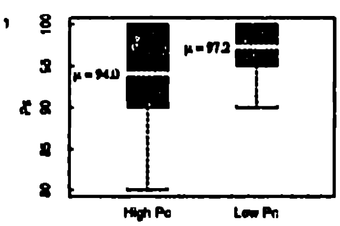
NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = -0.82$ $p = 0.435$ (F.K., Stem-Past)

not+ $t(9) = -1.16$ $p = 0.274$ (A.P., Stem-Past) ⟶

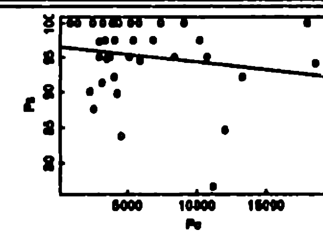


Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 9.8: All-Classes Study: production likelihood for attracted regulars

Predictiveness of Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glided*) as prod. like. (% subjs)
under Rule and Associative Theories for Attracted Regulars from Reaction Time Study

by a simple correlation: r_{PcPs}

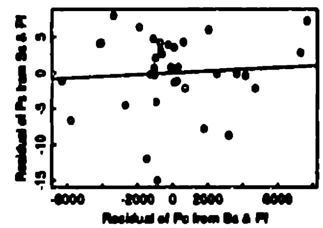


R:not+ A: + (prediction)

not+ $r(33) = -0.01$ $p = 0.951$ (F.K., Stem-Past)

not+ $r(33) = -0.17$ $p = 0.318$ (A.P., Stem-Past) ⟶

partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$



R:not+ A: + (prediction)

not+ $r(31) = 0.01$ $p = 0.954$ (F.K., Stem-Past)

not+ $r(31) = 0.07$ $p = 0.693$ (A.P., Stem-Past) ⟶

partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

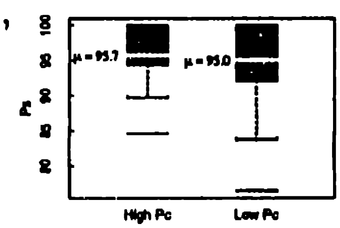
partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair



R:not+ A: + (prediction)

not+ $t(16) = 0.92$ $p = 0.373$ (F.K., Stem-Past)

not+ $t(16) = 0.32$ $p = 0.754$ (A.P., Stem-Past) ⟶

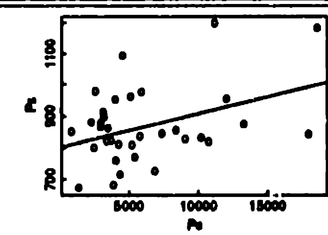
Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 9.9: Reaction Time Study: production likelihood for attracted regulars

Predictiveness of Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glided*) as generation time (ms)
under Rule and Associative Theories for Attracted Regulars from Reaction Time Study

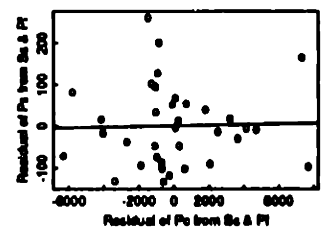
by a simple correlation: r_{PcPs}

R:not– A: – (prediction)
not– $r(33) = 0.18$ $p = 0.295$ (F.K., Stem-Past)
not– $r(33) = 0.39$ $p = 0.022$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

R:not– A: – (prediction)
not– $r(31) = -0.01$ $p = 0.946$ (F.K., Stem-Past)
not– $r(31) = 0.03$ $p = 0.881$ (A.P., Stem-Past) ⟶



partialing out *Ps'*: $r_{PsPc.Ps'}$

NA

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

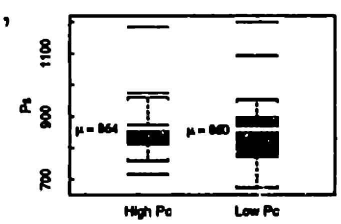
NA

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not– A: – (prediction)
not– $t(16) = -0.19$ $p = 0.851$ (F.K., Stem-Past)
not– $t(16) = 0.10$ $p = 0.919$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/4 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 4/4 (100%)

Table 9.10: Reaction Time Study: production time for attracted regulars

9.2.1 Discussion

Attracted regulars show no evidence of being supported by their surrounding regulars. In fact, the vast majority of analyses are in the *opposite* direction than we expect. I have three possible explanations for this unexpected result.

First, these unexpected results could simply emerge from the cluster clumping described above. Since the regular cluster strength of regulars will generally be positive, and since most attracted regular pasts (as all other pasts) are generally better than worse, there will be a clumping in one corner of the scatterplot — where Past Tense Success is high and cluster strength zero. One way to test this hypothesis is to perform analyses on only those verbs with cluster strength some distance from zero, thus avoiding the clump (I described this approach above, where I presented the clumping problem). I have not yet carried out these analyses. However, the clumping explanation is highly unlikely because the surprising negative correlation also holds for Past cluster strength, which I did *not* divide by past frequency, and thus should not show clumping effects.

The second explanation is the possible existence of an unexpected distribution of verbs over cluster strength. Upon examination of the verbs I discovered that almost all the attracted regulars with the lowest cluster strength (closest to zero) end in vowels (or *r*'s, which in the British transcription that I use is phonologically extremely similar to a vowel), while almost all the verbs with the highest cluster strength end in *t* or *d*. Furthermore, these vowel-ending verbs all have very high Past Tense Success values, while those ending in the dentals have low Past Tense Success values. Although I have not yet looked at this phenomenon in a statistically rigorous way, this explanation is supported by the graph of cluster strength *before* being divided by past frequency — here the two groups are extremely obviously independent to the naked eye in the scatterplot. This finding has led me to two possibilities: First, that this distinction between verbs exists for some independent reason (e.g., articulation difficulty); second, that this distinction is in fact due to some clustering phenomenon which I have yet to explain.

The third explanation is that, apart from the verb-ending phenomenon, there is some other clustering effect which should result in a negative correlation. For example, perhaps there are some interference effects with surrounding attracted regulars which I have not predicted.

9.3 Over-Irregulars (*glid*): The Predictiveness of Past Tense Cluster Strength (*hid, bit*)

If over-irregular pasts (*glide-glid*) are associatively computed over stem-past mappings shared with irregulars (*hide-hid, bite-bit*), the presentation of these other irregular pasts (*hid, bit*) should facilitate the latter's computation. That is, irregular cluster strength (*hid, bit*) should predict Past Tense Success (*glid*). In this case the first, third, fourth and last cells of the Display Tables should all show analyses revealing the significance of these predictions.

However, if over-irregular pasts are produced by a symbol-processing system, there should be no such irregular cluster strength effects. In this case these cells should show analyses revealing the *lack* of significance of these predictions.

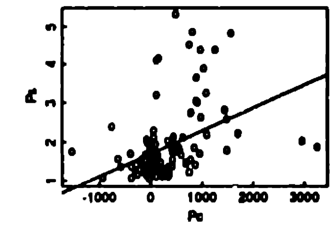
Predictiveness of Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glid*) as accept. ratings (1-7)
under Rule and Associative Theories for Over-Irregulars from All-Verbs Study

---

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

+	$r(109) = 0.48$	$p < 0.001$	(F.K., Stem-Past)
+	$r(109) = 0.41$	$p < 0.001$	(A.P., Stem-Past) ⟶



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partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

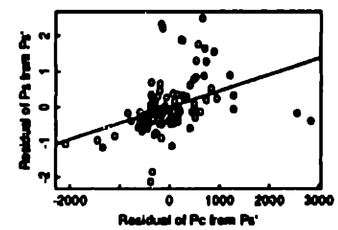
NA

---

partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

+	$r(108) = 0.39$	$p < 0.001$	(F.K., Stem-Past)
+	$r(108) = 0.37$	$p < 0.001$	(A.P., Stem-Past) ⟶

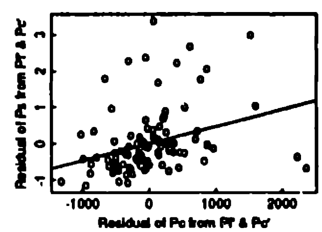


---

partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

+	$r(107) = 0.38$	$p < 0.001$	(F.K., Stem-Past)
+	$r(107) = 0.32$	$p < 0.001$	(A.P., Stem-Past) ⟶



---

partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

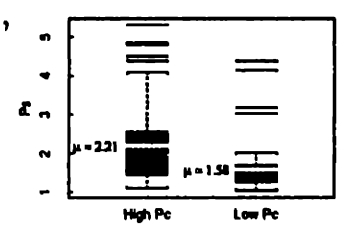
NA

---

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+	$t(54) = 0.70$	$p = 0.486$	(F.K., Stem-Past)
+	$t(54) = 4.08$	$p < 0.001$	(A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 5/6 (83%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 1/6 (17%)

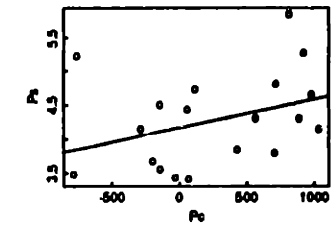
Table 9.11: All-Verbs Study: acceptability ratings for over-irregulars

Predictiveness of Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glid*) as accept. ratings (1-10)
under Rule and Associative Theories for Over-Irregulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = 0.38$ $p = 0.098$ (F.K., Stem-Past)
not+ $r(18) = 0.34$ $p = 0.138$ (A.P., Stem-Past) ⟶



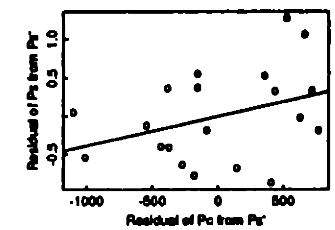
partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

NA

partialing out *Ps′*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

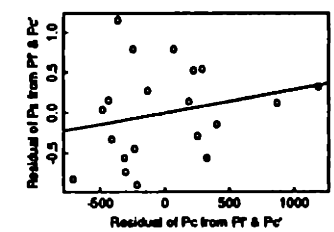
not+ $r(17) = 0.34$ $p = 0.160$ (F.K., Stem-Past)
not+ $r(17) = 0.36$ $p = 0.130$ (A.P., Stem-Past) ⟶



partialing out *Pf′*, *Pc′*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(16) = 0.16$ $p = 0.528$ (F.K., Stem-Past)
not+ $r(16) = 0.23$ $p = 0.358$ (A.P., Stem-Past) ⟶



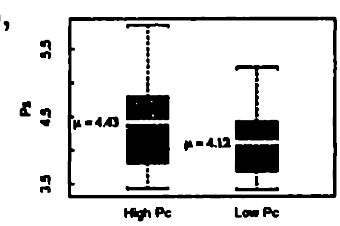
partialing out *Ss*, *Pf*, *Pf′*, *Pc′*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*),
given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 1.38$ $p = 0.201$ (F.K., Stem-Past)
not+ $t(9) = 1.95$ $p = 0.083$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/6 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 6/6 (100%)

Table 9.12: All-Classes Study: acceptability ratings for doublet irregulars

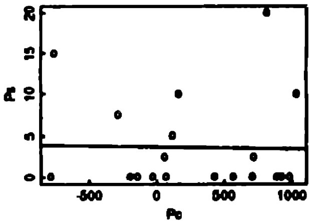
Predictiveness of Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glid*) as prod. like. (% subjs)
under Rule and Associative Theories for Over-Irregulars from All-Classes Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)

not+ $r(18) = 0.03$ $p = 0.915$ (F.K., Stem-Past)

not+ $r(18) = -0.02$ $p = 0.931$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

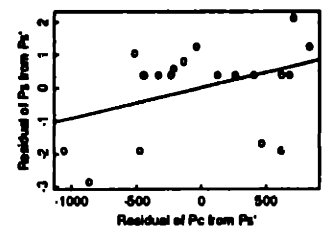
NA

partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)

not+ $r(17) = 0.32$ $p = 0.186$ (F.K., Stem-Past)

not+ $r(17) = 0.39$ $p = 0.100$ (A.P., Stem-Past) ⟶

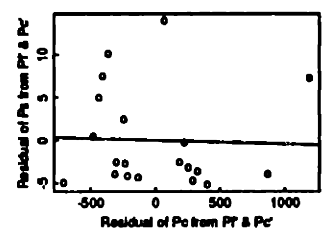


partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)

not+ $r(16) = -0.09$ $p = 0.726$ (F.K., Stem-Past)

not+ $r(16) = -0.04$ $p = 0.889$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

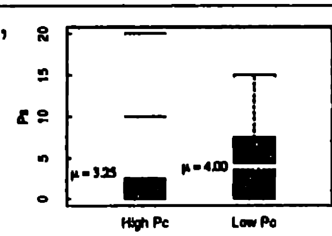
NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)

not+ $t(9) = 0.26$ $p = 0.803$ (F.K., Stem-Past)

not+ $t(9) = -0.71$ $p = 0.496$ (A.P., Stem-Past) ⟶



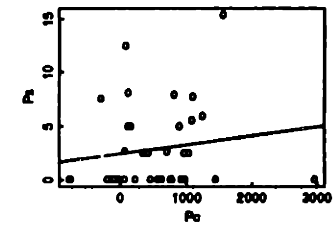
Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/6 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 6/6 (100%)

Table 9.13: All-Classes Study: production likelihood for over-irregulars

Predictiveness of Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glid*) as prod. like. (% subjs)
under Rule and Associative Theories for Over-Irregulars from Reaction Time Study

by a simple correlation: r_{PcPs}

R:not+ A: + (prediction)
not+ $r(33) = 0.08$ $p = 0.647$ (F.K., Stem-Past)
not+ $r(33) = 0.15$ $p = 0.380$ (A.P., Stem-Past) ⟶

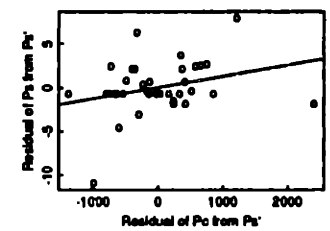


partialing out *Ss*, *Pf*: $r_{PsPc.SsPf}$

NA

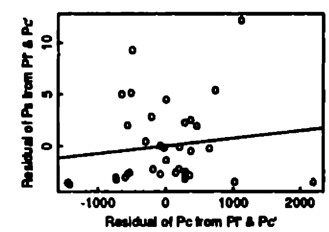
partialing out *Ps'*: $r_{PsPc.Ps'}$

R:not+ A: + (prediction)
not+ $r(32) = 0.19$ $p = 0.286$ (F.K., Stem-Past)
not+ $r(32) = 0.29$ $p = 0.095$ (A.P., Stem-Past) ⟶



partialing out *Pf'*, *Pc'*: $r_{PsPc.Pf'Pc'}$

R:not+ A: + (prediction)
not+ $r(31) = 0.15$ $p = 0.391$ (F.K., Stem-Past)
not+ $r(31) = 0.13$ $p = 0.459$ (A.P., Stem-Past) ⟶

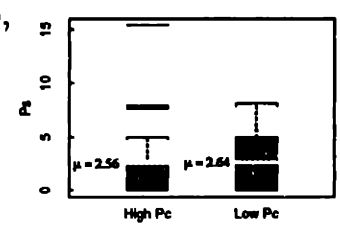


partialing out *Ss*, *Pf*, *Pf'*, *Pc'*: $r_{PsSs.PfPcPf'Pc'}$

NA

by a *t*-test comparing (*Ps* with high-*Pc*) with (*Ps* with low-*Pc*), given similar *Pf* values for each *Ps* pair

R:not+ A: + (prediction)
not+ $t(16) = 0.28$ $p = 0.781$ (F.K., Stem-Past)
not+ $t(16) = -0.06$ $p = 0.957$ (A.P., Stem-Past) ⟶



Predictive power of Past Tense Cluster Strength under Stem-Past Assoc Theory = 0/6 (0%)
Predictive power of Past Tense Cluster Strength under Rule Theory = 6/6 (100%)

Table 9.14: Reaction Time Study: production likelihood for over-irregulars

9.3.1 Discussion

There is evidence for moderate support of over-irregulars (*glide-glid*) by their surrounding irregulars. Over the 12 analyses for Stem-Past cluster strength analyses, all but 3 were in the expected direction, and those 3 were all highly non-significant (see Table 9.13) and were from the production likelihood measure of the All-Classes study, which I already know is subject to floor/ceiling effects. Of the 9 analyses which were in the expected direction, 4 were highly significant (all 4 from the All-Verbs study — see Table 9.11), and two others were approaching significance (significant for one-tailed tests). It is unlikely that this finding is due solely to the clumping effect because the same correlations hold for cluster strength *before* being divided by Altern. Past Tense Cluster Strength(past frequency of attracted regulars).

9.4 Attracted Regulars (*glided*): The Predictiveness of Altern. Past Tense Cluster Strength (*hid, bit*)

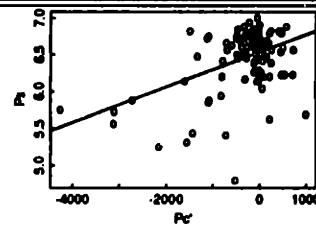
If attracted regulars (*glided*) are associatively computed alongside irregulars with similar stems, their computational success should be affected by these irregular neighbours (*hid, bit*). The higher the irregular cluster strength (the less the irregulars block *glided*, and perhaps even the more they support *glided*), the more successfully the doublet regulars (*glided*) should be computed. In this case the first five cells in the Analysis Tables should show these predictions.

Predictiveness of Altern. Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glided*) as accept. ratings (1-7)
under Blocking Theory for Attracted Regulars from All-Verbs Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

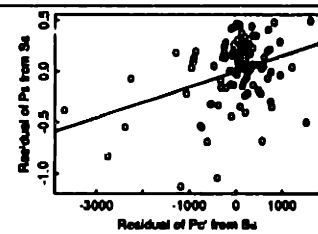
+	$r(109) = 0.44$	$p < 0.001$	(F.K., Stem-Past)
+	$r(109) = 0.45$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

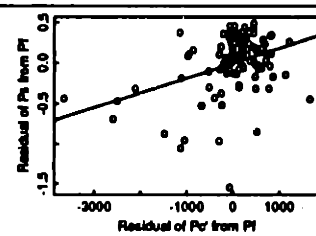
+	$r(108) = 0.43$	$p < 0.001$	(F.K., Stem-Past)
+	$r(108) = 0.37$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

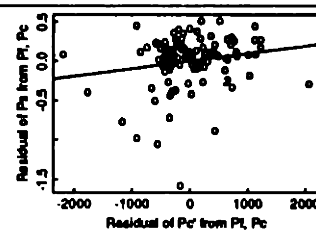
+	$r(108) = 0.37$	$p < 0.001$	(F.K., Stem-Past)
+	$r(108) = 0.38$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Pf, Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

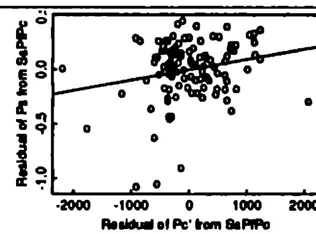
+	$r(107) = 0.20$	$p = 0.037$	(F.K., Stem-Past)
not+	$r(107) = 0.18$	$p = 0.060$	(A.P., Stem-Past) ⟶



partialing out *Ss, Pf, Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

+	$r(106) = 0.30$	$p = 0.001$	(F.K., Stem-Past)
+	$r(106) = 0.21$	$p = 0.029$	(A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 9/10 (90%)

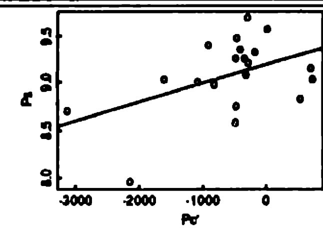
Table 9.15: All-Verbs Study: acceptability ratings for attracted regulars

Predictiveness of Altern. Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glided*) as accept. ratings (1-10)
under Blocking Theory for Attracted Regulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

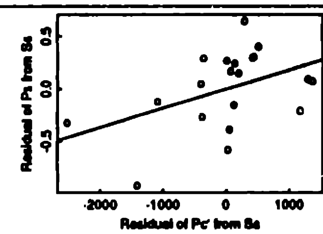
not+ $r(18) = 0.32$ $p = 0.162$ (F.K., Stem-Past)
\+ $r(18) = 0.46$ $p = 0.042$ (A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

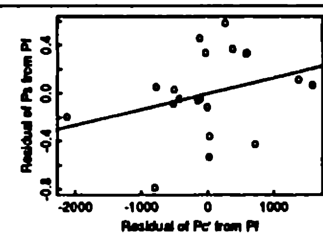
not+ $r(17) = 0.34$ $p = 0.152$ (F.K., Stem-Past)
not+ $r(17) = 0.45$ $p = 0.055$ (A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

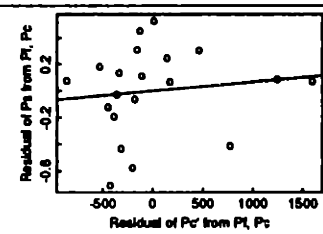
not+ $r(17) = 0.19$ $p = 0.439$ (F.K., Stem-Past)
not+ $r(17) = 0.30$ $p = 0.207$ (A.P., Stem-Past) ⟶



partialing out *Pf, Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

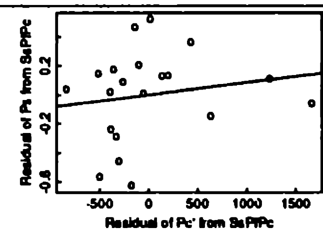
not+ $r(16) = 0.21$ $p = 0.393$ (F.K., Stem-Past)
not+ $r(16) = 0.13$ $p = 0.620$ (A.P., Stem-Past) ⟶



partialing out *Ss, Pf, Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

not+ $r(15) = 0.25$ $p = 0.328$ (F.K., Stem-Past)
not+ $r(15) = 0.16$ $p = 0.530$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 1/10 (10%)

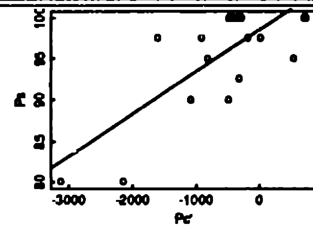
Table 9.16: All-Classes Study: acceptability ratings for attracted regulars

Predictiveness of Altern. Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glided*) as prod. like. (% subjs)
under Blocking Theory for Attracted Regulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

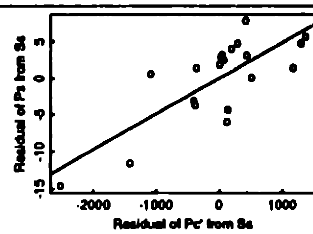
+	$r(18) = 0.64$	$p = 0.002$	(F.K., Stem-Past)
+	$r(18) = 0.75$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

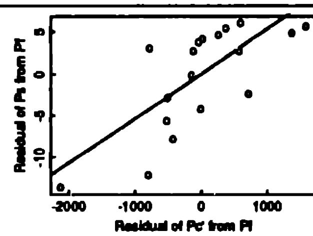
+	$r(17) = 0.70$	$p < 0.001$	(F.K., Stem-Past)
+	$r(17) = 0.77$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

B: + (prediction)

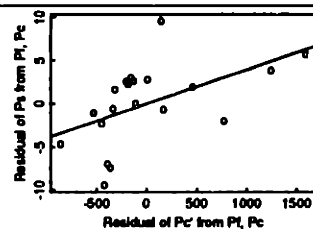
+	$r(17) = 0.61$	$p = 0.006$	(F.K., Stem-Past)
+	$r(17) = 0.72$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out *Pf, Pc*: $r_{PsPc'.PfPc}$

B: + (prediction)

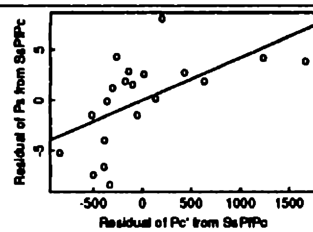
+	$r(16) = 0.51$	$p = 0.030$	(F.K., Stem-Past)
+	$r(16) = 0.52$	$p = 0.028$	(A.P., Stem-Past) ⟶



partialing out *Ss, Pf, Pc*: $r_{PsPc'.SsPfPc}$

B: + (prediction)

+	$r(15) = 0.61$	$p = 0.010$	(F.K., Stem-Past)
+	$r(15) = 0.58$	$p = 0.015$	(A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 10/10 (100%)

Table 9.17: All-Classes Study: production likelihood for attracted regulars

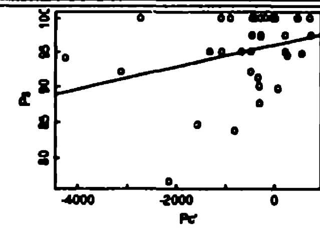
Predictiveness of Altern. Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glided*) as prod. like. (% subjs)
under Blocking Theory for Attracted Regulars from Reaction Time Study

by a simple correlation: $r_{Pc'P_s}$

B: + (prediction)

not+ $r(33) = 0.26$ $p = 0.131$ (F.K., Stem-Past)

not+ $r(33) = 0.32$ $p = 0.064$ (A.P., Stem-Past) ⟶

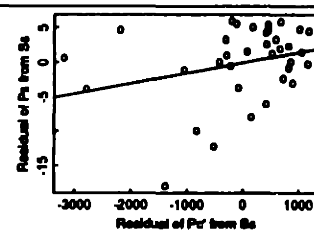


partialing out *Ss*: $r_{P_sPc'.S_s}$

B: + (prediction)

not+ $r(32) = 0.23$ $p = 0.186$ (F.K., Stem-Past)

not+ $r(32) = 0.29$ $p = 0.097$ (A.P., Stem-Past) ⟶

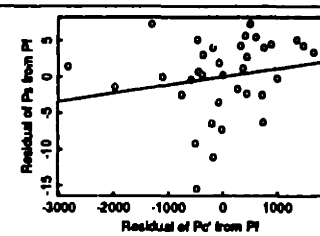


partialing out *Pf*: $r_{P_sPc'.Pf}$

B: + (prediction)

not+ $r(32) = 0.27$ $p = 0.120$ (F.K., Stem-Past)

not+ $r(32) = 0.19$ $p = 0.273$ (A.P., Stem-Past) ⟶

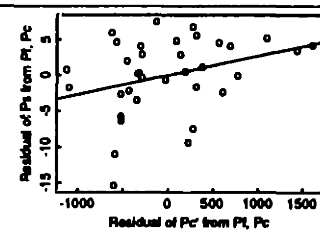


partialing out *Pf, Pc*: $r_{P_sPc'.PfPc}$

B: + (prediction)

\+ $r(31) = 0.35$ $p = 0.045$ (F.K., Stem-Past)

not+ $r(31) = 0.33$ $p = 0.064$ (A.P., Stem-Past) ⟶

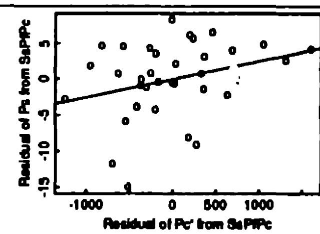


partialing out *Ss, Pf, Pc*: $r_{P_sPc'.S_sPfPc}$

B: + (prediction)

not+ $r(30) = 0.33$ $p = 0.066$ (F.K., Stem-Past)

not+ $r(30) = 0.30$ $p = 0.090$ (A.P., Stem-Past) ⟶



partialing out *Pf'*: $r_{P_sPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 1/10 (10%)

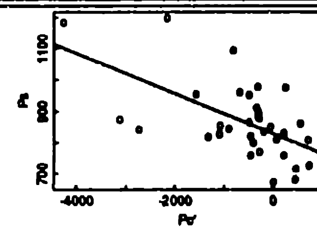
Table 9.18: Reaction Time Study: production likelihood for attracted regulars

Predictiveness of Altern. Past Tense Cluster Strength(*hid, bit*)
on Past Tense Success(*glided*) as generation time (ms)
under Blocking Theory for Attracted Regulars from Reaction Time Study

by a simple correlation: $r_{Pc'Ps}$

B: – (prediction)

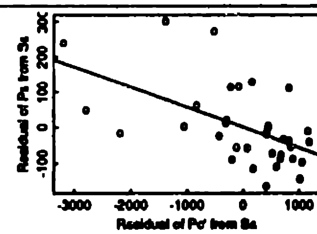
–	$r(33) = -0.49$	$p = 0.003$	(F.K., Stem-Past)
–	$r(33) = -0.58$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out Ss: $r_{PsPc'.Ss}$

B: – (prediction)

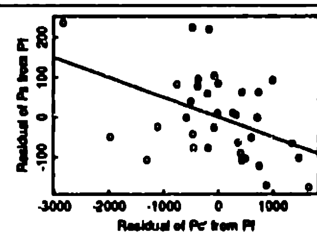
–	$r(32) = -0.45$	$p = 0.007$	(F.K., Stem-Past)
–	$r(32) = -0.55$	$p < 0.001$	(A.P., Stem-Past) ⟶



partialing out Pf: $r_{PsPc'.Pf}$

B: – (prediction)

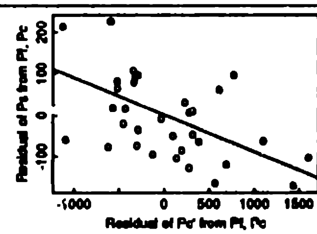
–	$r(32) = -0.45$	$p = 0.008$	(F.K., Stem-Past)
–	$r(32) = -0.44$	$p = 0.009$	(A.P., Stem-Past) ⟶



partialing out Pf, Pc: $r_{PsPc'.PfPc}$

B: – (prediction)

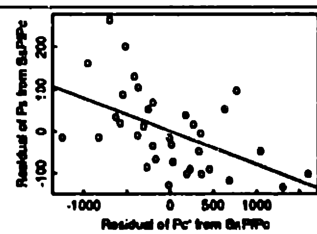
–	$r(31) = -0.57$	$p < 0.001$	(F.K., Stem-Past)
–	$r(31) = -0.55$	$p = 0.001$	(A.P., Stem-Past) ⟶



partialing out Ss, Pf, Pc: $r_{PsPc'.SsPfPc}$

B: – (prediction)

–	$r(30) = -0.54$	$p = 0.001$	(F.K., Stem-Past)
–	$r(30) = -0.52$	$p = 0.002$	(A.P., Stem-Past) ⟶



partialing out Pf': $r_{PsPc'.Pf'}$

NA

Evidence for Blocking under Stem-Past Assoc Theory = 10/10 (100%)

Table 9.19: Reaction Time Study: production time for attracted regulars

9.4.1 Discussion

There is evidence for moderately strong blocking (or support) of attracted regulars (*glide-glided*) by their surrounding irregulars (*ride-rode, drive-drove*). Of the 40 analyses for Stem-Past cluster strength, all 40 were in the expected direction. 23 of these analyses were significant under two-tailed tests, and another 9 were significant under one-tailed tests. It is highly unlikely that these results were caused solely by the clumping phenomenon because the same pattern emerged for cluster strength *before* division by past frequency.

9.5 Over-Irregulars (*glid*): The Predictiveness of Altern. Past Tense Success (*glided*)

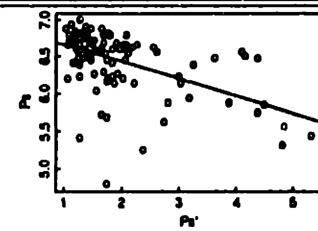
If over-irregulars (*glid*) are associatively computed, and their corresponding attracted regulars (*glided*) are as well, these attracted regulars should weaken the stem-past mappings over which the over-irregulars are computed. Thus the more successfully the attracted regulars (*glided*) are computed, the less successfully the over-irregulars (*glid*) should be computed. This should be reflected in a negative correlation between the computational success of over-irregulars (*glid*) and of their corresponding attracted regulars (*glided*). In this case the first five cells in the Analysis Tables should show these predictions.

Predictiveness of Altern. Past Tense Success(*glid*) as accept. ratings (1-7)
on Past Tense Success(*glided*) as accept. ratings (1-7)
under Blocking Theory for Attracted Regulars from All-Verbs Study

by a simple correlation: $r_{P_s{}'P_s}$

B: – (prediction)

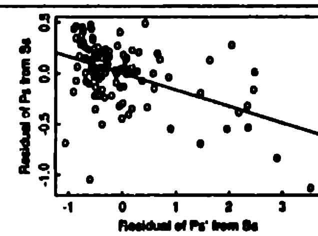
– $r(109) = -0.53$ $p < 0.001$



partialing out *Ss*: $r_{P_sP_s{}'.S_s}$

B: – (prediction)

– $r(108) = -0.48$ $p < 0.001$

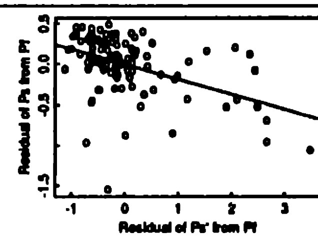


partialing out *Pf*: $r_{P_sP_s{}'.P_f}$

B: – (prediction)

– $r(108) = -0.44$ $p < 0.001$ (F.K.)

– $r(108) = -0.46$ $p < 0.001$ (A.P.) ⟶

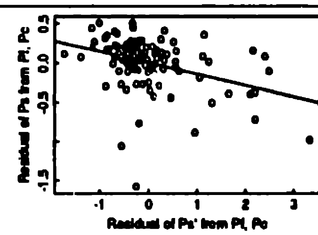


partialing out *Pf*, *Pc*: $r_{P_sP_s{}'.P_fP_c}$

B: – (prediction)

– $r(107) = -0.34$ $p < 0.001$ (F.K., Stem-Past)

– $r(107) = -0.37$ $p < 0.001$ (A.P., Stem-Past) ⟶

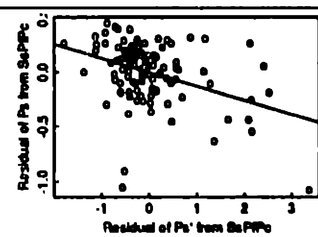


partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s{}'.S_sP_fP_c}$

B: – (prediction)

– $r(106) = -0.38$ $p < 0.001$ (F.K., Stem-Past)

– $r(106) = -0.39$ $p < 0.001$ (A.P., Stem-Past) ⟶



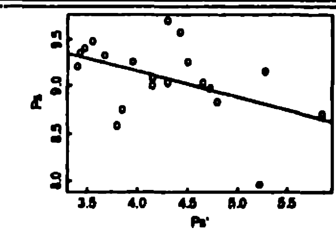
NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

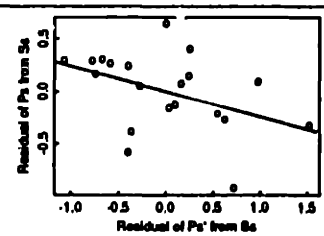
Table 9.20: All-Verbs Study: acceptability ratings for attracted regulars

Predictiveness of Altern. Past Tense Success(*glid*) as accept. ratings (1-10)
on Past Tense Success(*glided*) as accept. ratings (1-10)
under Blocking Theory for Attracted Regulars from All-Classes Study

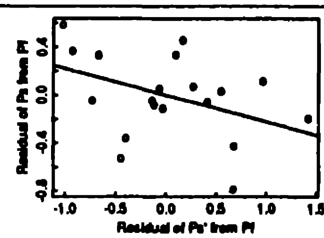
by a simple correlation: $r_{P_s'P_s}$
B: – (prediction)
– $r(18) = -0.47$ $p = 0.038$



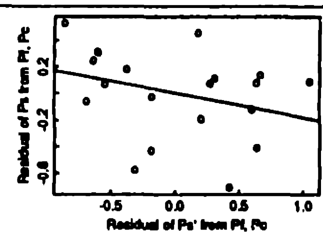
partialing out *Ss*: $r_{P_sP_s'.S_s}$
B: – (prediction)
not– $r(17) = -0.43$ $p = 0.067$



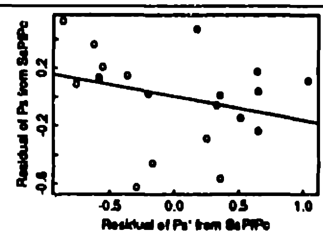
partialing out *Pf*: $r_{P_sP_s'.Pf}$
B: – (prediction)
not– $r(17) = -0.39$ $p = 0.096$ (F.K.)
not– $r(17) = -0.42$ $p = 0.077$ (A.P.) ⟶



partialing out *Pf*, *Pc*: $r_{P_sP_s'.PfPc}$
B: – (prediction)
not– $r(16) = -0.42$ $p = 0.086$ (F.K., Stem-Past)
not– $r(16) = -0.31$ $p = 0.213$ (A.P., Stem-Past) ⟶



partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s'.SsPfPc}$
B: – (prediction)
not– $r(15) = -0.39$ $p = 0.123$ (F.K., Stem-Past)
not– $r(15) = -0.30$ $p = 0.246$ (A.P., Stem-Past) ⟶

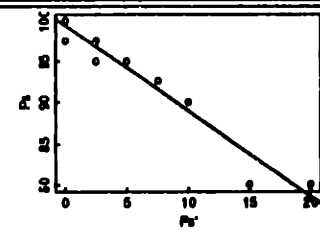
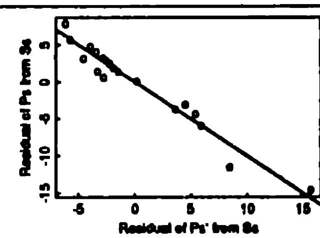
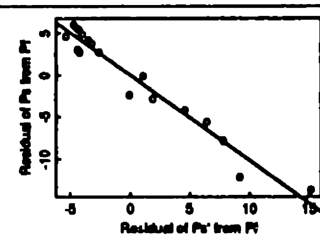
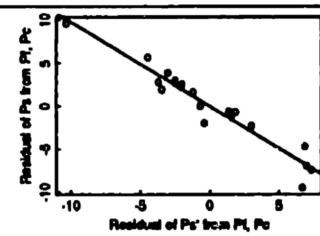
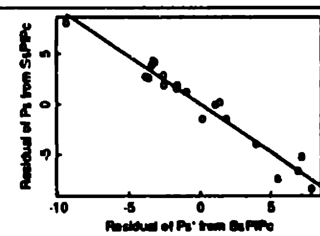


NA

Evidence for Blocking under Stem-Past Assoc Theory = 1/8 (12%)

Table 9.21: All-Classes Study: acceptability ratings for attracted regulars

Predictiveness of Altern. Past Tense Success(*glid*) as prod. like. (% subjs)
on Past Tense Success(*glided*) as prod. like. (% subjs)
under Blocking Theory for Attracted Regulars from All-Classes Study

by a simple correlation: $r_{P_s'P_s}$ B: – (prediction) – $r(18) = -0.97$ $p < 0.001$	
partialing out *Ss*: $r_{P_sP_s'.S_s}$ B: – (prediction) – $r(17) = -0.98$ $p < 0.001$	
partialing out *Pf*: $r_{P_sP_s'.Pf}$ B: – (prediction) – $r(17) = -0.97$ $p < 0.001$ (F.K.) – $r(17) = -0.98$ $p < 0.001$ (A.P.) ⟶	
partialing out *Pf*, *Pc*: $r_{P_sP_s'.PfPc}$ B: – (prediction) – $r(16) = -0.97$ $p < 0.001$ (F.K., Stem-Past) – $r(16) = -0.96$ $p < 0.001$ (A.P., Stem-Past) ⟶	
partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s'.S_sPfPc}$ B: – (prediction) – $r(15) = -0.97$ $p < 0.001$ (F.K., Stem-Past) – $r(15) = -0.97$ $p < 0.001$ (A.P., Stem-Past) ⟶	
NA	

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

Table 9.22: All-Classes Study: production likelihood for attracted regulars

Predictiveness of Altern. Past Tense Success(*glid*) as prod. like. (% subjs)

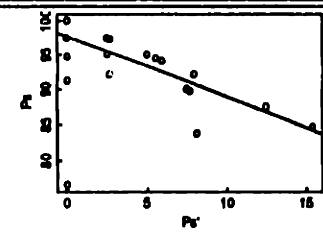
on Past Tense Success(*glided*) as prod. like. (% subjs)

under Blocking Theory for Attracted Regulars from Reaction Time Study

by a simple correlation: $r_{P_s{}'P_s}$

B: – (prediction)

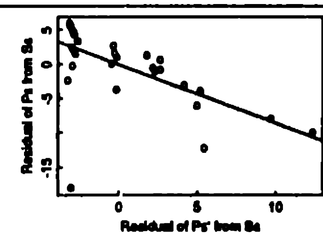
– $r(33) = -0.62$ $p < 0.001$



partialing out *Ss*: $r_{P_sP_s{}'.S_s}$

B: – (prediction)

– $r(32) = -0.62$ $p < 0.001$

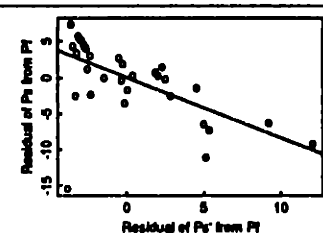


partialing out *Pf*: $r_{P_sP_s{}'.Pf}$

B: – (prediction)

– $r(32) = -0.62$ $p < 0.001$ (F.K.)

– $r(32) = -0.61$ $p < 0.001$ (A.P.) ⟶

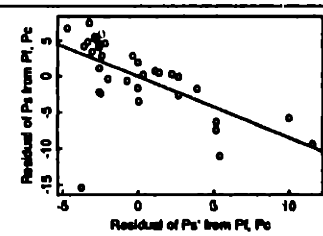


partialing out *Pf*, *Pc*: $r_{P_sP_s{}'.PfPc}$

B: – (prediction)

– $r(31) = -0.67$ $p < 0.001$ (F.K., Stem-Past)

– $r(31) = -0.62$ $p < 0.001$ (A.P., Stem-Past) ⟶

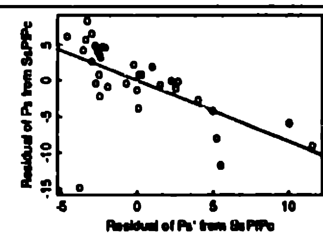


partialing out *Ss*, *Pf*, *Pc*: $r_{P_sP_s{}'.S_sPfPc}$

B: – (prediction)

– $r(30) = -0.67$ $p < 0.001$ (F.K., Stem-Past)

– $r(30) = -0.63$ $p < 0.001$ (A.P., Stem-Past) ⟶



NA

Evidence for Blocking under Stem-Past Assoc Theory = 8/8 (100%)

Table 9.23: Reaction Time Study: production likelihood for attracted regulars

9.5.1 Discussion

There is a strong blocking effect from attracted regulars (*glide-glided*) to their corresponding over-irregulars (*glide-glid*). Of the 32 analyses for Stem-Past cluster strength, all 32 were in the expected direction. 25 were significant for two-tailed tests, and another 3 were approaching significance (significant for one-tailed tests). Note, however, that care must be taken when interpreting the two production likelihood experiments, since the production success measures of attracted regulars and over-irregulars are expected to be nearly complements of each other.

9.6 Over-Irregulars (*glid*): The Predictiveness of Altern. Past Tense Frequency (*glided*)

If over-irregulars (*glid*) are associatively computed, and their corresponding attracted regulars (*glided*) are as well, these attracted regulars should weaken the stem-past mappings over which the over-irregulars are computed. Thus the more frequent the attracted regulars (*glided*), the more successfully they will be computed, and the less successfully the over-irregulars (*glid*) should be computed. This should be reflected in a negative correlation between the computational success of over-irregulars (*glid*) and the past tense frequency of their corresponding attracted regulars (*glided*). In this case the first and last cells in the Analysis Tables should show these predictions.

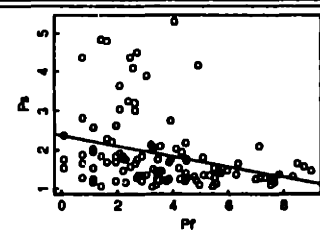
Predictiveness of Altern. Past Tense Frequency(*glided*)
on Past Tense Success(*glid*) as accept. ratings (1-7)
under Blocking Theory for Over-Irregulars from All-Verbs Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

– $r(109) = -0.34$ $p < 0.001$ (F.K.)

– $r(109) = -0.30$ $p = 0.001$ (A.P.) ⟶

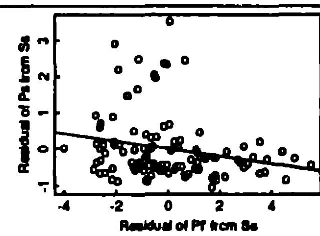


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

– $r(108) = -0.26$ $p = 0.006$ (F.K.)

– $r(108) = -0.22$ $p = 0.019$ (A.P.) ⟶



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

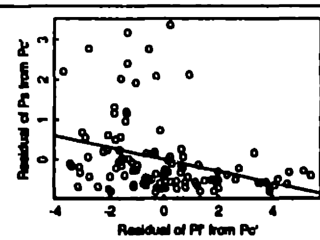
NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

– $r(108) = -0.36$ $p < 0.001$ (F.K., Stem-Past)

– $r(108) = -0.34$ $p < 0.001$ (A.P., Stem-Past) ⟶



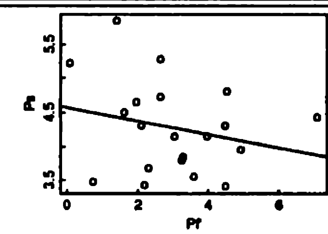
Evidence for Blocking under Stem-Past Assoc Theory = 6/6 (100%)

Table 9.24: All-Verbs Study: acceptability ratings for over-irregulars

Predictiveness of Altern. Past Tense Frequency(*glided*)
on Past Tense Success(*glid*) as accept. ratings (1-10)
under Blocking Theory for Over-Irregulars from All-Classes Study

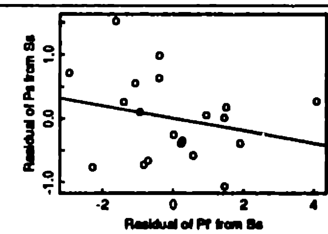
by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)
not– $r(18) = -0.29$ $p = 0.213$ **(F.K.)**
not– $r(18) = -0.24$ $p = 0.317$ **(A.P.)** ⟶



partialing out Ss**:** $r_{PsPf'.Ss}$

B: – (prediction)
not– $r(17) = -0.26$ $p = 0.291$ **(F.K.)**
not– $r(17) = -0.24$ $p = 0.320$ **(A.P.)** ⟶



partialing out Pf**:** $r_{PsPf'.Pf}$

NA

partialing out Pf**,** Pc**:** $r_{PsPf'.PfPc}$

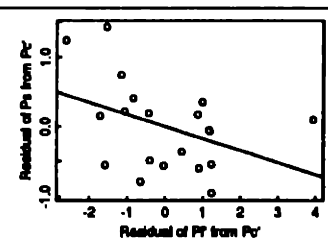
NA

partialing out Ss**,** Pf**,** Pc**:** $r_{PsPf'.SsPfPc}$

NA

partialing out Pc'**:** $r_{PsPf'.Pc'}$

B: – (prediction)
not– $r(17) = -0.28$ $p = 0.249$ **(F.K., Stem-Past)**
not– $r(17) = -0.41$ $p = 0.084$ **(A.P., Stem-Past)** ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 9.25: All-Classes Study: acceptability ratings for doublet irregulars

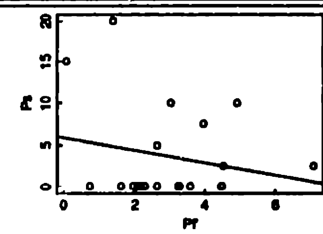
Predictiveness of Altern. Past Tense Frequency(*glided*)
on Past Tense Success(*glid*) as prod. like. (% subjs)
under Blocking Theory for Over-Irregulars from All-Classes Study

by a simple correlation: $r_{Pf'Ps}$

<u>B: – (prediction)</u>

not– $r(18) = -0.23$ $p = 0.319$ (F.K.)

not– $r(18) = -0.21$ $p = 0.380$ (A.P.) ⟶

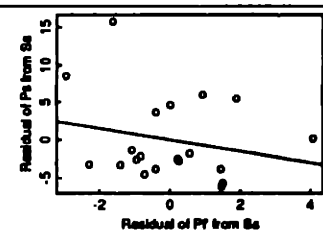


partialing out *Ss*: $r_{PsPf'.Ss}$

<u>B: – (prediction)</u>

not– $r(17) = -0.18$ $p = 0.465$ (F.K.)

not– $r(17) = -0.22$ $p = 0.369$ (A.P.) ⟶



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

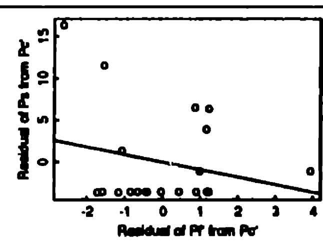
NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

<u>B: – (prediction)</u>

not– $r(17) = -0.23$ $p = 0.348$ (F.K., Stem-Past)

not– $r(17) = -0.23$ $p = 0.346$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 9.26: All-Classes Study: production likelihood for over-irregulars

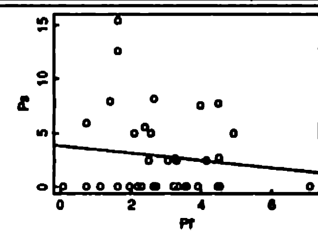
Predictiveness of Altern. Past Tense Frequency(*glided*)
on Past Tense Success(*glid*) as prod. like. (% subjs)
under Blocking Theory for Over-Irregulars from Reaction Time Study

by a simple correlation: $r_{Pf'Ps}$

B: – (prediction)

not– $r(33) = 0.13$ $p = 0.470$ (F.K.)

not– $r(33) = -0.13$ $p = 0.469$ (A.P.) $\longrightarrow$

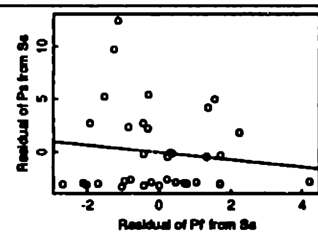


partialing out *Ss*: $r_{PsPf'.Ss}$

B: – (prediction)

not– $r(32) = 0.13$ $p = 0.447$ (F.K.)

not– $r(32) = -0.12$ $p = 0.486$ (A.P.) $\longrightarrow$



partialing out *Pf*: $r_{PsPf'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPf'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPf'.SsPfPc}$

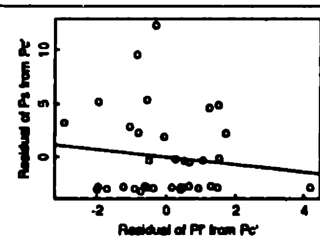
NA

partialing out *Pc'*: $r_{PsPf'.Pc'}$

B: – (prediction)

not– $r(32) = 0.12$ $p = 0.488$ (F.K., Stem-Past)

not– $r(32) = -0.12$ $p = 0.488$ (A.P., Stem-Past) $\longrightarrow$



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 9.27: Reaction Time Study: production likelihood for over-irregulars

9.6.1 Discussion

There are moderate blocking effects from the past frequency of attracted regulars to their corresponding over-irregulars. 35 out of 36 analyses were in the expected (negative) direction. Of these 35 however, 6 were significant at under two-tailed tests, and one more under a one-tailed test.

9.7 Over-Irregulars (*glid*): The Predictiveness of Altern. Past Tense Cluster Strength*chided, cited*)

If over-irregulars (*glid*) are computed in associative memory, and if regulars whose stems are similar to the stems of irregulars (*chided, cited*) have a certain probability of being learned in associative memory, we should find weak neighborhood effects of these regulars on the over-irregulars. In this case we would expect a positive correlation between the regular cluster strength (*chided, cited*) of the over-irregular (*glid*) and the computational success of that over-irregular. If this is the case the first and last cells of the Display Tables should show analyses revealing this positive correlation.

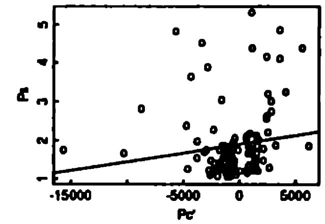
However, if over-irregulars are rule-produced, or if no regulars are associatively learned and computed, the frequency and similarity of their regular neighbours should not correlate at all with the computational success of the over-irregulars. If this is the case the first and last cells of the Display Tables should show analyses revealing no positive correlation.

Predictiveness of Altern. Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glid*) as accept. ratings (1-7)
under Blocking Theory for Over-Irregulars from All-Verbs Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

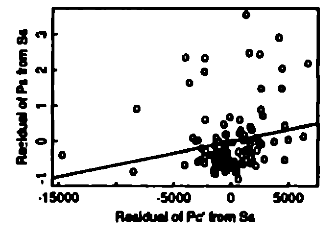
+	$r(109) = 0.20$	$p = 0.039$	(F.K., Stem-Past)
not+	$r(109) = 0.14$	$p = 0.141$	(A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

+	$r(108) = 0.23$	$p = 0.016$	(F.K., Stem-Past)
+	$r(108) = 0.20$	$p = 0.033$	(A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

NA

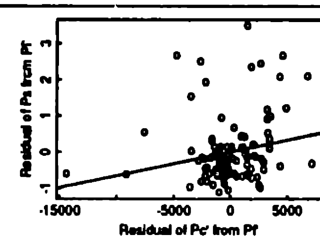
partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

+	$r(108) = 0.22$	$p = 0.020$	(F.K., Stem-Past)
+	$r(108) = 0.21$	$p = 0.031$	(A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 5/6 (83%)

Table 9.28: All-Verbs Study: acceptability ratings for over-irregulars

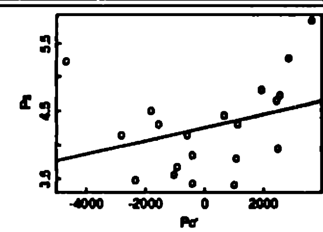
Predictiveness of Altern. Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glid*) as accept. ratings (1-10)
under Blocking Theory for Over-Irregulars from All-Classes Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

not+ $r(18) = 0.42$ $p = 0.067$ (F.K., Stem-Past)

not+ $r(18) = 0.32$ $p = 0.176$ (A.P., Stem-Past) $\longrightarrow$

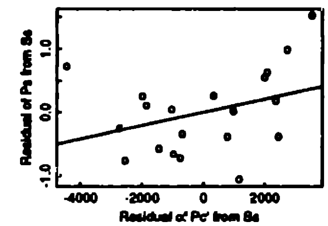


partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(17) = 0.42$ $p = 0.074$ (F.K., Stem-Past)

not+ $r(17) = 0.35$ $p = 0.142$ (A.P., Stem-Past) $\longrightarrow$



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

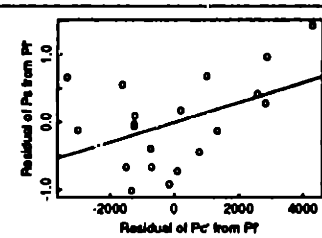
NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(17) = 0.41$ $p = 0.082$ (F.K., Stem-Past)

not+ $r(17) = 0.45$ $p = 0.052$ (A.P., Stem-Past) $\longrightarrow$



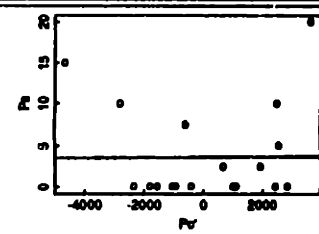
Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 9.29: All-Classes Study: acceptability ratings for doublet irregulars

Predictiveness of Altern. Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glid*) as prod. like. (% subjs)
under Blocking Theory for Over-Irregulars from All-Classes Study

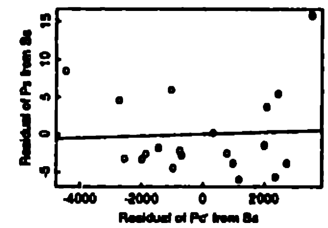
by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)
not+ $r(18) = 0.09$ $p = 0.698$ (F.K., Stem-Past)
not+ $r(18) = 0.01$ $p = 0.970$ (A.P., Stem-Past) ⟶



partialing out *Ss*: $r_{PsPc'.Ss}$

B: + (prediction)
not+ $r(17) = 0.09$ $p = 0.725$ (F.K., Stem-Past)
not+ $r(17) = 0.05$ $p = 0.848$ (A.P., Stem-Past) ⟶



partialing out *Pf*: $r_{PsPc'.Pf}$

NA

partialing out *Pf*, *Pc*: $r_{PsPc'.PfPc}$

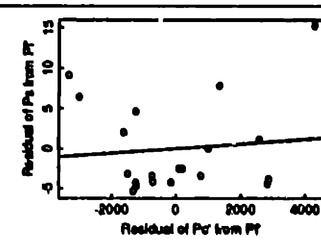
NA

partialing out *Ss*, *Pf*, *Pc*: $r_{PsPc'.SsPfPc}$

NA

partialing out *Pf'*: $r_{PsPc'.Pf'}$

B: + (prediction)
not+ $r(17) = 0.07$ $p = 0.768$ (F.K., Stem-Past)
not+ $r(17) = 0.10$ $p = 0.688$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

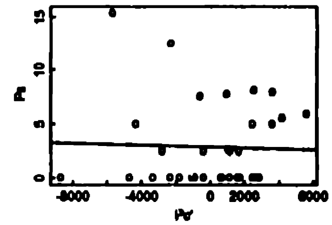
Table 9.30: All-Classes Study: production likelihood for over-irregulars

Predictiveness of Altern. Past Tense Cluster Strength(*chided, cited*)
on Past Tense Success(*glid*) as prod. like. (% subjs)
under Blocking Theory for Over-Irregulars from Reaction Time Study

by a simple correlation: $r_{Pc'Ps}$

B: + (prediction)

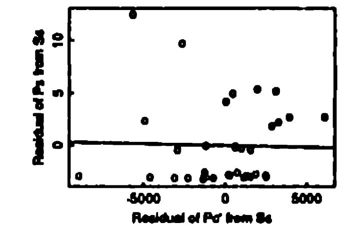
not+ $r(33) = -0.08$ $p = 0.659$ (F.K., Stem-Past)
not+ $r(33) = -0.03$ $p = 0.857$ (A.P., Stem-Past) ⟶



partialing out Ss: $r_{PsPc'.Ss}$

B: + (prediction)

not+ $r(32) = -0.07$ $p = 0.693$ (F.K., Stem-Past)
not+ $r(32) = -0.03$ $p = 0.884$ (A.P., Stem-Past) ⟶



partialing out Pf: $r_{PsPc'.Pf}$

NA

partialing out Pf, Pc: $r_{PsPc'.PfPc}$

NA

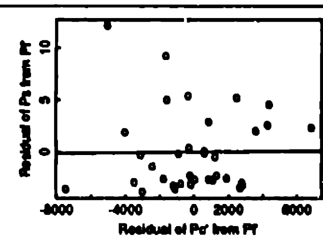
partialing out Ss, Pf, Pc: $r_{PsPc'.SsPfPc}$

NA

partialing out Pf': $r_{PsPc'.Pf'}$

B: + (prediction)

not+ $r(32) = -0.07$ $p = 0.686$ (F.K., Stem-Past)
not+ $r(32) = 0.01$ $p = 0.955$ (A.P., Stem-Past) ⟶



Evidence for Blocking under Stem-Past Assoc Theory = 0/6 (0%)

Table 9.31: Reaction Time Study: production likelihood for over-irregulars

9.7.1 Discussion

The attracted regulars (*bided, jived*) (regular cluster strength) surrounding over-irregulars (*glide-glid*) weakly block (or support) those over-irregulars. 13 out of the 16 analyses were in the expected direction, although only 2 of these 13 were significant for two-tailed analyses, and another 2 were significant for one-tailed analyses. This is consistent with attracted regulars being learned and computed in the associative memory.

Chapter 10

Summary and Discussion

10.1 Summary

True irregulars (*blow-blew*) show past tense frequency and irregular cluster strength (*grow-grew, throw-threw*) effects.

True regulars (whose stems are not similar to the stems of irregulars — for example, *walk-walked*) show neither past tense frequency nor regular cluster strength (*balk-balked, stalk-stalked*) effects.

Over-regulars (*blow-blowed*) are strongly blocked by their corresponding irregulars (*blow-blew*). Irregular past frequency also strongly blocks over-regulars. The surrounding irregulars (irregular cluster strength) of over-regulars weakly block over-regulars. However, surrounding regulars (regular cluster strength) do not support over-regulars.

Doublet irregulars (*dive-dove*) show past irregular frequency effects, and doublet regulars (*dive-dived*) show past regular frequency effects. However, the doublet regular past frequency effects are clearly weaker than the doublet irregular past frequency effects. The doublet irregulars do not show irregular cluster effects, and the doublet regulars do not show regular cluster effects.

There is very strong blocking between doublet irregulars and doublet regulars. The past frequency of doublet irregular pasts strongly blocks doublet regulars, while the past frequency of doublet regular pasts is less good at blocking doublet irregulars. Irregular cluster strength has a possible weak blocking effect on doublet regulars, while regular cluster strength has no effect on doublet irregulars.

Attracted regulars (*glide-glided*) show regular past frequency effects. These effects are weaker than for doublet regulars (*dive-dived*). Attracted regulars are moderately well blocked (or supported) by their surrounding irregulars (irregular cluster strength), while they are not at all supported by their surrounding regulars.

Over-irregulars (*glide-glid*) are strongly blocked by their corresponding attracted regulars (*glide-glided*). Over-irregulars are moderately blocked by the past frequency of their corresponding regulars, and weakly blocked by their surrounding regulars (regular cluster strength). Moreover, over-irregulars (*glide-glid*) are moderately well supported by their surrounding irregulars (irregular cluster strength).

10.2 Discussion

The irregular past frequency effects of true irregulars as well as doublet irregulars support both rote and associative models of irregulars. The Stem-Past irregular cluster effects of true irregulars support the Stem-Past associative model for irregulars.

The Hybrid model is supported by the contrasting lack of both word frequency and regular cluster effects for true regulars.

The Stem-Past associative model is further supported by the regular past frequency effects for doublet regulars and attracted regulars, since the model predicts that any regulars with stems similar to the stems of irregulars will be learned and computed in the same associative memory as the irregulars. Moreover, the stronger regular past frequency effects for doublet regulars than for attracted regulars also supports the Stem-Past model — because the stems of attracted regulars are less similar to the stems of irregulars than are the stems of doublets, attracted regulars should have a lower probability of being stored in the memory. Similarly, the stronger effects of irregular past frequency on doublet irregulars than regular past frequency on doublet regulars supports the Stem-Past model — the doublet irregulars can only be learned and computed in the memory, while the doublet regulars have a chance of being computed by the rule system (which should be particularly likely if the doublet regulars are infrequent, in which case they resemble over-regulars).

This decrease in word frequency effects from doublet irregulars to doublet regulars to attracted regulars is also evidence in favor of the Hybrid model, and against the single-net All-Associative model: The main argument of the All-Associative model against the lack of word or cluster strength effects for true regulars is that function has been so well approximated that the /ed/ is added to the stem with equal strength, no matter the phonological shape of the stem. However, for regulars phonologically closer to irregulars, this "over-learning" is highly unlikely, and therefore both doublet regulars and attracted regulars should show regular past frequency and regular cluster strength effects — in particular, doublet regulars should show past frequency effects just as strong as those for irregulars. However, we find that frequency effects are *weaker* for doublet regulars and for attracted regulars than for irregulars (even when their stems are *identical* with the stems of irregulars, in the case of doublets).

Both the Stem-Past model and the Hybrid model are supported by the irregular cluster blocking (or support) for attracted regulars, in contrast with the lack of regular cluster support for them.

The doublet blocking supports the Stem-Past model — in particular, the evidence that doublet irregular past frequency blocks doublet regulars while doublet regular past frequency blocks doublet irregulars. Furthermore, the Hybrid model is supported by the asymmetrical nature of this blocking, with irregular past frequency blocking doublet regulars (*dived*) more than regular past frequency blocking doublet irregulars (*dove*): If regulars were completely associatively learned and computed, they should block irregulars as much as vice versa. Instead, their weaker blocking of irregulars suggests that they have a certain probability of being rule-produced, which prevents them from blocking irregulars according to the theory of Associative Blocking.

The blocking of over-irregulars by their corresponding attracted regulars supports the Stem-Past model, as does their moderate blocking by their surrounding attracted regulars (regular cluster strength). The irregular cluster strength of over-irregulars also supports the Stem-Past model.

The blocking of over-regulars by irregular past frequency as well as (weakly) by their surrounding irregulars (irregular cluster strength) supports the Stem-Past model, as does the lack of support by surrounding regulars (regular cluster strength). However, since attracted regulars show the same clustering pattern as over-regulars, it is not clear to me that over-regulars are rule-produced; rather it is still open as to whether they are rule-produced, associatively computed along with attracted regulars and doublet regulars, or some of both (as I believe both doublet regulars and attracted regulars are computed).

The far stronger blocking of over-regulars by irregulars than of over-irregulars by doublet regulars is evidence for both the Stem-Past model and the Hybrid model — because attracted regulars should have a lower probability of being associatively learned and computed than irregulars.

10.3 Conclusion

Irregulars (*blow-blew*) are learned and computed in associative memory which resembles a function approximation system mapping stem-past phonological features. Regulars (*walk-walked*) are produced by a distinct symbol-manipulating-like rule — unless two conditions hold: If the stem of a regular is similar to the stems of irregulars, and if the regulars have already been computed (occured in the input), then the regular will be learned in and retrieved from associative memory. Thus doublet regulars (*dive-dived*) and attracted regulars (*glide-glided*), whose stems are similar to the stems of irregulars *and* which have been heard, will be associatively computed. But over-regulars (*blow-blowed*), which have not previously been heard, will not be successfully computed in associative memory.

These distinctions and interactions between regular and irregular linguistic forms suggest in turn that associative memory and grammatical symbol-processing are distinct cognitive components.

Bibliography

[Anderson, 1992] Anderson, S. (1992). *Amorphous morphology.* Cambridge University Press, New York.

[Armstrong et al., 1983] Armstrong, S., Gleitman, L., and Gleitman, H. (1983). What some concepts might not be. *Cognition*, 13:263–308.

[Aronoff, 1976] Aronoff, M. (1976). *Word formation in generative grammar.* MIT Press, Cambridge, MA.

[Aronoff and Sridhar, 1983] Aronoff, M. and Sridhar, S. (1983). Morphological levels in English and Kannada. In Richardson, J., Marks, M., and Chukerman, A., editors, *Papers from the parasession on the interplay of phonology, morphology, and syntax.*, Chicago. Chicago Linguistics Society.

[Bellugi et al., 1991] Bellugi, U., Bihrle, A., Jernigan, T., Trauner, D., and Doherty, S. (1991). Neuropsychological, neurological, and neuroanatomical profile of Williams Syndrome. *American Journal of Medical Genetics Supplement*, 6:115–125.

[Berko, 1958] Berko, J. (1958). The child's learning of English morphology. *Word*, 14:150–177.

[Bolinger, 1980] Bolinger, D. (1980). *Language: The loaded weapon.* Longman, New York.

[Brinkmann, 1993] Brinkmann, U. (1993). *Unpublished doctoral dissertation.* PhD thesis, University of Heidelberg, Germany.

[Brown, 1973] Brown, R. (1973). *A first language: The early stages.* Harvard University Press, Cambridge, MA.

[Bybee, 1985] Bybee, J. L. (1985). *Morphology: A study of the relation between meaning and form.* Benjamins, Philadelphia.

[Bybee, 1991] Bybee, J. L. (1991). Natural morphology: The organization of paradigms and language acquisition. In Huebner, T. and Ferguson, C., editors, *Crosscurrents in Second Language Acquisition and Linguistic Theories.*, pages 67–92, Amsterdam.

[Bybee and Moder, 1983] Bybee, J. L. and Moder, C. L. (1983). Morphological classes as natural categories. *Language*, 59:251–270.

[Bybee and Slobin, 1982] Bybee, J. L. and Slobin, D. I. (1982). Rules and schemas in the development and use of English past tense. *Language*, 58:265–289.

[Chapman, 1986] Chapman, R. L., editor (1986). *New Dictionary of American Slang.* Harper and Row, New York.

[Chomsky, 1957] Chomsky, N. (1957). *Syntactic structures.* The Hague, Mouton.

[Chomsky, 1965] Chomsky, N. (1965). *Aspects of the theory of syntax.* MIT Press, Cambridge, MA.

[Chomsky and Halle, 1968] Chomsky, N. and Halle, M. (1968). *The sound pattern of English.* Harper and Row, New York.

[Clark, 1982] Clark, E. V. (1982). The young wordmaker: A case study of innovation in the child's lexicon. In Wanner, E. and Gleitman, L. R., editors, *Language acquistion: the state of the art.*, New York.

[Clark, 1987] Clark, E. V. (1987). The principle of contrast: a constraint on language acquisition. In MacWhinney, B., editor, *Mechanics of language acquistion.*, Hillsdale, NJ.

[Clark, 1990] Clark, E. V. (1990). On the pragmatics of contrast. *Journal of Child Language*, 17:417–431.

[Daugherty and Seidenberg, 1992] Daugherty, K. and Seidenberg, M. (1992). Rules or connections? the past tense revisited. In *Proceedings of the Fourteenth Annual Conference of the Cognitive Science Society.*, Hillsdale, NJ.

[de Saussure, 1960] de Saussure, F. (1960). *A course in General Linguistics.* Peter Owen, London.

[Egedi and Sproat, 1991] Egedi, D. M. and Sproat, R. W. (1991). Connectionist networks and natural language morphology. Unpublished manuscript.

[Fodor, 1968] Fodor, J. A. (1968). *Psychological explanation.* Random House, New York.

[Fodor and Pylyshyn, 1988] Fodor, J. A. and Pylyshyn, Z. (1988). Connectionism and cognitive architecture: a critical analysis. *Cognition*, 28:3–71.

[Francis and Kucera, 1982] Francis, N. and Kucera, H. (1982). *Frequency analysis of English usage: Lexicon and grammar.* Houghton Mifflin, Boston, MA.

[Gordon, 1985] Gordon, P. (1985). Level-ordering in lexical development. *Cognition*, 21:73–93.

[Halle, 1973] Halle, M. (1973). Prolegomena to a theory of word formation. *Linguistic Inquiry*, 4:3–16.

[Halle and Mohanan, 1985] Halle, M. and Mohanan, K. P. (1985). Segmental phonology of modern English. *Linguistic Inquiry*, 16:57–116.

[Hare and Elman, 1992] Hare, M. and Elman, J. A. (1992). A connectionist account of English inflectional morphology: Evidence from language change. In *Proceedings of the Fourteenth Annual Conference of the Cognitive Science Society.*, pages 265–270, Hillsdale, NJ.

[Hays, 1988] Hays, W. L. (1988). *Statistics (4th edition).* Holt, Rinehart and Winston, Inc., Orlando, Florida.

[Hebb, 1949] Hebb, D. O. (1949). *The Organization of Behavior.* Wiley, New York.

[Hoard and Sloat, 1973] Hoard, J. E. and Sloat, C. (1973). English irregular verbs. *Language*, 49:107–120.

[Jackendoff, 1975] Jackendoff, R. S. (1975). Morphological and semantic regularities in the lexicon. *Language*, 51:639–671.

[Jacobs et al., 1991] Jacobs, R. A., Jordan, M. I., and Barto, A. G. (1991). Task decomposition through competition in a modular connectionist architecture. *Cognitive Science*, 15.

[James, 1890] James, W. (1890). *Psychology (Briefer Course).* Holt, New York.

[Janda, 1990] Janda, R. D. (1990). Frequency, markedness, & morphological change: on predicting the spread of noun-plural *-s* in Modern High German and West Germanic. *ESCOL '90*, pages 136–153.

[Jespersen, 1942] Jespersen, O. (1942). *A modern English grammar on historical principles.* George Allen & Unwin Ltd., London.

[Keil, 1989] Keil, F. C. (1989). *Concepts, kinds, and cognitive development.* MIT Press, Cambridge, MA.

[Kempley and Morton, 1982] Kempley, S. T. and Morton, J. (1982). The effects of priming with regularly and irregularly related words in auditory word recognition. *British Journal of Psychology*, 73:441–454.

[Kim et al., 1991] Kim, J. J., Pinker, S., Prince, A., and Prasada, S. (1991). Why no mere mortal has ever flown out to center field. *Cognitive Science*, 15:173–218.

[Kiparsky, 1982a] Kiparsky, P. (1982a). From cyclical to lexical phonology. In van der Hulst, H. and Smith, N., editors, *The structure of phonological representations.*, Dordrecht.

[Kiparsky, 1982b] Kiparsky, P. (1982b). Lexical phonology and morphology. In Yang, I. S., editor, *Linguistics in the morning calm.*, pages 3–91, Seoul.

[Kopcke, 1988] Kopcke, K. M. (1988). Schemas in German plural formation. *Lingua*, 74:303–335.

[Kucera and Francis, 1967] Kucera, H. and Francis, N. (1967). *Computational analysis of present-day American English.* Brown University Press, Providence, RI.

[Kuczaj, 1977] Kuczaj, S. (1977). The acquisition of regular and irregular past tense forms. *Journal of Verbal Learning and Verbal Behavior*, 16:589–600.

[Lachter and Bever, 1987] Lachter, J. and Bever, T. G. (1987). The relation between linguistic structure and associative theories of language learning—A constructive critique of some connectionist learning models. *Cognition*, 28:195–247.

[Lakoff, 1987] Lakoff, G. (1987). Connectionist explanations in linguistics: Some thoughts on recent anti-connectionist papers.

[Lashley, 1950] Lashley, K. S., editor (1950). *In search of the engram.* Society of Experimental Biology.

[Leiber, 1980] Leiber, R. (1980). *On the organization of the lexicon.* PhD thesis, MIT.

[Ling and Marinov, 1993] Ling, C. X. and Marinov, M. (1993). Answering the connectionist challenge: A symbolic model of learning the past tenses of English verbs.

[MacWhinney and Leinbach, 1991] MacWhinney, B. and Leinbach, J. (1991). Implementations are not conceptualizations: Revising the verb learning model. *Cognition*, 40:121–157.

[Mandler and Mandler, 1964] Mandler, J. M. and Mandler, G. (1964). *Thinking: From Association to Gestalt.* John Wiley and Sons, Inc., New York, London, Sydney.

[Marchman, 1992] Marchman, V. (1992). Language learning in children and neural networks: plasticity, capacity, and the critical period.

[Marchman, 1993] Marchman, V. (1993). Constraints on plasticity in a connectionist model of the English past tense. *Journal of Cognitive Neuroscience*, 5:215–234.

[Marcus et al., 1992] Marcus, G. F., Pinker, S., Ullman, M., Hollander, M., Rosen, T. J., and Xu, F. (1992). Overregularization in language acquisition. *Monographs of the Society for Research in Child Development*, 57.

[McCullock and Pitts, 1943] McCullock, W. S. and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5:115–133.

[Mencken, 1936] Mencken, H. (1936). *The American language.* Knopf, New York.

[Minsky, 1967] Minsky, M. L. (1967). *Computation: Finite and Infinite Machines.* Prentice-Hall, Englewood Cliffs.

[Newell and Simon, 1981] Newell, A. and Simon, H. A. (1981). Computer science as empirical inquiry: Symbol and search. In Haugeland, J., editor, *Mind design: Philosophy, psychology, artificial intelligence.*, Cambridge, MA. MIT Press.

[Pinker, 1984] Pinker, S. (1984). *Language learnability and language development.* Harvard University Press, Cambridge, MA.

[Pinker, 1990] Pinker, S. (1990). Of mice and men. Unpublished manuscript.

[Pinker, 1991] Pinker, S. (1991). Rules of language. *Science*, 253:530–535.

[Pinker and Prince, 1988] Pinker, S. and Prince, A. (1988). On language and connectionism: Analysis if a Parallel Distributed Processing model of language acquisition. *Cognition*, 28:73–193.

[Pinker and Prince, 1989] Pinker, S. and Prince, A. (1989). The nature of homan concept: evidence from an unusual source.

[Pinker and Prince, 1991] Pinker, S. and Prince, A. (1991). Regular and irregular morphology and the psychological status of rules of grammar. In Sutton, L. A., Johnson, C., and Shields, R., editors, *Proceedings of the Seventeenth Annual Meeting of the Berkeley Linguistics Society: General Session and Parasession on the Grammar of Event Structure.* Berkeley Linguisitcs Society.

[Pinker and Prince, 1992] Pinker, S. and Prince, A. (1992). Regular and irregular morphology and the psychological status of rules of grammar. In Sutton, L. A., Johnson, C., and Shields, R., editors, *Proceedings of the 17th Annual Meeting of the Berkeley Linguistics Society: General Session and Parasession on the Grammar of Event Structure.*, Berkeley, CA. Berkeley Linguistics Society.

[Plunkett and Marchman, 1990] Plunkett, K. and Marchman, V. (1990). From rote learning to system building.

[Plunkett and Marchman, 1991] Plunkett, K. and Marchman, V. (1991). U-shaped learning and frequency effects in a multi-layered perceptron: Implications for child language acquisition. *Cognition*, 38:43–102.

[Prasada and Pinker, 1993] Prasada, S. and Pinker, S. (1993). Similarity-based and rule-based generalizations in inflectional morphology. *Language and Cognitive Processes*, 8.

[Prasada et al., 1990] Prasada, S., Pinker, S., and Snyder, W., editors (1990). *Some evidence that irregular forms are retreived from memory but regular forms are rule-generated.* Psychonomic Society.

[Quillian, 1967] Quillian, M. R. (1967). Word Concepts: A Theory and Simulation of Some Basic Semantic Capabilities. *Behavioral Science*, 12:410–430.

[Quirk et al., 1985] Quirk, R., Greenbaum, S., Leech, G., and Svartvik, J. (1985). *A comprensive grammar of the English language.* Longman, New York.

[Rosenblatt, 1962] Rosenblatt, F. (1962). *Principles of Neuroscience.* Spartan, New York.

[Rumelhart and McClelland, 1986] Rumelhart, D. and McClelland, J. (1986). On learning the past tenses of English verbs. Implicit rules or parallel distributed processing? In McClelland, J., Rumelhart, D., and the PDP Research Group, editors, *Parallel distributed processing: Explorations in the microstructure of cognition.*, Cambridge, MA.

[Seidenberg and Bruck, 1990] Seidenberg, M. and Bruck, M., editors (1990). *Consistency effects in the generation of past tense morphology.* Psychonomic Society.

[Sproat, 1992] Sproat, R. (1992). *Morphology and computation.* MIT Press, Cambridge, MA.

[Stanners et al., 1979] Stanners, R. F., Neiser, J. J., Hernon, W. P., and Hall, R. (1979). Memory representation for morphologically related words. *Journal of Verbal Learning and Verbal Behavior*, 18:399–41.

[Stemberger and MacWhinney, 1988] Stemberger, J. and MacWhinney, B. (1988). Are inflected forms stored in the lexicon? In Hammond, M. and Noonan, M., editors, *Theoretical Morphology: Approached in Modern Linguistics.*, New York.

[Swift, 1977] Swift, D. (1977). *The effects of context, word frequency, and internal redundancy in reading and word perception.* PhD thesis, University of New Hampshire.

[Tversky, 1977] Tversky, A. (1977). Features of similarity. *Psychological Review*, 84:327–352.

[Ullman et al., 1993] Ullman, M., Corkin, S., Pinker, S., Coppola, M., Locascio, J., and Growdon, J., editors (1993). *Neural modularity in language: Evidence from Alzheimer's and Parkinson's diseases*, Washington D.C. 23rd Annual Meeting of the Society for Neuroscience.

[Ullman et al., 1992] Ullman, M., Hickok, G., and Pinker, S., editors (1992). *Irregular and regular morphology in an aphasic*, Montreal. Theoretical and Experimental Neuropsychology/Neuropsycholgie Experimentale et Theoreticale Conference.

[Whaley, 1978] Whaley (1978). Word-nonword classification time. *Journal of Verbal Learning and Verbal Behavior*, 17:143–154.

[Williams, 1981] Williams, E. (1981). On the notions of 'lexically related' and 'head of a word'. *Linguistic Inquiry*, 12:245–274.

[Winograd and Cowan, 1963] Winograd, S. and Cowan, J. D. (1963). *Reliable Computation in the Presence of Noise.* MIT Press, Cambridge, MA.

[Xu and Pinker, 1992] Xu, F. and Pinker, S., editors (1992). *Weird past tense forms.* Seventeenth annual Boston University Conference on Language Development.

[Zwicky, 1975] Zwicky, A. M. (1975). Settling on an underlying form: The English inflectional endings. In Cohen, D. and Wirth, J., editors, *Testing linguistic hypotheses.*, New York.