

A Cognitive Categorization-Based Approach for Understanding Identity Representation Online

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by

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S.B., Massachusetts Institute of Technology (2010)

Submitted to the Department of Electrical Engineering and Computer Science

in partial fulfillment of the requirements for the Degree of
Master of Engineering in Electrical Engineering and Computer Science
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Abstract

Computationally representing social identities using social networking profiles traditionally involves the reduction of identities to fit into simplistic categories such as “friends.” In contrast, this thesis proposes that the data structures underlying user identities can be algorithmically processed and interpreted in ways that assist in understanding more nuanced aspects of identity such as “subculture” or “personality”

Building upon an interdisciplinary computational identity model developed by Fox Harrell in his NSF-supported Advanced Identity Representation Project, this thesis proposes an algorithm based on theories of cognitive categorization[6, 7] to reveal implicit categories in computational identity systems. The algorithm has been applied to social networking site Facebook and a suite of graphical user interfaces was developed to enable users to explore individual and group identities. In a qualitative study, we found that most of the generated categories coherently represented social groups and would be useful for applications such as expressing the groups’ collective identities.

Thesis Supervisor: D. Fox Harrell
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CHAPTER I

INTRODUCTION

1.1 Motivation

As digital technologies become further integrated into our lives, the number of technologies we use to represent ourselves is growing rapidly. Between social networking sites, computer and video games, and e-commerce sites, computational representations of our identities have become important tools for communicating with other people and systems. On social networking sites like Facebook, profiles help define context for conversations, hold clues to help link carefully crafted online personas with the real-life offline people, and display connections between users and their friends. By playing video games, users are able to project identities onto their characters to shape their own experiences, adopt new identities through role playing, or play roles in teams to help other players defeat enemies. Representations of identity on e-commerce sites like Amazon.com support the system's offering of accurate and useful recommendations as well as provide a place to store information about the user like credit card numbers and shipping addresses.

While these examples of systems provide valuable new forms of identity representation, they also necessitate a reduction of expression from the possibilities of the non-virtual

world. In face-to-face interactions, aspects of the participants' identities are conveyed through our words, facial expressions, body language, verbal intonation, fashion, and other forms of implicit communication like inflection and tone. While understanding and performing these communicative acts is second nature to us in face-to-face conversations, they are extremely complex and important forms of communication. Through these, we can provide complex representations of the aspects we find most important to our identities (e.g. personality, gender, race, sexual orientation, fashion, and taste). We can explain the subtleties of our identities by displaying membership in different subcultures or accentuate the juxtapositions we use to define our identities. All of these combined help us express the full range of our identities.

In computer systems, any representation of identity must fit into an explicit categorization structure made up of discrete elements, forcing a reduction of the fidelity of identity representation with respects to the non-virtual world. As a consequence of this reduction, information like sexuality or gender presentation is often simplified and represented by a small set of discrete choices, which can flatten the nuance of the way these concepts are often enacted and understood. While additional information about identity can be communicated through pictures and text, these are much harder for the system itself to understand.

Computational identity systems (e.g. social networking systems, computer and video games, and e-commerce sites) perform this reduction by constructing specific categorization structures to enable computation in whatever way seems most beneficial. For example, categorization structures such as gender or race can be conveniently simplified to a drop-down menu without considering the broader effect this simplification might have. No matter how rich these categorization structures may be, they remain a simplified model of identity representation and important aspects of the user's identity often fall through the cracks or require a significant effort to communicate.

Luckily, the explicit categorization structures built into an identity representation can be combined and interpreted in ways that reveal implicit categories. For example, we

can take markers of explicit categories, such as interests in programming languages (e.g., “likes Lisp”), organizations (e.g., “likes the EFF”), or activities (e.g., “likes soldering”), and infer that the user might fit into a category loosely called “computer people”. Note that this category is quite subjective; in social circles involving non-computer experts, “likes Macs” and “likes Facebook” may be enough for someone to be placed in the “computer people” category, whereas in a highly technical set of users these interests might not necessarily place that person in a “computer people” category. This subjective aspect of categorization, that is, how categories arise in local networks rather than globally, is important to note. To take another example of implicit categorization, in a massively-multiplayer online (MMO) role-playing game like *World of Warcraft*¹, category markers like class, race, gear, and specialization combine to form implicit categories of *combat role* such as “damage dealer,” “tank,” or “healer.”² The process of identifying specific implicit categories can be implemented computationally with a high degree of specificity. For example, Gilbert and Karahalios[5] automate the process of categorizing “tie strength” or “friendliness between” by combining explicit categories from social networking systems such as “mutual friends”, wall posts, and education level.

Developers of computational identity systems often recognize the value of implicit categories and make efforts to help expose them to users. For instance, the computer game company Blizzard Entertainment implemented a feature in *World of Warcraft* that lets players specify which combat role they want to take when looking for a group, which made those implicit roles more explicit (shown in Figure 1-1³)[14]. When a user of the social media application Twitter views another person’s profile, she is also shown who, among the people she follows, also follows the other person’s profile (shown in Figure 1-2), i.e. if Alice follows Bob and Bob follows Cathy, when Alice views Cathy’s profile, she will see that Bob also follows Cathy. This can help Alice place Bob into one of her implicit categories (Bob might be in the category of people interested in HCI, or from

¹*World of Warcraft*. Blizzard Entertainment. <http://us.battle.net/wow/en/>

²These are common roles that players fulfill in the game. For instance, a “tank” is a character that can withstand a lot of damage and pulls attention away from the rest of the group, allowing them to proceed more safely.

³Image from WoWWiki. The copyright for the image is held by Blizzard Entertainment. http://www.wowwiki.com/File:Patch_3.3_LFD_in_queue.jpg

Alice's high school). Facebook shows shared interests and photos when viewing a friend's profile or "friends who like this" when viewing a page to help the user fit the friend or page into the right implicit categories.

While these efforts represent some small, isolated steps toward using software to reveal implicit identity categories, much more can be done. In particular, none of these systems take a holistic view of the problem and sees it as an instance of a general problem related to identity categorization. In the examples above, the systems either add another explicit category for the user to choose or simply present the user with data that is easy to compute, but require the user to do all the work of interpretation.



Figure 1-1: Screenshot of the Dungeon Finder feature in Blizzard Entertainment's *World of Warcraft*. The shield represents the "tank" role, the cross represents the "healer" role, and the dagger represents the "damage dealer" role.



Figure 1-2: Screenshot of Twitter's "Followers you follow" feature from the sidebar of EFF's profile page.

We believe that systems such as social networks carry a great deal of implicit information related to identity categories that has not yet been taken advantage of to provide for richer functionality. For instance, comparing the two examples of Facebook's "Friendship" feature in Figure 1-3, we can see the overlap between the user's Likes and those of the user's friends – i.e., the system displays items that both users Like. The first of the examples in Figure 1-3 provides the user with much more information because the shared Likes (the

Harry Potter books and films, the book *American Gods*, and the animated films *Spirited Away* and *Princess Mononoke*) potentially belong together in an implicit category of fantasy-related media (suggesting that the user may belong in an implicit category of fantasy-lovers), whereas the data in the second example is less strongly connected and provides less information. The musical groups Pink Floyd and Radiohead, and the television shows *How I Met Your Mother*, and *The Daily Show* are liked by a wider range of people and are not unique to any subset. With a better understanding of these implicit categories, we can take these interfaces further. For instance, we could prioritize interests that are less common and therefore more significant, which would enable the user to more easily fit their friends into the right implicit category.



Figure 1-3: Two examples of the preview of Facebook's "Friendship" feature

With better understanding of these implicit categories, we can support interfaces that help construct and present these categories in ways that better support understanding, dynamically change the presentation of identity for different groups, identify and reduce potentially stigmatizing categorization structures, and more. For example, an application could help the user quickly identify a person in a "friend request" by suggesting groups of friends that person is similar to, or an application could help the user find other people who like a TV show even if that TV show doesn't appear on any of the user's friends' profiles. Another application could help a user working at Planned Parenthood conceal that information from relatives who might disapprove.

Toward that end, the Advanced Identity Representation (AIR) Project, a 5-year NSF-supported endeavor lead by Professor Fox Harrell, to which this thesis contributes, pro-

poses using models of categorization based on theories drawn from cognitive science and sociology literature to help build new technologies to reveal these implicit categories for use in creative, utilitarian, or critical systems[6, 7]. This thesis builds on the work from the AIR Project by presenting the first components of a toolkit that takes abstract data structures representing identity and uses them to model social identity phenomena such as implicit social categories.

1.2 System

The system introduced here is comprised of several portions: an algorithm designed to work on a wide range of computational identity systems and a specific implementation of the algorithm and user interface built using Facebook as a case study. The algorithm takes as input a network of abstract data structures representing identities as connections between user profiles and the attributes associated with them. It outputs categories of Likes that hold information about identity hidden in the data. Instead of these categories being a discrete set of attributes, they are a set of scores representing a level of membership for each attribute in the network. First, the algorithm calculates the correlation between each pair of attributes on the network. Then, given a set of user profiles or attributes from within the network, the algorithm uses the correlation data to find attributes most central to defining that group, or the attributes that are the *best examples* of what it means to be a member of that group.

These categories of attributes are meant to serve as representations of categories of people. They are best thought of as a category of attributes that can define what types of people form the category of people. To continue an example from above, a category consisting of attributes like “likes Lisp”, “likes EFF”, and “likes soldering” can be a representation of the social category of “computer person.” As we shall see in the theoretical framework below, these categories can be used to describe examples of prototypical members, which are *best example* members of a category[8]. For instance, in the case of Facebook Likes,

the algorithm is able to reduce a group of people to a representative profile, or generalize a small set of likes and determine which are most central to the group or the level of membership for people who like those things. Chapter 2, describes the concepts of membership and centrality in detail.

The algorithm draws heavily from Hugo Liu's work on taste representation in social networks[12], though we propose several changes to address smaller networks (e.g. the user's friends) instead of more global networks (e.g. all users on a particular system). In particular, the primary algorithm starts by constructing an $n \times n$ matrix of all the possible features of a particular identity representation present on a portion of the network. The entries of this matrix are the Pointwise Mutual Information that each pair shares[2]. This matrix is referred to by Liu as a *taste fabric*. From there, we provide ways of seeding that matrix with values and through a technique called Spreading Activation. To extend this work and incorporate a cognitive science-based approach, we bring in network information to implement various models of categorization phenomena such as levels of membership and *best example* members of a category. This algorithm comprises the first components of the AIR Toolkit.

As a case study, we present an implementation of this algorithm using Facebook Likes (things people have liked on Facebook) as an example source of identity information. The toolkit downloads the user's and the user's friend's Facebook Likes and some profile information, then computes the correlation between Likes. This toolkit allows various interfaces to be built quickly and efficiently to harness the power of the algorithm. We present three interfaces built on top of the algorithm, each with a different purpose: Explore, Reflect, and Group Persona.

The Explore Interface is built to help explore category creation and the potential outcomes of different techniques. The Reflect Interface is an interface meant to show how previously constructed categories are represented on the user's profile. Finally, the Group Persona Interface (shown in Figures 1-4 and 1-5) is meant to help people explore the relationships between the explicit categories built into Facebook and the categories of Likes that those

explicit attributes imply.

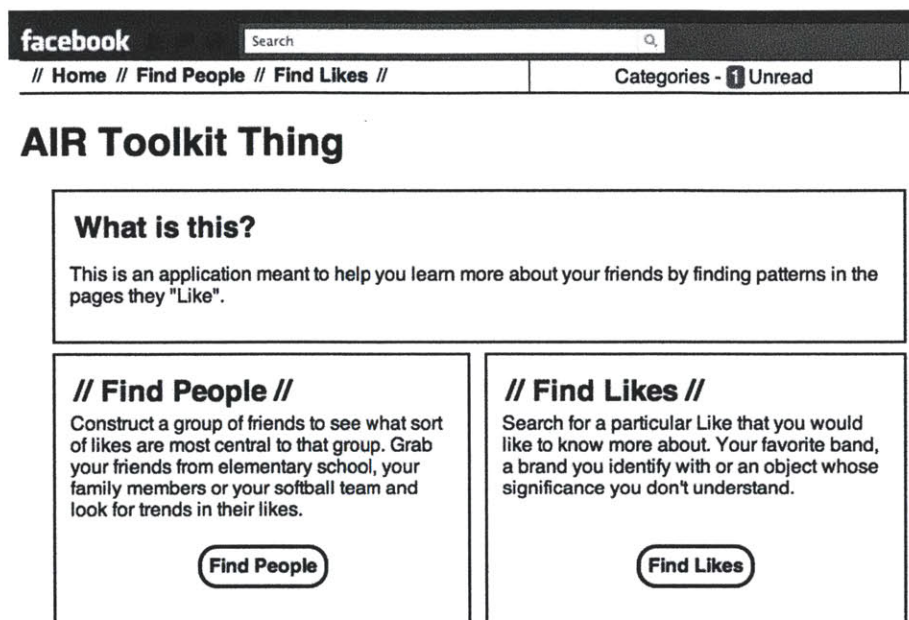


Figure 1-4: Screenshot of the Group Persona Interface's home page.

1.3 Thesis Outline


In this thesis, first Chapter 2 presents discussion of the theoretical framework underlying the work. Section 2.1 describes the relevant models proposed by the AIR project and the insights used here. Work related to the technical approaches used here is described in Sections 2.2 and 2.3. Chapter 3 first describes the algorithm in detail and relates it to the models suggested in Chapter 2, beginning with a description of the construction of the attribute matrix and the category creation built on top of it in Section 3.1. Section 3.2 then follows with a description of the implementation of the algorithm using Facebook Likes. Also included in Section 3.2 is a discussion of the benefits and drawbacks of using Facebook Likes as a source of identity information and the technical aspects of obtaining the necessary data.

Chapter 4 describes the design of three interfaces built on top of the current implemen-

facebook

// Home // Find People // Find Likes // Categories - 0 Unread

People who like San Francisco Giants edit



[See More](#)

Top Pages


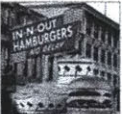






















 San Francisco Giants	 In-N-Out to Watsonville	 Buster Posey	 Tim Lincecum	 The 831	 Tosh.0
 Golden State Warriors	 San Francisco 49ers	 The Hangover	 I Love 831	 MEXICAN WORD OF THE DAY	 Santa Cruz, CA
 Family Guy	 South Park	 Santa Cruz Beach Boardwalk	 What's there to do? Nothing, we live in Watsonville.	 Step Brothers	 Santa Cruz
 In-N-Out Hamburgers			 SHARKS OFFICIAL FACEBOOK PAGE	 Rob & Big	

Figure 1-5: The display of a category using the Group Persona Interface.

tation of the toolkit and one built on an earlier implementation. Chapter 5 covers the results of the study conducted using the Group Persona Interface and the lessons learned from it.

Finally, Chapter 6 concludes the thesis and discuss future directions both for extending the toolkit from its current form and for interfaces that can be built with the toolkit.

1.4 Brief Glossary

Attribute: any explicit annotation of a profile connecting it to another concept. In social networking systems this includes annotations like profile info such as gender, location, education, work history, likes, etc. In video games, this could include choices made in character creation (race, class), attributes chosen throughout the game (skills, talents, equipment), or things that happen through gameplay (achievements, story accomplishments). On e-commerce sites, this could include things like previous purchases.

Computational Identity System: any system that represents a user's identity

Profile: an identities representation on a computational identity system

1.4.1 Common Acronyms and Shorthands

AIR Project: Advanced Identity Representation Project.

PMI: Pointwise Mutual Information

SNS: Social networking system

1.4.2 Proprietary Shorthands

Like: Facebook Like—explicit connections made when a Facebook user “Likes” a Page)

Page: Facebook Page—a cultural object (book, movie, musical artist, person, idea, place)
that can be

CHAPTER 2

THEORETICAL FRAMEWORK

This chapter provides a description of the theory that will underlie the approach of modeling cognitive categorization and computational identity representation. First, Section 2.1 forms the theoretical underpinning of the work by discussing Harrell's work on the AIR Project. Next, Section 2.2 discusses work on common sense reasoning. Finally, Section 2.3 discusses analogy as well as Liu's work on understanding taste in social networks and how each of these approaches influenced this work.

Besides the work discussed in this chapter, this thesis draws upon ideas from collaborative filtering (filtering for information based on large sets of user data). There are many techniques that scale up to the demands of e-commerce sites, but either have trouble working with relatively small, sparse data sets or would be difficult to integrate with the cognitive models of categorization discussed here. These systems did, however, raise issues to consider, such as gray sheep (users who do not consistently align with any group of people) and synonymy (when a single object has multiple entries)[16]. Systems meant to model analogy and conceptual blending such as SME[4], and Divago[13], provided helpful insights, but were not designed to address networks at the scale of the computational identity networks addressed here.

2.1 AIR Project

This work is part of the larger Advanced Identity Representation (AIR) Project, which proposes using cognitively grounded models of categorization to help build new technologies to reveal these implicit categories for use in creative, utilitarian or critical systems. These systems would be able to support user-representation that can change dynamically based on the user's preferences and actions or by who is viewing it. These representations would have the ability to be significantly more expressive than current computational systems and be empowering for diverse and underrepresented groups.

This project is an attempt to actualize some of the ideas presented by the AIR Project. We do this by developing early components of the AIR Toolkit to tackle the problem of using models proposed and collected in the AIR Project to help reveal implicit categories in computational identity systems.

We first discuss the technical components of a *sociodata ecology*, then a cognitive model of computational identity, followed by a description of cognitive categorization.

2.1.1 Technical Components of a Sociodata Ecology

One insight that can help understand that problem at hand is that computational identity systems use a limited number of technical components in their representation of identity. These components, Harrell notes, exist together in a *sociodata ecology*[7] where they can be used by computational systems and subjective user interpretations to infer information about social concepts, relationships and cultural values. The components are:

- Static media assets
- Flat text profiles
- Modular graphical models

- Statistical/numerical representation
- Formal annotation
- Procedural/Behavioral rules

Together, these components underlie technologies as diverse as a user's social networking site (SNS) profile, an e-commerce account, or a video game avatar.

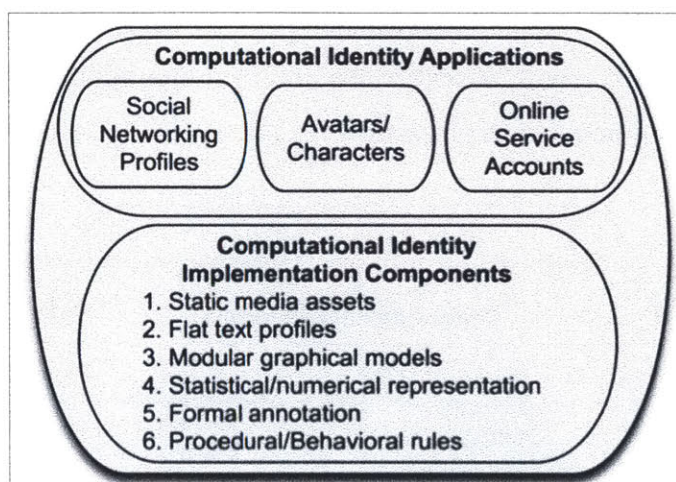


Figure 2-1: Shared Technical Underpinnings of Computational Identity Applications[6]

From this framework can emerge a better understanding of similarities between disparate computational identity applications that might allow us to create models of identity phenomena that can be implemented across many systems. The current work focuses on components falling under the description of formal annotations, which are explicit connections made in the data representation of an identity. Examples of formal annotations in social networks include choices like gender, location, hometown, and education. Specifically, we focus on Facebook Likes (connections made between a profile and Facebook's representation of a cultural object or concept—referred to as a Facebook Page—when a user “likes” that concept).

2.1.2 Cognitive Model of Computational Identity

The AIR Model of Cognitively Grounded Computational Identity is based on the understanding that people create and interpret presentations of identity through imaginative cognitive processes such as categorization. It is through these processes that both social classification infrastructures and technical identity classification infrastructures are created. When creating or interpreting a presentation of identity, people look through the lens of the technical way it is presented and the cultural context in which it exists.

Cognitive scientists have proposed that people form “idealized cognitive models” (ICMs) as building blocks upon which to build categories[8]. By using examples of these ICMs, we suggest that we can improve the expressiveness of computational identity systems by more closely modeling human categorization.

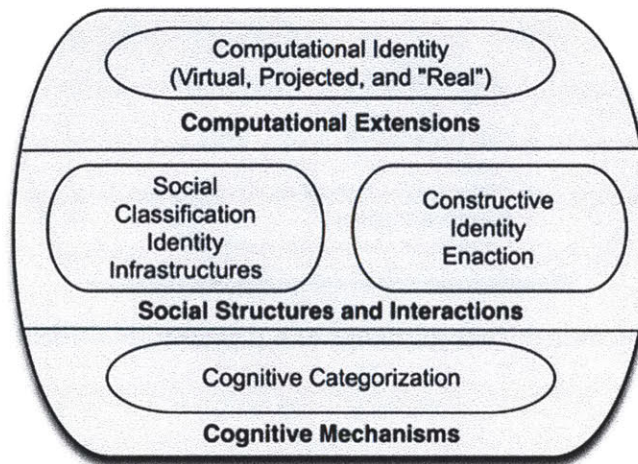


Figure 2-2: The AIR Model of Cognitively Grounded Computational Identity[6]

2.1.3 Cognitive Categorization

This work is further influenced by Eleanor Rosch’s prototype theory and George Lakoff’s work in categorization[8]. Lakoff’s work is highly influential in the study of metaphor and cognitive categorization. Lakoff notes that traditional or “folk” models of categorization

are based on shared properties. This definition is what most computational identity systems are built on, but it is incomplete. Human categorization is far more complex than that and cognitive models of categorization such as prototype theory hope to better address the complexity. Lakoff suggests a number of assumptions that the “folk” models rely on which do not align with our understanding of how human categorization actually work. Among these are things that many current computational identity structures assume:

- Meaning is based on truth and reference: it concerns the relationship between symbols and things in the world
- There is a correct, God’s eye view of the world—a single correct way of understanding what is and what is not true
- All people think using the same conceptual system. [8, p. 9]

Lakoff describes a metaphor- and metonymy-based structure of categorization that takes account themes such as:

Family resemblances: The idea that members of a category may be related to one another without all members having any properties in common that define the category.

Centrality: The idea that some members of a category may be “better examples” of that category than others.

Membership gradience: The idea that at least some categories have degrees of membership and no clear boundaries.

Centrality gradience: The idea that members (or subcategories) which are clearly within the category borders may still be more or less central. [8, p. 12]

Cognitive scientists have proposed that the categories humans form are based on idealized cognitive models (ICMs). An ICM is a model used to create categories that allow us

to understand and describe objects or concepts in the world. ICMs are *idealized* because the model may not represent something that actually exists, but is instead an idealized representation of a category of objects or concepts. For instance, Lakoff the concept of a “Bachelor” as an example of an ICM. While the definition of a bachelor is an unmarried adult male, the idealized model used to understand the concept of a bachelor also suggests that the unmarried adult male be single, heterosexual, and masculine. Lakoff builds off the prototype theory of the psychologist Eleanor Rosch to describe metaphor- and metonymy-based ICMs such as the ones below:

Representative (prototypes): “best example” members of categories.

Social stereotypes: normal, but often misleading, category expectations.

Ideals: culturally valued categories even if not typically encountered.

These ICMs are described as metonymic because they involve using a model of an individual member of the group to stand for the whole group. The prototype effects come in when someone uses this prototypical member to help understand and categorize a potential member of the group. This work focuses on using these ICMs (specifically representatives) as a model for revealing implicit categories. In particular, we argue that the categorization structures revealed by the algorithm implement concepts of family resemblances, category gradience, centrality and membership gradience.

2.2 AnalogySpace

The Common Sense Computing Initiative’s (CSC) work on using common sense knowledge in applications provides insights for the technical aspects of the system. Specifically, we draw on insights from AnalogySpace, which was created to help in reasoning over a large common sense knowledge base, such as ConceptNet[15]. This forms an important part of the background for this work. AnalogySpace focuses on problems of generalizing

sparsely-collected data, classifying information, creating “ad hoc categories”, and evaluating assertions from within the knowledge base. Since data from computational identity systems is also often sparse data, the problems of generalizing and creating categories largely parallel our own problems.

AnalogySpace consists of a collection of techniques built on top of a truncated singular value decomposition (SVD). AnalogySpace represents knowledge as a matrix with concepts along one axis and features along the other. From this sparse matrix, it computes a truncated SVD, which reduces the dimensionality and enables the data to be generalized in ways that support reasoning. The key insight here is that information about the meaning of the common sense knowledge in the knowledge base is hidden in the network itself and can be found through statistical techniques applied in clever ways. From the original sparse knowledge base, we can start to generalize the data to fill in the network and find implicit categories.

In the first version of the project, CSC’s Divisi library¹ was used to perform a truncated SVD using information from Facebook profiles to construct the matrix. This is discussed further in Section 4.1. This approach provided valuable insight for assessing the technical aspects of working with data related to identities and dealing with large networks; the next section discusses technical approaches more suitable to smaller networks.

2.3 Taste Performance in Social Networks

Presentations of user taste, in the form of lists of cultural interests, are commonplace on social network sites (SNSs). They can be found attached to profiles in Facebook, MySpace, Friendster, and Orkut. Hugo Liu has suggested in his work on taste performance in social networks that these lists of cultural interests serve as presentations of taste and are rich sources of information about identity. In [11], Liu studied the expressive potential of lists of interests by collecting data from 127,477 MySpace profiles. In this study, Liu

¹*Divisi*. Common Sense Computing Initiative. <http://csc.media.mit.edu/divisi>

suggests that while these cultural interests listed on social network profiles may not be the most accurate measure of the user's true taste, they primarily serve as a venue for taste performance. This insight comes from the finding that large groups of users either aligned their "taste statements" (these lists of cultural interests) with the most popular tastes or obscure and subcultural tastes. Additionally, users' taste statements tended to differ from those of their "Top 8" friends more than would be expected by chance, indicating that they served partially as a performance of uniqueness.

These findings indicate that lists of cultural interests on social network profiles (such as Facebook Likes) are important venues for expression of identity and that they would be a rich source of identity information.

2.3.1 Taste Fabrics

Liu's work was an important inspiration for the technical approaches used in this thesis. Liu et al.'s work in representations of taste on social network profiles provides techniques for constructing a "taste fabric" using lists of cultural interests[12]. Liu et al. describes a taste fabric as "an n by n correlation matrix, for all n interest items mentioned or implied on a social network (e.g. a book title, a book author, a musician, a type of food, etc.)." This taste fabric then takes a flat graph of explicit binary connections and starts to build up patterns that can be used to reveal implicit categories hidden in the data.

To build the correlation matrix, Liu et al. use a machine learning technique called Point-wise Mutual Information (PMI). The PMI is a measure of correlation between two attributes. A pair of attributes that appear frequently together, but infrequently across the whole graph will have strong PMI. The paper proposes to find groups of closely connected interests by treating the graph as a classic spreading activation network[3]. These two techniques combined form the base of the technical approaches in this thesis.

From there, Liu et al. focus on discovering what they call "taste neighborhoods" from the fabric. While this is a potentially rich direction to take in the future, the focus here is less

on algorithmic discovery and more on using user input to find categories in the network.

2.3.2 Challenges

Liu's work also provides a lot of insight into the potential limitations of the particular approach suggested here and of using taste information from social networking sites in general. As Liu et al.[12] suggests and reaffirms in Liu[11], taste performance on social networks should not be treated as a collection representative of all the things the user actually likes. On Facebook, the list of things a user Likes (has "liked" on Facebook) exists as an attempt to convey certain aspects of the user's identity. As such, the decision to Like something could be influenced more by how the user feels it fits the person they try to project and less by how much they like the object. For instance, a user might choose not to Like a band she listens to in private because it is unpopular amongst her friends. Another user may choose not to Like something because he knows his parents check his profile and he is afraid of getting in trouble for Liking it. A third user may choose to Like art films instead of blockbusters to try to appear more sophisticated than he feels himself to actually be. Additionally, users may not think about certain objects, others may not be available on the network and profiles may be out of date.

All of these factors would negatively affect the quality of this information for use in a recommendation system meant to choose things the user would like. Despite this, the representations of taste on social networks are still performances of identity. Each of the cases above is an example of a user trying to project a certain identity through their SNS profile. Some might Like objects they don't actually like, or choose not to Like an object they do like, but they are still trying to project a certain identity. The work in this thesis focuses on using these presentations of taste as a way to learn more about the identity the user is trying to represent.

Though taste presentations on SNS profiles serve can serve as a great source of identity-related information, the taste presentation is only a small part of the whole profile. Dif-

ferent people choose to use the taste presentation features to varying degrees. As a result of this and the problems mentioned before (forgetfulness, availability of data and profile age), the taste presentation data varies greatly in the amount of information it provides about each user. These insights motivate our decision to focus on *revealing* information about identity more than trying to use these techniques to try to *replicate* real-life categories.

Another important limitation and guiding factor is that while Liu's studies were done using *large-scale* scrapes of MySpace profiles (100,000 profiles in [12]), this thesis focuses on using relatively *small-scale* groups of Facebook profiles. The implementation of the algorithm using Facebook Likes only process one user's Facebook friends at a time. For the participants in our evaluation (Chapter 5), the number of friends' profiles range from 254 to 1590. This means that this focuses on revealing hidden identity information about the user's friends hidden in their network. Because of this, the data used here is even more sparse than the MySpace profile data and the difficulty of replicating real-life categories is even harder. On the other hand, using local networks, the systems built using this algorithm are able to focus on insights specific to the context of the user's friends.

2.4 Summary

Building upon the theoretical framework developed in the AIR project, the problem became finding a way to implement notions such as identity categories and prototypes computationally. The technical approaches that turned out to be most useful for the case study here were CSC's work on commonsense reasoning and Liu's work on taste performance in social networking systems.

CHAPTER 3

SYSTEM

Representations of identity using computational systems allow users to communicate their identities to both other users and the system. It would be impossible for users to communicate the complexity and nuance of their identities through the explicit categories provided by any computational identity system. Instead, we must construct profiles that indicate the aspects of identity deemed most useful by the system and its users. In efforts to increase the range of identity that users are able to express, computational identity systems provide limited sets of features meant to represent user identities. Because these representations are merely models of identity (as any computational representation must be), they often leave out or fail to fully describe many aspects of identity that users may find important. Currently, most representations of identity assume what Lakoff calls “folk” models of categorization[8]. These models make important assumptions about identity that don’t always hold true, such as the assumption that there exists a single categorization structure that will fully serve all users, or that an identity can be fully described with explicit links between the user and other concepts.

Importantly, these models tend to gloss over areas where connections exist in a gray area. For example, a friend link on an SNS could mean anything from “met once at a party” to “best friends since 6” to “friend’s friend who I don’t like, but felt bad declining”. This

distinction can be very important to the way the user uses the system or to how they are seen by other users or by the system itself. The user may want to share some things only with her or his closest friends, for instance, or the user's friends may make incorrect assumptions about the strengths of friendships. The system may also be able to make better recommendations when it knows which friends are closest.

Unfortunately, simply making categorization structures more complex is not the solution to this problem. Everyone has different ways of creating categories, so even a very intelligently constructed categorization structure will be interpreted differently to different people. Fortunately, information can be drawn from imperfect models of social identity to help users make the leaps to their own categorization structures themselves. Our job becomes less about creating perfect categories and more about better enabling users to construct their own categories, therefore making the systems more expressive.

To counteract the issues imposed by simple categorization structures, implicit information (information that is hidden in the network) can enable additional levels of categorization. In the case of labeling different strengths of friendships, for instance, Gilbert and Karahalios[5] managed to find indications of the tie strength (or friendliness between) "friends" on Facebook by examining data collected by the system, but not explicitly revealed. While this approach is very exciting, it is a tool to help create yet another explicit category. This thesis assists people in creating whole *new* categorization structures. These new structures are formed by revealing information that might help the user form his or her *own* categories, rather than attempting to replicate real-world categories.

Toward that end, we present an algorithm that seeks to help computational identity systems reveal identity-related phenomena by utilizing insights gained from cognitive models of categorization. The algorithm helps create categories of attributes that serve as a tool for thought to assist the user in the recreation of their own categorization structures. This algorithm is focused on building the base representation and providing a set of techniques, which will pave the way for increased nuance in representations of identity for the AIR Toolkit.

This chapter provides a detailed description of the technical workings of this system including the construction of the correlation matrix, the process of choosing seeds for a category, and the process used for creating categories. This is followed by a description of a case study applying this algorithm to Facebook profiles and their Likes as an example source of identity-related information. This chapter concludes with a discussion of the decisions made in the design of this algorithm and how they relate to the theory.

3.1 Algorithm

The purpose of this algorithm is to take a set of user profiles and the attributes associated with those profiles and construct categories of attributes that support the themes discussed in Section 2.1.3, namely *family resemblances*, *membership gradience*, and *centrality gradience*, given some set of data. These categories of attributes help provide information that can help users construct, alter, or reflect upon the categories they use to understand identity. In this case, the technical implementation of a category is a vector containing a score for each attribute in the matrix from 0 to 1. Instead of drawing clear lines for category boundaries, this implementation allows for attributes to have different levels of *membership* or *centrality* to the category.

The process of finding these implicit categories from the explicit data structures consists of three steps. The first step consists of constructing a correlation matrix, which is a matrix that stores information about the correlation between each pair of attributes. The second step consists of seeding the initial category scores, which serve as representations of the membership or centrality for each Page in the network. The third step consists of constructing the category by treating the Pages as nodes in a spreading activation network[3] to determine the final category scores. The following is a description of the technical processes for each of these three steps.

3.1.1 Building the Correlation Matrix

Starting with the collection of profiles and their attributes, we construct an $n \times m$ connection matrix relating profiles (SNS profiles, avatars, or characters) to their attributes (descriptors, skills, likes). From this $n \times m$ connection matrix we can construct an $m \times m$ correlation matrix relating attributes to attributes using a common machine learning technique from information theory called Pointwise Mutual Information (PMI)[2]. The PMI between two concepts is a measure of correlation, which will be useful for finding objects that frequently appear together. The PMI is calculated by the following formula:

$$PMI(n1, n2) = \log \left(\frac{p(n1, n2)}{p(n1) \times p(n2)} \right)$$

Where $p(n1)$ is the probability of $n1$ appearing on a randomly selected profile and $p(n1, n2)$ is the probability that both $n1$ and $n2$ appear on a randomly selected profile. The PMI metric is especially useful because it gives a proportionally higher score to objects that appear less frequently overall, but appear together when they do. When constructing categories, this phenomenon can help find attributes that are more central to the category or attributes that have a high signal-to-noise ratio when seen.

3.1.2 Seeding the Category

Categories begin with a *seed*. To seed the category, a set of attributes (potentially user defined) must be selected and its category scores must be set to some starting value. While there are many potential methods of choosing the set of attributes to serve as seeds and determining their starting scores, this work focuses on two ways that have shown promising results.

The **Page Method** consists of selecting a small group of related attributes and setting all of their category scores to a specified start value.

The **Profile Method** involves selecting a number of profiles from the network and using their collected attributes as seeds. To accomplish the Page Method, we find the most popular attribute, x , amongst those profiles and set its category score to a specified start value: $c[x] = s$. We then set the score of any other attribute, y , appearing on any of the selected profiles to a value proportional to the number of times it appears in that set compared to the number of times x appeared, or: $c[y] = s \times \frac{\text{num}(y)}{\text{num}(x)}$.

Each of these methods creates categories with different properties. The theoretical differences between the two methods are discussed in Section 3.3, followed by a more detailed discussion in Appendix B.

3.1.3 Constructing Categories with Spreading Activation

Starting from the seeded category vertex, the correlation matrix is used to calculate the category scores for the rest of the attributes. To do this, the $m \times m$ correlation matrix can be treated as a spreading activation network[3]. The algorithm finds other objects in the category by “activating” the nodes connected to nodes whose category scores are greater than some threshold t with a factor dependent upon the PMI between the two nodes. The algorithm works as follows for some threshold t and decay rate d :

1. Set the value of the initial seed nodes as described in Section 3.1.2.
2. While there are unfired nodes, whose value, $c[i]$ is greater than t :
 - (a) For each unfired node i whose value is greater than t :
 - i. set each connecting node’s value $c[j] = c[j] + (c[i] \times \text{pmi}[i, j] \times d)$
 - ii. if $c[j]$ is greater than 1, set it to 1
 - iii. Mark node i as having been fired
 - (b) set new decay rate $d = d^2$

Note that the PMI in the algorithm is normalized to a value between 0 and 1. Since the PMI network is highly connected (each object has a link to every object that appears on a profile with it) a high threshold for activation and a high decay rate produce the most meaningful categories. The methods for determining these parameters will be discussed in Section 3.2.2 and Appendix B.

The results of the spreading activation will be a vector of scores that can be used as a measure of *membership gradience* or *centrality gradience* for a category of attributes centered on the seed nodes or profiles.

3.1.4 From Categories to Profiles

From the vector of category scores, calculating a profile's category membership can be accomplished by simply computing a dot product between the category score vector and the profile's attribute vector. The profile's membership score is the sum of the category scores for each of the profile's attributes. This can be used to find top members in a category.

Similarly, the algorithm can compute a dynamic representation of a profile by filtering the profile's attributes to show how a category is affected by a profile. Given a profile, the algorithm can either filter out any attribute that has a category score below a certain value, creating a representation of the profile as seen through a particular category. An interface using this algorithm could also use the category scores themselves and create a more continuous representation of the profile by emphasizing attributes with high category scores and de-emphasizing attributes with low category scores.

3.2 Case Study With Facebook Likes

One common aspect of constructing an identity online is referencing shared cultural objects. Many social network sites allow the user to list a collection of these cultural objects in the form of books, movies, music, TV shows, and more. These lists can express a lot about the profile owner's identity in much the same way that posters on a bedroom wall or a bookshelf can tell you about them[9].

This thesis proposes an implementation of the algorithm above using Facebook Likes (pages, people, objects, brands, etc. people have "liked" on Facebook) as a source of identity information as a case study. While the algorithm could be used for a wide variety of computational identity systems, the first implementation addresses Facebook because it is popular, provides an ample resource of data and provides an example of a computational representation of identity as, in part, a category constructed by features such as preferences. The implementation has taken the form of a server application built using Django, a Python Web framework.

3.2.1 Using Facebook Likes

Facebook Likes are a particularly good starting point for a number of different reasons. With the introduction of Pages, Facebook formalized the process of Liking things and made the data structures much simpler. Previously, the presentations of taste on Facebook were essentially flat text with features to find other people who list the same things. With the introduction of formal Likes and Pages, the presentations of taste became formal links between objects, making the data structures much easier to perform computations with.

Obtaining Facebook data through Facebook's Graph API (the application programming interface used to download information from Facebook for use in applications) and the API's data structures is both very convenient and slightly restrictive. It is convenient in that it provides Likes as explicit connections between objects so the object Liked is unique and

unambiguous. There are some problems with multiple Pages for cultural objects because of the multiple spellings or other ambiguities, which can cause some needless distinctions, but, anecdotally, many people Like both Pages anyway. This data can be gathered relatively quickly and easily constructed into our $n \times m$ connection matrix.

Facebook's terms of service don't allow an application to use the data acquired from the API for anything besides an authenticated user's experience for privacy concerns. Because of this, compiling a taste fabric for a large portion of Facebook in the way that Liu et al. did for their Taste Fabric[12] is impossible. Instead, we focus on using data from a single user's local Facebook network (the user's Likes and the user's friends' Likes). This approach provides less data about the cultural aspects of the Likes in exchange for a greater focus on information specific to the user's group of friends. Certain cultural objects may have radically different meaning within the context of a user's friends than they do to a much larger group.

Because Facebook is a popular website, the features and APIs are often subject to change. It is important to note that this implementation was developed during the Spring and Summer of 2011. A description of the current state of the Facebook's API and its profile interface is included in Appendix A.

3.2.2 Seeding Categories

The same two methods discussed above in Section 3.1.2 are supported using Facebook profiles and Facebook Likes.

The Page Method consists of selecting a small group of related Likes and setting all of their category scores to a specified start value s . The Profile Method involves selecting a number of profiles from the network, finding the most popular Like and setting its value to the start value s and setting the rest of the values proportional to their relative popularity.

The parameters for the starting value, threshold and decay rate can be difficult to choose and vary significantly between the two methods. The parameters, combined with the seeds, determine how far the category spreads and how important the original seeds will be. For instance, in the Profile Method if the decay rate and threshold are too high, the category will end up just measuring the popularity of objects amongst the profiles without bringing network information in. Conversely, if the decay rate and threshold are too low, the whole graph ends up being activated and the scores saturate at 1, providing no information.

In Appendix B, we discuss the subtleties of selecting the right parameters for each of these methods.

3.3 Application of Theory

While these models can only do so much to create categories that align perfectly with the user's own categories, this work proposes that by strongly following insights from the cognitive categorization theory we have discussed[8], this algorithm will be useful in helping users create and improve *their own* categories through the system, which will in turn help improve understanding of the information on the computational identity systems. This section explains how insights from Lakoff's theories of categorization are applied in this algorithm.

To use Lakoff's terms, the results of the spreading activation can be used either as a measure of *membership gradience* or *centrality gradience*. When a category is seeded with individual attributes or Likes (the Page Method), the category score can become a measure of membership for the category. The attributes with a high category score are clearly in the category, while those with lower scores are not as definite. When the category is seeded with profiles instead, the question of membership is less important because we know which attributes are represented from the group of profiles. Instead, the category score serves as a measure of *centrality gradience*, suggesting that the attributes with the highest

category scores are most central or representative to the category.

Attributes that are central to the category are the most important attributes for defining membership for the category of people that the category of attributes suggests. This is reflected in the calculation of a category membership for profiles because the more central an object is, the more effect it has on the sum.

Similarly, when seeding a category with profiles (the Profile Method), the resulting collection of Likes, ordered by category score, can be seen as a *representative* (or *prototypical*) profile for members of the group. Chapter 5 provides an assessment of this hypothesis as a part of our empirical study.

This implementation also supports the concept of *family resemblances* through the process of spreading activation. By spreading through the network, the spreading activation can bring in attributes that weren't clearly related to the seeds or the most popular likes. These attributes may be part of the resultant category because of the network data surrounding them.

Most importantly, because of the way these categories are started, this system does not intend to make accurate predictions of the user's own categories, but rather uses user input to help construct categories that help the user make inferences and observations that might be useful or helpful. The algorithm is best thought of as a "tool to think with".

CHAPTER 4

INTERFACES

This chapter provides a discussion of the interfaces built on top of the Facebook implementation of the algorithm. Each of these interfaces reveals a different aspect of the algorithm. Each was also constructed relatively quickly using the affordances of the implementation.

4.1 SVD-based Exploration Interface

Before settling on the current set of techniques used in the algorithm, an alternate version was constructed using techniques similar to the ones in AnalogySpace. The interface was built using the Common Sense Computing Initiative's Divisi library for computing SVDs¹. The interface builds an $n \times m$ matrix relating concepts to features. In this case, profiles, Pages, and attributes are all concepts and the features are links between different concepts. It then computes a truncated SVD from this matrix and displays the results through a web interface.

The key features of the Divisi library that support the interface are the ability to make

¹*Divisi*. Common Sense Computing Initiative. <http://csc.media.mit.edu/divisi>

predictions about connections not present in the network and the ability to construct categories based on a number of users.

4.1.1 Interface Description

The interface provides functionality for exploring the output of the SVD based approach. It is structured like a read-only social network in which the user can view a representation of their friends' profiles and Likes. Two key features of this version of the site are viewing one user "projected" onto another user and creating categories of properties based on a small collection of users.



Figure 4-1: Screenshot of the projection of one user onto another user.

In the projection view, the user can view one of their friends' profiles filtered to only show Likes that another user would like, as determined by the algorithm and toolkit. This was an early experiment in creating dynamic representations of identity based on the viewer.

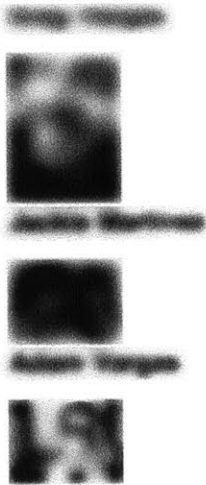
The *category* view allows the user to select a collection of profiles and create a category based around the properties those profiles have in common.

The website also has views for exploring the basic functions of the toolkit such as com-

explore

[categories](#) [add object](#)

Category



Top Features

likes [Princess Mononoke](#) | 0.3
likes [Neil Gaiman](#) | 0.3
isFrom [Watsonville, California](#) | 0.3
likes [Arcade Fire](#) | 0.2
likes [Arctic Monkeys](#) | 0.2
likes [PostSecret](#) | 0.2
likes [Spoon](#) | 0.2
likes [Watsonville Strawberry Festival at Monterey Bay](#) | 0.2
likes [City of Watsonville Parks and Community Services Department](#) | 0.2
likes [Gavin Newsom](#) | 0.2
likes [The Departed](#) | 0.2
likes [Modest Mouse](#) | 0.2
likes [TOTORO](#) | 0.2
likes [Barack Obama](#) | 0.2
likes [Howl's Moving Castle](#) | 0.2
likes [The Decemberists](#) | 0.2
likes [Serenity](#) | 0.2
likes [Spirited Away](#) | 0.2
likes [V for Vendetta](#) | 0.2
likes [Queen](#) | 0.2

Top Similarities

[\[blurred\]](#) | 2.04550947462
[\[blurred\]](#) | 1.4375805787

Figure 4-2: Screenshot of the category viewing interface before processing.

paring profiles, calculating predictions, creating categories, and adding profiles.

4.1.2 Lessons Learned

This interface helped us explore the range of possibilities for using identity data on Facebook profiles. Unfortunately, the predictions from the truncated SVD were inconsistent and the process was hard to understand. The decision was made to move to the techniques in Chapter 3. One hypothesis is that to make the most of AnalogySpace we would need to already have a lot of data and “blend” it with the data from the identity system similar to the way AnalogySpace uses ConceptNet as an external knowledgebase[15]. The system presented here aims to be self-contained and does not use a source of outside information like ConceptNet. As such, the results were not as easy to interpret because we did not capitalize on the system in the way it is most effectively used.

With this interface, we were able to experiment with different potential views like the

projection view and the category view. Though the later versions of the toolkit do not implement the projection view in the same way as this does because predictions are harder to make, the potential is still there.

4.2 Explore Interface

After implementing the toolkit using the PMI techniques, it became clear that an application was needed to assist in the exploration of the results. To that end, the Explore Interface was built. The Explore Interface presents all of the information downloaded from Facebook as well as the PMIs calculated by the algorithm (discussed in Section 3.1.1). In addition to that, the interface supports creating categories from small collections of seed objects and experimenting by adjusting the parameters of the category creation. It also supports viewing categories made through this interface or through any other with full information about category scores and spreading activation properties.

4.2.1 Interface Description

This interface was important for gaining an understanding of the behavior of the PMIs and the category creation. Figure 4-3 shows the Page view, which shows all of the Page's PMIs with other objects. This view by itself provides some key insights into the PMI metric. For instance, the more popular a Like is, the lower the top PMI is. The highest PMIs for any Page are going to be Pages that only appear along with that Page.

Another key feature of the interface is offering users the ability to choose seeds for a category. This interface utilizes the Page Method for seeding categories by setting a small set of Pages at a specified start value, as discussed in Section 3.1.2. The user is able to add Pages to the categories seeds, then adjust the parameters as they see fit as shown in Figure 4-4.

Princess Mononoke

first next last

 My Neighbor 0.78216546	 The News 0.78216546	 American Gods 0.78216546	 Princess Mononoke 0.78216546	 UC Berkeley 0.78216546	 The Elder Scrolls 0.78216546
 The Sims Social 0.78216546	 Michel Foucault 0.78216546	 The Beach 0.78216546	 Gossip 0.78216546	 $\int_a^b f(x) dx$ Calculus 0.78216546	 Mario Kart 0.78216546
 TOTORO 0.74336452	 UC Berkeley 0.73214235	 Gavin Newsom 0.73214235	 Howl's Moving 0.73214235	 Scott Pilgrim 0.71166185	 Salinas High 0.71166185
 Punk rock 0.71166185	 Godspeed You! Black 0.71166185	 Stars 0.71166185	 Super Smash 0.71166185	 Matt and Kim 0.71166185	 Spirited Away 0.69334142

first next last

liked by


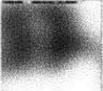
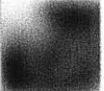
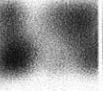


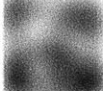
					
					

Figure 4-3: Screenshot of the Explore Interface's Page view.

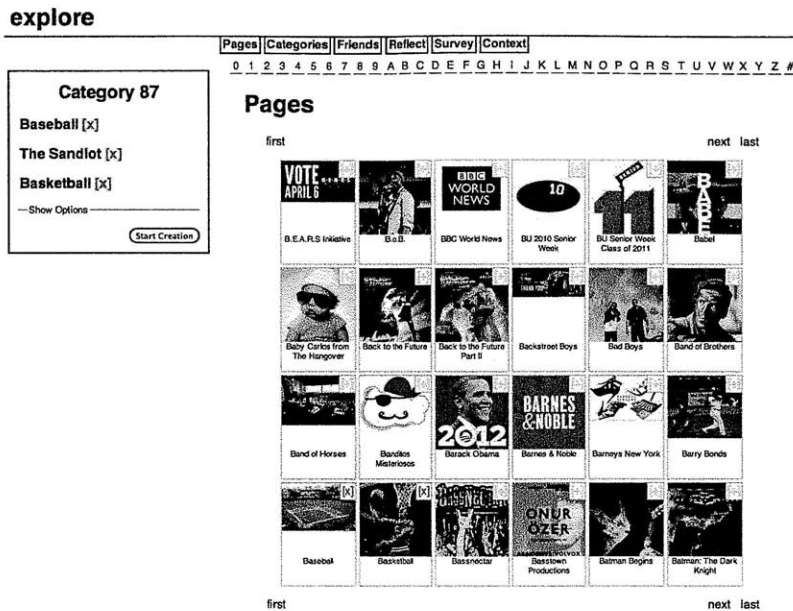


Figure 4-4: Screenshot of the Explore Interface's Category Creation feature.

When the category finishes its calculations, it can be viewed from the category page as shown in Figure 4-5. This view displays data about the category such as the seeds, parameters, and how many nodes were activated in the spreading activation process. It also shows the top Pages and members in the category with their respective scores.

4.2.2 Lessons Learned

This interface was the first opportunity to experiment with the construction of categories and quickly get a feel for the range of results from the toolkit. This interface was instrumental in understanding the effect different parameters and seeds can have on the resulting categories. Appendix B provides a more in-depth discussion about the specifics of choosing parameters.

explore

Pages Categories Friends Reflect Survey Context logout

Category 87

Baseball	Round: 3	Start Value : 0.5
The Sandlot	Round: 7	Threshold : 0.35
Basketball	Round: 39	Decay Rate : 0.3
	Round: 8	

[View Raw Data](#)

first next last

 Basketball	 Baseball	 The Sandlot	 Barry Bonds	 Fashawn	 I Love Being Black
0.993428561568	0.982331186222	0.951040189555	0.723278286834	0.699539646255	0.697549906477
 LeBron James	 Vernon Davis	 Jerry Rice	 Golf	 Rob Dyrdek's Fantasy Factory	 Chicago Bulls
0.695997266706	0.695039490583	0.692551060293	0.691710731169	0.685258987364	0.67556753133
 Contemporary R&B	 Football	 Rob & Big	 Half Baked	 How High	 Knocked Up
0.6530828397	0.651899582241	0.640952195141	0.632187707613	0.632118437297	0.631255192323
 Hot Rod	 The Last Airbender	 Michael Jordan	 Reggae	 Old School	 Zpac
0.627784781046	0.626985966654	0.620093989837	0.61006317522	0.609427122601	0.598395612938

first next last

top members

					
38.4004078284	25.7254484674	24.0155419026	22.4129916601	20.5265749524	19.967758233
					
15.3411878144	13.6351806298	13.3232002697	12.1613920937	11.8996247992	11.6408855504

Figure 4-5: Screenshot of the Explore Interface's Category view.

4.3 Reflect Interface

When users are deciding which Likes should or should not go on their profiles, it can be hard to get a feel for how each Like will be *seen*. Cultural objects may have meaning within the user's social network that they are not fully aware of. The Reflect Interface is a Facebook application that allows the user to view how previously constructed categories are represented on their profile. Using this interface, people may be able to better understand how their profile may be viewed by others in their network. It can help them see which groups of their own friends they share taste with.

The interface first displays the category for the purpose of helping the user understand and name categories that have been created either algorithmically, by other people, or through another interface. It then shows users' own Likes and gives them the ability to filter on their profile based on the categories previously constructed.

4.3.1 Interface Description

The Reflect Interface is intended to be a tool for viewing the effect of categories, but not for creating them. Because of that, it is important that the users familiarize themselves with the categories before they are able to fully assess their effect.




The category view, as shown in Figure 4-6, displays the twelve top Pages in the category and provides an interface for renaming the category. Renaming the category is an important task because it forces users to try to fit the information into their own categorization structures. When the users have familiarized themselves with each of the categories, they can move to the Profile view.

The profile view, as shown in Figure 4-7, initially resembles the structure of the default Facebook profile view, with a categorization scheme based more on the media of the object than on social or cultural context. On the sidebar, however, the user can apply a filter over the profile that shows only the objects in the chosen category. This view allows

Categories

- me and bff from home
- TV lovers
- friends from Cambridge
- fantasy/anime fans
- mainstream from CA
- sports fans
- indie music lovers
- friends from Berkeley**
- hipster nerds
- band geeks
- snarky people
- friends from home

friends from Berkeley

 Watsonville	 UC Berkeley	 Princess Mononoke	 My Neighbor Totoro
 How's Moving Castle	 Gossip	 UC Berkeley	 Neil Gaiman
 TOTORO	 Breast Cancer Awareness	 Saturn Cafe	 Ender's Game

friends from Berkel [Name this Category?](#)

[On to Profile](#)

Figure 4-6: Screenshot of the Reflect Interface's Category View.



Figure 4-7: Screenshot of the Reflect Interface's profile interface.

the user to reflect on how the profile serves as a representation of a user's identity by, for example, finding categories the user did not know were being represented or examining how noticeable each of the categories are.

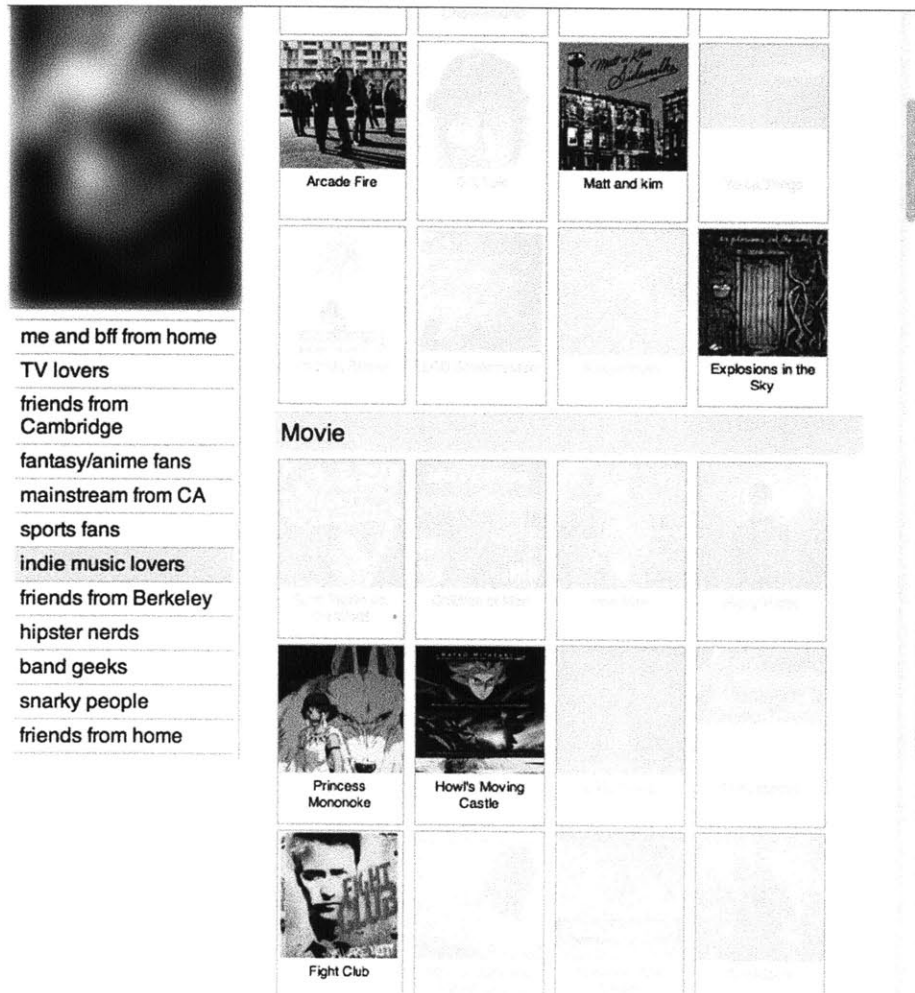


Figure 4-8: Screenshot of the Reflect Interface's Profile view filtered for Pages in the "indie music lovers" category.

4.3.2 Lessons Learned

The Reflect Interface is a valuable tool to help understand the identity the user's Facebook profile presents. The interface allows the user to find associations between her profile and

other groups of people by first situating information from a category into her own categorization structures and then viewing how that category is reflected on her own profile. This enables discoveries such as surprising categories the profile displays or discovering categories the user would like to represent, but her profile currently doesn't.

4.4 Group Persona Interface

The final interface we have created is the Group Persona Interface. Its purpose is to help users make sense of their friends' social identities by revealing trends associated with properties of their profiles. The interface enables users to seed categories with profiles that share certain attributes. To do this, the toolkit collects information from each of the friends' profiles such as gender, education history, and relationship status and provides filtering mechanisms to assist in the creation of groups.

4.4.1 Interface Description

The interface provides two distinct ways to construct categories: groups of friends who share profile information (the Find People view) and groups of friends who all share a particular Like (the Find Likes view).

The Find People view, shown in Figure 4-9, gives users facets to filter their friends on and construct a group based on shared attributes. The users can choose to filter for attributes on the left sidebar. The facets display the number of profiles in the current set that have each attribute. When multiple facets are selected, the system calculates the intersection of the groups determined by each individual facet. That is, everyone in the group will have all of the selected attributes.

To further narrow the category, users can select or deselect individual friends and create categories from their own knowledge combined with information the information in the

facebook Search

// Home // Find People // Find Likes // Categories - 0 Unread

Construct Group

Gender

- male (155)
- female (104)

Hometown

- Watsonville, California (60)
- Santa Cruz, California (9)
- Boston, Massachusetts (4)
- Aromas, California (3)
- Corralitos, California (3)
- more

Location

- Cambridge, Massachusetts (36)
- Watsonville, California (25)
- Boston, Massachusetts (19)
- San Francisco, California (9)
- Santa Cruz, California (9)
- more

School

- Massachusetts Institute of Technology (102)
- Watsonville High (48)
- Cabrillo College (17)
- Watsonville High School (14)
- University of California, Santa Cruz (10)

select: all none

Start

Figure 4-9: Screenshot of the Group Persona Interface's Find People view.

facets.

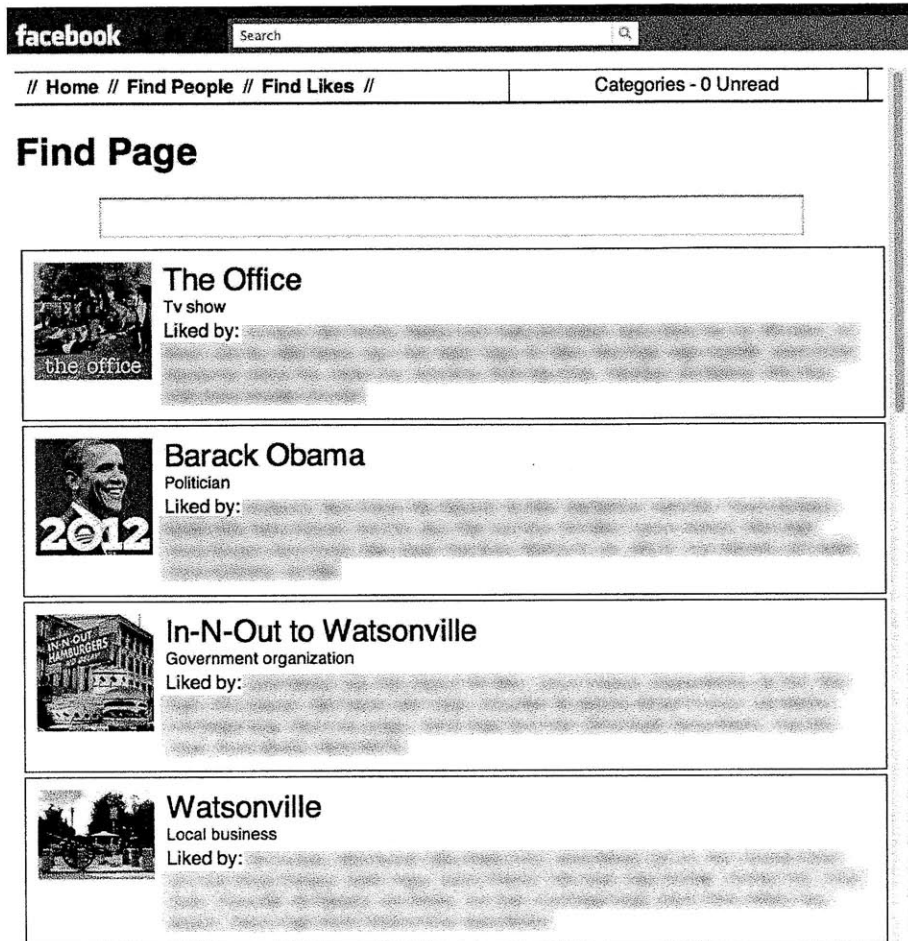
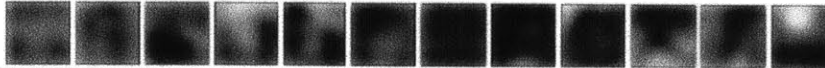


Figure 4-10: Screenshot of the Group Persona Interface's Find Likes view.

The Find Likes view, shown in Figure 4-10, gives the user the option of selecting any Page from their graph (that at least 2 people like) and turning those people into a category. To find Pages, the interface begins by showing some of the Likes within the user's network and provides a search bar with auto-complete functionality to find any other Page. The interface also tells the user who likes which Pages and begins by showing them the top 12 most popular Likes within their network. Clicking on a Page constructs a group using the profiles that Like that Page as seeds, then sends the user to the category view.





The category view, as shown in Figure 4-11, displays the profiles included in the category, the 24 top Pages and the 6 top members. In this case, members may include profiles from

Location-Cambridge, Massachusetts [edit](#)



[See More](#)

Top Pages

 Daft Punk	 CSAIL - MIT	 Barack Obama	 MIT EECS Department	 The Office	 Music
 Queen	 30 Rock	 Crystal Castles	 Girl Talk	 Radiohead	 Philosophy
 The Matrix	 Percolater	 Kanye West	 Muse	 How I Met Your Mother	 Pink Floyd
 Fight Club	 MGMT	 Seinfeld	 Vampire Weekend	 Red Hot Chili Peppers	 Wilco

Top Members

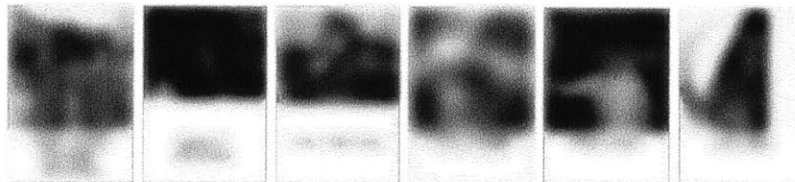


Figure 4-11: Screenshot of the Group Persona Interface's category view.

within the selected group as well as profiles from outside the group.

4.4.2 Lessons Learned

One area this interface has allowed us to explore is how the choices of parameters change the results of categories seeded by the Profile Method. All three parameters (start value, threshold, and decay rate) should be set to lower values than for categories seeded with the Page Method. Categories seeded from groups start with more distributed starting values, so if the parameters are too high, the category will spread too quickly. We provide a further discussion of the effects of the parameters in Appendix B.

This interface is also a useful tool for exploration because it is focused on building and viewing categories for the purpose of understanding more about the user's friends instead of using the category for an explicit purpose. While both types of interfaces are necessary, this interface helped to provide insights focused on improving the quality of the category results. Chapter 5 elaborates on the insights this interface provided in the discussion of the results of the study conducted using this interface.

CHAPTER 5

EVALUATION

This chapter presents the evaluation of the system and the Group Persona Interface described in Section 4.4 in a qualitative pilot user study aimed at learning the strengths and weaknesses of the system. Because this thesis comprises the first components of the AIR Toolkit, it is important to understand the strengths of the system as it is currently presented, but also to look for ways to improve it. The study presented here is a pilot study meant to help gain a better understanding of the system in its current state and to prepare for further studies on the system.

5.1 Method

5.1.1 Participants

We invited 8 participants to the lab to create and discuss categories they made with their own Facebook profiles and answer questions about a pre-made category. We began by soliciting participants from relevant lab-based mailing lists. We felt comfortable soliciting primarily university students because students are still a large portion of Facebook's

user-base[9].

Of the 8 participants, one did not respond to the demographic questionnaire. The remaining participants were ages 19-31 with a median age of 26 and were all male. Of the 7 participants who responded, five were students, two were MIT staff, and one was a postdoctoral researcher. Of the students, three were graduate students, and one was an undergraduate student. Among the four students, three were MIT students and one was visiting. All of the participants had been using Facebook for at least three years (the participant who had been using the site the longest had had a profile for 6 years). Facebook usage varied from “several times a day” to “monthly”. Three of the participants check Facebook several times a day, two check daily, one checks several times a week and the last checks monthly.

In terms of the size of the networks for each participant, the median number of profiles (the user and the user’s friends) was 524 (min 254, max 1590, mean 759.5), and the median number of Pages that were Liked by any of the profiles was 15,495.5 (min 5085, max 42,013, mean 18,961.5). When filtered for Pages that were Liked by more than one profile and for profiles that Liked at least one of those Pages, the median number of profiles became 297.5 (min 117, max 1138, mean 501.5), and the median number of Pages was 2176.5 (min 591, max 7416, mean 3449.25). There are were three reasons that a profile might not have Liked any pages Liked by at least one other profile: participants may have had friends that did not choose to Like anything on the site, participants’ friends may have had profile privacy settings that restricted access to either the participant or the use of applications, and participants’ friends may have Liked particularly unpopular objects – anything Liked by only one person in the participant’s network was not evaluated. The median number of links between Pages (a link only exists between Pages that appear together) was 582,348.5 (min 51,119, max 5,119,150, mean 1,289,220).

	Median	Mean	Min	Max
Number of Profiles	524	759.5	254	1590
Number of Pages	15,495.5	18,961.5	5085	42013
Filtered Profiles	297.5	501.5	117	1138
Filtered Pages	2176.5	3449.25	591	7416
Links between Pages	582,348.5	1,289,220	51,119	5,119,150

Table 5.1: Network sizes for the participants.

5.1.2 Procedure

Participants were invited into the lab for the study. A day prior to coming into the lab, participants were asked to authenticate the Facebook application and start the downloading process. This meant that time would be saved in the lab and we could solve any problems with the download and processing ahead of time. Downloading the data took between 30 minutes to 4 hours for all participants. Once in the lab, we gave participants a brief description of the system. We told them that the goal was to find out general information about groups of people on Facebook - for instance, what sort of people were their high school friends?

We began by assisting participants in creating two different groups to help introduce the interface. The first group was constructed using the filters on the Find People view, shown in Figure 5-1, to select their friends listed as having gone to their high school. We chose high school friends as a seed for category creation for two reasons. First, we surmised that it would be a relatively more cohesive group than a group of students from university. Universities (especially universities like MIT) generally have students with a wider range of backgrounds than high schools do, suggesting that a group of the participant's high school friends would form a largely distinct subset of the participant's friends. Second, we assumed that most, if not all, participants would have an appropriate number of friends with their high school listed to provide meaningful results. This second assumption turned out to not entirely be the case, which we discuss in Section 5.2.1.

Participants were instructed to construct the second category by selecting the 12th most

popular Page within the participant's network. The 12th most popular Page was chosen for two reasons. First, *all* participants would have a 12th most popular Page in the data. Second, the 12th most popular page might be able to strike a balance between popularity across the network and specificity to an individual group of people. This was done using the Find Pages view, shown in Figure 5-2, which lists the twelve most popular Pages within the participant's network as well as providing search functionalities for finding any other Like represented in their network. Participants were instructed to use this method because all participants would have a 12th most popular Page with a moderate level of popularity. The Page would be not so popular that the data returned would be noise, but not so unpopular that it would return no results.

Participants were then directed to construct two more categories in whatever way they found most interesting: using either the Find Likes or Find Pages interfaces described. For each category (including the first two), the participant was asked to fill out a survey using the interface provided with questions about the category.

5.1.3 Survey Questions

After participants created and viewed each category, we asked each of them a series of questions about the category.

Question 1: *How well does this group of Likes represent the likes of any individual person?* The interviewer clarified this question by asking if the participant could imagine someone who liked all of these things. This was a 7-point ordinal scale question.

Question 2: *Please fill in the following blanks with descriptive titles of subgroups you would make if you were to divide this set of Likes.* The interviewer clarified this question by explaining that we were looking for higher-level descriptions than just the type of media, but instead something about the people who might like each subgroup or at least genres that might apply across media. As we discuss later, this was not always effective.

Gender

male (155)

female (104)

Hometown

Watsonville, California (60)

Santa Cruz, California (9)

Boston, Massachusetts (4)

Aromas, California (3)

Corralitos, California (3)

more

Location

Cambridge, Massachusetts (36)

Watsonville, California (25)

Boston, Massachusetts (19)

San Francisco, California (9)

Santa Cruz, California (9)

more

School

Massachusetts Institute of Technology (102)

Watsonville High (48)

Cabrillo College (17)

Watsonville High School (14)

University of California, Santa Cruz (10)


more

Work

Google (8)

Figure 5-1: Screenshot of the filters on the Find People Interface

Find Page



The Office

Tv show

Liked by: [blurred text]

Figure 5-2: Screenshot of the Find Likes interface, showing the top Like and the searchbar.

Question 3: *If I showed you this collection of Likes without telling you how it was generated, what would you see as the unifying factor? (It's okay if it's the same or different than what we actually used.)* For this, we encouraged participants to work backward from the list of Pages to try to understand what might have been the unifying factor for the group of people. We also explained that if it was clear that the unifying factor was what we actually used, they didn't have to try to come up with a different answer.

Question 4: *Are there any Likes you are surprised about? Please choose up to two and describe what about them you find surprising.*

Question 5: *If you were hiring an actor to play someone in this group of people, how useful would this list be in describing what sort of persona they should take?* This was given in the form of a 7-point ordinal scale.

Question 6: *How much have you learned from this group of Likes that you didn't know or didn't realize about the people before?* This was also given as a 7-point ordinal scale.

Question 7: *Do you have any further thoughts about the category?*

In Section 6.2.3, we discuss the changes we would make for the next round of the study to better address our research questions.

5.2 Results

Here we discuss technical issues encountered in the study, followed by a discussion of the results broken up into two main questions, followed by some thoughts about the application.

#	Question	Clarifications	Key observations
1	How well does this group of Likes represent the likes of any individual person?	This was clarified by asking if the participant could imagine someone who liked all of these things. This was a 7-point ordinal scale question.	Median score of 6 indicating that the categories can serve as strong representations of people. The lack of 7's, however, indicates the representations are not perfect.
2	Please fill in the following blanks with descriptive titles of subgroups you would make if you were to divide this set of Likes.	The interviewer explained that we were looking for higher-level descriptions than just the type of media, but instead something about the people who might like each subgroup or at least genres that might apply across media. As we discuss later, this was not always effective.	41 of the 74 responses clearly described implicit categories in the data. This indicates that participant's often drew from their implicit social categories to understand the data presented.
3	If I showed you this collection of Likes without telling you how it was generated, what would you see as the unifying factor? (It's okay if it's the same or different than what we actually used.)	We encouraged participants to work backward from the list of Pages to try to understand what might have been the unifying factor for the group of people. We also explained that if it was clear that the unifying factor was what we actually used, they didn't have to try to come up with a different answer.	Most of the responses described some sort of implicit category either based around shared interests or descriptions of the people. One third of the responses were either the same as the factor used in the creation of the group or a slight variation in scope from that factor.
4	Are there any Likes you are surprised about? Please choose up to two and describe what about them you find surprising.	No clarifications needed.	The most common types of surprising Pages were surprising because the object was assumed to have few Likes across the network, the Page didn't fit the group of people, or the Page didn't fit with the other Pages in the category.
5	If you were hiring an actor to play someone in this group of people, how useful would this list be in describing what sort of persona they should take?	This was given in the form of a 7-point ordinal scale.	High responses to this question indicate that the categories can often be useful for describing a group of people to someone without knowledge of the group.
6	How much have you learned from this group of Likes that you didn't know or didn't realize about the people before?	This was also given as a 7-point ordinal scale.	While the responses indicate that many of the categories taught the participants something about their friends, none of the variables we collected were found to correlate strongly with how much the participant learned.
7	Do you have any further thoughts about the category?	No clarifications needed.	Example responses: "This group describes people from a location more than common likes or interests," "Very accurate set of likes!"

Table 5.2: The questions asked of the participants for each category.

5.2.1 Limitations

Two technical issues came up over the course of the study that should be noted. First, there are times when the spreading activation parameters (as discussed in Section 3.2.2 and Appendix B) allow the spreading activation process to enter a positive feedback loop. In the spreading activation process, when a Page activates, it adds its value to any Page it appears on a profile with (altered by a multiplier consisting of the PMI between the two Pages and the decay rate). If too many Pages fire early in the process before the multiplier decays, high values spread across the network and cause more and more Pages to activate. When this happens, the category scores can get saturated (capped at 1.0). When many of the Pages in the network have category scores of 1.0, the information about which of those Pages are most central is essentially lost. Our implementation has a fail-safe built in that stops the spreading activation process when too many category scores are set to fire, displaying the results as is. Of the 32 categories created through the study, six tripped the fail-safe on the algorithm. Of these six, two stopped before the category scores became saturated, but four ended up saturating a large portion of the graph's category scores. The two that stopped before the scores became unsaturated were indistinguishable from the categories that avoided the positive feedback loop. The four categories that had large numbers of saturated scores all received poor responses from the questions and were removed from our analysis. In Appendix B, we go into more depth about why this happened.

Secondly, two of the participants had very few friends from their high school in the system. We asked one to manually find anyone from their high school, but the category ended up being too small for this method of setting seeds. This category was one of the four categories that entered a positive feedback loop and had large numbers of saturated scores. The second time the same issue came up, we asked the (graduate student) participant to use their friends from their undergraduate university instead. The category had similar results to the ones created from other participants' high school friends, and we believe it was a suitable substitute.

All of our results should be interpreted in light of our group of participants. Our participants are *not* necessarily representative of the general user base of a site like Facebook. They are all male¹, and they are all highly educated and technology-oriented. In a small-scale study such as this one, the number of participants also indicates that the findings may not generalize across all populations. However, many of the results provided here are likely to apply more widely, and provide a useful initial look for future work.

Finally, the questions asked in the category surveys were often difficult to communicate and may have been misunderstood by the participants. Specifically, it was particularly hard to properly convey that Question 2 (labeling subgroups) was looking for subgroups that said more about the people who Like the Pages than the Pages themselves. When asked to find subgroups in the Pages, it is very easy to use explicit categories like type of media to divide the groups (this is what Facebook does). However, that data provides information that is potentially less useful for describing identity, so we tried to encourage the participants to avoid labels like these (even potentially replacing a label like Movies with a label like Movie-lovers). The fact that the most common type of label still referred to either media or genre indicates that this was potentially not properly communicated. Though these labels may hold important information about identity for the participants, for the purposes of analysis, we chose to keep them all in the same category. In future studies, we may be able to learn a bit more about how people might divide these groups by making this question clearer.

5.2.2 Question 1: Representing an Individual

The ratings received for Question 1 (*How well does this group of Likes represent the likes of any individual person?*) were generally quite high with a median of 6 out of 7

¹The lack of female participants is unfortunate and is based on who responded to a query on a mailing list that addresses all members and affiliates of the MIT Computer Science and AI Laboratory. The low female response rate can perhaps be partially explained by the low number of students on campus during the summer, which accentuates the already low representation of women in tech related labs on campus. In future work, more effort will be made to ensure a distribution of gender that more accurately represents the distribution of Facebook users.

(mean 5.407, stdev 1.152). Interestingly, of the five categories that got below a 5, in four of them there was one individual who Liked at least 21 of the 24 top Pages. Of the categories receiving a score greater than 4, only 8 of 22 had a profile that Liked 21 or more of the top 24 Pages. This may be an indication of two things. First, it's possible that even though there was one individual who was well represented in the network, the Pages chosen from that individual or the order in which they appeared made the representation less strong. We hypothesize that this could happen easily for people who have many Likes that have high PMI with other objects, so when a high number of those objects fire, they end up with disproportionate representation. This would cause the profile's less popular Likes to have a bigger effect on the category and since it's just the less popular ones, it may not serve as a particularly strong representation.

The strength of these scores on average suggests that these categories can serve as strong representations of people, but the lack of 7s (there were only two) reaffirms the belief that the categories may not be fully accurate and it may take some help from the users to turn them into full representations.

5.2.3 Question 2: Labeling Subgroups

For Question 2 (*Please fill in the following blanks with descriptive titles of subgroups you would make if you were to divide this set of Likes.*), we split the 74 responses into 6 categories: groups based on type of media, traits, associations, interests, descriptions of people, and miscellaneous.

The most common subgroup labels were descriptions of the Pages themselves. Descriptions like type of media ("games" and "books") or genre ("british [*sic*] bands," "offbeat comedy" and "fantasy fiction") were common in this category. The interviewer tried to encourage subgroups that said more about the people who Like these Pages than the Pages themselves, but this may not have been entirely clear as discussed in the Limitations section (Section 5.2.1). That said, these descriptions could carry implicit categories

with them, but the information provided wasn't enough to clearly make that assumption across the board. 30 of the 74 responses fit in this category.

The next most common labels were those that described traits a person or group of people might have. These were labels like "cosmopolitan," "cultured," "nerds," and "attentive." These subgroups are clearly reflective of implicit categories of people in their network. Seventeen of the 37 responses fit into this category, indicating that the system was presenting implicit categories in the data.

Eleven of the 37 responses involved things associated with groups of the participants' friends. We placed responses like "people from college," "female," and "people who are in EECS" in this category. These subgroups were primarily labeled as reflecting explicit categories, though since they were descriptions of the objects, the labels actually reflect an implicit category of things the participants associate with the explicit category.

Nine of the 37 responses described shared interests between the members of the group. These were responses like "movie lovers," "geek culture," and "comedy fans." These responses are very clearly implicit categories of social identity based on taste or shared interests. It's possible that many of the subgroups with labels describing the Pages themselves would fit into this category (e.g. "people who like fantasy fiction").

Four of the responses described the people associated with that subgroup of Pages. For instance, "lives near where they went to school," and "people with regional or school pride." These descriptions indicate that they reflect aspects of the identities of the people associated with them.

Finally, there were three labels that described a lack of information in the Pages presented: "vague," "broad," and "no links between the likes."

Of these labels, the labels of *traits*, *associations*, *shared interests*, and *descriptions of people*, are clearly labels that associate implicit categories with the Likes presented. These labels include 41 of the 74 responses, indicating that information about implicit categories is indeed being presented.

5.2.4 Question 3: Unifying Factor

We split the responses to Question 3 (*If I showed you this collection of Likes without telling you how it was generated, what would you see as the unifying factor?*) into 6 categories: factors that were the exactly the same as the factor used to construct the group, factors that were either a slight generalization or specification of the original factor, factors describing implicit categories based on taste or shared interests, factors describing implicit categories based on descriptions of the people, factors describing implicit categories based on both the Likes and the People, and factors that don't describe any particular category.

Three of the 27 responses reiterated the factor used to construct the profile. All three of these were based around the participant's high school friends indicating that they felt these Likes could only represent those friends. A further six responses described a slight variation of scope surrounding the original factor. For instance, for the participant's high school friends category, they often said the unifying factor was the city where the high school is located. Two of these descriptions described a smaller scope than the original factor would suggest. For instance, one response was "close friends from [my university] (even limited to people I lived with!)." These results indicate that these categories clearly identified a particular group of the participant's friends.

Sixteen of the remaining responses described some sort of implicit category either based around shared interests or descriptions of the people. Eight of these 16 described the unifying factor based around attributes of the people such as "open-minded, well traveled, self conscious," "liberal whites," or "people in their 20s who live near a large metropolitan area." Six describe shared interest or taste such as "Technology Enthusiast," "someone who reads Slashdot/hackernews," or "preference for slightly alternative media while still staying mainstream." The final two contained descriptions of both the people and the Likes: "Transhumanism, contrarians"; and "People [who] live in NY who like to watch TV shows and listen to pop music." The prevalence of these types of unifying factors suggests that this system is indeed presenting information related to implicit categories.

The remaining two responses were described as being too general to be particularly helpful. For example, one of the descriptions was “something to do with movies generally.” Both of these categories received 3s on Question 1 (representation of an individual).

5.2.5 Question 4: Surprising Pages

For this question (*Are there any Likes you are surprised about?*) we took the 38 responses and put each into one of six categories, based on why the result was surprising: because the object was unfamiliar, because the object was assumed to have few Likes across the network, because the Page didn't fit the group of people, because the Page doesn't fit with the other Pages in the category, because people chose to Like it on Facebook, and because of the absence of similar Pages.

The most common type of surprise was Likes that were surprising because they weren't associated with the people in the group. Phrases that indicated that a Page belonged in this category were “wouldn't expect close friends to like _____”, or “seems like it would be more appropriate for an older generation.” Of the 38 Likes, 11 fit this category. Surprises in this category indicate usefulness for discovering trends that may suggest recommendations or aspects of the user's friends they didn't know about.

Ten Likes were surprising because they didn't seem to fit thematically with the rest of the category. Phrases like “sort of separate from everything else”, or “totally different to anything else that is listed” placed Likes in this category. These surprises could indicate a connection between the user's implicit categories that may have been unexpected and helpful in refining those categories.

Eight Likes were surprising because they either had few Likes or were expected to have fewer Likes than they actually had. Phrases such as “this felt like it wasn't liked by enough people”, or “seems a bit obscure” placed a Page in this category. These surprises might suggest two things. First, if the group of people involved in constructing the category is small and doesn't have much in common, it's possible that something that is Liked by

more than one person in the group, but very rarely overall, will have a high impact on the category. This is primarily evidence that the people involved have very little in common. Pages that the user felt were obscure, but ended up having a high category score suggests that there may be something more to that Page (or the concept to which the Page refers) than the user expected — that Like may actually be popular amongst those people, despite the participant's lack of knowledge about it.

There were five Likes that were surprising because the participant didn't expect the Page itself to exist or be represented on their network. These comments focused mostly on either the fact that the concept (institution, idea) had a Facebook Page or around the fact that a number of people had explicitly Liked something that seemed so banal. Phrases like "wasn't even aware this existed, so surprised to see it :)" or "sort of an odd thing to be a fan of" were indicators for this category. These surprises can provide insights into the types of things people Like on Facebook. They may suggest the creation of a future category to gain information about why a surprising Page exists or why someone would Like it on Facebook.

There were two Pages that were surprising because they seemed to indicate a particular thread amongst the group, but there were no other related Pages. For instance, one participant noticed a Page in a foreign language that many of the people in the group spoke, but none of the rest of the Pages were specific to that group. Only two of the surprising Pages ended up in this category, but they suggest that the ability to compare the results from multiple groups would be helpful.

Finally, there were two Pages that were surprising because the participant didn't know what they were. The surfacing of these pages can help introduce the user to things their friends Like.

5.2.6 Question 5: Hiring an Actor

The responses to Question 5 (*If you were hiring an actor to play someone in this group of people, how useful would this list be in describing what sort of persona they should take?*) had an average score of 5.11 out of 7 (median 6, stdev 1.78). The results were largely positive here, but not quite as consistent as the individual scores. 70.0% of the responses were 5 or above, indicating good overall results.

Five categories received below a four. Of these, three of them were generated using the Find Likes interface and participants noted that the resulting category was too general to provide a good picture for the actor. The remaining two were based on high school friends (one category was based on people who Liked a high school; the other simply the category generated by high school friends). Some problems that the participants noted with these are that they were largely location-based (or centered around the high school itself) and though that was a good representation from the participant's perspective, those Likes didn't carry enough information for someone without context.

High responses to this question indicate that the categories can often be useful for describing a group of people to someone without knowledge of the group.

5.2.7 Question 6: Learned

When we asked participants how much they had learned from the category (*How much have you learned from this group of Likes that you didn't know or didn't realize about the people before?*), the average score was 4.04 out of 7 (median 5, stdev 1.63). Most of the categories received a score of 5 or greater, so many of the categories are helping to reveal information from the network and display them to the user in ways that teach them about their friends' identities. The results are fairly inconsistent though, and many of the categories didn't provide much new information.

For the most part, none of the variables we collected correlate strongly with how much

the participant learned. One interesting result is that when only looking at the categories created from high school friends, the average score drops to 3.14 (median 3, standard deviation 1.77). This makes sense because these are groups the participants probably know well, and when aggregated like this, hold few surprises.

How to make categories to teach people things, however remains a largely unanswered question. Though this supports the observation that the results may not hold enough novel information, it may indicate that a better approach may be to view many categories quickly. We hypothesize that, in some cases, these categories simply told people about things they already knew, which could provide more direction to help understand this issue in the next study.

5.2.8 Across Participants

This section discusses the results from the category of the interviewer's high school group. We asked questions about this category so we could get an idea about how consistent these results are even from a different user's network. None of the participants were Facebook friends with any of the profiles in the category (4 of the 8 participants were Facebook friends with the interviewer), so the answers to these questions enabled us to assess the quality of the results from a more objective standpoint.

The first question asked participants to rate how well the category represented the Likes of an individual. All but one of the participants rated it either 5 or 6 out of seven, indicating that it represented an individual well. One participant rated it at 2 for unknown reasons, indicating that the category did not represent a person well. That participant elaborated on his rating by adding "yeah, I can reasonably imagine someone who likes all of these things, but I wouldn't really know how to describe them." Comments from the other participants describing their stronger ratings include "it seems like a very unified story for one person", and "it is a useful window into someone's identity."

The second question asked the participant to label any subgroups they observed in the

category. There were 20 labels provided across all participants. Seven of them focused on location-based commonalities (e.g. “Person active in the community”, “cities in california”), 6 focused on the types of TV shows or movies (e.g. “movie lovers”, “pop tv shows for young adults”), 4 focused on celebrities or popular culture (e.g. “Hot Female Celebrity”), and 3 were miscellaneous.

The third question asked participants to work backward and attempt to identify the group based on what was seen. Of the 7 responses, 6 mentioned something about location (“Watsonville”, “California”, or “local”), and the 7th was “Sunny dispositions/ good humour/ attitude towards life”, which are stereotypical Californian descriptors. Three of the responses mentioned age (“young adult”).

5.3 Findings

There are two main purposes of this study. The first is to assess how coherent the categories constructed by the system are. The second is to understand for what situations the system might be useful. Two smaller purposes of the study are to try to improve the Group Persona Interface and to prepare for a second round study.

5.3.1 Are the Categories Coherent?

One of the main goals of this study is to find out how coherent the categories the system makes are. The more coherent a category is, the more easily a user will be able to incorporate the information shown by the system into the implicit categories they use to understand social identities. To understand how coherent the categories are, we can look at the participants’ responses to try to determine how often they employ their own categories of social identities to answer the questions we asked. This section focuses on the responses to the first three questions: representation of an individual, labeling subgroups and describing a unifying factor.

Our findings from Question 2 and 3 (labeling subgroups and describing a unifying factor, respectively) indicate that the participants made frequent use of their own category structures to understand the information presented. In labeling subgroups, 41 of the 74 labels were descriptions of an implicit category that the participant saw represented in the group. It's possible that many of the 30 labels describing more explicit categories could also be stand-ins for implicit categories. We will make sure to address that in future studies.

In Question 3, nine of the 27 categories of Likes were described as representing a group similar to the one that was stated. For many of these the fact that the unifying factor was similar to the original group, but different in scope, indicates even more strongly that the participants' implicit categories were important to their understanding of the data.

These together make it quite clear that many of the participants were able to situate the information presented to them into their implicit categories. When asked "What types of insights about social categories could this site help discover?" one participant responded: "The categories by which people define themselves: movies+music vs politics vs aspirations." This indicates that the participant made a clear connection between the Likes presented by the system and the categories they use in everyday situations to understand the identities of their friends.

In Question 1, we asked whether or not the category was easily understandable by asking participants if the category provided a good representation of an individual person. The responses to the question were largely positive, as discussed before, suggesting that the categories were quite coherent. This indicates that the results of the category were strong enough that the participants were able to make the connection between the group of Likes as they were presented and a clear representation of an individual. As one participant noted in the final questionnaire: "people can be identified by the media they consume."

Additionally, the responses to the questions asked of the interviewer's high school friends suggest that the implicit categories shown by the system are consistent enough for some to be seen in a category based on an unfamiliar group of people. The fact that the re-

sponses to Question 1 were high and the responses to Questions 2 and 3 were largely consistent across all participants indicates that the categories created by the system might be understandable even without the context of knowing the people involved.

5.3.2 Are the Categories Useful?

To address the question of how useful the categories can be, we want to find out both whether or not these categories are currently useful for anything, and what about them makes them useful. With this knowledge, we can inform the design of future applications. This section focuses on the responses to questions 4, 5 and 6 (surprising Likes, hiring an actor, and how much you have learned).

Question 5 proposes a situation (hiring an actor) and asks whether or not this category would be useful in such a situation. While the situation itself is unlikely, the situation suggests the more general use of providing a representation of one of these categories to someone as a way of communicating the persona of a member that group. The positive responses to this category suggest that the categories could in fact be useful for such a situation. For instance, one could imagine an interface where a user could create a category for a group of friends and send it to another friend as a way of quickly introducing the group. For the categories that weren't as highly rated, an interface that allowed the user to start with this group and manually edit it could allow the user to add necessary context to the group when it is missing from the results.

Question 6 asks a fairly straightforward question to understand how useful the category might be in teaching the participant something they didn't know or revealing something they hadn't realized. While there were many positive responses to this question, the responses were inconsistent across the data set and we were unable to find reasonable predictors of whether or not a category would teach something to the user. This question will be a primary goal in future studies.

Though we weren't able to find any clear predictors of how much a user may learn from

the category, we were able to find what types of insights the user might learn by asking the participants to identify particularly surprising Likes in the category (Question 4). We found that the insights could be categorized into six different groups: Pages that didn't fit the group of people, Pages that don't fit with the other Pages in the category, Pages that were perceived to be unpopular, Pages that were not expected to exist or be Liked on Facebook, Pages that weren't recognized, and Pages that were surprising because of the lack of similar Pages. We found that surprises in the categories of not fitting the people, not fitting the other Pages, or perceived to be unpopular were the most common, though surprises based on Like activity were also quite common.

These results indicate that there are clearly areas where these categories are useful and that there are also still many open questions regarding how to use them.

Finally, when asked whether or not this system might be useful, one participant responded: "Yes because it aggregates this data in a way that Facebook does not." This indicates that the categories we create are useful ways to extend representations of identity on systems like Facebook.

5.3.3 Improving the Group Persona Interface

The most salient thing learned from having people use the system is that it takes some amount of skill and familiarity to get the most out of the system. There are ways we can improve the results of the system given difficult groups, but there are many groups that might be constructed that simply don't have much in common. In that situation, it would be most helpful to simply take note of that and move on to create another category. This suggests two design changes. The first is that we should make it clear that the system works well for creating many categories quickly and revisiting them when they have finished calculating. Second, a clear way of indicating on the interface when the system is unsure about a category would help to keep a user from trying too hard to find patterns that may not exist.

Another important insight is that a lot of the usefulness of the system came from being able to compare categories created with similar features to see what the salient differences are. One participant suggested that “side-by-side comparison of groups would be interesting.” Comparing categories could help reveal important but subtle distinctions between similar groups of friends.

Another common request was for a more flexible way of selecting groups of people. For instance, one participant commented that “adding ‘or’ search would be cool, if you want to see larger groups.” This would be especially useful in situations where there are multiple Pages for the same concept. Another participant noted that it was difficult to construct groups with information not provided by Facebook and that the interface could be better streamlined for that process.

5.3.4 Future Study Improvements

While this study was very informative, there remain a number of questions that haven’t been tested well. First and foremost, we were unable to find predictors for how much a user might learn from each category. We feel that this is an important question to answer. Figuring out what additional data to collect to help answer this question will be an integral part of any future study.

In terms of structure, an interesting variant on this study would be to have people use the system for some set amount of time, then answer questions about the most interesting categories they created. This would help people explore the system and gain familiarity with it, which will hopefully allow them to come up with ways to use the system that we haven’t thought of before.

5.3.5 Further Insights

There were two themes that some of the users brought up discussed here. One user commented: “It surfaced some ‘obvious’ things that I would have expected people in my group to like (since I, e.g., watched it with them, or lent/had lent to me books etc.). It was fun to see it all summarised and laid out visually.” We see this as particularly motivating because it shows that these types of insights are not only potentially useful, but also potentially fun and entertaining.

Another participant commented that “using the tool was interesting but felt kind of creepy / voyeuristic.” Even though this data is readily available through Facebook itself (the data we have is actually more restricted than what they can see through facebook.com) there is still enough information here to make this particular participant feel like he was learning something about the participants that weren’t meant to be shown. We feel that this insight is important and something that deserves more research in the future.

CHAPTER 6

CONCLUSION AND FUTURE WORK

This chapter first summarizes the contributions made by this thesis. This is followed by a discussion of future directions this project may take and proposes examples of potential ways both the algorithm and current implementation can be used to make more expressive and empowering identity-related systems.

6.1 Contributions

We designed an algorithm for revealing implicit categories in network representations of identity. We developed relevant algorithmic techniques from the field of Machine Learning and used them to design an algorithm to reveal implicit categories hidden in the explicit category structures of social identity systems. To accomplish this, we used models of categorization based on cognitive science literature.

We implemented the algorithm using Facebook Likes as a source for information about identity. For the first implementation of the algorithm, we used Facebook Likes as a source of identity-related information as a case study. This implementation has taken the form of a server application built on Django (a Python web application framework).

We developed two interfaces for exploring the results of the algorithm. We describe the design and implementation of two interfaces built for the purpose of exploring the results of the algorithm. The first is based on an earlier version of the algorithm based on the technique of Singular Value Decomposition. The second uses the current implementation using Facebook Likes. These interfaces have allowed us to experiment with the parameters of the algorithm and the potential results of the categories.

We developed the Reflect Interface for viewing a user's own profile through the lens of different categories. We present the design and implementation of the Reflect Interface, which is a tool for helping users understand the implicit categories represented by their own profile.

We developed the Group Persona Interface for finding trends and implicit categories hidden in Facebook Likes by constructing groups of people and viewing the Likes that are central to them. We present the design and implementation of the Group Persona Interface, which is a tool for exploring trends in the Likes of different groups of the user's friends.

We evaluated the system using the Group Persona Interface to help understand how coherent and useful the results of the algorithm can be. We present the results of an evaluation of the system using the Group Persona Interface as a pilot study. From the evaluation, we have shown that the categories do provide information that is otherwise hard to find and can provide useful information about the user's social categories.

6.2 Suggestions for Future Work

The suggestions for directions for future work presented here fall into two different categories. The first category is things that can be done with the system built for this thesis. The second is potential extensions to either the system or the algorithm described here.

6.2.1 Future Work Using the Current Implementation

The implementation of the algorithm using Facebook Likes as a case study has not been fully explored. There is still a lot we can learn from the system about the range of possibilities for increasing the expressiveness of Facebook Likes.

Section 5.3.4 describes the future directions for studies built upon of the insights gained from this pilot study. In addition to obtaining stronger data to help test the hypotheses suggested by this study, finding out what about a category contributes to its usefulness as a learning tool and gaining insights about the potential of this application by having people use it in more extended and unstructured sessions could provide very valuable insights.

The insights gained from the study also suggest possible applications that can be built off the current system. For instance, the positive results of the question regarding using the categories as a way of communicating a persona to an actor suggests the possibility of building an interface to help with the process of introducing friends to a group of other friends.

The description of the Reflect Interface in Section 4.3 suggests a possible use of the system to develop multiple representations of the user's identity by dynamically filtering the user's profile based on certain categories. For instance, a user could make a set of categories for different groups of friends in her network and when one of those friends visits the user's profile, the friend would only see the Likes that are consistent with the category that friend belongs to. This could be useful for presenting a particular identity to different groups of people or for applications related to privacy. In the data collected for the study, the percentage of the participant's friends who either didn't Like anything or had restrictive privacy settings varied from 21.5% to 53.9% (mean 37.6%, median 39.0%) indicating that a lot of people choose not to represent their taste on social networking systems. It is possible that some people choose not to share this data because they are afraid of the associations that people might make or they want to keep that data from getting into

the wrong hands. With better understanding of these implicit categories, we can support interfaces that help construct and present these categories in ways that better support understanding, dynamically change the presentation of identity for different groups, identify and reduce potentially stigmatizing categorization structures, and more. Computational identity systems that give their users further control over the identities they represent can help those present their identities in ways they feel comfortable. For example, users may want to show they like a certain activity, but don't want to be associated with other people who might like those things. Applications could also help users target or hide profile information for different viewers. For example, an application could help a user working at Planned Parenthood keep that information from relatives who might disapprove.

6.2.2 Potential Extensions to the System

Though the application for the algorithm to Facebook Likes has proven to be a solid case study, there are many further directions to take the project in the future. This work presents the first of many components constituting the AIR Toolkit.

One of the key components of the algorithm presented here is that it can work using many different sources of identity-related information. While the implementation uses Facebook Likes, the algorithm could be applied to easily to character attributes in video games providing help for new players, or increasing the amount of expression possible in MMOs, for example.

Additionally, by incorporating techniques from fields like Natural Language Processing (NLP), one could increase the amount of identity-related data available to the system by parsing status updates or biographies on profiles. Using techniques like these, one could expand the focus of the identity representations beyond aspects of taste and get closer to a representation of more complex identity-related concepts like personality, race, sexuality, and gender. For example, in *Brown Tide Rising*, Otto Santa Ana examined the metaphors used in the discussion of issues related to immigration in articles from the *Los Angeles*

Times to help understand how these metaphors reveal the ways people conceptualize immigration issues[1]. NLP techniques combined with the algorithmic techniques presented in this thesis could assist in research like Santa Ana's by helping to find patterns in the ways people use metaphors amongst large sets of data.

The AIR Project also proposes using identity-related data across applications to allow the user's identity on one system affect their identity on other systems.

6.2.3 Recommendations for Study Questions

After the study, we realized that there are a lot of areas where we could improve the questions to better target the questions we actually want to ask. Here we suggest some areas where we saw the need for improvement.

Individual: This question was consistently hard to describe and often misunderstood. Future studies will want to make sure this question properly addresses the question of whether the categories presented are representative of an individual.

Subgroups: We feel it could be very useful to ask how strongly each subgroup is represented in the results to provide extra information to help the analysis.

Unifying: Especially when asking this question about a category not created from the participant's friends, not providing the participant with the actual factor used to construct the group would help get more objective answers.

Surprising: This question could be improved by asking more information to determine whether or not the Page was helpful in refining the participant's social categories.

6.3 Concluding Reflections

Identity is an extremely important phenomenon to get right when it comes to our interactions online. Online representations of identity help us communicate with friends on social networking sites, communicate with systems on e-commerce sites or adopt new personas on computer and video games. As these digital technologies become further integrated into our lives, the importance of having computational identity systems that can help users express their identities becomes increasingly important. It is our hope that the ideas and techniques presented in this thesis will help in the creation of systems that are better able to do so.

APPENDIX A

FACEBOOK INTERFACES AND APIS

This appendix is an attempt to freeze the state of Facebook’s interfaces and APIs regarding Facebook Likes. The Facebook website is continually being developed and new features are introduced quite frequently. As such, it is important to document the aspects of the website discussed in this thesis as they were during the development of this work—the Spring and Summer of 2011.

A.1 Pages

Facebook’s Pages are representations of concepts including people, places, people, objects, brands, and ideas. These differ from profiles in that they can be operated by more than one person, may not refer to a particular person and they are “Liked” instead of “friended.” In April 2010[10], Facebook made the decision to convert the textual lists of cultural objects (e.g. “Favorite Movies,” “Favorite Music”) to explicit links to the Pages representing these cultural objects. Figure A-1 shows an example of how Likes are represented in the Info section of a Facebook Profile.

Sports

Edit

Favorite Athletes



Lee, Jung-Hoon

Artosis

Tasteless

LiquidJinro

Arts and Entertainment

Edit

Music



Janelle Monae

The Beatles

Modest Mouse

Matt and Kim

More ▾

Books



Scott Pilgrim

The Invention of Air

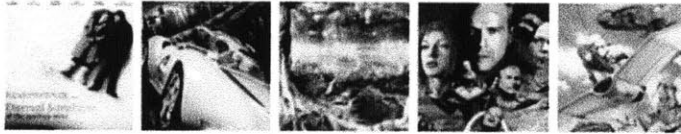
American Gods

Harry Potter

Watchmen

More ▾

Movies



Eternal Sunshine of the Spotless Mind

Speed Racer

The Fountain

The Fifth Element

Nausicaä of the Valley of the Wind

More ▾

Television



Figure A-1: Screenshot of the Likes portion of a Facebook Profile's Info section.

A.2 Facebook's Graph API

The conversion of textual lists to explicit links to Pages made the information much easier to access and use in computations. In April 2010[17], along with that conversion, Facebook introduced the Graph API, which is the interface the work in this thesis uses to obtain data about the user's network. The Graph API allows the system presented here to download the user's profile information, the user's friends' profile information and all of the Likes for those profiles. This is the data the algorithm uses to construct the correlation matrix.

APPENDIX B

ALGORITHM PARAMETERS

There are three important parameters involved in the spreading activation process described in Section 3.1.3: the starting value, the activation threshold and the decay rate. These parameters help determine how many nodes (referring to attributes or Pages) on the graph become activated and how much effect that has on the final category scores. This appendix provides further explanation about the effects the parameters have and some guidance on how to choose parameters for different tasks.

The description in the following sections focuses on Facebook profiles and Pages as the relevant identity-related data. While the descriptions and insights could carry over to many other sources of identity information, the techniques and numbers were generated using Facebook data.

B.1 Parameter Descriptions

The **starting value** helps determine the scores of the seeded nodes prior to the spreading activation process. When using the Page Method for seeding the category (as discussed in Section 3.2.2), the algorithm simply sets the category scores for each seed to the starting

value. When using the Profile Method (also discussed in Section 3.2.2), the algorithm sets the category scores of all Pages liked by any of the seed profiles to the starting value times a multiplier. That multiplier is determined by how popular the given Page is compared to the popularity of the most popular Page within the seed profiles. For instance, imagine a group of 4 people, each of whom Like the TV show *The Office* and two Like the TV show *Family Guy*. The algorithm would set the category score for *The Office* to the starting value and the score for *Family Guy* to half of the starting value.

The **activation threshold** determines which nodes fire at the beginning of each round. In each round of the spreading activation process, all unfired nodes with a category score greater than or equal to the threshold fire (as described in Section 3.1.2). The firing of each node raises the category scores of all nodes connected to it, causing some to cross the threshold and fire in the next round. The parameter defining that threshold is important because the graph is big and highly connected, so having every node fire would take a long time to compute and potentially cause positive feedback loops that could de-emphasize the effect of the seeds.

The decay rate determines how much effect the subsequent rounds of node firings effect the final category scores. When a node fires, its value times a multiplier is added to all other connected nodes. The multiplier is determined by the weight of the link between the two nodes (their PMI) and the decay rate. Because the graphs used in the algorithm are highly connected, if the process didn't decay in subsequent rounds, the fired nodes would spread quickly throughout the graph, eliminating the effect of the original seeds. To solve this problem, the algorithm uses a decay rate, which gets squared at the end of each round. In this implementation, the decay rate is a number between 0.0 and 1.0, meaning that a higher decay rate causes a slower decay, which may be counterintuitive.

B.2 Potential Failures

Choosing parameters to produce meaningful results is a balancing act. If the threshold is too high and the decay rate too low, only a small number (if any) of nodes fire, resulting in category scores that reflect little about the network. If the threshold is too low and the decay rate too high, there is danger of entering a positive feedback loop causing too many nodes to fire and losing most of the effects of the starting seeds. The term “category spread” is used in this section to refer to how large of a portion of the graph fired.

B.2.1 Low Category Spread

When the category spread is too low, the resulting category has the danger of not being very affected by properties of the network. In the case of seeds determined by the Page Method, if only the original Pages fire, the information the category carries can be determined largely by other Pages that show up with those original Pages. While this information is potentially useful, much of the information about the Pages from other users may be omitted. For instance, if the Pages used to seed a category are relatively unpopular, it may take the influence of the network data surrounding those Pages to help find their similarities.

When using the Profile Method to seed a category, low category spread can result in the category simply displaying how many people in the chosen group of profiles Like each of these objects. Again, this data might be useful or interesting by itself, but the amount of network data used would be minimal. For example, imagine a group of ten people. All ten of these people Like *Barack Obama*, and eight of the ten Like the *MIT Media Lab*. In this network, *Barack Obama* is the most popular Like, but the only people who Like the *MIT Media Lab* are the eight people in this group. *MIT Media Lab* is arguably more central to this group of people because it only appears within this group, while *Barack Obama* is popular across the network. If few nodes fire, this information may not have a chance to come into effect.

B.2.2 High Category Spread

If too many Pages fire early in the process before the multiplier decays, high values spread across the network and cause more and more Pages to activate. Because category scores are measured between 0.0 and 1.0, when this happens, the category scores can get saturated (all set to 1.0). When many of the Pages in the network have category scores of 1.0, the information about which of those Pages are most central is essentially lost.

To avoid this, our implementation has a fail-safe built in that stops the spreading activation process when too many category scores are set to fire, displaying the results as is. In the current implementation, this fail-safe is tripped when over 600 nodes are set to fire at the beginning of a new round. While this number does catch many categories before they spread too far, the number was chosen primarily to save computing power from runaway categories. One way of potentially improving the effectiveness of this fail-safe could be to adjust the number that causes it to stop based on which round the process is in. In later rounds, the process may decay enough to minimize the effect of a high number of fired nodes. In earlier rounds, the numbers have not decayed much and a smaller number of fired nodes can cause the category scores to saturate.

B.3 Numbers

For the implementation of the algorithm, we settled on values for the parameters. Some of these values are set beforehand and others are adjusted based on certain features of the category. The values and techniques we use here are based off of experimentation primarily with a single user's Facebook network. As such, there is still much work to be done in finding values and techniques that work well across many different data sets.

This section presents two different sets of values and techniques. The first is for categories seeded with the Page Method and the second is for categories seeded with the Profile Method.

B.3.1 The Page Method

The parameters used by default for categories seeded with the Page Method are:

Starting Value : 0.5

Activation Threshold : 0.4

Decay Rate : 0.4

It is important to note that these values are best thought of as starting points. These values are known to be fairly unstable, but they may provide a useful starting point for creating categories using the algorithm presented in this thesis.

In practice, these values tend to produce fairly stable categories for groups of 3 or 4 seeds. While discovering techniques for adjusting these values dynamically based on the input of seeds is beyond the scope of this work, it is an important issue to tackle for any system using this method of seeds.

B.3.2 The Profile Method

The values and techniques used to determine the values of the parameters for categories seeded with the Profile Method have been more thoroughly tested and are therefore more stable. The techniques used in the implementation presented here are as followed:

Starting Value : 0.3

Activation Threshold : the value of the third highest score, unless that score is either above 0.2 or below 0.12.

Decay Rate : The minimum of 0.18 and 0.03 times the popularity of the most popular Like.

Since the Profile Method gives starting values to more nodes, these values are significantly lower than the values for the Page Method.

The activation threshold is chosen to be the value of the third highest score so at least three nodes fire in the first round. Because the pattern of Likes for different groups tend to take the shape of a long tail, setting the threshold below the third most popular Page is usually close enough to the lower end of the tail to allow more nodes to fire in the second round. The bounds are there for more unusual cases. If there are three or more very popular Pages in a group, the threshold may be set too high for any other nodes to fire after the first round, so the threshold must be 0.2 or below. If the most popular Page is way more popular than the rest of the Pages, the threshold may be set low enough that too many nodes fire on the first or second round, resulting in a positive feedback loop.

The decay rate is chosen to help keep groups with few Likes in common from spreading too far. When a group has few Likes in common, the seeded scores are fairly flat, making the category susceptible to positive feedback loops. For example, if the most popular Page in a group has two Likes and it is tied with eight other Pages, if all eight Pages fire on the first round, nearly all of the Pages Liked by the people in the group could end up crossing the threshold. Choosing a low decay rate for groups like this helps to prevent positive feedback loops.

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