Identifying Customer Needs from User-Generated Content

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by

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Identifying Customer Needs from User-Generated Content

Abstract

Firms traditionally rely on interviews and focus groups to identify customer needs for marketing strategy and product development. User-generated content (UGC) is a promising alternative source for identifying customer needs. However, established methods are neither efficient nor effective for large UGC corpora because much content is non-informative or repetitive. We propose a machine-learning approach to facilitate qualitative analysis by selecting content for efficient review. We use a convolutional neural network to filter out non-informative content and cluster dense sentence embeddings to avoid sampling repetitive content. We further address two key questions: Are UGC-based customer needs comparable to interview-based customer needs? Do the machine-learning methods improve customer-need identification? These comparisons are enabled by a custom dataset of customer needs for oral care products identified by professional analysts using industry-standard experiential interviews. The analysts also coded 12,000 UGC sentences to identify which previously identified customer needs and/or new customer needs were articulated in each sentence. We show that (1) UGC is at least as valuable as a source of customer needs for product development, likely more-valuable, than conventional methods, and (2) machine-learning methods improve efficiency of identifying customer needs from UGC (unique customer needs per unit of professional services cost).

Keywords: *Customer Needs; Online Reviews; Machine Learning; Voice of the Customer; User-generated Content; Market Research; Text Mining; Deep Learning; Natural Language Processing*

1. Introduction

Marketing practice requires a deep understanding of customer needs. In marketing strategy, customer needs help segment the market, identify strategic dimensions for differentiation, and make efficient channel management decisions. For example, Park, Jaworski, and MacInnis (1986) describe examples of strategic positioning based on fulfilling customer needs: "attire for the conservative professional" (Brooks Brothers) or "a world apart—let it express your world" (Lenox China). In product development, customer needs identify new product opportunities (Herrmann, Huber, and Braunstein 2000), improve the design of new products (Krishnan and Ulrich 2001; Sullivan 1986; Ulrich and Eppinger 2004), help manage product portfolios (Stone, et al. 2008), and improve existing products and services (Matzler and Hinterhuber 1998). In marketing research, customer needs help to identify the attributes used in the conjoint analysis (Orme 2006).

Understanding of customer needs is particularly important for product development (Kano, et al. 1984; Mikulić and Prebežac 2011). For example, consider the breakthrough laundry detergent, "Attack," developed by the Kao Group in Japan. Before Kao's innovation, firms such as Procter & Gamble competed in fulfilling the (primary) customer needs of excellent cleaning, ready to wear after washing, value (quality and quantity per price), ease of use, smell good, good for me and the environment, and personal satisfaction. New products developed formulations to compete on these identified primary customer needs, e.g., the products that would clean better, smell better, be gentle for delicate fabrics, and not harm the environment. The market was highly competitive; perceived value played a major role in marketing and detergents were sold in large "high-value" boxes. Kao Group was first to recognize that Japanese customers wanted "a detergent that is easy to transport home by foot or bicycle," "in a container that fits in limited apartment space," but "gets my clothes fresh and clean." Guided by this insight, Kao launched a highly-concentrated detergent in an easy-to-store and easy-to-carry package.

Despite a premium price, Attack quickly commanded almost 50% of the Japanese laundry market (Kao Group 2016). American firms soon introduced their own concentrated detergents, but by being the first to identify an unfulfilled and previously unrecognized customer need, Kao gained a competitive edge.

There is an important distinction between customer needs and product attributes. A customer need is an abstract context-dependent statement describing the benefits, in the customer's own words, that the customer seeks to obtain from a product or service (Brown and Eisenhardt 1995; Griffin, et al., 2009). Product attributes are the means to satisfying the customer needs. For example, when describing their experience with mouthwashes, a customer might express the need "to know easily the amount of mouthwash to use." This customer need can be satisfied by various product attributes (solutions), including ticks on the cap and textual or visual descriptions on the bottle.

To effectively capture rich information, customer needs are typically described with sentences or phrases that describe in detail the benefits the customers wish to obtain from products. Complete formulations communicate more precise messages compared to "bags of words," such as developed by latent Dirichlet allocation (LDA), word counts, or word co-occurrence (e.g., Büschken and Allenby 2017; Lee and Bradlow 2011; Netzer, et al. 2012; Schweidel and Moe 2014). For example, consider one "bag of words" from Büschken and Allenby (2017):

> *"Real pizza:" pizza, crust, really, like, good, Chicago, Thin, Style, Best, One, Just, New, Pizzas, Great, Italian, Little, York, Cheese, Place, Get, Know, Much, Beef, Lot, Sauce, Chain, Got, Flavor, Dish, Find*

Word combinations give insight into dimensions of Italian restaurants—combinations that are useful to generate attributes for conjoint analysis. However, for new product development, product-development teams want to know how the customers use these words in context. For example:

- *Pizza arrives to the table at the right temperature (e.g., not too hot and not cold).*
- *Pizza that is cooked all the way through (i.e., not too doughy).*
- *Ingredients (e.g., sauce, cheese, etc.) are neither too light nor too heavy.*
- *Crust that is flavorful (e.g., sweet).*

- *Toppings stay on the pizza as I eat it.*

Our paper focuses on the problem of identifying the customer needs. While relative importances of customer needs are valuable to product-development teams, methods such as conjoint analysis and self-explicated measures are well-studied and in common use. We assume that preference measures are used later in product development to decide among product concepts (Ulrich and Eppinger, 2016; Urban and Hauser, 1993).

The identification of customer needs in context requires a deep understanding of a customer's experience. Traditional methods rely on human interactions with customers, such as experiential interviews and focus groups. However, traditional methods are expensive and time-consuming, often resulting in delays in time to market. To avoid the expense and delays, some firms use heuristics, such as managerial judgment or a review of web-based product comparisons. However, such heuristic methods often miss customer needs that are not fulfilled by any product that is now on the market.

User-generated content (UGC), such as online reviews, social media, and blogs, provides extensive rich textual data and is a promising source from which to identify customer needs more efficiently. UGC is available quickly and at a low incremental cost to the firm. In many categories, UGC is extensive—for example, there are over 300,000 reviews on health and personal care products on Amazon alone. If UGC can be mined for customer needs, UGC has the potential to identify as many, or perhaps more, customer needs than direct customer interviews and to do so more quickly with lower cost. UGC provides additional advantages: (1) it is updated continuously enabling the firm to update its understanding of customer needs and (2) unlike customer interviews, firms can return to UGC at low cost to explore new insights further.

There are multiple concerns with identifying customer needs from UGC. First, the very scale of UGC makes it difficult for human readers to process. We seek methods that scale well and, possibly, make human readers more efficient. Second, much UGC is repetitive or not relevant. Sentences such as

"I highly recommend this product" do not express customer needs. Repetitive and irrelevant content make a traditional manual analysis inefficient. Third, we expect, and our analysis confirms, that most of UGC concentrates on a relatively few customer needs. Although such information might be useful, we seek methods to efficiently search more broadly in order to obtain a reasonably complete set of customer needs (within cost and feasibility constraints), including rarely mentioned customer needs. Fourth, UGC data are unstructured and mostly text-based. To identify abstract context-dependent customer needs, researchers need to understand rich meanings behind the words. Finally, unlike traditional methods based on a representative sample of customers, customers self-select to post UGC. Self-selection might cause analysts to miss important categories of customer needs.

Our primary goals in this paper are two-fold. First, we examine whether a reasonable corpus of UGC provides sufficient content to identify a reasonably complete set of customer needs. We construct and analyze a custom dataset in which we persuaded a professional marketing consulting firm to provide (a) customer needs identified from experiential interviews with a representative set of customers and (b) a complete coding of a sample of sentences from Amazon reviews in the oral-care category. Second, we develop and evaluate a machine-learning hybrid approach to identify customer needs from UGC. We use machine learning to identify relevant content and remove redundancy from a large UGC corpus, and then rely on human judgment to formulate customer needs from selected content. We draw on recent research in deep learning, in particular, convolutional neural networks (CNN; Collobert, et al. 2011; Kim 2014) and dense word and sentence embeddings (Mikolov, et al. 2013a; Socher, et al. 2013). The CNN filters out non-informative content from a large UGC corpus. Dense word and sentence embeddings embed semantic content in a real-valued vector space. We use sentence embeddings to sample a diverse set of non-redundant sentences for manual review. Both the CNN and word and sentence embeddings scale to large datasets. Manual review by professional analysts remains necessary in the last step because of the context-dependent nature of customer needs.

We evaluate UGC as a source of customer needs in terms of the number and variety of customer needs identified in a feasible corpus. We then evaluate the efficiency improvements achieved by the machine learning methods in terms of the expected number of unique customer needs identified per unit of professional services costs. Professional services costs, or the billing rates of experienced professionals, are the dominant costs in industry for identifying customer needs. Our comparisons suggest that, if we limit costs to that required to review experiential interviews, then UGC provides a comparable set of customer needs to those obtained from experiential interviews. Despite the potential for self-selection, UGC does at least as well (in the tested category) as traditional methods based on a representative set of customers. When we relax the professional services constraint for reviewing sentences, but maintain professional services costs to be less than would be required to interview and review, then UGC is a better source of customer needs. We further demonstrate that machine learning helps to eliminate irrelevant and redundant content and, hence, makes professional services investments more efficient. By selecting a more-efficient content for review, machine learning increases a probability of identifying low-frequency customer needs. UGC-based analyses reduce research time substantially avoiding delays in time-to-market.

2. Related Research

2.1. Traditional Methods to Identify Customer Needs (and Link Needs to Product Attributes)

Given a set of customer needs, product-development teams use a variety of methods, such as quality function deployment, to identify customer solutions or product attributes that address customer needs (Akao 2004; Hauser and Clausing 1988; Sullivan 1986). For example, Chan and Wu (2002) review 650 research articles that develop, refine, and apply QFD to map customer needs to solutions. Zahay, Griffin, and Fredericks (2004) review the use of customer needs in the "fuzzy front end," product design, product testing, and product launch. Customer needs can also be used to identify attributes for conjoint

analysis (Green and Srinivasan 1978; Orme 2006). Kim, et al. (2017) propose a benefit-based conjoint-analysis model which maps product attributes to latent customer needs before estimation.

Researchers in marketing and engineering have developed and refined many methods to elicit customer needs directly from customers. The most common methods rely on focus groups, experiential interviews, or ethnography as input. Trained professional analysts then review the input, manually identify customer needs, remove redundancy, and structure the customer needs (Alam and Perry 2002; Goffin, et al. 2012; Kaulio 1998). Some researchers augment interviews with structured methods such as repertory grids (Wu and Shich 2010).

Typically, customer-need identification begins with 20-30 qualitative experiential interviews. Multiple analysts review transcripts, highlight customer needs, and remove redundancy ("winnowing") to produce a basic set of approximately 100 abstract context-dependent customer-need statements. Affinity groups or clustered customer-card sorts then provide structure for the customer needs, often in the form of a hierarchy of primary, secondary, and tertiary customer needs (Griffin and Hauser 1993; Jiao and Chen 2006). Together, identification and structuring of customer needs are often called voice-of-the-customer (VOC) methods. Recently, researchers have sought to explore new sources of customer needs to supplement or replace common methods. For example, Schaffhausen and Kowalewski (2015; 2016) proposed using a web interface to ask customers to enter customer needs and stories directly. They then rely on human judgment to structure the customer needs and remove redundancy.

2.2. UGC Text Analysis in Marketing and Product Development

Researchers in marketing have developed a variety of methods to mine unstructured textual data to address managerial questions. See reviews in Büschken and Allenby (2016) and Fader and Winer (2012). The research closest to our goals uses word co-occurrences and variations of LDA to identify word groupings in product discussions (Archak, Ghose, and Ipeirotis 2016; Büschken and Allenby 2006; Lee and Bradlow 2011; Tirunillai and Tellis 2014; Netzer, et al. 2012). Some researchers analyze these

word groupings further by linking them to sales, sentiment, or movie ratings (Archak, Ghose and Ipeirotis 2016; Schweidel and Moe 2014; Ying, Feinberg, and Wedel 2006). The latter two papers deal explicitly with self-selection or missing ratings by analyzing UGC from the same person over different movies or from multiple sources such as different venues. We address the self-selection concern by comparing customer needs identified from UGC to the customer needs identified from the interviews with a representative sample of customers. We assume that researchers can rely on standard methods to map customer needs to the outcome measures such as preferences for product concepts in each customer segment (Griffin and Hauser 1993; Orme 2006).

In engineering, the product attribute elicitation literature is closest to the goals of our paper, although the focus is primarily on physical attributes rather than more-abstract context-dependent customer needs. Jin, et al. (2015) and Peng, Sun, and Revankar (2012) propose automated methods to identify engineering characteristics. These papers focus on particular parts of speech or manually identified word combinations and use clustering techniques or LDA to identify product attributes and levels to be considered in product development. Kuehl (2016) proposes identifying intangible attributes together with physical product attributes with supervised classification techniques. Our methods augment the literatures in both marketing and engineering by focusing on the more-context-dependent, deeper-semantic nature of customer needs.

2.3. Deep Learning for Natural Language Processing

We draw on two literatures from natural language processing (NLP): convolutional neural networks (CNNs) and dense word and sentence representations. A CNN is a supervised prediction technique which is particularly suited to computer vision and natural language processing tasks. A CNN often contains multiple layers which transform numerical representations of sentences to create input for a final logit-based layer, which makes the final classification. CNNs demonstrate state-of-the-art performance with minimum tuning in such problems as relation extraction (Nguyen and Grishman

2015), named entity recognition (Chiu and Nichols 2016), and sentiment analysis (dos Santos and Gatti 2014). We demonstrate that, on our data, CNNs do at least as well as a support-vector machine (SVM), a multichannel CNN (Kim 2014), and a Recurrent Neural Network with Long Short-Term Memory cells (LSTM; Hochreiter and Schmidhuber 1997).

Dense word and sentence embeddings are real-valued vector mappings (typically 20-300 dimensions), which are trained such that vectors for similar words (or sentences) are close in the vector space. The theory of dense embeddings is based on the Distributional Hypothesis, which states that words that appear in a similar context share semantic meaning (Harris 1954). High-quality word and sentence embeddings can be used as an input for downstream NLP applications and models (Lample, et al. 2016; Kim 2014). Somewhat unexpectedly, high-quality word embeddings capture not only semantic similarity, but also semantic relationships (Mikolov, et al. 2013b). Using the convention of bold type for vectors, then if $\boldsymbol{v}(\text{'word'})$ is the word embedding for 'word,' Mikolov et al. (2013b) demonstrate that word embeddings trained on the Google News Corpus have the following properties:

$$\boldsymbol{v}(\text{king}) - \boldsymbol{v}(\text{man}) + \boldsymbol{v}(\text{woman}) \approx \boldsymbol{v}(\text{queen})$$

$$\boldsymbol{v}(\text{walking}) - \boldsymbol{v}(\text{swimming}) + \boldsymbol{v}(\text{swam}) \approx \boldsymbol{v}(\text{walked})$$

$$\boldsymbol{v}(\text{Paris}) - \boldsymbol{v}(\text{France}) + \boldsymbol{v}(\text{Italy}) \approx \boldsymbol{v}(\text{Rome})$$

We train word embeddings using a large unlabeled corpus of online reviews. We then apply the trained word embeddings (1) to enhance the performance of the CNN and (2) to avoid repetitiveness among the sentences selected for manual review.

3. A Proposed Machine Learning Hybrid Method to Identify Customer Needs

We propose a method that uses machine learning to screen UGC for sentences rich in a diverse set of context-dependent customer needs. Identified sentences are then reviewed by professional analysts to formulate customer needs. Machine-human hybrids have proven effective in a broad set of

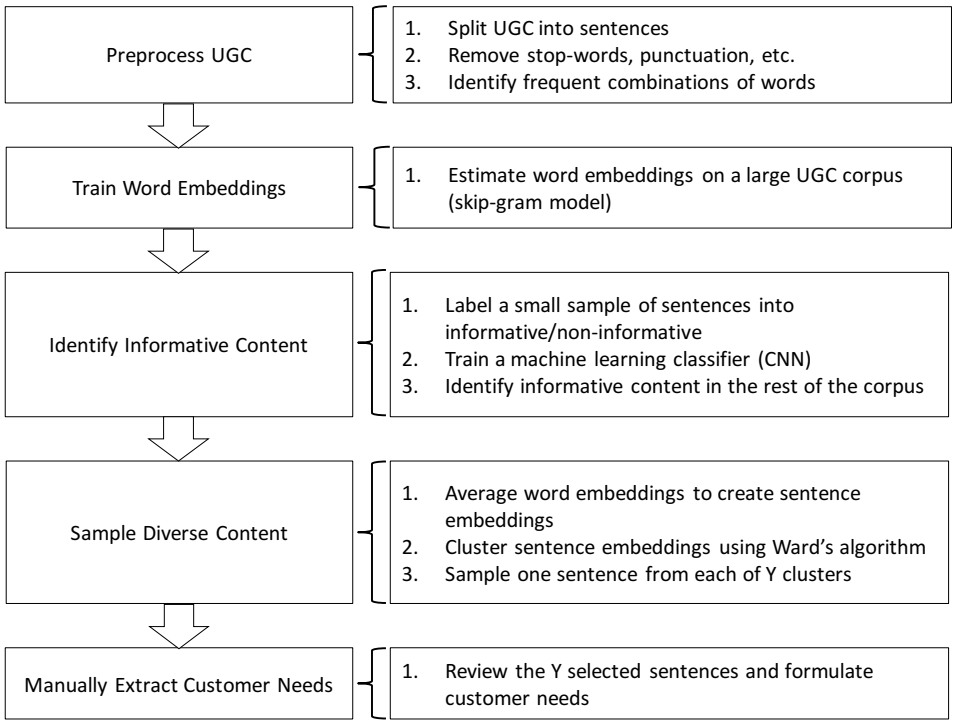
applications. For example, Qian, et al. (2001) combine machine learning and human judgment to locate research when authors' names are ambiguous (e.g., there are 117 authors with the name Lei Zhang). Supervised learning identifies clusters of similar publications and human readers associate authors with the clusters. The resulting hybrid is more accurate than machine learning alone and more efficient than human classification. Colson (2016) describes Stitch Fix's machine-human hybrid in which machine learning helps create a short list of apparel from vast catalogues, then human curators make the final recommendations to consumers.

Figure 1 summarizes our approach. The proposed method consists of five stages:

1. **Preprocess UGC**. We harvest readily available UGC from either public sources or propriety company databases. We split UGC into sentences, eliminate stop-words, numbers, and punctuation, and concatenate frequent combinations of words.
2. **Train Word Embeddings**. We train word embeddings using a skip-gram model (§3.2) on preprocessed UGC sentences, and use word embeddings as an input in the following stages.
3. **Identify Informative Content**. We label a small set of sentences into informative/non-informative, and then train and apply a CNN to filter out non-informative sentences from the rest of the corpus. Without the CNN, human readers would sample content randomly and likely review many uninformative sentences.
4. **Sample Diverse Content**. We cluster sentence embeddings and sample sentences from different clusters to select a set of sentences likely to represent diverse customer needs. This step is designed to identify customer needs that are different from one another so that (1) the process is more efficient and (2) hard-to-identify customer needs are less likely to be missed.
5. **Manually Extract Customer Needs**. Professional analysts review the diverse, informative sentences to identify customer needs. The customer needs are then used to identify new opportunities for product development.

Figure A1 in the Appendix illustrates each of the four steps with an example drawn for one product review. Our architecture achieves the same goals as voice-of-the-customer approaches in industry (§2.1). The preprocessed UGC replaces experiential interviews, the automated sampling of informative sentences is analogous to manual highlighting of informative content, and the clustering of word embeddings is analogous to manual winnowing to identify as many distinct customer needs as feasible. Methods to identify a hierarchical structure of customer needs and/or methods to measure the tradeoffs (preferences) among customer needs, if required, can be applied equally well to customer needs generated from UGC or from experiential interviews.

Figure 1 System Architecture for Identifying Customer Needs from UGC



3.1. Stage 1: Preprocessing Raw UGC

Prior experience in the manual review of UGC by professional analysts suggests that sentences are most likely to contain customer needs and are a natural unit by which analysts process experiential

interviews and UGC. We preprocess raw UGC to transform the UGC corpus into a set of sentences using an unsupervised sentence tokenizer from the natural language toolkit (Kiss and Strunk 2006). We automatically eliminate stop-words (e.g., 'the' and 'and') and non-alphanumeric symbols (e.g., question marks and apostrophes), and transform numbers into number signs and letters to lower case.

We join words that appear frequently together with the '_' character. For example, in oral care, the bigram 'Oral B' is treated as a combined word pair, 'oral_b.' We join words 'a' and 'b' into a single phrase if they appear together relatively often in the corpus. The specific criterion is:

$$\frac{count(a,b) - \delta}{count(a) \cdot count(b)} \cdot M > \tau$$

where M is the total vocabulary size. The tuning parameter, δ, prevents concatenating very infrequent words, and the tuning parameter, τ, is balanced so that the number of bigrams is not too few or too many for the corpus. Both parameters are set by judgment. For our initial test, we set $(\delta, \tau) = (5,10)$. We drop sentences that are less than four words or longer than fourteen words after preprocessing. The bounds are selected to drop approximately 10% of the shortest and 10% of the longest sentences. (Long sentences are usually an artifact of missing punctuation. In our case, the dropped sentences were subsequently verified to contain no customer needs that were not otherwise identified.)

As is typical in machine learning systems, our model has multiple tuning parameters. We indicate which are set by judgment and which are set by cross-validation. When we set tuning parameters by judgment, we draw on the literature for suggestions and we choose parameters likely to work in many categories. When there is sufficient data, these parameters can also be set by cross-validation.

3.2. Stage 2: Training Word Embeddings with a Skip-Gram Model

Word embeddings are the mappings of words onto a numerical vector space, which incorporate contextual information about words and serve as an input to Stages 3 and 4 (Baroni, Dinu, and Kruszewski, 2014). To account for product-category and UGC-source-specific words, we train our word

embeddings on the preprocessed UGC corpus using a skip-gram model (Mikolov, et al. 2013a). The skip-gram model is a predictive model which maximizes the average log-likelihood of words appearing together in a sequence of c words. Specifically, if I is the number of words in the corpus, V is the set of all feasible words in the vocabulary, and $\boldsymbol{v}_i$ are *d*-dimensional real-vector word embeddings, we select the $\boldsymbol{v}_i$ to maximize:

$$\frac{1}{I}\sum_{i=1}^{I}\sum_{\substack{-c\leq j\leq c\\ j\neq 0}} log\, p\left(word_{i+j}\middle|word_i\right)$$

$$p\left(word_j\middle|word_i\right)=\frac{exp\left(\boldsymbol{v}_j\boldsymbol{v}'_i\right)}{\sum_{k=1}^{|V|}exp\left(\boldsymbol{v}_k\boldsymbol{v}'_i\right)}$$

To make calculations feasible, we use ten-word negative sampling to approximate the denominator in the conditional probability function. (See Mikolov, et al. 2013b for details on negative sampling.) For our application, we use $d = 20$ and $c = 5$.

The trained word embeddings in our application capture semantic meaning in oral care. For example, the three words closest to 'toothbrush' are 'pulsonic', 'sonicare' and 'tb', with the last being a commonly-used abbreviation for toothbrush. Similarly, variations in spelling such as 'recommend', 'would_recommend', 'highly_recommend', 'reccommend', and 'recommed' are close in the vector space.

3.3. Stage 3: Identifying Informative Sentences with a Convolutional Neural Network (CNN)

Depending on the corpus, UGC can contain substantial amounts of content that does not represent customer needs. Such non-informative content includes evaluations, complaints, and non-informative lists of features such as "This product can be found at CVS." or "It really does come down to personal preference." Informative content might include: "This product can make your teeth super-sensitive." or "The product is too heavy and it is difficult to clean." Machine learning improves the efficiency of manual review by eliminating non-informative content. For example, suppose that only

40% of the sentences are informative in the corpus, but after machine learning screening, 80% are informative. If analysts are limited in the number of sentences they can review (professional services costs constraint), they can identify customer needs much more efficiently by focusing on a sample of Y prescreened sentences rich in informative content than on Y randomly selected sentences. With higher concentration of informative sentences, low-frequency customer needs are more likely be found in the Y prescreened sentences than in the Y randomly selected sentences.

To train the machine learning classifier, some sentences must be labeled by professional analysts as informative ($y = 1$) or non-informative ($y = 0$). There are efficiency gains because such labeling requires substantially lower professional services costs than formulating customer needs from informative sentences. Moreover, in a small-sample study, we found that Amazon Mechanical Turk (AMT) has a potential to identify informative sentences for training data at a cost below that of using professional analysts. With further development to reduce costs and enhance accuracy, AMT might be a viable source of training data.

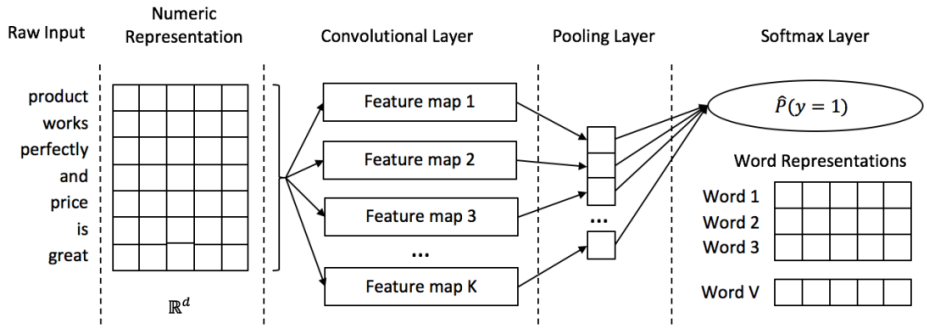
We use a convolutional neural network (CNN) to identify informative sentences. A major advantage of the CNN is that CNNs quantify raw input automatically and endogenously based on the training data. CNNs apply a combination of convolutional and pooling layers to word representations to generate "features," which are then used to make a prediction. ("Features" in the CNN should not be confused with product features.) In contrast, traditional machine-learning classification techniques, such as a support-vector machine or decision trees, depend critically on handcrafted features, which are the transformations of the raw data designed by researchers to improve prediction in a particular application. High-quality features require substantial human effort for each application. CNNs have been proven to provide comparable performance to traditional handcrafted-feature methods, but without substantial application-specific human effort (Kim 2014; Lei, Barzilay, and Jaakkola 2015).

A typical CNN consists of multiple layers. Each layer has hyperparameters, such as the number of

filters and the size of the filters. We custom select these hyperparameters, and the number and type of layers, by cross-validation. Each layer also has numerical parameters, such as the parameters of the filters used in the convolutional layers. These parameters are calibrated during training. We train the CNN by selecting the parameter values that maximize the CNN's ability to label sentences as informative vs. non-informative.

Figure 2 illustrates the architecture of the CNN in our application. We stack a convolutional layer, a pooling layer, and a softmax layer. This specification modifies Kim's (2014) architecture for sentence classification task to account for the amount of training data available in customer-need applications.

Figure 2 Convolutional Neural Network Architecture for Sentence Classification



3.3.1. Numerical Representations of Words for Use in the CNN

For every word in the text corpus, the CNN stores a numerical representation of the word. Numerical representations of words are the real vector parameters of the model which are calibrated to improve prediction. To facilitate training of the CNN, we initialize representations with word embeddings from Stage 2. However, we allow the CNN to update the numerical representations to enhance predictive ability (Lample, et al. 2016). In our application, this flexibility enhances out-of-sample accuracy of prediction.

The CNN quantifies sentences by concatenating word embeddings. If $\boldsymbol{v}_i$ is the word embedding for the i^{th} word in the sentence, then the sentence is represented by a vector $\boldsymbol{v}$

$$\boldsymbol{v} = [\boldsymbol{v}_1, \dots, \boldsymbol{v}_n] \in \mathbb{R}^{d \times n}$$

where n is the number of words in the sentence and $d = 20$ is the dimensionality of the word embeddings.

3.3.2. Convolutional Layer

Convolutional layers create multiple feature maps by applying convolutional operations with varying filters to the sentence representation. A filter is a real-valued vector, $\boldsymbol{w}_t \in \mathbb{R}^{d \times h_t}$, where h_t is a size of the filter. Filters are applied to different parts of the vector $\boldsymbol{v}$ to create feature maps ($\boldsymbol{c}^t$):

$$\boldsymbol{c}^t = [c_1^t, \dots, c_{n-h_t+1}^t]$$

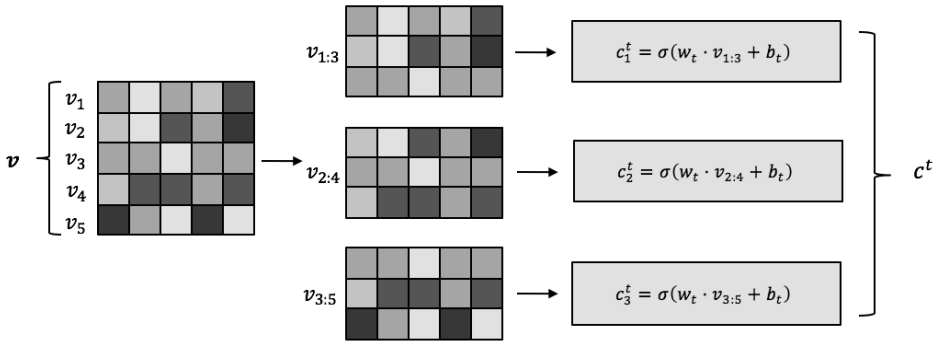
$$c_i^t = \sigma\left(\boldsymbol{w}_t \cdot \boldsymbol{v}_{i:i+h_t-1} + b_t\right)$$

where t indexes the feature maps, $\sigma(\cdot)$ is a non-linear activation function where $\sigma(x) = \max(0, x)$, $b_t \in \mathbb{R}$ is an intercept, and $\boldsymbol{v}_{i:i+h_t-1}$ is a concatenation of representations of words i to $i + h_t - 1$ in the sentence:

$$\boldsymbol{v}_{i:i+h_t-1} = [\boldsymbol{v}_i, \dots, \boldsymbol{v}_{i+h_t-1}]$$

We consider filters of the size $h_t \in \{3, 4, 5\}$, and use three filters of each size. The number of filters and their size are selected to maximize prediction on the validation set. The numerical values for filters, $\boldsymbol{w}_t$, and intercepts, b_t, are calibrated when the CNN is trained. As an illustration, Figure 3 shows how a feature map is generated with a filter of size, $h_t = 3$. On the left is a sentence, $\boldsymbol{v}$, consisting of five words. Each word is a 20-dimenional vector (only 5 dimensions are shown). Sentence $\boldsymbol{v}$ is split into triplets of words as shown in the middle. Representations of word triplets are then transformed to the real-valued c_i^t's in the next column. The t^{th} feature map, $\boldsymbol{c}^t$, is the vector of these values. Processing sentences in this way allows the CNN to interpret words that are next to one another in a sentence together.

Figure 3 Example Feature Map, c^t Generated with a Filter, w_t, of Size $h_t = 3$.



3.3.3. Pooling Layer

The pooling layer transforms feature maps into shorter vectors. The role of the pooling layer is to reduce dimensionality of the output of the convolutional layer to be used in the next layer. Pooling to the k^{th} largest features or simply using the largest feature has proven effective in NLP applications (Collobert, et al. 2011). We selected $k = 1$ with cross-validation. The output of the pooling layer is a vector, $\boldsymbol{z}$, that summarizes the results of pooling operators applied to the feature maps:

$$z_t = max[c_1^t, \dots, c_{n-h_t+1}^t]$$

$$\boldsymbol{z} = [z_1, z_2, \dots, z_9]$$

The vector, $\boldsymbol{z} \in \mathbb{R}^9$, is now an efficient numerical representation of the sentence and can be used to classify the sentence as either informative or not informative. The nine elements in $\boldsymbol{z}$ represent filter sizes (3) times the number of filters (3) within each size.

3.3.4. Softmax Layer

The final layer of the CNN is called the softmax layer. The softmax layer transforms the output of the pooling layers, $\boldsymbol{z}$, into a probabilistic prediction of whether the sentence is informative or not informative. Marketing researchers will recognize the softmax layer as a binary logit model which uses the $\boldsymbol{z}$ vector as explanatory variables. The estimate of the probability that the sentence is informative,

$P(y = 1|\boldsymbol{z})$, is given by:

$$\hat{P}(y = 1|\boldsymbol{z}) = \frac{1}{1 + e^{-\boldsymbol{\theta z}}}$$

The parameters of the logit model, $\boldsymbol{\theta}$, are determined when the CNN is trained. In our application, we declare a sentence to be informative if $P(y = 1|\boldsymbol{z}) > 0.5$, although other criteria could be used and tuned to a target tradeoff.

3.3.5. Calibration of the Parameters of the CNN

For our application, we calibrate the nine filters, $\boldsymbol{w}_t \in \mathbb{R}^{d \times h_t}$, and the nine intercepts, b_t, in the convolutional layer, and the vector $\boldsymbol{\theta}$ in the softmax layer. In addition, we fine tune the word embeddings, $\boldsymbol{v_i}$, to enhance the ability of the CNN's predictions (e.g., Kim 2014). We calibrate all parameters simultaneously by minimizing the cross-entropy error on the training set of professionally labeled sentences ($\boldsymbol{w}$ is a concatenation of the $\boldsymbol{w}_t$'s):

$$\widehat{\boldsymbol{w}}, \widehat{\boldsymbol{b}}, \widehat{\boldsymbol{\theta}}, \widehat{\boldsymbol{v}} = argmax_{\boldsymbol{w},\boldsymbol{b},\boldsymbol{\theta},\boldsymbol{v}} L(\boldsymbol{w}, \boldsymbol{b}, \boldsymbol{\theta}, \boldsymbol{v})$$

$$L(\boldsymbol{w}, \boldsymbol{b}, \boldsymbol{\theta}, \boldsymbol{v}) = -\frac{1}{N}\sum_{n=1}^{N}[\gamma y_n \, log \, \hat{y}_n + (1 - y_n) \, log(1 - \hat{y}_n)]$$

N is the size of the training set, y_n are the manually assigned labels, and $\hat{y}_n$ are the predictions of the CNN. The parameter, γ, enables the user to weight false negatives more (or less), than false positives. We initially set $\gamma = 1$ so that identifying informative sentences and eliminating non-informative sentences are weighed equally, but we also examine asymmetric costs ($\gamma > 1$) in which we place more weight on identifying informative sentences than eliminating uninformative sentences.

We solved the optimization problem iteratively with the RMSProp optimizer on mini-batches of size 32 and a drop rate of 0.3. Optimization terminated when the cross-entropy error on the validation set did not decrease over five consecutive iterations. See Tieleman and Hinton (2012) for details and definitions of terms such as "drop rate."

3.3.6. Evaluating the Performance of the CNN

We evaluate the quality of the CNN classifier using an F_1 score (Wilson, Wiebe, and Hoffmann 2005):

$$F_1 = \frac{precision \cdot recall}{\frac{1}{2}(precision + recall)}$$

where precision is the share of informative sentences among the sentences identified as informative and recall is the share of informative sentences correctly identified by the classifier. Accuracy, when reported, is the percent of classifications that were correct.

3.4. Stage 4: Clustering Sentence Embeddings and Sampling to Reduce Redundancy

UGC is repetitive and often focuses on a small set of customer needs. Consider the following sentences:

- "When I am done, my teeth do feel `squeaky clean.'"
- "Every time I use the product, my teeth and gums feel professionally cleaned."
- "I am still shocked at how clean my teeth feel."

These three sentences are different articulations of a customer need that could be summarized as "My mouth feels clean." Manual review of such repetitive content is inefficient. Moreover, repetitiveness makes the manual review onerous and boring for professional analysts, causing analysts to miss excitement customer needs that are mentioned rarely. If the analysts miss excitement customer needs, then the firm misses valuable new product opportunities and/or strategic positionings. To avoid repetitiveness, we seek to "span the set" of customer needs. We construct sentence embeddings which encode semantic relationships between sentences, and use sentence embeddings to reduce redundancy by sampling content for manual review from maximally different parts of the space of sentence embeddings.

Researchers often create sentence embeddings by taking a simple average of word embeddings corresponding to the words in the sentence (Iyyer et al., 2015), explicitly modeling semantic and

syntactic structure of the sentences with neural methods (Tai, Socher and Manning 2015), or training sentence embeddings together with word embeddings (Le and Mikolov, 2014). Because averaging demonstrates similar performance to other methods and is both scalable and transferable (Iyyer et al., 2015), we use averaging in our application.

Being the average of word embeddings, sentence embeddings represent semantic similarity among sentences. For example, the three similar sentences mentioned above have sentence embeddings that are reasonably close to one another in the sentence-embedding vector space. Using this property, we group sentences into clusters. We choose Ward's hierarchical clustering method because it is commonly used in VOC studies (Griffin and Hauser 1993), and other areas of marketing research (Dolnicar 2003). To identify *Y* sentences for professional analysts to review, we sample one sentence randomly from each of *Y* clusters. If the clustering worked perfectly, sentences within each of the Y clusters would articulate the same customer need, and each of the Y clusters would produce a sentence that an analyst would recognize as a distinct customer need. In real data, redundancy remains, but, hopefully less redundancy than that which would be present in Y randomly sampled sentences.

3.5. Stage 5: Manually Extracting Customer Needs

To achieve high relevancy in formulating abstract context-dependent customer needs, the final extraction of customer needs is best done by trained analysts. We evaluate in §5 whether manual extraction becomes more efficient using informative, diverse sentences identified with the CNN and sentence-embedding clusters.

4. Evaluation of UGC's Potential in the Oral-Care Product Category

We use empirical data to examine two questions. (§4) Does UGC contain sufficient raw material from which to identify a broad set of customer needs? And (§5) Do each of the machine-learning steps enhance efficiency? We address both questions with a custom dataset in the oral-care category. We selected oral care because oral-care customer needs are sufficiently varied, but not so numerous as to

overcomplicate comparisons. As a proof-of-concept test, our analyses establish a key example. We discuss applications in other categories in §6.

4.1. Baseline Comparison: Experiential Interviews in Oral Care

We obtained a detailed set of customer needs from an oral-care voice-of-the-customer (VOC) analysis that was undertaken by a professional market research consulting firm. The firm has almost thirty years of VOC experience spanning hundreds of successful product-development applications across a wide-variety of industries. The oral-care VOC provided valuable insights to the client and led to successful new products. The VOC was based on standard methods: experiential interviews, with transcripts highlighted by experienced analysts aided by the firm's proprietary software. After winnowing, customer needs were structured by a customer-based affinity group. The output is 86 customer needs structured into six primary and 22 secondary need groups. An appendix lists the primary and secondary need groups and provides an example of a tertiary need from each secondary-need group. Examples of customer needs include: "Oral care products that do not create any odd sensations in my mouth while using them (e.g. tingling, burning, etc.)" or "My teeth feel smooth when I glide my tongue over them." Such customer needs are more than their component words; they describe a desired outcome in the language that the customer uses to describe the desired outcome.

The underlying experiential interview transcripts were based on a representative sample of oral care customers and were not subject to self-selection biases. If UGC can identify a set of customer needs that is comparable to the benchmark, then we have initial evidence in at least one product category that UGC self-selection does not undermine the basic goals of finding a reasonably complete set of customer needs.

Professional analysts estimate that the professional-service costs necessary to review, highlight, and winnow customer needs from experiential-interview transcripts is slightly more than the professional services costs required to review 8,000 UGC sentences to identify customer needs. The

professional services costs required to review, highlight, and winnow customer needs is about 40%-55% of the professional services costs required to schedule and interview customers. At this rate, professional analysts could review approximately 22,000 to 28,000 UGC sentences using the methods and professional services costs involved in a typical VOC study.

4.2. Fully-Coded UGC Data from the Oral-Care Category

To compare UGC to experiential interviews and evaluate a proposed machine learning method, we needed a fully-coded sample of a UGC corpus. In particular, we needed to know and classify every customer need in every sentence in the UGC sample. We received in-kind support from professional analysts to generate a custom dataset to evaluate UGC and the machine-learning efficiencies. The in-kind support was approximately that which the firm would have allocated to a typical VOC study—a substantial time-and-cost commitment from the firm.

From the 115,099 oral-care reviews on Amazon spanning the period from 1996 to 2014, we randomly sampled 12,000 sentences split into an initial set of 8,000 sentences and a second set of 4,000 sentences (McAuley, et. al. 2015). To maintain a common level of training and experience for reviewing UGC and experiential interview transcripts, the sentences were reviewed by a group of three experienced analysts from the same firm that provided the interview-based VOC. These analysts were not involved in the initial interview-based VOC. Using a team of analysts is recommended by Griffin and Hauser (1993, p. 11).

We chose 8,000 sentences for our primary evaluation because the professional services costs to review 8,000 sentences are comparable, albeit slightly less than, the professional services costs to review a typical set of experiential-interview transcripts. For these sentences, the analysts fully coded every sentence to determine whether it contained a customer need and, if so, whether the customer need could be mapped to a customer need identified by the VOC, or whether the customer need was a

newly identified customer need. Matching needs from the UGC to the interview-based needs is fuzzy. For example, the three sentences that were mapped to "My mouth feels clean." were judged by the analysts to articulate that customer need even though the wording was not exact (§3.4).

In addition to the fully-coded 8,000 sentences, we were able to persuade the analysts to examine an additional 4,000 sentences to focus on any customer needs that were identified by the traditional VOC, but not identified from the UGC. This second dataset enables us to address whether there exist customer needs that are not in UGC per se, or whether the customer needs are sufficiently rare that more than 8,000 sentences are required to identify them. Finally, to assess coding reliability, we asked another analyst, blind to the prior coding, to recode 200 sentences using two different task descriptions.

4.3. Descriptive Statistics and Comparisons

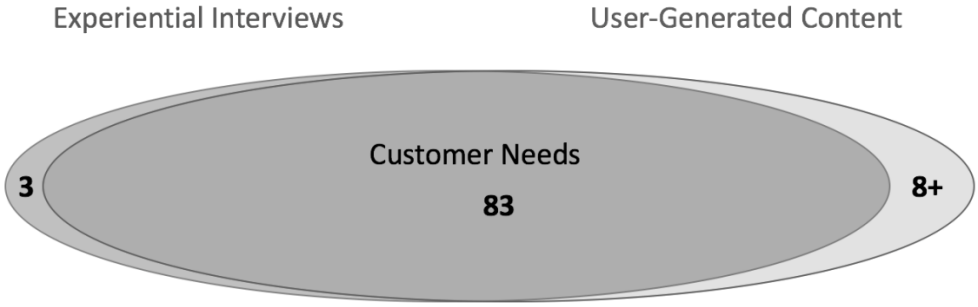
Using Amazon reviews, the three human coders determined that 52% of the 8,000 sentences contained at least one customer need and 9.2% of the sentences contained two or more customer needs. However, the corpus was highly repetitive; 10% of the most frequent customer needs were articulated in 54% of the informative sentences. On the other hand, 17 customer needs were articulated no more than 5 times in the corpus of 8,000 sentences.

We consider first the 8,000 sentences—in this scenario analysts allocate at most as much time coding UGC as they would have allocated to review experiential interview transcripts. This section addresses the potential of the UGC corpus, hence, for this section, we do not yet exploit machine-learning efficiencies. From the 8,000 sentences, analysts identified 74 of the 86 tertiary experiential-interview-based customer needs, but also identified an additional 8 needs.

We now consider the set of 4,000 sentences as a supplement to the fully-coded 8,000 sentences—in this scenario analysts still allocate substantially less time than they would to interview customers and review transcripts. From the second set of 4,000 sentences, the analysts identified 9 of 12 missing customer needs. With 12,000 sentences, that brings the total to 83 of the 86 experiential-

interview-based customer needs and 91 of the 94 total needs (97%). In the second set of 4,000 sentences, the analysts did not try to identify any customer needs other than the 12 missing needs. Had we had the resources to do so, we would likely have increased the number of UGC-based incremental customer needs. Overall, analysts identified 91 customer needs from UGC and 86 customer needs from experiential interviews. These results are summarized in Figure 4. At least in oral care, analyzing UGC has the potential to identify at least as many, possibly more, customer needs at a lower overall cost of professional services, even without machine-learning efficiencies. Furthermore, because the experiential-interview benchmark is drawn from a representative sample of consumers, the potential for self-selection in UGC oral-care postings does not seem to impair the breadth of customer needs contained in UGC sentences. We cannot rule out self-selection issues for other product categories. When self-selection is feared, we recommend analyses that build on multiple sources such as the methods developed by Schweidel and Moe (2014).

Figure 4. Comparison of Customer Needs Obtained from Experiential Interviews with Customer Needs Obtained from an Exhaustive Review of a UGC Sample



Whether or not customer needs are based on interviews or UGC, the final identification of customer needs is based on imperfect human judgment. We asked an analyst, blind to the prior coding, to evaluate 200 sentences using two different approaches. For the first evaluation, the analyst (1) explicitly formulated customer needs from each sentence, (2) winnowed the customer needs to remove duplicates, (3) matched the identified customer needs to the interview-based hierarchy, (4) added new

needs to the hierarchy if necessary, and (5) mapped each of the 200 sentences to the customer needs. For the second evaluation, the analyst followed the same procedures that produced Figure 4. These two evaluations were conducted two weeks apart.

We compare the codes produced by the additional analyst versus the codes produced by the three analysts. Inter-task accuracy (first vs. second evaluation by the new analyst) was 80%, which is better than the inter-coder accuracy (new analyst vs. previous analysts) of 70%. The additional analyst identified 71.4% of the customer needs that were previously identified by the three analysts. The additional analyst's hit rate compares favorably to Griffin and Hauser (1993, p. 8) who report that their individual analysts identified 45-68% of the needs, where the universe was all customer needs identified by the seven analysts who coded their data. This evidence suggests that Figure 4 is a conservative estimate of the potential of the UGC as a source of customer needs.

4.4. Prioritization of Customer Needs

To address whether the eight incremental UGC customer needs and/or the three incremental experiential-interview customer needs were important, we conducted a prioritization survey. We randomly selected 197 customers from a professional panel (PureSpectrum), screened for interest in oral care, and asked customers to rate the importance of each tertiary customer need on a 0-to-100 scale. Customers also rated whether they felt that their current oral-care products performed well on these customer needs on a 0-to-10 scale. Such measures are used commonly in VOC studies and have proven to provide valuable insights for product development. (Review citations in §2.1.)

Table 1 summarizes the survey results. On average, the customer needs identified in both the interviews and UGC are the most important customer needs. Those that are unique to UGC or unique to experiential interviews are of lower importance and performance. We gain further insight by categorizing the customer needs into quadrants via median splits. High-importance-low-performance customer needs are almost perfectly identified by both data sources. Such customer needs provide insight for product improvement.

Table 1. Importance and Performance Scores for Customer Needs Identified from UGC and from Experiential Interviews (Imp = Importance, Per = Performance)

Source of Customer Need	Count	Average Imp	Average Per	Quadrant (median splits)			
				High Imp High Per	High Imp Low Per	Low Imp High Per	Low Imp Low Per
Interviews ∩ 8,000 UGC [a]	74	65.5	7.85	29	11	11	23
Interviews ∩ 4,000 UGC [b]	9	63.9	7.97	6	0	0	3
UGC only	8	50.3	7.12	0	0	1	7
Interviews only	3	52.8	7.47	0	1	0	2

[a] Based on the first 8,000 UGC sentences that were fully-coded
[b] Based on the second 4,000 UGC sentences that were coded to test for interview-identified customer needs

Focusing on highly important customer needs is tempting, but we cannot ignore low-importance customer needs. In new product development, identifying hidden opportunities for innovation often leads to successful new products. Customers often evaluate needs below the medians on importance and performance when they anticipate that no current product fulfills those customer needs (e.g., Corrigan 2013). If the new product satisfies the customer need, customers reconsider its importance, and the innovator gains a valuable strategic advantage. Thus, we define low-importance–low-performance customer needs as hidden opportunities. By this criterion, the UGC-unique customer needs identify 20% of the hidden opportunities and the interview-unique needs identify 8% of the hidden opportunities. For example, two UGC-unique hidden opportunities are “An oral-care product that does not affect my sense of taste,” and “An oral care product that is quiet.” An interview-based hidden opportunity is “Oral care tools that can easily be used by left-handed people.”

In summary, UGC identifies the vast majority of customer needs (97%), opportunities for product improvement (92%), and hidden opportunities (92%). UGC-unique needs identify at least seven hidden opportunities while interview-only needs identify two hidden opportunities. We have not been able to identify any qualitative insights from the comparison of the customer needs between two sources suggesting that there is nothing systematic that is missing in the UGC. Table A2 in the appendix lists all eleven customer needs that are unique to either UGC or experiential interviews.

4.5. Tests of Non-Machine-Learning Prescreening of UGC Data

4.5.1. Helpfulness Ratings

Reviews are often rated by other users based on their helpfulness. In our data, 41% of the reviews are rated on helpfulness. Because helpful reviews tend to be longer, this corresponds to 52% of the sentences. We examine whether or not helpful reviews are particularly informative using the 8,000 fully-coded sentences. Fifty-four percent (54%) of non-rated reviews contain a customer need compared to 51% of rated reviews, 48% of reviews with rating above the median, and 48% of reviews with rating in the upper quartile. Helpfulness is not correlated with informativeness ($\rho = -0.01, p = 0.56$). When we examine individual sentences, we see that a sentence can be rated as helpful, but not necessarily describe a customer need (be informative). Two examples of helpful but uninformative sentences are: "I finally got this toothbrush after I have seen a lot of people use them." or "I'm so happy I'm just about beside myself with it!" Overall, helpfulness does not seem to imply informativeness.

4.5.2 Number of Times a Customer Need is Mentioned

For experiential interviews, the frequency with which a customer need is mentioned is not correlated with the measured importance of the customer need (Griffin and Hauser 1993, p. 13). However, in experiential interviews, the interviewer probes explicitly for new customer needs. The lack of correlation may be due to endogeneity in the interviewing process. In UGC, customers decide whether or not to post, hence frequency might be an indicator of the importance of a customer need. For oral-care, frequency of mention is marginally significantly correlated with importance ($\rho = 0.21, p = 0.06$). Frequency of mention is not significantly correlated with performance ($\rho = 0.09, p = 0.44$). However, if we were to focus only on customer needs with frequency above the median of 7.9 mentions, we would miss 29% of the high-importance customer needs, 44% of the high-performance customer needs, and 72% of the hidden opportunities. Thus, while frequency is related to importance, it does not enhance the efficiency with which customer needs or new-product ideas can be identified.

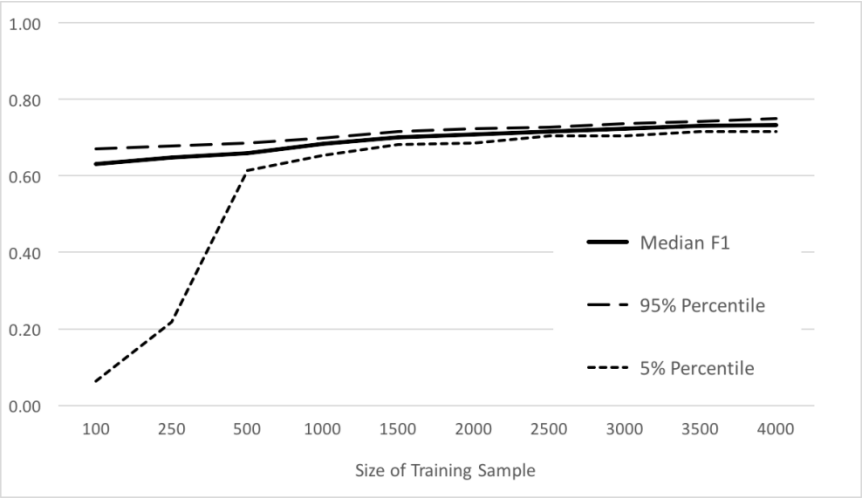
5. Oral Care: Evaluation of Machine-Human Hybrid Method

5.1. CNN to Eliminate Non-Informative Sentences

There is a tradeoff to be made when training a CNN. With a larger training sample, the CNN is better at identifying informative content, but there is an opportunity cost to using analysts to classify informative sentences. Fortunately, labeling sentences as informative or not is faster and easier than identifying abstract context-dependent customer needs from sentences. The ratio of time spent on identifying informative sentences vs. formulating customer needs is approximately 20%. Furthermore, as described earlier, exploratory research suggests that Amazon Mechanical Turk might be used as a lower-cost way to obtain a training sample.

Figure 5 plots the F_1-score of the CNN as a function of the size of the training sample. We conduct 100 iterations where we randomly draw a training set, train the CNN with the architecture described in §3.3, and measure performance on the test set. Figure 5 suggests that performance of the CNN stabilizes after 500 training sentences, with some slight improvement after 500 training sentences. We plot precision and recall as a function of the size of the training sample in the appendix, Figure A2.

Figure 5. F_1 score as a Function of the Size of the Training Sample



To test whether we might improve performance using alternative natural-language processing methods, we train a multichannel CNN (Kim 2014), a support-vector machine, and a recurrent neural

network with long short-term memory cells (LSTM, Hochreiter and Schmidhuber 1997). We also train a CNN with a higher penalty for false positives ($\gamma = 3$) to investigate the effect of asymmetric costs on the performance of the model. The evaluation is based on the 6,700 of 8,000 fully-coded sentences that remain after we eliminated sentences that were too short and too long. From the 6,700 sentences, we randomly select 3,700 sentences to train the methods and 3,000 to act as holdout sentences to test the performance of the alternative methods. We summarize the results in Table 2.

Table 2. Alternative Machine-Learning Methods to Identify Informative Sentences

Method	Precision	Recall	Accuracy	F_1
Convolutional Neural Network (CNN)	74.4%	73.6%	74.2%	74.0%
CNN with Asymmetric Costs ($\gamma = 3$)	65.2%	85.3%	70.0%	74.0%
Recurrent Neural Network-LSTM	72.8%	74.0%	73.2%	73.4%
Multichannel CNN	70.5%	74.9%	71.8%	72.6%
Support Vector Machine	63.7%	67.9%	64.6%	65.7%

Focusing on F_1, the CNN outperforms the other methods, although the other deep-learning methods do reasonably well. Conditioned on a given F_1, we favor methods that miss fewer informative sentences (higher recall, at the expense of a lower precision). Thus, in subsequent analyses, we use the CNN with asymmetric costs.

The deep learning methods achieve accuracies in the range of 70-74%, which is lower than that achieved in some sentence-classification tasks. For example, Kim (2014) reports accuracies in the range of 45-95% across seven datasets and eighteen methods (average 80%). A more-relevant benchmark is the capabilities of the human coders on which the deep-learning models are trained. The deep-learning models achieve higher accuracy identifying informative sentences than the inter-coder accuracy of 70%. The abstract context-dependent nature of the customer needs appears to make identifying informative content more difficult than typical sentence-classification tasks.

To be effective, the CNN should be able to correctly identify both sentences that contain frequently mentioned customer needs and sentences that contain rarely mentioned customer needs.

We conduct iterations to evaluate this property. In each iteration, we randomly split the 6,700 preprocessed sentences into 3,700 training and 3,000 holdout sentences, and train the CNN using the training set. We then compare the needs in the holdout sentences and the needs in the sentences identified by the CNN as informative. On average over iterations, the CNN identified sentences with 100% of the frequently mentioned customer needs, 91% of the rarely mentioned customer needs, and 84% of the customer needs that were new to the holdout data. Because all customer needs were identified in at least one iteration, we expect these percentages to approach 100% if it were feasible to expand the holdout set from 3,000 sentences to a larger number of sentences, such as the 12,000 sentences used in Figure 4.

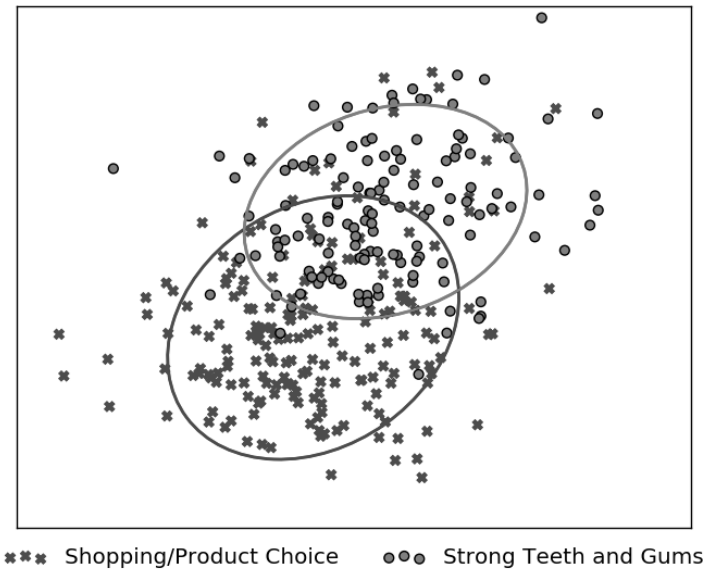
5.2. Clustering Sentence Embeddings to Reduce Redundancy

In Stage 4 of the proposed hybrid approach, we encode informative sentences into a 20-dimensional real-valued vector space (sentence embeddings), group sentence embeddings into Y clusters, and sample one sentence from each cluster. To visualize whether or not sentence embeddings separate the customer needs, we use a principle components analysis to project the 20-dimensional sentence embeddings onto two dimensions. Information is lost when we project from 20 dimensions to two dimensions, but the two-dimensional plot enables us to visualize whether sentence embeddings separate sentences articulating different customer needs. (We use principle components analysis purely as a visualization tool to evaluate Stage 4. The dimensionality reduction is not a part of our approach.)

Figure 6 reports the projection for two primary needs. The axes correspond to the first two principal components. The red dots are the projections of sentence embeddings that were coded (by analysts) as belonging to the primary customer need: "strong teeth and gums." The blue crosses are sentence embeddings that were coded as "shopping/product choice." (Review Table A1 in the appendix.) The ovals represent the smallest ellipses inscribing 90% of the corresponding set. Figure 6

suggests that, while not perfect, the clusters of sentence embeddings achieved separation among primary customer needs and, hence, are likely to reduce redundancy and enable analysts to identify a diverse set of customer needs when they analyze *Y* sentences, each chosen from one of *Y* clusters. Sampling diverse sentences likely increases the probability that low-frequency customer needs are contained in a sample of Y sentences.

Figure 6. Projections of 20-Dimensional Embeddings of Sentences onto Two Dimensions (PCA). Dots and Crosses Indicate Analyst-Coded Primary Customer Needs.



5.3. Gains in Efficiency Due to Machine Learning

We seek to determine whether the proposed combination of machine-learning methods improves efficiency of identifying customer needs from UGC. Efficiency is important because the reduced time and costs enable more firms to use advanced VOC methods to identify new product opportunities. Efficiency is also important because it enhances the probability of identifying low-frequency needs given a constraint on the number of sentences that analysts can process.

In our approach, machine learning helps to identify content for review by professional analysts.

We compare content selection approaches in terms of the expected number of unique customer needs identified in *Y* sentences. The baseline method for selecting sentences for review is current practice—a random draw from the corpus. The second method uses the CNN to identify informative sentences, and then randomly samples informative sentences for review. The third method uses the sentence-embedding-clusters to reduce redundancy among sentences identified as informative by the CNN. For each method, and for each value of *Y*, we (1) randomly split the 6,700 preprocessed sentences, which are neither too short nor too long, into 3,700 training and 3,000 hold-out samples, (2) train the CNN using the training sample, and (3) draw *Y* sentences from the hold-out sample for review. We count the unique needs identified in the *Y* sentences and repeat the process 10,000 times. An upper bound for the number of customer needs identified in the *Y* sentences is the number of customer needs contained in 3,000 hold-out sentences—this is fewer customer needs than are contained in the entire corpus.

From 3,000 sentences in the holdout sample, the largest possible value of *Y* for which we can evaluate the CNN is the number of sentences that the CNN classified as informative. The number of sentences identified by the CNN as informative varies across iterations, and in our experiment the minimum is 1,790 sentences. While it is tempting to consider *Y* in the full range from 0 to 1,790, it would be misleading to do so. At $Y = 1{,}790$, there would be 1,790 clusters—the same number as if we sampled all available informative sentences. To minimize this saturation effect on the oral-care corpus, we consider $Y = \{200, 300, \ldots, 1200\}$ to evaluate efficiency.

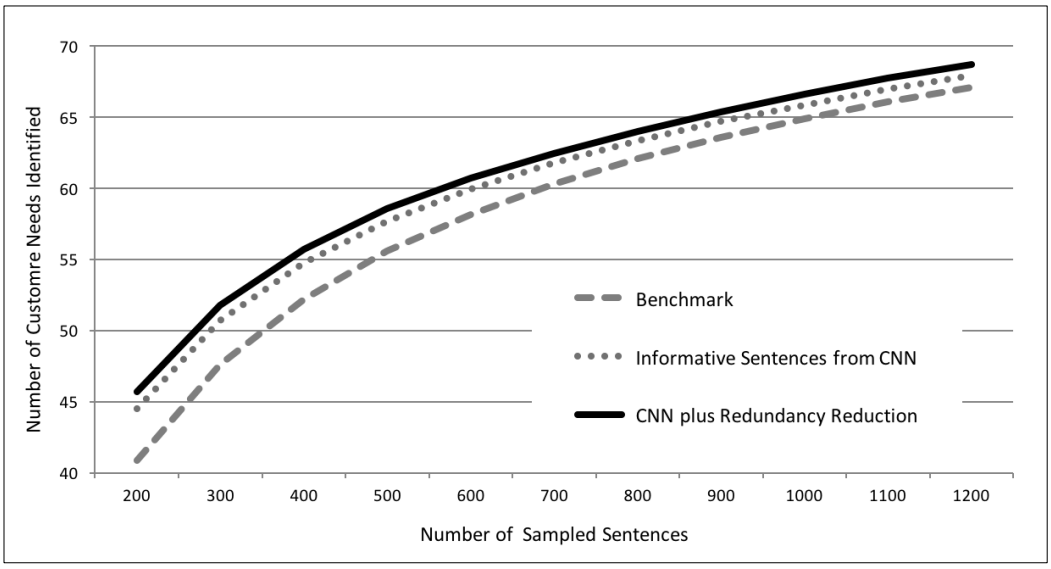
The blue dashed line in Figure 7 reports benchmark performance. The CNN improves efficiency as indicated by the red dotted line. Using the CNN and clustering sentence embeddings increases efficiency further as indicated by the solid black line. Over the range of *Y*, there are gains due to using the CNN to eliminate non-informative sentences and additional gains due to using sentence embeddings to reduce redundancy within the corpus.

We also interpret Figure 7 horizontally. The benchmark requires, on average, 824.3 sentences to

identify 62.4 customer needs. If we prescreen with machine learning to select non-redundant informative sentences, analysts can identify the same number of customer needs from approximately 700 sentences—85% of the sentences required by the baseline. The efficiencies are even greater at 200 sentences (78%) and 400 sentences (79%). At professional billing rates across many categories, this represents substantial time and cost savings and could expand the use of VOC methods in product development. VOC customer-need identification methods has been optimized over almost thirty years of continuous improvement; we expect the machine-learning methods, themselves, to be subject to continuous improvement as they are applied in the field.

Figure A3 in the Appendix provides comparable analyses for lower-frequency and for higher-frequency customer needs using a median split to define frequency. As expected, efficiency gains are greater for lower-frequency customer needs. Figure A4 pushes the comparison further to the least frequent customer needs (lowest 10%) and for those customer needs unique to UGC. As expected, machine-learning efficiencies are even greater for the least-frequent customer needs.

Figure 7. Efficiencies among Various Methods to Select UGC Sentences for Review



5.4. Scalability of the Machine-Learning Methods

The proposed methods scale well. With a training sample size of 1,000-4,000, the CNN typically converges in 20-30 epochs (stochastic gradient descent iterations) and does so in under a minute on a standard MacBook Pro. We use the *fastcluster* package implementation of the Ward's clustering algorithm. The asymptotic worst-case time complexity is $O(N^2)$. In our experiments, clustering of 500,000 informative sentences was completed in under 5 minutes. Once programmed, the methods are relatively easy to apply as indicated by the applications in §6.

5.5. Efficiency Gains in terms of the Professional Services Costs

Professional services costs dominate the expenses in a typical VOC study. Analysts and managers estimate that these costs are allocated about 40% to interviewing customers, 40-55% to identifying and winnowing customer-needs from transcripts, and 5-20% to organizing customer needs into a hierarchy and preparing the final report (§4.1). UGC eliminates the first 40% (§4.2). The proposed machine-learning hybrid approach allows a 15-22% reduction in the time allocated to identifying and winnowing customer needs (§5.3). Applying our methods thus eliminates approximately 46%-52% of the overall professional services costs. These are the substantial savings to the firm and its clients, which can facilitate market research for new product development. Furthermore, machine-learning methods enhance the probability that the lowest-frequency customer needs are identified within a given cost constraint. The lowest-frequency customer needs may be the customer needs that lead to new product success.

6. Additional Applications

The proposed human-machine hybrid methods have been applied three more times for product development. In all cases, the firm identified attractive new product ideas.

Kitchen appliances. During this application, the firm identified 7,000 online product reviews

containing more than 18,000 sentences. The firm wanted to evaluate the efficiency of the machine learning method and devoted sufficient resources to manually review 4,000 sentences. From these, 2,000 sentences were selected randomly from the corpus and 2,000 were selected using machine-learning methods. The two sets of sentences were merged, processed to identify unique customer needs (blind to source), and then re-split by source. Ninety-seven (97) customer needs were identified in the machine-learning corpus and 84 customer needs were identified in the random corpus. While 66 customer needs were in both corpora, more unique customer needs (31) were identified from the machine-learning corpus than from the random corpus (18). The firm found the combined customer needs extremely helpful and will continue to use UGC in the future. In particular, insights obtained from UGC tended to be closer to the customer's moment of experience. Customers post when the experience is fresh in their minds. These posts are more likely to describe malfunctions, difficulties in use or repair, challenges with customer service, or unique surprises. Such customer needs are often among the most useful customer needs for product development.

Skin treatment. This was a pure application in which the firm identified a relevant set of over 11,000 online reviews, used machine-learning to select sentences for review, and then identified customer needs from the selected sentences. The firm used a follow-up quantitative study to assess the importances of the customer needs. Important customer needs, that were previously unmet by any competitor, provided the basis for the firm to optimize its product portfolio with new product introductions. The firm feels that it has enhanced its ability to compete successfully in the market for skin-treatment.

Prepared foods. One of the largest prepared-food firms in North America applied machine learning to analyze a combined corpus of over 500,000 sentences extracted from its social-listening tool and over 10,000 sentences from product reviews. The social listening sources included forums, blogs, micro-blogs, and social media. The product reviews were obtained from five difference sources. In this

application, there were synergies between social-listening UGC and product-review UGC with about two-thirds of the customer needs coming from one or the other source. By combining the two UGC corpora, the firm identified more than thirty categories of customer needs to provide valuable insight for both new product development and marketing communications. As a result, the firm is now applying the machine-human hybrid method to adjacent categories.

7. Discussion, Summary, and Future Research

We addressed two questions: (1) Can UGC be used to identify abstract customer needs? And (2) can machine learning enhance the process? The answer to both questions is yes. UGC is at least a comparable source of customer needs to experiential interviews—likely a better source. The proposed machine-learning architecture successfully eliminates non-informative content and reduces redundancy. In our initial test, machine learning efficiency gains are 15-22%, but such gains are likely to increase with more research. Overall gains of analyzing UGC with our approach over the traditional interview-based VOC are 46-52%.

Answering these questions is significant. Every year thousands of firms rely on voice-of-the-customer analyses to identify new opportunities for product development, to develop strategic positioning strategies, and to select attributes for conjoint analysis. Typically, VOC studies, while valuable, are expensive and time-consuming. Time-to-market savings, such as those made possible with machine learning applied to UGC, are extremely important to product development. In addition, UGC seems to contain customer needs not identified in experiential interviews. New customer needs mean new opportunities for product development and/or new strategic positioning.

While we are enthusiastic about UGC, we recognize that UGC is not a panacea. UGC is readily available for oral care, but UGC might not be available for every product category. For example, consider specialized medical devices or specialized equipment for oil exploration. The number of customers for

such products is small and such customers may not blog, tweet, or post reviews. On the other hand, UGC is extensive for complex products such as automobiles or cellular phones. Machine-learning efficiencies in such categories may be necessary to make the review of UGC feasible.

Although our research focuses on developing and testing new methods, we are beginning to affect industry. Further research will enhance our ability to identify abstract context-dependent customer needs with UGC. For example,

- Deep neural networks and sentence embeddings are active areas of research in the NLP community. We expect the performance of the proposed architecture to improve significantly with new developments in machine learning.
- UGC is updated continuously. Firms might develop procedures to monitor UGC continuously. Sentence embeddings can be particularly valuable. For example, firms might concentrate on customer needs that are distant from established needs in the 20-dimenional vector space.
- Future developments might automate the final step, or at least enhance the ability of analysts to abstract customer needs from informative, non-redundant content.
- Other forms of UGC, such as blogs and Twitter feeds, may be examined for customer needs. We expect blogs and Twitter feeds to contain more non-informative content, which makes machine learning filtering even more valuable.
- Self-selection to post UGC is a concern and an opportunity with UGC. For oral care, the effectiveness of product reviews did not seem to be diminished by self-selection, at least compared to experiential interviews of a representative set of customers. In other categories, such as the food category in §6, self-selection and a non-representative sample issues might have a larger effect. Firms might examine multiple channels for a complete set of customer needs.
- Field experiments might assess whether, and to what degree, abstract context-dependent customer needs provide more insights for product development than insights obtained from lists of words.

- Amazon Mechanical Turk is a promising means to replace analysts for labeling training sentences, but further research is warranted.

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Appendix

Table A1. Voice of the Customer for Oral Care as Obtained from Experiential Interviews (22 examples of the 86 tertiary customer needs are shown—one for each secondary group. A full list of tertiary customer needs is available from the authors.)

Primary Group	Secondary Group	#Needs	Examples of Tertiary Customer Needs (22 of 86 shown)
Feel Clean And Fresh (Sensory)	Clean Feeling in My Mouth	4	My mouth feels clean
	Fresh Breath All Day Long	4	I wake up without feeling like I have morning breath
	Pleasant Taste and Texture	3	Oral care liquids, gels, pastes, etc. are smooth (not gritty or chalky)
Strong Teeth And Gums	Prevent Gingivitis	5	Oral care products and procedures that minimize gum bleeding
	Able to Protect My Teeth	5	Oral care products and procedures that prevent cavities
	Whiter Teeth	4	Can avoid discoloration of my teeth
Product Efficacy	Effectively Clean Hard to Reach Areas	3	Able to easily get all particles, even the tiniest, out from between my teeth
	Gentle Oral Care Products	4	Oral care items are gentle and don't hurt my mouth
	Oral Care Products that Last	3	It's clear when I need to replace an oral care product (e.g. toothbrush, floss)
	Tools are Easy to Maneuver and Manipulate	6	Easy to grasp any oral care tool—it won't slip out of my hand
Knowledge And Confidence	Knowledge of Proper Techniques	5	I know the right amount of time to spend on each step of my oral care routine
	Long Term Oral Care Health	4	I am aware of the best oral care routine for me
	Motivation for Good Check-Ups	4	I want to be motivated to be more involved with my oral care
	Able to Differentiate Products	3	I know which products to use for any oral care issue I'm trying to address
Convenience	Efficient Oral Care Routine (Effective, Hassle-Free and Quick)	7	Oral care tasks do not require much physical effort
	Oral Care "Away From the Bathroom"	5	The oral care items I carry around are easy to keep clean
Shopping / Product Choice	Faith in the Products	5	Brands of oral care products that are well known and reliable
	Provides a Good Deal	2	I know I'm getting the lowest price for the products I'm buying
	Effective Storage	1	Easy to keep extra products on hand (e.g. packaged securely, doesn't spoil)
	Environmentally Friendly Products	1	Environmentally friendly products and packaging
	Easy to Shop for Oral Care Items	3	Oral care items I want are available at the store where I shop
	Product Aesthetics	5	Products that have a "cool" or interesting look

Note to Table A1. Each customer need is based on analysts' fuzzy matching. For example, the customer need of "I want to be motivated to be more involved with my oral care" is based on fourteen sentences in the UGC, including: "Saves money and time (and motivates me to floss more)..." "This floss was able to do the impossible: get me to floss every day." "Makes flossing much more enjoyable err...tolerable …" "…this tool is the lazy person's answer to flossing."

Figure A1. Demonstration of the Application of the Proposed Machine Learning Hybrid Approach to an Amazon Review

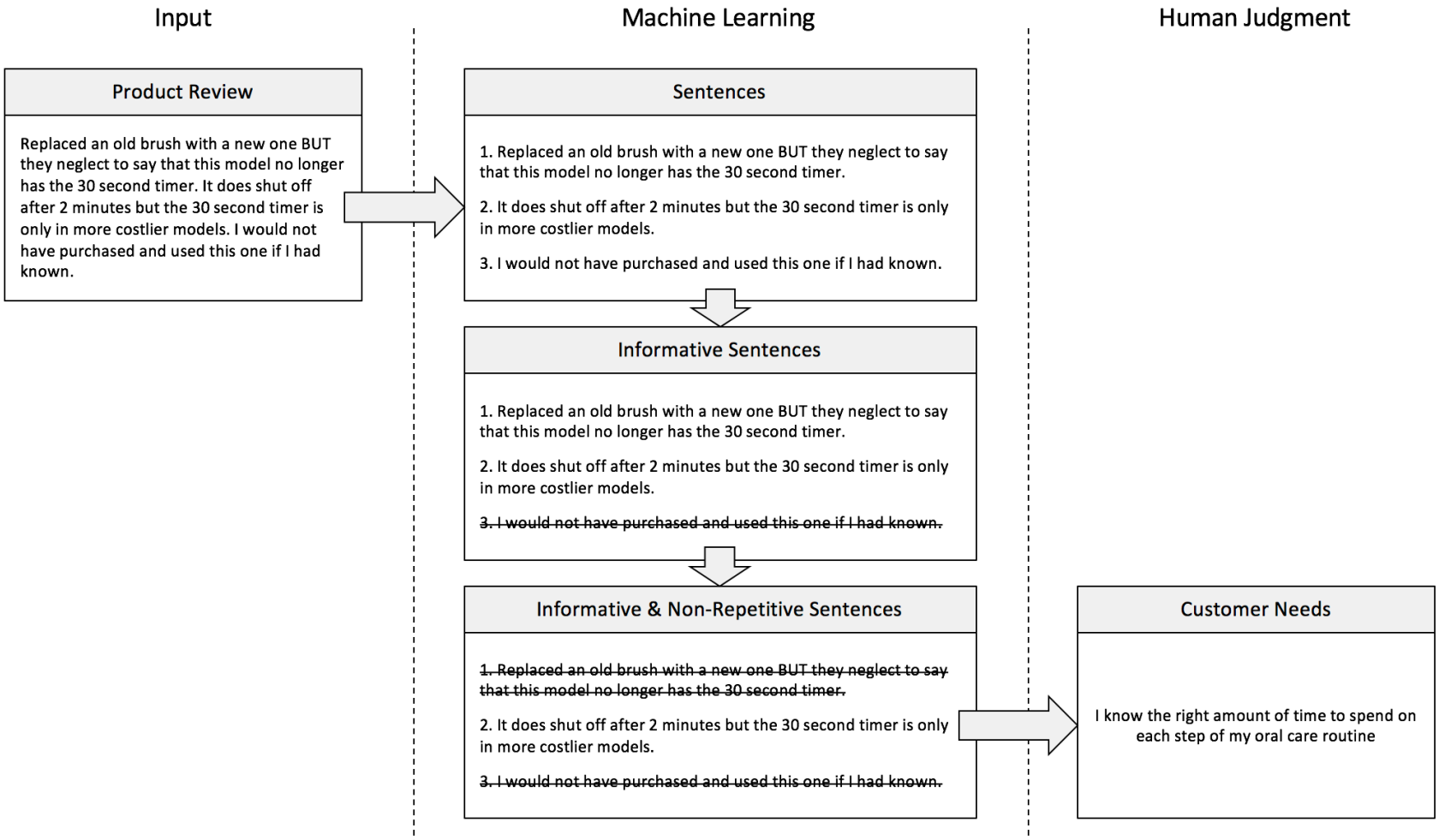
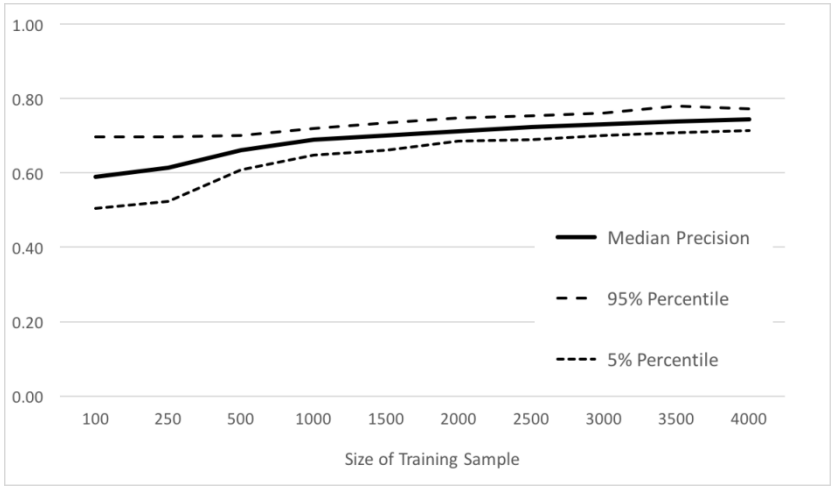
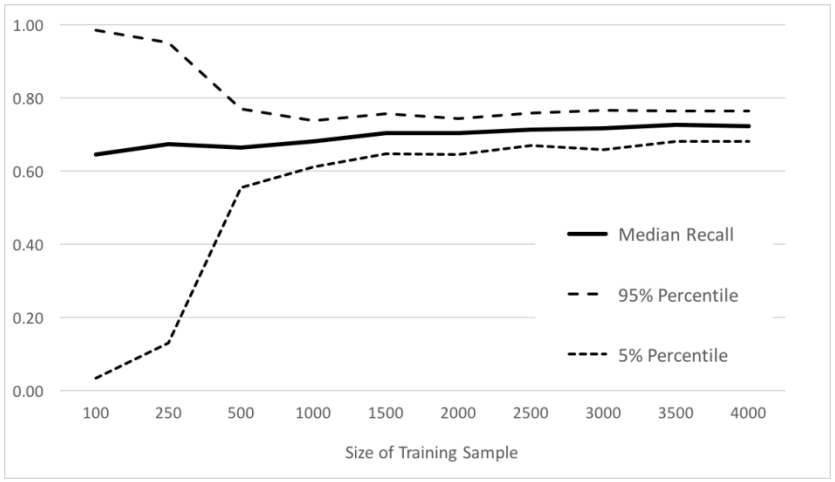


Figure A2. Precision and Recall as a Function of the Size of the Training Sample



(a) Precision



(b) Recall

Note to Figure A2. Below 500 sentences, the confidence bounds on recall are large in Figure A2. The effect on the confidence bounds on F_1 (Figure 5) is asymmetric. F_1 is a compromise between precision and recall. When either precision or recall is low, F_1 is low. When recall is extremely high, precision is likely to be low, hence F_1 will also be low. This explains why the lower confidence bound for 500 sentences in Figure 5 is extremely low, but the upper confidence bound tracks the median well.

Table A2. Complete Set of Customer Needs that Were Unique to Either UGC or Experiential Interviews

Customer Needs Unique to UGC	Customer Needs Unique to Experiential Interviews
Easy way to charge toothbrush.	Oral care tools that can be easily used by left-handed people.
An oral care product that is quiet.	I am able to tell if I have bad breath.
Responsive customer service (e.g., always answers my call or email, doesn't make me wait long for a response).	Advice that is regularly updated so that it is relevant to my current oral care needs—recognizes that needs change as I age.
An oral care product that does not affect my sense of taste (e.g. doesn't affect my taste buds).	
Oral care that helps me quit smoking.	
Easy to store products.	
Maintenance and repairs are simple and quick.	
Customer service can always resolve my issue.	

Figure A3. Efficiencies among Various Methods to Select UGC Sentences for Review (Low- and High-Frequency Customer Needs)

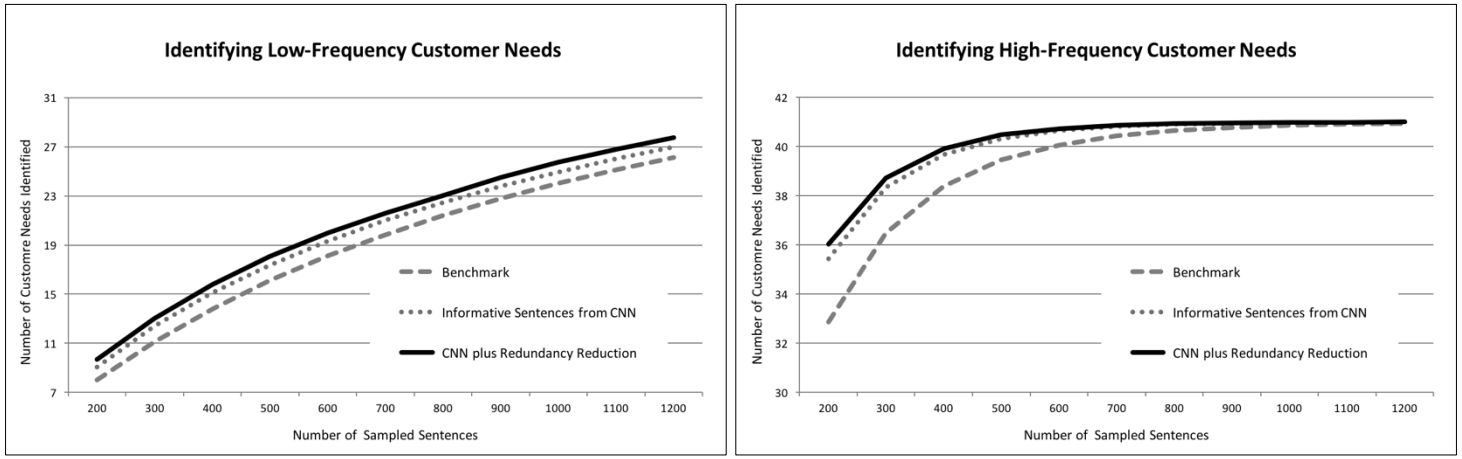


Figure A4. Machine Learning Hybrid Can Efficiently Identify the Least Frequent Customer Needs and Customer Needs Unique to UGC