Understanding Big Consumer Opinion Data for Market-driven Product Design

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Abstract

Big consumer data provide new opportunities for business administrators to explore the value from them and fulfill customer requirements (CRs). Generally, they are presented as purchase records, online behavior, emotions, etc. However, the distinctive characteristics, "4Vs", lead to many conventional methods for customer understanding potentially fail to handle such data. A visible research gap with practical significance is to develop a framework and several approaches to deal with big consumer data for CRs understanding. Accordingly, a pioneer research work is conducted to exploit the value of these data from the perspective of product designers. It starts with the identification of product features and sentiment polarities from big consumer opinion data. A Kalman filter method is then employed to forecast the trends of CRs and a Baysian method is proposed to compare products. The objective is to help designers to understand changes of CRs and the competitive advantages. Finally, with opinion data in Amazon.com, a case study is presented to illustrate how the proposed techniques are applied. This research is argued to incorporate an interdisciplinary collaboration between computer science and engineering design. It aims to facilitate designers by exploiting the valuable customer information from big consumer data for market-driven product design.

Keywords: big data; customer requirement; sentiment analysis; product comparison; trends analysis; product design; conceptual design; text mining;

1. Introduction

According to an IDC report in 2009, the volume of data doubles every 18 months (IDC, 2009). Another news report in ACM Communication estimated that about "2.5 exabytes of personal data were created each day" and "more than 2.5 petabytes of data are collected in every hour by Walmart from their customer transactions" (Hyman, 2012). Nowadays, it is referred as the big data revolution. With the advent of the era of big data, business leaders and interdisciplinary researchers are facing increasingly more data, which provides considerable opportunities for innovation and productivity. It implies that data scientists in diverse disciplines are facing new challenges.

Take e-business for instance. The growth of e-commerce makes a big volume of online consumer data being generated from time to time. Tmall.com and Taobao.com, two of China's biggest e-commerce sites owned by Alibaba Group, profited more than CNY 19 billion during the 24-hour promotional period in 11th Nov, 2013. Indeed, for instance, hundreds of mobile phones are on sales; web log servers track tens of thousands of visits a day about phones; millions of transactions are processed a year; and hundreds of reviews are posted even for a single hot phone. Now, how to analyze a big volume of consumer data becomes a hot topic and those experts whose skill sets include managing very large consumer datasets will be highly demanding.

In the past, if designers wanted to launch a new model, customer requirements (CRs) are collected from interviews, questionnaires or surveys, which are often a long haul and laborious. Nowadays, big consumer opinion data are pervasive in twitters, blogs and product reviews, which reveal consumers' interests. These data enable designers to obtain CRs, monitor trends of consumer interests and make comparisons with similar products, which facilitate designers to improve their new products and response to consumers accordingly. One typical consumer opinion data of Samsung Galaxy S III I9300 in Amazon.com is presented in Figure 1.

[*Insert Figure 1. One typical online review*]

Hence, it is of great worth to explore the value of big consumer data and make products to fulfill CRs. However, conventional methods for customer understanding often deal with limited consumer concerns. These concerns are usually collected in a short time from formulated tables or questionnaires with a clear purpose and only a small number of consumers are covered and suggested to give their feedbacks. Nonetheless, compared with conventional customer survey data, big consumer opinion data present contrastive and distinguish characteristics. For instance, a huge number of customer opinion are generated from time to time in different ecommerce websites, such as Amazon.com and Tmall.com, and in social network websites, such as Twitters.com and Weibo.com. Moreover, these customer emotions are diversified to point out pros and cons of products without any purposeful guidance. It induces that not all of these data transmit helpful information for consumers and designers. Generally, these characteristics are referred as Volume, Variety, Velocity and Value, or "4Vs of big data". 4Vs surpass the ability of theoretical models which were built based on conventional survey data. Algorithms that are devised exclusively to help business administrators, research engineers as well as data scientists to understand CRs effectively and efficiently from big opinion data are currently not available. Hence, the visible and significant gap wants a elaborately designed framework and approaches on the extraction of insightful information from big opinion data for those who are dedicating to launch a new model and fulfill CRs in market-driven product design. The success of effective analysis on big opinion data requires both algorithms in the field of computer science to identify sentimental information from textual data and knowledge in the field of design area to understand CRs. It will make no doubt to be helpful to solve critical and practical problems in market-driven product design and promote the theoretical work of interdisciplinary research.

To fill this gap, in this research, a framework regarding how consumer opinion data are utilized in market-driven product design is presented. In particular, online reviews, as one representative category of consumer opinion data, are analyzed. Firstly, reviews of similar products are collected. Sentiment polarities of consumers are then extracted from these textual opinion data by a supervised learning approach. In this supervised learning approach, pros and cons reviews in Cnet.com are utilized. It helps to identify sentiment polarities over product features. Next, a probabilistic model is built to make comparisons on similar products in the product feature level. This probabilistic model is utilized to facilitate designers to understand CRs. Moreover, a Kalman filter approach is employed to predict the trends of potential CRs.

The rest of this research is organized as follows. In Section 2, relevant studies are reviewed and the significance of this research is highlighted in Section 3. In Section 4, a framework to exploit big consumer opinion data is presented and details of the proposed models are explained. In Section 5, a case study is elaborated to demonstrate how big customer opinion data are utilized by designers to understand CRs in market-driven product design. In Section 6, this research is concluded.

2. RELATED WORK

2.1 Market analysis for product design

In the design area, numerous methods are reported to help designers to understand CRs for market analysis. How to identify CRs and balance their importance is the first concern in market analysis, which is widely studied in the research field.

Due to the impreciseness of CRs, some researchers began to cope with the inherent vagueness. For instance, linguistic variables were utilized to represent the imprecise CRs (Karsak, 2004). Then, the Fuzzy Delphi Method (FDM) was utilized to gain the consensus of customers to determine the importance of CRs. Similarly, linguistic variables, expressed in fuzzy numbers, were found to be more appropriate for the descriptions of CRs (Chen et al., 2006) and, accordingly, the relative weights of CRs were proposed to be expressed as fuzzy numbers. Some researchers also argued that the transformation of CRs should be made as little as possible to prevent information loss. For this purpose, a nonlinear programming approach was proposed to estimate the relative importance of CRs, which allowed customers to express preferences on the relative importance of CRs in their familiar formats (Wang, 2012).

To balance the relative importance of CRs, analytic hierarchy process (AHP) is often employed in various studies. In AHP, several candidates in the same hierarchy are analyzed by a pairwise comparison through individual assessments with concrete numerical values. Numerical values are utilized to rank possible candidates. In the product design area, a fuzzy AHP with an extent analysis approach was reported to determine the weights of CRs (Kwong and Bai, 2003). In this method, triangular fuzzy numbers were utilized for pairwise comparisons of the fuzzy AHP and comparisons of fuzzy numbers were conducted to prioritize CRs. Many researchers also utilized Kano's Model to quantify the importance of CRs. Kano's Model serves as a tool for the understanding of CRs and their impacts on customer satisfaction (CS). In Kano's Model, different CRs are categorized to must-be attributes, one dimensional attributes, attractive attributes, indifference attributes, etc. Chen and Chuang presented a robust design approach to achieve higher level of customer satisfaction in aesthetic qualities (Chen and Chuang, 2008). In such robust design approach, the Grey relational analysis with the Taguchi method was proposed to optimize the subjective quality with multiple-criteria characteristics. Then, Kano's Model was employed to balance weights of multiple-criteria to facilitate designers in understanding of the relationship between performance criteria and customer satisfaction. In the process to decide the weights of multiple-criteria, some studies applied regression methods with dummy variables to recognize critical attributes. However, such kind of methods were argued to potentially lead to an inaccurate classification of multiple-criteria in some specific condition (Lin et al., 2010). Hence, a moderated regression approach was suggested to improve the performance of the dummy regression method with dummy variables in order to obtain a more accurate attribute classification.

With different methods, including the rough set theory, the scale method and Kano's model, AHP was reported to be utilized in an integrated approach to estimate the importance of CRs (Li et al., 2009). The importance of CRs was determined by three steps. First, the initial importance of CRs was decided according to the relative positive field in rough set. Next, the ratio of CS to a CR was calculated by the integration of scale method and AHP. Finally, the importance of CS was decided by the initial importance of CRs, the ratio of CS to a CR and its sales point. Recently, a rating method for customer preferences and a rating method for CS were described (Nahm et al., 2013). The rating method for customer preference aims to provide relative importance of CRs and outputs a partial ordering of CRs. The rating method for CS suggests the CR priority according to competitive benchmarking analysis.

2.2 Analyzing consumer requirements for QFD

In the research field of CR analysis, one of the most famous approaches is Quality Function Deployment (QFD) (Akao, 2004). QFD is commonly used in conceptual design, process planning, project management, etc (Chan and Wu, 2002). With a planning matrix, QFD links CRs to engineering characteristics (ECs) and, eventually, outputs the values of ECs.

How to balance the importance of CRs is often regarded as one essential problem in QFD since it affects the selection of the final target value of ECs. A framework that incorporates fuzzy set and AHP was shown to prioritize CRs in target planning for QFD (Nepal, Yadav and Murat, 2010). Then, an example from automotive product development was illustrated to verify the availability of this framework. In this example, alignments with business strategies, product improvement opportunities and financial considerations are included and these three criteria are further divided to 13 CR attributes. With the proposed framework, these attributes are prioritized. Some researchers also argued that the determination of the importance of CRs should consider not only the degree of CR fulfillment but also competitive products (Lai et al., 2008). They proposed a method that considering competitive products, current performance of the product and customer satisfaction to determine the importance of CRs. Later, this method was applied to help designers to decide the final target value of ECs in QFD. An adaptive neuro-fuzzy inference system is proposed to generate CS models for QFD (Kwong, Wong and Chan, 2009). First, fuzzy rules were generated based on the market survey data. Next, important fuzzy rules and the corresponding internal models were extracted by considering the determination of the active range and active membership function for each fuzzy variable. Finally, a non-linear and explicit CS models was inferred by the weights in the system.

There are also research studies to investigate how to determine the target values of ECs for QFD. A decision model for robot selection was introduced by a fuzzy linear regression and QFD (Karsak, 2008). The fuzzy linear regression was utilized to decide target values of ECs when uncertain CRs are presented and imprecise relationship between ECs are found in QFD. Similarly, a fuzzy linear regression, QFD and zero–one goal programming were utilized to decide which Enterprise resource planning (ERP) system satisfys CRs of companies (Karsak and Ozogul, 2009). In this method, QFD made decision-makers consider the relationship between CRs of companies and the characteristics of ECs as well as the interactions of characteristics between ERP system. However, in these approaches, the single objective is to maximize CS. A framework was then proposed to determine target values of ECs for QFD by a fuzzy linear regression and fuzzy multiple objective programming (Sener and Karsak, 2011). The fuzzy linear regression was to find the functional relations between CRs and ECs, and among ECs. Fuzzy multiple objective programming was formulated to decide the values of ECs by maximizing CS under budget constraints. At the same time, other objectives such as technical difficulties and extendibility of ECs were considered in this fuzzy multiple objective programming.

To balance CS and the development cost, a fuzzy multi-objective method was proposed for uncertain and vague CRs (Mu et al., 2008). In this method, Kano's Model was combined into QFD with the consideration of the inherent vagueness of CRs as well as the nonlinear relationship between CRs and ECs. Some researchers also found that consumers tend to give a higher importance level to basic CRs (Tontini, 2007). Accordingly, a model that combined Kano's Model into QFD was proposed to adjust the importance of CRs. Some others developed a similar model that combined Kano's Model into QFD (Sireli, 2007). But it was utilized in the scenario of simultaneous multiple product design to understand CRs and balance the importance of CRs. The integration of Kano's Model with QFD was also utilized to monitor the dynamic changes of CRs (Raharjo et al., 2010). In their research, Kano's Model was to identify how fast a certain Kano's category changes over time and how to improve the current model to meet probable future CRs. With the integration of Kano's Model with QFD, the importance of CRs was adjusted dynamically. However, sometimes, CRs are dynamic and they will change along the time. To capture the fast changes of CRs, the grey theory was seen to combine with QFD (Wu, Liao and Wang, 2005). With that model, the importance of CRs was monitored to fulfill dynamic and future CRs. From a probabilistic viewpoint, a Markov chain model was also reported to analyze the fast changes of CRs (Wu and Shieh, 2006).

3. THE ARRIVAL OF BIG CONSUMER OPINION DATA

In the coming era of big data, a paradigm shift is observed in scientific research methods, which means that data scientists in different disciplines are facing new challenges. In ACM Queue, Jacobos pointed out several problems with the analysis of big data (Jacobs, 2009), including "the inability of many off-the-shelf packages to scale to large problems", "the paramount importance of avoiding suboptimal access patterns as the bulk of processing moves down the storage hierarchy", and "replication of data for storage and efficiency in distributed processing", and defined the big data as "data whose size forces us to look beyond the tried-and-true methods that are prevalent at that time." For the arrival of big data, some researchers began to describe how changes will influence information system and social science research (Chang et al. 2013) or started to build a conceptual framework for service-oriented decision support system (Demirkan and Delen, 2013).

It is also noticed that a big volume of public consumer concerns are observed in Amazon.com, Twitter.com, Cnet.com, etc. Most of them are presented in the form of natural textual language. Valuable information about customer praises and concerns are provided in these textual data, which helps potential customers to make purchase decisions or facilitate designers to improve their products or services. Generally, these helpful concerns are named as big consumer opinion data.

The fast development of information technology (IT) and information communication technology (ICT) makes big consumer opinion data widely available in many e-commerce websites, social networks, professional review sites, etc. Some may contain thousands of words with elaborated user experiences and affluent personal feeling on products. Some are only a few sentences, but insightful user comments and critical analysis may be offered. Grasp the ground truth meaning of customer feedback effectively will enable product designers to understand consumers in a finer granularity. As noted in the previous section, many approaches are innovated to conduct market analysis and analyze CRs for product design. However, nearly all of them are based on a small number of conventional customer survey data. Compared with conventional survey data, big consumer opinion data have some distinctive characteristics. First, a huge number of consumer opinion data can be easily obtained without conducting laborious survey. Also, consumer opinion data are generated and diffused in different sites, many of which have their own structures and encourage consumers to post their comments. Moreover, these data are submitted in different sites from time to time. It makes a difficult task to collect all of them like what are always claimed in conventional surveys. In addition, only a few of them contain sufficient information for potential consumers and product designers, although a large number of them are available, since the quality of data is often inversely related with the size of the community (Otterbacher, 2009). Four remarkable characteristics, which are usually referred as 4Vs of big data, surpass the ability of many approaches for survey data to handle big consumer opinion data and it imposes critical research challenges to designers to exploit the value.

Efficiently making use of big consumer opinion data helps designers to identify customer behavior, understand customer preferences, sense customer responses, track the trend of product, which will undoubtedly make the business to gain competitive advantages in the fiercely competitive market. However, in many state-of-the-art studies, few researchers outline a clear blueprint to take the great advantage of big consumer data for product design, which include the knowledge in computer science to handle big data and the experiences in product design to understand CRs.

Hence, analytical methods in different research areas are welcome to be involved to analyze the big consumer opinion data, such as, algorithms and models in information management and computer science, domain knowledge in product design, material and manufacturing, etc.

4. RESEARCH METHODOLOGY

4.1 A framework to exploit big consumer opinion data

To present how big consumer opinion data can be exploited for market-driven product design, a framework is shown in consideration of the four distinct characteristics.

As shown in Figure 2, in this framework, it starts from crawling a big volume of consumer data. However, big consumer opinion data can be found in a variety of hot websites, such as Twitter.com, Amazon.com, Cnet.com, etc. Hence, different web parsers for social network websites, e-commerce websites and review sites should be designed to extract such opinion data. Part-of-Speech (POS) tagging is then conducted on big consumer opinion data since consumers tend to utilize nouns or noun phrases to refer to product features and adjective or adverbs for sentiment polarities. Next, product features and customer sentiments are identified from consumer opinion data with the help of many latest innovated algorithms in opinion mining.

[*Insert Figure 2. A framework of exploting big consumer opinion data*]

In our previous work, the helpfulness of online consumer opinion data and what makes them more helpful are analyzed from the perspective of designers (Liu et al., 2013). The objective is to cope with the problem of value sparseness in online consumer opinion data and to help product designers to evaluate and predict the value of these data in the viewpoint of domain users. Based on this approach, a relatively small number of online consumer opinion data are available and it facilities product designers to be able to utilize high-quality data.

However, CRs may change along the time. Effective analysis of online customer opinion data makes it possible to sense the changes of CRs and avoid time-consuming repetitive surveys in conventional methods. Moreover, analyzing online customer opinion data also promotes business professionals to investigate the requirements of consumers about competitive products in the fierce market. Hence, in this research, some approaches regarding the recognition of the trends of CRs and the comparisons of CRs on similar products are suggested to show how big consumer opinion data can be exploited for market-driven design. Specially, in this research, online reviews, as one important type of big consumer opinion data, are taken as an example and technical details about how online reviews are analyzed intelligently will be elaborated in this section. Indeed, there exist other forms of big consumer data, such as twitters, threads in BBS, blogs, etc. But the techniques explained in this section can be modified and applied to analyze those type of big consumer data.

4.2 Product feature identification

One of the first tasks to analyze online reviews is the identification of which product features are mentioned by consumers. Different models for the extraction of product features from online reviews are reported. Some are built on the techniques of the topic model. But they are not able to be applied directly due to the efficiency to analyze a big volume of consumer data. Many methods that based on manually labeled corpus are also not applicable since the difficulty of obtaining sufficient training data. In consideration of the aforementioned arguments, in this research, with the help of WordNet, product features are extracted from pros and cons reviews.

As pointed out by various studies, product features are usually nouns or noun phrases. Thus, nouns are firstly extracted. In this research, the Stanford parser, a statistical POS tagging tool, is utilized to obtain nouns from reviews and these nouns are regarded as candidates of product features. However, there exist many noises in these candidates, which means many nouns are not product features. To filter out noises and identify product features, pros and cons reviews are utilized. An exemplary pros and cons review of Samsung Galaxy i9300 in Cnet.com is illustrated in Figure 3.

[*Insert Figure 3. One typical pros and cons review*]

As seen from Figure 3, pros and cons of this product are mentioned explicitly. Also, pros and cons are observed to be described by nouns or noun phrases. Accordingly, frequent nouns in pros and cons reviews are employed as seed words to identify product features from consumer opinion data. Moreover, in this task, stop words and a limited small number of manually defined stop words in a specific product domain are removed from product feature candidates.

However, different nouns are utilized to describe the same product features. For instances, "memory ", "ram" and "storage" are all utilized by consumers to describe the memory of mobile phones. Another case is that, "app", "applications", "apps" and "applications" may occur to refer to applications of mobile phones. A single word, such as "app", may be an infrequent noun. If such case is neglected, it will lead to probable inaccuracy in the identification of product feature. Thus, another relevant task is to cluster semantically similar words together.

In the first step, nouns are stemmed by the PlingStemmer, a tool to stem an English noun to its singular form. Then, the semantic similarity of words is calculated. For such purpose, different methods can be used to evaluate the similarity between words. In this research, one important source, WordNet, is utilized. WordNet is a large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each of which expresses a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations. In this research, words that occur in the same WordNet synset are regarded to be semantic similar.

In particular, different WordNet synsets of the same word with diverse meanings and the same WordNet synset of different words with the same meaning are utilized. The above assumption results in a semantic word graph, in which nodes are words with POS tags in WordNet and edges denote the connection between each pair of synonymous words. Notice that, nodes are words with POS tags rather than words themselves since POS tags contributes to identify synsets with the same POS. Besides WordNet synset, in this research, other relations in WordNet are also utilized to define the graph, such as, the "similar to" and the "related" WordNet synsets.

The WordNet distance is then defined as the length of the shortest path between two words in the graph. The distance is utilized to calculate the similarity between two product features. If two features occur in the same synset, the WordNet distance is defined as "1". Similarly, if two features are connected by one same word, the WordNet distance is defined as "2", etc. For example, the WordNet distance between "audio" and "headphone" is 3 since they are sequentially connected by "sound" and "phone" in WordNet. In addition, some words are frequently utilized with a short form, which makes the above approach unable to find the shortest path. For instance, "apps" vs. "applications" and "wifi" vs. "wireless network" frequently appear in electronic product reviews. Then, distances for both two examples are manually defined as "1". Accordingly, the WordNet distance between all pairs of product features can be calculated. Now, if the distance between two product features is smaller than a threshold, they are clustered together, which means two features imply comparable meanings. Accordingly, with the removal of the contextual stop word "phone", the exemplary word cluster becomes "audio, headphones, sound". Finally, given feature word clusters, those clusters with low frequency are pruned from feature candidates.

4.3 Sentiment analysis

After product features are identified from opinion data with the help of WordNet and pros and cons reviews, the next task is to analyze corresponding sentiment polarities.

Notice that, in pros and cons reviews, sentiment polarities in the feature level are presented. Take the pros and cons review in Figure 3 for instance. This consumer is satisfied with the image quality and innovative features, but not with the battery life and software stability. Taken this information into consideration, in this research, a two-step method is proposed to analyze sentiment polarities of consumer data.

The first step is to classify whether each sentence in consumer data is objective or subjective. In this step, a public dataset is utilized, which include 5,000 subjective and 5,000 objective sentences (Pang and Lee, 2004). With this training dataset, each sentence is denoted as a bag of words and a Naive Bayes classifier is built. With this classifier, subjective and objective sentences are distinguished. If one sentence is predicted as an objective one, in this study, it is assumed that this consumer presents neutral sentiment towards product features mentioned in the sentence.

The second step is to classify whether one subjective sentence is positive or negative. A simple method is to calculate the WordNet distance between adjective/adverb words and seed words. Specially, after some seed words are labeled as positive or negative, sentiment polarities of adjective/adverb words are estimated by the WordNet distance since synonyms of positive words are positive and synonyms of negative words are negative. However, a sentence may contain one or more adjective/adverb words with diversified sentiment polarities. Then, the sentiment of subjective sentence will be controversial if it is simply regarded to count whether the number of positive terms is bigger than that of the negative. To avoid arbitrarily predict the sentiment polarity of the overall sentence, in this study, each sentence is represented by the subjective lexicon in MPQA project (Wilson et al., 2005). Also, since nouns, adjectives, adverbs and verbs are generally considered to be utilized to express sentiment polarity, words with other POS are filtered out. Subsequently, given sentimental information presented in pros and cons reviews and the subjective lexicon representation of each sentence, a Naive Bayes sentiment classifier is built to estimate sentiment polarities of product features. Actually, other types of classification methods are tested, such as SVM, logistic regression, etc. However, it is found that the Naive Bayes classifier performs the best.

4.4 Trend recognition of CRs

Another critical task for customer-driven product design is to recognize the changing trends of CRs. Specially, in this research, the average opinion of a specific product feature is regarded as CRs of this feature and a Kalman filtering approach is proposed to analyze the dynamic change of CRs in the product feature level.

In this approach, sentiment polarities of a specific feature are firstly modeled as a linear system. It is denoted as,

$$z_t = Az_{t-1} + \varepsilon_t$$

z_t is a latent variable to represent the average real opinion of a specific feature at time t in a noisy environment. A is a designed linear transition matrix. ε_t is the system noise at time t and it is assumed to follow a zero mean Gaussian, which is denoted as,

$$\varepsilon_t \sim N(0, Q_t)$$

Q_t is the variance of ε_t at time t. To simplify the model, Q_t is assumed to be equal to a constant Q and it does not change along the time. y_t is the actual observation of the average opinion of a specific feature at time t. It can be inferred from a linear observation model.

$$y_t = Cz_t + \delta_t$$

C is a designed linear observation matrix. δ_t is the observation noise at time t. Similarly, it is also assumed to follow a zero mean Gaussian,

$$\delta_t \sim N(0, R_t)$$

Also, R_t is assumed not to change along the time and it equals to R.

The objective here is to estimate CRs of a specific product feature, z_t, based on the actual observation, y_t, at time t. Specially, since z_t and y_t is a scalar at time t, the designed linear transition matrix A and the linear observation matrix C equal to one.

According to the above settings, a Kalman filter approach is employed, which is a Bayesian filtering method for linear-Gaussian state space model. The Kalman filter approach has been widely proven to be a useful approach for time series analysis. It is a recursive algorithm that updates parameters at each time when a new observation is available at time t. In particular, it estimates CRs at time t and obtains feedback in the form of noises, which are utilized in the update step. Since both ε_t and δ_t follow Normal distribution, the prediction about CRs and the update about the parameters can be performed in a closed form at each iteration. In the prediction step, it follows,

$$
\begin{aligned}
p(z_t \mid y_{1:t-1}) &= N(z_t \mid \mu_{t|t-1}, \Sigma_{t|t-1}) \\
\mu_{t|t-1} &= A\mu_{t-1} \\
\Sigma_{t|t-1} &= A\Sigma_{t-1}A^T + Q
\end{aligned}
$$

In the update step, it follows,

$$
\begin{aligned}
p(z_t \mid y_{1:t}) &= N(z_t \mid \mu_t, \Sigma_t) \\
\mu_t &= \mu_{t|t-1} + K_t(z_t - C\mu_{t|t-1}) \\
\Sigma_t &= (I - K_t C)\Sigma_{t|t-1} \\
K_t &= \Sigma_{t|t-1} C^T S_t^{-1} \\
S_t &= C\Sigma_{t|t-1} C^T + R
\end{aligned}
$$

K_t is the Kalman gain matrix and it can be simplified to,

$$
K_t = \Sigma_{t|t-1} C^T (C\Sigma_{t|t-1} C^T + R)^{-1} = (C^T R C + \Sigma_{t|t-1}^{-1})^{-1} C^T R^{-1}
$$

With this approach, given the initial sentiment polarities from online opinion data, changing trends of CRs in the specific feature level can be estimated dynamically for product designers.

4.5 Comparison analysis of CRs

When designers conceive new models, customer satisfaction of competitive products in different feature dimensions is often compared. Through the comparisons, the strengths and the weaknesses of products are shown clearly. Accordingly, the next goal is to develop a model for the comparisons by exploiting online opinion data.

However, the number of customer referring to specific features on various products is different. For instance, there are $N^{p,k}$ and $N^{q,k}$ consumers mention product feature f_k of product *p* and product *q*, respectively. It can be expected that it is a rare case that $N^{p,k}$ is equal to $N^{q,k}$. In all of $N^{p,k}$ consumers, suppose that $N^{p,k}_{positive}$ consumers are satisfied with f_k of product *p*, $N^{p,k}_{negative}$ consumers are dissatisfied f_k of product *p*, and $N^{p,k}_{neutral}$ consumers express a neutral opinion. Obviously, $N^{p,k}$ equals to the sum of $N^{p,k}_{positive}$, $N^{p,k}_{negative}$ and $N^{p,k}_{neutral}$. The corresponding number of consumers presenting positive, negative and neutral on f_k of product *q* is $N^{q,k}_{positive}$, $N^{q,k}_{negative}$ and $N^{q,k}_{neutral}$. Now, the problem is, given these observations, how to infer which product is more favorable on product feature f_k.

On the face of it, one intuitive method is to compare which product receive a higher ratio of positive opinions. However, it might induce a misleading conclusion. For instance, there are 3 out of 3 consumers are satisfied with f_k of product *p* and

90 out of 100 consumers are satisfied with f_k of product *q*. If the simple method is applied, product *p* is assumed to be better. Nonetheless, only a weak confidence is shown since it does not have sufficient consumers referring to it. Accordingly, in this research, a Baysian analysis method is proposed to make comparisons between products.

Suppose the customer satisfaction of f_k is distributed over positive, negative and neutral opinion dimensions and it follows the Dirichlet distribution. Let $\alpha^{p,k}$ be three-dimension parameters of the Dirichlet distribution on f_k of product *p*, denoting the probabilities of customer with positive, negative and neutral sentiment. Now, suppose the customer satisfaction initially follows a uniform distribution and it is then denoted as,

$$\alpha^{p,k} \sim Dir(1,1,1)$$

In particular, the first, the second and the third dimension denote the prior of positive, negative and neutral sentiment, respectively. Now, suppose one positive customer opinion on f_k of product p is observed, $\alpha^{p,k}$ is updated as $\alpha^{p,k} \sim Dir(2,1,1)$. Similarly, if one negative customer opinion on f_k of product *p* shows, $\alpha^{p,k}$ is updated as $\alpha^{p,k} \sim Dir(1,2,1)$. A similar update can be conducted on the third dimension if one neutral perspective is observed.

Accordingly, $\alpha^{p,k}$ can be updated sequentially after a series of customer opinion data are reported. Now, given $N^{p,k}_{positive}$ consumers presenting positive, $N^{p,k}_{negative}$ consumers presenting negative and $N^{p,k}_{neutral}$ consumers presenting neutral opinion on product feature f_k of product p, α^{p} can be updated as,

$$\alpha^{p,k} \sim Dir(1+N^{p,k}_{positive}, 1+N^{p,k}_{negative}, 1+N^{p,k}_{neutral})$$

Similarly, $\alpha^{q,k}$ on feature f_k of product q can be updated after $N^{q,k}_{positive}$ consumers presenting positive, $N^{q,k}_{negative}$ consumers presenting negative and $N^{q,k}_{neutral}$ consumers presenting neutral opinion on product feature f_k of product q. It is represented as,

$$\alpha^{q,k} \sim Dir(1+N^{q,k}_{positive}, 1+N^{q,k}_{negative}, 1+N^{q,k}_{neutral})$$

Let $\alpha^{p,k}_{positive}$ be the probability of customers with positive sentiment on product feature f_k of product p and $\alpha^{q,k}_{positive}$ be the probability of that of product q. Define $\delta^{k}_{positive} = \alpha^{p,k}_{positive} - \alpha^{q,k}_{positive}$ as the difference of probabilities. It is desired to calculate the probability that $\delta^{k}_{positive}$ is bigger than zero, which means the probability of product feature f_k of product p is more favorable than that of product q. The statistic can be computed by a double integration as,

$$\begin{aligned} &p(\delta^{k}_{positive} > 0) \\ &= \int_0^1\int_0^1 I(\alpha^{p,k}_{positive} - \alpha^{q,k}_{positive}) \cdot Dir(\alpha^{p,k} \mid 1+N^{p,k}_{positive}, 1+N^{p,k}_{negative}, 1+N^{p,k}_{neutral}) \\ &\qquad \cdot Dir(\alpha^{q,k} \mid 1+N^{q,k}_{positive}, 1+N^{q,k}_{negative}, 1+N^{q,k}_{neutral}) d\alpha^{p,k} d\alpha^{q,k} \end{aligned}$$

Generally, it is difficult to calculate the integration directly. However, a simple yet effective method is to approximate the statistic $p(\delta^{k}_{positive})$ by the Monte Carlo sampling method. Specially, since $\alpha^{p,k}$ and $\alpha^{q,k}$ are independent, they can be sampled separately from the Dirichlet distribution. Next, according to the sampled $\alpha^{p,k}$ and $\alpha^{q,k}$, the ratio of the case that $\alpha^{p,k}_{positive}$ is bigger than $\alpha^{q,k}_{positive}$ can be calculated. Given sufficient samples, the integration can be estimated, which infers whether the probability of product feature f_k of product p is generally more favorable than that of product q.

5. CASE STUDY

5.1 Data preparation

To explain how the proposed methods facilitate designers for market-driven product design, a case study about the analysis of online consumer opinion data is illustrated.

In this case study, product features and the corresponding sentiment polarities are firstly identified from reviews in Amazon.com with the help of WordNet and pros and cons reviews in Cnet.com. Next, in this case study, dynamic changes of CRs are presented and predicted by the proposed Kalman filtering approach. Also, CR comparisons are conducted on similar products by the analysis of online opinions.

Particularly, 21,952 reviews of 583 intelligent mobile phones are collected from Cnet.com, which include 10,976 compliments and 10,976 critical comments. These reviews are firstly utilized as training data to identify product features and analyze sentiment polarities from big consumer opinion data. According to the proposed techniques in Section 4.1 and Section 4.2, a list of product features is found. In Table 1, some frequently discussed features are shown.

[*Insert Table 1. Some frequently discussed features in pros and cons reviews*]

Product feature words are identified using pros and cons reviews. The frequency denotes how often they are referred in the pros and cons review dataset. These features are represented in terms of noun clusters with a similar meaning. Taken words in noun clusters as seeds, product features can be identified from consumer opinion data. Specially, in this case study, mobile phone reviews in

Amazon.com are taken as exemplary customer opinion data and only those products with more than 30 reviews are taken into considerations. As a result, a web crawler collected 113,467 reviews of 661 products. The distribution of the number of reviews in terms of the number of products is illustrated in Figure 4.

[*Insert Figure 4. Statistics of reviews*]

As seen from Figure 4, in this dataset, most of products have less than 120 reviews and only a few products receive more than 480 reviews. Another consideration regarding the number of reviews is to investigate whether they are distributed evenly in terms of posting time. Accordingly, some statistics are presented in Figure 5.

[*Insert Figure 5. # of reviews vs. elapsed months*]

As seen from Figure 5, most reviews are posted in less than 15 months and the number of reviews declines gradually along the time. However, after 36 months, there are still about 2.62% reviews are posted by consumers. It can be inferred that, for some hot products, although they are not very popular after three years, there still exist some potential consumers. In addition, for the number of sentences and the number of words about these reviews, some statistics are described in Figure 6.

[*Insert Figure 6. # of reviews vs. # of sentences and # of words*]

As seen from Figure 6, the number of sentences and the number of words do not distribute evenly and, roughly speaking, they follow a Zipfian distribution. Most reviews contain less than five sentences and only a few of them have more than 50 sentences. Similarly, most reviews are observed to have less than 60 words and merely a few of reviews are longer than 480 words.

Moreover, on average, there are 124.31 words in each review. However, they are also not distributed evenly with the maximum of 14,104,898 words in a single review. A similar case can be also observed in terms of the number of sentences with an average 6.44 and a maximum 730,359 sentences in one review. All these 113,467 phone reviews in Amazon.com are employed in this case study to demonstrate how online opinion data are utilized by designers in market-driven product design.

5.2 Product feature identification and sentiment analysis

In Table 2, top five frequently mentioned product features of 661 mobile phones are listed. The screen (cover and screen), the battery (battery and batteries), the access of internet (internet, net, network, networks, web and wifi), the applications (app, application, applications and apps) as well as the memory of mobile phones are found to become top hot topics. It is reasonable since the majority of today's hot products are all intelligent models. Indeed, a big screen usually becomes the first appealing feature for consumers to choose. However, a big screen always means high power consumption. Hence, a second consideration is then how frequently consumers are bothered to recharge phones. Indeed, perhaps the most charming characteristics of modern phones are the access of the internet as well as the supported applications, which make mobile phones become one important type of intelligent devices and enable consumers to visit internet conveniently. Accordingly, it is understandable that applications as well as internet receives a substantial number of comments.

[*Insert Table 2. Top 5 frequently discussed features in mobile phone reviews*]

Next, sentiment polarities of online consumer opinion data are analyzed. In particular, with the proposed approach, the analysis result about sentiment polarities of one typical Amazon review is illustrated in Table 3.

[*Insert Table 3. An example of sentiment analysis*]

In the sentiment column of Table 3, "-1" represents a negative opinion and "0" denotes an objective opinion. In the "Features" column, the identified product features are listed. If one sentence does not refer to any product feature, "-" is filled in the corresponding "sentiment" cell and the "features" cell. Notice that, in this example, this consumer presented either a negative opinion or an objective opinion towards product features. In other cases, if a positive opinion is presented, "1" is utilized to denote the sentiment. An exemplary sentence is that "Battery life while using data has also been improved, an hour of internet browsing hit my battery only 10% ..." In this sentence, the battery life is mentioned and "1" will be filled automatically in the corresponding sentiment cell by the proposed method.

Accordingly, average sentiment polarities of top 5 frequently discussed features of 661 phones are listed in Table 4. As seen from this table, generally speaking, a slightly negative opinion is presented towards all of these hot product features.

[*Insert Table 4. The average sentiment polarities of top 5 frequently discussed features in mobile phone reviews*]

To investigate frequently referred product features and sentiment polarities of a specific product, in this case study, Samsung Galaxy i9300, which is a popular phone during 2012 and 2013, is selected. For this product, 954 reviews are collected from Amazon.com. The number of reviews and the frequency referring product features as well as the number of reviews with a specific opinion are presented in Table 5.

[*Insert Table 5. Frequently referred product features in reviews of Samsung i9300*]

As seen from Table 5, top five frequently referred product features coincide with that appears in the entire dataset of 113,467 reviews, which are shown in Table 2, and the difference between two tables lies in the percentage of reviews that refers product features. In these 954 reviews, consumers present different opinions towards these frequently referred features. An interesting phenomenon is that 49% consumers are not satisfied with the battery of i9300 and the figure for the memory goes to 46.9%. It suggests that designers of i9300 are recommended to consider how to improve the performance of battery and provide a larger memory space to consumers.

5.3 The changes analysis of CRs for a specific product

As mentioned in the previous sections, the average sentiment polarities of consumers are regarded as CRs of a specific product feature. However, frequently referred features may change along the time. Accordingly, which product features are frequently referred should be highlighted at first. The investigation about the changes of frequently referred features assists designers to observe the interest of consumers. In Table 6, top three frequently referred product features as well as the percentage of reviews that discuss these features are listed.

[*Insert Table 6. Top three frequently referred features in different years*]

As seen from Table 6, "battery" and "screen" are often discussed by consumers. It is easily understandable since consumers always prefer those products with suitable size of clear screen and they are reluctant to be bothered to recharge frequently. Another phenomenon is that the top referred features change from years to years. For some early products, consumers pay attention to the pictures taken by phones. However, with the fast development of ICT, phones are utilized as an intelligent device to access the internet. Also, various interesting applications in phones were then becoming hot topics, which are rarely seen in customer feedback of early products.

Next, the concentration turns to the analysis about CR changes of a specific product feature and 954 reviews of Samsung i9300 are still taken as an example. In Figure 7, the number of reviews is described in terms of elapsed days. As seen from this figure, all reviews are posted in 630 days and the number of reviews decreases gradually after 210 days. This result meets what are described in Figure 5, which implies that most reviews are generated in less than 15 months.

[*Insert Figure 7. # of reviews vs. elapsed days (954 Samsung i9300 reviews)*]

In Figure 8, the number of reviews referring top three hot product features is compared. As seen from this figure, the number of reviews referring to product features fluctuates from time to time. To obtain convincing results, in this research, at least four consumers mentioned the specific product feature in a fixed time slot is considered and the averaged opinion is regarded as the CR of this product feature.

[*Insert Figure 8. # of reviews that refers to a product feature vs. elapsed days (954 Samsung i9300 reviews)*]

The averaged sentiment polarities of top three product features are compared in Figure 9. CR over a specific product feature is seen not to be constant along the time. For instance, although, generally, consumers are not satisfied with the battery life, the average opinion changes from one time slot to another. To help designers estimate the potential CR in the next time slot, the introduced models in Section 4.4 are utilized.

[*Insert Figure 9. CR of a product feature vs. elapsed days (954 Samsung i9300 reviews)*]

In all of three sub figures in Figure 10, predicted CRs of three frequently mentioned product features are denoted as a red line, while CRs identified from online customer opinion are denoted as a blue line. As seen from this figure, the predicted CR and the observed CR demonstrate a small error, which means the proposed method is capable to predict CRs of a specific product feature in a high performance.

[*Insert Figure 10. Observed CR vs. Predicted CR (954 Samsung i9300 reviews)*]

5.4 The comparison analysis of CRs

In this section, the objective is to make comparisons of CRs between competitive products for QFD. Specially, four competitive mobile phones are selected. They are Samsung Galaxy i9300, Apple iPhone 4S, Nokia Lumia 920 and HTC One X. For short, "i9300", "iPhone4S", "Lumia920" and "OneX" are utilized. The number of reviews and frequently discussed features as well as average opinions are listed in Table 7 and Table 8 respectively.

[*Insert Table 7. The number of reviews and top frequently referred features*]

[*Insert Table 8. # of reviews with a certain sentiment that refers to product features*]

As seen from this table 7 and table 8, the total number of reviews of different sentiment that mentions a specific product feature does not distribute evenly. This phenomenon makes it not convincing to simply regarding the proportion of positive opinion as a factor to consider which product is better in a specific feature dimension. Accordingly, the proposed Baysian analysis method is applied to compare CRs of different products. The comparison results between i9300 and other phones are shown in Table 9.

[*Insert Table 9. The comparison between i9300 and three products on five features*]

Taken the comparison with iPhone4S for instance. It means that the probability that the screen of i9300 is better than iPhone4S is 0.791. Comparing with the percentage of positive reviews in Table 5 and Table 8, some interesting phenomena are found. As seen in Table 5 and Table 8, 78 out of 188 (41.49%) consumers are satisfied with the screen of i9300 and the figure for Lumia920 goes to

50.9%. However, in Table 9, a probabilistic explanations are provided. It can be found the probability that the screen of i9300 is better than that of Lumia920 is only 0.061. When the battery life and compatible applications are major concerns, i9300 seems to be much more favorable than that of Lumia920.

6. CONCLUSION

Nowadays, opinion data are generated online from time to time and presented in a variety of forms, such as customer reviews, twitters, blogs, etc. These opinion data reveal consumers' major requirements. The ability to promote a product that meets CRs from big consumer opinion data plays a significant role in market-driven product design, especially when competitive products are available. At its core, it is the CRs understanding from big opinion data at a deep level, which means processing and analyzing consumer opinion data effectively becomes urgent and highly in demand.

In this research, a big volume of consumer opinion data are analyzed for market-driven product design from the designers' point of view. Specially, online customer reviews, as an important type of consumer opinion data, are examined. At first, with the help of WordNet and pros and cons reviews, product features and sentiment polarities are identified from big consumer opinion data. Based on the identified product features and the recognized sentiment polarities, a Kalman filter approach is employed to recognize the trends of CRs, which helps designers to alert potential changes of CRs. Moreover, a Baysian method is proposed to make comparisons between different products in feature level. This study investigates the possibility that helps designers on how to handle the 4Vs of big consumer opinion data and how to process them by the latest development of the interdisciplinary collaboration.

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408 of 474 people found the following review helpful

☆☆☆☆☆ **iPhone or Galaxy S3? no way!!**, June 22, 2012

By **Luca Cascianini** - See all my reviews

This review is from: **Samsung Galaxy S3 i930016GB - Unlocked International Version No Warranty (Unlocked Phone)**

I got the S3 yesterday, since I owned a iPhone 4S here the comparison:

DESIGN: Galaxy S3 design is stunning, the feeling on hands is incredible. The ergonomics makes all the difference. The iPhone 4S is very squarish and definitely more solid but heavier too (way heavier);
SCREEN: Galaxy S3 screen is wonderful with vivid colours and sharp imaages, 4,8 inches vs 3.5 of the iPhone, after you make the transition you wont never come back, impossible.
OPERATING SYSTEM: S3 usability is a boom. iPhone is good but never at the level of the S3, way way slower.
BATTERY: S3 gets full day + 30% remaining battery, iPhone last till four or five PM;
GPS: Galaxy S3 gets locked in less than 10 seconds inside a building, iPhone searches and searches with no success;
CAMERA: they are very similar, S3 is faster and iPhone is may be a bit better in term of quality. No dramatic difference.
S-VOICE vs SIRI: they are both very basic and more fun than usefull.
USB-BLUETOOTH: iPhone only works with iTunes, no Bluetooth, no radio. Galaxy S3 can be usb-connected to computers and flashmemory, it has easy bluetooth connection and yes ... it has an amazing radio :)
APPS: to be sincere, all relevants apps in iPhones are present in Android. They have better design but they are at payment while in Android are always free. No mayor differences.

Galaxy S3 is an extraordinary good purchase. Recommended for all ex-iPhone users. You wont regret, there is a world outside iTunes :)

Help other customers find the most helpful reviews | Report abuse | Permalink

Was this review helpful to you? Yes No | Comments (36)

Figure 1. One typical online review

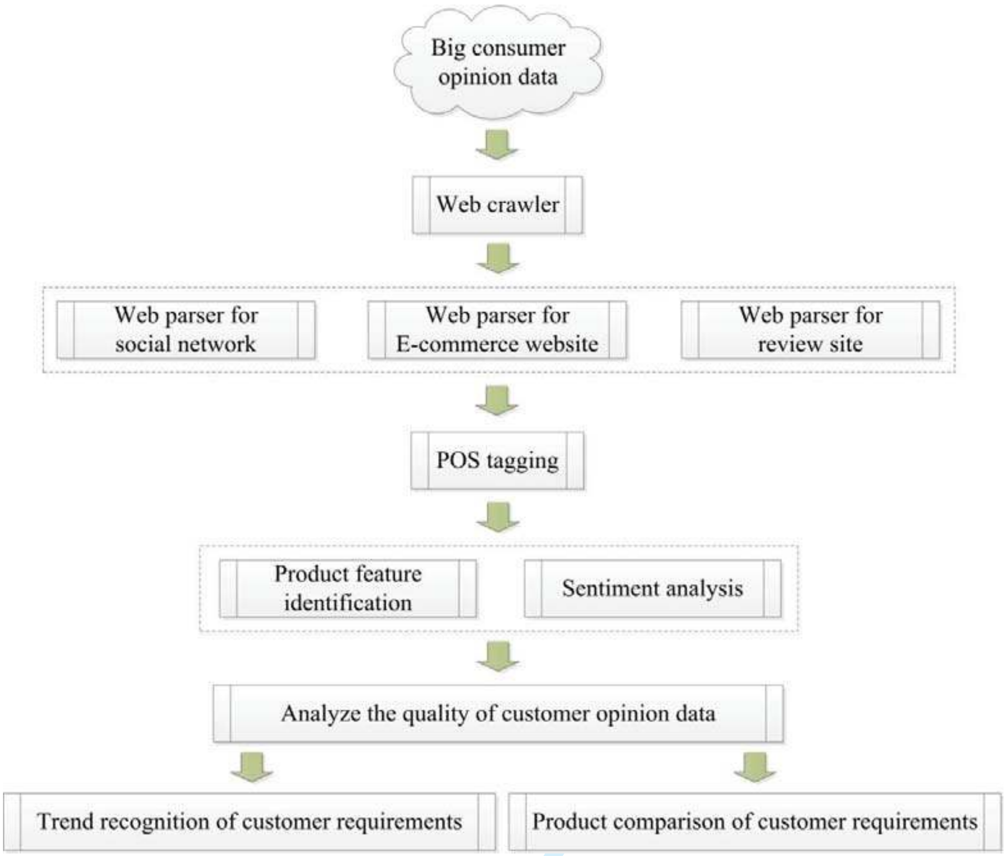


Figure 2. A framework of exploting big consumer opinion data

"I don't miss my IPhone"

★★★★★ Joyful422

Pros:

My favs are the Amazing customization!!!, widgets, screen size, several keyboard options, live wallpapers, light weight, direct call, dedicated back button and the multifunctional home screen button.

Cons:

I wish the battery lasted longer

Summary:

I researched this phone for at least a month because I was nervous about giving up my iPhone 4S. After watching YouTubes and convincing myself to try something other than Apple products, I purchased the phone figuring that if I didn't like it, I still had my iPad to fall back on. I have to say that this phone is the best! I love the freedom of customizing the phone and adding widgets to the home screen. I didn't realize how limited I was with my iPhones so all of these android features, like being able block numbers, live wallpapers, widgets, etc, are new to me. I still think the iPhone is a quality product, but this phone is much more fun. It's easy... I don't have to have an app for everything. Some things are just THERE on the home screen and I don't have to go into layers of apps to turn on WiFi or Bluetooth or anything else. Also, I thought the phone would be too big and awkward looking but it's actually very comfortable. The odd part is just last month I was making fun of my friend for having a phone this size. I never thought that I would even like a phone this big.
If you're like me and became a little bored with your iphone, I think that the SGS3 is worth a try.

Figure 3. One typical pros and cons review

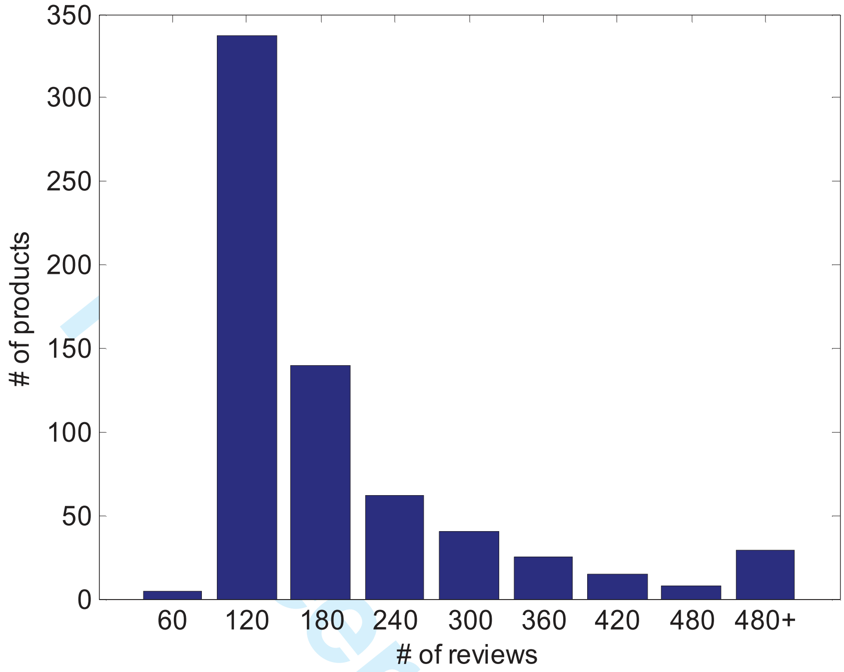


Figure 4. Statistics of reviews

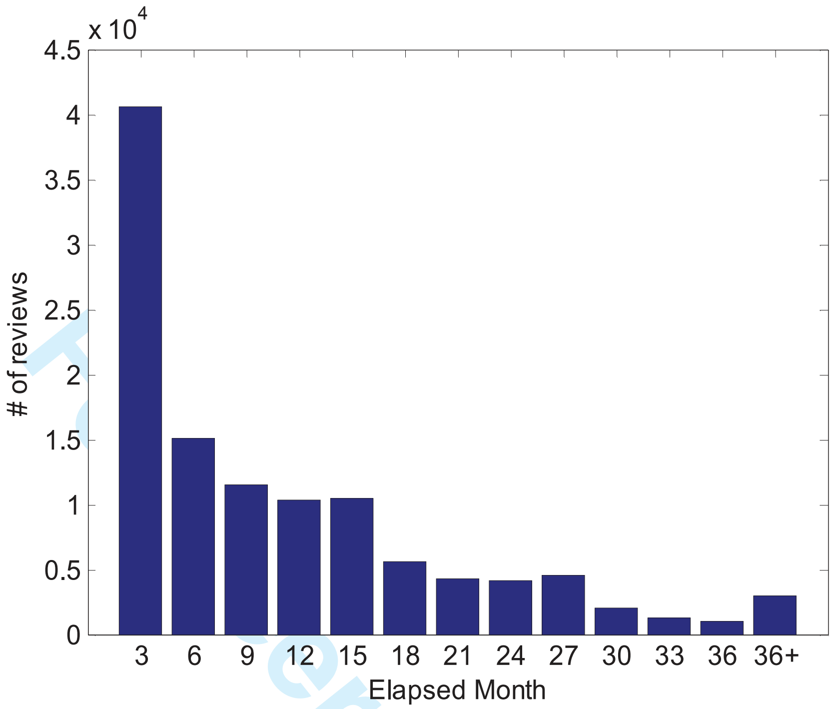
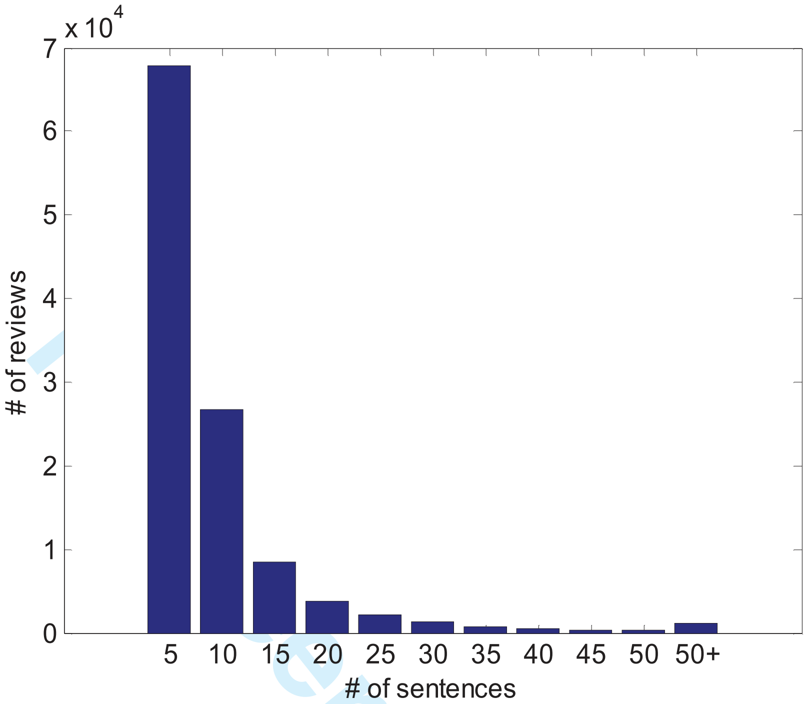
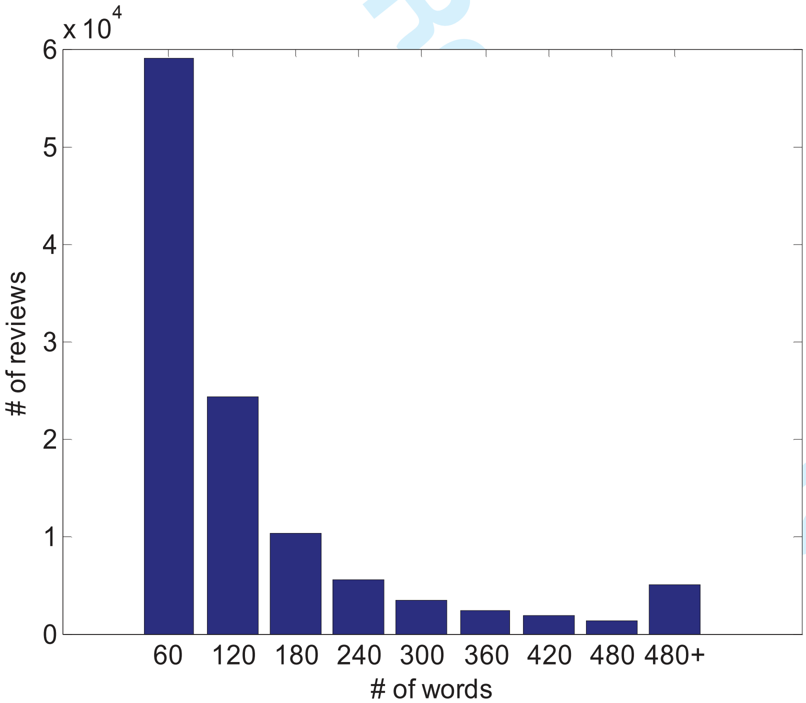


Figure 5. # of reviews vs. elapsed months



(a) # of reviews vs. # of sentences



(b) # of reviews vs. # of words

Figure 6. # of reviews vs. # of sentences and # of words

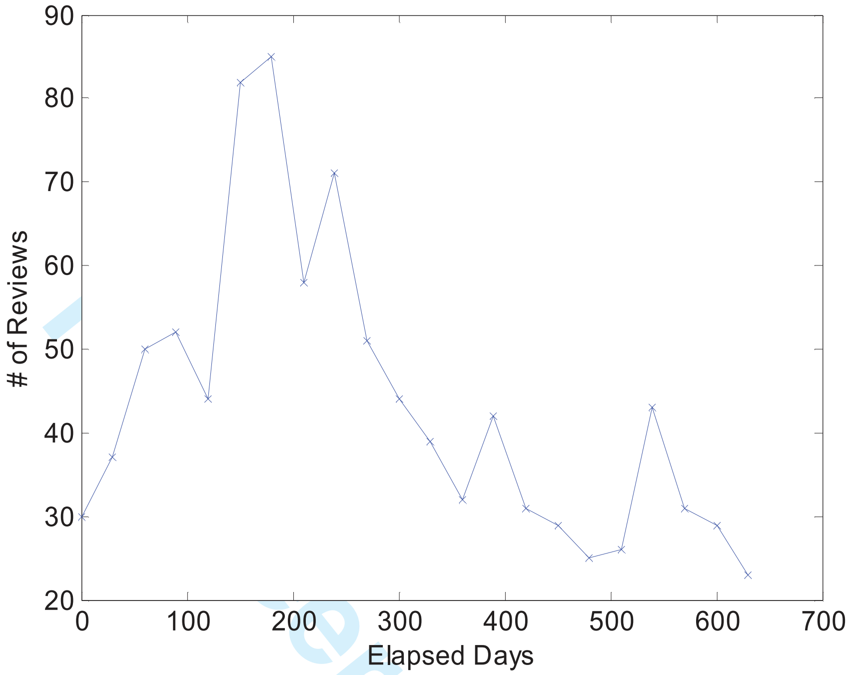


Figure 7. # of reviews vs. elapsed days (954 Samsung i9300 reviews)

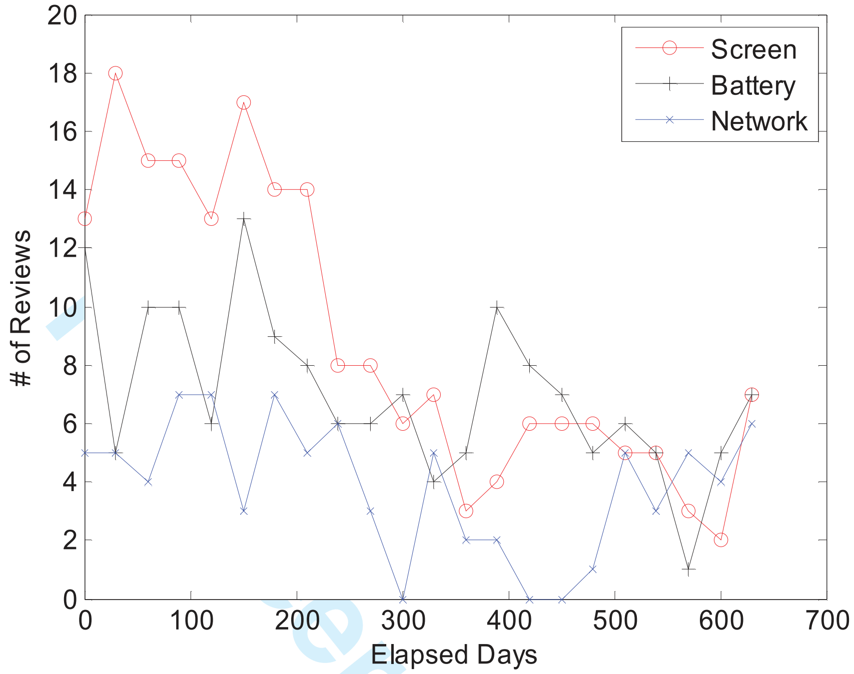


Figure 8. # of reviews that refers to a product feature vs. elapsed days (954 Samsung i9300 reviews)

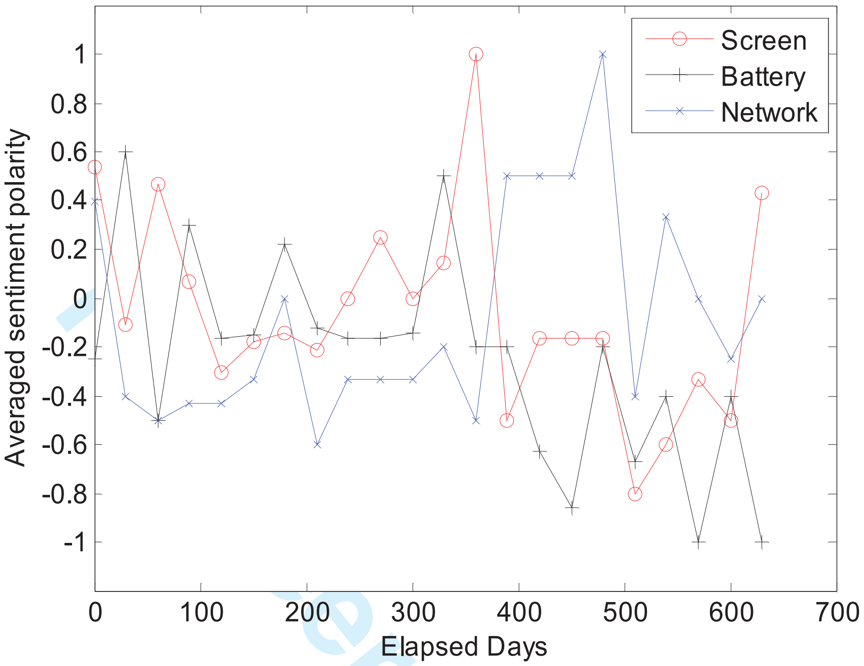


Figure 9. CR of a product feature vs. elapsed days (954 Samsung i9300 reviews)

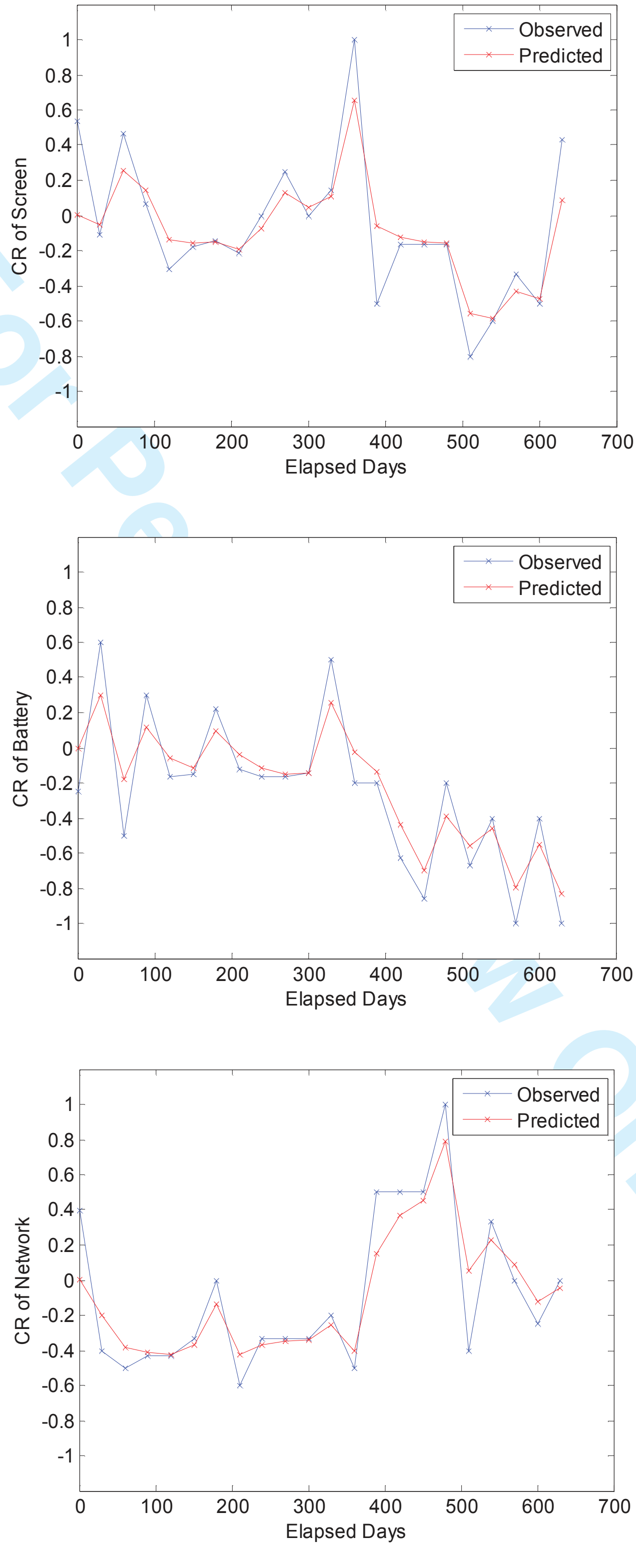


Figure 10. Observed CR vs. Predicted CR (954 Samsung i9300 reviews)

Product features	% of reviews referred features
cover screen screens	17.04%
batteries battery	14.87%
keyboard keyboards qwerty	8.09%
app application applications apps	7.24%
internet net network networks web wifi	6.41%

Table 1. Some frequently discussed features in pros and cons reviews

Product features	% of reviews referred features
cover screen screens	20.49%
batteries battery	18.23%
internet net network networks web wifi	13.28%
app application applications apps	13.21%
memory ram sd storage store	11.38%

Table 2. Top 5 frequently discussed features in mobile phone reviews

#	Sentence	Sentiment	Features
1	3months after I got the phone it stopped charging.	-	-
2	We waited for more than 2 weeks while it was "repaired" in Texas.	-	-
3	When the phone was returned it still would n't charge.	-	-
4	After a couple more calls a new charger and battery was sent to us.	0	charger, battery
5	With the new battery it started charging , but would drop phone calls a few minutes into a phone call.	-1	battery
6	Once again we had to send it to Texas for repair.	-	-
7	We received the phone this morning and it is missing the SIM card and the back cover.	0	cover
8	They say they 've lost the SIM card and I have to go buy a new one.	0	card
9	I 've had to call half a dozen times to get things fixed and each time I get transferred to 2 or 3 different departments and it takes 30-60 minutes or more.	-	-
10	It 's been over a month and I still don't have a working phone -- and all this time I 've been paying for service.	-1	service
11	Ilike the phone when it works , but the Samsung support model is such a disaster that I will never purchase a Samsung product again.	-1	support
12	When my iPhone failed I took it to the Apple store and they replaced it in less than half an hour.	-	-

Table 3. An example of sentiment analysis

Product features	Avg. opinions
cover screen screens	-0.051
batteries battery	-0.232
internet net network networks web wifi	-0.237
app application applications apps	-0.351
memory ram sd storage store	-0.311

Table 4. The average sentiment polarities of top 5 frequently discussed features in mobile phone reviews

Features	# of reviews referred features	% of reviews referred features	# of positive	# of negative	# of neutral	% of positive
Screen	188	19.7%	78	80	30	41.49%
Battery	149	15.6%	40	73	36	26.85%
Application	93	9.75%	25	35	33	26.88%
Network	81	8.49%	13	31	37	16.05%
Memory	81	8.49%	13	38	30	16.05%

Table 5. Frequently referred product features in reviews of Samsung i9300

Year	Feature	%	Feature	%	Feature	%
2003	Screen	38.60%	Picture	26.32%	Color	24.56%
2004	Screen	30.09%	Battery	23.82%	Picture	19.12%
2005	Battery	25.40%	Screen	25.08%	Speaker	23.49%
2006	Screen	27.29%	Battery	26.71%	Picture	24.56%
2007	Battery	24.35%	Menu	18.39%	Screen	17.10%
2008	Battery	25.86%	Screen	23.03%	Menu	19.19%
2009	Network	26.46%	Screen	25.31%	Battery	24.37%
2010	Screen	27.70%	Network	26.32%	Battery	23.33%
2011	Screen	23.92%	Battery	20.32%	Network	19.71%
2012	Screen	23.98%	Battery	21.11%	Network	16.45%
2013	Screen	19.10%	Battery	17.02%	Application	11.79%
2014	Screen	17.16%	Battery	15.70%	Application	11.53%

Table 6. Top three frequently referred features in different years

Product	# of reviews	Top referred features	# of reviews referred features	% of reviews referred features
iPhone4S	258	Screen	21	8.14%
		Battery	20	7.75%
		Application	19	7.36%
		Network	19	7.36%
		Memory	19	7.36%
Lumia920	227	Operating system	166	60.1%
		Application	157	56.9%
		Screen	112	40.6%
		Battery	87	31.5%
		Picture	86	31.2%
OneX	276	Battery	45	19.8%
		Screen	38	16.7%
		Menu	28	12.3%
		Picture	28	12.3%
		Network	27	11.9%

Table 7. The number of reviews and top frequently referred features

Product	Top referred features	# of positive	# of negative	# of neutral	% of positive
iPhone4S	Screen	7	13	1	33.3%
	Battery	4	12	4	20.0%
	Application	7	10	2	36.8%
	Network	2	10	7	10.5%
	Memory	2	6	11	10.5%
Lumia920	Operating system	40	68	58	24.1%
	Application	23	81	53	14.6%
	Screen	57	44	11	50.9%
	Battery	21	44	22	24.1%
	Picture	41	29	16	47.7%
OneX	Battery	11	25	9	24.4%
	Screen	25	12	1	65.8%
	Menu	1	19	8	3.57%
	Picture	14	10	4	50.0%
	Network	8	9	10	29.6%

Table 8. # of reviews with a certain sentiment that refers to product features

Features	iPhone4S	Lumia920	OneX
Screen	0.791	0.061	0.004
Battery	0.731	0.672	0.618
Application	0.206	0.990	-
Network	0.674	-	0.066
Memory	0.676	-	-

Table 9. The comparison between i9300 and three products on five features