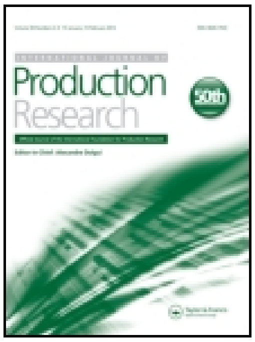

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Understanding big consumer opinion data for market-driven product design

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Big consumer data provide new opportunities for business administrators to explore the value to fulfil customer requirements (CRs). Generally, they are presented as purchase records, online behaviour, etc. However, distinctive characteristics of big data, Volume, Variety, Velocity and Value or '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 to deal with big consumer data for CRs understanding. Accordingly, a research study is conducted to exploit the value of these data in 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 Bayesian method is proposed to compare products. The objective is to help designers to understand the changes of CRs and their competitive advantages. Finally, using 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 valuable 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 a business report of International Data Corporation (IDC) in 2009, the volume of data doubles every 18 months (IDC 2009). Another news report in ACM (Association for Computing Machinery) Communication estimated that about 2.5 exabytes (one exabyte equals to 10^{18} bytes) of personal data were created each day and more than 2.5 petabytes (one petabyte equals to 10^{15} bytes) 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 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-h promotional period in 11 Nov 2013. Indeed, 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 analyse 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.

Hence, it is of great worth to explore the value of big consumer data and make products to fulfil CRs. Actually, studies on market-driven product design are favourable by researchers in the field of customer management or

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engineering design. Their concerns often include the descriptions of CRs (Karsak 2004), the transformation of CRs into quality function deployment (QFD) (Chen, Fung, and Tang 2006) and the relative importance of CRs (Mu et al. 2008). 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 big volume of online opinions are posted in e-commerce websites, such as Amazon.com and Taobao.com, without any purposeful guidance. In these websites, customers are encouraged to share their opinions from time to time. Besides e-commerce websites, consumer opinion data are also found in social network websites like Twitter.com, in review websites like Epinions.com, in media websites like Cnet.com, etc. In these sites, varieties of formats are hosted, which help consumers to articulate their concerns clearly. However, these data are not equally important for potential consumers and product designers. Some reviews might be lengthy and many details are described, while others might be short but critical opinions are pointed out. Generally, these characteristics are referred as Volume, Variety, Velocity and Value, or '4Vs', which are typical characteristics of big data and these characteristics make online consumer opinion data become one representative type of big data. 4Vs surpass the ability of many conventional models on the analysis of CRs for market-driven product design in the field of customer management or engineering design, which were built based on a limited customer 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.

The visible and significant gap wants an 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 fulfil 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 employed in market-driven product design is presented. In particular, online reviews, as one representative category of consumer opinion data, are analysed. Firstly, reviews of similar products are collected. Sentiment polarities 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 utilised. It helps to identify sentiment polarities over product features. Next, a Kalman filter approach is employed to predict the trends of potential CRs. Moreover, a probabilistic model is built to make comparisons on similar products in the product feature level, which aims to help designers for CR understanding on competitive products.

Notice that, various factors might be considered to affect CRs, such as, demographic customer characteristics of age or gender, financial considerations, social changes, macroeconomic fluctuations and market segmentation (Chen and Yan 2008; Ota et al. 2013). But the research focus is narrowed to highlight the imperative about the introduction of big customer opinion data into the design community and the objective is to bridge the gap between studies for understanding consumer opinion data and studies for market-driven product design. It aims to message designers about the significant value of big consumer opinion data. The analysis about different factors on CRs is out of the scope of this research. However, it highlights a critical research question and some additional studies will be conducted in the future.

The rest of this research is organised 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 benefit designers on CRs understanding 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 (Karsak 2004; Chen, Fung, and Tang 2006). For instance, linguistic variables were utilised to represent the imprecise CRs (Karsak 2004). Then, the Fuzzy Delphi Method was borrowed 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, Fung, and Tang 2006) and, accordingly, the relative weights of CRs were proposed to be expressed as fuzzy numbers. Wang also argued that the transformation of CRs should be made as little as possible to prevent information loss (Wang 2012). For this purpose, a nonlinear programming approach was proposed to estimate the relative importance of CRs according to customer satisfaction (CS), which allowed customers to express preferences on the relative importance of CRs in their familiar formats. Besides the CS, other factors might also be considered to affect CRs. Chen's group explained that, in a macro perspective, CRs might be influenced by sociocultural factors, such as multicultural factors, competitions and customer trends, which help to achieve better CS in the global marketplace (Chen, Khoo, and Yan 2002). Later, according to investigations on human behaviour and performance in the fields of physiology or psychology, his group pointed out physiological factors, psychological perspectives and technological considerations as potential factors that might influence CRs (Shieh, Yan, and Chen 2008).

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 analysed by a pairwise comparison through individual assessments with concrete numerical values. These numerical values are introduced for possible candidates ranking. 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 utilised for pairwise comparisons of the fuzzy AHP and comparisons of fuzzy numbers were conducted to prioritise CRs. Many researchers also employed 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 CS. In Kano's model, different CRs are categorised 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 CS in aesthetic qualities (Chen and Chuang 2008). In such robust design approach, the Grey relational analysis with the Taguchi method was proposed to optimise 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 CS. To decide the weights of multiple-criteria, regression methods with dummy variables are often utilised to recognise critical attributes. However, they 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 integrated 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, Ishikawa, and Inoue 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 *Analysing consumer requirements for QFD*

In the field of CR analysis, one famous approach is 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 prioritise 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 into CR attributes. With the proposed framework, these attributes are prioritised. Some also argued that the determination of the importance of CRs should consider both the degree of CR fulfilment and competitive products (Lai et al. 2008). They proposed a method that considering competitive products, current performance of the product and CS to determine the importance of CRs. Later, this method was applied 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 nonlinear 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 to decide target values of ECs when uncertain CRs are presented and imprecise relationship between ECs is found in QFD. Similarly, a fuzzy linear regression, QFD and zero–one goal programming were applied to decide which Enterprise resource planning (ERP) system satisfies CRs of companies (Karsak and Özogul 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 systems. However, in these approaches, the single objective is to maximise 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 maximising 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, Kauffmann, and Ozan 2007). But it was utilised 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 seen 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 fulfil dynamic and future CRs. From a probabilistic viewpoint, a Markov chain model was also reported to analyse the fast changes of CRs (Wu and Shieh 2006).

2.3 *Sentiment analysis on customer online opinions*

Approaches for the extraction of product features were argued that they need to cluster features into the same category (Mukherjee and Liu 2012). For this purpose, with some seed words for a few aspect categories as the initialisation, two probabilistic graphical models were proposed to extract and cluster features simultaneously. To extract aspects and the corresponding sentiment polarity from online reviews, a probabilistic modelling framework was proposed (Lin and He 2009). In this framework, a four layer model was built. Topics are generated dependent on sentiment, and words are generated on sentiment as well as topic pairs. Later, a reverse modelling framework was presented where sentiments are generated dependent on topic distributions (Lin, He, and Everson 2010). An unsupervised model was proposed to identify aspects and evaluate sentiment polarities from online reviews (Jo and Oh 2011). First, a probabilistic generative model was proposed, in which words in a single sentence are generated from one aspect. Then, one extended model was introduced, in which both aspect and sentiment are to analyse the sentiments in different aspects. However, it was found that it fails in the identification of sentiments specific to one aspect and does not separate sentiment words from the factual information. Then, a joint aspect and sentiment model was proposed for the extraction of aspects and sentiment words from online reviews (Xu et al. 2012).

Ding and Liu proposed an opinion aggregation function to estimate the sentiment polarities of product features (Ding and Liu 2007). To handle context-dependent opinions, three linguistic rules are utilised in this function, which include intra-sentence conjunction rules, pseudo intra-sentence conjunction rules as well as inter-sentence conjunction rules. A four-step architecture was proposed to extract sentiment polarity from online reviews (Cataldi et al. 2013). They include the extraction of frequent noun words, the identification of dependency graph based on Part-of-Speech (POS) tagged phrase structure tree, the sentiment polarity calculation of words using seed words and WordNet, and the sentiment estimation of product features based on word sentiment polarities. An unsupervised learning approach was proposed to select seed words in different domains automatically (Zagibalov and Carroll 2008). This approach was built based on a simple observation that positive words can be utilised in negation but these words occur more often in positive texts than negative. Some traditional methods in text classification are also utilised by researchers to identify whether a document is positive or negative, such as an SVM-based approach (Polpinij and Ghose 2008), a frequency statistic term weighting method (Hu and Wu 2009), a method using the association rule and the naive Bayesian method (Yang, Wong, and Wei 2009), etc.

2.4 *Consumer online opinions for product design*

By analysing online reviews, a three-step method was developed for customer-driven product design selection (Wang et al. 2011). First, product attributes were extracted from online reviews. Next, considering product ratings, category ratings, attribute ratings and product specifications, a hierarchical customer preference model was built by an approach of the Bayesian linear regression. At last, an optimisation problem was formulated to maximise potential profit by considering engineering constraints. A comprehensive user study regarding what induce consumers to make final purchase decisions was conducted and it is found that not only static features of products but also social features will impact it (Chen and Qi 2011). Accordingly, a framework to identify sentiment polarities of product features was built. In this framework, a method based on conditional random fields was applied to tag the sentiment of product features. The utility function that captures consumer behaviour on attribute value risk was also analysed by online reviews (Kannan, Goyal, and Jacob 2013). The sentiment polarities over different features were utilised to calculate the utility of products. The distribution of sentiment polarities over different features was regarded as a Beta distribution and the natural decline of sentiment polarities over time was regarded as a Poisson process. These modelling methods were utilised to analyse the dynamic change on the utility value of a product.

A graph propagation method was proposed to compare products in considerations of online reviews and community-based question answering (Li, Bhowmick, and Sun 2010). Comparative sentences were extracted from online reviews and the information about the number of preferences between two products was utilised in this graph method. Then, weights of product pairs, defined by the number of preference between products, were utilised for the information propagation. Online opinions were also reported to be utilised in the prediction about product design trends (Tucker and Kim 2011). First, sentiment polarities were extracted from online reviews. Next, the Holt-Winters exponential smoothing method was borrowed to track the trends of customer preferences.

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, Jacobs 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, Kauffman, and Kwon 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 is 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, general review sites, media websites, 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. Actually, the efficient understanding of consumer opinion data interests researchers in the field of computer science. With techniques in natural language processing and text mining, different models were reported in terms of opinion mining and sentiment analysis (Hu and Liu 2004; Lin and He 2009). The focus of these studies is primarily on the extraction of customer opinion from online textual data, such as customer online reviews, complains and compliments in twitters. But the current dilemma is that, given results from these studies, designers might still confuse potential applications in engineering design.

Also, as noted in the previous section, many approaches in engineering design are innovated to conduct market analysis and analyse 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 to 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 behaviour, understand customer preferences, sense customer responses and track the trend of product, which will undoubtedly make the business to gain competitive advantages in the fiercely competitive market. The analytical results from big consumer opinion data are expected to benefit designers in making wise decisions on whether breakthrough products, platform products and incremental products are required (Koen 2004). 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 experiences in product design to understand CRs. Hence, the interdisciplinary collaboration is welcome to analyse the big consumer opinion data for market-driven product design, such as, algorithms and models in information management and computer science, domain knowledge in product design, material and manufacturing.

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 1, 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 and Cnet.com. Hence, different web parsers for social network websites, e-commerce websites and review sites should be designed to extract such opinion data. POS tagging is then conducted on big consumer opinion data since consumers tend to utilise nouns or noun phrases to refer to product features and adjective or adverbs for sentiment polarities. Next, product features in terms of nouns and noun phrases and customer sentiments are identified from consumer opinion data with the help of many latest innovated algorithms in opinion mining. Similar assumptions using nouns and noun phrases as product features and adjective or adverbs as sentiment polarities are also made in different approaches for the identification of product features and the sentiment analysis on customer online opinions (Lin and He 2009; Alam and Lee 2012; Mukherjee and Liu 2012; Cataldi et al. 2013). In addition, notice that, some verbs or adjectives might also be utilised to refer to product features and, also, some verbs or nouns also bear the sentiment polarities of consumers. But all these are still open questions and not fully investigated. More dedicated models are expected to boost the accuracy of these two tasks.

In the research area of opinion mining, different approaches are reported to identify the sentiment polarity from online reviews. Some are supervised learning approaches based on the techniques of the topic model, in which a large number of manually labelled data are utilised as training samples (Lin and He 2009; Alam and Lee 2012; Xu et al. 2012). But it is generally time-consuming to obtain sufficient data. Also, they are not able to be applied directly due to the efficiency to analyse a big volume of consumer data. In addition, some are unsupervised learning approaches or semi-supervised learning approaches, in which only a small number of seed instances are provided (Yang, Wei, and Yang 2009; Zhai et al. 2010). However, these approaches are often observed not to perform well compared with supervised learning ones and they have to handle the case regarding the domain-dependent sentiment. Also, some approaches are difficult to understand for data practitioners in other fields. Hence, it motives this research to explore simple but effective approaches to extract product features and to identify sentiment polarities from big consumer opinion data.

Moreover, in our previous work, the helpfulness of online consumer opinion data and what makes them more helpful are analysed in the perspective of designers (Liu et al. 2013). The objective is to cope with the problem of value sparseness in consumer opinion data and to evaluate and predict the value of these data from the viewpoint of domain

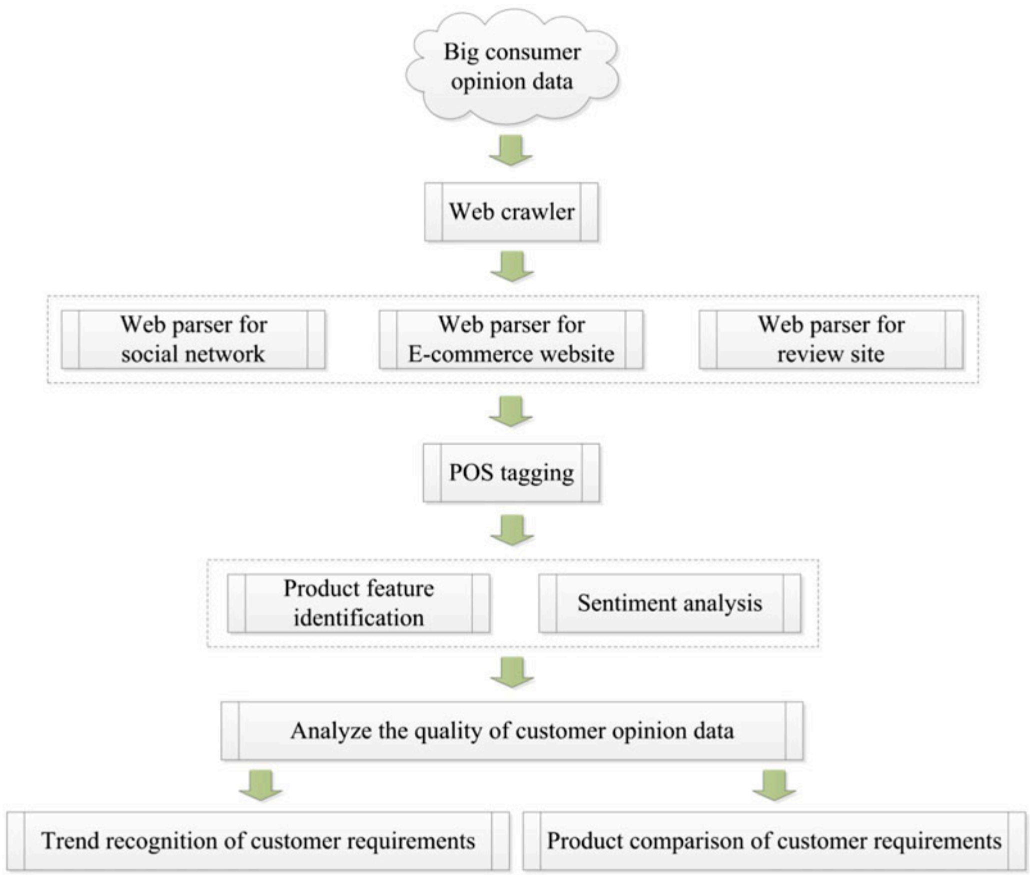


Figure 1. A framework of exploiting big consumer opinion data.

users. Based on this approach, a relatively small number of online consumer opinion data are available and it facilities product designers to obtain 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, analysing 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 analysed intelligently will be elaborated in this section. Indeed, there exist other forms of big consumer data, such as twitters, threads in BBS and blogs. But the techniques explained in this section can be modified and applied to analyse those types of big consumer data.

4.2 *Product feature identification*

One of the first tasks to analyse online reviews is the identification of which product features are mentioned by consumers. In consideration of the aforementioned arguments, in this research, with the help of WordNet, product features are extracted from pros and cons reviews. WordNet is an English lexical database that is developed by Princeton University. It can be simply regarded as a dictionary and it is widely utilised for text analysis. Some public programming interfaces of WordNet, such as the MIT Java WordNet Interface and the Java API for WordNet Searching, are freely available and, in this study, the MIT Java WordNet Interface is utilised.

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

As presented, 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 used to describe the same product features. For instances, 'memory', 'ram' and 'storage' are all used 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, WordNet synset is utilised. In WordNet, 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. Hence, words that occur in the same WordNet synset can be 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 used. This 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 considered 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 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 used 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 analyse corresponding sentiment polarities. Notice that, in pros and cons reviews, sentiment polarities in the feature level are presented. Taken this information into consideration, in this research, a two-step method is proposed to analyse 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 data-set is borrowed, which include 5000 subjective and 5000 objective sentences (Pang and Lee 2004). With this training data-set, 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. A famous book by Pang and Lee (2008) in the area of sentiment analysis refers that 'the label neutral is sometimes used as a label for the objective class'. Also, it is noted that 'Neutral indicates the absence of subjectivity. Strength classification thus subsumes the task of classifying a sentence as subjective or objective' (Liu 2012). Accordingly, in this research, if a sentence is predicted as an objective one, the sentiment towards product feature mentioned in the sentence is assumed to be neutral. A similar assumption is also adopted in (Esuli and Sebastiani 2006).

The second step is to classify whether one subjective sentence is positive or negative. A simple method is to calculate the WordNet distance between seed words and adjective/adverb words. Specially, after seed words are labelled 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 more 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 this dilemma, in this study, each sentence is represented by the subjectivity lexicon provided by the MPQA group (Wilson, Wiebe, and Hoffmann 2005). MPQA stands for the Multi-Perspective Question Answering and it is a research group in The University of Pittsburgh. This research group provides a list of subjectivity lexicon, which is widely utilised in the field of sentiment analysis. Also, since nouns, adjectives, adverbs and verbs are generally considered to express sentiment polarity, words with other POS are filtered out. Subsequently, given sentimental information 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 data classification algorithms are tested, such as SVM (Support Vector Machine) and logistic regression. But 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 recognise the changing trends of CRs. Specially, in this research, the average online opinion of one specific product feature is regarded as CRs of this feature and a Kalman filter approach is borrowed to analyse the dynamic change of CRs in the product feature level. The Kalman filter is a probabilistic algorithm, which is often utilised for analysing a series of ever-evolving data (Kwon et al. 2009; Sikora and Chauhan 2012; Nobrega and Oliveira 2015). Specifically, sentiment polarities of one specific feature in different time slot are analysed by the Kalman filter method. The motivation is to help designers to grasp the changes of CRs efficiently from big consumer opinion data.

In this approach, sentiment polarities of a specific feature are firstly modelled 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. Suppose that $N(\mu, \Sigma)$ denotes a random variable that follows a Normal distribution with the mean μ and the variance Σ. Accordingly, the distribution of ε_t can be denoted as,

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

Q_t is the variance of ε_t at time t. As suggested by Murphy (2012) and some similar studies (Sikora and Chauhan 2012), 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. Likewise, R_t is also assumed not to be a constant R along the time.

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

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. It estimates CRs at time t and obtains feedback in the form of noises, which are utilised 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,

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

In the first equation, the probability function is denoted as p and it denotes that, given the actual observations of the average opinions in all the previous time $t-1$, the conditional probability of the average real opinion at time t can be estimated with a Normal distribution with the mean $\mu_{t|t-1}$ and the variance $\Sigma_{t|t-1}$. $\mu_{t|t-1}$ and $\Sigma_{t|t-1}$ refer to the posterior mean and the variance at time t given previous states.

In the update step, it follows,

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

K_t is the Kalman gain matrix that minimises the posterior error covariance and S_t calculates the residual covariance at time t. Specially, K_t can be simplified to,

$$\begin{aligned} K_t &= \Sigma_{t|t-1}C^T(C\Sigma_{t|t-1}C^T + R)^{-1} \\ &= (C^TRC + \Sigma_{t|t-1}^{-1})^{-1}C^TR^{-1} \end{aligned}$$

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, CS 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 $N^{p,k}_{\text{positive}}$ consumers are satisfied with f_k of product p, $N^{p,k}_{\text{negative}}$ consumers are dissatisfied f_k of product p, and $N^{p,k}_{\text{neutral}}$ consumers express a neutral opinion. Obviously, $N^{p,k}$ equals to the sum of $N^{p,k}_{\text{positive}}$, $N^{p,k}_{\text{negative}}$ and $N^{p,k}_{\text{neutral}}$. The corresponding number of consumers presenting positive, negative and neutral on f_k of product q is $N^{q,k}_{\text{positive}}$, $N^{q,k}_{\text{negative}}$ and $N^{q,k}_{\text{neutral}}$. Now, the problem is, given these observations, how to infer which product is more favourable on product feature f_k.

On the face of it, one intuitive method is to compare which product receives 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, a Bayesian analysis method was proposed to make comparisons between products.

To model the outcomes of this three-dimensional overall CS, a multinomial distribution is utilised. Let $x^{p,k}$ be a random vector, where $x^{p,k} = (N^{p,k}_{\text{positive}}, N^{p,k}_{\text{negative}}, N^{p,k}_{\text{neutral}})$. Then, $x^{p,k}$ has the following probability mass function,

$$Mu(x|N^{p,k}, \alpha^{p,k}) = \binom{N^{p,k}}{N^{p,k}_{\text{positive}}, N^{p,k}_{\text{negative}}, N^{p,k}_{\text{neutral}}} \alpha^{p,k}_{\text{positive}}\alpha^{p,k}_{\text{negative}}\alpha^{p,k}_{\text{neutral}},$$

where $\alpha^{p,k}$ denotes the probability that is observed regarding the distribution over positive, negative and neutral opinions on feature k of product p, where $\alpha^{p,k} = (\alpha^{p,k}_{\text{positive}}, \alpha^{p,k}_{\text{negative}}, \alpha^{p,k}_{\text{neutral}})$. $\binom{N^{p,k}}{N^{p,k}_{\text{positive}}, N^{p,k}_{\text{negative}}, N^{p,k}_{\text{neutral}}} = \frac{N^{p,k}}{N^{p,k}_{\text{positive}} + N^{p,k}_{\text{negative}} + N^{p,k}_{\text{neutral}}}$ is the multinomial coefficient. To simplify the estimation on $\alpha^{p,k}$ when more online opinions are observed, a conjugate prior is widely utilised since the prior and the posterior have the same form. In the case of the multinomial distribution, the conjugate prior is the Dirichlet distribution. Hence, $\alpha^{p,k} \sim Dir(\alpha^{p,k}_{\text{positive}}, \alpha^{p,k}_{\text{negative}}, \alpha^{p,k}_{\text{neutral}})$ is assumed.

Notice that, $\alpha^{p,k}$ is expected to be estimated from online opinions. However, at first, little knowledge is supposed regarding $\alpha^{p,k}$. Considering an unbiased assumption and an uninformative prior, one intuition is that the initial probability $\alpha^{p,k}$ should follow a uniform distribution over three dimensions. An equivalent denotation of the uniform distribution in terms of the Dirichlet distribution can be 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 $N^{p,k}_{\text{positive}}$ consumers presenting positive, $N^{p,k}_{\text{negative}}$ consumers presenting negative and $N^{p,k}_{\text{neutral}}$ consumers presenting neutral opinion on product feature f_k of product p, $\alpha^{p,k}$ can be updated as,

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

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

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

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

$$p(\delta^k_{\text{positive}} > 0) = \int_0^1 \int_0^1 I(\alpha^{p,k}_{\text{positive}} - \alpha^{q,k}_{\text{positive}}) \quad \begin{array}{l} \cdot Dir(\alpha^{p,k} | 1 + N^{p,k}_{\text{positive}}, 1 + N^{p,k}_{\text{negative}}, 1 + N^{p,k}_{\text{neutral}}) \\ \cdot Dir(\alpha^{q,k} | 1 + N^{q,k}_{\text{positive}}, 1 + N^{q,k}_{\text{negative}}, 1 + N^{q,k}_{\text{neutral}}) d\alpha^{p,k} d\alpha^{q,k} \end{array}$$

Generally, it is difficult to calculate the integration directly. However, a simple yet effective method is to approximate the statistic $p(\delta^k_{\text{positive}})$ by the Monte Carlo sampling method. Also, product p and product q are two exemplary competing products. Reviews of two products are posted by two different sets of consumers independently. Hence, it is reasonable to supposed that $\alpha^{p,k}$ and $\alpha^{q,k}$ are independent and 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 $\alpha^{p,k}_{\text{positive}}$ is bigger than $\alpha^{q,k}_{\text{positive}}$ 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 favourable 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 filter 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 taken as training data to identify product features and analyse sentiment polarities from big consumer opinion data. In Table 1, some frequently discussed features in pros and cons reviews are shown.

Product feature words are identified using pros and cons reviews. The frequency denotes how often they are referred in the pros and cons review data-set. 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.

Table 1. Some frequently discussed features in pros and cons 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

Notice that some irrelevant data may be found in these 113,467 reviews. To make few transformations about online opinion data, all these reviews are considered. However, if the data quality is one central concern from the perspective of product designers, research studies in Liu et al. (2013) can be applied. In Liu et al. (2013), how to identify helpful online consumer opinion data from the viewpoint of product designers was investigated, which will facilitate designers to filter opinion data in a certain degree according to different precision requirements. On the other hand, some reviews might be related with others, which imply that opinions in later reviews might be influenced by previous ones. The investigation about the relevance between different reviews might be a sparkling research question. In the future, investigations will be made towards how these reviews are influenced by others, how these influence the customer understanding by designers, etc.

To obtain a general description of all these 113,467 reviews, the number of products in terms of the number of reviews is explored and it is illustrated in Figure 2.

As seen from Figure 2, in this data-set, 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, the number of reviews in terms of the elapsed months is presented in Figure 3.

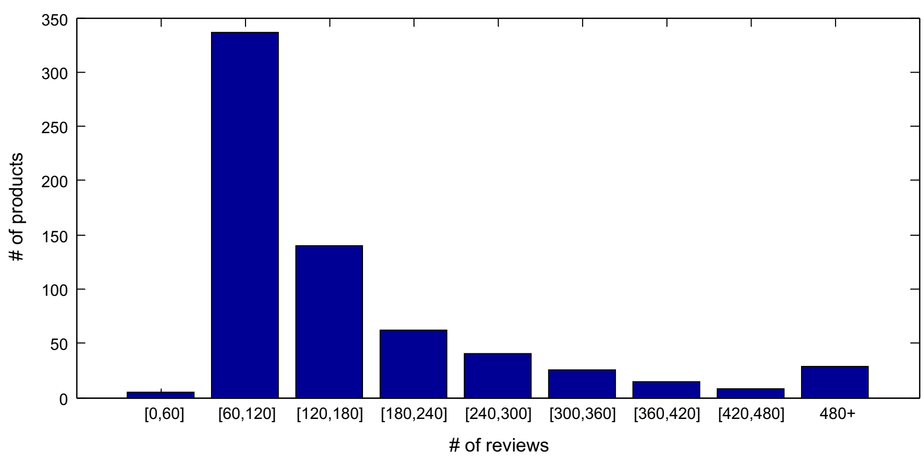


Figure 2. # of products vs. # of reviews.

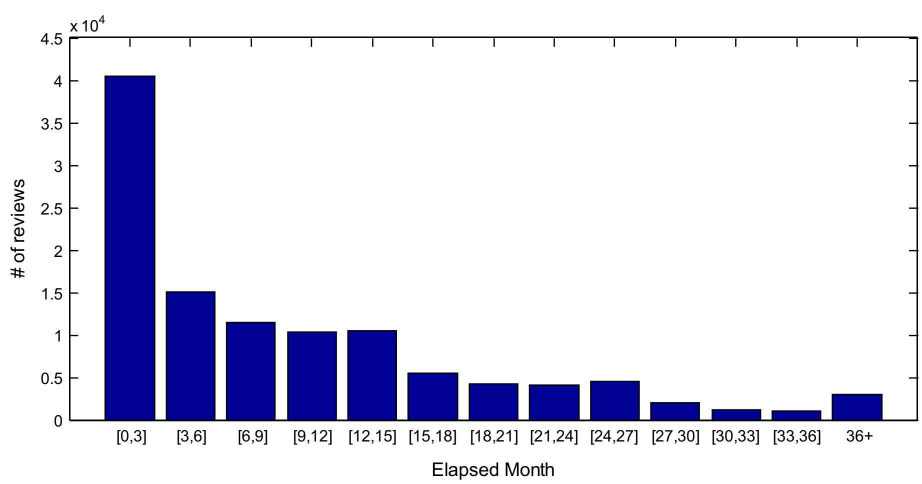


Figure 3. # of reviews vs. elapsed months.

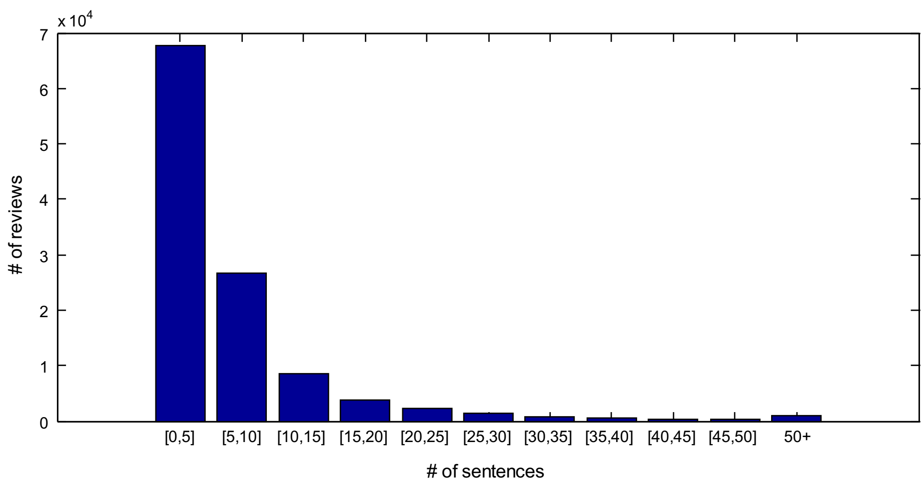
As seen from Figure 3, most reviews are posted in less than 15 months and the number of reviews declines gradually along the time. However, after 36 months, there are still about 2.62% reviews are posted by consumers. It can be inferred that, for some hot products, although they are not very popular after three years, there still exist some potential consumers. In addition, the number of reviews in terms of the sentence number and that in terms of the word number are described in Figure 4.

As seen from Figure 4, the number of sentences and the number of words do not distribute evenly. Most reviews are observed to contain less than five sentences and only a few are more than 50 sentences. Similarly, most reviews are found to have less than 60 words and merely a few of reviews are longer than 480 words.

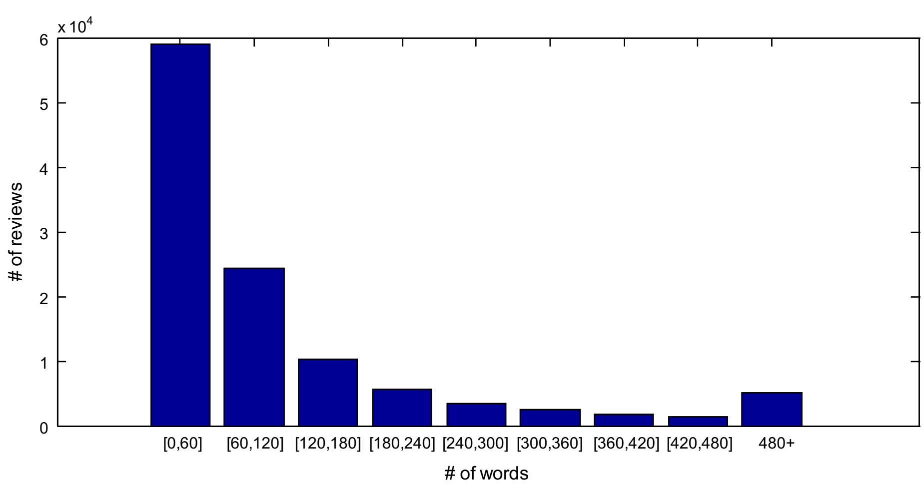
Moreover, on average, there are 124.31 words in each review. However, they are also not distributed evenly with the maximum of 14,104,898 words in a single review. A similar case can be also observed in terms of the number of sentences with an average 6.44 and a maximum 730,359 sentences in one review.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

5.2 *Product feature identification and sentiment analysis*

According to the proposed techniques in Sections 4.2 and 4.3, with the help of pros and cons reviews as training data, product features and corresponding sentiment polarities can be identified from consumer opinion data efficiently. These results help designers to obtain customer preferences in the product feature level.



(a) # of reviews vs. # of sentences



(b) # of reviews vs. # of words

Figure 4. # of reviews vs. # of sentences and # of words.

First, product features are required to be extracted from consumer opinion data. With the proposed WordNet-based approach, 21,952 pros and cons reviews in Cnet.com are at first utilised as training data. Frequently occurred nouns and noun phrases in the pros and cons list are viewed as candidates of product features and these candidates are later filtered by a shortlist to remove irrelevant ones. Then, with the help of synonyms in WordNet and manually defined synonyms, words that referring to product features can be found customer opinion data with a general form such as reviews in Amazon.com.

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 the 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 the Internet conveniently. Accordingly, it is understandable that applications as well as the Internet receive a substantial number of comments.

Next, sentiment polarities of each feature related sentence are analysed. As presented in Section 4.3, a two-step approach is utilised to analyse the sentiment polarities of one particular product feature. In this approach, at first, each sentence is represented as a bag of words. With the public data-set that contains subjective and objective sentences (Pang and Lee 2004), a Naive Bayesian classifier is required to classify whether one sentence is object or subjective. Next, each sentence is represented by the MPQA subjectivity lexicon. With the help of pros and cons reviews, another Naive Bayesian classifier is expected to classify whether a positive opinion is expressed. With this approach, the analysis result about sentiment polarities of one typical Amazon review is illustrated in Table 3.

Table 2. Top 5 frequently discussed features in mobile phone 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 3. An example of sentiment analysis result.

#	Sentence	Sentiment	Features
1	3 months 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 min 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	–	–

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 used 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 five 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 these hot product features.

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 are presented in Table 5.

As seen from Table 5, top five frequently referred product features coincide with that appears in the entire data-set 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*

Notice that sentiment polarities in the product feature level might be changed along the time. Efficient identification about the changes of sentiment polarities benefits designers in market-driven product design. It helps to give back reasonable responses and improve products for the sake of CS in time. In this study, a Kalman filter-based approach is proposed to recognise the changes of customer sentiments in product feature level.

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.

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

Product features	Avg. opinions
Cover screen screens	−0.051
Batteries battery	−0.232
Internet net network networks web Wi-fi	−0.237
App application applications apps	−0.351
Memory ram sd storage store	−0.311

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

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 6. Top three frequently referred features in different years.

Year	Feature	%	Feature	%	Feature	%
2003	Screen	38.60	Picture	26.32	Colour	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

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 accepted as an intelligent device to access the Internet. Also, 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 5, 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 3, which implies that most reviews are generated in less than 15 months.

In Figure 6, 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.

The averaged sentiment polarities of top three product features are compared in Figure 7. 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 are applied.

In all of three subfigures in Figure 8, 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

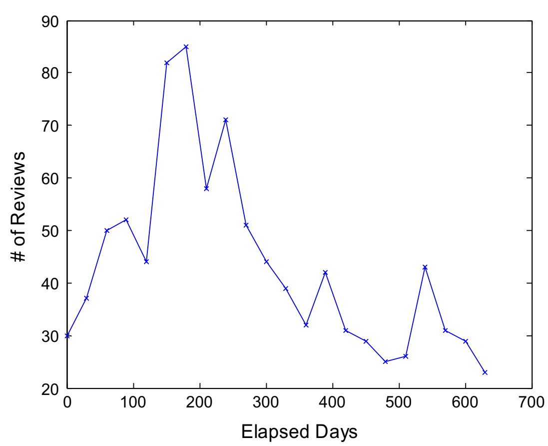


Figure 5. # of reviews vs. elapsed days (954 Samsung i9300 reviews).

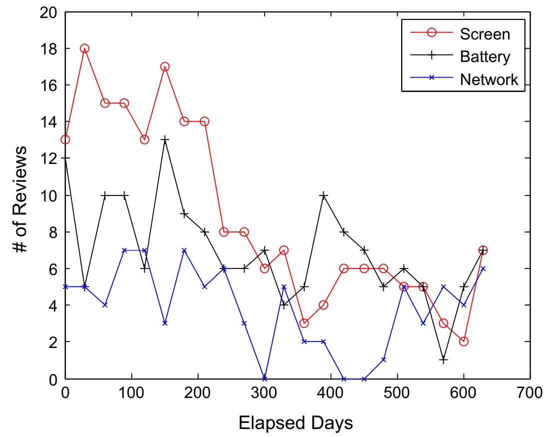


Figure 6. # of reviews that refers to a product feature vs. elapsed days (954 Samsung i9300 reviews).

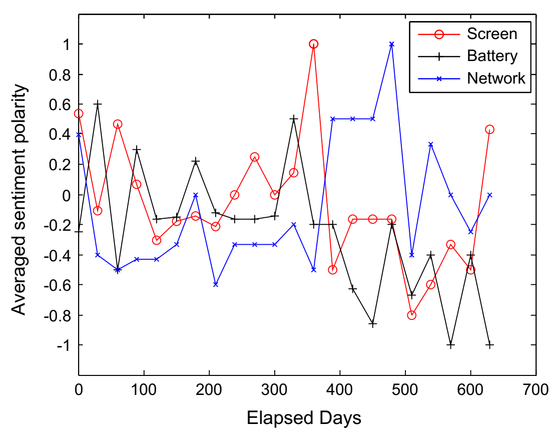


Figure 7. CR of a product feature vs. elapsed days (954 Samsung i9300 reviews).

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. These results will help designers to capture the dynamic changes of sentiment polarities for market-driven product design as well as help to give back reasonable and efficient responses for the sake of higher levels of CS.

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 utilised. The number of reviews and frequently discussed features as well as average opinions are listed in Tables 7 and 8 respectively.

As seen from this Tables 7 and 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 Bayesian analysis method is applied to compare frequently discussed product features of different products. The comparison results between i9300 and others are shown in Table 9. Note that, rather than all features, only frequently discussed features are concerned. For instance, the network and the memory are not frequently referred in reviews of Nokia Lumia 920. Also, reviews of HTC One X infrequently refer product features such as 'application' and 'memory'. Accordingly, experiments about product comparison do not reckon these features and results in the corresponding blanks are shown as '–' in Table 9.

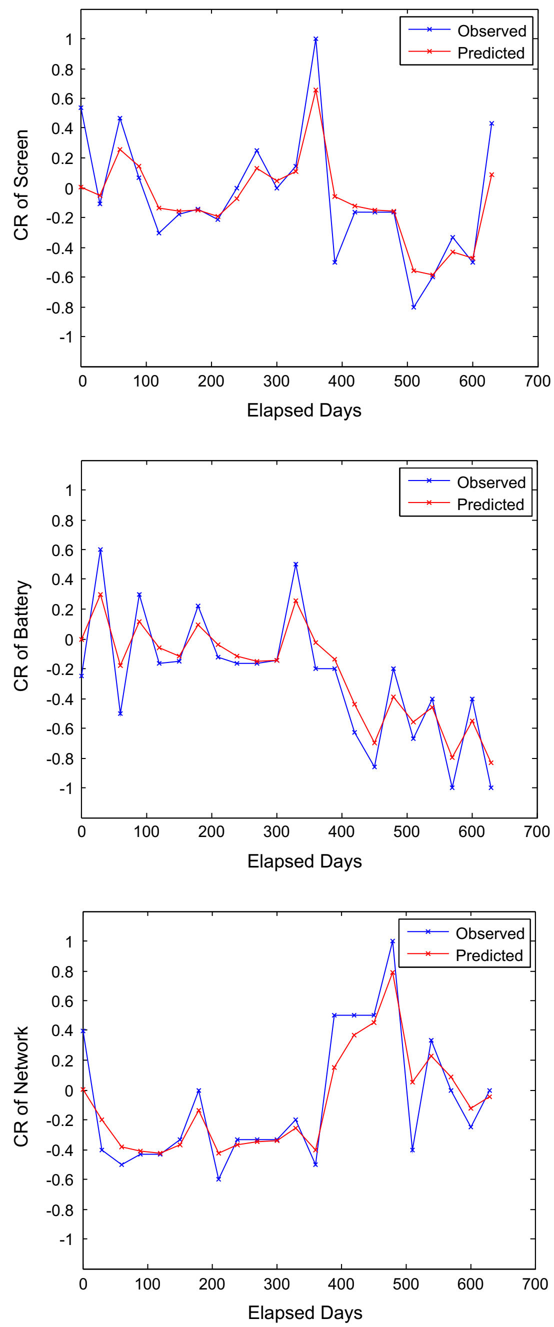


Figure 8. Observed CR vs. Predicted CR (954 Samsung i9300 reviews).

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 Tables 5 and 8, some interesting phenomena are found. As seen in Tables 5 and 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, 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 favourable than that of Lumia920. All these results in Table 9 help designers to make a reliable justification regarding whether i9300 is significantly better than others in the product feature level without considering the difference in number of consumers that actually refer to product features. In addition, these results motivate designers to explore further detailed investigations on some specific product features about customer concerns on competitive products.

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

Product	# of reviews	Top referred features	# of reviews referred features	% of reviews referred features
i9300	954	Screen	188	19.7
		Battery	149	15.6
		Application	93	9.75
		Network	81	8.49
		Memory	81	8.49
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 8. # of reviews with a certain sentiment that refers to product features.

Product	Top referred features	# of positive	# of negative	# of neutral	% of positive
i9300	Screen	78	80	30	41.49
	Battery	40	73	36	26.85
	Application	25	35	33	26.88
	Network	13	31	37	16.05
	Memory	13	38	30	16.05
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 9. The probabilities that i9300 is better than other products in five different feature level.

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	–	–

In this research, two of major tasks are to analyse whether CRs change along the time and whether one product is more favourable than a competitive one in the feature level. However, one of the first limitations about this research is that, besides the changes of sentiment polarities, designers also intend to know whether some particular features are missing in the current model or whether the current model meets the popular trend of CRs. Hence, in the future, some more details are expected to be presented when changes of CRs are analysed. Also, notice that the competitor analysis does not always means products in competing brands. Comparisons of products in the same brand are in need as well. For products in the same brand, especially for products in the same product family, common drawbacks are often required to be stressed and more details about these common drawbacks should be summarised clearly, which aims at the understanding of some critical reasons about consumers' preferences in the brand level. Accordingly, another limitation of this research lies in that the analysis of CRs for competitive products should be conducted for products in the same brand and in competing brands. All these tasks will help designers to better understand the pros and cons of different products.

6. Conclusion

Nowadays, opinion data are generated online from time to time and presented in a variety of forms, such as customer reviews, twitters and blogs. These opinion data reveal consumer major requirements. The ability of promoting product and service that meet 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 understanding of CRs from big opinion data at a deep level in the perspective of product designers, which implies that processing and analysing consumer opinion data effectively has become urgent and highly in demand for market-driven design.

In this research, a big volume of consumer opinion data were analysed for market-driven product design from the designers' point of view. The objective is to highlight the imperative of introducing big consumer data to design community. It is about how a large volume of CRs are obtained, how these online customer concerns are analysed from the viewpoint of product designers, and how these results will benefit designers for market-driven product design, etc. Specifically, online customer reviews, as an important type of consumer opinion data, were examined. At first, with the help of WordNet and pros and cons reviews, product features and sentiment polarities were identified from big consumer opinion data. Based on the identified product features and the recognised sentiment polarities, a Kalman filter approach was employed to recognise the trends of CRs, which helps designers to alert potential changes of CRs. Moreover, a Bayesian method was proposed to make comparisons between different products in feature level. Based on a big number of mobile phone reviews in Amazon.com, a case study was presented and categories of experiments were conducted to testify the effectiveness of the proposed approaches. This study introduces the big consumer opinion data to engineering community for market-driven product design and showcases the possibility how designers can be aided to handle big consumer opinion data through an interdisciplinary collaboration.

In the future, there are some critical tasks that need to be conducted to exploit the value from big consumer opinion data for market-driven product design. For instance, how to generate a brief yet insightful summarisation and how to sample a small set of representative review sentences from consumer opinion data of one particular product will facilitate designers to obtain customer concerns efficiently. Also, some popular products are welcomed around the world and customer opinions are generated in different e-commerce websites. How to employ online opinion data in various regions to differentiate CRs will significantly reduce tasks on the labour-intensive market investigations for international products. In addition, some further research investigations, such as applications of big consumer opinion data for product design, the integration of big consumer opinion data with design information and effective product design for different types of products using big consumer opinion data, are still not well studied. Moreover, the opinion analysis in consideration about the customer network, including how to find who are opinion leaders in the customer network or how lead opinions diffuse in the network, is another valuable research topic worthy of exploring for customer understanding in market-driven new product design, which complement greatly to the analysis of consumer opinion data.

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