Understanding Customer Regional Differences from Online Opinions: A Hierarchical Bayesian Approach

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Abstract: A large volume of customer reviews is generated from time to time and customer requirements are presented between lines of online opinions. Many studies about online opinions mainly focus on the extraction of customer sentiment, but practical concerns regarding the integration into new product design are far from extensively discussed. To enlighten designers about how consumers differ geographically in terms of their preferences, which is possessing important research significance and practical values, is not well investigated. Specifically, in this study, online reviews are invited to explore market regional heterogeneity. With identified product feature related subjective sentences from online reviews, a straightforward applied approach is to assume the ratio of the number of satisfied customers to the total number of customers as the expected percentage of satisfied customers across different regions. However, such frequency based approach becomes unreliable in case that the number of reviews do not distribute evenly. Accordingly, the Bayesian school of thought is utilized in which statistics of data-rich regions are invited to help to analyze that of data-poor regions. Then, a hierarchical Bayesian model is proposed and it assumes that the expected percentages of customer satisfaction in different regions follow a certain probability distribution. Finally, taking 9,541 mobile phone online reviews on Amazon as an example, categories of experiments were conducted. It informs the significance to product designers about the value of online concerns on analyzing market regional heterogeneity and presents the effectiveness of the proposed approach in terms of discovering customer regional differences.

Keywords: hierarchical Bayesian model; market regional heterogeneity; sentiment analysis; online reviews; customer satisfaction; regional distribution

1 Introduction

To stand out in the fierce market competition, product designers need to improve the quality and adjust their strategies quickly according to market dynamics. Especially, in the e-commerce environment, increasingly more customers are willing to share their opinions on products online. These online opinions, with distinctive characteristics, Volume, Velocity, Variety and Value or '4Vs', which mirror raw customer requirements (CRs), help product designers understand the market dynamics [1], analyze development trends [2] and sales rank [3], and provide new opportunities for managers to make effective responses regarding customer concerns [4]. They interest many researchers to explore how to obtain valuable information intelligently for potential consumers [5], business enterprises [6, 7] and product designers [8, 9]. Many studies regarding

CRs elicitation from online opinions for product designers are reported and they pay attentions on how to extract sentiment polarity from online reviews in different level [10, 11], how to identify customer insights from online opinions [12], how to connect online opinions with engineering technical considerations [13], how to predict future importance of product features [14], etc. But the underlying assumption of all these studies is that CRs are uniformly distributed and wholly undifferentiated across various regions.

However, CRs might vary from region to region and local markets have particular tastes. When companies enter an international market or a market with different levels of economic development and complex cultures, it is critical to pay much attention to customer requirement differences due to the region heterogeneity as customer requirement might vary from region to region and local markets have particular tastes. From the economic perspective, the overall development level and per capita income level of each region are different, and, from the perspective of cultural factors, historical heritage, religious culture, and customs may affect consumer behavior. For instance, to fulfill local taste buds, McDonald's introduced red bean pies in China and salmon McLaks burger in Norwegian restaurants [15], and they began to "regionalize its offerings in the U.S. with different sauces or flavors to appeal to local tastes" [16], although it contradicts the stated goal of simplifying the menu. Also, the first KFC outlet open in Bangalore in the mid-1990s, but all KFC restaurants were closed in India in just a few years until relaunched in 2004 due to that chicken wings and wraps were too alien for Indian [15]. Another case from FT.com reports that some foreign companies is failed to connect with local consumers in Africa [17] and, reported by MSN.com, even Apple is also, "planning dual-SIM card slots for the two larger iPhones in at least some regions." [18]. All these experiences explain that, regional uniformity leaves much obvious opportunities to design a tailor-made and differentiated product that meets the needs of local segments and if product designers fail to recognize regional differences of CRs, the customer satisfaction may be affected, which will potentially affect sale indicators.

Accordingly, the positioning of this study aims to enlighten designers about how consumers differ geographically in terms of their preferences on the same product. A straightforward approach is to analyze CRs individually in various regions. But it is generally time-consuming for product designers to collect sufficient CRs in various regions to explore market heterogeneity. On the basis of the findings by Timoshenko and Hauser [19], product online reviews can be invited to explore customer regional differences for market heterogeneity investigation in new product development. However, a further question becomes that the distribution of customer online concerns is often not uniformly distributed in terms of different regions. Particularly, for example, in some region, a large number of online reviews can be obtained. These reviews mirror customer compliments and complains and facilitate designers to understand concerns of customer in that region. Comparatively, in some region, due to various reasons, such as low-income regional economies or ineffective local promotion activity, only a small number of online opinions might be gained. Insufficient number of samples alone may fail to uncover real opinion distribution in that region. Note that, a widely applied approach to analyze a corresponding expected percentage of a given criteria, i.e., expected percentage of satisfied customers across different regions in this study, is a frequency-based statistics. That is, the percentage is assumed to be estimated by the ratio of the number of satisfied customers to the total number of customers. Obviously, the expected statistic is more reliable when there is a large number of sample available and otherwise it becomes contingent and unreliable with insufficient number of samples. It actually challenges the reliability of such widely applied approach. In order to eliminate this kind of error caused by the difference in the number of samples, different from the traditional frequency school view that the parameters, i.e., customer satisfaction level in different regions, are fixed, in this study, the Bayesian school of thought is utilized. It believes that the parameters also obey some kind of probability distribution. Then, in particular, it motivates this study to invite statistics of data-rich regions to help to analyze that in data-poor regions.

Specifically, a regional difference analysis framework is put forward for market heterogeneity by leveraging a big number of customer online opinions. First, a WordNet-based approach to obtain product features from customer online reviews and a classification approach was conducted to obtain customer sentiment polarity. Then, to reduce the dependence on the number of samples available in different regions, from the perspective of multi-task learning, a hierarchical Bayesian model is proposed to further analyze customer regional differences. In this model, rather than to estimate the percentages of satisfied customers in different regions independently, in this study, that statistics across different regions are assumed to follow a Beta distribution, which is a conjugate probability distribution to Binomial distribution. Finally, taking customer online opinions of mobile phone in the six major regions of the United States as an example, categories of experiments were conducted to evaluate the effectiveness. With the help of the proposed framework, product designers are enabled to grasp market preferences across various regions, make corresponding adjustment and tune their products in response to CRs.

The contributions of this study are at least two folds. First, a framework regarding regional difference analysis is proposed by leveraging customer online reviews. It highlights the significance to product designers about the value of product online concerns on analyzing market regional heterogeneity and help to make strategic adjustment in various regions. Theoretically, it intends to make up many studies which fail to explore the customer geographical heterogeneity investigation for new product development. Second, a hierarchical Bayesian model was innovated to analyze customer preference regional differences at the product feature level, in which analysis result for data-poor regions is borrowed from statistics in data-rich regions. Practically, it provides designers an efficient and effective solution to understand how consumers differ geographically in terms of their preferences by analyzing online concerns.

The rest of this study is organized as follows. In Section 2, some relevant studies are briefly reviewed. In Section 3, a framework regarding customer regional differences is depicted and technical details of the proposed approach are explained. Section 4 elaborates the proposed hierarchical Bayesian model for the analysis of customer regional differences. Using a large Amazon.com dataset, a case study is presented in Section 5 to show how the proposed framework benefit product designers. Section 6 concludes this research.

2 Literature review

2.1 Survey-based customer satisfaction analysis

Customer satisfaction is usually defined as the total consumption perception of consumers [20]. Conventionally, studies regarding customer satisfaction are conducted according to a small number of formatted questionnaires [21 - 24]. For instance, a customer satisfaction strategy was discussed in banking by analyzing advantages and disadvantages of service quality models for customer satisfaction [25]. To avoid the customer sentiment into either satisfied or unsatisfied qualitatively, the grey theory was introduced to evaluate customer satisfaction degree [26].

According to customer survey data, different studies intend to explore critical indicators that affect customer satisfaction. A probabilistic feature-selection technique was applied to measure the significance of product features and then a rule-based method was proposed to analyze the relation between product features and customer satisfaction [27]. Similarly, a hierarchical Bayesian model was built to estimate the relative importance of predictors in the presence of small customer survey samples [28]. Besides, various regression methods were utilized to examine relations between customer satisfaction and the effect of brand measures [29]. Then, feature selection approaches were applied to find out the most important indicators among all components of different brand measures. However, customer satisfaction is a kind of psychological feeling and different customers have different feelings about the same product or service. As a result, there might be a huge discrepancy in the setting of specific indicators and a lack of unified conclusions regarding customer satisfaction.

2.2 Online opinion-based customer satisfaction analysis

In the e-commerce environment, as an important type of online opinions, online reviews mirror customers' spontaneous opinions and emotional details are presented. These advantages satisfy both product designers and business retailers to measure customer satisfaction by online opinions.

For instance, the approaches Naive Bayes and logistic regression were utilized to estimate the overall customer satisfaction by analyzing features mined from online reviews [30]. Chen, Huang and Chen examined the relations among customer satisfaction and e-Loyalty based on the satisfaction-loyalty model and proved that customer satisfaction had a positive impact on customer e-Loyalty [31]. Besides, the extent to which online reviews influence consumer beliefs and participation in online group-buying was examined [32]. According to customer opinions and clues regarding customer satisfaction, the helpfulness [8, 33] and the trustfulness [34] of reviews were also investigated.

In addition, with the help of opinions extracted from online reviews, an integer programming model was proposed to analyze how to prioritize engineering characteristics [35]. Similarly, Wang, Lu and Tan [36] extracted the sentiment polarity of various product features from customer online reviews and utilized the logistic regression to analyze their impacts on customer satisfaction. They argued that customer satisfaction is significantly affected by various product features and influences begin to fluctuate with the change of price. Also, the latent semantic analysis was applied to identify critical factors that affect customer satisfaction by analyzing hotel online reviews [37].

Moreover, online opinions and customer satisfaction were introduced to analyze the overall market performance. For instance, Ghose and Ipeirotis investigated the customer expected helpfulness of online reviews as well as the relation between online reviews and product sales [38]. Then, a consumer-oriented ranking mechanism and a manufacturer-oriented ranking mechanism were designed. They argued that customer subjective opinions present useful clues in both two ranking mechanisms. A large volume of customer opinions was obtained from weblog [39]. Then, these online opinions were found to be a strong correlation with the of the movie box office and it confirms that customer opinions are a better predictor for movie box offices than the volume of discussions only, especially before the opening of the film. The naive Bayesian classifier was also utilized to examine the impact of Internet stock message boards on stock market and stock messages were found to help predict market volatility [40].

2.3 A brief summary

As presented, many studies regarding customer satisfaction from online opinions mainly focus on how to identify clues to predict customer satisfaction, how customer attitude affect customer behavior, how to identify critical indicators that influence customer satisfaction, how online customer satisfaction affect market performance, etc. What they neglect is to disclose CRs cautiously and help decision-makers to provide effective and efficient response to customer concerns. As one fundamental aspect, the analysis on customer regional differences point to fine-grained customer preferences, which is important in competitive market to adjust strategies and customize products cautiously on the basis of their regional expectations and differences.

Accordingly, several associated questions are put forward. Are customer preferences in different regions the same? Are customer preferences with the product or service different due to the region? In view of mentioned problems, in this study, a comprehensive discussion will be conducted towards these interesting and valuable questions and a framework is proposed to highlight customer regional difference by analyzing online reviews.

3 A framework for analyzing customer regional difference

3.1 Framework

In Figure 1, a three-step approach is proposed for the analysis of customer regional difference according to online reviews.

As presented, a large volume of online reviews with customer regional information are collected from review sites. Initially, some preliminary tasks, such as word normalization, word stemming, POS tagging (Part-of-Speech, POS), are involved to extract instructive information from customer reviews. Particularly, in this study, the software from the Stanford Natural language processing group was utilized for these tasks, which is a famous and widely utilized tool in the field of natural language processing. Then, two major tasks become how to extract product features and how to obtain customer sentiment opinions in the product feature level. Actually, different models were proposed in the field of computer science. For instance, some of them built Bayesian graph models to extract product features and analyze the sentiment polarity [41, 42]. However, many of them are too complex for practitioners in the field of business analyzers since that a solid mathematic background and skillful programming techniques are often required. Then, in this study, a simple yet effective approach is applied. Similar approaches for product feature extraction and sentiment analysis were also reported in [13, 43, 44].

3.2 Product feature extraction and sentiment analysis

Note that, some review sites encourage customers to express both compliments and criticisms clearly in a pros and cons list before a full detailed review. Take a review of the Samsung Galaxy I9300 in Epinions.com for instance. In a pros and cons list, pros are described as "Great battery life, 4.8 HD Super Amoled Display" and the section of cons is that "Images tend to get overexposed, and Screen dim for outdoor use". Note that, in this example, different features are listed, such as, battery life, display, image, screen, etc., and they are presented as nouns or noun phrases. Accordingly, as assumed in other studies, frequently appeared nouns and noun phrases in the pros and cons list are considered as product features.

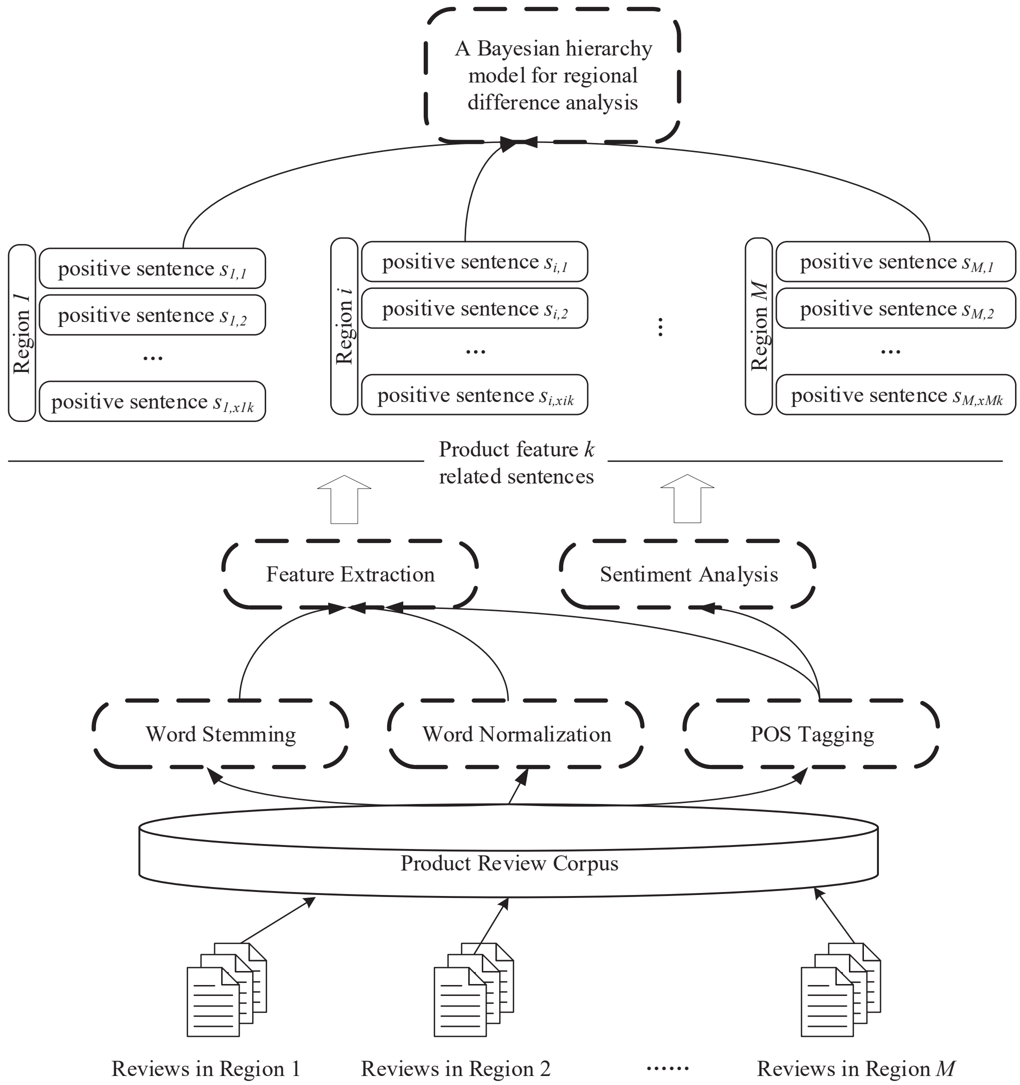


Figure 1. A framework for analyzing customer regional difference based on online reviews

Also, various words might be utilized to refer to the same product features. For instance, in the above example, rather than "image", the word "picture" might be used. It requires that noun words that refer to the same product feature should be clustered. In this study, a WordNet distance-based approach is applied to estimate the word similarity. WordNet is a lexical database for the English language, which groups English words into sets of synonyms [45]. Moreover, some abbreviations, such as "apps" and "pic", can be also utilized to indicate "applications" and "pictures" respectively. However, these oral abbreviations are seldom formally defined in WordNet or other thesauruses. Then, a short manually defined synonym list is provided to help noun words that often refer to the same product features to be clustered unambiguously. Finally, with the help of pros and cons list and WordNet, clusters of words can be obtained, and they help to identify product features from online reviews in a general format, such as reviews in Amazon.com.

The next task is to analyze customers' sentiment polarity of feature related sentences automatically. In this study, these sentences are categorized to positive, negative or objective. As assumed in other studies [43, 46, 47], a sentence is regarded to be subjective if a positive or a negative opinion is expressed. Otherwise, it is assumed to be objective. Note that, in this study, the focus is on customer regional differences in product feature level, then only feature related subjective sentences are taken into considerations. Accordingly, two subtasks are whether a sentence is subjective or objective and whether a sentence is positive or negative. For the first subtask, a publicly available dataset [48], including 5,000 subjective and 5,000 objective sentences, is borrowed and. It helps to build a classifier to classify whether a sentence is subjective or objective. Specifically, the bag of words representation is applied to symbolize each sentence and a binary Support Vector Machine (SVM) classifier is built. The second subtask is to classify whether a sentence is positive or negative. Note that, compliments and criticisms are identified clearly in the pros and cons list, which provide rich sentiment information. Then, the sentiment polarity of one sentence in the section of detailed reviews can be identified according to the associated pros and cons list and these sentences can be utilized to train a positive or negative classifier. Furthermore, rather than the bag-of-words representation, sentimental terms defined in the MPQA (Multi-Perspective Question Answering, MPQA) project are employed, which defines a list of sentimental terms that help to capture opinions [49]. With the MPQA representation, another binary SVM classifier to classify whether a sentence is positive or negative.

4. A Bayesian hierarchy model for regional difference analysis

The objective of this study is to explore customer regional differences by analyzing a large volume of online reviews. Conventionally, customer responses are categorized according to regional sections and sentiment analysis is conducted in the feature level independently in each region. Then, percentage of customers who are satisfied with a particular product feature can be estimated. Note that, the underline assumption in such straightforward approach is that a sufficient number of customer responses are obtained, and the number of responses does not differ significantly. Such frequency-based approach assumes that the percentage of preferred customers can be estimated independently. However, it does not hold if customer online reviews are borrowed for regional difference analysis and customer reviews are not evenly distributed in different regions. Then, it induces that the reliability of customer analysis in different regions may not be always reliable.

To eliminate the influence from the number of samples available, different from the viewpoint of Frequency School that parameters are fixed and invariant, in this study, the Bayes School's point of view is adopted. It is assumed that parameters, i.e. the percentage of preferred customers regarding a particular product feature in different regions, should follow a probability distribution. Specifically, rather than to estimate the percentage of preferred customers in different regions independently, the percentage in a particular region can be referred as an independent sample from a true distribution about the percentage of preferred customers. Then, the estimation about the percentage of preferred customers in different regions becomes a multi-task learning practice. Accordingly, a hierarchical Bayesian model can be built to estimate the percentage of preferred customers regarding a particular product feature in different regions.

Now, suppose there are M regions and a specific product feature k is taken into considerations. For a particular region i, where $i \in [1, M]$, $N_{i,k}$ customers mention the product feature k, and, among $N_{i,k}$ customers, $x_{i,k}$ customers are satisfied with k. Let a latent variable $\theta_{i,k}$ be the probability that a customer satisfies with k in region i. Then, it can be denoted as $x_{i,k} \sim Bin(N_{i,k}, \theta_{i,k})$.

One brute approach is to assume all $\theta_{i,k}$ are the same and it implies that the percentages of customer satisfaction are the same over different regions. But this assumption is so strong that it completely erases customer regional differences. Another naïve approach is to assume $\theta_{i,k}$ in each region is independent. It implies that the classical frequency-based approach is applied and the percentage is assumed to be estimated by the ratio of the number of satisfied customers to the total number of customers. However, as mentioned, it may suffer from the imbalanced number of customers in various regions, which induces that the estimated results are not reliable. In this study, the Bayes School's point of view is adopted. Specifically, it is believed that $\theta_{i,k}$ are not stationary but obeying a kind of probability distribution. Then, from a higher level perspective, regions with a small sample size can borrow statistics from the regions with a large sample size. For instance, there exist a shared prior η_k regarding the generation of $\theta_{i,k}$. Hence, it can be denoted as, the probability of a customer who is satisfied with k in region i be $p(\theta_{i,k} \mid \eta_k)$. As mentioned, a binomial distribution is applied regarding $x_{i,k}$, i.e., $x_{i,k} \sim Bin(N_{i,k}, \theta_{i,k})$. Then, in this study, for the convenience of deduction, a conjugate prior about $\theta_{i,k}$, a beta distribution, is assumed to follow and it can be denoted as $\theta_{i,k} \sim Beta(\alpha_k, \beta_k)$, where the shared prior η_k is defined as a pair of parameters (α_k, β_k).

Accordingly, the probability that customers satisfy with feature k in M different regions is represented by a joint probability distribution, which can be written as,

$$\begin{aligned} & p(X_k, \theta_k \mid N_k) \\ &= \prod_{i=1}^{M} p(x_{i,k} \mid N_{i,k}, \theta_{i,k}) p(\theta_{i,k}) \\ &= \prod_{i=1}^{M} Bin(x_{i,k} \mid N_{i,k}, \theta_{i,k}) Beta(\theta_{i,k} \mid \eta_k) \end{aligned} \quad (1)$$

In this way, the estimated $\theta_{i,k}$ fully considers sample information for all regions, and meanwhile, differences of each region are well preserved. Given this proposed Bayesian hierarchy model, the technique about the estimation on Dirichlet parameters which is proposed by Minka (Minka, 2000) can be applied to estimate η_k and $\theta_{i,k}$. Finally, regional differences of customers can be explored by analyzing the expected $\theta_{i,k}$.

On this basis, the probability that customers satisfy with product feature k in region i, $\theta_{i,k}$, is bigger than that in region j, $\theta_{j,k}$, can be estimated as,

$$\begin{aligned} & p(\theta_{i,k} > \theta_{j,k}) \\ &= \int_0^1 \int_0^1 \begin{pmatrix} (I(\theta_{i,k} > \theta_{j,k}) \cdot N(\theta_{i,k} \mid \theta_{i,k}, \sigma_{i,k}^2) \\ \cdot N(\theta_{j,k} \mid \theta_{j,k}, \sigma_{j,k}^2)) \end{pmatrix} d\theta_{i,k} d\theta_{j,k} \end{aligned} \quad (2)$$

$\theta_{j,k}$ and $\sigma^2_{j,k}$ are estimated probability of satisfied customers on feature k in region i and the corresponding estimated variance. $I(x)$ is an indicator function and $N(\theta, \sigma^2)$ is the probability distribution function of a normal distribution with a mean as θ and a standard deviation as σ. The above probability can be estimated by a Monte Carlo approach.

5 Case Study

5.1 Data preparation

To present how the proposed approach facilitates customers' regional differences, a case study about online mobile opinions are conducted.

Particularly, 2,684 pros and cons mobile reviews regarding different brands such as Apple, Samsung, Nokia, etc., are obtained by a web crawler from Epinions.com, which are utilized as training data to extract product features and obtain a customer's sentiment polarity. With the help of the Stanford Part-Of-Speech Tagger and the WordNet, nouns mentioned by customers more than 50 times in pros and cons sections are preserved as word candidates regarding product features. Then, these nouns are manually filtered to identify non-feature words.

To identify product features from online opinions in free text and understand regional differences of CRs, a web crawler is designed to get reviews from Amazon.com. In total, 9,541 mobile reviews were obtained. Within these 9,541 mobile reviews, 2,763 reviews mention at least one product features. Then, these reviews are divided into 95,458 sentences for further analysis.

Culling out reviews which missing regional values, 2,763 reviews referring to five hot features in the six major regions of the United States were obtained. According to Hall [50], six major regions of the United States are listed in Table 1 and the number of reviews in six regions are illustrated in Figure 2.

Table 1. Six major regions in US

Region	States
New England	Connecticut (CT), Massachusetts (MA), Maine (ME), Vermont (VT) New Hampshire (NH), Rhode Island (RI)
The Middle Atlantic	Washington DC (DC), Delaware (DE), Maryland (MD), New Jersey (NJ), New York (NY), Pennsylvania (PA)
The Midwest	Iowa (IA), Illinois (IL), Indiana (IN), Kansas (KS), Michigan (MI), Minnesota (MN), Missouri (MO), North Dakota (ND), Nebraska (NE), Ohio (OH), South Dakota (SD), Wisconsin (WI)
The West	California (CA), Colorado (CO), Idaho (ID), Montana (MT), Nevada (NV), Oregon (OR), Utah (UT), Washington (WA), Wyoming (WY)
The South	Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Kentucky (KY), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), Virginia (VA), West Virginia (WV)
Southwest	Arizona (AZ), New Mexico (NM), Oklahoma (OK), Texas (TX)

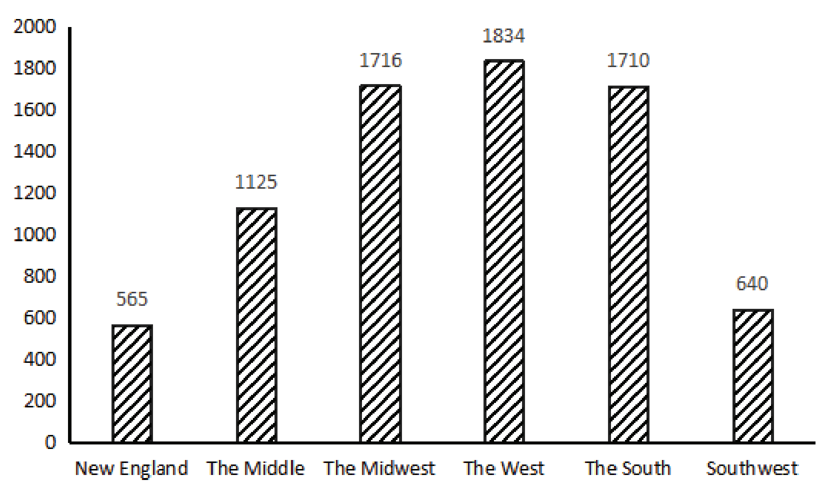


Figure 2. The number of reviews in six regions

As presented by Figure 2, reviews in different regions are not distributed evenly. For instance, the number of reviews from the West is more than three times of that from the New England with the lowest number. It implies that the frequency-based approach might be inaccurate on the estimation about the probability of satisfied customers with a particular product feature and it is necessary to invite a Bayesian hierarchical model for the estimation.

5.2 Product feature extraction and sentiment analysis

In this experiment, 102 words representing product features of mobiles are eventually gained, which are shown in Figure 3.

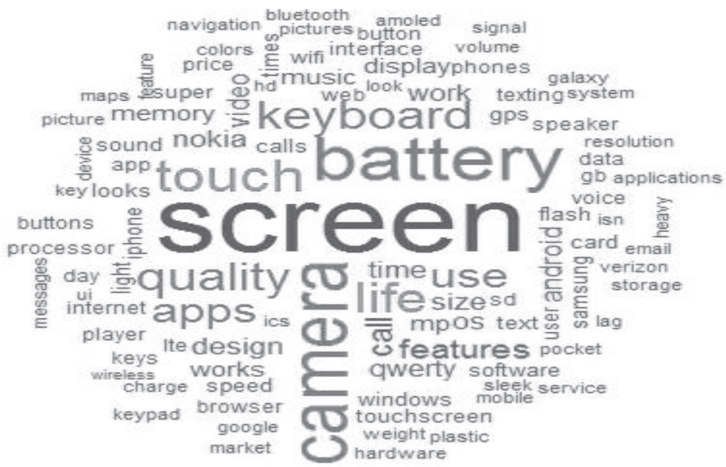


Figure 3. Product feature words of mobile phone frequently mentioned by customers

To present the effectiveness of identified features, as mentioned, those nouns referring to the same product feature are clustered together and the share of top 5 product feature groups which most frequently mentioned by customers are listed in Table 2. As seen from this table, ‘screen’, ‘battery’, ‘camera’, ‘keyboard’ and ‘applications’ are product feature groups with the highest customer attention. It is suggested that a higher priority should be given to these features when a new mobile is planned to be launched. In fact, a larger screen perhaps is one of the most attractive elements. However, it often leads to a higher degree of power consumption.

Table 2. Top 5 frequently discussed features in 2,763 reviews

Product features	# of reviews referred features	% of reviews referred features
screen, display, touch, touchscreen	1470	27.38
battery, charge, life, time, times	1083	20.18
camera, pictures, picture	939	17.49
keyboard, qwerty, keys, key, keypad, button, buttons	803	14.96
applications, apps, app, software	627	11.68

Using the techniques introduced in Section 3.2, 7, 234 review sentences referring at least one of top 5 frequently discussed feature are focused and utilized for further sentiment analysis. Note that, in this study, two classical SVM binary classifiers are utilized for sentiment analysis. As explained, there exist two subtasks for sentiment analysis. They are whether a sentence is subjective or objective and whether a sentence is positive or negative. For the first subtask, 500 sentences are manually labeled regarding subjective or objective to evaluate the performance of the SVM classifier that is trained by the 5,000 subjective and 5,000 objective sentences in Pang and Lee's subjective dataset [48]. With these manually labeled sentences, the precision is 0.89. Then, this classifier was applied to 7, 234 review sentences and 5, 387 subjective sentences were found. For the second subtask, 2,684 pros and cons mobile reviews were utilized for training and another SVM classifier were obtained to classify whether a sentence is positive or negative in these 5, 387 subjective sentences. Similarly, another categories of 500 sentences are manually labeled regarding positive or negative to evaluate the performance of the second SVM classifier and the precision is 0.76.

As can be seen, the binary SVM classifier helps to gain an acceptable result for two sentiment analysis tasks respectively. Also, the focus is on the analysis of market regional heterogeneity, and the simple but effective classifier is applied then.

5.3 Parameter estimation and model comparison

To understand customer regional difference in the product feature level, in this study, a hierarchical Bayesian model is built and Minka's approach [51] was applied to estimate parameters with the help of R programming language. Top five groups of the most frequently mentioned product features are analyzed and compared, including 'screen', 'battery', 'camera', 'keyboard' and 'applications'.

In Table 3, estimated parameters, i.e., η_k, regarding five product feature groups respectively, are listed. The standard errors of means (SEM), which reflects the variation of the sample mean to the population mean, is often used in hypothesis testing and parameter estimation. As seen from this table, SEM is relatively low. It indicates that the parameter estimation on η_k of different features is stable and it does not fluctuate significantly.

Table 3. The parameter estimation of η_k

Features	η_k	Means	SEM
Screen	α_1	69.6149	0.5131
	β_1	58.6322	0.4600
Battery	α_2	42.0242	0.2916
	β_2	71.9570	0.4713
Camera	α_3	55.1271	0.7904
	β_3	18.8344	0.2909
Keyboard	α_4	58.7730	0.8070
	β_4	42.7749	0.7010
Applications	α_5	63.6427	0.4642
	β_5	70.7609	0.4738

According to the estimated percentage of satisfied customers, a Monte Carlo approach was used to compare regional differences of customer satisfaction according to Equation (2). Take the differences between customers' satisfaction with battery in New England as an example. The comparison results are resented in Figure 4. It can be found that the probability of customer satisfaction on battery in New England is higher than that in other regions by more than 50% and it shows that the customer satisfaction with battery in New England is probability the highest.

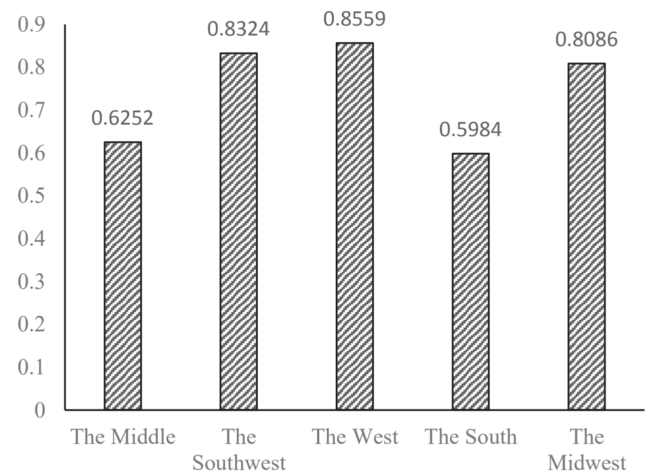


Figure 4. The comparative probability of customer satisfaction on battery in New England

Expected percentage of satisfied customers across different regions by the proposed approach are also compared with the classical frequency-based approach, which are listed in Table 4 and Table 5 respectively. To examine the effectiveness of the proposed approach, the technique of variation coefficient [52], which is a standardized measure of dispersion of a probability distribution or frequency distribution, is employed to quantify the degree of customer regional differences regarding the hierarchical Bayesian model.

Table 4. Expected percentage of satisfied customers across different regions

Regions	Screen	Battery	Camera	Keyboard	Applications
New England	0.5362	0.3988	0.7563	0.6174	0.4390
The Middle	0.5886	0.3803	0.7260	0.5761	0.4623
The Midwest	0.5295	0.3458	0.7025	0.5493	0.4956
The West	0.5127	0.3418	0.7395	0.6034	0.5003
The South	0.5607	0.3850	0.7335	0.5206	0.4587
Southwest	0.5414	0.3458	0.8399	0.6309	0.4717
Means	0.5449	0.3663	0.7496	0.5830	0.4713
Standard deviation	0.0242	0.0225	0.0435	0.0387	0.0213
Variable coefficient	0.0445	0.0615	0.0580	0.0663	0.0451

Table 5. Frequency-based estimated percentage of satisfied customers across different regions

Regions	Screen	Battery	Camera	Keyboard	Applications
New England	0.5135	0.4681	0.7742	0.7391	0.3636
The Middle	0.6512	0.3951	0.7108	0.5682	0.4483
The Midwest	0.5140	0.3258	0.6703	0.4706	0.5214
The West	0.4859	0.3226	0.7350	0.6316	0.5217
The South	0.5843	0.4000	0.7241	0.4167	0.4435
Southwest	0.5385	0.3036	1.0000	0.8750	0.4706
Means	0.5479	0.3692	0.7691	0.6169	0.4615
Standard deviation	0.0604	0.0629	0.118	0.1707	0.0589
Variable coefficient	0.1103	0.1703	0.1535	0.2767	0.1277

The practical significance is well reported in the measurement of the expected percentage of satisfied customers with camera in Southwest. As can be seen from Table 5, with the classical frequency-based approach, the expected percentage of satisfied customers with camera in Southwest is 100% and it implies that all potential customers in Southwest are satisfied with the camera. Obviously, it is an unreasonable and implausible conclusion and it can be guessed that, such unreasonable result is caused by the insufficient number of customer reviews that discuss about the camera. The small number of samples aggravates the innate defect of the classical frequency-based approach and lead to an unreliable. Comparatively, as reported in Table 4, the proposed Bayesian hierarchy model is expected to draw lessons from other regions, which leads to a more reasonable result and the estimated percentage turns to be 0.8399. It makes that the estimated satisfied percentage with camera in Southwest by the proposed model is more reliable. It shows that the proposed model can significantly reduce the statistical error caused by the number of samples. Besides, to evaluate the effectiveness of the proposed approach, the technique of variation coefficient is applied, which is a standardized measure of dispersion of a probability distribution or frequency distribution. As can be seen from Table 4, the estimated standard deviation and variation coefficient from the hierarchical Bayesian model are smaller than that in Table 5. It shows that the frequency-based model is suffered from a greater impact from the statistical error of sample size difference in various regions.

5.4 Customer regional difference analysis

Figure 5 compares the expected percentage of satisfied customers, i.e., the expected value of the interval estimation of customer satisfaction, i.e., $\theta_{i,k}$, and Figure 6 presents $\theta_{i,k}$ of the top five product features in the six major regions of the United States with 95% confidence interval.

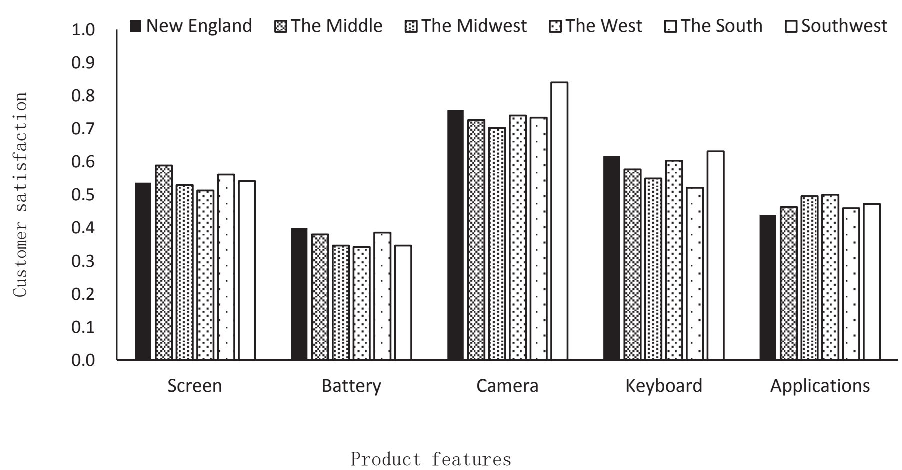
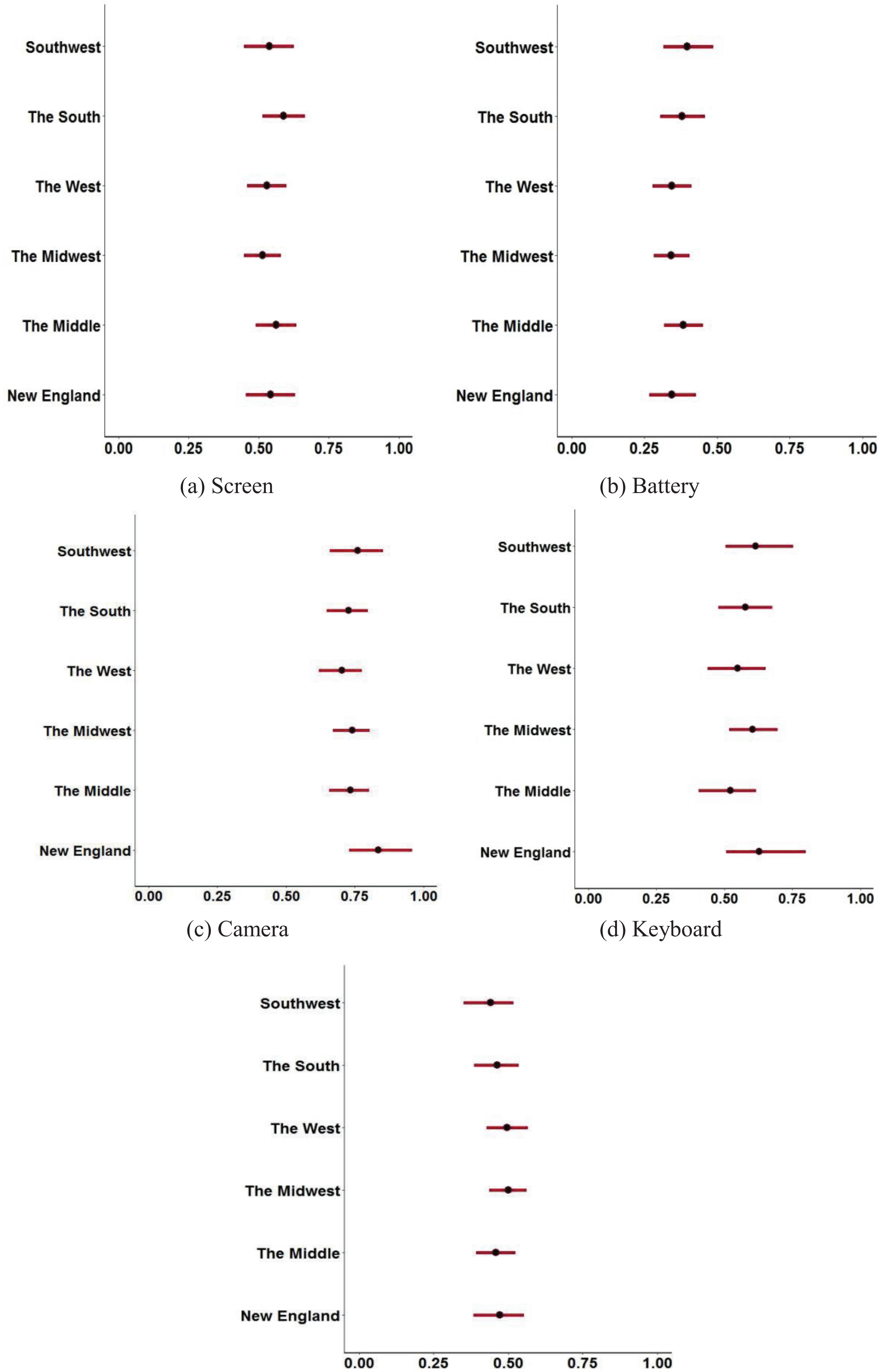


Figure 5 Comparison of regional differences on customer satisfaction



(a) Screen (b) Battery

(c) Camera (d) Keyboard

(e) Applications

Figure 6. The interval estimation of customer satisfaction regarding five product features with 95% confidence interval

It can be found that there are significant differences regarding customer satisfaction towards different product features in six regions. Among them, customers are seen to be more satisfied with keyboard and camera at present, while screen, power and application are still far away from customers' expectations. Therefore, when designing new models of mobiles, designers are suggested to give a higher priority to improve features with lower satisfaction to better meet CRs. In addition, as seen from Figure 5, for battery, the expected percentage of satisfied customers in The Midwest (0.3458), The West (0.3418) and Southwest (0.3458) are lower than that of New England (0.3988), The Middle (0.3803) and The South (0.3850).

For geographical reasons, it may be due to that The Midwest, The West and Southwest are mainly dominated by grasslands, mountains, deserts, and great lakes. People living in these areas may spend more time outdoors, so their demands for phone power is higher. Meanwhile, New England, The Middle and The South, are mainly dominated by cities and towns, people living in these areas may spend fewer time outdoors, where charging the mobile phone is more convenient, so their demands for phone power are relatively lower.

To further explore the effectiveness of these findings by the proposed approach, frequently referred brands in different regions and advantage remarks from professional editors in gsmarena.com are compared. Specifically, top four frequently referred brands in each region are listed in Table 6 and advantages and grades of four brands regarding screen, battery, camera and applications, which are collected and summarized from gsmarena.com, are listed in Table 7.

In terms of the number of most frequently referred mobiles, Apple phones and Samsung phones are taken as examples to explain the phenomenon that customers in different regions have various requirements. According to Table 6, the total number of customer reviews referring Apple phones in the West, the South and the Southwest (159) is close to the total number of reviews referring Samsung phones in the New England, The Middle and The Midwest (155). It implies that the comprehensive battery life of Apple phones has always been relatively good and consistent, and can better meet the requirements of customers in different regions. However, there is a visual gap regarding the total number of reviews referring Samsung phones and the corresponding total number in the West, the South and the Southwest is 151 and that in the New England, The Middle and The Midwest is only 125. The large sales gap between different regions may be induced by the fact that Samsung phones are not so outstanding in terms of battery. It coincides with scores described in Table 7, which come from professional testing and comments. Especially the negative impact brought by the server explosion and overheating problems of Samsung batteries, which makes it unfeasible to meet the intensive customer requirements on mobile battery in some regions.

Table 6. Top four frequently referred brands in each region

	New England	The Middle	The Midwest	The West	The South	The Southwest
Apple	25	50	80	87	47	25
Samsung	24	39	62	81	51	19
Nokia	25	34	60	68	41	24
Google	8	20	18	42	27	2

Table 7 Professional comparative remarks of product features of different mobile phone brands from gsmarena.com

		Apple	Samsung	Google	Nokia
Mobile phone models		IPhone 6s, IPhone 6 plus, IPhone 7, IPhone 6 plus	S5, S6, S6 edge+, Galaxy S7, Galaxy S7_edge, Galaxy Note7	pixel, pixel XL	Lumia 630, Lumia 730, Lumia 930, XL
Screen	Parameter	size: 4.7-5.5 inches resolution: 750*1334px, 1080*1920px	size: 5.1-5.7 inches resolution: 1080*1920px, 1440*2560px	size: 5.0 inches, 5.5 inches resolution: 1080*1920px, 1440*2880px	size: 4.5-5.0 inches resolution: 450*800px, 480*845px, 720*1280px, 1080*1920px
	Remark	Grade: better appropriate screen size, good feel and operation	Grade: good Large size, Super AMOLED, good color display and energy saving; innovatively launched curved, increased the share	Grade: excellent Use Samsung AMOLED screen	Grade: general
Battery	Parameter	Capacity: 1715-2900mAh battery life: 61-85h	Capacity: 2550-3600mAh battery life: 73-92h	Capacity: 2770mAh, 450mAh battery life: 64h, 78h	Capacity: 1830-2420mAh battery life: 46-66h
	Remark	Grade: excellent Although the capacity is low, but the life is long.	Grade: poor A short battery life, fast power consumption and fatal defects.	Grade: better High battery capacity, long battery life.	Grade: general
Camera	Parameter	front-facing camera: 5-7MP main camera: 12MP	front-facing camera: 5MP main camera: 12-16MP	front-facing camera: 8MP main camera: 12.3MP	front-facing camera: 0-5MP main camera: 5-20MP
	Remark	Grade: better Powerful photo taking, good restoration and permeability.	Grade: better Night photography is powerful, but photos lack authenticity.	Grade: excellent Excellent performance, built-in HDR+ function, provide a brighter and more gorgeous picture. The camera is not raised.	Grade: general

Keyboard	Parameter	Key type: physical home key, touch home key	Key type: physical home key	Key type: virtual key	Key type: virtual key
	Remark	Grade: excellent Touch button can supports force sensing, and provides tactile feedback. Keyboard supports multilingual typing, learns from content, and contextual predictions.	Grade: good Home key equips with a fingerprint sensor.	Grade: better Virtual key makes the front of mobile phone simpler. AI - based offline voice input function is introduced.	Grade: general
APPs	Remark	Grade: good The software ecology is excellent, the system is simple and easy to operate and safe, which brings good experience to users.	Grade: general Rich software resources, basically meet user needs; Lack of android software management, poor experience.	Grade: better Integrates all the services provided by Google and comes with Google Assistant.	Grade: poor Application software is limited, part of the function is missing, lack of complete ecology; Operation trivial.
Summary		Pros: Powerful IOS system, high fluency, good security and stability, excellent power consumption control. Cons: single product line	Pros: large screen and high configuration Cons: the negative impact brought by "Samsung Battery Explosion Problem" caused a sharp decline in brand value	Pros: the operating system is developed by Google itself with high brand value Cons: glass shell easy to leave scratches; Poor waterproof function	Pros: Durable and cost-effective Cons: compared with IOS and Android systems, Windows phone system has poor cognition and incomplete functions, and its brand value lags behind that of apple and Samsung.

It shows that customers in the West, the South and the Southwest of the United States have higher requirements for battery life. Meanwhile, Samsung phones received significantly fewer reviews in areas with higher battery requirements than in areas with lower battery requirements. Also, Apple's battery life is reported to be better than Samsung and the number of referred reviews varies little by region. According to these observations, in terms of battery life, the advantages of different brands in the battery feature level are consistent with regional preferences. Accordingly, mobile phone companies are suggested to develop targeted marketing strategies in different regions.

Admittedly, some products are a little out of date. These products were very popular and have been discussed by many consumers in different e-commerce websites. It helps to gain a large volume of valuable online opinions. Also, in this study, these well-discussed products are taken as examples to verify the effectiveness of the proposed hierarchical Bayesian model. It shows that the proposed method is reliable for market regional heterogeneity analysis, which helps to highlight customer requirement differences to a certain extent.

5.5 Discussions on the hierarchical Bayesian approach

The Hierarchical Bayesian model helps to combine the prior knowledge and sample information to make inference analysis on the data. It is an effective data modeling approach that integrates the prior knowledge and sample information, which helps to improve the accuracy of inference or reduce the cost of sampling. The form of hierarchy Bayesian model is flexible and it is often utilized to mirror complex data relations in various context. For instance, in this study, the Hierarchical Bayesian model is invited to analyze regional customer satisfaction in reviews-poor regions with the help of that in reviews-rich regions. The behind assumption is that the percentage of preferred customers regarding a particular product feature in different regions, should follow a probability distribution and it helps to give a more reliable analysis result for data-poor regions.

One of the most famous hierarchical Bayesian model is the latent Dirichlet analysis (LDA), which is widely utilized to infer hidden topic distribution of a given corpus. It is a generative hierarchical Bayesian model, in which documents are represented as random mixtures over latent topics and each topic is characterized by a distribution over words.

However, there exist some innate disadvantages of hierarchical Bayesian model. First, the deduction of hierarchical Bayesian models is complex for a junior researcher and an engineer, which needs solid math reasoning ability on various probabilities. Another obvious disadvantage is that, in many hierarchical Bayesian models, such as LDA, a series of hyper parameters are often invited. It induces that categories of experiments should be conducted to obtain the best overall performance. In this study, the Minka’s approach was applied to estimate these parameters. Besides, in many hierarchical Bayesian models, data are assumed to be drawn independently from a given distribution. For instance, in LDA, words are assumed to be drawn independently from a multinomial distribution and, for the convenience of deduction, a conjugate Dirichlet distribution is often applied on the parameters of the multinomial distribution. In this study, a binomial distribution is applied to estimate the distribution of customer satisfaction about a particular product feature across various regions and a conjugate Beta distribution is applied for the estimation of the binomial distribution. However, to make the assumption more reliable, different distributions can be utilized and some of these assumptions might be too strong. It makes that different models should be benchmarked. Specially, in this study, the multinomial distribution with a conjugate Dirichlet distribution was actually evaluated. It does not improve the performance but invite more parameters. Then, a binomial distribution is employed in this study.

6 Managerial implications

Insightful suggestions need to be highlighted to companies from the perspective of market driven product design, differentiate strategies for customer regional heterogeneity and after-sales service improvement with regional specialty.

(1) Market driven product design

In some competitive markets, it suggested that enterprises always need to listen to the voice of their customers, make corresponding improvement, and give rapid and effective response for market driven product design. At its core, they need to obtain sufficient valuable customer needs efficiently. A large volume of online opinions, which are posted from time to time, facilitate them to conduct real-time monitoring on consumers' social media and review sites where consumers are actively discussing about the pros and cons of products. It requires enterprises empower the review mining ability to uncover customer preferences, understand their detailed evaluations on products, pay attention to their compliments and complaints, discover aspects that do not meet their expectations, and pick out the "culprit" that affects product sales. Specially, for instance, in this study, customer satisfaction on mobile phone battery in regions show significantly lower than other aspects. Thus, in the case of limited resources, enterprises are suggested to give priorities to improve the battery, such as to increase the battery capacity, to improve the battery endurance or to reduce energy consumption of different components.

(2) Differentiate strategies for customer regional heterogeneity

It is suggested that, for some enterprises, when a series of products are planned to be launched, customer requirements from various regions needs to be reckoned. Targeted responses that mirror customer expectations can be given by the exploration of customer hints that are behind lines of online opinions in regional market segments as well as the improvement and expansion of corresponding product lines, so as to distinguish their products from those within a similar category. It also helps to promote products to customers in different regions with more precise marketing strategies.

(3) After-sales service improvement with regional specialty

With the more attentions on safeguarding rights and the continuous change of consumption patterns, consumers begin to put forward higher requirements for enterprises when they purchase products or services. They will not only consider the product quality itself, but also pay more attention to the value of after-sales service. Especially for mobile phones, electrical appliances, cars and other expensive products, to provide customers with complete after-sales service is not only the basis of sales, but also an indispensable part of promoting products to the market. As presented, customer satisfaction with the same product feature in different regions is not the same. In addition to customer diverse preferences in different regions, the level of after-sales service of offline stores in different regions may also become one critical reason for regional differences in customer satisfaction.

In this regard, it is suggested that enterprises build a regional after-sales service system. In the after-sales service, those areas where customer satisfaction is significantly lower than the average should be focused and made improving according to local tastes. Specially, in the experiment of this study, the lowest customer satisfaction about the screen is in the Western of the United States. Then, enterprises are suggested to call offline stores in the Western to improve the existing deficiencies or provide higher standards of after-sales service to customers correspondingly. For example, the after-sales personnel should make regular return visits after customers purchase products, record the use of customers timely, answer the difficult questions of customers patiently, so that customers can truly feel the concern from the enterprise, thus establishing the emotional connection between customers and the enterprise, and enhancing customers' loyalty to the brand. When customers come to the store for maintenance, orderly guidance with professional and considerate service help to improve customer satisfaction and enhance customer stickiness, which make after-sales service play an important role in the whole product marketing process, and, eventually, improve the competitiveness of enterprises.

7 Conclusions and future studies

Customer preferences on products and services may vary from region to region. It is of great practical efficiency and commercial value for designers to explore customer heterogeneity in different regions via a large volume of publicly available online opinions, which avoids conventional time-consuming and labor-intensive questionnaire-based survey. In this study, taking valuable customer online reviews as data source, a framework is proposed to investigate regional differences of customer preferences at the product feature level for market heterogeneity analysis. In this framework, two essential tasks, i.e., feature extraction and sentiment analysis, are initially conducted via a simple and effective approach with the help of pros and cons reviews. At its core, a hierarchical Bayesian method is proposed to analyze regional differences of customer preferences at the product feature level. Different from conventional frequency-based approaches, statistics in reviews rich regions are borrowed to help the analysis of customer preferences on reviews poor regions, which intends to minimize the influence from the number of samples available in different regions. Categories of experiments were conducted to show the practical value of the proposed approach. It demonstrates that the proposed framework enables data from different regions to communicate with each other and statistical errors from different sample size in different regions is reduced.

In this study, a WordNet-based approach to obtain product features from customer online reviews and a SVM-based classification approach were conducted to obtain customer sentiment polarity. However, with the fast development of deep learning, different approaches on opinion mining were proposed to improve the performance of feature identification and sentiment classification without the introduction of pros and cons reviews. Then, in the future, a valuable research is to integrate the state-of-the-art techniques of opinion mining to gain more accurate sentiment analysis results and provide more reliable suggestions to product designers. Also, in this study, six major geographic regions of the United States are taken as an example to analyze market regional differences of customer satisfaction. However, note that, regional differences between countries are often more striking than regions within one country, which have a significant impact on the globalization of multinational enterprises. For instance, in Amazon.com, different sub sites are offered to consumers in different countries, such as Amazon.cn, Amazon.co.jp, Amazon.com.br, Amazon.ae, etc. and, as indicated, online opinions are presented in different languages. Then, online translation services, such as Google translate and Microsoft Translator, can be utilized. Such translation service API helps to translate non-English reviews to English. With translated reviews, customer concerns from various regions can be analyzed to explore the market regional heterogeneity. Accordingly, in the future, customer online opinions from different countries need to be investigated from global e-commerce sites, such as Amazon.com, Alibaba.com, etc., which is believed to uncover more interesting results about customer requirements and invite more research studies to explore global customer heterogeneity intelligently. Another further step needs to be taken to obtain more details regarding customer regional differences. For instance, whether there is a significant difference regarding customer requirements between some recent opinions or a bigger set of opinions across along timespan in various regions and a relevant question is how to apply the methodology in this study to the recent published products. Admittedly, some recent published products may not acquire sufficient number of online opinions if customer opinions are collected from review sites only and the data sparseness in all regions may embarrass the proposed framework to obtain reliable results. However, online opinions about some recently published products may not only appear in review sites but also in social networks websites, such as, Twitter, Facebook, etc. For instance, some recently published hot products might be widely discussed by a large number of potential customers. In the future, textual clues in online opinions in different platforms regarding customer regional differences, such as review sites and social networks websites, need to be summarized and more categories of products should be tested with online opinions that are post in different time span to examine this interesting hypothesis. These details are bound to facilitate designers make strategic responses to customer concerns for new product design. Besides, to estimate the parameters of hierarchical Bayesian model, the R programming language is applied. But the whole workflow in this study was implemented by Java. In the future, an integrated software package should be developed without the data exchange between different languages, which helps to provide designers with much convenience to gain the final result.

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Conflict of interest statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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