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Identifying Critical Factors for Customer Satisfaction in Mobile Application Service: A Semantic Text Mining and Bayesian Network Approach

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Abstract. The strategic importance of achieving customer satisfaction has become more apparent in mobile application services given the rapidly changing markets and fierce competition. Knowledge from customer review data in App stores can be helpful in enhancing understanding of customers. This paper proposes an approach to identifying critical factors for customer satisfaction in mobile application services using the customer review data. To this end, a semantic text mining and Bayesian network are employed to analyze customer opinion in review data and model the customer satisfaction and its determinants. The proposed approach consists of three stages: data collection and preprocessing, evaluation of customer reviews, and identification of critical factors for customer satisfaction. We believe our method can facilitate the understanding of customers in mobile application services, and serve as a starting point of more general model.

Keywords: mobile application services, customer satisfaction, customer review, semantic text mining, Bayesian network.

1. Introduction

The strategic importance of achieving customer satisfaction has become more apparent in mobile application services given the rapidly changing markets and fierce competition. The growing markets for mobile application services and opportunities for new business have made numerous services to spring up everywhere, but many of them have disappeared from the competition. As can be seen in an article that reported 75% of mobile applications were deleted within 72 hours of being downloaded [1], customers are impatient with poor services due to low switching barrier and a lot of alternative services. In this situation, companies and mobile application developers are focusing increasing attention on developing innovative and useful services as well as delivering quality and reliable services from the customer perspectives. In this regard, understanding of what customers like or dislike about services is crucial, but as for the mobile application services, it is impeded in many cases due to a lack of quantitative data and systematic processes.

With respect to data, voice of the customers (VOC) can be helpful in enhancing understanding of customers. Knowledge from the VOC enables us to identify customer needs and ultimately accomplishes the quality from the customer perspectives. Various ways have been employed to collect the VOC, such as customer survey, focus group or individual interviews, contextual inquiry, ethnographic techniques, etc [2]. With the development of information and communication technology, data in the Web, which are generally in the form of reviews in the blogs, forums, communities, etc., have emerged as ample sources that allow gathering information and intensively interacting with customers beyond the geographical boundary at a relatively low cost [3]. Among the aforementioned ways, in the case of mobile application services, customer reviews in the App stores, which are marketplaces for mobile application services, can be helpful for the following reasons. First, in terms of the availability of data, customer reviews can be obtained more easily

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since most App stores include channels for reviews where customers can freely express their opinions about certain services. In addition to the customers' increased willingness to express their satisfaction or dissatisfaction with services, the built-in review systems that make reviewing a less burdensome lead to the large number of reviews in the App stores. Moreover, sine the review data in the App stores are open to everyone, service providers can monitor customers' opinion about not only their own services but also competing services. Second, in terms of the reliability of data, reviews in App stores are likely to contain more accurate information of customer experiences and assessments. The traditional ways of gathering VOC depending on inquiring of customers like surveys and interviews could be limited in the perceived and actual reliability by the number of subjects and the inherent bias in the wording the questions or the subjects' interpretation. Third, as far as the influence of data is concerned, the requirements or complaints expressed in customer reviews should be resolved and mirrored in updated versions or new services, since customers usually check out what others think about a mobile application service as well as the description of the service before they make a decision whether they download it or not. It has been pointed out that customer-generated information is sometimes considered to be more credible and relevant, and has a greater affect on customer decision making than company-provided information [4].

Thanks to the recent advances in computational methods and software, analyzing such review data written in natural language in unstructured textual format can gain benefits from the use of information retrieval, natural langue processing and machine learning techniques. To obtain useful knowledge from the customer review data, this paper proposes an approach to analyzing customers' opinions and identifying critical factors for customer satisfaction in mobile application services. To this end, a semantic text mining and Bayesian network are employed to analyze customer opinion in the review data and model the customer satisfaction and its determinants.

The remainder of this paper is organized as follows. In Section 2, the underlying methodologies of the proposed approach are briefly introduced. In section 3, the proposed approach is explained. Finally, this paper ends with conclusions in Section 4.

2. Methodological background

2.1. Semantic text mining

Text mining has been devised to deal with unstructured textual data, thereby discovering valuable information from large collections of texts [5]. Text mining includes various methods and algorithms in the research field of information retrieval, information extraction, data mining, statistics, etc. [6]. Since text has been one of the most common means of delivering and storing knowledge or information, authomatic extraction of useful information from the textual data is compelling.

In the past, text mining usually depended on frequencies of selected words within texts. However, due to highly skewed interpretation of texts, judgments based on simple frequencies could be biased to a large extent in many cases. It was also incapable of taking into account the interrelations among themes in texts.

Recent advances in computational algorithms have facilitated the development of many theories about text structures using text-parsing software, allowing advanced text mining techniques to be added to traditional methods. The representative one is semantic text mining, which examines the interrelationships among words and phrases at various levels of a text from individual clauses up to the entire content. Consideration of such semantic structures can present the meanings of documents more accurately so that the method can fill in the gaps in understanding that are not covered by earlier text mining techniques [7].

The basic procedure of semantic text mining is as follows. Firstly, data are collected and pre-processed. Secondly, the structural elements are identified through a linguistic analysis of domain- and situation-related elements [8]. A variety of semantic structures could be employed for different purposes. For instance, [9] encoded blocks of text as subject-action-object (SAO) triplets. The structural elements extracted at this step should be rearranged to consider abbreviations, synonyms, and singular/plural forms as several different words may represent the same meaning and some extremely common words are of little value in texts [10]. Thirdly, sampled pieces of texts are mapped as syntactic components within this template. To this end, many algorithms such as parsing, pattern recognition, and syntactic analysis could be incorporated to improve the performance of the process. Finally, the results are evaluated by experts who have domain knowledge or experience.

2.2. Bayesian network

Bayesian network is a directed acyclic graph that represents the probabilistic relationships among a set of random variables [11]. It consists of nodes, arcs, and probability tables. A node represents a random variable, and an arc asserts a dependence relation between the pair of variables. In Bayesian network, nodes at the tails of the arrows and nodes at the heads of the arrows are called parents and children, and the states of the parent nodes affect the states of the child nodes. Each node is associated with a probability table according to its dependence relationships with other nodes. Nodes without incoming arcs, i.e. root nodes, have prior probability tables which contain the probabilities of associated random variables taking on each of their possible values. On the other hand, all other nodes with parents have conditional probability tables (CPTs) that provide the conditional probabilities of associated random variables given all possible combinations of their parents' values.

The procedure for constructing a Bayesian network is as follows. First, random variables are selected as the nodes of the network. Next, the topology of the Bayesian network is constructed by connecting pairs of nodes with arcs based on the dependence relationships between corresponding random variables. Finally, the probability distribution of each node is specified in its probability table. The construction procedure can be implemented in two different ways: i) utilizing prior knowledge of domain experts or literatures and ii) learning from the data. The two approaches can be utilized in conjunction with each other. Once the Bayesian network is constructed, probabilistic inference of prior and posterior probabilities is possible by using a conditional independence property and Bayes' theorem [11]. In particular, when some variables are observed (*evidence* in Bayesian parlance), information on the state of the other variables is updated by calculating the posterior distributions of them, given the evidence.

The advantages of a Bayesian network are as follows [12]. First, a Bayesian network is suitable to deal with incomplete data. Instances with missing attributes can be handled by summing or integrating the probabilities over all possible values of the attribute. Second, a Bayesian network can be used to learn causal relationships, and hence could be used to gain an understanding of a problem domain and to predict the consequences of intervention. Third, constructing the network can be time consuming and require a large amount of effort. Once the structure of the network has been determined, however, adding a new variable is quite straightforward. Fourth, since the data can be combined with prior knowledge probabilistically, the method is quite robust to model over-fitting.

3. Proposed approach

As Fig. 1 shows, the suggested approach is designed to be executed in three stages: data collection and preprocessing, evaluation of customer reviews, and identification of critical factors for customer satisfaction.

3.1. Data collection and preprocessing

Customer review data on the target service are collected from the App stores. A review consists of structured items such as the name of the service, name of reviewer, and date of review, and unstructured items containing what a reviewer think in the form of complement, proposal, consulting, complaint, etc. The collected review data are transformed into keyword vectors for further analyses, each of which is comprised of the aforementioned structured items and customer opinions in unstructured textual format. While the structured items in consistent semantics and formats can be extracted easily by parsing the documents, a systematic approach is needed to deal with unstructured data in the textual format. Moreover, judgement of customer opinions requires considering the contextual information of phrases or sentences. Thus, semantic text mining is employed in this study to extract customer opinions from the review data. The major structural elements in the form of SO (sentiment-object) are first extracted out of documents at the sentence level. For instance, in the sentence "The design is excellent", customer opinion on the "design" (O) is represented in the positive adjective "excellent" (S). For developing the set of SOs, sentiment-related and object-related keywords should be identified. The text mining software can yield the importance of each keyword based on various indexes such as TF-IDF. After the keywords with high importance are derived from the dataset, they are assigned to the sentiment-related keywords and object-related keywords. The sentiment-related keywords are subdivided into positive and negative sentiments. The final keyword lists are rearranged to consider the abbreviation, synonyms, singular, and plural forms of words. If m object-related keywords are identified, the keyword vectors of ith review can be represented as $\overrightarrow{R_i} = (NS_i, NR_i, DR_i, \overrightarrow{PS_i})$; where NS_i is the name of reviewed service; NR_i is the name of reviewer; DR_i, is the date of review; and $\overrightarrow{PS_i} = (PS_{i1}, \ldots PS_{im})$ is the set of ith reviewer's opinions, where PS_{ik} stands for the ith reviewer's opinion on the kth object. The value of PS_{ik} is determined as the following: if a sentence in the ith review includes kth object and positive sentiments at the same time, the value of PS_{ik} becomes one; if a sentence in the ith review includes kth object and negative sentiments at the same time, the value of PS_{ik} becomes minus one; otherwise, it becomes zero.

3.2. Evaluation of customer reviews

Some reviews express the positive sentiments, whereas some reviews exhibit the negative opinion on the same services. Moreover, some reviews contain only a few sentences expressing opinions on the services, while some reviews contain very detailed opinions. Therefore, individual reviews should be evaluated in terms of their polarity and the relevance of information. Whether ith review is positive or negative on the service is determined by comparison on the sum of PS_{ik} with a threshold value: the polarity of ith review is positive if the sum of PS_{ij} is larger than the threshold value; otherwise, the polarity of ith review is negative. On the other hand, relevance score of ith review (RS_i) is determined depending on the number of features that the review mentioned, and calculated by dividing the absolute value of PS_{ik} by the average absolute value of PS_{ik} over the all reviews: $RS_i = m \cdot \sum_{k=1}^{m} |PS_{ik}| \Big/ \sum_{i=1}^{n} \sum_{k=1}^{m} |PS_{ik}|$.

3.3. Identification critical factors for customer satisfaction

In this step, a Bayesian network representing customer satisfaction and its determinants is developed through machine learning based on the weighted keyword vectors. Weighted keyword vectors are obtained by firstly multiplying the $\overline{PS}$ of original keyword vectors by the relevance scores of the corresponding reviews, and secondly adding the overall satisfaction of reviewers as a new variable. The weighted keyword vector of ith review is as the following: $\overrightarrow{wR_i} = (NS_i, NR_i, DR_i, RS_i \cdot \overrightarrow{PS_i}, SR_i,)$; where SR_i is the overall satisfaction of the ith review. The value of SR_i becomes either *satisfactory experience* (*se*) or *dissatisfactory experience* (*dse*) when polarity of the ith review is positive and negative, respectively. To execute the learning algorithms of Bayesian network, continues values of the $RS_i \cdot \overrightarrow{PS_i}$ should be divided into several categorical values through discretization methods like Holte's one [13]. Possible results, for instance, are: *very satisfied*; *satisfied*; *neither satisfied nor dissatisfied*; *dissatisfied*; *very dissatisfied*.

Using weighted keyword vectors as input data, first, a network topology of Bayesian network is constructed by structural learning as the following: the overall satisfaction of customers (SR) is selected as a target node; among m objects, the j objects that significantly affect the value of SR_i are automatically selected and included as nodes in the network; the $j+1$ nodes are linked to each other based on the dependence relationships among them. The Bayesian network is finally constructed by generating probability distribution of the nodes through parameter learning.

The current situation of customer satisfaction with the service can be examined based on the structure of Bayesian network and the marginal probabilities of the nodes. We can know which features (incorporated objects in the networks) have significant affect on the customer satisfaction and their relationships. The marginal probabilities of the target node indicate how many customers are satisfied with the services and

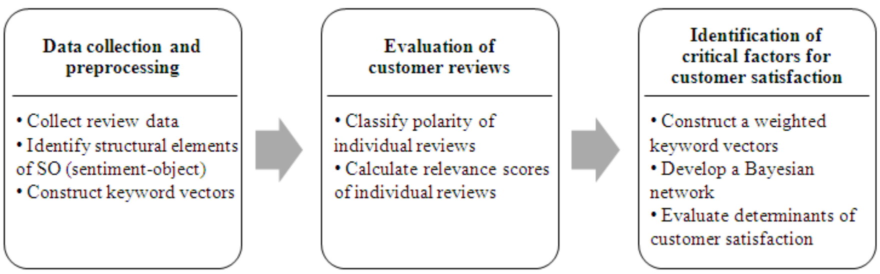

Fig.1: Overall process

how many are not. The marginal probabilities of the other nodes show that the degree of satisfaction with the corresponding objects. Moreover, the importance of the features in achieving greater customer satisfaction can be accessed by sensitive analysis that investigates changes in the probabilities of satisfied experience as the degree of satisfaction with the features changes.

4. Conclusions

We have proposed an approach to automatically analyzing customer opinion using customer review data and identifying critical factors for customer satisfaction in mobile application services. To this end, this study has suggested how to use semantic text mining with the structural elements in the form of SOs and develop a Bayesian network for modeling the customer satisfaction and its determinants in the mobile application services. We believe our method can facilitate the understanding of customers in mobile application services, and serve as a starting point of more general model.

The future research may include the following themes. Firstly, the development of other indexes is required to take into account other criteria in assessing the importance of features. For instance, comparison between the expected cost for meeting a certain customer need and their expected contribution to the customer satisfaction can be helpful. Secondly, our method can be expanded for more various purposes, such as evaluation and comparisons of multiple application services, and customization or personalization of mobile application service. Finally, the suggested approach should be actually implemented with the appropriate cases. These topics can be fruitful area for future research.

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