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Research on customer opinion summarization using topic mining and deep neural network

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Abstract

Product reviews are of great commercial value for online shopping market. The identification of customer opinions from product reviews is helpful to improve the marketing decisions of customers, sellers and producers. This paper proposes a novel framework for summarizing customer opinions from product reviews. Firstly, our framework identifies grammatically and semantically meaningful phrases which contain product attributes and their corresponding opinions from original product reviews by using grammar rules and the latent Dirichlet allocation (LDA) model. Secondly, our framework generates readable and simple summaries from the identified phrases automatically by using the deep neural network. The summaries provide users the valuable opinions on product attributes. Moreover, our framework provides an interactive mode for users to choose product attributes which they are interested for generate personalized summaries to help users focus on the most concerned opinions. Experimental results on six datasets demonstrate effectiveness of our framework.

Keywords: Product reviews; Topic mining; Deep neural network

1. Introduction

With the rapid development of e-commerce, the online shopping market has become larger and larger. Customers tend to write product reviews on their purchased products. In recent years, with the wide range of use of the text mining techniques, the commercial value of products reviews is capturing more and more attention in customer behavior analysis. The mining of product reviews has been effectively used in various applications recently, such as product promotion [80], purchasing decision making [52,69], marketing strategies for sellers [70], product ranking [7,38], product design or development [24,78], customer satisfaction analysis [35,75] and product recommendation for customers [13,74]. In summary, the analysis of product reviews is beneficial for customers, sellers and producers. Firstly, customers are able to get important information from product reviews to make better purchasing decisions. Secondly, sellers can order, arrange and promote their products according to results of product review analysis to achieve better marketing profits. Last but not least, producers are able to understand the advantages and disadvantages of their products according to opinions extracted from product reviews in order to design and develop better products.

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Due to the importance of product reviews on online marketing, it is practically valuable to generate a comprehensive summary from the large quantities of product reviews for customers, sellers and producers to better make their marketing decisions. Various methods have been designed in recent researches to extract feature vectors, latent representation, user preferences, customer behaviors, topics and sentiment contents from product reviews. However, these kinds of information are unable to present a comprehensive summary of product reviews. The reasons are as follows: On the one hand, feature vectors and latent representations are hard to be interpreted because they are processed as numeric representations instead of the form of text. These numeric representations are unable to be understood by people. On the other hand, most recent studies on product reviews do not combine user preferences, customer behaviors, topics or sentiment contents to generate comprehensive summaries to reflect detailed information of various features of products. Customers, sellers and producers mostly concern the quality and practicability of products. A comprehensive and useful summary for customers, sellers and producers should provide information of customer opinions on product attributes in order to present thorough understanding on the quality and practicability of products. According to the above discussions, this paper extends the limitation of recent researches, aiming to generate comprehensive summaries which provide valuable and practical information of product attributes so that customers, sellers and producers can more effectively determine their marketing decisions or strategies.

The task of providing comprehensive summaries for product reviews involves two core sub tasks: feature extraction and information organization.

(1) Feature Extraction: grammar rules and topic mining

Feature extraction is used to identify product attributes and their corresponding opinions.

Recent researches have proposed various methods for feature extraction. However, these methods are relatively complex to cause considerable computational cost. In the cases of our practice, the simple part-of-speech (POS) grammar rules are effective to identify POS phrases in product reviews. The POS phrases are the grammatically important information which includes product attributes and their corresponding opinions. Moreover, under the premise of effective feature extraction, the POS grammar rules are designed as simple as possible to save computational cost. For the goal of high efficiency and good effectiveness, we use the POS grammar rules for feature extraction.

The number of POS phrases is usually large because these phrases are extracted from tremendous amount of product reviews. Moreover, the POS phrases still contain a certain number of noisy phrases due to the simplicity of POS grammar rules. Users (customers, sellers and producers) are still overwhelmed by the information overload of POS phrases. Therefore, the POS phrases should be evaluated and filtered to reflect the most valuable information of product reviews. The evaluation and filtering of POS phrases can be completed by topic mining, the technique which summarizes text into topics and evaluates importance of words in their corresponding topics. The use of topic mining has two advantages. Firstly, contents of product reviews can be deeply analyzed. A particular product review usually contains many product attributes and their corresponding customer opinions. The complex information can be organized by topics to provide a more interpretable information structure. Last but not least, the POS phrases are sorted according to their importance in topics so that the most important POS phrases in each topic can be selected automatically by computer programs. In summary, topic mining conducts a two-level evaluation of POS phrases. In the first level, POS phrases are summarized in topics. In the second level, the most important POS phrases in each topic are selected as semantic phrases for further summarization. Semantic phrases are grammatically and semantically valuable and contain the core information of POS phrases.

The latent Dirichlet allocation (LDA) model is the simplest and popular topic mining model [23,28]. It has been applied in various research fields, such as text classification [33], text clustering [86], sentiment analysis [46], service recommendation or discovery [21,63] and analysis of network sensitive information [76], user interests [87] as well as spamming information of product reviews [67]. We choose the LDA model for POS phrases evaluating and filtering due to its simplicity and effectiveness in practical applications.

In summary, the feature extraction task identifies POS phrases from product reviews according to POS grammar rules and selects semantic phrases from POS phrases by conducting LDA topic mining. The selected semantic phrases are both grammatically and semantically valuable.

(2) Information Organization: feature selection and deep neural network

The task of information organization is about how to rearrange the semantic phrases selected after feature extraction. The semantic phrases need to be further processed to generate an interpretable and readable summary for users. The two reasons are stated in the following two paragraphs, respectively.

As mentioned above, users mostly concern about product attributes and their corresponding opinions. For example, the product attributes of a computer include operation system, screen resolution, appearance, price and so on. The opinions of operation system can be "The operation system is hard to use...". There usually exists the case that a certain number of product reviews contain the same product attributes. Consider a simple example of a case of three product reviews: "**The operation system is hard to use...The screen is bad...**", "**The operation system works well...The price is high...**" and "**The operation system is not good...The appearance is not ideal**". Users have to read through all of them to get an overview of opinions on operation system, which causes extremely low efficiency and readability, especially in the case of large number of semantic phrases. Efforts should be made to identify product attributes for users. When users desire for contents of operation system, the generated summary should only provide semantic phrases of operation system, such as "**The operation system is hard to use**; **The operation system works well; The operation system is not good**". Feature selection is one of the ideal solutions for selecting product attributes. In text domain, feature selection is used to select the important words from text. Product attributes are the "important words" in product reviews. Some feature selection methods such as term-frequency (TF), document-frequency (DF), term-variance (TV) are easy to be applied for text feature selection, so we choose feature selection to select product attributes from the semantic phrases.

The quantity of semantic phrases of a particular product attribute may still be large because the semantic phrases are from large quantities of product reviews. The semantic phrases need to be further compressed under the premise that the most important information is maintained. In this paper, we choose the typical long-short term memory (LSTM) neural network which owns the powerful learning and generating abilities on text for the compression of semantic phrases. The LSTM network is a typical deep neural network. It can be applied to learn from the semantic phrases of a particular product attribute and generates a compressed version of the original semantic phrases. Users are able to spend less time and efforts to get the most valuable information of product attributes from the compressed version. The LSTM network has been successfully applied in domains including text classification [44], entity recognition [62], positional text matching [6], text summarization [57], text similarity analysis [79] and sentiment analysis [88].

In summary, our information organization task selects product attributes by using feature selection and generates summaries by using the LSTM network.

According to the above discussions, we proposed a framework for summarizing customer opinions from product reviews. The proposed framework aims to generate a more interpretable and readable summary from tremendous amount of product reviews so that users are able to determine their marketing decisions more efficiently and effectively. Our framework contains two core modules: feature extraction and information organization. In the feature extraction module, POS phrases are extracted from original product reviews. The POS phrases are further processed by the LDA model to achieve semantic phrases. In the information organization module, a feature selection method is used to identify product attributes from semantic phrases. The LSTM network is used to generate the final summary by learning and summarizing the semantic phrases. After feature selection, a list of product attributes is displayed for users. The module provides an interactive mode for users to choose their concerned product attributes. Consider the case of computer. A user may choose the product attributes battery and appearance to input to LSTM separately. The final summary only offers customer opinions on battery and appearance. Contents of the final summary are dependent on the user's interest in product attributes.

Contribution of this paper is the proposal of an effective framework for summarizing customer opinions from product reviews. The framework provides a more interpretable and readable summary for users. Our framework has four advantages. Firstly, in our framework, the summary is generated in the view of product attributes. Product attributes and their corresponding opinions are mostly concerned by users. Secondly, our framework performs a deep-level feature extraction so that important information contained in product reviews can be discovered thoroughly. The feature extraction model extracts POS phrases from product reviews according to POS grammar rules in a relatively shallow level and then selects semantic phrases by using LDA model in a deeper level. The semantic phrases are grammatically and semantically valuable. Thirdly, our framework is flexible because it provides an interactive mode for users. Users are allowed to select concerned product attributes to generate their personalized summaries. Last but not least, the summary generated by our framework is more readable and simple. LSTM network is used in our framework to automatically generate contents of summaries. Semantic phrases of product attributes are further summarized by LSTM. Compared with the original semantic phrases, the contents of the summaries are shorter but still contain important information of product attributes. Our framework can be directly implemented for the analysis of product reviews in practical scenarios. According to our literature review of product review analysis, few researches have designed such a thorough framework for customer opinion summarization.

The rest of the paper is organized as follows: Section 2 discusses recent researches on product reviews, LDA model and LSTM network. Research motivation is given according to literature review. Section 3 presents the research objective and methodology of our framework. Section 4 conducts experiments on real-world datasets of product reviews to demonstrate effectiveness of our framework. Section 5 gives conclusions.

2. Literature review

2.1. Product review analysis

Research directions on product reviews in recent researches include helpfulness analysis, important feature extraction, impact factors investigation, customer perception analysis, product recommendation, sentiment analysis and rating prediction.

Some researchers focus on helpfulness of product reviews. Craciun and Moore [16] investigated the mechanisms of both reviewer reputation cues and gender stereotypes to affect the helpfulness of negative product reviews. Cu et al. [17] empirically demonstrated that sentiment content of product reviews had a positive but dynamic impact on the diffusion process of digital products. Li [39] used the method of scene simulation verification to experimentally analyze customers' perceptions on the usefulness of product reviews. Li et al. [41] proposed a joint model for the extraction of topics and sentiments from product reviews, in order to analyze the helpfulness of product reviews for product sales. Piao et al. [51] proposed a method for product reputation mining. The method evaluated helpfulness of product reviews according to the three-level of information of words, sentences and aspects. Sun et al. [59] used informativeness measurements and classification thresholds for analyzing the helpfulness of product reviews to ease the problem of information overload. Wang and Karimi [68] experimentally analyzed the relationship between the use of first-person singular pronouns by reviewers in their product reviews and readers' perception of product review helpfulness.

Another research area is the important feature extraction of product reviews. Chen et al. [15] presented an intelligent Kano framework for extracting, qualifying and classifying product features of product reviews. Chen et al. [14] proposed a feature extraction methodology for product reviews. The methodology extracted feature vectors according to the semantic similarity of synonyms. The local patterns, word-order information and discriminative ability were then considered for further processing the feature vectors. Hou et al. [24] proposed a summarization model to analyze words and expressions reflecting customers' preferences in product reviews. The summarization results contained multi-dimensional user preferences including product affordances, emotions and usage conditions. Lee et al. [38] presented a product ranking method based on deep neural network. The method extracted high-level latent representations and learned the optimal representations of products from product reviews. Wang et al. [67,69,70] presented a deep learning method to extract affective opinions from product reviews. The opinions were classified into seven groups to reflect different aspects of customer behaviors. Yang et al. [78] proposed a methodology to extract user experience information from product reviews for the applications of market-driven design paradigm.

There are also researches on analysis of impact factors of product reviews. Gallo et al. [20] discussed the influence of experiential framing of products on product reviews. Mumuni et al. [49] analyzed the impact of attributes toward product reviews on customers' reliance on product reviews. Reed et al. [52] conducted experiments on taste perception of customers on food products by analyzing product reviews, in order to identify the factors which affected the purchasing decisions. Tsao and Mau [64] analyzed the influence of sponsorship information on customers' perception of helpfulness, credibility and purchase intention. Wang et al. [70] investigated the relationship between cultures of customers and the concentrated types of product features according to product reviews. Yi et al. [80] discussed the product reviews highlighted by firms to help firms understand the way to actively manage product reviews.

The analysis of customer perception is other research direction. Hu and Krishen [25] analyzed the relationship between information of product reviews and customer decision satisfaction. Jiao and Qu [31] established the relationship between features of products and perceptions of customers by using a rational extraction method. Shihab and Putri [56] investigated how the proportion and quality of negative product reviews affected attitudes and purchase intentions of customers. Xu [75] analyzed the relationship between core attributes contained in product reviews and customers' satisfaction.

Researchers also pay attention to product recommendation according to product reviews. Cao et al. [13] proposed a recommendation model to make adequate use of characteristics contained in product reviews. Huang et al. [26] designed a product recommendation method which integrated the information of price, trust and product reviews to generate final recommendation. Liu and Teng [45] proposed a probabilistic linguistic method to rank products according opinions extracted from product reviews. The results were able to recommend customers the alternative products. Xing et al. [74] proposed a hierarchical attention model to fuse the information of user ratings and product reviews for product recommendation.

A few researches are about sentiment analysis and rating prediction. Bi et al. [7] proposed an approach based interval type-2 fuzzy numbers to represent the sentiment analysis results, in order to address the impact of the limited accuracy rates of sentiment analysis on decision analysis quality. Zablocki et al. [82] empirically investigated the relationship between emotional content in product reviews and customer attitudes on products. Kumar et al. [35] applied their multimodal framework for rating prediction of products. The framework predicted ratings by fusing the information of both physiological signals and product reviews.

The emotions contained in product reviews are important because user preference and advantages (or disadvantages) of products can be analyzed according to user emotions. The techniques of sentiment analysis and active computing can be used to analyze the emotions of product reviews. The common tasks and categorization of sentiment analysis and active computing can be seen in [12]. Stacked ensemble methods are also helpful for sentiment analysis. Isik et al. [27] proposed a new ensemble method for sentiment analysis. The method combined two different classifiers and two different methods for feature extraction. Akhtar et al. [3] proposed a stacked ensemble method for predicting sentiment intensity. The method used a multi-layer perceptron network to combine outputs from several deep learning and classical feature-based models. The word polarity disambiguation is also important for sentiment analysis on product reviews. Yin et al. [81] used context-independent part-of-speech chunks to construct sentiment lexicon, in order to solve the problem of lexical sentiment ambiguity. Cai et al. [11] used Apriori algorithm to construct ambiguous lexicon by expanding sentiment ambiguous words. Jose and Chooralil [32] performed sentiment classification by using lexical resources SentiWordNet and WordNet along with Word Sense Disambiguation. Umar et al. [65] introduced a word sense disambiguation method for determining the sense of a word within a context.

Recent semi-supervised methods for social data can also be used for product review analysis. Ji et al. [29] proposed a LSTM based attention framework for sentiment analysis. The framework used an unsupervised LSTM encoder–decoder to attain high dimensional representations of text and the applied a supervised attention based LSTM model to extract features. Zhao et al. [86] proposed a semi-supervised auto-encoder for event detection. The model used a pre-trained auto-encoder to guarantee that the achieved embeddings of segments contained semantic and order information of the text. Ma et al. [47] proposed a framework to qualify the tendency of a user-generated sentence and incorporate user information without connection between users, so as to ease the problem of data sparsity. Akba et al. [2] evaluated the effectiveness of semi-supervised feature selection methods in sentiment analysis.

2.2. LDA model in text domain

As the typical model in the field of topic mining, LDA model has captures much attention in recent researches.

Some researches apply LDA model for the task of topic discovery. It is also the basic task for LDA model. Jia and Wu [30] applied LDA model to analyze articles of new energy vehicles (NEVs), in order to understand the evolution in policy and development of NEVs. Li et al. [40] introduced WordNet to LDA model to identify the dynamics of topics from corpora with large quantities of documents. Wu et al. [72] proposed a knowledge discover model based on LDA model for the task of interpreting biomedical literature into more understandable forms by detecting burst topic and semantic information. Zhu et al. [89] applied LDA model to solve the problem that the biterm topic model is more suitable for short text but it ignored the topic information of documents.

Recent research field also covers the application of LDA in typical text mining tasks. Text classification is one of these tasks. Kim et al. [34] used LDA model to constructed document representations based on topic distribution. The document representations were further used for text classification. Kim and Gil [33] proposed a system for research paper classification. The system selected keywords and topics by using LDA model and clustered the papers by using K-means clustering algorithm. Zhang et al. [83] introduced a supervised topic model based on LDA to remove the noisy terms which negatively affected performance of multi-label text classification. Another task is sentiment analysis. Laddha and Mukherjee [36] proposed a method for sentiment analysis of reviews. The method extracted sentiment expressions from reviews by using conditional random field (CRF) and grouped the expressions into topics by using LDA model. Luo [46] proposed a method which combined LDA and convolutional neural network (CNN) for sentiment analysis. The method constructed feature vectors based on topic distribution which was generated by LDA model.

Another research area of LDA model is service discovery or recommendation. Lee et al. [37] proposed an approach based on LDA model for service robots. The model was used for understanding linguistic expressions to recommend suitable service for users. Nabi et al. [50] proposed a semantic crawler based on LDA model to collect and classify cloud services on the internet. Tian et al. [63] focused on the task of web service discovery for users and used the Gaussian LDA model to construct service description representation from text. Tajbakhsh and Bagherzadeh [61] proposed a method based on LDA model to construct topics which are in the form of clusters for hashtag recommendation in Twitter. Zhang et al. [84] modified LDA model for product recommendation. The modified model used only rating data for the task of predicting user interest.

A certain number of other researchers focus on text analysis of various kinds of text. Bastani et al. [5] used a method based on LDA model to summarize topics from customer complaint text and explored associated trends of topics over time. Gurcan and Cagiltay [22] used LDA model to identify important contents from online job advertisements of big data software engineering, aiming to help education programs to update their development projects. Xu et al. [76] proposed a topic recognition method based on LDA model for network sensitive information. The model embedded the sensitive words in LDA model to improve the recognition ability of sensitive words and quality of topic words. Hagen [23] described a framework for training and validating LDA model in the field e-petition analysis. Experimental results indicated that most of the topics generated by LDA model made sense to judges of people. Wang et al. [67] proposed an unsupervised method based on LDA for detecting spamming information in product reviews. LDA model was used to group the suspicious spammers into clusters of small sizes. Wang and Xu [71] designed a method by combining LDA model and deep learning model for automobile insurance fraud analysis. The method used LDA model to select features which were hidden in the text of accident description. Daud et al. [18] introduced a method based on LDA model and POS tags for plagiarism detection. The method analyzed sentences of documents by using LDA model and then converted the sentences by using POS information.

2.3. LSTM network in text domain

The LSTM network is a kind of typical and useful deep neural network. It has been involved in important tasks of text mining.

Researchers have paid attention to employ LSTM network for text classification. Ali et al. [4] applied bidirectional LSTM network for feature extraction and text classification of social media text. Liu and Guo [44] proposed an architecture for text classification. The architecture employed bidirectional LSTM network to achieve preceding and succeeding context representations from text. Sachan et al. [54] introduced a training strategy using cross-entropy loss for simple bidirectional LSTM for the purpose that LSTM was able to achieve competitive text classification performance compared with other complex text classification methods. She and Zhang [55] presented a hybrid model which combined Word2Vec, CNN and LSTM network. The LSTM network was used for saving historical information and extracting context information. Xiao et al. [73] proposed a text classification method based on Word2Vec and LSTM network to address the problem of patent text classification in the security field.

Another research area is sentiment analysis based on LSTM network. Abdullah et al. [1] applied a model based on CNN and LSTM network for the task of sentiment analysis of Arabic tweets. Ren [53] used LSTM network to perform sentiment analysis on investors' comment text from the stock bar forum. Su et al. [58] proposed a method based on LSTM network for recognizing sentiment from text. The LSTM network was used to model the emotion evolution from feature sequences of text. Zhang et al. [85] introduced a coordinated CNN-LSTM-Attention model to learn sentence representations which contained semantic and sentiment information. Zhou and Long [88] presented a sentiment analysis methods for product reviews of Chinese text. The method used bidirectional LSTM network to solve the problem of long-term dependency in text and identify context of text. Wang and Cao [66] applied alternative optimization function and loss function for the training process of LSTM network in order to improve performance of sentiment analysis.

There are also researches on various text mining tasks based on LSTM network. Entity recognition is one of the tasks. Tang et al. [62] proposed a model which combined CNN, LSTM network and CRF for the entity recognition of Chinese clinical text. Gafurov et al. [19] performed recognition of named entity by using bidirectional LSTM network. Another task is text summarization. Song et al. [57] proposed a text summarization framework based on LSTM and CNN. The framework firstly identified semantic phrases from text and secondly generated summaries for text by using deep learning models. Xu et al. [77] introduced a sequence-to-sequence model based on LSTM network to summarize Chinese text. The method analyzed the features of characters and words, and used keywords to modify the generated summaries. Some researchers focus on other tasks. Lim and Choi [43] applied LSTM network to identify the relationships among time and events from Korean text to solve the problem of temporal relation extraction. Makarenkov et al. [48] used LSTM network to analyze implicit knowledge, intent or belief of users from news articles and text of community question answering. Yao et al. [79] proposed a LSTM encoder for short text similarity measurement. The training strategy of the encoder improved LSTM network on processing relationships of word sequences. Li et al. [42] introduced a network which combined attention-based LSTM network and CNN. The attention-based LSTM network was used for presenting semantic information of words. Sun et al. [60] presented a method for text entailment recognition. The method employed bidirectional LSTM network with average pooling to construct sentence representations.

2.4. Research motivation

This paper is motivated by the following three observations.

Current researches on product review analysis include helpfulness evaluation, feature extraction, impact factor identification, customer perception analysis, product recommendation, rating prediction and sentiment analysis. These researches focus on one of the single aspects of information in product reviews. Few researches provide an overview of product reviews. However, in practical scenarios, customers, sellers and producers need to understand the information from reviews thoroughly to make effective and accuracy marketing decisions. Current researches are unable to fulfill the practical need for marketing decision making. In order to provide an effective solution for generating comprehensive product review summary for marketing decisions, this paper is motivated to propose an effective framework to summarize customer opinions for product reviews. Our framework provides highly interpretable and readable summaries for customers, sellers and producers. The generated summaries contain the most important information (product attributes and their corresponding opinions) in order to help users understand the core ideas of large quantities of product reviews efficiently and effectively. Moreover, our framework allows users to choose product attributes to generate their personalized summaries to further simplify the contents of summaries and fulfill the demand that different users may pay attention to different product attributes.

The LAD model has been successfully used in various text mining tasks. The core idea that LDA model decomposes text documents into topics and corresponding topic words is helpful for deep-level analysis of product reviews. Furthermore, LAD model also evaluates the significance of POS phrases in each topic. In the analysis of product reviews, we can choose the most important POS phrases from each topic for further analysis. This strategy has two advantages. Firstly, the strategy selects the most important information in topic level so that all the aspects of information in product reviews are considered. Secondly, the removal of the less important information helps to improve computational performance of our framework and filter out noisy information. Motivated by the above discussion in this paragraph, we use the LDA model to identify the most important information from product reviews in our framework.

The LSTM network has captured much attention in text domain. It is useful to capture contextual information from text and generate new text automatically after learning from given text. A few researches have applied LSTM network for text summarization. Considering the powerful learning ability of the LSTM network, we choose the LSTM network for the task of learning and summarizing semantic phrases to generate final summaries.

3. Methodology

3.1. Research objective

According to the research motivation in Section 2.4, our research objectives are stated as follows:

(1) To design thorough and flexible framework for product review summarization

For the purpose of extending the limitation of current researches, this paper aims to propose a novel framework for summarizing customer opinions from product reviews. The framework generates summaries of product attributes and their opinions for customers, sellers and producers to make more effective marketing decisions. Moreover, the framework is flexible to allow users to determine product attributes which they are interested in to generate personalized product review summarization. Our framework contains two modules: feature extraction module and information organization module.

(2) To develop a deep-level feature extraction module

The effectiveness of summaries is dependent on the quality of feature extraction from original product reviews. In order to achieve better features, feature extraction module in our framework extract features in two levels. In the first level, our framework uses POS grammar rules to select POS phrases. The POS phrases are the grammatically meaningful phrases which contain the important information of product reviews. They need to be further processed. On the one hand, the number of the POS phrases is still large because of the tremendous number of product reviews. On the other hand, due to the simplicity of POS grammar rules, POS phrases also contain a certain number of noise information. Our framework performs the second level feature extraction by using LDA model to deeply analyze the POS phrases and generate more informative semantic phrases. The semantic phrases are both grammatically and semantically meaningful.

(3) To develop a flexible and effective information organization module

Our framework offers an interactive mode for users to select product attributes which they are interested in. The information organization module identifies product attributes from semantic phrases to provide a list of product attributes by using feature selection. Users are allowed to select product attributes to generate summaries. The LSTM network is used to summarize semantic phrases automatically for users to save users' time to read through all the semantic phrases.

In summary, this paper aims to provide an effective framework for customers, sellers and producers to improve their practical marketing decisions. Our framework offers thorough summaries in the view of product attributes and their corresponding opinions. The proposed framework performs deep-level feature extraction in order to achieve the most important information and remove as much noisy information as possible. Moreover, our framework provides an interactive mode for users to generate their personalized summaries.

3.2. Basic theories

3.2.1. LDA model

The LDA model is a generative model. It assumes that text documents are reflected by a fixed number of topics [9]. The generative process of the LDA model for a set of text documents D is described in Fig. 1 mathematically.

The LDA model assumes that text documents in the collection D are generated by selecting the suitable words form K predefined topics. The kth topic β_k is a distribution over words and the topics are generated according to the symmetric Dirichlet distribution $Dir(\eta)$ with constant η as parameter. The ith text document d_i is represented as a collection of variables under the bag-of-word assumption. The text document d_i has a topic distribution θ_i. The distribution θ_i determines which topics of the K predefined topics should be used to generate d_i. $v_j^{(i)}$ is the jth variable in d_i. A statistically suitable words from a topic should be assigned to $v_j^{(i)}$ in order to generate d_i. $z_j^{(i)}$ is the topic assignment for $v_j^{(i)}$ according to the multinomial distribution $Mult(\theta_i)$ with θ_i as parameter. $z_j^{(i)}$ determines that the $z_j^{(i)}$th topic $\beta_{z_j^{(i)}}$ of the K predefined topics should be used to select words for $v_j^{(i)}$. In the topic $\beta_{z_j^{(i)}}$, the statistically suitable word $w_j^{(i)}$ is selected according to multinomial distribution $Mult(\beta_{z_j^{(i)}})$ with $\beta_{z_j^{(i)}}$ as parameter. V represents the collection of total words in D. The core task of the LDA model is to infer the latent variables β_k, θ_i, and $z_j^{(i)}$ by approximation techniques, according to the observation of D. Blei [8] introduces several approximation techniques for the LDA model.

Given a collection of documents $D = \{d_i | i = 1,2, \ldots, |D|\}$,

(1) Draw K topics from a symmetric Dirichlet distribution: $\beta_k \sim Dir(\eta)$, $k \in \{1,2, \ldots, K\}$

(2) For each document d_i, $d_i = \{v_j^{(i)}\}_{1 \times |d_i|}$:

Draw topic distribution from a symmetric Dirichlet distribution: $\theta_i \sim Dir(\alpha)$

For each word variable $v_j^{(i)}$ in d_i, $j = 1,2, \ldots, |d_i|$:

Draw a topic assignment from θ_i: $z_j^{(i)} \sim Mult(\theta_i)$, $z_j^{(i)} \in \{1,2, \ldots, K\}$

Draw the word from the corresponding topic: $w_j^{(i)} \sim Mult(\beta_{z_j^{(i)}})$, $w_j^{(i)} \in \{1,2, \ldots, |V|\}$

Fig. 1. The pseudo-code of generative process of LDA.

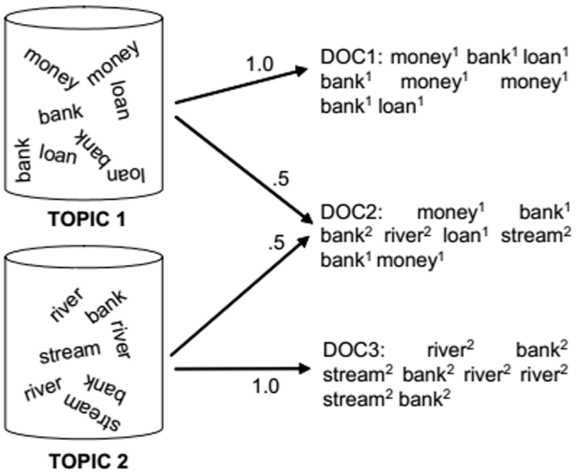

Fig. 2. A simple example for illustrating generative process of LDA model.

The generative process of LDA model can more simply stated as follows: For the text document collection $D = \{d_i | i = 1, 2, \ldots, |D|\}$:
(1) Predefine topic set $\beta = \{\beta_k | k = 1, 2, \ldots, K\}$.
(2) Generate topic distribution set $\theta = \{\theta_i | i = 1, 2, \ldots, |D|\}$ according to β.
(3) Generate topic assignment set $z = \{\left(z_j^{(i)}\right)_j | i = 1, 2, \ldots, |D|, j = 1, 2, \ldots, |d_i|\}$ according to θ.
(4) Generate text documents of D with words in β according to z.
It is obvious that the generative process of the LDA model is a "$\beta \to \theta \to z \to D$" process. The task of LDA model is a "$D \to (\beta, \theta, z)$" process to infer latent variables from the observed text document collection D.

A simple example is given for better understand of generative process of the LDA model. In Fig. 2, $D = \{\text{DOC1, DOC2, DOC3}\}$, $\beta = \{\text{TOPIC1, TOPIC2}\}$, $\theta = \{(1.0, 0), (0.5, 0.5), (0, 1.0)\}$ (values above or below arrows) and $z = \{(1, 1, 1, 1, 1, 1, 1, 1), (1, 1, 2, 2, 1, 2, 1, 1), (2, 2, 2, 2, 2, 2, 2, 2)\}$ (superscripts of the words in each text documents). For β, TOPIC1 $= \{\left(\text{bank}: \frac{3}{8}\right), \left(\text{money}: \frac{2}{8}\right), (\text{loan}: \frac{3}{8})\}$. TOPIC2 $= \{\left(\text{bank}: \frac{2}{7}\right), \left(\text{river}: \frac{3}{7}\right), (\text{stream}: \frac{2}{7})\}$. For example, $\left(\text{bank}: \frac{3}{8}\right)$ in TOPIC1 means the probability of the word "bank" is $\frac{3}{8}$ in TOPIC1. Now, consider the case of DOC2. The topic distribution for DOC2 is $(0.5, 0.5)$, which means DOC2 is generated by TOPIC1 and TOPIC2 under the same probability 0.5. The topic assignment for DOC2 is $(1, 1, 2, 2, 1, 2, 1, 1)$ indicating that the 3rd ("bank^2"), 4th ("river^2") and 6th ("streram^2") words of DOC2 are selected from TOPIC2 while the rest words are selected from TOPIC1.

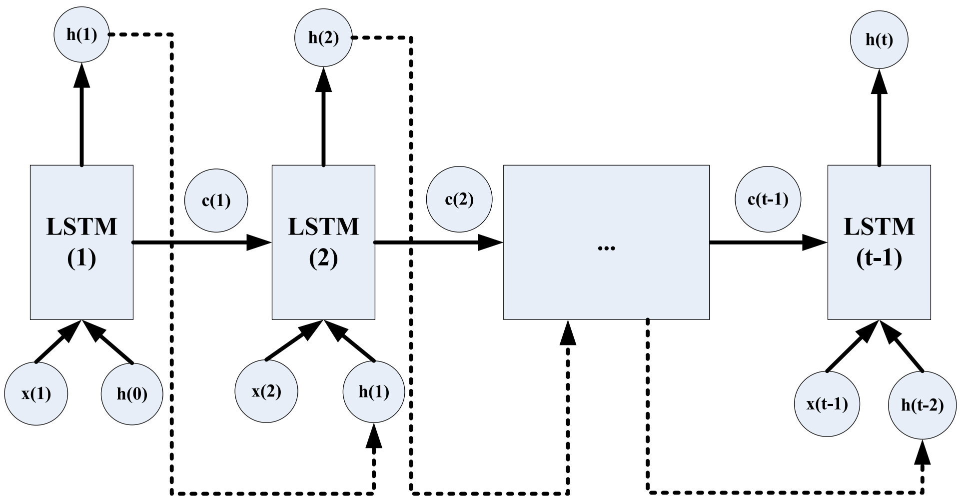

Fig. 3. The structure of LSTM network.

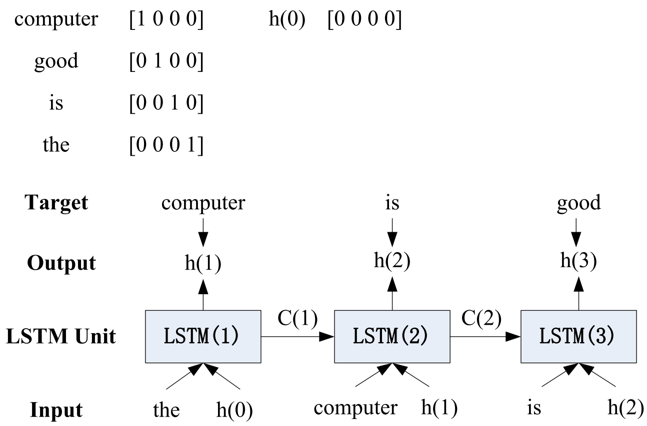

Fig. 4. An example of the mechanism of the LSTM network.

3.2.2. LSTM network

The LSTM network is a typical deep recurrent neural network. The structure of the LSTM network is shown in Fig. 3. The LSTM network contains changeable number of LSTM units. For a text document of t words, the LSTM network for the text documents contains t-1 LSTM units. In a word, the LSTM network is self-adaptive according to the length of text documents. Consider an example of a t-word text document $d = \{x\,(1)\,, x\,(2)\,, \ldots, x(t)\}$. In the first time step, x(1) and hidden state h(0) is input to the first LSTM unit to achieve hidden state h(1) and cell state C(1). h(0) is usually a zero vector. h(1) is the predicted result for x (2). Moreover, x (2) is used as the target for the first LSTM unit in training process. In the second step, x(1), h(1) and C(1) are input to the second LSTM unit to achieve h(2) and cell state C(2). The process continues until $x(t-1)$ is used as input. x(t) is used as the target for the $(t-1)$th LSTM unit. Each LSTM unit receives the contextual information from its previous LSTM units from the cell states.

Fig. 4 gives an example to show the mechanism of the LSTM network. The text document is "**The computer is good**". Each word in the text document is encoded as numeric vectors. One of the common numeric forms for words is the binary one-hot vectors. Word vectors (e.g. word vectors created by Word2Vec) or frequency vectors of words can also be used as input. The output of each LSTM unit is also the numeric vector of the same length as numeric vectors of words. h(0) is set as [0 0 0 0]. In the first time step, vector of "the" and h(0) are input to

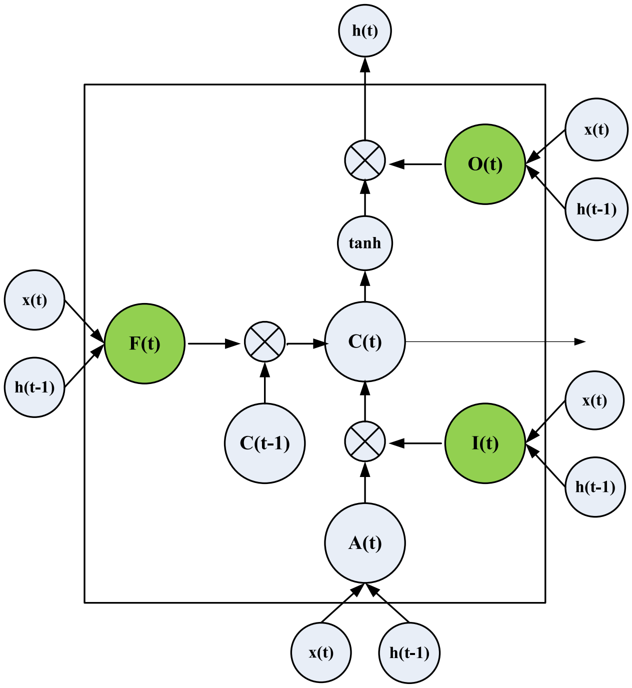

Fig. 5. The structure of the LSTM unit in time step t.

LSTM unit to output h(1). Vector of "computer" is the target for h(1). The loss for training process is the difference between output of each LSTM unit and its corresponding target.

The structure of the LSTM unit in time step t is shown in Fig. 5. The LSTM unit contains an input structure and three gates. The input structure A(t) is used to create input by fusing the information of $h(t-1)$ and x(t). The input gate I(t) is used to control how much information of A(t) should be input to the current unit. The forget gate F(t) is designed for controlling how much information of $C(t-1)$ should be filtered out of the current unit. The output gate O(t) is the control gate for measuring how much information should be output for current unit. h(t) is the final output of current unit. The cell state C(t) is also the output for the next unit. The mechanisms of A(t), I(t), F(t) and O(t) for handling $h(t-1)$ and x(t) are given by Formulas (1) to (4), respectively. W_* and U_* are the weight matrix for x(t) and h(t), respectively. The outputs of the three gates are probability vectors to control the quantity of information for the LSTM unit.

$$A(t) = \tanh[W_A x(t) + U_A h(t-1)] \tag{1}$$

$$I(t) = \mathrm{sigmoid}[W_I x(t) + U_I h(t-1)] \tag{2}$$

$$O(t) = \mathrm{sigmoid}[W_O x(t) + U_O h(t-1)] \tag{3}$$

$$F(t) = \mathrm{sigmoid}[W_F x(t) + U_F h(t-1)] \tag{4}$$

The cell state C(t) is calculated by Formula (5). The symbol "⊗" represents element-wise operation. Formula (5) clearly reflects the effects of information control of I(t) and F(t) on A(t) and $C(t-1)$, respectively.

$$C(t) = I(t) \otimes A(t) + F(t) \otimes C(t-1) \tag{5}$$

The final output of the LSTM unit is given by Formula (6).

$$h(t) = O(t) \otimes \tanh[C\,(t)] \tag{6}$$

3.3. The proposed framework

Our framework for product review summarization is shown in Fig. 6. Our framework contains two modules: feature extraction module and information organization module.

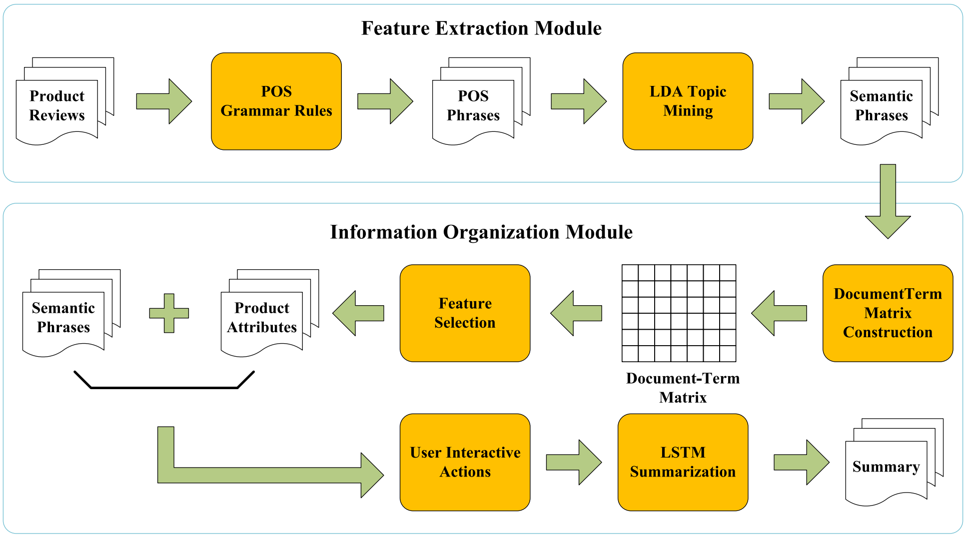

Fig. 6. Our framework for product review summarization.

In the feature extraction module, POS grammar rules are designed according to the structures of product reviews manually, in order to achieve POS phrases from original product reviews. The POS phrases contain grammatical information and a certain number of noisy information. LDA topic mining is then performed to achieve semantic phrases from POS phrases. The semantic phrases contain the important semantic information of POS phrases and much less noisy information.

In the information organization module, the semantic phrases are input for two tasks: feature selection and LSTM summarization. Before feature selection, the semantic phrases are usually transformed into Document-Term Matrix. A list of product attributes is generated after feature selection. The framework is interactive for users to select product attributes which they interest in. The user-interested product attributes and the corresponding semantic phrases are input to the LSTM network to generate personalized summaries.

Sections 3.3.1 to 3.3.3 respectively give detailed description of the two modules. A simple example is given in Section 3.3.4 to illustrate the working mechanism of our framework.

3.3.1. Feature extraction module

The feature extraction module is designed to identify important information from product reviews. Researchers have developed methods for discovering meaningful phrases from Chinese or English text. These methods are complex because they are developed based on LSTM, CRF, association rules or other theories. According to our practical experience and the analysis of product reviews, we find that meaningful phrases can be relatively effective identified according to POS of words. For example, the Chinese phrase “质量很好” (“Quality is very good” in English, “质量” for “quality”, “很” for “very”, “好” for “good”) is the sequence of a noun (“质量”), an adverb (“很”) and an adjective (“好”). Moreover, the English phrase “Quality is very good” is the sequence of a noun (“Quality”), a verb (“is”), an adverb (“very”) and an adjective (“good”). Based on the grammar and structure of product reviews, the POS rules for Chinese and English text of product reviews are given as follows:

In Chinese text, the notional words reflect most of the information in text. Notional words include nouns, verbs, adverbs and adjectives. Sometimes, the prepositions are used to connect notional words. In summary, the meaningful phrases should be the sequences of nouns, verbs, adverbs, adjectives and prepositions. In summary, the POS grammar rule for Chinese product reviews is stated as “**The POS phrases for Chinese product reviews are the sequence of nouns, verbs, adverbs, adjectives and prepositions**”. Similar to Chinese text, the English text also replies on notional words to convey most of its information. Moreover, the words of comparative and superlative are related to adjectives and adverbs. In addition, articles are related to nouns. In summary, the POS grammar rule for English product reviews is stated as “**The POS phrases for English product reviews are the sequence of nouns,**

	W_1	W_2	…	$W_{\|W\|}$
b'_1	w_{11}	w_{12}	…	$w_{1\|W\|}$
b'_2	w_{21}	w_{22}	…	$w_{2\|W\|}$
⋮	⋮	⋮	…	⋮
$b'_{(NK^*)}$	$w_{(NK^*)1}$	$w_{(NK^*)2}$	…	$w_{(NK^*)\|W\|}$

Fig. 7. The Document-Term matrix.

verbs, adverbs, adjectives, comparatives, superlatives, prepositions and articles". The two POS rules are used to respectively generate Chinese and English POS phrases.

POS phrases still contain noisy information due to the simplicity of POS grammar rules. Moreover, the number of POS phrases may still be large because they are extracted from tremendous product reviews. LDA topic mining is performed to select the most important POS phrases and filter out noisy information. The process of LDA topic mining for a collection POS phrases contains three steps. In the first step, the optimal topic number is determined by the perplexity of topic mining in repeated experiments on candidate topic numbers. The perplexity of a text document collection D is given by Formula (7) [10]. The candidate topic number with the largest value of perplexity is considered as the optimal topic number for D.

$$\text{perplexity}\,(D) = \exp\{-\frac{\sum_{i=1}^{|D|} log\, P(d_i)}{\sum_{i=1}^{|D|} |d_i|}\} \tag{7}$$

The probability $P(d_i)$ is processed by logarithmic function as $log\, P(d_i)$ in order to prevent the case that $\sum_{i=1}^{|D|} |d_i| \gg \sum_{i=1}^{|D|} P(d_i)$. However, the length of POS phrases is usually small, so the case that $\sum_{i=1}^{|D|} |d_i| \gg \sum_{i=1}^{|D|} P(d_i)$ is unlikely to happen. We use the simplified form of perplexity given by Formula (8) to determine the optimal topic number. Obviously, $\text{s} - \text{perplexity}\,(D)$ is positively correlated with $\text{perplexity}\,(D)$. The optimal topic number for the collection of POS phrases is represented as K^*.

$$\text{s} - \text{perplexity}\,(D) = \exp\{\frac{\sum_{i=1}^{|D|} P(d_i)}{\sum_{i=1}^{|D|} |d_i|}\} \tag{8}$$

In the second step, the LDA model is used to decompose the collection of POS phrases into K^* topics. In the final third step, the top N POS phrases from each of the K^* topics to achieve totally NK^* important POS phrases as semantic phrases.

3.3.2. Information organization module

The NK^* semantic phrases are input to the information organization module to achieve the final summary of product reviews. This module contains two core tasks: feature selection and LSTM summarization.

Product attributes are identified by using feature selection. The collection B' of the NK^* semantic phrases is needed to be transformed into a Document-Term matrix before feature selection. The Document-Term matrix of B' is shown in Fig. 7. $B' = \{b'_i | i = 1, 2, \ldots, NK^*\}$ where d'_i represents the ith semantic phrase. $W = \{W_j | j = 1, 2, \ldots, |W|\}$ represents the set of total words in B'. w_{ij} represents the term frequency of W_j in b'_i.

The feature selection method TF is a typical method and has been effectively used in various feature selection tasks. We use TF to identify product attributes from semantic phrases. The TF value for the jth word W_j is calculated by Formula (9). The top Q words with high TF values are considered as product attributes. Usually, $Q \ll |W|$. The Q product attributes is grouped as a list L of product reviews.

$$TF\left(W_j\right) = \sum_{i=1}^{Nk^*} w_{ij} \tag{9}$$

A user is allowed to select their interested product attributes from the Q product attributes to create a personalized list L' of product reviews ($L' \in L$). $L' = \{l_1, l_2, \ldots, l_{|L'|}\}$. For a product attribute $l_q \in L'$, its corresponding set

```
Input: D, a collection of product reviews
Output: S, summary of D
Begin
    # Feature Extraction
    D_1 = POS_grammar_rules(D);
    K* = LDA_optimal_topic(D_1)
    D_2 = LDA_semantic_phrases(D_1, K*, N)
    #Information Organization
    dtm = DTM_matrix(D_2);
    D_3 = Feature_selection(dtm, N');
    S = LSTM_summarization(D_2, D_3, index);
    # output results
    Return S;
End
```

Fig. 8. Pseudo code of our framework.

$B'(l_q)$ of semantic phrases is generated according to Formula (10).

$$B'\left(l_q\right) = \{b'_i | l_q \in b'_i, i = 1, 2, \ldots, NK^*\} \tag{10}$$

$B'\left(l_q\right)$ is input to the LSTM network to achieve summary for l_q. Other product attributes in L' can be processed similar to l_q.

3.3.3. Algorithm of our framework

Our framework can be convenient implemented by computer programs. The pseudo code of our framework is given in Fig. 8. In the two modules of our framework, each core step can be implemented by a corresponding function. In Fig. 8, the input of our framework is a collection D of product reviews, and the output is the generated summary S for D. Function POS_grammar_rules analyzes the POS of all the words in D and then generates the collection D_1 of POS phrases. Function LDA_optimal_topic performs LDA topic mining on D_1 under the candidate numbers of topics to determine the optimal number of topic K^*. Function LDA_semantic_phrases performs LDA mining to analyze POS phrases and selects the top N POS phrases as semantic phrases from each topic to create the collection D_2 of NK^* semantic phrases. The parameter N is determined by users. Function DTM_matrix transforms D_2 into Document-Term matrix dtm for feature selection. Function Feature_selection generates the top N' words with high TF values to generate list D_3 of product reviews. The parameter N' is determined manually. Function LSTM_summarization summarizes D_2 according to D_3 and index. The parameter index is the words of product attributes selected by users in D_3. The pseudo code of Function LSTM_summarization is given in Fig. 9.

Function LSTM_summarization generates collection $D_2(i)$ of semantic phrases for the ith product attributes $D_3[i]$ in D_3. Function LSTM_train trains $D_2(i)$ to create summary for $D_3[i]$. The process is repeated until the index list of product attributes is fully iterated once.

3.3.4. A simple example

This section gives a simple example to illustrate the working mechanism of our framework. We use our framework to achieve summary from the collection D' of three product reviews on a kind of computer. $D' = \{d'_1, d'_2, d'_3\}$. The contents of the three product reviews are given as follows:

d'_1: "The system works well. I like it. Its appearance is beautiful. My brother used it for work".
d'_2: "System is fast. The battery is not good. Anyway, my wife likes it. The appearance is excellent"

```
Function LSTM_summarization(D_2, D_3, index)
Output: S, summary of D
Begin
  # LSTM training
  For i in index
    D_2(i) = D_2[D_3[i] ∈ D_2];
    net = LSTM_train(D_2(i));
    S[i] = net(D_2(i));
  End For
  Return S;
End
```

Fig. 9. Pseudo code of LSTM_summarization.

TOPIC1	TOPIC2	TOPIC3
"system works well" **"system is fast"** "wife likes"	**"appearance is beautiful"** **"appearance is excellent"** "appearance is great" "brother used"	**"battery is not good"** **"battery is enough for work"** "works well"

Fig. 10. Topic mining result for D'_1.

d'_3: "The battery is enough for work. The appearance is great. It works well".

The following processes are performed according to pseudo code in Fig. 8:

(1) D'_1 = POS_grammar_rules(D')

The output of D'_1 is shown as follows:

d'_1: "system works well"
"appearance is beautiful"
"brother used"
d'_2: "system is fast"
"battery is good"
"wife likes"
"appearance is excellent"
d'_3: "battery is enough for work"
"appearance is great"
"works well"

It is obvious that D'_1 contains the important POS phrases for product attributes, for example, the POS phrase "operation system works well". However, D'_1 also contains less important phrases such as the POS phrase "brother used". D'_1 needs to be further processed by LDA topic mining to generate a smaller but more effective subset.

(2) K^* = LDA_optimal_topic(D'_1) and D'_2 = LDA_semantic_phrases(D'_1, K^*, N)

Repeated LDA topic mining tasks are performed to determine the optimal number of topics K^*. Here, K^* is set as 3. The result of LDA topic mining in Function LDA_semantic_phrases is shown in Fig. 10. The parameter N is set as 2, meaning that the top 2 POS phrases (bold in Fig. 10) in each of the three topics are selected.

	appearance	battery	beautiful	excellent	fast	for	good	is	system	well	work	works
1	0	0	0	0	0	0	0	0	1	1	0	1
2	0	0	0	0	1	0	0	0	1	0	0	0
3	1	0	1	0	0	0	0	1	0	0	0	0
4	1	0	0	1	0	0	0	1	0	0	0	0
5	0	1	0	0	0	0	1	0	0	0	0	0
6	0	1	0	0	0	1	0	0	0	0	1	0

Fig. 11. Document-Term matrix for D_2'.

appearance	battery	system	is	beautiful	excellent	fast	for	good	well	work	works
2	2	2	2	1	1	1	1	1	1	1	1

Fig. 12. TF values for all the words in D_2'.

D_2' is shown as follows:
"system works well"
"system is fast"
"appearance is beautiful"
"appearance is excellent"
"battery is not good"
"battery is enough for work"
Although the POS phrase "appearance is great" is filtered out, D_2' still contains the important information of "appearance". After topic mining, the less important POS phrases "wife likes", "brother used" and "works well" are removed. As mentioned above, the collection of POS phrases also contains noisy information. This example intuitively illustrates why LDA topic mining is necessary to be applied to achieve the collection of semantic phrases. In addition, this example also shows the effectiveness of the LDA model to deeply analyze the content of text in the view of topics. Each topic in Fig. 10 contains one of the product attributes. The LDA model is effective to rearrange the text according to semantic contents.

(3) dtm = DTM_matrix(D_2') and D_3' = Feature_selection(dtm, N')

The Document-Term matrix of D_2' is shown in Fig. 11. Each row represents a semantic phrase. Each column represents a word in all the semantic phrases. The "1" row indicates that the first semantic phrase "system works well" in D_2' contains words "system", "well" and "works" and, all the three words exist once. The "appearance" column indicates that the word "appearance" only exists in the third and the fourth semantic phrases ("appearance is beautiful" and "appearance is excellent") in D_2'. The Document-Term matrix is then input for feature selection.

The feature selection method TF shown in Formula (9) is used to select product attributes according to Document-Term matrix for D_2' in Fig. 11. The TF values of all the words are shown in Fig. 12.

It is obvious that most of the words with larger TF values are product attributes, including "appearance", "battery" and "system". The words are sorted according to their TF values decreasingly for users to select product attributes. We set the value of N' as 5. Finally, D_3' = {"appearance", "battery", "system", "is", "beautiful"}. D_3' contains important product attributes but also contain a certain number of noisy words which are not related to product attributes.

(4) S = LSTM_summarization(D_2', D_3', index)

Here, we choose the product attributes "appearance" and "system" to generate summary. According to Fig. 9, index ={"appearance", "system"}, D_2'("appearance") ={"appearance is beautiful", "appearance is excellent"}, D_2'("system") ={"system works well", "system is fast"}. D_2'("appearance") and D_2'("system") are respectively sent to the LSTM network to generate final summary: S["appearance"] ={"appearance is excellent"}, S["system"] ={"system is fast"} and $S = \{S[\text{"appearance"}], S[\text{"system"}]\}$.

Table 1
Summary of the six datasets for experiments.

Name	Number of product reviews	Language	Description
Cars	10 000	English	Product reviews of cars
Hotels	10 000	English	Product reviews of hotels
Amazon	12 000	English	Product reviews of office equipments from Amazon
Macbook	9706	Chinese	Product reviews of Apple MacBook
Jiudian	7766	Chinese	Product reviews of hotels
Douban	20 000	Chinese	Product reviews of movies

In this simple example, the summary can be done manually. However, in the practical scenarios, D_2' ("appearance") usually contains large number of semantic phrases. The LSTM network is necessary and effective to help users to achieve summaries automatically.

4. Experiments

4.1. Datasets and experimental settings

In order to demonstrate the effectiveness of our framework, six datasets from real-world business scenarios are used to conduct experiments. The six datasets are summarized in Table 1. The datasets Cars and Hotels are achieved from the UCI repository. The dataset Amazon contains product reviews on office equipments. The dataset Macbook is collected from a famous e-commerce platform in China. The datasets Jiudian and Douban are achieved from the website https://www.csdn.net/. The datasets Cars, Hotels and Amazon are the English datasets while the rest of the three are Chinese datasets. The datasets for experiments are helpful to demonstrate effectiveness of our framework because they cover various kinds of products including hotel services, cars, movies and other common products.

The styles of English and Chinese product reviews are different. English users tend to write detailed-style comments on product attributes while Chinese users are more likely to write short-style comments on product attributes in their product reviews. It is another reason why the experiments are capable of demonstrating the effectiveness of our framework that the datasets contain the product reviews of two typical styles (detailed-style and short-style) in practical scenarios.

4.2. Experimental results

4.2.1. Optimal numbers of topics

As mentioned above, the optimal number of topics for LDA topic mining is determined by perplexity in experiments. This section discusses the results of perplexity of candidate numbers of topics in each dataset in Fig. 13. It is obvious that the optimal number of topics (topics under the biggest perplexity values) for English datasets (Cars, Hotels and Amazon) is smaller than those for Chinese datasets (Macbook, Jiudian and Douban).

Experimental results show that our framework is suitable for analyzing both the detailed-style and short-style product reviews. The reason is as follows: Our framework performs two-level feature extraction for product reviews. For the case of detailed-style product reviews, the collection of POS phrases contains much noise phrases and relatively small numbers of product attributes because product reviews contain much detailed descriptions. However, many of the noise phrases will be removed by the LDA topic mining. Compared with numbers of noise phrases, numbers of phrases which are directly related to product attributes are small. As we can see in Fig. 13(a) to (c), the LDA model is able to understand the product reviews properly because it groups the product reviews into a relatively small number of topics. For the case of short-style product reviews, collections of the POS phrases contain a few noise phrases and relatively large number of product reviews. The LDA model is also capable of assigning proper numbers of topics for the product reviews. As we can see in Fig. 13(d) to (f), the POS phrases are arranged in relatively large numbers of topics. In summary, our framework is capable of understanding the semantic information of both detailed-style and short-style product reviews.

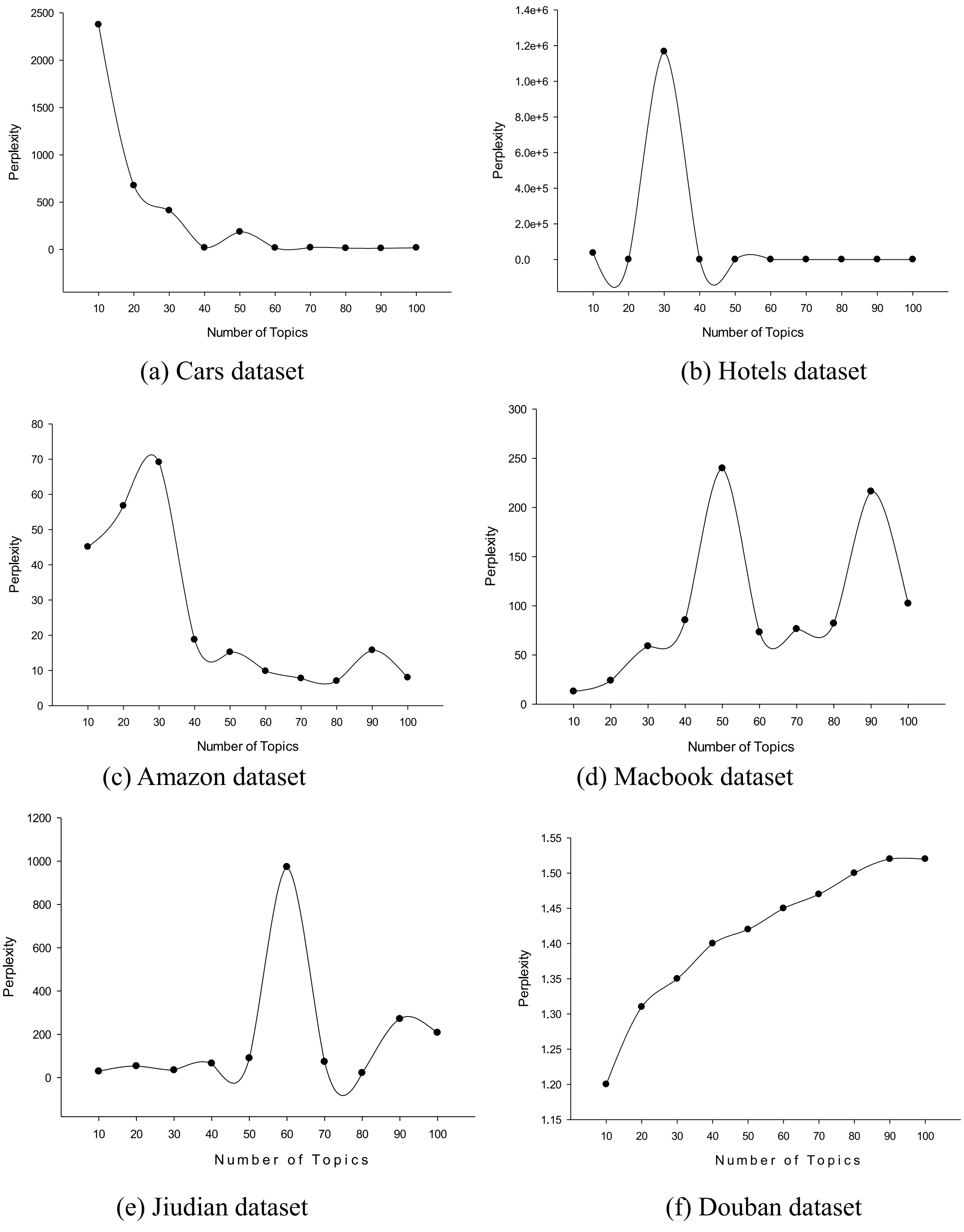

Fig. 13. Results of perplexity in the six datasets.

4.2.2. Semantic analysis of the summaries

The important product attributes which we selected from the six datasets are shown as follows: These product attributes are used to generate summaries for the corresponding datasets. For Amazon dataset, the product attributes are the office equipments (see Table 2).

The generated summaries for the six datasets are shown as follows: Noisy and duplicate text is possible contained in the output of the LSTM network due to the uncontrollable auto learning characteristics of the network. The results of our summaries are the pure customer opinions on product attributes after removing meaningless noisy and duplicate text from the original output of the LSTM network. The following results of summaries also indicate

Table 2
Important product attributes.

Dataset	Product Attributes
Cars	“gas”, “power”, “engine”, “seats”, “sound system”, “design”, “price”
Hotels	“room”, “staff”, “shower”, “food”, “location”, “water”, “price”
Amazon	“printer”, “pen”, “binder”, “paper”
Macbook	“系统” (“system”), “外观” (“appearance”), “性能” (“performance”), “分辨率” (“resolution”), “价格” (“price”)
Jiudian	“房间” (“room”), “早餐” (“breakfast”), “空调” (“air conditioner”), “宽带” (“broadband”), “卫生间” (“bathroom”), “环境” (“environment”), “价格” (“price”)
Douban	“剧情” (“plot”), “特效” (“special effect”), “情节” (“story”), “剧本” (“script”), “角色” (“roles”)

Table 3
The summary for cars dataset.

gas
Gas mileage is very good gas mileage is wonderful the gas mileage is average gas mileage is not the best gas mileage is terrible

power
The power gives a real sense of confidence on the road powerful engine has good power power is good enough incredible power love the power power is great incredible engine great power adequate power enough power power is enough lacks the power very powerful

engine
Engine is smooth engine is quiet engine is strong quiet engine very quiet engine the engine is powerful very powerful engine powerful engine the engine is more powerful engine is great the engine is weak great engine the engine sounds great the engine is so smooth strong engine the engine is very quiet

seats
Cloth seats the leather seats are very comfortable very comfortable seats the seats are very comfortable the seats are not comfortable seats are comfy seats are very comfortable leather heated seats very comfy seats heated seats comfortable seats memory seats seats are uncomfortable heated leather seats eats are comfortable the seats are comfy the heated seats the seats are very supportive the seats are exceptionally comfortable the seats get dirty very easily the seats are uncomfortable leather seats great seats love the seats the seats are comfortable uncomfortable seats

sound system
Good sound system the sound system is excellent the sound system is wonderful excellent sound system sweet sound system love the sound system the Bose sound system is awesome the sound system is awesome the standard sound system stereo system sounds great the sound system is great great sound system outstanding sound system the sound system is amazing sound system is great nice sound system

design
Sleek design nice design well designed well designed vehicle the interior design is simple love the design love the exterior design love the new design great design design flaws beautiful design a design flaw excellent design nice design well designed

price
A great price great price the price was very reasonable very reasonably priced the price was great best price low price good price great car for the price the price was unbeatable

that our framework is capable of generating meaningful and useful summaries for both detailed-style and short-style product reviews.

(1) Summary for Cars dataset

Customers show attitudes of three levels on gas mileage: good, average and bad, indicating that the gas mileages of cars are necessary to be improved. Generally, customers are satisfied with the good power, smooth and quiet engines, nice sound systems and reasonable prices of the cars. Most of the opinions on seats indicate that the seats of cars are comfortable. However, some customers complain that the seats are uncomfortable and get dirty easily. Although the attitudes of designs of the cars are positive in most cases, there are some opinions on design flaws (see Table 3).

Table 4
The summary for hotels dataset.

room	The rooms are very large very clean room room service is very good the bathroom had no window rooms are cozy room had a queen sized bed room was exceptionally quiet room was very comfortable the rooms are a little worn the rooms are lovely standard rooms the room was tiny the rooms are clean room was tiny the room was fairly clean rooms were cleaned the room was very large the rooms were fine the room was very small old rooms room was very clean the room was fine rooms are spacious the bathroom spotless the rooms are beautiful room spotless room was warm the room was a good size good sized rooms room was very comfortable
staff	Staff were fantastic the staff was always helpful the staff is super friendly the best part was the staff the staff was quite friendly staff were great the staff are helpful the staff were very nice the staff were amazing the staff is very nice the staff very helpful the staff were very helpful
shower	The shower was good with a good shower the shower had great water pressure the showers are hot with a great shower the shower worked great a nice shower nice shower good shower good shower pressure no shower gel
food	Great food the food was awful decent food wonderful food food excellent like Chinese food the food delicious the food is delicious food was great
location	Location was good very safe location location was OK excellent location the location is also great the location is incredible best location ever best location was perfect the location is super the location was perfect the location is super the location was perfect great location great hotel the location of the hotel is excellent the hotel location is fabulous location is fine was in a pretty good location found excellent location location was OK excellent location the location is also great the location is incredible best location ever the location is in a great location the location is also great the location is incredible best location ever best location was perfect the location is also the perfect location the best thing about this hotel is excellent the location is very quiet great location fantastic location the location was awesome the location was perfect great location
water	Was plenty of hot water the shower had good water pressure the water pressure was good no hot water constant hot water free bottled water lots of hot water the shower had great water pressure was plenty of hot water the shower had good water pressure the water pressure was good no hot water constant hot water free bottled water
price	Great prices good for the price not bad for the price was a great value for the price high price well priced over priced average priced got a great deal on priceline get a fair price great place for the price great place great price expected for the price a good price was worth the price the price is very reasonable very reasonably priced good price reasonable prices get a good price got an excellent price great prices good for the price

(2) Summary for Hotels dataset

Locations, staff, food and prices of hotels are generally satisfactory for customers. Hotels should continuously offer the high quality of staff and food service to keep good customer experience. Although rooms, water and shower of hotels are reviewed positively in most cases, there are still problems of old and small rooms, no shower gel and, no hot water (see Table 4).

(3) Summary for Amazon dataset

The summary for Amazon dataset is given in Table 5. According to the summary, all the four equipments are highly satisfactory for customers.

(4) Summary for Macbook dataset

The summary for Macbook dataset is given in Table 6. From this summary, we can get the customer opinions on some important attributes of the Apple MacBook. Most of the opinions reflect unfriendliness of the system for customers to use. Similarly, the quality of screen resolution of the computer is not acceptable. Opinions on the appearance of the computer are all positive, indicating customers are satisfied with the appearance. Most of the opinions show high approval on the performance of the computer. However, it is also not accepted by some customers. Some customers are satisfied with the price of the computer while others show the opposite opinions. In summary, screen resolution and system of the computer are necessary to be improved.

Table 5
The summary for amazon dataset.

printer
Great printer reliable printer the printer is fast get a decent page count out of this printer professional printers the labels did not get stuck in the printer have a dedicated photo printer of extremely high print quality excellent printer particular printer a professional printer great printer reliable printer the printer is fast
pen
Pen of choice a bit of a pen fanatic most comfortable pen either the sharpies have the best pen tips in several pen tip sizes this pen writes well pen of choice a bit of a pen fanatic the sharpies have the best pen tips this pen writes well
binder
The binder is sturdy
paper
Great quality paper this are excellent paper have tried the inexpensive paper good paper good graph paper

(5) Summary for Jiudian dataset

The summary for Jiudian dataset is given in Table 7. Some customers are not satisfied with the quality of rooms and breakfast while others give positive opinions. Most of the opinions of air conditioner/conditioning and bathroom are of negative sentiment. Customers give positive opinions on the fast speed of the broadband. Moreover, some hotels charge for the broadband and others do not. Generally, environments of hotels are satisfying. Opinions on prices of hotels contain nearly equal quantity of positive and negative contents.

(6) Summary for Douban dataset

The summary for Douban dataset is given in Table 8. According to the summary, the plots and special effects of some movies cause bad experience of customers. Opinions of scripts and stories of movies have nearly equal positive and negative contents. Opinions of roles are either positive or neutral.

5. Conclusions

This paper proposes a novel framework for product reviews summarization. Our framework identifies semantic phrases which are related to product attributes and the corresponding opinions from original product reviews by using POS grammar rules and LDA topic mining. The LSTM network is used to analyze and generate summaries of product attributes from semantic phrases.

Our framework has several advantages: (1) It extracts semantic phrases in views of both grammar and semantics. POS grammar rules are applied to find the POS phrases which are grammatically meaningful. The LDA model is used to filter the POS phrases in the view of topics to generate semantic phrases which are grammatically and semantically meaningful. (2) It analyzes and summarizes semantic phrases automatically by the LSTM network to free users from reading the large quantities of semantic phrases. Moreover, the semantic phrases are also relatively long and rough for reading. Users are still likely to be overwhelmed by the semantic phrases. The LSTM network provides users more readable and simple summaries. (3) It provides an interactive mode for users to choose product attributes which they are interested in to create personalized summaries to help user focus on valuable product attributes. (4) Experimental results also indicate that our framework is suitable for both detailed-style product reviews and short-style product reviews.

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Table 6
The summary for Macobook dataset.

系统 (system)

系统需要熟悉　系统用起来还不错　系统很方便　系统很快适应　系统正在熟悉　不习惯电脑系统　系统用不习惯　系统运行流畅　系统还在摸索　系统用不来　系统难适应　还在摸索系统　正在适应系统　系统难用　系统不麻烦

system is need to be familiar with　system works well　system is very convenient　system is fast to be adapt to　system is being familiar with　not used to computer system　system is not be used to　system works smoothly　system is being explored　system is tough to be used　system is hared be adapt to　is exploring system　is adapting to system　system is hard to be used　system is not troublesome

外观 (appearance)

外观漂亮　外观仍然十分值得入手　外观很喜欢　外观设计非常漂亮　外观精美　外观挺好　外观不错　外观就不必说　外观很正　大气外观　外观没话说　外观赞　外观好看　外观很好

appearance is beautiful　appearance is still extremely worthy　like the appearance very much　appearance design is extremely beautiful　appearance is exquisite　appearance is pretty good　appearance is nice　appearance is no need to be talk about　appearance is very nice　impressive appearance　appearance is nothing to be talk about　appearance is excellent　appearance is good looking　appearance is very good

性能 (performance)

性能不是一般好　性能超好　性能阔以　性能完美　性能不够　性能还算可以　性能不错　可能性能不是很好　性能够用　性能超棒　性能优异　性能挺好　性能很好　性能优越　性能稳定

performance is very good　performance is extremely good　performance is ok　performance is perfect　performance is not enough　performance is fairly ok　performance is good　performance is possibly not very good　performance is enough　performance is excellent　performance is extremely good　performance is fairly good　performance is very good　performance is impressive　performance is stable

分辨率 (resolution)

屏幕分辨率太低　屏幕分辨率稍微差点　屏幕分辨率一般　屏幕分辨率不是很好　屏幕分辨率有点低　屏幕分辨率比较低　屏幕分辨率高　分辨率好　分辨率低　分辨率不是太高　分辨率实在是低　分辨率不好

screen resolution is too low　screen resolution is a little bit bad　screen resolution is mediocre　screen resolution is not very good　screen resolution is a little bit low　screen resolution is relatively low　screen resolution is high　resolution is good　resolution is low　resolution is low　resolution is not very high　resolution is really low　resolution is not good

价格 (price)

价格还可以　价格太贵　价格实惠　价格一直在波动　价格偏高　价格也比实体店便宜　价格好

price is ok　price is high　price is affordable　price is fluctuating　price is lower than physical stores

Table 7
The summary for Jiudian dataset.

房间 (room)

房间装修很时尚　房间布局也很整齐　房间挺大　房间不干净　房间干净整洁时尚　房间偏小　房间太差　房间很旧　房间阴暗　房间装修不错　房间较大　房间太脏　房间环境不错

room decoration is very fashionable　room layout is also very neat　room is big　room is not clear　room is clear, neat and fashionable　room is a little bit small　room is too bad　room is old　room is dark　room decoration is nice　room is relatively big　room is too dirty　environment of the room is nice

早餐 (breakfast)

早餐很素　早餐没有酸奶　早餐极差　早餐地点太挤　早餐品种较少　早餐简单　早餐品种丰富　早餐非常丰富　早餐很丰盛　早餐还可以

much vegetable dishes for breakfast　no yogurt for breakfast　breakfast is too bad　spot for breakfast is too crowded choices for breakfast is too limited　breakfast is simple　choices for breakfast is rich　choices for breakfast is very rich　breakfast is sumptuous breakfast is ok

空调 (air conditioner/conditioning)

空调很足　空调制冷制热效果差　空调整夜发出流水　空调声音太大　空调还没有暖风　空调都有噪音　空调不太好　空调都是自动感应　冷暖空调都有　没有热空调　没有空调　空调不太凉　空调几乎感觉不到　空调声音也比较大　空调还好　空调噪音大　空调根本没开　中央空调

air conditioning is enough　air conditioner has pool cooling and heating effects　air conditioner drops water all night　air conditioner is loud　air conditioner has no heating　air conditioner is noisy　air conditioner is not good　air conditioner is automatic　air conditioner has both cooling and heating function　no heating air conditioning　no air conditioning　air conditioning is not cool　the air conditioning effect is hardly to be felt　air conditioner is relatively loud　air conditioning is ok　air conditioner is very noisy　air conditioner is not turned on　central air conditioning

宽带 (broadband)

宽带速度很快　放假宽带免费　宽带免费　宽带流畅　没有宽带　宽带还需要收费　宽带上网速度挺快　宽带速度也比较快　免费宽带　宽带要服务台开通才可使用　宽带竟然是收费

broadband is very fast　broadband is free in holiday　broadband is free　broadband is broadband is fluent　no broadband　broadband is not free of charge　broadband is fast　broadband is relatively fast　free broadband　broadband is need to be opened at the service desk　broadband charges

卫生间 (bathroom)

卫生间较小　卫生间不干净　卫生间都不错　卫生间没有电吹风机　卫生间太小

bathroom is relatively small　bathroom is not clear　bathroom is nice　bathroom is not equipped with hair dryer　bathroom is too small

环境 (environment)

环境不错　环境还可以比较安静　环境一般　环境安静　环境极好

environment is nice　environment is ok and relatively quiet　environment is mediocre environment is quiet　environment is excellent

价格 (price)

价格适中　价格不成正比　价格也不便宜　价格也高　价格比较合理　价格太贵　价格偏高　价格便宜

price is moderate　price is not worthy　price is also not cheap　price is also high　price is relatively reasonable　price is expensive　price is relatively high　price is cheap

Table 8
The summary for Douban dataset.

剧情 (plot)

剧情紧凑 剧情还行 剧情也算流畅 剧情没改好 关键剧情全都是强设定 剧情一般 剧情方面无可挑剔 脑残剧情 剧情简单 剧情不含糊 剧情欠佳 剧情很散 剧情狗血 优点在于反转剧情 剧情很好看 剧情都是套路 剧情太垃圾 忽略剧情

plot is fast-paced plot is ok plot is relatively smooth plot is not modified well key plot is farfetched plot is mediocre plot is found no fault with fool plot plot is simple plot is good plot is not good plot is not concentrated plot is bad the advantage is the reversed plot plot is very good plot is routine plot is very bad ignore the plot

特效 (special effect)

特效不错 特效很好 特效是相当不错 特效超棒 特效很棒 特效烂 特效好棒 风景特效死板 特效渲染过度到像动画片 特效还可以 特效孱弱 特效很差 特效还是可以 电影特效强大 电影没上映就一直在宣传特效 特效也值回票价

Special effect is nice special effect is very good special effect is excellent special effect is extremely good special effect is pretty good special effect is bad special effect is impressive landscape effect is inflexible special effect is over rendering as cartoon special effect is still ok special effect is weak special effect is very bad special effect is still ok special effect is technical special effect is promoting before movie release special effect is worthy

情节 (story)

情节很吸引人 情节都让人寻味 故事情节吸引人 情节斧凿痕迹略重 情节很老 情节猎奇

story is very appealing story is worth thinking story is appealing story is designed intentionally story is old story is strange

剧本 (script)

剧本太厉害 剧本有很大问题 剧本实在太聪明 剧本无敌 剧本真心不错 剧本立意深刻 剧本扎实

script is very talented script has big problems script is really smart script is prefect script is really nice script is of deep meaning script is content-rich

角色 (roles)

角色比较讨喜 角色都很生动 角色区别挺大 角色都记不住 角色很压抑 融入角色 不同角色反应不同社会现状 角色不错 角色也挺难演 人都比较贴合角色

roles are appealed roles are acted vividly roles are characterized roles are not remembered roles are depressed diving into the roles different roles are related to different social situations roles are good roles are still hard to be acted actors relatively fit the roles

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