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An Empirical Study on the Fusion Model of Online Review Information Service Oriented to User Emotional Experience

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Abstract

[Objective / Meaning] This paper proposes an automatic recognition model for online reviews that integrates emotional experiences.The purpose is to use this method to help users quickly and accurately obtain valuable information from massive review information, thereby assisting users in making demand decisions. In this paper, neural network models and clustering models are used to build an automatic recognition model, in order to solve the problem of lack of semantic understanding in traditional sentiment dictionary methods and the lack of data annotation in traditional neural network models. [Method / Process] Collect network review information, use recognition model for automatic recognition, extract information from different angles based on the fine-grained recognition results, perform data mining from the angle required by the user, and provide the best information to the user. [Results / Conclusions] The automatic identification model can effectively solve the problem of overloading user information in massive network reviews, reduce the cost of obtaining information for users, help users analyze comment information from multiple perspectives, and allow users to make better demand decisions.

Keywords

Semantic understanding; user needs decision making; information mining; fine-grained emotion recognition.

1. Introduction

With the continuous development of e-commerce, the number of product reviews on e-commerce websites has also increased with the expansion of the user scale, which also increases the cost of users digging valuable information from the massive review information. On the contrary, comments that originally had a supporting role invisibly increase the user's cognitive and decision-making burden. How to screen out valuable information that can serve users from a large number of comments has become a hot topic of research in recent years. Faced with this problem, this paper designs a network review information service fusion model oriented to user emotional experience. This model can help users discover valuable information in reviews, assist users to better understand products and make decisions, and improve the efficiency and quality of user decisions..

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2. Related research

Comments are a special kind of text, which often contains rich emotional information. Comments with high emotional intensity contain a large amount of information, and they can often effectively represent essential characteristics. That is to say, if the emotional intensity of the review can be identified and filtered according to the emotional intensity, then the part of the content with the most information value can be selected. For the recognition of emotion intensity in comments, the earliest domestic and foreign scholars used emotion calculation formulas to construct an emotion dictionary, and then calculate the text emotion intensity through the emotion dictionary[1]. However, this method only mechanically expresses the sentences in the text as a combination of words, and then queries the emotional color of the words according to the emotional dictionary. Finally, the emotional color of the entire sentence is judged based on the statistical results of the emotional color of the words, ignoring the connection between words and the understanding of semantics, so it is suitable for processing short texts in simple contexts. The processing of texts in complex contexts is beyond support

3. Theoretical basis

3.1. Theories related to emotional experience

3.1.1. PAD three-dimensional emotional model

The model points out that emotion has three dimensions: Pleasure-displeasure, Arousal-nonarousal, and Dominance-submissiveness. Pleasure-displeasure is the essence of emotion, which represents the positive and negative of the emotional state, representing the nature of like or dislike, negative or positive; Arousal-nonarousal refers to the individual emotional and physiological alertness, which is related to the degree of activation of the positive and negative of the emotional state; Dominance-submissiveness is the degree of subjective control of an individual's emotional state, which is manifested in the control and influence of the external environment and others [2]. Some domestic scholars also proposed the AVP model, which is similar to PAD, including emotional arousal, valence and potency/preference.It can also explain the user's emotional value and emotional evolution [3] . The PAD model divides human emotions into 8 categories. If the emotional polarity is positive, then the user's perception is positive emotion, otherwise, it is negative emotion. For example, +P+A+D means excitement, -P-A-D means boring. In addition, D.Nahl proposed the Affective Load, which regarded the widespread information environment as an emotional information environment, because people's behaviors such as query, processing, and utilization are all to meet information needs, and these behaviors must be accompanied by emotional experience [4]. Emotions affect people's cognition and decision-making behavior in many ways. For example, when people are dissatisfied with the search results and have negative emotions, "frustration" emotions will stop people's behaviors of continuing to solve problems[5]. Mapping to the research object of this article—Internet reviews. A large number of product reviews contain users' emotional information. Semantic mining and emotional analysis of these reviews will not only help the emotional design of products, narrow the gap between people and products and shorten the distance between people, but also promote the efficiency and quality of user decision-making.

3.2. Neural network related theories

Artificial Neural Network(ANN) is the core of deep learning. The purpose is to build an artificial neural network similar to the structure of human brain neural network to make the computer have a certain ability to process complex data intelligently. A supervised learning artificial neural network requires a large amount of high-quality labeled data for training, so that the parameters it learns are more intelligent, that is, the prediction effect of the network will be better. This is the so-called "how artificial, there is more intelligence ". Artificial neural

networks have different functions according to their internal structures. For example, the CNN ,Convolutional Neural Network shines in image recognition, and the RNN ,Recurrent Neural Network performs well in processing time series information. Artificial neural network is the core of deep learning. The purpose is to build an artificial neural network similar to the structure of human brain neural network to make the computer have a certain ability to process complex data intelligently. A supervised learning artificial neural network requires a large amount of high-quality labeled data for training, so that the parameters it learns are more intelligent, that is, the prediction effect of the network will be better. This is the so-called "how artificial, there is more intelligence ". Artificial neural networks have different functions according to their internal structures. For example, the CNN convolutional neural network shines in image recognition, and the RNN recurrent neural network performs well in processing time series information. Compared with traditional machine learning methods, deep artificial neural networks trained through complex network structure connections and large amounts of data have significantly improved the depth and complexity of learning. Faced with an increasingly complex information environment and increasing user information service needs, artificial intelligence can better meet user needs, and at the same time drive the entire society toward intelligence, and further improve and liberate social productivity.

LSTM stands for Long Short-Term Memory,which is a recurrent neural network (RNN). It is proposed by Hochreiter & Schmidhuber (1997). Compared with the traditional RNN,it enhances the memory capacity for long sequence information, so that the network can better process long sequence information such as text, so it is often used for modeling time series data. Such as text data, voice data, etc. The core idea of LSTM is to construct a meta-cell composed of input gates, output gates and forget gates, and connect many meta-cells to form a network. The complete LSTM model is composed of input words at time T, cell state, temporary cell state, hidden layer state, forget gate, memory gate, and output gate. The calculation process of LSTM can be described as: through the forgetting of the old information in the cell state and the memory of the new information, the useful information in the subsequent calculations can be transmitted. The useless information is discarded, and the hidden layer state is output at each time step. The functions of forgetting, memory and output are controlled by the hidden state of the last moment and the forgetting gate, memory gate, and output gate calculated from the current input. It can be simply considered that the LSTM cell structure includes a reservoir and three gated switches, which are input gate, forget gate and output gate. The function of this reservoir is to store information. When the input door, forget door and output door are closed, the water in the reservoir will not leak out, thus playing a role in preserving information. Open the input door, and the information from the outside world can flow into the reservoir; open the output door, and the information in the reservoir can flow out; open the forget door, and the information in the reservoir will be dissipated and forgotten little by little [6]. When using LSTM to process text data, it can establish a connection between words with a relatively long distance. For example, in the sentence "playing football is a passionate and charming sport", LSTM can recognize and remember that "playing football" is a "sport". LSTM allows us to overcome the problem of ignoring the connection between words in the traditional sentiment dictionary . But when using forward LSTM to analyze the problem of fuzzy understanding of the fine-grained intensity of emotion, for example, "Chinese men's football is so bad, I want to vomit". Nothing here is a degree of modification of bad, which means bad, and represents a strong derogatory color. But the forward LSTM cannot recognize this information. This is because when expressing strong commendation, weak commendation, strong derogation, weak derogation, etc., you need to pay attention to the interaction between emotion words, degree words, and negative words. At this time, it is very important to encode information from back to front. In order to solve this problem, we adopt Bidirectional LSTM, also known as BILSTM, to better establish bidirectional semantic model. The full name of BILSTM is Bi-directional Long

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Short-Term Memory, which is a combination of forward LSTM and backward LSTM, and is often used to model contextual information in natural language processing tasks. The use of the BILSTM model means that a double insurance is applied in semantic understanding, which avoids the problem of semantic ambiguity in the use of positive semantic understanding, and further improves the accuracy of semantic understanding. If we use high-quality emotional annotation data to train the BILSTM model, the model can recognize emotions. Under the same model complexity, the higher the quality of the training data set used, the better the prediction effect of the obtained model.

4. Model building

The overall framework is shown in Figure 1:(1) Coarse-grained analysis of emotional tendency intensity is completed through BILSTM. (2) Perform clustering through coarse-grained analysis results to obtain fine-grained analysis results.(3) Write fine-grained results.(4) Extract fine-grained results according to requirements. (5) Perform LDA topic analysis or TFIDF analysis based on the extracted results.

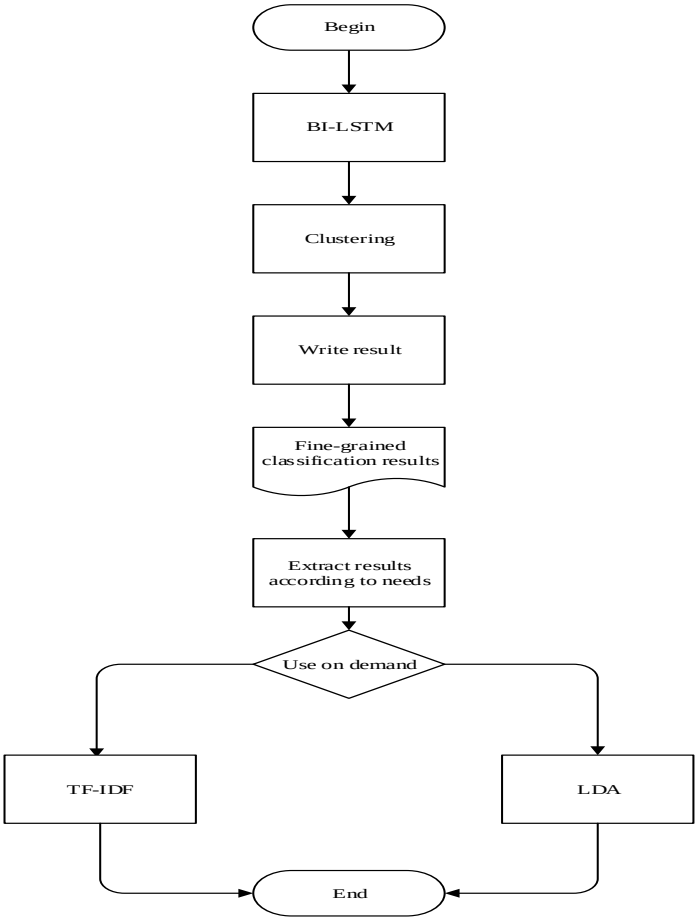

Figure 1 Overall framework

If you want to extract valuable information from a large number of online reviews to assist users in making decisions, you need to divide the emotional strength of the reviews first, and then extract the information from the selected reviews. Therefore, three problems need to be solved in sequence: (1) How to evaluate a large number of reviews (2) How to select valuable reviews based on the evaluation; (3) How to extract information from the selected reviews. The most important one is the first question, how to subdivide and evaluate the emotional intensity of a large number of online comments, in other words, how to build a fine-grained analysis model of emotional intensity, which is also the core model constructed in this article. The construction ideas of this model are discussed below.

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4.1. A fine-grained analysis model of emotion intensity

The emotional strength is related to the text information content, that is, the greater the amount of information contained in the text with greater emotional strength, the more valuable it is. Therefore, if the evaluation of the emotional strength of the text can be achieved, the information value of the text can also be evaluated. When analyzing the sentiment intensity of texts, this article chooses the BILSTM model and abandons the traditional sentiment dictionary, because this model can better understand the semantic relationship of the text, making the sentiment analysis results more accurate. Compared with the traditional LSTM model, the BILSTM model can understand the bidirectional semantics. Compared with more accurate models such as BERT, the BILSTM model is relatively lightweight, easy to understand and use, and is not much different from the accuracy of BERT in sentiment analysis. In summary, we choose the BILSTM model as our model for understanding text semantics and outputting sentiment analysis results. After selecting the BILSTM model, through comparative testing on the same data set, it was found that the Baidu training model has the best accuracy due to the high quality of Baidu's self-built training set. When using the Baidu pre-training model, you can choose the fine-tuning mode, that is, let the model change its own parameter settings slightly with the training data, or you can choose the mode without fine-tuning. Through comparative tests, it is found that the accuracy of the two modes is almost the same, and the fine-tuning mode is slower and more performance-consuming, so we choose the mode without fine-tuning.

The processing of text data in the Baidu BILSTM model is as follows: the text is segmented into a combination of words through the model, and each word is embedded into a vector containing contextual semantics through word vector embedding. Input each word vector in turn to the Bidirectional LSTM memory network, so that the network will memorize the semantic information of the entire text, and finally output the emotional tendency probability of the text. After comparing it with the original tags manually labeled, the parameters of the entire network are continuously modified to make the effect of the network is the best. All supervised artificial neural networks have an assumption, that is, that the characteristics of the training data are very similar to the characteristics of the data to be predicted. The BILSTM also follows this assumption, because there are only positive and negative labeled data, so the BILSTM on the market Including Baidu, all can only output positive and negative sentiment intensity analysis results. If there are only two sentiment intensities, it will not be of substantial help to the target service to be provided in this article, so we need more detailed results. However, due to the lack of labeled data, it is unrealistic to obtain the segmentation results directly. But the original model can output accurate positive and negative probabilities, and we can use this result for fine segmentation. It is definitely unscientific to divide the probability equally from 0 to 100%. We can use the predicted probability and predicted label of each text as coordinate values, so that each text is mapped to a point in the space. If points with similar characteristics can be clustered together, a more scientific subdivision result can be obtained. We use the clustering method to process the results of the BILSTM , and we can get the results of scientific emotional intensity segmentation. At the same time, we use the Calinski-Harabaz Index to score the clustering methods and evaluate different clustering methods: By calculating the square of the distance between points in the cluster to the center of the cluster, the tightness of the cluster is measured, then calculate the sum of the squares of the distance between the various center points and the center point of the data set to measure the separation of the data set, finally, the CH index is obtained from the ratio of the separation degree to the compactness. The larger the CH, the closer the cluster itself, the more dispersed the cluster, and the better the clustering results. Since some clustering methods need to specify the center number K, some do not, the method of specifying K requires a unified control variable of 5. The scores of each clustering method are shown in Table 1:

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Table 1: Three Scheme comparing

Clustering method	KMeans	Birch (K is not specified)	Birch (specify the K)	DBSCAN
CH score	40549.20	20279.91	22425.60	20279.91

It was found that K-Means performed the best in this task by comparison. K-Means belongs to the non-supervised learning model, which requires the center number of the cluster (divided into several categories). K-Means belongs to the non-supervised learning model, which requires the center number of the cluster (divided into several categories). Therefore, there is a need for a scientific score standard to evaluate different central numbers. This article selects the result of the inertia to measure the result of clustering under different values.This value is the properties of the K-Means object, which is a non-supervising assessment indicator without the label of the real classification result. Indicates the sum of the distance to the nearest cluster center. The smaller the value, the smaller, because the smaller indicates the more concentrated the distribution of samples between cluster. The inertia values under different K values are shown in Figure 2: When K is 7, the inertia value is the smallest. When K is 6, the last turning point occurs. Based on experience, we choose 6 to be the best. Because the difference between the inertia of 6 and 7 is not large, and if you choose 7, the classification will be too fragmented, and the degree of aggregation of the points will be too scattered.Therefore, the 6-class value is the smallest, the effect is best. Through the combination of two methods and select reasonable parameters, we can evaluate a large number of online comments into six types of emotional intensity.

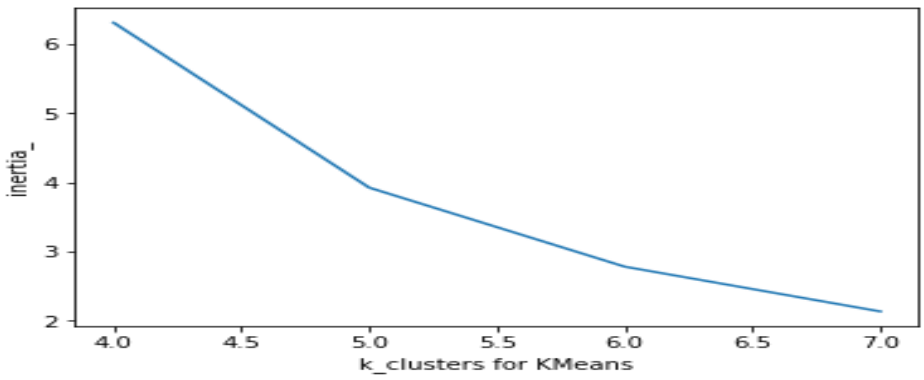

Figure 2 Inertia values under different K values

5. Data acquisition and experiment

5.1. Experimental data source

Due to the limited number of data sets crawled by crawler software, and the quality is uneven, the data set used in this article is the waimai_10k data set, which is a user evaluation collected by a certain food delivery platform, with 4,000 positive and about 8,000 negative. The data has two dimensions, one is the processed text, and the other is the 0/1 label manually labeled, 0 represents negative, and 1 represents positive. In this experiment, we only need to use the processed text, not the label item. The advantage of this data set is that it is provided by the food delivery platform, the source is relatively reliable, the amount of data is large, and it has been preprocessed.

5.2. Experimental data processing

According to the above six types of emotional intensity segmentation results, the classification results of each comment are written into the original data set, so that the required text can be extracted according to needs. According to sentiment theory and user needs, we need to extract

the most valuable comments, that is, the most emotional comments. This article chooses pandas to extract, because this tool has high processing efficiency when facing a large amount of data. After the comments are extracted, put the strongest positive ones in one group for analysis, and put the strongest negative ones together for analysis to avoid mutual interference.

5.2.1. Information extraction

According to the above selection results, the hidden information is extracted from the two sets of results. First, use TF-IDF in SKlearn to extract the feature information of each group. SKlearn is an open source machine learning toolkit that is easy to use, effective, and supports rich. TF-IDF (Term Frequency-Inverse Document Frequency) is a commonly used weighting technique for information retrieval and data mining. TF means term frequency, and the calculation method of term frequency is the number of keywords used / the total number of words in the text , IDF is the Inverse Document Frequency , IDF calculation method is to use the total number of documents / the number of documents containing a word and take the log value. The reason for using TF-IDF is to determine the weight of a word in a document (a word's contribution to the topic of the document).If only the word frequency is used to measure it, it will cause inaccuracy. For example, function words in Chinese have a high frequency of occurrence in various texts, but these words are basically useless for determining the theme of the text. These words are called "stop words" and their frequency should not be considered when measuring relevance. In addition, there is the issue of the importance of keywords. Take the search for "Atomic Energy Application" as an example. "Atomic energy" is a more professional word, while "application" is a more general word. Obviously, the former is more important than the latter in the relevance ranking, but the difference between the two cannot be distinguished only by word frequency. If a keyword appears in a few texts, it is easy to determine the search target through it, then this word can better represent the information topic of the text, and its weight should be greater. Conversely, if a word appears in a large amount of text, it is still not clear what to look for, that is, the word cannot represent the subject information of the text, and its weight should be small. Therefore, the index IDF can just meet the above two characteristics. The TF-IDF represents the weight of a certain keyword in the document. The formula for measuring a certain keyword in the text is defined as TF·IDF, that is, the influence of word frequency and IDF is comprehensively considered. The processing process of text data in TF-IDF is described as follows: First calculate the word bag composed of all texts, then count the word frequency vector of each text according to the word bag, and input the word frequency vector matrix into the next IDF statistics, and finally you can get TF-IDF value. Through the above process, TF-IDF can be used to mine the feature data of the text.

In addition, LDA can also be used to extract the main topic information discussed in each group of texts. LDA (Latent Dirichlet Allocation), or latent Dirichlet Allocation, was proposed by Blei in 2002 [7]. The LDA model is the generation probability model of the text collection. Assume that each text is represented by a polynomial distribution of topics, and that each topic is represented by a polynomial distribution of words. It is especially assumed that the topic distribution of the text and the prior distribution of the word distribution are Dirichlet distributions. Due to the import of the prior distribution, LDA can better deal with the over-fitting phenomenon in topic model learning. LDA can identify potential topic information from the text collection, and input the EM and other algorithms to get the potential topic information of the text collection. The identification process is: Probabilistic text information is generated through LDA, and then the observed real text information and the generated probabilistic text information are calculated by algorithms such as EM to obtain the potential topic information of the text collection. The text generation process of LDA is described as follows: First, multiple word distributions are generated based on the prior distribution of word distributions, that is, multiple topic content is determined. Then, multiple topic distributions are generated based on the prior distribution of topic distributions, that is, multiple text content is determined.Finally,

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a topic sequence is generated based on the distribution of each topic. For each topic, words are generated based on the word distribution of the topic. The whole constitutes a word sequence, that is, text is generated, and this process is repeated to generate all text. We can find that the word sequence of the text is an observation variable, the topic sequence of the text is a hidden variable, and the topic distribution of the text and the word distribution of the topic are also hidden variables. Through algorithms such as EM, the hidden variables are derived from the observed variables, that is, the topic sequence, topic distribution, and topic word distribution of the text are derived from the observed text word sequence. The processing of text information in LDA is described as follows: the text is processed into a word frequency matrix, and the word frequency matrix is input into the LDA model. LDA can obtain the number of topics, the distribution of keywords under each topic, and the topic distribution of each text according to the input word frequency matrix (observed variables calculate the topic distribution and the word distribution under the topic). However, to use LDA, you need to specify the number of topics. We need to choose a reasonable standard to score different topics. We choose to use the lda.perplexity(X) function to know the current training perplexity. The definition of perplexity in sklearn is exp(-1. * log-likelihood per word). The lower the perplexity value, the better the convergence effect, that is, the better the selected topic. When adjusting parameters, we can choose to use fully automatic VC, but this method takes a long time and is not flexible. At present, manual adjustment and selection of the best parameters are commonly used. Different topics and corresponding perplexity are shown in Table 2:

Table 2 Topic corresponds to perplexity table

topic	perplexity
2	190.87
3	219.68
4	240.29
5	281.04
6	271.38
7	329.13
8	341.70
9	331.31
10	332.95
11	371.53
12	411.12

Through comparative experiments, we found that the number of the best topics for this task is 2.

5.2.2. Discussion of experimental results

The results of the segmentation we get are shown in the following figure3:

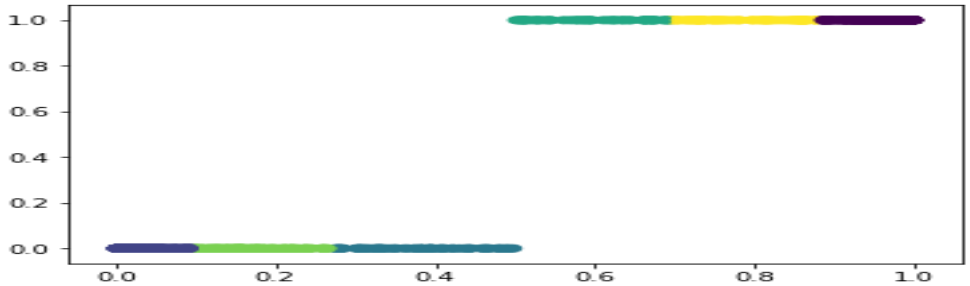

Figure 3 Results of fine-grained analysis of emotional intensity

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The horizontal axis in the figure is the positive probability of emotional tendency, that is, the leftmost end is the strongest derogatory meaning, and the rightmost end is the strongest commendation. The vertical axis is the emotion coarse-grained label 0 or 1. Different colors represent different fine-grained divisions, and the length of the color represents the proportion of the whole. From the figure, we find that the division result is not equal division, and the most negative to the most positive proportions are 9%, 18%, 22%, 20%, 19%, 12%. This is very close to our daily cognition. When evaluating a hot-selling product on an e-commerce website, you will find that the default comments account for the majority, that is, the middle two paragraphs in the figure. The slightly more emotional comments come next. The least is the real positive and negative reviews, which are the two ends. This shows that the subdivision results of the emotional model in this paper are consistent with the actual situation, confirming the effectiveness of the model.

Next, extract the strongest sentiment comments for TF-IDF feature mining, and the results are as follows:

Table 3 Characteristic result table

Ten keywords with large TF-IDF value	Ten keywords with small TF-IDF value
Chicken	Well
Parsley	Very delicious
Dumplings	High speed
Sauce	Attitude
Steamed buns with soy sauce	Service
Chinese sauerkraut	Thanks
Patty	very nice
Soybean curd	Praise
Lotus root box	On time
syrup	Taste

From the above table 3, it can be found that keywords with larger TF-IDF values are mostly product names, while keywords with smaller values are often user reviews. This shows that the model can help the store understand the worst dishes and services, so as to make targeted improvements, improve the store's service quality and product quality, and help obtain higher benefits. For users, they can select products that meet their needs without having to spend time and effort searching for popular dishes and store reviews, thereby improving decision-making efficiency.

Next, extract the best comments for LDA topic mining. Through LDA mining, you can clearly discover the salient topics in the user reviews, that is, which aspects of the merchant service users are most satisfied with. This is different from TF-IDF because TF-IDF does not have the function of focusing on topics and describing them in detail. The LDA results are shown in the following table 4:

Table 4 Topic Keywords

Topic1	Meal delivery; Quickly; Delivery; Deliverer; On time; Speed ;Rider ;Fast
Topic2	Pretty good; Taste; Delicious; Praise; Price; Dishes; Portion; Ingredient; Flavor; Delicacy

We can see that topic 1 with the best user reviews is about delivery, and keywords express the aspects of delivery service that satisfy users. Similarly, the user reviews of topic 2 are about the

taste of the dishes. For merchants, extracting the topics and keywords in the negative reviews can make targeted specific improvements, reduce the merchant's investigation burden for improving services, and increase the merchant's benefits. This model enables users' feedback to be timely and accurately delivered to merchants, improves the efficiency of information dissemination, makes merchants and users mutually beneficial, and improves both parties' satisfaction.

6. Conclusion

The innovation of this article lies in: From a technical perspective, (1) A model that realizes fine-grained analysis of emotional intensity in the absence of fine-grained annotation data is proposed. This model is based on deep semantic understanding and solves the semantic problems that traditional emotional dictionaries cannot. And it cleverly bypasses the problem of not being able to directly train neural network models that output fine-grained results with fine-grained annotated data. (2) The method and parameters of machine learning are scientifically selected based on the actual task, rather than based on experience or guesswork, so that the results we extract can be more in line with the actual task, which can greatly improve the accuracy. From a management perspective, (1) Our method can greatly reduce the cognitive burden of users. (2) Our method can improve the efficiency of user decision-making. (3) Our method can improve the quality of user decision-making. (4) Our method strengthens the communication function of online comments.

This article has done some exploratory work on the fine-grained analysis of emotional tendency intensity and the results of the analysis. While it can solve some practical problems, it hopes to bring some inspiration to others. However, there are deficiencies and omissions in this research. For example, due to the lack of labeled data, BILSTM and clustering methods are used to achieve division. There may be a better method than clustering to achieve division, which needs to be explored later. With the development of unsupervised learning, automatic labeling methods may be able to directly provide high-quality fine-grained labeling data of emotional orientation intensity. Whether the neural network model is used to directly output different granular results is better than the current method, which requires continued research in the future. Similarly, if there are high-quality feature description data and topic and topic word annotation data in the future, is the effect of using neural network models to directly output feature results of different emotional tendencies better than extracting and then mining based on the division results? Is the effect of directly outputting topics and keywords with different emotional tendencies using neural network models better than the current method? These are worthy of our continued research in the future. In addition, the network comment environment in this article is not sufficient. In the future, we can conduct comparative experiments in a variety of network comment environments, and use questionnaires and other methods to directly investigate users' feedback on improved methods.

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