Research Article

A Deep Learning-Based Text Emotional Analysis Framework for Yellow River Basin Tourism Culture

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As an important carrier of cultural communication, tourism can play a positive role in promoting regional ecology and cultural heritage. Therefore, this paper takes tourist attractions in the Yellow River basin as the research object and constructs mining and comment sentiment analysis for tourism text information in the Yellow River basin that appears on social media platforms. Based on the theory of the social center network, the tourism culture network of the Yellow River basin based on tourists’ emotion analysis is constructed. In addition, based on the linear fusion algorithm of semantic orientation pointwise mutual information and word2vec, this paper constructs an emotion dictionary in the field of tourism review and proposes a set of comprehensive emotion calculation rules based on Chinese text expression structure. The experimental results of 32 scenic spots in the Yellow River basin show that the proposed algorithm can achieve better sentiment classification of tourism texts, broaden the scope of application of the domain sentiment dictionary construction method, and improve efficiency.

1. Introduction

The intelligent analysis and mining of information released by tourists with the help of Internet platforms have a wide range of influence on all kinds of subjects in the tourism industry. Travel tourists’ perceptions of tourism destinations come from the transmission of tourism information [1]. Because of this, nowadays more and more tourists will record their beautiful moments of travel through photos and MVs on the microblog, short video platforms, and other new social platforms. Tourists can like, comment, and share, which results in online travel review text [2]. In view of the research and mining of online tourism review text, it provides tourists’ perception feedback on tourism destinations [3]. The “Internet + tourism” model promotes the explosive growth of online tourism review information. As an intangible wealth, online review text data plays an important role in the management and decision-making of scenic spot management institutions [4]. In order to ensure the effectiveness, objectivity, and scientificness of tourism review data, it is necessary to carry out sufficient tourism text mining analysis [5]. As one of the most commonly used methods of text mining, sentiment analysis can analyze and process the massive text data of tourists’ comments, extract the key theme words of tourists’ comments, and perceive the emotional tendency of tourists toward the tourism destination [6]. Scenic spot review data is written by tourists to express their intuitive feelings about the scenic spot, and its content involves all aspects of information affecting the popularity of scenic spots, which have the characteristic of a distinct theme. Choosing the scenic spot online review data as the research object and making a fine-grained emotional analysis for each image attribute set of a scenic spot (i.e., the factor set affecting tourists’ choice) is conducive to mining the emotional tendency of different topics in the review data and providing users with more valuable and accurate reference information.

The Yellow River, which originated in the Bayan Har Mountains on the Qinghai-Tibet Plateau, is the most important birthplace of Chinese civilization and the mother
river of the Chinese nation. In November 2020, at the China Travel Service Industry Development Forum and “The Belt and Road Initiative” Urban Tourism Alliance Annual Meeting, Dai Bin, President of China Tourism Research Institute, said [7], “we need to protect the Yellow River in the name of ecology, inherit the Yellow River in the name of culture, and develop the Yellow River in the name of tourism.” How to restore the Yellow River basin ecology and tap the Yellow River culture has become an urgent problem that must be solved. At present, the Yellow River basin plays an important role in carrying forward the ecological quality of the Yellow River basin. However, it is undeniable that research on the Yellow River basin plays an important role in promoting the ecological quality of the basin. Culture needs to be presented through a certain carrier, and the best carrier of the Yellow River culture is the tourist attractions formed by relying on the Yellow River culture.

It is of great significance to build a tool for mining and sentiment analysis of the Yellow River basin tourism text information on the social media platform. This paper first designs a mining system for tourism information in the Yellow River basin and proposes an algorithm of mutual information with emotional orientation points.

2. Literature Review of Sentiment Analysis Model

The sentiment analysis model based on the Chinese text sentiment dictionary contains a specific text sentiment dictionary built automatically in advance. The analysis rules corresponding to the algorithm model are defined in advance. According to the established analysis rules, the sentiment analysis of text content is carried out, and the results of text analysis are obtained. Li analyzed the specific emotional tendency of the text content of microblogging network public opinion based on the emotion dictionary, which not only re-established the emotion dictionary of the text but also added the emotion dictionary of the expression package [8]. Shaonpiuie et al. added part of speech analysis to the basic emotion dictionary to complete the subjective and objective classification analysis of text data [9]; Xu et al. expanded the emotional dictionary to include basic emotion words, domain emotion words, and polysemous emotion words, which improved the accuracy of emotion analysis [10]. The naive Bayes (NB) classifier is used to determine the text area where the polysemous emotional words are located and then get the emotional value of polysemous emotional words in this field. These analysis methods based on an emotion dictionary often use a general basic emotion dictionary, which is not universal in different fields. Therefore, the construction of a domain-specific emotion dictionary is of great significance for improving the accuracy of sentiment recognition in comment text. At the same time, the machine learning algorithm makes up for the shortcomings of the emotion dictionary method. The sentiment analysis method based on a machine learning algorithm can use a certain amount of data to train the algorithm model so as to identify the emotional tendency of short text [11, 12]. Experiments by Cui et al. showed that when the data set is large, the performance of the recognition classifier based on a high-order language model is better than the classifier proposed in the previous literature [13]. While training a small amount of data, the NB classifier has better performance. Santos et al. constructed a text model based on a new deep convolutional neural network, using information from character to sentence level to conduct sentiment propensity analysis of short texts [14].

3. Tourism Information Mining System of Yellow River Basin

The function of the system includes data acquisition, data management, emotional analysis, and comparative analysis of scenic spots. The overall process is as follows: firstly, get the tourists’ comments data from one or more tourism social media platforms through the data acquisition function, and then monitor the tourists’ emotions from the perspective of the whole scenic spot and fine-grained theme through the integrated algorithm in the system. Finally, combined with the time dimension of the data, the paper makes a visual comparison of the tourists’ emotions in the specified time period of the scenic spot, so as to provide the tourists with information in line with their personal preferences and assist the scenic spot managers to improve the management quality of the scenic spot.

3.1. Overall Structure. This system is a web service platform based on the Java language. Tomcat is used for service publishing, and open-source MySQL software is used for the database. The overall framework of the system uses Spring + Spring MVC + MyBatis. With Spring’s IOC feature, dependencies between objects are put under Spring’s control, which facilitates decoupling and simplifies the development of AOP features through Spring. SpringMVC is a lightweight web framework that uses MVC design ideas to decouple the web layer and make our development simpler. It includes the data acquisition layer, the data processing layer, the business module layer, and the function display layer. Among them, the data collection layer is mainly responsible for collecting relevant data, and the scope of the collection website includes Meituan, Ctrip, Tongcheng, and Tuniu. The data processing layer mainly provides a series of operations, such as data cleaning and warehousing, retrieval, use, and delivery. The business module layer is used for algorithm module loading and data interaction, and the function display layer is for system users, which is used for data acquisition, management, and feedback of intelligent analysis and mining results. The overall framework is shown in Figure 1.

3.2. Data Acquisition and Management. Data acquisition is mainly used for users to obtain real-time user review data of the corresponding scenic spots in the Yellow River basin from the designated tourism social website. Firstly, parameters such as province name, city name, scenic spot name, start and end time, and corresponding tourism social website are set. Then, the system will automatically obtain
data from the corresponding tourism social networking sites. After the data is obtained, the system will automatically carry out further cleaning operations, including traditional Chinese conversion, half-width conversion, and deduplication. The final data will be stored in the background database in a structured form. Data management is mainly used for users to obtain the data of the specified time and website of the designated scenic spot. Firstly, parameters such as province name, city name, scenic spot name, start and end time, and corresponding tourism social networking website are set. The data are classified and managed according to the user’s name, comment, release time, score, and usefulness. Among them, four functions are provided for tourists, including viewing number, time, rating, and usefulness. By classifying and managing the review data, the comments can be analyzed according to the attributes of each category, which is also convenient for subsequent research.

3.3. Text Emotion Analysis. The module is mainly used for users to analyze and mine tourism information that can be used for research according to the obtained review data. The system can classify user comments into topics, and users can choose emotion categories and topic categories independently. Therefore, we propose a mutual information algorithm of sentiment propensity points to analyze the sentiment propensity of tourism review texts in the Yellow River basin by using a domain dictionary and sentiment scoring rules.

4. Construction of Tourism Network Structure in the Yellow River Basin Based on Emotional Analysis

4.1. Node Network Index. According to different analysis perspectives, social network theory can be divided into relationship elements and structural elements. The relationship elements mainly explain the social relationship connection between actors through intensity, density, and scale; structural elements focus more on the position of actors in the social network and the formation and evolution of social structure. Social network theory mainly involves three elements: node, relationship, and connection [15]. Corresponding to the structure of the tourism flow network, each tourism destination is equivalent to a node in the social network structure, the connection between tourism destinations is equivalent to the connection between points, and the transfer of tourists between tourism destinations, namely, traffic channels, is equivalent to the connection. Actors in the form of all individuals, social entities, or events constitute the basic elements of the social network. They appear in the form of “points” or “nodes” and aggregate into
groups through the strong and weak relations formed in direct or indirect ways.

### 4.1. Degree Centrality

Degree centrality is to measure the number of connections between a tourism node and other nodes, so as to reflect which tourism nodes are in the central position. If tourists flow from other tourism nodes to a tourism node i, the tourism node is an inward tourism node.

\[ C_{D_{in}}(n_i) = \sum_{j=1}^{l} x_{ij,in}, C_{D_{out}}(n_i) = \sum_{j=1}^{l} x_{ij,out}. \]  (1)

Where \( C_{D_{in}}(n_i) \) and \( C_{D_{out}}(n_i) \) represent the centrality of introversion and extroversion relationship between a node and other nodes, respectively. \( \sum_{j=1}^{l} x_{ij} \) is used to calculate the number of direct connections between node i and other j – 1 nodes.

### 4.1.2. Closeness Centrality

Closeness centrality is used to measure the degree of closeness between a tourism node and other tourism nodes through distance. As with the same degree of centrality, proximity centrality can also be divided into extroversion proximity centrality and inward proximity centrality, which respectively characterize the extroversion or introversion relationship between a node and other nodes.

\[ C_{C}(n_i) = \frac{1}{\sum_{j=1}^{l} d(n_i,n_j)}. \]  (2)

Where \( d(n_i,n_j) \) represents the shortest path distance between tourism node \( n_i \) and \( n_j \), \( C_{C}(n_i) \) represents proximity to centrality, that is, the sum of distances between tourism node \( n_i \) and other tourism nodes is reciprocal. The higher the tightness, the stronger the connection to other nodes, and vice versa.

### 4.1.3. Betweenness Centrality

Betweenness centrality is mainly used to measure the key degree to which tourism node acts as an intermediary in a region. If the tourism node has a higher intermediary centrality, it means that the node plays a more intermediary role among other nodes, and tourists tend to turn around here, which can be a tourist distribution center.

\[ C_{B}(n_i) = \sum_{j=1}^{l} \sum_{k=1}^{l} \frac{glk(n_i)}{gjk} (j \neq k \neq i). \]  (3)

Where \( glk(n_i) \) represents the shortest number of tourist paths from node j to node k through tourist node i, and \( gjk \) represents the shortest number of tourist paths from node j to node k.

### 4.2. Construction of Emotion Dictionary

#### 4.2.1. Emotional Seed Dictionary

From the 15000 comment texts of Hebei tourist attractions crawled from the https://ctrip.com, \( T_{set} \), a word set of comment texts, is obtained by using jieba tool for word segmentation, and is intersected with the HowNet emotional dictionary to get an emotional word set \( T_{set} = \{ s_{j1} \} \). \( s_{j1} \) refers to j emotion words with an emotional tendency of i. The word2vec model is used to transform the words in the emotion word set into word vectors (\( s_{ki} \)). In order to achieve a better clustering effect of emotion seed words, a seed word set selection criterion based on cosine similarity is constructed, as shown in formulas (4) and (5).

\[ ADIS (s_{ki}) = \frac{1}{n} \sum_{j=1}^{l} \text{Dis}(s_{ki}, s_{kj}) = \frac{1}{n} \sum_{j=1}^{l} \frac{s_{ki} \cdot s_{kj}}{\| s_{ki} \| \times \| s_{kj} \|} \]  (4)

Where \( s_{ki} \) and \( s_{kj} \) represent the word vectors of different emotion words with an emotional tendency of k; \( ADIS(s_{ki}) \) represents the average distance of the i-th sentiment word with sentiment tendency k.

\[ S_{Threshold} = \frac{1}{n} \sum_{i=1}^{m} ADIS (s_{ki}). \]  (5)

Where \( S_{Threshold} \) represents the distance threshold of emotion words with emotion tendency k.

When \( ADIS (s_{ki}) > S_{Threshold} \), the word \( s_{ki} \) was stored in the seed emotion dictionary, and its emotional tendency was marked as k.

#### 4.2.2. Domain Emotion Dictionary

The SO-PMI algorithm is based on the PMI method to calculate the emotional orientation of words. The basic idea of SO-PMI is to select a group of positive words (P words) and negative words (N words) in a specific domain emotion dictionary to get a group of positive phrases and negative phrases. Then calculate the point mutual information difference between the candidate word and the positive/negative phrase, and then compare the difference with the set threshold to judge the emotional tendency of the candidate word, as shown in the following formula (6):

\[ S_{PMI}(\text{word}) = \frac{1}{N_{pos}} \sum_{i=1}^{N_{pos}} \text{PMI}(\text{word, pos}_i) - \frac{1}{N_{neg}} \sum_{i=1}^{N_{neg}} \text{PMI}(\text{word, neg}_i). \]  (6)

Where \( N_{pos} \) and \( N_{neg} \) represent the number of emotion words in positive and negative phrases, \( pos_i \) and \( neg_i \) represent the number of positive and negative emotion words in positive and negative phrases, respectively.
Threshold is a super-parameter in the experiment, which will directly affect the number of emotion words recognized by the emotion dictionary. After analysis of several experiments, a nonnegative threshold of 0.3 is set to judge the emotional polarity of candidate emotion words, and the judgment formula is shown in the following formula (7):

$$\text{alarity (word)} = \begin{cases} 
\text{positive } SO_{PMI}(\text{word}) > 0.3 \\
\text{neutral } -0.3 \leq SO_{PMI}(\text{word}) \leq 0.3 \\
\text{negative } SO_{PMI}(\text{word}) < -0.3
\end{cases}$$ (7)

$SO_{PMI}(\text{word}) > 0.3$ indicates that the propensity score of candidate emotion words is greater than the threshold of 0.3, and the candidate words are recognized as positive words and added to the positive emotion dictionary. $SO_{PMI}(\text{word}) < -0.3$ indicates that the propensity score of candidate emotion words is less than the threshold value of -0.3, and the candidate words are recognized as negative words and added to the negative emotion dictionary. While $-0.3 \leq SO_{PMI}(\text{word}) \leq 0.3$ indicates that the propensity score of a candidate emotional word is between -0.3 and 0.3, and the candidate word is identified as a neutral word.

The word2vec tool needs to train on the specified data set to obtain the training result word vector, and then calculate the cosine value of the angle between the two vectors to analyze the semantic relationship between the two words. Assuming that $w_1$ and $w_2$ represent two or more words or phrases, respectively, word2Vec is used to map the words to a n-dimensional vector $w_1 = (x_1, x_2, \ldots, x_n)$ and $w_2 = (y_1, y_2, \ldots, y_n)$. The cosine angle formula is used to calculate the average semantic similarity between the candidate emotion words and all the emotion words in the seed dictionary, and the emotional tendency score of the candidate emotion words is obtained, as shown in the formula (8):

$$\cos (w_1, w_2) = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}.$$ (8)

Where $\cos (w_1, w_2)$ represents the semantic similarity between words $w_1$ and $w_2$.

Formula (9) indicates that the emotional propensity score of candidate words is calculated based on the word2Vec algorithm, and the symbolic meaning of variables is the same as the above meaning.

$$\text{Word 2 Score (word)} = \frac{1}{N_{pos}} \sum_{i=1}^{N_{pos}} \cos \text{ (word, } pos^i \text{)} - \frac{1}{N_{neg}} \sum_{i=1}^{N_{neg}} \cos \text{ (word, } neg^i \text{)}.$$ (9)

In order to fully consider the advantages and disadvantages of the two algorithms and realize the significant improvement of the effect of sentiment polarity division of candidate words, this paper uses the linear weighting method to effectively fuse the two algorithms, where the final candidate sentiment score is obtained by weighting the candidate sentiment score based on semantic similarity calculation and the candidate sentiment score based on point mutual information calculation, so as to give full play to the advantages of the two algorithms. The calculation formula is shown in formulas (10) and (11)

$$\text{SentiScore (word)} = w_1 \ast \text{Word2Score (word)} + w_2 \ast SO_{PMI} \text{(word)},$$ (10)

$$\text{polarity (word)} = \begin{cases} 
\text{positive } \text{sentiScore (word)} > 0 \\
\text{neutral } \text{sentiScore (word)} = 0 \\
\text{negative } \text{sentiScore (word)} < 0
\end{cases}$$ (11)

where $w_1$ and $w_2$ represent the weight parameters of the two algorithms, respectively.

4.3. Text Emotion Calculation. In this paper, the Yellow River basin tourism review data is divided into short sentences and complex sentences according to punctuation marks. The emotional score of each comment text is calculated by using the above semantic rules and emotional scoring formula. As shown in Figure 2, the specific emotional score calculation process can be divided into the following three steps:

1. Emotional score calculation of short sentences. In the constructed domain emotion dictionary, the emotional words in each short sentence comment text are searched. If the emotional words are not found, the emotional score is 0; if the emotional words are found, the location (index) of the emotional words is located, the degree of adverbs and negative words before and after the search are matched, and the weights are obtained according to the different combination patterns, and then multiplied by the basic score of the emotional words to get further scores. In this process, the total number of negative words is counted. When the number of negative words is odd, the emotional score becomes the current opposite number. While the number is even, the emotional score remains unchanged. The final emotional score is regarded as the emotional score of a single sentence.

2. Calculate the emotional score of complex sentences. Search the conjunctions that connect the short sentences, match the weights of the conjunctions according to the semantic rules, and multiply the emotional scores of the short sentences with the weights of the conjunctions to get the emotional scores of the complex sentences.
5. Experiment and Analysis

5.1. Experimental Parameters. The data source of this experiment is the same as the previous Yellow River Basin tourism information mining system, including 1000 positive tourism reviews and 1000 negative tourism reviews. After manual inspection, it is found that the accuracy can meet the experimental requirements. Precision, recall, and F value are used to evaluate the effectiveness of the algorithm.

5.2. Results and Discussion

5.2.1. Characteristic Distribution of Different Scenic Spots. 32 scenic spots in the Yellow River basin are selected to test their characteristic distribution. The corresponding serial numbers of their names are shown in Table 1. The results of the characteristic distribution are shown in Figures 3 and 4.

It can be seen from the figure that Hukou Waterfall Scenic Area has the maximum value of degree centrality and closeness centrality, with values of 42.000 and 39.000, respectively, which are significantly higher than other tourism nodes. It shows that the scenic spot has a strong agglomeration and radiation capacity and is the most important tourist destination and tourist transit place in the Yellow River scenic spot of Shaanxi, Shaanxi, and Henan, which has a strong tourism attraction. The value of extroversion centrality and introversion centrality of Yulin Hongshi Gorge is the smallest, less than 1%, indicating that it is not a key scenic spot. In addition, the distribution law of internal/external degree centrality of different scenic spots is almost the same (except for the Terracotta Warriors, Lijiashan, and other scenic spots).

The smaller the value of closeness centrality is, the higher the proximity is, and the closer it is to other tourism nodes. From the point of view of the location of the scenic spots such as Baima Mountain, Taifeng Temple, and other scenic spots, the location of these scenic spots is relatively weak.

5.2.2. Emotion Classification Accuracy under Different Weights. The above results show that the model proposed in this paper has a good effect on tourism information mining in the Yellow River basin and can accurately analyze the feature distribution of different tourist attractions. On this basis, the classification accuracy of emotion dictionary of tourism reviews under different parameters is analyzed, and the results are shown in Table 2.

From the data in the table, it can be seen that, when the weight combination changes, the classification accuracy rate presents a process of increasing and then falling. This is because the mutual information of emotional points has a great impact on the sentiment classification of candidate words when the sentiment polarity is divided. The introduction of semantic similarity information is to avoid the extreme situation where the cooccurrence rate of candidate emotion words and seed words is 0, which leads to a large deviation in emotion classification. Therefore, when the weight combination is \( w_1 = 0.6, w_2 = 0.4 \), the accuracy is the highest.

In addition, the classification accuracy of different single algorithms is compared, and the results are shown in Figure 5. Compared with the method based on a single emotion dictionary, the proposed method has higher
accuracy in sentiment analysis and overcomes the disadvantage of relying too much on an emotion dictionary.

Compared with the single word2vec model, our model can improve the classification effect the most. The precision of positive comment text is improved by 6.1%, recall by 6.6%, and $F$ value by 6.4%; while the index of negative comment text is improved by 6.0%, 7.2%, and 6.6%, respectively. The proposed method takes the emotional information of words into account in the process of word vector representation. The outcome shows that the method of using the established domain-specific emotion dictionary combined with the emotional information word vector sentiment analysis method proposed in this paper is better than using the open

| $W_1$ | $W_2$ | Precision |
|------|------|---------|
| 0.2  | 0.8  | 0.700   |
| 0.3  | 0.7  | 0.740   |
| 0.4  | 0.6  | 0.762   |
| 0.45 | 0.55 | 0.763   |
| 0.5  | 0.5  | 0.775   |
| 0.55 | 0.45 | 0.761   |
| 0.6  | 0.4  | 0.793   |
| 0.65 | 0.35 | 0.79    |
| 0.7  | 0.3  | 0.715   |
| 0.8  | 0.2  | 0.660   |

Table 2: Classification accuracy of emotion dictionary under different weight combinations.
emotion dictionary. The results show that the accuracy and recall rate of the model proposed in this experiment are higher than those of the single model in the test set, and the model can better solve the problem that the single algorithm based on SO-PMI and word2vec is not universal in the implementation of domain dictionary construction tasks. The proposed linear fusion algorithm based on SO-PMI and word2vec has high accuracy and availability.

6. Conclusion

This paper first constructs the Yellow River basin tourism information mining system, which can analyze the huge amount of tourism data on the current social media platform. In addition, the tourism network structure of the Yellow River basin based on an emotional tendency is constructed, and the tourism information mined by the above system is analyzed. The results show that it is feasible to use the extended domain sentiment dictionary to achieve the sentiment classification accuracy of Chinese comment texts, which can avoid a lot of manual annotation and greatly save the time and energy of constructing the satisfaction model of scenic spots.

In this paper, the tourism text information of the Yellow River basin that appeared on the social media platform is mined, which provides a tool for the tourism sentiment analysis of the region, and is of great significance for promoting the tourism culture of the Yellow River basin.

Data Availability

The dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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