Research on Museum Evaluation Model Based on Emotional Perception Text Analysis

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Abstract. Museums are an important component of the public service cultural system. At present, the museum as a whole is in a state of overall prosperity. However, there is still a situation of supply homogenization in some local museums, which requires improving their own characteristics, carrying out supply side structural reforms, and achieving innovative transformation and creative development of public cultural services. This article establishes an emotion perception text model, identifies the emotional types of museum comments, calculates evaluation scores, and finally proposes feasible suggestions to help museums adhere to integrity and innovation, and alleviate awkward situations. This article uses user feedback data on Chaotian Palace, Zhanyuan, Ganxi Mansion, Jiangning Weaving Museum, and Six Dynasties Museum in Nanjing to establish an emotional discrimination model. By locating and quantitatively analyzing the emotional keywords in the comment content, calculate the corresponding emotional score of the user's comment content. Then, set a score threshold to determine the positive, neutral, and negative emotional types of user evaluations for each museum. Obtain the emotional distribution of each museum through statistical analysis.

Keywords: Emotion Perception Model, Sensors Method, Emotion Discrimination Model.

1. Introduction

Museums are an important component of the public cultural service system. As preservers and disseminators of cultural heritage, they play an important role in promoting social development, shaping national image, and enhancing public cultural literacy[1]. According to the statistics of the National Cutural Heritage Administration, in recent years, museum culture has made remarkable development in China[2]. The number of museums is growing day by day, and the reception capacity is gradually improving. However, as the number of museums increases, the phenomenon of homogenization becomes increasingly apparent, and some local museums lack distinctive positioning and other issues[3]. This poses a challenge for museums, requiring them to develop their own characteristics, adhere to integrity and innovation, and achieve their own creative transformation and innovative development. Therefore, based on the evaluations of users on the Dianping platform towards five museums in Nanjing, namely Chaotian Palace, Zhanyuan, Ganxi Mansion, Jiangning Weaving Museum, and Six Dynasties Museum, this article establishes a relevant sentiment analysis model and proposes feasible suggestions for museums to improve their public service level[4].The four issues of emotional analysis in museum reviews are closely related, addressing the emotional tendencies of reviews. By ranking the five museums based on the emotional scores of reviews, key events or influencing factors that affect their emotions were extracted. Based on this, feasible suggestions for improving the public service level of museums were proposed[5]. The overall approach to solving the four problems in this article is to establish different emotional models to analyze comment texts. Firstly, establish emotional discrimination criteria; The second is to determine the impact of keywords on emotional scores; The third is to determine methods to extract key events or influencing factors; Finally, extract and merge comments with neutral and negative emotional tendencies from each museum.

2. Establishing an emotion discrimination model based on the sentiments method

2.1. Emotional discrimination model

$$P(\omega_1, \cdots, \omega_n) = P(\omega_1, \cdots, \omega_n | c_1) \times P(c_1) + P(\omega_1, \cdots, \omega_n | c_2) \times P(c_2) + P(\omega_1, \cdots, \omega_n | c_3) \times P(c_3) \quad (1)$$

$$P(c_1 | \omega_1, \cdots, \omega_n) = \frac{P(\omega_1, \cdots, \omega_n | c_1) \times P(c_1)}{P(\omega_1, \cdots, \omega_n)} \quad (2)$$

$$P(c_2 | \omega_1, \cdots, \omega_n) = \frac{P(\omega_1, \cdots, \omega_n | c_2) \times P(c_2)}{P(\omega_1, \cdots, \omega_n)} \quad (3)$$

$$P(c_3 | \omega_1, \cdots, \omega_n) = \frac{P(\omega_1, \cdots, \omega_n | c_3) \times P(c_3)}{P(\omega_1, \cdots, \omega_n)} \quad (4)$$

c_1, c_2, c_3represents three emotions: positive, neutral, and negative; $\omega_1, \cdots, \omega_n$represents n features in comments;$P(c_1 | \omega_1, \cdots, \omega_n)$, $P(c_2 | \omega_1, \cdots, \omega_n)$, $P(c_3 | \omega_1, \cdots, \omega_n)$represents the emotional score of three types of emotions.

The model calculation process is as follows: first, the comment text is split into sentences, and each sentence is segmented[6]. For each segmented word, this model will search for the presence of that word in the sentiment dictionary and determine its emotional polarity (positive or negative). This model will consider the positional weight of the word. Generally speaking, words located at the beginning of a sentence have a greater impact on emotions, so they have higher weights. This model also considers the influence of negative words. If a word is preceded by negative words such as "no", "no", etc., its emotional polarity will be reversed. This model ultimately weights the emotional polarity of all words to obtain the emotional score of the comment. The score is between 0 and 1, with the closer it is to 1 indicating positive emotions and the closer it is to 0 indicating negative emotions.

2.2. Calculate the proportion distribution of various emotional categories

This article uses the sentiments method in the Snownlp library to establish an sentiment discrimination model, analyzes all comments in five museums, and calculates the corresponding sentiment score for each comment. Based on the emotional score, determine the emotional type that the comment belongs to, and the classification criteria are shown in Table 1:

Table 1. Classification of emotional discrimination criteria

Emotional score	Emotional type
Below 0.4 points	Negative emotions
0.4-0.6 points	Neutral emotions
0.6 points or above	Positive emotions

Based on the above analysis results, calculate the number of comments on various emotional types in each museum and draw a bar chart for intuitive comparison. Further calculate the proportion distribution of emotions in various directions for each museum review, and draw five pie charts for analysis and research purposes[7].

2.3. Analysis of calculation results

This article presents the number of positive, neutral, and negative comments for each museum, as shown in Fig 1:

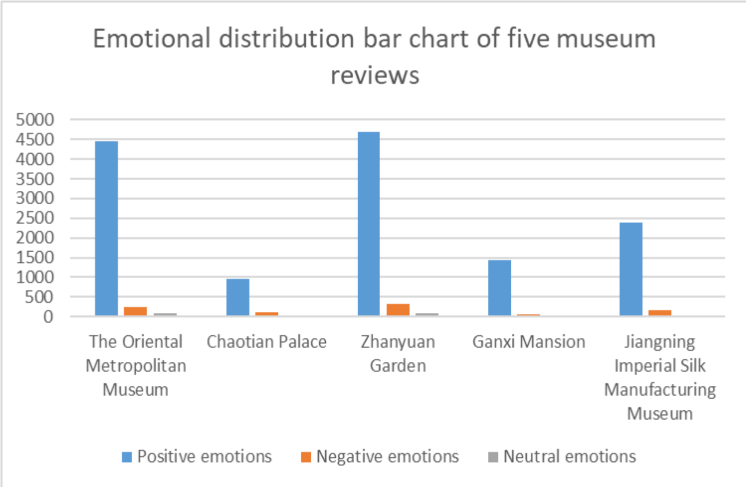

Fig. 1 Emotional distribution bar chart of five museum reviews

This article further calculates the emotional proportion distribution of positive, negative, and neutral directions in five museum reviews, as shown in Figs 2-6:

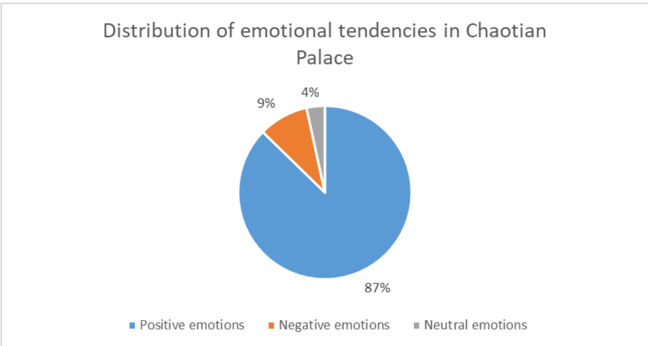

Fig. 2 Distribution of emotional tendencies in Chaotian Palace

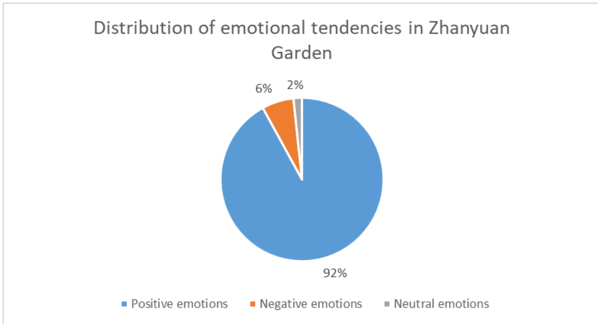

Fig. 3 Distribution of emotional tendencies in Zhanyuan Garden

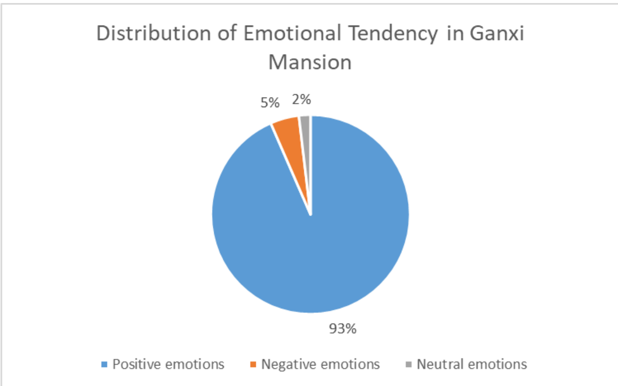

Fig. 4 Distribution of Emotional Tendency in Ganxi Mansion

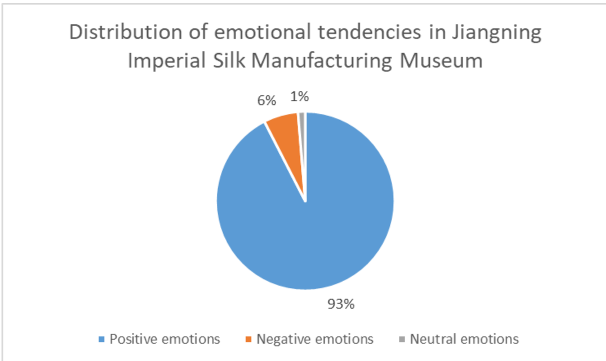

Fig. 5 Distribution of emotional tendencies in Jiangning Imperial Silk Manufacturing Museum

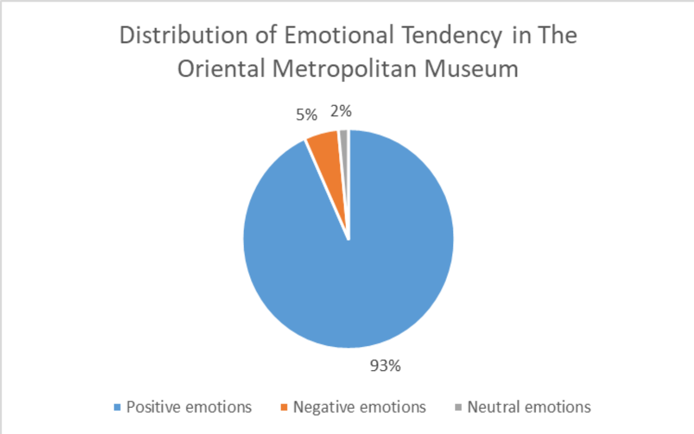

Fig. 6 Distribution of Emotional Tendency in The Oriental Metropolitan Museum

3. Establishment of Emotional Perception Text Model

Emotional perception text model: If there are negative words in the evaluation, assign negative words a score of -0.5; If there are degree adverbs in the evaluation, assign them a score of 2 points; If there are positive emotional words, the score will be calculated and the comment score will be multiplied by 2; If there are negative emotional words, start calculating the score, and multiply the comment score by -2;If there is an exclamation mark, the comment score is multiplied by 2. The final emotional score is positive or negative emotional words multiplied by negative words multiplied by degree adverbs multiplied by exclamation marks[8].

3.1. Calculation steps

Calculate the emotional scores of all user comments using an emotional score evaluation model. A positive emotional score indicates positive emotions, a zero score indicates neutral emotions, and a negative score indicates negative emotions[9]. Compare the emotional labels determined based on the scores in this article with the emotional tendencies studied in question one, calculate the accuracy of the emotional label judgment, verify the accuracy of the emotional score evaluation model, calculate the average score of each museum evaluation, and compare the average score to generate the final museum ranking.

3.2. Calculation results

Firstly, the sentiment score evaluation model is used to calculate the sentiment score for each comment. The results are shown in the table below. The emotional labels in the table are determined based on the score of this question[10,11]. A positive emotional score indicates positive emotions, a zero score indicates neutral emotions, and a negative score indicates negative emotions Compare the sentiment labels determined based on the scores in this article with the sentiment tendencies studied to verify the accuracy of the sentiment score evaluation model. The accuracy rates of each museum are listed in Table 2:

Table 2. Accuracy of each museum

museum	Accuracy
Chaotian Palace	84.35%
Zhanyuan	87.49%
Ganxi Mansion	86.51%
Jiangning Weaving Museum	86.93%
The Six Dynasties Museum	89.45%

Finally, calculate the average score of each museum evaluation, as shown in Fig 7.

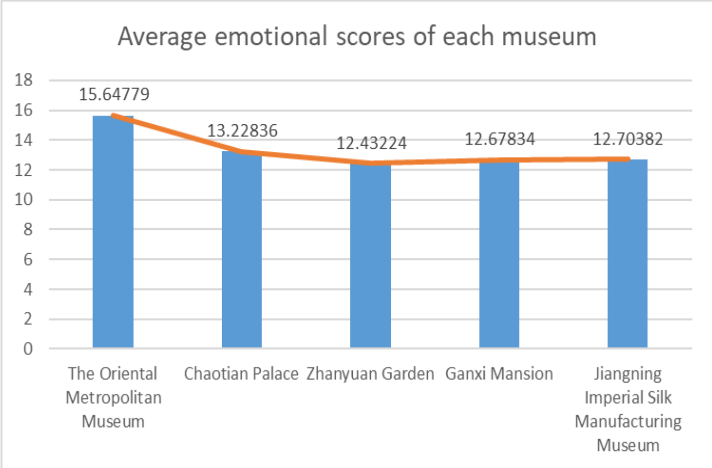

Fig. 7 Average emotional scores of each museum

Based on this, the ranking is shown in Table 3 (scores from high to low):

Table 3. Ranking Table of Five Museums

Ranking	museum	Average score
First place	The Six Dynasties Museum	15.64779
Second place	Chaotian Palace	13.22836
Third place	Jiangning Weaving Museum	12.70382
Fourth place	Ganxi Mansion	12.67834
Fifth place	Zhanyuan	12.43224

4. Establish event extraction and entity extraction models

(1). TF-IDF algorithm:

$$TF = \frac{The\ number\ of\ times\ word\ W\ appears\ in\ the\ document}{Total\ number\ of\ documents} \tag{5}$$

$$IDF = \log\left(\frac{The\ total\ number\ of\ documents\ in\ the\ corpus}{Number\ of\ documents\ containing\ word\ W+1}\right) \tag{6}$$

Among them, TF represents word frequency; IDF stands for inverse document frequency; The word W represents a specific keyword in the text.

(2). TextRank algorithm:

$$PR(p_i) = \frac{1-\alpha}{N} + \alpha \sum_{p=M_{p_i}} \frac{PR(p_j)}{L(p_j)} \tag{7}$$

$PR(p_i)$represents the importance ranking of the i-th keyword; a represents the damping coefficient, usually set to 0.85; N is the total number of comments; M_{p_i}represents the set of keywords for the i-th comment; $L(p_j)$represents the number of occurrences of the jth keyword.

4.1. Calculation results

The top ten important factors that affect the user's emotional evaluation of various museums based on key events and keywords are listed in Figs 8-12:

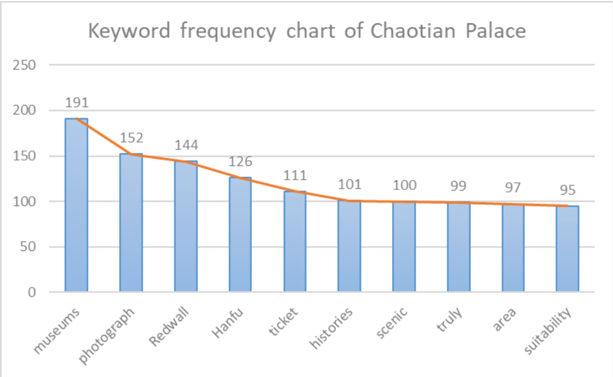

Fig. 8 Keyword frequency chart of Chaotian Palace

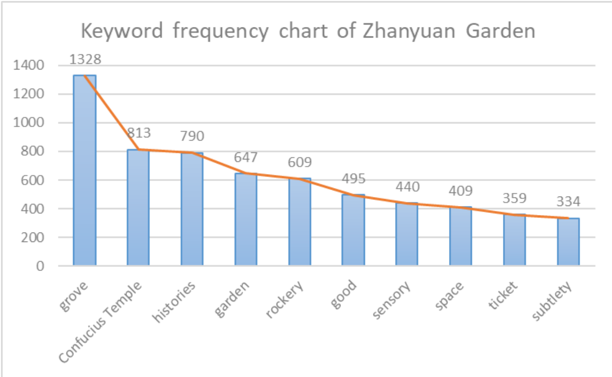

Fig. 9 Keyword frequency chart of Zhanyuan Garden

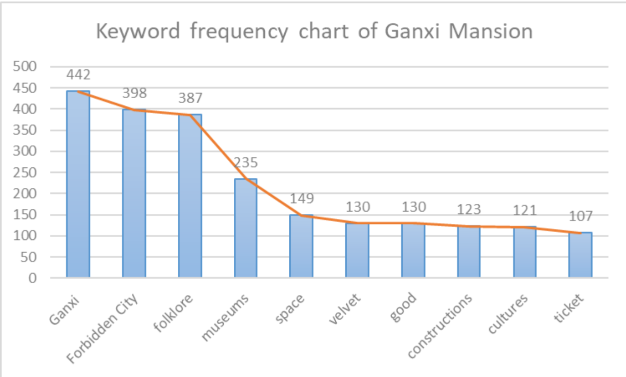

Fig. 10 Keyword frequency chart of Ganxi Mansion

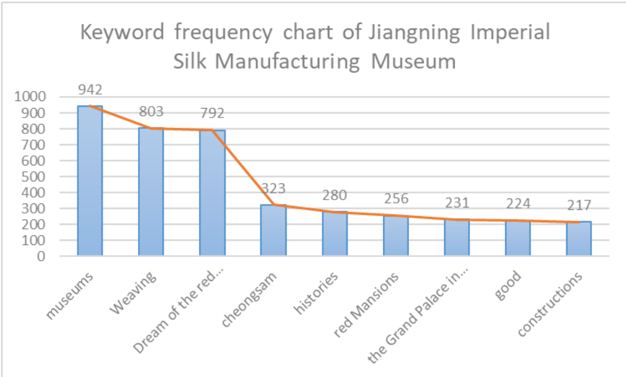

Fig. 11 Keyword frequency chart of Jiangning Imperial Silk Manufacturing Museum

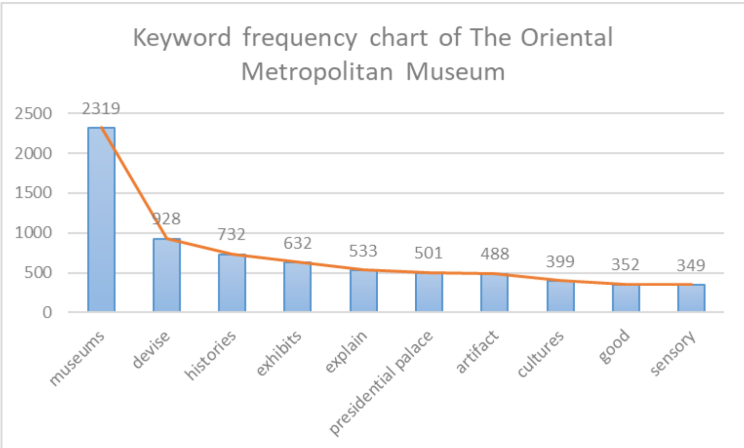

Fig. 12 Keyword frequency chart of The Oriental Metropolitan Museum

4.2. Result analysis

This article uses the IF-IDF algorithm to obtain key events in the comment content, and then uses the IF-IDF algorithm and Text Rank algorithm to obtain keywords in the comment content. Finally, the summarized results are obtained, and the results are visualized as a word cloud map. By comparing the word cloud obtained from this question with the word cloud obtained from the data preprocessing stage, it was found that there were significant changes in the extracted keywords. Among them, the word cloud obtained from the data preprocessing stage focused on the frequency of keyword appearances, while in this question, more attention was paid to factors that affect user emotions. Therefore, comparison can better reflect the accuracy and scientificity of the algorithm application in this article.

5. Conclusions

This article first converts the comment star rating, the comment text type to string type, the conversion time format to string type, the missing values for complete likes and responses to 0, and draws a word cloud map of five museum comments. These steps make known data more convenient to process using the model, greatly reducing runtime and facilitating the resolution of keywords and other issues. Furthermore, the relevant sentiment model established in this article is relatively simple, and the formulas of the model are easy to understand and explain, without involving overly complex mathematical concepts. When distinguishing emotional types and calculating emotional scores, reducing computational resources and time to train the model makes the implementation process relatively easy. Finally, a large number of mutual verification and comparison processes are used to make the calculation results more scientific and accurate. Comparing the sentiment tendency results of the comment labels pointed to by the sentiment score evaluation model, it was found that the accuracy of the sentiment type results obtained by the sentiment score evaluation model for each museum comment is close to 90%, indicating that the calculated comment score is relatively accurate. Simultaneously using event extraction algorithm and entity extraction algorithm, it not only compares but also complements each other, making the final extracted key events and influencing factors the most accurate and comprehensive.

References

[1] Su Jianlin, Text Sentiment Classification (1): Traditional Models, https://kexue.fm/archives/3360 Visited on March 10, 2024.

[2] Zhao Yanyan, Qin Bing, Liu Ting, Text Emotional Analysis, Journal of Software Science, Volume 21, Issue 8: 1834-1848, 2010.

[3] Amjady N. Short-term hourly load forecasting using time series modeling with peak load estimation capability [J]. IEEE Transactions on Power Systems, 2001, 16(4): 798-805.

[4] Wang Kangjing,Qian Jianghai. A sentiment classification algorithm incorporating improved TF-IDF and dictionary model[J]. Journal of Shanghai Electric Power University,2024,40(01):80-86.

[5] H. C. Yan,P. C. Li,J. T. Gu. An automatic TextRank digest generation algorithm based on co-occurring keywords[J]. Computer Engineering and Science,2023,45(11):2060-2069.

[6] Zhang, W.C.. Sentiment analysis of online word-of-mouth in public libraries[D]. Qufu Normal University, 2023.

[7] PENG Mei,HU Bibo. Sentiment analysis of e-commerce user reviews based on big data artificial intelligence[J]. Computer Programming Skills and Maintenance,2022(06):123-126.

[8] Shu Zhang. Research on Online Review Text Classification Based on Sentiment Analysis[D]. Jiangnan University,2023.

[9] GUO Qing,JIA Guojun. Research on sentiment analysis method of travel reviews based on tree LSTM[J]. Computer Application Research,2020,37(S2):63-65.

[10] Feng Shanshan. Research on event extraction method based on deep learning [D]. Changchun University of Technology,2024.

[11] Zhao Chongshuai. Research on Complex Event Extraction Methods for News Texts [D]. China University of Mining and Technology, 2023.