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Computer model-based analysis of user behaviour and emotional disposition on social platforms

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ABSTRACT
In order to be able to accurately identify user behavior and emotional tendency, this paper firstly adopts the neural network structure to build the emotion analysis model, and divides the model into four parts to analyze the text and emotion in social media, and obtains the information of semantics and emotion-related content in social media text. Secondly, from the semantic and emotional symbol content of the text in social media, the public emotional tendency model is built, and the sharing content and behavior of a large number of users in social media are analyzed. Finally, the association rule mining algorithm is used to extract the text and emotional symbols in social media, to improve the accuracy of the user's emotional tendency analysis model, and to be able to accurately derive the user's behavioral habits. In order to verify the analytical effect of the model, the model was tested, and the training speed of the BLSTM model was fast, and the training time was 1.5 hours in the first iteration of the test with a data set of 1 million. The model is more accurate in analyzing the user's positive emotions, with accuracy and precision around 85% and 90% respectively, and the results obtained are more accurate, meet the user's needs, and enhance the user's experience.

Keywords: user behavior, emotional tendency, neural network, sentiment analysis model, social media

1. Introduction

In the context of the rapid development and popularization of social media, social platforms have gradually become part of people's daily life, providing channels for people to share their lives and emotions. And the content shared by users contains information about users' behavior and emotions, which provides corresponding references for social scientific research and public opinion analysis [1]. User behavior analysis is mainly used to analyze the characteristics and social relationships of users through their likes, comments and retweets, and to derive behaviors such as their interests and

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usage habits. While the emotional tendency analysis is to mine the user's emotion and identify the content of the user's emotional expression by analyzing the content such as text and images, so as to derive the user's emotional tendency [2-3]. The analysis of users' emotional tendency and behavior can not only understand users' behavioral habits and decision-making, but also formulate reasonable marketing strategies based on users' preferences, which is of great significance to the management of social networks and the prediction of public opinion, and makes the operation of social platforms more scientific [4-5].

In this paper, firstly, the bottom-up neural network structure is used to establish a sentiment analysis model, and the model is divided into four parts: word vector representation layer, semantic acquisition layer, semantic synthesis layer, and sentiment computation layer, to analyze the text and the sentiment in social media, and to get the information and content of the semantics in the social media text. Secondly, according to the semantic and emotional symbols content of the text in social media, the public emotional tendency model is established, so as to derive the results of users' emotional tendency, and obtain users' preferences and habits. Finally, the association rule mining algorithm is used to extract the text and content features in social media, so as to improve the accuracy of the user emotional tendency analysis model, which is able to accurately derive the emotional tendency of users based on their behavior such as liking and sharing on social platforms, to understand the habits of users, and to improve the satisfaction and experience of users. The proposed research can formulate accurate marketing strategies for enterprises, which is of great significance to public opinion management and promotes the scientific management and development of social platforms.

2. Related Works

In the analysis of users' behavior and emotional tendency, Miao, R. et al. investigated and discussed the emotions of social network users to derive the emotional expression and tendency of social network users. BiLSTM algorithm was used to analyze the behavior and emotion of the users to obtain the emotional tendency of the users. According to the test, BiLSTM algorithm can reach 97.32% of F1 value, and its function loss can be reduced to 1.33%, which can reduce the impact of function loss on emotion recognition and can accurately predict the user's emotions [6]. Mehra, P. et al. used the sentiment-based analysis to predict the behavior of the user-generated comments after travelling to three Asian countries, and to derive the user's and psychological activities of users while traveling, which were used to build a model to analyze the emotional tendencies of users. According to the test, the approach can accurately calculate the user's emotional tendency, and the accuracy of the calculation is high [7]. Park, E. et al. investigated and researched the user's emotions and established the emotion ontology framework, which was used to analyze the user's emotions and behaviors, and to study the user's emotional tendency. According to the test, it was concluded that the framework can accurately analyze the user's emotions and behaviors with high accuracy [8]. Chen, J. et al. used the USON model to learn the user's emotional orientation in the social network and incorporated the user's interactions and opinions into the model, and defined the scores of the user's emotional orientation based on the distribution of emotional polarity in the opinion dataset. In this way, the user social network is established, and the user emotional orientation is taken as the node attribute and the social relationship as the edge of the attribute network, and the user's emotion is analyzed by the user social network. According to the experimental results, the performance of the proposed model is significantly higher than the state-of-the-art methods, the analysis is better and the results are more accurate [9]. Liu, B. et al. proposed a new model for performing context-aware user sentiment analysis, which includes semantic correlation of different modalities and the influence of Twitter contextual information to improve the accuracy of user sentiment analysis. Based on the experimental results, it was concluded that the method outperforms other existing methods in analyzing user sentiment and can accurately derive the user's emotional tendency [10]. Zou, X. et al.

proposed collaborative microblogging sentiment analysis method and constructed two classifiers in the method, a global microblogging sentiment analysis model that can utilize the sentiments that are shared by all the users, and the other one is a community-specific microblogging sentiment analysis model which can extract the emotions influenced by user's personality, in order to complete the analysis of user's emotional tendency, according to the experiments, the model can effectively improve the performance of microblogging sentiment classification and significantly outperforms the state-of-the-art methods, and can accurately analyze the user's emotional tendency [11]. Chouchani, N., et al. used a heterogeneous map to infer user-level emotional polarity, and analyze the user's emotion unfolding analysis, and according to experiments, this approach can accurately analyze the user's emotions, understand the user's preferences and behaviors, and enhance the user's sense of experience [12].

In the age of information technology, social media has become the mainstream way of information dissemination, gradually involved in people's daily life, more and more users publish and share content on social media, which contains the user's own emotions and behaviors.

3. Computational modeling of affective dispositions

3.1. Model structure

In order to improve the accuracy of sentiment analysis, the attention mechanism was introduced into the sentiment analysis of social platforms, and the emotions used in the social platforms were double-encoded, and the sentiment analysis model based on the dual attention mechanism was established to complete the analysis of users' emotional tendencies [13-14].

The dual-attention sentiment analysis model is shown in Fig. 1, and the sentiment analysis model is mainly constructed using a bottom-up neural network structure, which can be divided into four parts: the word vector representation layer, the semantic acquisition layer, the semantic synthesis layer, and the sentiment calculation layer.

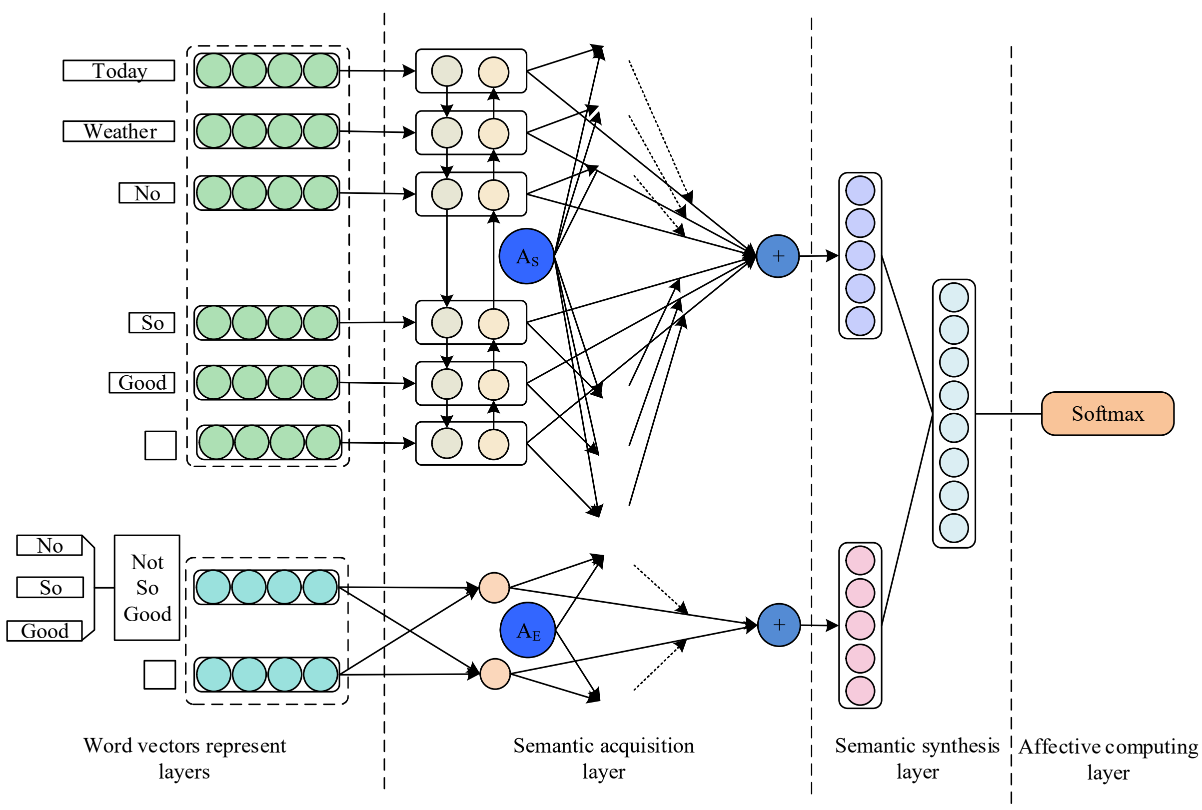

Fig. 1. Dual Attention Sentiment Analysis Model

3.2. Word Vector Representation Layer

In the sentiment analysis model, the word vector representation layer is the input layer of the model, which mainly converts the user's social platform culture that needs to be analyzed into word vectors, which can be divided into the word vector matrix R_E of the social platform sentiment symbols and the word vector matrix R_T in the social platform text.

Typically, the word vectors of words and sentiment symbols are obtained from the word vector dictionary $\mathrm{R}^{d\times N}$, while the word vector dictionary $\mathrm{R}^{d\times N}$ is obtained based on a large corpus and using a model for training word vectors, where D represents the dimension of the word vectors in $\mathrm{R}^{d\times N}$, and N represents the number of words in $\mathrm{R}^{d\times N}$.

In the word vector dictionary $\mathrm{R}^{d\times N}$, any word is a high dimensional vector that can be mapped to the vector space, and the positional relationship of the mapping indicates the semantic relationship between words, that is, the distance of words with similar lexical meanings in the vector. Using Word2Vec model to train the word vector dictionary, let the text sequence be $T=\{w_1,w_2,\cdots,w_n\}$, and the corresponding word vectors $v_i(i\in[1,n])$ of the words $w_i(i\in[1,n])$ in the text are spliced with each other, so as to obtain the word vector equation of the text sequence as follows:

$$R=v_1\oplus v_2\oplus\cdots\oplus v_n \tag{1}$$

where $\oplus$ represents a matrix R into which the word vectors are spliced, the number of rows of the matrix R represents the number of words, and the number of columns of the matrix R represents the dimension of the word vectors.

The word vectors in the words of the social platform text and the emotionally compliant word vectors in the emotionally compliant set are expanded and spliced using the above equation to obtain the matrix $R-$ of the social platform text and the matrices R_E, R_T, and R_E of the set of emotionally compliant symbols, and the rows of the matrices are the number of words and the number of emotionally compliant symbols contained in the social platform text.

3.3. Semantic Acquisition Layer

The semantic acquisition layer is to encode the social platform text matrix R and the sentiment symbol matrix in the sentiment analysis model to obtain the corresponding semantics for sentiment categorization. When encoding the matrices, it is necessary to consider the relationship between word contexts and capture the words in the comparison of sentiment representations to improve the accuracy of sentiment analysis. Since the sentiment symbols in the social platform belong to the discrete form, in which the sentiment symbols are the relationship between strengthening and weakening the sentiment, and there is no strong semantic dependence, so it is necessary to utilize the combination of bidirectional long and short memory networks and attention mechanisms to encode the semantics and improve the attention to the sentiment [15-16].

Long-short memory network has strong long-distance semantic capture ability, which can better solve the semantic encoding problem of long text, and can be widely used in text processing occasions. Since the common long-short memory network model can only capture the semantic information in the text in one direction, it can't capture the semantic information comprehensively, which leads to the situation of semantic loss. In order to obtain the comprehensive information in the semantics, a bidirectional length memory network is used to semantically encode the text of the social platform, so that the forward and reverse information in the semantics can be obtained, and the content in the semantics can be obtained in a comprehensive and complete way. Bidirectional length memory network adopts the structure of three gates and one memory unit to control the flow of information in the model, so as to capture the information in the semantics, and the structure diagram in the bidirectional length memory network is shown in Figure 2. In the bidirectional length memory network, c is used to represent the information of the node memory unit at the current moment, and the output is h_t, x_t represents the input at the current moment, and c_{t-1} is used to represent the information of the memory unit at the previous moment. The state of the output gate at the current moment is o_t, with f_t representing the state of the forgetting gate at that moment, and the output of the previous moment is h_{t-1}.

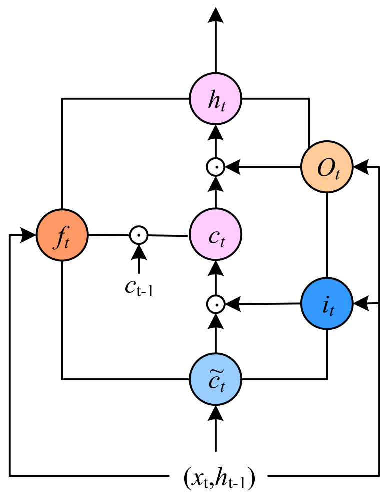

Fig. 2. Structure of long and short memory networks

This leads to the following relationships between the various structures:

$$\begin{aligned}
i_t &= sigmoid\left(W_i x_t + U_i h_{t-1} + b_i\right) \\
\tilde{c}_t &= \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \\
o_t &= sigmoid\left(W_o x_t + U_o h_{t-1} + b_o\right) \\
f_t &= sigmoid\left(W_f x_t + U_f h_{t-1} + b_f\right) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
h_t &= o_t \odot \tanh\left(c_t\right)
\end{aligned} \tag{2}$$

where x_t represents the input at moment t, W_i、W_c、W_o、W_f、U_i、U_c、U_o and U_f represent the weight matrices of each structure, b_i, b_c, b_o and b_f represent the corresponding biases of the structures, i_t, o_t, f_t and represent the state values of the input gate, the output gate, and the forget gate at moment t, and $\tilde{c}_t$ represents the state value of the memory cell at moment t. With h_t representing the output value at moment t, with $c-1$ representing the state value of the memory cell at moment c_{t-1}, with h_{t-1} representing the output value at moment c_{t-1}, and $\odot$ representing the operation of multiplication.

In the t moment, the data transfer relationship in the two-way length memory network is as follows:

$$\begin{aligned}
\overrightarrow{c_t}, \overrightarrow{h_t} &= G\left(x_t, \overrightarrow{c_{t-1}}, \overrightarrow{o_t}, \overrightarrow{f_t}, \overrightarrow{h_{t-1}}\right) \\
\overleftarrow{c_t}, \overleftarrow{h_t} &= G\left(x_t, \overleftarrow{c_{t-1}}, \overleftarrow{o_t}, \overleftarrow{f_t}, \overleftarrow{h_{t-1}},\right)
\end{aligned} \tag{3}$$

In the formula, the overall output is $o_t = \left[\overrightarrow{o_t}, \overleftarrow{o_t}\right]$, so that both forward and reverse semantic information in the text of the social platform is completely and comprehensively attended to.

When capturing the semantics of sentiment symbols in the text of the social platform, the attention mechanism is utilized to encode the text of the social platform and the set of sentiment symbols in order to obtain the sentiment symbols and words that are more important for the expression of sentiment. The attention mechanism is mainly used to find the more important parts of the input text for the results of sentiment analysis, using the input state h to weight the more important parts of the comparative text, so as to establish a vector v that is relevant to the context and can highlight the focus of the sentiment in the text, the specific formulas are as follows:

$$v = \sum_{t=1}^{T} \alpha_t h_t \tag{4}$$

where T represents the number of input states and α_t represents the weight of input state h. where α_t is related to the input state h and the randomly initialized context vector A, and A represents a representation of the overall input for the final classification result as in the following equation:

$$\begin{gathered} \alpha_t = \frac{\exp\left(e_t^{\,T} A\right)}{\sum_{k=1}^{T} \exp\left(e_k^{\,T} A\right)} \\ e_t = \mathrm{Tanh}\left(W h_t + b\right) \end{gathered} \tag{5}$$

where W and b represent the weights and biases of the model, respectively, and the randomization vector A serves as a parameter of the model, which can be obtained through learning and training. According to the attention mechanism described above, context-dependent vectors can be built for the input social platform text and sentiment symbols, and the importance of the input state to the sentiment expression can be represented in the vectors.

According to the semantic acquisition layer, the representation matrix R of the social platform and the representation matrix R_E of the corresponding set of emotion symbols can be encoded to build the corresponding semantic representations S_T and S_E, S_T and S_E, which contain the contextual semantic information of the entire social platform text, as well as some information that is important for the expression of the emotion.

4. Public Emotional Tendency Analysis Model Construction

In the emotional analysis of users, it is concluded that the emotional tendency of individual users is usually reflected using the content of social platforms, while the emotional tendency of the public is reflected using social platforms related to specific social events. Therefore, when analyzing emotional tendencies, it is necessary to study and explore the emotions of users by combining various factors to determine the overall emotional tendencies of the public [17-18]. The degree of inclination of various emotional tendencies is shown below:

$$t_x^e \frac{\sum x, e}{\sum x} \tag{6}$$

where x represents a specific social security event, e represents a specific emotional tendency, which includes positive, negative, and neutral emotions. $\sum$ The social platforms associated with x represent the number of social platforms associated with social security event x, and $\sum$ social platforms associated with x and with an emotional tendency of e represent the social security event x. In addition, the number of social platforms with an affective tendency of e can be used to determine the public's affective tendency according to the degree of various affective tendencies.

Let set $I = \{I_1, I_2, \ldots, I_m\}$ be composed with sample data from m different social platforms, Let the transaction database be D, and each transaction T in database D represents a collection of sample data, denoted by $T \subset I$. Transaction T contains itemset X if set $X \subset I$, and $X \subset T$.

In order to improve the accuracy of the public sentiment tendency model, it is necessary to utilize association rules to mine and extract features from social platform data. Association rules are usually implicit formulas like $X \Rightarrow Y$, where $X \subset I$, $X \subset T$, $X \cap Y \neq \varnothing$.

The association rules usually contain support and confidence, which are mainly used to mine the target data, i.e., to find out the association rules whose support and confidence are higher than the threshold value in the database of things D, and the setting of the threshold value is related to the specific situation. The association rules are mainly divided into two parts, one is to find out the frequent itemsets from the data collection, and the other is to utilize the frequent itemsets to generate association rules.

In the association rule, the support degree is the probability that the data set D contains X and Y at the same time, if the probability of X and Y appearing at the same time is relatively small, it means that the relationship between X and Y is not very big, if the probability of appearing at the same time is large, it means that the relationship between X and Y is relatively large. The calculation of support is shown below:

$$\sup port(X->Y) = P(X \cup Y) \tag{7}$$

And the confidence in the association rule is the probability of occurrence of Y if the database of things D already contains X. If the confidence level is high, it means that Y will appear with the appearance of X. If the confidence attitude is high, it means that the appearance of X has little to do with whether Y appears or not [19]. The calculation of confidence level is shown below:

$$confidence(X \rightarrow Y) = P(X| \ Y) = \frac{P(XY)}{P(Y)} \tag{8}$$

The Apriori algorithm is utilized to launch association rule mining on user social platform data as a way to improve the accuracy of the analysis of users' emotional tendencies.The Apriori algorithm is mainly a frequency set method based on data dimensions, which utilizes an iterative method of layer-by-layer searching, and scans the transactional database D multiple times [20-21]. Database scanning is required to find each Lk, Fig. 3 shows the flow of Apriori algorithm, the main process of Apriori algorithm is to find the set of frequent 1-item sets and notate the set as $L1$. Set $L1$ is used to find the set of frequent 2-item sets $L2$, while $L2$ is used to find L. And so on until K-item sets cannot be found.

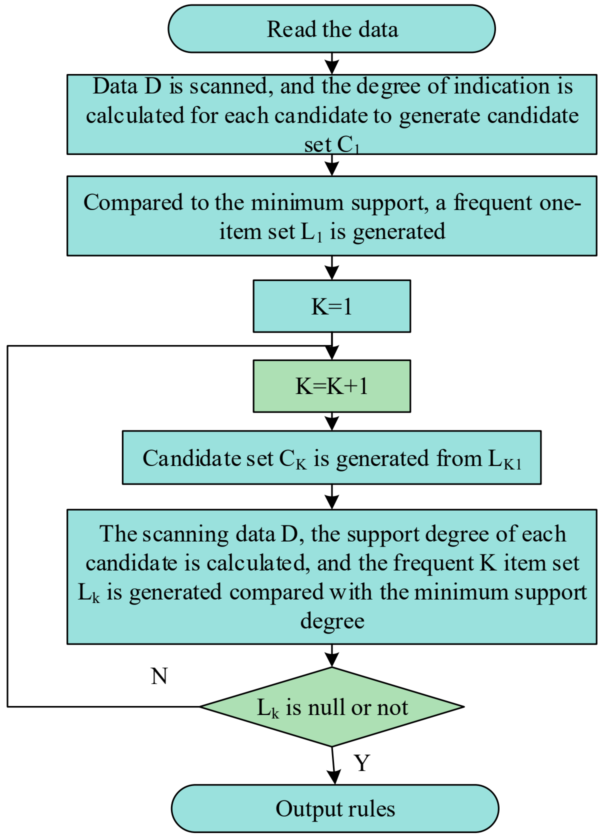

Fig. 3. Apriori algorithm flow

According to the above process to complete the extraction of social platform data collection features, to improve the correctness of the emotional tendency analysis, can better predict the user's emotional trend.

5. Social platform user behavior and emotional tendency analysis

5.1. Test preparation

In order to be able to derive the effect of the two-way attention mechanism network on the analysis of user sentiment, the model needs to be tested. In the test before the need to accurate corresponding equipment, the equipment in accordance with the requirements of the interconnection, adjust the required parameters, and debugging equipment, to ensure that the equipment is intact, to avoid the test results are affected. Table 1 shows the parameters of the test environment, the operating system used to select Windows 10 64 bit, the graphics card for the CTX965, used to protect the stability of the test process.

Table 1. Test environment parameters

Hardware and Software Configuration	Configuration information
Operating System	Windows10 64 bit
RAM/GB	16
CPU	I7-6700HQ2.60GHZ
Graphics card	CTX965

5.2. Sentiment Analysis Accuracy Test

Sentiment analysis accuracy test is mainly used to measure the accuracy of the model's analysis of the user's emotions, if the model's accuracy is high, it means that the model can accurately analyze the user's emotional trends, understand the user's preferences and habits, so as to accurately recommend the marketing strategy that meets the user's needs, and improve the user's satisfaction. If the accuracy of the model is low, it means that the model is difficult to accurately analyze the user's emotions, and cannot accurately recommend the corresponding marketing strategies according to the user's preferences and habits, and the user's satisfaction is low, so it is necessary to analyze the accuracy of the emotional analysis of the model.

Table 2 shows the results of the accuracy of emotion analysis, the model is more accurate in analyzing the positive emotions of users, at about 85%, and the accuracy of positive emotions is about 90%. The model analyzes the user's negative emotions at about 80%, with an accuracy of 75%, while the accuracy and precision of the analysis of the user's neutral emotions are 78% and 89%, respectively, and the overall accuracy and precision of the user's emotions are 78% and 89%, respectively. This shows that the model can accurately analyze the user's emotions and derive the user's emotional tendency, so that it can better manage the social platform, recommend corresponding marketing strategies according to the user's preferences and habits, and control the public opinion of the social platform. This makes the management and operation of social platforms more scientific, promotes the development of social media, and enhances user satisfaction with social platforms.

Table 2. Sentiment analysis accuracy results

Emotional Category	Accuracy	Precision
Positive	85%	90%
Negative	80%	75%
Neutral	70%	87%
Overall	78%	89%

5.3. Analysis of model training speed

Model training speed is mainly used to measure the speed of the model in learning user emotions, the faster the speed indicates that the model is faster in learning and finding user emotions, and can quickly get the results of the analysis of user emotions and reduce the time cost. If the speed is slower, it indicates that the model is slower in learning and analyzing user emotions, and cannot get the results of user emotion analysis in time, and the time cost is higher. So the training speed of BLSTM, GRU and RNN models need to be analyzed, and the comparison of the training speed of each model is shown in Table 3.The training speed of BLSTM model is faster, and in the first test, the dataset is 1 million, and the time used for training is 1.5 hours, while the time used for the GRU model is 2.5 hours, and the time used for training the RNN model is 3.2 hours. At the third test, the dataset was 1 million and the time used for training was 1.2 hours, while the time used for the GRU model was 3.1 hours and the training time for the RNN model was 4.1 hours. In the fifth test, the dataset was 1 million and the time used for training was 1.5 hours, while the time used for the GRU model was 2.1 hours and the training time for the RNN model was 4.6 hours. It can be concluded that the training time of BLSTM model is shorter than that of the other two models, which can quickly complete the learning and analysis of user's emotions and produce the results of user's emotional tendency analysis.

Table 3. Comparison of training speed of each model

Number of iterations	Dataset size	BLSTM training speed (hours)	GRU training speed (hours)	RNN training speed (hours)
1	One million.	1.5	2.5	3.2

2	One million.	1	3	3.5
3	One million.	1.2	3.1	4.1
4	One million.	1.3	3.3	4.5
5	One million.	1.5	2.1	4.6
6	One million.	1.1	2.3	4.2
7	One million.	1.2	2.1	4.3

5.4. Analysis of User Behavior and Emotional Tendencies

User behavior and emotional tendency analysis, mainly based on the user's social media liking and sharing behavior to analyze the user's emotional trends and tendencies. It analyzes and researches the positive and negative tendencies of users, derives the positive and negative emotions of users on social media, understands the preferences and habits of users, and recommends the contents that users are interested in, improves user satisfaction, and promotes the scientific management of social media platforms.

Table 4 shows the results of the analysis of user behavior and emotional tendency, and most of the emotions of the content posted by users on social media platforms are positive, which can reach 90.206%. However, due to the different behaviors of users, there is a large gap in the distribution of emotional tendencies. Among users without content forwarding, the proportion of positive emotions is around 99.907%, which is 9.701% higher than the overall, indicating that when users make behavior without content forwarding, there is a high probability that they will keep positive emotions towards the content on social media. As for the users who made the behavior of forwarding with content, the proportion of their positive emotions was 88.182%, which was 2.024% less than the overall, and for the users who made the behavior of commenting, the survey concluded that the proportion of their positive emotions was 82.068%, which was 8.138% less than the overall. For users who communicate with other users, the proportion of positive emotions is 62.712%, a decrease of 27.5% compared with the overall, and a decrease of 37.2% compared with the highest proportion of no content forwarding behavior. It can be concluded that the proportion of positive sentiment declined when users made content forwarding, commenting or communicating behaviors, especially commenting and communicating behaviors, indicating that there is a higher possibility that users have different opinions about the content of the neuromedia.

Table 4. Results of user behavior and emotional tendency analysis

Element	Count	Positive Count	Negative Count	Positive %	Negative %
LIKE	150	150	0	100	0
With Content Forwarding	660	582	78	88.182	11.818
Retweeted without content	1078	1077	1	99.907	0.093
Comments	1093	897	196	82.068	17.932
Exchange	59	37	22	62.712	37.289
Overall	2961	2671	285	90.206	9.625

5.5. Analysis of user activity

The user's activity analysis is mainly to analyze and speculate on the user's interactive behavior on the social platform, which is used to measure the user's participation, so as to reflect the user's browsing preferences and habits, to improve the accuracy of the analysis of the user's emotions, and to improve the user's satisfaction level. The results of the analysis of the user's activity are shown in Table 5, the user's activity on the social platform, user 1 logged in 3 times on the social platform, browsed for 50 minutes, the number of likes is 10 times, while the number of times browsing is 23 times. While browsing the above content, the user's sentiment is positive, while user 2 has logged in 1 time, used it for 30 minutes, liked it 3 times and viewed it 15 times, the user's sentiment is negative. From this, the user's activity level on the social platform can be derived, and the user's emotion can be analyzed based on the browsing time and other information, which can always keep an eye on the user's emotional trend and make the management of the social platform more scientific.

Table 5. Results of user activity analysis

User	Number of logins (times)	Length of use (minutes)	Number of likes (times)	Views (times)	Emotions
User 1	3	50	10	23	Positive
User 2	1	30	3	15	Negative
User 3	5	45	5	13	Negative
User 4	3	55	2	27	Positive
User 5	5	65	8	21	Neutral

6. Conclusion

In this paper, firstly, the neural network structure is used to build a sentiment analysis model to get the information and content of semantics in social media texts. Secondly, based on the semantic and emotional symbol content of the text in social media, the public emotional tendency model is constructed to obtain the user's preferences and behavioral habits. The association rule mining algorithm is used to extract the text and content features in social media as a way to improve the accuracy of the user emotional tendency analysis model. The analysis of the user behavior analysis and emotional tendency model yields that the BLSTM model is faster to train, with a dataset of 1 million, and the fastest time used for training is 1.1 hours. Meanwhile, the model is more accurate in analyzing the user's positive emotions, which is around 85%, and the accuracy of positive emotions is around 90%. The accuracy and precision of analyzing users' negative emotions are 80% and 75% respectively, while the accuracy and precision of analyzing users' neutral emotions are 78% and 89% respectively. This shows that the BLSTM model analyzes the tendency of users' emotions faster, with higher accuracy and precision, and the results of the analysis are more reliable and stable, which can promote the scientific management of social platforms, and enhance users' experience and satisfaction.

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