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Big Data Analysis and User Behavior Prediction of Social Networks Based on Artificial Neural Network

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The prediction of user behavior in social networks is of great significance for understanding user dynamics, personalized recommendation, and information dissemination. With the development of artificial intelligence (AI) technology, especially the application of artificial neural networks in big data analysis, new solutions and technical means have been provided for the analysis of user behavior in social networks. This study constructs a social network user behavior prediction model based on artificial neural networks. The article first reviews related research, establishes a research framework, and then describes in detail the functional structure of the user behavior prediction system. The key data structure design is meticulously constructed and the model is built through steps such as data preprocessing module, 3D feature frame construction module, feature mapping module, and feature prediction module. In addition, the article also constructs a group behavior theme probability prediction model based on an improved encoder-decoder model, which further enhances the understanding of group behavior of users in social networks. Through comparative experiments, the model proposed in this paper demonstrates its effectiveness in predicting individual and group user behaviors. The experimental results show that the model can accurately predict the behavior patterns of users in social networks and is superior to existing methods in terms of prediction accuracy and computational efficiency. This research shows that artificial neural networks are a powerful tool for analyzing big data in social networks and for predicting user behavior. The success of the study verifies the effectiveness of the model, provides a new technical path for future analysis of user behavior in social networks, and is expected to be widely applied in areas such as personalized recommendation and information dissemination analysis.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning approaches → Neural networks

Keywords: artificial neural network, social network, prediction of user behaviors

1. Introduction

Thanks to the rapid development of the Internet and information technology, social networks like Facebook, Twitter, QQ, and WeChat have attracted more and more users. About 5% of all smartphone apps are about social networks [1–3]. Suffice it to say that social networks have become the main platform for information acquisition. However, the huge amount of user behaviors on social networks, such as reposts, comments, and likes, easily brings the problem of information overload, and boasts an immense value of big data [4, 5]. Social network-based user behavior prediction has received extensive attention from domestic and foreign scholars, along with the wide application of text mining, personalized recommendation system, and big data analysis in various fields.

With a wealth of user behaviors, emotions, and communication resources, social networks today have a far greater influence than newspapers and televisions [6, 7]. After establishing an emotion prediction model, Shokouhyar *et al.* [8] pinpointed the emotional trends and preferences of users through user interaction analysis. They analyzed two key attributes of social network users, namely, the time correlation between current and past emotions and the friend-dependent social relevance, and carried out relevant simulations.

Big data analysis of user behavior on online social networks is of great significance to human behavior research [9–11]. Rosa *et al.* [12] developed a dynamic model of user behavior, which characterizes individual and group issues such as social pressure, social identity, social participation, and social relationships. This model offers a scientific method for discovering trending topics, extracts the power-law distribution characteristics within the time series intervals of topics, and identifies the reasons for the power-law distribution of behaviors with different power exponents. Dietel [13] analyzed how the interaction and behaviors of social network users affect their next behavior. He created the corresponding group dynamic model and extracted the attributes and distribution of group features through distributed clustering of social pressure and social recognition of users, revealing individual and group features of user behaviors.

The aforementioned studies indicate that despite the scattered, fragmented, and loose nature of Internet user behavior data, this data can be effectively captured and analyzed using appropriate methods and models, thereby extracting valuable information. The research results suggest that the use of big data analysis techniques can overcome the incompleteness and irregularity of data, revealing deeper patterns and trends in user behavior. Overall, these studies reflect the current trend of combining social sciences with data science, by constructing complex models and algorithms to parse and predict human behavior in social networks, further enhancing the understanding of group dynamics and individual behavior prediction.

Despite their immense value, online data on user behavior are scattered, fragmented, and loose [14–17]. Baranov *et al.* [18] conducted multi-dimensional, multi-level, fine-grained dynamic analysis of user behavior processes in fields like e-commerce and online education. They captured user preferences with two-way gated recurrent unit (GRU) encoders, and accurately predicted the behavior of user series; their model has been effectively applied to guidance and assisted control of the behavior of social network users. Tulu *et al.* [19] recognized the behavior patterns of anonymous users based on their personalized multi-dimensional trajectory set and introduced the idea of association rules to cut down the number of dataset scans and improve the elimination of abnormal data.

In addition, Wang *et al.* [20] implemented the collaborative filtering algorithm in the series recommendation model, and successfully mined the cascading attributes of social network users, such as interaction relevance and interaction frequency. Drawing on the theory of homogeneity, Bhattacharya *et al.* [21] discussed the relationship between the attributes of social network users (*e.g.*, gender, age, and nationality) and their behavior (*e.g.*, posting and reposting). They forecasted the gender proportion of users posting the same class of content and the click-through rate (CTR) of the same websites based on multiple linear regression (MLR) and support vector regression (SVR). They realized the search for users with similar interests and the construction of social groups through a fast search algorithm called linear discriminant analysis (LDA).

To sum up, the existing research on social network user behavior mostly focuses on sentiment prediction, preference analysis, and correlation analysis of user interactions. To predict the user behavior in actual social networks, it is necessary to forecast the various behaviors of the user with multiple time intervals. Therefore, this paper carries out a big data analysis on user behavior data of social networks based on artificial neural network (ANN), and thereby predicts the individual and group behavior of users [22–24].

In real social networks, user behavior is dynamic and multi-dimensional, influenced by various factors including personal interests, social influence, current hot topics, and changes in platform algorithms. Predicting user behavior in social networks is important for platform operators, content creators, marketing strategists, and social science researchers. User behavior on social networks is not static but evolves and changes over time. Predictions over multiple time intervals can help better understand these dynamic changes, providing a temporal perspective for formulating corresponding strategies. Predicting user behavior at different time intervals takes into account both long-term and short-term trends, enhancing the comprehensiveness and accuracy of predictions. Short-term predictions can capture immediate changes, while long-term predictions help understand underlying, deeper trends.

The remainder of this paper is organized as follows: Section 2 sets up a behavior prediction model for social network users, builds up the functional framework of the behavior prediction system for such users, and details the design of the key data structure for the model, as well as the construction flow of core modules (*e.g.*, data preprocessing, three-dimensional (3D) feature frame construction, feature mapping, and feature prediction). Section 3 improves the encoder-decoder model to realize the topic probability prediction of the group behaviors of social network users. Section 4 verifies the good performance of our model in user behavior prediction through experiments.

2. Construction of Behavior Prediction Model for Social Network Users

Figure 1 shows the functional framework of the behavior prediction system for social network users. The system receives a list of historical behaviors and attributes of social network users in a fixed period, and outputs the predicted future behaviors of such users in another fixed period. The fixed period can be 1 week or 1 day long.

The entire system is built around the central "Model Training" section, which is the core of the system. The system is divided into two main input sections: "Historical Data" on the left and "Future Behavior" on the right. Both sections are closely related to the timeline at the top, which controls the input flow of historical data and future behavior, respectively. Historical data, after data preprocessing, is transformed into 3D feature vectors and daily behavior distribution. This transformation indicates that the system might format and encode the original historical data to create a data structure suitable for model training. Future behavior is also preprocessed, but the output is only the daily behavior distribution, highlighting a focus on the temporal distribution characteristics of future behavior. The purpose of this system is likely to predict users' future behavior on social networks, to enhance the understanding of user behavior, and thereby optimize social network services or enable precise user recommendations and advertising. Overall, this structural diagram presents a data-driven process, centered on machine learning models, with an iterative learning and optimization approach.

To satisfy the demand of data processing, the behavior prediction system for social network users should at least include a data preprocessing module responsible for data cleaning, feature translation, and feature aggregation, a 3D feature frame construction module responsible for constructing 3D feature frames, and a target behavior construction module responsible for constructing target behaviors.

To satisfy the demand of model learning, the system must at least include a feature mapping module responsible for mapping 3D feature frames to eigenvectors, a feature prediction module responsible for predicting future eigenvectors, a target behavior analysis module responsible for parsing the eigenvectors into target behaviors, and a model optimization module responsible for parsing the eigenvectors into the target behavior model.

To satisfy the demand of model management, the system must at least include a model management module responsible for cyclic iterations of the model.

To satisfy the demand for target behavior perdition, the system must at least include a target behavior prediction module responsible for forecasting future target behaviors according to the optimal model and 3D feature frames.

The four modules, namely, feature mapping, feature prediction, target behavior analysis, and model optimization, were composited into our model as four layers with the same names.

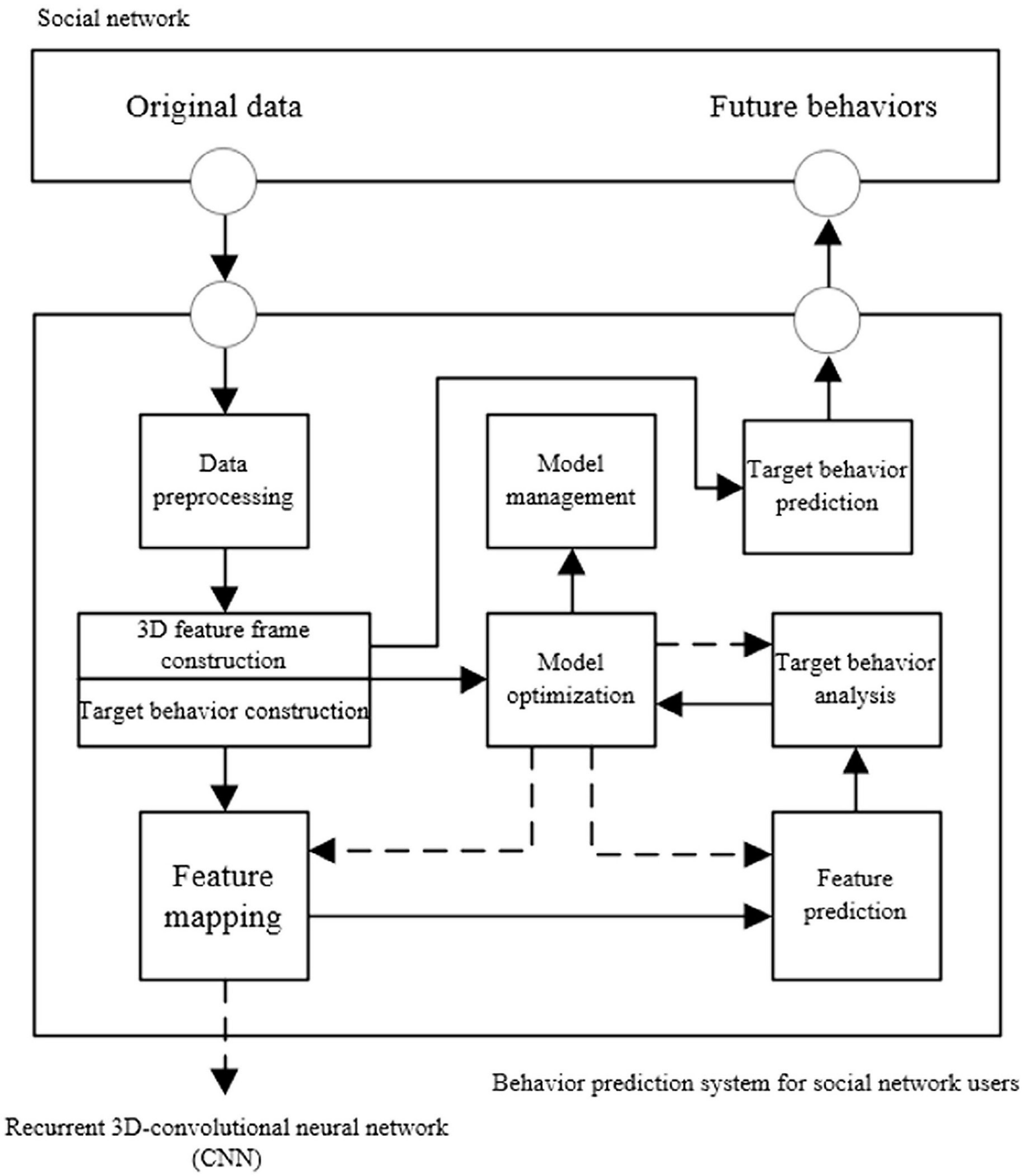


Figure 1. Functional framework of the behavior prediction system for social network users.

2.1. Design of the Key Data Structure

The original data on the behavior of social network users was constructed as a one-dimensional (1D) vector, in which each column represents the behavior features of social network users in an hourly interval. The original eigenvector was obtained by clustering the historical behavior of social network users at intervals of each second, and then connecting them with the attributes of such users.

From the original eigenvector, a two-dimensional (2D) eigenvector was derived, whose width are the features of user behaviors and its height represents the multiple sets of original eigenvectors after duplication and confusion.

The 2D eigenvector was used to characterize the behavior features of social network users in an hourly interval.

By the 3D feature frame construction module, 3D feature frames with a daily interval were generated to facilitate the operations of feature mapping and target behavior prediction in the system. The features of 3D feature frames can be expressed as f_1, f_2, SC_1, and SC_2, which are the same as those of 2D feature frames.

The overall eigenvector of the system is a 1D vector generated by the feature mapping module. The width of the vector represents the daily behavior features of social network users, which will be used for feature prediction and target behavior analysis. The overall eigenvector, which is derived from 3D feature frames, simplifies the data structure, making it easier to be used by the prediction module. Through target behavior analysis and prediction, the system produces target behaviors, each of which is a scalar and nonnegative integer. The produced results characterize the daily behaviors of social network users.

2.2. Construction of the Data Preprocessing Module

The data preprocessing module mainly preprocesses the original data of social network users. To obtain high-quality original data for 3D feature frame construction, the preprocessing module must process the data sequentially through data cleaning, feature translation, and feature aggregation.

Data cleaning, feature transformation, and feature aggregation are key steps in data preprocessing. Firstly, data cleaning involves removing or correcting errors, anomalies, duplicates, or incomplete data in the dataset to improve data quality. Then, feature transformation refers to the transformation or encoding of raw data, such as normalization, standardization, or one-hot encoding, to make the data suitable for specific machine learning models. Finally, feature aggregation involves combining multiple features into higher-level or more meaningful features, for example, through operations like averaging, summing, taking maximum or minimum values, aimed at enhancing the model's explanatory power and prediction accuracy.

Figure 2 shows the process of crawling and preprocessing the behavior data of social network users. Dirty data refers to data within a dataset that has quality issues, which may include errors, inconsistencies, duplicates, missing elements, or data that does not meet expected standards or business rules. Dirty data typically has a negative impact on data analysis and decision-making, thus necessitating identification and correction through a data cleaning process. The original data being crawled contains dirty data, mainly because of the inevitable software/hardware errors and intrinsic complexity of the social networks. The dirty data are in the form of duplicate items, missing items, abnormal items, and format errors. The data cleaning submodule cleans the list of historical behaviors and user attributes independently. During data cleaning, each piece of data must be constrained by the corresponding cleaning rule. If one or more cleaning rules are not satisfied, then the data will be deemed dirty; otherwise, the data will be considered as clean enough for the construction of 3D feature frames. The flow of data cleaning is explained in Figure 3.

To transform the form and dimensionality of features, the cleaned data on the eigenvalues of social network users need to be imported to the feature translation submodule for feature translation. Rather than change the essential meaning of the original features, feature translation should merely modify the name and size of features. Similar to data cleaning, the feature translation submodule translates the list of historical behaviors and user attributes independently. During the operation, each piece of data must be constrained by the corresponding translation rule and replaced with the translated piece of data. Each translation rule only acts on one feature. After being processed by all translation rules, a new detailed list of social network communication can be obtained. The flow of feature translation is explained in Figure 4.

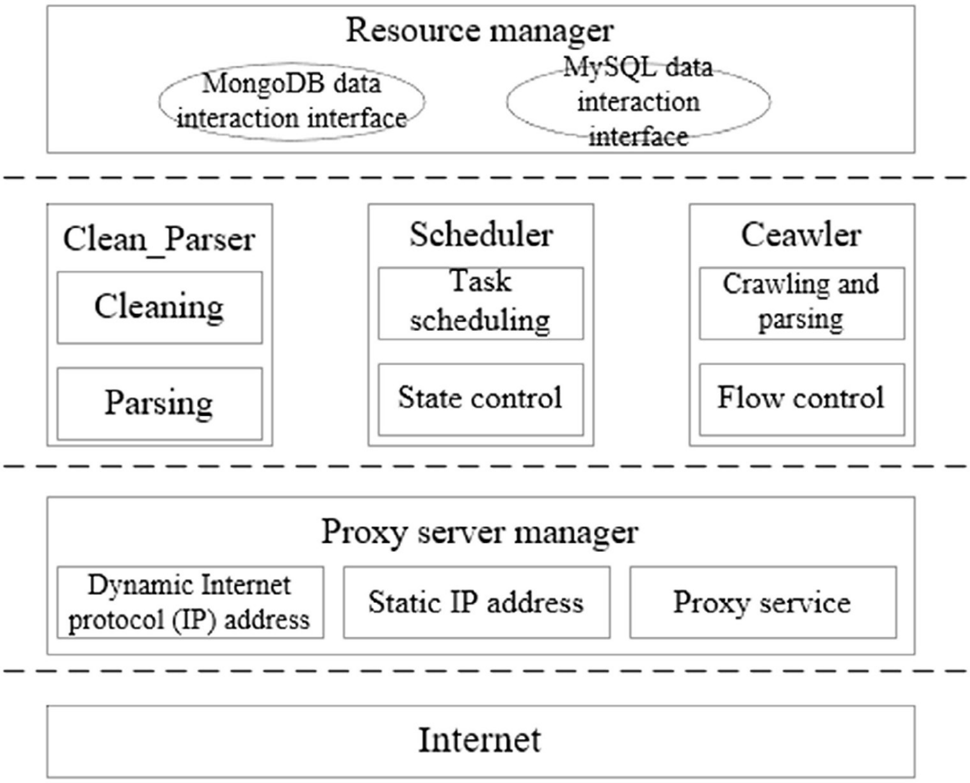


Figure 2. Crawling and preprocessing of behavior data of social network users.

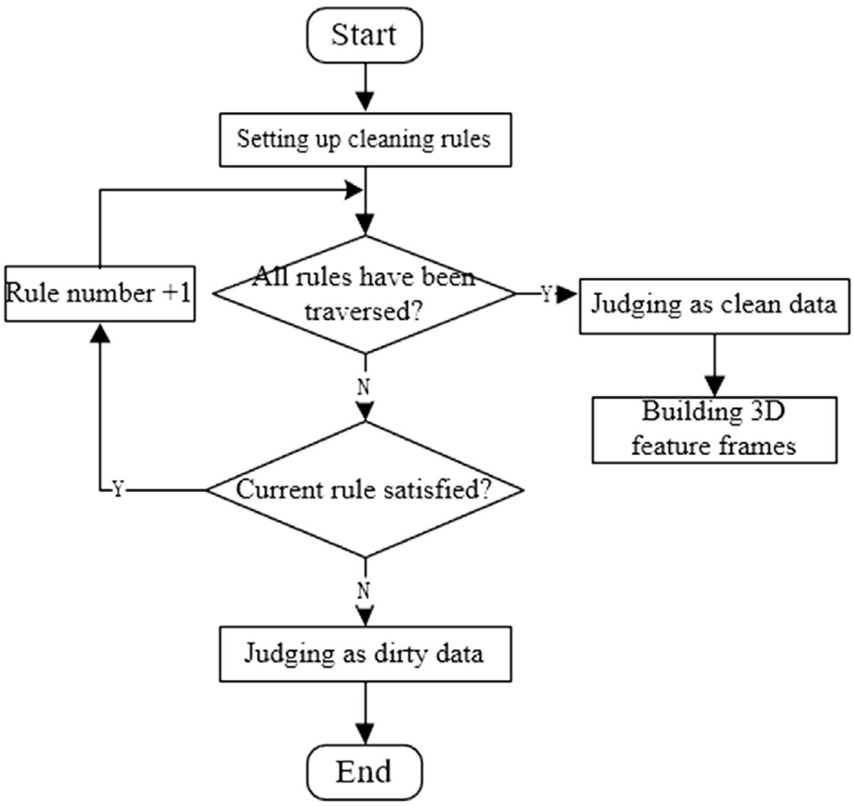


Figure 3. Flow of data cleaning.

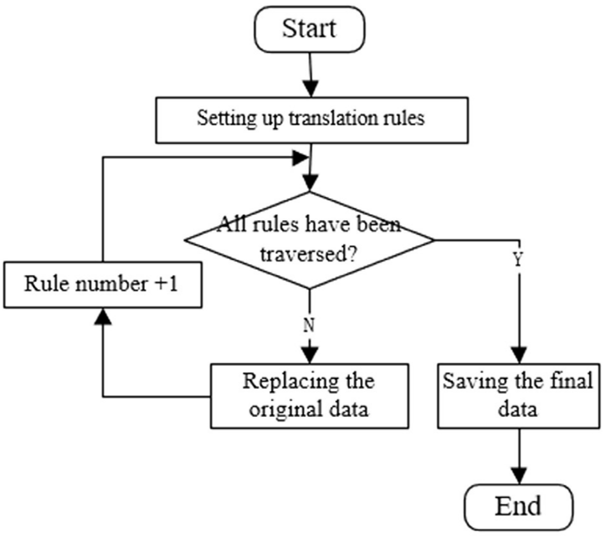


Figure 4. Flow of feature translation.

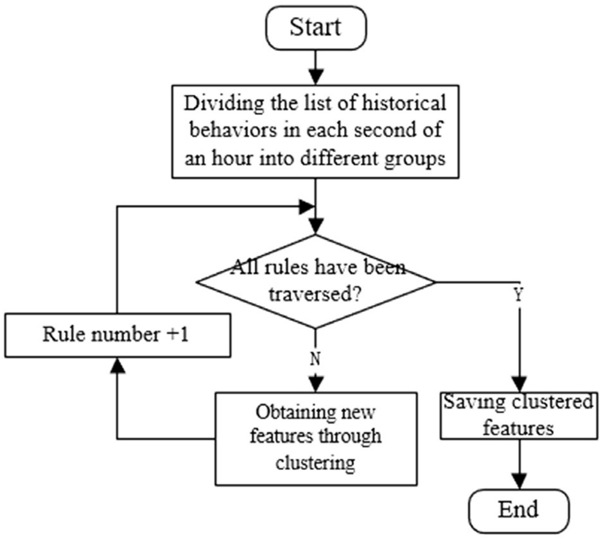


Figure 5. Flow of feature clustering.

The eigenvalues of social network user behaviors with intervals of one second is meaningless. By contrast, the behavior features with an hourly interval, that is, the distribution of features like the duration of each behavior class and each behavior, the interaction duration of each behavior, the mean of interaction durations, and the variance of interaction durations, are meaningful elements of the desired feature set.

To obtain the specific meaning of the aggregated features in the list of historical behaviors of social network users, it is necessary to cluster the social network user behavior with intervals of one second into behavior features with an hourly interval in the feature clustering submodule.

Firstly, the list of historical behaviors of the same user in each second of an hour was divided into different groups. Then, the multiple pieces of data in each group were integrated into a piece of data by the clustering rules, *e.g.*, the durations of the same behavior in the group were added up into the total duration. The flow of feature clustering is illustrated in Figure 5.

2.3. Construction of 3D Feature Frames

Figure 6 explains the construction flow of 2D feature frames, which characterize the features of the hourly behaviors of social network users. Based on the 2D feature frames, the 3D feature frames with day as the depth were constructed through the filling operation of the 3D feature frame construction module. The construction flow of 3D feature frames is explained in Figure 7. Since there is no 2D feature frame in a period with no social network behavior, it is necessary to design a "zero frame" that has no side effect on the pooling of the convolution kernels of the CNN, which guarantees the stability of data processing.

2.4. Construction of Feature Mapping Module

Both 3D feature frames and the overall eigenvector of the system reflect the daily behavior features of social network users. Therefore, the feature mapping module only needs to map the features of user behaviors, without needing to perform any task of feature prediction. This paper chooses the 3D CNN as the baseline module for feature mapping, and optimizes the feature extraction and behavior prediction by adjusting the model structure and training parameters. The established network contains a total of 8 layers, including 3 convolutional layers, 2 pooling layers, 1 fully connected layer, 1 input layer, and 1 output layer.

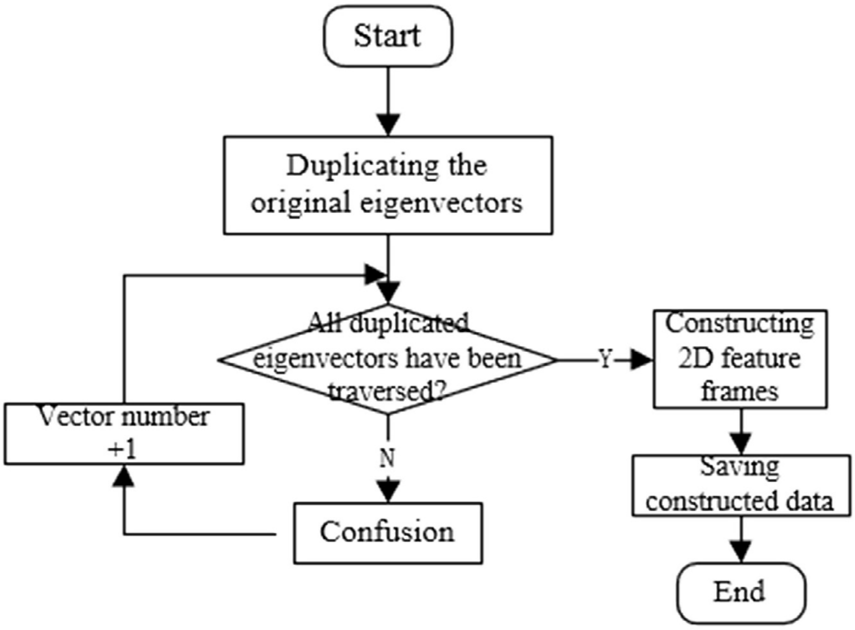


Figure 6. Flow of 2D feature frame construction.

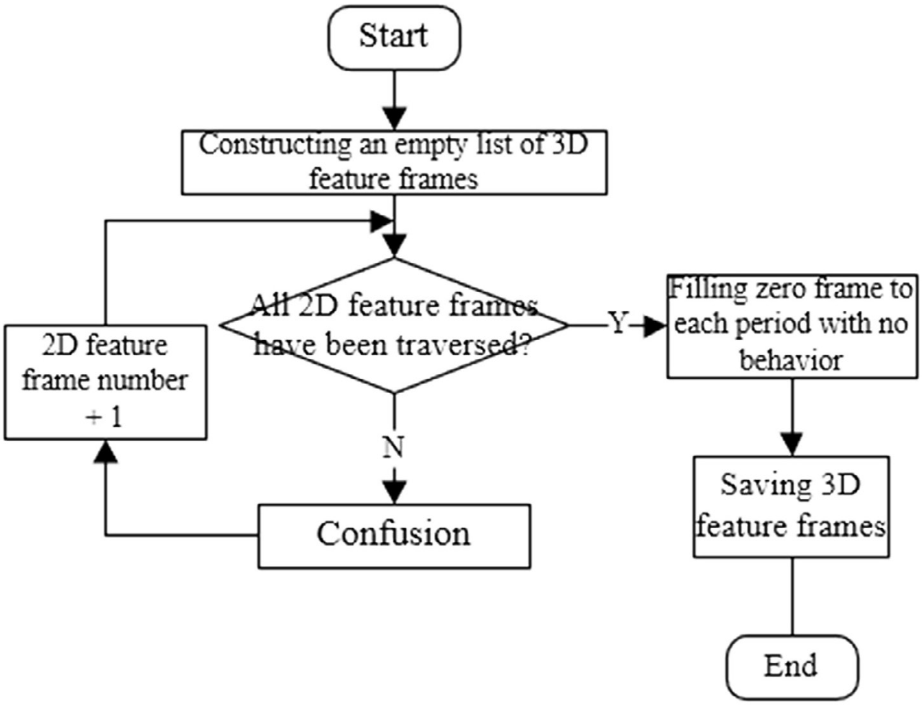


Figure 7. Flow of 3D feature frame construction.

The feature extraction process of social network language involves deep understanding and analysis of the text data generated by users on social networks. Initially, the raw text data needs to be preprocessed, such as cleaning meaningless symbols and punctuation, and then the text is converted into numerical features. For complex features like semantic relationships and emotional tendencies, deep learning models may be required for extraction. Additionally, feature extraction of social network language might also consider the structural characteristics of social networks, such as the frequency of interactions between users, community structures, *etc.*, to obtain a more comprehensive understanding of user behavior characteristics.

Let Q be a 3D feature frame imported to the feature mapping module; LS be a 3D convolution kernel in the convolutional layers; W and ε be the weight and bias of the fully connected layer, respectively; let the subscript "j, i, l" be the position of coordinates $<j, i, l>$ in the 3D matrix; let $<m, n, u>$ be the size of the convolution kernel L. Then, the 3D convolution can be expressed as:

$$3\mathrm{D}-C(k)_{j,i,l} = \sum_m \sum_n \sum_V Q_{m,n,v} LS_{j-m,\, i-n,\, l-v} + \varepsilon_{j,i,l} \tag{1}$$

Let $<m, n, u>$ be the size of max pooling operator. 3D max pooling can be expressed as:

$$3\mathrm{D}-S(Q)_{j,i,l} = \max\left\{Q_{j+m,\, i+n,\, l+u}\right\} \tag{2}$$

The fully connected operation can be expressed as:

$$3\mathrm{D}-FC(Q)_j = W \cdot Q + \varepsilon_j \tag{3}$$

The eigenvector R obtained by feature mapping can be expressed as:

$$R = 3\mathrm{D}-FC^{(m)}\left(3\mathrm{D}-C^{(m-1)}\left(3\mathrm{D}-S^{(m-2)}(\ldots)\right)\right) \tag{4}$$

2.5. Construction of the Feature Prediction Module

The long short-term memory (LSTM) neural network was adopted as the baseline model for feature prediction. Let $a^{(t)}$ be the eigenvector of the daily interval of historical user behaviors imported to the module; $g^{(t)}$ and sigmoid be the output vector and activation function of the hidden layer, respectively; N_{Cell} and t be the number of stacked layers and timestamp of LSTM unit, respectively; let d^{SC}, IN^{SC}, and W^{SC} be the bias, input weight, and hidden layer weight of the forget gate, respectively. Then, the output of the forget gate can be obtained by:

$$SC_t^{(t)} = sigmoid\left(d_t^{SC} + \sum_t IN_{j,i}^{SC} a_i^{(t)} + \sum_i W_{j,i}^{SC} g_i^{(t-1)}\right) \tag{5}$$

Let d^e, IN^e, and W^e be the bias, input weight, and hidden layer weight of the input gate, respectively. Then, the output of the input gate can be obtained by:

$$e_t^{(t)} = sigmoid\left(d_t^e + \sum_t IN_{j,i}^e a_i^{(t)} + \sum_i W_{j,i}^e g_i^{(t-1)}\right) \tag{6}$$

Let d^u, IN^u, and W^u be the bias, input weight, and hidden layer weight of the output gate, respectively. Then, the output of the output gate can be obtained by:

$$U(a(t)) = u_j^{(t)} = sigmoid\left(d_j^u + \sum_t IN_{j,i}^u a_i^{(t)} + \sum_i W_{j,i}^u g_i^{(t-1)}\right) \tag{7}$$

Let d_j, $IN_{j,i}$, and $W_{j,i}$ be the bias, input weight, and hidden layer weight of the LSTM unit, respectively. Then, the output of the LSTM unit can be obtained by:

$$z_j^{(t)} = SC_j^{(t)} z^{(t-1)} + e_j^{(t)} sigmoid\left(d_j + \sum_t IN_{j,i} a_i^{(t)} + \sum_i W_{j,i} g_i^{(t-1)}\right) \tag{8}$$

The operation of the hidden layer can be described by:

$$g_j^{(t)} = tanh\left(z_j^{(t)}\right) u_j^{(t)} \tag{9}$$

In the stacked LSTM neural network, the input of the current layer is the output of the previous layer. Hence, the output gate operation can be modified as:

$$u_j^{(t)} = U\left(u_{j-1}^{(t)}\right), 1 < j \le N_{Cell} \tag{10}$$

Suppose the LSTM neural network of the feature prediction module has 1 layer. Then, the eigenvector containing the user behavior features in a week (7 days) can be described as <$a^{(1)}$, $a^{(2)}$, ..., $a^{(7)}$>. Through the operation of the stacked LSTM neural network, the eigenvector of the user behavior features on the 8th day can be predicted as the output $u^{(7)}$1 of the forget gate on the 7th day.

3. Topic Probability Prediction Model for Group Behaviors of Social Network Users

The prediction of group behaviors of social network users is essentially a time series prediction problem of topic probability. This paper applies the probabilistic prediction model, which is popular in the translation field, to forecast the topic probability of group behaviors of social network users, and extracts the behavior features of group behaviors in periods of different lengths to for model training. Figure 8 shows the structure of the proposed decoder-encoder model. The encoder can transform a variable length series into a fixed length eigenvector, while the decoder can transform the eigenvector into another variable length series. Let $cp(b_1, ..., b_{L*}| a_1, ..., a_L)$ be the conditional probability of one series on another series. From the angle of probability, our model is actually learning that conditional probability. The length L of the input variable length series can be equal or unequal to that L* of the output series.

The baseline structure of the encoder was defined as a recurrent neural network (RNN), capable of retaining the influence of the previous inputs. Except the last character AL, the hidden state of the network changes with the input of each character of the input sentence:

$$g_t = SC(g_{t-1}, a_t) \tag{11}$$

The network outputs the semantic vector v^{SE} of the sentence. The basic properties of the RNN ensure that the v^{SE} contains all the information of the sentence, after all characters of the sentence have been imported to the network.

The decoder is also an RNN. After being trained, the RNN needs to output an ideal target series by predicting b_t^*. Unlike the RNN of the encoder, the RNN of the decoder generates an output based on bt and $g^*_{<t>}$, and this process solely depends on B_{t-j} and the semantic vector v_{SE}. The hidden state of this RNN at the timestamp t can be calculated by:

$$g_t^* = SC\left(g_{t-1}^*, b_{t-1}, v_{SE}\right) \tag{12}$$

With softmax as the activation function, the conditional probability of the next character can be calculated by:

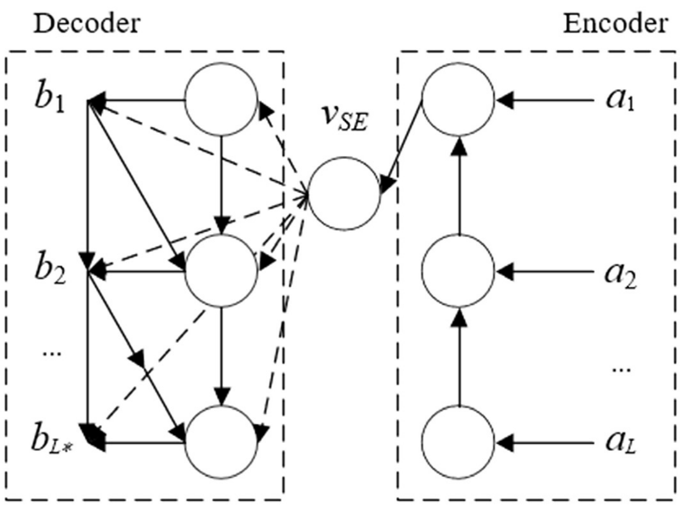


Figure 8. Structure of proposed decoder-encoder.

$$V\left(b_t \mid b_{t-1}, b_{t-2}, ..., b_1, v_{SE}\right) = \text{soft max}\left(g_t^*, b_{t-1}, v_{SE}\right) \tag{13}$$

The training objective of the model is to maximize the sum of the probabilities of the predicted results, namely the future behavior of the user groups. This is a training method that uses maximum likelihood estimation. By maximizing the probability of the predicted outcomes, the model is able to learn the mapping relationship from historical behavior to future behavior, thereby completing the training.

To complete the training of the encoder-decoder model, the sum of probabilities $cp(b_1, ..., b_{L'} \mid a_1, ..., a_L)$ for taking the entire historical data on group behaviors of social network users as the training samples:

$$\max_{\upsilon} \sum_{m-1}^{M} log\left(b_m \mid a_m, \upsilon\right) \tag{14}$$

where, υ is the parameter set to be determined for the encoder-decoder model. Considering the complexity of encoding-decoding of the model, the semantic vector v_{SE}, which acts on the model at any moment, was arranged to act on the encoder at the first moment only. After that, the output of the current model was always taken as the input of the model at the next moment.

Figure 9 presents the structure of the improved model. It can be seen that the RNN unit of the model is an LSTM unit. Then, the prediction probability outputted by the decoder at time t can be updated as:

$$g_t^* = SC\left(g_{t-1}^*, b_{t-1}\right) \tag{15}$$

The improved model has 1 input layer, 2 hidden layers, and 1 output layer. The nodes in each layer are all LSTM units. In chronological order, the historical data on group behaviors of social network users were imported to the input layer of the improved model for *m* times. Then, the *n* target probability prediction results were obtained from the output layer, laying the basis for model learning and training. In other words, the obtained topic probability model forecasts the group behaviors of the next *n* users, according to those of the previous *m* users.

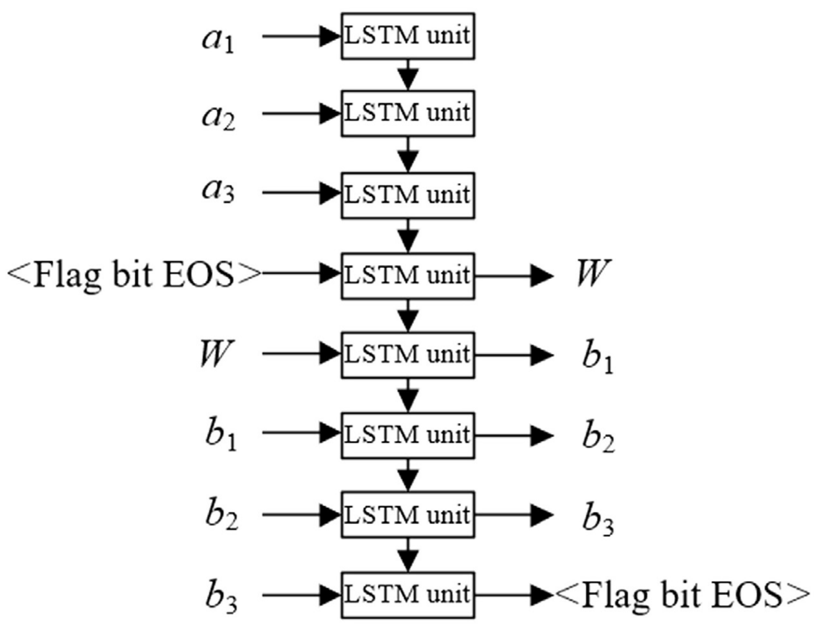


Figure 9. Structure of improved model.

In real life, the behavior features of people with different habits will not change suddenly during social networking, because the social behaviors online are a mirror of users' actual life. Apart from the topic of different behaviors (*e.g.*, clicking, responding, and questioning), the crawled data on user behavior contains the specific time of each behavior. By actual experience, it can be found that different users use social networks in different periods, and the behavior patterns of users vary from holidays to workdays. Therefore, it can be assumed that the group behaviors of social network users change with time. Figure 10 provides the framework of the corresponding topic probability prediction model.

Because of the nonlinear relationship between time (from morning to night) and user behaviors, the time of group behaviors was categorized as morning, afternoon, and evening according to the above assumption. Besides, whether the time belongs to holidays was extracted as an additional behavior feature. Then, the model input is no longer the topic probability of group behaviors alone, but a combination of five items: the topic probability, whether the time belongs to morning, whether the time belongs to afternoon, whether the time belongs to evening, and whether the time belongs to holidays. After the improvement, the behavior data of each user was not only processed by word segmentation and topic probability extraction, but also subject to feature extraction of four periods (*i.e.*, morning, afternoon, evening, and holidays). The weighted sum of the five features was imported to the LSTM unit. The optimal weights were obtained by error backpropagation training of the network.

The structure of the improved model is described in Figure 11. The features of whether the time of a behavior takes place in each period can be expressed as $[IIM_t, IIA_t, IIE_t, IIW_t]$.

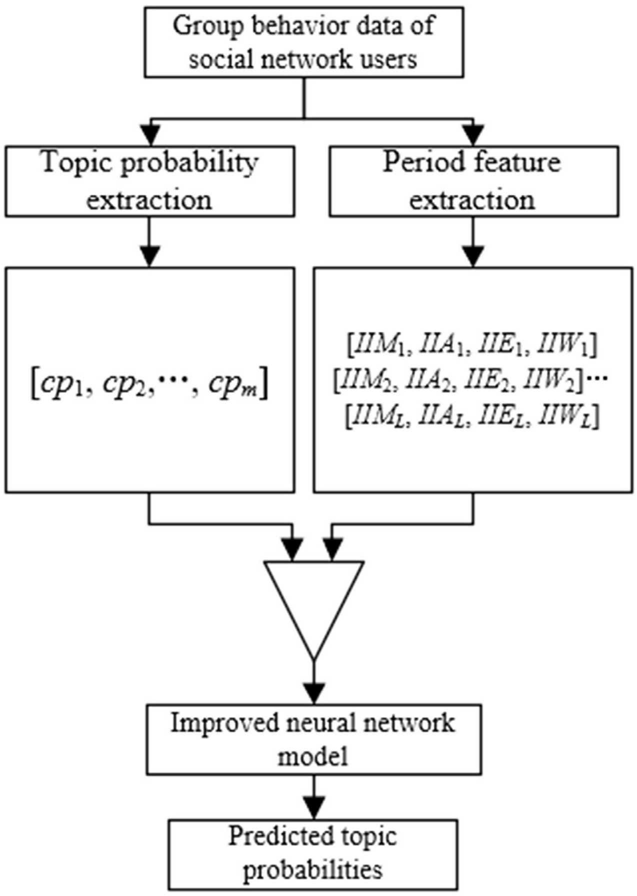


Figure 10. Framework of the topic probability prediction model for group behaviors of social network users.

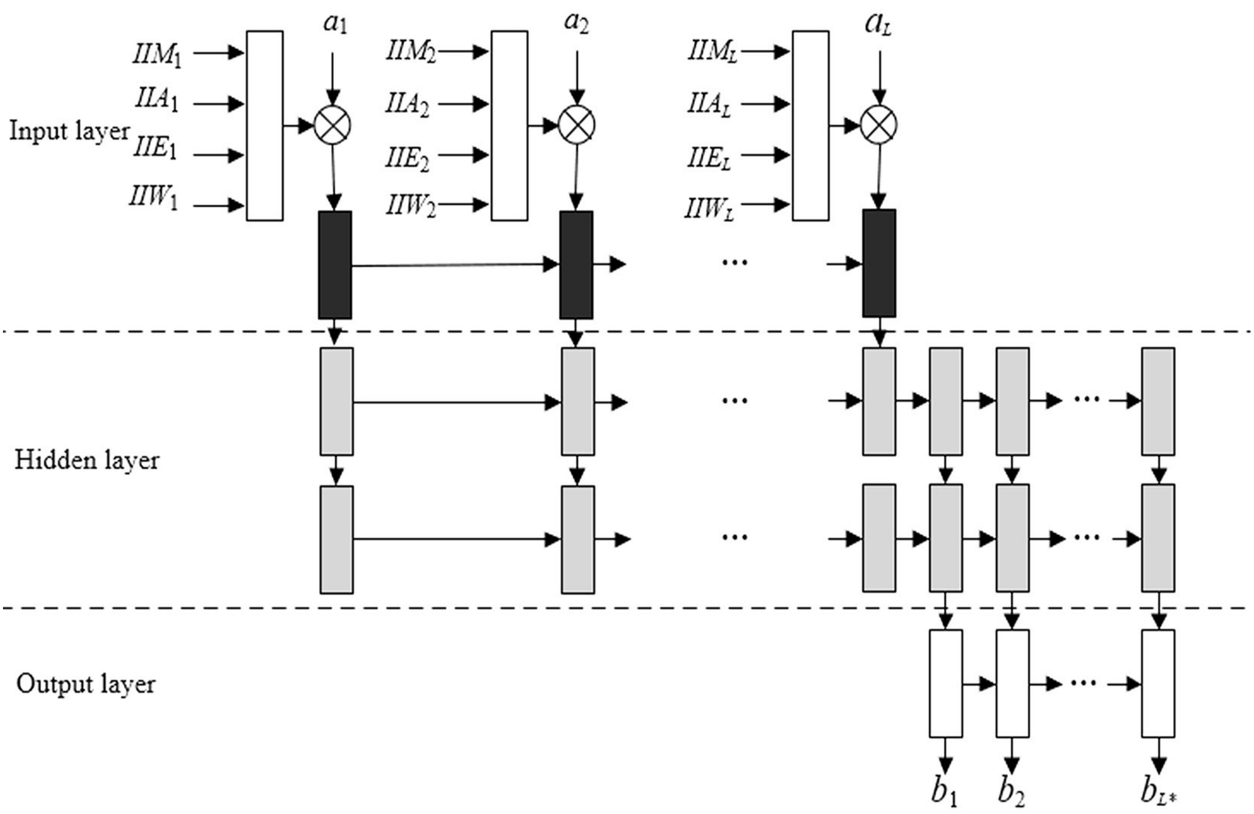


Figure 11. Structure of the improved neural network model for topic probability prediction of group behaviors for social network users..

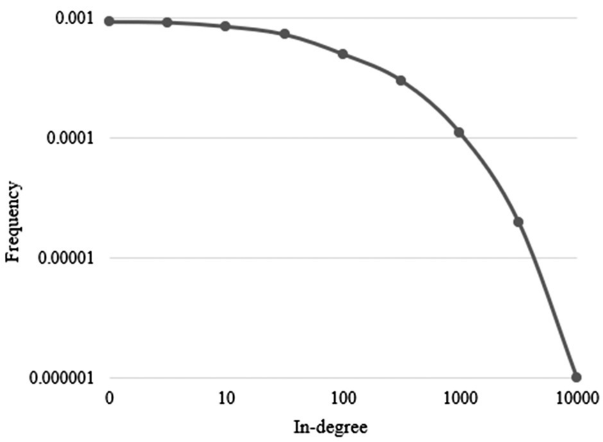
If the behavior does take place in a period, the value of the corresponding feature equals 1; otherwise, it equals 0. Let ω and γ be the weight and coefficient of each period, respectively. Then, the final input a_t^* to the LSTM unit can be obtained by multiplying the weighted [IIM_t, IIA_t, IIE_t, IIW_t] with the current input at:

$$a_t^* = a_t \bullet \gamma \bullet \begin{pmatrix} \omega_{IIM} \bullet IIM_t + \omega_{IIA} \bullet IIA_t \\ +\omega_{IIE} \bullet IIE_t + \omega_{IIW} \bullet IIW_t \end{pmatrix} \tag{16}$$

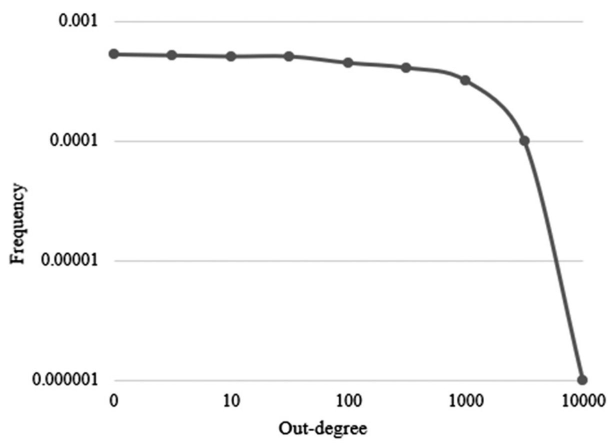
4. Experiments and Results Analysis

The data was collected from a social network with more than 10,000 users. Figure 12 shows the distribution of in-degree and out-degree of the network. The established dataset contains a total of 12,000 statistical nodes. The number of directed edges, the number of nodes in the strongest connected subgraph, and the number of nodes in the weakest connected subgraph were 487,656, 8,977, and 120,000, respectively; the mean out-degree of the network was 47.863. From Figure 12, the curve changes significantly as the value on the horizontal axis increases. This situation is likely due to the "Power Law" or "Long Tail" distribution in social networks. That is, according to the power law distribution, most users in a social network may have only a few followers (low in-degree) or follow only a few people (low out-degree), while only a few users have a large number of followers (high in-degree) or follow many people (high out-degree).

Table 1 compares the prediction results of our model and traditional CNN at Top-K=12 over the datasets of user behaviors in four different social networks. Obviously, our model achieved a much higher hit rate and normalized discounted cumulative gain than the contrastive model over each dataset.



(a) In-degree.



(b) Out-degree.

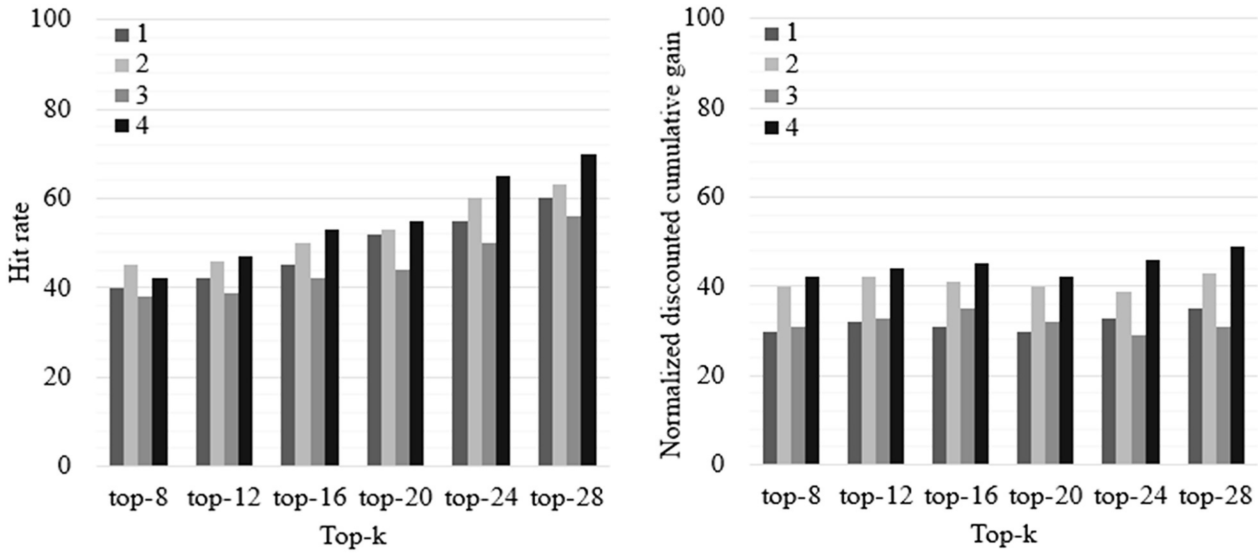
Figure 12. Statistics on the in-degree and out-degree of social networks.

Table 1. Comparison of prediction results of different models at Top-K=12.

	Top-K=12	**Traditional CNN**	**Our model**
1	Hit rate	0.5321	0.5846
	Normalized discounted cumulative gain	0.2383	0.3424
2	Hit rate	0.6365	0.7692
	Normalized discounted cumulative gain	0.3189	0.4347
3	Hit rate	0.6828	0.7135
	Normalized discounted cumulative gain	0.5476	0.5498
4	Hit rate	0.7843	0.7631
	Normalized discounted cumulative gain	0.5691	0.5379

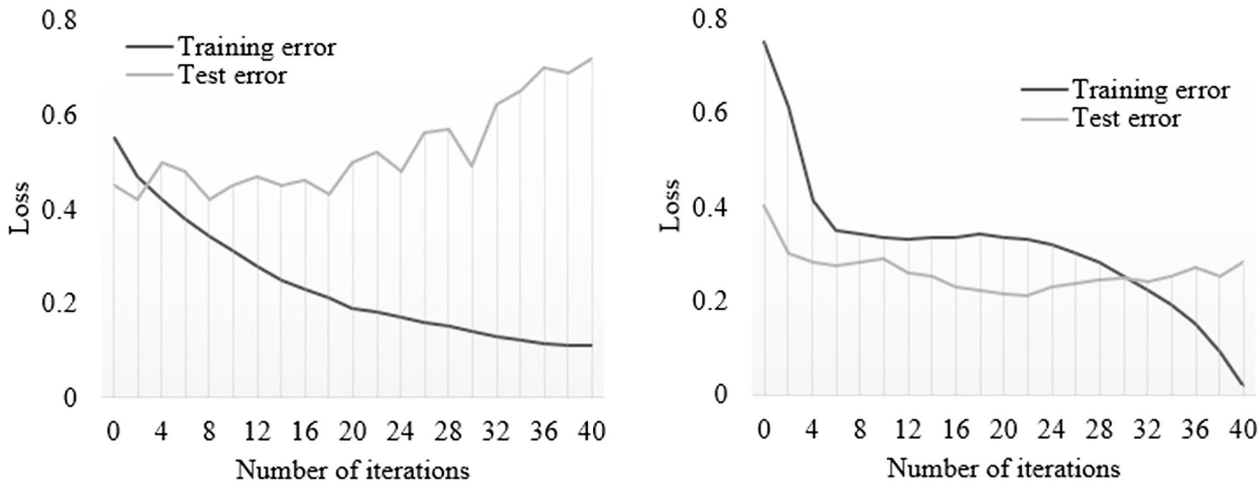
Figure 13 compares the prediction effects of our model at different Top-K values over the four different datasets. It can be seen that, as Top-K increased from 8 to 28, the hit rate and normalized discounted cumulative gain of our model increased to different degrees. Since the model operation should not be too fast, it is important to determine a suitable Top-K value for the model.

Figures 14(a) and 14(b) display the training and test error curves of the traditional CNN and our model, respectively. For the traditional CNN, the training loss dropped below the desired level after multiple iterations, while the test loss continued to increase with the number of iterations; the convergence was rather slow. For our model, the training efficiency was relatively high (the loss dropped to below 0.4 after only 5 iterations), and the convergence speed was satisfactory. The results demonstrate that, in the process of algorithm optimization, this study has taken into account both the iteration accuracy and the number of iterations, finding the optimal balance between the two. This approach ensures the performance of the algorithm while also making efficient use of computational resources.



(a) Hit rate. *(b)* Normalized discounted cumulative gain.

Figure 13. Prediction effects of our model at different Top-K values.



(a) *(b)*

Figure 14. Comparison of log loss curves of different models.

5. Conclusion

To accurately predict individual and group behaviors of social network users, this paper carries out big data analysis on social network user behaviors based on ANN. Firstly, a behavior prediction model was constructed for these users, the functional framework was set up for the prediction task, and the core modules of the model were introduced in turn, including data preprocessing, 3D feature frame construction, feature mapping, and feature prediction. Next, the current encoder-decoder model was improved to realize topic probability prediction of the group behaviors among social network users. Finally, our model was compared with traditional CNN at the Top K=12 in terms of prediction effect and was found to have a higher hit rate and normalized discounted cumulative gain than the CNN. Besides, the training and test curves of the two models were compared. The results confirm that our model has better training efficiency and prediction effect.

This study develops a social network user behavior prediction model based on artificial neural networks. Although it shows superior performance in terms of prediction accuracy and computational efficiency, there may be limitations in handling large-scale data, model interpretability, and adaptability to emerging social behaviors. Future research can further optimize the complexity of the model, enhance its interpretability, and continually track and study emerging social behaviors. Additionally, on the application level, integrating this prediction model more deeply with actual social network services and personalized recommendation systems could be considered to improve user experience and commercial value. The value of this research lies not only in advancing the technology of social network user behavior prediction but also in providing new technological pathways for future user behavior analysis in social networks, holding broad application prospects.

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