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Analysis of the influence of social networks on leadership decision-making behavior based on deep learning models

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Abstract

The study of factors influencing the decision-making behavior of leaders is one of the key problems in social network analysis. In this paper, based on recurrent neural networks in deep learning to study the influence weights of different social network factors, an improvement method based on random perturbation of parameters is proposed for the problem of slow convergence of RNN and easy to fall into local optimal solutions, and random perturbation parameters are introduced in the hidden layer as a way to optimize the weight update function. Then, the sample data sets of network density, structural holes, centrality and linkage points are established and input to different deep learning networks for testing respectively. The classification accuracy of PRP-RNN is 7.38% and 6.45% higher than CNN and LSTM for network density, respectively. The classification accuracy rate for network structure hole is 9.67% and 5.35% higher for PRP-RNN than CNN and LSTM, respectively. The classification accuracy for network centrality is 10.30% and 7.36% higher for PRP-RNN than CNN and LSTM, respectively. The classification accuracy rate for network association points is 9.71% and 8.63% higher for PRP-RNN than CNN and LSTM, respectively. Based on the analysis of deep learning, the closed and dense social network is more conducive to narrowing the invisible minefield of decision making, and the leaders who occupy the structural hole and the central position of the network have easier access to diversified information and resources, which is more conducive to improving the quality of decision making.

Keywords: *deep learning; PRP-RNN algorithm; stochastic perturbation parameters; social networks; leadership decision-making behavior*

Introduction

Leadership decision making is the key to success or failure in the behavior of organizational activities. With the changes in the external environment and the internal structure of the organization, leadership decisions are influenced by a variety of factors, and it becomes more complex and difficult for leaders to make rational and effective decisions(Jemison, 2021) (Rong P, 2019). For countries and regions in social transition, the reality of formal systems such as laws, contracts and the market transaction mechanisms built on them still need to be gradually improved. In this context, leadership decisions rely heavily on knowledge and information obtained from informal institutions (Sergis, Sampson, & Giannakos, 2018; Van de Calseyde, Evans, & Demerouti, 2021).

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Social networks are often seen as an informal institution that compensates for the absence of formal institutions and has a complementary role to formal institutions (Siyu & Xue, 2021; Sliwa & Freiwald, 2017). Specifically, a social network is a collection of stable relationships formed through interaction between individuals or collectives in a society. The main purpose of individuals or collectives embedded in social networks is to obtain the needed resources, i.e., social capital. Based on the network mosaic theory, social networks consist of points, lines, and facets; points refer to participants in the network in the form of individuals or collectives also known as network members, lines represent the relationships that individuals or collectives associate in the network, and facets refer to the structures constructed in the network (Siyu & Xue, 2021)-(Lavy & Sand, 2019). The leader is not only the decision maker who occupies the top of the organizational structure, but also the participant who is embedded in a complex and diverse social network(Baird & Vue, 2017). The leader plays a leading role in connecting the organization with the outside world and obtains various resources for the organization through the embedded social network, while the knowledge and information in the social network also influence the decision making behavior of the leader.

Social networks were earlier applied to the study of relationships between people in the social field(Saxton & Wang, 2014).The literature argues that emerging social network applications offer new ways for nonprofit organizations to engage communities in fundraising efforts, noting that giving on social networking sites is not driven by the same factors as traditional social networks. The literature(Webber et al., 2016)quantified the interactions of big brown bats in tree-roosting colonies based on social networks, dividing the population into multiple trees or the same building on a daily basis to the spread of pathogens in both groups of networks. The literature(Mills, 2017)investigated the application of social network analysis in archaeology, arguing that it is the connections between participants (or nodes) that define social ties.

Social network relationships play an important relationship in leadership decision making. The literature(Zaman & Andriyanty, 2021)examined the relationship between national leadership decisions and younger generation groups in the Republic of Indonesia and suggested that national leaders develop ideal leadership decisions according to the times. The literature(Qiang, Huiqi, Ali, & Nazir, 2021)argues that in social networks, an opinion leader is a powerful individual who is often an expert in a specific field and has a large number of people following his or her comments or ideas. Large collectives or even governments may use opinion leaders to influence sales or guide public opinion. The literature (Jolly, Krylova, & Phillips, 2022)studied the value of the ethical decision-making paradigm and analyzed the impact of followers' reactions to leaders' misbehavior. The literature (Motlaghzadeh, Kerachian, & Tavvafi, 2020)suggested that in multi-intelligent decision making, the decisions of the intelligences are coherently interdependent and the goals of the intelligences may not be aligned. In this type of decision making, agents need to act rationally and strategically.

This paper firstly composes the algorithmic steps based on the algorithmic idea of recurrent neural network, and analyzes and compares the differences between RNN forward propagation and backward propagation. Secondly, based on the network structure of RNN, we point out that RNN has the problems of easily falling into local optimal solutions and poor generalization ability, and propose the improvement algorithm of adding random perturbation parameters to the hidden layer to establish the PRP-RNN model. Compared with RNN, the introduction of random perturbation parameters in PRP-RNN changes the way of updating the weights of the input layer in the forward propagation process, and accordingly also corrects the objective function from the original mean expectation to the mean square error. Then, based on the analysis of the relationship between the number of nodes, the number of edges and the number of network layers of different types of social networks, the influence factors of social networks on leaders' decision-making behaviors are explored, so as to establish a sample dataset for deep learning. Finally, the sample dataset is divided into a training set and a test set, and different deep learning networks are used for training, and the specific effects of different social network factors on leadership decision-making behaviors are analyzed by comparing the training and test results.

RNN-based deep learning model

Recurrent Neural Network

The algorithmic idea of RNN

The output of traditional neural networks depends only on the current input, which leads to the inability of traditional neural networks to make good predictions for data that change over time (Pathirage et al., 2018).The output of recurrent neural network (RNN), on the other hand, is determined by both the input of the current moment and the output of the previous moment, which is like adding a memory space to the neural network so that the neural network can remember the behavior of the previous moment and react according to the behavior of the previous moment and the characteristics of this moment, the traditional neural network is like disconnected, while the recurrent neural network is like continuous.

Recurrent neural networks compute the weights of the same position repeatedly at different moments, and as the time series unfolds, they can theoretically transfer the past state to the present, i.e., today's results are not only influenced by today's events, but also related to countless yesterday. Recurrent neural network's rely on this way of its computation and have been widely used in problems such as speech recognition, natural language processing, and stock prediction.

Suppose that the input of the RNN at T moment is $X=\{x_1,\cdots,x_t,\cdots,x_T\}$, where $x_t=\left(x_{1t},x_{2t},\cdots,x_{Nt}\right)^T$. The output of the RNN at T moments is $O=\{o_1,\cdots,o_t,\cdots,o_T\}$, where $o_t=\left(o_{1t},o_{2t},\cdots,o_{Lt}\right)^T$. The output value of the RNN algorithm at t moments is not only related to the input value at t moments, but also depends on the output value of the hidden

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layer at $t-1$ moments.

The RNN forward propagation process is as follows:

$$o_t = g\left(V_{L\times M} \cdot h_t + by_{L\times 1}\right)_{L\times 1} \quad (1)$$

$$h_t = f\left(U_{M\times N} \cdot x_t + W_{M\times M} \cdot h_{t-1} + bh_{M\times 1}\right)_{M\times 1} \quad (2)$$

Where U is the weight of the input layer to the hidden layer, W is the weight of the hidden layers h_{t-1} to h_t, V is the weight of the hidden layer to the output layer, bh and by are the bias of the hidden layer and the output layer, respectively, and f, g are the activation functions.

Assuming that X corresponds to the true value of $Y = \{y_1, \cdots, y_t, \cdots, y_T\}$, where $y_t = \left(y_{1t}, y_{2t}, \cdots, y_{Lt}\right)^T$, the objective function is set to:

$$E = \sum_{t=1}^{T} E_t = \frac{1}{2}\sum_{t=1}^{T}\sum_{l=1}^{L}\left(y_{lt} - o_{lt}\right)^2 \quad (3)$$

The RNN backpropagation process is as follows:

$$\frac{\partial E}{\partial V} = -\sum_{t=1}^{T}\left(y_t - o_t\right) \cdot g'\left(\text{ ney } y_t\right) \cdot h_t \quad (4)$$

$$\frac{\partial E}{\partial by} = -\sum_{t=1}^{T}\left(y_t - o_t\right) \cdot g'\left(\text{ ney}_t\right) \quad (5)$$

$$\frac{\partial E}{\partial U} = -\sum_{t=1}^{T}\sum_{t=1}^{t}\left(\delta_\tau\right)^T \cdot x_t \quad (6)$$

$$\frac{\partial E}{\partial bh} = -\sum_{t=1}^{T}\sum_{\tau=1}^{t}\left(\delta_\tau\right)^T \quad (7)$$

$$\frac{\partial E}{\partial W} = -\sum_{t=1}^{T}\sum_{\tau=1}^{t}\left(\delta_\tau\right)^T \cdot h_{\tau-1} \quad (8)$$

Among them, there are:

$$\delta_\tau = \delta_t \prod_{\tau}^{t-1} W \cdot \mathrm{diag}\left(f'\left(\mathrm{net}_\tau\right)\right) \tag{9}$$

$$\delta_t = \left(y_t - o_t\right)_{L\times 1}^{T} \cdot \mathrm{diag}\left(g'\left(ney_t\right)\right) \cdot V_{L\times M} \cdot \mathrm{diag}\left(f'\left(net_t\right)\right) \tag{10}$$

The network structure model of RNN is shown in Figure 1.

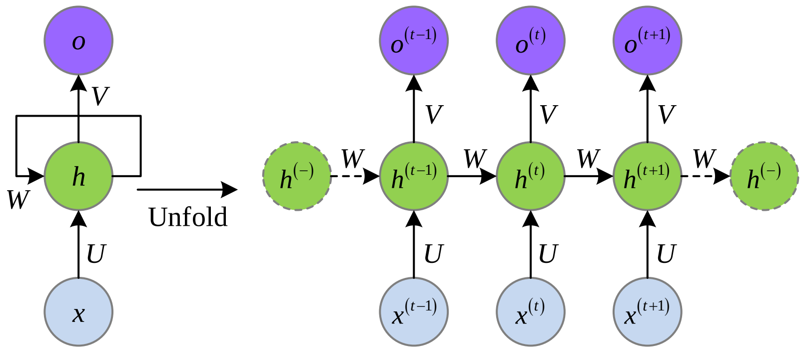

Figure 1 Structural model of recurrent neural networks

Algorithmic steps of RNN

The algorithm steps of RNN are as follows:

Step 1: Initialize output $h_0 = (0, 0, \cdots 0)_{1\times M}^{T}$ of the hidden layer, initialize the values of weight U, W, V and codeword bh, by.

Step 2: The input value x_1 at the moment $t = 1$ is substituted into the forward propagation equations (1) and (2), and after the initial value and the value of initial weight U, W, V and bias bh, by given in step 1, the hidden layer output value h_1 at the moment $t = 1$ is calculated, and after the value of initial weight V and bias by and the value of h_1 is calculated, the output layer output value o_1 is calculated.

Step 3: The input value x_2 at the moment of $t = 2$ is substituted into the forward propagation equations (1) and (2), and the hidden layer output value h_2 and the output layer output value o_2 are calculated after the values of h_1 and initial weight U, W, V and bias bh, by obtained in step 2.

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Step 4: Repeat the process of step 2 and step 3, and substitute the input value $ABCD$ at the $t=1,2,\cdots,T$ moment into the forward propagation equations (1) and (2) in turn, and after the $h_0,h_1,\cdots,h_{T-1}$ and initial weight U,W,V obtained at the previous moment, the value of bias bh,by is calculated to obtain the hidden layer output value $h_1,h_2,\cdots,h_T$ and output layer output value $O_1,O_2,\cdots,O_T$ at the $t=1,2,\cdots,T$ moment.

Step 5: Substitute the output layer output value $O_1,O_2,\cdots,O_T$ and the training set output value into Equation (3) to obtain the loss function.

Step 6: The values of o_T,ney_T,h_T obtained in step 4 are substituted into the back propagation equations (4) and (5) to calculate the bias derivatives of the objective function at the moment of $t=T$ with respect to the weights V and bias by.

Step 7: Substitute the value of o_T,ney_T,h_T obtained in step 4 into the back propagation equation (10) and calculate the value of $t=T$ moments δ_T.

Step 8: Substitute the value of net_{T-1} obtained in step 4 into the back propagation equations (9) and (10) to calculate the value of $t=T$ moments δ_{T-1}.

Step 9: Repeat the process of steps 7 and 8, and substitute the values into the back propagation equations (6) ~ (10) in turn to obtain the values of $t=T$ moment $\delta_T,\delta_{T-1},\ldots,\delta_1$. Summation is obtained for the choreography of the objective function at $t=T$ moments for weights U,W and bias bh.

Step 10: Repeat the process of steps 6, 7, 8, and 9, and calculate the derivatives of the objective function at the moment of $t=1,2,\cdots,T$ for weight U,W,V and codimension bh,by in turn, and sum up to obtain the complete partial derivatives.

RNN based on parameter random perturbation

With its special structure, the RNN algorithm has a good effect in predicting time series data, but because of the large randomness of initial weight selection, it is easy to make the prediction results reach the local optimal solution and converge slowly. To address this situation, this chapter introduces the random perturbation term into the RNN algorithm so that the improved RNN algorithm can converge faster compared to the traditional recurrent neural network, and the prediction effect is also better than the traditional recurrent neural network, which avoids reaching the local optimal solution and prevents overfitting thus improving the generalization ability of the model.

Although traditional recurrent neural network has good results in predicting temporal data, its initial weights are random, and this randomness will make the convergence speed of the model decrease. The existing improvement methods for initial weights are only applicable to specific data of a certain work type and do not have generalization ability. Therefore, this paper proposes an improved RNN network (PRP-RNN) based on random perturbation of parameters, which not only reduces the problem of slow convergence caused by random initial weights, but also the improved RNN network can converge to a better local optimal solution compared with the traditional RNN.

It is known that the training set input data, training set output data are X, Y. A column of time series data $x_1, x_2, \ldots, x_T$ is represented as the value of T time steps, where $x_t = \left(x_{1t}, x_{2t}, \cdots, x_{Nt}\right)^T$. In this paper, a small batch stochastic gradient descent algorithm is selected for weight update, i.e., the training set data X, Y is randomly disrupted into S groups. Each group consists of J columns of time series data. The input data and output data of the training set in the S th group j column t moment can be represented as that. Each update of the weights is a forward propagation and backward propagation calculation for the training set data of the S th group J column T time step. For the sake of concise presentation, the $p \times S + s$ th weight update is denoted by ps where $p = 0, 1, 2 \cdots, s = 1, 2, \cdots, S$.

The number of nodes in the hidden layer is known to be M. The weights U, W, V of the recurrent neural network are initialized to a Gaussian distributed random number matrix with mean 0 and standard deviation 0.1 for $M \times N, M \times M, L \times M$.

The algorithmic idea of PRP-RNN

In order to make the RNN algorithm converge faster, the random perturbation parameter $\mu_{M \times N}$ is introduced into the hidden layer of the RNN algorithm in this chapter, and the new weights are obtained by adding them with the input layer weights. The improved RNN network forward propagation process is as follows:

$$\tilde{U}_{M \times N} = U_{M \times N} + \mu_{M \times N} \tag{11}$$

$$\left(h_t\right)_{M \times 1} = f\left(\tilde{U}_{M \times N} \cdot \left(x_t\right)_{N \times 1} + W_{M \times M} \cdot \left(h_{t-1}\right)_{M \times 1} + (bh)_{M \times 1}\right) \tag{12}$$

$$(o_t)_{L\times 1} = g\left(V_{L\times M}\cdot(h_t)_{M\times 1} + (by)_{L\times 1}\right) \tag{13}$$

where, $f:R\to R, g:R\to R$ is the activation function. The mean square error is chosen for the objective function.

Due to the involvement of the random perturbation parameters in the forward propagation process, the objective function differs compared to the original RNN. To ensure the randomness of the random perturbation parameters for each weight update, the backpropagation process only biases the original input layer weights. The backpropagation process of the improved RNN network is as follows:

$$\frac{\partial E^{ps}}{\partial V_{lm}^{ps}} = \sum_{j=1}^{J}\sum_{t=1}^{T}\frac{\partial E_{tj}^{ps}}{\partial o_{tl}^{sj}}\frac{\partial o_{tl}^{sj}}{\partial ney_{tl}^{sj}}\frac{\partial ney_{tl}^{zj}}{\partial V_{lm}^{ps}} = -\sum_{j=1}^{J}\sum_{t=1}^{T}\left(y_{tl}^{sj}-o_{tl}^{sj}\right)\cdot g'\left(ney_{tl}^{sj}\right)\cdot\left(h_{tm}^{sj}\right) \tag{14}$$

$$\frac{\partial E^{ps}}{\partial (by)_{l}^{ps}} = \sum_{j=1}^{J}\sum_{t=1}^{T}\left(y_{tl}^{sj}-o_{tl}^{sj}\right)\cdot g'\left(ney_{tl}^{sj}\right) \tag{15}$$

$$\begin{aligned}\frac{\partial E^{ps}}{\partial U_{mn}^{ps}} &= \sum_{j=1}^{J}\sum_{t=1}^{T}\frac{\partial E_{tj}^{ps}}{\partial ney_{tm}^{sj}}\frac{\partial ney_{tm}^{sj}}{\partial U_{mn}^{ps}}\\ &= \sum_{j=1}^{J}\sum_{t=1}^{T}\frac{\partial E_{tj}^{ps}}{\partial ney_{tm}^{sj}}\frac{\partial ney_{tm}^{sj}}{\partial \tilde{U}_{mn}^{ps}}\frac{\partial \tilde{U}_{mn}^{ps}}{\partial U_{mn}^{ps}}\\ &= -\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{\tau=1}^{t}\left(\delta_{\tau m}^{sj}\right)^{T}\cdot x_{\tau n}^{sj}\end{aligned} \tag{16}$$

$$\frac{\partial E^{ps}}{\partial (bh)_{m}^{ps}} = -\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{\tau=1}^{t}\left(\delta_{\tau m}^{jj}\right)^{T} \tag{17}$$

$$\frac{\partial E^{ps}}{\partial W_{ik}^{ps}} = \sum_{j=1}^{J}\sum_{t=1}^{T}\frac{\partial E^{ps}}{\partial net_{ti}^{jj}}\frac{\partial net_{ti}^{jj}}{\partial W_{ik}^{ps}} = -\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{\tau=1}^{t}\left(\delta_{ti}^{sj}\right)^{T}\cdot h_{(\tau-1)k}^{sj} \tag{18}$$

The flow block diagram of the RNN algorithm based on parameter random perturbation is shown in Figure 2.

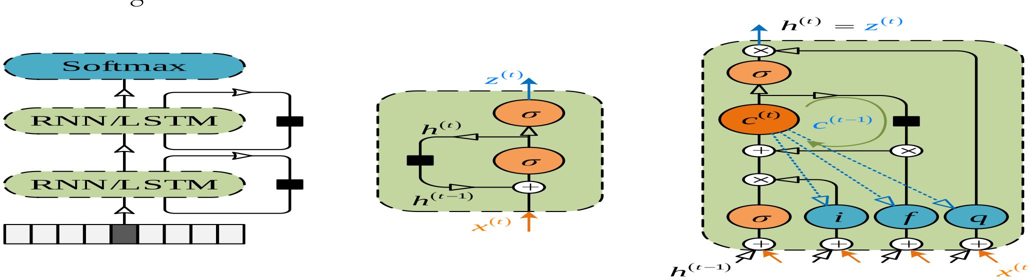

Figure 2. RNN algorithm flow based on parameter random perturbation

Algorithmic steps of PRP-RNN

The algorithm steps of PRP-RNN are as follows:

Step 1: Initialize the output of the hidden layer $h_0 = (0, 0, \cdots 0)^T_{1\times M}$, initialize the weighting U, W, V, compose the values of bh, by and random perturbation term $\mu_{M\times N}$.

Step 2: Substitute the training set group 1, column 1 input data $\left\{\left(x_{1t}^{11}, x_{2t}^{11}, \cdots, x_{Nt}^{11}\right)^T\right\}$ into the improved recurrent neural network forward propagation equations (11) ~ (13), and obtain the output value $\left\{\left(o_{1t}^{11}, o_{2t}^{11}, \cdots, o_{Lt}^{11}\right)^T\right\}$ after each layer weight, hidden layer activation function and output layer activation function.

Step 3: Repeat the process of Step 2 and substitute the input data $\left\{\left(x_{1t}^{1j}, x_{2t}^{1j}, \cdots, x_{Nt}^{1j}\right)^T\right\}$ in group 1 and column $j = 1, 2\cdots, J$ into the improved recurrent neural network forward propagation formulas (11) to (13) in turn to obtain the output values $\left\{\left(o_{1t}^{11}, o_{2t}^{11}, \cdots, o_{Lt}^{11}\right)^T\right\}$ in group 1 and column $j = 1, 2\cdots, J$ after each layer weight, hidden layer activation function and output layer activation function.

Step 4: The output value of step 3 is substituted into equation (11) to calculate the objective function, and the partial derivatives of the objective function of the 1st set of training data with respect to $U^{01}, W^{01}, V^{01}, by^{01}, bh^{01}$ are obtained by substituting into the back propagation equations (14) ~ (18), multiplying with the learning rate to obtain $\Delta U^{01}, \Delta W^{01}, \Delta V^{01}, \Delta by^{01}, \Delta bh^{01}$, and then the updated weight $U^{02}, W^{02}, V^{02}, by^{02}, bh^{02}$ is calculated.

Step 5: Repeat steps 3 and 4 process ps times to get the weight $U^{ps+1}, W^{ps+1}, V^{ps+1}, by^{ps+1}, bh^{ps+1}$.

Step 6: Suppose there is K set of test set input data $\left\{\left(\overline{x}_{1t}^{k}, \overline{x}_{2t}^{k}, \cdots, \overline{x}_{Nt}^{k}\right)^T\right\}$ and output data $\left\{\left(\overline{y}_{1t}^{k}, \overline{y}_{2t}^{k}, \cdots, \overline{y}_{Lt}^{k}\right)^T\right\}$. Substitute K sets of test set input data into the improved recurrent neural network forward propagation formulas (11) to (13) in turn, and obtain the output value $\left\{\left(\overline{O}_{1t}^{k}, \overline{O}_{2t}^{k}, \cdots, \overline{O}_{Lt}^{k}\right)^T\right\}$ of K sets of test set input data after weight

$U^{ps+1}, W^{ps+1}, V^{ps+1}, by^{ps+1}, bh^{ps+1}$, hidden layer activation function and output layer activation function, where $k = 1, 2, \ldots, K$.

Step 7: Find the objective function $E^k = \frac{1}{2}\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{l=1}^{L}(y_{tl}^k - o_{tl}^k)^2$ for output value $\left\{\left(\bar{o}_{1t}^k, \bar{O}_{2t}^k, \cdots, \bar{o}_{Lt}^k\right)^T\right\}$ and test set output data $\left\{\left(\bar{y}_{1t}^k, \bar{y}_{2t}^k, \cdots, \bar{y}_{Lt}^k\right)^T\right\}$, and the prediction error of the recurrent neural network after finding the expectation for the objective function.

The influence of social networks on leadership decision-making behavior

Establishment of social network

The term social network first appeared in the study of social capital theory, and subsequently the related research on social networks has grown exponentially(Bennion, 2022).The N participants with complex and diverse connections together form a social network I, and the network I can be viewed as a matrix of $N \times N$. The position (i, j) in the matrix I is marked as 1 if there is a connection between participant i and participant j, and 0 otherwise. The number of connections that participant i has is called the degree of that participant, a series of non-repeating connections between participant i and participant j is called a path, and the shortest path is called the distance between participant i and participant j. When any two participants in a social network I are connected to each other, that is, there is a path between any nodes, the social network I is called a network closure, and the network density is highest at that time. However, if there is no direct connection relationship between two random participants in the social network I, the social network is considered as a sparse social network.

In a sparse network structure, certain individuals or collectives are not directly connected to each other or appear to have intermittent relationships, and in terms of the overall network structure, it is like the appearance of caves, the so-called structural holes. In a social network structure with a structural hole, the third party that connects two without direct connection is called an intermediary or middleman. In other words, that participant occupies the structural hole position. The structural hole theory is mainly thought in terms of structural embeddedness, and tends to emphasize whether there is a connecting relationship between other individuals or collectives with direct connection to the self, and the individual or collective occupying the structural hole position plays a mediating role in the network. Scholars have also analyzed the influence of social networks on participants' behavior in terms of the strength of relational embeddedness.

The most commonly used analytic metric to reveal the relational embeddedness of participants in

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social networks is network centrality. The analysis of network centrality can exist not only in sparse network structures, but also in network-closed structures. Unlike structural hole theory, the more dense the social network structure is, the more favorable the network centrality is. In this paper, social networks are divided into 3 categories, and different types of social network structures are shown in Table 1. Among them, the network with no direction and no power has 41 network nodes and 245 edges, and the number of network layers is 2.

Table 1 Different types of social network structures

Type	Number of nodes	Number of sides	Number of network layers
Undirected and powerless	41	245	2
Undirected right	65	623	5
Undirected and directed mixing	512	427	3

Factors influencing leadership decision-making behavior

Leaders embedded in social networks use social relationships to obtain information and resources needed for unit management. The more dense the embedded social network, the deeper the exchange of knowledge and information between leaders and other members of the network, and the more opportunities to share relevant policy norms, which facilitates leaders to interpret external environmental information more comprehensively and thoroughly, and reduces the interference caused by external environmental uncertainty on decision-making behavior. A more closed and dense network means richer social relationships, more social capital available, and smoother information flow, reducing the problem of information asymmetry. Usually, in the case of denser social networks, the size and strength of the network is greater, which can lead to more knowledge units for the leader's cognitive schema. When the hierarchical relationship between multiple knowledge units is clearer and more reasonable in structure, the more conducive to the achievement of organizational goals the decision scheme made by the leader is. However, in reality, social networks often present small-world characteristics, that is, the average path between participants in the network is shorter and presents higher aggregation, especially when the participants in a high-density social network have more similar characteristics. The emergence of structural holes is due to the disruption of the relationship between network members. Network members who occupy the structural hole position act like intermediaries, they become bridges between network members without direct connection, and their greatest advantage is that they can control, integrate or draw on information and resources in the network according to their needs. Specifically, network members occupying the structural hole position can obtain diversified information and have stronger bargaining power when negotiating with other members, and the stronger the structural embeddedness of the position, the stronger the control ability of the network members in that position. In addition, because the local network around the structural hole location does not have high aggregation and the related network nodes are all weakly connected to each other, for this reason, the network members in this location have

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higher autonomy and can be free from the constraints of other network members. Network centrality is an analysis of the advantages of being located at the center of the network from the perspective of relational embeddedness. From the perspective of the whole social network, the network member who occupies the central position can gain more social capital. For example, the network member can obtain more information in the network, and at the same time the network member has stronger influence and control over the activity behavior of other network members, etc. At the same time, the activity behavior of the member in the center of the network is less interfered by other network members, which means that the network member has more space to exercise autonomy. Because of their strong influence and control, the members at the center of the network have a dominant role in the values and thinking activities prevailing in the whole network, so the convergence principle is less effective for the members at the center of the network.

Deep learning dataset construction for impact factors

Based on the above analysis, this paper classifies the factors influencing social networks on leadership decision-making behavior as network density, network structure hole, network centrality, and linkage point. In this paper, by examining the social network and leadership decision-making behavior of different circles, we establish a sample data set D as shown in Table 2. Test set D There are 100 samples, and this paper is divided into training set and test set according to the ratio of 7:3, i.e., there are 70 samples in the training set and 30 samples in the test set.

Table 2 Deep learning sample dataset

Number	Network density	Network structure holes	Network centrality	Junction points
1	0.04	13	0.12	8
2	0.49	29	0.33	5
3	0.02	26	0.9	7
4	0.3	13	0.4	5
5	0.18	1	0.81	9
……	……	……	……	……
96	0.47	6	0.23	7
97	0.34	7	0.39	5
98	0.78	12	0.46	7
99	0.34	2	0.5	9
100	0.35	18	0.53	7

Results and analysis

The dataset for deep learning has been constructed above, and next we input the dataset into the deep network for learning. In order to verify the feasibility of PRP-RNN network, this paper also compares convolutional neural network (CNN) and long short-term memory neural network (LSTM) at the same time.

After the CNN was trained and learned, the test results were expressed in a confusion matrix, as in Figure 3. When the true value is social network density, the accuracy of CNN classification as network density is 66.5%, the accuracy of classification as structural hole is 1.4%, the accuracy of classification as centrality is 14.3%, and the accuracy of classification as linkage point is 17.7%. When the true value is structural hole, the accuracy of CNN classification as network density, structural hole, centrality, and association point is 16.4%, 59.5%, 8.9%, and 15.3% in order. When the true value is centrality, the accuracy of CNN classification as network density, structural hole, centrality, and linkage point is 11.9%, 10.9%, 75.1%, and 2%, respectively. When the true value is the linkage, the accuracy of CNN classification as network density, structural hole, centrality, and linkage is 22.3%, 3.7%, 7.8%, and 66.2%, respectively. According to the confusion matrix, the accuracy of CNN can be found as 63.4% and the recall rate as 69.5%.

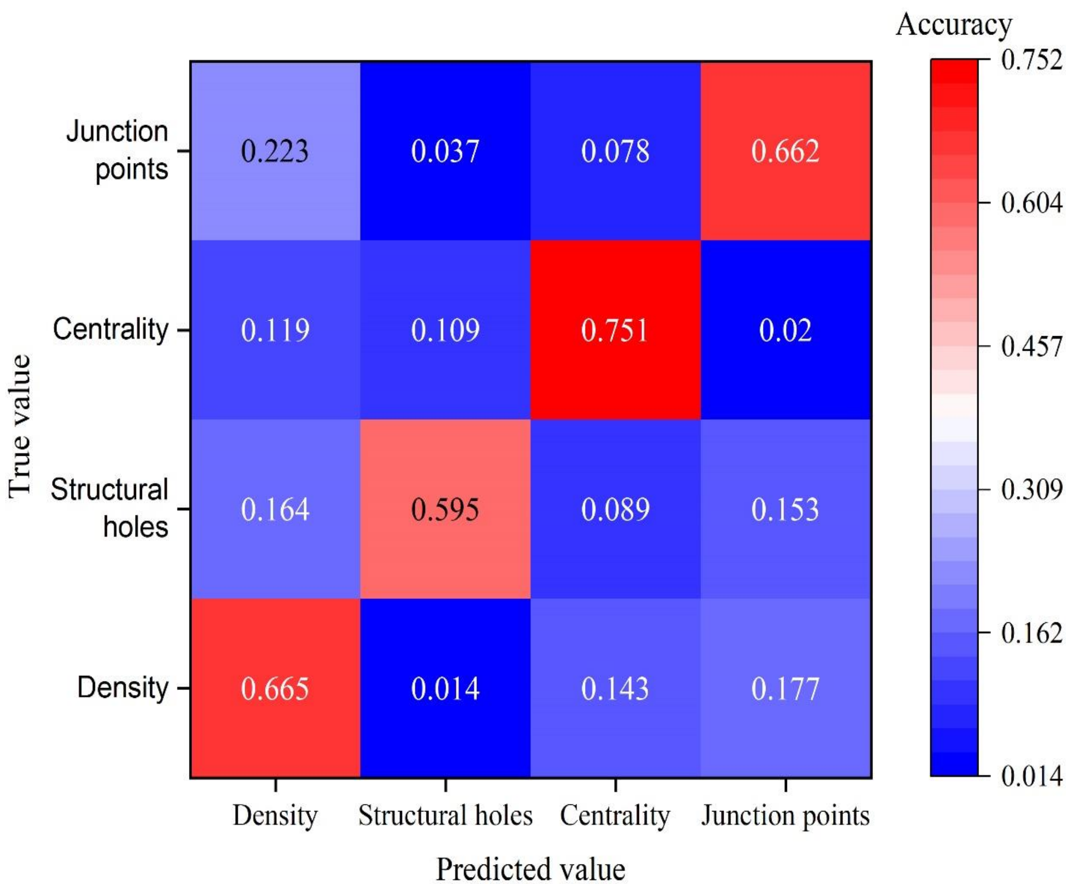

Figure 3 Convolutional neural network test result confusion matrix

After the LSTM was trained and learned, the test results were expressed in confusion matrix as in Figure 4. the classification accuracy of LSTM for social network density, structural hole, centrality, and linkage points were 65.3%, 66.7%, 63.5%, and 68.2% in order, which were -1.81%, 12.10%, -15.45%, and 3.02% higher than CNN, respectively. In terms of precision rate LSTM and CNN have comparable performance.

In terms of recall, LSTM has 66.4% recall for network density, 68.5% recall for structural holes, 65.2% recall for centrality, and 70.2% recall for conjunction points. Reflecting this in practice, LSTM considers the number of linked points in social networks to have a more significant effect on leadership decision-making behavior, while CNN considers network centrality to have the highest influence weight.

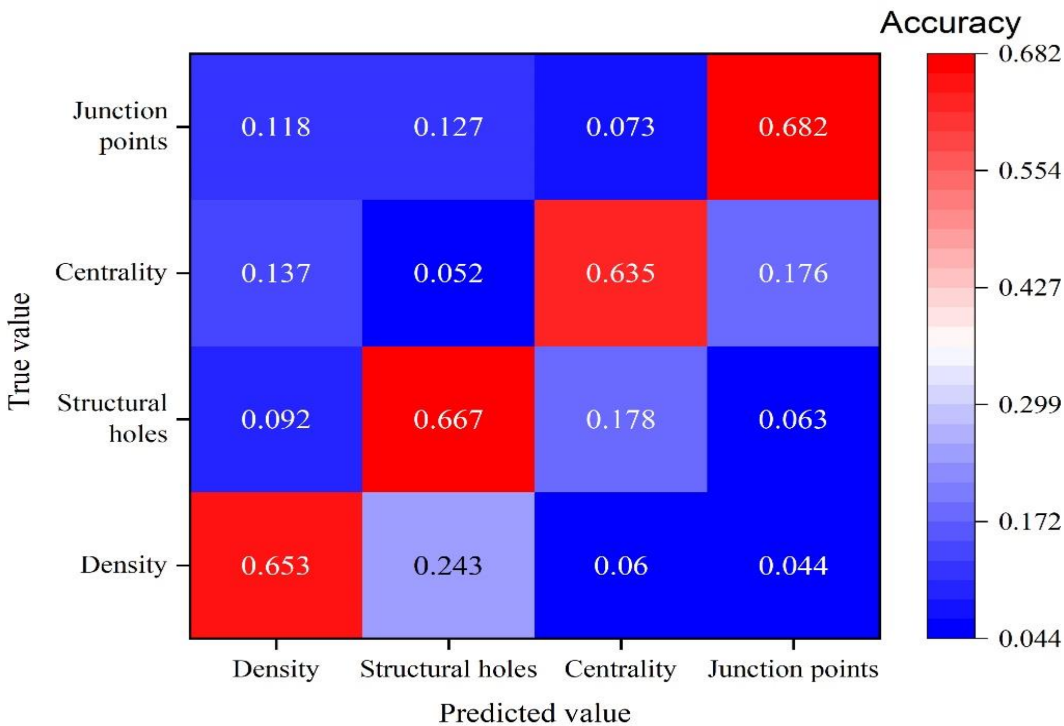

Figure 4 Long short-term memory neural networks test result confusion matrix

Training learning is also performed for PRP-RNN. The accuracy, precision, recall and F1 values of the test results of these three networks are shown in Figure 5. The PRP-RNN has higher performance compared to CNN and LSTM for both accuracy and recall. For the prediction accuracy of network density, PRP-RNN is 7.38% higher than CNN and 6.45% higher than LSTM. For the prediction accuracy of network structure hole, PRP-RNN is 9.67% higher than CNN and 5.35% higher than LSTM. For the prediction accuracy of network centrality, PRP-RNN is 10.30% higher than CNN and 7.36% higher than LSTM. Meanwhile, the recall rate of PRP-RNN is on average 9.71% higher than CNN and 8.63% higher than LSTM.

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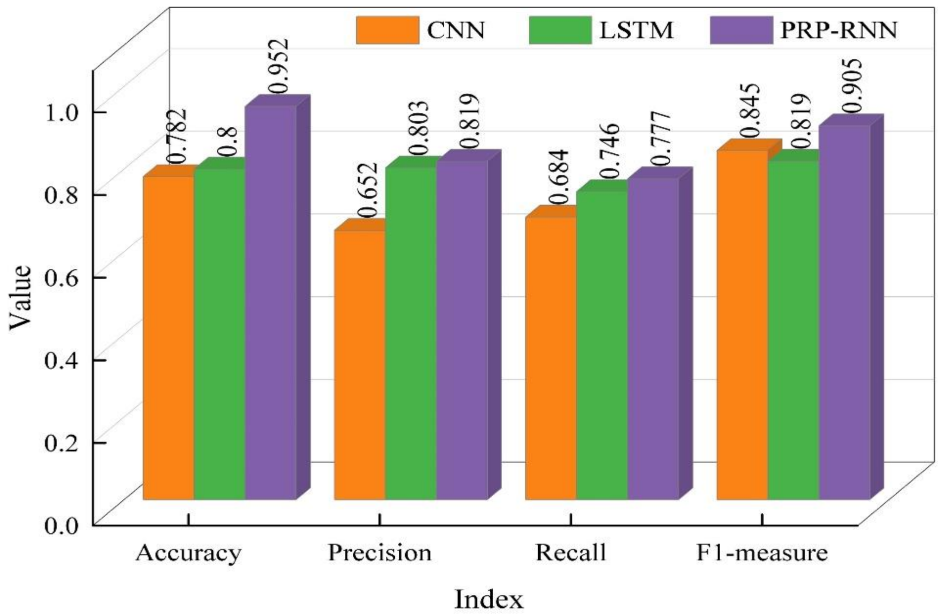

Figure 5 Comparison of test results of three neural networks

Reflected in practice, the impact of social network density on leaders' decision-making behavior has two sides. Specifically, one is considered from the perspective of social capital, when the more closed and dense the social network is, the richer the leader's social relationships are, the more social capital is available, and the more the leader's cognitive framework and belief structure are not affected by the uncertainty of the external environment, thus narrowing the scope of the invisible minefield of decision making. Secondly, considering from the perspective of convergence psychology, the more similar characteristics the network members have among themselves, the more solid the established social network is, and under the trend of convergence principle, the ideology and activity behavior among the network members maintain a high degree of consistency.

Network members who occupy structural holes act as information bridges. When the leader occupies the structural hole position, he/she can obtain more non-redundant information in the social network through the role of information bridge, and at the same time, the social network will have less binding effect on the network members who occupy the structural hole position, which means that the effect of the so-called convergence principle is reduced.

In the absence of information, resources and limited autonomy, members at the edge of the network are largely dependent on those at the center of the network to adjust their strategic decisions, most often by imitating the behavior of those at the center of the network. If the leader is at the center of the network, he or she has access to a wealth of information and resources, and has more influence and control. In this case, the leader's decision-making behavior can be independent of the other members of the network.

Conclusion

In this paper, we propose an improved algorithm based on parameter random perturbation for the problem of slow convergence of recurrent neural networks to build a PRP-RNN deep learning model, and also build a sample dataset based on the relationship between social networks and leaders' decision-making behaviors, and input the dataset into different deep learning networks for training. The accuracy and recall rates of PRP-RNN are higher than those of CNN and LSTM, and the PRP- RNN has an average recall rate of 9.71% higher than CNN and 8.63% higher than LSTM. Based on this, this paper draws the following conclusions:

(1) Social networks have a non-negligible influence on the decision-making behavior of leaders in unit management. Leaders should deeply understand and appreciate the role played by social networks, give full play to the positive influence of social networks, and thus improve the quality of decision-making.

(2) Leaders should pay more attention to the non-redundant information obtained in social networks and comprehensively interpret the signals of changes in the external environment. Especially for leaders embedded in highly dense social networks, they should improve their own cognitive ability to avoid being influenced by the ideology and activity behavior of other members in the social network, and to ensure that the strategic decisions made are more in line with the needs of unit development.

(3) Leaders should occupy the structural hole position or network center position in the embedded social network as much as possible, enhance their influence and control in the social network, create an autonomous and independent space for their own decision making, and then promote decision-making behavior more conducive to the achievement of organizational goals.

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