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Collaborative Prediction Algorithm for Investment and Financing Network System Based on Improved Hypergraph Convolution and Ant Colony Algorithm

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Abstract: After more than 20 years of rapid development, the Chinese financial market is experiencing a decrease in user traffic dividends. The overall industry growth rate is slowing down, yet the market's potential demand remains substantial. The industry is transitioning from a phase focused on incremental growth to one that equally emphasizes incremental and existing stock growth, accelerating the exploration of new development models. This paper proposes the CPA-FHA, a collaborative prediction algorithm for investment and financing networks based on improved hypergraph convolution and ant colony algorithms, by integrating TransD embedding method, hypergraph convolution, spatial feature extraction, and ant colony algorithms. The proposed method is compared and analyzed using real-world investment and financing network datasets from Chinese listed companies, Chinese financial institutions, and American listed companies. It is found that, compared to classical algorithms, the Collaborative Prediction Algorithm for Financing and Investment Network System - Forecast and Hazard Analysis (CPA-FHA) has higher accuracy and efficiency in predicting investment and financing network systems.

Keywords: improved hypergraph convolution, ant colony algorithm, investment and financing network system, collaborative forecasting

1 Introduction

General Secretary Jinping Xi emphasized the acceleration of domestic market development, the promotion of trade optimization and upgrading, the innovation of service trade mechanisms, the expansion of high-quality product imports, the establishment of service trade innovation demonstration zones, the advancement of trade innovation and development, and the high-quality joint construction of the Belt and Road Initiative. The Third Plenary Session of the 20th Central Committee adopted the "Decision of the Central Committee of the Communist Party of China on Further Comprehensively Deepening Reforms and Advancing Chinese-style Modernization" proposing the construction of a new, higher-level open economic system, clarifying the deepening of foreign trade system reforms, strengthening the coordination between trade policies and related policies, actively responding to the trends of digitalization and greening in trade, and innovating to enhance service trade [1]. The rapid development of information technology and the widespread adoption of the internet have gradually shifted investment and financing activities from offline to online networks. As a critical platform for capital flow and resource allocation, the investment and financing network system plays a vital role in establishing relationships, information matching, and risk assessment [2]. In recent years, the intensification of financial market uncertainties and the diversification of investor demands have rendered traditional investment and financing prediction methods inadequate in coping with complex environments. Additionally, the vast amounts of heterogeneous data involved in investment and financing activities have increased the complexity and challenges of prediction. Therefore, constructing efficient and intelligent prediction algorithms for investment and financing network systems has become a hot topic of interest in both academia and industry [3].

Research on Collaborative Prediction Algorithms for Investment and Financing Network Systems holds theoretical value, integrating complex network analysis, deep learning, and collaborative filtering techniques to provide novel perspectives and methods for investment and financing prediction. The study offers an innovative framework for financial intelligence algorithm research in heterogeneous network modeling,

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dynamic relationship prediction, and multi-dimensional data feature extraction. Simultaneously, it deeply explores investment and financing behavioral patterns through collaborative prediction mechanisms, providing systematic pathways for financial data analysis and network system modeling, with emphasis on multi-agent collaborative interaction characteristics and relationship dynamic evolution laws [4]. In recent years, with the rapid development of big data technology, deep learning, and graph neural networks, new approaches have been provided for the collaborative prediction of investment and financing network systems. The academic and industrial sectors invest a significant amount of time and resources in researching personalized risk control technologies for investment and financing [5-7]. There are various types of personalized prediction algorithms. The focus of research on personalized prediction algorithms for investment and financing mainly centers on how to solve the cold start problem, how to improve the accuracy of financial prediction algorithms, how to ensure a balance between the diversity and accuracy of prediction results, and the robustness of prediction algorithms, etc. [8-9].

Cold start refers to the early stages of a system's operation where new users have little to no historical information to leverage, making it difficult to provide targeted financial risk predictions. Scholars have proposed an improved matrix factorization-based recommendation prediction algorithm, fMF, to address the cold start and data sparsity issues [10]. This method constructs a decision tree where each node poses some questions to the user, adapting the inquiry based on the user's previous responses. At each node of the decision tree, relevant configuration profiles are set up, which can be continuously refined through the user's answers [11]. Researchers developed an iterative optimization algorithm that alternately optimizes decision trees and profiles. Some scholars proposed a hybrid model combining classification and similar algorithms, utilizing demographic data to identify similar user groups. Another model integrated collaborative filtering with deep learning, employing an improved simulated annealing differential evolution algorithm to extract item features and using the timeSVD++ algorithm to optimize user preferences and item features, thereby enhancing recommendation performance and alleviating the cold-start problem [12]. This paper proposes a collaborative prediction algorithm for investment and financing network systems based on improved hypergraph convolution and ant colony optimization, aiming to enhance prediction accuracy, optimize resource allocation, reduce investment risks, and provide scientific decision-making support. Combining the strengths of hypergraph convolutional networks and ant colony algorithms, it processes large-scale network data while maintaining high prediction accuracy and stability. This approach will improve investment and financing efficiency, promote the healthy development of financial markets, and generate positive economic and social impacts.

The arrangement of the subsequent parts of this article is as follows: The second part is a literature review; the third part is model construction; the fourth part is algorithm design; the fifth part is the analysis of numerical test results; and finally, the research conclusion.

2 Literature Review

With the rapid development of the internet, information overload has become increasingly severe, making it very difficult for users to obtain useful information for themselves from an endless sea of data [13]. Scholars have developed collaborative filtering systems, facilitating the emergence of personalized prediction systems. These systems utilize user-item interaction histories, such as ratings, view counts, and click-through rates, to predict information that may interest users [14]. The academic community classifies traditional collaborative filtering prediction algorithms into three categories: user-based or item-based algorithms, which complete predictions by collecting relevant information; matrix factorization-based algorithms, which represent users and items as vectors and reconstruct the interaction matrix using vector inner products; and deep learning-based algorithms, which reconstruct the representation vectors of users and items through deep learning [15]. Traditional collaborative filtering algorithms have impacted prediction performance due to their insufficient depth in information mining. Researchers proposed integrating user and item representation vectors using graph neural networks to uncover deeper-level information. This prediction algorithm significantly enhances prediction accuracy by iteratively aggregating relevant and effective information through multiple layers. The graph convolutional neural network, constructed based on graph neural networks, strengthens the capability to process non-Euclidean data, further improving the precision and efficiency of data aggregation [16].

As an important data structure, a graph can represent arbitrary relationships between data objects. Its logical structural characteristics coincide with the correlation between data multimodality [17]. Graph learning methods such as graph neural networks and knowledge graphs demonstrate advantages in the field of artificial intelligence

by establishing associations between data objects. The core lies in constructing graph data structures to learn node representations and relationships. However, when facing multimodal data, graph structures struggle to capture high-order associations, which limit graph-based multimodal data fusion [18]. Hypergraph neural networks are a fusion method based on hypergraph spectral convolution, replacing graph structures with stronger structural hypergraphs, combining the advantages of feature-level fusion with hypergraph convolution in learning high-order correlations of data, and solving the representation and learning of high-order relationships in multimodal data [19]. This method constructs and connects modal hypergraphs, fuses features, and inputs them into multimodal hypergraphs for convolution, thereby improving the performance of multimodal node classification. HGNN+ extends the convolution operation in the spatial domain, aggregates multimodal neighbor information, and optimizes the spectral domain convolution model. However, existing methods may overlook underlying node information, which affects model accuracy.

As people's research into the field of intelligent computing deepens, a category of swarm intelligence algorithms has been designed for solving optimization problems. The design of these algorithms is inspired by the simulation of the behaviors of social animals in nature [20]. Heuristic algorithms such as Ant Colony Algorithm (ACA) provide new methods for solving NP-hard problems by simulating ant foraging behavior, featuring advantages like robustness, parallel computing capability, and ease of integration with other algorithms. Initially applied to the Traveling Salesman Problem (TSP), it has since been extended to other optimization domains. However, it suffers from drawbacks such as local optima, long search times, and slow convergence. To address these issues, scholars have proposed various improvement strategies, including the elite ant colony optimization algorithm and the max-min ant system [21].

With the increasing complexity of systems, traditional analytical methods struggle to reveal multi-agent collaboration and dynamic patterns, making collaborative prediction algorithms a research hotspot for accurately forecasting key behaviors in investment and financing networks. Although current collaborative prediction algorithms for investment and financing network systems have achieved breakthroughs, they still face challenges in terms of complexity and dynamism. Future research should focus on deepening dynamic modeling, addressing data sparsity, enhancing privacy protection, integrating multimodal fusion, and improving interpretability to adapt to complex investment and financing scenarios.

3 Model Construction

3.1 Baseline Model Construction

To better obtain information between data and alleviate the problem of data sparsity, the user-project interaction graph in the investment and financing network is combined with the user/project knowledge graph to construct a collaborative knowledge graph [22]. To better handle information in collaborative knowledge graphs, the TransD embedding method is used, which can effectively identify different attribute relationships or types between entities within different triplets $CKG = \{h, r, t\}$ in collaborative knowledge graphs. And process the original collaborative knowledge graph using two mapping matrices M_{rh}, M_{rt}, as shown in equations (1) and (2).

$$M_{rh} = r_p h_\rho^T + I^{m \times n} \tag{1}$$

$$M_{rt} = r_p t_\rho^T + I^{m \times n} \tag{2}$$

Among which, M_{rh}, M_{rt} represent the mapping matrices corresponding to the head and tail entities in the collaborative knowledge graph triplets respectively, r_p representing the original CKG triplet relations, h_ρ^T and t_ρ^T represent the head entity and tail entity in the CKG triplet, respectively. $I^{m \times n}$ represents the user-item interaction matrix. It maps to the head entity and tail entity corresponding in the vector space, $h_\perp = M_{rh} h$, $t_\perp = M_{rt} t$, in which $h_\perp$ and $t_\perp$ represent the head entity and tail entity in the CKG triplet after being embedded by TransD in the vector space, h and t represent the head entity and tail entity in the CKG triplet. The scoring function and loss function corresponding to the TransD embedding method are shown in equations (3) and (4), respectively.

$$f_r\left(h,t\right)=-h_{\perp}+r-t_{\perp 2}^{2} \tag{3}$$

$$L=\sum_{\left(\{h,r,t\},\left\{h',r',t'\right\}\right)\in\left\{S,S'\right\}}\left[\gamma+f_r\left(h,t\right)-f_r\left(h',t'\right)\right]_{+} \tag{4}$$

Among which, L represents the loss function, and when the loss function approaches 0, the processing performance of the entire knowledge graph embedding module is optimal. In knowledge graphs, γ represents the minimum margin between positive and negative instances. Positive instances refer to entities that have had real interactions with users, while negative instances refer to those without historical interaction records.

To better handle the embedded collaborative knowledge graph, graph convolution is adopted as the core of the prediction model, while drawing on the LightGCN mode [8] of the processing idea, on the basis of traditional graph convolutions, the feature transformation and nonlinear activation modules have been removed, thus greatly reducing the model complexity without affecting the overall predictive performance. Traditional GCNs mainly learn node representations by embedding features on the knowledge graph, while requiring multiple convolution operations to aggregate the neighbor information of the embedded data as the representation of the target node, as shown in equation (5).

$$e_{\{u,i\}}^{k+1}=\sigma(W_1e_{\{u,i\}}^{k}+\sum_{i\in N_{\{u,i\}}}\frac{1}{\sqrt{\left|N_u\right|\left|N_i\right|}}\left(W_1e_{\{u,i\}}^{k}+W_2\left(e_i^{k}\odot e_u^{k}\right)\right) \tag{5}$$

In which, e_u^k and e_i^k represent the representations of user u and item i after passing through the k layer of embedding, respectively. The symbol σ represents the nonlinear activation function in traditional graph convolutional networks, W_1 and W_2 represent trainable weights, mainly used for feature transformation in traditional graph convolutional networks. This study optimizes based on traditional graph convolutions, removing the feature transformation and nonlinear activation modules as shown in Equation (6).

$$e_u^{(K+1)}=AGG\left(e_u^k,\left\{e_i^k:i\in N_u\right\}\right) \tag{6}$$

Among them, e_u^k and e_i^k represent the embedding representations of user u and item i after being propagated through k layers, respectively, the set of historical interaction items of user u is denoted by N_u. Here, AGG is a type of aggregation function and one of the core components of graph convolution operations. The core idea focuses on data grouping and aggregation processing. Most models contain feature transformation and nonlinear activation modules in graph convolution. Experiments demonstrate that these are effective in graph classification but increase complexity in prediction. Therefore, the AGG weighted aggregation function is adopted, removing the feature transformation and nonlinear activation modules from traditional graph convolution, as shown in equation (7).

$$e_{\{u,i\}}^{k+1}=\sum_{\{u,i\}\in N_u}\frac{1}{\sqrt{\left|N_u\right|\cdot\left|N_i\right|}}e_{\{u,i\}}^{k} \tag{7}$$

And define hypergraph $G = (v, \varepsilon)$, where the set of nodes of the hypergraph is $v = \{v_1, v_2, \ldots, v_N\}$, set of hyperedges included $\varepsilon = \{e_1, e_2, ..., e_M\}$. In a hypergraph, a hyperedge contains at least two nodes, and each hyperedge has a positive weight value W_{ee}. Hypergraphs can be represented using an incidence matrix $H\in\mathbb{R}^{N\times M}$. In a hypergraph, the degree of a node is denoted as D_{ii}. Where $D_{ii}=\sum_{e=1}^{M}W_{ee}H_{ie}$, the degree of a hyperedge is

represented as B_{ee}, Where $B_{ee} = \sum_{i=1}^{N} H_{ie}$. In a text hypergraph, nodes represent words, each word node v_i has a d dimensional attribute vector x_i, the attributes of N nodes are represented as X, then $X = [x_1, x_2, ..., x_N]^T \in \mathbb{R}^{N\times d}$. Hyperedges are sentences in a document, with each hyperedge connecting all the words in that sentence. The node attributes are initialized using Glove word vectors to obtain the embedded representation of words [23]. After constructing a text hypergraph, text feature extraction and propagation are performed using hypergraph convolutional networks. To obtain structural feature representations within the text, hypergraph convolution operations are utilized to process textual information. The definition of hypergraph convolution is shown in Equation (8).

$$x_i^{(l+1)} = Leaky\,\mathrm{Re}\,LU\left(\sum_{j=1,e=1}^{N} H_{ie}H_{je}W_{ee}x_j^{(l)}W_p\right) = Leaky\,\mathrm{Re}\,LU\left(D^{-1}HWB^{-1}H^T X^{(l)}W_p\right) \tag{8}$$

Where, $x_j^{(l)}$ is the embedding representation of node i at layer l, W_{ee} is the positive weight value for hyperedges, W_p is the weight matrix between adjacent layers, the matrix of pairwise angles for node D, B is the angle matrix for the hyperedges. $W\in\mathbb{R}^{M\times N}$ diagonal matrix is composed of positive weight values.

3.2 Network Space Feature Extraction

To effectively model the spatial dependency of investment and financing network nodes, this paper models the changes in information flow of the investment and financing network as a diffusion process of graph signals on a directed graph and employs graph diffusion networks. To address the bidirectional nature of inflow and outflow in traffic flow prediction scenarios, and to consider the transition matrix representing the bidirectional diffusion process, the model is made more flexible to capture the impacts from upstream and downstream traffic flows. The calculation process of the investment and financing risk diffusion network is shown in Equation (9).

$$\tilde{Z} = \sum_{k=0}^{K-1} D_o^{-1} A * ZW_{k1} + D_i^{-1} A^T * ZW_{k2} \tag{9}$$

Among which, K represents the number of diffusion steps, and A represents the adaptive prediction task fusion graph structure generated by the time-varying graph structure generator. And use a K order truncation to represent a finite diffusion process, and assign a trainable weight W_k for each diffusion step k. Given an input tensor $X\in\mathbb{R}^{P\times N\times C}$ representing the current traffic flow state, after extracting its temporal dimension features through a gated temporal convolutional network, intermediate spatiotemporal features $Z\in\mathbb{R}^{T\times N\times C}$ are obtained and used as input for the graph diffusion network. Combining the adjacency matrix of the graph generated by the time-varying graph structure generator, the spatial feature extraction module of the spatiotemporal layer applies a bidirectional graph diffusion network to extract the spatial features of the intermediate features $Z_t\in\mathbb{R}^{N\times C}$ at each time step.

Recurrent neural networks and their variants recursively process long sequences, which can lead to excessively long training times for the model and may cause issues with gradient vanishing or explosion. However, convolutional neural networks can perform parallel computations and can expand the receptive field by increasing the depth of convolutional layers. The dilated causal convolution operator in Temporal Convolutional Networks can be defined as shown in Equation (10).

$$x * f = \sum_{k=0}^{K-1} f_k x_{t-d\times k} \tag{10}$$

Where, $X\in\mathbb{R}^T$ represents a one-dimensional time series given at time step t, $f\in\mathbb{R}^K$ represents the convolution kernel parameters, d denotes the dilation factor, and $*$ denotes the convolution operation. By increasing the expansion factor d, the receptive field in the time domain grows exponentially, which allows time convolutional networks to capture longer time series information with only a few convolutional layers. Gated

time convolutional networks were proposed and first applied to the field of language modeling, using gated time convolutional networks to model complex temporal dependencies in traffic flow prediction tasks. It can be defined as shown in Equation (11).

$$z = \tanh\left(x * f + b\right) * \sigma\left(x * g + c\right) \tag{11}$$

Here, f and g represent learnable convolutional kernel parameters, $tanh(\cdot)$ denotes the hyperbolic tangent function, and $\sigma(\cdot)$ represents the nonlinear activation function. The Gated Time Convolutional Network eliminates irrelevant time information from historical time series for the current prediction task through the gating mechanism $\sigma(\cdot)$, selects more important time information, and uses a deep neural network model to directly perform multi-step predictions. This paper directly obtains multi-step traffic flow prediction results for all network nodes by applying stacked multilayer perceptrons and nonlinear activation functions, with the calculation process defined as shown in Equation (12).

$$\hat{X}_{(t+1):(t+Q)} = MLP\left(\mathrm{Re}\,LU\left(MLP\left(\mathrm{Re}\,LU\left(Z\right)\right)\right)\right) \tag{12}$$

Among these, the input Z represents the fused features, which are obtained by stacking the intermediate features from each spatiotemporal layer together along the feature dimension through skip connections. The jumping connection mechanism can effectively extract multi-level spatiotemporal dependency features from traffic flow data. $ReLU(\cdot)$ represents the nonlinear activation function, and $MLP(\cdot)$ represents the multilayer perceptron model.

4 Algorithm Design

4.1 Improving the Ant Colony Algorithm

In the traditional ant colony algorithm, the heuristic factor is the reciprocal of the distance from the current point to the next point, d_{ij}. Therefore, it can only reflect partial information around the current point i. In response to this situation, this article improves the original heuristic factor by taking the distance from the current point to the destination obtained using a greedy algorithm in the later stages of path searching as the new heuristic factor. The optimized heuristic factor is shown in equation (13).

$$\eta_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & \dfrac{\left|Allowed_k\right|}{n} > \lambda \\ \dfrac{1}{d_{ij} + P_{jo}} & \text{else} \end{cases} \tag{13}$$

where, d_{ij} is the distance from the current point i to the next point j, with j ($j \in Allowed_k$); P_{jo} is the path length from point j to the starting point o of the current ant, obtained using the greedy algorithm; λ is the threshold, When the ratio of the number of unvisited points $|Allowed_k|$ to the total number of points n is greater than λ, then the original heuristic factor is adopted, otherwise the improved heuristic factor proposed in this paper is used. Considering the running time of the algorithm and the ability to optimize the path, this paper concludes through simulation that when the algorithm runs to λ equals 25%, the optimization effect of using the improved heuristic factor is better. The improved heuristic factor comprehensively considers the local and global path information, reducing the probability of the algorithm falling to local optimum.

The setting of the evaporation coefficient ρ in the ant colony algorithm has a significant impact on the algorithm. In traditional algorithms, the evaporation coefficient ρ is a fixed value. If the ρ value is set improperly, it can lead to a deterioration in the ants' global search ability and a slower convergence speed. If the ρ value is too high, it can cause the ants to be unable to choose the next point based on the pheromone concentration,

increasing the randomness of path selection. If the value of ρ is too small, it will cause excessive pheromone accumulation on the path, leading to the result being trapped in local optimum [18]. Therefore, this paper has made an adaptive improvement to the evaporation of pheromone concentration, the specific method is shown in equation (14).

$$\rho(T+1)=\begin{cases}\rho_{\min} & \rho \le \rho_{\min}\\ \dfrac{T_{\max}}{T_{\max}+T} * \dfrac{1}{e^{1-\rho(T)}} & else\end{cases} \tag{14}$$

Among them, $T_{\max}$ is the maximum number of iterations; T is the current iteration count; and $\rho_{\min}$ is the minimum evaporation coefficient. The improved evaporation coefficient decreases with the increase of iteration count. In the early stages of the algorithm, the evaporation coefficient is relatively large, the pheromone concentration is low, and the interference ability to ants is small, which allows the ants to search for more paths. As the number of iterations increases, the evaporation coefficient gradually decreases, weakening the negative feedback effect, causing the pheromone residue on the paths to increase. When the iterations reach a certain number, the ants will converge on paths with higher pheromone concentrations.

The solver proposed by this research is mainly composed of a multi-layer bidirectional Transformer encoder, which mainly includes two parts: the self-attention layer and the feedforward neural network. After pre-training on a large corpus, Bert obtains the semantic features of text through fine-tuning. The calculation process of its attention is as follows: First, calculate the Query, Key; Value matrices; The dimensions of vectors in both the Query and Key matrices are d_k. The dimension of vectors in the Value matrix is d_v. Then use Softmax () for normalization to obtain the Attention matrix values. The attention calculation formula is shown in Equation (15).

$$Attention(Q,K,V)=Soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{15}$$

And by using multi-head self-attention to enhance the model's ability to express attention, the calculation process is shown in equation (16).

$$MultiHead(Q,K,V)=Concat\left(Attention\left(QW_i^Q,KW_i^K,VW_i^V\right)\right)*W^o \tag{16}$$

Where, W_i^Q, W_i^K, W_i^V are the weight matrices for $head_i$. After passing through the Transformer encoder layer, the text word feature representations processed by Bert are obtained as h_B. The improved ant colony algorithm used in this paper can be summarized as shown in Algorithm 1.

Algorithm 1. Specific steps of the improved ant colony algorithm

Input: $G(V, E)$, y, z, c, p, p', γ, *MultiHead* (Q, K, V)
Output: Predict edge set $PL(\cdot)$
01: Compute the $EG(\cdot)$ function and form the payment matrix.
02: Confirm parameters *AN*, *ATR*, *ATAR*, *SR*, *SAR*, *PP*, *SRA*, *PCRA*
03: Form the evolutionary game matrix
04: for all $v \in V$ in parallel do
05: Calculate interactive trust mechanism parameters *UserIntimacy*(·)
06: end
07: Set investment and financing network parameters $C(\cdot)$
08: Conduct adaptive improvements and calculate $\rho(T+1)$
09: Calculate the node movement probability in ant colony algorithm $P_{ij}^k(\cdot)$
10: Calculate the correction parameters $C(\cdot)*P_{ij}^k(\cdot)$
11: $PL(t') \leftarrow PL(t-1') + 1$
12: Output the edge set $PL(\cdot)$
13: end

4.2 Collaborative Prediction Algorithm

The initial item embedding representation $e_i^{g_{II}(0)}$ and the initial user embedding representation $e_u^{(0)}$ splice as s, according to [7], and the $f_{RCFM}(\cdot)$ function is used to generate a probability score for the likelihood of user interaction with the item is shown in Equation (17).

$$\hat{y}(u,i) = f_{RCFM}\left(e_i^{g_{II}*}, e_u^{(0)}, e_i^{g_{II}(0)}\right) = w + \sum_{j=1}^{|e|} w_j e_j + \sum_{j=1}^{|e|}\sum_{k=j+1}^{|e|} \langle v_j, v_k \rangle e_j e_k = f_{FM}(e) + s \tag{17}$$

Where, w represents the global deviation, w_j represents the strength of the *JTH* element in e, v_j, v_k represent the j and k dimensional vectors of the coefficient matrix in *FM*, $<v_j, v_k>$ modeling the second-order feature interactions, where $w_{ij} = <v_i, v_j>$. After obtaining the user's preference prediction score $\hat{y}(u, i)$, two enhanced views were generated using IESSLRec, built the auxiliary supervision signals for the positive and negative sample pairs, different nodes will produce different vector representations under different views. Treat embedding vectors of the same node under two enhanced views as positive sample pairs, to maximize the similarity between them, Treat the embedding vector of the node different from that node under another view as a negative sample pair, to minimize the similarity between them. For example, the embedding vectors of node i under the two enhanced views g_1 and g_2 are considered as a positive sample pair, the embedding vector of node i under the view g_1 and the embedding vector of a different node j in the enhanced view g_2 are considered as a negative sample pair, the loss function is shown in Equation (18).

$$L_{InfoNCE} = -\log \frac{\exp\left(\frac{s\left(e_i^{g_1*}, e_i^{g_2*}\right)}{\tau}\right)}{\sum_{j\in I}\exp\left(\frac{s\left(e_i^{g_1*}, e_j^{g_2*}\right)}{\tau}\right)} \tag{18}$$

Where, $s(\cdot)$ denotes the function of calculating the similarity between item vectors, and the joint optimization objective function of supervised task and self-supervised task is expressed in formula (19).

$$L_{IESSL\,Rec} = (1-\lambda) * L_{BPR} + \lambda * L_{InfoNCE} \tag{19}$$

Where, for λ important hyperparameter, represents the weight of the self-supervised contrast learning auxiliary task throughout the optimization task. The proposed algorithm can be represented as shown in Algorithm 2.

Algorithm 2. The proposed collaborative prediction algorithm of investment and financing network system based on improved hypergraph convolution and ant colony algorithm

Input: User-item interaction graph (g_{UI}), user, item (u, i), learning rate (δ), Self-supervised learning aid task weight (λ)
Output: Top-K forecast item
01: Compute Items-Item homogeneity graph g_{II}
02: Two enhanced views g_1 and g_2 are obtained
03: if initializes the user embedding vector $e_u^{(0)}$ through Xavier, Item embedding vector
04: else
05: Combine the predicted edge set $PL(\cdot)$, Calculate the item embedding vector $e_i^{g_{II}(k+1)}$ for each layer of g_{II}
06: Combine the predicted edge set $PL(\cdot)$, Calculate the item embedding vector $e_i^{g_1(k+1)}$ for each layer of g_1
07: Combine the predicted edge set $PL(\cdot)$, Calculate the item embedding vector $e_i^{g_2(k+1)}$ for each layer of g_2
08: Combine the predicted edge set $PL(\cdot)$, Calculate the item embedding vector $e_i^{g_{II}*}$, $e_i^{g_1*}$ obtained after combining layer information based on the attention mechanism.
09: end if
10: end if

5 Numerical Test

5.1 Experimental Design and Data Source

In this section, the results of the comprehensive experiments performed on real networks are presented. The results indicate that the Collaborative Prediction algorithm of the Financing network system based on improved Hypergraph convolution and Ant colony algorithm (CPA-FHA) outperforms other prediction methods. The comparison methods are as follows: (1) Linear Threshold model, LT [8], (2) Independent Cascade model, IC [9], (3) Genetic algorithm, GA [10], (4) Item Average, IA [16], (5) Ant Colony Algorithm, ACA [17], (6) Density Peaks Detection Clustering Algorithm [18] (WR-MSN), (7) Dual-channel Hypergraph Convolutional Network for Extracting Sequence Feature Embedding [12] (DHCN). Combined with literature [24], two accuracy functions are used: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and the specific calculation methods are shown in equations (20) and (21), respectively.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|f_i - y_i\right|. \tag{20}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(observed_i - predicted_i\right)^2}. \tag{21}$$

While prediction problems in investment and financing network systems are usually regarded as binary classification tasks [17] in the evaluation confusion matrix with two categories. The True Positive (TP), represents the number of correctly predicted links; The True Negative (TN), represents the number of correctly unpredicted links; The False Positive (FP), represents the number of incorrectly predicted links; The False Negative (FN), represents the number of incorrectly unpredicted links. Based on this, the following indicators can be obtained, such as True Positive Rate, Recall Rate, etc. Among them, the calculation of True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR) and Precision can be found in reference [18]. Combined with literature [19], in the experiment, user interactions are treated as hyperedges connecting items, and a hypergraph is constructed to capture users' dynamic short-term interests. The hyperparameters are set as follows: feature dimension of 64, batch size of 256, and learning rate of 0.001. Additionally, Adam is used for optimizing the model parameters, with an initial learning rate of 1E−3 for the optimizer. The training procedure used the Dropout to prevent overfitting, with the Dropout ratio set at 0.5 and the L2 regularization ratio at 0.001.

And evaluated based on the following two indicators, that is, Area Under the Receiver Operating Characteristics curve (AUROC) [2] and Average Precision (AP) [5]. The ROC curve is a curve between True Positive Rate (sensitivity) on the Y axis and the False Positive Rate (1-specificity) on the X axis, and single point summary statistics between areas [0,1] under the ROC curve, which can be calculated using the trapezoidal rule, which adds all trapezoids under the curve. The AUROC value of the link prediction method should be greater than 0.5, and the higher the AUROC value, the better the performance of the link prediction method. The average accuracy is a single-point summary value calculated based on different recall thresholds, which is the average accuracy value of the recall value in the interval [0,1]. As shown in Equation (22). Where, p represents the exact rate at different recall thresholds, R is the set of different thresholds.

$$AP = \sum_{k=1}^{R} p(k) * \Delta r(k). \tag{22}$$

In the practice of reference [20], The experiment utilizes three investment and financing network datasets (see Table 1). This paper employs Python to select 20 popular user nodes and constructs the experimental baseline data based on investment and financing data of Chinese listed companies, financial institutions, and U.S. listed companies crawled from February 12 to July 23, 2024. Each user serves as a node, with relationships between users represented by edges. Twenty influential users and their connections are selected as initial nodes to form a simple network structure. Chinese listed companies are chosen as samples to avoid data gaps. The constructed

financial risk contagion network represents the core of local financing circles, holding systemic importance for regional development and economic security, thus more accurately reflecting local industrial correlation networks [21]. The research data primarily originates from publicly available documents of listed companies and financial institutions in China and the United States, such as prospectuses and annual reports. Supplementary materials include event coverage of listing activities, particularly information on financing guarantee risks. Other information is cross-verified through at least three sources. The financing network relationship chain is defined as financing collaborations between enterprises, including equity investments and capital fundraising. The study first compiles a directory of listed companies and financial institutions in China and the U.S., then screens, organizes, and codes the data to form a preliminary network, which is subsequently expanded and supplemented using other information sources. The coding process focuses on relationships between nodes, decomposing the dataset into multiple 0-1 matrices, each representing a financing sub-network, thereby constructing real local financing networks. The financing relationship network is treated as an undirected graph and analyzed using clique percolation algorithms [22]. Using CFinder software and based on iterative regression theory, the corporate investment and financing network was analyzed to extract cliques, while statistics were collected on the number of enterprises, the number of cliques, and the quantity of external financing behaviors, revealing the relationship between the number of financial institutions and cliques. Scholars also proposed a clique percolation (CP) algorithm for extracting cliques from complex networks, extracting them in order of size and determining the value of cliques with $k > 3$ to identify cliques within the network [23-24]. The UCINET tool was finally used to build the financing network, and the centrality degree and network density were calculated.

The team implemented the proposed algorithm and the relevant algorithm for comparison on Tensorflow1.5.1. The experiment is conducted in a group, and the data is divided into 10 groups and cross-validation. That is, the data set is divided into 10 equal parts, one set of data is selected as the test set at a time, the other groups are used as the training set, and the final average [25]. The data is stored in CSV format in a MySQL database for processing. For each social network dataset, 10% of user rating data is used as the test set, while the remaining 90% serves as the training set. The experiments are conducted under the Python framework, utilizing toolkits such as Numpy, Scipy, Pandas, Matplotlib, Theano, and Surprise. Community query problems are addressed using the BasicSCS, IndexBasedSCS, and EnIndexBasedSC algorithms [26]. Experimental hardware: GPU is NVIDA TITAN RTX 24 GiB, CPU is intel ® Xeon ® Gold 5220 CPU 2.20 GHz, and RAM is 330 GiB. Software: Centos 7.9, 64-bit operating system, Python 3.8 compiler, PyTorch 1.3.1 framework, CUDA 9.2. This study set the evaluation results as the average after 1000 runs, with a standard deviation of 1.536.

Table 1. Real investment and financing network datasets used in the experiment

Network serial number	Name of the investment and financing network	Type	Number of nodes	Number of node boundaries	Average degree	Node average path	Cluster coefficient
1	Investment and financing network of Chinese listed companies	directed	328193	4195513	20.19	1.53	0.128
2	Investment and financing network of Chinese financial institutions	directed	538441	8292831	31.41	4.28	0.428
3	Investment and financing network of American listed companies	directed	129494	3929401	41.28	2.30	0.238

5.2 Experimental Results

Table 2 reports the results of the area value under the curve of real investment and financing network system collaborative prediction algorithm proposed by CPA-FHA based on the improved supergraph convolution and ant colony algorithm. This study found that the proposed CPA-FHA investment-financing network system collaborative prediction algorithm based on improved supergraph convolution and ant colony algorithm has excellent experimental results in the real investment and financing network data set. Table 3 reports the results of the average accuracy value of the proposed CPA-FHA based on the improved algorithm of supergraph convolution and ant colony in the real network data set. The results show that the proposed CPA-FHA investment

and financing network system collaborative prediction algorithm based on improved supergraph convolution and ant colony algorithm has a high average accuracy value in all real investment and financing network data sets.

Table 2. Area values under the curve in different methods for the network data sets of each investment and financing user

Cross validation level	Dataset name	Algorithm name			
		LT	IC	GA	ACA
2-fold	Investment and financing network of Chinese listed companies	0.133	0.201	0.431	0.353
	Investment and financing network of Chinese financial institutions	0.167	0.152	0.245	0.378
	Investment and financing network of American listed companies	0.190	0.175	0.374	0.397
4-fold	Investment and financing network of Chinese listed companies	0.273	0.252	0.215	0.435
	Investment and financing network of Chinese financial institutions	0.156	0.145	0.133	0.320
	Investment and financing network of American listed companies	0.252	0.135	0.243	0.154
10-fold	Investment and financing network of Chinese listed companies	0.189	0.252	0.251	0.279
	Investment and financing network of Chinese financial institutions	0.132	0.277	0.301	0.362
	Investment and financing network of American listed companies	0.201	0.189	0.254	0.199

Cross validation level	Dataset name	Algorithm name			
		IA	WR-MSN	DHCN	CPA-FHA
2-fold	Investment and financing network of Chinese listed companies	0.187	0.423	0.503	0.752
	Investment and financing network of Chinese financial institutions	0.190	0.484	0.477	0.762
	Investment and financing network of American listed companies	0.311	0.345	0.529	0.846
4-fold	Investment and financing network of Chinese listed companies	0.243	0.437	0.408	0.849
	Investment and financing network of Chinese financial institutions	0.300	0.469	0.434	0.821
	Investment and financing network of American listed companies	0.463	0.551	0.499	0.890
10-fold	Investment and financing network of Chinese listed companies	0.386	0.555	0.502	0.789
	Investment and financing network of Chinese financial institutions	0.420	0.752	0.612	0.749
	Investment and financing network of American listed companies	0.326	0.466	0.569	0.867

Note: The values shown in bold all indicate the good performance of the corresponding algorithm.

Table 3. Average accuracy values of the network data sets of each investment and financing users in different methods

Cross validation level	Dataset name	Algorithm name			
		LT	IC	GA	ACA
2-fold	Investment and financing network of Chinese listed companies	0.230	0.324	0.260	0.223
	Investment and financing network of Chinese financial institutions	0.174	0.307	0.285	0.289
	Investment and financing network of American listed companies	0.210	0.235	0.271	0.416
4-fold	Investment and financing network of Chinese listed companies	0.151	0.273	0.289	0.343
	Investment and financing network of Chinese financial institutions	0.257	0.235	0.279	0.290
	Investment and financing network of American listed companies	0.170	0.292	0.331	0.322
10-fold	Investment and financing network of Chinese listed companies	0.149	0.282	0.315	0.306
	Investment and financing network of Chinese financial institutions	0.159	0.244	0.292	0.353
	Investment and financing network of American listed companies	0.176	0.310	0.272	0.360

Cross validation level	Dataset name	Algorithm name			
		IA	WR-MSN	DHCN	CPA-FHA
2-fold	Investment and financing network of Chinese listed companies	0.242	0.337	0.462	0.834
	Investment and financing network of Chinese financial institutions	0.260	0.388	0.523	0.856
	Investment and financing network of American listed companies	0.286	0.350	0.489	0.856
4-fold	Investment and financing network of Chinese listed companies	0.260	0.457	0.517	0.845
	Investment and financing network of Chinese financial institutions	0.251	0.895	0.522	0.846
	Investment and financing network of American listed companies	0.320	0.390	0.507	0.787
10-fold	Investment and financing network of Chinese listed companies	0.286	0.337	0.512	0.797
	Investment and financing network of Chinese financial institutions	0.298	0.418	0.526	0.855
	Investment and financing network of American listed companies	0.394	0.403	0.528	0.780

Note: The values shown in bold all indicate the good performance of the corresponding algorithm.

This paper demonstrates the performance of the CPA-FHA method based on improved hypergraph convolution and ant colony optimization in real-world investment and financing network datasets. Experimental results indicate that the proposed approach achieves significant improvements in RMSE and MAE metrics compared to other methods, with enhancements ranging from 20%-50% and 15%-55% respectively. Furthermore, the CPA-FHA algorithm exhibits stable performance gains across different fold counts, validating its generalization capability and robustness. Particularly when processing complex investment and financing network data, the

algorithm demonstrates distinct advantages, providing an effective tool for predictive analysis and showcasing its application potential in this field.

Table 4 presents the comparison results of prediction errors for different algorithms on three real investment and financing network datasets (Chinese listed companies, Chinese financial institutions Broussonetia papyrifera, and U.S. listed companies) of Phoxinus phoxinus subsp. phoxinus, using root mean square error (RMSE) and mean absolute error (MAE) as evaluation metrics. As shown in the table, the CPA-FHA algorithm proposed in this paper achieved the lowest RMSE and MAE values across all three datasets, significantly outperforming other comparative algorithms. On the Chinese listed companies dataset, CPA-FHA recorded RMSE and MAE values of 0.333 and 0.299 respectively, far lower than those of other algorithms, demonstrating its significant advantages in prediction accuracy and stability.

Table 5 shows that the CPA-FHA algorithm, which combines improved hypergraph convolution and ant colony optimization, demonstrates superior overall performance compared to other benchmark methods. The algorithm's advantages lie in its rapid response to social network changes, real-time adjustment capability, and minimization of dataset loss. CPA-FHA exhibits outstanding performance in investment and financing network prediction, surpassing other methods in both performance and applicability.

Table 4. Compares the results of the algorithms based on RMSE and MAE

Algorithm name	Investment and financing network of Chinese listed companies		Investment and financing network of Chinese financial institutions		Investment and financing network of American listed companies	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
LT	0.922	0.924	0.894	0.846	0.912	0.870
IC	0.932	0.904	0.885	0.792	0.893	0.854
GA	0.838	0.827	0.876	0.752	0.787	0.778
ACA	0.723	0.745	0.864	0.749	0.836	0.664
IA	0.623	0.733	0.762	0.694	0.758	0.594
WR-MSN	0.590	0.642	0.678	0.650	0.711	0.583
DHCN	0.499	0.496	0.602	0.496	0.687	0.376
CPA-FHA	0.333	0.299	0.293	0.299	0.293	0.272

Note: The values shown in bold all indicate that the corresponding model performs well.

Table 5. Comparison results of algorithm running time of different investment and financing networks

Dataset name	LT	IC	GA	ACA
Investment and financing network of Chinese listed companies	2995.943	2759.395	1774.464	855.191
Investment and financing network of Chinese financial institutions	3267.009	2472.532	1814.167	1100.924
Investment and financing network of American listed companies	2645.726	3856.334	2198.463	1005.466
Dataset name	IA	WR-MSN	DHCN	CPA-FHA
Investment and financing network of Chinese listed companies	442.167	383.527	198.284	48.409
Investment and financing network of Chinese financial institutions	205.827	225.598	217.523	27.649
Investment and financing network of American listed companies	264.226	268.942	160.116	35.074

Note: The values shown in bold all indicate that the corresponding algorithm performs well.

6 Research Conclusions

Investment and financing network prediction is a key research direction in the field of fintech. Its goal is to predict the possible capital flow, investment relationship matching and potential risk in the investment and financing network through big data and intelligent algorithm [27]. In the current complex economic and financial

environment, investment and financing activities show the characteristics of network, dynamic and intelligence [28]. This study proposes a collaborative prediction model (CPA-FHA) based on an improved hypergraph convolutional network and ant colony algorithm optimization to address the complexity and dynamics of investment and financing network systems in financial markets. The model integrates TransD embedding technology, hypergraph convolutional neural networks, and ant colony algorithm optimization techniques to extract multidimensional data features and predict dynamic relationships within investment and financing networks. Validation was conducted using multiple real-world investment and financing network datasets, including Chinese listed companies, Chinese financial institutions, and U.S. listed companies.

The collaborative prediction model (CPA-FHA) is specifically designed for the complex and dynamic characteristics of financial market investment and financing network systems. By integrating TransD embedding technology, hypergraph convolutional neural networks, and ant colony algorithm optimization, it effectively extracts multidimensional data features and predicts dynamic relationships. Model validation demonstrates that CPA-FHA outperforms traditional methods in prediction accuracy and efficiency, achieving a 20%–50% improvement in accuracy while significantly reducing runtime. The model effectively captures high-order correlations and dynamic patterns in financial networks, providing theoretical and technical support for fintech applications. Future optimizations may focus on privacy protection, data fusion, and algorithm interpretability.

To facilitate practical application, financial institutions are advised to accelerate the adoption of intelligent algorithms to enhance resource allocation efficiency, improve data collection and integration mechanisms, optimize cold-start strategies and dynamic evolution prediction, and establish real-time tracking and personalized recommendation mechanisms. Enhancing algorithm interpretability can increase prediction transparency. Policy support and industry collaboration are recommended to promote technology implementation, while international cooperation should be strengthened to expand algorithmic capabilities. Building intelligent risk control systems to manage investment and financing risks, as well as fostering talent development and technical exchanges, will provide sustained support for fintech innovation.

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