Journal of Computers Vol. 37 No. 1, February 2026, pp. 173-184
https://doi.org/10.63367/199115992026023701011

Research on Ant Colony Link Prediction Algorithm of Cross-border Social E-commerce Based on Trust Community Mechanism

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Received 1 January 2025; Revised 27 April 2025; Accepted 28 April 2025

Abstract. In recent years, with the rapid development of information technology, social e-commerce has become the main place for users to buy goods, and effective link prediction and recommendation in social e-commerce environment has played an important role in the directions of academic circles. In this research, combining with the credit mechanism, the traditional infectious disease model is used for modeling of the trade route of Chinese cross-border social e-commerce. Based on the link prediction method, social network data sets and efficient ant colony optimization algorithm, the solution of the model in this study is realized. Under data sets from cross-border social e-commerce platforms such as Amazon, Netflix, and Facebook, TCAC-LP method has obvious advantages over other algorithms in terms of some error analysis values, accuracy, recall rate, F1 value, etc., which well reflects the high accuracy and precision of TCAC-LP method. Hence, some practical and effective suggestions for international social e-commerce trade can be provided from the perspective of customer evaluation emotion and psychological needs.

Keywords: value transfer, information dissemination, trust mechanism, social e-commerce, link prediction, ant colony algorithm

1 Introduction

According to the data of *Data Report of Cross-border E-commerce Market in the First Half of 2022*, Chinese cross-border e-commerce market reached RMB 7.1 trillion in the first half of 2022, accounting for 35.86% of the value from imports and exports which belong to Chinese commodity transaction in the first half of 2022, which was amounted to RMB 19.8 trillion. It is estimated that the market size will reach RMB 15.7 trillion in 2022, an increase of 10.5% compared with the market size of RMB 14.2 trillion in 2021. Thanks to the global Internet economy which has developed in a high speed and a great number of preferential policies which has been introduced by Chinese government to provide support for the cross-border e-commerce, so that they bring the high speed of development for cross-border social e-commerce. Currently, cross-border e-commerce platforms are actively expanding their presence in Southeast Asia, Europe, and North America through localized operations and strategic partnerships. Meanwhile, Chinese merchants are leveraging social media and influencer marketing to engage global consumers, particularly through live streaming and interactive content formats. The integration of artificial intelligence and big data analytics has also become a standard practice for optimizing inventory management, personalizing product recommendations, and improving logistics efficiency.

Since 2020, because of the influence which comes from the COVID-19 epidemic, the global retail chain has undergone tremendous changes. The online shopping demand of consumers has surged, and the global online retail has entered a period of rapid growth. With the intensification of competition, enterprises are forced

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to transform and upgrade for branding [1-2]. In addition, with the increasing diversification and personalized needs of overseas users, cross-border e-commerce companies are urged to seek more diversified trading ways to make overseas users achieve their needs [3]. However, how cross-border e-commerce companies can improve cross-border users' not only interaction but stickiness, meet customers' evaluation emotion and psychological needs with the increasing seller credit on E-commerce platforms, and enhance consumers' shopping experience to finally obtain higher customer retention and enhance brand value has become an urgent problem for numerous cross-border e-commerce companies. The main way to solve this problem is cross-border social e-commerce platform. There are many social media platforms having become important traffic portals for cross-border social e-commerce companies, for example, such as Facebook, Instagram, YouTube, Tik Tok and Twitter. Therefore, researching cross-border social e-commerce link prediction method based on trust community mechanism is quite significant when practicing and applying. The application scenarios of cross-border social e-commerce enterprises in the trade process, studying the method to optimize and match shared resources and efficiently schedule tasks is the research core for this paper. By taking advantage of the decentralization, consensus mechanism, incentive mechanism and smart contract characteristics of blockchain technology, mode innovation is achieved from the aspects of trust mechanism, sharing security and value transfer, and a high-credit and high-security social e-commerce capacity sharing platform and the governance mechanism have been established [4].

Community trust mechanism refers to a kind of trust mechanism that takes space as the boundary rather than human boundary in social networks, which shows the degree of trust between people within a certain range of space. While the community trust mechanism in social e-commerce can be expressed as a certain degree of trust generated by users for communication and communication in social platforms [5], which is also the basis for the development of social e-commerce. Social e-commerce refers to a new e-commerce way of commodity trade through communication and interaction on some network platforms according to the social relations in the network platform. It uses the powerful Internet and active users in the social platform for a long time to recommend products to the appropriate users, so as to improve the business rate of products. In social e-commerce platforms, the community trust mechanism is constructed through multi-dimensional factors such as user interaction frequency, content quality evaluation, and transaction history records. Advanced algorithms analyze user behavior patterns to identify opinion leaders and trustworthy nodes, forming decentralized trust networks. Social e-commerce has various characteristics, fast sales speed, wide range of users, obvious social elements and shopping guide effect, and is the practical application of science and technology in the information age.

Ant colony algorithm is a heuristic bionic optimization algorithm proposed by Italian scholars such as M. Dorigo and Maniezzo to get inspiration from observing ant colony foraging behavior. By means of global search, Ant colony algorithm can reduce the risk of traditional optimization algorithms falling into local optimal solutions in the process of solving, and because of its self-organization, distribution, global parallelism and other characteristics, Ant colony algorithm performs well in resource scheduling and other aspects of excellent performance. Moreover, Ant colony algorithm has many advantages, such as: it has strong self-organization and positive feedback, has distributed and parallel characteristics, good reliability, and is easy to combine with other algorithms [6].

This study employs traditional infectious disease modeling techniques and combines them with an innovative credit mechanism, leveraging the powerful capabilities of ant colony algorithms to design a method that is both efficient and accurate for predicting the local structure of community information links on social e-commerce platforms. The method aims to address and overcome challenges related to forecasting the future trend development of cross-border social e-commerce, thereby providing a solid solution to an increasingly important issue in the digital market. At the same time, this method combines the path search mechanism of the ant colony algorithm with the propagation dynamics of the infectious disease model to simulate the information diffusion pattern in the social e-commerce ecosystem. By assigning credit values to nodes based on transaction credibility and content quality, the algorithm dynamically adjusts the pheromone concentration to prioritize the identification of high-quality information links. This method can effectively identify key opinion leaders and influential nodes, helping merchants optimize marketing strategies and enhance user stickiness in cross-border transactions.

2 Literature Review

With the Internet developing quickly, the social link prediction in application has been constantly expanded, and link prediction has been applied to predict unknown links of social e-commerce in order to help merchants on the e-commerce platform to conduct psychological needs analysis based on customers' existing evaluation, so as to better build merchants' credit and improve the profits obtained from cross-border e-commerce. Some research results on link prediction from other researchers are as follows. For the purpose of clarify the network behavior how to evolve, Li et al. [7] put forward one kind of link prediction method according to learning automata and firefly algorithm. The experiments which combine real data show that FA-LP method has higher accuracy and better stability. After considering the effect of link direction, Pastor-Satorras et al. [8] extended the algorithm based on common neighbor (CN) to the algorithm based on direction pattern, and added the weight and time information of the link, effectively utilizing the institutional information of the network and further improved the accuracy of link prediction. Afassinou et al. [9], on the basis of the past, considers the role of common neighbors which are located between a pair of connected nodes and adds other nodes' role in the local community where the nodes are located into the influencing factors. Using rough similarity set theory and rough similarity, the knowledge is classified by the inherent in-degree and out-degree sets of nodes. This study will propose innovative link prediction algorithms to provide development solutions for cross-border social e-commerce.

Some scholars believe that graph embedding-based link prediction ensemble models are one of the important research hotspots in complex network studies in recent years. A graph embedding-based link prediction ensemble model is a powerful tool that can deeply mine the intrinsic features of graph data and predict the future connection state between nodes. The core idea of link prediction is to predict whether there will be a new relationship between two nodes or to discover hidden links in the network [10]. In addition, many studies have used graph embedding methods for link prediction, effectively retaining the network structure and converting node information into low-dimensional vector space. It has shown great application value in many aspects, such as social networks and e-commerce.

This study is to provide scientific and effective directional suggestions for the development of social e-commerce through the link prediction method, and the link prediction of this study is conducted in social networks, so some other researchers' research results on link networks are mentioned here. Soundarajan et al. [11] designed two efficient incremental dynamic algorithms to improve users' loyalty and experience in the dynamic network, which established a potential space for each node in the network, and then predicted the future links according to the potential space position of each node, so as to improve the prediction accuracy for a long time. Aghabozorgi et al. [12] proposed that the strength should be assigned to the links in the weighted directed network to predict the future dominant nodes. Therefore, getting all the attribute data about a social e-commerce in real life is very hard, and the link prediction in the future social environment should make full use of the methods of node similarity, likelihood analysis and weighting to build a complex network evolution model. These all provide ideas for the research of link prediction in cross-border social e-commerce.

In order to further develop our research on social e-commerce link prediction and clarify the trust community mechanism mentioned, some relevant research from other scholars was mentioned. To improve users' experience in the social e-commerce environment and spread the positive product information in the social e-commerce environment, Jiang et al [13] put forward SISR (Susceptibility-Infection-Susceptibility-Recovery) model, in which users who receive social e-commerce information will not enter the immune state. Ahmed et al [14] found that the trust degree and speed of social e-commerce products can be effectively improved by enhancing users' subjective identity, trust degree and expert effect. It is not easy to find a central authority that can not only spread social e-commerce information but also be accepted by most users, so the friendship among users can be regarded as another source to enhance users' awareness. With regard to the domain relationship, Sa et al. [15] studied the domain model to release the social e-commerce information trusted by users, however, they did not take the concept of trust between users into consideration. Xu et al. [16] analyzed the designed e-commerce information dissemination based on the evolutionary game framework, and believed that users thought that social e-commerce information dissemination is bound to face the risk of being punished. Besides, the results have revealed the effective influence of the designed e-commerce information dissemination after advance the ability of making judgment or the cost of punishment. However, most existing studies think that users only accept social e-commerce messages from neighboring nodes, while ignoring the trust among friends. These demonstrate the effectiveness and reliability of the Community trust mechanism in cross-border social e-commerce. Hsu and colleagues [17] believe that companies use social media to reach new markets by engaging potential global buyers, expanding their target markets, and increasing brand awareness. Cross-border social commerce is an emerging business model. Studies on cross-border e-commerce suggest that perceived risk is a key factor that reduces individuals' willingness to purchase unfamiliar foreign products, thus necessitating the mitigation of perceived risk through trust transfer.

After an in-depth analysis of the work of other researchers, the distinctive feature of this study lies in its focus on constructing more precise and efficient models and algorithms to predict the future development trends of cross-border social e-commerce. By employing these advanced tools and methods, the market dynamics and consumer behaviors can be more accurately grasped, providing strong support and guidance for the future development strategies of cross-border social e-commerce. This not only helps companies to formulate more scientifically sound strategic plans but also enables consumers to receive more personalized and high-quality service experiences. Furthermore, this study aims to fill in the gaps identified in existing research by addressing the limitations and challenges faced by cross-border social e-commerce. By leveraging a comprehensive understanding of the literature, this research endeavors to propose innovative solutions and insights that can contribute to the advancement of the field. The integration of diverse perspectives and methodologies from various disciplines ensures a holistic approach to understanding the complexities of cross-border social e-commerce. Ultimately, this study seeks to provide a robust framework for future research and practice in this rapidly evolving domain.

3 Model Building and Algorithm Design

3.1 Model Building

In the classical evolutionary game model, the two sides put forward a static strategy game based on specific rules [12]. Evolutionary game is a game repeatedly played by players randomly selected from a large number of users. The whole population becomes dynamic and stable with time [18-19].

With regard to this research, one kind of evolutionary game model has been built based on social e-commerce graph. Firstly, it is necessary to model the process of spreading/ counter-spreading information in social e-commerce environment. It is considered to cite three user states: spreader (s), rebutter (r) and ignorant (i). Equation (1) shows the evolution model matrix. Wherein, *AN* is the general anxiety state of users; *ATR* is the general attitude of users towards social e-commerce information; *ATAR* tells the general attitude of users towards e-commerce trust information; *SR* describes the strength of social e-commerce information; *SAR* describes the strength of social e-commerce information; *PP* is the probability whether users participate in the discussions; *PCRA* is the probability of users consulting authoritative subjects; *SRA* is the influence of social e-commerce authoritative subjects; are respectively control parameters of the word-of-mouth correction mechanism of social e-commerce authority trust; *c* is the overall control parameters of the proposed TRP control model. The parameters which belong to the profitability matrix have been simplified and merged into variables E_s, E_r, E_i. Among them, E_s is the sum of social e-commerce intensity, users' general attitude towards social e-commerce and their attention state; E_r is the sum of trust information intensity and users' general attitude towards trust information; E_i is the difference between 1 and E_s, E_r. After the social e-commerce information is spread, it can continue to evolve or be removed from the group according to the payment matrix parameters.

$$EG(\bullet)=\begin{array}{c c} & \begin{array}{ccc} S & R & I \end{array} \\ \begin{array}{c} S \\ R \\ I \end{array} & \begin{pmatrix} 0 & (SR+ATR+AN-SAR-ATAR)/3 & 0 \\ (SAR+ATAR-SR-ATR-AN)/3 & 0 & 0 \\ (1-SAR-ATAR-2SR-2ATR-2AN)/3 & (1-2SAR-2ATAR-SR-ATR-AN)/2 & 0 \end{pmatrix} \end{array} \quad (1)$$

In this study, it is believed that trust word-of-mouth correction is an effective communication method of social e-commerce. Thus, introducing the social e-commerce trust model is supposed to. In addition, the evolutionary game method is adopted to include the social e-commerce control mechanism considering the trust mechanism. The graph $G = (V, E)$ can usually represent E-commerce, in which V can be described as the set about users and E can be described as the link set. In this study, consulting users' trusted friends is the way to control the spread of social e-commerce. The nodes which own interests in social e-commerce information are Users' trusted friends, which often have a strong willingness to cooperate in the interaction about social e-commerce. Choosing trusted friends is an important part for the proposed social e-commerce control model, and the important factor to consider is the word-of-mouth correction mechanism that friends respond to users' inquiries about social e-commerce. Therefore, through the calculation of interactive trust mechanism (*UserIntimacy*) and professional trust mechanism (*UserAuthority*), friends who have strong links when answering questions can be found. Interactive trust mechanism and professional trust mechanism can be used for measurement. Interactive trust mechanism refers to the similarity obtained by users according to their common relationship. The stronger the interactive trust, the more likely friends are to respond to users' interaction needs. Trust mechanism parameters are shown in Equation (2).

$$UserIntimacy(\bullet) = [Simility(u,o) + Simility(u,i))] / 2 \quad (2)$$

Among it, u and o represent the two sides of friend interaction respectively, and u, $o \in A$. The vector *Simility* (u, o) is the cosine similarity of outgoing friend number in user degree link, and the vector *Simility* (u, i) is the cosine similarity of incoming friend number in user degree link. Because the number of in-degree between users is different from the one for out-degree links between users, the above two functions are not equal, and they need to be calculated separately and averaged. The professional trust mechanism can also be used to measure users' trust in word-of-mouth correction. The more authoritative a user node is, the faster it will respond to interaction. The user's authority depends on the historical interaction information between users. In this study, the reposts, browsings, likes and replies of consulted expert users are used to measure the degree of trust of users in their friends. The social authority between the consultation request user u and his friend f_i in the social e-commerce environment can be defined as shown in Equation (3).

$$UserAuthority(\bullet) = [\sum(\frac{Retweet(u,o,n)}{\max Retweet(A)} + \frac{Browse(u,o,n)}{\max Browse(A)} + \frac{Like(u,o,n)}{\max Like(A)} + \frac{Reply(u,o,n)}{\max Reply(A)})] / 4 \quad (3)$$

Among it, *Retweet* (u, o, n), *Browse* (u, o, n), *Like* (u, o, n), *Reply* (u, o, n) are respectively the reposts, browsings, likes and replies of the consulted users, and n is the number of published social e-commerce information. *MaxRetweet* (A), *maxBrowse* (A), *maxLike* (A), *maxReply* (A) are respectively the maximum repost, the maximum browsing, the maximum like and the maximum reply of all users in the set. The friends of users who own interests in social e-commerce information are trusted friends, and they usually have a high degree of interactive trust and professional trust in interaction request users, while the *Trust* (·) of consultation request user u in friend o can be calculated by Equation (4).

$$Trust(u,o,n) = y * UserIntimacy(\bullet) + z * UserAuthority(\bullet) \quad (4)$$

Among it, y, z respectively represent the importance weights of repost, browsing, like and reply, etc. In practice, the above coefficients can be optimized based on actual data training.

3.2 Algorithm Design

Based on the above-mentioned trust mechanism, the neighborhood of nodes and community information are coupled to form an overall mechanism to realize link prediction under uncertain conditions. Local measurement is often considered to be simple and universal, and the effectiveness of prediction has been proved in many social network fields [20]. Therefore, there are more probabilities that links which connect similar nodes exist. On the contrary, when locating in plenty of social networks which are real, compared with those who have no common characteristics, participants with similar experiences or points of interest are more likely to be related to each other, so community information can better reflect the connection between nodes and effectively improve not only the efficiency but the accuracy which belongs to link prediction. On top of that, two types of evidences about whether edges exist are as follows: firstly, if no one knows whether a link exists actually, the uncertainty can be quantified for each edge. In the second case, the existence of the link is unknown. That is, there is no quality function at the edge. Based on this, the link prediction system which is structured in this paper takes the above two situations into consideration, and optimizes the link prediction method by combining local topology information and community membership information so that it can be more in line with the research background of cross-border social e-commerce.

Therefore, the link prediction problem under uncertain conditions proposed in this study can be designed as follows: $\mathcal{G}^e(\mathcal{V}^e, \mathcal{E}^e, \mathcal{C}^e)$ is set as a social network model based on evidence theory. Among it, $\mathcal{V}^e=\{v_1, ..., v_{|v|}\}$ is node set; $\mathcal{E}^e = \{(v_iv_j, m^{v_iv_j} * Trust\ (u, o, n)), m: 2^{\Theta v_iv_j} \rightarrow [0,1]$, and $Trust\ (u, o, n) * \Theta v_iv_j = \{E_{v_iv_j}, \neg E_{v_iv_j}\}\}$ is a specified sedge set; $C(\cdot) = \{C_1, \ldots, C_{|C|}\}$ is a set which combines overlapping communities. L is the set which combines analyzed links. There may be no initial set of links in L. Updating or estimating the initial set which combines query links based on whether the prior information about the query links exists, and predicting links with the help of considering the information of local structure and community are the goals which are hoped to achieve.

The ant colony algorithm is substituted into the social network environment which integrates the community mechanism. Q is the pheromone enhancement coefficient of the pheromone increment on the adjustment path, and L_k is defined as the length which belongs to the object discovered by the k-th ant. For this research, the classical ant colony algorithm is optimized, so that the ants are more eager to decide the path with low pheromone quantity as their choices, and are able to explore more unexplored parts of the graph. That is, equation (5) shows the percentage of the probability of ant k moving between node i and node j.

$$P_{ij}^{k}(\bullet)=\frac{\left(\frac{1}{\tau_{ij}}\right)^{\alpha}}{\sum_{L\in N_i^k}\left(\frac{1}{\tau_{ij}}\right)^{\alpha}},i,j\in allowed_k \tag{5}$$

Combined with ant colony algorithm, the steps of link prediction method for predicting node pair (u, v) are shown below. The proposed algorithm of Trust Community Ant Colony Link Prediction (TCAC-LP) is summarized according to whether there is prior knowledge about u, v, as shown below.

Algorithm 1. Specific steps of the proposed trust community link prediction algorithm

Input: $G(V, E)$, y, z, c, p, p', γ, $Trust\ (u, o, n)$
Output: prediction edge set $PL(\cdot)$
01: Calculate $EG(\cdot)$ and form a payment matrix
02: **repeat**
03: Confirm parameters AN, ATR, $ATAR$, SR, SAR, PP, SRA, $PCRA$
04. Form an evolutionary game matrix
05: **for all** $v \in V$ in **parallel do**
06: Calculate the parameter $UserIntimacy\ (\cdot)$ of interactive trust mechanism
07: Calculate the authority $UserAuthority\ (\cdot)$ of social trust
08: Calculate the trust degree $Trust\ (\cdot)$
09: **end**
10: Set community parameters $C\ (\cdot)$
11. Calculate the moving probability $P_{ij}^{k}(\cdot)$ of nodes in ant colony algorithm.
12. Calculate the correction parameter $C\ (\cdot) * P_{ij}^{k}(\cdot)$
13: $PL(t') \leftarrow PL(t-1')+1$
14: Output edge set $PL(\cdot)$
15: **end**

4 Experimental Results

4.1 Data Description and Experiment Settings

For the sake of proving the excellent efficiency of the TCAC-LP method developed in this study, the real social e-commerce data sets are used for numerical simulation to observe the adaptability of the model to the real situation. According to the practice of Reference [14], the real network data sets are used in the experiment.

Amazon was chosen as the source of experimental data because it is the largest online e-commerce company in the United States and has a leading representative position in the social e-commerce industry worldwide. In the past few decades of Amazon's operation, it has been selling products through e-commerce and has begun to accept social comments from consumers. People around the world's comments on Amazon's sales services, product quality, etc. are an important manifestation of the achievements of social e-commerce. With the development of the times and science and technology, Amazon has also added social shopping functions on its platform, which makes the social e-commerce comment data on the Amazon platform effectively reflect the effectiveness of social e-commerce and can be a representative symbol of social e-commerce.

The reason for choosing Facebook as the experimental data is that Facebook is a social networking service website, and its main functions on the internet are developed and expanded based on social methods. Similar to Amazon, Facebook has launched its own Facebook store model, where merchants conduct social e-commerce transactions in a more convenient and socially distinctive way by sending product information on their social accounts. Facebook, combined with its vast number of social accounts and leading position in online socializing, not only provides users with a better dual experience of social and e-commerce shopping, but this social e-commerce method also brings new hope to the new cross-border e-commerce. Therefore, social e-commerce data originating from Facebook can significantly represent the current development status and future trends of cross-border social e-commerce.

Netflix, a streaming platform in the United States, is the world's largest audiovisual streaming giant and, like Amazon and Facebook, is a giant enterprise in the field of network technology. Netflix has ventured into the field of social cross-border e-commerce by adding e-commerce advertisements in movies and TV series, and with the support of a large amount of funds, it has gained a foothold and grown in the field of social e-commerce. Choosing Netflix's social e-commerce data for this study has significant representativeness in social e-commerce and provides positive guidance for the successful development of future social e-commerce enterprise platforms.

Amazon, Facebook, and Netflix are all new leaders in cross-border social e-commerce, and they have achieved excellent performance in cross-border social e-commerce. Choosing them as experimental data for this study can greatly enhance the effectiveness and symbolism of this study, and can truly and effectively lead and guide the development of future cross-border social e-commerce trends. As we all know, people live in interpersonal communication, daily life and social activities are closely related, and some activity records of users in daily life fully reflect the characteristics of social interaction, so we choose data sets on these large platforms as the research basis of cross-border social e-commerce.

The Amazon, Facebook, and Netflix data sets used in this study exhibit social attributes in network structure, fully reflecting their social connections at the e-commerce level. Amazon's various users have established social relationships through product reviews, browsing reviews, and other methods, and have built a social e-commerce framework through product transactions. Facebook users establish social relationships through content sharing, multimedia interaction, and other methods, and implement social e-commerce based on Marketplace functions and shop stores. Netflix has performed well in overseas marketing of social media, combining user preferences for content recommendation and interaction, and adding e-commerce business based on existing social advantages. Therefore, each node from these three data sets has social attributes and establishes connections based on social interactions and e-commerce. Their social attributes at the e-commerce level can be explained from the perspectives of local topology, degree centrality, feature vector centrality, community structure, etc.

In this study, Python software is used with 30 recent hot purchase user nodes as initial nodes to crawl user data sets from Amazon, Facebook and NetFlix platforms as the basic data of experimental simulation (crawling time is from July 23, 2022 to August 21, 2022). The specific information is shown in Table 1.

Our research team used Tensorflow1.5.1 to implement the algorithm proposed in this paper and related algorithms for comparison. The experiment was conducted in groups, and the data were equally divided into 10 groups. Cross-validation was adopted, that is, dividing data sets and making sure that they can become 10 parts which are equal. From one time to the next, the data belonging to one group was aggregated into the set for testing, and the other groups were aggregated into the set for training. Finally, it was needed to take the average value. For the network data set, 10% of each user's rating data was randomly selected as the test set by using Rapidminer data mining tool, and the remaining 90% of user data was used as the training set. Since the graph coloring solution algorithm in the experiment may have different results every time it runs, the evaluation result of the algorithm was set as the average value after 10000 iterations, and the standard deviation of running was 1.493. The process of transforming a directed graph into a weighted undirected graph was carried out under the compiling environment of Matlab7.0. [8] The TCAC-LP method mentioned in this research was taken with the following algorithms: (1) CN [8], (2) JC [8], (3) AA [7], (4) RA [2], (5) CNG [9] and (6) WOCG [17] for comparison.

Table 1. Social network data set

Network serial number	Social network name	Type	Number of nodes	Number of node edges	Average degree	Average path of nodes	Clustering coefficient
1	Amazon	Directed	32711	829383	28.31	3.23	0.492
2	Facebook	Directed	52422	728192	17.14	4.19	0.472
3	NetFlix	Directed	42812	901932	31.29	5.09	0.529

4.2 Experimental Results

Table 2 to Table 4 reports the comparison results of RMSE, MAE and AUROC indexes between TCAC-LP method and other classical algorithms the real social e-commerce network data sets. It is not difficult to find that the RMSE and MAE values of the TCAC-LP algorithm are significantly lower than those of the other six algorithms in the Amazon, Netflix, and Facebook data sets, which fully demonstrates that the TCAC-LP algorithm can maintain excellent low error rates when facing different types of cross-border social e-commerce data. At the same time, the AUROC value of the TCAC-LP algorithm also performs well among the seven algorithms, indicating that the TCAC-LP algorithm will bring higher prediction efficiency. It can better solve the link prediction problems when locating at the real social e-commerce environment with higher accuracy.

Table 2. Comparison results of Amazon data set in different link prediction methods

Index name	CN	JC	AA	RA	CNG	WOCG	TCAC-LP
RMSE	0.8263	0.7459	0.7391	0.6649	0.6371	0.5281	**0.2526**
MAE	0.7942	0.7162	0.6403	0.5728	0.5289	0.4727	**0.2143**
AUROC	0.2128	0.3184	0.4628	0.6728	0.6911	0.6702	**0.8172**

Note: The values shown in bold indicate that the corresponding algorithm has good performance.

Table 3. Comparison results of Netflix data set in different link prediction methods

Index name	CN	JC	AA	RA	CNG	WOCG	TCAC-LP
RMSE	0.7693	0.7293	0.7342	0.6748	0.5829	0.5233	**0.3242**
MAE	0.7863	0.7481	0.7211	0.6820	0.5922	0.5431	**0.2849**
AUROC	0.8584	0.8193	0.8038	0.6283	0.5860	0.5054	**0.2685**

Note: The values shown in bold indicate that the corresponding algorithm has good performance.

Table 4. Comparison results of Facebook data set in different link prediction methods

Index name	CN	JC	AA	RA	CNG	WOCG	TCAC-LP
RMSE	0.7438	0.6839	0.7342	0.7938	0.5738	0.5386	**0.2019**
MAE	0.7629	0.8922	0.7211	0.6491	0.6011	0.5081	**0.2480**
AUROC	0.9019	0.8048	0.8038	0.7039	0.5273	0.4928	**0.2548**

Note: The values shown in bold indicate that the corresponding algorithm has good performance.

In addition, precision, recall rate and F1 value calculation methods are used to further compare the algorithms in this study. Among them, True Positive (TP) indicates the number which can predict links correctly; True Negative (TN) indicates the correct number whose links are unpredictable; False Positive (FP) indicates the number whose links are mispredicted; then False Negative (FN) indicates the number of wrong unpredictable links. For the sake of observing the experimental results, Table 5 to Table 7 have shown them clearly. Obviously, the proposed TCAC-LP method has better accuracy than other algorithms.

Table 5. Accuracy analysis of Amazon data set in different link prediction methods

Index name	CN	JC	AA	RA	CNG	WOCG	TCAC-LP
Accuracy	0.4392	0.5281	0.5383	0.5281	0.6192	0.5829	**0.8293**
Recall rate	0.3812	0.3284	0.6201	0.4285	0.3182	0.7829	**0.8675**
F1 value	0.4281	0.2425	0.5282	0.4284	0.5820	0.5290	**0.8294**

Note: The values shown in bold indicate that the corresponding algorithm has good performance.

Table 6. Accuracy analysis of Netflix data set in different link prediction methods

Index name	CN	JC	AA	RA	CNG	WOCG	TCAC-LP
Accuracy	0.3415	0.4828	0.5848	0.6839	0.7492	0.7485	**0.8495**
Recall rate	0.3719	0.4572	0.5629	0.6583	0.6928	0.7602	**0.8920**
F1 value	0.3851	0.4695	0.6891	0.7102	0.6801	0.7861	**0.8762**

Note: The values shown in bold indicate that the corresponding algorithm has good performance.

Table 7. Accuracy analysis of Facebook data set in different link prediction methods

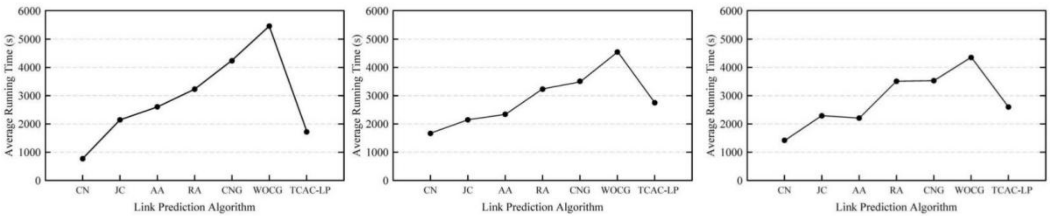
Index name	CN	JC	AA	RA	CNG	WOCG	TCAC-LP
Accuracy	0.4381	0.3910	0.5382	0.5960	0.6010	0.6819	**0.8769**
Recall rate	0.2494	0.3585	0.4192	0.5182	0.6295	0.6432	**0.8389**
F1 value	0.3172	0.4102	0.5284	0.5655	0.6384	0.6019	**0.8901**

Note: The values shown in bold indicate that the corresponding algorithm has good performance.

In the Amazon data set, the accuracy value of the TCAC-LP algorithm is 0.8293, and the highest accuracy value among the other six algorithms is 0.6192 of the CNG algorithm. In the Netflix data set, the accuracy value of the TCAC-LP algorithm is 0.8495, while the highest accuracy value among the other six algorithms is 0.7492 of the CNG algorithm. In the Facebook data set, the accuracy value of the TCAC-LP algorithm is as high as 0.8769, while the highest accuracy value among the other six algorithms is the WOGC algorithm, which is only 0.6819. Through the above comparison, it is evident that the accuracy value of the TCAC-LP algorithm is the highest among the seven comparison algorithms under three different data sets validation. Similarly, the TCAC-LP algorithm performs the best among the seven algorithms in terms of recall rate and F1 value, and is significantly higher than the other six algorithms. This fully reflects the high accuracy of the TCAC-LP algorithm's prediction, which is significantly better than the other six algorithms.

According to the link prediction results obtained by TCAC-LP method, trade merchants of social e-commerce can predict whether there will be relevant links in the social direction between different users, analyze the similarity of the emotional and psychological needs of customers who may have links, recommend products with similar interests to them, and specify international e-commerce strategies such as how to select customers, how to optimize product structure and enhance brand effect in social networks. Finally, the time complexity of the proposed TCAC-LP method was analyzed. For this purpose, the average running time of the algorithms was compared (Fig. 1 has shown the results). Obviously, the proposed TCAC-LP method has better operation efficiency compared with other methods. It is because the method proposed this study has higher operation efficiency after combining the advantages of trust mechanism and ant colony algorithm in link prediction in social e-commerce network environment.

Furthermore, the experimental results also indicate that the TCAC-LP method demonstrates precision in link prediction tasks. By comparing with other benchmark algorithms, this method performs more outstandingly in terms of accuracy, recall, and F1 score, thus proving the performance advantages of TCAC-LP. In particular, the integration of the trust mechanism with the ant colony algorithm enhances the model's ability to capture complex social dynamics and accurately predict potential user links. This is particularly crucial for the social e-commerce field, as it enables platforms to adjust marketing strategies and product recommendations more precisely, thereby increasing user interaction and satisfaction. Additionally, by applying the TCAC-LP method on datasets of different sizes, its scalability has been verified, and the results further confirm its stability and broad applicability in practical applications.



(1) Amazon.com (2) Facebook network (3) Netflix network

Fig. 1. Time complexity of real social e-commerce data set in different link prediction algorithms

In subsequent studies, in order to verify the superior performance of the algorithm model proposed in this study and the social attributes of the selected dataset at the e-commerce level, multiple validations were conducted based on data from other social e-commerce platforms. The experimental results all showed that the algorithm model proposed in this study, when faced with other social e-commerce datasets, it also demonstrated excellent results similar to the application of the three social e-commerce business datasets in this article. These results further consolidate the robustness and versatility of the TCAC-LP algorithm across diverse social e-commerce scenarios. The algorithm's ability to consistently outperform other methods in terms of accuracy, recall rate, and F1 value underscores its potential for widespread adoption in the field. Additionally, the analysis of time complexity revealed that the TCAC-LP method maintains high operational efficiency, making it a practical choice for real-time link prediction in social e-commerce networks. The promising outcomes from these validations suggest that the TCAC-LP algorithm could serve as a benchmark for future research in link prediction within social e-commerce contexts. As social e-commerce continues to evolve, the TCAC-LP algorithm stands ready to provide valuable insights and drive innovations in personalized recommendation strategies and international e-commerce planning.

5 Conclusion and Prospect

In this study, the traditional infectious disease model was used to model the trade route of Chinese cross-border social e-commerce, and the classical community information link prediction method of local structure of social e-commerce was improved by combining ant colony algorithm for the sake of making adaption to the speed of development and scale of Chinese cross-border social e-commerce. By combining traditional infectious disease models with ant colony algorithm, the fusion of this algorithm model is very novel and has significant originality. The data sets for the experiment were all sourced from international large-scale network platforms that have been involved in the field of cross-border social e-commerce in recent years, indicating that this study has grasped the current trends and hotspots, has high innovation, and has high representativeness for future predictions. The proposed link prediction method was verified by crawling real cross-border social e-commerce data sets including Amazon, Facebook and Netflix. Meanwhile, the proposed method performs in a better situation and higher efficiency in cross-border social e-commerce scenarios, compared with the existing link prediction methods. It can provide countermeasures and suggestions for making the social e-commerce trade process develop steady and making the international social e-commerce trade facilitation on earth develop in the coordinated and sustainable situation. In the follow-up work, we will try to apply this method to the directed weighted network, and consider the proposed link prediction algorithm and other node importance indexes in a comprehensive manner. This study combines epidemiological models with ant colony optimization to tackle the complexity of cross-border social commerce ecosystems. It uses a hybrid algorithmic approach to simulate information diffusion, creating a new analytical paradigm that merges biological and computational methods. The method focuses on adaptive learning to capture market trends and user behaviors, offering a complete view of community evolution. It improves predictive link analysis and introduces a framework for evaluating trust in decentralized networks. This interdisciplinary approach advances e-commerce theory and provides practical insights for creating resilient, user-focused business models in the global digital economy.

This research team intends to conduct an in-depth exploration of the performance of the ant colony algorithm in directed weighted network environments and to discuss strategies for adjusting and optimizing the algorithm to meet the specific needs of different network structures and weight distributions. The study will focus on precise adjustments of algorithm parameters and in-depth analysis of network topology features to ensure the accuracy and efficiency of predictive results. At the same time, this research will also explore the combined use of link prediction algorithms and node importance indicators (such as PageRank, HITS algorithm, etc.), aiming to achieve a more comprehensive network analysis. This will help identify key nodes in the network and potential trade hubs, providing stronger data support for decision-makers in the field of cross-border e-commerce. To better serve practical application needs, we plan to cooperate with cross-border e-commerce platforms to collect more real-time data to test and optimize our models. The study will include an analysis of market dynamics in different countries and regions, as well as research into trade patterns of different categories of goods. In addition, we will use current trade data for analysis to predict emerging markets and potential growth opportunities. Future research work will focus on further optimization of the algorithm, testing and verification of practical applications, predictive analysis of market trends, and the formulation of policy recommendations, dedicated to providing more accurate, efficient, and sustainable solutions for the global cross-border e-commerce field.

Acknowledgement

This paper is an educational science planning project of Zhejiang Province: The Construction of “1+3+N” Digital Collaborative Education Mode Based on the Integration of Production and Education —— Taking Cross-border E-commerce Specialty as an Example (project number: 2022SCG062).

The 2021 Cooperative Education Project of Industry-University Cooperation in Vocational Colleges of the Education Department Office of Zhejiang Province: Exploration on the Construction of Curriculum System and Teaching Content of Cross-border E-commerce Specialty Based on the Integration of “Job, Course, Competition, Certificate and Training”.

Practice research project of Digitization Empowering High-quality Education Development of China Association of Higher Education: Research and Practice on the Application Mode of Teaching Resources Sharing of Cross-border E-commerce Virtual Simulation Training (Project No.: 22SZH0412).

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