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Research Article

Discovering Potential Partners via Projection-Based Link Prediction in the Supply Chain Network

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ABSTRACT

As reserving a certain number of potential partners plays a significant role in alleviating existing partners' collaborative interruption risks, we investigate the process of discovering potential partners to improve the supply chain network's resilience. Most of the existing research confines its focus on discovering potential partners in the supply chain on the basic of sufficient partners' information, but very few works consider discovering potential partners in the supply chain network according to the structure of the supply chain network when the partner information is insufficient. In this situation, a novel model which applies projection-based link prediction method to discover potential partners in the supply chain network is proposed. The proposed model is composed of three stages. The first stage is predicting the candidate partnerships links based on the projection one-model graph which is transformed from the supply chain network according to its structure. The second stage is discovering potential partners by comparing the acquired connectivity of candidate partnership links with the maximal connectivity of existent partnerships. In the third stage, a resilience evaluation framework considering the both connectivity and flexibility indexes is presented to determine whether the supply chain network's agility is improved. In the experimental design, a supply chain network which is formed from a real dataset containing mobile phone suppliers, manufacturers and packers is used to evaluate the proposed algorithm's prediction accuracy. The results reveal that the algorithm achieves highest area under curve (AUC) scores and the supply chain network's resilience is improved by discovering potential partners.

1. INTRODUCTION

Traditionally, discovering potential partners in the supply chain is considered as a process of ranking candidates according to sufficient partners' information, such as the factors of cost, quality, delivery time, supply capacity and the precedence of tasks, etc. However, in order to adapt to the course of economy and technology globalization [1], discovering potential partners in the supply chain has evolved into discovering partners in the supply chain network. Compared with the simple linear supply chain, the structure of supply chain network is complex. As a result, there is now a widespread need to take into consideration the influence of the supply chain network structure on discovering potential partners [2,3]. To characterize the supply chain network's structure, some models on the basic of network theory have been presented [4], in which the network involves a series of nodes and links which refer to the suppliers, manufactures, packers and connections among them respectively. In order to make transactions or provide products and services, companies in the supply chain network work on interplay relationships with other enterprises, which generates various links including cooperation links, material links, information links, capital links and logistics links [5].

Recently, discovering potential partners in the supply chain network has led to a spectrum of attention by researchers. As stated by Hua, Sun and Xu [5], discovering potential partners in the supply chain network plays a significant role when enterprises are facing the interruptions of cooperations with their existing partners. Mensah *et al.* [6] put emphasis on the necessity of discovering potential partners by revealing that any suppliers' unexpected events may have a catastrophic influence on operations of the supply chain and cascade throughout the entire supply chain network. To understand how to discover potential partners in the supply chain network, others have suggested adopting the mathematical approach to explore this process. Salo and Jarimo [7] established a mixed-integer linear model to discover candidates in the virtual enterprise supply chain network. Sarkis *et al.* [8] proposed a strategic discovering agile candidates model on the basic of analytical network process (ANP) methodology. Guneri and Yucel [9] provided a weighted additive fuzzy programming method for predicting potential partners in the supply chain network. Chuang and Yeh [10] introduced two multi-objective genetic algorithms building an optimum mathematical discovering potential partners model. Han and Shin [11] applied fuzzy sets theory (FST) to discovering potential partners in the supply chain network.

Although the above methods have advantages in different contexts, partner information's scarcity is a large obstacle of exploring the

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potential partnerships in their implementations. Some papers aiming at discovering potential partners have tried to employ FST to overcome the incompleteness and uncertainty of partner information in the supply chain network [11–14]. The FST is an effective method to handle uncertain information, which can deal with the incomplete and uncertain information about the candidates and their performances [12]. Zhao *et al.* further pointed out that the FST can be applied to solve the problem of prediction [15]. However, the method of using fuzzy sets and fuzzy logic theories ignores the structure of the supply chain network and needs to select an adaptive initial set-point to complement an optimum value search. If the structure of the network is complex, the loss ratio and the delay must be increased.

In reality, discovering potential partners in the supply chain network can effectively alleviate the bad influence that existent cooperation partnership disruptions bring. Once the supply chain network members' cooperation is interrupted, the situation of sharp increase in supply costs, loss in profits, even brand damage and worse social impact will appear and the supply chain network will have difficulty in restoring normal operations in a short period of time. The purpose of this paper is to present a model of discovering potential partners to reconstruct possible supply chain network on the basic of projection-based link prediction in the supply chain network to avoid the losses in the early stage. The innovation of the work lies in that we shed light on how to use projection-based link prediction to discover potential partners in the supply chain network. This application of link prediction provides a technical basic for the further supply chain management's advance. Specifically, the contributions of this article are the following:

- The model depicting discovering potential partners in the supply chain network as predicting potential partnerships links in the network composed of participating enterprises nodes is proposed.
- Projection-based link prediction converts the supply chain network into projection one-model graphs according to the supply chain network's structure and compares the acquired connectivity of candidate partnership links with the maximal connectivity of existent partnerships to discover potential partners.
- The resilience evaluation framework of supply chain network considering the connectivity and flexibility index is presented to evaluate the supply chain network agility after discovering potential partners.

The reminder of this article is arranged as follows: Section 2 introduces the concepts and applications of link prediction. Section 3 depicts the link prediction for discovering potential partners in the supply chain network. Section 4 proposes a novel model based on projection-based link prediction. Section 5 presents the experiments and results of proposed algorithm in a real mobile phone supply chain network. Section 6 makes conclusions and provides directions for future research.

2. THEORETICAL BACKGROUND

Discovering potential partners in the supply chain network is able to be implemented successfully by formulating evaluation criteria according to valid partner information, but it will be difficult under the circumstance of partner information inaccuracy. There is a novel way of discovering potential partners in the supply chain network, which uses link prediction to predict potential partnerships links by analyzing the supply chain network's structure. Link prediction refers to how to make use of the structure of network or the label of known nodes to predict the connection probability of potential links which have not been connected yet in the network.

Link prediction has been applied to many significant fields for various goals. In the popular online social networks including Facebook and LinkedIn, a list of people you may know can be suggested [16]. In the ecommerce websites, personal recommendations can be generated to recommend products that customers most likely need [17]. Especially, the bipartite network is a classical form of complex networks in link prediction, where the nodes are divided into two disjoint parts, and the links connect with nodes which belong to different parts [18]. Link prediction in the bipartite network has gained a large-scope applications. For example, in the scientist-papers cooperation network [19], long-term collaboration trends in scientific collaborations are able to be identified by using link prediction. In the author-topic network, appropriate topics can be provided for academic authors according to the citations number of a publication and the condition of collaboration between authors [20]. In the term-document network [21], documents which have possibility to have substantial impact in a term can be discovered. In the club members–activities network [22], the relationships of club members can be predicted which is similar to recommend friends in the social network. In the disease–gene, drug–target and drug–therapy network, interactions in medical sciences also can be predicted [23].

Recently, many scholars have proposed various approaches to predict potential links in bipartite networks [24–29]. Benchettara *et al.* [24] introduced new indicators of network structure characteristics to measure the appearance possibility of potential links and applied classical supervised machine learning approaches to modelling prediction problems. Kunegis *et al.* [25] used the odd element of the underlying spectral conversion to transform graph kernels into bipartite networks resulting in several new link predictions. Li and Chen [26] proposed a recommendation approach based on kernel to predict whether there existed a potential link. Shams and Haratizadeh [27] presented a SibRank approach, which represented users' preferences as a signed bipartite network in order to improve the neighbor-based collaborative ranking methods. Zhang *et al.* [28] identified false and missing links in bipartite networks by employing the processes of local diffusion to evaluate the internal similarity. Chang *et al.* [29] predicted potential links in Wikipedia which is a characteristic bipartite network by making use of a strengthened supervised machine learning method.

A common way of predicting potential links in a bipartite network is to project the bipartite network into a projection one-model graph. Allai *et al.* [30] introduced novel approaches of the weighted projection graph and internal links to analyze bipartite networks. In their approaches, all nonexistent links are listed, then those whose internal links weights are greater than predetermined threshold value are potential links. However, listing all nonexistent links spent a large amount of calculation time and the selection of a suitable threshold in advance is difficult. Aslan and Kaya [20] put forward a link prediction approach on the basic of strengthening weighted projection then applied it to discovering the possible citation links in a real-world author-topic network. The drawback of their method lies in that the dataset and application affect the selection of threshold greatly. Gao *et al.* [31] presented an approach that predicts candidate node pairs by mapping the bipartite network onto a projected graph. Due to lack of a proper threshold value, it is difficult to assess whether potential links are superior to previous links. To fill these gaps, we presented a model on the basic of projection-based link prediction [31] to discover potential partners in the supply chain network.

Mathematically, the concept of link prediction is defined in the following: Suppose $G = (V, E)$ is a network in which V is the nodes set, E is the links set. Link prediction is aimed to discover a potential link (u, v) connecting with nodes u and v, of which $u, v \in V$ and $(u, v) \notin E$ [32]. Based on the definitions, link prediction in the bipartite network can be viewed as a particular case of link prediction. The bipartite network can be represented by a bipartite graph, denoted as a triple $G = (U, V, E)$, in which U and V are nodes sets that are disjoint, $u \in U$, $v \in V$, $E \subseteq |U| * |V|$ is the links set of the bipartite network G [20]. There exists no links connecting nodes in the same U or V part. Link prediction in a bipartite network is a process of discovering potential links between nodes in U and V, as displayed in Figure 1, the solid lines indicate existent links and dashed lines indicate potential links.

3. THE LINK PREDICTION FOR DISCOVERING POTENTIAL PARTNERS IN THE SUPPLY CHAIN NETWORK

Figure 2 illustrates a supply chain network consisting of participating enterprises such as suppliers, manufacturers, packers, distributors and retailers, spans undirected links representing partner interrelationships between upstream and downstream parties along the network. Discovering potential partners in the supply chain network is imperative stimulated by the dynamic market. To launch better cooperation, existing enterprises may consider choosing better parties as their potential partners. Although some enterprises may have their relatively fixed partners, they still have the rights to reserve a number of potential partners to avoid economic losses in case of market failure or cooperation disruption. Discovering potential partners in the supply chain network can be viewed as predicting potential partnerships links in a network composed of participating enterprise nodes.

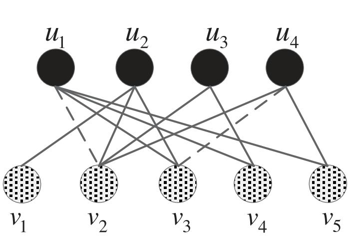

Figure 1 Discovering potential links of the bipartite network.

The network shown in Figure 2 can be divided into four bipartite networks comprising of suppliers-manufacturers, manufacturers-packers, packers-distributors, distributors-retailers relationship, as displayed in Figure 3. Suppose $G = (S, M, E)$ is a suppliers-manufacturers bipartite network which is a segment of the supply chain network, wherein $S = \{s_1, s_2, ...s_m\}$ is the suppliers set and $M = \{m_1, m_2, ...m_n\}$ is the manufacturers set, $(s, m) \in E$, S and M are disjoint node sets. E is the links set in the bipartite supply chain network G. Figure 4 shows prediction of potential partnerships links in the suppliers-manufacturers bipartite network. The

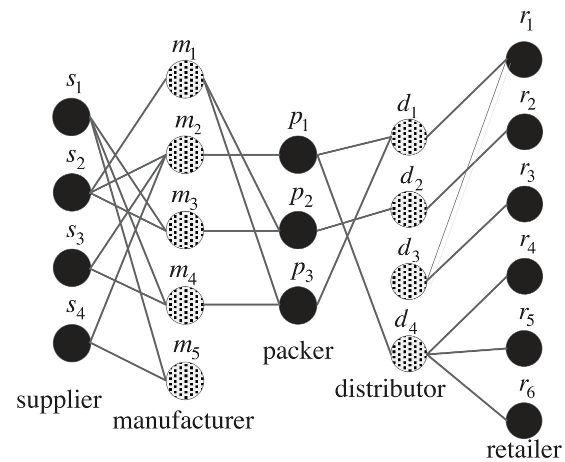

Figure 2 A traditional supply chain network.

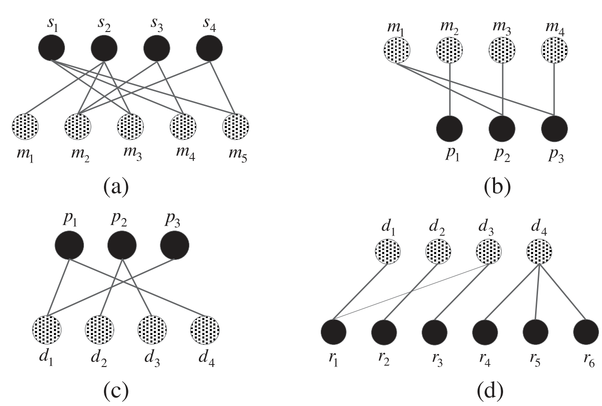

Figure 3 A traditional supply chain network is divided into four bipartite networks: (a) suppliers–manufacturers bipartite network, (b) manufacturers–packers bipartite network, (c) packers–distributors bipartite network, (d) distributors–retailers bipartite network.

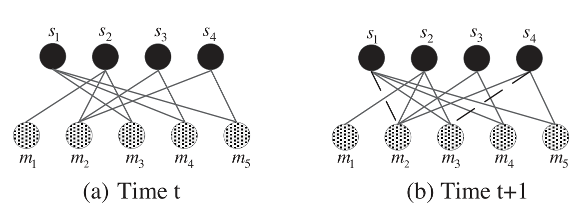

Figure 4 Prediction of potential partnerships links at time in a suppliers–manufacturers bipartite network at time t.

top circular dark nodes imply suppliers and the bottom circular dash nodes imply manufactures, the solid lines refer to the already existent partnerships and dashed lines refer to the potential partnerships links between suppliers and manufacturers, which refers the fact that the supplier already cooperated with the manufacturer and that the supplier will collaborate with the manufacturer in the future respectively. The objective of link prediction is to discover the potential partnerships links (dashed links) at time t + 1 in the suppliers-manufacturers bipartite network on the basis of the existent partnerships links (solid links) observed at time t. We only illustrate the link prediction for discovering potential partners in a suppliers-manufacturers bipartite network, the proposed model also applies to manufacturers-packers, packers-distributors and distributors-retailers bipartite networks.

4. THE PROPOSED MODEL

A model of discovering potential partners was proposed to improve the supply chain network's resilience. It is made up of three significant stages. Firstly, the candidate partnerships links are predicted according to the supply chain network's structure and its projection one-model graph. Secondly, comparing the acquired connectivity of candidate partnership links with the maximal connectivity of existent partnerships to discover potential partners. Thirdly, to determine whether the supply chain network's resilience is improved, we presented the resilience evaluation framework according to the supply chain network connectivity and flexibility index.

In the model, to predicate the potential partnerships links in the supply chain network, the suppliers-manufactures bipartite network is first converted into projection one-model graphs, which is given in Definition 1.

Definition 1. Let $G = (S, M, E)$ be a suppliers–manufacturers bipartite network, its S-projection one-model graph is defined as a unipartite graph $G_s = (S, E_s)$ where the set of links is

$$E_s = \left\{\left(s_i, s_j\right) | s_i, s_j \in S, \exists m_i \in M, m_i \in \Gamma(s_i) \cap \Gamma\left(s_j\right)\right\}.$$

Similarly, its M-projection one-model graph is defined as a unipartite graph $G_m = (M, E_m)$, where the set of links is

$$E_m = \left\{\left(m_i, m_j\right) | m_i, m_j \in M, \exists s_i \in S, s_i \in \Gamma(m_i) \cap \Gamma\left(m_j\right)\right\},$$

where $\Gamma(s_i)$ and $\Gamma\left(s_j\right)$ are the sets of partners of s_i and s_j respectively in the bipartite supply chain network. We may find that if nodes s_i and s_j have at least one common partner in the M, there will be a link connecting with nodes s_i and s_j in the S-projection one-model graph. Figure 5(a) shows that a suppliers-manufacturers bipartite network is projected into two one-model graphs which are S-projection one-model graph $G_s = (S, E_s)$ as Figure 5(b) shown and M-projection one-model graph $G_m = (M, E_m)$ as Figure 5(c) shown.

4.1. Predicting Candidate Partnership Links

To discover the potential partners in the bipartite network, we define the candidate partnership link based on the projection one-model graph.

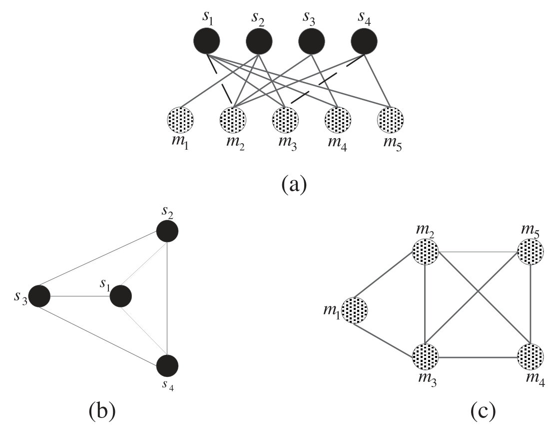

Figure 5 A suppliers–manufacturers bipartite network is projected into two one-model graphs: (a) suppliers–manufacturers bipartite network, (b) S-projection one-model graph, (c) M-projection one-model graph.

Definition 2. Let $G = (S, M, E)$ be a suppliers–manufacturers bipartite network. By adding a new link $\left(s_i, m_j\right) \in S * M$ to G, we structure a new suppliers–manufacturers bipartite network $G' = \left(S, M, E'\right)$, where $E' = E \cup \left\{\left(s_i, m_j\right)\right\}$. Let $G'_s = \left(S, E'_s\right)$ and $G'_m = \left(M, E'_m\right)$ be the S-projection one-model graph and M-projection one-model graph of G'. If $G_s = G'_s$ and $G_m = G'_m$, $\left(s_i, m_j\right)$ is defined as the candidate partnership link in the suppliers–manufacturers bipartite network.

For example, the unlinked node pair (s_1, m_2) in Figure 5 (a) is the candidate partnership link. In fact, in Figure 5 (b), are the nodes s_2, s_3 and s_4 are linked with s_1 in the original S-projection one-model graph. In Figure 5 (c), all the nodes m_1, m_3, m_4 and m_5 are linked with m_2 in the original M-projection one-model graph. Therefore, adding the new link (s_1, m_2) makes no change to the S-projection and M-projection one-model graph.

To estimate the connecting possibility of candidate partnership links, pattern and pattern covered by the candidate partnership are given in Definitions 3 and 4 respectively.

Definition 3. Suppose s_i and s_j are two supplier nodes in a suppliers–manufacturers bipartite network $G = (S, M, E)$. If there exists a node $x \in M$ such that $(s_i, x) \in E$ and $\left(s_j, x\right) \in E$, the link $\left[s_i, s_j\right]$ in the S-projection one-model graph is defined as a pattern.

Definition 4. Suppose (s_i, x) is a candidate partnership link in a suppliers–manufacturers bipartite network G. For each supplier node $s_j \in \Gamma_s(s_i) \cap \Gamma(x)$, we call $\left[s_i, s_j\right]$ a pattern covered by the candidate partnership link (s_i, x),

where $\Gamma_s(s_i)$ is the neighbors set of supplier s_i in the S-projection one-model graph G_s, and $\Gamma(x)$ is the partners set of manufacturer x in a suppliers–manufacturers bipartite network.

There are one or more patterns can be covered by a candidate partnership link in the projection one-model graph. If a candidate partnership link covers more patterns, the connecting possibility of the candidate partnership link will be higher. Thus, the number of patterns covered by the candidate partnership link can represent the probability of its link appearance.

In Figure 5(a), the concrete links (s_1, m_3) and (s_2, m_3) indicate that manufacture m_3 cooperates with suppliers s_1 and s_2 simultaneously. It forms a pattern $[s_1, s_2]$, which means there is a link $E(s_1, s_2)$ in the S-projection one-model graph G_s. In Figure 5(a), we also see that manufacturer m_2 doesn't cooperate with s_1. By adding a new link $E(s_1, m_2)$ in the bipartite network, we assume that manufacturer m_2 cooperates with the supplier s_1, then all patterns covered by (s_1, m_2) are $[s_1, s_2]$, $[s_1, s_3]$ and $[s_1, s_4]$ which are identical to the existing ones in the S-projection one-model graph. This indicates that the candidate partnership (s_1, m_2) has similarity to the current existing partnerships and high probability to exist in the discovery of potential partners. If a pair of unconnected nodes (s_1, m_2) is not a candidate partnership link, and $\Gamma_s(s_1) \cap \Gamma(m_2) = \emptyset$, there will be no pattern it covers, which means that there are no existing partnerships similar to (s_1, m_2) and nodes s_1 and m_2 should not be linked. Therefore, we are able to carry out the link prediction just in the set of candidate partnerships and overlook all noncandidate links, which will scope down the search range of potential partners.

We also note that the number of patterns which are covered by the candidate partnership link (s_i, x) is equivalent to the size of the set $\Gamma_s(s_i) \cap \Gamma(x)$. The larger the size is, the larger the number of patterns that are covered by the candidate partnership link (s_i, x) is, which means the linking probability of nodes s_i and x is higher. For example, in Figure 5(a), node pairs (s_4, m_3) and (s_1, m_2) are all candidate partnerships links, however, the number of patterns which are covered by them are diverse. The candidate partnership link (s_4, m_3) only covers pattern $[s_4, s_1]$ and $[s_4, s_2]$, whereas the candidate partnership (s_1, m_2) covers patterns $[s_1, s_2]$, $[s_1, s_3]$ and $[s_1, s_4]$. Obviously, the candidate partnership link (s_1, m_2) has a higher possibility to appear than the candidate partnership link (s_4, m_3).

4.2. Discovering Potential Partners

In this work, the potential partners set is extracted by using both the structural information of the weighted projection network and the candidate bipartite network with connectivity values.

In a projection one-model graph, each pattern is given a weight to its corresponding link. To obtain the pattern weight of $\left[s_i, s_j\right]$, we need to take three impact factors into account:

- The number of communal partners of nodes s_i and s_j in a suppliers–manufacturers bipartite network

The pattern covered by the candidate partnership link is showed by a link in the projection one-model graph. Every link $E\left(s_i, s_j\right)$ in the projection one-model graph G_s refers to that the supplier nodes in pattern $[s_1, s_2]$ have communal partners in the bipartite supply chain network G. Nevertheless, the link $E\left(s_i, s_j\right)$ in G_s does not specify the number of their partners. For example, two different suppliers–manufactures bipartite networks are given in Figure 6(a) and Figure 6(b). However, their projection one-model graphs are identical as can be seen in Figure 6(c). In order to prevent this situation from happening, we need to make use of a weighted projection one-model graph where each link (s_1, s_2) is given to a weight in the light of the number of communal partners of supplier nodes s_1 and s_2 in a suppliers–manufactures bipartite network. Nodes s_1 and s_2 in Figure 6 (a) have only one communal partner, so their link in the projection one-model graph ought to be given to a lower weight. Whereas, supplier nodes s_1 and s_2 in Figure 6(b) have four communal partners, thus, the link between them in the projection one-model graph ought to be given to a higher weight.

- The degree of communal partners of nodes s_i and s_j in a suppliers–manufactures bipartite network

In the pattern $[s_1, s_2]$, the degree of communal partners of nodes s_1 and s_2 in a suppliers–manufactures bipartite network ought to be taken into account. If the communal partners of nodes s_1 and s_2 have smaller degrees, and we deem that the weight of pattern $[s_1, s_2]$ is higher. For example, the projection one-model graph of Figure 7(a) is represented in Figure 7(b) and the projection one-model graph of Figure 8(a) is represented 8(b). Links $\left(s_1, m'\right)$ of the two suppliers–manufacturers bipartite networks above are both candidate partnerships links, and the pattern $[s_1, s_2]$ is both covered by them. In Figure 7(a), the degree of communal partner m between nodes s_1 and s_2 is two, the degree of communal partner m between nodes s_1 and s_2 in Figure 8(a) is six. In Figure 7(a), the manufacture m only collaborates with suppliers s_1 and s_2. However, in Figure 8(a), the manufacture m collaborates with six suppliers, and s_1, s_2 have less similarity because m is a communal partner of six suppliers. Obviously, s_1 and s_2 in Figure 7(b) have higher similarity because m is a communal partner of only two suppliers s_1 and s_2. Therefore, the link $E(s_1, s_2)$ ought to be assigned higher weight.

- The degree of nodes s_i and s_j in a suppliers–manufacturers bipartite network

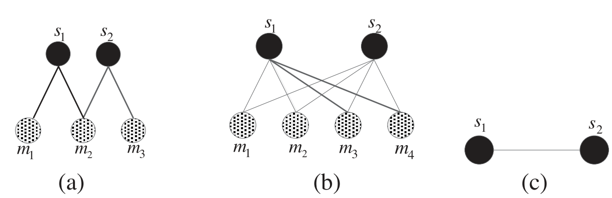

Figure 6 | Two different suppliers–manufacturers bipartite networks and their projection one-model graph.

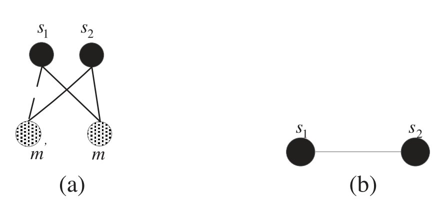

Figure 7 | Candidate partnership link and its projection.

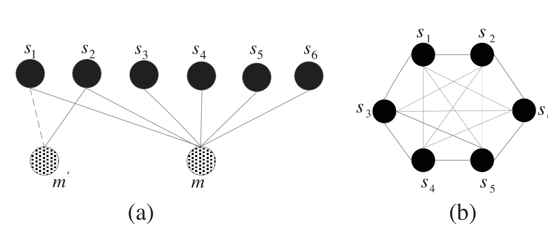

Figure 8 | Candidate partnership link and its projection.

The degree of nodes s_i and s_j also affects the pattern $[s_i, s_j]$ weight in a suppliers–manufacturers bipartite network. If s_i and s_j nodes have smaller degrees, we give higher weight to the pattern. For instance, two different suppliers–manufacturers bipartite networks which have the same candidate partnership link (s_1, m') are displayed in Figure 7(a) and Figure 9(a). In Figure 7(a), the degree of node s_1 is one and the degree of node s_2 is two. In Figure 9(a), the s_1 node's degree is three and the s_2 node's degree is four. In Figure 7(a), the supplier s_1 only cooperates with the manufacturer m, and supplier s_2 cooperates with manufacturers m and m'. However, in Figure 9(a), suppliers s_1 and s_2 cooperates with other manufacturers except m and m', and the manufacturer m is the only manufacturer they cooperates with in common. Therefore, supplier s_1 and s_2 in Figure 9(a) have less similarity, and pattern $[s_1, s_2]$ weight in Figure 7(b) could be higher than pattern $[s_1, s_2]$ weight in Figure 9(b).

According to the above analysis, the pattern weight can be defined as follows:

Definition 5. Suppose that $G_s = (S, E_s)$ is the S-projection one-model graph of a suppliers–manufactures bipartite network $G = (S, M, E)$. Let $(s_i, s_j) \in E_s$ be a link in G_s, the weight of a pattern $[s_i, s_j]$ is defined as

$$pw\left(s_i, s_j\right) = \frac{2}{d\left(s_i\right) + d\left(s_j\right)} \sum_{m \in \Gamma(s_i) \cap \Gamma\left(s_j\right)} \frac{1}{d\left(m\right)}. \tag{1}$$

where $d(s_i)$ is the supplier s_i node's degree, $d(s_i)$ is the supplier s_j node's degree and $d(m)$ is the manufacturer m node's degree in a suppliers–manufacturers bipartite network $G = (S, M, E)$. $\Gamma(s_i)$ and $\Gamma(s_j)$ are the sets of partners s_i and s_j in a suppliers–manufactures bipartite network.

In Definition 5, if s_i and s_j nodes have more communal partners with lower degree in a suppliers–manufacturers bipartite network, we will learn that link $E(s_i, s_j)$ in the S-projection one-model graph will be given to a higher weight. Obviously, candidate partnership link which covers the patterns whose weights are higher will have higher possibility to be connected.

In the model, each candidate partnership link is given to an indicator named connectivity, which is a metric of the candidate partnership link appearance probability. The connectivity of candidate partnership link can be defined in the following:

Definition 6. The connectivity of candidate partnership link (s_i, x) in a suppliers–manufacturers bipartite network $G = (S, M, E)$ is defined as

$$C(s_i, x) = \sum_{\{s_i, s_j\} \in \ell(s_i, x)} pw\left(s_i, s_j\right). \tag{2}$$

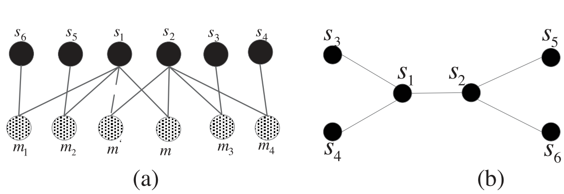

Figure 9 Candidate partnership link and its projection.

where $pw(s_i, s_j)$ is the weight of pattern $[s_i, s_j]$, $\Gamma_s(s_i)$ is the set of neighbors of supplier s_i in the S-projection one-model graph $G_s = (S, E_s)$, $\Gamma(x)$ is the partners set of manufacturer x in a suppliers–manufacturers bipartite network $G = (S, M, E)$ and $\ell(s_i, x)$ is the set of patterns which are covered by the candidate partnership link (s_i, x) with

$$\ell(s_i, x) = \left\{\left\{s_i, s_j\right\} | s_j \in \Gamma_s(s_i) \cap \Gamma(x)\right\}. \tag{3}$$

In the Definition 6, the connectivity of the candidate partnership link (s_i, x) indicates the sum total of the weights of pattern covered by the candidate partnership link (s_i, x). According to the formula (2), if the number of patterns covered by the candidate partnership link (s_i, x) which has higher weights is larger, the connectivity of the candidate partnership link (s_i, x) will be higher.

A significant index of network structure, called clustering coefficient of link, characterizes the connectivity between a link's two corresponding nodes and other surrounding nodes [33]. With the aim of discovering potential partners in the supply chain network accurately, we adopt the link's clustering coefficient to measure the existent partnership link's connectivity.

Definition 7. The connectivity of existent partnership link (s, m) in a suppliers–manufacturers bipartite network $G = (S, M, E)$ is defined as

$$C(s, m) = \frac{Z(s, m)}{\min\left(d_{s-1}, d_{m-1}\right)}. \tag{4}$$

where $Z(s, m)$ represents the number of unclosed triangles which include the existent partnership links in a suppliers–manufacturers bipartite network, d_s and d_m denote degrees of existent supplier node s and existent manufacturer node m respectively.

Since the weight of pattern reveals the links' similarity, the connectivity of candidate partnership link indicates the probability of candidate partnership link to be connected. Only when the connectivity of the candidate partnership link is greater than or equal to the maximal connectivity of existent partnership, will we recognize it as a potential partner relationship.

4.3. The Resilience Evaluation Framework

The resilience evaluation framework is a metric of a supply chain network's capability of making preparations for accidents, making response to interruptions and reverting to the same or a better operation state and thus includes network rejuvenation [34]. The framework takes the connectivity and flexibility of the supply chain network as criteria to assess the resilience improvement after discovering potential partners. The connectivity index quantifies connecting changes of the supply chain network after discovering potential partners. The analysis of supply chain network's flexibility can unveil configuration variation of the network which is affected by discovering potential partners [35,36]. Connectivity index indicates the speed of the supply chain network respond to market disruptive events and flexibility index means the capacity of transforming the supply chain network's range number and range heterogeneity to handle a series of turbulent market changes [37]. According to Scholten and Schilder [38], increased connectivity value and flexibility value resulted in a more resilient supply chain network.

The resilience evaluation framework is formulated as follows:

$$R = f\left(connectivity, flexibility\right). \quad (5)$$

wherein, the connectivity is described as,

$$connectivity = \left(\frac{C\left(s_i, x\right) + C\left(s, m\right)}{C\left(s, m\right)}\right) * 100. \quad (6)$$

It evaluates the ratio of total connectivity of links after discovering potential partners to the connectivity of the existent network. If the value of connectivity is greater than 1, it means that the connecting relationship of the supply chain network is improved by introducing new potential partners.

The flexibility of the network is depicted as

$$flexibility = \left(\frac{e_{\max} - v + 1}{e - (v - 1)}\right) * 100. \quad (7)$$

where $e_{\max}$ indicates the number of discovered candidate partnership links whose connectivity is greater than or equal to the maximal connectivity of existent partnership links, e denotes the number of candidate partnership links whose connectivity is smaller than the maximal connectivity of existent partnership links and v represents the number of existent partnership links. If the value of flexibility assumes greater than 1, it implies that the adaptability of the network is increased by the process of discovering potential partners.

4.4. The Algorithm of Proposed Model

Based on the proposed model, we present a discovering potential partnerships (DPPs) algorithm in supply chain bipartite network. The first step is to projectively transform the given suppliers–manufacturers bipartite network into projection one-model graphs. The second step is to calculate the weights of patterns covered by the candidate partnership links in the light of formula (1). Then, the connectivity of each candidate partnership link (s_i, x) is calculated according to formula (2) and if the acquired connectivity of candidate partnership links is greater than or equal to the maximal connectivity of existent partnership links, we will find the potential partners. In the end, the algorithm evaluates the resilience of original and post-experiment supply chain networks. The algorithm of proposed model is described as follows:

Algorithm of discovering potential partners
Input: The suppliers-manufactures bipartite network $G = (S, M, E)$;
Output: Potential partners and the resilience comparison results of original and post-experiment supply chain network;
Step 1: Construct the set of patterns
1. $E_s = \varnothing$
2. For each supplier node s_i in S do
3. For each manufacturer node x in $\Gamma_s\left(s_i\right)$ do
4. For each supplier node s_j in $\Gamma(x)$ do
5. $E_s = E_s \cup \left\{\left(s_i, s_j\right)\right\}$
6. End for
7. End for
8. End for
Step 2: Compute the weight of each pattern
9. For each link $E\left(s_i, s_j\right)$ in E_s do
10. Compute the weight of pattern $\left[s_i, s_j\right]$ based on the formula (1);
11. End for
Step 3: Compute the connectivity of candidate partnership link
12. For each supplier node s_i in the projection one-model graph G_s **do**
13. For each partner s_j of s_i in the projection one-model graph G_s **do**
14. For each manufacturer node x connected with s_2 in the suppliers-manufactures bipartite network G **do**
15. If $\left(s_i, x\right) \notin E$ then
16. $C\left(s_i, x\right) = C\left(s_i, x\right) + pw\left(s_i, s_j\right)$;
17. End if
18. End for
19. End for
20. End for
Step 4: Compute the connectivity of existent partnership link according to formula (4);
21. If $C\left(s_i, x\right) \geq \max\left(C\left(s, m\right)\right)$
22. Output potential partners.
23. End if
Step 5: Evaluate the resilience of supply chain network
24. For original and post-experiment supply chain network
25. Compare the *connectivity* value based on the formula (6)
26. Calculate *flexibility* value based on the formula (7)
27. Output the resilience comparison results of original and post-experiment supply chain network.
28. End for

5. ANALYSIS AND DISCUSSION OF THE EXPERIMENTAL RESULTS

To evaluate the proposed DPP algorithm for discovering potential partners in the supply chain network, we test it by performing experiments on a realistic mobile phone bipartite supply chain network. The experiments were carried out on computer with 4GB memory and operating system of Intel Core i5 Windows 7. The algorithm was operated in Matlab R2018a and the experimental results are visualized by Gephi.

5.1. Dataset

A real mobile phone supply chain network dataset is used to perform our experiments. Unlike some of the traditional link prediction literatures which use experimental dataset available to be downloaded from open-source and free websites, such as www.gephi.org, www.linkprediction.org, the dataset in this work is collected and integrated from the Mobile Phone Newspaper, Economic Daily, the Logistic Business of Headscm and Alibaba.com. In our test, we consider cellular phone brands such as Apple, Huawei and Mi and their suppliers, manufactures and packers.

Figure 10 illustrates a bipartite network of mobile phone suppliers and manufacturers. It depicts the participation of 125 suppliers and 9 manufacturers. They are marked as yellow and green respectively in the figure. If a supplier provides the manufacturer some mobile components such as chips, batteries and screens, the corresponding nodes will be connected by a link in the bipartite network. There are 941 links in total connecting suppliers with manufacturers. Figure 11 shows a manufacturers–packers bipartite network. The

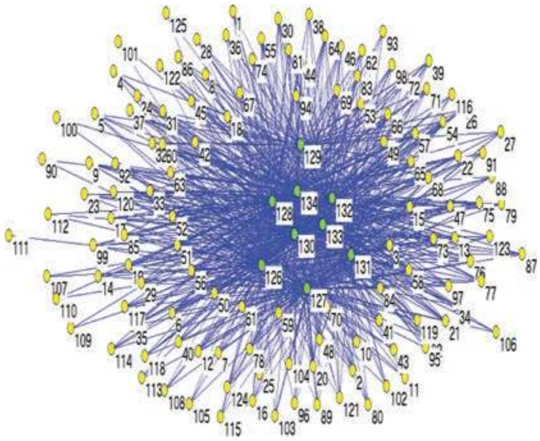

Figure 10 | Original structure of suppliers–manufacturers bipartite network.

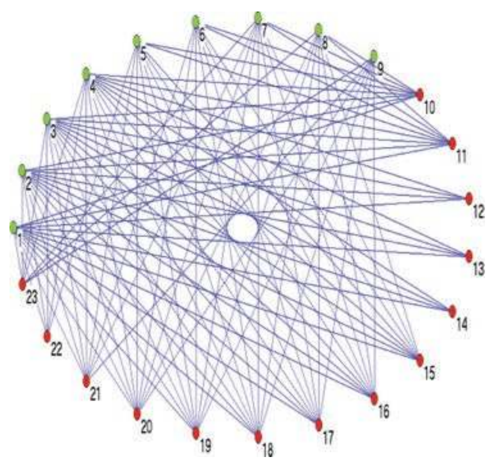

Figure 11 | Original structure of manufacturers–packers bipartite network.

dataset characterizes 23 firms including 9 manufacturers and 14 packers, as marked in green and red in the graph. Each link reflects a manufacturer cooperates with a packer, and there are totally 126 of it shown in the figure.

5.2. Evaluation Metric

To evaluate the prediction result of the DPP algorithm, we divide all the existent links into E^T and E^P which are the training set and the testing set respectively, satisfying $E^T \cup E^P = E$, $E^T \cap E^P = \emptyset$. In our experiment, a random 10-fold cross-validation (CV) is conducted, where the nodes of a suppliers–manufactures bipartite network is portioned into 10 subsets randomly, for which, one of the subset acts as the testing set and the remaining 9 subsets play as the training sets. The procedure of CV is implemented 10 times on training sets and each of the 10 subsets served as the validation set exactly. In a random 10-fold CV, the proposed algorithm's final area under curve (AUC) value is obtained by calculating the average AUC value of the 10 tests.

AUC was initially a metric to assess the prediction quality of the algorithms [39], which refers to the area under the receiver operating characteristic (ROC). ROC curve aims to assess the effect of classifier. In our experiments, the AUC value is able to be regarded as the probability when the similarity score of an existent link is higher than the similarity score of a nonexistent link. To compare the links' similarity scores, existent links and nonexistent links can be chosen randomly. In n comparisons, assume that there are n' times where the existent link's similarity score is higher than nonexistent link's similarity score and there are n' times where the existent link's similarity score is equal to nonexistent link's similarity score. The AUC is defined as

$$AUC = \frac{n' + 0.5n''}{n}. \tag{8}$$

In general, if the AUC score is higher, the prediction quality of the proposed algorithm is better. It is clear that the highest AUC score in formula (8) is 1, which represents a complete correct result. In fact, if all similarity scores are random, the AUC score is 0.5 approximately.

5.3. Comparison Baselines

With the goal of comparing the proposed algorithm's AUC value with other link prediction algorithms' AUC value, we choose three algorithms from the baselines of Preferential Attachment (PA) index, Local Naive Bayes common neighbor (LNBCN) index and Local Naive Bayes Adamic-Adar (LNBAA) index for performance comparison.

PAindex is based on the probability that a potential link connects with the node x which is proportioned to its degree k_x. The probability that a potential link connects with node x and y, which is proportioned to $k_x \times k_y$ [40], the PA is defined as

$$S_{xy}^{PA} = k_x \times k_y. \tag{9}$$

LNBCN index is formed by Local Naive Bayes Model and common neighbor index which obtains similarity score by calculating all common neighbors' number and it is defined as $S_{xy}^{CN} = |\Gamma(x) \cap \Gamma(y)|$, in which $\Gamma(x)$ denotes the x node's neighbor set [41], the LNBCN is defined as

$$r_{xy}^{LNBCN} = |S_{xy}^{CN}| \log s + \sum_{v_w \in O_{xy}} \log R_w. \tag{10}$$

where v_w indicates a node, $s = P(A_O)/P(A_1)$, $P(A_1)$ refers to the probability of connected links and $P(A_0)$ represents he probability of unconnected links, $R_W = N_{\Delta w} + 1/N_{\wedge w} + 1$, $N_{\Delta w}$ counts the number of v_w's neighbor node pairs which are connected, $N_{\wedge w}$ is the number of v_w's neighbor pairs which are not connected.

LNBAA index is combined with Local Naive Bayes Model and Adamic-Adar index which is different from common neighbors and the definition of it is $S_{xy}^{AA} = \sum_{w \in \Gamma(x) \cap \Gamma(y)} 1/\log k_w$, where k_w denotes the degree of node w which is the common neighbor of node x and node y [42]. The LNBAA is defined as

$$r_{xy}^{LNBAA} = \sum_{v_w \in O_{xy}} S_{xy}^{AA} \left(\log s + \log R_w\right). \tag{11}$$

where the meaning of s and R_w are identical with the parameter of formula (9).

5.4. Results and Discussion

In this section, we discuss the presented results in relation to the experiment. Table 1 displays the main structure of the suppliers–manufacturers bipartite network, which lists the numbers of suppliers, manufacturers, total links, links in testing set and training set. Table 2 reflects the main structure of the manufacturers–packers bipartite network. Table 3 lists the number of discovered potential partnerships links by the proposed algorithm of DPP, and other algorithms based on PA, LNBCN and LNBAA respectively in the suppliers–manufacturers bipartite network. Table 4 enumerates the number of discovered potential partnerships links by the aforementioned algorithms in the manufacturers–packers bipartite network. As the experimental results of the different algorithms summarized in Tables 3 and 4 shows, DPP finds the most potential partners in both suppliers–manufacturers and manufacturers–packers bipartite networks, followed by PA, LNBCN and LNBAA.

Table 5 displays the AUC values of the four algorithms in 10 tests on the suppliers–manufacturers dataset. In this table, we find that the AUC values of DPP is highest in 10 tests, which reveals that the DPP algorithm has highest prediction accuracy compared with other three algorithms. Table 6 displays the AUC values of four algorithms in 10 tests on the manufacturers–packers dataset. From this table, it is clear to see that DPP algorithm achieves highest AUC scores in 10 tests compared with PA, LNBCN and LNBAA algorithms. Compared with results in Table 5, Table 6 displays more significant advantages of DPP over the other three algorithms. This is due to the fact that the manufacturers–packers bipartite network has sparser nodes and links than the suppliers–manufacturers bipartite network. By adding some new potential partners to a sparse network, will the graph show bigger improvement than a dense structured network.

Figures 12 and 13 shows the updated structures of suppliers–manufacturers and manufacturers–packers networks after potential partner discovery respectively. Compared with Figure 10, there are 124 potential manufacturers partners for suppliers are discovered in Figure 12. Similarly, there are 16 potential packers partners for manufacturers are discovered in Figure 13 compared with Figure 11. As we implement that resilience evaluation framework, the *connectivity* of the updated suppliers–manufacturers network in Figure 12 is 1.257 which is greater than the value of 0.843 in the original network. And the *flexibility* value of the updated suppliers–manufacturers network 1.364 which is higher than the value of 0.982 its corresponding original network. In the same measure for the updated manufacturers–packers networks, the *connectivity* is imcreased from 0.621 to 1.048, and the *flexibility* ascends from 0.764 to 1.115. Obviously, by discovering potential partners via projection-based link prediction improves the resilience of the supply chain network significantly.

Figure 14 illustrates the suppliers–manufacturers–packers tripartite supply chain network after discovery of potential partners in the suppliers–manufacturers and manufacturers–packers networks. In the figure, each yellow node represents a supplier, green node symbolizes a manufacturer and red node refers to a packer, the links among the parties refer to their partnerships. To show the effect

Table 1 Structure information of the suppliers–manufacturers bipartite network.

Suppliers	Manufacturers	Links	Links in Testing Set	Links in Training Set
125	9	941	94	847

Table 2 Structure information of the manufacturers–packers bipartite network.

Manufacturers	Packers	Links	Links in Testing Set	Links in Training Set
9	14	126	13	113

Table 3 The number of discovered potential partnerships links by algorithms in the suppliers–manufacturers bipartite network.

DPP	PA	LNBCN	LNBAA
124	119	97	92

DPP, discovering potential partnerships; PA, Preferential Attachment; LNBCN, Local Naive Bayes common neighbor; LNBAA, Local Naive Bayes Adamic-Adar.

Table 4 The number of discovered potential partnerships links by algorithms in the manufacturers–packers bipartite network.

DPP	PA	LNBCN	LNBAA
16	11	9	5

DPP, discovering potential partnerships; PA, Preferential Attachment; LNBCN, Local Naive Bayes common neighbor; LNBAA, Local Naive Bayes Adamic-Adar.

Table 5 Comparison of AUCs of DPP with other algorithms on the suppliers–manufacturers dataset.

Test	DPP	PA	LNBCN	LNBAA
1	**0.9976**	0.9917	0.9760	0.9759
2	**0.9980**	0.9920	0.9777	0.9776
3	**0.9970**	0.9913	0.9750	0.9749
4	**0.9968**	0.9908	0.9786	0.9785
5	**0.9963**	0.9889	0.9765	0.9765
6	**0.9964**	0.9899	0.9773	0.9772
7	**0.9982**	0.9923	0.9770	0.9769
8	**0.9973**	0.9913	0.9763	0.9761
9	**0.9978**	0.9917	0.9747	0.9747
10	**0.9969**	0.9905	0.9769	0.9769
Average	**0.9972**	0.9910	0.9766	0.9765

AUC, area under curve; DPP, discovering potential partnerships; PA, Preferential Attachment; LNBCN, Local Naive Bayes common neighbor; LNBAA, Local Naive Bayes Adamic-Adar.

Table 6 Comparison of AUCs of DPP with other algorithms on the manufacturers–packers dataset.

Test	DPP	PA	LNBCN	LNBAA
1	**0.9740**	0.8938	0.7482	0.7482
2	**0.9781**	0.9096	0.7556	0.7548
3	**0.9841**	0.9246	0.7524	0.7524
4	**0.9746**	0.8980	0.7526	0.7518
5	**0.9790**	0.9035	0.7542	0.7538
6	**0.9805**	0.9108	0.7607	0.7599
7	**0.9632**	0.8742	0.7436	0.7432
8	**0.9738**	0.8890	0.7464	0.7456
9	**0.9762**	0.9064	0.7558	0.7554
10	**0.9842**	0.9194	0.7568	0.7556
Average	**0.9768**	0.9029	0.7526	0.7521

AUC, area under curve; DPP, discovering potential partnerships; PA, Preferential Attachment; LNBCN, Local Naive Bayes common neighbor; LNBAA, Local Naive Bayes Adamic-Adar.

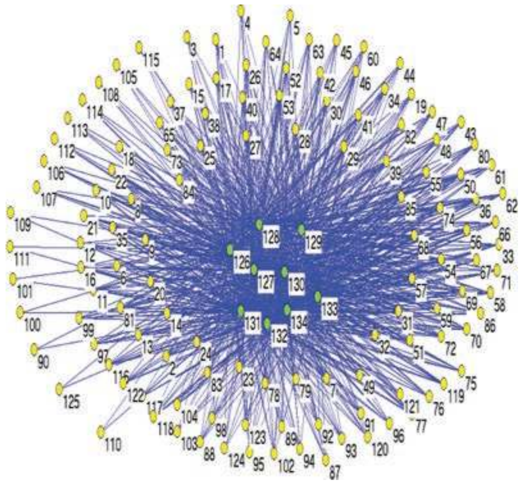

Figure 12 | Structure of suppliers–manufacturers after potential partner discovery.

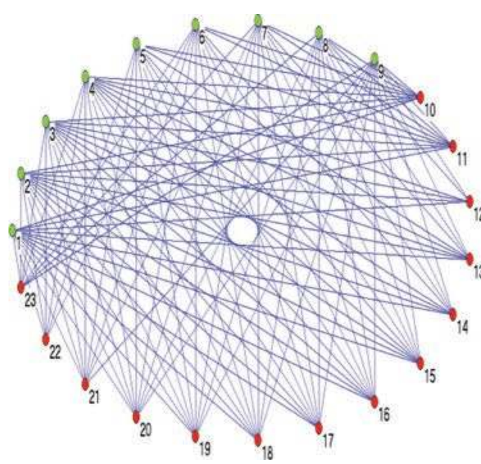

Figure 13 | Structure of manufacturers-packers after potential partner discovery.

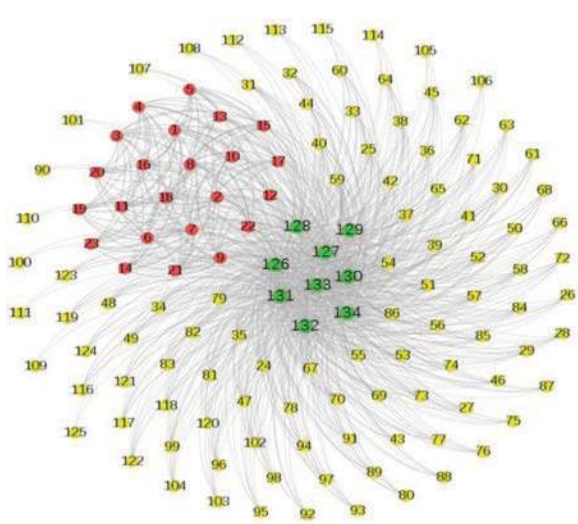

Figure 14 | Structure of supply chain network after experiment.

of the network by fulfilling the discovering task, we take the node labeled 126 as an example, which is a Huawei mobile phone manufacturer and connects with 89 upstream suppliers and 6 downstream packers. There are 534 combinations of supply chain from the suppliers to packers. By implementing the partner discovery process, it is found that 12 suppliers and 1 packers that are nonexistent nodes in the original bipartite networks can be its potential partners. This results in 707 possible combinations, a 32% increase to the original network. From this point, it also implies that the longer the supply chain extends, the more potential supply chains could we have. Furthermore, the connectivity of the tripartite network centered at node 126 increased from 0.647 to 1.176, and the flexibility increased from 0.851 to 1.370, indication great resilience improvement by implementing potential partner discovery. Obviously, the process of discovering potential partners helps the manufacture increase its robustness and reduce the vulnerability when there is a turbulence in the market. It could also enhance the risk response capacity of the supply chain network and ensure the profitability for the participants of the network.

6. CONCLUSIONS

Enterprises that fail to provide necessary supply chain visibility often find too late that interruptions, delays, scrap, risk exposure and quality failures were due to a dangerous reliance on inherent and insufficient supply chain partners. Discovering potential partners in supply chain network helps to improve resilience, visibility and collaboration throughout the partner network. This study proposes a projection-based link prediction approach to discover potential partners in the supply chain network to increase supplier chain resilience and reduce cooperation challenges. The model firstly predicts candidate partnership links based on the supply chain network's structure and its projection one-model graphs. Secondly, it discerns the potential partners by comparing the connectivity of the acquired candidate partnership links with the maximal connectivity of existent partnership links. Thirdly, a resilience evaluation framework is used to assess to what extent that supply chain network's connectivity and flexibility are improved. The application of the model is demonstrated through an experiment of a mobile phone supply chain network. Results of experiment reveals that the proposed algorithm exceeds three other link prediction algorithms in the aspect of AUC index showing higher prediction precision over them. Both connectivity and flexibility are improved in terms of the resilience of the post-discovery network to the original one.

Future research directions on the basic of this paper are as follows:

- The proposed potential partner discovery algorithm obtains divides the multi-tier supply chain network into bipartite supply chain networks, which ignores the globality of the supply chain network. Further work will be needed to concentrate on the integrity of the supply chain network.
- The proposed model is based on the static supply chain network and ignores the new entrants to the network. Further studies should consider the significance of the supply chain network evolution.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

AUTHORS' CONTRIBUTIONS

The study was conceived and designed by Zhigang Lu and experiments performed by Qian Chen. All authors read and approved the manuscript.

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