Network Community-based Technological Cooperation Identification

Lu Huang [1] Wen Miao [2] Yi Zhang [3] Huizhu Yu [4] Kangrui Wang [5]

[1] *huanglu628@163.com*
Beijing Institute of Technology (China)

[2] *a2689813532@126.com*
Beijing Institute of Technology (China)

[3] *yi.zhang@uts.edu.au*
Centre for Artificial Intelligence, Factulty of Engineering and Information Technology, University of Technology Sydney (Australia)

[4] *675244410@qq.com*
Beijing Institute of Technology (China)

[5] *kangruiwbb@163.com*
Beijing Institute of Technology (China)

Abstract

Technological cooperation becomes necessary in extending ~~technology~~ technological application and improving market competitiveness, and thus, ~~.~~ ~~For technology owners,~~ it is important to identify collaborative technologies that meet strategic purposes. This paper aims to construct a technological network based on the core terms derived from patent documents to help ~~the~~ technology owners ~~find the cooperative technology~~achieve such target. ~~Four steps are conducted~~A four-step analytic framework is constructed, including: 1) community division, which allows the selection of cooperative technology to be controlled within a more relevant technical range~~.~~; 2) indicators analysis that can be ~~,~~ used to understand the technical situation within the community from three main aspects, i.e., ~~, include~~ degree, clustering coefficient and line weight~~.~~; 3) the purpose of cooperation, which is an important basis for the ~~choice~~ selection of cooperative technology~~, include extend technology applications, improve technology level and identify possible technological connection~~;~~.~~ and 4) technology choice, which is to combine cooperation purposes and indicator~~s~~ analysis to select technology. Finally, a case study ~~about~~ on China's artificial intelligence (AI) technology is conducted to demonstrate the feasibility of this method, and the findings ~~benefit experts of AI field to make technological decisions~~will also help decision making in related AI fields.

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Conference Topic

Patent analysis; Social network analysis; Mapping and visualization;

Introduction

With the continuous development of science and technology, the degree of knowledge specialization ~~of knowledge~~ is getting higher and higher. To improve the ability of technological innovation and market competitiveness, technology cooperation has received increasing attention (Tu, Mohler & Ma, 2017; Kotsemir, Kuznetsova & Nasybulina, 2016). In addition, it's hard for an individual enterprise to bear high risk and huge capital investment requirement in the process of new product development, and technology cooperation can reduce the adverse impact of failure on enterprises.

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With advantages in value-added information, structured data format and low acquisition cost, patent has been widely used to analyse modern technologies, such as technical information flows, technological trends (Segev & Kantola, 2012), technological innovation (Lee & Kim, 2010), and technological strategy (Ernst, 2003). Bibliometrics have been commonly used in patent analysis due to its simplicity and convenience (Bellotti, Kronegger & Guadalupi, 2016; Landini, Malerba & Mavilia, 2015; Chen & Fang, 2014), but the shortage is that it heavily depends on bibliographic information, which doesn't include detailed technology information (Yoon & Park, 2004). As a remedy, a content-based approach fills the deficiency by analysing detailed information extracted from text, and keyword-based analysis (KWA) is a representative method of content-based approaches. The combination of KWA and network models (Huang, Zhu & Guo, 2014; Sternitzke, Bartkowski & Schramm, 2008), known as keyword-based network, can directly reveal the relationships between keywords and help to analyse technologies within the theoretical framework of networks (Wu, 2016; Zhang, Shang & Huang, 2016; Choi & Hwang, 2014), and the engagement of advanced information technologies (e.g., machine learning) further enhances such ability in relationship identification (Zhang et al. 2016).~~.~~

Community structure is a feature of networks. Node in a network can be divided into groups, and nodes in a group are tightly connected while node connections between different groups are sparse. Here group is called as community. Community in actual systems has significance meanings, and can help solve many actual problems. In social network, community may be based on human occupation, age or other factors (Girvan & Newman, 2001); in citation network, community may be divided according to research areas (Redner, 1998); in World Wide Web, different communities may represent different themes on web pages (Flake, Lawrence & Giles, 2002). Under this circumstance, i~~I~~ndicator analysis becomes~~is~~ an important way to understand~~study~~ the ~~network~~ topology of networks, and some common indicators include~~.~~ Degree, density, compactness, line weight, closeness, clustering coefficient, etc. ~~are common indicators.~~

This paper ~~presents~~ proposes a method that ~~identifying~~ identifies technological cooperation based on network community structure. Community division allows the selection of cooperative technologies to be controlled within a more relevant technical range and makes the selection result more accurate. We ~~classify~~ identify technology cooperation purposes into three categories, ~~include~~ i.e., extending technology applications, improving~~e~~ technology level and identifying possible technological connection. Network indicator analysis is adopted to select cooperative technology. Different purposes need different indicators. This paper mainly conduct the following research: community division, indicators analysis, purpose of cooperation and technology choice. Finally, a case of China's artificial intelligence technology is studied to illustrate the availability of the proposed method.

This paper is organized as follows: In the next section, we introduce the methodological framework, including patent collection, network construction, community analysis and identification of technological cooperation. A case study of China's artificial intelligence technology is discussed in the following section to demonstrate the feasibility of our method. Finally, we draw some conclusions and discuss the future study.

Method

The proposed method is comprised of four steps: patent collection, network construction, community analysis and ~~Identification~~ identification of technological cooperation. The process is showed in Figure1.

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Zhang, Y., Zhang, G., Zhu, D., Lu, J. 2016. Scientific evolutionary pathways: identifying and visualization relationships for scientific topics, *Journal of the Association for Information Science and Technology*, accepted.

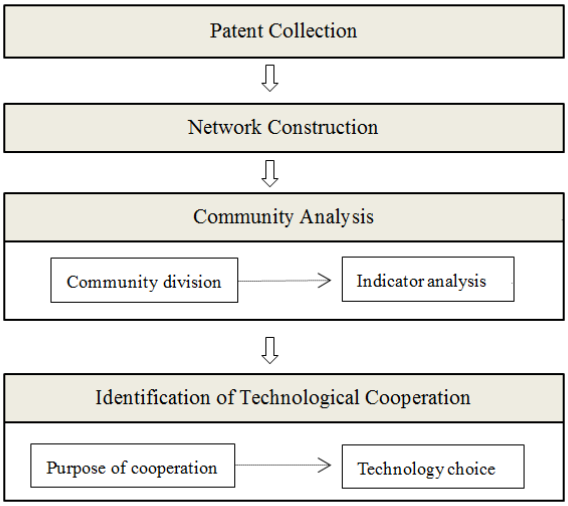

Figure1. Process of network community-based technological cooperation identification

Patent Collection

This step aims to propose a search strategy and collect patents. To make a good search strategy, some necessary factors should be considered, including the features of patent databases, actual research purpose and time span. For example, special patent database does not reveal enough information about the legal status, the same family, the patent.

Network Construction

Before we construct keyword-based patent networks, keyword acquisition is required, i.e., extracting keywords from patent abstracts, filtering invalid words (such as number, academic terms and other basic words) and selecting a number of keywords as the research objects. According to a co-occurrence matrix, we construct a keyword-based network, where each node represents a keyword and the line represents the co-occurrence relationship between the two end nodes.

Community Analysis

Based on the network constructed in the above step, we divide the whole network into some communities based on the connection tightness between nodes, allows the selection of cooperative technology to be controlled within a more relevant technical range. Then, we adopt network indicators (e.g., degree, clustering coefficient and line weight) to explore each community, providing theoretical basis for technological cooperation identification.

1) Community Division

Intuitively speaking, community refers to a set of nodes, and the connections within a community are dense while the connections between different communities are sparse. Network community indicates a set of nodes that have some common attributes or some similar effects. The algorithm for community division is as follows.

$$Q=\frac{1}{2m}\sum_{i,j}\left[A_{ij}-\frac{k_i k_j}{2m}\right]\delta(c_i,c_j)$$

$$,\quad \delta(c_i,c_j)=\begin{cases}1, & c_i=c_j\\ 0, & c_i\neq c_j\end{cases},\ m=\frac{1}{2}\sum_{ij}A_{ij},\ 1\leq i,j\leq n \qquad (1)$$

Where A_{ij} is the line weight between node i and node j (1), $k_i=\sum_j A_{ij}$ denotes the sum of all the line weights connecting node i, c_i and c_j are the community indexes of node i and node j respectively, m is the sum of all line weights of network and Q represents modularity, whose value is between [0, 1]- the higher Q value the better community division.

In the initial state, every node is a separate community, and the community number is n. Then, communities merge together one by one. The iteration ends when Q gets the maximum value.

2) Indicator Analysis

Before choosing a target technology, we need to understand the technology situation by analyzing nodes connection within the community, such as the influence and connection tightness of nodes, ~~nodes connection tightness~~ and node cohesion. Indicator which is used to analyze ~~nodes~~ the relationship of nodes can be taken to research the above situations. Considering the diverse implications of indicators in handling diverse technological problems (Yan & Luo, 2016; Jeong, Kim & Choi, 2015; Koseoglu, 2016), we try to summarize certain common indicators and their technological implications in Table 1.

~~Different indicators have different implications, and are used to handle different technological problems (Yan & Luo, 2016; Jeong, Kim & Choi, 2015; Koseoglu, 2016). Some common indicators are sorted, as shown in Table 1.~~

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TABLE1. Detailed network indicators introduction

Indicator	*Description*	*Technology implication*	*Paper Case*
Density	The tightness of nodes connection in the network	A high value means the network is highly connected, indicating the technology is well developed. While a low value means a sparse network whose development is immature.	(Flake, Lawrence & Giles, 2002)
Degree	The number of direct links between target node to others	A high value means target node is highly linked to other nodes, indicating the node technology is important.	(Harten & Retèl, 2016)
Component	The number of parts that make up the network	A small value means the network is highly connected, and technologies are closely linked.	(Taibi, Gualberti & Bazilian, 2016)
Clustering coefficient	The extent of links between neighbour nodes of target node	A high value means the links between neighbour nodes is dense, which indicates the target node surrounded by strong connections is very important. This indicator judges the importance of node by the density of its neighbour nodes' links.	(Urban, Zhou & Nordensvard, 2015)
Line weight	The strength of the relationship between the two nodes connected	Representing the intensity of the interaction between individuals, a high value indicates the two technologies are highly relevant.	(Tao & Xue, 2016)
Closeness	The extent of difficulty from target node to all other nodes in the network	A high value means the information of target node can be easily spread to all other nodes, indicating the target technology has an important influence in the network.	(Lu, 2010)
Betweenness	The number of the shortest path passing through the node to the total number of the shortest paths.	Reflecting the effect and influence of nodes in the whole network. Used to measure the intermediary and brokerage capability of technology.	(Radicic, Douglas & Pugh, 2015)

In our paper, we select indicators based on cooperation purpose, and different purposes will be analyzed with different indicators. Considering actual requirements on technology management and analysis, we specifically select three indicators in this paper, i.e., ~~Below three objectives are mentioned, the required indicators are three kinds:~~ degree, line weight and clustering coefficient. Degree reflects the influence of a node, line weight expresses the connection tightness between two nodes and clustering coefficient corresponds to the cohesion of a node. The detail explanation of these indicators is given below.

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- Degree

In a network, the degree of one node means the number of direct links between the node and other nodes. High degree value means the node is highly linked with other nodes, indicating the technology reflected by this node is important. The calculation formula (Jeong, Kim & Choi, 2015) is given below.

$$d_i = \sum_{j=1}^{n} l_{ij} \text{ , where } i \neq j \text{ and } l_{ij} \begin{cases} 1 & \text{if } w_{ij} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where w_{ij} denotes the line weight between node i and node j, and d_i denotes the number of lines connected to node i, and can reflect the importance of node in a large level.

- Clustering coefficient

The clustering coefficient of one node denotes the extent of links between the neighbor nodes of a target node. A high value means the links between neighbor nodes is dense, which indicates the target node surrounded by strong connections is very important. This indicator measures the importance of a node by the density of its neighbor nodes' links. The calculation formula (Yan & Luo, 2016) is as follows.

$$cc_i = \frac{2l'}{k(k-1)} \quad (3)$$

Where cc_i represents clustering coefficient of node i, k denotes the number of lines connect to node i directly, l' denotes the number of lines existed in the k nodes, and $k(k-1)/2$ denotes the number of possible links between those k nodes.

- Line weight

Line weight describes the relationship between two nodes. In this paper, the value means the co-occurrence frequency of two technologies in the patent set. The definition of line weight (Barrat, Barthélemy & Pastorsatorras, 2004) is introduced bellow.

$$w_{ij} = \frac{n_{ij}}{N} \quad , \ i \neq j \quad (4)$$

Where w_{ij} represents the line weight of node i and node j, N denotes the patent number of patent set, n_{ij} denotes the number of patents which contain both technologies of node i and node j. A high value of w_{ij} means node i and node j are highly related.

These indicators are used to choose technology cooperation object, and different technology cooperation purposes need different indicators analysis. Next, we will introduce cooperation purposes.

Identification of technological cooperation

This step aims to select target technology based on the results from indicators analysis. To do that, we need firstly figure out the purpose of the cooperation. ~~This paper summarizes three types of cooperation purposes, as follows:~~

1) Purpose of cooperation

In this paper, we mainly focus on three types of technological cooperation purposes, and the definitions are given below:

- Extend technology applications:
- The aim of the cooperation is to extend the application scope of own technology. The ideal cooperative technology should be those that are widely connected with other technologies.
- Improve technology level:
- Representing cooperate with professional technology to innovate own technology, which can improve the market competitiveness of own technology compared with similar technology.
- Identify possible technological connection:
- If technology a1 and technology a2 both connect closely with Technology b respectively, there is great possibility that a1 and a2 will connect tightly in the future. So, the cooperation between this two technologies is in line with technology development trends and easy to succeed.

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2) Technology choice

Based on the above research of cooperation purposes and indicators analysis, we select different indicators to realize the three cooperation purposes, and realize the choice of technology.

In a community, the node with high degree value is widely connected with other nodes, which means this technology is easily to build connection with other technologies. Those technologies with high degree are good choice for extending technology applications.

Clustering coefficient indicates the relationship between node and its surrounding nodes. A high value shows strong cohesion, which means the surrounding nodes are highly connected and form a topic group. If one aims to improving technology level, the member technologies of the group are suitable to cooperate.
Line weight measures the connection tightness between two nodes. Technology couple with high value shows the close contact of existing connection, can be used to identify possible technological connection.
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Case study: China’s Artificial Intelligence

To demonstrate the feasibility of our proposed method, china’s artificial intelligence technology is selected as a case. Artificial intelligence (AI), a technical science, aims to research and develop theories, methods, and application system for simulating, extending and expanding human intelligence. The reason we choose China’s artificial intelligence is that China has the world's leading voice and visual recognition technology, and its research ability of artificial intelligence is impressive. Besides, according to two important reports of the White House released in October 2016, *Preparing for the Future of Artificial Intelligence* and *The National Artificial Intelligence Research and Development Strategic Plan*, China has surpassed the US in the total number of cited journal articles that relate to deep learning techniques in 2014. What’s more, on March 5, 2017, at the opening ceremony of the National People's Congress, Premier Li Keqiang announced that China would speed up the research and development of new industries such as artificial intelligence. This is the first time that China's highest national conference has incorporated artificial intelligence into government work reports. This shows that artificial intelligence has become the priority of China's economic agenda, and the government has decided to support its growth. China's artificial intelligence has indeed made great achievements, and technology cooperation will broaden this field's future development.

Data

To study the development of AI in china, the patent set of Chinese AI technology was collected. The search strategy is "TS= ("artif* intelli*" OR "comput* intelli*" OR "deep learn*" OR "machine learn*" OR "big data" OR "cloud comput*" OR "pattern recogn*" OR "neural network*" OR "data mining*") AND PN= (CN*)". As a result, 10,229 China's patents between 2012 and 2016 were acquired from Derwent Innovations Index (DII).

Result

We draw a keyword-based network where nodes represent keywords and lines represent the co-occurrence relationships between two end nodes. Conducting community division, we got three communities displayed in Figure 4 (b1, b2 and b3 are the independent part of each community). Next, we combine figures and indicators analyse technology situation of each community.

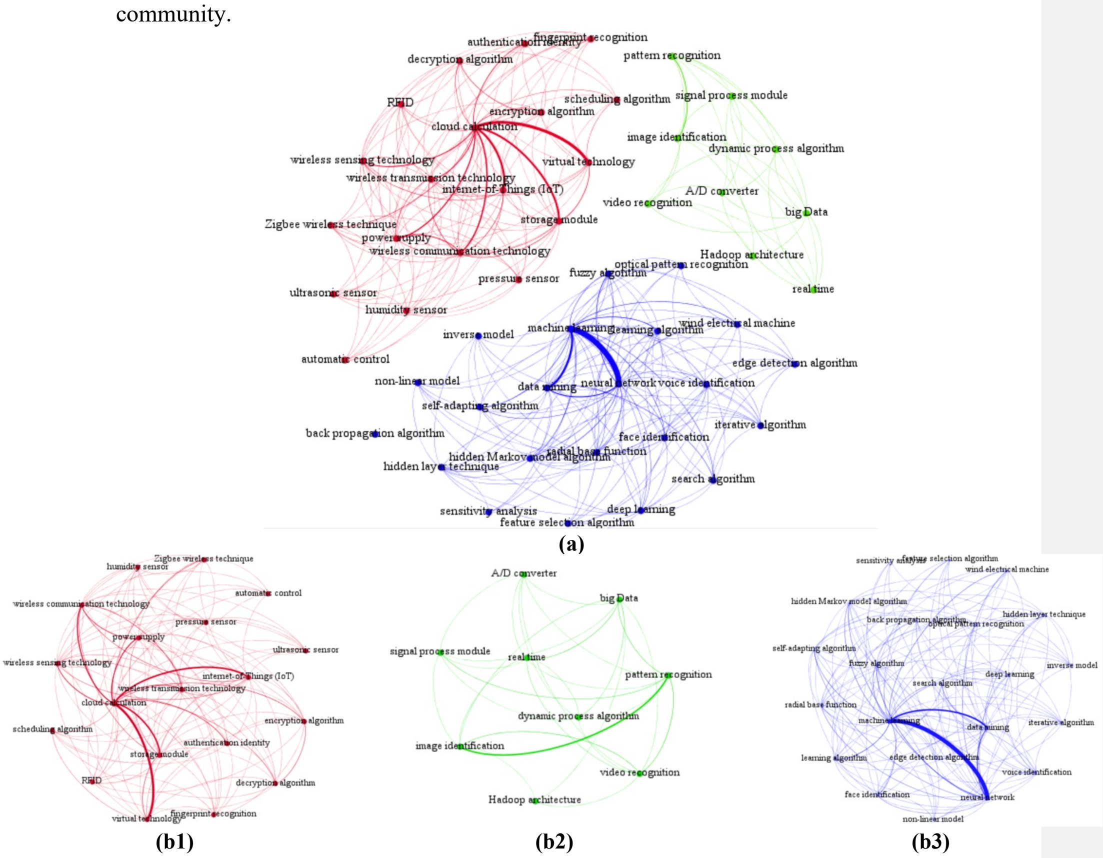

Figure4. Community division result of the technology network.

(a) shows the overall division effect. (b1), (b2) and (b3) are community1, community2 and community3 respectively.

TABLE 2 displays the results of degree and clustering coefficient analysis of three communities.
In degree analysis, we list out the top three technologies of each community. Comparing the degree values with community size, we find that in each community these technologies are almost all connected with other technologies, indicating these technologies are the best choice to cooperate with to extend technology application. From Figure 4-(b1), (b2) and (b3) we can find out the sparse nodes, and expand their technology application. The results are as follows:

- ~~In~~ C~~c~~ommunity 1:
- Automatic control can cooperate with cloud calculation, internet-of-Things (IoT) or wireless sensing technology.
- In community 2
  Hadoop architecture can cooperate with big Data, video recognition or real time.
- In community 3
  Sensitivity analysis can choose machine learning, neural network or data mining.

In clustering coefficient analysis, the top three technologies of each community are displayed. These technologies are highly professional, can promote own technology to have rapid growth. Improve own technology in the same type of technology in the competitiveness. From Figure 4-(b1), (b2) and (b3) we can identify the potential technology cooperation as follows:

- In community 1
  Ultrasonic sensor can choose to cooperate with automatic control.
- In community 2
  Dynamic process algorithm can choose to cooperate with image identification.
- In community 3
  Feature selection algorithm can choose to cooperate with Hidden markov model algorithm.

TABLE2. Top 3 technologies of degree and clustering coefficient in each community

Partition	*Size*	*Degree*		*Clustering coefficient*	
		Node	*value*	*Node*	*value*
		cloud calculation	18	automatic control	1
Community1	19	internet-of-things (IoT)	18	pressure sensor	0.96
		Wireless sensing technology	17	humidity sensor	0.96
		big data	8	Hadoop architecture	1
Community2	9	video recognition	7	dynamic process algorithm	0.93
		real time	7	A/D converter	0.93
		machine learning	21	feature selection algorithm	1
Community3	22	neural network	21	optical pattern recognition	0.93
		data mining	20	inverse model	0.93

TABLE 3 reflects the result of line weight analysis, listing out the top 5 technology couples of each community. Fig.5 is the network diagrams of these technologies.
In community 1, Fig.5-(c1) is the corresponding network diagram of these technologies, where we can see that there are other connections between the six technologies besides the top 5 lines. For example, internet-of-things (IoT) and wireless communication technology. For both of them are closely connected with cloud calculation, there are great possibility that internet-of-things (IoT) and wireless communication technology can cooperate with each other and build close connection in future. After a similar analysis, we find in community 2

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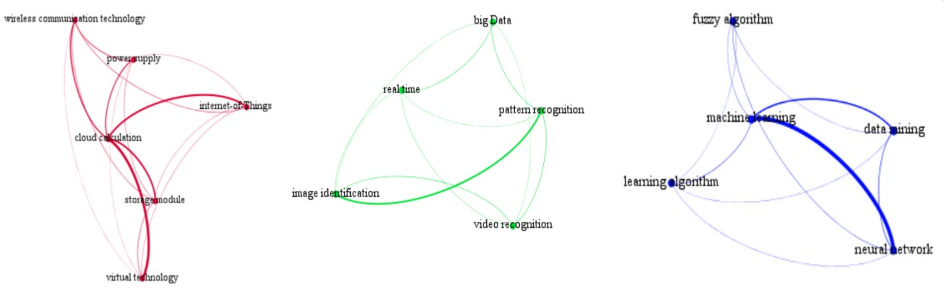
that pattern recognition and real time is possible close connection in the future and can cooperate with each other. In community 3 machine learning and fuzzy algorithm, data mining and fuzzy algorithm are potential technology combinations.

TABLE3. Top 5 technology couples of line weight in each community

Partition	*Ranking*	*Node Couple*	*Value*
Community1	1	cloud calculation——virtual technology	0.023
	2	cloud calculation——internet-of-things (IoT)	0.016
	3	cloud calculation——storage module	0.015
	4	cloud calculation—wireless communication technology	0.011
	5	cloud calculation——power supply	0.009
Community2	1	pattern recognition——image identification	0.007
	2	pattern recognition——video recognition	0.002
	3	pattern recognition——big data	0.002
	4	image identification——video recognition	0.002
	5	big data ——real time	0.002
Community3	1	machine learning——neural network	0.043
	2	machine learning——data mining	0.016
	3	neural network——data mining	0.007
	4	machine learning——learning algorithm	0.005
	5	neural network——fuzzy algorithm	0.004



(c1) **(c2)** **(c3)**

Figure5. Top 5 technology couples of line weight in each community.

(c1), (c2) and (c3) correspond to community1, community2 and community3 respectively.

Discussion and Key Findings

We constructed networks based on keywords extracted from Chinese AI patents, and divided it into 3 communities. In each community, we took indicator analysis to select cooperation technologies according to different cooperation purposes.

According to the connection tightness between nodes in the network, the network is divided into three communities. The contribution of community division is to refine the area of technical selection to a more relevant scope. We grasp the technical situation within each community by indicator analyse. When choosing cooperation partners, cooperation purposes are considered. This paper summarizes three kinds of cooperation purposes: extend technology applications, improve technology level and identify possible technological connection. Corresponding analysis indicators are: degree, clustering coefficient and line weight. Based on the above research, we can identify the following technology cooperation:

1) Cooperate with high degree technologies to extend technology applications, e.g., XXX in Figure XXX.~~.~~
2) Cooperate with high clustering coefficient technologies to improve technology level.

3) Identify possible close technological connection by existing technology connections.

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CONCLUSIONS AND FUTURE STUDY

In this paper, we propose a method based on network community to identify technological cooperation, mainly include community division, indicators analysis, purpose of cooperation and technology choice. This article is characterized by using community division and combining with technology purposes. Community division filtered out unrelated technologies and made the results more accurate. Different technology purposes adopt different network indicator analyses, according to the analysis results selecting technical cooperation object. Finally, we select China's artificial intelligence technology as a case to demonstrate the feasibility of our method. This paper has following contributions: proposing a method to identify technology cooperation and benefit experts of technical cooperation identification.

There are some limitations on our research. For example, in this paper, the network is divided into three communities. Applying other community division algorithm may get different results. Besides, this paper adopt three indicators based on research purposes, there are some other indicators can be used to analyse network topology, such as density, closeness and so on. Those indicators may have other new findings. In future, more accurate community division algorithm and more diverse indicators analysis should get further research.

Acknowledgments

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