Send Orders for Reprints to reprints@benthamscience.ae

Open Access

The Modeling and Analyzing Methods of Weighted Knowledge Network for Domain Knowledge Based on Keywords Clustering

Xiao Liao, Zhihong Li and Yunjiang Xi*

School of Business Administration, South China University of Technology, Guangzhou, 510641, China

Abstract: Keywords clustering, as the basic method of domain knowledge analysis, has some problems such as difficult to understand the clustered tree diagram, scarce of further analysis methods, etc. The paper proposed a new approach to analyze domain knowledge based on keywords clustering. The proposed weighted knowledge model (WKN) is composed of two types of nodes (nodes of high-frequency keywords and nodes of clusters which come from keywords clustering and named as keywords nodes). Based on WKN, some new methods are suggested to analyze domain knowledge, such as main sub-fields analysis and representation, important sub-fields and hot spots of domain knowledge identification, research fronts analysis, etc., and all the analysis results can be illustrated as a sub-network of WKN. In the end, a case study was conducted to verify the feasibility and validity of the methods. Compared with the existing methods, the proposed methods seem more clearly, deeply and conveniently, and present new tools for researchers to study and utilize domain knowledge.

Keywords: Domain knowledge analysis, keywords clustering, knowledge management, knowledge network.

1. INTRODUCTION

Domain knowledge is defined as the knowledge of an area to which a set of theoretical concepts is applied and is fundamental to all disciplines [1, 2]. The researches of domain knowledge mainly focus on analyzing the knowledge structure and the research trend in a specific domain. Besides, domain knowledge is often used in data mining research. The role of domain knowledge in data mining is highlighted in many researches. Anand *et al.*, (1995) defined domain knowledge as a specific domain information that collected from previous systems or documentation, or elicited from a domain expert, and in their research, domain knowledge was applied to reduce the search space before the data mining analysis to make patterns more intuitive [3]. LU Rnqian and JIN Zhi (2002) pointed out that the analysis on domain knowledge or domain analysis is the activity of identifying and representing the relevant information in a domain. Through domain analysis, the information can be shared and reused in similar systems [4]. Lima *et al.*, (2009) found that domain knowledge can be used for meaningful information discovering, which can be used as a guide in the discovery process [5]. Therefore, the acquisition of domain knowledge seems more and more valuable in research. In this paper, we proposed a modelling and analyzing method based on weighted knowledge networks to discover and analyze domain knowledge.

2. LITERATURE REVIEW

2.1. Analysis on Domain Knowledge

The commonly used methods on studying domain knowledge include knowledge mapping and bibliometrics analysis.

As an approach to knowledge management, knowledge mapping is the process of creating a knowledge map which is a constructed architecture of a knowledge domain [6]. Most current researches on knowledge mapping tend to focus on the application of knowledge maps in diverse situations and for different purposes [6-11]. Hellstrom T (2004) studied the intellectual capital management in academic environments and argued that knowledge mapping may provide a fruitful avenue for it [6]. Seitan O (2009) discussed knowledge mapping processes in the knowledge management system of tourist destination, and explored the possible knowledge map structures by different types of tourist destinations [7]. Ebener S *et al.*, (2006) studied the application of knowledge mapping process in health care [11].

The term “bibliometrics” proposed by Prtichard in 1969 means “the application of mathematics and statistical methods to books, journals and other communication media”. Roy (1983) defined bibliometrics as “a study of the process of information use by analyzing the characteristics of documents and their distribution by statistical methods” [12-14]. There have been a great number of bibliometric studies on a single journal or a specific research domain [14-19]. Hsing-Chau Tseng *et al.*, (2010) analyzed 20,670 citations of 460 articles published in SSCI journals in the expatriate field from 2000 to 2008 by utilizing the bibliometrics and techniques of social network analysis to map the research paradigms of expatriate research domain [20]. Pinto C. F. *et al.*, (2014) analyzed how national culture has been impacting international business research by conducting a bibliometric study of articles published in 7 leading international business journals over the recent three decades [21]. Samiee, S., & Chabowski, B. R. (2012) applied the bibliometrics techniques to evaluate the knowledge structure of international marketing publications from 1999 to 2008 and provided a supplemental examination of the findings for the next two years (2009 to 2010) [22].

With the help of the information visualization tool Citespace, which was developed by Dr. Chen Chaomei of Drexel University based on Java platform, the analysis of domain knowledge in academic field combines well of the methods of knowledge mapping and bibliometircs. The domain analysis often focused on the content analysis and connection analysis. Content analysis is based on keywords analysis which is often used to analyze the research fronts and hot spots in a specific domain, while connection analysis is based on network analysis approach such as citation and co-citation network. Connection analysis is often used to analyze the institutional distribution, annual distribution, journal co-citation analysis and author co-operation analysis. Citation analysis is a major bibliometric approach that authors cite documents they consider important to their research. Documents with highly citation are likely to have a great influence on research field [23]. Co-citation analysis is to analyze the frequency of 2 papers which are cited by same publications [24]. It is often used to measure the similarity of the content in two documents [25, 26].

In keyword analysis, keyword cluster is a major approach that keywords are clustered into several groups according to their closeness and similarity and then expressed as a knowledge tree diagram. However, the detail relations between keywords in the same group and the differences between groups cannot be expressed clearly. Moreover, the importance of each keyword in a group and the importance of each group in the domain cannot be expressed clearly in the tree diagram either.

To better analyze the knowledge structure of a specific domain, we need to identify the relations between domain keywords and their importance as well. Therefore, in this paper, we proposed a modelling and analyzing method for domain knowledge analysis which called as clustered network. Here, clustering network is a weighted knowledge network which is based on the keywords clustered results. Different from the knowledge mapping method and the bibliometrics analysis, clustered network visually shows the hierarchical relationships and the importance of each knowledge point in a specific knowledge domain. This model helps to explore the knowledge structure and research status in a research domain.

2.2. Knowledge Networks

A knowledge network was defined as "a co-operation of individuals who produce, share, or use a common repository of knowledge" [27, 28]. Pugh, K., & Prusak, L. (2013) defined knowledge networks as collections of individuals or teams who come together across organizational and disciplinary boundaries with aims to invent and share knowledge. The focus of such knowledge networks is on developing, distributing and applying knowledge [29].

Besides, researchers pointed out that there were two types of nodes in a knowledge network: human and non human agents. Human nodes included individuals as well as aggregates of individuals, such as groups, departments, organizations, and agencies; and non human agents included knowledge repositories, Web sites, content and referral databases, avatars and "webbots" [30, 31]. Increasingly, the type of nodes was enriched. Xi (2005) pointed out that there were four types of nodes including knowledge owners such as individuals, groups and organizations; knowledge carriers such as knowledge repositories, database and Web sites; knowledge points such as knowledge elements or knowledge unit; and other mixed type of nodes [32].

In this paper, we adopted the knowledge points as the nodes in a domain knowledge network which was used to analyze the structure of domain knowledge. The network model was established based on the knowledge nodes and their relationships such as co-occurrence relations. And the model is expressed as $G = (K, E)$, in which, $K = \{k_1, k_2, ..., k_n\}$is the nodes set (K), and the edge set is expressed as $E = \{(e_{ij}) \mid i, j = 1, \cdots, n\}$.

3. LITERATURE RETRIEVING AND KEYWORD CLUSTERING

3.1. Literature Retrieving

To assure the retrieving effects, some domain experts are needed to qualify the subject terms, retrieving logistics, and literature databases. The retrieved literature set is denoted as:

$$D = \{(d_i) \mid i = 1, \cdots, a\} \tag{1}$$

3.2. Keywords Pre-Processing and High Frequency Keywords Identifying

The keywords set of the field and their frequencies are acquired based on the literature set, and all the keywords need be pre-processed, which may include the following works: 1) all the keywords be translated into English; 2)plural Nouns be modified as singular forms; 3)abbreviations be changed into full forms; 4)different forms of the same meaning terms be changed into the general terminology of the field; 5)some papers with no keywords be replenished according to suggestions of fields experts. Then the standardized keywords set can be obtained, denoted as:

$$T = \{(t_i) \mid i = 1, \cdots, b\} \tag{2}$$

Then the frequencies of keywords can be re-calculated, and can be denoted as follows:

$$Q = \{(q_i) \mid i = 1, \cdots, b\} \tag{3}$$

According to the frequencies, keywords of high frequencies can be identified as:

$$T' = \{(t_i) \mid q(t_i) > q_0\} \tag{4}$$

Here q_0 is a threshold, and generally it should be set according to the common selection rules which meet the following formulation [18]:

$$\sum [q_i \mid q_i > q_0] \Big/ \sum q_i \approx 0.3 \tag{5}$$

3.3. Keywords Clustering

Based on the keyword set T, the word-paper matrix can be constructed, and then the clustering analysis can be conducted through the SPSS19.0 software. Generally only the high frequency words are used for clustering analysis. The word-paper matrix is presented as follows:

$$M = \{(m_{ij}) \mid i = 1, \cdots, a; j = 1, \cdots, b\} \tag{6}$$

In Equ.6, if t_i is one of the keywords of literature d_j, $m_{ij} = 1$; if not, $m_{ij} = 0$.

Through clustering we get many classes which are illustrated as a tree graph. All the classes no matter big or small can are marked as C_1, C_2,…, C_l, then the class set can be the acquired and presented as:

$$C = \{(C_i) \mid i = 1, 2, \cdots, l\} \tag{7}$$

4. NETWORK MODELLING PROCESS FOR DOMAIN KNOWLEDGE

4.1. Clusters Naming

Each cluster is a subset of keyword set (T), *i.e.* $C_i \subset T$. According to the keywords and their relations, each cluster in Cwill be named with the help of some domain experts. Let c_i denote the name of cluster C_i, and generally c_i may be presented as a terminology in the domain. Then the cluster set C can be presented as a set of terminologies acquired above:

$$C' = \{c_i \mid i = 1, 2, \cdots, l\} \tag{8}$$

4.2. Domain Knowledge Points Acquiring

According to literature [12, 15], each keyword actually represents a knowledge point (KP) in a domain, and a KP actually represents a knowledge sub-field. Since each cluster is consisted of some related keywords, it cab can be concluded that a cluster actually represents the high-layer sub-field of the domain, and can be seen as a high-layer knowledge point. Let K represent the set of KPs in the domain, and then it can be acquired as follows:

$$K = T \cup C' \tag{9}$$

4.3. KP Links Acquiring and Network Modelling

The links of KPs represent the hierarchical relations between keywords and clusters according to the clustering results. Let $e_{ij} = 1$ represent k_i is subordinate to k_j directly, else $e_{ij} = 0$, then the set of links can be represented as follows:

$$E = \{(e_{ij}) \mid e_{ij} = 1; i, j = 1, 2, \cdots, n\} \tag{10}$$

And then the network model of domain knowledge can be constructed as:

$$G = (K, E) \tag{11}$$

As shown in Equ.11, G is a hierarchical network with KPs as nodes and links as edges.

4.4. Weighted Knowledge Network (WKN) Modelling

The above knowledge network model can be weighted based on the frequencies of keywords. Let $q(k_j)$ denote the weight of k_j. If $k_j \in T$, then:

$$q(k_j) = [q_i \mid k_j = t_i] \tag{12}$$

Else if $k_j \notin T$, then:

$$q(k_j) = \sum_{i=1}^{n} [q_i \mid e_{ij} = 1, k_i \in K] \tag{13}$$

Let $K(k_j)$ denote the set of all the nodes which are subordinate to k_j directly or indirectly (including k_j itself), then Equ. 12-13 can be combined as:

$$q(k_j) = \sum_{i=1}^{n} [q_i \mid k_i \in T, k_i \in K(k_j)] \tag{14}$$

Then the weighted knowledge network model (WKN) can be constructed as follows:

$$WKN = (K, E, Q(K)) \tag{15}$$

5. THE ANALYZING METHODS BASED ON WKN MODEL

5.1. Main Sub-Fields Identifying and Analyzing

The WKN model can help to identify the main research sub-fields easily: the high-weighted son-nodes of the root node usually represent the important sub-fields, and their structures can be described through the sub-networks of the WKN model. For example, the structure of sub-field k_j can be described as:

$$WKN(k_j) = (K(k_j), E(k_j), Q(k_j)) \tag{16}$$

Here $K(k_j)$ denotes all the nodes in the sub-fields k_j (including k_j itself), $E(k_j)$ denotes the set of direct hierarchical relations between nodes of $K(k_j)$, and $Q(k_j)$ denotes the weight set of nodes in $K(k_j)$. Then the sub-fields can represented as hierarchical sub-network of WKN model.

5.2. Research Hot Spots Identifying and Representing

Let K' denotes the set of research hot spots. It can be identified and obtained by the following equation:

$$K' = \{(k_j) \mid q(k_j) > q_1\} \tag{17}$$

Here q_1 is the threshold and can be qualified by researchers. Then the research hot spots can be represented as a sub-network of WKN:

$$G(K') = (K', Q(K'), E(K')) \tag{18}$$

Here $Q(K')=\{q(k_j)\,|\,k_j \in K'\}$ denotes the weight set of hot spots, and $E(K')=\{e_{ij}\,|\,e_{ij}=1, k_i \in K', k_j \in K'\}$ denotes the edge set between hot spots nodes.

From Equ. 17-18, it can be seen that hot spots of the fields can be identified and illustrated as hierarchical network easily through WKN model.

5.3. Research Fronts Identifying and Analyzing

Research fronts usually refer to the latest research hot spots in 1~2 years, which can be identified and analyzed easily through WKN model.

Let $D^1 \subset D$ denote all the literature published in 2 years, $T^1=\{t_1,\cdots,t_c\}$ denotes the set of all the keywords of papers of D^1, it can be deduced that T^1 is a sub set of T and K, *i.e.*, $T^1 \subset T \subset K$.

Let KN^1 denote the minimal connected graph in the sub-network of WKN which is composed of all the keywords in T^1, and it can be represented as follows:

$$KN^1=(K^1,E^1) \tag{19}$$

Here K^1 denotes the set of nodes in KN^1, E^1 denotes the set of edges between nodes of K^1. Let $q^1(t_i)$ denotes the frequencies of all the keywords in T^1, then the weights of the nodes in K^1 can be obtained as follows:

$$\text{If } k_j=t_i \in T^1, \text{ then: } q^1(k_j)=q^1(t_i) \tag{20}$$

Else if $k_j \notin T^1$, let $K^1(k_j)$ denotes all the nodes in KN^1 that are subordinate to k_j directly or indirectly, then the weights of k_j can be obtained as follows:

$$q^1(k_j)=\sum_{i=1}^{n}[q_i\,|\,k_i \in T^1, k_i \in K^1(k_j)] \tag{21}$$

Let $Q^1(K^1)$ denotes the weights set of all the nodes in K^1, then the weighted knowledge network model for KN^1 can be constructed as follows:

$$WKN^1=(K^1,E^1,Q^1(K^1)) \tag{22}$$

Based on the WKN^1 model, the research fronts can be identified through the following method:

Let K^2 denotes the set of nodes which represent the knowledge points of research fronts, and then it can be represented as follows:

$$K^2=\{k_i\,|\,q^1(k_i)>q_2\} \tag{23}$$

Here q_2 is the threshold, and the Equ. 24 means nodes with weights higher q_2 than are identified as KPs of the research fronts.

Denote E^2 as the hierarchical relations between nodes of K^2, it can be deduced that E^2 is a subset of E^1, *i.e.*, $E^2 \subset E^1 \subset E$, denote $Q^1(K^2)=\{q^1(k_i)\,|\,k_i \in K^2\}$ as the weights set of the nodes in K^2, then the research frontiers of the fields can also be represented as a sub-network of WKN^1:

$$WKN^2=(K^2,Q^1(K^2),E^2) \tag{24}$$

5.4. Other Applications of WKN

The proposed WKN model can also be used to analyze the evolution of domain knowledge. Together with the co-author data and paper citation/co-citation data, further analysis can be conducted based on the model.

6. A CASE STUDY

6.1. Data Sources and Literature Retrieving

The selected research field for the case study is "super-network / hypernetwork". The data sources are Web of Science and CNKI database. While retrieving in the web of science database, the subject words and the main heading are "supernetwork or hypernetwork", the retrieving date is limited to Nov. 30, 2013, and the retrieving result contains 237 papers. With some low relevant papers canceled, 162 relevant papers are remained. While retrieving in CNKI, with the same limitations, 228 papers are retrieved and 171 relevant papers are remained. In the end 337 relevant papers are remained totally for the case study.

6.2. Data Pre-Processing and Keywords Clustering

According to the suggested processes, we processed all the keywords into standard forms, calculated frequencies, founded word-paper matrix, and last clustered the keywords. According Equ.5, q_0 was set as 3, therefore those with frequencies higher than 3 were selected as high frequency keywords, and were clustered through SPSS. The clustering result is illustrated as a tree graph as Fig. (**1**).

6.3. The WKN Model for Supernetwork Domain

The clustering of high-frequency keywords generates 28 clusters. According to above methods, all the clusters are marked and given names by 2 experts in the domain. Then the WKN model for "supernetwork study field" is constructed after founding the sets of KPS, edges, weights sequentially (shown as Fig. **2**).

Comparing the Figs. (**1** and **2**), we can see that the tree graph only illustrated how many clusters for the keywords and the hierarchical relations between them, however the meanings of the clusters are not shown directly, while those are shown directly through names in WKN model. In the case the WKN model shows there are 8 nodes under the root

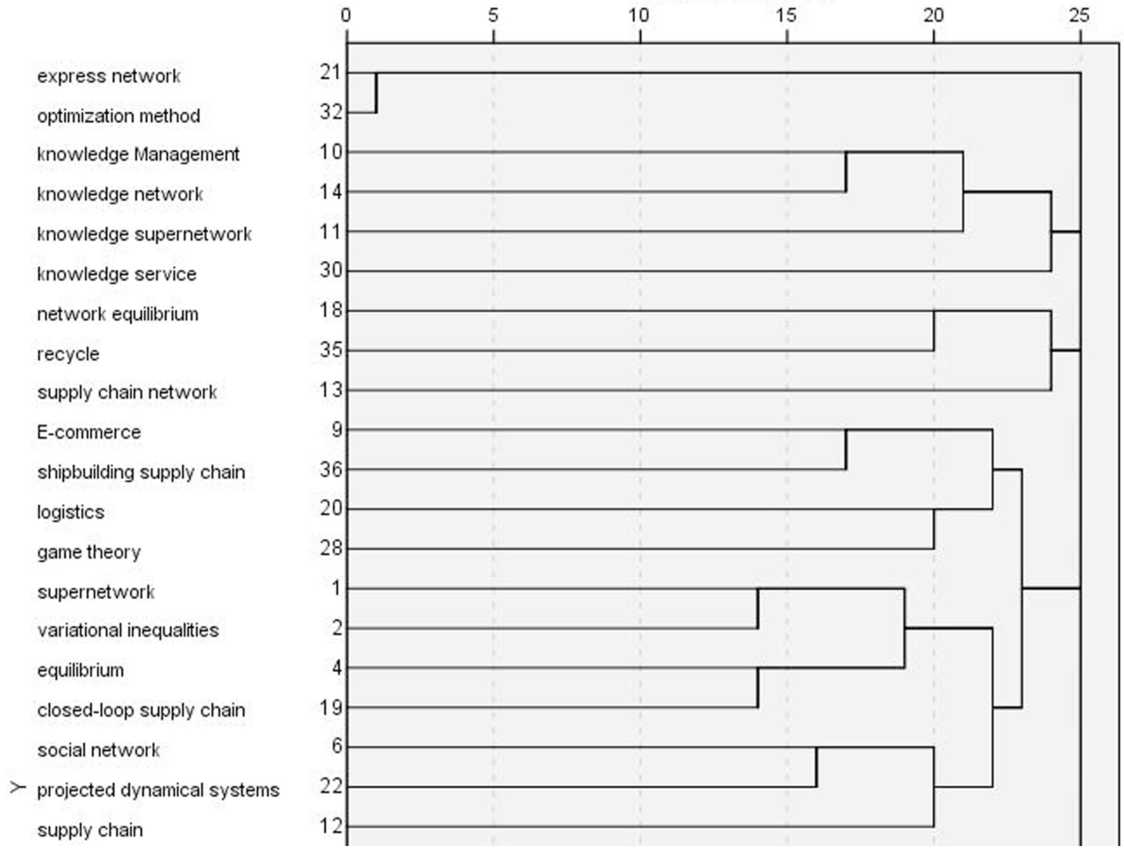

Fig. (1). Part of keywords clustering results.

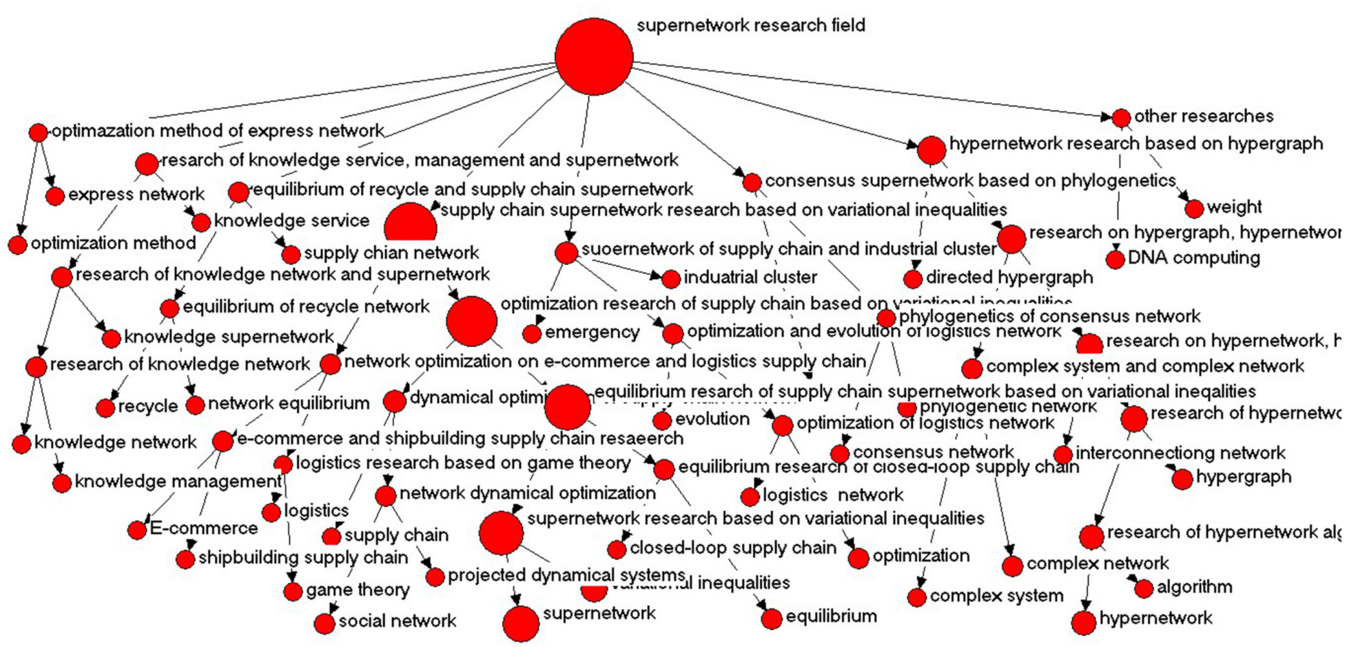

Fig. (2). WKN model of supernetwork domain.

node, which means there are 8 main sub-fields in the supernetwork field, and the node names indicate what the subfields are directly. Furthermore, the WKN model can also illustrate the importance of the sub-fields through the size of nodes based on their weights. Therefore it is easy to discover the important sub-fields and KPs in the research of supernetwork based on the WKN model.

6.4. Analysis on the Research of Supernetwork Field

6.4.1. Main Sub-Fields Identifying and Analyzing

As can be seen from Fig. (**2**), the research on supernetwork contains 8 sub-fields with the nodes size denoting their importance, and the structure of each field can be represented through a sub-graph of the WKN model (shown as Fig. **3**).

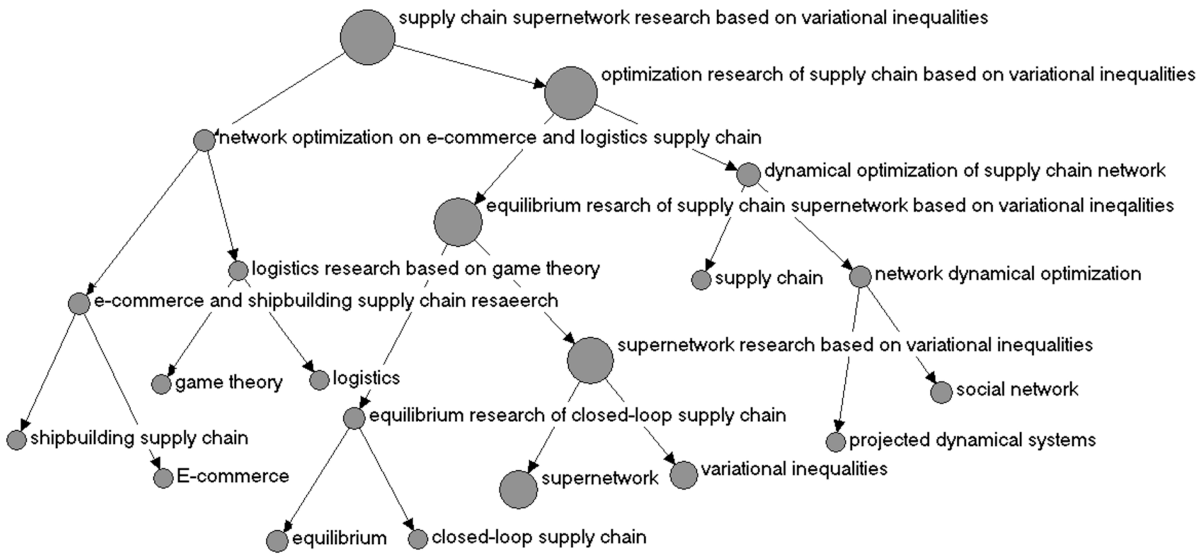

Fig. (3). WKN Structure of a sub-graph.

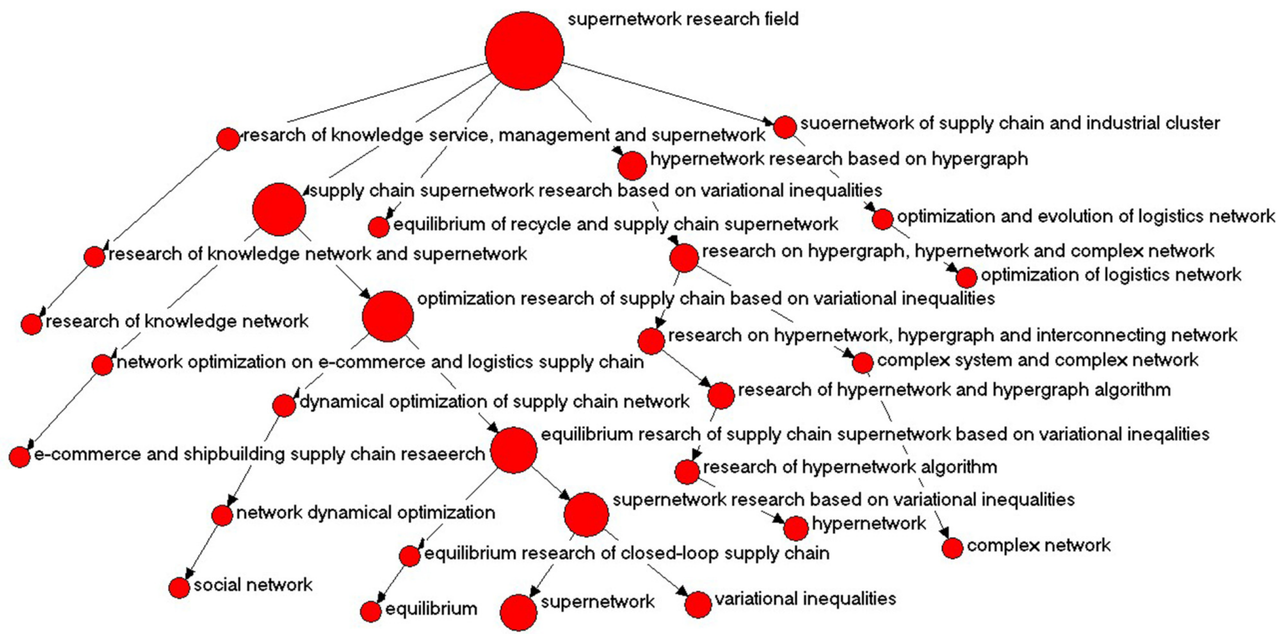

Fig. (4). WKN of research hot spots on supernetwork.

6.4.2. Research Hot Spots Identifying

In this paper, we set KPs with weights higher than 15 as hot spots. According to the above mentioned method, all the hot spots can be represented as the weighted network graph (Fig. **4**). In Fig. (**4**) it can be seen that the research hot spots form 5 sub-fields: research on knowledge service and management supernetwork, research on supply chain and industrial clustering supernetwork, research on supply chain network based on variational inequality, research on supernetwork based on hypernetwork. The structure and the importance of the hot spots are illustrated clearly in Fig. (**4**).

6.4.3. Research Fronts Identifying and Analyzing

In this paper, we select all papers from Jan.1 2012 to the retrieving time for the analysis of fronts, and 103 papers are selected. According to the above mentioned methods, the sub-network of WKN on research fronts is constructed as Fig. (**5**) and sub-network of hot spots in these two years is constructed as Fig. (**6**) in which the threshold of weights is set as 4.

From Fig. (5**2**) we can see that the fronts of supernetwork research include: the research of system evolution supernetwork, research of transferring network of accidents, supply chain and traffic supernetwork for regional industries and so on. As for Fig. (**6**), the hot spots in recent 2 years mainly focus on the following sub-fields: research on accident spread supernetwork, supply chain traffic supernetwork for regional industry, e-business supply chain supernetwork based on variational inequality, complex coupling system supernetwork based on hypernetwork, etc.

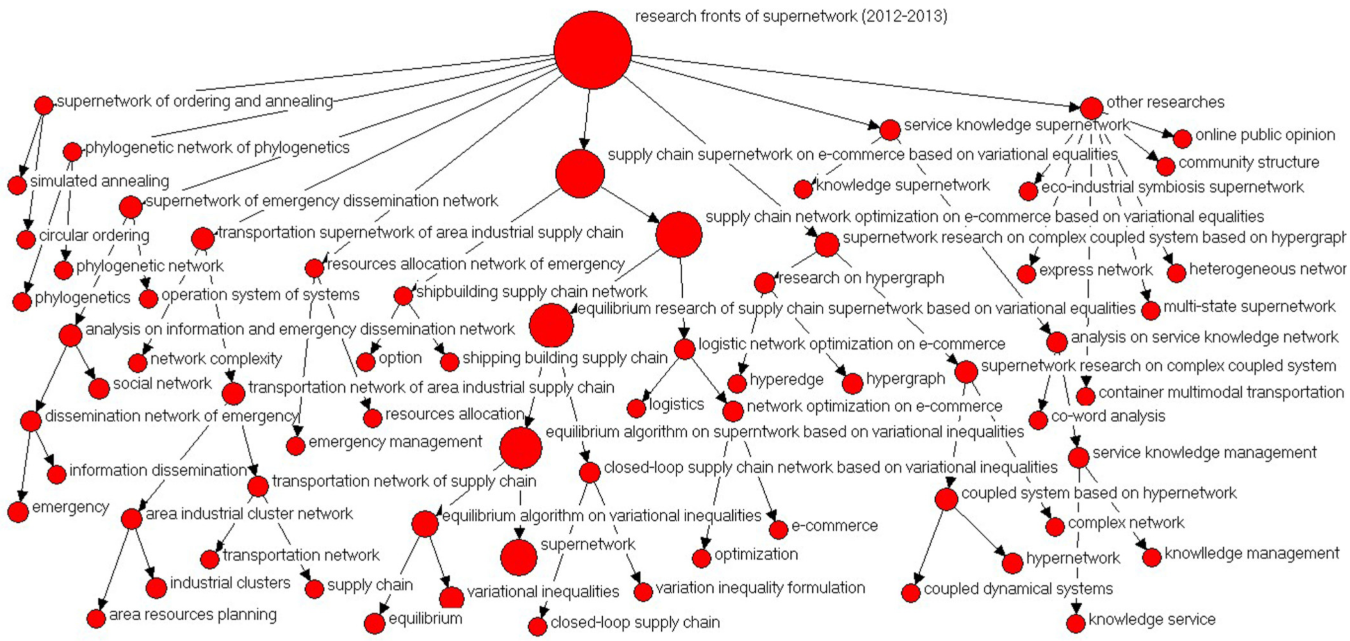

Fig. (5). WKN of research fronts of supernetwork.

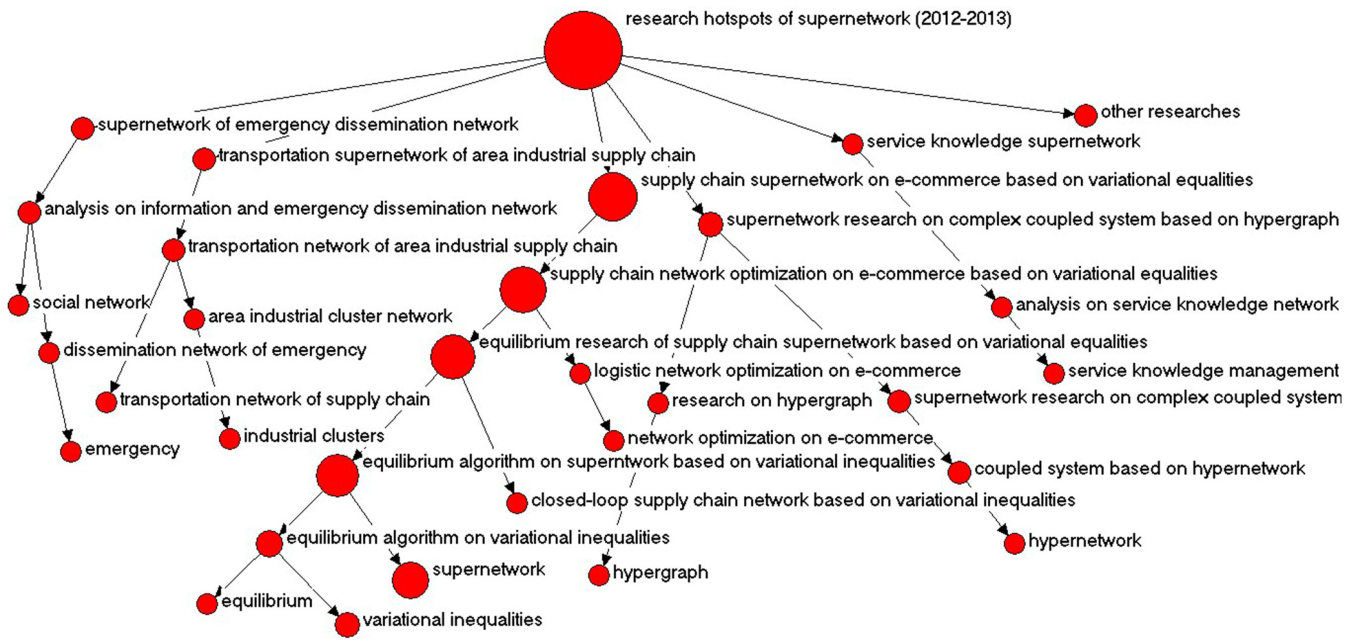

Fig. (6). WKN of research hot spots on supernetwork in year 2012-2013.

Furthermore, as also shown in Figs. (**5** and **6**) that: hot spots with name "e-business supply chain supernetwork based on variational inequality" owes the highest weights, which means the researches on this sub-fields catch highest focuses in recent 2 years. Besides, the node with name "accident spread supernetwork" has a high weight, which implies that this sub-field catches a great deal of attentions of researchers recently. Taking into account of the popularity of micro-blogs in China, the above analysis seems reasonable.

CONCLUSION

The proposed methods, *i.e.*, the modeling and analyzing methods of WKN based on keyword clustering, is easy to analyze and represent domain knowledge. The model provides some new ways to identify and illustrate the main subfields, to analyze the hot spots, frontiers, and represent the results as sub-graphs visually. As proved in the case study, the proposed methods seem more clearly, deeply and conveniently, which may help researchers to learn and utilize domain knowledge conveniently. However, there also exist some deficiencies, *e.g.*, the clustering result of keywords need be promoted, and the names of classes need more experts to ensure the adjustment, etc. All these deficiencies may be modified and promoted in further studies.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

This paper belongs to the project of the "National Natural Science Foundation of China", No.71371077, and the "Major Program Fund of National Science Foundation of China" No.71090403/71090400.

REFERENCES

[1] P.A. Alexander, "Domain knowledge: Evovling themes and emerging concerns", *J. Educational Psychology,* 1992, 27(1), 33-51.

[2] T.L. Dinh, and G. Fillion, "Acquiring Domain Knowledge of Information Systems: The Information System Upon Information System Approach", *J. Academy of Information and Management Sciences Journal,* 2007, 10(2), 57-77.

[3] S.S. Anand, D.A. Bell, and J.G. Hughes, "The role of domain knowledge in data mining", In: Pissinou N, Silberschatz A, Park EK and Makki K (eds). *Proceedings of the Fourth International Conference on Information and Knowledge Management.* Baltimore. ACM: New York, 1995, pp 37–43.

[4] R. Lu, and Z. Jin, "Formal ontology: Foundation of domain knowledge sharing and reusing", *J. Journal of Computer Science and Technology,* 2002, 17(5), 535-548.

[5] E. Lima, C. Mues, and B. Baesens, "Domain knowledge integration in data mining using decision tables: Case studies in churn prediction", *J. The Journal of the Operational Research Society,* 2009, 60(8), 1096-1106.

[6] T. Hellstrom, and K. Husted, "Mapping knowledge and intellectual capital in academic environments: A focus group study", *J. Journal of Intellectual Capital,* 2004, 5(1), 165-180.

[7] O. Seitan, "Knowledge Map an Important Tool of Knowledge Management in Tourist Destinations", *Bulletin of the Transilvania University of Brasov.Economic Sciences.Series* 2009, V, 2, 137-142.

[8] G. Yun, D. Shin, H. Kim, and S. Lee, "Knowledge-mapping model for construction project organizations", *J. Journal of Knowledge Management,* 2011, 15(3), 528-548.

[9] J. Lee, and D. Fink, "Knowledge mapping: Encouragements and impediments to adoption", *J. Journal of Knowledge Management,* 2013, 17(1), 16-28.

[10] R.A. Franks, Spalding, D.J. Albert, "Business Ethics as an Accreditation Requirement: A Knowleddge Mapping Approach", *J. Business Education & Accreditation,* 2013, 5(1), 17-30.

[11] S. Ebener, A. Khan, R. Shademani., L. Compernolle, "Knowledge mapping as a technique to support knowledge translation", *J. World Health Organization.Bulletin of the World Health Organization,* 2006, 84(8), 636-42.

[12] A. Prtichard, "Statistical bibliography or bibliometrics", *J. Journal of Documentation,* 1969, Vol. 25 No. 4, pp. 348-9.

[13] P.M. Roy, "Towards a theory of citing in citation analysis studies", in Sharma, C.D. and Vyas, K. (Eds), *Developing Horizons in Library and Information Science,* 1983, Vol. 1, Print Well, Jaipur, pp. 223-35.

[14] L.J. Kamal, D.K. Swain, and K.C. Sahoo, "Scholarly communication in journal of financial crime, 2006-2010: A bibliometric study", *J. Journal of Financial Crime,* 2012, 19(4), 371-383.

[15] B.C Biswas, A. Roy, and B.K. Sen, "Economic botany: a bibliometric study", *J. Malaysian Journal of Library & Information Science,* 2007, Vol. 12 No. 1, pp. 23-33.

[16] K.L Jena, "A bibliometric analysis of the journal 'Indian Journal of Fibre and Textile Research, 1996-2004'", *J. Annals of Library and Information Studies,* 2006, Vol. 53 No. 1, pp. 22-30.

[17] S. Kumar, and B.H. Gupta, "Modeling the growth of literature in the area of chemical science", *J. Library Herald,* 2003, Vol. 14 No. 4, pp. 225-39.

[18] A. Serenko, N. Bontis, L.D Booker, K.W. Sadeddin, and T. Hardie, "A scientometric analysis of knowledge management and intellectual capital academic literature (1994-2008)", *J. Journal of Knowledge Management,* 2010, Vol. 4 No. 1, pp. 3-23.

[19] P. Willett, "A bibliometric analysis of the literature of chemo informatics", *Aslib Proceedings: New Information Perspectives,* 2008, Vol. 60 No. 1, pp. 4-17.

[20] H.C. Tseng, L.Y. Chou, K.H. Yu, "Current research paradigms in expatriate(s) research: a bibliometric approach", *J. International Journal of Organizational Innovation*, 2010, 2,3,22-39

[21] C.F. Pinto, F.R. Serra, and M.P. Ferreira, "A bibliometric study on culture research in international business", *J. Brazilian Administration Review,* 2014, 11(3), 340-363.

[22] S. Samiee, and B.R. Chabowski, "Knowledge structure in international marketing: A multi-method bibliometric analysis", *J. Academy of Marketing Science.Journal,* 2012, 40(2), 364-386.

[23] M.J. Culnan, C.A. O'Reilly, and J.A. Chatman, "Intellectual structure of research in organizational behavior, 1972-1984: A co-citation analysis", *J. Journal of the American Society for Information Science,* 1990, Vol. 41, No. 6, pp. 453-458.

[24] E. Garfield, "Is citation analysis a legitimate evaluation tool?", *J. Scientometrics,* 1979, vol. 1, No. 4, pp. 359-375.

[25] A.R. Ramos-Rodriguez, and J. Ruiz-Navarro, "Changes in the intellectual structure of strategic management research: A bibliometric study of the Strategic Management Journal, 1980-2000", *J. Strategic Management Journal,* 2004, Vol. 25, No. 10, pp. 981-1004.

[26] T. Lin, and Y. Cheng, "Exploring the Knowledge Network of Strategic Alliance Research: A Co-citation Analysis", *J. International Journal of Electronic Business Management,* 2010, 8(2), 152-160.

[27] R. Sharda, G.L. Frankwick, and O. Turetken, "Group knowledge networks: A framework and an implementation", *J. Information Systems Frontiers,* 1999, 1(3), 221-239.

[28] WRJ. Baets, "Organizational learning and knowledge technologies in a dynamic environment", Boston, MA: Kluwer Academic Press, 1998.

[29] K. Pugh, and L. Prusak, "Designing effective knowledge networks", MIT *Sloan Management Review,* 2013, 55(1), 79-88.

[30] K. Carley, "Smart agents and organizations of the future". In L. Lievrouw&S. Livingstone (Eds.) Handbook of new media 2002, pp. 206-220.London: sage.

[31] N.S. Contractor, and P.R. Monge, "Managing knowledge networks", *J. Management Communication Quarterly: McQ,* 2002, 16(2), 249-258.

[32] Y.J. Xi, and Y.Z. Dang, "The Discovery and Representation Methods of Expert Domain Knowledge Based on Knowledge Network", *J. Systems Engineering,* 2005, 08:110-115.

Received: September 16, 2014 Revised: December 23, 2014 Accepted: December 31, 2014