

<http://ansinet.com/itj>

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSI*net*

Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Visual Knowledge Recommendation Service Based on Intelligent Topic Map

¹G. Li and ²H. Lu

¹Shandong Jiaotong University Maritime College, Weihai, 264200, People's Republic of China

²School of Electronic and Information Engineering, Xi'an Jiaotong University,
Xi'an, 710049, People's Republic of China

Abstract: Aiming to help users to effectively acquire and visualize target knowledge from massive, distributed and heterogeneous information sources, we designed a visual knowledge recommendation service system based on intelligent topic map. It includes knowledge organization, knowledge recommendation and visualization display. Knowledge logical organization model based on intelligent topic map extends the conventional topic map in structure and enhances its reasoning functions. Hot resources mining distinguish the different importance degree of knowledge nodes (topics or knowledge elements), interest trends predict the interested knowledge of users in the future and knowledge navigations provide a personalized navigation path for users. Moreover, recommendation results visualization based on intelligent Topic Map provides users with an intuitive, graphic and pellucid visual interface. Finally, a demonstration is given to elaborate the knowledge recommendation providing process.

Key words: Knowledge service, knowledge recommendation, topic map, intelligent topic map

INTRODUCTION

With the increase of information, the amount of information stored in information management systems is very large. In such an environment, users have to rely on active search to obtain desired knowledge. Finding relevant knowledge has become a tedious task. If the systems can initiatively recommend knowledge based on users interests, there must be great improvement in users satisfaction (Fan *et al.*, 2008). A knowledge recommendation system helps users to select items of interest from a huge stream of data. How to understand users demands more comprehensively and provide more effective knowledge for them is a focal point of research. For example, navigation recommendation was introduced for website visitors, based on their past navigation behavior or web log and cache data (Velásquez *et al.*, 2004; Wang and Li, 2006). A recommendation system prototype was built, which suggested websites to users by collecting browsing events at routers without neither user nor website effort (Jia *et al.*, 2007). Knowledge service-oriented recommendation mechanism for e-learning was studied, combined with the Knowledge Supply Chain (KSC), content-based filtering method and fuzzy logic to construct a Knowledge-Intensive Recommendation. Service Model (KIRSM) (Chao *et al.*, 2005). The ontology-based matchmaking approach was also proposed for Context-Aware Recommendations

(Naudet *et al.*, 2008). Recently, there have been considerable interests in applying graph-based methods for generating recommendations (Gori and Pucci, 2007; Cheng *et al.*, 2007). The architecture of the multi-agent recommendation system was described, which could provide personalized content to users based on their preferences more efficiently and more concisely (Shi, 2006). However, the previous works can not accurately represent and efficiently manage the multi-level, multi-granularity knowledge. The existing logical organization models based on metadata don't take the semantic features of knowledge into account and are difficult to express the inner relevance of knowledge, since they organize knowledge solely on the basis of the external features of the documents (e.g., curriculum, title, author, etc.). So it is difficult to recommend knowledge structure based on person's own cognitive pattern.

Personalized recommendations are a powerful vehicle to reduce information overload and to help users to effectively acquire target knowledge. Moreover, how to display the target knowledge for users is the problem we have to solve. Visual knowledge map overcomes the shortcoming of linear display. Visual navigation capabilities of exploiting the created knowledge structures are based on hyperbolic geometry concepts and provide users with intuitive access mechanisms to the required knowledge (Smolnik and Erdmann, 2002). In this study, we

organize knowledge resources based on Intelligent Topic Map (ITM) (Lu and Feng, 2009, 2010) which extends the conventional topic map in structure and enhances its reasoning functions. ITM establishes a novel multi-resource knowledge organization model which depicts the hierarchical relationship of cluster-topic-knowledge element-occurrence. ITM organizes knowledge from four levels: cluster level, topic level, knowledge element level and resource level. It constructs multi-granularity knowledge representation architecture which includes clusters, topics, knowledge elements, associations and occurrences. Based on ITM, we propose a new architecture for visual knowledge recommendation system by analysing users retrieval logs. Then, we propose the algorithms for mining hot resources, interest trend degree and knowledge access path by user logs analysis and knowledge path analysis. We realize graph-based methods for generating recommendations. It provides a visual knowledge map, which is available for users to acquire knowledge and associations among them.

SYSTEM FRAMEWORK

With the ITM as infrastructure, we define a system framework of visual knowledge recommendation. It mainly includes knowledge organization, knowledge recommendation and visualization display, which is shown in Fig. 1. When the web client sends a query request to the knowledge portal, the knowledge search application will acquire knowledge from ITM base. Then the user's logs and knowledge access path will be recorded and stored in the database. With user's historical records, knowledge recommendation services can employ the algorithm proposed in this study to provide recommendation by knowledge visualization display. Knowledge recommendation services include hot resources discovery, interest trend prediction and knowledge navigation.

Hot resources discovery: In order to distinguish the different importance degree of nodes (topics or knowledge elements), we define the node hot degree (H_a), which is the times of topics or knowledge elements visited (V), marked (M) and annotated (A) by all users. It is shown as follows:

$$H_a = w_1 \times V + w_2 \times M + w_3 \times A \quad (1)$$

w_1, w_2, w_3 is respectively stands for the weight of visit times, marking times, annotating times of the users. In the progress of operation, the VSM (Value Stream Mapping) vector model method is adopted for cluster of ITM. Using a hash mapping table variables corresponding to each

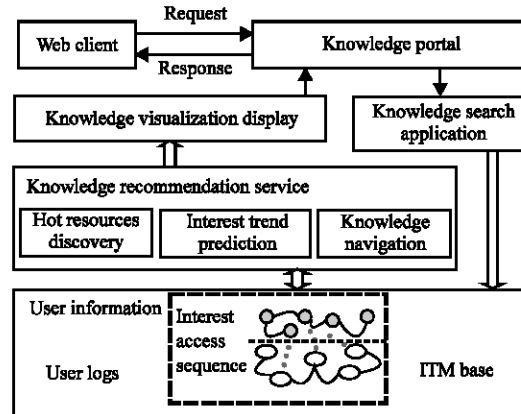


Fig. 1: The system framework based on ITM

cluster, the corresponding relation is established between nodes (topics or knowledge elements) and node hot degrees. Cluster variable is defined as follows:

```
Hash_map<String, Double>
Cluster [i] = New Hash_map<String, Double>
```

The information is recommended based on ITM for users to help them focusing on the hot resources, it can realize pertinent knowledge recommendation.

Interest trend prediction: Interest trend predicts the user interested knowledge in the future. It includes interest groups division and interest trend prediction.

Interest groups division: We provide an indicator of relationship degree to measure the similarity degree between users. Let $R(i, j)$ indicates the relationship degree between the user i and j , $R(i, j)$ is equal to the number of their same nodes divided by the number of all their nodes visited. Thus, the relationship degree between i and j can be calculated by formula Eq. 2 as follows:

$$R(i, j) = \frac{\text{num}(i^{\text{nodes}} \cap j^{\text{nodes}})}{\text{num}(i^{\text{nodes}} \cup j^{\text{nodes}})} \quad (2)$$

i^{nodes} stands for the set of i 's nodes visited and j^{nodes} stands for the set of j 's nodes visited, $\text{num}(x)$ denotes the function of calculating the number of elements in a set x . For example, i^{nodes} is the set $\{T_1, T_2, T_4, Ke_1, Ke_2\}$, while j^{nodes} is the set $\{T_2, T_4, Ke_1\}$, so, the relationship degree between i and j is equal to:

$$R(i, j) = \frac{\text{num}(\{T_1, T_2, T_4, Ke_1, Ke_2\} \cap \{T_2, T_4, Ke_1\})}{\text{num}(\{T_1, T_2, T_4, Ke_1, Ke_2\} \cup \{T_2, T_4, Ke_1\})} = \frac{\text{num}(\{T_2, T_4, Ke_1\})}{\text{num}(\{T_1, T_2, T_4, Ke_1, Ke_2\})} = \frac{3}{5}$$

Interest trend prediction: Interest trend degree is defined as the following expression:

$$T_{s^l}(i) = \text{Trend}_{\text{access}}(i) + \text{Trend}_{\text{topic}}(i) \quad (3)$$

$\text{Trend}_{\text{access}}(i)$ is interest trend degree based on access logs, it is defined as follows:

$$\text{Trend}_{\text{access}}(i) = \sum_{i \in S_j} \frac{1 \leq j \leq m}{f(\text{Spt}(s_j), \text{Sim}(s_i, s_j), \text{pos}(i, s_j))} \quad (4)$$

f is Harmonic Function, which adjusts the weight of three parameters in trend degree calculation. $\text{Spt}(s_j)$ represents the support of frequent sequences. $\text{Sim}(s_i, s_j)$ stands for the similarity between the frequent sequence s_i and s_j . $\text{pos}(i, s_j)$ represents the i 's position in matched frequent sequence s_j . $\text{Trend}_{\text{topic}}(i)$ is the interest trend degree based on ITM, it is defined as follows:

$$\text{Trend}_{\text{topic}}(i) = g(\text{weight}(a, i)), a \in s^l, i \in I_{\text{topic}}, (a, i) \in E \quad (5)$$

I_{topic} is the set of all topics which are associated with interest nodes of the sequence accessed lately in ITM, it is defined as follows:

$$I_{\text{topic}} = \{i \mid \forall a \exists i(a \in s^l, (a, i) \in E)\} \quad (6)$$

$\text{weight}(a, i)$ is the weight of association in ITM. E represents the set of associations.

Knowledge navigation: Knowledge navigation is to provide a personalized navigation path by means of topic maps. Moreover, based on expert rules or data mining method, users are provided with navigation recommendations. Such cognitive processes can be expressed as the sequence of clusters, topics and knowledge elements. Knowledge navigation extracts the most probable path as a new user's guide and this path could be learned from old user's a large number of interest paths.

It is assumed that N users visited the topic maps in a specific field. The topic node set is $T = \{T_i \mid 1 \leq i \leq p\}$, the knowledge element node set is $K = \{K_j \mid 1 \leq j \leq q\}$, m is arbitrary user in N users, the visited sequence C is $\{N_{T_1}^m, N_{T_2}^m, \dots, N_{T_p}^m\}, 1 \leq L \leq p$, the visited sequence K is $\{N_{K_1}^m, N_{K_2}^m, \dots, N_{K_M}^m\}, 1 \leq M \leq q$ so, P_u is defined as follows:

$$P_u(T_i) = \sum_{m=1}^N f_{ut}(m)/p \quad (7)$$

$P_u(T_i)$ represents the probability of every topic node appears in the navigation path at the u place. $f_{ut}(m)$ is defined as follows:

$$f_{ut}(m) = \begin{cases} 1, N_{T_u}^m = T_i \\ 0, N_{T_u}^m \neq T_i \end{cases} \quad (8)$$

$P_u(K_i)$ represents the probability of every knowledge element node appears in the navigation path at the u place.

$$P_u(K_i) = \sum_{m=1}^N f_{uk}(m)/q \quad (9)$$

$f_{uk}(m)$ is defined as follows:

$$f_{uk}(m) = \begin{cases} 1, N_{K_u}^m = K_j \\ 0, N_{K_u}^m \neq K_j \end{cases} \quad (10)$$

Navigation path is defined as follows:

$$\{T_1, T_2, \dots, T_u, \dots, T_p \mid T_u = T_i, \text{if}(T_i \mid \max\{P_u(T_i)\}), 1 \leq i \leq p\} \quad (11)$$

$$\{K_1, K_2, \dots, K_u, \dots, K_q \mid K_u = K_j, \text{if}(K_j \mid \max\{P_u(K_j)\}), 1 \leq j \leq q\} \quad (12)$$

An example of navigation path is shown in Fig. 2. The bold lines in the topic map represent cognitive path tendency, the numbers on the bold line indicate the sequence of cognitive steps.

Knowledge visualization display: Recommendation results will be displayed based on ITM in order to provide users with an intuitive, graphic and pellucid visual interface. The process of ITM building is shown as follows:

- **Step 1:** Establishing the relationships between Ke (the knowledge element) and T_i and setting the correlation degree to 1

$T_i \in C_T, C_T$ is the set of topics contained in the knowledge element texts:

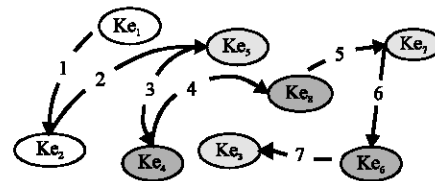


Fig. 2: An example of knowledge navigation

- **Step 2:** C_i is extended to get C_{i+1} according to the relationships between topics
- **Step 3:** For each topic $T_{i+1,j}$ in C_{i+1} , calculating the correlation degree with $T_{i+1,j}$
- **Step 3-1:** If r_i is the relationship between $T_{i+1,j}$ and a topic $T_{i,j}$, the correlation degree between $T_{i+1,j}$ and Ke is defined as follows:

$$w_{i1} \times s \tag{13}$$

s is the correlation degree between $T_{i,j}$ and Ke , w_{i1} is the weight and $w_{i1} \geq 1$

- **Step 3-2:** If existing many kinds of relationships between $T_{i+1,j}$ and n topics, calculating each correlation degree by the same as formula Eq. 14. The correlation degree between $T_{i+1,j}$ and Ke is defined as follows:

$$\bar{s} / n \tag{14}$$

\bar{s} is the correlation degrees average of all kinds of relationships

- **Step 3-3:** If the correlation degree exceeds a certain threshold, there is no relationship between $T_{i+1,j}$ and Ke , $T_{i+1,j}$ will be removed from C_{i+1}
- **Step 4:** Repeat Step 3, until each topic has been dealt in C_{i+1}
- **Step 5:** If $C_{i+1} = \emptyset$, the algorithm will be end, otherwise, $i = i+1$, go to Step 2

KNOWLEDGE RECOMMENDATION PROCESS

Take the ITM about the domain of Computer Network as an example. First, the system locates the interest node of the target user and then constructs the knowledge structure which takes the user interest node as core and selects the knowledge navigation path most reasonable to user requirements by case-based reasoning. Finally, visualizes them to the target user. The top-down method is adopted to define the abstract workflow as following:

- **Step 1:** Defining the top-level composite processes. As shown in Fig. 3, two composite processes which named locate interest node and knowledge service case, respectively are defined. The input of process locate interest node is the target user interest node, while the output of it is a part of ITM which includes

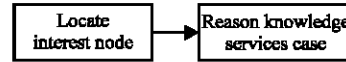


Fig. 3: The top-level definition of composite processes

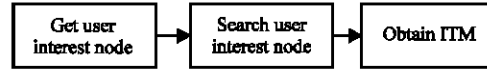


Fig. 4: The process of locate interest node

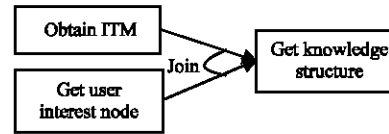


Fig. 5: The process of getting knowledge structure

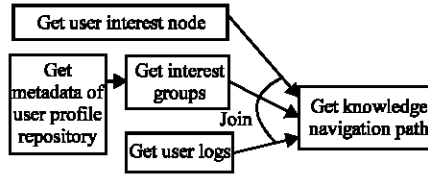


Fig. 6: The process of getting navigation path

the user interest node. The inputs of processing knowledge service case are user logs, the target user interest node and the ITM while the outputs of it are the visual knowledge structure and the visual knowledge navigation path

- **Step 2:** Refining the definition of processing locate interest node and processing knowledge service case, respectively. As shown in Fig. 4, the process locating interest node includes three atomic processes of which the functions are getting the user interest node, searching the user interest node and obtaining a part of ITM which includes the user interest node. The knowledge service case processing includes three parts of getting knowledge structure, get navigation path and visualize knowledge. As shown in Fig. 5, the process getting knowledge structure includes three atomic processes of which the functions are getting the user interest node, obtaining ITM and getting the knowledge structure which takes the user interest node as core within a certain knowledge radius. Join denotes the former processes must be finished before the last one is started. As shown in Fig. 6, the process getting navigation path includes five atomic processes of which the functions are getting the user interest node, obtaining the metadata of the users

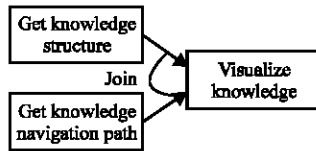


Fig. 7: The process of visualizing knowledge

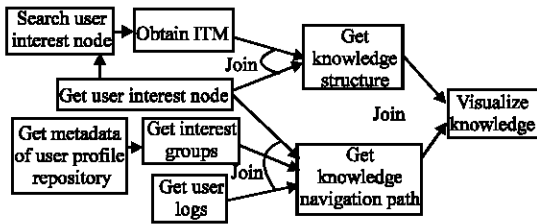


Fig. 8: The final definition of the knowledge services providing processes

profile repository where the profile of the users are stored, getting the user logs, finding the interest groups of the same class with target user profile repository, as well as getting knowledge navigation path. As shown in Fig. 7, the process visualizing knowledge includes three atomic processes of which the functions are getting the knowledge structure, getting knowledge navigation path and visualizing knowledge

- **Step 3:** Integrating the processes. The same atomic processes in different composite processes are merged into one. The final workflow definition is shown in Fig. 8. Given the profile of target user as input, the workflow execution generates corresponding knowledge services results for the target user

EXPERIMENT

To evaluate the effectiveness of our visual knowledge recommendation system based on ITM, network layer is applied to a part of the knowledge domain of computer network. Experimental data includes 1394 topics, 3104 knowledge elements, 816 associations between topics, 906 associations between knowledge elements and 617 associations between topics and knowledge elements. After system running some time, when the user’s interest node is protocol definition, the results of knowledge recommendation are shown as follows:

- **Hot resource discovery:** In descending order of the node hot degrees (H_v), hot resources ranking are shown as follows:

Table 1: The experimental results of knowledge structure

Node type	Node content
Topic	(TCP/IP Protocol family, 1), (Network Communication Protocol, 1), (TCP Protocol, 1), (IP Protocol,1) (Internet Protocol, 2), TCP/IP Protocol Model, 2), (TCP/IP Transport Layer, 2), (Transmission Control Protocol,2), (TCP/IP Network Layer, 2)
Knowledge Element	(TCP/IP Protocol definition, 1), (TCP Protocol definition, 2), (IP Protocol definition, 2), (TCP/IP Transport Layer functions, 3), (TCP/IP Network layer functions, 3), (TCP/IP Protocol Architecture, 3)

TCP/IP Protocol, IP Protocol, TCP Protocol, TCP Protocol, TCP/IP Protocol Model, IP Protocol Definition, etc

- **Knowledge structure:** Knowledge architecture return the cluster, topics and knowledge elements associated with protocol definition. The experimental results are shown in Table 1, when knowledge element TCP/IP protocol is the center and knowledge radius is set to 2. The node is expressed by Binary Group (node name, knowledge radius)
- **Knowledge navigation:** When the user’s interest node is IP protocol, the knowledge navigation path is given as follows:

TCP/IP protocol model"→"tcp/ip Protocol"→"IP Protocol"→"IP Protocol definition"

The result of visual recommendation is shown in Fig. 9. All the topics and knowledge elements associated with TCP/IP protocol within a certain knowledge radius is shown on the web page. Resource entity list based on the order in accordance with hot degree and reliability are list out, making the top list of high-quality resources on the bottom of web page. The black bold lines on the topic map represent cognitive path tendency, the numbers on the black bold line indicate the sequence of cognitive steps.

Compared with other relative methods about knowledge recommendation service, our system is established on Intelligent Topic Map. It realizes the efficient management of complex knowledge and embodies the multi-level, multi-granularity and inherent relevant characteristics of knowledge. We found that the system returns all the knowledge elements and topics which are associated with the knowledge point within a certain knowledge radius. It not only expresses the knowledge, but also fully reflects the association between the knowledge and the information resources related to the knowledge. Graphic display based on intelligent Topic Map is more perceivable, it can provide visual knowledge navigation mechanism. Using intelligent Topic Map in

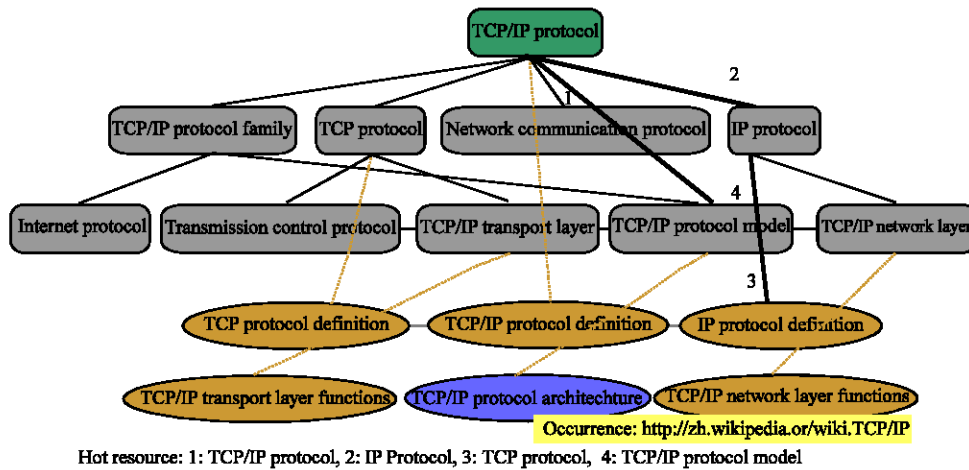


Fig. 9: A demonstration of knowledge navigation

visual knowledge recommendation service field is a novel direction and presents a new way for high-quality knowledge services.

CONCLUSION

We define knowledge mining for recommendation mechanism based on user logs and knowledge access path. And we propose the algorithms for customized recommendation by analyzing hot resources, knowledge navigation and interest trend degree. We establish a service-oriented knowledge recommendation architecture with the intelligent Topic Map as infrastructure, which provides a semantically interactive environment for users. It is useful for users to understand knowledge services more easily and accurately and choose the services they really need. Additionally, knowledge recommendation is provided by visual intelligent topic map.

ACKNOWLEDGMENT

This research is supported by the National High-Tech Research and Development Plan of China under Grant No. 2008AA01Z131; the Key Research Programs of China Institute of Communication Education under Grant No. JJY1001-3.

REFERENCES

Chao, R., J. Huang and C. Yang, 2005. The study of knowledge service-oriented recommendation mechanism-a case of e-learning platform. Proceedings of 2005 International Conference on Machine Learning and Cybernetics, Aug. 18-21, Guangzhou, China, IEEE Computer Society, pp: 2228-2233.

Cheng, H., P. Tan, J. Sticklen and W.F. Punch, 2007. Recommendation via query centered random walk on k-partite graph. Proceedings of the 2007 7th IEEE International Conference on Data Mining, Oct. 28-31, Omaha, NE, United States, IEEE Computer Society, pp: 457-462.

Fan, B., L. Liu, M. Li and Y. Wu, 2008. Knowledge recommendation based on social network theory. Proceedings of the 2008 IEEE Symposium on Advanced Management of Information for Globalized Enterprises, Sept. 28-29, Tianjin, China, IEEE Computer Society, pp: 322-324.

Gori, M. and A. Pucci, 2007. ItemRank: A random-walk based scoring algorithm for recommender engines. Proceedings of the 20th International Joint Conference on Artificial Intelligences, Jan. 6-12, Hyderabad, India, pp: 2766-2771.

Jia, J., S. Ye, X. Li and J. Dickerson, 2007. Web site recommendation using HTTP traffic. Proceedings of the 7th IEEE International Conference on Data Mining, Oct. 28-31, Omaha, NE, United States, IEEE Computer Society, pp: 535-540.

Lu, H. and B. Feng, 2009. An intelligent topic map-based approach to detecting and resolving conflicts for multi-resource knowledge fusion. Inform. Technol. J., 8: 1242-1248.

Lu, H. and B. Feng, 2010. Distributed knowledge integration based on intelligent topic map. Inform. Technol. J., 9: 132-138.

Naudet, Y., S. Mignon, L. Lecaque, C. Hazotte and V. Groues, 2008. Ontology-based matchmaking approach for context-aware recommendations. Proceedings of the 4th International Conference on Automated Solutions for Cross Media Content and Multi-Channel Distribution, Nov. 17-19, Florence, Italy, IEEE Computer Society, pp: 218-223.

- Shi, X., 2006. An intelligent knowledge-based recommendation system. *Intel. Inform. Process.*, 163: 431-435.
- Smolnik, S. and I. Erdmann, 2002. Visual navigation of distributed knowledge structures in groupware-based organizational memories. *Proceedings of 6th International Conference on Information Visualization*, July 10-12, London, England, IEEE Computer Society, pp: 353-360.
- Velásquez, J.D., A. Bassi, H. Yasuda and T. Aoki, 2004. Mining web data to create online navigation recommendations. *Proceedings of the Fourth IEEE International Conference on Data Mining*, Nov. 1-4, Brighton, UK, IEEE Computer Society, pp: 551-554.
- Wang, X. and B. Li, 2006. Intelligent knowledge recommendation system based on web log and cache data. *Proceedings of the 5th International Conference on Web Based Learning*, July 19-21, Penang, Malaysia, Springer Verlag, pp: 48-56.