ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 1, January 2014

Association Rule Mining Based a Personalized Mobile Search Engine

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Abstract: In the mobile based search the user and search interaction is limited to certain factor .To overcome this problem mobile search engine must returns the relevant results that satisfies the user's interest. By observing of necessitate for dissimilar types of concepts, present PMSE, it captures the user preferences sorted in an ontology-based, multifacet user profile to form a personalized ranking function that is used for future search results. It classifies the concepts into two types content concepts and location concepts by considering the importance of location information. GPS is used to attain regular travel patterns and query patterns, and the clickthroughdatas are used to enhance the personalization effectiveness. Proposed system introduce an association rule mining algorithm to collect the travel related query patterns and travel patterns from the original personal mobile search engine profile. Association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. The association rule mining analysis the query related patterns of the user and will form rules discovered in databases by measuring the user interest. The association rules is introduced for discovering regularities between normal patterns and query related patterns

Keywords: PMSE, Ontology, Multifacet, Clickthrough, Pattern

I. INTRODUCTION

Data mining commonly encompasses a variety of algorithms namely clustering, classification, association rule mining and more. Among these algorithms, Association rule mining (ARM) technique is one of the most effective data mining techniques to discover hidden or desired pattern among large amount of data. Since it's introduced in 1993 by Agrawal et al, the task of association rule mining has received a great deal of attention.

Generally an association rule mining algorithm contains the following steps

i. The set of candidate k-item sets is generated by 1-extensions of the large (k-1) item sets generated in the previous iteration.

ii. Supports for the candidate k-item sets are generated by a pass over the database.

iii. Item sets that do not have the minimum support are discarded and the remaining item sets are called large k-item sets.

A. **Limitations of association rule mining**

The frequent itemsets identified by ARM does not reflect the impact of any other factor except frequency of the presence or absence of an item. Frequent itemsets may only contribute a small portion of the overall profit, whereas non-frequent itemsets may contribute a large portion of the profit. Recently, to address the limitation of ARM, many types of association rule mining was defined.

B. **Frequent item set mining**

The problem of mining frequent itemsets arose first as a sub problem of mining association rules. Frequent itemsets play an essential role in many data mining tasks that try to find interesting patterns from databases such as association rules, correlations, sequences, classifiers, clusters and many more of which the mining of association rules is one of the most popular problems. The major challenge found in frequent pattern mining is a large number of result patterns. As the minimum threshold becomes lower, an exponentially large number of itemsets are generated. Therefore, pruning unimportant patterns can be done effectively in mining

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ISSN (Online) : 2278-1021

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process and that becomes one of the main topics in frequent pattern mining.

C.**Constraints based on association rule mining**

Many data mining techniques consist in discovering patterns frequently occurring in the source dataset. The goal is to discover all the frequent patterns in the database from the user-specified threshold value. In order to discover the patterns, the constraints specified can be classified into following groups

- Post-processing- filtering out patterns that do not satisfy user-specified pattern constraints.
- Pattern filtering- integration of pattern constraints into the actual mining process in order to generate only patterns satisfying the constraints.
- Dataset filtering- restricting the source dataset to objects that can possibly contain patterns that satisfy pattern constraints.

There are several more techniques that are available for efficient mining of association rules. Some of the techniques and advances in the association rule discovery are illustrated as follows:

- Hash-based technique
- Transaction reduction
- Partitioning
- Redundant association rules
- Interestingness measures of an association
- Negative association rules

II. Introduction Of Research

The introduction of location preferences offers PMSE an additional dimension for capturing a user's interest and an opportunity to enhance search quality for users. Here to attain the context information the physically visited locations of users are taken into account. GPS device is used to get the relevant information.

For example, if the user searches for college information, who is now located in "Chennai, Tamilnadu", his/her location can be used to personalized the search results to get information about the nearby colleges. In this paper the GPS location and the location preferences are coimbined for personalization.

It design for PMSE follows the client-server model. Here the queries will be send to server for the reranking and training purpose. The clients working prototype was implemented on the Google Android platform, and the server on a PC.

Privacy preservation is one of the hard issue in this work, here the users will send their profiles and the queries to the server for personalized search results. Here the minDistance and expRatio are the two parameters used to control the privacy levels.

III. Objective Of Research

1 GPS locations is an important factor in todays mobile web search. For example, if the user likes to search for the colleges information, who is now located in "Chennai, Tamilnadu," his/her position can be attaind by using GPS. By that the colleges located near to his location can be find easily.

2 Objective of the research is to exploit the regular travel patterns and query patterns by using GPS and the clickthrough data by the user.

3 Association rule mining algorithm is used to collect the travel related query patterns and travel patterns from the original personal mobile search engine profile.

IV. Motivation Of Research

The user's clickthrough data will be analized by taking the user's interests. Leung et al. developed a search engine personalization method based on users' concept preferences and showed that it is more effective than methods that are based on page preferences.Important motivation of the work is to improve personalization results and finds the most important query based results to satisfy the user preference profiles based on concepts and locations. The privacy pattern is also important and it will be controlled at client.

V. Problem Statement

The interaction between the user and the search engine was not so efficient, this is the main problem in the mobile search. The mobile user was not able to attain the relevant results they need.

In order to attain the relevant results the GPS is used and here the association rule algorithm is used.

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VI. EXISTING SYSTEM

The personalized mobile search engine will use the GPS location to attain the relevant results for the mobile search. Here the content and the location preference is used for the ranking function.

Issues

- It was found that a significant number of queries were location queries focusing on location information and doesn't consider mobile based search engine.

- All of these methods require the location based services with the manually retrieved local sensitive topics only and doesn’t exactly match with query results.

PMSE

PMSE is designed by using meta search approach, in that it will give reply on the commercial search engines like Google, Yahoo, Bing etc.

Here the client will receive the users request and it will submit that result to the server and will display the result and also it will collect the clickthroughs of the user inorder to derive his/her personal preferences

On the other hand the server will handle heavy task like forwarding the requests to the search engine, as well as training and also reranking the results.

Advantages

- Improve the efficiency of the user profile based result with concept and location.

- Improve the security of the system with privacy

- The privacy exposure while maintaining good ranking quality.

Disadvantages

The PMSE doesn’t exploit regular travel patterns and query patterns from the GPS

VII. PROPOSED SYSTEM

The regular travel patterns and query patterns from the GPS is further enhanced. For this we apply the association rule mining based system to mine the regular pattern with user and location. Association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. In this project association rule mining analysis the query related patterns of the user to identify strong rules discovered in databases using different measures of interestingness. Apart from the antecedent (the "if" part) and the consequent (the "then" part), an association rule has two numbers that express the degree of uncertainty about the rule.

First is **Support:** It is simply the number of transactions that include all items in the antecedent and consequent parts of the rule that is the number of patterns in the user click through data with travel patterns.

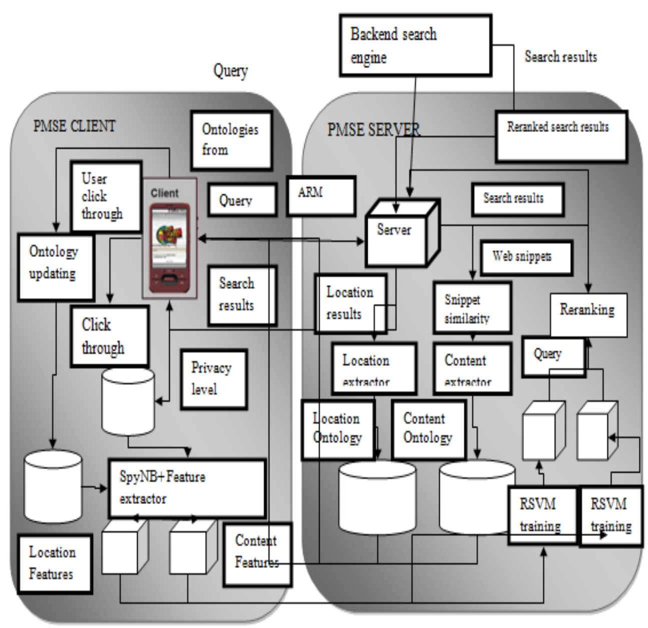
Second is **Confidence:** It is the ratio of the number of transactions that include all items in the consequent as well as the antecedent to the number of transactions that include all items in the antecedent.

Advantages

- Clickthrough data to further enhance the personalization effectiveness of PMSE.

- Improve personalization result with best association result for each regular patterns

VIII. ARCHITECTURE DIAGRAM



Architecture diagram

A. Methodologies Of Research

It first reviews the preference mining algorithms SpyNB it can be adopted with PMSE, and after that converse how PMSE conserve user privacy. SpyNB learn user behaviour

ISSN (Print) : 2319-5940
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preferences that are extracted from clickthrough data. The SpyNB method P be the positive set, U the unlabeled set, and PN the predicted negative set obtained from the. Thus, user partiality pairs can be obtaining as follow:

$$d_i < d_j, \forall l_i \in P, l_j \in PN$$

The PMSE clients supply the user's clickthrough data and have control on the confidentiality situation. It would generate a feature vector based on its clickthrough data and the filtered ontology according to the privacy values at dissimilar expRatio. If the feature vector is less than the expRatio then the query is forwarded to the PMSE server for the personalization. PMSE server simply knows regarding the filtered concept that the client prefer in the structure of a feature vector. PMSE employ mindistance to filter the concepts in the ontology. If a concept C_{i+1} is a child of one more concept C_i in ontology-based user profile C_i and C_{i+1} are associated with an edge whose distance is defined by $D(C_{i-1}, C_k)$ and concept C_i will be pruned and it satisfies the following condition .

Here SpyNB is used it will attain user behaviour models by attaining the preferences from the clickthroughdatas, by assuming that the clicked documents is clicked by the user only of his interest, now SpyNB takes that document as a positive sample and by using that it will predict the negative document. For this purpose the"spy" technique uses a novel voting procedure into Naive Bayes for predicating the negative set of documents.

$$\frac{D(C_{i-1}, C_k)}{D(C_{i-1}, C_k) + D(root, C_{i-1})} < mindistance$$

where $C_{i-1}$is the direct parent of C_i, and C_k is the leaf concept. The concept entropy $H_C(U_{Q,P})$ of the user profiles can be computed using the following equation:

$$H_C(U_{Q,P}) = -\sum_{C_i \in U_{Q,P}} pr(C_i) \log pr(C_i)$$

$$expRatio_{Q,P} = \frac{H_C(U_{Q,P})}{H_C(U_{Q,0})} - \sum_{C_i \in U_{Q,P}} pr(C_i) \log pr(C_i)$$

By getting the user content and location content the Ranking SVM will learn the ranking function to attain rank for the search results. The content concept and the location concept for a given set of queries will be extracted.By the search results a set of location concept is extracted for a given query. As taking the preference pairs as input the RSVM will find a linear ranking function. An adaptive implementation, SVMlight available is used in our experiments. Upon response of the user's preferences, Ranking SVM is employed to learn an adapted ranking function for investigate results according to the user contented and location preferences. For a given query, a set of content concepts and a set of location concepts are extracted on or after the search outcome as the document features. Using the first choice pairs as the input, RSVM aim at result a linear ranking function, this holds for as many document preference pairs, To extract the concepts measure similarity and parent-child associations of the concepts in the extracted concept ontologies are also included in the training based on the different types of relationships such as Similarity, Ancestor, Descendant and Sibling. Content feature vector C_i is extracted from the web snippet and corresponding values are incremented in the content feature vector their values are incremented in the content feature vector $\phi_C(Q, d_k)$ with the following equation:

$$\forall C_i \in s_k, \phi_C(Q, d_k)[C_i] = \phi_C(Q, d_k)[C_i] + 1$$

For other content concepts $C_j$that are related to the content concept C_i

$$\begin{aligned}\forall C_i \in s_k, \phi_C(Q, d_k)[C_j] \\ = \phi_C(Q, d_k)[C_j] + \text{Ancestor}(C_i, C_j) \\ + \text{Descendant}(C_i, C_j) + \text{Sibling}(C_i, C_j) \\ + \text{similarity}_\text{R}(C_i, C_j)\end{aligned}$$

Location feature vector l_i is extracted from the web snippet and corresponding values are incremented in the location feature vector their values are incremented in the location feature vector $\phi_l(Q, d_k)$ with the following equation

$$\forall C_i \in s_k, \phi_l(Q, d_k)[l_i] = \phi_l(q, d_k)[l_i] + 1$$

$$\begin{aligned}\forall C_i \in s_k, \phi_l(Q, d_k)[l_j] \\ = \phi_C(Q, d_k)[l_j] + \text{Ancestor}(l_i, l_j) \\ + \text{Descendant}(l_i, l_j) + \text{Sibling}(l_i, l_j) \\ + \text{similarity}_\text{R}(l_i, l_j)\end{aligned}$$

To optimize the personalization effect, we use the following formula to combine the two weight vectors, linearly according to the values of and to obtain the final weight vector for user U'0. s ranking. The two weight vectors are first normalized before the combination

$$\overrightarrow{w_{Q,U}} = \frac{e_C(Q,U)}{e_C(Q,U) + e_L(Q,U)} \overrightarrow{w_{C(Q,U)}} + \frac{e_L(Q,U)}{e_C(Q,U) + e_L(Q,U)} \overrightarrow{w_{L(Q,U)}}$$

Let $e(Q,U) = \frac{e_C(Q,U)}{e_C(Q,U)+e_L(Q,U)}$

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 1, January 2014

$\overrightarrow{w_{Q,U}} = e(Q,U)\overrightarrow{w_{C(Q,U)}} + (1 - e(Q,U)\overrightarrow{w_{L(Q,U)}}$ will rank the documents in the returned search according to the following equation , F(Q,d)=$\overrightarrow{w_{Q,U}}.\phi(Q,d)$

IX. Modules Description

A. PMSE clients for user clickthroughs

In this work client-server architecture is used, here the main task for client is to store the clickthroughs and the ontology's which areobtained from the server. The client will perform simple tasks like updating the clickthroughdatas and ontology's, displaying the results and creating the feature vectors. Here privacy is preserved by storing the user profiles in the client side itself.

B. User Interest Profiling

Assign thet the degrees of importance for the same content concept or location concept will be differ for each user and every query. According to the need of user we characterize the diversity of concepts associated with a query we introduced the content and location entropies to measure the amount of content and location information associated with a query. Like that the click content and location entropies are used to measure the percentage user interest in content and location information. Before returning the results to the client the reranking function will be done on the results by attaining the users content and location preferences.

Content Ontology

Our content concept extraction method first extracts all the keywords and phrases (excluding the stop words) from the web-snippets arising from q. If a keyword/phrase exists frequently in the web-snippets arising from the query q, would treat it as an important concept related to the query, as it coexists in close proximity with the query in the top documents. The following support formula, which is inspired by the well-known problem of finding frequent item sets in data mining, is employed to measure the importance of a particular keyword/phrase c_i with respect to the query q:

$$support(c_i) = \frac{sf(c_i)}{n} \cdot |c_i|,$$

where sfc_i is the snippet frequency of the keyword/ phrase c_i (i.e., the number of web-snippets containing c_i), n is the number of web-snippets returned and $|c_i|$ is the number of terms in the keyword/phrase c_i. If the support of a keyword/phrase c_i is higher than the threshold s (s =0:03in our experiments), we treat c_i as a concept for q.

Location ontology

The method for extracting content from concept is differ from the approach used for location concepts. There are two important methods in the formulation of location ontology. First, to extract location concept from the full documents this methods will alleviate a problem that a document usually embodies only a few location concepts, and thus only very few of them co-occur with the query terms in web-snippets. Second, the similarity and parent-child relationship cannot be accurately derived statistically because the limited number of location concepts embodied in documents. Furthermore, many geographical relationships among locations have already been captured as facts.

C. Diversity of Content and Location Information

Different queries may be associated with different amount of content and location information. To formally characterize the content and location properties of the query, we use entropy to estimate the amount of content and location information retrieved by a query. In information theory, entropy indicates the uncertainty associated with the information content of a message from the receiver's point of view. In the context of search engine, entropy can be employed in a similar manner to denote the uncertainty associated with the information content of the search results from the user's point of view. Since we are concerned with content and location information only define two entropies, namely, content entropy HC_q and location entropy HL_q, to measure, respectively, the uncertainty associated with the content and location information of the search results.

$$H_C(q) = -\sum_{i=1}^{k} p(C_i)\log p(C_i)$$

$$H_L(q) = -\sum_{i=1}^{k} p(L_i)\log p(L_i)$$

Click entropies reflect the user's events in response to the search results; it can be used as a suggestion of the variety of the user's wellbeing. Formally, the click content entropy and click location entropy $H_{\bar{L}}(q,U)$of a query q submitted by the user u are defined as follows

$$H_{\bar{C}}(q,U) = -\sum_{i=1}^{k} p\ (\overline{C_{i,U}})\log p(\overline{C_{i,U}})$$

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 1, January 2014

$$H_{\overline{L}}(q, U) = -\sum_{i=1}^{k} p(\overline{L_{i,U}}) \log p(\overline{L_{i,U}}).$$

Where t is the number of content concepts clicked by user U, $C_U = C_{1U}, C_{2U}, \ldots, C_{tU}$ is the number of times that the content concept C_i has been clicked by

$$||\overline{C_U}| = |\overline{C_{1U}}| + |\overline{C_{2U}}| + \cdots \ldots \ldots + |\overline{C_{tU}}|, p(\overline{C_{i,}}U) = \frac{|\overline{C_{iU}}|}{|\overline{C_U}|}, v$$

is the numeral of location concepts,

$$\overline{L_U} = \{\overline{l_{lU}}, \overline{l_{2U}}, \ldots \ldots .., \overline{l_{vU}}\}$$

The corresponding effectiveness of the location and content concepts can be measured between the concepts and user clicked concepts,

$$e_C(q, Uq) = \frac{H_C(Q)}{H_{\overline{C}}(UQ, U)}$$

$$e_L(q, Uq) = \frac{H_L(q)}{H_{\overline{L}}(q, U)}$$

In all of the above mentioned concepts the user preference doesn't provide the security methods in the profile.

D. Personalized Ranking Functions

By using the user content and location preferences the ranking SVM is used to observe a ranking function for the adaption of rank of the search results. By the search results a set of location concept is extracted for a given query. As taking the preference pairs as input the RSVM will find a linear ranking function.

E. Association rule mining travel patterns

To find a query traveler's interest extracted from search based user click through files when the personal user search the results from mobile .When user enter query based path or traversal patterns are identified firstly and then we generate frequent itemset that is number of time the user click thorough files and find most important travel patterns in the clickthrough files. This research focuses on the travelers who use mobile search have most frequent based links in both location and concept based ontology ,before that we find the frequent itemset that is more number of times user search the similar web pages or concept and location .From this we calculate the support and confidence values of the click through files and most relevant frequent itemset results are considered as user most important concepts and location then again we proceed the basepaper concept to rank the feature for both content and location ontology.

Performance evaluation

In this module measure performance of PMSE and ARM-PMSE system with precision, recall and accuracy.

- **Precision**

Precision value is calculated is based on the retrieval of information at true positive prediction, false positive.
Precision =TP/ (TP+FP)

- **Recall**

Recall value is calculated is based on the retrieval of information at true positive prediction, false negative. Recall is the fraction of relevant instances that are retrieved,
Recall =TP/(TP+FN)

- **TP (True positive)**

In a statistical hypothesis test, there are two types of incorrect conclusions that can be drawn. The hypothesis can be inappropriately. A positive test result that accurately reflects the tested-for activity of an analyzed. If the outcome from a prediction is p and the actual value is also p, then it is called a true positive (TP);
True positive rate (TPR) =TP/P
P= (TP+FN)

Where P is the positive. TP is the True Positive

- **TN (True negative)**

A result that appears negative when it should not. A true negative (TN) has occurred when both the prediction outcome and the actual value are n is the number of input data.
True negative rate (TNR) =TN/N
N= (TN+FN)
Where
N is the Negative value.
TN is the True Negative.

- **FP (False positive)**

A result that indicates that a given condition is present when it is not. However if the actual value is n then it is said to be a false positive (FP).
False positive rate (α) = FP / (FP + TN)

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 1, January 2014

- **FN (False negative)**

False negative (FN) is when the prediction outcome is n while the actual value is p.
False negative rate (β) =FN / (TP + FN)

X. CONCLUSION

PMSE extract the clickthrough data and get the user preferences for content and location. It also integrated the user's GPS locations with the personalization procedure to attain the location and will help to develop retrieval effectiveness. Proposed association rule method get the query travel patterns system and it contributes new knowledge, that gathers mostly on database to satisfy the user profiles results. The system will collect the newly clicked datas andanalyze them by ontology system. When several users click more data's the system will rerank the data's. It will analize more data and repeatedly using the newly obtained data. This will increase the knowledge discovery pattern in database. If the traveller changes his behaviour, the ranking will change and alsothe pattern in the database will changes.

REFERENCES

[1].Nauman, Mohammad Khan and Shahbaz, "Using Personalized Web Search for Enhancing Common Sense and Folksonomy Based Intelligent Search Systems," International Conference on Web Intelligence (IEEE/WIC/ACM), Pp. 423 – 426, 2007.
[2]. Zhengyu Zhu, JingqiuXu, Xiang Ren, YunyanTian and Lipei Li, "Query Expansion Based on a Personalized Web Search Model," Third International Conference on Semantics, Knowledgeand Grid, Pp. 128 – 133, 2007.
[3]. P. Palleti, H. Karnick and P. Mitra, "Personalized Web Search Using Probabilistic Query Expansion," International Conferences on Web Intelligence and Intelligent Agent Technology Workshops (IEEE/WIC/ACM), Pp. 83 – 86, 2007.
[4]. Jie Yu and Fangfang Liu, "Mining user context based on interactive computing for personalized Web search," 2nd International Conference on Computer Engineering and Technology (ICCET), Vol. 2, Pp. 209-214, 2010.
[5].Fang Liu, C. Yu and WeiyiMeng, "Personalized Web search for improving retrieval effectiveness," IEEE Transactions on Knowledge and Data Engineering, Vol. 16, No. 1, Pp. 28 – 40, 2004.
[6]. Xuwei Pan, Zhengcheng Wang and XinjianGu, "Context-Based Adaptive Personalized Web Search for Improving Information Retrieval Effectiveness," International Conference on Wireless Communications, Networking and Mobile Computing, Pp. 5427 – 5430, 2007.
[7]. Kyung-Joong Kim and Sung-Bae Cho, "A personalized Web search engine using fuzzy concept network with link structure," Joint 9th IFSA World Congress and 20th NAFIPS International Conference, Vol. 1, Pp. 81 – 86, 2001.
[8]. Chen Ding, J.C. Patra and Fu Cheng Peng, "Personalized Web search with self-organizing map," The 2005 IEEE International Conference on e- Technology, e-Commerce and e-Service (EEE '05), Pp. 144 – 147, 2005.
[9]. C. Biancalana and A. Micarelli, "Social Tagging in Query Expansion: A New Way for Personalized Web Search," International Conference on Computational Science and Engineering (CSE '09), Vol. 4, Pp. 1060 1065, 2009.
[10]. K.W.-T. Leung, D.L. Lee and Wang-Chien Lee, "Personalized Web search with location preferences," IEEE 26th International Conference on Data Engineering (ICDE), Pp. 701 – 712, 2010.
[11]. J. Lai and B. Soh, "Personalized Web search results with profile comparisons," Third International Conference on Information Technology and Applications (ICITA 2005), Vol. 1, Pp. 573 – 576, 2005.
[12]. B. Smyth, "A Community-Based Approach to Personalizing Web Search," IEEE Journals, Computer, Vol. 40, No. 8, Pp. 42 – 50, 2007.
[13]. O. Shafiq, R. Alhajj and J.G. Rokne, "Community Aware Personalized Web Search," International Conference on Advances in Social Networks Analysis and Mining (ASONAM), Pp. 351 – 355, 2010.
[14]. Han-joon Kim, Sungjick Lee, Byungjeong Lee and Sooyong Kang, "Building Concept Network-Based User Profile for Personalized Web Search," 9th International Conference on Computer and Information Science (ICIS), Pp. 567 – 572, 2010.
[15]. Yan Chen, Hai Long Hou and Yan-Qing Zhang, "A personalized context-dependent Web search agent using Semantic Trees," Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS), Pp. 1 – 4, 2008.
[16]. Wen-ChihPeng and Yu-Chin Lin, "Ranking Web Search Results from Personalized Perspective," The 8th IEEE International Conference on and Enterprise Computing, E-Commerce, and E-Services, The 3rd IEEE International Conference on E-Commerce Technology, Pp. 12, 2006.
[17]. M. Kutub, R. Prachetaa and M. Bedekar, "User Web Search Behaviour," 3rd International Conference on Emerging Trends in Engineering and Technology (ICETET), Pp. 549 – 554, 2010.
[18]. B. Arzanian, F. Akhlaghian and P. Moradi, "A Multi- Agent Based Personalized Meta-Search Engine Using Automatic Fuzzy Concept Networks," Third International Conference on Knowledge Discovery and Data Mining, Pp. 208 – 211, 2010.
[19]. DikLun Lee, W. Ng and K.W.-T. Leung, "Personalized Concept-Based Clustering of Search Engine Queries," IEEE Transactions on Knowledge and Data Engineering, Vol. 20, No. 11, Pp. 1505 – 1518, 2008. 20.

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ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 1, January 2014

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