Effcient Semantic Similarity Based Fcm For Inferring User Search Goals With Feedback Sessions

L.Suganya M.phil[1], Dr.B.Srinivasan , M.C.A, M.Phil , M.B.A, Ph.D [2]

[1] *Mphil Scholar, Department of Computer Science, Gobi Arts and Science College, Gobi. Tamilnadu, India*

[2] *Associate professor, Department of Computer Science, Gobi Arts and Science College, Gobi.*

Abstract— **Web search applications represent user information needs by submission of query to search engine. But still the entire query submitted to search engine doesn't satisfy the user information needs, because users may want to get information on diverse aspects when they submit the same query. From this discovering the numeral of dissimilar user search goals for query and depicting each goal with several keywords automatically become complicated. The suggestion and examination of user search goals can be very valuable in improving search engine importance and user knowledge. Discovering the numeral of dissimilar user search goals for query by k-means clustering with user feedback sessions. Efficiently reflect user information needs generate a pseudo-document to map the different user feedback sessions. Clustering Pseudo documents with K means clustering result are computationally difficult and semantic similarity between the pseudo terms is also important while clustering. To conquer this problem proposed a FCM clustering algorithm to group the pseudo documents and it also measure the semantic similarity between the pseudo terms in the documents using wordnet. The FCM algorithm divides pseudo documents data for dissimilar size cluster by using fuzzy systems. FCM choosing cluster size and central point depend on fuzzy model. The FCM clustering algorithm it congregate quickly to a local optimum or grouping of the pseudo documents in well-organized way. Semantic similarity between the pseudo terms with Wordnet based similarity is used for comparing the similarity and diversity of pseudo terms. Finally experimental result measures the clustering results with parameters like classified average precision (CAP), Voted AP (VAP), risk to avoid classifying search results and average precision (AP). It shows FCM based system improve the feedback sessions outcome than the normal pseudo documents.**

Keywords— **User search goals, feedback sessions, pseudo-documents, classified average precision (CAP), Voted AP (VAP), average precision (AP), Fuzzy C means clustering, K-means clustering.**

I. Introduction

In web search based applications user enters the query in the website to search the efficient information. The needs of the information may differ from each user and goal to achieve the user need are still becomes difficult. Because the user given queries may not understandable by system or it becomes less sometimes queries may not exactly represented by users. To achieve the user specific information needs many uncertain queries may cover a broad topic and dissimilar users may want to get information on different point of view when they submit the same query. User information need is to desire and obtain the information to satisfy the needs of each user. To satisfy the user information needs by considering the search goals with user given query. We cluster the user information needs with different search goal .Because the interference and examination of user search goals with query might have a numeral of advantages by improving the search engine significance and user knowledge. So it is necessary to collect the different user goal and retrieve the efficient information on different aspects of a query. Capture different user search goals in information retrieval outcome becomes changes than the normal query based information retrieval.

Major advantages from this search engine based query results are the first restructure web pages result according to user search goals. X. Wang and C.-X Zhai et.al [1] presented a user boundary that organizes Web search consequences into hierarchical category. Text classification algorithms are used to repeatedly classify subjective search consequences into an obtainable group organization. A user study compared our new category interface with the typical ranked list interface of search results. Here the author group user search goal with similar results

Hua-Jun Zeng et.al [2] suggested a query based search results for user goal and the rank list of documents return by a certain Web search engine, it first extracts and ranks most important phrases as candidate cluster names, base on a regression model learned beginning human labeled training data. The documents are assigned to applicable most important phrases to form candidate clusters, and the final cluster are generated by assimilation these candidate clusters. But this method only produces the result with higher level of the documents only and it doesn't make the results for all search based user goals.

Clustering search results is an efficient method to systematize investigates results, which allows a user to find the way into applicable documents quickly. Wang and Zhai [1] learning "interesting aspects" of a topic beginning Web search logs and organize search results therefore and generate further significant cluster labels using history query words entered by users. However, this method has limits because the numeral of dissimilar clicked URLs of a query may be small. To discover the user information automatically at different point of view with user given query and collects the similar search goal result with URL first we collect similar feedbacks sessions.

Reorganize the web structure environment based on the link in the URL clicked and unclicked by the URL. First the infer user search goals for a query by clustering the similar documents from the web search. Then, map feedback sessions from the pseudo documents to collect the similar pages of links to satisfy user goals and retrieve the user information. The K means clustering algorithm can be used to cluster the similar pseudo documents and group them according to the search goal. But these methods doesn't support the semantic similarity between the pseudo terms before clustering ,so we proposed wordnet based similarity measure and FCM based clustering to group the similar pseudo documents. Fuzzy c-means (FCM) is a method of clustering which allows one piece of documents data to belong to two or more clusters.

Represent the URL using Feedback session that includes the URLs, it consists of the clicked URL and Unclicked URL links. Usually language because users will scan the URLs single by single from top to down, we can believe that in addition the three clicked URLs, four unclicked ones in the rectangular box contain also be browsed and evaluate by the user and they be supposed to rationally be a division of the user feedback. Within the feedback session, the clicked URLs tell what user necessitates and the unclicked URLs reflect what user does not care about. It is supposed to be well-known that the unclicked URLs after the last clicked URL should not be included into the feedback sessions since it is not certain whether they were scanned or not. Each feedback session can tell what a user requires and what he/she does not care about. Furthermore, there is abundance of miscellaneous feedback sessions in user click-through logs. Consequently, for inferring user search goals, it is well-organized to analyze the feedback sessions than to observe the search results or clicked URLs straight.

The major contribution of the work as follows:

1. First collect the different user query based results in the web based search engine and then generated the different feedback session are collected infer user search goals for a query by clustering the similar documents from the web search.
2. After the collection of feedback session introduce a method to collect the similar pages of links to satisfy user goals and retrieve the user information.
3. The K means clustering algorithm can be used to cluster the similar pseudo documents.
4. Then measuring the semantic information makes result better than the normal keywords information. Measuring the semantic similarity between the pseudo terms we proposed a wordnet based similarity measure.
5. After that similarity measure again group the pseudouments using FCM means algorithm.
6. Finally compare the results with parameters classified average precision (CAP), Average Precision (AP), Voted AP(VAP) and risk to evaluate the performance of the restructured web search results.

II. LITERATURE REVIEW

The problem of clustering investigate results has been investigate in a numeral of previous works. All of the previous work apply clustering algorithms which first group documents into similar groups according to content similarity, and produce expressive summary for clusters. Though, these summaries are often illegible which construct it difficult for Web users to recognize relevant clusters.

Zamir and Etzioni [3] introduced a Suffix Tree Clustering (STC) which first identifies sets of documents that split common phrases, and after that create clusters according to these phrases. Our applicant phrase extraction procedure is similar to STC but we supplementary calculate a number of significant properties to identify salient phrases, and make use of learning methods to rank these salient phrases. Some topic finding or text trend analysis mechanism is also related to our method. The dissimilarity is that we are specified titles and short snippets somewhat than whole documents. For the meantime, we train regression model for the ranking of cluster which is closely related to the efficiency of users' browsing.

Web search engines challenge to satisfy users' information needs by standing web pages with reverence to queries. But the realism of web search is that it is frequently a procedure of querying, learning, and reformulating. A sequence of interactions among user and search engine can be essential to satisfy a solitary information need [4].

Though users query search engines in order to achieve tasks at a diversity of granularities, issue numerous query as they effort to accomplish tasks. R. Jones and K.L. Klinkner [5] learning real sessions manually labeled into hierarchical tasks, and demonstrate that timeouts, anything their length, are of incomplete utility in identifying task boundaries, achieving a greatest precision. Though, their method only identifies whether a pair of queries belongs to the same goal or mission and does not mind what the goal is in aspect.

U. Lee, Z. Liu, and J. Cho [6] study the "goal" at the back based on a user's Web query, so that this goal can be used to get better the excellence of a investigate engine's results. Preceding studies encompass mainly focused on manual query-log investigation to recognize Web query goals. Identify the user goal automatically with no any explicit feedback from the user. User search goals represented by a number of keywords can be utilized in query suggestion [7], [8], [9]; thus, the suggested queries can assist user to form their query more accurately.

A previous exploitation of user click-through logs is to get user implicit feedback to expand training data when knowledge ranking functions in information retrieval. Adapt a recovery system to challenging groups of users and exacting collections of documents promise further improvement in retrieval quality for at least two reasons. Since physically adapting retrieval function is instance consuming or even not practical, investigate on automatic adaptation by means of machine learning is in receipt of a great deal notice.

T. Joachims [10] explore and evaluate strategies for how to mechanically produce training example for learning retrieval functions from experiential user behavior. Yet, implicit feedback is more hard to interpret and potentially noisy. First examine which types of implicit feedback can be dependably extracted from experiential user behavior, in particular clickthrough data in WWW search. To assess the reliability of implicit feedback signals, we conduct a user study. The learn is intended to examine how users interrelate with the list of ranked consequences from the Google search engine and how their behavior can be interpret as significance judgments.

Thorsten Joachims did lots of works on how to use implicit feedback to get better the retrieval quality [11], [12]. In our effort we believe feedback sessions as user implicit feedback and suggest a novel optimization method to merge both clicked and unclicked URLs in feedback sessions to discover what users really necessitate and what they do not mind. One submission of user search goals is restructuring web investigate results. There are also some related works focuses on organize the search results [13], [1], [2]. In this work we infer user search goals beginning user click-through logs and reorganize the search results according to the inferred user search goals and then finally measure the results.

III. Semantic Similarity and FCM ,K Means Clustering Based Pseudocuments

In this paper first the section are majorly divided into two parts user query based information are extracted, user search goals are conditional by clustering these pseudo-documents and depicted with some keywords and then the original query based information are extracted from the web pages from that restructure the webpages based on user profile Then, we evaluate the performance of restructuring search results by evaluation criterion CAP, VAP, AP and Risk. In first step of the process is the collection of the web pages with similar query .For example when the user Given query as sun then collect all the log files that related to the web pages based on query with link pages clicked by user .Before that copy all the links and copy the contents from the link that contains information about the link pages .After these process finished then only we Map the feedback session of the each user.

A. Feedback session

Feedback session is a session for web search is a sequence of consecutive queries to satisfy a single information require and some clicked investigate results focal point on inferring user search goals for a exacting query. Consequently the single session contain simply one query is introduce, which distinguish from the conservative session. For the moment, the feedback session is based on a solitary session, though it can be comprehensive to the entire session. It consists of both clicked and unclicked URLs and ends with the last URL that be clicked in a single session. It is forced that previous to the last click, all the URLs have been scanned and evaluate by users. Each feedback session can tell what a user requires and what he/she does not care about. Moreover, there are plenty of diverse feedback sessions in user click-through logs. Consequently, for inferring user search goals, it is additional efficient to examine the feedback sessions than to examine the investigate consequences or clicked URLs in a straight line. To represent the feedback session efficiently some demonstration methods needed, because each and every user based search goal feedback sessions are differs and their corresponding log files also changed.

Represent a feedback session to Pseudo-Documents with Binary vector technique to characterize a feedback session search consequences are the URLs return by the search engine when the question “the sun” is submits, and “0” represent “unclicked” in the click sequence. The binary vector [0110001] can be second-hand to symbolize the feedback session, where “1” represent “clicked” and “0” represents “unclicked.

Building a pseudo documents

In the primary step, we primary augment the URLs with extra textual inside by extracting the titles and snippets of the returned URLs appear in the feedback session. Each URL in a feedback session is represent by a little text subsection that include of its title and snippet. Then, a number of textual process are implement to persons text paragraphs, such as transforming all the letters to lowercases, stemming and remove stop words. Finally, every URL’s title and snippet are generated by a Term Frequency-Inverse Document Frequency (TF-IDF) vector, correspondingly

$$T_{u_i} = \{T_{W_1}, T_{W_2}, \ldots \ldots, T_{W_n}\}^T \longrightarrow (1)$$
$$S_{u_i} = \{S_{W_1}, S_{W_2}, \ldots \ldots, S_{W_n}\}^T \longrightarrow (2)$$

Where

T_{u_i}- TF-IDF vectors of the URL’s title

$S_{u_i}$are the TF-IDF vectors of the URL’s snippet .

u_i- i^{th} URL in the feedback session.

$W_{j=}\{1; 2; \ldots ; n\}$ -j^{th} term appear in the enriched URLs. Each term in the URL is defined as a word or a numeral in the vocabulary of document collections. t_{wj} and s_{wj} characterize the TF-IDF significance of the j^{th} term in the URL’s title and snippet, correspondingly. Taking into consideration that URLs’ titles and snippets have dissimilar significances, we symbolize the enriched URL by the weighted sum of T_{ui} and S_{ui} , namely,

$$F_{u_i} = T_{u_i}\omega_t + S_{u_i}\omega_s = \{f_{W_1}, f_{W_2}, \ldots \ldots, f_{W_n}\}^T \rightarrow (3)$$

Where F_{ui} means the feature representation of the i[th] URL in the feedback session, and weights of the ω_t titles and ω_s the snippets, respectively. In order to obtain the feature demonstration of a feedback session, suggest an optimization method to merge both clicked and unclicked URLs in the feedback session. Attain such a F_{f_s} with the purpose of the calculation of the distance between F_{f_s} and each F_{uc_m} is minimize and the sum of the distance between F_{f_s} and each F_{uc_l} is maximize. Based on the supposition that the terms in the vectors are self-governing, perform optimization on each dimension separately,

$$F_{f_s} = \left[f_{f_s}(\omega_1), \ldots\ldots f_{f_s}(\omega_n)\right)]^T \longrightarrow (4)$$

Infer user search goals and represent them with a number of significant keywords. Then the similarity between the pseudocuments is evaluated as the cosine similarity score

$$Sim_{\,i,j} = \cos\left(f_{fs_i}, f_{fs_j}\right) = \frac{f_{fs_i} f_{fs_j}}{|f_{fs_i}||f_{fs_j}|} \longrightarrow (5)$$

$$Dis_{\,i,j} = 1 - Sim_{\,i,j} \longrightarrow (6)$$

B. Cluster pseudo-documents with K means

In this investigate we cluster pseudo-documents by K-means clustering which is straightforward and efficient. Because we not recognizable with the precise figure of user search goal for every query, we position K to be five different values.

$$F_{center_i} = \frac{\sum_{k=1}^{C_i} F_{fs_k}}{C_i}, \left(F_{fs_k} \subset Cluster\ i\right) \longrightarrow (7)$$

where F_{center_i}- i[th] cluster's center and C_i is the numeral of the pseudo-documents in the i[th] cluster. F_{center_i} is utilize to finish the investigate goal of the i[th] cluster. Finally, the conditions with the highest values in the F_{center_i} are second-hand as the keywords to represent user search goals, it is a keyword based explanation is that the extracted keywords be able to in addition be utilized to form a more significant query in query suggestion and thus can represent user information needs most effectively.

C. Semantic similarity and FCM based Clustering

WordNet is tool to measure the semantic similarity between the terms or words in the pages of documents that was selected by user .When a user given the words taken as input it finds the similarity to terms with the connections among four types of Parts of Speech (POS) - noun, verb, adjective, and adverb. The minimum unit in a WordNet is synset, which represent an exact meaning of a word. It includes the word, its clarification, and its synonyms. The specific connotation of one word under one type of POS is called a sense. Each sense of a word is in a dissimilar synset. Synsets are corresponding to senses = structures contain sets of terms with identical meanings. Each synset has a gloss that defines the concept it represents.

Synsets are connected to one another through explicit semantic relations with pseudo terms. Some of these relationships (hypernym, hyponym for nouns, and hypernym and troponym for verbs) comprise is-a-kind-of (holonymy) and is-a-part-of hierarchies. For one word and one type of POS, if there is further than one sense, WordNet organize them in the order of the majority frequently used to the least frequently used (Semcor) terms in the pseudocuments and most frequently occurs user to find the relevant or most similar documents in the user feedback sessions .

Fuzzy c-means (FCM) is a technique of clustering which allows one piece of pseudocuments data to belong to two or more clusters. It is the way to solve how the data with similar psedocuments are clustered according to best semantics similarity of the pseudo terms in the documents. In this algorithm the same given data or pseudocuments does not go completely to a well definite cluster, based on the fuzzy membership function only the psedocuments the cluster groups are formed in efficient manner with possible number of the groups at user feedback sessions. In the FCM approach, instead, the same given datum does not belong exclusively to a well defined cluster, but it can be placed in a focal point way. In this case, the membership function follows a flatter line to designate that each datum may go to frequent clusters with different standards of the membership constant. In fuzzy clustering, each position has a degree of belong to clusters, as in fuzzy logic, rather than belong totally to just one cluster. Thus, points on the edge of a cluster might be *in the cluster* to a smaller degree than points in the midpoint of cluster. It is based on selection of the degree membership function,

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^m \,||x_i\text{-}x_j||^2 \qquad 1 \le m \le \infty$$

where m is any real numeral greater than 1, u_{ij} is the degree of membership of x_i documents based data in the cluster j, x_i is the i[th] of measured data, C_j is the numeral of the pseudo-documents in the j[th] cluster and ||*|| is any norm expressing the similarity between any measured data of the pseudocuments and the center. Fuzzy separating is carried out concluded iterative optimizations of the objective function with the modernize of membership u_{ij} and the cluster centers c_j by:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left\{\frac{||x_i - c_i||}{||x_i - c_k||}\right\}^{\frac{2}{m-1}}}$$

This iteration will stop when $\max_{ij}\{|\mu_{ij}^{(k+1)} - \mu_{ij}^{(k)}|\} < s$, where s is a termination criterion between 0 and 1, whereas k is the repetition steps. This technique converges to a local smallest or a saddle point of J_m.

The algorithm is collected of the subsequent steps:

1) Initialize $U=[U_{ij}]$matrix, $U^{(0)}$ pseudocuments
2) At each and every position K calculate the midpoint vectors of each pseudocuments

$C^{[K]} = [C_j]$ with $U^{(k)}$

$$C_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{m} - x_i}{\sum_{i=1}^{N} \mu_{ij}^{m}}$$

3) Update $U^{(k)}$, $U^{(k+1)}$ the pseudocuments datapoints with membership function

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left\{ \frac{||x_i - c_i||}{||x_i - c_k||} \right\}^{\frac{2}{m-1}}}$$

4) if $|| U^{(k+1)} - U^{(k)}|| < \in$ then stop .It satisfies the condition then group the pseudocuments .Otherwise else to step 2 and again find the best pseudocuments data with user search goal.

IV. EXPERIMENTAL RESULTS

Before conclusion of the results and remarks of the paper the major part is the evaluation of the results from the experiments with classification results from each user search goal inference us a major problem , since user search goals are not predetermined and there is no ground truth. It is necessary to develop a metric to evaluate the performance of user search goal inference objectively. In this section finally measure the performance of the semantic similarity with FCM and accessible pseudocuments based clustering Measure the performance of the system with parameters like Classified Average Precision (CAP), Voted AP (VAP) which is the AP of the class including more clicks namely, risk to avoid classifying search results and average precision (AP).The corresponding AP,VAP,CAP and Risk values are measured Between user search Goal with cosine similarity and User search Goal with semantic similarity values are shown in Figure 1,2,3 and 4. It shows that the User search goal With Semantic similarity results are better than User search goal with cosine similarity measure.

A. Average precision (AP)

In order to be appropriate the assessment method to large-scale data, the solitary sessions in user click-through logs are second-hand to reduce physical work. Since beginning user click-through logs, we can get implied significance feedbacks, specifically "clicked" means applicable and "unclicked" means inappropriate. A probable evaluation principle is the average precision (AP) which evaluate according to user implicit feedbacks. AP is the average of precisions compute at the position of each applicable document in the ranked sequence

$$AP = \frac{1}{N^+} \sum_{r=1}^{N} rel(r) \frac{R_r}{r}$$

where N^+ is the numeral of applicable (or clicked) documents in the retrieved ones, r is the rank, N is the total numeral of retrieved documents, rel() is a binary function on the relevance of a given rank, and R_r is the number of relevant retrieved documents of rank r or less.

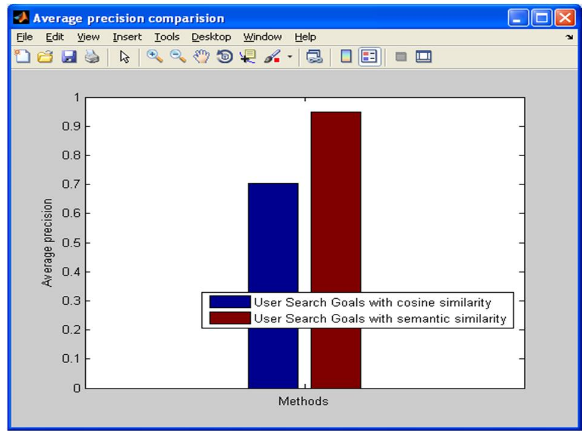

Figure 1: Average Precision (AP) comparison

B. Voted AP(VAP)

VAP of the modernized search result the AP of class 1, It is defined as ,

$$VAP = \frac{1}{NC} \sum_{r=1}^{NC} rel(r) \frac{R_r}{r}$$

where N is the total numeral of retrieved documents with class label one , rel() is a binary function on the relevance of a given rank, and R_r is the number of relevant retrieved documents of rank r or less.

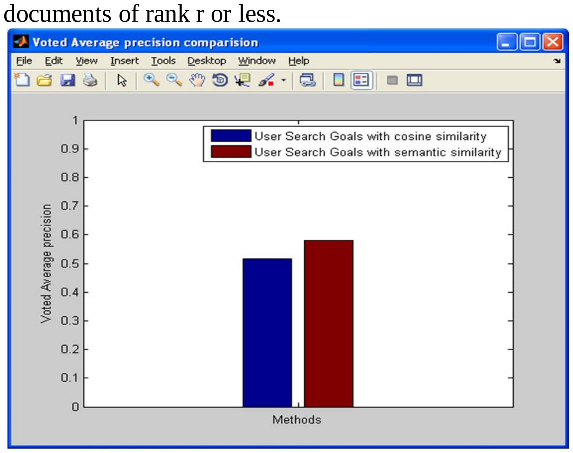

Figure 2: Average Precision (AP) comparison

C. *Classified Average Precision (CAP)*

Extend VAP by introducing the above Risk and propose a new criterion Classified AP(CAP)

$$\text{CAP} = \text{VAP} * (1 - \text{risk})^{\gamma}$$

Where $\boldsymbol{\gamma}$ is used to adjust the influence of Risk on CAP. CAP select the AP of the class with the aim of user is interested with the most clicks/votes and takes the risk of wrong classification into account.

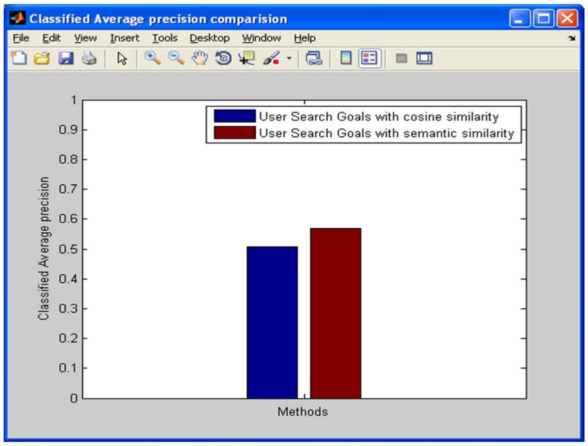

Figure 3: Classified Average Precision (AP) comparison

D. ***Risk***

VAP is still an unsatisfactory criterion. Taking into consideration an extreme case, if every URL in the click session is categorized into one class, VAP will forever be the highest value that is 1 no matter whether user contain so many investigate goals or not. Consequently present be supposed to be a risk to avoid classify exploration results into too many classes by error. They propose the risk as follows:

$$Risk = \frac{\sum_{i,j=1(i<j)}^{m} d_{ij}}{C_m^2}$$

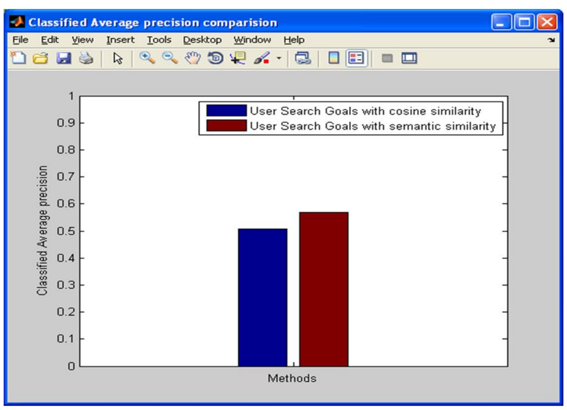

Figure 4: Risk comparison

V. CONCLUSIONS AND FUTURE WORK

In this paper Semantic similarity based FCM approach has been proposed to infer user search goals for a query by clustering its feedback sessions represented by pseudo-documents. Primarily we introduce feedback sessions to be analyzed to infer user search goals rather than search results or clicked URLs. Second, we map feedback sessions to pseudo documents to approximate goal texts in user minds with semantic similarity based measures and then pseudo-documents can supplement the URLs with additional textual contents including the titles and snippets. It cluster the different pseudocuments of the user search goals with feedback session and those pseudo-documents, user search goals can then be exposed and depict with a number of keywords Finally Semantic similarity based FCM approach and Cosine similarity based K means approach were measured the presentation on new criterion CAP, AP, VAP and Risk is formulate of user search goal inference. Experimental results on client click-through logs from a commercial search engine reveal the efficiency of our proposed methods.In future work can be done in the following manner user can search the query in the feedback we automatically derive the optimal value to improve the feedback session results.

References

[1] X. Wang and C.-X Zhai, "Learn from Web Search Logs to Organize Search Results," *Proc. 30th Ann. Int'l ACM SIGIR Conf. Research and Development in Information Retrieval (SIGIR '07)*, pp. 87-94, 2007

[2] H.-J Zeng, Q.-C He, Z. Chen, W.-Y Ma, and J. Ma, "Learning to Cluster Web Search Results," *Proc. 27th Ann. Int'l ACM SIGIR Conf. Research and Development in Information Retrieval (SIGIR '04)*, pp. 210-217, 2004.

[3] Zamir O., Etzioni O. Grouper: A Dynamic Clustering Interface to Web Search Results. *In Proceedings of the Eighth International World Wide Web Conference (WWW8)*, Toronto, Canada, May 1999.

[4] A. Spink, B. J. Jansen, and H. C. Ozmultu." Use of query reformulation and relevance feedback by Excite users" *Internet Research: Electronic Networking Applications and Policy,* 10(4):317–328, 2000.

[5] R. Jones and K.L. Klinkner, "Beyond the Session Timeout: Automatic Hierarchical Segmentation of Search Topics in Query Logs," *Proc. 17th ACM Conf. Information and Knowledge Management (CIKM '08)*, pp. 699-708, 2008.

[6] U. Lee, Z. Liu, and J. Cho, "Automatic Identification of User Goals in Web Search," *Proc. 14th Int'l Conf. World Wide Web (WWW '05)*, pp. 391-400, 2005.

[7] R. Baeza-Yates, C. Hurtado, and M. Mendoza, "Query Recommendation Using Query Logs in Search Engines," *Proc. Int'l Conf. Current Trends in Database Technology (EDBT '04)*, pp. 588-596, 2004.

[8] H. Cao, D. Jiang, J. Pei, Q. He, Z. Liao, E. Chen, and H. Li, "Context-Aware Query Suggestion by Mining Click-Through," *Proc. 14th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (SIGKDD '08)*, pp. 875-883, 2008.

[9] C.-K Huang, L.-F Chien, and Y.-J Oyang, "Relevant Term Suggestion in Interactive Web Search Based on Contextual Information in Query Session Logs," *J. Am. Soc. for Information Science and Technology,* vol. 54, no. 7, pp. 638-649, 2003.

[10] T. Joachims, L. Granka, B. Pang, H. Hembrooke, and G. Gay, "Accurately Interpreting Clickthrough Data as Implicit Feedback," *Proc. 28th Ann. Int'l ACM SIGIR Conf. Research and Development in Information Retrieval (SIGIR '05)*, pp. 154-161, 2005.

[11] T. Joachims, "Evaluating Retrieval Performance Using Clickthrough Data," *Text Mining, J. Franke, G. Nakhaeizadeh, and I. Renz, eds.*, pp. 79-96, Physica/Springer Verlag, 2003.

[12] T. Joachims, "Optimizing Search Engines Using Clickthrough Data," Proc. Eighth ACM SIGKDD *Int'l Conf. Knowledge Discovery and Data Mining (SIGKDD '02)*, pp. 133-142, 2002.

[13] H. Chen and S. Dumais, "Bringing Order to the Web: Automatically Categorizing Search Results," *Proc. SIGCHI Conf. Human Factors in Computing Systems (SIGCHI '00)*, pp. 145-152, 2000.