Enhancing Web Search with Semantic Identification of User Preferences

Naglaa Fathy[1], Nagwa Badr[1], Mohamed Hashem[1], Tarek F. Gharib[1, 2]

[1]**Faculty of Computer and Information Sciences, Ain-Shams University, Cairo, Egypt**
[2]**Faculty of Computing and Information Technology, King Abdul-Aziz University, KSA**

Abstract

Personalized web search is able to satisfy individual's information needs by modeling long-term and short-term user interests based on user actions, browsed documents or past queries and incorporate these in the search process. In this paper, we propose a personalized search approach which models the user search preferences in an ontological user profile and semantically compares this model against user current query context to re-rank search results. Our user profile is based on the predefined ontology Open Directory Project (ODP) so that after a user's search, relevant web pages are classified into topics in the ontology using semantic and cosine similarity measures. Moreover, interest scores are assigned to topics based on the user's ongoing behavior. Our experiments show that re-ranking based on the semantic evidence of the updated user profile efficiently satisfies user information needs with the most relevant results being brought on to the top of the returned results.

Keywords *Search Personalization, user profile, ODP, re-rank, semantic similarity*

1. Introduction

With the massive growth of the information available on the World Wide Web, it becomes more difficult for search engines to provide the desired results due to the ambiguity of user needs. Different users have different goals including research, entertainment, finding new jobs or purchasing items. Moreover, current search engines generally process search queries without considering user interests or contexts in which users submit their queries. This can be explained with the search query "Racetrack" One user may need information about Racetrack game. Another user might be looking for results of racetrack playa, while other users might be searching for the memory device racetrack. Obviously, different users would prefer different answers, However, Users surfing the Web in search of relevant information have less time and patience to formulate queries and filter the results returned. Therefore, most web search engines prefer to provide a large set of search results while the users have to determine what is relevant and what is not.

In order to address this problem, recent researches proposed Personalized search which aims to provide users with results that are relevant to their interests by considering user's search history in the retrieval process. It is challenging to identify and exploit the user profile so that search quality could be improved. In particular, personalized search observes all web pages visited by the user, together with the user's search behavior to build a user model which is then used to re rank the top search results returned by a non-personalized web search engine.

The easiest way to get more information about the user and incorporate it in the search process is to ask the user explicitly about his interests and preferences and save them in the user profile. The main disadvantage of this method is that users are reluctant to spend time to provide their intensions before each search. Moreover, it is very difficult for users to define their own interests accurately. Another complex method is based on implicitly observing user's browsing activities and adapting the system according to them. Information stored in user profile can be used to disambiguate or to infer user's query context. Studies in personalized search include [2] which provided the searcher with different search topics and monitored clicked search results so as to learn user's current interests and re-order web search result accordingly. Another approach in [1] models user interests as a vector of weighted terms from visited URLs, and apply a snippet scoring method to re rank search results. In [10] the user profile is composed of each submitted query with its clicked URLs and their corresponding topics, then re-rank is achieved by boosting results with similar topics to topics of queries in the profile that are relevant to current query.

In [3][4][5] [6] the user profile is created based on reference ontology to link information extracted from visited web pages, whereas re ranking is based on a numerical estimate of the results' relevance to the user's profile.

In this paper, we propose a personalized ranking approach for web search results in two main modules. The first module includes capturing the user's preferences and interests from past searches in an ontological user profile which is defined by assigning interest scores to existing categories in the Open Directory Project (ODP) [9]. As user preferences change over time, the user profile is maintained up-to-date by modifying the interest scores for each category after a user's search. Then in the second module search results returned from a user query are re-ordered to match user interests by measuring the *semantic similarity* in conjunction with the *cosine similarity* between the user's current search context and the ontological user profile.

The remainder of the paper is organized as follows. Section 2 reviews related work. Section 3 describes the architecture of our proposed approach. Section 4 defines the detail of building and maintaining the ontological personal profile. Section 5 illustrates the re ranking process. Section 6 reports the experimental evaluation of our approach and finally, we conclude our approach in section 7.

2. Related Work

Personalized systems are being developed to help users find relevant information. The main challenge of effective personalization systems is to accurately identify the user search interests, and re order the returned web pages in such a way that meets these interests. Most personalized techniques model the user's preferences in the form of a user profile or personal profile. In [4] the user has to explicitly select the categories that best fit her interests from the ODP and the user profile is then defined by storing the whole path of each category of interest. when a new query is issued Search results are classified according to the ODP, and then the distance between the hierarchical structure of the user profile and the results' topics is calculated to re rank results. One deficiency of this approach is that it does not maintain the user's changing preferences.

Another personalization method is presented in [8] that defined the user profile as a long term model to be a part of the Google Directory that stored topics of visited pages with the number of visits for each. Additional short term model is defined to store user's recently visited page-history with an adaptation strategy to update the user profile. Re-rank is done by measuring the hierarchical similarity between topics in the user profile and topics of current search results. One disadvantage of this approach is that not all web pages are classified under Google Directory.

An ontological user profile approach is presented in [7] which learned the user preferences after a period of one month then extracted information from user's search history and matched it to concepts of the predefined ontology (ODP). For a user's new search, Query ontology is defined from WordNet by expanding query meaning into semantic hierarchy which is then matched with the user profile to re rank results. However, they do not consider that user's interests over time may get degraded in certain topics and improved in others.

Another ontological user profile is defined in [5] [6] based on the ODP. Each category in the profile contains a vector of weighted terms from web pages originally indexed under such category. Clicked results are classified using the vector space model (VSM) and interest scores for each category which are used for the re-rank process are maintained based on the user's ongoing behavior. This approach does not consider the likeness of the meaning when classifying web pages.

The user model in [3] is defined by an acyclic tree of nodes as concepts from the WordNet ontology[1]. Each node has a vector of weighted terms considered as synonyms and are extracted from a user's past queries. A time stamp is associated with each concept to define its last appearance in user's query to dynamically adapt the profiles. However, this approach is deficient when a user submits query words that are not present in dictionary or ontology used by the system.

3. Proposed approach Architecture

The architecture of our proposed personalized search is shown in Figure 1 which includes two main modules: (a) Modeling the user context as an ontological profile with interest scores derived implicitly for existing concepts (categories) of a predefined domain ontology. Interest scores for each category are updated as the user interacts with the system. (b) Re-ranking the search results based on the semantic relatedness of the user's current query context and the updated ontological user profile. A preprocessing module is used to extract relevant knowledge from web pages.

3.1. Data Pre-Processing Module

Our Personalized approach is based on measuring the semantic similarity between set of senses from WordNet. Therefore, we should convert all words extracted either from the ODP topics or from the search results into set of related senses. To improve the performance of our approach and achieve more accurate results, we apply the preprocessing module on:

a) User search queries
b) Words extracted from ODP topics' titles and descriptions,

[1] WordNet is a lexical database that groups English words of same part of speech (i.e. noun, verb...) into sets of synonyms called *synsets or senses.* It stores general definitions for each sense, and provides various semantic relations between these synsets.

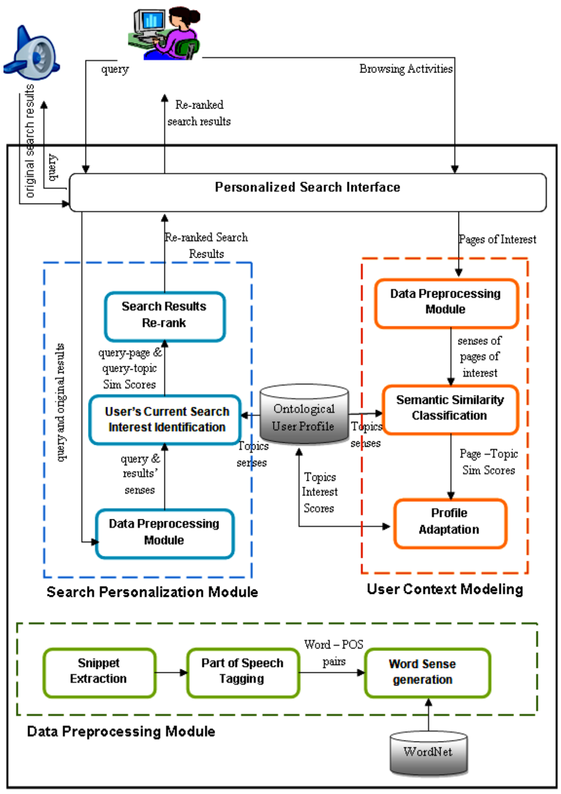

Figure 1 the Proposed Personalized Search Architecture

c) Snippets extracted from search results retrieved from search engine for a given query, where snippets could be obtained from result's URL, title, summary and meta tags.

The first step in generating word senses is to identify the correct part of speech POS (i.e. noun, verb, pronoun, adverb ...) of each word in a sentence. We applied TreeTagger [12] which takes a sentence as input and produces a single best POS tag for each word as output. Each word is followed by two or more characters indicating the part-of-speech. For example, in the sentence, "He/PP passed/VBD the/DT exam/NN", the PP tag indicates a personal pronoun, the VBD tag indicates a verb in the past tense, the DT tag denotes a determiner, and the NN tag is used for a singular noun. We removed stop words using the stop list in [17] as they occurred frequently and insignificant for our approach.

4. User Context Modeling

In our approach, we define the personalized ontology as a hierarchy of topics associated with interest scores initialized to 1. The aim of using ontology is to classify web pages to identify topics that might be of interest to a specific user. As the user interacts with the system, the ontological user profile is updated to maintain the user preferences. User's interests must be accurately collected and represented with minimal user involvement. This can be achieved by passively monitoring the user's browsing behavior over time and collecting Web pages that are shown of interest to the user.

Several factors might be used to indicate the relevance of a web page to the user. These include the frequency of visits to a page, the amount of time spent on the page, and other user actions such as saving, copying, or printing a page. For each document of interest, a set of related senses are defined as described in 3.1

4.1. Ontological User Profile

Our ontological user profile is constructed by matching user interests to the predefined ontology, (Open Directory Project). ODP, also known as dmoz, is an open content directory of the World Wide Web pages that is created and maintained by a community of volunteer editors. ODP uses a hierarchical ontology schema to organize web pages of similar topic into categories which can then include smaller categories, called concepts. Each concept in the user profile is associated with an interest score which has an initial value of one. The interest scores are updated as the user interacts with our system. To implement the personalized ontology, we first imported the structure of topics from the open directory project directly into Microsoft SQL Server Database [16] where each topic is defined by title and description. Next we applied the data preprocessing module, discussed below, so that words extracted from title and description of each topic and its subtopics are then matched to a set of related senses to such topic. Figure 2 shows an instance of our ontological user Profile where each node represents a topic associated with an interest score and set of related senses in the form *word#pos#sense* (i.e. car#n#1 refers to the third WordNet noun sense of *car*

4.2. Similarity-based Classification

Each webpage in which the user has shown interest is classified into a set of topics from the user profile.

For this task we used a combination of two similarity measures which come from different points of view.

The first measure is the semantic similarity between two sets of words that is based on the likeness of their meaning / semantic content. This could be visualized by grouping closer related words together and spacing more distantly related ones.

To calculate the semantic similarity Ssim (s1, s2) between two senses s1 and s2, we measure the distance between them in WordNet [13] as presented by Leacock-Chodorow [11]. This can be done by finding the shortest path from s1 to s2 using the formula below,

$$\text{Ssim}_{\text{LCH}}(s1, s2) = -\log \frac{length(s1, s2)}{2D} \qquad (1)$$

Where length (s1, s2) is the number of nodes along the shortest path from (s1) to (s2) and D is the maximum depth (from the lowest node to the top) in the taxonomy in which s1 and s2 occur. The Leacock-Chodorow measure assumes a virtual top node controlling all nodes, resulting in two taxonomies; one for all verbs and another for all nouns. As long as the two senses compared can be found in WordNet, this measure will always return a value greater than zero; since there always will be a path between them. We then calculate the overall semantic similarity Ssim (D, T) between document D and category (or topic) T as follows,

Ssim (D, T) =

$$\frac{1}{|t(D)||t(T)|} \sum_{\forall d \in t(D), \forall t \in t(T)} ssim(d, t) \qquad (2)$$

Where |t (D)| and |t (T)| denote the number of terms in document D and topic T.

The second measure is the cosine similarity where documents and topics are represented as frequency vectors and the similarity is measured by the cosine of the angle between these vectors on the (0, 1) scale, the higher the cosine of the angle between two vectors the more similar the documents represented by the vectors. The cosine similarity [20] of two vectors *t* and *d* is defined as follows: $\cos(\vec{t}, \vec{d}) =$

$$\frac{\vec{t} \bullet \vec{d}}{|\vec{t}||\vec{d}|} = \frac{\vec{t}}{|\vec{t}|} \bullet \frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} t_i d_i}{\sqrt{\sum_{i=1}^{|V|} t_i^2} \sqrt{\sum_{i=1}^{|V|} t_i^2}} \qquad (3)$$

where t_i, d_i denote the weight of word *i* associated to topic t and weight of term *i* in the document d respectively and can be calculated as:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \qquad (4)$$

where $n_{i,j}$ denotes the number of occurrences of the considered term (t_i) in document dj and $\sum_k n_{j,k}$ denotes total occurrences of all terms in document dj.

The final similarity score between a topic t and a document d is defined with a coefficient α added for accuracy improvement as follows:

Sim_Final (t, d) =

α * Semantic_Similarity (t, d) +

(1- α) * Cosine_Similarity (t, d) (5)

Table 1 shows an example of the Leacock-Chodorow Similarity matrix between *two set of senses* for terms extracted from the web page 'http://www.csa.com/' and the Topic 'Top/Science/Publications' with a total semantic similarity score between the two sets equals 2.98. While the cosine similarity between term vectors of such page and topic equals 0.825

Table 1: Web Page-Topic Semantic Similarity Matrix

terms extracted from Topic Top/Science/Publications	terms extracted from webpage http://www.csa.com							
		print	research	science	list	database	journal	subject
	science	1.39	1.39	**3.47**	1.39	1.27	1.27	2.77
	publication	2.08	1.16	1.52	1.67	1.86	2.37	2.08
	print	**3.47**	1.07	1.39	1.52	1.67	2.08	1.86
	journal	2.08	0.98	1.27	1.39	1.52	**3.47**	1.67
	audience	1.52	1.07	1.39	1.52	1.39	1.39	1.52
	magazine	1.67	0.69	0.9	0.98	0.9	2.08	1.27
	book	1.86	1.07	1.39	1.86	2.08	2.77	1.86
	list	1.52	1.07	1.39	**3.47**	2.77	1.39	1.86
	subject	1.86	1.39	2.77	1.86	2.08	1.67	**3.47**

4.3. Profile Adaptation

As the user's interests and preferences change over time, then we must maintain and update the user profile to represent user's real interests. After a user's web search, *all topics* in the ontological user profile are updated based on their relevance to user's pages of interest as follows:

Score_update (C_j) =

IS (C_j) + IS (C_j) * sim (D_i, C_j) (6)

where Ssim (D_i, C_j) is the semantic similarity between the topic and the page of interest as calculated in 4.1and IS (C_j) is the existent interest score for the topic C_j stored in the personalized ontology. The interest scores for all topics can be considered as a vector which is normalized to a predefined constant, L *as the vector length*. Normalization prevents the interest scores from constantly escalating, as the user expresses interests in some topics, the score for other topics have to decrease. The topics in the ontological user profile are updated with the normalized scores as follows:
New_Score (C_j) =

Score_Update (C_j) * L / n (7)

where n is the square root of sum of squared interest scores of all topics. Figure 3 shows an example of the Profile Adaptation. Suppose that a number of web results of interest are related to the topics *Books* and *Science*. Then a new higher score is assigned for the topics *Shopping; Publications; Books* and *Science*, *i.e.*, for the concepts where the user has shown interest and for those belonging to the same direct path of the hierarchy; a new lower score is allocated to the other sub-concepts, *i.e.*, *Magazines*,

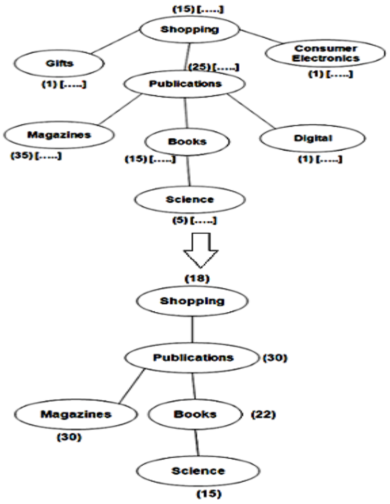

Figure 2 part of an ontological user profile with the topics' Interest scores updated after a user's search.

5. Search Personalization

In this section, we describe the personalized re-ranking strategy of search results based on our ontological user profile. When user issues a new query, it is passed to a search engine and a list of search results is returned. Both the query and the list of the search results are converted to sets of related senses as discussed in 3.2. We then classified these search results into their corresponding topics from the user profile. Next, the scores of the relevance of each result and the importance of such result's topic to the query are calculated respectively. Finally we incorporate both scores together with the topics' interest scores in document re-ranking.

5.1. User's Current Search Interests Identification

The user's short-term information needs are determined by a search query. Each search result for a given query is represented with a set of related senses and is then classified into the best matching topic using Eq. (2). Next, we identify the user's current query context using the similarity measure defined by Eq. (2) in:

(i) Finding the relevance of each search result to current query.
(ii) Finding the importance of such result's topic for current query.

5.2. Document Re-rank

For a given query, search results are re-ranked in order to bring those results that are most similar to the user preferences to the top of the results page. We calculate the Result's score S (R_i) by multiplying the interest score of the result's topic, I (T_i), the similarity of this result to the query, Sim (q_i, R_i), and the similarity of this result's topic to the query, Sim (q_i, Ti), as follows,

$$S(R_i) = I(T_i) * Sim(q_i, R_i) * Sim(q_i, Ti) \qquad (8)$$

Once all documents have been covered, the search results are sorted in descending order with respect to their new rank scores.

6. Experimental Evaluation

In this section, we discuss the experiments we have performed to evaluate our proposed method for web search personalization. We used WordNet.Net library [18] and WordNet 2.1 [19] to retrieve the senses of words in WordNet. In order to evaluate the effectiveness of our proposed approach, 6 volunteers were invited to install our personalized plug-in which recorded the queries our participants issued to Google. A period of one month of browsing history has been logged and stored for each. In this paper, we used the top four levels ODP hierarchy to conduct experiments. We examined users' browsing history and accordingly built our ontological users profiles discussed in 4.

6.1. Accuracy of Topic preference identification

In this section, we evaluate the efficiency of our similarity based classification method of search results. During the logging period of browsing history, each participant is asked to specify the top 3 topics of interest (T_{real}) for each query. Then we compute the overlap between such them and the top 3 topics (T_{sim}) which received highest number of clicks for *a given query* as follows:

$$Sim(T_{real}, T_{sim}) = \frac{|T_{real} \cap T_{sim}|}{n} \qquad (9)$$

where n is the total number of topics considered for a given query (=3 in our experiment).

The results are shown in Table 2, where we report the fraction of queries for which our method managed to correctly identify real topics of interest. Our model has a promising potential in identifying suitable results topics for most queries which in turn results in effective re ranking of search results.

Table 2: Distribution of participants' queries from browsing history across different values for overlapping between real topics of interests and topics defined by our method

Sim(T_{real}, T_{sim})	**Fraction of queries (%)**
1	9
2/3	68.4
1/3	17.6
0	5

6.2. Quality of Personalized Search

Effectiveness of a personalized system is determined by the user satisfaction. An efficient rank mechanism should place relevant pages close to the top of the rank list. In this experiment, each participant is presented with 12 queries and is asked to select the pages they consider relevant from the top 50 results returned from Google. Results were placed in random order to avoid result's position bias. Participants were asked to evaluate 5 of multi-intended queries presented in Table 3. These queries were used to assess the quality of personalized re-ranking of results. Next, each participant were asked to repeat 5 queries they issued in the logging period which they remembered the returned results could have been better. These queries were used to assess the efficiency of our personalization approach in case of re-finding known. The quality of our system is measured as:

$$\text{AvgRank}_s = \frac{1}{|p_s|}\sum_{p\in P_s} R(p) \qquad (10)$$

Here P_s denotes the set of clicked web pages on test query s, R (p) denotes the rank of page p. The final average rank on test query set S is computed as:

$$\text{AvgRank} = \frac{1}{|S|}\sum_{s\in S} AvgRank_s \qquad (11)$$

Smaller average rank value indicates better placements of relevant result, or better result quality. In Figure 3, demonstrate the overall effectiveness of our personalized ranking scheme for each of our study participants. We can see that our personalized method outperforms *non personalized search* in all cases.

Table 3: Multi intended test queries

Q1	AJAX	- Ajax web based development - the Dutch football team Ajax Amsterdam - Ajax cleaning product
Q2	Opera	- a form of musical and dramatic work - a very common used web browser
Q3	Eagle	- Kind of Birds - the American musical group - the British comic book - Electronic design automation software
Q4	Apple Company	- company that develops and sells computers products - Mountain Apple Company related to music - "Little Apple Brewing Company" related to entertainment
Q5	Sphinx	- Great Sphinx of Giza - Open Source Search Server - Sphinx speech recognition toolkit

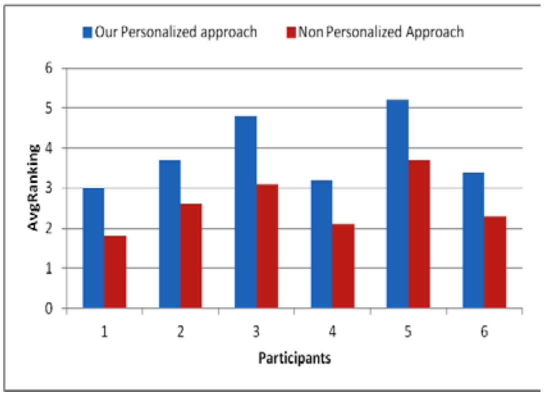

Figure 3 Average rankings of the examined pages by participant. Lower values indicate improved

The distribution of the relevance judgments for the non Personalized Google rank and our re-ranking approach shown in Figure 4 denotes that the default web rank is already able to place the largest portion of the Very Relevant results in the top 5 results. Our personalized search manages to add more Very Relevant results along the top rankings. The Relevant results are equally distributed across all ranks with few more relevant results added to the top rankings. Irrelevant results exist at all ranks, but become more prevalent after rank 12. Our Personalized search succeeds.

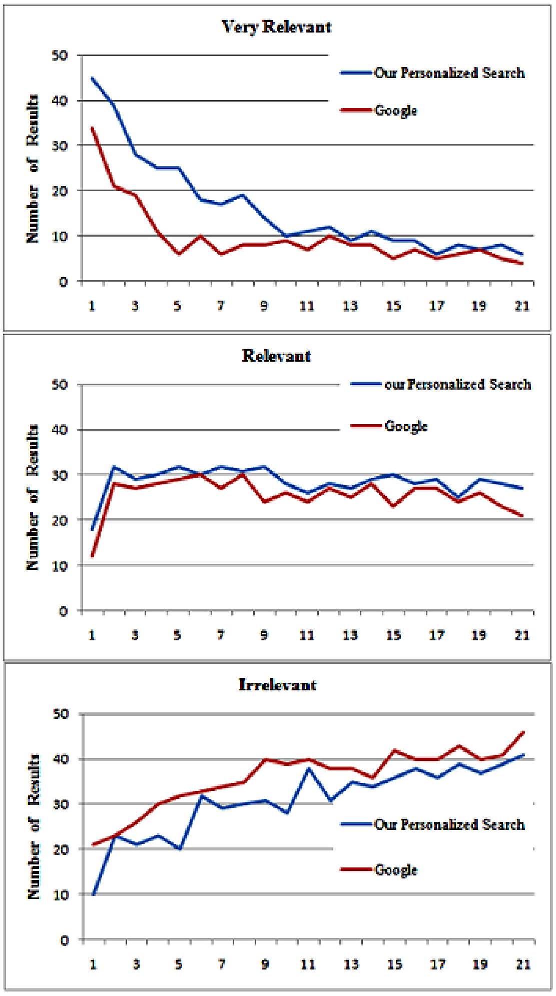

Figure 4 Distribution of Relevance for our approach and Google

6. Conclusion

In this paper we introduced how to capture user context in an ontological user profile from click-history data and incorporate this profile in the re-rank process of the search results, thus creating personalized views of the web. First, we designed an ontological user profile with reference to a pre-existing topic hierarchy of ODP .Topics in the profile are annotated with an interest score together with its description extracted from the ODP structure. Then, we adapted the user profile to the accumulation and degradation changes of user preferences by updating topics interest scores after each user search. Finally, we semantically identify user current query context to re-rank search results.

We measured the degree of relevance of each result and its topic against the query using a combination of semantic similarity and cosine similarity measures. Search results are re-ranked based on the interest scores of their topics together with their relevance scores against the query. Experimental results demonstrate that our personalized approach performs effectively in satisfying user needs even with the existence of ambiguous queries.

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Naglaa Fathy is a Teacher Assistant, Faculty of computer and information sciences, Ain shams university, Egypt. She received the B.S. degrees in Computer Science in 2006.

Dr.Nagwa Badr is an associate Professor, Faculty of computer and information science, Ain shams University, Egypt. She received the B.S. degrees in Computer Science in 1996, and PhD 2000-2003, in Software engineering and distributed system, Liverpool John moorse university, U.K. Postdoctoral in Glasgow University, U.K 2003-2006.

Prof.Mohamed Hashem is the vice dean for students affairs, Faculty of Computer and Information Sciences, Ain Shams University, Egypt. His research interests are computer networks, Ad-hoc and wireless networks, Qos Routing of wired and wireless networks, Modeling and simulation of computer networks, VANET and computer and network security.

Prof.Tarek Fouad Gharib is a Professor of Information Systems at Department of Information Systems, Ain Shams University, Cairo, Egypt. He received his Ph.D. degree in Theoretical Physics from the University of Ain Shams in 1994. His research interests include data mining techniques, bioinformatics, graph and sequential data mining and information retrieval. He received the National Science Foundation Award in 2001. Prof Gharib currently is in sabbatical at Faculty of Computing and Information Technology, King Abdul-Aziz University, Kingdom of Saudi Arabia.