Efficient Internet Search Engine Service Provisioning exploiting a Collaborative Web Result Ranking Mechanism

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***Abstract*— In the context of this paper, a meta-search third-party web result ranking mechanism is proposed, which is capable of adapting over the continuous changes that occur on the web, providing in parallel personalized information acquisition considering the user's navigation behaviour. The designed meta search engine service rates, re-organises and combines the results acquired from search services for a specific user information resource request in accordance with a weighted combination of a performance related factor (tightly related to the ranking of the web result as given by the search engine service) and a reliability related factor (corresponding to the user's satisfaction stemming from the specific web result that he/she browses), while the performance of each search engine with respect to adequately adapting to the web evolution is taken into account. Assuming a group of users falling within the same category with respect to the information/resource needs, the web result reliability rating system is collaborative in the sense that it considers both first-hand information (acquired from the user's past experiences with the search engine services) and second-hand information (corresponding to other users' experiences with search engine services), while the matching degrees of the users' profiles have been taken into account. A set of results indicative of the efficiency of our proposed scheme is provided. Transparency is achieved for both personalization and web evolution adaptation mechanisms, requiring virtually none effort from the user's part.**

***Index Terms*— Meta Search Engine Service, collaborative mechanisms, performance and reliability related factors.**

I. INTRODUCTION

The vast increase of web resources has boosted the demand for effective personalized information resources search and acquisition. In this perspective, web search engine services have a vital role, since they form an information broker between the user and the huge amounts of disseminated information. Considering the fact that (in most cases) it is difficult for the users to adequately and/or accurately describe their requirements and constraints with keywords, the search services return a vast amount of results, presenting lower precision in the first recall levels (top-ranked results). Thus, the construction of user profiles for personalized information search is necessitated.

The subject of this study falls into the overall web search service provisioning procedure, trying to extend pertinent previous work in the literature in the context of personalized search techniques based on user profiling [1], [2]. Specifically, the aim of this paper is, in accordance with efficient Internet search service operation objectives, to propose enhancements to the sophistication of the functionality offered by search engine services. A *meta-search third-party web result ranking mechanism* is proposed, which is capable of adapting over the continuous changes that occur on the web, providing in parallel personalized information with respect to the user's navigation behaviour. Transparency is achieved for both personalization and web evolution adaptation mechanisms, requiring virtually none effort from the user's part. In essence, the proposed meta search engine rates, re-organizes and combines the results acquired from search services for a specific user request in accordance with a weighted combination of a *performance related factor* (tightly related to the ranking of the web result as given by the search engine part) and a *reliability related factor* (corresponding to the user satisfaction stemming from the investigated web result). The reliability criterion is motivated by the fact that there may be different levels of user satisfaction with respect to the disseminated content of each web result. In this respect, there may be web results that, in principle, do not meet user requirements and preferences. Hence, recording the previous experience can easily assist the meta-search engine service in deciding how to present to the user the results obtained from the search services.

For the evaluation of the web results reliability, a *collaborative reputation mechanism* is utilized, which helps estimating their quality and predicting their future usability, taking into account their past performance in consistently satisfying user expectations. Specifically, assuming a group of users falling within the same category with respect to the information/resource needs, the web result reliability rating

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system considers both *first-hand information* (acquired from the user's past experiences with the search engine services) and *second-hand information* (corresponding to other users' experiences with search engine services), while in parallel the matching degrees of the users' profiles are taken into account.

The rest of the paper is organized as follows. Section II presents the fundamental concepts of our proposed third-party results ranking mechanism, aiming to offer an efficient way of personalized information resource search and acquisition. Section III provides the formal description and mathematical formulation of the designed third-party web results reliability rating system. In Section IV the overall ranking mechanism is mathematically formulated. Section V provides a set of results indicative of the performance of our proposed scheme. Finally, in Section VI conclusions are drawn and future plans are given.

II. Fundamental Ranking Mechanism Elements

Assuming the presence of a user group G consisting of K users belonging to the same category with respect to their information needs, M Search Engine Services (*SESs*) each providing N web results (*WRs*) to the Meta Search Engine Service (*MSES*) with respect to a specific user u_k information resource request, MSES can combine and present to the user u_k the web results acquired in re-organized manner on a basis of a third-party result ranking mechanism. The proposed mechanism rates the WRs in accordance to a weighted combination of the evaluation of the quality of each SES returned WR, and an estimation, which takes into account whether the information needs of the user u_k concerning the specific WR raised in the past have been met. In our approach, the first factor constitutes the performance related factor, while the second factor contributing to the overall WR ranking is referred to hereafter as the reliability related factor. The performance factor is introduced in order to take into account in our model the expected quality of each WR as given by each SES. To this end, the WRs ranking returned by each SES is considered. Taking into account the fact that the precision over the first recall level (top-ranked results) as given by each SES may be low, the reliability factor is considered in order to reflect whether WRs finally provide to the user u_k the information resource that corresponds to his/her personalized requirements, preferences and constraints. Reliability of a WR is reduced whenever the specific WR does not match the user's expectations.

For the evaluation of the WRs reliability, a collaborative WR reputation mechanism is used, which helps estimating WRs quality and predicting the future (expected) usability, taking into account their past performance in consistently satisfying user expectations. In research literature, reputation mechanisms are employed to provide a "soft" security layer (considered to be sufficient for many applications [3]) by establishing trust relationships among system participants and/or resources [4], [5], [6], [7], [8], [9], [10], [11]]. Feedback received from participants related to an entity's past behaviour may be formulated as a reputation measure exploiting learning from experience concepts [12], [13], [14], [15]. The reputation related information obtained may be used by the parties in order to adjust their decisions and behaviour. In general, a reputation system is considered to sustain rational cooperation and serve as an incentive for good behaviour because good players are rewarded by the society, whereas bad players are penalized [3]. In this study, a reputation mechanism is exploited in order to collectively determine if a specific WR corresponds to user requirements and preferences with respect to a specific information resource search request. The reliability criterion is motivated by the fact that there may be different levels of user satisfaction with respect to the various WRs. In this respect, there may be WRs that, in principle, do not meet user requirements and preferences. Hence, recording the previous experience can easily assist the MSES in deciding how to present to the user the results obtained from the SESs. In our approach it has been assumed that past search behaviour is an indicator of the user's future behaviour, as a basis for user modeling.

For the formation of the WRs reliability ratings (and overall ratings) a centralized approach has been adopted (i.e., the MSES maintains and updates a collective record of the SES WRs reputation ratings, after taking into account each group user's view on the WRs quality). User's experience on the WRs quality is formed taking into account two factors. First, the time spent for his/her exploration as well as the 'depth' of the search. Time is considered as an important factor in determining user satisfaction upon a specific WR, since the more time the user spends exploring a specific result, the more this result is possible to be relevant and vice versa. As depth we have considered the number of hyperlinks used from the initiation of the search with starting point the SES WR result, until the session is closed. Every time the user browses a URL from the provided SES WRs, upon the end of the session, a reward function is calculated based on the aforementioned features, which is exploited in order to respectively update the WRs reliability value.

The proposed scheme is collaborative in the sense that it considers information acquired from various users in order to determine the reliability rating of each WR, enabling thus WRs reliability rating formation in a time efficient manner. At this point it should be noted that in the context of this study all users u_k ($k = 1,...K$) belonging to the same group G posing a specific search request for information resources differ with respect to their information needs. Specifically, different matching degrees with respect to their profiles have been considered. Additionally, the reliability value of each WR is formed irrespective of the SES that provided it. WRs reliability related information is acquired from each user session in a fully transparent way, without any interference in the user's browsing behaviour. Specifically, the user's personalized interaction patterns are monitored within the context of his/her sessions with a SES, while MSES results are presented to the user in the form of a text paragraph regarding the URL (as most web search engines do) without labeling their source, ensuring this way that the user is completely unbiased to a preference that may has in a particular SES.

The highly dynamic nature of the web necessitates effective information management. Thus, SESs should adequately adapt to the web evolution by indexing new information as quickly as possible and constantly checking the validity of their results (information resources do not live for ever or they are moved to another location or they are renamed). In general, SESs may demonstrate a different performance level with respect to the aforementioned issues. For example, results that no longer exist may be provided (dead links, errors 404), active but temporarily unavailable results may be given (web server internal errors, bad gateway, service/host unavailability), while new or updated information may be incorporated at a different pace by various SESs. This fact is taken into account in order to reward efficient SESs and penalize those that fail to perform effective information management. To this respect, a SESs Web Evolution Rating Mechanism [16] is utilized in order to assign a ranking value to each SES, reflecting its ability to follow the dynamic nature of the web.

A learning period is required in order for the MSES to obtain fundamental information for the WRs. In case where reliability specific information is not available to the MSES, the reliability related factor is not considered for the WRs re-organisation. It should be noted that the reputation mechanism comes at the cost of keeping reputation related information at the MSES and updating it after each user session has taken place.

III. Formulation of the Web Result Reliability Rating System

Let us assume the presence of K users belonging to the same group G and M SESs each providing N WRs to the MSES with respect to a specific user $u_k \in G$ information resource request. MSES will estimate the reliability of the WRs and rate the WRs accordingly, on the basis of two factors: the direct past of experiences of user u_k with SESs and other users $u_l \in G$ ($l \in \{1,...K\}$, $l \neq k$) experiences in the past with SESs.

A. Estimating WRs reliability rating based on user's direct experiences

Concerning the formation of the web result WR_i reliability rating $RR_{post}^{u_k}(WR_i)$, the MSES may rate WR_i after a user session d has taken place at time t_d in accordance with the following equation:

$$RR_{post}^{u_k,t_d}(WR_i) = RR_{pre}^{u_k}(WR_i) + k_r \cdot l(RR_{pre}^{u_k}(WR_i)) \cdot \{rr(WR_i) - E[rr(WR_i)]\} \quad (1),$$

where $RR_{post}^{u_k}(WR_i)$ and $RR_{pre}^{u_k}(WR_i)$ are the web result WR_i reliability based rating after and before the updating procedure. It has been assumed that $RR_{post}^{u_k}(WR_i)$ and $RR_{pre}^{u_k}(WR_i)$ lie within the $[0,1]$ range, where a value close to *0* indicates a web result that does not satisfy the user. The (reward) function $rr(WR_i)$ reflects the level of user satisfaction at the current session and $E[rr(WR_i)]$ is the mean (expected) value of the $rr(WR_i)$ variable. In general, the larger the $rr(WR_i)$ value, the more satisfied is the user with the web result WR_i, and therefore the more positive the influence on the rating of the WR_i. Factor k_r ($k_r \in (0,1]$) determines the relative significance of the new outcome with respect to the old one. In essence, this value determines the memory of the system. Small k_r values mean that the memory of the system is large. However, greater usability will gradually improve the web results WR_i reliability ratings. $l(RR_{pre}^{u_k}(WR_i))$ is a function of the WR_i reputation rating $RR_{pre}^{u_k}(WR_i)$ and is introduced in order to keep the WR_i rating within the range $[0,1]$. In the current version of this study, $l(RR_{pre}^{u_k}(WR_i)) = \frac{1}{1-e} \cdot [1 - \exp(1 - RR_{pre}^{u_k}(WR_i)]$, for which it stands $\underset{RR_{pre(WR_i)}^{u_k} \to 0}{l(RR_{pre}^{u_k}(WR_i)) \to 1}$ and $\underset{RR_{pre(WR_i)}^{u_k} \to 1}{l(RR_{pre}^{u_k}(WR_i)) \to 0}$.

It should be noted that web results deterioration of its previous quality leads to a decreased post rating value, since the $\{rr(WR_i) - E[rr(WR_i)]\}$ quantity is negative. The $rr(WR_i)$ function may be implemented in several ways. In the context of this study, it was assumed without loss of generality that the $rr(WR_i)$ values vary from 0.1 to 1, while it is calculated on the basis of two factors: time spent exploring a specific web result WR_i and the respective depth of the search.

Specifically, the personalization algorithm considered for the calculation of $rr(WR_i)$ is a client-side agent that weights the relevancy of the provided web results, based on the users' web search interactions.. We have assumed that past search behaviour is an indicator of the user's future behaviour. The construction of the personalized browsing behaviour is performed in a totally transparent way, while the merged WRs are presented without labelling their source. Personalization patterns are recorded and updated continuously according to the WRs visited by the user, the time spent for their exploration as well as the depth link of the investigated results. Thus, the user's profile is also adjusted to any possible changes in respect to his/her navigation patterns. More information regarding the way we measure the similarity of a WR in respect to the user's behaviour, can be found in [16].

B. Estimating WRs overall reliability rating

The web result reliability rating $RR^{u_k}(WR_i)$ may be estimated by the MSES for user u_k at time t_c an information resource has been requested in accordance with the following formula:

$$RR^{u_k,t_c}(WR_i) = w_{u_k} \cdot RR^{u_k,t_c}(WR_i) + \sum_{\substack{l=1 \\ (l \neq k)}}^{K} w_{u_l}(WR_i) \cdot RR^{u_l,t_c}(WR_i) \quad (2),$$

where $RR^{u_x,t_c}(WR_i)$ denotes the reliability rating of the target web result WR_i as formed by user u_x on the basis of its direct experiences with WR_i in the past and is a function of $RR_{post}^{u_x,t_d}(WR_i)$ given by (1), where t_d denotes the time instance at which WR_i was last time accessed by user u_x and the respective reliability value was accordingly updated. As may observed from (3), the reliability rating of the target WR_i is a weighted combination of two factors. The first factor contributing to the reliability rating value is based on the direct experiences of the requestor user u_k, whereas the second factor depends on user $u_l \in G$ ($l \neq k$) opinion regarding WR_i usability.

Concerning the calculation of $RR^{u_l,t_c}(WR_i)$ ($l = 1,...K$), a wide range of functions may be defined. We restrict our attention to the polynomial family of functions. Other functions could be defined as well. A formal model of the polynomial related family of functions concerning the $RR^{u_l,t_c}(WR_i)$ reliability rating, is provided according to the following expression:

$$RR^{u_l,t_c}(WR_i) = [1 - (\frac{t_c - t_d}{t_c})^{1/\vartheta}] \cdot RR_{post}^{u_l,t_d}(WR_i) \quad (3),$$

As may observed from (3), it stands $\underset{t_c \to t_d}{RR^{t_c}(WR_i) \to RR_{post}^{t_d}(WR_i)}$ and $\underset{t_c >> t_d}{RR^{t_c}(WR_i) \to 0}$. Specifically, the bigger the quantity $t_c - t_d$ is, the lower is the reliability value considered for the WR_i. Thus, (3) models the fact that more recent user interactions with a specific WR should weigh more in the overall WR ranking evaluation. As it may be observed, these families of functions represent an infinite number of different members, one for each value of ϑ. Parameter ϑ has been included in order to highlight the different patterns with respect to the adopted rate of decrease.

Weight $w_{u_x}(WR_i)$ provide the relative significance of the reliability rating of the web result WR_i as formed by the user u_x (i.e., $RR^{u_x}(WR_i)$) to the overall WR reliability rating estimation by the evaluator MSES for user u_k. In general, $w_{R_x}(WR_i)$ is a measure of the credibility of user's u_x opinion and may be a function of the matching degree of users u_k and u_x profiles (i.e., preferences & requirements with respect to information resource requested), the number of sessions user u_x has begun with web result WR_i, the total number of sessions user u_x has been involved to considering all WRs and the number of times WR_i has been accessed considering all K users using the MSES till time instance t_c, whenupon user u_k information resource request has originated.

Thus, weight $w_{u_x}(WR_i)$ is given by the following equation:

$$w_{u_x}(WR_i) = PMD^{u_k}(u_x) \cdot \frac{NS^{u_x}(WR_i)}{\sum_{i=1}^{N} NS^{u_x}(WR_i)} \cdot \frac{NS^{u_x}(WR_i)}{K \cdot \sum_{l=1}^{K} NS^{u_l}(WR_i)} \quad (4),$$

Where $PMD^{u_k}(u_x)$ denotes the profile matching degree of users u_k and u_x (it stands $PMD^{u_k}(u_x) \in [0,1]$ with $PMD^{u_k}(u_k) = 1$), $NS^{u_x}(WR_i)$ is the number of sessions user u_x has begun with web result WR_i, $\sum_{i=1}^{N} NS^{u_x}(WR_i)$ is the number of sessions user u_x has been involved to considering all WRs returned by the MSES, and $\sum_{l=1}^{K} NS^{u_l}(WR_i)$ is the total number of times WR_i has been accessed, considering all K user sessions till time instance t_c, whenupon user u_k information resource request has originated.

IV. Web Results Ranking Mechanism Formulation

The target web result provided by search engine service SE_j ($j = 1,...,M$) is rated by the evaluator MSES at time t_c that a user u_k request has to be served in accordance with the following formula:

$$WPR_{SE_j}^{u_k,t_c}(WR_i) = WEAS_{SE_j}^{t_c} \cdot \{w_p \cdot PR_{SE_j}^{t_c}(WR_i) + w_r \cdot RR^{u_k,t_c}(WR_i)\} \quad (5),$$

where $WPR_{SE_j}^{u_k,t_c}(WR_i)$ denotes the overall rating of the web result WR_i provided by SES SE_j at time instance t_c for user u_k. As may observed from (5), the rating of the target WR_i is a weighted combination of two factors. The first factor contributing to the overall WR_i rating value (i.e., $PR_{SE_j}^{t_c}(WR_i)$) is based on the performance of the WR_i as given by SES SE_j and forms the performance related factor.

In a similar manner to the WRs reliability rating value, it has been assumed that $PR_{SE_j}^{t_c}(WR_i)$ lie within the $[0,1]$ range, where a value close to *0* indicates that the performance of the web result as given by the SES is low. In the context of this study, $PR_{SE_j}^{t_c}(WR_i)$ is given by the following expression:

$$PR_{SE_j}^{t_c}(WR_i) = 1 - \frac{k}{N} \quad (6),$$

where k is the rank level of WR_i as returned to the MSES by SES SE_j at time instance t_c and N is the number of WRs provided by SE_j.

The second factor (i.e., $RR^{u_k,t_c}(WR_i)$) depends on user satisfaction stemming from WR_i, collectively formed considering all user service search requests in the past. In essence, this factor constitutes the reliability related factor given by (2).

Weight $WEAS_{SE_j}$ is the SES web evolution rating value and is introduced in order to reward SES that perform efficient information management, while penalizing those that fail to follow the web evolution dynamics [16]. Finally, weights w_p and w_r provide the relative value of the anticipated WR performance as given by each SES and the reliability related part. It is assumed that weights w_p and w_r are normalized to add up to 1 (i.e., $w_p + w_r = 1$). It should be noted that in certain variants of the problem one of the two factors may be ignored.

Taking into account the fact that a specific WR may be returned from various SESs, for the WR reliability evaluation we considered the WR of the SES yielding the higher weight $WEAS_{SE_j}$.

V. Performance Evaluation

In order to evaluate our web results ranking mechanism formulation, we created a virtual population of four users ($K = 4$).

In parallel, for each of the four users we submitted 100 different randomly generated four-term queries in Google, MSN and Yahoo! per week for three months. The queries were generated by using the Mangle Random Link Generator [17], which is an API that creates randomly a set of words, from one up to five terms simultaneously, in several languages. In our case the randomly generated queries were in English, since according to the creators of this application, Mangle Random Link Generator, works best in English in case you want to create randomly a test set that consists of more than two terms.

For each submitted query per user, we took under consideration the top-twenty results per SES, and we randomly labeled some of those as relevant by simulating this selection as a toss of a virtual coin, which for each examined result has a probability value equal to *0.4* of showing heads. In other words, if it showed heads the corresponding result was considered as relevant, meaning that we expected to have nearly eight relevant results per query. The total labeled results during this procedure produced the initial generated population.

We then resubmitted the same 100 queries per user in Google, MSN and Yahoo! twice, but this time we randomly excluded one and two terms (three-term and two-term queries respectively). Similar to the previous case, for each submitted query we took under consideration the top-20 results, and we randomly labeled some examined result as relevant. However, if a result, which was labeled as relevant during the initial generated population, appeared again in the tested population was labeled as relevant with a probability value equal to one. In all other cases, results were considered as relevant according to a lower probability value equal to *0.3* and *0.2* for the three-term and two-term queries, respectively.

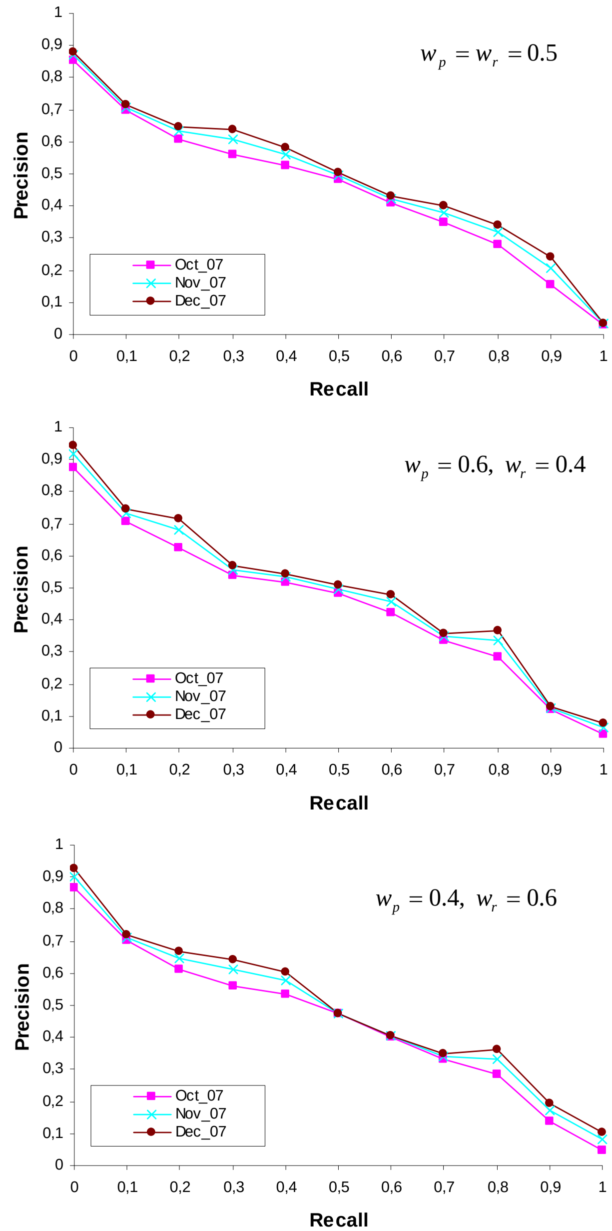

Fig. 1. Averaged Precision-Recall (PR) diagrams for one of the four users and for several values of w_p, w_r

By this mechanism we managed to find correlations between the web result reliability rating $RR^{u_k}(WR_i)$ for user

u_k according to (2) as well as the overall rating of the web result WR_i $WPR_{SE_j}^{u_k,t_c}(WR_i)$, provided by Google, MSN and Yahoo! at time instance t_c for user u_k. Finally, as far as the web evolution rating value $WEAS_{SE_j}$ is concerned, we used the experimental values as derived from the work described in [16]. The final assessment was made with Precision-Recall (PR) diagrams, having averaged the respective PR values in a monthly basis from October to December of 2007. We observed that the precision over different recall levels for the top-twenty merged returned results was increased for all four users. Figures 1a up to 1c illustrate the positive influence of the proposed web results ranking mechanism formulation for different values of w_p and w_r in the averaged PR values of one of the simulated users, when $w_p = w_r = 0.5$, $w_p = 0.6, w_r = 0.5$ and $w_p = 0.4, w_r = 0.6$, respectively.

VI. Conclusions

In accordance with efficient web search service operation objectives, the aim of this paper is to propose enhancements to the sophistication of the functionality that can be offered by search engine services. Specifically, a meta-search third-party web result ranking mechanism is proposed, which enables for personalized information acquisition, taking into account the user's preferences, requirements and constraints, implicitly, by monitoring his/her navigation behaviour. The proposed mechanism is capable of adapting over the continuous changes that occur on the web, rewarding search engines performing effective information management, while penalizing those that fail to follow the dynamic nature of the web. Transparency is achieved for both personalization and web evolution adaptation mechanisms, requiring virtually none effort from the user's part. In essence, the proposed meta search engine rates, re-organises and combines the results acquired from search services for a specific user information resource request in accordance with a weighted combination of a performance related factor and a reliability related factor (corresponding to the user satisfaction stemming from the specific web result that he/she browses), while the performance of each search engine with respect to adequately adapting to the web evolution is taken into account.

Assuming a group of users falling within the same category with respect to the information/resource needs, the web result reliability rating system is collaborative in the sense that it considers both first-hand information (acquired from the user's past experiences with the search engine services) and second-hand information (corresponding to other users' experiences with search engine services), while the matching degrees of the users' profiles have been taken into account. Experimental results have been obtained over a nearly three month period (October to December of 2007) by creating a virtual population of queries and relevant results. It was observed that the precision over several recall levels was increased, for all time intervals for the tested period and for all virtual users. Directions for future work include, the realization of further wide scale experiments considering user groups with different information needs, so as to evaluate the applicability and the response of the framework presented herewith.

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