EXPLORING MULTI-FACTOR TAGGING ACTIVITY FOR PERSONALIZED SEARCH

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Abstract: Coping with ambiguous queries has long been an important part in the research of Web Information Systems and Retrieval, but still remains to be a challenging task. Personalized search has recently got significant attention to address this challenge in the web search community, based on the premise that a user's general preference may help the search engine disambiguate the true intention of a query. However, studies have shown that users are reluctant to provide any explicit input on their personal preference. In this paper, we study how a search engine can learn a user's preference automatically based on a user's tagging activity and how it can use the user preference to personalize search results. Our experiments show that users' preferences can be learned from a multi-factor tagging data and personalized search based on user preference yields significant precision improvements over the existing ranking mechanisms in the literature.

1 INTRODUCTION

Users often have different intentions when using search engines (Xu et al., 2008). According to (Qiu and Cho, 2006), queries provided by users to search engines are under-specified and, thus, poorly translate fully the meaning users have in mind. As a consequence, according to (Jäschke et al., 2007), only 20% to 45% of the results match a user's intentions. One approach to increase user satisfaction is to personalize search results.

Recently, strategies intended to disambiguate the true intention of a query began to collect and analyze user preferences in order to personalize the search retrievals. The user preferences have been modeled in many ways in the literature (Biancalana, 2009; Xu et al., 2008; Qiu and Cho, 2006), including analysis of explicit data such as user profile and preference models, or the implicit collection of data such as user click history, visited pages log, or tagging activity. All of these are indicators of user preferences utilized by search engines to decide which items in the collection of search results are more or less relevant for a particular individual.

In this work, we analyze user's tagging activity to learn the user preferences and personalize the search results. For this purpose, we consider tags because they represent some sort of affinity between user and resource. By tagging, users label resources freely and subjectively, based on their sense of value. Tags, therefore, become a potential source for learning user's interests (Durao and Dolog, 2009).

In our approach, we build our user model incorporating various tag indicators of user's preference, i.e., each indicator relates to a factor for personalizing searches. We therefore formalize the term *factor* as an indicator of user's preference denoted by a particular set o tags. For instance, a factor Z may represent the set of tags assigned to the most visited pages of a user and a factor Y may represent the set of tags assigned to the pages marked as favorites by the same user. Our belief is that a multi-factor approach can produce a more accurate user model, and thereby facilitate the search for what is more suitable for a given user. The contributions of this paper are:

- We provide a personalized component to investigate the problem of learning a user's preference based on his tagging activity. We propose a sim-

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ple yet flexible model to succinctly represent user preferences based on multiple factors.

- Based on the formal user model, we develop a method to automatically estimate the user's implicit preferences based on his and the community's tagging activity. We provide theoretical and experimental justification for our method.
- Finally, we conduct an experimental and comparative analysis to evaluate how much the search quality improves through this personalization. Our experiments indicate reasonable improvement in search quality — we observed about **61.6%** of precision improvement over traditional text-based information retrieval and **6,13%** of precision gain over the best method compared — demonstrating the potential of our approach in personalizing search.

The rest of this paper is organized as follows. We first provide an overview of personalized search and social tagging activity in section 2, on which our work is mainly based. In section 3 we describe our models and methods. Experimental evaluation, results and discussion are presented in section 4. In section 5, we review the related work and finally conclude the paper in section 6.

2 BACKGROUND

In this section we briefly revise traditional text-based information retrieval concepts followed by an overview of collaborative tagging systems.

2.1 Information Retrieval and Personalized Search

Traditionally, search engines have been the primary tool for information retrieval. Usually the search score is computed in terms of *term frequency* and *inverse document frequency* (i.e. tf-idf) (Baeza-Yates and Ribeiro-Neto, 1999). The tf-idf weighting scheme assigns to term t a weight in document d given by:

$$\text{tf-idf}_{t,d} = \text{tf}_{t,d} \times \text{idf}_t \tag{1}$$

In other words, $\text{tf-idf}_{t,d}$ assigns to term t a weight in document d that is: i)highest when t occurs many times within a small number of documents (thus lending high discriminating power to those documents); ii) lower when the term occurs fewer times in a document, or occurs in many documents (thus offering a less pronounced relevance signal); iii)lowest when the term occurs in virtually all documents.

Eventually the search score of a document d is the sum, over all query terms q, of the tf-idf weights given for each term in d.

$$\text{Score}(q,d) = \sum_{t \in q} \text{tf-idf}_{t,d} \tag{2}$$

In order to achieve personalization, a further step consists of selecting which documents d are relevant or not for a given user. Technically, the traditional scoring function must be adapted/integrated with a personalization model capable of modeling the users' preferences. This is usually done by adding new terms to the query and re-weighting the original query terms based on the user profile.

2.2 Collaborative Social Tagging

Collaborative tagging systems have become increasingly popular for sharing and organizing Web resources, leading to a huge amount of user generated metadata. Tags in social bookmarking systems such as *Del.ici.ous*[1] are usually assigned to organize and share resources on the Web so that users can be reminded later on. Invariably, tags represent some sort of affinity between user and a resource on the Web. By tagging, users label resources on the Internet freely and subjectively, based on their sense of values. Tags then become a potential source for learning user's interests.

2.2.1 Tagging Notation

Formally, tagging systems can be represented as hypergraphs where the set of vertices is partitioned into sets: $U = \{u_1,...,u_k\}, R = \{r_1,...,r_m\}$, and $T = \{t_1,...,t_n\}$, where U, R, and T correspond to users, resources, and tags. A tag annotation, i.e. a resource tagged by a user, is an element of set A, where: $A \subseteq U \times R \times T$. The final hypergraph formed by a tagging system is defined as G with: $G = \langle V,E \rangle$ with vertices $V = U \cup R \cup T$, and edges $E = \{\{u,r,t\} \mid (u,r,t) \in A\}$.

Particularly to understand the interests of a single user, our models concentrate on the tags and resources that are associated with this particular user, i.e. in a *personalized* part of the hypergraph G. We then define the set of interests of a user as $I_u = (T_u, R_u, A_u)$, where A_u is the set of tag annotations of the user: $A_u = \{(t,r) \mid (u,t,r) \in A\}$, T_u is the user's set of tags: $T_u = \{t \mid (t,r) \in A_u\}$, R_u is the set of resources: $R_u = \{r \mid (t,r) \in A_u\}$.

The introduction on information retrieval as well as on tagging notations will serve as basis for describing our personalized search model in the following sections.

[1] http://delicious.com

3 MULTI-FACTOR TAG-BASED PERSONALIZED SEARCH

We now discuss how we personalize search results. In Section 3.1 we first describe our multi-factor representation of user preferences. Then in Section 3.2, we describe how to use this preference information in ranking search results.

3.1 User Preference Representation

In this work, tags from different factors such as tags assigned to the user's bookmarks and his own tags serve as our learn units of user preferences. Further, we understand that some tags are preferred over another, meaning that the frequency of usage of a given tag can denote its affinity with the tagger. In this sense, we define the tag preference set, for each factor, as a tuple $(tag, tagFreq(tag))$, where $tagFreq(tag)$ is a function that measures the user's degree of interest in that tag. Formally, we define this set for a particular user u and factor $f \in F$ (let F be the set of all possible factors) as:

$$T_f = \{(t, tagFreq(t)) \mid t \in T_f\}, \tag{3}$$

where $tagFreq(t) = \frac{n_t}{|T_f|}$, n_t is the number of occurrences of the tag $t \in T_f$ and $|T_f|$ is the amount of tags in a given factor f. The set T_f is normalized such that $\sum_{i=1}^{|T_f|} tagFreq(i) = 1$. To illustrate the user tagging preference representation, suppose a user has only two tags in one particular factor: "semantic web" and "data mining", and the first has been utilized three times while the second has been utilized only once. This means the user has been interested in "semantic web" three times as much as he has been interested in "data mining". Then, the tag preference set of the user for that factor will be represented as {("semantic web",0.75),("data mining",0.25)}.

The composition of our multi-factor tag-based user model T'_u extends the traditional set of user tags T_u (see subsection 2.2.1), with a disjoint union of tag sets:

$$T'_u = \bigsqcup_{f \in F} T_f, \tag{4}$$

where T_f is the set of tags assigned to each factor $f \in F$. Next section explains how the tag-based multi-factor approach is applied to personalize search results.

3.2 Tag-based Personalization Approach

The tag-based personalization approach decides which resource $r \in R$ is relevant to each user $u \in U$ based on his preferences established in the multi-factor tag-based user model. In the context of this work, we re-rank the search results by measuring the similarity of tags that denote user preference and the tags assigned to the retrieved items. With this, we promote the items closer to user's preferences at the first positions in the collection of search results.

Technically, we calculate the cosine similarity (Baeza-Yates and Ribeiro-Neto, 1999) between *each* vector of tag frequencies $\overrightarrow{T}_f \subset \overrightarrow{T}'_u$ from $T_f \subset T'_u$ and the vector of tag frequencies $\overrightarrow{T}_r$ from the retrieved resources T_r of a given user query q. Further, we weigh each vector $\overrightarrow{T}_f$ with a coefficient, α_f that determines its degree of importance over the other factors in the model. We incorporate the coefficients because different users may rely on tag factors differently. As a consequence, the importance of each factor may vary accordingly.

The coefficient values for each factor are automatically estimated using the Ordinary Least Square (OLS) linear regression. The goal of using OLS is to minimize the sum of squared distances between the observed tag frequencies of each factor in the dataset and the best coefficient values predicted by linear approximation (Williams, 2007).

Once the coefficient values are estimated, the Tag-based Similarity Score (TSS) can be calculated as:

$$TSS(\overrightarrow{T}_r, \overrightarrow{T}'_u) = \sum_{f=1}^{|F|} \alpha_f * \frac{\overrightarrow{T_r}.\overrightarrow{T_f}}{|\overrightarrow{T_r}||\overrightarrow{T_f}|}, \tag{5}$$

The TSS value is then utilized to weigh the ordinary search score and thereby promote the items matching the user interests to higher positions in the search ranking. The Personalized Search Score (PSS) over a resource r triggered by a query q in the set of resources R is then defined as follows:

$$\text{PSS}(q, r, u) = \sum_{t \in q} \text{tf-idf}_{t,r} * TSS(\overrightarrow{T}_r, \overrightarrow{T}'_u). \tag{6}$$

In the following section, with the intuit of demonstrate the how the personalized search takes place, we simulate a user search since the user's initial query until the re-ranking of search results.

3.3 Personalized Search in Action

In this section we describe how the personalized ranking is realized when a user $u \in U$ submits a query q for a search engine:

1. Assume that a user u, whose preferences are denoted by the multi-factor tag-based model T'_u, submits a query q for a given search engine;
2. The search engine returns a set of resources $S \subseteq R$ that matches the entry query q. Each retrieved resource $s \in S$ is assigned with a set of tags defined by $T_s = \{t1, .., t_z\}$. The retrieved items in S are initially ranked respecting the tf-idf (Baeza-Yates and Ribeiro-Neto, 1999) ordering $\tau = [s_1, s_2, ..., s_k]$, where the ordering relation is defined by $s_i \geq s_j \Leftrightarrow$ tf-idf$(q, s_i) \geq$ tf-idf(q, s_j).
3. For each $s \in S$, we weigh the τ with $TSS(\vec{T}_s, \vec{T'}_u)$. The outcome is a personalized ranking list of pages represented by S'. The rank list will follow a new ordering $\tau' = [s_1, s_2, ..., s_k]$, where $s_i \in S'$ and the ordering relation is defined by $s_i \geq s_j \Leftrightarrow PSS(q, s_i, u) \geq persScore(q, s_j, u)$.
4. The personalized result set $S' \subseteq R$ is then returned to the user.

4 EXPERIMENTAL EVALUATION

To evaluate our approach, we analyze and compare how the different similarity measures re-rank the returned result list. For the matter of comparison, the best personalization approaches will rank the relevant/preferable retrieved items to the higher positions in the result list.

We utilize the precision metric to measure and compare the performance of our personalization approach over other similarity measures. By doing so, the research goal of this evaluation is *to assess whether the multi-factor tags improve the precision of traditional text-based information retrieval mechanism in leading users to find the information they are actually looking for*. We intend to address (and attenuate) the problem witnessed by searchers when the search results do not meet their real needs and, instead, present them with undesired information.

4.1 MovieLens Dataset

We have utilized the MovieLens dataset for evaluating our approach. The data set contains 1,147,048 ratings and 95,580 tags applied to 10,681 movies by 13,190 users. The dataset was chosen because it allowed us to build multi-factor user model base on two distinct factors corresponding to two different user activities: tagging and rating. The first factor refers to T_u as the set of user' tags and the second refers to V_u, the set of tags assigned by other users to the pages rated four or five stars by user u. In a scale from one to five, we consider movies rated four or five as strong indicators of user's preferences. The evaluated multi-factor user model is defined as follows:

$$T'_u = \gamma.T_u + \beta.V_u \tag{7}$$

where γ and β are the coefficients used to weigh the importance of each tag factor.

Because the MovieLens dataset only provides little information about the movies such as title and category, we crawled the synopses of the movies in order to create our search space. The synopses were extracted from *The Internet Movie Data Base* (IMDb) [2], a movie repository that catalogs information about movies, including information about casting, locations, dates, synopses, reviews, and fan sites on the Web.

4.2 Methodology and Evaluation Metrics

In order to evaluate whether the proposed approach matches our research goal, we performed a quantitative evaluation in terms of precision of the search results. Precision refers to the proportion of retrieved items that are actually relevant to the user's query (Baeza-Yates and Ribeiro-Neto, 1999). We calculated the precision as $prec(q,u) = \frac{|R_{q,u}| \cap |R'_{q,u}|}{|R_{q,u}|}$, where $|R_{q,u}|$ is the amount of retrieved items for a query q triggered by an user u and $|R'_{q,u}|$ is the amount of *relevant* pages expected to be retrieved. This set was composed by movies rated four or five stars besides the query q as a term in the text content. In this way, we could distinguish what was relevant or not for each user. Further, we statistically computed the most representative number of users to be assessed. The sample size was calculated with confidence level set to 95% and confidence interval set to 2%.

4.2.1 Queries and Search Space

For each user, we ran the top n queries using the most popular terms that appeared in all indexed pages. We prioritized the most frequent terms along all documents and the most frequent ones in each document. It is important to mention that we filtered out the stop words prior to processing the list of indexed terms.

[2] http://www.imdb.com/

Table 1: Size of different datasets we utilized in this paper. *Count* is the number of movies the dataset contains. *N. users* is the number of users that generated those entities. For example, the second and third columns of the second row indicate that 4,009 users assigned 95,580 tags to movies. Total is the number of times the users rated or tagged the movies. The last three columns indicate the same numbers after the pruning is being applied.

	Before Pruning			After Pruning		
Dataset	Count	N. Users	Total	Count	N. Users	Total
Movies rated	8,358	9,753	1,147,048	7,075	6,476	211,746
Movies tagged	7,601	4,009	95,580	4,029	3,871	88,181

This list was calculated as a mean of tf-df (Baeza-Yates and Ribeiro-Neto, 1999). This decision was taken to avoid that any particular group of individuals was favored over another.

Once we have selected the queries, we focused on defining the most appropriate search space. Since our goal was centered on the precision, we decided to focus the search only at the top 30 ranked items. This focused observation was motivated by the fact that users usually don't go further to encounter what they are looking for, instead they reformulate queries to better convey the information they are actually seeking (Baeza-Yates and Ribeiro-Neto, 1999).

4.2.2 Pruning

Although substantial data was available, we pruned the dataset for our analyses of the personalized search. We focused on a set of movies with a minimum threshold of tags and ratings. We began pruning the present dataset by selecting items that had been tagged with at least 5 distinct tags. We wanted to focus on tag sets with high lexical variability and less redundancy. This care was taken to prevent that tags from distinct factors could overlap with tags from expected documents in the case of low tag variability. We iteratively repeated this pruning until reach a stable set of items and tags. Further, since we wanted to explore the precision of the personalized search, we only included users that had distributed ratings higher than or equal to four stars. Otherwise we would not have any source of information on user's preference about the retrieved items. The complete overview of the dataset size is shown in Table 1.

4.2.3 Similarity Measure Comparison

The core of the tag-based personalization approach is the computation of the Tag-based Similarity Score (TSS) (see in section 3.2). In order to compare our approach with other similarity measures, we changed the TSS algorithm using other similarity algorithms without considering the coefficients assigned to the factors involved. Besides the cosine similarity, the other similarity measures utilized are the *Matching Coefficient*, *Dice*, *Jaccard* and *Euclidean Distance* (all refer to (Boninsegna and Rossi, 1994)).

- The *Matching Coefficient* approach is a simple vector based approach which simply counts the number of terms (tags in our case), (dimensions), on which both vectors are non zero. So, for vector set $\overrightarrow{v}$ and set $\overrightarrow{w}$ the matching coefficient is calculated as $matching(\overrightarrow{v},\overrightarrow{w}) = |\overrightarrow{v} \cap \overrightarrow{w}|$. This can be seen as the vector based count of similar tags.
- The *Dice Coefficient* is a term based similarity measure (0-1) whereby the similarity measure is defined as twice the number of terms common to compared entities divided by the total number of tags assigned in both tested resources. The Coefficient result of 1 indicates identical vectors (e.g. $\overrightarrow{v}$ and $\overrightarrow{w}$) as where a 0 equals orthogonal vectors. The coefficient can be calculated as $dice(\overrightarrow{v},\overrightarrow{w}) = \frac{2|\overrightarrow{v} \cap \overrightarrow{w}|}{|\overrightarrow{v}|+|\overrightarrow{w}|}$.
- The *Jaccard Coefficient* measures similarity between sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets. The coefficient can be calculated as: $jaccard(\overrightarrow{v},\overrightarrow{w}) = \frac{|\overrightarrow{v} \cap \overrightarrow{w}|}{|\overrightarrow{v} \cup \overrightarrow{w}|}$.
- The *Euclidean Distance* approach works in vector space similar to the matching coefficient and the dice coefficient, however the similarity measure is not judged from the angle as in cosine rule but rather the direct euclidean distance between the vector inputs. The standard Euclidean distance formula between vectors $\overrightarrow{v}$ and $\overrightarrow{w}$ is defined as follows: $euclidean(\overrightarrow{v},\overrightarrow{w}) = \sqrt{\sum_{i=1}^{n}(\overrightarrow{v}_i - \overrightarrow{w}_i)^2}$.
- The *Cosine Similarity* is utilized to measure the similarity between two vectors of n dimensions by finding the cosine of the angle between them. The cosine similarity for two vector between vectors is calculated as: $cosSim(\overrightarrow{v},\overrightarrow{w}) = \frac{\overrightarrow{v} \cdot \overrightarrow{w}}{|\overrightarrow{v}||\overrightarrow{w}|}$.

Unlike our proposed TSS algorithm, here we do not consider the coefficients assigned to the tag factors. For the sake of differentiation, we call the cosine similarity with coefficient applied to our TSS algorithm as Cosine^{Coef}.

Table 2: Mean of Precision.

	$Cosine^{Coef}$	Cosine	Jaccard	Dice	Euclidean	Matching
Min.	0.723	0.616	0.576	0.575	0.600	0.510
1st Qu.	0.765	0.710	0.576	0.577	0.600	0.583
Median	0.776	0.761	0.634	0.633	0.634	0.583
Mean	**0.796**	**0.755**	**0.694**	**0.694**	**0.667**	**0.641**
3rd Qu.	0.841	0.845	0.841	0.842	0.756	0.766
Max.	0.912	0.909	0.912	0.913	0.886	0.865
Std.Dev	0.052	0.087	0.131	0.130	0.083	0.105

4.3 Evaluation Results

Figure 1 shows the mean of precision (Subfigure 1(a)) and the box plot displays the distribution differences between the five similarity measures (Subfigure 1(b)). The higher precision values correspond to better performance. The precision of our approach is displayed in the first bar ($Cosine^{Coef}$) followed by the compared similarity measures with their respective standard errors. We also include the non-personalized precision result for the sake of comparison. This ranking was based on the traditional tf-idf weighting scheme where the text-based search has no support from personal tags. It is important to emphasize that all compared similarity measures produce a personalized score except the non-personalized search.

Table 2 summarizes the statistics from our sample of precision values regarding the evaluated metrics. It shows the five-number summary (sample minimum, lower quartile, median, upper quartile and sample maximum), the mean value, and the standard deviation of the samples. It is worth noting that the sample minimum value of our approach has higher precision than any other similarity measure compared. This behavior is also noticed when compared with the sample maximum value. Similarly, the standard deviation of the sample of our approach is lower than the standard deviation of the other samples. This indicates less dispersion within the precision values of our approach. Furthermore, differences between all pairs of similarity measures are significant ($p \leq 0.01$) except for those between Jaccard and Dice similarity.

As results show, our approach (Cosine^{Coef}) achieved the highest precision rates. In particular, it achieved 61.6% of precision improvement over traditional text-based information retrieval (non-pers) and 6,13% of precision gain over cosine similarity. The overall result also indicates that the cosine-based similarity measures (regarding or not the coefficients) perform better than the other approaches. As expected, all similarity measures applied to the personalized search outperformed the non-personalized method.

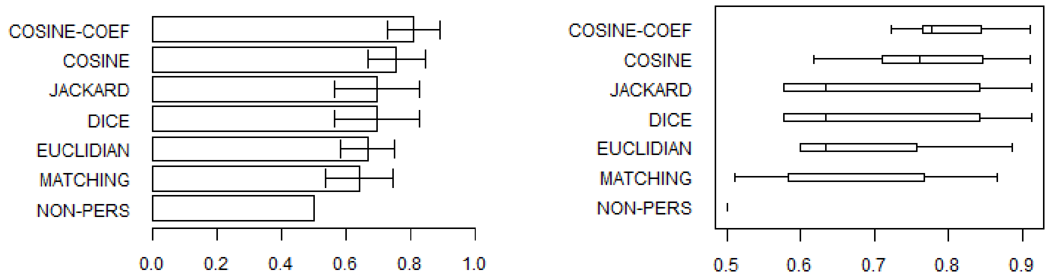
4.4 Discussion and Limitations

Concerning the role of tags as means of personalizing traditional information retrieval, we evidenced that tags indeed can be used as learning units of user's preference. As results showed, this hypothesis was confirmed when the precision of our solution considerably outperformed the precision of non-personalized search. The immediate benefit of personalized search is the reduction of undesired retrievals at the first positions and thereby not distracting users with unsolicited information. Part of this success relates to the best estimation of coefficients applied to each factor considered in the search. The adoption of coefficients helped us to efficiently determine which tag factors are more representative for an individual over the others. Regarding the applicability of the approach, we are quite positive that existing tag-based systems can utilize and/or adapt our solution to their reality.

The main limitation of the current approach is the lack of tags. In this work we are not addressing this problem since the goal is to emphasize the benefits with the multi-factor approach. A potential solution is seen in the work of (Jäschke et al., 2007) that studies tag prediction in social bookmarking environments. Performance is another issue that was not formally evaluated in the current study but we empirically observed that the personalization process is at least 10% more expensive than the basic keyword-based search. However this cost cannot be judged isolated since the personalized outcome can compensate the investment. Further investigation is necessary and planned for future works.

5 RELATED WORK

In recent years many researchers utilize query log and click-through analysis for web search personalization. In (Qiu and Cho, 2006), the authors combine a topic-sensitive version of PageRank (Haveliwala, 2002) with the history of user clicks data for search



(a) Mean of Precision

(b) Box Plot

Figure 1: Overall result and statistics from the experiment. Note that each of the similarity measure are utilized in the TSS algorithm to personalize the search.

result personalization. Joachims et al. (Joachims et al., 2005) study clicks applicability as implicit relevance judgments. They show that users' clicks provide a reasonably accurate evidence of their preferences. These studies are relevant to our work in context of predicting user preferences but our approach takes into account user annotations which are called tags as user feedback. Tan et al. (Tan et al., 2006) propose a language modeling approach for query history mining. Their small-scale study demonstrates significant improvement of personalized web search with a history-based language model over regular search. The user modeling approach described in (Shen et al., 2005) is based on a decision-theoretic framework to convert implicit feedback into a user profile that is used to re-rank search results.

While user models are usually targeted at search personalization, they could also be applied for personalized information filtering, as was shown in (Yang and Jeh, 2006) which analyzes click history for the identification of regular users' interests. (Teevan et al., 2009) shows that combining implicit user profiles from several related users has a positive impact on personalization effectiveness. Recently, new approaches for adaptive personalization focus on the user task and the current activity context. There are several approaches trying to predict applicability of personalization while considering the current context of the user's task on query submission (Teevan et al., 2008; Dou et al., 2007).

Collaborative Filtering (CF) (Bender et al., 2008) has become a very common technique for providing personalized recommendations, suggesting items based on the similarity between users' preferences. One drawback of traditional CF systems is the need for explicit user feedback, usually in the form of rating a set of items, which might increase users' entry cost to the recommender system. Hence, leveraging implicit user feedback (Au Yeung et al., 2008), such as views, clicks, or queries, has become more popular in recent CF systems. In this work, we leverage implicit tagging information, which can be viewed as a variant of implicit user feedback. (Carmel et al., 2009) proposes a solution which considers the structure of the user's social network assuming that people which share same social ties have similar interests. In addition to social network, they have another approach similar to our study taking into account user tags to understand user interest. Comparing these two approaches they noted that tagging activity gives efficient information about user preferences for active taggers. In order to measure relevance between user and search result, (Gemmell et al., 2008) considers topic matching instead of tags which we used in our approach. They propose a ranking algorithm which ranks web pages by the term matching between user interest and resource's topic. In (Sieg et al., 2007), there exists a different approach to personalizing search result by building models of user as ontological profiles. They derive implicit interest scores to existing concepts in domain ontology.

Focused mostly on tags, (Xu et al., 2008) proposes an algorithm for personalizing search and navigation based on personalized tag clusters. Slightly similar to our model, they measure the relevance between user and tag cluster and try to understand user interest while we calculate the similarity between user and tags. Tags are used in different manners to find search personalized results answering user needs since tags are chosen by users personally. Similar to our study, in (Noll and Meinel, 2007), a tag based reranking model is presented taking into account tags from *Del.icio.us*. Likewise our model, they compare tags of search results and users to calculate new scores of search results.

6 CONCLUSIONS AND FUTURE WORKS

This study introduces a multi-factor tag-based model to personalize search results. We analyze user's tagging activity to learn users' preferences and use this information to personalize the search. We evaluated our approach with other personalization methods and as a result we realized significant improvement of precision. As a future work, we intend to analyze the semantic relationship between tags in order to catch hidden similarities that are not undertaken by this model. In addition, we aim at enhancing the model by considering the tag decay. The goal is to perform a temporal analyzes and filter the results according to the actual users' preferences.

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