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A Novel Framework for Image Search in Social Networking

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ABSTRACT: Most Internet users, you probably spend a decent amount of time using a search engine to find content and answers. Social network search engines are designed to do Search they can filter out all the unnecessary results we might get if we used a regular search engine. The large-scale user-generated meta-data not only facilitate users in sharing and organizing multimedia content, but provide useful information to improve media retrieval and management. Personalized search serves as one of such examples where the web search experience is improved by generating the returned list according to the modified user search intents. In this paper, we propose a novel framework simultaneously considering the user and query relevance to learn to personalized image search. The proposed framework contains two components: one is a Ranking based model and another one is User-specific modeling to map the query relevance and user preference. We did experiments on large scale data to demonstrate the effectiveness of the proposed method. In this paper we consider the simple case of one word-based query. As well as topic based.

Keywords**:** Social Networking, Image Search, search engine, Tagging.

I. INTRODUCTION

A social network is a theoretical construct useful in the social sciences to study relationships between individuals, groups, organizations, or even entire societies. Image search is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be Meta tags, colour distribution in images, region/shape attributes. Image Meta search - search of images based on associated metadata such as keywords, text, etc. Content-based image retrieval– the application of computer vision to the image retrieval. It aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colours, shapes etc.) to a user-supplied query image or user-specified image features. A selection-based search system is a search engine system in which the user invokes a search query using only the mouse. A selection-based search system allows the user to search the Internet for more information about any keyword or phrase contained within a document or webpage in any software application on his desktop computer using the mouse. Traditional browser-based search systems require the user to launch a web browser, navigate to a search page, type or paste a query into a search box, review a list of results, and click a hyperlink to view these results. Three characteristic features of a selection-based search system are that the user can invoke search using only his mouse from within the context of any application on his desktop (for example Microsoft Office, Adobe Reader, Mozilla Firefox, etc.), receive categorized suggestions which are based on the context of the user-selected text (or in some cases the wisdom of crowds), and view the results in floating information boxes which can be sized, shared, docked, closed and stacked on top of the document that has the user's primary focus.Personalizing the search process, by considering the searcher's personal attributes and preferences while evaluating a query, is a great challenge that has been extensively studied in the information retrieval (IR) community but still remains a stimulating task.

It is of great interest since user queries are in general very short and provide an incomplete specification of individual users' information needs. For example, searching for "IR" by an information retrieval student has completely different meaning than searching by another who is interested in infra-red radiation. Search personalization requires the capability of modeling the users' preferences and interests. This is usually done by tracking and aggregating users' interaction with the system.

In general, such aggregation includes users' previous queries, click-through analysis, and even eye tracking during the search session. Users' interactions are structured into a user profile that can be utilized during search. A user profile is usually employed in two main scenarios, either through personalized query expansion, i.e., adding new terms to the query and re-weighting the original query terms based on the user , or through reran king and filtering[1] the search results while incorporating users' interests accordingly. For most of the history of the web, search engines have only had access to two major types of data describing pages. These types are page content and link structure. Today a third type of data is becoming available: user generated content (e.g., tags, bookmarks) describing the pages directly. Unlike the two previous types of data, this new source of information is neither well studied nor well understood. Our aim in this paper is to quantify the size of this data source, characterize what information it contains, and to determine the potential impact it may have on improving web search. Since the beginning of the web, people have used page content to aid in navigation and searching. However, almost as early Eiron and McCauley suggest as early as 1994 users were suggesting the use of anchor text and link structure to improve web search. Creswell et al. also give some early justification for use of anchor text to augment web search. Meanwhile, there has of also been a current users attempting to annotate their own pages with metadata. This began with the <Meta> tag which allowed for keywords on a web page to aid search engines. However, due to search engine spam, this practice has lost favor. The most recent instance of this idea is Google Co-op, 3 where Google encourages site owners to label their sites with “topics.” Co-op allows Google to refine search results based on this additional information. However, unlike social bookmarking, these metadata approaches require site owners to know all of the labels a user might attach to their site. This leads to the well studied “vocabulary problem” (see [2]), whereby users have many different types of terminology for the same resources.

Ultimately, unlike previous metadata, social bookmarking systems have the potential to overcome the vocabulary problem by presenting many terms for the same content created by many disparate users. Independently of web search, there has been a growth of interest in tagging. This is primarily due to its usefulness as a lightweight organizational tool and as a way to increase text for video and image search. Golder and Huberman [9] were two of the earliest researchers to look at the dynamics of tagging, but many others soon followed ([3, 4, 5]).While a number of papers have looked at del.icio.us, only a few have looked at its relationship to web search.

However, neither looked at whether del.icio.us (or any other social bookmarking site) was producing data of a sufficient quantity, quality or variety to support their methods. Both also use relatively small datasets Bao et al. use 1, 736, 268 web pages and 269, 566 annotations, while Yanbe et al. use several thousand unique URLs. Also, both of these papers are primarily interested in the popularity and tags of the URLs studied, rather than other possible uses of the data. The ultimate test of whether social bookmarking can aid web search would be to implement systems like those of Bao et al. or Yanbe et al. and see if they improve search results at a major search engine. However, such a test would be expensive, time consuming, and might not really get to the root of why (or why not) social bookmarks help. Our paper aims to provide these insights.

II. PERSONALIZED SOCIAL SEARCH

There are several alternative definitions of the concept social search. In this work we use the notion of social search to describe the search process over social" data gathered from Web 2.0 applications, such as social book marking systems, wikis, blogs, forums, social network sites (SNSs), and many others. Such a social search system represents different entity types (documents, persons, communities, tags) and their interrelations, and allows searching for all object types related to the user's query.

Social search provides an ideal test bed for personalization due to the explicit user interactions through Web 2.0 tools. A user profile that is derived from user feedback such as bookmarking, rating, commenting, and blogging, provides a very good indication of the user's interests. Furthermore, user profiles that are only based on explicit public social activity can be safely utilized without disrespecting the user's privacy1. Consequently, several previous works studied search personalization by profiling user interests based on public bookmarks aggregated from a social bookmarking system.

A. SN-BASED PERSONALIZED SOCIAL SEARCH

Here we focus on re-ranking of search results by considering their relationships to users that belong to the searcher's social network. The assumption behind this personalization approach is that the preferences of other people, who are expected to have similar" interests as the searcher, provide a good prediction for the searcher's preferences and can thus assist in revealing the search results that might subjectively satisfy the searcher's needs. Personalized re-ranking of search results is done as follows: given a list of (non-personalized) results retrieved for the user's query, and a list of related users extracted from his/her social network, search results are re-ranked by considering their relationship strength with those users. Thus, documents that are strongly related to the user's related people are boosted accordingly.

B. SOCIAL SEARCH

The amount of social data is rapidly growing and has become a main focus of research on social search. Recent work [6] reports that in 2008 around 115 million bookmarks were available on the del.icio.us social bookmarking site. A page popularity measure, SB Rank, proposed in [7], is proportional to a number of existing social bookmarks.

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Following the language modeling approach, a theoretically sound generative model for social annotations is presented in [8].Tags and other conceptual structures emerging in social systems are called folk sonom ies and are typically modeled as graphs. A formal model for folksonomies and ranking algorithms called Adapted Page Rank and Folk Rank are Dunedin. Folk Rank is used for the generation of personalized rankings of entities within the folksonomy and for the recommendation of tags, users and resources. Lately, Bao et al [9]. propose two alternative algorithms, Socialism Rank and Social Page Rank. Both are based on social annotations and corresponding connections between pages, annotations and users. A comparative evaluation study of these algorithms and a few novel algorithms are described in [10].

C. USE PROFILES

Dogear[11], LC's social bookmarking application, allows users to store and tag their favorite web pages. Over 90% of the bookmarks are public (visible to all other users) and about half are intranet pages, while the other half are external internet pages. Dogear includes 743,239 public bookmarks with 1,943,464 tags by 17,390 users. Blog Central [12], LC's blogging system, has 16,337 blogs, 144,263 blog entries, with 69,947 users.LC's communities service contains over 2,100 online communities, each with shared resources and discussions, with a total of over 50,000 members. Social Networks and Discovery (SaND) [12], is an aggregation tool for information discovery and analysis over the social data gathered from all LC's applications. It leverages complex relationships between content, people and tags, and its integrated index supports a combination of content-based analysis and people-based analysis. SaND provides several social aggregation services including social search, personalized item recommendations, personalized people recommendations, finding social paths between people, and additional social network services. SaND provides social search over the social data using a unified approach [3] in which all system entities (documents, persons, groups, and tags) are searchable and retrievable. As part of its analysis, SaND builds an entity-entity relationship matrix that maps a given entity to all related entities, weighted according to their relationship strength. The entity-entity relationship strength is composed of two types of relations: Direct relations, indirect relations. The relative relationship strengths appear on the graph's edges. Familiarity relations are colored red (bolded).The overall relationship strength between two entities is determined by a linear combination of their direct and indirect relationship strengths User profile types: there are different types of user profiles they are,

1. FAMILIARITY SN

Familiarity between two individuals is considered according to indicators that they know each other [11]. A direct familiarity relation exist if both persons are marked as friends in one of the enterprise SNSs, or when one is the direct manger/employee of the other. In addition a person is familiar with those s/he tagged, but not vice versa. Indirect familiarity relations are defined when the two persons are both authors of the same paper, patent, or wiki-page, or when both have a common manager (team members). In order to extract the user's Familiarity network, we use SaND to extract the entire user's related people and to filter out all non-familiar people which do not obey the above constraints. In addition, the relationship strength between the two is modified to be based on familiar relations only. More details on the familiarity relationships and the calculation of the familiarity score can be found in [10].

2. SIMILARITY

Similarity between two individuals is considered according to common activity in the context of LC's social software: co-usage of the same tag; co-tagging of the same document; co-membership of the same community, or co-commenting on the same blog entry. Similarly to the familiarity case, in order to extract the user's Similarity network, we use SaND to extract all related people and retrieve (and re-weight) only people which obey the above constraints.

3. OVERALL SN

Besides the Familiarity and Similarity networks, we also examine the user's overall social network, which contain all related persons according to the full relationship model.

Topic-based: The user's topics of interests are represented by a set of terms that are closely related to the user. Directly related terms are tags used by the user to tag documents and other people, and tags used by others to tag that user. Indirectly related terms are those that are related to the user through other entities (e.g. all tags of a document bookmarked by the user). The user's top related terms retrieved by Sand serve as the user's Topic-based profile.

Personalizing the search: A user profile is constructed on the y when a person logs into the system. For a user u, SaND retrieves N(u) the ranked list of users related to u, and T(u) the ranked list of related terms. These two lists are then used as the user profile to personalize the search results for all user's queries during the search session.

Given the user profile, P(u) = (N(u); T(u)), the search results are re-ranked as follows:

$$S_p(q, e|P(u)) = \alpha S_{np}(q, e) + (1-\alpha)[\beta \sum_{v \in N(u)} w(u, v) \cdot w(v, e) + (1-\beta) \sum_{t \in T(u)} w(u, t) \cdot w(t, e)]$$

Sp(q; e|P(u)) is the personalized score of entity e to query q given the profile of user u. Snp(q; e) is the non-personalized SaND score of e to q. Since we only re-weight the search results, only entities with positive score are considered (u; v) and w (u; t) are the relationship strength of user v and term t to u, as given by the user profile. Similarly, w(v; e) and w(t; e) are the relationship strength between v and t to entity e, as given by SaND. Thus, an entity is first scored by SaND according to its non-personalized scoring mechanism, and then the entity score is modified according to its relationship strength with users and terms in the user profile. The equation has several parameters that control the amount of personalization.

III.EVALUATION

Evaluating personalized search is a great challenge since relevance judgments can only be assessed by the searchers themselves only the users can subjectively judge whether a specific result answers their personal need. Therefore, existing IR evaluation benchmarks based on judged queries, each associated with a set of relevant results objectively assessed by experts, cannot be utilized for personalized search evaluation. Existing evaluation approaches for personalized search are often based on a user study, where participants are asked to judge the search results for their personal queries in a personal manner, thus alternative personalization techniques can be comparatively analyzed. However, appropriate user studies with a reasonable number of participants are very expensive to accomplish, therefore, such studies are uncommon and often limited to a small and a biased sample. Alternatively, users' implicit feedback such as clicking on a specific result (while un-clicking other results), can be interpreted as personal relevance judgment. Clicks, however, they are not necessarily the best indicators for user satisfaction
with results - clicking on a result does not necessarily mean it is relevant, while un-clicking does not always imply irrelevance. Furthermore, such evaluation is only feasible for a live system with enough users who use it on a regular basis. Social search applications provide richer sources for user feedback that can be used for regular personalized search evaluation. User feedback such as rating, tagging, and commenting, indicates the user's interest in a specific document.

Recently, several works utilized data from Delicious to evaluate personalized search methods [5, 8]. In this approach, any bookmark (u; d; t) which represents a user u who book marked a document d by a tag t, can be used as a test query for personalized search evaluation. The main assumption behind is that any document tagged by u with t (including d) is considered relevant for the personalized query (u; t) (i.e. submits the query t).Therefore, the bookmark triplets (u; d; t) extracted from a social bookmarking system provide an almost unlimited source of personalized test queries to be used for personalized search evaluation. Given the bookmark (u; d; t), a personalized search system is evaluated according to its ability to highly rank the corresponding documents. A good personalization policy is expected to differentiate between two similar tested queries (u1; d1; t) and (u2; d2; t), promoting d1 while serving (u1; t), and d2 for the query (u2; t).There is a delicate issue with bookmark-based evaluation. The search system is already aware of" the association between d and t, as realized by u, hence this information can be exploited for over tuning. For example, given the query (u; d; t), a personalization approach that retrieves only the documents tagged by u with t will inevitably outperforms other personalization alternatives, since any other document is considered irrelevant. However, this over-tunned personalization policy is restricted to queries that were previously used as tags by the user; hence it will totally fail for other personalized queries. This limitation cannot be disclosed by the bookmark-based evaluation methodology.

In order to eliminate the dependency between personalization and evaluation, and to simulate the personal query (u; d; t) with no prior knowledge on the user's association between t and d, we have to mask u bookmarking of d. Masking is done as follows: for each personal query (u; d; t), we hide" that bookmark from the search system before handling the query (u; t). The system is instructed as this specific bookmarking has never happened content is not enriched by the tag t (unless d was tagged with t by others), t is taken out from the user profile (unless t relations with u is derived from other resources) and u's relations with other entities that are based on this bookmark are modified accordingly. This masking guarantees that personalization is evaluated without any prior knowledge on u relations with d and t. Note that personalized methods that better predict their users' interests, as reacted by their tagging activity, will be favored by that evaluation methodology. This is definitely one of the main characteristics that are expected from a personalized search system, hence such evaluation can successfully prioritize alternative personalization strategies.

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However, the bookmark-based evaluation approach still suffers from the incompleteness problem not all documents tagged by u with t are relevant for u while searching for t, and not all documents not tagged by u with t are necessarily irrelevant. This limitation is partially handled by the huge amount of personalized queries available for evaluation. But we believe that conclusions based on such evaluation should be supported by alternative evaluation methods, an approach that was taken by us in this work. We first evaluate and tune our personalized social search system with the bookmark-based evaluation, using Dogear's bookmarks as personalized queries, and confirm our findings with an extensive user survey based on 240 participants that subjectively judge the results for their 577 personal queries. To the best of our knowledge, this is the first study that (1) eliminates the dependency between personalization and evaluation that inherently exists in bookmark-based evaluation ;(2) validates the bookmark-based evaluation methodology for personalized search by comparing its findings with the results of an independent user survey. Query Refinement, also called Query Expansion, refers to the modification to the original query according to the user information. It includes augmenting the query by other terms [11], [5] and changing the original weight of each query term [2]. Kraft *et al.* [8] utilized the search context information collected from users' explicit feedback to enrich the query terms. Chirita *et al.* [2] proposed five generic techniques for providing expansion terms, ranging from term and expression level analysis up to global co-occurrence statistics and external thesauri. Result Processing can be further classified into result filtering and re-ranking. Result filtering aims to filter irrelevant results that are not of interest to a particular user. While, result re-ranking focuses on re-ordering the results by the degree of users' preferences estimated. Since our work falls into this category, we mainly review the related work on result re-ranking. Chirita *et al.* conducted an early work by re ranking the search results according to the cosine distance between each URL and user interest profiles constructed. Qiu *et al.*extended Topic-Sensitive Page Rank by incorporating users' preference vectors. By aggregating the search results from multiple search engines, Liu *et al.* [22] introduced a new method for visual search reranking called Crowd Reranking.

A typical work is performed by Xu *et al.* [2], in which the overall ranking score is not only based on term similarity matching between the query and the documents but also topic similarity matching between the user's interests and the documents' topics.

IV.RANKING BASED MULTI-CORRELATION TENSOR FACTORIZATION

In this section, we present the algorithm for annotation prediction. There are three types of entities in the photo sharing websites. The tagging data can be viewed as a set of triplets. Let U*;* I;T denote the sets of users, images, tags and the set of observed tagging data is denoted by µ=U × I × T i.e., each triplet(*u; i; t*) ,µ means that user *u* has annotated image *i* with tag *t*. The ternary interrelations can then constitute a three dimensional tensor $Y \in$ R |U|×|I|×|T|, which is defined as:

$$y_{u;i;t} = \begin{cases} 1 & \text{if } (u, i, t) \in \mu \\ 0 & \text{otherwise} \end{cases}$$

where *y is* user-image-tag tensor, *U; I; T* represent user, image, tag factor matrices, |U|×|I|×|T| represents sets of users, images and tags, respectively, *u; i; t represents* represent user, image, tag index and feature vectors. Predicting the users' annotations to the images are related to reconstructing the user-tag-image ternary interrelations. We use Tucker decomposition [13], a general tensor factorization model, to perform the low-rank approximation. In Tucker decomposition, the tagging data *Y* are estimated by three low rank matrices and one core tensor:

$$\hat{\mathcal{Y}} := \mathcal{C} \times_u U \times_i I \times_t T$$

Where c is the core tensor. To better leverage the observed tagging data, we first introduce a novel ranking based optimization scheme for representation of the tagging data. Then the multiple intra-relations among users, images and tags are utilized as the smoothness constraints to tackle the sparsity problem. Below figure shows the proposed frame work.

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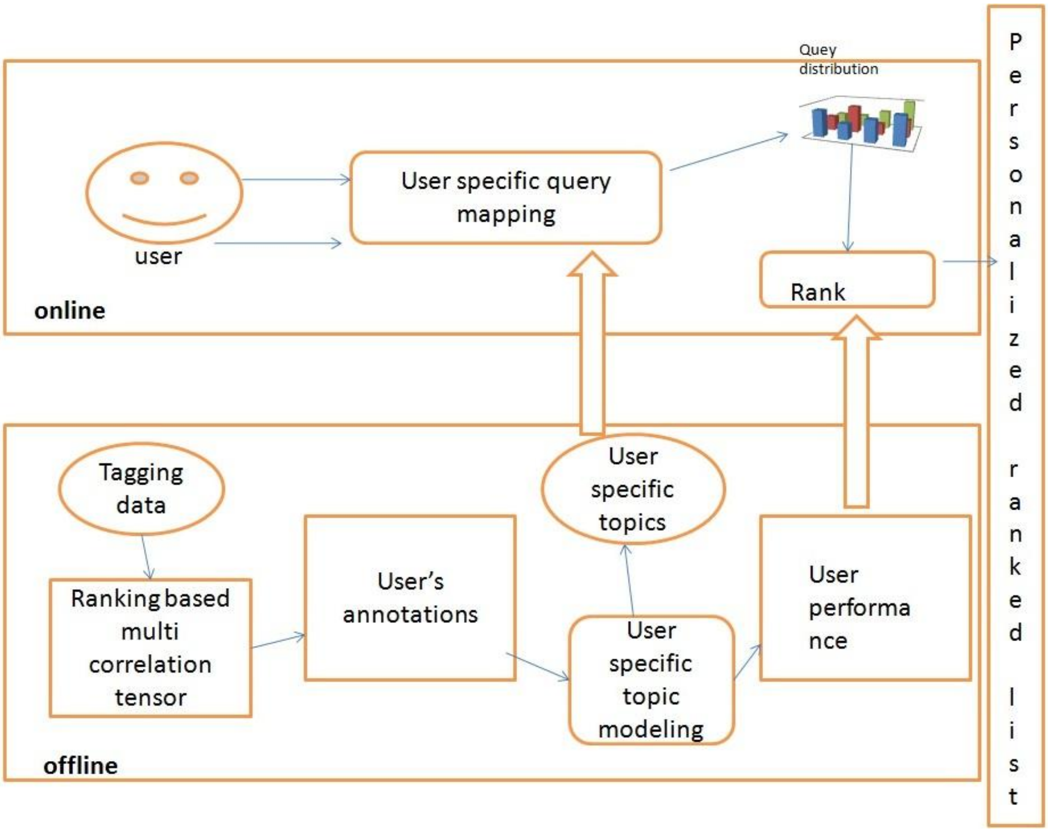

Figure 1: The proposed framework

V. EXPERIMENTAL RESULTS

In the research community of personalized search, evaluation is not an easy task since relevance judgment can only be evaluated by the searchers themselves. The most widely accepted approach is user study [14], [15], [17], [16], where participants are asked to judge the search results. Obviously this approach is very costly. In addition, a common problem for user study is that the results are likely to be biased as the participants know that they are being tested. Another extensively used approach is by user query logs or click through history [10], [15]. However, this needs large-scale real search logs, which is not available for most of the researchers. Social sharing websites provide rich resources that can be exploited for personalized search evaluation. User's social activities, such as rating, tagging and commenting, indicate the user's interest and preference in a specific document. Recently, two types of such user feedback are utilized for personalized search evaluation. The first approach is to use social annotations [2], [11], [3]. The main assumption behind is that the documents tagged by user *u* with tag *t* will be considered relevant for the personalized query (*u; t*). Another evaluation approach is proposed for personalized image search on Flickr, where the images marked *Favorite* by the user *u* are treated as relevant when *u* issues queries. The two evaluation approaches have their pros and cons and supplement for each other. We use both in our experiments and list the results in the following. We select two state-of-the-art models as the baseline.(i) Topic-based: topic-based personalized search using folksonomy[2].(ii) Preference-based: personalized image search by predicting user interests-based preference.

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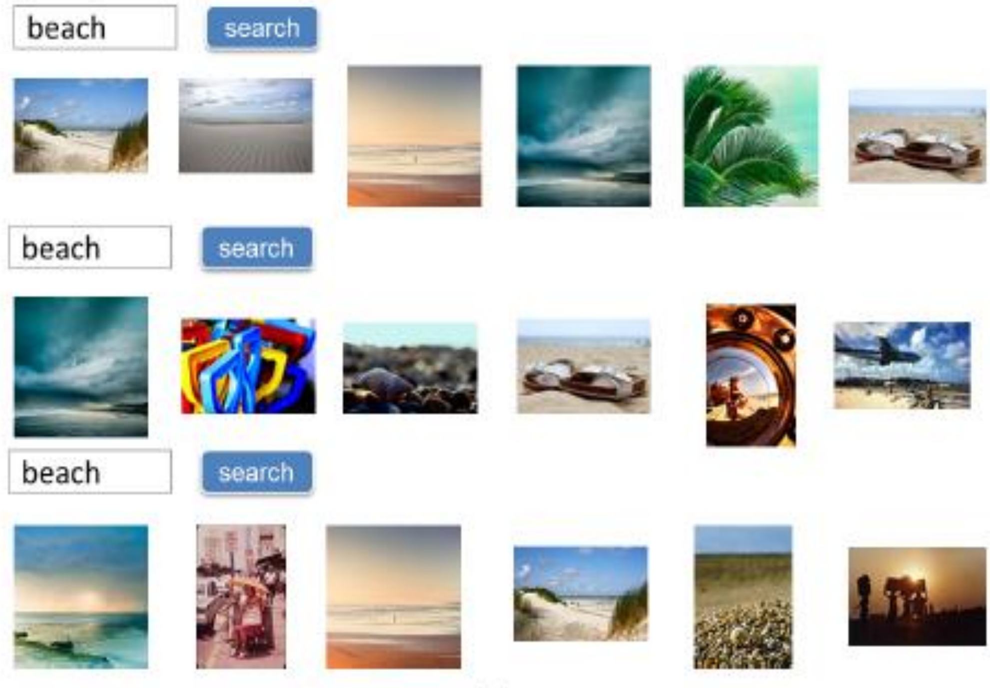

Figure 2: Topic-based method: Example of non-personalized (top) and personalized (middle for User A and bottom for User B) search results for query "beach".

Here we consider a simple word based method also in that the Searching is done depends upon word it is most efficient we are also done experiments with query based also. Similarly image Search also done by tagging mechanism.

VII. CONCLUSION AND FUTURE WORK

In this paper, we propose a novel framework simultaneously considering the user and query relevance to learn to personalized image search in social networks. The proposed framework contains the components: one is a Ranking based model and another one is User-specific modeling to map the query relevance and user preference. here we are also considering user profiles and and tagging mechanism also for Effective query processing and image search, we also found that tags were overwhelmingly relevant and objective. Furthermore, the tags which annotate URLs, while relevant, are often functionally determined by context. In the future, we will improve our current work, i.e for batch of new data (new users or new images), we directly restart the RMTF and user-specific topic modeling process. While, for a small amount of new data, designing the appropriate update rule is another future direction. and in future only considering user profiles all the searching done in social net works.

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