Image Retrieval Using Personalized and Non-Personalized Search

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ABSTRACT: 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, etc. Image meta search - search of images based on associated metadata such as keywords, text, etc.Content-based image retrieval (CBIR) – the application of computer vision to the image retrieval. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colors, shapes etc.) to a user-supplied query image or user-specified image features.

KEYWORDS: Image Retrieval, Social Annotation, Content Based, Text Based

I.INTRODUCTION

TEXT-BASED search has been the most popular search paradigm in today's search market. Despite of simplicity and efficiency, the performance of the text – based search is far from satisfying. Poor user experience has investigation on Google search, for 52% of 20 000 queries, the searchers did not find any relevantresults. This is due to two reasons:
1) queries are in general short and nonspecific, e.g., the query of   "IR"   has   the   interpretation of both information retrieval and infra-red, and   2) users may have different intentions for the same query, e.g., searching for "Samsung laptop"
by a   charger battery CD-Drive has a completely different meaning from searching. One thing is there to address these problems is, where the user specific information is considered to distinguish the exact intentions of the user queries and rerank the   results lists.Given the large and growing importance of search engines like google, yahoo etc,. personalized search has   the   potentialto   significantly   improve that searching   experience.   Compared   with   non- personalized search, the ranking type of a document like (web page, image, audio, message, video, etc.) in the result list is decided not only by the user query, but by the preference of user. shows the example for non-personalized and personalized image search results   from   the   search engines. The non-personalized search returned results only   based on the user query relevance and displays Samsung laptop images as well as it can displays the Samsung   charger   battery   on   the above   image   in figure1. While personalized search results   consider as both user query relevance and user preference, so the personalized results from an laptop lover rank the laptop images on the top.
This provides a natural two step solution scheme. Most of the existing work [2]–[5] follow this scheme and decompose   personalized   search   into   two   steps: computing   the   non-personalized relevance score between the query, the document, and computing their personalized score by estimating the user's preference over the document. After this, a merge operation is conducted to generate a   ranked list. It suffers from two problems.

1) The interpretation is less straight and its not that much convinced. The intuition of personalized search is to rank the returned documents by estimating the user's preference over documents under the particular queries. In this we can   directly analyzing the user query document   correlation,   the   existing   system scheme approximates it by separately computing a user query document relevance score and a user document relevance score.

2) How to determine the merge strategy is not trivial. In   this   research,   we   simultaneously   considers   the Typically a weighting parameter will be optimized to balance the two scores, or the learnt user preference is used to rerank the query relevance-based original list .user and   query   dependence   and   present   a   novel framework   to tackle the personalized image search problem. To investigate on user preference, perform and user modeling, and the popular social activity of tagging also included. Combined tagging has become most popular for sharing and organizing resources to user preferences, its leading to a huge amount of user is generating the   annotations. Online photo sharing websites   using   network,   such as   Flickr, Picasa, Photobucket,

Pixable, Piczo, Zooomr, and Pinterest its allows a users as owners to tags the image as taggers, and comment the image as commenters for their contributed contents to interact and collaborate with each other in a social media dialogue. the original annotations available is not enough for user preference mining. Therefore, we can transfer the problem of personalized   image search to   users   annotation prediction. Moreover, as user queries and tags do not follow the simple one to one communication, we build user specific topic spaces to exploit the relations between the queries and tags. A formal assumption is that, *the users is tagged actions is to   reflect their personal relevance judgement.* For example, if a user tagged "Birthday" to an image, it is probable that the user will consider this image as relevant if he/she issues "Birthday" as a user query. Illustrated by this, the intuition of this research is that if the users annotations to the images are available, we can estimate directly to the   users preference under certain queries.

The framework of this research is shown in Fig. 2. It contains only two - stages: first one is offline model training stage   and   the   another   one   is   online personalized search response stage. For the offline stage, three types of data including users, two images and tags as well as their ternary interrelations and intra-relations are first collected. To alleviate the sparsity and noisy problem, we present a novel method Following the assumption, we can straightly utilize the predicted user annotations for personalized image search, if a   user has a   high probability to assign the tag to an image, the image should be ranked higher when the user issues query . However, this formulation has two problems:

1) it is unreasonable to assign the query to a single tag in the tag vocabulary, e.g., when a user searches "barbie dolls" would like the images that he/she annotated   with   semanticrelated tag barbiestills" are also ranked as higher.

2) there are variations in individual user's tagging patterns and vocabularies, e.g., the tag "singam movie images" from an tamil movie specialist should be related to "Movies", while a Hindi singam movie images or Telugu singam imgaes will consider "singam movie images" more related to "films". To address the two problems, we perform *user-specific topic modeling* to build the semantic topics for every user. The user's annotation for an image is view like an *document*. The separate tag to the image is an *word*. User annotations for all the images constitute the *corpus.* Named (RMTF-*ranking-based multicorrelation   tensor   factorization*)   to   better leverage the observed   tagging data for users' annotation prediction. The contributions of this research are summarized as three-folds. • We propose a novel personalized image search framework by   simultaneously   considering   user   and   query information of the image. The user's preferences over images under certain query are estimated by how probable he/she assigns the query related tags to the images. • A tensor factorization model named RMTF is proposed to predict the user annotations using ranking based to the images. • We have build the user specific topics and map the queries as well as the users' preferences onto the learned topic spaces to represents the better query tag relationship.

II. RELATED WORK

In recent years, extensive efforts have been focusing on personalized search. Regarding the explicit user profile, relevance feedback , user history data (browsing log , click-through data , and social annotations etc.), context information is   time and location, etc. and social network   are   also   exploited For the implementation there are two basic stages
1) query refinement and 2) result processing.

III. RANKING BASED RETRIEVAL

In this section, we present the algorithm for annotation prediction. ists the key notations used in this research. There are three types of entities, we have to share our image to many websites like google, piczo, photobucket, flickr etc. The tagged data can be viewed as a set of triplets. Predicting the users' annotations tohe images are related to reconstructing the user-tag- image   ternary interrelations.   The   low-rank approximation isperform to   use   Tucker decomposition in a general tensor factorization model . In this research, a model named RMTF is proposed to designed as   objective function. We first introduce a novel   ranking based optimization   scheme   for   presentation of the tagging data or tag the image to perform a better leveraged images. The users   may among multiple inter relations images and tags are utilized as the smoothness constraints to take on it.

A. Ranking Based Optimization Scheme

However, under this type of situation of social image tagging data,   the   semantics   of   encoding   all   the unobserved data as 0 are incorrect, which is illustrated with the running example.

• Firstly, the fact that *user3* has not given any tag to *image2* and *image4* does not mean *user3* considering all the tags are bad for set forth the images. Maybe man/women does not want the image to tag or it has no chance to see the fifth image
• Secondly, *user1* annotates *image1* with only the third *tag*. It is also indefensible to assume that other tags should not be annotated to the image, as   many concepts may be missing in the user generated tags and individual user may not be familiar to all the relevant tags in the large tag vocabulary.

According to the optimization function is

(3), *0/1 scheme* tries to predict 0 for both cases.   the above two issues, in this research, we present a ranking optimization scheme which intuitively takes the user tagging behaviors into reflection. First of all we have to note that only the soft difference is important and fitting   to   the   numerical   values   of   1   and   0   is unnecessary.

B. Multicorrelation Smoothness Constraints

Photo sharing websites differentiate from other social tagging systems by its characteristic of self-tagging: most images are only tagged by their users or owners. Fig. 4(a) shows the #tagger statistics for picasa and thewebpage tagging system photobucket. We can see that in picasa, 90% images have no more than four taggers and the average number of tagger for each image in picasa is 1.9 . All the same , the average tagger in photobucket is 6.1. The severe default or lack of problem   calls   for   external   resources   to   enable information propagation.

TABLE - 2
THE TWO EXAMPLE USERS FOR USER-SPECIFIC TOPICS

User A	Topic 1	military, **aircraft**, battleship, navy, artillery, iraq, aircraftcarrier, barracks
	Topic 2	apple, computer, art, girl, cellphone, cool, vintage, digital
	Topic 3	athlete, basketball, baseball, actor, sports, art, film, black
	. . .	. . .
User B	Topic 1	buddha, buddhist, temple, religion, buddhism, thailand, asia, ancient
	Topic 2	blossoms, blooms, nature, macro, flower, bravo, butterfly, spring
	Topic 3	airplane, boeing, **aircraft**, airport, aviation, jet, aeroplane, cockpit
	. . .	. . .

IV. USER-SPECIFIC TOPIC MODELING

 The reconstructed user-tag-image ternary conjunction or combination, so the personalized image search is to perform directly. When user submits a query, the rank of image is inversely proportional to the probability ofannotating with tag q. However in practice, the queries and tags do not follow one-to-one relationship query usually corresponds the tag vocabulary is to several related tag . In any case, the query-tag correspondence differs from user or owner to user or owner. Hence, we build topic spaces for each user to exploit this user- specific one-to-many relationship. We investigate on a
Flickr dataset of 270-K images that the average number of annotated images per user is only 30.From the user-specific topics, we can see:
• user's interest profile, e.g., user is likely to be a art who also likes flowers, natural and butterfly, while user is keen at religion and interests in gardening and blossoms;
• the same tag may have different topic posterior distributions for different users, e.g., for user , "aircraft" occurs frequently in a military-related topic, while for user ,"aircraft" returns to its literal sense of air vehicle.

V. EXPERIMENTS

In the research community of personalized search, is not an easy task since relevancy judgment can only be evaluated by the users or the searchers themselves. The most   accepted approach is user study , where participants are asked to judge the search results. Obviously this approach is so costly. In addition, a main 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   history. However, this needs a 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 is evaluate. User's social activities, such as rating as rate the image , tagging as tag the image or document to our friends and commenting as comment the image, indicate the user's interest and user preference in a specific
document. Nowadays, two types of such user feedback are utilized for personalized search evaluation. The annotations is used to be a first approach. The documents has tagged by user with tag will be considered relevant for the personalized query its behind the main assumptions. The other evaluation approach is proposed for personalized image search on Flickr, where the images marked *Favorite – based* by the user are treated as relevant when the queries issues. The two valuation approaches have their supplement for each other. We have to use both approaches in our experiments and list the results in the following. At the baseline we select two state of the art model.

• Topic-based: topic-based personalized search using folksonomy. • Preference-based: personalized image search by predicting user interests-based preference. Note that both methods follow the two-step scheme: the overall ranking is decided by separately computing query relevance and the user preference. In addition, we also compared the performances of the proposed model with variety of settings.
• TF-Tensor Factorization 0/1 LDA- Latent Dirichlet Allocation : Tensor Factorization without smoothness constraints, optimization under the *0/1 scheme*, using user-specific topic modeling.• MTF – Multicorrelation Tensor   Factorization   0/1   LDA   Latent   Dirichlet Allocation: Tensor factorization with multicorrelation smoothness constraints, optimization under the *0/1 scheme*, using user-specific topic modeling.• RMTF – Ranking Based Multicorrelation Tensor Factorization LDA - Latent Dirichlet Allocation, the proposed model:
annotations predictions by Ranking based tensor   factorization,   using   user-specific   topic modeling.
• RMTF: Directly using the RMTF-based predicted annotations   for   personalized   rank

Outperform   to the   non-personalized   scheme. Comparison between the two test scenarios of NUS-WIDE15 A10 30 and NUS-WIDE15 A100, the performances of personalized methods improve as the test users original annotations increase. This is reasonable as   these   methods utilize the social annotation resources and the more user feedback is available, the more accurate user preferences can be estimated. What is interesting is that the preference- based model and the proposed model are more sensitive to the amount of original annotations. The reason may be that and our methods extract topic spaces by explicitly exploiting the tagging data, while in the topic-based model , the topic space is predefined and the original annotation is just used to generate the topic vector. Focusing on either test scenario, the performance of the proposed RMTF/ LDA, even MTF 0/1 LDA, is superior than the baseline methods, which demonstrate   the   advantage   Of simultaneously considering query relevance and user preference over the separate schemes. Depending on one-to-one query- tag assumption, the performance of RMTF deteriorates dramatically without the user-specific topic modeling. Moreover, RMTF LDA outperforms MTF 0/1 LDA, showing the advantage of the proposed ranking scheme over the conventional 0/1scheme. Without smoothness priors, TF 0/1 fails to preserve the affinity structures and achieves inferior results. The metric of mMAP is utilized to evaluate the performance and the results . We have the following observations.

• The mMAP is relatively low compared with Annotation - based evaluation. This phenomenon reflects the problem of Favorite-based evaluation scheme: the *Favorite- based* images are considered relevant for   all the test queries. As   no   query information is involved, for those queries non- relevant with the topic of the *Favorite based* images, the AP tends to be low;
• Comparing between the two test scenarios, the average performance of NUS-WIDE15 F100 also improves overNUS-WIDE15 F10 30, but not as significant as in Annotation-based evaluation. One possible reason for the improvement is that those users having more *Favorite* marks are active users who are likely to also attend more interest groups and tag more images. While, the improvement is not so significant demonstrates that the Favorite based   evaluation scheme is less Sensitive to the amount of original annotations.
• Another obvious difference from the results of annotation based evaluation is that the performance of TF

0/1and MTF 0/1 LDA degrade dramatically. The mMAP ofTF 0/1 is even lower than the non-personalized method. Parable results due to the implicit prior knowledge provided by the original annotations. By utilizing the *Favorite based*   marks, a heterogeneous resource to eliminated the implicit priror for evaluation. Fig. 8 displays exemplary search results for the query "rose". The top six non-personalized results and the personalized results of User A and User B . We can also considering the query relevance   and   user information, to the proposed system (RMTF – Ranking based multi correlation tensor factorization) and (LDA- Latent Dirichlet Allocation) captures   the   user's preference under certain topics. As a result of mapping "art , flower etc" to Topic 2 of Table II, the top search results for user A mainly focus on blossom, butterfly etc. While, for user B, the above search results are basically military related, which coincides with user B preference. For the baseline method which is having the separate query relevance and user preference, sometimes its very hard to interpret the search results. For example, the 2nd image and 3rd images for user B in Fig. 8(a) are ranked as higher because user B has a major interest in   navy and butterfly. From   these images is having the little relation with natural. We note that for some general queries which search intents have clear, its tends to fail the personalized search. In Fig. 9 one of such examples, With "computer" having common understanding   to   the variant   users, incorporating user information will generate confusing search results. There are literatures are discussing the issue about when to perform personalization. Benefit of   personalization is   highly dependent on   the ambiguity of the user query. Since there is no conclusion to this problem, in this research we focus on the problem of how to perform personalization and discussion of   when to   perform personalization is beyond the scope of this research.

VI. CONCLUSION

 personalized search is challenging as well as significant. In this research we propose a novel framework to exploit the users social activities for personalized image search, such as annotations and the participation of interest groups. The   query relevancy   and   user   preference   are simultaneously integrated into the final rank list. Experiments on a large-scale Flickr data set show that the proposed framework greatly out performs well. In future, we will develop our current work along   with the four directions.

1) In this research, we only consider the simple case of one letter based queries. The actual construction of topic space provides a possible solution to handle the complex multiple letter-based queries. We will leave it for our future work.

2) During the user-specific topic modeling process, the obtained user specific topics represent the user's distribution on the topic space and can be considered as user's interest profile. Hence, this framework can be extended to any applications based on user's interest profiles.

3) For batch of new data (new users or new images), we   can   directly restart   the   RMTF- ranking multicorrelation tensor factorization and user-specific topic modeling process. While, for a small bulk of new data, designing the appropriate update rule is another future direction.

4) Utilizing large tensors brings challenges to the computation cost. We plan to turn to parallelization (e.g., parallel MATLAB) to speedup the RMTF converging the   process. Moreover, the distributed storing mechanism of parallelization will provide a convenient way to store very large matrices and further reduce the storage cost.

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