IMPROVING PERSONALIZED IMAGE RETRIEVAL FROM THE PHOTO SHARING SOCIAL NETWORKS

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Abstract--Data mining, or Knowledge discovery, is the process of digging through and analyzing enormous sets of data and then extracting the meaning of the data. Photo sharing websites helps in publishing or transferring user's digital_photos online, thus enabling the user to share them with others publicly or privately . This function is provided through both websites and applications that facilitate the upload and display of images. Nowadays, there has been an increase in the photo sharing websites which allows users not only to create, share, annotate and comment multimedia contents, but also provide useful information to improve media retrieval and management. But, most of the photo sharing websites used today, results in poor user experience (i.e.) when given a query, the searchers did not find any relevant results. To overcome this problem, a framework is proposed that contains the following three components 1) a ranking-based multicorrelation tensor factorization model (RMTF), 2) user-specific topic modeling,3)Latent Semantic Indexing. In this paper, a proposed framework is used to handle the complex multiple words-based queries and simultaneously considering the user and query relevance for personalized image search By using the above method, the image retrieved results in what the user's had expected.

Index terms – annotation, tensor factorization, data mining, multicorrelation, sparse**,** personalize.

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I. INTRODUCTION

Over the past few years, current web search engines have become the dominant tool for accessing information online. However, even today's most successful search engines struggle to provide high-quality search results: Approximately 50 percent of Web search sessions fail to find any relevant results for the searcher. This is due to two reasons: 1) queries are in general short and nonspecific; For example, the query "AM expansion" stands for both Ante Meridiem and Amplitude Modulation and 2)users may have different intentions for the same query e.g., searching for "jaguar" by a car fan has a completely different meaning from searching by an animal specialist. Since the social annotations require the users to create explicitly, many users may be reluctant to maintain such personal data[1]. Similar to the document terms, the synonymy and polysemy problem also exist in social annotations. It cannot be suitable for social data out of the firewall, typically with lower quality.

One solution to address these problems is *personalized search*, where user-specific information is considered to distinguish the exact intentions of the user queries and rerank the list results. 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 expansion" by an information retrieval student has a 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. Given the large and growing importance of search engines, personalized search has the potential to significantly improve searching experience. When searching the photos by submitting a query, a user may receive hundreds or thousands of returned results, e.g., 118,147 photos are returned by searching with "*Great Wall*". Obviously, users need a tool to assist them in getting access to interested photos more easily. Flickr encourages users to perform various activities such as sharing photos with tags, joining in interested groups, contacting other users with similar interest as friends, as well as expressing their preference on photos by adding favorite marks[1]. These social activities offer valuable information for solving personalized search problem. Typically, users are interested in more than one field, and the searcher may share different interests with different friends. The variety of users' implicit interests can be mined and encoded into the latent interest dimensions. Friends may contribute differently to searcher's preference prediction according to the submitted query and the interest distribution. For example, a friend distributed consistently with the searcher on the latent dimensions related to *Travel* and *Landscape* will contribute much to a query like '*Great Wall*'. Therefore, determining the relevant dimensions for a specific query is essential to accurately predict the searcher's preference on returned photos Personalized search serves as such a tool which rearranges the returned results based on the preference of the searcher.

The personalized search is decomposed into to steps: computing the non-personalized relevance score between the query and the document, and computing the personalized score by estimating the user's preference over the document. After that, a merge operation is conducted to generate a final ranked list. While this two-step scheme is extensively utilized, it suffers from two problems. 1) The interpretations less straight and not so convinced. The intuition of personalized search is to rank the returned documents by estimating the user's preference over documents under certain queries. Instead of directly analyzing the user-query-document correlation, the existing scheme approximates it by separately computing a query-document relevance score and a user-document relevance score. 2) How to determine the merge strategy is not trivial.

To investigate on user preference and perform user modeling, the popular social activity of tagging is considered. Currently, collaborative tagging systems become more and more popular and many social resource sites support tagging mechanism.

For example, bookmarks on Del.icio.us 3 may be tagged in terms of topics interesting to the user; in Flickr, users can upload and annotate their own photos. A fundamental assumption is that, *the users' tagging actions reflect their personal relevance judgment*. For example, if a user tagged "rose" to an image, it is probable that the user will consider this image as relevant if he/she issues "rose" as a query. Moreover, as queries and tags do not follow simple one-to-one relationship, a user-specific topic spaces is built to exploit the relations between queries and tag.

Query expansion refers to the modification to the original query according to the user information. It includes augmenting the query by other terms and changing the original weight of each query term. The first is a novel user interface and interaction model for obtaining high quality search context for a given query. Instead of guessing search context, it allows users or publishers to explicitly and conveniently define context. Search precision can be significantly improved by filtering tag search results by user's contacts or a larger social network that includes those contact's contacts. The Topic-Sensitive Page Rank scheme (TSPR) proposed can potentially provide different rankings for different queries.

II. PROPOSED SYSTEM

For the offline stage, three types of data including users, images and tags as well as their ternary interrelations and intra-relations are first collected. Then users annotation prediction is performed, Since the photo sharing websites utilize a different tagging mechanism that repetitive tags are not allowed for unique images, besides the common noisy problem, it has more severe sparsity problem than other social tagging systems.

To alleviate the sparsity and noisy problem, a novel method named *ranking-based multicorrelation tensor factorization* (RMTF)[8] is presented to better leverage the observed tagging data for users' annotation prediction. 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 tagging patterns and vocabularies, e.g., the tag "jaguar pictures" from an animal specialist should be related to "leopard", while a car fan will consider "jaguar" more related to "autos". To address the two problems, *user-specific topic modeling* is used to build the semantic topics for each user. The user's annotation for an image is viewed as *document*. The individual tag to the image is *word*. User's annotations for all the images constitute the *corpus*.

a)RMTF:

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 $O \subset U \times I \times T$ i.e., each triplet (u,i,t) € O means that user has annotated image with tag 't'. The ternary interrelations can then constitute a three dimensional tensor , which is defined as,

$$y_{u,i,t} = \begin{cases} 1, & if\ (u,i,t) \in O \\ 0, & Otherwise. \end{cases}$$

Photo sharing websites differentiate from other social tagging systems by its characteristic of self-tagging. The severe sparsity problem calls for external resources to enable information propagation. To serve the ranking based optimization scheme, a tag affinity graph is built[11]. The tag relevance are classified into semantic as well as context relevant. Based on the affinity value as well as the user topics images were ranked. The method used together with it is the 0/1 scheme while helps to represent the data in matrix format As this optimization scheme tries to fit to the numerical values of 1 and 0, it is referred as the 0/1 scheme. However, under the 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.

0	0	0	0
0	1	0	0
1	0	0	0
0	1	0	0
0	0	0	0

a)

?	+	-	-
-	+	?	-
-	-	+	+
-	-	-	-
?	?	-	-

b)

Fig 1 (a)0/1 scheme (b) Ranking Scheme

Firstly, the fact that user3 has not given any tag to image2 and image4 does not

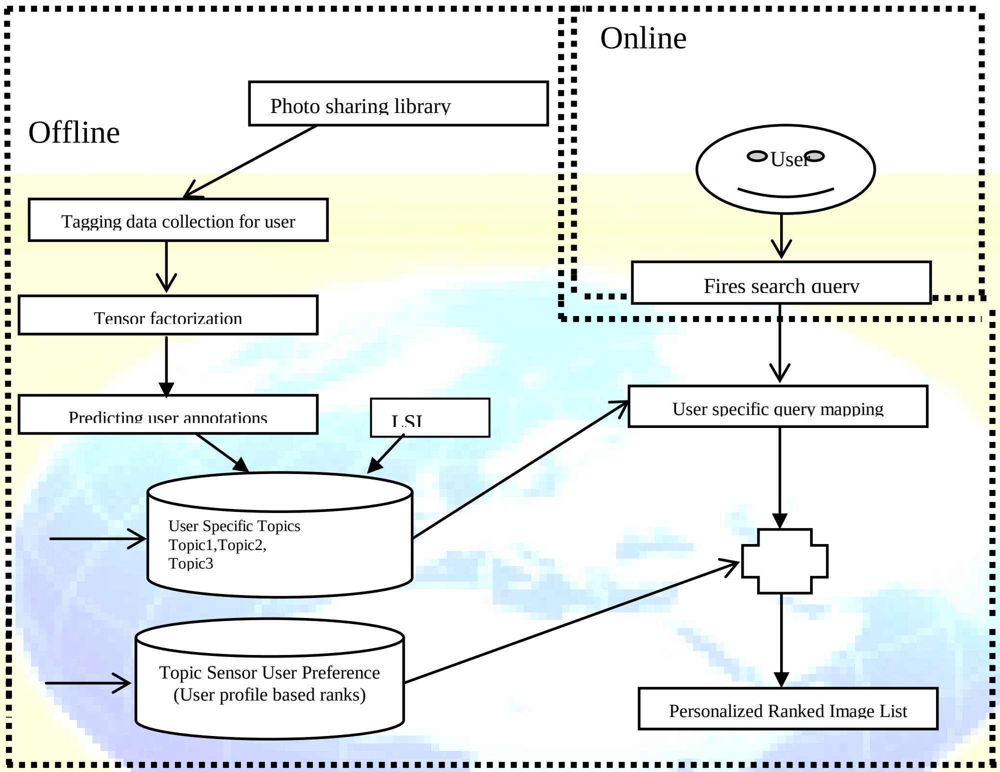

Fig 2 .Architectural Framework.

mean user3 considering all the tags are bad for describing the images. Maybe he/she does not want to tag the image or has no chance to see the image. Secondly, user1 annotates image1 with only tag3. It is also unreasonable to assume that other tags should not be annotated to the image, as some concepts may be missing the user-generated tags and individual user may not be familiar to all the relevant tags in the large tag vocabulary.

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 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. 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 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 Another evaluation approach is proposed for personalized image search on Flickr , where the images marked Favorite by the user are treated as relevant when issues queries.[4] By conducting experiments with various methods, the personalized search results in more specific results than non-personalized search and RMTF technique works better than other methods.

Firstly, the qualitative difference is important and fitting to the numerical values of 1 and 0 is unnecessary. Therefore, instead of solving an point-wise classification task, it is formulated as a ranking problem which uses tag pairs within each user-image combination (u,i) as the training data and optimizes for correct ranking. Each user image combination (u,i) is defined as a post. The set of observed posts is denoted as ,

$$P_O = \{(u,i,t) \mid \exists t \in T, y_{u,i,t} = 1\}$$

Secondly, for the training pair determination, The neutral triplets constitute a set M,

$$M = \{(u,i,t) \mid (u,i) \square P_O\}$$

The tags co-occurring frequently are likely to appear in the same image are called context-relevant . On the other hand, users will not bother to use all the relevant tags to describe the image[3]. The tags semantic-relevant with the observed tags are also the potential good descriptions for the image. To perform the idea, a tag affinity graph is built based on tag semantic and context intra-relations. The tags with the highest affinity values are considered semantic-relevant and context-relevant. Given a post (u,i)∈ P_O ,the positive tag set is found out as,

$$T_{u,i}^{+} = \{t \mid (u,i) \in P_O \square y_{u,i,t} = 1\}$$

The negative tag set is calculated by,

$$T^{-}{}_{u,i} = \left\{ t \middle| (u,i) \in P_O \square y_{u,i,t} \neq 1 \square t \square N_{T_{u,i}{}^{+}} \right\}$$

By using this in the above figure the minus sign indicate the negative triplets and the filtered triplets are indicated by question marks.

To serve the ranking based optimization scheme, the tag affinity graph based on the tag semantic relevance and context relevance is built. The context relevance of tag t_m and t_n is simply encoded by their weighted co-occurrence in the image collection,

$$t^{c}{}_{m,n} = \frac{n(t_m, t_n)}{n(t_m) + n(t_n)}$$

The semantic relevance of tag t_m and t_n are based on their WordNet distance,

$$t^{s}{}_{m,n} = \frac{2.IC(lcs(t_m, t_n))}{IC(t_m) + IC(t_n)}$$

where IC(.) is the information content of tag, and lcs(t_m, t_n) is their least common subsume in the WordNet taxonomy.

b)Latent Semantic Indexing:

Latent semantic indexing (LSI) is an indexing and retrieval method that uses a mathematical technique called singular value decomposition (SVD) to identify patterns in the relationships between the terms and concepts contained in an unstructured collection of text. LSI is based on the principle that words that are used in the same contexts tend to have similar meanings. A key feature of LSI is its ability to extract the conceptual content of a body of text by establishing associations between those terms that occur in similar contexts. LSI is also an application of correspondence analysis, a multivariate statistical technique developed by Jean-Paul Benzécri in the early 1970s, to a contingency table built from word counts in documents. It is Called Latent Semantic Indexing because of its ability to correlate semantically related terms that are latent in a collection of text, it was first applied to text at Bell Laboratories in the late 1980s[10]. The method, also called latent semantic analysis (LSA), uncovers the underlying latent semantic structure in the usage of words in a body of text and how it can be used to extract the meaning of the text in response to user queries, commonly referred to as concept searches. Queries, or concept searches, against a set of documents that have undergone LSI will return results that are conceptually similar in meaning to the search criteria even if the results don't share a specific word or words with the search criteria. LSI overcomes two of the most problematic constraints of Boolean keyword queries: multiple words that have similar meanings (synonymy) and words that have more than one meaning (polysemy). Synonymy is often the cause of mismatches in the vocabulary used by the authors of documents and the users of information retrieval systems. As a result, Boolean or keyword queries often return irrelevant results and miss information that is relevant. LSI begins by constructing a term-document matrix, A, to identify the occurrences of the m unique terms within a collection of n documents. In a term-document matrix, each term is represented by a row, and each document is represented by a column, with each matrix cell, a_{ij}, initially representing the number of times the associated term appears in the indicated document, $\mathrm{tf_{ij}}$. This matrix is usually very large and very sparse.

Once a term-document matrix is constructed, local and global weighting functions can be applied to it to condition the data. The weighting functions transform each cell, a_{ij} of A, to be the product of a local term weight, l_{ij}, which describes the relative frequency of a term in a document, and a global weight, g_i, which describes the relative frequency of the term within the entire collection of documents[8]. These LSI helps to predict the annotations of the multi word queries in the data collection.

c)User Specific Topic Modeling:

When user 'u' submits a query 'q' , the rank of image 'I' is inversely proportional to the probability of 'u' annotating 'i' with tag 'q'.

User A	Topic 1	Great Wall,Paper making,bronze dagger-axe
	Topic 2	The Secret Of Monkey Island, Grim Fandango, The Longest Journey

User B	Topic 1	Maruti Alto, Audi Q5, Maruti WagonR
	Topic 2	BBQ ribs, Pavlova, Som tam

Fig.3 Topic Spaces

Each user's annotations to all the images constitute one corpus, and Latent Dirichlet Allocation is chosen to perform topic modeling. The individual tag is viewed as word, while the user's annotation to one image corresponds to one document.

LDA assumes that in one corpus, documents are generated from a set of 'K' latent topics $\{topic_1,\ldots topic_K\}$ Document 't_i' is the tags assigned to image' i' by individual user. Each topic is characterized by its eight most probable tags. The rank of the user u-specific topics is decided by $p(topic_j|u)$,the probability that user 'u' is interested in topic ''j is found out as,

$$p(topic_j|u) = \frac{\sum_i^{|I|} p(topic_j|i,u)}{\sum_j^K \sum_i^{|I|} p(topic_j|i,u)}$$

The above things are done at the offline stage and in case of the online the user specific query mapping is estimated as,

$$p(topic_j|q,u) = \frac{p(topic_j|u).p(q|topic_j,u)}{p(q)}$$

$$\propto p(topic_j|u).p(q|topic_j,u)$$

j=1,….K

When user searches "aircraft plane", the images likely to be annotated by military-related tags are ranked higher according to While, when user searches "aircraft plane", the images likely to be annotated by aircraft-related tags will be ranked higher.

d)User Specific Query Mapping:

In here, when an user fires a query the query distribution over topics are found out by using a graph. The graph can be constructed by comparing the query given by the user with the user specific topics found out. Then the rank of the images were found out by comparing the query distribution over topics with the topic sensitive user preferences founded. This results in a personalized ranked list of the images.

III. Experimental Results

Experiments are performed on a large-scale web image dataset, NUS-WIDE . It contains 269 648 images with 5018 unique tags collected from Flickr. The images' are crawled with owner information and obtained owner user ID of 247 849images. The collected images belong to 50 120 unique users. A novel RMTF model is used for users' annotation prediction. In this subsection, the performance of RMTF is evaluated for annotation prediction. Following the evaluation process from ,for each user all triplet he/she has annotated for one image to constitute the test set$\mathbb{s}_{test}$ are randomly removed.The remaining observed user-image-tag triplets are used for regularized tensor factorization. Learn the model and predict top- lists for each of the removed posts$\mathbb{p}_{\mathbb{s}_{test}}$based on the reconstructed tensor $\hat{Y}$.The recall and precision of the top- recommended tags and report the F1 score of the average recall and precision are computed.

Precision(N)=

$$\frac{1}{|\mathbb{s}_{test}|}\sum_{(u,i)\in\mathbb{p}_{\mathbb{s}_{test}}}\frac{|Top(u,i,N)\cap\{t|(u,i,t)\in\mathbb{s}_{test}\}|}{N}$$

Recall(N)=

$$\frac{1}{|\mathbb{s}_{test}|}\sum_{(u,i)\in\mathbb{p}_{\mathbb{s}_{test}}}\frac{|Top(u,i,N)\cap\{t|(u,i,t)\in\mathbb{s}_{test}\}|}{\{t|(u,i,t)\in\mathbb{s}_{test}\}}$$

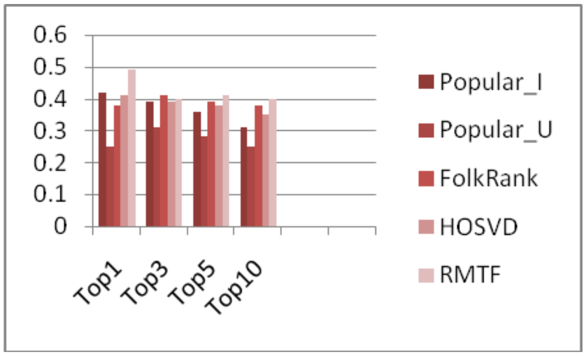

Fig 4. F1 score of annotation prediction for different methods.

Fig. 4 illustrates the results. It is shown that RMTF generally performs the best, and with the increasing number of recommended tags, the F1 score decreases less steeper for RMTF than the other methods. This coincides with the discussions in the introduction that the proposed ranking scheme as well as exploiting the tag semantic-and-context relevance better alleviates the severe sparsity and noisy problem for Flickr dataset.

IV. CONCLUSION

Personalized image search ,such as annotations and the participation of interest groups. The query relevance and user preference are simultaneously integrated into the final rank list. Experiments on a large-scale Flickr dataset show that the proposed framework greatly outperforms the baseline. How to effectively utilize the rich user metadata in the social sharing websites for personalized search is challenging as well as significant. Searching the images with these multiple word queries help us to retrieve data’s in more relevant manner.

References

[1] B. Smyth, "A community-based approach to personalizing web search," Computer, vol. 40, no. 8, 2007.

[2] D. Carmel, N. Zwerdling, I. Guy, S. Ofek-Koifman, N. Har'El, I.Ronen, E. Uziel, S. Yogev, and S. Chernov, "Personalized social search based on the user's social network," in *Proc. CIKM*, 2009.

[3] Y. Cai and Q. Li, "Personalized search by tag-based user profile and resource profile in collaborative tagging systems," in *Proc. CIKM*, 2010.

[4] D. Lu and Q. Li, "Personalized search on flickr based on searcher's preference prediction," in Proc. WWW, 2011, pp. 81–82, companion volume.

[5] S. Bao, G.-R. Xue, X.Wu, Y. Yu, B. Fei, and Z. Su, "Optimizing web search using social annotations," in *Proc. WWW*, 2007.

[6] M. J. Carman, M. Baillie, and F. Crestani, "Tag data and personalized information retrieval," in *Proc. SSM*, 2008.

[7] R. Jäschke, L. B. Marinho, A. Hotho, L. Schmidt-Thieme, and G. Stumme, "Tag recommendations in social bookmarking systems," *AICommun*., vol. 21, no. 4.

[8] J. Teevan, M. R. Morris, and S. Bush, "Discovering and using groups to improve personalized search," in *Proc. WSDM*, 2009.

[9] K. Lerman, A. Plangprasopchok, and C. Wong, "Personalizing image search results on flickr," J. CoRR, 2007.

[10] J. E. Pitkow, H. Schütze, T. A. Cass, R. Cooley, D. Turnbull, A. Edmonds, E. Adar, and T. M. Breuel, "Personalized search," Commun. ACM, vol. 45, no. 9, 2002.

[11] J.Sang, C.Xu,"Learn to Personalized Image Search From The Photo Sharing Websites",*Aug 2012*,vol 14.

[12] J. Teevan, S. T. Dumais, and D. J. Liebling, "To personalize or not to personalize: Modelingqueries with variation in user intent," in *Proc. SIGIR*, 2008.

BIBLIOGRAPHY

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