

Personalized Image Search Using Complex Multiple Words-Based Queries

Nishant Singh Chauhan
Galgotias University
Greater Noida, India.
chauhan.singh@live.com

Mr. S .Madhu
Galgotias University
Greater Noida, India.
smadhugu@gmail.com

Abstract—In today’s world internet produces a huge amount of data and to search content among this data keyword based search is commonly used among web users. To improve the search experience of the searchers the metadata can be used which is being generated by internet. Social networking and sharing websites like Facebook, Flickr and YouTube give features to users that allow them to share, create, tag, comment and annotate. This creates the user-generated metadata in a bulk amount which can be utilized for management and media retrieval. We consider the user preferences and returned the result list accordingly in Personalize Search to improve the web search experience. In this paper, we propose a model in which user and query relevance considered simultaneously to learn to personalized image search. This model is tested for complex multiple based query and it’s showing satisfactory results. In this crucial work is to insert the user preference and query-related search intent into user-specific topic spaces.

Keywords—Personalized image search; annotation; Ranking base multicorrelation tensor factorization; Metadata; User specific topic.

I. INTRODUCTION

Over a past few decades web search engines have played the main role in accessing the information available online. But still even today’s best search engine is not able to provide quality search results. Approximately 50% of the web search sessions fails to find any relevant results for searcher[3][4]. This all happens because of generally short and nonspecific queries. For example “HP” could be a petroleum company Hindustan Petroleum or a computer manufacturing company Hewlett Packard. Another reason may be that user may have different meaning for the same word. For example query for word “cricket” could be an insect or it could be a sports game played. Therefore to overcome this problem the solution is Personalize search. In Personalize search the information related to user is considered to predict exact intention of the user and then the result is ranked accordingly. Whereas in Non-personalized results are given directly without focusing on user assumptions.

The components of proposed framework:

1. A improved ranking-based multicorrelation tensor factorization model is proposed to perform annotation prediction, this is considered as user’s potential annotations for images;
2. User-specific topic modelling is introduced, which map query relevance and user preference into same user-specific topic space. Two resources involved with user’s social activities are employed for evaluating better performance.

Problem of missing and noisy tags may occur in a large scale web dataset, which in turn may restrict the working of social systems which are based on tag retrieval system. Therefore to solve this problem refinement of tag to make it free from noise and enrich it for images is necessary. Earlier

existing methods for tag refinement mainly focus on either on images and tag or images and user but not on all the three entities together. As discussed above, user creates the tagging activity and this user interaction with tagging gives remarkable results.

We sincerely consider that the integration of user information adds to a superior understanding and explanation of the tagging data. Let’s consider the following examples to understand this observation. In Figure. 1 User A has tagged the image of Taj Mahal monument as Taj and another User B has tagged hotel Taj as Taj. Second picture in the same figure shows a aero plane, in which the tagging done by an engineer is aircraft and a businessman tags as aero plane. Our main motive is to improve the original relations between the images and tags which is supported with unprocessed tagging data on web.

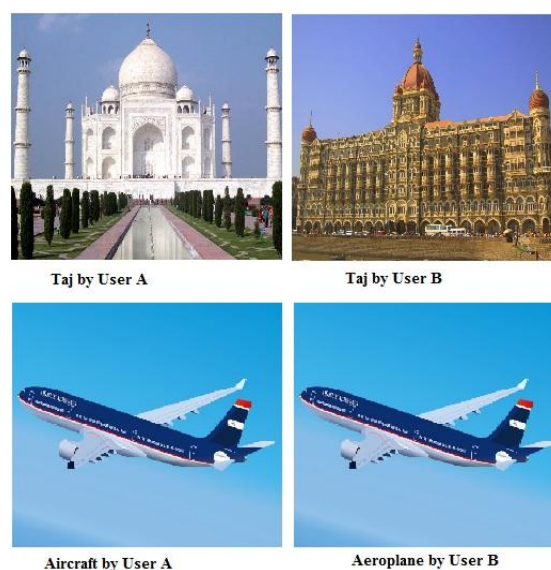


Figure1.

This module is expanded to find out complex multiple word-based queries result with the modified ranking tensor factorization model.

II. LITERATURE REVIEW

We have first surveyed some previous work on personalize search in this section. After that we have examined and discussed the limitation of these works in terms of the user interest and user profiling that is relevance measurement and improving results.

1. Personalized Image Search

To personalize the image search is a challenging task because images contains very less text that can be used to explain them. In an example, where user is seeking for the photos of “jaguar”. Now what should system return picture of wild animal or images of luxurious cars? To sort out such ceases, personalization helps to remove uncertainty from the keywords used in image search or to remove irrelevant images from search results. Hence, if the given user is concerned in nature, the system will show the images of the predatory cat of South America and not of an automobile [2].

With the help of user generated metadata and query expansion personalize system helps to weed out irrelevant result.

Personalization techniques traditionally falls in one of two categories: collaborative-filtering or profile based. The first thing that in collaborative filtering [15] is that it recommends new items to user of similar class by aggregating opinions of many users. This all can be done by asking users to rate items on a universal scale, and designing such rating system is itself challenging task

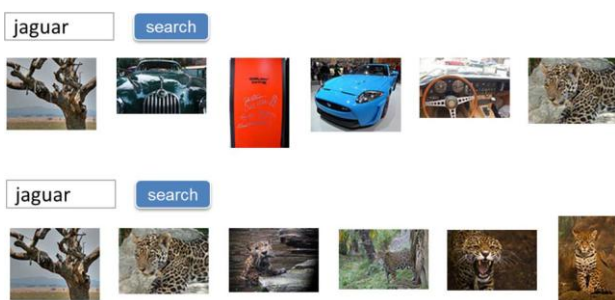


Figure 2. Examples for (Top) Non-personalize search and (Bottom) Personalized search result for the query “jaguar”.

and process to bring out high quality ratings from users are equally important. In spite of this there is no assurance that users getting higher returns for making suggestions is less and therefore will be hesitant to make the extra effort[14].

Personalization systems for second class uses individual user’s interest profile. There are some problems associated with this approach, one problem is that it would be very time consuming for every user to maintain their explicit profiles current and second problem is that this approach use the personal information of the users and no one wants to share that information which makes it difficult to access for researchers[15]. Where as in most cases these data mining methods have proven commercially successful and helpful.

One of the important resource of metadata are tags, user can easily understand and identify the data with the help of these tags as they are user defined keywords. Many challenges got arise in these tagging systems when user try to attach semantics to objects though keywords [8][12]. These challenges can be elaborated as a single tag has multiple related meanings, multiple tags have same meaning and the same tag may have different meaning. There are many methods used by many social websites one of them is that they display images in the result based on their “interestingness,” having the most “interesting” images on the top [14]. The information contained in user-generated metadata, especially the tags are fully utilized by machine learning-based method, which in turn shows the result for personalize search for given user. But this method also fail if user has not shown any interest in that domain in past [13]. Personalize search is divided into two steps as almost all the existing work uses this scheme: the non-personalize relevance score is computed between the document and the query and personalized is calculated by estimating the user’s preference over the document. After that merging these two scores a final ranked list of images is produced [5] [12].

While using this two-step scheme some problems arises. i) The explaining way is not realistic and straight. The main purpose of personalize search is by estimating the users preference over documents, rank the returned documents for certain queries. Individually by computing a user-document relevance score and a query-document relevance score all present schemes estimates user-query-document correlation, however it could be done at once by just finding user-query-document correlation.

ii) How merging operation is to be done this question is not of great importance [11]. Since the searcher themselves judge the appropriate matter in hand therefore in personalize search, verification is not an easy task. User study is the most popular and usual method in which various participants judge the result coming from various searches. But this way of finding result is very expensive as it requires a lot of research and even the results are unfair as the participant knows that they are being tested. There is an additional way by click through history or user query logs,

but it requires really massive and scalable real search logs, which is not easily available for the researchers [10].

Every one wants to keep their personnel information confidential because of the privacy issues therefore they don't share their profiles, which makes updating these profiles difficult. As personalize system require user data this becomes a problem. To overcome this problem social media plays an important role, here user uploads a picture, mark some object as favorite and write blogs. From this we get the required user generated data without interfering the user's privacy [9].

2. Problem Identification

World Wide Web contains a large number of photo sharing websites having large image collections available online, such as Zoomr, Picasa, Flickr and Pintrest4. To form a communication channel in a social media these websites assign their users as the owner, tagger, and commenter for their all contributed images which in turn work together and they are able to relate with each other [9] [8].

Since this web contain a huge amount of dataset, missing of tags and noisy tags are unavoidable, due to which the performance of social tag-based retrieval system is limited [7] [6] [5]. To solve this problem refinement of tags noise removal from tags and enriching them for images is necessary. The more efforts are being done on tag refinement to tackle with missing and noisy tags issues, while the most important source of user study that is the data of user's communication in social tagging is neglected [8]. In this paper the solution is provided by doing personalize search by considering the user's query online and by analyzing the user's information offline simultaneously. User annotation to the image is predicted by using ranking based tensor factorization model system.

III. PROPOSED FRAMEWORK

There are two stages in the framework of this paper: Online stage and offline personalize search stage as shown in Fig.3. The basic idea is to embed the user preference and query-related search intent into user-specific topic spaces. Since for topic modeling the user's original explanation is scattered, therefore we need to improve quality of explanation pool giving user's notes before user-specific topic spaces construction.

Components of framework:

1. To perform the basic search as per by predicting user's interest related with the query, considering it as the main annotations for the images, a ranking-based multi correlation model is proposed.

2. To map the user preference and query relevance into the same user-specific topic space a user-specific topic modeling is done.

According to the calculated user's choices, considering the query and user information at the same time, the images are ranked finally. With the three tier architecture the projected system is implemented. The first tier is client site where user submits query, then in second tier at server site searching is done and then in third tier contains remote database site where results are stored. This framework is also tested for complex multiple word-based queries.

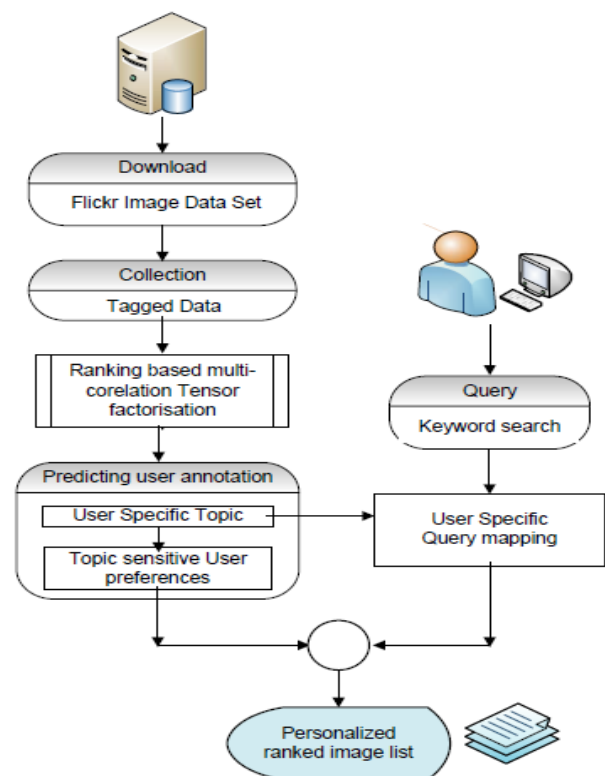


Figure.3. Three tier architecture system[1].

A. Ranking Based Multi-correlation Tensor Factorization (RMTF)

There are three types of entities of entities considered in all photo sharing social websites for tagging data. We can view this classified data as a set of triplets, in which let U be the set of users, I be the set of images and T the set of tags and the set of observed tagging is denoted by O, i.e., each triplet (U,I,T) ∈ O means that user has annotated image with tag. The ternary interrelations can then constitute a three dimensional tensor, which is defined as

$$Y_{u,i,t} = 1, \text{ if } (u,i,t) \in O \quad (1)$$

$$0, \text{ otherwise}$$

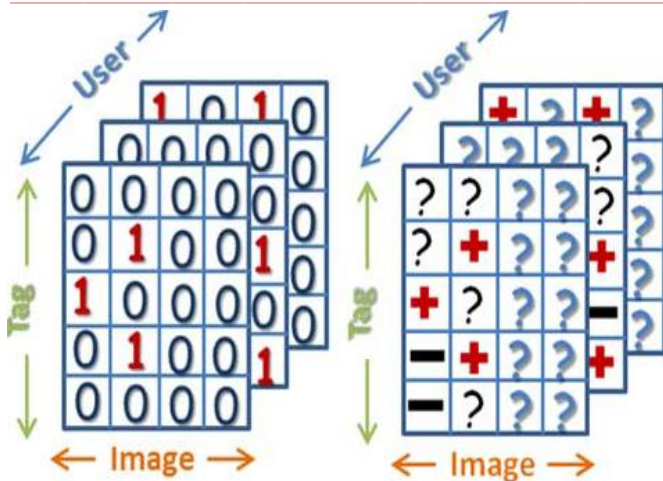


Figure.4. Tagging data interpretation (a) 0/1 scheme (b) Ranking Scheme

A three dimensional matrixes constructed for individual user is called tensor and initially it is created for individual user per image. If a user gives a tag to the image 1s entered into the matrix otherwise 0. We refer this as the 0/1 scheme since this optimization scheme uses 1 and 0 numerical values. All observed data is given value 1 and unobserved data as value 0. There is a problem associated with it, that is if a user doesn't give a tag to an image it assigns a value 0 to it but it doesn't mean that if a user is not giving tag to an image then the user doesn't like the image. Maybe that user does not want to tag that image or has no chance to see that image As some concept may be missing in 0/1 scheme, therefore to address this problem ranking optimization scheme is used as it considers user tagging behavior.

Every user image combination is defined as post, on each of this post ranking scheme is performed and a positive tag set and negative tag set is constructed in post (u,i). These sets form training pairs and we have considered that all positive tag sets give better description of images than negative tag set. There is a possibility that user generated tags may have some concept missing. All context relevant tags (tags that occur frequently) are supposed or likely to occur in the same image but user will not bother for all the relevant tags to express the image. The good description for image is possible by the tags which are semantic-relevant with noticed tags.

B. Constraint for Muticorrelation Smoothness

The average number of tagger for each image in Flickr is about 1.9, because 90% images in Flickr have not more than four taggers. In Del.icio.us have 6.1 average tagger for each web page. To enable information propagation information system considers the external resources because of limitations and multiple relations between users, images and tags are collected by the system. System also collect ternary interrelations among user-query-document. In learnt

factor subspaces we assume that two items with high affinities should be mapped closed to each other.

C. User Specific Topic Modeling

Personalized search can be directly performed once the remodeling of user-tag-image ternary interrelations are done: for a user's query, the rank of image is inversely proportional to the probability of annotating with tag.

D. Online Personalize Search

In an online personalize search first user-specific query mapping-estimate is performed after user submits a query which is the conditional probability that belongs to user-specific topics. A list of topics is generated from the user which is compared with user query and a prediction is made that user has interest in certain area to rank images accordingly.

IV. ALGORITHM

There are two sets of records in database, one set contains records of image and tags associated with the images given by the users and other set contains the description of images.

1. In the beginning a three dimensional matrix tensor is created containing user, image and tag.

$$Y_{u,i,t} = 1, \text{ if } (u,i,t) \in O$$

$$0, \text{ otherwise}$$

2. Then all the records from the database are retrieved and query is matched with all the records to find the relevance between them. All the tags present in dataset are compared with query word one by one. We have set threshold value in our system to 0.5. if value of comparison is 0.5 or more than that we take the value as 1 in a tensor otherwise 0 is taken.

If $\text{matchtopic} \geq 0.5$

then $\text{tensorvalue} = 1$ else 0

3. Now for multiple words query if query is "apple puma" we compare the first word of query with the first tag present in the database after that we compare it with second word of the query.
4. A graph is formed based on tags semantic and context intra-relations using all above information, which generates lists of topic for user.
5. After that a calculated matrix value is taken and placed in an array which contains images and values.

6. There may be multiple tags for the same images that could be relevant with the query and it may create duplicates. Therefore those duplicates need to be removed from the final list as many images may occur several times in the result.
7. With the help of sorted array images are arranged in an order from highest to lowest value of relevance.
8. Final sorted and personalized search result for complex multiple word-based query is generated.

V. EXPERIMENTAL RESULTS

The result based on user’s intent are shown by personalize search and are more accurate as compared to non-personalize search which contains many irrelevant images. For showing Personalize search in our experiment we have considered two users User A and User B who searches for word “Apple”. Now an “Apple” could be a fruit to a user or it could be a product from Apple Company. Let’s assume according to User A it’s a fruit therefore he tags Apple as a fruit and User B tags Apple as a product from Apple company. In the figure (i) It shows non-personalize search result for both the users it contains the picture of apple and apple company products like ipad and iphone. (ii) It shows the personalize search result and it have the picture of apple fruit for User A (iii) It shows the personalize search result for User B and shows the images oh iPhone.

Here we created a huge database containing the several images of apple, iphone, jaguar cat, jaguar car and with this we created two users profile. Now this whole system was tested for Personalize and Non-personalize search.

Now we have done some advancement in previous system and we took it to another level of searching.



Figure.5. Showing Non-personalize and personalize search for User A and User B

In our second experiment we tested our system for complex multiple word-based query and we got the desired results.

In this experiment User A tagged another image of a car named “Alto” as “Alto” and User B tagged a music instrument named “Alto” as “Alto”. After that multiple word query “Apple Alto” was given to system.



Figure.6. Showing Non-personalize and personalize search for User A and User B for complex multiple word-base query.

In above figure (i) First row shows the result for the non-personalize search for both the users and it shows the images of an Alto car, Alto music instrument, Apple fruit and Apple iphone. (ii) Second row shows the result for User A, as he has tagged “Alto” as a car and “Apple” as a fruit, therefore it shows the images of car and fruit. (iii) Third row shows the result for User B, as he has tagged “Alto” as a music instrument and “Apple” as an Iphone, therefore it shows the images of music instruments and Iphones.

It was observed that proposed framework gave the desired output and greatly performs the outline.

VI. CONCLUSION

In today’s world every searcher wants that the result returned for his query should be according to his intent (semantic) which a very challenging task is as web contains a lots of data and which accordingly generates a huge amount of metadata. This metadata is created by user itself in form of tag, like and post which they perform on social media sites. Now to utilize this user generated information in social sharing websites for personalized search is a challenging task is an important part of the framework. In our proposed framework we found that by utilizing user’s

social activities and user created metadata for personalized search has performed extremely well and shows satisfactory result. We have even extended our work to complex multiple word-based queries and got the same satisfactory and outperforming results. One of the important advantage of this multiple word search is user can save its time by simultaneously searching for two queries in one search operation.

Hence for future work (i) current work can be extended and embedded to any application based on searching according to user's intent. (ii) It may increase the computation cost while using large tensors therefore parallelization can be done by using different platform for this framework (e.g. parallel MATLAB).

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