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Image Tag Refinement with Ranking based Multicorrelation Tensor Factorization (RMTF) Model

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ABSTRACT
Web 2.0 has become principle tool for accessing information. With Photo sharing websites like Flickr, Picassa, Zoomr images uploaded by user and their tags are available. But Missing tags and Noise problems among image and tag make it difficult to retrieve relevant image based on user's preference. This requires tags refinement. We propose a model that utilizes Ranking based multicorrelation tensor factorization model for enriching tags pool. This model does it by constructing ternary relation between User, Image and Tag. RMTF does qualitative analysis on available tag set and find positive example and negative example by finding user, image tag interrelations. Tags are compared based on context relevance and semantic relevance. The proposed model finds better result than previous solutions. Given module is tested for multiple word query and shown attractive results.

Introduction

Popularity of web made information access and organizing easy for the user. With the help of web search engines it becomes easy to access any kind of information online. Web is generating enormous amount of data. Organizing such data is the biggest challenge. Its fact that today's most successful search engines struggle to find out specific search results. Same is the case with Photo sharing websites. Photo sharing websites are used to upload and access images and are very popular. Approximately 50 percent of Web search sessions fail to find any relevant results for the searcher. This happens due to reasons that queries are generally short and nonspecific. For example query "reva" could be name of some person or it could be First electric car of India. For query "tablet" what system should return medicine or tablet computer picture.

A solution to address this problem is to perform Personalize search. In personalize search information related with the user is learned in order to predict exact intention of the user.

Non personalized search returns results without considering user priorities. Personalized search results are returned based on both user query and liking of the given user and final ranking is done.

But then question is 'How to rank and order results?' Few researchers found solution on this problem by improving ranking through evaluating the significance or trustworthiness of a particular document. It is possible to assess its relative importance within the wider Web by studying a pattern of links in and out. Example is Google search engines PageRank algorithm which assigns higher score to a document if it is itself linked to by many other documents with a high page-rank score, and it iteratively evaluates the page-rank scores for every document in its index for use during results ranking. Other researchers began exploring alternative ranking options. One of the alternatives is used in the Direct Hit search engine. This technique states that results be supposed to be ranked by their popularity among searchers. This method isn't preferred one as the technology proved incompetent in recognizing new sites or less visited one [4].

We sincerely consider that the integration of user information adds to a superior understanding and explanation of the tagging data. Following simple examples explain this observation. In this figure one user has tagged image of apple fruit as apple and another user has tagged image of ipod as apple. Another pictures shows tagging by fans of football from different continent. One fan has tagged image as football and another fan has tagged the same image by soccer. The purpose of our work is to improve the original relations between the images and tags supported with the unprocessed tagging data available on photo sharing websites.

The implemented model contains three components:

1) A ranking-based multicorrelation tensor factorization model is proposed to perform annotation prediction. This is considered as users' potential annotations for the images;

2) We introduce user-specific topic modelling. This scheme is used to map the query relevance and user preference into the same user-specific topic space. For better evaluating performance, two resources involved with users' social activities are employed.

3) Given module is expanded to find out double word query results by combining distance vector algorithm used by Google with Ranking tensor factorization model.

Figure 1 Example of images their tags and taggers

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Literature Review

This section basically focuses on some existing work on Personalize Search done by research community. Later we look at and talk about the boundaries of these works in terms of the user profiling and user interest that is relevance measurement and improving results.

Personalized Image search

Personalize image search is challenging task to do specially with images as unlike documents here we don’t have free flowing text. Images contain very less text that can be used to explain them. Consider, for example, a user searching for photos of “jaguars.” What should the system return?, Images of luxury cars or wild animal picture? In such cases, personalization can help to find out actual intention of user by disambiguating query keywords used in image search and then to filter out irrelevant images from search results. Hence, if a given user is interested in nature, the system will show images of the voracious cat of South America and not of an automobile [13].

Through query expansion and user generated metadata personalization system help to weed out irrelevant result.

Traditionally, personalization techniques fall in one of two categories: collaborative-filtering or profile based. The first, collaborative filtering [11], aggregates opinions of many users to recommend new items to users of similar class. Since users are asked to rate items on a universal scale, designing such rating system is itself challenging task and how 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 [12].

The second class of personalization systems uses a profile of user's interests. One problem with this approach is that it is time-consuming for users to keep their explicit profiles current. Another problem is that while most of data mining methods have proven helpful and commercially successful, in most cases these data used contain personal information no one like to share and hence difficult to access to researchers [11].

Issues with Tagging

Tags are one of important resource of metadata. Tags are user defined keywords so that user can easily identify and understand the data. But tagging systems has many challenges that arise when users try to attach semantics to objects through keywords [8][9]. These challenges are the same tag may have different meanings, tag has multiple related meanings, and multiple tags have the same meaning.

One more method used by many social websites is that they display images by their “interestingness,” with the most “interesting” images on top [12].

A machine learning-based method exploits information contained in user-generated metadata, specifically tags, in order to perform personalize image search for given user and showing results for same. This method fails if user has not shown any interest in past in that domain [15].

Existing Scheme

Most of the existing work follow this scheme and decompose personalized search into two steps: computing the non-personalized relevance score between the query and the document, and personalized score is calculated by estimating the user’s preference over the document. Following this merge operation is done to produce a final ranked list of images [4][9].

While this two-step scheme is extensively utilized, it is subject to problems. 1) Way of explaining is less straight and not very realistic. The purpose of personalized search is to rank the returned documents by estimating the user’s preference over documents under certain queries. All present scheme estimates user-query-document correlation by individually computing a query-document relevance score and a user-document relevance score, however this could be done at once to find user-query-document correlation. 2) Question of how to determine the merging operation is not trivial [14].

In Personalized search, verification is not an easy task since judgment of appropriate matter in hand can only be evaluated by the searchers themselves. The most usual and popular method is user study. In user study different participants are asked to judge the results coming from various searches. Apparently this way of finding the results requires lots of research and hence is very costly. And results are unfair as the participants know that they are being tested. An additional way is by user query logs or click through history, this requires really massive and scalable real search logs, which is not easily available for most of the researchers [10].

Personalization system requires user data. But people wanted to keep personnel information confidential because of the privacy issues hence not interested in sharing their profiles. Keeping these profiles updated is one more problem. In such case social media plays very important role. Users upload pictures, mark objects as favourite, and write blogs. From this it becomes possible to derive user interests without disrespecting user privacy [7].

Problem Identification

On the web, there are many photo sharing websites with large-scale image collections available online, such as Flickr, Picasa, Zooomr and Pinterest4. These websites on the web allow their users as owners, taggers, or commenter’s for their contributed images to work together and able to relate with each other in order to form channel of communication in a social media [7][8].

Because of large-scale web dataset, noisy and missing tags are inevitable, which limits the performance of social tag-based retrieval system [1][3][4]. Therefore, the tag refinement is necessary to remove noise and enrich tags for images to solve this problem. However more efforts are done on tag refinement to address the noisy and missing tags issues, while the user communication in the social tagging data is neglected which is one of the most important source of user study [8].

This paper proposes solution by doing personalize search by simultaneously considering online user query and offline it will analyze users information. Using ranking based tensor factorization model system predicts user annotation to the image.

Proposed Framework

Following figure contains the structure of system implemented in this paper. This model contains two stages: offline stage and online stage where user is submitting query.

In this scheme we are embedding user’s preference and query-related search intent into user-specific topic spaces. Since the users' original explanation for a given topic is too thin, correct topic modeling is difficult hence; we need to improve quality of users' notes giving explanation pool before user-specific topic spaces construction.

The framework will contain following components:

1. Presenting user related information into the form of social tagging and processing it to mutually modeling numerous factors of user, image and tag by using three order tensor.
2. A ranking-based multi correlation model is proposed to perform basic search as per by predicting users’ interest related with the query, which is taken into account as users' main annotations for the images.

3. User-specific topic modeling to map the query relevance and user preference into the same user-specific topic space.
4. Extending it for searching multiple word queries.

Lastly, the images are ranked according to the calculated user's choices, which at the same time consider the query and user information as well. The anticipated system implemented as simple three tier architecture where first is client site, then server site and finally data site. At client site which acts as a frontend for user where user submits query, then searching is done at server site and then remote database site where results are stored.

Process contain component: RMTF (Ranking Based Multi-correlation Tensor Factorization)

In all photo sharing websites three types of entities are considered when comes to tagging data. These entities are user, Image and Tag. This classified data can be viewed as a set of triplets. Let U denote the set of users, I the set of images and T the sets of tags and the set of observed tagging data is denoted by O, i.e., each triplet (u,i,t) € O means that user has annotated image with tag.

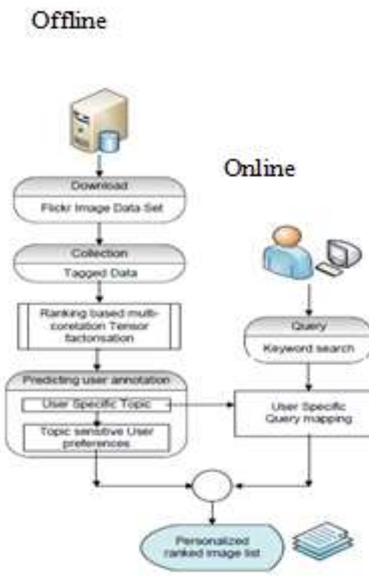

Figure 2. Work Flow Diagram

The ternary interrelations can then constitute a three dimensional tensor, which is defined as otherwise.

$$Y_{u,i,t} = \begin{cases} 1, & \text{if } (u,i,t) \in O \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Fig. 3(a) shows the tensor constructed from the design in Fig. 2.

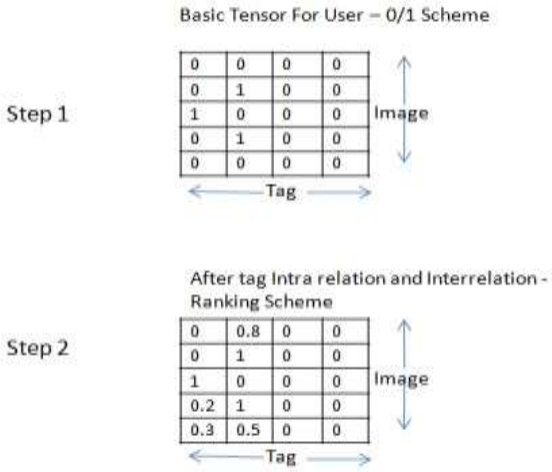

Figure 3. Interpretation of Tagging data

In simple words a tensor is three dimensional matrix formed for individual user. At initial stage it is created for individual user per image if the user has given tag then 1 is entered in matrix otherwise 0. As this optimization scheme tries to fit to the numerical values of 1 and 0, we refer it as the 0/1 scheme. All unobserved data is treated as 0. But 0/1 scheme has problem that firstly, the fact that some user has not given any tag to certain images that does not mean that user is considering all the tags are bad for describing the images. Maybe that user does not want to tag the image or has no chance to see the image. Secondly, let user annotates image with only tag3. It is again irrational to assume that other tags should not be annotated to the image, as some concepts may be missing in 0/1 scheme. To address this problem ranking optimization scheme is presented. This scheme considers user tagging behavior.

Steps are as follows:

1. Basic tensor is formed offline for individual user is shown in step1 of figure 3.
2. Each user-image combination (u,i) is defined as post. If user is tagging for certain image 1 will be stored in matrix.
3. Ranking optimization scheme is performed over each post and within each post (u,i) a positive tag set T^{+}u,i and negative tag set T^{-}u,i are constructed. These sets form training pair. Here we have considered that all positive tag sets give better description of images than negative tag set as all tags cannot be relevant at one point. In Ranking optimization scheme first users tags for a set of image are taken into consideration. In our model we kept threshold of 0.4 for an objective function. So all tags having values more than 0.4 for specific image will be considered as positive tag set and values below will be considered as negative tag set.
4. Since we have very limited information about images system has to consider external resources to enable information propagation. System collects multiple intra relations among the users, images and tags.

System contains many images, if given user is not tagging for certain image then it does not mean that given image is irrelevant. We call it as Multicorrelation smoothness constraint. We assume that two items with high affinities should be mapped close to each other in the learnt factor subspaces.

5. Hence this scheme considers all the tags available in the database given by other users and compares' those tags with user tags. We call it finding interrelation and intrarelation amongst tags.
8. All the context relevance tags that is tags those are frequently co-occurring in same context and semantic relevance tags are found out with the help of WordNet.

Semantic relevance between two tags is based on their WordNet distance. WordNet is a lexical database which is available online, and provides a warehouse of English lexical items. WordNet was designed to establish the connections between four types of Parts of Speech (POS) - noun, verb, adjective, and adverb. More the score means higher is the similarity between two tags. These graphs are used to impose the smoothness constraint and to reconstruct the tensor.

It may also happen that some concepts may be missing in the user-generated tags. We assume that all context relevant tags (the tags that occurring frequently) are likely to appear in the same image. On the other hand, users will not bother to use all the relevant tags to express the image. The tags which are semantic-relevant with the noticed tags are also the possible good descriptions for the image.

6. Taking this intra relation affinity graphs are created. Tag affinity graph is based on tag semantic and context intra-

relations. The tags with the -highest affinity values are considered semantic-relevant and context-relevant. We only keep the unobserved tags semantic-irrelevant and context-irrelevant to any of the observed tags, to form the negative tag set. These graphs are used to impose the smoothness constraint and to reconstruct the tensor. It is shown in step 2 of figure 3.

Figure 4 shows sample Tag Affinity Graph. Each vertex in graph is Tag. In our model we kept threshold as 0.4. Hence if in any two tags semantic is more than 0.4 then they are connected which is shown by arrow.

Parsing this graph gives list of topics for a given user.

For example if user has tagged three images earlier with tags Apple, Jaguar. All other images with the related tags based on WordNet distance are found out by the system and topics are generated.

Topic 1: Apple, Fruit, Juice, Vitamin.

Topic 2: Jaguar , cat, leopard, wild.

Examining above topics we can easily predict users interest.

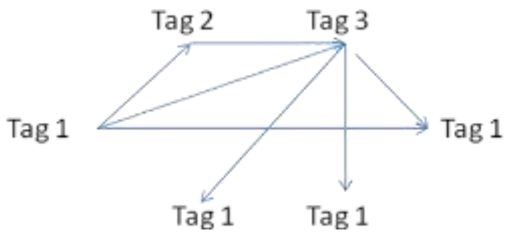

Figure 4. Tag affinity graph

7. Once the remodeling of user-tag-image ternary interrelations are done, we can directly perform the personalized image search: when user submits a query, the rank of image is inversely proportional to the probability of annotating with tag q. This stage is called as User Specific Topic Modeling.

8. In the online stage, when user submits a query, we first perform user-specific query mapping—estimate the conditional probability that belongs to user-specific topics. User query is compared with list of topics generated from the user and prediction made that user has interest in certain area. After that images are ranked accordingly. This stage is called as Online Personalize Search.

Experimental Results

In our experiment we had created dataset containing hundred images of Jaguar car and Jaguar animal for query Jaguar. Two users had tagged the image and Search operation is performed for both Personalize search and non personalize search. It is found that non Personalize search contains many irrelevant images. Personalize search results are based on user search intent and hence more accurate. Following chart shows the result for both type of search and comparison.

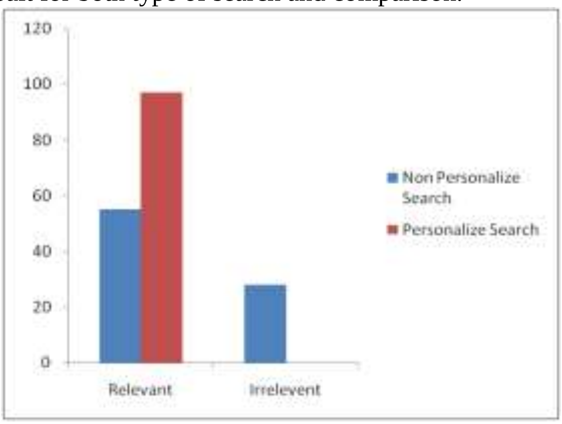

Figure 5. Chart showing result for query "jaguar"

We come across single words with two meanings as in case of word "jaguar", it may also happen with double words. In the testing we found that our system is capable to find relevant results in that case. For this we have taken example of images related to famous brand "mother care" and word "mother care". The prior will show the images of baby products to the user if the user has tagged to it and later will show the images of mother and baby.

Search results for the double word query Mother Care are shown in figure 6 that shows non personalize search containing pictures of mother and daughter as well as product of the brand Mother Care. In result of personalize search has shown where user has explicitly shown interest by tagging on products of brand Mother Care.

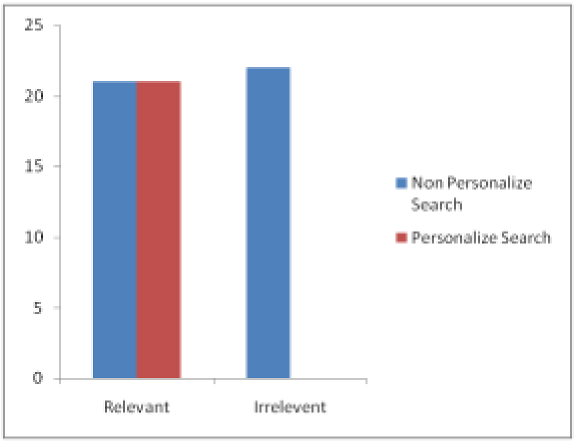

Figure 6. Chart showing result for query "mother care"

It is seen that the proposed framework greatly outperforms the baseline.

Conclusion

In today's fast world user wants accurate results. Getting accurate search results is challenging task as web contains lots of data. Large quality of metadata generated by web is in the form of tag and posts on social networking site, groups to which they submit images. Proficiently utilizing this rich user information is not easy task but equally important to merit attention. In this paper we have found that proposed framework to exploit the users' social activities for personalized image search is outperforming and showing good results. Also the framework extended to work for double word query, tested and is showing desirable results.

During user specific topic modeling process the obtained user specific topic spaces can be used to generate user's interest report. Hence in future current work can be extended to any application based on interest profiles. Large developed tensor brings challenges in terms of number of comparisons done and hence to the cost of computation. We can plan to use parallelization which will offer suitable method to store very large matrices and helps in additional cut in the storage cost.

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