

Personalized Tag Recommendation Using Social Contacts

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ABSTRACT

Tag recommendation encourages users to add more tags in bridging the semantic gap between human concept and the features of media object, which provides a feasible solution for content-based multimedia information retrieval. We study personalized tag recommendation within a popular online photo sharing site - Flickr. Contact relationship information of Flickr users is collected to generate an online social network. From the perspective of network topology, we propose node topological potential to characterize its ability of affecting other nodes. With the topological potential metric of the users in contacts network, we can distinguish different social relations between users and find out those who really have influence to the target users. On these social contacts, we acquire the implicit personalized information. Tag recommendations are based on user's tagging history and the latent personalized preference learned from social contacts. We evaluate our system on large scale real-world data crawled from Flickr. The experimental results demonstrated that our algorithm can significantly outperform the non-personalized global tag co-occurrence method. We also analyze the further usage of our approach for the cold-start problem of tag recommendation.

Author Keywords

Recommendation System, Social Tagging, Personalization, Social Networks, Flickr

ACM Classification Keywords

H.3.3 Information Search and Retrieval: information filtering

INTRODUCTION

Social tagging has been enjoying a great deal of success in recent years. These tags provide meaningful descriptors of the objects, and allow the user to organize and index her content. This becomes even more important, when dealing with multimedia objects that provide little or no textual context, such as bookmarks, photos and videos [8].

The availability of rich media annotations is essential for large-scale retrieval systems to work in practice. The current state-of-the-art in content-based image retrieval is progressing, but has not yet succeeded in bridging the semantic gap between human concepts, e.g., keyword-based queries, and low-level visual features that are extracted from the images [2]. However, the success of Flickr proves that users are willing to provide this semantic context through manual annotations. Recent user studies on this topic reveal that users do annotate their photos with the motivation to make them better accessible to the general public [1]. Photo annotations provided by the user reflect the personal perspective and context that is important to the photo owner and her audience. This implies that if the same photo would be annotated by another user it is possible that a different description is produced. In Flickr, you can find many photos on the same subject from many different users, which are consequentially described by a wide variety of tags.

While social tagging have many benefits, they also present some challenges. Unsupervised tagging integral to the open nature of Folksonomy, results in a wide variety of tags that can be redundant, ambiguous or entirely idiosyncratic. Tag redundancy, in which several tags have the same meaning, can obfuscate the similarity among resources [5]. Redundant tags can hinder algorithms that depend on identifying similarities between resources. On the other hand, recent studies reveal that in the case of the Flickr photo sharing system, most of the time users add very few tags or even none at all., at least 20% of public photos have no tag at all and cases with 1-3 tags constitute 64% of the cases with any tags [8]. One of the reasons for this seems to be that users are often reluctant to enter many useful tags or indeed any at all. Tagging an object takes considerably more time than just selecting it for upload. Also note that any particular image is only tagged by a single user (the owner). This has to be contrasted with the setting for social bookmarking services such as del.icio.us, where a single object (a website) can be tagged by multiple users. Only in this case can standard collaborative filtering techniques be applied [6].

Tag recommendation can deal with these challenges by suggesting a set of tags that users are likely to use for a media resources. The motivation of tag recommendation is twofold [10]. From the system point of view, it aims at expanding the set of tags annotating a resource, thus enriches the content information of resources. At the same time, through tag suggestion, what tag the user choose to some extent will be constrained to the candidate tag list. Tag redundancy will

apparently decrease. From the user point of view, like all other recommendation systems, the target is to improve the experience of the user in her tagging process. Personalized tag recommendations which take a user's preference into account when making suggestion usually have better performance compared with general tag recommenders. In short, the goal of a personalized tag recommendation is to predict tags for each user specifically and effectively, give a tagging object [3].

We study personalized tag recommendation within a popular online photo sharing site - Flickr. Based on the analysis of user tagging motivations, tagging contents and tagging behaviors in Flickr, we investigate and implement the tag suggestion using global tag co-occurrence, and find that the global algorithm lacks the ability for personalized recommendation. In later work we will use this recommendation as a baseline for measuring the effectiveness of our personalized recommender.

One way to address personalization issue is using social network, but how to use it? In Flickr, the user can interact with others through contacts, who then can be further identified to be their friends, family members, fans etc. In this paper we propose a personalized tag recommendation algorithm which aggregates user tagging history and her social contacts. In our approach the focus on the user personalized information mining is central; therefore we make much more efforts to exploit the potential knowledge which exists in social network. A network of contacts is derived for the data we crawled using APIs from the Flickr website, based on the actual contacts information of the users. Inspired by the classic physics field theory, which depicted that in the physical world, objects interact with each other via physical field, for example the gravitation field. From the perspective of topology, we think that the locality of a node in contacts network reflects its position potential, named as topological potential, which characterizes its ability of affecting other nodes, and the result of other nodes interaction effect overlay. The potential field in contacts networks does not like other classic field owning Euclidean distance, so we replace Euclidean distance by hops between two nodes.

With the topological potential metric of the users in contacts network, we can distinguish different social relations between users; find out those who really have influence to the target users, which are the user communities with common preferences. As these communities are discovered, we acquire the potential personalized information of the user. Our personalized tag recommendation algorithm is on the foundation of global tag co-occurrence, combined with personal tagging history and potential personalized information. Our evaluation using the data set of Flickr with 300 users. All users received personalized tag recommendations for a Flickr image. We also compare our suggestion result with the global tag co-occurrence method. Our main contributions are (1) demonstrating that personalized recommendation combined with user contact network is effective (In our study we get a raise of the success ratio $S@3$ from 68% to 87% when compared with other non-personalized recom-

mendation); (2) presenting a novel measurement metric of users influence in social network for mining the implicit user personalized preference - finding the contacts who really affect the user (not only 1-hop contact).

The remainder of the paper is structured as follows. We start with discussing the related work in Section 2. In Section 3 we propose a novel measurement of user influence in online social network. In Section 4 we present our tag recommendation framework for extending photo annotations in Flickr. The setup of the experimental evaluation and the results of the experiment are presented in Section 5. Finally, in Section 6 we come to the conclusions and explore future directions.

RELATED WORK

Tag recommendation is an interesting and well defined research problems. There are three pieces of work, which are most closely related to our current work. Sigurbjörnsson and van Zwol proposed a method of tag recommendation using the collective knowledge of a large collection of Flickr photos [8]. Their approach used global tag co-occurrence to make recommendations for partially tagged photos. Their approach will be used as a baseline in our experimentation. Garg and Weber proposed a personalized approach to tag recommendation for Flickr photos [4]. They highlight the good performance of a hybrid method combining the personal and general contexts that gives improvement over either context alone. Adam Rae et al. [7] propose a personalized recommender system that aggregates and exploits the knowledge that exists at four different contextual layers in an extendable probabilistic framework. They suggest that the tagging behavior of a user's contacts poorly reflects that of the user, and so is unhelpful when making tag recommendations. The tagging behavior of contacts is harmful for making tag suggestions. In our work we present a novel measurement metric of influence in user's contact network to find the contacts who really affect the user (not only one hop contact). We combine their tagging behavior into our personalized tag recommendation method. Evaluation results demonstrate using social contacts can improve the performance of tag recommendation system.

MEASUREMENT OF USER INFLUENCE IN CONTACT NETWORK

In this section, we present a novel measurement to characterize the user influence in online social network. From the point of view of network topology, we propose that the locality of a node in contact network reflects its position potential, named as topological potential, which characterizes its ability of affecting other nodes, and vice versa.

From physical field to topological potential

From the classic concept of field introduced by M. Faraday in 1837, the field as an interpretation of non-contact interaction between particles in every different granularity, from atom to universe, had attained great success. In the physical world, objects interact with each other via physical field, such as gravitation field. According to the field theory in physics, the potential in a conservative field is a function of position, which is inversely proportional to the distance

and is directly proportional to the magnitude of the particles mass or charge. Inspired from the above physical idea, we introduce the theory of fields into the network topology structure to describe the relationship among the nodes being linked by edges and to reveal the general characteristic of the underlying importance distribution.

Given the network $G = (V, E)$, V is the set of nodes, E is the set of edges and $—E—=m$. For $\forall u \in G$, let $\varphi_v(u)$ be the potential at any point v produced by u . Then $\varphi_v(u)$ must meet all the following rules:

- (1) $\varphi_v(u)$ is a continuous, smooth, and finite function;
- (2) $\varphi_v(u)$ is isotropic in nature;
- (3) $\varphi_v(u)$ monotonically decreased in the distance $\|v - u\|$. When $\|v - u\|=0$, it reaches maximum, but does not go infinity, and when $\|v - u\| \rightarrow \infty$, $\varphi_v(u) \rightarrow 0$.

So the topological potential can be defined as the differential position of each node in the topology, that is to say, the potential of node in its position. This index reflects the ability of each node influenced by the other nodes in the network, and vice versa.

Gaussian-type definition of topological potential

As the modularity structure of real-world network implies that the interaction among nodes has local characteristic. Topological potential and its distribution focus on the structural localization conducted by node activity. Considering a node in network as a potential source, it can affect others along with paths connecting each other. Hence all of nodes in a network affect each other by their potential fields overlapping. Each node's influence will quickly decay as the topology distance increases. Hence, we tend to define the topological potential in the form of Gaussian function. The potential field in networks does not like other classic field owning Euclidean distance, so we replace Euclidean distance by jumps between two nodes.

Given a network $N = (V, E)$, where $V = \{v_1, v_2, \dots, v_n\}$ is the set of nodes, E is the set of edges. The potential of node $V_i \in V$ in the network can be defined as follow:

$$\varphi(v_i) = \frac{1}{n} \sum_{j=1}^n \varphi(j \rightarrow i) = \frac{1}{n} \sum_{j=1}^n \left(m_j \times e^{-\left(\frac{d_{j \rightarrow i}}{\sigma}\right)^2} \right) \quad (1)$$

where m_j is the mass of v_j , describing activity of the node, σ reflects the influence range. $d_{j \rightarrow i}$ is the shortest distance between node v_j and v_i . Other type definitions, such as reciprocal-type, inverse-square-type, and etc. have been studied and compared.

Optimizing the influence factor

In the definition of topological potential, the mass m_j , the shortest distance $d_{j \rightarrow i}$ and the influence factor σ are three

most important factors.

In order to minimize the uncertainty, Shannon entropy principle is used as Equation 4 to optimize the influence factor.

$$\min H = \frac{1}{\sigma} \left(- \sum_{i=1}^n \frac{\varphi(v_i)}{Z} \log\left(\frac{\varphi(v_i)}{Z}\right) \right) \quad (2)$$

We take no consideration of node mass, while optimizing the influence factor σ .

Ranking of user influence

Now we come back to the user contact network in Flickr. According to the definition of topological potential, each node in contact network affects all other nodes, are also subject to the combined effects of other nodes, meaning that user behavior on Flickr can affect other users on her contact network, but also at the same time be influence by other users.

In this paper, we use topological potential to measure the user influence, through the value of topological potential to reflect the level of user's influence to other users. The greater the topological potential value, the greater the influence of the user. For user's contacts, not necessarily all of them will have a significant impact on the target user, there are a lot of weak ties, and preferences of the user's interest is not very good coincidence. Therefore, based on potential value, we get the ranking of the user influence. Select some of the contacts with high rank in the ranking list to generate the user's preference community. In this community, close interaction between users, they have a common interest. Those who have real influence to the target user are all in the preference community, it is the base of our personalize recommendation.

There are two steps to rank user influence based on topological potential. First we have to choose the optimal influence factor, here we use the shannon entropy to get the optimized value of σ . Second, sort the user with topological potential value in descend order.

RECOMMENDATION FRAMEWORK

In this section we provide a detailed description of the personalized tag recommendation framework. We start with a general view of our research task, followed by an introduction of the non-personalized global tag co-occurrence recommendation strategy. Finally, we explain the personalized tag recommendation method that are used by our system and evaluated in the experiment.

Task

We study the problem of personalized tag suggestion. In this work, we describe algorithms which help to semi-automate the tagging process by suggesting relevant tags to the user, who can then choose to add them(by clicking) or ignore them (by adding different tags manually). More clearly, we propose a recommendation system for the following task:

Given the tagging object (a kind of online multimedia resource) and an initial (small or empty) set of tags. We use the identity of a user and her social contacts network, as well as tagging history of all user in the contact network, suggest a ranked list of related tags to the tagging object to the given user.

The task is independent of any particular application, but we only evaluated our algorithm in the context of Flickr. Under this context our task simplified to: Given a Flickr photo and a set of user-defined tags, the system has to recommend some tags that are good descriptors of the photo, at the same time the recommended tags reflect the user's personalized preference.

Tag co-occurrence

Concept co-occurrence in daily life contains useful information to measure their similarity in the semantic domain. The semantic about the concepts is related to human cognition. Since 80% of the human cognition is formed from the visual information in daily life, the occurrence of concepts in daily life contributes a lot to their semantics [9].

Tag co-occurrence is that there are two tags T_1 and T_2 which are used to annotate a resources at the same time, we called tag T_1 and tag T_2 co-occurrence one time. Tag co-occurrence on Flickr can partially capture the conceptual relationship in daily life. We assume that if two tags are frequently assigned to the same image, the corresponding concepts also have a high probability to co-occur in daily life. Since our task is to recommend some tags that are good descriptors of the photo, tag co-occurrence is the foundation of our tag recommendation approach, and only works reliable when a large quantity of supporting data is available. Obviously, the amount of user-generated content that is created by Flickr users, satisfies this demand and provides the collective knowledge base that is needed to make tag recommendation systems work in practise.

The calculation of the tag co-occurrence on Flickr has already been investigated by the recent work [8]. Here we adopt the similar method to calculate the tag co-occurrence over our data collection of 23 million images crawled from Flickr. This dataset is sufficiently large for generating the statistics about the tag co-occurrence. Using the raw tag co-occurrence for computing the quality of the relationship between two tags is not very meaningful, as these values do not take the frequency of the individual tags into account. Therefore it is common to normalize the co-occurrence count with the overall frequency of the tags. There are essentially two different normalization methods: symmetric jaccard coefficient and asymmetric conditional probability. The coefficient takes the number of intersections between the two tags t_i and t_j , divided by the union of the two tags. The Jaccard coefficient is known to be useful to measure the similarity between two objects or sets. The conditional probability captures how often the tag t_j co-occurs with tag t_i normalized by the total frequency of tag t_j . We can interpret this as the probability of a photo being annotated with tag t_i given the it was annotated with tag t_j .

Based on tag co-occurrence, for the given photo and user-defined tags, we calculate the tag co-occurrence coefficient for each of the user-defined tags and the global tag cloud. Then an ordered list of m is derived according to the value of co-occurrence coefficient. The lists of candidate tags are then used as input for tag aggregation and ranking, which ultimately produces the ranked list of n recommended tags. This method we called global tag co-occurrence.

Tagging history

For the purpose of sharing, managing and retrieval, Flickr users usually actively add some tags for pictures. Furthermore they often upload a group of pictures at a short period of time. For example, a user upload a group of photos of her tour to some place, or record a set of photos about an certain event. These images often contain the same content, with a high degree of close contact, the user often annotate these images with same tags. So what the tags used on the latest upload pictures can reflect these temporal link between these pictures, and these tags can be used for tag recommendation.

The tagging history a given user is made up of all instances of tags used on all the images that the user has uploaded. These sets vary between users, but consist solely of information relevant to that particular user. These sets tend to be far smaller and less comprehensive than that of the general tag cloud for global user, but better reflect a user's personal ontology of keywords. It is this user-specific nature of the tagging history that should allow it to make more relevant annotation recommendations to particular users. Based on tagging history, we calculate the tag co-occurrence coefficient for each of the user-defined tags and user's historical tags, especially the latest used tags. We can get the ranked list of recommended tags. This method we called personal tagging history.

Social contacts

Flickr user can maintain contacts with other users, who then can be further identified to be their friend, family member, or other type of contact. A user in Flickr can explicitly connect themselves to other users by giving them the label 'Contact'. These inter-personal connections form a social contact network between many of the users in the system.

As depicted in section 3, using topological potential, we characterize user influence and find those who have large impact to whom recommendations are being generated. These users are not only 1-hop contact, even including 2-hops contacts. By taking all the photos and tags from these contacts, we get the tag list of contacts, excluding the tags from the photos of the user themselves. These tags capture the vocabulary not of the user but of their social contact, possibly sharing attributes like language, geographical proximity and to some degree photographic interests, which are considered to be helpful in providing a more focused set of recommendations. Through tag co-occurrence for each of the user-defined tags and contact's tags. We also get the ranked list of recommended tags. This method we called social contact.

Aggregation methods

In our recommendation framework, we need two aggregation strategy, one is for the tag co-occurrence results of each user-defined tags, another is for the combination of candidate recommendation tag list comes from different method.

When the lists of candidate tags for each of the user-defined tags are known, a tag aggregation step is needed to merge the lists into a single ranking. Here we also adopt the similar aggregation method with [8]. We use two aggregation method: Vote and Sum.

Vote: Calculators the occurrences of tags in all the candidate list, ranking the tags according to the score of occurrences and select the final recommended results.

Sum: The summing strategy also takes the union of all candidate tag lists (T), and sums over the co-occurrence values of the tags.

We will evaluate these two aggregation strategies in our tag co-occurrence algorithm during the evaluation as is presented in Section 5.

For the case of combination of candidate recommendation tags comes from different approach, we used Borda Count method. The Borda Count is a single-winner election method in which voters rank candidates in order of preference. The Borda Count determines the winner of an election by giving each candidate a certain number of points corresponding to the position in which he or she is ranked by each voter. Once all votes have been counted the candidate with the most points is the winner. Because it sometimes elects broadly acceptable candidates, rather than those preferred by the majority, the Borda count is often described as a consensus-based electoral system, rather than a majoritarian one.

In our work we call the Borda Count method mentioned above a basic Borda Count. In basic Borda voting method each candidate is treated equally, but our proposed recommendation algorithm based on three different information are independent, and maybe the length of the recommended list are different. When we make the tag aggregation in the end, they weighed different proportion in the final recommended list. So when we conduct the Borda Count voting, we need to give different weight w to different candidate list.

EVALUATION

In this section, we will evaluate the performance of our personalized recommendation framework. We first define the experimental setup. Then we examine the performance of individual method in isolation. The performance of the combination of different method are shown at last part.

Evaluation setup

Our evaluation task is to recommend tags for a partial tagged photos in Flickr. We randomly select 300 users within the scope of 2-hop from the seed user in our data set. The selected user are all satisfy a condition that they should have 10 photos with at least 8 tags. For each user we choose 10 photo, finally we get 3000 photos as our evaluation photo

pool. Half of the tags in one photo are used as the training set, the other half as the test sets. Using this method, we get five different data set. The final performances result is the average of the five evaluation data.

For the evaluation of the task, we adopted three metrics, that capture the performance at different aspects:

Mean Reciprocal Rank (MRR) MRR measures where in the ranking the first relevant tag is returned by the system, averaged over all the photos. This measure provides insight in the ability of the system to return a relevant tag at the top of the ranking.

Success at rank k ($S@k$) We report the success at rank k for three values of k : $S@1$, $S@3$ and $S@5$. The success at rank k is defined as the probability of finding a good descriptive tag among the top k recommended tags.

Precision at rank k ($P@k$) We report the precision at rank 5 ($P@5$) and 10 ($P@10$). Precision at rank k is defined as the proportion of retrieved tags that is relevant, averaged over all photos.

Evaluation results

We start with evaluating the performance of our framework using different method in isolation and then evaluate the method in combination. We use the global tag co-occurrence method as baselines for these two stages of the evaluation.

Global tag co-occurrence

In this section we choose the symmetric jaccard coefficient and asymmetric conditional probability to calculate the tag co-occurrence coefficient. Furthermore we use the vote and sum aggregation strategy to produce different tag recommendation list. We compared four different experimental on our full data collection, the results are depict in Table 1. Here we only use three metric: MRR, $p@5$ and $S@5$.

As Table 1 shown, the symmetric jaccard coefficient with the sum aggregation strategy, success at rank 5 is 47%, precision at rank 5 is 36%; asymmetric conditional probability with the sum aggregation strategy, success at rank 5 is 52%, precision at rank 5 is 41%. Hence, for the same sum aggregation strategy, conditional probability outperforms jaccard coefficient in all metrics. Even for the vote aggregation strategy, we can get the same conclusion. Additionally, conditional probability with vote aggregation strategy, success at rank 5 is 45%, precision at rank 5 is 34%, only get a 1% compared with jaccard coefficient. So for the vote aggregation strategy, the performance of the symmetric jaccard coefficient and asymmetric conditional probability has no apparent difference. On the other hand, when choose the jaccard coefficient, sum outperform vote 3%, but for the conditional probability, the improvement reach 7%.

In summarize, we find on tag recommendation, the asymmetric conditional probability is better than the symmetric jaccard coefficient, sum do well than vote. In our later experiment, we use the asymmetric conditional probability to

Table 1. Comparison of different tag co-occurrence recommendation method on full data collection

Method	MRR	S@5	P@5
jaccard+vote	0.3561	0.4404	0.3306
jaccard+sum	0.3956	0.4751	0.3631
probo+vote	0.3717	0.4564	0.3423
probo+sum	0.4645	0.5261	0.4118

Table 2. Evaluation results for the individual recommendation method (we only use the top10 of the candidate list)

Method	MRR	S@1	S@3	P@5	P@10
PT	0.2483	0.3427	0.6313	0.2437	0.3864
PC	0.3221	0.6836	0.8368	0.4459	0.6033
SC	0.2731	0.4003	0.5359	0.2618	0.3632
CC	0.2658	0.4173	0.6899	0.3015	0.4575

calculate the tag co-occurrence coefficient, use the sum strategy to produce the recommendation tag list. This method is simplified labeled as CC. The performance of our global tag co-occurrence method on the evaluation data is presented in Table 2.

User tagging history

We evaluate two recommendation method on tagging history as we introduce in section 4. One is directly use the latest used 10 tags as the recommendation results, this method is simplified labeled as PT. The other is to calculate the tag co-occurrence coefficient of the user’s whole tag list used before, furthermore use the sum strategy to produce the recommendation tag list. This method is simplified labeled as PC. It is different from the global tag co-occurrence method, we only use the use’s personal tag information. Table 2 give the performance of two methods.

Table 2 shows the performance of tag co-occurrence on user tagging history outperform the global tag co-occurrence. The precision at rank 5 is 44.6%, even reach 60.3% at rank 10. The success at rank 1 is 68%, at rank 3 is 83.7%. The PC algorithm show excellent performance in personalized tag recommendation. Compared with PC, the performance of latest used tags (PT) is not so good. In our experiment, for the continuous upload photos which the tag used are almost the same, the PT method get a good performance.

User social contact

Using the topological potential, we get the ranking of user influence in social contact network. We choose the top N(here N=10) contacts to form a preference community, as another source of personalized information. We then calculate the tag co-occurrence coefficient of these contact’s personal tag list, use the sum strategy to produce the recommendation tag list. This method is simplified labeled as SC. Table 2 also give the performance of this method.

Table 2 shows that only using social contact, we can get some personalized tag recommendation, even though the precision and success is very low(about 60% of the PC method). This suggest that only use contact’s tags in recommendation

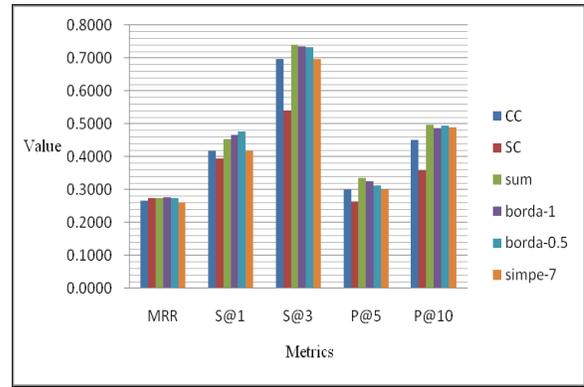


Figure 1. The aggregation results of global tag co-occurrence and social contact

is not enough, but it can be combined with other method to improve the personalization of recommendation list.

Combination performance

Combining different methods has been shown to be useful for tag recommendation. Figure 1 shows the results of combining global tag co-occurrence and social contact using different aggregation strategy. Here sum refer to the sum aggregation strategy; borda-1 is the basic Borda Count, the wight of global tag co-occurrence and social contact are equal; borda-0.5 represent the wight of social contact is half of global tag co-occurrence. Simple-7 use the first seven tags in global tag co-occurrence, other three selected from the highest ranked tags in social contact and not in the global tag co-occurrence.

Figure 1 shows the performance get improved when combine global tag co-occurrence and social contact. Especially, the sum aggregation strategy make the P@10 raised 4.5% for global tag co-occurrence and 14% for social contact. Furthermore the s@3 raised to 74%. Figure 2 shows the results of combine global tag co-occurrence with user history using different aggregation strategy. Figure 3 shows the results of combine social contact with user history using different aggregation strategy. Figure 2 and Figure 3 all show that when introducing user tagging history, the performance of combined method decrease in all metric, this suggest that the user history does not fit for direct combination. In order to merge all information in the final tag list, we combine global tag co-occurrence with social contact at first, then the user history is added at the second step. The aggregation results of all three method are presented in Figure 4. By combing all method together, we find that under the boada-1 strategy, S@3 reach 87.3%, which is the peak performance of our recommendation system. Compared with any other recommendation strategy, our system get a good performance, the details are shown in Table 3.

In summarize, on combination of different method, we find that we can first combine global tag co-occurrence with social contact using sum aggradation strategy. Then using basic Borda Count voting to combine the tag list of user history. A significant improvement of personalized tag recommenda-

Table 3. Evaluation results for the combination of three recommendation method using different aggregation strategy (we only use the top10 of the candidate list)

Mertrics	CC+SC	PC	Sum	borda-1	borda-0.5	simple-7
MRR	0.2734	0.3275	0.2883	0.3085	0.2886	0.2608
S@1	0.4527	0.7030	0.5233	0.6423	0.5813	0.4170
S@3	0.7397	0.8427	0.8087	0.8717	0.7977	0.6973
P@5	0.3351	0.4525	0.3925	0.4244	0.3633	0.2992
P@10	0.4972	0.6017	0.5645	0.6074	0.5830	0.4886

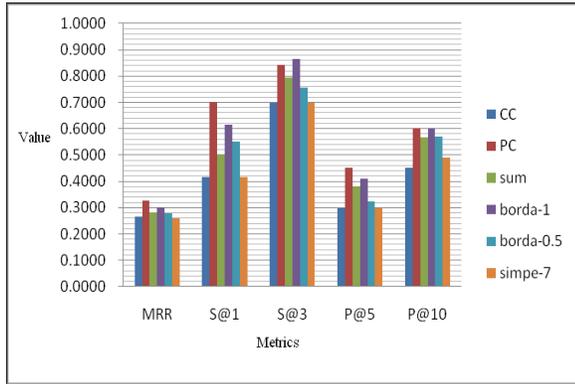


Figure 2. The aggregation results of global tag co-occurrence and user tagging history

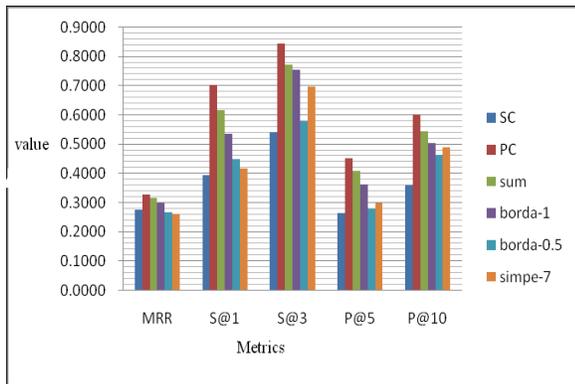


Figure 3. The aggregation results of global tag co-occurrence and user tagging history

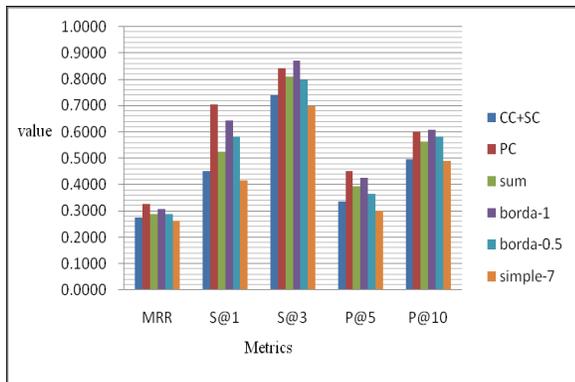


Figure 4. The aggregation results of global tag co-occurrence, social contact and user tagging history

tion performance will be achieved.

CONCLUSIONS

We have demonstrated how to measure user influence in an online social network. The social contacts data can be used to provide more personalized recommendations of tags for a user when annotating photos. We have further shown that by combining this potential personalized data with user tagging history and global tag co-occurrence, we can significantly improve the performance of our recommendation system. We have presented a framework of personalized tag recommendation in Flickr and shown how this can be evaluated with respect to established information retrieval performance measures. The framework can be extended with additional contexts (activity we hope to undertake in the future) to gain a better understanding of the relative usefulness of social contact network defined by different inter-user relationships.

The model we have presented has benefits for the cold start problem of tag recommendation. With the topological potential metric of the users in contacts network, we can distinguish different social relations between users; find out those who really have influence to the target users, which are the user communities with common preferences. For a new photo without any user-defined tags, we are able to make relevant recommendations only using the contact information from to perspective of network topology.

We are confident that through further exploration of rich social data available within online media sharing sites like Flickr, we can improve performance further still. We also think that learning weighings for the combination of our different strategy can be done on a more sophisticated, community level which could also increase our ability to make good tag recommendations – an area we will investigate in future.

ACKNOWLEDGEMENT

This work has been supported by the National Grand Fundamental Research 973 Program of China under Grant No. 2007CB310803, the National Natural Science Foundation of China under Grant No.61035004, No.60974086 and the Project (No.SKLSDE-2010ZX-16) of the State Key Laboratory of Software Development Environment.

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