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Personalized Tag Recommendation Using Social Influence

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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. In this paper, we study personalized tag recommendation in a popular online photo sharing site — Flickr. Social relationship information of users is collected to generate an online social network. From the perspective of network topology, we propose node topological potential to characterize user's social influence. With this metric, we distinguish different social relations between users and find out those who really have influence on the target users. Tag recommendations are based on tagging history and the latent personalized preference learned from those who have most influence in user's social network. We evaluate our method on large scale real-world data. The experimental results demonstrate that our method can outperform the non-personalized global co-occurrence method and other two state-of-the-art personalized approaches using social networks. We also analyze the further usage of our approach for the cold-start problem of tag recommendation.

Keywords recommendation system, social tagging, personalization, social network, Flickr

1 Introduction

Social tagging has been enjoying a great deal of success in recent years, with millions of users visiting sites like: Delicious for social bookmarking; Flickr and YouTube for photo and video sharing, respectively; CiteULike and Connotea for sharing of bibliographic references; and Last.fm for the sharing of music listening habits. These tags provide meaningful descriptors of the objects, and allow the user to organize and index his/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[1].

The availability of rich media annotations is essential for large-scale retrieval systems to work in practice. Take image retrieval for example, the state-of-the-art technique in content-based image retrieval is progressing, but it 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 shows that users are willing to provide this semantic context through manual annotations. Recent studies on this topic reveal that users do annotate their photos with the motivation to make them better accessible to the general public[3]. Photo annotations provided by the user reflect the personal perspective and context that is important to the photo owner and his/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 of the same subject from different users, which are consequentially described by a wide variety of tags.

While social tagging has many benefits, it also presents 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[4]. 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[1]. One of the reasons for this seems to be that users are often reluctant to enter 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

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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[5].

Tag recommendation can deal with these challenges by suggesting a set of tags that users are likely to use for a media resource. The motivation of tag recommendation is twofold[6]. 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 chooses 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 his/her tagging process. Fig.1 shows an example of tag recommendation in Del.icio.us, the recommended tags are presented for a certain bookmark, users can choose or ignore them. 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, given a tagging object[7].

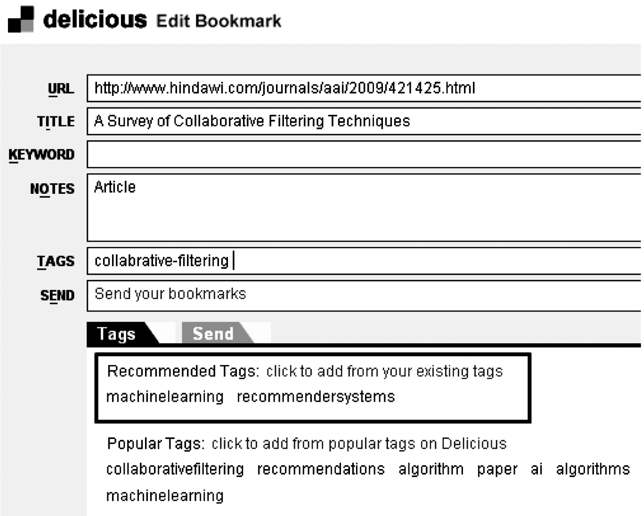

Fig.1. Tag recommendation in Del.icio.us. The user is presented with recommended tags and selects any preferred by typing them in the provided text box.

We study personalized tag recommendation within a popular online photo sharing site — Flickr. We investigate and implement the tag suggestion using global tag co-occurrence, and find that the global algorithm lacks the ability to make personalized recommendation. For personalization issue, using social network is a good solution, but how to use it? In Flickr, the user can interact with others through contacts, who then can be further identified to be his/her friends, family members, fans, *et al.* In this paper we propose a personalized tag recommendation algorithm which aggregates user tagging history and his/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 from 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 depicts that in the physical world, objects interact with each other via physical field, for example, the gravitation field. From the perspective of topology, we consider that the locality of a user in contacts network reflects its position potential, named as topological potential, which characterizes its ability of affecting other users. The potential field in contacts networks does not like other classic field owning Euclidean distance, so we replace Euclidean distance by link hops between two users.

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 on 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 uses the dataset of Flickr with 1 000 users. All users received personalized tag recommendations for some given Flickr images. We also compare our suggestion result with the global tag co-occurrence method and other two personalized methods using social networks. Our main contributions are 1) demonstrating that personalized recommendation combined with user social influence is effective (in our study we get a raise of the success ratio S@3 from 68% to 87% when compared with other social contact personalized recommendations); 2) presenting a novel measurement 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, followed by the analysis of our data collection in Section 3, where we focus on data description and limitations. In Section 4 we propose a novel measurement of user influence in online social network. In Section 5 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 6. Finally, in Section 7 we come to the conclusions and explore future directions.

2 Related Work

Tag recommendation is an interesting and well-defined research problems. The main directions for the research can be divided into graph-based approaches and content-based approaches[8-9]. Jächke *et al.*[10] proposed a graph-based tag recommendation system based on FolkRank, an adaptation of PageRank to folksonomy graph. Given a resource-user pair the system increases their weights in the folksonomy graph and runs FolkRank to spread the weights in the graph. Tags with the highest weights are returned as recommendations. The process has to be run for each incoming post, which makes the system inefficient. Guan *et al.*[6] proposed a framework based on graph Laplacian to model interrelated multi-type objects involved in the tagging system. Tags are ranked by a graph-based ranking algorithm which takes into consideration both relevance to the document and preference of the user. Recently, tensor factorization models (also considered as graph-based approaches) show very successful evaluation results on personalized tag recommendation problems. Symeonidis *et al.*[11] used a generalization of Singular Value Decomposition to model the relations between users, resources and tags. Each of such triplets is assigned a probability value. Given a user and resource, the system simply returns the most probable tags related to them. The idea was extended by Randle *et al.*[12]

Content-based approaches extend the folksonomy graph by adding the resource content dimension. The content allows them to process posts, for which there is little information in the graph, making them more practical. Since it usually encode user's preferences from textual information (e.g., web pages, academic papers, tags), content-based methods can predict tags for new users and new items. Tatu *et al.*[13] proposed a system based on tags extracted from resource and user profile. The set of tags is extended using NLP (Natural Language Processing) techniques and later merged with content-based tags. A tag recommendation system[14] utilized several tag sources including item content and user history to build both profiles for users and tags. New tags are checked against user profiles, which are rich but imprecise sources of information about user interests. The result is a set of tags related to both the resource and the user. Depending on the characteristics of processed posts, this set can be an extension of the common tag recommendation sources, namely resource title and resource profile.

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[1]. Their approach uses global tag co-occurrence to make recommendations for partially tagged photos, which is the base of our tag recommendation approach. Garg and Weber proposed a personalized approach to tag recommendation for Flickr photos[15]. They highlight the good performance of a hybrid method combining the personal and general contexts that gives improvement over either context alone. Rae *et al.*[16] proposed a personalized recommender system that aggregates and exploits the knowledge that exists at four different contextual layers in an extendable probabilistic framework. They suggested 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. Their approach will be used as a baseline in our experiment.

For recommendation with social network, recently Ma *et al.*[17] proposed a method to recommend with explicit and implicit social relations. Based on the intuition that every user's decisions on the Web should include both the user's characteristics and his/her trusted friends' recommendations, the authors proposed a probabilistic matrix factorization framework for recommender systems. The experimental analysis shows that this method generates better recommendations than nonsocial collaborative filtering algorithms. However, the disadvantage of this work is that although the users' social trust network is integrated into the recommender systems by factorizing the social trust graph, it only includes one-hop neighbors. The authors did not consider trust propagation. This drawback definitely affects the recommendation qualities. In our work, with the measurement of user social influence, we use not only one-hop contacts information for recommender. We combine 2-hop contacts' tagging behavior into our personalized tag recommendation method. Experimental results show our method outperforms theirs.

3 Data Collections

In this section we introduce Flickr (a popular photo sharing website) and describe the data collection on which we do our experiment.

3.1 Flickr

Flickr is a popular website for users to share and organize personal photographs. In September 2010, it reported that it was hosting more than 5 billion images. Flickr is also an online community, in which users can create networks of friends, join groups, send messages to other users, and comment on photos. Flickr allows annotation of photos in the form of tags or unstructured textual labels. Tags in Flickr are mostly assigned by the users who upload the image and provide multiple benefits[18]. In addition to making the photo searchable by the contributing user, tags enable users to discover other users' photos.

Flickr encourages users to designate others as contacts by making it easy to view the latest images submitted by them through "Contacts" interface. Users add contacts for a variety of reasons, including keeping in touch with friends and families, as well as tracking photographers whose work is of interest to them. We claim that the latter reason is the most dominant of the reasons. Therefore, we view user's contacts as an expression of the user's interests.

3.2 Data Description

In order to collect the state of the online social network, we crawled a subset of the Flickr user network. We started with a randomly selected Flickr user and followed all of the contacts links in a breadth-first search (BFS) strategy. In this way we get a "snowball" sample of Flickr online social network. Since the number of Flickr users is so large, we only collect the users 3-hop away the seed user. We call our sample data the *user contact network*. Here the nodes are different Flickr users, the edges are the apparent contact relationships created through the "Contact" button provided by the Flickr system.

According to the user contact network, we used Flickr API to download the list of photos uploaded after January 1, 2010 for all users. All tags of these photos were also downloaded at the same time. For the evaluation requirement, these photos should at least have two tags. We crawled the Flickr website for the user contact network, photos and tags on July 2010. As Table 1 depicts, we observed 0.25 million Flickr users and 1 million contact relations in the contact network. We also collected information about 5 million tags over 23 million photos.

Table 1. Summary of Flickr Dataset

Statistic	Numbers
Users	258 869
Photos	23 715 143
Tags	5 046 975
Contact Relationships	1 170 408

3.3 Limitations

Although the data provide us with an actual scenario of tag recommendation, it has two limitations. One is that our data collection methodology of user contact network does not get the entire Flickr social network that is reachable for the seed user. We only collect users 3-hop away. This does not affect our analysis results because the use of tag has local effect, most of the tags were used by few users. Furthermore, the information propagation in the Flickr social network is limited to individuals who are within close proximity of the upload and spreading takes a long time at each hop. The content popularity is often localized in the network[19-20].

Another limitation is that we can only observe the contact network, photos and tags, but we cannot manipulate them. We are not able to make change to the Flickr website or run tests in a controlled environment. We cannot get the real-time user's feedback on our personalized tag recommendation. On this problem, when we do the evaluation, we divide the original dataset into training set and testing set.

4 Measurement of User Influence in Social Network

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

4.1 From Physical Field to Topological Potential

From the classic concept of field① introduced by M. Faraday in 1837, the field as an interpretation of noncontact interaction between particles in every different granularity, from atom to universe, had achieved great success. In 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 particle's mass or charge. Inspired by the above physical idea, we introduce the theory of field into network topology structure to describe the relationship among the nodes being linked by edges and to reveal the general characteristic of the underlying potential distribution.

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

① http: //en.wikjpedia.org/wiki/Field_(physics).

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 decreases in the distance $\|v-u\|$. When $\|v-u\|=0$, it reaches maximum, but does not go infinity, and when $\|v-u\| \to \infty$, $\varphi_v(u) \to 0$.

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 other nodes in network, and vice versa.

4.2 Gaussian-Type Definition of Topological Potential

The modularity structure of real-world network implies that the interaction among nodes has the properties of localization. Topological potential and its distribution focus on the structural locality conducted by node activity. Considering a node in network as a potential source, it can affect others along the paths connecting each other. Each node's influence will quickly decay as the topology distance increases. We tend to define the topological potential in the form of Gaussian function.

Given a network $G = (V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$ 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:

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

where m_j is the mass of v_j, describing activity of the node. Generally each node is supposed to be equal in mass and meets a normalization condition $\sum_{i=1}^{n} m_i = 1$; $d_{j\to i}$ is the topological distance between v_j and v_i; σ is the influence factor, which reflects the influence range. If σ is too small, the range of interaction is very short, and the potential function will become the superposition of n sharp pulses centered at the nodes. The extreme is that there exists no interaction between the nodes and the potential at the location of each node nearly equals $\frac{1}{n^2}$. On the other hand, if σ is very large, there is strong interaction between the nodes, and the potential function will become the superposition of n broad, slowly changing functions. The extreme is that the potential at the location of each node approximately equals $\frac{1}{n}$. Since the difference between the probability density function and the potential function in the form of Gaussian function is only normalization constant, obviously the potential in the above extreme cases cannot produce a meaningful estimation of the underlying distribution. Thus, the value of σ should be learned from the actual network topology.

Other types of definitions, such as reciprocal-type, inverse-square-type, have been studied and compared.

The reciprocal-type is:

$$\varphi(v_i) = \frac{1}{n}\sum_{j=1}^{n}\varphi(j \to i) = \frac{1}{n}\sum_{j=1}^{n}\Big(m_j \times \frac{1}{\sigma d_{j\to i}+1}\Big). \quad (2)$$

The inverse-square-type is:

$$\varphi(v_i) = \frac{1}{n}\sum_{j=1}^{n}\varphi(j \to i) = \frac{1}{n}\sum_{j=1}^{n}\Big(m_j \times \frac{1}{(\sigma d_{j\to i})^2+1}\Big). \quad (3)$$

4.3 Optimizing the Influence Factor

As the definition of topological potential depicts, there is a positive correlation between the influence degree of each node and the influence factor. A node generally affects more widely with the increasing of influence factor σ. Suppose all mass of nodes are equal, and let them be 1. When $\sigma = 0$, there is no interaction among nodes, and the topological potential of all nodes are the same. When $\sigma \to \infty$, usually the value of σ is larger than D (the diameter of the network), interaction among all nodes gets similar again, and the topological potential of all nodes trends to reach to the same value again. When $0 < \sigma < D$, interaction among nodes is much different, and the same to the node topological potential. So σ should be optimized so as to make the topological potential of each node most different, then the distribution of potential field is as consistent with the underlying distribution of original data as possible.

Entropy was used as a measurement of the amount of thermal energy showing the disorder or randomness in a closed thermodynamic system. However, Shannon's entropy is a useful measure of uncertainty in an information system. The higher the entropy is, the more uncertain the associated physical system is. In order to minimize the uncertainty, Shannon entropy principle is used as (4) to optimize the influence factor.

Let $\varphi(v_1), \varphi(v_2), \ldots, \varphi(v_n)$ be the node topological potential of $v_1, v_2, \ldots, v_n$, respectively. The optimization function can be defined as,

$$\min(H) = \min\Big(-\sum_{i=1}^{n}\frac{\varphi(v_i)}{Z}\log\Big(\frac{\varphi(v_i)}{Z}\Big)\Big), \sigma \geqslant 0, \quad (4)$$

where $Z = \sum_{i=1}^{n}\varphi_i$ is a normalization factor. For any $\sigma \in [0, +\infty)$, the Shannon entropy H satisfies $0 \leqslant H \leqslant \log(n)$, and $H = \log(n)$ if and only if $\varphi(v_1) = \varphi(v_2) = \cdots = \varphi(v_n)$. Here we take no consideration of node mass, while optimizing the influence factor σ. For example, Fig.2(a) shows a typical network with 30 nodes and 34 edges, we just use it as a demo network. Fig.2(b) depicts the relationship between the influence factor σ and the Shannon entropy. When $\sigma = 2.03$ the entropy reaches the minimum value, and under current optimizing rule this value of σ is the best.

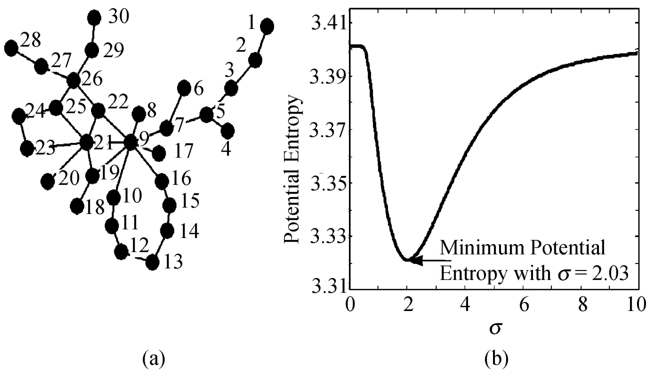

Fig.2. (a) Topology of a typical network, which contains 30 nodes and 34 edges. (b) Optimal choice of influence factor for a data field produced by the typical network. When $\sigma \to 0$ the Shannon entropy H tends to be $H_{\max}$. H decreases at first as σ increases from 0 to ∞ and at a certain σ ($\sigma = 2.03$), H achieves a global minimum; as σ further increases, H trends to reach the maximum again when $\sigma \to \infty$.

4.4 Calculating the Topological Distance

In physical space, the distance between two points is measured by Euclidian distance, but in virtual network space the Euclidian distance does not exist. Furthermore in order to characterize the social influence propagation in different paths between users, traditional metrics such as hops or shortest path length which are widely used in social network analysis are insufficient. Thus, we redefine the topological distance as follows based on cognitive physics[21] and shunt-wound circuit theory in electricity.

For a given network $G = (V, E)$, $V = \{v_1, \ldots, v_n\}$ is the set of nodes, $E \in V \times V$ is the set of edges and $|E| = m$ is the number of edges. If there exists a set of nodes $P = \{v_i, v_k, \ldots, v_l, v_j\}$, and no node appears repeatedly in P, P can be considered as a reachable path between v_i and v_j. The set of all reachable paths between v_i and v_j are noted as S_{ij}. As Fig.3(b) describes, each reachable path in set S_{ij} is mapped to a resistance in a branch, the topological distance between v_i and v_j is changed to the equivalent resistance R_e between electric potential U_i and U_j, which satisfies the following function,

$$\sum_{k \in S_{ij}} \frac{1}{R_k} = \frac{1}{R_e}. \tag{5}$$

If there is only one reachable path between v_i and v_j, the topological distance between them is equal to the length of the reachable path. When there are k reachable paths between v_i and v_j, which are defined as $P_1, P_2, \ldots, P_k$, and their lengths are defined as $L_1, L_2, \ldots, L_k$ respectively. The topological distance D_{ij} between v_i and v_j should be $0 < D_{ij} \leqslant \min(L_1, L_2, \ldots, L_k)$.

The definition above is similar to the resistance in shunt-wound circuit, where the equivalent resistance is smaller than any resistance in branches. Here nodes v_i and v_j are mapped to two electric potentials U_i and U_j in shunt-wound circuit, and those k reachable paths are mapped to k branches in the circuit. Then the resistance in each branch can be represented as the function of reachable path lengths, and the topological distance between v_i and v_j can be reckoned by mapping inversely the equivalent resistance R_e between U_i and U_j, as depicted in Fig.3.

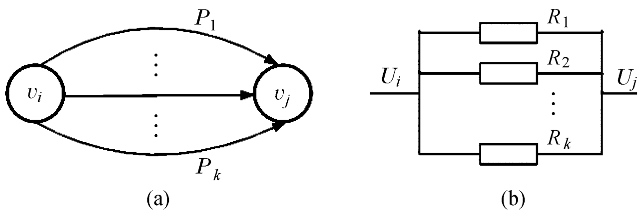

Fig.3. Topological distance between two nodes are discussed in virtue of electricity. In (a), there are k reachable paths between v_i and v_j, which are $P_1, P_2, \ldots, P_k$ respectively. In (b), v_i and v_j are mapped to U_i and U_j, the path P_k is mapped to the resistance R_k in a branch circuit, and the whole topological distance can be achieved by mapping inversely equivalent resistance between U_i and U_j.

Suppose there exists a function correlation between path length L_k of the k-th reachable path and R_k, that is $R_k = f(L_k)$. From the definition of topological potential, it decreases rapidly with the increase of the distance, and there is the exponential correlation between them. Usually it is hoped that resistance function would have the same characteristic. Hence the exponential function is chosen as the resistance function

$$f(x) = e^x - 1. \tag{6}$$

Join (5) to (6), the topological distance D_{ij} between v_i and v_j is finally formalized as:

$$D_{ij} = \ln\Big(\frac{1}{\sum_{k \in S_{ij}} \frac{1}{e^{L_k} - 1}} + 1\Big). \tag{7}$$

5 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, which is the base of our personalized approach. Finally, we present our personalized tag recommendation method and different aggregation strategies.

5.1 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), an initial (small or empty) set of tags and a target user, we use the identity of the user and his/her online social network, as well as tagging history and social influence of all users in the contact network, to suggest a personalized list of related tags for the tagging object.

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

5.2 Tag Co-Occurrence

Concept co-occurrence in daily life contains useful information to measure concept similarity in the semantic domain. The semantic about the concepts is related to human cognition. Since 80% of the human cognition is formed by the visual information in daily life, the occurrence of concepts in daily life contributes a lot to their semantics[22].

Tag co-occurrence means that there are two tags t_1 and t_2 which are used to annotate a resource at the same time, we call t_1 and t_2 co-occurrence once. 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 reliably 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 practice.

The calculation of the tag co-occurrence on Flickr has already been investigated by the recent work[1]. 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 (8) and asymmetric conditional probability (9).

Jaccard Coefficient:

$$C(t_i, t_j) = \frac{|t_i \cap t_j|}{|t_i \cup t_j|}. \tag{8}$$

The coefficient takes the number of intersections between t_i and t_j, divided by the number of union of the two tags. The Jaccard coefficient is known to be useful to measure the similarity between two objects or sets.

Conditional Probability:

$$C(t_i|t_j) = \frac{|t_i \cap t_j|}{|t_j|}. \tag{9}$$

The conditional probability captures how often t_j co-occurs with t_i normalized by the total frequency of t_j. We can interpret this as the probability of a photo being annotated with t_i given that it was annotated with t_j before.

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 tags 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 is called global tag co-occurrence.

5.3 User 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 within a short period of time. For example, a user uploads a group of photos of his/her tour, or records a set of photos about a certain event. These images often contain the same content, with a high degree of close relation, and the user often annotates these images with same tags. So what the tags used on the latest upload pictures can reflect temporal link among these pictures, and these tags can be used for tag recommendation.

The tagging history of 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 users, 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 is called personal tagging history.

5.4 Contacts with Social Influence

Flickr users can maintain contacts with other users, who then can be further identified to be their friends, family members, or other type of contact. A user in Flickr can explicitly connect him/herself to other users by giving them the label "Contact". These interpersonal connections form a social network between many of the users in the system.

Now we come back to the collected social network of Flickr users. According to the definition of topological potential, each user in contact network has social influence, which means that not only the user's behavior on Flickr can affect other users in his/her social network, but also at the same time him/herself will subject to the combined influence from others.

In this paper, the topological potential is used to measure the social influence of each user. The value of topological potential reflects the degree of a user's influence to other users. The higher the topological potential value, the stronger the influence of the user. For the user's contacts, not necessarily all of them have a significant impact on the target user. There are a lot of weak ties, and preferences of these users' interests are not very good coincidence. Therefore, based on potential value, we can get the ranking of user social influence. Some of the contacts with high rank in the ranking list are selected to generate the user's preference community. In this community, there are close interaction between users, who have common interest. Those who have real influence on the target user are all in the preference community, which is the core of our personalize recommendation.

The user influence ranking algorithm is summarized as Fig.4. There are two steps to rank user influence based on topological potential. First we choose the optimal influence factor. Here we use the Shannon entropy to get the optimized value of σ. Second, we sort the users with topological potential value in descend order.

Algorithm 1. User Influence Ranking
Input: Initial search range $[a, b]$, precision threshold ε;
Output: Optimized σ and ranking list.
Step 1: Choose the optimal influce factor
Given $\sigma_l = a + (1-\tau)(b-a), \sigma_r = a + \tau(b-a)$; $\tau = \frac{\sqrt{5}-1}{2}$;
//Calculate the Shannon entropy
$H_l = H(\sigma_l)$ and $H_r = H(\sigma_r)$
while $|b-a| > \varepsilon$ **do**
  if $H_l < H_r$ **then**
    Let $b = \sigma_r$, $\sigma_r = \sigma_l$, $H_r = H_l$
    Calculate $\sigma_l = a + (1-\tau)(b-a)$ and $H_l = H(\sigma_l)$
else
    Let $a = \sigma_l$, $\sigma_l = \sigma_r$, $H_l = H_r$
    Calculate $\sigma_r = a + r(b-a)$ and $H_r = H(\sigma_r)$
  end if
end while
if $H_l < H_r$ **then** $\sigma = \sigma_l$
else $\sigma = \sigma_l$
Return σ
Step 2: Calculate and evaluate the topological potential value of each user, and sort it descendingly

Fig.4. Algorithm of user influence ranking.

With topological potential, we characterize user social influence and find those who have large impact on recommendations being generated. These users are not only 1-hop contacts, even including 2-hop contacts. 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 him/herself. These tags capture the vocabulary not only the user but also their social contacts, 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. Calculating tag co-occurrence for each of the user-defined tags and contacts' tags, we finally get the ranking list of recommended tags. This method is called contacts with social influence.

User social influence is related to user similarity. In [23], user similarity is calculated using random walk algorithms. As the definition of topological potential depicts, we suppose that the mass of all nodes in social network are the same, so the user similarity is not included. In our future work, the user similarity may be used as a factor of node mass. Furthermore, user influence can be explicit or implicit, [24] discusses implicit user relations. In our user social influence calculation, we discuss explicit influence from 1-hop contacts and implicit influence propagated from 2-hop contacts.

5.5 Aggregation Methods

In our recommendation framework, we need two aggregation strategies: one is for the tag co-occurrence results of each user-defined tag, the other is for the combination of candidate recommendation tag lists from different methods.

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 [1]. We use two aggregation method: Vote and Sum.

Vote. Calculate the occurrences of tags in all the candidate lists, rank the tags according to the score of occurrences and select the final recommended results.

$$vote(t,u) = \begin{cases} 1, & \text{if } t \in T_u, \\ 0, & \text{otherwise}, \end{cases} \tag{10}$$

$$score(t) = \sum_{u \in U} vote(t,u). \tag{11}$$

Here, t is the candidate tag, T_u are the co-occurrence tags for a user-defined tag u. U refers to the set of tags the user assigned to a photo.

Sum. The summing strategy also takes the union of all candidate tag lists (T), and sums over the co-occurrence values of the tags, thus the score of a candidate tag $t \in T$ is calculated as

$$score(t) = \sum_{u \in U} C(t,u), \quad \text{if } t \in T_u. \tag{12}$$

Here, $C(t,u)$ refers to the co-occurrence value.

We will evaluate these two aggregation strategies in our tag co-occurrence algorithm during the evaluation as presented in Section 6.

For the case of combination of candidate recommendation tags from different approaches, we use two strategies, one is *Borda Count*, the other is *Simple Combination*. Borda Count is a single-winner election method in which voters rank candidates in the order of preference. 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, Borda Count is often described as a consensus-based electoral system.

In our work we call the Borda Count method mentioned above basic Borda Count. In basic Borda Count voting method each candidate is treated equally, but our proposed recommendation algorithm is based on three different kinds of independent personalized information, and maybe the length of each recommended list is not the same. When making the tag aggregation in the end, they weigh different proportions in the final recommended list. So when we conduct the Borda Count voting, we need to give different weights to different candidate lists.

The Simple Combination method is a user-defined aggregation. For the final recommender list, the user can explicitly define which part comes from which method. For example, in the top 10 tag list, the first 7 tags come from method A, the last 3 come from method B. The Simple Combination rule is pre-defined to reflect the special preference for individual method. The Simple-7 strategy in Subsection 6.2.4 is a use case of this method.

6 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 methods and the comparison with other personalized methods are shown at the last part.

6.1 Evaluation Setup

Our evaluation task is to recommend tags for a partial tagged photo in Flickr. In order to collect the state of the social network, we started the first crawl by selecting a well-known user as a seed, who has a large amount of contacts in our dataset. In each step, we retrieved the list of contacts for a user we had not yet visited and added these users to the list of users to visit. We then continued until we exhausted the list, thereby performing a BFS of the social network graph, starting from the seed user. Finally 1 000 users within the scope of 3-hop to the seed user were chosen from the achieved social network. These selected users all satisfy the condition that they should have 10 or more photos with at least 8 tags. For each user we chose 10 photos, finally we got 10 000 photos as our evaluation photo set. For each of the photos, half of their tags are used as the training sets, the other half as the test sets. In order to make the evaluation data more diverse, we chose 5 different well-known users as the seed users to get 5 different evaluation datasets. The final performance data are the average of testing results on these 5 evaluation sets.

For the evaluation of the task, we adopted 3 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 3 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 are relevant, averaged over all photos.

6.2 Evaluation Results

We start with evaluating the performance of our framework using different methods in isolation and then evaluate the methods in combination. First we use tag co-occurrence as the base for the individual strategy evaluation. Then for the combination cases, we use other personalized recommendation methods that also exploit social network in [16-17] as baseline for the evaluation.

6.2.1 *Global Tag Co-Occurrence*

In this subsection we choose the symmetric Jaccard coefficient and asymmetric conditional probability to calculate the tag co-occurrence coefficient. Furthermore we use Vote and Sum aggregation strategies to produce different tag recommendation lists. We compared 4 different experiments on our full data collection, the results are depicted in Table 2. Here we only use 3 metrics: MRR, P@5 and S@5.

Table 2. Comparison of Different Tag Co-Occurrence Recommendation Methods 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

Note: "Jaccard" indicates symmetric Jaccard coefficient, "Vote" indicates Vote aggregation strategy, "Sum" indicates Sum aggregation strategy, "Probo" indicates asymmetric conditional probability.

As Table 2 shows, for the symmetric Jaccard coefficient with the Sum aggregation strategy, success at rank 5 is 47.51%, precision at rank 5 is 36.31%; for asymmetric conditional probability with the Sum aggregation strategy, success at rank 5 is 52.61%, precision at rank 5 is 41.18%. 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, for conditional probability with Vote aggregation strategy, success at rank 5 is 45.64%, precision at rank 5 is 34.23%, only getting a 1% improvement compared with Jaccard coefficient. So for the Vote aggregation strategy, the performances of the symmetric Jaccard coefficient and asymmetric conditional probability have no apparent difference. On the other hand, for the Jaccard coefficient, Sum outperforms Vote by 3%, but for the conditional probability, the improvement reaches 7%.

In summary, we find that on tag recommendation, the asymmetric conditional probability is better than the symmetric Jaccard coefficient, and Sum does better than Vote. In our later experiment, we use the asymmetric conditional probability to calculate the tag co-occurrence coefficient, and use the Sum strategy to produce the recommendation tag list. This method is simply labeled as CC. The performance of our global tag co-occurrence method on the evaluation data is presented in Table 3.

Table 3. Evaluation Results for the Individual Recommendation Method

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

Note: we only use the top 10 in the candidate list.

6.2.2 *User Tagging History*

We evaluate two recommendation methods on tagging history as we introduced in Section 5. One is directly using the latest used 10 tags as the recommendation results, which is simplifiedly labeled as PT. The other is first to calculate the tag co-occurrence coefficient of the user's whole tag list used before, further use the Sum strategy to produce the recommendation tag list. This method is simply labeled as PC. It is different from the global tag co-occurrence method. We only use the user's personal tag information. Table 3 gives the performance of the two methods.

Table 3 shows PC on user tagging history outperforms the global tag co-occurrence. The precision at rank 5 is 44.59%, even reaches 60.33% at rank 10. The success at rank 1 is 68.36%, at rank 3 is 83.68%. The PC algorithm shows excellent performance in personalized tag recommendation. Generally speaking, it is difficult for a single approach to get so high performance. This result may have some relations with our evaluation setup. The disadvantage of this method is apparent, and all recommended tags only come from the user him/herself. Lacking of diversity, the PC algorithm should be combined with other approaches. Compared with PC, the performance of the latest used tags

(PT) is not so good. In our experiment, for the continuously uploaded photos whose tags are overlapped, the PT method gets a good performance.

6.2.3 User Social Contacts

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 contacts' personal tag lists, use the Sum strategy to produce the recommendation tag list. This method is simply labeled as SC. Table 3 also gives the performance of this method.

Table 3 shows that only using social contact, we can get some personalized tag recommendation, even though the precision and success are not very well (only 60% of the PC method). This suggests that only use contacts' tags in recommendation is not enough, while it can be combined with other methods to improve the diversity of recommendation list.

6.2.4 Combination Performance

Combining different methods has been shown to be useful for tag recommendation. Fig.5 presents the results of combining global tag co-occurrence with social contacts using different aggregation strategies. Here Sum refers to the Sum aggregation strategy; Borda-1 is the basic Borda Count, the weights of global tag co-occurrence and social contact are equal; Borda-0.5 represents the weight of social contact is half of the global tag co-occurrence. Simple-7 is a *Simple Combination* as mentioned in Subsection 5.5, which uses the first 7 tags in global tag co-occurrence, and other 3 selected from the highest ranked tags in social contacts (not in the global tag co-occurrence list).

Fig.5 shows the performance gets improved when combining global tag co-occurrence with social contact. Especially, the Sum aggregation strategy makes P@10 raise to 4.5% for global tag co-occurrence and 14% for social contact. Furthermore S@3 raises to 74%. Fig.6 shows the results of combining global tag co-occurrence with user history using different aggregation strategies. Fig.7 shows the results of combining social contact with user history using different aggregation strategies. Figs. 6 and 7 all show that when introducing user tagging history, the performance of combined method decreases in all metrics, which suggests that the user

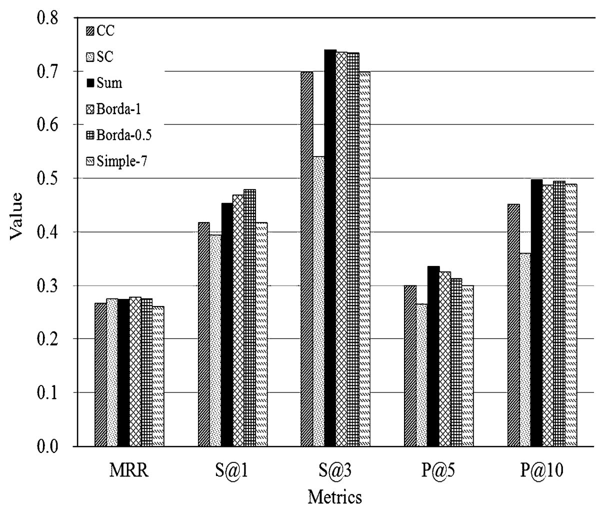

Fig.5. Aggregation results of global tag co-occurrence and social contact.

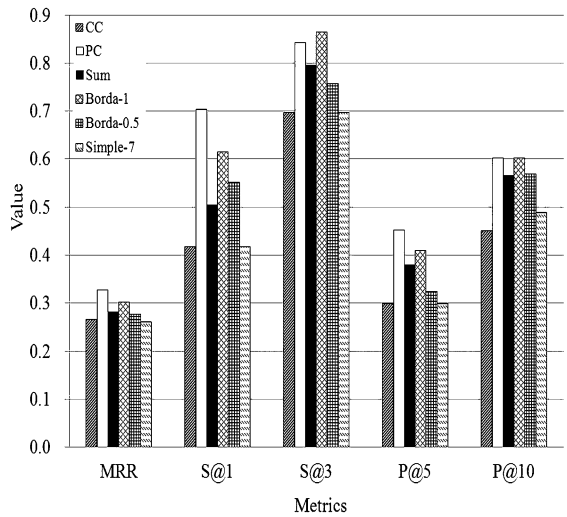

Fig.6. Aggregation results of global tag co-occurrence and user tagging history.

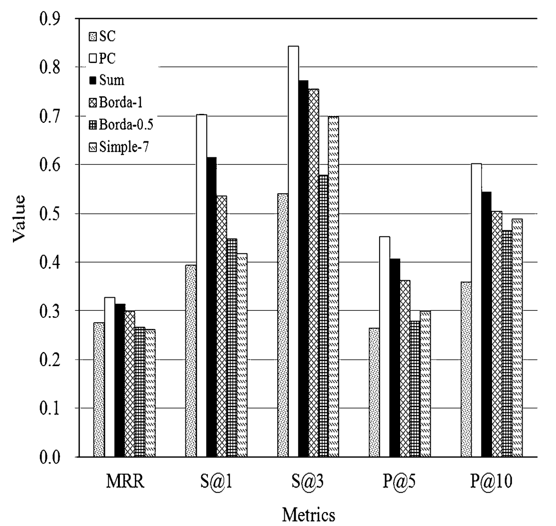

Fig.7. Aggregation results of social contact and user tagging history.

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 3 methods are presented in Fig.8. By combing all methods together, we find that under the Boada-1 strategy, S@3 reaches 87.3% and P@10 gets 60.7%, which are the peak performance of our recommendation system. The details of performance results with different aggregations are shown in Table 4.

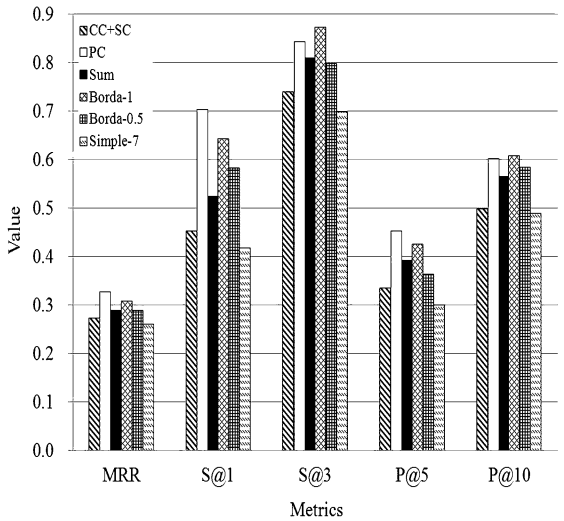

Fig.8. Aggregation results of global tag co-occurrence, social contact and user tagging history.

In summary, on combination of different methods, we find that we can first combine global tag co-occurrence with social contact using Sum aggregation strategy, then use basic Borda Count voting to combine the tag list of user history. A significant improvement of personalized tag recommendation performance will be achieved.

6.2.5 Comparison with Other Personalized Methods

In [16] Adam *et al.* collect inter-personal connections to form a social graph between many of the users in the Flickr system. They produce a tag network from this data by taking all the photos from the contacts of the user for whom recommendations are being generated and aggregating them, excluding the tags from the photos of the user him/herself. Finally they use a probabilistic prediction framework to generate the candidate tags. Fig.9 shows the performance of the Social Contact method compared to the Collective Context and their combination for users with increasing number of contacts (i.e., Bucket 0 contains the users with the small number of contacts and Bucket 5 contains users with the greatest number of contacts). Their conclusions are that the Social Contact is poor for all groups and always detrimentally affects the combination run. This seems to suggest that the tagging behavior of a user's contacts poorly reflect that of the user, and so is unhelpful when making tag recommendations.

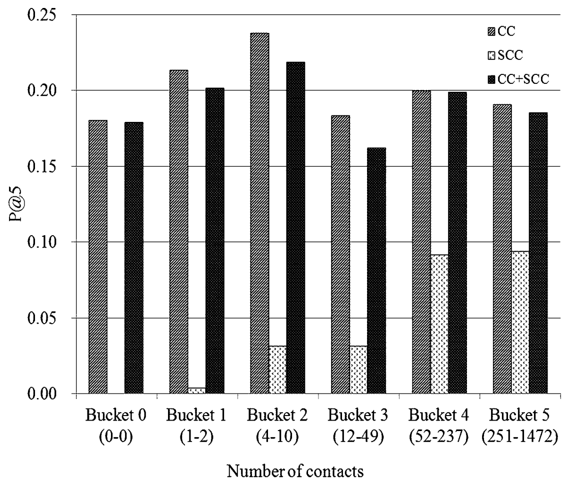

Fig.9. Relative performance of Social Contact Context (SCC) compared to the Collective Context (CC) depending on the user's contact count[16].

In our case, as depicted in Fig.5, the social contact information is combined with the global tag co-occurrence. We see a statistically significant improvement in the performance of the combined run for all our metrics. The social contacts appear to perform well when used in combination with other approaches. Our findings are different from [16]. We think the main reason is that Adam *et al.* use all 1-hop contacts tagging information for tag recommendation, and too many noises have been brought to the final tag list. While in our framework, first we introduce 2-hop contacts

Table 4. Evaluation Results for the Combination of Three Recommendation Methods Using Different Aggregation Strategies and Comparison with Other Methods

Mertrics	CC+SC	PC	Sum	Borda-1	Borda-0.5	Simple-7	RSTE
MRR	0.2734	0.3275	0.2883	0.3085	0.2886	0.2608	0.2812
S@1	0.4527	0.7030	0.5233	0.6423	0.5813	0.4170	0.5641
S@3	0.7397	0.8427	0.8087	**0.8727**	0.7977	0.6973	0.7826
P@5	0.3351	0.4525	0.3925	0.4244	0.3633	0.2992	0.3775
P@10	0.4972	0.6017	0.5645	**0.6074**	0.5830	0.4886	0.5233

Note: we only use the top 10 in the candidate list.

tagging information to make the recommendation more diverse, then through measurement of user social influence to find those who really have impact on the target user to ensure the precision of our algorithm.

Finally, in order to show the performance of our tag recommender, we compare our method with RSTE approach proposed by Ma *et al.* in [17]. In this method, two recommender systems are created, one utilizes only the user-item matrix to make recommendations, while the other uses only a trust-based system. A parameter α is used to fuse these two systems into one, which is called: Social Trust Ensemble by the authors. If $\alpha = 1$, the system only mines the user-item matrix for matrix factorization; if $\alpha = 0$, the system only extracts information from the social trust graph. For our tag recommendation task, the inputs are tags, items and users, which do not include apparent user-item matrix and social trust information. So in our experiment, according to the rules of RSTE, we set $\alpha = 0$ and use similarity to replace social trust. From Table 4, we can observe that our approach with social influence outperforms the RSTE method in each metric. The detailed comparison results are depicted in Fig.10. This demonstrates that using 2-hop contacts for tag recommender and considering the possible social influence diffusions of users in online social network are reasonable. Our topological potential model on social influence is effective.

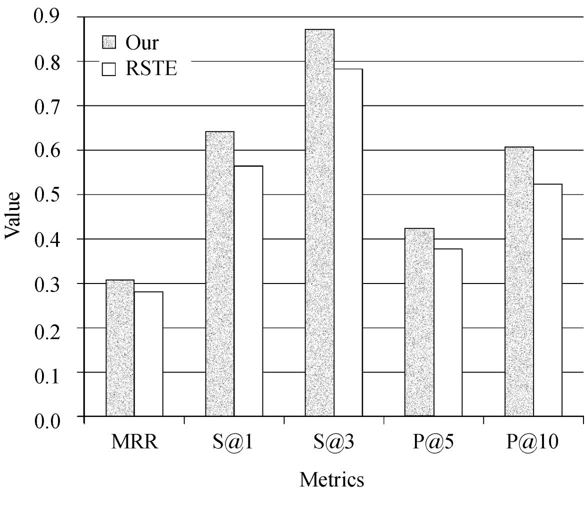

Fig.10. Comparison results of our approach with RSTE.

7 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 recommender. 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 metrics. 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 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 on 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 the perspective of social 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 strategies 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.

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