USER SPECIFIC FRIEND RECOMMENDATION IN SOCIAL MEDIA COMMUNITY

Cong Guo[1], *Xinmei Tian*[1], *Tao Mei*[2]

[1]CAS Key Laboratory of Technology in Geo-spatial Information Processing and Application System,
University of Science and Technology of China, Hefei Anhui, China.
[2]Microsoft Research, Beijing, China.
gcong18@mail.ustc.edu.cn, xinmei@ustc.edu.cn, tmei@microsoft.com

ABSTRACT

Social networks nowadays have become an important form of communication in which users can post their current status or share their lives by mobile phones or the Web. In this paper, we develop an effective and efficient model to estimate continuous tie strength between users for friend recommendation with the heterogeneous data from social media community. We categorize those multimodal data into two classes: interaction data (e.g., comments, marking favorite photos) and similarity data(e.g., common friends, groups, tags, geo, visual). We propose to use asymmetric relationship in the interaction data for tie strength estimation instead of using the conventional symmetric ones. Furthermore, by exploring the behavior of users in a social media community, we find that the tie strength between users can be approximately modeled as a linear function of their social connections. Based on this observation, we propose an effective and highly efficient user specific linear model for the tie strength estimation. The experiments on a popular social network show promising results and demonstrate the effectiveness of our proposed method.

Index Terms**—** Multimedia, Friend prediction

1. INTRODUCTION

With the concept of WEB 2.0 becoming popular in late 2004, many famous social networks appeared successively. Social networks have made it simple for people to communicate with others and have become an online community for internet users. The community members share common interests and can experience an alternative lifestyle by browsing posts of others. This kind of online community attracts more attentions of netizens and their members do at an ever-growing rate. In fact, researchers find that there is a tendency that more friends will bring more logins [1]. So in social networks, an effective and efficient friend recommendation system really plays an important role among thousands of social network applications.

This work is supported by the NSFC under contract No. 61201413, Specialized Research Fund for the Doctoral Program of Higher Education No. WJ2100060003, the Fundamental Research Funds for the Central Universities No. WK2100060007 and No. WK2100060011 to Dr. Xinmei Tian.

Many studies about social networks are conducted on Flickr-a popular online photo sharing community. Users of Flickr can build their contact lists and browse posts of their friends. While scanning the photos, users can make comments and mark the photos as favorite. To make users with common interests communicate conveniently, users can build or join interest groups in Flickr. Since Flickr is a photo-sharing network, the photos are the mainly posts. The photos usually contain rich information such as geo-information, user-annotated tags and visual-information. So Flickr contains rich information, and it arouses the interest of researchers to study such a famous social network.

A concept describing the relationship between users in social networks is the tie strength [2]. To understand the tie strength between users, researchers analyzed the social networks data and summarized some basic rules which are helpful for understanding the behavior of users [3], [4], [5], [6]. Mislove et al. [3] studied the link formation processes and found that a user tend to create and receive links in proportion to their outdegree and indegree. Schifanella et al. [4] found users with similar topical interests are more likely to be friends. Zwol [5] found that views on photos is closely linked with geographic distribution. Lerman and Jones [6] showed that social browsing through the photo streams of contacts is one of the primary methods by which users find new images on Flickr. Those efforts provide the basis for the latter research. Meanwhile researchers also tried to combine the rich data from Flickr to model their recommend tasks. Yu et al. [7] tried to combine visuals and tags to build a group recommendation model. Phan et al. [8] combined tags and favorite photos of users to model the tie strength between users. Yao et al. used visual similarity and geo similarity for characterizing user relationship [9].

There are two forms to build the tie strength: binary tie strength and continuous tie strength. Most of the previous work has focused on social networks with binary relational ties (e.g., friends or not). A binary relational tie provides only an inaccurate indication of the relationship. Recently, Zhuang et al. [10] studied a continuous tie strength model using MKL [11] method which combined seven heterogeneous data from Flickr. A two-stages learning method was used to tackle the data to build kernels into a holistic similarity space and learn a weight vector to combine the different kernels. Such a linear combination of various tie strength can be used to describe the probability of two users to be friends.

The method proposed in [10] assumed that all the Flickr users share the same behavior mode and the relationship between users is symmetric. However, in fact different users should have different behavior modes. For example, popular users usually have more followers and make posts more frequently than ordinary users. Also, Flickr is an asymmetric network. It allows a user to follow updates from other users who are in his/her contact list but do not follow him/her. So applying such a fixed behavior mode and the symmetric relationship will ignore some information.

In this paper, we propose two useful kernels inspired by the efforts of former researchers.The two kernels well describe the unsymmetrical relationship in Flickr. Furthermore we study a user specific linear model for friend recommendation in Flickr. We separate those data into two classes : interaction data (e.g., comments, marking favorite photos) and similarity data(e.g., common friends, groups, tags, geo, visual). They separately describe the symmetric and asymmetric relationships. By exploring the behavior mode of users, we assume that the tie strength is a linear function of the interaction/similarity approximately. Therefore we propose an effective and efficient linear model for the tie strength estimation. To capture the unique behavior model of different users, our tie strength model is query specific.

In summary, this paper makes the following contributions:

- We analyze the heterogeneous data and find two useful asymmetric kernels to capture the asymmetric social relationship. Those asymmetric kernels largely boost the friend recommendation accuracy.
- We assume that the tie strength between users is approximately a linear function of their interaction/similarity. It inspires that we can build a simple linear model for tie strength estimation.
- Instead of learning a universal model which is applied for all users, we propose to build a user specific model for different users to reflect their own behavior.

The rest of the paper is organized as follows. Section 2 introduces our kernels and user specific linear model for friend recommendation. Section 3 presents the experiment results, followed by the conclusion in Section 4.

2. FRIEND RECOMMENDATION WITH USER SPECIFIC LINEAR MODEL

In this section, we will first analyze the multimodal social media data and then present our user specific linear model for friend recommendation. We conduct our analysis on Flickr and use the heterogeneous data such as comments, marking photos, common friends, groups, tags, geographic distribution, visual information and contact lists.

2.1. Interaction and similarity Features

In this subsection we describe two kinds of interaction features which are comments and marking photos data from Flickr. We also extract some similarity features in this part. To pretreat these similarity features, we follow the method in [10].

• Users' interaction by comments

It seems like users have a trend to browse photos of their friends and make comments [6]. First we use breadth-first search manner to get 5000 users and extract the complete comments information from the profiles. For a user u_j, we count the the number of comments from his friends and non-friends, and then we count the numbers of friends and non-friends who make comments. We find that the average number for comments of a user from the friends is 5.06 times as that of a user from the non-friends.

In the directed relation graph of the 5000 users, there are 37318 edges. We find that there is mutual communication on 30.03% of the edges, but in fact there is one-way communication on 50.34% of the edges. If we only use the mutual comments, we'll miss amounts of information. Thus if a user u_i makes comments on photos belong to u_j frequently, we can guess that u_i has put u_j in his contact list. It should be noted that the number of comments that u_i has made on u_j does not equal to the number of comments that u_j has made on u_i. So we define that the interaction of u_i to u_j is the number of comments which u_i makes on u_j

$$K^1(u_i, u_j) = \#comments\ u_i\ makes\ on\ u_j$$

• Users' interaction by marking photos

As mentioned above, users tend to browse their friends' photos. Another behavior between users is marking photos as favorite. We find that the frequency that a user marks the photos of his friends is 3.12 times more than his non-friends. So if u_i always marks $u_j's$ photos, we may guess that u_i has put u_j in his contact list. The interaction of u_i to u_j is the number of photos of u_j which u_i marks as favorite:

$$K^2(u_i, u_j) = \#photos\ of\ u_j\ which\ u_i\ marks\ as\ favorite$$

• Users' similarity by common friends

Using common friends number to recommend friends is the most popular method which most social networking websites apply. The similarity between u_i and u_j is the number of friends both belong to u_i and to u_j:

$$K^3(u_i, u_j) = \#friends\ u_i\ and\ u_j\ both\ have$$

When $i = j$, the kernel value is the number of friends u_i has

• Users' similarity by common interest groups

If two users have many common groups, they may become friends. The similarity between u_i and u_j is the number of groups both u_i and u_j join in:

$$K^4(u_i, u_j) = \#groups\ u_i\ and\ u_j\ both\ join\ in$$

When $i = j$, the kernel value is the number of groups u_i joins in.

• Users' similarity by common tags

We adopt the bag-of-word model to compute the similarity of users. We use traditional tf-idf method to get the weight of tags and use a tag vector z_i to represent the tag information of u_i. We adopt the normalized linear kernel to measure the similarity between u_i and u_j:

$$K^5(u_i, u_j) = z_i^T z_j / (\sqrt{z_i^T z_i}\sqrt{z_j^T z_j})$$

• Users' similarity by geo-information

If two users have been to many same places, they may have some similarity.

$$K^6(u_i, u_j) = \#places\ u_i\ and\ u_j\ both\ have\ been$$

When $i = j$, the kernel value is the number of places u_i has been.

• Users' similarity by visual features

Like the method we use to get the similarity of tags, we adopt the bag-of-(visual) word (BoW) model. First we get the SIFT for each photos and quantize them into d_x groups by a K-means clustering process. Thus a photo can be assigned to a visual vector $x \in R^{d_x}$. We use an average visual vector to present a user's visual features.

$$V_i = \frac{1}{n_i}\sum\nolimits_{k=1}^{n_i} x_k$$

n_i is the number of photos belong to u_i. So the similarity between u_i and u_j can be given by a Gaussian kernel:

$$K^7(u_i, u_j) = exp(-\frac{\|V_i - V_j\|}{\sigma^2})$$

For K^1 andK^2, we divide the elements in each row by the maximum value in the row. For K^3 toK^7, we normalize them as

$$K(i, j) = \frac{K(i, j)}{\sqrt{K(i, i)}\sqrt{K(j, j)}} \quad (1)$$

2.2. The relationship between users' tie strength and their interaction/similarity

In Flickr, every user has his/her own contact list which contains all the users who he/she adds as friends.

$$Y(u_i, u_j) = \begin{cases} 1\ if\ u_j\ in\ the\ friend\ list\ of\ u_i \\ 0\ otherwise \end{cases}$$

To understand the distribution of each kernel, we analyze the relationship between users' tie strength and their interaction/similarity degrees. We use the conception of friend recommendation precision to estimate the probability of two users to be friends. For an arbitrary kernel $K^{(i)}$ and a user u_j, if the iteration/similarity value between u_j and u_k is $s \in [0, 1]$, i.e., $K^{(i)}(u_j, u_k) = s$, the probability that u_k to be $u_j's$ friend, i.e., the tie strength $T^{(i)}$ between u_j and u_k , can be defined as

$$\begin{aligned} T^{(i)}(u_j, s) &= P(y(u_j, u_k) = 1 | K^{(i)}(u_j, u_k) = s) \\ &= \frac{TP_{j,k}^{(i)}}{TP_{j,k}^{(i)} + FP_{j,k}^{(i)}} \end{aligned} \quad (2)$$

where $TP_{j,k}^{(i)}$ is the number that $u_j's$ friends whose interaction/similarity is above s under kernel $K^{(i)}$. $FP_{j,k}^{(i)}$ is the number that $u_j's$ non-friends whose interaction/similarity is above s under kernel $K^{(i)}$. Eqn.(2) means that if we assume u_k is u_j's friend, all other users whose interaction/similarity with u_j is larger than s should also have the same probability to be u_j's friends. Therefore, we can use the friend recommendation precision to estimate the tie strength $T^{(i)}(u_i, s)$.

For user u_j, by exploring all other users in $\mathcal{U}$, we can get a series $T^{(i)}(u_j, s)$ with s varying from 0 to 1 under Kernel $K^{(i)}$. We quantify s with interval 0.05 and plot $T^{(i)}(u_j, s)$ as a T-s curve. Figure 1 shows two users' $T - s$ curves under K^3. From this figure we can observe that the T is approximately a linear function of s . To further confirm this observation, we get the statistic $T - s$ over all users,

$$T^{(i)}(s) = \sum\nolimits_{u \in \mathcal{U}} T^{(i)}(u_j, s)/|\mathcal{U}| \quad (3)$$

Figure 2 shows the $T - s$ curves under 7 kernels and all 7 curves can be approximately fitted by a linear model.

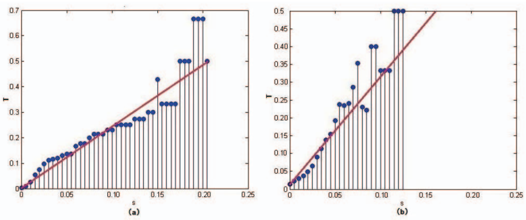


Fig. 1. Two users T-s curve under common friends kernel.

2.3. User Specific Linear Model for Friend Recommendation

Based on the phenomenon shown in Fig.2, we can assume that the tie strength between users is approximately a linear function of their similarity for all 7 kernels. In other words, if we know the similarity between two users, we can directly derive their tie strength, i.e., the probability that those two users could be friends, from the linear model. The next problem is to derive a linear model for each of the 7 kernels. The straightforward way is to approximate the linear function on training set via the regression algorithms, such as least-squares linear regression and super vector regression. The linear models derived in such way reflect the statistical behaviors of all users. As aforementioned, beyond the common social behavior, different users also have their specific behavior which cannot be captured by the average model. Therefore, instead of learning

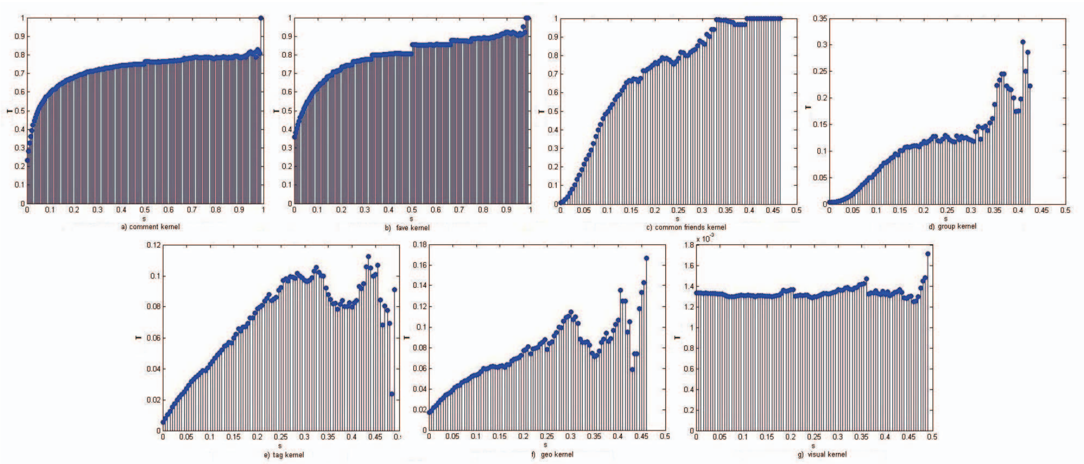


Fig. 2. The T-s (Tie strength vs. similarity/interaction) curve over 7 kernels. It shows that the tie strength between users is approximately a linear function of their similarity/interaction.

a universal model for all users, we propose to estimate the user specific model to reflect their own behaviors. For a user u_j, we assume his/her tie strength vs. similarity/interaction with other users can be modeled via a linear model,

$$t^{(i)}(u_j, u_k) = {a_j}^{(i)} K^{(i)}(u_j, u_k) + {b_j}^{(i)} \tag{4}$$

where $t^{(i)}(u_j, u_k)$ is the objective tie strength between users u_j and an arbitrary u_k. ${a_j}^{(i)}$ and ${b_j}^{(i)}$ are the parameters of the linear model for user u_j under the i-th Kernel. Fig.1 shows the tie-strength vs. similarity/interaction curves of one user under $K^{(3)}$ kernel.

To estimate the parameters ${a_j}^{(i)}$ and ${b_j}^{(i)}$ in the linear model, we propose an efficient and effective method. For the intercept ${b_j}^{(i)}$, it is defined as the tie strength when $K^{(i)}(u_j, u_k) = 0$. For the slope ${a_j}^{(i)}$, we first derive the average similarity/interaction between u_j and his/her friends,

$$s^{(i)}_{u_j,1} = \sum\nolimits_{u_k \in \mathcal{U}} K^{(i)}(u_j, u_k) * Y(u_j, u_k) / n^{(i)}_{u_j,1}$$

$$n^{(i)}_{u_j,1} = |\{u_k | u_k \in \mathcal{U}, Y(u_j, u_k) = 1, K^{(i)}(u_j, u_k) \neq 0\}|$$

where $n^{(i)}_{u_j,1}$ is the number of users which satisfy a) are friends of u_j and b) have non-zero similarity/interaction with u_j. Similarly, we can get the average similarity/interaction between u_j and his/her non-friends,

$$s^{(i)}_{u_j,0} = \sum\nolimits_{u_{(k)} \in \mathcal{U}} K^{(i)}(u_j, u_k) * (1 - Y(u_j, u_k)) / n^{(i)}_{u_j,0}$$

$$n^{(i)}_{u_j,0} = |\{u_k | u_k \in \mathcal{U}, Y(u_j, u_k) = 0, K^{(i)}(u_j, u_k) \neq 0\}|$$

where $n^{(i)}_{u_j,0}$ is the number of users which satisfy a) are not friends of u_j and b) have non-zero similarity/interaction with u_j.

The slope $a^{(i)}_j$ is defined as the gradient around the middle of $s^{(i)}_{u_j,1}$ and $s^{(i)}_{u_j,0}$, i.e.,

$$a^{(i)}_j = \frac{t^{(i)}_{u_j}(\bar{s}) - t^{(i)}_{u_j}(0)}{\bar{s}} \tag{5}$$

where $\bar{s} = \frac{1}{2}(s^{(i)}_{u_j,1} + s^{(i)}_{u_j,0})$.

The reasons why we define slope $a^{(i)}_j$ in this way are twofold. First, the t-s curve is not smooth especially when s is extremely big or small which corresponds to users are mostly friends and non-friends respectively. Therefore, we adopt the gradient around a middle s value - $\bar{s}$ to get a more stable model. Second, compared with conventional regression algorithms, the proposed estimation algorithm is highly efficient since we only need to know four values, i.e., $s^{(i)}_{u_j,1}$, $s^{(i)}_{u_j,0}$, $t^{(i)}_{u_j}(\bar{s})$ and $t^{(i)}_{u_j}(0)$. The high efficiency guarantees that our proposed user specific model can be applied for online applications on social networks.

For each user, after getting the linear models for each of the 7 kernels, we have to combine them together to derive the final tie strength. Here we adopt two combination ways. The first one is the linear combination with equal weights.

$$R1(u_j, u_k) = \frac{1}{7} \sum\nolimits_{i=1}^{7} T(u_j, s^{(i)}_k)) \tag{6}$$

where $s^{(i)}_k = K^{(i)}(u_j, u_k)$

As aforementioned, we category the heterogeneous data into two categories, i.e., the interaction kernels (K^1 and K^2) and similarity kernels (K^3 to K^7). In the second combination, we first equally combine the kernels within the same category.

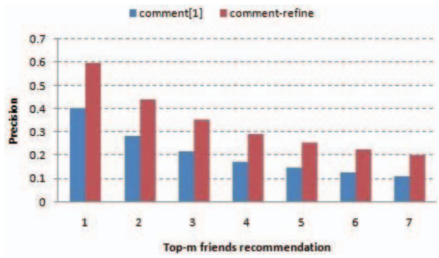
$$R_I(u_j, u_k) = \frac{1}{2} \sum\nolimits_{i=1}^{2} T(u_j, s^{(i)}_k) \tag{7}$$

$$R_S(u_j, u_k) = \frac{1}{5} \sum\nolimits_{i=3}^{7} T(u_j, s^{(i)}_k) \tag{8}$$

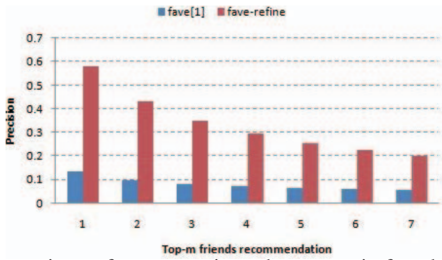
Then the final tie strength is derived according to the following formulation

Table 1. The statistics of the collected Flick data

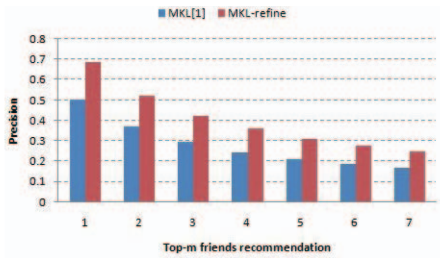
#user	#group	#tag	#contact
5000	101408	117680	37318



(a) Comparison of asymmetric and symmetric comment kernels



(b) Comparison of asymmetric and symmetric fave kernels



(c) MKL of 7 kernels using asymmetric and symmetric kernels

Fig. 3. The average accuracy of Top-7 friend recommendation by using asymmetric and symmetric kernels.

$$R_2(u_j, u_k) = \frac{e^{R_I(u_j,u_k)} \times e^{R_S(u_j,u_k)}}{e^{R_I(u_j,u_k)} + e^{R_S(u_j,u_k)}} \quad (9)$$

This combination will give a better balance between the tie strength estimated from interaction kernels and similarity kernels. Only when interaction and similarity tie strength are both high, the final tie strength will be tight.

3. EXPERIMENT

We evaluated the proposed model on the same data set as [10] comprised of multimodal information of 16346 users from Flickr. We also start from a random user as seed and expand the crawling according to its friend list in a breadth-first search manner. We stopped at 5000 users. Extracting the profile of the 5000 users, we can build the kernels mentioned in section 2.1. Table 1 shows some basic statistics of the component we build.

3.1. Comparison of asymmetric and symmetric kernels

In this section, we evaluate the friend recommendation by using the asymmetric kernels and make a comparison with the symmetric kernels [10].

We first randomly choose 4000 users for training purpose and the rest 1000 users to be the candidates in the testing process. In [10], the method of normalizing a kernel is dividing each row with the maximal value at that row and then making it symmetry by computing $K = (K + K^T)/2$. We follow the same method to pretreat our kernels, then use MKL [11] to combine the seven kernels. Given a test user with 1000 candidates, we sort the values in a descending order and extract the top users as recommended friends. The top-7 friend recommendation results are plotted in Figure 3. As shown in Figure 3, the blue bars are the kernels mentioned in [10], and the red ones are ours. Obviously our kernels get a better performance on both single and combined multiple kernels.

Figure 3(a) shows a 20% growth at Top-1 recommendation since we use the asymmetric comment kernel. Another visible improvement is the favorite kernel in Figure 3(b). Asymmetric favorite kernel makes Top-1 recommendation increased by almost 50% and gets a similar accuracy with the comment kernel we proposed. These two asymmetric kernels really perform an extreme high prediction ability to extract friends from numerous candidates. The good results show that the comments are the most frequently way for users to convey kindness to others. Compare the results of different treatment methods on comments kernel, directed comments instead of mutual comments are more general in social networks and contain more information that we cannot ignore. Figure 3(c) is the MKL result of 7 kernels. Since we use the same method as [10] for the rest 5 kernels, the only difference is that we change from the two symmetric kernels to two asymmetric kernels. MKL is well integrated of the heterogeneous data and performs the best than every single kernel.

Combine the observation of comment kernel and favorite kernel, we may guess that the directed communication in social networks will present more relationship and users have a trend to browse their friends' photos or posts and then make feedbacks.

3.2. User specific friend recommendation

We evaluate the performance of our user specific model approach presented in section 2.4. We use all the kernels that presented in section 2.2. and make a comparison with MKL using the same kernels. As what we did in section 3.1, we use 4000 users for training, but differently we normalize K^3 to K^7 using Eqn.(1). Also given a test user with 1000 candidates, we sort the values in a descending order and extract the top users as recommended friends. In fact, the contact kernel Y is really sparse. So it sometimes appears that in the training process for a user u_j, there is no u_j's friend in the kernel Y. Consequently, in the testing process, once u_j's friend appear, we cannot find him. To avoid this case happen, we choose the users who have at least n friends in the training process. In the testing process, we give these users 1000 candidates to find their friends.

Firstly, we compare our R2 model with the MKL method

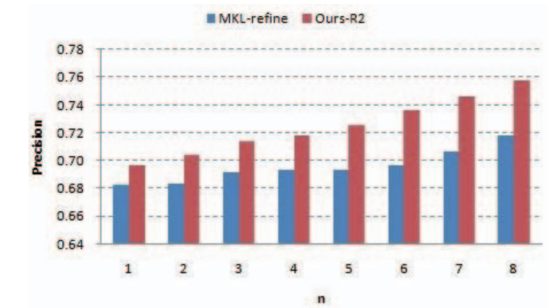


Fig. 4. Average accuracy of top-1 friend recommendation with different testing users.

proposed in [10], We present the Top-1 friend recommendation with different testing users by changing n. The result is plotted in Figure 4. As shown in Figure 4, our R2 model yields a better performance than MKL. Moreover by the increase in n, the difference between two models gets larger. This indicates that users have their specific behavior modes. More information between users can help build more precision behavior modes for users. Figure 5 shows that when $n = 8$ the average accuracy of top-7 friend recommendation under our R_2 combination model and MKL model. Our model efficient extracts the friend relationship. Since our contact kernel Y is really sparse, users have not many friends in the testing process. So when m gets bigger, the difference of accuracy between R2 model and MKL gets smaller.

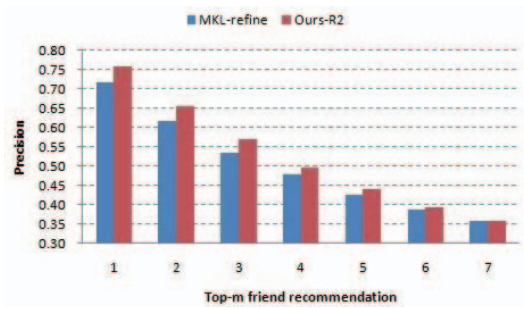


Fig. 5. Average accuracy of top-7 friend recommendation under R2 model and MKL model (n=8).

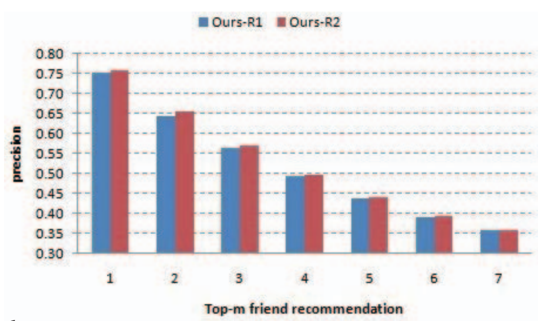


Fig. 6. Average accuracy of top-7 friend recommendation by R1 and R2 combination of our model.

Then we make comparison between our R_1 and R_2 combination models. We set n to be 8 and then get Figure 6. Our R_2 model works better than our R_1 model. Only interaction and similarity tie strength are both get the high scores, the R_2 final tie strength will get a high score. This makes the prediction more accurate.

4. CONCLUSION

Instead of using a fixed form to calculate the continuous tie strength with the method of MKL, this paper studies a user specific model for the friend recommendation task combining the rich heterogeneous data. Our key ideas are threefold: 1) separating the multiple data sources into two classes which are interactions and similarities. 2) employing a relatively simple linear model under the concept of precision to evaluate tie strength within each single kernel. 3) using a normalized exponent combination method to tackle the interaction and similarity kernels. Evaluated on a real-world dataset, our method achieves promising results. We hope this work could call for more attention to the social strength modeling in the community with a user-specific way.

5. REFERENCES

[1] Michael Moricz, Yerbolat Dosbayev, and Mikhail Berlyant, "Pymk: friend recommendation at myspace," in *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*. ACM, 2010, pp. 999–1002.

[2] Mark S Granovetter, "The strength of weak ties," *American journal of sociology*, pp. 1360–1380, 1973.

[3] Alan Mislove, Hema Swetha Koppula, Krishna P Gummadi, Peter Druschel, and Bobby Bhattacharjee, "Growth of the flickr social network," in *Proceedings of the first workshop on Online social networks*. ACM, 2008, pp. 25–30.

[4] Rossano Schifanella, Alain Barrat, Ciro Cattuto, Benjamin Markines, and Filippo Menczer, "Folks in folksonomies: social link prediction from shared metadata," in *Proceedings of the third ACM international conference on Web search and data mining*. ACM, 2010, pp. 271–280.

[5] Roelof Van Zwol, "Flickr: Who is looking?," in *Proceedings of the IEEE/WIC/ACM international Conference on Web intelligence*. IEEE Computer Society, 2007, pp. 184–190.

[6] Kristina Lerman and Laurie Jones, "Social browsing on flickr," *arXiv preprint cs/0612047*, 2006.

[7] Jie Yu, Dhiraj Joshi, and Jiebo Luo, "Connecting people in photo-sharing sites by photo content and user annotations," in *Multimedia and Expo, 2009. ICME 2009. IEEE International Conference on*. IEEE, 2009, pp. 1464–1467.

[8] Nhat Hai Phan, Van Duc Thong Hoang, and Hyoseop Shin, "Adaptive combination of tag and link-based user similarity in flickr," in *Proceedings of the international conference on Multimedia*. ACM, 2010, pp. 675–678.

[9] Ting Yao, Chong-Wah Ngo, and Tao Mei, "Context-based friend suggestion in online photo-sharing community," in *Proceedings of the 19th ACM international conference on Multimedia*. ACM, 2011, pp. 945–948.

[10] Jinfeng Zhuang, Tao Mei, Steven CH Hoi, Xian-Sheng Hua, and Shipeng Li, "Modeling social strength in social media community via kernel-based learning," in *Proceedings of the 19th ACM international conference on Multimedia*. ACM, 2011, pp. 113–122.

[11] Corinna Cortes, Mehryar Mohri, and Afshin Rostamizadeh, "Two-stage learning kernel algorithms," in *Proceedings of the 27th International Conference on Machine Learning (ICML-10)*, 2010, pp. 239–246.