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When a Friend Online is More Than a Friend in Life: Intimate Relationship Prediction in Microblogs

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Abstract. Microblogging services such as Twitter and Sina Weibo have been an important, if not indespensible, platform for people around the world to connect to one another. The rich content and user interactions on these platforms reveal insightful information about each user that are valuable for various real-life applications. In particular, user offline relationships, especially those intimate ones such as family members and couples, offer distinctive value for many business and social settings. In this study, we focus on using Sina Weibo to discover intimate offline relationships among users. The problem is uniquely interesting and challenging due to the difficulty in mining such sensitive and implicit knowledge across the online-offline boundary. We introduce deep learning approaches to this relationship identity problem and adopt an integrated model to capture features from both user profile and mention message. Our experiments on real data demonstrate the effectiveness of our approach. In addition, we present interesting findings from behavior between intimate users in terms of user features and interaction patterns.

Keywords: Intimate relationship · Relationship identification · Deep learning · Microblogging platform

1 Introduction

Online microblogging services provide popular public platforms where users can establish their own social networks online. For example, Sina Weibo[1], which is widely used in China, now has 76 million active users every day and 1.67 hundred million users every month, and still counting. With the common usage of such social networks, some interesting questions arise. For example, profiling a user's topic interests can benefit product recommendation and advertisements to serve targeted customers [14,15]; profiling a user's location helps push localized news or weather information [1]. Such profiling can not only offer personalized services to users but also give potential commercial opportunities to businesses.

[1] http://www.weibo.com.

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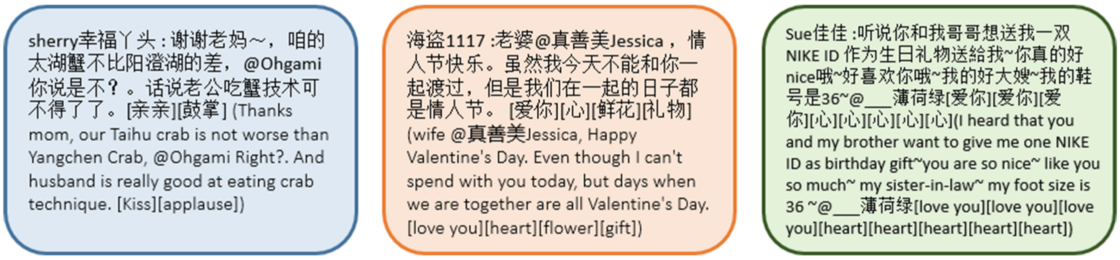


Fig. 1. Examples of intimate relationship

A closely related task to user profiling is the task of identifying offline friends from online microblogging platform. This task has also attracted researchers' attention and been applied to applications such as friend recommendation and product recommendation, since offline friendship is arguably a more reliable connection between users.

In this paper, we are particularly interested in identifying intimate relationships in Weibo. We define an intimate relationship as the relationship between romantic partners, parents and children, and other close relatives. Some examples are shown in Fig. 1. An intimate relationship is a much stronger relationship than general offline relationship which represents an elevated level of mutual trust and association in many aspects such as financial ones. As such, it is of great value to leverage these relationships among users for a great number of business and financial applications.

For example, Word-of-mouth marketing has been observed to be more effective among users with intimate relationships as a result of deeper trust and shared lifestyle. On the other hand, in banking industry, it is crucial to be able to identify customers of potential credit issues and one useful approach is to propagate credit-related labels from identified ill-credit users to those unknown ones. As people with intimate relationships are usually financially connected, these user attributes and labels such as personal credit and financial status are only legitimate to be propagated among users of intimate relationships [16].

Intuitively, a user's profile and Weibo mention messages provide valuable signals for identifying her intimate relationships. In this work, we have the following assumptions: (1) Intimate user pairs share certain common properties such as their geolocations and interests. (2) Intimate user pairs would more likely mention each other in specific messages. The challenges of the problem lie in the difficulty in inferring these implicit sensitive user information from noisy social data across the online-offline boundary.

In this paper, we employ an integrated model to combine user profile information as well as mention interaction. The main contributions of our work are as follows:

- We identify the important and interesting problem of mining user intimate offline relationship from microblogging platforms, which offers unique value for a wide range of real-life applications.

- We introduce effective TransE and CNNs models to the problem and propose an integrated model which captures both user profile and interaction features.
- We conduct experiments on real data sets to demonstrate the effectiveness of our model. We also summarize specific features and behavior patterns between pairs of intimate users to offer a better understanding of the characteristics of intimate relationships on microblogging platform.

In the rest of this work, we introduce related work in Sect. 2 and then formulate our research approaches in detail in Sect. 3. The dataset is introduced in Sect. 4. Experiments and result analysis are described in Sect. 5. We conclude this work in Sect. 6.

2 Related Work

2.1 Strong Tie

Strong tie plays an important role in social network systems. Researchers are interested in identifying strong ties since they give us more reliable information. A strong tie is typically "embedded" in a social network, with more mutual friends [11] or homogeneity. It benefits us in identifying the most important individuals in a social network. Recently, some work developed methods analyzing social network structures and measuring tie strengths [12,13]. Most of their methods take advantage of the number of mutual friends as embeddedness between two users.

2.2 Intimate Relationships

In the work of [2], the author proposed a new network-based characterization for intimate relationships, those involving spouses or romantic partners. For our research, we broaden the definition of intimate relationships. The intimate relationships can be between romantic partners, parents and children, and relatives. Such relationships are important to study for several reasons. From a substantive point of view, romantic relationships are of course singular types of social ties that play powerful roles in social processes over a person's whole life [6], from adolescence [5] to older age [7]. They also form an important aspect of the everyday practices and uses of social media [8]. There are important challenges from a methodological point of view: they are evidently among the very strongest ties, but it has not been clear whether standard structural theories based on embeddedness are sufficient to characterize them, or whether they possess singular structural properties of their own [9]. In comparison, our work utilizes additional rich context features to identify intimate relationship.

3 Model

3.1 Profile-Based Model

As we introduced above, people usually use friendship to measure similarity of users online, however, as we know, it is not enough to predict intimate relationships. More useful information like profiles of users may also contribute to intimate relationship prediction. Based on this motivation, we extend a social relation network into a knowledge network and characterize users with rich information.

To better explain our model, we demonstrate in a precise way. In network graph G, triplets can be displayed as $< h, r, t > \in G$, where $h, t \in E$ represents a head entity and a tail entity, E is a set of all entities, and $r \in R$ is a set containing all relationships between entities.

Given the above definition, we construct our knowledge network graph, which is a collection of relational fact triplets but with many missing parts in need of completion. We leverage TransE [4], which is an advanced deep learning technique for knowledge graph completion problems. This model learns embeddings of entities and relationships by mapping entities and relations into the same vector space where entity embeddings occupy positions in the knowledge graph space and relation embeddings connect them. Such low-dimensional continuous representation encodes inherent relationships between entities and relations [18]. Its high performance and low complexity triggered many modifications and applications [17,19]. The basic idea behind the TransE framework is the following. For a true triplet, $h+r$ is approximately equal to t, that is, $h+r \approx t$, while $h+r$ should be far away from t for a false triplet. For some dissimilarity measurement d, if $< h, r, t >$ holds, $d(h+r, t)$ should be relatively small compared with a false triplet $d(\acute{h}+r, t)$ or $d(h+r, \acute{t})$. In order to ensure $d(h+r, t)$ is smaller than a false triplet, we minimize the following margin-based penalty function:

$$L_1 = \sum_{(h,r,t) \in S} \sum_{(\acute{h},r,\acute{t}) \in \acute{S}} [\gamma + d(h+r, t) - d(\acute{h}+r, \acute{t})]_+ \tag{1}$$

where all $h, r, t \in R^{k*1}$, $[x]_+$ denotes positive part of x, γ is a margin hyper parameter, and

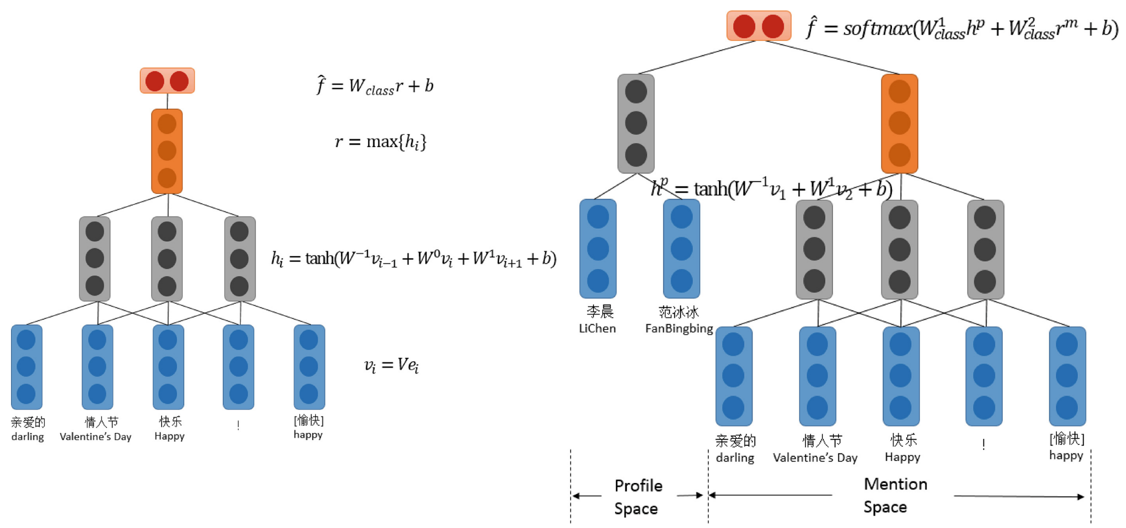
$$\acute{S} = \{(\acute{h}, r, t) | \acute{h} \in E\} \cup \{(h, r, \acute{t}) | \acute{t} \in E\} \tag{2}$$

Which means false triplet is obtained from replacing one entity in triplet with another one in E randomly. When there are many same relationships attached to two entities, their embeddings will be much similar.

3.2 Mention-Based Model

Since Weibo is a microblogging platform where users can interact with each other by repost or @ or reply, and interactions between intimate users and regular friends may be distinct, we would like to investigate Weibo mention messages between two users to predict whether they have an intimate relationship.

In the mention space, definition m is a sequence of many tokens $\{e_1, e_2, ..., e_n\}$, which is Weibo message in practice. $m \in M_{h,t}$ represents existing mentions, which include entities h and t, and M means the set of all mentions. We would like to build a convolutional neural network (CNN) [10] to classify it into target classes, i.e., intimate relationship or not. CNNs are an effective type of sentence-level neural networks extensively applied in social media tasks, like Tweet sentiment



(a) CNNs applied to mention space (b) Integrated Model

Fig. 2. Neural network model architecture

analysis [20]. Figure 2(a) shows the neural network architecture. In the first layer, input is a parsed mention message. Then every token is mapped into a vector v_i using embedding matrix V. Then convolution layer convolutes input by windows, and a position-specific parameter W implies weight of feature at different positions. After that, a max pooling operation is applied to select the most significant feature for every dimension among the various windows. Finally, the output of the convolution layer is sent to the classifier layer, and classified into two classes. The objective function is as follows:

$$L_2 = argmin \sum_{m \in M_{h,t}} \parallel f_m - \hat{f_m} \parallel_2, \tag{3}$$

where $\hat{f_m}$ is the predicted label. The reason why we choose CNNs is that this neural network can capture relatively global features inside a sequence instead of local features. For example, two sequences containing *Valentine's Day*, convolutional neural network tells difference between *Happy Valentine's Day* and *Valentine's Day is a holiday.*

In our model, the embedding of tokens are all pre-trained by Word2Vec, and we keep embedding matrix static and feed CNNs model Weibo mention messages to learn parameters.

3.3 Integrated Model

Even though mention message can be a powerful evidence to decide whether there is an intimate relationship between two users, we still cannot say as long as two users communicate with an intimate expression then they have an intimate relationship. So we attempt to integrate these two models. In the prediction part, we combine profile information and mention information together and make predictions jointly.

Figure 2(b) shows the architecture of the integrated model. The left side is in profile space, where we leverage pre-trained embedding from profile-based model. The right side is in mention space, where we still use pre-trained Word2Vec embeddings. But we finally connect these two sides together by applying a linear combination of these two sides and finally send into a softmax layer to obtain output.

In the profile space, the output of the convolution layer is obtained in a similar way as in mention-based model, that is:

$$h^p = tanh(W^{-1}v_1 + W^1 v_2 + b), \tag{4}$$

Where v_1 and v_2 are entity embeddings learned from Profile-based model. The output of the mention space is the output of the max pooling layer denoted as r^m. So the classifier layer tries to merge this two linearly and obtain the final label with a softmax function:

$$\hat{f_m} = softmax(W^1_{class} h^p + W^2_{class} r^m + b) \tag{5}$$

Thus the parameter W^1_{class} and W^2_{class} will act as projectors projecting two spaces into a single space. And this model carries both types of information from the profile space as well as the mention space. The objective function is the same as the one in the mention-based model.

4 Dataset

The Weibo dataset we collected contains details of their online activities on Weibo of 1622 user pairs between October 2012 and June 2013. These users are randomly picked from Weibo.

The ground truth is manually labeled based on their Weibo messages by major votes. From the content of each Weibo, we distinguish whether a user and his mentioned user may have any intimate relationship by specific and distinct words. The intimate relationships include three types: romantic partners, parents and children, and other close relatives. Since many user pairs have fuzzy intimate relationships and certain relationship has rare samples, we narrow down all kinds of intimate classes into one, even though our model can handle multi-classes classification problem well theoretically.

Overall, we have 642 pairs who have certain intimate relationship; 980 pairs who are not shown any evidence that can prove that they have any intimate relationship. In our research, based on the collected user pairs, we extend their social relation network by collecting information of both themselves and their neighbors.

For baseline, we consider three forms of network. Forming with only followee relationship, only follower relationship and only mutual follow relationship, denoted as Follower&Followee (Table 1). Obviously, network forming with Follower&Followee contains much fewer edges than the other two.

Table 1. Network specification

Network	Avg degree	Nodes	Edges
Followee	4.2881	185241	397168
Follower	2.0212	209372	211594
FollowerFollowee	1.9042	57510	54756

Besides follower and followee relationship, details of users' gender, interests, education and Weibo messages .etc are collected, allowing for an analysis of their profile and mention.

4.1 Weibo Mention Message

For these 1622 user pairs, we crawled their Weibo messages from users' homepages. These Weibo messages are also randomly picked which can be employed as evidence to predict intimate relationship between two users in literal way.

For every mention message containing a mentioned user, we replace the mentioned username with specific symbol *\$account\$* in the sentence, since it doesn't matter who is mentioned in our mention-based model. In terms of pre-processing, all the emotion is transformed into text and text are simplified and tokenized by the tool Jieba[2]. Thus we obtain clear mention message for every user pair.

4.2 User Profile

We extract 8 types of data from user profiles to define the relationships between entities. Table 2 contains a summary of this data.

Table 2. Relation summary

Relation	Description
StudyIn	Schools that users have studied in. A user can have this kind of relation with several schools
WorkIn	City and district where a user is working
LiveIn	City and district where a user is living
GenderIs	Gender of user, right entities are "male" or "female"
InterestedIn	Topics that users are interested in which is extracted from description of Weibo user
BelongTo	A user belongs to "celebrity" if he is verified by official Weibo, always celebrity is very influential user among other people
Follower	User's Follower, left and right entity of this triplet are users
Followee	User's Followee, left and right entity of this triplet are users

[2] https://github.com/fxsjy/jieba.

We collected 966705 triplets about listed relations. Finally, we add "IntimateWith", "UnitimateWith" triplets inside together to comprise all triplets for profile-based model.

5 Experiment

5.1 Experiment Setup

In the experiment, given two users, we are going to identify whether they have intimate relationship between them, based on dataset we collected.

For baseline, we construct Weibo social relation network by connecting two users if there is online friendship between them, these online friendships variate as Follower, Followee and Follower&Followee. Some widely-used algorithms for link prediction are implemented to measure similarity between user pair. $Jaccard$ and $AdamicAdar$ coefficients [3] represent how many common neighbors two users are sharing, which may reveal how intimate they are. $Dispersion$ [2] motivates from the idea that people can easily have common neighbor online in a cluster but intimate users would more likely to have common neighbors from different clusters and . And $MutualFollow$ is binary feature applied in Followee&Fllower network, which values 1 if there is an edge holding between two users.

In the training part, we split dataset into two train and test part by 80 % and 20 % randomly. We obtain similarity scores for every user pairs, then we apply SVM^{light} to do classification.

For the profile-based model, in TransE, we apply L_2 distance to measure dissimilarity $(h+r)$ and t, and learning rate is set as 0.01 and iterate 1000 times, we learn 50 dimension embedding for every entity. All these parameters are tuned to achieve best performance for validation set. When predicting relationship of one user pair, we rank triplet containing "IntimateWith" and "UnitimateWith", relation with smaller dissimilarity will be our predicted label.

For mention-based model, all embedding of tokens are pre-train from a large corpus collected from Weibo[3]. Here, we still learn 50 dimension for every word, and set windows size as 3, learn rate as 0.05 for every step, iterate for 100 times. Same parameters are also used in integrated model.

For evaluation, we use recall, precision, F1 and accuracy index, which are widely used in classification problem.

5.2 Experiment Result

The result can be seen in Table 3. Notice traditional $Jaccard$ gains a low F1 score, while $Adar$ performs relatively better. Both of them use information of common neighbors, but $Jaccard$ reduces common neighbor's effect by adding union of their neighbor inside. $Dispersion$, which was proved to have impressive performance, however obtains a low recall, this may because most of people would not

[3] We randomly picked 100 active Weibo users, and crawled all their Weibo messages and constituted corpus with 12 k Weibo messages.

Table 3. Experiment results

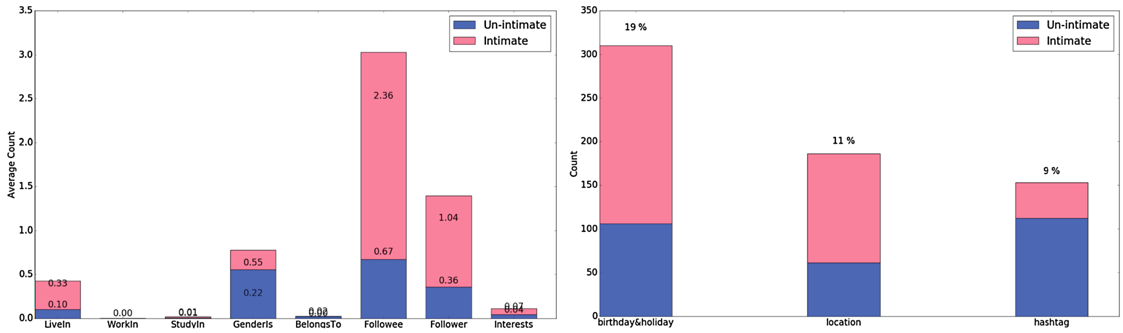
Method	Algorithm	Recall	Precision	F1	Accuracy
Followee	Jaccard	3.68	83.33	7.05	59.88
	Adar	41.18	90.32	56.57	73.86
	Dispersion	35.29	94.12	51.33	72.34
Follower	Jaccard	1.47	100	2.90	59.27
	Adar	26.47	92.31	41.14	68.69
	Dispersion	17.65	92.31	29.63	65.35
Follower&Followee	Mutual	47.06	72.73	57.14	70.82
	Jaccard	3.68	100	7.10	60.18
	Adar	13.64	100	24.01	64.13
	Dispersion	8.82	100	16.21	62.13
Profile-based model		99.26	67.17	71.42	67.17
Mention-based model		58.82	73.39	65.30	74.16
Integrated model		88.24	75.47	**81.35**	**83.28**

like to establish their neighbors circle in Weibo, so the feature is unavailable, which leads to performance depreciation. From the table, the followee relationship performs better than follower relationship which may indicates that followee relationship is more reliable and applicable compared with follower relationship in this dataset.

Profile-based method performs not very well, even if it captures not only friendship between users but also their interest or education or work information, its low precision indicates it tends to make false positive prediction.

Mention-based method doesn't meet our expectation, note that even though CNNs is a powerful tool to capture text features in Weibo mention message, during learning process, it gives high weight to some intimate tokens or phrases, like *I love you*, *miss you*. Moreover, some specific names entities like *IKEA*, *Resort hotel* are also given high weights implying intimate relationship. However, in Weibo, even though text maybe the most straightforward for us to recognize intimate users, the precision is relatively low, this may because intimate expression does not mean intimate relationship between users, most false positive prediction happens because of this. Many Weibo on Valentines' Day contains intimate expression, but it turns out to be advertisement from one company reposted by user. Meanwhile, fans would like to express intimate words to their idols but there is no intimate relationship between them. Thus it's reasonable for us to combine these two spaces together and make prediction.

When we combine these two features together, integrated model outperforms all other models, improving mention-based model F1 score by 16.05 % and profile-based model by 9.93 %. Integrated model consider not only distance of two users, but also their message interaction on Weibo, so that it can achieve highest performance.



(a) user profile statistic (b) mention message statistic

Fig. 3. Profile and interaction understanding

5.3 Result Analysis

More than prediction, it would be interesting to figure out significant feature and understand interaction behavior of intimate users online. We analyze average sharing relation statistics for both intimate and un-intimate users and plot Fig. 3(a). Obviously, intimate user pairs share more relations especially followee and follower. However, intimate user pairs in our dataset seems to have different genders, this implies majority of intimate user pairs are couple. Figure 3(b) records count of specific text appearing in Weibo mention message like, birthday or holiday name, location, or hashtag. 19 % Weibo messages mention birthday or specific holiday like *Valentines' Day*, *Mother's Day* etc., 11 % Weibo messages contain location name like hotel, restaurant. Intimate user pairs mention them more frequently by comparison. However, hashtag appear in un-intimate user pairs more often, because actually, Weibo message containing hashtag is likely to be advertisement.

Table 4 displays particular examples we extracted from dataset, the Weibo mention message in first example shows nothing about intimate literally, but our mention-based model can learn it as intimate expression because of *ResortHotel* is likely to be some romantic place, meanwhile, profile-based model implies they are intimate user pair for the sake of relations they share in their profile; in second example, Weibo content seems to happen between father and son,

Table 4. Case study

Golden Standard	Profile-based	Mention-based	user&user mention	Weibo mention message
+	+	+	Devil_住在云上的人&奚小慕(regular user&regular user)	我在千湖馨度假酒店。与 $account$ 在一起。湖景房～真心美哦～晚上要多拍照片 (I'm in Thousand - Islet Lake Cozy Island Resort Hotel with $account$. Lake house˜really great˜I'll take lots of photo tonight)
-	-	+	維尼小標題&微博搞笑排行榜(regular user&celebrity user)	Dad happy father's day.I love you//$account$: 親愛的爸爸，父親節快樂！愛你 (Dad happy father's day. I love you//$account$: Dear father happy father's day! love you)
+	-	+	Scarlet-Jason&Miss-小甲菌菌子(regular user&regular user)	$account$ 老婆，我沒有這感覺你有嗎？[偷笑][偷笑] ($account$ wife, I don't have such feeling, do you?)

but profile-based model tells us the distance of two users are quite far, actually, this Weibo happens when one user repost a Weibo posted by a celebrity user; but profile-based method in third example indicates two users have un-intimate relationship while mention-based method obviously reveals their intimate relation. Thus judging with both user profile and mention message is more reasonable.

6 Conclusion

Exploring the structural roles of significant users in microblogging platform is a broad question which requires a combination of different approaches.

In this paper, we introduce TransE to profile space, which reveals similarity among users based on user profile, as well as CNNs to mention space which encodes mention messages, then an integrated model is proposed to adopt both rich context features and contribute to prediction.

Overall, predicting intimate relationship in microblogging platform depends heavily on various signature we extract. In the future, photo and URL link can be used as other useful signals for prediction; sounder baseline should be employed for comparison and more fine-grained intimate classes would like to be explored. To better investigate specific relationship within microblogging platform, more potential feature and methods should be considered in the right way.

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