# Predicting User Mention Behavior in Social Networks

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**Abstract.** Mention is an important interactive behavior used to explicitly refer to target users for specific information in social networks. Understanding user mention behavior can provide important insights into questions of human social behavior and improve design of social network platforms. However, most previous works mainly focus on mentioning for the effect of information diffusion, few researches consider the problem of mention behavior prediction. In this paper, we propose an intuitive approach to predict user mention behavior using link prediction method. Specifically, we first formulate user mention prediction problem as a classification task, and then extract new features including semantic interest match, social tie, mention momentum and interaction strength to improve the performance of prediction. To evaluate the proposed approach, we conduct extensive experiments on Twitter dataset. The experimental results clearly show that our approach has 15% increase in precision compared with the best baseline method.

**Keywords:** Social network · Mention behavior · Link prediction · Classification

## 1 Introduction

In recent years, social network platforms such as Sina Weibo, Twitter and Facebook have become more and more popular, because they allow users to freely post a short message named tweet or status for sharing viewpoints and acquiring knowledge in real time. According to the latest statistics, approximately 500 million tweets are generated per day in Twitter[1]. As a result, the rich information in social networks not only expands our horizon, but also has wide applications in public opinions supervision, natural disaster prediction and political upheaval detection.

In order to better exchange ideas among users, Twitter provide mention function as a new feature to encourage interaction and conversation in social activities. Mention is enabled in a tweet by using "@username". It is placed anywhere in the body of the tweet and contains one or more target users. If a tweet

[1] https://about.twitter.com/company


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contains more than one username, these people will all see the tweet in their own Mentions tabs. By using mention ensures that these tweets which usually have a higher priority to the target user do not get lost by the overwhelming stream of other tweets in the user timeline. Most studies on Twitter's mention function have focused on constructing mention network to explore the pattern of information diffusion and recommending the mentioned users to improve the visibility of the tweets. Although exist research works has been obtained some significant progress, these works neglect the most important fact: *the purpose of mentioning between users is not always to expand information diffusion, sometimes more to let a user know about a tweet or build a good relationship that a mentioned user is interested in information.*

In the paper, we try to predict who will be mentioned for a new coming tweet, it is important to predict future mention links since these links are a bridge for future spread of influence. To this end, we first formulate the user mention prediction problem as a classification task, and then extract a set of feature for the prediction. We would expect that exploiting these features for user's mention prediction would help improve the performance of prediction.

Our contributions are summarized as follows:

- We model mention behavior prediction problem as a supervised classification task combine user, textual, social tie and temporal information features.
- We use semantic enrichment technique to measure interest match between users and topic interest between tweet and user. We also propose a notion of mention momentum to quantify the mention behavior from the pairwise angle.
- We construct a large collection of dataset from Twitter service. The experimental study shows that these features can effectively improve the performance of user mention prediction comparing with other baseline methods.

The rest of the paper is organized as follows. Section 2 surveys the previous work on analysis of user mention in social networks. In Section 3, we formulate the user mention prediction problem and investigate the properties of the problem. Section 4 proposes our model. The empirical experiment results are reported in Section 5. At last, we conclude our work and give the future research directions in Section 6.

## 2 Related Work

There has been a number of efforts that study the properties of mention mechanism in social networks. We can roughly divide these works into two categories of models in this scope: (i) information diffusion models and (ii) recommend models. In the following, we will briefly summarize some representative works as follow.

The goal of information diffusion models is to study on analyzing how mention effect information diffusion. Yang et al. [13] construct a diffusion network based on @username mentioning to analyze the speed, scale and range of tweets on the same topic spread in Twitter. Itakura et al. [7] characterize the structural differences of the retweet graph, the mention graph and the reply graph. They employee PageRank and HITS algorithms to measure each graph, the result suggest that using the mention function is the most efficient method of reaching the mass audience in Twitter. Yu et al. [14] proposes a directed tree model based on user interaction that considering the history, type and frequency of interaction to describe the process of information diffusion.

Beside, mention function has a widely used in recommender systems. Tang et al. [10] present a context-aware recommendation framework and employ ranking support vector machine model to locate target users for posting promotion-oriented messages. Pramanik et al. [8] develop a Twitter app to recommend the best set of users to be mentioned in a tweet in order to maximise the spread of an information. Wang et al. [12] propose a new recommendation scheme to expand the diffusion of tweets by recommending proper users to mention. They formulate the problem as a ranking problem and use all the new features, including user interest match, user social ties and user influence, to achieve the best performance of the algorithm. Those recommendation models aim to find the right users to mention in a tweet for expanding the diffusion of tweets.

However, as far as I know, few research work predict whom to mention. To fill this gap, we now present an approach to predict user mention behavior through link prediction method.

## 3 Problem Statement

Mention is an important interactive behavior in social networks. The intuition behind is that the purpose of mention is to attract the attention of other people for specific information and to form interactions each other.

Mention forms a "tweet-to-user" interaction link between mentionee and mentioner, thus we formulate the problem of mention behavior prediction as a link prediction task. The link prediction problem can also be regarded as a classification problem.

For the convenience and simplicity of description, we formally define mention behavior prediction as follows.

**Definition 1 Mention Prediction.** We use a triple $(u, t, v)$ to represent that user $u$ mentioned $v$ in tweet $t$. For user $u$, we denote all mentioned users as the mention candidate $C$. Given a tweet $t$ that is to post by user $u$, the goal is to find whether $u$ mention $v(\in C)$ in $t$ or not.

Note that publisher $u$ may mention multiple users within one mention tweet $t$, we will consider as multiple mention instances.

As above discussed, the problem of user mention prediction is modeled as a classification task and exist lots of the popular classification methods can be employed. But, the key challenge in this approach is to extract a set of features for the classification task. Next we will discuss the set of features that have been used successfully for mention prediction task.

# 4 User Mention Prediction Model

In this section, we present the process of extracting features used in our model and propose user mention behavior prediction model for task. These features are extracted from the content of tweets, the structure of network topology and interaction knowledge to predict user potentially mention behaviors in the future.

## 4.1 Feature Extraction

**User-to-User Interest Match.** This feature assumes that a user is more likely to mention these users who share similar topics of interests. However, profiling user interest is a challenge task due to the informal nature and ungrammatical language of tweets in Twitter [9]. For instance, given a tweet such as "#Gravity is beautiful http://fb.me/3SkiI5DND" it is difficult to understand to talk about movie or space based on topic modeling technics like LDA. Hong et al. [6] show that topic model techniques like LDA can not accurately depict the topic of tweet due to the short-length, ambiguous, noisy data feature in Twitter. Therefore, we use a semantic enrichment technique to construct user interest profile.

[5] have been shown some web services providing semantic enrichment such as Dbpedia Spotlight[2], TextRazor[3] and Zemanta[4], we opt for OpenCalais[5] due to its state-of-the-art semantic functionality and a high rate limit of 50,000 document per day. We use OpenCalais API to assign each tweet to known topics which now have 18 categorizations, such as sports, education, environment and politics. Then, for each user $u$, we measure the distribution of his/her interests, $D(u)$, represented as a vector over the set of topic categories:

$$D(u) = (\frac{N_{c_1}}{N}, \frac{N_{c_2}}{N}, \cdots, \frac{N_{c_n}}{N}) \quad where \quad N = \sum_i N_{c_i} \tag{1}$$

$N_{c_i}$ is the number of tweets classified into category $c_i$ published by user $u$ in sampled dataset. $N$ is the total number of tweets posted by user $u$. Thus, $D(u)$ represent the proportion of tweets made by the user $u$ publishing about each topic category and also reflect the importance of each of interests.

As discussed in previous studies [1] for topics of interests of Twitter's user, we also propose to use Cosine Similarity (CS) to measure *interest match degree* between mentionee $u$ and mentioner $v$ through their interests distributions. That is,

$$UUIM(u,v) = \frac{D(u) \cdot D(v)}{\parallel D(u) \parallel \parallel D(v) \parallel} \tag{2}$$

**Tweet-to-User Topic Match.** In order to expand the visibility of tweets, publisher always prefers to mention these users who are interested in the new

[2] http://spotlight.dbpedia.org/
[3] https://www.textrazor.com/
[4] http://www.zemanta.com/
[5] http://www.opencalais.com/

coming tweet and more likely to retweet it. Therefore, in this paper we also calculate topic match degree between mentioner $v$ and the new coming tweet $t$.

As is mentioned above, we also exploit OpenCalais API to represent the topic of tweet $t$ as follow:

$$D(t) = (p_{c_1}, p_{c_2}, \cdots, p_{c_n}) \tag{3}$$

where $p_{c_i}$ is the probability of tweet $t$ belong to the $i$-th topic. Similarity, *topic match degree* between the new coming tweet $t$ and mentioner $v$ can be computed as Cosine Similarity as follows:

$$TUTM(t, v) = \frac{D(t) \cdot D(v)}{\parallel D(t) \parallel \parallel D(v) \parallel} \tag{4}$$

**User Social Tie.** Intuitively, the more common neighbors, the more they are familiar with each other. They are more likely to mention each other compared with a total stranger. In simple words, if user $u$ follow $w$ and $v$ follow $w$, then there is a high probability that between $u$ and $v$ form a social tie. So, the number of common neighbors can be measure as the chance that $u$ and $u$ will have a mention between them. However, the common neighbors metric is not normalized. Therefore, we use Adamic/Adar [2] as a metric of the strength of *social tie* between two users. For a set of features $z$, it is defined as below.

$$UST(u, v) = \sum_{z \in \Gamma(u) \cap \Gamma(v)} \frac{1}{log\,|\Gamma(z)|} \tag{5}$$

$UST(u, v)$ gives each common neighbor of user $u$ and $v$ a weight, $\frac{1}{log|\Gamma(z)|}$ , to denote its importance. According to exist works on link prediction, Adamic/Adar works better than common neighbors metrics.

**Mentioner Influence Score.** In social marketing, the goal of mentioning users in a tweet mainly hope to attract more people for discussing or retweeting it. Consequently, the influence of mentioners is an important consideration factor of information diffusion with publisher. Therefore, we can define *influence* for mentioner $v$ who is to mentioned in a tweet $t$ as follow:

$$MIS(t, v) = Num.Follower_v \tag{6}$$

where $Num.Follower_v$ is the number of mentioner $v$'s followers.

**Mention Momentum Based Time.** We assume both of users often mentioned each other in the past, this tends to point out that they have been having a conversation and therefore share a good relation in social networks. Furthermore, they are more likely to mention each other in the near future. Specifically, given mentionee $u$ and mentioner $v$, we denote the timestamp of $u$ first mention $v$ as $m_f(u, v)$, and the timestamp of $u$ last mention $v$ as $m_l(u, v)$. We define *mention time span* from $u$ to $v$ as below:

$$MTS(u,v) = m_l(u,v) - m_f(u,v) \tag{7}$$

Correspondingly, we also define *mention frequency* as the average mention interval from $u$ to $v$ as follow:

$$MF(u,v) = \frac{N(u,v)}{MTS(u,v)} \tag{8}$$

where $N(u,v)$ is the mention number of from $u$ to $v$ in the given time interval.

Furthermore, we also calculate *recent mention interval*, which is defined as the interval between $m_l(u,v)$ and the posted timestamp $t_t$ of tweet $t$:

$$RMI(u,t,v) = t_t - m_l(u,v) \tag{9}$$

Finally, we formulate *mention momentum* as below:

$$MMT(u,t,v) = \frac{MF(u,v)}{RMI(u,t,v)} \tag{10}$$

**Interaction Score.** A lot of studies [7,13,14] show that interaction network such as retweet network, reply network and mention network are much more important than follow network in terms of link prediction. Therefore, we use *interaction score* to measure the strength of user interaction as below:

$$IS(u,v) = \sum_{i=1}^{K} \alpha_i N_i(u,v) \tag{11}$$

where $K$ is the number of types for interaction behaviors. $\alpha_i$ and $N_i(u,v)$ is the weight of $i$-th interaction behavior and the number of times, respectively.

### 4.2 Mention Behavior Prediction

Now we have extracted all features of predicting user mention behavior, and then in this section we will discuss how to model the user mention prediction model (named as UMPM) using these features. As discussed in Section 3, the mention behavior prediction can be regarded as a classification problem: given a tweet $t$ that is to posted by user $u$ and a set of candidate $C$ at a specific time point $T$, the goal is to find whether $u$ mention $v(\in C)$ in $t$. We denote the classification label as $m_{u,t,v}$. $m_{u,t,v} = 1$ indicates that $u$ will mention $v$ in t, and $m_{u,t,v} = 0$ otherwise. The classification model is very flexible, thus we can integrate different combinations of the features into the model conveniently.

To solve the classification problem, many classification models for supervised learning can be used. In this paper, we opt to choose SVM, because SVM has a strong theoretical foundations and practical advantages [11], and [15] result shows that SVM is better than others, including Naive Bayes, decision trees, etc. in link prediction.

$$f(m_{u,t,v}|X) = sign(w^T X + b) \quad (12)$$

where $X$ is the feature vector introduced above, and $w$ are weights of the features and $b$ is a bias.

# 5 Experiments and Analysis

In this section, we design the experiment with three goals: (1) show two sampling methods to collect Twitter dataset and then preprocess the dataset; (2) compare link prediction methods for evaluating our proposed approach; (3) leverage common metrics to evaluate the performance of our model.

## 5.1 Data Collection

For this experiment, our objective is to construct a dataset that reflects a comprehensive history of user mention over an extended period. Thus we devise two different sampling schemes - a snowball sample and an activity sample in order to obtain a more comprehensive dataset.

**Snowball Sample.** We first randomly select 10 seed users to perform a snowball sampling. For each seed user, we crawl all tweets on which that Twitter user has been published, and all followers list and all followees list. We then crawl all users appearing in the "list of lists". We repeat these last two steps. In total, our obtain 5,140 Twitter users. Our dataset also contains all tweets ever posted by the collected users, which consists of 11,104,955 tweets.

**Activity Sample.** To avoid potentially biased by the snowball sampling method, we also run a sample of users based on their activity. Specifically, we carefully choose 10 fields of celebrity users that those are verified, and crawl their all tweets and follow networks. Table 1 shows a more detailed information.

**Table 1.** Data Description of Activity Sample

| Users' Category | Num.User | Num.Tweet | Example |
|---|---|---|---|
| Athletes | 16 | 34645 | TheRock, JohnCena, KAKA |
| Brands | 15 | 45086 | McDonalds, YouTube, CocaCola |
| Celebrities | 17 | 37492 | Justinbieber, katyperry |
| Games | 19 | 49896 | PlayStation, AngryBirds |
| Movies | 17 | 33169 | Starwars, SpiderManMovie |
| News | 19 | 61367 | CNN, espn, FoxNews, nytimes |
| Organizations | 18 | 58019 | NASA,Harvard,PBS,RED |
| Politicians | 17 | 39928 | BarackObama, MittRomney |
| Sport Teams | 17 | 54890 | Realmadrid, LFC, NBA |
| TV Shows | 16 | 39857 | BigBang_CBS, Discovery |

In order to our prediction task, we need to run some steps to extract the data requested. From the tweets we only consider these tweets that user directly publish with @ symbol. To improve data quality, strict filtering is employed:

1. Only keep tweets that reference them using "@username".
2. Only keep alphanumeric characters and #. Remove URLs from tweet.
3. Remove all tweets containing RT as a stand-alone term.
4. Remove all tweets that reply other user.
5. Remove all tweets that are determined not to be English.

Figure 1 lists the results of this filtering where we only keep the roughly 21% tweets that does not match any of the filter criteria.

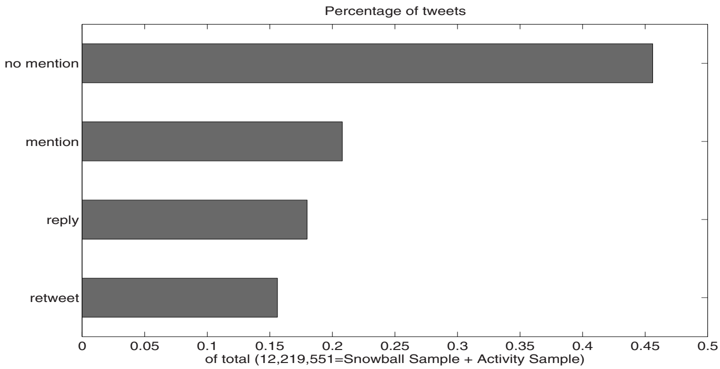


**Fig. 1.** Results of filtering tweet data to improve data quality

### 5.2 Comparison Methods and Evaluation Metrics

In [3], the authors survey a variety of techniques for link prediction. Here, we choose some typical link prediction methods for evaluating our proposed approach are described as follows:

- **Common Neighbors(CN).** $CN(u, v)$ uses the number of shared neighbor as the proximity score of user $u$ and $v$. The proximity score can be formally defined as:

$$CN(u, v) = |\Gamma(u) \cap \Gamma(v)| \tag{13}$$

  The more $CN(u, v)$ is, the closer user $u$ and $v$ are in the network.
- **Jaccard Coeficient (JC).** $JC(u, v)$ normalizes the size of common neighbors in their neighbors as the proximity score of user $u$ and $v$ as below:

$$JC(u, v) = \frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|} \tag{14}$$

- **Adamic/Adar (AA).** $AA(u,v)$ also employees the common neighbors, and weighs the common neighbors with smaller degree of user $u$ and $v$ as below:

$$AA(u,v) = \sum_{z \in \Gamma(u) \cap \Gamma(v)} \frac{1}{log\,|\Gamma(z)|} \tag{15}$$

- **Preferential Attachment (PA).** $PA(u,v)$ gives higher scores to pairs of nodes for user $u$ and $v$ as below:

$$PA(u,v) = \Gamma(u) \cdot \Gamma(v) \tag{16}$$

We divide the constructed data set into training and testing data, and perform 10-fold cross validation. We evaluate the performance of mention behavior prediction in terms of Precision and the area under the ROC curve (AUC).

### 5.3 Results and Discussion

**Overall Results and Analysis.** As shown in Figure 2, we can see conclude that our proposed user mention prediction model (UMPM) significantly better other baseline methods in AUC metrics. We draw the following conclusions from these results. First, the performance of node neighborhood based link prediction methods outperform that of node feature aggregation based link prediction methods. The former show that the best results is Adamic/Adar (AA) method that correctly classifies 75.06% of all instances, but the latter (PA) obtain only the precision with 60.95% of correctly classified instances. The performance has a relatively well improvement for 23.15%. A reasonable explanation is the number of common neighborhood of both users can better measure user's relationship than node's attribute, they are more likely to mention each other in a new coming tweet in the future. In addition, the performance of AA is better than that of Common Neighbors (CN), this is in accordance with the conclude in [3]. Second, the performance of our proposed method (UMPM) outperforms all the comparison algorithms in the experiment. Even comparing the best result with AA, it shows 15% increase in precision. This indicates that the features that we had selected have good discriminating ability. Finally, the result also indicates that the proposed model can improve the performance of mention behavior prediction as we increase the observation period.

**Feature Analysis.** As discussed in Section 4.1, we extract a set of features for the mention prediction task, namely User-to-User Interest Match, Tweet-to-User Topic Match, User Social Tie, Mentioner Influence Score, Mention Momentum based Time and Interaction Score. To analyze how effectiveness of each feature used in our proposed algorithm contribute to the learned model, we design this contrast experiment by eliminating one feature at a time and observe how the performance of our model changes. Specifically, we mark without User-to-User Interest Match feature as No_UUIM, without Tweet-to-User Topic Match feature as No_TUTM, without User Social Tie feature as No_UST, without Mentioner Influence Score feature as No_MIS, without Mention Momentum based Time

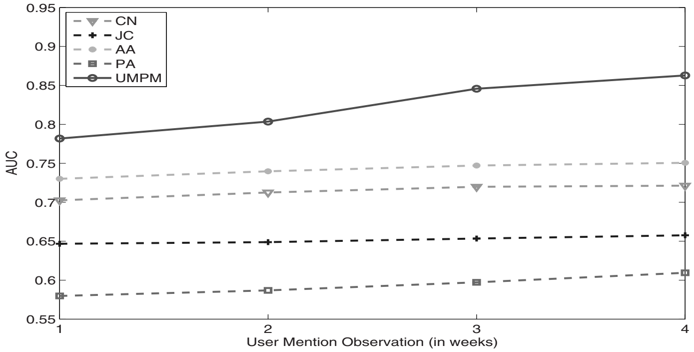


**Fig. 2.** AUC on link prediction with baseline methods

feature as No_MMT and without Interaction Score feature as No_IS. Similarly, we summarize performance for feature evaluation using the Precision metric as mentioned in Section 5.2.

All the results are shown in Figure 3, where the higher the precision is, the less important the feature is. Note that, when we remove User-to-User Interest Match feature (No_UUIM) and Tweet-to-User Topic Match feature (No_TUTM), the precision suffers from a 5.8% decline and 10.4% decline, respectively. The result shows the prediction importance of both features is lowest. It is in accordance with our instinct that both users who have the similarity interests or tastes are not necessarily mention each other. Moreover, when we eliminate Mention Momentum based Time feature (No_MMT) and Interaction Score feature (No_IS), the model suffers a 35.8% decline of precision and 27.7% decline of precision, respectively. We can conclude that although user interest match and user influence help to improve the prediction result, user interactions play a much more significant role in the mention prediction task. As discussed earlier, past user mentions has a high correlation with the user mention data in the future. This is as we expected because the users who often mention each other are more likely to have a mention relationship in the future than the users who have not mentioned each other in the past.

**Discussion.** In total, we aim to predict user mention behavior using machine learning method, but, as shown in the picture above, the accuracy is not more higher. One of the reasons being that the tweet feature is sparse and user profile information contributes very little to the classifier performance. In addition, our observation for Twitter is that the neighborhood does not completely identify the area of influence. For example, in our experimental dataset, we define four types of user relationship, namely stranger (both of users no follow each other), follower (one is following another user), followee (one is followed by another user), friend (both of users mutual follow each other). We extract the link relationship between mentionee $u$ and montioner $v$. The result is shown in Figure 4. From

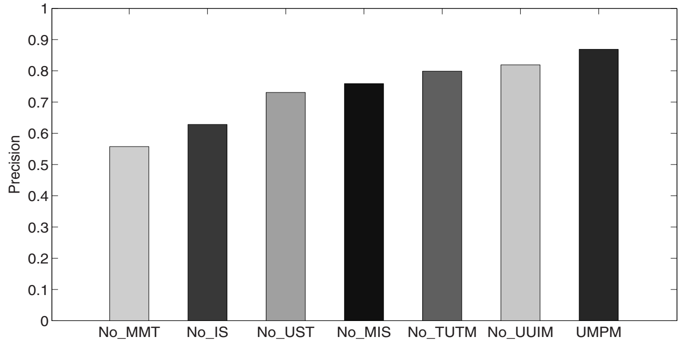


**Fig. 3.** Comparison on how different features affect the performance of UMPM

the figure, we can clearly see that most of mention behaviors are more likely to occur between friends. Meanwhile, we also find an interest fact that in second place is mentions between strangers, where the lowest is 13% in SportTeams and the highest is up to 44% in Brands. We can conclude that the purpose of a user mentions others in a tweet is very different in social networks. The set of our mentioned candidate have no consider the strangers, this is one of reasons that why the precision is not high in the above mentioned.

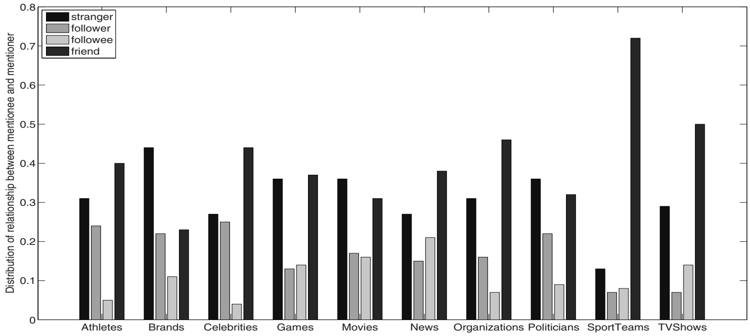


**Fig. 4.** Distribution of tweets per user relationship in activity sample

## 6 Conclusions and Future Work

In this paper we model the problem of user mention prediction as a classification task. Our analysis focuses on whom to be mentioned for a new coming tweet. To this end, we extract a series of prediction features and carefully choose prediction model. The experiment result shows that our proposed method outperform the baseline link prediction methods which only consider network topology or node attribute. Moreover, we find that novel users who never mentioned for the publisher in the past are refer to in a tweet. Although it is more difficult for predicting these novel users and the prediction accuracy may be lower, we will try to address this issue in the future due to the need of information diffusion monitoring. Meanwhile, we also will consider location-based feature in our mention prediction model.

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