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User emotion for modeling retweeting behaviors

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ABSTRACT

Twitter and other microblogs have rapidly become a significant mean of information propagation in today's web. Understanding the main factors that make certain pieces of information spread quickly in these platforms has emerged as a popular topic. Therefore, as a simple yet powerful way of disseminating useful information, retweeting has attracted much interest. Existing methods for retweets have been conducted for analyzing the social network structure, or understanding the retweeting mechanism. However, little attention is paid to whether users' emotion will affect users' retweeting behavior. In this paper, we study the user emotion problem in a large social network. Particularly, we consider users' retweet behaviors and focus on investigating whether users with a certain emotional status will retweet the tweet corresponding with users' current mood from their friends. In order to achieve this goal, we propose a retweeting prediction framework. First, we construct a model of emotion detection via considering two kinds of emotional signals; second, we extract possible retweeted friends and tweets; third, based on the first two steps, we obtain Top-N retweets using Learn-to-Rank method. Experiments are performed on two real-world datasets, the Twitter network and Obama–McCain Debate dataset, with comprehensive measurements. Experimental results demonstrate that our retweeting prediction framework has substantial advantages over commonly used retweeting prediction approaches in predicting retweeting behaviors. Consider Precision in Twitter network as an example. For the Top-N stage, our method can, on average, increase by 15.2% and 11.2% in relation to Tweet(+SV) and User(+ED), respectively. We find that emotion is a vital feature which affects retweetability.

1. Introduction

Social network has emerged as a vital tool for information dissemination, search and marketing. Meanwhile, with the increasing of people's requirements, more and more social networks are appearing, like Twitter,[1] Facebook,[2] and Sina Weibo.[3] Taking Twitter as an example, through Twitter, users can post tweets whose length is up to 140 characters, which tells your family or friends anything in your daily life, such as what you are doing, what you are thinking, or what is happening around you. So far, the number of Twitter users has climbed to 288 million (Urabe, Rzepka, & Araki, 2013) and the number of tweets published on Twitter every day is over 65 million.[4]

As a result of the rapidly increasing number of tweets, more and more researchers pay attention to mining people's emotions expressed in tweets (He, Zheng, & Bao, 2014; Jiang, Yu, & Zhou, 2011). As Bollen, Pepe, and Mao (2011) said, users argued that the events in the social, political and cultural fields did have a significant influence on users' mood. Usually, different emotions may be expressed by users towards different topics, where users may be happy with some aspects of an entity but unhappy with other aspects. Thus, by analyzing the semantic orientation of tweets posted by users, we can obtain the current sentiment of users, like positive, negative or neutral. Nowadays, some web sites constructed on the Internet have already been emerging in order to provide a Twitter sentiment search service, like Tweetfeel,[5] Twendz,[6] and Twitter Sentiment.[7] However, most of the current research or services focus on sentiment analysis itself, such as sentiment classification (Jiang et al., 2011; Lin & He, 2009), inferring individual emotional states (Kim, Yoo, & Lim, 2013; Tang, Zhang, & Sun, 2012), and disclosing the emotions in tweets (Zhao, Dong, & Wu, 2012). Few research works involve how emotions affect

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1 https://twitter.com/
2 https://www.facebook.com/
3 The most popular Chinese microblogging service,
4 http://en.wikipedia.org/wiki/Twitter
5 http://www.tweetfeel.com/
6 http://twendz.waggeneredstrom.com/
7 http://twittersentiment.appspot.com/

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people's behaviors, like retweeting behaviors, which motivates our work.

Here, retweeting behavior is a strong indication of the direction of information flow in the Twitter social graph in that people explicitly identify the source, and is also a social practice that occurs in Twitter so as to quickly share a piece of information (Recuero, Araujo, & Zago, 2011). In a certain extent, retweet action indicates that the original tweet contains valuable information (Suh, Hong, & Pirolli, 2010). Also, retweets have been a measure of the tweet's popularity and influence (Kwak, Lee, & Park, 2010). Retweeting behavior is an important feature for personalized Tweet recommendation (Chen, Chen, & Zheng, 2012) and learning to rank of Tweets (Duan, Jiang, Qin, & Zhou, 2010). Understanding retweeting mechanism and predicting retweeting behavior is an important and essential step for various social network applications, such as user behavior analysis, business intelligence, and popular event prediction (Liang, Jiang, Yin, Wang, Tan, & Bai, 2016; Zhang, Gong, Guo, & Huang, 2015).

Currently, there exist many studies about retweets. One important branch of these studies is retweeting the prediction model. It contains two main points: one is which tweet will be retweeted (Chen et al., 2012), the other one is finding retweeters in Twitter (Luo, Osborne, & Tang, 2013). However, few works pay attention to which tweet a certain user will repost, which also motivates our research work.

From the previous research, major factors affecting the retweeting behaviors are categorized into the following: (1) content and contextual features of the tweets, such as URLs and hashtags; (2) users' features, such as users' interests, the age of the account, and social influence (Zhang, Liu, & Tang, 2013). Unluckily, emotions can never be considered as a vital feature of users to affect retweetability. Intuitively, users with good mood are likely to follow the positive tweets and ones with bad mood would like to follow the negative tweets. In this paper, we investigate how different emotions in the context of online social media affect users' retweeting behaviors. To the best of our knowledge, this is the first attempt towards studying that human's emotions somehow influence retweeting behaviors in a large scale and real world setting.

The main contributions of this research can be summarized as follows:

- We study the problem of the retweeting behavior prediction in Twitter social network.
- We present a novel retweeting prediction framework consisting of three stages: emotion detection, capturing the possible retweets, and finding Top-N retweets.
- We propose a emotion detection model to generate users' mood by leveraging two kinds of emotional signals, emoticons and word-level emotions.
- Experiments on real dataset indicate that our proposed method can predict retweeting behavior with high accuracy compared with the state-of-the-art prediction methods.

The remainder of this paper is organized as follows. We first introduce the related work in Section 2. We next present several necessary definitions and denote the task of retweeting behavior prediction in Section 3. We further show a novel three-stage prediction framework to predict the users' retweeting behavior in Section 4. We report our experiments and results in Section 5, and conclude the study in Section 6.

2. Related work

In this section, we review two categories of related work: studies on emotion mining and modeling retweeting behaviors in social networks.

Emotion Mining. Emotion mining has recently emerged as a popular way to help better understand a user's online behavior and benefit a set of applications relevant to online campaign and recommender systems (Gao, Mahmud, & Chen, 2014; Mohammad, Zhu, Kiritchenko, & Martin, 2015; Rangel & Rosso, 2016). Early works mainly focused on how to understand users' emotions in social media, such as qualitative and quantitative analysis of how an individual's emotional state can be inferred from her/his historic emotion log (Tang et al., 2012).

In Aoki and Uchida (2011), authors proposed a method by which emotional vectors of emoticons can be automatically generated via using emotional words that co-occur with emoticons derived from many weblog articles. In He et al. (2014), they first investigated emotion entrainment in the context of online social media and then showed a framework which can model entrainment phenomenon. Jiang et al. (2011) addressed target-dependent sentiment classification of tweets. Specifically, given a query, the sentiments of the tweets can be classified as positive, negative or neutral according to whether they contained positive, negative or neutral sentiments about that query. Similarly, Shen, Kuo, and Yeh (2013) tried to solve a clinical problem, depression detection. A two-stage supervised learning framework was proposed to identify potential depression candidates based on their write-ups. In Urabe et al. (2013), they described an emoticon recommendation system by which users can express their feelings with their input. In Calais Guerra, Veloso, and Meira (2011), authors handled the task of real time sentiment analysis as a relational learning task via using the network structure formed from the mutual endorsements among social network users. In Hu, Tang, and Tang (2013), they investigated whether social relations can help sentiment analysis and presented a sociological approach to addressing noisy and short texts for sentiment classification. Zhao et al. (2012) built an online sentiment analysis system for Chinese tweets in Weibo, which generated sentiment labels for tweets by employing the emoticons, and constructed an incremental learning Naive Bayes classifier for the categorization of four types of sentiments. In Hu, Tang, and Gao (2013), authors detected a new problem of interpreting emotional signals for unsupervised sentiment analysis. Li, Wang, and Hovy (2014) tried to answer the long-lasting question about mood-weather correlation by showing a framework that harnessed Twitter data. In Guillory, Spiegel, and Drislane (2011), they emphasized the importance of the intensity of specific emotions, in other words, emotions impacted text-based communication, and pointed out that the process of emotion contagion in this context was more complex than previously thought.

Another line similar to our research problem is how to use emotion to guide users' behavior (Calais Guerra et al., 2011; Gao et al., 2014; Kramer, 2012; Mohammad et al., 2015; Yang, Jia, & Zhang, 2014). In Yang et al. (2014), they presented a novel emotion learning method, that is, they modeled the comments and visual features of images and bridged these two pieces of information via learning a latent space. In Gao et al. (2014), they proposed a computational model to infer a user's attitude according to sentiment, opinion and likelihood of taking an action towards controversial topics in social network. In order to recommend mood-specific movies, Calais Guerra et al. (2011) put forward a novel mood-specific movie similarity concept. To be specific, they used a joint matrix factorization model to factorize both the user-movie rating matrix and the mood-specific movie similarity matrix. In this work, we also try to extract users' emotions from social media, like Twitter, but our aim is to detect whether users' emotions will affect their retweeting behaviors.

Modeling Retweeting Behaviors. In recent years, retweeting behavior has attracted much interest because of the importance of retweet practice (Bi & Cho, 2016; Starbird & Palen, 2012; Zeng, Luo, & Chen, 2013). However, most of the research works focused on how to utilize retweet behavior to analyze the phenomenon in social network, such as cascade prediction (Cheng, Adamic, & Dow, 2014; Galuba, Aberer, & Chakraborty, 2010; Wang, Yan, Hu, Yu, & Li, 2015), information propagation (Starbird & Palen, 2012; Wang, Hu, Yu, & Li, 2014; Zhang, Sun, & Wang, 2013), and inferring users' affiliation (Zeng et al., 2013).

In Nagarajan, Purohit, and Sheth (2010), authors qualitatively analyzed the properties of the retweet behavior surrounding the most viral content pieces. Welch, Schonfeld, and He (2011) compared the retweeting graph with the following graph in Twitter. Further, they found that the retweeting graph can better preserve topical relevance than the following graph via using PageRank on both graphs. In Zhao and Rosson (2009), they detected to understand how and why people use Twitter, a popular microblogging tool, and probed microblog's potential effects on informal communication. Also, Macskassy and Michelson (2011) sought to understand what makes people spread information in tweets or microblogs through the use of retweeting. Bakshy, Hofman, and Mason (2011) presented a predictive model of influence in order to predict cascade sizes of posted URLs by leveraging the individuals' attributes and average size of past retweets. In Cha, Haddadi, and Benevenuto (2010), authors analyzed the influence of Twitter users by adopting three measures that captured different perspectives: indegree, retweets, and mentions. In Chen et al. (2012), a collaborative ranking model was proposed for recommending useful tweets to Twitter users. Moreover, extra contextual information, like tweet content, retweet history and other explicitly defined features, is helpful for detecting personal interests. Hong, Dan, and Davison (2011) investigated the problem of predicting the popularity of messages as measured by the number of future retweets and highlighted on what kind of factors affect information propagation in Twitter.

Also, some research exploited the retweet behavior at a different angle, namely what will influence users' retweet behaviors. In Maximilian, Kasneci, and Naumann (2013), authors detected how "obvious" and "latent" tweets and users' features will impact the retweet behavior. Zi (2010) predicted users' retweet behaviors based on a semi-supervised framework on a factor graph model. Zhang et al. (2013) modeled users' retweet behaviors in the microblogging network by studying a novel idea of social influence locality and figured their defined influence locality functions have strong predictive power. Stieglitz and Dang-Xuan (2012) sought to check whether sentiment occurring in politically relevant tweets has an effect on their retweetability (i.e., how often these tweets will be retweeted). In Petrovic, Osborne, and Lavrenko (2011), they used a machine learning approach based on the passive–aggressive algorithm to predict whether a tweet will be retweeted. In this work, we also exploit which factors will influence retweeting behaviors, but we are more interested in detecting whether users with a certain emotional status will retweet the tweet corresponding with users' current mood from their friends.

3. Research objective

3.1. Notation definition

In this work, to model the retweeting behavior, we first formalize each user u in the dataset as a pair $(u.F, u.T)$, where $u.F = \{f_1, f_2, \ldots, f_q\}$ is a set of friends of u (i.e., some users whom u is following) and $u.T = \{t_1, t_2, \ldots, t_k\}$ is a set of tweets that are posted by u. We consider two types of entities: a set of users $U = \{u_1, u_2, \ldots, u_n\}$, and a set of tweets $P = \{t_1, t_2, \ldots, t_m\}$. Here, we assume that there are n users, and m tweets.

Table 1
Emotional categories and the typical emoticons in each class.

Emotion	Typical emoticons
Anger	
Disgust	
Sadness	
Fear	
Surprise	
Happiness	

Table 2
Emotional categories and the typical words in each class.

Emotion	Typical emoticons
Anger	aggravated, sore, irritated, rage, angry, outraged, enraged
Disgust	offensive, bored, regret, hatred, annoying, loathing, dislike
Sadness	sad, sick, depressed, sorrow, cold, crying, tears, pitiful
Fear	scared, crazy, awake, afeard, scary, dangerous, terrifying
Surprise	fantastic, elated, excited, amazed, splendid, stunned, fierce
Happiness	great, cheerful, jubilant, fortunate, thankful, satisfied

3.2. Problem definition

In this section, we first show several necessary definitions and then present a formal description of the problem.

A heterogeneous social network can be defined as $G = (V, E)$, where nodes V include all users (i.e. followers and followees) and all tweets (i.e. posts), and edges E include all links from users to tweets and all connections from users to users. In addition, our social network data consists of a collection of posts with emotional signals. This is a general setting in our social network.

Definition 1 (*Emotion*). Let $\mathcal{Y}$ be the space of the emotional state. A user u_i's emotional state at time period $TP = [tp_0, tp_1]$ can be represented as a S dimensional emotional vector $y_i^t = \langle y_{i1}^t, y_{i2}^t, \ldots, y_{iS}^t \rangle$ $(y_{ij}^t \in \mathcal{Y}, j \leq S$, where each dimension indicates one of u_i's mood dimensions (e.g., happiness, surprise, anger, etc.) Further, we can denote the historic records of all users' emotional states up to time t as $\mathcal{Y}_U = \left\{y_i^t\right\}_{i,t}$. In addition, we consider the mood feature with highest weight as the user's emotional state at time period TP.

In this work, for users' emotional status, we mainly consider six emotions: $\mathcal{Y} =$ {happiness, surprise, anger, disgust, fear, sadness} according to Yang et al. (2014).

Definition 2 (*Emotional Signals*). The emotional signals could be any information correlated with sentiment of a post or words in the post from the social network. In terms of the emotional signals, we extract the sentiments a certain post expresses and further we obtain the users' emotional status. Here, we adopt two methods to mine the users' emotional signals from the dataset: emoticon detection and word-level emotion detection, as described below.

Emoticons are consistent with sentiments expressed in posts, and they are frequently used on different social network platforms, like Twitter, Facebook, and Yelp. Intuitively, for a user he/she may not simultaneously contain a positive emoticon in a post expressing thinking negative. Similarly, according to emotion consistency theory (Abelson, 1983), it shows that two frequently co-occurrent words should have similar sentiment polarity. Intuitively, users may not simultaneously express negative and positive words together in a short post. As shown in Tables 1 and 2, we have emoticons and word-level emotions examples, including some publicly available sentiment lexicons.

Learning Task. (Retweeting Prediction Problem) Given a heterogeneous social network G and datasets manually labeled sentiment

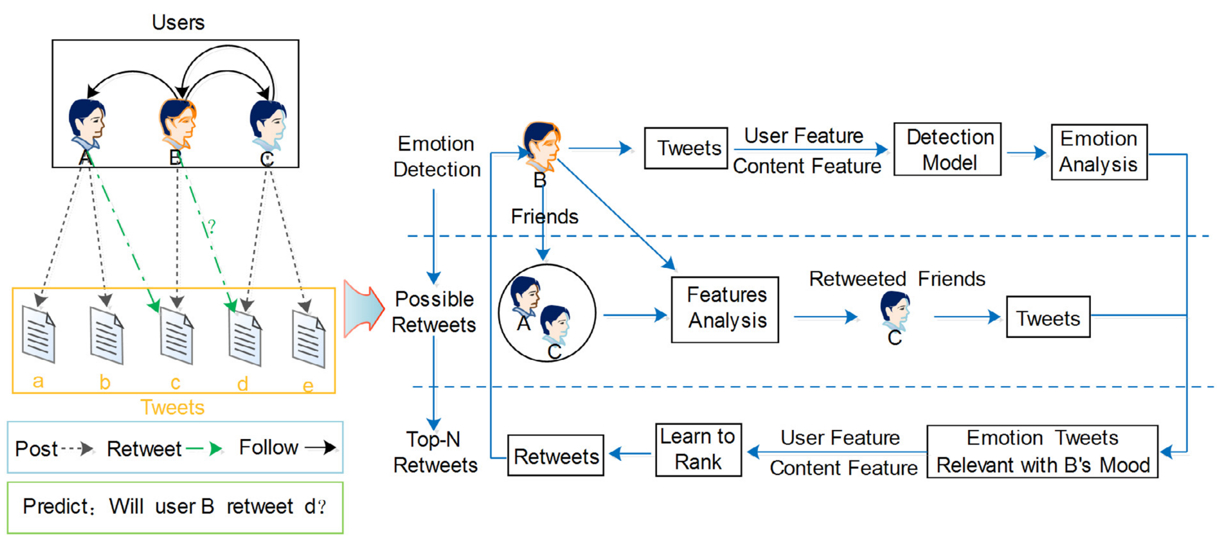

Fig. 1. The General Framework. In the left side of the figure, it shows an information network. Based on the network information, we further introduce our framework of modeling retweeting behaviors in the right side of the figure. It contains three stages: emotion detection, capturing the possible retweets, and finding Top-N retweets.

lexicon, we aim to predict (1) if users' emotional status can be detected from their posts or words in the post (2) if users with a certain emotional status will retweet the tweet t corresponding with users' current mood from their friends after viewing it.

4. Method

We now introduce the overview of the whole processing. The workflow consists of three phrases, as shown in Fig. 1. It mainly comprises three phases: emotion detection, capturing the possible retweets, and finding Top-N retweets.

4.1. Emotion detection

In this paper, we present a method of emotion detection, a semi-supervised graph model (SGM), with the aim of handling the short-text tweet. SGM attempts to classify each emotional signal into one of the several specific emotional categories. As depicted at the phase 1 in Fig. 1, our goal is to detect a user u_i's emotion (e.g., six emotional states) at time period TP.

As illustrated in Fig. 2, SGM consists of two parts: (1) Modeling an emotional category distribution and (2) Modeling a word distribution within an emotional category. Through SGM, we can transfer a user u_i's tweets at time period $T = [t_0, t_1]$ into a series of emotional states, and then we can obtain u_i's emotion.

4.1.1. Defining the prior knowledge

We divide our prior knowledge into two categories: emoticons and word-level emotions.

For emoticons, like Zhao et al. (2012), we also manually choose 95 ones as the sentiment labels from more than 1000 emoticons, but we divide them into six different sentiment categories, including happiness, surprise, anger, disgust, fear, sadness (An example in Table 1).

For word-level emotions, they are obtained from sentiment lexicons. We use two types of sentiment lexicons to analyze the impact of sentiment prior, SentiWordNet (Li, Huang, & Zhu, 2011) and MPQA Opinion Corpus (Wilson, Wiebe, & Hoffmann, 2005). However, these two kinds of sentiment lexicons only distinguish between positive and negative sentiment and omit the rich emotional states of users. Like Li et al. (2014), we additionally use Profile of Mood States (POMS) (Norcross, Guadagnoli, & Prochaska, 1984; Pollock, Cho, Reker, & Volavka, 1979; Shacham, 1983), a

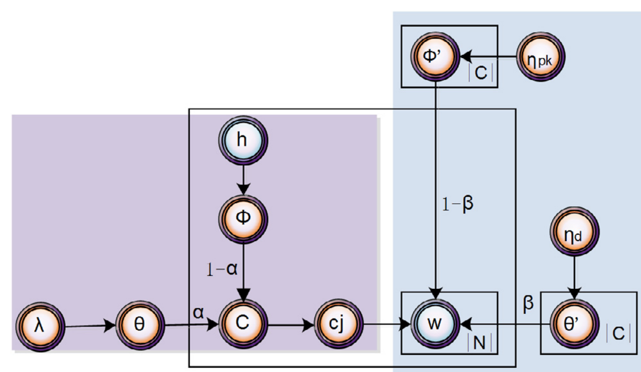

Fig. 2. Graphical representation of the emotion detection model. The purple block can be regarded as one part of SGM, which models an emotional category distribution. The blue block can be regarded as another part of SGM, which models a word distribution within an emotional category. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

psychological rating scale used to assess transient, to differentiate emotional states. Specifically, we detect three dimensions of emotional state based on POMS, anger, disgust, sadness, and three manually added fear, surprise, and happiness dimensions. At last, we explore six dimensions of mood state (An example in Table 2). Practically, we used the way proposed by Bollen, Mao, and Zeng (2010), who expanded the original topic list offered by POMS questionnaire from context patterns analysis in a set of 5-grams computed from the web-scale Google Web (Bergsma, Lin, & Goebel, 2009). Thus, each tweet term that maps expanding topics is matched back to original POMS terms. The distensible lexicon list contains 152 terms and allows us to obtain the amount of emotional state related tweets.

4.1.2. Probabilistic graph model construction

The above analysis intuitively reflects that the category prediction task comprises two estimations: emotional category distribution and emotional category-word distribution.

1. Emotional category distribution. SGM catches two different kinds of emotional category distributions in order to transfer emotional signals into emotional states. Let θ define the emotional category obtained from emotional signals in users' original posts, P. This is a weight vector representing the weight of each emotional

category. In the same way, let ϕ denote the emotional category distribution obtained from emotional signals in our prior knowledge. The emotional category distribution for the combined two kinds of sources is then assumed to be a linear combination of θ and ϕ. Here, we employ parameter α as a weight to control the contributions of different sources (i.e., original posts, or a priori knowledge). λ is used to denote the contribution of unlabeled data when generating the emotional category distribution for P.

2. Emotional category-word distribution. The emotional category-word distribution also has two parts: θ' denotes the distribution of different words over different emotional categories in the input collection of posts, which is a $|C| \times |N|$ matrix. Here, $|C|$ is the number of emotional categories, and $|N|$ is the number of words in the collection. Similarly, ϕ' denotes the emotional category-word distribution from information derived from prior knowledge. The emotional category-word distribution for the combined collection is also assumed to be a linear combination of θ' and ϕ', weighted by the parameter β.

Based on SGM, we formally denote the probability of a tweet t falling into a category c as

$$P(c|t) = \frac{P(c)P(t|c)}{\sum_c P(c)P(t|c)} \tag{1}$$

where $P(c)$ is the prior probability of category in the dataset. Assumed that the presence of a word w is independent to the presence of any other word in t, we obtain

$$P(t|c) = \prod_{w \in t} P(w|c) \tag{2}$$

4.1.3. Parameter estimation

In this section, we use EM approach to infer parameters. In the expectation step, we estimate the distributions θ, ϕ, $\hat{\theta'}^{w_k}_{c_j}$, $\hat{\phi'}^{w_k}_{c_j}$. For the parameter estimations, we utilize the labeled data, prior knowledge, and the unlabeled data. Initially, we assign category labels to unlabeled data with a uniform distribution, i.e., the probability is $\frac{1}{|C|}$ for each emotional category. In the next iterations, labels of unlabeled data and SGM are alternatively updated and reinforced until convergence.

θ **Estimation**. θ represents the probability of each emotional category in the original tweets. It is proportional to the expected number of tweets assigned to this emotional category.

$$\begin{aligned}\hat{\theta_{c_j}} &\equiv P(c_j|\hat{\theta}) \\ &= \frac{1 + \sum_{i=1}^{|P^l|} P(y_i = c_j|t_i) + \sum_{i=1}^{|P^u|} \lambda P(y_i = c_j|t_i)}{|C| + |P^l| + \lambda|P^u|}\end{aligned} \tag{3}$$

As aforementioned, the dataset consists of labeled tweets P^l and unlabeled tweets P^u. They have different contributions to the emotional category probability estimation.

ϕ **Estimation**. ϕ defines the prior category probability distributes over prior knowledge. Here, the prior probability of category c_j for a emotional hashtag h depends on the relation between the corresponding hashtag h and the predefined emotional category names,

$$\hat{\phi_{c_j}} \equiv P(c_j|\hat{\phi}) = \frac{D(h, c_j) + \mu}{\sum_{j=1}^{|C|} D(h, c_j) + \mu|C|} \tag{4}$$

where μ is a smoothing factor and $D(h, c_j)$ is employed to calculate semantics distance between the tag h and the category c_j. As aforementioned, our prior knowledge consists of two kinds of emotional signals. They have different contributions to $D(h, c_j)$. The function $D(h, c_j)$, denoted as in the following equation, is employed to achieve that goal.

$$D(h, c_j) = \begin{cases} 1 & \text{if } h \text{ belongs to Emoticons} \\ \dfrac{1}{NGD(h, c_j)} & \text{otherwise} \end{cases} \tag{5}$$

where $NGD(h, c_j)$ is the Normalized Google Distance.[8] Actually, it can be observed that a smaller value of NGD leads to more contribution of c_j for the specific emotional signals.

θ' **and** ϕ' **Estimation**. θ' and ϕ' are used to denote the emotional category-word distributions over original tweets and prior knowledge, respectively. We can define them as the following equations.

$$\hat{\theta'}^{w_k}_{c_j} \equiv P(w_k|c_j, \hat{\theta'}) = \frac{n^{w_k}_{d_{c_j}} + \eta_d}{\sum_{i=1}^{|N|} n^{w_i}_{d_{c_j}} + |N|\eta_d} \tag{6}$$

$$\hat{\phi'}^{w_k}_{c_j} \equiv P(w_k|c_j, \hat{\phi'}) = \frac{n^{w_k}_{pk_{c_j}} + \eta_{pk}}{\sum_{i=1}^{|N|} n^{w_i}_{pk_{c_j}} + |N|\eta_{pk}} \tag{7}$$

where $n^{w_k}_{d_{c_j}}$ and $n^{w_k}_{pk_{c_j}}$ are, respectively, the times of the word w_k that has occurred in the category c_j from original tweets and prior knowledge. η_d and η_{pk} are hyperparameters with a small value close to zero for smoothing purpose.

For a given tweet t_i, we can get the category label which is assigned using the maximum likelihood estimator.

$$\begin{aligned} y_i &= argmax_{c_j} P(c_j|t_i, \hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}') \\ &= argmax_{c_j} \frac{P(c_j|\hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')P(t_i|c_j, \hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')}{P(t_i|\hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')} \\ &= argmax_{c_j} \frac{P(c_j|\hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')P(t_i|c_j, \hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')}{\sum_{c_j} P(c_j|\hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')P(t_i|c_j, \hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}')} \end{aligned} \tag{8}$$

Here, the prior probability of emotional category c_j is denoted as a linear combination of the estimates from both the input tweets and prior knowledge:

$$P(c_j|\hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}') = P(c_j|\hat{\theta}, \hat{\phi}) = \alpha P(c_j|\hat{\theta}) + (1 - \alpha)P(c_j|\hat{\phi}) \tag{9}$$

where α is a balance parameter to control the contributions between $\hat{\theta}$ and $\hat{\phi}$.

Finally, the maximum likelihood probability for the each tweet t_i can be derived as follows:

$$\begin{aligned} P(t_i|c_j, \hat{\theta}, \hat{\phi}, \hat{\theta}', \hat{\phi}') &= P(t_i|c_j, \hat{\theta}', \hat{\phi}') = \prod_{k=1}^{|t_i|} P(w_k|c_j, \hat{\theta}', \hat{\phi}') \\ &= \prod_{k=1}^{|t_i|} \left\{ \beta P(w_k|c_j, \hat{\theta}') + (1 - \beta)P(w_k|c_j, \hat{\phi}') \right\} \end{aligned} \tag{10}$$

where β plays a similar role as α.

4.2. Possible retweets

In order to capture a user u_i's possible retweets, we first detect u_i's possible retweeted friends $u_i.F'$, and then through combining u_i's emotion with tweets from $u_i.F'$ at the time period TP, we can catch the possible retweets corresponding with u_i's emotion.

We adopt the method in Merritt, Jacobs, Mason, and Clauset (2013) to obtain u_i's possible retweeted friends $u_i.F'$. Specifically, we leverage the logistic regression model to obtain u_i's possible retweeted friends. Given each training pair of users $\langle u_i, f_j \rangle (f_j \in u_i.F')$, let x_i be the $(d+1)$ dimension vector consisting of constant 1 and d users' features between u_i and f_j, and y_i be the flag of whether they will be possible retweeted friends. By utilizing the users' features, we can denote the probability P_i which follows binomial distribution as follows: $P_i = P(z_i = 1|x_i) = \frac{1}{1+e^{-x_i \delta}}$, where $z_i = 1$ if

8 http://en.wikipedia.org/wiki/Normalized_Google_distance

two users will be possible retweeted friends, otherwise 0. δ is the $d+1$ coefficient weights associated with the constant and each user feature. Here, besides the features like retweet history, friend status, friend active time, and follower interests in their method, we also consider the other important feature, friend emotion.

Intuitively, a user u_i is likely to retweet tweets from her/his friends sharing the similar emotion with u_i. This information can be a valuable hint when detecting retweeted friends. Here, we still leverage the SGM model to catch the emotion vectors of u_i's friends at the time period *TP*. We can then compute a cosine similarity between the user u_i's emotion and her/his friend's emotion. We call this feature the SimEmotion.

4.3. Top-N retweets

Given a set of possible tweets P_i^R from u_i's friends, our aim is to learn a function F that estimates the likelihood of a tweet $t_i (t_i \in P_i^R)$ being retweeted by u_i in future. We consider this as a ranking problem and find the Top-N retweets, which are most likely to be retweeted. This is because a user u_i might still have variable numbers of retweeting choices, though tweets corresponding with u_i's emotion have been mined, and potentially we might want to rank them.

To get a good function F which ranks P_i^R according to whether they are likely to be retweeted, we investigate a wide range of features. We develop the features in a Learning to Rank (i.e., ListNet) scenario (Cao, Qin, & Liu, 2007). As we all known, Learning to Rank is a data driven approach which incorporates a set of features in a model for ranking task (Liu, 2009). Every tweet t_i is tagged whether it will be retweeted by user u_i in training data. This gives tweet-user pairs. From these tweet-user pairs, a set of features related to the possibility of being retweeted is extracted.

In order to identify features that affect how tweets get retweeted by u_i and thus spread in the Twitter network, we have analyzed a wide variety of tweets and user features. Here, we show only the main features that were most impactful with regard to the retweets frequency. Next, we will introduce these two kinds of features: tweets' features and users' features.

4.3.1. Tweets' features

According to Luo et al. (2013) and Maximilian et al. (2013), the following tweets' features can be employed: tweet length, hashtags and mentions, the times of tweets retweeted. Besides, we consider two other features: sentiment valence and content influence.

Sentiment valence (SV). As Maximilian et al. (2013) said, the sentiment of a tweet is a possible factor influencing the retweet frequency. From the sentiment analysis, we can see that tweets with different sentiment undergo a different diffusion process. By combining Bayes' Theorem with the previous works (Maximilian et al., 2013; Pfitzner, Garas, & Schweitzer, 2012; Thelwall, Buckley, Paltoglou, Cai, & Kappas, 2010), the probability of a retweet given a sentiment valence like sadness is

$$P(retweet|sadness) = \frac{P(sadness|retweet) * P(retweet)}{P(sadness)} \tag{11}$$

Similarly, we can, respectively, get the probability of a retweet for other five emotional states. The conditionals in the above formula can be estimated by their maximum likelihood estimations.

Content influence (CI). As Zi (2010) said, we can measure the importance of the content by estimating the frequency of the terms used by all the tweets of all the users within this period of time. We also admit the fact that a hot tweet is discussed by a relative majority of the community and the tweets of special interests are known by few users. Here, we calculate the content influence using the sum of tf-idf values of keywords in the content of the original tweet,

$$TF-IDF(t) = \sum_{K} N(K, t) \cdot log|P|/N(K, P) \tag{12}$$

where $N(K, t)$ is the number of occurrences of the keyword K in tweet t, $N(K, P)$ is the number of occurrences of the keyword K in the whole tweet collection P, and $|P|$ is the total number of tweets.

4.3.2. Users' features

According to Suh et al. (2010), Luo et al. (2013) and Zi (2010), the following users' features can be employed: the number of friends, followers, statuses (total number of tweets written by a user), retweet history, users' status, users' active time, the age of users' account, and users' interests. Here, we also consider three other features: emotional divergence, co-retweet state, and users' influence.

Emotional divergence (ED). Following (Pfitzner et al., 2012), we can get different sentiment scores of tweets, as returned by the SentiStrength algorithm. And then, we can combine these scores into a single score reflecting the emotional divergence of the user. For a given user u_i, we can calculate the user's emotional divergence using the following equation:

$$u\_ED(u.T) = \sum_{i=1}^{n} \sum_{t \in u.T} s\_score_i(t) \tag{13}$$

where $u.T$ represents all tweets the user u_i has posted at the time period *TP*, $s\_score_i()$ represents different sentiment scores of tweets and n represents the number of emotional states.

Co-retweet state (CS). This feature captures the similarity of retweet sets of the user and the retweeter. If two users tweet (or retweet) many identical tweets, it is likely that they retweet each other. Given a user u_i and a retweeter u_j, we use Jaccard similarity to measure this score,

$$Jaccard(u_i, u_j) = \frac{Tweet(u_i) \cap Tweet(u_j)}{Tweet(u_i) \cup Tweet(u_j)} \tag{14}$$

where $Tweet(u_i)$ refers to the tweet set a user u_i posts or reposts.

Users' influence (UI). As Eytan, Karrer, and Adamic (2009) indicated, if a user u_i holds some influence, his/her opinions will be easily adopted by his/her friends, which means u_i's tweets will be propagated or retweeted. So users' influence is also a potential factor affecting retweets. Here, we use the method in Li, Wang, and Deng (2012) to model a user's influence scope. They chose a Gaussian distribution to capture a node's influence model.

5. Experiments

In this section, we show that our method based on *SGM* (M_SGM) can improve the retweeting prediction accuracy compared with the state-of-the-art retweeting prediction methods on the Stanford Twitter Sentiment (STS) dataset generated by Hu et al. (2013) and Obama–McCain Debate (OMD) dataset created by Shamma, Kennedy, and Churchill (2009).

5.1. Dataset

The original Twitter dataset does not contain social relations. Xia et al. enrich this dataset with social network metadata, using Twitter's publicly available API. Finally, this dataset contains 22,262 tweets and 8467 users. The average tweets of a user is 2.63. Additionally, the max degree and min degree of the users is 897 and 1, respectively. For Obama–McCain Debate dataset, it contains 3269 tweets published during the presidential debate on September 26, 2008. Further, we deleted the users who have no friends or have posted fewer than fifteen tweets regarding the social network.

5.2. Experiment setup

In this work, we adopt two-fold cross-validation (i.e., half training and half testing) to evaluate the performance of the retweeting prediction on Twitter network. Also, we manually determine the emotional category in which a small part of tweets belong to in order to detect the users' emotional states. Generally, given a past time period $Time_0 = [time_0, time_1]$, we seek to use the training M_SGM extracted from the Twitter network in the time period $Time_0$, to predict the retweeting relationship in a future time period, say $Time_1 = [time_1, time_2]$. In the training stage, we first sample a set of retweet pairs (i.e, user-retweet) that have never occured in $Time_0$, collect their associated features in $Time_0$, and record whether a retweeting relationship is to appear between them in the future interval $Time_1$. A training model is then built to learn the best coefficients associated with each feature by maximizing the likelihood of relationship building. In the test stage, we apply the learned coefficients to the features for the test pairs, and compare the predicted retweeting relationship with the ground truth. Here, the parameters are set as $\alpha = 0.5$, $\beta = 0.8$, $\lambda = 0.4$ for OMD and $\alpha = 0.9$, $\beta = 0.9$, $\lambda = 0.3$ for STS, respectively.

For evaluating our method we utilize the standard information retrieval measures such as *Precision*, *Recall*, *F1-Score*, and mean reciprocal rank (*MRR*). *MRR* is the inverse of the position of the first correct list in the ranked set of lists produced by our model. For *Precision*, we evaluate how many of Top-N retweets suggested by the methods actually have links from users. This metric has been used in online social media (i.e., Facebook, Twitter, etc.). For *Recall*, we evaluate how many of Top-N retweets suggested by the methods belong to the retweet set, which is formed by retweets having links from users.

5.3. Comparison methods

We compare our proposed approach (*M_SGM*) with the following methods.

LRC-BQ. It combines the influence locality function and basic features including personal attributes, instantaneity and topic propensity, to train the logistic regression classifier and to predict retweeting behaviors (Zhang et al., 2013).

ListRec. It leverages the dynamically varying tweet content, the network of twitterers and the popularity of lists to collectively model the users' preference towards social lists (Rakesh, Singh, & Vinzamuri, 2014).

TS. It adopts a machine learning approach based on the passive–aggressive algorithm to predict whether a tweet will be retweeted (Petrovic et al., 2011).

CRFs. It proposes using conditional random fields to model and predict the retweet patterns with three types of user-tweet features, i.e., content influence, network influence and temporal decay factor (Peng, Zhu, & Piao, 2011).

ASC-HDP. It proposes a novel method based on hierarchical Dirichlet process to predict retweet behavior by combining structural, textual, and temporal information (Zhang et al., 2015).

RTPMF. It puts forward a probabilistic matrix factorization model to predict the retweeting behavior by exploiting user social embedding and message semantic embedding (Liang et al., 2016).

5.4. Result and analysis

In this section, we first evaluate the performance of *SGM* for detecting the users' mood. And then, we compare the performance of our proposed *M_SGM* with other baselines.

Table 3
Performance comparison between different methods using Precision, Recall, F-Measure and MRR (on STS Dataset).

Method	Precision	Recall	F-Measure	MRR
SGM	**0.732**	**0.771**	**0.751**	**0.699**
SVM	0.712	0.765	0.738	0.651
LS	0.715	0.693	0.704	0.659
L-LDA	0.710	0.761	0.735	0.643
Semi-NB	0.722	0.756	0.739	0.672

5.4.1. Emotion detecting

To demonstrate the effectiveness of our proposed approach, we compare it against the following classifying methods.

SVM It is a supervised learning method. We use the SVM-light package to implement SVM.

LS It is a widely used supervised classification method for i.i.d. data (Friedman, Hastie, & Tibshirani, 2008).

L-LDA It incorporates supervision by constraining LDA model to use only those topics that correspond to an observed label set (Ramage, Hall, & Nallapati, 2009).

Semi-NB It is a famous semi-supervised text classification method (Nigam, McCallum, & Thrun, 2000). We employ it by leveraging only unlabeled tweets as a prior.

From Table 3, in terms of *Precision*, it can be seen that our proposed *SGM* apparently beats all the other four methods and produces the best prediction accuracy. Specifically, *SGM*, respectively, achieves a 2%, 1.7%, 2.2%, and 1% improvement compared with *SVM*, *LS*, *L-LDA*, and *Semi-NB*. Similarly, for other three measures, we can also see that our proposed *SGM* significantly outperforms the other four methods. These comprehensive improvements are due to the fact that the integrated two kinds of emotional signals enrich the tweet representation and the leveraging intrinsic information detected from abundant unlabeled data enhances the prediction accuracy.

5.4.2. The performance of proposed method

In this section, we compare the predictive performance of our proposed *M_SGM* with a number of baselines mentioned above. First, we illustrate how our *M_SGM* can serve as a powerful model for predicting potential retweeting relationships. The prediction processing performance results can be found in Figs. 3–9.

In Fig. 3, it can be clearly seen that our proposed *M_SGM* method significantly outperforms other prediction methods. In terms of *Precision*, *M_SGM* achieves a 3.3–12.6% average improvement compared with other six methods. Here, *CRFs* does not outperform any other five methods under any measure. The possible reason is that *CRFs* mainly considers the basic users' and tweets' features, and ignores other important features, like users' emotion, users' influence, sentiment valence. It can be seen that *RTPMF* and *ASC-HDP* outperform other four methods. The main reason is that these two methods consider more features like structural, textual, and temporal information. Also, *LRC-BQ* obviously beats *LS*. The main reason is *LRC-BQ* models social influence locality for the retweeting behaviors, while *LS* omits the feature of social influence. Additionally, for *LRC-BQ* and *ListRec*, when *N* is less than 10, *LRC-BQ* slightly exceeds *ListRec*, and vice versa. The possible reason is that *ListRec* detects to learn an optimal ranking list of retweets, while *LRC-BQ* does not consider this point. Actually, our proposed *M_SGM* has the similar thoughts, obtaining Top-N list, with *ListRec*, but *ListRec* ignores some vital features, such as users' emotion and sentiment valence. Because of the space limit, the similar analysis is shown in Figs. 4–8, respectively.

In Fig. 10, it shows the effect on prediction performance from varying the amount of data used for training. We gradually increase the amount of training data, at incremental steps of 20%. As a whole, an upward trend can be observed in prediction performance

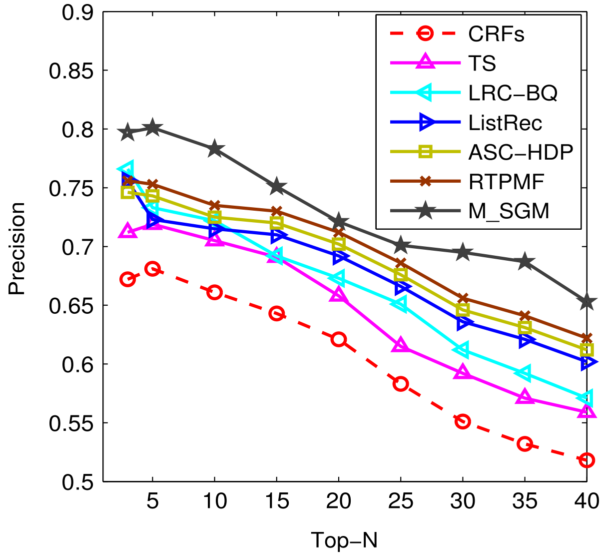

Fig. 3. Precision on STS Dataset.

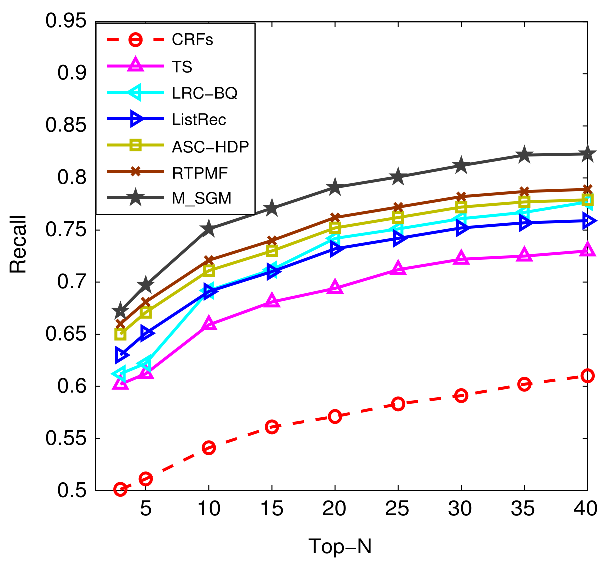

Fig. 4. Recall on STS Dataset.

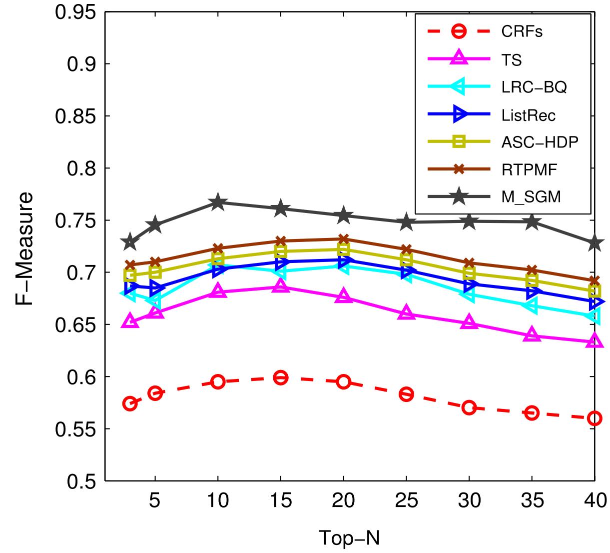

Fig. 5. F-Measure on STS Dataset.

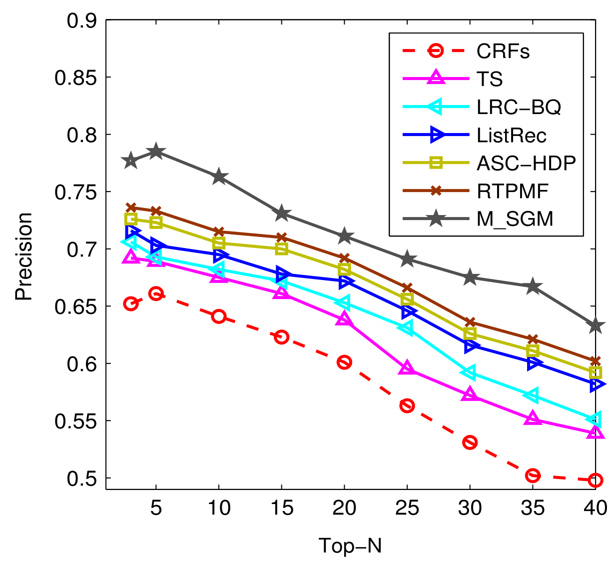

Fig. 6. Precision on OMD Dataset.

as more training data is made available, which is intuitive. It is worth mentioning that, by considering standard deviation (values of *MRR* in different training datasets), *M_SGM* is shown to be the most stable method, indicating its excellent performance is relatively stable across all the datasets.

5.4.3. Feature contribution analysis

From Table 4, it contains three main parts corresponding to the three stages of our proposed framework, respectively. In the *SGM* stage, we analyze impacts on emotion detection from two kinds of emotional signals, emoticons and word-level emotions. It shows that emotion detection based on emoticons produces better performances than word-level emotions, which consists with our intuition. The possible reason is that emoticons more intuitively reflect users' emotional state compared with word-level emotions. Also, for the Top-N stage, we detect impacts on Top-N retweets from user's and tweets' features. We can see that both Tweet(+SV) and User(+ED) play an important role in improving the accuracy of retweeting behaviors. It also indicates that emotion is a vital feature of users which affects retweetability. For the *PR* stage, we have the similar analysis to the Top-N stage.

5.4.4. Different sentiments' contribution analysis

We will further check whether different emotions have different impacts on retweeting behavior prediction. Surprisingly, from Fig. 10, it can be seen that our method based on anger obtains a better performance compared with other five emotions. It shows that anger is more influential than other emotions like happiness, and indicates that the angry tweets can spread quickly and broadly in the network, which is consistent with Fan, Zhao, & Chen (2009).

6. Conclusion

In this work, we first present the problem of predicting the retweeting behaviors in Twitter network. Different from previous works, we probe whether different emotions in the context of online social media will affect the users' retweeting behavior.

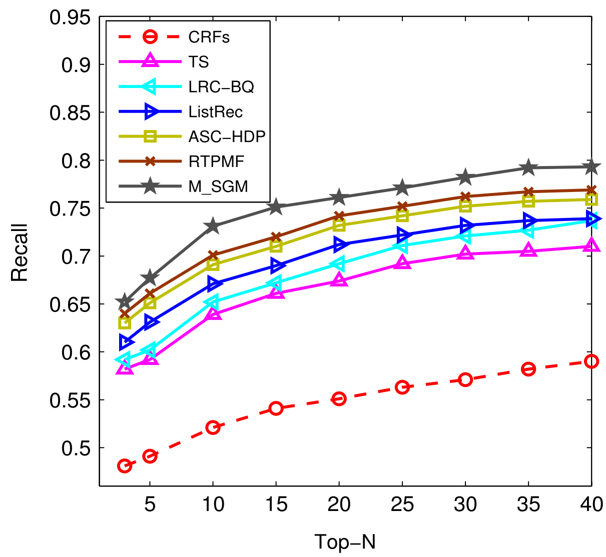

Fig. 7. Recall on OMD Dataset.

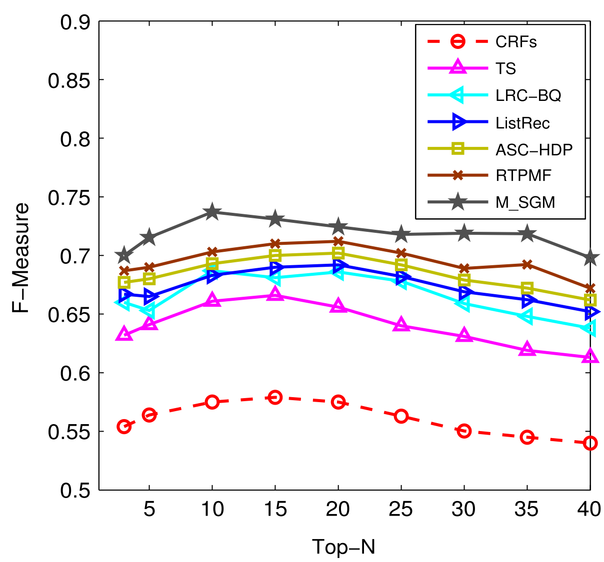

Fig. 8. F-Measure on OMD Dataset.

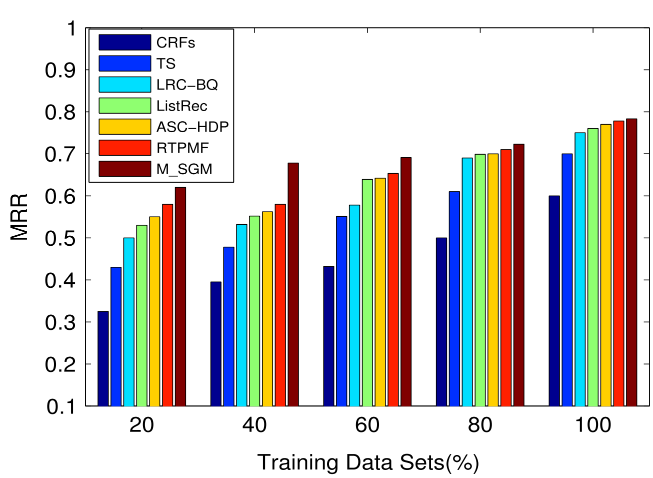

Fig. 9. MRR on STS Dataset. The influence of the amount of available training data on overall retweeting behavior prediction performance.

Table 4
Factor contribution analysis (on STS Dataset). Here, stages represent the stages of our framework, *SGM* represents the emotion detection stage, *PR* represents the stage of capturing possible retweets, and Top-N represents the stage of obtaining Top-N retweets. Additionally, *SE* represents the feature of SimEmotion.

Stages	Features	Precision	Recall	F-Measure	MRR
SGM	Emoticons only	0.423	0.461	0.442	0.405
	Words only	0.315	0.347	0.331	0.301
	Basic features	0.66	0.676	0.668	0.582
PR	User	0.732	0.771	0.751	0.699
	(+SE)	**+7.2%**	**+9.5%**	**+8.3%**	**+11.7%**
	Basic features	0.541	0.583	0.561	0.41
	Tweet	0.693	0.737	0.714	0.635
	(+SV)	**+15.2%**	**+15.4%**	**+15.3%**	**+22.5%**
	Tweet	0.633	0.687	0.659	0.565
	(+CI)	+9.2%	+10.4%	+9.8%	+15.5%
Top-N	User	0.653	0.714	0.682	0.579
	(+ED)	**+11.2%**	**+13.1%**	**+12.1%**	**+16.9%**
	User	0.638	0.68	0.658	0.539
	(+CS)	+9.7%	+11.3%	+9.73%	+12.9%
	User	0.628	0.67	0.648	0.509
	(+UI)	+8.7%	+10.5%	+8.7%	+10.9%

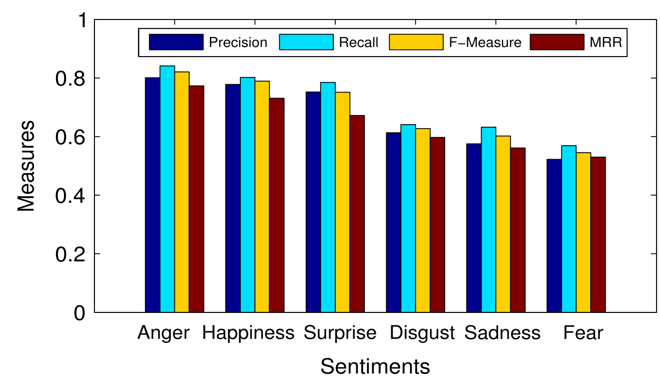

Fig. 10. Impacts of different emotions on retweeting behavior prediction (on STS Dataset). Here, *x*-axis represents different sentiments and *y*-axis represents different measures.

Further, we put forward a novel retweeting prediction framework in order to predict retweeting behaviors effective and efficiently. This framework consists of three stages: emotion detection, capturing the possible retweets, and finding Top-N retweets. At last, experiments on the Twitter network show that via considering user's emotion feature, our proposed method can detect retweeting behaviors with much higher accuracy compared with the state-of-the-art prediction methods.

In the future, we intend to extend our work in the following three directions. First, we attempt to apply retweeting prediction study on different information networks, like Facebook, and Weibo. Second, we will gather fine-grained data from two social networks, like Twitter and Facebook, and try to infer users' emotional status. Third, we will further study our proposed framework for improving the predictive performance by incorporating more users' features, e.g., users' home location.

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