User Interest and Social Influence Based Emotion Prediction for Individuals

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ABSTRACT

Emotions are playing significant roles in daily life, making emotion prediction important. To date, most of state-of-the-art methods make emotion prediction for the masses which are invalid for individuals. In this paper, we propose a novel emotion prediction method for individuals based on user interest and social influence. To balance user interest and social influence, we further propose a simple yet efficient weight learning method in which the weights are obtained from users' behaviors. We perform experiments in real social media network, with 4,257 users and 2,152,037 microblogs. The experimental results demonstrate that our method outperforms traditional methods with significant performance gains.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioral Sciences

Keywords

Emotion prediction; Social influence; User interest; Social network

1. INTRODUCTION

Nowadays, emotions are playing important roles in daily life, ranging from market selling [4] to stock prediction [3]. What people feel may directly affect what decision they will make, which makes emotion prediction important.

Recent years have witnessed increasing research efforts on emotion prediction from text or image domain. For example, Picard's work [6] inferred sentence-level emotional affinity based on text. Takamura, Inui, and Okumura [8] expressed the impression of a word with the positive or negative emotion polarity value and applied the value to extract evaluation expressions. Not only from the text domain, affective image classification is also emerging from image perspective. One of the first affective image filtering system is K-DIME [2], which builds a retrieval system for users to retrieve affective images. Another work was done by Jana et al. [5], using the features inspired by psychology and art theory to classify affective images.

Previous works mainly focus on predicting the emotion for the masses. Since different people may have different emotions, it makes emotion prediction approach for the masses invalid for individuals. It's desired to develop emotion prediction methods for individuals.

The problem of emotion prediction for individuals is not trivial. So far, there are fewer works on emotion prediction for individuals. Emotions have long been viewed as passions produced on their own interest [7]. However. from social aspect, [11] has shown that how happy you're is influenced by your social links to people in social networks. More recently, Tang's work [10] quantitatively studies how an individual's emotion is influenced by his friends in social network.

It can be seen from the above that existing emotion prediction methods for individuals either focus on user interest or social influence. However, neither user interest or social influence alone can predict individual's emotion accurately. In this work, we propose a novel method jointly considering user interest and social influence in social network platform to predict user's emotion. We further propose a simple yet efficient weight learning method to balance the weights of user interest and social influence to figure out exactly what kind of roles they are playing in the final emotion prediction. Fig. 1 illustrates the conceptual framework of our proposed emotion prediction for individuals.

The contributions of our work can be summarized as follows:

- We present a novel emotion prediction method for individuals taking both user interest and social influence into account.
- We propose a simple yet efficient weight learning method to balance the user interest and social influence in which the weights are obtained from users' behaviors.

2. EMOTION PREDICTION FOR INDIVIDUALS

In this section, we first define some notions and problem setting, then elaborate emotion prediction by user interest and social influence separately. Finally we propose a simple weight learning method to combine these two factors together.

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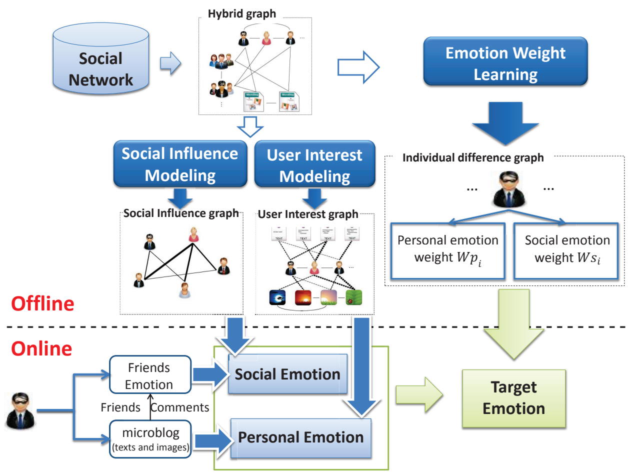

Figure 1: Conceptual framework of emotion prediction for individuals.

2.1 Problem Setup

The social network is a hybrid graph which can be represented as $G = (\{V, B\}, E)$, where V is the set of $|V| = N$ users, B is the microblog set posted or retweeted by users and $E \subset V \times V$ is the set of directed/undirected links between users. Given this, we can define the problem as follows:

Definition 1. **Personal emotion:** personal emotion is the subjective feeling when user seeing the microblog. It's the kind of emotion produced by user interest. We use $Ep_i^t(b)$ as the personal emotion for use v_i when seen microblog b at the time t.

Definition 2. **Social emotion:** social emotion is the emotion produced by the impact of other people's emotion (social influence). Here we use $Es_i^t(b)$ as the social emotion for user v_i when seeing friends' comments of microblog b at the time t.

Definition 3. **Target emotion:** a user v_i's target emotion is the final emotion user will make, it's a combination of personal emotion and social emotion, we use $y_i^t(b)$ as the target emotion for user v_i when seeing the microblog b at the time t, $y_i^t(b) \subset \mathcal{Y}$, where $\mathcal{Y}$ is the emotion space.

In this work the emotion space is covered by two categories: positive and negative, which is enough for most of applications. Thanks to [1], the dictionary has 23,419 Chinese regular words with positive or negative emotion polarity value with which we can get the groundtruth of users' emotions by their comments.

With all these definitions, we can represent our goal as follow:

Learning task: Given a dynamic continuous network G^t, the goal is to learn a prediction function f to infer the emotion of a user when seeing microblog b at the time t by taking both user interest and social influence into consideration. Mathematically, we have

$$G = f(\{V, B\}, E) = f(Ep_i^t(b), Es_i^t(b)) \rightarrow y_i^t(b) \tag{1}$$

where $y_i^t(b) \subset \mathcal{Y}$.

2.2 Personal Emotion Prediction

It is said that everyone has their own minds, different people may have different emotions even meeting the same situation or seeing the same thing. For example, someone may get excited when mentioned "shopping", while some may feel exhausted. Not only in text, users also have interest in images, some like bright colors while some prefer delicate ones. Under the circumstances, we construct user interest model by taking text and image two domains into consideration.

2.2.1 *Emotion prediction from text*

Based on users' historical microblogs, we can get user interest in different topics and calculate the positive and negative probability of the words for each user, which is much like constructing a personalized dictionary other than [1] for the masses. In this way, we can get to know users well and make the emotion prediction more precise from text domain.

We use $p_{pos_i}(w)$ and $p_{neg_i}(w)$ to represent the positive and negative probability of word w for user v_i.

$$p_{pos_i}(w) = \frac{|\{b|b \in B_H(i), y_i(b) > 0, w \in b\}|}{|\{b|b \in B_H(i), w \in b\}|} \tag{2}$$

where $B_H(i)$ is the microblog set commented by user v_i in historical dataset. The $p_{neg_i}(w)$ is similar to $p_{pos_i}(w)$.

Therefore, the personal emotion from text domain for microblog b can be summarized as follow:

$$Ep_i(b) = \sum_{w \in b} (p_{pos_i}(w) - p_{neg_i}(w)) \tag{3}$$

where w is the word contained in the microblog b.

2.2.2 *Emotion prediction from image*

Nowadays, more than 60% microblogs are illustrated with images making microblogs more vivid and more expressive. In the meantime, images not only bring the physical scene content, but also have the ability to convey emotional information which makes people feel happy, or sad, etc. Generally, the visual features of an image include color, shape, composition and so on, while among all these features, color has been shown to play an important role in image affective analysis [9].

Here we use three basic kinds of color features to present images, brightness, colorfulness and hue, which are also used in most of the affective image classification or detection work [5]. We cluster positive and negative images separately for each user to find out the representatives in the two categories. When comes a new image, the distances between the image and representatives are measured to find out which category the image should belong to.

2.3 Social Emotion Prediction

With the popularity of social network, i.e. `Facebook, Twitter and Flicker`, more and more people are willing to share their own feelings towards hot events or their experiences in daily life, whether delivering positive or negative emotions, which makes it easier for people to know others' minds. More or less, users are getting increasingly easier to be influenced by others in social network.

However, different friends may have different extents of influences on the user based on how close they are or how much similarity they have in common. We use the emotion similarity when treated the same microblog to measure the social influence. $w(v_i, v_j)$ is defined as the influence of user v_j to user v_i. Here, user $v_j \in F(i)$ where $F(i)$ is the friend set of user v_i:

$$w(v_i, v_j) = \frac{|\{b|y_i(b) \cdot y_j(b) > 0, b \in B_H(i), b \in B_H(j)\}|}{|\{b|b \in B_H(i), b \in B_H(j)\}|} \quad (4)$$

where $B_H(i)$ is the microblog set commented by user v_i in historical dataset and $y_i(b)$ is the user v_i's emotion value for the commented microblog b.

We suppose when user v_i visits microblog b, he will also see all the comments made by his friends to microblog b within one day. Here, we only consider the emotion polarity made by their friends, whether positive or negative, rather than how strong the emotions are. In conclusion, we use the following equation to predict the social emotion for user v_i of microblog b.

$$Es_i^t(b) = \sum_{j \in F(i), t-1 < t' < t} w(v_i, v_j) sign(y_j^{t'}(b)) \quad (5)$$

where t' can be anytime before t within one day.

2.4 Emotion Weight Learning

Different people have different characters. Some of them are independent and have their own minds, while some of them are more susceptible. We propose a simple weight learning method to measure the individual difference in the weights of personal emotion and social emotion for the target emotion.

We use Wp_i and Ws_i to represent the weights of personal emotion and social emotion for the target emotion of the user v_i. Through mining users' historical behavior, we find that prediction precisions of personal emotion and social emotion can very well measure the weights and more importantly, it is simple and make our method efficient.

$$Wp_i = \frac{|\{b|Ep_i(b) \cdot y_i(b) > 0, b \in B_H(i)\}|}{|\{b|b \in B_H(i)\}|} \quad (6)$$

$$Ws_i = \frac{|\{b|Es_i(b) \cdot y_i(b) > 0, b \in B_H(i)\}|}{|\{b|b \in B_H(i)\}|} \quad (7)$$

where $B_H(i)$ is the microblog set commented by user v_i from historical dataset.

In conclusion, we can summary our method as below:

$$Y^t = f(\{V, B\}, E) = f(Ep^t, Es^t) = Wp_i \cdot Ep_i^t + Ws_i \cdot Es_i^t \quad (8)$$

3. EXPERIMENTS

In this section, we first describe our experimental setup, and then present the performance of the proposed method and the comparison methods. Finally, we give our analysis and discussions based on the results.

3.1 Dataset

The dataset for our experiment is crawled from Tencent Weibo which is one of the biggest microblogging service with more than 780 million users in China. We collect all the microblogs between November 20th and November 30th of year 2011, as well as the relationship between the users. It turns out to have large number of users but only a few are active. For the efficiency and effectiveness of the experiments, we select 4,257 users who have more than 40 microblogs in 10 days and have strong relationship with others. 2,152,037 microblogs was produced within 10 days by these users.

On Tencent Weibo platform, users post microblogs with texts as well as images. Besides posting, users can also comment others' microblogs and retweet, which makes another new microblog authoring the reviewer. The original content will still exist in this new microblog, from which multimedia content can be analyzed. On the other hand, reviewer's comments can be an evidence showing his or her emotions when seeing the original microblog. We use traditional lexicon-based methods to find out the emotion polarity of the comments with a predefined Chinese words dictionary [1], which is the groundtruth for our experiments.

3.2 Evaluation Metric

We use *precision, recall* and *F1-Measure* as our metrics for positive and negative microblogs. The dataset is unbalanced, which needs to be mentioned. The number of microblogs conveying positive emotion is way much higher than the negative, which makes the proportion about 5:1. In this condition, predicting the negative emotion correctly will be more important than the positive ones. As the comprehensive metric, we need take the unbalanced situation into consideration. Therefore, we use the $F1_{avg}$ to measure the overall performance as a comprehensive metric.

$$F1_{avg} = \frac{F1_{pos} + F1_{neg}}{2}$$

3.3 Baseline Methods

Besides our proposed method which combines personal emotion and social emotion together with learned weight, we also implement the following baselines for comparison.

- General emotion prediction using images: the three basic kinds of color features [5], brightness, colorfulness and hue, was also used in this method. Different from our method, it's the prediction for the masses.
- General emotion prediction using texts: like Takamura et al. did in [8], the dictionary [1] was used to make predictions from original microblog as the emotion prediction result for users.

3.4 Evaluation

We first compare our method which combine personal emotion and social emotion together to the two baselines (based on images and texts) respectively. From Fig. 2 (a) and (b) we observe that our method achieve the best $F1$ performance in both positive and negative microblogs, which makes the comprehensive metric $F1_{avg}$ in our method huge success with 13% and 6.14% improvements compared to the other two baselines from (c).

Furthermore, we systematically study the effects of personal emotion and social emotion to our joint method. From Fig. 3 (a) and (b) we can observe that prediction from social emotion is better than the personal emotion for both positive and negative microblogs. That means most of the users have the same emotion (positive or negative) with others towards the same microblog. However, with the help of user interest, our method which combines the two factors together outperforms the social prediction. It indicates that there are particular some kinds of users who actually have their own minds and don't echo the sentiment of others.

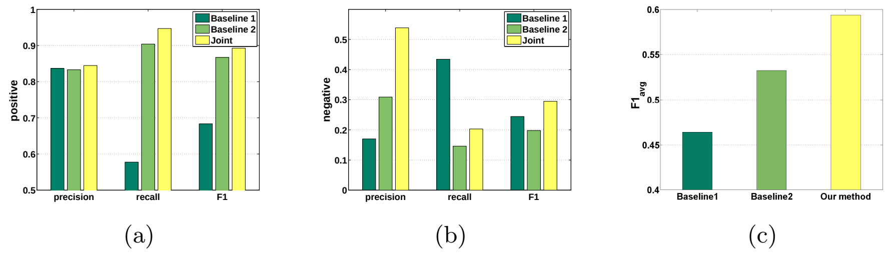

Figure 2: Comparison of our joint method based on personal emotion and social emotion with two baselines (based on image and text separately). (a) and (b) compare the three methods for positive and negative microblogs separately. (c) compares the three methods for all the microblogs using comprehensive measure $F1_{avg}$ which demonstrate our method outperform other two with 13% and 6% improvement.

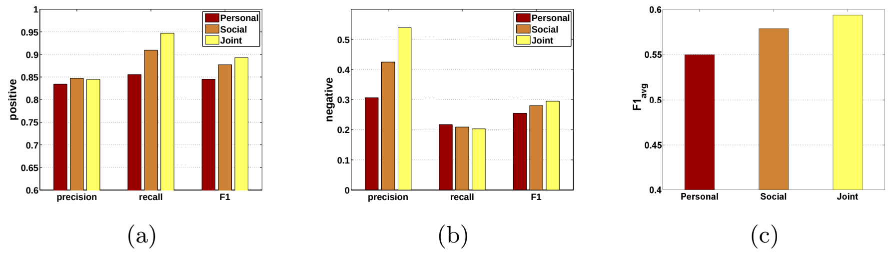

Figure 3: Comparison of our joint method with personal emotion prediction and social emotion prediction. From (a) and (b) we can observe social emotion prediction is more accurate than personal emotion prediction in both positive and negative microblogs. However, with the help of personal information, the joint method achieve the best performance from (c).

4. CONCLUSION AND FUTURE WORK

In this paper, we proposed a novel method taking both user interest in text and image domains and social influence among friends into consideration in social network for emotion prediction for individuals. A simple yet efficient weight learning method was proposed to balance the effects of the two factors to the target emotion. We conduct a set of comprehensive experiments to validate the effectiveness of our approach. From the experimental results, we can observe user interest and social influence play different roles in the target emotion, and our method which considers the both factors outperforms traditional emotion prediction methods with significant improvements.

5. ACKNOWLEDGMENTS

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