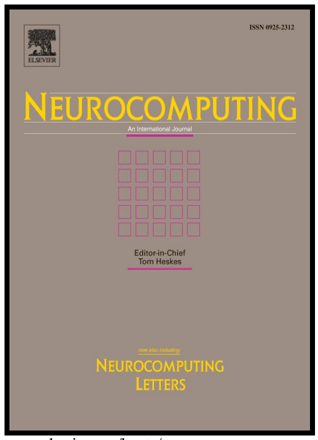
Author's Accepted Manuscript

Joint user-interest and social-influence emotion prediction for individuals

Ting Rui, Peng Cui, Wenwu Zhu



www.elsevier.com/locate/neucom

PII: S0925-2312(16)31469-2
DOI: http://dx.doi.org/10.1016/j.neucom.2016.11.054
Reference: NEUCOM17811

To appear in: *Neurocomputing*

Received date: 23 April 2016
Revised date: 12 November 2016
Accepted date: 29 November 2016

Cite this article as: Ting Rui, Peng Cui and Wenwu Zhu, Joint user-interest anc social-influence emotion prediction for individuals, *Neurocomputing* http://dx.doi.org/10.1016/j.neucom.2016.11.054

Joint User-interest and Social-influence Emotion Prediction for Individuals

Ting Rui

PLA University of Science and Technology, Nanjing, China

Peng Cui

Tsinghua University, Beijing, China

Wenwu Zhu

Tsinghua University, Beijing, China

Abstract

Emotions are playing significant roles in daily life, making emotion prediction important. Since emotions are highly subjective for users, we focus on emotion prediction for individuals instead of for the masses. Existing works on emotion prediction for individuals either focus on media content or social-influence alone, which are incomprehensive in predicting users' emotions. In this paper, we design a joint user-interest and social-influence emotion prediction framework for individuals, in which user-interest in multimodal media content and social-influence in social relations are both considered. To address the issue that for different users, the impacts of these two factors are different, a probabilistic graphical model is proposed to combine these two factors together, where a set of parameters are used to measure their importance in influencing the user's emotions, and they are learnt from the user's historical behaviors. We conduct experiments using real social media network to verify our algorithm and evaluate its performance. The results demonstrate the effectiveness of our approach and show that our approach can substantially improve the emotion prediction performance.

Keywords: Emotion prediction, social-influence, user-interest, social network.
2010 MSC: 00-01, 99-00

1. Introduction

Emotions affect people's behaviors and contribute to plenty of fields, ranging from social economy to individual decision-making[1]. [2] has shown public mood states have large correlation to stock market. What is more, emotions also show effective roles in influencing customers' purchase intentions [3]. The significant roles emotions play in daily life make the study of users' emotion an important issue.

Recent years have witnessed increasing research efforts on emotion detection or sentiment analysis from multimedia aspects [4][5][6][7]. However, just finding out what kinds of features express emotions well is far from enough. We are eager to learn users' emotions in advance so that we can provide real-time recommendation service, which makes emotion prediction more important. To date, most works in emotion prediction focus on predicting emotions for the masses [8][9][10], discovering the general emotions media have expressed. These are similar to sentiment analysis, finding out the representative features and turning the problem into classification problem in machine learning. Since the emotions are highly subjective for users, emotions predicted from the masses cannot present individual emotion effectively, making emotion prediction for individuals more targeted.

The success of many large-online social networks has made users' behavior in social network available for further study of individual emotions [11]. However, it is still a challenging problem due to the following reasons:

- **Complexity and subjectivity of individual emotion.** Individual emotion is a subjective, conscious experience characterized by multiple factors. Besides the diversity of emotion influence factors, the uncertainty of their roles in influencing different users' emotions make emotion prediction for individuals a challenging task.
- **Heterogeneous multimodal media in emotion prediction.** The prevalence of digital photography devices has caused the proliferation of heterogeneous and multimodal media in social networks. Different media domains may raise different emotions for users. How to integrate these heterogeneous media to find out the correlation between multimodal media in emotion prediction is also an unsolved problem.

*Corresponding author
Email address: cuip@tsinghua.edu.cn (Peng Cui)

As will be discussed in details in Section III, our data-driven analysis of real social media network shows that user-interest and social-influence are two important factors affecting users' emotions in social networks. For example, when watching the Super Bowl game, a football fan is more likely to get excited than others who are not interest in football, which shows that user-interest plays an important role in emotions. Besides, it is easier to get excited when watching the game and sharing their feelings with online friends, indicating social-influence is also an important factor in emotions. Based on this, we propose a joint user-interest and social-influence emotion prediction framework for individuals.

- In our framework, user-interest in multimodal media content and social-influence in social relations are both considered. Note that for different users the two factors play different roles, and some users are more easily influenced by others. To address this issue, we propose a probabilistic graphical model, where a set of parameters are used to quantify the impact of user-interest and social-influence on the user's emotions. These parameters are learnt from the user's historical behavior.

- Besides the multi-factors, we also consider both images and texts in our content-based emotion prediction, and propose a Bayesian model to integrate these heterogeneous media content in our analysis.

Fig. 1 illustrates the concept design, where user U_1's emotion towards microblog B_2 is predicted from both B_2's media contents and U_1's social relations in social networks. Specifically, our proposed framework first considers the two factors, user-interest and social-influence, separately. From user-interest perspective, user U_1's emotion towards microblog B_2 is predicted from the content similarity between B_2 and a previous microblog B_1 and U_1's emotion toward B_1. From social-influence perspective, user U_1's emotion for microblog B_2 is predicted from the already known emotion user U_2 had for microblog B_2 and the influence of user U_2 on user U_1. With the emotions predicted by two aspects, a probabilistic graphical model is used to model the roles user-interest and social-influence play in emotion prediction for individuals.

The contributions of our work can be summarized as follows:

- To the best of our knowledge, we are the first to consider both user-interest in multimodal media content and social-influence between friends in emotion prediction for individuals, which makes emotion prediction for individuals more effective and accurate.

- For each user, given that user-interest and social-influence play different roles in emotion, we assign each user a unique parameter set and propose a probabilistic graphical model to model their roles in emotion prediction for individuals.

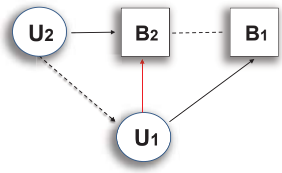


Figure 1: Joint user-interest and social-influence emotion prediction. The solid red line between users and microblogs represents the corresponding emotions we will predict. The solid black lines linking users to microblogs represent the corresponding emotions we have already known. The dotted black lines between users measure their social influence and the dotted black lines between microblogs measure the content similarities.

- A Bayesian model is proposed to integrate heterogenous media (text and image domains) in emotion prediction so as to represent user-interest more comprehensive.

- We conduct a set of comprehensive experiments showing the effectiveness of our algorithm. In addition, from our experiments, we also observe interesting patterns on how user-interest and social-influence affect different users' emotions in different situations, which make the work more interesting and exciting.

The remainder of this paper is organized as follows. Related works are summarized in Section 2. In Section 3, the data-driven approach is used to study which factors affect users' emotions and how their impacts vary from person to person. The framework of our algorithm and notions will be clarified in Section 4. In Section V, our proposed emotion prediction framework will be discussed in details, including the endogenous and the exogenous emotion prediction modules, and the probabilistic graphical model to combine them together. We evaluate the performance of our proposed framework and present a few interesting observations in Section 6. Finally, conclusion is drawn in Section 7.

2. Related Work

In this section, we survey literature on sentiment analysis as well as emotion prediction.

2.1. Sentiment Analysis

As people gradually realize the important roles emotions play in daily life, sentiment analysis has been a hot topic for quite a few years. Texts are the most common way to express users' emotion, which makes texts become the most popular domain in sentiment analysis area. Sentiment analysis from texts has been widely used on product and movie reviews [12][13] and various social media applications [14], including poll rating prediction [15], stock market prediction [2], event analysis [16], etc. Like traditional machine learning problems, most existing methods in sentiment analysis can fall into unsupervised and supervised learning methods. The basic idea of these methods is to build a sophisticated feature space, which can effectively represent the sentiment status of the texts. The most representative way to perform unsupervised sentiment analysis is the lexicon-based method [9]. The methods rely on a pre-defined sentiment lexicon to determine the general sentiment polarity of a given document. However, unsupervised sentiment analysis in social networks faces greater challenges due to following reasons: 1) microblogs in social networks are more casual and limited to 140 characters of text, compared to reviews, it includes more noise. 2) the rapid development of vocabularies, such as "T_T" or "coooooool", make the unsupervised sentiment learning methods difficult to get their emotions in time [17]. While in supervised methods, with the help of annotations and tags, it is much easier to learn the emerged cyberwords emotions in social networks. In order to train a classifier, supervised learning usually requires hand-labeled training data. With the large range of topics discussed in social networks, it would be very difficult to manually collect enough data to train a sentiment classifier for microblogs. Under the circumstances, star ratings [18], distant supervision [19] or social relations [20] in social networks has become the polarity signals in training dataset, solving the problem to some extent.

With the prevalence of digital devices, multimedia such as images and audio have been popular in social networks. Compared to texts, these multimedia messages convey emotions more vivid and diverse [21]. One of the first affective image filtering system is K-DIME [22], which builds a retrieval system for users to retrieve affective images. Another work was done by Jana et al. [5], using features inspired by psychology and art theory to classify affective images. Work [8] has shown the colors' important roles in image emotion prediction and some researches [23][24] specialize in emotion color. Besides images features, multiple domains [6][25] information has been preliminarily combined together.

2.2. Emotion Prediction

Compared to sentiment analysis, finding out what kinds of features express emotions well, we are eager to learn users' emotions in advance so that we can provide real-time recommendation service, making emotion prediction more important. Currently, emotion prediction can be divided into two categories: prediction for the masses and for individuals.

2.2.1. Emotion Prediction for The Masses

To date, most works in emotion prediction focus on predicting emotions for the masses, discovering the general emotions media have expressed. It can be seen as an application of sentiment analysis, finding out the representative features and turning the problem into classification problems in machine learning. [9] proposes a methods for extracting the words' semantic orientations regarding semantic orientations as spins of electrons. [8] tries to find the fundamental features that reflect the affects of the authors in images and infer the trend of public affects for images. [26] focuses on the prediction of users' favorite photos by combining social, visual and textual signals into a single prediction system.

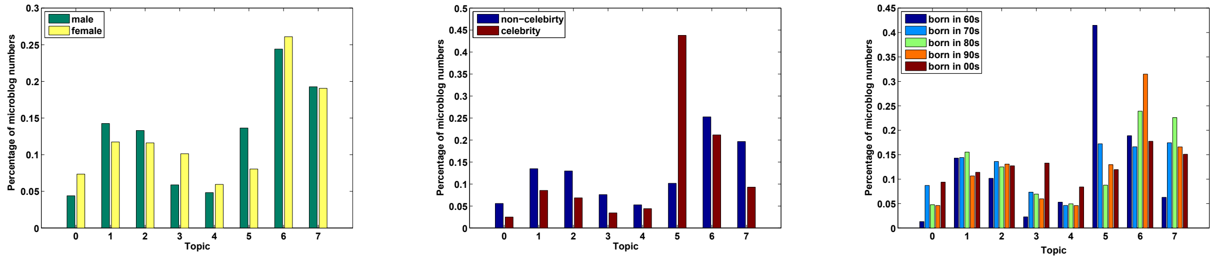
2.2.2. Emotion Prediction for Individuals

However, different people have different tastes, making emotion prediction for the masses less valid for individuals [27]. Therefore, user-interest has long been viewed as the major factor affecting users' emotions. Besides, with the successful of many large-scale online social networks, users can easily observe and influence each other's emotions and social-influence has also become another factor influencing users' emotions. Current works on individual emotion prediction also can be divided into these two parts: user-interest based and social-influence based.

From user-interest perspective, users' interest toward different topics and different images can be learnt from their historical behavior dataset, similar to user-level recommendation [28], content-based filtering and collaborative filtering [29]. With the learnt user behavior and media content, users' emotion can be predicted from user-interest aspect.

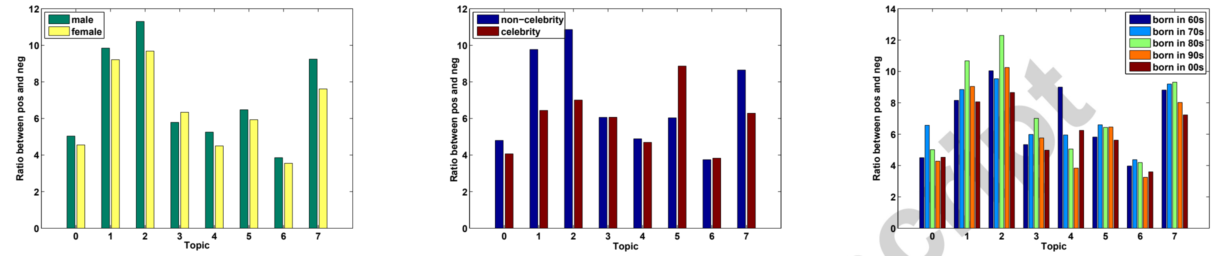
The popularity of social networks makes it available to study the social-influence in social networks [30]. Winter et al. [31] investigated several models of social-influence from an interdisciplinary view. Anagnostopoulos et al. [32] theoretically interpreted social-influence as a source of social correlation when the time series of user actions is available. Crandall et al. [33] further investigated the correlation between social similarity and influence. Meanwhile, plenty of works have shown the effect of social-influence made in emotion prediction. [34] has shown that how happy you are is influenced by your social links to people in social networks. The work for sentiment analysis in microblogging [20] also found that social relation helps in handling noisy and short tweets. [35] gives us a better clue of using social relationship in sentiment analysis by user-user "connected" in tweets. More recently, Tang's work [36] quantitatively studies how an individual's emotion is influenced by his friends in social network.

As user-interest and social-influence are both important factors influencing users' emotions, in our earlier work [37], the two factors are both considered. However, as for joint strategy, the two factors weights are gotten from direct statistics, which cannot depict the two factors roles in individual emotions well. In this paper, we explore how information from user-interest and social-influence can be used jointly to improve emotion prediction performance and how the two factors work for different users in emotions.



(a) (b) (c)

Figure 2: User interest distributions on different topics for different user groups. (a) shows the relationship between user interest distributions and gender. (b) reveals the relationship between user celebrity status and their interest distributions. (c) presents the relationship between user age and the interest distributions.



(a) (b) (c)

Figure 3: Correlation between positive-negative microblog ratios and users' profile on different topics. (a) presents the relation between the ratio and user's gender. (b) reveals the correlation between user celebrity status and the ratios. (c) shows how user's age influences the ratio on different topics.

3. Data-driven Observations

Before describing our proposed emotion prediction framework for individuals, we first use data-driven approach to conduct a series of analysis on social media networks and validate that emotions shown in microblogs are affected by user-interest and social-influence. In this section, we use Tencent Weibo as our platform and randomly select more than 1K users and their 773,287 microblogs. In our work, emotions are divided into two categories, positive and negative, which are common in studies on sentiment recognition [38] [39] and enough for most applications. More details of the dataset are in Section 6.1.

User-interest towards multimodal media content and social-influence between users are two important factors that influence users' emotions. To find out the relationship between user-interest, social-influence and users' emotions in online social networks, in this section, we focus on the following aspects:

- Do users have personal user-interest in online social networks? Are their emotions affected by the content in different ways?
- Do microblogs on different topics tend to trigger different emotions in online social networks?
- As friends tend to share similar emotions, do they influence each other's emotions in online social networks?

3.1. Correlation Between User Profile and Topics of Interest

Users are interested in different topics and post different microblogs. To determine the relationship between user profile and their preferences in posting or sharing microblogs, we first collect users' gender, celebrity status and age information from user profile and group them into several groups. Then we apply Latent Dirichlet Allocation (LDA) [40] to the microblogs and extract 8 topics. For each user group, among all microblogs they post, we calculate their distributions among the 8 topics and plot the results in Fig. 2.

Fig. 2(a) shows the relationship between user interest distributions and gender. From Fig. 2(a), women are more interested in *Topic* 0 (about Beauty) and *Topic* 3 (about Women) than men, and men show more interest in *Topic* 5 (about Global news and the World) than women. For the rest of the topics, they show approximately the same level of interest. These findings agree with the general consensus that men are more concerned about politics and finance, while women are more interested in beauty and fashion. Fig. 2(b) shows that around 45% of the microblogs posted by celebrities are on *Topic* 5 (about Global news and the World), which is much larger than that by

Table 1: Ratios of the numbers of microblogs showing positive and negative emotions on different topics.

Topic	0	1	2	3
pos/neg	4.78	9.64	**10.73**	6.06
Topic	4	5	6	7
pos/neg	4.88	6.37	**3.74**	8.58

non-celebrities. This is because celebrities often consider themselves as the role models of many people and take more social responsibilities. When looking at the topics of interests for users in different age groups in Fig. 2(c), we can observe that users born in 1960s are more concerned about global news and world (*Topic* 5), while younger generations born in 1990s post more microblogs on *Topic* 6 (about bitter jokes or black humor).

From the above discussions, we observe that different users have different topics of interest.

3.2. Emotion Biases

In the following, we study whether different topics tend to trigger different emotions, and whether different user groups show different feelings towards the same topic. To answer the first question, for each topic, we first calculate the numbers of microblogs showing positive and negative emotions, respectively, and show their ratios in Table 1. Here, a larger ratio indicates a higher chance to see microblogs showing positive feelings. The average ratio across all topics in our test dataset is 6.17. From Table 1, *Topic* 2 is about "love and happiness" and its positive-negative ratio is far above the average. *Topic* 6 is on bitter jokes and black humors, and we tend to see more microblogs showing negative feelings, such as self-mockery and satire of the society. This shows that different topics indeed tend to trigger different emotions.

To answer the second question, same as in Section 3.1, we group users into groups according to their gender, celebrity status and age. For each group, we calculate their positive-negative ratio distributions among all topics and show the results in Fig. 3. From Fig. 3(a), we can observe that almost for all the topics, men tend to have more positive emotions than women. From Fig. 3(b), non-celebrities tend to be more positive when concerned about "Beauty", "Friends", "Love" and "Treasure", while celebrities tend to post more positive views on global news including finance and governments. Fig. 3(c) shows that different age groups show different emotion biases towards different topics.

All these patterns show that users have different emotions towards microblogs on different topics, elaborating the importance of users' self-interest in emotion prediction.

3.3. Social Influence in Users' Emotion

With the prevalence of social networks, users can easily observe and influence each other's emotions. In the following, we study the correlation between friends' emotions and its impact on users' emotions.

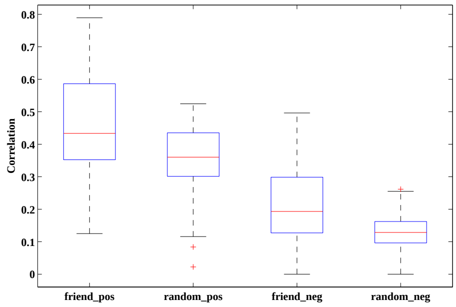


Figure 4: The correlation between users' interest vectors in emotion analysis.

As will be explained in details in Section 5.1, we mine users' historical microblogs, and extract features from texts and images that are important for emotion analysis. We then use two interest vectors to represent the likelihood that the user shows positive and negative emotions, respectively, when presented with these features. For any two users, the cosine similarities between their interest vectors are used to measure the correlations between their emotions. The results are shown in Fig. 4. From the box plot, we can observe that for both positive and negative emotions, the correlations between friends (directly connected users in social networks) are higher than that between two randomly picked users. As influence in one of the primary explanations for social correlation [32], it shows that influence between friends actually exists and does affect users' emotions. (In this section, we only discuss the influence from social relations qualitatively. The quantitative analysis of social influence between friends and its impact on users' emotion will be discussed in Section 5 in details.)

Summary To briefly summarize, we have the following observations in online social networks:

1. Users have their personal preference and characteristics, which must be taken into consideration in emotion prediction for individuals.
2. Different contents trigger different emotions, and emotion prediction must analyze the microblogs' contents and its impact on users' emotions.
3. Friends influence each other's emotions, and social-influence must be considered in individual emotion prediction.

4. The Framework and Problem Definition

Based on the above observations, we propose a novel framework that considers both user-interest and social-influence in emotion prediction for individuals. Fig. 5 shows the proposed framework. It includes two parts, the offline training to extract user-interest in multimodal media content and social-influence in social relations, and the online emotion prediction. We will discuss them one by one.

Social network G is a hybrid graph composed of nodes and edges, where nodes contain user set U and microblog set B. There are 3 types of edges: $e_u \subset U \times U$ is the set of directed links between users, $e_b \subset B \times B$ includes all edges connecting microblogs, and an edge in the set $e_{ub} \subset U \times B$ means a user shared or commented on a microblog b, from which user's emotion can be revealed. The social network G can be presented as $G = \{Node, Edge\} = \{U, B, e_u, e_b, e_{ub}\}$.

In the offline training phase, given this hybrid social network graph, we first extract keywords and image features from microblog contents, and then mine users' historical behavior to build the user-interest graph, which represents users' likes and dislikes towards these keywords and image features. It includes two bipartite subgraphs, one for positive emotions and the other for negative ones, where an edge links a user to a keyword or an image feature and indicates the likelihood that the keyword or image feature triggers the user's positive/negative emotions. We also obtain a social-influence graph that describes how users influence each other's emotions. It includes two subgraphs, one for positive emotions and the other for negative ones. In this graph, a directed edge from user U_1 to user U_2 indicates the influence that U_1 has on U_2. The last step in the offline training is to combine these two different factors in user emotion analysis. To address the issue that for different users, user-interest and social-influence have different impacts on their emotions, we assign each individual a unique vector set (α, β) to represent the weights user-interest and social-influence play in his/her emotions, respectively, and use probabilistic graphical model to learn these parameters from users' past behavior.

With the above offline training results, in online prediction phase, a user's emotion when seeing a new microblog in online social network is predicted as follows:

We first extract keywords and image features from the new microblog, and based on the user-interest graph, we estimate the user's endogenous emotion, which is defined as follows.

Definition 1. ***Endogenous emotion:*** *Endogenous emotion is the intuitive feelings users have when seeing the microblog. It is the emotion triggered by the content of the microblog and the user's self-interest. We use $Eu_u^t(b)$, the endogenous emotion vector, to denote the probabilities that user u has positive and negative emotions, respectively, when seeing microblog b at time t.*

We then use the social-influence graph to estimate how others' reactions to the microblog b may influence the user's emotion and predict the exogenous emotion.

Definition 2. ***Exogenous emotion:*** *Exogenous emotion is the emotion produced by the impact of friends' emotion (social-influence). Here, we use $Es_u^t(b)$ as the exogenous emotion vector showing the probabilities that user u has positive and negative emotions, respectively, when seeing microblog b at time t.*

Table 2: Notations

Symbol	Definition
G	The social network graph
B	The microblog set
U	The user set
Eu	The 1×2 endogenous emotion vector
Es	The 1×2 exogenous emotion vector
E	The true emotion the user has when seeing the microblog, $E = 1$ for positive emotions, and $E = 0$ otherwise
Y	The predicted emotion, $Y = 1$ when the predicted emotion is positive, and $Y = 0$ otherwise
$Tx(b)$	A vector representing the microblog b's text information extracted from the text portion
$Im(b)$	A vector representing the microblog b's image information extracted from the images in b
$p_u^e(Content)$	The probability that user u has positive ($e = 1$) and negative ($e = 0$) emotions when seeing the content ($Tx(b)$ or $Im(b)$ or both)
inf_{u_1,u_2}	User u_2's influence on u_1's emotions
$N(u)$	A set including user u's friends who commented before user u.
$p_u^e(E_{N(u)}, inf)$	The probability that user u has positive ($e = 1$) or negative ($e = 0$) emotions when seeing his friends' emotions $E_{N(U)}$

In the last step, we combine the two emotions using the weights learnt from the probabilistic graphical model and output the overall predicted individual emotions.

Definition 3. ***Individual emotion:*** *Individual emotion is the overall emotion users have, with considerations of both user-interest and social-influence. The output is a binary number $Y_u^t(b)$, the predicted individual emotion user u has when seeing microblog b at time t. It is 1 when the predicted emotion is positive and 0 otherwise.*

In summary, in this work, given a dynamic network G at time t, the goal is to design a predictive function f to infer users U's emotion when seeing microblog B at time t with the historical user-interest information and the known friends' emotions for microblog B. Mathematically, we have:

$$Y_U^t(B) = f(B, U, E_{N(U)}^t(B) | G^t)$$

5. Joint User-interest and Social-influence Emotion Prediction

In this section, we will present the details of the proposed joint user-interest and social-influence emotion prediction for individuals. Endogenous emotion and exogenous emotion prediction will be discussed first, followed by the probabilistic graphical model to combine them together.

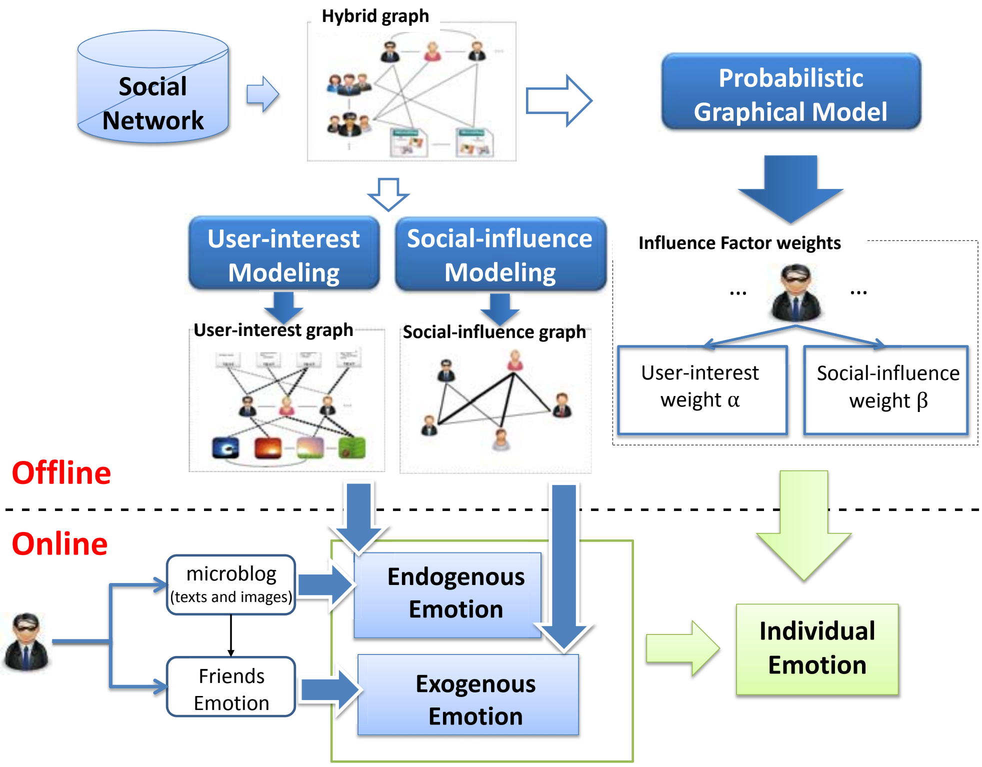


Figure 5: Framework of joint user-interest and social-influence emotion prediction for individuals.

5.1. Endogenous Emotion Prediction Based on Bayesian Model

Texts and images are the most common ways to convey information. In this work, we consider both texts and images in our endogenous emotion prediction. Given the trained user-interest graph and a new microblog, we first estimate users' reactions to the keywords extracted from the new microblog's text and the features extracted from the attached image separately. Then, a Bayesian model is used to combine these two results to predict the user's endogenous emotion.

5.1.1. Text Domain

There have been extensive researches on text based emotion analysis. In our work, in the offline training stage, we first use Term Frequency Inverse Document Frequency (TF-IDF) [41] to determine which words in corpus of microblogs might be more important for emotion analysis and filter the microblog texts accordingly. Then we use the bag-of-word model, which is widely used in information and text mining [42], and let each word correspond to one dimension in the resulting data space. Here we assume that words appear independently and the order is irrelevant. Let $B = \{b_1, ...b_n\}$ be a set of microblogs and $W = \{w_1, ...w_m\}$ be the set of distinct words occurring in B. So a microblog b can represented as an m-dimensional vector,

$$Tx(b) = (I_b(w_1), ...I_b(w_m))^{\mathrm{T}}$$

where $I_b(w) = 1$ when microblog contains word w and $I_b(w) = 0$ otherwise.

As we said before, each word conveys different emotions for different users, and users' historical behaviors give us a clue to find out their personal interest. $pos_u(w)$ and $neg_u(w)$ are used to represent the word w's probability of triggering positive and negative emotions for user u, and they are estimated using

$$pos_u(w) = \frac{|\{b|b \in B_H(u), E_u(b) = 1, w \in b\}|}{|\{b|b \in B_H(u), w \in b\}|} \quad (1)$$

$$neg_u(w) = \frac{|\{b|b \in B_H(u), E_u(b) = 0, w \in b\}|}{|\{b|b \in B_H(u), w \in b\}|} \quad (2)$$

where $B_H(u)$ is the historical microblog dataset for user u and $E_u(b)$ is the emotion user u has for microblog b, $E_u(b) = 0$ for negative and 1 for positive.

Based on Eqs. (1) and (2), each user gets a personal dictionary represented as an $m \times 2$ word-emotion matrix W_u, in which each word has two entries denoting the probabilities of triggering positive and negative emotions.

$$W_u = \begin{pmatrix} pos_u(w_1) & neg_u(w_1) \\ \vdots & \vdots \\ pos_u(w_m) & neg_u(w_m) \end{pmatrix}$$

In the online prediction stage, with the new microblog b and user's word-emotion matrix W_u, $p_u^{pos}(Tx(b))$ and $p_u^{neg}(Tx(b))$, the probabilities that user u has positive and negative emotions, respectively, from text domain can be calculated as:

$$[p_u^{pos}(Tx(b)), p_u^{neg}(Tx(b))] = Tx(b)^{\mathrm{T}} W_u \tag{3}$$

5.1.2. Image Domain

Nowadays, more than 60% microblogs are illustrated with images, which make microblogs more vivid and expressive of users' emotions.

In [23], color emotions features have shown to be effective in image affective classification. Color emotions can be described as emotional feelings evoked by a single color or color combinations. They belong to the cognitive aspects of color and describe an image using aesthetical measurements. Compared to traditional color histogram, it defines similarity between images in a semantic way. Moreover, it can be quickly extracted, and characterizes images with three emotion values, *activity, weight and heat.*

In the offline training stage, for each microblog illustrated with images, we follow the work in [23], use the following equations to compute the mean score for each emotion value and define as a 1×3 vector $Im(b)$ to represent the image's emotion features.

$$\begin{aligned} activity &= -2.1 + 0.06 \\ &\times \left[(L^* - 50)^2 + (a^* - 3)^2 + \left(\frac{b^* - 17}{1.4} \right)^2 \right]^{\frac{1}{2}} \end{aligned} \tag{4}$$

$$weight = -1.8 + 0.04(100 - L^*) + 0.45\cos(h - 100°) \tag{5}$$

$$heat = -0.5 + 0.02(C^*)^{1.07}\cos(h - 50°) \tag{6}$$

$$h = \arctan\left(\frac{b^*}{a^*}\right) \tag{7}$$

$$C^* = \sqrt{a^{*2} + b^{*2}} \tag{8}$$

where L^*, a^* and b^* are CIELAB coordinates, h is the CIELAB hue angle and C^* is the CIELAB chroma.

In the offline training stage, for all microblogs attached with an image where the user shows positive emotions, we compute their image feature vector $Im(b)$ as above, and calculate the mean μ_u^{pos} and the covariance matrix Σ_u^{pos} over all such images. Here, we consider the mean μ_u^{pos} as the most representative color emotion feature point to trigger user u's positive feelings, and for image feature points that are far away from the mean μ_u^{pos}, the probabilities that user u shows positive feelings are small. We model the user's personal positive feelings towards color emotion features as multivariate normal distributions with mean μ_u^{pos} and covariance matrix Σ_u^{pos}, which shows superior effects. Similarly, for all microblogs illustrated with images where the user shows negative emotions, we follow the same procedure and calculate the mean vector μ_u^{neg} and the covariance matrix Σ_u^{neg}. The parameter set $(\mu_u^{pos}, \Sigma_u^{pos}, \mu_u^{neg}, \Sigma_u^{neg})$ describe user u's personal feelings toward image contents.

$$Im_u^{pos} \sim \mathcal{N}(\mu_u^{pos}, \Sigma_u^{pos})$$

$$Im_u^{neg} \sim \mathcal{N}(\mu_u^{neg}, \Sigma_u^{neg})$$

In the online prediction, given an image represented by its feature vector $Im(b)$, the probability that it triggers user u's positive emotions is:

$$\begin{aligned} p_u^{pos}(Im(b)) = \frac{1}{(2\pi)^{d/2}|\Sigma_u^{pos}|^{\frac{1}{2}}} exp\{-\frac{1}{2}(Im(b) - \mu_u^{pos})^{\mathrm{T}} \\ \Sigma_u^{pos\,-1}(Im(b) - \mu_u^{pos})\} \end{aligned} \tag{9}$$

The probability that user u shows negative emotions when seeing the image can be computed in the same way.

5.1.3. The Bayesian Model

When seeing a new microblog online, the above discussions predict a user's emotions in these two different domains separately. However they cannot be separated from each other. Images make texts more vivid and texts clarify the content. With above independent analysis of the text and the image in microblog b, a Bayesian model is used to combine them together based on users' historical behavior, where the probabilities that user u has positive and negative emotions when seeing microblog b are

$$p_u^{pos}(Tx(b), Im(b)) = \frac{p_u^{pos}(Tx(b)) \cdot p_u^{pos}(Im(b)) \cdot p_u(pos)}{\sum\limits_{e=pos,neg} p_u^e(Tx(b)) \cdot p_u^e(Im(b)) \cdot p_u(e)} \tag{10}$$

$$p_u^{neg}(Tx(b), Im(b)) = \frac{p_u^{neg}(Tx(b)) \cdot p_u^{neg}(Im(b)) \cdot p_u(neg)}{\sum\limits_{e=pos,neg} p_u^e(Tx(b)) \cdot p_u^e(Im(b)) \cdot p_u(e)} \tag{11}$$

where $p_u^e(Tx(b))$ for $e \in \{pos, neg\}$ are in Eq. (3), $p_u^e(Im(b))$ are in Eq. (9), and $p_u(pos)$ and $p_u(neg)$ are the percentages of microblogs where user u shows positive and negative emotions, respectively.

So, the predicted endogenous emotion vector $Eu_u(b)$ when user u sees a microblog b can be presented as:

$$Eu_u(b) = [p_u^{pos}(Tx(b), Im(b)), p_u^{neg}(Tx(b), Im(b))] \tag{12}$$

5.2. Exogenous Emotion Prediction Based on Weighted Bernoulli Distribution

In this section, we will investigate how users influence each other's emotions and how to predict a user's exogenous emotions.

We first discuss the offline training stage. We first consider the simple scenario with two users only and study how they influence each other's emotions. Any time a contagious user u_2 tries to influence user u_1, we suppose he has a fixed probability to make u_1 have the same emotion as himself. If user u_1 actually has the same emotion as user u_2, it is a successful attempt. Each attempt can be viewed as a Bernoulli trial [43]. The Maximum Likehood Estimator(MLE) of the success probability is the ratio of the number of successful attempts to the total number of trials.

$$inf_{u_1,u_2} = \frac{|B_{u_1,u_2}|}{|B_{u_2}|} \tag{13}$$

where B_{u_2} is the microblog set shared by user u_2 and B_{u_1,u_2} is the microblog set user u_2 has successfully influenced u_1.

We now consider the scenario where several users may influence another user's emotions. For one microblog, a user's emotion may be influenced by all his friends who shared their comments before. Thus, it is reasonable to infer that all these predecessors share the "credit" for influencing the user to have the same emotion as them, and in this work, we give the same credit to all such predecessors. The credit given to user $u_2 \in N(u_1)$ who have commented on microblog b before u_1 can be defined as:

$$credit_{u_1,u_2}(b) = \frac{1}{\sum\limits_{f \in N(u_1)} I(E_f(b) = E_{u_1}(b))} \tag{14}$$

where $N(u_1)$ includes all user u_1's friends who make comments on microblog b before user u_1, and I is the indicator function.

Combing Eqs. (13) and (14), user u_2's influence on u_1 to have the same emotion as him/her is estimated using the following MLE:

$$inf_{u_1,u_2} = \frac{\sum\limits_{b \in B_{u_1}} credit_{u_1,u_2}(b)}{|B_{u_2}|} \tag{15}$$

In addition, the work in [43] showed that timeliness also plays an important role in influencing others' emotions, and the earlier a user sees his friends' comments, the more easily he will be influenced by them. Following their work, an exponential decay function is used in this paper to update the influence factor at time t:

$$inf^t_{u_1,u_2} = inf_{u_1,u_2} e^{-(t-t_{u_2})/\tau_{u_1,u_2}} \tag{16}$$

where inf_{u_1,u_2} is the influence of u_2 on u_1 calculated in Eq. 15. τ_{u_1,u_2} is the average time for user u_1 responding to user u_2's comments and is estimated using

$$\tau_{u_1,u_2} = \frac{\sum\limits_{b \in B_{u_1,u_2}} (t_{u_1}(b) - t_{u_2}(b))}{|B_{u_1,u_2}|} \tag{17}$$

where $t_u(b)$ is the time that user u comments on microblog b.

Based on above discussion, in the online exogenous emotion prediction stage, the probability for user u to have positive emotions when seeing microblog b at time t is:

$$p^{pos}_u(E_{N(u)}(b), inf_{u,N(u)}) = \frac{1}{\sum\limits_{u_2 \in N(u_1)} inf^t_{u_1,u_2}} \sum_{u_2 \in N(u_1)} inf^t_{u_1,u_2} E_{u_2}(b) \tag{18}$$

where $E_{u_2}(b) = 1$ when user u_2 expresses positive emotions towards microblog b, and the probability to have negative emotion is:

$$p^{neg}_u(E_{N(u)}(b), inf_{u,N(u)}) = 1 - p^{pos}_u(E_{N(u)}(b), inf_{u,N(u)}) \tag{19}$$

So, the vector $Es_u(b)$ representing user u's exogenous emotion when seeing microblog b is:

$$Es_u(b) = [p^{pos}_u(E_{N(u)}(b), inf), p^{neg}_u(E_{N(u)}(b), inf)] \tag{20}$$

5.3. The Probabilistic Graphical Model

In the previous two subsections, the impact of user-interest and social-influence on users' emotions have been considered separately. Note that these two factors affect different users differently, and even for the same person, the impact of these two factors may vary for positive and negative emotions. Therefore, for each user, we use four parameters to measure how these two factors affect a user's emotions in the positive and negative ways, respectively. α^0_u, α^1_u measure the weights of user-interest for negative and positive emotions, respectively, and β^0_u, β^1_u are the weights of social-influence for negative and positive emotions, respectively. A probability graphical model is used to combine these two factors in emotion prediction. More specifically, by combing Eqs. (10), (11) and (18) together, we define the the probability that user u's individual emotion for microblog b is Y as

$$\begin{aligned} P(Y) = &\frac{1}{Z} exp\Big\{ \sum_{u \in U} \sum_{b \in B_u} \alpha^Y_u (p^{pos}(b))^Y (p^{neg}(b))^{1-Y} \\ &- \beta^Y_u \Big(\frac{1}{\sum\limits_{v \in N(u)} inf^t_{u,v}} \sum_{v \in N(u)} inf^t_{u,v} E_v(b) - Y \Big)^2 \Big\} \end{aligned} \tag{21}$$

where Z is a normalization factor.

5.3.1. Parameter Estimation

In the offline training stage, the key component in learning the probabilistic graphical model is to estimate a parameter configuration $\theta = (\alpha^0_u, \alpha^1_u, \beta^0_u, \beta^1_u)$ from a given historical behavior that maximizes the log-likelihood objective function $\mathcal{L}(\theta) = \log P_\theta(Y)$,

$$\theta^* = \arg\max_\theta \log P(Y|\theta) \tag{22}$$

For parameter estimation, we use SampleRank algorithm [44] that updates the parameters from atomic gradients. The proposed algorithm includes two steps: (1)

Algorithm 1: Emotion Parameter Learning Algorithm

Require: Number of iterations and learning rate η.
Ensure: $\alpha_u^0, \alpha_u^1, \beta_u^0, \beta_u^1 > 0$

```
Initialize θ = {α_u^0, α_u^1, β_u^0, β_u^1}
Randomly initialize Y
for i:=1 to Number of Steps do
    Y^new := Sample(Y);
    if (Perf(Y^new, Y) > 0&ΔθF < 0) then
        //performance is better, objective function is lower
        θ := θ + ηΔθF
    end if
    if (Perf(Y^new, Y) < 0&ΔθF > 0) then
        //performance is worse, objective function is higher
        θ := θ − ηΔθF
    end if
    if (Perf(Y^new, Y) > 0) then
        Y := Y^new;
    end if
    if convergence then
        break;
    end if
end for
```

a nondeterministic transition function, which yields Y^{new} from current emotion prediction Y, and (2) parameter update according to training performance. In the following, we explain the algorithm in details.

As summarized in Algorithm 1, in each iteration of the learning algorithm, we first sample a new emotion set Y^{new} using *Sample* function. When updating the parameters, we calculate two scores: the $Perf(Y^{new}, Y)$ which calculates the difference between the $F1_{avg}$ scores for sampled emotions Y^{new} and Y, and the log-likelihood ratio $\Delta\theta F$ of new sample Y^{new} to previous configuration Y:

$$\Delta\theta F = \log(\frac{P(Y^{new})}{P(Y)}) = \log(P(Y^{new})) - \log(P(Y)) \tag{23}$$

where F is the function $log(P)$. Here, $Perf$ is the real performance based on the real emotion we have in the historical dataset, while $\Delta\theta F$ is our predicted performance metric based on our proposed objective likelihood function.

When the predicted and the real performance metrics match, that is, when $Perf$ and $\Delta\theta F$ give the same trend (either both increase or both decrease), it shows that the current parameter configuration θ can correctly describe the two factors' roles and they do not need to be updated. Otherwise, they give different trends (one increases while the other decrease), and we update the parameters with learning rate η until it converges.

5.3.2. Individual Emotion Prediction

Algorithm 2: Individual Emotion Prediction Algorithm

Require: Learned parameter θ
Ensure: Emotion $Y \in \{0, 1\}$

```
output ← Y
for Each user u do
    if P(Y = 1|α_u^1, β_u^1) > P(Y = 0|α_u^0, β_u^0) then
        //the probability of being positive is larger;
        Y ← positive
    else
        //the probability of being negative is larger;
        Y ← negative
    end if
end for
```

In online prediction stage, with the learned parameters, we can predict users' emotions based on their interest and social friends. Specifically, for each user, given the learned parameters θ and historical dataset, we plug them into Eq. 21 and get the emotion that can maximize the objective likelihood function. Mathematically, our problem is an instance of the maximum a posteriori probability problem:

$$\arg\max_{y\in\{0,1\}} P(Y = y|\theta) \tag{24}$$

Details of the individual emotion prediction algorithm are in Algorithm 2.

5.3.3. Complexity Analysis

The complexity of Algorithm 1 in this paper is dominated by the step of *Random* function and calculating the value of $\Delta\theta F$. And from Eq. 23, we know the complexity of calculating $\Delta\theta F$ is decided by calculating the value of $P(Y)$. The complexity of $P(Y)$ is $O(m + n)$, where m is the size of microblog set and n is the user set. And the complexity of *Random* function is $O(n)$. With considering that only constant time operations is involved in the for-loop in Algorithm 1, therefore, the complexity of Algorithm 1 is O(m+n). And the complexity of Algorithm 2 in this paper is O(n).

6. Experimental Results

In this section, we first describe our experimental setup, and then show experimental results of our proposed algorithm to evaluate its effectiveness and efficiency. Finally, we will discuss some interesting phenomena that we observed from our simulation results.

6.1. Experimental Setup

Dataset: We perform our experiment on real social media network, Tencent Weibo, which is one of the biggest microblogging service in China with more than 780 million users. We collect all the microblogs between November 20 and November 29, 2011, as well as the relationship between the users. Even though there are a large number of users, only a few are active. For the efficiency and effectiveness of the experiments, we select 5,261 users who posted more than 50 microblogs in the 10-day window and had strong relationship with others. 1,385,475 microblogs were posted within these 10 days by these users.

On the Tencent Weibo platform, users post microblogs with texts as well as images. Besides tweeting, users can also comment on others' microblogs and retweet, which generates another new microblog authored by the follower. The original content still exists in this new microblog, from which multimodal media content can be analyzed. On the other hand, followers' comments can be an evidence showing his or her emotions when seeing the original microblog. We use lexicon-based methods to find out the emotion polarity of the comments with a predefined Chinese emotional words dictionary [45], which is used as the groundtruth in our experiments.

Performance Evaluation Metrics: Precision, Recall and F1-Measure are used to evaluate the performance of the proposed algorithm. Through mining of users' emotions from microblogs' comments, we find that there are much more microblogs with positive emotions and the ratio of positive to negative is about 5:1. In this case, correct prediction of the negative emotions is more difficult and we need to take this unbalanced dataset into consideration. Therefore, with the F1-Measure for positive and negative emotions $F1_{pos}$ and $F1_{neg}$, $F1_{avg}$ was used to measure the overall performance as a comprehensive metric.

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

Besides $F1_{avg}$, we also use the receiver operating characteristics (ROC) graph to evaluate our algorithm. ROC is a generally useful performance graphing method. The properties of the graph make it more useful for unbalanced classes [46]. For each measurement, we set a threshold, if $P(Y = positive) > threshold$, we predict the emotion as positive. Otherwise, it is predicted as negative. The Eq. 24 and Algorithm 2 can be seen as an example with $threshold = 0.5$.

Baseline Methods Besides our proposed algorithm that combines endogenous emotion and exogenous emotion together with learned weights, we also implement the following baseline algorithms for comparison.

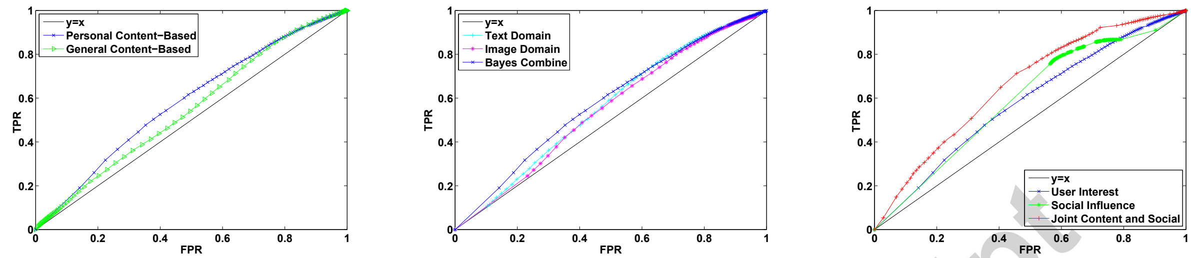
- *Document Clustering Methods:* Unsupervised learning has been extensively used in data mining. From Section 5, each user can be presented as a vector in the text and image domains. Then we choose the most representative clustering method, the support vector machine (SVM), as a baseline method in this study.
- *Traditional Lexicon-Based Methods:* These methods employ a word-matching scheme to perform unsupervised emotion classification. In particular, emotion polarity of a word is obtained from the predefined sentiment lexicon. The overall emotion score of a microblog is computed as the summation of sentiment scores of the words in the microblog [9].
- *Content-Based Bayesian Model for General Emotion Prediction:* Traditional methods for sentiment analysis mostly target general emotions media generate. Different from emotion prediction from user-interest described in our algorithm, these method make predictions for the masses. In this baseline method, contents extracted from texts and images will both be considered and a Bayesian model will be used to combine them together.
- *Joint Content and Social With Direct Parameter Estimation:* In our earlier work [37], content and social information were both used in emotion prediction. However, when combining these two factors, the weight factors were estimated through direct statistics information. αs are the precision results when user-interest and microblog content are considered only, and βs are the precision results when social-influence is considered only.

6.2. Emotion Prediction Performance

To illustrate the effectiveness of our algorithm, we first compare it to the baseline algorithms mentioned above. Table 3 shows the performance of different approaches when predicting positive and negative emotions, and the overall performance, respectively. For the first three baselines that are content-based methods, we can observe that with unbalanced dataset, traditional approaches fail to predict negative emotions well and tend to predict the emotions as the one having large proportions in the dataset. With the joint consideration of user-interest in historical behavior and social relation, method [37] can improve the negative emotion prediction $F1_{neg}$ by 4.32% compared with Bayesian Algorithm, but the simple parameter selection method used there cannot well depict how user-interest and social-influence influence users' emotions. Comparing the last two columns in Table 3, we can see that the proposed probabilistic graphical model and the parameter learning algorithm in Algorithm 1 can further improve the negative emotion prediction $F1_{neg}$ by 10.72%. It should be noted that in the positive emotion prediction task, our method achieves comparable but not the best performance in recall measure. We attribute this to the imbalance of the dataset. As the proportion of positive-emotional images is much larger than negative-emotional images, the predictive models are prone to produce positive predictions on images, leading to high recall rate in positive emotions. However, in our method, the imbalance problem is successfully alleviated by introducing the social influence factor, and thus our method can achieve much better performance in negative emotion prediction. A side

Table 3: Performance comparison of different emotion prediction approaches.

Emotion	Method	SVM	Lexicon-Based	Bayesian	Joint with precision [37]	Joint with learned parameter
Positive	precision	81.67%	82.80%	82.97%	83.90%	85.55%
	recall	93.76%	94.87%	85.78%	93.22%	91.77%
	$F1_{pos}$	87.30%	88.43%	84.22%	88.32%	**88.55%**
Negative	precision	13.76%	31.36%	22.36%	38.10%	44.17%
	recall	4.51%	9.92%	18.58%	18.19%	29.46%
	$F1_{neg}$	6.80%	15.07%	20.30%	24.62%	**35.34%**
Overall	$F1_{avg}$	47.05%	51.75%	52.26%	56.47%	**61.95%**



(a) (b) (c)

Figure 6: ROC graph for simulation results. (a) the performance improvement with personal user-interest in content-based emotion prediction. (b) the performance improvement with heterogeneous multimodal media. (c) the performance improvement with joint consideration of user-interest and social-influence.

effect is the tiny degradation of recall performance in positive emotion prediction, which we think is reasonable and acceptable.

To gain more insights on emotion prediction for individuals, we analyze the problem from the following aspects:

- User are different, and we need to take user's unique characteristics and personal user-interest into consideration. How does user-interest affect the emotion prediction results for individuals?
- Both texts and images affect users' emotions. Do images and texts complement each other in content-based emotion prediction?
- Media content and social influence are both important in emotion prediction. How much performance gain can we obtain if we jointly consider user-interest and social-influence?

To answer the first question, we focus on content-based emotion prediction only, and compare two different approaches. The first (personalized emotion prediction) is the same as in Section V.A, where a unique word-emotion matrix W_u and parameter set (μ_u^{pos}, σ_u^{pos}, μ_u^{neg}, σ_u^{neg}) are used to describe user u's user-interest and used to predict his emotions. In the second approach (the general content-based emotion prediction), a single word-emotion matrix and parameter set (μ^{pos}, σ^{pos}, μ^{neg}, σ^{neg}) are trained from all users' historical behavior and are used to predict all users' emotions. As shown in Fig. 6(a), every user has his own interest, likes and dislikes. Thus, personalized content-based emotion prediction gives more accurate results than the generalized scheme. As for the second question, we can see from Fig. 6(b) that text and image domain have almost the same performance when used separately, and when combined together using the Bayesian Model, the overall performance becomes better. It shows that images and texts in social networks do complement each other in emotion prediction, and both should be used in emotion prediction. Fig. 6(c) answers the third question, and shows that both user-interest and social-influence play important roles in influencing users' emotions. Note that user's friends' information is sparse in social network. Therefore, the exogenous emotion is sometimes predicted just based on one or two friends' emotions, causing both high false alarm and high sensitivity. Even so, with little information about users' friends, our joint algorithm can achieve much better performance compared to using content information alone.

6.3. Observations and Discussions

In our algorithm, each user will get four parameters: content positive α_u^1, content negative α_u^0, social positive β_u^1 and social negative β_u^0, which quantify how user's self-interest and social factors influence users' emotions in positive and negative ways. These parameters can reveal users' characteristics. For example, a user with a larger social positive parameter is easier to be influence by others' happy and positive emotions.

To analyze the relationship between users' profiles and their parameters, we did further analysis and observed

Table 4: The percentage of users whose social-influence parameters are larger than user-interest parameters with different gender and celebrity status.

		Pos emotions	Neg emotions
Gender	Female	36.44%	38.06%
	Male	39.55%	41.540%
Celebrity	Yes	39.68%	53.97%
	No	37.95%	38.61%
	All users	37.62%	43.44%

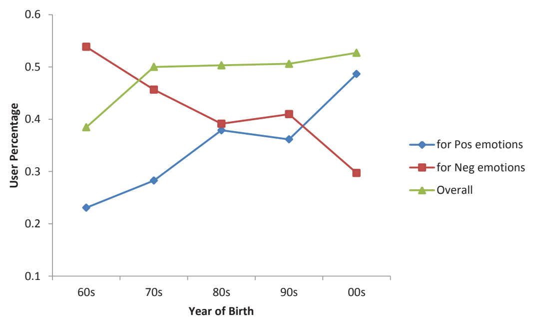


Figure 7: The percentage of users whose social-influence parameters are larger than user-interest parameters in different age groups.

some interesting patterns. As we group users into several groups in Section 3, we calculate the percentage of users whose social-influence parameters βs are larger than user-interest parameters αs for each group.

From Table 4, we can observe that for all users, social-influence parameters are larger for negative emotions (43.44%) compared to positive emotions (37.62%), meaning that negative emotions are easier to spread in social networks, and this is consistent with the saying "Bad news travel fast" [47]. In addition, we find that celebrities have larger social-influence parameters for both positive and negative emotions, indicating they are important in emotion spreading in social networks. From age perspective in Fig. 7, we observe that younger users are more easily influenced by others' positive emotions. While for negative emotions, the observations are quite the opposite and the elder users are much more easily influenced by social negative emotions. In our Tencent Weibo platform, most of the negative emotions reflect the unhappy scenes in our society, which are paid more attentions by the elders.

These interesting observations can help in social recommendations and other applications.

7. Conclusion

In this paper, we propose to jointly use information from user-interest in multimodal media content and social-influence in social relations to predict users' individual emotions, and a probabilistic graphical model was proposed to combine these two factors. The RankSample based algorithm was proposed to learn the parameters quantifying how user-interest and social-influence affect the user's emotions and the Bayesian model was used to integrate heterogenous media in emotion predictions. We conduct a set of comprehensive experiments to validate the effectiveness of our approach, as well as to discover interesting patterns for different users and different events. From the experimental results we can observe that user-interest and social-influence do help and interact with each other in emotion prediction. Our algorithm, jointly considering user-interest and social-influence, outperforms traditional emotion prediction methods with significant improvements.

References

[1] P. Cui, W. Zhu, T.-S. Chua, R. Jain, Social-sensed multimedia computing, IEEE MultiMedia 23 (1) (2016) 92–96.

[2] J. Bollen, H. Mao, X. Zeng, Twitter mood predicts the stock market, Journal of Computational Science 2 (1) (2011) 1–8.

[3] K. A. Goyal, A. Sadasivam, A critical analysis of rational & emotional approaches in car selling, International Journal of Business Research and Management (IJBRM) 1 (2) (2010) 59–63.

[4] R. W. Picard, Affective computing: challenges, International Journal of Human-Computer Studies 59 (1) (2003) 55–64.

[5] J. Machajdik, A. Hanbury, Affective image classification using features inspired by psychology and art theory, in: Proceedings of the international conference on Multimedia, ACM, 2010, pp. 83–92.

[6] N. Sebe, I. Cohen, T. Gevers, T. S. Huang, Emotion recognition based on joint visual and audio cues, in: Pattern Recognition, 2006. ICPR 2006. 18th International Conference on, Vol. 1, IEEE, 2006, pp. 1136–1139.

[7] Q. You, J. Luo, H. Jin, J. Yang, Robust image sentiment analysis using progressively trained and domain transferred deep networks, arXiv preprint arXiv:1509.06041.

[8] J. Jia, S. Wu, X. Wang, P. Hu, L. Cai, J. Tang, Can we understand van gogh's mood?: learning to infer affects from images in social networks, in: Proceedings of the 20th ACM international conference on Multimedia, ACM, 2012, pp. 857–860.

[9] H. Takamura, T. Inui, M. Okumura, Extracting semantic orientations of words using spin model, in: Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics, Association for Computational Linguistics, 2005, pp. 133–140.

[10] Q. You, J. Luo, H. Jin, J. Yang, Cross-modality consistent regression for joint visual-textual sentiment analysis of social multimedia, in: Proceedings of the Ninth ACM International Conference on Web Search and Data Mining, ACM, 2016, pp. 13–22.

[11] P. Cui, S.-W. Liu, W.-W. Zhu, H.-B. Luan, T.-S. Chua, S.-Q. Yang, Social-sensed image search, ACM Transactions on Information Systems (TOIS) 32 (2) (2014) 8.

[12] B. Pang, L. Lee, Opinion mining and sentiment analysis, Foundations and trends in information retrieval 2 (1-2) (2008) 1–135.

[13] M. Hu, B. Liu, Mining and summarizing customer reviews, in: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2004, pp. 168–177.

[14] S. Prentice, E. Huffman, Social medias new role in emergency management, Idaho National Laboratory (2008) 1–5.

[15] B. O'Connor, R. Balasubramanyan, B. R. Routledge, N. A. Smith, From tweets to polls: Linking text sentiment to public opinion time series., ICWSM 11 (2010) 122–129.

[16] E. Kim, S. Gilbert, M. J. Edwards, E. Graeff, Detecting sadness in 140 characters: Sentiment analysis and mourning michael jackson on twitter, Web Ecology 3.

[17] F. Wu, Y. Huang, Y. Song, Structured microblog sentiment classification via social context regularization, Neurocomputing 175 (2016) 599–609.
[18] B. Pang, L. Lee, S. Vaithyanathan, Thumbs up?: sentiment classification using machine learning techniques, in: Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10, Association for Computational Linguistics, 2002, pp. 79–86.
[19] A. Go, R. Bhayani, L. Huang, Twitter sentiment classification using distant supervision, CS224N Project Report, Stanford (2009) 1–12.
[20] X. Hu, L. Tang, J. Tang, H. Liu, Exploiting social relations for sentiment analysis in microblogging, in: Proceedings of the sixth ACM international conference on Web search and data mining, ACM, 2013, pp. 537–546.
[21] P. Cui, Z. Wang, Z. Su, What videos are similar with you?: Learning a common attributed representation for video recommendation, in: Proceedings of the 22nd ACM international conference on Multimedia, ACM, 2014, pp. 597–606.
[22] N. Bianchi-Berthouze, K-dime: an affective image filtering system, Multimedia, IEEE 10 (3) (2003) 103–106.
[23] M. Solli, R. Lenz, Color emotions for image classification and retrieval, in: Conference on Colour in Graphics, Imaging, and Vision, Vol. 2008, Society for Imaging Science and Technology, 2008, pp. 367–371.
[24] L.-C. Ou, M. R. Luo, A. Woodcock, A. Wright, A study of colour emotion and colour preference. part i: Colour emotions for single colours, Color Research & Application 29 (3) (2004) 232–240.
[25] S. Poria, E. Cambria, N. Howard, G.-B. Huang, A. Hussain, Fusing audio, visual and textual clues for sentiment analysis from multimodal content, Neurocomputing 174 (2016) 50–59.
[26] R. van Zwol, A. Rae, L. Garcia Pueyo, Prediction of favourite photos using social, visual, and textual signals, in: Proceedings of the international conference on Multimedia, ACM, 2010, pp. 1015–1018.
[27] G. Zhao, X. Qian, X. Xie, User-service rating prediction by exploring social users' rating behaviors, IEEE Transactions on Multimedia 18 (3) (2016) 496–506.
[28] M. J. Pazzani, D. Billsus, Content-based recommendation systems, in: The adaptive web, Springer, 2007, pp. 325–341.
[29] J. B. Schafer, D. Frankowski, J. Herlocker, S. Sen, Collaborative filtering recommender systems, in: The adaptive web, Springer, 2007, pp. 291–324.
[30] P. Cui, F. Wang, S. Liu, M. Ou, S. Yang, L. Sun, Who should share what?: item-level social influence prediction for users and posts ranking, in: Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval, ACM, 2011, pp. 185–194.
[31] W. A. Mason, F. R. Conrey, E. R. Smith, Situating social influence processes: Dynamic, multidirectional flows of influence within social networks, Personality and social psychology review 11 (3) (2007) 279–300.
[32] A. Anagnostopoulos, R. Kumar, M. Mahdian, Influence and correlation in social networks, in: Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2008, pp. 7–15.
[33] D. Crandall, D. Cosley, D. Huttenlocher, J. Kleinberg, S. Suri, Feedback effects between similarity and social influence in online communities, in: Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2008, pp. 160–168.
[34] J. Whitfield, The secret of happiness: grinning on the internet, Nature.
[35] C. Tan, L. Lee, J. Tang, L. Jiang, M. Zhou, P. Li, User-level sentiment analysis incorporating social networks, in: Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2011, pp. 1397–1405.
[36] J. Tang, Y. Zhang, J. Sun, J. Rao, W. Yu, Y. Chen, A. C. M. Fong, Quantitative study of individual emotional states in social networks, Affective Computing, IEEE Transactions on 3 (2) (2012) 132–144.
[37] Y. Yang, P. Cui, W. Zhu, S. Yang, User interest and social influence based emotion prediction for individuals, in: Proceedings of the 21th ACM international conference on Multimedia, ACM, 2013.
[38] M. Pantic, L. J. Rothkrantz, Toward an affect-sensitive multimodal human-computer interaction, Proceedings of the IEEE 91 (9) (2003) 1370–1390.
[39] N. Sebe, I. Cohen, T. S. Huang, Multimodal emotion recognition, Handbook of Pattern Recognition and Computer Vision 4 (2005) 387–419.
[40] D. M. Blei, A. Y. Ng, M. I. Jordan, Latent dirichlet allocation, the Journal of machine Learning research 3 (2003) 993–1022.
[41] G. Salton, M. J. McGill, Introduction to moderm information retrieval (1983).
[42] R. Batza-Yates, B. Ribeiro-Neto, Moderm information retrieval (1999).
[43] A. Goyal, F. Bonchi, L. V. Lakshmanan, Learning influence probabilities in social networks, in: Proceedings of the third ACM international conference on Web search and data mining, ACM, 2010, pp. 241–250.
[44] M. Wick, K. Rohanimanesh, A. Culotta, A. McCallum, Samplerank: Learning preferences from atomic gradients, Advances in Ranking (2009) 69.
[45] http://www.pudn.com/downloads462/sourcecode/math/detail1943885.ht
[46] T. Fawcett, An introduction to roc analysis, Pattern recognition letters 27 (8) (2006) 861–874.
[47] N. N. T. G. J. Kunegis, A. C. Alhadi, Bad news travel fast: A content-based analysis of interestingness on twitter.