**INTRODUCTION**

With the fast development of the online social networks (OSNs) platforms (e.g., Twitter, Face book, etc), expressing emotions or sharing meaningful moments with friends in OSNs has become people’s daily activities. Lots of published contents in OSNs provide good opportunity to study users’ emotions, therefore enabling the rapid development of emotion-aware applications. For example, an activity management system or personalized advertisement system can make valuable suggestions or schedule in an emotion sensing way. A personalized recommendation system can recommend personalized products, movies or songs according to individuals’ current emotions. When facing with public emergencies, such as earthquakes or pandemic disease, emotion detection in OSNs can be utilized to monitor public opinions, which provide support for government decision making.

Therefore, emotion detection has become a critical task in OSNs and attracted more and more attentions both in academia and industry [1][3][43][27]. Among the literatures, existing approaches for emotion detection in OSNs could be divided into two major lines: lexicon based methods [16] and machine learning based methods [1]. The lexicon based methods extracted emotional keywords using kinds of dictionaries, for example, the Linguistic Inquiry and Word Count (LIWC) [16]. Coviello et al. [5] utilized LIWC to measure emotions of the published posts and detected emotional contagion in large scale online social networks. Golder et al. [12] measured positive affect and negative affect of Tweets using LIWC and discovered individual-level diurnal and seasonal mood rhythms across different cultures. The machine learning based approach [11] considered emotion detection as a prediction problem and adopted classification/regression algorithms to infer emotions. For example, Hu et al. predicted polarity sentiments of tweet texts by considering social relations [15]. However, existing methods for emotion detection in online social media did not take the following aspects into consideration. First, emotion detection is usually inferred in sentence level, which could not reveal the a user’s emotional state in a period. For instance, a user may publish multiple Tweets with various emotions at the same time.

Therefore a comprehensive analysis of emotions in user level is necessary. Second, existing approaches mainly consider single emotion classification, which ignores the co occurrence of multiple emotions in a period. Based on our observations, it is very common for a user to express multiple emotions in a period, and multiple emotions might even coexist in one sentence or one tweet. For instance, Table I illustrates some examples of tweets with multiple emotions, where more than one kind of emotions, such as “Happy” and “Surprise” might co-appear in one single tweet, which is quite different from the assumption of traditional single emotion classification.

Based on the above observations, we consider the emotion detection in online social media as a multiple motions classification problem, and technically the existing single emotion classification approaches are not suitable for this problem. Further, to the best of our knowledge, multiple emotions detection in OSNs has not been addressed very well. To this end, in this paper, we design a multi-label learning approach for the problem of multiple emotions detection in OSNs. Specifically, as illustrated in Fig. 1, we comprehensively extract three different user-level characteristics, the social contextual features (e.g., an individual’s emotion may be influenced by his friends on social networks), temporal features (e.g., an individual’s emotion could be correlated to his past emotion states), and textual features (the emotions revealed in is tweets), for emotion detection. The Ekman’s emotion model [8] is first employed to express six basic categories of emotions: Happy, Surprise, Anger, Disgust, Sad, and Fear. Then we systematically and thoroughly study the influential factors of individuals’ emotions from an annotated Twitter dataset, in which three significant correlations can be observed: the emotion label correlation, the social correlation and the temporal correlation.

Definitely, the emotion label correlation denotes that several emotion pairs such as happy and surprise are more likely to co-exist in one instance than other emotion label pairs such as happy and fear. The social correlation denotes that neighboring users are more likely to have similar emotions in OSNs. Finally, the temporal correlation means that a user’s present emotions have high correlation with his/her emotions in the past. After that, we propose a factor graph based model by introducing emotion label correlation, social correlation, and temporal correlation comprehensively for the multi-emotion detection problem. To be specific, the factor graph regards each variable which includes observed textual feature variables and hidden label variables as a node in a graph, and the edges denote the correlations among variables, which is usually called factor function that can be utilized to represent the emotion label correlation, social correlation and temporal correlation naturally.

Then, a multi-label learning algorithm is proposed through maximizing the joint probability of the factor functions. The experimental study shows that our proposed approach outperforms state-of-the-art algorithms in terms of multiple metrics. Our contributions are summarized as follows: We present the multiple emotions detection problem in OSNs from users’ perspective which is different from traditional sentence level emotion analysis, and formulate the multiple emotions detection as a multi-label learning problem. We make several observations on a human-annotated Twitter dataset and discover the correlations between emotion labels, the social relationships as well as the temporal correlations, which can be utilized as features for the multiple emotions detection. We propose to incorporate emotion label correlations, social correlations, and temporal correlations into a unified framework based on factor graph, and solve the emotion detection problem by a multi-label learning algorithm. We conduct comprehensive experiments based on humanannotated dataset, and the results show that the proposed approach can achieve better performance comparing with the state-of-the-arts.

The rest of the paper is organized as follows. Section 2 introduces the emotion model and the related works on emotion analysis on texts of OSNs. Section 3 formalizes the multiple emotions detection problem. Section 4 introduces the Twitter dataset and makes observations on the annotated dataset. Section 5 proposes solutions to the multiple emotions detection problem including feature extraction, feature selection and factor graph model building. Section 6 reports experimental results, and demonstrates the performance of the proposed factor graph model. Section 7 concludes the work.