Emotion Detection in Online Social Networks A Multi-label Learning Approach

ABSTRACT

Emotion detection in online social networks (OSNs) can benefit kinds of applications such as personalized advertisement services, recommendation systems, etc. Conventionally, emotion analysis mainly focuses on the sentence level polarity prediction or single emotion label classification, however, ignoring the fact that emotions might co-exist from users’ perspective. To this end, in this work, we address the multiple emotions detection in OSNs from user level view, and formulate this problem as a multi-label learning problem. First, we discover emotion labels correlations, social correlations, and temporal correlations from an annotated Twitter dataset. Second, based on the above observations, we adopt a factor graph based emotion recognition model to incorporate emotion labels correlations, social correlations and temporal correlations into a general framework, and detect the multiple emotions based on multi-label learning approach. Performance evaluation demonstrates that the factor graph based emotion detection model can outperform the

existing baselines.

**EXISTING SYSTEM**

* The goal of sentiment analysis was usually to predict the polarity (positive, negative or neutral) of an object, which was studied in analyzing movie reviews [21], product views [14], opinion mining [38] etc. Emotion detection is usually regarded as a fine-grained sentiment analysis. Emotion analysis can include more categories compared with sentiment analysis about polarity prediction. About the emotion detection in traditional human social network, Fowler et al. claimed that happiness [9], or depression [26] can spread from individual to individual based on clinical trial. However, the amount of data collected from traditional human social network could be very limited. Thanks to the fast development of online social medias, such as Facebook, Twitter, much more data can be obtained for researchers to analyze.
* For instance, Moodcast [52][35] inferred individuals’ emotions by considering the social influence, temporal correlation, and location information as features. Yang et al. modeled the comment information and visual features of images jointly to further improve the performance on detecting individuals’ emotions based on images [43]. Wang et al. proposed an emotion prediction model by quantifying individuals’ emotion influence in online image social networks such as Flicker [40]. Zhan et al. proposed a noise-aware classification framework on crowdsourcing emotion detection datasets in OSNs [44]. Tang et al. designed a hidden topic emotion transition model to detect both the document-level emotion and the sentence-level emotion [34].
* Obviously, detecting emotions in OSNs, such as Facebook or Twitter, is always a hot topic [3][39][49]. Generally, two main methods were widely adopted for emotion detection in OSNs: lexicon based method and machine learning based method. The target of the lexicon based method is to extract emotions from texts based on some well-known dictionaries, such as the Linguistic Inquiry and Word Count (LIWC) dictionaries [16]. For instance, Bollen et al. extracted six kinds of mood states (depression, tension, vigor, anger, confusion, fatigue) from Twitter texts using the LIWC dictionary, and comparing the results with several important events [3]. However, the lexicon based methods are heavily dependent on the quantity and quality of words within the dictionaries.
* The machine learning based methods usually detect emotions by extracting kinds of features from contents in OSNs, and then predict sentiments or emotions utilizing various kinds of classification or regression models [15][19][20][23][39]. We compare kinds of emotion detection work as shown in Table II. In details, Vo et al. [39] analyzed individuals’ emotions in Twitter when in earthquake situations, and then proposed kinds of emotion categories for the earthquake situations including unpleasantness, calm, anxiety, sadness, relief and fear. Balabantaray et al. [2] analyzed emotions on sentence level in Twitter and built a classifier to determine the emotion class of the published tweets.
* Hasan et al. [13] trained supervised classifiers to automatically detect and classify the emotions expressed by Twitter messages, in which avoiding high dimensional and sparse feature vectors. Besides training emotion classifiers, Roberts et al. [25] analyzed the linguistic style of the utilized corpus for expressing emotions. Zhou et al. [7] learned emotion distributions from social media texts by capturing the relations of emotions based on the Plutchikâ˘A ´ Zs wheel of emotions. However, most existing literature just consider the single emotion detection, however, ignoring that multiple emotions might co-exist. Different from the existing literature, we considers to detect the multiple emotions in OSNs, which has not been well addressed in the past.
* In our previous work [50], we addressed the multiple emotions detection problem in OSNs by proposing a factor graph based model to incorporate emotion labels correlations and social correlations into a general framework. Compared with the previous work, we have re-built our multiple emotions detection model due to the newly observed temporal correlation. We have added the temporal correlation factor function in the updated factor graph model. We also have conducted comprehensive experiments to show the effectiveness of our proposed model.

Disadvantages

* + In the existing work, emotion detection is not usually regarded as a fine-grained sentiment analysis.
  + This system is less performance due to the existing system which is not addressed the multiple emotions detection problem in OSNs by not proposing a factor graph based model to incorporate emotion labels correlations and social correlations into a general framework.

**PROPOSED SYSTEM**

* The system proposes 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.
* The system presents the multiple emotions detection problem in OSNs from users’ perspective which is different from traditional sentence level emotion analysis, and formulates the multiple emotions detection as a multi-label learning problem.
* The system makes 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.
* The system proposes 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.
* The system conducts comprehensive experiments based on human annotated dataset, and the results show that the proposed approach can achieve better performance comparing with the state-of-the-arts.

**Advantages**

* The proposed system an efficient design a multi-label learning approach for the problem of multiple emotions detection in OSNs.
* To The system is more effective due to presence of the social correlation denotes that neighboring users are more likely to have similar emotions in OSNs.

**SYSTEM REQUIREMENTS**

➢ **H/W System Configuration:-**

➢ Processor - Pentium –IV

➢ RAM - 4 GB (min)

➢ Hard Disk - 20 GB

➢ Key Board - Standard Windows Keyboard

➢ Mouse - Two or Three Button Mouse

➢ Monitor - SVGA

**Software Requirements:**

* Operating System - Windows XP
* Coding Language - Java/J2EE(JSP,Servlet)
* Front End - J2EE
* Back End - MySQL