Daily Mood Detection In Social Networks Entangle With Emoticons

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Abstract - *In recent, Psychological Research have a significant importance to stress detection. With the development of social networks more and more people are willing to share their daily events and moods, and interact with friends through the social networks. As these social media data timely reflect users' real life states and emotions in a timely manner, it offers new opportunities for representing, measuring, modeling, and mining users behavior patterns through the large-scale social networks, and such social information can find its theoretical basis in psychology research and knowledge engineering. Our analysis is empowered by a state-of-the-art machine learning tool that computes the embedding's of emoji's and words in a semantic Space.*

Key Words: Mood detection, Micro-blog, Social media, healthcare, FGM, Social interaction, Sentiment analysis

1. INTRODUCTION

The Rise of Social Media is Changing People's Life, as Well as Research in Healthcare and Wellness. Employing real-world social media data as the basis, we studied the correlation between user' psychological stress states and their social interaction behaviours. To fully leverage both content and social interaction information of users' tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN) tangling with sentiment analysis.

1.1 Research on Tweet-Level Emotion Detection in Social Networks

Computer-aided detection, analysis, and application of emotion, especially in social networks, have drawn much attention in recent years. Relationships between psychological stress and personality traits can be an interesting issue to consider. Daily stress can be reliably recognized based on behavioral metrics from user's mobile phone activity. Many studies on social media based emotion analysis are at the tweet level, using text-based linguistic features and classic classification approaches. On the Chinese micro-blog platform Weibo, classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad.

Problem in social networks, and found that anger has a stronger correlation among different users than joy, indicating that negative emotions could spread more quickly and broadly in the network.

The prevalence of emoji's has been an amazing phenomenon of social innovation and appreciation. Emoji's, graphic symbols carrying specific meanings, are created, quickly adopted into online conversations, supported by multiple platforms, and inducted into Unicode standards

1.2 Research on User-Level Emotion Detection in Social Networks.

Our recent work proposed to detect user's psychological mood states from social media by learning user-level presentation via a deep convolution network on sequential tweet series in a certain time period.

Based on the semantic emoji/word embedding's learned from this data set, we present the first in-depth analysis of how the semantics of an emoji affect its popularity.

2. PROPOSED SYSTEM DESIGN

To maximally leverage the user-level information as well as tweet-level content information, we propose a novel hybrid model of factor graph model combined with a convolutional neural network (CNN). This is because CNN is capable of learning unified latent features from multiple modalities, and factor graph model is good at modeling the correlations. The overall steps are as follows: 1) we first design a convolutional neural network (CNN) with cross auto encoders (CAE) to generate user-level content attributes from tweet-level attributes; and 2) we define a partially labeled factor graph (PFG) to combine user-level social interaction attributes, user-level posting behavior attributes and the learnt user-level content attributes for stress detection

Sentiment Analysis: Both emoticons and emoji's have been widely used to express the emotions, which relate our work to the sentiment analysis literature. Sentiment analysis has long been a core problem of natural language processing. Although various advanced sentiment analysis techniques have been proposed, accurately identifying sentiments and emotions from free text is still very challenging.

Table -1: Comparison of Efficiency and Effectiveness Using Different Models (%)

Method	Acc.	Rec.	Prec.	F1	CPU time
LRC	76.18	87.94	78.58	83.00	39.43 s
SVM	72.58	87.39	75.16	80.82	≈10 min
RF	77.73	89.63	79.35	84.18	67.71 s
GBDT	79.75	82.99	85.90	84.43	262.86 s
FGM	91.55	96.56	90.44	93.40	≈20 min

Attribute Contribution Analysis: We have defined several set of tweet-level and user-level attributes from a single tweet's content as well as users' posting behaviors and social interactions in a weekly period. To evaluate the contribution of different attributes and compare the effectiveness of our model of leveraging different attributes, we compared the proposed model with other existing models by using different combinations of attributes as input.

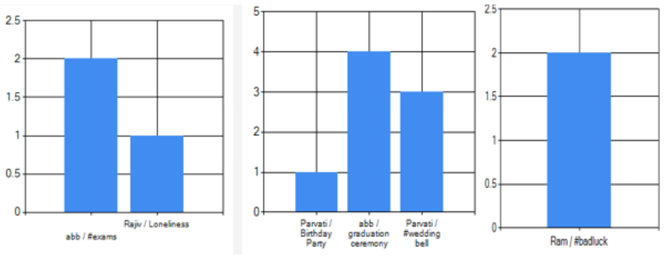

Chart -1: Social structure (Positive, Negative, Stressed)

First, we design a CNN with cross auto encoders (CAE) to generate user-level interaction content attributes from tweet-level attributes. The CNN has been found to be effective in learning stationary local attributes for series like images and audios.

Fig -1: Evaluation of Social Moods from Tweets

Then, we design a partially-labeled factor graph (PFG) to incorporate all three aspects of user-level attributes for user stress detection. Factor graph model has been widely used in social network modeling. It is effective in leveraging social correlations for different prediction tasks. Instead of using the official descriptions, we decide to characterize the meaning from the context where emoji's are used. And instead of describing an emoji, we would like to represent it with the words that are most similar to it. The similarity is measured semantically. That is, similar emoji's are used in similar semantic contexts. To qualitatively measure the semantic similarity, and to find representing words for each emoji, we apply a network embedding algorithm that projects all language tokens on to the same high-dimensional space. In such space, words that are close to each other are semantically similar to each other.

3. CONCLUSION

We presented a framework for detecting users' psychological stress states from users' daily social media data, leveraging tweets' content as well as users' social interactions. Employing real-world social media data as the basis, we studied the correlation between user' psychological stress states and their social interaction behaviors. To fully leverage both content and social interaction information of users' tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN). We train embedding's of both words and emoji's and construct a k-nearest neighbor graph. With the kNN graph, we are able to characterize the semantic relationship between emoji's and words with structural property of the ego net. We also quantitatively measure the complementarity of emoji's to words.

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