Detecting Adolescent Psychological Pressures from Micro-Blog

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***Abstract*— Under the rapid social and economic development and intensive competition pressures, adolescents are experiencing different psychological pressures coming from study, communication, affection, and self-recognition. If these psychological pressures cannot properly be resolved and released, it will turn to mental problems, which might lead to serious consequences, such as suicide or aggressive behavior. Traditional face-to-face psychological diagnosis and treatment cannot meet the demand of relieving teenagers' stress completely due to its lack of timeliness and diversity. With micro-blog becoming a popular media channel for teenagers' information acquisition, interaction, self-expression, emotion release, we envision a micro-blog platform to sense psychological pressures through teenagers' tweets, and assist teenagers to release their stress through micro-blog. We investigate a number of features that may reveal teenagers' pressures from their tweets, and then test five classifiers (Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier) for pressure detection. We also present ways to aggregate single-tweet based detection results in time series to overview teenagers' stress fluctuation over a period of time. Experimental results show that the Gaussian Process Classifier offers the highest detection accuracy due to its robustness in the presence of a large degree of uncertainty that may be encountered with previously-unseen training data on micro-blog tweets. Among the features, tweet's emotional degree combining negative emotional words, emoticons, exclamation and question marks, plays a primary role in psychological pressure detection.**

I. Introduction

A. Motivation

1) Teenagers' Adolescent Psychological Pressures Are Increasing: With the coming of information age and the rapid development of society, human beings are under unprecedented competition pressures. Unavoidably, growing teenagers have to experience various adolescent psychological pressures, coming from study, communication, affection, self-recognition, etc. Facing the radical reform of society and economy, teenagers usually more easily get confused and become over-stressed due to their immature development of self-cognition and discrimination ability towards things. Too much stress will result in psychological health problems. When these mental issues are too serious and do not get resolved promptly and properly, adolescents with some mental problems will turn to hurt either themselves or others for stress release. For instance, at the primary school shooting event in Connecticut, USA on December 14, 2012, 20 children and 6 adults were killed by a gunman named Adam Lanza, who is suspected suffering from the mental disease - autism [1]. Statistics from [2], [3] show that over 17% of 1000 college students from over 10 universities in Chongqing Province of China feel stressful and have suicidal thoughts or behaviors. In Japan, about one in ten college students who are under the pressure of job searching stated that they really want to die and to disappear [3]. Suicide has become teenagers' no.1 killer in the past two years in Korea[2]. Currently, 20% teenagers have psychological illness around the world, 10%-30% in China, and 14%-20% in America [1]. Annual increase of adolescent suicide rate has become a world-wide common problem.

Adolescence is a critical period for one's growth and development. Most mental, emotional, and behavioral disorders of adults have their roots in childhood and adolescence [1]. Youth is strong, and the country will be strong; Youth progresses, and the country will progress [4]. Close attention to and proper treatment of teenagers' pressures is critical to further development of our human society. To do this, we first need to timely sense teenager's psychological pressures, and then provide effective guidance to assist pressurized teenagers to shape the right attitudes when facing difficulties.

So far, the most traditional and common form of psychological guidance is via one-to-one instruction, which requires a *patient* to talk with a psychological consultant face to face. However, as most teenagers' psychological pressures cannot timely be found out, plus teenagers usually hesitate to share and talk with others about their mental issues, the traditional psychological guidance mode cannot meet the demand of relieving teenagers' stress alone for its lack of timeliness and diversity.

2) Micro-blog Has Become a New Channel for Sensing and Easing Teenagers' Psychological Pressures: With micro-blog becoming the most popular information broadcast and communication media nowadays, more and more teenagers go to micro-blog for information acquisition, self-expression, emotion release, and personal interaction due to its instantiation, interactivity, unique equality, freedom, fragmentation, and individuality characteristics.

Micro-blog origins from twitter created in 2006, on which people can post any information less than 140 words, and

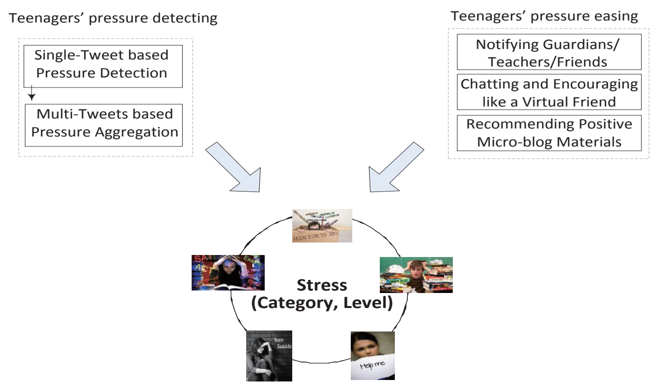

Fig. 1. A micro-blog platform for detecting and easing adolescent psychological pressures

easily share materials such as news, opinions, and entertainments with others through personal computer, mobile phone, etc., no matter where they are. As of July 2012, twitter users have topped 517 million in the world according to the data released by Semiocast, a French research company [5]. Micro-blog users in China also reached 415 million according to the New Media Development Report of China (2012) [6]. The majority of micro-blog users are teenagers. Statistics from Pew Research Center in May 2013 show that more and more teenagers have been drawn to Twitter from Facebook in America. In China, teenagers aged from 10 to 29 account for 55.78% of all micro-blog users based on the data released by New Media Development Report of China (2013) [7]. According to the Chinese Academy of Social Sciences [8], self-expression is still the main usage of tweets (covering around 74.3%), compared to other usage like daily life and experience description, information and comments sharing, etc.. This makes the detection of teenagers' pressures through their tweets on micro-blog feasible.

On the other hand, micro-blog constitutes another media-rich and lively communication channel between teenagers and their friends/teachers/other micro-blog users, through which prompt attention and care can reach stressed teenagers. For instance, in the previous examples, if we could detect the psychological disorder from Adam Lanza's twitter and take appropriate actions, we might be able to avoid the tragedy. Many times, teenagers in the growth hesitate to express their feelings to their parents and teachers. Micro-blog, as a new kind of social communication mode, could play positive roles to some extent. To those pessimistic adolescents, if we could discover psychological pressures from their micro-blog (if they have micro-blog) timely and guide them to think in a positive and optimistic way, we may hopefully save more lives.

B. Our Work

Adolescent psychological problems arouse multi-disciplinary research for its particular importance to teenagers' health and multi-variant complexity. How to combine the modern information technology with psychological guidance effectively is the major consideration to us. In this study, we envision a micro-blog platform solution for detecting and easing adolescent psychological pressures, as shown in Figure 1. It is comprised of two components. The first *pressure detecting component* analyzes and detects from a teenager's tweets whether s/he has some stress, and the stress category and stress level. Four typical common teenagers' pressure categories (i.e., *academic stress, interpersonal stress, affection stress*, and *self-cognition stress*) are considered in this work. Based on the detected stress category and level, the second *pressuring easing component* encouragingly recommends r elevant materials, chats like a virtual friend, or brings guardians' attention at the worst case to assist stressful teenagers.

The focus of this work is on the first pressure detection component. The challenge here is that most teenagers write short tweets (less than 140 characters) spontaneously and informally, conveying author's ideas and modes though linguistic sentences, emoticons, punctuations, music, etc. The tweet contents are thus usually obscure, fragmentary, and incomplete with topic-obvious words missing. The tweet post time and frequency also vary from different contexts (on holiday or school/working day).

In order to timely and effective detect teenagers' psychological pressures status and psychological pressures changes from micro-blog, we investigate a number of such features that may reveal some adolescent psychological pressures, including tweet's content (whether containing negative emotion words), emoticons (showing negative facial expressions), punctuation (exclamation and question marks), post time and frequency (whether deviating from the usual patterns), content of re-tweeted tweet posted by other user, and music (whether containing some negative emotion) that the teenager posts. Based on the extracted and analyzed features, we examine the performance of five classifiers (Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier). We also present ways to aggregate single-tweet based detection results in time series, which is helpful in predicting implicit stress tendency, dealing with stress overlooked by individual tweet's detection, and getting an overview of stress fluctuation over a period of time. Experimental results show that the Gaussian process classifier offers the highest detection accuracy compared to other popularly used approaches. Among the features, tweet's emotional degree combining negative emotional words, emoticons, exclamation and question marks, plays a primary role in psychological pressure detection. Although this study focuses on Chinese tweets, the techniques developed could be extended to tweets in other languages.

The contributions of the paper can be summarized as follows.

- We propose to exploit the micro-blog platform for detecting and easing adolescent psychological pressures, and particularly formulate the problem of detecting adolescent psychological pressures from teenager's tweets.
- After the investigation of teenagers' micro-blog behaviors, we construct four teenagers' stress-related linguistic

lexicons on micro-blog. We further select a number of tweet features that may reveal teenager's psychological pressures and test five classifiers (Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier) for pressure detection.

- We also provide two methods to aggregate single-tweet based detection results from one or multiple teenagers' tweets in time series to get an overview of teenagers' stress fluctuation and variation over a certain period of time.

To our knowledge, sensing and helping release adolescent psychological pressures through micro-blog, and turning micro-blog into a new kind of adolescent mental education mode and platform are a new exploration in the world. From both scientific and social aspects, it will lead to a number of teenager-oriented micro-blog research and utilization questions as well as possible solutions. We believe that combining traditional adolescent mental education with micro-blog media will have great benefits to our human society.

The remainder of the paper is organized as follows. We review some closely related work in Section 2. We provide the problem statement in Section 3, and present techniques for teenager's single-tweet based pressure detection in Section 4. We also discuss methods of aggregating multiple tweet's detection results into a time series in Section 5. Detection performance is evaluated in Section 6. We conclude the paper with a brief discussion of future work.

II. Related Work

Research into micro-blog contents mainly focuses on short text mining, topic detection, and sentiment analysis. Among them, sentiment analysis, a.k.a. opinion mining, is the most related work of this study. Previous work on sentiment analysis take blogs, reviews, and tweets as research objects, aiming to extract people's opinions towards some subjects or products. Usually, people's opinions are classified into two polarities: positive and negative, and sometimes including neutral, while peoples' emotions are classified into six categories, i.e., joy, fear, sadness, surprise, anger, and disgust.

Techniques of natural language processing and machine learning are popularly used in sentiment analysis. [9], [10], [11] employed the lexicon-based strategy to obtain the overall polarity of a document by computing the number of positive words and negative words in blogs or reviews. [12] also developed a syntactic parser and sentiment lexicon to discover the semantic relationship between target and expression. [13] detected the sentiment orientations to products according to the natural language expression conventions. [14] collected 40 emoticon classes found in Yahoo! blog articles, and utilized sentences containing these emoticons to automatically detect user's emotions from messenger logs.

To overcome the limitation that the performance of natural language processing techniques in sentiment analysis relies on the domain of corpus, and thus cannot easily be extended to other application fields, [15] researched the performance of three machine learning methods over movie reviews, including Naive Bayes, Maximum Entropy, and Support Vector Machines. Their experimental result showed that the performance of SVM classifier with unigram presence features is superior to others. [16] improved the precision of sentiment analysis based on unsupervised learning by analyzing features of textual contents and iteration mechanisms. [17], [18], [19] studied effective techniques of feature selection and feature combination. [20] utilized both text features and text theme such as description, comment, background, etc. in sentiment analysis. Multi-classifier fusion techniques were employed in [21] to improve the performance of sentiment classification. [22] estimated the emotional tendency of a document by combining the prior lexicon-based emotional tendency and the posterior training-based emotional tendency.

Most of sentiment analysis on micro-blog also makes use of [23], [24]. [25] used emoticons as labels to reduce dependency in machine learning techniques for sentiment classification. [23] employed Twitter hashtags and smileys to enhance sentiment learning. [26] improved target-dependent Twitter sentiment classification by taking target-dependent features as well as related tweets into consideration. [27] built a graph model for sentiment classification at the hashtag level in Twitter, where three approximate classification algorithms were investigated. [28] presented a two-staged SVM classifier for robust sentiment detection from biased and noisy data on Twitter.

In terms of application areas, most research in sentiment analysis aims at offering techniques to business domains by detecting users' opinions towards a product or proposal. [29] randomly sampled and analyzed users' reviews to specific brands of products on micro-blog, and extracted users' emotion polarities using an automatic classification method. [30] predicted the direction of stock markets by analyzing the micro-blog data. [31], [32] provided a lexicon-based natural language processing method to investigate the debate performance of candidates in the 2008 US president election.

To our knowledge, this paper is the first to detect and analyze adolescents' psychological pressures from micro-blog, aiming to combine traditional adolescent mental education with micro-blog media and turn micro-blog into a new kind of adolescent mental education mode and platform.

III. Problem Statement

Before providing the problem statement for adolescent psychological pressure detection on micro-blog, we conduct a user study by looking into tweets of 1000 high-school teenagers (aged from 11 to 24 with a self-label "after-1990s", each posting a few to thousands of tweets) on the Chinese Sina Micro-blog (http://blog.sina.com) to examine the characteristics of teenagers' micro-blog behaviors.

A. Characteristics of Teenagers' Tweets on Micro-Blog

Compared with other micro-blog user groups, teenagers have their own micro-blog characteristics in terms of tweets'

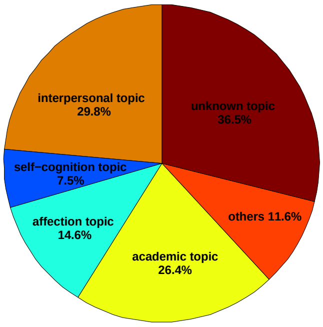

Fig. 2. Topic proportions of tweets posted by 3 teenagers

Translation: Aha. I am the school bully. I must be perseverant. Finish homework and no sleep.

Translation: I stare blankly even with good mood. No idea what to think. No one comes to rescue.

Translation: The weather makes one sleepy. I should review my language course, but I slept lazily.

Fig. 3. Three tweet examples on Chinese Sina micro-blog

Number	**Negative Emoticons**
11	cry, sick, spit, curse, disappointed, angry, crazy, sorrow, bad-luck, feel-wronged, heart-broken
Number	**Positive Emoticons**
25	haha, hehe, lovely, sinister, clap-hand, love, kiss, titter, happy, digging-nose, cool, bye, money, heart, fickle-in-love, wink, hug, shy, xixi, gluttonous, ok, great, victory, thumb-up, birthday cake
Number	**Neural Emoticons**
24	dizzy, despise, shut-up, surprise, ignoring, tired, sleepy, silence, miserable, speechless, candle, yaw, hum, thinking, questionable, hum-to-right, embarrassing, clock, hum-to-left, thumb-down, microphone, no, pig, seduce

Fig. 4. Popularly used emoticons by teenagers on micro-blog

content, expression style, post time and frequency, tweeting and forwarding (retweeting), etc.

1) Tweet's Content: Teenagers' tweet contents are mainly centered about personal feelings and emotions, daily life recording, hobbies, chasing stars, social events, etc. As illustrated in Figure 2, tweets about interpersonal topic occupy 29.8%, tweets about academic topic occupy 26.4%, tweets about affection topic occupy 12.6%, tweets about self-cognition topic occupy 14.6%, tweets whose topics are not obvious thus unknown are about 36.5%, and tweets about some other topics occupy 11.6%. As some tweets talk about more than one topic, the sum of the proportions is bigger than 1. Figure 3 gives some example tweets in Chinese with English translation below, where The first and third reveal some pressure in study, and the second reveals some interpersonal pressure. Based on the above observations, we decide to take four common typical teenagers' pressure categories (i.e., *academic stress, interpersonal stress, affection stress*, and *self-cognition stress*) as our micro-blog detection targets.

2) Tweet's Expression Style: Young teenagers like to compose a tweet using short linguistic sentences to express themselves and record information. Besides, pictorial emoticons are widely used in teenagers' micro-blog to imply their emotions like laughing, shy, angry and crazy because of its vividness, as well as multiply-used punctuations like exclamation and question marks for emphasis purposes. The Sina micro-blog service offers 46 emoticons in total, as shown in Figure 4.

Example tweets in Figure 3 contain text, emoticons, and punctuations. We found that these emoticons can significantly help discriminate teenagers' emotional feelings. In addition, a majority of teenagers are fond of posting and forwarding multi-media information like music, pictures, videos, etc. As most teenagers are music lovers, they like to share their favourite music with peers or just enjoy themselves through micro-blog, and the music genres ($happiness$ or $sadness$) may indicate and further influence teenagers' moods. For example, a lovelorn teen with the feelings of affection pressures prefer sad music, which could represent his/her mood at the moment rather than happy music, but his/her moods will gradually get better when s/he chooses happy music. We discover some picture and video contents can imply the pressure themes when teens are under psychological pressures. For instance, if a teen suffers from academic pressures, he/she would like to pay more attention to the subjects related to study and thus post corresponding pictures or videos.

3) Tweet's Post Time and Frequency: Despite the fact that one can post a tweet anytime, because of environmental constraints and personal habits, a teenager's tweet post time and frequency exhibit certain patterns and vary from time to time. For instance, during school semesters, teenagers would not post tweets during class and the probability of posting tweet at midnight is fairly low normally. However, during school breaks and public holidays, their tweeting time and frequency may have a radical change. In our study, we notice a teen released several tweets at midnight and this action is different from his usual tweeting behavior. Looking into his tweets over, we found he deeply struggled in love-matters. In another case, a keen released 16 tweets in one day, which is about five times as usual. By examining her tweets in detail, we found she argued with a classmate at that morning. So, discovery of these abnormalities in post time and post frequency is helpful for us to estimate a teenager's psychological pressure state.

4) Tweeting and Forwarding: Besides posting original tweets, teenagers may also once in a while forward (retweet) tweets from peers or well-known people, who may either have the same opinions with forwarders or be adored by forwarders. The retweeted contents may imply forwarder's concerns and attitudes to a certain extent.

B. Problem Definition

Taking the characteristics of teenagers' micro-blog into account, we provide our single-tweet based adolescent pressure detection problem statement as follows.

Let $\mathcal{C}_{ategory}$ = {`NULL, academic, interpersonal, affection, self-cognition`} be the set of pressure categories. We use `NULL` to denote an unknown category. Let $\mathcal{L}_{evel}$ = {`none, very light, light, moderate, strong, very strong`} be the set of pressure levels, where `none` means no pressure level.

Given a tweet $tweet$, the pressure detection result from $tweet$ is either null (meaning no pressure detected) or a few tuples $PressureDetect(tweet) = \langle (C_1, L_1), \cdots, (C_n, L_n) \rangle$, where $C_i \in \mathcal{C}_{ategory}$ and $L_i \in \mathcal{L}_{evel}$ $(1 \leq i \leq n)$ correspond to the detected pressure category and pressure level.

IV. Detecting Pressures from a Teenager's Tweet

Selecting relevant features for building robust pressure learning and classification models is critical to the detection performance. We first extract and analyze eight features from a teenager's tweeting and forwarding behavior, and then classify a tweet's revealed pressure level in $\mathcal{L}_{evel}$.

A. Tweet's Feature Space

1) Linguistic Association between Pressure Category and Negative Emotion Words: We construct four teenagers' stress-related linguistic lexicons on micro-blog (Table I).

- A **stress-category lexicon** contains 399 words, categorized into four typical types, i.e., *academic, interpersonal, affection,* and *self-cognition* stress.
- A **negative-emotion lexicon** contains 250 words like disgusting, boring, depressed, hating, dislike, scared, painful, miserable, sad, bad, etc.
- A **degree lexicon** contains 219 words, classified into five degree levels, i.e., *very light, light, moderate, strong,* and *very strong*.
- A **negation lexicon** contains 18 words like no, not, none, neither, nothing, nobody, nothing, never, seldom, infrequent, etc.

For each sentence in a tweet, we apply a graph-based Chinese parser [33], [34] to find out associated word pairs.

TABLE II
24 TYPES OF WORD ASSOCIATIONS IN CHINESE GRAMMAR [35]

No.	*Association Type*	*No.*	*Association Type*
1	ADV (adverbial)	13	HED (head)
2	APP (apposite)	14	IC (independent clause)
3	ATT (attribute)	15	IS (independent structure)
4	BA (ba-construction)	16	LAD (left adjunct)
5	BEI (bei-construction)	17	MT (mood-tense)
6	CMP (complement)	18	POB (preposition-object)
7	CNJ (conjunctive)	19	QUN (quantity)
8	COO (coordinate)	20	RAD (right adjunct)
9	DC (dependent clause)	21	SBV (subject-verb)
10	DE (de-construction)	22	SIM (similarity)
11	DEI (dei-construction)	23	VOB (verb-object)
12	DI (di-construction)	24	VV (verb-verb)

Table II illustrates totally 24 linguistic association relationships like subject-predicate, attributive, adverbial, etc. in Chinese grammar [35].

The discovered associated word pairs form a directed word-association tree, where each node denotes a word token, and each edge between two nodes denotes a word association. If there exists a path between a stress-category-related word node and a negative emotion word node and no negation lexicon word in between, a stress in the corresponding category is detected. A Chinese word-association tree example is given in Figure 5. It is derived from a Chinese sentence, translated into English as "*My world is really bad - terrible grade, hypocritical friendship.*", Two word pairs, ($grade$, $terrible$) and ($friendship$, $hypocritical$), reveal more or less the pressure in the stress categories of $study$ and $interpersonal$. The path length is the number of edges in the path, showing the linguistic tightness between the two words. In the example, both path lengths are 2. To normalize the contribution of different features' values, we apply a mapping function to transform a path length to an integer in [1,6] (corresponding to six different pressure levels), that is, we map a path length in [0,3] to 5, (3,5] to 4, (5,10] to 3, over 10 to 2, and 0 to 0, If there is no path but with some negative emotion word and stress category word, the integer result is set to 1.

From the tweet content, we search for stress category related words by scanning. If no such words exist, we search the teenager's forwarded tweet contents posted by others under the assumption that teenagers tend to have emotional resonance. If both do not success, we set the pressure category detected from the tweet's text `NULL` and pressure level to `no-pressure`.

2) Number of Negative Emotion Words: Negative emotion words may reveal teenagers' negative emotions, and the number of negative emotions is a good indicator to pressure level. We map the number of negative-emotion words in a tweet to an integer in [0, 5]. They are equal if the number of negative-emotion words is in [0,5]. If the former number is greater than 5, the mapped value is 5.

3) Numbers of Positive and Negative Emoticons: Negative/positive emoticons (Figure 4) usually indicate one's bad/good mood. We map the number of negative emoticons in a tweet to an integer in [0,5], and the number of positive

TABLE I

FOUR TEENAGERS' STRESS-RELATED LINGUISTIC LEXICONS ON MICRO-BLOG

Stress-Category Lexicon		
Stress Category	*#Word*	*Examples*
Academic	50	study, examination, test, school, assignment, homework, class, recession, examination paper, grade, etc.
Interpersonal	238	classmate, deskmate, friend, teacher, parent, trust, home, grow-up, friendship, trust, etc.
Affection	50	love, girl-friend, boy-friend, sorrow, sad, tired, courage, mood, infatuation, etc.
Self-cognition	61	fat, ugly, silly, terrible, failure, timid, bad, mediocrity, negligible, etc.
Negative-Emotion Lexicon		
	#Word	*Examples*
	227	disgusting, dislike, hating, boring, depressed, painful, scared, miserable, sad, sorrow, terrible, bad, etc.
Emotional Degree Lexicon		
Degree Level	*#Word*	*Examples*
Very Light	12	more or less, slightly, a few, a little, etc.
Light	27	some, somewhat, a bit, slightly, a little, a few, etc.
Moderate	31	relatively, comparatively, etc.
Strong	65	very, very much, so much, great, etc.
Very Strong	84	extreme, particular, utmost, the most, excessive, undue, extravagant, extra, extraordinary, etc.
Negation Lexicon		
	#Word	*Examples*
	13	no, not, none, neither, nor, nothing, nobody, nothing, nowhere, never, seldom, hardly, scarcely, barely, little, few, etc.

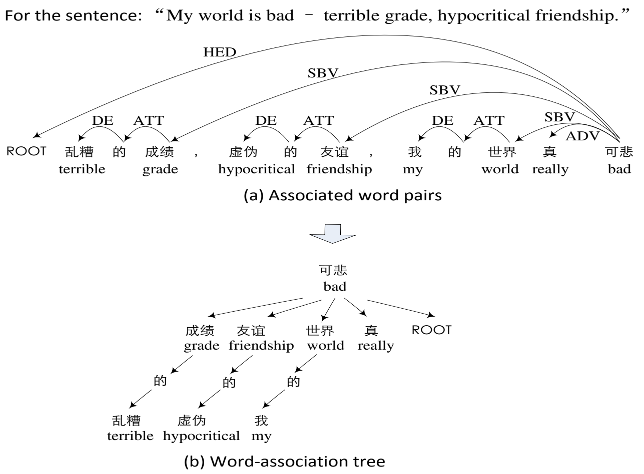

Fig. 5. Identifying associated-word pairs and generating a word-association tree from a Chinese sentence, translated into English "*My world is bad - terrible grade, hypocritical friendship.*"

emoticons to an integer in [-5,0]. Here, the mapping strategy is similar to the mapping method of negative-emotion words.

4) Numbers of Exclamation and Question Marks: Special marks such as exclamation and question marks are most commonly used by teenagers in their tweets to express their emotions. Exclamation marks are used to indicate extreme emotions such as angry, whiny, etc., and question marks are used to imply confused emotion. The mapping strategy is also similar to the above mapping one.

5) Emotional Degree: Emotional degree denotes the intensity of emotion in a tweet. For example, "I hate so much!!!" owns a high level of emotional intensity because of "so much" lexicon and three exclamation marks. We consider 5 elements including negative-emotion word, adverb of degree, negative emoticon, exclamation mark and question mark. We firstly separately count the numbers of these elements in a tweet, and then, we use formula $ED = (N_{NegEmoticon} + N_{NegEmotionWord} + N_{AdvDegree} + 1)$*$(N_{Exclamation} + N_{Question} + 1)$ to compute the tweet's emotional degree. Where ED denotes the emotional degree, and $N_{NegEmoticon}, N_{NegEmotionWord}, N_{AdvDegree}$, $N_{ExclamationMark}$, $N_{QuestionMark}$ denote the number of emoticons, negative emotion words, adverb of degree, exclamation, and question marks, respectively. Finally, we map the result ED (an integer great than or equals to 0) to an integer in [0, 5]. The mapping strategy is that if $ED = 0$, the mapped value is 0; if $ED \in (0, 3]$, the mapped feature value is 1; if $ED \in (3, 6]$, the mapped feature value is 2; if $ED \in (6, 10]$, the mapped feature value is 3; if $ED \in (10, 20]$, the mapped feature value is 4; and otherwise, the mapped feature value is 5.

6) Shared Music Genres: Sad music conveys sorrow emotion and many teenagers who sink into stress are attracted to share it through micro-blog to express their low moods. We regard it as a feature for detecting teenagers' depression.

7) (Un)usual Post Time: In macroscopic view, the time when teenagers post tweets is quite random. Each teen posts tweets on relative fixed time points. For instance, teenagers are used to post tweets at spare time rather than class time and they prefer to update tweets frequently on holidays. When a tweet is posted on an abnormal time point, it may be a special tweet with probably a strange emotion. In our work, we design two rules below based on the assumption that if teenagers post tweets at abnormal time on weekdays, maybe s/he has mood swing, and if teenagers post tweets at abnormal time on weekends or holiday, we consider it is normal because most teenagers will break up their usual customs on holidays: a) If a teen posts a tweet at an abnormal post time on weekdays, we set the feature value of post time corresponding with this tweet with 1, and otherwise 0; b) If a teen posts a tweet at an abnormal post time on weekends or holidays, we ignore it. Here, we take all weekends and holidays into account. For the sake of teenagers' different posting habits, there is no uniform

TABLE III

TWEET'S EIGHT FEATURES

f_1:	linguistic association between pressure category and negative emotion words
f_2:	number of negative emotion words
f_3:	numbers of positive and negative emoticons
f_4:	numbers of exclamation and question marks
f_5:	emotional degree
f_6:	shared music genres
f_7:	(un)usual post time
f_8:	(un)usual post frequency

abnormal post time we can get. We locate abnormal post time based on individuals by day (only consider weekdays here).
- Get the total number of teen' s tweets, and put it in a variable NUM.
- Divide a day into 24 points corresponding to 24 hours. Assign each tweet to corresponding point according to post time, calculate tweets number on each point and put it into an array $numHour[i]$, where i denotes the index in the array and corresponding to points from 1 to 24.
- Calculate the average value of $NUM/24$, and put it in a variable $avgNum$. For each time point i, if $numHour[i] < avgNum/2$ or $numHour[i] > avgNum * 2$, we look this point i as a abnormal post time point of this teenager, and mark the feature value of tweet's post time (corresponding to point i) with 1, otherwise 0.

8) (Un)usual Post Frequency: As post time, tweet's post frequency also looks like random and not related to psychological pressures on the whole. Actually when a teenager posts tweets much more or much less than usual, s/he may experience some pressures. We design a schema below to exam abnormal post frequency in a teenager's whole tweets.
- Get the total number of a teen' s tweets, and put it in a variable NUM.
- Count the total days (spanning from first tweet to last tweet), and put it in a variable N.
- Calculate the average value of NUM/N, and put it in a variable $avgFrequency$.
- Count the number of tweets posted in each day j , which is during the span time period, and put it into an array $numFrequency[j]$, where j is the array index corresponding to day j.
- If $numFrequency[j] < avgFrequency/2$ or $numFrequency[j] > avgFrequency * 2$, we deem the post frequency of day j is exception, and mark the feature value of post frequency with 1 for each tweet posted during day j, otherwise 0.

Similar to tweet's post time, if a tweet is posted with a abnormal frequency on weekends or holidays, we consider this tweet's post frequency as normal, namely the feature value is 0.

Table III summarizes all the eight features of a teenager's tweet.

B. Pressure Detection

Based on the features, we then perform single-tweet based pressure detection. The task is to classify the pressure level to one category in $CSet = \{C_1, \cdots, C_n\}$ (n=6 in the study, corresponding to `none, very light, light, moderate, strong, very strong` pressure level. We test five different classifiers, which are Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier.

1) Naive Bayes: Naive Bayes (NB) is a simple probabilistic classifier based on the Bayes theorem with strong (naive) independent assumptions. It performs well on text categorization [36]. For an m-featured tweet $t = (f_1, f_2, \cdots, f_m)$ (m=7 in this study), class $C \in CSet$ is assigned to tweet t, $C \propto \text{argmax}_{C \in CSet}\ P_{NB}(C|t)$, where $P_{NB}(C|t) = P_{NB}(C|f_1, f_2, \cdots, f_m) = P(C)\ \Pi_{i=1}^{m}\ P(f_i|C)$, and parameters $P(C)$ and $P(f_i|C)$ are obtained through maximum likelihood estimates. The advantage of Naive Bayes is that it only requires a small amount of training data to estimate the parameters (means and variances of the variables), necessary for classification. As independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix.

2) Support Vector Machines: Support Vector Machines (SVMs) are supervised learning models that are popularly used for classification and regression analysis [37]. Given a set of training examples, each marked as belonging to one of two classes, the basic SVM training algorithm builds a model that assigns new examples into one class or the other. It represents the examples as points in space, mapped so that the examples of the separate classes are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a class based on which side of the gap they fall on.

As our pressure detection involves 6 classes (corresponding to 6 pressure levels), we adopt the multiclass SVM which reduces the multiclass classification problem into multiple binary classification problems. It distinguishes between one of the class labels and the rest (one-versus-all) by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class [37].

3) Artificial Neural Network: We employ the back propagation algorithm [38], one of the best known and widely used learning algorithm in training multi-layer neural network perceptions, to classify a tweet's pressure level. The multi-layer perceptions refer to the network consisting of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, from left to right and on a layer-by-layer basis. Back propagation is a multi-layer feed forward, supervised learning network based on gradient descent learning rule. The back propagation neural network provides a computationally efficient method for changing weights in the feed forward network with differentiable activation function units, to learn a training set of input-output data, aiming to minimize the total squared error of the output computed by the network.

4) Random Forests: Random Forests [39] are an ensemble of separately trained binary decision trees. These decision trees are trained to solve a problem together optimally. For that, the predictions of all trees (named as votes) are combined together to a final vote. Maximizing the information gain and minimizing the information entropy are the goals of the training of these trees to optimally separate the data points or predict a continuous variable.

Random Forests utilize bootsrap resampling method to extract multiple samples from an original dataset. Through building a decision tree for each bootsrap sample, Random Forests combine them and make final prediction using a mutual voting algorithm. The classifier function over tweet t can be formed as follows: $H(C,t) \propto \quad \text{argmax}_{C \in CSet} \sum_{i=1}^{\#Tree} I(C, h_i(t))$, where $H(C,t)$ represents a classifiers combination model, C is the output category variable in $CSet$, $h_i(t)$ is a single decision-tree classifier function which returns a classified category, $\#Tree$ is the total number of binary decision trees, and indicator function $I(C, h_i(t))$ returns 1 if $h_i(t) = C$, and 0 otherwise.

A bagging method is adopted to generate the training set for each decision tree, and to randomly select the splitting feature set. For an input tweet t and an output category $C \in CSet$, Random Forests define the following margin function, $MG(t,C)$:

$$\begin{aligned} MG(t,C) =& \frac{1}{\#Tree} * [\sum_{i=1}^{\#Tree} I(C, h_i(t)) - \\ & \max_{C_j \in CSet} \sum_{i=1}^{\#Tree} I(C, h_i(t)) * (1 - I(C, C_j))] \end{aligned}$$

The larger the value $MG(t,C)$ is, the better the performance of classifying t into category C is.

5) Gaussian Process Classifiers: The Gaussian process (GP) framework offers a principled means of performing inference over noisy data. Of fundamental importance is the notion of GP as a distribution over functions, which is suitable to analyze teenagers' tweets on micro-blog. Through GP, we can perform inference over functions. Given a tweet set $TSet$, we define a GP prior distribution over latent (unobserved) functions $\mathbf{f}= \{f(t) \mid t \in TSet\}$, according to $f(t) \sim \mathcal{GP}(\mu(t), k(t,t'))$, where $t, t' \in TSet$, $\mu(t)$ is the mean function, and $k(t,t')$ is the squared-exponential covariance function:

$$k(t,t') = \delta_s^2 \exp(-\frac{\|t-t'\|^2}{2\delta_l^2}) \tag{1}$$

where $\|\cdot\|$ is the ℓ_2-norm, δ_l and δ_s are hyperparameters giving the length-scale in the t-direction and the variance of s. Considering additive Gaussian noise $\varepsilon \sim \mathcal{N}(0, \delta_t^2)$ over the latent function, we can obtain the object function $C = f(t) + \varepsilon$, where $C \in CSet$ are the classified categories. Further, the prior GP distribution of C can be defined for some observed data:

$$C_o \sim \mathcal{N}(0, K(TSet, TSet) + \varepsilon_n^2 I_n) \tag{2}$$

where C_o is the observed prior category set, $K(TSet, TSet) = K_w = (k_{ij})$ is a $w-$order symmetric covariance matrix, and k_{ij} measures the correlation between t_i and t_j ($t_i, t_j \in TSet$). Through prior GP distribution, we can define joint prior distribution between observed and predicted category set C_o, C^*. The posterior distribution of C^* can be formalized as follows:

$$f_* | TSet, C_o, C^* \sim \mathcal{N}(\overline{f_*}, \text{cov}(f_*)) \tag{3}$$

where $\overline{f_*}$ and $\text{cov}(f_*)$ are the mean value and variance of the classification results. Expectation propagation algorithm proposed by [40] is to approximate inference in GP classification and get the best results of accuracy and speed based on the latent function.

V. Aggregating Single-Tweet Based Pressure Detection Results

Aggregating sensed stress from a sequence of tweets posted by one or multiple teenagers is helpful in predicting implicit stress tendency, dealing with stress overlooked by individual tweet's detection method, and getting an overview of stress fluctuation over a period of time. One challenge here is that most teenagers write tweets using an informal language, and some stress category related and/or degree words may be missing from a tweet. Detecting pressures from a tweet sequence needs to cope with such incomplete elements.

Considering that a teenager's stress may last for a while (say, during an exam period), we take neighbor tweets' stress category as the implicit one. Also, stress from neighbor tweets affects the current tweet due to the continuity of emotions. We fill in the missing stress levels based on the previous tweets' stress levels, and the closest tweet has the highest influence.

Given a tweet sequence $\langle t_1, t_2, \cdots, t_n \rangle$, without loss of generality, different aggregation operations (like Avg, Sum, Count, Max, Min) can enforced. For instance, let $\langle (C, L_1)$, $\cdots$, $(C, L_x) \rangle$ be a sequence of sensed stress in category C from a teenager's 1-week tweets. We can have $Avg(C, \langle (C, L_1), \cdots, (C, L_x) \rangle)$=$(C, \sum_{i=1}^{x} L_i / x)$.

VI. Evaluation

A. Experimental Settings

Tweets of 459 middle-school students (of age 14-20) are collected from Chinese Sina micro-blog from the first time they launched micro-blog to July 7, 2013. All of the students label themselves with a micro-blog tag named "The Generation After 90s". This tag is the clue via which we find out these teenagers. We randomly pick up 23 teenagers' tweets as our experimental data. Each of the 23 teenagers posted around 300-1000 tweets with a total number of tweets to 10,872, and an average number to 473 per teenager.

Three experiments are conducted on this data set, aiming to examine: 1) the single-tweet based pressure detection performance of five different classifiers, including Naive Bayes, SVM, ANN, Random Forest, and Gaussian Process classifier; 2) the impact of different features on micro-blog pressure detection; and 3) aggregation performance, showing teenager's emotion fluctuation within a certain period of time.

From each tweet $tweet$, we preprocess and obtain its pressure category, together with its eight features in Table III. We compare the stress detection results obtained from the classification experiments with the ones given by our human being.

B. Experiment 1: Performance of Single-Tweet based Pressure Detection

1) Pressure Category-Independent Detection Performance: Firstly, we randomly select 80% data from 23 teenagers' tweets for training, and the rest 20% for testing without distinguishing tweets' revealed pressure categories.

The results in Table IV show that Gaussion Processing performs the best. Both Gaussion Processing and Random Forest classifiers perform the best with high precision and recall rates over 0.8. SVM and ANN achieve precision and recall recall rates, close to 0.8, and Naive Bayes performs the worst whose precision and recall rates are less than 0.8. This verifies the GP classifier's good robustness in the presence of the large degree of uncertainty that may be encountered with previously-unseen training data. We further look into the confusion matrix results returned from Gaussian Process and Random Forest, as shown in Table VI, and Table V. It is interesting to note that neighboring class pairs (e.g., `very light`, `light`, `very strong`, `strong`) are easily miss-classified.

TABLE V

THE CONFUSION MATRIX TABLE OF GAUSSIAN PROCESS RESULT

Pressure Level	None	Very Light	Light	Moderate	Strong	Very Strong
None	5819	415	54	39	11	7
Very Light	268	1533	238	38	15	1
Light	37	192	637	95	20	5
Moderate	19	18	80	333	111	10
Strong	4	5	18	93	321	61
Very Strong	0	4	4	15	75	277

TABLE VI

THE CONFUSION MATRIX TABLE OF RANDOM FOREST RESULT

Pressure Level	None	Very Light	Light	Moderate	Strong	Very Strong
None	5796	436	61	33	14	5
Very Light	264	1543	231	37	14	4
Light	45	205	624	86	17	9
Moderate	16	27	76	328	106	18
Strong	15	9	17	117	271	73
Very Strong	4	8	7	7	80	269

For example, in Table V, 415 records belonging to class `None` are miss-classified to its neighbor class `Very Light`, but only 7 records are miss-classified to class `Very Strong` which is far from class `None`. Table VII shows results of Root Mean Square Error. The GP method is great for improving our understanding of the dataset, while SVM, ANN, and NB will probably give the relatively worse results.

TABLE VII

THE RMSE OF 5 CLASSIFICATION RESULTS

Classifier	NB	Random Forest	LibSVM	ANN	GP
RMSE	0.2408	0.2133	0.2175	0.231	0.2099

2) Impact of the Number of Pressure Levels: Considering that six pressure levels might be too fine-grained, we collapse the two pressure levels `very light` and `light` into `light`, and `strong` and `very strong` into `strong`, so that only four pressure levels (`none, weak, moderate, strong`) are taken as the classifier output domain. Table VIII shows that precision and recall rates obtained from five classifiers are all increased and all over 0.8. The performance all gets improved by reducing the number of pressure levels from 6 classes to 4, demonstrating the influence of classification grain to in classification.

3) Pressure Category-Dependent Detection performance: We conduct this experiment to find out pressure level from teenager's tweet under different stress categories `unknown, academic, interpersonal, affection, self-cognition` stress. Teenagers may exhibit different post behaviors under different stress categories. For example, exclamation mark seldom appears in a tweet with affection stress, especially about love. But it is frequently used when teenagers talk about academic stress. So we train stress category specific classification models. Firstly, we divided data into 5 subsets according to five stress categories. The tweet number of each data set is 3143 (interpersonal category), 1518 (self-cognition category), 433 (academic category), 217 (affection affection category), and 5527 (unknown stress category), respectively. Within each pressure category, we take 80% of tweets for training and 20% for testing. The pressure detection results are presented in Table IX. Comparing these results with the first experimental results in Table IV, the difference is not much.

We further choose tweet sets, falling into the interpersonal and self-cognition stress category. For experiment in each category, we use 80% data for training and 20% data for testing. Results under interpersonal stress category are given in Table X. We can see most precision and recall rates reach a high value 0.8, except for the Naive Bayes method, indicating specific category condition increases the classification performance. Average results under two different categories (interpersonal and self-cognition) are given, and self-cognition category owns higher average precision and recall rates, though the training data is less than that in the interpersonal category.

C. Experiment 2: Impact of Tweet's Features on Pressure Detection Performance

We use *information gain* to measure the impact of tweet's features on the detection result (i.e., pressure level class) based on the entropy and conditional entropy.

TABLE IV

PRESSURE CATEGORY-INDEPENDENT DETECTION BY FIVE CLASSIFICATION METHODS

Pressure Level	**Naive Bayes** (Pre. Rec. F-measure)	**Random Forest** (Pre. Rec. F-measure)	**SVM** (Pre. Rec. F-measure)	**ANN** (Pre. Rec. F-measure)	**Gaussian Processing** (Pre. Rec. F-measure)
None	0.817 0.920 0.866	0.944 0.913 0.928	0.907 0.924 0.915	0.875 0.927 0.901	0.947 0.917 0.932
Very Light	0.608 0.364 0.455	0.693 0.737 0.714	0.677 0.659 0.668	0.720 0.690 0.705	0.707 0.732 0.720
Light	0.495 0.569 0.529	0.614 0.633 0.623	0.609 0.528 0.566	0.619 0.602 0.611	0.618 0.646 0.632
Moderate	0.543 0.504 0.523	0.539 0.574 0.556	0.515 0.590 0.550	0.630 0.459 0.531	0.543 0.583 0.563
Strong	0.574 0.502 0.536	0.540 0.540 0.540	0.604 0.560 0.581	0.615 0.500 0.552	0.580 0.639 0.609
Very Strong	0.753 0.741 0.747	0.712 0.717 0.714	0.763 0.797 0.780	0.773 0.744 0.758	0.767 0.739 0.753
Avg.	0.720 0.734 0.719	0.818 0.812 0.815	0.796 0.798 0.797	0.794 0.802 0.796	0.826 0.820 0.823

TABLE VIII

COLLAPSING PRESSURE LEVELS FROM 6 TO 4

Pressure Level	**Naive Bayes** (Pre. Rec. F-measure)	**Random Forest** (Pre. Rec. F-measure)	**SVM** (Pre. Rec. F-measure)	**ANN** (Pre. Rec. F-measure)	**Gaussian Processing** (Pre. Rec. F-measure)
None	0.810 0.897 0.851	0.940 0.899 0.919	0.920 0.899 0.909	0.924 0.892 0.908	0.943 0.905 0.924
Light	0.720 0.587 0.647	0.783 0.853 0.816	0.786 0.817 0.801	0.785 0.814 0.799	0.800 0.867 0.832
Moderate	0.555 0.504 0.528	0.553 0.562 0.557	0.525 0.512 0.519	0.511 0.562 0.535	0.586 0.479 0.527
Strong	0.807 0.793 0.800	0.815 0.788 0.801	0.778 0.804 0.791	0.795 0.821 0.808	0.772 0.849 0.809
Avg. after Collapse	0.769 0.775 0.769	0.862 0.857 0.859	0.847 0.845 0.846	0.849 0.845 0.847	0.867 0.866 0.865
Avg. before Collapse	0.720 0.734 0.719	0.818 0.812 0.815	0.796 0.798 0.797	0.794 0.802 0.796	0.826 0.820 0.823

TABLE IX

CATEGORY-DEPENDENT PRESSURE DETECTION BY FIVE CLASSIFIERS

Pressure Level	**Naive Bayes** (Pre. Rec. F-measure)	**Random Forest** (Pre. Rec. F-measure)	**SVM** (Pre. Rec. F-measure)	**ANN** (Pre. Rec. F-measure)	**Gaussian Processing** (Pre. Rec. F-measure)
None	0.796 0.912 0.85	0.930 0.917 0.924	0.938 0.915 0.926	0.943 0.912 0.927	0.936 0.923 0.929
Very Light	0.6 0.315 0.413	0.703 0.726 0.714	0.695 0.718 0.706	0.682 0.726 0.703	0.702 0.742 0.722
Light	0.446 0.597 0.51	0.578 0.597 0.587	0.563 0.581 0.571	0.540 0.548 0.544	0.655 0.581 0.615
Moderate	0.412 0.233 0.298	0.467 0.467 0.467	0.432 0.533 0.478	0.485 0.533 0.508	0.514 0.633 0.567
Strong	0.519 0.583 0.549	0.609 0.583 0.596	0.667 0.667 0.667	0.583 0.583 0.583	0.619 0.542 0.578
Very Strong	0.81 0.654 0.723	0.846 0.846 0.846	0.909 0.769 0.833	0.885 0.885 0.885	0.889 0.923 0.906
Avg. Dependent	0.694 0.707 0.687	0.813 0.811 0.812	0.817 0.809 0.813	0.814 0.808 0.810	0.828 0.825 0.826
Avg. Independent	0.720 0.734 0.719	0.818 0.812 0.815	0.796 0.798 0.797	0.794 0.802 0.796	0.826 0.820 0.823

TABLE X

PRESSURE CATEGORY-DEPENDENT DETECTION PERFORMANCE

Pressure Category	**Naive Bayes** (Pre. Rec. F-measure)	**Random Forest** (Pre. Rec. F-measure)	**SVM** (Pre. Rec. F-measure)	**ANN** (Pre. Rec. F-measure)	**Gaussian Processing** (Pre. Rec. F-measure)
interpersonal	0.694 0.707 0.687	0.813 0.811 0.812	0.817 0.809 0.813	0.814 0.808 0.810	0.828 0.825 0.826
self-cognition	0.724 0.730 0.712	0.848 0.825 0.829	0.827 0.810 0.810	0.839 0.816 0.823	0.857 0.832 0.836

$$InformationGain(C|f) = H(C) - H(C|f),\ where$$

$$H(C) = -\sum_{i=1}^{n} P(C = C_i) log P(C = C_i);$$

$$H(C|f) = \sum_{j=1}^{m} P(f = f_i) H(C|f_j) =$$

$$\sum_{j=1}^{m} P(f = f_j) \sum_{i=1}^{n} P(C = C_i|f = f_j) log P(C = C_i|f = f_j)$$

It means the change of information amount when bringing in feature f. The bigger the value of information gain is, the more important the feature is. Thus the impact degree of features on the detection performance can then be evaluated by sorting the values of information gain. Based on the training tweets, we compute the information gain of different features, shown in Table XI. In the test, we treat positive and negative emoticons, as well as question and exclamation marks, separately.

Among the features, tweet's emotional degree combining negative emotional words, negative emoticons, exclamation and question marks, plays the most significant role in psychological pressure detection. Negative emotion words and word association relationship between stress category and negative emotion words are also top ranked. (Un)usual post frequency and shared music genre have the least impact on pressure detection. This result demonstrates features related to tweet's content are important to the pressure level detection. This is because text is most often posted element by teenagers. Next, we test the classification performance with features ranked top 2, top 3, top 4, and top 5, respectively with Gaussian process method, and found out the more features we use, the more accurate detection performance we can achieve, as illustrate in Figure XII. However, such performance increasing trend

TABLE XII

FEATURES UTILIZED BY GAUSSIAN PROCESS CLASSIFIER

Pressure Level	**Top2 Features** (Pre. Rec. F-measure)	**Top3 Features** (Pre. Rec. F-measure)	**Top4 Features** (Pre. Rec. F-measure)	**Top5 Features** (Pre. Rec. F-measure)
None	0.634 0.986 0.772	0.778 0.861 0.817	0.773 0.883 0.825	0.790 0.884 0.834
Very Light	0.000 0.000 0.000	0.323 0.265 0.291	0.536 0.324 0.403	0.553 0.319 0.405
Light	0.000 0.000 0.000	0.368 0.357 0.362	0.473 0.578 0.520	0.524 0.598 0.559
Moderate	0.327 0.694 0.444	0.544 0.463 0.500	0.527 0.479 0.502	0.556 0.612 0.583
Strong	0.000 0.000 0.000	0.489 0.431 0.458	0.494 0.373 0.425	0.567 0.500 0.531
Very Strong	0.000 0.000 0.000	0.613 0.494 0.547	0.565 0.506 0.534	0.629 0.727 0.675
Avg.	0.378 0.598 0.463	0.615 0.638 0.624	0.663 0.682 0.664	0.688 0.704 0.688

TABLE XI

IMPACT OF DIFFERENT TWEET'S FEATURES ON PRESSURE DETECTION PERFORMANCE

Rank	Feature	InfoGain
1	emotional degree	0.285675
2	negative emotion words	0.279034
3	linguistic association between stress category and negative emotion words	0.212512
4	exclamation marks	0.208379
5	negative emoticons	0.137678
6	positive emoticons	0.048038
7	question Marks	0.036773
8	(un)usual post time	0.023496
9	(un)usual post frequency	0.010988
10	shared music genre	0.000319

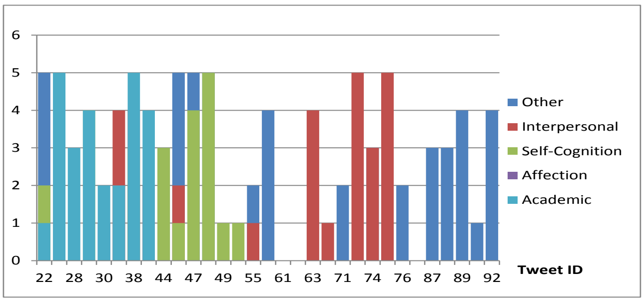

Fig. 6. Stress levels detected from one teenager's different tweets

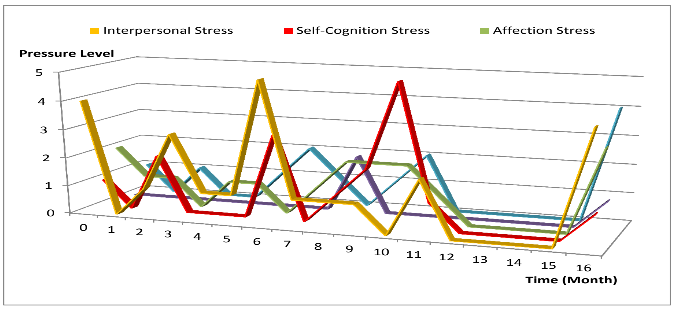

Fig. 7. A teenager's average stress level on a monthly basis

becomes slowly when more features are added in. For instance, when only top 2 features are considered, we get a low precision rate 0.378, and the precision increases abruptly to 0.615 when top 3 features are used. The precision reaches 0.688 when top 5 features are used. This verifies the importance of features with big information gain.

D. Experiment 3: Aggregating Single-Tweet Based Pressure Detection Results

We focus on category-dependent pressure detection, and try to find out how a teenager's emotion fluctuates within a certain time period. We randomly select 244 tweets posted from 2011/8/31 to 2013/7/18 (172 days and 17 months) by one teenager. To get a global view of his emotional fluctuation, we search for topics in each tweet according to the constructed stress category lexicon, perform Gaussian process classification to obtain single-tweet based pressure levels, and aggregate these results by months. We calculate the average pressure level on a monthly basis with the results presented in Figure 6 and 7.

VII. CONCLUSION

Adolescent mental health cannot be ignored, and psychological pressure is one of the prominent problems of current teenagers. Micro-blog, as the most important information exchange and broadcast tool in the current society, is becoming an important channel for teenagers' information acquisition, inter-interaction, self-expression, emotion release due to its unique equality, freedom, fragmentation, individuality characteristics. In this paper, we propose a pressure detection strategy on micro-blog to timely and effective detect teenagers' psychological pressures status and psychological pressures changes. we first extract and analyze features associated with expression of teenagers' psychological pressures from their tweets. We then test five popular classification algorithms (Naive Bayes, SVM, Artificial Neural Network, Random Forest, and Gaussian Process Classifier) for timely and effective detection of teenagers' psychological pressures status and psychological pressures changes. Going one step further, we aggregate multi-tweets in a time series to find out the variation of teenagers' psychological pressures. We applied our strategy to 23 teenagers' tweets collected from Chinese Sina micro-blog, and each teenager posted 300-1000 tweets. Experiment results show that the Gaussian Process Classifier has the highest detection accuracy due to its robustness in the presence of a variety of uncertainty existing in teenagers' micro-blog tweets. Among the features, tweet's synthesized emotional degree, negative emotional words, emoticons, exclamation and question marks, plays important roles in pressure detection.

We are currently implementing the micro-blog based strategies for assisting teenagers to relieve the stress. 1) Considering teenagers in the growth many times hesitate to express their feelings to their parents and teachers, when a teenager is detected to have a strong consistent stress, the micro-blog platform will notify his/her guardians and friends to care for his/her psychological change and issue helps immediately to avoid tragedy. 2) For a teenager experiencing a moderate stress, the micro-blog platform can chat and encourage him/her like a personal virtual friend. 3) For a teenager experiencing a weak stress, the micro-blog platform can search and recommend relevant encouraging messages or micro-bloggers of positive attitudes to him/her.

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