

# TeenSensor: Gaussian Processes for Micro-blog based Teen's Acute and Chronic Stress Detection

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Stress is a common problem all over the world. More and more teenagers today have to cope with different stressor events coming from school, family, peer relation, self-cognition, romantic relation, etc. Over-stress without proper guidance will lead to a series of potential problems including physical and mental disorders, and even suicide due to the shortage of teen's psychological endurance and controllability. Therefore, it is necessary and important to timely sense adolescents' stress and help them release the stress properly. In this paper, we present a micro-blog based system called TeenSensor, aiming to detect teens acute and chronic stress from their tweeting contents (including linguistic text, song, picture, emoticon, punctuation) and tweeting context (time, and frequency) on micro-blog. We conduct a user study where 69 16/17-year-old high-school students got involved. The result shows that sensing teenagers acute and chronic stress is feasible through the open micro-blog, achieving 69.6% accuracy for acute and 72.2% for chronic, respectively. TeenSensor performs better in detecting the stress of introvert teens than extrovert teens. Among the four typical types of teens stress, self-cognition stress is revealed the least from micro-blog, compared to the study, inter-personal, and affection stress types.

Keywords: Teen stress; sense; micro-blog.

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## 1. INTRODUCTION

### 1.1 Background

Stress is the body's adaptation response to any demand or pressure called stressors. For teenagers, school demands, negative thoughts and feelings about themselves, changes in their bodies, exploring his or her own identity, problems with peer group, unsafe living environment, separation/divorce of parents, chronic illness within the family unit, death of a loved one, moving or changing schools, being involved in too many activities, or family financial problems, etc., may easily bring stress to teens.

Stress in general can be divided into *acute stress* or *chronic stress*. Mild acute stress can be considered playing a positive role to some extent - it may enhance alertness and improve productivity [1]. But when the level of acute stress is beyond a limit,

physical and psychological health problems may be induced. Relatively, chronic stress is the long-standing stress which generates heavier damage compared to acute stress. It is one of the risk factors for mental disorder, such as depression [2]. It can also lead up to many physical disorders.

Being short of psychological endurance and controllability due to the immature development of self cognition and discrimination ability, teens are ill-equipped to cope with either acute or chronic stress that they face, leading to various negative manifestations of that stress in their daily lives. Psychologically changes in behavior (such as moodiness, irritability, inability to concentrate, crying, changes in eating patterns, changes in sleeping patterns, worrying, mood swings, frustration, nervousness, depression, exhibiting a negative attitude, low productivity, confusion, lack of creativity, lethargy, forgetfulness, and/or boredom) may become more prevalent than usual for adolescents. Socially increased stress may be exhibited through isolating his

or her self from others, loneliness, decreased general communication skills, lashing out at others, nagging, or simply a refusal to engage verbally [3]. A new survey from the Washington, D.C. based American Psychological Association [4] finds that teens across the USA are feeling high levels of stress that they say negatively affect every aspect of their lives, and more than a quarter (27%) say they experience "extreme stress" during the school year, vs. 13% in the summer, and 34% expect stress to increase in the coming year. These stressors range from school to friends, work and family, and teens aren't always using healthy methods to cope. Some teens become overloaded with stress. When it happens, inadequately managed stress can lead to anxiety, withdrawal, aggression, physical illness, or poor coping skills such as drug and/or alcohol use. To the extreme, injury to either teenagers themselves or others will happen. The campus gunman, Adam Lanza who shot 20 children and 6 adults at the primary school in Connecticut, USA on December 14, 2012, was suspected suffering from the mental disease - autism [5]. Research [6] shows the major risk factor for suicide comes from mental disorder and depression. In the USA, suicide is the third leading cause of death for youth between the ages of 10 and 24 [7]. In China and Korea, suicide has become youth's no.1 killer [8]. Annually increased adolescent suicide rate in the world is becoming a world-wide serious problem nowadays. Therefore, timely sensing teens' stress and providing effective intervention to help them release the stress are desirable.

## 1.2 Existing Solutions

Traditional methods on stress detection in psychology use some *subjective* scales and questionnaires, whose effective time length is one week, and one month at most. Observing human's physiological and physical signals change with the variation of psychological stress status, in the recent ten years, many researchers used various sensors to *objectively* monitor the changes and predict the trends of *physiological signals* (e.g., galvanic skin response (GSR), heart rate variability (HRV), electroencephalogram (EEG), electrocardiogram (ECG), blood pressure, electromyogram, and respiration) and *physical signals* (e.g., voice, gesture and interaction, facial expressions, eye gaze, pupil dilation and blink rates) for mining people's abnormal behavior patterns causing by stress [9, 10, 11, 12]. Smart phones as a kind of speech sensors were also exploited in [13, 14], focusing on cognitive stress and stressor frequency estimation rather than the type and severity of stress. Compared with these body contact and invasive stress measurements, the open micro-blog arises as another low-cost sensing channel to obtain people's self-expressed contents and behaviors, from which some emotional signals could be captured and analyzed. For example, [15, 16, 17, 18, 19] evaluated whether people are in the risk of depression by analyzing their twitting behaviors. Recently, [20, 21] presented a micro-blog based platform to specifically sense and help ease teenagers' adolescent stress, where four typical types of adolescent stress (*study, communication, affection, self-recognition*) and five ranked stress levels (*very strong, strong, moderate, light, very light*) were considered in stress detection.

## 1.3 Our Work

Unlike [20, 21] making no distinction between teen's acute and chronic stress, this paper presents a system called TeenSensor, which constructs a Gaussian Process Framework to detect the occurrence of teens acute and chronic stress from two categories of tweeting behaviors (i.e., *tweeting content* and *tweeting context*), and reports its performance through a user study at a high school where 69 students of age 16-17 participated. The advantages of turning to micro-blog for teens stress detection are: Firstly, teenagers tend to record details of their daily life and give vent to their feelings on microblog rather than to their parents and teachers directly, making the acquisition of teens' emotional states as well as their experienced stress types possible. Secondly, as micro-blog can keep track of teens' long-term tweeting contents and behaviors, from micro-blog, it is possible to detect and associate stress within different time scopes, while the traditional physiological questionnaires usually only hold for a limited amount of time (maximally one month). Third, without using any body sensors or mobile phones, stress detection through micro-blog is low-cost and can reach broad audience. Furthermore, based on the sensing results, effective and prompt intervention and interaction with teens under stress can be easily realized through the colorful micro-blog media. The contributions of this paper are as follows. We experimentally show that: 1) Teen's acute and chronic stress can be revealed and detected from micro-blog, achieving 69.6% accuracy for acute and 72.2% for chronic, respectively. 2) TeenSensor performs better in detecting the stress of introvert teens than extrovert teens. 3) Among the four typical types of teens stress, self-cognition stress is revealed the least from micro-blog, compared to the study, inter-personal, and affection stress types. 4) Teen's tweeting content play a more important role in stress detection than tweeting context.

## 2. RELATED WORK

### 2.1 Stress Detection from Physiological Signals

Some physiological measures for stress detection include galvanic skin response (GSR), heart rate variability (HRV), electroencephalogram (EEG), electrocardiogram (ECG), blood pressure, electromyogram, and respiration. The experiments of [9] verified that GSR can be used as a real-time objective and reliable indicator of human's stress and arousal level. [22] measured an individual's stress level when he/she plays a competitive virtual game through GSR. [23] found skin conductivity and heart rate metrics have close correlations with driver's stress level, and used electrocardiogram, electromyogram, skin conductance, and respiration for driver's stress detection [24]. [25] combined the physiological signals (GSP, heart rate, skin temperature, and figure pressure) collected by an emotional mouse with other physical appearance information to monitor a user's stress level. [26] evaluated the cardiovascular and subjective stress response to the combined physical and mental workload via HRV and blood pressure, showing that HRV is a more sensitive and selective measure for mental stress. [27] applied the non-linear system identification technique to HRV for continuous mental

stress monitoring. The above experimental results came from the laboratories where subjects were under a stationary state. For people on the move, [28] combined ECG, GSR, and accelerometer gathered from 20 participants across three activities (sitting, standing, and walking) to differentiate physiological signals generated between physical activity and mental stress. [10] found that the ratio of EEG Power Spectrum is negatively correlated with the Perceived Stress Scale (PSS) and suggested to use PSS and the ratio of EEG Power Spectrum for human mental stress detection [29]. [11] developed an emotional recognition system based on GSR, HRV, EEG, and respiration.

## 2.2 Stress Detection from Physical Signals

Although physiological measures can achieve good accuracy in mental stress detection, it may make people discomfort, slightly conflicting air, or even stress increase due to its invasiveness. Some physical measures (e.g., voice, gesture and interaction, facial expressions, eye gaze, pupil dilation and blink rates) are thus taken for stress detection as non-invasive measures, since they do not need to put the contact sensors on human bodies. Voice-based stress detection has received much attention in recent years due to its observable variability when response to stressors. [30, 31] investigated the change characteristics of speech signals when people under stress. [32] presented a stress detection method by computing prosodic, voice quality, and spectral features on variable window sizes. Smart phones were also used as a kind of sensor to detect people's mental stress by analyzing their voice variation in diverse conversational situations [13, 14]. Besides voice, [25] analyzed people's mouse movements and found that people click mouse button harder as their stress decrease. [33] applied optical computer recognition (OCR) algorithms to facial change detection while people experience stress, and suggested that an OCR algorithm using mouth and eyebrow regions has the potential performance for stress discrimination. [34] proposed a stress recognition method based on pupil videos obtained from video camera. Pupil dilation was also examined for stress detection in [35, 36]. [25] measured mental stress by observing a series of changes caused by head and mouth movements as well as eye movement including eye gaze, eye blink, and pupil dilation. Considering the contact sensors need specialists to install and monitor, causing inconvenience to people's daily life, [37] used a low-cost webcam that recovers the instantaneous heart rate signal from video frames of human faces for mental stress detection. [38] further trained four types of classifiers using features extracted from GSR and/or speech signals, and the result showed that SVM classifiers can reach better accuracy than other classifiers for stress detection. [39] employed both Situation-awareness paradigm and LZ78 loss-less algorithm to detect and predict potential anomalous and dangerous situations for cognitive impaired people.

## 2.3 Stress Detection from Micro-blog

The popularity of micro-blog offers another medium for sensing people's mood. [15] found that the depressed individuals look twitter as a tool for emotional interaction and they pre-

fer to consume emotional content over information content and non-depressed individuals regard twitter as a information exchanging tool. [16, 17] built a statistical classifier to estimate whether people are in the risk of depression before been diagnosed by analyzing their twitting behaviors. The experimental results demonstrated that social media contains useful cues in predicting individual's depression tendency. In a similar manner, [18] proposed a two-stage supervised learning framework to detect whether the user is suffering from depression currently by evaluating content and temporal features of his/her postings on BBS. [33] constructed a depression detection model based on a sentiment analysis method and 10 features extracting from the postings on micro-blog.

The most closely related work of this study is [20, 21], which envisioned a micro-blog platform for specifically sensing and helping ease teens' stress. [20] investigated a few tweeting features (i.e., tweeting content, tweeting time, and frequency) that may reveal adolescent stress, and tested five classifiers for stress detection. Based on the detection result, three timely intervention steps (encouraging teens to read something or do something, notifying teens' guardians at the worst case) were designed to help pressurized teenagers cope with their stress [21]. This paper distinguishes from [20, 21] in the following three aspects. 1) We take two types of stress (*acute stress* and *chronic stress*) into account, and present corresponding sensing techniques, while [21] treated the stress in general with no distinction. 2) We categorize tweet-related features systematically into two (*content features* and *context features*) and evaluate respective importance and effectiveness, while [20] considered only a limited number of features. 3) We invite 69 high-school students to participate in our user study for performance evaluation, and this was not done in [20, 21].

## 3. PROBLEM STATEMENT - TEENS ACUTE AND CHRONIC STRESS DETECTION

Before giving the problem statement for teens stress detection on micro-blog, we first examine the characteristics of teenagers' micro-blog behaviors 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>).

### 3.1 Characteristics of Teens Micro-blog Behaviors

Compared with other user groups, teenagers exhibit different micro-blog behaviors in tweeting/retweeting content, topic, and tweeting context, etc.

#### 3.1.1 Tweeting Content

Besides using short linguistic sentences, young teenagers many times like to add some pictorial emoticons (like laughing, shy, angry, and crazy symbols) to vividly expression their minds, or use multiple exclamation and question marks for emphasis

purpose, like the example tweets in Fig. 3. Some popularly used emoticons by teenagers on the Sina micro-blog are listed in Fig. 1. They can significantly help us 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 favorite music with peers or just enjoy themselves through micro-blog. The genres (*happiness* or *sadness*) of the music may more or less reveal and further influence teens moods. For example, a lovelorn teen under the affection stress more likely listens to some sad rather than happy music, but his/her mood will gradually get better once s/he starts to choose and share some happy music. Also through the color of the posted picture, the emotional state of the teenager could be conveyed. Psychological studies [40, 41] have shown that the image color conveys emotion through a kind of color theme/template, and images with the same content but different color theme may have totally different emotions.

### 3.1.2 Tweeting Topic

Teenagers' tweeting contents are mainly about daily records, personal feelings, hobbies, social events, start chasing, etc., as illustrated in Fig. 2. As some tweets are about more than one topic, the sum of the topic proportions is not equal to 1. Fig. 3 gives some example tweets in Chinese with English translation below, where the first and third tweets reveal some stress in study, and the second one reveals interpersonal stress. As in [20], we consider four typical types of adolescent stressors (i.e., *academic stress*, *interpersonal stress*, *affection stress*, and *self-cognition stress*) as micro-blog detection targets.

### 3.1.3 Tweeting Context

Tweeting context refers to the circumstances under which a tweeting action happen. Time, frequency, location, concurrent activity, surrounding people, etc. Are typical tweeting contextual elements. Besides tweeting contents, tweeting context could also help us estimate teens emotional states. Considering the two most important contextual elements (*tweeting time* and *tweeting frequency*), despite the fact that people can freely and easily tweet anytime, because of environmental constraints and personal habits, teens' tweeting time and frequency exhibit a certain regular patterns and vary from time to time. It is very common that during school semesters, teens post less tweets during class or at midnight. However, during school breaks and public holidays, their tweeting time and frequency may have a radical change. For instance, among the tweets we studied, we notice a teen posted several tweets at midnight, deviating from his normal behavior. Looking into his tweets over, we found he struggled in love-matters deeply. Another teen released 16 tweets within one day, which was about five times as usual. After examining her tweeting contents in detail, we found out she quarreled with a classmate at that morning. Therefore, abnormalities in tweeting time and frequency may have some association with some abnormal emotions. In this study, we consider tweeting time and tweeting frequency as the tweeting context.

### 3.1.4 Retweeted (Forwarded) Tweet Content

Besides posting original tweets, teenagers once in a while retweet (forward) some tweets authored by their peers or their adorable well-known people, where they find an echo. These retweeted contents may imply forwarder's concerns and attitudes to a certain extent.

## 3.2 Problem Definition

Taking the characteristics of teenagers' micro-blog behaviors into account, we define the problem of teens acute and chronic stress detection as follows.

As in [20], this study considers four typical types of teens stress, i.e.,  $T = \{\textit{academic}, \textit{interpersonal}, \textit{affection}, \textit{selfcognition}, \textit{general}\}$ , where general denotes a stress in general whose type is unknown. Six ranks are adopted to measure a stress level, i.e.,  $L = \{\textit{very strong}, \textit{strong}, \textit{moderate}, \textit{light}, \textit{very light}, \textit{none}\}$ , where none means no stress.

**Definition 1.** Let  $s = (s.type, s.level)$  be a stress with stress type  $s.type \in T$  and stress level  $s.level \in L$ . The **stress detection result from a single teen's tweet**  $t$  is a set:  $SingleTweetDetect(t) = \{s_1, s_2, \dots, s_n\}$ , where  $s_1, s_2, \dots, s_n$  are the stresses with different stress types. An empty set indicates no stress being detected.

To further sense whether a stress belongs to the *acute* or *chronic* category, a sequence of teen's tweets during a certain time period are to be investigated, with single tweet based detection results being aggregated. We call a stress  $s$  a chronic stress within the time period  $[t_s, t_e]$ , if it occurs *frequently* and *relatively evenly* across the whole time period. That is, the occurrence frequency of  $s$  within  $[t_s, t_e]$ , as well as any of its equally divided  $k$  phases, is greater than a certain threshold  $\tau$ . Otherwise, it is an acute stress.

**Definition 2.** Given a sequence of teen's tweets  $T = \langle t_1, t_2, \dots, t_m \rangle$  posted during the time period  $[t_s, t_e]$ , let

$$sense(s, t) = \begin{cases} 1 & \text{if } \exists s' \in SingleTweetDetect(t) \text{ such that} \\ & (s.type = s'.type) \\ 0 & \text{otherwise} \end{cases}$$

The **occurrence frequency of  $s$  sensed from  $t_s$  within  $[t_s, t_e]$**  is computed as:

$$freq(s, T, t_s, t_e) = \frac{1}{m} \sum_{i=1}^m sense(s, t_i)$$

**Definition 3.** Stress  $s$  is a **chronic stress** detected from  $T = \langle t_1, t_2, \dots, t_m \rangle$  posted during the time period  $[t_s, t_e]$ , if and only if its occurrence frequency within  $[t_s, t_e]$  and any of the equally divided  $k$  phases of  $[t_s, t_e]$  is greater than a threshold  $\tau$  by satisfying the following two conditions:

- 1)  $freq(s, T, [t_s, t_e]) \geq \tau$ ;
- 2)  $\forall i (0 \leq i < k) (freq(s, T_i, [t_s + i\Delta t, t_s + (i+1)\Delta t]) \geq \tau)$ , where  $\Delta t = \frac{t_e - t_s}{k}$  is the phase length after equally dividing time period  $[t_s, t_e]$  into  $k$  phases, and  $T_i$  is the tweet sequence posted within  $[t_s + i\Delta t, t_s + (i+1)\Delta t]$ .

Number	Negative Emoticons
11	cry  sick  spit  angry  disappointed  heart-broken
	sorrow  bad-luck  feel-wronged
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

Figure 1 Some popularly used emoticons by teenagers on the Chinese Sina micro-blog.

Otherwise, stress  $s$  is an acute stress.

The setting of  $\tau$  is subject to individual’s introverted/extrovert and optimist/pessimistic character, male or female gender, and daily behavior, and thus varies from different teens groups. Here, it is set to 0.3 in detecting high-school teens’ acute and chronic stress across a 4-month semester. We divide the 4-month period  $[t_s, t_e]$  into 4 equal phases ( $k=4$ ) where each phase time length is 1 month.

**Definition 4.** The stress detection result from a list of teen’s tweets  $T = \langle t_1, t_2, \dots, t_m \rangle$  posted during the time period  $[t_s, t_e]$  is a set of chronic and acute stresses,  $MultipleTweetsDetect(T) = \{s_{a1}, \dots, s_{an}, s_{c1}, \dots, s_{cn}\}$ , where  $s_{a1}, \dots, s_{an}$  are the acute stresses, and  $s_{c1}, \dots, s_{cn}$  are the chronic stresses.

For a chronic stress, we can further evaluate the mean and fluctuation variance of the stress level within the time period through a distribution function (say, normal distribution which assumes that a very strong/weak stress level occurs far less than a medium stress level).

## 4. METHOD - GAUSSIAN PROCESS FRAMEWORK

Selecting relevant features for building robust stress detection models is critical to the detection performance. We categorize two kinds of features related to tweeting content and tweeting context on micro-blog. From each teen’s tweeting/retweeting behavior, we extract and analyze these features, and then employ a Gaussian Process classifier to perform single-tweet based stress detection.

### 4.1 TeenSensor Feature Space

#### 4.1.1 Tweeting Content Features

A teen’s tweeting content may contain linguistic text, emoticon, exaggerated punctuation, image, and/or music/video, from which the following seven features are derived.

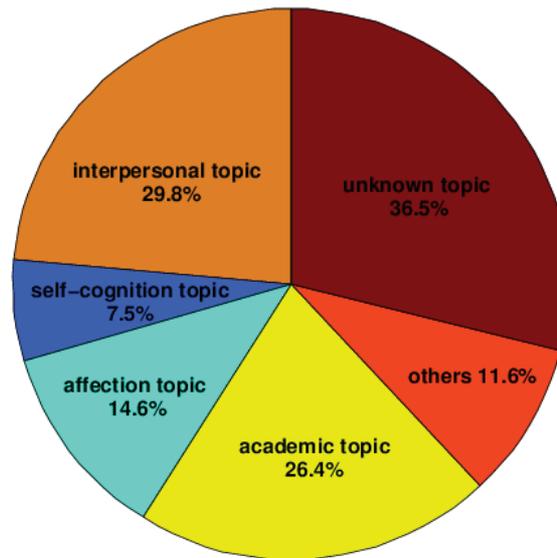


Figure 2 Tweeting topics by three teenagers.



Figure 3 Three tweet examples on the Chinese Sina micro-blog.

### 1. Source [Text]

Feature 1: Linguistic association strength between stress type and negative emotion words.

To facilitate linguistic text analysis, we construct four teenagers' stress-related linguistic lexicons on microblog, as shown in Table 1.

- The *stress type lexicon* contains 399 words, categorized into four typical types, i.e., *academic*, *interpersonal*, *affection*, and *self-cognition* stress.
- The *stress level lexicon* contains 219 words, classified into

five degree levels, i.e., *very light*, *light*, *moderate*, *strong*, and *very strong*.

- The *negative emotion lexicon* contains 250 words like disgusting, boring, depressed, hating, dislike, scared, painful, miserable, sad, bad, etc.
- The *negation lexicon* contains 18 words like no, not, none, neither, nothing, nobody, nothing, never, seldom, infrequent, etc.

Based on the four lexicons, from each sentence of a tweet, we apply a graph-based Chinese parser [42, 43] to find out associated

**Table 1** Four Teens Stress-related Linguistic Lexicons on Micro-blog.

<b>I.Stress Type Lexicon</b>	
<i>Academic: Interpersonal: Affection: Self-cognition:</i>	Study, examination, test, school, assignment, homework, class, recession, examination paper, grade, etc. Classmate, deskmate, friend, teacher, parent, trust, home, grow-up, friendship, trust, etc. Love, girl-friend, boy-friend, sorrow, sad, tired, courage, mood, infatuation, etc. Fat, ugly, silly, terrible, failure, timid, bad, mediocrity, negligible, etc.
<b>II.Stress Level Lexicon</b>	
<i>Very Light: Light: Moderate: Strong: Very Strong:</i>	More or less, slightly, a few, a little, etc. Some, somewhat, a bit, slightly, a little, a few, etc. Relatively, comparatively, etc. Very, very much, so much, great, etc. Extreme, particular, utmost, the most, excessive, undue, extravagant, extra, extraordinary, etc.
<b>III.Negative Emotion Lexicon</b>	
<i>Negative Emotion:</i>	Disgusting, dislike, hating, boring, depressed, painful, scared, miserable, sad, sorrow, terrible, bad, etc.
<b>IV.Negation Lexicon</b>	
<i>Negation:</i>	no, not, none, neither, nor, nothing, nobody, nothing, nowhere, never, seldom, hardly, scarcely, barely, little, few, etc.

word pairs. Table 2 illustrates totally 24 linguistic association relationships like subject-predicate, attributive, adverbial, etc. in Chinese grammar [44]. All 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 type related word node and a negative emotion word node and no negation lexicon word in between, a stress of the corresponding type is detected. Here, the path length is the number of edges in the path, showing the linguistic tightness between the two words.

To normalize the contribution of different features' values, we map the path length in [1,3], [4,5], [6,10], [11, ] to 5, 4, 3, 2 (corresponding to *very strong*, *strong*, *moderate*, *light* stress level), respectively. If there is no path but with some negative emotion word and stress type word, the mapping result is 1 (corresponding to *very light* stress level). Note that although this study focuses on Chinese tweets, the techniques developed could be extended to tweets in other languages.

From the tweeting content text, we search for stress type lexicons by scanning. If they do not 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, there is no stress being detected from the linguistic tweeting text.

**Feature 2: Number of negative emotion words.**

Negative emotion words may reveal a teenager's negative emotion, and the number of negative emotions is a good indicator to stress level. We normalize the number of negative emotion words in a tweet into an integer in [0,5] (corresponding to the five different stress level plus no stress level). If over 5 negative emotion words exist, the mapping value will be 5.

#### 1. Source [Music]

**Feature 4: Music emotion.**

Sad music conveys sorrow emotion. Teenagers sinking into stress likely post resonance music through micro-blog. We maintain a sad music repository containing hundreds of sad music that are popular among the teenagers. The music emotion feature takes value 1 for sad music, and 0 otherwise.

#### 1. Source [Picture]

**Feature 3: Color emotion.**

Images convey emotions like excitement and sadness, and psychological experiments have shown that color themes are crucial for the recognition of emotions. We apply the affective image classification technique developed in [45] to evaluate the emotion of an image from the five aesthetic perspectives, including image's five-color combination, saturation, brightness, warm-or-cool color, and clear-or-dull color. We map the image color emotion to The result is mapped to a two-dimensional image-scale space (*warm-cool* and *hard-soft*) which is well-recognized in art design [46].

#### 1. Source [Emoticon]

**Feature 5: Number of positive and negative emoticons.**

Negative/positive emoticons (Figure 1) 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 emoticons to an integer in [-5,0]. When there are more than 5 negative or positive emoticons, the mapping result will remain as 5 or -5.

#### 1. Source [Punctuation]

**Feature 6: Number of exclamation and question punctuation.**

**Table 2** 24 Types of Word Associations in Chinese Grammar.

No. Word Association	No. Word Association
1 adverbial	13 head
2 apposite	14 independent clause
3 attribute	15 independent structure
4 ba-construction	16 left adjunct
5 bei-construction	17 mood-tense
6 complement	18 preposition-object
7 conjunctive	19 quantity
8 coordinate	20 right adjunct
9 dependent clause	21 subject-verb
10 de-construction	22 similarity
11 dei-construction	23 verb-object
12 di-construction	24 verb-verb

Multiple exclamation and question marks are commonly used by teenagers in their tweets to express emotions, where exclamation marks often indicate some extreme emotions such as angry, whiny, etc., and question marks often represent confusion. We perform the same mapping as the one on emoticons.

### 1. Source [Text+Emoticon+Punctuation]

Feature 7: *Emotion intensity*.

In general, emotion intensity can be reflected from negative emotion words, adverb of degree, number of negative emoticons, and number of exclamation and/or question marks in a tweet. For example, “*I hate it so much!!!*” reveals a high emotion intensity due to the negative emotion word “*hate*”, adverb “*so much*”, and three consecutive exclamation marks. We compute a tweet’s emotion intensity as:  $(\#NegEmoticon + \#NegEmotionWord + \#AdvDegree + 1) * (\#ExclamationMark + \#QuestionMark + 1)$ , where  $\#NegEmoticon$ ,  $\#NegEmotionWord$ ,  $\#AdvDegree$ ,  $\#ExclamationMark$ , and  $\#QuestionMark$  are the number of emoticons, negative emotion words, adverb of degree, exclamation, and question marks, respectively. The result is further normalized into an integer in [0,5] by mapping the value in (0, 3], (3, 6], (6, 10], (10, 20], (20, ) to 1, 2, 3, 4, 5, respectively. A value 0 is mapped to 0 as well.

#### 4.1.2 Tweeting Context Features

Tweeting context refers to the circumstance under which a teen tweets/retweets on micro-blog. Time, frequency, location, concurrent activity, surrounding people, etc. are typical tweeting contextual elements. This work considers the two most important contextual elements (*tweeting time* and *tweeting frequency*).

### 1. Source [Context]

Feature 8: *Tweeting time*.

Teens tweet in a relatively regular manner. For example, they tweet at spare time more often than at class time, and tweet more frequently on holidays than on school. An abnormal tweeting time may have some association with some abnormal emotion. To capture the abnormality of a teen’s tweeting time, we analyze his/her daily tweeting history on weekdays without considering weekends and holidays when most teenagers tend to break

up their usual customs. We count the number of posted tweets within different hours of a day, and divide it by the average number of hourly posted tweets on that day to obtain the proportion of tweeting amount per hour. The average proportion of hourly tweeting number in the teen’s tweeting history provides a reference for us to judge whether a tweeting time on weekdays is abnormal or not. That is, if a tweeting time falls into the hour whose tweeting amount proportion is less than 50%, we regard it as abnormal, and thus set the feature value to 1, otherwise, to 0. If the tweeting day is holiday and weekend, we set the feature value to 0.

Feature 9: *Tweeting frequency*.

We examine an abnormal tweeting frequency in a similar way as an abnormal tweeting time. The only difference is that the former is done on a daily basis rather than on a hourly basis. Also, we do not consider tweeting frequency’s abnormality during holidays and weekends. The feature value is set to 1 if the tweeting frequency is abnormal, and 0 otherwise.

## 4.2 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  $\mathbf{f} = \{f(t) | t \in TSet\}$ , according to  $f(t) \sim GP(\mu(t), k(t, t'))$ , where  $t, t' \in TSet$ ,  $\mu(t)$  is the mean function, and  $k(t, t')$  is the squared-exponential covariance function:

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

where  $\|\cdot\|$  is the  $\ell_2$ -norm,  $\delta_l$  and  $\delta_s$  are hyperparameters giving the length-scale in the  $t$ -direction and the variance of  $s$ . Considering additive Gaussian noise  $\varepsilon \sim N(0, \delta_\varepsilon^2)$  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:

$$C_0 \sim N(0, K(TSet, TSet) + \varepsilon_n^2 I_n) \quad (2)$$

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:

$$f_* | TSet, C_o, C^* \sim N(\bar{f}_*, cov(f_*)) \quad (3)$$

where  $\bar{f}_*$  and  $cov(f_*)$  are the mean value and variance of the classification results. Expectation propagation algorithm proposed by [47] is to approximate inference in GP classification and get the best results of accuracy and speed based on the latent function.

## 5. USER STUDY

To show the benefit of using unobtrusive open micro-blog to detect teen's acute and chronic stress, we conduct a user study to see what accuracy TeenSensor can reach by comparing its detection result with the ground-truth of stress obtained through the Cohen's Perceived Stress Scale (PSS-14) [48], which is commonly used to measure human stress level worldwide in psychology.

### 5.1 Experimental Set-up

We invite 300 students (146 females and 154 males, aged 16 to 17) from 10 classes of Xining No.4 High School to participate in our study, as shown in Fig. 4 (a). The reasons we choose these students are: most of them use micro-blog, and are suffering various stresses to one degree or another confronted with the upcoming national college entrance examination (as evidenced by our user study result). Before the user study, we introduce the aim and procedure of the study to them. After having their consents, we let the students fill in the Chinese PSS questionnaire [49], containing 14 questions (Table 3) to answer based on their emotional feelings in the recent last month (from Nov.26, 2013 to Dec.26, 2013). According to [50], PPS-14 score value 26 is the boundary value, score falling into [26, 56] indicates a strong stress, score in [1, 26] indicates a light stress, and score 0 indicates no stress. We collect 258 complete questionnaires out of 300, and further filter out 69 students (32 females and 37 males) who were active micro-blog users in the recent month as our study participants. Fig. 4 (b) gives the Chinese PPS score distribution from the 69 students.

### 5.2 Experimental Results

As the PSS indicator returns four stress levels (i.e, none, light, moderate, strong) without stress type consideration, for comparison purpose, we merge our "very light" and "light" stress ranks into "light" stress level, "very strong" and "strong" into "strong" stress level to match the PSS result. Four experiments are conducted to evaluate the performance of TeenSensor's 1) teens general stress detection, 2) chronic and acute stress detection, 3) features impact on stress detection, and 4) stress type aware single-tweet based detection, respectively.

#### 5.2.1 Performance of Teens General Stress Detection

We train our TeenSensor model based on the identified 69 students' historic tweets. For each teen, TeenSensor performs a single-tweet based stress detection upon his/her last month's tweets in [Nov.26,2013 to Dec.26,2013], and then computes this teen's average stress level based on the single-tweet based detection results. Fig. 5 (a) compares the two detected stress levels of PSS and TeenSensor for each of the 69 teens. The average detection accuracy of TeenSensor is 56.5%. Fig. 5 (b) (c) (d) show the ranking variance between the two detected stress levels under the 69 teens, 30 introvert teens, and 39 extrovert teens, respectively. The closer the two results, the more accuracy TeenSensor achieves. The average errors of ranking distribution between the two detected stress levels in Fig. 5 (b) (c) (d) are 13, 10 and 16 respectively. Along with the result presented in Fig. 5 (c), we can find TeenSensor works the best in detecting introvert teens' stress. It reveals the fact that teens with different characters have different attitudes against stressors, and introvert adolescents are more vulnerable to depression, and thus more likely express themselves on micro-blog for stress release than extrovert adolescents.

#### 5.2.2 Performance of Chronic and Acute Stress Detection

We appraisal TeenSensor for detecting teens chronic and acute stress based on micro-blog. To achieve a reasonable ground-truth on acute and chronic stress detection, we invite a mental health counselor at the school to join us to help estimate teens' stress categories. The counselor observes all the tweets posted by the 69 participants during a semester and labels each of them with chronic, acute or none stress category in advance. Then we compare the TeenSensor detection results with these marks. Table 4 shows the accuracy of both of chronic and acute stress detection by TeenSensor, achieving 72.2% for chronic and 69.6% for acute, respectively. This implies the potential that sensing teens' chronic and acute stress through micro-blog is feasible.

Fig. 6 shows the two TeenSensor detection result interface regarding chronic and acute stress, respectively. In the figures, distinct differences between the chronic stress and acute stress can be observed.

#### 5.2.3 Features Impact on Detection Performance

We evaluate the importance and effectiveness of tweeting content and tweeting context upon stress detection. Tweets of 69 students in the period of a month are used as the data set. Firstly, we train and test the tweets only with tweeting content features, then we calculate the average stress level in a month for each teenager. The results are ranked by order, and compared with the ranking list of PSS scores, as shown in Fig. 7 (a). In contrast, we conduct another experiment with both tweeting context and content features included, the same ranking method in the last step are applied here. Results in Fig. 7 shows that the join of context features reduces the experiment average error rate from 17.25% to 14.49%, but tweeting content features still dominate.

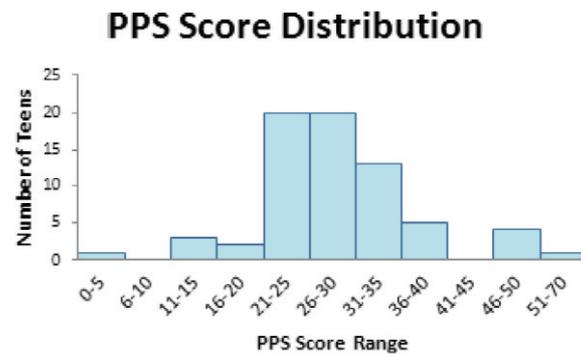
**Table 3** The Cohen's Perceived Stress Scale (PSS-14) at a 5-point Scale.

(from 1="never" to 5="very often")

In the last month, how often have you ...
Q1 : been upset because of something that happened unexpectedly?
Q2 : felt that you were unable to control the important things in your life?
Q3 : felt nervous and "stressed"?
Q4 : dealt successfully with day to day problems and annoyances?
Q5 : felt that you were effectively coping with important changes that were occurring in your life?
Q6 : felt confident about your ability to handle your personal problems?
Q7 : felt that things were going your way?
Q8 : found that you could not cope with all the things that you had to do?
Q9 : been able to control irritations in your life?
Q10 : felt that you were on top of things?
Q11 : been angered because of things that happened that were outside of your control?
Q12 : found yourself thinking about things that you have to accomplish?
Q13 : been able to control the way you spend your time?
Q14 : felt difficulties were piling up so high that you could not overcome them?



(a)



(b)

**Figure 4** (a) Participants from Qinghai No.4 High School; (b) PSS score distribution from 69 teens.**Table 4** Teens Acute and Chronic Stress Detection Performance.

	<i>acute stress</i>	<i>chronic stress</i>
By mental health counselor	23	18
By TeenSensor	15	13
Detection accuracy	69.6%	72.2%

**Table 5** Number of Tweets of Different Stress Types.

<i>inter-personal</i>	<i>self-cognition</i>	<i>affection</i>	<i>study</i>
14725	7450	3552	2232

#### 5.2.4 Performance of Stress Type Aware Single-Tweet based Detection

As PSS is designed for measuring the level of stress in general without distinguishing stress types, in the last experiment, we examine the stress type aware single tweet based detection per-

formance of TeenSensor by categorizing 69 teens' tweets into five subsets, corresponding to inter-personal, self-cognition, affection, and study stress type. Besides, while the previous experiments work on 69 teens' tweets posted only in the last month (the valid time of PSS), we enlarge the data set by including all the tweets posted by the 69 teens since their micro-blog start-

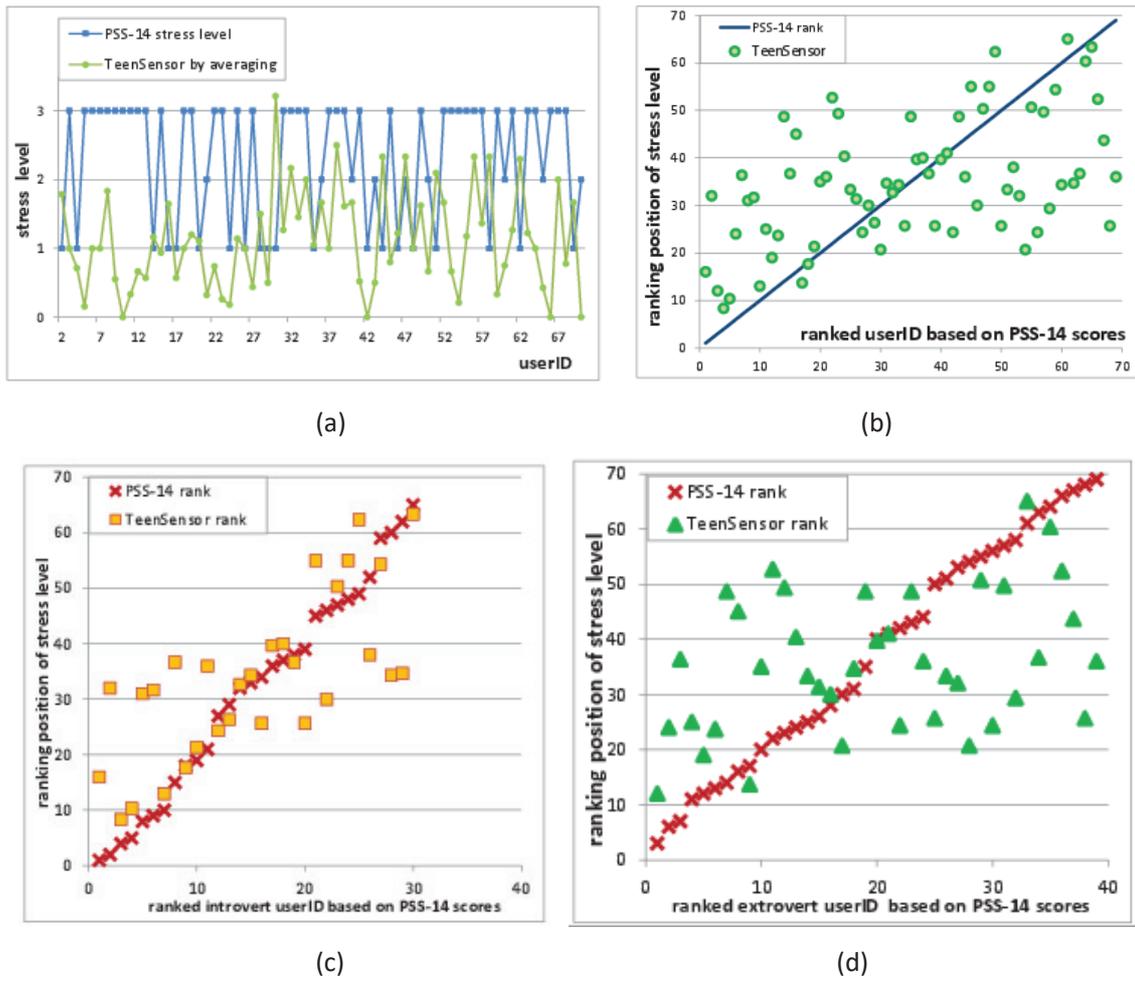
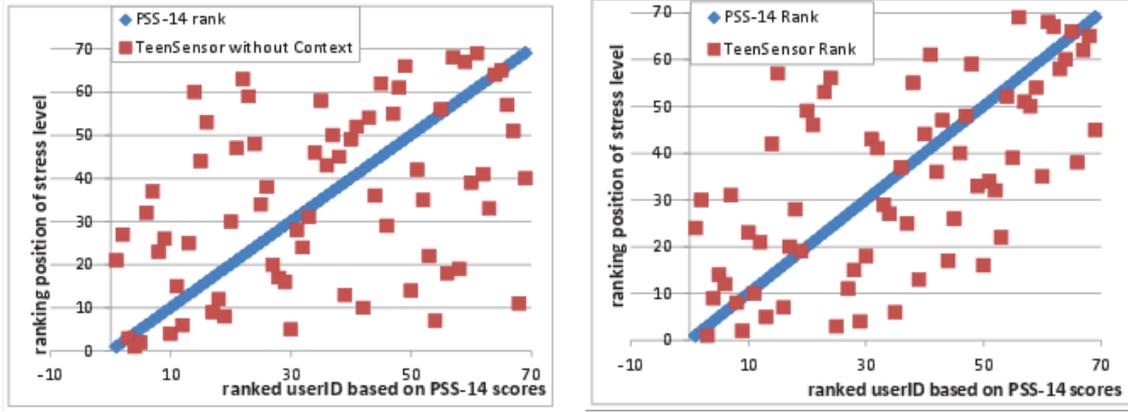


Figure 5 Stress levels detected by TeenSensor and PSS.



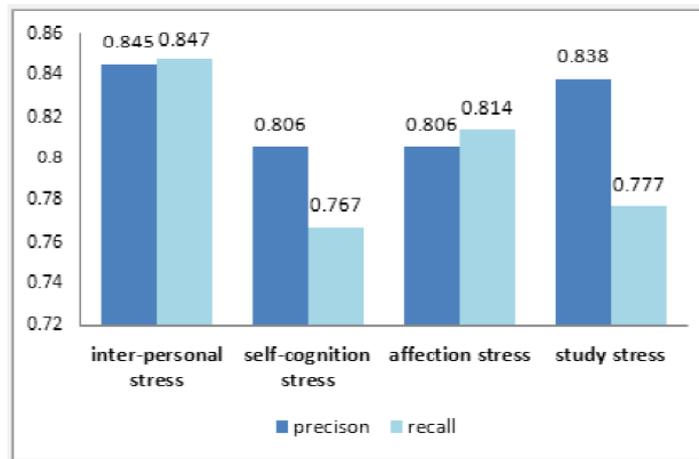
Figure 6 (a) TeenSensor's chronic stress detection result; (b) TeenSensor's acute stress detection result.



(a)

(b)

Figure 7 (a) Stress level ranking based on tweeting content features (b) Stress level ranking based on tweeting content and context features.



(a)

Train Set	Interpersonal		Self-Cognition		Affection		Study	
	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.
1	87.2%	82%	85%	80.6%	72.6%	79.6%	87%	78%
2	88.4%	87.7%	75.2%	72.8%	82.8%	82%	77.2%	84.4%
3	85.8%	81%	80.2%	79.8%	90.3%	82.3%	86%	71%
4	84.4%	85.3%	90%	82.6%	77.8%	84%	78.4%	75.6%
5	81.2%	87.5%	84.5%	77.8%	77.2%	82.2%	90.3%	83.3%
6	84.4%	80.2%	74.2%	69.2%	83.6%	79.8%	85.3%	74.3%
7	86%	84.8%	77.6%	72.8%	76.2%	76.8%	86.8%	77.2%
8	82.6%	84.5%	71.8%	72.8%	77.2%	82.4%	87.8%	78.2%
9	77.5%	86.6%	83.8%	81.8%	86%	78.2%	79.2%	77%
10	87.4%	87.1%	83.3%	76.6%	82.8%	85.5%	80%	78.5%
AVG	84.5%	84.7%	80.6%	76.7%	80.6%	81.4%	83.8%	77.7%

(b)

Figure 8 Stress type aware detection precision and recall.

ups in the experiment. Table 5 gives different numbers of tweets, whose revealed stress types and stress levels are annotated by our invited mental health counselor at the school.

For each stress type, we use 10% of its tweets for testing and

among the rest 90% of its tweets. To ensure the experimental efficiency and rationality, we randomly generate 10 different training sets, each containing 2000 tweets. We run TeenSensor 10 times, and calculate the average precision and recall values

under each stress type.

As Fig. 8 (a) (b) demonstrate, TeenSensor achieves the highest detection precision 84.5% and recall 84.7% for interpersonal stress type. This may be due to its largest training set We also notice that detection of self-cognition stress type has the lowest precision and recall, for teenagers often feel shy to negatively express themselves directly through tweets, compared to other stress types.

## 6. CONCLUSION

Stress can adversely impact individuals by leading to a series of physical and mental health problems. For adolescents, it may result in more serious consequences such as suicide due to their shortage of psychological endurance and controllability. Therefore, it is particularly necessary to timely detect stress and guide adolescents when they are under stress. Nowadays, micro-blog offers a new channel to get in touch with adolescent's real-time emotion and behavior expression through their tweeting content and tweeting context. In this paper, we propose a system called TeenSensor to detect teens acute and chronic stress from their micro-blog behaviors. It extracts and analyzes and extract a number of tweeting features which reflect teen's stress emotion and behavior expression, and then implements a Gaussian Processes framework to detect the teens' stress based on the features features. A user study is conducted at a high school with 69 students of age 16-17 to evaluate the performance of TeenSensor. We compare the PSS stress indicators with the TeenSensor detection results. The result of the study show that TeenSensor can achieve 56.5% accuracy in stress detection. In the future, we plan to implant a personalization model upon TeenSensor to automatically or semi-automatically adapt to different teens' stress detection.

## ACKNOWLEDGMENTS

The work is supported by National Natural Science Foundation of China (61872214, 61532015, 61521002) and Chinese Major State Basic Research Development 973 Program (2015CB352301).

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