Analyzing the Restoring Impact of Uplift Events on Overwhelmed Teenagers via Microblogs

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Abstract—**As an important concept in traditional psychological theory, restoring is an essential process in human's stress coping system. Timely and efficient restoring of stress could help teenagers get out of overwhelmed status as soon as possible. Previous research has explored the possibility of detecting teenagers' stress series and mining the impact of stressor events from social media. On the contrary, the research on auto-analyzing the restoring ability of uplift events still stays empty, due to the uncertainty on identifying uplift events and the complexity of various restoring situations. In this paper, we give a deep inside into the restoring impact of uplifts on the real data set of xx teenagers from three high schools, and correlate the stress restoring patterns with uplift events. A two-sample based statistical model is conducted to analyze the stressful behavioral correlation between uplift (U-SI) and non-uplift (SI) stressful intervals from both linguistic and stress intensity perspectives. Our research provides guidance for school and parents that which kind of uplift events could help relieve students' overwhelmed stress in both stress prevention and stress early stopping situations. Experimental results show that our method could measure the restoring impact of uplift events in three experimental situations, and obtains high performance (0.0756 MSE, 0.1145 RMSE, 29.27% MAPE and 0.1015 MAD) on real data set.**

Index Terms—**uplift event, stress, correlation, microblogs**

I. Introduction

Life is always full of ups and downs. According to the transactional model of stress [1], our stress mainly comes from daily hassles. The cumulative stress caused by the small and frequent stressful life events could drain people's inner resources, leading to psychological maladjustment, ranging from depression to suicidal behaviours [2]. As a global public health concern, suicide has become the second leading cause of death among young adults in college (Centers for Disease Control and Prevention, 2012).

On the other hand, positive life events (called *uplifts* in psychological theory) such as satisfying social interactions, excellent academic performance and pleasant entertainment activities are conceptualized in psychological literature as exerting a protective effect on emotional distress [3] [4] [5]. Compared with adults, young people exhibite more explousure to uplift events, as well as hassles [6], due to the immature inner status and lack of experience. Researchers indicate that positive events mitigate the relation between negative events and maladjustment in samples of adolescents experiencing family transitions [7]. The written expression of positive feelings has also be shown to prompt increased cognitive reorganization among an undergraduate student group [8].

Positive uplifts can not only help reinforce adolescents' sense of well-being, and help restore the capacity for dealing with stress, but also have been linked to medical benefits, such as improving mood, serum cortisol levels, and lower levels of inflammation and hypercoagulability [9]. Through examining the relationship between self-reported positive life events and blood pressure (BP) in 69 sixth graders, researchers found that increased perceptions of positive life events might act as a buffer to elevated BP in adolescents [10].

The protective effect of uplift events is hypothesized to operate in two ways: directly and indirectly by 'buffering' [4]. In the direct way, the more positive uplift events people experienced, the less distress they experience. While in the indirectly way, positive life events play its role by buffering the effects of negative events on distress. A pioneer experiment conducted by Reich and Zautra provided enlightening evidence for us [11]. In this experiment, sampled college students who reported initial negative events were encouraged to engage in either two or twelve pleasant activities during one-month, and compared with controlled students. Results indicated that participants in the two experimental groups reported greater quality of life compared with controlled students, and participants who engaged in twelve uplift events exhibited lower stress compared with whom engaging two or none uplifts, implicating the protective effect of uplift events on adolescents.

Previous exploration for the protective effect of uplift events on adolescents are mostly conducted in psychological area, relying on traditional manpower-driven investigation and questionnaire. The pioneer psychological researches provide us valuable implications and hypothesis, while limited by labor cost, data scale and single questionnaire based method. With the high development of social networks, today adolescents tend to express themselves and communicate with outside world through posting microblogs, at anytime and anywhere. The self-motivated expressions could delivery much information about their inner thoughts and life styles. In recent years, some research on psychological stress analysis based on microblog platform has emerged, from basically detecting stress intensity from microblog content [12], [13], predicting future stress level in time series [14]–[17], to extracting stressor events and stressful intervals [18]. These researches explored applying psychological theories into social network based stress mining, offering effective tools for adolescent stress sensing. Nevertheless, few work takes an insight into the restoring function of uplift events, which plays important role opposite to stress, as the essential way for adolescent psychological stress easing.

In this paper, we aim to continually mine the restoring impact of uplift events leveraging abundant data source from microblogs, to further provide guidance for school and parents that when and which kind of uplift events could help relieve students' overwhelmed stress in both stress prevention and stress early stopping situations. To model such a complex real-life problem, several challenges exist.

- *How to extract uplift events from microblogs and identify corresponding impact time range*? The impact of uplift events is highlighted when the teen is under stress, with various relative temporal order. Extracting such scenarios from teen's messy microblogs is the first and basic challenge for further analysis.
- *How to qualitatively and quantitatively measure the restoring impact conducted by uplift events*? There are multiple clues related to teens behaviors from microblogs, i.e., depressive linguistic content, abnormal posting behaviors. The teen might act differently under similar stressful situations when the uplift event happens or not. It is challenging to find such hidden correlation between uplift events and teen's behavioral characters.

Moreover, for different types of uplift events, the restoring impact might be different. And for each individual, the protective and buffering effect for stress might also varies according to the personality. All these questions guide us to solve the problem step by step.

To answer the above questions, our contributions are summarized as follows.

- Case study on real data set. To observe the posting behaviors and contents of stressful teens under the impact of uplift events, we conduct the case study from real data set from 124 high school students associated with the scheduled event list. Several observations are conducted to guide next step research.
- Extracting uplift events and impacted interval. We define and extract structural uplift events from posts using linguistic parser model based on six-dimensional uplift scale[] and LIWC[] lexicons. Independent stressful intervals (SI) and stressful intervals impacted by uplifts (U-SI) are extracted considering temporal orders.
- Quantify the restoring impact of uplift events. We describe a teen's stressful behaviors in three groups of measures (stress intensity, posting behavior, linguistic), and model the impact of uplift events as the statistical difference between the sets of SI and U-SI in two aspects: the two-sample based method is employed for variation detection; the t-test correlation is conducted to judge the monotonous correlation.

The rest of the paper is organized as follows. We introduce related works in section 2, and conduct the data observation in section 3. The preliminaries and problem formulation are presented in section 4. We introduce the detailed method to analyze the restoring impact of uplift events in section 5. We present the experimental results in section 6, discuss some implications in section 7 and conclude the paper in section 8.

II. Related Work

A. Protective function of uplift events

Many psychological researchers have focused on the restorative function of positive events and emotions with respect to physiological, psychological, and social coping resources. [19] identified three classes of coping mechanisms that are associated with positive emotion during chronic stress: positive reappraisal, problem-focused coping, and the creation of positive events. Work [4] hypothesized that protective effect of uplift events operates in both directly (i.e., more positive uplift events people experienced, the less distress they experience) and indirectly ways by 'buffering'. [20] considered the possible roles of positive emotions in the stress process, and incorporated positive emotion into a revision of stress and coping theory. They conducted a longitudinal study of the care giving partners of men with AIDS and described coping processes that were associated with positive psychological states in the context of intense distress.

Work [21] investigated the protective effect of positive events in a sample of 327 adults, and found that the positive association between loneliness and psychological maladjustment was found to be weaker for those who experienced a high number of positive life events, as opposed to those who experienced a low number of positive life events. This is assistant with the conclusion made by [22] that positive events act as protective factors against suicide individually and synergistically when they co-occur, by buffering the link between important individual differences risk variables and maladjustment. Through exploring naturally occurring daily stressors, [23] found that over time, the experience of positive emotions functions to assist high-resilient individuals to recover effectively from daily stress. In the survey of [24], strategies of positive psychology are checked as potentially tools for the prophylaxis and treatment of depression, helping to reduce symptoms and for prevention of relapses. Through a three-week longitudinal study, [25] examined the correlation between employee stress and health and positive life events, and concluded that naturally occurring positive events are correlated with decreased stress and improved health.

B. Measuring the Impact of Uplift Events

To measure the impact of uplift events, [26] conducted *Hassles and Uplifts Scales*, and concluded that the assessment of daily hassles and uplifts might be a better approach to the prediction of adaptational outcomes than the usual life events approach. Work [27] presented the *Hassles & Uplifts Scale* to assess the reaction to minor every-day events in order to detect subtle mood swings and predict psychological symptoms. To measure negative interpretations of positive social events, [28] proposed the interpretation of positive events scale (*IPES*), and analyzed the relationship between social interaction anxiety and the tendency to interpret positive social events in a threat-maintaining manner. Article [29] proposed the *Perceived Benefit Scales* as the new measures of self-reported positive life changes after traumatic stressors, including lifestyle changes, material gain, increases in selfefficacy, family closeness, community closeness, faith in people, compassion, and spirituality. Specific for college students, work [30] investigated in 282 college students using the *Adolescent Self-Rating Life Events Checklist*, and found that the training of positive coping style is of great benefit to improve the mental health of students.

C. Analyzing adolescent stress from social media

With the high development of social network, researchers tend to digging user' psychological status from the self-expressed public data source. Billions of people record their life, share multi-media content, and communicate with friends through such platforms, e.g., Tencent Microblog, Twitter, Facebook and so on. Inspired by rich microblogging content, [12], [13] proposed to detect adolescent stress from single microblog utilizing machine learning methods by extracting stressful topic words, abnormal posting time, and interactions with friends. [31] construct a deep neural network to combine the high-dimensional picture semantic information into stress detecting. Based on the stress detecting result, [14] [16] [15] adopted a series of multi-variant time series prediction techniques (i.e., Candlestick Charts, fuzzy Candlestick line and SVARIMA model) to predict the future stress trend and wave. Taking the linguistic information into consideration, [17] employed a NARX neural network to predict a teen's future stress level referred to the impact of co-experiencing stressor events of similar companions. All above pioneer work focused on the generation and development of teens' stress, providing solid basic techniques for broader stress-motivated research from social networks.

To find the source of teens' stress, previous work [18] developed a frame work to extract stressor events from microblogging content and filter out stressful intervals based on teens' stressful posting rate. Based on such research background, this paper starts from a completely new perspective, and focuses on the buffering effect of positive events on restoring stress. Thus we push forward the study from how to find stress to the next more meaningful stage: how to deal with stress.

D. Correlation analysis for multivariate time series

Basic correlation analysis methods on time series focused on univariate data have been well studied. As the most widely adopted method, the Pearson correlation analysis [32] measures the linear correlation between two variables X and Y. One inevitable defect is that Pearson correlation is too sensitive to outlier values. To overcome such drawback, Spearman Rank correlation [33] and Kendall Rank correlation [34] are proposed based on Pearson correlation. While Pearson correlation estimates linear relationships, Spearman correlation estimates monotonic relationships (whether linear or not), and are calculated as the Pearson correlation between the rank values of two variables. The Kendall correlation mainly assesses the similarity of the orderings of the data when ranked by each of the quantities. The above correlation methods are usually used to estimate relationship between single-dimensional variables, and cannot be adopted directly in our microblog content based scenario.

For multivariate time series analysis, two-sample based methods are widely adopted. Such kind of methods are deduced to check whether two samples come from the same underlying distribution, which is assumed to be statistically unknown. Correspondingly, various kernel [35] and distance-based methods [36](e.g., the nearest neighbor based method two-sample method) are proposed. Work [35] proposed to transform the distance between two variables and nearest neighbors into a reproducing kernel Hilbert space (RKHS), and solve the problem using Maximum Mean Discrepancy. In work [36], the author adopted the r-nearest neighbor based method to partition two set of event driven time series data. The global proportion of the right divided neighbors are calculated to estimate whether there exists statistically difference between the two sets. We use the r-nearest neighbor based two-sample method in our problem, thus to measure the distance and correlation between two multi-dimension variables.

III. Data Observation

We built our dataset based on two sources: 1) the microblogs of high school students coming from Taicang High School1, from January 1st, 2012 to February 1st, 2015; and 2) list of scheduled school events, with exact start and end time. We filtered out 124 active students according to their posting frequency from over 500 students, and collected their microblogs throughout the whole high school career. Totally 29,232 microblogs are collected in this research, where 236 microblogs per student on average, 1,387 microblogs maximally and 104 posts minimally.

Uplift events and stressor events. The list of weekly scheduled school events from February 1st, 2012 to August 1st 2017 are obtained from the official website[1] of the school, with detailed event description and grade involved. There are 122 stressor events and ?? uplift events in total. Here we give the examples of scheduled uplift and stressor events in high school life, as shown in Table I. There are 2-3 stressor events and ?? uplift event scheduled per month.

Stress detected from microblogs. We aim to observe the impact conducted by stressor events, as well as the restoring influence of uplift events. Based on previous research [12], we detected the stress level (ranging from 0 to 5) for each post, and aggregated a students stress in each day by calculating the average stress of all posts. Figure 1 shows three examples of a students stress fluctuation during three mid-term exams, where the uplift event campus art festival was scheduled ahead of the first exam, the uplift event holiday happened after the second exam, and no scheduled uplift event was found nearby the third exam. The student exhibited differently in above three situations, with the stress lasting for different length and with different intensity.

To further observe the influence of uplift events for students facing stressor events, we statistic all the stressful intervals [18] detected surround the scheduled examinations over the 124 students during their high school career. For each student, we divide all his/her stressful intervals into two sets: 1)stressful intervals under the influence of neighbouring uplift events (e.g., *Halloween activity*), and 2)independent stressful intervals. Figure 2 shows five measures of each student during the above two conditions: the *accumulated stress*, the *average stress* (per day), the *length of stressful intervals*, the *frequency of academic topic words*, and the *ratio of academic stress among all types of stress*. For each measure, we calculate the average value over all eligible slides for each student.

[1] http://www.tcsyz.com/col/col11201/index.html

Fig. 1: Examples of school related stressor events, uplift events and stress fluctuation

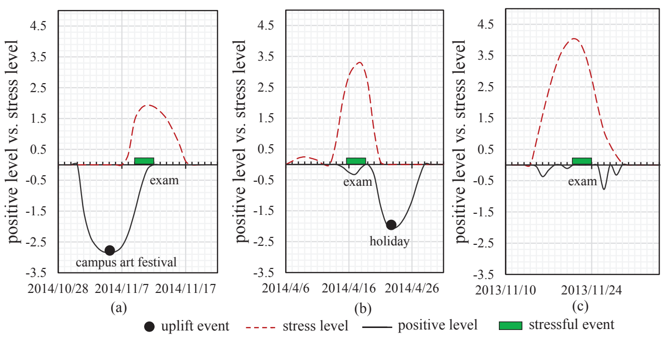


TABLE I: Examples of school scheduled uplift events and stressor events.

Type	Date	Work Content	Grade
stressor event	2014/4/16	*first day of mid-term exam*	grade1,2
uplift event	2014/11/5	*campus art festival*	grade1,2,3

Findings. Comparing each measure in scheduled exam slides under the two situations (influenced by neighbouring uplift events or not), we find that students during exams with neighbouring uplift events exhibit less average stress intensity (both on accumulated stress and average stress), and the length of stress slides are relatively shorter. Further, we statistic the frequency of academic topic words (as listed in Table xx) for each exam slide, and look into the ratio of academic stress among all five types of stress. Results in Figure 2 shows that most students talked less about the upcoming or just-finished exams when uplift events happened nearby, with lower frequency and lower ratio. The stress intensity and type distribution detected from each student's microblogs varies due to personal life experience, posting habits and express styles. The statistic result shows clues about the stress-relieving ability of scheduled uplift events, and help shape our problem as how to quantify the influence of uplift events, thus to provide further guidance for planning campus activities to help relive high school students' psychological stress effectively.

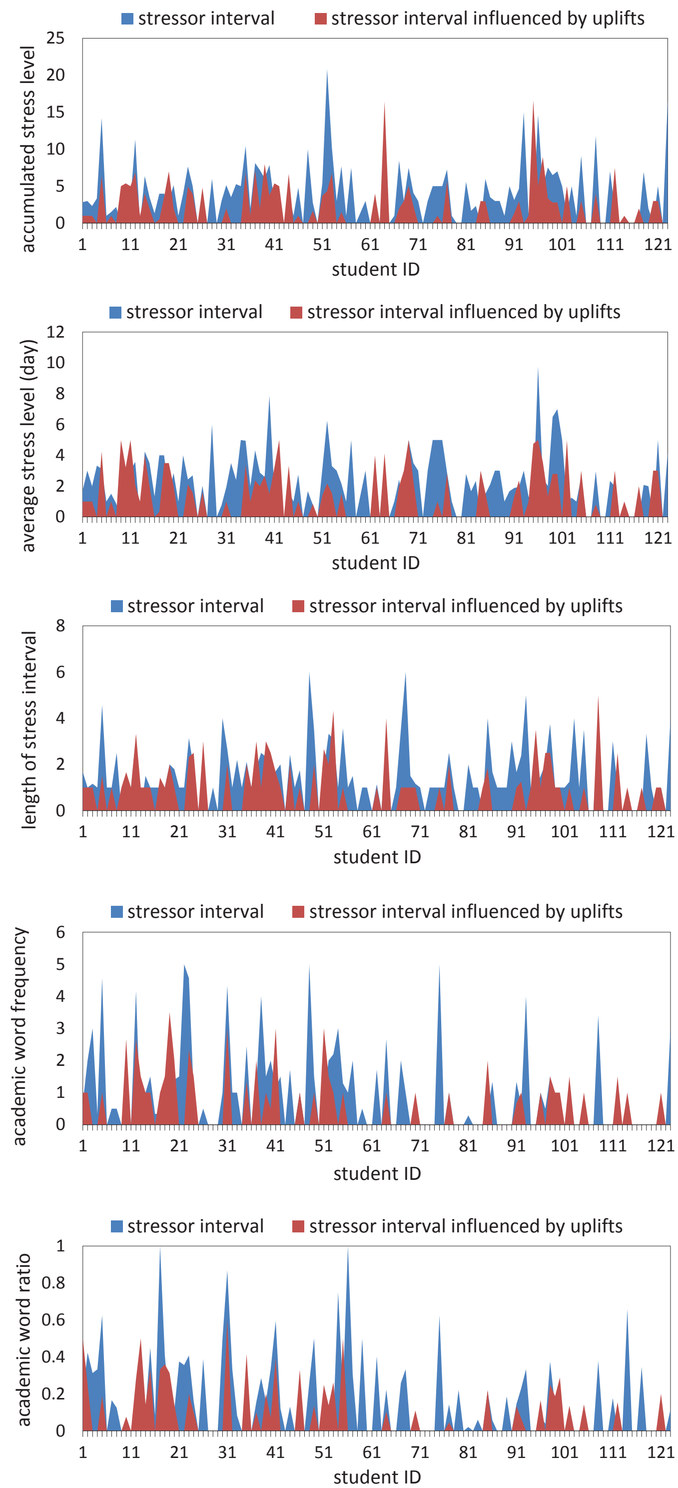
IV. Preliminaries

Based on the observation and psychological theory, we conduct our research in the assumption that uplift events can ease stress, namely the positive impact of uplift events. While stressor events stimulate human's stress, uplift events bring positive influence and restore ability to stressed people[] in various situations with multi-types, resulting in different restoring impact. Taking the three stress curves in Figure 1

TABLE II: Examples of topic words for stressor events.

school life	exam, fail, review, score, grade, test paper, rank, pass
romantic	blind love, willing, heart, secret, miss, be infatuated with
pear relation	betrayal, friend, friendship, crowd out, desolate, envy
self-cognition	humble, fate, confused, hopeless, despaired, death
family life	parental, divorce, home, relatives, scold, expectations

Fig. 2: Compare students' stress during exams with/without uplift events nearby.



for example, comparing the stress curves *a)*, *b)* with *c)*, when uplift happens, the overall stress intensity during a time period is reduced. An uplift event might happen before teen's stress caused by scheduled stressor events (*example a)*), conducting lasting easing effect. Meanwhile, an uplift event might also happen during (*example b)*) or at the end of the stressful period, which might promote the teen out of stress more quickly. To study the restoring impact of an uplift event, we structure its impact from three aspects:

- **Impact interval of uplifts**. To study uplifts from microblogs, two fundamental temporal factors are identifying the exact time point when the uplift event happens, and the corresponding stressful interval it impacts. The temporal order between uplifts and teen's stress varies in different situations, and its a challenge to match the uplift to the right stressful interval it actually impacts.
- **Restoring patterns of uplifts**. As the restoring impact of uplifts relieve teen's stress and exhibit in multiple aspects (e.g., the changing in posting behavior, linguistic expression, and stress intensity from microblog content), it's meaningful to abstract the stress-related changing patterns and describe the impact structurally.
- **Quantified impact of uplifts**. Different types of uplifts might conduct restoring impact with different intensity. In this paper, the ultimate problem we target to solve is how to quantify the restoring impact both qualitatively and quantitatively from both the positive behaviors and stressful behaviors from teenagers microblogs.

Given an uplift event with specific type, we consider its restoring influence by comparing teen's behavioral measures under two situations. As shown illustrated in Figure 2, in the original situation (i.e., subseries A), teen's stress is caused by a stressor event, lasting for a period, and no other intervention (namely, uplift event) occurs. We call such stressful intervals as *SI*. In the other comparative situation (i.e., subseries B), teen's stressful interval caused by the same type of stressor is impacted by uplift events, called U-SI. Thus the difference under the two situations SI and U-SI could be seen as the restoring impact conducted by the uplift.

Next, we give the formal definition for uplift events and stressor events from the perspective of linguistic structure.

Definition 1: **Uplift event**. Let $u = [type, \{role, act, descriptions\}]$ be an uplift event, where the element *role* is the subject who performs the *act*, and *descriptions* are the key words related to e. According to psychological questionnaires [xx, xx], teenagers' uplift stressors mainly focus on six aspects, as $\mathbb{U} = \{$ *'school life', 'family life', 'pear relation', 'self-cognition', 'romantic', 'entertainment'*$\}$, $\forall u$, $u_{\cdot type} \in \mathbb{U}$.

Definition 2: **Stressor event**. Similar to stressor event, let $e = [type, \{role, act, descriptions\}]$ be a stressor event. According to psychological theories [xx], we divide stressor events into five types, as $\mathbb{S} = \{$ *'school life', 'family life', 'pear relation', 'self-cognition', 'romantic'*$\}$, $\forall e$, $e_{\cdot type} \in \mathbb{S}$.

The examples of teen's microblogs describing uplifts and stressors are listed in Table xx. For the post *'I have so much homework today!!!'*, its elements are *role* = *'I', act='have', descriptions* = *'homework'*, and the *type* = *'school life'*. For the post *'Expecting Tomorrow' Adult Ceremony[Smile][Smile]* ', we translate it into *act* = *'expecting', description* = *'Adult Ceremony'*, and the *type* = *'self-cognition'*.

TABLE III: Examples of uplift events in teens' posts.

I am really looking forward to the spring outing on Sunday now. (Doer:*I*, Act:*looking forward*, Object:*spring outing*)
My holiday is finally coming [smile]. (Doer:*My holiday*, Act:*coming*, Object:*[smile]*)
First place in my lovely math exam!!! In memory of it. Object:*first place, math, exam, memory*)
You are always here for me like sunshine. (Doer:*You*, Object:*sunshine*)
Thanks all my dear friends to take the party for me. Happiest birthday! (Doer:*friends*, Act:*thanks*, Object:*party, birthday*)
Be yourself. Trust yourself and follow your heart. (Doer:*yourself*, Act:*trust*, Object:*heart*)
Feel proud of our play in the Games. Our class is always the family!!! (Doer:*Our*, Object:*class, family*)
A good film always makes bring comfort and happiness to me. (Doer:*me*, Act:*bring*, Object:*comfort, happiness*)
I know my mom is the one who support me forever, no matter when and where. (Doer:*mom*, Act:*support*)

Problem: For a stressor event e with type $S^{'}$, an uplift event u with type $U^{'}$, let $F : (e, S^{'}, u, U^{'}) \rightarrow \alpha$ $(\alpha \in (-1, 1))$ be the restoring influence of uplift event u conducted on the stress caused by stressor event e. Our target is to quantify the influence of u over e, from multi-perspectives.

V. Identify Uplifts and Impact Interval

In this section, we first introduce the procedure to extract uplift events and stressful intervals from teen's microblogs. For each stressor event, the corresponding stressful interval is identified using probability based statistical method according to teen's stressful posting frequency. The uplift events are extracted from posts applying LTP natural language processing models.

A. Uplift Events

Lexicon. We construct our lexicon for uplift events from two sources. The basic positive affect words are selected from the psychological lexicon LIWC (e.g., *expectation*, *joy*, *love* and *surprise*). Then we build the uplift event lexicon by expanding the basic positive words from the data set of teens' microblogs, and divide all candidate words into six dimensions corresponding to six types of uplift events, containing 452 phrases in *entertainment*, 184 phrases in *family life*, 91 phrases in *friends*, 138 phrases in *romantic*, 299 phrases in *self-recognition* and 273 phrases in *school life*, with totally 2,606 words. Additionally, we label *role* words (*teacher*, *mother*, *I, we*) in the uplift lexicon.

Parser relationship. For each post, after word segmentation, we parser current sentence to find the main structure, and then match with topic words for each uplift dimension. The and parser model in Chinese natural language processing platform [xx] is adopted in this part, which identify the central verb first, namely the *act*, and construct relationship between the central verb and corresponding *role* and *objects*. By searching these main elements in uplift lexicon, we identify the existence and type of any uplift event. Due to the sparsity of posts, the *act* may be empty. The *description* of current uplift is collected by searching all nouns and adjective words in current post. In such way, we extract the structured uplift event from teens microblogs.

B. Impact Interval

When the uplift event happens, it conducts positive impact on stressed teens, exhibiting in teen's stress intensity, stress interval length, and stressful behaviors. Basically, in this part, we identify stressful intervals from stress series to support further quantifying the influence of a stressor event. Splitting interval is a common time series problem, and various solutions can be referred. Here we identify stressful intervals impacted in three steps. In the first step, we extract uplift events, stressor events and filter out candidate intervals after smoothing process. Then, on the basis of Poisson based method proposed in [18], we judge the existence of stressful interval. Finally, we divide the stressful intervals into two sets: the SI and U-SI, according to its temporal order with neighbour uplift events.

Regression. Since teen's stress series $S = \{s_1, s_2, \cdots, s_n\}$ detected from microblogs (per day) are discrete points, we adopt the loess (local regression using weighted linear least squares and a 2nd degree polynomial model) method [xx] to highlight characteristics of the stress curve. In loess method, we need to set the parameter *span*, which represents the percentage of the total number of data points in the whole data set (ranging from 0 to 1), and determines the degree of smoothing. We discuss the effect of different *span* settings on the result of interval segmentation in experiment section.

Candidate intervals. Then we filter out candidate intervals on the smoothed stress series $S^{'} = \{s_1^{'}, s_2^{'}, \cdots, s_n^{'}\}$. As illustrated in Figure xx, we define the sub-series $w_{<a,b>} = [s_a^{'}, \cdots, s_b^{'}]$ as a *wave*, where $s_a^{'} = vally(w_{<a,b>})$ is the minimum value, and $s_p^{'} = peak(w_{<a,b>})$ is the maximal value during $\{s_a^{'}, \cdots, s_b^{'}\}$. A candidate interval $I =< w_1, \cdots, w_i, \cdots, w_m >$ with the peak value α ($peak(w_i) = \alpha$) is identified using following rules:

- $s_1^{'} = 0$, $s_m^{'} = 0$. $\forall s_j^{'} \in \{s_2^{'}, \cdots, s_{m-1}^{'}\}$, $s_j^{'} > 0$.
- For waves w_k before the interval peak α , i.e., $w_k \in < w_1, \cdots, w_i >$, $peak(w_{k+1}) >= peak(w_k)$, $vally(w_{k+1}) >= peak(w_k)$.
- For waves w_k behind the interval peak α, i.e., $w_k \in < w_{i+1}, \cdots, w_m >$, $peak(w_{k+1}) <= peak(w_k)$, $vally(w_{k+1}) <= peak(w_k)$

Poisson based method. For each candidate interval, a poisson based probability model is adopted to measure how confident the current interval is a stressful interval. Here teen's stressful posting rate under stress (λ_1) and normal conditions (λ_2) are modeled as two independent poisson process

$$Pr[N = n|\lambda_i] = \frac{e^{-\lambda_i T}(\lambda_i T)^n}{n!} \tag{1}$$

where $i \in \{0, 1\}$, $n = 0, 1, \cdots, \infty$ We expect that $\lambda_1 > \lambda_0$, and measure the probability as $P(\lambda_1 > \lambda_0|N_1, T_1, N_0, T_0)$, where N_1, N_0 are the number of stressful posts, and T_1, T_0 are time duration corresponding to λ_1 and λ_0. Without loss of generality, we assume a Jeffreys non-informative prior on λ_1 and λ_0, and infer the posterior distribution $P(\lambda_1|N_1)$ and $P(\lambda_0|N_0)$ according to Bayes Rule. Thus for current interval I_1 and historical normal interval I_0, the quantified probability $\beta = P(\lambda_1 > \lambda_0|I_1, I_0) \in (0, 1)$ indicates the confidence if I_1 is a stressful interval.

Interval impacted by Uplift events. In this part, we filter out two sets of stressful intervals: stressful intervals without the interference of uplift events (SI), and stressful intervals under the impact of uplift events (U-SI). For a detected stressful interval $I =< t_1, \cdots, t_n >$, we consider the temporal order between I and any detected uplift event u happened at time point t_u:

- If an uplift event happens during stressful interval, i.e., $t_u \in [t_1, t_n]$, the uplift interval I is judged as $I \in SI$.
- For uplift event happens nearby a stressful interval, we also consider the probability that it conducts impact teen's stressful interval. Here the gap between t_u and I is limited to ξ, i.e., $t_u \in [t_{1-\xi}, t_1) \cup (t_n, t_{n+\xi}]$.

The setting of parameter ξ is discussed in experiment section.

VI. Impact of Uplift Events

To quantify the impact of uplift event, in this section, we propose to model the impact as the correlation between two situations: 1) stressful interval (SI), and 2) stressful interval impacted by uplift events (U-SI). Multi stress-related measures are proposed to describe the correlation between SI and U-SI, and we quantify such correlation using a two-sample method.

A. Restoring Patterns and Behavioral Measures

To extract the restoring patterns of uplift events, we describe teen's stressful behavioral measures during SI and U-SI from both the temporal and linguistic perspectives.

Posting behavior. Stress could lead to teen's abnormal posting behaviors, reflecting teen's changes in social engagement activity. For each stressful interval, we consider three measures of posting behaviors on each time unit (day), and present as corresponding series. The first measure is *posting frequency*, representing the total number of posts per day. Research in [] indicates that over whelmed teens usually tend to post more to express their stress for releasing and seeking comfort from friends. Further, the second measure *stressful posting frequency* shows the number of stressful posts per day. This measure is based on previous stress detection result and highlights the stressful posts among all posts. The third measure *original frequency* shows the number of original tweets. Compared to forwarded posts, original posts indicate higher probability that teens are talking about themselves. Thus for each day in current interval, teen's posting behavior is represented as a three-dimension vector.

Stress Intensity. We describe the stress intensity during stressful intervals through four measures: *sequential stress level, length, RMS,* and *peak*. Basically, *stress level* per day construct a sequential measure during a stressful interval, recording stress value and fluctuation on each time point. The *length* measures the length of current stressful interval. As uplift events might conduct impact on overwhelmed teens, postpone the beginning or promote the end of the interval, we take the *length* as a factor of the interval stress intensity. To quantify the intensity of stress changes, we adopt the *RMS* (root mean square) of stress value through the interval as the third measure. In addition, *peak* stress value is also a measure to show the maximal stress value in current interval.

Linguistic. We extract teen's stressful expressions from the content of posts during SI and U-SI, respectively. The first linguistic measure is the frequency of *topic word* for each of the five stressor event dimensions, which represents how many times the teen mentioned about a stressor event, indicating the degree of attention for each type of stressor event. The frequency of *pressure word* is the second measure, reflecting the degree of general stress emotion of the teen. We adopt measure specifically because in some cases teens post very short tweets with only emotional words, and type-based words are omitted. Another important factor to describe the impact of stressor events is wether existing *self-mention word* (i.e., *'I','we','my'*). Self-mention words show high probability that the current stressor event and stressful emotion is related to the author, rather than the opinion about a public event or life events about others. Except stressful linguistic descriptions, we also take the frequency of *positive word* as a measure, which is opposite with stress-related measures, and also offers information from the opposite perspective.

Based on the posting behavior, stress intensity and linguistic measures, we quantify the correlation between SI and U-SI, thus to measure the impact of uplift events.

B. Quantify the Correlation

In our problem, there are two sets to compare: the set of SI and the set of U-SI, containing stressful intervals without uplifts and stressful intervals impacted by up lift events, respectively. As the basic elements in each set are intervals, the series value in time line, we formulate this comparison problem as finding the correlation between two sets of multi-dimension points, where each time unit is represented as a point with multi-dimension stress measures. Specifically, we adopt the multivariate two-sample hypothesis-testing method [] to model such correlation. In this two-sample test problem, the hypothesis is that the points in set SI and U-SI are under different unknown distribution. Assume points in SI and U-SI are randomly sampled from unknown distribution F and G respectively, the hypothesis is denoted as:

$$\begin{cases} H_0 : F = G \\ H_1 : F \neq G \end{cases} \tag{2}$$

Under such hypothesis, H_0 indicates points in SI and U-SI are under similar distribution, while H_1 means SI and U-SI are under statistically different distributions, namely uplift events conduct obvious restoring impact on stressed teens.

We handle this two-sample tests problem based on teens three groups of stressful behavioral measures, thus to quantify the restoring patterns of uplift events from multi perspectives. As a classic statistical topic, various algorithms have been proposed to solve the two-sample testing problem. For the two sets SI and U-SI, each point is depicted using multi measures, and we mine the correlation for each measure. Here the KNN (k nearest neighbour) based method is conducted to judge the existence of correlation between SI and U-SI, and two distance algorithms are adopted according to the type of different stress measures. To analyze the correlation for a multi-dimension measure, is . For each single-dimension measure, Pearson based correlation algorithm are adopted.

1) Correlation for multi-dimension measures: To measure the correlation for each multi-dimension measure, the Euclidean distance is used to calculate the distance of structured points in SI and U-SI. Following section xx, multi-dimension measures considered here are *posting behavior* and *linguistic*, indicated as D_p and D_l.

To measure the distance between κ-dimension points in two sample sets S_y^{pre} and S_r, we adopt the nearest neighbor based method here for our two-sample test problem [xx]. The basic idea is that for each point ℓ_x in the two sets, we hope its nearest neighbors (*most similar points*) belonging to the same set of ℓ_x.

Given the two sample sets composed of stress intervals $A_1 = S_y^{pre}$ and $A_2 = S^r$, for each point $\ell x \in A = A_1 \bigcup A_2$, we define function $NN_r(\ell_x, A)$ as the $r-$th nearest neighbor of ℓ_x. Specifically, let $SNN_r(\ell_x, A)$ and $LNN_r(\ell_x, A)$ be two sub-functions of $NN_r(\ell_x, A)$ based on temporal pattern and linguistic distribution, respectively. For point ℓ_x with temporal pattern matrix $\mathbf{P}_x$ and linguistic distribution vector $\mathbf{d}_x$, the $r-$th temporal-based neighbor is:

$$SNN_r(\ell_x, A) = \{y | min\{||\mathbf{P}_x - \mathbf{P}_y||_2 | y \in (A/\ell_x)\}\} \tag{3}$$

We define function $I_r(\ell_x, A1, A2)$ to indicate whether the r-th nearest neighbor $NN_r(\ell_x, A)$ belongs to the same sub-set with ℓ_x:

$$I_r(\ell_x, A_1, A_2) = \begin{cases} 1, if \ell_x \in A_i \&\& NN_r(\ell_x, A) \in A_i, \\ 0, otherwise \end{cases} \tag{4}$$

We use $T_{r,n}$ to indicate the proportion that pairs containing two points from the same set among all pairs formed by $\ell_x \in A$ and its nearest neighbors:

$$T_{r,n} = \frac{1}{nr} \sum_{i=1}^{n} \sum_{j=1}^{r} I_j(x, A_1, A_2) \tag{5}$$

The ratio of above neighbors indicates the difference of the two sample sets. We expect that $T_{r,n}$ is close to 1 thus the two underlying distribution F and G for S_y^{pre} and S^r is significantly different, meaning stressor events of type y have obvious impact on teens' stress series.

According to the hypothesis test theory [xx], when the size of S_y^{pre} and S_r are large enough, the statistic value $Z = (nr)^{1/2}(T_{r,n} - \mu_r)/\sigma_r$ obeys a standard Gaussian distribution, with the expectation μ_r and variance ${\sigma_r}^2$

$$\mu_r = (\lambda_1)^2 + (\lambda_2)^2 \tag{6}$$

$${\sigma_r}^2 = \lambda_1\lambda_2 + 4{\lambda_1}^2{\lambda_2}^2 \tag{7}$$

where $\lambda_1 = |A_1|$ and $\lambda_2 = |A_2|$. Thus we judge whether stressor events of type y has intensive correlation with teens' stress series as: if $C = (nr)^{1/2}(T_{r,n} - \mu_r)/{\mu_r}^2 > \alpha$ (here

α = 1.96 for P = 0.025), the stressor events E_y has intensive correlation with stress series, where $C^L = C$ if $NN_r = LNN_r(.)$, $C^T = C$ if $NN_r = SNN_r(.)$.

2) Correlation for single dimension measure: For measures in single-value format, we simplify the distance measure between SI and U-SI, and represent the nearest neighbour as

$$SNN_r(\ell_x, A) = \{y|min\{|\mathbf{P}_x - \mathbf{P}_y||y \in (A/\ell_x)\}\} \quad (8)$$

C. Temporal Order

To measure the impact intensity of SI and U-SI in temporal order, we further quantify intensity on time series by comparing with the neighbouring front and rear intervals, respectively. For a stressful interval $I =< t_i, t_{i+1}, \cdots, t_j >$, let $I^{front} =< t_m, \cdots, t_{i-1} >$ be the interval front of I, and $I^{rear} =< t_{j+1}, \cdots, t_n >$ be the interval behind of I. The length of I^{front} and I^{rear} are set to threshold l. For the set of stressful intervals SI composed of $< I_1, I_2, \cdots, I_N$, the corresponding sets of front and rear neighbouring intervals are denoted as SI^{front} and SI^{rear}. Similarly, for the set of stressful intervals $U - SI = < UI_1, UI_2, \cdots, UI_M >$ impacted by uplift events, the corresponding sets of front and rear neighbouring intervals are denoted as USI^{front} and USI^{rear}. We compare the difference of impact intensity of SI with USI in following four situations, where $g(.)$ is the function comparing two sets.

① $g(SI, SI^{front})$ returns if intensive change happens when stressful intervals begin.
② $g(SI, SI^{rear})$ returns if the teen's stress change intensively after the stressful intervals end.
③ $g(USI, USI^{front})$ returns if intensive change happens when stressful intervals affected by uplift events appears.
④ $g(USI, USI^{rear})$ returns if stress change intensively after stressful intervals affected by uplift events end.

Here we adopt the t-test as intensity computation function $g(.)$. The t-test algorithm measures if intensive positive or negative correlation exists between two sets. In our situation, taking the comparison between SI and SI^{rear} for example, the computation elements I_k in both sets are multi-dimension intervals. The function $g(.) = t_{score} \in$ (-1,1) is represented as

$$t_{score} = \frac{\mu_{SI} - \mu_{SI^{rear}}}{\sqrt{\frac{(n_1-1)\sigma_{SI}^2 + (n_2-1)\sigma_{SI^{rear}}^2}{n_1+n_2-2}(\frac{1}{n_1} - \frac{1}{n_2})}} \quad (9)$$

where μ_{SI} and $\mu_{SI^{rear}}$ are the mean values in the set of stressful intervals SI and SI^{rear}, respectively. σ_{SI} and $\sigma_{SI^{rear}}$ are the variance values in SI and SI^{rear}. If $g(SI, SI^{rear}) > \alpha$, values in SI^{rear} show significant decrease compared with SI (monotonic negative effect). If $g(SI^{front}, SI) < -\alpha$, values in SI show significant increase compared with SI^{front} (monotonic positive effect). Here we adopt α = 1.96, P = 0.025.

D. Overall Algorithm

We present the overall algorithm in using pseudo code xx. To quantify the restoring impact of uplift events, we first extract uplift events from post content. Then we divide the set of stressful intervals SI, and the set of stressful intervals impacted by uplift events USI. The KNN based two-sample method are conducted on the two sets in multi stressful behavioral measures (posting behavior, linguistic and intensity), to judge if SI are statistically different with USI. Then next step comes to comparing SI and USI with neighbouring intervals, respect to temporal order. The output of the whole algorithm is represented as .. *Parameter settings.*

VII. Experiments

In this section, we integrate the impact of uplift events into traditional stress series prediction problem in time line, and verify whether the deduced restoring pattern of uplift events could help improve the prediction performance, thus to show the effectiveness of our method for quantifying the impact of uplift events, as well as the easing function of uplift events during teens' stress dealing process.

A. Experimental setup

1) Data set: We take the same data set in previous case study (Section 3), which contains 29,232 microblogs of 124 students from Taicang High School of Jiangsu Province from Tencent Microblog platform[2], posted from 2012/1/1 to 2015/2/1. To protect privacy, usernames are anonymized in the experiment. We collect the school's weekly plans published on its official website[3]. Among the 273 school scheduled events filtered out, 122 events are study-related stressors, xx events are uplift events. Based on the scheduled time of stressors and uplift events, we identified xxx stressful intervals (SI) and xxx stressful intervals impacted by uplift events (USI). Further experiments are conducted on the two sets to verify the impact of uplift events from multi perspectives.

2) Baseline methods: To show the effectiveness, we adopt the commonly used average value based and Pearson correlation algorithms to compare with the knn-based two-sample method in this paper. As a widely adopted measure of the linear correlation between two variables, the Pearson correlation method computes a value in the range $(-1, 1)$, where 1 denotes total positive linear correlation, 0 denotes no linear correlation, and -1 is total negative linear correlation. The Pearson correlation between two variables X and Y is presented as:

$$\rho_{X,Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (10)$$

where μ_X and μ_Y is the mean value of X and Y, respectively; $E(.)$ is the expectation function; $E[(X-\mu_X)(Y-\mu_Y)]$ is the covariance of the two variances X and Y.

In the KNN (k nearest neighbours) based two-sample procedure, to calculate the distance between two n dimension points X and Y from different perspectives, we adopt both the L_1 and L_2 measures, denoted as $L_1 = \sum_{i\in[1,n]} |X_i - Y_i|$, and $L_2 = \sqrt{\sum_{i\in[1,n]}(X_i - Y_i)^2}$ (the Euclidean metric).

[2]http://t.qq.com/
[3]http://stg.tcedu.com.cn/

TABLE IV: Comparison of the uplift event impact based method with the baseline forecast approach

	Uplift (S&L)				Uplift (S|L)				Uplift (S)				Uplift (L)			
	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD
School	0.0356	0.1138	0.2574	0.1009	0.1153	0.1933	0.3355	0.1798	0.1753	0.2530	0.3953	0.2396	0.0853	0.1631	0.3036	0.1496
Romantic	0.0234	0.0945	0.2716	0.0834	0.1031	0.1732	0.3437	0.1616	0.1632	0.2334	0.4041	0.2219	0.0731	0.1432	0.3127	0.1316
Peer	0.2461	0.1575	0.3742	0.1405	0.3251	0.2375	0.4080	0.2202	0.3851	0.2975	0.4679	0.2802	0.2951	0.2072	0.3660	0.1898
Healthy	0.0248	0.0975	0.2684	0.0864	0.1044	0.1760	0.3441	0.1645	0.1645	0.2363	0.4045	0.2247	0.0744	0.1460	0.3138	0.1344
Family	0.0481	0.1094	0.2919	0.0961	0.1279	0.1882	0.3428	0.1747	0.1879	0.2481	0.4041	0.2345	0.0978	0.1581	0.3136	0.1445
All	0.0756	0.1145	0.2927	0.1015	0.1552	0.1936	0.3548	0.1802	0.2152	0.2537	0.4152	0.2402	0.1251	0.1635	0.3219	0.1500

Fig. 3: Correlation towards each types of stressor events

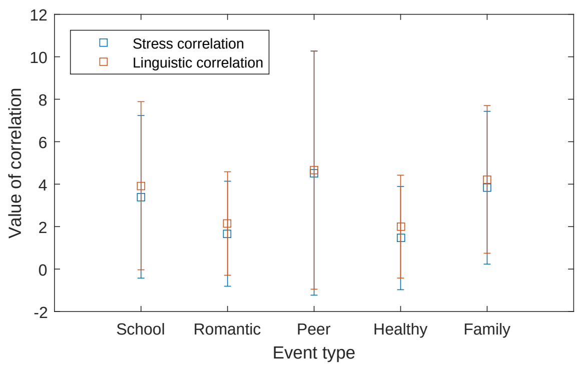
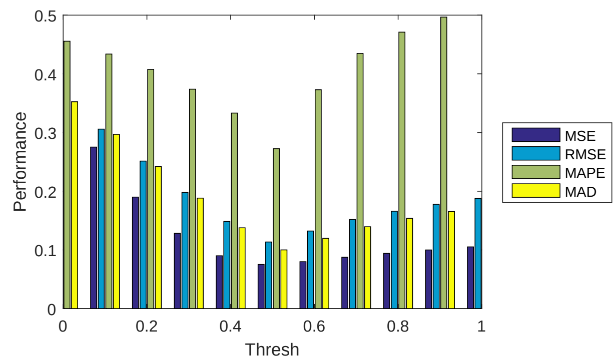


Fig. 4: Stress prediction performance under S&L pattern.



3) Metrics: To measure the effectiveness of our method for quantifying the impact of uplift events, we integrate the impact of uplift events into traditional stress series prediction problem in time line, and verify whether the deduced restoring pattern of uplift events could help improve the prediction performance. Here we choose the SVARIMA (Seasonal Autoregressive Integrated Moving Average) algorithm [**?**], which is proved to be suitable for teenagers' stress series prediction problem [14], due to the data seasonality and non-stationarity.

The basic stress prediction is conducted using SVARIMA approach, in the set of stressful intervals impacted by uplift events (USI). Since stressor events cause the fluctuation of stress series from normal states, and the simple series prediction method is difficult to handle such exception. To eliminate the interference, we simply consider the prediction problem in those stressful intervals rather than randomly picked out stress series. Further, the impact of uplift events are utilized as 'adjust value' to modify the stress prediction result.

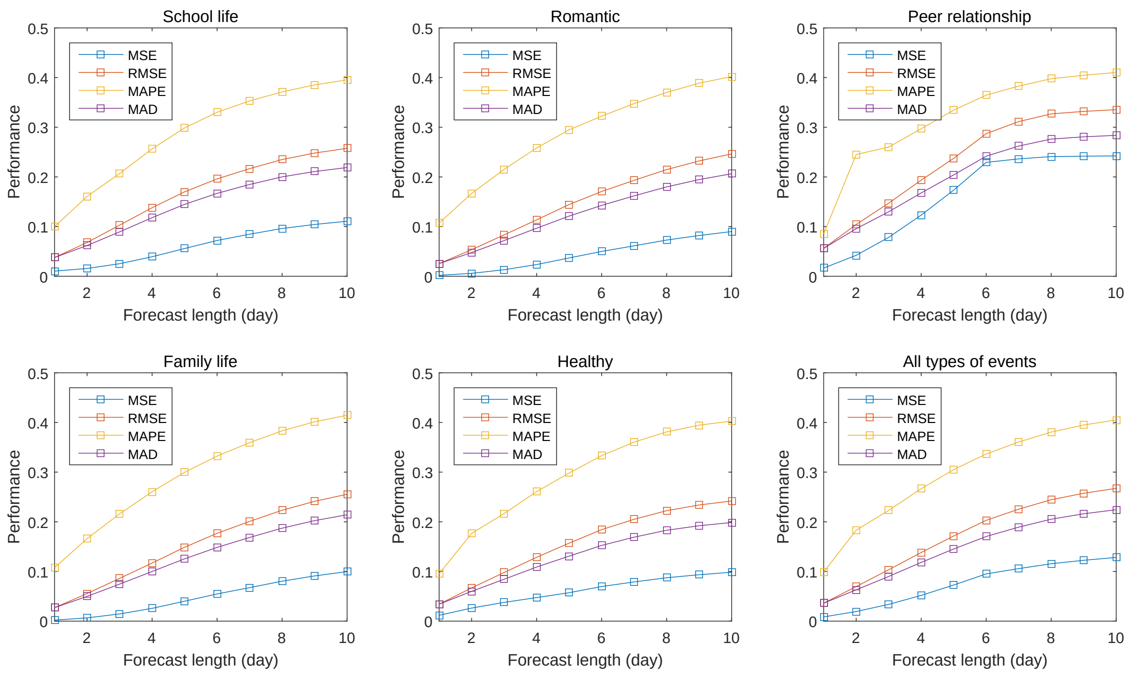
We adopt three metrics to measure the stress forecasting problem, where *MSE* and *RMSE* measure absolute error and *MAPE* measures relative error. For all real stress $\overline{s_i}$ and predicted stress s_i in predicting sequence, $MSE = \sum(s_i - \overline{s_i})^2$, $RMSE = \sqrt{MSE}$, and $MAPE = \sum |s_i - \overline{s_i}|/\overline{s_i}$.

B. Impact of uplift events

We first apply the impact of uplift events into stress prediction. The experimental set contains xxx stressful intervals under the impact of uplift events (USI). The number of each type of uplift events and stressful intervals are lists in Table xx. The original prediction result using only SVARIMA is showed in Table IV, with the highest performance (0.0847 MAPE, 0.2167 MSE, 0.4153 RMSE, and 28.38%MAPE) in 'school life' uplifts restoring the stress from 'self cognition', and the total performance achieves 0.2003 MAD, 0.22544 MSE, 0.42432 RMSE and 0.3893 MAPE($L = 7$, $\alpha = 0.5$). The distribution of both linguistic and stress intensity correlations of all testing students is shown in 3 in each of the five stress types, among which 'school life' and 'peer relation' stress exhibit most intensive correlations. Then we take the impact of each type of uplift events into consideration on the prediction result. Specifically, for uplifts with obvious restoring function, the average stress level during historical restoring patterns are integrated to modify the result (details in Section IV). After the modification, the prediction performance achieves 0.1015 MAD, 0.0756 MSE, 0.1145 RMSE, and 29.27% MAPE, with 49.32%, 66.46%, 73.20% and 54.63% improvements respectively. The highest improvement is observed for the uplift event 'school life', which appears most frequently in our collected data set.

We present the prediction result under the impact of uplift events for five types stressor events, with prediction interval ranging from 1 to 10 days, as shown in 5. With the increasing of period length, the prediction performance shows the decreasing trend in all metrics. The reason is that the longer prediction takes the previous predicted result, and the error accumulated with more predicted values taken into the next step prediction. Among the five types of events, the prediction for school life stress achieve the best performance. On one side, more uplift events and stressors about school life events are detected from teens microblogs, providing more sufficient data in prediction. On the other side, stress coming from school life is the most common stress in the student group, with

Fig. 5: Teens' stress prediction performance under different length.



relative stable periodicity and high frequency. And ...

C. Contribution of each measure

We conduct experiments with each measure included respectively to show its contribution for the correlation during prediction. Four situations are considered here, considering 1) both the stress intensity correlation and linguistic correlation (the S&L pattern), 2) the linguistic correlation or the stress intensity correlation (the S|L pattern), 3) only the linguistic correlation (the L pattern), and 4) only the stress intensity correlation (the S pattern). We integrate the impact of uplift events under the four patterns into stress prediction using the parameter α, as overlapping $\alpha \times S_{historical}$, where $S_{historical}$ is the average stress level. The detailed adjust process is presenting in section VII-D. Here we present the prediction result when $\alpha = 0.5$. The performance are presented in Table IV, with each type of stress respectively, and the overall performance for all types of stress. Results show that the correlation in the S&L pattern outperforms other three patterns (0.0756 MSE, 0.1145 RMSE, 29.27% MAPE and 0.1015 MAD), showing the effectiveness of considering both the two correlations. The restoring impact performs best in *school* dimension, achieving 25.74% MAPE, reflecting teens' relative higher stress in school life and the necessary of timely restoring and prevention.

D. Parameter settings

We further adjust the parameter α when integrate the impact of correlation into future stress prediction. For each of the for restoring patterns (S&L, S|L, S and L), we adjust α in the effect of $\alpha \times L$. We calculate the corresponding prediction result for each teen respectively, and show the result of the whole testing group using the averaging performance. Fig. 4 shows the changing trend in the S&L pattern. The performance is improved first and then deteriorates, and the best performance is achieved when α is nearby 0.5, with 0.1015 MAD, 0.0756 MSE,0.1145 RMSE, and 29.27% MAPE as the average performance of whole experimental data set.

VIII. Discussion

A. Limitation and advantage of correlation analysis

B. Exploring the spread of positive power in social networks

IX. Conclusion

In this paper, we give a deep inside into the restoring impact of uplifts on the real data set of xx teenagers from three high schools, and correlate the stress restoring patterns with uplift events. A two-sample based statistical model is conducted to analyze the stressful behavioral correlation between uplift (U-SI) and non-uplift (SI) stressful intervals from both linguistic and stress intensity perspectives. Experimental results show that our method could measure the restoring impact of uplift events in three experimental situations, and obtains high performance (0.0756 MSE, 0.1145 RMSE, 29.27% MAPE and 0.1015 MAD) on real data set. Our research provides guidance for school and parents that which kind of uplift events could help relieve students' overwhelmed stress in both stress prevention and stress early stopping situations. Our future work will focus on digging the overlap impact of multiple uplift events in more complex situations, as well as the frequent appearing patterns of uplift events and stressors, thus to provide more accurate analysis and restoring guidance for individual teenagers.

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