Examining Accumulated Emotional Traits in Suicide Blogs with an Emotion Topic Model

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***Abstract*—Suicide has been a major cause of death throughout the world. Recent studies have proved a reliable connection between the emotional traits and suicide. However, detection and prevention of suicide are mostly carried out in the clinical centers, which limits the effective treatments to a restricted group of people. To assist detecting suicide risks among the public, we propose a novel method by exploring the accumulated emotional information from people's daily writings (i.e. Blogs), and examining these emotional traits which are predictive of suicidal behaviors. A complex emotion topic (CET) model is employed to detect the underlying emotions and emotion-related topics in the Blog streams, based on eight basic emotion categories and five levels of emotion intensities. Since suicide is caused through an accumulative process, we propose three accumulative emotional traits, i.e., accumulation, covariance, and transition of the consecutive Blog emotions, and employ a generalized linear regression algorithm to examine the relationship between emotional traits and suicide risk. Our experiment results suggest that the emotion transition trait turns to be more discriminative of the suicide risk, and that the combination of three traits in linear regression would generate even more discriminative predictions. A classification of the suicide and non-suicide Blog articles in our additional experiment verifies this result. Finally, we conduct a case study of the most commonly mentioned emotion-related topics in the suicidal Blogs, to further understand the association between emotions and thoughts for these authors.**

***Index Terms*—Suicide risk prediction, accumulated emotional traits, emotion accumulation, emotion covariance, emotion transition**

I. Introduction

According to the World Health Organization (WHO), suicide has been among the top three causes of death in the worldwide, leading to one death in every forty seconds [1]. And the problem is even more severe among the young people of fifteen to nineteen years old [2]. Researchers find that among all the risk factors of suicide, the mental health problem has been a major cause [3][4][5][6][7][8].

In the psychological research of suicide risk, it has been well-proved that some emotional factors such as the emotional dysregulation [9], the emotion-driven loss of control characteristic of negative urgency [10], and some particular emotion expressions like anger [11] and anxiety [12] are closely related to the high risks of suicide, based on Joiner's interpersonal-psychological theory of suicidal behavior (IPTS) [13][14][15]. Some other emotional factors such as emotional reactivity [16], emotional intensity [17], and emotional instability [18] have also been proved to be associated with the suicide schema, the elaboration of which could cause increment in suicide risks. Besides, people's emotion regulations which both internally and externally [19] affect the non-suicide self-injury (NSSI) have also been found a strong predictor of suicide attempts [20].

For a specific group of people within clinical centers [21][22], the current interventions of suicidal behavior are accurate and effective, by evaluating the patients' physiological and biochemical indicators, and by delivering physician education in depression recognition and proper treatments [21]. It is also noticeable that the wearable activity recognition techniques have recently been experimented in the analysis of mental diseases including bipolar disorder [23][24][25][26] and mental stress [27], which offer automatic transformation of patients' physical statistics to the clinical centers. However, it could still be too expensive to deliver such resources to large mount of people outside the clinical centers [28], who are potentially at the suicide risk.

To assist detecting suicide risks among the public, we propose a novel method by exploring the emotional information from people's daily writings, i.e. Blog articles on the social network, and examining several important emotional traits in Blog streams for suicide risk prediction. Public Blog streams have been collected from two groups of people: those who have publicly committed suicide and those who have been randomly chosen from Blog sites with a post-examination of their suicidal ideation. All private information has been previously removed. The Blogs are fed to a complex emotion topic (CET) model [29] to find the emotional information as well as the emotion-related topics. For example, for the sentence "Jo:2|Lo:2 *Life* was *bitter*, but I was *glad* to have you around."[29], emotions of Joy and Love have been found with corresponding intensity scores of 2, representing an intensity level between low and median. Words of "Life", "bitter", and "glad" are detected as the emotion-related topics, since their existence are associated with certain emotions.

The basic emotion categories in this study follows the definition of human emotions in the Chinese emotion corpus (Ren-CECps) [30], including three positive emotions of Joy, Love, Expectation, four negative emotions of Anxiety, Sorrow, Anger, Hate, and a special emotion Surprise which could be either positive or negative depending on the context. The emotion intensity covers five levels from weak to strong,

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with the corresponding intensity score ranging from 1 to 5[1]. Because people usually express mixture emotions in their writings [29][31], we use a complex emotion representation which composes multiple emotion entries in this study.

Psychological studies [32][33] suggest that suicidal behaviors are caused by an accumulative process, and the study of connection between unstable emotions and suicide risks [18] also suggests that the repeated bursts of negative emotions in a long history could strengthen or elaborate the suicide schema and increase the suicide risks. Following these researches of the emotional factors in suicide, we develop three accumulated emotional traits, i.e. emotion accumulation, emotion covariance, and emotion transition based on the detected complex emotions in Blog streams. These emotional traits represent the Blog authors' mental states and characterize their emotion expression properties within a period of time. We compare these emotional traits in the suicide and non-suicide groups, and use them to predict the suicide risks.

In this study, we define a severity score to evaluate the suicide risk, and further assume that risk scores of people who have committed suicide should be higher than those of the normal people. This gives rise to a linear regression model which associates the risk scores with our emotional traits in Blog articles, as well as the accumulation of these risk scores for suicide prediction. Besides evaluating the suicide risk, we would also like to understand the particular reasons of these suicides, by looking into the emotion-related topics underlying the authors' writings. Each topic corresponds to a collection of words with similar word distributions and similar word-emotion co-occurrences through the Blog stream. By observing the emotion-related topics, we can better understand the concerns in people's writings, as well as their emotions particularly related to these concerns.

The rest of this paper is organized as follows. In section II, we review the recent studies of emotional traits in suicide prediction, suicide predictions from texts, and methods of text emotion recognition. In section III, we describe CET model for complex emotion recognition in Blog articles, and briefly explain the emotion inference method in this model. In section IV, we illustrate the idea of accumulated emotional traits in Blog streams for evaluating the authors' suicide risks, and compare the distribution of these traits in the suicide and non-suicide groups. In section V, we propose a linear regression model to detect the Blog authors' suicide risks, based on the emotional trait features in Blog streams. In section VI, we illustrate the suicide and non-suicide Blog streams in our experiment and the Ren-CECps emotion corpus for developing the CET model. In section VII, we describe the experiment of suicide risk detection, show the accumulated suicide risks, evaluate the regression results, and analyze the emotion-topic associations. Finally, in section IX we conclude this paper.

II. Related work

Recent psychological studies have found close connections between people's emotion expression and their suicide risk, based on Joiner's IPTS (interpersonal-psychological theory of suicidal behavior) theory [13][14][15]. For example, anger and the constructs of aggression and hostility were found closely related to the triggering of regular interpersonal conflicts and relationship problems [34][35], which explained the generation of a suicide ideation [11]. Anger was also found responsible for the violent or aggressive behavior [36][37] and self-injury [38], which indirectly contributed to the exposure to painful and provocative events and would increase the individual capability to complete lethal suicide actions. In a study of affect dysregulation and suicide [12], anxiety was found closely related to the suicidal ideation and suicide attempt history.

Suicide schema as a general idea of latent suicidogenic cognitive structure [39] is another indicator of the suicide risk. The development of suicide schema was found consistently linked with the increased suicide risk [40][17]. Recent findings suggested that the emotional traits of increased emotional reactivity, range, and experience were responsible for the activation of suicide schema [16]. Other emotional traits like instability and intensity, as demonstrated in the studies [17][18], would repeatedly trigger and eventually elaborate the suicide schema.

The accumulated burden over life trajectory of suicide people was found in Séguin and colleagues' study [33], by collecting the third-party information on consecutive suicides for every five-year life-history. A more recent study by Carlborg and colleagues [32] also suggested the previous suicidal attempts significantly contributed in the suicide risks, by examining the association between accumulated suicide attempts and the committed suicides, according to the suicidal attempt histories from the medical records of 224 inpatients with schizophrenia spectrum psychosis.

There have been also researches and attempts of detecting suicide risks through analyzing people's words, such as the poems of suicidal poets [41], the recorded memories of suicide attempts [42], and the suicide notes [43][44]. The analysis of language usage in poems suggested that the frequency of individual self mentions was significantly higher in the suicide poets than in the non-suicide poets [41]. The examination of personal memories indicates that emotionally negative memories are biased towards people who recently attempted suicide [42]. And the emotion classification of suicide notes [43][44] showed promising results for physicians to detect suicidal messages and to assess suicide risks.

Text emotion prediction is to find emotions in words, sentences, and documents. For example, [45][46] predicted emotion labels for words with CRF (Conditional Random Fields) models, by considering the context features. To predict complex emotions in words and phrases, [31][47] proposed a Bayesian model to infer multiple emotions and emotion intensities for words and to generate emotion-related topics for further analysis of word emotion variation. For sentence emotion prediction, massive examples from Internet were investigated by [48], and a kernel-based method was proposed by [49] to generate sentence emotions directly from the inside word emotions. Enlightened by the unsupervised and supervised topic models [50][51][52][53], a recent work [29] incorporated the complex document emotions in a revised topic model, and studied the association between emotions

[1]The original definition of emotion intensity in Ren-CECps covers ten scores, ranging from 0.1 to 1.0. In this study we simplify this representation by mapping ten intensities to five categorical levels.

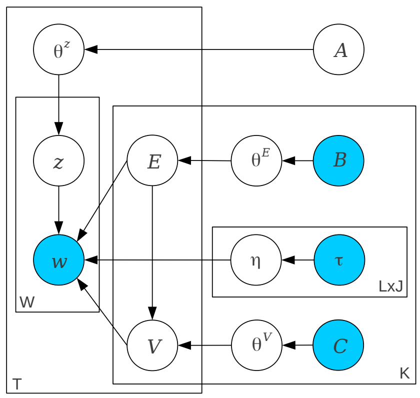

Fig. 1. The complex emotion topic model, where nodes represent the random variables and edges represent the dependencies.

in documents and semantic meanings in topics. Other studies such as [54] and [55] also specified significant emotional features for the multi-class document emotion classification.

III. Complex emotion topic model

The complex emotion topic (CET) model [29] is employed to retrieve complex emotions from Blog articles. Specifically, for each Blog article this model would recognize any basic emotions of Joy, Love, Expectation, Surprise, Anxiety, Sorrow, Anger, and Hate, as well as the associated emotion intensities from weak to strong in five levels. Besides, the model also generates a set of emotion-related topics, as lists of words with similar semantic meanings. The graph representation of the CET model is shown in Figure 1.

Basic emotions are explicitly represented as binary random variables E_{tk} within the overlapping Blog plate T and emotion category plate K. A plate is used to replicate the inside variables, with the number of replications on its corner. Each Blog article t is associated with K latent emotion variables E_{tk}, with $k \in \{1, \dots, K\}$ and several latent emotion intensities V_{tk}. Inside these Blog articles, words are represented by observed variables w_{ti} within the overlapping word plate W and topic plate T, with W counting the number of words in Blog t and $i \in \{1, \dots, W\}$. Topics, as the semantic clustering of words, are denoted as the latent variable z_{ti}.

The CET model is a generative model, which means the values of words w_{ti}, topics z_{ti}, Blog emotions E_{tk}, and emotion intensities V_{tk} could be generated by sampling through a set of probabilistic distributions as

$$\begin{aligned} z_{ti} &\sim \mathrm{Cat}(\theta^z_t), \\ E_{tk} &\sim \mathrm{Ber}(\theta^E_k), \\ V_{tk}|E_{tk} &\sim \mathrm{Cat}(\theta^V_k), \\ w_{ti}|z_{ti}, E_t, V_t &\sim \mathrm{Cat}(\eta_{E_t V_t z_{ti}}), \end{aligned} \tag{1}$$

where Cat and Ber are the Categorical and Bernoulli distributions, respectively, and θ^z_t, θ^E_k, θ^V_k, and $\eta_{E_t V_t z_{ti}}$ are the distribution parameters. In Bayesian models, the distribution parameters are also treated as random variables, with the corresponding distributions of

$$\begin{aligned} \theta^z_t &\sim Dir(A), \\ \theta^E_k &\sim Beta(B_k), \\ \theta^V_k &\sim Dir(C_k), \\ \eta_{klj} &\sim Dir(\tau_{klj}), \end{aligned} \tag{2}$$

where Dir and $Beta$ specify the Dirichlet and Beta distributions, respectively, k, l, j correspond to the assignment of document emotion E, emotion intensity V, and word topic z, respectively, and A, B, C, τ indicate the concentration parameters in these Dirichlet and Beta distributions.

As a generative model, the CET model is associated with a joint probability over all the inside random variables. Therefore, the values of latent variables of interest can be easily inferred through Gibbs sampling in Algorithm 1, with the following derived conditional probabilities of these variables. Detailed derivations can be found in [29].

$$\begin{aligned} p(E_t|w, z, E_{-t}, V; A, B, C, \tau) \propto \frac{n_{E_t} + B_{E_t}}{T + B_*} \times \\ \exp\left(\frac{a}{|W_t|}\sum_{i\in W_t} \log\frac{n_{E_t V_t z_{ti} w_{ti}} + \tau_{E_t V_t z_{ti} w_{ti}}}{n_{E_t V_t z_{ti} *} + \tau_{E_t V_t z_{ti} *}}\right), \end{aligned} \tag{3}$$

$$\begin{aligned} p(V_t|w, z, E, V_{-t}; A, B, C, \tau) \propto \frac{n_{E_t V_t} + C_{E_t V_t}}{n_{E_t *} + C_{E_t *}} \times \\ \exp\left(\frac{a}{|W_t|}\sum_{i\in W_t} \log\frac{n_{E_t V_t z_{ti} w_{ti}} + \tau_{E_t V_t z_{ti} w_{ti}}}{n_{E_t V_t z_{ti} *} + \tau_{E_t V_t z_{ti} *}}\right), \end{aligned} \tag{4}$$

$$\begin{aligned} p(z_{ti}|w, z_{-ti}, E, V; A, B, C, \tau) \propto \frac{n_{t z_{ti}} + A_{z_{ti}}}{W_t + A_*} \times \\ \frac{n_{E_t V_t z_{ti} w_{ti}} + \tau_{E_t V_t z_{ti} w_{ti}}}{n_{E_t V_t z_{ti} *} + \tau_{E_t V_t z_{ti} *}}. \end{aligned} \tag{5}$$

Algorithm 1 Gibbs sampling algorithm.

```
for m = 1 to M do
  for t = 1 to T do
    Compute p(E_t|w, z, E_{-t}, V; A, B, C, τ) in Eq.3
    Draw a sample of the document emotion E_t
    Compute p(V_t|w, z, E, V_{-t}; A, B, C, τ) in Eq.4
    Draw a sample of the emotion intensity V_t
    for i = 1 to W_t do
      Compute p(z_ti|w, z_{-ti}, E, V; A, B, C, τ) in Eq.5
      Draw a sample of the topic z_ti
    end for
  end for
end for
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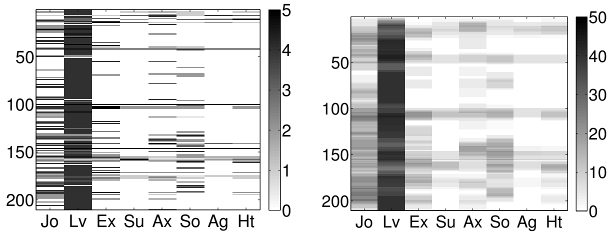
IV. Accumulated emotional traits

We propose three accumulated emotional traits as the special statistics of emotions expressions in Blog streams. Specifically, we use the emotion accumulation trait as the summarization of emotion distribution within continuous Blog articles, the emotion covariance trait as the connection between different



(a) Separate emotions (b) Accumulated emotions

Fig. 2. Separate and accumulated emotions in the Blog streams. Corresponding emotion intensities in each Blog emotion are mapped to the gray-scale. The separate emotion intensity ranges between 1 to 5, while the accumulated emotion intensity (over 10 continuous emotion intensities) ranges between 1 to 50.

emotion categories, and the emotion transition trait as the patterns in emotion changes. To simplify the problem, time intervals of the Blog postings are assumed to be the same. These accumulated emotional traits describe the Blog authors' mental states in time series, and provide important features in detecting the authors' suicide risks.

A. Emotion accumulation

Complex emotions can be accumulated through a period of time for representing people's mental states. The emotion accumulation is calculated by summing over emotion intensities in the most recent L Blog articles as

$$\mathrm{Acc}(V_{t-L+1}, \ldots, V_t) = \sum_{t'=t-L+1}^{t} V_{t'}, \tag{6}$$

where V_t is the emotion intensity vector of length K in Blog t. The separate emotion expression shows randomness in a single Blog article as shown in Figure 2(a), while the accumulated emotion represent significant patterns with $L = 10$, as shown in Figure 2(b). Because the emotion distributions in Blog streams are sparse as illustrated below, for mental states representation we would prefer the accumulated emotions to leverage the patterns in emotion expressions.

In Figure 2(a) we plot the emotion intensities in complex emotions for 210 continuous Blog articles, with the intensity scores mapped to the gray scales. A lot of Blog articles express Love with different emotion intensities, indicating some of the author's mental states could be dominated by Love. Some other emotions like Joy, Expect, Anxiety, and Sorrow tend to be sparser, and some emotions like Surprise, Anger, and Hate are even sparser. Such significant difference in text emotion frequency is not unique in our study. It has been found in a number of studies in developing the emotion corpus [30][56][57][58] and recognizing emotions in the texts [29][31][59] that the number of different emotions are far from balance. In Blog posts, most authors are prone to hide their negative or weak aspects from the public and willing to impress others with the positive feelings. And for our Blog emotion recognition, the most significantly positive emotion is Love, which explains the frequent observations of Love.

Emotions expressed in the Blog articles reflect the author's mental states, with a lot of noise as shown before. These noises can be reduced through accumulation, as the mean variance of emotion intensity decreases from 0.0686 to 0.0107 in Figure 2. The accumulated emotion distribution appears smoother than the original, while still represents the similar emotion distributions.

A more important reason of employing the accumulated emotions is that the cause of mental states is an accumulative process. In this process, the hidden mental state varies much slower than the observed emotion expressions. We sum the complex emotions in Blogs through previous L time points, to reflect the accumulative construction of mental states.

We look into the emotion accumulation trait of different Blog authors and further examine its discrimativeness of the suicide risk. Figure 3 shows emotion accumulations in four specified suicide Blog streams and four randomly chosen non-suicide Blog streams. Specifically, all Blog streams present the favor of Love, which is because Love is the most common emotion in Blog articles. For the suicide samples A to D, the second favored emotions are Anxiety and Sorrow. While for the non-suicide samples F and G, the second favored emotion is Joy, and for the non-suicide samples E and H, the emotions tend to be more evenly distributed. We also find that the consecutive Anxiety and Sorrow are more common in the suicide group (i.e., counting 36.70% and 65.35% of Blog articles for macro average) than in the non-suicide group (i.e., 22.13% and 25.99% respectively), while that the consecutive Joy and Expect are less common in the suicide group (i.e., 9.87% and 19.28% respectively) than in the non-suicide group (i.e., 79.33% and 25.30 respectively). This comparison implies that the favor (or concentration) of accumulated emotions in Blog streams could construct an important trait for representing the authors' mental states. Further, the accumulated emotion intensities of Anxiety and Sorrow are higher in the suicide group than in the non-suicide group, which suggests that they could be an important indicator for predicting suicide risk.

B. Emotion covariance

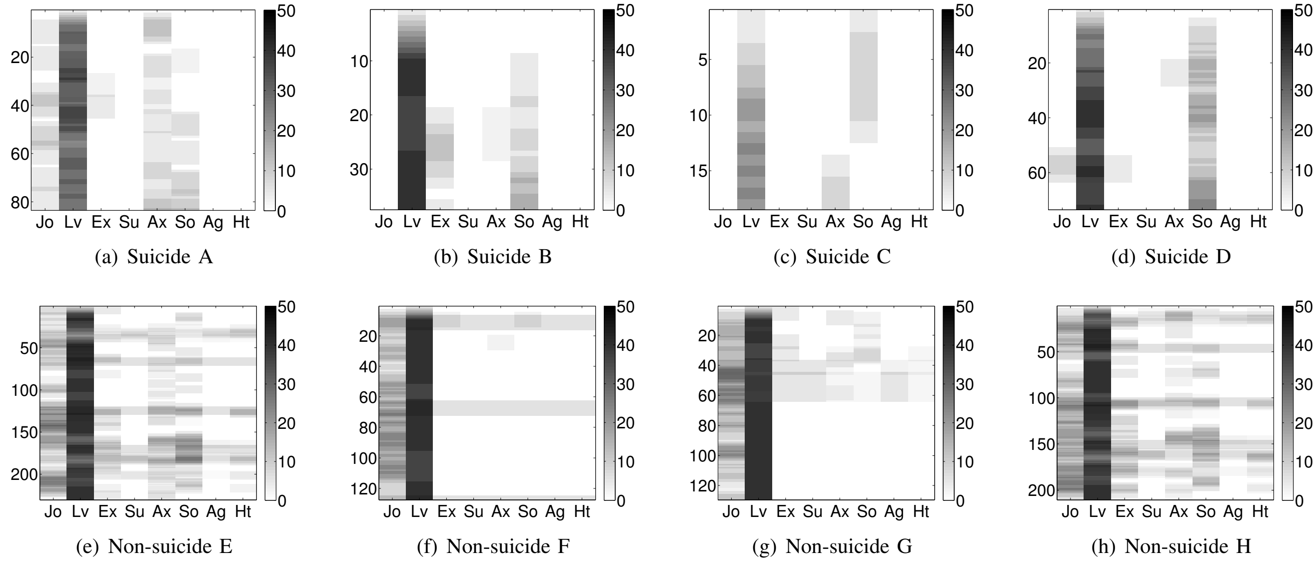
To evaluate the emotion covariance trait for an author, we assume the blog articles are independent in continuous L Blogs and employ Spearman's rank correlation coefficient for every two emotion entries, i.e. E_i and E_j, in these Blogs by

$$\mathrm{R}(E_i, E_j) = 1 - 6\frac{\sum_{t=1}^{L} d_t^2}{L(L^2-1)}, \tag{7}$$

where d_t is the difference in emotion intensity rankings at time point t

$$d_t = \mathrm{rank}(V_{it}) - \mathrm{rank}(V_{jt}). \tag{8}$$

Spearman's rank correlation coefficient evaluates how closely two emotion entires E_i and E_j vary together, and is appropriate for the skewed emotion intensities. We calculate the correlation coefficients in every continuous $L = 20$ Blog articles. To give an overview of the emotion covariance, we plot the mean of emotion covariances in four specified suicide Blog streams and four randomly chosen non-suicide Blog streams in Figure 4. The gray-scale of a square located at (E_i, E_j) corresponds to the correlation coefficient $\mathrm{R}(E_i, E_j)$.



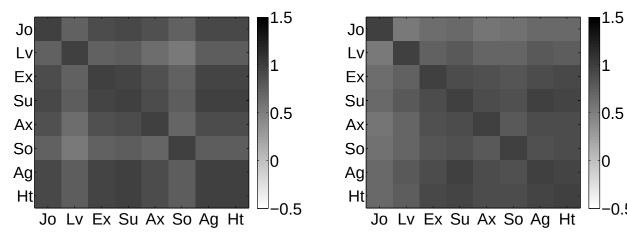
(a) Suicide A (b) Suicide B (c) Suicide C (d) Suicide D

(e) Non-suicide E (f) Non-suicide F (g) Non-suicide G (h) Non-suicide H

Fig. 3. Accumulated emotions in four specified suicide Blog streams and four randomly chosen non-suicide Blog streams. These plots use gray-scales to represent the accumulated emotion intensities in Blog streams.

Because emotion E_i co-varies perfectly with itself, the Spearman's rank correlation coefficient $\mathrm{R}(E_i, E_i)$ equals 1. These correspond to the diagnoal squares in Figure 3. In the suicide group, the squares at (Sorrow, Love) are lighter than the rest squares, which suggests that Sorrow and Love retains the expression of each other in these author's mental states. Other significant emotion covariances are in (Anxiety, Love) and (Expect, Sorrow), which have not been observed in the non-suicide group. In the non-suicide group, emotion covariances are either evenly spread like in streams F and G, or randomly located like in streams E and H.

To have a more general comparison of emotion covariances in the suicide and non-suicide groups, we plot the mean of emotion correlation coefficients for both groups in Figure 5(a) and Figure 5(b), respectively. In the suicide group, squares with respect to Anger, Hate, Expect, and Surprise are darker than those in the non-suicide groups, which indicates that negative emotions are more strongly correlated in the suicide group than in the non-suicide group. The squares with respect to Sorrow in the suicide group are much lighter than those in the non-suicide group, which suggest that Sorrow is more likely to retain the other emotions in the suicide group. While in the non-suicide group, positive emotions of Joy and Love tend more likely to retain the other emotions compared to the suicide group, as implied by the relevant lighter squares. These observations also suggest that the emotion covariance could be an important trait for predicting suicide risk.



(a) Suicide mean (b) Non-suicide mean

Fig. 5. Mean of emotion covariances for the suicide and non-suicide groups. We calculate the average of emotion covariances in the suicide and non-suicide Blogs streams separately, and represent them in the gray-scaled plots.

C. Emotion transition

Consecutive emotions in a Blog stream could reflect the transition patterns of the author's emotion expression. Formally, we explore the emotion transition as the counts of emotion pairs (E_{t-1}, E_t) within ten continuous Blog articles, where E_{t-1} and E_t are the complex emotions in the previous and current Blog articles for time point t. We propose an emotion transition matrix, with the row entries corresponding to emotions in the previous time point and the column entries corresponding to emotions in the current time point, to represent the emotion transition patterns for a Blog author.

The emotion transition matrix for a single time point t can be calculated as

$$\mathrm{Trs}(E_{t-1}, E_t) = 1\{E_{t-1}\} \times 1\{E_t\}^T, \tag{9}$$

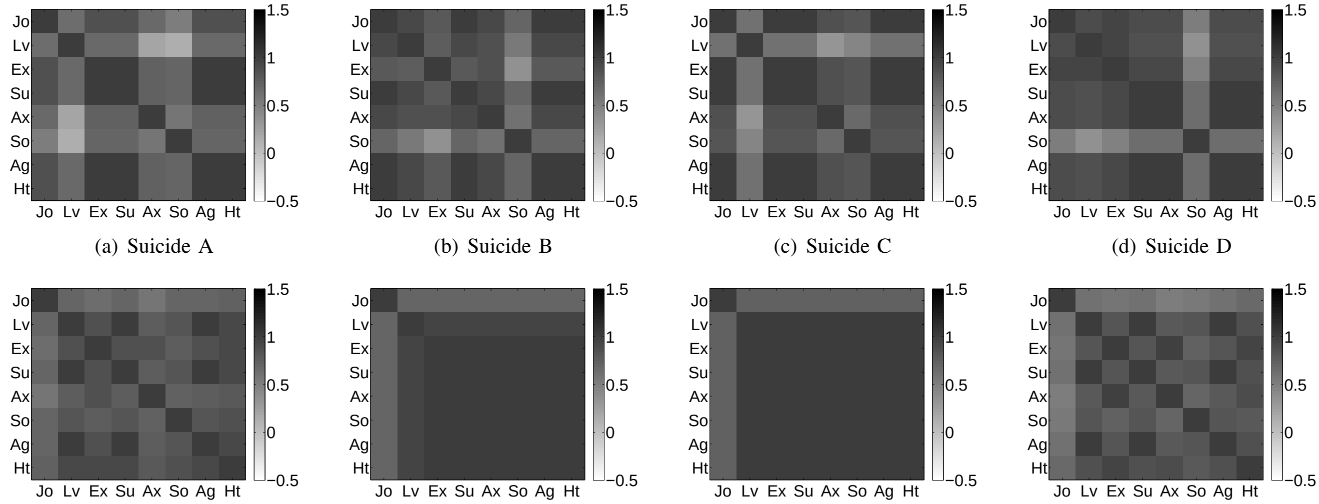
where

$$1\{E_t\} = (1\{E_{t1}\}, 1\{E_{t2}\}, \ldots, 1\{E_{tK}\})^T \tag{10}$$

is an indicator function and E_t and E_{t-1} are binary-valued vectors of length K. The emotion transition in L consecutive Blog articles, i.e. $E_{t-L}, \cdots, E_t$, is given by accumulating the emotion transition matrices for every time point in $\{t-L+1, \ldots, t\}$

$$\mathrm{Trs}(E_{t-L}, \cdots, E_t) = \sum_{t'=t-L+1}^{t} \mathrm{Trs}(E_{t'-1}, E_{t'}). \tag{11}$$

We represent emotion transition matrix in a gray-scaled plot, by plotting the emotion transition counts with different gray-scales. Figure 6 shows the mean of emotion transition matrices



(a) Suicide A (b) Suicide B (c) Suicide C (d) Suicide D

(e) Non-suicide E (f) Non-suicide F (g) Non-suicide G (h) Non-suicide H

Fig. 4. Emotion covariances in four specified suicide Blog streams and four randomly chosen non-suicide Blog streams. We calculate the correlation coefficients for emotion pairs (E_i, E_j), and plot the mean of correlation coefficients for each Blog stream. These plots use gray-scales to represent the correlation coefficients, with the dark squares representing the strong positive correlations and the light squares representing the strong negative correlations.

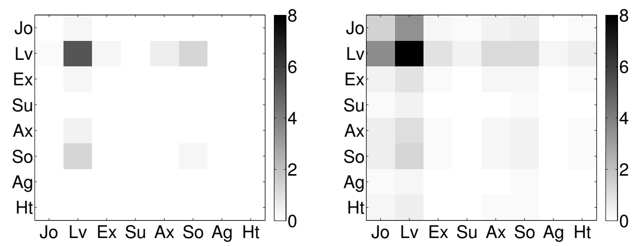
of every ten consecutive articles in four specified suicide Blog streams and four randomly chosen non-suicide Blog streams.

The transition of (Love, Love) is the most regular pattern for both groups, which explained why Love is also the most common emotion in emotion accumulation. In the suicide group, we find that Love is more regularly followed by Anxiety and Sorrow, while in the non-suicide group, Love is more regularly followed by Joy. Similarly, there are significant patterns of transitions from Anxiety and Sorrow to Love in the Suicide group, and a significant pattern of transition from Joy to Love in the non-suicide group. These observations are consistent with the finding in Palmier and colleague's research [18], which suggested that the fluctuation between the positive and negative emotions could predict the development of suicidal ideation and behavior. Besides, we also find a lot more emotion transition patterns in the non-suicide group, e.g., the transitions among Joy and Expect, Anxiety and Hate, Sorrow and Hate, than in the suicide group.

We plot the average of emotion transition matrices for the suicide and non-suicide groups respectively in Figure 7. Transitions between the positive emotion (Love) and the negative emotions (Sorrow, Anxiety) are the major patterns in the suicide group, while in the non-suicide group transitions among positive emotions (Love, Joy) count the major patterns. These observations imply that the emotion transitions could be an important trait in detecting the authors' suicide risks.

V. Suicide risk detection

People often go through a long psychological process before committing suicide, which consists the generation of suicide ideation, the increment of tolerance to painful events, the development of capability to complete the lethal suicide actions, and many attempts to committing the suicide. The suicide risk varies for people under different psychological conditions. In this section, we would like to employ a generalized linear regression model for predicting such suicide risks, based on our proposed emotional traits.



(a) Suicide mean (b) Non-suicide mean

Fig. 7. Averaged emotion transition matrices over the Blog streams for the suicide and non-suicide groups, respectively.

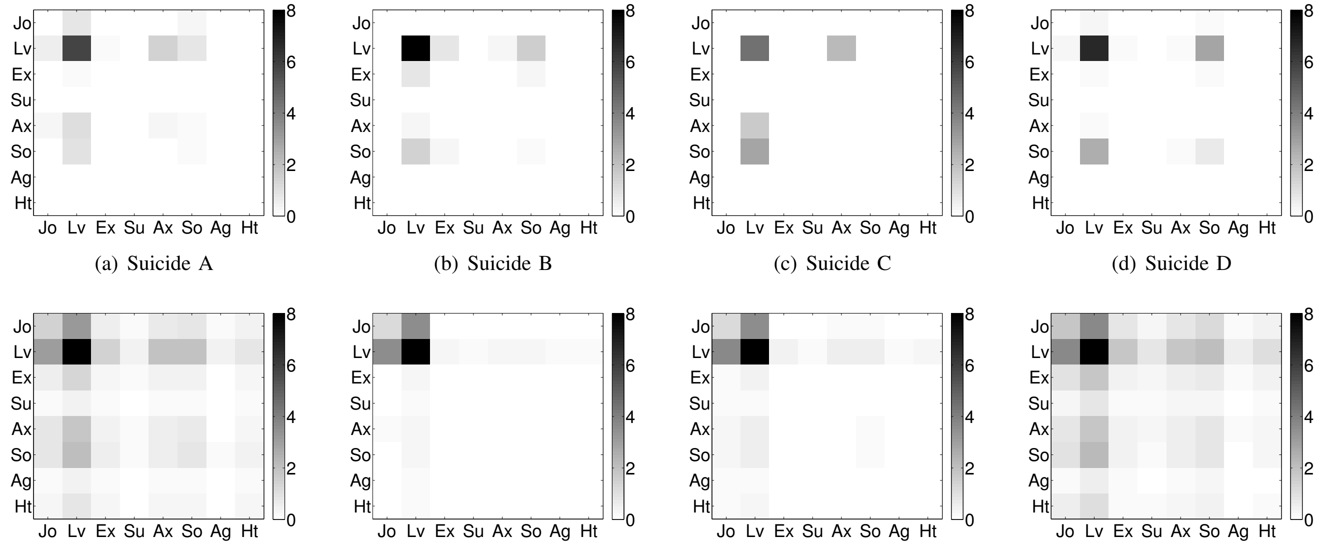
Specifically, we employ the Ridge regression model and fit it by minimizing the following cost function

$$f(w) = \|Xw - y\|^2 + \alpha\|w\|^2, \tag{12}$$

where X is the matrix of accumulated emotional traits in the training set, and y is the vector of corresponding suicide risk scores. w is the vector of weighting parameters which we would like to fit, and $\alpha \geq 0$ is the regularization parameter, which retains the variability of weighting parameters to avoid over-fitting. We use 1.0 and 0.0 as the risk scores for Blogs in the suicide and non-suicide groups. Although these scores are not necessarily accurate, we can still expect an acceptable linear regression model, which goes through both the high risk samples and the low risk samples, and also generates high risk scores for those similar to the high risk samples and generates low risk scores for those similar to the low risk samples. We predict suicide risk score by

$$y_t = X_t w, \tag{13}$$

where X_t is a vector of the accumulated emotional traits for the tth test Blog and y_t is the suicide risk score.



(a) Suicide A (b) Suicide B (c) Suicide C (d) Suicide D

(e) Non-suicide E (f) Non-suicide F (g) Non-suicide G (h) Non-suicide H

Fig. 6. Emotion transitions in four specified suicide Blog streams and four randomly chosen non-suicide Blog streams. We calculate the emotion transition matrices for every ten consecutive articles in the Blog stream, and plot the mean matrices. These plots use gray-scales to represent the counts of emotion transitions in consecutive Blog articles, with the row and column entries representing the emotions in the previous and current Blog articles.

As we have discussed, suicide is caused through an accumulative process. Therefore, we would like to further calculate the accumulated suicide risk by time t in a Blog stream, by summing over the current and previous suicide risks as

$$s_t = \frac{1}{n} \sum_{t'=t-n+1}^{t} y_{t'}, \tag{14}$$

where n is the number of time points for which we are accumulating.

VI. Data Collection

We collect public Blog articles from authors who have publicly committed suicide and some normal authors, separately. The suicide authors have been reported in official news sources. For selecting normal authors, we randomly choose some Blog sites and manually examine the contents to make sure the authors have no suicidal ideation. We remove all the private information relevant to the Blog authors from the data, and arrange the Blog articles for each author into a stream according to the publish time. Totally 907 Blog articles were collected in our data set, with four specified suicidal Blog streams and four randomly chosen non-suicidal Blog streams, respectively. Besides, to train a complex emotion topic (CET) model for Blog emotion recognition, we employ the emotion corpus Ren-CECps [30] which consists 1147 Blog articles with the fine-grained emotions labeled in each article.

VII. Experiment and evaluation

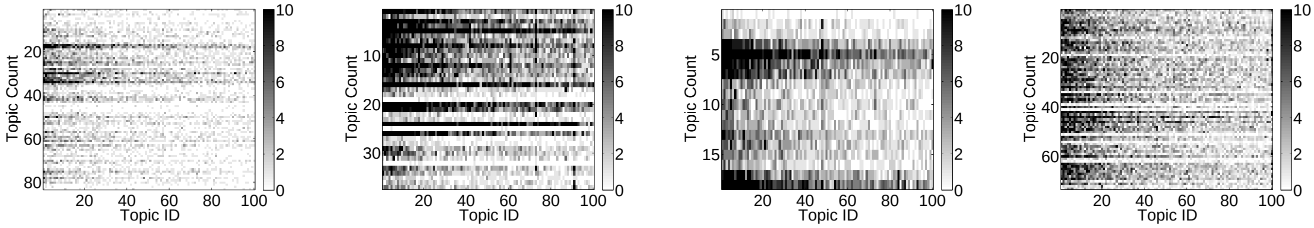
Before predicting Blog authors' suicide risks, we infer the complex emotions and the emotion-related topics in Blog articles, with the CET model. A maximum of 2000 Gibbs sampling iterations has been set for the CET inference, with a saving step of 10 and a burn-in iteration of 1500. All parameters are selected based on a five-fold cross validation over Ren-CECps. The complex emotions and topics in the Blog streams are generated from a majority voting based on the Gibbs sampling results. The predicted emotions are shown in Figure 3 in an accumulated form, while the topic distributions in Blog streams are shown in Figure 8.

In the next step, we extract the accumulated emotional traits form Blog streams, and train a linear regression model for suicide risk detection based on these trait features, through a five-fold cross validation. Concretely, we generate five independent train / test splits for each Blog stream. For each validation fold, we combine all train splits as the training set to train a linear regression model, and combine all test splits as the test set for evaluating the model performance. We employ the coefficient of determination by

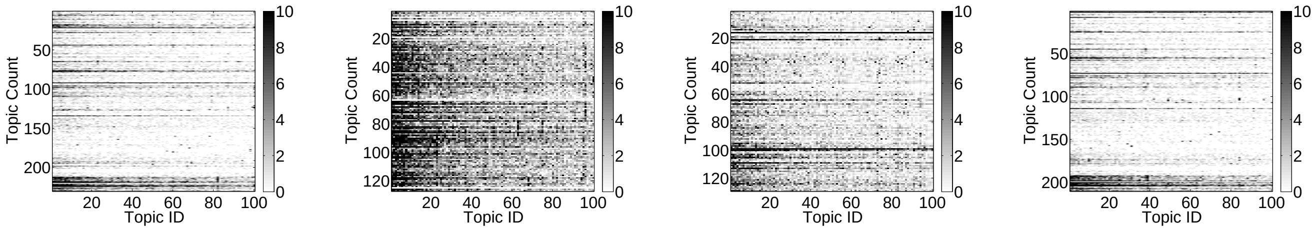
$$\mathrm{R}^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}, \tag{15}$$

for linear regression evaluation based on the average of cross validation, where m is the number of samples in the test set, y_i and $\hat{y}_i$ are the true and predicted risks for the ith sample, and $\bar{y}$ is the average of true risks in y_i. For models based on the emotion accumulation, emotion covariance, and emotion transition traits respectively, we achieved the R^2 scores of 0.3870, 0.4989, and 0.6286. With the combined emotional traits, the linear regression model achieves the highest R^2 of 0.7071.

Then, we report the detected suicide risks in Figure 9. The suicide risks are accumulated through the nearest $n = 7$ time points, as in Equation 14. In the suicide group, we find risk scores are mostly over 0.5. While in the non-suicide group, risk scores are below 0.5 and close to 0. Therefore, we propose a division line $y = 0.5$ in Figure 9 for separating the risk scores into a high-risk region and a low-risk region. For suicide risk



(a) Suicide A (b) Suicide B (c) Suicide C (d) Suicide D



(e) Non-suicide E (f) Non-suicide F (g) Non-suicide G (h) Non-suicide H

Fig. 8. Topic distribution in suicide and non-suicide groups, with topic indices on the X-axis and the counts of topics on the Y-axis. We count topics in each Blog article and represent the topic counts in a gray-scale plot.

detection, we prefer discriminative models, i.e. models which generate higher scores for the suicide group and lower scores for the non-suicide group.

In Figures 9(a) to 9(d), the emotion transition trait renders higher risk scores (0.7013 on average) than the scores generated by emotion accumulation and emotion covariance traits (0.6568 and 0.6921 on average, respectively). While in Figures 9(e) to 9(h), the emotion transition trait renders lower risk scores (0.0843 on average) than the scores generated by accumulation and covariance traits (0.1312 and 0.0988 on average, respectively). By combining these traits together, the regression model generates even more discriminative risk predictions, with a mean score of 0.7337 for the suicide-group and a mean score of 0.0582 for the non-suicide group. Our results suggest that different representativeness exists in three emotional traits, and combining these emotional traits could render a better model for suicide risk detection.

Finally, we would like to understand the authors' emotions, especially for the suicide group, by revealing the emotion-related topics in the Blogs. We evaluate the association between emotions and topics by the point-wise mutual information (PMI). Table I shows the most commonly mentioned topics, their positively associated emotions, and the PMI scores, for each suicide Blog stream. By reviewing these topics and associated emotions, we can interpret the thoughts of there authors. Blog stream A recorded the sad feelings of a divorced woman, in which the most common topic "seem, come out, cry, ..." was related to Anxiety and Sorrow. Blog stream B recorded the memories of a father who lost the only child in an earthquake, in which the most common topics "home, hometown, father, mother, ..." and "wait, earthquake, son, schoolbag, ..." were related to Love and Sorrow. Blog stream C was the cancer-struggling diaries from a single mother, in which the most common topic "divorce, suffer, care, illness, hospital, daughter, ..." was related to Anxiety and Love. Blog stream D was the memory of a wife who lost husband in an accident, in which the most common topic "leave, think of, love, mother, ..." was related to Sorrow. These semantic topics also provide an opportunity of dividing the suicide people into groups, and extract important information for further study of suicidal behaviors. More general examples of topical words and the related emotions are shown in Table IV in Appendix.

To further understand the favor of word usage in emotion expressions for different authors, we report the association between commonly used words and the most commonly expressed emotions in Table II for each suicide Blog. The result indicates that when expressing emotions each author has a different selection of words. More importantly, the same words (e.g. "confront" and "words") might trigger different emotions for different authors. Even for expressing an emotion with the same word, the associations could still diverse for different authors (e.g. "friend" in A and C).

VIII. Additional Experiment

We report the result of a binary classification of the suicide and non-suicide Blog articles, based on the proposed emotional traits with a Logistic Regression classifier. As the linear regression experiment, we evaluate the classification results with a five-fold cross validation on the Blog streams. The detailed Precision, Recall, F1, and Accuracy scores are depicted in Table III. The representativeness of different emotional traits for suicide and non-suicide classification has been found consistent with the regression experiment. The emotion transition trait renders higher classification scores than the emotion accumulation and emotion covariance traits, and the combined emotional trait achieves the best classification result.

IX. Conclusion

Suicide has been a severe problem in the modern society, which takes around one million people's lives every year throughout the world. In this paper, we try to find the connections between the level of people's suicide risks and the

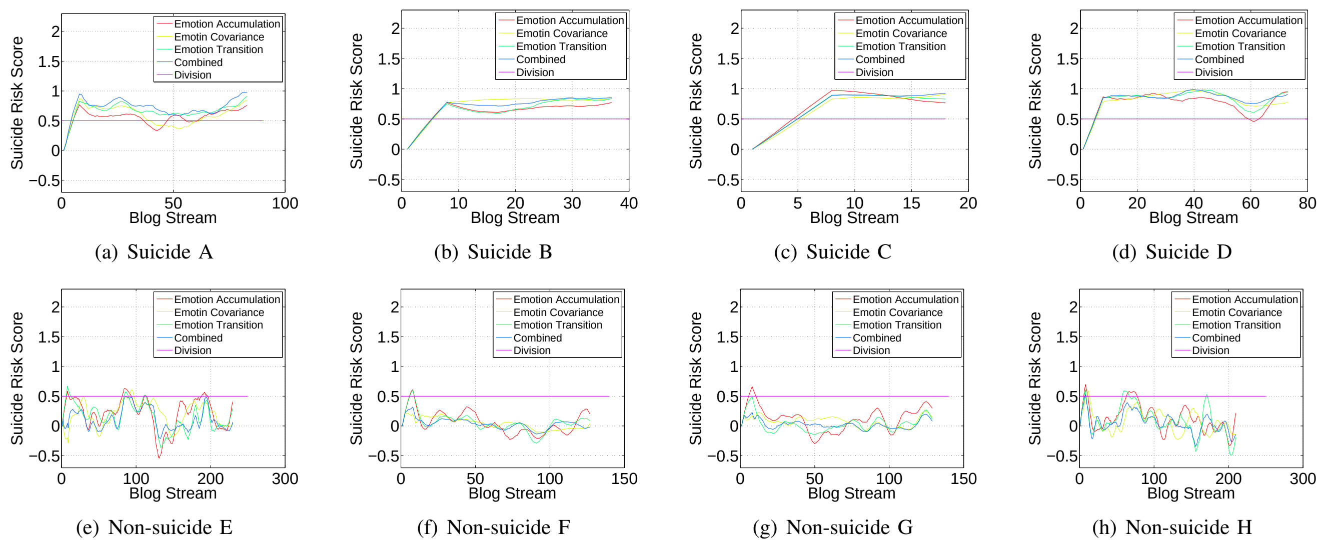


Fig. 9. Accumulated suicide risk scores in the suicidal and non-suicidal groups. The suicide risk scores are plotted separately for each author, with different colors distinguishing the accumulated emotional traits for the prediction.

TABLE I
TOPICS AND RELATED EMOTIONS IN THE SUICIDE BLOG STREAMS.

	Topics	Emotions
A	far, Beijing, cry, at last, ability, seem, feel, come out, look	Anxiety(0.3021), Sorrow(0.0012)
	home, month, phone call, feeling, story, curiosity, friend, happy, automatically, begin, listen	Love(0.0737)
	child, Christmas Eve, Saturday, TV, lover, dining table, again, at last, feel, lyric	Joy(0.5440), Love(0.0080), Anxiety(0.0058)
	classmate, they, you, she, age, wrong, once, already, bad, encounter, forget, to turn out to be	Expect(0.3829), Anxiety(0.1798)
	smile, appearance, she, game, really, again and again, international, unexpectedly, feel, depend on	Love(0.0936)
B	home, hometown, father, mother, child, life, happiness, friend, name, little, forever, missing	Love(0.0582)
	wait, earthquake, son, schoolbag, world, heaven, heart, cake, years of age, once, pumpkin, in a hurry	Sorrow(0.0444), Love(0.0197)
	teach, will, become, county, mother, wife, she, son, only, once, many, new, leave, stay, nothing	Expect(0.3237)
	smile, see, come out, return to, think of, used to, little, heaven, son, Dad, Mom, month, day, now	Love(0.05822)
	arrange, guide, Beichuan, support, treatment, son, leader, winter, last year, for ever, already	Anxiety(1.3918), Expect(1.1124)
C	divorce, suffer, care, illness, hospital, daughter, husband, friend, doctor, hospitalized, always	Anxiety(0.02760), Love(0.0222)
	feel, wish, encounter, be caught in, heart, doctor, Mom, home, school, month, however, why	Sorrow(0.8589)
	smile, believe, thank, daughter, home, friend, phone call, truth, happiness, really, for purpose, a little	Love(0.0336)
	feel, money, problem, house, other people, temper, she, Mom, life, teacher, only, special, still further	Sorrow(0.3418)
	hospitalized, remove, heart, pain, midnight, determination, coolness, no matter, excuse, fight for	Sorrow(0.2396), Love(0.0232)
D	leave, think of, love, mother, she, appearance, world, small, quietly, tough, all at once, already	Sorrow(0.0438)
	love, stay, as if, before, happiness, heart, all one's life, angle, really, she, sometimes, phone call	Joy(1.5269), Love(0.0197)
	see, think of, feel, leave, meet, refuse, drop, love, day, world, used to, already, always, everything	Love(0.0351), Anxiety(0.0172)
	leave, come back, accompany, smile, happy, appearance, doctor, anymore, together, every	Expect(4.2896), Joy(1.7046), Sorrow(0.0419)
	promise, come back, go, cry, cut, girl, she, small, like, time, however, still, why, here, sometimes	Joy(1.7168), Sorrow(0.1151)

accumulated emotional traits which are reflected in their online Blog streams. Specifically, we propose three accumulated emotional traits based on the complex emotion predictions with the CET (Complex Emotion Topic) model. These emotional traits represent special statistics on a series of complex emotions in Blog streams, including the emotion accumulation which summarizes the emotion distribution within consecutive Blog articles, the emotion covariance which describes the co-occurrence of different emotions in emotion expressions, and the emotion transition which reveals the patterns in emotion changes. We carefully study these emotional traits, explicitly represent them in gray-scaled plots, and examine their patterns in Blog streams for the suicide and non-suicide groups respectively. To generalize these accumulated emotional features in suicide risk detection, we employ a linear regression model with a regularization term on these trait feature parameters.

We examine the accumulated emotional traits in suicide risk detection, by calculating and comparing the suicide risk scores in both suicide and non-suicide groups. The emotion transition trait turns to be more discriminative of the suicide risk in our linear regression model, since it renders higher risk scores for the suicide group while lower scores for the non-suicide group. And by combining three accumulated emotional traits, the model generates even more discriminative predictions. The

TABLE II
EMOTIONS AND RELATED WORDS IN THE SUICIDE BLOG STREAMS.

Love	A	always(0.6443)	open(0.5374)	everybody(0.5288)	classmate(0.5288)	wear(0.5068)	go home(0.4923)
	B	think of(0.2366)	sofa(0.2366)	leave(0.2366)	cousin(0.2366)	brother(0.2366)	ask(0.2366)
	C	pick(0.2826)	die(0.2826)	hit(0.2826)	someone(0.2826)	husband(0.2826)	again(0.2826)
	D	new year(0.3753)	message(0.3753)	pretty(0.3753)	familiar(0.3753)	gift(0.3753)	or(0.3753)
Sorrow	A	last night(2.3789)	dream of(2.3789)	road(2.3085)	will(1.9383)	body(1.7939)	friend(1.5209)
	B	sleep(3.9927)	soal(3.8817)	death(3.0213)	dreamworld(2.8228)	not at all(2.5597)	do not(2.5597)
	C	life(3.3210)	words(2.9584)	friend(2.8064)	confront(2.7360)	they(2.6954)	perhapse(2.5434)
	D	next life(1.0693)	doctor(1.0670)	humble(1.0242)	encounter(1.0022)	be alright(0.9698)	left(0.9471)
Anxiety	A	king(2.3844)	son(2.2969)	at that time(2.2324)	three(1.7994)	words(1.6068)	writing(1.3844)
	B	miss(6.8837)	Mo(6.7428)	pain(6.5841)	forever(4.7767)	earthquake(3.2895)	Beichuan(1.7897)
	C	Chinese yuan(2.3039)	who(2.0409)	however(1.7190)	in fact(1.5670)	look as if(1.4739)	same(1.4739)
	D	confront(5.9176)	turn out to(5.8410)	nothing(5.4701)	others(5.3770)	silence(5.2896)	except(5.2071)

TABLE III
RESULT OF THE SUICIDE AND NON-SUICIDE CLASSIFICATION.

	Emotion Accumulation		Emotion Covariance		Emotion Transition		Combined	
	Suicide	Non-suicide	Suicide	Non-suicide	Suicide	Non-suicide	Suicide	Non-suicide
Precision	94.39	75.10	95.03	78.29	96.57	82.12	98.88	84.51
Recall	90.29	83.48	92.00	85.22	93.14	89.57	93.71	96.52
F1	92.22	78.54	93.45	81.38	94.75	85.15	96.16	89.64
Accuracy	88.60		90.32		92.26		94.41	

additional experiment of suicide and non-suicide Blog article classification also verifies this result. Finally, we look into the causes of people's suicidal behaviors, by revealing the associated emotions in the most commonly mentioned topics in the suicide Blog streams. The point-wise mutual information (PMI) evaluation of association between emotions and topics offers further opportunities for analyzing the suicidal behaviors and for studying the personal emotion expressions.

In this paper, we introduce a leading edge study of detecting suicide risks for Blog authors, based on a relatively small set of data, i.e. around 1000 Blog articles, which was restricted to the finding of suicide Blog authors. One of the future directions of this study might be incorporating an active learning algorithm, with human expert interactions, to incrementally find authors with suicide risks from the Blog websites. Active learning provides a loop for both data collection and model training, with positive feedbacks. Based on a larger corpus, we could develop the subtle sequence analysis algorithms (e.g., CRFs) among Blog streams for more accurate suicide prediction. The exact time of Blog postings would also be considered for a better calculation of the emotional traits and a better prediction of the suicide risks. We would also hope to cooperate with the clinical centers, to deliver interventions for people with high level suicide risks and to provide more information for the suicide studies in the future.

APPENDIX

We show emotions and related topical words in general Blog articles, sampled from the suicide Blog streams in Table IV.

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REFERENCES

[1] W. H. Organization *et al.*, "Public health action for the prevention of suicide: a framework," *Geneva, Switzerland: WHO Press*, 2012.

[2] G. C. Patton *et al.*, "Global patterns of mortality in young people: a systematic analysis of population health data." *Lancet*, vol. 374, no. 9693, pp. 881–892, 2009.

[3] J. I. Manuel, M. L. Martinson, S. E. Bledsoe-Mansori, and J. L. Bellamy, "The influence of stress and social support on depressive symptoms in mothers with young children," *Social Science & Medicine*, 2012.

[4] M. Lasgaard, L. Goossens, and A. Elklit, "Loneliness, depressive symptomatology, and suicide ideation in adolescence: Cross-sectional and longitudinal analyses," *Journal of abnormal child psychology*, vol. 39, no. 1, pp. 137–150, 2011.

[5] K. Storrie, K. Ahern, and A. Tuckett, "A systematic review: Students with mental health problemsa growing problem," *International journal of nursing practice*, vol. 16, no. 1, pp. 1–6, 2010.

[6] K. C. Richards, C. E. Campenni, and J. L. Muse-Burke, "Self-care and well-being in mental health professionals: The mediating effects of self-awareness and mindfulness," *Journal of Mental Health Counseling*, vol. 32, no. 3, pp. 247–264, 2010.

[7] W. H. Organization *et al.*, "mhgap: Mental health gap action programme: scaling up care for mental, neurological and substance use disorders," *Geneva, Switzerland: WHO Press*, 2008.

TABLE IV
TOPIC AND RELATED EMOTION SAMPLES IN THE SUICIDE BLOG STREAMS.

	Emotions	Samples
A	Anxiety, Sorrow	I am in an awful state. I can laugh but cannot feel the slighest smile. I hope that I can truly laugh **our** or **cry out**, but I just cannot feel anything.
	Love	I am **happy** that Lao Zhang is online, or I would not **call** hime for the meeting.
	Expect, Anxiety	The man kept saying: we were inappropriate together; I am more appropriate with **her**; I like **her** more; we were different people; …; I am more appropriate with **her**.
	Love	Haha, it is **really out of my expection**. I met Ren Yu **unexpectly**!
B	Love	The **little** guy was **named** Mo before he was born, and everyone liked this **name**. …**Father** took the **little** guy playing at the town square …
	Sorrow, Love	When the **earthquake** happened, …I saw your **son** protecting his head and staying aside the teacher. …I miss the last seven years living with my **son**. The sights of him taking **bag** to school and protecting his head in the **earthquake** forever fixed in my head.
	Expect	After transferring to Beichuan, **she** rented a house near the farmers market in the **country**. **Mother** followed them there to take care of their lives. …Her eyes became **much** brighter when **she** was talking (about her life), showing expectations for the new life in the future.
	Love	My **son** always behaved well. …Before coming, **mother** dug some potatoes in the ground, which were my **son**'s favorite food. …The **little** guy wiped out two **small** bowls of rice together with the delicious potato silk. …I **used to** forbid watching TV after lunch. My **son** …kept saying, "**Dad**, I dont take nap and I am so bored."
	Anxiety, Expect	My hometown **Beichuan** is on an earthquake zone. …I was very worried about my family in **Beichuan**. …My wife and I felt a sense of foreboding when we heard the death number has become seven thousand in **Beichuan**. …I immediately contact people to go back to **Beichuan**, but the high way was **already** closed.
C	Anxiety, Love	Yesterday I called my **daughter**. My **daughter** was very excited and told me what happened at school. She said "I wish you recover soon. Then we can play together." As a child who had not experienced death before, she didn't know how serious my **illness** was. Hearing her laughter, I quickly wiped my tears from eyes.
	Sorrow	I asked myself thousands of times in my **heart**: What was I doing wrong? **Why** should God punish me? I just **suffered** a divorce, and now I have to confront illness, which may affect my whole life.
	Love	My **friends** are very concerned about me. A few close **friends** have been staying with me, calling me, or texting me. With cares from **friends**, I am feeling more comfortable. As the saying goes, Misfortune tests the **sincerity** of **friends**. I am touched in heart by my good **friends**, and feel owning them too much.
	Sorrow	**She** (my daughter) got **only** a few votes for class cadre election (in the first semester) and **only** 19 votes in the second semester, which made her **feeling** disgraced. …**She** cannot answer the **teacher**'s question in class, and the other students laughed at her, which caused the antagonism between her and the **teacher**. **She** even talked back to the **teacher** once.
	Sorrow, Love	Deep in my **heart**, I am grateful to my net friends "**NO MATTER**" and "XIN YUAN". In my most difficult and dark time, they did not leave me but came closer to me. This is a really big favor in my life.
D	Sorrow	After your **leaving**, everything about you in this **world** has been forced to remove from my **world**. …Looking at the empty house, **thinking of** every Tuesday we spent here, my heart seems emptied up. …I cannot hold back the sorrow in my heart any more, with tears **quietly** dropping out.
	Joy, Love	Today is my 25th birthday. …My **Mom** and I went to your family. …After your leaving, it **seems** our two families have not been so lively for a long time. …I remember that you used to keep me from helping in kitchen you **before**. **Sometimes** I would sneak in and acted up, before you drove me out.
	Love, Anxiety	Today is the 111st day since you **left**, but it seems 111 years (to me). Sometimes I wake up at night, I **feel like** an aged person **already**. I cannot help **thinking of** so much time we **used to** be together. …We were **always** happy together. …I want to forget **everything** we **used to** have, but no matter I am sleeping or waking your shadow is everywhere in my **world**.
	Expect, Joy, Sorrow	I remember we used to be **together** at late night. …We were so **happy**. Just running made us so **happy**. …I have never thought what it would be if one day I could not find you **anymore**. If we were not loving each so deeply, I should have strength to smile **again**, and I could have loved **every** one who loves me, and I could have fallen in love with someone **again**.
	Joy, Sorrow	I had a very long dream, in which I saw little Bei (a cat) **came back**, and you **came back** too. Little Bei **still like** before jumped up to the sofa, got into my arms, and refused to leave. You were **still like** every **time** before when you **came back** from work, with a full smile, saying: little Bei, I am **back** to take over her. …It was just a dream, but I **still** scared to cry. This is not the first **time** when I dreamed of the blood on your face.

[8] D. Wasserman, "A stress-vulnerability model and the development of the suicidal process," *Martin Dunitz*, pp. 13–27, 2001.

[9] M. D. Anestis, C. L. Bagge, M. T. Tull, and T. E. Joiner, "Clarifying the role of emotion dysregulation in the interpersonal-psychological theory of suicidal behavior in an undergraduate sample," *Journal of psychiatric research*, vol. 45, no. 5, pp. 603–611, 2011.

[10] M. D. Anestis and T. E. Joiner, "Examining the role of emotion in suicidality: Negative urgency as an amplifier of the relationship between components of the interpersonal–psychological theory of suicidal behavior and lifetime number of suicide attempts," *Journal of affective disorders*, vol. 129, no. 1, pp. 261–269, 2011.

[11] K. A. Hawkins, J. L. Hames, J. D. Ribeiro, C. Silva, T. E. Joiner, and J. R. Cougle, "An examination of the relationship between anger and suicide risk through the lens of the interpersonal theory of suicide," *Journal of psychiatric research*, vol. 50, pp. 59–65, 2014.

[12] D. W. Capron, A. M. Norr, R. J. Macatee, and N. B. Schmidt, "Distress tolerance and anxiety sensitivity cognitive concerns: Testing the incremental contributions of affect dysregulation constructs on suicidal ideation and suicide attempt," *Behavior therapy*, vol. 44, no. 3, pp. 349–358, 2013.

[13] T. E. Joiner Jr, K. A. Van Orden, T. K. Witte, E. A. Selby, J. D. Ribeiro, R. Lewis, and M. D. Rudd, "Main predictions of the interpersonal–psychological theory of suicidal behavior: Empirical tests in two samples of young adults." *Journal of abnormal psychology*, vol. 118, no. 3, p. 634, 2009.

[14] T. Joiner, "Why people die by suicide," *Harvard University Press*, 2009.

[15] K. A. Van Orden, T. K. Witte, K. H. Gordon, T. W. Bender, and T. E. Joiner Jr, "Suicidal desire and the capability for suicide: tests of the interpersonal-psychological theory of suicidal behavior among adults." *Journal of Consulting and Clinical Psychology*, vol. 76, no. 1, p. 72,

2008.

[16] N. Tarrier, P. Gooding, L. Gregg, J. Johnson, and R. Drake, "Suicide schema in schizophrenia: The effect of emotional reactivity, negative symptoms and schema elaboration," *Behaviour research and therapy*, vol. 45, no. 9, pp. 2090–2097, 2007.

[17] P. S. Links, R. Eynan, M. J. Heisel, and R. Nisenbaum, "Elements of affective instability associated with suicidal behaviour in patients with borderline personality disorder." *The Canadian Journal of Psychiatry/La Revue canadienne de psychiatrie*, 2008.

[18] J. Palmier-Claus, P. Taylor, F. Varese, and D. Pratt, "Does unstable mood increase risk of suicide? theory, research and practice," *Journal of affective disorders*, vol. 143, no. 1, pp. 5–15, 2012.

[19] O. Rodav, S. Levy, and S. Hamdan, "Clinical characteristics and functions of non-suicide self-injury in youth." *European psychiatry: the journal of the Association of European Psychiatrists*, 2014.

[20] S. E. Victor and E. D. Klonsky, "Correlates of suicide attempts among self-injurers: A meta-analysis," *Clinical psychology review*, vol. 34, no. 4, pp. 282–297, 2014.

[21] J. J. Mann, A. Apter, J. Bertolote, A. Beautrais, D. Currier, A. Haas, U. Hegerl, J. Lonnqvist, K. Malone, A. Marusic *et al.*, "Suicide prevention strategies: a systematic review," *Jama*, vol. 294, no. 16, pp. 2064–2074, 2005.

[22] T. N. I. of Mental Health. (2013) National institute of mental health, transforming the understanding and treatment of mental illness through research. [Online]. Available: http://www.nimh.nih.gov/index.shtml

[23] A. Grunerbl, A. Muaremi, V. Osmani, G. Bahle, S. Ohler, G. Tröster, O. Mayora, C. Haring, and P. Lukowicz, "Smart-phone based recognition of states and state changes in bipolar disorder patients," 2014.

[24] A. Lanata, G. Valenza, M. Nardelli, C. Gentili, and E. Scilingo, "Complexity index from a personalized wearable monitoring system for assessing remission in mental health," 2014.

[25] A. Greco, G. Valenza, A. Lanata, G. Rota, and E. P. Scilingo, "Electrodermal activity in bipolar patients during affective elicitation," 2014.

[26] G. Valenza, L. Citi, C. Gentili, A. Lanatá, E. Scilingo, and R. Barbieri, "Characterization of depressive states in bipolar patients using wearable textile technology and instantaneous heart rate variability assessment," 2014.

[27] Q. Xu, T. Nwe, and C. Guan, "Cluster-based analysis for personalized stress evaluation using physiological signals," 2015.

[28] E. OConnor, B. Gaynes, B. Burda, C. Williams, and E. Whitlock, "Screening for suicide risk in primary care: A systematic evidence review for the us preventive services task force [internet]." *ESE Preventive Services Task Force Evidence Syntheses*, 2013.

[29] F. Ren and X. Kang, "Employing hierarchical bayesian networks in simple and complex emotion topic analysis," *Computer Speech & Language*, 2012.

[30] C. Quan and F. Ren, "A blog emotion corpus for emotional expression analysis in chinese," *Computer Speech & Language*, vol. 24, no. 4, pp. 726–749, 2010.

[31] X. Kang and F. Ren, "Sampling latent emotions and topics in a hierarchical bayesian network," in *2011 International Conference on Natural Language Processing and Knowledge Engineering (NLP-KE)*. IEEE, 2011, pp. 37–42.

[32] A. Carlborg, J. Jokinen, A.-L. Nordström, E. G. Jönsson, and P. Nordström, "Attempted suicide predicts suicide risk in schizophrenia spectrum psychosis," *Nordic journal of psychiatry*, vol. 64, no. 1, pp. 68–72, 2010.

[33] M. Séguin, A. Lesage, G. Turecki, M. Bouchard, N. Chawky, N. Tremblay, F. Daigle, and A. Guy, "Life trajectories and burden of adversity: mapping the developmental profiles of suicide mortality," *Psychological medicine*, vol. 37, no. 11, pp. 1575–1584, 2007.

[34] K. G. Baron, T. W. Smith, J. Butner, J. Nealey-Moore, M. W. Hawkins, and B. N. Uchino, "Hostility, anger, and marital adjustment: Concurrent and prospective associations with psychosocial vulnerability," *Journal of behavioral medicine*, vol. 30, no. 1, pp. 1–10, 2007.

[35] K. A. Van Orden, T. K. Witte, K. C. Cukrowicz, S. R. Braithwaite, E. A. Selby, and T. E. Joiner Jr, "The interpersonal theory of suicide." *Psychological review*, vol. 117, no. 2, p. 575, 2010.

[36] B. M. Wilkowski and M. D. Robinson, "The cognitive basis of trait anger and reactive aggression: An integrative analysis," *Personality and Social Psychology Review*, vol. 12, no. 1, pp. 3–21, 2008.

[37] R. C. Tafrate, H. Kassinove, and L. Dundin, "Anger episodes in high- and low-trait-anger community adults," *Journal of Clinical Psychology*, vol. 58, no. 12, pp. 1573–1590, 2002.

[38] P. H. Soloff, J. A. Lis, T. Kelly, J. Cornelius, and R. Ulrich, "Risk factors for suicidal behavior in borderline personality disorder," *American Journal of Psychiatry*, vol. 151, no. 9, pp. 1316–1323, 1994.

[39] D. Pratt, P. Gooding, J. Johnson, P. Taylor, and N. Tarrier, "Suicide schemas in non-affective psychosis: An empirical investigation," *Behaviour research and therapy*, vol. 48, no. 12, pp. 1211–1220, 2010.

[40] K. Hawton, L. Sutton, C. Haw, J. Sinclair, and J. J. Deeks, "Schizophrenia and suicide: systematic review of risk factors," *The British Journal of Psychiatry*, vol. 187, no. 1, pp. 9–20, 2005.

[41] S. W. Stirman and J. W. Pennebaker, "Word use in the poetry of suicidal and nonsuicidal poets," *Psychosomatic Medicine*, vol. 63, no. 4, pp. 517–522, 2001.

[42] J. M. Williams and K. Broadbent, "Autobiographical memory in suicide attempters." *Journal of abnormal psychology*, vol. 95, no. 2, p. 144, 1986.

[43] C. Cherry, S. M. Mohammad, and B. De Bruijn, "Binary classifiers and latent sequence models for emotion detection in suicide notes," *Biomedical informatics insights*, vol. 5, no. Suppl 1, p. 147, 2012.

[44] B. Desmet and V. Hoste, "Emotion detection in suicide notes," *Expert Systems with Applications*, vol. 40, no. 16, pp. 6351–6358, 2013.

[45] D. Das and S. Bandyopadhyay, "Word to sentence level emotion tagging for bengali blogs," in *Proceedings of the ACL-IJCNLP 2009 Conference Short Papers*. Association for Computational Linguistics, 2009, pp. 149–152.

[46] Y. Wu, K. Kita, F. Ren, K. Matsumoto, and X. Kang, "Exploring emotional words for chinese document chief emotion analysis," *25th Pacific Asia Conference on Language, Information and Computation (PACLIC 25)*, 2011.

[47] K. Xin and R. Fuji, "Predicting complex word emotions and topics through a hierarchical bayesian network," *China Communications*, vol. 9, no. 3, pp. 99–109, 2012.

[48] R. Tokuhisa, K. Inui, and Y. Matsumoto, "Emotion classification using massive examples extracted from the web," in *Proceedings of the 22nd International Conference on Computational Linguistics-Volume 1*. Association for Computational Linguistics, 2008, pp. 881–888.

[49] X. Kang, F. Ren, and Y. Wu, "Bottom up: Exploring word emotions for chinese sentence chief sentiment classification," in *Natural Language Processing and Knowledge Engineering (NLP-KE), 2010 International Conference on*. IEEE, 2010, pp. 1–5.

[50] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *the Journal of machine Learning research*, vol. 3, pp. 993–1022, 2003.

[51] D. Ramage, D. Hall, R. Nallapati, and C. D. Manning, "Labeled lda: A supervised topic model for credit attribution in multi-labeled corpora," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 1-Volume 1*. Association for Computational Linguistics, 2009, pp. 248–256.

[52] D. Ramage, C. D. Manning, and S. Dumais, "Partially labeled topic models for interpretable text mining," in *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2011, pp. 457–465.

[53] D. M. Blei and J. D. McAuliffe, "Supervised topic models." in *NIPS*, vol. 7, 2007, pp. 121–128.

[54] K. Lin, C. Yang, and H. Chen, "Emotion classification of online news articles from the reader's perspective," in *Web Intelligence and Intelligent Agent Technology, 2008. WI-IAT'08. IEEE/WIC/ACM International Conference on*, vol. 1. IEEE, 2008, pp. 220–226.

[55] S. Aman and S. Szpakowicz, "Using roget's thesaurus for fine-grained emotion recognition." in *IJCNLP*, 2008, pp. 312–318.

[56] C. Strapparava and R. Mihalcea, "Semeval-2007 task 14: Affective text," in *Proceedings of the 4th International Workshop on Semantic Evaluations*. Association for Computational Linguistics, 2007, pp. 70–74.

[57] K. R. Scherer and H. G. Wallbott, "Evidence for universality and cultural variation of differential emotion response patterning." *Journal of personality and social psychology*, vol. 66, no. 2, p. 310, 1994.

[58] E. C. O. Alm, "Affect in text and speech," *ProQuest*, 2008.

[59] R. A. Calvo and S. Mac Kim, "Emotions in text: dimensional and categorical models," *Computational Intelligence*, vol. 29, no. 3, pp. 527–543, 2013.