Title of submission to PLOS journals

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Abstract

Suicide is a global phenomenon and the fourth leading cause of death between 15-19-year-old people. More than 700,000 people died by suicide every year. It is urgently important for suicide prevention at an early stage. Prior research has shown that people with suicidal ideation are more likely to post suicide-related messages on social media. [1] Their posts usually contain strong intensity of negative emotions [2], and the change of those emotions may reflect the change of mental state, which would, in turn, trigger suicide attempts. As a result, early detection of emotion shifts may effectively prevent suicide attempts. In this work, we use binary segmentation to detect the change points of negative emotions from Twitter posts (1) 30 days before the attempt and (2) six months before the attempt. We use the dataset provided by the CLPsych 2021 Shared Tasks. Further, for each user, we compute approximate entropy (ApEn) and sample entropy (SampEn) of negative emotions, and test corresponding P values. On the 30-day sub-dataset, we successfully detected negative-emotion shifts within 2 weeks before the real suicide attempt over 61.76% of the users. However, we see mixed negative-emotion patterns over suicidal users and control users. On the 182-day sub-dataset, We find differentiable patterns of anger, sadness, and disgust emotions among suicidal and control users, but didn't detect negative-emotion shifts before the real suicide attempt on majority of the users.

1 Introduction

Globally, close to 800,000 people die by suicide every year – roughly one person every 40 seconds. Unfortunately, the rates of suicide are on the rise. From 1999 to 2018, suicide rates increased by over a third. During the COVID-19 pandemic, a CDC survey found 10.7% of US adults had suicidal thoughts in the past month, rates as high as 25.5% in the 18-25 year old age group. Due to the increasing concerns around suicide, better prevention approaches and identification of high-risk individuals, especially young people, are needed. Traditional clinical assessments in outpatient or emergency room settings tend to occur sporadically and require the patients' motivation and cooperation. Due to concerns of involuntary psychiatric hospitalization, patients may not want to share their suicidal thoughts. Current suicide risk assessments must consider many covariates – demographic characteristics, past history of suicidality, psychiatric illness, and psychosocial stressors. These factors have high heterogeneity and may contribute differentially to overall suicide risk for individuals. Thus, there is great clinical value in moving suicide assessments from hospital and clinic settings to real-world monitoring to gauge longitudinal risk on an individual level for a broad population. There is increasing interest in using NLP and unstructured text to detect and understand suicide risk. Advantages of using social media and NLP approaches include the ability to conduct passive sensing on publicly available data, the availability of 24-7 longitudinal data, the ability to perform real-time risk assessment, and the access to unfiltered and frank thoughts. In particular, social media may offer insights for populations who are less likely to seek clinical care – such as younger adults and minoritized populations. Unlike clinical assessments which occur sporadically and require the patients' motivation and cooperation, social media data does not have such barriers. Previous work has used Reddit posts to extract information on methods of suicide attempts [3], Twitter posts to detect suicidality prior to attempts [4], and online postings to identify individuals at high risk for self-injurious behaviors [5]. Some studies have used handcrafted features, including TF-IDF [6], Linguistic Inquiry and Word Count (LIWC) [7], N-gram, Part-of-Speech (PoS) and emotions [8–11], while others explored language embeddings [12–15]. We hypothesized that(1)we can detect break points before suicide attempt day based on negative emotions which generated from suicide users' posts to prevent them from suicide.(2)we can compare the negative emotion complexity of suicide and control group to find if there is regularity of suicide attempt users' post emotion.

2 Related Work

The 2021 Workshop on Computational Linguistics and Clinical Psychology (CLPsych 2021) created a shared task [16] with an aim of predicting suicide risk from social media data. It contains two sub-tasks, including prediction of a suicide attempt 30 days prior and prediction of suicide 6 months prior on the data donated to the OurDataHelps.org platform. In the five accepted papers, [17] extracted several hand-crafted features included Part-of-Speech (PoS) tags, fine-mined emotion and emotion intensity, and custom dictionary-based features. This approach proposed C-Attention Network and tested a few other machine learning models on both sets of features. A frame which combined an ensemble model and a majority voting over individual tweets approach was introduced in [18]. [19] used Bayesian modeling to predict suicide attempts based on Twitter posts. Several theory-based features used in the model included behavioral information feature which was counted by the number of replies for each user, LIWC based features and a few other dictionary-based features. A Self-Harm Topic Model was proposed in [19]to generate SHTM-based features and further a LSTM network along with a dense layer were used to predict suicide attempts. In [20], the team compared the performance of a few simple traditional models with fine-tuned deep learning models on both sub-tasks. They used syntax features and character TF-IDF features in the work.

Similarly, the CLPsych 2019 Shared Task introduced an expert-labeled dataset from Reddits, and three sub-tasks of assessing suicide risk of each user into one of the four levels: no, low, moderate, or severe risk. Among the submissions to the shared task, [21] introduced a deep learning model consists of an SVM on top of a set of CNN, Bi-LSTM, BiRNN and Bi-GRU neural networks. Glove [22] and ELmo [23] were used as the pretrained word embeddings in the work. [24] used BERT features generated separately from SuicideWatch and non-SuicideWatch posts. Further more, proposed a model used a stacked parallel CNN with LIWC and a universal sentence encoder [25].

Apart from the CLPsych series, there are other works using social media platforms to examine and predict suicide risk [26–34]. [28] analyzed and learned the connectivity and communication characteristics of Twitter users. Subsequently, observed the association between those features and post content which reflects suicidal ideation. Attention was specifically paid to suicide risk among young adults in [33], through a retrospective clinical interview. The study also analyzes the role of text communications in differentiating the suicidality from depression. [31] used TF-IDF to automatically identify the tweets that are strongly related to suicide. A similar approach was introduced in [32] on Chinese online communities. More recently, [34] used several neural networks to estimate the weight of psychological factors (like stress, loneliness, burdensomeness etc), using psychological metrics to predict suicidal ideation from tweets.

Further, a few other research focused on discovering the shift points of mental health status in social media. In work [35], lexicon-based features were extracted from text to instantly detect suicide-related posts on Twitter. [36] developed language and interactional measures and a propensity score matching based statistical approach on data from Reddit users who shifted from mental health concerns to suicidal ideation. [37] aimed to analyze the seasonality decreased over time by examining all suicides occurring in Norway during 1969–2007.

However, there is no previous work of finding change point for emotions, especially for negative emotions for suicide ideation users. This is important to learn the sudden change of emotions before suicide attempt to prevent from it. Also it is imperative to study how different suicide and control users' negative emotion different. In this work, we apply binary segment to detect break points of negative emotions of posts before user suicide attempt. Meanwhile we compute ApEn and SampEn to learn the pattern difference of suicide and control users' negative emotions.

3 Data and Features

In this section, we describe the summary of dataset and emotion features we generate from dataset.

3.1 Data Description

We use the data released by CLPsych 2021 shared task [38]. This data set includes suicide users and control users with their posts on Twitter. Suicide users have tag suicide attempt which related to their actual suicide attempt date and naturally control users don't. CLPsych 2021 contains two sub-tasks: sub-task 1 to predict suicide attempt 30 days prior suicide attempt and sub-task 2 to predict suicide attempt 182 days prior. For sub-task 1, there has 114 suicide and control users' data for training and 22 for test. For sub-task2, there has 164 suicide and control users' data for training and 30 for test.

3.2 Emotion Features

Emotions play an important role for indicating suicide ideation from social media posts [39–42], so we generated emotion intensity scores based on suicide and control posts from data set above. We use NRC lexicon [43] and generate emotions like anger, anticipation, disgust, fear, joy, sadness, surprise and trust. We apply anger, fear, sadness and disgust these negative emotion tags to our research.

4 Methods

4.1 Change Point Detection

Change points describe the instantaneous change for time-series data [44]. Change point detection(CPD) will reveal the pattern of time-series data [45].CPD has been implemented to numerous areas [46] [47] [48].We use python package ruptures to perform binary segmentation. Ruptures [49] is a great python library to detect change point through time-series data. It has multiple algorithms which can be implemented to detect exactly and approximately for models which either various parametric or non-parametric. We have tried 4 built-in methods, which were binary segmentation, pelt, window based searching and dynamic programming. After experiments, we find binary segmentation is the best method for our data set in which other three methods will lose plenty change points during implementation. Binary segmentation [50] is a mature and fast algorithm [51]. The process of the algorithm is iterative in which once a change point has been detected the whole series data will be split around this change point and this procedure will repeat on these two separate series [52]. It is an greedy sequential algorithm and will execute detection for single change point and perform estimate t(k) in each iteration. .

4.2 Approximate Entropy and Sample Entropy

Approximate entropy(ApEn) and sample entropy(SampEn) can be applied to measure the regularity of time-series data. These two algorithms describe the repeatability or predictability of the data. The higher value of ApEn and SampEn indicate fluctuate and unpredictable of data where lower value shows regularity and predictable. The basic idea of ApEn as follows: For time-series data u(1), u(2),...,u(N), we can form a a sequence of vectors x(1), x(2),...,x(N-m+1) in real m-dimension space. We fix an integer m which represent the length of compared data and positive real number r which specifies a filtering level. We can define x(1),x(2),. . . ,x(N-m+1) by x (i)=[u(i),u(i+1),. . . ,u(i+m-1)]. For each i(1≤ i≤ N-m+1), we can construct:

$$C_i^m(r) = (\text{number of } x(j) \text{ such that } d[x(i), x(j)] \leq r)/(N-m+1) \tag{1}$$

We then can define:

$$\Phi^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \log(C_i^m(r)), \tag{2}$$

ApEn can be defined as:

$$\text{ApEn} = \Phi^m(r) - \Phi^{m+1}(r). \tag{3}$$

The SampEn is similar to ApEn. We form a template vector of length m, tolerance r of given time-series data u(1), u(2),...,u(N) with length N.The SampEn can be computed as:

$$SampEn = -\log \frac{A}{B} \tag{4}$$

where

$$A = d[X_{m+1}(i), X_{m+1}(j)] < r \tag{5}$$

$$B = d[X_m(i), X_m(j)] < r \tag{6}$$

The SampEn value will be low due to the similarity of time series and highly on account of great difference between time series.

5 Experiments and Results

5.1 Change Point Detection

We detect the change point of users' posts from 4 negative emotions, which are fear, anger, sadness and disgust. They were generated from original posts by NRC lexicon. We set different window size of change point for 30 days sub-task and 182 days sub-task which 30 days as 2 weeks while 182 days as 1 month. The original training data set for 30 days include 114 users, 57 of them are suicide attempted users and 57 of them are control. We also compute the test data set of 30 days which contains 11 suicide attempted users and 11 control users. As for 182 days sub-task, the training data set include 82 suicide attempted users and 82 control users. Identically we compute test data set which include 15 suicide attempted users and 15 control users. After experiment we find that change point can be detected if the time-series data has 10 or more data, which 10 or more posts for our circumstance. Since there are quite a number of users who has less than 10 posts, the final result reduce from original amount. After computation we find that:(1)For 30 days sub-task, the change point which less than 2 weeks before suicide attempt are 21. The number of change point which more than 2 weeks before suicide attempt are 13.(2)For 182 sub-task, the change point which less than 1 month before suicide attempt are 19.The number of change point which more than 1 month before suicide attempt is 61. Table 1 shows the change point date within and beyond 2 weeks before suicide attempt date for suicide users in 30 days sub-task. Table 2 shows the change point date within and beyond 1 month before suicide attempt date for suicide users in 182 days sub-task.

Table 1. Table of CPD for suicide users in 30 days sub-task.

Sub-task	Change Point in 2 weeks	Change Point beyond 2 weeks
30 days	21	13

Table notes that the number of change point detected in 2 weeks and beyond2 weeks for suicide users in sub-task 30 days.

Table 2. Table of CPD for suicide users in 182 days sub-task.

Sub-task	Change Point in 1 month	Change Point beyond 1 month
182 days	19	61

Table notes that the number of change point detected in 1 month and beyond 1 month for suicide users in sub-task 182 days.

Table 5 shows the change point date within and beyond 2 weeks before last date for control users in 30 days sub-task. Table 6 shows the change point date within and beyond 1 month before last date for control users in 182 days sub-task.

Table 3. Table of CPD for control users in 30 days sub-task.

Sub-task	Change Point in 2 weeks	Change Point beyond 2 weeks
30 days	24	10

Table notes that the number of change point detected in 2 weeks and beyond2 weeks for control users in sub-task 30 days.

Table 4. Table of CPD for control users in 182 days sub-task.

Sub-task	Change Point in 1 month	Change Point beyond 1 month
182 days	25	55

Table notes that the number of change point detected in 1 month and beyond 1 month for control users in sub-task 182 days.

5.2 ApEn and SampEn

We calculate the ApEn and SampEn for 4 negative emotions which are fear, sadness, disgust and anger for control and suicide users on 30 days and 182 days sub-tasks. Since the control users and suicide users are alternatively presented for both 2 sub-tasks data set and each group of suicide and control users' posts length are roughly the same, we implement kernel density estimation(KDE) for control and suicide user's ApEn and SampEn to see the overall difference of two groups. KDE is a really useful statistical tool with an intimidating name, which is a technique that can create a smooth curve of given data. From figure 2, figure 3, figure 4, figure 1, we can see the KDE plot of 4 negative emotions' ApEn values comparing control and suicide group in 30 days sub-task. KDE plots depict the probability density at different values in a continuous variable. We can see that fear and sad emotion ApEns are roughly similar within suicide and control groups where suicide users highest values are higher than control groups. Suicide users show larger anger ApEn on maximum region which indicate that for those suicide and control users who have ApEn values close to peak value, suicide ApEns will larger than control ApEns. This shows that there are more suicide users are not predictable in fear emotion than control users.

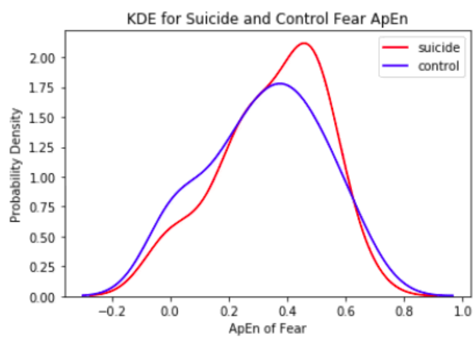

Fig 1. KDE of Fear ApEn(30 days sub-task)

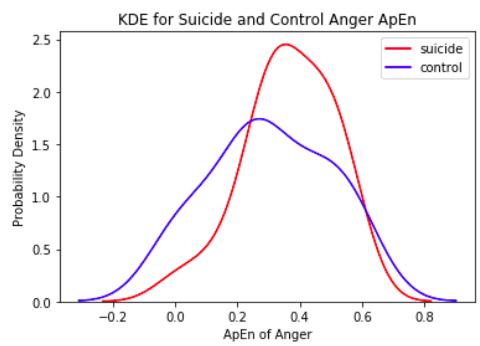

Fig 2. KDE of Anger ApEn(30 days sub-task)

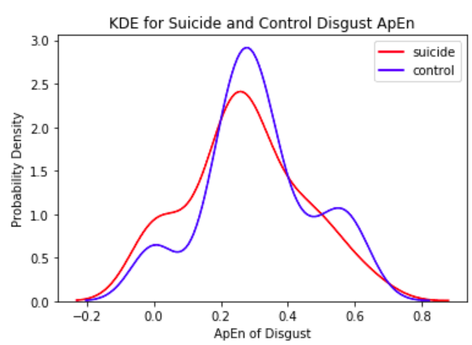

Fig 3. KDE of Disgust ApEn(30 days sub-task)

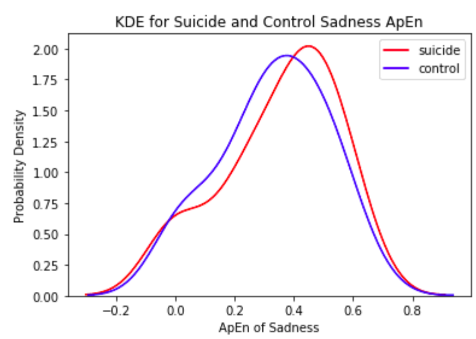

Fig 4. KDE of Sad ApEn(30 days sub-task)

From figure 6, figure 7, figure 8, figure 5, we can see the KDE plot of 4 negative emotions' ApEn values comparing control and suicide group in 182 days sub-task. Comparing result to KDE plot in 30 days sub-task, there is no sign that suicide users will have higher ApEn on anger emotion as time period extended. In opposite, control users show more unpredictable on anger emotion. Also observing other 3 emotions KDE plots, we can see the differences between suicide and control curve has becoming greater since the gaps are not as tight as 30 days sub-task.

From figure 10, figure 11, figure 12, figure 9, we can see the KDE plot of 4 negative

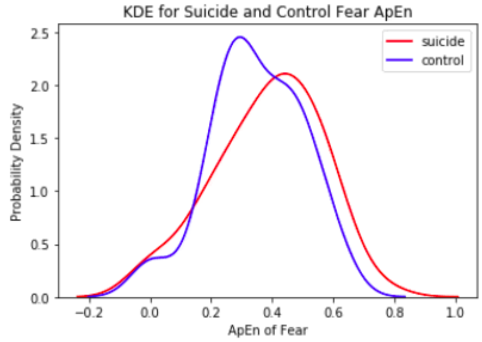

Fig 5. KDE of Fear ApEn(182 days sub-task)

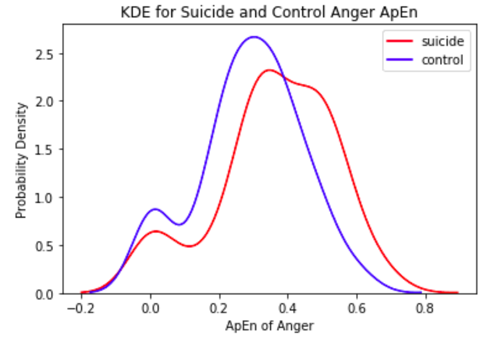

Fig 6. KDE of Anger ApEn(182 days sub-task)

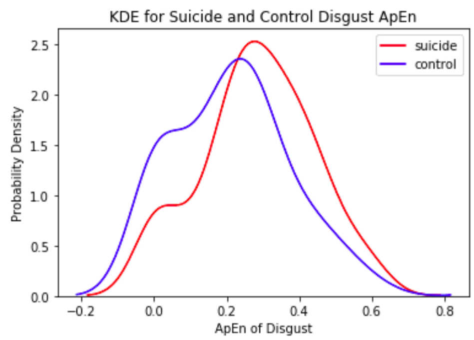

Fig 7. KDE of Disgust ApEn(182 days sub-task)

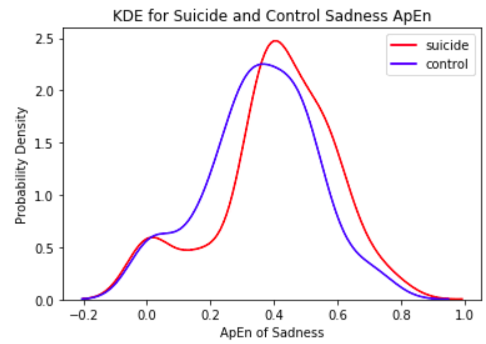

Fig 8. KDE of Sad ApEn(182 days sub-task)

emotions' SampEn values comparing control and suicide group in 30 days sub-task. We can conclude from figures that there are more suicide users show unpredictable on disgust emotion. Besides we can draw that the complexity of fear, anger and sadness are closely similar between suicide and control group.

From figure 14, figure 15, figure 16, figure 13, we can see the KDE plot of 4 negative emotions' SampEn values comparing control and suicide group in 182 days sub-task. We can see it is also that suicide group's 4 emotion complexities reduce as time period extend from 30 days to 182 days. In addition we can see that suicide and control curves more apart from 30 days plots which indicate that as time period extend, we can separate the complexity from 4 emotions of suicide and control users.

We compute P-values of ApEn and SampEn for control and suicide users based on the above results to see if we can differentiate them as time period extend. The P-value is a parameter used to determine the results of hypothesis testing, and can also be compared according to different distributions using the rejection domains of distributions. P-value was first proposed by R. A. Fisher. P-value is the probability of a more extreme outcome than the sample observation obtained when the null hypothesis is true. If P is small, the probability of the null hypothesis happening is small, and if it does, according to the small probability principle, we have a reason to reject the null hypothesis, and the lower the P is, the more reason we have to reject the null hypothesis. We can conclude that the smaller the P-value, the more significant the result. But whether the test results are "significant," "moderately significant," or "highly significant" depends on the size of the p-value and the actual problem. For

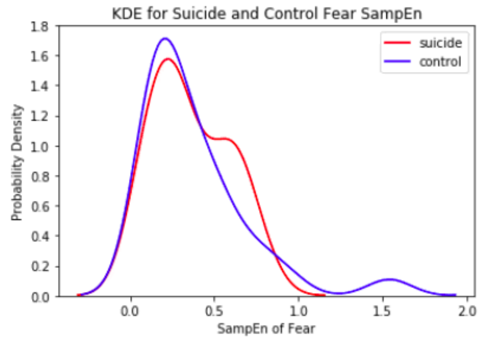

Fig 9. KDE of Fear SampEn(30 days sub-task)

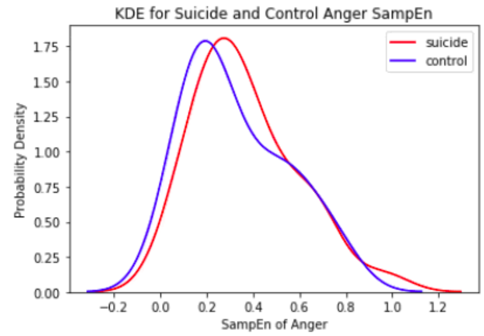

Fig 10. KDE of Anger SampEn(30 days sub-task)

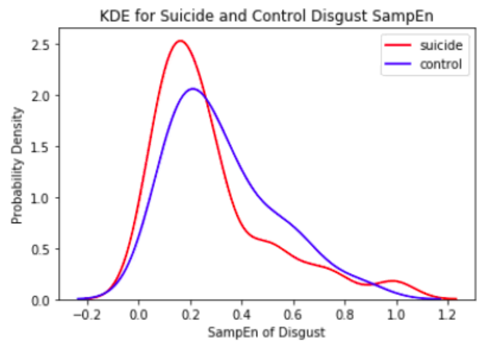

Fig 11. KDE of Disgust SampEn(30 days sub-task)

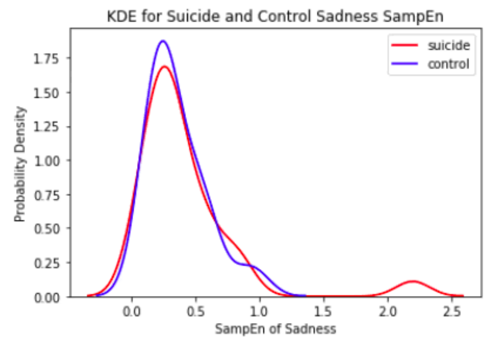

Fig 12. KDE of Sad SampEn(30 days sub-task)

ApEn, table 5 shows the p-values for each emotion's ApEn value in sub-task 30 days. Table 6 shows the p-values for each emotion's ApEn value in sub-task 182 days.

Table 5. Table of P values for emotions' ApEn values in 30 days sub-task.

Sub-task	P value for Anger	P value for Fear	P value for Sadness	P value for disgust
30 days	0.0876	0.490	0.964	0.490

Table notes that the p values for 4 emotions in sub-task 30 days.

Table 6. Table of P values for emotions' ApEn values in 182 days sub-task.

Sub-task	P value for Anger	P value for Fear	P value for Sadness	P value for disgust
182 days	0.025	0.317	0.066	0.025

Table notes that the p values for 4 emotions in sub-task 182 days.

For SampEn, table 7 shows the p values for each emotion's SampEn value in sub-task 30 days. Table 8 shows the p values for each emotion's SampEn value in sub-task 182 days.

From the ApEn and SampEn p-values if we assume 90% confidence (i.e., P-value ¡= 0.1) for the sub-task 182 days data, the motion of anger, sadness and disgust complexities are able to differentiate between suicidal and control. Besides, as time gap increase form 30 days to 182 days, all the emotions' complexities show distinctly different since p-values reduced when days gap increased. We can also see that ApEn

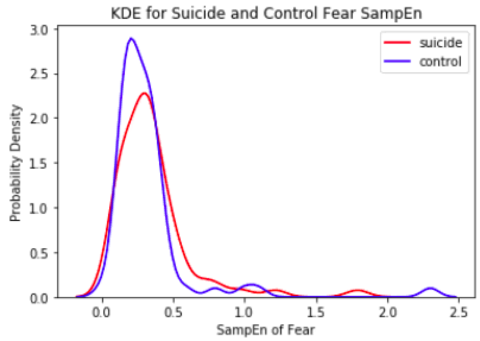

Fig 13. KDE of Fear SampEn(182 days sub-task)

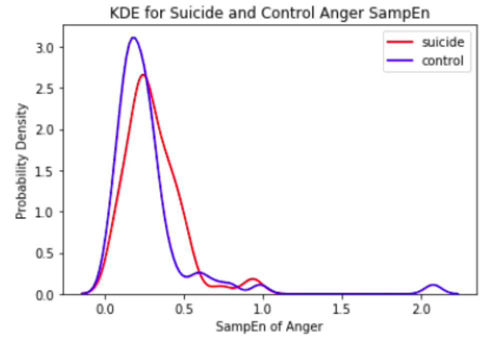

Fig 14. KDE of Anger SampEn(182 days sub-task)

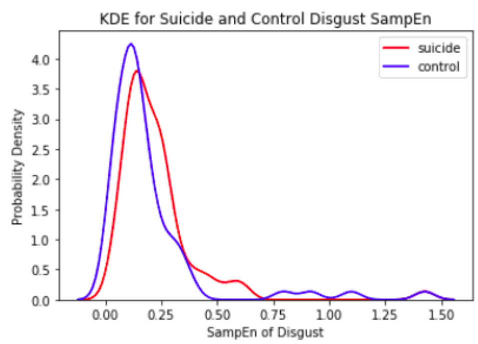

Fig 15. KDE of Disgust SampEn(182 days sub-task)

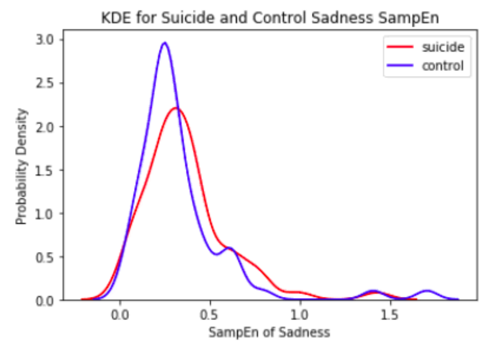

Fig 16. KDE of Sad SampEn(182 days sub-task)

Table 7. Table of P values for emotions' SampEn values in 30 days sub-task.

Sub-task	P value for Anger	P value for Fear	P value for Sadness	P value for disgust
30 days	0.490	0.917	0.995	0.490

Table notes that the p values for 4 emotions in sub-task 30 days.

Table 8. Table of P values for emotions' SampEn values in 182 days sub-task.

Sub-task	P value for Anger	P value for Fear	P value for Sadness	P value for disgust
182 days	0.066	0.224	0.102	0.008

Table notes that the p values for 4 emotions in sub-task 182 days.

and SampEn of Fear emotion stays on a high level even when time gap increase which may indicate that the fear emotion complexity is hard to classify suicide and control group.

6 Conclusion

In this work, we introduce Binary Segmentation, which one of change point detection methods to detect the break points through suicide group time-series negative emotions, which are sadness, anger, disgust and fear from text based on suicide group posts from Twitter. We also calculate the ApEn(Approximate Entropy) and SampEn(Sample Entropy) based on four negative emotions above. Our change point detection results indicate that (1)we can detect 21 out of 34 suicide users' negative emotion break points before 2 weeks from suicide attempt for data which recorded suicide users' posts for 1 month.(2)we can detect 61 out of 80 suicide users' negative emotion break points beyond 1 month from suicide attempt for data which recorded suicide users' posts for 182 days. Also for ApEn and SampEn results, we compute p-values of 4 negative emotions based on suicide and control group posts' ApEn and SampEn values. We find that(1)the emotion of anger, sadness and disgust complexities are able to differentiate between suicidal and control if we assume 90% confidence (i.e., P-value ¡= 0.1) for the sub-task 182 days data. (2)As data time gap increase form 30 days to 182 days, all the emotions' complexities show distinctly different since p-values reduced when days gap increased. (3) ApEn and SampEn of Fear emotion stays on a high level even when time gap increase which may indicate that the fear emotion complexity is hard to classify suicide and control group.

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