Exploring Timelines of Confirmed Suicide Incidents through Social Media

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***Abstract*—Suicide is one of leading causes of death worldwide, yet little data is available about the lives of suicide victims because most people do not seek treatment. Research has shown that people express suicidal ideation in social media, which can potentially be tapped to improve our understanding of the thoughts and behaviors of people prior to suicide. In this work, we introduce a novel dataset of Chinese social media accounts of 130 people who committed suicide between 2011 and 2016. We describe the demographic and geographic composition of the users, then conduct a longitudinal text analysis of their post histories, showing observable changes in content leading up to the time of death. With encouraging exploratory findings, we discuss directions for future research.**

***Keywords*-Suicide; Mental Health; Social Media; Topic Model; Time Series Analysis;**

I. Introduction

Suicide is a major public health concern and one of the leading preventable causes of death. According to global statistics from the World Health Organization (WHO), over 800,000 people die from suicide each year globally. Suicide was the second leading cause of death among 15 to 29 year-olds in 2012, and the 5th leading cause of death among 30 to 40 year-olds [1]. Early intervention can be effective in preventing suicide [1], yet evidence shows that people are reluctant to seek clinical help [2].

Compared to many problems in healthcare informatics, suicide has a particular shortage of data due to patients' lack of engagement with clinical services. Some researchers have turned to other data sources to understand the causes leading up to death, such as suicide notes [3] and diaries [4]–[6], but these studies generally represent small-scale case studies rather than providing population-level insights. A potentially larger-scale source of first-person information is social media, where people may discuss suicide more openly than in clinical settings [2]. Not only do people post suicide notes online, but their social media histories can provide a naturalistic window into their thoughts and behaviors before death, potentially giving insights into the risk factors of suicide.

In this work, we use a social media corpus to understand suicide in China. Suicide in China has unique characteristics, yet is currently understudied and underreported, in part due to lack of data and centralized reporting [7]. Even with the subset of suicide incidents that are recorded, official government statistics do not provide fine-grained demographic and geographic information [8]. Suicide is also under-treated in China—only an estimated 5% of individuals with depression receive treatment in China, and only 7% of people who committed suicide had received mental health treatment [7]. Therefore, there is a strong need to identify new sources of data regarding suicide in China.

Chinese social media platforms are increasingly common platforms for people to broadcast suicidal ideation [2], [9]. This is especially true for Sina Weibo, a microblogging platform similar to Twitter (hereafter referred to as Weibo). As of 2016, Weibo has approximately 300 million active users per month, 82% of whom are below 30 years old, which matches the age group most at risk of suicide (15-29 years) according to WHO [1]. In this work, we create a novel dataset of 130 Weibo users who committed suicide. We describe the characteristics of the dataset and present a preliminary examination of temporal patterns in content of users' feeds. We observe shifts in content close to the time of death, as well as content differences between users who died for different reasons (specifically, those who committed suicide due to relationship problems and those with other reasons). Given these findings, we suggest aspects of the dataset that merit deeper investigation, proposing paths for future work.

II. Suicide Studies on Social Media

The rise of social media has been accompanied by an increasing interest in the role of social media on suicide-related behavior [10]. Social media reduces communication barriers while also making it possible to obtain information from vulnerable populations, including those at risk of suicide. The use of social media platforms to post suicide notes or messages of suicidal ideation is well documented [11], and may provide opportunities for immediate intervention [12].

In contrast to traditional measurement, such as structured surveys and interviews, social media provides a rich, easily accessible, and less intrusive source of information. Research based on social media data has addressed topics including, but not limited to, influenza vaccination [13], cancer support [14], diabetes [15], drugs [16], and bereavement-based grief [17].

A number of studies have used statistical approaches to understand suicide-related behavior, including suicide and depression prediction on Twitter [18], [19] and the measurement of suicide ideation transmission on Reddit [20], [21]. A number of studies using computational and statistical approaches have explored suicide on microblogs in Sina Weibo, including the prediction [22], [23] and categorization [24]–[27] of microblogs and users. Together, these studies show that suicide involves multiple factors, such as self-reference, family, social issues, and community, as well as the potential of social media to explore and assess suicidal behavior. However, the research in these previous studies did not focus on verified suicides, which is an important contribution of our work.

III. Privacy and Ethics

Understanding online suicidal behavior is important for potential intervention, but this research also brings ethical challenges. Social media research is often fraught with conflicting ethical issues, without fully consistent norms in the community [28], but suicide is a particularly sensitive topic, with greater potential for harm than many (for example, by catalyzing further suidical ideation [29]). In a strict sense, this work does not consistitute human subjects research, both because we are using publicly available data without interacting with users, as well as the fact that the subjects in the dataset are deceased. However, there is still an ethical obligation to handle the data carefully and establish privacy protections for sensitive information. We therefore include only aggregated information in this paper, and do not publish information associated with individual accounts (including example messages). We do, however, provide a description of how the data was collected and from where, so that the methodology can be replicated. One difficult tradeoff involves sharing our dataset, which allows other researchers to work on this important problem, but could expose sensitive information widely. Our approach is to make data available on a case-by-case basis upon request, sharing subsets of the data needed to fulfill a research request.

IV. Dataset

We now introduce and characterize our dataset of 130 Weibo users who were verified to have died of suicide.

A. Data Collection

We identified Weibo users who died of suicide through two Weibo accounts, "早逝女孩祭奠平台" and "逝者如斯夫dead", that publish user-submitted reports of death. Reports are sent to these accounts by others, usually friends or relatives, as a way of making a public announcement of the death. The "早逝女孩祭奠平台" account only publishes deaths of female users, and "逝者如斯夫dead" publishes both genders.

We manually read through every post of these two accounts and identified reports that matched the following criteria:

- The cause of death is clearly identified as suicide.
- The report includes the Weibo account identifier for the deceased person.
- The Weibo account still exists and is publicly viewable (6 accounts did not meet this criterion).

We manually reviewed each account and removed three:

- The cause of death for one user appeared to be something other than suicide upon further inspection, indicated by this comment to correct the record: "是先天性心脏病突发而死根本没有自杀这一说 (She died of congenital heart disease instead of committing suicide)".
- One user attempted suicide but did not succeed.
- One user was the account of a celebrity (an actor and singer). While celebrities may be important to include for certain research questions, we believed this would represent too much of an outlier for the purpose of understanding the timelines of ordinary people.

From the death reports, we manually extracted the following information for each user: gender, location of suicide, date of death, and age. Sometimes these attributes could not be ascertained, in which case they were marked as unknown.

We crawled the 5,000 most recent posts from each user's account. For each post, we also collected interaction data: replies to the post, and repost and "like" counts. We also collected information about each user's social network, collecting the account IDs of up to the 200 most recent followers and 200 most recent followees.[1]

We collected account IDs of deceased Weibo users from these reports from December 15, 2016 to January 15, 2017. Data from the deceased users was crawled from February 9, 2017 to April 2, 2017.

In total, we collected 104,229 messages from 130 users who died of suicide (30 male, 100 female). We also collected 37,610 account IDs of followers and followees, and 2,362,910 interaction events (1,363,813 comments; 536,687 reposts; 462,410 likes), though we do not analyze these additional attributes in the present study. Our dataset is openly available,[2] with directly identifiable information removed out of respect for the privacy of the users.

B. Dataset Characteristics

Table I shows the breakdown of the number of users in our dataset by year of death, as well as the distribution by demographic group (gender and age). Gender is known for all users in the dataset, and age is known for 115 users.

Gender: The dataset is heavily skewed toward female users, which is in part an artifact of our data sources for suicide reports (one account only reported female suicides),

[1] 200 is a limitation of the platform. Weibo will only display a maximum of 20 pages of users, where each page contains 10 users. Users are listed in descending chronological order (i.e., most recent first).

[2] https://drive.google.com/open?id=0ByISRszIs-h5YTBTNlduWlF2d2M

Table I
OF USERS BY YEAR OF DEATH (LEFT) AND BY DEMOGRAPHICS (RIGHT)

2011	12
2012	39
2013	18
2014	22
2015	17
2016	22

Age / Gender	Male	Female	**Overall**
13–20	9	29	38
21–30	14	49	63
31–40	6	8	14
Unknown	1	14	15
Overall	30	100	130

but this also turns out to be fairly reflective of the estimated gender distribution of suicides in China. Unlike in most countries, where male suicides outnumber female suicides, existing research has found that female suicides are more common in China by a ratio of 3:1 [7].

Age: The average age of the deceased at time of death in our dataset is 23.5 years. The vast majority (88.6%) are under age 30, with a minimum of 13 and maximum of 40. This largely reflects the age distribution of Weibo (where 82% of users are under age 30 according to a 2017 report [30]), though a World Health Organization (WHO) report [1] found that the risk of suicide is more than twice as high in the 15–29 age group as the 30–40 group, which our statistics agree with. However, the highest risk of suicide is among the elderly in China [31], who are not represented in our dataset at all—a common limitation of using social media data [32].

Location: We also analyzed the dataset's geographic distribution. We identified the location of death (at the granularity of provinces) for users based on their death reports. If this information was not available from the report, we used the user's birth location if mentioned in the report, and the static location from the user's profile otherwise. For each province, we calculated the number of users in our dataset who died in that location, divided by the population of the province to adjust for differences in overall population.[3]

Figure 1 summarizes the normalized counts by province. All provinces in Southeast China have coverage in our dataset, though Tianjin and provinces in comparatively less developed parts of China have no users. Even after normalizing by population, the highest rates of suicide in our dataset are from Beijing and Shanghai, China's two most populated cities. One explanation is that urban areas are overrepresented in Weibo in general (67% users are from cities [30]), though Beijing and Shanghai are still overrepresented in our dataset (24.6% of users) compared to the full population of Weibo (16% of Weibo users [30]). It is also possible that users from the largest cities have larger social networks and therefore increased likelihood of having their deaths reported to the two Weibo accounts we

[3]Data from Wikipedia: https://en.wikipedia.org/wiki/Provinces_of_China We note that a more appropriate way to normalize the counts would be to adjust for the number of Weibo users from each province, rather than the real world population, but we were unable to obtain these statistics.

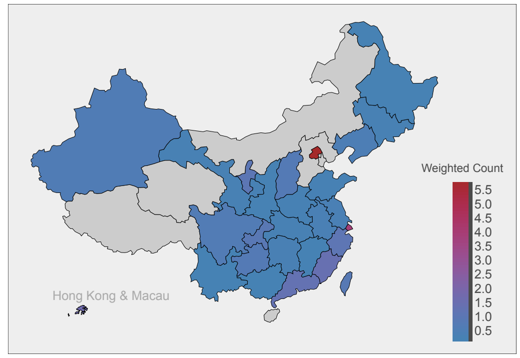

Figure 1. Number of users in each location of death, normalized by the population of each location. Gray indicates no users in our dataset from that province. Hong Kong and Macau were counted as one province (bottom left).

used as sources. Finally, it is interesting to note that recent research finds that urbanization of China is changing the epidemiology of suicide, with urban suicide rates increasing relative to rural suicide [31]. Our dataset may support the study of suicide in urban areas.

C. Affordances and Limitations

We now discuss what types of research questions we believe one can and cannot investigate with this dataset. While a general limitation of the dataset is the small number of users, which will make it hard to achieve statistical power in some experiments, the data is richer than traditional suicide records, with longitudinal details about people's everyday lives. As a result, these social media feeds can provide unique insights into the context of a suicide, through a person's history that was likely not captured in clinical data. We describe three areas below in which social media could inform suicide research. For each area, we discuss ways in which this particular dataset is an appropriate tool, as well as its limitations.

Intelligence: Our dataset provides a new source of intelligence for suicide. A common use of social media for public health is to estimate population-level statistics, such as the prevalence of influenza in a given week [33], or the level of fitness in a geographic location [34]. In the case of China, social media is especially promising. There is a strong need to find alternative data sources to supplement official suicide data from China, which does not have a comprehensive system for collecting suicide data [7]. Public suicide statistics from the Chinese Center for Disease Control and Prevention do not contain geographic information (other than urban and rural designations [8]) and cases are believed to be undercounted [7]. Unfortunately, it is unlikely a dataset collected in this way could yield reliable population-level estimates. The biggest challenge is our source for identifying suicide users. Relying on user-submitted reports likely results in a strong selection bias that is difficult to characterize and adjust for. It is also difficult to correct for demographic biases inherent to Weibo, as comprehensive demographic data on Weibo users is not available. Moreover, unlike Twitter, Weibo does not have a streaming API that can provide a random sample that can be used to evaluate the population distributions.

However, as suicide incidents are not widely cataloged, there is still enormous value in using social media to identify new cases of suicide, akin to how a project like the Gun Violence Database [35] mines media to identify new incidents of violence. Now that we have examples of suicide user accounts, it may be possible to construct a predictive model that can detect if there has been a suicide (if not from the user, then from other comments). Given the need for better intelligence on suicide in China, this will be an important direction to pursue.

Network analysis: The Weibo population forms a high-dimensional and sparse social network of which the 130 suicide users are a tiny subset. Moreover, the network is incomplete, due to the platform's display limit of 400 users. Finally, of this partial network (with a maximum of 400 edges between each node pair), we can only collect a small subset due to the length of time needed to crawl each page.

In this sparse and incomplete network, paths between the suicide users will be sparse. If a path exists at all, we expect that most connections will likely go through a small number of popular users rather than users with more personal connections.[4] Therefore, without additional expansion, we expect that this dataset will not be reliable for analyzing network effects between suicide users.

However, the ego-centric networks that we can obtain are valuable for studying interactions between suicide users and their direct contacts. With each user's first-order connections, we can measure effects that the friends had on the suicide user's timeline (e.g., support) and vice versa (e.g., grief).

Text analysis: Our dataset is most appropriate for analyses of text content, since our dataset contains mostly complete message histories of each user. A user's post history, as an artifact similar to a diary [36], can be studied to help understand the user's thoughts and actions (disclosed by the user online) and state of mind (revealed through unconscious linguistic behaviors [5]) leading up to death. Additionally, the demographic information we have for each user can be used to measure linguistic and behavioral differences between these groups in the period before suicide.

[4]Surprisingly, we did find direct interactions between 18 pairs of users. 10 of these pairs included the most popular user in the dataset, and all interactions were in one direction. We plan to study these interactions in more depth to understand what kind of relationship these users had.

Daily Life Topic 26	睡觉 (sleep); 吃 (eat); 回家 (back home); 一天 (a day); 下雨 (raining); 工作 (work); 天气 (weather); 洗澡 (shower); 起床 (get up); 学校 (school)
Entertainment Topic 6	演员 (actor); 相声 (crosstalk); 曲艺 (Beijing Opera); 演出 (perform); 嘉宾 (guest on show); 单曲 (single song); 电影票 (movie ticket); 电影院 (movie theater)
News/opinions Topic 16	国家 (nation); 社会 (society); 人民 (the people); 政府 (government); 老百姓 (civilian); 教育 (education); 文化 (culture); 法律 (law); 制度 (social system)
Family Topic 21	老婆 (wife); 老公 (husband); 爸爸 (Dad); 妈妈 (Mom); 弟弟 (Brother); 姐姐 (Sister); 家里 (home); 闺蜜 (best friend)
Sentiment (-) Topic 3	难过 (frustrated); 悲伤 (sad); 害怕 (fear); 孤独 (lonely); 寂寞 (lonely); 伤心 (sad); 哭 (cry)
Sentiment (+) Topic 18	哈哈 (laugh); 偷笑 (laugh); 好 (good); 可爱 (cute); 赞 (awesome); 给力 (awesome); 酷 (cool); 鼓掌 (applause)

Table II
EXAMPLES OF TOPICS FROM EACH CATEGORY.

V. LONGITUDINAL CONTENT ANALYSIS

We now characterize the content of the users' social media messages, and how it changes over time.

A. *Temporal Aggregation*

We calculated statistics to summarize the activity levels and content of the users' social media feeds in time intervals with respect to the date of death— the 10 months, 10 weeks, and 10 days prior to death. At each granularity, we calculate statistics within 10 intervals spanning d days, where $d \in \{1, 7, 30\}$ to represent days, weeks, and months, respectively. This approach is similar to prior work that summarized the content of cancer-related search queries with respect to the date of diagnosis [14], [37].

To measure uncertainty in our estimates in each time period, we performed bootstrap resampling. We created 100 estimates of the statistics, where each estimate was calculated by randomly sampling with replacement from the 130 users. We then used the 5th and 95th percentiles of the distribution of estimates as lower and upper bounds.

We considered three measurements:

Posting frequency: As a measurement of the level of participation in Weibo, we measured the number of messages posted by each user in each time interval. We calculated the average number of messages posted by active users in each month, week, and day, shown in the top row of Figure 2. For each time interval, we only included users in the average who had active accounts beginning before that interval, since not all users had accounts going back 10 months. The average posting frequency is fairly consistent over the period of months, but we see an increase in posting

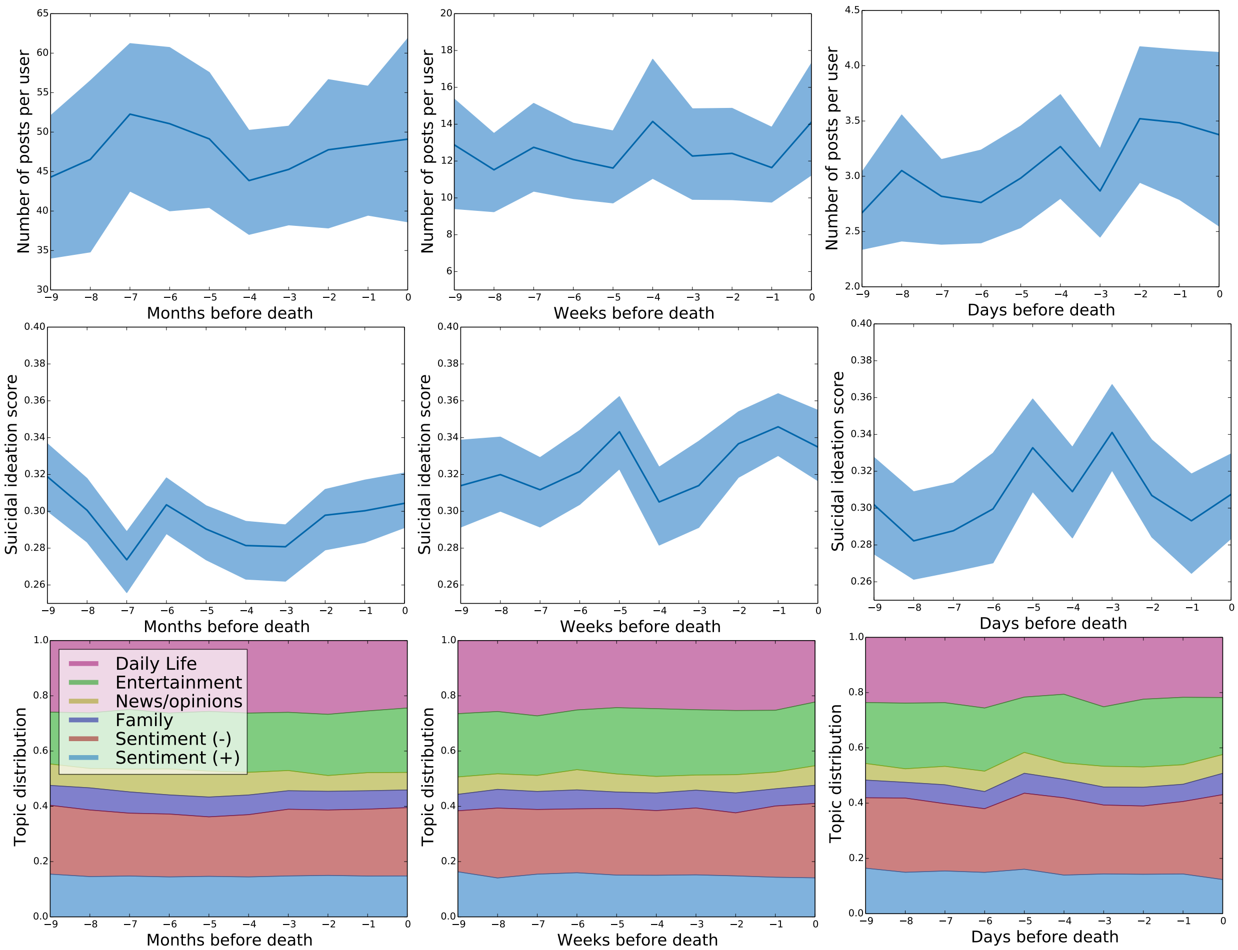

Figure 2. The average number of posts (top row), the linguistic suicidal ideation score indicating suicide-associated language use (middle row), and the distribution of topic categories (bottom row) for ten time intervals at three granularities: monthly (left), weekly (center), and daily (right). In the top two rows, shaded area corresponds to a 90% confidence interval estimated with bootstrap sampling.

frequency in the last week before death, with a fairly steady increase through the final days.

Linguistic indicators: We measured the use of language that is associated with suicide. We utilized a large Chinese suicide lexicon (3,453 entries) developed in previous work [22] in collaboration with psychologists. The lexicon includes words carrying negative affect as well as other words used in suicide notes such as self-references and family references. The lexicon was validated by using it to identify messages containing suicide ideation in Weibo with 79% precision [22].

We define a suicidal ideation score $s(t)$ for a time interval t as the sum of the probabilities of the lexicon words in that time interval, where word probabilities are proportional to their frequencies in the messages posted in the interval t. Using $\mathcal{L}$ to denote the set of words in the suicide lexicon, the linguistic score is defined as:

$$s(t) = \sum_{w \in \mathcal{L}} P(w|t) \tag{1}$$

A higher score indicates higher use of language associated with suicide, as defined by the lexicon. The ideation scores are shown in the middle row of Figure 2. We see that scores are noticeably higher at the granularity of weeks compared to months, showing an increase in levels of language suggestive of suicidal ideation in the weeks leading up to death. There is high variability in the scores in the daily plot, so it is less clear what the trend is in the final days, but the score reaches high points in the 3–5 days before death.

Topic composition: We also broadly characterized the various topics of discussion in the corpus using probabilistic topic modeling. We used Latent Dirichlet Allocation (LDA) [38] to estimate the proportions of 30 latent topics (distributions over words) in each message using `MALLET` [39]. Text was preprocessed following [22] and using the Python

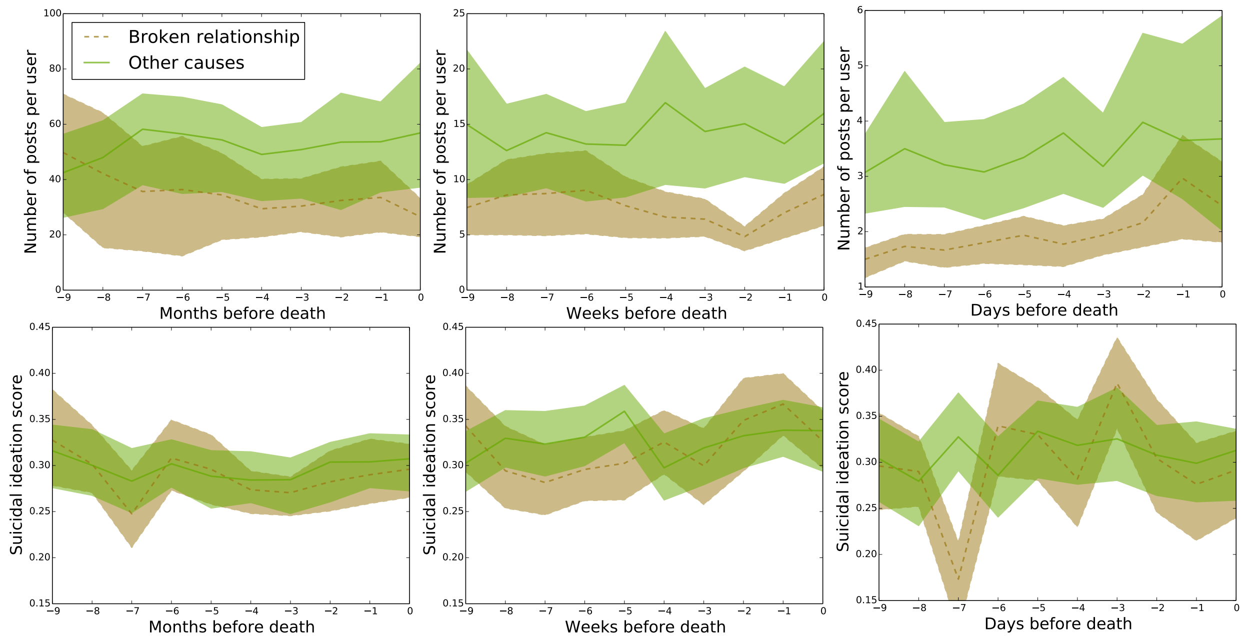

Figure 3. The average number of posts (top row) and the suicidal ideation score indicating suicide-associated language use (bottom row) comparing two sets of users: those whose reason for suicide was a broken relationship, and a matched sample of all other users. Shaded area shows the 90% confidence interval.

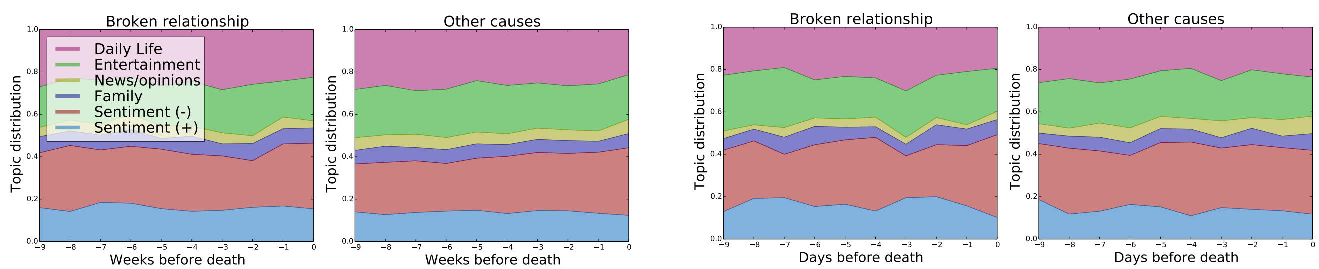

Figure 4. The topic distribution by week (left) and day (right) for the same two groups of users compared in Figure 3.

package `jieba`[5] for word segmentation.

We examined the top words in each of the 30 topics and determined labels for the topics. We grouped the 30 topics into six general categories: daily life (e.g., meals and work), entertainment (e.g., music), news and opinion (e.g., politics and business), negative sentiment, and positive sentiment. Examples of topics within each category are shown in Table II.

We calculated the average proportion of each topic z in each time interval t:

$$P(z|t) = \frac{1}{|\mathcal{D}(t)|} \sum_{d \in \mathcal{D}(t)} P(z|d) \tag{2}$$

where $\mathcal{D}(t)$ is the set of documents posted during time period t. We aggregated the individual topic proportions into proportions over time for the six general categories, shown in the bottom row of Figure 2. We find that the entertainment and daily life topic categories are the most common topics of discussion, and negative topics are discussed more than positive topics in this corpus. The topic distribution is surprisingly stable over time, suggesting that users largely share similar content leading up to their suicide. However, we do observe an increase in negative sentiment topics close to the time of death, with a decrease in "everyday" content, the entertainment and daily life topics.

[5]https://github.com/fxsjy/jieba

B. Comparing Suicide Contexts

While there appear to be general patterns in the behavior and content of users in our dataset, it may be more meaningful to separately analyze different groups of users based on the context of their suicide. Many of the death reports from which we identified suicide users (Section IV) described *why* the user had committed suicide. One of the most common and easy to identify reasons for suicide was a broken relationship. We now repeat our analysis above for the subset of users who committed suicide for this reason and compare to the other users in the dataset.

The first two authors, native Chinese speakers, labeled each of the 130 users to indicate whether the reason for suicide appeared to be due to relationship problems. They agreed on all but two users (Cohen's $\kappa = 0.90$). We identified 35 such users, which we refer to the "Broken relationship" dataset. We then compare temporal patterns within this set to patterns in the complement of this set, users who died for "Other causes".

Only 11% of users in the "Broken relationship" set were male, compared to 23% of users in the entire dataset. Thus, differences between these two groups could be due to gender differences. To control for bias from this confounding variable, we downsampled the "Other causes" set to match the gender distribution of the "Broken relationship" set, resulting in an "Other causes" set of 8 male users and 62 female users.

Figure 3 shows the average posting frequency and suicidal ideation score for the two different groups of users, and Figure 4 shows the topic distributions for the two user groups. We find that the "Broken relationship" users have a significantly lower posting frequency in general (with the largest gap two weeks before death), but a sharper increase in frequency in the final days and weeks before death. There is also differences in the users' topic distributions, with "Broken relationship" users having smaller proportions of news/opinion topics and higher proportions of sentiment topics.

VI. Discussion and Conclusion

In this exploratory work, we constructed and examined a dataset of 130 social media accounts of people who we verified to have died of suicide. We found temporal patterns that suggest there are commonalities in how people express themselves in the time leading up to their suicide: increased frequency of posts, increased suicidal ideation, and increased negative sentiment in the final weeks and days before suicide. The overall changes are small, which is perhaps a function of aggregating across every user without regard for their individual context. When comparing patterns of users grouped by their reason for committing suicide, we see more variation in social media behavior. We therefore might find richer insights by examining social media patterns within more focused groups of individuals.

Another direction for future work is to consider the other data attributes: comments, reposts, and likes. Whether these interactions influence the trajectory of a user's suicide timeline would be important to study. There is also promise in using this dataset to understand how a suicide affects not just the individual, but others in their network, by measuring attributes like grief [17]. Finally, while we focused on Chinese social media, the approach outlined in this work—finding social media accounts of people who died of suicide, and calculating temporal patterns in social media content with respect to the date of death—could serve as a framework for other social media platforms in other languages and locations. Longer term, we hope that social media can augment traditional data sources to expand our understanding of the causes suicide.

Acknowledgments

We would like to thank Casey Fiesler for useful discussion and feedback on this work, and the reviewers for their valuable comments.

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