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Analyzing Sanctioned Suicide: a case study on pro-choice suicide sites

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Elisa Sartori, December 2022

I hereby declare that the undersigned and author of this document is responsible for its content, and for the parts taken from other works, these are expressly reported by citing sources.

Abstract

According to the World Health Organization, close to 700'000 people take their own lives every year. Suicide has always been a socially important topic, so much so that free hotlines, help bots and automatic banners are displayed and easily accessible to people that search related keywords on the web. In the last year, it has come to light the existence of Sanctioned Suicide, a pro-choice forum discussing suicide, where users can both look for help with their recovery or research and asks questions about methods and how to acquire them. These types of sites have yet to be extensively researched in the literature. Their analysis could allow us to better understand what are the topics discussed and how these communities act, very useful knowledge for suicide prevention and help of suicidal individuals.

In this thesis, we use Sanctioned Suicide as a case study and investigate how it is organized, what knowledge can be found and how users communicate in this environment. We have collected data for a total of 53K threads, 700K comments and 16K users. We use this dataset to analyze user trends, extract the topics of conversation in the forum and uncover hidden relations. Our analyses show that 30% of the topics found in Sanctioned Suicide discussions deal with suicide methods. We also discover that Covid has been a distress factor for users, especially during the first lockdown, highlighting a strong connection between talks of suicide and Covid.

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1 Introduction

Suicide has always been an important and challenging topic to tackle. Not only because of the loss of life of a suffering individual but also because it has a lifelong impact on their surviving family members, colleagues and close friends that have to cope with the premature departure of their loved one. According to the World Health Organization (WHO) [119], as many as $700'000$ people die every year due to self-immolation. Suicide is also the fourth leading cause of death among teenagers and young adults (15 to 29 years old).

In 2014, with the publication of the suicide report "Preventing suicide: a global imperative" [120], WHO recognized suicide as a public health priority. With this publication, WHO aims to 1) raise public awareness about the repercussions of suicide and suicide attempts on public health and 2) increase the priority of suicide prevention on the global agenda. In fact, according to WHO, "Suicides are preventable. Much can be done to prevent suicide at individual, community and national levels".

Prevention can take many forms: from organized events to more practical tools like free help hotlines, chat-bots [1, 104] and banners with helpful contacts triggered by a search for suicide-related keywords. In all forms, however, knowledge of terms employed and methods commonly used has a crucial role and needs to be constantly up-to-date for it to be effective. Keeping information current is imperative since, as Anderson et al. indicate, "Early and successful treatment can significantly reduce the length and severity of episodes of depression and associated suicidal thoughts or behaviour"[5].

In the Internet and Social Media age, information can be published and found everywhere. It is impossible to track everything, which is why social networks have started relying on Artificial Intelligence models more and more to take care of undesired content or identify and help suicidal users (e.g. Facebook [26]).

It is no surprise that the literature also addresses the problem of detecting suicidal individuals in an online environment. Generally, these studies tend to focus on detecting whether a user is experiencing suicidal ideation or his level of risk. This goal is achieved by building AI models able to discern warning signs and indicators in texts posted by users. However, they rely on pre-existing knowledge gathered from previous studies to distinguish these keywords and indicators, which may not be current, given how quickly language changes online [123]. Taking into consideration the sheer amount of online content posted every day, Big Data analysis could be instrumental in discovering terms and methods used by suicidal individuals directly from their posts.

Recently, a site called Sanctioned Suicide has been brought into the spotlight by Italian and International media, given its connection to a series of teenage suicides close to each other [111]. Allegedly, this site is a community where users seem to be able to find information on methods, how and from whom to acquire the correct components and even dosages. The site has received a lot of negative press, with some sources accusing it of instigating suicide [38, 60, 112].

The goal of this thesis is to analyze Sanctioned Suicide to determine how users interact on and with the site and to extract information that improves our knowledge on the subject, which could ultimately support experts in planning interventions. The information that can be inferred from sites like Sanctioned Suicide could be invaluable in keeping information up-to-date and improving already existing tools to aid with this complex problem. In addition, based on news articles related to the site that we have read, we believe Sanctioned Suicide is an echo chamber[1], so we want to verify if our assumption is correct. Since multiple sources have mentioned inciting suicide, we will also investigate this possibility. We make the following contributions:

- We collect a dataset of Sanctioned Suicide discussions composed of 53K threads, 700K comments and 16K users, from March 2018 up to July 2022.
- We investigate how users utilize the site through the analysis of trends and discussions.
- We show that Sanctioned Suicide is an echo chamber.
- We show that it is possible to discover terms and methods using Big Data analysis on the site's discussions.

This thesis is organized as follows. In Chapter 2 is the background study. Chapter 3 presents the website Sanctioned Suicide along with its contents. To answer the objectives of this thesis we had to create a dataset based on the site's contents, Chapter 4 discusses the dataset collection and provides some summary statistics on how users interact with the site. Chapter 5 presents the analyses made to understand what information can be extracted from the site and how users interact within it, for which we used Topic Modeling and Word Embedding. Chapter 6 discusses a work still in progress in regards to suicide incitement. Finally, Chapter 7 contains our conclusions and some possible future extensions.

[1] An environment in which a person encounters only beliefs or opinions that coincide with their own, so that their existing views are reinforced and alternative ideas are not considered [70].

2 Background

As introduced in Chapter 1, our primary goal is to analyze the site Sanctioned Suicide. Data-driven approaches have already proven useful in the context of websites and social media. The enormous amount of information available on the Web has made these techniques more and more relevant. One field in particular, Social Data Analysis[2], has shown its utility by employing information from social media in conjunction with Big Data and Artificial Intelligence (AI) to improve the online environment.

In this chapter, we discuss the work done in the field, and explore the two main topics covered in this thesis: *echo chambers* and *cybersuicide*. Cybersuicide refers to a suicide mediated by the Internet in some way. The term has evolved into including pro-suicide websites and sites that contain graphic suicide-related content like images.

2.1 Social Data Analysis for good

Recently, we had the opportunity to see the importance and relevance of technology up close, even outside of Social Data Analysis. When Coronavirus forced everyone into social isolation and lockdowns, the ability to continue attending lessons and working remotely meant that many people did not have to put their lives on hold.

Nevertheless, those were not the only benefits brought by technology. Academically, we have seen a substantial increase in publications that use Big Data and AI in response to Covid [75], both to fight it and to preserve people's well-being. Some of these works include but are not limited to deep learning models able to detect drugs that could fight Covid [62], models that can diagnose Covid from coughs recordings [47, 55] and from x-rays [20], models that can detect fake news [71] and models able to make hypothesis on the number of cases and their potential longevity [46, 105].

Even before Covid, this sector presented work of great value in numerous fields, including:

- **Environment monitoring**, where Big data and AI are used to monitor an environment and its quality. Both have been beneficial in the context of agriculture, to monitor food safety and farming. Examples of works done in the field are Faid et al. [28] discussing an AI-powered IoT-based platform,

[2] Analyses of how people interact using data from socials.

where the authors use a model for weather forecasting in conjunction with drones to help with crop management and Chen et al. [18] presenting a model for water quality monitoring, to detect environmental pollution.

- **Healthcare**, where Big Data and AI have been used to improve people's health, identify diseases and enhance hospital processes. Examples of works in this field include Hong-tan et al. [45] tackling monitoring and personalized health care suggestions for students, Celi et al. [15] researching artificial intelligence tools to predict fluid requirement in the intensive care unit and Chen et al. [17] discussing a model to evaluate the risk for certain diseases, like Alzheimer, based on a patient's information.

- **Homelessness**, where Big Data and AI have been used as a support to deal with this issue, with Fisher et al. [30] presenting a simulation model to assist governments in making decisions and testing the effects of policies beforehand or VanBerlo et al. [114] discussing a model to predict chronic homelessness (individuals who have spent more than 6 months in a shelter) to help with shelter management.

Since our goal is oriented toward online communities' well-being, we will limit discussions to prior works that deal with similar themes or employ Social Data Analysis.

2.1.1 Mental state

Welfare in communities has multiple aspects and can be investigated in many ways. Some works focus on users' mental state in social networks by observing emotions expressed in text. Singh et al. [102] aimed to understand people's mental condition during the pandemic. The authors achieve this by using sentiment analysis on online comments, utilizing *Bert4rec* [106], a natural language processing model. The analysis is conducted using two distinct datasets of Covid-related posts collected from Twitter [113], one with users from India and the other with users from the rest of the world. They found that tweets from the Indian dataset had more positive sentiments if compared with the word dataset, which they connected to a positive response to the actions taken by the Indian government during the pandemic.

Prabhakar et al. [74] wanted to understand if misinformation was present on Twitter during the pandemic and how people reacted to Covid. To achieve this, they examined coronavirus tweets (i.e., posts from Twitter) using sentiment analysis and performed Topic Modeling using Latent Dirichlet Allocation (LDA) [11].

They calculate the presence of 8 emotions, as well as the general valence of the post (i.e., *positive* or *negative*). They found that most of the topics identified referred mainly to reliable information on Covid, with very little misinformation present. Results also show that both *negative* and *positive* sentiments are present, with fear, trust and anticipation being the most occurring emotions in people during that time.

Rajput et al. [81] conduct a statistical study on worldwide Covid-related tweets to investigate if there were patterns or trends in the words used at the time and what was the mindset of Twitter users. They achieve the first objective by evaluating the frequency of n-grams using word clouds. For the second they perform sentiment analysis using a classification with labels *positive*, *negative* or *neutral* and compare results with tweets from the World Health Organization. Results show the most frequent words to be "coronavirus", "covid19", "china" and "wuhan" and that the most expressed sentiment was *positive* for WHO's posts and *neutral* for those of the general public. After removing the neutral class the authors compared results again, where they determined that the general public was more focused on the positives rather than the negatives, following WHO's general attitude.

2.1.2 Content moderation

Another branch of the field aims to protect people from harmful web content. Content moderation is the process of detecting inappropriate posts (e.g., nudity, swearing, violence, racism or self-harm) on web platforms. Reliable identification of such contents is necessary to remove it, apply a warning label, or report user misconduct. In content moderation, a combination of human and AI moderators is typically used [41], human for their reliability and AI for their speed. The literature on the topic is quite broad as it covers all types of social media content: images, videos or text. We will see an example for each.

Karabulut et al. [53] explore the problem of identifying and censoring nudity in photos. The authors present an automatic pipeline organized into two parts. The first identifies which areas of the image contain nudity, the second obfuscates only those parts in the image and leaves the rest untouched.

Chaudhari et al. [16] investigate the detection and censorship of profane content in a video. The authors present a machine-learning model that silences audio and pixelates lips in video segments that contain profanity. The model detects profanity by converting audio to text and checking for profane words. Once a profane word has been detected, the time segments where it appears are stored.

Later, they will be provided as input to suppress the sound and blur the lips in these time segments using facial markers (the facial points collectively representing a specific part of the face).

Tahmasbi et al. [107] investigate sinophobic behavior on Covid-related tweets. They create and analyze word occurrences and embeddings to understand how the use of words changes over time. By scrutinizing occurrences, they discover an increase in the words “china”, “chinese” and slurs related to them (e.g., chink). Lastly, they use cosine similarity on embeddings to create a two-hop graph around the word “chinese”, confirming a close connection between the term, related slurs and Covid.

2.1.3 Misinformation and Disinformation

Another related field is combatting misinformation (false or inaccurate information) and disinformation (deliberately misleading information). The dangers of these practices are many, such as reducing trust in the media, tarnishing people’s reputations or influencing people’s opinions. Research in the field can go from fake news identification to persuasion detection. Kaliyar et al. [52] present in their work a deep convolutional neural network able to achieve 98.36% accuracy on fake news detection. The proposed model does not rely on premade features; instead, they are learned automatically through the input text.

Da San Martino et al. [22] identify and discuss 18 propaganda technique. Propaganda is a type of persuasion commonly used in the news, which aim is to promote a specific narrative by influencing peoples’ opinions. This work presents a manually annotated corpus of 350K tokens. On top of that, the authors design a multi-granularity network that can identify techniques both at sentence level (i.e., text contains persuasion) and at fragment level (i.e., type of technique and where).

Iyer et al. [48] present a baseline model that can discern persuasion based on the structure of sentences. This model does not require annotated data as they use parse trees to detect structure similarity within persuasion tactics.

2.1.4 Empathy

The theme of empathy has also been addressed in the domain of online communities. The work of Sharma et al. [98] presents *EPITOME*, a new conceptual framework to measure empathy expressed through text. The authors use a dataset composed of conversations on mental health collected from *Talklife* [108] and *Red-*

dit [83][3]. Using this framework, they discover that these platforms have a shallow expression of empathy (averaging 1 out of 6). This problem was addressed later in Sharma et al. [99], proposing a new task of empathic rewriting (i.e., transforming posts from low-empathic to higher empathy) and *PARTNER*, a trained model to achieve that.

2.2 Cybersuicide

In general, the relationship between the Web and suicide is strongly investigated. The theme of cybersuicide has been addressed in the literature from many different points of view and ways.

Some studies focus on identifying what influences suicides. Niederkrotenthaler et al. [66] examine the association between celebrities' suicide news coverage and suicides in the public following the reports. They find that after the media reports the death of a celebrity, the risk of suicide increased by 13% if compared to the trend before the reportage. Researchers are also linking Internet and media reports of suicides to have an impact on suicidal behavior, in particular for the choice of method used. Biddle et al. [9] investigate this by conducting semi-structured interviews to 22 individuals that survived suicide attempts. They uncovered that the most common sources for their choice of the method were television, news and websites.

Other studies investigate what role other people play in cybersuicides, such as that of Fratini et al. [32]. The authors investigate the practice of livestreaming suicides over the Internet, specifically they analyze the role of the audience. They determine that spectators play a key role with people actively encouraging or trying to dissuade the individual from suicide.

2.2.1 Prevention

A big part of the research in the field is dedicated to prevention and methods restriction. In the work of Gunnel et al. [42], the authors raise awareness on the possibility of an increment in suicides due to Covid. Historically there has been evidence that deaths by suicide increased during the 1918 influenza pandemic and even during the 2003 SARS epidemic. The authors encourage enhanced surveillance of COVID-19-suicide-related risk factors in patients. Bonvoisin et al. [13] discuss the effects of pesticide restriction in India. Pesticide ingestion is one of the most common methods of suicide in India, particularly in the most

[3]Restricted to the 55 subreddits found in the work of Sharma et al. [100].

rural countries. They found some legislations were more effective than others, impacting previous trends of both pesticide suicides and suicides in general.

However, most researches focus on detecting suicidal ideation and behavior risks in individuals. Detection might include physical approaches, such as using Closed Circuit Television (CCTV, i.e., security camera) surveillance to detect potential suicides by train [2] or by hanging [57]. Other works, instead, use statistical data (e.g., gender, sexuality, age) to improve screening of suicidal people [3]. But the largest branch is text-based detection, using text in online conversations to identify suicidal users in Web platforms [43, 101]

The identification of topics in suicide discussions is also related to detecting suicidal individuals. Some work has shown that using information on latent topics and feelings expressed in texts can improve model performance [50, 51]. Instead, Franz et al. [31] apply topic modeling to detect self-injurious thoughts and behaviors.

2.2.2 Pro-choice sites

Sanctioned Suicide is not the only pro-choice suicide site in existence, there are many more. These websites may also be referred to as "pro-suicide" given the large amount of content in regards to methods that can be found. People don't come across these sites by accident, but they aren't hard to find either.

Biddle et al. [10] investigate what resources can be found by a suicidal individual on the Web. The authors query four of the most popular search engines (Ask [6], Google [39], MSN [63], and Yahoo [121]) with typical terms that might be used by a suicidal user (e.g., suicide, suicide method). They consider the first ten sites obtained from each query and discover that the three most frequently occurring sites were all pro-suicide. In addition to that prevention sites, academic sites and all news reports of suicides also contained information about methods.

Pro-choice sites and their contents are being analyzed. Murray [65] aims to explain the existence of these types of websites that encourage discussion on suicide from a pro-suicide or pro-choice perspective. The study presents the results of interviews conducted with two groups: users of such sites and those who fight to make them illegal. The results show a duality; some users have found comfort in the possibility of talking openly about suicide, which helped them recover. However, during the work, the author analyzed suicide websites to better understand the domain. The investigation was restricted to a visual analysis of the three most relevant and frequented, *alt.suicide.holiday*, *alt.suicide.methods* and *alt.suicide.bus.stop*. There, the author finds detailed compilations on suicide methods, plans to prepare for the consequences (pets, funeral, etc.), information on how to erase all data relating to the site and how to write a suicide note. On one site, a Lethality-Time-Agony Method calculator was found, where users could input the importance they gave to each aspect and were returned a recommendation for a method according to the given preferences. The author also finds evidence of specific terms being used, with *"asher"* referring to members and *"catch the bus" or "ctb"* to suicide.

It is confirmed that the information on these websites is being used. In 2019 Mudan et al. [64] reported an unusual cluster of deaths due to intentional ingestion of sodium nitrite over the course of 6 months. They had 5 patients between the ages of 16 to 27 presenting to the emergency room. The authors determined, through patients themselves or family members, that they obtained information about this method of suicide online. Similarly, McCann et al. [58] indicate that their medical toxicology service encountered similar cases. They had 5 patients between the ages of 17 and 35 presenting after the voluntary ingestion of sodium nitrite. Two of the patients indicated having purchased it online, and another explained that this method was recommended to him in a public depression support group on Facebook.

Researchers are also discussing the pros and cons of banning pro-suicide websites. Pirkis et al. [73] discuss in their work the benefits and limitations of the Australian 2006 ban on such online places. While off-shore sites remain primarily unsusceptible to legislations, they find that limiting access to domestic pro-suicide sites may make it more difficult to know where to acquire certain substances.

For what concerns Sanctioned Suicide, Alvarez [4] mentions the site in the introduction. The main body of the research, however, investigates *SuicideForum.com*, a pro-recovery site. The author analyzes the discursive meaning of the concept of space. The results show duality in meaning. For some, it evokes a sense of comfort ("home", "this site"), for others, a sense of entrapment ("hostile", "alien"). To the best of our knowledge, no prior works have tried to investigate Sanctioned Suicide, nor the possible influences of echo chambers in these communities.

2.3 Echochambers

On Oxford Languages dictionary [70], an *echo chamber* is defined as "an environment in which a person encounters only beliefs or opinions that coincide with their own, so that their existing views are reinforced and alternative ideas are not considered".

Literature on echo chambers is centered around proving their existence [25, 95, 109] and discussing their relation to *filter bubbles*[4] [24, 95], how they influence people and their risks [24, 118], as well as how to mitigate their effects [49].

Considering the definition, it would appear evident that these types of environments could thrive on the web. In particular on social media, where people can join communities that share their same views on the world. However, the literature is divided on the matter, with some studies finding evidence of echo chambers [34, 95] and others not [25].

Terren et al. [109] give a thorough review of the literature on echo chambers on social media. They consider 55 studies done in the field and classify them according to similarities and differences. They discovered that studies that found no evidence of echo chambers were based on self-reported data and thus could be biased, whereas those that found evidence of their existence were data-driven.

Other works, instead, try to quantify how common it is to come across an echo chamber. Cinelli et al. [21] set out to investigate four social media platforms (Facebook [27], Twitter [113], Reddit [83], and Gab [33]) by analyzing the posts produced by 1M users. In their work, they give a formal definition of an echo chamber. To define an echo chamber there must be a coexistence of two factors: opinion polarization concerning a topic and homophilic interactions between users. In other words, users must have a common opinion on a strongly controversial topic and show a preference for interacting with like-minded people. They achieve this by reconstructing the interaction networks built on social media platforms and seeing how users interact among themselves. Their findings show differences between social media: while echo chambers were predominant on Facebook and Twitter, the same cannot be said for Reddit and Gab. Discussions are mostly centered around science, conspiracy and politics. Furthermore, by analyzing news consumption between Facebook and Reddit, they are able to determine that algorithms targeting users' preferences (i.e., filter bubbles) favor the creation of echo chambers.

This finding is supported by Donis [24], whose goal was to examine how negative beliefs and misinformation are spread and reinforced on social media. It discusses how people may get stuck in a feedback loop of constant reinforcements of their values, behaviors and interests through filter bubbles and echo chambers which may lead to the exasperation of negative or dangerous beliefs.

Echo chambers and filter bubbles are not harmful per se, but while it makes it easier to connect with content and people whose values they share, there needs

[4] Algorithms filtering and presenting only information in accordance to user preferences.

to be opposing views in case of negative opinions. Echo chambers and their effect of reinforcing ideas can be a severe problem when involving extremist ideas. Rhodes [118] tests this hypothesis by conducting a randomized experimental study on 96 Twitter users. They were divided into a control group, with the usual Twitter content filtering, and a treatment group, with an algorithm suppression mechanism. All participants were considered at risk of radicalization due to their geographical location. After 4 months of observation, users received a survey on radicalization (on the justifiability of suicide bombings). The results show that the control group users had a statistically significant increase in radicalization.

The same effect can be seen in communities that are online echo chambers. The *Incel* community has become quite infamous in recent years. The term Incel stands for "involuntary celibate" and indicates someone unable to find a partner. The community is quite toxic, characterized by extreme misogyny and racism. Incels are known to spread extremist views and encourage violence, so much so that some of their members committed mass murder [7, 110].

Young [122] analyses contents on Incels' communities across social media platforms. The goal was to understand Incel's ideology better and identify what impact hatred and violence had on them. They find that social media has not only had a crucial role in the existence of these communities, but also plays a key role in instigating the passage of violence from the online world into the real one. The discovery is confirmed by Salojarvi et al. [84], where the authors also find that echo chambers and lack of exposure to different ideas have fueled both the Incel movement and its radicalization.

As we have discussed, there exist a lot of echo chambers. Some centered around politics, medicine, and other common topics whereas others, like Incels, are dedicated to more complex topics(e.g., politics). Other known echo chambers of this type are *Pro-Ana* (sites that support anorexia) and *Pro-Mia* (sites that support bulimia). These are not communities that someone comes across by chance, but are sought after by users.

Osler et al. [69] investigate the echo chamber effect on Pro-Ana sites, particularly what motivates people to join them. Pro-Ana sites provide support, solidarity, tips, and a sense of community. The feeling of being understood can help reinforce and maintain anorexic practices in individuals with Anorexia Nervosa. The authors also identify two key components that explain why individuals join and stay in these communities: *affective allure* (sense of comfort and belonging provided) and *affective stickiness* (emotional support, understanding and compassion make leaving more difficult).

3 Sanctioned Suicide

As introduced in Chapter 1, Sanctioned Suicide [89] is a pro-choice site where suicidal people gather to discuss the topic. From our preliminary observations, the site is quite peculiar since there is a duality in contents. Users access it to both research methods and to get help from people who are going through similar emotions. To better understand the nature of the site and its users, an initial visual study of its rationale, organization and resources is necessary. In this chapter, we will present the website and its content. Lastly, we will discuss our findings.

3.1 Site organization

In Figure 1, we can see the site's landing page. On the left is a menu, where users

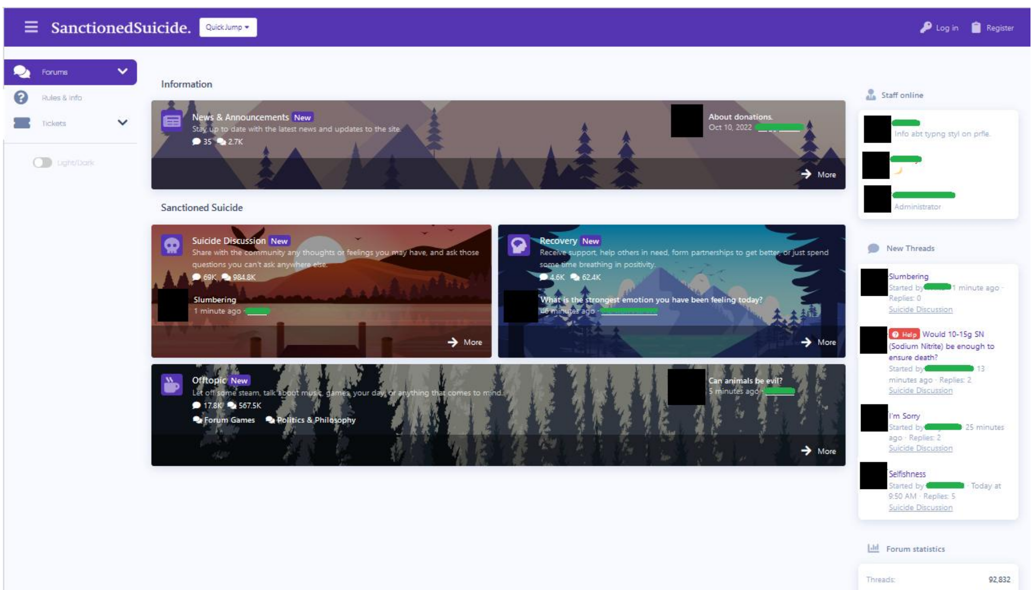


Figure 1: Sanctioned Suicide landing page. Usernames and profile pictures were censored to ensure anonymity.

can access the forums, view the rules, open tickets to appeal bans or rejections, report bugs, or make inquiries. On the right can be seen which moderators are online, new threads opened, forum statistics and last donations made. At the center are shown four forums:

- *News & Announcements*, where are posted rules, news and changes about site policies.

- *Suicide Discussion*, where users can discuss thoughts and feelings, and ask questions about the topic.

- *Recovery*, for giving or receiving support with the goal of getting better.

- *Offtopic*, for discussions not inherent to suicide or recovery (games, music, opinions and feelings/fears).

Each forum has a brief introduction, an overview of the total number of threads and replies and the last active thread. From this pieces of information we can gather that, at the time of writing, *Suicide Discussion* is the most active one (with $69K$ threads), followed by *Offtopic* ($17.8K$ threads) and lastly *Recovery* ($4.6K$ threads).

Sanctioned Suicide is quite open about its stance and code of conduct. In the *News & Announcements* section, all threads concerning rules, info on the site's origin and updates can be found.

3.1.1 Purpose and Ideology

According to the thread "The principles of sanctioned suicide" [86] found in *News & Announcements*, the site was created on March 2018, after the *r/sanctionedsuicide* subreddit was banned from the Reddit platform for encouraging violence [82]. On the origin of the site name, it is said that the term *sanctioned* expresses an "acceptance of something, a principle that dictates an ethical choice".

Here an important distinction is made between acknowledging and encouraging. The creators accept that suicide is an ethical and personal choice and is valid as long as an individual is in a rational and non-impulsive state of mind. They continue explaining that while bodily autonomy is respected, they do not encourage suicide. For this reason, all visitors are asked to respect users' decisions or to stop browsing the site. They also declare their willingness to collaborate with authorities if someone is "caught attempting to force users to commit acts against their will", since helping with the act is considered unethical.

On this page is expressed how they believe closing the site will not fix the issue of suicide but will only remove a space where people in need can talk about their problems. They state that the site's purpose is to provide "an uncensored safe place for the discussion of the subject".

This stance is confirmed in the rules [85, 87, 88, 90] where it is stated: "Please understand that the information offered on this site is for educational purposes only, and provided only by other users like you. We do not encourage, promote, advise, suggest, or aid suicide in any way or form; we only provide a space to talk about it. Understand that there is information on this site that if used could kill you. Be responsible, know the laws of your country, follow the forum rules, and know that the way you use any information posted on the forum is fully and solely your responsibility."

For these reasons, users must be at least 18 years of age and of sound mind: "By using this site, you represent, acknowledge, and agree that you are at least 18 years of age, that you do not have intellectual disabilities, and that you have read and agreed with all our rules". The rules discuss:

- General information (e.g., no NSFW profile images, only one account allowed per user, permissions to create threads, send PMs and use the chatroom will be granted after a certain amount of posts, how to block or follow users or threads.).
- How to communicate with others (e.g., be respectful, do not bully, do not impose your views, report misbehaving users.).
- How to maintain anonymity (e.g., be mindful of what details to share, do not post or request personal information, use a unique username for every website, use VPN, remove EXIF in pictures before uploading.).
- Reiterations that users are not to assist others in committing the act (e.g., do not encourage, manipulate, coerce or help other users commit the acts, only provide information, do not sell, offer or gift anything.).

The site is moderated, and users that break the rules can incur in various types of sanctions:

- **Warning -** can have various degrees of severity from (10% to 99%) at the moderator's discretion. Once a user reaches 100%, they will be banned.
- **No PMs -** moderators have the right to remove access to PMs if a user sends personal messages that violate the rules.
- **Hard Ban -** reserved for extreme cases, the user will be permanently removed from the website.
- **Auto-ban -** users can request an auto-ban (i.e., voluntary removal). This can be revoked up to one time. The second time a user requests an auto-ban, they will be permanently removed (i.e., hard ban).

Banned users cannot post nor interact in the forum. Bans can be appealed in the appropriate section where the request will be evaluated. Hard bans, however, cannot be appealed.

3.1.2 Forums

News & Announcements is mostly informative. In the following analyses, we will consider the main forums: *Suicide Discussion*, *Recovery* and *Offtopic*.

The forums use the same TAGS to differentiate between discussions, it is their occurrence that changes based on which forum is being observed. The TAGS are:

- **Story**, used to tell a personal story.
- **Venting**, used for venting.
- **Help**, used to ask for help.
- **Discussion**, used to start discussions.
- **News**, used for posting News and articles.
- **NSFW**, used for posting NSFW content.
- **Method**, used when talking about suicide methods.
- **Resource**, used when talking about available resources (e.g., books, tutorials, videos, researches).

Table 1 shows examples of threads for each TAG and Forum. TAGS, however, are not mandatory: users can open threads without specifying them.

3.1.2.1 Suicide Discussion

Discussions are centered around:

- Feelings (e.g., hopelessness, acceptance, venting about a personal story or situation).
- Plans and experiences (e.g., failed attempts, plans to depart).
- Asking for advice or information on methods.

The most prevalent TAGS are Venting, Discussion, Help, Method and Story.

Forum	TAG	Title
Suicide	Story	Contemplations on my whole life, eternal suffering, and my goodbye letter.
Suicide	Story	Story of my last attempt
Suicide	Venting	I'm sick of people telling me to be positive!
Suicide	Venting	semi-vent about medical help
Suicide	Help	Any fellow Australians know where to buy SN?
Suicide	Help	Is this the right regulator for my nitrogen cylinder?
Suicide	Discussion	What is something that you regret doing
Suicide	Discussion	What if life and death are sides of the same coin?
Suicide	News	Scammers, trolls, and spammers
Suicide	News	Google, Bing, And Yahoo Isn't Indexing This Site Anymore - Not Like It Use To
Suicide	NSFW	Video showing a man falling off a cliff
Suicide	NSFW	I self harmed today.
Suicide	Method	Why is partial hanging less effective?
Suicide	Method	How reliable is cynide?
Suicide	Resource	Seeking Legit USA SN Sources (Please PM)
Suicide	Resource	SN attempts: failures / successes - detailed methods and experiences information [google docs]
Recovery	Story	I just survived an attempted overdose and I have a new outlook on life
Recovery	Story	Thinking of running away/moving out instead of ctb
Recovery	Help	Every relapse is worse than the last
Recovery	Help	Have I fucked myself over?
Recovery	Discussion	Anyone else here avoid going to the doctor?
Recovery	Discussion	What do you do all day to try and minimize the boredom and loneliness?
Recovery	Resource	Size Discrimination And Getting Equitable Medical Care - HAES Health Sheets
Recovery	Resource	Chromium Pincolate for depression and Bipolar - research info
Offtopic	Story	How do you ask someone to live with you?
Offtopic	Story	I just graduated
Offtopic	Venting	caregiver's fatigue and pain
Offtopic	Venting	My plant was cut to the ground :(
Offtopic	Help	What happened to the search function?
Offtopic	Help	Why am I spending so much money?
Offtopic	Discussion	Anybody else feel like they are reliving the same day over and over again?
Offtopic	Discussion	star wars megathread
Offtopic	News	Jason Vukovich, 'The Alaskan Avenger', who attacked pedophiles, sentenced to 28 years in prison
Offtopic	News	"Wobbly" moon could lead to catastrophic flooding in coastal cities...
Offtopic	NSFW	Fetishes
Offtopic	NSFW	There are dark and disturbing places on the internet
Offtopic	Resource	Stand up Comedy
Offtopic	Resource	A tool for determining what is and isn't working in a relationship

Table 1: Examples of discussions for each TAG and Forum.

3.1.2.2 Recovery

On this forum are present banners with links to recovery threads and mental health resources. On our first visit to the site, this banner was shown in all of the main forums. Unfortunately, it seems that it was removed from *Suicide Discussion* and *Offtopic* as of late.

Discussions are centered around:

- Feelings (e.g., venting, hopeful messages, asking for support).
- Experiences.

- Asking for advice.
- What helps and what is not helping (e.g., coping mechanisms, therapy).
- Medications.

The most prevalent TAGS are Help, Discussion, Story and Resource.

3.1.2.3 Offtopic

In this forum are two subforums; one for games and one dedicated to discussions around politics and philosophy. Discussions are centered around:

- Games, shows, social media, hobbies.
- General opinions and discussions not related to suicide nor recovery.
- Asking for advice for personal topics not related to suicide nor recovery.

The most prevalent TAGS are Discussion, Venting, Help and Story.

3.1.3 Layout

All of the forums use the same layout, which can be seen in Figure 2. On the

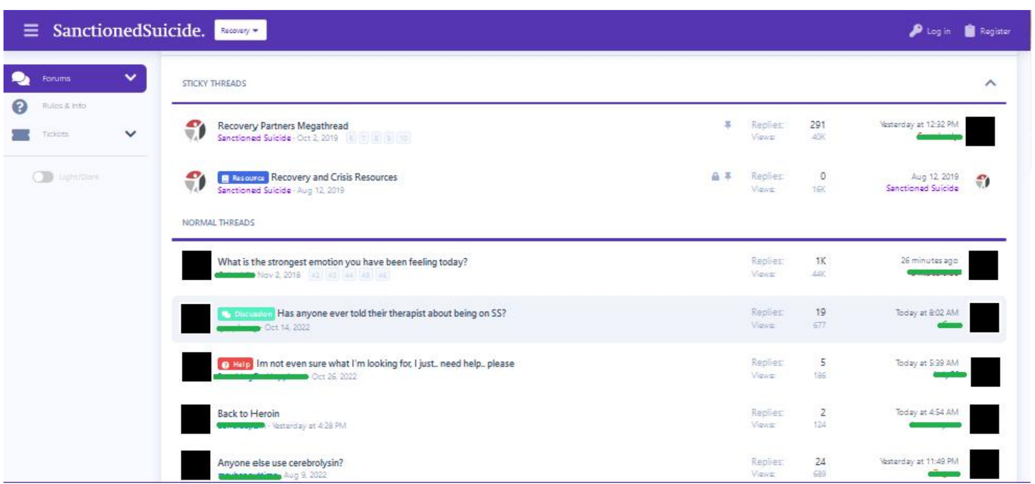


Figure 2: Sanctioned Suicide layout. Usernames and profile pictures were censored to ensure anonymity.

forum's initial page are the *Sticked threads* (i.e., important or popular threads) and the *Normal threads* (i.e., the rest of the threads).

For each thread, several details can be retrieved just from this page:

- *TAG* associated.
- Title.
- Author.
- Creation date.
- Number of replies.
- Number of views.
- User that replied last.
- Time of last reply.

Clicking on one of the threads opens up the thread detail page (Figure 3), where the full thread discussion can be seen. On this page the following information can

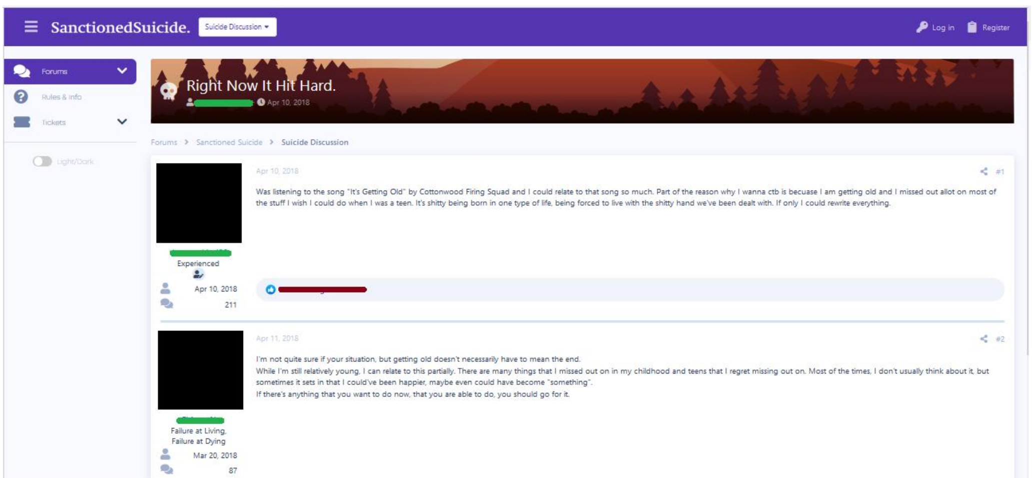


Figure 3: Sanctioned Suicide thread. Usernames and profile pictures were censored to ensure anonymity.

be found:

- User's profile picture (top left).
- Username of poster and personal phrase (center left).
- User's registration date and total number of posts (bottom left).

- Comment number in the thread (top right).
- Date of posting (top center).
- Body of comment (center).
- Other users' interactions (bottom center).

3.2 Contents discussion

On the site, we have found threads called *megathreads*, which are particularly extensive in terms of comments and are commented on even years later after their creation. These threads generally discuss methods, suicide resources, and where to buy substances. However, some are used to seek out suicide or recovery partners or to introduce new members. In addition to any information found in threads, there are also links to resources outside of the site. In particular, we have seen:

- A suicide wiki.
- Guides and tutorials.
- Researches and articles.
- Books, such as Peaceful Pill Handbook[5].
- Documentaries and videos.
- References to Exit International[6].

Furthermore, while the rules explicitly forbid the sale of substances, they do not prohibit the publication of information about where to buy them and from whom. As a result, email contacts of potential sellers can be found on the site.

During our examination we have seen several references to other platforms like Twitter [113] and Discord [23]. This suggests that conversations may move outside of the site to other platforms. We also discovered that users employ specific terms inside the forum. We collected them in Table 2. Most of them appear to be acronyms. However, we see *CTB*, which previously appeared in Murray [65]. This suggests that terminology is not site-specific, but that users

[5] A series of books that provide research and information on voluntary euthanasia and assisted suicide.

[6] A site that provides information and guidance on assisted suicide and end-of-life matters [https://www.exitinternational.net/].

Term	**Refers to**	**Meaning**
PPH or PePH	Peaceful Pill Handbook	Guide
SS	Sanctioned Suicide	The site
OT	Off Topic	Outside the thread topic
OP	Original Poster	The author of the post
CTB	Catch The Bus or Cease To Be	Suicide
Getting tickets	Planning	Preparing to suicide
Exit	Exit International	Site on assisted suicide
N	Nembutal	Suicide method
SN	Sodium Nitrite	Suicide method
CO	Carbon Monoxide	Suicide method
SA	Sodium Azide	Suicide method
Partial	Partial Suspension Hanging	Suicide method
H2S	Hydrogen Sulfide	Suicide method
AE	Antiemetic	Medication to prevent vomining
SI	Survival Instinct or Suicidal Ideation	Depends on the context
SSRI	Selective Serotonin Reuptake Inhibitors	Medication for mental health

Table 2: Sanctioned Suicide terminology.

transfer it from one site to another. Some appear to persist over time since the study was conducted in 2008.

The author also compiled a list of methods found in the same work, visible in Table 3. In Sanctioned Suicide terminology, we can see many more methods involving substances and gasses (e.g., Hydrogen Sulfide, Sodium Azide, Nembutal). Unfortunately, we are unable to confirm all available methods of Sanctioned Suicide, as we do not have access to all conversations. Although the site has a search bar, it is only available to people registered on the site after an undisclosed amount of comments. Furthermore, in addition to personal messages, there is also an internal subforum that is not publicly accessible but invite-only.

From the posts we have seen, users appear to be empathetic towards one another, which could indicate that *affective allure* and *affective stickiness*, terms defined by Osler et al. [69], may be present on the site. We also did not notice any comments explicitly inciting users to do the gesture (e.g., “You should kill yourself”), confirming what is stated in the rules. We did find a significant amount of discussions on failed attempts, requests for more information on procedures, and people discussing their preferred suicide method.

Users also discuss a lot about their problems, whether they are personal, mental or physical health-related. They share with others how much they are struggling and their desire to end it all, talking about their personal stories,

Method
Carbon Monoxide
Overdose Rx drugs
Overdose non-Rx drugs
Overdose illegal drugs
Household toxins
Cyanide
Gunshot of head
Gunshot of chest
Gunshot of abdomen
Shotgun to head
Shotgun to chest
Explosives
Electrocution
Set fire to self
Structure fire
Cut throat
Cut wrists/arms/legs
Stab of Chest
Stab of abdomen
Auto crash
Jump from height
Hit by train
Hit by truck/auto
Hanging
Plastic bag over head
Drowning ocean/lake
Drowning bathtub
Drowning pool

Table 3: Methods found in the work of Murray.

motivations and view of the world. They talk about feeling guilty about their plans and not wanting to leave behind certain people because of how they will feel after their departure. Quite a few posts express feelings of loneliness and isolation, or feeling out of place. We even found some that were related to lockdown and Covid. However, users also share their achievements, their hobbies and ask for advice in personal matters.

3.3 Discussion

Sanctioned Suicide has a duality in content, there are both people looking for support to get better and people looking for ways to kill themselves. The latter are much more frequent than the former, as we have seen in Chapter 3.1 that *Suicide Discussion* is by far the most active. Taking this into consideration we decided to focus only on the *Suicide Discussion* forum.

We have confirmed that various information about methods can be found on the site. However, more detailed analyses are needed to understand the full extent of the contents accessible on the site. Given the site's limitations on guests as opposed to registered users, we have to resort to topic modeling to confirm the arguments of discussions and all knowledge the site offers.

We have seen how terminology is not necessarily site-specific but that users may transfer it from site to site. We also found references to other social media platforms, which could be problematic as it could result in information being shared there as well, as we saw happening in McCann et al. [58].

We have not found instances of explicit instigation on the site. However, we took into consideration the formal definition of echo chambers described in [21], which states that to define an echo chamber there must be the coexistence of two factors: opinion polarization concerning a topic and homophilic interactions between users. Both are present in Sanctioned Suicide. We have opinion polarization as the site discusses the topic of suicide from a pro-choice point of view. Homophily of interactions is given by the fact that Guests cannot comment as one must be registered, and trying to dissuade someone while registered will occur in a ban. While not explicitly condemning different ideas and stating that they do not promote suicide, Sanctioned Suicide has a rule on not imposing personal views, which makes it so that one cannot explicitly discourage a suicidal individual from committing the act.

Since we confirmed that SS is an echo chamber, while explicit persuasion may not be present, idea reinforcement, typical in echo chambers as discussed in Chapter 2.3, might be. In order to continue with these analyses, we need to collect some of the contents from *Suicide Discussion* to create a dataset.

4 Dataset

As discussed in the previous chapter, to carry out a more in-depth analysis on the use of the site, we need to collect posts and some knowledge about users. In this chapter, we first present the adopted methodology for the data collection, followed by an overview of the collected dataset.

4.1 Collection

We collected data on *threads*, *comments* and *users* using the information described in Chapter 3.1.3. We included the entire period of activity of the *Suicide Discussion* forum, from March 2018 to July 2022. We automated the whole process using *python* [80] in combination with *selenium* [96]. *Selenium* is a tool for automating browser interactions. This library is able to identify certain elements within a web page and perform interactions that users can perform (e.g., click). In our work, we have used it to browse Sanctioned Suicide and collect texts and values. *Python* is a high-level programming language, often used for data analysis and automation due to its ease of use and readability. In our work, we used it to implement our collection script and, later on, to process and analyze our data.

The collection process results into three distinct CSV file:

- `threads.csv`, containing information about *threads* (e.g., title, author, date of creation, number of replies).
- `comments.csv`, containing details about *comments* (e.g., comment number, body of comment, date of posting, author).
- `users.csv`, containing *users* data (e.g., username, registration date, total number of posts). No sensitive user data has been collected.

In total we have collected 54'359 *threads*, containing 739'549 *comments*, posted by 16'285 *users*. These numbers will be reduced after preprocessing.

4.2 Preprocessing

We began by deleting from `threads.csv`, `comments.csv` and `users.csv` all entries that were missing significant values (e.g., date, text) or were duplicates. After that, as discussed in Chapter 3.3, we needed to create a dataset suitable for topic modeling, so we performed some additional steps. Our preprocessing pipeline follows what is described in the literature, discussed in Chapter 2.1, resulting in the following steps:

1. removal of citations.
2. concatenation of thread title with all comments.
3. replacement of multiple whitespaces with a single one.
4. removal of unicode and newline characters.
5. substitution of digits with text (e.g., from 10 to "ten").
6. lowercase all text.
7. substitution of web addresses[7], emails and usernames with the tokens "[URL]", "[email]" and "[username]".
8. removal of non-English threads.

To remove citations, we consider all comments belonging to a same thread. We go from oldest comment to youngest and remove a sentence if it matches one in a previous comment. We repeat that for all comments in all threads. After this step, we retrieved the title from `threads.csv` and create a new csv, containing the union between the thread title and all of its comments. Pattern matching was used to delete or replace unicode, newline characters, whitespaces, urls, email addresses and usernames. We converted digits to text using the library num2words [72]. Lastly, to remove non-English threads, we used langdetect [56], a library for multi-language detection. If the classification of the whole thread was not English we removed it from the corpus.

After following all these steps we have obtained our final dataset, that we will call *union.csv*, containing 53'610 threads and 733'225 comments from 16'158 users.

4.3 Dataset summary statistics

To contextualize our future findings, we first need to have an understanding of how the site is being used. We begin by analyzing how users engage with Sanctioned Suicide. Table 4 shows some general statistics. We calculated the metrics in the following way:

- **Average n. of comments -** we sum up the total number of comments made by each user and divide it by the number of users.

[7]Starting with "http://" and "https://".

Metric	Value
Average n. of comments	45.45
Average n. of days to first post	28.44
Average n. threads interaction	29.53
Average n. days of activity	177.57
Average n. daily comments	0.84
Average n. threads created	3.32
Average n. comments per thread	13.64
Average n. words per comment	88.09

Table 4: Dataset statistics.

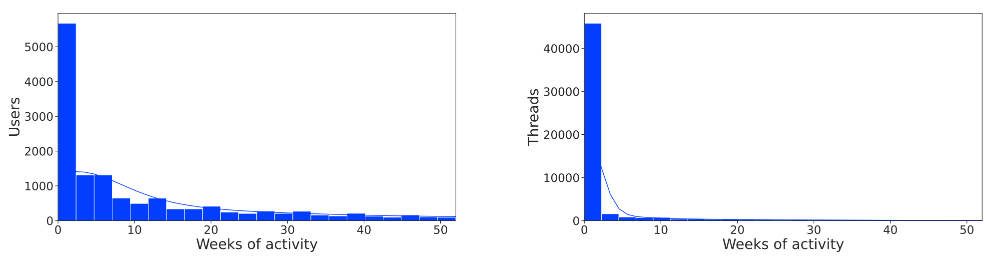
- **Average n. of days to first post -** for each user, we calculated the number of days between the date of registration to the site and the date of the first comment made. We then summed these values and divided the result by the number of users.
- **Average n. threads interaction -** for each user, we calculate the number of threads they commented on, without duplicates in case of multiple comments in the same thread. We then sum up the values and divide by the total number of users.
- **Average n. days of activity -** for each user, we calculated the number of days between the date of registration to the site and the date of the last comment made. We then summed these values and divided the result by the number of users.
- **Average n. daily comments -** for each user, we divide the total number of threads by the days of activity previously computed. We then sum up the values and divide again by the number of users.
- **Average n. threads created -** was calculated by dividing the total number of threads created by the number of users.
- **Average n. comments per thread -** was calculated by summing the number of comments in each thread and dividing by the total number of threads.
- **Average n. words per comment -** was calculated by summing the number of words in each comment and dividing by the total number of comments.

The results show that the average user does not interact much on the site. In fact, users tend to post less than 1 daily comments. Users also tend to make their first post a month after signing up and stay on the site for a 6 month period on average, during which time they make a total of 45 comments in 29 threads and create 3 new threads. Threads tend not to be very deep, averaging 14 comments, and comments tend to be of medium length (88 words).

These calculations already give us some insight. However, we have to consider that outliers might taint the results. For this reason, we proceed by doing some analysis using distributions. Our goals are to determine 1) how long users and threads stay active on the site, 2) how long users actually take to make the first comment, 3) how much users actually interact with the threads and 4) the general trends of activity in Sanctioned Suicide.

4.3.1 Users and threads period of activity

In Figure 4a, we can see the distribution of users per week of activity and in Figure 4b that of threads. For each user, we compute the weeks of activity as



(a) Users period of activity. (b) Threads period of activity.

Figure 4: Users and threads period of activity.

the number of weeks from the registration date to the last comment made. We have followed a similar process for threads; however, we used their creation date. On the x-axis, we have the weeks of activity, and on the y-axis, the number of users that were active for that many weeks. We show the results within a year of activity, but the trends displayed do not change outside this period. For users, we previously computed the average days of activity to be 177 per user, meaning 25 weeks. However, from the distribution it is immediate to see that most users are active just for a couple of weeks, with very few being active in the long term. This trend is more evident in threads. Almost all of them have a lifespan of two weeks, after which they are never commented on again.

4.3.2 First comment

Figure 5 shows the distribution of users according to the number of weeks they took before making their first comment. We show the results within a year of

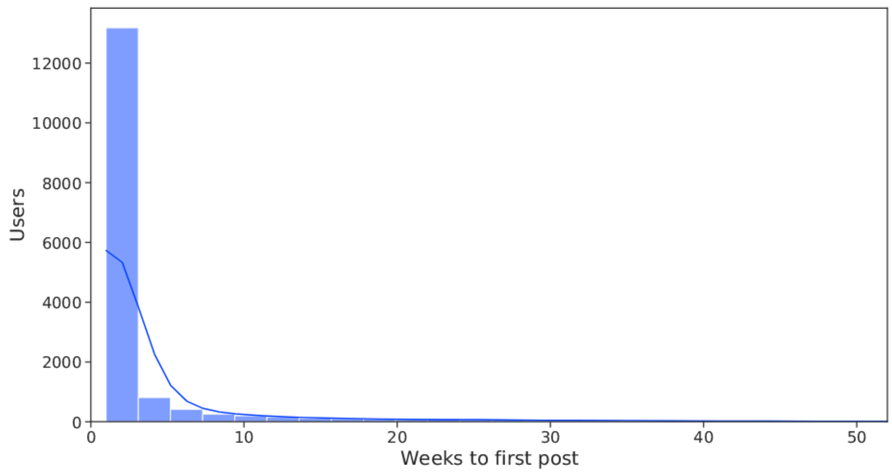


Figure 5: Users first posts.

activity, but the trends displayed do not change outside this period.

Previously, we calculated the average number of days between registration and first post to be 28, meaning 4 weeks. From the figure, however, we can see that the majority of users make their first post within a couple of weeks.

4.3.3 Thread interaction

Figure 6 shows the average amount of interactions[8] per user, according to their period of activity in months[9]. We can see that users who stay longer tend to interact more within threads, whereas those who are active just for a few months participate very little.

4.3.4 General activity levels

In Figure 7 we can see the monthly trends of registered users, threads created and total comments made. We can see five points of interest: $P1$ on September

[8] Average number of threads they commented on.
[9] Number of months from the registration date to the last comment made.

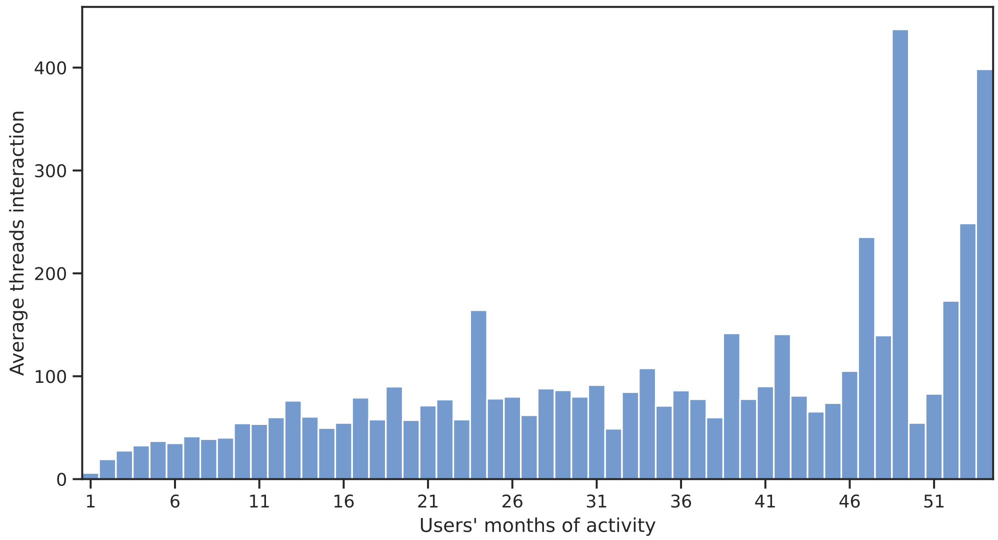


Figure 6: Users' interactions average.

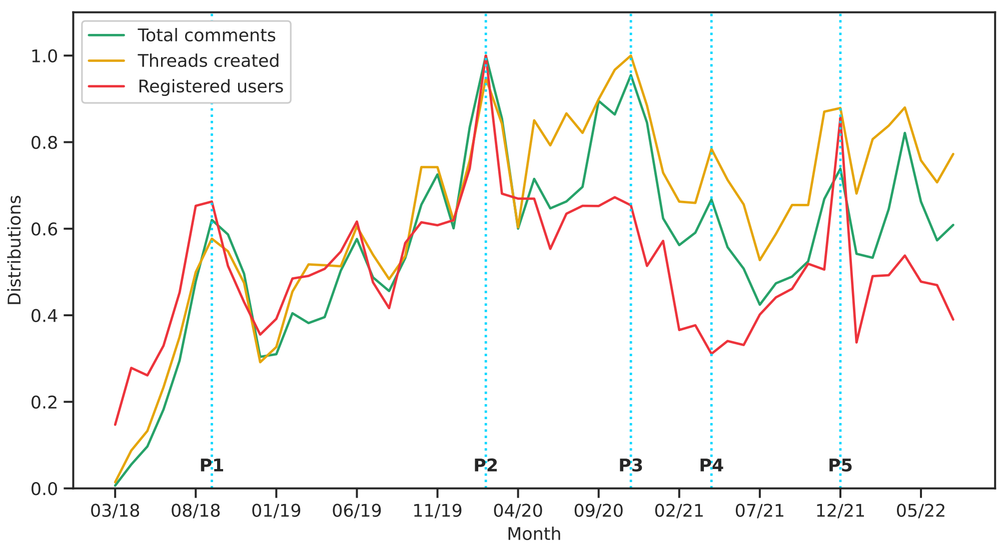


Figure 7: Site's general trends.

2018, $P2$ on February 2020, $P3$ on November 2020, $P4$ on April 2021 and $P5$ on December 2021. In $P1$, $P2$ and $P5$ we can see an increase in all trends. In $P3$, there is a slight user increase but high activity levels and in $P4$ user decrease, but activity on the site is high. However, we do not proceed to investigate them further, as they will not provide us with additional information about the site.

4.3.5 Word cloud

Lastly, we create a word cloud. A word cloud is a graphical representation of the most frequent words within a corpus. The bigger the word, the most occurrences it has. To achieve this, we use the Python library *wordcloud* [79]. Before using wordcloud, we have removed all punctuation marks and stop words from the text. Figure 8 shows the 1000 most common n-grams in the discussions.

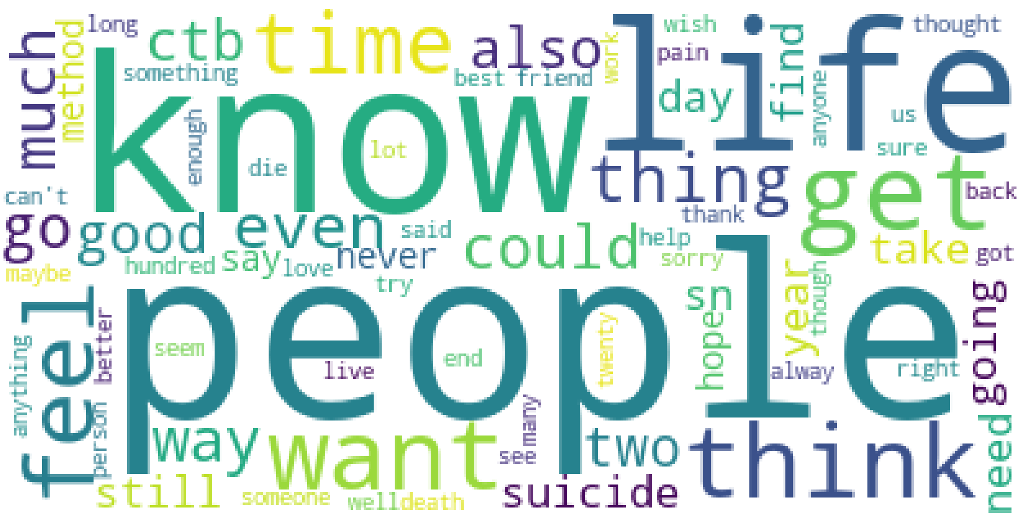


Figure 8: Word cloud of 1000 most frequent words.

As we can see, there are references to suicide ("suicide","method","ctb", "die") and expressions of unease ("help", "pain"). However, there are also words generally associated with positive meanings ("love", "hope","live", "better", "best friend"). Nonetheless, they could be used in a negative way (e.g., "I hope to die"). Further analyses are needed to understand how users employ these words in discussions.

4.4 Discussion

We have discovered that users do not stay active on the site for very long (less than 2 weeks) and that, similarly, most threads have a short lifespan (less than 2 weeks). Users also tend to make their first post rather quickly after their registration, a few weeks at most. We have found that, on average, users that stay active longer tend to be more active and participate in more threads. However, as we discussed previously, they are not that many. We have also seen how there are some points of interest in the general trends of the site. Regardless, their exploration goes beyond the scope of this thesis, as it will not provide further information on the site or how users interact within it. Lastly, we discussed how the 1000 most frequent words in the corpus contain both negative and positive meanings and how further analyses are needed to understand their context.

5 Analyses

In Chapter 3, we discussed some of the contents found on Sanctioned Suicide, however limitations made it impossible to confirm all knowledge available. In this chapter, we aim to better understand the topics covered on the website and how users interact within it. To achieve this, we conduct investigations using *Topic Modeling*, to identify the main themes in discussions, and *Word Embeddings*, to analyze in which context words are used. Understanding the context of words can give us a better idea of user interactions with both the site and other users. Each investigation has its own section where we describe the methodology (i.e., an overview and introduction to which analyses we performed) and the findings, the results of our examinations.

5.1 Topic Modeling

In this chapter, we explain our approach to Topic Modeling. Topic Modeling is a Natural Language Processing (NLP) task that aims to identify the primary topics discussed in a set of documents.

5.1.1 Methodology

Several models can solve the task of Topic Modeling. To determine the one most suitable for our objectives, we performed a comparative analysis between three of the most popular: *Latent Dirichlet Allocation*, *Non-Negative Matrix Factorization* and *BERTopic*.

5.1.1.1 Topic modeling comparison

Latent Dirichlet Allocation [11] (LDA) is a generative probabilistic model that assumes documents as a set of topics, which in turn are composed of a set of words. By observing the contents of a group of documents, LDA can learn a distribution of words per topic, defining the main themes discussed in the documents. The number of topics to be found must be set a priori.

Non-Negative Matrix Factorization [29] (NMF) uses the same assumptions as LDA but employs a statistical approach. Documents are seen as high-dimensional representations that must be factorized into a lower-dimensional one. This factorization is composed from two matrices, one representing the distribution of words over topics and the other the distribution of topics over documents. The first identifies the topics found in the documents, and the second identifies which topics are discussed in which document. NMF has been shown to perform better than LDA when working with short text documents [19]. Even for this strategy, the number of topics to find must be provided first.

BERTopic [40] is a recently proposed method to perform Topic Modeling. It uses a clustering approach in which documents are first processed into embeddings, vectorial representations of the documents. These embeddings are then compressed into a lower-dimensional representation using *UMAP* and clustered with *HDBSCAN*. UMAP [59] is a dimension reduction algorithm that takes high-dimensional data as input and produces a low-dimensional representation that is as much structurally similar as possible, to reduce loss of information. HDBSCAN [14] is a clustering algorithm that, given some data, can identify clusters based on the density of their representation. It is not necessary to provide any preliminary information. Only after these steps are the topics extracted [8], taking into account the clustering of documents performed previously. This approach results in consistent topics since the documents were already grouped based on their similarity. The great advantage of this technique is that the number of topics is found automatically during the process; there is no need to fix it beforehand. For the comparison, we have used the following implementations:

- **LDA -** we have used the scikit-learn implementation [92], with settings *n_components* = 15 and *random_state* = 0. To process the text we have used CountVectorizer [91] with settings *ngram_range* = (1,3), *max_features* = 1000 and *max_df* = 0.95.

- **NMF -** we have used the scikit-learn implementation [93], with settings *n_components* = 15 and *random_state* = 0. To process the text we have used TfidfVectorizer [94] with settings *ngram_range* = (1,3), *max_features* = 1000 and *max_df* = 0.95.

- **BERTopic -** we have installed the model using pypi [76], as described in the official GitHub repository [37]. BERTopic allows direct instantiation with models. As vectorizer model, we have used CountVectorizer [91] with settings *ngram_range* = (1,3), *max_features* = 1000 and *max_df* = 0.95. As the embedding model, we have used 'all-mpnet-base-v2' from SentenceTransformer [97]. We have used the official UMAP model [78] with settings *n_components* = 10 and *metric* = 'cosine'. We have used the official HDBSCAN implementation [77] with settings *min_cluster_size* = 15 and *metric* = 'euclidian'. To ensure the comparability of the models, we set the number of topics to find at 15 using the parameter *nr_topics*.

We trained the models on a subset of 400 threads taken from `union.csv`, the dataset presented in Chapter 4.2. We used the library Natural Language Toolkit (NLTK) to stem all threads with PorterStemmer [67] and remove all stopwords [68], words and connectors that lack significance in determining the context of a text (e.g., "I", "and","the", etc.). Stemming is the process of truncating words at their roots. When analyzing the context of a text, we are not interested in the exact words but in their meaning. Having terms like "going" or "gone" adds noise to the analyses, so stemming is usually applied to transform both into their root, "go". We have not used Stemming with BERTopic as the guidelines did not suggest it.

In Table 5, we compare the 10 most important words for some of the topics obtained. We selected all those who discussed two specific methods: poisoning and death by gasses. We made this limitation to make a fair comparison between all models. Both methods appeared to be popular on the site as we found several threads and megathreads discussing them during our visual exploration. They also have very identifiable words (e.g., **visine** and **yew** for poisoning, **argon** and **bag**[10] for death by gas) that make recognizing these topics easier. The complete list of all the topics obtained from the three models is available in the Appendix A.

Model	Topic	Top 10 keywords
LDA	poisoning	seed, yew, poison, hotel, url, drink, make, lethal, use, neighbor
LDA	gasses	use, bag, would, need, neck, ga, thank, method, get, around
LDA	gasses	bag, would, peopl, vegan, method, ga, know, one, argon, nitrogen
NMF	gasses	bag, plastic, co2, ga, mask, regul, method, tape, dri, ice
NMF	poisoning	visin, poison, eye, yew, drop, method, seed, tetrahydrozolin, url, lethal
NMF	gasses	argon, nitrogen, ga, gase, inert, inhal, air, regul, cylind, use
BT	poisoning	seeds, yew, visine, url, meto, eye, heroin, lethal, dose, poisoning
BT	gasses	gas, bag, regulator, inert, cylinder, nitrogen, tank, argon, n2, flow

Table 5: Topic Modeling results comparison.

LDA found two topics related to death by gas. However, while there are words clearly consistent with the theme (e.g., **bag**, **argon**, **nitrogen**), there are others that have little to do with it (e.g., **neck**, **vegan**). The same is true for the topic related to poisoning, where we can see the telltale words **yew** and **poison** alongside **hotel** and **neighbor**. NMF performs better if compared to LDA. The top 10 keywords found in the topics are consistent for both methods. However, there are still two topics related to death by gas. Lastly, BERTopic found two topics, one for each method. In addition to that, the top 10 keywords also appear

[10] The method is also known as exit bag.

to be consistent with the methods identified (**seeds** refers to the poisonous yew seeds and **eye** to eye drops containing **tetrahydrozolin**, a toxic substance).

BERTopic appeared to have the highest quality results, so we continued with the analyses using this model.

5.1.1.2 BERTopic optimization

With the parameters used during the comparison, BERTopic produced a large number of topics (more than 400), many of which were mini-topics (less than 15 documents) and not very important. We ran several tests with different parameters to obtain more compact and significant results.

In this chapter, we describe our final model. As introduced before, BERTopic allows direct instantiation with models, which are:

1. `vectorizer_model`, a CountVectorizer [91] with settings *ngram_range* = (1,3), *max_features* = 50000 and *stop_words* = NLTK stopwords [68]. This model is used to manage the vocabulary of words in BERTopic. *ngram_range* indicates what n-grams to consider and *max_features* corresponds to the maximum dictionary size.

2. `embedding_model` is 'all-mpnet-base-v2' from SentenceTransformer [97]. This is the model used to produce document embeddings.

3. `umap_model`, a UMAP model [78] with settings *n_components* = 10 and *metric* = 'cosine'. This model is used to reduce document embeddings to a lower dimensional representation. *n_components* indicates the dimensionality of the reduced embeddings, *metric* indicates how the distance is computed between embeddings.

4. `hdbscan_model` a HDBSCAN model [77] with settings *min_cluster_size* = 30 and *metric* = 'euclidian' and *prediction_data* = True. This is the model that forms clusters from the reduced embeddings. *min_cluster_size* is the minimum number of documents in a cluster, *metric* indicates how the distance between points is computed, and *prediction_data* allows us to predict the topics for unseen documents after the model is trained.

To set the parameters, we have followed the official code and guidelines [37]. We adjusted some parameters (*min_cluster_size* and *max_features*) based on the results. We trained the model using `union.csv`, presented in Chapter 4.

We initialized BERTopic with the following parameters:

- **diversity** = 0.2, this parameter is used to discourage the selection of words with very similar meanings in the same topic.
- **top_n_words** = 10, this parameter indicates the number of words used to represent a topic, and 10 is the default value.
- **umap_model** = `umap_model`.
- **hdbscan_model** = `hdbscan_model`.
- **embedding_model** = `embedding_model`.
- **vectorizer_model** = `vectorizer_model`.
- **nr_topics** = "auto", reduces automatically the topics found if they are very similar.
- **calculate_probabilities** = True, this parameter is used to calculate or not the probabilities of all topics in each document.

The trained BERTopic model produced three distinct csv. The first is `topics.csv` containing all topics and their top 10 keywords. The second is `union_pred.csv` containing the topic predictions for each thread in `union.csv`, one topic per thread. The third and last document is `comments_pred.csv` containing the topic predictions for each comment, one per comment.

5.1.1.3 Analyses performed

BERTopic recognized 89 topics in total. We start by discussing the topics found and categorizing them into thematic groups, called *areas*, to visualize the results better. After that step, we proceed with analyzing some monthly trends:

- **Thread thematic areas distribution**, where we consider the prediction of the *area* for each thread and display for each month the total number of threads created discussing that *area*.
- **Comments thematic areas distribution**, where we consider the prediction of the *area* for each comment and show for each month the total number of comments posted about that *area*.
- **First posts thematic areas distribution**, where we analyze in which *areas* users posted their first comment. We display this trend based on the date the comment was made. In case of multiple comments made on the first

day of user activity, we considered them all, since we could not distinguish which one was the first. We consider only posts made within a week of user registration, as they will most likely be the reason why they joined the site.

- **Keywords distribution**, where we look for specific keywords in threads. We display for each month the total number of threads posted that contained that keyword. We also investigate co-occurrences, threads in which keywords appear simultaneously.

Lastly, we examine the correlation between *areas*. Since multiple *areas* may be present in a thread, we wanted to understand which other arguments are likely to be addressed, given a thread discussing a specific *area*.

To answer this, we use the threads' predictions in *union_pred.csv* to isolate all the threads that discuss a specific *area*. For each of those threads, we then took the prediction of the single comments from *comments_pred.csv*. Set n as the number of *areas*, we create a nxn matrix in which the rows correspond to the comments' *areas* and the columns to the threads' *areas*. The value in cell $c_{(i,j)}$ corresponds to the number of threads classified with *area* j, which had at least one comment classified in *area* i. We then divide each column j by the total number of threads classified with *area* j and transform them into percentages by multiplying by 100. We have now obtained a matrix that, for each thread's *area*, indicates how likely it is to find a comment about a particular subject.

5.1.2 Findings

In this chapter, we discuss our findings. We start by discussing the topics and methods found. Then we examine the monthly trends of threads, comments, first posts and keywords.

5.1.2.1 Topics

Table 6 shows all 89 topics identified on Sanctioned Suicide by BERTopic.

Topic	Top words
-1	life; people; want; know; think; suicide; something; someone; hope; die
0	life; people; think; suicide; know; death; time; world; die; said
1	sn; ordered; hundred; pm; use; package; seller; address; bottle; uk

2	rope; neck; knot; method; noose; carotid; belt; hang; partial hanging; door
3	fentanyl; benzos; drugs; pills; drug; overdose; heroin; meds; use; five
4	jump; jumping; land; jumped; building; method; landing; cliff; one hundred; survive
5	therapist; therapy; help; hospital; mental health; psych; psychiatrist; therapists; suicidal; psych ward
6	nitrogen; gas; regulator; tank; exit bag; cylinder; inert gas; hose; flow rate; welding
7	peace; find peace; hope find peace; goodbye; peaceful; travels; wish peace; safe travels; wish best; peaceful journey
8	peace; sn; find peace; journey; hope find; hope find peace; peaceful; good luck; going; wishing
9	hotel; room; home; find; forest; place; hotels; hotel room; dead; house
10	charcoal; carbon monoxide; coals; smoke; chimney; exhaust; burning; briquettes; bbq; chimney starter
11	birthday; christmas; year; happy birthday; happy; holidays; twenty; family; birthdays; new year
12	write; writing; notes; suicide note; letter; leave note; suicide; leaving; written; write note
13	gun; shotgun; bullet; shooting; brainstem; guns; firearm; firearms; recoil; handgun
14	funeral; cremation; cremated; family; money; burial; buried; want funeral; funerals; estate
15	blood; artery; cutting; knife; arteries; wrists; stabbing; femoral artery; carotid; methods
16	bottle; one bottle; two bottles; pentobarbital; hundredml; lethal; amount; one hundredml; use; twenty fiveg
17	chronic; doctors; chronic pain; disease; health; doctor; symptoms; nerve; suffering; illness
18	covid; virus; vaccine; lockdown; coronavirus; pandemic; flu; covid nineteen; health; vaccines
19	song; songs; listen; playlist; lyrics; album; funeral; radiohead; linkin park; linkin

20	sleep; sleeping; insomnia; hours; waking; asleep; mornings; fall asleep; nights; nightmares
21	job; work; jobs; working; boss; life; money; interview; unemployed; fired
22	self harm; harm; cutting; scars; cuts; harming; self harming; blade; self harmed; scar
23	drowning; water; method; swim; drown; underwater; bathtub; hyperventilate; swimming; tub
24	last; last day; go; music; things; one last; final; love; plan; bucket list
25	dignitas; euthanasia; switzerland; assisted suicide; belgium; netherlands; suicide; law; doctors; foreigners
26	trains; tracks; method; decapitation; train method; speed; suicide; methods; jumping front; train drivers
27	alcohol; drink; drinking; drunk; alcoholic; alcohol poisoning; vodka; poisoning; liver; vomit
28	lifers; pro lifers; people; choice; pro life; suicide; pro choice; think; suicidal; anti
29	cyanide; sodium; seeds; sodium nitrite; apricot; potassium cyanide; cherry; apple seeds; poisoning; cyanide poisoning
30	starvation; dehydration; days; starving; hunger; eating drinking; without food; starve; thirst; without water
31	partner; partners; together; die alone; suicide pact; pacts; meet; trust; idea; partners megathread
32	india; uk; north; hi; looking partner; country; italy; south east; london; nhs
33	cat; pets; pet; animals; love; animal; sorry loss; shelter; family; heart
34	hydrogen; sulfur; bleach; hydrogen sulfide; lime sulfur; detergent; chemicals; hydrochloric; hydrochloric acid; detergent suicide
35	talk; someone talk; chat; lonely; friend; free pm; talk someone; need someone talk; want talk; loneliness
36	ugly; die want die; looks; want die want; die want; face; appearance; want die; beauty; body
37	dream; dreams; nightmares; dreaming; woke; nightmare; waking; lucid dreams; dreamed; lucid dream

38	seeds; plant; hemlock; poisonous; ricin; poison; poisoning; poisonous plants; symptoms; tincture
39	trans; gender; dysphoria; people; straight; lgbt; trans people; lesbian; bi; transgender
40	ctb; ready; time; know; things; life; think; day; feeling; end
41	background check; firearm; firearms; states; buy gun; gun laws; gun show; background checks; handgun; legally
42	college; school; university; degree; uni; grades; education; high school; exams; student
43	fasting; fast; eight hours; stomach; eat; eating; meal; food; drink; taking sn
44	salt; capsules; vomiting; dissolve; table salt; swallow; sodium; vomit; take; tastes
45	taste; bitter; neotame; two hundredml; tongue; tastes; tasted; honey; tasting; syrup
46	tinnitus; noise; deafening; hyperacusis; ear; hearing; anxiety; calm; sound; quiet
47	bipolar; psychosis; voices; schizophrenia; manic; delusions; hallucinations; meds; psychotic; disorder
48	data; reset; devices; wipe; hard drive; factory reset; deleting; encryption; erase; iphone
49	eating; eat; eating disorder; anorexia; diet; lose weight; eating disorders; appetite; anorexic; stomach
50	organs; organ; organ donation; body; donate organs; organ donor; transplant; brain; body science; cremation
51	poem; bad boy; poems; poetry; prince; snake; love; written; writing; flower
52	world; species; human; nature; humanity; life; planet; earth; society; climate
53	bpd; disorder; diagnosed; bipolar; personality disorder; mental; people bpd; therapy; disorders; borderline personality
54	goodbye; tribute; goodbye thread; forum; rest peace; ctb; gone; self ban; rip; threads
55	hotel; noise; room; loud; noises; death rattle; hear; bed; snoring; take sn
56	caffeine; caffeine powder; heart attack; coffee; energy drinks; caffeine od; caffeine overdose; overdose; pills; caffeine pills

57	welcome; thank; welcome back; back; community; forum; support; hello; hugs; thank much
58	hypothermia; cold; winter; frostbite; temperatures; cold water; shivering; freeze; freezing death; die hypothermia
59	rebreather; mask; oxygen; rtwod rebreather; air; scrubber; exit bag; rebreather ii; breathing; masks
60	scale; tablespoon; scales; measuring; grams; tablespoons; spoons; teaspoons; kitchen; weighing
61	autism; autistic; asperger; aspergers; social; diagnosed; spectrum; autistic people; society; high functioning
62	death; fear; afraid; fear death; afraid death; nothingness; scary; afterlife; scares; death fear
63	car; speed; cars; driving; car crash; seatbelt; train; traffic; vehicle; steering
64	azide; sodium azide; sodium; nitrite; sodium nitrite; antidote; explosive; lethal; metals; cyanide
65	thousand; movies; favorite; one thousand nine; thousand nine; thousand nine hundred; one thousand; nine hundred; hundred; anime
66	sorry loss; love; died; hear; condolences; peace; grief; heart; life; hugs
67	regret; life; back; time; regrets; biggest regret; go back; could go back; ago; change
68	emails; email; gmail; mail; spam; messages; delayed email; app; encrypted; delayed emails
69	attempts; failed; hanging; hospital; pills; overdose; suicide; enough; four; method
70	electrocution; electricity; electric; electrical; circuit; electrocuted; shock; bath; wire; outlet
71	phenobarbital; barbiturate; pentobarbital; pills; drug; lethal; phenobarb; barbiturates; nembutal; lethal dose
72	hate; fcking; etc; life; hatred; whatever tf; want; however tf; hate life; hating
73	nde; near death; death; death experience; consciousness; near death experience; death experiences; near death experiences; afterlife; dmt

74	autopsy; look accident; toxicology; cause death; natural death; suicide; bottle; body; tests; methemoglobinemia
75	homeless; homelessness; debt; money; housing; food; need; financial; income; shelter
76	anxiety; panic; panic attacks; panic attack; anxious; breathing; depression; symptoms; calm; medication
77	stream; streaming; livestream; live stream; suicide; live; ctb; recording; share; audience
78	bag; plastic bag; method; sleeping pills; suffocation; unconscious; plastic bag head; survival; exit bag; rip bag
79	dnr; medical; resuscitate; life support; hospital; paramedics; cpr; attorney; advanced directive; document
80	hotline; hotlines; samaritans; help; suicide hotline; suicide; suicide hotlines; suicidal; chat; helplines
81	happy; happiness; life; two thousand; childhood; felt; nostalgia; memories; never happy; past
82	suicide; suicide selfish; selfishness; suffering; selfish act; life; suicidal; selfish people; world; society
83	cops; police; suicide cop; gun; kill; suicide; guns; prison; knife; police officer
84	poison; rat; rat poison; poisoning; pesticide; pesticides; kill; poisons; blood; rats
85	insurance; life insurance; suicide; insurance company; insurance policy; insurance companies; life insurance policy; beneficiaries; benefit; ctb
86	ocd; anxiety; obsession; obsessive; rituals; disorder; severe ocd; things; intrusive thoughts; compulsive
87	gore; video; liveleak; suicide videos; hanging videos; gore sites; suicide; best gore; documenting; website
88	revenge; people; life; suicide; suffer; spite; hate; abused; anger; blame
89	insulin; diabetic; blood sugar; inject; glucose; low blood; diabetes; overdose; type one; syringes

Table 6: Topics found by BERTopic.

There are several themes identified thanks to BERTopic. First, -1 are the outliers, threads that couldn't be classified within a topic. We can see several topics about methods (e.g., 1 ,2 ,3 ,4 , etc.), but we discuss them in the following chapter. The topic 41, which seems to revolve around how to buy guns and inquiries about background checks, is noteworthy.

Many topics are about suicide. The topics 7, 8, 54 appear to be about *goodbye threads*, threads where people say goodbye before committing the act. They can be identified through commonly used terms like **find peace**, **goodbye**, **safe travels** and **journey**. Similarly, topic 40 seems to express a readiness to suicide (**ctb**, **ready**, **feeling**, **end**). Also related to this theme are 69 about failed attempts, 25 discussing assisted suicide, 31 concerning the practice of suicide pacts and 77. Topic 77 is particularly peculiar because we can see keywords like **stream**, **streaming**, **suicide**, **live**, **ctb**, **share** and **audience**. This combination suggests that the practice of live-streaming suicide, seen in the work of Fratini et al. [32], might be present in Sanctioned Suicide.

Some topics examine post-suicide matters, with 12 tackling suicide notes and 14 discussing **funeral**, **cremation** and **burial**. The topic 48 seems to be about deleting personal data from devices. Some topics cover medical aspects, such as 74 about autopsies (**autopsy look accident**), 50 talking about organ donation and 53 inquiring about **dnr** and related normatives. Lastly, 85 is about life insurance. Some topics concern mental health like 5 with keywords **therapy**, **hospital** and **mental health**. In addition to that, 22 discusses self-harm and topics 47, 49, 53, 76 and 86 discuss mental health disorders (e.g., **bipolar**, **psychosis**, **schizophrenia**). Other topics appear to be about interpersonal relationships. Topic 11 seems to be around social events, with keywords **birthday**, **christmas**, **holidays** and **family**, and topic 33 refers to pets.

Users also appear to be sharing personal problems. The topic 61 is related to autism, and 17 to chronic pain. Other are about social problems like 21 linked to **job**, 42 discussing college and school in general, 75 about homelessness and 39 about LGBTQ+ related problems, with keywords such as **trans** and **dysphoria**. Instead, topic 36 seems to be related to issues of personal appearance, with keywords **ugly**, **appearence**, **looks** and **want die** that is repeated multiple times.

Interestingly, there is a topic dedicated to Covid, topic 18 with keywords **covid**, **lockdown** and **pandemic**. The site has been active since 2018, for Covid to appear as a topic that must mean that it has been a much-discussed argument.

Some topics are about support. In 35, users seem to express loneliness and desire to talk with other people (**someone talk**, **need someone talk**, **loneliness**). Topic 80 discusses hotlines and support chats. Similarly, 57 seems to express that

Sanctioned Suicide is a place of comfort for some, with keywords **welcome back**, **community**, **forum** and **support**. That would confirm prior works' findings, indicating that users may find comfort in pro-choice sites [65].

Some topics seem pretty light, like 65 appearing to be about hobbies. However, others appear to be about serious matters. Topic 67 seems to be talking about life regrets (**life**, **regret**), 62 about fear of death, 72 deals with hatred, 88 tackles feeling of **revenge**, **hate**, **abuse**, **anger** and **blame**. Some users appear to be feeling conflicted about suicide. In topic 82 we can see keywords like **suicide selfish**. Other keywords are **selfish people**, **world** plus **society**, which may express that society is selfish. Lastly, in topic 66 appear a lot of empathetic words: **sorry**, **loss**, **love**, **condolences**, **peace**, **grief**, **heart**, **life** and **hugs**. Even from our visual analysis (in Chapter 3), users appeared to be very attentive and supportive.

Managing such a large number of topics is complicated. Therefore, we have grouped the topics into broader thematic areas to continue the analysis. Table 7 shows how we have divided the topics into the following *areas*:

- *Methods*, grouping all topics discussing suicide methods and necessary tools.
- *Suicide*, grouping all topics inquiring about suicide and post-suicide matters.
- *Covid*, that contains topic 18 linked to Covid.
- *Social and health problems*, groups all topics discussing physical and social problems.
- *Social interactions*, contains all topics discussing relationships with other people.
- *Hobbies*, groups all typical hobbies (e.g, songs, music).
- *Mental health*, collects all mental health related topics.

We discard some of the topics: outliers, topics that are very generic like 0 (**life**, **people**, **think**), topics discussing emotions and those difficult to categorize. In the tables they are indicated as *Ignored*. In Table 8 can be seen the total number of threads that belong in each *area*.

5.1.2.2 Methods

In total, 27 out of 89 topics are about methods. The full list is:

Area	Topics
Ignored	-1 0 32 55 57 87 9 37 77 66 72 81 88
Methods	1 2 3 4 6 10 13 15 23 26 27 29 30 34 38 41 43 56 58 59 63 70 71 78 84 60 64 83 89
Suicide	12 14 24 25 40 48 50 54 62 79 85 74 31 7 8 73 69 16 44 45 82
Covid	18
Social and health problems	21 28 36 39 42 52 67 75 61 17 46
Social interactions	11 33 35 68
Hobbies	19 51 65
Mental health	5 22 47 49 53 76 80 86 20

Table 7: Division of topics in *areas*.

Area	Total Threads
Ignored	32129
Methods	14061
Suicide	3399
Covid	221
Social and health problems	1182
Social interactions	811
Hobbies	312
Mental health	1495

Table 8: Total threads per *area*.

- **Topic 1** sodium nitrate.
- **Topic 2** hanging. Some keywords give more details on the different ways (noose, belt, partial hanging, door).
- **Topic 3** overdose. Other words indicate the substances used (fentanyl, benzos, heroin, meds).
- **Topic 4** jumping, more ways to achieve that (building, cliff).
- **Topic 6** death by gas. Keywords indicate both substances (nitrogen) and necessary items (tank, regulator, cylinder, hose).
- **Topic 10** carbon monoxide. Other words indicate the ways it can be achieved (charcoal, coals, exhaust, bbq).
- **Topic 13** guns. Keywords refer to weapons (gun, shotgun) and location (brainstem).
- **Topic 15** stabbing/cutting. Keywords refer to the locations where to cut (artery, wrists, femoral artery, carotid).
- **Topic 16** pentobarbital. The other keywords appear to be about dosages (bottles, hundredml).
- **Topic 23** drowning. Both open water (swim) and at home (bathtub).
- **Topic 25** assisted suicide. Other keywords discuss where is accessible (switzerland, belgium, netherlands) and inquire about the legality (law, foreigners).
- **Topic 26** death by train. Discussions about ways (tracks, jumping front) and consequences (decapitation).
- **Topic 27** alcohol poisoning.
- **Topic 29** cyanide. Keywords discuss the possible ways (cherry, apple seeds, apricot, cyanide poisoning).
- **Topic 30** starvation/dehydration.
- **Topic 34** detergent. Some other keywords are about substances (hydrogen, sulfur, lime, hydrochloric acid).
- **Topic 38** poisonous plants (seeds, hemlock, ricin).

- **Topic 56** caffeine overdose (heart attack). Other keywords refer to possible ways it can be ingested (caffeine powder, caffeine pills).
- **Topic 58** hypothermia (freezing death).
- **Topic 63** car crash.
- **Topic 64** various methods. Some of the keywords are sodium azide, sodium nitrite, explosive.
- **Topic 70** electrocution. It seems that there are multiple ways (bath, wire, outlet).
- **Topic 71** pentobarbital and nembutal.
- **Topic 78** suffocation. Other keywords are plastic bag head, unconscious.
- **Topic 83** suicide by cops.
- **Topic 84** poisoning with various substances (rat poison, pesticide).
- **Topic 89** insulin overdose.

Overall, not many are repeated, and for the most, they are well-defined. If we compare our results with those reported in the work of [65], we can find most of them in our list. The one that does not appear is **death by fire**. However, BERTopic has identified some methods which do not appear in the previous work, which are **suicide by cop**, **caffeine overdose**, **freezing**, **alcohol poisoning**, **poisoning with plants**, **starvation/dehydration**, **assisted suicide** and **death by gas** (nitrogen). Still, some of these methods might not be actually employed but just discussed in terms of feasibility.

5.1.2.3 Thread thematic areas distribution

Figure 9 shows the distribution of thematic areas in threads across the months. It is a stacked area plot [103], meaning that the values on the y-axis are summed together. The most discussed *areas* are *Methods*, followed by *Suicide*, which are the main themes of the forum. *Mental health* is the third most popular. There is a peak in *Covid* on March 2020 (during the first lockdown), which means that *Covid* was a hot topic, combined with a decrease of *Social Interaction* and *Social and Health problems*. There is an increase of *Mental Health* and *Social and Health problems* discussions during the period from August 2020 to May 2021, some months before and after the second lockdown in most of Europe [115–117] (October 2020 to January 2021). *Hobbies*, instead, is relatively constant.

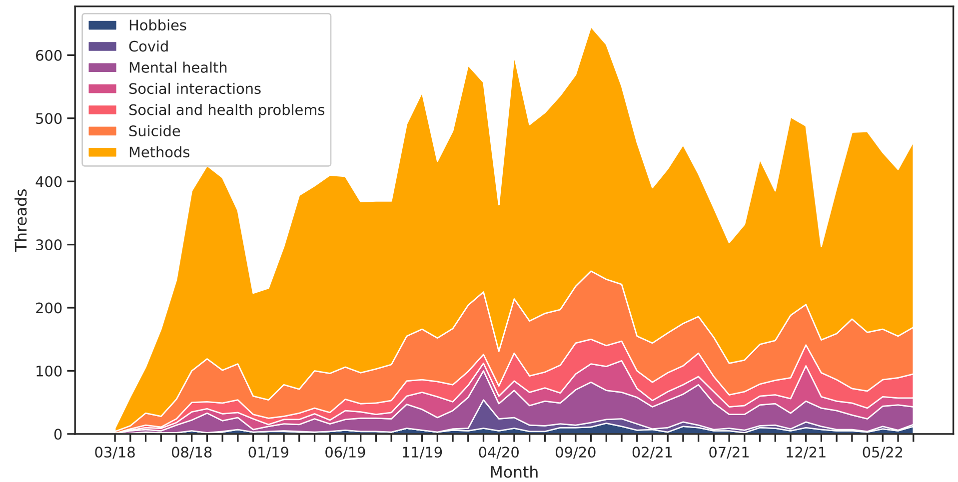


Figure 9: Threads thematic areas distribution.

5.1.2.4 Comments thematic areas distribution

Figure 10 shows the monthly distribution of comments' thematic areas. It is

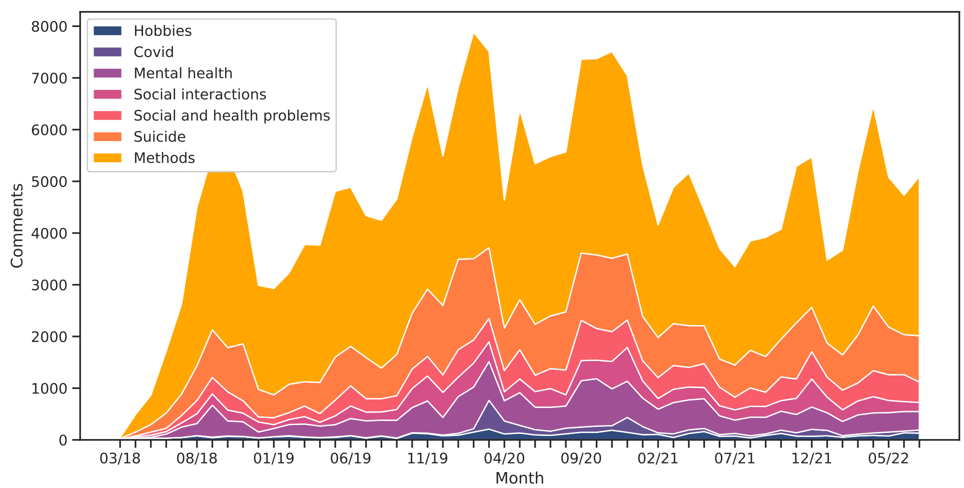


Figure 10: Comments thematic areas distribution.

a stacked area plot [103], meaning that the values on the y-axis are summed together. The trends are mostly the same as shown in the treads distribution, however, we see a second increase in *Covid* discussions during a period consistent with the second lockdown in most of Europe. Also, *Social Interactions* appears to have cyclical increases. These are in the months of December, most likely due to Christmas since the keyword was present in topic 11 one of the original BERTopic topics.

5.1.2.5 First posts thematic areas distribution

In Figure 11 we can see the distribution of first posts thematic areas over time. It is a stacked area plot [103], meaning that the values on the y-axis are summed

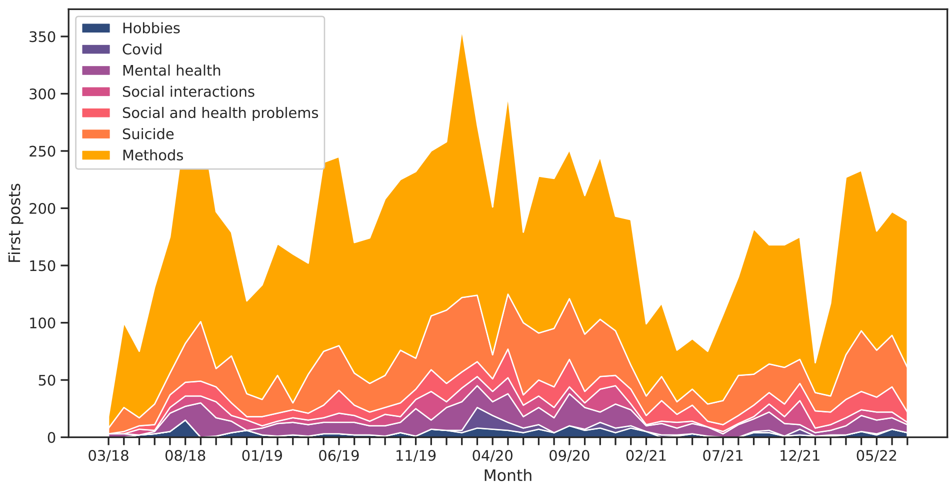


Figure 11: First posts thematic areas distribution.

together. As we can see the majority of first posts are in regard to *Methods* and *Suicide*. We can see that *Social Interactions* has cyclical peaks. This is in correspondence to the Christmas period (that is a keyword in topic 11, as we have previously seen). We can see a peak in *Covid* discussion on March 2020, the period of the first lockdown. This trend suggests that *Covid* was one of the reasons for which users joined the forum even if it was not the main one, as *Methods* and *Suicide* are still relatively high. The second *Covid* peak seen in the comments distribution is not visible, which suggests that the second lockdown was perceived by users as less destabilizing. Quite a lot of first post appear to be about *Mental Health*, but overall the trend confirms what we saw in previous distributions.

5.1.2.6 Keywords distribution

The previous trends were made considering BERTopic topics, however, these are not precise as a thread might be tackling multiple arguments. To get a better idea of the true distributions we search for specific keywords in threads.

We look at keywords related to topics that we have seen to be most popular in the forum during the visual inspection, discussed in Chapter 3. We consider the following trends:

- **Total threads**, showing the number of created threads per month.
- **Methods** shows the trend of threads with methods-related keywords **method** and **methods**.
- **Suicide** shows the trend of threads with suicide-related keywords **ctb** and **suicide**.
- **Loneliness** shows the trend for threads with loneliness-related keywords **alone**, **loneliness** and **lonely**.
- **Covid** shows the trend of threads with Covid-related keywords **covid**, **pandemic** and **lockdown**.
- **Methods/Suicide** shows the occurrences of threads where methods-related and suicide-related keywords appear simultaneously.
- **Suicide/Loneliness** displays the occurrences of threads where suicide-related and loneliness-related keywords appear simultaneously.
- **Suicide/Covid** shows the trend for threads where suicide-related and covid-related keywords appear simultaneously.
- **Loneliness/Covid** shows the trend of threads where loneliness-related and covid-related keywords appear simultaneously.

Figure 12 shows the distribution of keywords in threads across the months. It is immediately noticeable that both peaks in **Covid** discussions are visible and are compatible with the lockdown periods (March 2020 to June 2020 and October 2020 to January 2021). However, conversations about **Covid** in the interim span averaged 100 threads per month, whereas in previous graphs they seemed to disappear. After February 2021, threads related to **Covid** start to decline. Note that the peak around April 2020 occurs when there is a decline in the total amount of threads posted.

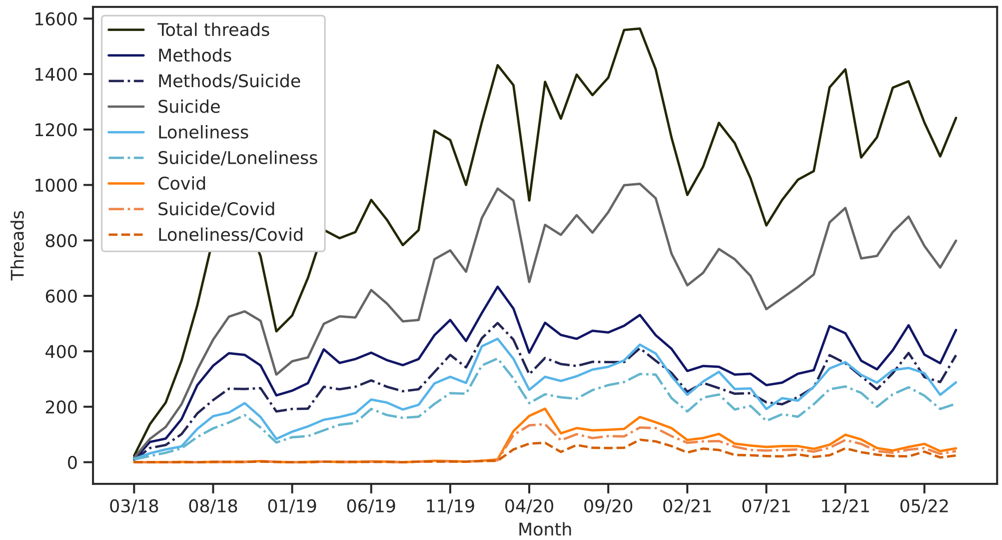


Figure 12: Distribution of keywords in threads.

Contrary to what might have appeared in the previous distributions, suicide-related keywords are more frequent in threads than methods-related ones. Concerning the correlations in the threads, **Suicide** and **Methods** keywords seem to appear frequently together, even if not as much as **Loneliness** with **Suicide**. However, the highest correlation is observed between **Covid** and **Suicide** keywords. Surprisingly, even during lockdowns, **Loneliness** and **Covid** are not highly associated.

5.1.2.7 Topics correlation

With this analysis, described in Chapter 5.1.1.3, we aim to understand how the thematic areas previously identified are associated with each other. Figure 13 illustrates the correlations among *areas* as percentages. **M** stands for *Methods*, **S** for *Suicide*, **C** for *Covid*, **SHP** for *Social and health problems*, **SI** for *Social interactions*, **H** for *Hobbies* and **MH** for *Mental health*.

As expected, we can see from the diagonal that threads discussing a certain *area* also have comments discussing it. Overall comments about *Methods* can be found in most threads, regardless of the *area* they pertain to.

Surprisingly both *Social interactions* and *Hobbies* threads have a non-negligible correlation with *Suicide* and *Methods*. *Social interactions* has the highest: 65% of threads discussing the *area* also relate to *Suicide* and 60% to Methods. For

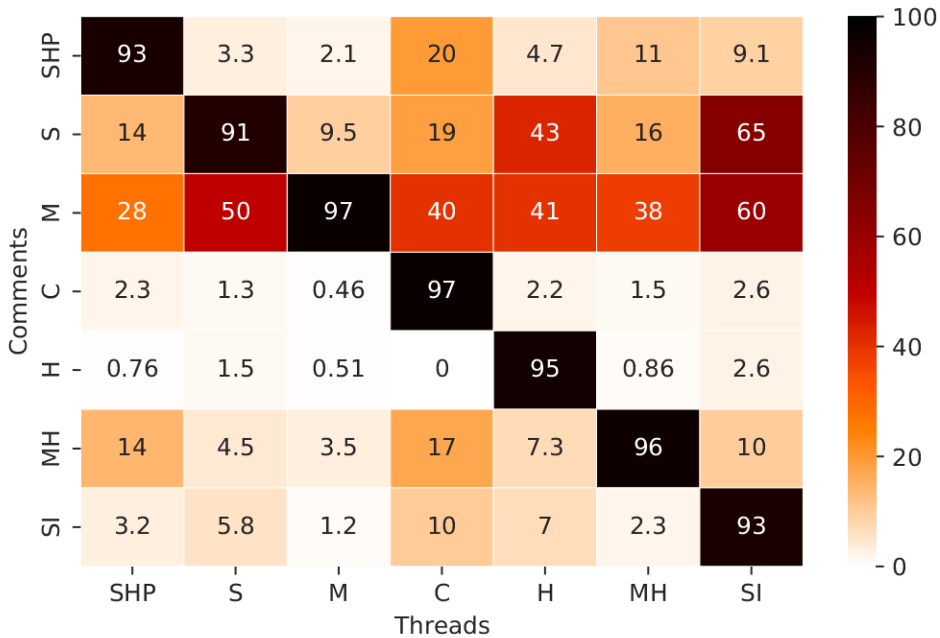


Figure 13: Matrix of *areas* correlations.

Hobbies the numbers are slightly lower: 43% of threads discussing the *area* also discuss *Suicide* and 41% discuss Methods. A possible explanation is that some of their interests are related to suicide. This is supported by topic 87 where some of the keywords are **best gore** and **suicide videos**.

Half of the threads discussing *Suicide* also discuss *Methods*, as one would expect, but a lower percentage if compared to *Social interactions*. This seems to indicate that issues related to the social sphere are particularly felt by Sanctioned Suicide users. Lastly, it appears that methods are also mentioned in 40% of threads related to *Covid*. This could indicate that *Covid* has induced strong discomfort among users and/or that they were discussing it as a possible method, seeing as the correlation with *Suicide* is low.

5.2 Word embeddings

In this chapter, we explain our approach to Word embeddings. Inspired by the work of Tahmasbi et al. [107], we used word embeddings to better understand the relations and similarities between words. Word embeddings capture the context in which words are used in the text to create similar representations for terms with similar meanings. Similarity is measured using the metric *cosine similarity*.

5.2.1 Methodology

Word2Vec [61] is a popular model used to produce word embeddings. This model takes a set of documents as input and learns the representation of words as vectors in a latent space, based on their context in the text. Learned vectors can be compared against each other to determine similarities between the use of words in the original documents.

In previous analyses, we have seen some interesting correlations between words. In this chapter we want to go deeper into them by exploiting the similarities between embeddings. We have also discovered an interesting relationship between users and Covid that we want to monitor.

For this reason, we create two models. One is trained on the totality of Sanctioned Suicide posts, whereas the second is limited to the pandemic period, starting from January 2020 with the first cases of Covid [115, 117]. We make this distinction so as not to include relationships between words that were created before the pandemic; otherwise, they would pollute the results on the connection between users and Covid. We refer to the models as `complete_model` and `covid_model`.

5.2.1.1 Model training

Our dataset was `comments.csv`, presented in Chapter 4. We used this instead of `union.csv` to be able to remove all comments outside the pandemic period when training the `covid_model`.

We preprocessed the text by removing stopwords using NLTK [68], and we stemmed all words using Gensim [36] implementation of PorterStemmer [35]. We initialized both models with the following settings: **window** = 7 (dimension of the context), **min_count** = 5 (minimum frequency for words) and **max_final_vocab** = 50000 (vocabulary size).

5.2.1.2 Analyses performed

We proceed with doing two types of analyses, the first based on embeddings similarity and another one more visual presented in the work of Tahmasbi et al. [107], two-hop graphs.

With the first analysis, we observe which words are most similar to specific stemmed terms. The keywords selected are:

- **suicide**, **method**, **ctb**, **die** to explore the relationship between users and the main themes of the site.
- **help**, **pain**, that are the expressions of unease we identified in Chapter 4.3.5.
- **love**, **hope**, **live**, **better**, **friend**, that are the positive words we identified in Chapter 4.3.5.
- **covid**, **lockdown**, **pandem**, to explore the relationship between users and Covid.

In Chapter 2 we have discussed previous works finding on online communities and cybersuicide: 1) sinophobic behaviour [107], 2) sense of belonging and support [4, 65, 69] and 3) livestreamed suicides [32]. To corroborate if their finding apply to Sanctioned Suicide, we have also included the following keywords: 1) **china**, **chines**, 2) **home**, **support**, **site**, **sanctionedsuicid**, **recovery** and 3) **stream**, **livestream**.

With the second analysis, we observe in a graphical way the use of language and we build a two-hop graph. Starting from certain keywords, we then identify their neighbors, embeddings with a cosine similarity greater or equal than a certain threshold. They are considered at distance one-hop from the keywords. We repeat the process with the neighbors to obtain the two-hop graph. As threshold we fix an embedding similarity of 0.6. To better visualize how words are grouped, we further cluster the resulting graph using the Louvain algorithm [12], a method to detect communities (i.e. densely connected clusters) in large networks.

We create a two-hop graph for covid-related keywords (**covid**, **pandem** and **lockdown**) and one for suicide-related keywords (**ctb** and **suicide**). Nodes' sizes represent the frequency of words in the corpus and edge thickness is proportional to the similarity between words.

5.2.2 Findings

In this chapter, we discuss our findings. We start by discussing embeddings similarity, then we examine the two-hop graphs of covid-related and suicide-related keywords.

5.2.2.1 Embeddings similarity

Table 9 shows, for each term, the 5 most similar words and their cosine similarity. We have used the embeddings obtained from `complete_model`. When necessary, to properly answer some of the questions, we integrate the data shown on the table with a direct comparison between terms.

Term	W1	Sim1	W2	Sim2	W3	Sim3	W4	Sim4	W5	Sim5
suicide	lgbtqia+	0.55	dieit	0.53	mateev	0.53	itselfi	0.53	hyperextend	0.52
method	reliabl	0.60	option	0.59	painless	0.58	hang	0.56	rout	0.55
ctb	ctbing	0.80	cbt	0.67	die	0.62	end	0.61	postpon	0.55
die	dy	0.76	kill	0.68	end	0.66	ctb	0.62	death	0.56
help	counsel	0.61	support	0.59	"help"	0.59	better	0.57	talk	0.55
pain	agoni	0.82	suffer	0.72	discomfort	0.70	anguish	0.68	excruci	0.63
love	cherish	0.73	ador	0.67	dearli	0.64	uncondit	0.63	uncondition	0.61
hope	hopefulli	0.72	solac	0.64	wish	0.62	glad	0.62	relief	0.52
live	life	0.70	miser	0.63	continu	0.58	exist	0.58	world	0.56
better	wors	0.70	improv	0.65	happier	0.61	easier	0.61	least	0.57
friend	"friends"	0.75	acquaint	0.70	boyfriend	0.67	classmat	0.65	girlfriend	0.65
recov	recoveri	0.60	heal	0.58	miracul	0.50	relaps	0.48	improv	0.44
site	websit	0.91	forum	0.85	ss	0.78	internet	0.67	fixthe26	0.64
ss	forum	0.85	site	0.78	commun	0.70	lurker	0.68	fixthe26	0.66
sanctionedsuicid	rsuicidewatch	0.75	rdepress	0.73	rss	0.73	reddit	0.72	sub	0.70
stream	broadcast	0.58	footag	0.52	viewer	0.52	realtim	0.51	livestream	0.51
livestream	shuaibi	0.66	r9k	0.66	viewer	0.65	broadcast	0.65	liveleak	0.64
recoveri	recov	0.60	"recovery"	0.59	section	0.51	improv	0.49	speedi	0.48
home	hous	0.80	roommat	0.72	bedroom	0.64	dorm	0.63	flatmat	0.62
support	compassion	0.65	commun	0.64	guidanc	0.63	compass	0.59	help	0.59
covid	corona	0.83	coronaviru	0.81	viru	0.81	covid19	0.81	pandem	0.80
lockdown	pandem	0.81	quarantin	0.79	covid	0.77	corona	0.69	coronaviru	0.67
pandem	lockdown	0.81	covid	0.80	corona	0.77	coronaviru	0.75	covid19	0.75
chines	china	0.80	indian	0.73	taiwan	0.70	european	0.68	mainland	0.67
china	chines	0.80	russia	0.77	taiwan	0.76	india	0.73	vietnam	0.73

Table 9: Top 5 similar words for each term.

The term **suicide** appears to be related to **lgbtqia+** maybe in the context of social problems, but the rest of the keywords are difficult to interpret. Interestingly enough, the correlations **suicide - methods** and **suicide - ctb** are very low and negative (-0.26 and -0.02 respectively). A possible motive is that, since it is the major theme of the forum, it is being used in so many different contexts and has so many associations that it makes it very difficult to contain all of them in an embedding. Another one is that **ctb** is the preferred word of choice inside the site when one is referring to committing the act. For the term **ctb**, we can see a significant correlation (more than 0.6 similarity) to the words **die** and **end** that we know are indicative of its actual meaning (suicide). We can also see a relation with **postpon**, possibly indicative of discussions about postponing the act. For the term **method**, we can observe a significant correlation to **reliability** and **painless**. Which may indicate what they consider important when choosing a method.

For the keyword **help**, we can see associations with **counsel**, **support**, **talk** and **better**, associations that we expect to see when discussing getting help. We can see that **better** is linked to **happier**, indicating a positive outlook. However, for **recov** we can see an association with **relaps**, even if under 0.5. For **support**, we can see a significant correlation to **compassion**. The term **live** its associated with **life** but also **misery** and **exist**, clear indicators of their distress.

Words **site**, **ss**[11] and **sanctionedsuicid** have only associations to other sites. Both have very low correlations with **home**, but **ss** has a similarity of 0.43 with **support**. So the site might be seen by some as a place offering support and compassion that they cannot find elsewhere. To confirm this we checked the most similar words to the term **world**. While not in the top 5 there were significant correlations with **evil** (0.59) and **injustic** (0.58), which supports our theory. Also in Chapter 5.1.2.1 we found topic 57 with keywords **community**, **forum** and **support**.

We can see that both **ss** and **site** have a significant correlation with **fixthe26**, which is a site aimed at changing laws and shutting down pro-choice forums. This signifies that they might be talking about this possibility. Both words have a correlation between 0.4 and 0.5 with **ban**, however, ban might be linked to Sanctioned Suicide regulations, so we can neither rule out nor disprove this hypothesis.

The keywords **stream** and **livestream** display only connections to streaming terms or other websites. They also have a low correlation with the terms **suicide** and **ctb**, with the highest being 0.26. However, in Chapter 5.1.2.1 we found topic 77 that seemed to relate to this theme, so we cannot rule out nor confirm the possibility of suicide livestreams.

Words **pain**, **love**, **hope**, **home** and **die** all show correlations to the traditional meanings. The word **friend** shows connections to the social sphere and various levels of relationships. Terms **covid**, **lockdown**, **pandem** are strongly interconnected, all appearing on the top 5 of one another and all showing similarities higher than 0.8. The keywords **china**, **chines**[12] show correlations with other nationalities. The most common slurs identified in the work of Tahmasbi et al. [107] are not present in our Word2Vec dictionary, excluding strong sinophobic behavior on Sanctioned Suicide.

We have checked if results obtained with `covid_model` embeddings presented

[11] Abbreviation of Sanctioned Suicide.

[12] Stemming of chinese.

interesting differences, but they did not differ that much.

5.2.2.2 Covid two-hop graph

Figure 14 shows the two-hop graph for the keywords **covid**, **pandem** and **lockdown**, obtained using `covid_model`. We can see that there are three communities,

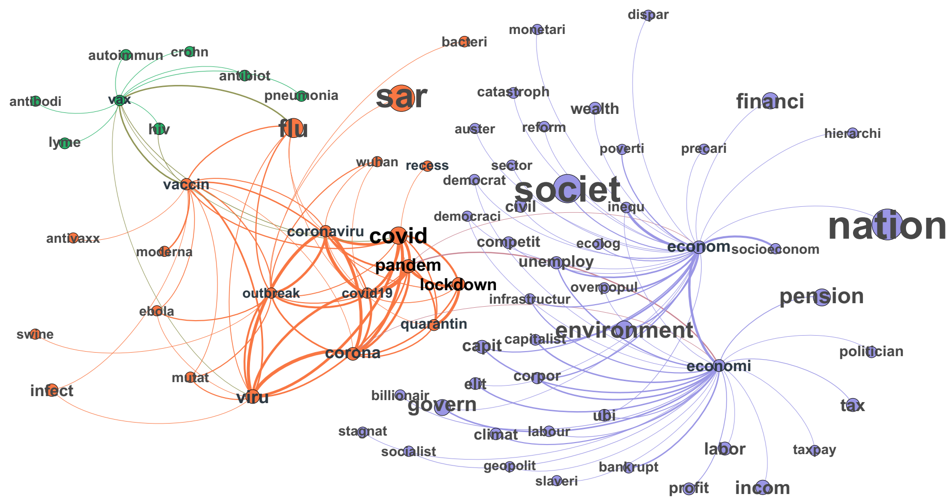


Figure 14: Two-hop graph for keywords covid, pandem and lockdown.

the one in orange appears related to the pandemic, the green one to medical terms related to vaccines, and the purple one to economic and sociopolitical problems.

In the pandemic cluster, we can see the strong correlation among Covid-related words like **covid**, **pandem**, **lockdown**, **conoravirus**, **corona**, **viru**, **outbreak**, **covid19**. We can also see words having correlations with the pandemic like **vaccin**, **antivaxx**, **moderna**, **flu**, **infect**, **mutat**. These relations indicate that there were discussions centered around vaccination during the pandemic. As part of the group, we can also see some interesting words like **wuhan**, where the pandemic originated and **recess**. The term **recess** is particularly interesting since it indicates users were worried about the possibility of a recession due to Covid. We can also see connections between the word **outbreak** and other pandemics like **swine** and **ebola**.

In the medical cluster can see talks about **vax antibodi antibiot autoimmun** and other diseases like **crohn lyme** and **hiv**. Noteworthy is that the word **antivaxx** is not part of this community but is connected to the world **vaccin** and is part of the Covid cluster.

Connected to **pandem** is the cluster related to economic and socio-political problems, which is quite varied. Strongly associated with **econom** is **inequ**. This suggests that several discussions on the site tackle economic inequality. In fact, there are many words associated with the theme of money like **monetari**, **poverti**, **financi**, **wealth**, **tax**, **taxpay** **bankrupt**, **billionair**. It appears that on the site, there are also economic discussions on the theme of **environment** with associated keywords as **catastroph**, **ecolog** and **climat**. We can observe that some economic discussions on the site are related to the themes of society (**overpopul**, **labor**, **incom**, **pension**, **corpor**) and politics (**govern**, **politician**, **capitalist**, **democtrat**, **reform**).

5.2.2.3 Ctb two-hop graph

In Figure 15 we can see the two-hop graph for the keywords **ctb** and **suicide**, obtained using `total_model`. It is immediate that **suicide** has no associations,

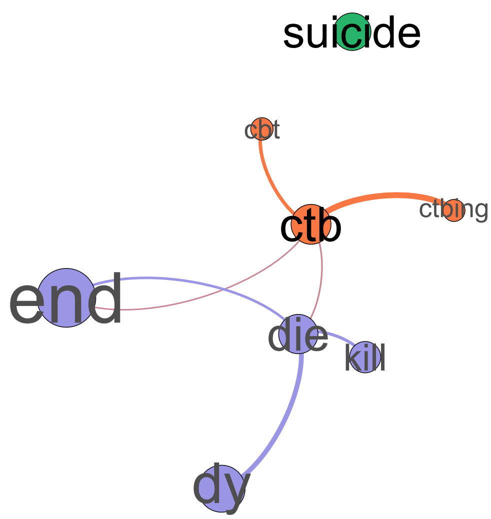


Figure 15: Two-hop graph for keywords ctb and suicide.

as we have seen from Table 9 ever the five most similar words have a similarity lower than 0.6, the threshold for the graph.

Two communities are identified. The first is composed from the cluster **ctb** its variation **ctbing** and a typo, **cbt**. The second from keywords associated to its meaning **end**, **die**, **kill** and **dy**. We can notice how **ctb** is the only link between the two communities. Furthermore, **dy** and **kill** are the only node distant two-hops from one of the initial keywords (**ctb**). Differently from the graph centered around Covid this one in very restricted. This probably indicates that conversations that start around **ctb** remain on this theme and do not branch in other discussions.

6 Incitement detection

In Chapter 3 we have established how Sanctioned Suicide is an echo chamber and how, while we have not seen any attempts at suicide incitement through explicit persuasion, *idea reinforcement* might be present. Idea reinforcement is the constant exposure to the same ideas, which can lead to self-convincing and rationalizing a belief. In this chapter, we discuss our proposal to identify if *idea reinforcement* is present on the site through persuasion detection. This is still a work in progress.

6.1 Methodology

Persuasion is the action of trying to influence others' attitudes, beliefs, or behavior through written or verbal exchanges. Usually, this is done by employing various techniques (e.g., urgency, ultimatums, peer pressure) to induce a specific state of mind in the victim. Artificial Intelligence models that can detect persuasion have been proposed [22, 52]. However, they rely on techniques used in explicit persuasion. In Sanctioned Suicide case, we are looking for comments that may have a persuasive effect but that might not necessarily employ explicit techniques. Detecting this type of persuasion in comments is extremely nuanced and requires depending on people to get a reliable classification. We plan to submit this task to both volunteers and crowdsourcing workers and to use the platform Inception to present the comments to participants.

Inception [54] is a semantic annotation web application that can be used for various annotation tasks in written text. It is designed to work on sentences, so we had to adapt it to work with comments. Participants will be asked to evaluate if a comment:

- contains negative persuasion, when the comment worsens someone's state of mind and instills negative ideas.
- contains positive persuasion, when the comment improves someone's state of mind and instills positive ideas.
- is neutral does not contain persuasion.

If for any reason, participants feel affected by what they are reading, we encourage them to stop participating. Given the sensitivity of the topic, we are working with the HIT ethical committee [44] to ensure that our procedures are safe for participants and that we are providing them with all the support they need.

7 Conclusions

Suicide has always been an important and difficult subject to address, being the fourth leading cause of death among young adults between the ages of 15 and 29. Since 2014 the World Health Organization has made suicide prevention a public health priority. Knowledge of terms and methods commonly employed has a crucial role in suicide prevention, and Big Data analysis could prove to be an important tool to determine them directly from sites like Sanctioned Suicide. Keeping information up-to-date is necessary to ensure the effectiveness of prevention measures, but this can be a challenge given how rapidly language changes online.

Sanctioned Suicide is a pro-choice community where users can find information on methods, dosages and how and from whom to acquire the correct components or substances. The goal of this thesis was to analyze this website to determine how users interact on and with the site and to extract information that improves our knowledge on the subject. We also wanted to verify if Sanctioned Suicide was an echo chamber and if suicide incitement was present on the forum.

We find that terminology is not site-specific but moves across platforms. We also find that users tend to stay active on the site for a brief period (less than 2 weeks) and similarly, most discussions are short-lived (less than 2 weeks of activity). Users seem to have a tendency to make their first post within a couple of weeks of signing up, and those who are only active for a few months intervene in just a few discussions.

By using Topic Modeling to identify the main themes in discussions, we discover that 30% of the topics found in Sanctioned Suicide are related to methods, substances or tools used to commit suicide. Users appear very preoccupied with the topics of suicide and methods, so much so that even topics concerning hobbies are also related to these themes. We determined that Covid has affected users as it appears as a topic and has a strong correlation with the theme of suicide, in particular during the first lockdown. Among the topics we found several uncommon methods (e.g., topic 56 caffeine overdose and topic 58 hypothermia), and identified several substances (e.g., sodium nitrite, sodium azide, nitrogen and phenobarbital) and tools (e.g., rebreather, tank, hose) used for committing suicide. Specific terminology also appears, like **ctb** (suicide), **exit bag** (death by gas) and **sn** (sodium nitrate). In addition to that, we used Word Embeddings to compare the similarity between terms and how they are used in discussions, highlighting that users were particularly concerned about the economic fallout from Covid, and that some seem to see Sanctioned Suicide as a place of support. Finally, we showed that Sanctioned Suicide is an echo chamber using a formal definition and, while not yet finished, we have outlined our plan to verify if suicide incitement is present on the site.

We believe this work has shown the importance of sites such as Sanctioned Suicide in supporting suicide prevention efforts and hope it will stimulate further investigations on the topic in the literature.

7.1 Future Works

BERTopic results are quite unstable and vary from run to run. In a previous run using the same parameters used for the final model, we obtained 35 topics. The results can be viewed in Table B1 in the Appendix. The inconsistency is due to the stochastic nature of UMAP and the quality of the initial clustering obtained with HDBSCAN.

BERTopic is an excellent model for extracting keywords and finding the main topics. A little less in regards to the classification of documents, as it associates a topic to a document only if sure of its prediction, otherwise it tends to assign it to the cluster of outliers, as can be seen in Table C1 in the Appendix. Future works could entail an ablation study on the components to see their effect on the results' quality. Also, it could be tested if removing the words in the more general topics (such as topic 0 in the final model) or using stemming improves the classification results. Another possible extension of our work could be defining a procedure that, provided the topics identified by BERTopic and related keywords, automatically associates a label to the topics or associates topics to documents in a less conservative way.

We also attempted to explore the presence of *affective allure* and *affective stickiness* presented by Osler et al. [69]. We asked Sharma et al. for access to the model presented in their work [98], which can recognize empathy expressed in a text. Unfortunately, they could not provide it to us. Future works could be to use Sentiment Analysis or other techniques to determine the level of empathy present in Sanctioned Suicide and see if *affective allure* and *affective stickiness* may be present or how empathy levels change over time or across topic.

A Model comparison results

This Section shows the full 15 topics obtained during the model comparison described in Chapter 5.1.1.1. Table A1 shows the topics found by NMF, Table A2 those found by LDA and in Table A3 those found by BERTopic.

Topics	**Top words**
0	life, live, suffer, never, peopl, born, want, die, love, exist
1	sn, bottl, drink, nitrat, nitrit, stan, tast, test, sodium, read
2	peac, hope, wish, find, best, plan, sorri, luck, go, thank
3	pm, india, sourc, pleas, order, abl, sn, reliabl, get, ship
4	peopl, human, ugli, person, care, suicid, world, other, think, friend
5	bag, plastic, co2, ga, mask, regul, method, tape, dri, ice
6	argon, nitrogen, ga, gase, inert, inhal, air, regul, cylind, use
7	visin, poison, eye, yew, drop, method, seed, tetrahydrozolin, url, lethal
8	method, surviv, suicid, si, fear, jump, ctb, fail, die, want
9	feel, cut, pain, im, tire, wish, know, cri, self, hurt
10	hang, partial, rope, full, suspens, knot, neck, carotid, weight, ligatur
11	server, join, invit, discord, send, channel, pm, pleas, mod, interest
12	day, year, go, feel, time, get, life, thing, even, want
13	meto, metoclopramid, pill, dose, tablet, paracetamol, take, guid, nausea, drug
14	would, money, hotel, food, make, situat, want, home, live, eat

Table A1: NMF test full results.

Topics	Top words
0	use, bag, would, need, neck, ga, thank, method, get, around
1	would, use, get, gun, think, go, time, make, death, even
2	go, life, hope, peac, feel, know, one, want, get, day
3	sn, im, id, stan, guid, updat, pleas, need, info, take
4	evil, parent, life, peopl, natur, man, want, kid, would, one
5	sn, get, meto, pain, method, bodi, url, 10, use, order
6	want, feel, life, peopl, would, get, know, go, thing, live
7	method, sn, would, know, use, test, get, still, way, think
8	life, peopl, one, feel, think, make, get, would, want, go
9	day, get, sn, terezi, peac, joe, one, hope, know, pleas
10	work, job, peopl, want, virgin, school, life, singl, get, would
11	peopl, life, would, live, suicid, one, think, human, look, world
12	server, join, send, pleas, pm, invit, channel, discord, messag, member
13	seed, yew, poison, hotel, url, drink, make, lethal, use, neighbor
14	bag, would, peopl, vegan, method, ga, know, one, argon, nitrogen

Table A2: LDA test full results.

Topics	Top words
-1	people, life, want, one, know, think, get, even, feel, time
0	life, feel, want, get, know, even, years, things, job, people
1	seeds, yew, visine, url, meto, eye, heroin, lethal, dose, poisoning
2	people, life, world, think, suffering, want, evil, even, parents, humans
3	email, pph, pm, contact, anyone, sn, new, know, source, url
4	sn, taste, also, hope, im, feel, back, took, get, know
5	life, feel, therapy, suffering, sorry, peace, pain, even, get, always
6	neck, full, suspension, partial, hanging, rope, ratchet, method, knot, carotid
7	peace, hope, wish, find, day, last, luck, best, looking, good
8	gas, bag, regulator, inert, cylinder, nitrogen, tank, argon, n2, flow
9	server, join, servers, discord, please, send, interested, pm, ss, invite
10	alone, know, feel, life, one, time, sorry, want, good, go
11	memory, symptoms, meds, caused, adhd, loss, term, bad, years, taking
12	sn, test, bottle, bottles, opened, stored, one, shelf, sealed, since
13	organs, ctb, bucket, donate, want, list, could, think, afraid, death
14	gun, taw122, 45, 357, use, 45acp, calibers, shotgun, revolver, round

Table A3: BERTopic test full results.

B BERTopic previous run

Table B1 shows the topics found by BERTopic in a previous run than the model presented in Chapter 5.1.

Topic	Top words
-1	people; life; want; know; think; things; suicide; hope; someone; find
0	know; think; life; want; way; method; take; said; suicide; hundred
1	jump; jumping; bridge; land; water; method; jumped; building; one hundred; ground
2	gun; shotgun; guns; firearm; shooting; brain; firearms; method; bullet; handgun
3	charcoal; carbon monoxide; generator; gas; coals; smoke; chimney; grill; burning; exhaust
4	hotel; room; home; find; family; forest; hotels; door; hotel room; dead
5	writing; notes; suicide note; letter; suicide; family; leaving; leave note; written; closure
6	bottle; sealed; stored; opened; shelf; shelf life; bottles; expiration; fridge; nitrate
7	job; work; jobs; money; life; want; homeless; make; find; live
8	covid; vaccine; lockdown; coronavirus; pandemic; flu; die; covid nineteen; health; world
9	song; songs; music; listen; playlist; lyrics; listening; album; funeral; suicide
10	birthday; year; christmas; want; two thousand twenty; dates; month; plan; holidays; set date
11	driver; method; trains; front train; train driver; track; suicide; decapitation; train method; speed
12	last; day; go; music; ctb; last day; days; final; life; one last
13	bottle; one bottle; two bottles; one hundred; hundredml; twenty fiveg; one hundredml; bottle enough; amount; one bottle enough
14	cat; dog; pets; pet; love; care; home; leave; life; family
15	dream; dreams; dreaming; woke; nightmare; reality; waking; lucid dreams; dreamed; lucid dream
16	ugly; people; looks; attractive; want die want; face; body; appearance; beauty; hate

17	taste; drink; bitter; capsules; neotame; tastes; two hundredml; honey; tasted; tasting
18	school; college; degree; university; uni; classes; semester; career; education; grades
19	gay; trans; gender; women; people; dysphoria; life; straight; body; things
20	scale; tablespoon; scales; measuring; grams; tablespoons; teaspoons; tbsp; weigh; fiftyml
21	tinnitus; noise; ears; loud; deafening; hyperacusis; anxiety; hearing; hammering; calm
22	birthday; happy birthday; happy; birthdays; birthday happy; twenty; happy birthday happy; birthday happy birthday; celebrate; love
23	phone; reset; wipe; hard drive; factory reset; laptop; deleting; encryption; erase; everything
24	organs; organ; body; organ donation; donor; donate organs; organ donor; transplant; brain; science
25	poem; bad boy; poetry; poems; love; snake; written; write; writing; flower
26	cold; hypothermia; alcohol; winter; frostbite; temperatures; cold water; death; shivering; freeze
27	debreather; rebreather; mask; oxygen; air; rtwod rebreather; scrubber; exit bag; rebreather ii; masks
28	car; truck; crash; cars; driving; car crash; train; road; seatbelt; death
29	christmas; holidays; family; holiday; xmas; merry; celebrate; new year; merry christmas; thanksgiving
30	suicide; thousand; movies; favorite; one thousand nine; hundred; thousand nine; book; one thousand; thousand nine hundred
31	email; emails; delayed; gmail; mail; spam; boomerang; scheduled; delayed email; delayed emails
32	electrocution; electricity; voltage; electric; electrical; circuit; electrocuted; outlet; wire; toaster
33	dnr; medical; directive; resuscitate; legal; life support; hospital; suicide; paramedics; cpr

34	insurance; life insurance; suicide; policies; insurance company; insurance policy; insurance companies; companies; life insurance policy; ctb
35	insulin; diabetic; blood sugar; inject; glucose; low blood; overdose; iv; diabetes; type one

Table B1: Topics found by BERTopic in a previous run.

C BERTopic threads distribution in topics

Table C1 shows the distribution of topics found by BERTopic using the model presented in Chapter 5.1.

Topic	Threads Occurrences
-1	27278
0	3696
1	3673
2	3179
3	2738
4	902
5	793
6	684
7	645
8	600
9	531
10	520
11	516
12	365
13	313
14	288
15	256
16	243
17	242
18	221
19	186
20	182
21	178

22	175
23	170
24	169
25	157
26	160
27	158
28	136
29	133
30	130
31	126
32	126
33	127
34	120
35	119
36	119
37	120
38	120
39	110
40	102
41	100
42	92
43	86
44	85
45	84
46	81
47	80
48	79
49	75
50	74
51	71
52	70
53	68
54	69
55	67
56	67
57	64
58	65
59	64

60	62
61	62
62	61
63	60
64	59
65	55
66	50
67	50
68	49
69	47
70	47
71	47
72	46
73	45
74	42
75	42
76	43
77	42
78	42
79	41
80	41
81	39
82	39
83	37
84	38
85	38
86	38
87	36
88	34
89	31

Table C1: Total threads per topic.

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