

PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA  
MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH  
UNIVERSITY OF MOHAMED BOUDIAF - M'SILA

FACULTY: Mathematics and Informatics

Department of computer science

N: 80



DOMAIN: Mathematics and Computer Science

FIELD: Computer Science

SUB-FIELD: Information Communication  
Technologies

**A Dissertation in Fulfillment  
For the Requirements of the Degree of Master**

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**SUBJECT**

**A data mining tool for the detection of suicide in  
social networks**

**Defended publicly on: 06/ 11 / 2017, to the jury:**

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**Academic year: 2016 /2017**

## **Acknowledgments :**

I would like to use these lines to express my profound and sincere gratitude To my beloved mother. to all those who have collaborated in the achievement of this work. In particular, to tahar mehenni, the supervisor of this thesis, for the guidance, supervision, and support.

Finally, thanks to my family and friends and my best friend for the support they have given me during these months because they have been my primary support and source of motivation.

To all of them, thank you.

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## ***GENERAL INTRODUCTION***

At present, the suicide phenomenon is raising, having a relevant impact on our society. Each year about one million people die as a result of suicidal behavior becoming an economic, social and human problem. On the other hand, the use of Social Networks as a means of communication is becoming extremely popular, through which their emotional states and impressions are exchanged, and people find that writing about their feeling and sharing it to the world through this social networks is much easier than talking about it in real life so they will not be embarrassed or humiliated by other people, which they of course do not know their condition or they do know their conditions but do not care, and doing it any way for fun or other reasons. So people are more comfortable in these social networks and they feel more secure in it, especially when they talk anonymously, therefore, it is no surprise that more and more people with depression publish their suicide notes in these communication channels.

In this context, Information Technologies, Communications and more specifically Language Technologies play an important role in the early detection of suicide, their causes and their terrible consequences. Based on these considerations, it is mandatory to provide societal, environmentally approaches and solutions to tackle these societal challenges. This work is an exhaustive survey of the different researches in this scope, in order to explain which methodologies, technologies and resources are used in the detection of suicide by means of the Social Networks analysis as well as to preventing it.

Our program here has the same role, which is to detect suicidal people only from their publication into social networks like Facebook or tweeter. In this search paper we are going to focus in the social network twitter, also we want to note that when we detect the suicidal person then we could prevent it's suicide, we can talk to him about his conditions, and perhaps he does not know that he is doing things which they are signs of suicide, or even we could recommend some authority or divisions or organization all over the world that take good cares of suicidal people, and treat them in wherever suicide level they are in, or where ever they are from, also whatever their financial state.

In the first chapter we are going to talk about suicide, and all the risk factors and protective ones, and how it evolved over the years in two or three countries, after that we'll see if suicide effects health and or does it affect on others, then we will explain each of the three levels in detection, and

in here where our work start to be more and more clear, after that we mention some of the myths which are out there, and we correct them, we will mention the most common suicide warning signs that could happen to the suicidal person and in that point we could detect if there is suicidal thought or not, and by that we could interfere and prevent him or her from committing suicide, then finally we jump to the protective factors where everyone can fort and protect himself to fall for this kind of things other than the suicidal person.

In the second chapter, we will talk about identify text mining methods and sentiment analysis for social media content ,and then social networks,and recognition of Homophily and Influence, then we define the meaning of social network sites SNS, its characteristics, its history and what people do on SNS also we will see the usage of social networks, we will talk about the impact and the affects of the SNS in work productivity, and we will see some tips about how we could remain safe from SNS.

In the third chapter will start from the results of a previous Research Where it was studied on Twitter and Reddit and extracting the most frequently used sentences by people who had attempted suicide and notes from people who committed suicide then we will propose a solution to solve the problem of zero probability (document) in the sentiment classification.

In the fourth chapter, the creation of our program or the implementation of the early work, so we will create a program which is capable of detecting suicide tweets,

The program will be divided into three sections : download tweets and pre-process these tweets ,After pre-processing we pass this data in our trained classifier, which then classify them into positive or negative or suicidal class, and we classify the person as “**The user has suicidal tendencies**” or not based on trained results

# CHAPTER 1

## SUICIDE ANALYSIS AND DETECTION

### 1 Introduction

Suicide is when people direct violence at themselves with the intent to end their lives, and they die as a result of their actions. Suicide is a leading cause of death in the United States.

A suicide attempt is when people harm themselves with the intent to end their lives, but they do not die as a result of their actions. Many more people survive suicide attempts than dying, but they often have serious injuries. However, a suicide attempt does not always result in a physical injury.

According to the analysis carried out by the World Health Organization (WHO) in 2012 every 40 seconds a person died by suicide, becoming more than 800,000 people per year. The WHO estimates that suicide is the 13th leading cause of death in the world and the third one between youth aged 15-44; and it is estimated to be a major cause of mortality during adolescence, particularly at ages 15-19. In a western society such as the United States, 13% of all deaths among youth and young adults aged 10-24 years result from suicide [1]. On top of this, research results, unfortunately, suggest a high lifetime prevalence of self-injurious behaviors in adolescents .

Suicidal behaviors can be conceptualized as a complex process that can range from suicidal ideation, which can be communicated through verbal or non-verbal means, to planning of suicide, attempting suicide, and in the worst case, suicide. Suicidal behaviors are influenced by interacting biological, genetic, psychological, social, environmental and situational factors.

### 2 Suicidal Behavior

Suicidal behavior includes:

- Suicidal ideation (thinking about ending one's life)
- Suicide attempt (non-fatal suicidal behavior)
- Suicide (ending one's life)

### 3 Understanding Suicide

Although some people may perceive suicide as the act of a troubled person, it is a complex outcome that is influenced by many factors. Individual characteristics may be important, but so

are relationships with family, peers, and others, and influences from the broader social, cultural, economic, and physical environments.

There is no single path that will lead to suicide. Rather, throughout life, a combination of factors, such as a serious mental illness, alcohol abuse, a painful loss, exposure to violence, or social isolation may increase the risk of suicidal thoughts and behaviors.

## **4 Risk and Protective Factors**

### **Risk factors**

They are characteristics that make it more likely that a person will think about suicide or engage in suicidal behaviors. Although risk factors generally contribute to long-term risk, stressful events, such as relationship problems, financial difficulties, or public humiliation could provide the impetus for a suicidal act.

### **Protective factors**

They are not just the opposite or lack of risk factors. Rather, they are conditions that promote strength and resilience and ensure that vulnerable individuals are supported and connected with others during difficult times, thereby making suicidal behaviors less likely. [2]

Risk and protective factors for suicidal behaviors can be found at many levels, from the individual to the community and society at large. The social ecological model (see **Figure 1.1**) provides a useful framework for viewing these factors along four levels of influence: individual, relationship, community, and societal. The figure lists the major risk and protective factors for suicidal behaviors identified in the literature, [2] [3] and these factors can vary between individuals and across settings.

Suicide is closely linked with mental and substance use disorders [4] and shares risk and protective factors with other types of self-directed violence, interpersonal violence, 15 and other related problems. As a result, efforts to reduce the risk factors and to increase the protective factors for suicide are likely to also help prevent or reduce these and other problems. [5]

## **5 How does suicide affect health?**

People who attempt suicide and survive may experience serious injuries, such as broken bones, brain damage, or organ failure. These injuries may have long-term effects on their health. People who survive suicide attempts may also have depression and other mental health problems.

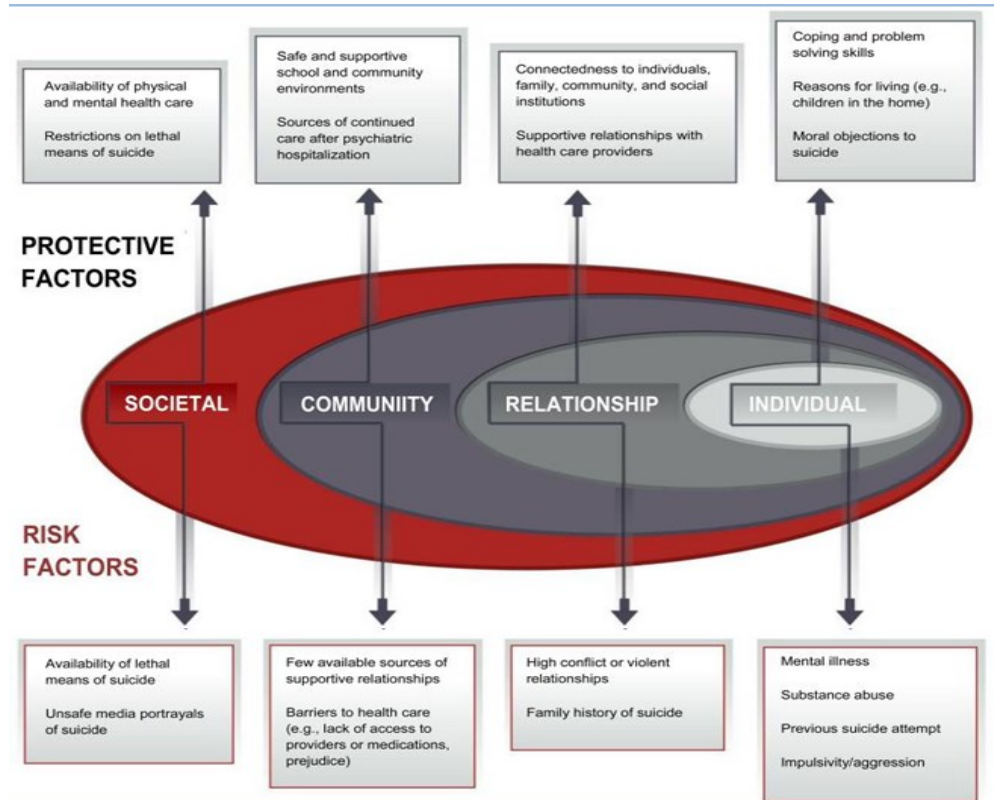


Figure 1.1 protective and risk vectors. [6]

Suicide also affects the health of others and the community. When people die by suicide, their family and friends often experience shock, anger, guilt, and depression. The medical costs and lost wages associated with suicide also take their toll on the community.

## 6 How suicide affects others

There is no blueprint for how we react to and cope after a suicide. We each have our own relationship with the person who died and we all grieve in our own way and at our own pace.

When someone grieves in a different way to you, it doesn't mean that they don't care – they are just finding their own way to cope. But it can be hard if they behave in a way that you can't relate to. It can also be difficult to express our own grief around others if they are reacting differently, especially if those people also had a close relationship with the person who died.

Patience and understanding are helpful and it is important that you try and find somewhere you can share your feelings. And remember that there is support available from others from outside friends and family – this can provide a space to “be yourself” without having to worry about how others will react. [6]

## 7 Why is suicide a public health problem?

- Myth – Suicide in youth is not a problem
- Truth - Suicide in young people is a serious and prevalent problem:
  - ❖ Suicide is the 10th leading cause of death in the US.
  - ❖ Each year 42,773 Americans die by suicide. See the **(Figure 1.2)**
  - ❖ For every suicide 25 attempts.
  - ❖ Suicide costs the US \$ 44 Billion Annually
  - ❖ On average, there are 117 suicides per day.
  - ❖ 494,169 people visited a hospital for injuries due to self-harm.
  - ❖ Top methods used - firearms, suffocation, poisoning [7]

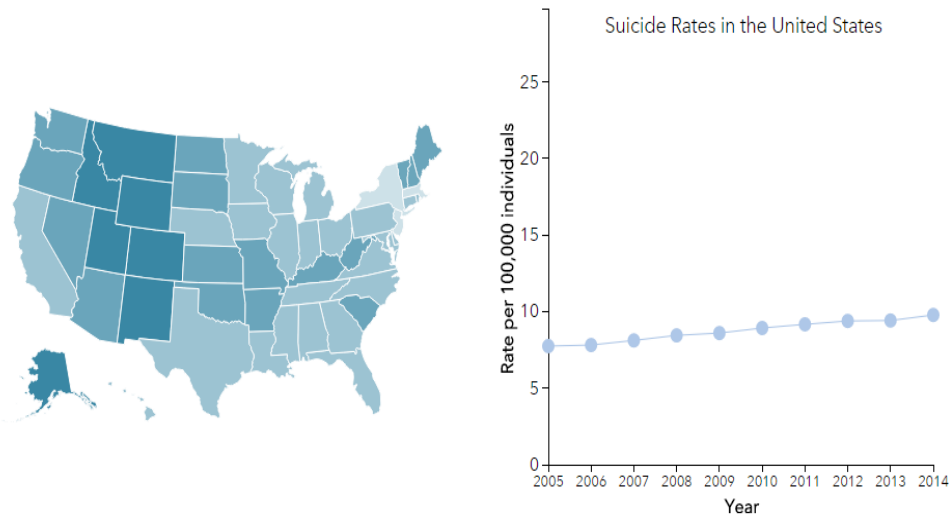


Figure1.2 Suicide rates in the US. [7]

## 8 Ten Commonalities of Suicide

- The common purpose of suicide is to seek a solution: A suicidal person is seeking a solution to a problem that is "generating intense suffering" within him or her.
- The common goal of suicide is a cessation of consciousness: The anguished mind of a suicidal person interprets the end of consciousness as the only way to end the suffering.
- The common stimulus of suicide is a psychological pain: Shneidman calls it "psychache," by which he means "intolerable emotion, unbearable pain, and unacceptable anguish."

- The common stressor in suicide is frustrated psychological needs: A suicidal person feels pushed toward self-destruction by psychological needs that are not being met (for example, the need for achievement, for nurturance or for understanding).
- The common emotion in suicide is hopelessness-helplessness: A suicidal person feels despondent, utterly unsalvageable.
- The common cognitive state of suicide is ambivalence: Suicidal people, Schneidman says, "wish to die and they simultaneously wish to be rescued."
- The common perceptual state in suicide is constriction: The mind of a suicidal person is constricted in its ability to perceive options, and, in fact, mistakenly sees only two choices—either continue suffering or die.
- The common action in suicide is an escape: Shneidman calls it "the ultimate egression (another word for escape) besides which running away from home, quitting a job, deserting an army, or leaving a spouse ... pale in comparison."
- The common interpersonal act in suicide is communication of intention: "Many individuals intent on committing suicide ... emit clues of intention, signals of distress, whimpers of helplessness, or pleas for intervention."
- The common pattern in suicide is consistent with life-long styles of coping: A person's past tendency for black-and-white thinking, escapism, control, capitulation and the like could serve as a clue to how he or she might deal with a present crisis. [8]

## **9 Early Detection**

We are going to talk about students who attend school because that's the place we can detect mostly where a young boy or a girl is thinking of suicide.

The school is the environment where youngsters spend most of their time. By providing a safe and healthy environment where mental health is promoted, the school can contribute greatly to the prevention of student suicide.

‘There is no health without mental health’. Mental health is ‘a state of emotional and social well-being that enables people to undertake productive activities, experience meaningful interpersonal relationships, adapt to change and cope with adversities.’ Promotion of mental health for all students can enhance their ability to cope and feel positive about people and events in life, increase resilience and reduce the incident of suicidal behavior. In the multi-level ‘Health Promoting Schools Framework’ advocated by The World Health Organization (WHO), promotion of mental health is the basis of suicide prevention. [9]

### **10 Warning Signs that could lead to suicide**

Research has demonstrated that in over 80% of completed suicide, a warning sign or signs were given. The following is a list of warning signs grouped into seven categories:

❖ Unexpected reduction of academic performance

- Drop in grades and academic performance
- Apathy in class
- Failure to complete assignments
- Inability to concentrate on school work and routine tasks
- Increased absences or truancy
- Increased aggression, frequent trouble-making in school

❖ Expression of ideas and themes about death and suicide

- Written essays, conversation, and artwork contains ideation about death/suicide
  - ✓ -Direct statements indicating a wish to die or escape or a final departure

‘I wish I were dead.’

‘I am going to kill myself.’

‘I am going to end it all.’

- ✓ Indirect or subtle statements indicating feelings of hopelessness and helplessness

‘I am so tired of it all.’

‘You will be better off without me.’

‘What’s the point of living?’

‘Who cares if I’m dead’

‘Very soon you won’t have to worry about me.’

‘I should never have been born.’

- Exploring various lethal means such as sleeping pills, hanging, charcoal burning, etc. from different sources, e.g. peers, the internet, etc.
- Making plans and/or final arrangements e.g. giving away prized possessions, putting affairs in order
- ❖ Change in mood and marked emotional instability
  - Anger at self, increased irritability, moodiness, aggressiveness
  - Pervasive sadness, sudden tearfulness
  - Overwhelming guilt, shame
  - Increased hopelessness, helplessness and worthlessness
- ❖ Significant stress events
  - Grief about a significant loss e.g. death of friend/family member, breakup with boy/girl friends, the suicide of a peer, the anniversary of someone else's suicide, etc.
  - Situational stress e.g. unwanted pregnancy, trouble with the law/disciplinary crisis, severe family disruption, physical/sexual abuse, etc.
- ❖ Withdrawal from relationships
  - Loss of interests in surroundings, friends, hobbies or activities previously enjoyed
  - Drop out of sports and clubs
  - Isolation
- ❖ Physical symptoms with emotional cause
  - Increased physical complaints such as a headache, stomachaches, fatigue, body aches
  - Change in sleep or eating patterns, nightmares, eating disturbances
  - Neglecting personal hygiene/physical appearance
  - Disorientation, frequent accidents
- ❖ High-risk behaviors
  - New involvement in high-risk activities
  - Increased use of drugs or alcohol
  - Repeated self-injuries behaviors [10]

It is estimated that as many as 90% of individuals who have ended their lives by committing suicide had a mental disorder, 60% of which were depressed at the time. In fact, all types of mood disorders have been clearly linked to suicidal behavior. Depression and its symptoms

(e.g., sadness, lethargy, anxiety, irritability, sleep and eating disturbances) should alert all counselors to the potential risk of suicide.

Elevated risk for suicide also has been associated with schizophrenia, substance abuse disorders, personality disorders, anxiety disorders including Post-traumatic stress disorder (PTSD), and diagnostic comorbidity.

Approximately 10-15% of individuals with schizophrenia complete suicide, which is consistently the most common cause of death among individuals experiencing psychosis. Increased personal insight into the mental disorder, fewer years in treatment and severe depressive symptoms are associated with a heightened risk of suicide among individuals within the psychotic population. Alcoholism, particularly in the presence of depression and personality disorder, also can increase the risk of suicide. [11]

### 11 The five domains that comprise the proposed risk factor matrix

Five domains of risk factors comprise the proposed theoretical model of suicidal behavior. It is suggested that these five domains, organized as a matrix or multiaxial approach, provide a simple model for considering risk factors for education and clinician intervention as well as clinical investigation (see Figure 1.3).

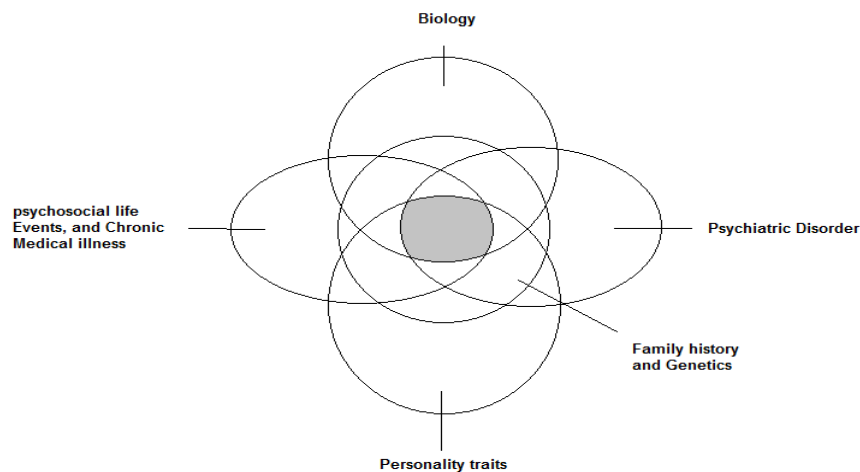


Figure 1.3 Overlap model (five domains). [12]

1. The first is a careful clinical description according to psychiatric diagnosis. Current research shows that affective disorders, conduct disorders, and substance abuse are the most highly associated psychiatric diagnoses with suicide in young people. As found in the adult literature where over 90% of persons who end their lives by suicide have an

associated psychiatric illness, the few studies on adolescent suicide suggest high percentages as well. [13]

2. Second, personality traits relating to suicide, such as aggression, impulsivity, and hopelessness, are important in and of themselves in characterizing suicide since they may represent personality styles that cross diagnostic groupings. In addition, this domain includes certain personality disorders, such as borderline personality disorder and antisocial personality disorder, which are more highly correlated with suicidal behavior and represent risk factors.
3. The third domain is concerned with psychosocial factors, social supports, life events, and chronic medical illness. For example, early loss, increased negative life events, the presence of a chronic medical illness, and decreased social supports increase the risk for suicide. In addition, most young people who end their lives have had a recent humiliating life experience. [14]
4. The fourth area is the identification of both genetic and family factors that predispose an individual to suicide. Previous investigators have suggested. That the genetics of suicide may be independent of the genetics in a family history relating to specific psychiatric disorders such as affective disorder or alcoholism.
5. The final factor in this matrix is the neurochemical and biochemical variables currently under active investigation in an attempt to identify either a biologic abnormality or a vulnerability state for suicide.

## **12 Detection Levels**

The three levels of detection require greater elaboration. A brief over-view of each level and several examples are now presented. Individuals who would be placed in **Level I**, which can best be labeled "detection awareness", are not actively suicidal or in immediate danger of suicide completion (**Table 1.1**). However, individuals at this level do have certain risk factors. For example, the offspring of affectively ill or substance-abusing parents, the offspring of a person who has died by suicide, close contacts with suicides and suicidal people, and abused and neglected children would comprise the Level I group. Level I would also include children who have recently been under extreme stress, such as that relating to the divorce of parents, moves, the presence of a chronic illness either in the children or in the family, or the recent death of a parent or a close

relative. It should be pointed out that one can think of the individual as having relatively little control over Level I problems.

1. Offspring of affectively ill or substance-abusing parents.
2. Offspring of suicides and suicide attempters.
3. Close contacts of suicides and suicidal people (prevention of contagions).
4. Abused and neglected children.
5. Children who have recently been under severe stress.
  - (a) The divorce of parents.
  - (b) Move.
  - (c) The death of parent/relative.

Table 1.1 Level I-Detection Awareness. [12]

**Level II**, shown in (**Table 1.2**), is characterized by major problems that do not meet criteria for a psychiatric disorder. Young individuals who fit into Level II may require assessment, intervention, and perhaps even treatment, but the treatment is not for a Diagnostic and Statistical Manual of Mental Disorders, Third Edition, Revised (DSM-III-R) psychiatric diagnosis. Individuals at this level generally show some amount of distress, the presence of symptoms, and/or decrease in function. Examples of problems at this level may include pronounced academic problems, the presence of learning disabilities, increasing interpersonal relationship difficulties, a major loss, or severe self-esteem problems. These individuals maybe exemplified by youth who run away, adolescents who have an unwanted pregnancy, or children who are undergoing major stresses and become symptomatic. Personality problems including extreme aggressivity or feelings of hopelessness are also characteristic of Level II in young people. Individuals at Level II may indeed become suicidal, and are at risk for suicide attempts and suicide completion.

**Level III**, represents the detection of suicidal youth who have major psychiatric disorders (**Table 1.3**). When any individual is identified at this level, assessment and an intervention component are required, with the intervention representing active treatment aimed at a specific psychiatric diagnosis. Such diagnoses in children and youth may include affective disorders, conduct disorders, schizophrenia, eating disorders, substance abuse, and adjustment reactions.

1. Requires assessment and intervention/treatment (not related to psychiatric diagnosis)
  2. Anything that is not a major psychiatric disorder.
  3. Symptomatic, but does not meet criteria for a DSM-III-R, Axis I disorder
- (a) Academic problems
  - (b) Learning disability
  - (c) Interpersonal relationship difficulties
  - (d) Self-esteem and sexual identity problems
  - (e) Runaways
  - (f) Having an unwanted pregnancy
  - (g) Children who are undergoing major stress or loss and are symptomatic
  - (h) Aggressivity, hopelessness, personality traits and styles.

Table 1.2 Level II - Major Problem Awareness. [12]

Even though personality disorders are not diagnosed before the age of 18, they can be diagnosed in those youth between the ages of 18-24. In addition, as was previously discussed, certain disorders of childhood and adolescence may be predictive of adult disorders. In fact, there is a stability of these personality characteristics developmentally. Most individuals with antisocial personality disorder have had a conduct disorder in their youth. [15]

1. Necessitates appropriate assessment and evaluation
  2. Has a treatment component aimed at a specific psychiatric diagnosis
- (a) Affective disorder
  - (b) Schizophrenia
  - (c) Conduct disorder
  - (d) Substance abuse and/or alcoholism
  - (e) Adjustment reactions
  - (f) Eating disorder
  - (g) Identity disorder

Table 1.3 Level III--Major Psychiatric Disorder. [12]

### 13 Protective factors

Researchers and practitioners refer those conditions that may increase a person’s risk of attempting or completing a suicide as ‘risk factors’ and those that protect a person, promote resilience and reduce the potential for suicidal behaviors as ‘protective factors’. From a developmental perspective, youth, in particular, face different challenges at different ages.

Suicidal behaviors, ranging from suicidal ideation to suicide death, are often triggered by certain very stressful life events and an unbearable state of mind (e.g. hopelessness, helplessness, shame, etc.).

Suicide usually happens with warning signs. For suicide prevention, we should aim at early detection and intervention so that warning signs can be timely identified risk factors at individual, family and environmental levels mitigated and protective factors effectively enhanced. Our conceptual framework is given below (**Figure 1.4**).

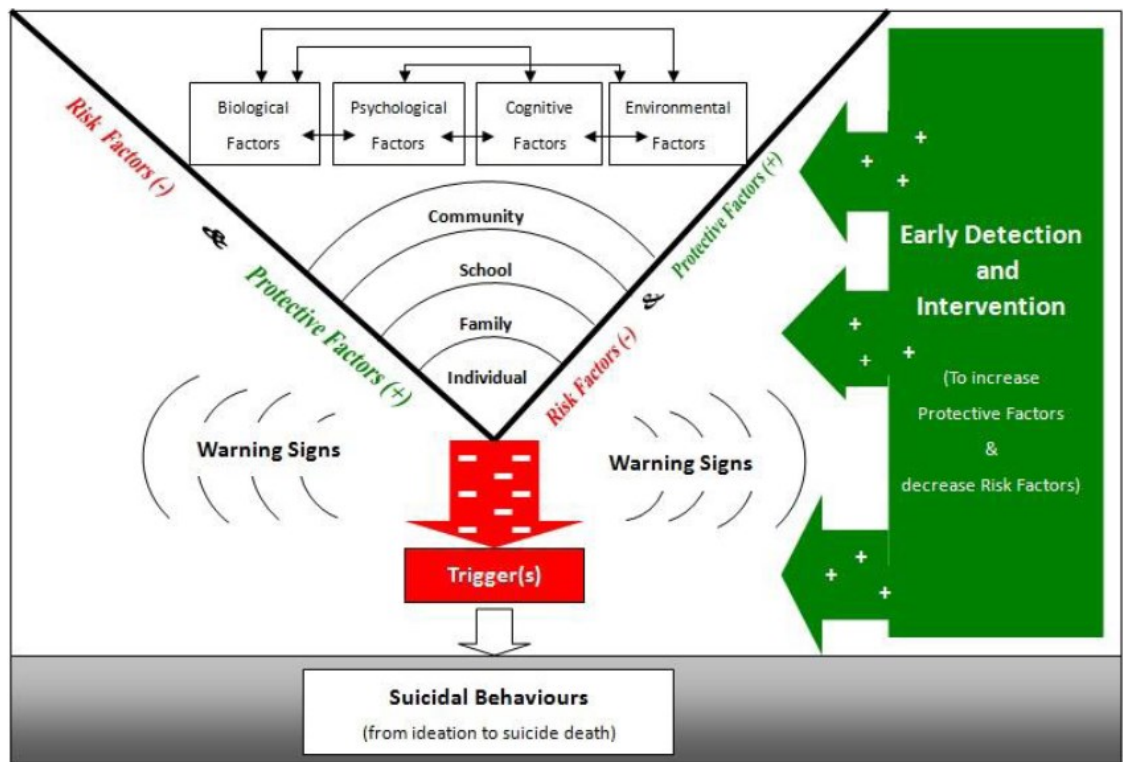


Figure 1.4 A Conceptual Framework for Understanding Suicide. [16]

They are positive conditions that promote resilience. Although such protective factors ‘do not negate the risk of suicide, they can counterbalance the extreme stress of life events. [17] Below are examples of protective factors found in suicide literature:

- Strong sense of self-worth

- Strong sense of personal control
- Positive attitude and life value
- Religious, cultural and ethnic beliefs
- Effective coping skills e.g. problem-solving, conflict resolution, social skills, anger control, communication, etc.
- Good impulse control
- Supportive significant others (e.g. best friends, parents)
- Positive family environment and healthy family relationships
- A satisfying social life (e.g. constructive use of leisure time)
- Community involvement e.g. opportunity to participate and contribute to school/community activities
- Safe and supportive environment (e.g. difficult access to lethal means)
- Access to mental health care, medical compliance

## **14 Conclusion**

Suicide is a priority condition globally and has been identified as such by the World Health Organization (WHO). A national suicide prevention strategy should be developed through a stepwise approach. Such a strategy acknowledges, as a first step, that suicide is a major problem and that it is preventable. The process of developing a national strategy provides an impetus to suicide prevention by improving awareness among government representatives and local communities. Internet Technologies and Communication and, more specifically, the Human Language Technologies can help to resolve part of these problems through the early detection of suicidal thoughts and/or behavior expressed through the Social Media. The words and the way people use to communicate on their blogs, social networks, etc. provide information about the psychological state and personality of individuals. The processing and analysis of natural language texts shared via the Internet help record and detect changes in an emotional state of the people. Unfortunately, although there are available resources and tools for sentiment analysis and opinion mining, even in the field of the depression detection and using different approaches and features, there is neither system nor platform that deals with the full process of suicide prevention.

# CHAPTER 2

## Data Mining Of Social Media

### 1 INRODUCTION :

Humans are social creatures by nature, we always try to group ourselves instinctively within communities and societies. We also tend to group ourselves with people with somewhat similar ideologies and backgrounds, as this would facilitate easier understanding and communication. The communication patterns also tend to intensify for members in the same group, in comparison to members from the outside. All of these facts are the essence of the sociological principles of Influence and Homophily; where people eventually tend to develop similar views and opinions over different issues, based on the characteristics of these groups.

The Social Network, or the virtual social world in general, is a reflection of the real world. People in the virtual world still instinctively group themselves with people sharing similar backgrounds, forming a kind of virtual communities. Detecting these virtual groupings might be of special importance for the analysis and monitoring of Social network, as it provides a disciplined view of the network in which people connect to each other. and identify text mining methods and sentiment analysis for social media content .

### 2 Text Mining

Text mining can be defined as the process at which text is transferred into data that can be analysed. This incurs the procedures of creating an index for the individual terms, based on the location of the term within the original text, or based on other techniques or protocols. The words and indexes can then be used for a variety of analysis methods.

The idea behind indexing is not to store the abstract word's location, the indexing process in text mining is rather about storing the word's meaning, or concept, within the given context. The concepts are then stored in database, concepts database, and used for further analysis and processing. The concepts are extracted from the given text via a series of computational linguistic techniques for extraction processes. [30]

Data mining, in contrast to text mining, is the process of discovering patterns and trends within large datasets. Data mining is an interdisciplinary field, involving constructs from the fields of

machine learning, artificial intelligence, database systems, and statistical methods. The two most essential operations in the data mining process are clustering and classification.[18]

## **2.1 Clustering and Classification**

Clustering is the process of automatically aggregating or grouping similar items and records together, based upon sharing similar attributes' values. Clustering usually assumes no prior information regarding the number of available clusters. Classification in its essence is similar to clustering in the process of segmenting the available items into separate classes. However, unlike clustering, it is required that the user analyst knows beforehand how each of these classes is defined, and what are the different attributes. It is also required that each of the available items should have values for the segmenting attributes. Classification is considered less exploratory than clustering.[18]

As in clustering, many different algorithms can be used for classification purposes. One of the most important approaches is via decision trees, where new items can be classified by traversing the tree to the leaf which represents a class. Much effort is needed to properly obtain the decision tree and evaluate it. K-means can also be used as a classification approach, as mentioned above. Other algorithms include Support Vector Machines (SVM), and many others.

## **2.2 Reasons for text mining**

- Enriching the content, by improving the indexing of the text.
- Systematic Review of Literature, by systematically reviewing a large content. This process can help reduce time and effort needed in general literature review.
- Discovering new insights: as I have mentioned earlier text mining on its own does not bring about new insights or knowledge. However, data mining the resulting indexed content of the text mining process might actually obtain new knowledge.
- Computational Linguistics Research, where text mining is considered as a tool for bigger linguistic researches.[18]

## **2.3 Text mining procedures**

1. Information retrieval (IR): The process of selecting the most appropriate or relevant content or documents to be mined, by matching the desired query to the possible content. If the content was structured, as in scientific publications of a certain field for example, the information retrieval process would be relatively easier. However, if there weren't a

structured content to refer to, the process will have to include as much content as possible to be able to derive the required results, and will be computationally more consuming to map content to locations.

2. Natural language processing (NLP): In a simple notation, NLP is about transferring or interpreting the human readable text into data that the computer can read and process. It utilises linguistic and grammatical principles and tools for the interpretation procedures. Such tools include Part Of Speech (POS), parsing tools, dictionaries, and others.

3. Information extraction (IE): By structuring the resulting data of the NLP step. Terms and named-entities are identified here, in addition to the possible connections or relationships between the entities and terms. The results of this steps are considered facts, or assertions and are usually collected in a database for future analysis. The starting point of the extraction[19]

process is usually a set of templates for the kinds of information to be obtained. A simple example from chemistry is a pattern where two chemicals, A and B are found close to the phrase "reacts with". [19]

4. Data mining (DM): identifying trends and patterns in the dataset, to find new knowledge insights.

A special kind of text mining, although uses some different approaches, is opinion mining and sentiment analysis. A more comprehensive review follows.

## **4 Sentiment Analysis**

Sentiment Analysis is the automatic procedure in which the overall polarity of the content is measured. It involved Natural Language Processing (NLP), computational linguistic, and textual analytics to obtain the subjective and sentimental information from a given text. The sentiment analysis process entails a number of tasks or procedure after which the overall polarity or the subjectivity of the content can be specified.

Throughout the next sections I will be outlining the different tasks associated with sentiment analysis, and some of the approaches and algorithms that current researchers are using.

### **4.1 Polarity Classification**

Classification here at a simple notation is the process of classifying the opinions in an opinionated piece of text, under two opposite sentiment polarities. The opinion in the text is assumed to be covering a single topic, field or context. The process may be utilized for summarization processes, or simply to extract the overall sentiment, say negative.[20]

The opinionated text may be addressing subjective or objective issues, where the author may be addressing an issue by stating his/her own opinions, or stating a fact or a piece of news that might be

considered as polarised (e.g: good news or bad news) within a specific context. But it's worth mentioning here that the distinction between subjective and objective information can be subtle.[16]

A number of related problems to the polarity classification include the Related Categories, which explores the reasons on why the users had an overall positive or negative sentiment. Identifying the pros and cons in this manner helps at improving the overall polarity, in addition to enriching the helpfulness of individual reviews, where judgments that are reinforced by reason are more trustworthy. Other problems include Rating Inference, by measuring the "degree of positiveness", and having a multi-point scale for the overall output.

An important issue in this context is Agreement; in the opposite manner of polarity classification, lies the issue of determining whether two different texts should receive similar or different sentiment label.

## **4.2 Subjectivity Detection**

As illustrated above, polarity classification operates under the assumption that the content of the text being opinionated. However, real life texts might be objective or might include both objective and subjective content that are related to the given context.

Subjectivity detection can be thought of as an independent process. However, it was found that having subjectivity detection as a preceding process for polarity classification increases the efficiency of the sentiment analysis. Subjectivity Detection is a harder problem than polarity classification, so improvements in the subjectivity detection promises better results for the sentiment analysis process as a whole.[19]

When we discussed polarity classification we have made the assumption that the given text to be processed covers a single and certain topic. However, this might not be the general case. An enhancement to the subjectivity detection can be done by first operating topic-based text filtering, then progressing with the subjectivity detection system. This procedure is called Joint Topic-Sentiment Analysis.

Another similar class of problems is determining view points and perspectives. This problem is characterised by a collection of bundled attitudes and beliefs within the given text, which means that simple polarity classification techniques might not be suitable here, and techniques based on extraction will have to be utilised.

### 4.3 Features/Aspects extraction

The feature extraction processes are one of the fundamental steps for data-driven analysis for textual content. Converting a plain text into a features vector enables more comprehensive and rigorous procedures of data mining and sentiment analysis.

### 4.4 General Approaches

- Term Presence vs. Frequency: Term frequency has been an important factor for regular information retrieval and topic-based analysis procedures. However, for sentiment and opinion analysis, it has been shown that just the presence of the term has a big impact on the sentiment analysis and subjectivity detection procedures, regardless of its frequency.
- Term-based Features: Corresponding to the position of the term within the text, which might have a big influence on the overall sentiment. The location can be encoded within the feature vector to be utilised in the analysis process. Another factor is the N-gram based analysis, where having a unigram, bigram and trigram-based analysis will affect

the analysis process and results. The actual effect of each is debatable though. [20]

- Parts of Speech: Which refers to the morphological behavior of the lexical item within the text. It is important for both topic-based and sentiment analysis. Adjectives are commonly utilised for both sentiment analysis and subjectivity detection. [20] There were also many studies on the utilisation of certain verbs and nouns for

sentiment analysis. [20]

- Syntax: The syntax is quite important for analysing short texts.
- Negation: Where despite that a negation term might be present only once in a certain sentence, it transforms it into the total opposite. An interesting research was conducted by combining the parts-of-speech approach with negation, to detect whether the presence of a negation term does indeed reverse the polarity, or to obtain which parts of the sentence

the negation is affecting. [21]

- Topic-Oriented Features: Where similar sentences might refer to totally different sentiments if addressing different topics. In addition to the fact that the classifiers trained for certain domain will give erroneous results if used for different domains.

## 5 Supervised and Unsupervised approaches

One way to classify the algorithms used for the sentiment analysis process is to divide them into those that utilise machine learning constructs, and those that use some form of lexical inference based on specific terms and applying certain lexical rules. However, many approaches utilize both techniques together.[21]

The two major machine learning classes for the learning process are supervised and unsupervised learning methods. Supervised learning relies on pre-existing set of labeled data, or lexicons in our case, to be used to infer the overall sentiment of the text. Whereas unsupervised learning assumes no previous knowledge or training of the text at hand. Supervised learning based sentiment analysis requires an already labeled dataset to train the classifier. This training dataset is fed to the classifier to train upon what features' values produce which classifications. Probabilistic and non-probabilistic supervised machine learning algorithms are used for this learning process, like the Naive Bayesian Classifier, and Support Vector Machines (SVM). The main mathematical rule behind the Naive Bayesian Classifier is:

Unsupervised learning utilises machine learning methods used for classifying and extracting the sentiment lexicons and their degree of polarity. The advantage of these approaches is that it can be utilised to crude content without or with little background information or evidence. It can also be used to bigger content in comparison to other supervised approaches.[19]

- Sample method includes Unsupervised Lexicon Induction, by first obtaining sentiment lexicon from the text using unsupervised algorithm. Then the degree of subjectivity for that lexicon can be measured by the available indicators at the text. The polarity can be measured by propagation from seed terms whose polarities are already known.

The unsupervised algorithm used to extract the sentiment lexicons could utilise linguistic heuristics, like opposite connectors (e.g: "but"), to obtain separate polarities and then separate them. [19] Or a number of other techniques.

- Another approach is by bootstrapping, where an initial classifier is used to obtain labeled data, which is then used as an input for supervised learning based algorithm.

## 6 Classification Based on Relationship Information

Another way to enhance the analysis process is by utilising Classification Based on Relationship Information. The main idea is to take advantage of the relationship connections between deferent documents, deferent classes, deferent features and discourse participants within the content at hand. Going into the details won't be beneficial here as it's a quite lengthy discussion about the size of this report.

A possible way to make use of relationship information within the context of Social Media is to investigate the usage of Social Network Analysis constructs to facilitate or enhance the sentiment analysis. Which this project will try research in more detail. [30]

## **7 Challenges:**

\_ The scarcity of the possible classes, as in "positive or negative" or the star rating system, in movies rating for example. And the interleaving nature of the context, which makes it hard to distinguish a certain distinct classification for a certain context.

\_ The fact that sentiments and opinions are usually expressed in a more subtle way than regular fact based text. This makes sentiment analysis a harder problem than regular facts based analysis in terms of the used algorithms and techniques. The problem gets intensified when observing isolated chunks of text or small sentences. This makes applying sentiment analysis techniques for Social Media content a quite challenging process, due to the fact that the content in Social Media means is usually short.

\_ Sentiment analysis is context sensitive and domain dependent. The same phrase or expression can mean different things at different contexts. [30]

\_ Unlike in topic analysis for documents, where the topic is based on what the majority of the content is focusing on, regardless of the order, opinion analysis is quite affected by the overall order of the ideas. e.g: "A is better than B" represents the exact opposite opinion from "B is better than A." [18]

## **8 Sentiment Analysis for Social Media Content**

In addition to the previously Mentioned challenges for documents-based sentiment analysis, the application of sentiment analysis and opinion mining techniques for Social Media content, like Twitter and Facebook, imposes a set of new challenges. These include:

\_ The relatively short content (140 characters for Twitters). This imposes a big restriction for the application of many document or blog based sentiment analysis techniques.

\_ The unstructured nature of the content, and the necessity to work with unstructured information extraction methods. [30]

\_ The issue of spam and fake reviews, posts, and comments.

Sarcasm and irony detection. A very difficult problem to be addressed rigorously. Sarcasm can shift the entire polarity

\_ Grammatical mistakes, broken sentence boundaries, spelling problems, context specific terminology, slang terminology, etc.

\_ Lack of contextual data.[21]

## **9 Social Network Analysis (SNA)**

The Social Network Analysis field is not new, however, this field has been revived recently by the current outbreak of Social Media and Social Media tools.

Modeling communities of people (nodes) and interactions (connections) in a structured manner are of great importance for understanding how information gets propagated and spread in a system of people. The resulting structure builds upon two basic facts:

1. People tend to group into clusters as a result of communication opportunities for which people tend to meet, both physically and virtually.
2. Communication is more influential and frequent within these clusters, such that people within the same cluster tend to develop similar views. [21]

The main purpose of structure-based social network analysis is the detection of communities within a system of people, and to obtain the main opinion makers or opinion leaders within these communities. The resulting structure of the system can be viewed as a graph. Many graph-based techniques and algorithms can then be used to process the resulting network and

extract subgroups or communities. These methods include cliques-based, degree, and matrix perturbation methods.

### **9.1 Social Network**

The Social Network: is a network structure composed of social entities (might be people, organisations or groups) as nodes. And connections in the form of edges, that represent the connection or relationship amongst these entities. Such connections might be friendships, acquaintanceship, or business connection etc.

Structural Holes in Social Networks People, or nodes, within a single cluster tend to share similar views and knowledge. The process of making explicit data or knowledge into insider or local knowledge within the group is passed through certain channels, or relations, between two nodes of different clusters. This process of knowledge passing produces structural holes in the structure of the social network.

People (nodes) in groups separated by structural holes focus more on their local knowledge and interaction rather than the general network correspondence. One way to look at these holes is like a buffer, or like an insulator in an electric circuit isolating the different components of the network. It is also worth mentioning here that holes represent non-redundant sources of information, amongst the different clusters. [22]

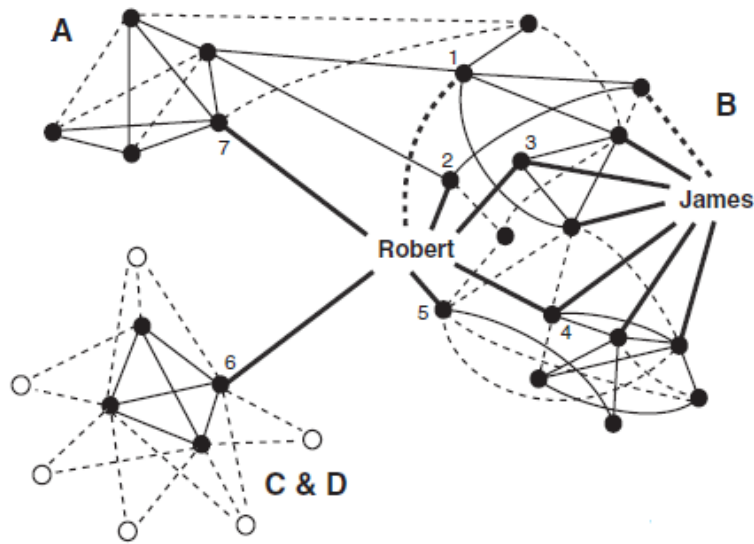


Figure 2.1: A sample social network, showing closure and brokerage nodes. [21]

Nodes inside the network can be classified as either:

1. Closure: nodes within the cluster or group. Closure nodes are important to strengthen the connections, by constantly doing the same thing or having similar data, they get better at they do or know. Closure nodes also incur more trust within the networks,

where reputation tends to propagate more sensitively for nodes within the clique, as the connections tend to transfer reputation status more efficiently.

2. Brokerage: nodes connecting two different clusters. Brokerage nodes are important to diversify the knowledge in the cluster by bringing in new data from other clusters. [22]

In the figure above it can be observed that James at clique B represents a closure node, a local node that strengthens the connections within the clique. Whereas Robert is a part of clique B, but at the same time he has connections with both cliques A, C and D. Robert here represents the Brokerage node at the network. Robert has a vital access to less redundant knowledge, and new knowledge and activities going on at other cliques.

## 9.2 Opinion Leaders

Robert in Figure 2.1 above also has the capability of transferring new knowledge and data from other cliques to the local one. The structural holes within the network graph present Robert with the opportunity of brokering interactions and communication amongst several cliques, while displaying different beliefs to other contacts. Robert in the graph above is what researchers have identified as an opinion leader.

Brokerage nodes, or opinion leaders, present a valuable opportunity for action amongst different cliques representing different communities. Brokerage nodes build bridges amongst the communities, bridges between markets and organizations for example. [22]

## 9.3 Rule of Agency and Personality

It's worth mentioning here that the structure of the network and the presence of Brokerage nodes is not the main factor for the efficiency of the structure, after all it's the people that act, not networks. Taking advantage of the structural holes is mainly dependent upon the skills or the performance of the Brokerage node at transferring and decoding of potentially useful knowledge.

Another point in this area is regarding the dynamics of the network structure. Modern technologies facilitate easy and continuous change in the connections and general structure of the network. However, researches have indicated that Opinion Leaders or brokerage nodes tend in previous structures tend to maintain their rule at consequent changes, and that structural holes tend not to change much, which provides some sense of stability and equilibrium for the observed structure over time. [22]

## 10 Structural Holes and Opinion Leaders Detection

The following parameters are used to identify and evaluate the potential Opinion Leaders.

These parameters can be considered as metrics when it comes to the community detection and opinion leaders identification.

1. Network density: network density can be defined by the strength of the connections amongst the network. It is calculated by dividing the number of the available connections in a sample network, by the number of all possible connections.
2. Hierarchy: which is the degree at which the contacts are connected to a single contact within the network
3. Non-redundant contacts: The count of the unique contacts, without the contacts redundant with other contacts in the network. Which primarily refers to the count of different cliques or clusters that the contact is connected with.

4. Betweenness index: A measure of the structural holes that the agent or the contact has access to within the network.

## **11 Dimensions of Connection**

The communication and interaction patterns within the context of social networks in general, and Social Media in particular, is of a multidimensional heterogeneous form[23]. The different nodes, or users, tend to use different forms of communication and knowledge sharing. A good example would be the Twitter content, where the interaction dimensions could be in the shape of Retweeting, Replying, Mentioning or Hashtags similarity.

## **12 Recent Challenges Facing SNA**

Making the shift of traditional Social Network Analysis, to the Social Media Analysis incurs many challenges that didn't exist before, or weren't as challenging. Such issues include:

- Scalability: Social Network Analysis at the age of Social Media has to deal with millions of different nodes and even much more edges. This explosive outbreak of nodes and connections requires capable tools to carry out the required analysis.
- Heterogeneity: The communication and interaction patterns within the context of Social Media in general, is a multidimensional heterogeneous form. The different nodes, or users, tend to use different forms of communication and knowledge sharing
- Evolution: The Social Media network evolves constantly, which requires a dynamic and adaptive analysis techniques and modeling with snapshots of the general system.
- Evaluation: The main issue here is the lack of ground truth, or complete information due to many reasons, like privacy.

## **13 Homophily and Influence**

Homophily can be defined as the tendency of people to associate and bond with other people who share similarities with them. This concept is directly correlated with the well-known saying of "birds of a feather flock together". A more abstract definition has been provided in the literature as the "love of the same".

Homophily forms a very fundamental principle in social networks in general. Miller McPherson, et al, have explained the presence of the Homophily within social networks, and explained how Homophily has powerful effects and implications for the information people receive, the attitudes they form, and the interactions they experience. The Social Media's recent outbreak provides a

fertile scene for the Homophily as a principle affecting the people's choices of other people to connect to. The explanation above illustrates how Homophily affects the people's connections and interactions within a social network. Influence Models, on the other hand, study the information diffusion patterns and the spread of new ideas within the network as a result of the people's connections. Influence can be considered as a core principle affecting the knowledge propagation and new ideas generation. Some sample influence modeling approaches include: [31]

- Linear Threshold Model (LTM).
- Independent Cascade Model (ICM).

## 14 Community Detection

The virtual communities within Social Media contents are the direct effect of the Homophily Principle, and the effect these communities have over their members is the result of the Influence principle.

As we have illustrated before, contacts or nodes within a Social Media mean can be represented with graphs. Communities are then identified from the resulting graphs via utilizing conventional graphs parsing algorithms. One way towards community detection is via identifying which nodes are more densely connected in comparison to the rest of the nodes. [31]

In this context, the community structure can be defined as essentially a form of grouping or clustering of the nodes. The resulting clusters are characterized by having dense connections amongst the nodes within the community, and sparse connections for the inter-clusters nodes.

These connections might have different semantics, as shall be illustrated at the next section, but they all contribute to the communities' structure.

Community types:

1. Explicit: based on conscious human decisions.
2. Implicit: stemming out of the interactions and communication amongst the users, considerably more difficult to observe and analyze.

Community attributes: [31]

1. Overlapping: Networks not containing clear cuts in terms of possible cliques or communities, having a number of common nodes.
2. Weighted Participation: Nodes having different participation metrics' measures amongst the network or clique.

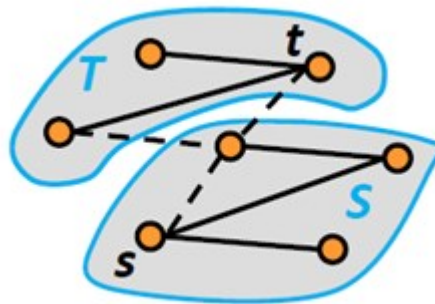
3. Roles: Where nodes can be assigned to roles based on their location/importance within the network.
4. Hierarchy: Hierarchical structure can be observed in the clique or network. [23]

### 14.1 Clustering

Clustering is the process of automatically aggregating or grouping similar items and records together, based upon sharing similar attributes' values. The clustering analysis process is usually aiming at exploring new insights at the given content, as the clustering process does not require the user to know the different clusters beforehand. Actually, clustering sometimes aims at exploring the attributes and parameters of the clusters that the content might be representing.

There are a number of different algorithms for clustering. However, most of these algorithms are based on iteratively assigning items to clusters, calculating some measure, then reassigning items to clusters until no much of change is observed at the measure, i.e until the process converges. This measure can be based upon statistical variability, spatial distance, and others. Some of the most used clustering algorithms include: [31]

- K-means, an exclusive clustering algorithm. K predefined clusters, which might be a problem sometimes. In that sense, K-means can also be considered as a classification algorithm
- Fuzzy C-means, an overlapping clustering method.
- Hierarchical clustering.
- Mixture of Gaussians, a probabilistic clustering approach.



[Figure 2.2: A sample network, showing possible Graph cuts. Source [18]

### **15 Conclusion:**

Modeling communities of people (nodes) and interactions (connections) in a structured manner is of great importance for understanding how information gets propagated and spread in a system of people. And as in the real world, people in the virtual world also tend to aggregate themselves within communities and clusters of close interests and backgrounds. Many different algorithms and approaches can be utilised to capture and detect these virtual communities of a Social Media content. Given the illustrated community definition, and it's importance within a Social Media context, raises the questions of potential practical applications. should look for a good way to classify the text to discover suicidal tendencies and improve the data mining in this field.

# CHAPTER 3

## CLASSIFICATION OF Suicide Detection In Social Network

### 1 Introduction :

The advent of social media—e.g., Facebook, Twitter, Reddit or Instagram—and their heavy use by young adults has raised concerns about the possible effects it might have on suicidal ideation and the imitation of suicidal behaviour—the so-called “Werther Effect”—. In addition to the feasibility of monitoring such media to prevent self-harming actions (including those of suicidal nature). In this chapter I will start from the results of a previous Research Where it was studied on Twitter and Reddit and extracting the most frequently used sentences by people who had attempted suicide and notes from people who committed suicide. and studied this by using psychology students to do manual sorting classification, And for the method of classification, I will use Naive Bayesian method(unigram multinomial NB model) , which has proven its strength in the text classification and I will propose a solution to solve the problem of zero probability (document) in the sentiment classification.

### 2 previous work:

the work by AMAIA ESKISABEL (2016) where he use machine learning since he count with the help of experts to label. In addition to the versatility of these techniques compared to lexical analyses, where he was studying on Twitter and Reddit and extracting the most frequently used sentences by people who had attempted suicide and notes from people who committed suicide. and studied this by using psychology students to do manual sorting classification[26]

### 3 Introduction to Supervised Machine learning Classifiers

Supervised machine learning is a technique whose task is to deduce a function from tagged training samples. The training samples for supervised learning consist of

large set of examples for a particular topic. In supervised learning, every example training data comes in a pair of input (vector quantity) and output value (desired

result). These algorithms analyze data and generate an output function, which is used to mapped new data sets to respective classes. Different machine learning classifiers which we are going to use to build our classifier are: MultinomialNB Classifier

#### 4 Naive Bayes Classifiers :

The Naive Bayes algorithm is a widely used algorithm for document classification. Given a feature vector table, the algorithm computes the posterior probability that the document belongs to different classes and assigns it to the class with the highest posterior probability. There are two commonly used models (i.e., multinomial model and multi-variate Bernoulli model) for using Naive Bayes approach for text categorization. In this paper, and without loss of generality, we run the multinomial model adopted by numerous authors (McCallum & Kamal, 1998).

Bagofwords :The intuition of the classifier is shown in Fig. 6.1. We represent a text document as if it were a bag-of-words, that is, an unordered set of words with their position ignored, keeping only their frequency in the document. In the example in the figure, instead of representing the word order in all the phrases like “I love this movie” and “I would recommend it”, we simply note that the word I occurred 5 times in the entire excerpt, the word it 6 times, the words love, recommend, and movie once, and so on.



Figure 3.1 bag of words [24]

Intuition of the multinomial naive Bayes classifier applied to a movie review. The position of the words is ignored (the bag of words assumption) and we make use of the frequency of each word.

Naive Bayes is a probabilistic classifier, meaning that for a document  $d$ , out of all classes  $c \in C$  the classifier returns the class  $\hat{c}$  which has the maximum posterior probability given the document. In Eq. 3.1 we use the hat notation to mean “our estimate of the correct class”.

$$\hat{c} = \operatorname{argmax}_{c \in C} P(c|d) \quad 3.1$$

### 5 Bayesian inference:

This idea of Bayesian inference has been known since the work of Bayes (1763) and was first applied to text classification by Mosteller and Wallace (1964). The intuition of Bayesian classification is to use Bayes’ rule to transform Eq. 3.1 into other probabilities that have some useful properties. Bayes’ rule is presented in Eq. 3.2; it gives us a way to break down any conditional probability  $P(x|y)$  into three other probabilities:

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} \quad 3.2$$

We can then substitute Eq. 3.2 into Eq. 3.1 to get Eq. 3.3:

$$\hat{c} = \operatorname{argmax}_{c \in C} P(c|d) = \operatorname{argmax}_{c \in C} \frac{P(d|c)P(c)}{P(d)} \quad 3.3$$

We can conveniently simplify Eq. 3.3 by dropping the denominator  $P(d)$ . This is possible because

we will be computing  $P(x|y) = \frac{P(y|x)P(x)}{P(y)}$  for each possible class. But  $P(d)$  doesn’t change for each class; we are always asking about the most likely class for the same document  $d$ , which must have the same probability  $P(d)$ . Thus, we can choose the class that maximizes this simpler formula:[27]

$$\hat{c} = \operatorname{argmax}_{c \in C} P(c|d) = \operatorname{argmax}_{c \in C} P(d|c)P(c) \quad 3.4$$

We thus compute the most probable class  $\hat{c}$  given some document  $d$  by choosing the class which has the highest product of two probabilities: the prior probability of the class  $P(c)$  and the likelihood of the document  $p(d | c)$ :

$$\hat{c} = \operatorname{argmax}_{c \in C} \overbrace{P(d|c)}^{\text{likelihood}} \overbrace{P(c)}^{\text{prior}} \quad 3.5$$

Without loss of generalization, we can represent a document  $d$  as a set of features  $f_1, f_2, \dots, f_n$ :

$$\hat{c} = \operatorname{argmax}_{c \in C} \overbrace{P(f_1, f_2, \dots, f_n | c)}^{\text{likelihood}} \overbrace{P(c)}^{\text{prior}} \quad 3.6$$

Unfortunately, Eq. 3.6 is still too hard to compute directly: without some simplifying assumptions, estimating the probability of every possible combination of features (for example, every possible set of words and positions) would require huge numbers of parameters and impossibly large training sets. Naive Bayes classifiers therefore make two simplifying assumptions. The first is the bag of words assumption discussed intuitively above: we assume position doesn't matter, and that the word "love" has the same effect on classification whether it occurs as the 1st, 20th, or last word in the document. Thus we assume that the features  $f_1, f_2, \dots, f_n$  only encode word identity and not position. [31]

## 6 Training the Naive Bayes Classifier:

How can we learn the probabilities  $P(c)$  and  $P(f | c)$ ? Let's first consider the maximum likelihood estimate. We'll simply use the frequencies in the data. For the document prior  $P(c)$  we ask what percentage of the documents in our training set are in each class  $c$ . Let  $N_c$  be the number of documents in our training data with class  $c$  and  $N_{doc}$  be the total number of documents. Then: [31]

$$\hat{P}(c) = \frac{N_c}{N_{doc}} \quad 3.7$$

To learn the probability  $P(f_i | c)$ , we'll assume a feature is just the existence of a word in the document's bag of words, and so we'll want  $P(w_i | c)$ , which we compute as the fraction of times the word  $w_i$  appears among all words in all documents of topic  $c$ . We first concatenate all

documents with category  $c$  into one big “category  $c$ ” text. Then we use the frequency of  $w_i$  in this concatenated document to give a maximum likelihood estimate of the probability:

$$\hat{P}(w_i|c) = \frac{\text{count}(w_i, c)}{\sum_{w \in V} \text{count}(w, c)} \quad 3.8$$

Here the vocabulary  $V$  consists of the union of all the word types in all classes, not just the words in one class  $c$ .

There is a problem, however, with maximum likelihood training. Imagine we are trying to estimate the likelihood of the word “fantastic” given class positive, but suppose there are no training documents that both contain the word “fantastic” and are classified as positive. Perhaps the word “fantastic” happens to occur (sarcastically?) in the class negative. In such a case the probability for this feature will be zero: [31]

$$\hat{P}(\text{“fantastic”}|\text{positive}) = \frac{\text{count}(\text{“fantastic”}, \text{positive})}{\sum_{w \in V} \text{count}(w, \text{positive})} = 0 \quad 3.9$$

But since naive Bayes naively multiplies all the feature likelihoods together, zero probabilities in the likelihood term for any class will cause the probability of the class to be zero, no matter the other evidence!

The simplest solution is the add-one (Laplace) . While Laplace smoothing is usually replaced by more sophisticated smoothing algorithms in language modeling, it is commonly used in naive Bayes text categorization:

$$\hat{P}(w_i|c) = \frac{\text{count}(w_i, c) + 1}{\sum_{w \in V} (\text{count}(w, c) + 1)} = \frac{\text{count}(w_i, c) + 1}{(\sum_{w \in V} \text{count}(w, c)) + |V|} \quad 3.10$$

Note once again that it is a crucial that the vocabulary  $V$  consists of the union of all the word types in all classes, not just the words in one class  $c$

What do we do about words that occur in our test data but are not in our vocabulary at all because they did not occur in any training document in any class? The standard solution for such unknown words is to ignore such words—remove them from the test document and not include any probability for them at all.[24]

<p>Training algorithm: generate lexicon <math>V</math>, priors and conditional probability based on multinomial model</p> <p>Input : classes <math>C</math>, document space <math>D</math></p> <p>Output: classifier</p> <hr/> <p>Method:</p> <ol style="list-style-type: none"> <li>1. <math>V \leftarrow</math> extract vocabulary from document space <math>D</math></li> <li>2. <math>N \leftarrow</math> count the number of document in <math>D</math></li> <li>3. For each <math>c \in C</math></li> <li>4. <math>N_c \leftarrow</math> count the number of document contained in class <math>c</math></li> <li>5. <math>priors \leftarrow N_c/N</math></li> <li>6. <math>T_c \leftarrow</math> count the number of document contained in class <math>c</math></li> <li>7. For each <math>t \in V</math></li> <li>8. <math>T_{ct} \leftarrow</math> count the frequency of term in <math>T_c</math></li> <li>9. conditional probability <math>\leftarrow</math> according to the step 8 and the Equation (4) in section 3.1</li> </ol> <hr/> <p>Classification algorithm: generate a correct class label</p> <p>Input: classes <math>C</math>, lexicon <math>V</math>, priors, conditional probability and test document <math>d</math></p> <p>Output: a correct class label</p> <hr/> <p>Method:</p> <ol style="list-style-type: none"> <li>1. <math>W \leftarrow</math> extract the term <math>t</math> from the test document <math>d</math></li> <li>2. For each <math>c \in C</math></li> <li>3. <math>score_c \leftarrow priors</math></li> <li>4. For each <math>t \in W</math></li> <li>5. <math>score_c \leftarrow score_c + conditional\ probability</math></li> <li>6. Obtain the maximum score</li> </ol> <hr/>
--

Figure 3.2 training nave bayes[24]

Naive Bayes algorithm based multinomial model: training and test

### 7 Example multinomial naive Bayes classifier:

	docID	words in document	in $c = China?$
training set	1	Chinese Beijing Chinese	yes
	2	Chinese Chinese Shanghai	yes
	3	Chinese Macao	yes
	4	Tokyo Japan Chinese	no
test set	5	Chinese Chinese Chinese Tokyo Japan	?

Figure 3.3 Example multinomial naive Bayes classifier[24]

Decide:

whether document  $d_5$  belonging to class  $c=China?$

- **Training:**  $\hat{P}(c) = 3/4, \hat{P}(\bar{c}) = 1/4$   
 $\hat{P}(Chinese | c) = (5 + 1)/(8 + 6) = 6/14 = 3/7$   
 $\hat{P}(Tokyo | c) = \hat{P}(Japan | c) = (0 + 1)/(8 + 6) = 1/14$   
 $\hat{P}(Chinese | \bar{c}) = (1 + 1)/(3 + 6) = 2/9$   
 $\hat{P}(Tokyo | \bar{c}) = \hat{P}(Japan | \bar{c}) = (1 + 1)/(3 + 6) = 2/9$
- **Testing:**  $\hat{P}(c|d_5) \propto 3/4 \cdot (3/7)^3 \cdot 1/14 \cdot 1/14 \approx 0.0003 \Rightarrow c=China$   
 $\hat{P}(\bar{c}|d_5) \propto 1/4 \cdot (2/9)^3 \cdot 2/9 \cdot 2/9 \approx 0.0001$

Figure 3.4 result of example multinomial naive Bayes classifier[24]

### 8 Data Pre-processing:

The goal behind preprocessing is to represent each document as a feature vector, that is, to separate the text into individual words. In the proposed classifiers, the text documents are modeled as transactions. Choosing the keyword that is the feature selection process.

Preprocessing text is called tokenization or text normalization. Things to consider include

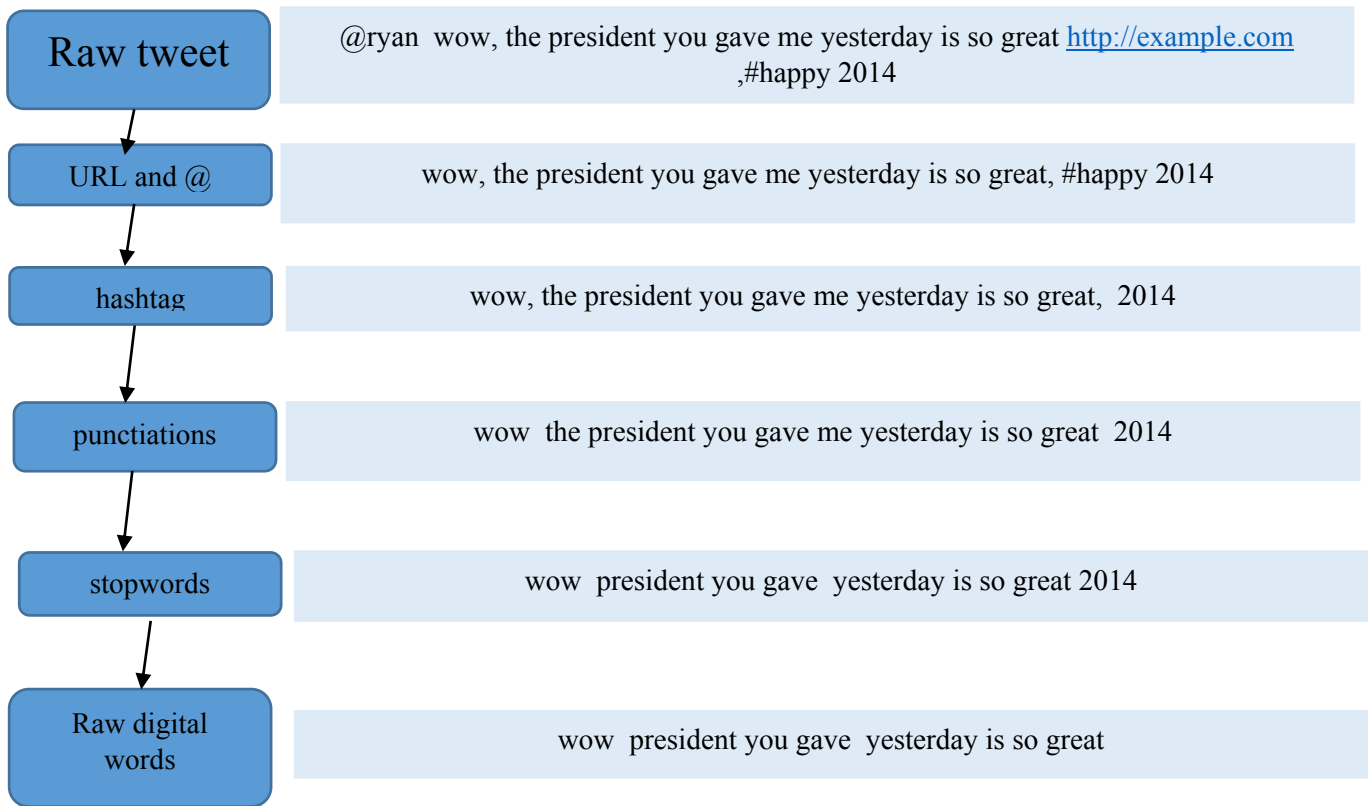


Figure Data Pre-processing[25]

## 9 URLs and '@' Removal

The first step is to remove URLs and the word starts with '@' symbol. We will not track the content of the web links, so the URLs are deleted. The '@' symbol always has a username followed, which is useless, so the entire word starts with '@' could be removed.

## 10 Hashtag Removal

The word starts with '#' is a hashtag. The hashtag is different from other words; it gives a tag or a topic to the tweet. Usually, the tag is talking about the topic people saying about in this tweet, not about people's attitudes. This word might provide some information but not that important. So I decided not to remove the entire word, but to just remove the '#' symbol, and treat the tag as a normal word in a tweet.

## 11 Punctuations Removal

We do not need punctuations as the features, they are just symbols to separate sentences and words, so they should be removed.

12 **Spelling Correction:** In natural language, misspelled errors are encountered.

## 13 Digital words Removal

Some words start with a digit, like '1990', '4:00 pm' etc. These words also have no relationship with attitudes or feelings. So these words should be removed. After the pre-process of the dataset, all tweets will only have some plain words. Through this pre-process, noises are removed so that we can build better vocabulary and have a smaller dimension of the term vector.

## 14 Proposed classification:

Each sentence is first preprocessed and then passed into three categories of classifiers, each deciding whether the sentence belongs to the corresponding category or not.

The first category "positive" This category contains positive and regular sentences.  
the second category "negative" Contains negative sentences that do not contain suicidal phrases like "the taste of pizza today very bad".

The third category contains suicidal phrases that are classified as emergency phrases in the previous search

#### **14.1 Examples :**

*“Each day, each hour, each minute is just torture. I want it to end.”*

*“Waking up every day wishing I hadn’t “*

*“I feel like the only way to no longer carry this pain is to die.”*

*“I am weird and slow. Every social interaction is painfully awkward. “*

*“I want to finish my life.”*

*“No one understands me in this life, I’m leaving.”*

#### **15 Proposal Solution for Zero problem(document):**

This happens in case the probability of each category is 0, that is when we pass a new text (tweet) entirely on our classification and we do not have any word from this text in the dataset, then we will resort to our proposed solution by switching each word from the new text with synonyms and search for the new word in the dataset ,If we find the new word in the dataset then will pass to the next word, Then we re-categorize the new sentence ( the same meaning ) . But what if we don't find any word(synonym) that matches the text we have in the dataset?

In this case, we rely on the second solution.the solution depends on the extraction of sentiment from the sentence using the textblob library.

The sentiment property returns a namedtuple of the form Sentiment(polarity,subjectivity). The polarity score is a float within the range [-1.0, 1.0]. The subjectivity is a float within the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective.

Then categorize the sentence using the new data if the number of “polarity” is greater than 0, we categorize it as positive, and if it's less than 0, we classify it as negative.

The second solution we can not rely on it to classify the tweet in the category "suicidal", because the category "suicidal" is sensitive, so we classify any value below zero in the negative category.

#### **16 Conclusions:**

In this chapter we chose to use machine learning, we propose a naive Bayesian classification for classifying and predicting text based on three different probability models (

positive, negative, suicidal ) and solve the problem of zero probability(document) To get a better result than previous works in this field(Suicide detection in social network), machine learning methods often use supervised learning techniques. These are techniques to infer a function from training data . The training data are collections of pairs based on an input and the desired output. In the wake of the results, it can be concluded that a baseline system has been developed capable of detecting suicidal ideation analysing written text.

## CHAPTER 4

### Implementation Of The System

#### 1 Introduction :

The use of Social Media as a mean of communication is becoming extremely popular, through which their emotional states and impressions are exchanged. Therefore, it is no surprise that more and more people with depression publish their suicide notes in these communication channels. In this context, Information Technologies and Communications, and more specifically Language Technologies. In this chapter we will explain the system that we have implement to detect suicide notes and tweets in tweeters and we choose tweeter because it is a free broadcast social media site that enables registered users to communicate with others in real-time using 140 character statements.

Users create a network by following other accounts; although, the large majority of Twitter accounts are public which allows anyone to view their content. Twitter content can be posted via a web interface, SMS or a mobile device. It is available in almost all countries except China, Iran and North Korea, and has no minimum age requirement. Approximately 23% of online adults use Twitter and over 500 million tweets are sent per day.

The program will be divided into three sections : download tweets and pre-process these tweets ,After pre-processing we pass this data in our trained classifier, which then classify them into positive or negative or suicidal class based on trained results.

#### 2 Python:

Python is an interpreted, object-oriented programming language similar to PERL, that has gained popularity because of its clear syntax and readability. Python is said to be relatively easy to learn and portable, meaning its statements can be interpreted in a number of operating systems, including UNIX-based systems, Mac OS, MS-DOS, OS/2, and various versions of Microsoft Windows 98. Python was created by Guido van Rossum, a former resident of the Netherlands, whose favorite comedy group at the time was Monty Python's Flying Circus. The source code is freely available and open for modification and reuse. Python has a significant number of users.

### **3 Natural Language Toolkit:**

NLTK is a leading platform for building Python programs to work with human language data. It provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries, and an active discussion forum.

Thanks to a hands-on guide introducing programming fundamentals alongside topics in computational linguistics, plus comprehensive API documentation, NLTK is suitable for linguists, engineers, students, educators, researchers, and industry users alike. NLTK is available for Windows, Mac OS X, and Linux. Best of all, NLTK is a free, open-source, community-driven project.

NLTK has been called “a wonderful tool for teaching and working in, computational linguistics using Python,” and “an amazing library to play with natural language.”[29]

### **4 TextBlob :**

*TextBlob* is a Python (2 and 3) library for processing textual data. It provides a simple API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more.[30]

### **5 Definition Of The System**

Below are a series of sections that will explain how to implement an application that provides a service for monitoring tweets to identify suicidal ideation based on its text content.

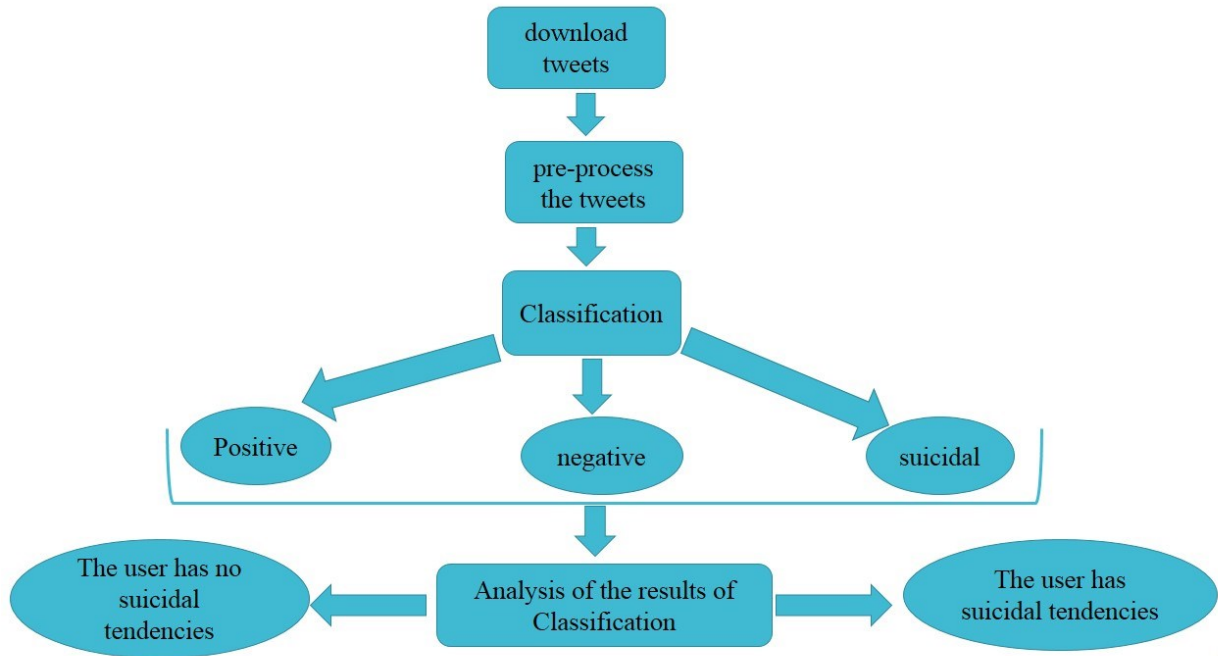
The system should be able to display tweets identify as suicidal to users, The system must be able to retrieve tweets from user profile without interruption using **REST APIs** methods. In addition, it must be able to communicate with machine learning software and create classification models in real time. Then classify the text(tweet) into the appropriate category, then calculate percentage of each class and classify the user depend on this result.

#### **Proposed Architecture**

As our goal is to achieve suicide analysis for data provided from Twitter. We are going to build a classifier which consists of machine learning classifier.

Once our classifier is ready and trained we are going to follow the steps shown in

Figure 4.1



16

Figure 4.1 Proposed Architecture

**Step-1** First we are going to download tweets in our build classifier with the help of Tweepy library in python

**Step-2** Then we pre-process these tweets, so that they can be fit for mining and feature extraction.

**Step-3** After pre-processing we pass this data in our trained classifier, which then classify them into positive or negative or suicidal class based on trained results.

Since, Twitter is our source of data for analysis. We are going to download the tweets from twitter in our dataset. For this we are going to use Twitter Application.

## 6 Twitter API (Application Programming Interface)

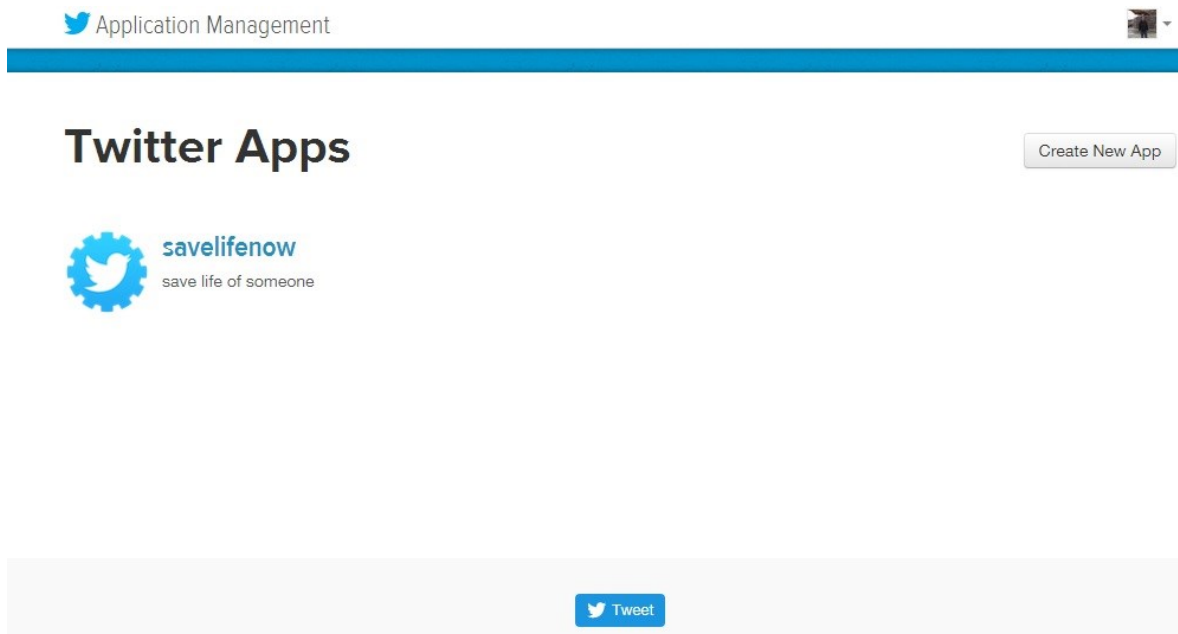
Twitter allows users to collect tweets with the help of Twitter API. Twitter provides two kinds of APIs: REST API and Streaming API. The differences between these are: REST APIs support connections for short time interval and only limited data can be collected at a time, whereas Streaming API provides tweets in real-time and connection for long time. We use REST API for our analysis.

## 7 Data Collection

### Twitter Data

To use Twitter API we must first have a twitter account. It can be easily created by filling the sign up details in twitter.com website. After this you will be provided with a username and password which is use for login purpose. Once your account is created, you can now read and send tweets on any topic you want to explore.

Twitter provider a platform from which we can access data from twitter account and can use it for our own purpose. For this we have to login with our twitter credentials in dev.twitter.com website.



**Figure 4.2** twitter api interface[27]

In this website, we first create an application which will be used for streaming tweets by providing necessary details. Once our API is created we can get to know customer key, customer secret key, access token key and access secret key. These keys are used to authenticate user when user want to access twitter data.

The screenshot displays the Twitter Application Management page for an application named "savelifenow". The page is divided into several sections:

- Application Settings:** This section contains a warning about the "Consumer Secret" and a table of application details.
 

Consumer Key (API Key)	oQTRjxzT8q5JJ5GoxT0Sdzqx
Consumer Secret (API Secret)	VpC5R3ZsUqrthR1tE84SmLFrgJtzRRzthMekhoCICXvLVNgl
Access Level	Read and write (modify app permissions)
Owner	yassine_simple
Owner ID	2727887263
- Application Actions:** This section contains two buttons: "Regenerate Consumer Key and Secret" and "Change App Permissions".
- Your Access Token:** This section contains a warning about the access token and a table of token details.
 

Access Token	2727887263-JN4MMxmxUH3BwJSvltgwVxjw5TZLOlvdmmUSRBN
Access Token Secret	ooagnRPV301qih4rG0VBWUJEJWYs5WIRIA1pBJZZuk2k
Access Level	Read and write
Owner	yassine_simple
Owner ID	2727887263
- Token Actions:** This section contains two buttons: "Regenerate My Access Token and Token Secret" and "Revoke Token Access".

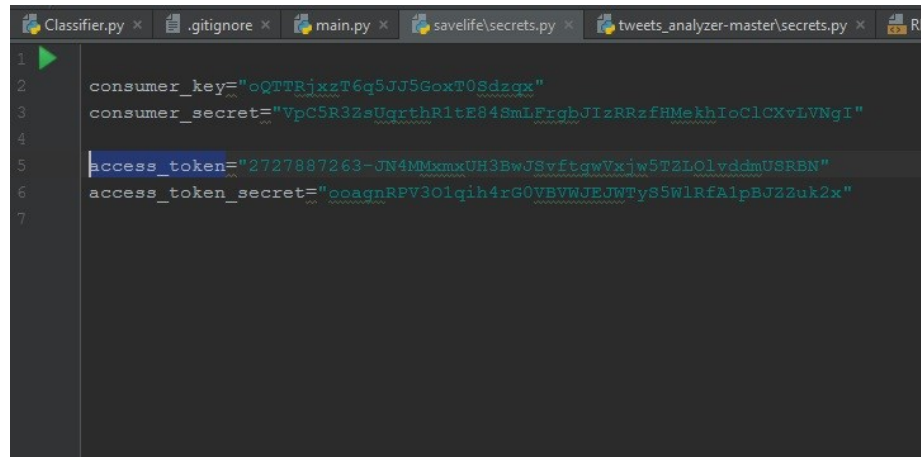
At the bottom of the page, there are links for "About", "Terms", "Privacy", and "Cookies", and a copyright notice for "© 2017 Twitter, Inc."

**Figure 4.3** twitter screen of the access token key[27]

Now we create a Python script which will be used to fetch tweets from twitter . Before creating this script we first install a library in Python called **tweepy**.

Python is a very powerful language which provides many services with the help of many Python libraries. Tweepy is one of the open source Python library which enables Python to communicate with twitter and use its API to collect data so that we can use it in our program. To install tweepy, just provide a command ‘pip install tweepy’ in command prompt or bash and we ready to go with our script.

In this script we use all the keys and secrets which we got in API, we first create listener class which is used to load the data from the twitter. Now to gather data we first set up ‘OAuth’ protocol.

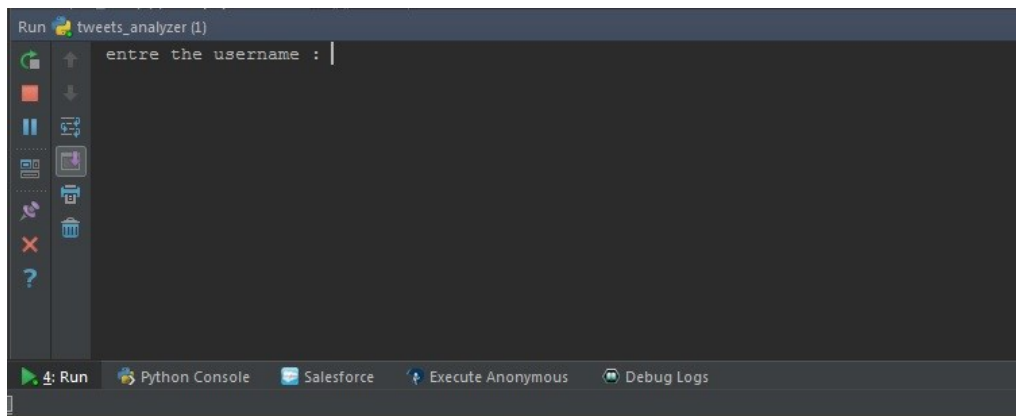


```
Classifier.py x .gitignore x main.py x savelifelife\secrets.py x tweets_analyzer-master\secrets.py x RE
1
2 consumer_key="oQTTRjxzT6q5JJ5GoxT08dzqx"
3 consumer_secret="vpC5R3ZsUqrthR1tE848mLFrgbJIzRRzfHMekhIoClCXvLVNgI"
4
5 access_token="2727887263-JN4MMxmxUH3BwJSyftgwVxjw5TZL0lvdmUSRBN"
6 access_token_secret="ooagnRPV3O1qih4rG0VBVWJEJWty85W1RfA1pBJZ2uk2x"
7
```

**Figure 4.4** code of authorization

OAuth is a standard protocol which is used for authorization. It allow user to log in any third party websites by using any social network website account without exposing passwords. OAuth provides security and authorization to user.

The first screen in our program requires the user name of the person we want to search his tweets



**Figure 4.5** first screen requires the user name

The script which we use to access data with the help of twitter is shown is Figure 4.4

```

309 #print(datetime.datetime.now().strftime("%Y-%m-%d %H:%M:%S"))
310 #print(user_info.created_at)
311 #average number per days = (user_info.statuses_count) / float((datetime.datetime.now().strftime("%Y-%m-%d %H:%M:%S")) - (user_info.created_at))
312 #print(float(datetime.datetime.now()) - (user_info.created_at))
313
314
315 print("[+] lang : \033[1m%\033[0m" % user_info.lang)
316 print("[+] geo_enabled : \033[1m%\033[0m" % user_info.geo_enabled)
317 print("[+] time_zone : \033[1m%\033[0m" % user_info.time_zone)
318 print("[+] utc_offset : \033[1m%\033[0m" % user_info.utc_offset)
319
320 if user_info.utc_offset is None:
321     print("\033[91m!\033[0m Can't get specific timezone for this user")
322
323 if args.utc_offset:
324     print("\033[91m!\033[0m Applying timezone offset %d (--utc-offset)" % args.utc_offset)
325
326 print("[+] statuses_count : \033[1m%\033[0m" % user_info.statuses_count)
327
328 # Will retrieve all Tweets from account (or max limit)
329 num_tweets = numpy.amin([args.limit, user_info.statuses_count])
330 print("[+] Retrieving last %d tweets..." % num_tweets)
331
332 # Download tweets
333 get_tweets(twitter_api, args.name, limit=500)
334 #num_tweets

```

**Figure 4.6** Code for getting tweets using Twitter API

Since we do not need to download a lot of data we will collect data in one object

## 8 Data Pre-Processing

Data obtained from twitter is not fit for extracting features. Mostly tweets consists of message along with usernames, empty spaces, special characters, stop words, emoticons, abbreviations, hash tags, time stamps, URL's ,etc. Thus to make this data fit for mining we pre-process this data by using various function of NLTK. In preprocessing we first extract our main message from the tweet, then we remove all empty spaces, stop words (like is, a, the, he, them, etc.), hash tags, repeating words, URL's, etc.. Once we are done with it, we are ready with processed tweet which is provided to classifier for required results.

## 9 Classification System

The classification system .will use machine learning techniques to classify tweets.

The system can be divided in two parts: (1) the training phase and (2) the prediction phase. In the training phase, the classification system takes the data that will be stored in the dataset to train the system and create a predictive model that will be updated in real time. In the case of the prediction phase, it will take the new tweets and classify them.

```

Classifier.py x trainedData.py x trainer.py x ExceptionNotSeen.py x naive-bayes-classifier\...\classifier.py x main.py x savelifelife\secrets.py x
1 from naiveBayesClassifier import tokenizer
2 from naiveBayesClassifier.trainer import Trainer
3 from naiveBayesClassifier.classifier import Classifier
4
5 newsTrainer = Trainer(tokenizer.Tokenizer(stop_words=..., signs_to_remove=...["?!#&"]))
6
7 # You need to train the system passing each text one by one to the trainer module.
8 tweetSet =
9     {'text': 'not to eat too much is not enough to lose weight', 'category': 'positive'},
10    {'text': 'go to sleep forever', 'category': 'suicidal'},
11    {'text': 'tired of living', 'category': 'suicidal'},
12    {'text': 'tramp is bad president', 'category': 'negative'},
13    {'text': 'you not buitifull', 'category': 'negative'}
14
15
16 ]
17
18 for degree in tweetSet:
19     newsTrainer.train(degree['text'], degree['category'])
20
21 # When you have sufficient trained data, you are almost done and can start to use
22 # a classifier.
23 tweetClassifier = Classifier(newsTrainer.data, tokenizer.Tokenizer(stop_words=..., signs_to_remove=...["?!#&"]))
24
25 # Now you have a classifier which can give a try to classify text of news whose
26 # category is unknown, yet.
27 unknownInstance = "# what do you think @xxxxx"

```

Figure 4.7 Code of the dataset

```

naive-bayes-classifier naiveBayesClassifier trainer.py
Classifier.py x trainedData.py x trainer.py x ExceptionNotSeen.py x naive-bayes-classifier\...\classifier.py x m
1 from naiveBayesClassifier.trainedData import TrainedData
2
3 class Trainer(object):
4
5     """docstring for Trainer"""
6     def __init__(self, tokenizer):
7         super(Trainer, self).__init__()
8         self.tokenizer = tokenizer
9         self.data = TrainedData()
10
11     def train(self, text, className):
12         """
13         enhances trained data using the given text and class
14         """
15         self.data.increaseClass(className)
16
17         tokens = self.tokenizer.tokenize(text)
18         for token in tokens:
19             token = self.tokenizer.remove_stop_words(token)
20             token = self.tokenizer.remove_punctuation(token)
21             self.data.increaseToken(token, className)
22

```

Figure 4.8 Code for Training data

When we ran the script shown in Figure 4.6, it will extract the features( token ) from the

training data, Training different classifiers on the dataset will result in comparison for their accuracies.. For text classification, three Naïve Bayes classifier classes will be trained and tested on the dataset.

When the training is completed we can try a new text classification, passing the text to the classification code

```

27     for className in classes:
28
29         # we are calculating the probability of seeing each token
30         # in the text of this class
31         # P(Token_1|Class_i)
32         tokensProbs = [self.getTokenProb(token, className) for token in tokens]
33
34         # calculating the probability of seeing the the set of tokens
35         # in the text of this class
36         # P(Token_1|Class_i) * P(Token_2|Class_i) * ... * P(Token_n|Class_i)
37         try:
38             tokenSetProb = reduce(lambda a,b: a*b, (i for i in tokensProbs if i))
39         except:
40             tokenSetProb = 0
41
42         probsOfClasses[className] = tokenSetProb * self.getPrior(className)
43
44     return sorted(probsOfClasses.items(),
45                 key=operator.itemgetter(1),
46                 reverse=True)
47
48
49     def getPrior(self, className):
50         return self.data.getClassDocCount(className) / self.data.getDocCount()
51
52     def getTokenProb(self, token, className):
53         #p(token|Class_i)
54         classDocumentCount = self.data.getClassDocCount(className)
55
56         # if the token is not seen in the training set, so not indexed,
57         # then we return None not to include it into calculations.
58         try:
59             tokenFrequency = self.data.getFrequency(token, className)
60         except NotSeen as e:
61             return None
62
63         # this means the token is not seen in this class but others.
64         if tokenFrequency is None:
65             return self.defaultProb
66
67         probability = tokenFrequency / classDocumentCount
68         return probability
69

```

Figure 4.9 Code for classify the tweet

## 10 Proposal Solution for Zero problem(document):

But what if the probability of each class is 0, that is when we pass a new text (tweet) entirely on our classification and we do not have any word from this text in the dataset, then we will resort to our proposed solution :

**first solution:** switching each word from the new text with synonyms and search for the new word in the dataset ,If we find the new word in the dataset then will pass to the next word, Then we re-categorize the new sentence ( the same meaning ) .

### **second solution:**

the solution depends on the extraction of sentiment from the sentence using the textblob library. Sentiment(polarity,subjectivity). The polarity score is a float within the range [-1.0, 1.0].

The subjectivity is a float within the range [0.0, 1.0], if the number of “polarity” is greater than 0 Then positive, else negative

```

64         if tagged[i][1] == 'NNP' or tagged[i][1] == 'DT':
65             break
66
67         # The tokenizer returns strings like NNP, VBP etc
68         # but the wordnet synonyms has tags like .n.
69         # So we extract the first character from NNP ie n
70         # then we check if the dictionary word has a .n. or not
71         word_type = tagged[i][1][0].lower()
72         if syn.name().find("."+word_type+"."):
73             # extract the word only
74             r = syn.name()[0:syn.name().find(".")]
75             replacements.append(r)
76
77     if len(replacements) > 0:
78         # Choose a random replacement
79         replacement = replacements[randint(0,len(replacements)-1)]
80         output = output + " " + replacement
81     else:
82         # If no replacement could be found, then just use the
83         # original word
84         output = output + " " + words[i]
85

```

Figure 4.10 Code of the 0 probability solution



## **12 Conclusion:**

While moving forward, there is a key point to consider, which is that Suicide prevention activities should be implemented simultaneously with data collection .The collection of accurate data on suicide and suicide attempts are important and have been a major challenge in most countries; however, waiting for a perfect surveillance system is not the answer. Improvements to surveillance should be made as the country moves forward in implementing suicide prevention interventions, as we have seen in the this chapter.

as we have seen in the last chapter, that our program detects suicidal tweets, and it will give the percentage of been suicidal or negative or positive or suicidal , and experiences Training also will be more effective and more accurate of detecting a suicidal tweet from negative or positive or suicidal, then calculate percentage of each class and classify the user depend on this result.

## **GENERAL CONCLUSION**

Due to various reasons, people may not have an appropriate way to alleviate their depressions in real life, which is a symptom that leads to committing suicide, so this kind of people will try to express such feeling with the world, and they begin searching for ways.

In the present most of them use the social network for that, so as you saw in the previous chapters that we gave a better looking to this phenomenon, and how we can detect it in social network also preventing it.

This work aims to create a program, which will be capable of detecting suicide in social networks, so the results obtained from this study or this program were acceptable.

While we have identified some interesting and promising results, future work we will work to compare the results of this work with previous work, future, and will be setting a machine classification which means that the classification will be automatic, and perhaps we could integrate another data mining tool in our work.

We could develop a machine classification method, which could automatically distinguish between text containing suicidal ideation, and other forms of suicidal communication, and could be used to derive a much larger dataset from social media streams for further validation and experimentation.

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## الملخص:

يشكل الانتحار شاغلا صحيا رئيسيا في جميع انحاء العالم ، ومعظمه في صفوف المراهقين والبالغين. التكنولوجيات التي ظهرت تمثل نهجا مشجعا للعثور علي الناس الذين ينوون الانتحار. وبالتالي فاننا في هذه المذكرة قمنا باقتراح نظام لكشف التغريدات الانتحارية التي من الممكن ان ينشرها اشخاص يشتبه في نواياهم في الاقدام على الانتحار، لتحقيق هذا النظام استخدمنا لغة بايثون وبعض المكتبات مثل Textblob و NLTK .

**الكلمات المفتاحية :** اكتشاف الانتحار، الشبكات الاجتماعية ، التنقيب في البيانات ، تصنيف النصوص

## Abstract:

Suicide is a major health concern worldwide, mostly in adolescents and young adults. Popping up technologies represent an encouraging approach for find people who intend to commit suicide. So in this work we have proposed a system to detect suicidal tweets that can be published by people who suspect by their suicidal intentions. To realize this system we used the Python language, and libraries like Textblob and NLTK.

**Key words:** Suicide detection, social networking, data mining, text classification

## Résumé:

Le suicide est une préoccupation majeure pour la santé dans le monde, principalement chez les adolescents et les jeunes adultes. Les technologies qui apparaissent représentent une approche encourageante pour trouver des personnes qui ont l'intention de se suicider .Donc, dans ce memoire thèse, nous avons proposé un système permettant de détecter les tweets suicidaires qui peuvent être publiés par des personnes suspectes par leurs intentions suicidaires. Pour réaliser ce système, nous avons utilisé le langage Python, et des bibliothèques comme Textblob et NLTK.

**Mots-clés:** détection du suicide, réseaux sociaux, exploration de données, classification des textes