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# Automatic Detection of Suicidal Tendencies of Poets

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### Abstract

How easy is it for a human to detect suicidal tendencies of a writer when reading pieces of their work? How useful would it be to have a tool for exactly that? For centuries, humans have used language to express themselves. Poetry has been around since Ancient Greece, allowing poets to put feelings into words, or to just describe what they see around them the way they see it. To conduct this research, we have gathered 80 poems to create a small database in order to train a machine learning algorithm to detect suicidal tendencies in poetry. We examined characteristics such as the length of a poem, number of unique elements, type-token ratio, lexical richness, polarity and number of certain parts of speech and word groups. Results have shown that we can have predictions as accurate as 73.75%. We also report on other features that seem to be most important for the algorithm and argue that methods from natural language processing may provide important insights into the analysis of language in general. This can be particularly helpful in today's society, when almost everyone posts something on social media almost everyday.

Keywords: suicide, suicide prediction, machine learning, poetry

## 1. Introduction

To write poetry, the poet is often forced to search the language for the perfect word. In poetry, each word is chosen carefully, as it has to fit with the rhythm and style of the whole piece. Writing poetry forces the poet to deepen their understanding of language and how they use it. Many well known poets, and their readers, have experienced the astounding and transformational power of a beautiful poem, either by writing, or by reading their pieces. Research has already been done to examine the features that may be useful in offering a glimpse of the mental health of a writer, professional or not. Previous researchers have worked on training machine learning algorithms to detect suicidal tendencies in songs, texts, social media posts and some have even gone as far as to try

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and distinguish between genuine and elicited suicide notes.

The focus of this research is to develop a completely automated way to extract features for every instance. The selection of the poems was random and none of the features used were handpicked or extracted by humans, in contrast with other similar papers, even though some of them weren't completely accurate. Also, we focused on examining only poems, while other existing work has focused on songs [6], texts, essays [2] and suicide notes [3]. To our knowledge, there isn't any published research that has poems and automated feature extraction as a focal point of their work.

In this paper, we present an attempt to determine the role of computational algorithms in understanding a suicidal poet's thoughts, as represented by their work. It focuses on developing methods of natural language processing that distinguish between suicidal and non-suicidal poets. It is hypothesized that machine learning algorithms can classify poems written by poets with suicidal tendencies, as it has been shown by similar research on the field. The database we used is comprised of 40 poems by poets who have committed suicide and 40 poems by poets who have died of natural causes. The next sections review previous computational work on poetry and motivate the features we use; we then introduce our corpus, our analyses, and results.

## 2. Methodology

First, a corpus of songs by both male and female poets was constructed, which makes up the training and test sets. The whole database is comprised of 80 songs, of which 40 were written by four poets who have died of natural causes and 40 by four poets who did commit suicide. The selection of the poems was completely random. We have used the 10-fold cross-validation technique. It's a technique to evaluate predictive models by partitioning the 80 poems into a training set(72) to train the model, and a test set to evaluate it(8).

In our search for poets who committed suicide, we looked for poets who met the following prerequisites: the suicide had to be relatively unambiguous and they had to speak English as their native language. That is because we didn't want to use translated poems, as our features are based on the poets' selection of words, and since a translated poem is a translator's selection of words, we felt that wouldn't reflect the feelings of the original creator genuinely enough.

To determine which features we should take into consideration for our research, we studied similar published papers on the field. The paper "A Computational Analysis of Style, Affect, and Imagery in Contemporary Poetry" [1] has used the following features to distinguish poems that were written by award winning poets and amateur poets: the type-token ratio, the lexical richness, the polarity, and the word grouping (concrete, abstract, generalization words). The features of I-words and social words were also used in "Language Use of Depressed and Depression-vulnerable College Students" [2] to determine whether the writer of an essay suffers from or is about to be diagnosed with depression. The part of speech tagging of words as nouns, verbs, adverbs and adjectives was also used in "Suicide Note Classification Using Natural Language Processing: A Content Analysis" [56], where they trained algorithms to distinguish between genuine and elicited suicide notes.

## 3. Features

The suicide poets are Sylvia Plath (1932 − 1963, USA), Anne Sexton (1928 − 1974, USA), Sara Teasdale (1884 − 1933, USA) and Ernest Hemingway (1899 − 1961, USA). The non-suicide poets are Emily Bronte (1818 − 1848, UK), Elizabeth Bishop (1911 − 1979, USA), Robert Frost (1874 − 1963, USA) and Langston Hughes (1902 − 1967, USA). 10 poems from each poet were used and every poem was originally written in the English language.

We loaded all the poems on the Python IDLE and we used NTLK commands to extract some of the features. We also used some websites to get others. Each poem is an instance and we have examined the following features:

### *3.1 Length (Tokens)*

One of our features is the length of the poems (count of words). The shortest poem was

20 words long and the longest was 500. We attempted grouping poems in groups per 50 words (0-50, 51-100, …), but the algorithms' performance was worse than when using just the number of words. We used the "len(poem)" command.

### *3.2 Unique Elements (Type)*

Another feature examined is the count of unique elements in each poem, for which we used the "len(set(poem))" command.

### *3.3 Type-token Ratio*

We used the type-token ratio, which calculated by dividing the number of unique elements of the poem (the total number of different words) by its length (the total number of words). A high TTR indicates a high degree of lexical variation while a low TTR indicates the opposite. We used the "len(set(poem))/len(poem)".

### *3.4 Lexical Richness*

For each poem, we calculated the lexical richness using the Python command "len(poem)/len(set(poem))". It measures the poem's diversity, essentially expressing how many different words are used.

### *3.5 Polarity*

We entered each poem on the site of "Sentiment Analysis with Python NLTK Text Classification" [4] to get the sentiment classification on whether the poem is *positive*, *negative* or *neutral*.

### *3.6 Nouns, Adjectives, Verbs, Adverbs*

For each poem, we used NLTK for Python to count the *verbs*, the *adjectives*, the *nouns* and the *adverbs*. We used the command "pos_tag(word_tokenize(sentence))".

### *3.7 I-words (I, me, my, mine), Social Words*

To get a count of *first person singular pronouns* (which includes "I", "me", "my" and "mine") and a count of *social* references (which includes mentions of friends, family or communication) we used the LIWC2015 engine [5].

### *3.8 Concrete, Abstract, Generalization Words*

Due to lack of a tool to automatically classify words as *concrete* (words that refer to physical objects that we can use our senses to experience), *abstract* (words that express ideas, concepts, or qualities) and *generalization* words (such as all, none, most, many, always, everyone, never, sometimes, some etc) we have used a list of the most common words of each group that appeared in poems of another research paper [1].

### *3.9 Class*

The class for each instance is either *suicide* or *nosuicide*. Each poem is an instance, and they are classified according to the way their creator died.

## 4. Results Analysis

All features were input into Weka and a number of different machine learning algorithms were run to create a classifier. The classifier was trained using the 10 fold cross-validation technique on the 80 instances (poems). The most successful algorithm was the K-Star algorithm, which correctly classified the poems as either suicide or non-suicide (nosuicide) 73.75% of the time. This is after we removed the length of the poems and the count of the verbs, the adverbs and the generalization words. In *Table 1* below, we report the confusion matrix for the test set. Using the same algorithm, but by removing other features such as the length, lexical richness, the verbs and the adverbs, and the generalization words (in different combinations each time), we reached a percentage of 72.5%.

Other, less successful, algorithms that we run were:

- the LogitBoost, which classified the poems correctly 70% of the time, when we removed the count of the abstract words, the adjectives and the type/token ratio
- the Bayes Net, which had a result of 65% correct classifications, with the count of

verbs, concrete words and the length removed

- the Naive Bayes algorithm, that correctly classified instances as high as 61.25%, when we removed the count of social words, abstract words and adjectives.

While our classification statistics do not reach a satisfactory level, we believe that they indicate that we are on the right track and that this task can be tackled using NLP.

```
=== Confusion Matrix ===

  a  b   <-- classified as
 30 10 |  a = suicide
 11 29 |  b = nosuicide
```

*Table 1*

## 5. Conclusion

While our approach reveals some interesting patterns, they are not as clear as we feel like they can be. It should be noted that we have used poems that lay on the more traditional side of poetry. Results may differ when examining more modern pieces from modern poets, as traditional and modern poetry are quite distinct from each other. We believe our study has shed light on some elements of writing that can be used as a groundwork for more development, in order to draw more conclusive results and achieve a higher performance of machine learning algorithms.

Some ways to improve the results for future research on the topic are adding different styles of poems, e.g. more modern poetry, using a larger database and utilizing more accurate tools for feature identifying. Besides expanding the corpus to include many more styles and poets from many different time frames, it would also be worthwhile to extend the analysis to other types of features, since it has been demonstrated that Natural Language Processing and Machine Learning can be used effectively for researches similar to this one.

In summary, we believe our research can provide a solid foundation to discover potential features of poetic elements to experiment with, test and confirm on suicide prediction, and it can also expand on other topics. We have concluded that by processing elements of poetry, it is possible to take a look at the way the poet thinks and perhaps to also analyze his psychology and feelings, which can be exceptionally useful, not only when examining poems, but every kind of text and natural language.

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