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Identifying Suicide Notes Using Forensic Linguistics and Machine Learning*

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Lee, Yong-hun & Joh, Gihyun. (2019). Identifying suicide notes using forensic linguistics and machine learning. *The Linguistic Association of Korean Journal, 27*(2), 171-191. This paper presents how to identify the characteristic properties of suicide notes using the analysis methods in forensic linguistics and how to apply the knowledge to the machine learning research. For this purpose, a corpus was compiled with Virginia Woolf's literary works and suicide notes, which contained six texts. Then, each text was analyzed with the LIWC (Linguistic Inquiry and Word Count) software. Since the analysis results were complicated, a dimensionality reduction was conducted using a Principal Component Analysis (PCA). In the PCA analysis, it was found that, even though all the texts were written by the same author, the suicide notes were clearly identified from the literary works. The analysis results of LIWC analyses were applied to a machine learning technique (especially a Support Vector Machine; SVM), and the classification accuracy was measured using six real texts and three hypothetical texts. Through the analysis, it was found that the SVM machine identified the suicide notes from the literary works with 100% of accuracy. The current study demonstrates that the linguistic properties of texts can be used to identify the suicides notes from the other types of writings and that they can be used in machine learning research.

Key Words: suicide notes, forensic linguistics, Linguistic Inquiry and Word Count, principal component analysis, machine learning

1. Introduction

Those who decided to commit a suicide leave a suicide note which says the motivation and their psychological states. It is important to judge the truth of suicide notes because

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fake documents can be used for various forms of criminal activities. Accordingly, it is necessary to analyze the suicide notes from the forensic linguistic point of view, because the suicide note is an important evidence in the identification of the authenticity and it can be used as a piece of evidence in various judicial proceedings or individual cases. Many previous studies in suicide notes have been conducted mainly from a psychological point of view (Leenaars, 1988; Shneidman and Farberow, 1957), but the studies from a linguistic point of view are still insufficient (Giles, 2007; Shapero, 2011; Roubidoux, 2012).

This paper tries to provide an example technique by which the suicide notes are scientifically analyzed with forensic linguistics. The current study especially focuses on demonstrating how various linguistic features may help identify or detect the suicide notes from the ordinary writings. That is, the goal of this paper is to demonstrate how linguistic features contribute to identifying or detecting the suicide notes.

For this purpose, a corpus was constructed with four literary works by Virginia Woolf and her two suicide notes. The reason why only Woolf's writings were chosen was as follows: it is possible to investigate whether the forensic linguistic analysis can clearly identify the suicide notes from the other ordinary writings (even in the case where the same person wrote both types of writings). After the compilation of the corpus, all the text files are analyzed using several linguistic factors with the Linguistic Inquiry and Word Count (LIWC) software. The analysis results were stored in a text file format, and they were analyzed with Principal Component Analysis (PCA) as a statistical analysis and with a Support Vector Machine (SVM) method.

Among many machine learning methods, this paper employed an SVM to identify the suicide notes from the other ordinary texts. The reasons why SVM was chosen were that this technique is one of the most frequently-used methods in machine learning literature and that its classification accuracy is fairly high.

This paper is organized as follows. In Section 2, previous studies are reviewed. Section 3 introduces a research method, which covers a corpus structure, PCA (a statistical method), and SVM (a machine learning method). Section 4 enumerates the analysis results, and Section 5 includes discussions. Section 6 summarizes this paper.

2. Previous Studies

2.1. Forensic Linguistics

Forensic linguistics is a branch of applied linguistics (especially, a branch of corpus linguistics), which applies linguistic knowledge, analysis methods, and linguistic insights to the context of fields including law, crime investigation, trial, and judicial procedure. Its scope includes not only various parts in crime investigation and judicial procedures but also the fields of authorship identification (such as authorship verification, authorship profiling, and authorship attribution).

Traditionally, 'forensic' refers to the application of scientific methods to crime investigation, which covers the legal standards of admissible evidences and criminal procedures. The roles of forensic scientists are to collect, preserve, and analyze the evidence during the investigation. Whereas some forensic scientists visit the place of the crime to collect the evidence, others perform an analysis on objects in the laboratory. The evidence includes various physical and abstract entities, such as fingerprints, hair, DNA detection, and transfusion examination. Digital forensics, on the other hand, collects and analyzes the digital data which are commercially and/or are closely used in everyday life, when the data become the subject of investigation. Usually, the digital data are stored in digital media and tend to be transmitted through a network. Scientists in digital forensics collect, preserve, and analyze such data and submit them to the judicial procedure as evidence.

Forensic linguistics was first initiated in 1968 by a professor Jan Svartvik (Svartvik, 1968), where he analyzed the writings by Timothy John Evans (a prominent murder suspect). He analyzed four writings with several linguistic features and found considerable discrepancies among the writings. It implied that the writings might not have been written by the same author. In 1993, the International Association of Forensic Linguists (IAFL) was founded, and an international journal *The Law and the International Journal of Law, Language and Discourse* was started to be published in 1994.

There are roughly three areas of application of linguistic knowledge in the forensic contexts: (i) understanding of lexis and languages in the law, (ii) understanding language use in the judicial processes, and (iii) the provision of linguistic evidence for the judicial decisions. More specifically, forensic linguistics handles the followings: the language of legal documents, the language of the police and law enforcement, interviews with children and vulnerable witnesses in the legal system, courtroom interaction, linguistic evidence and expert witness testimony in courtrooms, authorship attribution and plagiarism, forensic phonetics, and speaker identification (Coulthard & Johnson, 2007, p. 5). The discipline of forensic linguistics is not homogenous in nature, and a range of experts and researchers in different areas of the field are involved in this field.

Olsson (2004) defines forensic linguistics as an application of linguistic knowledge to a particular (social) environment (i.e., a legal situation), which is located in the interface between language, crime and law. According to Olsson (2008), all spoken and written texts can be forensic texts if they are implicated in judicial or criminal situations. This study also mentions that a suicide note generally includes the sentences which suggest a way to kill themselves and that an analysis on the suicide note must also be included in the investigation. The application of linguistic knowledge to the study of suicide notes plays an important role in investigation of the authenticity and intention of suicide notes.

2.2. Studies on Suicide Notes

As forensic linguistics develops, several studies have been conducted on the suicide notes. Durkheim (1992) classified suicide into four types in terms of integration and regulation. The first one is an 'egoistic suicide', which occurs when the social group is not integrated with suicide committers and they do not get any help from the social group. In this type of suicide, people often feel lonely or hopeless when they are in a difficult situation. The second type is an 'altruistic suicide', which occurs when the degree of social cohesion is very low. It is a type of suicide associated with the individuals who have a very strong relationship with the group where their personal identity is considered to be important. In this type of suicide, the people generally ignore their own needs but think the goals of group more important. The third is an 'anomic suicide', which occurs when the degree of social regulation is too low, when people faces a chaos or an unexpected economic collapse, when they loses moral norms or social common values which regulate their behaviors, or when they loses a lover due to death or divorce. In this type of suicide, people decide to kill themselves because they are overwhelmed by a big change in their lives. The fourth is a 'fatalistic suicide', which occurs due to an excessive oppression or a despair. People think that they have no future and that their freedom is suppressed an authority.

Shneidman (1996) considers suicide as a result of psychological needs that have not been met. The study classifies the sources of suicide into five categories: (i) frustrated love or possessions, (ii) disorganized or disordered control power (related to their own accomplishment), (iii) insulted image of self (including an attempt to avoid shame), (iv) failure in relationship with other people which makes them feel sad, and (v) excessive rage and aggression which is caused by unfulfilled desire. He argues that all suicides are caused by an 'extreme psychache', which is an unbearable psychological distress.

Chaski (2012) enumerates some phrases which are frequent in the suicide notes. They present apologize (*I'm sorry* or *Please forgive me*), love (*I love you* or *I cannot live without you*), anger (*I cannot please you* or *I hope you are happy now*), complaint (*The situation is not acceptable* or *I can no longer tolerate*), or psychological shock (*since the divorce*). Chaski (2012) claims that suicide notes do not have the complete form of writing, but that they contain 1 to 4 different writing styles. The study also points out that none of suicide notes demonstrates the 6 types of writing styles.

Sboev, Gudovskikh, Rybka, & Moloshnikov (2015) mentions that the psychological state of the author(s) can be analyzed by the psycholinguistic markers at the moment of writing. These markers include pronouns, nouns, adjectives, verbs, adverbs, the ratio of adjectives and verbs in the writings, word count (i.e., word tokens in corpus linguistics), the average number of words used in the sentence (i.e., mean sentence length), the ratio of nouns to verbs, number of exclamation punctuation, the number of emoticons, and so on.

From a forensic linguistic point of view, the suicide notes contain typical (linguistic) properties. For the purpose of analyzing suicide notes in forensic linguistics, it is necessary to get help from all of the theoretical linguistics (including phenetics, phonology, morphology, syntax, semantics, pragmatics, and discourse analysis). Most of the early linguistic studies on suicide texts have been conducted based on a corpus which is compiled by Shneidman. The corpus contains 66 writings, and they are mixtures of genuine and fake suicide notes. The texts are linguistically analyzed with the techniques in discourse analysis, the uses of various auxiliary verbs (including modals), or the verbs which show the difference between the genuine and the fake.

Some studies have analyzed the suicide notes using discourse analysis (Edelman & Renshaw, 1982) or semantic space (Matykiewicz, Wlodzislaw, & Pestian, 2009). Edelman & Renshaw (1982) uses the so-called Syntactic Language Computer Analysis, they analyzed not only syntactic features such as parts of speech (POS) but also semantic properties of nouns, verbs, and adjectives, and so on. (Pestian, Matykiewicz, & Grupp-Phelan, 2008; Pestian, Nasrallah, Matykiewicz, Bennett, & Leenaars, 2010).

Nowadays, as corpus linguistics and machine learning develop, there are several trials to apply the techniques to the analysis of suicide notes, which frequently use statistical analysis of various linguistic units such as personal pronouns, past tense verbs, nouns, and various semantic types (Olsson, 2009). In recent years, there are a clear tendency to rely on the automated corpus analysis techniques for the detection of suicide notes. In order to identify and classify typical suicide notes, scholars adopt the corpus-analysis methods (Shapero, 2011) or automated machine-learning techniques (Pestian et al., 2010).

The Linguistic Inquiry and Word Count (LIWC) program is an output of such trials (Pennebaker, Francis & Booth, 2001; Tausczik & Pennebaker, 2010). The program has been widely used in various disciplines such as psycholinguistics or computer science. The software analyzes the writings of ordinary people with 72 linguistic factors and obtain the statistical data of certain semantic types of words (Pennebaker & King, 1999). The variables (i.e., linguistic factors) in the LIWC can be divided into the categories of Standard Linguistic Dimension, Psychological Process, Relativity, and Personal Concerns. The program counts the frequencies of 72 variables and classifies them into the above four categories. The proportions of words in each category reflect the psychological states and mechanisms of the author of writings. LIWC not only contains more than 3,000 content words (which are commonly used in everyday life) but also various types of function words (article, preposition, first/second/third person pronouns) and word length (Pennebaker et al., 2001). By counting function words and pronouns, it is possible to accumulate the analysis results in various individual differences in the psychological fields which cannot be obtained from the previous studies.

2.3. Machine Learning

Machine learning means “fields of study that gives computers the ability to learn without being explicitly programmed” (Samuel, 1959). Mitchell (1997) mentioned as follows: “A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P* if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.” (p. 2) Summarizing these two famous definitions, machine learning can be defined as one of the fields in Computer Science (especially in Artificial Intelligence) which makes a machine (a computer) automatically learn from the training data (which can be referred to *E*) and perform some class of tasks *T* (either classification or regression) with the performance measure of *P*.[1)]

1) For detailed explanations for machine learning and deep learning, see Mitchell (1997). For an example application to linguistic data, see Lee, Yu, & Yoon (2017).

There are several different types of machine learning methods in the literature: *k* nearest neighbors (*k*NN), naive Bayes, decision trees, regressions, artificial neural networks (ANN), SVM, association rules, and so on. Each machine learning method has its pros and cons, and the choice of the method depends on the problems which must be solved.

3. Research Method

3.1. Corpus Compilation

In order to identify the characteristic properties of suicide notes, it is necessary to compile a corpus both with suicide notes and ordinary texts. For this purpose, a corpus was compiled with the suicide notes and the literary works by Virginia Woolf. The reason why the corpus contained only the texts by one person was that we wanted to examine whether the linguistic properties of the suicide notes were distinguished from those of other ordinary works by the same writer.

Two suicide notes of Virginia Woolf came from Joh (2019)'s study, and the literary works were from the text archives of Project Gutenberg (http://www.gutenberg.org/). The detailed information is shown in Table 1.

Table 1. Organization of Corpus

Text Type	Title	Year	Code
Novel	The Voyage Out	1915	Voyage
	Night and Day	1922	Night
	Jacob's Room	1922	Jacob
Short Story	Monday or Tuesday	1921	Monday
Suicide Notes	To Younger Sister	1941	Woolf01
	To Her Husband	1941	Woolf02

For the first four literary works, after the text files were downloaded from the Project Gutenberg, the header and footer were removed from the texts using the R script.[2] The texts for suicide notes came from Joh (2019)'s study and were used without any change.

2) The R script was programmed by the first author.

3.2. LIWC Analysis

After a corpus was compiled with the suicide notes and her literary works, all the texts were analyzed with the LIWC software. LIWC is a text-analysis software, which can be used for psycholinguistics (Tausczik & Pennebaker, 2010) or sentiment analysis (Liu, 2015). This program counts the frequencies of each word in the given text(s) and calculates the percentage of categories to which various words are classified in the given text(s). The program can handle various types of texts, ranging from short e-mail messages to long speeches, poems, and transcribed natural language. The input file can be either a plain text file or a Word format file.

As Chaski (2012) points out, it is a rare care where all the relevant linguistic factors in a single suicide note. In addition, it is difficult to identify the factors with naked eyes. That is why computational and statistical tools were employed in this paper. Although the LIWC analysis produces about 100 values for each text, this paper adopted only nine values in two groups of category. Table 2 shows the analysis results of the texts in Table 1.

Table 2. LIWC Analysis Results

Text	Jacob	Monday	Night	Voyage	Woolf01	Woolf02
LIWC Dimension						
I Words	0.20	1.00	0.00	0.00	9.20	9.80
Social Words	9.30	6.50	10.70	11.70	13.50	11.90
Positive Emotions	2.40	3.00	3.00	1.60	4.30	5.20
Negative Emotions	2.20	0.80	0.40	3.00	1.80	2.10
Cognitive Processes	7.60	7.30	9.10	8.20	20.20	20.70
Summary Variables						
Analytic	79.90	90.40	88.40	91.40	1.00	3.10
Clout	71.80	64.20	79.60	80.90	42.70	32.10
Authenticity	2.80	61.00	17.50	16.30	96.50	79.30
Emotional Tone	29.10	67.80	73.60	8.90	71.80	81.70

As you can observe, the first four texts are the literary works, and the last two are the suicide notes.

In some statistics (such as *I words*, *social words*, *positive emotions*, or *cognitive process*), the values of the suicide notes were higher than those of literary works. In other statistics (such as *analytic* or *clout*), on the other hand, the values of the suicide notes were much lower than those of literary works. In some statistics (such as *negative emotions*, *authenticity*, or *emotional tone*), the values were in the fuzzy boundary.

3.3. Principal Component Analysis

Although the analysis results in Table 2 illustrates some (linguistic) properties which distinguished the suicide notes from the literary works, it is difficult to identify the suicide notes from the others. There are two reasons for this difficulty. First, some values (such as those in *negative emotions*, *authenticity*, or *emotional tone*) were located in the fuzzy boundary, and it made us hard to decide which category the texts belong to. Second, the dimensionality of values was high (9 dimensions), and it made us to take long time in the comparison. It also made the visual identification impossible. In order to solve these problems, a Principal Component Analysis (PCA) was taken in this paper.

PCA (Pearson, 1901; Hotelling, 1933; Hotelling, 1936) is a statistical method which utilizes an orthogonal transformation. That is, it converts a set of observations in the *correlated* variables into a set of values in linearly *un-correlated* variables (i.e., principal components). This transformation process is conducted in such a way that the first principal component (*comp 1*) has the largest possible variance (i.e., explanatory power), and the other succeeding components are ordered with the values of variance. PCA performs the transformation under the strict constraint that the values are orthogonal to the preceding components. The resulting vectors (i.e., eigenvectors) consist of an un-correlated orthogonal basis set, in which each value is a linear combination of all the variables in the model. PCA is known to be very sensitive to the relative scaling of the original variables.

In this paper, a PCA was conducted to the values in Table 2, and the first two components were selected for the representation. They were visually represented in the plot, and two types of texts were clearly identified in the plot.

3.4. Support Vector Machine

Among several machine learning techniques, this paper took an SVM method. It is one of the most frequently-adopted method in the machine learning literature and its (classification) accuracy is very high.

SVM (Cortes & Vapnik, 1935; Ben-Hur, Horn, Siegelmann, & Vapnik, 2001) is a supervised machine learning model which can be used for classification and regression analysis.[3) After the algorithm/machine is given a set of training data, the SVM machine builds a statistical model in which new examples are assigned to one of categories. An SVM machine represents the examples as points in space, and the mapping is proceeded so that all the examples of different categories are divided by a clear gap. New examples in the test sets are then mapped into the same space and they are predicted to belong to one of the categories based on properties of the examples. The SVM model can be used both for a linear and a non-linear classification.

For the SVM method, three more texts were made using the six texts in Table 1. The new texts were named *Test01*, *Test02*, and *Test03* respectively. *Test01* was made by the combination of *Jacob* and *Monday*, *Test02* was made with *Night* and *Voyage*, and *Test03* was made *Woolf01* and *Woolf02* respectively. As you can guess, these three texts have intermediate properties of their two components.

In the current study, the six text files in Table 1 consisted of a training set, and the newly-constructed texts (i.e., *Test01*, *Test02*, and *Test03*) formed a test set. All the text files were labeled as either *suicide* (suicide notes) or *non-suicide* (literary works). What the SVM had to do in this pilot test was to learn the characteristic properties from the training set and then to decide whether the newly-constructed texts (i.e., *Test01*, *Test02*, and *Test03*) belonged to either *suicide* or *non-suicide*.[4) Of course, the labels of the test sets were removed before they went into the SVM machine, and the decision of the machine was compared with the answers (i.e., the removed label for each text).[5)

3) The word 'regression' in the machine learning literature has a slightly different meaning in statistics. That is 'regression analysis' in the machine learning literature does not imply that in statistics.

4) The SVM machine was designed and programmed in Python, by the first author of this paper.

5) An expert in machine learning points out that this type of test is unreasonable and unreliable, because the numbers of the training set (i.e., six texts) and the test set (i.e., three texts) are too small to be reliable. Usually, the data sets in the machine learning literature (both in the training set and the test set) contain thousands of data points. We also know the limitation of our trial. However, the trial of this section is for illustratory purpose. Our goal is to check whether the machine learning algorithm (specifically the SVM algorithm) can identify the suicide notes purely based on the linguistic properties, not to get a reliable

4. Analysis Results

4.1. Results of Principal Component Analysis

Figure 1 illustrates the analysis results of PCA. As mentioned in Section 3.3, the PCA analysis was conducted based on the data in Table 2.

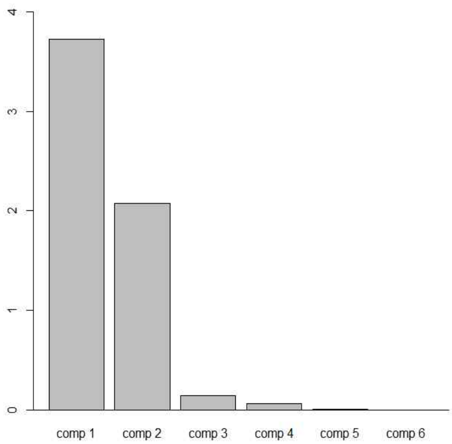

Figure 1. Bar Plot Showing the Eigenvalues of Components

As you can see, the first two components (*comp1* and *comp2*) can provide an explanation to the most variations of data. In order to measure how each component can explain the given data, the eigenvalues are calculated and Table 3 shows the values.

accuracy for the classification. There is also a practical reason. Although it is easy to get ordinary texts for a person, it is very difficult to obtain suicide notes for the same person, due to legal and ethnical problems. That is why we conducted a pilot study with tiny data sets.

Table 3. Eigenvalues of Components

Component	Eigenvalue	Percentage (%)	Cumulative %
comp 1	3.728	62.137	62.137
comp 2	2.072	34.541	*96.679*
comp 3	0.138	2.307	98.985
comp 4	0.060	1.002	99.987
comp 5	0.001	0.011	99.998
comp 6	0.000	0.002	100.000

As you can find, the first two components (*comp1* and *comp2*) can explain 96.679% of data. Accordingly, the data set in Table 2 can be investigated with these two components.

The following plot is a result of mapping all the six texts using the first two components in the PCA.[6)]

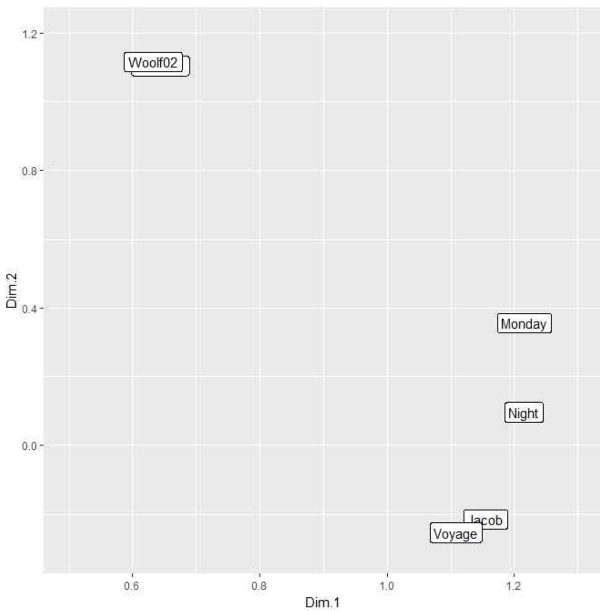

Figure 2. Plot for PCA Analysis Results

Here, *Woolf01* and *Woolf02* were represented with overlapping in the upper left corner. *Woolf02* is located in front of *Woolf01*. This overlapping implies that two texts are very

6) Here, 'Dim.1' is the value of the first principal component, and 'Dim.2' is that of the second principal component.

similar in the linguistic properties.

What you may find in this plot is that the suicide notes (*Woolf01* and *Woolf02*) are clearly separated from the others. Two suicide notes are located in the upper left corner, and the others (literary works including novels and short stories) are located in the lower right corner. It implies that suicide notes can be clearly identified from the ordinary writings (such as literary works) with purely their linguistic characteristics, even in the case where the same person wrote both the literary works and the suicide notes.

If a hypothetical line is inserted as in Figure 3 by a machine learning algorithm, the classification becomes more clear.[7)]

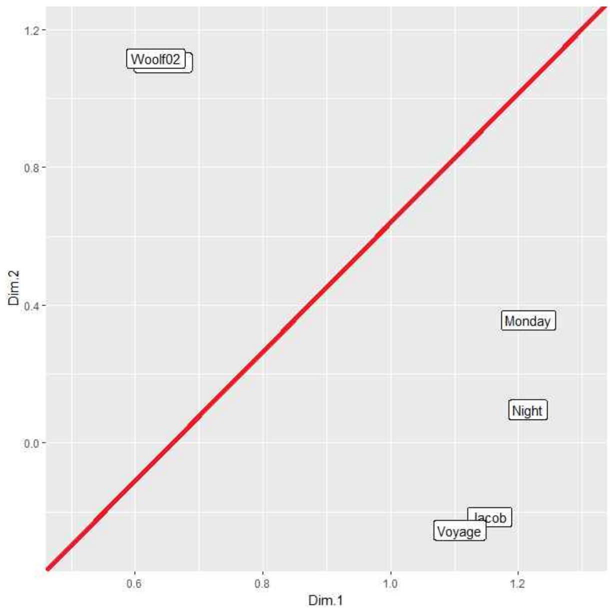

Figure 3. Classification of Six Text Files

The red line clearly separates two types of texts, and this line can be a border line of the classification.

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7) Note that the 9-dimensional data set in Table 2 was used in the SVM analysis. Although the actual analysis was performed in the 9-dimensional space, it was impossible to graphically represent the analysis process. That is why the plots for PCA (Figure 4 and Figure 5) were adopted here. The plots are 2-dimensional objects and the data can visually be represented with *x*-axis and *y*-axis.

4.2. Results of the SVM Classification

When the SVM classification was performed with the training set (six files in Table 2) and the test set (*Test01*, *Test02*, and *Test03*), the machine predicted the text files in the test set as *non-suicide* (*Test01*), *non-suicide* (*Test02*), and *suicide* (*Test03*) respectively. That is, the SVM model predicted the type of texts with 100% of accuracy.

In order to provide an explanation why this was possible, the plots for PCA in Section 4.1 was used again. If the information for three text files had added to Table 2 and the resulting data set had been analyzed with PCA, the result would have been the plot in Figure 4.

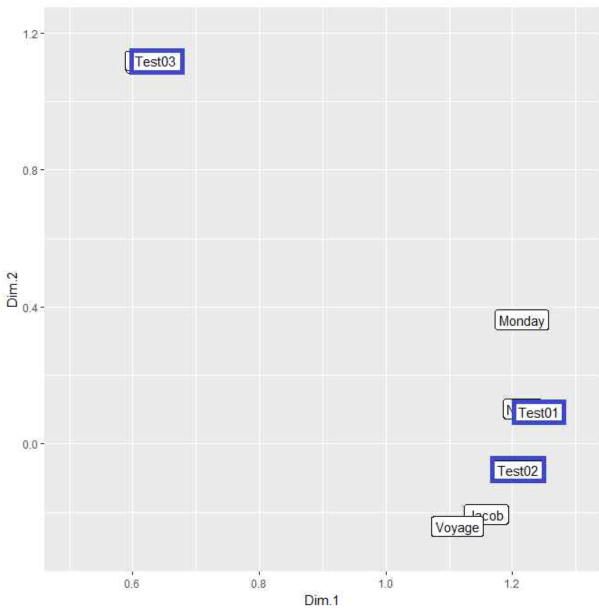

Figure 4. Graphical Representation of PCA (Including Test Set)

Here, three text files (*Test01*, *Test02*, and *Test03*) in the test set were marked with a bold-faced border line. Note that they are located in the intermediate positions of its two component files.

If the SVM algorithm had been applied in this space, the result would have been as in Figure 5.

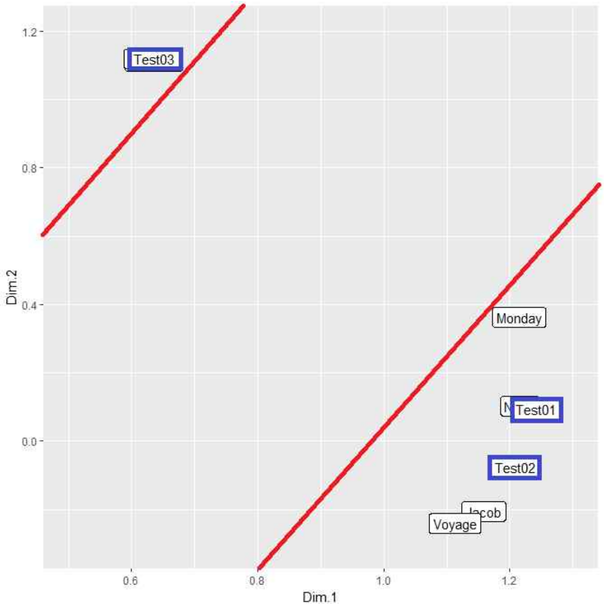

Figure 5. Graphical Representation of Machine Learning (SVM) Classification

Here, two (red) lines represents two support vectors which separate two categories, *suicide* and *non-suicide*. The SVM algorithm makes the distance of these two lines as far as possible.

Although the above accounts are based on the hypothetical space, the same mechanisms are applicable to the 9-dimensional space. From this accounts, it was found that the 100% of accuracy was possible because two types of texts (i.e., *suicide* and *non-suicide*) contained clearly-distinguished linguistic properties.

5. Discussions

In this paper, a corpus was compiled with both suicide notes and other ordinary writings (in the current study, literary works by the same author). The text files in the corpus were linguistically analyzed with a software LIWC, which utilized tens of linguistic features and four category types. Since the analysis results were a high dimensional object (9 dimensions), they are statistically analyzed with PCA so that dimensionality can be reduced. In the analysis of PCA, it was found that two dimensions were enough to represent and analyze all the texts in corpus.

In the two dimensional space in Figure 2 and Figure 3, it was found that the suicide notes (*Woolf01* and *Woolf02*) were clearly separated from the other literary works (*Jacob*, *Monday*, *Night*, and *Voyage*). The reason why this separation was possible was that the linguistic properties of suicide notes were clearly different from those of literary works. It implies that the suicide note can be identified and classified from the other types of writings using (purely) linguistic properties.

A promising result was that the identification of suicide notes and the classification of text types even in the case where the same person wrote both types of writings. As noted in Section 3.1, all the texts were collected from the writings of Virginia Woolf, whether it is a suicide note or a literary work. The analysis results of this paper demonstrated that the identification of suicide notes and the classification of text types were possible even in the case where the same person wrote both types of writings. It implies that the analysis method in this paper can safely applied to the writings of same author.

This paper also applied a machine learning technique (an SVM method in this paper) to classify the suicide notes from the others and found that the machine performed the classification with high accuracy. If more corpus data (especially, the data of suicide notes) can be collected and analyzed, the machine learning methods can effectively be used to identify the suicide notes from the other types of writings. In fact, the task in this paper was a classification problem in the machine learning literature. If a regression problem is applied to the data, it is possible to calculate the probability by which the given text belongs to a suicide note. Then, it is possible to issue an alarm message, when the possibility of suicide exceeds a threshold value. Then, it is possible to use linguistic knowledge to face a social danger (here, a suicide).

6. Conclusion

This paper investigated whether various linguistic features may contribute to the identification and classification of suicide notes from the other types of writings. For the purpose of investigation, a corpus was constructed with four literary works by Virginia Woolf and her two suicide notes. Then, all of the texts are linguistically analyzed with the LIWC software. The analysis results were, in turn, analyzed with a PCA, and an SVM was constructed for the classification.

In the analysis results of PCA, it was found that the first two components can explain about 97% of data set and that the suicide notes were clearly separated from the other literary writings. In the analysis results of SVM, it was found that the machine classified two groups of writings with high accuracy. This paper demonstrated how the suicide notes could be analyzed linguistically and statistically using forensic linguistics and how the analysis results could be applied in the machine learning literature. The techniques and analysis results of this paper can be used in the future research for the correct detection of suicide notes.

This paper also illustrated how linguistic knowledge could be used to face or solve social problems such as suicide. That is, some linguistic factors could be used to detect the psychological states of authors, and the factors could be used to avoid unhappy results of suicides. This shows showed a case where linguistic knowledge could be used to face social problems such as suicide. However, since the corpus data on the suicide notes are not enough, it is difficult to generalize the analysis results in this paper. If more corpus data can be collected, it will be possible to construct a system where many suicide trials are detected in advance.

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Appendix A. Woolf01.txt (To Her Younger Sister)

Sunday Dearest, You can't think how I loved your letter. But I feel I have gone too far this time to come back again. I am certain now that I am going mad again. It is just as it was the first time, I am always hearing voices, and I shan't get over it now. All I want to say is that Leonard has been so astonishingly good, every day, always; I can't imagine that anyone could have done more for me than he has. We have been perfectly happy until these last few weeks, when this horror began. Will you assure him of this? I feel he has so much to do that he will go on, better without me, and you will help him. I can hardly think clearly anymore. If I could I would tell you what you and the children have meant to me. I think you know. I have fought against it, but I can't any longer. Virginia.

Appendix A. Woolf01.txt (To Her Husband)

Tuesday Dearest, I feel certain that I am going mad again. I feel we can't go through another of those terrible times. And I shan't recover this time. I begin to hear voices, and I can't concentrate. So I am doing what seems the best thing to do. You have given me the greatest possible happiness. You have been in every way all that anyone could be. I don't think two people could have been happier 'till this terrible disease came. I can't fight any longer. I know that I am spoiling your life, that without me you could work. And you will I know. You see I can't even write this properly. I can't read. What I want to say is I owe all the happiness of my life to you. You have been entirely patient with me and incredibly good. I want to say that — everybody knows it. If anybody could have saved me it would have been you. Everything has gone from me but the certainty of your goodness. I can't go on spoiling your life any longer. I don't think two people could have been happier than we have been. V.

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