https://doi.org/10.24303/lakdoi.2023.31.2.101

Analyzing Suicide Notes with Forensic Linguistics and Deep Learning Techniques

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Lee, Yong-hun & Gihyun Joh. (2023). Analyzing suicide notes with forensic linguistics and deep learning techniques. *The Linguistic Association of Korea Journal*, *31*(2), 101-122. This paper provides an analysis of suicide notes and ordinary texts using forensic linguistics and deep learning techniques. For the analysis, two types of corpora were compiled. One corpus was composed of suicide notes (SNs), and the other was for ordinary texts (OTs). Seven files were included in the first group, and eight files were contained in the second group. After these two types of corpora were compiled, each text in the corpora was linguistically analyzed with Linguistic Inquiry and Word Count (LIWC). Since the analysis results had 72 dimensions per text, both PCA and t-SNE (dimensionality reduction techniques in deep learning) were applied for the visualization of results. Then, the results were analyzed. Through the analysis, the following facts were observed: (i) suicide notes could be distinguished from ordinary texts, (ii) even though the same author wrote both types of texts, suicide notes could be distinguished from ordinary texts, and (iii) the novels with the 1st person protagonist's point of view were also different from the suicide notes, though both types of texts preferred to use the 1st person pronoun 'I'.

Key Words: suicide notes, forensic linguistics, Linguistic Inquiry and word count, PCA, t-SNE

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1. Introduction

As suicides increase nowadays, it becomes more important to detect the suicide signs before the actual suicides were committed. In order to identify the suicide signs from the suicide notes, various kinds of cues can be used, whether they can be either linguistic or non-linguistic cues (e.g., psychological states).

This paper conducts a linguistic analysis of suicide notes, especially based on forensic linguistics. Forensic linguistics is originally a subfield of corpus linguistics, whose goal is to linguistically analyze the texts which are related to the law. However, it can also be used to identify suicide notes. Among the tools that can be used in forensic linguistics, this paper employed the Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2001; Tausczik & Pennebaker, 2010) to analyze suicide notes.

Two corpora were constructed. One was for the suicide notes (SNs) and the other was for the ordinary texts (OTs). Seven files were used for the corpus of SNs, and eight files were employed for the OTs. Among the fifteen files, six files (2 SNs and 4 OTs) were written by the same author, Virginia Woolf. The reason why these files were included in the corpora was that we want to examine if the linguistic analysis in forensic linguistics can correctly identify the SNs from OTs, even though they were written by the same author.

After two types of corpora were compiled, each file in the corpora was analyzed with the LIWC, using the method in forensic linguistics. Then, since the result of LIWC contained 72-dimensional vectors, the analysis result was converted into 2-dimensional vectors and visualized, using the principal component analysis (PCA) and t-SNE.

This paper was organized as follows. In Section 2, a basic introduction to forensic linguistics and deep learning was provided with an overview of the studies on suicide notes. Section 3 was on corpus compilation and analysis methods. Section 4 presented the analysis result, and Section 5 included discussions. Section 6 summarizes the paper.

2. Previous Studies

2.1. Forensic Linguistics

As a subfield of applied linguistics, forensic linguistics applies linguistic information, analysis techniques, and linguistic insights to the areas of law, criminal investigation, court proceedings, and judicial procedure. It is actually a subfield of corpus linguistics. Its purview extends to authorship identification as well as numerous aspects of criminal investigations and judicial processes (such as authorship verification, authorship profiling, and authorship attribution).

The term ‘forensic’ has historically been used to describe the use of scientific techniques in criminal investigations, which usually includes the legal requirements for admissible evidence and criminal procedure. The gathering, preservation, and analysis of the evidence during the investigation are the responsibilities of forensic scientists. Some forensic scientists go to the scene of the crime to gather evidence, while others examine items in the laboratory. The evidence consists of a variety of tangible and intangible items, including fingerprints, hair, DNA testing, and transfusion analysis. On the other hand, when digital data become the focus of an inquiry, digital forensics gathers and examines the digital data that are closely used in daily life. The majority of the time, digital data is usually communicated through a network after being saved on digital media. These data are gathered, preserved, and examined by experts in digital forensics, who then present them as evidence in court.

Professor Jan Svartvik introduced forensic linguistics for the first time in 1968 (Svartvik, 1968), when he examined Timothy John Evans’ writings (a prominent murder suspect). He examined four texts with various linguistic traits and discovered significant differences across the texts. It suggested that the authors of those writings might not be the same. The *International Association of Forensic Linguists* (IAFL) was established in 1993; and in 1994, the publication of the international journals *The Law and the International Journal of Law, Language and Discourse* began.

The use of linguistic expertise in forensic circumstances can be divided into roughly three categories: (i) knowing lexis and languages in the law, (ii) comprehending language use in the judicial processes, and (iii) providing linguistic evidence for judicial decisions. More specifically, forensic linguistics deals with the following: the language of legal papers, the language of the police and law enforcement, courtroom interaction, interviews with minors and vulnerable witnesses, linguistic evidence, and expert witness testimony in courtrooms, authorship attribution and plagiarism, forensic phonetics, and speaker identification (Coulthard & Johnson, 2007, p. 5). The field of forensic linguistics is not uniform in nature, and various specialists and researchers from other fields are involved.

Forensic linguistics is defined by Olsson (2004) as the application of linguistic knowledge to a specific (social) setting of a legal scenario, which is situated at the intersection of language, crime, and law. Olsson (2008) asserts that any spoken or written words that are referenced in legal or criminal proceedings might be considered forensic texts. The study also points out that an analysis of the suicide notes must be included in the investigation since a suicide note typically contains lines that suggest a means to kill oneself. The use of linguistic expertise in the investigation of suicide notes plays an important role in the investigation of the authenticity and intention of suicide notes.

2.2. Studies on Suicide Notes

The above previous studies produced the so-called Linguistic Inquiry and Word Count (LIWC) program (Pennebaker et al., 2001; Tausczik & Pennebaker, 2010).[1] Several academic fields, including computer science and psycholinguistics, have made extensive use of the application. The software uses 72 linguistic parameters to assess the writings of regular people and gather statistics about certain semantic word patterns (Pennebaker & King, 1999). Four categories (Standard Linguistic Dimension, Psychological Process, Relativity, and Personal Concerns) can be used to categorize the variables (linguistic aspects) in the LIWC. The program divides the 72 variables into four categories based on their frequencies. The percentages of words in each category reveal the psychological processes and states of the writer(s). LIWC includes more than 3,000 content words (the words used often in everyday speech), as well as different word lengths and types of function words (such as articles, prepositions, and first-, second-, and third-person pronouns). It is also possible to compile the analysis results in numerous individual variations in the psychological sectors, which cannot be obtained from the earlier studies, by counting function words and/or pronouns (Pennebaker et al., 2001).

2.3. Deep Learning

Machine learning can be defined as "fields of study that give computers the ability to learn without being explicitly programmed" (Samuel, 1959). Mitchell (1997) also says 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) By combining these two well-known definitions,

1) Recently, LIWC-22 was published.

machine learning is an area of computer science, particularly artificial intelligence, that enables a machine (a computer) to automatically learn from training data (which can be referred to as *E*) and perform a class of tasks *T* (either classification or regression) with the performance metric *P*.

Machine learning techniques come in a variety of forms in the literature, including *k* nearest neighbors (*k*NN), naive Bayes, decision trees, regressions, artificial neural networks (ANN), SVM, association rules, and more. Each machine learning technique has advantages and disadvantages, and the best technique relies on the problems that need to be solved. Deep learning is an extension of machine learning. Various kinds of deep learning methods can be applied such as Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short Term Memory (LSTM), and more recently Transformer-based models.

3. Research Method

3.1. Corpus Compilation

In order to analyze the properties of suicide notes, ordinary texts were necessary against which suicide notes were compared. For this purpose, two types of corpora were compiled. One was for the SNs, and the other was for the OTs. Seven files were included in the first type of corpus, and eight files were included in the second type of corpus. The following table shows us basic information on the files.

Table 1. Organization of Corpora

File	Token	Type
OT01.TheVoyageOut.txt	165,442	9,903
OT02.NightAndDay.txt	202,759	11,040
OT03.Jacob'sRoom.txt	67,035	7,501
OT04.MondayOrTuesDay.txt	22,659	3,833
OT05.JaneEyre.txt	227,236	13,989
OT06.WutheringHeights.txt	146,282	9,954
OT07.GreatGatsby.txt	61,329	6,243
OT08.HuckleberryFinn.txt	140,151	7,140

File	Token	Type
SN01.Noh.txt	124	74
SN02.Noh.txt	343	160
SN03.Choi.txt	530	237
SN04.Cobain.txt	671	287
SN05.Woolf-S.txt	190	105
SN06.Woolf-H.txt	229	105
SN07.CEASE.txt	76,593	7,195

The detailed information on each corpus file was as follows.

The corpus of SNs contained seven files. The first two corpus files (SN01 and SN02) were the suicide notes which were written by two politicians in Korea. SN03 was another suicide note written by a Korean. All these three files (SN01, SN02, and SN03) were originally written in Korean, but they were translated into English for analysis. Because the number of available suicide notes was very small, these translated suicide notes were included in the analysis. Even though there might be some variations in the translations, the variations were not big enough to change the overall patterns of the LIWC analysis. SN04 was a suicide note by Kurt Cobain, who was a musician in the USA. SN05 and SN06 were the suicide notes written by Virginia Woolf, each of which was written to her sister and husband respectively. SN07 was a corpus of suicide notes (Ghosh et al., 2020). As the number of tokens and types indicated, this corpus file contained various types of suicide notes, even though they were anonymous.

The corpus of OTs contained eight files. The first four files (OT01~OT04) were the novels of Virginia Woolf. The reason why they were included in the analysis was that we want to examine if the linguistic analysis in forensic linguistics can correctly identify the SNs from OTs, even though they were written by the same author. The second four files (OT05~OT08) were the novels which were written from the 1st person protagonist's point of view. In forensic linguistics, one of the important characteristics of SNs was that they used the 1st person pronouns very frequently. It looked natural because most suicide notes were written on the self. However, the novels with the 1st person protagonist's point of view also used the 1st person pronouns very frequently. Thus, it was necessary to compare the novels with the SNs, in order to examine how much the 1st person pronouns behaved in the identification of suicide notes.

3.2. LIWC Analysis

After two types of corpora were compiled, each corpus file was analyzed with the LIWC. Originally, the analysis program was provided through the website. However, in this paper, the analysis program was programmed by the first author using Python.[2] The reason why the LIWC was re- programmed was that additional statistics in corpus linguistics were added to the original LIWC analysis, even though all of them were not used in this paper. The original LIWC analysis results contained the following four categories of dimensions: Standard Linguistic Dimensions, Psychological Processes, Personal Concerns, and Spoken Categories. Section 4 provides a detailed analysis of these four dimensions of analysis.

3.3. Visualization

Since the results of LIWC analysis contained 72 vector spaces, it would be impossible to visually compare the texts in the corpora. Therefore, PCA and t-SNE were applied to the analysis results for the visual representation. Originally, PCA and t-SNE are techniques in *unsupervised* machine learning and deep learning, which are used for dimensionality reduction.

Principal component analysis (PCA; Pearson, 1901) is a technique for analyzing the large size of the dataset which contains a high number of dimensions per data point, which increases the interpretability of observations but preserves the maximum amount of information and enables the visualization of multidimensional data. Originally, PCA is a statistical technique which is employed for reducing the dimensionality of a dataset. The PCA analysis is accomplished by linearly transforming each vector into a new coordinate system where the variation in the data points can be described with fewer dimensions than that of the original dataset. Many studies usually utilize the first two or three principal components in order to plot the data points in 2D and 3D space. PCA also visually identifies clusters of closely related data points. PCA has many applications in various fields such as population genetics, microbiome studies, and atmospheric science.

t-distributed stochastic neighbor embedding (t-SNE; Rowei & Hinton, 2002) is a statistical technique for visualizing high-dimensional data points by giving each data point a location in a 2D or 3D map. It is based on Stochastic Neighbor Embedding (SNE), where the t-distributed variant was incorporated. t-SNE is a *nonlinear* dimensionality reduction

2) https://www.liwc.app/

technique for embedding high-dimensional data points for visualization in a low-dimensional vector space (2D or 3D). Especially, t-SNE can make a model of each high-dimensional object by 2D or 3D points in such a way that similar objects are modelled by nearby points and dissimilar objects are modelled by distant points with high probability.

4. Analysis Results

4.1. Results of LIWC Analysis

In this section, the results of LIWC analysis were examined in detail based on the four different categories. The following two tables enumerated the analysis results from the first perspective, Standard Linguistic Dimensions.[3)]

Table 2. Standard Linguistic Dimensions (Ordinary Texts)

File	OT01	OT02	OT03	OT04	OT05	OT06	OT07	OT08
funct	47.591	48.163	43.176	45.077	48.190	46.566	44.594	48.040
pronoun	12.759	13.922	9.073	11.302	14.100	15.040	12.912	13.610
ppron	8.710	9.755	5.891	7.233	10.741	12.090	9.286	9.513
i	**1.338**	**1.337**	**0.519**	**1.942**	**5.176**	**4.401**	**3.248**	**3.453**
we	0.303	0.290	0.234	1.090	0.238	0.443	0.525	0.885
you	0.821	0.868	0.453	0.728	1.630	1.617	0.969	1.213
shehe	4.765	6.369	3.841	2.511	3.139	5.154	4.037	2.891
they	1.480	0.888	0.835	0.949	0.559	0.474	0.507	1.071
ipron	4.049	4.167	3.182	4.069	3.359	2.950	3.626	4.096
article	6.394	5.903	7.759	7.613	5.664	4.938	6.524	5.763
verb	10.272	9.844	8.606	7.706	10.545	9.475	9.087	9.304
auxverb	5.374	5.165	4.436	4.215	6.374	5.472	3.952	4.138
past	**6.078**	**5.753**	**4.877**	**3.270**	**4.858**	**4.039**	**5.831**	**4.632**
present	2.806	2.625	2.651	3.270	3.770	3.443	2.552	3.575
future	0.599	0.674	0.534	0.587	1.074	1.058	0.277	0.444
adverb	3.394	3.028	3.171	3.261	3.186	2.692	3.101	4.165
preps	11.869	12.511	11.566	11.077	10.823	10.616	11.623	10.614

3) Detailed explanations of the abbreviations are included in the Appendix.

File	OT01	OT02	OT03	OT04	OT05	OT06	OT07	OT08
conj	5.669	5.349	5.479	5.477	5.937	6.205	4.932	8.120
negate	0.985	1.058	0.825	0.993	1.458	1.316	0.538	0.956
quant	1.996	2.129	1.560	1.761	1.740	1.524	1.637	2.005
number	1.076	0.915	1.064	1.143	0.828	0.700	1.042	1.008
swear	0.037	0.035	0.058	0.093	0.021	0.052	0.038	0.163

As for the 1st person pronouns, the ratios (the percentage) in the SNs were the highest compared to those of OTs. In OTs, the ratios of the 1st person pronouns in the second four text files (OT05~OT08) were higher than those in the first four text files (OT01~OT04). Even though the ratios of the 1st person pronouns in the novel of the 1st person protagonist's point of view were higher than those of ordinary novel texts, they were not as high as the ratio in the SNs. As for tense, OTs preferred past tense, whereas SNs present tense. The reason for this tendency of tense seems to be the fact that most of the SNs were on the recent event.

Table 3. Standard Linguistic Dimensions (Suicide Notes)

File	SN01	SN02	SN03	SN04	SN05	SN06	SN07
funct	55.645	47.522	52.830	53.651	60.526	57.205	54.104
pronoun	12.097	11.370	13.585	15.499	24.211	24.454	17.391
ppron	8.065	6.997	10.377	10.283	16.842	16.594	12.209
i	**7.258**	**6.122**	**7.358**	**7.303**	**10.000**	**10.917**	**8.181**
we	0.000	0.292	0.755	0.894	0.526	0.873	0.534
you	0.000	0.292	1.887	1.490	3.684	4.803	1.927
shehe	0.000	0.000	0.189	0.447	2.632	0.000	0.910
they	0.806	0.292	0.189	0.149	0.000	0.000	0.651
ipron	4.032	4.373	3.208	5.216	7.368	7.860	5.182
article	6.452	6.414	8.491	5.812	1.053	1.747	4.619
verb	15.323	11.953	11.887	11.475	22.632	23.581	14.087
auxverb	12.903	8.163	7.358	6.408	14.737	15.284	8.682
past	0.806	5.248	3.396	1.490	4.737	3.930	3.415
present	**10.484**	**5.248**	**7.170**	**7.154**	**14.737**	**15.721**	**8.214**
future	0.806	1.458	0.566	1.192	2.105	0.873	1.188
adverb	4.032	2.041	3.962	4.620	6.316	1.310	3.617

File	SN01	SN02	SN03	SN04	SN05	SN06	SN07
preps	12.097	9.913	12.453	12.668	6.842	6.987	11.176
conj	3.226	5.248	7.736	6.557	6.316	3.493	5.511
negate	2.419	2.915	0.943	0.447	0.526	0.437	2.021
quant	3.226	3.207	1.509	3.279	3.684	3.930	2.770
number	0.000	1.458	0.189	0.745	0.526	0.873	0.595
swear	0.000	0.000	0.000	0.149	0.000	0.000	0.261

The following two tables showed the analysis results from the second perspective, Psychological Process.

Table 4. Psychological Processes (Ordinary Texts)

File	OT01	OT02	OT03	OT04	OT05	OT06	OT07	OT08
social	11.666	12.534	9.480	8.699	9.067	11.084	9.731	9.349
family	0.327	0.412	0.260	0.265	0.292	0.366	0.249	0.279
friend	0.072	0.078	0.076	0.049	0.091	0.135	0.116	0.065
humans	1.347	0.880	1.516	1.064	0.969	0.690	0.864	0.571
affect	**4.266**	**4.201**	**3.403**	**3.654**	**4.501**	**4.709**	**3.724**	**3.102**
posemo	**2.664**	**2.502**	**1.911**	**2.290**	**2.733**	**2.361**	**2.183**	**2.003**
negemo	**1.543**	**1.611**	**1.437**	**1.337**	**1.735**	**2.315**	**1.512**	**1.092**
anx	**0.329**	**0.404**	**0.300**	**0.243**	**0.374**	**0.474**	**0.442**	**0.166**
anger	**0.349**	**0.380**	**0.355**	**0.366**	**0.340**	**0.662**	**0.329**	**0.252**
sad	**0.467**	**0.447**	**0.528**	**0.424**	**0.654**	**0.728**	**0.494**	**0.323**
cogmech	13.278	14.326	11.120	12.309	12.925	12.792	11.826	14.506
insight	2.081	2.543	1.141	1.651	1.780	1.538	1.536	1.033
cause	0.867	1.001	0.585	0.812	0.787	0.872	0.655	0.894
discrep	1.209	1.498	0.934	1.042	1.435	1.490	0.804	1.120
tentat	2.100	2.424	1.754	1.911	1.887	1.676	1.759	1.787
certain	1.294	1.382	1.141	1.359	1.155	0.952	1.070	1.334
inhib	0.428	0.520	0.440	0.578	0.505	0.552	0.486	0.355
incl	4.382	4.153	4.465	4.321	4.314	4.798	4.918	7.020
excl	1.890	2.067	1.557	1.827	2.087	1.937	1.386	1.697
percept	3.517	2.991	4.047	3.676	2.893	2.398	3.246	2.913
see	1.470	1.188	1.827	1.801	1.116	0.857	1.401	0.973

File	OT01	OT02	OT03	OT04	OT05	OT06	OT07	OT08
hear	1.230	1.063	1.244	0.918	0.931	0.844	1.014	1.334
feel	0.750	0.662	0.867	0.808	0.727	0.612	0.677	0.512
bio	1.897	1.394	2.197	2.185	1.797	1.727	2.009	1.429
body	1.057	0.749	1.332	1.156	0.998	0.941	1.123	0.867
health	0.403	0.266	0.309	0.424	0.375	0.367	0.307	0.233
sexual	0.169	0.186	0.146	0.221	0.163	0.163	0.126	0.060
ingest	0.317	0.207	0.467	0.419	0.285	0.275	0.465	0.295
relativ	11.973	11.074	13.054	12.110	11.165	10.637	13.972	12.555
motion	1.792	1.570	2.039	1.915	1.680	1.861	2.226	1.861
space	6.054	5.702	6.895	6.170	5.204	4.856	6.773	6.250
time	4.087	3.607	4.102	3.959	4.237	3.798	4.947	4.240

In the second dimension of perspective, both types of texts (OTs and SNs) preferred words with positive emotions to words with negative emotions. However, SNs contained more words which represented anxiety, anger, and sadness.

Table 5. Psychological Processes (Suicide Notes)

File	SN01	SN02	SN03	SN04	SN05	SN06	SN07
social	3.226	10.787	8.868	9.091	11.579	10.480	9.502
family	0.000	0.000	0.755	0.298	0.000	0.000	0.697
friend	0.000	0.000	0.377	0.000	0.000	0.000	0.225
humans	0.806	2.041	0.755	1.788	0.526	0.873	0.977
affect	**4.839**	**12.245**	**7.170**	**8.346**	**5.789**	**6.114**	**6.986**
posemo	**0.806**	**7.872**	**4.717**	**5.812**	**4.211**	**4.367**	**4.036**
negemo	**4.032**	**4.373**	**2.453**	**2.534**	**1.579**	**1.747**	**2.906**
anx	**0.000**	**0.875**	**0.377**	**0.447**	**0.526**	**0.000**	**0.380**
anger	**0.806**	**1.458**	**0.377**	**0.745**	**1.053**	**0.873**	**0.994**
sad	**0.806**	**0.000**	**0.755**	**0.447**	**0.000**	**0.000**	**0.704**
cogmech	11.290	12.536	14.151	15.946	17.895	18.341	16.163
insight	1.613	1.166	3.019	3.428	4.211	3.930	2.398
cause	1.613	1.166	1.698	1.788	0.526	0.000	1.417
discrep	0.806	1.749	1.887	1.341	2.632	3.930	1.833
tentat	1.613	0.292	0.377	1.788	2.105	3.057	2.311

File	SN01	SN02	SN03	SN04	SN05	SN06	SN07
certain	0.806	1.458	1.887	2.086	4.211	3.493	1.918
inhib	0.000	1.749	0.189	0.149	0.000	0.000	0.537
incl	1.613	3.790	4.151	4.918	2.632	3.493	3.799
excl	2.419	1.166	1.698	1.639	2.632	1.310	2.780
percept	0.806	0.292	0.943	1.788	2.632	3.057	1.334
see	0.000	0.000	0.000	0.000	0.000	0.437	0.407
hear	0.000	0.000	0.000	0.745	1.579	1.747	0.349
feel	0.806	0.292	0.566	0.745	1.053	0.873	0.492
bio	2.419	0.583	1.132	2.534	1.053	1.747	2.417
body	0.000	0.583	0.189	0.447	0.000	0.000	0.547
health	2.419	0.000	0.566	0.447	0.000	1.747	1.025
sexual	0.000	0.000	0.377	1.639	1.053	0.000	0.764
ingest	0.000	0.000	0.000	0.000	0.000	0.000	0.129
relativ	10.484	8.746	7.170	7.899	13.684	6.987	10.090
motion	0.806	3.790	0.755	0.596	2.105	2.183	1.478
space	7.258	3.207	3.019	3.428	1.579	0.873	4.179
time	2.419	2.915	3.396	3.130	10.000	3.493	4.331

The following two tables illustrated the analysis results from the third perspective, Personal Concerns.

Table 6. Personal Concerns (Ordinary Texts)

File	OT01	OT02	OT03	OT04	OT05	OT06	OT07	OT08
work	0.636	0.758	0.741	0.931	0.706	0.656	0.509	0.425
achieve	0.740	0.922	0.574	0.693	0.878	1.075	0.667	0.714
leisure	0.728	0.567	0.964	0.781	0.436	0.420	0.874	0.455
home	0.560	0.658	0.792	0.719	0.678	0.708	0.998	0.445
money	0.262	0.246	0.303	0.349	0.282	0.228	0.310	0.536
relig	0.227	0.199	0.310	0.459	0.390	0.330	0.140	0.149
death	0.114	0.083	0.148	0.238	0.177	0.259	0.173	0.250

Table 7. Personal Concerns (Suicide Notes)

File	SN01	SN02	SN03	SN04	SN05	SN06	SN07
work	0.806	2.332	3.019	0.298	0.000	0.873	1.219
achieve	0.806	2.332	1.509	1.043	1.579	1.310	1.328
leisure	0.806	3.499	0.566	1.192	0.000	0.437	0.601
home	0.806	0.000	0.943	0.000	0.000	0.000	0.356
money	1.613	1.458	0.566	0.000	0.000	0.437	0.478
relig	0.000	0.000	0.566	0.596	0.000	0.000	0.547
death	2.419	0.000	0.000	0.149	0.000	0.000	0.631

In the third perspective, SNs contained many '0.000'. The reason seemed to be originated from the short length of the SNs. Therefore, it was doubtful that this dimension could be used as a reliable criterion.

The following two tables demonstrated the analysis results from the fourth perspective, Spoken Categories.

Table 8. Spoken Categories (Ordinary Texts)

File	OT01	OT02	OT03	OT04	OT05	OT06	OT07	OT08
assent	0.146	0.147	0.160	0.291	0.173	0.157	0.160	0.133
nonfl	0.100	0.103	0.100	0.106	0.157	0.103	0.116	0.343
filler	0.245	0.102	0.248	0.216	0.175	0.107	0.199	0.191

Table 9. Spoken Categories (Suicide Notes)

File	SN01	SN02	SN03	SN04	SN05	SN06	SN07
assent	0.000	0.000	0.000	0.000	0.000	0.000	0.072
nonfl	0.000	0.000	0.000	0.149	0.000	0.000	0.077
filler	0.000	0.000	0.189	0.000	0.000	0.000	0.259

As in the third perspective, SNs contained many '0.000' in this table. The reason seemed to be originated from the short length of the SNs. Therefore, it was doubtful that this dimension could be used as a reliable criterion.

4.2. Visualization with PCA

The following is the result of the visualization with PCA.

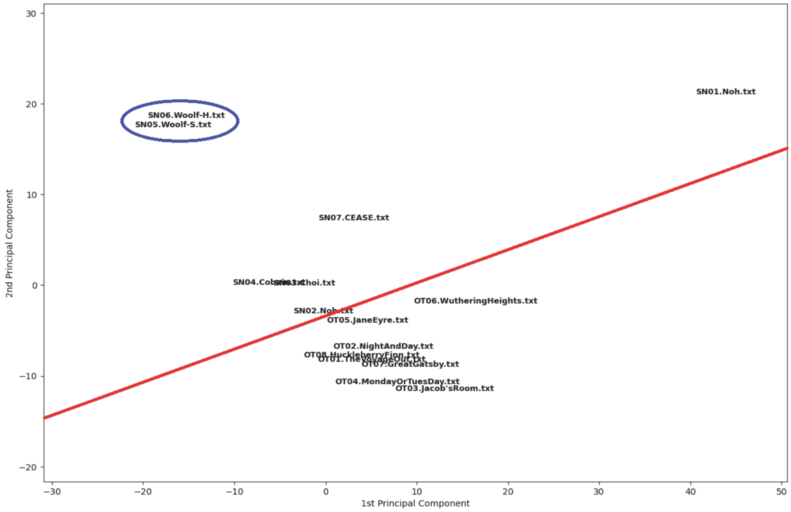

Figure 1. Visualization with PCA

Here, the red line was the line which divided two groups of texts (OTs vs. SNs).

As you observed, the red line divided the SNs from OTs. Note that SN05 and SN06 were located in a similar location. It implied that these two texts were very similar, because they were written by the same author. Also, note that SN05 and SN06 were located very far from the location of OT01~OT04. It implied that the SNs could clearly be identified from the OTs even though they were written by the same author. Also, note that the novels with the 1st person protagonist's point of view (OT05~OT08) were intermixed with the other types of novels (OT01~OT04). This implied that the novels with the 1st person protagonist's point of view were similar to the other types of novels, even though they had more 1st person pronouns. Once again, note that the novels with the 1st person protagonist's point of view (OT05~OT08) were located very far from the location of SNs (SN01~SN07). It implied that the SNs were linguistically far from the novels with the 1st person protagonist's point of view (OT05~OT08), although both types of texts contained many 1st person pronouns.

4.3. Visualization with t-SNE

The following is the result of visualization with t-SNE.

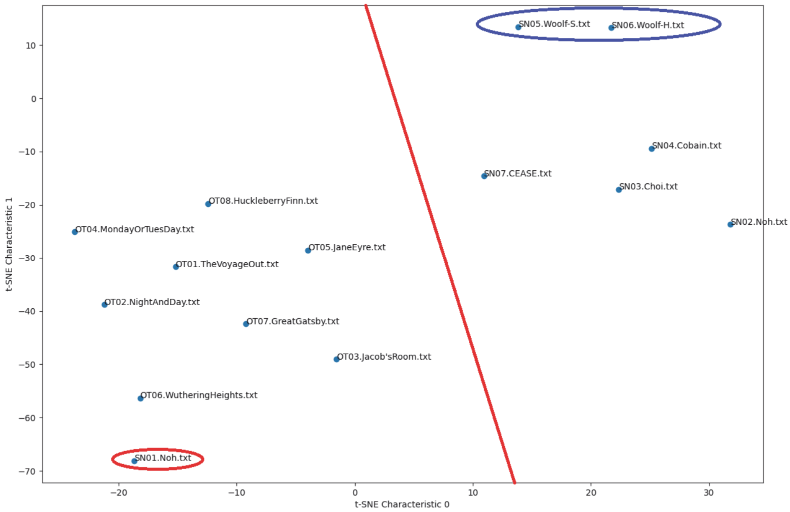

Figure 2. Visualization with t-SNE

Here, the red line was the line which divided two groups of texts (OTs vs. SNs).

As you observed the red line divided the SNs from OTs. One exception was SN01. Note that SN05 and SN06 were also located in the near location. It implied that these two texts were very similar from the linguistic perspective, and it indicated that they could be written by the same author. Also, note that SN05 and SN06 were located very far from OT01~OT04. It implied, once again, that the SNs could clearly be identified from the OTs even though they were written by the same author. Also, note that the novels with the 1st person protagonist's point of view (OT05~OT08) were indistinguishable from the other types of novels (OT01~OT04). This implied that the novels with the 1st person protagonist's point of view were similar to the other types of novels, though they had more 1st person pronouns. Once again, notice that the novels with the 1st person protagonist's point of view (OT05~OT08) were located very far from the positions of SNs (SN01~SN07). It implied that the SNs were linguistically far from the novels with the 1st person protagonist's point of view (OT05~OT08), although both types of texts contained many 1st person pronouns.

5. Discussions

Suicide notes have their own linguistic characteristics, and it is important to analyze them from a linguistic perspective. Even though deep learning can be applied to detect suicide notes from ordinary texts, linguistic analysis is also important to detect not only suicide signs but also the cause/reason for the suicide commitment.

From this perspective, this paper is important in that it tries to analyze suicide notes from a linguistic point of view. The linguistic analysis in this paper is conducted with the LIWC (Pennebaker & King, 1999; Pennebaker et al., 2001; Tausczik & Pennebaker, 2010). Even though the deep learning techniques (PCA and t-SNE) are utilized in this paper, their goal is just for the visualization of the analysis results.

For the study of the SNs, two types of corpora were constructed. One was composed of seven SNs, and the other was made of eight OTs. In order to examine if the linguistic analysis could correctly detect SNs from OTs, the writings of Virginia Woolf were included in the corpora. In addition, four more novels were included in the corpora which were written from 1st protagonist's point of view. Then, all the texts in the corpora were analyzed with 72 features in the LIWC. Then, two deep learning techniques (PCA and t-SNE) were applied to visualize the results.

The comparison of tables in Table 2 ~ Table 9 revealed the following. Among the four dimensions of the LIWC, two dimensions illustrated clear differences. In the Standard Linguistic Dimension, SNs used the 1st person pronoun 'I' more frequently than the OTs. Even though the novels with 1st protagonist's point of view also preferred to use the 1st person pronoun 'I' frequently, its frequencies were much lower than those of SNs. In addition, SNs preferred to use the past tense, while OTs preferred to use the present tense. In the Psychological Process, SNs contained more negative words than OTs, In the Relativity and the Personal Concerns, it was hard to say any characteristic because of the short length of the SNs.

Figure 1 and Figure 2 clearly showed that SNs could be distinguished from OTs only with the (purely) linguistic analysis (i.e., with the LIWC analysis). In the PCA analysis (Figure 1), even though the texts in OTs were slightly clustered, they were clearly separated from the SNs. In the t-SNE analysis (Figure 2), SNs were clearly separated from the OTs, too. Therefore, it could be said that SNs could be distinguished from OTs only with the (purely) linguistic analysis.

Though the same author wrote both types of texts, SNs have different linguistic properties from OTs. As Figure 1 and Figure 2 illustrated, SN05~SN06 and OT01~OT04 were written by the same author Virginia Woolf, and two groups of texts were clearly distinguished. This analysis result showed that SNs have different linguistic properties from the OTs, although the same author wrote both types of texts. An interesting fact was that two SNs (SN05~SN06) were located very closely while OT01~OT04 were distributed in more wide space.

Figure 1 and Figure 2 also demonstrated that SNs were also clearly distinguished from the novel with 1^{st} protagonist's point of view. In these figures, OT05~OT08 were the novel with 1^{st} protagonist's point of view. the common property between SN01~SN07 and OT05~OT08 was that both types of texts contained more 1^{st} person pronouns. From Table 2 and Table 3, it was shown that, though the novels with 1^{st} protagonist's perspective also preferred to use the 1^{st} person pronoun 'I' frequently, its frequencies were much lower than those of SNs. It made SN01~SN07 clearly distinguished from OT05~OT08.

However, the analysis of this study had some limitations. First, we only contained a few SNs and OTs in the analysis. More various types of SNs and OTs must be included in the analysis. Second, in the PCA representation of Figure 1, the texts in OTs were slightly clustered, and they were closer to SN01 or SN04, though such a tendency didn't appear in Figure 2. In the t-SNE representation of Figure 2, however, though no clustering appeared, SN01 showed different behavior. Accordingly, more advanced techniques are necessary to face this problem.

6. Conclusion

In this paper, we analyzed SNs and OTs using forensic linguistics and deep learning techniques. For the analysis, two types of corpora were compiled. One corpus was composed of SNs, and the other was for OTs. Seven files were included in the first group, and eight files were contained in the second group.

After two types of corpora were compiled, each text in the corpora was linguistically analyzed with 72 linguistic features in the LIWC. Because the analysis results had 72 dimensions, the PCA and t-SNE were applied for the visualization. Then, the result was analyzed.

Through the analysis, the following facts were observed: (i) suicide notes could be distinguished from ordinary texts, (ii) even though the same author wrote both types of texts, suicide notes could be distinguished from ordinary texts, and (iii) the novels with the 1st person protagonist's point of view were also different from the suicide notes, though both types of texts preferred to use the 1st person pronoun 'I'.

As mentioned in Section 5, linguistic analysis is also important to detect not only suicide signs but also the cause/reason for the suicide, because the language in the suicide notes provided us with some cues for suicide committing. We hope that this study contributes to detecting and analyzing the SNs more accurately.

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Appendix. LIWC Variable Information

Dimension	Abbrev	Examples
I. STANDARD LINGUISTIC DIMENSIONS		
Word Count	WC	
Words per sentence	WPS	
Sentences ending with ?	Qmarks	
Unique words (type/token ratio)	Unique	
% words captured, dictionary words	Dic	
% words longer than 6 letters	Sixltr	
Total pronouns	Pronoun	I, our, they, you’re
1st person singular	I	I, my, me
1st person plural	We	we, our, us
Total first person	Self	I, we, me
Total second person	You	you, you’ll
Total third person	Other	she, their, them
Negations	Negate	no, never, not
Assents	Assent	yes, OK, mmhmm
Articles	Article	a, an, the
Prepositions	Preps	on, to, from
Numbers	Number	one, thirty, million
II. PSYCHOLOGICAL PROCESSES		
Affective or Emotional Processes	Affect	happy, ugly, bitter
Positive Emotions	Posemo	happy, pretty, good
Positive feelings	Posfeel	happy, joy, love
Optimism and energy	Optim	certainty, pride, win
Negative Emotions	Negemo	hate, worthless, enemy
Anxiety or fear	Anx	nervous, afraid, tense
Anger	Anger	hate, kill, pissed
Sadness or depression	Sad	grief, cry, sad
Cognitive Processes	Cogmech	cause, know, ought
Causation	Cause	because, effect, hence
Insight	Insight	think, know, consider
Discrepancy	Discrep	should, would, could
Inhibition	Inhib	block, constrain

Dimension	Abbrev	Examples
Tentative	Tentat	maybe, perhaps, guess
Certainty	Certain	always, never
Sensory and Perceptual Processes	Senses	see, touch, listen
Seeing	See	view, saw, look
Hearing	Hear	heard, listen, sound
Feeling	Feel	touch, hold, felt
Social Processes	Social	talk, us, friend
Communication	Comm	talk, share, converse
Other references to people	Othref	1st pl, 2nd, 3rd per prns
Friends	Friends	pal, buddy, coworker
Family	Family	mom, brother, cousin
Humans	Humans	boy, woman, group
III. RELATIVITY		
Time	Time	hour, day, oclock
Past tense verb	Past	walked, were, had
Present tense verb	Present	walk, is, be
Future tense verb	Future	will, might, shall
Space	Space	around, over, up
Up	Up	up, above, over
Down	Down	down, below, under
Inclusive	Incl	with, and, include
Exclusive	Excl	but, except, without
Motion	Motion	walk, move, go
IV. PERSONAL CONCERNS		
Occupation	Occup	work, class, boss
School	School	class, student, college
Job or work	Job	employ, boss, career
Achievement	Achieve	try, goal, win
Leisure activity	Leisure	house, TV, music
Home	Home	house, kitchen, lawn
Sports	Sports	football, game, play
Television and movies	TV	TV, sitcom, cinema
Music	Music	tunes, song, cd

Dimension	Abbrev	Examples
Money and financial issues	Money	cash, taxes, income
Metaphysical issues	Metaph	God, heaven, coffin
Religion	Relig	God, church, rabbi
Death and dying	Death	dead, burial, coffin
Physical states and functions	Physcal	ache, breast, sleep
Body states, symptoms	Body	ache, heart, cough
Sex and sexuality	Sexual	lust, penis, fuck
Eating, drinking, dieting	Eating	eat, swallow, taste
Sleeping, dreaming	Sleep	asleep, bed, dreams
Grooming	Groom	wash, bath, clean
APPENDIX: EXPERIMENTAL DIMENSIONS		
Swear words	Swear	damn, fuck, piss
Nonfluencies	Nonfl	uh, rr*
Fillers	Fillers	youknow, Imean

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Received on April 25, 2023
Revised version received on June 13, 2023
Accepted on June 30, 2023