Abstract

In this paper, we describe the results of our research aimed at detecting depression in Japanese sentences. Machine learning approaches to detect depression from language have been demonstrated in the United States and other countries. However, in Japanese, there are only two studies that have tackled the detection of depression from natural language. In order to be able to detect depression based on linguistic features, even in documents that do not explicitly mention the topic of depression, we build a machine learning model that detects depression in Japanese by eliminating topics that suggest depression or depression. We also examine the accuracy when the parts of speech are limited and when the ratio of the number of labels is aligned, to verify the significance. In the performances of our models with 5-fold cross-validation, we were able to obtain a high evaluation.

1 Introduction

Depression is a common illness that affects over 264 million people worldwide. Depression and other mental health conditions are becoming more common around the world. At its worst, depression can lead to suicide. A resolution passed by the World Health Assembly in 2013 advocated for a comprehensive, coordinated approach to mental illness at the national level\(^1\).

According to a patient survey conducted by the Ministry of Health, Labor and Welfare (MHLW), an official organization in Japan, the total number of patients with mood disorders such as depression in Japan has increased 2.9 times in 21 years, from 433,000 in 1996 to 1,276,000 in 2009. Depression also affects the economy, and the annual social loss due to depression in Japan is estimated to be 2 trillion yen (Sato, 2014). Therefore, “stress check system”\(^2\) has been introduced into the public system as a mandatory requirement for business establishments with 50 or more employees since 2015 to prevent mental health problems such as depression. As can be seen from these examples, clearly, depression is an issue of high importance in Japan.

In psycholinguistics, linguistic features have been studied as one of the behavioral indicators of depression. (Fine, 2008) reported that the idea that language use reflects the speaker’s mind. Psychiatrists also have used it to assess mental health conditions. There are many studies that focus on the linguistic features of depression and analyze natural language. (Yip, 2018) manifested the communicative patterns of anxiety and depression communication using the framework of discourse analysis. Unfortunately, lack of resources, a shortage of trained health-care providers, and the social stigma associated with mental illnesses are all obstacles to effective treatment of depression. Therefore, they sometimes miss the appropriate time for taking care of depression. The detection of depression by machine learning will be more important.

In this study, we use blog data to limit topics with LDA, vectorize documents with TF-IDF, reduce dimensions with SVD, and build classifiers with SVM.

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\(^1\)https://www.who.int/news-room/fact-sheets/detail/depression
\(^2\)https://www.mhlw.go.jp/stf/houdou/0000082587.html
Our contributions are summarized as follows:

- We demonstrated the usefulness of depression detection in Japanese.

- We focused on eliminating not only depression but also topics associated with depression, which has not received much attention in the research community.

- We showed that it is important to adjust the number of labels for the depressed group in the same ratio as the number of labels for the control group, such as after eliminating topics.

- We found that the linguistic features of depression require more strong than minimal preprocessing.

2 Related Work

A myriad of studies also have been conducted to detect depression from natural language (Rinaldi et al., 2020; Morales et al., 2018). The most widely used feature engineering method is to extract lexical features from the Linguistic inquiry word count (LIWC) lexicon, which contains over 32 psychological construct categories (Pennebaker et al., 2007). Many studies have applied depression detection from natural language, such as predicting depression from social media (Choudhury et al., 2013; Song et al., 2018; Orabi et al., 2018), analyzing the impact of COVID-19 using a depression predictor (Wolohan, 2020) and detecting suicidal attempt (Coppersmith et al., 2016; Gao et al., 2017). The ability of machine learning approaches to detect depression-related cues from language has been demonstrated in the United States and other countries. However, only two studies (Hiraga, 2017; Tsugawa et al., 2015) have addressed the detection of depression from natural language in Japanese. Despite the fact that most foreign studies are able to provide publicly available datasets, there are currently no datasets on depression in Japanese. (Hiraga, 2017) obtained blog data from 111 people and used a total of 7,358 articles to build a corpus. After eliminating topics related to depression and comparing the accuracy of several algorithms, the best performing model had accuracy of 95.5. (Tsugawa et al., 2015) obtained Twitter data from 209 volunteers, and built a corpus of up to 3,200 Tweets per person. The user’s behavioral history was also used as a feature, and the accuracy of the constructed model was 69.

In this paper, we present machine learning approach for depression detection in Japanese which departs from this previous work in four main ways:

First, in this study, we prepare more training data than in previous studies. (Tsugawa et al., 2015) uses data from Twitter. Although depression detection from multimedia such as Twitter is important, this study aims to improve the accuracy by using blog data and increasing the number of characters. (Hiraga, 2017) uses the same data from blogs as in this study. In this study, we increase the number of data from (Hiraga, 2017) to verify accuracy. We obtain the data of approximately 900 bloggers from blogs and build a corpus using approximately 300,000 articles.

Second, in this study, we compare the use of limited parts of speech with the use of all parts of speech. Many related studies have limited the number of parts of speech, believing that it is possible to capture the characteristics with a small number of parts of speech, and others have maximized the use of parts of speech, believing that all parts of speech, such as prepositions and conjunctions, have important functions. In this study, we compare the use of limited parts of speech with the use of all parts of speech.

Third, our approach erases not only depression, but also topics that are associated with depression. It is important to detect depression from linguistic features, even if they are not directly related to depression. Hence, there are some studies that address this issue by eliminating topics related to depression. In many studies, only topics related to ”depression” are eliminated. However, topics that include words that are far from the control group, such as ”sleeping pills,” ”hospital,” and ”dying,” are also considered to be topics that indirectly suggest depression. In order to be able to detect depression from topics that are similar to those of the control group, in this study, we eliminate topics that are associated with depression as well as depression.

Fourth, in this study, we adjust the number of the control group and the number of the suppression the
group to be the same when the above topics are eliminated. If we do obtain valuable results, it could be due to an imbalance in the ratio of the number of data in the depressed group to the number of data in the control group. Numerous studies have not corrected for this point. Thus, in this study, when the topics related to depression are eliminated, the number of topics in the control group is also examine together.

3 Data

In this study, we obtained data on depression patients from TOBYO : Depression Fighting Blog, one of the largest disease fighting portals to access patients’ valuable experiences and knowledge. This site compiles articles on depression from several blog platforms. We obtained 441 users’ information from Ameeba blog, which does not prohibit scraping, has not terminated its service, and has a large number of users. All the articles of the users were retrieved, and 149,997 articles were retrieved. For data on people who are not depressed, we randomly selected 460 users from several Ameeba blog genres like "Marriage/Pregnancy/Child Care", "Lifestyle", "Married Couples", "Pets", "Entertainment/Hobbies", "Travel/Regional", and "Fashion/Cosmetics" to get a total of 166,312 articles.

4 Method

The purpose of this study is to detect depression in Japanese. We construct a model that can detect depression based on linguistic features, even if depression is not explicitly mentioned. In this study, we perform the following three tasks.

1. When we limit the parts of speech, we examine our models.

2. When we remove topics related to depression and topics associated with depression, we examine our models.

3. When the number of data in the depressed group and the control group is the same, we compare our models.

4.1 Preprocessing

To avoid removing necessary information from the analysis target, we perform the minimum necessary preprocessing. First, we remove pictograms, URLs, stop words, convert numbers, and normalize words.

Unlike English, which has clear word boundaries in most parts of the text, Japanese does not have clear word boundaries. The word segmentation process is more complicated in the case of Japanese. The merit of the N-gram method used in the previous research (Hiraga, 2017) is that it does not cause retrieval omissions because the documents are mechanically divided and written. On the other hand, the disadvantage is that it generates many noise. For example, if we search for a document with the keyword "Kyoto", we get a hit for "Kyoto", which is the last two letters of "Tokyo", and the document is returned as it is. Because POS-based models have the highest accuracy in previous studies, in this study, all bases are separated by parts of speech. We use a Japanese tokenizer, called sudachi, which is resistant to word shaking.

For Task 1, "When we limit the parts of speech, we examine our models.", we prepare data using all parts of speech and data limited to only nouns, verbs, adjectives, adjectival verbs, and adverbs. We use articles with more than 50 words. For the data with all parts of speech, the number of depressive labels is 33,806 and the number of control labels is 47,275. For the data with limited parts of speech, the number of depression labels was 25,704, and the number of control labels was 38,442.

4.2 Depression topic withheld by LDA

For Task 2, "When we remove topics related to depression and topics associated with depression, we eliminate documents by Latent Dirichlet Allocation (LDA) that explicitly mention depression or topics that suggest depression. LDA is a probabilistic generative model that assumes that a document consists of multiple topics. (Resnik et al., 2015) uses LDA for depression detection. As a clue to determine the number of topics, we use perplexity as a measure of the accuracy of the probabilistic model. Figure 1 shows the change in perplexity when the number of topics $k$ is varied. As the minimum value was ob-
tained when k=5 for both the case of using all parts of speech and the case of limiting the number of parts of speech, the number of topics was set to 5. The topic with the highest percentage of the five topics is considered as the topic of the blog post, and the blog posts are classified by topic.

Table 1 shows the top 10 words for each topic when all parts of speech are used. When the top 100 word probabilities are displayed, Topic2 is the only topic that contains the word ”depression”. In addition to ”depression,” words such as ”hospital,” ”medicine,” ”symptom,” ”disease,” ”spirit,” ”live,” ”work,” and ”anxiety” were also observed. Although it did not contain the word ”depression,” Topic 1 contained words that were associated with depression, such as ”medicine,” ”sleeping pills,” and ”prescription.” On top of that, Topic 1 included words such as ”diet” and ”teacher.” Thus, we eliminate topic 1 and topic 2.

Table 2 shows the top 10 words for each topic when the parts of speech are limited to nouns, verbs, adjectives, adjectival verbs, and adverbs. When the top 100 word probabilities are displayed, Topic1 is the only topic that contains the word ”depression”. In addition to ”depression,” other words such as ”company,” ”medicine,” ”symptom,” ”disease,” ”spirit,” ”die,” ”work,” ”understanding,” ”family,” “work hard,” ”stress,” and ”disorder” were also observed. On top of that, although it did not contain the word ”depression,” Topic 5 contained words associated with depression such as ”medicine,” ”sleeping pills,” ”hospital,” ”mental,” ”examination,” and ”prescription.” Moreover, Topic 5 included words such as ”teacher,” ”work hard,” ”weight,” ”tired,” and ”work.” Thus, we eliminate topic 1 and topic 5.

### 4.3 Classification

For Task 3, ”When the number of data in the depressed group and the control group is the same, we compare our models.”, the first step is to align the number of labels for all the data to be compared. In this study, we vectorize sentences using a count-based method, TF-IDF, the inverse of Term Frequency and Document Frequency. This method evaluates the importance of a word by multiplying its Term Frequency by its Inverse Document Frequency. Because TF-IDF has as many features as there are morphemes, it is likely to be a sparse matrix and the processing time will be long. In order to reduce the amount of computation, we use singular value decomposition (SVD) to reduce the dimensionality to a low level. SVD is a method of matrix factorization in linear algebra for matrices with complex or real components. This SVD brings the dimensionality to 250 dimensions. We then use Support Vector Machine (SVM) classification method to perform binary classification task between the depressed group and the control group. SVM is a pattern recognition method that uses supervised learning based on margin maximization.

### 5 Results

The evaluation indices are accuracy and F1 value. For each evaluation index, we took the average value of five parts by cross-validation. Table 3 shows the
### Table 1: Using all parts of speech Top 10 probabilities of a word occurring in a topic.

| Topic 1 n=6808 | Topic 2 n=15879 | Topic 3 n=8303 | Topic 4 n=18077 | Topic 5 n=4801 |
|----------------|------------------|----------------|------------------|----------------|
| kusuri(drugs) | demo(but)        | toki(time)     | nomu(drink)      | taberu(eat)    |
|               | watashi(I)       | jibun(myself)  | nu(not)          | hito(people)   |
|               | iu(say)          | hito(people)   | iu(say)          | hito(people)   |
|               | kuru(come)       | nani(what)     | ne(ne)           | yo(yo)ne       |
|               | kuru(people)     | ne(ne)         | nu(not)          | ya(ya)         |
| hi(people)    | o(o)             | o(o)           | demo(but)        | demo(but)      |
| o(o)           | demo(but)        | demo(but)      | demo(but)        | demo(but)      |

### Table 2: Using limited parts of speech Top 10 probabilities of a word occurring in a topic.

| Topic 1 n=13130 | Topic 2 n=3863 | Topic 3 n=5078 | Topic 4 n=18328 | Topic 5 n=13469 |
|-----------------|----------------|----------------|------------------|------------------|
| omou(think)     | burougublog    | iu(say)        | kyou(today)       | toki(time)       |
| jibun(myself)   | honjitsu(today)| miru(see)      | iku(go)          | nomu(drink)      |
| hito(people)    | mura(village)  | omou(think)    | hi(day)          | neru(sleep)      |
| iu(say)         | en(yen)        | sensei(teacher)| omou(think)      | taberu(eat)      |
| ima(now)        | gozarugozaru   | hito(people)   | iu(say)          | kyou(today)       |
| kuru(come)      | rankinguranking| kiku(listen)   | kyou(today)       | iku(go)          |
| kangaeru(consider)| itasu(itasu)| hanashi(story) | iku(go)          | hi(day)          |
| sigoto(work)    | ouen(support)  | nihon(japan)   | kau(buy)         | kyou(today)       |
| dou(how)        | itadaku(itadaku)| jyosei(woman)| toki(time)       | kyou(today)       |
| koto(koto)      | koto(koto)     | kuru(come)     | ie(house)        | deru(get out)    |

Table 2: Using limited parts of speech Top 10 probabilities of a word occurring in a topic.
results of all the models.

In Task 1, “When we limit the parts of speech, we examine our models.” is to examine the accuracy of model1(all topic / all part of speech) and model2(all topic / limited part of speech). When model1 and model2 are compared, model2 has higher accuracy, which indicates that higher accuracy can be obtained by limiting the part of speech.

In Task 2, “When we remove topics related to depression and topics associated with depression, we examine our models.” we compared model1(all topic / all part of speech) with model3(depression topic withheld / all part of speech), and model2(all topic / limited part of speech) with model4(depression topic withheld / limited part of speech). When comparing model2(all topic / limited part of speech) and model3(depression topic withheld / all part of speech), the accuracy of the model using the data of all topics was higher than the model eliminating depression and depression-related topics. This indicates that when all parts of speech are used, topics related to depression provide cues to recognize characteristics of depressed groups. On the other hand, when comparing model2(all topic / limited part of speech) and model4(depression topic withheld / limited part of speech), the accuracy of the model that eliminated the topics related to depression and depression was higher than the model that used the data of all topics. When we limit the part-of-speech, the accuracy was lower when we delete topics related to depression. However, it is possible that this is due to the fact that the percentage of data showing the control group became larger by we eliminated topics related to depression. We will demonstrate this problem in Task 3.

In Task 3, “When the number of data in the depressed group and the control group is the same, we compare our models.”, we compare model1(all topic / all part of speech) and model5(all topic / all part of speech / adjustment), model2(all topic / limited part of speech) and model6(all topic / limited part of speech / adjustment), model3(depression topic withheld / all part of speech) and model7(depression topic withheld / all part of speech / adjustment), and model4(depression topic withheld / limited part of speech) and model8(depression topic withheld / limited part of speech / adjustment). The scores for model1 and model5, model2 and model6, and model3 and model7 varied slightly. On the other hand, large changes were observed in model4(depression topic withheld / limited part of speech) and model8(depression topic withheld / limited part of speech / adjustment), indicating that the large number of the control group improved the accuracy. The model with the highest accuracy in this study is Model 4, but the most convincing model is Model 8. There are several studies that eliminate topics related to depression, but no studies that have subsequently adjusted the number of labels. We found that adjusting the number of labels when eliminating topics related to depression produced more useful results.

The most useful and accurate model was the model trained by eliminating depression and depression-related topics, keeping the number of depressed group and the control group equal, and limiting the parts of speech to nouns, verbs, adjectives, adjectival verbs, and adverbs, which resulted in its accuracy of 0.956 and its F1 value of 0.959. These results are higher than those of previous studies (Hiraga, 2017; Tsugawa et al., 2015).

6 Conclusion

In this study, we constructed a machine learning model for detecting depression from natural language with the aim of detecting depression in Japanese. In Task 1, “When we limit the parts of speech, we examine our models.”, we found that by limiting the part of speech, the features of the depressed group can be better recognized. In Task 2, "When we remove topics related to depression and topics associated with depression, we examine our models.”, we confirmed the accuracy by eliminating topics related to depression and depression, and found that we could detect depression from linguistic features even in materials where the topic of depression is not explicitly mentioned. In Task 3, "When the number of data in the depressed group and the control group is the same, we compare our models.”, we found that we can build a more useful model by balancing the labels.

The most useful and accurate model was
| Model                                                                 | Accuracy | F1  |
|----------------------------------------------------------------------|----------|-----|
| model1(all topic / all part of speech)                              | .922     | .921|
| model2(all topic / limited part of speech)                          | .923     | .924|
| model3(depression topic withheld / all part of speech)              | .899     | .876|
| model4(depression topic withheld / limited part of speech)          | .971     | .962|
| model5(all topic / all part of speech / adjustment)                 | .921     | .921|
| model6(all topic / limited part of speech / adjustment)             | .925     | .925|
| model7(depression topic withheld / all part of speech / adjustment) | .884     | .884|
| model8(depression topic withheld / limited part of speech / adjustment) | .956     | .959|

Table 3: Performance of our model with 5-fold cross-validation.

the model trained by eliminating depression and depression-related topics, keeping the number of depressed and the control group equal, and limiting the parts of speech to nouns, verbs, adjectives, adjectival verbs, and adverbs. Its accuracy was 0.956 and its F1 value was 0.959. The results of this study show that it is possible to extract the linguistic features of depression from Japanese documents, Even if there are no topics related to depression. This will help in the early detection of depression in people who are not aware of it and in the establishment of a system to prevent depression.

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