Detection of Compound-Type Dark Jargons Using Similar Words

Takuro Hada[1,2][a], Yuichi Sei[1,3][b], Yasuyuki Tahara[1][c] and Akihiko Ohsuga[2][d]

[1]*The University of Electro-Communications, Tokyo, Japan*

[2]*First Organized Crime Countermeasures Division, Organized Crime Department, Criminal Investigation Bureau, National Police Agency, Japan*

[3]*JST PRESTO, Saitama, Japan*

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Abstract: Recently, drug trafficking on microblogs has increased and become a social problem. While cyber patrols are being conducted to combat such crimes, those who post messages that lead to crimes continue to communicate skillfully using so-called “dark jargon,” a term that conceals their criminal intentions, to avoid using keywords (“drug,” ”marijuana,” etc.) of the target of monitoring. Evading detection by the eyes of monitoring, they continue to communicate with each other skillfully. Even if the monitors learn these dark jargons, they become obsolete over time as they become more common, and new dark jargons emerge. We have proposed a method for detecting dark jargons with criminal intent based on differences in the usage of words in posts and have achieved a certain level of success. In this study, by using similar words, we propose a method for detecting compound-type dark jargons that combines two or more words, which have been difficult to detect using existing methods. To confirm the effectiveness of the proposed method, we conducted a detection experiment with compound words and a detection experiment with dark jargons. As a result, we confirmed that the proposed method enabled to detect compound-type dark jargons that could not be detected by existing methods.

1 INTRODUCTION

With the rapid spread of social media, the number of cybercrime has increased. A news article based on a United Nations Office on Drugs and Crime report noted increases in online drug trafficking via Facebook, Twitter, and Instagram (Wongcha-um and Allard, 2020). The Special Narcotics Control Law also applies to social media postings that use dark jargons, and as shown in Figure 1, the number of arrests has dramatically increased in recent years.

Posters who aim to drug trafficking are wary of having their posts deleted by cyber patrols, the police, or social media operators, having their accounts frozen, or being arrested by the police. Therefore, they tend to avoid words directly related to crimes (“marijuana,” ”methamphetamine,” etc.) and use dark jargons, as depicted in Figure 2, to conduct drug trafficking only with those who know the meaning of the dark jargons.

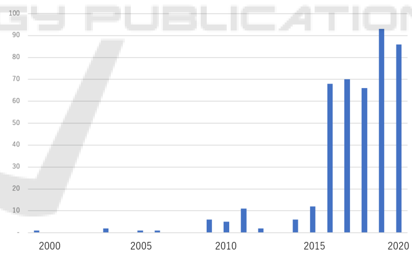

Figure 1: Number of arrests for violation of the Narcotics Control Law (stirring up and instigation) based on data from the Ministry of Justice (MOJ, 2021).

Dark jargons are commonly used in the drug trade, for example, “ganja,” “grass,” “weed,” and “joint” for marijuana and “es,” “shabu,” “ice,” and “crystal” for methamphetamine in Japanese. Even if these dark jargons are regularly detected by keyword searches, the effect tends to be limited. This is because, as a characteristic of dark jargons, when they are generally recognized, new dark jargons are created to avoid surveillance, or the meaning of a dark jargon is given to a common word that has not been used before (Yuan et al., 2018). For example, in Japan, for marijuana, the terms “grass,” “weed,” and “joint” are

[a] https://orcid.org/0000-0003-2853-9211
[b] https://orcid.org/0000-0002-2552-6717
[c] https://orcid.org/0000-0002-1939-4455
[d] https://orcid.org/0000-0001-6717-7028

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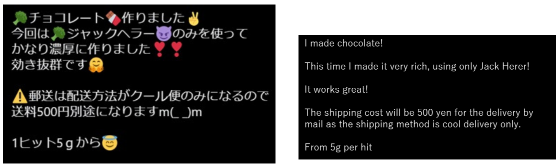

(a) Writing in Japanese (Example).

(b) Translation of (a).

Figure 2: Example sentences with dark jargons from Twitter.

used, and for methamphetamine, “ice” and “crystal” are used. As a result, the monitors must continually keep track of new dark jargons and add them to the list of targets for detection, which places a heavy burden on them. Therefore, to support cyber patrols to prevent crimes such as drug trafficking, we aim to detect posts that induce crimes, including dark jargons.

We have previously proposed a method for detecting crime-inducing dark jargons by similar words based on the hypothesis that similar related words (hereafter “Related word”) appear around the words used in illicit transactions.

Here, we focused on Twitter and classified tweets related to dark jargons into four types:(Hada et al., 2021)

1. Tweets that feature only known dark jargons (and words directly related to crime).
2. Tweets containing only unknown dark jargons.
3. Tweets featuring a mixture of known dark jargons (and words directly related to crime) and unknown dark jargons.
4. Tweets that feature neither known nor unknown dark jargons.

Moreover, we purposed to detect unknown dark jargons based on the known dark jargons (and words directly related to crime), assuming that the tweets in (3) exist. Specifically, we used a corpus of tweets targeting (1) and (3) above (hereinafter the “Bad Corpus”) and a corpus of tweets targeting (4) above (hereinafter the “Good Corpus”).

We then proposed a method that focuses on the difference in similarity of the same word in two groups of tweets by classifying them into the above two corpora (Good Corpus, Bad Corpus).

Using our method, we succeeded in detecting unknown dark jargons (Hada et al., 2021), (Hada et al., 2022). However, our method has a problem in that it cannot detect dark jargons that are compound words combining two or more words. In this study, we call words that are both compound words and dark jargons “compound-type dark jargons.”

The ability to detect compound-type dark jargons is very significant because it will expand the range of dark jargons that can be detected using our method. Therefore, this study proposes a method for detecting compound-type dark jargons based on similar words and conducts dark jargon detection experiments in conjunction with existing dark jargon detection methods.

This paper is organized as follows. Section 2 describes the background of this study. Section 3 describes the methodology proposed in this study. Section 4 describes the experimental setup and the results of the experiments, and Section 5 describes the dark jargon detection experiments using existing methods based on the results of Section 4. In Section 6, we discuss the proposed method through experiments. Finally, Section 7 presents the conclusion of this study.

2 BACKGROUND

2.1 Increase in the Number of Crimes Involving Drug Trafficking

In Japan, there have been many cases related to drug trafficking using microblogs such as Twitter, which have become a social problem. For example, Figure 3 shows the number of arrests for marijuana offenses by age group. As shown in the figure, the number of arrests increases every year, particularly among teenagers and those in their 20s.

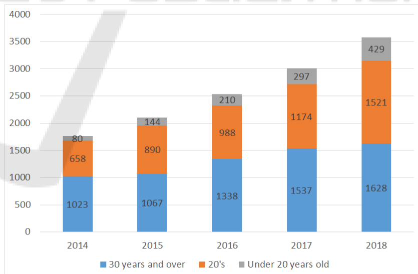

Figure 3: Based on the number of arrests for marijuana offenses by age group (data from the National Police Agency (NPA, 2018)).

Therefore, this study focuses on Twitter because of its large number of users, its accessibility to an unspecified number of people, its environment in which illegal transactions are likely to occur, and the tendency to use dark jargons in such transactions.

2.2 Dark Jargon

Dark jargon is defined as a special word that is used only within a specific society or group. The target of this study is words used in crime, particularly those related to drug trafficking, that evade the attention of police and others.

We targeted the following dark jargon types.

1. The name of the object itself that constitutes a criminal act.
   - Words with High Recognition.
     For example, "marijuana" and "LSD" fall under this category. Since these words are generally recognized and do not have the effect of making people hide their transactions, they were classified as "related word" rather than "dark jargon".
   - Words with Low Recognition.
     Since the target word itself is not generally recognized, even if it is used as it is, only a specific group of people will understand it.
     For example, the types of cannabis "White Kush," "White Widow," and "Gorilla Glue" fall into this category.
2. Not the name of the criminal offense itself
   - Diversion (camouflage).
     Words used to camouflage commonly used words by giving them a cryptic meaning fall under this category. For example, as words related to drug trafficking, there are "vegetable" and "grass" for marijuana, and "ice" and "crystal" for methamphetamine.
   - Coined words.
     Words intentionally coined for illegal transactions fall under this category. For example, in Japan, words related to drug trafficking include "hashishi" and "pot" for marijuana, and "shabu" and "gankoro" for methamphetamine.

2.3 Changes of Dark Jargon

Words gradually change in meaning over time, with dark jargons used in crime changing as their meaning becomes more generally recognized. Words gradually change their meanings over time (Mihalcea and Nastase, 2012), (Wijaya and Yeniterzi, 2011), and among them, dark jargons used in crime change when their meaning is generally recognized (Yuan et al., 2018).

Therefore, we prepared actual tweet data for the years 2016 and 2020 to explore the situation with respect to social media and conducted two studies (Hada et al., 2022). The first was to investigate the occurrence rate of dark jargons, and we found that words that were barely detected as dark jargons in the 2016 tweet data appeared in the 2020 tweet data, see Table 1. Second, we examined the extent to which commonly used dark jargons such as "vegetable (meaning marijuana)" and "handcart (meaning direct sales)" were used as dark jargons in 2016 and 2020, respectively, and found that in the range of tweets collected, neither "handcart" nor "vegetable"were dark jargons in 2016 (Table 2).

In the range of tweets collected, the percentage of tweets in which the meaning of handcart or vegetable was defined as dark jargon was 0% in 2016, whereas, in 2020, the percentage was 81.8% for handcart and 2.5% for vegetable, due to their several occurrences in the general meaning; however, the percentage of words that had never been used as dark jargons by that time was 0.3%. In 2020, however, words that have never been used as dark jargons will be used with the meaning of a dark jargon. The results show that words that were not used as dark jargons at all before are being used as dark jargons in 2020.

Table 1: Difference in the number of tweets in which each word appeared as dark jargons between the two years(2016,2020).

Word			Quantity	
Japanese	English	Meaning	2016	2020
クッシュ	Kush	Marijuana	1	157
ウィドー	Widow	Marijuana	0	70
野菜	Vegetable	Marijuana	0	894
手押し	Handcart	deal face-to-face	0	1,163
Total number of tweets			111,408,818	69,301,877

Table 2: Difference in the percentage of tweets in which each word was used as dark jargons between the two years(2016,2020).

	Vegetable		Handcart	
	2016	2020	2016	2020
Number of detections	37,931	35,490	290	1,472
Number used as dark jargons	0	894	0	1,163
Percentage of s dark jargon	0%	2.5%	0%	81.8%

2.4 Compound Word

The compound word is defined as two or more originally independent words combined to form a new word with a new meaning and function. Examples of compound words are "hon·bako (book box)" and "yama·zakura" (mountain cherry blossom). ("·" denotes the concatenation of words.)

Alternatively, as examples of compound-type dark jargons, we have identified "lemon·skunk," "gorilla·glue," and "white·widow" as dark jargons for marijuana in the tweets we have confirmed thus far.

The dark jargon detection method proposed by

Hada et al. (Hada et al., 2021), (Hada et al., 2022) relied on a word segmentation unit. Thus we had the problem that words that were originally compound words could not be detected in their correct forms if they were word segmented. For example, for the words mentioned earlier, the words "lemon" "skunk," "gorilla" "glue," and"white" "widow," respectively, were separated by single-word phrases, and although "gorilla" could be detected, the word "gorilla·glue" could not be detected.

One possible countermeasure to prevent compound-type dark jargons from being separated by phrases during segmentation is to adjust the segmentation unit, but as segmentation is based on an internal dictionary, words that do not exist in the internal dictionary are not segmented into compound units.

Because there are many coined words and words with low recognition among those used as dark jargons, they are typically not registered in segmentation dictionaries and are unlikely to be automatically added to the dictionary. Even if recognized compound-type dark jargons are registered in the dictionary, it is required human hand to catch up with the latest changing dark jargons. Furthermore, when a common word such as "lemon" is included in a clause, for example, "lemon skunk," the clause is considered separated from the rest of the sentence. If we can register compound clauses in the dictionary in advance, we can expect to detect compound clauses using existing methods.

3 RELATED WORKS

Several studies have been reported on the detection of dark jargons on Web sites such as BBS (Lee et al., 2007) (Ohnishi and Tajima, 2013). There have also been several reports on dark jargon detection for platforms other than websites and BBS. For example, Yuan et al. proposed a method for automatically identifying dark jargons from the Dark Web, as marijuana is exchanged under the names of popcorn and blueberries and child pornography under the name of cheese pizza on the Dark Web(Yuan et al., 2018). In doing so, since a single corpus by Word2vec (Mikolov et al., 2013a) cannot detect cryptic terms, multiple corpora are prepared and cryptic terms are detected based on semantic discrepancies between terms that appear in two different corpora. However, the aforementioned study targets cryptic terms on the Dark Web, but does not target short, context-free microblogs that are widely used by young people in general. Regarding Chinese, Zhao et al. focus on dark jargons used for cybercrime in the underground market in China and implement dark jargon detection using unsupervised learning (Zhao et al., 2016). They concluded that the combination of "CBOW + Negative Sampling" is the optimal setting for Word2vec and is about 20% higher than the LDA approach. However, according to the aforementioned authors, it is still described as a first-stage study (Yuan et al., 2018). Alternatively, A study of dark jargon detection for Japanese has been reported for ID-Exchange BBS as a platform (Satoshi ABIKO and SAKUTA, 2018). Abiko et al. classified harmfulness using text classification (supervised learning) for ID-Exchange BBS with short sentences and no context. However, they note that it is difficult to deal with camouflaged dark jargons such as "vegetable" and "ice".

For Twitter, the subject of this study, research has been conducted with the goal of reducing crime (O'Day and Calix, 2013), (Kansara et al., 2016). Among them, research has also been conducted on detecting offensive or illegal words (Xiang et al., 2012),(Wiedemann et al., 2018), (Hakimi Parizi et al., 2019). Aoki et al.'s method detects uncommon usage by using the word vector of the word of interest and its surrounding words to evaluate the degree to which the surrounding words of the word of interest differ from the surrounding words in the case of common usage(Aoki et al., 2017) . Aoki et al.'s method requires prior recognition of the dark jargons and the preparation of sentences in which the dark jargons appear. However, since dark jargons are characterized by their ability to evade surveillance and be known only to certain people, it is very labor intensive to keep track of new dark jargons. In other words, the biggest difference between our method and Aoki et al.'s is that Aoki et al.'s research does not find new unknown dark jargons, while our method detects words that are used similarly from similar words of a word, and it can discover unknown dark jargons that even we do not recognize. As for Aoki et al.'s method, we believe that our method can find new dark jargons and recognize them as dark jargons and that our method is essential for the effective use of Aoki et al.'s method.

Regarding the detection of dark jargons, it would be difficult to apply the dark jargon detection methods used on the web and bulletin boards directly to microblogs such as Twitter. This is because the following characteristics of microblogs have been described(Dela Rosa and Ellen, 2009).

- Short character length.
  Microblogs comprise as little as a single word to less than a paragraph at most. For Twitter, there is a limit of 140 characters per post.
- Informal and unstructured formats.

Microblogs contain slang, misspellings, and abbreviations.

An analysis of tweets related to dark jargons on Twitter revealed that not only do many short sentences appear, but tweets used for criminal transactions, among others, are often even more disembodied sentences because they attempt to conceal the criminal intent. Therefore, it is considered difficult to conduct analysis and machine learning using sentence entailment. Alternatively, in order to conclude a transaction in the shortest possible exchange, it is necessary to include necessary information in a single post, such as the target of the transaction, location, amount, quality, etc. Therefore, we found a tendency for crime-related words to appear around dark jargons, which we defined as related words. Therefore, we thought that we could effectively find dark jargons and similar words used in criminal transactions by using word-distributed expressions, taking advantage of the tendency of crime-related words to appear around dark jargons in tweets related to transactions. Note that Word2vec was used in this study as the word variance representation, and although several studies using Word2vec and cosine similarity have been reported recently, there are no examples of using it to detect unknown dark jargons(Yao et al., 2021),(Huang et al., 2021). Therefore, we believe that detecting unknown dark jargons in short sentences targeting Twitter is very significant because it is expected to prevent crimes before they occur and to deter crimes through early detection. Therefore, we detect unknown dark jargons by using known dark jargons as clues and focusing on their similar words.

4 ON THE DETECTION OF COMPOUND-TYPE DARK JARGONS

4.1 Approach to Detect Compound Words

Existing methods (Hada et al., 2021), (Hada et al., 2022) detect dark jargons based on segmented words, and thus compound-type dark jargons consisting of words separated by phrases are difficult to detect.

Therefore, the detection of compound words is a challenge for us. For example, one word "green crack," which is used as a cloaking word for marijuana, is separated into "green" and "crack" when Japanese segmentation processing is performed.

Because compound words, particularly compound-type dark jargons, are assumed to occur more frequently in the same context, i.e., such words are considered strongly related to each other, we hypothesized that words separated by compound phrases would appear at the top of each other as similar words.

Therefore, we constructed a word distribution model for the Bad corpus with a window size of 2, which is smaller than the setting used to construct word distribution models for dark jargon detection and examined the similarity between the words "green" and "crack" for the word "green crack." The top similarity word for "green" was "crack," whereas the top similarity word for "crack" was "green," indicating that the two words are similar.

From this result, we hypothesized that it would be possible to automatically detect compound words by detecting words that match the top similar words in both words.

Therefore, we propose the following method for detecting compound words.

1. Search for the top i similar words of α. ($\mathcal{S}(\alpha)_{1st} \ldots \mathcal{S}(\alpha)_{ith}$)
("$\mathcal{S}(\alpha)$" denotes sequence of similar words of α.)
2. Next, similar words of each of $\mathcal{S}(\alpha)_{1st} \ldots \mathcal{S}(\alpha)_{ith}$ are searched respectively.
$(\mathcal{S}(\mathcal{S}(\alpha)_{1st})_{1st} \ldots \mathcal{S}(\mathcal{S}(\alpha)_{1st})_{ith}, \mathcal{S}(\mathcal{S}(\alpha)_{2nd})_{1st} \ldots \mathcal{S}(\mathcal{S}(\alpha)_{2nd})_{ith}, \mathcal{S}(\mathcal{S}(\alpha)_{ith})_{1st} \ldots \mathcal{S}(\mathcal{S}(\alpha)_{ith})_{ith})$
3. And if $\alpha = \mathcal{S}(\mathcal{S}(\alpha)_{ith})_{ith}$, then the words "$\alpha \cdot \mathcal{S}(\alpha)_{ith}$" and "$\mathcal{S}(\alpha)_{ith} \cdot \alpha$" are created as candidate compound words.
4. We compare these words with the original bad corpus, check the number of occurrences in the original bad corpus, and consider the words that exceed a certain number of occurrences to be compound words.

In this paper, words that are close to each other in the distributed representation model are considered as "similar words" even if they have different meanings.

4.2 Process of Registering Compound Words

The following process was used to detect compound words.

1. Word search among the top 5 (i = 1…5) similar words
   - Word distributed expression model for compound word detection was constructed using Word2Vec (Mikolov et al., 2013a) by splitting tweets in the Bad corpus.

- The words in the constructed word-distributed representation model are extracted and listed to create a word group $\mathcal{A}$.
- For each word α_j (j = 1...n) in the listed word group $\mathcal{A}$, retrieve the top 5 similar words. $(\mathcal{S}(\alpha_j)_{1st} \ldots \mathcal{S}(\alpha_j)_{5th})$
- For each of the retrieved words $(\mathcal{S}(\alpha_j)_{1st} \ldots \mathcal{S}(\alpha_j)_{5th})$, the top 5 similar words $(\mathcal{S}(\mathcal{S}(\alpha_j)_{1st})_{1st} \ldots \mathcal{S}(\mathcal{S}(\alpha_j)_{5th})_{5th})$ are also searched.
- Match α_j against each of $\mathcal{S}(\mathcal{S}(\alpha_j)_{ith})_{ith}$ to determine if they match.
- If $\alpha_j = \mathcal{S}(\mathcal{S}(\alpha_j)_{ith})_{ith}$, swap the two words to create two compound word candidates("$\alpha_j \cdot \mathcal{S}(\mathcal{S}(\alpha_j)_{ith})_{ith}$" and "$\mathcal{S}(\mathcal{S}(\alpha_j)_{ith})_{ith} \cdot \alpha_j$").

2. Match all created "$\alpha_j \cdot \mathcal{S}(\mathcal{S}(\alpha_j)_{ith})_{ith}$" and "$\mathcal{S}(\mathcal{S}(\alpha_j)_{ith})_{ith} \cdot \alpha_j$" against the Bad corpus one by one, and count the number of occurrences of each word.
3. Only words with $\mathcal{X}$ or more occurrences ($\mathcal{X}$ is specified separately) are added to the internal dictionary for word segmentation as compound words.

4.3 Considerations for Improving Accuracy

To suppress the detection of unnecessary words and improve the detection accuracy of dark jargons, we verified several functions and added the following three effective functions to the proposed method in Section 4.2 (no functions added described as "proposed method w/0 added func").

4.3.1 Comparison with the Good Corpus

To avoid a risk of decrease rate of detecting compound-type dark jargons by detecting general compound words, we searched for similar words of the same word α between the two corpora (Good and Bad corpora) and considered that words α in which the same word appeared did not appear in the context as dark jargon. Therefore, we also searched for similar words in the Good corpus when searching for similar words, and if the word appeared in the top 20, we stopped a process of registering compound words.

4.3.2 Filtering by Morphological Analysis

Because most of the compound-type dark jargons consisted mainly of nouns, part-of-speech classification was performed before combining compound words, allowing only nouns to be extracted.

4.3.3 Deletion of Words in the Dictionary

Among the words detected as candidates for compound words, single words were also detected. Words that were already registered in the dictionary for word segmentation were excluded from the candidate compound words.

5 EXPERIMENT (COMPOUND WORDS DETECTION)

5.1 Summary

Experiments were conducted to verify compound word detection using the proposed method.

5.2 Experimental Process (Compound Words Detection)

5.2.1 Data Collection

Using the Twitter API, we collected Twitter data for approximately one year (from 2019/07/19 to 2020/07/27), of which only the text data were used. Then, based on the keywords related to drug dark jargons, we extracted a list of accounts tweeting about drug trafficking using dark jargons. Then, using the list as a key, we again collected Tweets during the same period and created a corpus (hereinafter the "Bad Corpus").

5.2.2 Preprocessing

Words that were irrelevant for dark jargon detection were removed in advance. The deleted items are as follows.

1. URL
2. newline characters
3. Words frequently appearing on Twitter
   (e.g., "RT," "Favorite," etc.)

5.2.3 Creating Corpora

The following two corpora were prepared.

1. Bad corpus
   See section 5.2.1.
2. Good corpus
   As a general corpus, we chose to use a large-scale tweet corpus and used a large-scale Japanese social media + Web corpus created by Hotlink Corporation (Shogo Matsuno and Sakaki, 2019).

Note that the Good corpus is used in the additional feature Section 4.3 of the proposed method.

5.2.4 Morphological Analysis

Japanese sentence structure is not separated by spaces, etc. Therefore, morphological analysis processing and segmentation are essential before word distribution processing. Segmentation is the process of dividing sentences into word units based on an internal dictionary of words. This allows for the word-by-word segmentation of sentences. The problem here is how to divide sentences appropriately. Because Twitter is microblog and it is characterized by short sentences, many new words and slang, and many sentences that are intentionally cut off, which may result in incorrect segmentation. In addition, because the target words of this study are dark jargon, some of the words may be close to coined words and thus need to be correctly segmented.

Thus, SUDACHI(Takaoka et al., 2018) was chosen as the morphological analyzer for the following two reasons.

1. The internal dictionary is updated regularly, and it is maintained to correspond to new words as much as possible.
2. The viewpoint of availability to select the word segmentation unit for new words.

5.2.5 Adding Compound Words to the User Dictionary for Word Segmentation

The following process was repeated 10 times on the preprocessed Bad corpus.

1. Segmentation
   The prepared corpus is split into separate words using SUDACHI (Takaoka et al., 2018).
2. Building a word distribution model
   Word2Vec was used to perform the modeling. The parameters of Word2Vec for compound word detection are presented in Table3.
3. Detecting compound words from the corpus

Table 3: Parameters of Word2Vec for compound word detection.

Parameter	Value
Size	300
Min-Count	3
Window Size	2
Negative	20
Methods	Skip-Gram (Mikolov et al., 2013b)

   From the constructed distributed word representation model, a set of words registered in the model is extracted, and the compound word detection algorithm described in Section 5.2.1 is applied to each word to create compound word candidates.
4. Checking the number of occurrences
   Pick up words that appear two or more times in the original corpus before segmentation.
5. Register words in SUDACHI's (Takaoka et al., 2018) user dictionary
   Registering a word in the user dictionary allows the compound word to be segmented as a single phrase.

5.3 Experimental Conditions

In addition to the proposed method, comparative evaluations were performed using the following two methods.

For the experiment, a baseline method was developed for comparative evaluation.

5.3.1 Baseline Condition

To verify the effectiveness of the proposed method, we used the baseline condition in which all bi-grams were obtained for sentences after segmentation (hereinafter the "baseline method"). Because the proposed method also prepares candidate compound words with their front and rear parts swapped, we also prepared candidate compound words with their front and rear parts swapped for the above words. When the proposed method was used to create compound word candidates from the Bad corpus, 686,561 words were created, and when the threshold for the number of occurrences was set to twice when referring to the Bad corpus before preprocessing, 105,266 words were created, which is a huge number compared with other conditions. Therefore, we relaxed the threshold for the frequency of occurrence from twice to 14 times or more and selected 14,218 words as the number of target words.

5.3.2 Detection of Related Words

Generally, transactions require information such as "the object of the transaction," "something descriptive of the object of the transaction (e.g., high quality)," "time," "place," "transaction method," "transaction amount," "amount of money," and so on. As words to express these information, dark jargons can occur if a common understanding arises among those who conduct transactions. However, in situations where there are no words established as dark jargons yet, common

Table 4: Classification of compound word candidates.

Method	Compound word candidates (Before applying threshold filter)	Compound word candidates (After applying threshold filter)	True compound words	Rate[b]
Proposed	61,731[a]	295[a]	264[a]	89.5%
Proposed w/o Added Func	101,573[a]	521[a]	308[a]	59.1%
Baseline	686,561	14,218	388	2.73%

[a] Total of 10 trials of the process in section 5.2
[b] Number of True compound words/Number of candidate compound words

Table 5: Percentage of compound-type dark jargons under each condition.

Method	Quantity of Compound word	Dark Jargons		Related Words		SUM	
		Quantity	Rate	Quantity	Rate	Quantity	Rate
Proposed	264	19	6.4%	23	7.8%	42	14.2%
Proposed w/o Added Func	308	25	4.8%	24	4.6%	49	9.4%
Baseline	388	30	0.2%	102	0.7%	132	0.9%

words are used to avoid misunderstandings among each other. As words to express this information, dark jargons can occur if a common understanding arises among those who conduct transactions. However, in situations where there are no words established as dark jargons yet, common words are used to avoid misunderstandings among each other. Therefore, even if one tries to conduct a transaction cleverly using a dark jargons without being aware of the intention, it is considered necessary to include at least three pieces of information: “object of the transaction,” “location (e.g., in Tokyo),” and “amount of money. Furthermore, in order to realize a speedy exchange while evading surveillance,

it is necessary to include “transaction method (hand delivery, mail, etc.)” and “something descriptive of the transaction object (high quality, etc.)” in the text.

We defined these words as related words, which do not constitute dark jargons by themselves, but tend to appear together with the dark jargons.

The words were classified into the following categories.

1. “Dark Jargon”
   Words defined in Section2.2.Words judged to have a meaning different from their original meaning.
2. “Related word”
   Although these words could not be categorized as codewords, they tended to appear alongside codewords and were judged as rarely appearing in general tweets (e.g., “stock” and “price”).
3. “Unrelated word”
   Words that do not meet the criteria of the previous two categories.

5.4 Results

The three methods detected candidate compound words and classified them into two categories: compound or not. Words identified as compound words were further classified as either dark jargons or related words. The results of the compound word detection are presented in Table 4. The number of occurrences of compound word candidates (Section 4.2 3) was set to X=2 for the proposed method and the proposed method (w/o added func) and X=14 for the baseline.

Table 4 shows that the proposed method significantly outperforms the baseline in terms of compound word detection accuracy. Furthermore, when comparing the proposed method with the proposed method without func, the proposed method outperforms the”proposed method without added functionality” by 30.1%.

The results for the compound-type dark jargons that appeared in the compound words are presented in Table 5.

The experimental results show that there is a significant difference between the proposed method and the baseline method in terms of the detection rate of compound-type dark jargons, with the proposed method without added func, the proposed method, and the baseline method detecting 9.4%, 14.2%, and 0.9% of the compound words that contain dark jargons and related words, respectively.

5.5 Consideration (Compound Words Detection Experiment)

Tables 4 and 5 show that the proposed method significantly outperformed the baseline in detecting compound words, indicating that the proposed method is an effective method for compound word detection.

Furthermore, the proposed filter function was 30.1% more effective than the"proposed method without added func," demonstrating that the filter function was effective in detecting compound words.

We also analyzed whether our method, which focuses on similar words, is an effective method for detecting compound words from the perspective of detecting proper nouns. This is because we thought that the proper nouns of compound words are more likely to be detected by the proposed method as they appear more frequently in the same word and thus are more related to each other than to other words. Table 6 shows that proper nouns accounted for approximately half of the compound words detected by the proposed method, at 48.5%. This indicates that the proposed method is effective in detecting compound words based on similar words, focusing on the degree of word relatedness because proper nouns appeared at a high frequency among the detected compound words. Additionally, the proposed method with the added functionality was the most accurate, so it can be said that the added functionality worked effectively.

Among the parameters of Word2Vec, four types of parameter values (1, 2, 3, and 4) are prepared for"Window Size," which sets the maximum distance between the current and predicted words within a sentence. Because of the experiments, the best result was obtained with Window Size = 2; thus, we adopted Window Size = 2 as the parameter this time.

Table 6: Number and percentage of proper nouns.

Method	Compound Word	Proper Noun	Rate
Proposed	264	128	48.5%
Proposed w/o Added Func	308	112	36.4%

6 EXPERIMENT (DARK JARGONS DETECTION)

6.1 Outline of Experiment

Using a set of words in a corpus, we experimented to detect dark jargons and compound-type dark jargons, which have not been detected by existing methods. We expected that compound-type dark jargons would be detected by registering them in the dictionary and then executing the program of the existing method (Hada et al., 2021). Specifically, we prepared 18 of 21,210 words as a word list for collation and aimed at detecting dark jargons.

6.2 Experimental Environment

Because the proposed method with added functions was the most accurate in the compound word detection experiment, a compound word dictionary was created using the proposed method.

6.3 Experimental Process (Dark Jargon Detection)

6.3.1 Creation of the User Dictionary for Word Segmentation

Compound words were added to the dictionary for word segmentation, and the process described in section 4.2 was repeated 10 times to create a compound word dictionary to enable word segmentation in units of compound words.

6.3.2 Creating Corpora

The process described in Section 5.2.1, Section 5.2.2, Section 5.2.3, and Section 5.2.4 was followed until the corpus was created.

6.3.3 Word Distributed Expression Processing

After the morphological analysis process, Word2Vec was used to process the word distribution. The parameters were set as follows (Table 7).

Table 7: Parameter of Word2Vec.

Parameter	Value
Size	300
Min-Count	3
Window Size	4
Methods	Skip-Gram (Mikolov et al., 2013b)

6.3.4 Execution of the Proposed System

As input to the system, a word list was created by extracting words that commonly occur in both corpora and words that only occur in the Bad corpus from the word distribution model. The number of words that commonly occur in both corpora was 19,068, and the number of words that only occur in the bad corpus was 2,152.

6.4 Results

Because of the experiment, 115 words were detected as candidates for dark jargons, and the classification results are presented in Table 8. We could also identify compound-type dark jargons detected by the proposed method, which could not be detected by existing methods. For example, 10 compound words such as "pineapple chunk," "jack-heller," and "blue dream," which refer to marijuana, were included in the classified words.

Table 8: Classification results.

Classification	Quantity	Rate
Dark jargons	74	64.3%
Related Words	20	17.4%
Part of Compound-Type dark jargons	14	12.2%
Unrelated	7	6.1%

In terms of precision, we compared our method, the baseline, and the existing method(Hada et al., 2022) by separating the case for including a part of the compound-type dark jargons in true and the case for not including it, see Table 9. The results showed that the proposed method performed better than both of the baseline and existing methods.

Furthermore, regarding the difference in accuracy between our method and the existing method, our method was 0.095 points more accurate when a part of the compound-type dark jargons was not included in true. When a part of the compound-type dark jargons were included in true, the difference between the two methods widened further, with the proposed method being 0.152 points more accurate.

Table 9: Comparison of precision.

Evaluation Method	Precision	
	a	b
Proposal method	0.765	0.643
the existing method	0.613	0.548
Baseline method	0.057	0.052

a) Include "Part of Compound-Type dark jargons" in true

b) Do not include "Part of Compound-Type dark jargons" in true

7 CONSIDERATION

In this experiment, those classified as "a part of compound word-type secret words" in Table 8 were classified as false positives. These were words that were used for malicious purposes, but when the original sentence was divided into spaces, a segment was cut off, and part of it was detected. Therefore, the part of the word alone did not have any meaning as a dark jargon. For example, "big" ("big · bats," "big · bat," etc. were identified) and "super" ("super · lemon · haze," "super · lemon · skunk," etc. were identified). These words were not detected as compound words by the proposed method based on similar words, because they appeared more frequently with other common words. For example, "super" and the top similar words were unrelated to dark jargons. Therefore, a method for detecting compound words that include words with a high frequency of occurrence with common words is a challenge for future study. Additionally, we will continue to study other words such as "doctor" ("Dr. · Greenspoon" and "Dr. · Jamaica" were identified), which could not be detected as compound-type dark jargons because a clause of compound-type dark jargon appeared as dark jargon.

8 CONCLUSIONS

To support cyber patrol, we proposed a method for detecting detect compound-type dark jargons, which has been a limitation of existing methods, and conducted dark jargon detection experiments after creating a compound word dictionary, aiming to detect dark jargons and compound-type dark jargons. The experimental results showed that the precision and accuracy of the proposed method were improved compared with existing methods and that the proposed method could detect 10 compound-type dark jargons that had not been detected by existing methods. These findings indicate that the combination of the proposed method and existing methods for compound word detection can be expected to provide efficient automatic detection of dark jargons.

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