Semantic Entanglement on Verb Negation

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Abstract: The word2vec, developed by Mikolov et al. in 2013, is an epoch-creating method that embeds words into a vector space to capture their fine-grained meaning. However, the reliability of word2vec is inconsistent. To evaluate the reliability of word vectors, we perform Mikolov's word analogy task, where $\mathrm{word_A}$, $\mathrm{word_B}$, and $\mathrm{word_C}$ are provided. Under the condition that $\mathrm{word_B}$ exhibits a particular relation with $\mathrm{word_A}$, the task involves searching the vocabulary and returning the most relevant word for $\mathrm{word_C}$ for the same relation. We conduct an experiment to return negative words for verbs using word2vec for 100 typical Japanese verbs and investigate the effect of context (i.e., surrounding words) on correct or incorrect responses. It is shown that the task fails when the sense of verbs and negative relation are entangled because the semantic calculation of verb negation does not hold.

1 INTRODUCTION

Recently, the automatic generation of natural language sentences has progressed significantly owing to the development of artificial intelligence (AI) technology. For example, the advent of technology that uses AI to generate fake news articles that appear real (Brown et al., 2020) has surprised humans, and Google Translate (Wu et al., 2016) can now provide translations that are similar to those written by humans.

Several methods have been developed to generate word vectors, the representative of which is word2vec, published by (Mikolov et al., 2013). The word2vec is based on the "distributional hypothesis" (Harris, 1954) pertaining to the meaning of a word, i.e., the hypothesis that the meaning of a word is determined by the context (originally, "a word is characterized by the company it keeps" (Firth, 1957)). More specifically, word2vec vectorizes words such that the inner product of word vectors that appear in similar contexts is a high value.

For example, the following are sentences using the verb "go" and its negation "do not go."

- I go to school.
- I go to the office.
- I do not go to school.
- I do not go to the office.

In this example, "go" and "do not go" are used in similar contexts, i.e., both are used with content words that represent a destination. Therefore, word2vec is expected to represent these words as similar vectors (i.e., two vectors with a high inner product value).

Conversely, the negation of verbs, such as "do not go" and "do not choose" are used in similar contexts. For example, they are often used in contexts with conjunctions to clarify reasons, as in the following examples:

- I do not go to school because it is far away.
- I do not choose it because I hate it.

However, it seems that these contexts share only function words, such as conjunctions, and not content words. Therefore, word2vec is not expected to represent the negation of these verbs as extremely similar vectors.

Conversely, word2vec is expected to yield vectors with similar differences regardless of verbs, i.e., vectors that represent the difference between the negation and affirmation of verbs. In other words, the following holds:

$$v_{\text{do not go}} - v_{\text{go}} \fallingdotseq v_{\text{do not choose}} - v_{\text{choose}} \quad (1)$$

This is because the part where the content words contribute to the vector construction is canceled, and

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only the negative function remains in the difference vectors.

1.1 Word Analogy Task

Mikolov et al., the developers of word2vec, reported in an experiment involving the "word analogy task" that the following equation holds when using word vectors generated by word2vec:

$$\mathrm{argmax}_{w \in \mathrm{Vocabulary}} \cos\left(v_{\mathrm{woman}} + \left(v_{\mathrm{king}} - v_{\mathrm{man}}\right), v_w\right) = \mathrm{queen} \tag{2}$$

Here, "Vocabulary" is a set of words, and cos (a, b) is an operation that calculates the cosine of the angle between vectors a and b.

Specifically, the word analogy task is as follows: First, $\mathrm{word_A}$, $\mathrm{word}_{\mathbf{B}}$, and $\mathrm{word_C}$ are provided, where $\mathrm{word_A}$ and $\mathrm{word_B}$ exhibit some relation (the type of relation is not specified). In this setting, the word analogy task requests to return the word ($\mathrm{word_D}$) that will be obtained when this relation is applied to $\mathrm{word_C}$.

In the example presented by Mikolov et al., $\mathrm{word_A}$ = man, $\mathrm{word_B}$ = king, $\mathrm{word_C}$ = woman, and $\mathrm{word_D}$ = queen. The problem was to infer, "If the man who governs the country is called the king, then what is the woman who governs the country?" This query can be returned correctly using word vectors generated by word2vec (the correct response is "queen").

1.2 Challenges to Be Addressed in This Study

Mikolov et al. showed some successful examples of the word analogy task when in fact, it failed in many cases. In particular, (Yoshii et al., 2015) reported that it was difficult to return the negation of a verb in Japanese.

For example, suppose $\mathrm{word_A}$ = go, $\mathrm{word_B}$ = do not go, $\mathrm{word_C}$ = choose, and $\mathrm{word_D}$ = do not choose. The task is to return the negation of "choose." The correct response is "do not choose." This is exactly the calculation problem using the following equation:

$$\mathrm{argmax}_{w \in \mathrm{Vocabulary}} \cos\left(v_{\mathrm{choose}} + \left(v_{\mathrm{do\ not\ go}} - v_{\mathrm{go}}\right), v_w\right) \tag{3}$$

If Eq. (1) holds, then it should be calculated as follows to obtain the correct response:

$$\begin{aligned}
&\mathrm{argmax}_{w \in \mathrm{Vocabulary}} \cos\left(v_{\mathrm{choose}} + \left(v_{\mathrm{do\ not\ go}} - v_{\mathrm{go}}\right), v_w\right) \\
&\fallingdotseq \mathrm{argmax}_{w \in \mathrm{Vocabulary}} \cos\left(v_{\mathrm{choose}} + \left(v_{\mathrm{do\ not\ choose}} - v_{\mathrm{choose}}\right), v_w\right) \\
&= \mathrm{argmax}_{w \in \mathrm{Vocabulary}} \cos\left(v_{\mathrm{do\ not\ choose}}, v_w\right) \\
&= \text{do not choose}
\end{aligned}$$

However, the equation was not calculated in this manner. In general, it is difficult to return a negative word for a verb when using word vectors generated by word2vec. In this study, we investigate the contributing factors.

The remainder of this paper is organized as follows: In Section 2, we present an experiment to return negative words for verbs using word2vec for 100 typical Japanese verbs. We report that $\mathrm{word_C}$ and $\mathrm{word_D}$, not $\mathrm{word_A}$ and $\mathrm{word_B}$, which affect the difficulty of the word analogy task. In Section 2, we report the following observation regarding the frequency of word occurrence in the corpus: When $\mathrm{word_C}$ and $\mathrm{word_D}$ appear frequently in the corpus, the analogy of the negation of a verb tends to be successful. Subsequently, in Section 3, we investigate the effect of context (i.e., surrounding words) on correct or incorrect responses and report the following observation: When $\mathrm{word_C}$ and $\mathrm{word_D}$ are likely to appear in common contexts, the analogy of the negation of a verb tends to be successful. Finally, in Section 4, we conclude the paper by summarizing the results and presenting some future directions.

2 WORD ANALOGY TASK EXPERIMENT FOR NEGATION OF VERBS

Using the word vectors generated by word2vec, we conducted an experiment wherein we performed a word analogy task to obtain negative words for specified verbs.

2.1 Method

2.1.1 Corpus

First, we extracted text from 10,000 web pages of Japanese Wikipedia and used them as the corpus for word2vec.

2.1.2 Morphological Analysis

Next, we used the morphological analyzer MeCab[1] to convert the text into word sequences. In addition, we combined the word labeled as "auxiliary verb" by MeCab with the verb that is the target of the auxiliary verb to form a synthetic word of the form "do not verb" ("ない" in Japanese = auxiliary verb = "do not" in English). Hence, we were able to obtain the negation of verbs as words.

2.1.3 Generating Word Vectors using Word2vec

We used word2vec to generate word vectors to increase the similarity (inner product) between words appearing in similar contexts in the corpus. Table 1 lists the values of the word2vec parameters used in this experiment.

Table 1: Parameter values used for word2vec.

Parameter	Value
window size	8 (default = 5)
# epochs	15 (default = 5)
# negative samplings	25 (default = 5)

- The parameter window size represents the number of surrounding words that define the context. The number of surrounding words required to generate word vectors may vary depending on the corpus used. In this experiment, we used text from Japanese Wikipedia, which includes various topics, as the corpus. We used a window size larger than the default value to precisely capture the meanings of various words appearing in this corpus.
- Because the quality of word vectors tends to improve when the numbers of epochs and negative samplings are high, these values are set to be larger than the default values.

2.1.4 Verbs Used in Experiment

The verbs used for the word analogy task in this experiment were the top 100 verbs that appear frequently in the corpus. Figure 1 shows a list of these verbs and their negative words.

2.1.5 Experimental Procedure

In the word analogy task, we first assume that the word for $\mathrm{word_A}$ is $\mathrm{word_B}$; subsequently, the word for $\mathrm{word_C}$ is obtained, i.e., $\mathrm{word_D}$. The experimental procedures are as follows:

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('する', 'しない'), ('なる', 'ならない'), ('ある', 'ない'), ('行う', '行わない'), ('できる', 'できな
い'), ('持つ', '持たない'), ('呼ぶ', '呼ばない'), ('受ける', '受けない'), ('見る', '見ない'), ('い
る', 'いない'), ('使う', '使わない'), ('いう', 'いわない'), ('言う', '言わない'), ('知る', '知らな
い'), ('用いる', '用いない'), ('含む', '含まない'), ('入る', '入らない'), ('考える', '考えない'), ('異
なる', '異ならない'), ('伴う', '伴わない'), ('出る', '出ない'), ('よる', 'よらない'), ('作る', '作らな
い'), ('得る', '得ない'), ('与える', '与えない'), ('描く', '描かない'), ('務める', '務めない'), ('思
う', '思わない'), ('示す', '示さない'), ('続く', '続かない'), ('除く', '除かない'), ('書く', '書かな
い'), ('出す', '出さない'), ('認める', '認めない'), ('語る', '語らない'), ('置く', '置かない'), ('加え
る', '加えない'), ('取る', '取らない'), ('行く', '行かない'), ('出来る', '出来ない'), ('求める', '求め
ない'), ('挙げる', '挙げない'), ('ちる', 'ちらない'), ('終わる', '終わらない'), ('結ぶ', '結ばない'),
('述べる', '述べない'), ('至る', '至らない'), ('始まる', '始まらない'), ('かける', 'かけない'), ('生ま
れる', '生まれない'), ('みる', 'みない'), ('つく', 'つかない'), ('残す', '残さない'), ('残る', '残らな
い'), ('とる', 'とらない'), ('果たす', '果たさない'), ('入れる', '入れない'), ('変わる', '変わらな
い'), ('含める', '含めない'), ('向かう', '向かわない'), ('選ぶ', '選ばない'), ('基づく', '基づかな
い'), ('進む', '進まない'), ('走る', '走らない'), ('合わせる', '合わせない'), ('来る', '来ない'), ('見
せる', '見せない'), ('失う', '失わない'), ('戻る', '戻らない'), ('経る', '経ない'), ('もつ', 'もたな
い'), ('つける', 'つけない'), ('読む', '読まない'), ('やる', 'やらない'), ('ひる', 'ひらない'), ('送
る', '送らない'), ('設ける', '設けない'), ('付ける', '付けない'), ('見える', '見えない'), ('現れる',
'現れない'), ('起こす', '起こさない'), ('迎える', '迎えない'), ('決める', '決めない'), ('聞く', '聞かな
い'), ('戦う', '戦わない'), ('開く', '開かない'), ('伝える', '伝えない'), ('続ける', '続けない'), ('扱
う', '扱わない'), ('定める', '定めない'), ('目指す', '目指さない'), ('くる', 'こない'), ('立つ', '立た
ない'), ('進める', '進めない'), ('起こる', '起こらない'), ('比べる', '比べない'), ('超える', '超えな
い'), ('演じる', '演じない'), ('違う', '違わない'), ('なす', 'なさない')
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Figure 1: List of 100 pairs of Japanese verbs and their negated words used in experiment.

(1) Based on the list shown in Figure 1, select a pair of verbs and their negative words (e.g. "go" and "do not go").

(2) Let the verb selected in (1) be $\mathrm{word_A}$ and the negative word of the selected verb be $\mathrm{word_B}$. (e.g., $\mathrm{word_A}$ = "go," $\mathrm{word_B}$ = "do not go").

(3) Select another pair from the list in Figure 1.

(4) Let the verb selected in (3) be $\mathrm{word_C}$ and the negative word of the selected verb be $\mathrm{word_D}$.

(5) Using the word vectors generated by word2vec, obtain the cosine similarity between $v_{\mathrm{word_C}} + v_{\mathrm{word_B}} - v_{\mathrm{word_A}}$ and each word vector for all Japanese words. Next, select the top 10 Japanese words with the highest cosine similarity.

(6) From the 10 words selected, 1 point is assigned if $\mathrm{word_D}$ (i.e., the correct answer) matches the word with the highest cosine similarity (the first place word), 0.5 points if it matches the second place word, and 0.25 points if it matches the third place word (if it does not match the words up to the third place, points are not assigned).

(7) Do not modify the pair selected in (1), replace the pair selected in (3) with another pair, and repeat steps (4) to (6).

(8) Replace the pair selected in (1) with another pair, and repeat steps (2) to (7).

2.2 Results

Table 2 shows the experimental results. Each row corresponds to a specific word analogy task and its results. Columns A, B, C, and D are $\mathrm{word_A}$, $\mathrm{word_B}$, $\mathrm{word_C}$, and $\mathrm{word_D}$, respectively. Columns E to N

[1] https://taku910.github.io/mecab/

Table 2: Experimental results (excerpt).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1					単語の類推タスクの結果(水色で塗られているセルは，単語Dと一致している単語)										
2	単語A	単語B	単語C	単語D(答え)	1	2	3	4	5	6	7	8	9	10	点数
3	する	しない	なる	(['ならない'])	('なった', 0.	('変わりなし	('変わらなし	('同じであそ	('言えない',	('いえない',	('同じであっ	('思える', 0.	('呼べない',	('重なる', 0	0
4	する	しない	ある	(['ない'])	('無い', 0.85	('ない', 0.83	('有る', 0.80	('多い', 0.7	('見当たら	('あった', 0.	('出ない', 0	('なかった',	('ありませ	('少なくない	0.5
5	する	しない	行う	(['行わない'])	('行わない',	('行なう', 0.	('行わなか	('おこなう',	('伴わない',	('行える', 0.	('行えない',	('使わない',	('避ける', 0.	('できない',	1
6	する	しない	できる	(['できない'])	('できない',	('出来ない',	('可能であ	('出来る', 0	('可能な', 0	('不可能な'	('可能だ', 0	('不可能で	('難しい', 0.	('無い', 0.74	1
7	する	しない	持つ	(['持たない'])	('持たない',	('もつ', 0.79	('持った', 0.	('併せ持つ'	('もたない',	('有する', 0.	('持ち', 0.67	('持たず', 0	('もった', 0.	('示さない',	1
8	する	しない	呼ぶ	(['呼ばない'])	('よぶ', 0.77	('言う', 0.74	('称する', 0.	('言わない'	('呼ばない',	('略す', 0.7	('言い換え	('呼べない',	('呼んだ', 0	('見なす', 0	0
9	する	しない	受ける	(['受けない'])	('受けない',	('受けた', 0.	('与えない',	('受けなか	('免れる', 0.	('受けず', 0	('与えなか	('うける', 0.	('行わなか	('行わない'	1
10	する	しない	見る	(['見ない'])	('見えない',	('見ない', 0.	('見た', 0.65	('知らない',	('映す', 0.6	('観る', 0.63	('読む', 0.6	('見える', 0.	('撮る', 0.62	('見せない'	0.5
11	する	しない	いる	(['いない'])	('いない', 0.	('いなかっ	('おらず', 0.	('います', 0	('いた', 0.75	('いません'	('おり', 0.69	('しまった',	('しまう', 0.6	('こなかっ	1
12	する	しない	使う	(['使わない'])	('使わない',	('用いない',	('用いる', 0.	('使えない',	('使える', 0.	('持たない',	('つけない',	('仕込む', 0	('覚える', 0.	('消せる', 0	1
13	する	しない	いう	(['いわない'])	('言う', 0.77	('いえない',	('言えない',	('限らない',	('言った', 0.	('言わない'	('思えない',	('呼べない',	('思う', 0.67	('云う', 0.66	0
14	する	しない	言う	(['言わない'])	('言わない',	('言えない',	('言った', 0	('いえない',	('思う', 0.73	('いう', 0.73	('思える', 0	('呼ばない',	('思った', 0	('呟く', 0.71	1

Table 3: Summary of experimental results (part of entire table).

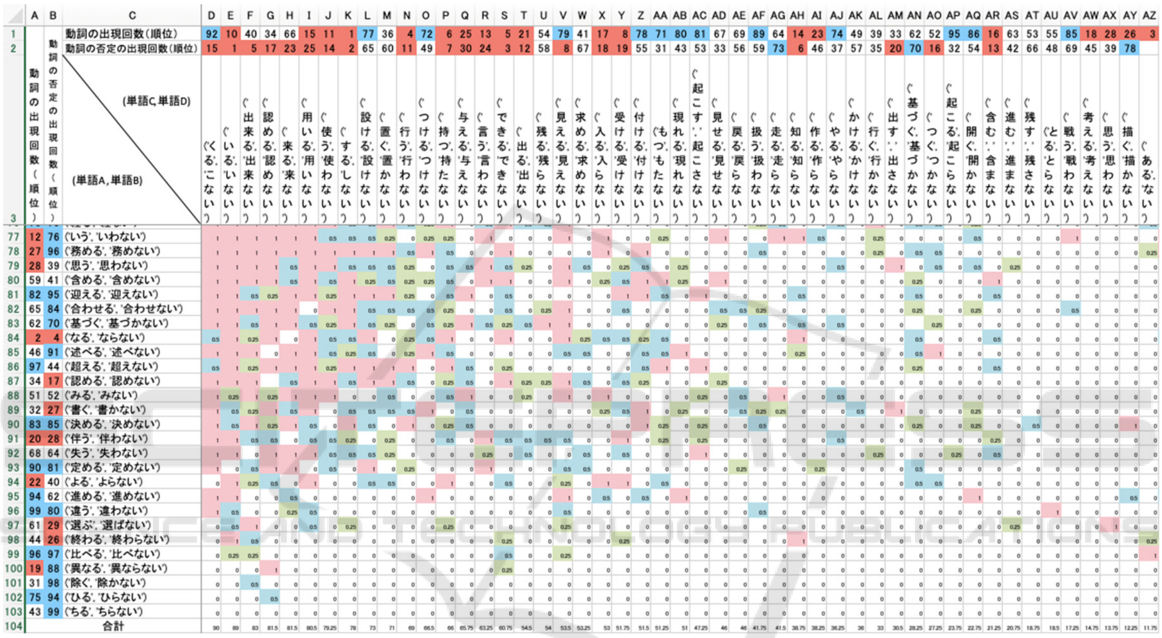
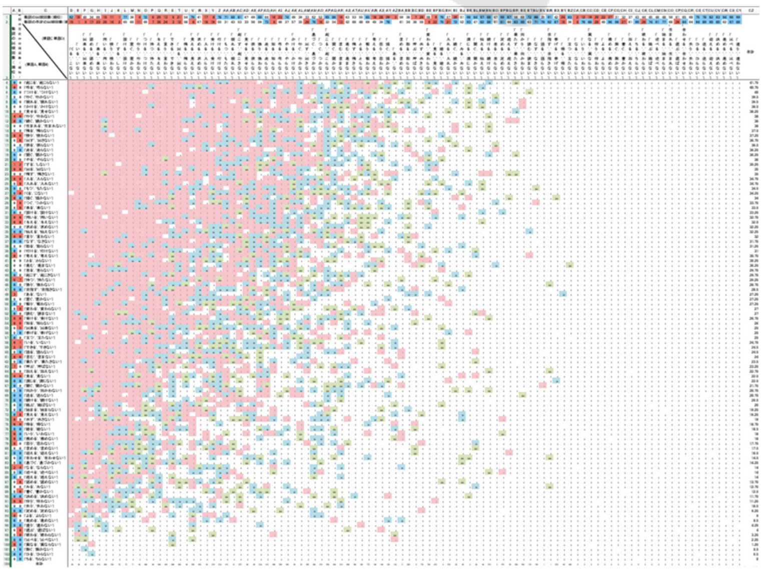


Table 4: Summary of experimental results (entire table).



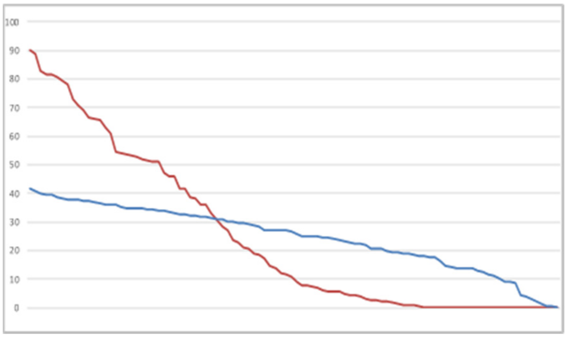


Figure 2: Plot of vertical sums of points (red graph); plot of horizontal sums of points (blue graph) in Table 3.

show a ranked list of words from the 1st to 10th in the descending order of cosine similarity with $v_{\mathrm{word}_\mathrm{C}} + v_{\mathrm{word}_\mathrm{B}} - v_{\mathrm{word}_\mathrm{A}}$. The words in the blue cells matched with the correct answers (i.e., they matched with word_D). The numerals in the rightmost column show the points earned based on step (6). It is noteworthy only the partial results are shown in Table 2, whereas the overall results were obtained in the same format.

Table 4 is a summary of Table 2, with the pair of word_A and word_B in column C, and the pair of word_C and word_D in the third row. Table 3 shows an enlarged version of the top three rows and the lower rows of the left part of Table 4.

- For example, in cell E84 of Table 3 where row 84 and column E coincide, word_A and word_B are "become" and "do not become," respectively, and word_C and word_D are "exist" and "do not exist," respectively. In this setting for the word analogy task, the point earned is 1.0, as indicated in cell E84; this means that the first place word matches the correct answer.

- In Tables 3 and 4, cells with values of 1, 0.5, and 0.25 are indicated in pink, light blue, and light green, respectively.

- The numerals in the bottom row cells of Tables 3 and 4 are the total scores, i.e., the vertical sums of the points. Additionally, pair word_C and word_D in the third row are sorted from left to right in the descending order of their total scores.

- The maximum value of the total scores is 99 because the 100 pairs of verbs and their negation shown in Figure 1 are used to generate a word analogy task alternately.

- Owing to space limitations, the right side of column AZ is not shown in Table 3; however, the horizontal sums of the points were calculated. Pair word_A and word_B in column C were sorted from top to bottom in the descending order of the sums.

- The numerals in the first and second rows are the ranking of word_C among 100 verbs and the ranking of word_D among 100 verb negations used in the experiment with respect to the number of occurrences in the corpus, respectively. Similarly, the ranking of word_A among 100 verbs and the ranking of word_B among 100 verb negations are shown in columns A and B, respectively. The red and blue cells indicate the top and bottom 30 rankings, respectively.

2.3 Discussion

In Figure 2, the red graph is a plot of the vertical sums of the points shown in Table 4, and the blue graph is a plot of their horizontal sums. We observed that the red graph varied more significantly than the blue one. This implies that the difficulty of the word analogy task depends primarily on word_C and word_D rather than word_A and word_B.

Therefore, we focused on word_C and word_D. As shown in the second row of Table 4, many cells on the left side are red, whereas many cells on the right side are blue. Because the red and blue cells in the second row indicate high and low frequencies of word_D occurrence, respectively, if word_D appears frequently in the corpus, then the vertical sum of the points tends to be large, and vice versa. Furthermore, if word_D appears frequently in the corpus, then the word vector of word_D generated by word2vec is sufficiently precise to return a correct response to the word analogy task. Therefore, the vertical sum of points can be interpreted as a success indicator for the word analogy task.

In this experiment, the top 100 verbs that appear frequently in the corpus were used as word_C, and the word vector of word_C generated by word2vec should always be precise.

However, the right side of the second row in Table 4 contained red cells, where the vertical sum of the points indicated a low value. These red cells reflect the difficulty of the word analogy task despite the high occurrence frequency of word_D in the corpus.

3 STUDY OF SURROUNDING WORDS

In the previous section, we mentioned that word analogy tasks are often difficult, although $\mathrm{word_C}$ (i.e., the verb) and $\mathrm{word_D}$ (negation of the verb) appear frequently in the corpus. We presume that the difficulty emerges from the words around $\mathrm{word_C}$ and $\mathrm{word_D}$ because word2vec generates a word vector using the surrounding words. Therefore, we analyzed the surrounding words of $\mathrm{word_D}$, i.e., the red cells in the second row of Table 4. Furthermore, we analyzed the words surrounding $\mathrm{word_C}$ paired with $\mathrm{word_D}$.

The surrounding words are the two words preceding the word of interest. We analyzed the two preceding words because in Japanese, words that describe verbs appear immediately before the verbs.

3.1 Method

For pair $\mathrm{word_C}$ and $\mathrm{word_D}$, the following procedures were used:

(1) Let $\mathrm{Surrounding_C}$ be a set of surrounding words for $\mathrm{word_C}$, and $\mathrm{Count_C}(w)$ be the number of co-occurrences of the surrounding word $w \in \mathrm{Surrounding_C}$ with $\mathrm{word_C}$ in the corpus. For $\mathrm{word_C}$, we calculated the total number of co-occurrences, $\mathrm{TotalCount_C} = \sum_w \mathrm{Count_C}(w)$. For example, when $\mathrm{word_C}$ = "come" (= "来る" in Japanese), $\mathrm{TotalCount_C} = 8533$.

(2) For the word $w \in \mathrm{Surrounding_C}$, calculate the probability that w co-occurs with $\mathrm{word_C}$, i.e., $\mathrm{Prob_C}(w) = \mathrm{Count_C}(w) \div \mathrm{TotalCount_C}$. For example, when $\mathrm{word_C}$ = "come," because the word "out" co-occurs with "come" 236 times, $\mathrm{Prob_C}(\text{"out"}) = 236 \div 8533 \fallingdotseq 0.028$.

(3) Let $\mathrm{Surrounding_D}$ be a set of surrounding words of $\mathrm{word_D}$, and $\mathrm{Count_D}(w)$ be the number of co-occurrences of the surrounding word $w \in \mathrm{Surrounding_D}$ with $\mathrm{word_D}$ in the corpus. For $\mathrm{word_D}$, we calculated the total number of co-occurrences, $\mathrm{TotalCount_D} = \sum_w \mathrm{Count_D}(w)$. For example, when $\mathrm{word_D}$ = "do not come" (= "来ない" in Japanese), $\mathrm{TotalCount_D} = 915$.

(4) For the word $w \in \mathrm{Surrounding_D}$, calculate the probability that w co-occurs with $\mathrm{word_D}$, i.e., $\mathrm{Prob_D}(w) = \mathrm{Count_D}(w) \div \mathrm{TotalCount_D}$. For example, when $\mathrm{word_D}$ = "do not come," because the word "out" co-occurs with "do not come" 63 times, $\mathrm{Prob_D}(\text{"out"}) = 63 \div 915 \fallingdotseq 0.069$.

(5) For the word $w \in \mathrm{Surrounding_C} \cup \mathrm{Surrounding_D}$, compare the values of $\mathrm{Prob_C}(w)$ and $\mathrm{Prob_D}(w)$ to identify the smaller value. Subsequently, the total value $\mathrm{HistIntersect} = \sum_w \min(\mathrm{Prob_C}(w), \mathrm{Prob_D}(w))$ is calculated. In other words, the histogram intersection of the two discrete probability distributions, $\mathrm{Prob_C}(w)$ and $\mathrm{Prob_D}(w)$, is calculated. The larger the value of HistIntersect, the more likely is the verb and its negated word to share the surrounding words, i.e., the verb and its negated word are more likely to be used in the same context.

3.2 Results

The results of this study are summarized in Table 5. Columns B, C, and D contain $\mathrm{word_C}$, $\mathrm{word_D}$, and HistIntersect, respectively. Column A contains the vertical sum of the points in Table 4 for pair $\mathrm{word_C}$ and $\mathrm{word_D}$, i.e., a success indicator of the word analogy task. As presented in Table 5, the value of HistIntersect tends to be large for pair $\mathrm{word_C}$ and $\mathrm{word_D}$, whose success indicator of the word analogy task is high.

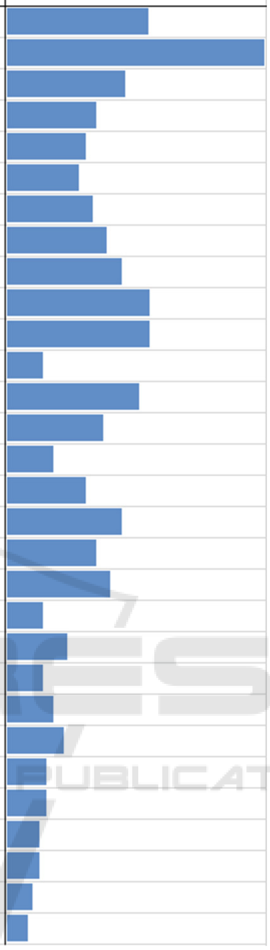
3.3 Discussion

We discovered that the word analogy task is easy when a verb and its negative word share the same surrounding words, that is, when they are used in the same context. For example, the word that appears most frequently as a surrounding word for "come" is "out," which is the most frequently used word around "do not come" as well. Specifically, the expressions "come out" (= "出て来る" in Japanese) and "do not come out" (= "出て来ない" in Japanese) appear frequently in the corpus. When expressions in which the verb can be replaced with the negative word of the verb and vice versa appear frequently in the corpus, the analogy task is easy.

Conversely, when the surrounding words are only used with either a verb or its negative word, then the analogy task becomes difficult. For example, the word that appears the most frequently as a surrounding word for the negative word "do not get" (= "得ない" in Japanese) is "any choice but to do" (= "せざるを" in Japanese). By contrast, "any choice but to do" has never appeared as a surrounding word for "get" (= "得る" in Japanese) in the corpus. When surrounding words co-occur only with either a

Table 5: Results of this study.

	A	B	C	D	E
1	Vertical sum of points in Table 2.3.2	word C (verb)	word D (negation of verb)	HistIntersect	Bar Chart of HistIntersect
2	90.00	くる	こない	0.50	
3	89.00	いる	いない	0.72	
4	83.00	出来る	出来ない	0.33	
5	81.50	認める	認めない	0.25	
6	81.50	来る	来ない	0.22	
7	80.50	用いる	用いない	0.20	
8	79.25	使う	使わない	0.24	
9	78.00	する	しない	0.28	
10	69.00	行う	行わない	0.32	
11	66.00	持つ	持たない	0.40	
12	65.75	与える	与えない	0.40	
13	63.25	言う	言わない	0.10	
14	60.75	できる	できない	0.37	
15	54.50	出る	出ない	0.27	
16	53.50	見える	見えない	0.13	
17	53.00	入る	入らない	0.22	
18	51.75	受ける	受けない	0.32	
19	38.75	知る	知らない	0.25	
20	30.50	出す	出さない	0.29	
21	21.75	つく	つかない	0.10	
22	21.25	含む	含まない	0.17	
23	7.25	変わる	変わらない	0.10	
24	6.75	見る	見ない	0.13	
25	5.75	入れる	入れない	0.16	
26	0.50	得る	得ない	0.11	
27	0.00	書く	書かない	0.11	
28	0.00	なる	ならない	0.09	
29	0.00	伴う	伴わない	0.09	
30	0.00	選ぶ	選ばない	0.07	
31	0.00	終わる	終わらない	0.06	



verb or its negative word (such as in idiomatic expressions), the analogy task becomes challenging.

4 CONCLUSIONS

We discovered that the following two conditions were necessary to correctly respond to the word analogy task for a verb and its negated word:

(1) Both the verb and its negated word appear frequently in the corpus.

(2) The verb and its negated word share the same surrounding words, i.e., they are used in the same context.

In particular, regarding (2), we assumed that the surrounding words shared by word_C and word_D represented their base meanings. Moreover, the operation of $v_{\mathrm{word}_\mathrm{D}} - v_{\mathrm{word}_\mathrm{C}}$ canceled the base meaning, causing only the relation between word_C and word_D (i.e., negation) to remain. However, if no surrounding word is shared by word_C and word_D, then the operation $v_{\mathrm{word}_\mathrm{D}} - v_{\mathrm{word}_\mathrm{C}}$ will not cancel the base meaning.

In addition, the correct and incorrect responses to the word analogy task depended on the method of word vector generation. In this study, word vectors were generated using the surrounding words defined by a fixed window. However, the word vectors changed based on the definition of the surrounding words. In fact, an attempt to generate word vectors using an attention mechanism instead of a fixed window has been reported (Sonkar et al., 2020). Furthermore, word vectors can be generated using not only surrounding words, but also grammatical information, such as part of speech and conjugations of words. A future task is to generate word vectors that can decompose the meaning of each word and the relation between words with fine granularity.

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