

Metonymy Analysis Using Associative Relations between Words

Takehiro Teraoka

School of Media Science, Tokyo University of Technology
1404-1, Katakura, Hachioji, Tokyo, 192-0914 Japan
teraokatkh@stf.teu.ac.jp

Abstract

Metonymy is a figure of speech in which one item's name represents another item that usually has a close relation with the first one. Metonymic expressions need to be correctly detected and interpreted because sentences including such expressions have different meanings from literal ones; computer systems may output inappropriate results in natural language processing. In this paper, an associative approach for analyzing metonymic expressions is proposed. By using associative information and two conceptual distances between words in a sentence, a previous method is enhanced and a decision tree is trained to detect metonymic expressions. After detecting these expressions, they are interpreted as metonymic understanding words by using associative information. This method was evaluated by comparing it with two baseline methods based on previous studies on the Japanese language that used case frames and co-occurrence information. As a result, the proposed method exhibited significantly better accuracy (0.85) of determining words as metonymic or literal expressions than the baselines. It also exhibited better accuracy (0.74) of interpreting the detected metonymic expressions than the baselines.

Keywords: Metonymy, Associative Concept Dictionary, Verb, Noun

1. Introduction

Metonymy is a figure of speech, in which one item's name represents another item that usually has a close relation to the first. The relations shown in Table 1 (Lakoff and Johnson, 1980; Yamanashi, 1988) have various patterns based on contiguity. Below is a Japanese metonymic example of the spatial contiguity for 'Container for Content' and its direct English translation:

kare-ga isshoubin-wo nomihoshita
'He drank a 1.8-liter bottle.'

The Japanese sentence does not mean that he drank the bottle itself, but its contents, usually Japanese sake. Japanese sake is generally served from a 1.8-liter glass bottle, called *isshoubin*. Therefore, the above example sentence, where *isshoubin* is a metonymic expression, means that he drank Japanese sake from a 1.8-liter bottle. Since a sentence including metonymy is grammatical on a literal level and metonymic relations have many patterns, it is difficult for computers to analyze these expressions.

Previously, rule-based or statistical approaches have been used to detect and interpret metonymy. Rule-based approaches use semantic networks and rules to discriminate metonymy (Bouaud et al., 1996; Fass, 1991). Statistical approaches use corpus-based metonymy resolution on location names, which is done with machine learning techniques (Markert and Nissim, 2003). Moreover, by using syntactic or semantic information as machine learning features, five different studies classified the large data set of metonymic and literal meanings in the SemEval-2007 Task 08: *Metonymy Resolution at SemEval-2007* (Nicolae et al., 2007; Poibeau, 2007). Previous studies in the Japanese language also used thesauri to detect metonymy and statistical approaches with example-based information extracted from newspaper corpora in interpreting metonymy (Murata et al., 2000).

| Metonymic patterns -spatial contiguity- | Examples of sentences (metonymic reading) |
|--|---|
| Container for Content | <i>kare-ha glass-wo nonda</i> 'He drank the glass (liquid).' |
| Producer for Product | <i>kare-ha Mahler-wo kiita</i> 'He listened to <u>Mahler</u> (symphony).' |
| Controller for Controlled | <i>Nixon-ga Hanoi-wo bakugekishita</i> ' <u>Nixon</u> (government) bombed Hanoi.' |
| Object Used for User | <i>gakuseifuku-ga aruiteiru</i> ' <u>The school uniform</u> (student) is walking.' |
| Material for Product | <i>kare-ha caffeine-wo nonda</i> 'He drank <u>caffeine</u> (soft drink).' |
| Others | <i>riron-ga sore-wo jisshoushita</i> ' <u>The theory</u> (proposer) claimed that.' |

Table 1: Metonymic expressions with spatial contiguity

However, from our conversations and reading, metonymic expressions in sentences are understood using associative relations between words. The metonymic relations listed in Table 1 are psychologically associative (Yamanashi, 1988). For the present study, I argued that computers also require associative information to analyze metonymies more accurately. In a previous study, using associative information to detect metonymic expressions was confirmed to be effective (Teraoka et al., 2012; Teraoka et al., 2013). It was argued that associative information will also improve the accuracy of interpreting metonymic expressions as well as their detection.

An associative approach is therefore proposed for metonymy analysis with the associative concept dictionary for verbs and nouns (referred as to Verb-ACD and Noun-ACD) (Teraoka et al., 2010; Okamoto and Ishizaki, 2001). To evaluate this approach, test sentences used in the previous study were prepared and the results from the proposed method were compared with those of the previous study.

2. ACD Construction

In this section, I describe the Verb-ACD (Teraoka et al., 2010) and Noun-ACD (Okamoto and Ishizaki, 2001) used to extract associative information for detecting and Interpreting metonymic expressions.

2.1. Verb-ACD

The Verb-ACD consists of the following three elements: stimulus words, associated words from the stimulus words with semantic relations, and word distances among them. To collect associative information on verbs, large-scale association experiments were conducted on the web where the stimulus words were basic verbs with semantic relations corresponding to deep cases. These verbs were from Japanese elementary school textbooks (Kai and Matsukawa, 2001), and the entries were prioritized in a basic Japanese dictionary (Morita, 1989).

By using the linear programming method, the word distance between the stimulus word and associated one was quantified. As shown in Eq. (1), the distance $D(x, y)$ between the stimulus word x and associated word y is expressed with the following formulas:

$$D(x, y) = \frac{7}{10}F(x, y) + \frac{1}{3}S(x, y) \quad (1)$$

$$F(x, y) = \frac{N}{n(x, y) + \delta} \quad (2)$$

$$\delta = \frac{N}{10} - 1 (N \geq 10) \quad (3)$$

$$S(x, y) = \frac{1}{n(x, y)} \sum_{i=1}^{n(x, y)} s_i(x, y). \quad (4)$$

Table 2 lists the deep cases and examples when the stimulus word is the Japanese word *hakobu* ‘convey’. The distance consists of the inverse frequency of an associated word $F(x, y)$ and the average associated word order $S(x, y)$. Each coefficient was obtained using the simplex method. Let N denote the number of participants in the experiments, and $n(x, y)$ denote the number of participants who responded with the associated word y to the stimulus word x . Let δ denote a factor introduced to limit the maximum value of $F(x, y)$ to 10, and let $s(x, y)$ denote the associated word’s order of each participant. Three elements, the stimulus verbs, associated words, and their distances, were used to construct the Verb-ACD.

There are currently 519 stimulus verbs in the Verb-ACD, and the total number of participants is approximately 2,200. All participants are undergraduates and graduate students of Keio University. For this study, each stimulus verb was presented to 40 participants. There were approximately 220,000 associated words. When all overlapping words were eliminated, there were approximately 45,000 associated words.

2.2. Noun-ACD

The Noun-ACD also consists of stimulus words, i.e., nouns, associated words with semantic relations, and word distances among these words (Okamoto and Ishizaki, 2001). Table 3 lists the semantic relations and examples when the

| Deep case | Associated words (Word distance) |
|-----------|----------------------------------|
| Agent | I (3.60), Mover (4.21) |
| Object | Package (1.36), Furniture (7.78) |
| Source | House (1.45), School (3.81) |
| Goal | House (1.92), Station (3.73) |
| Duration | Morning (2.71), Midnight (5.88) |
| Location | Warehouse (3.73) |
| Tool | Car (1.62), Hands (3.47) |
| Aspect | Desperately (3.17) |

Table 2: Example of associated words in Verb-ACD (stimulus word: ‘convey’)

| Semantic relation | Associated words (Word distance) |
|-------------------|------------------------------------|
| Hypernym | Book (1.17) |
| Hyponym | English-Japanese dictionary (2.31) |
| Part / Material | Paper (1.23), page (3.31) |
| Attribute | Heavy (2.00), Difficult (5.54) |
| Synonym | Encyclopedia (5.60) |
| Action | Consult (1.63), Investigate (1.86) |
| Situation | Library (1.66), Book store (2.22) |

Table 3: Example of associated words in Noun-ACD (stimulus word: ‘dictionary’)

stimulus word is the Japanese word *jisho* ‘dictionary’. Currently, the number of stimulus words in the Noun-ACD is 1,100 and there are over 5,000 participants. For this study, each stimulus word was presented to 50 participants. There were approximately 280,000 associated words. After eliminating all overlapping words, there were approximately 64,000 associated words.

3. Proposed Method

To detect metonymic expressions in sentences and interpret them, the Verb-ACD, Noun-ACD, Japanese Word-Net (Isahara et al., 2008), and *Goi-Taikei*—A Japanese Lexicon (Ikehara et al., 1999) were used. The proposed method extracts attribute values of input sentences and detects metonymic expressions with decision tree learning. Figure 1 shows the ‘Detecting Phase’ with my basic idea and the attributes of decision tree learning and ‘Interpreting Phase’.

3.1. Detecting Metonymic Expressions

By using noun properties in the *Goi-Taikei*, this detecting phase was slightly enhanced from the previous system (Teraoka et al., 2012; Teraoka et al., 2013). As shown in Figure 1, the proposed method basically detects metonymic expressions with associative information by using the relations of two paths of synset nodes in Japanese Word-Net. One is the path from the synsets of associated words to their hypernym synsets. The other is from the synsets of each word in a sentence to their hypernym synsets. If there is a shared synset node between these two paths and this node distance is short, the word in the sentence is regarded as ‘Literal’. On the other hand, it is possible to be a metonymic expression if there is no shared synset or the

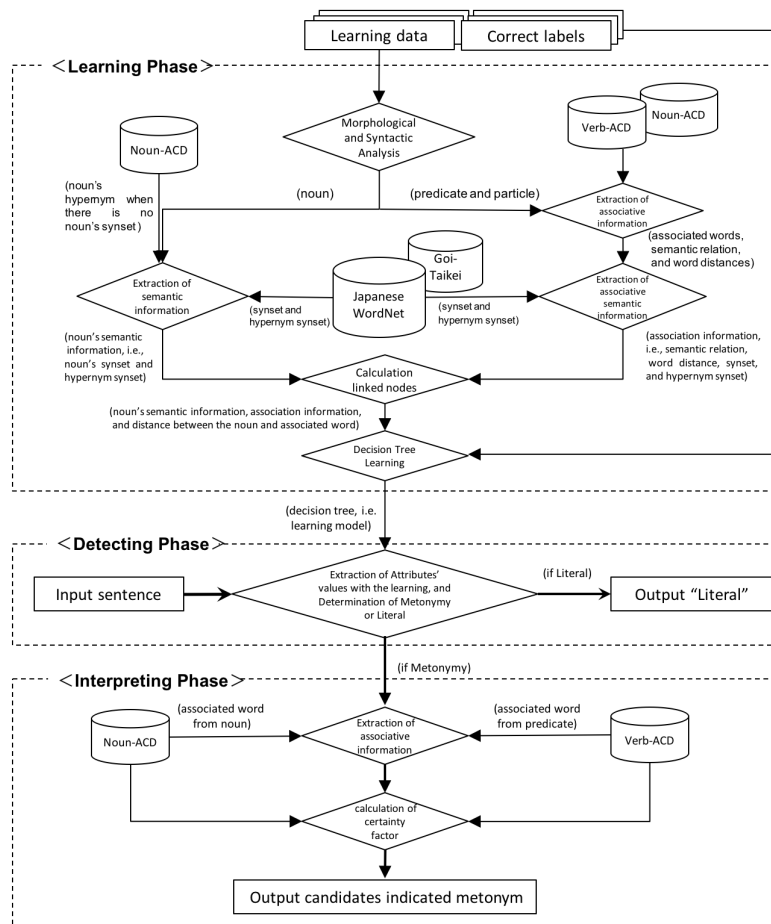


Figure 1: Method outline

node distance is long. In the same way, the method also obtains the node distance with the noun properties in Goi-Taikei and uses the longer of these node distances. A method for artificially determining whether the distance is short or long has the potential to be ad-hoc. I used decision tree learning for detecting metonymic expressions. Extracting the attributes of the learning phase consists of the following four steps.

1. **Morphological and Syntactic Analyses.** The proposed method analyzes each sentence in the learning data morphologically¹ and syntactically².
2. **Extraction of Associative Information.** From the results of the morphological and syntactic analyses, the proposed method extracts a predicate in the sentence and its modification relations. When the predicate is a verb or a verb formed by adding *suru* to a noun, e.g., *taiho-suru* ‘arrest (verb)’ where *suru* is added to *taiho* ‘arrest (noun)’, the shortest and second-shortest associated words from a pair of predicate verb and particle corresponding to the semantic relation in Table 4 are then extracted from the Verb-ACD. If the sentence has more than one particle, the method extracts the associated words from each noun with the particle. If the

| Japanese particle | Deep case |
|--------------------|----------------|
| <i>ga, wa</i> | Agent |
| <i>wo, ni</i> | Object |
| <i>kara, yori</i> | Source |
| <i>made, e, ni</i> | Goal |
| <i>de</i> | Location, Tool |

Table 4: Japanese particles corresponding to deep cases in Verb-ACD

predicate is anything but a verb, two stimulus words of the noun as an associated word with the semantic relation Attribute in Table 3 are extracted from the Noun-ACD. In the same manner as with the predicate verb, these word distances are the shortest and second-shortest between the predicate, i.e., the associated and stimulus words.

3. **Extraction of Noun Information.** The proposed method extracts synsets and hypernym synsets of all nouns in a sentence from Japanese WordNet. These hypernym synsets are all synsets that the method obtains from nouns in the sentence to each third upper level for the synset hierarchy. If there are proper nouns in the sentence, it extracts each synset of properties from the result of the morphological analysis because

¹Using MeCab 0.996.

²Using CaboCha 0.69.

| Attribute | Description | Value |
|----------------------------------|--|---|
| <i>Semantic_relation</i> | Semantic relations corresponding to particles with nouns in sentence | Agent, Object, Source, Goal, Location, Tool, Noun |
| <i>Distance_1st_candidate</i> | Shortest word distance between predicate and associated words | Continuous |
| <i>Distance_2nd_candidate</i> | Second shortest word distance between predicate and associated words | Continuous |
| <i>Number_A_synset</i> | Number of synsets of associated words | Continuous |
| <i>Number_A_property</i> | Number of noun properties (Goi-Taikai) of associated words | Continuous |
| <i>Number_A_hyponym</i> | Sum of hyponym synsets from associated words for three upper levels | Continuous |
| <i>Number_A_hyponym_property</i> | Sum of hyponym noun properties (Goi-Taikai) from associated words for three upper levels | Continuous |
| <i>Number_N_synset</i> | Number of synsets of nouns in sentence | Continuous |
| <i>Number_N_property</i> | Number of noun properties (Goi-Taikai) of nouns in sentence | Continuous |
| <i>Number_N_hyponym</i> | Sum of hyponym synsets from nouns for three upper levels | Continuous |
| <i>Number_N_hyponym_property</i> | Sum of hyponym noun properties (Goi-Taikai) from nouns for three upper levels | Continuous |
| <i>Number_HN_synset</i> | Number of synsets of hyponyms of nouns in sentence | Continuous |
| <i>Number_HN_hyponym</i> | Sum of hyponym synsets of hyponyms of the nouns in sentence | Continuous |
| <i>Match_node</i> | Degree of linked nodes from each synset (or noun property) of associated words and nouns in sentence to shared one | None, Near, Middle-Near, Middle, Middle-Far, Far |

Table 5: Attributes and values with decision tree learning

Japanese WordNet does not have enough synsets of proper nouns. For example, if one of the proper nouns in the sentence in Table 1 is *hanoi* ‘Hanoi’, the method extracts synsets and hyponym synsets of *chiiki* ‘LOCATION’, which is a property from the result of morphological analysis.

4. **Confirmation of Shared Synset.** By comparing synsets and hyponym synsets of the associated words with those of nouns or properties of proper nouns in a sentence, the proposed method confirms whether a shared synset node is between both paths of synset nodes. If there is one or more shared synset, the method obtains the node. Moreover, it obtains the other node distance with the noun property hierarchy in Goi-Taikai. It prioritizes the farther node distance as the attribute of decision tree learning.

Let *Match_node* denote the degree of linked synset nodes (or noun property nodes) from each synset (noun property) of associated words and nouns in the sentence to the shared one. By using the sum of linked nodes, this degree was separated into the following six levels: ‘None’, ‘Near’, ‘Middle-Near’, ‘Middle’, ‘Middle-Far’, and ‘Far’. ‘None’ means that there was no shared synset (or noun property), i.e., the noun was determined as ‘Metonymic’. ‘Near’ means that either the synset (or noun property) of the associated word or that of the noun in the sentence was at least the shared one, i.e., the average number of linked nodes was between 0 and 1. ‘Middle-Near’ means that the average number of nodes was between 1 and 2, i.e., the sum of linked nodes was 3 or 4. ‘Middle’ means that the sum of linked nodes was 5 or 6. ‘Middle-Far’ means that the sum of all nodes was between 7 and 8. ‘Far’ means that the sum

of linked nodes was more than 8.

Therefore, in this learning phase, the proposed method extracts the attributes of decision tree learning in Table 5 and determines each noun as ‘Metonymic’ or ‘Literal’ with the decision tree.

3.2. Interpreting Metonymic Expressions

When the proposed method detects ‘Metonymic’ in the interpreting phase, it presents candidates indicated by the metonym by using the Verb-ACD and Noun-ACD. There are three steps of outputting candidates.

1. **Extraction of predicate word information.** The proposed method extracts associated words of the predicate verb with deep cases corresponding to the Japanese particles in Table 4. It extracts these words from mainly the Verb-ACD. If the predicate word is a noun or adjective, the method extracts words of the predicate word with Attribute in Table 3.
2. **Extraction of noun information.** The proposed method also extracts words associated with nouns in a sentence with Part/Material and Situation in Table 3. If there are no words with the above semantic relations, the method extracts the noun’s hyponym in the Noun-ACD then extracts words of the hyponym with Part/Material and Situation.
3. **Output of candidates by certainty factor.** If there are words shared between extracted words from the Verb-ACD and those from the Noun-ACD, the method determines these words as interpretation candidates and calculates certainty factors using both their word distances. To prevent incorrect interpretations with a

| Metonymic sentence (English translation) | Literal sentence (English translation) |
|--|--|
| <i>isshoubin-wo nonda</i> (Someone drank the issho-bottle.) | <i>sake-wo nonda</i> (Someone drank the sake.) |
| <i>kasetsu-ga genri-wo setsumei-suru</i> (The hypothesis explains the elements.) | <i>hito-ga genri-wo setsumei-suru</i> (People explain the elements.) |
| <i>shirobai-ga ihansha-wo taiho-shita</i> (The police motorcycle arrested the criminals.) | <i>keisatsukan-ga ihansha-wo taiho-shita</i> (The police man arrested the criminals.) |
| <i>shikisha-ha sono-clarinet-wo waratta</i> (The conductor laughed at the clarinet.) | <i>shikisha-ha sono-ensosha-wo waratta</i> (The conductor laughed at the player.) |
| <i>kao-wo soru</i> (Someone shaves own face.) | <i>hige-wo soru</i> (Someone shaves a beard.) |

Table 6: Examples of test sentences (in Japanese)

low certainty factor, the method uses a threshold k expressed by the average of certainty factors of all candidates shown in Eq. (6). The certainty factor C is defined as

$$C = \frac{1}{L_V(L_N + L_H)} \quad (L_V L_N \neq 0) \quad (5)$$

$$k = \frac{1}{n} \sum_{i=1}^n C_i \quad (0 < C_i \leq 1) \quad (6)$$

Let L_V , L_N , and L_H denote the word distance between a candidate and predicate verb, that between a candidate and noun in a sentence, and that between a noun in a sentence and its hypernym, respectively. If no hypernym is used, L_H is zero. Let n denote the number of all candidates. Finally, the method outputs candidate words in descending order of certainty factors that are more than or equal to the threshold.

4. Experiment

To detect and interpret metonymic expression, Murata used mainly case frame data and co-occurrence data from newspaper corpora, respectively. To evaluate the proposed method, I prepared two baseline methods in which the Case Frame (Kawahara and Kurohash, 2006) and newspaper corpora were used to automatically detect metonymies in the previous study (Murata et al., 2000). I prepared test sentences with literal and metonymic expressions and evaluated the proposed method by comparing its accuracy, recall, precision, and F-measure rates with those of the baselines. In this section, I describe the baselines, test sentences, and evaluation results.

4.1. Baseline Method

One baseline method (Case Frame-Goi-Taikai (CF-GT)) consisted of case frame structures in the Case Frame and noun properties in Goi-Taikai, which were used for detecting metonymies (Murata et al., 2000). It first selects a case frame of the predicate after morphological and syntactic analyses of an input sentence. To detect metonymies, it uses the highest and second highest collocation frequencies of the noun in each case frame of the predicate verb. It then obtains nouns in the syntactic information and their properties. These noun properties consist of nouns and are

expressed by the hypernyms and hyponyms in the noun semantic hierarchy. As with the proposed method, CF-GT also uses decision tree learning to determine the word as ‘Metonymic’. After detecting metonymies, it interprets them as metonymic understanding words by using the collocation frequencies of the noun in the sentences in the newspaper corpora.

Another baseline method (Case Frame-Japanese WordNet (CF-JWN)) uses the Case Frame and synsets in Japanese WordNet to detect metonymies. It uses synsets to obtain node distance and the rest to do the same as CF-GT. It also uses the collocation frequencies in the newspaper corpora to interpret metonymies.

4.2. Test Sentences

For this evaluation, I prepared 90 test sentences that consisted of 45 sentences with metonymic expressions and 45 with literal expressions. As shown in Table 6, most of the former were extracted from previous studies (Murata et al., 2000; Yamanashi, 1988). The latter included metonyms that were metonymic understanding words from previous studies and grammar books. In the 90 test sentences, there were 108 nouns the proposed method and baselines determined as ‘Metonymic’ or ‘Literal’.

4.3. Results and Discussion

4.3.1. Detection of Metonymies

To determine each noun as ‘Metonymic’ or ‘Literal’, I extracted attributes from the 90 test sentences and constructed 108 cases. I then trained 107 cases and tested the other case with the training data. By running 108 folds, each case was determined automatically as ‘Metonymic’ and ‘Literal’. From Table 7, we can see that the proposed method correctly determined 92 cases determined as ‘Metonymic’ or ‘Literal’ in 108 cases. On the other hand, the two baselines correctly determined 66 and 69 cases, respectively. As a result, the proposed method exhibited higher accuracy (0.85) than the two baselines. Additionally, there was significant difference ($p < 0.05$) between them. The statistical difference was determined using McNemar’s test. The evaluation measurements were recall, precision, and F-measure calculated using the number of correct detections above. The proposed method expressed higher recall (0.78), precision (0.85), and F-measure (0.81) than the baselines, as shown in Table 7.

| | Accuracy | Precision | Recall | F-measure |
|-----------------|-------------------|--------------|------------------|-----------|
| CF-GT | 0.61 (66/108) | 0.53 (25/47) | 0.56 (25/45) | 0.54 |
| CF-JWN | 0.64 (69/108) | 0.57 (24/42) | 0.53 (24/45) | 0.55 |
| Proposed method | 0.85 (92/108)**++ | 0.85 (35/41) | 0.78 (35/45)**++ | 0.81 |

Table 7: Results of accuracy in determining whether expressions are metonymic or literal and precision, recall, and F-measure rates in detecting metonymic expressions. The asterisks and + indicate statistical significance over CF-GT and CF-JWN, respectively. (* + p<0.05, ** ++ p<0.01)

| Candidate | Certainty | Score |
|----------------------------------|-----------|-------|
| <i>mayuge</i> ‘Eyebrow’ | 0.28 | 4 |
| <i>kami</i> ‘Hair on head’ | 0.27 | 2 |
| <i>hige</i> ‘Beard or moustache’ | 0.24 | 7 |
| <i>ke</i> ‘Hair’ | 0.22 | 7 |

Table 8: Rating scores for interpretation candidates in example sentence

4.3.2. Interpretation of Metonymies

To evaluate the interpreting phase with the proposed method, I used the rating score of a linguistic specialist between 1 and 7, which expresses a certain level of acceptability for metonymic reading. The higher the rating, the higher the suitability to a metonymic reading. Table 8 lists candidates with certainty factors and rating scores of the following example:

kao-wo soru ‘Someone shaves his face.’

Here, ‘face’ is a metonymic expression, and the sentence generally means that someone shaves oneself. As shown in Table 8, candidates that the proposed method output contain some words determined as metonymic reading, i.e., *hige* ‘Beard or moustache’ and *ke* ‘Hair’. However, the baselines (CF-GT and CF-JWN) could not analyze this example because there was an insufficient amount of appropriate example-based data.

Table 9 lists two rates of correctness for each metonymic concept. The first rate is that of correct words in all candidates. I used candidates that were rated more than 4 as being correct. The second rate is that of sentences containing at least one correct word. These results show that, while the numbers of test sentences were not the same, the proposed method had different correct rates in each metonymic concept. It output correct words in each sentence with ‘Container for Content’. However, its ability in selecting candidates with a certainty factor needs to be improved because the first rate was generally lower than the second one.

Results with the top N accuracy (N= 1, 5) are shown in Table 10. Each rate means whether the first correct word was in rank of top 1 and top 5, respectively. In other words, each is an accuracy of the first correct word in the top N. As shown on the table, the proposed method expressed higher accuracies than the baselines. Therefore, the proposed method had a higher possibility of being used to interpret metonymic expressions than the baseline methods.

| Metonymic concept | Correct rate -word | Correct rate -sentence |
|---------------------------|-----------------------|---------------------------|
| Container for Content | 0.61 (17/28) | 0.86 (12/14) |
| Producer for Product | 0.50 (4/8) | 1.00 (5/5) |
| Controller for Controlled | 0.50 (1/2) | 1.00 (1/1) |
| Object used for User | 0.50 (7/14) | 0.75 (6/8) |
| Way for Agent | 1.00 (1/1) | 1.00 (1/1) |
| Material for Product | 1.00 (1/1) | 1.00 (1/1) |
| Others | 0.71 (5/7) | 0.80 (4/5) |
| All | 0.59 (36/61) | 0.86 (30/35) |

Table 9: Correct rates in metonymic concepts with spatial contiguity

| | Accuracy (top 1) | Accuracy (top 5) |
|-----------------|------------------|------------------|
| CF-GT | 0.28 (7/25) | 0.44 (11/25) |
| CF-JWN | 0.21 (5/24) | 0.42 (10/24) |
| Proposed method | 0.74(26/35) | 0.86 (30/35) |

Table 10: Results with Top N Accuracy in interpreting metonymic expressions

5. Conclusion

The proposed method exhibited a higher accuracy, particularly in detecting metonymic expressions and interpreting them, than the previous method with co-occurrence information. Thus, associative information can be used in systems that analyze metonymic expressions.

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