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Idea Generation Support Using Conceptual Attributes

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Abstract

We support idea generation from the conceptual attribute database. We make it possible to make analogies, such as “If we make a cat larger, it becomes a tiger,” from the conceptual attribute database. We also confirmed the usefulness of the McRae dataset. Against the results of using the two analogy methods, we made a four-level evaluation (“very good,” “good,” “OK,” and “bad”). In the first analogy method, the accuracy rate of the proposed method was 0.84 when the cases other than “bad” were judged to be correct. The accuracy rate of using word2vec was 0.13. In the second analogy method, the accuracy rate of the proposed method was 0.67 when the cases other than “bad” were judged to be correct. The accuracy rate of using word2vec was 0.19. The performance of the proposed methods was reasonably high. It was also higher than using word2vec. Consequently, we obtained that the McRae database used in the proposed methods was useful.

Keywords: Idea generation support, conceptual attribute, analogy, database.

1 Introduction

The idea support aims to expand existing ideas and come up with new ideas [6, 9, 12]. One of the idea support methods is the checklist method [10]. The checklist is an idea method created by Alex F. Osborn [3, 5, 10]. For example, if we make a cat larger, it becomes a tiger. We support idea generation using the conceptual attribute database. A concept attribute database is a database in which a concept represented by a certain word has many attributes. In this study, we used the McRae dataset [7] as the conceptual attribute database. We make it possible to make an analogy from the conceptual attribute database. The analogy is like, “If we make a cat larger, it becomes a tiger.” We examine the usefulness of the McRae dataset. The main contributions of this study are summarized as follows.

- This study aims to enable idea support, such as the checklist method, from the conceptual attribute database.
- In this paper, we proposed two analogy methods using the conceptual attribute database. To the best of our knowledge, these methods are original and have not been reported previously.

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Table 1: Example of conceptual attribute database

Word	Conceptual attribute
cat	an_animal, has_4leg, a_pet, has_fur, $\cdots$
tiger	a_cat, an_animal, has_4leg, has_fur, is_large, $\cdots$
gun	a_weapon, made_of_metal, is_dangerous, $\cdots$
pistol	a_gun, a_weapon, made_of_metal, is_small, $\cdots$
rifle	a_gun, a_weapon, made_of_metal, is_long, $\cdots$

- We proposed two analogy methods. Against the results of the analogy, we made a four-level evaluation ("very good," "good," "OK," and "bad") using five subjects. In the first analogy method, the accuracy rate of the proposed method was 0.84 when the cases other than "bad" were judged to be correct. The accuracy rate of using word2vec [8] was 0.13. Meanwhile, the accuracy rate of the proposed method was 0.67 in the second analogy method when the cases other than "bad" were judged to be correct. The accuracy rate of using word2vec was 0.19. The performance of the proposed methods was reasonably high. It was also higher than using word2vec. Consequently, we obtained that the McRae database used in the proposed methods was useful.

2 Our Proposed Method

This section describes the proposed method. Section 2.1 describes the conceptual attribute database. Sections 2.2 and 2.3 describe Analogy methods 1 and 2, respectively.

2.1 Conceptual attribute database

In this study, we make an analogy using the McRae dataset as a conceptual attribute database. The McRae dataset consists of 7,521 semantic attribute data given by 725 annotators for 541 English word concepts that belong to the basic level. The semantic attribute data of the McRae dataset is used as the conceptual attribute. Table 1 shows an example of the conceptual attribute database.

2.2 Analogy method 1

An analogy is made from the conceptual attribute database, as shown in Table 3.1. The procedure is described as follows.

- Procedure 1: We extract a word with an attribute of a_word (a_cat, etc.). Here, the a_word (a_cat, etc.) represents the type of word.

- Procedure 2: We find the attribute (is_large, etc.) we would like to add to the extracted word.

- Procedure 3: We extract words with the same two attributes as the two attributes extracted in Procedures 1 and 2.

For example, if we would like to make a cat larger, we add the attribute is_large to the attribute of the cat. Then, the item with the added attributes is taken out. We expect that tigers will be extracted. An example is shown below.

We extract a word that has a_cat.

tiger: a_cat, an_animal, has_4leg, has_fur, is_large, $\cdots$
lion: a_cat, an_animal, has_4leg, has_fur, is_large, $\cdots$
cheetah: a_cat, an_animal, has_4leg, has_fur, is_fast, $\cdots$

We extract a word that has both a_cat and is_large.

tiger: a_cat, an_animal, has_4leg, has_fur, is_large, $\cdots$
lion: a_cat, an_animal, has_4leg, has_fur, is_large, $\cdots$

2.3 Analogy method 2

In Analogy method 1, an analogy is made with a_word (a_cat, etc.) as an attribute. Analogy method 2 makes it possible to infer things that do not have any a_word (such as a _cat) as attributes. The procedure is described as follows.

- Procedure 1: We add the attribute (is_large, etc.) we would like to add to all words.
- Procedure 2: We find the cosine similarity between an original word and a word with the added attribute.
- Procedure 3: It is assumed that the top 10 items with high cosine similarity can be inferred.

We add the attribute we would like to add to all words, such as is_large, and then sort them in descending order of cosine similarity. An example is given as follows.

We add the attribute (is_large) we would like to add to all words.

cat: an_animal, has_4leg, a_pet, $\cdots$ + is_large
gun: a_weapon, made_of_metal, is_dangerous, $\cdots$ + is_large

We find the cosine similarity.

tiger: a_cat, an_animal, has_4leg, has_fur, is_large, $\cdots$
cat + is_large: an_animal, has_4leg, a_pet, $\cdots$ + is_large
The cosine similarity: 0.700

The words with added attributes are sorted in descending order of cosine similarity.

tiger cat + is_large: (Cosine similarity) 0.700
lion cat + is_large: (Cosine similarity) 0.600
rifle gun + is_large: (Cosine similarity) 0.500

Table 2: Part of the experimental outputted results of Analogy method 1

Original word	Word to add	Result of analogy	Example of analogy
cat	is_large	tiger	If we make a cat larger, it becomes a tiger.
gun	is _large	bazooka	If we make a gun larger, it becomes a bazooka.
jacket	is_large	parka	If we make a jacket larger, it becomes a parker.
pillow	is_small	cushion	If we make a pillow smaller, it becomes a cushion.
gun	is_small	bullet	If we make a gun smaller, it becomes a bullet.
rock	is_small	stone	If we make a rock smaller, it becomes a stone.
gun	is_fast	bullet	If we make a gun faster, it becomes a bullet.
cat	is_fast	cheetah	If we make a cat faster, it becomes a cheetah.
van	is_fast	ambulance	If we make a van faster, it becomes an ambulance
toy	made_of_wood	kite	If we make a toy a thing made of wood, it becomes a kite.
toy	made_of_wood	slingshot	If we make a toy a thing made of wood, it becomes a slingshot.
aex	made_of_wood	wagon	If we make an aex a thing made of wood, it becomes a wagon.

3 Experiment of Analogy Method 1

3.1 Experimental results

We made 623 analogies from the experiment. Table 2 presents some of the experimental results. Some cats can be correctly analogized by making them larger (is_large) to become tigers. However, there were errors such that if guns are made faster (is_fast), they become bullets.

3.2 Evaluation method

To verify the accuracy of the analogical results, we perform an evaluation experiment on five subjects.

The evaluation was made on the following four-point scale.

- Very good: We can infer the output.

  Original word: stone. Word to add: is_beautiful. Results of analogy: emerald. Example: "If we make stone beautiful, it becomes emerald."

- Good: We can almost infer the output. The output is a bit weird.

Table 3: Results of the proposed method in subject evaluation of Analogy method 1

Subject	Very Good	Very good + good	Very good + good + OK
Subject 1	0.37	0.70	0.93
Subject 2	0.21	0.47	0.70
Subject 3	0.56	0.68	0.81
Subject 4	0.37	0.61	0.88
Subject 5	0.16	0.47	0.88
Total	0.33	0.59	0.84

Original word: toy. Word to add: has_hair. Results of analogy: doll. Example: "If we make a toy a thing with hair (has_hair), it becomes a doll."

- OK: We can infer the output in certain special circumstances.

  Original word: pillow. Word to add: is_square. Results of analogy: cushion. Example: "If we make a toy square, it becomes a cushion."

- Bad: We cannot infer the output.

  Original word: truck. Word to add: has_door. Results of analogy: van. Example: "If we make a truck a thing with doors, it becomes a van." (The analogy is bad because both a truck and a van have doors.)

  Original word: tiger. Word to add: is_small. Results of analogy: bullet. Example: "If we make a tiger small, it becomes a bullet." (The analogy is bad because a tiger and a bullet are very different.)

3.3 Evaluation results

The results of Section 3.1 were evaluated for 57 items with the highest frequency of attributes. Table 3 presents the evaluation results.

3.4 Comparison between the proposed method and word2vec

In word2vec [8], a word is expressed with a vector. Word2vec can make an analogy such that king − man + woman = queen. The analogy is performed using the vectors of king, man, woman, and queen [2, 4, 11, 1]. However, if we perform the calculation of "cat − small + large" in word2vec, we may make an analogy of "If we make a cat larger, it becomes a tiger." Therefore, we conducted comparison experiments between our proposed method and word2vec.

We used text8 (100 Mb) attached with word2vec for the training of word2vec. We examine whether what is obtained using the proposed method can also be obtained using word2vec [8]. We consider the case where a word (e.g., tiger) is inferred from a word (e.g., cat) and an attribute word (e.g., large) in the proposed method. In this case, a word (e.g., cat) and an attribute word (e.g., large) are handled as an input, and a word (e.g., tiger) is handled as an output. Using the proposed method, we obtained 47 different inputs from the 57 data items (sets of three words) obtained. The 47 inputs were used in the experiments of this section. In the proposed method, if there are n outputs for one input, multiply the number of correct answers by $1/n$. We also use antonyms of attribute words in word2vec. For example,

Table 4: Results of the proposed method in subject evaluation of Analogy method 1 (ad-justment)

Subject	Very Good	Very good + good	Very good + good + OK
Subject 1	0.33	0.69	0.91
Subject 2	0.21	0.45	0.71
Subject 3	0.54	0.69	0.81
Subject 4	0.34	0.58	0.87
Subject 5	0.17	0.41	0.88
Total	0.32	0.56	0.84

Table 5: Results of word2vec in subject evaluation against Analogy method 1 (adjustment)

Subject	Very Good	Very good + good	Very good + good + OK
Subject 1	0.02	0.09	0.19
Subject 2	0.00	0.02	0.09
Subject 3	0.02	0.02	0.09
Subject 4	0.00	0.06	0.21
Subject 5	0.02	0.02	0.09
Total	0.01	0.04	0.13

we consider the case where a word (e.g., cat) and an attribute word (e.g., large) is an input. In this case, we add the vector of "cat" and the vector of "large" and subtract the vector of "small" (the antonym of "large") from the sum. Finally, the word with the maximum similarity to the vector obtained from this calculation is used as an output. Tables 4 and 5 present the results of the proposed method and word2vec, respectively.

4 Experiment of Analogy Method 2

This section describes experiments using Analogy method 2.

4.1 Experimental results

Table 6 presents some of the experimental results. As presented in Table 6, some cases could be inferred correctly such that if we make an orange smaller (is_samll), it becomes a tangerine. Some could not be inferred correctly such that if we make a squid larger (is_large), it becomes an octopus.

4.2 Evaluation results

We evaluated the results of Section 4.1 for 70 items with the highest frequency of attributes. The attributes with the highest frequency are "large," "small," "long," "round," "fast," "white," and "black." Table 7 presents the evaluation results. We used the evaluation method as the same as in Section 3.2. We conducted comparison experiments between the proposed method and word2vec. Here, we explain the method of using word2vec. In

Table 6: Part of the experimental outputted results of Analogy method 2

Original word	Word to add	Result of analogy	Example of analogy
deer	is_large	moose	If we make a cat larger, it becomes a tiger.
squid	is_large	octopus	If we make a squid larger, it becomes an octopus.
pheasant	is_large	raven	If we make a pheasant larger, it becomes a raven.
orange	is_small	tangerine	If we make an orange smaller, it becomes a tangerine.
blackbird	is_small	sparrow	If we make a blackbird smaller, it becomes a sparrow.
trout	is_small	perch	If we make a trout smaller, it becomes a perch.
moose	is_fast	caribou	If we make a moose faster, it becomes a caribou.
tricycle	is_fast	scooter	If we make a tricycle faster, it becomes a scooter.
van	is_fast	car	If we make a van faster, it becomes a car.
broccoli	is_white	cauliflower	If we make a broccoli white, it becomes a cauliflower.
duck	is_white	goose	If we make a duck white, it becomes a goose.
spinach	is_white	cabbage	If we make a spinach white, it becomes a cabbage.

word2vec, we use all the combinations of all the 541 entry words in McRae and seven attributes words (“large,” “small,” “long,” “round,” “fast,” “white,” and “black”) as inputs. We also use antonyms of attribute words as the same as in Section 3.4. We used the word with the maximum similarity to the vector obtained by the addition/subtraction of attribute word vectors among all the 541 entry words as an input. We limit outputs in word2vec to the 541 entry words so that the words handled by the proposed method are equal to those handled by word2vec.

5 Discussion

5.1 Discussion on Analogy method 1

As shown in Table 3, we obtained that the accuracy rate based on “very good + good” was about 0.59, which was useful to some extent. However, 0.16 of outputs were judged as “bad.” The reasons for bad outputs would be as follows.

- Existence of wrong attributes in the conceptual attribute database.

  There are some wrong conceptual attributes. For example, a_gun is included in the conceptual attribute of “bullet.” a_gun is included in the conceptual attribute of “bullet” as a thing related to a gun, but since “bullet” is not a gun itself, a_gun is not

Table 7: Results of the proposed method in subject evaluation of Analogy method 2

Subject	Very Good	Very good + good	Very good + good + OK
Subject 1	0.34	0.50	0.73
Subject 2	0.46	0.64	0.69
Subject 3	0.07	0.26	0.43
Subject 4	0.39	0.73	0.91
Subject 5	0.17	0.44	0.60
Total	0.29	0.51	0.67

Table 8: Results of word2vec in subject evaluation of Analogy method 2

Subject	Very Good	Very good + good	Very good + good + OK
Subject 1	0.01	0.04	0.14
Subject 2	0.07	0.13	0.20
Subject 3	0.00	0.03	0.07
Subject 4	0.01	0.07	0.34
Subject 5	0.00	0.04	0.17
Total	0.02	0.06	0.19

suitable for the conceptual attribute here. Due to the existence of such incorrect attributes, it is possible that making the gun smaller (is_small) will result in an incorrect analogy, such as a bullet.

- Analogies that cannot be associated

  There was an analogy that we could not associate with. For example, false analogies were made such that if a toy is made of wood (made_of_wood), it becomes a wagon, and if a stick is made black (is_black), it becomes a wand. Many subjects could not associate a toy with a wagon and a stick with a wand.

- Unchanged analogy

  There was an analogy that did not change. An erroneous analogy was made that making the frog smaller (is_small) would make it a toad, and making a dish white (is_white) would make it a plate. These were judged as bad because the things before analogy and the thing after analogy were judged to be small and white.

In this paper, we conducted comparison experiments between the proposed method and word2vec. Tables 4 and 5 show that the proposed method and word2vec were 0.84 and 0.13 in "very good + good + OK," respectively. Thus, the proposed method outperformed word2vec.

5.2 Discussion on Analogy method 2

As presented in Table 7, the accuracy rate based on "very good + good" was about 0.51, which was useful to some extent. However, 0.33 of outputs were judged as "bad." The reasons for bad outputs would be as follows.

- Small difference in change

  Many analogies about birds came out in our proposed method. For example, a false analogy was made that if a nightingale is made smaller (is_small), it becomes a starling. It was sometimes judged that the nightingale and starling were almost the same in length, and they could not be inferred because they did not change much. For analogy with such a small change, the evaluation is "OK" or "bad," and it is considered that the correct answer rate decreases.

- Reverse analogy

  A false analogy was made that if the mackerel is made smaller (is_small), it becomes a perch. This is "bad" because a mackerel is smaller than a perch.

- Analogies that cannot be associated

  There was an analogy that could not be inferred that when a squid was made large (is_large), it became an octopus.

In this study, we compared the proposed method and word2vec. As presented in Tables 7 and 8, the proposed method and word2vec were 0.67 and 0.19 in "very good + good + OK." Thus, the proposed method outperformed word2vec.

6 Conclusions

In this study, we provided idea support from the conceptual attribute database. We used McRae's dataset to make analogies using two analogy methods in the conceptual attribute database. Against the results of the experiments of Analogy methods 1 and 2, five subjects were evaluated on a four-level scale ("very good," "good," "OK," and "bad"). In Analogy method 1, the accuracy rate of the proposed method was 0.84 when the cases other than "bad" were judged to be correct, whereas that of the word2vec was 0.13. In Analogy method 2, the accuracy rate of the proposed method was 0.67 when the cases other than "bad" were judged to be correct, whereas that of the word2vec was 0.19. The performance of the proposed methods was reasonably high, and it was higher than using word2vec. Therefore, we obtained that the McRae database used in the proposed methods was useful. In future studies, we will create a new conceptual attribute database from a large amount of text data to make more analogies.

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References

[1] Carl Allen and Timothy Hospedale. Analogies explained: Towards understanding word embeddings. In *Proceedings of the 36th International Conference on Machine Learning*, pages 223–231, 2019.

[2] Kenneth Ward Church. Word2vec. *Natural Language Engineering*, 23(1):155–162, 2017.

[3] Kurt Gaubinger, Michael Rabl, Scott Swan, and Thomas Werani. Creativity techniques. In *Innovation and Product Management*, pages 115–133, 2014.

[4] Giovanni Di Gennaro, Amedeo Buonanno, and Francesco A. N. Palmieri. Considerations about learning word2vec. *The Journal of Supercomputing*, 77:12320–12335, 2021.

[5] Hassan Hassan. Creativity and innovation for electrical and computer engineering researchs. In *Proceedings of the 2004 American Society for Engineering Education Annual Conference & Exposition*, pages 1–9, 2004. https://peer.asee.org/creativity-and-innovation-for-electrical-and-computer-engineering-research.pdf.

[6] E.E. Klein and D.G. Dologite. The role of computer support tools and gender composition in innovative information system idea generation by small groups. *Computers in Human Behavior*, 16(2):111–139, 2000. https://doi.org/10.1016/S0747-5632(00)00013-3.

[7] Ken McRae, George S Cree, Mark S Seidenberg, and Chris McNorgan. Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods*, 37:547–559, 2005.

[8] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems*, 26:3111–3119, 2013. https://proceedings.neurips.cc/paper/2013/file/9aa42b31882ec039965f3c4923ce901b-Paper.pdf.

[9] Jun Munemori, Kohei Komori, and Junko Itou. Gungen-heartbeat: A support system for high quality idea generation using heartbeat variance. *IEICE Transactions on Information and Systems*, E103-D(4):796–799, 2019.

[10] Alex F. Osborn. *Applied Imagination*. Creative Education Foundation Press, 1993.

[11] Pavel Rychly. Evaluation of the sketch engine thesaurus on analogy queries. In *Proceedings of RASLAN 2016 Recent Advances in Slavonic Natural Language Processing*, pages 147–152, 2016. https://nlp.fi.muni.cz/raslan/2016/paper18-Rychly.pdf.

[12] Takashi Yoshino, Jun Munemori, Tomohiro Shigenobu, and Kazutomo Yunokuchi. A spiral-type idea generation method support system for sharing and reusing knowledge and information among a group. *IPSJ Journal*, 41(10):2794–2803, 2000.