Context-Dependent Metaphor Interpretation Based on Semantic Relatedness

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Abstract. The previous work of metaphor interpretation mostly focused on single-word verbal metaphors and ignored the influence of contextual information, leading to some limitations(e.g. ignore the polysemy of metaphor). In this paper, we creatively propose the aspect-based semantic relatedness, and we present a novel metaphor interpretation method based on semantic relatedness for context-dependent nominal metaphors. First, we obtain the possible comprehension aspects according to the properties of source domain. Then, combined with contextual information, we calculate the degree of relatedness between the target and source domains from different aspects. Finally, we select the aspect which makes the relatedness between target and source domains maximum as comprehension aspect, and the metaphor explanation is formed with corresponding property of source domain. The results show that our method has higher accuracy. In particular, when the information of target domain is insufficient in corpus, our method still exhibits the good performance.

Keywords: Metaphor interpretation · Semantic relatedness · Contextual information · Comprehension aspect

1 Introduction

Metaphor, as a kind of common phenomenon in natural language, is not only a rhetorical means, but also a cognitive style of human beings. In recent years, the research of metaphor interpretation has attracted attention of people gradually. The existing methods of metaphor interpretation paid more attention to single-word metaphors expressed by verbs, such as “stir-excitement”. Instead, the interpretation mechanism of nominal metaphors is more complex than verbal metaphors. It not only needs to find the relevance between target and source domains, but also requires the consideration about contextual background of metaphors. Hobbs [1] regarded metaphor interpretation as a part of the general discourse processing problem. Only in context the metaphorical expression can be properly interpreted. To avoid misunderstandings, speaker will guide people toward the desired direction to understand metaphor through the adjustment and supplement of discourse. Consider the following examples:

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(1) 他是猫。(He is a cat.)
(2) 他是只晒太阳的慵懒的猫。(He is a lazy cat and enjoys the sunshine.)

When the contextual information is insufficient, metaphor interpretation is hard to determine. The source domain "猫(cat)" of examples has the properties, such as "顽皮(naughty)", "敏捷(quick)", "慵懒(lazy)" and so on. According to these properties of source domain, we can find different comprehension aspects to make target and source domain relevant. In the example (1), we might have multiple explanations, such as "他是顽皮的(He is naughty)", "他是敏捷的(He is quick)" and so on. In the example (2), based on the contextual information, we can make sure that the explanation "他是慵懒的(He is lazy)" is much better.

In nominal metaphors, a seemingly unrelated concept is usually associated with another concept. And metaphor interpretation is finding the appropriate aspect in line with knowledge background to make the relatedness between target and source domains maximum. In this paper, we present a metaphor interpretation method based on semantic relatedness, aiming at the context-dependent nominal metaphors. First, we extract the properties of source domain, and select possible comprehension aspects according to these properties. Then, we apply vector representations of words and integrate the relatedness between context and source domain to calculate the relatedness between target and source domains from different aspects. Finally, we choose the aspect which makes the relatedness of target and source domains maximum as the comprehension aspect, and metaphor explanation is formed with corresponding property of source domain.

The contributions of this paper are as follows: 1. We creatively propose the aspect-based semantic relatedness computational method. 2. We consider the influence of contextual information to comprehend metaphors, and apply the aspect-based semantic relatedness to context-dependent nominal metaphor interpretation. Combined with the contextual information, we calculate the relatedness between target and source domains, and obtain the metaphor explanation. The experiment results show that our method is effective.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of related work. In Section 3, we show the theoretical basis at first. Then we introduce the aspect-based semantic relatedness computational method and the context-dependent nominal metaphor interpretation method. Section 4 shows the experimental results and evaluation. Our conclusions and future work are given in Section 5.

2 Related Work

2.1 Metaphor Interpretation

Shutova [2] proposed a method which first extracted a set of potential substitutes by selecting all words that appeared in a particular syntactic relation with the metaphorical verb in the BNC. Then it narrowed down the list of candidates by selecting the verbs that shared a hypernym with the metaphorical verb in WordNet. She used automatically induced selectional preferences to discriminate between figurative and literal paraphrases. Shutova et al.[3] presented a novel approach to metaphor interpretation with a vector space model using a non-negative matrix factorization to compute the meaning list of target verbs. Bollegala and Shutova [4] presented an unsupervised metaphor interpretation method that used the Web to find literal paraphrases for metaphorical expressions. Ekaterina et al. [5] presented a metaphor interpretation approach based on abduction. They mapped linguistic metaphors to conceptual metaphors, and interpreted conceptual metaphors in terms of both logical predicates and natural language expressions.

Comparing to other work that focused on single-word verbal metaphors, we utilize contextual information to deal with nominal metaphor interpretation through aspect-based semantic relatedness.

2.2 Semantic Relatedness

There are two kinds of semantic relatedness calculation model, knowledge-based and corpus-based approaches.

Knowledge-based methods employ information extracted from manually constructed lexical taxonomies, e.g., WordNet. Previous studies have focused on gloss [6] and the structure of the lexicon [7], such as the semantic path and depth. Siblini and Kosseim [8] used all 26 semantic relations found in WordNet in addition to information found in glosses.

Corpus-based approaches mainly use context information and structural pattern of corpus, such as using paths in the Wikipedia category structure, using the contents of the articles, or using the hyperlinks between articles. For example, Explicit Semantic Analysis (ESA) [9] as well as Salient Semantic Analysis (SSA) [10] was proposed to incorporate large amounts of human knowledge such as Wikipedia into word relatedness computation. They both represented a word as a concept vector, where each dimension corresponds to a Wikipedia concept. Yazdani and Popescu-Belis [11] used the contents and links for computing text semantic relatedness. Agirre et al. [12] studied the different types of links in Wikipedia, and applied random walk algorithm on the full graph based on those links for word relatedness and named-entity disambiguation. Mikolov et al. [13] used machine learning techniques to compute continuous vector representations of words from large datasets, and then calculated the word vector distance to measure semantic relatedness. They observed large improvements in accuracy at much lower computational cost.

In this paper, we adopt the corpus-based method. Compared with knowledge-based methods, our method has the advantage that information content is much richer. However, the existing corpus-based methods regard a concept as a whole. For example, compare all attributes of concepts, the more their common attributes the higher relatedness they are. Thus, they ignored that the semantic relatedness between concepts will change with comprehension aspect. And aspect-based semantic understanding is a noticeable phenomenon in natural language; aspect-based semantic relatedness computation can help understand natural language. Therefore, based on the previous researches, we propose an aspect-based semantic relatedness computational method.

3 Our Method

Our method consists of the following steps. Given the nominal metaphor with context, which has marked target and source domains, we extract the properties of source domain. Then, we obtain the possible comprehension aspects according to these properties. And from different aspects, we calculate the degree of relatedness between target and source domains combined with contextual information. Finally, we select the aspect which makes relatedness maximum as the comprehension aspect, and the corresponding property of source domain forms the metaphor explanation. Section 3.1 illustrates the theoretical basis of our methods. Section 3.2 presents the aspect-based semantic relatedness computation method and our method for the context-dependent nominal metaphor interpretation.

3.1 Theoretical Basis

Davidson [14] indicated that, generally speaking, the literal meaning of metaphor is clear error or absurd. In other words, the target domain and the source domain are not related literally. But, according to relevance theory, any words of discourse are related on the semantics, and the process of discourse understanding is looking for the relevance of discourse to support the "contextual effect" of discourse. Thus, although the target and source domains are not related in literal meaning. From some comprehension aspects, the semantic relatedness will be found, which we call aspect-based semantic relatedness. The process of metaphor interpretation is to find the appropriate aspect from which the relevance between target and source domains is constructed.

Semantic relatedness is based on the aspect, the related concepts from a certain aspect may be irrelevant from another aspect. For example, from the aspects "色彩(color)" "智慧(intelligence)" "行为(behavior)", "狐狸(fox)" has the properties "红色(red)" "聪明(smart)" " 敏捷(quick)", respectively. Based on the aspect "色彩(color)", target domain "律师(lawyer)" and source domain "狐狸(fox)" are irrelevant. But they are relevant from the aspect "智慧(intelligence)", because both of them have the property "聪明(smart)". Thus, the key to metaphor interpretation is the comprehension aspects.

What is more, because of the openness and uncertainty of metaphorical meaning [14], people might find multi-aspects to produce different explanations. For example, "张三是狼(Zhangsan is a wolf)" can be interpreted as "张三很凶狠(Zhangsan is cruel)" "张三很狡猾(Zhangsan is crafty)" "张三很多疑(Zhangsan is suspicious)". To avoid misunderstanding, speaker will guide listener to the correct understanding direction through the selection and adjustment of context, such as emphasizing on the typical properties of target domain, extending and stating the non-significant properties of source domain. When the contextual information is sufficient, the optimal explanation can be determined. According to relevance theory, the optimal metaphor comprehension should have the greatest relatedness with intent of discourse, and the context will make certain properties of source domain salient [15]. In this sense, the relatedness between context and source domain will help determine the best explanation.

Searle's metaphor theory [16] also supported our idea to some extent. It mainly explained how to interpret metaphor. For simple example, "S is P" which means "S is R". He pointed out that metaphor interpretation is utilizing context or existing knowledge base to obtain the relations among S,P and R. For this kind of metaphor, "S is P", he proposed six principles to get R through P. 1. R is in the definition of P. For example, because of the definition of "giant" is "big", the metaphor "Sam is a giant" can be interpreted as "Sam is big". 2. Under certain conditions, P is R, R is an important and well known feature of P. For example, "Sam is a pig" can be interpreted as "Sam is filthy, gluttonous, and sloppy, etc". 3. P is often said to be R, although P does not have the feature R. For example, the feature of P in a familiar myth. 4. As a result of natural or cultural reasons, we feel that there is a relation between P and R. For example, "I am in a black mood" can be interpreted as "I am angry and depressed". 5. P and R are not similar, but the situations which they are in are similar. For example, the metaphor "You have become an aristocrat" means the living conditions is similar to an aristocrat. 6. In some cases, P and R are same or similar in the sense, but the applied range of R is limited, then people use P. For example "His brain is addled", although "addled" only applies to "egg". These principles are to obtain the related features R of P from different aspects, then construct the semantic relatedness between S and P based on these aspects.

3.2 Metaphor Interpretation Based on Semantic Relatedness

Given the metaphor with context, we first extract the notional words(nouns, verbs, adjectives and adverbs), which are denoted as w_1, w_2, ..., w_N (except the marked target domain $Target$ and source domain $Source$).

The knowledge of source domain is crucial to metaphor interpretation. In this paper, we select possible comprehension aspects according to the properties of source domain, and calculate the aspect-based semantic relatedness between the target and source domains. We extract the properties of the source domain by using *Attribute Database*[1] and *Sardonicus*[2], which are denoted as p_1, p_2, ..., p_M, the corresponding aspects are r_1, r_2, ..., r_M, respectively.

Then, metaphor interpretation can be regarded as a problem to find the comprehension aspect $\mathbf{r} = r_i$, which makes the semantic relatedness between target and source domains $Rel(Target, Source, \mathbf{r})$ maximum, and the property p_i of source domain which is corresponding to the aspect r_i will be salient. Thus, we express the metaphor explanation briefly as "$Target\ Be\ p_i$".

[1] A database developed by NLP Lab of Xiamen University.

[2] An adjective classification retrieval. http://afflatus.ucd.ie/sardonicus/tree.jsp.

In order to measure the semantic relatedness between words, a word w is represented by a vector $\overrightarrow{w}$, as follows:

$$\overrightarrow{w} =< c_1, c_2, ..., c_q > \tag{1}$$

where, q is the dimension of vector, $c_i (1 \leq i \leq q)$ is the value of dimension i.

Mikolov et al. [13] proposed two model architectures for computing continuous vector representations of words from large data sets, Continuous Bag-of-Words (CBOW) model and distributed Skip-gram model. They measured the quality of these representations in a word similarity task and compared their methods with different types of neural networks. The results revealed their methods had large improvements in accuracy at much lower computational cost. In this paper, we apply CBOW model[3] to obtain the vector representations of words.

Assuming source domain $Source$ has the property p from the aspect r, then the semantic relatedness between word w and word $Source$ based on aspect r, $Rel(w, Source, r)$, could be computed using cosine distance measure as follows:

$$Rel(w, Source, r) = dis_{cos}(\overrightarrow{w}, \overrightarrow{p}) \tag{2}$$

$$dis_{cos}(\overrightarrow{w}, \overrightarrow{p}) = \frac{\sum_{j=1}^{q} c_j e_j}{\sqrt{\sum_{j=1}^{q} c_j^2} \sqrt{\sum_{j=1}^{q} e_j^2}} \tag{3}$$

where, w is represented as $\overrightarrow{w} =< c_1, c_2, ..., c_q >$, p is represented as $\overrightarrow{p} =< e_1, e_2, ..., e_q >$.

Combined with the relatedness between context and source domain, we can obtain the semantic relatedness between target domain $Target$ and source domain $Source$ based on aspect r, $Rel(Target, Source, r)$, as follows:

$$\begin{aligned} Rel(Target, Source, r) &= dis_{cos}(\overrightarrow{Target}, \overrightarrow{p}) + \frac{1}{N} \sum_{i=1}^{N} Rel(w_i, Source, r) \\ &= dis_{cos}(\overrightarrow{Target}, \overrightarrow{p}) + \frac{1}{N} \sum_{i=1}^{N} dis_{cos}(\overrightarrow{w_i}, \overrightarrow{p}) \end{aligned} \tag{4}$$

where, N is the number of extracted notional words(except the marked target domain $Target$ and source domain $Source$). If $Target$(or w_i) absents in the corpus, let $dis_{cos}(\overrightarrow{Target}, \overrightarrow{p}) = 0$(or $dis_{cos}(\overrightarrow{w_i}, \overrightarrow{p}) = 0$).

We obtain the semantic relatedness between target and source domains from all possible aspects. Then we choose the aspect **r** which makes the relatedness between target and source domains maximum as the comprehension aspect, as shown in Eq(5).

[3] https://code.google.com/p/word2vec/.

$$
\begin{aligned}
\mathbf{r} &= \underset{r_i}{\operatorname{argmax}}\{Rel(Target, Source, r_i)\} \\
&= \underset{r_i}{\operatorname{argmax}}\{dis_{cos}(\overrightarrow{Target}, \overrightarrow{p_i}) + \frac{1}{N}\sum_{j=1}^{N} Rel(w_j, Source, r_i)\} \\
&= \underset{r_i}{\operatorname{argmax}}\{dis_{cos}(\overrightarrow{Target}, \overrightarrow{p_i}) + \frac{1}{N}\sum_{j=1}^{N} dis_{cos}(\overrightarrow{w_j}, \overrightarrow{p_i})\}
\end{aligned} \tag{5}
$$

where $r_i \in \{r_1, r_2, ..., r_M\}$.

The corresponding property $\mathbf{p}=p_i$ of source domain from the aspect $\mathbf{r}=r_i$ will become salient. The property p_i forms the metaphor explanation which is expressed briefly as "$Target$ Be p_i".

4 Experiment and Evaluation

In our experiments, we use *Reader Corpus*[4] as the corpus, and use *Segtag*[5] to support CBOW model in computing the vector representations of words. Considering the data sparse problem in corpus, we extend the synonyms of the property word p using the *Tongyi Cilin (Extended)*[6]. The synonyms set of p is represented as $S = \{v_1, v_2, ..., v_{|S|}\}$, where $|S|$ is the number of synonyms. If r is the corresponding aspect of property p, the semantic relatedness between word w and word $Source$ based on aspect r, $Rel(w, Source, r)$, could be computed as follows:

$$
Rel(w, Source, r) = dis_{cos}(\overrightarrow{w}, \overrightarrow{p}) = \frac{1}{|S|}\sum_{i=1}^{|S|} dis_{cos}(\overrightarrow{w}, \overrightarrow{v_i}) \tag{6}
$$

Specially, if w and p is synonym, let $Rel(w, Source, r) = 1$.

For the metaphor "如今的华为已经成了狮子，成为电信行业当之无愧的王者(Now Huawei has become a lion, who is the king of the telecommunications industry)", the marked target domain is " 华为(Huawei)" and source domain is "狮子(lion)". We extract the properties of "狮子(lion)" and select possible comprehension aspects according to the properties. Table 1 contains the semantic relatedness between target and source domains from different aspects(the corresponding aspects are given by *Adjectives Database*[7]).

As shown in Table (1), we see the relatedness between word "王者(king)" and source domain " 狮子(lion)" are higher from the aspects "心情(mood)" and "神情(manner)", thus the corresponding properties " 恼怒(irritated)" and "威严(august)" become more salient.

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[4] A Chinese Corpus. URL: www.duzhe.com.

[5] A word segmentation tool of NLP Lab of Xiamen University.

[6] A Chinese Thesaurus, http://ir.hit.edu.cn/.

[7] An adjective classification database developed by NLP Lab of Xiamen University.

Table 1. The relatedness between word “王者(king)” and source domain “狮子(lion)” from different aspects

w	Source	p	r	Rel($w, Source, r$)
王者 king	狮子 lion	饥 hungry	衣食 subsistence	0.1135108
		凶猛 fierce	行为 behavior	0.1261268
		恼怒 irritated	心情 mood	0.1703408
		威严 august	神情 manner	0.1515766

In order to better illustrate the performance of our method, we compare our method with the following three simple methods:(1)RT: Ignoring the contextual information, it just calculates the semantic relatedness between the target and source domains from different aspects, which represents as RT($Target, Source, r$); (2)RS: Select the most salient property of source domain and we use aspect-based semantic relatedness to measure the degree of saliency, which represents as RS($Source, Source, r$); (3)RTS: Combined RT with RS, it not only utilizes the semantic relatedness between the target and source domains, but also the saliency of properties, which represents as RTS($Target, Source, r$). The computational formulas are as follows:

$$RT(Target, Source, r) = dis_{cos}(\overrightarrow{Target}, \overrightarrow{p}) \quad (7)$$

$$RS(Source, Source, r) = dis_{cos}(\overrightarrow{Source}, \overrightarrow{p}) \quad (8)$$

$$RTS(Target, Source, r) = RT(Target, Source, r) + RS(Source, Source, r) \quad (9)$$

where, p is the corresponding property of source domain from the aspect r.

Considering the following examples, the words with underline are the extracted notional words of context:

(1) “高龄 八十九岁的萧乾，仍然是一匹生气勃勃的野马。”
“XiaoQian with the advanced age of eighty-nine is still a vibrant wild horse.”
The marked target domain is “萧乾(XiaoQian)”, source domain is “野马(wild horse)”.

(2) “不用 上班，不用 上学，就躺着晒太阳，多 好啊！我是一只没有 忧虑 烦恼的猫。”
“How wonderful to just lay in the sun without work and school ! I am a no-worry cat.”
The marked target domain is “我(I)”, source domain is “猫(cat)”.

(3) “这个塞维利亚球员长着一张娃娃脸，但在球场上却是个不折不扣的魔鬼。”
“The baby-faced Sevilla player is a real devil on the pitch.”
The marked target domain is “球员(player)”, source domain is “魔鬼(devil)”.

(4) "古老的济南，城内那么狭窄，城外又那么宽敞，山坡上卧着些小 村庄，小村庄的房顶上卧着点雪，这是张小 水墨画，也许是唐代的名手 画的吧。"
"Old Jinan is so narrow in the city, but it is so spacious outside the city, small villages lay on the hillside, little snow lies on the roof of the villages. It is a little wash painting, and perhaps drawn by a famous artist of Tang Dynasty."
The marked target domain is "这(it)"(refer to the scenery), source domain is "水墨画(wash painting)".

The results of four methods are demonstrated in Table 2.

As the example (1) shows, the source domain "萧乾(XiaoQian)" does not appear in the corpus, thus we do not have access to relevant information of source domain. It conforms to the common phenomenon in the metaphor that listeners are not familiar with the target domain, thus they are guided by the source domain and the current context to understand the metaphor. RT can not get a result. RS and RTS choose the most salient property "魁梧(strapping)" as the result. Our method considers the relevance between context and source domain, which get the best interpretation and the chosen property is "矫健(strong and vigorous)". The example shows that our method still has a good effect in the absence of the target domain information, and proves the guidance of the context information for metaphor interpretation.

As the example (2) shows, the property "顽皮(naughty)" is obviously more salient than other properties of source domain "猫(cat)". Thus, RS and RTS choose the "顽皮(naughty)" as the results. The effect of context makes the property "慵懒(lazy)" become more salient in our method. It reveals that contextual information emphasizes the properties of the target domain.

As the example (3) shows, the results of RT reveal the semantic relatedness between target domain "球员(player)" and source domain "魔鬼(devil)" from the aspect "感觉(sense)" is greatest. Then, RT chooses the corresponding property "可怕(horrible)". But, the most salient property of source domain "魔鬼(devil)" is "邪恶(evil)" according to RS and the saliency is obviously higher than others, which results in the most salient property is still "邪恶(evil)" in RTS. And in our method, combined the relatedness between context and source domain, the property "可怕(horrible)" becomes the most salient property.

As the example (4) shows, the marked target domain "这(it)" refers to the scenery of Jinan. In other words, the marked target domain does not provide available information. The results of RT show there is not significant difference among the relatedness from various aspects. From the results of RS, we see the property "简洁(concise)" of source domain "水墨画(wash painting)" is more salient than others obviously. Our method obtains the better result than RS and RTS. It reveals our method still work well when the information of target domain is absent. It also shows the computation of aspect-based semantic relatedness between context and source domain utilizes the contextual information validly.

We evaluate the experiment with the help of human annotators that annotate 80 instances of nominal metaphors with context from the Web, Blogs, and the Books. The data contains various genres: news/journal articles, politics, finance,

Table 2. The results of four methods

Target	Source	p	RT	RS	RTS	Our Method
萧乾 XiaoQian	野马 wild horse	高大 tall	NIL	0.09607011	0.09607011	0.092578129
		魁梧 strapping	NIL	0.18563326	0.18563326	0.110308271
		强壮 strong	NIL	0.12608944	0.12608944	0.127122275
		矫健 strong and vigorous	NIL	0.11942509	0.11942509	0.134411583
我 I	猫 cat	贴心 intimate	0.01600922	0.01757664	0.03358586	0.070006938
		灵活 flexible	0.03114080	0.07590316	0.10704396	0.075094045
		敏捷 quick	-0.0261091	0.02083970	-0.0052694	-0.00909032
		顽皮 naughty	0.09468020	0.21980882	0.31448899	0.174238095
		慵懒 lazy	0.09193315	0.0590001	0.15093327	0.197266790
球员 player	魔鬼 devil	可怕 horrible	0.029382963	0.06316606	0.092549023	0.091602731
		残忍 cruel	0.009653102	0.14321677	0.152869872	0.059492234
		邪恶 evil	0.008303388	0.17595066	0.184254048	0.077411169
这 it	水墨画 wash painting	名贵 valuable	0.043466200	0.08059552	0.08059552	0.045615660
		简洁 concise	0.056759820	0.12486820	0.12486820	-0.00535744
		美丽 beautiful	0.088287376	0.06179154	0.06179154	0.061062775
		相同 same	0.057834150	0.06957777	0.06957777	0.026469391
		简单 simple	0.058563670	0.05398252	0.05398252	0.023385722

essays, fiction and speech. We have 5 volunteer annotators who are all native speakers of Chinese and their agreement on the preliminary test was 0.66(κ) [17], which is considered reliable. Then we evaluated our method against their judgments in terms of accuracy and compared with other methods. We divided the acceptability into five levels instead of simple binary decision(accept/decline), because the five-level method makes the evaluation finer-grained. We asked annotators to score the acceptability of each result and took average acceptability below three as the incorrect results. The results are demonstrated in Table 3.

Table 3. The results of four methods

	RT	RS	RTS	Our Method
Accuracy	0.59	0.55	0.61	**0.84**

The results show our method achieves higher accuracy and it has obvious improvements compared with other three methods, which reveals our method has the good performance. Then, we analyze the errors and propose the solutions to improve our approach in the future.

1. We use the *AttributeDatabase* and *Sardonicus* to obtain the properties of source domain, but some properties are still difficult to be extracted, causing that the method is unable to obtain the appropriate comprehension aspect. In the future, we will improve the extraction mechanism of properties to solve this problem.
2. Context information provides the cues of proper comprehension aspect, at the same time, it may also bring some noise. In the future, we can introduce the weights to reduce the influence of noise.

5 Conclusions

The previous researches of metaphor interpretation mostly focus on single-word metaphors expressed by verbs and are lacking in the effective use of context information. In this paper, we creatively propose the aspect-based semantic relatedness and present a novel metaphor interpretation method based on semantic relatedness for context-dependent nominal metaphors. We obtain the possible comprehension aspects according to the properties of source domain. Then, combined with the relatedness between context and source domain, we calculate the relatedness between target and source domain from different aspects. Finally, we select the aspect which makes the relatedness between target and source domains maximum as the comprehension aspect, and the corresponding property of source domain will be salient, forming the metaphor explanation. The experimental results show that the aspect-based semantic relatedness computation is reasonable and the context information can effectively guide to the appropriate understanding of metaphor. We evaluate our method and compare it with other methods, the results show that our method has good performance. In future work, we will improve our approach and apply the method to other NLP tasks such as word sense disambiguation and text clustering.

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