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Automatic detection and interpretation of nominal metaphor based on the theory of meaning

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ABSTRACT

Automatic processing of metaphors can be explicitly divided into two subtasks: recognition and interpretation. This paper presents an approach to recognize nominal metaphorical references and to interpret metaphors by exploiting distributional semantics word embedding techniques and calculating semantic relatedness. In terms of detection, our idea is that nominal metaphors consist of source and target domains and that domains present in metaphors will be less related than domains present in non-metaphors. We represent the meaning of the concept as a vector in high-dimensional conceptual space derived from the corpus and compute the relatedness between the vectors to complete the task of detection. Relatedness here is based on the semantics of concepts. Thus, the model we present deals with metaphors where target and source have the same direct ancestors, such as "*A surgeon is a butcher*".

Then, using the relatedness between target and source domain, based on the properties of source domain and dynamic transfer of properties, we present an approach to interpret metaphors with dynamic transfer. Based on the view that metaphor interpretation is the cooperation of source and target domains, we divide metaphor interpretation into two subtasks: properties extraction and properties transfer. Creatively, we use annotations to express a non-binary evaluation, and we take the degree of the annotators' acceptability to evaluate our interpretation of metaphors.

1. Introduction

A metaphor is a kind of figurative language or trope. For instance, the uses of the noun "*butcher*" in the sentences "*He is a butcher*." and "*A surgeon is a butcher*." are different. In the first sentence, according to WordNet, the noun "*butcher*" means "*a person who slaughters or dresses meat for market*". In the second sentence, "*butcher*" exhibits its metaphorical use of "*someone who makes mistakes because of incompetence*". According to *Metaphor Theory* [1], a metaphor is defined as an analogy between two distinct domains – source and target domains. The target domain is what is actually being talked about; the source domain is the domain used as a basis for understanding the target (e.g., in the metaphor "*Time is money*", "*time*" is a concept in the target domain, and "*money*" is a concept in the source domain.). In the 1980s, Lakoff and Johnson proposed a Conceptual View and emphasized that, rather than being a rare form of creative language, metaphors are primarily a cognitive phenomenon, and metaphorical language serves as evidence for cognitive phenomena.

Metaphor research plays an important role in Natural Language Processing (NLP) [2]. Many sentences convey emotional tendency through underlying meaning [3]. Metaphor research has been applied to many NLP problems, such as machine translating, information retrieving, question answering [4], discourse understanding, and text summarizing. As a widespread phenomenon in natural language and a basic method of human thinking, the way we identify and interpret metaphors attracts the attention of not only linguists, but also cognitive scientists. The method for automatically processing metaphors is a simulation of the way humans identify, interpret and generate metaphors. It is believed that conceptual metaphors are not a barrier to, but a resource for cognition. Metaphors are integral to the human understanding of a myriad of abstract or complex concepts [1].

Following Krishnakumaran and Zhu [5], we divide metaphors into three types: Type I, II and III metaphors. In Type I metaphors(*nominal metaphors*), a noun is associated with another noun through the verb "be", such as in the case of "*Love is a journey*." In Type II metaphors(*verbal metaphors*), a verb acts on a noun such as in the instance, "*He kills a process*." For Type III metaphors(*adjective metaphors*), an adjective acts on a noun. Differing from other authors, who focus on Type II and III metaphors, in this paper, we focus only on Type I metaphors which are subject-verb pairs.

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Our method represents the concept by exploiting distributional semantics word embedding techniques and calculates semantic relatedness to determine whether or not the sentence is metaphorical. The core of metaphor interpretation is to extract similarities from target and source domains. Thus, properties of source domain play an important role in the dynamic metaphor process. Our method uses databases to extract a source's properties and then calculates the semantic relatedness between target and source concepts based on those properties. Finally, our method selects the property with the highest relatedness as interpretation output.

Compared with other works in metaphor detection, the main contributions of this paper are as follows:

1. We exploit distributional semantics word embedding techniques and semantic relatedness in the metaphor detection and interpretation fields.
2. Our method is based on the theory of meaning. We consider that the difference between source and target domains is in the semantic level, rather than that the domains belong to two different categories.
3. Our method can be flexibly applied to Chinese and English languages. In the Chinese language, we achieve detection accuracy of 85% and interpretation accuracy of 87%. In the English language, we achieve detection accuracy of 85.2% and interpretation accuracy of 85%.

2. Related work

2.1. Automatic metaphor detection

According to Wilks [6,7], metaphors represent an anomalous breaking of selectional preference in a given context. He believes that an occurrence of a metaphor necessarily leads to a semantic preference violation. Wilks' system divides metaphor understanding into two stages: recognition and interpretation.

One of the first attempts to identify and interpret metaphorical expressions automatically is the work of Fass [8]. The approach of Fass has its origins in the work of Wilks and uses a selectional preference violation technique to detect metaphors. For NLP, Fass introduces Collative Semantics, which extends many of the main ideas of preference semantics. Fass proposes a system ("met*") that discriminates among literalness, metonymy, metaphor and anomaly. However, this system relies on hand-coded declarative knowledge bases and leads to a number of limitations.

The CorMet system, developed by Mason, is the first attempt to discover source-target domain mappings automatically [9], which is accomplished by "finding, in a domain-specific selectional preference, systematic variations that are inferred from large, dynamically mined Internet corpora". Mason built the CorMet system with a statistical approach; the system is a corpus-based system for discovering metaphorical mapping between concepts. The CorMet system dynamically mines domain specific corpora to locate less frequent usages and identifies conceptual metaphors. Verbs selected for a concept in a source domain tend to be selected for their metaphorical equivalent in the target domain.

The method of Gedigian et al. [10] discriminates between literal and metaphorical use. For this purpose, they trained a Maximum Entropy (ME) classifier. They obtained their data by extracting the lexical items, whose frames are related to MOTION and CURE, from FrameNet [11], whereby highly conventionalized metaphors ("dead metaphors") are taken to be negative examples.

Kintsch [12,13] developed a computational system ($CI - LSA$ framework) of "X is Y" metaphoric references using semantic vector space. This system first uses of Latent Semantic Analysis (LSA) [14] and, by computing semantic distances through the bag-of-words representation, attempts to obtain the relevant or similar meaning to X and Y. Then, a Construction-Integration (CI) model [15] is added to select words that have a semantic distance close to the target domain, Y. As a result, words having a high semantic association with X are selected to represent the meaning of the metaphor "X is Y".

Krishnakumaran and Zhu [5] used hyponymy relation in WordNet [16], and selection preference violation based on knowledge learned from bigram frequencies on the web, to automatically classify sentences into metaphoric or normal usages. They dealt with verbs, nouns and adjectives as parts of speech.

Veale and Hao [17] proffered the argument that the same concepts and properties are described in either case. They automatically acquired a large simile case-base from the web and used the examples to both understand property-attribution metaphors and generate apt metaphors for a given target on demand.

Shutova et al. [18] presented a novel approach to identify metaphors by using verb and noun clustering. Starting from a small seed set of manually annotated metaphorical expressions, the system they presented can distinguish a large number of metaphors of similar syntactic structure from a corpus. This approach is different from former work in that it does not employ any hand-crafted knowledge. In contrast, this approach captures a metaphor by means of verb and noun clustering. The first to employ unsupervised methods for metaphor identification, their system operates with a precision of 0.79.

Based on the view that a metaphor usually involves mapping of a relatively concrete concept to a relatively abstract one, Turney et al. [19] proposed a new approach to identify metaphor expressions from literal usages. Thus, they presented the hypothesis that a metaphorical word is related to the abstractness of the context. Based on this hypothesis, they introduced a method to (1) differentiate metaphorical or literal expressions within a given context and (2) evaluate the algorithm with Type 3 (adjective-nouns) metaphors (as in dark thought) and with the TroFi Example Base for verbs. Therefore, to deal with the identification of metaphorical phrases, they used only one element: the abstractness of nouns in the phrase. Their algorithm has an average accuracy of 0.79 in adjective-nouns metaphors and an accuracy of 0.734 in verbal metaphors.

Neuman et al. [20] described three algorithms for three types of metaphor identification. According to them, the traditional selectional preference applied to metaphor identification has the main problem that using the common sense of phrases as an indication does not work very well in types such as subjective-nouns metaphors. They identified metaphors from two approaches: selectional preference and abstractness-based identification. They emphasize the method of measuring abstractness level, which is viewed as an indirect approximation of a noun's embodied nature. They combine measuring abstractness and selectional preference(Concrete Category Overlap) and first check a noun's selectional preference to obtain its literal sense. Their algorithms achieve an average 0.71 precision for the three types of metaphors. For type I metaphor identification, their approach is to compare the semantic categories of the nouns. They achieve 0.839 precision for Reuters corpus and 0.841 precision for NYT corpus. However, the category-based method is weak in dealing with metaphors of which the source and target concepts come from the same category. Our method avoids such mistakes by calculating the relatedness of nouns.

Tsvetkov et al. [21] used a method of combining abstractness degree and extracted CSF-common semantic features from cross-lingual metaphor distinguishing, especially in Russian and English. The classifier they presented is trained on English expressions first and then applied to another language; therefore, other than English, it does not require any hand-crafted lexical resource, such as TroFi, MRC and WordNet. They distinguish between metaphorical and literal usages by extracting syntactic relations (e.g. subject-verb-object (SVO) and adjective-nouns (AN)) as their features. Regarding SVO relations, they extract three types of features– semantic categories, abstractness degree, and types of named entities – and apply a logistic regression