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Latent semantic similarity based interpretation of Chinese metaphors

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ABSTRACT

As a ubiquitous usage in both text and speech, metaphor now attracts more and more attention. Automatic metaphor processing can be divided into two subtasks: metaphor detection and metaphor interpretation. This paper describes an algorithm to interpret the Chinese nominal and verbal metaphors based on latent semantic similarity which we define in this paper. Our method extends the perceptual features of the source and target concepts using the synonyms in WordNet to discover the latent semantic similarity between them and thereby generates the interpretation of nominal metaphors. It is considered that if two words are latent semantic similar, not only is there an extension path in WordNet from one to the other, but also their sentiments should be consistent. So the sentiment of the word is used to constrain the extension. Without a context, we think that the results of interpretation may be multiple because there are several features of the source that can be used to describe the target. Thus, we use Google Distance to rank the interpretation results. This model achieves 85% accuracy in nominal metaphors and 86% accuracy in verbal metaphors.

1. Introduction

Metaphor research, which has been applied to many NLP problems, such as machine translation, information retrieval, question answering, discourse understanding and text summarizing, plays an important role in Natural Language Processing (NLP). Research shows that some errors in machine translation and word segmentation are caused by metaphors. Thus, a good approach, dealing with metaphors, will effectively improve the performance and precision of the existing models in other NLP items, such as machine translation. Metaphor is a widespread phenomenon in natural language, and a basic method of human thinking, and the way we identify and interpret metaphors attracts not only the attention of linguists, but also that of cognitive scientists. The method for automatically processing metaphors simulates 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 (Lakoff and Johnson, 1980).

The automatic processing of metaphors can be divided into two subtasks: metaphor detection and metaphor interpretation. Metaphor detection is to distinguish between metaphorical and literal usages; metaphor interpretation is to identify the intended literal meaning of a metaphorical expression. We consider that interpretation is the following three-way correspondence between source domain and target domain: (1) the source and target share common properties; (2) the properties of source and those of target have some similarities; and (3) the target is matched to one of the source domain's properties. In this paper, we define (1) as shallow semantic similarity and (2) as latent semantic similarity (see Section 3).

Following Krishnakumaran and Zhu (2007), we divide metaphors into three types: Type I (Nominal Metaphors), II (Verbal Metaphors) and III (Adjective Metaphors). For example:

Type I : A noun is associated with another noun through the verb "be", e.g., "Love is a journal."

Type II: A verb acts on a noun such as in the instance "He kills a process."

Type III: An adjective and the noun it describes, e.g., "sweet child," or "The book is dead." (Gandy et al., 2013)

In this paper, we focus on Type I and Type II metaphors. Regarding Type III metaphors, we take the metaphors formed as "⟨target⟩ BE [a/an/the] ⟨source⟩" as our database. Regarding Type II metaphors, we take the ones formed as "Verb–DirectObject" and "Subject–Verb" as our database.

In this paper, we claim that a metaphor is a process that creates similarity between two concepts in cases where such similarity does not already exist. If it were simply a matter of highlighting existing similarity, many relations between concepts which are not

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metaphoric would be predicted to be metaphoric. Thus, the similarity between concepts may not be present in a knowledge-base, unless, like WordNet (Miller, 1995), a metaphor is already implicitly present. Therefore, in this paper, WordNet is used to obtain the latent semantic similarity between concepts.

Our method is divided into three steps: (1) the extraction of perceptual features of the source and target concepts; (2) the synonymous extension of extracted features using WordNet; and (3) the ranking of interpretation results based on Google Distance. In the section on extracting the perceptual features, we use the features extracted by the online database, *Sardonicus* (Veale and Hao, 2007). Then we use the synonyms in WordNet to extend the perceptual features to interpret the metaphors. Because the extension is non-directional, we use the sentiment of each feature to constrain the extension's direction, guaranteeing the extension's consistency. At last, when there is no context, we think that there should be more than one interpretation result. There should be different interpretation results related to the different features of the source concept. Thus, we use Google Distance to rank the results.

The main contributions of this paper are as follows (Baroni et al., 2009):

(1) We do not need to develop a corpus or other statistic resources for the system, but, instead employ the latent semantic similarity based on WordNet. The latent semantic similarity actually reflects the mapping of image schema between the source and target concepts.
(2) Compared with Shutova (2010), our system deals with, not only verbal, but also nominal metaphors.
(3) Our system achieves 85% accuracy for nominal metaphors and 86% accuracy for verbal metaphors.

2. Related work

2.1. Models based on inference

Martin (1994) described a metaphor comprehension system (MIDAS) and applied it to teaching software based on Unix.

Martin takes KODLAK, the extended sematic system of KL2ONE, as its knowledge interpretation language, which connects elements through an inheritance mechanism and concept hierarchy. When dealing with novel metaphors, MIDAS extends the existing ones to interpret them by the metaphor extending system (MES). Firstly, the metaphor algorithm searches the metaphors related to the given novel ones and then selects the most related ones by calculating the concept distance of the two. The most related ones is the results of the interpretation. MIDAS relies on inference, and deals with novel metaphors without any corpus.

Veale and Hao (2008) described a “fluid knowledge presentation for metaphor interpretation and generation”, which is called Talking Points. Talking Points extracts the conceptual properties from WordNet and the web. The properties extracted by Talking Points are then organized in Slipnet, which contains rules of insertions, deletions and substitutions and constructs the connection between concepts, thus completing the interpretation of the metaphors. However, Veale and Hao have not declared the useable range of Talking Points.

2.2. Models based on word paraphrasing

According to Shutova (2010), the result of interpretation should be directly embedded in other systems. They thus define metaphor interpretation “as a paraphrasing task” and describe a system that automatically derives literal interpretation in unrestricted text. The method is divided into two subtasks: generate literal paraphrasing and disambiguate from literal and metaphorical ones. Differing from the normal word disambiguate, paraphrasing must distinguish literal and metaphorical ones from the generated interpretations.

Bollegala and Shutova (2013) presented a fully unsupervised model of metaphor interpretation using paraphrases extracted from the web. According to them, given a metaphorical verb and its arguments, metaphor interpretation is extracting a paraphrase and replacing it in a literal way. They confirm that the main difference between metaphor interpretation and common paraphrase extraction is how to find paraphrases with literal usage, especially in a given context with given arguments.

In this paper, we apply the idea that views the interpretation of verbal metaphor as a paraphrasing task. Different from Shutova, when choosing a literal verb to paraphrase the metaphorical verb, we apply the semantic information of the source and target domains, not only statistic data or selectional preference.

2.3. Model based on term vector

Shutova et al. (2012) presented a novel approach to metaphor interpretation with a vector space model, which focuses on verb metaphorical usages. Using a non-negative matrix factorization to compute the meaning list of target verbs, paraphrase candidates are extracted. After annotating the text with UKwac corpus (Baroni et al., 2009) and Stanford Part-of-Speech Tagger (Toutanova et al., 2003), the similar word (candidate paraphrase) is followed by adapting a probability distribution added to some dependency features. Because they assume that target verbs also restrict the interpretation, they score the obtained paraphrases with the supplementary target verb itself. The method using vector space model is also viewed as computing the similarity between the source and target domains. Compared to such similarity, this paper proposes the latent semantic similarity, which reflect how the source and target domains are similar, not only implying that the source and target domains are similar.

Overall, in terms of the previous studies on metaphor interpretation, a majority of work focus on verbal metaphors and some statistic methods are applied in metaphor interpretation. In this paper, we focus on Chinese nominal and verbal metaphor. Specially, we propose the idea of latent semantic similarity (See Section 3). Based on latent semantic similarity, this paper tries to explore the latent relation between the target and source domains. Such relation implies the semantic relation between the target and source domains, not only some statistic data.

3. Some definitions and assumptions

In this paper, we propose that the key of metaphor interpretation is to comprehend the “meaning” of the source and target concepts and to find the relationships between the two concepts. Ogden et al. (1946) gave 22 definitions of “meaning” in *The Meaning of Meaning*, three of which we focus on as follows: *“An Intrinsic property”*, which points out that the meaning of a word is its features; *“Emotion around by anything”*, which points out that sentiment is also a part of a word's meaning, and *“That which is actually related to a sign by a chosen relation”*, which points out that the meaning of a concept contains the relation to other concepts.

To build a system for metaphor interpretation, based on Ogden's definition to the “meaning”, we give some definitions and assumptions in this section.