Metaphor Detection and Interpretation: A Survey

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ABSTRACT: Metaphor is a very widely used non-literal language. It is a figure of speech in which two unrelated concepts are compared. In this paper, we review several approaches in the detection of metaphors across domains, genres, and discourse. Also, figures out computationally detecting metaphors based on certain features like abstractness and concreteness, lexical cohesion, global/ local contextual features. The evaluated approaches are focused on two datasets: Online Breast Cancer discussion forum dataset and VU Amsterdam metaphor annotated dataset.

1 INTRODUCTION

Metaphor can be defined as a figure of speech in which a word or phrase is given for an object or any action to which it cannot be literally applied. It arises when two different concepts are compared. It is highly frequently seen in language, and though makes the computational processing of languages indispensable for real-world NLP tasks pointing certain semantic processes. Demonstration of metaphor is pervasive in language and reasoning, which makes its computational processing a necessary task within Natural Language Processing. According to corpus studies, explaining up to twenty percent of all word meanings, the metaphor is a bottleneck, especially in semantic tasks. An accurate and scalable metaphor processing system is an important component for many practical NLP applications.

Humans often use metaphors to describe certain abstract concepts like feelings, emotions, relationships etc. by reference to some concrete or physical experiences. Actually, metaphors are originated when one concept is used in terms of the properties of another. For example, we can interpret the metaphorical expression "Her heart was *dancing* with pleasure," in this expression *dancing* is used as a metaphor, where her feeling is expressed through reference to some physical experience.

For about 2,500 years, from the time of Aristotle believed that metaphor was just a matter of language, or it was a word with a literal meaning that have a second meaning, which Aristotle demanded was "similar" to the first. Thus, a metaphor would be reduced to a set of literal similarity expressions for any cognitive content, based on this comparison theory. Also, metaphors were considered nonessential for stating the basic truth claims, which could be reduced to propositions and literal concepts. They were seen as strong rhetorical and poetic plots of language. This Aristotelian perspective was proven to be wrong by the last half of the 20th century. An innate rethinking of the nature and processing of metaphor was brought forth by a progressing body of cognitive-science as a result of their research on the meaning, knowledge and language, reasoning, and conceptualization. This cognitive research was the basis for what came to be known as Conceptual Metaphor Theory (Lackoff & Johnson 1980).

Metaphor did not become a focal topic of research until the 1960s, all the works on metaphor identification have published from then. Most of them relied on the task-specific hand-coded knowledge and state-of-the-art accurate parsing. There were also certain works on computational lexical semantics which have created many avenues for the creation of metaphor processing system.

According to Lackoff & Johnson 1980, the metaphor is not only a language property (a linguistic phenomenon), but it is also a property of thought (a cognitive phenomenon). This was then used and extended by multiple approaches (Grady 1997, Narayanan 1997, Fauconnier & Turner 2002, Feldman 2006, Pinker 2007) Conceptual metaphors include "source domain" frames which are mapped to "target domain" frames. Most of the inference structure in the source domain is mapped to the corresponding target-domain structure. Few examples of metaphor include:

(1) She was on the *road* to success.
(2) Millen *invested* himself completely in this project.
(3) How can I *kill* a process? (Martin 1988)

The dissimilar features of a concept are viewed in terms of another concept. In Example (1), *road* is not the one which the vehicles pass by, instead it describes that she is on the way or moving through the steps to succeed. In Example (3), *invested* is used instead of involved fully in this project. While in Example (4), a computational process is considered as something *alive* and, though, its forced stop or termination is related with the act of killing. Processing of metaphor can be divided into two subtasks: Identification, or recognition (differentiating between metaphorical and non-metaphorical language in text) and metaphor interpretation (identifying the intended literal meaning of a metaphorical expression). A best metaphor processing system should point both of these two tasks.

In the natural language texts the usage of customary metaphor is omnipresent. It is a commonly used linguistic tool in day to day communication, hence it makes difficult for natural language applications to detect it in discourse. It is useful for several NLP applications, like summarisation, machine translation, text simplification, Information retrieval, question answering, Information extraction and opinion mining. Thus metaphor processing is indispensably necessary for automatic text understanding. In this paper, various metaphor detection and interpretation methods are discussed and evaluated.

Metaphor understanding processing needs resolving non-literal meanings through analogical comparisons. The development of a complete and computationally practical account of this phenomenon is a complex and challenging task. Various methodologies are proposed for identifying the metaphors in sentences and discourse.

Classification based on features makes use of various classes of features like abstractness and concreteness, lexical cohesion, global and contextual features etc. Figure 1. Depicts the classification of the various approaches based on the features they used. Also, uses machine learning algorithms like Logistic Regression and Support Vector Machine (SVM), as classifiers. Figure 2. depicts the classification of previously proposed metaphor detection methodologies based on the classifiers they used. In the coming sections, we will discuss and compare the different approaches for the detection of metaphors.

2 METAPHOR DETECTION

The Various approaches are put forth for metaphor detection in computational linguistics. Some of them are discussed here. The major methodologies for computationally detecting metaphors can be divided into work that considers the following classes of features: selectional preference, abstractness and concreteness, lexical cohesion, and global/local contextual features.

Earlier, most of the metaphor identification system made use of the selectional preferences features. These features relate, how the semantically compatible predicates are associated with any specific arguments. The main notion for the use of selectional preferences features for detecting metaphors is, the non-literal (metaphorical) words tend to break these features. In the metaphorical expression, "*the clouds sailed across the sky,*" here *sailed* is used metaphorically, as *clouds* being a subject infringes its selectional restriction. The use of selectional preferences has studied well over several previous approaches (Martin 1996, Shutova et al. 2010, Shutova et al. 2013, Huang 2014). This methodology can be again classified into methods that use lexical resources and those uses corpus-based methods in order to obtain selectional preferences.

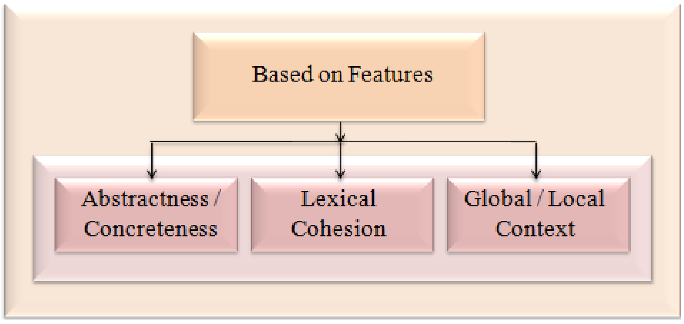

Figure 1. Classification of methodologies based on the features used.

2.1 *Features Based Methods*

Klebanov et al. (2014), proposed an approach where metaphor is identified by the use of several lexical features like POS tags, concreteness ratings, and scores of topics of target words to identify word level metaphors. Metaphorical words in the source domain uses concrete and imaginative words than that of the target domain. The concreteness and abstractness methodologies measure computationally the degree of words in the sense of abstractness to find metaphors. Consider the phrases as examples: *green thoughts* (nonliteral-metaphorical expression) and *green valley* (literal-nonmetaphorical expression). The first one has a concrete word (*green*), used to modify the abstract concept (*thought*), thus making it as more likely to be metaphorical.

The approach used in Klebanov et al. (2014) describes about modeling a supervised machine learning system that classifies all content words in a running text as either metaphorically or non-metaphorically used. Also, it enables the quantification of how much a given text make use of non-literal expressions like metaphor or to which similar kind of metaphors used by two unlike texts. This approach evaluates the effectiveness of a unigram baseline which gives fine results for few datasets and reveals that the system recall can be improved on this baseline. Uses two metaphor annotated datasets: VU Amsterdam metaphor annotated corpus (Steen et al. 2010) and a group of essays which was written for college graduates' assessment.

The VU Amsterdam corpus contains 117 fragments sampled over four genres. It contains the annotation of all content words in a running text in order to classify as metaphorical or not. The data comes from the British National Corpus (BNC): academic, fiction, news, and conversation. According to this approach, the baseline feature POS helps to improve recall over all datasets. Only for a few datasets the concreteness features were found to be effective. Also proved that the topical homogeneity can be exploited beyond unigrams.

According to Klebanov et al. (2015), using the re-weighting of training examples and features given by a concrete database, the system provides an essential improvement on baselines published previously. This approach starts with a baseline features set and training method (Klebanov et al. 2014) and investigates the influence of re-weighting of training examples and number of other features that relate to the concreteness of the desired notion, also to the concreteness dissimilarity within some types of dependency relations.

This methodology also uses the VU Amsterdam corpus data. Performance is measured by recall, precision, and F-1 score for the positive (metaphor) class. Uses the feature set by Klebanov et al. (2014). The baseline consist of the features such as unigrams, part of speech tags produced by Stanford POS tagger, mean concreteness values, and topic models. Found that the first approach of re-weighting of training examples is very effective and the second shows only very small. The main limitation of the discussed two approaches is that no features were used to represent the connection between the current word and its immediate context.

The limitations of the above discussed methods can be overcome through the new approach of metaphor detection in discourse (Jang et al. 2015). Most of the works aimed at identifying metaphors from a given single sentence thus focus mostly on local contextual hints within any short text. This methodology addresses a novel approach that explicitly uses global context of a discourse for metaphor detection. Also, shows that the syntactic information like dependency structure can help demonstrate local contextual information, thus improving the detection results when they are combined.

This approach has certain advantage over the previous ones in that most of them looked at lexical semantic features like selectional restriction violations or contrast in abstractness and concreteness. While these methodologies have shown to be succeeded in the detection of metaphors in single sentence, identifying metaphor in discourse is a novel method to the metaphor processing task. As metaphor, a semantic phenomenon it explains objects or actions with a perspective taken from a different sphere. Though, it is quite normal that metaphors cut a sentence's or a discourse's lexical coherence.

The major contribution of this approach is two-fold. First, proposes various textual descriptors which can hold global contextual shifts like category of semantic word in a discourse, homogeneity in topic distributions, and lexical chains. This method has achieved greater performance over several prior approaches (Klebanov et al. 2014), on metaphor disambiguation than the state-of-art systems. This work has put forth a different approach from others in that it gathers global contextual feature from discourse to detect metaphors and leverages syntactic structures to better represent local contextual information.

The global features spread over the whole document, while local contexts over the sentence with the interested expression. To represent the global contexts of a given text, the features used are as follows: semantic category, topic distribution, lexical chain, and context tokens. The local contextual information in a sentence is finite because it consist of only some words, but the information it conveys is somewhat direct and wider, as it gives the immediate context of the interested expression. Various semantic features are used to represents the local contextual information such as semantic category, semantic relatedness, lexical abstractness and concreteness, and grammatical dependencies. The dataset used for this approach is different from the previous approaches already discussed. Data is acquired from an online breast cancer support group discussion forum, by (Jang et al. 2015), which is a dataset of posts from a public breast cancer support group discussion form.

Jang et al. (2016) present a method that distinguishes literal and non-literal use of target words by evaluating sentence-level topic transitions and also identifies the motivation of speakers in expressing emotions, feelings and other abstract concepts metaphorically. Holding information from various area allows more effective method of expressing the abstract concepts like emotions, ideas, thoughts etc. than only using it as literal language.

Approaches the problem in two different ways to better find the important context around a metaphor. First, hypothesize that topic transition patterns between sentences in which metaphors are present, and their contexts are dissimilar from that of literal sentences. For that includes various sentence-level topic transition indicators like topic similarity between a sentence and neighborhood, evaluated using sentence Latent Dirichlet Association (Jo & Oh 2011) as features. Second, models the approach based on speakers' motivation in expressing the emotions by detecting that emotion and cognitive words in non-literal and literal sentences and their contexts.

The major contribution of this approach is of threefold. Provides topic transitions between a metaphor and its context and proposes to find emotional and cognition words to better understand the motivation of speaker behind the usage of that metaphor. Finally, evaluated that metaphor often occurs more frequently surrounding any personal topics. To encode the sensational and emotional features uses Linguistic Inquiry Word Count (LIWC) (Tausczik & Pennebaker 2010), a tool that count the use of words that fall into certain categories. Online breast cancer discussion forum dataset, annotated by Jang et al. (2015), is used. This approach makes use of two baseline features, features set of Jang et al. (2015), and context unigram model. Performance evaluation using five metrics, kappa, F1 score, precision, recall, and accuracy.

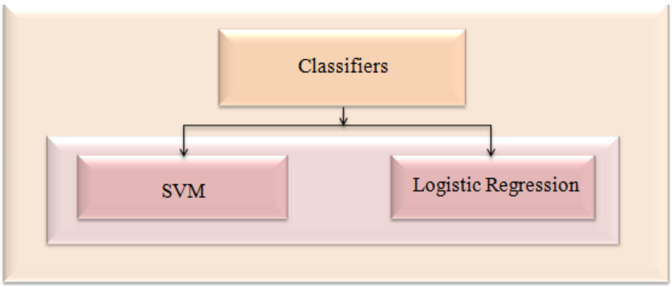

Figure 2. Classification of methodologies based on classifiers used.

2.2 *Classification Based methods*

The above discussed methodologies can be classified based on the classification algorithms they used as shown in the figure, Figure 2. The machine learning method used by all of these methodologies described here is supervised machine learning for binary classification. Specifically, Support Vector Machine (SVM) and Logistic Regression classifiers are used. In the approaches proposed by (Klebanov et al. 2014, Klebanov et al. 2015, Jang et al. 2015) uses Logistic Regression classifiers. While SVM with sequential minimal optimization (SMO) is used by the approach put forth by Jang et al. (2016).

Table 1. Summary of the proposed approaches and the datasets used.

Approaches	Types of Classification		Datasets
	Based on Features	*Based on Classifiers*	
(Klebanov et al. 2014)	Abstractness/ Concreteness	Logistic Regression	VU Amsterdam Metaphor annotated Corpus
(Klebanov et al. 2015)	Abstractness/ Concreteness	Logistic Regression	VU Amsterdam Metaphor annotated Corpus
(Jang et al. 2015)	Global/ Local Context	Logistic Regression	Online Breast Cancer discussion forum support group dataset
(Jang et al. 2016)	Lexical Cohesion	SVM	Online Breast Cancer discussion forum support group dataset

3 FUTURE DIRECTIONS

Overall, the results from various approaches conveys that the metaphor processing system can supply helpful and correct facts regarding metaphor to other NLP processes especially relied on lexical semantics. Hence, in order to show its utility for outer applications, a task-based evaluation is outstanding. In the further works, metaphor processing can be integrated with various NLP applications., in order to describe the donation of this ubiquitous yet sparsely marked phenomenon to natural language understandings.

Metaphor detection can be improved further by adding some more features. The proposed features in each methodology can be spread out to other domains. As the particular topic transition and emotion/cognition patterns will be different in other domains, these features for the detection of metaphors would nevertheless be relevant.

4 CONCLUSION

Metaphor makes our thinking more realistic and enriches our communication with new imagery, but most importantly it plays a major structural role in our understandings helping us organize and project our knowledge. There are various methods for processing metaphor. We have reviewed on some of the literature and have tried to give the comparison between them based on the features and classifiers they use to get better performance. The datasets used by the proposed approaches rely on Online Breast cancer discussion forum and VU Amsterdam annotated Corpus.

The processing of metaphor is inevitable in natural language understanding. Various approaches discussed through this survey focused on different kind of features to detect metaphor. The most successful features in metaphor detection are concreteness, distributional behavior of source and target domain, selectional preferences, textual coherence, and topical properties. These experiments in each of the approaches presented provide new insights on the process of detecting metaphors across domains, genres, and discourse.

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