High-Precision Abductive Mapping of Multilingual Metaphors

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Abstract

Metaphor is a cognitive phenomenon exhibited in language, where one conceptual domain (the target) is thought of in terms of another (the source). The first level of metaphor interpretation is the mapping of linguistic metaphors to pairs of source and target concepts. Based on the abductive approach to metaphor interpretation proposed by Hobbs (1992) and implemented in the open-source Metaphor-ADP system (Ovchinnikova et al., 2014), we present work to automatically learn knowledge bases to support high-precision conceptual metaphor mapping in English, Spanish, Farsi, and Russian.

1 Introduction

In everyday speech and text, people talk about one conceptual domain (the *target*) in terms of another (the *source*). According to Lakoff and Johnson (1980) and others, these *linguistic metaphors* (LMs) are an observable manifestation of our mental, *conceptual metaphors* (CMs). Computational research on metaphor is important: If natural-language systems treat metaphors at face value, meaning can be missed, resulting in absurd or trivial claims.[1] Additionally, understanding metaphors is a way to recognize the attitudes of different individuals, groups, or cultures. Metaphors express strongly felt emotions (e.g., "I'm *crushed* by taxes"—taxation is a burden or threat) and presupposed understandings of concepts (e.g., "She *won* the argument"—arguments are a form of conflict).

The full interpretation of linguistic metaphors is a difficult problem, but a first level of understanding is the identification of the conceptual source and target domains being invoked. For instance, we can map the linguistic metaphor "fighting poverty" to the ⟨source, target⟩ pair ⟨*War*, *Poverty*⟩.

In this paper, we present work that performs this mapping within the abductive reasoning framework proposed by Hobbs (1992) and implemented by Ovchinnikova et al. (2014). By handling metaphor mapping within a general framework for knowledge-based discourse processing, it is possible to extend conceptual mapping to give deeper analysis, as discussed in section 5. This paper's main contribution is the use of annotated collections of metaphors, describing seven target concepts in terms of 67 source concepts in four languages, to learn the lexical axioms needed for high-precision abductive metaphor mapping.

2 Related Work

Metaphor has been studied extensively in the fields of linguistics, philosophy, and cognitive science (e.g., Lakoff and Johnson, 1980; Lakoff, 1992; Gentner et al., 2002). Computational research on metaphor has focused on the problems of (1) identifying linguistic metaphors in text (e.g., Fass, 1991; Birke and Sarkar, 2006; Shutova et al., 2010; Li and Sporleder, 2010; Tsvetkov et al., 2014) and (2) identifying the source and target concepts invoked by each linguistic metaphor.

[1] Lakoff and Johnson (1980) give the examples, "This theory is made of cheap stucco"—blatantly false—and "Mussolini was an animal"—blatantly true.

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Knowledge-based approaches to identifying conceptual metaphors include that of Hobbs (1992), described in the following section, KARMA (Narayanan, 1997, 1999), and ATT-Meta (Barnden and Lee, 2002; Agerri et al., 2007). These have relied on the use of manually coded knowledge, limiting their ability to scale across domains and languages.

As an alternative to identifying source and target concepts and, potentially, performing deeper analysis, Shutova (2010) and Shutova et al. (2012) learned literal paraphrases for linguistic metaphors based on co-occurrence frequencies, focusing on LMs consisting only of a verb and its subject or object. E.g., they would rewrite "stir excitement" as "provoke excitement". One limitation of a basic paraphrasing approach to metaphor interpretation is that metaphors do not have fixed interpretations; their meaning is dependent on the discourse context in which they are used.[2]

3 Framework for Metaphor Interpretation

Hobbs et al. (1993) describe an approach to discourse processing based on abductive inference. Abduction is a form of reasoning that, given an observation, produces an explanatory hypothesis. For discourse processing, each sentence is an observation, and the interpretation of the sentence is the best explanation of why the sentence is true given what is already known: commonsense and linguistic knowledge and the content of the discourse up to that point. Hobbs (1992) described the applicability of this approach to the problem of interpreting linguistic metaphors. In this framework, metaphor interpretation is part of the general problem of discourse processing.

Ovchinnikova et al. (2011) presented a semantic discourse processing framework based on abduction, which uses the Mini-Tacitus reasoner (Mulkar et al., 2007) to interpret a sentence by proving its logical form, merging redundancies wherever possible, and making any necessary assumptions. This work was extended by Ovchinnikova et al. (2014) to address the interpretation of metaphor. They presented an end-to-end metaphor interpretation system, going from the recognition of linguistic metaphors in text through to basic natural language explanation of the conceptual metaphor identified by abduction. The effectiveness of this approach was validated by expert linguists for English and Russian metaphors.

[2] Hobbs (1992) gives an example: "John is an elephant" should be interpreted as meaning that he is clumsy if it follows "Mary is graceful". In other contexts it might mean that John is large, that he has a good memory, etc.

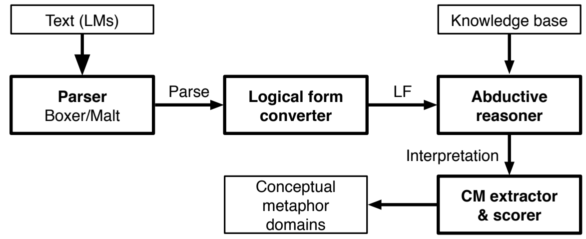

Figure 1: Abduction-based metaphor processing pipeline.

A diagram of the interpretation pipeline is shown in Figure 1. To process a text fragment containing a metaphor, this system generates logical forms (LFs) in the style of Hobbs (1985) by postprocessing the output of the Boxer (Bos et al., 2004) and Malt (Nivre et al., 2006) dependency parsers. A logical form is a conjunction of propositions, where argument links show the relationships among the constituents. An advantage of LFs over the direct use of dependency structures is that they generalize over syntax and they link arguments using long-distance dependencies. While this process is generally reliable, it can result in incorrect part-of-speech suffixes on predicates or inaccurate linking of arguments.

Along with appropriate knowledge bases, the sentential logical forms are input to an engine for weighted abduction based on integer linear programming (Inoue and Inui, 2012). The reasoner finds the most likely (i.e., lowest cost) explanation of the observations (the LF of the text) using knowledge about what conceptual domains explain the use of words and phrases. A conceptual metaphor (CM) extractor and scorer then selects the most likely source–target mappings based on the length of the path linking the source and target in the predicate-argument structure. For this paper, our task consists of the identification of seven target concepts (*Government*, *Democracy*, *Elections*, *Bureaucracy*, *Taxation*, *Poverty*, and *Wealth*) and 67 source concepts used to describe them. A selection of source concepts are listed in Figure 2, and the sizes of the development and test sets annotated with these concepts are given in Table 1.

Abyss	*Container*	*High Location*	*Physical Harm*
Accident	*Contamination*	*Journey*	*Plant*
Animal	*Crime*	*Leader*	*Portal*
Barrier	*Disease*	*Life Stage*	*Protection*
Blood Stream	*Emotion Experiencer*	*Light*	*Resource*
Body of Water	*Enslavement*	*Medicine*	*Science*
Building	*Fire*	*Monster*	*Servant*
Business	*Food*	*Movement*	*Struggle*
Competition	*Forward Movement*	*Obesity*	*Theft*
Confinement	*Game*	*Physical Burden*	*War*

Figure 2: A selection of source concepts.

4 Knowledge Bases and Mapping Performance

The metaphor mapping performance we have achieved is due to two advances over the work of Ovchinnikova et al. (2014): a focus on source and target spans in each sentence and the creation of new knowledge bases. A span is a minimal excerpt of a sentence that is sufficient to mentally trigger the source or target concept. We do not allows spans to overlap or cross sentence boundaries, which may limit our ability to deal with some metaphors. There are one source span and one target span identified per CM, even though a domain might also be supported by words outside the spans. While the spans in our data were annotated manually, they can also be found automatically by LM identification tools like those mentioned in section 2.

We modified the Metaphor-ADP mapping service to filter the logical forms generated by the parser so they only include literals directly related to these spans. We evaluated the contribution of this filtering and found that—for the cross-language average—this improved the precision of source identification significantly with only a small drop in recall:

	Source		Target	
	Prec.	Rec.	Prec.	Rec.
Sentence	39%	22%	84%	49%
Spans	79%	21%	99%	26%

Concentrating on the identified spans particularly helps with sentences containing multiple lexical items that suggest sources or targets, such as those with more than one distinct metaphor, e.g., "…move forward in advancing gun rights …[so] gun rights [will] be on a solid foundation." The drop seen in target recall is deceptive: The system only returns a mapping when it identifies both a source and a target concept. By no longer identifying erroneous sources from outside the source span, the system now returns no mapping for many sentences where the target could nonetheless be identified correctly. As source concept mapping is the harder problem, our focus is on improving those scores.

Performance at metaphor mapping also depends on the coverage of the knowledge bases (KBs) of *lexical axioms* for each language. These encode information about what words or phrases trigger which source and target concepts. Ovchinnikova et al. (2014) used collections of manually authored axioms for English and Russian, bootstrapped by finding related words and expressions in ConceptNet (Havasi et al., 2007). Manually authoring a knowledge base exploits the intuitions of the knowledge engineer, but these can fail to match the data. In addition, manual enumeration is not a scalable approach to ensure coverage for a wide variety of input LMs.

As such, a further improvement to precision and recall came from work to learn KBs automatically from annotated metaphors. This work sought to automatically generate new axioms from example sentences in our development set by identifying which source and target span words or phrases are most predictive of source and target concepts. We found that as the development sets grow larger, inevitably even those lexical items that seem unambiguous, e.g., "*riqueza*" mapping to the *Wealth* target concept, are ambiguous in our annotations. Sometimes this reflects a real ambiguity (e.g., does "Democrats" relate to *Democracy* or *Elections*?), but it can also be due to erroneous annotations.

	English	Spanish	Farsi	Russian
Dev.	7,963	8,151	7,349	4,851
Test	894	894	881	644

Table 1: The number of metaphoric sentences in the development and test sets for each language.

However, for a goal of high-precision mapping, sophisticated learning methods are not necessary. Instead, we require that a chosen percent of the instances of a logical form fragment correspond to a single source or target concept, in which case we output a lexical axiom mapping the LF to the concept. We found it helpful to enforce the mutual exclusivity of the text fragments that map to source concepts and those that map to target concepts. When a text fragment is ambiguous between a source mapping and a target mapping, we produce an axiom for whichever correspondence was more frequent. This reduces the likelihood of the axioms leading the system to identify, e.g., two source concepts in a sentence but no target concept. The results are axioms like

$$\begin{aligned}&\text{Source:Abyss}(e_0)\\&\quad\Rightarrow \text{bottomless-adj}(e_0, x_0) \wedge\\&\qquad \text{pit-nn}(e_1, x_0)\end{aligned}$$

If something is described as bottomless and as a pit, an explanation is that it is an instance of the source concept 'Abyss.'

The learned KBs contain approximately twice as many axioms as the manually authored (and bootstrapped) KBs:

	English	Spanish	Farsi	Russian
Manual	1,595	1,024	1,187	1,601
Learned	3,877	2,558	2,481	3,071

Hybrid KBs combining manual and learned axioms yielded the highest recall, at the expense of a loss of precision compared with the automatically learned axioms alone. We would expect manual axioms to perform with higher precision than automatically learned ones. However, this was not so. Learned and hybrid axioms generally outperformed manual ones, as indicated in Table 2. These results could suggest problems with the quality or generality of our manually authored axioms. It is also possible that this demonstrates the consistency of the automatically learned axioms with the annotation of the testing set. E.g., the annotated metaphors used for training and testing sometimes fail to include source concepts that were added later. This can give an advantage in our testing to axioms learned from training data that suffers from the same bias.

	Source		Target	
	Prec.	Rec.	Prec.	Rec.
Manual, Spans	79%	22%	84%	49%
Learned, Spans	85%	56%	99%	65%
Hybrid, Spans	81%	57%	99%	70%

Table 2: Impact of various axiom sources on span-selected Metaphor Mapping performance. Learned and Hybrid approaches generally outperform the Manual approach to axiom collection.

5 Future Work

There are two interesting lines of future work: The first is to devise more refined techniques that are able to take advantage of large dataset of annotated metaphors despite the increase in errors and inconsistencies that normally appear in large collections of annotated data. To this end, we are exploring the use of machine learning techniques to appropriately vary the weights of the learned axioms. The other line of work is to move beyond source and target concept mapping toward a richer interpretation of metaphors.

A target can be viewed differently depending on the role it occupies in a metaphor, which could be handled by axioms such as

$$\begin{aligned}&\text{Source:Physical\_Harm}(e_0) \wedge\\&\text{Role:Threat}(x_0, e_0) \wedge\\&\text{Role:Threatened}(x_1, e_0)\\&\quad\Rightarrow \text{crush-vb}(e_0, x_0, x_1)\end{aligned}$$

If something crushes something else, an explanation is that it is a threat causing physical harm to something that is threatened.

where predicates describing general roles related to the source concept are abduced, in addition to the concept itself. By identifying which roles in the source domain are instantiated by target domain elements, we get a more complete picture of the metaphor's meaning. E.g., for the LM "Democracy crushes our dreams", democracy is seen as a threat, while in "Corruption has crushed democracy", it is seen as threatened. The axioms necessary for this interpretation could be manually authored, learned from further annotation of data, or sought by the adaptation of existing work on semantic role labeling.

6 Summary

Understanding the meaning of linguistic metaphors depends, as a first approximation, on the ability to recognize what target concept domain is being discussed in terms of what source concept domain. Within a principled framework for general discourse processing, we have exploited a large body of annotated data to learn knowledge bases for high-precision metaphor mapping.

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