CEUR-WS.org/Vol-2347/1-Bolognesi.pdf

How do words vs. images construct and represent metaphor

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Abstract Metaphorical similarity is a peculiar type of semantic relation, based on a very limited number of features that are shared by the two metaphor terms. The nature of these shared features is still largely unknown. Similarly, we know little about whether different modes of metaphor expression (e.g., images, language) use the same types of features to construct metaphors. I hereby report a series of distributional analyses based on a representative sample of pictorial and linguistic metaphors. Three different types of similarity are operationalized through three different distributional methods that are based on the same underlying principle (the distributional hypothesis) but model semantic representations based on different information. Based on such analyses I show that the pictorial and the linguistic modes of expression afford different ways to construct metaphors, because they tend to exploit different types of features that are shared by the metaphor terms. The results are discussed within a cognitive linguistic framework, in which I defend a multi-layered view of conceptual metaphor, in which image schemas might constitute the most generic layer of representation, at which the difference between pictorial and linguistic metaphors may disappear.

Keywords. Semantic similarity, distributional semantics, conceptual richness, metaphors, multimodality.

1. Introduction

The growing interest in multimodal communication and in how meaning is constructed and expressed within the pictorial mode (Jewitt 2009; Kress 2010; Bateman 2014; Bateman et al. 2017) has attracted also scholars working on pictorial and multimodal metaphor (e.g., Forceville & Urios-Aparisi 2009), who conducted analyses across different genres, including advertising (e.g., Forceville 1996) and political cartoons (e.g., El Refaie 2009).

However, there are virtually no previous quantitative studies that aim specifically at comparing the structure and functioning of the pictorial and the linguistic modes of expression in relation to metaphor construction.

The cognitive view of metaphor, fathered by Lakoff and Johnson (1980) suggests that metaphors are matters of *thought*. In this view, (linguistic) metaphoric expressions are distinguished from conceptual structures in a binary manner: there are (linguistic) expressions on one hand, and there are conceptual structures on the other hand. Because conceptual metaphors are considered as 'supra-modality', one might expect to find the same conceptual structures expressed in different modes (e.g., in images and in language). However, such binary opposition between metaphoric

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expression and conceptual metaphor neglects the variety of different sub-levels that can be distinguished within the conceptual dimension. As Kovecses (2017) acknowledges, this is an issue commonly raised in relation to conceptual metaphors: at which level of generality should we formulate conceptual metaphors? Kovecses distinguishes between four levels - image-schemas, domains, frames and mental spaces - and claims that all these levels contribute to structure our conceptual system and the conceptual metaphors therein. The advantages of adopting a fine-grained and multi-layered view of conceptual metaphor enable researchers to investigate in a bottom-up and data-driven manner how different modes (e.g., images and language) construct metaphors, without imposing the straitjacket of a necessarily unique supra-modality conceptual structure onto which metaphoric expressions in all modalities shall converge. The analyses presented here show that, *at some level of conceptualization*, typical metaphors found in images and typical metaphors found in language differ quite consistently and do so in several ways[2].

2. Theoretical Background

Functional neuroimaging evidence show different patterns of neural activation during matched word and picture recognition tasks (Bright et al. 2004; Gates & Yoon 2005), suggesting that processing the pictorial and the linguistic expression of a concept activates different brain areas. Moreover, a variety of clinical studies report about patients with profound visual object recognition disorders, but relatively intact word comprehension (Binder et al. 2009). These findings suggest that pictorial ad linguistic stimuli afford different types of cognitive processing routes and tap into different conceptual representations, at least at some level of abstraction (see also Dual Coding Theory, Paivio 1971; 2010). Given the same concept, images and words, respectively, seem to favor the encoding of different types of information about such concept. For example, images trigger a deeper emotional response, compared to words (e.g. Kensinger & Schacter 2006).

Taking such findings in the field of metaphor, it can be argued that typical metaphors expressed through words and typical metaphors expressed through images might be constructed on the basis of different types of features, which are shared by the metaphor terms. This does not imply however that one of the two modalities constructs ‘more conceptual’ or ‘more embodied’ metaphors than the other.

Based on a literature review on conceptual richness in cognitive psychology (Recchia & Jones 2012; Kounios et al. 2009; Pexman et al. 2008) I argue that a fairly rich approximation of our general knowledge about a concept can be obtained by observing:

1) Its entity-related, attributive properties;
2) Its experience-based relational properties;
3) Its language-based contexts.

For example a fairly rich approximation of what MARGARITAS are, is given by:

[2] The analyses hereby reported are based on three studies published as outputs of the EU-Marie Curie awarded project CogViM (Cognitive Grounding of Visual Metaphor, FP7-IEF2013-629076).

- **Attributional properties**: e.g. <is_sour> (perceptual property), <has_tequila> (an ingredient of margaritas), <is_tangy> (perceptual property).
- **Relational properties**: e.g. <salt> (can be typically found in the same contexts as margaritas, on the glass rim), <summer_times> (season in which margaritas are typically consumed).
- **Linguistic contexts**: e.g. “blending margaritas”, “making smooth frozen margaritas”, “drinking too many margaritas”, which are exemplary sentences in which the word *margarita* can be used.

Although these three streams of semantic knowledge may contain overlapping information, they are theoretically distinct. Based on these different streams of semantic information, different types of semantic similarity between two concepts can be constructed. For example, MARGARITAS share attributional properties with LONG ISLANDS (they both contain tequila), but not as many relational properties (the latter cocktails are not served with salt and are less typical for summer beach parties). It follows that MARGARITAS and LONG ISLANDS are similar in their attributional structures, but not so much in their relational and linguistic structures. Contrariwise, based once again on the few properties mentioned above, the reader might argue that MARGARITAS share relational properties with, for example, SALADS (which are also served with salt and consumed especially in the summer), while these two concepts do not share attributive or linguistic properties. Finally, it could be argued that MARGARITAS share linguistic properties with MILKSHAKES (both are blended, smooth and frozen), but fewer attributive and relational properties.

In metaphor studies, the classic comparison view (e.g., Ortony 1979) defines similarity on the same lines as Tversky’s similarity definition (1977), that is, as a feature-matching process. Other views suggest that the similarity between two metaphor terms emerges specifically from their interaction (e.g.: Black 1979), or from the interaction of complex analogical structures (e.g., Bowdle & Gentner 2005). The approach used here leans toward the classic comparison view, that is, metaphorical similarity is operationalized as a function of shared properties across three streams of semantic information. The analyses discussed here are therefore ‘limited’ to the metaphorical similarity modelled as a feature-matching process. Nonetheless, such process includes the matching of entity-related, as well as relational properties, and the syntactic patterns plus lexical collocates in text corpora.

A growing body of scientific literature has previously tackled aspects of metaphor comprehension by means of distributional semantics. For example, a pioneering study conducted by Kintsch (2000) showed in a qualitative fashion how Latent Semantic Analysis (Landauer & Dumais 1997) can be used to model metaphor comprehension. In a more recent and extensive project (Utsumi 2011), categorization and comparison processes involved in metaphor comprehension were compared and modelled through distributional semantics. Within the nlp and machine learning communities the interest in statistical modelling of metaphor has also been growing recently (Veale et al. 2016). These studies typically aim at modelling metaphor structure (rather than the cognitive processes that lead to metaphor comprehension), and tackle problems such as metaphor detection in text corpora, or address specific types of metaphor, such as verb metaphoricity (Del Tredici & Bel 2016).

3. Method and Materials

A sample of 50 pictorial metaphors retrieved from the VisMet corpus (Bolognesi et al. 2018) and 50 linguistic metaphors retrieved from the Metaphor Corpus (Steen et al. 2010) were used for the analyses[3]. In order to compare the pictorial and the linguistic stimuli, the 100 metaphors were all formalized into A-IS-B statements by applying established procedures in formal content analyses featuring independent annotators and calculations of interrater reliability scores (MIPVU for the identification of linguistic metaphors, Steen et al. 2010; VISMIP for the identification of visual metaphors, Šorm & Steen 2018). Details about these procedures are reported in Bolognesi (2017).

The three distributional analyses are described in detail in the dedicated articles (Bolognesi 2016a; Bolognesi 2017; Bolognesi & Aina 2017). To summarize, attributional properties are operationalized as semantic features attributed to the concepts, collected in property generation tasks (as in McRae et al. 2005) (e.g. CAR: <has four wheels>, <is fast>). The similarity between each pair of metaphor terms is computed in terms of the amount of shared semantic features. For example: consider an advertisement where a car is represented as a rearing horse. The visual metaphor is formalized through the VISMIP procedure as CAR-IS-HORSE. Metaphorical similarity is quantified here as the cosine between the vectors of CAR and HORSE, whose dimensions are the semantic features of the two concepts. Relational properties are operationalized through Flickr Distributional Tagspace (Bolognesi 2014; Bolognesi 2016b): a corpus of roughly 100,000 tagsets for each metaphor term was created. The similarity between two metaphor terms is quantified here as the cosine between the vectors of CAR and HORSE, whose dimensions are the tags with which these concepts appear across tagsets. Language-based contexts are operationalized through *typedm*, (Distributional Memory, Baroni & Lenci 2010), a multi-purpose structured distributional model that encompasses syntactic as well as semantic information about words. The similarity between two metaphor terms is quantified here as the cosine between the vectors of CAR and HORSE, whose dimensions are the linguistic contexts of the two words in *type*-DM.

4. Analysis

The analyses of metaphorical similarity across the three different distributional spaces show different patterns for pictorial and linguistic metaphors[4]. The results are summarized in Table 1.

Table 1. Attributional, relational and linguistic similarity between pairs of metaphor terms.

	Attrib.Sim	Relat.Sim	Ling.Sim
Linguistic metaphors	M=0.012, SD=0.047	M=0.096, SD=0.057	M=0.192, SD=0.087
Pictorial metaphors	M=0.050, SD=0.067	M=0.156, SD=0.061	M=0.121, SD=0.089
t-test	t= 3.282, p < 0.05	t=5.169, p<0.05	t= -4.194, p<0.05

Table 1 shows that the three patterns of metaphorical similarity differ for the two samples of metaphors: pictorial and linguistic metaphors are constructed and represented

[3] The lists of metaphors can be found in the appendix to Bolognesi (2017:550).
[4] In the studies reporting these specific analyses, the measures of metaphorical similarity are also compared to the similarity emerging from to randomly paired concepts.

on the basis of different types of semantic information shared between metaphor terms. Moreover, the manual annotation of the features shared by the metaphor terms (based on the Wu and Barsalou 2009 taxonomy of feature types[5]) shows that pictorial metaphors are typically constructed on shared features that express entity-related properties (typically perceptual features and components of the predicated concept), and experience-based relational properties (typically locations in which the concepts appear and objects/participants that populate these environments). Conversely, linguistic metaphors appear to be typically constructed on features that are mainly taxonomic (such as, for example, hypernyms that are shared by the two terms of the linguistic metaphor). Taxonomic information is well-captured and represented in language use, and this is probably why a language-based distributional model (like DM) is more suitable for capturing metaphorical similarity for linguistic metaphors, as opposed to distributional models based on entity-related and experience-based relational properties.

5. Discussion and Conclusion

Linguistic categories (e.g. the word *car*) and visual categories (e.g. a pictorial representation of a car) classify perceptual experiences in different ways. These two semiotic systems have different 'preferences' in the type of information that can be more easily expressed. It is therefore to be expected that, at some level of abstraction, typical pictorial and linguistic metaphors behave in different ways, and construct comparisons on the basis of different types of features, which are shared by the metaphor terms. This is understandable only when we adopt a multi-layered view of conceptual metaphors, such as that offered by Kovecses (2017): when we talk about *conceptual* metaphors we need to take into account a variety of levels that constitute the so-called conceptual system. These levels of conceptual representations range from levels that contain more conceptually rich information (e.g., mental spaces) to highly schematic ones (e.g., image schemas). The first levels involve richer representations that are arguably more deeply influenced by modality-specific information, and therefore by the metaphoric expressions that can be typically found in specific semiotic systems. Contrariwise, deeper and more schematic levels of metaphor analysis, such as those based on image schemas, may see mode-specific differences disappear, and common embodied (but semantically impoverished) patterns based on image schemas emerge. The studies here reported tackle a level of metaphor analysis at which significant differences between pictorial and linguistic metaphors can still be operationalized and measured. It might be interesting to investigate, in further research, at what level of abstraction the conceptual metaphors extracted respectively from linguistic and from pictorial expressions become really independent from their semiotic manifestations, and therefore completely supra-modality. I believe that such equipollence can be established only at the image schematic level.

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