Can Knowledge Graphs and Deep Learning Approaches help in Representing, Detecting and Interpreting Metaphors?

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Abstract. This paper gives an introduction to Conceptual Metaphor Theory (CMT) as introduced by George Lakoff and discusses the possible research problems that can open in the context of Knowledge Graphs and Deep Learning Methods and Metaphors in different mediums.

1 Proposal

Typically when a human mind thinks of a metaphor, the mind tries to map one concept to the another concept based on their properties or functionality etc. In Conceptual Metaphor Theory (CMT) [9], George Lakoff discusses that in the presence of a metaphor there are cross-domain mappings, i.e., a mapping between a source domain and a target domain. For example, in

$$Corruption\ is\ infecting\ our\ society.$$

, the source domain is infection (i.e., a `Disease`) which is mapped to the target domain *Corruption* (i.e., a `Criminal Activity`).

A published resource is available on-line called MetaNet [1], which defines a list of such metaphors and each metaphor consists of a source and a target domain. In case of the above example, it evokes the metaphor `Crime is a disease`. Each of these domains are represented as a linguistic frame called as source frame and target frame respectively. These frames resembles the frames as introduced in FrameNet [2], however, there are only few exact matches between the frames in both the resources, meaning that MetaNet contains its own specific frames. For the running example, the source frame is a `Disease` and the target frame is a `Criminal Activity`, where each of the roles of source frame i.e., `disease` and `patient` map to the roles in the target frame `criminal activtiy` and `victim` respectively.

Can Knowledge Graphs Capture such kind of Semantics. While thinking in terms of Knowledge Graphs, can this information about cross-domain mapping be represented in the form of a Knowledge Graph? Amnestic Forgery [5, 6] is one of the attempts to integrate the metaphors from MetaNet to the existing linguistic linked data cloud based on Frame Semantics, Framester [4]. In

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this resource each metaphor is represented following the theory of Description & Situation (D&S) [7]. According to this, a metaphor is a description and its occurrence in the text is a situation. One of the drawbacks of this resource is that it keeps very general metaphors. There is a need to find a middle ground between the cross-domain mappings as represented by frames and mappings occurring in the text. In order to find such kind of mappings we need to process the textual resources rich in metaphors such as poems or corpora specifically created for metaphors.

One of the solutions is to use previously designed deep learning methods [8] for distinguishing between metaphoric and literal expressions. Then finally learning from these metaphoric expressions their specific domains and enrich the Knowledge Graph with this kind of information. Another solution would be to create such kind of mappings in the existing Knowledge Graphs such as DBpedia which contain those domains and are represented based on their literal meanings but are not connected to the other domains based on their possible metaphoric relation. This can help in better Identification/interpretation of metaphors or generation of new metaphors.

Metaphors in Different Mediums Metaphors not only occur in language but they also occur in different mediums such as visual metaphors (occurring in images which can be related to political comics, advertisement or art work). A metaphor can also be expressed in multiple mediums such as text with image or gestures which can be found in videos. The last kind of metaphors are referred to as multi-modal metaphors [3]. Tensors can help in dealing with multi-dimensionality in such kind of metaphors. Following these lines many other tasks come into play such as: (i) Metaphor identification along with their interpretation by combining the information present in different mediums, (ii) Capturing/Modeling cultural biases, meaning that the metaphor is interpreted differently based on cultural background.

References

1. E. Dodge, J. Hong, and E. Stickles. Metanet: Deep semantic automatic metaphor analysis. In *Proceedings of the Third Workshop on Metaphor in NLP*. Association for Computational Linguistics, 2015.
2. C. J. Fillmore. Frame semantics and the nature of language. *Annals of the New York Academy of Sciences*, 280(1), 1976.
3. C. J. Forceville and Eduardo Urios-Aparisi. *Multimodal Metaphor*. De Gruyter Mouton, Berlin, Boston, 2009.
4. A. Gangemi, M. Alam, L. Asprino, V. Presutti, and D. R. Recupero. Framester: A wide coverage linguistic linked data hub. In *EKAW*, 2016.
5. A. Gangemi, M. Alam, and V. Presutti. Amnestic forgery: An ontology of conceptual metaphors. In *FOIS*, 2018.
6. A. Gangemi, M. Alam, and V. Presutti. Linked metaphors. In *In: ISWC 2018 Posters & Demonstrations, Industry and Blue Sky Ideas Tracks with (ISWC 2018)*, 2018.

7. A. Gangemi and P. Mika. Understanding the semantic web through descriptions and situations. In *On The Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE - OTM Confederated International Conferences, CoopIS, DOA, and ODBASE*, 2003.
8. G. Gao, E. Choi, Y. Choi, and L. Zettlemoyer. Neural metaphor detection in context. In *EMNLP*, 2018.
9. G. Lakoff and M. Johnson. *Metaphors we Live by*. University of Chicago Press, Chicago, 1980.