The method of Graph Integration using AMR graph and ConceptNet Graph

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Abstract. Commonsense Reasoning is the process of deduction using commonsense knowledge in logic. Unlike humans, the machine requires to learn external knowledge and acquire them itself. In this paper, we propose the method of integrating the AMR graph with ConceptNet to leverage the reasoning ability of the machine. The integrated graph also gives the advantage of interpretability.

Keywords: Commonsense Reasoning, AMR, ConceptNet

1 Introduction

Commonsense Reasoning is the process of deduction using commonsense knowledge in logic. For example, humans choose the answer 'tree' for the question "Poison causes harm to which of the following?" as they used the commonsense "Poison is capable of kill something living" and "Living things include tree". This kind of commonsense knowledge is defined as the information that people share and experience within their life. Unlike a human, a machine is required to learn with external commonsense knowledge. To evaluate how much machine acquire the knowledge, several datasets [1, 2] have been suggested. This dataset is composed of diverse questions that require external multi-hop knowledge.

A pre-training model with a massive amount of raw text is one of the approaches that try to solve this problem. Although the fact that BERT and ALBERT leverage the reasoning ability of the machine, the interpretability of the model's learning process, or the reason for the answer is still limited. Another approach is the Graph-based models [3, 4] applied with Commonsense Knowledge Graph in part. The approach has the potential of interpretability using the Self-attention mechanism[attention] which shows the attention score. However, it only interprets the results based on the words of the sentence, and extract unnecessary graph to answer the question.

To extract the proper commonsense graph, the semantic interpretation of the question should be preceded. Semantic representation is one of the ways that interpret questions semantically. AMR (Abstract Meaning Representation) [5] is the semantic representation that expresses questions into the graph with specific logic. It consists of a single root node, concept nodes, and relations that connect the nodes. However, this semantic representation is lack of commonsense knowledge to solve the questions as the commonsense information is not included in the graph. Therefore, the integrated graph with AMR and ConceptNet [6] graph makes Graph-based models solve the above dataset.

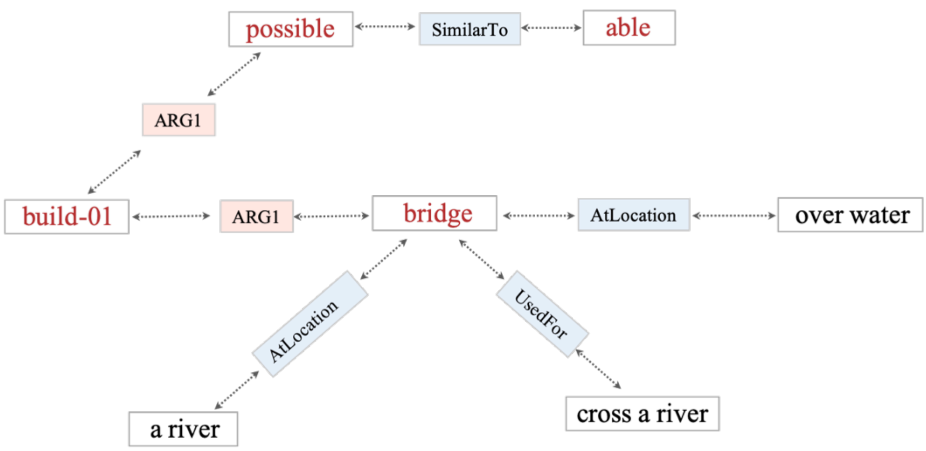
2 Related Works

2.1 AMR(Abstract Meaning Representation)

Abstract Meaning Representation graph represents the concept in the sentence with the relation defined in Propbank [7]. The relations consist of over 100 relations including ARG 0 ~ 4 which are core roles. Examples of the AMR graph are now open to the public.

3 Method

We first generate an AMR graph from any OpenBookQA question to interpret the question with semantic representation using Zhang's model [8]. As the generated graph has limited commonsense knowledge, connect the concept nodes to the relation from the ConceptNet. In this way, proper ConceptNet information is extracted as the concept nodes represent the core role within the question. For example, we made "How can a bridge be build?" question into the AMR graph, and integrate ConceptNet relations. The answer is 'over water' and this integrated graph includes the proper relation for the question.



4 Conclusion

In conclusion, we propose the method of integrating AMR graph and ConceptNet graph to effectively extract the necessary information according to the question. In future work, we make use of this graph into the diverse downstream tasks.

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