

CT5166 Knowledge Graphs - Assignment 1

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In the lecture, we have learnt that Knowledge Graphs is an informative linked network that use graphs as data. It is a combination of information from different sources with rapid evolvement hence making it a robust technique when comes to reasoning. To get a desired answer from knowledge graphs, we have to form a query with SPARQL. To form a query, it is important to figure out the appropriate relation candidates, which are the predicate of the N-Triples that are connecting the entities (the subject and object) in the questions in order to get the correct answer. This often comes with a challenge as there might be a various possible relations and it's difficult to narrow down the range to the most suitable one.

In this paper, we are going to discuss the Generative Relation Linking (GenRL) for Question Answering over Knowledge Bases (KBQA) proposed by Rossiello et al. in 2021. The researchers introduced a novel approach focusing on relation linking and adopted the BART, a pre-trained sequence-to-sequence (seq2seq) language model to solve such a generative issue.

The researchers are emphasizing to solve the following three challenges with their approach

- 1) Some of the relations between the text and the knowledge base (KB) are expressed uncommonly
- 2) Multiple relations questions had low performance
- 3) There are lack of training data.

However, a simple sequence-to-sequence models is not robust enough to handle the challenge of limited training data. Hence, the knowledge integration (KI) and knowledge validation (KV) processes are extended to the BART model.

The knowledge integration implies structured data from the knowledge base in order to enable the models to handle the meanings of the knowledge base and use the information from knowledge graphs as an additional point to enhance the performance of relation linking by handling unseen relations. Besides, the knowledge validation process is enabled by taking in a list of structured argument-relation pairs generated by the trained model as input. Such process increases the performance by removing the ambiguity and re-rank the multiple relations. This newly proposed approach is evaluated against the state-of-the-art models with four different datasets derived from DBpedia and Wikidata.

BART contains two components: 1) bi-directional encoder and 2) left-to-right decoder. The KI is tasked to generate the input of the BART model by getting information from the KB and enrich the question with a list of candidate relations base on the identified entities that created by an entity linker. Before passing the relation tokens to the seq2seq model, a pre-rank process is required to avoid exceeding the maximum limit of tokens which the BART can handle.

Secondly, a list of argument-relation pairs is generated by the decoder of BART model. Such data could consists either the entities extracted from the question or placeholders for multiple relations question.

Finally, analysis of the argument-relation pairs generated by the decoder is brought out by the KV module. In the analysis, temporary graphs are built from the possible pairs that are ranked descending to their confidence score and then being validated with the KB. If one of the pair is valid, the results preserved. In multi-hop relation cases, the GenRL substitute the placeholder

to up to two new unbound variable (e.g. ?x) as unknown. The final output is then being converted back to URIs by the KV.

In addition, the GenRL is applying Closed World Assumption on the ASK type SPARQL query with processing KV only on top N argument-relation pairs and return the default answer *false* if none is validated.

In short, the GenRL approach is a simpler model as it contains no NLP components hence reduce the error propagation being generated. With the Knowledge Integration and Knowledge Validation embedded, GenRL has better tolerance on rare questions template and enhanced generalisation when training with limited data. It also has high portability across different Knowledge Base. All these have led GenRL to achieve a higher F1 score from 9% to 59% more than the state-of-the-arts including SLING, Falcon, and KBPearl.

In spite of the strengths, there are still some challenges that the GenRL needs to focus on as the performance is lowered when facing implicit relation and lexical gap. Moreover, it has difficulties distinguishing appropriate namespaces hence introducing redundancy relations. Last but not least, researchers could focus on working with manually constructed datasets as GenRL is performing weaker on it when compared to template-based dataset.

Next, we are going to look at the similar work as GenRL. Firstly, A BERT-based Approach with Relation-aware Attention for Knowledge Base Question Answering proposed by Luo et al. in 2020. In terms of similarity, both BERT and GenRL are not integrating NLP components in their method but they are encoding the questions and matching them with KB in vector space. Both the method achieve good performance on SimpleQuestions dataset. Nevertheless, BERT is only evaluated on a single source and is only focusing on single-relation questions, hence it has no portability across different Knowledge Base nor tested to solve multi-hop questions.

Secondly, Naseem et al. conducted a research on A Semantics-aware Transformer Model of Relation Linking for Knowledge Base Question Answering (SemRL) in 2021. This research paper is highly similar with GenRL as they both are cross-Knowledge Graphs effective, evaluated on datasets derived from DBpedia and Wikidata and out-performed the state-of-the-arts. However, SemRL is using semantic parsing, Abstract Meaning Representation (AMR) for entities extractor and BERT model as their encoder. It also achieves a lower F-score than GenRL.

Last but not least, the GenRL paper is not working on the efficiency and weight evaluation on the model. Therefore, it would be interesting to see comparisons on computational cost and model size between GenRL and the state-of-the-arts. As those are important metrics that should be taken into considerations in the point of performance improving. Besides, KBQA is commonly applied in various forms including search engine on web or phone applications. Thus, it is important to have a reliable and light weight KBQA system that can be embedded in all kind.