Learning to Transform, Combine, and Reason in Open Domain Question Answering*

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1 Extended Abstract

Users seek direct answers to complex questions from large open-domain knowledge sources like the Web. Open-domain question answering has become a critical task to be solved for building systems that help address users’ complex information needs. Most open-domain question answering systems use a search engine to retrieve a set of candidate documents, select one or a few of them as context, and then apply reading comprehension models to extract answers. Some questions, however, require taking a broader context into account, e.g., by considering low-ranked documents that are not immediately relevant, combining information from multiple documents, and reasoning over multiple facts from these documents to infer the answer. In this paper, we propose a deep learning model based on the Transformer architecture that is able to efficiently operate over a larger set of candidate documents by effectively combining the evidence from these documents during multiple steps of reasoning, while it is robust against noise from low-ranked non-relevant documents included in the set.

For example, in Figure 1, in order to infer the correct answer to the question: “Who is the Spanish artist, sculptor and draughtsman famous for co-founding the Cubist movement?” given the top-ranked document, a reading comprehension system most likely will extract “Georges Braque” as the answer, which is not the correct answer. In this example, in order to infer the correct answer, one has to go down the ranked list, gather and encode facts, even those that are not immediately relevant to the question, like “Malaga is a city in Spain,” which can be inferred from a document at rank 66, and then in a multi-step reasoning process, infer some new facts, including “Picasso was a Spanish artist” given documents at ranks 12 and 66, and “Picasso, who was a Spanish artist, co-founded the Cubist” given the previously inferred fact and the document ranked third. In this example, and in general in many cases in open-domain question answering, a piece of information in a low-ranked document that is not immediately relevant to the question, may be useful to fill in the blanks and complete information extracted from the top relevant documents and eventually support inferring the correct answer.

In this paper, we propose TraCRNet (pronounced Tracker Net) to improve open-domain question answering by explicitly operating on a larger set of candidate documents during the whole question answering process and learning how to aggregate and

* This is an extended abstract of Dehghani et al. \cite{1}.
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Who is the Spanish artist, sculptor, and draughtsman famous for co-founding the Cubist movement? Answer: Pablo Picasso

Returning to the example in Figure 1 after learning representations for each top-ranked document and the question, TraCRNet updates them by applying multiple steps of the Universal Transformer in a layer called Multihop Reasoning.

We employ TraCRNet on two public open-domain question answering datasets, SearchQA and Quasar-T, and achieve results that meet or exceed the state-of-the-art.

Acknowledgments

This research was supported in part by the Netherlands Organization for Scientific Research through the Exploratory Political Search project (ExPoSe, NWO CI # 314.99.108). All content represents the opinion of the authors, which is not necessarily shared or endorsed by their respective employers and/or sponsors.

References