NLP-Applications

Project Proposal

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1.Problem Statement

Multi-hop question answering where answering to question requires reasoning and aggregation across several paragraphs. Most of the existing QA problems are confined to finding the answers from a single paragraph (single-hop). For example, in SQuAD (Rajpurkar et al., 2016[1]) questions are designed to be answered given a single paragraph as the context. This problem not only seeks to provide correct answers but also requires explanation through selection of supporting facts.

2.Dataset

We will be using HotPotQA[2] for training and evaluating the QA model. HotpotQA is a question answering dataset featuring natural, multi-hop questions, with strong supervision for supporting facts to enable more explainable question answering systems. It provides two different kinds of training pairs variants : a) distractor setting and b) full-wiki setting. Distraction setting contains collection of questions and 10 paragraphs for each: 2 gold paragraphs and the 8 distractors and are shuffled. Full wiki setting is an open-domain setting which contains the same questions as a distractor setting but contains first paragraphs of all Wikipedia articles without explicitly specifying the gold paragraphs. We will be working both on the distractor and full wiki setting for this problem.

3.Approaches

We will be analysing and implementing different QA models which solves this problem, most of them are from HotpotQA leaderboard[3] itself. We have selected these approaches to experiment with different architectures and to evaluate the model efficiency to reason with information taken from more than one document to arrive at the answer.

3.1 Baseline Model

We will be implementing the QA model as described in HotpotQA paper[2] as the base model which is basically the reimplementation of architecture described in Clark and Gardner (2017) model[5]. Apart from returning the answer span (sequence of words from paragraph), the model was modified to respond to the question with either "yes" or "no". It also incorporates the latest advances in QA including character-level models, self-attention (Wang et al., 2017[6]), and bi-attention (Seo et al., 2017[7]).

3.2 Question Decomposition & Rescoring (DecompRC)

This QA model[8] tackles the problem by decomposing the questions into sub-question of different reasoning types : bridging, intersection and comparison (it also contains sub-category like greater, smaller, larger, older, younger etc). Then it extracts the answer for each of the sub-question and scores different decomposition on the basis of the final answer and supporting facts prediction. The decomposition of the question is learned through a neural network trained only on 400 decomposition pairs. These decompositions are learned effectively using the span prediction over the main question.

3.3 Hierarchical Graph Networks

This QA model[9] aggregate clues from scattered texts across multiple paragraphs, a hierarchical graph is created by constructing nodes from different levels of granularity (i.e., questions, paragraphs, sentences, and entities). By combining heterogeneous nodes in a single unified graph, this hierarchical differentiation of node granularity enables this model to support variants question answering sub-tasks simultaneously (can work for both settings : distractor as well as full-wiki).

3.4 Exploiting Explicit Paths for Multi-hop Reading Comprehension

This QA model[4] (Kundu et al.(2018) proposes a path based reasoning approach for multi-hop reading comprehension. The proposed model named PathNet, attempts to extract implicit relations from text through entity pair representations and composes them to encode each path. It also composes the passage representations along each path. Question framing in Wikihop is in the form of a tuple comprising head entity, relationship entity and unknown tail entity. For path extraction head entities are extracted from question and tail entity from candidate keys. This model has been applied on wikihop dataset , however we will try to implement it on **HotpotQA** as well to test out the inferences on different datasets.

3.5 Learning to Retrieve Reasoning Paths Over Wikipedia Graphs for QA.

(Asai et al., 2020 [10]) introduces a new graph based recurrent retrieval approach that learns to retrieve reasoning paths over the Wikipedia graph to answer multi-hop open-domain questions. The retriever model trains a recurrent neural network that learns to sequentially retrieve evidence paragraphs in the reasoning path by conditioning on the previously retrieved documents. The reader model ranks the reasoning paths and extracts the answer span included in the best reasoning path.

Also if time permits, we can experiment with a new QA model based on a combination of mentioned above ideas and evaluate it on similar metrics.

4. References

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