Improving Question Answering with External Knowledge

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Abstract

Prior background knowledge is essential for human reading and understanding. In this work, we investigate how to leverage external knowledge to improve question answering. We primarily focus on multiple-choice question answering tasks that require external knowledge to answer questions.

We investigate the effects of utilizing external in-domain multiple-choice question answering datasets and enriching the reference corpus by external out-domain corpora (i.e., Wikipedia articles). Experimental results demonstrate the effectiveness of external knowledge on two challenging multiple-choice question answering tasks: ARC and OpenBookQA.

1 Introduction

External knowledge plays a critical role in human reading and understanding since authors assume readers have a certain amount of background knowledge gained from sources outside the text (McNamara et al., 2004; Salmerón et al., 2006; Zhang and Seepho, 2013).

A growing number of studies concentrate on the construction of multiple-choice machine reading comprehension (Mostafazadeh et al., 2016; Lai et al., 2017; Khashabi et al., 2018; Ostermann et al., 2018; Sun et al., 2019) or question answering tasks (Clark et al., 2018; Mihaylov et al., 2018). For machine reading comprehension tasks, the majority of the questions are still designed to be answerable based on the content of the provided reference documents. In this paper, we focus on multiple-choice question answering tasks: only a reference corpus is provided, and we require diverse types of knowledge to select the correct answer options (Clark et al., 2018).

It is still an open problem how to exploit external knowledge for multiple-choice question answering to replete with the knowledge gaps between humans and machines. Very recent studies (Peters et al., 2018; Radford et al., 2018; Devlin et al., 2018) leverage rich world knowledge by pre-training deep neural models such as LSTMs and Transformers (Vaswani et al., 2017; Liu et al., 2018) using language model objectives over large-scale corpora (e.g., BookCorpus (Zhu et al., 2015) and Wikipedia articles). We have seen significant improvements obtained on a wide range of natural language processing tasks by fine-tuning these pre-trained models on a downstream task. However, it is relatively time-consuming and resource-extensive to introduce external knowledge during the pre-training stage.

In this paper, we aim to utilize external knowledge to improve multiple-choice question answering during the fine-tuning stage. We investigate the effects of 1) augmenting training data by using external in-domain question answering datasets; 2) enriching reference corpora by retrieving additional knowledge from external open-domain resources via conducting entity discovery and linking based on questions and answer options.

We conduct preliminary experiments on two challenging multiple-choice question answering tasks collected from examinations – ARC (Clark et al., 2018) and OpenBookQA (Mihaylov et al., 2018) – by using BERT (Devlin et al., 2018) as the underlying question answering model. Experimental results we can obtain promising results by leveraging external knowledge.

2 Method

In this section, we first introduce the underlying question answering baseline we use (Section 2.1).
We then present two methods to introduce external in-domain (Section 2.2) and open-domain (Section 2.3) knowledge.

2.1 Basic Framework

By default, we employ the following framework unless explicitly specified. Following Sun et al., we first fine-tune a pre-trained language model on the largest multiple-choice machine reading comprehension dataset RACE (Lai et al., 2017) and then fine-tune the resulting model on target multiple-choice question answering datasets. In this paper, we use BERT (Devlin et al., 2018) as the pre-trained language model.

Given question \( q \), answer option \( o \), and reference document \( d \), we concatenate them with special tokens @ and # as the input sequence for BERT\(_{\text{LARGE}}\) by @d#q#o#, where @ and # stand for the [CLS] and [SEP] respectively in BERT. We add segmentation embedding \( \lambda \) to every token before \( q \) (exclusive) and \( B \) to the other tokens. For instances in ARC and OpenBookQA, \( d \) comes from the concatenation of the top 50 sentences retrieved by Lucene (McCandless et al., 2010) from their corresponding reference corpus with non-stop words in \( q \) and \( o \) as the query (Sun et al., 2018). The final prediction for each question is obtained by a linear plus softmax layer over the output of the final hidden state for the first token of each input sequence. We refer readers to Devlin et al.; Sun et al. for more details.

2.2 Utilization of In-Domain Data

Our basic framework consists of two stages: fine-tuning a pre-trained language model on a large-scale open-domain machine reading comprehension dataset (i.e., RACE) and then fine-tuning the resulting neural reader on target question answering datasets. For the latter step, instead of fine-tuning a neural reader on a single target dataset (Sun et al., 2018), we also investigate into fine-tuning a neural reader on multiple target datasets simultaneously.

2.3 Utilization of Open-Domain Data

We use entity discovery and linking (EDL) to help us enrich the reference documents.

Entity discovery is a task that extracts entity mentions from text. Most entity discovery systems are trained using pre-defined classes (e.g., Person, Location, Organization, etc.). However, in ARC and OpenbookQA, vast majority entity mentions are from scientific domain (e.g., “skin surface”, “oil”, “magnet”, and “iron”). As there is currently no potent system for scientific domain, we simply consider all noun phrases as entity mentions.

Entity Linking task can be divided into two sub-tasks: candidate generation and entity disambiguation. Given a set of extracted entity mentions \( M = \{m_1, m_2, ..., m_n\} \), we first generate an initial list of candidate entities \( E_m = \{e_1, e_2, ..., e_n\} \) for each entity mention \( m \), and then rank them to select the candidate entity with the highest score as the appropriate entity for linking.

A dictionary-based candidate generation approach (Medelyan and Legg, 2008) is adopted such that

\[
F_{\text{mention}}(e|m) = \frac{A_{m,e}}{A_{m,*}} \tag{1}
\]

where \( A_{m,*} \) is a set of anchor links with the same anchor text \( m \), and \( A_{m,e} \) is a subset of \( A_{m,*} \) that points to entity \( e \). Then each initial list of candidate entities is re-ranked based on three measures: salience, similarity, and coherence (Pan et al., 2015).

Salience is computed by using Wikipedia anchor links

\[
F_{\text{prior}}(e) = \frac{A_{e,*}}{A_{e,\text{s}}} \tag{2}
\]

where \( A_{e,*} \) is a set of anchor links that point to entity \( e \), and \( A_{e,\text{s}} \) is a set of all anchor links in Wikipedia.

Similarity refers to the context similarity between mention-entity pairs. We adopt a neural network model that jointly learns embedding of words and entities from Wikipedia (Yamada et al., 2017). For each entity mention \( m \), we build the vector representation of its context \( v_i \) using the vector representation of each word (excluding entity mention itself and stop words) in the context. Cosine similarity between the vector representation of each entity candidate \( v_e \) and \( v_i \) is computed to measure similarity between mention and entity \( F_{\text{sim}}(m,e) \).

Coherence is driven by the assumption that if multiple mentions appear together within a sentence, their referent entities are more likely to be coherent in the KB. Following Huang et al. (2017), we construct a weighted undirected graph \( G = (E, D) \) from KB, where \( E \) is a set of all entities in KB and \( d_{ij} \in D \) indicates that two entities \( e_i \) and \( e_j \) share some KB properties. The weight
of $d_{ij}$, $w_{ij}$ is computed as

$$w_{ij} = \frac{|p_i \cap p_j|}{\max(|p_i|, |p_j|)}$$ (3)

where $p_i$, $p_j$ are the sets of KB properties of $e_i$ and $e_j$ respectively. After constructing the knowledge graph, we apply the graph embedding framework proposed by Tang et al. (2015) to generate knowledge representations for all entities in the KB. Coherence between two entities $\text{coh}(e_i, e_j)$ is modeled using cosine similarity between the vector representations of these two entities. Given an entity mention $m$ and its candidate entity $e$, coherence score is defined as

$$F_{\text{coh}}(e) = \frac{1}{|C_m|} \sum_{c \in C_m} \text{coh}(e, c)$$ (4)

where $C_m$ is the union of entities for coherent mentions of $m$. Finally, we combine these measures to compute the final score for each entity candidate $e$.

We apply the EDL system described above to the text of all questions and answer options. For each discovered and linked entity, its Wikipedia abstract is extracted and appended to the corresponding reference document of each (question, answer option) pair.

## 3 Experiments

### 3.1 Datasets

In our experiment, we use RACE (Lai et al., 2017), which is the existing largest multiple-choice machine reading comprehension dataset, as the source task of transfer learning. We evaluate the performance of our methods on ARC (Clark et al., 2016, 2018) (including ARC-Easy and ARC-Challenge) and OpenBookQA (Mihaylov et al., 2018). All these tasks, which are collected from examinations that are carefully designed by human experts, contain a significant number of questions requiring external knowledge for question answering, and there still exists a big performance gap between humans and machines. We show the statistics of these datasets in Table 2.

### 3.2 Experimental Settings

We use the pre-trained uncased BERT$_\text{LARGE}$ released by Devlin et al. We set the batch size to 24, learning rate to $2 \times 10^{-5}$, and maximum sequence length to 512. We fine-tune for 5 epochs on RACE and 8 on the other datasets. We show the accuracy of our implemented BERT baseline on the RACE dataset in Table 3.

### 3.3 Experimental Results

As shown in Table 1, we see consistent improvements in accuracy across all tasks after we apply EDL to enrich the reference document for each question. For example, given the following question: "Which of the following statements best explains why magnets usually stick to a refrigerator door?" and its four answer options: "The refrigerator door is smooth."
“The refrigerator door contains iron.”
“The refrigerator door is a good conductor.”
“The refrigerator door has electric wires in it.” by using EDL, we link the mention “magnets” to its corresponding Wikipedia entry Magnet and attach its description in Wikipedia “A magnet is a material or object that produces a magnetic field. This magnetic field is invisible but is responsible for the most notable property of a magnet: a force that pulls on other ferromagnetic materials, such as iron, and attracts or repels other magnets.” after its reference document.

Based on our preliminary experiments, we see further improvements on all the datasets except ARC-Easy, by fine-tuning the baseline model on the training instances of all the multiple-choice question answering datasets (i.e., ARC-Easy, ARC-Challenge, and OpenBookQA).

4 Related Work

4.1 Question Answering

Recent years have seen numerous datasets (Richardson et al., 2013; Rajpurkar et al., 2016; Lai et al., 2017; Mihaylov et al., 2018; Clark et al., 2018; Choi et al., 2018; Reddy et al., 2018; Sun et al., 2019) and models (Chen et al., 2016; Wang et al., 2018b; Radford et al., 2018; Devlin et al., 2018; Sun et al., 2018) to drive progress in question answering. On the dataset side, our work primarily focuses on multiple-choice examination datasets designed by educational experts (Lai et al., 2017; Clark et al., 2018; Mihaylov et al., 2018; Sun et al., 2019) since questions from these datasets are generally clean, error-free, and challenging (Sun et al., 2019). On the model side, our work follows the general framework of discriminatively fine-tuning pre-trained language models on question answering tasks (Radford et al., 2018; Devlin et al., 2018; Sun et al., 2018).

4.2 Utilization of External Knowledge

Previous work have explored many ways to leverage external knowledge. Several work (Wang et al., 2018a; Sun et al., 2019) exploit the graph of general knowledge ConceptNet (Speer et al., 2017). Chen et al. propose to tackle open domain question answering using Wikipedia. Ni et al. study improving information retriever by essnetial terms (Khashabi et al., 2017). In comparison, our work primarily focuses on improving multiple-choice question answering by leveraging external in-domain and external open-domain knowledge, and, particularly is the first work to leverage knowledge via EDL.

5 Conclusion

In this work, we study improving question answering by utilizing in-domain external question answering datasets and utilizing out-domain external corpora to enrich the reference corpus. Preliminary experimental results on ARC and OpenBookQA datasets demonstrate the effectiveness of our proposed approaches.

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A Appendices

A.1 Engineering Details of the Strong Systems Used for Comparison

When we were in the middle of paper preparation, to make a competitive comparison, we put semi-complex engineering effort into making strong systems for ARC-Challenge, ARC-Easy, and OpenBookQA. These systems employed the approach of concurrently fine-tuning on multiple target datasets (Section 2.2), system ensembles based on a generalization of reading strategies (Sun et al., 2018), and different pre-trained language models (Radford et al., 2018; Devlin et al., 2018). We describe their details in this section.

A.1.1 Approach Overview

• Reference Documents Given a question and an option, we employed the same approach as Sun et al. to retrieve relevant sentences from the corpus provided by each dataset and regard the concatenation of the retrieved sentences as the reference document (Section 2.1). We did not leverage any further steps such as EDL (Section 2.3) to enrich the reference document.

• Pre-trained Language Models We mainly employed BERT (Devlin et al., 2018) as the pre-trained language model. We used uncased BERT\textsubscript{LARGE} for all our BERT-based models. Besides, we also employed GPT (Radford et al., 2018) for ARC-Challenge.

• Fine-Tuning Strategies Following Sun et al., all our models were first fine-tuned on the RACE dataset (Lai et al., 2017). In our GPT-based model, we employed self-assessment (SA) and highlighting (HL) reading strategies (Sun et al., 2018) and followed their input representation accordingly. In our BERT-based models, we generalized the back-and-forth reading strategy (Sun et al., 2018) by training models with more diverse input sequence order and ensembling them simultaneously rather than only ensembling model pairs with reverse or almost reverse input sequence order.

• Utilization of In-Domain Data We employed the approach of simultaneously fine-tuning on multiple target datasets described in Section 2.2 with the exception that we randomly dropped a portion of training instances in OpenBookQA when simultaneously fine-tuning on multiple target datasets for OpenBookQA.

A.1.2 Settings for Each Tasks

• ARC-Challenge The system for ARC-Challenge was composed of 29 models (Table 4). The final prediction for each question is the option with the largest weighted average logit, where we simply set weight 1 for all models that only use RACE and ARC-Challenge for fine-tuning and 3 for the other models. The BERT segmentation embedding settings for different input sequences are detailed in Table 7.

• ARC-Easy The system for ARC-Easy was composed of 18 models (Table 5). Different from ARC-Challenge, we only employed BERT\textsubscript{LARGE}, and all models have equal weights (i.e., the final prediction for each question is the option with the largest average logit).

• OpenBookQA The system for OpenBookQA was composed of 5 models (Table 6). Different from ARC, we employed only one model for each used input sequence. Moreover, we dropped 54.6% OpenBookQA training instances when fine-tuning on multiple datasets.

We trained our BERT-based models with the same settings as Section 3.2 and our GPT-based model with the same settings as Sun et al.
| Base Model         | Input Sequence | Finetuning Datasets | Weight | Count |
|--------------------|----------------|--------------------|--------|-------|
| GPT+SA+HL          | [o$qd]$        | R+C                | 1      | 1     |
| BERTARGE           | @d$qo$#o#      | R+C                | 1      | 4     |
| BERTARGE           | @q#o$#d#       | R+C                | 1      | 4     |
| BERTARGE           | @d$qo$#q#      | R+C                | 1      | 4     |
| BERTARGE           | @q#o$#d#       | R+C+E+O            | 3      | 2     |
| BERTARGE           | @o$q#o$#d#     | R+C+E+O            | 3      | 2     |
| BERTARGE           | @q#o$#o#      | R+C+E+O            | 3      | 3     |
| BERTARGE           | @q#o$#d#      | R+C+E              | 3      | 1     |
| BERTARGE           | @q#d$qo#      | R+C+E              | 3      | 1     |
| BERTARGE           | @o$#d$q#      | R+C+E              | 3      | 1     |

**Table 4:** Settings of ARC-Challenge Models. †: R (RACE), C (ARC-Challenge), E (ARC-Easy), O (OpenBookQA). ‡: $\{\text{start token in GPT}\}$, $\$\{\text{delimiter token in GPT}\}$, $\} \{\text{end token in GPT}\}$, @ \{\text{[CLS] token in BERT}\}, # \{\text{[SEP] token in BERT}\}.

| Input Sequence | Finetuning Datasets | Count |
|----------------|--------------------|-------|
| @d$qo$#o#      | R+E                | 2     |
| @q$#o$#d#      | R+E                | 2     |
| @d$qo$#q#      | R+E                | 1     |
| @q$d$#o#      | R+E                | 4     |
| @q#d$qo#      | R+E+C+O            | 1     |
| @d$qo#q#      | R+E+C+O            | 2     |
| @q#d#o#      | R+E+C+O            | 2     |
| @o$#d$q#      | R+E+C+O            | 1     |
| @o#d$q#      | R+E+C+O            | 1     |

**Table 5:** Settings of ARC-Easy Models. †: R (RACE), C (ARC-Challenge), E (ARC-Easy), O (OpenBookQA), ‡: @ \{\text{[CLS] token in BERT}\}, # \{\text{[SEP] token in BERT}\}.

| Input Sequence | Finetuning Datasets |
|----------------|--------------------|
| @d$qo$#o#      | R+O                |
| @d$qo#q#      | R+O                |
| @o$q#d#      | R+O                |
| @o$#d$q#      | R+O                |
| @d$#o$q#      | R+O*+E+C           |

**Table 6:** Settings of OpenBookQA Models. †: R (RACE), C (ARC-Challenge), E (ARC-Easy), O (OpenBookQA), O* (OpenBookQA with 54.6% instances dropped). ‡: @ \{\text{[CLS] token in BERT}\}, # \{\text{[SEP] token in BERT}\}.

**Table 7:** BERT Segmentation Embedding Settings for Different Input Sequences. We add segmentation embedding A to the underlined part and B to the rest.