Abstract

This paper presents a general approach for open-domain question answering (QA) that models interactions between paragraphs using structural information from a knowledge base. We first describe how to construct a graph of passages from a large corpus, where the relations are either from the knowledge base or the internal structure of Wikipedia. We then introduce a reading comprehension model which takes this graph as an input, to better model relationships across pairs of paragraphs. This approach consistently outperforms competitive baselines in three open-domain QA datasets, WEBQUESTIONS, NATURAL QUESTIONS and TRIVIAQA, improving the pipeline-based state-of-the-art by 3–13%.

1 Introduction

Open-domain question answering systems aim to answer any question a user can pose, with evidence provided by either factual text such as Wikipedia (Chen et al., 2017; Yang et al., 2019) or knowledge bases (KBs) such as Freebase (Berant et al., 2013; Kwiatkowski et al., 2013; Yih et al., 2015). Textual evidence, in general, has better coverage but KBs more directly support making complex inferences. It remains an open question how to best make use of KBs without sacrificing recall. Previous work has converted KB facts to sentences to provide extra evidence (Weissenborn et al., 2017; Mihaylov and Frank, 2018), but do not explicitly use the KB graph structure. In this paper, we show that such structure can be highly beneficial for fusing information across passages in open-domain text-based QA.

We introduce a general approach for text-based open-domain QA that models knowledge-rich interactions between passages using structural information from a knowledge base. Our goal is to combine the high coverage of textual corpora with the structural information and relationships apparent in knowledge bases, to improve both the recall and accuracy of the resulting model. Different from standard approaches where a model retrieves and reads a set of passages, we integrate graph structure at every stage to construct, retrieve and read a graph of passages.

Our approach first retrieves a graph using both text and KB, in which each node is a passage of text, and the relations are either from the knowledge graph or the internal structure of Wikipedia (Figure 1). Then, we introduce a reader model which takes this graph as an input, and considers relations between passage pairs in order to answer the question. Using the external knowledge base, our approach is able to synthesize the context over passages and build a knowledge-rich representation of text passages, which contributes to choosing the
Our experiments demonstrate significant improvements on three popular open-domain QA datasets: WEBQUESTIONS (Berant et al., 2013), NATURAL QUESTIONS (Kwiatkowski et al., 2019) and TRIVIAQA (Joshi et al., 2017). Our novel graph-based QA model improves the accuracy consistently, and significantly outperforms previous pipeline-based state-of-the-art by 3–13%. Our ablations show that both graph-based retrieval and reader model substantially contribute to the performance improvements, even when we fix the other component.

2 Related Work

Text-based Question Answering. Text-based open-domain QA is a long studied problem (Voorhees et al., 1999; Ferrucci et al., 2010). Recent work has focused on two stage approaches that combine information retrieval with neural reading compression (Chen et al., 2017; Wang et al., 2018; Das et al., 2019; Yang et al., 2019). We follow this tradition but introduce a new framework which retrieves and reads a graph of passages. Similar methods for graph-based retrieval were also developed concurrently to our approach (Godbole et al., 2019), and can be easily adapted to our framework. However, to best of our knowledge, reading passages by incorporating relations between passages has not been previously studied.

After the retrieval step, the next challenge is to find the answer given a set of passages. Most work concatenates passages into a single sequence (Swayamdipta et al., 2018; Yang et al., 2018; Song et al., 2018) or reads each in parallel (Clark and Gardner, 2018; Alberti et al., 2019; Min et al., 2019b; Wang et al., 2019). The most related work to ours includes Song et al. (2018) and Cao et al. (2019), which construct a graph of entities in the passage through entity detection and coreference resolution. In contrast, we focus on building a graph of passages, to better model the overall relationships between the passages.

Other lines of research in open-domain QA include joint learning of retrieval and reader components (Lee et al., 2019) or direct phrase retrieval in a large collection of documents (Seo et al., 2019). Although end-to-end training of our approach can further improve the performance, this paper only focuses on pipeline approaches since end-to-end training is computationally and memory expensive.

Knowledge Base Question Answering. Question answering over knowledge bases has also been studied (Berant et al., 2013; Kwiatkowski et al., 2013; Yih et al., 2015), typically without using any external text collections. However, recent work has augmented knowledge bases with text from Wikipedia (Das et al., 2017; Sun et al., 2018, 2019), to increase factual coverage. In this paper, we study what can be loosely seen as an inverse problem. The model answers questions based on a large set of documents, and the knowledge base is used to better model relationships between different passages of text.

3 Approach

We present a new general approach for text-based open-domain question answering, which consists of a knowledge graph based retrieval model GRAPHRETRIEVER and a reading comprehension model GRAPHREADER. GRAPHRETRIEVER constructs a graph of passages for the question from a large collection of documents (Section 3.1) and GRAPHREADER reads the input graph and finally returns an answer (Section 3.2).

3.1 Graph-Based Retrieval

Our retrieval approach leverages external knowledge to guide the selection of passages. GRAPHRETRIEVER retrieves a graph of passages in which vertices are passages and edges denote relationships between passages. The passages are retrieved from documents that are related to entities in the question or have high TF-IDF similarity score to the question. Retrieved passages are denoted by \( \{ p_1, \ldots, p_n \} \), and relations are denoted by \( \{ r_{i,j} \mid 1 \leq i, j \leq n \} \), where \( r_{i,j} \in \mathcal{R} \) is a relation indicating whether there is a relation between \( p_i \) and \( p_j \) or no relation. To achieve this, we use Wikipedia and WikiData as resources to retrieve passages, and combine two methods—entity-based retrieval and text-match retrieval.

Entity-based retrieval. Our first entity-based retrieval method uses the graph structure of Wikidata to extract text passages related to the question. It first identifies entities in the question using an entity linking system and then expands these seed entities with entities connected to them in Wikidata. Our method retrieves the Wikipedia documents corresponding to the selected entities and connects those passages according to the relation type in the WikiData graph. Formally, a relation \( r_{i,j} \in \mathcal{R}_{KB} \). 
between two passages $p_i$ and $p_j$ is a WikiData relation (e.g., performer and part of in Figure 1) if $p_i$ and $p_j$ are passages corresponding to entities that are connected in WikiData.

**Text-match retrieval.** Our text-match retrieval method extends TF-IDF-based retrieval from Chen et al. (2017) to select top $k$ articles from Wikipedia, split each article into passages, and then run BM25 (Robertson et al., 2009) on top of these passages to score them. We simply construct relations between passages if they belong to the same Wikipedia article: $r_{i,j}$ is child and $r_{j,i}$ is parent if $p_i$ is the first passage of the article and $p_j$ is another passage from the same article.

Retrieved passages from each retrieval method are sorted based on entity linking scores of originated seed entities from the entity-based retrieval or BM25 scores from the text-match retrieval. The $n$ highest scoring passages and their relations are used as the final graph.\(^1\)

### 3.2 Graph-Based Reading Comprehension

Our GRAPHREADER takes a question $q$ and $n$ retrieved passages $p_1, p_2, \ldots, p_n$ (and their relations $r_{i,j}$) and aims to output an answer to the question given the list of retrieved passages. Instead of processing each passage independently, the key idea of our approach is to improve passage representations using different fusion layers to integrate individual passages using the graph structure into account. The overall architecture is illustrated in Figure 2.

#### 3.2.1 Initial Paragraph Representation

Formally, given the question $q$ and a paragraph $p_i$, GRAPHREADER first obtains a question-aware passage representation:

$$P_i = \text{TextEncode}(q, p_i) \in \mathbb{R}^{L \times h},$$

where $L$ is the maximum length of each passage, and $h$ is the hidden dimension. This representation can be obtained from strong pretrained models such as BERT (Devlin et al., 2019), although not necessary. Additionally, GRAPHREADER encodes each representation $r_{i,j}$ through a relation encoder:

$$r_{i,j} = \text{RelationEncode}(r_{i,j}) \in \mathbb{R}^h.$$

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\(^1\)Although we considered Personalized PageRank (Haveliwala, 2002) following Sun et al. (2018), our preliminary result shows no improvement over this naive combination.

![Figure 2: A diagram of GRAPHREADER where the input graph is $p_1, p_2, \ldots, p_6$ in Figure 1 and $M$ fusion layers aggregate information from other passages. Details are described in Section 3.2.](image)

#### 3.2.2 Fusing Paragraph Representations

GRAPHREADER then builds $m$ graph-aware fusion layers to update passage representations by propagating information through edges of the graph. For each fusion layer $1 \leq m \leq M$, GRAPHREADER obtains new passage representation $\hat{z}_i^{(m)}$ based on all the adjacent passages and their relations through a composition function $f$ (described below). We investigate two variants of the fusion layers, one with a gating function and one without.

**Simple fusion.** Simple fusion combines $\hat{z}_i^{(m)}$ and the previous representation $z_i^{(m)}$ through a linear projection layer and finally obtains the updated representation $z_i^{(m+1)}$:

$$z_i^{(m+1)} = W_g[z_i^{(m)}; \hat{z}_i^{(m)}] + b_g \in \mathbb{R}^h,$$

where $z_i^{(0)} = \text{MaxPool}(P_i)$, and $W_g \in \mathbb{R}^{h \times 2h}$ and $b_g \in \mathbb{R}^h$ are both learnable parameters.

**Gated fusion.** Different from simple fusion, the gated fusion uses $\hat{z}_i^{(m)}$ and $z_i^{(m)}$ to compute a gating vector $g_i^{(m)}$ that controls how much information should be updated from the newly proposed
where $W$ is a relation-aware composition function: 

\[
\tilde{z}_i^{(m)} = \frac{1}{|G_i|} \sum_{j \in G_i} W_f z_j^{(m)} + b_f,
\]

where $W_f \in \mathbb{R}^{h \times h}$ and $b_f \in \mathbb{R}^h$ are learnable parameters.

**Relation-aware**. We then consider a more sophisticated, relation-aware composition function:

\[
\tilde{z}_i^{(m)} = \frac{1}{n} \sum_{j \in G_i} \left( W_f (r_{i,j} \odot z_j^{(m)}) + b_f \right),
\]

where $W_f \in \mathbb{R}^{h \times h}$ and $b_f \in \mathbb{R}^h$ are learnable.

We compare with alternative fusion methods in Section 5.1, where the result indicates that different ways to incorporate relation information do not give significantly different performance from each other, but this element-wise multiplication based method performs well consistently across all datasets.

### 3.2.3 Answering Questions

**GRAPHREADER** uses the updated passage representations $z_1^{(M)}, \ldots, z_n^{(M)}$ (denote $Z = [z_1^{(M)}, \ldots, z_n^{(M)}] \in \mathbb{R}^{h \times n}$) and computes the probability of each span $1 \leq j \leq k \leq L$ in the passage $p_i$ being an answer as $P_{\text{selected}}(i) \times P_{\text{start}}(i,j) \times P_{\text{end}}(i,k)$. Specifically,

\[
P_{\text{selected}}(i) = \text{softmax}(Z_i^T \mathbf{w}_{\text{selected}}),
\]

\[
P_{\text{start}}(i,j) = \text{softmax}(P_i^T \mathbf{w}_{\text{start}}),
\]

\[
P_{\text{end}}(i,k) = \text{softmax}(P_i^T \mathbf{w}_{\text{end}}),
\]

where $\mathbf{w}_{\text{selected}}, \mathbf{w}_{\text{start}}, \mathbf{w}_{\text{end}} \in \mathbb{R}^h$ are learnable vectors.

| Dataset             | Statistics | Graph density |
|---------------------|------------|---------------|
|                     | Train | Dev | Test | Cr. | In. | Tot. |
| WEBQ               | 3417  | 361 | 2032 | 0.9 | 1.9 | 2.8 |
| NATURALQ           | 79168 | 8757| 3610 | 0.7 | 2.2 | 2.9 |
| TRIVIAQA           | 78785 | 8837| 11313| 0.8 | 2.0 | 2.8 |

Table 1: The Statistics and density of the graph (% of passage pairs with a relation from **GRAPHRETRIEVER** are reported. Cr., In. and Tot. denote cross-document relations (WikiData relations) and inner-document relations (child, parent) and their sum.

### 4 Experiments

#### 4.1 Datasets

We evaluate our model on three open-domain question answering datasets: (1) **WEBQUESTIONS** (Berant et al., 2013) is originally a QA dataset designed to answer questions based on Freebase and the questions were collected through Google Suggest API. We use the same setting from Chen et al. (2017). (2) **NATURAL QUESTIONS** (Kwiatkowski et al., 2019) is a dataset where questions are collected from Google search engine and designed for end-to-end open-domain question answering. (3) **TRIVIAQA** (Joshi et al., 2017) is a dataset where questions are from trivia and quiz-league websites. For all these datasets, we only use question and answer pairs for training and testing (and discard the documents which are provided in the reading comprehension datasets). We following the data split from Chen et al. (2017) for **WEBQUESTIONS** and Min et al. (2019a) for **NATURAL QUESTIONS** and **TRIVIAQA**. We provide the statistics of the datasets and also the density of the graph retrieved by our **GRAPHRETRIEVER** in Table 1.

#### 4.2 Baselines

For retrieval, we compare our **GRAPHRETRIEVER** to a pure text-match based retriever that we described in Section 3.1 and investigate if leveraging the knowledge graph actually improves the retrieval component.

We also compare several different reader models as follows. (1) **PARREADER** reads each passage in parallel and predicts a candidate span from the passage and an answerable score (Min et al., 2019b; Wang et al., 2019). The passage with the highest answerable score during testing will be

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https://bit.ly/2q8mshc and https://bit.ly/2HK1Fgn.
We summarize important training details, where at least one of them contains the answer text. We use the uncased, base version of BERT (Devlin et al., 2019) for question-aware passage representation TextEncode. For the relation encoder, we keep top 90 relations on each dataset and train an embedding matrix for each relation. For each model, we experiment with \( M = \{1, 2\} \) and both simple and gated fusion layers, and choose the number that gives the best result on the development set. More detailed hyperparameters are provided in Appendix A.

### 4.4 Main Results

The main results are given in Table 2. We observed:

1. **GraphRetriever** offers substantial performance gains over text-match retrieval when we compare within the same reader, especially on *WEBQUESTIONS* and *NATURAL QUESTIONS*. This indicates that graph-based retrieval itself is beneficial to retrieve context passages.

2. **GraphReader** offers performance improvements over two ParReader baselines, demonstrating that GraphReader with cross-passage reading of the text is more effective than reading each passage in parallel.

3. Models using relation types offer consistent improvements over those with binary relations. However, the improvements are smaller than we expected, likely because the relation types are easily inferred based on text passages.

We also compare our results to the state-of-the-art, both pipeline and end-to-end approaches, in Table 2. In particular, our best performing model outperforms previous pipeline approaches state-of-the-art by 3–13%. Compared to the state-of-the-art end-to-end approaches where the retriever and the reader model are trained jointly, our model is behind on *WEBQUESTIONS*, comparable on *Natural Questions*, and outperforms previous pipeline approaches state-of-the-art by 3–13%.

![Table 2: Overall results on the development and the test set of three datasets. We also report state-of-the-art results, both with pipeline and end-to-end: *Lin et al. (2018), Min et al. (2019a), Min et al. (2019b), *Lee et al. (2019).* Note that the development sets used in Lee et al. (2019) are slightly different but the test sets are the same.](dumps.wikimedia.org/wikidatawiki/dumps/20190601/Wikidata2019QATrain/wikidata_en_qa_train.json)

| Retriever | Reader | WEBQUESTIONS | NATURAL QUESTIONS | TRIVIAQA |
|-----------|--------|--------------|------------------|---------|
|           |        | Dev | Test | Dev | Test | Dev | Test |
| Text-match | PARREADER | 23.6 | 25.2 | 26.1 | 25.8 | 52.1 | 52.1 |
| Text-match | PARREADER++ | 19.9 | 20.8 | 28.9 | 28.7 | 54.5 | 54.0 |
| GraphRetriever | PARREADER | 27.6 | 27.5 | 27.3 | 26.4 | 52.1 | 52.4 |
| GraphRetriever | PARREADER++ | 29.4 | 29.5 | 30.5 | 29.4 | 54.5 | 53.9 |
| GraphRetriever | GraphReader (binary) | 30.8 | 31.6 | 32.6 | 31.8 | 54.9 | 54.1 |
| GraphRetriever | GraphReader (relation) | 32.1 | 31.6 | 32.9 | 31.2 | 55.7 | 55.4 |

SOTA (pipeline) | - | 18.5\(^a\) | 28.8\(^b\) | 28.1\(^b\) | 50.7\(^b\) | 50.9\(^b\) |
SOTA (end-to-end) | 38.5\(^c\) | 36.4\(^c\) | 31.3\(^c\) | 33.3\(^c\) | 45.1\(^c\) | 45.0\(^c\) |

- \(^a\)This is a slight modification from Shared Normalization (Clark and Gardner, 2018); our preliminary result indicates this variant slightly outperforms original Shared Normalization.
- \(^b\)Min et al. (2019a), Min et al. (2019b), *Lee et al. (2019).* Note that the development sets used in Lee et al. (2019) are slightly different but the test sets are the same.
- \(^c\)Lin et al. (2018)
Although not explored in this paper, our framework benefits greatly from end-to-end training. To further advance the state-of-the-art, the presence of a relation, achieves strong results, sometimes outperforming other relation-aware models.

**5 Analyses**

In the following, we conduct ablation studies (Section 5.1) and analyze the effects of several design choices, including different relation types, composition functions and comparisons to concatenated-passage baselines. Finally, we present qualitative results in Section 5.2.

### 5.1 Ablation Studies

**Effect of different relation types.** Table 3 compares the effect of different relation types in the constructed graph of passages, showing results for the following settings: (a) **fully connected**, that ignores the relation types and connects all pairs of passages, (b) **empty**, that does not include any edge between passages, (c) **cross-doc**, that only includes edges between passages according to the Wikidata relation types, (d) **inner-doc**, that only include edges between passages within a document, and (e) **cross+inner**, that include both cross-doc and inner-doc, corresponding to the graph constructed by our approach. Note that (a) and (b) do not use any relation information from the input graph—they only consider input passages.

The results show that including cross-doc and inner-doc relations consistently outperforms other variants. In particular, using relation information is better than ignoring relation information (fully connected, empty), demonstrating the importance of selecting a good set of graph edges. Finally, cross edges play a more important role compared to inner edges, showcasing the importance of incorporating external knowledge from Wikidata.

**Effect of different composition functions for relations.** Table 4 demonstrates the effect of replacing the element-wise composition function for incorporating relations in **GRAPHREADER** (explained in Section 3.2) with other composition functions. (a) **Binary** does not include any relation type, (b) **Elm-wise** uses the element-wise function described in Section 3.2, (c) **Concat** concatenates the passage representation and the relation representation, (d) **Bilinear** uses a bilinear function, and (e) **Multi-task** uses a multi-task objective of answering the question and classifying the relation given a passage pair, instead of incorporating relation representations. Details are described in Appendix A.

Table 4 shows that incorporating different composition functions does not significantly impact the performance, while element-wise multiplication method (**GRAPHREADER** (Elm-wise)) achieves the best or near best performance across all datasets. Interestingly, we observe that the relation classification accuracy is 88-90% on WebQuestions and Natural Questions and 78% on TriviaQA, indicating that classifying the relation given a passage pair is relatively easy.6

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6The classification accuracy is high only when *whether there is a relation or not* is given, because when it is not given, the classifier always predicts no relation. This also supports why **GRAPHREADER** (Binary), which only considers the presence of a relation, achieves strong results, sometimes outperforming other relation-aware models.
Table 6: Examples from WebQuestions (top 2) and Natural Questions (bottom 3) where predictions from ParReader and GraphReader are denoted by red and blue text, respectively. For both models, GraphReader was used. Constructed graphs are reported; triples with no relation relation are omitted. The [Bold] text of each passage denotes title of the Wikipedia article where the passage is originated.

Comparison to passage concatenation. Table 5 compares the performance of our graph-based method with a model that concatenates passages for the reading stage. We compare with ParReader++ which is similar to ParReader++ but is additionally given concatenated passage pairs which are related based on the input graph, along with their relation text. For this baseline, we split each passage up to 140 tokens since concatenated passages should be up to 300 tokens. Table 5 shows that concatenating passages is not competitive, potentially because truncating each passage causes significant information loss.

5.2 Qualitative Results
Table 6 shows a few examples from WebQuestions and Natural Questions. The common observation across different datasets is that our method incorporates knowledge-rich relationships between passages to find the correct evidence and answer questions. This is in contrast to the independent reading of passages in ParReader.

For example, the first question in Table 6 seems straightforward since P1 explicitly mentions the evidence. However, ParReader selects P3 as the evidence context, potentially because it assumes “St. Louis Park” and “St. Louis County” are related. In GraphReader, the connection between P1 and P2 strongly hints that “St. Louis Park” is not in “St. Louis County”. For the second question ParReader assigns a very high probability to “China” because “China” is the only country name explicitly mentioned in the article “Nike, Inc”. However, the connection between P1 and P3 strongly hints that the answer should be “United States”, which helps GraphReader predict the correct answer. For the third example, ParReader predicts “Tom Scholz” as an answer, potentially because there is bias that the first person in the passage about a song is likely to be the singer. However, GraphReader which is aware of the connection...
between P1 and P3 predicts the correct answer. In the last two examples, independent reading of the passages in PARREADER lead to the wrong selection of the evidence passage. However, our GRAPHREADER reads P1 and P2 jointly and selects the correct evidence paragraph even when the two passages are not related based on an external knowledge base.

6 Conclusion

We proposed a general approach for open-domain question answering (QA) that models interactions between paragraphs using structural information from a knowledge base. Unlike standard approaches where a model retrieves and reads a set of passages, we integrate graph structure at every stage to construct, retrieve and read a graph of passages. Our approach consistently outperforms competitive baselines in three open-domain QA datasets, WEBQUESTIONS, NATURAL QUESTIONS and TRIVIAQA, and we also include a detailed qualitative analysis to illustrate where the cross paragraph reading contributes the most to the overall system performance.

References

Chris Alberti, Kenton Lee, and Michael Collins. 2019. A BERT baseline for the Natural Questions. arXiv preprint arXiv:1901.08634.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In EMNLP.

Nicola De Cao, Wilker Aziz, and Ivan Titov. 2019. Question answering by reasoning across documents with graph convolutional networks. In NAACL.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In ACL.

Christopher Clark and Matt Gardner. 2018. Simple and effective multi-paragraph reading comprehension. In ACL.

Rajarshi Das, Shehzaad Dhuliawala, Manzil Zaheer, and Andrew McCallum. 2019. Multi-step retriever-reader interaction for scalable open-domain question answering. In ICLR.

Rajarshi Das, Manzil Zaheer, Siva Reddy, and Andrew McCallum. 2017. Question answering on knowledge bases and text using universal schema and memory networks.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL.

Paolo Ferragina and Ugo Sciailia. 2011. Fast and accurate annotation of short texts with wikipedia pages. IEEE software.

David Ferrucci, Eric Brown, Jennifer Chu-Carroll, James Fan, David Gondek, Aditya A Kalyanpur, Adam Lally, J William Murdock, Eric Nyberg, John Prager, et al. 2010. Building Watson: An overview of the DeepQA project. AI magazine, 31(3):59–79.

Ameya Godbole, Dilip Kavarthapu, Rajarshi Das, Zhiyu Gong, Abhishek Singhal, Hamed Zamani, Mo Yu, Tian Gao, Xiaoxiao Guo, Manzil Zaheer, et al. 2019. Multi-step entity-centric information retrieval for multi-hop question answering. In Workshop on Machine Reading for Question Answering EMNLP.

Taher H Haveliwala. 2002. Topic-sensitive pagerank. In Proceedings of the 11th international conference on World Wide Web, pages 517–526. ACM.

Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. 2017. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In ACL.

Tom Kwiatkowski, Eunsol Choi, Yoav Artzi, and Luke Zettlemoyer. 2013. Scaling semantic parsers with on-the-fly ontology matching. In EMNLP.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Lion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. TACL.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In ACL.

Yankai Lin, Haozhe Ji, Zhiyuan Liu, and Maosong Sun. 2018. Denoising distantly supervised open-domain question answering. In ACL.

Todor Mihaylov and Anette Frank. 2018. Knowledgeable reader: Enhancing cloze-style reading comprehension with external commonsense knowledge. In ACL.

Sewon Min, Danqi Chen, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2019a. A discrete hard EM approach for weakly supervised question answering. In EMNLP.

Sewon Min, Eric Wallace, Sameer Singh, Matt Gardner, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2019b. Compositional questions do not necessitate multi-hop reasoning. In ACL.
Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in PyTorch.

Stephen Robertson, Hugo Zaragoza, et al. 2009. The probabilistic relevance framework: BM25 and beyond. *Foundations and Trends® in Information Retrieval*.

Minjoon Seo, Jinhuyuk Lee, Tom Kwiatkowski, Ankur P Parikh, Ali Farhadi, and Hannaneh Hajishirzi. 2019. Real-time open-domain question answering with dense-sparse phrase index. In *ACL*.

Linfeng Song, Zhiguo Wang, Mo Yu, Yue Zhang, Radu Florian, and Daniel Gildea. 2018. Exploring graph-structured passage representation for multi-hop reading comprehension with graph neural networks. *arXiv preprint arXiv:1809.02040*.

Nitish Srivastava, Geoffrey E Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. *Journal of machine learning research*.

Haitian Sun, Tania Bedrax-Weiss, and William W Cohen. 2019. Pullnet: Open domain question answering with iterative retrieval on knowledge bases and text. In *EMNLP*.

Haitian Sun, Bhuwan Dhingra, Manzil Zaheer, Kathryn Mazaitis, Ruslan Salakhutdinov, and William W Cohen. 2018. Open domain question answering using early fusion of knowledge bases and text. In *EMNLP*.

Swabha Swayamdipta, Ankur P Parikh, and Tom Kwiatkowski. 2018. Multi-mention learning for reading comprehension with neural cascades. In *ICLR*.

Ellen M Voorhees et al. 1999. The TREC-8 question answering track report. In *Trec*.

Shuohang Wang, Mo Yu, Xiaoxiao Guo, Zhiguo Wang, Tim Klinger, Wei Zhang, Shiyu Chang, Gerry Tesauro, Bowen Zhou, and Jing Jiang. 2018. R³: Reinforced ranker-reader for open-domain question answering. In *AAAI*.

Zhiguo Wang, Patrick Ng, Xiaofei Ma, Ramesh Nallapati, and Bing Xiang. 2019. Multi-passage BERT: A globally normalized bert model for open-domain question answering. In *ACL*.

Dirk Weissenborn, Tomáš Kočiský, and Chris Dyer. 2017. Dynamic integration of background knowledge in neural nlu systems. *arXiv preprint arXiv:1706.02596*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. HuggingFace’s Transformers: State-of-the-art natural language processing. *ArXiv*, abs/1910.03771.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019. End-to-end open-domain question answering with bertserini. In *ACL*.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W Cohen, Ruslan Salakhutdinov, and Christopher D Manning. 2018. HotpotQA: A dataset for diverse, explainable multi-hop question answering. In *EMNLP*.

Scott Wen-tau Yih, Ming-Wei Chang, Xiaodong He, and Jianfeng Gao. 2015. Semantic parsing via staged query graph generation: Question answering with knowledge base. In *ACL*.
A Training Details

We use WikiExtractor\textsuperscript{8}, TAGME (Ferragina and Scaiella, 2011)\textsuperscript{9} and Rank-BM25\textsuperscript{10} for Wikipedia dump parsing, entity extraction and BM25.

For a text-match retrieval, we use top 40 articles based on bi-gram TFIDF scores from Document Retriever in DrQA (Chen et al., 2017). Each article is split into paragraphs with up to 300 tokens, and fed into a BM25 ranker altogether. We only consider the first 20 hyperlinks for each article. We observe 9% of links are redirect pages and discard them.

All experiments are done in Python 3.5 and PyTorch 1.1.0 (Paszke et al., 2017). For BERT, we use BERT\textsubscript{BASE} and pytorch-transformers (Wolf et al., 2019)\textsuperscript{11}. Specifically, given a question $Q$ and a paragraph $P_i$ where the title of the originated article is $T_i$, we form a sequence $S_i = Q : [\text{SEP}] : <t> : T_i : </t> : P_i$, where $:$ indicates a concatenation and $[\text{SEP}]$ is a special token. This sequence is then fed into BERT and the hidden representation of the sequence from the last layer is chosen as a question-aware paragraph representation. When BERT is used for relation representations, we follow the similar strategy as above. When question-aware representations are used, we form a sequence $Q : [\text{SEP}] : R_{i,j}$. Otherwise, we just use $R_{i,j}$ as an input sequence. When an embedding matrix is used, we only consider 75 relations, including the top 74 relations from the training set\textsuperscript{12} and UNK.

For each fusion layer, we apply dropout (Srivastava et al., 2014) with a probability of 0.3. For training, we evaluate the model on the development set periodically, and stop training when Exact Match score does not improve 10 times. Other hyperparameter values are reported in Table 7. For all other hyperparameters not mentioned, we follow the default settings from pytorch-transformers. At training time, the $m = 20$ highest scoring passages with and without the answer text are used, mostly due to memory limitations.

Details for different composition functions

GRAPHREADER (Concat) concatenates the paragraph representation and the relation representation, $\hat{z}_i^{(m)} = \frac{1}{n} \sum_{j \in G_i} (W_f [r_{i,j} : \hat{z}_j^{(m)}] + b_f)$, where $W_f \in \mathbb{R}^{2h \times h}$ and $b_f \in \mathbb{R}^h$ are learnable. GRAPHREADER (Bilinear) uses a bilinear function as: $\hat{z}_i^{(m)} = \frac{1}{n} \sum_{j \in G_i} (r_{i,j}^T W_f \hat{z}_j^{(m)})$, where $W_f \in \mathbb{R}^{h \times h}$ is a learnable matrix. GRAPHREADER (Multi-task) uses a multi-task objective of answering the question and classifying the relation given a paragraph pair, instead of incorporating relation representations. Details are described in Appendix.

$\hat{z}_i^{(m)}$ is computed similar to GRAPHREADER (Binary). Relation classifier is trained as: $p_{i,j,\text{rel}} = \text{Softmax}(W_{\text{rel}} [z_i^{(M)} : z_{j}^{(M)}] + b_{\text{rel}}) \in \mathbb{R}^{N_{\text{rel}}}$, where $N_{\text{rel}}$ is a number of unique relations and $W_{\text{rel}} \in \mathbb{R}^{N_{\text{rel}} \times 2h}$ and $b_{\text{rel}} \in \mathbb{R}^{N_{\text{rel}}}$ are learnable. We train with a cross entropy objective using $p_{i,j,\text{rel}}$ and the groundtruth relation, only when the groundtruth relation is not no relation.

\textsuperscript{8}github.com/attardi/wikiextractor
\textsuperscript{9}github.com/gammaliu/tagme
\textsuperscript{10}github.com/dorianbrown/rank_bm25
\textsuperscript{11}github.com/huggingface/pytorch-transformers
\textsuperscript{12}They cover 93% of relations on the dev set.
| Hyperparameter                                           | WEBQUESTIONS | Others |
|----------------------------------------------------------|--------------|--------|
| Batch size for PARREADER                                 | 10           | 56     |
| Batch size for PARREADER++ and GRAPHREADER               | 8            | 16     |
| # of sampled paragraphs for each question during training | 20           | 20     |
| Interval for evaluation on the development set during training | 1k           | 2k     |
| # of paragraphs on the development set during training    | 80           | 20     |

Table 7: Hyperparameters used for experiments. We use the different values for WEBQUESTIONS because the dataset size is much smaller than others.