Abstract

Open-domain question answering (QA) is the task of identifying answers to natural questions from a large corpus of documents. The typical open-domain QA system starts with information retrieval to select a subset of documents from the corpus, which are then processed by a machine reader to select the answer spans. This paper describes Mindstone, an open-domain QA system that consists of a new multi-stage pipeline that employs a traditional BM25-based information retriever, RM3-based neural relevance feedback, neural ranker, and a machine reading comprehension stage. This paper establishes a new baseline for end-to-end performance on question answering for Wikipedia/SQuAD dataset (EM=58.1, F1=65.8), with substantial gains over the previous state of the art (Yang et al., 2019b). We also show how the new pipeline enables the use of low-resolution labels, and can be easily tuned to meet various timing requirements.

1 Introduction

In this paper, we introduce Mindstone, an open-domain question answering (QA) system, which answers user’s questions from a large collection of documents. We present our results for QA from Wikipedia using questions from SQuAD (Rajpurkar et al., 2016). One of the first significant open-domain QA systems was DrQA (Chen et al., 2017) that combined term-based information retrieval techniques with a multi-layer RNN-based reader to identify answers in Wikipedia articles. In a more recent work, BERTserini (Yang et al., 2019a) replaced the retriever with Anserini (Yang et al., 2017) and the reader with BERT (Devlin et al., 2018), to obtain large improvements over prior results. While BERT and other pre-trained transformer models have enabled machine comprehension systems to reach human-level performance on many paragraph-level datasets (e.g. the first place on the SQuAD (Rajpurkar et al., 2016) leaderboard achieves EM/F1=90.0/92.4 squ), the overall performance of open-domain QA with retriever-reader pipelines remains about half of these numbers.

We propose an improved pipeline structure that has enabled Mindstone achieve a new state-of-the-art QA pipeline performance on Wikipedia by a significant margin. Our experiments show that adding two specialized stages for ranking retrieval results and question expansion improves the end-to-end performance by 8 points, improves answer recall, and makes it easier to use larger datasets with lower-resolution labels (potentially gathered from users’ interaction with the QA system). We also measure the end-to-end time per query for our system and compare it to prior work.

2 Background and Related Work

The machine reading task of answering questions has made great progress in recent years. There are two primary reasons for this. The first is the creation of datasets such as QACNN/DailyMail (Hermann et al., 2015), SQuAD (Rajpurkar et al., 2016), and Natural Questions (Kwiatkowski et al., 2019). The second is the considerable progress in deep learning architectures like attention-based and memory augmented neural networks (Bahdanau et al., 2016; Weston et al., 2014), Transformers (Vaswani et al., 2017) and pre-trained models (Devlin et al., 2018).

Until recently, open-domain QA has been mostly addressed through the task of answering from structured knowledge bases such as Simple Questions (Bordes et al., 2015). However, KB limita-
tions such as incomplete or missing information and fixed schemas, have generated new interest in question answering from unstructured documents.

DrQA, the pioneering work of Chen et al. (2017), answers questions from the entire Wikipedia. Its pipeline combines a document retriever and a bi-directional RNN document reader. BERTserini (Yang et al., 2019a) uses a paragraph-level Anserini-based retriever and a fine-tuned BERT reader for answering questions. In a follow-up work, Yang et al. (2019b) discuss data augmentation using distant supervision. While this work established the previous best results on open-domain QA, our experiments show that adding a neural ranker and neural RM3 to the pipeline results in a faster and more accurate system.

3 Pipeline Architecture

In this section, we describe the Mindstone pipeline. Following Yang et al. (2019a), we first split the corpus articles into paragraphs. We also prepend article titles to each paragraph to provide some context from the full article. We will use paragraphs and documents interchangeably to refer to the resulting paragraphs. For each question, all documents travel through all stages of the pipeline or until it is apparent that they cannot score high enough to be included in top answers. Figure 1 depicts these stages and their relative order.

Assume the corpus has $N_{\text{corpus}}$ paragraphs. Given a question, retriever, ranker and reader each assign a score to every text span of every paragraph. We use $S_{\text{retriever}}$, $S_{\text{ranker}}$ and $S_{\text{reader}}$ to denote these scores. In practice, all text spans in the same paragraph have the same retriever and ranker scores, and we only calculate $S_{\text{ranker}}$ for top $N_{\text{retriever}}$ documents (when sorted by retriever score) to lighten the job of the slower ranker. The final score of a span of text is a weighted average of its three scores, where the weights are tuned to maximize the exact match metric on a small subset of the training set. We normalize all scores to have a value in $(-\infty, 1]$ before taking the average.

Retriever. We use a TF-IDF-based retriever to retrieve $N_{\text{retriever}}$ documents. More specifically, we use Anserini (Yang et al., 2017) based on Lucene version 8.0, and Okapi BM25. Our index only considers unigrams that are not in a predefined set of stop words. The main advantage of this

2Adding bigrams for a paragraph-level corpus slightly hurts the pipeline’s performance and speed. DrQA uses uni-grams and bigrams for indexing, which improves the performance on an article-level corpus.

stage is its speed, and it needs to have a high recall@N_{\text{retriever}} since the performance of the full pipeline is upper bounded by it.

Ranker. We use a BERT-Base (110M parameters) model for ranking the retrieved documents. The model is trained as a binary classifier on MS MARCO (Nguyen et al., 2016) using the same method as Nogueira and Cho (2019), and then fine-tuned on SQuAD. For more details on our fine-tuning approaches, see section 4. $S_{\text{ranker}}$ is the output of the classifier before softmax layer. Our ranker takes the first 448 tokens of the paragraph and the whole question as input and outputs whether the paragraph contains an answer to the question.

Neural RM3. Our experiments showed that using RM3 (Lavrenko and Croft, 2001) in retriever hurts its recall. Instead, we use a method similar to RM3, but using ranker document scores instead of retriever scores. Let $d_1,...,d_{N_{\text{retriever}}}$ denote the sorted output of retriever and $S_{\text{ranker}} \geq \ldots \geq S_{\text{retriever}}$ be the scores that ranker has assigned to them. Let $v(d)$ be the vector of TF-IDF scores of the top $T$ most common terms in document $d$ where $T$ is a hyperparameter. Then

$$q' = \alpha q + (1 - \alpha) \sum_{S_{\text{ranker}} \geq 0} v(d_i)$$

where $q$ is the original question vector and $\alpha \in [0, 1]$ is a hyperparameter, will be the expanded question in vector form. We use this new question to retrieve more documents from the corpus and feed them through the ranker. In the open-domain Wikipedia/SQuAD setting, neural RM3 increases recall@100 by 6 points. However, due to the slowdown it causes, in section 5 we report our results without neural RM3.

Reader. The reader finds the exact location of the answer in the ranked documents. We assume the answer is a contiguous span of text and use a linear layer for two token-level classification tasks to determine the start and the end position of the answer span (Devlin et al., 2018). Paragraph and question are truncated or padded to be exactly 384 tokens in total. Since we are using version 1.1 of SQuAD, the reader always returns an answer. We experiment with both base and large BERT models.
Figure 1: Mindstone pipeline architecture. Numbers are for the Wikipedia corpus.

4 Experiments

Data. Similar to DrQA (Chen et al., 2017), and BERTserini (Yang et al., 2019b), we use 2016-12-21 English Wikipedia dump, which has more than 5 million articles and 37 million paragraphs.

We use SQuAD version 1.1 to train the paragraph reader and MS MARCO to train the ranker. We have trained all models on the training set of the mentioned datasets. Since SQuAD’s test set is not publicly available, we use a small subset of its training set for development, and report the results on its development set.

Training Ranker. We train the ranker on MS MARCO, and then fine-tune it on a SQuAD-based binary classification dataset. We experimented with three different approaches for building this dataset:

1. (Fine-tuning) For every paragraph-question pair in SQuAD, add another paragraph from the same Wikipedia article that does not contain the answer string.
2. (Data augmentation 1) Use the retriever to retrieve \( n \) documents for each question in the dataset, and add them to the new dataset. Their labels are determined according to whether or not they include the answer string.
3. (Data augmentation 2) Similar to the second approach, use the retriever to obtain \( m \) paragraphs, then rank them with the ranker and use the top \( n \) results.

We use \( m = 100 \) and \( n = 5 \) for our experiments.

5 Results

Unless stated otherwise, we use the same metrics (exact match, F1 and recall) as defined in Chen et al. (2017). \( N_{\text{retriever}} \) is set to 100 to be comparable to prior work.

5.1 Full Pipeline Performance

In this section, times are measured on a machine with a single NVIDIA V100 GPU (16GB memory) and an 8-core CPU. Mixed precision\(^3\) is used for inference. All time measurements are averaged over 1000 queries in batch mode, and the minimum of 5 runs is reported. To have a fair comparison, we have partially re-implemented DrQA to use Anserini, which improves its speed. We have implemented Yang et al. (2019a) and Yang et al. (2019b) following their descriptions in the cited papers, and use our implementations to measure time. Exact match and F1, however, are directly copied from Chen et al. (2017), Yang et al. (2019a) and Yang et al. (2019b).

Our main results for open-domain QA from Wikipedia using SQuAD questions are shown in Table 1. Our best-performing system has a BERT-Large reader. The ranker training approach that resulted in the best performance is fine-tuning followed by data augmentation with neural ranker (the first and third approach from section 4).

Although DrQA uses a much smaller neural network, its end-to-end time per query is greater than Mindstone due to its larger index (DrQA uses unigrams and bigrams) and reader’s named entity recognition. BERTSerini and Yang et al. (2019b) are slower than Mindstone due to the additional time spent on reader’s token-level classification and processing multiple segments for documents that are longer than BERT’s maximum sequence length. Mindstone on the other hand, only reads 2.5% of documents and its ranker only processes the truncated version of long paragraphs.

One of our findings is that adding a ranker enables a better use of larger reader models. In previous approaches such as Yang et al. (2019a), using a BERT-Large reader would increase query time\(^3\)

\(^3\)https://github.com/NVIDIA/apex
Table 1: Open-domain results for SQuAD development set and Wikipedia. DrQA retrieves 5 articles, and all other systems retrieve 100 paragraphs.

| Model                          | EM  | F1  | Time per query |
|--------------------------------|-----|-----|----------------|
| DrQA (Chen et al., 2017)       | 29.8| -   | 988 ms         |
| BERTSerini (Yang et al., 2019a)| 38.6| 46.1| 887 ms         |
| Yang et al. (2019b)            | 50.2| 58.2| 887 ms         |
| Mindstone (ours)               | 58.1| 65.8| 738 ms         |

Table 2: The effect of different parts of Mindstone.

| Model                  | EM  | F1  | Time per query |
|------------------------|-----|-----|----------------|
| Mindstone (ours)       | 58.1| 65.8| 738 ms         |
| - BERT-Large reader    | 53.9| 62.7| 722 ms         |
| - ranker data augmentation | 47.8| 56.4|                |
| - ranker fine-tuning   | 44.3| 53.7|                |

5.2 Retriever and Ranker Performance

In Figure 3, retriever and ranker recalls show how much ranker improves the retrieval process.

Mindstone outputs a sorted list of answers, so we can calculate accumulative exact match and F1. Top-N exact match in Figure 3 shows the probability of finding at least one exact-match answer in the top N answers.

We also analyze the performance gap between retriever and the full pipeline. Prior work and other sections of this paper all use the exact match metric in the same way: if a paragraph includes the gold answer string, it is a hit in terms of recall. However, this approach can overestimate recall for queries that have a common phrase as their answer. As a more strict approach, we consider a retrieved paragraph to be a hit only if it is the same as the paragraph that crowdworkers used to write the query in the process of building SQuAD. Using this definition, Figure 3 shows that the top-N exact match and recall at N curves are almost identical. This means that Mindstone’s reader is not the performance bottleneck, and future attempts to improve the pipeline need to be focused on the retriever or ranker.

6 Conclusion and Future Work

Our system uses a conventional retriever supplemented with a neural ranker and neural RM3 relevance feedback. Our new pipeline design establishes new state-of-the-art results for end-to-end performance on question answering for Wikipedia/SQuAD dataset, with an 8 points gain over previous baseline (Yang et al., 2019b).

We have built a highly responsive QA system with a sub-second latency. While conventional re-

Figure 3: Retriever and ranker recall. The x-axis is log-scale.

Figure 2: Performance improves with more retrieved documents.

Since the version of Wikipedia dump we are using is different from that of SQuAD’s (and other processing differences), a simple string equality check would not work. Our solution is using a simple string similarity metric and a threshold.
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