MIX : a Multi-task Learning Approach to Solve Open-Domain Question Answering

Sofian Chaybouti, Achraf Saghe, Aymen Shabou
DataLab Groupe, Crédit Agricole S.A
Montrouge, France
sofian.chaybouti@ensta-paris.fr,
{achraf.saghe, aymen.shabou}@credit-agricole-sa.fr

Abstract

In this paper, we introduce MIX : a multi-task deep learning approach to solve Open-Domain Question Answering. First, we design our system as a multi-stage pipeline made of 3 building blocks : a BM25-based Retriever, to reduce the search space; RoBERTa based Scorer and Extractor, to rank retrieved documents and extract relevant spans of text respectively. Eventually, we further improve computational efficiency of our system to deal with the scalability challenge : thanks to multi-task learning, we parallelize the close tasks solved by the Scorer and the Extractor. Our system outperforms previous state-of-the-art by 12 points in both f1-score and exact-match on the squad-open benchmark.

1 Introduction

With huge quantities of natural language documents, search engines have been essential for the time saved on information retrieval tasks. Usually, deployed search engines achieve the task of ranking documents by relevance according to a query. Recently, research has focused on the task of extracting the span of text that exactly matches the user’s query through Machine Reading Comprehension and Question Answering.

Question Answering deals with the extraction of the span of text in a short paragraph that exactly answers a natural language question. Recent deep learning models based on heavy pretrained language models like BERT achieved better than human performances on this tasks (Devlin et al., 2019).

One could try to apply QA models for the Open-Domain Question Answering paradigm which aims to answer questions taking a big amount of documents as knowledge source. Two main issues emerge from this : first, applying 100M parameters language models to potentially millions of documents requires unreasonable GPU-resources. Then, QA models allow to compare spans of text coming exclusively from a single paragraph while in the open-domain QA paradigm, one needs to compare spans of text coming from a wide range of documents.

Our system, as done in previous work, deals with the resources issue thanks to a Retriever module, based on the BM25 algorithm, that allows to reduce the search space from millions of articles to a hundred of paragraphs. The second issue is tackled by adding a deep learning based Scorer module that re-ranks with more precision the paragraphs returned by the Retriever. Eventually, the Extractor module uses a QA deep learning model to extract the best span of text in the first paragraph returned by the Scorer. To avoid a heavy and hardly scalable pipeline consisting of two huge deep learning models, we parallelize the re-ranking and span extraction tasks thanks to multitask learning : while maintaining high performances, it allows to significantly reduce both memory requirements and inference time. Our system beats previous state-of-the-art (Yang et al., 2019a) by a wide margin of 12 points both in f1-score and exact-match.

2 Background and Previous Work

2.1 Machine Reading Comprehension

The construction of vast Question Answering datasets, particularly the SQuAD benchmark (Rajpurkar et al., 2016), has led to end-to-end deep learning models successfully solving this task, for
instance (Seo et al., 2018a) is one of the first end-to-end model achieving impressive performances. More recently, the finetuning of powerful language models like BERT (Devlin et al., 2019) has allowed to achieve better than human performances on this benchmark. Some researchers have adapted the pretraining task of language models to be better adapted to the extractive question answering down-stream task like SpanBERT (Joshi et al., 2020). Eventually, all these models rely on the same paradigm: building query-aware vector representations of the words in the context.

2.2 Open-Domain Question Answering

(Chen et al., 2017) introduce the Open-Domain Question Answering setting (figure 1) that aims to use the entire English Wikipedia as a knowledge source to answer factoid natural language questions. Considering Wikipedia as a collection of about 5 millions of textual documents without relying on its graph structure, this setting brings the challenge of building systems able to do Machine Reading Comprehension at scale. Most recent works ((Chen et al., 2017), (Raison et al., 2018), (Min et al., 2018)) explored the following pipeline to solve this task. First, retrieving a dozens of documents using statistical methods (bigrams, tf-idf, BM25, etc.) or similarity search between documents and questions (Karpukhin et al., 2020) and then applying a deep learning model trained for machine reading comprehension to find the answer. Some other works have been about designing methods to re-rank documents using more sophisticated methods like deep learning or reinforcement learning ((Wang et al., 2017), (Lee et al., 2018)).

Yang et al. designed in BERTserini (Yang et al., 2019a) a pipeline of 2 steps: first, reducing the search space thanks to BM25 algorithm, and then, extracting the spans of text in each document retrieved with a finetuned BERT. Eventually, the issue discussed in the introduction about scoring the relevance of spans of text coming from different paragraphs is tackled by taking the weighted average of the score from BM25 algorithm and the score of the QA model. The weight is an hyperparameter tuned manually. Seo et al (Seo et al., 2018b) introduced the Phrase-Indexed Question Answering (PIQA) benchmark in order to make machine reading comprehension scalable.

This benchmark enforces independent encoding of question and document answer candidates in order to reduce Question Answering to a simple similarity search task. Indeed, answer candidates are indexed off-line. Closing the gap between such systems and very powerful models relying on query-aware context representation would be a great step towards solving the open-domain question answering scalability challenge. The proposed baselines use LSTM-encoders trained in an end-to-end fashion. While achieving encouraging results, the performances are far from state-of-the-art attention based models.

DENSPI (Seo et al., 2019) is the current state-of-the-art model on the PIQA benchmark. This system makes use of the BERT-large language model to train a siamese network able to encode questions and indexed answer candidates independently. DENSPI is also evaluated on the squad-open benchmark. While being significantly faster than the other systems, it needs to be augmented by sparse representations of documents to be on par with them in terms of performances.
Ocean-Q (Fang et al., 2020) proposes an interesting approach to solve the Open-Domain QA task by building an ocean (a large set) of question-answer pairs using Question Generation and query-aware QA models. When a question is asked, the most similar question from the ocean is retrieved thanks to tokens similarity. This approach avoids the question-encoding step while being on par with previous models on the squad-open benchmark.

3 Model

In this section, the proposed model to solve the task is developed.

3.1 Pipeline Description

The complete MIX pipeline is shown in figure 2. It is made up of three fundamental building blocks.

When a question is asked, we first make a selection of a few paragraphs which are relevant to the question (i.e., more likely to contain the correct answer). Later, we call this step the Retriever module. It has to be highly efficient to tackle large corpora, with potentially several millions of documents.

After that, we refine the retrieval step by re-ranking these paragraphs with a classification by relevance step, that we call the Scorer.

Finally, we extract from each paragraph the snippet that best answers the question. This is the Extractor part.

3.2 BM25 algorithm

The Retriever uses the BM25 algorithm, which is one of the most successful algorithms for textual information retrieval. It evaluates the relevance of each document relative to a query written in natural language. Indeed, when a request is made, the algorithm computes a score for each document in the dataset. This score is a sum of terms over the words in the question. Each term of the sum grows with the term-frequency of the word in the document and is modulated by its inverse document frequency. Documents are finally sorted regarding their scores.

3.3 Scoring Documents

The Scorer allows to refine the classification of the paragraphs returned by the Retriever. We use deep learning to implement this step and we build a model that associates a relevance score to a pair (Question, Document) (figure 3). In this model, we use the classification token of the RoBERTa (Liu et al., 2019) language model to return the relevance score.

3.4 Question Answering

The Extractor part of the pipeline uses a vanilla Question Answering model : the RoBERTa language model finetuned to produce probability distributions on the paragraph tokens to identify the begining and the end of the span of text answering an input question (figure 4).

3.5 Multi-task Model

As we have just seen, our system is composed of two deep learning models, one for the Scorer and the other for the Extractor. These models solve respectively the re-ranking of documents and the QA tasks. This configuration can be heavy in terms of resources.

Since these two tasks are related in the sense that they require the understanding of a text in the light of a question asked, a multitask learning model could be designed instead. The goal is to learn both tasks by sharing part of their models parameters, allowing parallel classification of paragraphs and extraction of relevant spans of text (figure 5). This would save inference time and required memory.

The proposed multi-task model is depicted in the figure 6, where we can see that shared parameters are those of the language model (thus, the largest part of the set of parameters). We keep the layers that are specific to each task, i.e., the layer that takes as input the classification token in the Scorer and the layers of start and end positions in the Extractor.

3.6 Training Objectives

3.6.1 Paragraphs Scoring

When training our model to score paragraphs, we optimize the cross-entropy of the ground truth paragraph against the other ones. This corresponds to the following loss :

$$L(\Theta, Q, D) = -\text{score}(d^*) + \log \left(\sum_{d \in D} \exp\left(\text{score}(d)\right)\right)$$

(1)
with $\Theta$ the parameters of the model, $Q$ the question, $D$ the set of paragraphs returned by the Retriever and $d^*$ the correct paragraph.

### 3.6.2 Question Answering

Training the model for the Question Answering task is done by minimizing the cross entropy of the start and end positions of the correct answers. Given a document $D$ (tokenized as $D = \{d_1, d_2, ..., d_n\}$), a question $Q$, the answer $A$ characterized by $(s,e)$ its start and end positions in $D$, $\theta$ the model parameters, $P_{\text{start}}$ the probability distribution for the start of the response and $P_{\text{end}}$ the probability distribution for the end of the answer, we define the loss function $L(Q, D; \theta)$ as the following (eq. 2):

$$L(Q, D; \theta) = -\log(P_{\text{start}}(s|Q, D; \theta)) - \log(P_{\text{end}}(e|Q, D; \theta))$$

### 4 Experiment

In this section, we show our experiments and results.

#### 4.1 Data

**SQuAD v1.1:** SQuAD v1.1 (Rajpurkar et al., 2016) is a reading comprehension dataset consisting of 100,000+ questions-answers pairs from Wikipedia paragraphs. The span extraction part of our model is trained on the train set (87599
The proposed multi-task pipeline.

The proposed Multi-task model.

Figure 5: The proposed multi-task pipeline.

Figure 6: The proposed Multi-task model.

4.2 Training and Implementation Details

4.2.1 Indexation

For document indexation, we use the Python API of Elasticsearch (Gormley and Tong, 2015). It allows us to take advantage of its native implementation of B25 algorithm. When indexing, we used a sliding window with a stride of 400 tokens and considered paragraphs of 450 tokens. We end up indexing around 40M paragraphs.

We take advantage of Elasticsearch indexation to build the dataset to train the Scorer: we apply the BM25 algorithm for each question in the dataset to all paragraphs in SQuAD. We only retrieve 30 paragraphs for each question. Each time the paragraph containing the ground truth answer is in the retrieved texts, a new example is added to the dataset. We end up with 80k+ examples for the train set and 10k+ for the development set.

4.2.2 Training

The training details of the multi-task learning model are given in table 1. During the training, we alternate a Question Answering optimization step and a Scoring optimization step.

|                           | QA            | Scoring      |
|---------------------------|---------------|--------------|
| learning rate             | 5e-5          | 1e-5         |
| batch size                | 32            | 16           |
| optimizer                 | Adam          |              |

Table 1: Training details for the multi-task learning model.
4.3 Results

4.3.1 Metrics

The performances of the QA model are evaluated thanks to classic exact-match (EM, exact overlap between ground truth span and prediction) and f1-score (F1, partial overlap between ground truth span and prediction). The performances of the Scorer are evaluated by observing if the paragraph containing the right answer is ranked first (precision @ 1).

4.3.2 Results on SQuAD

Table 2 provides results of our multitask model on the SQuAD dataset for both Question Answering and re-ranking tasks. It shows that our model is on-par with state-of-the-art performances on Question Answering. In addition, the re-ranking task performs well as in 94.2 % of the examples the ground truth paragraph is ranked at the first place. The comparison with the finetuning of RoBERTa (Liu et al., 2019) on the only task of question answering shows that the performances of our model do not suffer from the multi-task learning.

|                | EM  | F1  | precision @ 1 |
|----------------|-----|-----|---------------|
| RoBERTa-base (Liu et al., 2019) on SQuAD | 83.0 % | 90.4% | - |
| multi-task     | 82.7% | 90.1% | 94.2%         |

Table 2: Results of MIX on the QA and the scoring tasks.

4.3.3 Results on the squad-open benchmark

In this section, we present the results obtained on the benchmark squad-open. Table 3 provides the results of MIX on different numbers of paragraphs returned by the Retriever (100 and 200) and for TOP 1, TOP 2 and TOP 3 snippets returned by the Extractor. We observe that the model is more limited by the performance of the paragraph reclassification step than by the number of paragraphs returned by BM25. Indeed, performances increase very quickly when going from top 1 to top 2 or from top 2 to top 3, while they increase less rapidly when going from 100 to 200 documents.

We also compare the performance of MIX to other state-of-the-art models evaluated on the squad-open benchmark (table 4). MIX’s performance is above the others by at least 12 points in both metrics (EM and F1). We explain it first by the performances achieved in QA thanks to the BERT type language models and then by the reclassification of documents, making it possible to circumvent much better the constraint of comparing two snippets coming from two different texts than other systems like BERTserini (Yang et al., 2019a), where BERT is also used but where the score of a span is a linear combination of the Retriever score (BM25 algorithm) and the Reader score (QA model).

|                | EM  | F1  |
|----------------|-----|-----|
| DrQA (Chen et al., 2017) | 29.8 | -   |
| R3 (Wang et al., 2017)    | 29.1 | 37.5|
| Paragraph ranker (Lee et al., 2018) | 30.2 | -   |
| Multi-step reasoner (Das et al., 2019) | 31.9 | 39.2|
| BERTserini (Yang et al., 2019b) | 38.6 | 46.1|
| MINIMAL (Min et al., 2018) | 34.7 | 42.5|
| Weaver (Raison et al., 2018) | -    | 42.3|
| DENSPI (Hybrid) (Seo et al., 2019) | 36.2 | 44.4|
| DENSPI (Dense Only) (Seo et al., 2019) | 20.5 | 13.3|
| Ocean-Q (Fang et al., 2020) | 32.7 | 39.4|
| MIX (ours) (100 documents) | 50.5 | 58.5 |

Table 4: Results on the squad-open benchmark.

5 Conclusion

We introduced MIX, a multi-task learning approach to solve open-domain question answering, relying on the BM25 algorithm as a Retriever to reduce the search space and the powerful RoBERTa language model finetuned to achieve both paragraph re-ranking (Scorer) and spans of text extraction (Extractor). Our system achieves state-of-the-art results on the squad-open benchmark by a wide margin. Our evaluation shows that the results are
more limited by the performance of the Scorer than by the Retriever that reduces the search space of million of paragraphs to a hundred.

References

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

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

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

Yuwei Fang, Shuohang Wang, Zhe Gan, Siqi Sun, and Jingjing Liu. 2020. Accelerating real-time question answering via question generation.

Clinton Gormley and Zachary Tong. 2015. Elastic-search: The Definitive Guide, 1st edition. O’Reilly Media, Inc.

Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S. Weld, Luke Zettlemoyer, and Omer Levy. 2020. Spanbert: Improving pre-training by representing and predicting spans.

Vladimir Karpukhin, Barlas Oğuz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen tau Yih. 2020. Dense passage retrieval for open-domain question answering.

Jinhyuk Lee, Seongjun Yun, Hyunjae Kim, Miyoung Ko, and Jaewoo Kang. 2018. Ranking paragraphs for improving answer recall in open-domain question answering.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach.

Sewon Min, Victor Zhong, Richard Socher, and Caiming Xiong. 2018. Efficient and robust question answering from minimal context over documents.

Martin Raison, Pierre-Emmanuel Mazaré, Rajarshi Das, and Antoine Bordes. 2018. Weaver: Deep co-encoding of questions and documents for machine reading.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text.

Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. 2018a. Bidirectional attention flow for machine comprehension.

Minjoon Seo, Tom Kwiatkowski, Ankur P. Parikh, Ali Farhadi, and Hannaneh Hajishirzi. 2018b. Phrase-indexed question answering: A new challenge for scalable document comprehension.

Minjoon Seo, Jinhyuk Lee, Tom Kwiatkowski, Ankur Parikh, Ali Farhadi, and Hannaneh Hajishirzi. 2019. Real-time open-domain question answering with dense-sparse phrase index. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4430–4441, Florence, Italy. Association for Computational Linguistics.

Shuohang Wang, Mo Yu, Xiaoxiao Guo, Zhiguo Wang, Tim Klinger, Wei Zhang, Shiyu Chang, Gerald Tesauro, Bowen Zhou, and Jing Jiang. 2017. R³: Reinforced reader-ranker for open-domain question answering.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019a. End-to-end open-domain question answering with. Proceedings of the 2019 Conference of the North.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019b. End-to-end open-domain question answering with bertserini. CoRR, abs/1902.01718.