EfficientQA : a RoBERTa Based Phrase-Indexed Question-Answering System

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Abstract

State-of-the-art extractive question answering models achieve superhuman performances on the SQuAD benchmark. Yet, they are unreasonably heavy and need expensive GPU computing to answer questions in a reasonable time. Thus, they cannot be used for real-world queries on hundreds of thousands of documents in the open-domain question answering paradigm. In this paper, we explore the possibility to transfer the natural language understanding of language models into dense vectors representing questions and answer candidates, in order to make the task of question-answering compatible with a simple nearest neighbor search task. This new model, that we call EfficientQA, takes advantage from the pair of sequences kind of input of BERT-based models (Devlin et al., 2019) to build meaningful dense representations of candidate answers. These latter are extracted from the context in a question-agnostic fashion. Our model achieves state-of-the-art results in Phrase-Indexed Question Answering (PIQA) (Seo et al., 2018b) beating the previous state-of-art (Seo et al., 2019) by 1.3 points in exact-match and 1.4 points in f1-score. These results show that dense vectors are able to embed very rich semantic representations of sequences, although these ones were built from language models not originally trained for the use-case. Thus, in order to build more resource efficient NLP systems in the future, training language models that are better adapted to build dense representations of phrases is one of the possibilities.

1 Introduction

Question answering is the discipline which aims to build systems that automatically answer questions posed by humans in a natural language. In the extractive question answering paradigm, the answers to a question are spans of text extracted from a single document. In the famous SQuAD benchmark (Rajpurkar et al., 2016) for instance, each answer lies in a paragraph from Wikipedia.

In the open-domain setting, the answers are sought in a large collection of texts such as the whole English Wikipedia (Chen et al., 2017). State-of-the-art performances in usual Question Answering are achieved thanks to powerful and heavy pretrained language models that rely on sophisticated attention mechanisms and hundreds of millions of parameters. Attention mechanisms (Bahdanau et al., 2016) are key components of such systems since they allow building contextualized and question-aware representations of the words in the documents and extract the span of text which is most likely the correct answer. These models are very resource-demanding and need GPUs to be scalable. Thus, they seem unsuitable to the open-domain real use cases, where the model has to be applied on hundreds of thousands of documents, even with a multi-GPU server.

A first approach to solve this issue would be first applying a filter based on a statistical algorithm like tf-idf (Sparck Jones, 1988) vectors or BM25 (Robertson and Jones, 1976) algorithm. Then, the heavy model is called on several dozens of paragraphs. This approach is still prohibitive with CPU-only resources for instance.

(Seo et al., 2018b) introduces a new benchmark, called Phrase-indexed Question Answering, which adds a constraint to the usual extractive question answering task. Indeed, document and question encoders are forced to be independent (figure 1).
First, a document is processed in order to provide a vector representation to each answer candidates, in an offline mode. Then, in the online step, the query is processed to be mapped to its own vector representation. Hence, the answer to the query is obtained by retrieving the nearest candidate vector to the query vector. The general form of such approach to solve the open-domain question answering could be reformulated as the following. First, all candidate answers from all documents of the database are indexed offline. Then, at inference time, the question is encoded and the best candidate is retrieved by a simple nearest-neighbor search. This way, the scalability challenge of QA-systems is improved, since a single pass forward in the deep learning model is needed to encode the question instead of several ones (one per each document) in previous settings.

In this paper, we propose a new algorithm to solve the PIQA benchmark (figure 1) and to close the gap between classic QA models. Our approach takes advantage of BERT-based models in two ways. First, it extracts the potential answer candidates in a question-agnostic fashion. Secondly, it takes two sequences as input to build powerful semantic representations of candidate answers. Finally, it trains a siamese network to map candidates answers and query in the same vector space.

Our model performs well, beating DENSPI (Seo et al., 2019), the previous state-of-the-art on the PIQA benchmark, by 1.4 points in f1-score and 1.3 points in exact-match, while being less resource-demanding both in training and at inference times. It requires indexing only a hundred answer-candidates dense vectors per context and finetuning a RoBERTa-based (Liu et al., 2019) model, while DENSPI uses a BERT-large model.

2 Background

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) allowed achieving superhuman performances on this benchmark. In SpanBERT (Joshi et al., 2020), the pre-training task of the language model is masked span prediction instead of masked word prediction to be better adapted to the down-stream task of QA which consists in span extraction. All these models rely on the same paradigm: building query-aware vector representations of the words in the context. This fundamental idea makes these model unsuitable to the Open-Domain setting.

2.2 Open-Domain Question Answering

(Chen et al., 2017) introduced the Open-Domain Question Answering setting that aims to use the entire English Wikipedia as a knowledge source to answer factoid natural language questions. This setting brings the challenge of building systems able to perform Machine Reading Comprehension at scale.

Most recent work explored the following pipeline to solve this task. First, documents of the dataset are indexed (or encoded) using either statistical methods like BM25 or dense representations of documents. Then, we retrieve a dozens of them by similarity search between documents and questions (Karpukhin et al., 2020). Finally, we apply a deep learning model trained for machine reading comprehension to find the answer. This approach has been developed in a number of papers (Chen et al., 2017), (Raison et al., 2018), (Min et al., 2018), (Wang et al., 2017), (Lee et al., 2018), (Yang et al., 2019). It takes advantage of the very powerful language models of SOTA but has the inconvenient of being resource-demanding. Moreover, its performances are capped by the capabilities of the documents retrieval step of the pipeline.
2.3 the PIQA Challenge

(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 the Question Answering task to a simple similarity search task. 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 baselines proposed 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 on the PIQA benchmark. This system uses the BERT-large language model to train a siamese network able to encode questions and indexed answer candidates independently. To represent candidate answers, DENSPI builds dense representations using the start and the end positions of each index phrase.

DENSPI is also evaluated on the SQuAD-open benchmark (Chen et al., 2017). While being significantly faster than 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 both the PIQA and the Open-Domain QA benchmarks by building an ocean 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 and significantly higher than the baselines on the PIQA challenge.

3 Model

In this section, the model and the algorithm to solve the task are developed.

3.1 Problem Definition

The problem tackled in this paper is Phrase-indexed Question Answering. Vanilla Question Answering is the task of building systems able to answer natural language questions with spans of text lying in the documents (figure with example 1). Formally, the goal is to design a function $F$ mapping a question $Q$ and a context $C$, both represented by a sequence of tokens $\{q_1, q_2, ..., q_n\}$ and $\{c_1, c_2, ..., c_m\}$ respectively, to a subsequence of $C$ as an answer $A = \{a_1, a_2, ..., a_p\}$ (eq. 1).

$$F(Q, C) = A$$

In PIQA, $F$ is constrained to be an $\text{argmax}$ over a set of answer candidates $\{A_1, A_2, ..., A_k\}$ ($k$ subsequences of the context $C$) of a similarity product between the encoding $G(Q) \in \mathbb{R}^l$ of the question and the encoding of each candidate $H(A_i) \in \mathbb{R}^l$ (eq. 2), where $l$ is the encoding size.

$$A = \text{argmax}_{A_i} G(Q) \cdot H(A_i)$$

3.2 Agnostic Extraction of Answer Candidates

The first step toward building the system is to define the set of answer candidates. A naive approach would be to consider all possible spans in a given context $C$ of length $m$. This would give $\frac{m(m+1)}{2}$ possible candidates, i.e. about $10^5$ candidates per context, if we assume contexts are made of about 500 tokens.

![Figure 2: Agnostic extraction of answer candidates](image)

Only a limited amount of all possible spans are potential answers to any question. Thus, we reduce the set of candidates by training a Question-Agnostic Answer Candidates Extraction model (figure 2). Formally, the context $C$ is mapped to the set of candidates $\{A_1, ..., A_k\}$ thanks to a function $f$.

To do so, a Roberta Base (Liu et al., 2019) model is finetuned taking the context as input and supervised by the answers provided in the SQuAD dataset. To extract the candidates, we use a beam search algorithm: the $s$ most likely candidate starts are first extracted thanks to a dense layer, then, their
Agnostic extraction of answer candidates with beam search. Paragraph tokens are provided to the language models to produce their embeddings, then a first dense layer allows to identify the $s$ most likely start positions of candidates. The embeddings of the paragraph’s tokens are concatenated to each start position and a second dense layer allows to identify the $e$ most likely end positions associated to each start position. We end up with $s \times e$ possible spans.

Embeddings are concatenated to each context word embeddings and fed into another dense layer to extract the $e$ most likely candidate ends associated to each start position as shown in figure 3. Thus, we end up processing $s \times e$ answer candidates. Ablation studies, developed in further sections, show that feeding the start position embeddings when extracting the end positions results gives better answer candidates.

### 3.3 Building of dense vectors of answer candidates and questions

After defining the set over which the $\text{argmax}$ function will be applied, we need to build the encoding functions for both the questions and the candidates answers. To this purpose, we finetune a Roberta Base as a siamese network (Koch et al., 2015) so that questions and candidates are mapped to the same euclidean space (eq. 3).

$$G \simeq H$$ (3)

#### 3.3.1 Answer Candidates Dense Representations

To build powerful answer candidates representations we take advantage from the pair of sequences type of input of pretrained BERT based models. The context is provided as first input and the candidate is provided as second input of the encoder as shown in figure 4. Eventually, the embeddings of each tokens are passed through a dense layer and their final embeddings are averaged to provide the encoding of the candidate.

#### 3.3.2 Question Dense Representation

To build its representation, the question is passed through the same network as the context-candidate pair, and the embeddings of all tokens are averaged as shown in figure 5.

### 3.4 Training Objectives

#### 3.4.1 Candidates Extraction

When training the Question-Agnostic Candidates Extraction model, we use the cross-entropy loss over start and end positions, just like most of deep
neural networks trained for vanilla Question Answering but without adding the question information as described in eq.4.

\[
L(C; \Theta) = -\log(P(s^*; \Theta)) - \log(P(e^*; \Theta))
\]  

(4)

3.4.2 Phrase-Indexed Question-Answering

To train the siamese network to build the questions’ and candidates’ representations, we use the candidates extracted previously. When the correct answer \(A^*\) is among these candidates, the loss described in eq.5, where \(\Gamma\) represents the parameters of the networks, is minimized.

\[
L(Q, A_i; \Gamma) = -H(A^*) \cdot G(Q)
+ \log(\sum_i \exp(H(A_i) \cdot G(Q)))
\]  

(5)

4 Experiment

In this section, we present our experiments and results.

4.1 Data

4.1.1 SQuAD v1.1

SQuAD v1.1 (figure 6) (Rajpurkar et al., 2016) is a reading comprehension dataset consisting of 100,000+ questions-answers pairs from Wikipedia.
paragraphs. Our model was trained on the train set (87599 pairs) and evaluated on the development set (10570 pairs).

Figure 6: Question-answer pairs for a passage in the SQuAD dataset (figure taken from (Rajpurkar et al., 2016))

4.1.2 FQuAD: The French Question Answering Dataset

In recent years, efforts have been done for the democratization of NLP powerful tools beyond the English language. To this purpose, new datasets in other languages have been designed. The French Question Answering Dataset, called FQuAD (figure 7) is one of them (d'Hoffschmidt et al., 2020). FQuAD is a French Question Answering corpus built from 326 Wikipedia articles which train and development sets consist of 20,731 and 5,668 question/answers pairs respectively.

4.2 Training Details

4.2.1 Agnostic Extraction Model

To train the agnostic extraction model, we used a learning rate of 1e-4 with a batch size of 32 and AdamW (Loshchilov and Hutter, 2019) optimization algorithm.

4.2.2 Dense Representations Model

To build the dataset to train and evaluate the model, we use our agnostic extraction model to retrieve 60 candidates for each question-context pair. Each time, the good answer were present in the extracted set of candidates, the whole example is added to the train set. To evaluate the model we extract 100 candidates for each question-context pair.

The training of the siamese network took approximately 1 week for 5 epochs on a single 24GB GPU NVIDIA Quadro RTX 6000. We used a learning rate of 1e-5 with AdamW optimizer and a linear scheduler. We also used mixed precision training (Miccikievicius et al., 2018) to reduce time requirements and 8 steps of gradient accumulation along with a batch size of 4 which is equivalent to a training batch size of 32.

4.3 Results

4.3.1 Answer Candidates Extraction Model

In this section, we justify the architecture of the Answer Candidates Extraction Model. Indeed, we might have chosen a simpler architecture where start positions and end positions likelihoods are computed independently as shown in figure 8. While the two models show equivalent results in vanilla Question Answering, the architecture we have chosen provides a much better set of candidates. Given the same number of selected candidates, the good answer is far more present as shown in table 1. The architectures are evaluated with exact-match and f1-score over all selected candi-
Figure 8: classic architecture for candidates extraction

dates. For fair comparisons, we evaluate the classic architecture using both optimal decoding and beam search. When doing beam search, we use 50 as beam size for start positions and 2 as beam size for end positions. We explain the differences in performances by the fact that the dependent computations between start and end positions provide better constituents that are more likely to be answers to questions. Indeed, the likelihood of a candidate is better modeled in this case:

\[ P(s, e) = P(s) \times P(e|s) \]

while in the classic architecture:

\[ P(s, e) = P(s) \times P(e) \]

Table 1: Comparison between classic decoding and ours for 100 extracted answer candidates

| model                  | exact-match | f1-score |
|------------------------|-------------|----------|
| classic architecture   | 65.1        | 80.3     |
| classic architecture   | 54.1        | 72.4     |
| with beam search       |             |          |
| our architecture       | 92.3        | 96.7     |

Table 2: Results on SQuAD v1.1

| model                  | EM   | F1   |
|------------------------|------|------|
| 1st baseline: LSTM + SA| 49.0 | 59.8 |
| (Seo et al., 2018b)    |      |      |
| 2nd baseline: LSTM + SA + ELMO | 52.7 | 62.7 |
| (Seo et al., 2018b)    |      |      |
| DENSPI                 | 73.6 | 81.7 |
| (Seo et al., 2019)     |      |      |
| Ocean-Q                | 63.0 | 70.5 |
| (Fang et al., 2020)    |      |      |
| EfficientQA            | 74.9 | 83.1 |
| RoBERTa (vanilla QA, our run) | 83.0 | 90.4 |
| (Liu et al., 2019)     |      |      |

4.3.2 Results on the SQuAD v1.1 benchmark (PIQA challenge)

Table 2 shows the results obtained by various systems on the PIQA challenge. We observe that EfficientQA beats previous sota DENSPI (+1.3 in exact-match and +1.4 in f1-score) while the encoding method of the latter is based on large version of BERT (340 million parameters) and ours is based on RoBERTa-base (125 million parameters). We can explain these performances by the quality of the representations on the one hand and in the other hand, by the fact that agnostic extraction drastically reduces the size of the set on which we are looking for the right answer. Hence, it leaves less room for error.

4.3.3 Results on the FQuAD benchmark

CamemBERT (Martin et al., 2020) is a pretrained French language model based on the RoBERTa architecture. We use it to build the dense representations of the French version of EfficientQA. Table 3 presents the results of EfficientQA on the FQuAD benchmark. (d’Hoffschmidt et al., 2020) have fine-tuned CamemBERT to perform vanilla Question Answering on their dataset. The results show that the gap between EfficientQA and finetuned models are closer in English than in French. This might be explained by the volume of data significantly lower in French than in English.

5 Conclusion

In this paper, we introduced EfficientQA, a phrase-indexed approach to solve question answering. Our system relies on question-agnostic extraction of
Table 3: Performances of EfficientQA on the FQuAD benchmark

| model                        | exact-match | f1-score |
|------------------------------|-------------|----------|
| EfficientQA (PIQA)           | 64.4        | 76.0     |
| CamembertQA (vanilla QA,     | 77.6        | 87.3     |
| our run) (d’Hoffschmidt et al., 2020) |             |          |

candidates that allows to reduce drastically the set of possible answers and to take advantage from the pair of sequences type of input of RoBERTa-base pretrained language model. EfficientQA achieves state-of-the-art performances on the PIQA benchmark and keep closing the gap with vanilla Question Answering models, while there is still room for further improvements by using heavier pretrained language models to build dense representations of questions and candidates. Future research will focus on mobilizing the necessary resources to extend EfficientQA representations to index a whole corpus such as the entire English Wikipedia and speed-up open-domain question answering.

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