Neural Retrieval for Question Answering with Cross-Attention Supervised Data Augmentation

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Abstract

Neural models that independently project questions and answers into a shared embedding space allow for efficient continuous space retrieval from large corpora. Independently computing embeddings for questions and answers results in late fusion of information related to matching questions to their answers. While critical for efficient retrieval, late fusion underperforms models that make use of early fusion (e.g., a BERT based classifier with cross-attention between question-answer pairs). We present a supervised data mining method using an accurate early fusion model to improve the training of an efficient late fusion retrieval model. We first train an accurate classification model with cross-attention between questions and answers. The accurate cross-attention model is then used to annotate additional passages in order to generate weighted training examples for a neural retrieval model. The resulting retrieval model with additional data significantly outperforms retrieval models directly trained with gold annotations on Precision at N (P@N) and Mean Reciprocal Rank (MRR).

1 Introduction

Open domain question answering (QA) involves finding answers to questions from an open corpus (Surdeanu et al., 2008; Yang et al., 2015; Chen et al., 2017; Ahmad et al., 2019). The task has led to a growing interest in scalable end-to-end retrieval systems for question answering. Recent neural retrieval models have shown rapid improvements, surpassing traditional information retrieval (IR) methods such as BM25 (Ahmad et al., 2019; Lee et al., 2019; Karpukhin et al., 2020).

When QA is formulated as a reading comprehension task, cross-attention models like BERT (Devlin et al., 2019) have achieved better-than-human performance on benchmarks such as the Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al., 2016). Cross-attention models are especially well suited for problems involving comparisons between paired textual inputs, as they provide early fusion of fine-grained information within the pair. This encourages careful comparison and integration of details across and within the two texts.

However, early fusion across questions and answers is a poor fit for retrieval, since it prevents precomputation of the answer representations. Rather, neural retrieval models independently compute embeddings for questions and answers typically using dual encoders for fast scalable search (Henderson et al., 2017; Guo et al., 2018; Gillick et al., 2018; Yang et al., 2019b). Using dual encoders results in late fusion within a shared embedding space.

For machine reading, early fusion using cross-attention introduces an inductive bias to compare fine grained text spans within questions and answers. This inductive bias is missing from the single dot-product based scoring operation of dual encoder retrieval models. Without an equivalent inductive bias, late fusion is expected to require additional training data to learn the necessary representations for fine grained comparisons.

To support learning improved representations for retrieval, we explore a supervised data augmentation approach leveraging a complex classification model with cross-attention between question-answer pairs. Given gold question passage pairs, we first train a cross-attention classification model as the supervisor. Then any collection of questions can be used to mine potential question passage pairs under the supervision of the cross-attention model. The retrieval model training benefits from additional training pairs annotated with the graded predictions from the cross-attention model augmenting, the existing gold data.

Experiments are reported on MultiReQA-SQuAD and MultiReQA-NQ, with retrieval models
establishing significant improvements on Precision at $N$ (P@N) and Mean Reciprocal Rank (MRR) metrics.

2 Neural Passage Retrieval for Open Domain Question Answering

Open domain question answering is the problem of answering a question from a large collection of documents (Voorhees and Tice, 2000; Chen et al., 2017). Systems usually follow a two-step approach: first retrieve question relevant passages, and then scan the returned text to identify the answer span using a reading comprehension model (Jurafsky and Martin, 2018; Kratzwald and Feuerriegel, 2018; Yang et al., 2019a). Prior work has focused on the answer span annotation task and has even achieved super human performance on some datasets. However, the evaluations implicitly assume the trivial availability of passages for each question that are likely to contain the correct answer. While the retrieval task can be approached using traditional keyword based retrieval methods such as BM25, there is a growing interest in developing more sophisticated neural retrieval methods (Lee et al., 2019; Guu et al., 2020; Karpukhin et al., 2020).

3 Retrieval Question-Answering (ReQA)

Ahmad et al. (2019) introduced the Retrieval Question-Answering (ReQA) task that has been rapidly adopted by the community (Guo et al., 2020; Chang et al., 2020; Ma et al., 2020; Zhao and Lee, 2020; Roy et al., 2020). Given a question, the task is to retrieve the answer sentence from a corpus of candidates. ReQA provides direct evaluation of retrieval, independent of span annotation. Compare to Open Domain QA, ReQA focuses on evaluating the retrieval component and, by construction, avoids the need for span annotation.

We explore the proposed approach on the MultiReQA-NQ and MultiReQA-SQuAD tasks. MultiReQA (Guo et al., 2020) established standardized training / dev / test splits. Statistics for the MultiReQA-NQ and MultiReQA-SQuAD tasks are listed in Table 1.

4 Methodology

Figure 1 illustrates our approach using a cross-attention classifier to supervise the data augmentation process for training a retrieval model. After training the cross-attention model, we retrieve additional potential answers to questions in the training set using an off-the-shelf retrieval system. The predicted scores from the classification model are then used to weight and filter the retrieved candidates with positive examples serving as weighted silver training data for the retrieval model.

| Dataset | Training Pairs | Test Questions | Test Candidates |
|---------|----------------|----------------|-----------------|
| NQ      | 106,521        | 4,131          | 22,118          |
| SQuAD   | 87,133         | 10,485         | 10,642          |

Table 1: Statistics of MutiReQA NQ and SQuAD tasks: # of training pairs, # of questions, # of candidates.

1 For each question, we sample a sentence from the 10 nearest neighbors returned by a term based BM25 (Robertson and Zaragoza, 2009) from a sentence pool containing all supporting documents in a corpus. Sampled sentences are paired with questions as negative examples.

2 Similar to our BM25 negatives and drawing from the same sentence pool, we sample the 10 nearest neighbors using the Universal Sentence Encoder - QA (USE-QA) (Yang et al., 2019b). Sampled sentences are paired with negative examples.

Note the approach can also be applied to any collection of questions, even for those without ground truth answers.
the question that selected it and labeled as negative.

3 Each question is paired with a sentence randomly sampled from its supporting documents, excluding the question’s gold answer.

A BERT model is fine-tuned following the default setup from the Devlin et al. (2019).

4.2 Dual-Encoder Retrieval Model

We follow Guo et al. (2020) and employ a BERT based dual-encoder model for retrieval. The dual encoder model critically differs from the cross-attention model in that there is no early interaction (cross-attention) between the question and answer. The resulting independent encodings are only combined in the final dot-product scoring a pair. The same BERT encoder is used for questions and answers with the output of the CLS token taken as the output encoding. For answers, the answer and context are concatenated and segmented using the segment IDs from the original BERT model. A learned input type embedding is added to each token embeddings to distinguish questions and answers within the encoding model.

4.3 Mining Augmented Training Pairs

We create an augmented training set for the retrieval model using the cross-attention model. For each question in the training set, we use USE-QA to mine the top 10 nearest neighbors from the entire training set, and then remove those retrieved pairs which are true positives. Next the cross-attention model is used to score the retrieved pairs. The neural retrieval model is trained on the combination the scored pairs and the original question-answer pairs from training set. The original pairs are assigned a score 1.

4.4 Weighted In-batch Softmax for Dual-Encoder Retrieval Model

The neural retrieval model is trained using the batch negative sampled softmax loss (Gillick et al., 2018) in equation 1. We modify the standard formulation to include a weight, \( w(x, y) \), for each pair.

\[
J' = \sum_{(x,y)\in \text{Batch}} w(x, y) \frac{e^\phi(x,y)}{\sum_{y'\in \mathcal{Y}} e^\phi(x,y')}
\]  

The \( w(x, y) \) is set to 1 if \( (x, y) \) is the ground truth positive pair and \( p(x, y)^2 \) otherwise, where \( p(x, y) \) is the probability output from the cross-attention model if it is not a ground truth example.

5 Evaluation

In this section we evaluate the proposed approach using the MultiReQA evaluation splits for NQ and SQuAD. Models are assessed using Precision at N (P@N) and Mean Reciprocal Rank (MRR). Following the ReQA setup (Ahmad et al., 2019), we report P@N for \( N=\{1, 5, 10\} \). The P@N score tests whether the true answer sentence appears as the top-N-ranked candidates. And MRR is calculated as 

\[
\text{MRR} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\text{rank}_i},
\]

where \( N \) is the total number of questions, and \( \text{rank}_i \) is the rank of the first correct answer for the \( i \)th question.

5.1 Configurations

We fine-tune the public English BERT cross-attention models using Batch size of 256; weighted Adam optimizer with learning rate 3e-5. Each model is fine-tuned for 10 epochs. We experiment with both Base and Large BERT models. All hyperparameters are set using a development set splitted out from the training data (10%). While mining for silver data, we keep only the mined examples with cross-attention model scores predicted as positive (with score \( \geq 0.5 \)).

The BERT Base model is used to initialize the dual encoder retrieval model. During training we use a batch size of 64, and a weighted Adam optimizer with learning rate 1e-4. The maximum input length is set to 96 for questions and 384 for answers. Models are trained for 200 epochs. Following Guo et al. (2020), we use the BERT CLS...
| Models       | NQ ACC | NQ AUC-PR | SQuAD ACC | SQuAD AUC-PR |
|-------------|--------|-----------|-----------|--------------|
| Majority    | 73.7   | –         | 74.8      | –            |
| BERTdual_encoder | 75.8   | 49.3      | 80.3      | 62.0         |
| (S) BERTBase | 84.3   | 92.8      | 92.6      | 96.5         |
| (S) BERTLarge| 84.9   | 93.5      | 93.6      | 97.1         |

Table 2: Accuracy (ACC) and area under the precision-recall curve (AUC-PR) for the classification task. **Majority** is a simple baseline that always predict false. **(T)** indicates the model is a supervisor model candidate.

token as the text embedding for retrieval. The embeddings are $l_2$ normalized. Hyper-parameters are manually tuned on a held out development set.

5.2 Performance for the Classification Task

The classification data created using the method from section 4.1 contains a total of 531k and 469k training examples for NQ and SQuAD, respectively. Test sets extracted from the SQuAD and NQ test splits contain 15k and 41k examples.

Table 2 shows the performance of the cross-attention models. We compare performance to the majority baseline which always predict false and the BERT dual encoder retrieval model which uses cosine similarity for prediction. BERT based models outperform the baselines by a wide margin, with the BERT large model achieving the highest performance on all metrics. This is consistent with our hypothesis that late fusion models outperform the retrieval model on the task. Both models achieve better performance on the SQuAD than NQ. The SQuAD task has higher token overlap, as described in 3, making the task somewhat easier. We use the BERT large model to supervise the data augmentation step in the next section.

5.3 Mined Examples

We mined the SQuAD and NQ training data to construct additional QA pairs. After collecting and scoring addition pairs using the method described in section 4.3, we obtained 53% (56,148) and 12% (10,198) more examples for NQ and SQuAD, respectively. Table 4 illustrated the examples retrieved by USE-QA and predicted as positive examples by the classification model. Both of the examples are clear positives.

Much less data is mined for SQuAD than NQ. We believe it is because of the way SQuAD was created, whereby workers write the questions based on the content of a particular article. The resulting questions are much more specific and biased toward a particular question types, for example Ahmad et al. (2019) shows almost half of the SQuAD questions are *what* questions. Another reason is that the candidate pool for SQuAD is only half that of NQ, resulting in questions having fewer opportunities to be matched to good additional answers.

5.4 Results on the Retrieval QA

Table 3 shows the P@N and MRR@100 of the retrieval models on MultiReQA-SQuAD and MultiReQA-NQ. The first two rows show the result from two simple baselines BM25 (Robertson and Zaragoza, 2009) and USE-QA reported from Guo et al. (2020). BM25 remains as a strong baseline, especially with 62.8% P@1 and 70.5% MRR for SQuAD. The performance on NQ is much lower, as there is much less token overlap between NQ questions and answers. USE-QA matches the performance of BM25 on NQ but performs worse on SQuAD.

BERTdual_encoder trained on the NQ and SQuAD training set performs very strong compared to the baselines, especially on NQ with a +20 point improvement on NQ. Our P@1 on SQuAD matches BM25, but we achieve an MRR that is +2.3 points better. Performance is further improved by including the augmented data from our cross-attention model, obtaining 53.3% P@1 and 65.9% MRR on NQ, which is an +8.6% and a +7.0% improvement on P@1 and MRR, respectively, comparing with the second best model.

Compare to NQ, the improvement on SQuAD is rather marginal. The augmented BERTdual_encoder retrieval model only achieves slightly improved performance on SQuAD, with +1 points for both of P@1 and MRR. As discussed in last section, we mine much less data on SQuAD compare with NQ, with only 10% more data on top of the original training set. As demonstrated by the strong BM25 performance and shown in (Guo et al., 2020), the SQuAD question answer pairs have higher token overlap between question and answers, eliminating the advantage of the neural methods to implicitly

5 We note that USE-QA can be fine-tuned using the training set, which will usually significantly outperform the default USE-QA model as demonstrated in Guo et al. (2020).

6 Our BERTdual_encoder performs much better than the one reported in Guo et al. (2020), we found simply train the model longer significantly improves the model performance.
Table 3: Precision at N(P@N) (%) N=[1, 5, 10] and Mean Reciprocal Rank (MRR) (%) on the MultiReQA tasks.

| Models                | NQ P@1 | NQ P@5 | NQ P@10 | NQ MRR | SQuAD P@1 | SQuAD P@5 | SQuAD P@10 | SQuAD MRR |
|-----------------------|--------|--------|---------|--------|-----------|-----------|-----------|----------|
| BM25                  | 24.7   | –      | –       | 36.6   | 62.8      | –         | –         | 70.5     |
| USE-QA                | 24.7   | –      | –       | 34.7   | 51.0      | –         | –         | 62.1     |
| BERTdual_encoder      | 44.7   | 77.1   | 85.1    | 58.9   | 62.8      | 85.4      | 91.0      | 72.8     |
| BERTdual_encoder Augmented | 53.3   | 82.3   | 88.5    | 65.9   | 63.8      | 86.1      | 91.6      | 73.7     |

Table 4: Scored examples from cross-attention classification model.

| Score | Silver QA Pair |
|-------|----------------|
| 0.92  | Q: what are the names of the two old muppets in the balcony that heckle everyone?  
A: Statler and Waldorf are a pair of Muppet characters known for their cantankerous opinions and shared penchant for heckling. |
| 0.90  | Q: where the phrase dressed to the nines come from  
A: It appears in book six of Jean-Jacques Rousseau’s Confessions, his autobiography... |

model more complex semantic relationships.

6 Conclusion

In this paper, we propose a novel approach for making use of an early fusion classification model to improve late fusion retrieval models. The early fusion model is used to supervised data mining that augments the training data for the later model. The proposed approach mines 53% (56,148) and 12% (10,198) more examples for MultiRQA-NQ and MultiRQA-SQuAD, respectively. The resulting retrieval models improve +8.6% and +1.0% on P@1 on NQ and SQuAD, respectively. The current pipeline assumes there exists annotated in-domain question answer pairs to train the cross-attention model. With a strong general purpose cross-attention model, our supervised data mining method could be modified to train in-domain retrieval models without gold question answer pairs. We leave this direction to the future work.

References

Amin Ahmad, Noah Constant, Yinfei Yang, and Daniel Cer. 2019. ReQA: An evaluation for end-to-end answer retrieval models. In Proceedings of the 2nd Workshop on Machine Reading for Question Answering, pages 137–146, Hong Kong, China. Association for Computational Linguistics.

Wei-Cheng Chang, Felix X. Yu, Yin-Wen Chang, Yiming Yang, and Sanjiv Kumar. 2020. Pre-training tasks for embedding-based large-scale retrieval. In International Conference on Learning Representations.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1870–1879, Vancouver, Canada. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1: Long Papers, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Daniel Gillick, Alessandro Presta, and Gaurav Singh Tomar. 2018. End-to-end retrieval in continuous space. CoRR, abs/1811.08008.

Mandy Guo, Qinlan Shen, Yinfei Yang, Heming Ge, Daniel Cer, Gustavo Hernandez Abrego, Keith Stevens, Noah Constant, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2018. Effective parallel corpus mining using bilingual sentence embeddings. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 165–176, Belgium, Brussels. Association for Computational Linguistics.

Mandy Guo, Yinfei Yang, Daniel Cer, Qinlan Shen, and Noah Constant. 2020. MultiReQA: A cross-domain evaluation for retrieval question answering models. arXiv preprint arXiv:2005.02507.

Kelvin Guu, Kenton Lee, Zora Tung, Panupon Pasupat, and Ming-Wei Chang. 2020. Realm: Retrieval-augmented language model pre-training. arXiv preprint arXiv:2002.08909.

Shuguang Han, Xuanhui Wang, Mike Bendersky, and Marc Najork. 2020. Learning-to-rank with bert in tf-ranking. arXiv preprint arXiv:2004.08476.
Matthew Henderson, Rami Al-Rfou, Brian Strope, Yun-Hsuan Sung, László Lukács, Ruqi Guo, Sanjiv Kumar, Balint Miklos, and Ray Kurzweil. 2017. Efficient natural language response suggestion for smart reply. arXiv preprint arXiv:1705.00652.

Daniel Jurafsky and James H. Martin. 2018. Speech and Language Processing (3rd Edition. in draft). Prentice-Hall, Inc., Upper Saddle River, NJ, USA.

Vladimir Karpukhin, Barlas Oğuz, Sewon Min, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. arXiv preprint arXiv:2004.04906.

Bernhard Kratzwald and Stefan Feuerriegel. 2018. Adaptive document retrieval for deep question answering. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 576–581, Brussels, Belgium. Association for Computational Linguistics.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. ArXiv, abs/1906.00300.

Ji Ma, Ivan Korotkov, Yinfei Yang, Keith Hall, and Ryan McDonald. 2020. Zero-shot neural retrieval via domain-targeted synthetic query generation.

Rodrigo Nogueira, Wei Yang, Kyunghyun Cho, and Jimmy Lin. 2019. Multi-stage document ranking with bert. arXiv preprint arXiv:1910.14424.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.

Stephen Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: Bm25 and beyond. Found. Trends Inf. Retr., 3(4):333–389.

Uma Roy, Noah Constant, Rami Al-Rfou, Aditya Barua, Aaron Phillips, and Yinfei Yang. 2020. Lareqa: Language-agnostic answer retrieval from a multilingual pool.

Mihai Surdeanu, Massimiliano Ciaramita, and Hugo Zaragoza. 2008. Learning to rank answers on large online QA collections. In Proceedings of ACL-08: HLT, pages 719–727, Columbus, Ohio. Association for Computational Linguistics.

Ellen M. Voorhees and Dawn M. Tice. 2000. Building a question answering test collection. In Proceedings of the 23rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’00, pages 200–207, New York, NY, USA. ACM.

Wei Yang, Rui Qiao, Haocheng Qin, Amy Sun, Luchen Tan, Kun Xiong, and Ming Li. 2019a. End-to-end neural context reconstruction in Chinese dialogue. In Proceedings of the First Workshop on NLP for Conversational AI, pages 68–76, Florence, Italy. Association for Computational Linguistics.

Yi Yang, Wen-tau Yih, and Christopher Meek. 2015. WikiQA: A challenge dataset for open-domain question answering. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 2013–2018, Lisbon, Portugal. Association for Computational Linguistics.

Yinfei Yang, Daniel Cer, Amin Ahmad, Mandy Guo, Jax Law, Noah Constant, Gustavo Hernandez Abrego, Steve Yuan, Chris Tar, Yun-Hsuan Sung, et al. 2019b. Multilingual universal sentence encoder for semantic retrieval. arXiv preprint arXiv:1907.04307.

Tianchang Zhao and Kyusong Lee. 2020. Talk to papers: Bringing neural question answering to academic search. arXiv preprint arXiv:2004.02002.