Encoder Adaptation of Dense Passage Retrieval for Open-Domain Question Answering

Minghan Li and Jimmy Lin
David R. Cheriton School of Computer Science
University of Waterloo
{m692li, jimmylin}@uwaterloo.ca

Abstract

One key feature of dense passage retrievers (DPR) is the use of separate question and passage encoder in a bi-encoder design. Previous work on generalization of DPR mainly focus on testing both encoders in tandem on out-of-distribution (OOD) question-answering (QA) tasks, which is also known as domain adaptation. However, it is still unknown how DPR’s individual question/passage encoder affects generalization. Specifically, in this paper, we want to know how an in-distribution (IND) question/passage encoder would generalize if paired with an OOD passage/question encoder from another domain. We refer to this challenge as encoder adaptation. To answer this question, we inspect different combinations of DPR’s question and passage encoder learned from five benchmark QA datasets on both in-domain and out-of-domain questions. We find that the passage encoder has more influence on the lower bound of generalization while the question encoder seems to affect the upper bound in general. For example, applying an OOD passage encoder usually hurts the retrieval accuracy while an OOD question encoder sometimes even improves the accuracy.

1 Introduction

Generalization of neural networks has been a hot topic in various applications, such as computer vision (Recht et al., 2019; Hendrycks and Dietterich, 2019) and natural language processing (Talmor and Berant, 2019; ElSahar and Gallé, 2019). In this paper, we are particularly interested in the generalization of dense passage retrievers (DPR) (Karpukhin et al., 2020) in open-domain question answering (Voorhees and Tice, 2000; Chen et al., 2017). DPR leverages a bi-encoder structure which uses separate encoders for questions and passages and take the dot product of their vector output as relevance scores for end-to-end retrieval.

Previous work have been focusing on testing the generalization of DPR as a whole on out-of-distribution (OOD) data, which is also known as domain adaptation (Ramponi and Plank, 2020; Thakur et al., 2021). This line of work analyzes how DPR responds to different types of data, such as compositional questions (Liu et al., 2021), novel entities (Sciavolino et al., 2021), and different languages (Zhang et al., 2021). The common conclusion is that DPR transfers poorly to novel data distributions in zero-shot, compared to traditional term-matching algorithms such as BM25 (Robertson and Zaragoza, 2009). However, it remains unclear how individual question/passage encoder of DPR affects generalization in those tests.

In this paper, we aim to answer more fine-grained questions about generalization w.r.t. DPR: (1) Can a single in-distribution (IND) question/passage encoder generalizes well if paired with another OOD passage/question encoder from a different domain? (2) Do the question encoder and passage encoder play different roles in the generalization of DPR? To clarify, an encoder is IND when tested on the domain where it is trained; an encoder is OOD when paired with another encoder and tested on a different domain.
To answer those questions, we evaluate various combinations of DPR’s question encoder and passage encoder trained on five different question answering tasks (but using the same corpus, e.g., Wikipedia), which we refer to as “encoder adaptation” as shown in Fig. 1.

For question (1), most IND × OOD pairs of question encoder and passage encoder under-perform the IND encoder pairs on most datasets. However, there are some “outlier” encoder pairs that perform quite well on across all datasets. For example, the question encoder trained on CuratedTREC (Baudiš and Šedivý, 2015) adapts reasonably well with different passage encoders, and the passage encoders trained on TriviaQA (Joshi et al., 2017) and Natural Questions (Kwiatkowski et al., 2019) achieve acceptable accuracy when paired with different question encoders.

For question (2), we observe that the passage encoder seems to have a bigger impact on the generalization lower bound, while the question encoder seems to affect the upper bound more. Specifically, if an IND question encoder is paired with an OOD passage encoder, then the performance would usually drop significantly on that dataset. However, in the reverse setting (i.e., IND passage encoder × OOD question encoder), the performance does not suffer too much and sometimes even get improved.

For future work, such observations indicate that a pre-trained passage encoder can be fixed during adaptation and one could just fine-tune or re-train the question encoder to transfer DPR on other domains. It is similar to the work from Sciavolino et al. (2021) and Zhan et al. (2021) but for more general transfer learning, saving both time and space by avoiding repeatedly encoding dense indexes.

2 Related Work

Retrieval in QA Term-matching methods such as tf-idf or BM25 (Robertson and Zaragoza, 2009; Lin et al., 2021) has established strong baseline in various QA tasks (Chen et al., 2017; Yang et al., 2019; Min et al., 2019). Recently, retrievers based on neural networks (Goodfellow et al., 2016) and pre-trained language models (Devlin et al., 2019) also make great advancement in open-domain question-answering (Seo et al., 2019; Lee et al., 2019; Guu et al., 2020). Particularly, dense passage retrieval (DPR) (Karpukhin et al., 2020) sets the milestone by encoding questions and passages separately with a bi-encoder design. Based on DPR, multiple work on compression (Yamada et al., 2021; Izacard et al., 2020), hard-negative mining (Xiong et al., 2021; Zhan et al., 2021), and QA pre-training (Lu et al., 2021; Gao and Callan, 2021) has further pushed the performance boundary of in-distribution dense retrieval.

Domain Adaptation in Retrieval BEIR investigates DPR’s transferability over multiple retrieval tasks containing different knowledge (Thakur et al., 2021), while Mr.TYDI evaluates DPR pretrained on English corpus in a multi-lingual setting (Zhang et al., 2021). The zero-shot cross-domain/language results of DPR are unsatisfactory as expected, while other works on in-distribution generalization also find that DPR performs poorly on certain types of questions. Liu et al. (2021) observes that neural-retrievers fail to generalize to compositional questions and novel entities. Sciavolino et al. (2021) also finds that dense models can only generalize to common entities or certain question patterns.

3 Dense Passage Retrieval

Retrieval/Inference Given a corpus of passages \{\(p_1, p_2, \ldots, p_n\)\} and a query \(q\), DPR (Karpukhin et al., 2020) leverages two encoders \(f_Q\) and \(f_P\) to encode the question and documents, respectively. The similarity between the question \(q\) and document \(p\) is defined as the vector dot product:

\[
s = E^T_q E_p,
\]

where \(E_Q\) and \(E_P\) are the output of \(f_Q\) and \(f_P\), respectively. The similarity score \(s\) will be used to rank the passages during retrieval. Both \(f_Q\) and \(f_P\) use the pre-trained BERT (Devlin et al., 2019) for initialization and use the \([CLS]\) vector as the representation.

Training As pointed out by Karpukhin et al. (2020), training the encoders such that EQ (1) becomes a good ranking function is essentially a metric learning problem (Kulis, 2012). Given a specific question \(q\), let \(p^+\) be the positive context that contains answers for \(q\) and \(P = \{p_1^+, p_2^-, \ldots, p_k^-\}\) be the negative contexts, the negative log likelihood objective w.r.t. \(q\) and \(P\) is:

\[
\mathcal{L}(q, p^+, \overline{p_1}, \overline{p_2}, \ldots, \overline{p_k}) = - \log \frac{\exp(E^T_q E_{p^+})}{\exp(E^T_q E_{p^+}) + \sum_{i=1}^{k} \exp(E^T_q E_{p_i^-})}.
\]
Table 1: IND/OOD Q-P encoder pairs: Top-20/Top-100 retrieval accuracy (%) on five benchmark QA test sets. Each score represents the percentage of top 20/100 retrieved passages that contain answers. “NQ-test” means the test data of NQ; “NQ-Q-P” means using the DPR’s question and passage encoder trained on NQ to encode the test questions and Wikipedia corpus.

| Encoder     | Test set  | NQ-test | Trivia-test | WQ-test | Curated-test | SQuAD-test |
|-------------|-----------|---------|-------------|---------|--------------|------------|
| BM25-Q-P    | 62.9/78.3 | 76.4/83.2 | 62.4/75.5 | 80.7/89.9 | 71.1/81.8    |
| NQ-Q-P      | 79.1/85.9 | 69.1/78.6 | 67.4/78.3 | 85.3/91.4 | 47.7/63.3    |
| Trivia-Q-P  | 62.5/72.4 | 78.9/84.5 | 70.0/80.6 | 88.2/92.9 | 53.2/68.7    |
| WQ-Q-P      | 46.3/61.9 | 58.0/71.4 | 71.0/80.2 | 75.8/86.5 | 41.4/59.1    |
| Curated-Q-P | 56.0/68.0 | 69.0/79.7 | 66.8/77.9 | 85.1/92.2 | 50.4/66.1    |
| SQuAD-Q-P   | 41.4/61.6 | 63.7/77.3 | 57.9/74.1 | 79.5/91.1 | 62.1/76.8    |

4 Experimental Setup

We follow the DPR paper (Karpukhin et al., 2020) to train and evaluate our dense retrievers. We replicate their results on 5 benchmark datasets, with a maximum score difference between ours and their numbers of 1%. This work only focuses on evaluating the retrieval performance and therefore we do not include the reader module into consideration. We report the top-20 and top-100 recall accuracy as the metrics for evaluation.

Datasets

We train individual DPR models on 5 standard benchmark QA tasks: Natural Questions (NQ) (Kwiatkowski et al., 2019), TriviaQA (Joshi et al., 2017), WebQuestions (WQ) (Berant et al., 2013), CuratedTREC (TREC) (Baudiš and Šedivý, 2015), SQuAD-1.1 (SQuAD) (Rajpurkar et al., 2016) as shown in Tbl. 2. We evaluate the retriever models on the test sets of the aforementioned datasets.

For retrieval, we chunk the Wikipedia collections (Guu et al., 2020) into passages of 100 words as in Wang et al. (2019), which yields about 21 million samples in total. We follow Karpukhin et al. (2020) using BM25 (Robertson and Zaragoza, 2009; Lin et al., 2021) to select the positive and negative passages.

Models and Training

We train individual DPR models on the training set of NQ, TriviaQA, WQ, CuratedTREC, and SQuAD-1.1 separately following Karpukhin et al. (2020). We optimize the objective function in EQ (2) with learning rate of 2e-05 using Adam (Kingma and Ba, 2015) for 40 epochs. The rest of the hyperparameter setting remains the same as described in Karpukhin et al. (2020).

5 Can IND Q/P-Encoders Generalize to OOD P/Q-Encoders?

5.1 IND/OOD Q-P Encoder Pairs

Tbl. 1 shows the zero-shot retrieval performance using different DPR models and BM25 on 5 benchmark QA datasets. Each question encoder is paired with its original passage encoder and evaluated on different test sets. Normally, the in-distribution DPR model is expected to outperform the OOD DPR, which is the situation that happens to most datasets such as NQ, Trivia, and SQuAD. However, for datasets such as WQ and Curated, we find that the DPR trained on Trivia has better zero-shot performance than the IND ones. We suspect the reason is that NQ and Trivia has much larger training data than WQ and Curated as shown in Tbl. 2, which potentially includes some similar questions in Curated and WQ. Moreover, BM25 outperforms the DPR model on SQuAD as SQuAD mainly contains entity-centred questions which is good for term-matching algorithms. In contrast, DPR has been shown to have poor generalization on novel entities (Liu et al., 2021; Sciavolino et al., 2021),
and therefore the OOD DPR perform poorly on SQuAD in general.

5.2 IND Q-Encoder × OOD P-Encoder

Tbl. 3 shows the adaptation performance using IND question encoders and OOD passage encoders trained on other domains. The performance immediately drops once the IND question encoder is paired with an OOD passage encoders on most datasets. However, compared to the zero-shot setting in Tbl. 1, most OOD passage encoders have significant improvement when paired with the IND question encoders, except for WQ where all OOD passage encoders have significant accuracy drop when paired with the WQ question encoder. This indicates that the representations learned from the WQ data are shifted towards some weird manifolds that do not align well with other encoders. In contrast, the passage encoders trained on NQ and Trivia still perform well on most datasets, which supports the argument that NQ and Trivia learns more general representations due to learning from more diverse training data.

5.3 IND P-Encoder × OOD Q-Encoder

Tbl. 4 shows the adaptation performance using IND passage encoders and OOD question encoders trained on other domains. Similar to the previous section, the IND passage encoders significantly improve the generalization compared to the zero-shot setting. The difference to Section 5.2 is that the accuracy is more robust against different question encoders with the IND passage encoder. Surprisingly, when the IND passage encoders are paired with particular OOD question encoders, the accuracy is sometimes even better than the in-distribution counterpart! For example, the Curated question encoder outperforms the IND question encoder on NQ, Trivia, WQ, and Curated when paired with the in-distribution passage encoder of each domain. Therefore, we propose two conjectures from the results in Tbl. 3 and Tbl. 4: (1) Using in-domain passage encoders is more important than using in-domain question encoders. (2) Curated question encoder learns more general question representations that align well with others with much less training data. We conjecture that it is because Cu-
Figure 2: Comparison between IND Q-encoder × OOD P-encoder and OOD Q-encoder × IND P-encoder. The x-axis represents different test sets, and the y-axis represents the best top-100 accuracy (%) relative to the IND question-passage encoder pair by replacing either the question or passage encoder with another one.

rated covers more question patterns or entities that might help to learn more general question encoders.

6 Does Q/P-Encoder Play a Different Role in the Generalization of DPR?

To analyze the role that the question encoder and passage encoder each plays in the generalization of DPR, we compare the relative top-100 retrieval test accuracy between using the best OOD question encoder and the best OOD passage encoder for each dataset as shown in Fig. 2. We can see that using an OOD passage encoder consistently underperforms using an OOD question encoder (except for Curated which has the best OOD question encoder as well, making the passage encoder bar looks like an outlier). It suggests that the passage encoder is the key to DPR’s generalization as it lower-bounds the IND question-passage encoder pair’s performance most of the time.

From the last section, using an OOD question encoder does not hurt the retrieval accuracy too much but sometimes even outperforms using an IND question encoder. Fig. 2 shows that using a best OOD question encoder outperforms the IND question-passage encoder pairs on most dataset, except for SQuAD whose data are biased towards certain data types (e.g., named entities). Such results are consistent with the findings in hard-negative mining (Zhan et al., 2021) and entity transfer learning (Sciavolino et al., 2021) for DPR.

7 Conclusions

We address two questions regarding the generalization of DPR: (1) Can its question/passage encoder generalize to another passage/question encoder of another DPR trained on a different domain? (2) What roles do the question encoder and passage encoder play in the generalization of DPR? To answer these questions, we examine different combinations of DPR’s question encoders and passage encoders trained on five different QA datasets, which we refer to as “encoder adaptation”. Despite most pairs of question encoder and passage encoder from different sources underperform the in-distribution DPR model, we find the passage encoders learned on Natural Questions and TriviaQA achieve reasonable accuracy due to more training data. In addition, the question encoder from the CuratedTREC dataset adapts particular well with different passage encoders, whose performance even outperform the in-distribution DPR model.

Finally, we observe that the passage encoder affects the generalization lower bound more while the question encoder seems to play a more vital role in the generalization upper bound, indicating the possibility of transferring DPR to another domain by just fine-tuning the question encoder while keeping the passage encoder fixed.

Acknowledgements

This research was supported in part by the Canada First Research Excellence Fund and the Natural Sciences and Engineering Research Council (NSERC) of Canada; computational resources were provided by Compute Ontario and Compute Canada.

References

Petr Baudiš and Jan Šedivý. 2015. Modeling of the question answering task in the YodaQA system. In International Conference of the Cross-Language Evaluation Forum for European Languages, pages 222–228. Springer.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Seattle, Washington, USA. Association for Computational Linguistics.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proceedings of the 55th An-
nual 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 and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Hady Eltaher and Matthias Gallé. 2019. To annotate or not? predicting performance drop under domain shift. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 2163–2173. Association for Computational Linguistics.

Luyu Gao and Jamie Callan. 2021. Unsupervised corpus aware language model pre-training for dense passage retrieval. CoRR, abs/2108.05540.

Ian J. Goodfellow, Yoshua Bengio, and Aaron C. Courville. 2016. Deep Learning. Adaptive computation and machine learning. MIT Press.

Kelvin Guu, Kenton Lee, Z. Tung, Panupong Pasupat, and Ming-Wei Chang. 2020. Realm: Retrieval-augmented language model pre-training. ArXiv, abs/2002.08909.

Dan Hendrycks and Thomas G. Dietterich. 2019. Benchmarking neural network robustness to common corruptions and perturbations. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net.

Gautier Izacard, Fabio Petroni, Lucas Hosseini, Nicola De Cao, Sebastian Riedel, and Edouard Grave. 2020. A memory efficient baseline for open domain question answering. CoRR, abs/2012.15156.

Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1601–1611, Vancouver, Canada. Association for Computational Linguistics.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6769–6781, Online. Association for Computational Linguistics.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In 3rd International Conference on Learning Representations, ICLR 2015.

Brian Kulis. 2012. Metric learning: A survey. Foundations and Trends in Machine Learning, 5(4):287–364.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Ilia 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. Transactions of the Association for Computational Linguistics, 7:452–466.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.

Jimmy Lin, Xueguang Ma, Sheng-Chieh Lin, Jheng-Hong Yang, Ronak Pradeep, and Rodrigo Nogueira. 2021. Pyserini: An easy-to-use Python toolkit to support replicable ir research with sparse and dense representations. ArXiv, abs/2102.10073.

Lingqing Liu, Patrick S. H. Lewis, Sebastian Riedel, and Pontus Stenetorp. 2021. Challenges in generalization in open domain question answering. CoRR, abs/2109.01156.

Shuqi Lu, Chenyan Xiong, Di He, Guolin Ke, Waleed Malik, Zhicheng Dou, Paul Bennett, Tie-Yan Liu, and Arnold Overwijk. 2021. Less is more: Pre-training a strong siamese encoder using a weak decoder. CoRR, abs/2102.09206.

Sewon Min, Danqi Chen, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2019. A discrete hard EM approach for weakly supervised question answering. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2851–2864, Hong Kong, China. Association for Computational Linguistics.

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.
Alan Ramponi and Barbara Plank. 2020. Neural unsupervised domain adaptation in NLP - A survey. In Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020, pages 6838–6855. International Committee on Computational Linguistics.

Benjamin Recht, Rebecca Roelofs, Ludwig Schmidt, and Vaishaal Shankar. 2019. Do imagenet classifiers generalize to imagenet? In Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA, volume 97 of Proceedings of Machine Learning Research, pages 5389–5400. PMLR.

Stephen E. Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: BM25 and beyond. Foundations and Trends in Information Retrieval, 3(4):333–389.

Christopher Sciavolino, Zexuan Zhong, Jinho Lee, and Danqi Chen. 2021. Simple entity-centric questions challenge dense retrievers. CoRR, abs/2109.08535.

Minjoon Seo, Jinho 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.

Alon Talmor and Jonathan Berant. 2019. MultiQA: An empirical investigation of generalization and transfer in reading comprehension. In Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers, pages 4911–4921. Association for Computational Linguistics.

Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2021. BEIR: A heterogenous benchmark for zero-shot evaluation of information retrieval models. CoRR, abs/2104.08663.

Ellen M. Voorhees and Dawn M. Tice. 2000. The TREC-8 question answering track. In Proceedings of the Second International Conference on Language Resources and Evaluation (LREC’00), Athens, Greece. European Language Resources Association (ELRA).

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 Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5878–5882, Hong Kong, China. Association for Computational Linguistics.