An Encoder Attribution Analysis for Dense Passage Retriever in Open-Domain Question Answering

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Abstract

The bi-encoder design of dense passage retriever (DPR) is a key factor to its success in open-domain question answering (QA), yet it is unclear how DPR's question encoder and passage encoder individually contributes to overall performance, which we refer to as the *encoder attribution* problem. The problem is important as it helps us identify the factors that affect individual encoders to further improve overall performance. In this paper, we formulate our analysis under a probabilistic framework called *encoder marginalization*, where we quantify the contribution of a single encoder by marginalizing other variables. First, we find that the passage encoder contributes more than the question encoder to in-domain retrieval accuracy. Second, we demonstrate how to find the affecting factors for each encoder, where we train DPR with different amounts of data and use encoder marginalization to analyze the results. We find that positive passage overlap and corpus coverage of training data have big impacts on the passage encoder, while the question encoder is mainly affected by training sample complexity under this setting. Based on this framework, we can devise data-efficient training regimes: for example, we manage to train a passage encoder on SQuAD using 60% less training data without loss of accuracy.

1 Introduction

Attribution analysis, or credit assignment, concerns how individual components of a system contribute to its overall performance (Minsky, 1961). In this paper, we are interested in the *encoder attribution* problem of dense passage retrievers (DPR) (Karpukhin et al., 2020; Zhan et al., 2020b) for open-domain question answering (Voorhees and Tice, 2000; Chen et al., 2017). DPR leverages a bi-encoder structure that encodes questions and passages into low dimensional vectors separately.

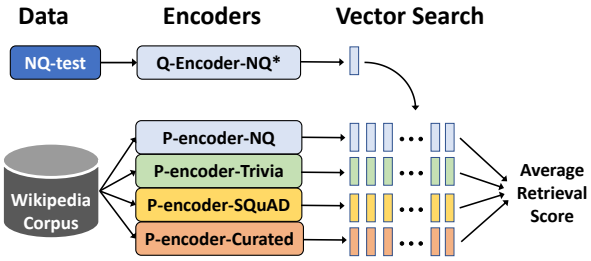

Figure 1: Encoder marginalization. Here, "*" denotes the target encoder we want to evaluate, where we use the Q-encoder of DPR trained on NQ as an example. The Q-encoder is evaluated on NQ-test data and paired with different P-encoders, and the final contribution is determined by averaging across the scores of different encoder pairings.

Follow-up work has proposed various methods to further improve and analyze DPR (Xiong et al., 2021; Luan et al., 2021; Mao et al., 2021; Gao and Callan, 2021). However, most of these methods only test the bi-encoder model in tandem, leaving two questions unanswered:

(1) *What are the individual contributions of each encoder of DPR?*

(2) *How to find the affecting factors for each encoder in different QA datasets?*

The first problem, which we refer to as *encoder attribution*, is important as it helps us understand which part of the DPR model might go wrong and identify possible sources of error in the data for the second problem. Therefore, it is important to separately inspect individual encoders of DPR.

In this paper, we perform an encoder attribution analysis of DPR under a probabilistic framework, where we model the evaluation function for DPR's predictions as a probabilistic distribution. The core component of our method is called *encoder marginalization*, where we target one encoder and marginalize over the other variables. We then use the expectation under the marginalized

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distribution as the encoder's contribution to the evaluation score. The marginalization can be approximated using Monte-Carlo, as illustrated in Fig. 1, where encoders trained from different domains are used as empirical samples, which will be discussed in Section 3.2.

For question (1), we introduce a technique we call encoder marginalization to compare the question encoder and passage encoder of the same DPR (Section 5.2). We find that in general, the passage encoder plays a more important role than the question encoder in terms of retrieval accuracy, as replacing the passage encoder generally causes a larger accuracy drop.

For question (2), we perform a case study where we analyze DPR's individual encoders under a data efficiency setting. We evaluate different DPR models trained with different amounts of data. Under this setting, we find that positive passage overlap and corpus coverage of the training data might be the affecting factors for the passage encoder, while the question encoder seems to be affected by the sample complexity of training data. Based on the discovery of these affecting factors, we develop a data-efficient training regime, where we manage to train a passage encoder on SQuAD using 60% less training data with very little drop in accuracy.

Our work makes the following four main contributions:

- To our knowledge, we are the first to perform an encoder attribution analysis for DPR under a probabilistic framework.
- We find that the passage encoder plays a more important role than the question encoder in terms of in-domain retrieval accuracy.
- Under a data efficiency setting, we identify that passage encoders are affected by positive passage overlap and corpus coverage of the training data, while question encoders are sensitive to the training sample complexity.
- Our framework enables the development of data-efficient training regimes where we are able to use up to 60% less training data.

2 Background and Related Work

Attribution analysis It is also known as *credit assignment* and has long been discussed in various areas and applications. In reinforcement learning (Sutton and Barto, 1998), the accumulated reward from the environment needs to be distributed to the agent's historical decisions (Sutton, 1984; Harutyunyan et al., 2019; Arumugam et al., 2021). In investment (Binay, 2005), it is used to explain why a portfolio's performance differed from the benchmark. Attribution analysis has also been used in NLP (Mudrakarta et al., 2018; Jiang et al., 2021) and CV (Schulz et al., 2020) to interpret models' decisions. Therefore, attribution analysis is an important topic for understanding a system's behavior, especially for black-box models like deep neural networks (Goodfellow et al., 2016).

Retrieval for QA First-stage retrieval aims to efficiently find a set of candidate documents from a large corpus. Term-matching methods such as BM25 (Robertson and Zaragoza, 2009; Lin et al., 2021) have established strong baselines in the first-stage retrieval of various QA tasks (Chen et al., 2017; Yang et al., 2019; Min et al., 2019). Recently, retrievers based on pre-trained language models (Devlin et al., 2019; Liu et al., 2019) also make great advancements (Seo et al., 2019; Lee et al., 2019; Guu et al., 2020; Khattab and Zaharia, 2020). Particularly, dense passage retrievers (DPR) (Karpukhin et al., 2020; Zhan et al., 2020b) set a milestone by encoding questions and passages separately with a bi-encoder design. Based on DPR, multiple works on compression (Yamada et al., 2021; Izacard et al., 2020; Ma et al., 2021), hard-negative mining (Xiong et al., 2021; Zhan et al., 2021), multi-vector encoding (Luan et al., 2021; Lee et al., 2021b), and QA pre-training (Lu et al., 2021; Gao and Callan, 2021) expand the boundary of dense retrieval.

Other Analyses of DPR BEIR investigates DPR's transferability to multiple domains and retrieval tasks (Thakur et al., 2021), while Mr.TyDi evaluates DPR pre-trained on English for retrieval in a multi-lingual setting (Zhang et al., 2021). Lewis et al. (2021) find that most of the test answers also occur somewhere in the training data for most QA datasets. Liu et al. (2021) observe that neural retrievers fail to generalize to compositional questions and novel entities. Sciavolino et al. (2021) also find that dense models can only generalize to common question patterns.

2.1 Open-Domain Question Answering

Open-domain question answering requires finding answers to given questions from a large collection

of documents (Voorhees and Tice, 2000). For example, the question *"How many episodes in Season 2 Breaking Bad?"* is given and then the answer "13" will be either extracted from the retrieved passages or generated from a model. The goal of open-domain question answering is to learn a mapping from the questions to the answers, where the mapping could be a multi-stage pipeline that includes retrieval and extraction, or it could be a large language model that generates the answers directly given the questions. In this paper, we mainly discuss the retrieval component in a multi-stage system, which involves retrieving a set of candidate documents from a large text corpus. Based on the type of corpus, we could further divide open-domain question answering into textual QA and knowledge base QA. Textual QA mines answers from unstructured text documents (e.g., Wikipedia) while the other one searches through a structured knowledge base. We will mainly focus on textual QA in this paper.

2.2 Dense Passage Retrieval

Given a corpus of passages $\mathcal{C} = \{d_1, d_2, \cdots, d_n\}$ and a query q, DPR (Karpukhin et al., 2020) leverages two encoders η_Q and η_D to encode the question and passages separately. The similarity between the question q and passage d is defined as the dot product of their vector output:

$$s = E_q^T E_d, \tag{1}$$

where $E_q = \eta_Q(q)$ and $E_d = \eta_D(d)$. The similarity score s is used to rank the passages during retrieval. Both η_Q and η_D use a pre-trained BERT model (Devlin et al., 2019) for initialization and its `[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 d^+ be the positive context that contains the answer a for q and $\{d_1^-, d_2^-, ...d_k^-\}$ be the negative contexts, the contrastive learning objective with respect to q, d^+, and $\{d_i^-\}_{i=1}^k$ is:

$$\begin{aligned}&\mathcal{L}(q, d^+, d_1^-, d_2^-, ...d_k^-)\\ &= -\log \frac{\exp(E_q^T E_{d^+})}{\exp(E_q^T E_{d^+}) + \sum_{i=1}^{k} \exp(E_q^T E_{d_i^-})}.\end{aligned} \tag{2}$$

The loss function in Eq. (2) encourages the representations of q and d^+ to be close and increases the distance between q and d^-.

Retrieval/Inference The bi-encoder design enables DPR to perform an approximate nearest neighbour search (ANN) using tools like FAISS (Johnson et al., 2021), where the representations of the corpus passages are indexed offline. It is typically used in first-stage retrieval, where the goal is to retrieve all potentially relevant documents from the large corpus. Therefore, we consider top-k accuracy as the evaluation metric in this paper, following Karpukhin et al. (2020).

Let R be an evaluation function (e.g., top-k accuracy) for first-stage retrieval. Given a question-answer pair (q, a) and a corpus $\mathcal{C}$, we use η_Q and η_D to encode questions and retrieve passages separately. We define the evaluation score r_0 given the above inputs to be:

$$r_0 = R(q, a, \mathcal{C}, \eta_Q, \eta_D) \tag{3}$$

For simplicity's sake, in the rest of the paper, we will omit the answer a and corpus $\mathcal{C}$ as they are held fixed during evaluation.

3 Methods

3.1 Encoder Marginalization

In this section, we propose a simple probabilistic method to evaluate the contributions of encoders η_Q and η_D, as well as to compare the same type of encoder across different datasets. The core idea is called encoder marginalization, where marginalization simply means summing over the probability of possible values of a random variable.

Typically, the evaluation function R in Eq. (3) outputs a deterministic score r_0. However, we could also view r_0 as a specific value of a continuous random variable $r \in \mathbb{R}$ sampled from a Dirac delta distribution $p(r \mid q, \eta_Q, \eta_D)$:

$$\begin{aligned}p(r \mid q, \eta_Q, \eta_D) &\doteq \delta(r - r_0)\\ &= \begin{cases}+\infty, & r = r_0\\ 0, & r \neq r_0,\end{cases}\\ \text{s.t.,} \int_{-\infty}^{+\infty} &\delta(r - r_0)\mathrm{d}r = 1\end{aligned} \tag{4}$$

where $r_0 = R(q, a, \mathcal{C}, \eta_Q, \eta_D)$. Again, the answer a and corpus $\mathcal{C}$ are omitted for simplicity's sake. The expectation of the evaluation score r under the

Dirac delta distribution $\delta(r - r_0)$ is:

$$\mathbb{E}_{p(r|q,\eta_Q,\eta_D)}[r] = \int_{-\infty}^{+\infty} r \cdot \delta(r - r_0)\mathrm{d}r = r_0 \quad (5)$$

which is the score of the evaluation function in Eq. (3). This is also known as the *sifting property*[1] of the Dirac delta distribution (Mack, 2008), where the delta function is said to "sift out" the value at $r = r_0$. The reason for such a formalization is that now we can evaluate the contribution of a single encoder to the evaluation score r by marginalizing the other random variables.

The contribution of an individual encoder η_Q or η_D to score r on a question q can be evaluated by marginalizing the other encoder of $p(r \mid q, \eta_Q, \eta_D)$ in Eq. (4). We assume that the question q is sampled from the training data distribution for learning η_Q and η_D. Let's take the question encoder η_Q as an example. The distribution of r after marginalizing over η_D is:

$$\begin{aligned} p(r \mid q, \eta_Q) &= \int_{\eta_D} p(r \mid q, \eta_Q, \eta_D) p(\eta_D)\mathrm{d}\eta_D \\ &\approx \frac{1}{K}\sum_{i=1}^{K} p(r \mid q, \eta_Q, \eta_D^{(i)}) \\ &= \frac{1}{K}\sum_{i=1}^{K} \delta(r - r_0^{(i)}) \end{aligned} \quad (6)$$

where the superscript (i) means the tagged random variables belong to the i^{th} out of K QA dataset (e.g., $\eta_D^{(i)}$ means the passage encoder trained on the i^{th} QA dataset). The second to the last step uses the Monte-Carlo approximation, where we use $\eta_D^{(i)}$ sampled from a prior distribution $p(\eta_D)$, which will be discussed in Section 3.2.

The integration step in Eq. (6) assumes independence between q, η_D, and η_Q. Although during the training of DPR, η_D and η_Q are usually learned together, the two encoders do not necessarily need to be evaluated together during inference. For example, a question encoder trained on NQ could be paired with a passage encoder trained on Curated and tested on the Trivia QA dataset, without assuming any dependency. Therefore, we assume here no prior knowledge about how η_D and η_Q are trained, but rather highlight their independence during evaluation to validate Eq. (6).

[1]This property requires the sifted function $g(r)$ (in this case, $g(r) = r$) to be Lipschitz continuous.

As for the contribution of η_Q, according to the expectation of Dirac delta distribution in Eq. (5), the expectation of r under the marginalized distribution in Eq. (6) is:

$$\begin{aligned} \mathbb{E}_{p(r|q,\eta_Q)}[r] &= \int_{-\infty}^{+\infty} r \cdot p(r \mid q, \eta_Q)\mathrm{d}r \\ &\approx \int_{-\infty}^{+\infty} r \cdot \frac{1}{K}\sum_{i=1}^{K} p(r \mid q, \eta_Q, \eta_D^{(i)})\mathrm{d}r \\ &= \frac{1}{K}\sum_{i=1}^{K} \int_{-\infty}^{+\infty} r \cdot \delta(r - r_0^{(i)})\mathrm{d}r \\ &= \frac{1}{K}\sum_{i=1}^{K} r_0^{(i)} \end{aligned} \quad (7)$$

which corresponds to the in-domain encoder marginalization in Fig. 1. In this way, we manage to calculate the contribution of a question encoder η_Q to the evaluation score r given a question q.

3.2 Encoder Prior Distribution, Sampling, and Approximation

In the previous section, we define the contribution of a single encoder for DPR using encoder marginalization. However, to approximate the expectation under the marginalized distribution in Eq. (6), we need to sample the encoder η_D from a prior distribution $p(\eta_D)$. In practice, we do not have access to $p(\eta_D)$ but instead, we need to train η_D on specific datasets as empirical samples.

In addition, we cannot consider every possible function for the encoder. Therefore, we need to put constraints on the encoder prior distribution, so that $p(\eta_D)$ becomes $p(\eta_D \mid \Phi)$ that implicitly conditions on some constraints Φ. In this paper, Φ could represent, for example, model structures, training schemes, optimizers, initialization, and so on. The (sampled) encoders we run in the experiments are initialized with the same pre-trained language model (e.g., `bert-base-uncased`) and optimized with the same scheme (e.g., 40 epochs, Adam optimizers...), to ensure the constraints we put are consistent for different DPR models.

In practice, we use empirical samples such as DPRs pre-trained on different QA datasets for approximation in Eq. (7). Although the sample size is not big enough as it is very expensive to train DPR and encode a large textual corpus, the samples themselves are statistically meaningful as they are carefully fine-tuned for the domains we want

Datasets	Train	Dev	Test
Natural Questions	58,880	8,757	3,610
TriviaQA	60,413	8,837	11,313
WebQuestions	2,474	361	2,032
CuratedTREC	1,125	133	694
SQuAD	70,096	8,886	10,570

Table 1: The number of questions in each QA dataset from Karpukhin et al. (2020). The "Train" column denotes the number of questions after filtering.

to evaluate, instead of using models with randomly initialized weights.

4 Experimental Setup

We follow the DPR paper (Karpukhin et al., 2020) to train and evaluate our dense retrievers. We reproduce their results on five benchmark datasets using Tevatron[2] (Gao et al., 2022), a toolkit for efficiently training dense retrievers with deep neural language models. Our reproduced results have only a maximum difference of $\sim$2% compared to their numbers. We report the top-20 and top-100 accuracy for evaluation.

Datasets We train individual DPR models on five standard benchmark QA tasks, as shown in Tbl. 1: Natural Questions (NQ) (Kwiatkowski et al., 2019), TriviaQA (Trivia) (Joshi et al., 2017), WebQuestions (WQ) (Berant et al., 2013), CuratedTREC (Curated) (Baudiš and Šedivỳ, 2015), SQuAD-1.1 (SQuAD) (Rajpurkar et al., 2016). We use the data provided in the DPR[3] repository to reproduce their results. We evaluate the retriever models on the test sets of the aforementioned datasets. For retrieval, we chunk the Wikipedia collection (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 as the initial training data for DPR.

Models and Training During training, each question is paired with 1 positive passage, 1 hard negative retrieved by BM25, and $2 \times (B-1)$ in-batch negatives where B is the batch size. We optimize the objective in Eq. (2) with a learning rate of 1e-05 using Adam (Kingma and Ba, 2015) for 40 epochs. The rest of the hyperparameters remain the same as described in Karpukhin et al. (2020).

[2]https://github.com/texttron/tevatron
[3]https://github.com/facebookresearch/DPR

5 Results and Analysis

5.1 Generalization of Tandem Encoders

This section aims to show the generalization ability of DPR's bi-encoder evaluated in tandem. Tbl. 2 shows the zero-shot retrieval accuracy of different DPR models and BM25 on five benchmark QA datasets. Each row represents one model's accuracy on five datasets and each column represents the accuracy of five different models on one dataset. Normally, the in-domain DPR model is expected to outperform the other DPR models trained using data from other domains, which is the situation we observe for most datasets, such as NQ, Trivia, and SQuAD. However, for Curated, the DPR trained on NQ and Trivia has better zero-shot retrieval accuracy than the in-domain one. We suspect it is because NQ and Trivia have much larger training data than Curated, as shown in Tbl. 1, which potentially covers some similar questions in Curated.

Moreover, BM25 outperforms all DPR models on SQuAD as SQuAD mainly contains entity-centered questions which are good for term-matching algorithms. Besides, the SQuAD dataset is mainly for machine-reading comprehension and therefore a passage could be used to answer multiple questions, which could cause potential conflicts in representation learning (Wu et al., 2021).

In the following sections, we will perform encoder attribution analysis to examine DPR's each encoder individually.

5.2 In-Domain Encoder Marginalization

This section aims to answer the question (1) "*What are the individual contributions of each encoder of DPR?*" from Section 1. To analyze the contributions of a single encoder on a specific QA dataset, we compare the marginalized top-20 retrieval accuracy of the encoder using in-domain encoder marginalization shown in Fig. 1 and Eq. (7).

Fig. 2 shows the in-domain encoder marginalization results relative to the tandem DPR results. The blue bars show the question encoder's contributions where we target the question encoder and marginalize over the passage encoders, and vice versa for the orange bars (passage encoder) on five datasets. We further divide those results by the in-domain DPR's top-20 accuracy, which is normalized to 100% (the horizontal line in Fig. 2). We do not compare across

Encoder \ Test set	NQ	Trivia	WQ	Curated	SQuAD	Average
BM25	62.9/78.3	62.4/75.5	76.4/83.2	80.7/89.9	**71.1/81.8**	70.7/81.7
DPR-NQ	**79.8/86.9**	73.2/81.7	68.8/79.3	86.7/92.7	54.5/70.2	**72.6/82.2**
DPR-Trivia	66.4/78.9	**80.2/85.5**	71.4/81.7	**87.3/93.9**	53.0/69.2	71.7/81.8
DPR-WQ	54.9/70.0	66.5/78.9	**76.0/82.9**	82.9/90.8	49.3/66.2	65.9/77.8
DPR-Curated	68.5/72.7	66.5/77.7	65.5/77.5	84.0/90.7	51.3/67.5	67.2/77.2
DPR-SQuAD	56.6/72.3	71.0/81.7	64.3/77.0	83.3/92.4	61.1/76.0	67.3/80.0

Table 2: Zero-shot evaluation of DPR's bi-encoder in tandem. Top-20/Top-100 retrieval accuracy (%) on five benchmark QA test sets is reported. Each score represents the percentage of questions that have at least one correct answer in the top-20/100 retrieved passages.

different datasets, but rather compare the question encoder and the passage encoder for each domain. We can see that in general, the passage encoder (orange bars) contributes more to the top-20 accuracy compared to the question encoder (blue bars) on all five datasets. Moreover, for the Curated dataset, marginalizing the out-of-domain question encoders even improves the marginalized accuracy of the passage encoder of Curated.

Overall, we can see that the passage encoder plays a more vital role compared to the question encoder in terms of in-domain retrieval accuracy, which makes sense as the passage encoder needs to encode the entire corpus (in our case, 21M passages), while the question sets are much smaller.

5.3 Affecting Factors for Encoders in QA Training Data

In this section, our goal is to answer question (2), "*How to find the affecting factors for each encoder in different QA datasets?*" from Section 1. We will use the data efficiency test as an example and show how using encoder attribution in the data efficiency test can help us locate possible affecting factors in the dataset. Specifically, we will train DPR models with different amounts of training data. The reason we choose to change the size of the training data is that data sizes often have a large influence on a model's generalization ability, which could help reveal relevant affecting factors.

In-Domain Data Efficiency Test We train the DPR model with different amounts of data and test each encoder's in-domain marginalization accuracy with respect to the training data amount. Since it is extremely resource-consuming to train different DPR models and encode the entire Wikipedia corpus into dense vectors, in this section, we mainly focus on NQ, Trivia, and SQuAD due to their relatively large dataset sizes.

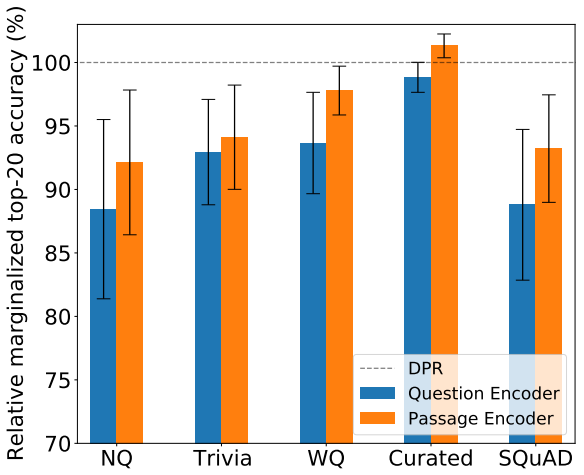
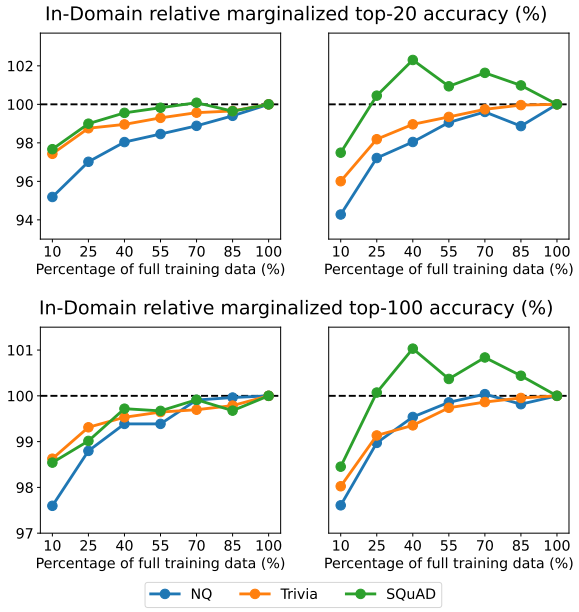


Figure 2: In-domain marginalized top-20 accuracy (%) of each encoder relative to the in-domain DPR for each dataset using Eq. (7). Each in-domain DPR's top-20 accuracy is normalized to 100%.

Fig. 3 shows the in-domain encoder marginalization results for both question encoder and passage encoder under a data efficiency setting, where we uniformly sample 10%, 25%, 40%, 55%, 70%, 85% of training data of each dataset to train DPR. We use in-domain encoder marginalization to evaluate each encoder's accuracy with different amounts of data. Specifically, to provide a fair comparison, we use DPR's encoders trained with 100% data as the samples for all marginalization. For example, for the question encoder trained with 10% data, it is paired with five passage encoders of DPR trained on five different domains with 100% data. This is to ensure that the comparison between different question encoders is not affected by different ways of marginalization.



(a) Question encoder (b) Passage Encoder

Figure 3: In-domain encoder marginalization results under a data efficiency setting. We train DPR on NQ, Trivia, and SQuAD with different amounts of training data. The marginalized top-20/100 accuracy (%) for each encoder is normalized. Note that the y-axis is shared in each row. The horizontal line is the accuracy of an encoder trained with 100% data.

As we can see, the accuracy of the question encoder with respect to different training data amounts (left column in Fig. 3) on three datasets improves as the amount of training data increases. For the passage encoder (right column in Fig. 3), NQ's and Trivia's behave similarly to the question encoder (blue and orange lines of the right column in Fig. 3). However, the accuracy of SQuAD's passage encoder (green line of the right column in Fig. 3) shows non-monotonic behaviour with respect to training data sizes in the [40%, 100%] interval, where the accuracy first rises before 40% and drops afterwards. This means that besides the training sample complexity, there are more affecting factors that influence the accuracy of the passage encoder, which we further analyze below.

Factor Analysis Based on the results in the previous section, we now propose two possible affecting factors in the training data for the question encoder and passage encoder: *corpus coverage* and *positive passage overlap*, defined as follows:

- **Corpus coverage**: Number of distinct positive passages in the training data (i.e., with different texts and titles in Wikipedia corpus).

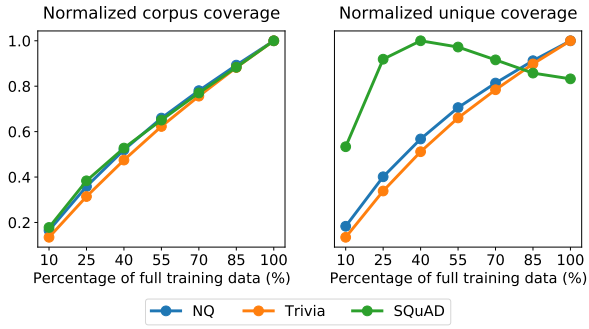


Figure 4: Dataset statistics for different amounts of data. Left: Normalized corpus coverage. Right: Normalized unique passage coverage. Note that the y-axis is shared in both plots.

Dataset	Coverage	Overlap	Unique
NQ	30,466	0.21	22,424
Trivia	**42,473**	0.14	**34,910**
SQuAD	3,247	**0.68**	738

Table 3: Corpus coverage and positive passage overlap, as well as the unique passage coverage, which equals corpus coverage $\times$ $(1 - \text{positive passage overlap})^{1.3}$ for each dataset.

- **Positive passage overlap**: Ratio between the number of positive passages that can answer more than two training questions and the total number of distinct positive passages.

In this paper, each question only has one positive passage. We further define an intermediate statistic called *unique passage coverage*:

- **Unique passage coverage**: Corpus coverage $\times$ $(1 - \text{positive passage overlap})^{\alpha}$.

where α is an empirical value and is used to adjust the weight between the coverage and overlap.

Despite there being other statistics, we find these statistics above reasonable to reflect the features of each dataset, as well as the correlation with the cross-domain marginalization.

Tbl. 3 shows the corpus coverage and positive passage overlap measures that we defined on three QA datasets, where we collect the aforementioned statistics for the training data of each dataset. We can see that despite having the most training data, SQuAD also has the largest positive passage overlap. Fig. 4 (right column) shows that the unique passage coverage of SQuAD (green line) also behaves similarly to the in-domain marginalization

P-encoder	NQ	Trivia	WQ	Curated	SQuAD	Average
SQuAD-100%	**63.3/77.1**	**73.5/82.4**	65.2/76.7	79.5/90.6	61.1/76.0	68.5/80.5
SQuAD-40%	62.8/76.4	72.8/82.3	**65.9/77.4**	**81.3/91.1**	**62.3/76.8**	**69.2/80.8**

Table 4: Top-20/100 (%) accuracy of passage encoders trained on all of SQuAD and 40% of SQuAD, paired with the question encoder trained on each domain and tested on each domain's test set. With only 40% of data, a better balance between the corpus coverage and positive passage overlap is achieved on SQuAD, and therefore these passage encoders are even better overall than the ones trained with 100% of SQuAD data.

results of SQuAD's passage encoder (Fig. 3, right column), which rises as the data amount increases and then drops after 40% of training data.

To further verify the robustness of the passage encoder trained with only 40% of training data of SQuAD, we test its passage encoder on five QA test sets and pair it with the in-domain question encoder trained with 100% data. Tbl. 4 shows the comparison between the passage encoders trained with full SQuAD and 40% of SQuAD, respectively. We can see that with only 40% of training data, the passage encoders manage to achieve similar and in some cases even higher accuracy compared to the ones trained with all data. Therefore, this analysis provides evidence leading us to believe that the unique passage coverage measure, which is related to the corpus coverage and positive passage overlap of the training data, indeed influences the passage encoder strongly.

5.4 Impact of Passage Encoders

In the previous sections, we manage to identify the importance of the passage encoder and its affecting factors such as positive passage overlap and corpus coverage of the training data. We find that our discoveries are consistent with some previous work's conclusions. For example, Zhan et al. (2021, 2020a); Sciavolino et al. (2021) all find that it is sufficient to achieve reasonable retrieval accuracy by just fine-tuning the question encoder with a fixed passage encoder, which demonstrates the importance of a robust passage encoder in domain adaptation and hard-negative mining.

However, how to learn such a robust passage encoder is challenging as pre-training DPR on a single QA dataset will introduce biases. Multi-task dense retrieval (Maillard et al., 2021; Li et al., 2021; Metzler et al., 2021) uses multiple experts learned in different domains to solve this problem. These solutions are effective but not efficient as they build multiple indexes and perform searches for each expert, requiring a lot of resources and storage space.

Another solution is to build a question-agnostic passage encoder so that the model is not biased towards particular QA tasks. DensePhrases (Lee et al., 2021a,b) pioneers this direction by building indexes using phrases instead of chunks of passages for multi-granularity retrieval. By breaking passages into finer-grained units, DensePhrases indeed improve the generalization of dense retrieval in different domains with query-side fine-tuning. However, similar to multi-task learning, it is not efficient as the phrase index can be enormous for a corpus like Wikipedia. Although techniques such as product quantization (Gray and Neuhoff, 1998) can be applied to improve efficiency, it comes at the cost of effectiveness.

Overall, it is desirable to have a robust passage encoder for efficient dense retrieval according to previous work and our analysis, but challenges still remain in the effectiveness-efficiency trade-off.

6 Conclusions

We propose an encoder attribution analysis of DPR using encoder marginalization to individually evaluate each encoder of DPR. We quantify the contribution of each encoder of DPR by marginalizing the other random variables under a probabilistic framework. We find that the passage encoder plays a more important role compared to the question encoder in terms of top-k retrieval accuracy. We also perform a case study under the data efficiency setting to demonstrate how to find possible affecting factors in the QA datasets for individual encoders. We identify that passage encoders are affected by positive passage overlap and corpus coverage of the training data, while question encoders are sensitive to the training sample complexity. Our framework is also very general and can be applied to other methods based on bi-encoders for encoder attribution analysis, but one needs to pay attention to the choice of the encoder prior distribution to ensure the marginalization is appropriate.

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