

Two-Step Question Retrieval for Open-Domain QA

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Abstract

The retriever-reader pipeline has shown promising performance in open-domain QA but suffers from a very slow inference speed. Recently proposed question retrieval models tackle this problem by indexing question-answer pairs and searching for similar questions. These models have shown a significant increase in inference speed, but at the cost of lower QA performance compared to the retriever-reader models. This paper proposes a two-step question retrieval model, **SQuID** (Sequential Question-Indexed Dense retrieval) and distant supervision for training. SQuID uses two bi-encoders for question retrieval. The first-step retriever selects top-k similar questions, and the second-step retriever finds the most similar question from the top-k questions. We evaluate the performance and the computational efficiency of SQuID. The results show that SQuID significantly increases the performance of existing question retrieval models with a negligible loss on inference speed.¹

1 Introduction

Retriever-reader models in open-domain QA require a long time for inference (Izcard and Grave, 2021; Lewis et al., 2020b; Sachan et al., 2021; Mao et al., 2021a; Karpukhin et al., 2020). This has been identified as a bottleneck in building real-time QA systems, and question retrieval and phrase-indexed QA have been proposed to resolve this problem (Seo et al., 2018, 2019; Lee et al., 2020, 2021a,b; Lewis et al., 2021a,b). These approaches directly search the answer of the input question from the corpus without conducting additional machine reading steps which are computationally inefficient. In phrase-indexed QA, retrievers pre-index all phrases in the corpus and find the most similar phrase to the input question. In question retrieval, synthetic

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¹The implementation of SQuID has been released at <https://github.com/yeonsw/SQuID.git>

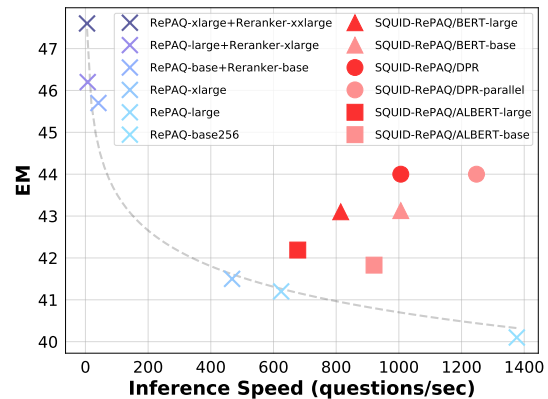


Figure 1: Trade-off relation between the open-domain QA performance and the inference time of existing question retrieval models (blue dots) and SQuID (red dots) on NaturalQuestions (NQ). The x-axis represents the inference speed and the y-axis represents the QA performance.

question-answer pairs are pre-indexed and referenced by retrievers (Du et al., 2017; Duan et al., 2017; Fabbri et al., 2020; Lewis et al., 2020a).

Although recent question retrieval models significantly increase the inference speed, this improvement accompanies QA performance degradation. Several approaches have been applied to question retrieval models to overcome the performance degradation, such as adopting the cross-encoder (Mao et al., 2021b; Xiong et al., 2020) for re-ranking and increasing the model size (Lewis et al., 2021b). However, these approaches cause a significant loss of computational efficiency. Figure 1 shows the trade-off between the open-domain QA performance and the inference speed of question retrieval models.

We propose **SQuID** (Sequential Question-Indexed Dense retrieval) which significantly improves QA performance without losing computational efficiency. Our work follows previous work on neural re-ranking methods, which use a cross-encoder to re-rank the top-k passages retrieved from the first-step retriever (Lewis et al., 2021b;

Xiong et al., 2020). Re-ranking methods have improved retrieval performance but require huge computation costs due to the cross-encoder architecture. We use an additional bi-encoder retriever in SQuID instead of the cross-encoder to prevent loss on computational efficiency. We also provide distant supervision methods for training the additional retriever in the absence of training data for question retrievers.

We evaluate SQuID on NaturalQuestions (NQ) (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017). We conduct three types of experiments: open-domain QA, computational efficiency evaluation, and analysis on distant supervision methods for training the second-step retriever. Experimental results show that SQuID significantly outperforms the state-of-the-art question retrieval model by 4.0%p on NQ and 6.1%p on TriviaQA without losing computational efficiency. Our main contribution is in proposing a sequential question retriever model that successfully improves both QA performance and inference speed, thereby making a meaningful step toward developing real-time open-domain QA systems.

2 Related Work

The research problem of reducing the computational cost of open-domain QA has received much attention recently. The main bottleneck of a retriever-reader model is the machine reading step, and Seo et al. (2018, 2019); Lee et al. (2021a) propose phrase-indexed QA, which directly retrieves the answer from the corpus without the machine reading step. These models pre-compute the context of phrases in a corpus and conduct lexical and semantic similarity searches between the given question and the context of phrases (Zhao et al., 2021; Yamada et al., 2021). Most related to our work are the question retrieval models with question-generation models to build question-answer pairs and conduct a similarity search between the input question and the pre-indexed questions (Lewis et al., 2021a,b). These models significantly reduce the computational cost but results in lower performance. Our work provides an efficient question retrieval pipeline with distant supervision methods for training, while previous question retrieval models focus on the indexing methods with less attention on the retrieval pipeline.

3 Method

Our method is constructed based on the question retrieval pipeline proposed by Lewis et al. (2021b), where question retrievers find the most similar question to the input question and return the answer of the selected question. In this study, we note that previous question retrievers are optimized not just for improving the retrieval performance but for maintaining the inference speed to cover millions of text (Lewis et al., 2021b). In this process, the performance of retrievers decreases as they are more optimized for computational efficiency. We propose to use an additional retriever that takes the top-k predictions from the first retriever and selects the most similar question from the top-k results. The second-step retriever has a lower constraint in the inference speed than the first retriever since its search space contains only a few samples. This enables us to focus only on the retrieval performance when designing the training method. The overall training and inference procedure of SQuID is illustrated in Figure 2. We describe the details of SQuID below.

3.1 Training

Since the annotated question-question pairs are unavailable, we distantly supervise SQuID with heuristically selected positive and negative samples. We first select top-k similar questions with the first-step retriever. Among the top-k questions, we choose the positive samples and the negative samples as the following. For positive samples, we choose questions with the most similar answer to the ground truth answer in terms of F1-score, the evaluation metric used in extractive QA (Rajpurkar et al., 2016). For negative samples, we sample questions with answers that differ from the ground truth answer (Karpukhin et al., 2020; Xiong et al., 2021).

When the input question is provided with a positive sample (q^+) and m negative samples (q_1^-, \dots, q_m^-), our second-step retriever is trained to distinguish the positive and negative samples. The loss function is as follows:

$$L(q, q^+, q_1^-, \dots, q_m^-) = -\log\left(\frac{e^{\text{sim}(q, q^+)}}{e^{\text{sim}(q, q^+)} + \sum_{i=1}^m e^{\text{sim}(q, q_i^-)}}\right). \quad (1)$$

The similarity function is defined as the dot product of two vectors: $\text{sim}(q_1, q_2) = E_Q(q_1)^T E_Q(q_2)$. Where $E_Q(\cdot)$ is the question encoder of the second-step retriever.

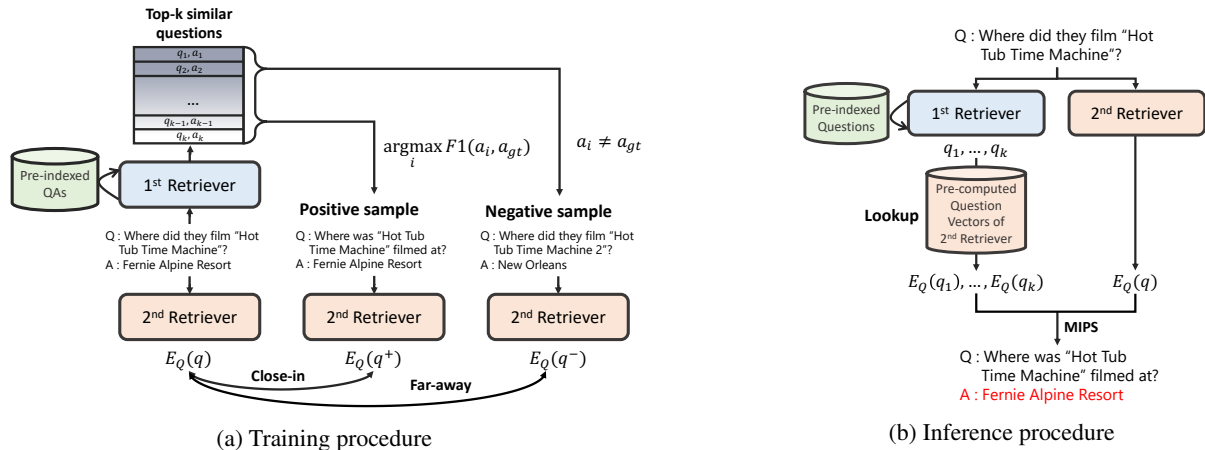


Figure 2: Illustrations of training and inference processes of SQuID. SQuID consists of two retrievers. The first-step retriever selects top-k similar questions among the pre-indexed QAs. From the top-k results, (a) the second-step retriever is trained to distinguish the positive sample from the negative samples, and (b) it selects the most similar question at the inference time.

3.2 Inference

Given a question q , the two retrievers of SQuID work in two steps. The first-step retriever selects top-k similar questions. The retrieved questions are then mapped to the question vectors pre-computed by the second-step retriever. The second-step retriever selects the most similar question q' from the top-k results with the question vectors. We use Maximum Inner Product Search (MIPS) for the second-step retrieval. Finally, SQuID puts the answer of q' as the answer for q .

4 Experimental Setup and Results

We evaluate the performance and computational efficiency of SQuID on two open-domain QA datasets: NaturalQuestions (NQ) and TriviaQA. We also compare various distant supervision methods for training SQuID. We use exact match (EM) (Rajpurkar et al., 2016) for performance evaluation and the number of questions per second (Q/sec) for evaluation of inference speed. The details of our experimental setup is described in Appendix A.2.

Question Retrievers on Open-Domain QA: We evaluate SQuID with two different first-step retrievers: BM25 and RePAQ-base256² (Lewis et al., 2021b). Table 1 shows that SQuID-BM25/DPR and SQuID-RePAQ/DPR achieve the best performance among question retrieval models on TriviaQA and NQ, respectively. Note that SQuID-RePAQ/DPR outperforms RePAQ-base256 significantly with a

²We use RePAQ-base256 provided by the official implementation. RePAQ-base256 has slightly lower performance than RePAQ-base.

negligible loss of inference speed; 4.0%p EM gain on NQ and 6.1%p gain on TriviaQA at 92.0% speed (1266 Q/sec vs. 1376 Q/sec).

Trade-off between QA Performance and Computational Efficiency:

Table 1 shows the trade-off between the open-domain QA performance and the inference speed of the three types of open-domain QA models. Comparing RePAQ-large and RAG-Sequence, we see a large performance gap of 3.3%p on NQ and 18.0%p on TriviaQA, and we also see a large speed gap of 624 Q/s and 0.8 Q/s. SQuID bridges this gap, achieving comparable performances to RAG-Sequence on NQ while maintaining the high inference speed. The performance gain on TriviaQA is not as high, and we conjecture that this is because RePAQ uses only questions from NQ in its filtering step. We leave a deeper study of this discrepancy for future research.

Figure 1 illustrates the QA performance and inference speed of various configurations of RePAQ SQuID. We vary the encoder of the second-step retriever with different pre-trained models: DPR (Karpukhin et al., 2020), BERT-base/large (Devlin et al., 2019), and ALBERT-base/large (Lan et al., 2019). The first and second-step question encoders can be executed concurrently, so we run them in parallel and set the batch size as half to measure the inference speed (SQuID-DPR-parallel). We use the maximum batch size possible on a single V100-16GB GPU. The figure shows that results of SQuID all lie to the top right of the curve fitted to the RePAQ results, meaning that SQuID succeeds in improving both QA performance and inference

Model Type	Model	NQ	TriviaQA	Inference speed (Q/sec)
Question retrieval	RePAQ-base256 (Lewis et al., 2021b)	40.0	38.8	1376
	RePAQ-base (Lewis et al., 2021b)	40.9	39.7	738
	RePAQ-large (Lewis et al., 2021b)	41.2	38.8	624
	SQuID-BM25/DPR	43.1	45.6	328
	SQuID-RePAQ/DPR	44.0	44.9	1006 (1266 [†])
Phrase-indexed	DensePhrase (Lee et al., 2021a)	40.9	50.7	20.6*
Retriever-reader	RAG-Sequence (Lewis et al., 2020b)	44.5	56.8	0.8
	FiD-large (Izacard and Grave, 2021)	51.4	67.6	0.5*

Table 1: The open-domain QA performance (EM) and inference speeds of SQuID and baselines on NQ test set and TriviaQA test set. We use the performance and the inference speed of each baseline reported from their results. * indicates the inference speed is from the original paper. [†] indicates that the inference speed is computed in the parallel computing setting.

Supervision	BM25	RePAQ
w/o 2nd retriever	34.4	40.0
+ Self	39.5	40.4
+ Similar	43.1	44.0
+ Similar / Self	43.6	44.1
+ Same Answer	43.4	44.4

Table 2: The open-domain QA performance (EM) of SQuID in four different distant supervision methods on NQ test set.

speed. The detailed results are in Appendix A.1.

Analysis on Positive Sampling Methods: We distantly supervise the second-step retriever because annotated question-question pairs are unavailable. We conduct experiments on various positive sampling methods for distant supervision: “Self”, “Similar”, “Similar/Self”, and “Same Answer”. Each method uses the following as the positive sample:

- 1) the input question itself (“Self”),
- 2) a similar question with a similar answer (“Similar”),
- 3) a similar question if it has the ground truth answer, or the input question itself (“Similar/Self”),
- and 4) a random question with the ground truth answer (“Same Answer”).

Table 2 shows the performance of SQuID-BM25 and SQuID-RePAQ-base256 on the NQ test set with the four distant supervision methods. The first row (w/o 2nd retriever) indicates the performance based only on the first-step retriever (BM25 or RePAQ-base256). The second-step retriever with “Self” method improves the performance slightly, and the others improve the performance more significantly. The large gap between “Self” and the

other methods shows that using the answer information is essential for distant supervision.

Error Propagation Analysis: The error rate of each stage in a multi-stage model provides a better understanding of the model’s performance boundary. In SQuID, the second-step retriever only predicts the correct answer when the top-50 question-answer pairs retrieved by the first-step retriever contain the answer. This indicates that the upper-bound performance of SQuID is determined by the performance of the first-step retriever. We measure the R@50 accuracy of the first-step retrievers on NQ and TriviaQA. The performance of BM25 and RePAQ are 64.07% and 64.34% on NQ and 61.73% and 59.10% on TriviaQA, respectively.

5 Conclusion

The trade-off between the performance and the inference speed is an important problem in open-domain QA. Recently proposed question retrieval models have shown significantly improved inference speed. However, this improvement came at the cost of a significantly lower QA performance by the question retrieval models compared to the state-of-the-art open-domain QA models. In this paper, we proposed a two-step question retrieval model, SQuID. We evaluated the open-domain QA performance and the inference speed of SQuID on two datasets: NaturalQuestions and TriviaQA. From the results, we showed that the sequential two-retriever approach in SQuID achieves a significant QA performance improvement over the existing question retrieval models, while retaining the advantage of faster inference speed. This improvement in both

QA performance and inference speed is a meaningful step toward the development of real-time open domain QA systems.

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Model	EM	Q/sec
SQuID-RePAQ/DPR-parallel	44.0	1266
SQuID-RePAQ/DPR	44.0	1006
SQuID-RePAQ/BERT-large	43.1	814
SQuID-RePAQ/BERT-base	43.1	1006
SQuID-RePAQ/ALBERT-large	42.2	677
SQuID-RePAQ/ALBERT-base	41.8	920
RePAQ-base256	40.0	1376
RePAQ-large	41.2	624
RePAQ-xlarge	41.5	467
RePAQ-base + Reranker-base	45.7	41
RePAQ-large + Reranker-xlarge	46.2	7

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All models we used are publicly available.

Table 3: EM score and inference speed on NQ for various configurations of SQuID and RePAQ

Wenhan Xiong, Xiang Li, Srini Iyer, Jingfei Du, Patrick Lewis, William Yang Wang, Yashar Mehdad, Scott Yih, Sebastian Riedel, Douwe Kiela, et al. 2020. Answering complex open-domain questions with multi-hop dense retrieval. In *ICLR*.

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A Appendix

A.1 Detailed results of Figure 1

Table 3 shows the detailed results of Figure 1.

A.2 Experimental Setup

Training Details: We set the batch size to 2 per GPU and the number of negative samples to 16. We used validation EM score for early stopping. SQuID was trained on a machine with four V100-16GB GPUs. We report the result of a single trial.

Computational Environment for Measuring the Inference Speed:

The inference speed of baseline models and SQuID is measured with a V100-16GB GPU and 32 CPUs (Intel Xeon E5-2686v4). We report mean of three separate trials.

A.3 License or Terms of Artifacts

We use BERT whose license is under the Apache License 2.0 free with modification and distribution. Also, we use RePAQ whose license is under the CC