Query Expansion Using Contextual Clue Sampling with Language Models

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Abstract

Query expansion is an effective approach for mitigating vocabulary mismatch between queries and documents in information retrieval. One recent line of research uses language models to generate query-related contexts for expansion. Along this line, we argue that expansion terms from these contexts should balance two key aspects: diversity and relevance. The obvious way to increase diversity is to sample multiple contexts from the language model. However, this comes at the cost of relevance, because there is a well-known tendency of models to hallucinate incorrect or irrelevant contexts. To balance these two considerations, we propose a combination of an effective filtering strategy and fusion of the retrieved documents based on the generation probability of each context. Our lexical matching based approach achieves a similar top-5/top-20 retrieval accuracy and higher top-100 accuracy compared with the well-established dense retrieval model DPR, while reducing the index size by more than 96%. For end-to-end QA, the reader model also benefits from our method and achieves the highest Exact-Match score against several competitive baselines.

1 Introduction

Despite the advent of dense retrieval approaches based on semantic matching for open-domain question answering such as DPR (Karpukhin et al., 2020), approaches based on lexical matching (e.g., BM25) remain important due to their space-efficiency and can serve as input to hybrid methods (Gao et al., 2021; Formal et al., 2021; Lin and Ma, 2021).

A core challenge for lexical retrieval is the vocabulary mismatch between the query and documents. Query expansion techniques dating back over half a century have proven effective in overcoming this issue (Salton, 1971; Robertson and Jones, 1976; Abdul-Jaleel et al., 2004). In recent work, GAR (Mao et al., 2021) explored removing the query expansion’s reliance on an external corpus and instead used a large language model to generate a context.

We argue that expansion needs to balance two key factors: (1) Diversity: Given the question, there can be multiple different reasoning paths (referred to as contextual clues) to reach the correct answer. (2) Relevance: Simply relying on a single generated context increases the risk of query drift, as the generated context could be semantically irrelevant or contain factual errors (Schütze et al., 2008). However, simply generating multiple contexts is prone to the hallucination problem – they can be unfaithful to the input or include false information (Tian et al., 2019; Maynez et al., 2020; Dziri et al., 2021). Thus, in this work, we wish to explore the question: How can we best generate a sufficiently rich set of contextual clues to answer a query?

Our proposed solution (Figure 1) overcomes these problems with two simple and efficient steps: Filtering and fusion. After sampling top-k outputs from the decoder of the fine-tuned language model,
we first cluster these generated contextual clues based on their lexical distance. In each cluster, where highly similar contextual clues are grouped together, we only keep a single generated output with the highest generation probability. The filtering step effectively reduces potential factual errors and redundant close duplicates. The query is then individually augmented with each filtered contextual clue. We retrieve documents separately for every single augmented query. As the last step, all the documents are ranked together (fusion) with the generation probability from the integral contextual clue in the augmented query.

We evaluate our approach on two established benchmarks: Natural Questions (Kwiatkowski et al., 2019) andTriviaQA (Lee et al., 2019). Our baseline model GAR (Mao et al., 2021) trails behind its dense retrieval counterpart DPR (Karpukhin et al., 2020) by a large margin when retrieving a small number of passages. We bridge this gap and outperform GAR by 3.1% and 2.9% on Top-5/Top-20 accuracy on the NQ dataset. Compared with DPR, our approach outperforms it by 0.6 and 1.0 points on Top-100 accuracy on the two datasets, while requiring 96% less index storage space. The accuracy can be further improved by 3.4% on the basis of DPR’s performance when fusing the documents retrieved from DPR and our method together. Furthermore, our retrieval performance also successfully transfers to downstream question answering tasks, where our methods increase by 3.2% and 0.8% Exact Match score compared with the DPR and GAR retrieved documents.

2 Methods

2.1 Contextual Clue Sampling and Filtering

We employ a sequence-to-sequence model that takes the question as input and generates the contextual clues for the answer as target. As our model, we use BART-large (Lewis et al., 2020a), but note that the generator can be replaced with any other sequence-to-sequence model. Contextual clues are the sentences in a passage that contains the ground-truth answer to the question. These sentences are either extracted from the passage provided by the dataset (when available), or from the matching passage used as a reference for the retriever.

At inference time, we first sample a diverse set of contextual clues from the fine-tuned model. Generally speaking, a single contextual clue can be broken into two main components; relational facts (“august 21, 2018”) and contextual description (“the game was released on”). Interestingly, we notice that many generations are identical in contextual descriptions, but inconsistent with the fact words (various dates, numbers or named entities). Previous works try to solve this inconsistency issue with an additional training loss (Elazar et al., 2021), adding a reasoning module (Nye et al., 2021), or by majority vote (Wang et al., 2022). Instead, we first cluster the contextual clues based on their edit distance. For most cases, contextual clues with the same contextual descriptions but varying relational facts, are grouped together in the same cluster. We then employ a simple filtering strategy for each cluster by keeping the top-ranked output with maximum generation probability, while discarding the rest outputs in the cluster. As a result, we could gather all possible reasoning paths to the answer, while reducing potential factual errors. As shown in Appendix A.2, the filtering strategy is crucial for the following retrieval step in terms of both retrieval efficiency (saves 70% for the retrieval process) and accuracy (consistently better than using full contextual clues).

2.2 Retrieval and Fusion

Defining the \( n \) generated and filtered contextual clues as \( \{c_i\}_{i=1}^{n} \), we augment the question \( q \) into \( \{[CLS] q \ [SEP] c_i\}_{i=1}^{n} \) by appending each individual context to it. Following GAR, we use BM25 as the backend for retrieval where it could be seen as a logical scoring model using a query encoder \( \eta_q \) and passage encoder \( \eta_d \) (Lin, 2022):

\[
s(q, d) = \phi(\eta_q(q), \eta_d(d))
\]

where \( \phi \) is a similarity function such as dot product or L2 distance. Note that we use \( c \) to denote the generated contexts and \( d \) to denote real passages in the corpus. To aggregate the retrieval results of different augmented queries, we perform retrieval individually for each augmented query and use the likelihood \( p(c_i \mid q) \) of the generated context \( c_i \) as the fusion weights. Therefore, the final retrieval score \( s_f(q, d) \) for each question-passage pair is calculated as:

\[
s_f(q, d) = \sum_{i=1}^{n} p(c_i \mid q) \cdot s([CLS] q \ [SEP] c_i, d)
\]
Table 1: Evaluation of generated answer contexts on the validation set of the NQ dataset.

| # Context | ROUGE-1 | ROUGE-2 | ROUGE-L | Ans Cover |
|-----------|---------|---------|---------|-----------|
| Top-1     | 35.27   | 22.82   | 31.84   | 29.02     |
| Full      | 48.32   | 32.43   | 42.64   | 46.01     |
| Filtered  | 47.14   | 31.44   | 41.80   | 43.17     |

3 Experiment

3.1 Datasets

We conduct the experiments on two widely used ODQA datasets: Natural Questions (NQ) (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017). NQ consists of 79,168 train, 8,757 dev, and 3,610 test question-answer pairs. We use the open-domain splits of TriviaQA which contains 78,785 train, 8,837 dev, and 11,313 test QA pairs (Lee et al., 2019).

3.2 Experiment Setup

We finetune the BART-large model (Lewis et al., 2020a) for contextual clue generation. Given the question, we generate 100 candidate outputs from BART using beam search with beam size 100. We first cluster candidates using fuzzy string matching with the built-in difflib Python module. The similarity cutoff is set to 0.8 and any string pairs scoring less than the cutoff are not kept in the same group. On average, for each question, there are 24 contextual clues for NQ and 33 for TriviaQA after filtering. More details on processing the contextual clues are in the Appendix A.1 and A.2.

For each contextual clue augmented query, we use the Pyserini (Lin et al., 2021) BM25 to retrieve top-1000 candidate passages. All the retrieved documents are then re-ranked according to Eq. (2). Further details are included in the Appendix A.3.

3.3 Baselines

Retriever DPR (Karpukhin et al., 2020) employs an extractive reader model based on BERT (Devlin et al., 2019) and predicts the answer span. RAG (Lewis et al., 2020b) combines the DPR dense retriever together with a BART answer generator, and jointly trains the two models end-to-end. FiD (Izacard and Grave, 2021) also uses DPR to retrieve relevant passages and the decoder attends over all the encoded passages to generate the final answer. For fair comparison, we evaluate the retrieval results of FiD, GAR, and SEAL on the same reader model, FiD-large which takes the question along with 100 top retrieved passages as input.

4 Results

4.1 Contextual Clues Evaluation

We are interested in understanding the quality of the generated contextual clues. In Table 1, Top-1 returns the top sequence with the highest probability during beam search, while Full contexts contain all top-ranked 100 sequences. Filtered is the set of contextual clues after filtering. We report the ROUGE F-measure scores between the ground-truth and generated contextual clues on the NQ validation set. We also report the answer coverage rate, measured as the percentage of contextual clues that contain the answer.

As shown in Table 1, rigorously increasing the number of generated candidates increases the ROUGE scores by at least 10% compared with only generating the top sequence, indicating it’s more probable to capture the potential ground-truth answer context. The filtering strategy effectively reduces the size of candidate contexts while maintaining high coverage and diversity (less than 1% difference in ROUGE scores). Moreover, Full significantly increases the answer coverage rate by ~17% compared with Top-1, suggesting that not only more semantics but also more fact words are captured in a larger sizes of candidates.

4.2 Main Retrieval Results

In Table 2, we show both the retrieval accuracy and index size. Note that the index size should be considered with salt since it largely depends on
| Methods | Natural Questions | TriviaQA |
|---------|------------------|----------|
|         | Top-5 | Top-20 | Top-100 | Top-5 | Top-20 | Top-100 |
| **Dense Retrieval** |     |       |        |       |       |        |
| DPR     | 61GB  | 68.3   | 80.1   | 86.1  | 72.7   | 80.2   | 84.8   |
| **Lexical Retrieval** |     |       |        |       |       |        |
| BM25    | 2.4GB | 43.8   | 62.9   | 78.3  | 67.7   | 77.3   | 83.9   |
| GAR     | 2.4GB | 60.8   | 73.9   | 84.7  | 71.8   | 79.5   | 85.3   |
| SEAL    | 8.8GB | 61.3   | 76.2   | 86.3  | -      | -      | -      |
| Ours-single | 2.4GB | 63.0   | 75.2   | 84.8  | 71.7   | 79.1   | 84.6   |
| Ours-multi | 2.4GB | **63.9** | **76.8** | **86.7** | **72.3** | **80.1** | **85.8** |
| **Fusion Retrieval** |     |       |        |       |       |        |
| BM25+DPR | 63.4GB | 69.7   | 81.2   | 88.2  | 71.5   | 79.7   | 85.0   |
| GAR+DPR | 63.4GB | 72.3   | **83.1** | 88.9  | 75.7   | 82.2   | 86.3   |
| Ours-single + DPR | 63.4GB | 72.7   | 82.6   | 88.1  | 76.0   | **82.6** | 86.4   |
| Ours-multi + DPR | 63.4GB | **72.7** | 83.0   | **89.1** | **76.1** | 82.5   | **86.4** |

Table 2: Top-5/20/100 retrieval accuracy (%) and index size (GB) of different models on Natural Questions and TriviaQA test sets. Each score in the right column represents the percentage of the top 20/100 retrieved passages that contain the answers. The DPR and BM25 indexes are downloaded from the Pyserini toolkit.¹

the system implementation. The baseline models are reported in their open-sourced versions. We additionally compare with other memory-efficient neural retrieval models in the appendix A.4 and report retrieval time latency in the appendix A.5.

Compared with other lexical retrieval models, our method significantly outperforms both GAR and SEAL, showing the effectiveness of extensively sampled contextual clues. We also find that **Ours-multi** consistently improves over **Ours-single**. We surmise that ground-truth answers serve as useful signals during retrieval and they are more likely to be covered when directly sampling answers. Most of the traditional lexical retrieval methods always trail behind dense retrieval by a large margin, as illustrated in Table 2. Surprisingly, our method even outperforms the DPR model by 0.6 and 1.0 points in terms of top-100 accuracy on two datasets, while requiring 96% less index storage space. For the purpose of pushing the limit of retrieval performance, we also show the accuracy of different lexical-based methods fused with DPR. Overall, our method fused with DPR achieves the highest accuracy across all baseline methods on both datasets.

### 4.3 End-to-end QA results

As shown in Table 3, Ours-multi achieves the highest exact-match scores compared with other baseline methods on both datasets. We have an interesting observation on TriviaQA dataset. The only difference between FiD and Ours is that FiD retrieves from DPR. Although ours-single is 0.2 points lower on Top-100 accuracy than that of DPR, the EM score of Ours-single is ~ 2 points higher than FiD. It demonstrates even with relatively same top-k retrieval accuracy, that our approach could retrieve qualitatively better passages that are easier for the reader model to answer.

| Methods | Natural Questions | TriviaQA |
|---------|------------------|----------|
| DPR     | 41.5             | 57.9     |
| RAG     | 44.5             | 56.1     |
| FiD     | 51.4             | 67.6     |
| GAR     | 50.6             | 70.0     |
| SEAL    | 50.7             | -        |
| Ours-single | 50.6 | 69.7     |
| Ours-multi | **51.7** | **70.8** |

Table 3: End-to-end exact-match results on the test sets.

5 Conclusion

We propose to narrow the lexical gap between the query and the documents by augmenting the query with extensively sampled contextual clues. To make sure the generated contextual clues are both diverse and relevant, we propose the strategy of context filtering and retrieval fusion. Our approach outperforms both the previous generation-based query expansion method and the dense retrieval counterpart with a much smaller index requirement.
References

Nasreen Abdul-Jaleel, James Allan, W Bruce Croft, Fernando Diaz, Leah Larkey, Xiaoyan Li, Mark D Smucker, and Courtney Wade. 2004. Umass at trec 2004: Novelty and hard. Computer Science Department Faculty Publication Series, page 189.

Michele Bevilacqua, Giuseppe Ottaviano, Patrick Lewis, Wen-tau Yih, Sebastian Riedel, and Fabio Petroni. 2022. Autoregressive search engines: Generating substrings as document identifiers. arXiv preprint arXiv:2204.10628.

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.

Nouha Dziri, Andrea Madotto, Osmar R Zaiane, and Avishek Joey Bose. 2021. Neural path hunter: Reducing hallucination in dialogue systems via path grounding. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 2197–2214.

Yanai Elazar, Nora Kassner, Shauli Ravfogel, Abhi-lasha Ravichander, Eduard Hovy, Hinrich Schütze, and Yoav Goldberg. 2021. Measuring and improving consistency in pretrained language models. Transactions of the Association for Computational Linguistics, 9:1012–1031.

Thibault Formal, Benjamin Piwowarski, and Stéphane Clinchant. 2021. Splade: Sparse lexical and expansion model for first stage ranking. Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval.

Peter I. Frazier. 2018. A tutorial on Bayesian optimization. ArXiv, abs/1807.02811.

Luyu Gao, Zhuyun Dai, and Jamie Callan. 2021. Coil: Revisit exact lexical match in information retrieval with contextualized inverted list. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3030–3042.

Gautier Izacard and Édouard Grave. 2021. Leveraging passage retrieval with generative models for open domain question answering. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 874–880.

Mandar Joshi, Eunsol Choi, Daniel S 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.

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.

Diederik P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In ICLR (Poster).

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion 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.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020a. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880.

Patrick Lewis, Barlas Oguz, Wenhan Xiong, Fabio Petroni, Wen-tau Yih, and Sebastian Riedel. 2021. Boosted dense retriever. arXiv preprint arXiv:2112.07771.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. 2020b. Retrieval-augmented generation for knowledge-intensive nlp tasks. Advances in Neural Information Processing Systems, 33:9459–9474.

Jimmy Lin. 2022. A proposed conceptual framework for a representational approach to information retrieval. In ACM SIGIR Forum, volume 55, pages 1–29. ACM New York, NY, USA.

Jimmy Lin, Xueguang Ma, Sheng-Chieh Lin, Jheng-Hong Yang, Ronak Pradeep, and Rodrigo Nogueira. 2021. Pyserini: A Python toolkit for reproducible information retrieval research with sparse and dense representations. In Proceedings of the 44th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 2356–2362.
Jimmy J. Lin and Xueguang Ma. 2021. A few brief notes on deepimpact, coil, and a conceptual framework for information retrieval techniques. *ArXiv*, abs/2106.14807.

Xueguang Ma, Minghan Li, Kai Sun, Ji Xin, and Jimmy Lin. 2021. Simple and effective unsupervised redundancy elimination to compress dense vectors for passage retrieval. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 2854–2859, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Yuning Mao, Pengcheng He, Xiaodong Liu, Yelong Shen, Jianfeng Gao, Jiawei Han, and Weizhu Chen. 2021. Generation-augmented retrieval for open-domain question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4089–4100.

Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1906–1919.

Maxwell Nye, Michael Tessler, Josh Tenenbaum, and Brenden M Lake. 2021. Improving coherence and consistency in neural sequence models with dual-system, neuro-symbolic reasoning. *Advances in Neural Information Processing Systems*, 34.

Stephen Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends in Information Retrieval*, 3(4):333–389.

Stephen E Robertson and K Sparck Jones. 1976. Relevance weighting of search terms. *Journal of the American Society for Information science*, 27(3):129–146.

Gerard Salton. 1971. *The SMART retrieval system—experiments in automatic document processing*. Prentice-Hall, Inc.

Hinrich Schütze, Christopher D Manning, and Prabhakar Raghavan. 2008. *Introduction to information retrieval*, volume 39. Cambridge University Press Cambridge.

Ran Tian, Shashi Narayan, Thibault Sellam, and Ankur P Parikh. 2019. Sticking to the facts: Confident decoding for faithful data-to-text generation. *arXiv preprint arXiv:1910.08684*.

Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, and Denny Zhou. 2022. Self-consistency improves chain of thought reasoning in language models. *arXiv preprint arXiv:2203.11171*.

Ikuya Yamada, Akari Asai, and Hannaneh Hajishirzi. 2021. Efficient passage retrieval with hashing for open-domain question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 979–986.
A Appendix

A.1 Contextual Clues Sampling and Filtering

Experimental Details

We finetune BART-large model (Lewis et al., 2020a) for contextual clue generation. For Natural Questions dataset, we extract the sentence containing the ground-truth answer from the provided positive passage. For TriviaQA dataset, since only pairs of questions and answers are provided in the original dataset, we extract the answer context sentence from the highest ranked passage retrieved by BM25. We train the model using Adam optimizer (Kingma and Ba, 2015) with a learning rate of $3 \times 10^{-5}$, linear scheduling with warm-up rate 0.01, and training batch size of 256 on 4 V100 GPUs.

Given the question, we generate 100 candidate outputs from BART using beam search with beam size 100. We first group similar candidates using fuzzy string matching with the built-in difflib python module. The similarity cutoff is set to 0.8 and any string pairs scoring less than the cutoff are not kept in the same group. On average, for each question there are 24 contextual clues for NQ and 33 for TriviaQA after filtering.

A.2 Effectiveness of Filtering Strategy

Directly augmenting question with the full set of sampled contextual clues is a sub-optimal solution due to the following reasons: 1) Retrieval efficiency: After filtering, for each query, we only need to perform 70% less times of the retrieval. As a result, it’s also saves the search space for the retrieval fusion step. 2) Retrieval accuracy: As shown in Table 4, the accuracy for the unfiltered contexts is consistently lower than that on the filtered contexts. We suppose it’s due to removal of hallucinated facts contained in the contextual clues during filtering.

A.3 Retrieval Fusion Experimental Details

We put all the passages belonging to the same question but different augmentation into a public pool after filtering duplicates. If a passage in the public pool does not appear in the top-1000 retrieval list of an augmented query, we use the minimum score of the augmented query’s top-1000 list as the default score for the missing passage from that augmented query. We then average the retrieval score for each passage in the pool according to Eq. (2) and re-sort the order of the fused passages. For fair comparison with GAR (Mao et al., 2021), we additionally fine-tune an answer generation model and a title generation model. We perform the same fusion steps above for all three generation models, and we linearly interpolate their fusion results by searching the best weighting on the development set using Bayesian Optimization (Frazier, 2018).

A.4 Comparison with Memory Efficient DPR techniques

We compare our approach with other memory efficient neural retrieval models in Table 5. Ma et al. (2021) show that the DPR could be furthered compressed to trade accuracy off against speed and storage. However, the accuracy of DPR could drop significantly if compressed to the same storage level of the lexical index. BPR (Yamada et al., 2021) integrates a learning-to-hash technique into DPR to represent the passage index using compact binary codes. The index size of BPR is slightly smaller than ours approach, but we achieve higher retrieval accuracy on both two datasets. We also include DrBoost (Lewis et al., 2021), a dense retrieval ensemble trained in stages. DrBoost outperforms ours approach on NQ dataset, while taking $6 \times$ times larger index size.

A.5 Latency Analyses

Retrieval time latency is an important factor to consider for deployment. We list the latency time in Table 6. It is notable that the latency listed in the table is tested on CPU, since we use BM25 as our retrieval backend and it only requires CPU to run. Dense retrieval methods (e.g. DPR) normally is running on GPU devices, which only takes 456.9ms (Lewis et al., 2021) per query without other device specific speed-up techniques.
**Methods**

**Natural Questions TriviaQA**

| METHOD                        | NATURAL QUESTIONS | TRIVIAQA |
|-------------------------------|-------------------|----------|
|                               | Top-5  | Top-20 | Top-100 | Top-5  | Top-20 | Top-100 |
| Ours-single (unfiltered)      | 61.1   | 73.7   | 84.1    | 70.9   | 78.7   | 84.3    |
| Ours-single                   | 63.0   | 75.2   | 84.8    | 71.7   | 79.1   | 84.6    |

Table 4: Top-5/20/100 retrieval accuracy (%) on Natural Questions and TriviaQA test sets. Filtering strategy effectively increases the retrieval accuracy and reduces the search space for the retrieval fusion step.

**Methods**

**Index Size**

| METHOD                      | INDEX SIZE | NATURAL QUESTIONS | TRIVIAQA |
|-----------------------------|------------|-------------------|----------|
| DPR                         | 61GB       | 80.1              | 86.1     | 80.2   | 84.8   |
| DPR + PCA-256               | 21GB       | 77.2              | 85.5     | 76.5   | 83.4   |
| DPR + PCA-256 + PQ          | 1.3GB      | 74.8              | 84.1     | 74.5   | 82.6   |
| BPR                         | 2.0GB      | 77.9              | 85.7     | 77.9   | 84.5   |
| DrBoost                     | 13.5GB     | 80.9              | 87.6     | -      | -      |
| Ours-single                 | 2.4GB      | 75.2              | 84.8     | 79.1   | 84.6   |
| Ours-multi                  | 2.4GB      | 76.8              | 86.7     | 80.1   | 85.8   |

Table 5: Comparison with other memory efficient neural retrieval models on index size.

**Methods**

**Latency**

| METHOD        | LATENCY | NATURAL QUESTIONS |
|---------------|---------|-------------------|
| DPR           | 7570ms  | 80.1              | 86.1     |
| DPR + PCA-256 | 2540ms  | 77.2              | 85.5     |
| DPR + PCA-256 + PQ | 765ms  | 74.8              | 84.1     |
| BM25          | 318ms   | 62.9              | 78.3     |
| GAR (ours)    | 962ms   | 73.9              | 84.7     |
| Ours-single   | 1545ms  | 75.2              | 84.8     |
| Ours-multi    | 2732ms  | 76.8              | 86.7     |

Table 6: Comparison on retrieval time latency, which is tested using 1 Intel Xeon CPU E5-2699 v4 @ 2.20GHz.