Unsupervised Dense Retrieval Deserves Better Positive Pairs: Scalable Augmentation with Query Extraction and Generation

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Abstract

Dense retrievers have made significant strides in obtaining state-of-the-art results on text retrieval and open-domain question answering (ODQA). Yet most of these achievements were made possible with the help of large annotated datasets, unsupervised learning for dense retrieval models remains an open problem. In this work, we explore two categories of methods for creating pseudo query-document pairs, named query extraction (QExt) and transferred query generation (TQGen), to augment the retriever training in an annotation-free and scalable manner. Specifically, QExt extracts pseudo queries by document structures or selecting salient random spans, and TQGen utilizes generation models trained for other NLP tasks (e.g., summarization) to produce pseudo queries. Extensive experiments show that dense retrievers trained with individual augmentation methods can perform comparably well with multiple strong baselines, and combining them leads to further improvements, achieving state-of-the-art performance of unsupervised dense retrieval on both BEIR and ODQA datasets.

1 Introduction

Text retrieval is one of the most impactful artificial intelligence applications nowadays. Billions of users access massive amounts of data on the Internet through common internet services powered by information retrieval techniques, such as web search and product search. Despite the fact that traditional lexical retrieval remains a simple yet effective solution, neural network based models, namely dense retrievers, have made great stride in recent years and demonstrated advantages on scenarios concerning semantic matching.

Nevertheless, most dense retrievers heavily rely on training with a large amount of annotated data. For example, MS MARCO (Nguyen et al., 2016) and Natural Questions (Kwiatkowski et al., 2019) are two most widely used datasets, and they contain hundreds of thousands of human annotated which is prohibitively costly to collect considering the scope of topics we care about.

A few efforts on unsupervised dense retrieval have been taken by recent studies such as Contriever and Spider (Izacard et al., 2021; Ram et al., 2021), but their performance still lags behind the classic lexical method BM25 by large margins. Thus training dense retrievers without any human-annotated data remains an unsolved challenge.

Under supervised settings, recent studies have observed that the ways of selecting negative examples can significantly impact the final performance. This is because when annotated query-doc pairs are at disposal to serve as perfect positives in contrastive learning, carefully selected negative examples can help models better determine the classification boundary. On the other side, unsupervised retrieval can be drastically different since only documents are available, where we think strategies for building positive pairs can be more influential on the final performance and need more investigations.

In this study, we propose two categories of strategies for constructing pseudo query-doc pairs, namely query extraction (QExt) and transferred query generation (TQGen). Given a document of arbitrary domain, both methods can produce pseudo queries in an unsupervised manner, then the resulting queries are paired with the original document to train dense retrievers with a contrastive loss. The contributions of this study can be summarized as follows:

1. We propose query extraction, a novel data augmentation method for training dense retrievers. Given a document, a list of random spans are sampled from it. We utilize various methods to gauge their salience to the source document, and select the spans with highest scores as pseudo queries.

2. We propose transferred query generation, in which we generate pseudo queries with the help of
language generation models for other NLP tasks, e.g., summarization. Even though query generation (QGen) has been studied for long, existing studies require annotated data for training query generation models. Instead, we utilize out-of-distribution generation models for this end, and the result demonstrates that the inductive bias of certain NLP tasks can be effective for training dense retrievers.

3. Extensive experiments show that the retriever trained with the proposed augmentation methods, named AUGTRIEVER, outperform existing unsupervised baselines and achieve state-of-the-art performance on both BEIR and open-domain QA benchmarks, greatly bridging the gap between lexical and dense methods.

2 Background

2.1 Bi-encoder Dense Retriever

We adopt a Transformer based bi-encoder architecture and contrastive learning for training a dense retriever (Karpukhin et al., 2020; Xiong et al., 2020; Izacard et al., 2021). Technically, two transformers ($E_q$ and $E_p$) are used for encoding queries $q$ and docs $d$ respectively. The $q$ and $d$ are represented by two low-dimensional vectors by average pooling all embeddings of the top layer. Then we can obtain the relevance score between $q$ and $d$ by calculating the inner product of the two vectors. The parameters of both encoders are shared and initialized with BERT-base (Devlin et al., 2019). The model is optimized by a contrastive objective, with other documents in the same batch as negative examples. Alternatively, recent works (Izacard et al., 2021; Yang et al., 2021; Xu et al., 2022) use a momentum encoder and a large queue to enable using more negative examples. We refer to as INBATCH the architecture using negative examples in the same batch and as MoCo the architecture with momentum encoder and negative queue.

2.2 Pseudo-positive Construction for Unsupervised Text Retrieval

Several methods have been proposed to construct pseudo-positive query/document pairs for training unsupervised dense retrieval. Some of these methods are summarized below. One may refer to (Shen et al., 2022) for other related methods.

- INVERSE CLOZE TASK (Lee et al., 2019): a sentence is randomly extracted from a given document, then a retriever is trained to retrieve the document using the sentence as a query.

- Masked salient span in REALM (Guu et al., 2020): REALM is a retrieval-augmented language model, where during the pre-training phase, a retriever and a generator cooperatively predict a masked named entity (predicted by an NER tagger).

- CONTRIEVER (Izacard et al., 2021): a simple yet robust method is proposed to construct pseudo query-doc pairs called random cropping (RANDOMCROP). Given a document $d$, two random spans (contiguous subsequences) are independently extracted from $d$ to form a positive pair.

- SPIDER (Ram et al., 2021): SPIDER uses two passages containing identical n-grams (recurring spans) in a document to serve as positive pairs. However, this method is not data-efficient, since recurring spans are not valid for all documents, especially for short ones.

- SPAR (Chen et al., 2021): It is trained to mimic the ranking of a sparse teacher retriever BM25 using contrastive learning. Original $\Lambda$ was trained with either annotated questions or random sentences.

- CPT (Neelakantan et al., 2022): Neighboring pieces from the same document are considered positive pairs.

3 Method

In this section, we introduce several data argumentation methods to create pseudo queries given a document (e.g., a passage from a Wikipedia article or a web document from CommonCrawl), without using any annotated queries or questions. And we train bi-encoder dense retrievers (either InBatch or MoCo) with those synthesized query-document pairs. We name the resulting models AUGTRIEVER.

3.1 Query Extraction (QEXT)

Given a document, we hypothesize that certain parts of it contain relevant information. Therefore, we can extract and utilize them to train models.

3.1.1 Query Extraction by Document Structural Heuristics

Documents usually contain rich structures. The idea of extracting information based on structures for weak supervision has been broadly explored and demonstrated effective (Chang et al., 2019;
Zhou et al., 2022; Wu et al., 2022). Following this strand, we propose to utilize document structure to construct pseudo queries for training a dense retriever. Specifically, we consider two types of information, titles (DOC-TITLE) and anchor texts (DOC-ANCHOR), that bear similar qualities to search queries and are widely available on the internet. They are deemed to be representative about the core content of the document, either by the authors of the document or of other documents that refer to it (Baiza-Yates et al., 1999). Both titles and anchor texts are relatively easy to extract using DOM structures and human-crafted heuristics.

3.1.2 Query Extraction by Salient Span Selection

The above method heavily relies on the quality and availability of distant labels embedded in the document structures, which may limit the training scale. To overcome this issue, we propose an alternative that directly extracts spans from a document. The hypothesis is that, a document can be segmented into multiple spans and some of them are more representative than the others. Then we can utilize different methods to select the most salient spans to serve as pseudo queries.

Formally, given a document \(d\), we randomly sample a number of text spans \(s_1, s_2, \ldots, s_N\) from it. We consider 16 random spans and their length ranges from 4 to 16 words. And then we propose three ways to measure the relevance between \(d\) and each of those spans:

- **QExt-Self**: selecting by the model itself. We simply feed the bi-encoder model with each span \(s_i\) paired with \(d\), and use the dot-product score as their salience.
- **QExt-BM25**: selecting by lexical models. BM25 is broadly used to measure the lexical relevancy between queries and documents. Thus it can also serve to select spans based on lexical statistics.

- **QExt-PLM**: selecting by pre-trained language models. Pre-trained language models have demonstrated great performance on text understanding and generation. In our setting, we consider PLMs as a means for measuring the relevancy by checking how likely each span can be generated given a document as the context. Technically, we can feed a T5-small LM-Adapted model (Raffel et al., 2020) with the document as a prefix, and use the likelihood \(p(s_i | d)\) as the salience score.

3.2 Transferred Query Generation (TQGEN)

Previous works have shown that query generation can work as an effective means for augmenting training data, whereas it requires a great amount of annotated data to obtain such a query generator. To avoid training with in-domain data, we propose to use text generator models for other tasks to produce pseudo queries, expecting the inductive bias for other tasks can be effective to bootstrap a dense retriever. Hypothetically, dense retrievers may benefit from the inductive bias of tasks such as summarization and keyphrase generation, since the outputs of those tasks are commonly regarded relevant and representative about the source text. As for implementation, we use a single T0 model as a meta generator, to avoid the hassle of choosing specific models for each generation task. We provide the T0 model with various prompts to elicit outputs for different tasks, including:

- **TQGen-Topic**: What is the main topic of the above text?
The reason we design a prompt for extractive summaries intentionally is that we ask the model to use words in the original text as much as possible to reduce the hallucinations in the outputs. We utilize nucleus sampling to generate a single pseudo query for each document with Top-p=0.9 and Top-K=0.

4 Experiments

4.1 Datasets

4.1.1 Training Data

We consider two datasets for training AUGTRIEVER, Wikipedia¹ and CommonCrawl by Pile (Gao et al., 2020) (Pile-CC). For Wikipedia, we process the original text dump by segmenting articles into paragraphs by line breaks and reserving titles and anchor texts (texts with hyperlinks, italics, or boldface), resulting in 22.6M paragraphs for training. Pile-CC contains 52.4M web documents. Since all its structure information is removed, DOC-ANCHOR is unavailable with Pile-CC. For DOC-TITLE, we simply take the first line of each document as its title, and truncate it to no longer than 64 words. We find it extracts correctly in about 50% of all cases.

4.1.2 Test Data

Two benchmarks are used for evaluation – BEIR (Thakur et al., 2021) and six ODQA datasets. We consider BEIR to be a better benchmark for information retrieval, as it covers a broader range of domains and a wide variety of query types. We discuss scores of MS MARCO (MM) separately, since it is one of the most studied IR testset.

On the other side, all ODQA datasets are based on Wikipedia and mainly designed for evaluating question answering systems, thus it may be subject to certain domain and task bias. We only use them for retrieval following previous studies (Karpukhin et al., 2020; Ram et al., 2021). We report scores on SQuAD v1.1 (SQ) and EntityQuestions (EQ) alone, as they tend to favor lexical models, which is different from the other four.

4.2 Implementation Details

We adopt most settings used in CONTRIEVER (Izacard et al., 2021) for unsupervised training, except for a smaller experiment scale to accommodate the number of model variants. All variants are trained with (1) 100k steps, (2) batch size of 1,024 for Wikipedia, 2,048 for most Pile-CC, (3) learning rate (lr) of $5\times10^{-5}$, and (4) queue size of 16,384 (for MoCo), which are considerably smaller comparing with CONTRIEVER (500k steps, batch size 2048, queue size 131,072). We do observe certain performance gain with longer training and larger batch size, but a queue size of larger than 16,384 deteriorates the performance. For domain adapatation, we train a pre-trained model with 5k steps, batch size of 1,024 and lr of $1\times10^{-5}$. For fine-tuning, we tune a model with extra 20k steps, batch size of 1,024 and 1,024 extra random negative examples (1 positive+2,047 negative), and lr of $1\times10^{-5}$.

4.3 Baselines

A number of unsupervised dense methods are discussed in Sec 2.2. We consider Bm25 as a lexical baseline and four dense baselines – CONTRIEVER, SPIDER, SPAR Λ (Wikipedia version). We report their scores if publically available (BEIR results of Bm25 and CONTRIEVER), or reproduce the results using public code and checkpoints († indicates a reproduced result). MoCo+RANDOMCROP can be regarded as our reproduced CONTRIEVER in a smaller scale. We also include results with generate queries (using a supervised Doc2Query (Nogueira et al., 2019)) and questions PAQ (Lewis et al., 2021), referred to as QGEN-D2Q and QGEN-PAQ respectively. We rerun all baselines on Touché-2020 since the data has been updated in BEIR.

4.4 Results

4.4.1 Unsupervised Retrieval Results

We present the main unsupervised results in Table 1 and will discuss the other results in Sec 4.5. As for baseline results, we can see that Bm25 leads on most benchmarks by a large margin. Among the three dense retrievers, the lexical-oriented retriever SPAR Λ performs the best on BEIR and SQ&EQ, which indicates that dense retrievers can achieve robust retrieval performance by lexical matching. CONTRIEVER performs comparably

¹enwiki-20211020-pages-articles-multistream.xml.bz2
with SPAR\textsubscript{A} on BEIR, and it outperforms others on MM and QA4. Supervised augmentation baseline QGEN-D2Q delivers very competitive results on both benchmarks, suggesting that query generation trained with MS MARCO can generalize well in other domains.

As for AUGTRIEVER\textsuperscript{2}, we find that multiple variants can outperform three dense baselines on BEIR significantly, especially the ones trained with domain-general data Pile-CC. It also achieves better scores than BM25 on MM and QA4. The empirical results strongly suggest the effectiveness of the proposed augmentation methods.

Among different variants, (1) TQGEN achieves the overall best performance, which evidences that the outputs of transferred generation tasks, e.g., keyword and summary generation (Meng et al., 2017; See et al., 2017), can be directly carried over into training dense retrieval models. (2) The gap between our best model MoCo+TQGEN-AbSum (CC) and the supervised QGEN is closed on BEIR, indicating our methods can help models reach a similar level of generalization ability. (3) MoCo+QExt-PLM (CC) exhibits comparable results to strong baselines such as CONTRIEVER. This signifies that query extraction can work as a fair unsupervised method, especially given enough variety in data.

### 4.4.2 Unsupervised Domain-Adaptation Results

We also explore the idea that whether any of the proposed methods can be useful as a means for unsupervised domain adaptation. Given an InBatch model pre-trained with TQGEN-Topic on Pile-CC, we further train the model with pseudo queries generated with in-domain data, i.e. the document corpus of each BEIR testset, without using annotated Q/D pairs. The results are shown in Table 2.

We can see that on most domains (BEIR testsets) this method can still lead to significant improvements, up to 30%, suggesting the efficacy of adapting models with in-domain data. Out of 15 BEIR datasets, domain adaptation leads to positive impacts on 11 of them, and it outperforms BM25 on 7 datasets (only 3 if without DA). The model gains the most in domains that are specific and distant from the pretraining distribution, such as finance (FiQA) and science (TREC-COVID, SciDocs). However, negative impacts are observed in four domains that only a small number of documents are available. Except for Touché-2020, the rest three testsets offer no more than 10k documents, which might have caused overfitting during the course. Additional regularizations and careful hyperparameter selection can be helpful, and we leave it to future work.

### 4.4.3 Fine-Tuned Results

We provide fine-tuned results with MS MARCO in Table 3, to demonstrate whether the proposed augmentation methods can be effective pretraining measures. Note that we only adopt a basic setting for fine-tuning, without sophisticated techniques such as negative mining (Izacard et al., 2021) or asynchronous index refresh (Xiong et al., 2020).

All AUGTRIEVER models attain significant improvements after fine-tuning. Our models outperform most baseline models by a clear margin, indicating the effectiveness of using proposed augmen-

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\textsuperscript{2}Here we train InBatch models using augmented query-document pairs, whereas we train MoCo models using a 50/50 mixed strategy (50% of pairs by RANDOMCROP and 50% by one of the proposed augmentation strategies). More details about the two settings will be discussed in Sec 4.5.
Table 2: Result of I

Table 3: Retrieval scores after fine-tuning with MS MARCO. Bold text indicates best scores among the three.

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4.5 Result Analysis

To better understand how individual augmentation strategies help the retrieval task and in what specific scenarios they perform well or poorly, we conduct a detailed analysis. We report unsupervised performance of AUGTRIEVER (trained on Wikipedia) and baselines in Fig 2, by averaging scores of 14 BEIR datasets and 6 ODQA datasets. We make the following key observations:

1. BEIR shows similar trend as ODQA, but BEIR results can be a more generic benchmark. In general, BEIR covers a wider range of domains and topics, which better reflects models’ generalization ability. In this case, we see that BM25 leads with a clear margin among all models, remaining a competitive unsupervised baseline. On the other hand, all ODQA datasets are considered in-distribution since models are trained with Wikipedia data. Since QA queries often require capturing lexical variants and semantic relationships, dense models demonstrate distinct advantages over BM25. Of note is that QGEN-PAQ, which is trained with 65M generated QD pairs on Wikipedia, excels on ODQA (in-distribution) but fails to generalize well on BEIR. This suggests BEIR can be a more indicative benchmark for evaluating text retrieval, and we use it for discussion in the rest of the paper.

2. Among all AUGTRIEVER variants, TQGEN achieves the best scores, outperforming all dense baselines significantly. The result suggests that the outputs of certain text generation tasks can be utilized as surrogate queries for training dense retrievers. Among the four strategies, shorter pseudo queries (TOPIC/TITLE) appear to be performing better on BEIR (even better than QGEN-D2Q). While on the contrary, longer ones (ABSUM/EXSUM) suit better on ODQA, probably because they bear a resemblance to questions by carrying more details. EXSUM works slightly better than ABSUM, and we conjecture this is because EXSUM tends to use original text and thus has fewer hallucinations.

3. InBatch performs well with queries of better quality, whereas MoCo can benefit more from noisy ones. Augmentations such as RANDOM-CROP and QEXT yield massive noisy queries (e.g., incomplete sentences, non-informative texts). In
those cases, MoCo demonstrates greater robustness against noisy pairs, which suggests that a rapidly changing encoder can be sensitive to noise and using momentum update can be an effective alternative. In contrast, InBatch performs notably better with “cleaner” queries (TQGEN and QGEN), revealing the advantage of each architecture.

4. We observe that RANDOMCROP can produce diverse pseudo QD pairs despite possible noise. To bring the best of both worlds, we consider blending RANDOMCROP with other strategies. The results are shown in Figure 3, and we find that MoCo obtains consistent gains by mixing individual augmentation methods with RANDOMCROP, performing on a par with the best results of InBatch without RANDOMCROP. This manifests that MoCo can take advantage of multiple strategies, resulting in better generalization ability. Conversely, the mixed strategy causes little help or even a performance drop on InBatch, which echoes our previous argument.

5. We plot the relative performance of different models in comparison with CONTRIEVER on BEIR in Figure 4. The left heatmap shows the relative performance on each BEIR dataset, and the right one presents the averaged scores after grouping from different aspects.

AUGTRIEVER models they perform significantly better on QA datasets (e.g. TREC-COVID, FiQA, NQ and HotpotQA), worse on fact checking datasets (e.g. FEVER, Climate-FEVER, Scifact and Quora), and similarly on the rest datasets. CONTRIEVER explicitly blends Wikipedia and CC-Net in training, to favor knowledge-rich testsets, but it does not show consistent benefits across all five Wikipedia related testsets. It is enlightening to see that, DOC-TITLE and QEXT-PLM with MoCo, which take certain contents from the original document for pseudo queries, can deliver comparable or better performance to CONTRIEVER, despite a much shorter training period. As for our TQGEN models, both models perform very well on TREC-COVID, which contributes to the major part of the improvement. But they consistently underperform DOC-TITLE and QEXT-PLM considerably on Climate-FEVER and Quora, indicating that each augmentation method may be most beneficial for certain tasks. But the training with hybrid strategies does not appear to bring the advantage of all. With regard to the effect of pseudo query length, TQGEN-TOPIC indeed performs better on datasets with short and medium length queries (SQ/MQ), and TQGEN-EXSUM shows more strength on medium and long queries.
Figure 4: Two heatmaps show the relative performance gain/loss of different models against CONTRIEVER. The left heatmap shows nDCG@10 difference on each BEIR dataset, and in the right figure we group BEIR datasets in different ways. SQ/MQ/LQ: datasets with short/medium/long queries. SD/MD/LD: datasets with short/medium/long documents. Phrase/Question/Sentence denotes datasets that use this form of queries. And the rest are categorized by text domains. Refer to A.1 for specific grouping of datasets.

5 Related Work

Recent years have seen a flourishing of research works for neural network based information retrieval and question answering. The interested reader may refer to (Lin et al., 2021; Guo et al., 2022; Zhao et al., 2022) for a comprehensive overview. Our study, along with a line of recent studies (Izacard et al., 2021; Ram et al., 2021), falls under the category of self-supervised learning using contrastive learning (Shen et al., 2022), in which a model is trained to maximize the scores of positive pairs and minimize the scores of negative ones. It has demonstrated effective for supervised dense retrieval (Karpukhin et al., 2020; Xiong et al., 2020; Liu et al., 2021) and pretraining (Izacard et al., 2021; Yu et al., 2022). Different from most prior studies, we target at unsupervised methods that can be directly and independently applied in retrieval tasks, without any further tuning using annotated data.

Previous works propose different ways to construct query-document pairs to fit the requirement of contrastive learning. Lee et al. propose the inverse cloze task (ICT), using a random sentence as a pseudo query to predict the surrounding context in a batch. REALM (Guu et al., 2020) pretrains a retriever and generator with a pair of a salient span (named entities) and its context. Spider (Ram et al., 2021) proposes to use recurring spans as pseudo queries. The above studies focus on ODQA tasks and their pseudo queries tend to be entity-like, but results from this study and Izacard et al. show that entity-like queries (e.g. anchor texts) fail to generalize well in a broad range of domains. Some studies propose more generic ideas for training unsupervised models. Specifically, Neelakantan et al.; Ma et al. use neighboring pieces of text as positive pairs. Izacard et al. adopt a random cropping strategy to independently sample two text spans, encouraging the model to learn lexical matching. Chen et al. use random sentences as queries and pair them with documents predicted by Bm25.

A few research works investigate techniques of data augmentation and domain adaptation for dense retrieval and text understanding (Tang et al., 2022; Wang et al., 2022; Iida and Okazaki, 2022). Query and question generation have been shown an effective means for augmenting retrieval training data (Thakur et al., 2021; Nogueira et al., 2019; Lewis et al., 2021; Ma et al., 2021a; Gangi Reddy et al., 2022; Cho et al., 2022; Liang et al., 2020). Wang et al. use cross-encoder to select a good set of synthetic query-document pairs for domain adaptation. Bonifacio et al.; Dai et al. propose to use generate questions using large language models in a few-shot manner. Xu et al. propose to use Dropout-as-Positive-Instance for pretraining retrievers. Fang et al. use positive pairs generated by back-translation. For hyperlinks, Chang et al. compare three pretraining tasks for retrieval – inverse cloze task, body first selection, and wiki link prediction. Zhou et al. and Wu et al. also utilize hyperlinks to construct pseudo query-document pairs.
Ma et al.; Ma et al. propose a representative words prediction task to optimize the semantic distance between a document and a pair of random word sets, estimated by language models.

6 Discussion and Conclusion

In this study, a series of scalable augmentation techniques are proposed to produce surrogate queries for training dense retrievers without using any annotated pairs. We achieve state-of-the-art performance on two collections of widely used benchmarks (BEIR and six ODQA datasets), demonstrating that the inductive bias of the synthetic query-doc pairs is effective for training dense retrievers, greatly bridging the gap between unsupervised dense models and Bm25 and inspiring us to rethink the necessity of using real queries.

For future work, we would like to continue investigating unsupervised methods for dense retrieval, to understand what causes the gap between lexical and dense retrievers. We observe that lexical features can be complementary to distributed representations, which motivates us to explore effective dense methods to represent lexical information.

Besides, it remains an open question that what the difference is between synthetic and annotated query-document pairs, and it is interesting to understand how different augmentation methods help with dense retrieval. Particularly, we would like to dive deeper into the salient span selection for query extraction, which is easy to scale and shows impressive results when training with domain-general data. Factors such as the length of spans, cropping methods, and ranking models are worth studying in the next step.

Limitations

We demonstrate that several data augmentation can be taken as an effective means for training unsupervised dense retrieval models. We acknowledge that this study suffers from the following limitations:

- We propose several methods to generate pseudo queries bringing different types of inductive bias. Though demonstrated effective in general, it remains not clear for what reasons and in what exact cases they are beneficial, and what the best way is to combine them.
- Our experiments with QExt is limited. Many key factors are underexplored, such as scoring models, span lengths and number of candidates.
- We manually select four language generation tasks in TQGen, nevertheless pseudo queries transferred from the other tasks may also be useful but are missing from this study. We heuristically define four prompts to elicit the corresponding outputs from T0, but the outputs often do not match what we expect (e.g. long sentences in TOPIC, abstractive contents in EXSUM). Besides, we only keep single output sequence by nucleus sampling. Experimenting with other generation models as well as more diverse outputs could be interesting.
- Due to computational constraints, we only explore very limited settings of backbones and hyperparameters and train all models for 100k steps. It is yet not clear whether other configurations can lead to significant performance changes.

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A Example Appendix
A.1 BEIR dataset groups
A.2 Examples of QEXT
A.3 Examples of TQGEN
A.4 Complete Results