Multi-Task Retrieval-Augmented Text Generation with Relevance Sampling

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Abstract

This paper studies multi-task training of retrieval-augmented generation models for knowledge-intensive tasks. We propose to clean the training set by utilizing a distinct property of knowledge-intensive generation: The connection of query-answer pairs to items in the knowledge base. We filter training examples via a threshold of confidence on the relevance labels, whether a pair is answerable by the knowledge base or not. We train a single Fusion-in-Decoder (FiD) generator on seven combined tasks of the KILT benchmark. The experimental results suggest that our simple yet effective approach substantially improves competitive baselines on two strongly imbalanced tasks; and shows smaller improvements on four of the other five tasks. Furthermore, we demonstrate our multi-task training with relevance label sampling scales well with increased model capacity and achieves state-of-the-art results in six out of seven KILT tasks.

1. Introduction

Retrieval augmented generation models are trained as a unified unit consisting of retrieval and generation modules (Lewis et al., 2020). The knowledge base accessed by the retriever module offers many benefits for practical use, such as maintainability through updates and domain adaptations. On the other hand, this setup brings additional complexity to the text generation tasks, as we now administer connections of a query-answer pair to relevant items in the knowledge base, for a more holistic view including retrieval performance (Zamani et al., 2022). The coverage sparsity of relevance judgements of large collections and the resulting reliability issues are well studied, yet still a timely problem in the retrieval community (Zobel, 1998; Voorhees, 2001; Craswell et al., 2021). This challenge is exacerbated when tasks are retroactively expanded (Kwiatkowski et al., 2019), repurposed (Bajaj et al., 2016) or adapt the collection (Petroni et al., 2021).

We propose a simple yet effective approach for training retrieval-augmented models for knowledge-intensive tasks with noisy labels. We use a confidence score for query-answer pairs and items in the knowledge base. This confidence can be sourced from manually annotated, heuristic, or model generated aspects. We filter training examples via a threshold of confidence on the relevance labels, whether a pair is answerable by the knowledge base or not. With this we aim to reduce noise in the training process, and produce better results with fewer training examples.

To study our training approach, we use a fixed T5-based dense retrieval module (Ni et al., 2021) and train a Fusion-in-Decoder (FiD) generator (Izacard & Grave, 2020) on multiple tasks of the KILT benchmark (Petroni et al., 2021). KILT aggregates and heuristically maps many different English Wikipedia-based generation tasks to a single Wikipedia snapshot, which introduces considerable noise in the label quality, due to the time-shifted nature of the task creations.

We apply our confidence threshold on relevance label filtering to remove a training example if no knowledge item could be identified as sufficiently relevant from the existing labels. Because of the time shifted knowledge base, if an answer is not available in the new passage text anymore, we have a lower confidence, that the query can be answered at all given the new passages. After this step, we apply downsampling on imbalanced tasks for a balanced multi-task training on all the seven tasks of KILT that have passage mappings; spanning open domain QA, fact verification, slot filling, and dialogue categories: HotpotQA (Yang et al., 2018), TriviaQA (Joshi et al., 2017), Natural Questions (NQ) (Kwiatkowski et al., 2019), T-REx (Elsahar et al., 2018), Zero Shot RE (zsRE) (Levy et al., 2017)), FEVER (Thorne et al., 2018), and Wizard of Wikipedia (WoW) (Dinan et al., 2018).

Furthermore, we demonstrate the robustness of our sampling strategy by creating an alternative to the prevalent original, aggregation method from Wikipedia paragraphs to retrievable units. Finally, we study the impact of our training method on increased capacities of the generator backbone.

We find that our training strategy significantly improves the

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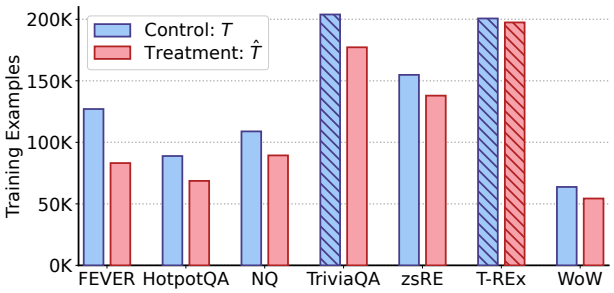

Figure 1. Training examples per task and sampling method. *Hatched bars indicate downsampling with potential more training data available.*

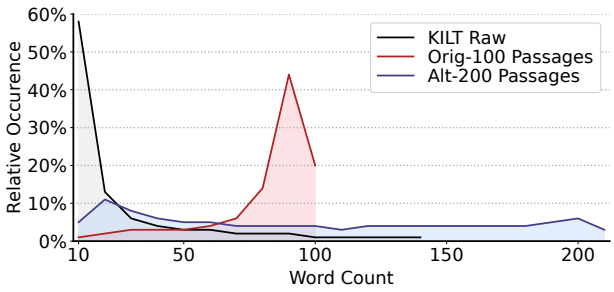

Figure 2. Statistics of the passage lengths of the raw KILT texts, its original chunking (Orig-100) and our alternative approach (Alt-200). *The word counts are binned to 10 words.*

effectiveness on the two strongly imbalanced datasets: TriviaQA (+ 11.9 EM) and T-REx (+5.2 Accuracy). This leads to a new state-of-the-art in TriviaQA, and is competitive in T-REx compared to more specialized models. It also improves four out of the remaining five tasks, albeit at a smaller rate. When scaling up the FiD backbone with our multi-task sampling technique from T5-Base to T5-Large and T5-XL, we observe expected quality gains across all our evaluated tasks and outperform the state-of-the-art on a total of six out of seven KILT tasks.

2. Relevance-Based Confidence Sampling

The main goal in retrieval-augmented generation is to generate an answer string a given a query q; with a secondary goal of identifying a set of relevant passages P from a collection C, which are the source of the answer. In a dataset, the relevant passage set $P_t^{(q,a)}$ using a threshold t, is:

$$P_t^{(q,a)} = \left\{ p \mid \Phi(p, q, a) > t, \forall\, p \in C \right\} \tag{1}$$

where Φ is a mapping function between a passage, query and answer triple, returning a confidence value, whether this passage is relevant or not. Only if the confidence is higher than our set threshold t, do we include the passage in the set. From the view of a dataset creator, it is usually unfeasible to conduct annotations for all possible pairs, therefore, those pairings without annotations return a null confidence for relatedness, even if it might be related.

As dataset creation is a very costly operation, many works adapt and evolve existing datasets. When knowledge intensive datasets are evolved, the query-answer pair may stay the same while the confidence values of the passage connections change. Therefore, we hypothesise it is beneficial not to include all possible training examples, rather only take into account query-answer pairs, where a higher confidence threshold on the relevance label is set, to reduce noise. A low or no confidence value might indicate a low quality query answer pair.

Starting from the training set T, which includes all possible pairs (q, a), we define a filtered version $\hat{T}_t$ as follows:

$$\hat{T}_t = \left\{ (q, a) \mid \exists\, p \in P_t^{(q,a)}, \forall\, (q, a) \in T \right\} \tag{2}$$

where we need to define a threshold t as our sampling boundary. The boundary needs to be adapted to the properties of the applied task.

In this work we apply our sampling approach on KILT which conducted a heuristic mapping process of passages for given query-answer pairs. We implement the confidence mapping Φ as the BLEU score in their mapping and set the threshold t to be > 0, filtering all pairs, where no overlap in the previously annotated document was found. Our sampling is not limited to KILT and could be extended to other resources with a similar setup or by mining weakly-supervised relevance signals, as proposed by Asai et al. (2021), and filtering for example based on the confidence of the labelling model.

3. Experiment Design

KILT multi-task training We train a single generator model on multiple tasks of the KILT benchmark, most of which already provide training sets of similar magnitude (50 to 150 thousand), except for: TriviaQA (1.8 million) and T-REx (12.5 million), accounting for 96% of training examples. FiD training requires considerable hardware resources, therefore we decided to downsample the oversized datasets, rather than upsample the others.[1]

Figure 1 shows the number of query-answer pairs available per sampling method: our control T and treatment $\hat{T}$. We apply our filtering before downsampling oversized tasks to balance our multi-task training set. For our unified training we downsample oversized tasks to 200K examples, then combine and shuffle all tasks. By applying the relevance-label filter method $\hat{T}$ we reduce our training set size by 25% (or 140K fewer examples) to 808K examples compared to our control.

[1] A T5-Base training run until convergence requires roughly one TPU month of compute with our downsample strategies.

Table 1. Comparing sampling strategies and model capacity scaling for multi-task training on the KILT dev set. Highest result in bold.

	Model	Generator	Open Domain QA *Normalized EM* NQ	HotpotQA	TriviaQA	Fact *Ex. Acc.* FEVER	Slot Filling *Exact Accuracy* T-REx	zsRE	Dialog *Norm. F1* WOW
Related Methods									
1	RAG (Petroni et al., 2021)	BART-Large	44.39	26.97	71.27	86.31	59.20	44.74	13.11
2	DPR + FiD (Piktus et al., 2021)	T5-Base	54.98	38.04	71.43	90.93	80.94	72.39	16.11
3	KGI (Glass et al., 2021)	BART-Large	–	–	–	–	84.04	71.32	–
4	Re2G (Anonymous, 2022)	BART-Large	46.70	–	74.01	91.05	**86.60**	–	19.35
Ours (DPR-100 passages)									
5	GTR + FiD with control T	T5-Base	53.82	31.53	64.09	89.60	77.38	71.38	19.53
6	GTR + FiD with treatment $\hat{T}$	T5-Base	54.88	30.79	77.50	90.01	82.88	71.67	19.33
Ours (Alt-200 passages)									
7	GTR + FiD with control T	T5-Base	55.23	31.39	66.49	89.88	77.36	70.11	19.54
8		T5-Base	56.61	31.46	78.41	88.60	82.60	71.75	19.70
9	GTR + FiD with treatment $\hat{T}$	T5-Large	62.07	35.68	82.45	92.01	82.94	73.31	19.84
10		T5-XL	**62.36**	**39.20**	**84.61**	**93.06**	83.86	**74.49**	**21.91**

Alternative retrievable units. The initial KILT release offers a fine-granular view on the Wikipedia collection. The raw paragraph collection contains 111.4 million items, with a strong concentration of very short sequences ($<$ 20 words), as shown in Figure 2. This is not a practical number of passages to index with dense retrieval methods (as the memory requirement is determined by the number of passages). A standard aggregation approach, proposed by Karpukhin et al. (2020) for DPR is to aggregate the raw data to passages of up to 100 words. It adds as many words to a new passage until 100 words or a changed document are reached, which breaks most paragraphs at the boundaries in half. Therefore, we propose an alternative aggregation strategy to relax the strict length requirement and favoring not to break up paragraphs. We aggregate whole raw-paragraphs until they reach 200 words, or start a new passage if they do not fit. This change results in a very different length distribution, as shown in Figure 2. It also results in only 27.7 million passages, compared to 35.7 million of the original chunking. In both cases the title of the page is added to all passages.

Implementation. All our experiments are based on the t5x framework (Roberts et al., 2022). We use a fixed GTR-Base dense retrieval model (Ni et al., 2021), which is pre-trained on the MSMARCO passage retrieval task (Bajaj et al., 2016) and has been shown to generalize well on the BEIR benchmark (Thakur et al., 2021). We train an FiD model (Izacard & Grave, 2020) with task specific markers on TPUs. For training we use a batch size of 128 with 50 retrieved passages, and a learning rate of 10^{-3} with the Adafactor optimizer (Shazeer & Stern, 2018). We do not tune our models to a specific checkpoint, rather train them all for 50K steps. The special case T5-XL uses a learning rate of $5 * 10^{-4}$ and trained for 16K steps.

4. Results

In this section we present and discuss our experimental results. An important note with every use of the KILT benchmark is that the numbers presented here are only comparable to other works also based on the KILT benchmark and not the original versions of the individual tasks. This is due to the changed collection as well as changed query sets, as described by Petroni et al. (2021).

The results are shown in Table 1. In the first section (lines 1-4) we show related works, which also report KILT-based scores: RAG (Lewis et al., 2020), as evaluated by Petroni et al. (2021); DPR + FiD (Piktus et al., 2021); KGI (Glass et al., 2021); and Re2G (Anonymous, 2022). We present our results using the original passage units in the second (lines 5 & 6) and our alternative retrieval units in the third section (lines 7 & 8). In both sections we compare the random downsampling and our proposed relevance-label guided sampling strategy.

Sampling strategies First, we focus on the two strongly imbalanced tasks (TriviaQA and T-REx), which had their training examples change the most under our relevance-label sampling strategy: We see that for both passage variants, both tasks improve considerably with the proposed sampling. Comparing lines 7 & 8 we observe a gain for TriviaQA of 11.9 EM and 5.2 Accuracy for T-REx. For the other tasks on our alternative passage-units, we observe small gains on NQ, HotpotQA, zsRE, and WOW; and the only regression on FEVER.

These results are a strong indicator for the viability and usefulness of our relevance-label sampling strategy considering that it has access to 140K fewer training examples than the

baseline. We want to emphasize that when we compare our already competitive results to related work our approach is handicapped in a few key areas: **1)** we are not training the retriever (which is out of scope, but orthogonal to our work and could lead to further improvements); **2)** we are training a single model, which gives us less chance to overfit on a single task; **3)** we do not employ multiple training loops, index updates, or knowledge distillation. Therefore, we conclude that multi-task training is a viable option for the community to build upon going forward.

Retrievable units To observe the impact of our alternative passage aggregation strategy we need to compare the pairs of lines 5 & 7 as well as lines 6 & 8. Even though the properties of the two passage collections are very different, the results of the retrieval augmented generation are very similar. Our alternative approach is slightly better on NQ, TriviaQA, and WOW; a virtual draw on ZsRE, T-REx, and HotpotQA, but worse on FEVER. Overall, we also notice, that our passage sampling strategy works slightly better on the alternative passages, resulting in the best overall results of our ablation, with the exception of FEVER. Therefore, we select this combination (line 8) for the following experiments.

Scaling the generator capacity In most NLP settings, increasing the capacity of a pre-trained model leads to effectiveness gains, at the cost of efficiency. Given how the related methods use varying generator capacities (such as BART-Large (Lewis et al., 2019)), we want to understand and measure the implications of scaling up the generator for our alternative passage aggregation and relevance-label sampling strategy $\hat{T}$. We show these results in Table 1 for T5-Base (line 8), T5-Large (line 9), and T5-XL (line 10).

We find that scaling the model size and compute resource consistently improve results over all tasks. This is an expected result. Nevertheless, we wanted to confirm that our sampling improvements observed in Table 1 is not just beneficial in the smaller setting.

Compared to related methods our FiD model with T5-Base is SOTA on 3/7, T5-Large is SOTA on 5/7 and T5-XL sets a new SOTA ceiling on 6/7 KILT tasks. Only our performance on T-REx is not as good as Re2G and KGI. This might be attributable to our downsampling of the T-REx training data, and the related methods are trained exclusively on the single task, without the need for training data adjustments.

Are we just gaming the benchmark? A valid concern we need to raise is whether we are really improving the quality of the model, or simply moving the training set construction closer to the way the tests sets have been constructed by Petroni et al. (2021). The KILT test sets filter an average 18% of queries compared to their original task versions. Petroni et al. (2021) removed a query if not at least one of the answers could be mapped to a passage at least once. Crucially, if one of the answers is partially mappable, all the other answers for this query were also kept as valid. Our analysis shows that, while the average ratio of mapped answers increases compared to the raw training data, especially exact mapped answers still only account for 10% to 67% of available answers. Therefore, we argue that we are not gaming the benchmark, as we exclusively select mapped query-answer pairs for our training, which differs from the test set construction. For a conclusive answer to this question future work should evaluate our trained models on other, independently created, evaluation tasks.

5. Related Work

Multi-task training To the best of our knowledge, the multi-task focus of the KILT community so far has been on the retriever module and not the answer generator. The foundational retrieval augmented architectures FiD (Izacard & Grave, 2020), RAG (Lewis et al., 2020), and REALM (Guu et al., 2020) are trained on individual tasks. In their initial baseline setup Petroni et al. (2021) already studied the impact of multi-task retrieval training; Maillard et al. (2021) continued to study various configurations for KILT multi-task single-model retrieval. Lewis et al. (2021) trained the RePAQ-retriever system on multiple tasks, but for their FiD defer mechanism used task-specific FiD checkpoints. For context-given question answering Khashabi et al. (2020) trained UnifiedQA on multiple QA tasks.

Improved RAG training Many of the recent papers improving RAG-style models optimized end-to-end processes (f.e. EMDR2 (Singh et al., 2021)), ensembling multiple modules (f.e. R2-D2 (Fajcik et al., 2021)), or creating multiple training loops to update the indexed documents multiple times (f.e. Hindsight (Paranjape et al., 2021)). Our approach differs, as we focus on the selection of the available training data in a multi-task setting. For more information on retrieval-enhanced machine learning models, we refer the reader to Zamani et al. (2022).

6. Conclusion

We proposed a simple yet effective approach for multi-task training of the FiD retrieval-augmented generation model on the KILT benchmark. We cleaned (& downsampled were necessary) the training set by removing query-answer pairs with low relevance confidence. We demonstrated that this approach substantially improves two imbalanced tasks, and has a smaller benefit on four of the remaining five tasks. By scaling the model capacity we achieve state-of-the-art results on six out of seven KILT tasks by even outperforming task-specific models.

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