

Evidentiality-guided Generation for Knowledge-Intensive NLP Tasks

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Abstract

Retrieval-augmented generation models have shown state-of-the-art performance across many knowledge-intensive NLP tasks such as open question answering and fact verification. These models are trained to generate the final output given the retrieved passages, which can be irrelevant to the original query, leading to learning spurious cues or answer memorization. This work introduces a method to incorporate *evidentiality* of passages—whether a passage contains correct evidence to support the output—into training the generator. We introduce a multi-task learning framework to jointly generate the final output and predict the *evidentiality* of each passage, leveraging a new task-agnostic method to obtain *silver* evidentiality labels for supervision. Our experiments on five datasets across three knowledge-intensive tasks show that our new evidentiality-guided generator significantly outperforms its direct counterpart with the same-size model and advances the state of the art on FaVIQ-Ambig. We attribute these improvements to both the auxiliary multi-task learning and silver evidentiality mining techniques.

1 Introduction

Knowledge-intensive tasks (e.g., open Question Answering (QA), fact verification) are designed to retrieve evidence passages related to an input query given a large collection of passages such as Wikipedia. Most successful methods for these tasks use retrieval-augmented generation (e.g., Izacard and Grave, 2021b) that is trained to generate the final output given the retrieved passages from a separately-trained retriever (e.g., DPR; Karpukhin et al., 2020). This training process disregards the *evidentiality* of passages (Lee et al., 2021)—if the passages correctly support the output or not—leading to leveraging spurious cues or generating hallucinations, as shown by the recent work (Xu

Open Question Answering (input x: question, output y: answer)

question 1: The Fate of the Furious release date in india?

answer: April 12, 2017 | **prediction:** April 14, 2017

The Fate of the Furious

The Fate of the Furious was released in the **United States** on April 14, 2017.

The Fate of the Furious

The release across major markets such as Australia, the United Kingdom, China, and **India**, beginning on April 12, 2017.

question 2: How many countries India share the border with?

answer: seven | **prediction:** seven

India

India is **seventh** largest country.

Borders of India

India **shares land borders with seven sovereign nations**.

Fact verification (input x: claim, output y: classification label)

claim: The first 'fast and furious' film was filmed in 2001.

gold class: REFUTE | **prediction:** SUPPORT

The Fast and the Furious (2001 film)

Fast & Furious is a media franchise, and the first film was **released in 2001**

The Fast and the Furious (2001 film)

principal photography began in **July 2000** and lasted until that October.

Figure 1: Examples where a trained generator ignores the evidential passages and generates an incorrect answer from passages that do not provide sufficient evidence. The red rounded rectangles indicate *positive* passages with evidence to answer while the green rounded rectangles are *negative* passages. The highlighted part indicates the supporting evidence.

et al., 2021). For example, for the QA task, an answer might be retrieved incorrectly from a passage with a high lexical overlap with the query (the first example in Figure 1). This could happen through memorization of outdated information especially when many passages during training are not evidential (Longpre et al., 2021). Adopting heuristics to train the generator with passages containing the target strings can partially solve this problem for some QA tasks. Still, these passages might lack sufficient evidence to answer questions (the second example in Figure 1). In addition, such heuristics cannot be applied for open-ended generation or classification tasks (the third example in Figure 1).

In this paper, we introduce a multi-task training framework to explicitly incorporate passage *evidentiality* during training to generate task outputs based

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on the supporting evidence, leveraging our new task-agnostic approach for mining *silver* evidentiality annotations. An evidentiality-positive passage (e.g., green passages in Figure 1) should provide evidence relevant to the task, while an evidentiality-negative passage (e.g., red passages in Figure 1) does not present sufficient information even when it happens to contain the answer string.

Our evidentiality-guided generator uses a multi-task learning framework over the two tasks of answer generation and evidentiality prediction trained using *silver* evidentiality labels. We introduce a new approach to collect evidentiality-positive and -negative passages for training. To this end, we train an evidentiality mining model that takes an input query, a gold output and a single passage and predicts if the passage supports the gold output or not. This model is trained on the combinations of existing gold passage annotation and data collected by our novel leave-one-out generation approach. In particular, this approach evaluates the relevance of each passage to a query through the correctness of the generated output when the passage is removed from the pool of retrieved passages. Human annotators find that the evidentiality labeling yields 95% accuracy, and often correctly identifies the negative passages with answer strings.

We run extensive experiments across representative knowledge-intensive tasks: open-domain QA (Natural Questions Open; Kwiatkowski et al., 2019, TriviaQA unfiltered; Joshi et al., 2017), fact verification (FaVIQ Ambig; Park et al., 2021, FEVER; Thorne et al., 2018) and knowledge-grounded dialogue (Wizard of Wikipedia; Dinan et al., 2019). Our experiments show large performance improvements across different datasets from their direct counterpart, FiD (Izacard and Grave, 2021b), achieving state-of-the-art performance on FaVIQ-Ambig. Our analysis shows both multi-task learning and silver evidentiality mining contribute to the performance improvement, helping the generator learn to focus on the more relevant passages without being distracted by high-ranked passages with more lexical overlap. Our code will be available at https://github.com/AkariAsai/evidentiality_qa.

2 Method

2.1 Overview

Problem. Knowledge-intensive tasks (e.g., open QA, fact checking) are designed to retrieve evi-

dence passages related to an input query x given a large collection of passages such as Wikipedia. Most successful previous work in this domain uses a retrieval-augmented generation framework such as Fusion-in-Decoder (FiD; Izacard and Grave, 2021b) that consists of two components: a retriever model \mathcal{R} and a generator model \mathcal{G} . The retriever model \mathcal{R} is trained to retrieve a set of passages $\mathbf{P} = \{p_1, p_2, \dots, p_i, \dots, p_N\}$ with the highest top N relevance score for each training query x : $\mathbf{P} = \mathcal{R}(x)$. The base generator model \mathcal{G} (Section 2.2) is then trained to generate the final output y given an input query and the top retrieved passages: $y = \mathcal{G}(x, \mathbf{P})$.

Our analysis (detailed in Section A.1) shows that a base generator \mathcal{G} trained in this manner often generates the answers from passages ranked high by the retriever, not passages that contain the correct evidence. In this work, our goal is to build a model that recognizes the *evidentiality* of each passage and generates answers based only on passages that contain relevant evidence. We define passages with evidence relevant to the task as positive and passages without evidence as negative, even if they happen to include some spurious cues a model can exploit (e.g., a gold answer string for QA).

Method overview. Our method extends the retrieval-augmented generation paradigm by improving the generator \mathcal{G} to generate answers from passages that provide a correct evidence for the answer. We train our new evidentiality-guided generator \mathcal{G}^+ using a multi-task learning framework (§2.4), sketched in Figure 2. Specifically, given an input query x , we combine the generation of the correct answer \hat{y} with the prediction of binary evidentiality labels for each passage in \mathbf{P} : $\hat{\mathbf{E}} = \{\hat{e}_1, \hat{e}_2, \dots, \hat{e}_i, \dots, \hat{e}_N\}$.

It is challenging to obtain *gold* evidentiality labels $\hat{\mathbf{E}}$ for many tasks since most datasets are curated with only query-answer annotations (x, \hat{y}) . Therefore, we heuristically obtain *silver* evidentiality data \mathbf{E}^{silver} (§2.3) by training an evidentiality mining model \mathcal{M} that assigns a silver evidentiality label \hat{e}_i to each passage p_i given the query x and the gold output \hat{y} . Training \mathcal{M} is feasible for a task with gold evidentiality annotation for training passages. For tasks with no human annotated gold evidence, we introduce a new approach to evaluate the relevance of passages in generating the correct answer by leaving one passage at a time in answer generation, sketched in Figure 3. After we train

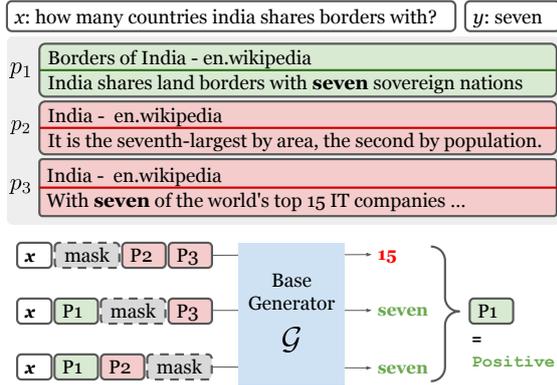


Figure 3: Overview and examples of our leave-one-out evidentiality mining.

trained model to generate the correct answer, sketched in Figure 3. In particular, we feed an input query x and retrieved passages \mathbf{P} to our trained base generator model k times, where we mask the i th passage in the i th iteration to evaluate if the model can still generate the correct answer without the information presented in i th passage. We consider i th passage *positive* if the model fails to generate \hat{y} when and only when i th passage is masked. We also consider i th passage *negative* if the model succeeds in generating \hat{y} when and only when i th passage is masked—this means that the i th passage confuses the model and can be a hard negative passage.

In our experiments, we combine the gold evidentiality data (i.e., long answers) from Natural Questions with task-specific leave-one-out data to train a separate evidentiality model \mathcal{M} for each task. See the details of the data mining for each task in Appendix.

2.4 Multi-task Learning with \mathbf{E}^{silver}

Our generator \mathcal{G}^+ has a single encoder and has two T5 decoders: an answer generator and an evidentiality predictor. We train \mathcal{G}^+ with a multi-task objective given the originally available data (x, \mathbf{P}, \hat{y}) and newly mined \mathbf{E}^{silver} .

Evidentiality predictor. The evidentiality classifier predicts the evidentiality of each passage. As the answer generator, we use the T5 decoder architecture for the classifier. Our evidentiality classifier generates the evidentiality e_i given encoded passage representation \mathbf{p}_i : $p(e_i|q, \mathbf{p}_i)$. The evidentiality predictor in \mathcal{G}^+ has a much harder problem than the evidentiality model \mathcal{M} from the previous section: \mathcal{M} has access to the gold answer \hat{y} , while

\mathcal{G}^+ does not. Intuitively, we can get reasonably accurate evidentiality labels from \mathcal{M} using the gold answer, then force \mathcal{G}^+ to predict those labels without access to the gold answer, hopefully teaching \mathcal{G}^+ 's encoder to better determine the relationship between x and p_i .

Multi-task Training. We conduct multi-task training of generation and evidentiality prediction. In particular, our framework minimizes a multi-task objective below:

$$\mathcal{L} = \mathcal{L}_{gen} + \lambda \mathcal{L}_{class}, \quad (1)$$

where λ is a weighting parameter to balance the two objectives, which would be tuned on the development set.

In Eq. (1), \mathcal{L}_{gen} is formulated as follows:

$$\mathcal{L}_{gen} = - \sum_j^T \log p(\hat{y}_j | y_{<j}, q, \hat{\mathbf{P}}), \quad (2)$$

where \hat{y}_j denotes the j th token of the annotated gold answer \hat{y} . Similarly, evidentiality prediction objective \mathcal{L}_{class} can be written as follows:

$$\mathcal{L}_{class} = - \sum_i^N \log p(e_k^{silver} | q, p_i). \quad (3)$$

Note that this probability is computed by a T5 decoder; even though $e_k^{silver} \in \{positive, negative\}$, the probability is normalized over T5's entire output vocabulary.

3 Experimental Setups

We experiment on three knowledge-intensive tasks: open QA, fact verification, and knowledge-enhanced dialogue. Comparing with the previous competitive methods shows our method's superiority across five datasets.

3.1 Tasks, Datasets, and Metrics

Statistics for each dataset are provided in Table 1.

Open QA. We use Natural Questions Open (Kwiatkowski et al., 2019) and TriviaQA-unfiltered (Joshi et al., 2017) to evaluate our method on open QA. Natural Questions consists of questions, long answers (e.g., gold evidence passages) and short answers (e.g., spans in the long answers), and the open QA version is created by discarding questions that only have long answers

Dataset & Task	# of examples			evaluation metric	Top-20 recall
	train	dev	test		
1. Open QA					
Natural Questions Open (Kwiatkowski et al., 2019)	79,168	8,757	3,610	EM	82.1
TriviaQA unfiltered (Joshi et al., 2017)	78,785	8,837	11,313	EM	75.2
2. Fact Verification					
FEVER (Thorne et al., 2018)	104,966	10,444	10,100	accuracy	98.1
FaVIQ-Ambig (A) (Park et al., 2021)	17,008	4,260	4,688	accuracy	100.0
3. Knowledge-enhanced Dialogue					
Wizard of Wikipedia (Dinan et al., 2019)	63,734	3,054	2,944	F1	96.2

Table 1: Dataset statistics. We experiment with three diverse knowledge-intensive NLP tasks across six datasets. “Top 20 recall” calculates if any of the top 20 passages include the answer strings (for open QA datasets and FaVIQ-A) or comes from the provenance article (for FEVER and Wizard of Wikipedia) in the development set. FEVER and Wizard of Wikipedia are based on the KILT (Petroni et al., 2021) version.

or short answers whose length is longer than five tokens (Lee et al., 2019). TriviaQA-unfiltered (Joshi et al., 2017) includes unfiltered 110K Trivia question and answer pairs. For both of the datasets, we use publicly available DPR retrieval results for training and inference data,¹ and do not further fine-tune retrievers. Only the Natural Questions dataset has gold paragraph annotations and we use the gold paragraph annotations to train the evidentiality mining model \mathcal{M} only. Following prior work (Lee et al., 2019), we use Exact Match (EM) as our primary metric.

Fact verification. We use FaVIQ Ambig (FaVIQ-A; Park et al. 2021) and FEVER (Thorne et al., 2018) via the KILT benchmark (Petroni et al., 2021) to evaluate our method on fact verification. FaVIQ-A is created from an information-seeking QA dataset, AmbigQA (Min et al., 2020) to pose realistic fact verification queries. We use the retrieved passages and baseline code provided by the authors of the FaVIQ dataset and KILT. We use accuracy as our evaluation metric.

Knowledge-enhanced dialogue. We use Wizard of Wikipedia (Dinan et al., 2019) to evaluate our method on knowledge-enhanced dialogue. We use the officially available KILT DPR baseline codes (Petroni et al., 2021)² to obtain top N passages and evaluate downstream F1 score using the original script.

3.2 Baselines

We use FiD (Izacard and Grave, 2021b) as our primary baseline using their official implementa-

¹<https://github.com/facebookresearch/dpr>

²<https://github.com/facebookresearch/kilt/blob/main/kilt/retrievers/README.md>

tion.³ In addition, we report results from the best published, publicly available generator models for each dataset including RAG (Lewis et al., 2020a) and DPR + BART (Petroni et al., 2021; Park et al., 2021).

3.3 Hyper parameters

Due to the computational budget, we use T5’s base-size models throughout our experiments. If not specified, we use the top 20 passages during training and inference, which also reduces the computational times from the original FiD model that uses top 100 passages. We train the models for 120k steps using 8 GPUs with 24 GB memory and take the checkpoint that achieves the highest score on the development set. The batch size is set to 1 and to imitate the larger batch size, we set the gradient accumulation step to be 4. The learning rate is set to 10^{-5} and the number of warm-up steps is 1000. We set λ to be 0.5 for open QA and dialogue, and 0.1 for fact verification.

4 Results and Analysis

Our evidentiality-guided generator \mathcal{G}^+ demonstrates large performance improvements over its direct counterpart (the base generator \mathcal{G} , which is equivalent to FiD) on all datasets, and it advances the state of the art on FaVIQ-A.

4.1 Task Results

Open QA. Table 2a shows experimental results on the two open QA datasets. On Natural Questions Open, we improve the performance over FiD by 1.5 EM score. We observe performance improvements over FiD on TriviaQA as well, demon-

³<https://github.com/facebookresearch/fid>

Models	NQ EM		TQA EM	
	dev	test	dev	test
RAG (large)	–	44.5	–	56.8
FiD (base)	46.9	48.3	67.1	67.2
Ours(base)	47.8	49.8	67.7	67.8
R2D2 (large*)	–	55.0	–	69.9

(a)

Models	FaVIQ-A		FEVER
	dev	test	dev
DPR+BART (large)	66.9	64.9	88.1
DPR+BART (base)	60.2	–	–
RAG (large)	–	–	87.7
FiD (base)	67.8	64.3	89.5
Ours (base)	69.6	65.7	89.8

(b)

Models	F1
DPR+BART (large)	15.5
RAG (large)	13.8
FiD (base)	16.9
Ours (base)	17.9

(c)

Table 2: **Main Results.** “base” and “large” denote the base generator model sizes (e.g., T5-large, BART-base). (a) Performance on Natural Questions Open and TriviaQA unfiltered. “NQ” denotes Natural Questions Open, “TQA” denotes TriviaQA unfiltered. The state-of-the-art model is R2D2 from Fajcik et al. (2021), which has 1.29 billion parameters (more than twice more parameters than our model), consisting of a ranker and two reader models with ELECTRA (Clark et al., 2020)-large and T5-large. (b) Performance on FaVIQ-A and FEVER. Previous best model is DPR+BART (large) from Park et al. (2021) and Petroni et al. (2021) on FaVIQ-A and FEVER, respectively. (c) Performance on Wizard of Wikipedia development set. The best published model on the development set is DPR+BART (large) from Petroni et al. (2021).

strating the effectiveness of evidentiality-guided training for open QA. It should be noted that on open QA, most of the recent models (e.g., Fajcik et al., 2021) contain a few times more parameters than our model or use improved retrievers (Izacard and Grave, 2021a), both of which are beyond our computational budgets. Our results represent state-of-the-art performance for models with access to similar computational resources, and our contributions on improving the generator should be complementary to work focusing on improving retrieval components.

Fact verification. Table 2b shows the experimental results on FaVIQ-A and FEVER. In addition to the original paper’s baseline, we have fine-tuned a BART-base baseline using their original public codebase (DPR+BART (base)) for a fair comparison.⁴ Our model significantly outperforms the prior best model (DPR+BART (large)) on FaVIQ-A by a large margin. Our model also significantly outperforms FiD on FEVER by 1.8% on the development set and 1.4% on the test set, yielding state-of-the-art performance on this dataset.

Knowledge-enhanced dialogue. Table 2c shows the experimental results on the Wizard of Wikipedia dataset. On Wizard of Wikipedia, our model outperforms prior work using larger base models and improves the F1 score from the base FiD model by 1.0. By explicitly training our model with evidentiality, we obtain performance improvements on knowledge-enhanced dialogue as well.

⁴<https://github.com/faviq/faviq>

4.2 Analysis

4.2.1 Ablation Study

We study the impact of different components of our method by comparing the full method with other variants.

- **Multi-task** does not use our multi-task objective and only trains with \mathcal{L}_{gen} , which is theoretically equivalent to FiD.
- **E^{silver} mining** uses the multi-task training but does not use our method to find evidentiality silver labels. Instead, it relies on the different task-specific heuristics to obtain evidentiality. For example, for QA it uses answer string matching to supervise our multi-task learning. As discussed, this distantly supervised approach cannot be directly applied to classification or open-ended generation tasks. For WoW, it uses *provenance* title and label all passages from provenance articles positive (Petroni et al., 2021). For FaVIQ-A, it uses the original answer annotations inherited from AmbigQA available in the dataset. It should be noted that that additional metadata is often unavailable in most of the datasets, and this variant for WoW and FaVIQ can be considered as a ground-truth setting.
- **LOO-gen.** uses the multi-task training but removes our leave-one-out-generation strategy for collecting evidentiality labels. It only incorporates the first step of training the evidentiality model over Natural Questions only.

Table 3 reports the ablation results. There is a clear drop by removing the multi-task auxiliary learning, especially on FaVIQ-A, where a model needs to precisely access the evidence and reason, without being distracted by a simple lexical over-

Models Metric	NQ EM	FaVIQ-A Acc	WoW F1
Ours	47.9	69.6	17.9
- multi-task	46.9	67.8	16.9
- E^{silver} mining	47.3	69.1*	18.0*
- Loo-gen.	47.6	69.2	17.7

Table 3: Ablation results. All results are based on the performance on development set of the four datasets. “NQ” denotes Natural Questions Open and “WoW” denotes Wizard of Wikipedia. * in the FaVIQ-A and WoW columns indicate that a model is trained with additional metadata our evidentiality-guided generator does not use during training.

lap (Park et al., 2021). Removing E^{silver} mining drops the performance on the three datasets, indicating the effect of mining evidentiality labels, instead of relying on string matching heuristics. Moreover, our method is easily applicable to a task or a new dataset where we do not have access to some heuristics like provenance as in KILT or FaVIQ-A. Finally, the performance drop by removing LOO-gen. shows the impact of our task-agnostic leave-one-out approach in collecting evidentiality labels to train \mathcal{M} .

4.2.2 Evaluating Evidentiality Labels

Table 4a shows human analysis over evidentiality positive and negative labels obtained by our method over randomly selected samples on the Natural Questions development set. In particular, we randomly sample 50 Natural Questions development questions and sample 2 positive passages and 2 negative passages (if applicable) with answer strings for each question. The authors manually analyze (i) if the positive passages actually provide sufficient evidence to answer, and (ii) if the negative passages actually *do not* provide sufficient evidence to answer, despite the existence of the gold answer strings. We found that in 95% of the mined positive passages provide sufficient evidence to answer, while only 4% of the negative passages do not; in other words, the predictions are correct 95% of the positive passages and 96% of the negative passages.

4.2.3 Comparing \mathcal{G} and \mathcal{G}^+

Qualitative evaluation of \mathcal{G} and \mathcal{G}^+ . We conduct a systematic qualitative analysis on the FaVIQ-A set predictions made by a base generator \mathcal{G} and our evidentiality-guided generator \mathcal{G}^+ . We study the claims in the evaluation set that \mathcal{G} and \mathcal{G}^+ pro-

e	\hat{e}	%	(category) relevance	%
pos	pos	95	(1) $p_{\mathcal{G}^+} > p_{\mathcal{G}}$	43
pos	neg	5	(2) $p_{\mathcal{G}^+} < p_{\mathcal{G}}$	14
neg	pos	4	(3) $p_{\mathcal{G}^+} = p_{\mathcal{G}} = 0$	29
neg	neg	96	(4) $p_{\mathcal{G}^+} = p_{\mathcal{G}} = 1$	14

(a)

(b)

Table 4: (a) Human analysis over evidentiality positive and negative labels obtained by our method. e denotes predictions made by \mathcal{M} while \hat{e} denotes the evidentiality annotation labeled by human annotators. pos denotes evidentiality-positive while neg denotes evidentiality negative. (b) Qualitative evaluation of \mathcal{G} and \mathcal{G}^+ . $p_{\mathcal{G}}$ and $p_{\mathcal{G}^+}$ denotes the relevance between the input query and the passages most attended by \mathcal{G} and \mathcal{G}^+ , respectively.

vide different prediction classes (793 out of the total 4,260 claims). We observe \mathcal{G}^+ provides the correct labels in 54% of these cases. We further filter out the cases where the two models provide the highest attention scores to similar passages, leading to 192 claims.

The authors of this paper manually inspect all of those 192 claims and classify them into four categories: (1) \mathcal{G}^+ attends to a more relevant passage ($p_{\mathcal{G}^+} > p_{\mathcal{G}}$), (2) \mathcal{G} attends to a more relevant passage ($p_{\mathcal{G}^+} < p_{\mathcal{G}}$), (3) the models attend on equally-irrelevant passages ($p_{\mathcal{G}^+} = p_{\mathcal{G}} = 0$), (4) both of them attend to equally-relevant passages ($p_{\mathcal{G}^+} = p_{\mathcal{G}} = 1$). The Table 4b (b) results show that \mathcal{G}^+ attends to the passages that are more relevant to the input claims. After further inspection, we found that \mathcal{G} sometimes generates the right class, even if it gives the highest attention to a less relevant passage, explaining a smaller accuracy gap between the two models. This probably happens due to the nature of the task (e.g., two-way classification). We show some examples in Table 8 in the Appendix.

Analyzing attentions of \mathcal{G} and \mathcal{G}^+ . To further understand our method’s behavior, we compare the attention scores assigned to the top retrieved passages of a base generator FiD (\mathcal{G}) and our evidentiality-guided generator (\mathcal{G}^+). Figure 4 shows that the attention scores of the base generator \mathcal{G} and \mathcal{G}^+ ; the x-axis is the attention values and the y-axis is probability. Figure 4 shows that the attention scores of the base generator \mathcal{G} are concentrated closely near the value of -5.0, whereas the attention scores of our \mathcal{G}^+ more widely spread out. We also found that our \mathcal{G}^+ more often gives

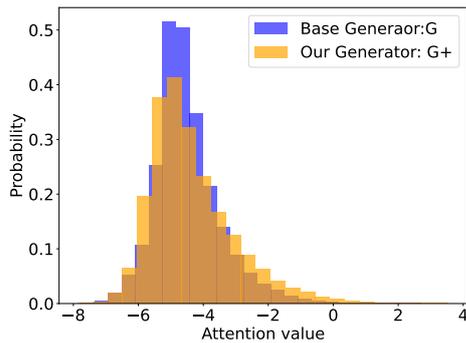


Figure 4: Attention score distributions over top 20 passages of the base generator \mathcal{G} and our evidentiality-guided generator \mathcal{G}^+ .

its highest attention value to the passages ranked lower by \mathcal{R} ; our generator \mathcal{G}^+ and base generator \mathcal{G} gives their highest attention scores to the passages ranked lower than top 10 by \mathcal{R} in 45.8% and 44.8% of the examples, respectively. We hypothesize that FiD mostly generates answers from more highly-ranked passages while our method enables shifting the attention scores to lower-ranked passages and generates answers from those, by explicitly training the models telling the evidentiality-negative and evidentiality-positive passages.

4.2.4 Performance on Hard Subsets.

To see if there is an even more notable gap between the base \mathcal{G} and \mathcal{G}^+ on those challenging questions, we automatically collect challenging instances from FaVIQ-A and Trivia QA development set. In particular, we feed the top one retrieved passages with the input queries to the two generators and label questions that both models can generate the right answers given top passages only *easy*, otherwise *hard*.

Table 5 shows the models’ performance on the easy and hard subsets. In FaVIQ-A, the performance gap between two models on the harder subset is larger than the gap on the easy subset (i.e., 1.7 % v.s. 1.1% accuracy gap). Interestingly on FaVIQ-A, both models show somewhat low performance on the easy subset, where two models originally succeed to answer correctly given a single passage only. This is probably because the models are distracted by other passages when questions are actually simple and can be answered by top passages. On the other hand, the full accuracy of these top one passage only-variants is low (Ours: 54.7 % accuracy, FiD: 53.4%), suggesting the effective-

dataset split(#)	FaVIQ-A (Acc.)		TQA (EM)	
	easy(1.7k)	hard(2.5k)	easy(4.0k)	hard(8.8k)
FiD	74.5	62.9	94.8	37.1
Ours	75.6	64.6	94.8	36.0

Table 5: Performance on *easy* and *hard* subsets of FaVIQ-A and TriviaQA (TQA), decided by top one only models’ predictions. The numbers inside parenthesis show the number of the examples included in the easy and hard subsets.

ness of reading more passages. On the TriviaQA easy subset, both models show nearly 95% EM, showing little performance gap between the two models, while there is a notable performance gap between the two models on the hard subset. These results indicate that our method is more effective on harder examples that require carefully assessing and reasoning the passages beyond the top one.

5 Related Work

Retrieval-augmented generation. Retrieval-augmented generators achieve competitive performance across many different knowledge-intensive NLP tasks (Izacard and Grave, 2021b; Lewis et al., 2020b; Glass et al., 2021; Paranjape et al., 2021; Park et al., 2021). These models leverage retrievers such as Dense Passage Retriever (Karpukhin et al., 2020) or BM25 (Robertson and Zaragoza, 2009) to find supporting evidence from large-scale passage collections, and then feed those retrieved passages with the original input query to competitive pre-trained generators such as BART (Lewis et al., 2020a) or T5 (Brown et al., 2020). The generators are typically trained to generate the annotated gold answers based on passages obtained by the retrievers, which results in its reliance on spurious clues or hallucinations through memorization of outdated knowledge at inference time (Xu et al., 2021; Longpre et al., 2021; Lewis et al., 2021). Recent work improves the retrieval component (Paranjape et al., 2021; Maillard et al., 2021) or introduces another passage re-ranking modules (Fajcik et al., 2021) and has shown performance improvements on some downstream tasks. They are complementary to our work, which focuses on improving the generator component.

Distantly supervised learning under under resource constrained settings. Distantly supervised learning obtains approximate supervisions by finding sentences or passages containing the

target strings (Mintz et al., 2009), and has shown to be effective across different tasks under limited supervisions such as information extraction (Hoffmann et al., 2011) or open QA (Chen et al., 2017). Especially on QA, prior work introduces some heuristics to map the weak supervision to full supervision (Joshi et al., 2017) or develop algorithms using gradient information to avoid spurious options (Clark and Gardner, 2018; Min et al., 2019).

Finding evidence to answer in Multi-hop QA without supervised annotations. Recently, Lee et al. (2021) introduce evidentiality-guided training for multi-hop question answering such as HotpotQA (Yang et al., 2018), which mine evident sentences by adding or removing them to create counterfactual cases, and train a QA model with a regularization term to avoid overconfidence on negative passages. Although this work and our work both attempt to mine evidentiality labels, there are several core differences. Their approach incorporates some task-specific assumptions of HotpotQA, which makes limits its applicability to a diverse set of knowledge-intensive tasks. We also further introduce an evidentiality labeling model and auxiliary multi-task learning approach, which can be directly applied to diverse NLP tasks. Several prior work attempts to learn to find evidence sentences in unsupervised manners in multi-hop QA (Chen et al., 2019; Yadav et al., 2019; Perez et al., 2020), whereas our work attempts to use evidentiality information to improve the generator components via multi-task training. This is the first work to introduce evidentiality-guided generation using a task-agnostic multi-task learning and evidentiality mining framework that goes beyond QA, showing successful results on other knowledge-intensive tasks including fact verification and dialog.

Entailment-based approaches to improve QA. Assessing evidentiality of a passage given a question and a final output can be framed as an entailment task. Using entailment models to enhance the performance of QA tasks has been extensively studied (Harabagiu and Hickl, 2006; Sacaleanu et al., 2008; Abacha and Demner-Fushman, 2019; Trivedi et al., 2019). Iyer et al. (2021) introduce a framework that conducts answer re-ranking using natural language inference framework to improve the performance in open QA. Chen et al. (2021) find NLI models specifically trained for QA can calibrate the answer reliability taking the input evi-

dence, question and answer. Those work focuses on improving the final answers by entailment-based answer re-ranking, while in our work, we use our evidentiality-mining model to collect silver evidentiality data.

6 Conclusion

Augmenting pre-trained generation models with retrievers has shown to be effective in many knowledge-intensive tasks but they often rely on spurious cues or generate hallucinations at inference. In this work, we introduce a multi-task learning objective of answer generation and evidentiality prediction. We propose task-agnostic data mining techniques to obtain *silver* evidentiality labels to enable this auxiliary training. Our experiments across five datasets show large performance improvements from the direct counterpart and our evidentiality-guided generator advances the state-of-the-art performance on FaVIQ-Ambig. Our analysis shows that multi-task learning and silver evidentiality mining both contribute to the performance improvements by helping the model learn to focus and generate answers on more relevant passages, and is more effective on harder examples.

Acknowledgements

This research was supported by NSF IIS-2044660, ONR N00014-18-1-2826, gifts from Google, the Allen Distinguished Investigator Award, the Sloan Fellowship, and the Nakajima Foundation Fellowship. We thank the members of the UW NLP group and Allen NLP for their insightful discussion and feedback on this paper.

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Appendix

A Preliminary Experiments and Analysis

A.1 Analysis on a Base Generator \mathcal{G}

Error Analysis. We conduct a detailed error analysis on the base generator, FiD. We manually analyzed 50 errors in the Natural Questions development set to understand what causes the errors. Although 23 errors are due to the annotation errors (e.g., correct answer aliases are not covered by the original data; questions are highly ambiguous as pointed by [Min et al. 2020](#); [Asai and Choi 2021](#)), we found that the model often succeeds in retrieving the right evidence but fails to attend the passages with supporting evidence. We show the top attended passages for sampled six questions in [Table 6](#). As you can see, although those passages have high lexical overlap with the questions, they are often irrelevant or about the different entities in the same genre (e.g., last name, movie). Yet, during training, the model is only given the final output supervision signal, making it difficult to distinguish the passages with sufficient evidence to answer from the ones without evidence.

Memorization issues. We also found that the model more often memorizes the answers without carefully accessing the context. In the questions where our models failed to generate the correct answers, more than 5% of the answers are not sub-spans of any of the retrieved passages, while in the questions FiD succeeds to answer 99.5% of the answers are copied from the passages. Moreover, in the success cases, the predicted answers are the sub-spans of the top 10 passages in 96% of the cases, while in the error cases, only 79% of the predicted answers are copied from the top passages. Those findings are consistent with the ones observed by [Xu et al. \(2021\)](#). Recently, [Longpre et al. \(2021\)](#) found that the generative QA models often generate the answers memorized during fine-tuning, when they observe more unreliable passages during training. We expect that the model may generate arbitrary answers when it does not have confidence in any of the retrieved passages.

A.2 Evidentiality Negative Passages among Top Retrieved Passages

We manually analyze 20 sampled Natural Questions training questions where at least of one of the top 3 passages retrieved by DPR include the

annotated gold answers, to see if answerability entails evidentiality. We found that in 30% of the cases, the passages do not actually support the answers. We shows the examples in [Table 7](#). Training a model with distantly supervised approaches have been widely used in open QA, but particularly in the current retrieved-augmented training schema, this approach can cause huge learning noises. It also should be noted that those passages are all from top 3 retrieved results, which are expected to be highly related to the input queries.

B Details about \mathcal{M} and Resulting E^{silver}

B.1 Task-specific Details for Leave-one-out Generation

Open QA. To collect new positive and negative data using leave-one-out generation, we consider top 20 passages retrieved for all of the original training data queries, and then split 20 passages into two ten-passage chunks. We then run a trained FiD model for 10 times, masking i th passage at the i th iteration. We consider i th passage p_i positive when and only when FiD fails to generate the correct answer when i th passage is masked. We also consider p_i (hard-)negative when and only when FiD succeeds to answer correctly when i th passage is masked, as we assume the i th passage can be highly distracting or confusing, resulting in generation errors.

Fact verification. As fact verification is a classification task, using the same methodology as open QA may not be desirable—when we run a model ten times, it is likely to predict both correct and incorrect classes for multiple times, and we may not be able to mine the useful positive and negative passages. For the two fact verification datasets, we consider the top 10 passages and we split them into two five-passage chunks. We consider the i th passage as a positive passage if the predictions based on the passage collections including i th passage unanimously agree on correct prediction whereas it fails to generate the correct class when i th passage is masked. We consider the i th passage as a negative passage when (i) the model succeeds to answer when and only when i th passage is masked, and (ii) the predictions unanimously agree on incorrect classes, which indicates all of the passages do not support the input claim.

Knowledge-enhanced dialogue. Unlike open QA or fact verification, the final output of a di-

Q: who played mary in christmas with the kranks

A: Felicity Huffman

Christmas with the Kranks: Christmas with the Kranks is a 2004 American Christmas comedy film based on the 2001 novel “Skipping Christmas” by John Grisham. It was directed by Joe Roth and written and produced by Chris Columbus. It stars Tim Allen and Jamie Lee Curtis as a couple who decide to skip Christmas one year since their daughter is away, much to the chagrin of their neighbors. .

Q: hyori bed and breakfast season 2 air date

A: February 4, 2018

Queen Sugar: On March 11, 2016, it was announced that Marycarmen Lopez also was cast as regular. On August 1, 2016, the series was renewed for a second season ahead of its television premiere which aired in a two-night premiere on June 20 and June 21, 2017. The second season premiered on OWN in a two episode special on June 20 and 21, 2017. The show was renewed for a third season on July 26, 2017. The third season premiered in a two-night special on May 29 and May 30, 2018. On August 8, 2018, the series.

Q:where does the last name waters come from

A: Wales and Yorkshire

Bywater (surname): Bywater (surname) Bywater is an uncommon English surname of Anglo-Saxon origin and can most frequently be found in the English region of Yorkshire. It is a topographical surname given to those who were situated near a body of water. Bywater is an uncommon surname of Anglo-Saxon origin. The name derives from the merger of the Old English words “bi” and “waeter” to form “biwaeter”. Topographical surnames are among the earliest created, because natural and artificial features in the.

Q:who was last person to be executed in us

A: Ruben Cardenas Ramirez

Billy Bailey: He became only the third person to be hanged in the United States since 1965 (the previous two were Charles Rodman Campbell and Westley Allan Dodd, both in Washington) and the first person hanged in Delaware in 50 years. As of 2018, he remains the last person to be executed by hanging in the United States.

Q: what is the largest ethnic group in mexico today

A: K’iche’

Mexican-American middle class: the Latino/a population of the United States is the nation’s largest racial/ethnic minority group, constituting 17.6 percent of the total population. At two thirds of the Latino/a ethnic category, Mexicans are by far the largest national origin group. .

Table 6: Examples of the top attended spurious passages in the questions where the base generator \mathcal{G} failed to generate the correct answers. The underlined phrases contradict the input queries, while those passages generally have high lexical overlap with the given input queries.

ologue system can be highly open-ended. For dialogue, we compare the average F1 score of the generated responses when i th passage is included and masked. If the average F1 when p_i is masked is higher by more than 0.1 than the F1 when p_i is

masked, we consider p_i provides useful evidence to generate the correct response, and therefore mark p_i positive. On the contrary, when the average F1 when p_i is presented is lower by more than 0.1 than the score when p_i is masked, we believe p_i can be

Q: who is in charge of enforcing the pendleton act of 1883

A: United States Civil Service Commission

1. Pendleton Civil Service Reform Act: Pendleton Civil Service Reform Act The Pendleton Civil Service Reform Act (ch. 27,) is a United States federal law enacted in 1883 that mandated that positions within the federal government should be awarded on the basis of merit.

2. United States Civil Service Commission: The Pendleton law was passed in part due to public outcry over the assassination of President Garfield.

3. Pendleton Civil Service Reform Act: The Act was written by Dorman Bridgman Eaton, a staunch opponent of the patronage system who was later first chairman of the **United States Civil Service Commission**.

Q: who plays skyler on lab rats elite force

A: Paris Berelc

1. Lab Rats: Elite Force: The series is a combined spinoff of “Lab Rats” and “Mighty Med” and stars William Brent, Bradley Steven Perry, Jake Short, **Paris Berelc**, and Kelli Berglund.

2. Lab Rats: Elite Force: Elite Force is an American comedy television series created by Chris Peterson and Bryan Moore that aired on Disney XD from March 2 to October 22, 2016. ... stars William Brent, Bradley Steven Perry, Jake Short, **Paris Berelc**, and Kelli Berglund.

3. Lab Rats: Elite Force: On September 3, 2015, it was announced that “Lab Rats” and “Mighty Med” would have a joint spinoff series called “Lab Rats: Elite Force”. Only William Brent, formerly credited as Billy Unger, and Kelli Berglund from “Lab Rats” and Bradley Steven Perry, Jake Short, and **Paris Berelc** from “Mighty Med” were announced as returning for the new spinoff series. .

Q: who developed the first periodic table with 8 columns

A: Dmitri Mendeleev

1. Periodic table: In 1923, Deming, an American chemist, published short (Mendeleev style) and medium (18-column) form periodic tables. Merck and Company prepared a handout form of Deming’s 18-column medium table, in 1928, which was widely circulated in American schools.

2. History of the periodic table: their decision by saying that such “theoretical” topics might be controversial. The importance of Newlands’ analysis was eventually recognised by the Chemistry Society with a Gold Medal five years after they recognised Mendeleev’s work.

3. History of the periodic table: the work of **Dmitri Mendeleev** had been published. In 1864, the English chemist John Newlands classified the sixty-two known elements into eight groups, based on their physical properties. Newlands noted that many pairs of similar elements existed, which differed by some multiple of eight in mass number, and was the first to assign them an atomic number.

Table 7: Examples of the passages that include the annotated answer strings but do not provide sufficient evidence to answer among the top passages retrieved by a \mathcal{R} (DPR).

highly distracting, and thus we mark p_i negative. As in fact verification, we use the top 10 passages and split them into two five-passage chunks.

B.2 Experimental Details

Implementation details of evidentiality labeling model \mathcal{M} . We use PyTorch (Paszke et al., 2019) via HuggingFace transformers RoBERTa (Liu et al., 2019) implementation. We tune our model from ROBERTa-base. We optimize the objective function using Adam (Kingma and Ba, 2015) with

learning rate 2×10^{-5} . We lowercase the input and set the maximum sequence length to 350. We train the model for 7 epochs. Per GPU batch size is 12 and we use 8 GPUs with 24 GB memory.

Training data. We mine new training data for each task using our leave-one-out generation approach and mix the data with Natural Questions (Kwiatkowski et al., 2019). For Natural Questions data, as human annotators annotate long-answer, from which final minimal an-

swers are extracted, we assume that those human annotate long answers are evidentiality-positive passages, while the other passages included in the same article are negative.

B.3 More Examples of E^{silver}

The newly mined examples can be seen in Figure 5. Although all of the passages here include the answer strings, we could see the red passages do not entail the answers. For instance, in the second example, the red passage from “The Chronicles of Narnia: Prince Caspian” only lists the names of the actors who reprise their roles from the first film, and does not mention show played ice queen. The first passage, on the other hand, clearly mentions that Tilda Swinton plays the White Witch (the ice queen) in the Chronicles of Narnia. In the third example shows that our model detects the case where we originally have distantly-positive passages, all of which are labeled as negative by our evidentiality mining model.

C More Analysis and Examples

C.1 Examples of FaVIQ-A most attended and final predictions.

Table 8 shows the most attended passages and final prediction results made by the base generator \mathcal{G} (FiD) and our evidentiality generator \mathcal{G}^+ (ours) from our qualitative analysis on FaVIQ-Ambig.

Question (Q) & Answer (A)	Evidentiality-Positive Passage	Evidentiality-Negative Passage
<p>Q: How many countries india shares borders with?</p> <p>A: seven</p>	<p>Borders of India</p> <p>India shares land borders with seven sovereign nations ...</p>	<p>India</p> <p>India is the seventh-largest country by area, the second-most populous country.</p>
<p>Q: who played ice queen in chronicles of narnia</p> <p>A: Tilda Swinton</p>	<p>Tilda Swinton</p> <p>Tilda Swinton is a British actress. She is also known for her performance as the White Witch in the "Chronicles of Narnia series" (2005–10).</p>	<p>The Chronicles of Narnia: Prince Caspian</p> <p>The Chronicles of Narnia: Prince Caspian is a 2008 American high fantasy film ... William Moseley... Tilda Swinton reprise their roles from the first film</p>
<p>Q: Season 2 this is us number of episodes</p> <p>A: 15</p>	<p>19-2 (2014 TV series)</p> <p>The first season originally aired from January 29 to April 2, 2014, while the second season aired from January 19 to March 23, 2015</p>	<p>Quantico (season 2)</p> <p>Quantico (season 2) The second season of American drama thriller series "Quantico" premiered on September 25, 2016, and concluded on May 15, 2017.</p>
<p>Q: What is the first book of percy jackson</p> <p>A: The Lightning Thief</p>	<p>The Sea of Monsters</p> <p>It is the second novel in the "Percy Jackson & the Olympians" series and the sequel to "The Lightning Thief".</p>	<p>Camp Half-Blood Chronicles</p> <p>The Lightning Thief is the first book in the Percy Jackson and the Olympians series. It features Percy Jackson.</p>
	<p>Camp Half-Blood Chronicles</p> <p>termed Book 8 in the Percy Jackson series by Amazon or the publisher. The British edition was published by Puffin Books in March as "Percy Jackson: The Ultimate Guide". "The Lightning Thief Graphic Novel" is an adaptation of "The Lightning Thief" into</p>	

Figure 5: Examples of newly mined evidentiality examples for Natural Questions.

Category 1 (40%): *Our model attends a more relevant passage.*

Claim: roger danuarta was the name of actress in munna michael as judge of dancing stars from jodhpur, rajasthan, india.

A: REFUTES

[**Ours (pred: REFUTES)**] **Munna Michael:** as Judge of Dancing Star (cameo appearance) Chitragada Singh as Judge of “Dancing Star” (cameo appearance) Pallavi Kulkarni (cameo appearance) **Roger Danuarta** (cameo appearance)

[**FiD (pred: SUPPORTS)**] **Dancing with the Stars (American season 24):** Dancing with the Stars (American season 24) The full list of celebrities and pros was announced on March 1, 2017, on Good Morning America. Hosts and judges. Tom Bergeron and Erin Andrews returned as hosts, and Carrie Ann Inaba, Len Goodman, Julianne Hough, and Bruno Tonioli returned as judges

Category 2 (10%): *FiD attends a more relevant passage.*

Claim: west was stacey’s surname in gavin and stacey before marrying.

A: SUPPORTS

[**Ours (pred: REFUTES)**] **List of Gavin & Stacey characters:** “Gavin & Stacey” is an award winning British television comedy series, following the lives of the title characters Gavin (Mathew Horne) and Stacey (Joanna Page), who, before marrying, live on opposite sides of the country, Gavin in Billericay, Essex, and Stacey in Barry, Vale of Glamorgan.

[**FiD (pred: SUPPORTS)**]**Gavin & Stacey:** Gavin & Stacey Other storylines that run throughout the course of the three series include Pam’s fake vegetarianism. Characters and cast.:Main characters. Gavin Shipman (Mathew Horne) – nicknamed “Gav”, “Gavlar”, or “Gavalar”, the funny and enthusiastic level-headed protagonist from Billericay, Essex. Stacey Shipman (“nee” **West**)

Category 3 (30%): *Both are equally irrelevant.*

Claim: sylvia fricker was the original singer of always on my mind.

A: SUPPORTS

[**Ours (pred: SUPPORTS)**] **For Once in My Life (Sylvia Syms album):** ‘For Once in My Life (Sylvia Syms album) For Once in My Life is an album by American vocalist Sylvia Syms recorded in 1967 and released on the Prestige label.

[**FiD (pred: REFUTES)**]**Follow Me...:** Follow Me... The song “You Were on My Mind” was originally recorded and released in 1964 by Ian & Sylvia, and was a major hit in the US when covered by the group We Five in 1965.

Category 4 (20%): *Both are equally relevant.*

Claim: the third party system ended in american politics in 1854.

A: REFUTES

[**Ours (pred: REFUTES)**]**Political parties in the United States:** The GOP dominated national politics during the Third Party System, **from 1854 to 1896**, and the Fourth Party System from 1896 to 1932.

[**FiD (pred: SUPPORTS)**] **Third Party System:** The Third Party System is a term of periodization used by historians and political scientists to describe the history of political parties in the United States **from 1854 until the mid-1890s.**

Table 8: Examples of the most attended passages and final prediction results made by the base generator \mathcal{G} (FiD) and our evidentiality generator \mathcal{G}^+ (ours) from our qualitative analysis on FaVIQ-Ambig.