Learning To Retrieve Prompts for In-Context Learning

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Abstract

In-context learning is a recent paradigm in natural language understanding, where a large pre-trained language model (LM) observes a test instance and a few training examples as its input, and directly decodes the output without any update to its parameters. However, performance has been shown to strongly depend on the selected training examples (termed prompt). In this work, we propose an efficient method for retrieving prompts for in-context learning using annotated data and a LM. Given an input-output pair, we estimate the probability of the output given the input and a candidate training example as the prompt, and label training examples as positive or negative based on this probability. We then train an efficient dense retriever from this data, which is used to retrieve training examples as prompts at test time. We evaluate our approach on three sequence-to-sequence tasks where language utterances are mapped to meaning representations, and find that it substantially outperforms prior work and multiple baselines across the board.

1 Introduction

The striking language skills and world knowledge embedded in large pre-trained language models (LMs) (Devlin et al., 2019; Raffel et al., 2020; Brown et al., 2020; Petroni et al., 2019) have recently led to in-context learning, a new paradigm in natural language understanding. Under this paradigm, a language model is given a prompt, which typically contains a few training examples, as well as a test instance as input, and then the LM generates the output for the test instance directly, without any update to its parameters. This approach was first introduced in GPT-3 (Brown et al., 2020), but has quickly spread to even larger LMs, such as Jurassic-1 (Lieber et al., 2021), and GLaM (Du et al., 2021).

An attractive property of in-context learning is that it provides a single model for multiple language understanding tasks. However, it has been shown that downstream performance can vary widely conditioned on the choice of in-context examples (Liu et al., 2021a). This has sparked interest in prompt retrieval (see Fig. 1), where given a test instance, training examples are chosen for the prompt based on some similarity metric. Recent work has either used off-the-shelf unsupervised similarity metrics, or trained a prompt retriever to select examples based on surface similarity (Das et al., 2021).

In this work, we suggest to use language models themselves to label examples that can serve as good prompts, and train a prompt retriever from this signal. To train the retriever (see Fig. 2), we assume access to a training set of input-output pairs and to a scoring LM, i.e., a language model that will be used to score prompts. For each training example \((x,y)\), we go over other candidate training examples, and estimate the probability, according to the scoring LM, of \(y\) conditioned on \(x\) and the
Given a training example, we use an unsupervised retriever $R_u$ to obtain a set of candidates. We then pass the candidates to a scoring LM and label the top-$k$ and the bottom-$k$ as positive and negative examples, respectively. Last, we use this training data to train a dense retriever.

Candidate prompt. We label training examples that lead to high probability as positive examples and low probability as negative examples and train a prompt retriever from this data using contrastive learning. We argue that using a LM for labeling examples is a better proxy for training a retriever compared to previously-proposed surface similarity heuristics. Importantly, when creating the training data, we have access to the gold label $y$, which can be used to obtain a high-quality set of candidate prompts. This leads to good positive examples and hard negative examples, which are beneficial for training with a contrastive objective.

Using a scoring LM to train an efficient retriever for a potentially different test time inference LM is beneficial in two scenarios. First, when the scoring LM is smaller than the inference LM and serves as a proxy for it. This results in cheap and efficient data generation for the retriever, accessible to a wide range of researchers. Second, our approach can be used even when the scoring and inference LMs are identical (e.g., both are GPT-3). This makes sense when we cannot access model weights and only use it as a service, an increasingly popular paradigm. In this case, we use the LM to train a much lighter-weight retriever that is only tasked with learning a similarity function. More generally, given that the scale of LMs is likely to keep increasing in the foreseeable future, one can view our approach for Efficient Prompt Retrieval, or EPR, as a method for interfacing and learning to interact with large LMs.

We empirically test EPR on three structured sequence-to-sequence tasks, where input natural language utterances are mapped to a meaning representation: MTOP (Li et al., 2021) and SM-CalFlow (Andreas et al., 2020), which focus on task-oriented dialogue, and BREAK (Wolfson et al., 2020), a benchmark for mapping questions to a language-based meaning representation. We observe that EPR substantially improves performance compared to prior work on prompt retrieval. When the scoring LM and inference LM are identical (using GPT-NEO (Black et al., 2021)), performance compared to the best baseline improves from 26%→31.9% on BREAK, from 57%→64.2% on MTOP, and from 51.4%→54.3% on SMCalFlow. When using GPT-NEO as a proxy for larger LMs (GPT-J, GPT-3, and CODEX), we observe similar results, where performance improves substantially in all cases.

To conclude, we propose a new approach for retrieving training examples for in-context learning in large language models, and show it substantially outperforms prior methods. Given recent developments in scaling language models, designing efficient methods for interacting with them is an important direction for future research. All of our code and data are publicly available at https://github.com/OhadRubin/EPR.

2 Background: Prompt Retrieval

Problem setup Given a training set $D = \{(x_i, y_i)\}_{i=1}^n$ of input-output sequences, and a test example $x_{\text{test}}$, our goal is to train a retriever model, $R(x_{\text{test}}, D)$, that will retrieve a subset of training examples $P = \{(x_j, y_j)\}_{j=1}^m \subset D$, where $m \ll n$. We succinctly refer to the set of training examples...
We first describe how to generate labeled data (Section 3.1), and then how to use the training data for training and inference (Section 3.2). Fig. 2 provides an overview of the training procedure.

3 Efficient Prompt Retriever

We now describe our method for training EPR, an efficient prompt retriever for in-context learning. We first describe how to generate labeled data (Section 3.1), and then how to use the training data for training and inference (Section 3.2). Fig. 2 provides an overview of the training procedure.

Prior work Liu et al. (2021a) investigated the effect of different prompts on the performance of GPT-3 and demonstrated that the choice of in-context examples strongly affects downstream performance. Consequently, they used an unsupervised sentence encoder to encode the training examples, and retrieved for every test instance the $k$ nearest training examples.

Das et al. (2021) proposed to train a supervised prompt retriever for knowledge-base question answering. The retriever was trained with supervision that is tailored for knowledge-base queries, and relies on surface similarity between formal queries. Conversely, our approach takes advantage of the generative LM itself and is thus more general.

Shin et al. (2021) used GPT-3 to select examples for the prompt in the context of few-shot semantic parsing. However, rather than training a retriever, they randomly sample a large set of question-program pairs from the training set, and choose those that are similar to the target instance question according to GPT-3. This results in an expensive inference procedure, where GPT-3 is run hundreds of times for each test instance, unlike our approach, which only uses a light-weight sub-linear retriever at test time.

3.1 Generating the Training Data

Our approach relies on finding which training examples can serve as good prompts for other training examples. Scoring all pairs of training examples is quadratic in $|D|$, and thus prohibitive. Hence, we need a method for choosing a set of candidate examples $\mathcal{E} \subset D$, from which we will choose positive and negative examples for training. Importantly, since we are not at test time and are only generating data for training, we can use the target sequence $y$ to retrieve a good set of candidates. This leads to a problem that can be attacked by simple retrievers, given that our goal is to retrieve training examples that are similar to the input in terms of their output sequence, $y$.

To obtain a high-quality candidate set of training examples, we take advantage of an unsupervised retriever, $\mathcal{E} = R_u((x, y), D)$. For the choice of the unsupervised retriever, we experiment with BM25 (Robertson and Zaragoza, 2009), a sparse retriever that relies on surface text similarity, and SBERT (Reimers and Gurevych, 2019), which is based on dense sentence encoding. For both BM25 and SBERT, we experimented with passing the retriever the training pair $(x, y)$ or the target sequence $y$ only, and found that using $y$ leads to slightly higher performance.

Scoring the candidate set Once we retrieve the set of candidates $\mathcal{E} = \{\bar{e}_1, \ldots, \bar{e}_L\}$ for a training example $(x, y)$,² we score each candidate $\bar{e}_l \in \mathcal{E}$ independently with a scoring LM, $\hat{g}$, which serves as a proxy for the inference LM, $g$. Specifically, the score for a candidate prompt is

$$s(\bar{e}_l) = \text{Prob}_g(y | \bar{e}_l, x),$$

which is the probability under the LM, $\hat{g}$, of the output sequence conditioned on the candidate prompt concatenated to the input sequence. This indicates how helpful this candidate is for decoding the target (independent of all other candidates). We argue this score is a better proxy for the utility of a training example at inference time compared to prior approaches.

We apply this scoring procedure to all training examples, and then define for each training example a set of positive examples $\mathcal{E}_{pos}$, which includes the top-$k$ candidates in $\mathcal{E}$ according to $s(\bar{e}_l)$, and a set of negative examples $\mathcal{E}_{neg}$, which includes the bottom-$k$ candidates in $\mathcal{E}$ according to $s(\bar{e}_l)$.

²The term prompt is often used to refer to a natural language template filled by an input example (Liu et al., 2021b), but here it denotes a set of training examples provided as input to the LM.

²Scoring the candidate set
This should lead to relevant positive examples, assuming that the set of candidates, $\hat{E}$ includes good prompt candidates, and hard negatives, since all candidates have high similarity with $(x, y)$ according to $R_d((x, y), D)$. With positive and negative examples at our disposal, we can now apply contrastive learning, which we describe next.

3.2 Training and Inference

Training  Our training procedure proceeds exactly like the contrastive learning procedure from DPR (Karpukhin et al., 2020). This procedure results in an input encoder $E_X(\cdot)$, which receives the sequence of input tokens, $x$, and a prompt encoder $E_P(\cdot)$, which receives a candidate prompt, namely, a concatenation of the tokens in an input-output pair. Both encoders are initialized from BERT-base (Devlin et al., 2019), and the output vector representation of both the input encoder and the prompt encoder is given by the CLS token, as usual. The goal of training is to learn a similarity metric such that given a test example $x_{\text{test}}$, it will be similar to training examples that lead to decoding of $y_{\text{test}}$.

In each training batch, we sample $B$ training examples. For every batch example $(x_b, y_b)$, we randomly sample one positive example $e_b^+$ from its corresponding set $E_{\text{pos}}^{(b)}$ and one negative example $e_b^-$ from $E_{\text{neg}}^{(b)}$. We define the similarity score between an input and an input-output pair to be the inner product $\text{score}(x, e) = E_X(x)^\top E_P(e)$. We can now define the typical contrastive learning objective and minimize for each example the negative log likelihood of the positive example:

$$L(x_b, e_b^+, e_b^-) = -\log \frac{e^{\text{score}(x_b, e_b^+)}}{\sum_{y'_b=1} e^{\text{score}(x_b, e_b^+) + e^{\text{score}(x_b, e_b^-)}}}.$$  

An advantage of this approach is that for a batch size $B$ the effective batch size is $B^2$, due to the use of the in-batch negatives trick (Henderson et al., 2017).

Inference  After training the input encoder and prompt encoder, we encode the entire set of training examples with $E_P(\cdot)$ in a pre-processing step using FAISS (Johnson et al., 2017). At test time, given an input sequence $x_{\text{test}}$, we compute its encoding $E_X(x_{\text{test}})$, and then use maximum inner-product search over the training data to find the $L$ most similar training examples, sorted by their inner product (from high to low): $\mathcal{P} = \{e_1, \ldots, e_L\}$. The final prompt $\mathcal{P}'$ is determined by the maximal context size supported by the inference LM, $g$. Specifically, $\mathcal{P}' = \{e_1, \ldots, e_{L'}\}$, where $L' \leq L$ is the largest $L'$ such that $\sum_{b=1}^{L'} |e_{i_b}| + |x_{\text{test}}| + |y'| \leq C$, where $|y'|$ is an upper bound on the length of the generated output, and $C$ is the maximal context size supported by $g$. Finally, we return the output of greedy decoding on $g(e_{L'}, e_{L'-1}, \ldots, e_1, x_{\text{test}})$.

We note that while at training time we score each training example independently, at test time the language model observes a prompt, i.e., a set of examples. We leave modeling the dependence between different training examples to future work.

4 Experimental Results

We now describe our experimental evaluation of EPR, where we compare EPR to a wide range of unsupervised and supervised baselines, both when the scoring LM, $\hat{g}$, is smaller than the inference LM, $g$, and when they are identical.

4.1 Datasets

We focus on tasks that map utterances to meaning representations, where in-context examples can be used to learn the mapping from inputs to outputs. Examples from each dataset and the number of examples are in Table 1.

- **BREAK** (Wolfson et al., 2020) is a dataset that maps complex natural language questions into a language-based meaning representation, where a question is decomposed into an ordered list of atomic steps expressed in natural language. We use the low-level BREAK subset, which provides a more fine-grained decomposition over a wide range of domains and modalities. BREAK contains 44K training examples and 8K development set examples.

- **MTOP** (Li et al., 2021) is a recent semantic parsing dataset, focused on task-oriented dialogues, where commands are mapped to complex nested queries across 11 domains, such as alarm, messaging, music, recipes, etc. Similar to past work (Pasupat et al., 2021), we use the English subset of MTOP, which contains 16K training examples and 2K development set examples.

- **SMCalFLOW** (Andreas et al., 2020) is a large English-language task-oriented dataset that covers tasks such as calendar, weather, places, and people. The meaning representation is a dataflow program, which includes API calls, function composition and complex constraints. SMCalFLOW
| Dataset     | Size | Utterance                                                                 | Meaning Representation                                                                 |
|-------------|------|---------------------------------------------------------------------------|----------------------------------------------------------------------------------------|
| BREAK       | 52K  | There are more birds in the image on the right than in the image on the left. | 1) return right image; 2) return birds in #1; 3) return number of #2; 4) return left image; 5) return birds in #4 6) return number of #5; 7) return if #3 is higher than #6; |
| MTOP        | 17K  | call Zoey’s wife.                                                         | [IN:CREATE_CALL = [SL:CONTACT = [IN:GET_CONTACT = [SL:CONTACT_RELATED = Zoey [SL:TYPE_RELATION = wife]]]] ] |
| SMCALFLOW   | 148K | Can you create me a new meeting on thursday morning?                      | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTimeConstraint (Morning) (NextDOW (Thursday))))))) |
|             |      | Schedule lunch for the late afternoon today.                              | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (& (Event.subject_? (?= "lunch") (Event.start_? (DateTimeConstraint (LateAfternoon) (Today))))))) |

Table 1: The size and 1-2 examples from each of the datasets we evaluate on.

includes 134K training examples and 15k development set examples, from which we sample a random 44K for training.

4.2 Baselines and Oracles
We consider the following unsupervised baselines, which are applied at test time only.

- **RANDOM:** we randomly sample $L$ examples from the training set $D$.
- **SBERT:** We use SentenceTransformers, a library providing BERT-based sentence embeddings. Specifically, we use paraphrase-mpnet-base-v2, a 110M parameter model to encode the test utterance $x_{test}$ and retrieve the $L$ examples with the most similar utterances for the prompt.
- **BM25:** We use the classical sparse retrieval method BM25 (Robertson and Zaragoza, 2009), which is an extension of TF-IDF, to retrieve for each test utterance $x_{test}$ the $L$ training examples with the most similar utterance.
- **BRUTEFORCE:** We apply the dynamic prompt selection method for few-shot semantic parsing from Shin et al. (2021). Given a test example $x_{test}$, we randomly sample 200 training examples. For each training example $(x_i, y_i)$, compute $\text{Prob}_y(x_{test} \mid x_i)$, and use the highest scoring examples for the prompt. Similar to us, this approach uses the inference LM to choose prompt examples. However, it does so at test time, which results in very slow inference compared to a sub-linear prompt retriever.

Next, we describe baselines that use the training set, $D$, to train a prompt retriever. All supervised methods share the following procedure. First, a candidate set $\tilde{E}$ is retrieved with the unsupervised retriever $R_u(y, D)$. We use BM25 as an unsupervised retriever, since it outperformed SBERT (see Section 4.4). Moreover, we retrieve with $y$ only, since this outperformed retrieving with the pair $(x, y)$. We then score each candidate prompt $\tilde{e}_i \in \tilde{E}$ with some scoring function, and label the top-$k$ prompts as positive examples and the bottom-$k$ as negative examples. Different supervised methods only differ in the scoring function itself.

- **DR-BM25:** Here, we use the original BM25 scores for labeling positive and negative examples and training a dense retriever.
- **CASE-BASED REASONING (CBR):** We adapt to our setup the scoring function from Das et al. (2021), who performed prompt retrieval in the context of knowledge-base question answering.

3https://www.sbert.net/index.html.
Specifically, Das et al. (2021) defined the weight for a pair of logical forms to be the $F_1$ score between the two sets of relations appearing in those logical forms, and use this weight to softly label their data. Since in our setting we do not assume logical forms, we define the score between two output sequence $y_i$ and $y_j$ to be the $F_1$ between the two sets of tokens in $y_i$ and $y_j$, omitting stop words.

- **EFFICIENT PROMPT RETRIEVAL (EPR):** Our full approach from Section 3, where we score candidate prompts with the scoring LM.

Last, we consider two oracle models.

- **BM25-ORACLE:** We score test examples using BM25 using the gold output sequence $R_{BM25}(y_{test}, D)$. This provides an upper-bound on what can be learned by DR-BM25. EPR can potentially outperform this oracle, since its training signal goes beyond surface text similarity.

- **LM-ORACLE:** We use the procedure for labeling training data at test time. Given a test example $(x_{test}, y_{test})$, we first retrieve $L$ candidate training examples with $R_{BM25}(y_{test}, D)$, then sort the candidate examples with the scoring LM $\hat{g}$, estimating the probability of $y_{test}$ given $x_{test}$ and the candidate prompt. This provides an upper bound for EPR, since EPR is trained to emulate this behaviour.

### 4.3 Experimental Details

**Language models** In this work, we only train a dense retriever, but use scoring and inference LMs. For our scoring LM, $\hat{g}$, we use GPT-Neo (Black et al., 2021), a 2.7B-parameter LM trained on The Pile (Gao et al., 2021), an 825 GB English text corpus, constructed from a wide range of high-quality resources. In addition, we consider the following inference LMs:

- **GPT-J** (Wang and Komatsuzaki, 2021): a 6B-parameter LM, also trained on The Pile. The advantage in this setup, is that GPT-J was trained on the same corpus as GPT-Neo. However, it is only 2.2x larger.

- **GPT-3** (Brown et al., 2020): A 175B-parameter model, trained mostly on a filtered subset of common crawl.

- **CODEX** (Chen et al., 2021): A 175B-parameter model, trained mostly on code from GitHub. Since our tasks involve mapping from utterances to programs or meaning representations, we consider the model, trained mostly on a filtered subset of common crawl.

**Evaluation** On BREAK, we evaluate performance with LF-EM (Hasson and Berant, 2021), proposed as an improvement to exact match (EM), as it measures whether two meaning representations are semantically equivalent. On MTREAK, and SMCALFLOW, we evaluate with EM, i.e., whether the string output by the inference LM is identical to the reference string.

We evaluate EPR in two settings: (a) LM-as-a-service, and (b) LM-as-a-proxy. In the first setting, we use GPT-Neo as both the scoring LM and inference LM. In this setting, we evaluate our approach on the full development sets of BREAK, MTOP, and SMCALFLOW. In the latter setting, as we access GPT-3 and CODEX through a paid API, we sample a random subset of 1,000 development examples from each dataset and evaluate a few methods on this subset only.

**Training details** In all cases the number of examples retrieved by the retriever $L = 50$, and the number of positive and negative examples $k = 5$. To train EPR, we use the Adam optimizer (Kingma and Ba, 2015) with batch size 120 and learning rate 1e-4 on eight RTX 3090. We run training for 30 epochs. We used the default DPR hyperparameters without tuning.

### 4.4 Results

**LM-as-a-service** Table 2 reports the results of the LM-as-a-service setup where the scoring and inference LMs are identical. We observe that EPR substantially outperforms all other baselines. Specifically it improves performance from...
Table 3: Development results on BREAK with GPT-NEO in the one-shot setting. Numbers shown are LF-EM. Full-context is the corresponding numbers from Table 2.

| Model           | One-shot | Full-context |
|-----------------|----------|--------------|
| **Unsuper.**     |          |              |
| RANDOM          | 1.1      | 1.7          |
| BM25            | 15.2     | 26.0         |
| **Super.**      |          |              |
| DR-BM25         | 14.1     | 23.6         |
| CBR             | 14.5     | 25.7         |
| EPR             | 23.0     | 31.9         |
| **Oracle**      |          |              |
| BM25-ORACLE     | 18.0     | 23.5         |
| LM-ORACLE       | 33.3     | 43.1         |
| ANYCORRECT-ORACLE| 53.6    | -            |

Table 3 shows the results of this experiment. Indeed we observe that EPR outperforms the best baseline by 8.5%, and even BM25-ORACLE by 5%. In addition, we examine ANYCORRECT-ORACLE, which tests whether any of the $L$ candidates returned by BM25 leads to the correct output. We observe that ANYCORRECT-ORACLE reaches 53.6%, 20 points above LM-ORACLE. This shows that quality of the list of candidates provided by BM25, as you can reach more than 50% LF-EM with just a single prompt. Moreover, it hints that a better scoring function can potentially further improve the efficacy of our approach.

**LM-as-a-proxy** Table 4 shows results in the setup where the scoring LM is GPT-NEO and the inference LM is a larger LM (we also report GPT-NEO for reference). First, we observe that the trends are very similar to the LM-as-a-service setup, i.e., EPR substantially outperforms prior baselines, including our best unsupervised baseline, BM25, and the best supervised baseline, CBR, by 2-8 points on all datasets and all pre-trained models. Thus, GPT-NEO serves as a good proxy for choosing training examples.

Zooming in on different inference LMs, GPT-J performs slightly better than GPT-NEO across the board. This is expected as the two models were trained on the same data and using the same procedure and only different in the number of their parameters. CODEX outperforms GPT-3, which can be explained by the fact that it was fine-tuned on code tasks, and the datasets we experiments with involve mapping to programs or meaning representations. Curiously however, GPT-J outperforms both CODEX (except on MTop) and GPT-3 despite the fact that it is 30x smaller. This perhaps can be explained by the fact that GPT-J was trained on a different dataset (The Pile (Gao et al., 2021)), but we leave investigation of whether performance with GPT-3 and CODEX can be further improved for future work.

**4.5 Analysis**

**Example prompts** Table 5 shows an example from BREAK where EPR decodes the correct output, while CBR does not. All training examples retrieved by EPR perform an argmax operation (argmin in the original utterance), and return in the final step “a code”, while the third example now closer, we can expect the advantage of EPR to be more pronounced.

**Figure**
Table 4: Results on a random sample of 1,000 examples from the development set when using GPT-Neo as a scoring LM across different inference LMs and datasets.

| Method     | RANDOM | BM25 | CBR | EPR | RANDOM | BM25 | CBR | EPR | RANDOM | BM25 | CBR | EPR |
|------------|--------|------|-----|-----|--------|------|-----|-----|--------|------|-----|-----|
| GPT-3      | 4.2    | 20.1 | 21.3| 25.3| 7.6    | 52.5 | 54.8| 62.6| 5.8    | 35.3 | 41.6| 46.5|
| CODEX      | 8.9    | 24.5 | 24.2| 29.5| 10.8   | 60.6 | 59.4| 66.1| 7.2    | 45.1 | 48.7| 50.3|
| GPT-I      | 3.3    | 26.7 | 26.7| 31.5| 8.8    | 56.6 | 58.0| 65.4| 10.6   | 50.4 | 50.9| 57.4|
| GPT-NEO    | 1.0    | 22.8 | 25.8| 29.9| 7.6    | 52.8 | 55.4| 63.6| 8.0    | 46.1 | 50.1| 53.5|

Table 5: An example from BREAK development set where EPR is correct and CBR is incorrect along with the top-3 training examples retrieved from each retriever.

| Test Example | Utterance | Meaning | Representation |
|--------------|-----------|---------|----------------|
| Top-1        | Give the code of the airport with the least flights. | 1) flights of #1 | 2) number of #2 for each #1 |
|              |           | 3) #1 where #3 is lowest | 4) code of #4 |
| Top-2        | What is the code of the city with the most students? | 1) cities | 2) students in #1 |
|              |           | 3) number of #2 for each #1 | 4) #1 where #3 is highest |
|              |           | 5) code of #4 | |
| Top-3        | Return the code of the city that has the most students. | 1) cities | 2) students in #1 |
|              |           | 3) number of #2 for each #1 | 4) #1 where #3 is highest |
|              |           | 5) code of #4 | |
|              | Find the count and code of the job has most employees. | 1) jobs | 2) employees of #1 |
|              |           | 3) number of #2 for each #1 | 4) #1 where #3 is highest |
|              |           | 5) employees of #4 | 6) number of #5 |
|              |           | 7) code of #4 | 8) #6 , #7 |
|              | What destination has the fewest number of flights? | 1) destinations | 2) flights of #1 |
|              |           | 3) number of #2 for each #1 | 4) #1 where #3 is lowest |
|              | Which destination has least number of flights? | 1) destinations | 2) flights to #1 |
|              |           | 3) number of #2 for each #1 | 4) #1 where #3 is lowest |

Recall@k of EPR To look more closely at the retrieval results of EPR, we perform the procedure for labeling positive examples using the scoring LM on the development set. We then measure, for various values of k, whether EPR returns at least one of the positive examples in its top-k prompts. We see that EPR performs quite well, retrieving at least one positive example in the top-50 prompts in more than 80% of the cases.
5 Related Work

Retrieval Research on training dense retrievers has skyrocketed recently, propelled by rising interest in open-domain question answering (Chen et al., 2017; Lee et al., 2019; Karpukhin et al., 2020; Guu et al., 2020; Khattab and Zaharia, 2020; Qu et al., 2021). Work on retrieval-based methods has also spread more widely to other knowledge-intensive tasks (Lewis et al., 2020), e.g., fact verification (Samarinas et al., 2021).

Similar to us, Pasupat et al. (2021) have recently proposed to use retrieval in the context of semantic parsing. However, their goal is not to improve in-context learning, but instead to control the output generated by a sequence-to-sequence model. Retrieval methods have also been successfully used in language modeling itself (Khandelwal et al., 2020; Borgeaud et al., 2021) and machine translation (Khandelwal et al., 2021).

Prompts Developing methods for interacting with large language models and extracting desired behaviours has attracted considerable attention recently, under the umbrella term prompting. In this work, prompts are simply a set of in-context training examples, but substantial effort has also been devoted to casting natural language tasks as language modeling by phrasing the target task in natural language (see extensive survey in (Liu et al., 2021b)). Such approaches include prompt engineering through the use of manual patterns (Petroni et al., 2019; Schick and Schütze, 2021), and also methods for extracting either hard (Shin et al., 2020; Haviv et al., 2021) or soft (Li and Liang, 2021; Zhong et al., 2021; Qin and Eisner, 2021) prompts automatically.

Constrained decoding Shin et al. (2021) used GPT-3 to select training examples for in-context learning. However, their focus was not on training a prompt retriever, but instead on representing logical forms with a pseudo-language, and applying constraints that are based on the formal language at decoding time to improve generation. Here, we do not explore constrained decoding, since this is orthogonal to our research question. However, when constraints can be applied, this is likely to further enhance performance.

6 Conclusions

Very large pre-trained LMs are becoming an inseparable part of the natural language understanding eco-system. However, accessing their weights or updating them through backpropagation can be prohibitive or even impossible for many researchers. In this work, we propose EPR, a method for learning to retrieve good prompts for in-context learning, by using language models themselves as the scoring function. This allows us to train a light-weight efficient retriever and substantially improve performance compared to strong baselines on three challenging sequence-to-sequence tasks.

More broadly, given that large language models are going to play a prominent role in developing language understanding models in the future, it is important to develop approaches for interacting with such models effectively. EPR can be viewed as a step in this direction, and future work can further expand on this idea by retrieving better training examples, composing effective prompts, and post-editing the output generated by language models.

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A Appendix

Tables 6, 7, and 8 provide more examples for cases where EPR is correct while CBR is incorrect along with the top-3 prompts for each method.
### Table 6: An example from MTTop development set where EPR is correct and CBR is incorrect along with the top-3 training examples retrieved from each retriever.

| Test Example | Utterance | EPR | CBR |
|--------------|-----------|-----|-----|
|               | Remind me to add 2 dozen eggs to my grocery list. | [IN:CREATE_REMINDER [SL:PERSON_REMINDED me ] [SL:TODO add 2 dozen eggs to my grocery list ] ] | \[IN:CREATE_REMINDER [SL:TODO a grocery list ] [SL:PERSON_REMINDED my ] [SL:DATE_TIME today ] ] |
| Top-1 | Remind me to get two bottles of water. | Please add a grocery list to my list of things to be reminded about doing today. | [IN:CREATE_REMINDER [SL:PERSON_REMINDED me ] [SL:TODO get two bottles of water ] ] | [IN:CREATE_REMINDER [SL:PERSON_REMINDED me ] [SL:TODO make a grocery list ] ] |
| Top-2 | Remind me to bring an extra pair of shoes to the river. | Remind me to make a grocery list. | [IN:CREATE_REMINDER [SL:PERSON_REMINDED me ] [SL:TODO bring an extra pair of shoes to the river ] ] | [IN:CREATE_REMINDER [SL:PERSON_REMINDED me ] [SL:TODO make a grocery list ] ] |
| Top-3 | Remind me to add bottled water to grocery list. | I need to make a grocery list; will you remind me when I get off work at 5:00 p.m.? | [IN:CREATE_REMINDER [SL:PERSON_REMINDED me ] [SL:TODO add bottled water to grocery list ] ] | [IN:CREATE_REMINDER [SL:TODO make a grocery list ] [SL:PERSON_REMINDED me ] [SL:DATE_TIME at 5:00 p.m.] ] |

### Table 7: An example from SMCALFLOW development set where EPR is correct and CBR is incorrect along with the top-3 training examples retrieved from each retriever.

| Test Example | Utterance | EPR | CBR |
|--------------|-----------|-----|-----|
|               | confirmed thanks | (PleasantryAnythingElseCombined) | Yes, but make sure to let me know the weather for that time. |
| Top-1 | it’s ok bye | (PleasantryAnythingElseCombined) | (let (x0 (Execute ("^"(Dynamic) ConfirmAndReturnAction))) (do (Yield x0) (Yield (WeatherForEvent ("^"(Dynamic) item x0)))))) |
| Top-2 | it’s ok | (PleasantryAnythingElseCombined) | Awesome, perfect |
| Top-3 | it’s ok | (PleasantryAnythingElseCombined) | Perfect... |
| Test Example | Utterance | EPR                                                                 | CBR                                                                 |
|-------------|-----------|----------------------------------------------------------------------|----------------------------------------------------------------------|
|             | Create a meeting with David Crim today | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "David Crim")))))))))) | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "David Crim")))))))))) |
| Top-1 Utterance | make a meeting with jeri today | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "jeri")))))))))) | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "jeri")))))))))) |
| Top-2 Utterance | put meeting with emlime on today | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "emlime")))))))))) | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (nextDayOfMonth (Today) 24L)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "David Largenstop")))))))))) |
| Top-3 Utterance | I want meet Dr Kennady from today | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "Dr Kennady")))))))))) | (Yield (CreateCommitEventWrapper (CreatePreflightEventWrapper (Event.start_? (DateTime.date_? (?= (Today)))) (Event.attendees_? (AttendeeListHasRecipient (Execute (refer (extensionConstraint (RecipientWithNameLike (^ (Recipient) EmptyStructConstraint) (PersonName.apply "bob")))))))))) |

Table 8: An example from SMCAFLOW development set where EPR is correct and CBR is incorrect along with the top-3 training examples retrieved from each retriever.