End-to-End Training of Multi-Document Reader and Retriever for Open-Domain Question Answering

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Abstract

We present an end-to-end differentiable training method for retrieval-augmented open-domain question answering systems that combine information from multiple retrieved documents when generating answers. We model retrieval decisions as latent variables over sets of relevant documents. Since marginalizing over sets of retrieved documents is computationally hard, we approximate this using an expectation-maximization algorithm. We iteratively estimate the value of our latent variable (the set of relevant documents for a given question) and then use this estimate to update the retriever and reader parameters. We hypothesize that such end-to-end training allows training signals to flow to the reader and then to the retriever better than stage-wise training. This results in a retriever that is able to select more relevant documents for a question and a reader that is trained on more accurate documents to generate an answer. Experiments on three benchmark datasets demonstrate that our proposed method outperforms all existing approaches of comparable size by 2-3 absolute exact match points, achieving new state-of-the-art results. Our results also demonstrate the feasibility of learning to retrieve to improve answer generation without explicit supervision of retrieval decisions.

1 Introduction

Open-domain question answering (OpenQA) is a question answering task where the goal is to train a language model to produce an answer for a given question. In contrast to many question answering tasks, an OpenQA model is only provided with the question as its input without accompanying documents that contain the answer. One of the most promising approaches to OpenQA is based on augmenting the language model with an external knowledge source such as Wikipedia (often referred to as the evidence documents). In this approach, the model consists of two core components (Chen et al., 2017): (i) an information retrieval system to identify useful pieces of text from the knowledge source (the retriever); and (ii) a system to produce the answer given the retrieved documents and the question (the reader).

We can view such a model as a latent variable model, where the latent variables represent retrieved documents that are used to produce answers given questions (Lee et al., 2019). End-to-end (joint) training of this model is challenging since we need to learn both to generate an answer given retrieved documents and what to retrieve. Previous work considers two potential solutions (see Table 1 for a high-level summary). First, they adopt a stage-wise training, where the retriever is trained while freezing the reader and vice versa (Karpukhin et al., 2020, Izacard and Grave, 2021b,a). Another
alternative is to constraint the reader to condition on each retrieved document individually\(^1\) (Guu et al., 2020)—sometimes with extra supervision for the latent variables in the form of the relevant document for a question (Lewis et al., 2020b).

In this paper, we consider a retrieval-augmented question answering model that combines information from multiple documents when generating answers. Expectation-maximization (Dempster et al., 1977) offers a principled template for learning this class of latent variable models. We present EMDR\(^2\): End-to-end training of Multi-Doc Reader and Retriever (§2). EMDR\(^2\) iteratively uses feedback from the model itself as “pseudo labels” of the latent variables for optimizing the retriever and reader parameters. We use two estimates of the latent variables: (i) prior scores for updating the reader parameters and (ii) approximate posterior scores given all observed variables for the retriever parameters.

We evaluate our proposed method by experimenting on three commonly used OpenQA datasets: Natural Questions, TriviaQA, and WebQuestions (§3). EMDR\(^2\) achieves new state-of-the-art results for models of comparable size on all datasets, outperforming recent approaches by 2-3 absolute exact match points. We also show that EMDR\(^2\) is robust to retriever initialization. It achieves high accuracy with unsupervised initialization, suggesting that supervised training of the retriever may not be an essential component of the training process as suggested in prior work (Karpukhin et al., 2020).

In summary, our contributions are as follows: (i) we present an end-to-end training method (EMDR\(^2\)) for retrieval-augmented question-answering systems; (ii) we demonstrate that EMDR\(^2\) outperforms other existing approaches of comparable size without any kind of supervision on the latent variables; (iii) we provide ablation studies for a better understanding of the contributions of different components of our proposed method; and (iv) we release our code and checkpoints to facilitate future work and for reproducibility.\(^2\)

EMDR\(^2\) is a framework that can be used to train retrieval-augmented text generation models for any task. We believe that our estimation technique in EMDR\(^2\) is also useful for learning similar latent variable models in other domains.

\footnote{This makes marginalization over the latent variables easier since we only need to consider one document at a time rather than multiple documents at once.}

\footnote{Our code is available at: https://github.com/DevSinghSachan/emdr2}

### 2 Model

Our proposed model EMDR\(^2\) consists of two components: (i) a neural retriever and (ii) a neural reader, which we train jointly in an end-to-end setting. Figure 1 shows an illustration of our model and training procedure. We discuss each component and our training objective in detail below.
2.1 Neural Retriever: Dual Encoder

Let the collection of evidence documents be denoted by \( \mathcal{D} = \{d_1, \ldots, d_M\} \). Given a question \( q \), the goal of the retriever module is to select a subset of documents \( Z \subset \mathcal{D} \) to answer the question. We model the retriever as a dual-encoder network (Bromley et al., 1994), where one encoder \( f_q \) encodes the question and another \( f_d \) encodes the evidence document (to a vector). The retrieval score is defined as the dot product between the two resulting vectors:

\[
score(q, d; \Phi) = f_q(q; \Phi_q)^\top f_d(d; \Phi_d),
\]

where \( \Phi = [\Phi_q, \Phi_d] \) denotes the retriever parameters. We select top-\( K \) documents for the question \( q \) from \( \mathcal{D} \) based on the retrieval scores. We denote the set of retrieved documents by \( Z = \{z_1, \ldots, z_K\} \).

We use transformer encoders (Vaswani et al., 2017) as our \( f_q \) and \( f_d \). Our transformer architecture is similar to BERT with 12 layers and 768 hidden size (Devlin et al., 2019). We use the final representation of the first token (i.e., the standard [CLS] token from BERT’s tokenization) as our question (and similarly document) embedding. Initializing \( f_q \) and \( f_d \) with BERT weights has been shown to lead to a poor retrieval accuracy (Lee et al., 2019, Sachan et al., 2021). Therefore, we initialize the retriever with an unsupervised training procedure. We discuss our initialization technique in detail in §3.2.

2.2 Neural Reader: Fusion-in-Decoder

The reader takes as input a question \( q \) and a set of retrieved documents (to be read) \( Z \) to generate an answer. Our reader is based on the Fusion-in-Decoder (FiD; Izacard and Grave, 2021b) model, which is built on top of T5 (Raffel et al., 2020). T5 is a pretrained sequence-to-sequence transformer that consists of an encoder \( g_e \) and a decoder \( g_d \).

In FiD, each retrieved document \( z_k \) is first appended with its title (\( t_{z_k} \)) and the question:

\[
x_k = [\text{CLS}]q[\text{SEP}]t_{z_k}[\text{SEP}]z_k[\text{SEP}],
\]

where [CLS] is used to indicate the start of a document and [SEP] is used as a separator for the different parts of the document as well as the final token.

Each \( x_k \) is then independently given as an input to the T5 encoder \( g_e \). The output representations corresponding to all of the retrieved documents are concatenated as:

\[
X_z = [g_e(x_1); \ldots; g_e(x_K)] \in \mathbb{R}^{(N \times K) \times H},
\]

where \( N \) is the number of tokens in each \( x_k \) and \( H \) is the hidden size of the T5 encoder \( g_e \). In this work, we use the T5-base configuration with \( N = 512 \) and \( H = 768 \).

\( X_z \) is then given as an input to the T5 decoder \( g_d \). When generating an answer token, the decoder attends to both previously generated tokens (i.e., causal attention) as well as the tokens encoded in \( X_z \) (i.e., cross attention). Since \( X_z \) contains information from multiple documents, the decoder has the ability to aggregate useful signals contained in multiple documents and jointly reason over them.

We define the probability of the answer as:

\[
p(a \mid q, Z; \Theta) = \prod_{t=1}^{T} p(a_t \mid a_{<t}, q, Z; \Theta), \tag{2}
\]

where \( \Theta \) denotes the reader parameters (i.e., T5 encoder and decoder) and \( T \) is the number of answer tokens. We keep generating answer tokens until the decoder outputs a special EOS token or a pre-specified maximum answer length is reached.

2.3 End-to-End Training of Reader and Retriever

In contrast to previous work on generative question answering, we train both the reader and the retriever jointly in an end-to-end differentiable fashion.

Denote our latent variable which represents a set of retrieved documents by \( Z \) and let \( Z \) be a possible value of \( Z \). The marginal likelihood of an answer (marginalizing over all the possible values of \( Z \))

\[3\]We truncate and pad as necessary such that every \( x_k \) has the same length \( N \). See §3.2 for details.
We need to be able to compute $\log p(a | q; \Phi)$, which contains trainable parameters.

We propose using two estimates of $Z$—$Z_{\text{reader}}$ and $Z_{\text{retriever}}$—for updating the two components of the model (reader parameters $\Theta$ and retriever parameters $\Phi$):

$$
\log p(a | q; Z_{\text{reader}}; \Theta) + \log p(Z_{\text{retriever}} | q; \Phi). 
$$

In the first term, we set the value of the latent variable $Z = Z_{\text{reader}}$ based on the prior scores. In the second term, we seek to maximize an approximate posterior of $Z = Z_{\text{retriever}}$. We discuss them in more detail below.

**Reader parameters $\Theta$.** For updating $\Theta$ (the first term of Eq. 3), we use the top-$K$ documents with the highest individual scores (as computed by Eq. 1 based on the current value of $\Phi$) to construct $Z_{\text{reader}}$. This is equivalent to relying on the prior $p(Z | q; \Phi)$ to estimate $Z_{\text{reader}}$ (without using information from the answer $a$). We choose to use the prior to train reader parameters since the prior scores are also used at evaluation time to obtain the top-$K$ documents. As a result, there is no mismatch between training and test computations when computing $p(a | q; Z; \Theta)$ (i.e., $Z$ that is used at test time is obtained in exactly the same way as $Z_{\text{reader}} = Z_{\text{top-K}}$).

**Retriever parameters $\Phi$.** For updating $\Phi$ (the second term of Eq. 3), we propose to use the posterior estimate. In other words, we use additional information from $a$ when evaluating $Z_{\text{retriever}}$ to train $\Phi$. Using the posterior allows our retriever to learn from richer training signals as opposed to relying only on the prior.

We need to be able to compute $p(Z_{\text{retriever}} | q, a; \Theta, \Phi)$ to maximize the retriever parameters. However, computing this quantity is difficult since it is a probability of a set.\(^4\) Consider a set of $K$ documents (e.g., $Z_{\text{top-K}}$), where $z_k$ denotes a document in the set. We approximate the maximization of the probability of the set by assuming that its probability is maximized if the sum of the probability of

\(^4\)Contrast our objective with REALM (Gau et al., 2020), where the reader only conditions on one retrieved document $z_k$ when generating an answer. In this case, the latent variable represents a document assignment instead of a set of retrieved documents.

\(^5\)This is true whether we choose to use the posterior probability or the prior probability.
We experiment with three commonly used open-domain question answering datasets: Algorithm 1:

while not converged do
    • Compute $Z_{\text{top-K}}$ using the current retriever parameters $\Phi$. // E-step
    • Compute $p(a \mid q, z_k)$ for each $z_k$ using the current reader parameters $\Theta$. // E-step
    • Update model parameters $\Theta$ and $\Phi$ to maximize the log-likelihood in Eq. 6. // M-step
end

3 Experiments

3.1 Datasets

We experiment with three commonly used open-domain question answering datasets:  

6 The intuition is that each element of the set contributes independently, which greatly simplifies the computation to find the maximum of the set.

7 We choose not to normalize with $p(a \mid q; \Theta, \Phi)$ since computing this quantity would require summing over all evidence documents $M$. While this makes the resulting objective that we optimize not correspond to a proper probability distribution anymore, we observe that our training method still behaves well in practice.
• **Natural Questions (NQ; Kwiatkowski et al., 2019).** NQ contains questions asked by users of the Google search engine. Similar to Lee et al. (2019), we use the short answer subset.

• **TriviaQA (Joshi et al., 2017).** TriviaQA is a collection of trivia question-answer pairs that were collected from multiple sources on the web.

• **WebQuestions (WebQ; Berant et al., 2013).** WebQ questions were collected using Google Suggest API and the answers were annotated using Mechanical Turk. We use the version from Chen et al. (2017) where Freebase IDs in the answers are replaced by entity names.

**Evidence documents \( D \).** We use the preprocessed English Wikipedia dump from December 2018 released by Karpukhin et al. (2020) as our evidence documents. Each Wikipedia article is split into non-overlapping 100 words long segments. Each segment corresponds to a document in our case. There are a total of 21,015,324 documents in total.

We provide descriptive statistics and other preprocessing details in Appendix A.

### 3.2 Implementation Details

**Hardware and library.** We run all of our experiments on a machine with 96 CPUs, 1.3TB physical memory, and 16 A100 GPUs. We use PyTorch (Paszke et al., 2019) to implement our proposed model and relevant baselines.

**Model configurations.** For both the retriever and reader, we use the base configuration that consists of 12 layers, 768 dimensional hidden size, and 12 attention heads. In all experiments, we retrieve 50 documents, unless stated otherwise. We only use the base configuration in our experiments due to GPU memory constraints. However, we believe that our results would generalize to larger configurations as well.

**Retrieval.** To support fast retrieval, we pre-compute evidence document embeddings and store them in a distributed fashion over all the GPUs. We refer to these document embeddings as the document index. For each question, we retrieve documents in an online (on-the-fly) manner by performing exact maximum inner product search (MIPS), implemented using asynchronous distributed matrix multiplication over the document index. These documents are converted to subwords using BERT’s tokenization and are given as input to the T5 reader. If a tokenized document is shorter than 512 tokens, it is padded using the tokens from the neighboring documents until the maximum token limit is reached. Such padding additionally helps to provide an extended context for answer generation.

**Initialization and training details.** We initialize the parameters of the model with unsupervised pre-training before performing supervised training using the question-answer training examples. Unsupervised pre-training is essential as it helps to warm-start the retriever so that it outputs relevant documents for a given question.

We first pre-train the retriever parameters with unsupervised Inverse Cloze Task training (Lee et al., 2019) for 100,000 steps. We then extract sentences containing named entities from the evidence documents. Next, we replace 15% of the named entity tokens with masked tokens, which are often referred to as masked salient spans (MSS; Guu et al., 2020). The masked sentence can be considered as the question and its salient spans (i.e., named entities) can be considered as the answer to train the model with Eq. 6. We train the model on these question-answer (masked sentence-named entities) pairs for 82,000 steps with a batch size of 64 using Adam (Kingma and Ba, 2015). We refer to this initialization method as unsupervised pre-training with masked salient spans. We provide further description in Appendix C.

After MSS training, we finetune the model on the dataset-specific question-answer training examples with EMDR\(^2\). We perform training for 10 epochs on NQ and TriviaQA with a batch size of 64, and for 20 epochs on WebQ with a batch size of 16. During training, we save a checkpoint every 500 steps and select the best checkpoint based on its performance on the development set.

During end-to-end training, since the parameters of the document encoder \( f_d \) are also updated at every step, the pre-computed document embeddings become stale as training progresses. We use the most recent document encoder checkpoint to compute fresh document embeddings asynchronously with which the document index is updated after every 500 training steps to prevent staleness.
Model | top-K | NQ | TriviaQA | WebQ | # of
<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td>dev</td>
<td>test</td>
<td>dev</td>
<td>test</td>
<td>dev</td>
</tr>
</tbody>
</table>

**Closed-Book QA Models**

<table>
<thead>
<tr>
<th>Model</th>
<th>NQ</th>
<th>TriviaQA</th>
<th>WebQ</th>
<th># of</th>
</tr>
</thead>
<tbody>
<tr>
<td>T5-base (Roberts et al., 2020)</td>
<td>0</td>
<td>-</td>
<td>25.7</td>
<td>-</td>
</tr>
<tr>
<td>T5-large (Roberts et al., 2020)</td>
<td>0</td>
<td>-</td>
<td>27.3</td>
<td>-</td>
</tr>
<tr>
<td>T5-XXL (Roberts et al., 2020)</td>
<td>0</td>
<td>-</td>
<td>32.8</td>
<td>-</td>
</tr>
<tr>
<td>GPT-3 (Brown et al., 2020)</td>
<td>0</td>
<td>-</td>
<td>29.9</td>
<td>-</td>
</tr>
</tbody>
</table>

**Open-Book QA Models**

<table>
<thead>
<tr>
<th>Model</th>
<th>NQ</th>
<th>TriviaQA</th>
<th>WebQ</th>
<th># of</th>
</tr>
</thead>
<tbody>
<tr>
<td>BM25 + BERT (Lee et al., 2019)</td>
<td>5</td>
<td>24.8</td>
<td>26.5</td>
<td>47.2</td>
</tr>
<tr>
<td>ORQA (Lee et al., 2019)</td>
<td>5</td>
<td>31.3</td>
<td>33.3</td>
<td>45.1</td>
</tr>
<tr>
<td>REALM (Guu et al., 2020)</td>
<td>5</td>
<td>38.2</td>
<td>40.4</td>
<td>-</td>
</tr>
<tr>
<td>DPR (Karpukhin et al., 2020)</td>
<td>25</td>
<td>41.5</td>
<td>-</td>
<td>56.8</td>
</tr>
<tr>
<td>ReConsider (Iyer et al., 2021)†</td>
<td>30</td>
<td>-</td>
<td>43.1</td>
<td>-</td>
</tr>
<tr>
<td>RAG-Sequence (Lewis et al., 2020b)†</td>
<td>50</td>
<td>44.0</td>
<td>44.5</td>
<td>55.8</td>
</tr>
<tr>
<td>Individual Top-K (Sachan et al., 2021)</td>
<td>-</td>
<td>-</td>
<td>45.9</td>
<td>-</td>
</tr>
<tr>
<td>Joint Top-K (Sachan et al., 2021)</td>
<td>50</td>
<td>-</td>
<td>49.2</td>
<td>-</td>
</tr>
<tr>
<td>FiD (Izacard and Grave, 2021b)</td>
<td>100</td>
<td>-</td>
<td>48.2</td>
<td>-</td>
</tr>
<tr>
<td>FiD-KD (Izacard and Grave, 2021a)</td>
<td>100</td>
<td>48.0</td>
<td>49.6</td>
<td>68.6</td>
</tr>
</tbody>
</table>

Table 2: Exact match scores on three evaluation datasets. Top-K denotes the number of retrieved documents that are used by the reader to produce an answer. To provide a fair comparison with our reimplementations, we show results from other papers with the base configuration, except for RAG-Sequence that uses BART-large (Lewis et al., 2020a). † indicates that their results on WebQ use NQ training data to pretrain the model.

**Inference.** We use greedy decoding for answer generation at inference time.

### 3.3 Baselines

We compare our model to other approaches for OpenQA that can be categorized under the following two classes:

- **Closed-book QA models.** Large-scale language models capture a lot of world knowledge in their parameters derived from the corpus they have been trained on (Petroni et al., 2019). We compare with the work of Roberts et al. (2020) who show that larger T5 models—when finetuned with question-answer pairs—can perform remarkably well. We also compare with the few-shot results of GPT-3 (Brown et al., 2020).

- **Open-book QA models.** Similar to this work, these models consist of retriever and reader components and adopt the retrieve then predict approach for answering questions given a collection of evidence documents. These models mainly differ in how the retriever is initialized (ORQA; Lee et al., 2019, DPR; Karpukhin et al., 2020), whether the reader processes a single document (ORQA, DPR, RAG; Lewis et al., 2020b) or multiple documents (FiD; Izacard and Grave, 2021b), or whether the reader and retriever are trained jointly or in a multistage process (REALM; Guu et al., 2020, FiD-KD; Izacard and Grave, 2021a).
3.4 Results

We follow standard conventions and report exact match (EM) scores using the reference answers included in each dataset. Table 2 shows our main results. We divide the table into three main sections: closed-book QA models, open-book QA models, and our implementation. The first two sections contain results from other papers, which we include for comparisons. The last section includes results from our proposed model, as well as our reimplementation of relevant baselines to control for our experimental setup.

Our reimplementation of T5-base provides strong baselines when the number of retrieved documents is set to 0 (no retrieval) and 1. From Table 2, we see that the setting of top-1 vastly improves performance over the setting with no retrieved documents, signifying the importance of retrieval for OpenQA tasks. When further increasing the top-\(k\) documents to 50, the performance of the FiD models substantially improves over the top-1 retrieval, verifying the observation from (Izacard and Grave, 2021b) about the importance of modeling the retrieved documents as a set.

Comparing EMDR\(^2\) with our reimplementation of FiD illustrates the benefit of our end-to-end training approach. The underlying model is similar in both cases, but the training method is different. FiD adopts a two-stage approach to first train the retriever and then the reader. We have three variants of FiD: (i) the reader and retriever are initialized with MSS training, (ii) the retriever is initialized with DPR training, which is the setting used in the original paper (Izacard and Grave, 2021b), and (iii) the retriever is initialized with MSS + DPR training from (Sachan et al., 2021), as it further improves DPR recall. EMDR\(^2\) outperforms all the variants by large margins on all the datasets.

The current best approach for training multi-document reader and retriever is FiD-KD (Izacard and Grave, 2021a). FiD-KD is a complex training procedure that requires multiple training stages and performs knowledge distillation with inter-attention scores. We take the results from the original paper when comparing our model with FiD-KD. EMDR\(^2\) outperforms the reported numbers of FiD-KD by more than 2.5 points on NQ and TriviaQA to obtain new state-of-the-art results on these benchmarks.

In addition to better performance, EMDR\(^2\) also has three other advantages compared to FiD-KD: (i) EMDR\(^2\) is more efficient since it only uses 50 evidence documents, whereas FiD-KD leverages 100 documents; (ii) FiD-KD is based on a distillation approach which requires multiple cycles of retriever and reader training, while EMDR\(^2\) only requires one cycle of end-to-end training; and (iii) FiD-KD relies on supervised initialization of the retriever to achieve its best performance. EMDR\(^2\) is more robust to the retriever initialization, as demonstrated by state-of-the-art results even with unsupervised initialization of the retriever.

For the WebQ dataset, the training set size is much smaller compared to the other datasets (Table 5). Previous approaches such as RAG rely on supervised transfer (i.e., they finetune a model pre-trained on NQ) to obtain good results. In contrast, EMDR\(^2\) improves over the results from this RAG model by 3.5 points without the supervised transfer step. This result demonstrates the applicability of our approach to the low-resource setting where we only have a limited number of training examples.

We also perform qualitative analysis of the model outputs, which is included in Appendix E.

3.5 Ablations

**Number of retrieved documents.** We investigate the performance of EMDR\(^2\) and FiD as we vary the number of retrieved documents \(K\) in Figure 2. We observe that when the number of retrieved documents is increased, both EMDR\(^2\) and FiD improve in performance. When \(K\) is small, the gap between EMDR\(^2\) and FiD is larger. This indicates the efficacy of EMDR\(^2\) in a more constrained setting where we can only retrieve a small number of documents (e.g., due to memory limitations).

**Retriever initialization.** We explore the effect of different parameter initialization strategies when training with EMDR\(^2\): (i) unsupervised MSS pre-training, (ii) supervised retriever training (DPR), and (iii) MSS pre-training followed by supervised retriever training (MSS + DPR, Sachan et al. (2021)). Table 3 shows our results. We can see that on NQ, MSS pre-training being unsupervised leads to a lower initial retriever recall than DPR. After EMDR\(^2\) training, the recall improves by 20% (highlighted in yellow cells). Training with DPR initialization leads to the same final recall as obtained by MSS.

\(\text{We note that GPT-3 is not trained on the full training examples that we use, so the results are not directly comparable.}\)
We compare EMDR\textsuperscript{2} objective (Eq. 6) to two alternative formulations for end-to-end training.

In the first alternative formulation, when training the retriever parameters $\Phi$, we simply factorize $p(Z \mid q; \Phi) = \prod_{k=1}^{K} p(z_k \mid q; \Phi)$ to arrive at the following objective:

$$L_{\text{alt-1}} = \log p(a \mid q, Z; \Theta) + \sum_{k=1}^{K} \log p(z_k \mid q, Z; \Phi).$$

The second term in this objective is maximized by a uniform retrieval, in other words, by removing any discrimination between documents in the retriever. We include it to show the impact of an adversarial objective.

In the second formulation, for each retrieved document, we approximate its posterior under the assumption that we have a uniform prior over the set of retrieved documents: $\tilde{p}(z_k \mid q, a, Z_{\text{top-}K}; \Theta) \propto p(a \mid q, z_k; \Theta) \times \frac{1}{K}$. We use this to train reader and retriever parameters as follows:

$$L_{\text{alt-2}} = \log p(a \mid q, Z; \Theta) + \text{KL}(\tilde{p}(z_k \mid q, a, Z_{\text{top-}K}; \Theta) \parallel p(z_k \mid q, Z; \Phi)).$$

Intuitively, we try to match the probability of retrieving a document $z_k$ with the “contribution” of that document to the generated answer $a$, regardless of whether the retriever is relatively more or less likely to retrieve the document a priori.

Table 4 shows our results on the development set of NQ. We observe that training with the adversarial objective $L_{\text{alt-1}}$ objective diverges, leading to poor performance, as expected. This shows that harming the retriever during training can significantly harm performance of the QA system. In contrast, although it disregards the estimated prior, the $L_{\text{alt-2}}$ objective still improves over the FiD baseline for NQ and
TriviaQA. However, it still lags behind EMDR². On WebQ, the $L_{alt-2}$ objective diverges and leads to a poor performance. We leave further analysis on the convergence of $L_{alt-2}$ objective as a part of future work.

4 Related Work

Our work is based on end-to-end training of neural readers and retrievers, which we discuss in §1, §2, and §3. Here we instead focus on discussing previous work related to standalone neural retrievers, neural readers, and their application in other natural language processing tasks.

Neural retrievers. There are two broad classes of neural retrievers based on the number of embeddings computed for a document: dual encoders (Yih et al., 2011, Lee et al., 2019) and multivector encoders (Khattab and Zaharia, 2020, Luan et al., 2021). Dual encoders store one embedding for each evidence document. Multivector encoders require multiple embeddings, which can be computationally expensive for large-scale retrieval. Due to the large size of the evidence document collection in OpenQA, our work uses the more efficient dual-encoder. Sachan et al. (2021) show that the performance of supervised dual encoders in OpenQA can be improved when pre-training with the Inverse Cloze Task for the high-resource setting or masked salient spans for the low-resource setting.

Neural readers. Neural readers output a result given retrieved documents as its input. There are also two broad classes of neural readers: extractive and generative. Extractive readers (Clark and Gardner, 2018, de Masson d’Autume et al., 2019, Wang et al., 2019, Guu et al., 2020, Karpukhin et al., 2020) extract a span from a retrieved document to produce an answer. Generative readers (Izacard and Grave, 2021b), on the other hand, generates an answer conditioned on the retrieved documents.

Other application areas. In addition to question answering, retrieval-augmented methods have been successfully applied to other natural language processing tasks. In left-to-right language modeling, retrieving similar words from an external memory has been shown to improve perplexity (Khandelwal et al., 2020, Yogatama et al., 2021). In machine translation, retrieving domain-specific target language tokens has improved performance in domain adaptation (Khandelwal et al., 2021). Finally, in dialog modeling, retrieving knowledge-informed text has helped improve factual correctness in the generated conversations (Fan et al., 2021).

We provide a detailed comparison of EMDR² with some of the previous work in Appendix C and D.

5 Discussion

Summary of contributions. We presented EMDR², an end-to-end training method for retrieval-augmented question answering systems. We showed how to arrive at our training objective using the expectation-maximization algorithm. We demonstrated that EMDR² achieves state-of-the-art performance on three benchmark OpenQA datasets.

Technical limitations. EMDR² shares a few limitations with other retrieval-augmented question answering models. In particular, as evidence documents are stored in an uncompressed format, maintaining them and searching for relevant documents can be expensive (both in terms of compute and memory consumption). In our experiments, we only focused on open-domain question answering. It would be interesting to see how EMDR² performs for other text generation models as well. We also note that training is relatively resource-heavy (requiring 16 GPUs), potentially having environmental concerns.

Potential negative societal impacts. While EMDR² has the potential to improve language models in the low-resource setting (as demonstrated by our results on WebQ in §3.4), it could exhibit typical biases that are associated with large language models. For example, our model does not have an explicit mechanism to generate answers that are calibrated for fairness across all spectra. As a retrieval-augmented method, it also could be more prone to generating fake answers if an attacker manages to have access and modify information in the collection of evidence documents.
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References


Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes] Please see the model (§2) and result (§3) sections that solidify the claims made in the abstract and introduction sections.

   (b) Did you describe the limitations of your work? [Yes] Please see limitations in §5.

   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Please see negative societal impact in §5.

   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...

   (a) Did you state the full set of assumptions of all theoretical results? [N/A]

   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...

   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We include the code, data, and instructions in the supplemental material and §3.2.

   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] We specify these details in the appendix included in the supplementary material.

   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] Our experiments are compute expensive and it is not feasible to perform multiple runs of the same experiment with different seeds. All our training runs use the same seed value (1234). As an alternative to running multiple seeds, we perform a number of ablation studies (§3.5).

   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] Please see §3.2 under hardware and library.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

   (a) If your work uses existing assets, did you cite the creators? [Yes] Please see §3.1 for the details.

   (b) Did you mention the license of the assets? [Yes] Our work is based on open-source data and framework. When applicable, we describe the license information in the appendix.

   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] We include our code in the supplementary material.

   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [N/A]

   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]

5. If you used crowdsourcing or conducted research with human subjects...

   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]