PEFA: Parameter-Free Adapters for Large-scale Embedding-based Retrieval Models

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ABSTRACT

Embedding-based Retrieval Models (ERMs) have emerged as a promising framework for large-scale text retrieval problems due to powerful large language models. Nevertheless, fine-tuning ERMs to reach state-of-the-art results can be expensive due to the extreme scale of data as well as the complexity of multi-stages pipelines (e.g., pre-training, fine-tuning, distillation). In this work, we propose the PEFA framework, namely **P**aram**E**ter-**F**ree **A**dapters, for fast tuning of ERMs without any backward pass in the optimization. At index building stage, PEFA equips the ERM with a non-parametric k-nearest neighbor (kNN) component. At inference stage, PEFA performs a convex combination of two scoring functions, one from the ERM and the other from the kNN. Based on the neighborhood definition, PEFA framework induces two realizations, namely PEFA-XL (i.e., extra large) using double ANN indices and PEFA-XS (i.e., extra small) using a single ANN index. Empirically, PEFA achieves significant improvement on two retrieval applications. For document retrieval, regarding Recall@100 metric, PEFA improves not only pre-trained ERMs on Trivia-QA by an average of 13.2%, but also fine-tuned ERMs on NQ-320K by an average of 5.5%, respectively. For product search, PEFA improves the Recall@100 of the fine-tuned ERMs by an average of 5.3% and 14.5%, for PEFA-XS and PEFA-XL, respectively. Our code is available at https://github.com/amzn/pecos/tree/mainline/examples/pefa-wsdm24.

CCS CONCEPTS

• **Computing methodologies** → **Supervised learning**; **Instance-based learning**.

KEYWORDS

embedding-based retrieval, bi-encoders, parameter-free adapters, k-nearest neighbor models

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1 INTRODUCTION

Given a user's query, large-scale text retrieval aims to recall a match set of semantically relevant documents in real-time from an enormous corpus, whose size can be 100 millions or more. Embedding-based retrieval models (ERMs) [6, 29, 58], namely bi-encoders [20, 43], have emerged as the prevalent paradigm for large-scale text retrieval, thanks to recent advances in large language models (LLMs). At the learning stage, ERMs fine-tune parametric Transformer encoders that map queries and documents into a semantic embedding space where relevant (query, document) pairs are close to each other and vice versa. At the inference stage, retrieving relevant documents from the enormous output space can be formulated as the maximum inner product search (MIPS) problem [60]. With proper indexing data structures, MIPS problem can be efficiently solved by approximate nearest neighbor (ANN) search libraries (e.g., Faiss [25], ScaNN [15], HNSWLIB [39]) in time sub-linear to the size of corpus.

Adapting ERMs to downstream retrieval tasks usually follows the full-parameter fine-tuning paradigm, which requires gradient computations and updates parameters of Transformer encoders. Such full-parameter fine-tuning approach faces challenges in the industrial setup, where learning signals are enormous. In modern e-commerce stores, for example, the number of relevant (query, product) pairs can be billions or more. Full-parameter fine-tuning ERMs on such scale may take thousands of GPU hours due to complicated multi-stage pipeline: pre-training [6, 12, 13], 1st stage fine-tuning with random negatives and BM25 candidates [29], 2nd stage fine-tuning with hard-mined negatives [58, 62], and 3rd stage fine-tuning with distilled knowledge from expensive cross-attention models [48, 63]. Furthermore, these fine-tuning approaches require access to models' gradient information, which is not accessible for many black box LLMs such as GPT-3 [4] and beyond.

In this work, we propose the PEFA framework (i.e., **P**aram**E**ter-**F**ree **A**dapters) for fast tuning of black-box ERMs, which doesn't

require any gradient information of the model. The scoring function of PEFA is a convex combination between the ERM and the new non-parametric k-nearest neighbor (kNN) model. The learning of kNN model reduces to constructing ANN index that stores key-value pairs of query embeddings and learning signals. Given a query at inference time, the kNN model seeks close-by training queries in the neighborhood, and aggregates the associated relevant documents as its scoring function. Depending on the definition of neighborhood, we introduce two kNN models under our PEFA framework:

- PEFA-XS: the neighborhood is defined by the relevant query-document pairs, which is independent to the test-time query.
- PEFA-XL: the neighborhood is an intersection of the one in PEFA-XS and kNN queries in the training set, which is dependent to the test-time query.

In Summary, we highlight four key contributions below.

- We propose PEFA, a novel *Parameter-free* adapters framework for fast tuning ERMs to downstream retrieval tasks.
- PEFA requires no gradient information of ERMs, hence applicable to black-box ERMs.
- PEFA is not only applicable to a wide-range of pre-trained ERM, but also effective to fine-tuned ERMs.
- We demonstrate the effectiveness and scalability of PEFA on two retrieval applications, including document retrieval tasks and industrial-scale product search tasks.

For document retrieval, PEFA not only improves the recall@100 of pre-trained ERMs on Trivia-QA by an average of 13.2%, but also lifts the recall@100 of fine-tuned ERMs on NQ-320K by an average of 5.5%. For NQ-320K dataset, applying PEFA to the fine-tuned GTR_{base} [42] reaches new state-of-the-art (SoTA) results, where the Recall@10 of 88.71% outperforms the Recall@10 of 85.20% in the previous SoTA Seq2Seq-based NCI [56], under similar model size for fair comparison. For product search consisting of billion-scale of data, PEFA improves the Recall@100 of the fine-tuned ERMs by an average of 5.3% and 14.5%, for PEFA-XS and PEFA-XL, respectively.

2 PRELIMINARY

2.1 Dense Text Retrieval

Dense text retrieval typically adopts the Embedding-based Retrieval Model (ERM) architecture, also known as bi-encoders [6, 29, 58]. For simplicity, we use the term passage/document interchangeably in the rest of paper. Given a query $q \in \mathcal{X}$ and a passage $p \in \mathcal{X}$, the relevance scoring function $f_{\text{ERM}}(q, p)$ of the ERM is measured by

$$f_{\text{ERM}}(q, p; \theta) = \left\langle E(q; \theta), E(p; \theta) \right\rangle, \tag{1}$$

where $E(\cdot; \theta) : \mathcal{X} \to \mathbb{R}^d$ is the encoder parameterized with θ that maps an input text to a d-dimensional vector space and $\langle \cdot, \cdot \rangle : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is the similarity function, including inner product and cosine similarity. Without loss of generality, we use inner product as the scoring function for the rest of paper.

Learning. Suppose the training data is presented as a set of relevant query-passage pairs $\mathcal{D} = \{(q_i, p_i)\}_{i=1}^{|\mathcal{D}|}$. The encoder parameters θ are often learned by maximizing the log-likelihood loss function [6, 29] $\max_\theta \sum_{(q,p)\in\mathcal{D}} \log p_\theta(p|q)$, where the conditional probability is defined by the Softmax function

$$p_\theta(p|q) = \frac{\exp\left(f_{\text{ERM}}(q, p; \theta)\right)}{\sum_{p' \in \mathcal{D}} \exp\left(f_{\text{ERM}}(q, p'; \theta)\right)}.$$

In practice, various negative sampling techniques [11, 29, 34, 58] have been developed to approximate the expensive partition function of the conditional Softmax. We direct interested readers to the comprehensive study [14] for more details of learning ERMs.

Inference. Given a query embedding $\boldsymbol{q} \in \mathbb{R}^d$ and a corpus of n passage embeddings $\mathcal{P} = \{\boldsymbol{p}_j\}_{j=1}^n$ where $\boldsymbol{p}_j \in \mathbb{R}^d$, $j = 1, \ldots, n$, ERMs retrieve k most relevant passages from $\mathcal{P}$ in real time, which is a Maximum Inner Product Search (MIPS) problem. Exact inference of MIPS problem requires $O(n)$ time, which is prohibited for large-scale retrieval applications. Thus, practitioners leverage Approximate Nearest Neighbor search (ANN) to approximately solve it in time *sub-linear* (e.g., $O(\log(n))$) to the size of corpus n.

To achieve sub-linear time complexity of ANN search, ANN methods require an additional *index building stage* to preprocess the corpus $\mathcal{P}$ into specific data structures, such as hierarchical graphs (e.g., HNSW [39], VAMANA [23], etc) and product quantization (e.g., FAISS [25], ScaNN [15], etc). Compared to the cost of full-parameter fine-tuning ERMs on GPU machines, the cost of building ANN index is often negligible as the latter takes place on the lower-cost single CPU machine, with much faster computational time.

2.2 Problem Statement

Notations. $\mathbf{Y} \in \{0, 1\}^{m \times n}$ is the query-to-passage relevant matrix, namely the supervised training data. The row indices of $\mathbf{Y}$ refer to the set of queries $\mathcal{Q}$, and the column indices of $\mathbf{Y}$ refer to the set of passages $\mathcal{P}$, respectively. Note that $\mathcal{P}$ is also the corpus space used for ANN inference of ERMs. The bold matrices $\mathbf{P} \in \mathbb{R}^{n \times d}$ and $\mathbf{Q} \in \mathbb{R}^{m \times d}$ denote the query and passage embeddings of $\mathcal{P}$ and $\mathcal{Q}$ obtained from the ERM, respectively. We denote $\mathbf{Y}_{i,:} \in \{0, 1\}^n$ as the relevant vector of ith query $\boldsymbol{q}_i$, representing which set of passages in $\mathcal{P}$ are relevant to this query $\boldsymbol{q}_i$. Similarly, $\mathbf{Y}_{:,j} \in \{0, 1\}^m$ is the relevant vector of jth passage $\boldsymbol{p}_j$, representing which set of queries in $\mathcal{Q}$ are relevant to this passage $\boldsymbol{p}_j$. Finally, $\hat{\boldsymbol{q}} \in \mathbb{R}^d$ is the query embeddings at inference time and $\text{NN}(\hat{\boldsymbol{q}}, \mathbf{P}; k)$ is the set of k nearest indices in the indexed database $\mathbf{P}$ given $\hat{\boldsymbol{q}}$.

Problem Setup. In this work, we propose PEFA, *parameter-free* adapters for ERMs via equipping it with a non-parametric kNN component. The non-parametric kNN model is learning-free which avoid any optimization step to fine-tune parameters of ERMs. The major computation of PEFA becomes building ANN index storing key-value pairs for serving efficiently at the inference stage. Thus, our PEFA is also applicable to both pre-trained and fine-tuned ERMs, even ones initialized from black-box LLMs. Note that PEFA is orthogonal and complement to most existing literature that aims to obtain better pre-trained or fine-tuned ERMs at the learning stage, including recent studies of the parameter-efficient fine-tuning of ERMs [28, 37, 44]. Finally, for the ease of discussion, we assume embeddings obtained from ERMs are unit-norm (i.e., ℓ_2 normalized), hence the inner product is equivalent to the cosine similarity. The techniques proposed in this paper can be easily extended to non-unit norm cases by replacing the distance metric used in kNN.

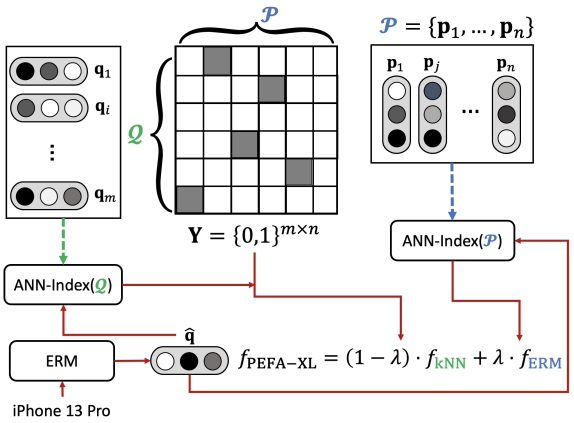


Figure 1: Illustration of the proposed PEFA-XL method. The green and blue dash line represents computation paths for building ANN index in *offline*. The red solid line represents computation paths for performing ANN search in *online*. PEFA-XL requires *two* ANN indices: one on the passage space $\mathcal{P}$ for fast inference of ERM, while the other on the query space Q for fast inference of kNN model.

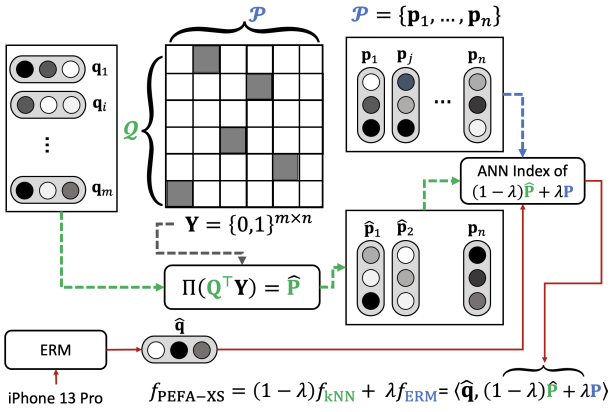


Figure 2: Illustration of the proposed PEFA-XS method. The green and blue dash line represents computation paths for building ANN index in *offline*. The red solid line represents computation paths for performing ANN search in *online*. PEFA-XS requires only *one* ANN index. As the neighborhood of kNN becomes independent to $\hat{q}$, interpolation of two score functions can be pre-computed in the embedding space, when building the ANN index *offline*.

3 PROPOSED FRAMEWORK

In this section, we propose PEFA, a *Parameter-free* Adapters framework for fast tuning of ERMs. Given a query embedding $\hat{\boldsymbol{q}}$ at inference time, our PEFA framework defines the relevant scoring function of a query-passage pair $(\hat{\boldsymbol{q}}, \boldsymbol{p}_j)$ as the convex combination between scoring functions of the black-box ERM and a non-parametric kNN model:

$$f_{\text{PEFA}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \lambda \cdot f_{\text{ERM}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) + (1-\lambda) \cdot f_{\text{kNN}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j), \quad (2)$$

where $\lambda \in [0, 1]$ is the interpolation hyper-parameter to balance the importance between the ERM and the kNN model. Note that the proposed PEFA framework is learning-free. In other words, the underlying parameters θ of ERM remains unchanged, and Equation 2 is only applied at the inference time.

Next, we present scoring functions of kNN models in a generic form as follows.

$$f_{\text{kNN}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \left\langle \hat{\boldsymbol{q}}, \mathbf{Q}^\top \mathbf{D}(\hat{\boldsymbol{q}}, \mathbf{Q}) \mathbf{Y}_{:,j} \right\rangle \quad (3)$$

where $\mathbf{D}(\hat{\boldsymbol{q}}, \mathbf{Q}) \in \mathbb{R}^{n \times n}$ is a normalized diagonal matrix, acting like a gating mechanism that controls which set of training queries the current test query $\hat{\boldsymbol{q}}$ should pay attention to.

Plugging Equation 3 back to Equation 2, we derive the scoring function of PEFA explicitly

$$f_{\text{PEFA}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \lambda \left\langle \hat{\boldsymbol{q}}, \boldsymbol{p}_j \right\rangle + (1-\lambda) \left\langle \hat{\boldsymbol{q}}, \mathbf{Q}^\top \mathbf{D}(\hat{\boldsymbol{q}}, \mathbf{Q}) \mathbf{Y}_{:,j} \right\rangle. \quad (4)$$

Based on the design of diagonal matrix $\mathbf{D}(\hat{\boldsymbol{q}}, \mathbf{Q})$, we present two realizations of kNN models under the PEFA framework, namely PEFA-XL (Section 3.1) and PEFA-XS (Section 3.2). We then discuss their intuitions, time and space complexity, and connections to the related literature. For the rest of the paper, We use HNSW [39] as the underlying ANN methods in our PEFA framework for complexity analysis and experiment results.

3.1 PEFA-XL

A standard realization of the kNN model is that the test query $\hat{\boldsymbol{q}}$ only pays attention to top-k most similar training queries in $\boldsymbol{Q}$. Specifically, $\mathbf{D}_{i,i} = 1$ if $i \in \text{NN}(\hat{\boldsymbol{q}}, \mathbf{Q}; k)$; otherwise $\mathbf{D}_{i,i} = 0$. We can then derive the kNN model of Equation 3 as following:

$$f_{\text{kNN}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \left\langle \hat{\boldsymbol{q}}, \sum_{i=1}^{n} (\mathbf{D}_{i,i} \mathbf{Y}_{i,j}) \cdot \boldsymbol{q}_i \right\rangle = \sum_{i \in \text{NN}(\hat{\boldsymbol{q}}, \mathbf{Q}; k)} \left\langle \hat{\boldsymbol{q}}, \boldsymbol{q}_i \right\rangle \cdot \mathbf{Y}_{i,j}. \quad (5)$$

By plugging the query-aware kNN model of Equation 5 into Equation 2, we present the scoring function of PEFA-XL explicitly

$$f_{\text{PEFA-XL}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \lambda \left\langle \hat{\boldsymbol{q}}, \boldsymbol{p}_j \right\rangle + (1-\lambda) \sum_{i \in \text{NN}(\hat{\boldsymbol{q}}, \mathbf{Q}; k)} \left\langle \hat{\boldsymbol{q}}, \boldsymbol{q}_i \right\rangle \cdot \mathbf{Y}_{i,j}. \quad (6)$$

Implementation. An illustration of PEFA-XL method is presented in Figure 1. Intuitively, the kNN model of PEFA-XL produces its match set by aggregating relevant passages $\mathbf{Y}_{i,j}$ of training queries $\boldsymbol{q}_i$ that are in the neighborhood of the test query $\hat{\boldsymbol{q}}$. Note that the scoring function of f_{ERM} in Equation 6 is bounded between $[-1, 1]$ as the inner product of two unit-form embeddings are bounded by the range of cosine similarity. On the other hand, the scoring function of f_{kNN} in Equation 6 needs an additional normalization so that its score is calibrated to f_{ERM}. In practice, we consider normalizing f_{kNN} by k, namely $D_{i,i} = 1/k$ if $i \in NN(\hat{\boldsymbol{q}}, \mathbf{Q}; k)$, so that f_{kNN} is still upper bounded by 1.

Complexity Analysis. At inference stage, retrieving the match set via PEFA-XL (Equation 6) requires ANN searches on **TWO** distinct output spaces. Specifically, the ERM requires ANN search on the passage space $\mathcal{P}$ of size n, while the kNN model requires ANN search on the query space $\mathcal{Q}$ of size m. According to the comprehensive review [55], the inference time complexity of HNSW

Methods	Scoring functions	HNSW index building time	HNSW index size	HNSW inference time
ERM	Equation 1	$O\big(n\log(n)\big)$	$O\big(nd + \lvert E_{\mathcal{P}}\rvert\big)$	$O\big(\log(n)\big)$
PEFA-XL	Equation 6	$O(n\log(n) + m\log(m))$	$O\big(nd + \lvert E_{\mathcal{P}}\rvert + md + \lvert E_{\mathcal{Q}}\rvert + \mathrm{nnz}(\mathbf{Y})\big)$	$O\big(\log(n) + \log(m)\big)$
PEFA-XS	Equation 8	$O\big(n\log(n)\big)$	$O\big(nd + \lvert E_{\mathcal{P}}\rvert\big)$	$O\big(\log(n)\big)$

Table 1: Comparing time and space complexity of ERM, PEFA-XS, and PEFA-XL at the inference stage. We use the competitive graph-based ANN algorithm HNSW [39] as the underlying method for ANN search. The time and space complexity of HNSW is induced from [55]. $E_{\mathcal{P}}$ and $E_{\mathcal{Q}}$ represents the edges of HNSW graph for $\mathcal{P}$ and $\mathcal{Q}$, respectively.

on a data set $\mathcal{S}$ is $O\big(\log(|\mathcal{S}|)\big)$. Thus, the inference time complexity of PEFA-XL becomes $O\big(\log(n) + \log(m)\big)$.

Next, we discuss the space complexity of PEFA-XL, which requires to store two HNSW indices as well as the query-to-passage relevant matrix $\mathbf{Y}$. The space complexity of an HNSW index on a data set $\mathcal{S}$ is $O\big(|\mathcal{S}|d + |E_{\mathcal{S}}|\big)$ where the former comes from saving the database vectors and the latter comes from saving edges of the HNSW graph. The space complexity of storing $\mathbf{Y}$ is $O\big(\mathrm{nnz}(\mathbf{Y})\big)$. Thus, the space complexity of PEFA-XL is $O\big(nd + |E_{\mathcal{P}}| + md + |E_{\mathcal{Q}}| + \mathrm{nnz}(\mathbf{Y})\big)$.

Finally, the time complexity of building HNSW indices for PEFA-XL is $O\big(n\log(n) + m\log(m)\big)$ because building a HNSW index for a set $\mathcal{S}$ takes $O\big(|\mathcal{S}|\log(|\mathcal{S}|)\big)$ [55]. The building time, inference time, and space complexity of PEFA-XL is summarized in Table 1.

Connections to kNN-LM. Using a non-parametric kNN model to improve a parametric neural network has also been studied in the context of k nearest neighbors language modeling (kNN-LM) [17, 30, 59] and retrieval-augmented LM pre-training [3, 16, 32]. kNN-LM interpolates the next-token predictive probability by the neural language model and the kNN model. While sharing similar intuitions, PEFA-XL is different from kNN-LM because PEFA-XL requires two ANN searches, one on the passage space $\mathcal{P}$ and the other on the query space $\mathcal{Q}$. In contrast, kNN-LM only needs one ANN search on the context space, while inference on the vocab space is exact since the size of vocabulary is small.

3.2 PEFA-XS

In practice, PEFA-XL can be too expensive to deploy due to storing two ANN indices, which double the model storage and inference latency. Thus, we seek an efficient alternative of PEFA-XL that only needs to maintain single ANN index, hence the name PEFA-XS.

Recall that PEFA-XL demands another ANN search because of finding k nearest queries in $\mathcal{Q}$, namely $\mathrm{NN}(\hat{\boldsymbol{q}}, \mathcal{Q}; k)$. We can approximate $\mathrm{NN}(\hat{\boldsymbol{q}}, \mathcal{Q}; k)$ by the set of relevant queries given a target passage $\boldsymbol{p}_j \in \mathcal{P}$. We denote this alternative query set as $\mathcal{I}(\boldsymbol{p}_j, \mathbf{Y}) = \{i | \mathbf{Y}_{ij} > 0, i = 1, \ldots, n\}$, which is a function of $\boldsymbol{p}_j$ that is independent to the test query $\hat{\boldsymbol{q}}$. In other words, the resulting diagonal matrix $\mathbf{D}_{i,i} = 1$ if $i \in \mathcal{I}(\boldsymbol{p}_j, \mathbf{Y})$; other $\mathbf{D}_{i,i} = 0$. The approximate kNN model of PEFA-XS becomes

$$f_{\mathrm{kNN}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \Big\langle \hat{\boldsymbol{q}}, \sum_{i \in \mathcal{I}(\boldsymbol{p}_j, \mathbf{Y})} \mathbf{Y}_{i,j} \cdot \boldsymbol{q}_i \Big\rangle = \big\langle \hat{\boldsymbol{q}}, \mathbf{Q}^\top \mathbf{Y}_{:,j} \big\rangle. \tag{7}$$

By plugging the query-independent kNN model of Equation 7 back to Equation 2, we present the scoring function of PEFA-XS

$$f_{\text{PEFA-XS}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \lambda \big\langle \hat{\boldsymbol{q}}, \boldsymbol{p}_j \big\rangle + (1 - \lambda) \big\langle \hat{\boldsymbol{q}}, \mathbf{Q}^\top \mathbf{Y}_{:,j} \big\rangle.$$

Implementation. An illustration of PEFA-XS method is presented in Figure 2. Similar to the implementation design of PEFA-XL, we need to normalize the scoring function of f_{kNN} in Equation 7 such that its score is upper bounded by 1. Thus, we introduce an ℓ_2 normalization operator $\Pi(\boldsymbol{x}) = \frac{\boldsymbol{x}}{\|\boldsymbol{x}\|}$ that projects an embedding back to the unit-sphere. We can then rewrite the scoring function of PEFA-XS as

$$f_{\text{PEFA-XS}}(\hat{\boldsymbol{q}}, \boldsymbol{p}_j) = \big\langle \hat{\boldsymbol{q}}, \lambda \cdot \boldsymbol{p}_j + (1 - \lambda) \cdot \Pi(\mathbf{Q}^\top \mathbf{Y}_{:,j}) \big\rangle, \tag{8}$$

where normalization step $\Pi(\cdot)$ can be absorbed in the design of $\mathbf{D}$.

Complexity Analysis. Note that the kNN model of PEFA-XS is independent to the test query $\hat{\boldsymbol{q}}$, so the interpolation of two scoring functions can be pre-computed in the embedding space, as derived in Equation 8. This suggests that PEFA-XS only requires a single ANN index, where a set of n interpolated passage embeddings are used. Therefore, the inference of PEFA-XS share the same time and space complexity as ERM alone. Specifically, the time complexity of constructing HNSW index and performing ANN search are $O\big(n\log(n)\big)$ and $O\big(\log(n)\big)$, respectively. The space complexity of storing ANN index is $O(nd + |E_{\mathcal{P}}|)$. Finally, the time and space complexity of PEFA-XS is summarized in Table 1.

Connections to XMC. Given a passage, aggregating its relevant (as defined by customer behavior signals) query embeddings to be an alternative passage embeddings of itself has also been explored in the extreme multi-label classification (XMC) literature. Specifically, XMC community terms such representation as **P**ostive **I**nstance **F**eature **A**ggregation, namely PIFA embeddings [5, 22, 61, 64]. However, PIFA embeddings are often an aggregation of sparse tfidf features, and mostly used for unsupervised clustering to partition label space in the XMC literature [61]. In contrast, PEFA-XS interpolates such alternative passage embeddings with the original passage embeddings, and conduct ANN search on the interpolated ASIN embedding space. As a side note, PIFA embeddings are also closely connected to the simple graph convolution layer in graph neural network [8, 36, 57], where the input-to-label relevant matrix is viewed as a bipartite graph.

4 EXPERIMENTS ON DOCUMENT RETRIEVAL

In this section, we empirically verify the effectiveness of PEFA on the document retrieval task. Experiment code is available at https://github.com/amzn/pecos/tree/mainline/examples/pefa-wsdm24.

4.1 Datasets & Evaluation Protocols

Datasets. We conducted experiments on two public benchmarks for document retrieval, namely the Natural Questions [31] dataset and the Trivia-QA [27] dataset.

- Natural Questions [31]: a open-domain question answering dataset which consists of 320k query-document pairs, where the documents containing answers are gathered from Wikipedia and the queries are natural questions. The version we use is often referred to as NQ-320K [2, 53, 56].
- Trivia-QA [27]: a reading comprehension dataset which includes 78k query-document pairs from the Wikipedia domain. We use the same version as in [56].

The State-of-the-art (SoTA) method, namely NCI [56] consider generated query-document pairs as additional training signals in NQ-320K and Trivia-QA datasets. Following the same setup of NCI [56], we also include those augmented query-document pairs when learning PEFA on NQ-320K and Trivia-QA datasets.

Evaluation Protocols. We measure the performance with recall metrics, which are widely-used in retrieval communities [6, 29, 41, 53, 56]. Specifically, given a predicted score vector $\hat{\boldsymbol{y}} \in \mathbb{R}^n$ and a ground truth label vector $\boldsymbol{y} \in \{0,1\}^n$, Recall@k is defined as Recall@$k = \frac{1}{|\boldsymbol{y}|} \sum_{j \in \text{top}_k(\hat{\boldsymbol{y}})} \boldsymbol{y}_j$ where $\text{top}_k(\hat{\boldsymbol{y}})$ denotes labels with the k largest predicted scores.

4.2 Implementation Details

Comparison Methods. Our PEFA framework is applicable to any black-box ERMs. We applied PEFA to various competitive ERMs, such as Sent-BERT$_{\text{distill}}$ [45], DPR$_{\text{base}}$ [29], MPNet$_{\text{base}}$ [50], Sentence-T5$_{\text{base}}$ [41] and GTR$_{\text{base}}$ [42]. We also compare PEFA with recent SoTA Sequence-to-Sequence (Seq2Seq) models, including Differentiable Search Index (DSI) [53], Search Engines with Autoregressive LMs (SEAL) [2] and Neural Corpus Indexer (NCI)[56].

Hyper-parameters. PEFA have two hyper-parameters, the interpolation coefficient λ in Eq. 2 and the number of nearest neighbors k in Eq. 6 used by PEFA-XL only. We present ablation studies on hyper-parameters in Section 4.4 where $\lambda = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ and $k = \{16, 32, 64\}$. For $\lambda = 1.0$, PEFA reduce back to its baseline ERM. We consider HNSW for ANN search and set hyper-parameters according to existing work [5, 38, 43]. At the index building stage, the maximum edge per node $M = 32$ and the size of priority queue for graph construction $efC = 500$. At the online serving stage, the beam search width for graph search $efS = 300$.

4.3 Main Results

NQ-320K. In Table 2, we applied PEFA-XS and PEFA-XL to fine-tuned ERMs: Sent-BERT$_{\text{distill}}$ [45], DPR$_{\text{base}}$ [29], MPNet$_{\text{base}}$ [50], Sentence-T5$_{\text{base}}$ [41] and GTR$_{\text{base}}$ [42]. These ERMs were full parameter fine-tuned on the NQ-320K dataset. The proposed PEFA framework achieved significant improvement for a wide range of black-box ERMs. The average gain of PEFA-XS over ERMs are +9.22% and +5.29%, for Recall@10 and Recall@100, respectively. The average gain of PEFA-XL over ERMs are +11.33% and +5.20% for Recall@10 and Recall@100, respectively. For competitive ERMs such as MPNet$_{\text{base}}$ [51] and GTR$_{\text{base}}$ [42], **PEFA further outperform the previous SoTA Seq2Seq method, namely NCI [56].** The Recall@10 and Recall@100 of MPNet$_{\text{base}}$ +PEFA-XL are 88.72% and 94.13%, which is considerably better than the previous SoTA NCI. On the other hand, the original MPNet$_{\text{base}}$ without PEFA can not outperform the previous SOTA method, NCI.

Methods	Recall@10	Recall@100
BM-25	32.48	50.54
DSI (base) [53]	56.60	-
NCI (base) [56]	85.20	92.42
SEAL (large) [2]	81.24	90.93
Sent-BERT$_{\text{distill}}$ [45]	67.08	81.40
+PEFA-XS (ours)	80.52	92.22
+PEFA-XL (ours)	85.26	92.53
DPR$_{\text{base}}$ [29]	70.68	85.19
+PEFA-XS (ours)	83.45	92.22
+PEFA-XL (ours)	84.65	92.07
MPNet$_{\text{base}}$ [50]	80.82	92.39
+PEFA-XS (ours)	86.67	<u>94.53</u>
+PEFA-XL (ours)	**88.72**	**95.13**
Sentence-T5$_{\text{base}}$ [41]	73.63	88.16
+PEFA-XS (ours)	82.52	92.18
+PEFA-XL (ours)	83.69	92.55
GTR$_{\text{base}}$ [42]	79.74	90.91
+PEFA-XS (ours)	84.90	93.28
+PEFA-XL (ours)	<u>88.71</u>	94.36
Avg. Gain of PEFA-XS over ERM	+9.22	+5.28
Avg. Gain of PEFA-XL over ERM	+11.82	+5.72

Table 2: Our PEFA framework on NQ-320K dataset. Both Seq2Seq models and ERMs are full-parameter fine-tuned. The results of BM-25, DSI [53], NCI [56] and SEAL [2] are taken from [56]. 1st/2nd place numbers are boldface/<u>underscore</u>, respectively.

Trivia-QA. In Table 3, we applied PEFA-XS and PEFA-XL to pre-trained ERMs. Note that these ERMs were not fine-tuned with any relevant query-document pairs from Trivia-QA. The setup examines the robustness and generalization of our PEFA framework. We observe PEFA-XS and PEFA-XL achieve larger average gain of Recall over the unsupervised ERMs, when comparing Table 3 to Table 2. When the underlying ERM are pre-traiend only (not fine-tuned to the downstream task), PEFA-XS seems to perform slightly better than PEFA-XL in Recall@20, where the former has an average gain of 18.67% while the latter has an average gain of 17.07%.

4.4 Ablation Studies

In Table 4, we present ablation studies of two hyper-parameters of our PEFA framework on the NQ-320K dataset. λ is the interpolation coefficient that balances f_{ERM} and f_{kNN} in Equation 2. When $0.0 < \lambda < 1.0$, the Recall@100 of both PEFA-XS and PEFA-XL are consistently higher the ERM alone ($\lambda = 1.0$). For PEFA-XS and PEFA-XL, $\lambda = 0.5$ and $\lambda = 0.1$ mostly yield the largest gain in average, respectively. Crucially, the linear interpolation of PEFA-XS can be pre-computed offline at the HNSW index building stage (see Figure 2) hence did not increase any inference latency overhead compared to the ERMs. For PEFA-XL, besides the hyper-parameter λ, it has another hyper-parameter k, controlling the number of nearest neighbors in the kNN model f_{kNN}. We observed that $k = 32$ generally saturate the performance.

Methods	Recall@20	Recall@100
BM-25	69.45	80.24
NCI (base) [56]	**94.45**	**96.94**
SEAL (large) [2]	81.24	90.93
Sent-BERT$_{\text{distill}}$ [45]	51.94	68.50
+PEFA-XS (ours)	<u>86.28</u>	<u>93.33</u>
+PEFA-XL (ours)	83.76	91.83
DPR$_{\text{base}}$ [29]	60.69	73.80
+PEFA-XS (ours)	82.97	91.06
+PEFA-XL (ours)	78.76	89.62
MPNet$_{\text{base}}$ [50]	77.03	87.34
+PEFA-XS (ours)	86.05	92.97
+PEFA-XL (ours)	86.13	92.42
Sentence-T5$_{\text{base}}$ [41]	62.74	77.21
+PEFA-XS (ours)	78.39	88.57
+PEFA-XL (ours)	75.13	87.24
GTR$_{\text{base}}$ [42]	71.75	82.05
+PEFA-XS (ours)	83.81	91.02
+PEFA-XL (ours)	85.30	92.38
Avg. Gain of PEFA-XS over ERM	+18.67	+13.61
Avg. Gain of PEFA-XL over ERM	+17.07	+12.80

Table 3: Our PEFA framework on Trivia-QA dataset. Seq2Seq models are full-parameter fine-tuned while ERMs are unsupervisedly pre-trained. ERMs +PEFA did not fine-tune or update any parameter of the underlying ERMs. 1st/2nd place numbers are boldface/<u>underscore</u>, respectively.

ERM	PEFA	Recall@100 of various λ				
		0.1	0.3	0.5	0.7	0.9
DPR$_{\text{base}}$	PEFA-XS	91.48	92.22	91.71	89.87	87.08
	PEFA-XL (k=16)	91.98	90.66	89.72	88.54	87.62
	PEFA-XL (k=32)	92.07	90.50	89.20	88.62	87.46
	PEFA-XL (k=64)	91.93	89.89	88.95	88.39	87.04
Sentence-T5$_{\text{base}}$	PEFA-XS	91.23	92.16	92.20	91.61	89.72
	PEFA-XL (k=16)	92.53	91.25	90.82	90.69	90.24
	PEFA-XL (k=32)	92.34	91.20	90.96	90.77	90.11
	PEFA-XL (k=64)	92.22	91.26	91.03	90.70	89.90
GTR$_{\text{base}}$	PEFA-XS	92.11	93.07	93.31	92.85	91.74
	PEFA-XL (k=16)	94.36	93.32	92.81	92.53	91.93
	PEFA-XL (k=32)	94.32	93.23	92.82	92.44	91.79
	PEFA-XL (k=64)	93.93	93.14	92.76	92.29	91.62

Table 4: Ablation study of our PEFA framework on NQ-320K dataset. PEFA-XS has only one hyper-parameter, namely the interpolation coefficient λ. PEFA-XL has two hyper-parameters: λ and k (number of nearest neighbors). For $\lambda = 1.0$, PEFA-XS and PEFA-XL reduce to the same underlying ERM in Table 2.

5 EXPERIMENTS ON PRODUCT SEARCH

For large-scale product search system, full-parameter fine-tuning may take thousands of GPU hours. In this section, we conducted experiments on such larger-scale datasets and demonstrated that our PEFA framework is an effective and fast technique that offers sizable improvements to not only a variety of pre-trained ERMs but also the full-parameter fine-tuned ERMs.

5.1 Datasets & Evaluation Protocols

Datasets. We follow similar procedure [5, 26, 36, 43], to collect datasets from a large e-commerce product search engine. Based on the size of catalog $n = |\mathcal{P}|$, we construct three subsets as follows.

- ProdSearch-5M: consists of roughly 30 millions of relevant query-product pairs, which covers around 10 millions of queries and 5 millions of products.
- ProdSearch-15M: consists of roughly 150 millions of relevant query-product pairs, which covers around 40 millions of queries and 15 millions of products.
- ProdSearch-30M: consists of roughly 500 millions of relevant query-product pairs, which covers around 100 millions of queries and 30 millions of products.

For all proprietary ProdSearch datasets, the data statistics do not reflect the real traffic of the e-commerce system due to privacy concerns. All relevant query-product pairs are random samples from anonymous aggregated search log. We further split those pairs into the training set and the test set by time horizon, where we use first twelve months of search logs as the training set and the last one month of search logs as the evaluation test set.

Evaluation Protocol. To eliminate evaluation bias toward our PEFA framework, all test queries are *unseen* in the training set. To avoid disclosing the exact performance of production systems, we report absolute gain of Recall@k metrics between the proposed PEFA framework and the baseline ERMs.

We also report the ANN index size (GiB) and the index building time (hours) in offline indexing stage. For online inference, following the ANN benchmark protocol [1], we consider the single thread setup and report the inference latency (milliseconds/query).

5.2 Main Results

In Table 5, we applied PEFA to pre-trained ERMs (e.g., MPNet$_{\text{base}}$ [50], Sentence-T5$_{\text{base}}$ [41], GTR$_{\text{base}}$ [42] and E5$_{\text{base}}$ [54]) and the fine-tuned ERMs (FT-ERM [40]). For privacy of the proprietary product search datasets, we only report the absolute gain of Recall metrics compared to the MPNet$_{\text{base}}$ baseline.

Without PEFA, pre-trained ERMs have much lower Recall metrics compared to FT-ERM, as the latter is carefully pre-trained and fine-tuned. Adding PEFA-XS and PEFA-XL to those pre-trained ERMs significantly lift the Recall to comparable, or even outperform, the fine-tuned FT-ERM. Take the largest dataset ProdSearch-30M as an example. Adding PEFA-XL to Sentence-T5$_{\text{base}}$, GTR$_{\text{base}}$ and E5$_{\text{base}}$ have a Recall@100 gain of 30.10%, 31.71% and 31.91%, respectively. These recall@100 gain is already outperform the Recall@100 of fine-tuned FT-ERM. On the other hand, PEFA-XS on pre-trained ERMs offer smaller Recall gain compared to PEFA-XL. Only E5$_{\text{base}}$ +PEFA-XS have a larger Recall@100 gain compared to the fine-tuned FT-ERM.

Similar to the finding of NQ-320K, we also see that PEFA can further improve the performance of fine-tuned ERMs. For example, on the largest dataset ProdSearch-30M, PEFA-XS and PEFA-XL further improve the Recall@100 of the fine-tuned FT-ERM by 5.3% and 14.50%, respectively.

Methods	ProdSearch-5M		ProdSearch-15M		ProdSearch-30M	
	Recall@100	Recall@1000	Recall@100	Recall@1000	Recall@100	Recall@1000
$\text{MPNet}_{\text{base}}$ [50]	0.00	0.00	0.00	0.00	0.00	0.00
+PEFA-XS (ours)	11.23	13.14	5.05	11.79	9.67	17.47
+PEFA-XL (ours)	22.83	12.31	23.48	21.56	27.22	18.96
$\text{Sentence-T5}_{\text{base}}$ [41]	0.44	3.42	1.32	3.44	1.89	5.17
+PEFA-XS (ours)	13.63	17.13	10.39	16.34	13.18	21.28
+PEFA-XL (ours)	23.09	13.43	23.91	23.72	30.10	21.25
GTR_{base} [42]	7.85	9.23	6.75	10.33	8.35	9.83
+PEFA-XS (ours)	17.32	19.55	16.83	25.00	18.49	24.38
+PEFA-XL (ours)	<u>27.79</u>	19.23	27.87	28.75	31.71	24.28
E5_{base} [54]	9.93	9.75	9.98	12.98	12.01	12.61
+PEFA-XS (ours)	19.23	19.18	17.21	27.78	20.11	26.08
+PEFA-XL (ours)	26.83	17.75	<u>30.48</u>	31.07	<u>31.91</u>	25.49
FT-ERM [40]	21.32	20.87	21.74	30.04	18.49	24.11
+PEFA-XS (ours)	23.42	<u>22.17</u>	26.34	<u>34.84</u>	23.79	<u>29.61</u>
+PEFA-XL (ours)	**29.32**	**22.87**	**36.54**	**37.24**	**32.99**	**30.01**
Avg. Gain of PEFA-XS	16.97	18.23	15.16	23.15	17.05	23.76
Avg. Gain of PEFA-XL	25.97	17.12	28.46	28.47	30.79	24.00

Table 5: Applying PEFA to pre-trained ERMs ($\text{MPNet}_{\text{base}}$ [50], $\text{Sentence-T5}_{\text{base}}$ [41], GTR_{base} [42] and E5_{base} [54]) and the fine-tuned ERMs (FT-ERM [40]) on three proprietary product search datasets: ProdSearch-5M, ProdSearch-15M and ProdSearch-30M. To avoid disclosing the exact performance of production systems for privacy concerns, all reported numbers are absolute gain of Recall metrics compared to the baseline method $\text{MPNet}_{\text{base}}$. 1st/2nd place numbers are boldface/<u>underscore</u>, respectively.

5.3 Indexing and Inference

In Table 6, we discuss the trade-off between the performance and the deployment efficiency for the proposed PEFA framework. Note that PEFA is a parameter-free method without updating model parameters of ERMs, which can be easily implemented in the offline HNSW index building stage. For the largest dataset ProdSearch-30M, the run-time of building HNSW indices for PEFA-XS and PEFA-XL are 1.0 and 4.7 hours, respectively. This is much faster than hundred of GPU hours when fine-tuning the FT-ERM on the billion-scale dataset.

Despite larger gain in recall metrics, PEFA-XL comes at the cost of larger HNSW index, longer index building time, and larger inference latency. Specifically, the HNSW index size of PEFA-XL is 3.6x larger than the HNSW index of ERM, as PEFA-XL requires two HNSW indices: One HNSW index on the product embeddings $\mathbf{P} \in \mathbb{R}^{n \times d}$, while the other HNSW index on the training query embeddings $\mathbf{Q} \in \mathbb{R}^{m \times d}$ for the kNN modeling. For product search datasets, the number of queries m can be larger than the number of products n. Due to similar reasons, the inference latency of PEFA-XL is 2.4x larger than the latency of ERM.

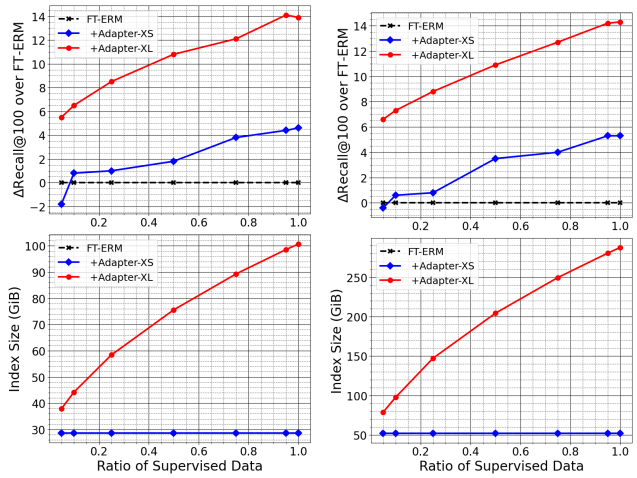
On the other hand, PEFA-XS not only achieves modest gains of recall metrics, but also maintains the same deployment efficiency (e.g., HNSW index size and inference latency) as its baseline ERM. Recall that PEFA-XS maintains only one ANN index because the interpolation of f_{ERM} and f_{kNN} is independent to test-time query, which can be pre-computed offline in a single ANN index (see Equation 8 in Section 3.2). From the deployment perspective, PEFA-XS may be a more practical choice as it introduces zero additional overhead to the production system at inference time.

Datasets	Methods	Indexing		Serving
		disk-size	run-time	Latency
ProdSearch-5M	FT-ERM	13.1	0.3	0.82
	+PEFA-XS	13.1	0.2	0.67
	+PEFA-XL	32.2	0.7	2.15
ProdSearch-15M	FT-ERM	28.6	0.6	0.91
	+PEFA-XS	28.6	0.5	0.94
	+PEFA-XL	100.7	1.9	1.94
ProdSearch-30M	FT-ERM	51.9	0.9	0.77
	+PEFA-XS	51.9	1.0	0.71
	+PEFA-XL	287.7	4.7	1.99

Table 6: For practical deployment consideration, we report the HNSW index size on disk (GiB) and the run-time (hours) of PEFA during offline index building stage. We also report the inference latency (millisecond/query) of the HNSW index for online serving.

5.4 Effect of Supervised Data Size

The amount of supervised data (i.e., relevant query-product pairs) consumed by PEFA plays a crucial role to the predictive power of PEFA-XS and PEFA-XL, run-time of HNSW index building, and the model size of resulting HNSW indices. Hence, we present such analysis in Figure 3. The amount of supervised data is controlled by the sampling ratio $\{0.05, 0.10, 0.25, 0.50, 0.75, 0.95\}$. In particular, we uniformly sample query-product pairs from the relevance matrix $\mathbf{Y} \in \{0, 1\}^{n \times m}$ in Equation 3.



(a) ProdSearch-15M (b) ProdSearch-30M

Figure 3: The amount of supervised data versus predictive power and model size for the proposed PEFA framework. The y-axis of the 1st row figures is the recall gain compared to the FT-ERM (black line). The y-axis of the 2nd row figures is the PEFA model size (GiB). The x-axis of all figures is the ratio of supervised data being used.

With 10% of the relevant query-product pairs sampled from $\mathbf{Y}$, PEFA-XS reaches the same level of Recall@100 compared to the fine-tuned FT-ERM. With more supervised data, PEFA-XS outperforms FT-ERM eventually. What's more, the model size of PEFA-XS do not increase as it consumes more supervised data.

For PEFA-XL, interestingly, it can achieve significant improvements in Recall@100 even with just 5% of the supervised data. At 5% of the supervised data usage, the resulting HNSW index is around 1.4x times larger than the HNSW index of FT-ERM and PEFA-XS. Also, the inference latency of PEFA-XL seems to be consistently 2x larger than the latency of FT-ERM and PEFA-XS across all datasets. Again, it is up to the practitioners to decide the trade-off between the additional performance gain brought by PEFA-XL and the cost of larger index size and inference latency.

6 RELATED WORK

6.1 Dense Text Retrieval

DSSM [21] and C-DSSM [49] utilize multi-layer perceptron and convolutional neural networks while DPR [29] deploys pre-trained neural language models (NLMs) like BERT [10]. Some studies attempt to improve ERMs by pre-training and adjusting results. Condenser [12] pre-trains NLMs with the idea of Funnel-Transformer [9] while Co-Condenser [13] re-ranks its retrieval results with an attentive cross-encoder. DPTDR [52] applies prompt-tuning [35] to further improve the quality dual encoders for ERMs. However, conventional ERMs could suffer from dealing with tail queries and labels, especially when we have an enormous industry-scale index [46]. Even though some lines of research attempt to address this issue by computing label-centric similarity [47] and multi-view representations [65], they are infeasible for industrial production due to the requirement of extensive pre-training and additional cross-attentive computations between queries and labels.

Different from existing approaches, our PEFA has no need of pre-training another embedding model, so the enhancement can be achieved within an acceptable short period of only ANN search indexing. Moreover, the kNN model of training queries can further benefit the representation capability of PEFA embedding.

6.2 Inference with Training Instances

Similar to our proposed PEFA framework, some studies also leverage training instances in inference for better performance in various research fields. k nearest neighbors language modeling (kNN-LM) [17, 30, 59] build a kNN model within the small vocabulary space while PIFA embeddings [5, 22, 61, 64] aggregate sparse representations of training instances for the label space. The derived coresets of training embeddings can be indexed with ANN search to shrink candidate labels and accelerate inference for recommender systems [24] and neural language models [7]. However, none of the above methods addresses the challenge of large-scale retrieval in an industry scale.

6.3 Parameter-Efficient Tuning of ERMs

To avoid the expensive full-parameter fine-tuning of ERMs for various downstream tasks, there are some preliminary studies on parameter-efficient fine-tuning of ERMs [28, 37, 44]. Nevertheless, as pointed out by [37], naively apply existing parameter-efficient fine-tuning methods in the NLP literature, such as Adapter [18], prefix-tuning [33] and LoRA [19], often results in limited success for ERM in the retrieval applications. Furthermore, parameter-efficient fine-tuning approaches still require access to the models' gradient, which may not be available for the recent powerful large language models (LLMs) such as GPT-3 [4]. Our proposed PEFA framework is complementary to any pre-trained and fine-tuned ERMs, namely including ERMs derived from parameter-efficient fine-tuning. Notice that our PEFA did not require any gradient information of the underlying ERMs, which can have a broader impact to black-box ERMs where the encoders are initialized from LLMs.

7 CONCLUSIONS

In this paper, we propose PEFA, *parameter-free* adapters for fast tuning of black-box ERMs. PEFA offers flexible choices (i.e., PEFA-XS and PEFA-XL) for practitioners to improve their pre-trained or fine-tuned ERMs efficiently, without any updates to model parameters of ERMs. PEFA-XL brings more significant gain of Recall@k at the cost of doubling the ANN index size and inference latency, while PEFA-XS yields modest gain of Recall@k without any overhead compared to the existing ERM inference pipeline. For document retrieval, PEFA not only improves the recall@100 of pre-trained ERMs on Trivia-QA by an average of 13.2%, but also lifts the recall@100 of fine-tuned ERMs on NQ-320K by an average of 5.5%. For NQ-320K dataset, applying PEFA to $\text{MPNet}_{\text{base}}$ [50] and GTR_{base} [42] reaches new SoTA results, where the Recall@10 of 88.72% outperforms 85.20% of previous SoTA Seq2Seq-based NCI [56]. For product search consisting of billion-scale of data, PEFA improves the Recall@100 of the fine-tuned ERMs by an average of 5.3% and 14.5%, for PEFA-XS and PEFA-XL, respectively.

ETHICAL CONSIDERATIONS

We discuss ethical implications of our PEFA framework in two perspectives: interpretability and privacy.

Interpretability. Given a query, embedding-based retrieval models (ERMs) retrieve the match set based on similarity search between the query embedding and the corpus of passage embeddings. However, the interpretability and explainability of ERMs is quite limited because we do not know which training examples contribute to or lead to the decisions of the retrieved match-set. Our proposed framework PEFA combines ERMs with a non-parametric kNN component, which enhances the interpretability of ERMs. The kNN component computes similarity scores between the test query and the set of training queries, hence we know which training examples contribute the most to the retrieved match-set.

Privacy. For e-commerce product search, it is crucial to protect customers privacy. Thus, we need to insure the underlying models do not explicitly memorize customers purchase history. When applying PEFA to the product search datasets, we carefully anonymized the search log, hence we never know which customer issues a specific query. Furthermore, we consider yearly-aggregated data of query-product pairs as the training signals in our kNN component. In other words, each query in our training set can not be traced back to its original query session.

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