Domain Adaptation for Memory-Efficient Dense Retrieval

Nandan Thakur\textsuperscript{1}, Nils Reimers\textsuperscript{2} and Jimmy Lin\textsuperscript{1}
\textsuperscript{1}David R. Cheriton School of Computer Science, University of Waterloo
\textsuperscript{2}Hugging Face
{nandan.thakur, jimmylin}@uwaterloo.ca

Abstract

Dense retrievers encode documents into fixed dimensional embeddings. However, storing all the document embeddings within an index produces bulky indexes which are expensive to serve. Recently, BPR (Yamada et al., 2021) and JPQ (Zhan et al., 2021a) have been proposed which train the model to produce binary document vectors, which reduce the index 32× and more. The authors showed these binary embedding models significantly outperform more traditional index compression techniques like Product Quantization (PQ). Previous work evaluated these approaches just in-domain, i.e. the methods were evaluated on tasks for which training data is available. In practice, retrieval models are often used in an out-of-domain setting, where they have been trained on a publicly available dataset, like MS MARCO, but are then used for some custom dataset for which no training data is available.

In this work, we show that binary embedding models like BPR and JPQ can perform significantly worse than baselines once there is a domain-shift involved. We propose a modification to the training procedure of BPR and JPQ and combine it with a corpus specific generative procedure which allow the adaption of BPR and JPQ to any corpus without requiring labeled training data. Our domain-adapted strategy known as GPL is model agnostic, achieves an improvement by up-to 19.3 and 11.6 points in nDCG@10 across the BEIR benchmark in comparison to BPR and JPQ while maintaining its 32x memory efficiency. JPQ+GPL even outperforms our upper baseline: uncompressed TAS-B model on average by 2.0 points.\textsuperscript{1}

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|}
\hline
Model & Index Size & Query Time & nDCG@10 \\
\hline
Dense Model & 65 GB & 456.9 ms & 0.415 \\
Dense Model + HNSW & 151 GB & 1.8 ms & 0.415 \\
Dense Model + PQ & 2.0 GB & 44.0 ms & 0.361 \\
BPR (Yamada et al., 2021) & 2.2 GB & 38.1 ms & 0.357 \\
BPR/GPL (ours) & 2.2 GB & 38.1 ms & 0.398 \\
JPQ (Zhan et al., 2021a) & 2.2 GB & 44.0 ms & 0.402 \\
JPQ/GPL (ours) & 2.2 GB & 44.0 ms & 0.435 \\
\hline
\end{tabular}
\caption{Index size and query time for retrieval on 21M passages from English Wikipedia from (Yamada et al., 2021). The Dense Model denotes TAS-B (Hofstätter et al., 2021) and nDCG@10 denotes the average of the model across 18 datasets from the BEIR benchmark (Thakur et al., 2021).}
\end{table}

1 Introduction

Dense retrievers perform retrieval by mapping queries and documents to a shared dense vector space and retrieve relevant hits by nearest-neighbor search. These models can significantly outperform traditional lexical or Bag-of-Words (BoW) models such as BM25 across multiple tasks in several downstream tasks such as question-answering (Lee et al., 2019; Karpukhin et al., 2020), semantic similarity (Reimers and Gurevych, 2019), conversational search (Yu et al., 2021), entity retrieval (Gillick et al., 2019), fact-checking (Samarinas et al., 2021) or passage retrieval (Gao et al., 2021; Xiong et al., 2021; Hofstätter et al., 2021; Zhan et al., 2021b; Luan et al., 2021). However, dense retrievers require to store all embeddings for all passages in a corpus. Once the corpus is of certain size, this becomes quite costly. Encoding 21 million passages from the English Wikipedia with a 768 dimensional dense retriever produces 65 GB of embeddings (Yamada et al., 2021). As nearest-neighbor search in large vector spaces is rather slow, a fast approximate nearest-neighbor approach like HNSW (Malkov et al., 2014) must be used, which increases the index size to 151GB. As this index must often be fully stored in memory, quite powerful and expensive servers are needed.

Hence, in large-scale search scenarios it is often necessary to compress the dense embedding index. Traditionally, unsupervised techniques like \textsuperscript{1}Code and data are publicly available at: https://github.com/NThakur20/income
Product Quantization (PQ) (Jegou et al., 2010) have been used. More recently, Binary Passage Retriever (BPR) (Yamada et al., 2021) and JPQ (Zhan et al., 2021a) have been proposed which trains a specific encoder to produce binary document vectors. The authors showed a significant performance gain in comparison to PQ. From Table 1, we can observe that using binary document embeddings reduces the index size $32 \times$ from 65 GB to 2 GB. Further, as nearest-neighbor search is more efficient in a binary vector space, we end up with an overall index size of just 2.2 GB instead of 151 GB.

In previous work, BPR and JPQ have just been evaluated “in-domain”, i.e. the binary vectors were tested on datasets for which training data is available. However, in many search applications, models are used out-of-domain (OOD): The model is trained on a publicly available dataset, like MS MARCO (Nguyen et al., 2016), and is then used on some application specific corpus. In this paper, as of our knowledge we are the first to evaluate several diverse vector compression algorithms (both supervised and unsupervised) in the out-of-domain setting for retrieval using the BEIR benchmark (Thakur et al., 2021). Our results show, that while BPR and JPQ have strong in-domain performance, they can perform poorly out-of-domain, sometimes even worse than unsupervised PQ.

BPR and JPQ use labeled training data to learn an $n$-dimensional binary document encoder with each dimension a binary value either -1 or 1. An example for a 2-dimensional vector space is illustrated in Figure 1. In the best case, the document embeddings are evenly distributed over the $2^n$ quadrants of the vector space. However, in the case of out-of-domain data, it can happen vectors are concentrated in a certain quadrant. For example, the TREC-COVID dataset just contains scientific documents on COVID-19, hence, document embeddings are all concentrated in a small sub-space. In the illustrative example of Figure 1, all these documents would be mapped to the $[1, 1]$ quadrant making them indistinguishable from each other. For higher dimensional vector spaces the effect is not as extreme as depicted in Figure 1, but we still observe for TREC-COVID that a high number of dimensions provide little or even no information anymore, making the compression sub-optimal.

To overcome the limitation of BPR & JPQ for out-of-domain data, we propose an extension using Generative Pseudo Labeling (GPL) (Wang et al., 2021). Our method does not require any labeled data from the target domain. Instead, we use a T5 encoder-decoder to first generate synthetic queries for our corpus. Next, we mine hard negatives using an ensemble of dense retrievers or a trained PQ index for the target domain which are then labeled using an existing cross-encoder. This generated training data is then used to learn an binary document encoder. BPR & JPQ use originally an InfoNCE ranking loss, which requires high data quality. As the synthetic queries can be of mixed quality, we...
adapt MarginMSE (Hofstätter et al., 2020) loss to the binary case. As we discuss later in Sec. 7, we find our technique to be robust against domain shifts, due to a strong cross-encoder teacher, providing a better recall and capturing higher dimensional efficiency within the 768 binary hash dimensions within the model.

Our method easy to use, broadly applicable to many retrieval settings and model-agnostic, i.e. our method is independent of the backbone model architecture and in future can be easily wrapped with the latest state-of-the-art dense retriever as the backbone model for our method. We use the BEIR benchmark (Thakur et al., 2021) to evaluate our models across 18 diverse out-of-domain IR tasks. We are able to achieve an improvement on 16 out of 18 datasets with an improvement of up-to 19.3 points nDCG@10 for BPR and 11.0 points nDCG@10 for JPQ. JPQ+GPL even outperforms the original uncompressed continuous TAS-B model on average by 2.0 points on BEIR.

2 Related Work

Dense vector compression primarily uses unsupervised compression techniques such as principal component analysis (PCA) or Product Quantization (PQ) (Izacard et al., 2020; Ma et al., 2021b; Min et al., 2021). Recently, more supervised techniques have been introduced for improving vector compression. The first work, Binary Passage Retriever (BPR) (Yamada et al., 2021) trains using a hashing algorithm with a dense layer on top to learn to represent hashes effectively within the dense retrieval space. Another work, JPQ (Zhan et al., 2021a) implements an algorithm to iteratively train a PQ index and query encoder together to improve first-stage retrieval and a subsequent work by the same authors, RepCONC (Zhan et al., 2022) implements a similar algorithm with constrained clustering and trains the PQ index jointly with the document encoder. Similarly another recent work, DrBoost (Lewis et al., 2021) iterative trains the multiple dense vector representations and distills the knowledge with gradient boosting. Table 1 shows the index size, query time and task performance for different model combinations.

All prior supervised compression techniques have been evaluated only "in-domain". As of our knowledge, we are the first which study the robustness of these approaches performed in an out-of-domain setting.

Domain adaptation: Liang et al. (2020); Ma et al. (2021a) use a T5 (Raffel et al., 2020) question generation model to generate synthetic data on Wikipedia to train a dense retriever. Similarly, Thakur et al. (2021) implemented it as a post-training step for domain adaptation of dense retrievers across specific domains. Xin et al. (2022) proposed MoDIR to use Domain Adversarial Training (DAT) (Ganin et al., 2016) for unsupervised domain adaptation of dense retrievers. MoDIR trains models by generating domain invariant representations to attack a domain classifier. Similarly, another recent work UDALM (Karouzos et al., 2021) first applies MLM training on the target domain; and it then applies multi-task learning on the target domain with MLM and on the source domain with a supervised objective. More recently, Wang et al. (2021) introduced GPL: a pseudo labeling approach involving a teacher cross-encoder model to learn the synthetic training data more effectively for dense retrieval. The authors showed GPL for domain adaptation outperformed both MoDIR and UDALM for dense retrieval on BEIR (Thakur et al., 2021). The focus of our work involves both memory compression and domain adaptation techniques, which we find crucial for performance boosts in models producing binary embeddings while keeping its memory efficiency constant.

3 Background Information

In this section, we explain about the BPR (Yamada et al., 2021) and JPQ (Zhan et al., 2021a) model architectures and provide details on model training and inference setup.

3.1 Binary Passage Retriever (BPR)

The BPR model design builds upon the existing dense retriever, DPR (Karpukhin et al., 2020) with an additional dense layer on the top of existing query and document encoders. Given any passage \( p_i \) from a corpus \( D \), DPR encodes the passage into a fixed-dimensional dense embedding \( e(p_i) \in \mathbb{R}^d \), where \( d = 768 \). Next, using the additional dense layer, BPR computes the hash as the sign function of the passage embedding as \( h(p_i) = \text{sign}(e(p_i)) \) where \( h(p_i) \in \{-1, 1\}^d \).

Training: During training, BPR learns to represent \( h(p_i) \) effectively using a combination of two loss functions. Let a training instance of a batch
size \( n \) be denoted as \((q_i, p_{i,1}^+, p_{i,1}^-, \ldots, p_{i,n-1}^-)\), where \( q_i \) is the input query, \( p_{i,1}^+ \) is the relevant passage for \( q_i \) and all rest \((p_{i,1}^-, \ldots, p_{i,n-1}^-)\) are in-batch negatives. The first loss function is used to learn a suitable hashing function algorithm. More formally this is defined as:

\[
\mathcal{L}_{\text{hash}} = \sum_{j=1}^{n-1} \max(0, -(h(q_i) \cdot h(p_{i,j}^+)) - h(q_i) \cdot h(p_{i,j}^-) + \alpha)
\]

where \( h(p_i) \) is the learned hash function of passage \( p_i \) and \( \alpha \) is a ranking constant. BPR also optimizes for InfoNCE (van den Oord et al., 2019) ranking loss function similar for learning to retrieve with in-batch negatives which is identical to the loss function of the DPR model.

\[
\mathcal{L}_{\text{InfoNCE}} = - \log \frac{e^{e(q_i) \cdot h(p_{i}^+)}}{e^{e(q_i) \cdot h(p_{i}^+)} + \sum_{j=1}^{n-1} e^{e(q_i) \cdot h(p_{i,j}^-)}}
\]

Finally, the model is trained with joint optimization of both the loss functions simultaneously: \( \mathcal{L} = \mathcal{L}_{\text{hash}} + \mathcal{L}_{\text{InfoNCE}}. \)

**Inference:** BPR inference is carried out in two steps. First, the model retrieves the top-\( k \) passages with the hamming distance function using the input hashed query \( h(q_i) \) and across all passages hashes \( h(p_i) \) in the corpus. Next, the model reranks the retrieved top-\( k \) hashed passages \( h(p_i) \) using the dot product with the dense query embedding \( e(q_i) \).

### 3.2 Joint Optimization of Query Encoder and Product Quantization (JPQ)

Product Quantization (PQ) typically involves first training a dense retriever using a ranking loss function. Next, after encoding all the documents with the dense retriever, the PQ index is finally trained to minimize the MSE (or reconstruction) loss. However, the retriever is unable to learn effectively due to the separation between encoding and compression. The PQ training cannot benefit from the supervised information. To improve upon this existing method, JPQ (Zhan et al., 2021a) jointly optimizes the query encoder and PQ index. JPQ learns to optimize the position of the PQ centroid embeddings, by changing the centroid embeddings to push the relevant document closer to the query embedding and the irrelevant documents further away. The JPQ authors subsequently worked on RepCONC (Zhan et al., 2022), a work built upon JPQ, involving quantization as a clustering problem. In our paper, we focus on domain adaptation of the JPQ model, and in future our technique can be easily extended to similar models such as RepCONC.

**Training:** The JPQ model is initialized from the STAR model (Zhan et al., 2021b) trained on the MS MARCO dataset using static hard negatives and random in-batch negatives. The STAR document encoder initializes the index assignment by computing the centroid embeddings using the PQ algorithm. For each training step, the JPQ query encoder module (also initialized with STAR) encodes the query \( q \) into vector \( e(q) \) and updates the PQ centroid embeddings using gradient descent. The gradients are computed with respect to the ranking loss helps jointly optimize the query encoder and the PQ centroid embeddings. Further, JPQ additionally includes end-to-end negative sampling which generates the top-ranked negatives from its own generated reconstructed PQ index at each training step. Its optimization technique penalizes the top-ranked irrelevant documents retrieved by the reconstruction of its own PQ index. The final loss function is given as:

\[
\mathcal{L}_{\text{JPQ}} = - \sum_{i=0}^{n-1} \sum_{i=0}^{n-1} l(e(q) \cdot h(p_i^+), e(q) \cdot h(p_i^-))
\]

where it tries to minimize the pairwise loss function \( l \) between the query embedding \( e(q) \) and reconstructed quantized positive \( h(p_i^+) \) and negative passage \( h(p_i^-) \).

**Inference:** JPQ inference is carried out similar to the dense retriever + PQ algorithm. The dense retriever by computing the similarity between the reconstructed quantized passage from our trained PQ (quantized) centroid embeddings \( h(p) \) and the original query embedding \( e(q) \). The approximate similarity score is denoted by: \( s(q, p) = e(q) \cdot h(p) \).

### 4 Adapting binary document encoders to new domains

As our experiments show, binary document encoders can have issues with out-of-domain data. These methods learn an encoder on which we can apply the \texttt{sign} function to map the continuous vector to a binary vector. At test time, it might be that the corpus focuses on a particular topic, i.e., document embeddings for this corpus are densely represented in only a particular sub-space of our overall vector space. For unsupervised methods
like PQ it is not an issue, as they learn the binarization at test time. For BPR, it can be a challenge as we illustrated in Figure 1 and analyze in more detail in Sec. 7.2: Due to the concentration of the corpus on a particular topic, the compression (i.e., binarization) is not optimal leading to a decrease in nDCG@10 performance on out-of-domain data.

To overcome this, we need queries and documents from our test distribution to update our binary document encoder. But as annotating (query, document) pairs is time-consuming, we opt for methods that can synthetically generate these pairs.

4.1 Binary Passage Retriever (BPR)

**BPR+GenQ: Thakur et al. (2021)** presented GenQ: A T5 encoder-decoder model is used to generate a query \( \hat{q} \) for a given passage \( p_i \) from our corpus, which can then be used to update dense embedding models to new domains. We follow the same approach for BPR and use \( (\hat{q}, p_i) \) pairs to learn our BPR encoder with the loss functions as presented in Section 3.1. So we replace our gold (query, passage) pairs with synthetically generated queries from the document.

**BPR+GPL:** Wang et al. (2021) showed that the generated queries can be of low quality, impacting the quality of the encoder. Instead, they propose to combine query generation with a pseudo-labeling approach: For a generated query \( \hat{q} \) from the passage \( p_i \), we retrieve top-\( k \) matching passages \( \{p_1^-, p_2^-, \ldots, p_k^-\} \) from our corpus using an existing retriever. We then randomly select a passage to create the triplet \( (\hat{q}, p^+, p^-) \). Then, a cross-encoder (CE) model is used to score \( s^+ = (\hat{q}, p^+) \) as well as \( s^- = (\hat{q}, p^-) \) and we compute the score-margin \( \delta = s^+ - s^- \).

Originally, BPR uses the InfoNCE loss which is sensitive to low quality data, which frequently happens with synthetically generated queries (Wang et al., 2021). Hence, we modify BPR to work with MarginMSE loss (Hofstätter et al., 2020). The first-stage hash loss function \( L_{\text{hash}} \) is unchanged. Instead of \( L_{\text{InfoNCE}} \), we will be using:

\[
L_{\text{GPL}} = -\sum_{i=0}^{n-1} \left[ (e(\hat{q}_i) \cdot h(p_i^+) - e(\hat{q}_i) \cdot h(p_i^-)) - (\text{CE}(\hat{q}_i, p_i^+) - \text{CE}(\hat{q}_i, p_i^-)) \right]^2
\]

where \( \text{CE}(\hat{q}_i, p) \) is the score from an existing cross-encoder model. Note, for the T5 query generation model as well as for the cross-encoder model we can use pre-existing models that have been trained on MSMARCO.

4.2 Joint Optimization of Query Encoder and Product Quantization (JPQ)

**JPQ+GenQ:** Similar to BPR, we follow the same approach and keep the training procedure identical with JPQ. We use synthetic generated queries from the T5 model for each target passage \( (\hat{q}_i, p_i) \) to train our model and PQ centroids with the loss function as presented in Section 3.2.

**JPQ+GPL:** Similar to BPR, we modify the JPQ loss function to MarginMSE loss (Hofstätter et al., 2020). The positive and negative margins are labeled between the top-\( k \) hard negatives retrieved using the trained PQ index and query with the teacher cross-encoder model at runtime. Since labeling all top-200 (query-passage) pairs is computationally expensive for each training sample using the cross-encoder, for JPQ+GPL we reduce and only label the top-25 hard negatives retrieved using the PQ algorithm.

5 Experiments

**Datasets and Evaluation:** For all our experiments, we use the MS MARCO passage ranking dataset (Nguyen et al., 2016) as the training data for our models. It has 8.8M passages and 532.8K query-passage pairs labeled as relevant in the training set. We use the BEIR benchmark (Thakur et al., 2021) to measure OOD generalization of retrievers. The benchmark contains 18 task distributions from diverse domains. We would like to refer the reader to Appendix B for a detailed overview of the datasets and domain statistics provided in BEIR.

**Datasets:** For all datasets in BEIR, we evaluate the performance of our model using the Normalised Cumulative Discount Gain (nDCG@10) metric.

**TAS-B Backbone model:** As stated earlier in Sec. 1, our method is **model agnostic**, i.e., we can apply our method to any backbone transformer model such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019) or DistilBERT (Sanh et al., 2019). In our experiments, we choose TAS-B (Hofstätter et al., 2021), a dense retriever based on DistilBERT as our backbone model. TAS-B was trained with balanced topic aware sampling using dual supervision from a cross-encoder and ColBERT (Khattab and Zaharia, 2020) teacher models. TAS-B is lightweight, efficient and robust in zero-shot first stage retrieval amongst its dense model.
Table 2: Zero-shot retrieval performance by different vector compression strategies on the BEIR benchmark (Thakur et al., 2021) using TAS-B (Hofstätter et al., 2021) as the backbone model. All scores denote NDCG@10. The best performance on a dataset achieving 0.32 compression is marked in bold, second best performance is underlined.

| Dataset (†) | Memory | nDCG@10 | Training BPR (TAS-B) | JPQ (TAS-B) |
|-------------|--------|---------|----------------------|-------------|
| MS MARCO    | 1×     | 0.408   | 0.407                | 0.408       |
| BQ2Q        | 2×     | 0.383   | 0.407                | 0.406       |
| NQ/CQADupStack | 3×   | 0.319   | 0.376                | 0.381       |
| HotpotQA    | 4×     | 0.463   | 0.407                | 0.407       |
| FIAQ-2018   | 32×    | 0.384   | 0.391                | 0.391       |
| Signal-1M (RT) | 0.289 | 0.377   | 0.377                | 0.381       |
| TRE-CR-NEWS | 0.377 | 0.377   | 0.377                | 0.381       |
| Robust-04   | 0.427  | 0.428   | 0.428                | 0.428       |
| ArgaAnA     | 0.429  | 0.429   | 0.429                | 0.429       |
| Touche-2020 | 0.162  | 0.156   | 0.156                | 0.156       |
| CQADupStack | 0.314  | 0.302   | 0.302                | 0.302       |
| Quora       | 0.835  | 0.835   | 0.835                | 0.835       |
| DBpedia     | 0.384  | 0.384   | 0.384                | 0.384       |
| SCIDOCS     | 0.149  | 0.149   | 0.149                | 0.149       |
| FEVER       | 0.700  | 0.600   | 0.571                | 0.571       |
| Climate-FEVER| 0.228 | 0.228   | 0.228                | 0.228       |
| SciFact     | 0.645  | 0.645   | 0.645                | 0.645       |
| AVERAGE     | 0.415  | 0.414   | 0.407                | 0.407       |

Figure 2: The number of training steps (in thousands) required to fine-tune TAS-B (Hofstätter et al., 2021) model for converting into BPR or JPQ. The y-axis denotes the nDCG@10 performance on the MSMARCO DEV (Nguyen et al., 2016) dataset.

counterparts such as ANCE (Xiong et al., 2021) or DPR (Karpukhin et al., 2020) as shown in (Thakur et al., 2021). In future, our method can be easily applied to better dense retrievers as backbones.

Training BPR and JPQ: We replicate the original training setup of BPR and JPQ and further fine-tune the TAS-B model in the Appendix, we find our BPR (TAS-B) and JPQ (TAS-B) model to outperform the original NQ trained BPR (Yamada et al., 2021) and original STAR-based JPQ (Zhan et al., 2021a) models. The fine-tuning is efficient and quick and only requires around 50K additional steps (5-6 hours in a single A100 GPU) to convert an existing dense retriever into a binary retriever model.

Baselines: We evaluate both unsupervised and supervised techniques for vector compression. (1) Floating point: We reduce the floating-point precision of the TAS-B model from default 32 bits to 16 (fp16) and 8 (fp8) bit respectively. (2) Dimensional reduction: we fit the principle component analysis (PCA) transformation across all the passage embeddings produced by TAS-B for each test dataset respectively. We apply the identical approach for evaluating TLDR (Kalantidis et al., 2021) as well. (3) Product Quantization (Jegou et al., 2010) decomposes the original d dimensional vector into k centroids, quantized and stored with n bits. (Jegou et al., 2010). (4) We adapt the TAS-B model with GPL to the respective domains and apply product quantization (GPL+PQ).

Experimental Setup: We implement all models using HuggingFace’s Transformers package (Wolf et al., 2020). For all our experiments we use a max sequence length of 350 and compute the similarity between query and passage using dot-product.
We use faiss (Johnson et al., 2019) for implementing various dense vector compression baselines. We use the faiss ScalarQuantizer in flat mode for implementing both fp8 and fp16. For the PQ implementation, we use faiss ProductQuantizer in flat mode. To achieve a compression of 32×, we configure PQ with $k = 96$ centroids and $n = 8$ bits respectively. For PCA, we use faiss PCAMatrix in flat mode and reduce original 768 dimensions into 256 dimensions. For TLDR, we train one additional multi-layer perceptron (MLP) layer with 2048 dimensions using 5 nearest neighbors to sample positive pairs, and downward project TAS-B model to 256 dimensions.

GenQ & GPL: To generate queries for both GenQ and GPL, we use the docT5query (Nogueira and Lin, 2019) model trained on MS MARCO and generate at max 3 queries per passage using nucleus sampling with temperature 1.0, $k = 25$ and $p = 0.95$. For GenQ, we use the default setting in (Thakur et al., 2021): 1-epoch training and batch size 75. For GPL, we follow the setting in (Wang et al., 2021) and train for 1 epoch or a maximum of 45K steps with a batch size 32. To retrieve hard negatives we use three dense retrievers trained on MS MARCO and generate at max 50 negatives using each retriever and uniformly sample one negative passage and one positive passage for each training query to form one training example. For CE labeling in GPL, we use the ms-marco-MiniLM-L-6-v2 cross-encoder as suggested by the original authors in (Wang et al., 2021).

| Dataset/Model | BPR | BPR +GenQ | BPR +GPL | JPQ | JPQ +GenQ | JPQ +GPL |
|---------------|-----|-----------|----------|-----|-----------|----------|
| TREC-COVID    | 0.236 | 0.315 | 0.310 | 0.283 | 0.360 | 0.380 |
| BioASQ        | 0.569 | 0.723 | 0.735 | 0.721 | 0.766 | 0.786 |
| NCORPUS       | 0.541 | 0.538 | 0.532 | 0.814 | 0.878 | 0.878 |
| NQ            | 0.937 | 0.944 | 0.943 | 0.967 | 0.963 | 0.969 |
| HotpotQA      | 0.712 | 0.704 | 0.728 | 0.808 | 0.802 | 0.823 |
| FiQA-2018     | 0.736 | 0.796 | 0.798 | 0.814 | 0.814 | 0.814 |
| Signal-1M (RT)| 0.366 | 0.414 | 0.439 | 0.463 | 0.438 | 0.485 |
| TREC-NEWS     | 0.546 | 0.618 | 0.430 | 0.641 | 0.683 | 0.708 |
| Robust04      | 0.391 | 0.462 | 0.454 | 0.534 | 0.546 | 0.562 |
| ArguAna       | 0.991 | 0.995 | 0.994 | 0.994 | 0.996 | 0.995 |
| Touche-2020   | 0.733 | 0.772 | 0.778 | 0.796 | 0.777 | 0.798 |
| CQADupStack   | 0.742 | 0.805 | 0.799 | 0.802 | 0.840 | 0.846 |
| Quora         | 0.996 | 0.997 | 0.998 | 0.998 | 0.998 | 0.998 |
| DBPedia       | 0.598 | 0.557 | 0.581 | 0.708 | 0.694 | 0.729 |
| SCIDOCs       | 0.464 | 0.505 | 0.532 | 0.528 | 0.547 | 0.557 |
| FEVER         | 0.934 | 0.938 | 0.928 | 0.958 | 0.962 | 0.964 |
| Climate-FEVER | 0.611 | 0.631 | 0.612 | 0.690 | 0.708 | 0.731 |
| SciFact       | 0.950 | 0.962 | 0.945 | 0.983 | 0.987 | 0.987 |

AVERAGE

0.671 | 0.704 | 0.696 | 0.736 | 0.749 | 0.763

Table 3: Recall@1000 evaluation scores by BPR, JPQ with and without GPL on the BEIR benchmark (Thakur et al., 2021) using the base TAS-B model (Hofstätter et al., 2021).

6 Experimental Results

**Zero-Shot Baselines** From Table 2, fp16 and fp8 are strong baselines to easily compress 2-4x memory within a single point difference on BEIR. This shows most of the information in TAS-B is contained well within the initial 16 or 8 bit float vectors. These techniques are practical to quickly compress the memory up-to 4x. On the other hand, we find PCA and TLDR to produce the lowest zero-shot scores on BEIR. These results indicate useful information contained in 768 dimensions of TAS-B model is lost projecting to lower dimensions using dimension reduction. In comparison, unsupervised PQ training is a strong baseline amongst others by achieve a 32x compression in memory and it even outperforms zero-shot BPR on average by 0.4 points (10/18 datasets).

**BPR** is competitive on in-domain MS MARCO Dev dataset by dropping only 1.1 points in comparison to TAS-B while achieving 32x in memory compression. This shows supervised compression techniques are effective in learning in-domain distributions. In contrast BPR fails to perform well on zero-shot and underperforms the PQ baseline. GenQ and GPL can both improve the out-of-domain performance of the BPR model. Both methods generate queries for the given documents in the corpus. While GenQ uses binary labels (relevant or not), GPL uses continuous pseudo-labels from a CrossEncoder with MarginMSE loss.

**BPR+GenQ** can only improve on datasets that focus on a single topic like FiQA, SciFact and BioASQ. For corpora that cover a broader set of topic (e.g. NQ, DBPedia), BPR+GenQ performs worse than the BPR model, due to the reasons discussed in (Wang et al., 2021; Thakur et al., 2021).

**BPR+GPL** is able to improve upon 16 out of 18 datasets compared to BPR, which was just trained on MSMARCO. (Wang et al., 2021) showed that the T5 model can generate bad queries which hurt the model performance if trained with InfoNCE loss. The only two datasets where we notice a performance drop is TREC-NEWS and FEVER.

**JPQ Results** In contrast to BPR, we find the JPQ model to be more robust across than BPR. In-domain, on MS MARCO, JPQ and BPR perform

---

3https://huggingface.co/cross-encoder/ms-marco-MiniLM-L-6-v2
Table 4: A comparison of dimensional efficiency (in %) across in the BEIR benchmark (Thakur et al., 2021) between BPR (zero-shot) and BPR+GPL. Overall, higher dimensional efficiency indicates the model captures more information within its 768 binary (either 1 or -1) dimensions.

| Dataset          | BPR    | BPR+GPL |
|------------------|--------|---------|
| TREC-COVID       | 78.2%  | 76.2%   |
| BioASQ           | 74.9%  | 88.3%   |
| NCF-corpus       | 86.7%  | 81.5%   |
| NQ               | 87.0%  | 87.0%   |
| HotpotQA         | 74.9%  | 90.4%   |
| FiQA-2018        | 87.5%  | 90.4%   |
| Signal-1M (RT)   | 88.3%  | 91.2%   |
| TREC-NEWS        | 86.7%  | 88.0%   |
| Robust04         | 86.7%  | 88.0%   |

Figure 3: Dimensional efficiency plot for BPR (zero-shot) and BPR+GPL on TREC-COVID. GPL helps train the model to utilize its dimensions effectively and capture more dimensional information. Figure 5 in the Appendix provides the dimensional entropy plots for all BEIR datasets.

comparably. But out-of-domain, JPQ is 4.1 better than BPR. As before, JPQ+GPL can improve the performance by 3.3, which even outperforms the original continuous TAS-B model by 2 points.

7 Further Analysis

7.1 Learning to rerank from the CE teacher

Recall that BPR implements a two stage inference: The first stage retrieves top-k (k = 1000) hashed passages using hamming distance, and the second stage “reranks” the binary passages retrieved with the continous query embedding. Our hypothesis is that BPR will effectively learn to rerank from a CE teacher as the first-stage hashing loss function $L_{hash}$ is unchanged during training with GPL.

From Table 3, we find that BPR+GenQ achieves the highest recall@1000 scores which are comparable to BPR+GPL. This shows arguably that both BPR+GenQ and BPR+GPL perform comparably at the first retrieval stage, i.e. the nDCG@10 performance gain of BPR+GPL Table 2 comes primarily from the second i.e. re-ranking stage. This is in support of our hypothesis of a CE teacher is able to teach well to improve BPR at the reranking stage.

7.2 Higher dimensional efficiency captures more information

Recall from Figure 1, some corpora like TREC-COVID are narrowly focused on a single topic such as COVID-19. There, the compression of BPR learned on MSMARCO can be sub-optimal and we can observe a dimension collapse, where all dimension are nearly always -1 or 1, which does not provide an information for the retrieval nor for the re-ranking stage of BPR.

To quantify the information captured in the 768 dimensional binary space or hash distribution for BPR, in this paper we propose a metric dimensional efficiency $E(d)$, which measures how much information a dimension $d$ can capture. Ideally, maximizing the dimensional efficiency of a dataset would capture more information within its model dimensions. More formally, for a given corpus $C$ with passages $\{p_1, ..., p_n\}$ with each passage hash $h(p_i)$ containing $d$ dimensional binary vectors $[h_1(p_i), ..., h_d(p_i)]$ where each $h_d(p_i) \in \{-1, 1\}$ and $d = 768$. We then define our dimensional efficiency as:

$$E = -\sum_{d=1}^{768} P_d \star (1 - P_d)$$

where $P_d$ denotes the relative frequency of a dimension being 1 and $P_d = 0.5$ provides the maximum dimensional efficiency. From Table 4 and Figure 3, we find rather surprising observations. Recall from Table 2, we observe that BPR+GPL is better than BPR in terms of nDCG@10 on the BEIR. However, BPR+GPL does not necessary use all dimensions i.e. some dimensions are found to be always either -1 or 1. For the dimensions BPR+GPL which model uses, the model uses them more effectively (multiple dimensions closer to $P_d = 0.5$). We keep a more in-depth theoretical investigation of dimensional efficiency as future work.
7.3 GPL is robust across PQ centroids

In above sections, we find GPL helps domain adapt JPQ to specialized domains for retrieval. However, we evaluated our technique for a single compression rate of $32 \times \cdot$ In this section, we change the number of PQ centroids required for JPQ and apply our domain adaptation algorithms: GPL and GenQ and check whether our technique still holds for even higher compression rates up until $200 \times \cdot$ The lesser the number of centroids $M$, the higher compression is achieved. We train and evaluate across four datasets from the BEIR benchmark: TREC-COVID, FIQA, SCIFACT and Robust04. We chose the centroid learning rates identical to the original authors of JPQ suggest: $5e^{-6}$ for $M \in \{16, 24\}$, $2e^{-5}$ for $M = 32$, and $1e^{-4}$ for $M \in \{48, 64, 96\}$. From Figure 4, we find JPQ+GPL is able to improve zero-shot binary retrieval even at higher compression rates like $64 \times$ or $128 \times \cdot$ The JPQ zero-shot performance drops at a higher rate in contrast to JPQ+GPL across all four datasets.

8 Conclusion

Supervised dense compression algorithms have been popular and effective in-domain in recent times, however can have difficulties to generalize well to unseen domains. The algorithms are memory efficient, but lack in performance when evaluated in specialized domains which contain no training data. In order to adapt these compression algorithms under severe domain shifts, In this paper we propose a solution to jointly optimize domain-adaptation algorithms along with vector compression. The recent technique, GPL in combination with BPR and JPQ provide a boost of 19.3 and 11.6 nDCG@10 points respectively.

9 Limitations and Future Work

Even though we find the GPL technique to provide a boost with memory compressed models: BPR and JPQ. Our work has a few limitations which we briefly mention them below and for future work:

Different compression algorithms: In our work, we considered JPQ and BPR due to its popularity and effectiveness shown in our preliminary results. In future, we can work on extending our methods to more recent memory compression algorithms such as RepCONC (Zhan et al., 2022).

Better backbone models: We suspect the performances on the BEIR can further improved with stronger backbone models in comparison with TAS-B. Due to the model agnostic nature of our method, we can easily extend our work to different state-of-the-art dense retrievers in the upcoming future.

Requires separate models: BPR and JPQ both require training separate models for each domain or task with our technique. This can be quite cumbersome for practical use-cases involving several hundreds of domains or retrieval tasks, for which one would need to train multiple models.

Compute intensive: Our method GPL is compute intensive: (1) For BPR+GPL, every dense retriever requires to separately compute embeddings for the whole corpus for hard-negative mining. (2) Cross-encoder teacher model although very effective, slows down the training significantly as required to label during training. In future, we can explore efficient and faster teachers instead of cross-encoders for GPL such as ColBERT (Khattab and Zaharia, 2020) or TILDE (Zhuang and Zuccon, 2021) for efficient and faster GPL training.

Acknowledgements

This research was supported in part by the Canada First Research Excellence Fund and the Natural Sciences and Engineering Research Council (NSERC) of Canada. Computational resources were provided by Compute Canada. We would additionally like to thank Kexin Wang for his helpful feedback and participation in the weekly research meetings.
References

Alexander Bondarenko, Maik Fröbe, Meriem Beloucif, Lukas Gienapp, Yamen Ajjour, Alexander Panchenko, Chris Biemann, Benno Stein, Henning Wachsmuth, Martin Potthast, and Matthias Hagen. 2020. Overview of Touché 2020: Argument Retrieval. In Working Notes Papers of the CLEF 2020 Evaluation Labs, volume 2696 of CEUR Workshop Proceedings.

Vera Boteva, Demian Gholipour, Artem Sokolov, and Stefan Riezler. 2016. A full-text learning to rank dataset for medical information retrieval. In Proceedings of the 38th European Conference on Information Retrieval (ECIR 2016), pages 716–722.

Arman Cohan, Sergey Feldman, Iz Beltagy, Doug Downey, and Daniel Weld. 2020. SPECTER: Document-level representation learning using citation-informed transformers. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2270–2282, Online. Association for Computational Linguistics.

Davind Corney, Dyaa Albakour, Miguel Martinez, and Samir Moussa. 2016. What do a million news articles look like? In Proceedings of the First International Workshop on Recent Trends in News Information Retrieval co-located with 38th European Conference on Information Retrieval (ECIR 2016), pages 42–47.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Thomas Diggelmann, Jordan Boyd-Graber, Jannis Bulian, Massimiliano Ciaramita, and Markus Leipold. 2020. Climate-fever: A dataset for verification of real-world climate claims. In Tackling Climate Change with Machine Learning workshop at NeurIPS 2020.

Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario March, and Victor Lempitsky. 2016. Domain-adversarial training of neural networks. Journal of Machine Learning Research, 17(59):1–35.

Luyu Gao, Zhuyun Dai, Tongfei Chen, Zhen Fan, Benjamin Van Durme, and Jamie Callan. 2021. Complement lexical retrieval model with semantic residual embeddings. In Advances in Information Retrieval, pages 146–160, Cham. Springer International Publishing.

Diego Garcia-Olano. 2019. Learning dense representations for entity retrieval. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 528–537, Hong Kong, China. Association for Computational Linguistics.

Faegheh Hasibi, Fedor Nikolaev, Chenyan Xiong, Kristian Balog, Svein Erik Bratsberg, Alexander Kotov, and Jamie Callan. 2017. Dbpedia-entity v2: A test collection for entity search. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’17, pages 1265–1268. ACM.

Sebastian Hofstätter, Sophia Althammer, Michael Schröder, Mete Sertkan, and Allan Hanbury. 2020. Improving efficient neural ranking models with cross-architecture knowledge distillation. arXiv preprint arXiv:2010.02666.

Sebastian Hofstätter, Sheng-Chieh Lin, Jheng-Hong Yang, Jimmy Lin, and Allan Hanbury. 2021. Efficiently Teaching an Effective Dense Retriever with Balanced Topic Aware Sampling, page 113–122. Association for Computing Machinery, New York, NY, USA.

Doris Hoogeveen, Karin M Verspoor, and Timothy Baldwin. 2015. Eqadupstack: A benchmark data set for community question-answering research. In Proceedings of the 20th Australasian document computing symposium, pages 1–8.

Gautier Izacard, Fabio Petroni, Lucas Hosseini, Nicola De Cao, Sebastian Riedel, and Edouard Grave. 2020. A memory efficient baseline for open domain question answering. arXiv preprint arXiv:2012.15156.

Herve Jegou, Matthijs Douze, and Cordelia Schmid. 2010. Product quantization for nearest neighbor search. IEEE transactions on pattern analysis and machine intelligence, 33(1):117–128.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2019. Billion-scale similarity search with GPUs. IEEE Transactions on Big Data, 7(3):535–547.

Yannis Kalantidis, Carlos Lassance, Jon Almazan, and Diane Larlus. 2021. Tldr: Twin learning for dimensionality reduction. arXiv preprint arXiv:2110.09455.

Constantinos Karouzos, Georgios Paraskevopoulos, and Alexandros Potamianos. 2021. UDALM: Unsupervised domain adaptation through language modeling. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2579–2590, Online. Association for Computational Linguistics.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of
Omar Khattab and Matei Zaharia. 2020. ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT, page 39–48. Association for Computing Machinery, New York, NY, USA.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee, Kristina N. Toutanova, Lilion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. Transactions of the Association of Computational Linguistics.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.

Patrick Lewis, Barlas Oğuz, Wenhan Xiong, Fabio Petroni, Wen-tau Yih, and Sebastian Riedel. 2021. Boosted dense retriever. arXiv preprint arXiv:2112.07771.

Davis Liang, Peng Xu, Siamak Shakeri, Cícero Nogueira dos Santos, Ramesh Nallapati, Zhiheng Huang, and Bing Xiang. 2020. Embedding-based zero-shot retrieval through query generation. arXiv preprint arXiv:2009.10270.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.02892.

Yi Luan, Jacob Eisenstein, Kristina Toutanova, and Michael Collins. 2021. Sparse, Dense, and Attentional Representations for Text Retrieval. Transactions of the Association for Computational Linguistics, 9:329–345.

Ji Ma, Ivan Korotkov, Yinfei Yang, Keith Hall, and Ryan McDonald. 2021a. Zero-shot neural passage retrieval via domain-targeted synthetic question generation. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 1075–1088, Online. Association for Computational Linguistics.

Xueguang Ma, Minghan Li, Kai Sun, Ji Xin, and Jimmy Lin. 2021b. Simple and effective unsupervised redundancy elimination to compress dense vectors for passage retrieval. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics.

Macedo Maia, Siegfried Handschuh, André Freitas, Brian Davis, Ross McDermott, Manel Zarrour, and Alexandra Balahur. 2018. WWW’18 open challenge: Financial opinion mining and question answering. In Companion Proceedings of the The Web Conference 2018, WWW ’18, page 1941–1942, Republic and Canton of Geneva, CHE. International World Wide Web Conferences Steering Committee.

Yury Malkov, Alexander Ponomarenko, Andrey Logvinov, and Vladimir Krylov. 2014. Approximate nearest neighbor algorithm based on navigable small world graphs. Information Systems, 45:61–68.

Sewon Min, Jordan Boyd-Graber, Chris Alberti, Danqi Chen, Eunsol Choi, Michael Collins, Kelvin Guu, Hannanen Hajishirzi, Kenton Lee, Jennimaria Palomaki, Colin Raffel, Adam Roberts, Tom Kwiatkowski, Patrick Lewis, Xuyiagang Wu, Heinrich Küttler, Linqing Liu, Pasquale Minervini, Pontus Stenetorp, Sebastian Riedel, Sohee Yang, Minjoo Seo, Gautier Izacard, Fabio Petroni, Lucas Hosseini, Nicola De Cao, Edouard Grave, Ikuya Yamada, Sonse Shimaoka, Masatoshi Suzuki, Shumpei Miyawaki, Shun Sato, Ryo Takahashi, Jun Suzuki, Martin Fajcik, Martin Docekal, Karel Ondrej, Pavel Smrz, Hao Cheng, Yelong Shen, Xiaodong Liu, Pengcheng He, Weizhu Chen, Jianfeng Gao, Barlas Oğuz, Xilun Chen, Vladimir Karpukhin, Stan Peshiterliev, Dmytro Okhonko, Michael Schlichtkrull, Sonal Gupta, Yashar Mehdad, and Wen-tau Yih. 2021. Neurips 2020 efficientqa competition: Systems, analyses and lessons learned. In Proceedings of the NeurIPS 2020 Competition and Demonstration Track, volume 133 of Proceedings of Machine Learning Research, pages 86–111. PMLR.

Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. 2016. Ms marco: A human generated machine reading comprehension dataset. In CoCo@ NIPS.

Rodrigo Nogueira and Jimmy Lin. 2019. From doc2query to docTTTTTquery.

Aaron van den Oord, Yazhe Li, and Oriol Vinyals. 2019. Representation learning with contrastive predictive coding. arXiv preprint arXiv:1807.03748.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21(140):1–67.

Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing.
and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Chris Samarinias, Wynne Hsu, and Meng Li Lee. 2021. Improving evidence retrieval for automated explainable fact-checking. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Demonstrations, pages 84–91. Online. Association for Computational Linguistics.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Ian Soboroff, Shudong Huang, and Donna Harman. 2019. Trec 2019 news track overview. In TREC.

Axel Suarez, Dyaa Albakour, David Corney, Miguel Martinez, and Jose Esquivel. 2018. A data collection for evaluating the retrieval of related tweets to news articles. In 40th International Conference on Information Retrieval Research (ECIR 2018), Grenoble, France, March, 2018., pages 780–786.

Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2021. BEIR: A heterogeneous benchmark for zero-shot evaluation of information retrieval models. In Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2).

James Thorne, Andreas Vlachos, Christos Christodouloupolous, and Arpit Mittal. 2018. FEVER: a large-scale dataset for fact extraction and VERification. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 809–819, New Orleans, Louisiana. Association for Computational Linguistics.

George Tsatsaronis, Georgios Balikas, Prodromos Malakasiotis, Ioannis Partalas, Matthias Zschunke, Michael R Alvers, Dirk Weissenborn, Anastasia Krithara, Sergios Petridis, Dimitris Polychronopoulos, et al. 2015. An overview of the biosaq large-scale biomedical semantic indexing and question answering competition. BMC bioinformatics, 16(1):138.

Ellen Voorhees. 2005. Overview of the TREC 2004 robust retrieval track. Special Publication (NIST SP), National Institute of Standards and Technology, Gaithersburg, MD.

Ellen Voorhees, Tasmeer Alam, Steven Bedrick, Dina Demner-Fushman, William R. Hersh, Kyle Lo, Kirk Roberts, Ian Soboroff, and Lucy Lu Wang. 2021. TREC-COVID: Constructing a pandemic information retrieval test collection. SIGIR Forum, 54(1).

Henning Wachsmuth, Martin Potthast, Khalid Al-Khatib, Yamen Ajjour, Jana Puschmann, Jiani Qu, Jonas Dorsch, Viorel Morari, Janek Bevendorff, and Benno Stein. 2017. Building an Argument Search Engine for the Web. In 4th Workshop on Argument Mining (ArgMining 2017) at EMNLP, pages 49–59. Association for Computational Linguistics.

Henning Wachsmuth, Shahbaz Syed, and Benno Stein. 2018. Retrieval of the best counterargument without prior topic knowledge. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 241–251. Association for Computational Linguistics.

David Wadden, Shanchuan Lin, Kyle Lo, Lucy Lu Wang, Madeleine van Zuylen, Arman Cohanim, and Hannaneh Hajishirzi. 2020. Fact or fiction: Verifying scientific claims. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7534–7550, Online. Association for Computational Linguistics.

Kexin Wang, Nandan Thakur, Nils Reimers, and Iryna Gurevych. 2021. GPL: Generative pseudo labeling for unsupervised domain adaptation of dense retrieval. arXiv preprint arXiv:2112.07577.

Lucy Lu Wang, Kyle Lo, Yoganand Chandrasekhar, Russell Reas, Jiangan Yang, Doug Burdick, Darrin Eide, Kathryn Funk, Yannis Katsis, Rodney Michael Kinney, Yunyao Li, Ziyan Liu, William Merrill, Paul Mooney, Dewey A. Murdick, Devvret Rishi, Jerry Sheehan, Zhihong Shen, Brandon Stilson, Alex D. Wade, Kuansan Wang, Nancy Xin Ru Wang, Christopher Wilhelm, Boya Xie, Douglas M. Raymond, Daniel S. Weld, Oren Etzioni, and Sebastian Kohlmeier. 2020. CORD-19: The COVID-19 open research dataset. In Proceedings of the 1st Workshop on NLP for COVID-19 at ACL 2020, Online. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yaccine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Ji Xin, Chenyan Xiong, Ashwin Srinivasan, Ankita Sharma, Damien Jose, and Paul Bennett. 2022. Zero-shot dense retrieval with momentum adversarial domain invariant representations. In Findings of the Association for Computational Linguistics: ACL 2022, pages 4008–4020, Dublin, Ireland. Association for Computational Linguistics.
A Appendices

We provide the following additional sections in detail and information that complement discussions in the main paper:

- A detailed description of all the 18 datasets present in the BEIR benchmark in Appendix B.
- Backbone analysis for BPR and JPQ in Appendix C.

B BEIR Datasets

In this section, we motivate the 18 datasets present in the BEIR benchmark (Thakur et al., 2021) used for evaluation in our experiments.

B.1 Bio-Medical Information Retrieval

TREC-COVID (Voorhees et al., 2021) is an ad-hoc search challenge based on the CORD-19 dataset containing scientific articles related to the COVID-19 pandemic (Wang et al., 2020). It originally contains 50 queries and 171K documents. The labels in TREC-COVID are 3-level (i.e. 0, 1 and 2) and there are on average 493.5 relevant documents for each test query.

NFCorpus (Boteva et al., 2016) contains natural language queries harvested from NutritionFacts (NF). The original corpus contains 3.6K annotated medical documents from PubMed as the corpus and 323 queries from all content sources from NF (videos, blogs, and Q&A posts) as queries. The labels in NFCorpus are 3-level (i.e. 0, 1 and 2) and there are on average 38.2 relevant documents for each test query.

BioASQ (Tsatsaronis et al., 2015) is a biomedical semantic question answering challenge dataset. The dataset originally contains 500 queries and 15M articles from PubMed as our corpus. The labels are binary in BioASQ and there are on average 4.7 relevant documents for each test query.

B.2 Open-domain Question Answering (QA)

Natural Questions (Kwiatkowski et al., 2019) contains Google search queries and documents with paragraphs and answer spans within Wikipedia articles. We use the NQ version provided by the authors in (Thakur et al., 2021). The dataset contains 2.68M documents and 3452 test queries. The labels are binary in NQ and there are on average 4.7 relevant documents for each test query.

HotpotQA (Yang et al., 2018) contains multi-hop like questions which require reasoning over multiple paragraphs to find the correct answer. We use the version provided by the authors in (Thakur et al., 2021). The dataset contains 2.68M documents and 3452 test queries. The labels are binary in HotpotQA and 2.0 on average relevant documents for each test query.
**FiQA-2018** (Maia et al., 2018) Task 2 consists of opinion-based question-answering. The corpus includes financial data by crawling StackExchange posts under the Investment topic from 2009-2017. We use the version provided by the authors in (Thakur et al., 2021). The dataset contains 57K documents and 648 test queries. The labels are binary in FiQA-2018 and on average 2.6 relevant documents are present for each test query.

**B.3 Tweet Retrieval**

**Signal-1M Related Tweets** (Suarez et al., 2018) task retrieves relevant tweets for a given news article title. The Related Tweets task provides news articles from the Signal-1M dataset (Corney et al., 2016) from which we get 97 queries and the corpus contains manually scraped 2.86M tweets. We use the version provided by the authors in (Thakur et al., 2021). The labels in Signal-1M (RT) are 3-level (i.e. 0, 1 and 2) and there are on average 19.6 relevant documents for each test query.

**B.4 News Retrieval**

**TREC-NEWS** (Soboroff et al., 2019) 2019 track involves background linking: Given a news headline, we retrieve relevant news articles that provide important context or background information. The corpus contains 595K documents and 57 test queries. The labels in TREC-NEWS are 5-level and there are on average 19.6 relevant documents for each test query.

**Robust04** (Voorhees, 2005) provides a robust dataset focusing on evaluating on poorly performing topics. The corpus contains 528K documents from the complete TREC disks 4 and 5 and 249 test queries. The labels in Robust04 are 3-level and there are on average 69.9 relevant documents for each test query.

**B.5 Argument Retrieval**

**ArguAna Counterargs Corpus** (Wachsmuth et al., 2018) involves the task of retrieval of the best counterargument to an argument. The corpus contains 8.6K documents as arguments and 1,406 test queries. The labels in ArguAna are binary and there are on average 1 relevant document for each test query.

**Touché-2020** (Bondarenko et al., 2020) Task 1 is a conversational argument retrieval task. The corpus contains the conclusion as title and premise for arguments present in args.me (Wachsmuth et al., 2017) for 382K documents and 49 test queries. We use the version provided by the authors in (Thakur et al., 2021). The labels are 3-level and there are on average 19.0 relevant documents for each test query.

**B.6 Duplicate Question Retrieval**

**CQADupStack** (Hoogeveen et al., 2015) is a dataset for community question-answering, built from 12 StackExchange subforums: Android, English, Gaming, Gis, Mathematica, Physics, Programmers, Stats, Tex, Unix, Webmasters and WordPress. The task is to retrieve duplicate question posts with both a title and a body text given a post title. It has 13.1K queries and 457.2k passages. The labels are binary and there are 1.4 passages in average labeled as relevant for each query. As in (Thakur et al., 2021), the average score of the 12 sub-tasks is reported.

**Quora** Duplicate Questions dataset identifies whether two questions are duplicates. We use the version provided by the authors in (Thakur et al., 2021). The corpus contains 522K queries as documents and 10K test queries. The labels present in Quora are binary and there are on average 1.6 relevant documents for each test query.

**B.7 Entity Retrieval**

**DBPedia-Entity-v2** (Hasibi et al., 2017) is an established entity retrieval dataset. It contains a set of 400 heterogeneous entity-bearing test queries containing named entities, IR style keywords, and natural language queries. The task involves retrieving entities from the English part of DBpedia corpus which contains 4.63M documents. The labels in DBPedia are 3-level and there are on average 38.2 relevant documents for each test query.

**B.8 Citation Prediction**

**SCIDOCS** (Cohan et al., 2020) contains a corpus of 30K held-out pool of scientific papers. We use the task and the version provided by the authors in (Thakur et al., 2021). The task includes 1k papers as queries with 5 relevant papers and 25 (randomly selected) uncited papers for each query. The labels are binary in SCIDOCS are there are on average 4.9 relevant documents for each query.

**B.9 Fact Checking**

**FEVER** (Thorne et al., 2018) The Fact Extraction and VERification dataset is collected to facilitate the automatic fact checking. We use the task
and the version provided by the authors in (Thakur et al., 2021). The dataset contains 5.41M pre-processed Wikipedia Abstracts (June 2017 dump) and 6,666 test queries. The labels are binary and on average there are 1.2 relevant documents for each query.

**Climate-FEVER** (Diggelmann et al., 2020) is a dataset for verification of real-world climate claims. We include the original 1,535 dataset claims as test queries and retrieve evidences from the the same FEVER Wikipedia corpus containing 5.41M pre-processed Wikipedia Abstracts (June 2017 dump). The labels are binary and on average there are 3.0 relevant documents for each query.

**SciFact** (Wadden et al., 2020) is for the task of verifying scientific claims using evidence from the abstracts of the scientific papers. It contains 300 queries and 5.2K passages built from S2ORC, a publicly-available corpus of millions of scientific articles. The labels are binary and there are 1.1 passages in average labeled as relevant for each query.

### C Backbone Analysis for BPR and JPQ

In this section, we discuss in depth regarding the backbone analysis for BPR and JPQ. As we can wrap any Huggingface dense retriever as a BPR model. We would like to investigate the research question: Which is the best backbone model for BPR and JPQ? To investigate the above question, we considered two approaches: (1) Fine-tuning from scratch i.e. the models have not been fine-tuned prior on MS MARCO. (2) Post fine-tuning of already fine-tuned NQ or MS MARCO models.

#### 1. Fine-tuned on MSMARCO:
We further fine-tune already MSMARCO trained models. For our analysis we chose four models: TAS-B, MSMARCO-v3 both with CLS Pooling and dot-product and with mean pooling and cosine similarity and MiniLM-L6 dense retriever models. All models are publicly available in the Sentence Transformers repository. From Table 5 We find the TAS-B model to perform the best in-domain and outperform others when evaluated across the MS MARCO dev dataset.

#### 2. Trained from scratch:
We trained from scratch two models: MSMARCO-v3 model both with CLS Pooling and dot-product and with mean pooling and cosine similarity. We found these models learn decently and even outperform models trained on the NQ dataset however they underperform fine-tuned models on MS MARCO.

#### 3. Fine-tuned on NQ:
The original BPR model trained in (Yamada et al., 2021), was unable to perform well on the MS MARCO dev dataset. Although the dataset evaluated is not in-domain for NQ, however from Table 7, we find BPR model trained NQ seems to not generalize well in the BEIR benchmark under performing BPR with TAS-B as backbone by a huge margin of 15.6 points.

### Table 5: Backbone model analysis for BPR (Yamada et al., 2021).

| Model                  | NDCG@10 | MRR@10 |
|------------------------|---------|--------|
| Fine-tuned models on MSMARCO |         |        |
| TAS-B                  | 0.397   | 0.336  |
| MSMARCO-v3 (Dot)       | 0.384   | 0.326  |
| MSMARCO-v3 (Cosine)    | 0.383   | 0.328  |
| MiniLM-L6              | 0.362   | 0.306  |
| Trained from Scratch   |         |        |
| MSMARCO-v3 (Dot)       | 0.368   | 0.312  |
| MSMARCO-v3 (Cosine)    | 0.375   | 0.320  |
| Fine-tuned model on NQ |         |        |
| NQ (Yamada et al., 2021) | 0.130   | 0.105  |

Table 5: Backbone model analysis for BPR (Yamada et al., 2021). We evaluated both fine-tuned on MS MARCO or NQ or trained from scratch as backbones. TAS-B overall achieves the best in-domain BPR performances on the MS MARCO DEV dataset.

#### Backbone analysis for JPQ
To maintain consistency between the zero-shot results with BPR and JPQ, we chose the best performing backbone model on BPR i.e. the TAS-B model also as a backbone for JPQ. From Table 7, we find that the JPQ model trained using TAS-B backbone outperforms the original STAR backbone by 1.3 points on average on BEIR.
| Split (→) | Domain (↓) | Dataset (↓) | Title | Relevancy | Train Dev Test Avg. Word Lengths |
|-----------|------------|-------------|-------|-----------|---------------------------------|
| Passage-Retrieval | Misc | MS MARCO | No | Binary | $532,761$ | $6,980$ | $8,841,823$ | $1.1$ | $5.96$ | $55.98$ |
| Bio-Medical | Bio-Medical | TREC-COVID | Yes | 3-level | $110,575$ | $324$ | $323$ | $3,633$ | $38.2$ | $3.30$ | $232.26$ |
| Information Retrieval (IR) | Bio-Medical | BioASQ | Yes | Binary | $32,916$ | $500$ | $14,914,602$ | $4.7$ | $8.05$ | $202.61$ |
| Question Answering (QA) | Wikipedia | NQ | Yes | Binary | $132,803$ | $3,452$ | $2,681,468$ | $2.0$ | $17.61$ | $46.30$ |
| | Wikipedia | HotpotQA | Yes | Binary | $170,000$ | $5,447$ | $5,233,329$ | $2.0$ | $17.61$ | $46.30$ |
| | Finance | FiQA-2018 | No | Binary | $1,406$ | $57,638$ | $2.6$ | $10.77$ | $132.32$ |
| Tweet-Retrieval | Twitter | Signal-1M (RT) | No | 3-level | $57$ | $594,977$ | $4.7$ | $15.27$ | $634.79$ |
| Argument Retrieval | Misc | ArguAna | Yes | Binary | $249$ | $10,000$ | $522,931$ | $1.1$ | $12.37$ | $213.63$ |
| Duplicate-Question Retrieval | StackEx | CQADupStack | Yes | Binary | $13,145$ | $55,977$ | $4.7$ | $15.27$ | $634.79$ |
| Entity-Retrieval | Wikipedia | DBPedia | Yes | 3-level | $49$ | $382,545$ | $4.7$ | $15.27$ | $634.79$ |
| Citation-Prediction | Scientific | SCIDOCS | Yes | Binary | $1,535$ | $5,416,568$ | $4.7$ | $15.27$ | $634.79$ |

Table 6: Statistics of datasets in BEIR benchmark taken from (Thakur et al., 2021). Few datasets contain documents without titles. Relevancy indicates the query-document relation: binary (relevant, non-relevant) or graded into sub-levels. Avg. D/Q indicates the average relevant documents per query.

| Dataset (↓) /Model (→) | JPQ (STAR) (Zhan et al., 2021a) | JPQ (TAS-B) (our work) | BPR (NQ) (Yamada et al., 2021) | BPR (TAS-B) (our work) |
|--------------------------|---------------------------------|------------------------|---------------------------------|------------------------|
|                         | $\text{Memory Efficiency}$ | $\text{JPQ (STAR)}$ | $\text{JPQ (TAS-B)}$ | $\text{BPR (NQ)}$ | $\text{BPR (TAS-B)}$ |
| MSMARCO                  | $0.402$ | $0.400$ | $0.130$ | $0.397$ | $0.400$ |
| TREC-COVID               | $0.654$ | $0.601$ | $0.201$ | $0.397$ | $0.400$ |
| BioASQ                   | $0.306$ | $0.326$ | $0.040$ | $0.285$ | $0.285$ |
| NRCorpus                 | $0.237$ | $0.312$ | $0.115$ | $0.287$ | $0.287$ |
| NQ                       | $0.446$ | $0.446$ | $0.399$ | $0.447$ | $0.447$ |
| HotpotQA                 | $0.456$ | $0.552$ | $0.240$ | $0.482$ | $0.482$ |
| FiQA-2018                | $0.295$ | $0.289$ | $0.081$ | $0.255$ | $0.255$ |
| Signal-1M (RT)           | $0.249$ | $0.269$ | $0.157$ | $0.241$ | $0.241$ |
| TRECEWS                  | $0.382$ | $0.366$ | $0.161$ | $0.338$ | $0.338$ |
| Robust04                 | $0.392$ | $0.398$ | $0.207$ | $0.309$ | $0.309$ |
| ArguAna                  | $0.415$ | $0.389$ | $0.201$ | $0.316$ | $0.316$ |
| Tōüche-2020              | $0.240$ | $0.176$ | $0.073$ | $0.167$ | $0.167$ |
| CQADupStack              | $0.296$ | $0.296$ | $0.110$ | $0.287$ | $0.287$ |
| Quora                    | $0.852$ | $0.830$ | $0.677$ | $0.852$ | $0.852$ |
| DBPedia                  | $0.281$ | $0.370$ | $0.236$ | $0.335$ | $0.335$ |
| SCIDOCS                  | $0.122$ | $0.134$ | $0.058$ | $0.130$ | $0.130$ |
| FEVER                    | $0.669$ | $0.664$ | $0.325$ | $0.571$ | $0.571$ |
| Climate-FEVER            | $0.198$ | $0.194$ | $0.121$ | $0.177$ | $0.177$ |
| SciFact                  | $0.507$ | $0.622$ | $0.221$ | $0.548$ | $0.548$ |
| AVERAGE                  | $0.389$ | $0.402$ | $0.201$ | $0.357$ | $0.357$ |

Table 7: JPQ (Zhan et al., 2021a) trained on $(M = 96)$ centroids with STAR (Roberta) as base model. Evaluated zero-shot, and with GenQ or GPL on the BEIR benchmark (Thakur et al., 2021). All scores denote nDCG@10.
Figure 5: A comparison of dimensional efficiency between BPR and BPR+GPL models for all datasets present in the BEIR benchmark (Thakur et al., 2021). For most of the datasets, BPR+GPL has a skewed distributed in the middle which denotes to utilize the dimensions better and capture more information within the 768 binary compressed vectors.