

Distill-VQ: Learning Retrieval Oriented Vector Quantization By Distilling Knowledge from Dense Embeddings

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ABSTRACT

Vector quantization (VQ) based ANN indexes, such as Inverted File System (IVF) and Product Quantization (PQ), have been widely applied to embedding based document retrieval thanks to the competitive time and memory efficiency. Originally, VQ is learned to minimize the reconstruction loss, i.e., the distortions between the original dense embeddings and the reconstructed embeddings after quantization. Unfortunately, such an objective is inconsistent with the goal of selecting ground-truth documents for the input query, which may cause severe loss of retrieval quality. Recent works identify such a defect, and propose to minimize the retrieval loss through contrastive learning. However, these methods intensively rely on queries with ground-truth documents, whose performance is limited by the insufficiency of labeled data.

In this paper, we propose Distill-VQ, which unifies the learning of IVF and PQ within a knowledge distillation framework. In Distill-VQ, the dense embeddings are leveraged as “teachers”, which predict the query’s relevance to the sampled documents. The VQ modules are treated as the “students”, which are learned to reproduce the predicted relevance, such that the reconstructed embeddings may fully preserve the retrieval result of the dense embeddings. By doing so, Distill-VQ is able to derive substantial training signals from the massive unlabeled data, which significantly contributes to the retrieval quality. We perform comprehensive explorations for the optimal conduct of knowledge distillation, which may provide useful insights for the learning of VQ based ANN index. We also experimentally show that the labeled data is no longer a necessity for high-quality vector quantization, which indicates Distill-VQ’s strong applicability in practice. The evaluations are performed on MS MARCO and Natural Questions benchmarks, where Distill-VQ notably outperforms the SOTA VQ methods in Recall and MRR. Our code is available at <https://github.com/staoxiao/LibVQ>.

CCS CONCEPTS

• **Computing methodologies** → *Continuous space search*.

KEYWORDS

Vector Quantization, Knowledge Distillation, Embedding Based Retrieval, Approximate Nearest Neighbour Search

ACM Reference Format:

Shitao Xiao, Zheng Liu, Weihao Han, Jianjin Zhang, Defu Lian, Yeyun Gong, Qi Chen, Fan Yang, Hao Sun, Yingxia Shao, Denvy Deng, Qi Zhang, Xing Xie. 2022. Distill-VQ: Learning Retrieval Oriented Vector Quantization By Distilling Knowledge from Dense Embeddings. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '22)*, July 11–15, 2022, Madrid, Spain. , 11 pages. <https://doi.org/10.1145/3477495.3531799>

1 INTRODUCTION

The embedding based retrieval (EBR) of documents plays an important role in many web applications, such as search engines and recommender systems [5, 12, 17, 23]: given an input query, the relevant documents are selected from the entire corpus based on embedding similarity. Knowing that brute-force linear scan is temporally infeasible, the embeddings need to be organized by ANN index in order to support real-world information retrieval. For the past decade, the vector quantization (VQ) techniques, e.g., Inverted File System (IVF) [1, 2, 19] and Product Quantization (PQ) [18, 40, 45], are widely applied, which enables ANN to be performed with competitive time and memory efficiency.

• **Typical learning paradigms of VQ.** VQ is typically learned to minimize the reconstruction loss, i.e., the minimization of distortions (e.g., l_2 distance) between the original dense embeddings and the reconstructed embeddings from quantization. Unfortunately, such an operation is inconsistent with the goal of retrieving ground-truth documents for the query, which may cause severe loss of retrieval performance. In recent works [45, 50], the dense embeddings and VQ are jointly learned to minimize the post-quantization retrieval loss. However, the existing methods typically rely on contrastive learning, which calls for a tremendous amount of queries labeled with ground-truth documents. As a result, it may suffer from inferior performance due to the insufficiency of labeled data.

• **Our Solution.** In this paper, we propose **Distill-VQ**, which jointly learns IVF and PQ via knowledge distillation. In Distill-VQ,

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SIGIR '22, July 11–15, 2022, Madrid, Spain

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ACM ISBN 978-1-4503-8732-3/22/07...\$15.00

<https://doi.org/10.1145/3477495.3531799>

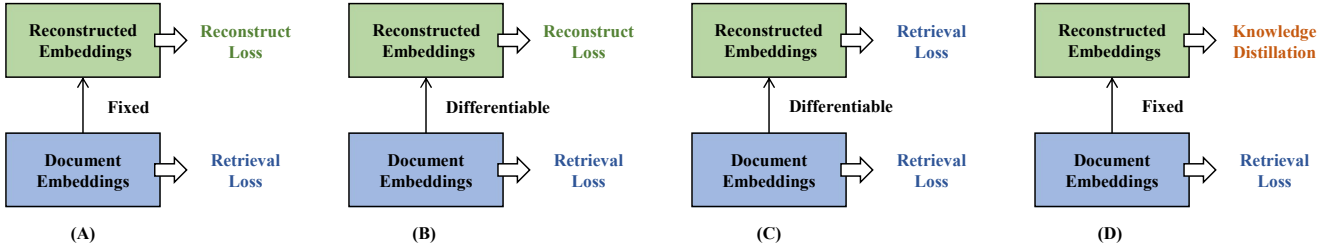


Figure 1: Development of vector quantization. (A): the reconstruction loss is minimized for the fixed document embeddings and reconstructed embeddings; e.g., PQ [18], OPQ [11]. (B): reconstructed embeddings are end-to-end differentiable and learned for reconstruction loss minimization; e.g., DPQ [8]. (C): reconstructed embeddings are end-to-end differentiable and learned for retrieval loss minimization; e.g., MoPQ [45], JPQ [50], RepCONC [51]. (D): quantized embeddings are learned by knowledge distillation based on fixed document embeddings (Distill-VQ).

we leverage well-trained dense embeddings¹ as the teachers: for each query, the teachers will predict its relevance scores towards a set of candidate documents. The predicted scores are used as the indicators of how likely the corresponding documents are the ground-truth to the query. The quantization modules are treated as the students, which are learned to reproduce the teachers’ predictions, such that the dense embeddings’ retrieval performance can be effectively preserved. Compare with the existing methods, Distill-VQ gives rise to the following merits.

First and foremost, Distill-VQ is able to exploit the data more effectively, which will significantly contribute to the retrieval quality. The current joint learning methods are typically based on contrastive learning and driven by labeled data: the model is learned to identify the document labeled as ground-truth to each query, where the remaining documents within the corpus are equally treated as negative samples. In contrast, Distill-VQ is to learn from the teachers (i.e., the well-trained dense embeddings), thus relaxing the limitation from labeled data. During the knowledge distillation process, the high-relevance documents to each query, whether labeled as ground-truth or not, will probably be given high relevance scores from the teachers. As a result, such documents will virtually serve as positive samples, which are huge supplements to the original labeled dataset. Besides, instead of treating all remaining documents equally as negative samples, Distill-VQ will penalize more for the documents which are predicted to be less relevant with the query. Therefore, it may also alleviate the false negative problems existed in the conventional methods.

In addition, Distill-VQ also contributes to higher applicability while working with those off-the-shelf document embeddings, e.g., CDSSM [24] and SBERT [35]. As discussed, the existing joint learning methods typically learn dense embeddings and VQ at the same time leveraging massive-scale of labeled data. However, it remains little explored of how to optimize the VQ’s performance on top of well-trained dense embeddings. Distill-VQ naturally alleviates this problem as it is designed to work with fixed document embeddings. Besides, knowing that the model is learned from knowledge distillation, the labeled data is no longer a necessity. In fact, it is experimentally verified that Distill-VQ may generate high-quality vector quantization without using ground-truth documents, which significantly relaxes the requirement on training data.

We perform comprehensive explorations for the optimal conduct of knowledge distillation, including the document sampling strategies (i.e., which documents to distill the teachers’ knowledge), and the function to preserve teachers and students’ similarity (which defines how to distill teachers’ knowledge from their predictions to the sampled documents). It is found that distilling knowledge from a sufficient large number of Top-K documents (the Top-K relevant documents to each query predicted by the teachers) with functions enforcing ranking order invariance, e.g., ListNet [4], may produce the most effective training outcome. Our evaluations are performed on two large-scale benchmarks: MS MARCO and Natural Questions, where Distill-VQ outperforms the SOTA vector quantization methods by notable margins. We also integrate Distill-VQ’s output into FAISS [22], which significantly improves the performance of its original VQ-based indexes, e.g., IVFPQ, IVF-Flat; and enables our method to be directly applicable to real-world applications. To summarize, our work is highlighted with the following points.

- We propose a novel framework Distill-VQ, which jointly learns IVF and PQ for the optimization of their retrieval performance.
- By distilling knowledge from the well-trained dense embeddings, Distill-VQ achieves much more effective exploitation of the data, and contributes to a higher applicability when working with off-the-shelf embeddings.
- Comprehensive explorations are performed for the optimal conduct of Distill-VQ, including the document sampling strategies and the functions to enforce teachers and students’ consistency.
- Experimental studies on MS MARCO and Natural Questions benchmarks verify the effectiveness of Distill-VQ.

2 RELATED WORKS

Embedding based retrieval has been widely applied in practice, such as search engines [30, 39], question answering [33, 34, 54], on-line advertising [26, 31], and content-based recommender systems [27, 44]. Knowing that the documents need to be retrieved from a large-scale corpus, where brute-force linear scan will be temporally infeasible, it calls for approximate nearest neighbour search (ANN) [28] such that documents with high embedding similarities can be efficiently selected. The ANN index needs to trade-off three key factors: time cost, memory usage, and recall rate. That’s to say, it is expected to recall high-quality candidates with the minimum consumption of time and memory. In recent years, the VQ based ANN indexes (e.g., IVFADC [19], IMI [1], IVFADC-G-P [2], DiskANN [40], SPANN [6]) have been widely recognized as effective solutions to realize this objective. For the family of VQ based ANN indexes: the

¹We target on optimizing the retrieval performance resulted from vector quantization. How to train dense embeddings is beyond the discussion of this paper.

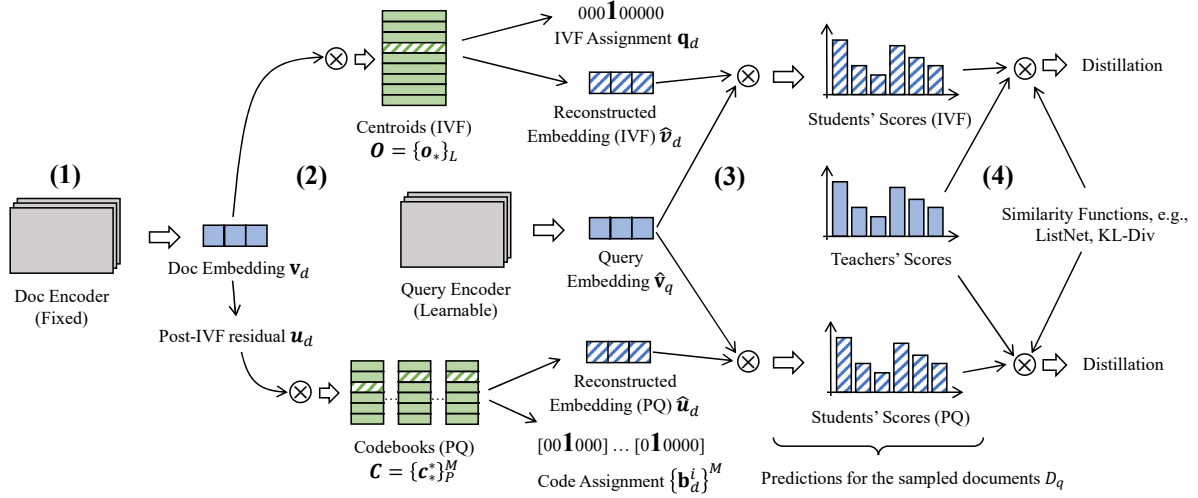


Figure 2: Distill-VQ. (1) The Doc Encoder (well-trained and fixed) infers the embeddings for all documents in the offline stage. (2) Each document embedding is assigned to IVF and PQ (the assigned entries are stripped); then, the embedding is reconstructed w.r.t. the assignments of IVF and PQ, respectively. (3) The Query Encoder infers the query embedding, which will interact (inner-product in our work) with the reconstructed embeddings for the relevance scores with the document. For each query: the relevance scores are computed for all the sampled documents. (4) The knowledge distillation is performed w.r.t. the relevance scores from teachers (computed in the offline stage).

original dense embeddings are quantized based on the codec of index, including the IVF’s centroids, and the PQ’s codebooks. With this operation, the document can be expressed as binary codes, which is much lighter than the original dense embeddings. What’s more, the retrieval process can be significantly accelerated based on the inverted file system and the approximate distance computation from the codebooks.

For the past decade, the learning of VQ has passed through different stages, with training objective evolving from reconstruction loss minimization to retrieval loss minimization. The detailed development is discussed as follows.

• **Reconstruction loss minimization.** VQ is originally learned to minimize the reconstruction loss, i.e., the minimization of the distortions (e.g., the l_2 distance) between the reconstructed embeddings and the original dense embeddings. Typical methods work with fixed document embeddings, and rely on unsupervised approach, such as clustering (e.g., k -means) or hierarchical clustering, for the learning of codebooks [18, 19] and inverted indexes [2, 6, 19], as Figure 1 (A). Knowing that the distribution of the original dense embeddings can be unfavorable for quantization, people propose OPQ [11], where the optimal rotation matrix is learned for a more effective reduction of the reconstruction loss. Later on, it is also proposed to jointly learn vector quantization and embedding models in an end-to-end differentiable way [3, 8, 49, 53] as Figure 1 (B), where the reconstruction loss can be further reduced.

• **Retrieval loss minimization.** One potential problem about the above works is that VQ is learned purely based on document embeddings, whereas the relationships with queries are not taken into consideration. Besides, it is also analyzed in [45] that the reduction of the reconstruction loss does not necessarily improve the retrieval quality. Realizing such defects, the latest works (e.g., MoPQ [45], JPQ [50], RepCONC [51]) propose to jointly learn VQ and the embedding models via contrastive learning, in which the discrimination of the ground-truth documents for each query can be

optimized (referred as retrieval loss minimization), as Figure 1 (C). Compared with the previous minimization of the reconstruction loss, the retrieval loss minimization achieves substantial improvements in terms of the retrieval performance.

• **Distinctions of our work.** Distill-VQ is similar with the existing works as it also targets on optimizing the retrieval quality rather than simply minimizing the reconstruction loss. However, Distill-VQ is differentiated in the following aspects, as Figure 1 (D). First and foremost, Distill-VQ is learned from well-trained dense embeddings via knowledge distillation, while the existing methods rely on contrastive learning. Secondly, Distill-VQ relaxes the requirement on labeled data, and can be effectively trained purely with unlabeled data. Thirdly, Distill-VQ works with fixed document embeddings instead of end-to-end optimization of the whole model.

• **Knowledge Distillation.** Finally, it should be noted that knowledge distillation (KD) [14] plays the fundamental role in Distill-VQ. KD used to be a powerful tool for model compression [21, 38, 41], where the student model (lightweight) is learned to imitate the predictions from the teacher model (heavyweight). In recent years, it becomes increasingly popular to apply KD for representation learning. For example, in [16, 36, 52], the representation models are distilled from the relevance scores predicted by the re-ranking models; and in [7, 46], the representation models are pretrained by distilling knowledge from the pseudo labels annotated by the teacher models. It is generally believed that KD contributes to the representation learning thanks to the exploitation of massive unlabeled data [46] and label smoothing [48]. Distill-VQ inherits such merits of KD, thus becoming more effective in preserving the dense embeddings’ retrieval performance.

3 DISTILL-VQ

The framework of Distill-VQ is shown as Figure 2, where both IVF and PQ modules are optimized. As a result, the developed techniques can be directly applied to generic VQ-based ANN indexes, such as PQ, IVFPQ, IVF-Flat, IVFADC-G-P, DiskANN, SPANN, etc.

The workflow of Distill-VQ is divided into four steps. Firstly, Distill-VQ works with a well-trained document encoder, which generates the embeddings for all documents in the offline stage. The document embeddings are fixed in Distill-VQ, which longer take any computation cost in quantization learning. Secondly, each document embedding is assigned to its nearest centroid in IVF and the nearest codeword in each codebook of PQ. The assignment results are represented in binarized forms (i.e., one-hot vectors indicating the assigned ID), and used to generate the reconstructed embeddings for the document. Thirdly, the query encoder is used to generate query embedding, which will interact (inner-product) with the reconstructed document embedding for the relevance score. Finally, the knowledge distillation is performed, which enables the relevance scores computed by students (i.e., the reconstructed embeddings) to imitate the predictions from the teachers (i.e., the well-trained dense embeddings of the queries and documents).

3.1 Quantization and Reconstruction

The document embeddings are quantized and reconstructed via the following steps. Firstly, the document embedding \mathbf{v}_d is generated for each document d from the well-trained document encoder. Secondly, the IVF's centroids ($\mathbf{O} = \{\mathbf{o}_i \in \mathbb{R}^h\}_L$; L : size of IVF) and PQ's codebooks ($\mathbf{C} = \{\mathbf{c}_i^j \in \mathbb{R}^{h/M}\}_P^M$; P : number of codewords per codebook; M : number of codebooks) are initialized from the document embeddings based on vanilla IVFPQ [19]:

$$\mathbf{O}, \mathbf{C} \leftarrow \text{IVFPQ}(\{\mathbf{v}_d\}_D). \quad (1)$$

The document embeddings can be quantized and reconstructed on top of the initialized IVF and PQ. For IVF, each document embedding is quantized by assigning to the closest centroid (using l_2 distance); and gets reconstructed as $\hat{\mathbf{v}}_d$ based on the assigned centroid²:

$$\mathbf{q}_d \leftarrow \arg \min_i \|\mathbf{v}_d - \mathbf{o}_i\|; \hat{\mathbf{v}}_d \leftarrow \mathbf{o}_{\mathbf{q}_d}. \quad (2)$$

For PQ, the post-IVF residue \mathbf{u}_d is computed for each document embedding based on its IVF assignment: $\mathbf{u}_d \leftarrow \mathbf{v}_d - \hat{\mathbf{v}}_d$. Then, the post-IVF residue is quantized into M one-hot vectors $\{\mathbf{b}_d^i\}^M$ by assigning each segment of $\mathbf{u}_d^i \in \{\mathbf{u}_d^i\}^{1 \dots M}$ to its closest codeword in the corresponding codebook, and gets reconstructed as $\hat{\mathbf{u}}_d$ by concatenating all the assigned codewords:

$$\mathbf{b}_d^i \leftarrow \arg \min_j \|\mathbf{u}_d^i - \mathbf{c}_j^i\|; \hat{\mathbf{u}}_d = \text{concat}([\mathbf{c}_{\mathbf{b}_d^1}^1, \dots, \mathbf{c}_{\mathbf{b}_d^M}^M]). \quad (3)$$

3.2 Knowledge Distillation

The reconstructed embeddings are learned from knowledge distillation, where the well-trained embeddings for the document (\mathbf{v}_d) and query (\mathbf{v}_q) are utilized as the **Teachers**. Particularly, for each query (q), the teachers' scores (T_q) are computed for its sampled candidate documents ($d \in D_q$) based on \mathbf{v}_d and \mathbf{v}_q :

$$T_q \leftarrow \{\langle \mathbf{v}_q, \mathbf{v}_d \rangle | d \in D_q\}, \quad (4)$$

where " $\langle \cdot \rangle$ " is the inner-product operator. The reconstructed embeddings are treated as the **Students**, which will generate their

Algorithm 1: Distill-VQ

Input : Well-trained dense embeddings: $\{\mathbf{v}_d\}_D, \{\mathbf{v}_q\}_Q$

Output: IVF, PQ, updated query encoder

```

1 begin
2   while Not converge do
3     for  $q \in Q$  do
4        $D_q \leftarrow$  sample candidate documents from  $D$ ;
5        $T_q \leftarrow$  generate teachers' scores as Eq. 4;
6        $S_q^\alpha, S_q^\beta \leftarrow$  generate students' scores as Eq. 5;
7       Update IVF, PQ and query encoder w.r.t. Eq. 6;

```

scores (S_q^α and S_q^β) towards each query's candidate documents:

$$\begin{aligned} \text{IVF} : S_q^\alpha &\leftarrow \{\langle \tilde{\mathbf{v}}_q, \hat{\mathbf{v}}_d \rangle | d \in D_q\}; \\ \text{PQ} : S_q^\beta &\leftarrow \{\langle \tilde{\mathbf{v}}_q, \hat{\mathbf{u}}_d + \hat{\mathbf{v}}_d \rangle | d \in D_q\}. \end{aligned} \quad (5)$$

Note that the query encoder is still learnable in knowledge distillation. Therefore, the query embedding $\tilde{\mathbf{v}}_q$ will become different from its original value \mathbf{v}_q (i.e., the one used for computing teachers' scores). The students' scores are required to preserve the teachers' predictions w.r.t. a certain similarity function " $f(\cdot)$ ". Finally, the objective for the knowledge distillation is formulated as:

$$\min_{\mathbf{O}, \mathbf{C}, \tilde{\mathbf{v}}_q} - \sum_q \left(f(T_q, S_q^\alpha | D_q) + f(T_q, S_q^\beta | D_q) \right). \quad (6)$$

The above optimization problem involves two groups of learnable parameters: the IVFPQ related parameters \mathbf{O} and \mathbf{C} , and the query encoder (which generates $\tilde{\mathbf{v}}_q$). Compared with the conventional joint learning methods [45, 50], the document embedding \mathbf{v}_d is fixed in Distill-VQ, meaning that the document encoder is excluded from the training process. Considering that the document is usually much larger than the query in terms of sequence length, and there are multiple candidate documents sampled for each query, such a difference will lead to a major saving of the computation cost.

Given the above formulation, the vector quantization is learned through the following iterative process (Alg. 1): for each query, the candidate documents D_q are sampled from the entire documents D ; then, teachers' scores are computed based on the well-trained dense embeddings, and the students' scores are computed based on the reconstructed embeddings; finally, the model is updated for the minimization of the distillation loss through gradient descent.

The knowledge distillation in Alg. 1 involves two critical factors: 1) the **Similarity Function** $f(\cdot)$, which determines what kind of similarity to be preserved between the teachers and students; and 2) the **Sampling Strategy** for the candidate documents D_q , which identifies the documents where the similarity needs to be preserved. In the next part, we'll make discussions on a series of alternative solutions for both factors, whose impacts will be comprehensively explored in our experimental studies.

3.2.1 Similarity Function. The students may preserve the teachers' predictions in two alternative ways. One is to enforce the **Score Invariance**, where the students are expected to generate the same relevance scores for the candidate documents as predicted by the teachers. It is a quite rigid requirement for the similarity between

²Considering the high time cost of reassignment over large-scale IVF centroids, we fix the assignment of IVF centroids in the training process.

teachers and students. In this place, we'll introduce the following similarity functions for the enforcement of score invariance.

- **Mean Square Error (MSE).** The simplest form of score invariance is to minimize the absolute difference between the scores predicted by the teachers and students:

$$f(T_q, S_q^* | D_q) = \sum_{d \in D_q} \|s_{q,d} - t_{q,d}\|, \quad (7)$$

where S_q^* are the students' predicted scores, i.e., S_q^α or S_q^β ; $s_{q,d}$ and $t_{q,d}$ are the students' and teachers' predictions towards each candidate document d , as Eq. 4 and 5.

- **Margin MSE.** A modification of MSE is utilized in [16]: instead of directly minimizing the absolute difference, it minimizes the difference between the margins of scores for two candidate documents d_1 and d_2 , as predicted by the teachers and students:

$$f(T_q, S_q^* | D_q) = \sum_{d_1, d_2 \in D_q} \| (t_{q,d_1} - t_{q,d_2}) - (s_{q,d_1} - s_{q,d_2}) \|. \quad (8)$$

Margin MSE is a relaxation of MSE, which emphasizes more of the pairwise relationships between the candidate documents rather than the absolute scores.

Aside from the above functions for the enforcement of score invariance, a more flexible option is to enforce the **Ranking Order Invariance**, where the students are merely expected to generate the same ranking orders for the candidate documents as predicted by the teachers. It is a highly relaxed requirement for the teachers and students similarity, which will probably become much easier to optimize. In this place, we introduce the following similarity functions to enforce the ranking order invariance.

- **RankNet.** The weighted RankNet (RankNet for short) was a pairwise ranking loss proposed in [15]. With RankNet, the teachers and students' consistency is to be kept in terms of the pairwise relationship between two candidate documents:

$$f(T_q, S_q^* | D_q) = - \sum_{d_1, d_2 \in D_q} (t_{q,d_1} - t_{q,d_2}) * \log \sigma(s_{q,d_1} - s_{q,d_2}). \quad (9)$$

It can be regarded as a variation of BPR loss [37] weighted by the teachers' prediction. Aside from the pairwise ranking loss, the functions on listwise similarity may also be leveraged.

- **KL-divergence.** The teachers and students' predicted scores towards the candidate documents are normalized into the following distributions (teachers: $\Phi_{q,*}^t$, students: $\Phi_{q,*}^s$):

$$\Phi_{q,d}^t = \frac{\exp(t_{q,d})}{\sum_{d \in D_q} \exp(t_{q,d})}, \quad \Phi_{q,d}^s = \frac{\exp(s_{q,d})}{\sum_{d \in D_q} \exp(s_{q,d})}. \quad (10)$$

A sufficient condition for ranking order invariance is that the students may generate the same distribution as the teachers. To this end, the KL-divergence is minimized for the above distributions:

$$f(T_q, S_q^* | D_q) = \text{KL}(\Phi_{q,*}^s || \Phi_{q,*}^t) = - \sum_{d \in D_q} \Phi_{q,d}^s \log \frac{\Phi_{q,d}^t}{\Phi_{q,d}^s}. \quad (11)$$

- **ListNet.** A close variant of KL-divergence is ListNet [4], which is a well-known function for ranking order preservation. In ListNet, the cross-entropy is minimized for the students and teachers'

distribution over the candidate documents (as Eq. 10):

$$f(T_q, S_q^* | D_q) = H(\Phi_{q,*}^t, \Phi_{q,*}^s) = - \sum_{d \in D_q} \Phi_{q,d}^t \log \Phi_{q,d}^s. \quad (12)$$

Both KL-divergence and ListNet require the listwise similarity between teachers and students. What's more, the teachers and students' similarities on the top-ranked documents can be naturally emphasized by both functions, which enables knowledge distillation to be more consistent with the retrieval metrics.

3.2.2 Candidate Document Sampling. The retrieval performance (reflected by metrics like Recall@K and MRR) is mainly determined by the top-ranked documents, i.e., whether the ground-truth can be covered by the Top-K retrieved documents. Therefore, the students are expected to emphasize more of its similarity with the teachers on such groups of documents. Intuitively, the following sources of candidate documents can be applied for this purpose.

- **Ground-Truth.** One straightforward option is to utilize the ground-truth documents of each query, as these documents are the targets to be retrieved. Ideally, the teachers' retrieval performance can be fully preserved if the students may always generate the same rankings for the ground-truth documents (as the teachers). However, it will probably take a huge amount of labeled data to ensure the knowledge distillation quality, which will be a challenging condition in reality.

- **Top-K Documents.** Another other option is to select the documents with the Top-K similarities to the query as the candidates (based on the original dense embeddings):

$$D_q = \text{Top-K}\{\langle v_q, v_d \rangle | d \in D\}. \quad (13)$$

The Top-K documents are plausible for two reasons. Firstly, the students will fully preserve the teachers' retrieval performance as long as they may generate the same Top-K documents. Secondly, it relaxes the limitation from labeled data, since plenty of training samples can be generated for knowledge distillation by getting the Top-K documents of arbitrary queries.

- **In-Batch Documents.** Aside from the top-ranked documents, the lower-ranked documents need to be introduced for the contrastive purpose, i.e., to make sure the lower-ranked documents from the teachers are safely excluded from the students retrieval results. In this place, we leverage **in-batch sampling** [23], where one query will make use of other queries' related documents within the same batch for knowledge distillation.

Finally, we may come up with the following sampling strategies.

- **All-Mixed.** The first one still uses labeled data, where the candidate documents are a mixture of all three sources: 1) ground-truth documents, 2) Top-K documents, 3) in-batch documents.

- **Top-K and In-Batch.** The second one purely works with the unlabeled data, where the candidate documents are merely a mixture of the Top-K and in-batch documents.

The impacts of both strategies are extensively analyzed in our experiment, together with explorations of other influential factors, such as the value of K, and how many documents to sample from the Top-K, etc. It is interesting to find that purely working with the unlabeled data, i.e., the Top-K and In-Batch combination, is sufficient to achieve highly competitive knowledge distillation performance.

Datasets	MS MARCO Passage	Natural Questions
#Train (original)	502,939	79,168
#Train (processed)	502,939	58,880
#Dev	6,980	8,757
#Test	–	3,610
#Documents	8,841,823	21,015,324

Table 1: Specifications of the datasets.

4 EXPERIMENTS

4.1 Experiment Settings

4.1.1 Datasets. Our experimental studies are based on the two popular benchmarks on document retrieval. The first one is the **MS MARCO (passage retrieval)** [32]³. It is a widely used benchmark on web search and embedding-based retrieval, where the targeted answers from MS MARCO corpus need to be retrieved for queries from Bing search. The second one is the **Natural Questions (NQ)** [25]. The queries are real-world questions collected from Google Search; each of the queries is paired with an answer span and ground-truth passages from the Wikipedia pages. The detailed specifications of the datasets are shown as Table 1. For both datasets, we expect the ground-truth answer to each query can be retrieved from the entire corpus. Therefore, the experiment performances will be measured by the recall rate for the top-K retrieval result. Besides, we’ll also report MRR@10 for more comprehensive evaluation.

4.1.2 Baseline methods. We consider the following groups of baselines in experiments (corresponding to the discussions in Section 2). Firstly, the typical vector quantization methods: **IVFPQ** [19], **IVFOPQ** [11], and **ScaNN** [13], where the vector quantization is learned for reconstruction loss minimization with fixed document embeddings. Secondly, the latest work on the joint learning of embedding models and vector quantization for reconstruction loss minimization: **Poeem** [53]. Thirdly, the latest work on the joint learning of embedding models and vector quantization for retrieval loss minimization: **JPQ** [50] and **RepCONC** [51]. Note that JPQ and RepCONC utilize the original IVF provided by FAISS rather than learn it as the PQ component. We further introduce a variant of **MoPQ**[45] for ablation study, which optimizes the IVF and PQ both by contrastive learning.

4.1.3 Implementation details. Distill-VQ (our approach) leverages BERT-based backbone [9] for text encoding. In our experiments, we work with the released well-trained encoders from the latest works: **AR2-G** [52] and **CoCondenser** [10], which are the most accurate models on MS MARCO and NQ benchmarks. For the sake of fair comparisons, all the baseline methods will use **the same document embeddings** as Distill-VQ (which will be more accurate than their original implementations). For PQ, OPQ, ScaNN: the quantization will be directly applied to document embeddings from AG2-G and CoCondenser; for Poeem: the query encoder and the quantization module will be jointly learned for reconstruction loss minimization; for JPQ, RepCONC, MoPQ: the query encoder and the quantization module will be jointly learned for retrieval loss minimization. We wrap up the learned quantization results with the IVFPQ index implemented by **FAISS** [22], which enables document

retrieval to be efficiently performed. The default configuration of index is specified as follows. For IVF: a total of 10,000 posting lists are deployed, of which the Top-100 posting lists (i.e., the Top 1%) will be visited for ANN search; for PQ, a total of 64 codebooks are deployed, each of which uses 8-bit codewords (i.e., 256 codewords per codebook). Aside from the default configuration, which we will also explore more settings of IVF and PQ in our experiments.

The experiments are based on clusters of 8* NVIDIA-A100-40GB GPUs and 2* AMD EPYC 7V12 64-Core CPUs. The algorithms are implemented with python 3.6 and PyTorch 1.8.0. We optimize the parameters with the AdamW optimizer. The learning rates for query encoder, IVF centroids and PQ codebooks are 5e-6, 1e-3 and 1e-4 respectively. More training details can be found in our released code: <https://github.com/staoxiao/LibVQ>.

4.1.4 Problems to be explored. Our experiments focus on three problems. First and foremost, Distill-VQ’s impact on retrieval quality against the existing VQ methods (Section 4.2.1). Secondly, analysis of knowledge distillation: the impact from different similarity functions and different sampling strategies for candidate documents (Section 4.2.2). Thirdly, exploration of Distill-VQ’s impact on each individual component: IVF and PQ, respectively, with variant configurations of both components (Section 4.2.3, 4.2.4).

4.2 Experiment Analysis

4.2.1 Overall performance. The overall performances of different methods are evaluated under the default settings (IVF: search Top-100 out of 10,000 posting lists; PQ: 64 codebooks, each codebook is 8-bit). All the methods utilize the same document embeddings from AR2-G and CoCondenser for fair comparisons. Distill-VQ’s general effectiveness can be verified given its huge advantages over the baselines (as Table 2). For MS MARCO: Distill-VQ achieves 0.3607 and 0.3523 on MRR@10 with AR2-G and CoCondenser, outperforming the strongest baselines by +1.36% and +1.53%, respectively. For NQ: Distill-VQ achieves 0.6235 and 0.5781 on MRR@10 with both embeddings, leading to +4.0% and +0.92% over the strongest baselines. The above performances are also the SOTA results of their kinds as compared with the reported results in the latest works [43, 50, 51]. Note that our evaluation is performed on top of IVF with merely 1% of the posting lists searched, which means there is a 100× acceleration over the previous works.

Besides, it is also interesting to find that although the joint learning baselines (Poeem, JPQ, RepCONC, MoPQ) are still generally better than PQ, OPQ and ScaNN, their advantages over IVFOPQ are not as significant as the observations in previous works [43, 50, 51]. Meanwhile, the performances of Poeem (minimizing the reconstruction loss) and other joint learning methods (minimizing the retrieval loss) are also close to each other in many cases. Much of these observations is probably due to the enhancement of document embeddings, as AR2-G and CoCondenser are more accurate than conventional models, like DPR [23], ANCE [47]. However, the joint learning methods for retrieval loss minimization may regain notable advantages when working with larger acceleration and compression ratios, as to be discussed in Section 4.2.3 and 4.2.4.

4.2.2 Explorations of knowledge distillation. We further explore the similarity function and candidate documents’ impact on knowledge

³Following the existing practice, MS MARCO is tested on its released validation set.

Encoder	Method	MS MARCO Passage (Dev)				Natural Questions (Test)			
		MRR@10	R@10	R@50	R@100	MRR@10	R@10	R@50	R@100
AR2-G [52]	IVFPQ	0.2403	0.4545	0.6615	0.7325	0.2823	0.5002	0.6764	0.7240
	IVFOPQ	0.3448	0.6013	0.7881	0.8385	0.5505	0.7260	0.8047	0.8279
	ScaNN	0.2670	0.4880	0.6953	0.7963	0.4137	0.6470	0.7742	0.8124
	Poem	0.3448	0.6077	0.7975	0.8487	0.5588	0.7443	0.8246	0.8445
	JPQ	0.3451	0.6107	0.8028	0.8558	0.5666	0.7512	0.8282	0.8504
	RepCONC	0.3449	0.6106	0.7983	0.8497	0.5500	0.7382	0.8141	0.8373
	MoPQ	0.3471	0.6119	0.8037	0.8564	0.5835	0.7634	0.8412	0.8606
	Distill-VQ	0.3607[†]	0.6276[†]	0.8221[†]	0.8719[†]	0.6235[†]	0.7927[†]	0.8627[†]	0.8783[†]
CoCondenser [10]	IVFPQ	0.2252	0.4380	0.6509	0.7202	0.3871	0.6177	0.7642	0.8047
	IVFOPQ	0.3340	0.5947	0.7810	0.8325	0.5447	0.7362	0.8385	0.8626
	ScaNN	0.2470	0.4602	0.6715	0.7442	0.4520	0.6540	0.7831	0.8193
	Poem	0.3363	0.6026	0.7908	0.8403	0.5522	0.7476	0.8354	0.8573
	JPQ	0.3360	0.5954	0.7810	0.8335	0.5436	0.7448	0.8335	0.8551
	RepCONC	0.3319	0.5895	0.7798	0.8342	0.5544	0.7495	0.8356	0.8602
	MoPQ	0.3370	0.6056	0.8019	0.8542	0.5689	0.7549	0.8395	0.8627
	Distill-VQ	0.3523[†]	0.6212[†]	0.8086	0.8612[†]	0.5781[†]	0.7654[†]	0.8543[†]	0.8762[†]

Table 2: Overall Performances on MS MARCO Passage Retrieval and Natural Questions, with embeddings from AR2-G and CoCondenser. [†] indicates the improvement over the strongest baseline is statistically significant on a paired t-test ($p < 0.05$).

Method	MS MARCO Passage (Dev)				Natural Question (Test)			
	MRR@10	R@10	R@50	R@100	MRR@10	R@10	R@50	R@100
MSE	0.3518	0.6158	0.7981	0.8457	0.5725	0.7545	0.8313	0.8520
Margin-MSE	0.3592	0.6207	0.8107	0.8595	0.5869	0.7573	0.8324	0.8504
RankNet	0.3519	0.6156	0.8044	0.8560	0.6052	0.7844	0.8623	0.8764
KL-Div	0.3633	0.6239	0.8153	0.8612	0.5846	0.7576	0.8315	0.8506
ListNet	0.3607	0.6276	0.8221	0.8719	0.6235	0.7927	0.8627	0.8783
GT+IB	0.3577	0.6240	0.8194	0.8710	0.6224	0.7910	0.8600	0.8703
GT+IB+Top-200 ¹	0.3607	0.6276	0.8221	0.8719	0.6235	0.7927	0.8627	0.8783
IB (*)	0.3543	0.6223	0.8115	0.8608	0.5992	0.7731	0.8457	0.8642
Top-3 ¹ +Top-200 ¹ (*)	0.3595	0.6215	0.8084	0.8541	0.5941	0.7603	0.8360	0.8545
IB+Top-200 ² (*)	0.3598	0.6237	0.8126	0.8616	0.6186	0.7883	0.8479	0.8662
IB+Top-3 ¹ +Top-200 ¹ (*)	0.3603	0.6265	0.8221	0.8727	0.6228	0.7915	0.8624	0.8786
IB+Top-10 (*)	0.3614	0.6285	0.8201	0.8698	0.6130	0.7853	0.8581	0.8753
IB+Top-100 (*)	0.3655	0.6312	0.8210	0.8690	0.6271	0.7933	0.8637	0.8800
IB+Top-200 (*)	0.3656	0.6298	0.8205	0.8871	0.6295	0.7969	0.8675	0.8806

Table 3: Knowledge distillation analysis. Upper: impact from similarity functions. Lower: impact from sampled documents (GT: ground-truth; IB: in-batch sampling; Top-K¹/Top-K²: sampling 1/2 document from Top-K; Top-K: using all Top-K documents; (*): w.o. ground-truth.)

Dataset	Method	Recall@100 with different number of posting lists to search						
		Top-1	Top-10	Top-30	Top-50	Top-100	Top-300	Top-500
MS MARCO	IVF + OPQ	0.4378	0.5299	0.5744	0.8180	0.8385	0.8658	0.8737
	IVF (Rctr) + OPQ	0.4550	0.7394	0.7988	0.8158	0.8366	0.8610	0.8687
	IVF (Rtrv) + OPQ	0.5018	0.7673	0.8147	0.8303	0.8493	0.8630	0.8690
	IVF (Distill) + OPQ	0.5203	0.7807	0.8289	0.8442	0.8614	0.8789	0.8838
NQ	IVF + OPQ	0.5168	0.7080	0.7731	0.7936	0.8279	0.8634	0.8759
	IVF (Rctr) + OPQ	0.5792	0.7484	0.7986	0.8218	0.8443	0.8684	0.8778
	IVF (Rtrv) + OPQ	0.6022	0.7750	0.8235	0.8401	0.8556	0.8711	0.8767
	IVF (Distill) + OPQ	0.6875	0.8326	0.8612	0.8706	0.8736	0.8875	0.8903

Table 4: Distill-VQ’s impact on IVF with different number of posting lists to search. The top-K (increased from 1 to 500, with acceleration ratio changing from 10,000× to 20×) out of the 10,000 deployed posting lists are searched for document retrieval.

distillation. The remaining experiments will be based on AR2-G unless otherwise specified, given the similar observations between the two embeddings.

• **Similarity function’s impact** The evaluation results are shown in the upper part of Table 3, where the five alternative functions discussed in Section 3.2.1: MSE, Margin-MSE, RankNet,

KL-divergence, and ListNet, are compared against each other. It can be observed that different similarities do lead to distinct distillation effects, where the overall performances from enforcing the ranking order invariance (KL-Div, ListNet, RankNet) are comparatively better than those enforcing the score invariance (MSE, Margin-MSE). As discussed, the ranking order invariance is a sufficient condition

Dataset	Method	Recall@100 with different number of deployed posting lists						
		100	500	1,000	5,000	10,000	50,000	100,000
MS MARCO	IVF + OPQ	0.5424	0.7525	0.7828	0.8231	0.8385	0.8639	0.8728
	IVF (Rctr) + OPQ	0.5390	0.7567	0.7908	0.8305	0.8366	0.8642	0.8735
	IVF (Rtrv) + OPQ	0.5916	0.7757	0.8083	0.8476	0.8493	0.8724	0.8795
	IVF (Distill) + OPQ	0.6123	0.7900	0.8200	0.8524	0.8614	0.8801	0.8850
NQ	IVF + OPQ	0.5814	0.7437	0.7700	0.8113	0.8279	0.8506	0.8592
	IVF (Rctr) + OPQ	0.5814	0.7581	0.7872	0.8337	0.8443	0.8604	0.8599
	IVF (Rtrv) + OPQ	0.7202	0.8132	0.8318	0.8487	0.8556	0.8609	0.8573
	IVF (Distill) + OPQ	0.7858	0.8445	0.8556	0.8725	0.8736	0.8819	0.8836

Table 5: Distill-VQ’s impact on IVF with different number of deployed posting lists. The number of deployment is increased from 100 to 100,000; 1% of the posting lists will be searched (e.g., Top-100 for 10,000) so that the acceleration ratio is always 100×.

for preserving dense embeddings’ retrieval performance. Besides, it is a largely relaxed requirement compared with the score invariance, which can be distilled more easily. The same reasons may also be applied to explain Margin-MSE’s advantage over MSE. We may also observe that ListNet remains competitive on both of the datasets; in contrast, KL-Div and RankNet only achieve competitive performance on one of the datasets. For RankNet, the unnormalized scores ($t_{q,d}$) from teachers are directly utilized; for KL-Div, the students’ distribution ($\Phi_{q,*}^s$) is implicitly regularized to be uniform (whereas the teachers’ distribution can be skewed in reality). Both issues may become adversarial factors for optimization under specific conditions of the teachers.

• **Candidate documents’ impact** The analysis for candidate documents’ impact are shown as the lower part of Table 3. In this place, the candidate documents come from the combinations of the following sampling sources: 1) using the ground-truth document, labeled as GT; 2) using in-batch document sampling, labeled as IB; 3) randomly sampling one/two candidate from the Top-K documents, labeled as Top- K^1 /Top- K^2 (e.g., Top- 3^1 means sample one document from the Top-3, and Top- 200^2 means sampling two documents from the Top-200); 4) using all Top-K documents, labeled as Top-K. We may have the following findings from the demonstrated results.

Firstly, the labeled data is no longer a necessity in knowledge distillation, and highly competitive retrieval performance can be achieved by distilling knowledge from the unlabeled data (marked with “*”). We may observe that the combination of in-batch sampling (IB) and Top-K documents outperforms the other sampling strategies in comparison, especially those simply working with ground-truth and in-batch. Besides, it is also interesting to find that the retrieval quality tends to benefit more from using an increased amount of Top-K documents: using the entire Top-200 is much more effective than simply using a few samples from them (IB+Top-200 against IB+Top- 200^2), and using Top-100 and Top-200 outperform the one simply using Top-10 (IB+Top-100/200 against IB+Top-10).

Secondly, although the top-ranked documents are important, the lower-ranked documents from in-batch sampling are still necessary for knowledge distillation. Comparing Top- 3^1 +Top- 200^1 with IB+Top- 3^1 +Top- 200^1 : the retrieval quality drops a lot on both datasets when in-batch sampling is disabled. However, it is also undesirable to simply work with the in-batch documents due to the lack of top-ranked documents, as the performance from IB alone is much lower than other methods.

4.2.3 Distill-VQ’s impact on IVF. Detailed exploration of Distill-VQ’s impact on IVF is shown in Table 4 and 5. To focus on the impact solely from IVF, all methods in comparison utilize the same product quantization: OPQ, as implemented by FAISS. A total of four methods are compared: 1) IVF: the original IVF implemented by FAISS, 2) IVF (Rctr): the IVF learned for reconstruction loss minimization (Poeem), 3) IVF (Rtrv): the IVF learned for retrieval loss minimization (MoPQ), and 4) IVF (Distill): the IVF learned from knowledge distillation (Distill-VQ).

For evaluations in Table 4, a total of 10,000 posting lists are deployed in IVF. The Top-K posting lists are searched for document retrieval, where a smaller K indicates a larger acceleration ratio, e.g., Top-10 indicates 1,000× speedup up (10,000/10). According to the experiment results, the retrieval quality can be continuously increased for all the methods with the growth of K; during this process, IVF (Distill) maintains notable advantages over other baselines. Besides, IVF (Distill) achieves more significant improvements when larger acceleration ratios are adopted (i.e., smaller K): when K equals to 1, IVF (Distill) outperforms the baselines by +2~6% on MS MARCO, and +8~17% on NQ. The advantages gradually diminish to +1% on both datasets when K increases to 500.

It is also interesting to see that both IVF (Rtrv) and IVF (Rctr) are no better than the original IVF when a large number of posting lists can be searched (e.g., K=500). This is probably because the jointly learning methods target on optimizing the Top-1 posting list of each query, whereas caring little of the retrieval quality from the Top-K posting lists.

Secondly, the number of deployed posting lists is increased from 100 to 100,000 in Table 5. The document retrieval will always be made by searching the top 1% posting lists (e.g., the Top-1 will be searched for 100, and the Top-50 will be searched for 5,000), thus keeping a fixed acceleration ratio of 100×. For both MS MARCO and NQ, IVF (Distill) achieves notable improvements over the strongest baselines in every setting. Besides, it is interesting to observe that although the acceleration ratio is fixed, the performances are gradually improved when more posting lists are deployed. Since an observation is consistent with the previous finding [1, 2] that fine-grained inverted indexes are beneficial to retrieval quality. The search for the Top-K indexes can be expensive when a large number of posting lists are deployed; in [2], the problem is mitigated by establishing another ANN index (e.g., HNSW) for the posting lists.

4.2.4 Distill-VQ’s impact on PQ. Further exploration of Distill-VQ’s impact on PQ is made as Table 6. To focus on the impact solely from PQ, all methods in comparison utilize the same IVF generated

		2×8		4×8		8×8		16×8		32×8	
Dataset	Method	MRR@10	R@100	MRR@10	R@100	MRR@10	R@100	MRR@10	R@100	MRR@10	R@100
MS MARCO	IVF + PQ	0.0066	0.0903	0.0051	0.0825	0.0094	0.1059	0.0489	0.2896	0.1431	0.5546
	IVF + OPQ	0.0123	0.1355	0.0444	0.3027	0.0772	0.4201	0.2599	0.7558	0.3220	0.8183
	IVF + ScaNN	0.0187	0.1559	0.0336	0.3220	0.0497	0.3778	0.1147	0.5273	0.1883	0.6553
	IVF + PQ (Poeem)	0.0122	0.1268	0.0459	0.2986	0.0934	0.4367	0.2760	0.7574	0.3253	0.8213
	IVF + PQ (JPQ)	0.0146	0.1350	0.0785	0.4412	0.1611	0.6273	0.2897	0.8118	0.3308	0.8351
	IVF + PQ (RepCONC)	0.0195	0.1760	0.0760	0.4371	0.1400	0.5789	0.2817	0.8048	0.3284	0.8372
	IVF + PQ (MoPQ)	0.0231	0.2120	0.0923	0.4855	0.1621	0.6222	0.2935	0.8089	0.3309	0.8406
	IVF + PQ (Distill)	0.0241	0.2406	0.1022	0.5274	0.1773	0.6476	0.3048	0.8106	0.3399	0.8410
NQ	IVF + PQ	0.0450	0.3479	0.0493	0.3523	0.0547	0.3679	0.0762	0.4457	0.1404	0.5673
	IVF + OPQ	0.0780	0.4254	0.1336	0.4986	0.1572	0.5772	0.3517	0.7565	0.4819	0.8127
	IVF + ScaNN	0.0828	0.4306	0.1521	0.5473	0.1610	0.5925	0.2014	0.6470	0.2923	0.7293
	IVF + PQ (Poeem)	0.0783	0.4224	0.1375	0.5198	0.1602	0.5912	0.3669	0.7686	0.4901	0.8244
	IVF + PQ (JPQ)	0.0675	0.4138	0.1587	0.5529	0.1937	0.6508	0.4080	0.8132	0.5040	0.8324
	IVF + PQ (RepCONC)	0.0847	0.4299	0.1452	0.5307	0.1853	0.6227	0.4133	0.8121	0.4988	0.8376
	IVF + PQ (MoPQ)	0.0917	0.4592	0.1642	0.5756	0.2163	0.6716	0.4613	0.8229	0.5220	0.8396
	IVF + PQ (Distill)	0.0945	0.4889	0.1802	0.6254	0.2661	0.7047	0.4776	0.8271	0.5401	0.8418

Table 6: Distill-VQ’ Impact on PQ, with the size of codebooks expanded from 2×8 to 32×8 (#Codebooks × Bit_Per_Codebook). All methods in comparison use the same IVF generated by FAISS (search Top-100 out of 10,000 posting lists for 100× acceleration).

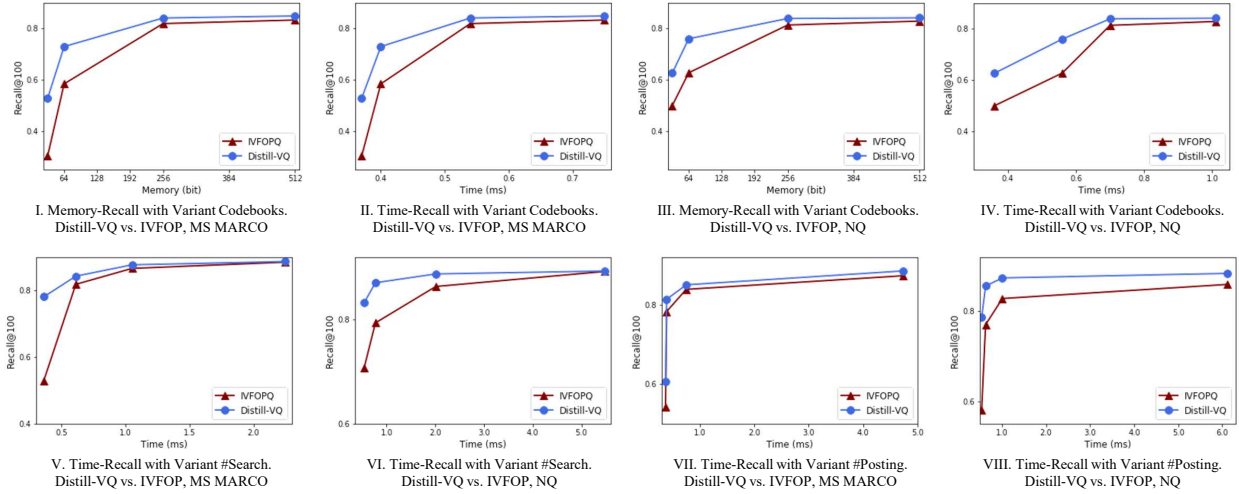


Figure 3: Efficiency and Retrieval Quality. I-IV: Recall@100 at different time/memory efficiency by changing the size of codebooks. V-VIII: Recall@100 at different time efficiency by changing 1) #Search: search the Top-#Search out of the 10,000 deployed posting lists, and 2) #Posting: the number of deployed posting lists (with the Top-1% searched).

by FAISS. The number of the codebooks is increased from 2 to 32: a smaller scale of codebooks means a larger compression ratio. With the growth of codebooks scale, the retrieval quality can be consistently improved for all the methods. When small-scale codebooks are used (meaning that the compression ratio is large), Distill-VQ is able to outperform all the baselines with notable advantages in both Recall and MRR. Besides, we may also compare different baselines more clearly when small-scale codebooks are used. Particularly, the jointly learning methods (Poeem, JPQ, RepCONC, MoPQ) achieve more significant and consistent advantages against the conventional methods (PQ, OPQ); and the methods on retrieval loss minimization (JPQ, RepCONC, MoPQ) are superior than the one minimizing the reconstruction loss (Poeem). Finally, Distill-VQ’s relative advantages gradually diminish; when codebooks become sufficiently large, some of the baselines (JPQ, RepCONC, MoPQ) are able to get close to Distill-VQ in terms of Recall. This is because

larger codebooks are more expressive than the smaller ones, which makes it easier to preserve the dense embeddings’ retrieval performance. However, Distill-VQ still maintains notable advantages in MRR@10 (more discriminative than Recall@100), indicating that the corresponding VQ is still much better than other baselines.

4.2.5 Efficiency and retrieval quality. We further analyze Distill-VQ’s retrieval quality at different working efficiency (Figure 3). The memory efficiency is measured by the bit-rate of each document; e.g., 64-bit is corresponding to the 8×8 codebooks, which leads to a 192× compression of the original dim-768 float-32 document embeddings. The time efficiency is measured by the latency of getting the Top-100 documents for each query. The evaluation is performed on top of FAISS, where the vector quantization results from Distill-VQ are loaded into the IVFPQ index in FAISS. The original IVFOPQ from FAISS is introduced for comparison.

In Figure 3 I-IV, Recall@100 is measured at different time and memory cost by changing the codebook size (correlation between recall and codebook size is discussed in Table 6). In Figure 3 V-VIII, Recall@100 is measured at different time cost by changing #Search: the amount of posting lists to search (10,000 deployed in total), and #Posting: the number of posting lists to deploy, with the Top 1% to be searched (correlations between recall and both factors are discussed in Table 4, 5). It can be observed that Distill-VQ outperforms IVFOPQ in all of these settings. Besides, the advantages become much more significant at small bit-rates and time latency, reflecting Distill-VQ’s importance in massive-scale scenarios where high compression and acceleration ratios are needed.

4.2.6 Summary of findings. The major findings of the experiments are summarized into the following points.

- Disitll-VQ notably outperforms the existing vector quantization methods on MS MARCO and Natural Questions.
- Both IVF and PQ modules may benefit from Disitll-VQ; the resulted advantages are more significant when larger compression and acceleration ratios are adopted.
- The knowledge distillation can be effectively performed based on ListNet (enforcing ranking order invariance) and documents sampled from Top-K+In-Batch (w.o. using labeled data).
- Distill-VQ results in better efficiency-recall trade-off as compared with the original IVFPQ in FAISS library.

5 CONCLUSION

We present a novel framework Distill-VQ, which jointly learns IVF and PQ for the optimization of their retrieval performances. In our framework, the VQ modules are learned by distilling knowledge from the well-trained dense embeddings, which enables massive-scale of unlabeled data to be exploited for the improvement of VQ’s performance. Our empirical explorations indicate that Distill-VQ can be effectively conducted by enforcing teachers-students ranking order invariance (ListNet) over documents sampled from unlabeled data (Top-K+In-Batch). Knowing that the proposed method may conveniently work with those off-the-shelf embeddings and easily be integrated with FAISS, we expect it to serve as a generic tool to facilitate high-quality and efficient document retrieval.

ACKNOWLEDGMENTS

This work is supported by the National Natural Science Foundation of China (Nos. U1936104, 62192784, 62022077 and 61976198) and CCF-Baidu Open Fund.

REFERENCES

- [1] Artem Babenko and Victor Lempitsky. 2014. The inverted multi-index. *IEEE transactions on pattern analysis and machine intelligence* 37, 6 (2014), 1247–1260.
- [2] Dmitry Baranchuk, Artem Babenko, and Yuri Malkov. 2018. Revisiting the inverted indices for billion-scale approximate nearest neighbors. In *ECCV*. 202–216.
- [3] Yue Cao, Mingsheng Long, Jianmin Wang, and Shichen Liu. 2017. Deep visual-semantic quantization for efficient image retrieval. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 1328–1337.
- [4] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to rank: from pairwise approach to listwise approach. In *Proceedings of the 24th international conference on Machine learning*. 129–136.
- [5] Wei-Cheng Chang, Felix X Yu, Yin-Wen Chang, Yiming Yang, and Sanjiv Kumar. 2020. Pre-training tasks for embedding-based large-scale retrieval. *arXiv preprint arXiv:2002.03932* (2020).
- [6] Qi Chen, Bing Zhao, Haidong Wang, Mingqin Li, Chuanjie Liu, Zengzhong Li, Mao Yang, and Jingdong Wang. 2021. SPANN: Highly-efficient Billion-scale Approximate Nearest Neighbor Search. *arXiv preprint arXiv:2111.08566* (2021).
- [7] Ting Chen, Simon Kornblith, Kevin Swersky, Mohammad Norouzi, and Geoffrey Hinton. 2020. Big self-supervised models are strong semi-supervised learners. *arXiv preprint arXiv:2006.10029* (2020).
- [8] Ting Chen, Lala Li, and Yizhou Sun. 2020. Differentiable product quantization for end-to-end embedding compression. In *International Conference on Machine Learning*. PMLR, 1617–1626.
- [9] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).
- [10] Luyu Gao and Jamie Callan. 2021. Unsupervised corpus aware language model pre-training for dense passage retrieval. *arXiv preprint arXiv:2108.05540* (2021).
- [11] Tiezheng Ge, Kaiming He, Qifa Ke, and Jian Sun. 2013. Optimized product quantization. *IEEE transactions on pattern analysis and machine intelligence* 36, 4 (2013), 744–755.
- [12] Daniel Gillick, Sayali Kulkarni, Larry Lansing, Alessandro Presta, Jason Baldridge, Eugene Ie, and Diego Garcia-Olano. 2019. Learning dense representations for entity retrieval. *arXiv preprint arXiv:1909.10506* (2019).
- [13] Ruiqi Guo, Philip Sun, Erik Lindgren, Quan Geng, David Simcha, Felix Chern, and Sanjiv Kumar. 2020. Accelerating large-scale inference with anisotropic vector quantization. In *International Conference on Machine Learning*. PMLR, 3887–3896.
- [14] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531* (2015).
- [15] 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* (2020).
- [16] 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. *arXiv preprint arXiv:2104.06967* (2021).
- [17] Jui-Ting Huang, Ashish Sharma, Shuying Sun, Li Xia, David Zhang, Philip Pronin, Janani Padmanabhan, Giuseppe Ottaviano, and Linjun Yang. 2020. Embedding-based retrieval in facebook search. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2553–2561.
- [18] Hervé Jegou, Matthijs Douze, and Cordelia Schmid. 2010. Product quantization for nearest neighbor search. *IEEE transactions on pattern analysis and machine intelligence* 33, 1 (2010), 117–128.
- [19] Hervé Jegou, Romain Tavenard, Matthijs Douze, and Laurent Amsaleg. 2011. Searching in one billion vectors: re-rank with source coding. In *ICASSP*. IEEE, 861–864.
- [20] Gangwei Jiang, Hao Wang, Jin Chen, Haoyu Wang, Defu Lian, and Enhong Chen. 2021. xLightFM: Extremely Memory-Efficient Factorization Machine. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 337–346.
- [21] Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. 2019. Tinybert: Distilling bert for natural language understanding. *arXiv preprint arXiv:1909.10351* (2019).
- [22] Jeff Johnson, Matthijs Douze, and Hervé Jegou. 2019. Billion-scale similarity search with gpus. *IEEE Transactions on Big Data* (2019).
- [23] 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 *EMNLP*. 6769–6781.
- [24] Yoon Kim. 2014. Convolutional Neural Networks for Sentence Classification. In *EMNLP*. Association for Computational Linguistics, Doha, Qatar, 1746–1751. <https://doi.org/10.3115/v1/D14-1181>
- [25] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. 2019. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics* 7 (2019), 453–466.
- [26] Chaozhuo Li, Bochen Pang, Yuming Liu, Hao Sun, Zheng Liu, Xing Xie, Tianqi Yang, Yanling Cui, Liangjie Zhang, and Qi Zhang. 2021. AdsGNN: Behavior-Graph Augmented Relevance Modeling in Sponsored Search. *arXiv preprint arXiv:2104.12080* (2021).
- [27] Sen Li, Fuyu Lv, Taiwei Jin, Guli Lin, Keping Yang, Xiaoyi Zeng, Xiao-Ming Wu, and Qianli Ma. 2021. Embedding-based Product Retrieval in Taobao Search. *arXiv preprint arXiv:2106.09297* (2021).
- [28] Wen Li, Ying Zhang, Yifang Sun, Wei Wang, Mingjie Li, Wenjie Zhang, and Xuemin Lin. 2019. Approximate nearest neighbor search on high dimensional data—experiments, analyses, and improvement. *IEEE Transactions on Knowledge and Data Engineering* 32, 8 (2019), 1475–1488.
- [29] Defu Lian, Haoyu Wang, Zheng Liu, Jianxun Lian, Enhong Chen, and Xing Xie. 2020. Lightrec: A memory and search-efficient recommender system. In *Proceedings of The Web Conference 2020*. 695–705.
- [30] Yiding Liu, Weixue Lu, Suqi Cheng, Daiting Shi, Shuaiqiang Wang, Zhicong Cheng, and Dawei Yin. 2021. Pre-trained Language Model for Web-scale Retrieval in Baidu Search. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 3365–3375.

- [31] Wenhao Lu, Jian Jiao, and Ruofei Zhang. 2020. Twinbert: Distilling knowledge to twin-structured compressed BERT models for large-scale retrieval. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. 2645–2652.
- [32] 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*.
- [33] Xiaoyu Qin, Xiaowang Zhang, Muhammad Qasim Yasin, Shujun Wang, Zhiyong Feng, and Guohui Xiao. 2021. SUMA: A Partial Materialization-Based Scalable Query Answering in OWL 2 DL. *Data Science and Engineering* (2021), 229–245.
- [34] Yingqi Qu, Yuchen Ding, Jing Liu, Kai Liu, Ruiyang Ren, Wayne Xin Zhao, Daxiang Dong, Hua Wu, and Haifeng Wang. 2021. RocketQA: An optimized training approach to dense passage retrieval for open-domain question answering. In *NAACL*. 5835–5847.
- [35] Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084* (2019).
- [36] Ruiyang Ren, Yingqi Qu, Jing Liu, Wayne Xin Zhao, Qiaoqiao She, Hua Wu, Haifeng Wang, and Ji-Rong Wen. 2021. RocketQAv2: A Joint Training Method for Dense Passage Retrieval and Passage Re-ranking. *arXiv preprint arXiv:2110.07367* (2021).
- [37] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2012. BPR: Bayesian personalized ranking from implicit feedback. *arXiv preprint arXiv:1205.2618* (2012).
- [38] 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* (2019).
- [39] Yelong Shen, Xiaodong He, Jianfeng Gao, Li Deng, and Grégoire Mesnil. 2014. Learning semantic representations using convolutional neural networks for web search. In *WWW*. 373–374.
- [40] Suhas Jayaram Subramanya, Rohan Kadekodi, Ravishankar Krishaswamy, and Harsha Vardhan Simhadri. 2019. Diskann: Fast accurate billion-point nearest neighbor search on a single node. In *Proceedings of the 33rd International Conference on Neural Information Processing Systems*. 13766–13776.
- [41] Siqi Sun, Yu Cheng, Zhe Gan, and Jingjing Liu. 2019. Patient knowledge distillation for bert model compression. *arXiv preprint arXiv:1908.09355* (2019).
- [42] Yongji Wu, Defu Lian, Neil Zhenqiang Gong, Lu Yin, Mingyang Yin, Jingren Zhou, and Hongxia Yang. 2021. Linear-time self attention with codeword histogram for efficient recommendation. In *Proceedings of the Web Conference 2021*. 1262–1273.
- [43] Shitao Xiao, Zheng Liu, Weihao Han, Jianjin Zhang, Chaozhuo Li, Yingxia Shao, Defu Lian, Xing Xie, Hao Sun, Denvy Deng, et al. 2022. Progressively Optimized Bi-Granular Document Representation for Scalable Embedding Based Retrieval. In *WWW*.
- [44] Shitao Xiao, Zheng Liu, Yingxia Shao, Tao Di, and Xing Xie. 2021. Training Large-Scale News Recommenders with Pretrained Language Models in the Loop. *arXiv e-prints* (2021), arXiv-2102.
- [45] Shitao Xiao, Zheng Liu, Yingxia Shao, Defu Lian, and Xing Xie. 2021. Matching-oriented Embedding Quantization For Ad-hoc Retrieval. In *EMNLP*. 8119–8129.
- [46] Qizhe Xie, Minh-Thang Luong, Eduard Hovy, and Quoc V Le. 2020. Self-training with noisy student improves imagenet classification. In *ECCV*. 10687–10698.
- [47] Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, Jialin Liu, Paul N. Bennett, Junaid Ahmed, and Arnold Overwijk. 2021. Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval. In *International Conference on Learning Representations*. <https://openreview.net/forum?id=zeFrfgYzLn>
- [48] Li Yuan, Francis EH Tay, Guilin Li, Tao Wang, and Jiashi Feng. 2020. Revisiting knowledge distillation via label smoothing regularization. In *ECCV*. 3903–3911.
- [49] C Yue, M Long, J Wang, Z Han, and Q Wen. 2016. Deep quantization network for efficient image retrieval. In *AAAI*. 3457–3463.
- [50] Jingtao Zhan, Jiaxin Mao, Yiqun Liu, Jiafeng Guo, Min Zhang, and Shaoping Ma. 2021. Jointly optimizing query encoder and product quantization to improve retrieval performance. In *CIKM*. 2487–2496.
- [51] Jingtao Zhan, Jiaxin Mao, Yiqun Liu, Jiafeng Guo, Min Zhang, and Shaoping Ma. 2022. Learning Discrete Representations via Constrained Clustering for Effective and Efficient Dense Retrieval. In *WSDM*. 1328–1336.
- [52] Hang Zhang, Yeyun Gong, Yelong Shen, Jiancheng Lv, Nan Duan, and Weizhu Chen. 2021. Adversarial Retriever-Ranker for dense text retrieval. *arXiv preprint arXiv:2110.03611* (2021).
- [53] Han Zhang, Hongwei Shen, Yiming Qiu, Yunjiang Jiang, Songlin Wang, Sulong Xu, Yun Xiao, Bo Long, and Wen-Yun Yang. 2021. Joint Learning of Deep Retrieval Model and Product Quantization based Embedding Index. *arXiv preprint arXiv:2105.03933* (2021).
- [54] Mingdong Zhu, Derong Shen, Lixin Xu, and Xianfang Wang. 2021. Scalable Multi-grained Cross-modal Similarity Query with Interpretability. *Data Science and Engineering* (2021), 280–293.