Compact Token Representations with Contextual Quantization for Efficient Document Re-ranking

Anonymous ACL submission

Abstract

Transformer based re-ranking models can achieve high search relevance through context-aware soft matching of query tokens with document tokens. To alleviate runtime complexity of such inference, previous work has adopted a late interaction architecture with pre-computed contextual token representations at the cost of a large online storage. This paper proposes contextual quantization of token embeddings by decoupling document-specific and document-independent ranking contributions during codebook-based compression. This allows effective online decompression and embedding composition for better search relevance. This paper presents an evaluation of the above compact token representation model in terms of relevance and space efficiency.

1 Introduction

Modern search engines for text documents typically employ multi-stage ranking. The first retrieval stage extracts top candidate documents matching a query from a large search index with a simple ranking method. The second stage or a later stage uses a more complex machine learning algorithm to re-rank top results thoroughly. Recently neural re-ranking techniques from transformer-based architectures have achieved impressive relevance scores for top k document re-ranking, such as MacAvaney et al. (2019). However, using a transformer-based model to rank or re-rank is extremely expensive during the online inference (Lin et al., 2020). Various efforts have been made to reduce its computational complexity (e.g. Gao et al. (2020)).

A noticeable success in time efficiency improvement is accomplished in ColBERT (Khattab and Zaharia, 2020) which conducts late interaction of query terms and document terms during runtime inference so that token embeddings for documents can be pre-computed. Using ColBERT re-ranking after a sparse retrieval model called DeepImpact (Mallia et al., 2021) can further enhance relevance. Similarly BECR (Yang et al., 2021), CEDR-KNRM (MacAvaney et al., 2019), and PreTTR (MacAvaney et al., 2020) have also adopted the late interaction architecture in their efficient transformer based re-ranking schemes.

While the above work delivers good search relevance with late interaction, their improvement in time efficiency has come at the cost of a large storage space in hosting token-based precomputed document embeddings. For example, for the MS MARCO document corpus, the footprint of embedding vectors in ColBERT takes up to 1.8TB and hosting them in a disk incurs substantial time cost when many embeddings are fetched for re-ranking. It is highly desirable to reduce embedding footprints and host them in memory as much as possible for fast and high-throughput access, especially when an online re-ranking server is required to efficiently process many queries simultaneously.

The **contribution** of this paper is to propose a compact representation for contextual token embeddings of documents called Contextual Quantization (CQ). Specifically, we adopt codebook-based quantization to compress embeddings while explicitly decoupling the ranking contributions of document specific and document-independent information in contextual embeddings. These ranking contributions are recovered with weighted composition after quantization decoding during online inference. Our CQ scheme includes a neural network model that jointly learns context-aware decomposition and quantization with an objective to preserve correct ranking scores and order margins. Our evaluation shows that CQ can effectively reduce the storage space of contextual representation by 32 times or more for the tested datasets with insignificant online embedding recovery overhead and a small relevance degradation for re-ranking passages or documents.

2 Problem Definition and Related Work

The problem of neural text document re-ranking is defined as follows. Given a query with multiple terms and a set of candidate documents, rank these documents mainly based on their embeddings and query-document similarity. With a BERT-based re-ranking algorithm, typically a term is represented by a token, and thus in this paper, word "term" is used interchangeably with "token".

Deep contextual re-ranking models. Neural re-ranking has pursued the representation-based or interaction-based algorithms (Guo et al., 2016; Dai et al., 2018; Xiong et al., 2017). Embedding interaction based on query and document terms shows an advantage in these studies. The transformer architecture based on BERT (Devlin et al., 2019) has been recently adopted to re-ranking tasks by using BERT's [CLS] token representation to summarize query and document interactions (Nogueira and Cho, 2019; Yang et al., 2019; Dai and Callan, 2019; Nogueira et al., 2019a; Li et al., 2020). Recently BERT is integrated in late term interaction (MacAvaney et al., 2019; Hofstätter et al., 2020c,b; Mitra et al., 2020) which delivers strong relevance scores for re-ranking.

Efficiency optimization for transformer-based re-ranking. Several approaches have been proposed to reduce the time complexity of transformer-based ranking. For example, architecture simplification (Hofstätter et al., 2020c; Mitra et al., 2020), late interaction with precomputed token embeddings (MacAvaney et al., 2020), early exiting (Xin et al., 2020), and model distillation (Gao et al., 2020; Hofstätter et al., 2020a; Chen et al., 2020b). We will focus on the compression of token representation following the late-interaction work of ColBERT (Khattab and Zaharia, 2020) and BECR (Yang et al., 2021) as they deliver fairly competitive relevance scores for several well-known ad-hoc TREC datasets. This late-interaction approach follows a dual-encoder design that separately encodes the two sets of texts, studied in various NLP tasks (Zhan et al., 2020; Chen et al., 2020a; Reimers and Gurevych, 2019; Karpukhin et al., 2020; Zhang et al., 2020).

Several previous re-ranking model attempted to reduce the space need for contextual token embeddings. ColBERT has considered an option of using a smaller dimension per vector and limiting 2 bytes per number as a scalar quantization. BECR (Yang et al., 2021) uses LSH for contextual embedding compression (Ji et al., 2019). PreTTR (MacAvaney et al., 2020) uses a single layer encoder model to reduce the dimensionality of each token embedding. Following PreTTR's work, the SDR method in Cohen et al. (2021) considers neural encoding and scalar quantization, and combines static BERT embeddings with contextual embeddings. SDR is substantially slower than ColBERT because SDR runs two transformer layers in online inference. Inspired by this work, our work decomposes contextual embeddings to decouple ranking contributions during vector quantization. Unlike SDR, the document-independent component does not use raw static embeddings of BERT, but exploits corpus-specific information using the output of the transformer layers of BERT.

Vector quantization. Vector quantization with codebooks was developed for data compression to assist approximate nearest neighbor search, for example, product quantizer (PQ) from Jégou et al. (2011), optimized product quantizer (OPQ) from Ge et al. (2013); residual additive quantizer(RQ) from Ai et al. (2015) and local search additive quantizer (LSQ) from Martinez et al. (2018). Recently such a technique has been used for compressing static word embeddings (Shu and Nakayama, 2018) and document vectors in a dense retrieval scheme called JPQ (Zhan et al., 2021). None of the previous work has worked on quantization of contextual token vectors for the re-ranking task, and that is the focus of this paper.

3 Contextual Quantization

Applying vector quantization naively to token embedding compression does not ensure the ranking effectiveness because a quantizer-based compression is not lossless, and critical ranking signals could be lost during data transformation. To achieve a high compression ratio while maintaining the competitiveness in relevance, we consider the ranking contribution of a contextual token embedding for soft matching containing two components: 1) document specific component derived from the self attention among context in a document, 2) document-independent and corpus-specific component generated by the transformer model. Since for a reasonable sized document set, the second component is invariant to documents, its storage space is negligible compared to the first component. Thus the second part does not need compression. We focus on compressing the first compo-

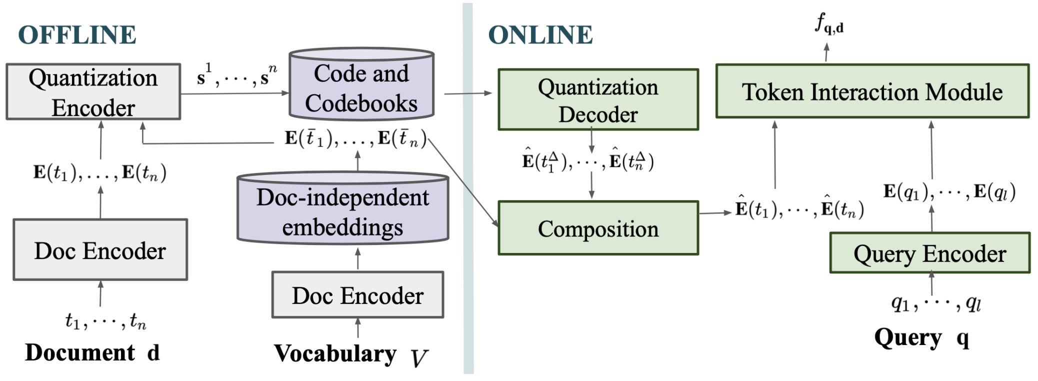

OFFLINE
Quantization Encoder
$\mathbf{s}^1, \cdots, \mathbf{s}^n$
Code and Codebooks
$\mathbf{E}(\bar{t}_1), \ldots, \mathbf{E}(\bar{t}_n)$
$\mathbf{E}(t_1), \ldots, \mathbf{E}(t_n)$
Doc-independent embeddings
Doc Encoder
Doc Encoder
$t_1, \cdots, t_n$
Document $\mathbf{d}$
Vocabulary V
ONLINE
$f_{\mathbf{q},\mathbf{d}}$
Quantization Decoder
Token Interaction Module
$\hat{\mathbf{E}}(t_1^\Delta), \cdots, \hat{\mathbf{E}}(t_n^\Delta)$
$\mathbf{E}(q_1), \cdots, \mathbf{E}(q_l)$
Composition
$\hat{\mathbf{E}}(t_1), \cdots, \hat{\mathbf{E}}(t_n)$
Query Encoder
$q_1, \cdots, q_l$
Query $\mathbf{q}$

Figure 1: Offline processing and online ranking with contextual quantization

nent using codebooks. This decomposition strategy can reduce the relevance loss due to compression approximation, which allows a more aggressive compression ratio. Our integrated vector quantizer with contextual decomposition contains a ranking-oriented scheme with an encoder and decoder network for jointly learning codebooks and composition weights. Thus, the online composition of decompressed document-dependent information with document-independent information can retain a good relevance.

3.1 Vector Quantization and Contextual Decomposition

A vector quantizer consists of two steps as discussed in Shu and Nakayama (2018). In the compression step, it encodes a real-valued vector (such as a token embedding vector in our case) into a short code using a neural encoder. The short code is a list of reference indices to the codewords in codebooks. During the decompression step, a neural decoder is employed to reconstruct the original vector from the code and codebooks.

The quantizer learns a set of M codebooks $\{\mathcal{C}^1, \mathcal{C}^2, \cdots, \mathcal{C}^M\}$ and each codebook contains K codewords ($\mathcal{C}^m = \{\mathbf{c}_1^m, \mathbf{c}_2^m, \cdots, \mathbf{c}_K^m\}$) of dimension h. Then for any D-dimensional real valued vector $\mathbf{x} \in \mathbb{R}^D$, the encoder compresses $\mathbf{x}$ into an M dimensional code vector $\mathbf{s}$. Each entry of code $\mathbf{s}$ is an integer j, denoting the j-th codeword in codebook $\mathcal{C}^m$. After locating all M codewords as $[\mathbf{c}^1, \cdots, \mathbf{c}^M]$, the original vector can be recovered with two options. For a product quantizer, the dimension of codeword is $h = D/M$, and the decompressed vector is $\hat{\mathbf{x}} = \mathbf{c}^1 \circ \mathbf{c}^2 \cdots \circ \mathbf{c}^M$ where symbol $\circ$ denotes vector concatenation. For an additive quantizerthe decompressed vector is $\hat{\mathbf{x}} = \sum_{j=1}^M \mathbf{c}^j$.

Codebook-based contextual quantization. Now we describe how codebook-based compression is used in our contextual quantization. Given a token t, we consider its contextual embedding vector $\mathbf{E}(t)$ as a weighted combination of two components: $\mathbf{E}(t^\Delta)$ and $\mathbf{E}(\bar{t})$. $\mathbf{E}(t^\Delta)$ captures the document-dependent component, and $\mathbf{E}(\bar{t})$ captures the document-independent component discussed earlier. For a transformer model such as BERT, $\mathbf{E}(t)$ is the token output from the last encoder layer, and we obtain $\mathbf{E}(\bar{t})$ by feeding [CLS] $\circ\, t \,\circ$ [SEP] into BERT model and taking last layer's output for t.

During offline data compression, we do not explicitly derive $\mathbf{E}(t^\Delta)$ as we only need to store the compressed format of such a value, represented as a code. Let $\hat{\mathbf{E}}(t^\Delta)$ be the recovered vector with codebook-based decompression, as a close approximation of $\mathbf{E}(t^\Delta)$. Let $\hat{\mathbf{E}}(t)$ be the final composed embedding used for online ranking with late-interaction. Then $\hat{\mathbf{E}}(t) = g(\hat{\mathbf{E}}(t^\Delta), \mathbf{E}(\bar{t}))$ where $g(.)$ is a simple feed-forward network to combine two ranking contribution components.

The encoder/decoder neural architecture for contextual quantization. We denote a token in a document $\mathbf{d}$ as t. The input to the quantization encoder is $\mathbf{E}(t) \circ \mathbf{E}(\bar{t})$. The output of the quantization encoder is the code vector $\mathbf{s}$ of dimension M. Let code $\mathbf{s}$ be $(s_1, \cdots, s_m, \cdots, s_M)$ and each entry s_m will be computed below in Eq. 4. This computation uses the hidden layer $\mathbf{h}$ defined as:

$$\mathbf{h} = \tanh(\mathbf{w}_0(\mathbf{E}(t) \circ \mathbf{E}(\bar{t})) + \mathbf{b}_0). \qquad (1)$$

The dimension of $\mathbf{h}$ is fixed as $1 \times MK/2$. The hidden layer $\mathbf{a}$ is computed by a feed forward layer with a softplus activation (Eq. 2) with an output dimension of $M \times K$ after reshaping, Let $\mathbf{a}^m$ be the m-th row of this output.

$$\mathbf{a}^m = \text{softplus}(\mathbf{w}_1^m \mathbf{h} + \mathbf{b}_1^m). \quad (2)$$

To derive a discrete code entry for s_m, following the previous work (Shu and Nakayama, 2018), we apply the Gumbel-softmax trick (Maddison et al., 2017; Jang et al., 2017) as shown in Eq. 3, where the temperature τ is fixed at 1 and ϵ_k is a noise term sampled from the Gumbel distribution $-\log(-\log(\text{Uniform}[0,1]))$. Here $\mathbf{p}^m$ is a vector with dimension K. $(\mathbf{p}^m)_j$ is the j-th entry of the vector. Similarly, $(\mathbf{a}^m)_j$ is the j-th entry of $\mathbf{a}^m$.

$$(\mathbf{p}^m)_j = \frac{\exp(\log((\mathbf{a}^m)_j + \epsilon_j)/\tau)}{\sum_{j'=1}^{K} \exp(\log((\mathbf{a}^m)_{j'} + \epsilon_{j'})/\tau)}. \quad (3)$$

$$s_m = \arg\max_{1 \le j \le K} (\mathbf{p}^m)_j. \quad (4)$$

In the decompression stage, the input to the quantization decoder is the code $\mathbf{s}$, and this decoder accesses M codebooks $\{\mathcal{C}^1, \mathcal{C}^2, \cdots, \mathcal{C}^M\}$ as M parameter matrices of size $K \times h$ which will be learned. For each m-entry of code $\mathbf{s}$, s_m value is the index of row vector in $\mathcal{C}^m$ to be used as its corresponding codeword. Once all codewords $\mathbf{c}^1$ to $\mathbf{c}^M$ are fetched, we recover the approximate vector $\hat{\mathbf{E}}(t^\Delta)$ as $\sum_{j=1}^{M} \mathbf{c}^j$ for additive quantization or $\mathbf{c}^1 \circ \mathbf{c}^2 \cdots \circ \mathbf{c}^M$ for product quantization.

Next, we perform a composition with a one-layer or two-layer feed-forward network to derive the contextual embedding as $\hat{\mathbf{E}}(t) = g(\hat{\mathbf{E}}(t^\Delta, \mathbf{E}(\bar{t}))$. With one feed-forward layer,

$$\hat{\mathbf{E}}(t) = \tanh(\mathbf{w}_2(\hat{\mathbf{E}}(t^\Delta) \circ \mathbf{E}(\bar{t})) + \mathbf{b}_2). \quad (5)$$

The above encoder and decoder for quantization have parameter $\mathbf{w}_0, \mathbf{b}_0, \mathbf{w}_1, \mathbf{b}_1, \mathbf{w}_3, \mathbf{b}_3$, and $\{\mathcal{C}^1, \mathcal{C}^2, \cdots, \mathcal{C}^M\}$. These parameters are learned through training. Once these parameters are learned, the quantization model is fixed and the code for any new token embedding can be computed using Eq. 4 in offline processing.

Figure 1 depicts the flow of offline learning and the online inference with context quantization. Given a query with l tokens $\{q_1, q_2, ..q_l\}$, and a documents with n tokens $\{t_1, t_2, ..t_n\}$, The query token embeddings encoded with a transformer based model (e.g. BERT) are denoted as $\mathbf{E}(q_1), \cdots, \mathbf{E}(q_l)$. The embeddings for document tokens through codebook base decompression are $\hat{\mathbf{E}}(t_1), \cdots \hat{\mathbf{E}}(t_n)$. The online inference then uses the interaction of query tokens and document tokens defined in a re-ranking algorithm such as ColBERT to derive a ranking score (denoted as $f_{\mathbf{q},\mathbf{d}}$).

The purpose of injecting $\mathbf{E}(\bar{t})$ in Eq. 1 is to decouple the document-independent ranking contribution from contextual embedding $\hat{\mathbf{E}}(t^\Delta)$ so that this quantization encoder model will be learned to implicitly extract and compress the document-dependent ranking contribution.

Table 1 gives an example with several token codes produced by CQ for different sentences representing different contexts, and illustrates context awareness of CQ's encoding with a small codebook dimension (M=K=4). For example, 1 in code [4, 4, 3, 1] means the 4-th dimension uses the first codeword of the corresponding codebook. Training of CQ uses the MS MARCO passage dataset discussed in Section 4 and these sentences are not from this dataset. Our observation from this example is described as follows. First, in general token codes in the same sentences are closer to each other, and token codes in different sentences, even with the same word "bank", are far away with a visible Hamming distance. Thus CQ coding allows a context-based separation among tokens residing in different contexts. Second, by looking at boldfaced tokens at each sentence, their distance in terms of contextual semantics and proximity is reflected to some degree in their CQ codes. For instance, a small Hamming code distance of three words "actor", "poet" and "writer" resembles their semantic and positional closeness. A larger code distance of two "bank"s in the 3rd and 4th sentences relates with their word sense and positional difference.

Training loss for parameter learning. We have explored three training loss functions. The first option is to follow a general quantizer (Shu and Nakayama, 2018) using the mean squared error (MSE) between the reconstructed and original embedding vectors of all token t_i. Namely $\mathcal{L}_{MSE} = \sum \|\mathbf{E}(t_i) - \hat{\mathbf{E}}(t_i)\|_2^2$.

The second option is the pairwise cross-entropy loss based on rank orders. After warming up with the MSE loss, we further train the quantizer using $\mathcal{L}_{PairwiseCE} = \sum(-\sum_{j=\mathbf{d}^+,\mathbf{d}^-} P_j \log P_j)$ where $\mathbf{d}^+$ and $\mathbf{d}^-$ are positive and negative documents for query q.

We adopt the third option which borrows the idea of MarginMSE loss from Hofstätter et al. (2020a) proposed for BERT-based ranking model distillation. In MarginMSE, a student model is trained to

Context	Token codes		
William Shakespeare was widely regarded as the world's greatest **actor**, **poet**, **writer** and dramatist.	writer [4,4,3,1]	actor [4,4,3,1]	poet [1,4,3,1]
I would like to have either a cup of **coffee** or a good **fiction** to kill time.	coffee [3,3,3,4]	fiction [3,1,3,4]	
She sat on the river **bank** across from a series of wide, large steps leading up a hill to the **bank** of America building.	1^{st} bank [3,1,4,2]	2^{nd} bank [4,1,3,1]	
Some language techniques can recognize word senses in phrases such as a river **bank** and a **bank** building.	1^{st} bank [4,3,2,2]	2^{nd} bank [3,1,1,4]	
If you **get** a cold, you should drink a lot of water and **get** some rest.	1^{st} get [2,2,4,2]	2^{nd} get [2,1,2,4]	

Table 1: Example context-aware token codes produced by CQ using M=K=4 for the illustration purpose.

mimic the teacher model in terms of both ranking scores as well as the document relative order margins. In our case, the teacher model is the ranking model without quantization and the student model is the ranking model with quantization. It is defined as $\mathcal{L}_{MarginMSE} = \sum((f_{\mathbf{q},\mathbf{d}^+} - f_{\mathbf{q},\mathbf{d}^-}) - (\hat{f}_{\mathbf{q},\mathbf{d}^+} - \hat{f}_{\mathbf{q},\mathbf{d}^-}))^2$, where $f_{\mathbf{q},\mathbf{d}}$ and $\hat{f}_{\mathbf{q},\mathbf{d}}$ denote the ranking score with and without quantization, respectively. The above loss function distills the ColBERT ranking characteristics into the CQ model for better preservation of ranking effectiveness.

3.2 Related Online Space and Time Cost

Online space for document embeddings. The storage cost of the precomputed document embeddings in a late-interaction re-ranking algorithm is dominating its online space need. To recover token-based document embeddings, an online server with contextual quantization stores three parts: codebooks, the short codes of tokens in each document, and the document-independent embeddings.

Given a document collection of Z documents of length n tokens on average, let V be the number of the distinct tokens. For M codebooks with $M * K$ codewords of dimension h, we store each entry of a codeword with a 4-byte floating point number. Thus the space cost of codebooks is $M * K * h * 4$ bytes, and the space for document-independent embeddings of dimension D is $V * D * 4$ bytes. When $M = 16, K = 256, D = 128$ as in our experiments, if we use the product quantization with the hidden dimension $h = 8$, the codebook size is 131 MB. In the WordPiece English token set for BERT, $V \approx 32K$ and the space for document-independent embeddings cost about 16.4 MB. Thus the space cost of the above two parts is insignificant.

The online space cost of token-based document embeddings is $Z * n * M * \log_2 K/8$ bytes. Here each contextual token embedding of length D is encoded into a code of length M and the space of each code costs $\log_2 K$ bits.

In comparison, the space for document embeddings in ColBERT with 4 bytes per number costs $Z * D * n * 4$ bytes. Then the space ratio of ColBERT without CQ and with CQ is approximately $\frac{32D}{M \log_2 K}$, which is 32:1 when $D = 128$, $M = 16$ and $K = 256$. BECR uses 5 layers of the refinement outcome with the BERT encoder for each token and stores each layer of the embedding with a 256 bit LSH signature. Thus the space cost ratio of BECR over ColBERT-CQ is $\frac{5 \times 256}{M \log_2 K}$, which is 10:1 when $M = 16$ and $K = 256$. We can adjust the parameters of each of ColBERT, BECR, and ColBERT-CQ for a smaller space with a degraded relevance, and their space ratio to CQ still remains large, which will be discussed in Section 4.

Time cost for online decompression and composition. Let k be the number of documents to re-rank. The cost of decompression with the short code of a token using the cookbooks is $O(M * h)$ for a product quantizer and $O(M * D)$ for an additive quantizer. Notice $M * h = D$. For a one-layer feed-forward network as a composition to recover the final embedding, the total time cost for decompression and composition is $O(\mathrm{k} * n * D^2)$ with a product quantizer, and $O(\mathrm{k} * n(M * D + D^2))$ with an additive quantizer. When using two hidden layers with D dimensions in the first layer output, there is some extra time cost but the order of time complexity remains unchanged.

Noted that because of using feed-forward layers in final recovery, our contextual quantizer cannot take advantage of an efficiency optimization called asymmetric distance computation in Jégou et al. (2011). Since embedding recovery is only applied to top k documents after the first-stage retrieval, the time efficiency for re-ranking is still reasonable without such an optimization.

4 Experiments and Evaluation Results

4.1 Settings

Please refer to the appendix for more details on datasets, implementation, training, and the source of relevance numbers cited for some models.

Datasets and metrics. The well-known MS MARCO passage and document ranking datasets are used. Following the official leader-board standard, for the development sets with sparse labels, we use mean reciprocal rank (MRR@10) for relevance. For the densely labeled TREC test sets, we use normalized discounted cumulative gain (NDCG@10). We also measure the dominating space need of the embeddings in bytes and re-ranking time latency in milliseconds.

To evaluate latency, we uses an AWS g4dn instance with an NVIDIA T4 GPU and 4 Intel Cascade Lake CPUs.

Choices of first-stage retrieval models. To retrieve top 1,000 results before re-ranking, we consider the standard BM25 method (Robertson and Zaragoza, 2009), and also the recent retrieval work including neural sparse retrievers: DeepCT (Dai and Callan, 2020), DeepImpact (Mallia et al., 2021), and uniCOIL (Lin and Ma, 2021; Gao et al., 2021); and dense retrievers: TCT-ColBERT(v2) (Lin et al., 2021) and JPQ (Zhan et al., 2021).

Re-ranking models and quantizers compared. We demonstrate the use of CQ for token compression in ColBERT in this paper. We compare its relevance with ColBERT, BECR and PreTTR. Other re-ranking models compared include: BERT-base (Devlin et al., 2019), a cross encoder re-ranker, which takes a query and a document at run time and uses the last layers output from the BERT [CLS] token to generate a ranking score; TILDEv2 (Zhuang and Zuccon, 2021), which expands each document and additively aggregates precomputed neural scores. We have also evaluated the use of other quantization methods discussed in Section 2 for ColBERT, including two product quantizers (PQ and OPQ), and two additive quantizers (RQ and LSQ).

4.2 A Comparison of Relevance

Table 2 and Table 3 show the ranking relevance in NDCG and MRR of the different methods and compare against the use of CQ with ColBERT (marked as ColBERT-CQ). We either report our experiment results or cite the relevance numbers from other

Model Specs.	Dev MRR@10	TREC DL19 NDCG@10	TREC DL20 NDCG@10
	Retrieval choices		
BM25*	0.167	0.488	0.480
docT5query*	0.277	0.642	–
DeepCT*	0.243	0.572	–
TCT-ColBERT(v2)	0.358	–	–
JPQ*	0.341	0.677	–
DeepImpact	0.326	0.662	0.602
uniCOIL	0.340	0.702	0.674
	Re-ranking baselines (+BM25 retrieval)		
BERT-base	0.349	0.682	0.655
BECR*	0.323	0.682	0.675
TILDEv2*	0.333	0.676	0.686
ColBERT	0.355	0.701	0.723
	Quantization (+BM25 retrieval)		
ColBERT-PQ	0.290 (-18.3%)	0.684 (-2.3%)	0.714 (-1.2%)
ColBERT-OPQ	0.324 (-8.7%)	0.691 (-1.4%)	0.688 (-4.8%)
ColBERT-RQ	–	0.675 (-3.7%)	0.696 (-3.7%)
ColBERT-LSQ	–	0.664 (-5.3%)	0.656 (-9.3%)
ColBERT-CQ	0.352 (-0.8%)	0.704 (+0.4%)	0.716 (-1.0%)
	(+uniCOIL retrieval)		
ColBERT	0.369	0.692	0.701
ColBERT-CQ	0.360 (-2.4%)	0.696 (+0.6%)	0.720 (+2.7%)

Table 2: Relevance scores for MS MARCO passage ranking. The % degradation from ColBERT is listed.

papers with a * mark for such a model. For quantization approaches, we adopt M=16, K=256, i.e. compression ratio 32:1 compared to ColBERT.

In Table 2, we choose two retrieval options (BM25 or uniCOIL) to select top 1,000 results for re-ranking. BM25 is the standard reference point, which is also the fastest method. UniCOIL delivers good relevance score compared to other retrievers. As a sparse retriever without the need of GPU, it is also faster than dense retrievers in general.

For the passage task, ColBERT outperforms other re-rankers in relevance for the tested cases. ColBERT-CQ after BM25 or uniCOIL retrieval only has a small relevance degradation with around 1% or less, while only requiring 3% of the storage of ColBERT. The relevance of the ColBERT-CQ+uniCOIL combination is also competitive to the one reported in Mallia et al. (2021) for the ColBERT+DeepImpact combination which has MRR 0.362 for the Dev query set, NDCG@10 0.722 for TREC DL 2019 and 0.691 for TREC DL 2020.

For the document re-ranking task, Table 3 similarly confirms the effectiveness of ColBERT-CQ. ColBERT-CQ and ColBERT after BM25 retrieval also perform well in general compared to the relevance results of the other baselines.

From both Table 2 and Table 3, we observe that in general, CQ significantly outperforms the other quantization approaches (PQ, OPQ, RQ, and LSQ). As an example, we further explain this by plotting the ranking score of ColBERT with and without a

Model Specs.	Dev MRR@10	TREC DL19 NDCG@10
Retrieval choices		
BM25*	0.278	0.523
docT5query*	0.288	0.597
DeepCT*	0.320	0.544
TCT-ColBERT(v2)	0.351	–
JPQ*	0.401	0.623
uniCOIL*	0.353	–
Re-ranking baselines (+BM25 retrieval)		
BERT-base*	0.393	0.670
ColBERT	0.410	0.714
Quantization (+BM25 retrieval)		
ColBERT-PQ	0.400 (-2.4%)	0.702 (-1.7%)
ColBERT-OPQ	0.404 (-1.5%)	0.704 (-1.4%)
ColBERT-RQ	–	0.704 (-1.4%)
ColBERT-LSQ	–	0.707 (-1.0%)
ColBERT-CQ	0.405 (-1.2%)	0.712 (-0.3%)

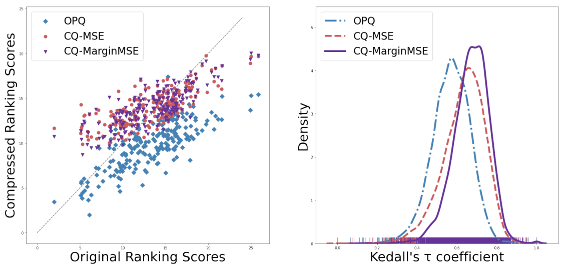
Table 3: Relevance scores for MS MARCO document ranking. The % degradation from ColBERT is listed.

quantizer in Figure 2(a). Compared to OPQ, CQ trained with two loss functions generates ranking scores much closer to the original ColBERT ranking score, and this is also reflected in Kendall's τ correlation coefficients of top 1,000 re-ranked results between a quantized ColBERT and the original ColBERT (Figure 2(b)). There are two reasons that CQ outperforms the other quantizers: 1) The previous quantizers do not perform contextual decomposition to isolate intrinsic context-independent information in embeddings, and thus their approximation yields more relevance loss; 2) Their training loss function is not tailored to the re-ranking task.

4.3 Effectiveness on Space Reduction

Model	Doc task Space	Passage task Space	Disk I/O	Latency	MRR@10
BECR*	575G	77.4G	>110ms	8ms	0.323
PreTTR*	1.8T	248G	>182ms	>1000ms	0.358
TILDEv2*	–	5.2G	–	–	0.326
ColBERT	1.8T	248G	>182ms	16ms	0.355
ColBERT-small*	172G	23G	–	–	0.339
ColBERT-OPQ	–	7.7G	–	56ms	0.324
ColBERT-CQ					
undecomposed	57.5G	7.7G	–	17ms	0.339
K=256	57.5G	7.7G	–	17ms	0.352
K=16	28.7G	3.9G	–	17ms	0.339
K=4	14.4G	1.9G	–	17ms	0.326

Table 4: Embedding space size in bytes for the document ranking task and for the passage ranking task. Re-ranking time per query and relevance for top 1,000 passages in milliseconds on a GPU using the Dev query set. M=16. For ColBERT-OPQ and ColBERT-CQ-undecomposed, K=256. We assume embeddings in BECR, PreTTR, and ColBERT do not fit in memory and we report their disk I/O for each query.



(a) (b)

Figure 2: (a) Ranking score by quantized ColBERT with OPQ and CQ using two loss functions, vs. original ColBERT score. (b) Distribution of Kendall's τ correlation coefficient between the 1,000 ranked results of quantized and original ColBERT.

Table 4 shows the space size in bytes for 3.2 million document embeddings in the MS MARCO document corpus and the 8.8 million passage embeddings in the passage corpus, and compares CQ with other approaches. To demonstrate the trade-off, we also list their estimated time latency and relevance in passage re-ranking as a reference and notice that more relevance comparison results are in Tables 2 and 3. The latency is the total time for embedding decompression/recovery and re-ranking.

For BECR, PreTTR, and ColBERT, we assume that their embedding data cannot fit in memory given their large data sizes. The disk I/O latency number is based on their passage embedding size and our test on a Samsung 870 QVO solid-state disk drive to fetch 1,000 passage embeddings randomly. Their I/O latency takes 110ms or 182ms with single-thread I/O and with no I/O contention, and their disk access can incur much more time when multiple queries are processed in parallel in a server dealing with many clients. For example, fetching 1,000 passage embeddings for each of ColBERT and PreTTR takes about 1,001ms and 3,870ms respectively when the server is handling 16 and 64 queries simultaneously with multiple threads.

For other methods, their passage embedding data is relatively small and we assume that it can be preloaded in memory. The query latency reported in the 4-th column of Table 4 excludes the first-stage retrieval time. The default ColBERT uses embedding dimension 128 and 4 byte floating numbers. ColBERT-small denotes an optional configuration suggested from the ColBERT paper using 24 embedding dimensions and 2-byte floating numbers with a degraded relevance performance.

As shown in Table 4, ColBERT CQ uses up to 57.5GB for document re-ranking and 7.7GB for passage re-ranking. It can fit in the memory of a mid-end server while the embedding footprint of original ColBERT is huge. It will be expensive to configure a server satisfying its memory requirement. By looking at the latency difference of ColBERT with and without CQ, the time overhead of CQ for decompression and embedding recovery takes 1ms per query, which is insignificant.

Compared with another quantizer ColBERT-OPQ, ColBERT-CQ can achieve the same level of space saving with $K = 256$ while having a substantial relevance improvement. ColBERT-CQ with $K = 4$ achieves the same level of relevance as ColBERT-OPQ while yielding a storage reduction of 75% and a latency reduction of about 70%. Comparing ColBERT-CQ with no contextual decomposition, under the same space cost, ColBERT-CQ's relevance is 4% higher. CQ with $K = 16$ achieves the same level relevance as ColBERT-CQ-undecomposed with $K = 256$, while the storage of CQ reduces by 50%. Comparing with ColBERT-small which adopts more aggressive space reduction, ColBERT-CQ with $K = 4$ would be competitive in relevance while its space is about 4x smaller. Comparing with other non-ColBERT baselines (BECR, PreTTR, and TILDEv2), ColBERT-CQ strikes a good balance across relevance, space and latency. For the fast CPU based model (BECR, TILDEv2), our model achieves better relevance with either lower or comparable space usage.

4.4 Design Options for CQ

	TREC19	TREC20
CQ, Product, 1 layer, MarginMSE	0.687	0.713
Different model configurations		
No decomposition. Product	0.663	0.686
No decomposition. Additive	0.656	0.693
CQ, Product, 1 layer, raw static embedding	0.655	0.683
CQ, Additive, 1 layer	0.693	0.703
CQ, Product, 2 layers	0.683	0.707
CQ, Additive, 2 layers	0.688	0.703
Different training loss functions		
CQ, Product, 1 layer, MSE	0.679	0.704
CQ, Product, 1 layer, PairwiseCE	0.683	0.705

Table 5: NDCG@10 relevance score of different design options for CQ in TREC DL passage ranking.

Table 5 shows the relevance scores for the TREC deep learning passage ranking task with different design options for CQ. As an alternative setting, the codebooks in this table uses M=16 and K=32 with compression ratio 51.2:1 compared to ColBERT. Row 1 is the default design configuration for CQ with product operators and 1 composition layer, and the MarginMSE loss function.

Different architecture or quantization options. Rows 2 and 3 of Table 5 denote CQ using product or additive operators without decomposing each embedding into two components, and there is about 4% degradation without such decomposition.

Row 4 changes CQ using the raw static embeddings of tokens from BERT instead of the upper layer outcome of BERT encoder and there is an up to 4.7% degradation. Notice such a strategy is used in SDR. From Row 5 to Row 7, we change CQ to use additive operators or use a two-layer composition. The performance of product or additive operators is in a similar level while the benefit of using two layers is relatively small.

Different training loss functions for CQ. Last two rows of Table 5 use the MSE and PairwiseCE loss functions, respectively. There is an about 1.2% improvement using MarginMSE. Figure 2 gives an explanation why MarginMSE is more effective. While CQ trained with MSE and MarginMSE generates ranking scores close to the original ranking scores in Figure 2(a), the distribution of Kendall's τ correlation coefficients of 1,000 passages in Figure 2(b) shows that the passage rank order derived by CQ with the MarginMSE loss has a better correlation with that by ColBERT.

5 Concluding Remarks

Our evaluation shows the effectiveness of CQ used for ColBERT in compressing the space of token embeddings with a 32:1 ratio or more while incurring a small relevance degradation in MS MARCO passage and document re-ranking tasks. The quantized token-based document embeddings for the tested cases can be hosted in memory for fast and high-throughput access. This is accomplished by a neural network that decomposes ranking contributions of contextual embeddings, and jointly trains context-aware decomposition and quantization with a loss function preserving ranking accuracy. The online time cost to decompress and recover embeddings is insignificant with 1ms for the tested cases. We plan to release the CQ implementation after the paper is accepted for publication. Our future work is to investigate the use of CQ in the other late-interaction re-ranking methods.

References

Liefu Ai, Junqing Yu, Zenbin Wu, Yunfeng He, and Tao Guan. 2015. Optimized residual vector quantization for efficient approximate nearest neighbor search. *Multimedia Systems*, 23:169–181.

Daniel Fernando Campos, Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, Li Deng, and Bhaskar Mitra. 2016. Ms marco: A human generated machine reading comprehension dataset. *ArXiv*, abs/1611.09268.

Jiecao Chen, Liu Yang, Karthik Raman, Michael Bendersky, Jung-Jung Yeh, Yun Zhou, Marc Najork, D. Cai, and Ehsan Emadzadeh. 2020a. Dipair: Fast and accurate distillation for trillion-scale text matching and pair modeling. In *EMNLP*.

Xuanang Chen, B. He, Kai Hui, L. Sun, and Yingfei Sun. 2020b. Simplified tinybert: Knowledge distillation for document retrieval. *ArXiv*, abs/2009.07531.

Nachshon Cohen, Amit Portnoy, Besnik Fetahu, and Amir Ingber. 2021. Sdr: Efficient neural re-ranking using succinct document representation. *ArXiv*, 2110.02065.

Nick Craswell, Bhaskar Mitra, Emine Yilmaz, Daniel Fernando Campos, and Ellen M. Voorhees. 2020. Overview of the trec 2020 deep learning track. *ArXiv*, abs/2102.07662.

Zhuyun Dai and J. Callan. 2019. Deeper text understanding for ir with contextual neural language modeling. *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Zhuyun Dai and Jamie Callan. 2020. Context-aware term weighting for first stage passage retrieval. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Zhuyun Dai, Chenyan Xiong, Jamie Callan, and Zhiyuan Liu. 2018. Convolutional neural networks for soft-matching n-grams in ad-hoc search. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*, pages 126–134. ACM.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *NAACL*.

Luyu Gao, Zhuyun Dai, and J. Callan. 2020. Understanding bert rankers under distillation. *Proceedings of the 2020 ACM SIGIR on International Conference on Theory of Information Retrieval*.

Luyu Gao, Zhuyun Dai, and Jamie Callan. 2021. COIL: revisit exact lexical match in information retrieval with contextualized inverted list. *CoRR and NAACL 2021*, abs/2104.07186.

Tiezheng Ge, Kaiming He, Qifa Ke, and Jian Sun. 2013. Optimized product quantization for approximate nearest neighbor search. *2013 IEEE Conference on Computer Vision and Pattern Recognition*, pages 2946–2953.

J. Guo, Y. Fan, Qingyao Ai, and W. Croft. 2016. A deep relevance matching model for ad-hoc retrieval. *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*.

Sebastian Hofstätter, Sophia Althammer, Michael Schröder, Mete Sertkan, and Allan Hanbury. 2020a. Improving efficient neural ranking models with cross-architecture knowledge distillation. *ArXiv*, abs/2010.02666.

Sebastian Hofstätter, Hamed Zamani, Bhaskar Mitra, Nick Craswell, and A. Hanbury. 2020b. Local self-attention over long text for efficient document retrieval. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Sebastian Hofstätter, Markus Zlabinger, and A. Hanbury. 2020c. Interpretable & time-budget-constrained contextualization for re-ranking. In *ECAI*.

Eric Jang, Shixiang Shane Gu, and Ben Poole. 2017. Categorical reparameterization with gumbel-softmax. *ArXiv*, abs/1611.01144.

Hervé Jégou, Matthijs Douze, and Cordelia Schmid. 2011. Product quantization for nearest neighbor search. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33:117–128.

Shiyu Ji, Jinjin Shao, and Tao Yang. 2019. Efficient interaction-based neural ranking with locality sensitive hashing. In *WWW*, pages 2858–2864, New York, NY, USA. ACM.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2017. Billion-scale similarity search with gpus. *arXiv preprint arXiv:1702.08734*.

V. Karpukhin, Barlas OÄ§uz, Sewon Min, Patrick Lewis, Ledell Yu Wu, Sergey Edunov, Danqi Chen, and Wen tau Yih. 2020. Dense passage retrieval for open-domain question answering. *ArXiv*, abs/2010.08191.

O. Khattab and M. Zaharia. 2020. Colbert: Efficient and effective passage search via contextualized late interaction over bert. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.

Canjia Li, A. Yates, Sean MacAvaney, B. He, and Yingfei Sun. 2020. Parade: Passage representation aggregation for document reranking. *ArXiv*, abs/2008.09093.

Jimmy Lin, Rodrigo Nogueira, and A. Yates. 2020. Pretrained transformers for text ranking: Bert and beyond. *ArXiv*, abs/2010.06467.

Jimmy J. Lin and Xueguang Ma. 2021. A few brief notes on deepimpact, coil, and a conceptual framework for information retrieval techniques. *ArXiv*, abs/2106.14807.

Sheng-Chieh Lin, Jheng-Hong Yang, and Jimmy J. Lin. 2021. In-batch negatives for knowledge distillation with tightly-coupled teachers for dense retrieval. In *REPL4NLP*.

Sean MacAvaney, F. Nardini, R. Perego, N. Tonellotto, Nazli Goharian, and O. Frieder. 2020. Efficient document re-ranking for transformers by precomputing term representations. *SIGIR*.

Sean MacAvaney, Andrew Yates, Arman Cohan, and Nazli Goharian. 2019. Cedr: Contextualized embeddings for document ranking. *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Chris J. Maddison, Andriy Mnih, and Yee Whye Teh. 2017. The concrete distribution: A continuous relaxation of discrete random variables. *ArXiv*, abs/1611.00712.

Antonio Mallia, O. Khattab, Nicola Tonellotto, and Torsten Suel. 2021. Learning passage impacts for inverted indexes. *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Julieta Martinez, Shobhit Zakhmi, Holger H. Hoos, and J. Little. 2018. Lsq++: Lower running time and higher recall in multi-codebook quantization. In *ECCV*.

Bhaskar Mitra, Sebastian Hofstätter, Hamed Zamani, and Nick Craswell. 2020. Conformer-kernel with query term independence for document retrieval. *ArXiv. and SIGIR 2021*, abs/2007.10434.

Rodrigo Nogueira and Kyunghyun Cho. 2019. Passage re-ranking with bert. *ArXiv*, abs/1901.04085.

Rodrigo Nogueira, W. Yang, Kyunghyun Cho, and Jimmy Lin. 2019a. Multi-stage document ranking with bert. *ArXiv*, abs/1910.14424.

Rodrigo Nogueira, Wei Yang, Jimmy J. Lin, and Kyunghyun Cho. 2019b. Document expansion by query prediction. *ArXiv*, abs/1904.08375.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In *EMNLP/IJCNLP*.

Stephen E. Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: Bm25 and beyond. *Found. Trends Inf. Retr.*, 3:333–389.

Raphael Shu and Hideki Nakayama. 2018. Compressing word embeddings via deep compositional code learning. *ArXiv*, abs/1711.01068.

J. Xin, Rodrigo Nogueira, Y. Yu, and Jimmy Lin. 2020. Early exiting bert for efficient document ranking. In *SUSTAINLP*.

Chenyan Xiong, Zhuyun Dai, J. Callan, Zhiyuan Liu, and R. Power. 2017. End-to-end neural ad-hoc ranking with kernel pooling. *SIGIR*.

Wei Yang, Haotian Zhang, and Jimmy Lin. 2019. Simple applications of bert for ad hoc document retrieval. *ArXiv*, abs/1903.10972.

Yingrui Yang, Yifan Qiao, Jinjin Shao, Mayuresh Vivekanand Anand, Xifeng Yan, and Tao Yang. 2021. Composite re-ranking for efficient document search with bert. *ArXiv*, abs/2103.06499.

Jingtao Zhan, J. Mao, Yiqun Liu, Min Zhang, and Shaoping Ma. 2020. Learning to retrieve: How to train a dense retrieval model effectively and efficiently. *ArXiv*, abs/2010.10469.

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. *ArXiv and CIKM 2021*, 2108.00644.

Y. Zhang, Ping Nie, Xiubo Geng, A. Ramamurthy, L. Song, and Daxin Jiang. 2020. Dc-bert: Decoupling question and document for efficient contextual encoding. In *SIGIR*.

Shengyao Zhuang and G. Zuccon. 2021. Fast passage re-ranking with contextualized exact term matching and efficient passage expansion. *ArXiv*, abs/2108.08513.

A Details on DataSets, Retrieval, Relevance Numbers, and Model Implementations

Dataset	# Query	# Doc	Mean Doc Length	# Judgments per query
MS MARCO passage Dev	6980	8.8M	55	1
TREC DL 19 passage	200	–	–	21
TREC DL 20 passage	200	–	–	18
MS MARCO doc Dev	5193	3.2M	1123	1
TREC DL 19 doc	200	–	–	33

Table 6: Dataset statistics

Datasets. As summarized the in Table 6, our evaluation uses the MS MARCO document and passage collections for document and passage ranking (Craswell et al., 2020; Campos et al., 2016). The original document and passage ranking tasks provide 367,013 and 502,940 training queries respectively, with about one judgment label per query. The development query sets are used for relevance evaluation. The TREC Deep Learning (DL) 2019 and 2020 tracks provide 200 test queries with many judgment labels per query for each task.

First-stage retrieval models considered. As a standard reference point, we use the popular BM25 method based on term frequency (Robertson and Zaragoza, 2009) to retrieve top 1,000 results before re-ranking. We have also considered the recent work in sparse and dense retrievers that outperforms BM25. For sparse retrieval with inverted indices, DeepCT (Dai and Callan, 2020) uses deep learning to assign more sophisticated term weights for soft matching. The docT5query work (Nogueira et al., 2019b) uses a neural model to pre-process and expand documents. Recently the sparse inverted index is enriched with document expansion and neural computation in the work of DeepImpact (Mallia et al., 2021) and uniCOIL (Lin and Ma, 2021; Gao et al., 2021). For dense retrieval, TCT-ColBERT(v2) (Lin et al., 2021) is a recent scheme that produces a dense document representation with knowledge distillation, and JPQ (Zhan et al., 2021) compresses dense document vectors with a jointly trained query encoder and PQ index.

Model relevance numbers cited from other papers. As marked in Table 2 and Table 3, for BM25, we cite its relevance performance in (Craswell et al., 2020; Gao et al., 2021). For docT5query, DeepCT, JPQ, TILDEv2 and BECR (Yang et al., 2021), we directly copy the relevance numbers they reported in their papers. For TCT-ColBERT(v2), DeepImpact and uniCOIL, we obtain their performance using the released checkpoints of pyserini [1]. For PreTTR (MacAvaney et al., 2020) on the passage task and BERT-base on the document task, we cite the relevance performance reported in Hofstätter et al. (2020a).

Model implementation and training. The ColBERT code follows the original version released [2] and BERT implementation is from Huggingface [3]. For BERT-base and ColBERT, training uses pairwise softmax cross-entropy loss over the released or derived triples in a form of $(\mathbf{q}, \mathbf{d}^+, \mathbf{d}^-)$ for the MS MARCO passage task. For the MS MARCO document re-ranking task, we split each positive long document into segments with 400 tokens each and transfer the positive label of such a document to each divided segment. The negative samples are obtained using the BM25 top 100 negative documents. The above way we select training triples for document re-ranking may be less ideal and can deserve an improvement in the future.

When training ColBERT, we use gradient accumulation and perform batch propagation every 32 training triplets. All models are trained using Adam optimizer (Kingma and Ba, 2015). The learning rate is 3e-6 for ColBERT and 2e-5 for BERT-base following the setup in its original paper. For ColBERT on the document dataset, we obtained the model checkpoint from the authors.

Our CQ implementation leverages the open source code [4] for Shu and Nakayama (2018). For PQ, OPQ, RQ, and LSQ, we uses off-the-shelf implementation from Facebook's faiss[5] library (Johnson et al., 2017). For MS MARCO documents, we split each document into passages of size 400 tokens with 65 overlapping tokens between two consecutive passages, following the ColBERT setup. To get training instances for each quantizer, we generate the contextual embeddings of randomly-selected 500,000 tokens from passages or documents using ColBERT.

When using the MSE loss, learning rate is 0.0001, batch size is 128, and the number of training epochs is 200,000. When fine-tuning with PairwiseCE or MarginMSE, we freeze the encoder based on the MSE loss, set the learning rate to be 3e-6, and then train for additional 800 batch iterations with 32 training pairs per batch.

[1] https://github.com/castorini/pyserini/
[2] https://github.com/stanford-futuredata/ColBERT
[3] https://huggingface.co/transformers/model_doc/bert.html
[4] https://github.com/mingu600/compositional_code_learning.git
[5] https://github.com/facebookresearch/faiss