Densifying Sparse Representations for Passage Retrieval by Representational Slicing

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Abstract

Learned sparse and dense representations capture different successful approaches to text retrieval and the fusion of their results has proven to be more effective and robust. Prior work combines dense and sparse retrievers by fusing their model scores. As an alternative, this paper presents a simple approach to densifying sparse representations for text retrieval that does not involve any training. Our densified sparse representations (DSRs) are interpretable and can be easily combined with dense representations for end-to-end retrieval. We demonstrate that our approach can jointly learn sparse and dense representations within a single model and then combine them for dense retrieval. Experimental results suggest that combining our DSRs and dense representations yields a balanced tradeoff between effectiveness and efficiency.

1 Introduction

Transformer-based bi-encoders have been widely used as a first-stage retriever for text retrieval. Previous work (Reimers and Gurevych, 2019; Chang et al., 2020; Karpukhin et al., 2020) trains models to project texts into a continuous embedding space for dense retrieval. Such dense retrievers are capable of tackling the vocabulary and semantic mismatch problems compared to traditional word matching approaches (e.g., BM25). Subsequent work further improves dense retrieval through knowledge distillation (Lin et al., 2021; Hofstätter et al., 2021), hard negative mining (Xiong et al., 2021; Zhan et al., 2021), or their combination (Qu et al., 2021; Gao and Callan, 2021). However, as Sciavolino et al. (2021) have shown, dense retrievers still fail in some easy cases and it remains challenging to interpret why they sometimes perform poorly.

Recently, another thread of work uses bi-encoders to learn sparse representations for text retrieval. For example, Dai and Callan (2020) demonstrate that replacing tf–idf with contextualized term weights via a regression model significantly improves retrieval effectiveness. Mallia et al. (2021) further improve the approach by combining contextualized term weights with passage expansion models based on sequence-to-sequence transformers Nogueira and Lin (2019), addressing the vocabulary mismatch problem with sparse retrieval.

Around the same time, Formal et al. (2021b); Zhuang and Zuccon (2021) propose bi-encoder designs for jointly learning contextualized term weights and expansions. These papers demonstrate that sparse retrievers generate representations that are more understandable for humans than dense retrievers. Furthermore, there is evidence (Luan et al., 2021; Gao et al., 2021b; Lin and Ma, 2021) that sparse representations compensate for the weaknesses of dense representations; these researchers fuse sparse and dense representations for text retrieval. Chen et al. (2021) recently propose to train another dense retriever (SPAR) to imitate sparse retrievers, and directly fuse the dense representations from SPAR and DPR.
The advantages of sparse retrievers motivate us to explore the following research question: Can we densify sparse representations? Our motivation comes from two reasons: (1) The densified representations are more likely to be interpretable and can serve as a good alternative to dense representations in scenarios where interpretability is important. (2) The densified representations can be directly combined with other dense representations under the same physical retrieval framework, which makes these techniques easier to deploy.

We present an approach to densifying sparse representations by representational slicing. Unlike previous work (Chen et al., 2021), our approach involves no training. In addition, we propose a gated inner product (or GIP) operation to compute the relevance scores between the densified sparse representations (DSRs) of queries and passages. This process is depicted in Fig. 1. Although our analysis indicates that GIP has higher time complexity compared to inner products for dense vectors, with our proposed retrieve-and-rerank approach, DSR retrieval can be further sped up without any retrieval effectiveness drop. Finally, our experiments show that combining DSRs with other dense representations yields performance tradeoffs that balance effectiveness, index size, and query latency.

2 Background

Following Lin et al. (2020), let us formulate the task of text (or ad hoc) retrieval as follows: Given a query \( q \), the goal is to retrieve a ranked list of documents \( \{d_1, d_2, \cdots, d_k\} \in C \) to maximize some ranking metric, such as nDCG, where \( C \) is the collection of documents.

Specifically, given a (query, document) pair, we aim to maximize the following:

\[
P(\text{Relevance}|q, d) \triangleq \phi(\eta_q(q), \eta_d(d)) = \phi(q, d)
\]

where \( \eta_q(q) \) and \( \eta_d(d) \in \mathbb{R}^h \) denote the functions mapping the query and document into \( h \)-dimensional vector representations, \( q \) and \( d \), respectively. The function that quantifies the degree of relevance between the representations \( q \) and \( d \) is denoted \( \phi(\cdot, \cdot) \), which can be a simple inner product or a much more complex operation (Nogueira and Cho, 2019; Humeau et al., 2020).

Dense retrieval. Transformer-based bi-encoders have been widely applied to the task of passage retrieval (Reimers and Gurevych, 2019; Chang et al., 2020; Karpukhin et al., 2020). The query and passage texts are first projected to low-dimensional dense vectors, and their inner product is computed as a measurement of relevance:

\[
P^{ds}(\text{Relevance}|q, d) \triangleq \langle q^{\text{CLS}}, d^{\text{CLS}} \rangle,
\]

where \( q^{\text{CLS}} \) and \( d^{\text{CLS}} \in \mathbb{R}^{768} \) are the query and passage dense representations encoded by the [CLS] token from the final layer of BERT-base.

Sparse retrieval. Zamani et al. (2018) was the first to demonstrate that neural networks can learn sparse representations for text retrieval. Recently, transformer-based bi-encoders have also been applied to sparse representation learning. Briefly, the solutions can be classified into two approaches. On the one hand, some researchers (Dai and Callan, 2020; Mallia et al., 2021; Zhuang and Zuccon, 2021; Lin and Ma, 2021) use BERT token embeddings to learn a contextualized term weight for each input token. On the other hand, some researchers (Formal et al., 2021b; Bai et al., 2020) design models to directly learn sparse representations on the entire BERT wordpiece vocabulary.

Generally, all these sparse retrieval approaches can be considered as projecting queries and passages into \( |V_{\text{BERT}}| \)-dimensional vectors, where \( |V_{\text{BERT}}| = 30522 \) is the vocabulary size of BERT wordpiece tokens:

\[
P^{sp}(\text{Relevance}|q, d) \triangleq \langle q^{sp}, d^{sp} \rangle,
\]

where \( q^{sp} \) and \( d^{sp} \in \mathbb{R}^{30522} \). The value in each dimension is the token’s term weight. The same as dense retrieval, the relevance score between a query and a passage is computed by the inner product of their vector representations.

Gap between dense and sparse retrieval. Although the inner product is the common operation for measuring relevance for both dense and sparse representations, there are still some major differences between them. (1) Unlike dense representations, sparse ones can be considered as bag of words and thus are more interpretable, since each dimension of the vectors represents a word in the BERT vocabulary. (2) Text retrieval using sparse representations are executed through inverted indexes due to their high dimensionality, while dense retrieval is often executed on flat indexes using Faiss (Johnson et al., 2017). This gap between the execution of dense and sparse retrieval increases
Sparse representations can be considered vectors with $|V|$ dimensions, i.e., $q^{sp} = (q_0, \ldots, q_{|V|-1})$; $d^{sp} = (d_0, \ldots, d_{|V|-1})$. We first divide the vectors into $M$ slices of smaller vectors, each of which has $N$ dimensions (i.e., $|V| = M \cdot N$). In terms of a standard “slice” notation:

\begin{align}
S^q_m &= q^{sp}[mN : mN + N] \in \mathbb{R}^N, \quad (1) \\
S^d_m &= d^{sp}[mN : mN + N] \in \mathbb{R}^N, \quad (2)
\end{align}

where $m \in \{0, 1, \ldots, M - 1\}$. Note that the slicing can be performed in different ways (e.g., contiguous, stride, \(^1\) or random); for simplicity, we use contiguous in our presentation. Thus, the inner product between $q^{sp}$ and $d^{sp}$ can be rewritten as the summation of all their slices’ dot products:

\begin{equation}
\langle q^{sp}, d^{sp} \rangle = \sum_{m=0}^{M-1} \langle S^q_m, S^d_m \rangle \quad (3)
\end{equation}

\(^1\)The array is sliced with $N$ stride.

**Approximate sparse representations.** Intuitively, if a representation is sparse enough, we can assume that for each slice, there is only one non-zero entry. Thus, we can approximate $S^q_m$ ($S^d_m$) by keeping only the entry with maximum value in each slice:

\begin{align}
S^q_m &\approx \max(S^q_m) \cdot \hat{u}(e^q_m) \quad (4) \\
S^d_m &\approx \max(S^d_m) \cdot \hat{u}(e^d_m), \quad (5)
\end{align}

where $\hat{u}(e^q_m)$ is a unit vector with the only non-zero entry at the entry $e^q_m = \arg\max(S^q_m)$. Thus, the inner product of $q^{sp}$ and $d^{sp}$ sparse vectors in Eq. (3) can be approximated as follows:

\begin{equation}
\langle q^{sp}, d^{sp} \rangle \approx \sum_{m=0}^{M-1} \max(S^q_m) \cdot \max(S^d_m) \cdot \langle \hat{u}(e^q_m), \hat{u}(e^d_m) \rangle
\end{equation}

**Densified sparse representations.** Observing Eq. (6), in order to compute the approximate inner product of sparse vectors, each query (document) can be alternatively represented as two $M$-dimension dense vectors:

\begin{align}
q^{ds} &= (\max(S^q_0), \ldots, \max(S^q_{M-1})) \in \mathbb{R}^M \\
d^{ds} &= (\max(S^d_0), \ldots, \max(S^d_{M-1})) \in \mathbb{R}^M \\
e^q &= (e^q_0, \ldots, e^q_{M-1}) \in \mathbb{N}^M \\
e^d &= (e^d_0, \ldots, e^d_{M-1}) \in \mathbb{N}^M,
\end{align}

where $q^{ds}$ ($d^{ds}$) is the dense vector storing the $M$ maximum values from the query (document) slices, and $e^q$ ($e^d$) is the integer dense vector storing the entries with the maximum value in the corresponding slices. We call the representations $q^{ds}$ and $e^q$ ($d^{ds}$ and $e^d$) the *densified sparse representations* (DSRs) for queries (documents).

**Gated inner product.** Using DSRs, Eq. (6) can be rewritten as:

\begin{equation}
\langle q^{sp}, d^{sp} \rangle \approx \sum_{m=0}^{M-1} q^{ds}[m] \cdot d^{ds}[m] \mathbb{1}_{\{e^q[m] = e^d[m]\}}, \quad (7)
\end{equation}

where $q^{ds}[m]$ ($d^{ds}[m]$) and $e^q[m]$ ($e^d[m]$) is the $m$-th entry of query (document) DSRs. We call the operation in Eq. (7) the *gated inner product* (GIP),...
which can be considered an approximation of the inner product of the original sparse vectors.

However, note that the gated inner product requires $4 \cdot M$ operations, which is more than the standard inner product of $M$-dimensional dense vectors, which only requires $2 \cdot M$ operations. When conducting brute-force search over corpus $C$, the differences are even larger: $4 \cdot M |C| > 2 \cdot M |C|$.

**Retrieval and reranking.** In order to address the issue of high time complexity, we propose a retrieve-and-rerank approach. In the first stage, we use approximate brute-force search by computing only partial dimensions of the gated inner product between the query and document DSRs:

$$\sum_{m \in M} q^{ds}[m] \cdot d^{ds}[m] 1_{\{e^q[m]=e^d[m]\}}, \quad (8)$$

where $M = \{m|q^{ds}[m] > \theta\}$ is the set of indices for the GIP computation, and $\theta$ is a hyperparameter. This first-stage retrieval only relies on the dimensions where $q^{ds}[m]$ has a large value. The intuition behind this design is that user queries usually contain only a few terms. Thus, only a few dimensions in the sparse query vector have impact on retrieval effectiveness, which might be also true for the DSRs. In the second (reranking) stage, the retrieved documents are sorted by the approximate gated inner product; then, the top-$k$ documents are reranked by gated inner product with all dimensions, as in Eq. (7).

**3.2 Fusion with Dense Representations**

One of the advantages of densifying sparse representations is to make the fusion of sparse and dense retrieval easier, since it actually becomes the fusion of two dense representations. Their fusion scores can be computed as follows:

$$\sum_{m=0}^{M-1} \lambda \cdot q^{[CLS]}[m] \cdot d^{[CLS]}[m] + q^{ds}[m] \cdot d^{ds}[m] 1_{\{e^q[m]=e^d[m]\}}, \quad (9)$$

where $\lambda$ is a hyperparameter. Note that the sparse and dense representations can be from the same model using joint training or from separately trained models. Eq. (9) can be implemented by existing packages that support common array operations. We use PyTorch in our experiments.

4 **Experimental Setup**

**Dataset descriptions.** (a) MS MARCO Dev: 6980 queries comprise the development set for the MS MARCO passage ranking test collection, with on average one relevant passage per query. We report MRR@10 and R@1000 as the top-$k$ retrieval measures. (b) TREC DL (Craswell et al., 2019, 2020); the organizers of the 2019 (2020) Deep Learning Track at the Text REtrieval Conferences (TRECs) released 43 (53) queries with multiple graded relevance labels, where (query, passage) pairs were annotated by NIST assessors. We report NDCG@10 and R@1000 for these evaluation sets.

**Sparse retrieval models.** In our experiments, we explore two previous sparse retrieval models based on BERT-base:

1. uniCOIL (Lin and Ma, 2021) uses token embeddings from the final layer in BERT to generate one-dimension representations (term weights) for each input query and passage token. In our experiments, we use uniCOIL without passage expansion for simplicity.

2. SPLADE (Formal et al., 2021b) uses the MLM technique to project each token embeddings from query (or passage) to a $|V_{BERT}|$-dimensional sparse representation, where $|V_{BERT}| = 30522$ is the vocabulary size of BERT wordpiece. Following Formal et al. (2021a), we conduct max pooling over all sparse representations generated by query (or passage) tokens. Note that unlike Formal et al. (2021a), we do not control the sparsity of generated representations while training.

We denote the densified sparse representations from uniCOIL (SPLADE) as DSR-uniCOIL (DSR-SPLADE). We train all models on the MS MARCO “small” triples training set for 100k steps with a batch size of 96 and learning rate 7e-6. In our experiments, we test retrieval latency using single NVIDIA Titan RTX with batch size 1.

We densify the 30522-dimensional representations into 768-dimensional vectors by (1) discarding the first 570 unused tokens in the BERT vocabulary; (2) divide the remaining 29952 tokens into 768 slices. Each of the slices contains 39 tokens according to token ids; i.e., $M = 768$ and $N = 39$. In addition, we also conduct experiments for densifying into 256 and 128 dimensions, where there are 117 and 234 tokens in each slice, respectively.
Table 1: Results of sparse representation densification experiments.

|                  | Dev DL 2019 | DL 2020 |
|------------------|-------------|---------|
|                  | M (Dims)    | MRR@10  | R@1K   | nDCG@10 | R@1K   | nDCG@10 | R@1K   |
|                  |             |         |        |         |        |         |        |
| DSR-uniCOIL      | 30K         | 0.312   | 0.925  | 0.621   | 0.775  | 0.633   | 0.794  |
| (no expansion)   | 768         | 0.309   | 0.923  | 0.615   | 0.769  | 0.632   | 0.792  |
|                  | 256         | 0.305   | 0.919  | 0.605   | 0.751  | 0.622   | 0.788  |
|                  | 128         | 0.300   | 0.913  | 0.605   | 0.744  | 0.614   | 0.782  |
|                  | DSRSPLADE   | 30K     | 0.340   | 0.965  | 0.684  | 0.851   |        |
|                  |             | 768     | 0.343   | 0.957  | 0.681  | 0.831   | 0.655  | 0.824  |
|                  |             | 256     | 0.338   | 0.953  | 0.667  | 0.820   | 0.651  | 0.822  |
|                  |             | 128     | 0.332   | 0.946  | 0.657  | 0.810   | 0.657  | 0.812  |

* These numbers are copied from SPLADE-max in Formal et al. (2021a) for reference only and are not directly comparable to our results.

Figure 3: Experiments with our retrieve-and-rerank approach using DSRSPLADE (768 dimensions) under different θ settings.

5 Results

5.1 Densifying Sparse Representations

Table 1 shows our results for densifying sparse representations. The first row (with 30K dimension) in each block reports the retrieval effectiveness of the original sparse representations, which can be considered an upper bound. Note that uniCOIL’s representation is highly sparse, and thus retrieval can be performed using an inverted index. However, since our SPLADE model is trained without any sparsity constraints, the output query and passage representations are actually quite dense and challenging for end-to-end retrieval; see Mackenzie et al. (2021) for more discussion. For reference, we report the retrieval effectiveness of the SPLADE-max model from the original paper (Formal et al., 2021a), which does include sparsification that renders the model amenable to inverted indexes.

As we can see from Table 1, our method is able to densify the original 30K-dimensional sparse vectors into 768-dimensional vectors with less than 1% retrieval effectiveness drop. In addition, only around 2% and 4% retrieval effectiveness degradation can be seen for $M = 256$ and 128, respectively. These results demonstrate the advantage of our approach, which does not require any training.

5.2 Retrieve and Rerank

In Section 3, we discussed the disadvantage of the gated inner product operation, that it is more expensive than the standard inner product. In these experiments, we test SPLADE with 768 dimensions on the MS MARCO development queries to demonstrate how our proposed retrieve-and-rerank approach remedies the issue.

In Fig. 3, the red lines show the effectiveness and efficiency of the retrieve-and-rerank approach under different settings of θ (which controls the value threshold in GIP), while the blue lines depict first-stage retrieval only. Note that the x axis is in log scale. The point $θ = 0$ represents the retrieval effectiveness upper bound of the model since the gated inner product is computed using all dimensions. As θ increases, the first-stage (approximate) retrieval efficiency improves dramatically but effectiveness drops. However, we see no effectiveness...
Table 2: Effectiveness/efficiency comparisons.

| Dim Dev DL 2019 DL 2020 storage latency | sparse | dense | MRR@10 | nDCG@10 | nDCG@10 | (GB) | (ms/q) |
|----------------------------------------|--------|-------|--------|---------|---------|------|-------|
| CoIBERT (Khattab and Zaharia, 2020)    | 0      | 128/tok | 0.360 | -       | -       | 154  | 458a  |
| COIL (Gao et al., 2021a)              | 32/tok | 768    | 0.355 | 0.704   | -       | 50   | 41a   |
| Dense-[CLS] (our dense baseline)      | 0      | 768    | 0.310 | 0.626   | 0.625   | 13   | 115   |
| DSR-uniCOIL                           | 768    | 0      | 0.309 | 0.615   | 0.632   | 20   | 40    |
| DSR-SPLADE                            | 768    | 0      | 0.343 | 0.681   | 0.655   |      |       |
| DSR-uniCOIL + Dense-[CLS]             | 768    | 768    | 0.350 | 0.678   | 0.704   | 32   | 2 x 24b |
| DSR-SPLADE + Dense-[CLS]              | 768    | 768    | 0.352 | 0.697   | 0.677   |      |       |
| DSR-uniCOIL + Dense-[CLS]             | 256    | 256    | 0.346 | 0.680   | 0.688   | 11   | 34    |
| DSR-SPLADE + Dense-[CLS]              | 256    | 256    | 0.348 | 0.711   | 0.678   |      |       |
| DSR-uniCOIL + Dense-[CLS]             | 128    | 128    | 0.337 | 0.679   | 0.671   | 5    | 32    |
| DSR-SPLADE + Dense-[CLS]              | 128    | 128    | 0.344 | 0.709   | 0.673   |      |       |

These numbers are copied from the original papers, with different execution environments.

b This condition cannot run on our single GPU; thus, we divide the index into 2 shards, each with a latency of 24 ms.

5.3 Comparisons to Other Dense Models

Table 2 compares the performance of DSR and other dense retrievers in terms of retrieval effectiveness, latency, and index size. For a fair comparison, here we exclude other dense models trained with more sophisticated techniques, such as knowledge distillation and hard negative mining. We implement a bi-encoder model (denoted “Dense-[CLS]”) trained under the same condition as our sparse models; this model takes the [CLS] token as the output representation. Note that the latency of “Dense-[CLS]” is measured using a Faiss flat index.

In the conditions denoted DSR-{uniCOIL, SPLADE} + Dense-[CLS], we train a bi-encoder model for sparse and dense representations jointly, where the loss takes into account inner products from both the [CLS] token and the sparse vectors. After training, we then densify the sparse model as described above. During inference, we apply our retrieve-and-rerank approach, where 10K candidates are first retrieved by only DSRs and then reranked by the fusion of DSRs and dense representations, as in Eq. (9). Here we set $\lambda$ to 1.

Among the dense retrievers considered here, CoIBERT is the most effective, and COIL, which can be thought of as a variant of CoIBERT, reduces the time complexity by adding a lexical match prior. However, both multi-vector designs still require much more storage for the index than single-vector dense retrievers. Our fusion models combining 768-dimensional DSRs with dense [CLS] representations show retrieval effectiveness close to COIL but with a much smaller index size. When reducing the dimensions of the DSR models, we can see a tradeoff between efficiency and effectiveness. However, it is worth noting that our fusion DSR models with 128-dimensional vectors shows better efficiency and effectiveness than the dense-only and DSR-model. This shows that our densified sparse representations exhibit complementary relevance signals than “pure” dense retrieval models.

5.4 Alternative Slicing Strategies

Finally, we examine different slicing strategies for densifying sparse representations using DSR-SPLADE with 768 dimensions in these experiments. Table 3 reports the results. Our default setting for the previous experiments is stride and we observe that stride has the same effectiveness as randomized slicing. Surprisingly, the contiguous slicing strategy shows degradation in ranking effectiveness. This indicates that max pooling over contiguous slices could lose information compared to the other strategies. It is worth exploring other slicing strategies, which we leave for future work.

Table 3: Ablation on slicing method.

|          | MS MARCO dev |
|----------|--------------|
| stride   | 0.343        | 0.957        |
| contiguous| 0.332      | 0.951        |
| random   | 0.343        | 0.957        |
6 Conclusions

In this paper, we study how to densify sparse representations for passage retrieval. Our approach requires no training and can be considered an approximation of sparse representations. The relevance score of the densified sparse representations (DSRs) can be computed through our proposed gated inner product (GIP), a variant of the standard inner product. Although our analysis indicates that GIP has higher time complexity than inner product, our experiments show that in practice, DSR retrieval can be conducted through a retrieve-and-rerank approach, which is 10 times faster without sacrificing any effectiveness. Finally, we empirically show that a bi-encoder model can be a more robust dense retriever by combining DSRs along with other “standard” dense representations.

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