Improved Learned Sparse Retrieval with Corpus-Specific Vocabularies

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Abstract. We explore leveraging corpus-specific vocabularies that improve both efficiency and effectiveness of learned sparse retrieval systems. We find that pre-training the underlying BERT model on the target corpus, specifically targeting different vocabulary sizes incorporated into the document expansion process, improves retrieval quality by up to 12% while in some scenarios decreasing latency by up to 50%. Our experiments show that adopting corpus-specific vocabulary and increasing vocabulary size decreases average postings list length which in turn reduces latency. Ablation studies show interesting interactions between custom vocabularies, document expansion techniques, and sparsification objectives of sparse models. Both effectiveness and efficiency improvements transfer to different retrieval approaches such as uniCOIL and SPLADE and offer a simple yet effective approach to providing new efficiency-effectiveness trade-offs for learned sparse retrieval systems.

Keywords: Learned sparse retrieval \cdot Language model vocabulary.

1 Introduction

Sparse term representations such as SPLADE [10], TILDE [41] or uniCOIL [12, 17] establish competitive retrieval performance using existing sparse retrieval techniques underpinned by standard *inverted indexes* data structures [42]. The inverted index has been optimized to be highly scalable, cost-efficient, update-able in real-time, and continue to be one of the core first-stage retrieval components in most commercial search systems today.

One of the key distinctions of state-of-the-art learned sparse representations compared to traditional ranking functions such as BM25 [32] is the tight integration between the vocabulary of the inverted index and the one of the model producing term importance representations for each document. While BM25 based inverted indexes contain potentially millions of unique tokens, learned sparse indexes generally restrict the vocabulary to tokens occurring in the underlying BERT [5] vocabulary. This vocabulary is usually restricted to say 30,000 entries to improve model efficiency.

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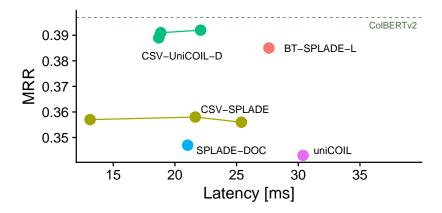


Fig. 1. Latency and effectiveness improvements achieved by leveraging Corpus Specific Vocabularies (CSV) (with different vocabulary sizes) compared to baseline learned sparse retrieval models.

While some work has elucidated the link between term score distribution and learned sparse representations [18, 24], in this work we explore the relationship between vocabulary selection, retrieval quality, and runtime efficiency of learned sparse representations.

Contribution. This work provides the following contributions:

- We show the benefit of creating corpus-specific vocabularies to pre-train underlying language models to retrieval quality.
- We explore trade-offs between vocabulary size, pre-training time, document expansion, and effectiveness improvements.
- We demonstrate that our approach is applicable to many state-of-the-art techniques such as SPLADE, and uniCOIL.
- We propose a corpus-specific modification to TILDE document expansion that leverages custom vocabularies as well as augmentation of hard negatives at training time.
- We analyze improvements in retrieval latency resulting from large corpusspecific vocabularies.

Overall our proposed approach is simple and offers new performance trade-offs for different learned sparse models (see Figure 1).

2 Background and Related Work

Learned Sparse Models. Usage of pre-trained contextualized language models (LMs) has resulted in improvements to search effectiveness, albeit with higher retrieval costs than traditional lexical models [22]. While models such as BM25 leverage term frequency statistics to estimate term importance in a document, LMs

can be leveraged to learn the importance of a term in a document by directly optimizing for the actual retrieval task. These term importance scores form the basis of many *learned sparse* retrieval techniques that still leverage the inverted index for query processing. Such models include SPLADE [10], TILDE [41], DeepImpact [23] or uniCOIL [12, 17] which differ in their handling of document and query processing, vocabulary selection, and training objective but offer state-of-theart retrieval performance while providing different efficiency and effectiveness trade-offs.

Pre-training. Pre-training refers to allowing a model to learn general language representations by performing tasks such as Masked Language Modeling (MLM) on large text corpora. In the search setting, techniques such as coCondenser [11] provide additional search-specific pre-training tasks to improve the performance of LMs on the actual retrieval task. Such pre-training objectives may operate on the target retrieval corpus, or larger potentially out-of-domain text corpora. Recent work has explored the relationship of vocabulary size in standard-pretraining arrangements [8] as well as the notion of rare-terms in pre-training requiring special consideration [39].

Document Expansion. To mitigate the vocabulary mismatch problem [40], learned sparse representations perform document expansion to augment the document with potentially relevant (future query) tokens. The DocT5Query [27] technique augments documents with tokens by appending generated queries from the source document, while TILDE [41] directly optimizes for both term importance estimation and document expansion.

Inverted Index and Dynamic Pruning. The inverted index stores one postings list for each unique term t produced by a ranking model. Each postings list comprises a sequence of the document ID and corresponding term importance score pairs [30, 42]. During query processing, the posting lists of all query terms are processed to retrieve the top-k highest-scoring documents. Query processing algorithms such as the MaxScore [37] or BlockMaxWand [7] dynamic pruning mechanisms enable skipping of large sections of postings lists. However, a relationship still exists between the length of each postings list and overall query latency [36].

3 Corpus-specific Vocabularies

This section introduces the notion of **Corpus-Specific Vocabularies** (CSV) and shows how it can be incorporated into different aspects of the overall training procedures of sparse retrieval models: vocabulary selection, pre-training, document expansion, and model training (see Figure 2 for an overview). We find that CSV provides greater coverage of query terms, can be easily incorporated into training procedure of different models, and better correspond to the actual usage of the vocabulary entries in the downstream ranking task inside the inverted index.



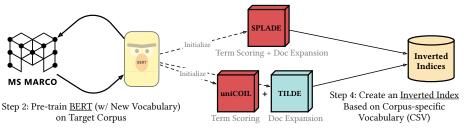


Fig. 2. A high-level overview of the workflow described in this work. As the vocabulary of the language model is learned on the target retrieval corpus, and that the sparse retrieval models (e.g., SPLADE and uniCOIL) and the document expansion models (e.g., TILDE) all use the language model as backbones, all the components in the learned sparse retrieval systems, including the acquired inverted index, are influenced by the corpus-specific vocabulary (CSV).

3.1 Vocabulary Selection

Before the advent of learned sparse models based on language models, it was common practice for an inverted index to contain lists for all unique tokens in the target corpus. Standard text collections such as Gov2 contain 25 million unique tokens [28] comprising parsing errors, named entities, numbers, etc. Indexing these unique tokens has the benefit of being able to precisely (and efficiently) retrieve documents containing rare tokens, a key benefit of sparse retrieval models over alternative dense retrieval systems.

On the contrary, due to computational restrictions (parameter memory usage, softmax inefficiencies among others) associated with Transformers, it is common practice to limit the number of unique tokens fed into such models to only tens of thousands (e.g., 30,000 in the case of standard BERT [5]). Algorithms such as byte-pair encoding (BPE) [35] or WordPiece [38] have been developed to tokenize text into sub-word units, to minimize the occurrence of out-of-vocabulary tokens during text processing with such limited vocabulary sizes. These vocabulary size restrictions are generally non-problematic, as these sub-word tokens are represented in the context of word sequences during standard NLP tasks such as machine translation.

However, in the context of sparse retrieval models such as uniCOIL, this contextualization of sub-word tokens only takes place at training time. At retrieval time when using a standard inverted index, each token is processed in isolation.

We propose to adjust the vocabulary used in sparse models such as uni-COIL (and the underlying language model) to better account for this mismatch. For simplicity, we train WordPiece tokenizers on our target corpus with varying, larger vocabulary sizes. While vocabulary selection could be enhanced by incorporating other signals such as query logs and term frequency counts into the learning process, we seek to isolate the effect of vocabulary size in this work and leave these extensions to future work. We refer to this process as leveraging Corpus-Specific Vocabularies (CSV). In this work, we specifically experiment with vocabulary sizes of 30,000, 100,000, and 300,000. As we will show in detail in Section 4, increasing vocabulary size has positive effects on both retrieval quality and runtime latency.

3.2 Pre-training Objectives

Since our model employs a different vocabulary from BERT, we cannot use pretrained BERT checkpoints. BERT is pre-trained with two objectives in mind: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) [5]. Pre-training is usually performed on the BooksCorpus (800M words) and English Wikipedia (2,500M words) datasets. Models such as coCondenser [11] and SPLADE [9, 10, 15] begin with a pre-trained BERT checkpoint and undergo further pre-training on the retrieval corpus, which is sometimes referred to as "middle-training" [15].

In this study, we *bypass* the pre-training step on large, out-of-domain text corpora (e.g. BooksCorpus and Wikipedia) and *only* pre-train on the target retrieval corpus. We make this choice due to (1) the aim of mitigating the cost and environmental impact associated with pre-training multiple LMs using multiple different vocabularies on large corpora, and (2) empirical evidence suggesting that LMs pretrained from scratch on the retrieval corpus exhibit improved effectiveness in retrieval tasks [16].

Note that pre-training with large vocabulary sizes can be computationally expensive but methods such as hierarchical or sampled softmax are standard, drop-in replacements for softmax cross entropy which improves scalability with regard to the number of classes (vocabulary entries).

3.3 Sparse Retrieval Models

We purpose to use CSV to enhance the efficiency and effectiveness of sparse retrieval models that rely on the underlying language model vocabulary as their index vocabulary. To demonstrate this, we leverage uniCOIL [12, 17] and SPLADE [9, 10] as examples. uniCOIL assigns an impact score to each query and passage token, and discards tokens with a non-positive impact. It relies on an additional model for document expansion.

SPLADE, on the other hand, projects queries and passages into |V|-dimensional embeddings, where |V| is the vocabulary size of the underlying LM, and calculates the matching score based on the dot product of these embeddings. To "sparsify" these dense representations for efficiency, SPLADE employs FLOPS regularizers [29] to restrict the number of tokens with non-zero weights. Unlike uniCOIL, SPLADE performs query and document expansion automatically, without the need for prior corpus expansion. Because query expansion significantly influences retrieval efficiency, which is not the focus of this study, we limit our experiments to SPLADE-DOC proposed in SPLADE-v2 [9]. SPLADE-DOC only performs token weighting and expansion on the passage side and assigns uniform weight to query tokens without expansion. Note that changing vocabulary size

affects how SPLADE should be regularized, as the FLOPS loss is calculated by *summing* the square of a token's average absolute weight in a mini-batch *across* the *vocabulary*.

3.4 Document Expansion

We use TILDE [41] for document expansion with uniCOIL, as it requires fewer resources for both training and inference and provides comparable performance to DocT5Query [27]. TILDE is initially trained using labeled relevant query-passage pairs. However, the shallow labeling of MS MARCO [1] and the presence of false negatives [21] make this approach restricted. To enhance TILDE for document expansion, we propose to aggregate the rankings of 12 dense rankers [31] using the Borda Count [2] into a consolidated ranking, and then use the top 10 passages from this ranking as training signals to train TILDE. We choose the Borda Count for ranking aggregation due to its simplicity. Note that TILDE can also leverage CSV as it predicts additional document tokens over the underlying LM vocabulary space which we adjust and fine-tune to the target corpus. We refer to this approach as Corpus-Specific Document Expansion leveraging augmentation (TILDE-AUG-CSV) as both the vocabulary used during expansion and the underlying expansion model fit directly to the target corpus. The positive benefits of these enhancements will be explored in detail in Section 4.

3.5 Distillation-based Training

Training a student model using the outputs of a trained teacher ranking model as training signals can considerably enhance learning outcomes [9, 15, 34]. We use KL Divergence [13, 14] as the training loss and a standard cross-encoder [26] as the teacher to train the uniCOIL and SPLADE-DOC models as suggested by Lassance and Clinchant [15].

Overall we seek to apply CSV to a variety of state-of-the-art techniques, showing they are broadly applicable and generalize to different approaches, which we will show in Section 4.

4 Experiments

4.1 Setup

Datasets. We use the MS MARCO v1 (referred to as MSM in tables; 8.8M passages) and MS MARCO v2 (138M passages) collections. For evaluation, we mainly use the 6,980 queries from the MS MARCO v1 Dev set. We also use the test queries of TREC 2019 [4] and 2020 [3] from the TREC Deep Learning track.

Latency experiments. We use the PISA engine [25] which substantially outperforms Lucene in terms of space usage and runtime efficiency for retrieval over learned sparse indexes [22]. We use the state-of-the-art BlockMaxWand [7] dynamic-pruning based query algorithm. All our indexes leverage recursive-graph-bisection [6, 19, 20] to optimize efficiency. Our code and experimental setup is available at https://github.com/PxYu/CSV-for-LSR-ECIR24. We report latency as mean retrieval time (MRT) in ms averaged over 5 runs.

Hardwares. All models are trained on $8 \times A100$ GPUs, whereas our latency experiments are performed on an Intel Xeon 8375C CPU in single-threaded execution mode.

Models and Baselines. While adjusting the underlying LM and pretraining on the target corpus is general, we focus specifically on the impact on sparse retrieval models. Here we experiment with SPLADE (abbreviated as SPL) and uniCOIL (abbreviated as uCOIL). For each, we experiment with vocabulary sizes of 30,000, 100,000, and 300,000. We pre-train our CSV models using the MLM objective (with a 15% masking probability) on MS MARCO (497M words) (and MS MARCO v2 as indicated) for 10 epochs. uniCOIL models can also leverage TILDE-AUG-CSV (abbreviated as TILDE-A) document expansion by first training TILDE-AUG-CSV with query likelihood and document likelihood for 5 epochs and take the top-200 tokens predicted in the document likelihood distribution as expansion, ignoring stop-words, sub-words and tokens in the original passage [41]. We also train a distillation based version of uniCOIL (abbreviated uCOIL-D) as discussed in Section 3.

As baselines, we retrain a uniCOIL model with the standard BERT vocabulary (to compare to our 30,000 vocabulary models, to which it has similar vocabulary size). We additionally report numbers for existing BT-SPLADE-L model [15] as competitive efficient and effective baselines. We also compare to standard BM25, DocT5Query and ColBERTv2 [34] baselines.

4.2 Vocabulary Selection and Index Statistics

First, we explore the effect of vocabulary selection on different index and query statistics without document expansion. Table 1 shows query statistics for a uni-COIL index (trained only on MS MARCO; no document expansion) with different vocabularies. We observe that the mean number of query tokens decreases as the vocabulary size increases. The number of queries where any sub-word token (compared to only having full word tokens) is present decreases from 48% for the default BERT vocabulary to 35% for our custom vocabulary of the same size. Larger vocabularies further decrease the number of queries containing sub-word tokens to 11% and 2% respectively. We also observe that passage length, postings per query, and mean retrieval time (MRT) decrease as the vocabulary size increases. Also, note that a custom vocabulary with 30k tokens outperforms the regular BERT-30k vocabulary on all metrics. Overall, CSV-300k is 20% faster compared to a standard BERT-30k based uniCOIL model.

Table 1. Mean query length (|Q|), percentage of split queries, passage length (|D|), in terms of tokens), postings per query, and MRT. Metrics are derived from uniCOIL models without document expansion.

Vocab	Q	%Split Qrys	D	Postings	MRT
BERT-30K	7.02	48.27%	47.6	6,482,729	22.88
CSV-30K	6.68	35.50%	46.2	$6,\!207,\!331$	19.70
CSV-100K	6.29	11.36%	42.5	5,502,811	18.66
CSV-300K	6.17	2.36%	41.3	$5,\!118,\!462$	18.62

Table 2. MRR and MRT for different pre-training, document-expansion and uniCOIL training objectives.

#	Vocab	Pretrain	D. Exp.	Model	MRR	MRT
1	BERT	BERT	TILDE	uCOIL	0.354	33.88
2	BERT	MSM	TILDE	uCOIL	0.343	29.29
3	CSV-100K	MSM	-	uCOIL	0.332	18.66
4	CSV-100K	MSM	TILDE	uCOIL	0.353	22.65
5	CSV-100K	MSM+v2	TILDE	uCOIL	0.370	22.45
6	CSV-100K	MSM+v2	TILDE-A	uCOIL	0.376	19.88
7	CSV-100K	MSM+v2	TILDE-A	uCOIL-D	0.391	18.85

4.3 Retrieval Quality

Table 2 explores pretraining, document expansion, and model distillation. Note that we omit certain configurations and metrics that do not provide additional insights to simplify presentation. Rows #1 and #2 represent reproduced standard baselines for reference.

First, comparing CSV-100k with no document expansion (row #3) and CSV-100k with standard TILDE expansion (row #4), we observe that latency increases but retrieval quality improves. Both pre-training on MS MARCO v2 (row #5) and augmented document expansion (TILDE-A) improve retrieval quality while remaining latency neutral or improving latency. Finally, we replace regular uni-COIL with a version trained with distillation (uCOIL-D, row #7). uCOIL-D provides the best retrieval quality (0.391 MRR). Note that this is competitive to state-of-the-art late interaction models such as CoIBERTv2 [34] (0.397 MRR on the same task). In subsequent experiments, we restrict our analysis and presentation to pre-training on MSM+v2, expansion using TILDE-A and uCOIL-D.

Table 3 shows the effect of increasing vocabulary sizes on uniCOIL based models. No substantial difference between the CSV-100k (row #10) and CSV-300k (rows #11-#13) can be observed, which indicates that 100k is a sufficient vocabulary size for MS MARCO v1. We also observe that latency *increases* for

Table 3. MRR and MRT for different custom vocabulary sizes and document expansion limits. # Kept Tokens refers to the number of expansion tokens provided by TILDE-A that are actually used for document expansion. It acts as a hyperparameter to control the balance between effectiveness and efficiency under the same vocabulary.

#	Vocab	# Tilde Tokens	# Kept Tokens	MRR	MRT
8	BERT-30K	37.5	37.5	0.379	20.00
9	CSV-30K	41.6	40.0	0.389	18.69
10	CSV-100K	46.6	40.0	0.389	17.24
11	CSV-300K	90.7	40.0	0.388	17.06
12	CSV-300K	90.7	50.0	0.391	18.72
13	CSV-300K	90.7	90.7	0.392	22.08

CSV-300k (row #13) compared to CSV-30k (row #9), which is contrary to the numbers reported in Table 1. We find TILDE-A expansion increases document size substantially with larger vocabulary size (90.71 extra tokens on average for CSV-300k, 41.63 for CSV-30k). This increase counteracts the decrease in postings list lengths we obtained through increasing vocabulary size. Adjusting the TILDE-A hyperparameter to only expanding with the top-40/50 tokens, in rows #10 - #12 we see latency in line with CSV-30k for larger vocabularies while showing a negligible improvement in retrieval performance. In summary, for MS MARCO v1, leveraging a custom vocabulary (rows #9 compared to #8) is more important to improving retrieval quality compared to increasing vocabulary size, which however has a positive impact on latency.

Table 4 shows the effect of corpus-specific vocabulary in different sizes on SPLADE. Similarly, as with uniCOIL (row #8 and #9), the CSV model (row #16) outperforms the model with BERT vocabulary in similar size (row #17) in terms of MRR and MRT. Again, retrieval quality does not increase with larger vocabulary sizes, however, the CSV-300k version (rows #20 and #21) is roughly 40% faster than the comparable SPL-DOC baseline (row #15). This effect is related to the FLOPS sparsity regularization leveraged by SPLADE interacting with vocabulary size. Experimenting with different regularization strengths (λ_d) while trying to keep MRR roughly constant (rows #17 - #21), we find larger vocabularies (300k) result in improved retrieval speed (13ms vs 25ms).

Similarly, Table 5 shows that our improvements also transfer to the TREC query sets. While standard BM25 and DocT5Query are still faster, CSV reduces mean latency relative to regular uniCOIL by 50% (17.63ms vs 33.73ms) and improves over state-of-the-art BT-SPLADE-L method. We conduct Bonferroni corrected pairwise t-tests, and report significance with p < 0.05.

4.4 Query Latency

Previous experiments show that CSV with both 100k and 300k tokens substantially reduces the latency of existing approaches. For example, standard uni-

SPL-DOC

SPL-DOC

21

Method Vocab λ_d MRR MRT 14 BT-SPLADE-L [15] 0.38027.62 15^{\dagger} SPL-DOC BERT-30K 0.008 0.34721.03 SPL-DOC 16 BERT-30K 0.008 0.339 27.28 SPL-DOC CSV-30K 17 0.008 0.35625.39SPL-DOC CSV-100K 0.009 0.35821.65SPL-DOC CSV-300K 0.0060.35918.47

Table 4. MRR and MRT for several SPLADE based methods.

0.007

0.008

0.357

0.354

13.12

14.21

CSV-300K

CSV-300K

COIL with BERT vocabulary (row 1; Table 2) exhibit a mean response time of 33.88ms, whereas our fastest method uniCOIL based method reduces mean response time to 17.06ms (row 11; Table 3), a 50% reduction. Similarly, SPLADE enhanced by CSV exhibits similar latency improvements (see Table 4). For comparison, CoIBERTv2 [34] accelerated by PLAID [33] provides similar effectiveness but is substantially slower (185ms single CPU; not run by us).

We observe that CSV-300K results in more lists (due to having a larger vocabulary) with larger list max scores referring to maximum score a term is assigned in any document in the collection as shown in Figure 3. This also creates more skewed list max score distribution (the score "band" in Figure 3 is more narrow for the standard BERT vocabulary) which is essential as pruning algorithms use list max scores to skip over low-scoring documents [7].

This has a direct effect on runtime performance which can be observed in the run-time statistics of the MaxScore algorithm shown in Table 6. Note that methods uniCOIL and BT-SPLADE-L which leverage smaller vocabularies score substantially more documents. This would be especially impactful in the case where a non trivial scoring function (e.g. scoring discovered documents with a more expensive secondary model as in proposed by Mallia et al. [24]) is used to score documents.

Interestingly, operation Insert which counts the number of insertions into the final top-k result heap during processing are similar. While more documents are scored, the amount of documents inserted into the resulting heap stays similar. This is an artifact of list max scores (plotted in Figure 3) being used to determine if a document should be scored and larger vocabularies provide more fine-grained

[†] This is initialized with a DistilBERT model that is further pretrained on MSMARCO using MLM+FLOPS [15]. In comparison, row #16 is initialized with a BERT model that is only pretrained on MSMARCO v2 using MLM.

Table 5. nDCG@10 and MRT, for TREC 19&20 queries. The symbol ∇ denotes a sig. difference viz. uCOIL-D-CSV-300K (#13).

Strategy	TREC 2019		TREC 2020	
	$\overline{\mathrm{nDCG}}$	MRT	$\overline{\mathrm{nDCG}}$	MRT
BM25	0.501^{\triangledown}	4.93	0.487^{\triangledown}	7.94
DocT5Query	0.643^{\triangledown}	4.87	0.607^{\triangledown}	7.80
UniCOIL-TILDE	0.660^{\triangledown}	31.59	0.647^{\triangledown}	33.73
BT-SPLADE-L	0.703	26.91	0.698	27.60
uCOIL-D-CSV-100K (#10)	0.718	15.00	0.706	18.01
uCOIL-D-CSV-300K (#11)	0.722	14.46	0.708	17.63
uCOIL-D-CSV-300K (#13)	0.729	17.55	0.728	22.13

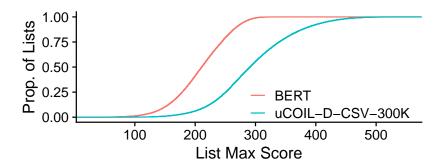


Fig. 3. Cumulative distribution of lists that have list max scores higher than a given value. BERT displaying less skew in list max scores which negatively affects performance.

"decision boundaries" as fewer high and low-scoring terms are conflated into a single vocabulary entry.

4.5 Pre-training Cost and Model Size

Not using existing LM checkpoints requires more time and resources for pretraining. We pretrain each LM on MS MARCO for 10 epochs with MLM. For experiments with uniCOIL, we train TILDE for 5 epochs for document expansion, and train uniCOIL for 5 epochs on the expanded corpus for retrieval. SPL-DOC is trained for 50k iterations using our pre-trained LM. We spend 4-13 hours pretraining LMs of different sizes due to the computational overhead of larger vocabulary sizes. Our pretraining does not currently leverage standard sampling/hierarchical softmax strategies used to deal with a large number of categories, which increases the cost. Increasing vocabulary size also increases model

Table 6. Query processing statistics (avg per query) for MaxScore and three index varieties.

Strategy	SCORE	INSERT	NEXT	NEXT-GEQ
uniCOIL	7,004,022	301,650	6,575,301	2,048,790
uCOIL-D-CSV-300K	$4,\!836,\!943$	$450,\!567$	$4,\!554,\!723$	1,336,857
BT-SPLADE-L	$6,\!400,\!831$	$556,\!829$	$6,\!110,\!824$	$1,\!175,\!790$

parameter size from 109M to 316M, similar to BERT-large with a 30k vocabulary. We experimented with pre-training BERT-large on our corpus to obtain a baseline with similar parameter size, but found that the MS MARCO corpora were too small to pre-train a model of this size. Note that search-specific pre-training tasks such as coCondenser [11] provide orthogonal benefits to vocabulary changes. We leave exploring potential interactions of these techniques to future work.

5 Conclusion and Future Work

We demonstrate that corpus-specific vocabularies are effective at improving both retrieval quality and query latency of learned sparse retrieval systems. They are simple yet effective and can be applied to a variety of different modeling types.

We believe there is a large body of future work exploring the effect of the vocabulary on sparse retrieval models. Promising directions are developing more sophisticated vocabulary selection strategies and training and document expansion strategies that take underlying inverted index-based retrieval into account when assigning term weights.

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