Dense Passage Retrieval for Open-Domain Question Answering - 2020

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1. Main Concepts

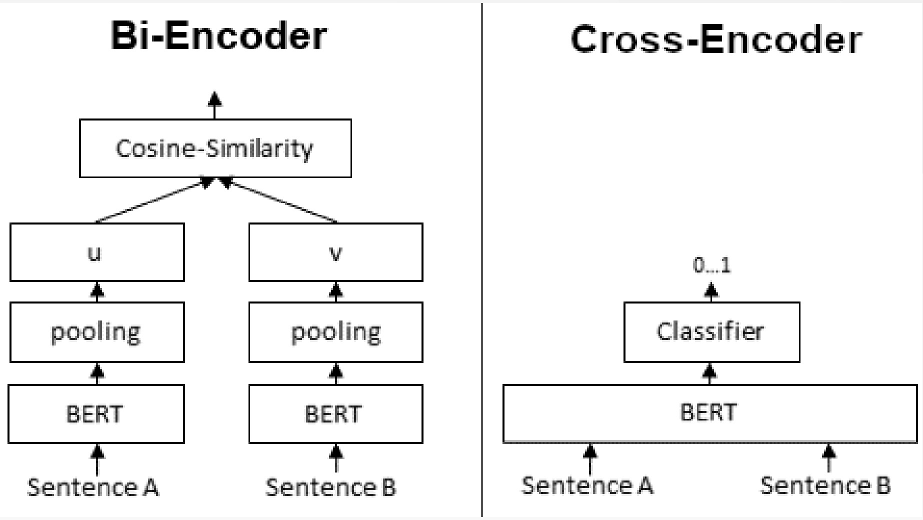
1. **Open Domain QA**: is a task that answers factoid questions using a large collection of documents.
2. **Passage retrieval**: effectively reduces the search space for answer extraction, but also identifies the support context for users to verify the answer
3. **Sparse Vectors**: contains mostly zero values, and only a few non-zero values. Sparse vectors are commonly used to represent documents in a text corpus, where each dimension represents a word in the vocabulary. **TFIDF** and **BOW**. Matches keywords efficiently with an inverted index and can be seen as representing the question and context in highdimensional, sparse vectors (with weighting).
4. **Dense Vectors**: contains non-zero values for every dimension, and are often generated using techniques such as **word embeddings**, which capture the semantic meaning of words in a language. Can also be learnable by task-specific goal representation.
5. **Retriever model**: component that can select a small set of relevant texts
6. **Reader model**: component to extract the answer from the relevant texts

2.1 Contribution

1. **Goal**:
   `can we train a better dense embedding model using only pairs of questions and passages (or answers), without additional pretraining?`
   1. the goal of the dense passage retriever (DPR) is to index all the passages in a low-dimensional and continuous space.
   2. uses a dense encoder which maps any text passage to a embedding vectors and builds an index for all the passages that we will use for retrieval.
2. Effective result on using dense vector for document retrieval

2.2 Architecture

1. dual-encoder (bi-encoder) with BERT
    1. encoder 1 = question
    2. encoder 2 = possible answers
    3. output = embedding from [CLS] 768dim
    4. cost function = max dot product between output vectors (ablation study showed that other similarity functions perform comparably)



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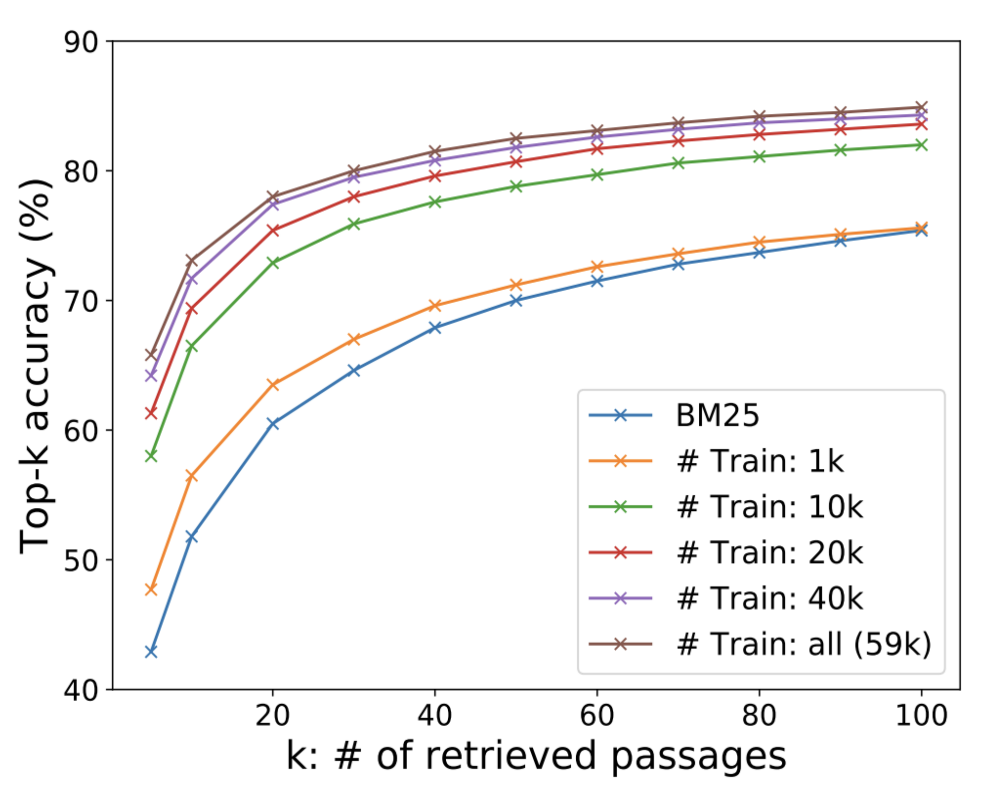
3. interesting/unexpected results

- empirical analysis and ablation studies indicate that more complex model frameworks or similarity functions do not necessarily provide additional values.
- simply fine-tuning the question and passage encoders on existing question-passage pairs is sufficient to greatly outperform BM25
- **Negative Selection Strategies**
  - Random: random passages from the corpus
  - BM25: top passages that don't contain the answer but matches most of the question tokens
  - Gold: positive passages paired with other questions which appear in the training set
- **in-batch negatives** approach and reuse gold passages fro the same batch as negatives (improve computation efficiency)
- **FAISS**: an extremely efficient, open-source library for similarity search and clustering of dense vectors, which can easily be applied to billions of vectors. Used to index the passages.

4.1 Results

1. Outperforms Lucene-BM25 by 9%-19% absolute top-20
2. Outperforms BM25 by 65.2% vs. 42.9% in Top-5 accuracy



4.2 Results

1. Stablish SOTA on multiple open domain QA benchmarks on models with the best retriever precision
2. `In the context of open-domain question answering, a higher retrieval precision indeed translates to a higher end-to-end QA accuracy.`
3. Demonstrated that dense retrieval can outperform and potentially replace the traditional sparse retrieval component in open-domain question answering. **Still holds?**

Training	Retriever	Top-20 NQ	Top-20 TriviaQA	Top-20 WQ	Top-20 TREC	Top-20 SQuAD	Top-100 NQ	Top-100 TriviaQA	Top-100 WQ	Top-100 TREC	Top-100 SQuAD
None	BM25	59.1	66.9	55.0	70.9	68.8	73.7	76.7	71.1	84.1	80.0
Single	DPR	78.4	79.4	73.2	79.8	63.2	85.4	**85.0**	81.4	89.1	77.2
	BM25 + DPR	76.6	79.8	71.0	85.2	**71.5**	83.8	84.5	80.5	92.7	**81.3**
Multi	DPR	**79.4**	78.8	**75.0**	**89.1**	51.6	**86.0**	84.7	**82.9**	93.9	67.6
	BM25 + DPR	78.0	**79.9**	74.7	88.5	66.2	83.9	84.4	82.3	**94.1**	78.6

Table 2: Top-20 & Top-100 retrieval accuracy on test sets, measured as the percentage of top 20/100 retrieved passages that contain the answer. *Single* and *Multi* denote that our Dense Passage Retriever (DPR) was trained using individial or combined training datasets (all the datasets excluding SQuAD). See text for more details.