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:

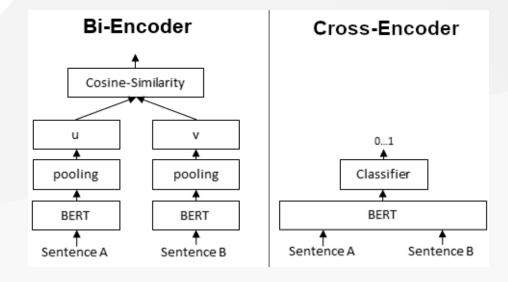
can we train a better dense embedding model using only pairs of questions and passages (or answers), without additional pretraining?

- 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)

image source

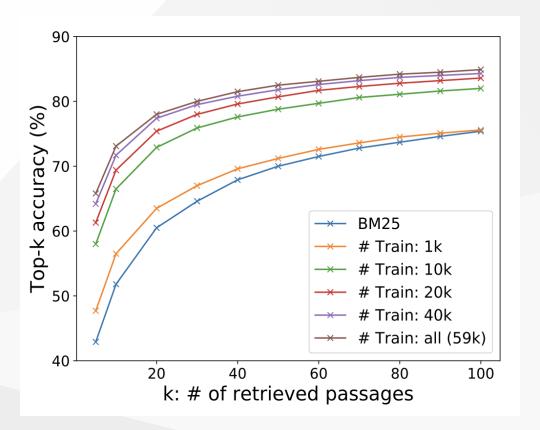


3. interesting/unexpected results

- 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 before the inference.

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
- In the context of open-domain question answering, a higher retrieval precision indeed 2. 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					Top-100				
_		NQ	TriviaQA	WQ	TREC	SQuAD	NQ	TriviaQA	WQ	TREC	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 BM25 + DPR	78.4 76.6	79.4 79.8	73.2 71.0	79.8 85.2	63.2 71.5	85.4 83.8	85.0 84.5	81.4 80.5	89.1 92.7	77.2 81.3
Multi	DPR BM25 + DPR	79.4 78.0	78.8 79.9	75.0 74.7	89.1 88.5	51.6 66.2	86.0 83.9	84.7 84.4	82.9 82.3	93.9 94.1	67.6 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.