A Replication Study of Dense Passage Retriever

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Abstract

Text retrieval using learned dense representations has recently emerged as a promising alternative to “traditional” text retrieval using sparse bag-of-words representations. One recent work that has garnered much attention is the dense passage retriever (DPR) technique proposed by Karpukhin et al. (2020) for end-to-end open-domain question answering. We present a replication study of this work, starting with model checkpoints provided by the authors, but otherwise from an independent implementation in our group’s Pyserini IR toolkit and PyGaggle neural text ranking library. Although our experimental results largely verify the claims of the original paper, we arrived at two important additional findings that contribute to a better understanding of DPR: First, it appears that the original authors underreport the effectiveness of the BM25 baseline and hence also dense–sparse hybrid retrieval results. Second, by incorporating evidence from the retriever and an improved answer span scoring technique, we are able to improve end-to-end question answering effectiveness using exactly the same models as in the original work.

1 Introduction

Replicability and reproducibility form the foundation of the scientific enterprise. Through such studies, we as a community gain increased confidence about the veracity of previously published results. These investigations are often under-valued, especially compared to work that proposes novel models, but they nevertheless make important contributions to advancing science.

This paper presents a replicability study of the dense passage retriever (DPR) technique proposed by Karpukhin et al. (2020) for end-to-end open-domain question answering (QA). To be precise, we use the term replicability in the sense articulated by the ACM, characterized as “different team, different experimental setup”. We are able to achieve comparable measurements (i.e., effectiveness on different test collections) based on an independently developed computational artifact (i.e., a different implementation). Specifically, our experiments rely on model checkpoints shared by the original authors, but we have otherwise built an entirely different implementation (other than the evaluation scripts).

DPR is worthy of detailed study because it represents an important exemplar of text retrieval using learned dense representations, which has recently emerged as a promising alternative to “traditional” text retrieval using sparse bag-of-words representations (Zhan et al., 2020; Xiong et al., 2020; Hofstätter et al., 2020; Lin et al., 2020). Our experiments largely verify the claims of Karpukhin et al. (2020) regarding the effectiveness of their proposed techniques. However, we arrived at two important additional findings, one of which is inconsistent with the original work, the other of which presents an enhancement:

1. Focusing on retrieval, we found that the effectiveness of the sparse retrieval (BM25) baseline is higher than values reported by Karpukhin et al. (2020). Whereas they reported that dense–sparse hybrid results do not meaningfully improve over dense retrieval alone, we arrived at the opposite conclusion, where hybrid techniques yield statistically significant gains. We are able to achieve on average a three-point improvement in top-20 accuracy over the best DPR results across five standard QA test collections.

2. Focusing on end-to-end QA effectiveness, we explored different techniques for evidence com-
The main contribution of this work is the replication of DPR, where our experimental results add a number of important refinements to the original work. Code associated with our retrieval experiments is packaged in our Pyserini IR toolkit\(^7\) (Lin et al., 2021) and code associated with our end-to-end QA experiments is part of our PyGaggle toolkit\(^8\) for neural text ranking.

2 Methods

DPR (Karpukhin et al., 2020) adopts the retriever–reader design proposed by Chen et al. (2017) for the open-domain QA task. Both the task formulation and the pipeline architecture for tackling the task date from the late 1990s (Voorhees and Tice, 1999), so this general approach has a long history that predates neural networks. The open-source code associated with the paper is available on GitHub (which we refer to as “the DPR repo”),\(^4\) but it does not appear to contain code and models necessary to reproduce all results reported in the paper (more detailed discussions below).

2.1 Retriever

In the retrieval stage, given a corpus \(\mathcal{C} = \{D_1, D_2, \ldots , D_m\}\), the task is to return for each query \(q\) a list of \(k\) most relevant documents (i.e., most likely to contain the answer) from \(\mathcal{C}\), where \(k << |\mathcal{C}|\). In the original DPR paper and also our replication study, the corpus refers to a version of English Wikipedia (dump from 2018-12-20), and the “documents” are non-overlapping 100-word splits from the articles.

To be clear, in most text ranking applications, the “unit of indexing” (and also retrieval) is usually referred to as a “document” \(D_j\), although in this case it is a passage (i.e., a split) from Wikipedia. For consistency with this parlance, we use “document” and “passage” interchangeably throughout this paper. To add to the potential confusion, results of the retriever are also referred to as “contexts” that are fed to the reader.

Dense retrieval with DPR uses a query encoder and a passage encoder, which are both based on BERT. Queries and passages are encoded as dense representation vectors as follows:

\[
q^* = \text{BERT}_q(q), \; D^*_j = \text{BERT}_D(D_j)
\]

where \(q^*\) and \(D^*_j\) are low dimensional vectors (768). The relevance score of a passage to a query is computed by dot product:

\[
\text{Sim}(q, D_j) = \langle q^*, D^*_j \rangle
\]

Thus, the top \(k\) retrieval problem can be recast as a nearest neighbor search problem in vector space. Operationally, this is accomplished via Facebook’s Faiss library (Johnson et al., 2017).

Karpukhin et al. (2020) also investigated hybrid retrieval, combining results from dense retrieval (DPR) and sparse retrieval (BM25) by computing the linear combination of their respective scores to rerank the union of the two initial retrieved sets:

\[
\lambda \cdot \text{Sim}(q, D_j) + \text{BM25}(q, D_j),
\]

where \(\lambda = 1.1\), an empirical value tuned on the development set. BM25 retrieval was performed using Lucene with parameters \(b = 0.4\) and \(k_1 = 0.9\). However, the DPR repo does not appear to contain code for reproducing the BM25 and hybrid fusion results.

We attempted to replicate the retriever results reported in Karpukhin et al. (2020) with Pyserini, an IR toolkit that our group has been developing since 2019 (Lin et al., 2021). The toolkit supports sparse retrieval (i.e., BM25) via integration with another toolkit called Anserini (Yang et al., 2017), which is built on Lucene. Like in the original DPR work, Pyserini supports dense retrieval via integration with Facebook’s Faiiss library. Combining dense and sparse retrieval, our toolkit supports hybrid retrieval as well.

To be clear, we started with model checkpoint releases in the DPR repo and did not retrain the query and passage encoders from scratch. Otherwise, our implementation does not share any code with the DPR repo, other than evaluation scripts to ensure that results are comparable.
Similar to the original work, we calculated hybrid retrieval scores by linear combination of dense and sparse scores, as follows:

$$\text{Sim}(q, D_j) + \alpha \cdot \text{BM25}(q, D_j).$$

Note that, contrary to the original work, we placed the $\alpha$ weight on the BM25 score because this yields a more natural way to answer the pertinent research question: Given dense retrieval as a starting point, does adding BM25 as an additional relevance signal provide any value? This question is answered by a setting of $\alpha = 0$, which is equivalent to discarding BM25 results.

Finally, there are a few more details of exactly how to combine BM25 and DPR scores worth exploring. As a baseline, we tried using the raw scores directly in the linear combination (exactly as above). However, we noticed that the range of scores from DPR and BM25 can be quite different. To potentially address this issue, we tried the following normalization technique: If a document from sparse retrieval is not in the dense retrieval results, we assign to it the the minimum dense retrieval score among the retrieved documents as its dense retrieval score, and vice versa for the sparse retrieval score.

To arrive at a final top-$k$ ranking, the original DPR paper generated top $k'$ results from DPR and top $k'$ results from BM25 (where $k' > k$), before considering the union of the two result sets and combining the scores to arrive at the final top $k$. Karpukhin et al. (2020) set $k' = 2000$, but after some preliminary experimentation, we decided to fix $k' = 1000$ in our experiments since it is a more common setting in information retrieval experiments (for example, $k = 1000$ is the default in most TREC evaluations).

2.2 Reader

As is standard in a retriever–reader design, the retriever in Karpukhin et al. (2020) returns $k$ candidate passages (i.e., splits from Wikipedia) for each query $q$. The reader extracts the final answer span from these candidate contexts, where each context $C_i$ is comprised of the Wikipedia article title $C_i^{\text{title}}$ and the content text $C_i^{\text{text}}$.

The reader in DPR uses BERT-base and takes as input each candidate context $C_i$ concatenated to the question $q$. Answer extraction is treated as a labeling task, and the reader identifies the answer by predicting the start and end tokens of the answer span in the contexts. To do so, the DPR reader adds a linear layer on top of BERT to predict the start logit and end logit for each token from the final hidden layer representations. The score of an answer span is calculated by adding the start logit of the first token and the end logit of the last token. The reader returns the $m$ highest scoring answer spans. In addition, the reader uses the learned representation of [CLS] to predict the overall relevance of the context to the question.

In more detail, the reader operates as follows:

$$r_i, S = \text{Reader}([\text{CLS}] q \ [\text{SEP}] \ C_i^{\text{title}} \ [\text{SEP}] \ C_i^{\text{text}})$$

where $r_i$ is the overall relevance score for context $C_i$, and $S$ comprises $m$ potential (answer span, span score) pairs extracted from context $C_i$:

$$\{(S_{i,1}, s_{i,1}), (S_{i,2}, s_{i,2}), \ldots, (S_{i,m}, s_{i,m})\}.$$  

In the original paper, the final answer span is the candidate with the maximum span score from the context with the highest relevance score.

We attempted to replicate exactly the DPR implementation of answer extraction using our open-source PyGaggle neural reranking library, which holds the code to many of our other search-related projects. Once again, we began with reader checkpoints released in the DPR repo, but otherwise our implementation is completely independent (other than, again, the evaluation code).

In addition to the answer extraction algorithm above, we also implemented the normalized answer span scoring technique described by Mao et al. (2020). Each answer span in each candidate context $C_i$ is rescored by:

$$s'_{i,j} = \text{softmax}(\vec{r})_{i,j} \cdot \text{softmax}(s_{i,j})$$

where $\vec{r} = \{r_1, \ldots, r_k\}$ is the set of relevance scores of all candidate contexts and $s_i = \{s_{i,1}, \ldots, s_{i,m}\}$ is the set of all span scores within context $C_i$. Duplicate answer spans across all contexts are scored by accumulating their individual scores. The answer span with the maximum final score is selected as the final prediction.

In summary, we compared two answer span scoring techniques in the reader: the “original” answer span scoring technique described by Karpukhin et al. (2020), and the span scoring technique described by Mao et al. (2020).
2.3 Final Evidence Fusion

In the original DPR paper, the final answer span is only selected based on scores from the reader. In our replication attempt, we additionally tried to exploit scores from the retriever to improve answer span selection. Our intuition is that predictions from both the retriever and the reader should contribute to the final answer. Concretely, instead of just using the relevance score \( r_i \) from the reader to score contexts, we fuse \( r_i \) with the retriever score \( R_i \), calculated by:

\[
\beta \cdot r_i + \gamma \cdot R_i
\]

Depending on the retrieval method, \( R_i \) can be the sparse retrieval score, the dense retrieval score, or the score after hybrid fusion. This final fused score replaces \( r_i \) as the relevance score for each context in the answer span scoring step. For example, with fusion, the answer span scoring technique of Mao et al. (2020) becomes softmax\((\beta \cdot \hat{r}^i + \gamma \cdot \hat{R}^i) \cdot \text{softmax}(\vec{s}^i)\).j.

Thus, to summarize, we explored four settings in our end-to-end QA replication: the original DPR span scoring technique, with and without retriever score fusion, and the answer span scoring technique of Mao et al. (2020), with and without retriever score fusion.

3 Experimental Setup

Models Our replication efforts began with model checkpoints provided in the DPR repo. Unfortunately, Karpukhin et al. (2020) did not appear to make available all models used in their experiments, and thus, to be precise, our experiments used the following models:

- **Retriever\textsubscript{NQ}:** DPR encoders trained using just the NQ dataset (for the retriever).
- **Retriever\textsubscript{Multi}:** DPR encoders trained using a combination of datasets (for the retriever).
- **Reader\textsubscript{NQ-Single}:** the DPR reader trained on NQ with negative passages from retrieval results by Retriever\textsubscript{NQ}.
- **Reader\textsubscript{TQA-Multi}:** the DPR reader trained on TriviaQA with negative passages from retrieval results by Retriever\textsubscript{Multi}.

Datasets We evaluated retrieval effectiveness on five standard benchmark QA datasets (NQ, TriviaQA, WQ, CuratedTREC, SQuAD), exactly the same as Karpukhin et al. (2020). We used the Retriever\textsubscript{Multi} model, which can be applied to all five datasets. For end-to-end QA, we evaluated on NQ and TriviaQA with the available models. More precisely, we used the Reader\textsubscript{NQ-Single} model to process the retrieved contexts from Retriever\textsubscript{NQ} for NQ and used the Reader\textsubscript{TQA-Multi} model to process the retrieved contexts from Retriever\textsubscript{Multi} for TriviaQA.

Metrics For retrieval, we measured effectiveness in terms of top-k retrieval accuracy, defined as the fraction of questions that have a correct answer span in the top-k retrieved contexts at least once. End-to-end QA effectiveness is measured in terms of the exact match (EM) metric, defined as the fraction of questions that have an extracted answer span exactly matching the ground truth answer.

Missing from the original DPR paper, we performed significance testing to assess the statistical significance of metric differences. In all cases, we applied paired t-tests at \( p < 0.01 \); the Bonferroni correction was applied to correct for multiple hypothesis testing as appropriate.

Hyperparameters In the hybrid retrieval technique described in the DPR paper, the \( \lambda \) weight for combining dense and sparse retrieval scores is fixed to 1.1. However, our implementation replaces \( \lambda \) with \( \alpha \) (see Section 2.1). We tuned the \( \alpha \) values on different datasets by optimizing top-20 retrieval accuracy: For datasets where we can obtain exactly same train/dev/test splits as the original DPR paper (NQ and TriviaQA), we tuned the weight on the development set. For the remaining datasets, where splits are not available or the original DPR paper does not provide specific guidance, we tuned the weight on a subset of the training data. We obtained the optimal weight by performing grid search in the range \([0, 2]\) with step size 0.05.

Similarly, for final evidence fusion, we tuned \( \beta \) (i.e., the weight for the relevance score) and \( \gamma \) (i.e., the weight for retriever score) on the development set of NQ and TriviaQA using grid search. For greater computational efficiency, we performed tuning in multiple passes, first with a coarser step size and then with a finer step size.
For the original DPR answer span scoring technique, we fixed $\beta$ to one and performed a two-step grid search on $\gamma$. We started with step size 0.05 and found the optimal $\gamma_1$. Then, we used step size 0.01 in the range $[\gamma_1 - 0.04, \gamma_1 + 0.04]$ to find the optimal $\gamma$.

For the answer span scoring technique of Mao et al. (2020), we defined $\delta = \frac{\beta}{\gamma}$ and performed a three-step grid search on $\beta$ and $\delta$ (i.e., the weight for the retriever score becomes $\gamma = \beta \cdot \delta$). We started with step size 0.2 for both $\beta$ and $\delta$ and found the optimal pair of values $\beta_1, \delta_1$. We then repeated this process with step size 0.05 and then 0.01 in a smaller range around the optimal $\beta_i$ and $\delta_i$ from the previous pass.

For final evidence fusion, we tuned the weight parameters together with the number of retrieval results ($k$) up to 500 with a step size of 20. Optimal parameters were selected based on the exact highest match score.

4 Results

4.1 Retrieval

Table 1 reports top-$k = \{20, 100\}$ retrieval accuracy from our replication attempt, compared to figures copied directly from the original DPR paper; here we focus on results from Retriever$_{Multi}$. The hybrid retrieval results reported in the original DPR paper is denoted Hybrid$_{orig}$, which is not directly comparable to either of our two techniques: Hybrid$_{norm}$ (with minimum score normalization) or Hybrid (without such normalization). We make the following observations:

First, our dense retrieval results are very close to those reported in Karpukhin et al. (2020). We consider this a successful replication attempt and our efforts add veracity to the effectiveness of the DPR technique. Yay!

Second, our Pyserini BM25 implementation outperforms the BM25 results reported in the original paper across all datasets. Furthermore, the gap is larger for $k = 20$. On average, our results represent a nearly seven-point improvement in top-20 accuracy and a nearly five-point improvement for top-100 accuracy. Since Karpukhin et al. (2020) have not made available their code for generating the BM25 results, we are unable to further diagnose these differences.

Nevertheless, the results do support the finding that dense retrieval using DPR is (generally) more effective than sparse retrieval. We confirmed that the effectiveness differences between DPR and BM25 in our replication results are statistically significant. In all datasets except for SQuAD, DPR outperforms BM25; this is consistent with the original paper. We further confirmed that for SQuAD, DPR is significantly better than BM25. As Karpukhin et al. (2020) noted, Retriever$_{Multi}$ was trained by combining training data from all datasets but excluding SQuAD; these poor results are expected, since SQuAD draws from a very small set of Wikipedia articles.

Third, the effectiveness of hybrid dense–sparse fusion appears to be understated in the original DPR paper. Karpukhin et al. (2020) found that

| Condition | Top-20 | Top-100 |
|-----------|--------|---------|
|           | orig   | repl    | orig   | repl    |
| NQ        |        |         |        |         |
| DPR       | 79.4   | 79.5    | 86.0   | 86.1    |
| BM25      | 59.1   | 62.9    | 73.7   | 78.3    |
| Hybrid$_{orig}$ ($\lambda = 1.1$) | 78.0   | -       | 83.9   | -       |
| Hybrid$_{norm}$ ($\alpha = 1.30$) | -      | 82.6    | -      | 88.6    |
| Hybrid ($\alpha = 0.55$) | -      | 82.7    | -      | 88.1    |
| TriviaQA  |        |         |        |         |
| DPR       | 78.8   | 78.9    | 84.7   | 84.8    |
| BM25      | 66.9   | 76.4    | 76.7   | 83.2    |
| Hybrid$_{orig}$ ($\lambda = 1.1$) | 79.9   | -       | 84.4   | -       |
| Hybrid$_{norm}$ ($\alpha = 0.95$) | -      | 82.6    | -      | 86.5    |
| Hybrid ($\alpha = 0.55$) | -      | 82.3    | -      | 86.1    |
| WQ        |        |         |        |         |
| DPR       | 75.0   | 75.0    | 82.9   | 83.0    |
| BM25      | 55.0   | 62.4    | 71.1   | 75.5    |
| Hybrid$_{orig}$ ($\lambda = 1.1$) | 74.7   | -       | 82.3   | -       |
| Hybrid$_{norm}$ ($\alpha = 0.95$) | -      | 77.1    | -      | 84.4    |
| Hybrid ($\alpha = 0.3$) | -      | 77.5    | -      | 84.0    |
| CuratedTREC|        |         |        |         |
| DPR       | 89.1   | 88.8    | 93.9   | 93.4    |
| BM25      | 70.9   | 80.7    | 84.1   | 89.9    |
| Hybrid$_{orig}$ ($\lambda = 1.1$) | 88.5   | -       | 94.1   | -       |
| Hybrid$_{norm}$ ($\alpha = 1.05$) | -      | 90.1    | -      | 95.0    |
| Hybrid ($\alpha = 0.7$) | -      | 89.6    | -      | 94.6    |
| SQuAD     |        |         |        |         |
| DPR       | 51.6   | 52.0    | 67.6   | 67.7    |
| BM25      | 68.8   | 71.1    | 80.0   | 81.8    |
| Hybrid$_{orig}$ ($\lambda = 1.1$) | 66.2   | -       | 78.6   | -       |
| Hybrid$_{norm}$ ($\alpha = 2.00$) | -      | 75.1    | -      | 84.4    |
| Hybrid ($\alpha = 28$) | -      | 75.0    | -      | 84.0    |

Table 1: Retrieval effectiveness comparing results from the original DPR paper (“orig”) and our replication attempt (“repl”). The symbol † on a BM25 result indicates effectiveness that is significantly different from DPR. The symbol ‡ indicates that the hybrid technique is significantly better than BM25 (for SQuAD) or DPR (for all remaining collections).
Table 2: The Jaccard overlap between sparse retrieval results and dense retrieval results.

| Condition | $k = 20$ | 100  | 500  | 1000 |
|-----------|---------|------|------|------|
| NQ        | 6.1     | 5.2  | 4.4  | 4.2  |
| TriviaQA  | 9.2     | 6.6  | 5.0  | 4.6  |
| WQ        | 5.9     | 5.9  | 5.8  | 5.7  |
| CuratedTrec| 6.9    | 7.2  | 6.3  | 5.9  |
| SQuAD     | 4.5     | 4.1  | 4.0  | 4.0  |

hybrid retrieval is less effective than dense retrieval in most settings, which is inconsistent with our experimental results. Instead, we found that dense–sparse retrieval consistently beats sparse retrieval across all settings. The gains from both hybrid scoring techniques are statistically significant, with the exception of top-20 for CuratedTREC. Our results might be due to better BM25 which suggests that they are effective in very different ways. This provides an explanation of why hybrid retrieval is effective, i.e., they are exploiting very different signals. These results also justify the DPR design choice of retrieving $k' > k$ results from dense and sparse retrieval and then rescoring the union to arrive at the final top-$k$.

4.2 End-to-End QA

Table 3 presents results for our end-to-end question answering replication experiments on the NQ and TriviaQA datasets in terms of the exact match score. The original results are shown in the “orig” column. The “repl” column reports our attempt to replicate exactly the span scoring technique described in the original paper, whereas the “GAR” column shows results from using the technique proposed by Mao et al. (2020). The version of each technique that incorporates retriever scores (see Section 2.3) is denoted with a * symbol, i.e., “repl*” and “GAR*”. For NQ, we used Retriever$_{NQ}$ and Reader$_{NQ-Single}$; for TriviaQA, we used Retriever$_{Multi}$ and Reader$_{TQA-Multi}$.

With retrieval using DPR only, the “orig” and “repl” scores on both datasets are close (within a point), which suggests that we have successfully replicated the results reported in Karpukhin et al. (2020). Again, yay!

With retrieval using BM25 only, our replicated results are quite a bit higher than the original DPR results; this is not a surprise given that our BM25 results are also better. When combining DPR and BM25 results at the retriever stage, the end-to-end effectiveness remains unchanged for NQ, but we observe a modest gain for TriviaQA. The gain for TriviaQA is statistically significant. So, it is not the case that better top-$k$ retrieval leads to improvements in end-to-end effectiveness.

Comparing the “repl” and “repl*” columns, we observe that combining scores from the retriever yields modest gains across all conditions. These gains are significant for four out of the six conditions, which suggests that retriever scores contribute to improving effectiveness. Comparing the “GAR” and “repl” columns, we also observe modest gains when adopting the answer span selection technique of Mao et al. (2020). These gains are significant for all except one condition. Comparing the “GAR” and “GAR*” columns, we find that in all cases, incorporating retriever scores significantly increases effectiveness.

Finally, putting everything together—using both the answer span scoring technique of Mao et al. (2020) and incorporating re-
triever scores—we observe statistically significant gains across all retrieval conditions, as can be seen in the “GAR*” vs. “repl” columns across all rows. Compared to the best replicated results, we obtained an improvement of approximately three points in end-to-end QA effectiveness compared to the best answer extraction approach described in Karpukhin et al. (2020). Note that we were able to obtain these improvements using exactly the model checkpoints provided in the DPR repo—we have simply added two relatively simple tricks to improve scoring and evidence combination.

In Figure 1, we plot exact match scores as a function of varying k retrieval results for NQ (left) and TriviaQA (right). That is, we show how end-to-end QA effectiveness changes as the reader is provided more contexts from the retriever to consider. There are two factors here at play: On the one hand, top-k accuracy increases monotonically, i.e., as k increases, so does the likelihood that the answer appears in the contexts fed to the reader. On the other hand, the reader is asked to consider more contexts, and thus needs to discriminate the correct answer from a larger pool of candidate contexts, some of which might be low quality and thus serve as “distractors” from the correct answer. How do these factors balance out? Similar analyses in previous work with BM25 retrieval have shown that end-to-end QA effectiveness increases with increasing k (Yang et al., 2019; Xie et al., 2020); that is, the reader does not appear to be “confused” by the non-relevant material. Indeed, in our BM25 results we also observe the same trend.

Interestingly, however, when we switch from BM25 results to DPR results, the behavior appears to change. For TriviaQA, the effectiveness curve behaves as expected, but for NQ, the exact match score trends up and then decreases after a peak. This means that while the likelihood of the reader seeing a correct answer in the candidate contexts increases with k, it is more likely to be negatively affected by increasing amounts of non-relevant contexts as well. This general behavior is also seen for the hybrid scoring techniques: as k increases, so does the exact match score, but only up to a certain point. Beyond this point, feeding the reader more candidate contexts leads to slight decreases in end-to-end effectiveness.

5 Conclusion

The breakneck pace at which NLP and IR are advancing, we argue, makes reproducibility and replicability critical to advancing science—to ensure that we are building on a firm foundation. Our study adds to the veracity of the claims made by Karpukhin et al. (2020), and our work indeed confirm that DPR is an effective dense retrieval technique. However, we arrived at two important additional findings, one of which is inconsistent with the original work, the other of which presents an enhancement. Together, they enrich our understanding of DPR.

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