Retrieval Oriented Masking Pre-training
Language Model for Dense Passage Retrieval

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Abstract
Pre-trained language model (PTM) has been shown to yield powerful text representations for dense passage retrieval task. The Masked Language Modeling (MLM) is a major sub-task of the pre-training process. However, we found that the conventional random masking strategy tend to select a large number of tokens that have limited effect on the passage retrieval task (e.g. stop-words and punctuation). By noticing the term importance weight can provide valuable information for passage retrieval, we hereby propose alternative retrieval oriented masking (dubbed as ROM) strategy where more important tokens will have a higher probability of being masked out, to capture this straightforward yet essential information to facilitate the language model pre-training process. Notably, the proposed new token masking method will not change the architecture and learning objective of original PTM. Our experiments verify that the proposed ROM enables term importance information to help language model pre-training thus achieving better performance on multiple passage retrieval benchmarks.

1 Introduction
Dense passage retrieval has drawn much attention recently due to its benefits to a wide range of downstreaming applications, such as open-domain question answering (Karpukhin et al., 2020; Qu et al., 2021; Zhu et al., 2021), conversational systems (Yu et al., 2021) and web search (Lin et al., 2021; Fan et al., 2021; Long et al., 2022). To balance efficiency and effectiveness, existing dense passage retrieval methods usually leverage a dual-encoder architecture. Specifically, query and passage are encoded into continuous vector representations by language models (LMs) respectively, then, a score function is applied to estimate the semantic similarity between the query-passage pair.

Based on the dual-encoder architecture, various optimization methods have been proposed recently, including hard negative training examples mining (Xiong et al., 2021), optimized PTMs specially designed for dense retrieval (Gao and Callan, 2021, 2022; Ma et al., 2022) and alternative text representation methods or fine-tuning strategies (Karpukhin et al., 2020; Zhang et al., 2022a, 2021). In this paper, we focus on studying the part of pre-trained language model. We observe that the widely adopted random token masking MLM pre-training objective is sub-optimal for dense passage retrieval task. Referring to previous studies, introducing the weight of each term (or token) to assist in estimating the query-passage relevance is effective in both passage retrieval and ranking stages (Dai and Callan, 2020; Ma et al., 2021; Wu et al., 2022). However, the random masking strategy does not distinguish the term importance of tokens. Further, we find that about 40% of the masked tokens produced by the 15% random masking method are stop-words or punctuation\textsuperscript{1}. Nonetheless, the effect of these tokens on passage retrieval is extremely limited (Fawcett et al., 2020). Therefore, we infer that LMs pre-trained with random token masking MLM objective is sub-optimal for dense passage retrieval due to its shortcoming in distinguishing token importance.

To address the limitation above, we propose alternative retrieval oriented masking (ROM) strategy aiming to mask tokens that are required for passage retrieval. Specifically, in the pre-training process of LM, the probability of each token being masked is not random, but is superimposed by the important weight of the token corresponded. Here, the important weight is represented as a float number between 0 and 1. In this way, we can greatly improve the probability of higher-weight tokens being masked out. Therefore, the pre-trained language model will pay more attention to higher-weight words thus making it more proper for downstreaming dense passage retrieval applications.

\textsuperscript{1}We used nltk and gensim stop-words lists.
To verify the effectiveness and robustness of our proposed retrieval oriented masking method, we conduct experiments on two commonly used passage retrieval benchmarks: the MS MARCO passage ranking and Neural Questions (NQ) datasets. Empirically experiment results demonstrate that our method can remarkably improve the passage retrieval performance.

2 Related Work

Existing dense passage retrieval methods usually adopt a dual-encoder architecture. In DPR (Karpukhin et al., 2020), they firstly presented that the passage retrieval performance of dense dual-encoder framework can remarkable outperform traditional term match based method like BM25. Based on the dual-encoder framework, studies explore to various strategies to enhance dense retrieval models, including mining hard negatives in fine-tuning stage (Xiong et al., 2021; Zhan et al., 2021), knowledge distillation from more powerful cross-encoder model (Ren et al., 2021; Zhang et al., 2021; Lu et al., 2022), data augmentation (Qu et al., 2022) and tailored PTMs (Chang et al., 2020; Gao and Callan, 2021, 2022; Ma et al., 2022; Liu and Shao, 2022; Wu et al., 2022).

For the pre-training of language model, previous research attend to design additional pre-training objectives tailored for dense passage retrieval (Lee et al., 2019; Chang et al., 2020) or adjust the Transformer encoder architecture (Gao and Callan, 2021, 2022) to obtain more practicable language models. In this paper, we seek to make simple transformations of the original MLM learning objective to improve the model performance, thereby reducing the complexity of the pre-training process.

3 Methodology

In this section, we describe our proposed pre-training method for the dense passage retrieval task. We first give a brief overview of the conventional BERT pre-training model with MLM loss. Then we will introduce how to extend it to our model with retrieval oriented masking pre-training.

3.1 BERT Pre-trained Model

MLM Pre-training Many popular Transformer Encoder language models (e.g. BERT, RoBERTa) adopts the MLM objective at pre-training phase. MLM masks out a subset of input tokens and requires the model to predict them. Specifically, the MLM loss can be formulated as:

\[ \mathcal{L}_{mlm} = \sum_{i \in \text{masked}} \text{CrossEntropy}(W h^L_i, x_i), \]

where \( h^L_i \) is the final representation of masked token \( x_i \) and \( L \) is the number of Transformer layers.

Random Masking In general, the selection of masked out tokens is random, and the proportion of masking in a sentence is set at 15%. Mathematically, for each token \( x_i \in x \), the probability of \( x_i \) being masked out \( p(x_i) \) is sampled from a uniform distribution between 0 and 1. If the value of \( p(x_i) \) is in the top 15% of the entire input sequence, then \( x_i \) will be masked out.

3.2 Disadvantages of Random Masking

The significant issue of the random masking method is that it does not distinguish the important weight of each token. Statistic analysis illustrates that 40% of the tokens masked by the random masking strategy are stop-words or punctuation. As shown in previous studies, it is valuable to distinguish the weights of different terms for passage retrieval. Whether for the query or passage, terms with higher important weights should contribute more to the query-passage relevance estimation process. Although the pre-train language model itself is contextualized aware, we still hope that the language model has a stronger feature of distinguishing term importance for retrieval task. However, the language model trained by the random masking strategy is flawed.

3.3 Retrieval Oriented Masking

As mentioned above, term importance is instructive for passage retrieval. Here, we explore to introduce term importance into the MLM training. More specifically, we incorporate the term importance information into token masking. Different from the random masking strategy, whether a token \( x_i \) is masked is not only determined by the random probability \( p_r(x_i) \), but also determined by its term weight \( p_w(x_i) \). Here, \( p_w(x_i) \) is normalized between value 0 and 1. The final probability of token \( x_i \) being masked out is \( p_r(x_i) + p_w(x_i) \).

Then the problem now is to calculate the term weight of each token. Previous studies have proposed different methods to calculate word weights (Mallia et al., 2021; Ma et al., 2021), which can be roughly divided into unsupervised and supervised categories. To maintain the unsupervised
A stomach is the result of an allergic reaction.

|        | A | stomach | is | the | result | of | an | allergic | reaction |
|--------|----|---------|----|-----|--------|----|----|----------|----------|
| Weight | 0.0| 0.4     | 0.0| 0.0 | 0.1    | 0.0| 0.0| 0.3      | 0.2      |

Figure 1: An illustration of our retrieval oriented masking (ROM) method. “stomach” is the token with the highest term weight in the input sentence, thus sharing a larger probability of being masked out.

4 Experiments

4.1 Datasets

We evaluate the proposed model on the following data sets. **MS MARCO Passage Ranking** is a widely used benchmark dataset for passage retrieval task, and which is constructed from Bing’s search query logs and web documents retrieved by Bing (Nguyen et al., 2016). **Neural Question** is another passage retrieval dataset derived from Google search (Kwiatkowski et al., 2019). For each dataset, we follow the standard data splits in previous work (Gao and Callan, 2022).

4.2 Compared Methods

To verify the effectiveness of our proposed method, we adopt the following methods which focused on PTM optimization as our main baselines: **Condenser** (Gao and Callan, 2021) adapts the Transformer architecture in LM pre-training to enhance the text representations thus facilitating downstreaming passage retrieval; **coCondenser** (Gao and Callan, 2022) is an extension of Condenser, which uses an unsupervised corpus-level contrastive loss to warm up the passage embedding space; **COSTA** (Ma et al., 2022) introduces a novel contrastive span prediction task in LM pre-training aiming to build a more discriminative text encoder.

We directly borrowed several other competitive baselines from the coCondenser paper, including lexical systems BM25, DeepCT (Dai and Callan, 2020), DocT5Query (Cheriton, 2019) and GAR (Mao et al., 2021); and dense systems DPR (Karpukhin et al., 2020), ANCE (Xiong et al., 2021), and ME-BERT (Luan et al., 2021).
Table 1: Experiment Results for MS MARCO Passage Retrieval and Natural Question Datasets. T-test demonstrates the improvements of ROM and coROM to the baselines are statistically significant ($p \leq 0.05$).

| Method                | MS MARCO Passage | Neural Question |
|-----------------------|------------------|-----------------|
|                       | MRR@10 | R@1000 | R@5  | R@20 | R@100 | R@200 |
| BM25                  | 18.6    | 85.7   | -    | 59.1 | 73.7  | 73.7  |
| DeepCT (Dai and Callan, 2019) | 24.3    | -      | -    | -    | -     | -     |
| DocT5Query (Cheriton, 2019)  | 27.7    | 94.7   | -    | -    | -     | -     |
| GAR (Mao et al., 2021)     | -      | -      | 60.9 | 74.4 | 85.3  | -     |
| DPR (Karpukhin et al., 2020) | -      | -      | -    | 74.4 | 85.3  | -     |
| BERT$_{base}$          | 33.4    | 95.5   | -    | -    | -     | -     |
| ANCE (Xiong et al., 2021) | 33.0    | 95.5   | -    | 81.9 | 87.5  | -     |
| ME-BERT (Luan et al., 2021) | 33.8    | -      | -    | -    | -     | -     |
| RocketQA (Qu et al., 2021) | 37.0    | 97.9   | 74.0 | 82.7 | 88.5  | -     |
| Condenser (Gao and Callan, 2021) | 36.6    | 97.4   | -    | 83.2 | 88.4  | -     |
| COSTA (Ma et al., 2022)  | 36.6    | 97.1   | -    | -    | -     | -     |
| ROM                   | 37.3    | 98.1   | 73.9 | 83.4 | 88.5  | -     |
| coCondenser (Gao and Callan, 2022) | 38.2    | 98.4   | 75.8 | 84.3 | 89.0  | -     |
| coROM                | 39.1    | 98.6   | 76.2 | 84.6 | 88.8  | -     |

4.3 Experimental Setup

Our ROM language model pre-training starts with a vanilla 12-layer BERT-base model. Following previous work, we use the same data as BERT in pre-training: English Wikipedia and the BookCorpus. In addition, like the coCondenser model, we also train a language model that adds a contrastive learning loss function based on the ROM model and target corpus (Wikipedia or MS-MARCO web collection). Here, the co-training drove ROM model is denoted as coROM\(^2\).

During the fine-tuning process, we adopt the AdamW optimizer with 5e-6 learning rate and batch size 64 for 3 epochs for the MS MARCO passage dataset. For the NQ dataset, we follow the hyper-parameter setting presented in the DPR toolkit (Karpukhin et al., 2020). For the MS MARCO passage dataset, the test set label is not available, we only report results on the dev set. We follow the evaluation methodology used in previous work (Gao and Callan, 2022). All experiments are conducted on 8 NVIDIA Tesla 32G V100.

4.4 Evaluation Results

The overall performance of all baselines and ROM are reported in Table 1. The results indicate that ROM achieves the best performance. Firstly, the improvement of the ROM model is extremely significant compared with the vanilla BERT model. For example, the MRR@10 metric on the MS MARCO dataset has increased from 33.4 to 37.3, which empirically proves the benefits of tailored LM. Compared with other dense retrieval tailored LMs, the ROM model achieves consistent improvement on both two datasets. Additionally, similar to the coCondenser model, coROM model will further improve the passage retrieval performance with the help of the contrastive co-training method, indicating that high-quality text representation is the foundation of dense passage retrieval.

Table 2: MRR@10 metric on the MS MARCO Passage Ranking leaderboard. We bold the best performances of both the dev and eval set.

| Model                        | dev  | eval |
|------------------------------|------|------|
| Search LM (SLM) + HLATR      | 46.3 | 45.0 |
| Listwise + Fusion reranker   | 45.4 | 44.0 |
| Cot-MAE (Wu et al., 2022)    | 45.6 | 43.8 |
| Lichene-xxlarge + deberta-v3-large | 45.2 | 43.6 |
| Adaptive Batch Scheduling (Choi et al., 2021) | 45.3 | 43.1 |
| coCondenser (Gao and Callan, 2022) | 44.3 | 42.8 |

\(^2\)The fine-tuned model on MS MARCO passage ranking dataset is available at [https://modelscope.cn/models/damo/nlp_corom_sentence-embedding_english-base/summary](https://modelscope.cn/models/damo/nlp_corom_sentence-embedding_english-base/summary). The original ROM and coROM models will be publicly available in the future.
Table 3: ROM results on MS MARCO passage dataset with different methods for producing term weights.

| Term Weights   | MRR@10 | R@1000 |
|----------------|--------|--------|
| BPROP          | 37.3   | 98.1   |
| DeepImpact     | 37.6   | 98.2   |

4.5 MS MARCO Passage Ranking LeaderBoard

To further verify the effectiveness of the ROM family model, we conduct an experiment with full retrieval-then-reranking pipeline and submit our result to MS MARCO LeaderBoard. Table 2 presents the top systems on the MS MARCO Passage Ranking leaderboard.* For the model description “Search LM (SLM) + HLATR”, “Search LM(SLM)” is the coROM model and HLATR (Zhang et al., 2022b) is a lightweight reranking module coupling both retrieval and reranking features thus further improving the final ranking performance. The final submission is an ensemble of multiple “reranking + HLATR” models trained on different pretrained language models (e.g. BERT, ERINE and RoBERTa).

4.6 Analysis

Quality of Term Weights Intuitively, the quality of term weights will directly affect the performance of the ROM model and the supervised method can produce higher quality term weight results. Thus, in addition to the BPROP method, we also conduct ROM pre-training by term weight distribution generated by the supervised DeepImpact method (Mallia et al., 2021). The experimental results of MS MARCO passage dataset are presented in Table 3. From which we can observe that: 1) High-quality term weight results do lead to better passage retrieval performance; 2) The improvement brought by DeepImpact is much smaller than that of the ROM model compared to the vanilla BERT LM, which indicates that the unsupervised term weight computation method is decent by considering that supervised method will inevitably introduce extra training cost.

Attention Weights Analysis To verify that the proposed ROM model is more discriminative for tokens with different weights, we compare the [CLS]-token distribution of the ROM and vanilla BERT models. In table 4, we present the top term weight tokens produced by these two different models. We can observe that the two sets have overlapping tokens. However, the higher attention weight tokens produced by the ROM model is obviously more reasonable, and the token set of the BERT model even contains stop-word marks.

5 Conclusion and Future Work

In this paper, we investigate that current random token masking MLM pre-training method is sub-optimal for LM pre-training, as this process tends to focus on stop words and punctuation. We suggested a novel retrieval oriented masking strategy which incorporates term importance information. We evaluated our ROM and extended coROM LMs on two benchmarks. The results showed that our method is highly effective, and our final model can achieve significant improvements compared to previous tailored LMs for dense passage retrieval.

In this paper, we intuitively use the BPROP method for term weight computation, and have not compared it with other unsupervised term weight methods. More detailed studies of term weight distribution based on the ROM model may produce an in-depth understanding. In further, we only conduct experiments based on BERT_base model, and validation based on extensive LMs pre-trained with MLM objective (e.g. RoBERTa) can further help to demonstrate the generality of the proposed ROM method.

References

Wei-Cheng Chang, Felix X. Yu, Yin-Wen Chang, Yiming Yang, and Sanjiv Kumar. 2020. Pre-training tasks for embedding-based large-scale retrieval. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020.

David R. Cheriton. 2019. From doc2query to docttttt-query.

Donghyun Choi, Myeongcheol Shin, Eunggyun Kim, and Dong Ryeol Shin. 2021. Adaptive batch scheduling for open-domain question answering. IEEE Access, 9:112097–112103.
Zhuyun Dai and Jamie Callan. 2019. Context-aware sentence/passage term importance estimation for first stage retrieval. *arXiv preprint arXiv:1910.10687*.

Zhuyun Dai and Jamie Callan. 2020. Context-aware term weighting for first stage passage retrieval. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval, SIGIR 2020, Virtual Event, China, July 25-30, 2020*, pages 1533–1536.

Yixing Fan, Xiaohui Xie, Yinqiong Cai, Jia Chen, Xinyu Ma, Xiangsheng Li, Ruqiang Zhang, Jiafeng Guo, and Yiqun Liu. 2021. Pre-training methods in information retrieval. *CoRR*, abs/2111.13853.

Emily Fawcett, Michelle Helena van Velthoven, and Edward Meinert. 2020. Long-term weight management using wearable technology in overweight and obese adults: Systematic review. *JMIR mHealth and uHealth*, 8.

Luyu Gao and Jamie Callan. 2021. Condenser: a pre-training architecture for dense retrieval. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*, pages 981–993.

Luyu Gao and Jamie Callan. 2022. Unsupervised corpus aware language model pre-training for dense passage retrieval. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pages 2843–2853.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick S. H. Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 6769–6781.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Lilion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. *Trans. Assoc. Comput. Linguistics*, 7:452–466.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers*, pages 6086–6096.

Jimmy Lin, Rodrigo Nogueira, and Andrew Yates. 2021. Pretrained Transformers for Text Ranking: BERT and Beyond. *Synthesis Lectures on Human Language Technologies*. Morgan & Claypool Publishers.

Zheng Liu and Yingxia Shao. 2022. Retromae: Pre-training retrieval-oriented transformers via masked auto-encoder. *arXiv preprint arXiv:2205.12035*.

Dingkun Long, Qiong Gao, Kuan Zou, Guangwei Xu, Pengjun Xie, Ruijie Guo, Jian Xu, Guanjun Jiang, Luxi Xing, and Ping Yang. 2022. Multi-cpr: A multi domain chinese dataset for passage retrieval. *CoRR*, abs/2203.03367.

Yuxiang Lu, Yiding Liu, Jiaxiang Liu, Yunsheng Shi, Zhengjie Huang, Shikun Feng, Yu Sun, Hao Tian, Hua Wu, Shuaiaiqiang Wang, Dawei Yin, and Haifeng Wang. 2022. Ernie-search: Bridging cross-encoder with dual-encoder via self on-the-fly distillation for dense passage retrieval. *CoRR*, abs/2205.09153.

Yi Luan, Jacob Eisenstein, Kristina Toutanova, and Michael Collins. 2021. Sparse, dense, and attentional representations for text retrieval. *Trans. Assoc. Comput. Linguistics*, 9:329–345.

Xinyu Ma, Jiafeng Guo, Ruqiang Zhang, Yixing Fan, and Xueqi Cheng. 2022. Pre-train a discriminative text encoder for dense retrieval via contrastive span prediction. *CoRR*, abs/2204.10641.

Xinyu Ma, Jiafeng Guo, Ruqiang Zhang, Yixing Fan, Yingyan Li, and Xueqi Cheng. 2021. B-PROP: bootstrapped pre-training with representative words prediction for ad-hoc retrieval. In *SIGIR ’21: The 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, Virtual Event, Canada, July 11-15, 2021*, pages 1318–1327. ACM.

Antonio Mallia, Omar Khattab, Torsten Suel, and Nicola Tonellotto. 2021. Learning passage impacts for inverted indexes. In *SIGIR ’21: The 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, Virtual Event, Canada, July 11-15, 2021*, pages 1723–1727.

Yuning Mao, Pengcheng He, Xiaodong Liu, Yelong Shen, Jianfeng Gao, Jiawei Han, and Weizhu Chen. 2021. Generation-augmented retrieval for open-domain question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pages 4089–4100.

Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. 2016. MS MARCO: A human generated machine reading comprehension dataset. In *Proceedings
Yingqi Qu, Yuchen Ding, Jing Liu, Kai Liu, Ruiyang Ren, Wayne Xin Zhao, Daxiang Dong, Hua Wu, and Haifeng Wang. 2021. Rocketqa: An optimized training approach to dense passage retrieval for open-domain question answering. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pages 5835–5847.

Ruiyang Ren, Yingqi Qu, Jing Liu, Wayne Xin Zhao, Qiaojiao She, Hua Wu, Haifeng Wang, and Jirong Wen. 2021. Rocketqa2: A joint training method for dense passage retrieval and passage re-ranking. ArXiv, abs/2110.07367.

Xing Wu, Guangyuan Ma, Meng Lin, Zijia Lin, Zhongyuan Wang, and Songlin Hu. 2022. Contextual mask auto-encoder for dense passage retrieval. CoRR, abs/2208.07670.

Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, Jialin Liu, Paul N. Bennett, Junaid Ahmed, and Arnold Overwijk. 2021. Approximate nearest neighbor negative contrastive learning for dense text retrieval. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021.

Shi Yu, Zhenghao Liu, Chenyan Xiong, Tao Feng, and Zhiyuan Liu. 2021. Few-shot conversational dense retrieval. In SIGIR ’21: The 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, Virtual Event, Canada, July 11-15, 2021, pages 829–838.

Jingtao Zhan, Jiaxin Mao, Yiqun Liu, Jiafeng Guo, M. Zhang, and Shaoping Ma. 2021. Optimizing dense retrieval model training with hard negatives. Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval.

Hang Zhang, Yeyun Gong, Yelong Shen, Jiancheng Lv, Nan Duan, and Weizhu Chen. 2021. Adversarial retriever-ranker for dense text retrieval. CoRR, abs/2110.03611.

Shunyu Zhang, Yaobo Liang, Ming Gong, Daxin Jiang, and Nan Duan. 2022a. Multi-view document representation learning for open-domain dense retrieval. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022, pages 5990–6000.

Yanzhao Zhang, Dingkun Long, Guangwei Xu, and Pengjun Xie. 2022b. Hlitr: Enhance multi-stage text retrieval with hybrid list aware transformer reranking. arXiv preprint arXiv:2205.10569.