RetroMAE: Pre-training Retrieval-oriented Transformers via Masked Auto-Encoder

Zheng Liu\textsuperscript{1}\textdagger, Yingxia Shao\textsuperscript{2}

\textsuperscript{1}: Huawei Technologies Ltd. Co., Shenzhen, China
\textsuperscript{2}: Beijing University of Posts and Telecommunications, Beijing, China
zhengliu1026@gmail.com, shaoyx@bupt.edu.cn

Abstract

Pre-trained models have demonstrated superior power on many important tasks. However, it is still an open problem of designing effective pre-training strategies so as to promote the models’ usability on dense retrieval. In this paper, we propose a novel pre-training framework for dense retrieval based on the Masked Auto-Encoder, known as RetroMAE. Our proposed framework is highlighted for the following critical designs: 1) a MAE based pre-training workflow, where the input sentence is polluted on both encoder and decoder side with different masks, and original sentence is reconstructed based on both sentence embedding and masked sentence; 2) asymmetric model architectures, with a large-scale expressive transformer for sentence encoding and a extremely simplified transformer for sentence reconstruction; 3) asymmetric masking ratios, with a moderate masking on the encoder side (15\%) and an aggressive masking ratio on the decoder side (50\%–90\%). We pre-train a BERT like encoder on English Wikipedia and BookCorpus, where it notably outperforms the existing pre-trained models on a wide range of dense retrieval benchmarks, like MS MARCO, Open-domain Question Answering, and BEIR.

1 Introduction

Dense retrieval plays the fundamental role in many important web applications, like search engines and recommender systems (Xiong et al., 2020; Qu et al., 2020). By having semantically correlated query and document represented as spatially close embeddings with dual-encoders, dense retrieval can be efficiently conducted via approximate nearest neighbour search, e.g., product quantization (Jegou et al., 2010) and HNSW (Malkov and Yashunin, 2018). In recent years, the pre-trained language models have been widely utilized as the backbone of dual-encoders (Karpukhin et al., 2020; Xiong et al., 2020; Luan et al., 2021). However, the mainstream pre-trained models, such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), XLNET (Yang et al., 2019), and T5 (Raffel et al., 2019), are typically pre-trained with token-level tasks, like masked language modeling and sequence-to-sequence. As a result, the sentence-level representation capability is not be properly developed, which will probably restrict the quality of dense retrieval.

Aware of the above defect, continuous effort has been made so as to better prepare pre-trained models for dense retrieval tasks. One popular strategy is to take advantage of self contrastive learning (SCL) (Chang et al., 2020; Izacard et al., 2021; Ni et al., 2021; Xu et al., 2022), where the models are pre-trained to recognize manually created positive samples from data augmentation. However, the SCL based methods can be limited by the data augmentation quality, and usually call for massive amounts of negative samples (Xu et al., 2022; He et al., 2020). Another popular strategy leverages auto-encoding (AE), which is freed from the requirements on data augmentation and negative sampling. The AE based strategy is differentiated in terms of reconstruction tasks: the existing methods leverage masked language modeling (MLM) (Gao and Callan, 2021), replaced token detection (RTD) (Chuang et al., 2022), and auto-regression ((Lu et al., 2021; Wang et al., 2021)), whose impacts on reconstruction difficulty and data efficiency are highly different. So far, it is still an open problem of exploring more effective AE based pre-training algorithms.

In this paper, we propose a novel masked auto-encoding (MAE) framework to pre-train retrieval-oriented language models, known as RetroMAE (Figure 1). The proposed pre-training framework not only simplifies the existing AE based methods, but also gives rise to surprisingly competitive per-
The Norwegian Forest cat is a breed of domestic cat originating in Northern Europe.

Figure 1: RetroMAE. The encoder adopts a large-scale network, whose input is moderately masked. The decoder is extremely simple in structure (one-layer transformer); the input is aggressively masked; the original sentence is reconstructed based on the sentence embedding and the aggressively masked input.

performances on downstream dense retrieval tasks. In particular, RetroMAE is featured for the following critical components and strategies.

- **Masked auto-encoding.** The pre-training follows a novel masked auto-encoding process. The input sentence is polluted twice with two different masks. One masked input is used by the encoder, where the sentence embedding is generated. The other masked input is used by the decoder, and together with the sentence embedding, the original sentence is reconstructed.

- **Asymmetric structure.** RetroMAE adopts an asymmetric model structure. The encoder is a large-scale transformer, e.g., BERT, which is learned to generate a discriminative embedding for the input sentence. In contrast, the decoder follows an extremely simplified structure, e.g., one single layer of transformer, which learns to reconstruct an masked sentence.

- **Asymmetric masking ratios.** The encoder’s input sentence is masked at a moderate ratio: 15%, which is the same as the typical MLM strategies. However, the decoder’s input sentence is masked with a much more aggressive ratio: 50–90%.

The above designs of RetroMAE are favorable to pre-training effectiveness thanks to the following reasons. Firstly, the auto-encoding task becomes much more challenging compared with the existing methods. The auto-regression may attend to the prefix during the decoding process; and the conventional MLM merely has a small portion (15%) of the input tokens masked. By comparison, RetroMAE aggressively masks most of the input during the decoding process, forcing the in-depth semantics to be encoded within the sentence embedding so as to ensure the reconstruction quality. Besides, the decoder is merely an one-layer transformer; the extremely simplified network further increases the difficulty of auto-encoding. Secondly, it ensures training signals to be fully generated from each pre-training sentence. For typical MLM style methods, the training signals may only be derived from 15% of the input tokens. Whereas for RetroMAE, the training signals can be derived from the majority of the tokens. Besides, knowing that the decoder only contains one-single layer, we propose the enhanced decoding with two-stream attention (Yang et al., 2019) and position-specific attention mask (Dong et al., 2019), where the training signals can be derived from the entire input tokens.

We perform comprehensive experimental studies with popular dense retrieval benchmarks, such as MS MARCO (Nguyen et al., 2016) and BEIR (Thakur et al., 2021). According to the evaluation results, RetroMAE notably improves both in-domain and out-of-domain performance in comparison with the existing generic and retrieval-oriented pretrained language models.

2 Related works

The related works are reviewed from two aspects: dense retrieval and pretrained language models.

Dense retrieval becomes increasingly popular in recent years. It represents query and document as embeddings within the same latent space, where the semantic relationship between query and document can be measured based on the embedding similarity. As a result, dense retrieval can be efficiently conducted leveraging approximate nearest neighbour search, like HNSW (Malkov and Yashunin, 2018) and Product Quantization (Jegou et al., 2010). The encoding model, i.e., the dual encoder, is fundamental to the retrieval quality. With the progress of deep learning, the model architecture is being continuously evolving, from simple linear transformations (Huang et al., 2013) to CNNs (Shen et al., 2014), RNNs (Kiros et al., 2015), etc. The adventure of large-scale pre-trained language models, e.g., BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), T5 (Raffel et al., 2019), brings about a major leap-forward for dense retrieval. Thanks to the equipment of such big expressive models, the retrieval quality
has been substantially enhanced (Karpukhin et al., 2020; Luan et al., 2021; Lin et al., 2021).

One important feature about the pre-trained language models is that the pre-training tasks are highly differentiated. One common practice is the masked language modeling (MLM) as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), where the masked tokens are predicted based on the rest of the context. The basic MLM is extended by tasks like entity masking, phrase masking and span masking (Sun et al., 2019; Joshi et al., 2020), which substantially contribute to the sequence labeling applications, such as entity resolution and question answering. Besides, tasks like auto-regression (Radford et al., 2018; Yang et al., 2019) and sequence-to-sequence (Raffel et al., 2019; Lewis et al., 2019) are also utilized, where the pre-trained models can be better fit into NLG related applications. However, all these generic approaches focus on token-level language modeling, where the sentence representation capability is not effectively developed (Chang et al., 2020). As a result, it usually calls for a large scale of labeled data (Nguyen et al., 2016; Kwiatkowski et al., 2019) and sophisticated fine-tuning strategies (Xiong et al., 2020; Qu et al., 2020) to guarantee the pre-trained models’ performance on dense retrieval.

To mitigate the above problem, recent works target on pre-training retrieval oriented language models. The mainstream approaches are based on two different strategies: self-contrastive learning (SCL) and auto-encoding (AE). The SCL based methods (Chang et al., 2020; Guu et al., 2020; Xu et al., 2022) require specific data augmentation, e.g., inverse cloze task (ICT), where positive samples are generated for each anchor sentence; then, the language model is trained to discriminate the positive samples from the negative ones via contrastive learning. However, the self-contrastive learning usually calls for huge amounts of negative samples, which is computationally challenging; besides, the pre-training effect can be severely restricted by the quality of data augmentation. The AE based methods are free from these restrictions, where the language models are learned to reconstruct the input sentence based on the sentence embedding. The existing methods utilize various reconstruction tasks, such as MLM (Gao and Callan, 2021), auto-regression (Lu et al., 2021; Wang et al., 2021), and token replace detection (Chuang et al., 2022), etc, which are quite differentiated in terms of data efficiency and reconstruction difficulty. For example, MLM learns from the masked tokens, which only consist 15% of each sentence; in contrast, the training signals can be derived from all the input tokens with auto-regression. Besides, the conventional auto-encoding leverages a large-scale decoder (Li et al., 2020; Wang et al., 2021); while in (Lu et al., 2021), a smaller decoder is used, which increases the reconstruction difficulty. Ideally, the auto-encoding should be data efficient, which ensures the pre-training corpus to be fully leveraged; meanwhile, it should also be made sufficiently challenging, which forces sentence embeddings to capture the in-depth semantics about the input sentences.

3 Methodology

We propose the following masked auto-encoding workflow for the retrieval-oriented pre-training. The model consists two components: a BERT-like transformer $\Phi^{\text{enc}}(\cdot)$ for sentence representation, and a light-weight transformer $\Phi^{\text{dec}}(\cdot)$ for sentence reconstruction. An input sentence $X$ is masked as $\hat{X}^{\text{enc}}$ and encoded for the sentence embedding $h_{\hat{X}}$; the sentence is masked once again as $\hat{X}^{\text{dec}}$, and together with $h_{\hat{X}}$, the original sentence $X$ is decoded. Detailed elaborations about the above workflow is illustrated as follows.

3.1 Encoding

The input sentence $X$ is polluted as $\hat{X}^{\text{enc}}$ for the encoding stage, where a small fraction of its tokens are randomly replaced by the special token [M] (Figure 1. A). We apply a moderate masking ratio, 15% by default, where the majority of information about the original sentence can be preserved. Then, the encoder $\Phi^{\text{enc}}(\cdot)$ is used to map the polluted input as the sentence embedding $h_{\hat{X}}$:

$$h_{\hat{X}} \leftarrow \Phi^{\text{enc}}(\hat{X}^{\text{enc}}).$$

We leverage a BERT-like transformer for the encoding operation, i.e., 12 layers and 768 hidden-dimension, where the in-depth semantic about the input may get effectively captured. Following the common practice, we select the [CLS] token’s last-layer hidden state as the sentence embedding.

3.2 Decoding

The input sentence $X$ is polluted once again as $\hat{X}^{\text{dec}}$ for the decoding stage (Figure 2. B). The
masking ratio is much more aggressive compared with the one used by the encoder, where up to 50~90% of the input tokens will be masked. The masked input is joined with the sentence embedding, based on which the original input sentence can be reconstructed by the decoder. Particularly, the sentence embedding and the masked input are combined into the following sequence:

\[
    h_X ⊕ E_{X,dec} = [h_X; e_{x_1}, ..., e_{x_N}].
\]  

(2)

In the above equation, \(e_x\) denotes the word embedding; \(x_1\) equals to the original token value if it is not masked, otherwise \([M]\). We add extra position embeddings \(P\) to the above sequence, which form the decoder’s input. Finally, the decoder \(Φ_{dec}\) is learned to reconstruct the original sentence \(X\) by optimizing the following objective:

\[
    \min \sum_{x_i \in \text{masked}} CE(x_i | h_X ⊕ E_{X,dec} + P),
\]

(3)

where \(CE\) indicates the cross-entropy loss. We adopt a light-weight network, i.e., an one-layer transformer by default, for the decoding operation. Given the aggressively masked input and the extremely simplified decoding network, it will force the generation of high-quality sentence embedding such that the original input can be reconstructed with good fidelity.

3.3 Enhanced Decoding

One shortcoming about the above decoding process is that the training signals, i.e., the cross-entropy loss, may only be derived from the masked tokens, instead of the entire input tokens. Besides, each masked token is reconstructed based on the same context, i.e., \(h_X ⊕ E_{X,dec} + P\). We argue that the pre-training effect can be further enhanced if 1) more training signals can be derived from the input, and 2) the reconstruction task can be performed based on different contexts. To this end, we propose the following enhanced decoding inspired by two-stream attention (Yang et al., 2019) and position-specific attention mask (Dong et al., 2019). Particularly, we will have the following two input sequences: \(H_1\) and \(H_2\), for decoding (Figure 2. C):

\[
    H_1 ← h_X + P, \quad H_2 ← E_X + P,
\]

(4)

where \(h_X\) is the sentence embedding, \(E_X\) is the word embedding for the original tokens, and \(P\) is the position embedding. Then, we introduce the position-specific attention mask \(M \in L × L\), based on which the self-attention is performed as:

\[
    Q = H_1 W^Q, \quad K = H_2 W^K, \quad V = H_2 W^V;
\]

\[
    M_{ij} = \begin{cases} 0, & \text{can be attended}, \\ -∞, & \text{masked}; \end{cases}
\]

(5)

\[
    A = \text{softmax}(\frac{Q^T K}{\sqrt{d}} + M)V.
\]

The output \(A\), together with \(h_X\) (because of the residual connection) are used to reconstruct the original input (other operations in transformers, like layer-norm and FFN, are omitted for simplicity.) Finally, the objective will be optimized:

\[
    \min \sum_{x_i \in X} CE(x_i | A, h_X)
\]

(6)

Knowing that the decoder only consists of one single transformer layer, each token \(x_i\) can only be
Algorithm 1: RetroMAE

1 begin
2 \( \tilde{X}_{\text{enc}} \leftarrow \text{mask}(X); \)
3 \( h_{\tilde{X}} \leftarrow \Phi_{\text{enc}}(\tilde{X}_{\text{enc}}); \)
4 \( H_1 \leftarrow h_{\tilde{X}} + P; \) % for \( Q \)
5 \( H_2 \leftarrow E_X + P; \) % for \( K \) and \( V \)
6 \( M \leftarrow \text{Eq. 7}; \)
7 \( A \leftarrow \text{based on } H_1, H_2, M \text{ as Eq. 5}; \)
8 model update w.r.t. Eq. 6;

reconstructed based on the information which are visible to the \( i \)-th row of matrix \( M \). In this place, the following rules are applied to generate the attention mask matrix \( M \):

\[
M_{ij} = \begin{cases} 
0, & x_j \in s(X_{\neq i}), \\
-\infty, & \text{otherwise}. 
\end{cases} \tag{7}
\]

In the above equation, \( s(X_{\neq i}) \) represents the random sampling of the input tokens. The sampled tokens will be visible when reconstructing \( x_i \). The diagonal elements, i.e., \( x_i \) for the \( i \)-th row, will always be excluded, which means they will always be masked; therefore, each token cannot attend to itself during the reconstruction stage.

We summarize the pre-training workflow of the encoding and enhanced decoding as Algorithm 1, where the following features need to be emphasized. Firstly, the reconstruction task is challenging given the aggressive masking ratio and the lightweight network about the decoder. Secondly, we may derive abundant pre-training signals from the unsupervised corpus since all tokens within each input sentence can be used for the reconstruction task. Finally, the pre-training is made simple and efficient: 1) there are no requirements on sophisticated data augmentation and negative sampling, and 2) the training cost is maintained to be comparable to the conventional BERT/RoBERTa style pre-training due to the simplicity of decoder.

4 Experiment

We explore the following issues in our experimental studies. 1) RetroMAE’s impact on dense retrieval, in comparison with the generic pre-trained language models and the retrieval-oriented pre-trained models. 2) The impact resulted from the four key factors in RetroMAE, the enhanced decoding, the size of decoder, the decoder’s masking ratio, and the encoder’s masking ratio.

4.1 Experiment Settings

The following datasets are utilized for the pre-training and evaluation of RetroMAE.

- Pre-training. We reuse the same pre-training corpus as the ones utilized by BERT (Devlin et al., 2019), i.e., the English Wikipedia and BookCorpus. Both datasets are also frequently leveraged by previous works on retrieval-oriented pre-training, such as SEED (Lu et al., 2021) and Condenser (Gao and Callan, 2021).

- Supervised evaluation. We make use of the MS MARCO passage retrieval dataset (Nguyen et al., 2016) to evaluate RetroMAE’s performance after supervision. It is one of the large-scale datasets for dense retrieval evaluation, which consists of real-world questions from Bing search. The questions are paired with their corresponding passages from web documents, where human annotated ground-truth answers to the questions are included. RetroMAE is fine-tuned on its training set and evaluated on its dev set.

- Zero-shot evaluation. We evaluate RetroMAE’s zero-shot retrieval performance on top of the recently released BEIR benchmark (Thakur et al., 2021). It contains a total of 18 datasets, covering dense retrieval tasks across different domains, such as question answering, fact checking, bio-medical retrieval, news retrieval, and social media retrieval, etc.

We consider three categories of baseline methods\(^1\) in our experimental studies.

- Generic models. The following generic pre-trained language models are included in our experiments. 1) BERT (Devlin et al., 2019), which is the most popular pre-trained language model in practice. It is also widely used as the backbone for the fine-tuning of dense retrievers (Karpukhin et al., 2020; Xiong et al., 2020). 2) RoBERTa (Liu et al., 2019), which is an enhanced replication of BERT with improved training settings and substantially augmented training data. 3) ELECTRA (Clark et al., 2020), introduces the generator-discriminator framework and the token replacement prediction task to further improve the pre-training effect.

- Constrained learning. The following contrastive learning based methods are considered. 1) SimCSE (Gao et al., 2021), where the language model is learned to discriminate different views of the anchor sentence augmented by drop-
### Methods and Performance

| Methods  | MRR@10 | MRR@100 | Recall@10 | Recall@100 | Recall@1000 |
|----------|--------|---------|-----------|------------|-------------|
| BERT     | 0.3170 | 0.3278  | 0.5801    | 0.8570     | 0.9598      |
| RoBERTa  | 0.3139 | 0.3245  | 0.5995    | 0.8155     | 0.9351      |
| ELECTRA  | 0.3136 | 0.3258  | 0.5638    | 0.8478     | 0.9579      |
| SimCSE   | 0.3191 | 0.3307  | 0.5833    | 0.8537     | 0.9602      |
| LaPraDoR | 0.3193 | 0.3307  | 0.5907    | 0.8653     | 0.9699      |
| SEED     | 0.3264 | 0.3374  | 0.5913    | 0.8535     | 0.9539      |
| DiffCSE  | 0.3202 | 0.3311  | 0.5832    | 0.8561     | 0.9607      |
| Condenser| 0.3357 | 0.3471  | 0.6082    | 0.8770     | 0.9683      |
| RetroMAE | 0.3501 | 0.3606  | 0.6306    | 0.8890     | 0.9757      |

Table 1: Supervised dense retrieval performance on MS MARCO.

out. Despite its simplicity, SimCSE achieves quite promising results on semantic textual similarity tasks. 2) **LaPraDoR**\(^2\) (Xu et al., 2022), which is a recently proposed unsupervised retriever on top of contrastive learning. It notably enhances the previous ICT based methods (Guu et al., 2020; Chang et al., 2020) with the alternative training of query and document encoder, where the scale of negative samples can be greatly increased.

- **Auto-encoding.** We also make comparison with three pre-trained models following the auto-encoding framework. 1) **Condenser** (Gao and Callan, 2021), where the sentence embedding is joined with the intermediate hidden-states from encoder for the masking language modeling task. 2) **SEED,** in which the sentence embedding is used to reconstruct the original sentence via auto-regression. 3) **DiffCSE** (Chuang et al., 2022), which is a combination of SimCSE and auto-encoding based pre-training: for one thing, the sentence embedding is learned by contrastive learning as SimCSE; for another thing, the sentence embedding is applied to the ELETRA-style pre-training, i.e., the prediction of replaced tokens generated by a generator.

The implementation settings are specified as follows. The encoder backbone of RetroMAE is the same as BERT base, i.e., with 12 layers, 768 hidden-dimensions, and a vocabulary of 30522 tokens. The decoder is a one-layer transformer. The encoder masking ratio is 0.5, and the decoder masking ratio is 0.15. The model is trained for 8 epochs, with the AdamW optimizer, a batch-size of 32 for each device, and a learning rate of 1e-

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\(^2\) The original LaPraDoR is an ensemble of dense retriever and BM25. We preserve its released dense retriever for our experimental studies.
Datasets:
- BERT
- LaPraDoR
- SimCSE
- DiffCSE
- SEED
- Condenser
- RetroMAE

TREC-COVID: 0.649, 0.495, 0.524, 0.492, 0.612, 0.754, 0.756
BioASQ: 0.262, 0.239, 0.264, 0.258, 0.297, 0.317, 0.383
NFCorpus: 0.257, 0.283, 0.250, 0.259, 0.256, 0.278, 0.301
NQ: 0.438, 0.415, 0.412, 0.412, 0.425, 0.459, 0.490
HotpotQA: 0.478, 0.488, 0.502, 0.499, 0.528, 0.537, 0.638
FiQA-2018: 0.237, 0.266, 0.240, 0.229, 0.244, 0.261, 0.301
Signal-1M(RT): 0.216, 0.245, 0.264, 0.260, 0.246, 0.258, 0.278
TREC-NEWS: 0.362, 0.206, 0.368, 0.363, 0.335, 0.353, 0.398
Robust04: 0.364, 0.310, 0.353, 0.343, 0.348, 0.352, 0.433
ArguAna: 0.357, 0.503, 0.436, 0.468, 0.347, 0.375, 0.481
Touche-2020: 0.270, 0.178, 0.178, 0.168, 0.180, 0.223, 0.243
CQADupStack: 0.284, 0.326, 0.295, 0.305, 0.285, 0.316, 0.382
Quora: 0.782, 0.843, 0.848, 0.850, 0.849, 0.855, 0.856
DBPedia: 0.298, 0.328, 0.304, 0.303, 0.324, 0.331, 0.385
SCIDOCS: 0.115, 0.145, 0.125, 0.125, 0.117, 0.136, 0.150
FEVER: 0.684, 0.518, 0.651, 0.641, 0.653, 0.682, 0.719
Climate-FEVER: 0.205, 0.172, 0.222, 0.200, 0.176, 0.199, 0.214
SciFact: 0.504, 0.483, 0.545, 0.523, 0.556, 0.570, 0.648
Avg. Performance: 0.376, 0.358, 0.377, 0.372, 0.377, 0.403, 0.448

Table 2: Zero-shot dense retrieval performances on BEIR benchmark (measured by NDCG@10).

denser, are generally better than other methods. Such an observation indicates that auto-encoding is probably a more suitable paradigm for the pre-training of retrieval-oriented language models. We would also attribute RetroMAE’s advantage over other auto-encoding based methods to its higher data-efficiency and reconstruction difficulty. More analysis about this point will be made in the following discussions.

Secondly, the contrastive learning based methods merely bring very limited improvements over the generic pre-trained models, as can be observed from the comparison between SimCSE, LaPraDoR and BERT in Table 1 and 2. In fact, similar observations are also made by previous study (Gao and Callan, 2021): although contrastive learning may equip the pre-trained models with preliminary capability on dense retrieval, the advantage is almost wiped out when the models are fine-tuned with labeled data.

Thirdly, despite that RoBERTa and ELECTRA are proved to be more effective than BERT on generic NLU tasks, like GLUE and MRC, they are no better than BERT on dense retrieval scenarios. Such an observation validates once again that the conventional token-level pre-training contributes little to the models’ dense retrieval capability; thus, retrieval-oriented pre-training is needed.

4.2.2 Ablation Studies

We ablate RetroMAE based on MS MARCO, where the following factors are analyzed: 1) decoding method, 2) decoder’s size, 3) decoder’s masking ratio, 4) encoder’s masking ratio. The experiment results are shown as Table 3, where the following observations can be made.

Firstly of all, we analyze the impact from the decoding method. It can be observed that the enhanced decoding outperforms the basic decoding with notable advantages. Such an empirical advantage can be explained by the higher data efficiency of the enhanced decoding. Particularly, the basic decoding (Section 3.2) samples 50% of tokens (the default masking ratio for decoder) for reconstruction, and all of the masked tokens are predicted based on the same context. In contrast, the enhanced decoding (Section 3.3) may use all of the input tokens for reconstruction, and each of the masked tokens is predicted based on a unique context sampled as Eq. 7. Therefore, the enhanced decoding may obtain augmented and diverse training signals from the input data.
| Factor     | Setting   | MRR@10 | MRR@100 | Recall@10 | Recall@100 | Recall@1000 |
|------------|-----------|--------|---------|-----------|------------|-------------|
| Decode     | Basic     | 0.3434 | 0.3548  | 0.6166    | 0.8832     | 0.9722      |
|            | Enhanced  | 0.3501 | 0.3606  | 0.6306    | 0.8890     | 0.9757      |
| Height (De)| $H_{de} = 1$ | 0.3455 | 0.3568  | 0.6212    | 0.8818     | 0.9716      |
|            | $H_{de} = 2$ | 0.3434 | 0.3548  | 0.6166    | 0.8832     | 0.9722      |
| Mask (De)  | $\gamma_{de} = 0.3$ | 0.3479 | 0.3596  | 0.6242    | 0.8890     | 0.9739      |
|            | $\gamma_{de} = 0.5$ | 0.3501 | 0.3606  | 0.6306    | 0.8890     | 0.9757      |
|            | $\gamma_{de} = 0.7$ | 0.3490 | 0.3604  | 0.6289    | 0.8910     | 0.9755      |
|            | $\gamma_{de} = 0.9$ | 0.3491 | 0.3602  | 0.6272    | 0.8870     | 0.9745      |
| Mask (En)  | $\gamma_{en} = 0.15$ | 0.3501 | 0.3606  | 0.6306    | 0.8890     | 0.9757      |
|            | $\gamma_{en} = 0.3$ | 0.3553 | 0.3665  | 0.6356    | 0.8922     | 0.9763      |
|            | $\gamma_{en} = 0.5$ | 0.3537 | 0.3649  | 0.6337    | 0.8910     | 0.9742      |

Table 3: Ablation studies of RetroMAE based on MS MARCO.

Secondly, we analyze the impact from the size of decoder. In this place, we use two different decoders for comparison: 1) the decoder with one single transformer layer ($H_{de} = 1$), and 2) the decoder with two transformer layers ($H_{de} = 2$). It can be found that the smaller decoder, which increases the difficulty of input reconstruction, gives rise to better empirical performances.

Thirdly, we further analyze the impact from different masking ratios of the decoder ($\gamma_{de}$), which is increased from 0.3 to 0.9. It can be observed that the decoder with an aggressive masking ratio, i.e., 0.5~0.7, results in a relatively better empirical performance. However, further increasing of the masking ratio, i.e., $\gamma_{de} = 0.9$, does not bring in additional improvements. It is probably because an over aggressive masking ratio will discard too much necessary information to reconstruct the original sentence.

Lastly, we also make analysis for the encoder’s masking ratio ($\gamma_{en}$). It is quite interesting that a slightly improved masking ratio, i.e., $\gamma_{en} = 0.3$, achieves better performances than the default one $\gamma_{en} = 0.15$. Similar as the decoder’s situation, an increased masking ratio on the encoder side will also increase the reconstruction difficulty. However, the empirical performance will not benefit from an even larger masking ratio; and the ideal value of $\gamma_{en}$ is smaller than $\gamma_{de}$. This is because a too large $\gamma_{en}$ will prevent the generation of high-quality sentence embedding, considering that too much useful information about the input sentence will be discarded.

### 4.2.3 Discussion

We draw the following conclusions based on our experimental findings in this paper. Firstly, the auto-encoding framework demonstrates strong potential in pre-training retrieval-oriented language models, and RetroMAE brings in substantially improvements over the existing auto-encoding based methods. Secondly, RetroMAE’s performance is optimized by the enhanced decoding strategy, the simplified network of decoder, and the proper setting of the masking ratios.

### 5 Conclusion

In this paper, we propose RetroMAE, which pre-trains retrieval-oriented language models based on masked auto-encoding: the input sentence is randomly masked twice for encoder and decoder, respectively; the sentence embedding from encoder is joined with the masked input of decoder to reconstruct the original sentence. We take advantage of asymmetric model structure (full-scale encoder and simplified decoder) and asymmetric masking ratio (a moderate one for encoder and an aggressive one for decoder), which improves the difficulty of reconstruction. We also introduce the enhanced decoding with two-stream attention and position-specific attention mask, which increases the data efficiency of pre-training. The experimental studies on MS MARCO and BEIR benchmark validate RetroMAE’s effectiveness, as significant improvements on retrieval quality can be achieved against the existing methods.
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