Abstract

In this work, we revisit the Transformer-based pre-trained language models and identify two problems that may limit the expressiveness of the model. Firstly, existing relative position encoding models (e.g., T5 and DEBERTA) confuse two heterogeneous information: relative distance and direction. It may make the model unable to capture the associative semantics of the same direction or the same distance, which in turn affects the performance of downstream tasks. Secondly, we notice the pre-trained BERT with Mask Language Modeling (MLM) pre-training objective outputs similar token representations and attention weights of different heads, which may impose difficulties in capturing discriminative semantic representations. Motivated by the above investigation, we propose two novel techniques to improve pre-trained language models: Decoupled Directional Relative Position (DDRP) encoding and MTH pre-training objective. DDRP decouples the relative distance features and the directional features in classical relative position encoding for better position information understanding. MTH designs two novel auxiliary losses besides MLM to enlarge the dissimilarities between (a) last hidden states of different tokens, and (b) attention weights of different heads, alleviating homogenization and anisotropic problem in representation learning for better optimization. Extensive experiments and ablation studies on GLUE benchmark demonstrate the effectiveness of our proposed methods.

1 Introduction

The paradigm of pre-training on large-scale corpus and fine-tuning on specific task datasets has swept the entire field of Natural Language Processing (NLP). BERT (Devlin et al., 2018) is the most prominent pre-trained language model, which stacks the encoder blocks of Transformer (Vaswani et al., 2017) and adopts MLM and Next Sentence Prediction (NSP) pre-training tasks, achieving the SOTA results in 2018. After that, a large number of Pre-trained Language Models (PLMs) (Liu et al., 2019; Lan et al., 2020; Raffel et al., 2019; Clark et al., 2020; He et al., 2021) that optimize the Transformer structure and pre-training objectives have emerged, which further improves the performance of the pre-trained language models on multiple downstream tasks.

In this work, we improve Transformer-based pre-trained language models with two straightforward yet effective techniques to facilitate the model’s optimization as follows:

(1) Decoupled Directional Relative Position Encoding. We associate the pre-trained language model with the way people understand semantics. We believe that the relative distance features and the directional features are heterogeneous information that reflects different aspects of positional information. However, a large number of relative position encoding methods confuse the relative distance and direction when building the relative position representations (Shaw et al., 2018; Yang et al., 2019; Wei et al., 2019; Raffel et al., 2019; He et al., 2021; Ke et al., 2021). We argue that in this case there is no explicit connection established between embedding vectors of the same direction or the same distance, which may result in serious information losses in position encoding. Inspired by this, we propose a novel Decoupled Directional Relative Position (DDRP) encoding. In detail, DDRP decomposes the classical relative position embedding (Shaw et al., 2018) into two embeddings, one storing the relative distance features and the other storing the directional features, and then multiply the two together explicitly to derive the final decoupled relative position embedding.

(2) Representation Differentiations. We notice that the pre-trained BERT has high consistency in last hidden states across different tokens and
attention weights (i.e., the dot product between Query and Key in the self-attention module) across different heads, respectively. Similar last hidden states will introduce the anisotropic problem (Ethayarajh, 2019), which will bound the token vectors to a narrow representation space and thus make it more difficult for the model to capture deep semantics during fine-tuning. Considering attention weights contain rich linguistic knowledge (Clark et al., 2019; Jawahar et al., 2019), we argue that high consistency in attention weights also constrains the ability of the model to capture multi-aspect information. Therefore, we propose two novel pre-training approaches to stimulate the potential of the pre-trained model to learn rich linguistic knowledge: Token Cosine Differentiation (TCD) objective and Head Cosine Differentiation (HCD) objective. Specifically, TCD attempts to broaden the dissimilarity between tokens by minimizing the cosine similarities between different last hidden states. In contrast, HCD attempts to broaden the dissimilarity between heads by minimizing the cosine similarities between different attention weights. We apply the values calculated from TCD and HCD as two auxiliary losses in pre-training, which in turn guides the model to produce more discriminative token representations and attention weights. Our enhanced pre-training task combines the original MLM objective with two proposed TCD and HCD objectives, noted as MTH.

Extensive experiments on the GLUE benchmark show that DDRP achieves better results than classical relative position representation (Shaw et al., 2018) on almost all tasks without introducing the additional computational overhead and consistently outperforms prior competitive relative position encoding models (He et al., 2021; Ke et al., 2021). Moreover, our proposed MTH outperforms MLM by a 0.96 average GLUE score and achieves nearly 2x pre-training speedup on BERT_BASE. Both DDRP and MTH are straightforward, effective, and easy to deploy, which can be easily combined with existing pre-training objectives and various model structures. Our contributions are summarized as follows:

- We propose a novel relative position encoding named DDRP, which decouples the relative distance and directional features, giving the model a stronger prior knowledge, fewer parameters, and better results compared to conventional coupled position encodings.
- We analyze the trend of self-similarity of last hidden states and attention weights during pre-training, and propose two novel Token Cosine Differentiation and Head Cosine Differentiation objectives, motivating pre-trained Transformer to better capture semantics in PLMs.
- We conduct extensive experiments on GLUE benchmark to verify the general and significant improvement of our proposed methods and analyze the characteristics of DDRP and MTH in detail.

2 Related Work

2.1 Pre-trained Language Models for NLU

In recent years, pre-trained language models have made significant breakthroughs in the field of NLP. BERT (Devlin et al., 2018), which proposes MLM and NSP pre-training objectives, is pre-trained on large-scale unlabeled corpus and has learned bidirectional representations efficiently. After that, many different pre-trained models are produced, which further improve the effectiveness of the pre-trained models. RoBERTa (Liu et al., 2019) proposes to remove the NSP task and verifies through experiments that more training steps and larger batches can effectively improve the performance of the downstream tasks. ALBERT (Lan et al., 2020) proposes a Cross-Layer Parameter Sharing technique to lower memory consumption. XLNet (Yang et al., 2019) proposes Permutation Language Modeling (PLM) to capture the dependencies among predicted tokens. ELECTRA (Clark et al., 2020) adopts Replaced Token Detection (RTD) objective, which considers the loss of all tokens instead of a subset.

2.2 Position Encoding in Pre-training

For text comprehension, position information is crucial, therefore there are several studies aiming at how to incorporate position information into pre-trained models. Transformer and BERT add the absolute position embedding and word embedding as the original input of the Transformer structure. Shaw et al. (2018) firstly proposes relative position encoding, which adds unshared relative position vectors to Key and Value representation spaces respectively. It is proved that relative position encoding can more effectively improve the performance
of downstream tasks compared to absolute position encoding. T5 (Raffel et al., 2019) adds the relative position biases after the Query-Key dot product, which are learnable scalars. TUPE (Ke et al., 2021) performs Query-Key dot product with different parameter projections for contextual information and positional information separately and then added them up, they also add relative position biases like T5 on different heads to form the final correlation matrix. DEBERTA (He et al., 2021) separately encodes the context and position information of each token and uses the textual and positional disentangled matrices of the words to calculate the correlation matrix.

3 Method

In this section, we first give a brief introduction to the self-attention module and several relative position encoding models (in Sec. 3.1). Next, we give the details of our proposed Decoupled Directional Relative Position Encoding (in Sec. 3.2), which conducts a deeper analysis of the positional information in pre-trained models. Finally, we introduce Representation Differentiations (in Sec. 3.3) in detail, which constructs a novel MTH pre-training objective to motivate the pre-trained Transformer to produce more discriminative token representations and attention weights.

3.1 Background

Multi-head self-attention plays a vital role in the BERT structure, and its core formula for a specific head is as follows:

\[
Q = HW^Q, \quad K = HW^K, \quad V = HW^V, \quad (1)
\]

\[
A = \frac{QK^T}{\sqrt{d}}, \quad (2)
\]

\[
Z = \text{softmax}(A)V, \quad (3)
\]

where \( H \in \mathbb{R}^{S \times D} \) represents the input hidden states; \( W^Q, W^K, W^V \in \mathbb{R}^{D \times d} \) represent the projection matrix of Query, Key, and Value respectively; \( A \in \mathbb{R}^{S \times S} \) represents attention weight; \( Z \in \mathbb{R}^{S \times d} \) represents the single-head output hidden states of self-attention module; \( S \) represents input sequence length; \( D \) represents the dimension of input hidden states; \( d \) represents the dimension of single-head hidden states.

Unlike BERT which adds the absolute position embedding to the word embedding as the final input of the model, Shaw et al. (2018) first proposes relative position encoding, which does not use absolute position embedding as the original input of the model, but adds relative position embedding into \( K \) in the self-attention module of each layer to make a more interactive influence. Its formula is as follows:

\[
A_{i,j} = \frac{Q_i (K_j + K_{s(i,j)})^T}{\sqrt{d}}, \quad (4)
\]

\[
\sigma (i, j) = \text{clip} (i - j) + r_s, \quad (5)
\]

where \( Q_i \) represents Query vector at the \( i \)-th position; \( K_j \) represents Key vector at the \( j \)-th position; \( A_{i,j} \) represents the attention value of \( i,j \); \( r_s \) represents maximum absolute position distance; \( \sigma (i, j) \) represents the index of relative position embedding \( K^r \in \mathbb{R}^{2r_s \times d}; \) relative position embedding for \( K \) are shared at all different heads. Note that Shaw et al. (2018) has experimentally demonstrated that adding relative position embedding to the interaction between \( A \) and \( V \) gives no further improvement in effectiveness, so the relative position embedding in \( V \) space is eliminated in all our experiments to reduce the computational overhead.

Due to the effectiveness of relative position encoding, there are several researches exploring various relative position encodings (Yang et al., 2019; Wei et al., 2019; Raffel et al., 2019; Su et al., 2021; He et al., 2021; Ke et al., 2021). Specifically, we will introduce two recently proposed state-of-the-art models: TUPE (Ke et al., 2021) and DEBERTA (He et al., 2021). TUPE computes the word contextual correlation and positional correlation separately with different parameterizations and then adds them together, plus additional relative biases. Its formula is as follows:

\[
Q_P = PW^Q_P, \quad K_P = PW^K_P, \quad (6)
\]

\[
A_{i,j} = \frac{(Q_P P^T + Q_P P^T)^T}{2d} + b_{o(i,j)}, \quad (7)
\]

where \( P \in \mathbb{R}^{n \times D} \) represents absolute position embedding; \( r_s \) represents maximum absolute position length; \( W^Q_P, W^K_P \in \mathbb{R}^{D \times d} \) represent different projection matrices for the absolute position embedding; \( b \in \mathbb{R}^{2r_s} \) represents relative position scalars. DEBERTA computes attention weights among words using disentangled matrices based on their contents and relative positions, respectively, and its formula is as follows:

\[
A_{i,j} = \frac{Q_i K_j^T + Q_i K_{s(i,j)}^T + K_j Q_{s(i,j)}^T}{\sqrt{3d}}, \quad (8)
\]
3.2 Decoupled Directional Relative Position Encoding

We argue that relative distance and direction, two different types of positional information, are both important for understanding semantics. However, existing relative position encodings mix relative distance and directional information for modeling, which makes information originally in different spaces entangled. It may affect the model’s perception of distance and direction, which in turn affect the performance. Therefore, we propose a novel Decoupled Directional Relative Position (DDRP) encoding.

DDRP decouples the relative distance and directional information and maintains them with two different embeddings. Its formula is as follows:

\[
A_{i,j} = \frac{Q_i (K_j + K'_{d(i,j)})^T}{\sqrt{d}}, \quad (9)
\]

\[
K'_{d(i,j)} = (D_{\rho(i,j)} \odot K''_{d(i,j)}) W_{K}^{rd}, \quad (10)
\]

\[
\rho(i,j) = \begin{cases} 
1, & \text{if } i-j < 0 \\
0, & \text{if } i-j = 0 \\
2, & \text{if } i-j > 0 
\end{cases}, \quad (11)
\]

\[
\delta(i,j) = \text{abs}(\text{clip}(i-j)), \quad (12)
\]

where \(\rho(i,j)\) represents the index of directional embedding \(D \in \mathbb{R}^{3 \times d}\); \(\delta(i,j)\) represents the index of relative distance embedding \(K^{rd} \in \mathbb{R}^{r_s \times d}\); \(W_{K}^{rd} \in \mathbb{R}^{4 \times d}\) represents projection matrix for relative position vectors; \(K'\) represents the relative position matrix. Note that in terms of implementation details, the only difference between DDRP and BETR-R is that DDRP decouples \(K^{rd}\) in BETR-R into the element-wise multiplication of \(D\) and \(K^{rd}\).

We also provide a specific example in Figure 1.

We summarize the advantage of DDRP as follows: (i) Unlike previous relative position encodings, which could only obtain entangled and coupled position information, DDRP can explicitly obtain clear relative distance and directional information for a better position encoding. (ii) Unlike previous relative position encodings, which require \(2r_s\) relative position vectors, DDRP only need \(r_s+3\) relative position vectors.

3.3 Representation Differentiations

Analyses on the similarities between different tokens and heads. Since it is confirmed that isotropic distributions of different tokens or heads may be beneficial to performance (Mu et al., 2017; Ethayarajh, 2019; Clark et al., 2019; Jawahar et al., 2019), we also wonder how self-similarity of tokens and heads changes during pre-training. Therefore, we first analyze the self-similarity trends of tokens and heads during the original MLM-based pre-training. For an input sequence \(S = [x_1, \ldots, x_n]\), we evaluate the last hidden states’ average self-similarity as the similarities across different tokens, noted as:

\[
f(S) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \cos(h_i, h_j), \quad (15)
\]

where \(h_i\) and \(h_j\) are the last hidden states of \(x_i\) and \(x_j\); \(\cos\) represents cosine similarity. For multiple heads \(H = [H_1, \ldots, H_m]\), we evaluate the attention weights’ average self-similarity as the similarities across different heads, noted as:

\[
f(H) = \frac{2}{L(m-1)} \sum_{l=1}^{L} \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} \cos(a^l_i, a^l_j), \quad (16)
\]

where \(L\) represents the number of Transformer layers; \(a^l_i\) and \(a^l_j\) are the attention weights of the \(i\)-th head and \(j\)-th head of the \(l\)-th layer.

We also provide a specific example in Figure 1.

Figure 1: Fig.1(a) represents the classical relative position matrix; Fig.1(b) represents the decoupled relative position matrices we proposed. Note that the parameter vectors of the same color have the same values.

Figure 2: Average self-similarity of last hidden states and attention weights during MLM pre-training.

Specifically, we sample 5,000 sentences from the validation set and evaluate the average self-
We interpret this as MLM can guide the model to a wide variety of multi-level semantic and syntactic training objectives.

Following the previous practice, we use a base-size uncompressed text corpus for pre-training. Following Devlin et al. (2018), we use Wikipedia and BooksCorpus (Zhu et al., 2015), a roughly 16G uncompressed text corpus for pre-training.

4 Experiments

4.1 Pre-training Text Corpora

Follow Devlin et al. (2018), we use Wikipedia and BooksCorpus (Zhu et al., 2015), a roughly 16G uncompressed text corpus for pre-training.

4.2 Baselines

We compare DDRP with competitive pre-trained models. BERT (Devlin et al., 2018) equips Transformer (Vaswani et al., 2017) with parametric absolute position encoding. BERT-R uses the relative position encoding proposed by Shaw et al. (2018), which couples relative distance information and positional information separately and then adds them up, plus the relative position biases like T5 (Raffel et al., 2019). DEBERTA (He et al., 2021) uses two vectors to encode content and position and uses disentangled matrices on their contents and relative positions respectively to compute the attention weights among words.

4.3 Experimental Settings

Following the previous practice, we use a base-size model for training, which consists of 12 Transformer layers, each containing 12 heads with an
input dimension of 768. During pre-training, we directly use the maximum training length of 512 without taking any form of random injection, and for examples less than 512 in length, we do not use the next document for padding. We remove Next Sentence Prediction (NSP) task and only keep Masked LM (MLM) as our pre-training task unless noted otherwise. Considering that shorter documents may be missing semantics, we discard documents of length less than 8. We adopt the whole word masking strategy and split the whole words longer than 4 into individual subtokens. Following Devlin et al. (2018), we set the batch size to 256 sequences, the peak learning rate to 1e-4, and the training steps to 1M. We grid search $\alpha_1$ and $\alpha_2$ of TCD and HCD in \{0.01, 0.1, 1.0\}. Eventually, we set $n' = 50$, $\alpha_1 = 1.0$ for TCD and set $m' = 2$, $\alpha_2 = 0.01$ for HCD. All the models are implemented based on the code practice of BERT\(^\dagger\) in Tensorflow. We conduct all experiments on 16 Tesla-V100 GPUs (32G). All the pre-training hyperparameters are supplemented in Appendix A. To make a fair comparison, we re-evaluate BERT, BERT-R, TUPE and DEBERTA\(^\dagger\). All the models mentioned in this paper (including DDRP) have the same pre-training hyperparameters and model configurations, which are consistent with vanilla BERT.

### 4.4 Results on GLUE Benchmark

We evaluate models on eight different English understanding tasks from General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2019). The datasets cover four types of tasks: natural language inference (RTE, QNLI, MNLI), paraphrase detection (MRPC, QQP), linguistic acceptability (CoLA), and sentiment classification (SST-2). For all experiments, STS-B and CoLA are reported by Pearson correlation coefficient and Matthews correlation coefficient, and other tasks are reported by Accuracy. All the fine-tuning hyperparameter configurations can be found in Appendix B. Following Ke et al. (2021), we fine-tune with five random seeds and report the median results.

#### 4.4.1 Comparing Prior Competitive Models with DDRP

The overall comparison results are shown in Table 1. While all the various relative position encoding models achieve better results than BERT, our proposed DDRP achieves the best, which demonstrates that decoupling relative distance and direction can extend the representation space of relative position encoding, and thus improve the upper limit of the model. Moreover, DDRP pre-trained with MTH can consistently outperform BERT-R/DEBERTA by a 1.11/0.91 average GLUE
Figure 3: The left figure (a) represents the trend of average cosine self-similarity of token representations and attention weights during pre-training. The right figure (b) represents the trend of GLUE average score during pre-training.

| Model       | RTE   | STS-B | MRPC   | CoLA  | SST-2 | QNLI  | QQP   | MNLI  | Avg.  |
|-------------|-------|-------|--------|-------|-------|-------|-------|-------|-------|
| MTH         | 73.64 | 90.16 | 88.48  | 62.31 | 92.43 | 91.21 | 91.12 | 84.67 | 84.25 |
| w/o HCD     | 73.28 | 90.41 | 87.25  | 60.85 | 92.23 | 91.37 | 91.00 | 84.22 | 83.83 |
| w/o TCD&HCD | 70.75 | 89.66 | 87.50  | 59.65 | 92.20 | 91.23 | 91.00 | 84.33 | 83.29 |

Table 3: Ablation study for MTH. Note that MTH (w/o TCD&HCD) equals simply using MLM in pre-training.

score. This demonstrates that DDRP can be effectively compatible with better pre-training objectives to perform stronger.

4.4.2 Comparing MTH with MLM

As illustrated in Table 2, BERT (MTH) outperforms BERT (MLM) by a 0.96 average GLUE score and is consistently better on 7 out of 8 tasks. When combining MTH with strong DDRP, it still brings an improvement by 0.59 GLUE average score. Besides the final performance, we also examine the efficiency of MTH. Notably, BERT (MTH) can achieve better results compared with well-trained BERT (MLM) while only using 50% training steps. Since MTH utilizes cosine similarity and sampling strategy for the penalty, only a very slight computational cost is introduced. We consider MTH to be a more effective and time-efficient approach.

5 Analysis and Discussion

5.1 Ablation Studies

Effect of DDRP. As shown in Table 1, BERT-R outperforms BERT by 0.6 points. Based on BERT-R, our proposed DDRP outperforms BERT-R by 0.52 points without imposing additional computational costs. It is worth noting that DDRP helps a great deal on low-resource tasks, such as CoLA, while further improving the performance on high-resource tasks, such as QNLI and MNLI.

Effect of TCD and HCD. MTH brings in two additional TCD and HCD losses besides the original MLM task. To further evaluate the relative contributions of the HCD and TCD, we develop one variation, which is BERT trained with MLM and TCD. Table 3 summarizes the results on the base-size models. Firstly, it shows a 0.42 average GLUE score drop when HCD is removed from MTH, especially on MRPC, CoLA, and MNLI. Secondly, there is a 0.54 average GLUE score drop when TCD is progressively removed, especially on RTE, STS-B, and CoLA. These results indicate that both TCD and HCD losses play a crucial role in improving performance.

5.2 Analysis on MTH

In Sec. 3.3, we have analyzed the average self-similarity of token representations and attention weights under the MLM pre-training objective. To further understand why MTH works, we compare MLM and MTH in terms of average self-similarity of token representations and attention weights and performance in Figure 3. As shown in Figure 3.(a), it is easy to find that MTH’s average self-similarity is much lower than MLMs’. We can also clearly notice from Figure 3.(b) that the average GLUE score of MTH is always about one point higher.
than MLM’s during the whole pre-training process. These confirm that (i) the differentiation of tokens and heads is important for model optimization; (ii) MTH can help to produce more discriminative token representations and attention weights, extend the representation space of tokens and heads, and thus improve the performance.

5.3 Analysis on DDRP

In previous sections, we have experimentally demonstrated that DDRP improves BERT-R by a large magnitude and outperforms the various state-of-the-art relative position encoding models. To further investigate why making only slight modifications on BERT-R can bring great gains, we analyze the attention maps of DDRP. To better examine and explain the ability of DDRP to capture information in the same direction or same distance, we divide multiple heads into two groups evenly, where all heads in the same group share the same set of DDRP and DDRPs are not shared among two groups. Taking the same configuration as BERT\(_{BASE}\), which will divide 12 heads when performing multi-head attention operations, we will divide heads 1/2/3/4/5/6 into group1, head 7/8/9/10/11/12 into group2 specifically.

Surprisingly, we can observe a distinct upper triangle effect in group 1 and a distinct lower triangle effect in group 2 from Figure 4, which indicates that DDRP can process and analyze contextual representations in a more targeted manner, reduce information redundancy, thus improve performance. (Note that it doesn’t mean that one group will definitely focus more on forward/backward, we choose the group that focuses more on the backward as "group1" and the group that focuses more on the forward as "group2") Besides the sampled batch, we also sample 5,000 sentences from the validation set and count the percentage of sentences with upper and lower triangular effects according to Algorithm 1 (more details can be seen in Appendix C). We observe the up-down triangle effect in 92.11% of sampled sentences. We also conduct the same process for BERT-R and find only 78.94% of the sentences have an up-down triangle effect. The above phenomena and statistics fully reveal that DDRP can effectively decouple the distance and directional features in the relative position encoding, so that different heads of the model can focus on the token information interaction in different directions, thus improving the effectiveness and rationality of the model.

Figure 4: Attention visualization for a sampled batch of sentences. From left to right is the attention visualization for group 1, group 2, and global, respectively.

5.4 Complexity Analyses

**DDRP.** Compared with BERT, DDRP introduces additional parameters: \( D \in R^{3 \times d} \), \( K^{rd} \in R^{rs \times d} \) and \( W^{rd} \in R^{d \times d} \). The total increase in parameters is \( 3 \times d + rs \times d + d \times d \). For base-sized model (\( D = 768, L = 12, S = 512, N = 12, d = 64 \))^3, the total increase amounts to 0.0084M, which is negligible. Compared with BERT, the additional computational complexity for BERT-R and DDRP is \( O(SD) \), and the additional computational complexity for DEBERTA is \( O(NSD) \). Overall, BERT-R and DDRP increase the computational cost about 5%, and DEBERTA increases the computational cost about 30%. Although DDRP introduces a slight computational cost compared to BERT, it saves a lot of computational overhead compared to DEBERTA and outperforms all the above models.

**MTH.** Since the two losses of TCD and HCD are based on cosine similarity and sampling strategy, they do not introduce too much computational cost. Compared with MLM, MTH only increases a slight computational cost of about 4% while bringing excellent improvement.

6 Conclusion

In this work, we propose DDRP (Decoupled Directional Relative Position) encoding and MTH (MLM aligned with TCD and HCD) pre-training objectives to optimize Transformer-based pre-trained models. Specifically, DDRP decouples relative distance features and directional features to eliminate unnecessary randomness in the self-attention module. MTH uses TCD and HCD losses to supervise the model to always maintain a certain level of critical thinking. The experimental results show that DDRP achieves better performance compared

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^3\( N \) is the number of head.
with various relative position encoding models and MTH outperforms MLM by a large margin. We will continue to validate the advantage of DDRP and MTH in larger models when sufficient computational resources are available, inspiring more research to explore the decomposability of confusing information and the discriminability of representation space.

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A Appendix A. Hyperparameters for Pre-Training

As shown in Table 4, we list the pre-training hyperparameter configurations. To make a fair comparison, all models’ pre-training hyperparameter configurations in our experiments are identical to vanilla BERT (Devlin et al., 2018).

| Hyperparameter       | Value                  |
|----------------------|------------------------|
| Vocab size           | 3,0522                 |
| Hidden size          | 768                    |
| Attention heads      | 12                     |
| Layers               | 12                     |
| Training steps       | 1M                     |
| Warmup ratio         | 0.01                   |
| Batch size           | 256                    |
| Learning rate        | 1e-4                   |
| Adam $\epsilon$      | 1e-6                   |
| Adam $(\beta_1, \beta_2)$ | (0.9, 0.999)        |
| Learning rate schedule | linear               |
| Weight decay         | 0.01                   |
| Clip norm            | 1.0                    |
| Dropout              | 0.1                    |

Table 4: Hyperparameters used for pre-trained models.

B Appendix B. Hyperparameters for Fine-Tuning

As shown in Table 5, we enumerate the hyperparameter configurations to fine-tune the tasks on the GLUE benchmark (Wang et al., 2019). We grid search these fine-tuning hyperparameter configurations for all models. Following the BERT, we do not show results on the WNLI GLUE task for the Dev set results.

| Hyperparameter | GLUE          |
|----------------|---------------|
| Batch size     | {16, 32}      |
| Learning rate  | {1e-5, 2e-5, 5.3e-5} |
| Epoch          | {4, 6}        |
| Adam $\epsilon$ | 1e-6          |
| Adam $(\beta_1, \beta_2)$ | (0.9, 0.999) |
| Learning rate schedule | linear       |
| Weight decay   | 0.01          |
| Clip norm      | 1.0           |
| Dropout        | 0.1           |
| Warmup ratio   | 0.1           |

Table 5: Hyperparameters used for fine-tuning on the GLUE benchmark.

C Appendix C. Details for Up-Down Triangle Effect

Here we provide more details for the up-down triangle effect (in Sec. 5.3). It is rather difficult and non-intuitive to analyze the directional information in 12 different attention heads. Since previous studies have considered parameter sharing in the self-attention module (Devendra Singh Sachan, 2018; H Gong, 2021), we try to divide the heads into two groups, sharing the DDRP within-group and not between two groups, which helps to explicitly reveal the directional information encoded in attention weights. We experimentally verified that this sharing approach could provide a better presentation of the directional information, achieving comparable or even slight better results based on both DDRP and BERT-R consistently. Therefore, we combined this approach to conduct a comparative analysis of DDRP and BERT-R to demonstrate the more powerful directional perception of DDRP.

As illustrated in Figure 4, group 1 is more focused on the front information (greater attention values in the upper triangle region) and group 2 is more focused on the back information (greater attention values in the lower triangle region). To further analyze the universality of this phenomenon, we empirically set a lower bound for the upper and lower triangle effect as $t$, and design the Algorithm 1 to quantitatively analyze the ability of DDRP to capture the front and back direction information. We also conduct the same process for BERT-R and compare DDRP with BERT-R.

**Algorithm 1 Count up-down triangle percentage**

**Require:** $N$: total number of sentences; $n$: total number of sentences that have been processed; $ms$: Maximum sentence length; $mn$: total number of sentences that match the upper and lower triangle

1: Initialize $ms \leftarrow 64$, $n \leftarrow 1$, $mn \leftarrow 0$
2: while $n \leq N$ do
3: Calculate the attention map of the groups corresponding to the current sentence and get: $amp_1, amp_2$.
4: // prepare for the upper and lower triangle
5: Sum the upper and lower triangles of $amp$ to get $amp_{up}, amp_{down}$ respectively.
6: $amp_{up} \leftarrow amp_{up}/ms$, $amp_{down} \leftarrow amp_{down}/ms$
7: $amp_{up} \leftarrow amp_{up}/ms$, $amp_{down} \leftarrow amp_{down}/ms$
8: // compute for the upper and lower triangle
9: if $amp_{up} \geq t$ and $amp_{down} \geq t$ then
10: $mn \leftarrow mn + 1$
11: else
12: Continue
13: $n \leftarrow n + 1$
14: return $mn/N$