Know What You Don’t Need: Single-Shot Meta-Pruning for Attention Heads

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Abstract

Deep pre-trained Transformer models have achieved state-of-the-art results over a variety of natural language processing (NLP) tasks. By learning rich language knowledge with millions of parameters, these models are usually overparameterized and significantly increase the computational overhead in applications. It is intuitive to address this issue by model compression. In this work, we propose a method, called Single-Shot Meta-Pruning, to compress deep pre-trained Transformers before fine-tuning. Specifically, we focus on pruning unnecessary attention heads adaptively for different downstream tasks. To measure the informativeness of attention heads, we train our Single-Shot Meta-Pruner (SMP) with a meta-learning paradigm aiming to maintain the distribution of text representations after pruning. Compared with existing compression methods for pre-trained models, our method can reduce the overhead of both fine-tuning and inference. Experimental results show that our pruner can selectively prune 50\% of attention heads with little impact on the performance on downstream tasks and even provide better text representations. The source code will be released in the future.

1 Introduction

Pre-trained language models (PLMs), such as BERT (Devlin et al., 2019), XLNet (Yang et al., 2019) and RoBERTa (Liu et al., 2019), have achieved state-of-the-art results across a variety of natural language processing (NLP) tasks. To fully utilize large-scale unsupervised data during pre-training, PLMs are becoming larger and larger. For example, GPT-3 (Brown et al., 2020) has 175 billion parameters. With the growing number of model parameters, the computational overhead, including memory and time, becomes tremendously heavy, which severely limits the application of PLMs to downstream NLP tasks. Therefore, model compression for PLMs is increasingly important.

Most PLMs are Transformer-based (Radford et al., 2018; Devlin et al., 2019), and they are utilized following a three-step paradigm: pre-training, fine-tuning and inference, as illustrated in Figure 1. Quite a few methods have been proposed to compress pre-trained Transformers during or after fine-tuning to reduce the computational overhead in the inference phase (Tang et al., 2019; Turc et al., 2019; Jiao et al., 2019; McCarley, 2019; Wang et al., 2019b; Fan et al., 2020), while little work attempts to perform model compression before fine-tuning.

In fact, compressing pre-trained Transformers before the fine-tuning phase is more significant. For one thing, computational overhead of pre-trained Transformers during fine-tuning is usually heavier than that during inference, because of extra
computations for gradient descent. Furthermore, compressing pre-trained Transformers before fine-tuning can reduce the overhead during both fine-tuning and inference, which is more helpful.

In this paper, we make the first attempt to conduct model compression for deep pre-trained Transformers before fine-tuning. According to previous work (Kovaleva et al., 2019; Michel et al., 2019), deep pre-trained Transformers are overparameterized, and only part of attention heads are actually useful for downstream tasks. Therefore, we propose to prune the unnecessary attention heads of pre-trained Transformers to reduce the overhead.

We train a pruner to measure the importance of attention heads and identify the unnecessary ones. We assume the unnecessary attention heads cannot provide useful information, and pruning them will have little effect on the distribution of the text representations learned by the pre-trained Transformers. Therefore, we design a self-supervised objective function for the pruner, which trains the model to maintain the distribution of representations after pruning. In addition, to make our pruner more general, we adopt a meta-learning paradigm to train it. To provide diverse task distributions, we sample data from multiple corpora to form the training set of meta-learning.

Our pruning strategy is single-shot, which means it can compress the pre-trained Transformers once before fine-tuning rather than using an iterative optimization procedure (McCarley, 2019; Voita et al., 2019). We name our model Single-Shot Meta-Pruner (SMP). In the experiments, we apply SMP to the representative pre-trained Transformer BERT, and conduct evaluations on GLUE (Wang et al., 2019a) and the semantic relatedness tasks of SentEval (Conneau and Kiela, 2018). Experimental results show that SMP can prune as many as 50% of attention heads of BERT without sacrificing much performance on GLUE, and even bring performance improvement on the semantic relatedness tasks of SentEval. In addition, SMP is also comparable to, if not slightly better than, the baseline method which conducts model compression after fine-tuning. Moreover, we find the patterns of unnecessary heads learned by SMP are transferable, which means SMP could work with different Transformer models and downstream tasks.

2 Related Work

To compress pre-trained Transformers, there are two mainstream approaches, namely knowledge distillation and parameter pruning.

(1) Knowledge distillation (Sanh et al., 2019; Chen et al., 2020a; Sun et al., 2020) treats the original large model as a teacher to teach a lightweight student network. Sun et al. (2019) design the student networks to learn from multiple intermediate layers of the teacher model. Jiao et al. (2019) propose to learn from both teachers’ hidden states and attention matrices.

(2) Parameter pruning aims to remove unnecessary parts of networks, such as weight magnitude pruning (McCarley, 2019; Li et al., 2020) and layer pruning (Fan et al., 2020; Sajjad et al., 2020). Given a complete BERT after fine-tuning, Michel et al. (2019) propose to prune attention heads according to the change of loss function when slightly perturbing the attention matrices. They argue that the loss function is situated in a local minimum after fine-tuning and sensitive to the change of important attention heads. Compared to this work, our SMP meta-learns the criterion and prunes PLMs before fine-tuning.

In addition to these two approaches, researchers also explore other methods, such as weight factorization (Wang et al., 2019b), weight sharing (Lan et al., 2020), and parameter quantization (Zafrir et al., 2019). Most of current compression studies focus on reducing the overhead of inference. There are also some researches trying to directly compress the models during pre-training (Gordon et al., 2020; Sanh et al., 2019), but this kind of compression has severe impact on the performance of downstream tasks. In this work, our SMP aims to reduce the overhead of both fine-tuning and inference and better maintain the performance of PLMs.

From the more general perspective of pruning neural networks, our SMP prunes models before training (fine-tuning), which is different from pruning after and during training. Pruning after training aims to identify unnecessary parts in a fully trained model based on weight magnitude (Han et al., 2015) or effects on the loss (LeCun et al., 1990). Pruning during training (Louizos et al., 2018; Voita et al., 2019) attempts to combine pruning and training procedures together. These methods require approximately the same computational overhead as training a full network.

Single-shot pruning (Lee et al., 2019b,a;
Sampled Data Representation Space Representation Space
Relative Distance Distribution for Relative Distance Distribution for

Dettmers and Zettlemoyer, 2019), which prunes networks before training, is more efficient than traditional pruning, which leads to lower computational overhead. Most existing studies of single-shot pruning focus on the weight pruning of randomly initialized networks by pre-defined criteria, but the models pruned by weight pruning are difficult to accelerate (Han et al., 2015). In this work, we focus on directly pruning the structures (attention heads) in Transformers, which makes pruned models easy to accelerate. We also consider how to maintain the knowledge in pre-trained models, which is different from pruning randomly initialized networks.

3 Method

In this section, we elaborate on our SMP model as well as its objective function and training method. Figure 2 illustrates the overall framework and workflow of SMP.

The goal of SMP is to find and prune the unimportant attention heads in pre-trained Transformers. To this end, SMP calculates the importance score of each attention head. Then the attention heads with low importance scores are pruned to obtain a pruned Transformer.

To train SMP, we design a self-supervised objective function, which aims to keep the output of the PLMs not changing a lot after pruning. Specifically, we propose to preserve the distribution of text representations.

Furthermore, we adopt the meta-learning paradigm in training to make SMP general and be able to apply to almost all sentence-level tasks.

3.1 Score Calculation

Transformer is composed of a stack of identical layers, and each layer has two sub-layers: a multi-head self-attention network and a point-wise feed-forward network. For the multi-head self-attention networks, each attention head yields an attention matrix. For example, as illustrated in the bottom left of Figure 2, a 3-layer 4-head Transformer has $3 \times 4 = 12$ attention heads in total. To obtain the importance score of an attention head, we first compute the importance scores of its attention matrices for all instances, and then average them out as the final result.

We formulate importance score calculation of an attention matrix as an image classification task, whose input is an attention matrix and output is its importance score. We adopt a convolutional neural network (CNN) as the encoder of attention...
matrices, which is widely used in image processing. SMP concatenates a sigmoid non-linear function to the matrix encoder to output a score ranging from 0 to 1.

Considering the difference between single-sentence and sentence-pair downstream tasks, SMP actually outputs a two-dimensional vector comprising two scores $s_{\text{sing}}$ and $s_{\text{pair}}$, which are designed for single-sentence and sentence-pair tasks respectively. Formally, the importance score of an attention matrix is calculated by

$$[s_{\text{sing}}, s_{\text{pair}}] = \sigma(\text{CNN}(M_{\text{att}})), \quad (1)$$

where $M_{\text{att}}$ represents an attention matrix.

After calculating the importance score of each attention head in the full pre-trained Transformer $T$, we can prune the unimportant heads and obtain a pruned Transformer $\hat{T}$:

$$\hat{T} = \text{SMP}(T). \quad (2)$$

### 3.2 Self-supervised Objective Function

Considering pre-trained Transformers essentially encode input instances into vector representations, it is reasonable to assume that the unimportant heads have little effect on the distribution of the representations of a set of sampled instances. In other words, the representation distribution of sampled instances should be maintained after pruning those unimportant attention heads. For example, given three instances $\{x_1, x_2, x_3\}$, we compute their representations before and after pruning by

$$h_i = T(x_i), \quad \hat{h}_i = \hat{T}(x_i).$$

An appropriately pruned model should make sure that if $h_i$ is closer to $h_j$ than $h_k$, $\hat{h}_i$ should also be closer to $\hat{h}_j$ than $\hat{h}_k$.

Based on this assumption, we design the training objective function for SMP. We parameterize the representation distribution of a set of sampled instances using the relative distance distribution. The relative distance distribution for an instance records the normalized distances between the instance and other instances.

Given a set of instances $\{x_1, \ldots, x_N\}$, the relative distance distribution for an instance $x_n$ is an $N$-dimensional normalized vector $r^n$, whose $i$-th entry is the relative distance between $x_n$ and $x_i$:

$$r^n_i = \frac{e^{\text{Dist}(h_n, h_i)}}{\sum_{j=1}^{N} e^{\text{Dist}(h_n, h_j)}}, \quad (3)$$

where $\text{Dist}$ is the function measuring the distance between two representations. In this work, we simply use cosine distance.

To quantify the variation of relative distance distribution after pruning, we use the Kullback-Leibler (KL) divergence (Kullback and Leibler, 1951). The KL divergence between the relative distance distributions associated with the original and pruned Transformers are

$$D_{KL}(r^n||\hat{r}^n) = -\sum_{i=1}^{N} r^n_i \ln(\frac{\hat{r}^n_i}{r^n_i}), \quad (4)$$

where $r^n$ and $\hat{r}^n$ denote relative distance distributions associated with the original and pruned Transformers respectively.

Our SMP intends to maintain the representation distribution after pruning, which means making $D_{KL}(r^n||\hat{r}^n)$ as small as possible for all instances. Therefore, the objective function of SMP is

$$\mathcal{L}_{\text{SMP}} = \sum_{n=1}^{N} D_{KL}(r^n||\hat{r}^n). \quad (5)$$

### 3.3 Model Training via Meta-learning

To train our SMP, we design a meta-learning process. We show a simple example of this training paradigm in Figure 2.

At the beginning of each episode, we sample $k$ instances from the training data to construct a mini dataset, which is a set of sentence pairs or single sentences.

During pruning, we first compute the importance score for each head according to the type of the mini dataset (sentence-pair or single-sentence), as in Equation (1). Then we apply Gumbel-softmax (Jang et al., 2016) to the importance scores of all heads, which is a common reparameterization method and can transform the importance scores to discrete 0 or 1. We multiply the outputs of an attention head by its discrete importance score of 0 or 1, and the unimportant heads, whose importance scores are 0, will be pruned. Meanwhile, Gumbel-softmax can make sure that the pruning operation is differentiable and we can conduct back-propagation for SMP.

After pruning the pre-trained Transformer for different synthetic mini datasets, SMP is trained to adapt to different corpora and master the meta-knowledge about pruning attention heads.

### 4 Experiments

In this section, we evaluate our SMP on GLUE (Wang et al., 2019a) and SentEval (Con-
neau and Kiela, 2018). The pre-trained Transformers used here are BERT$_{\text{BASE}}$ and BERT$_{\text{LARGE}}$.\footnote{https://github.com/google-research/bert}

\section{4.1 Experiment Setup}

**SMP architecture.** We set the size of input attention matrices to (128 × 128), which can cover most downstream tasks. Considering some tasks, such as question answering with some input sequences longer than 128, we downsize the attention matrices. Our SMP is composed of five CNN layers. The dimension of the output of the first layer is 8, and the following layers’ dimensions are twice as large as the former layers. As a result, the dimension of the output representation for the attention matrix is $8 \times 2^4 = 128$. To compute the matrix scores $s_{\text{pair}}$ and $s_{\text{simp}}$, we feed the output representation to a full-connected layer.

**Pruning.** In this work, we follow the head pruning paradigm of (Michel et al., 2019) and prune the same number of heads for each layer. We set the pruning ratio to 50%, which can significantly improve the computation efficiency and effectively maintain the original performance according to our experiments. We also report the influence of pruning ratio in this section.

**Training data for meta-learning.** We select seven datasets from GLUE (Warstadt et al., 2018; Socher et al., 2013; Dolan and Brockett, 2005; Williams et al., 2018; Rajpurkar et al., 2016; Dagan et al., 2006) as the training data. The statistics are shown in Table 1. In particular, we split the original training data of these datasets into the training and validation part in the ratio of 9:1.

| Size | Dataset | MNLI | QQP | SST-2 | CoLA | STS-B | MRPC | RTE |
|------|---------|------|-----|-------|------|-------|------|-----|
| 392k | Pair    | Pair | Sing| Sing  | Pair | Pair  | Pair | Pair |

Table 1: Statistics of the corpora used to train SMP. Sing refers to the single sentence task. Pair refers to the sentence-pair task.

We use two kinds of sequence-level representations of BERT: [CLS] token representation for sentence-pair data and mean pooling on the sequence outputs for single sentence data. For each training episode, we set the number of sampled instances $k$ to 60, which lets SMP make full use of the memory of the GPUs. The model is updated every 8 episodes. The quicker update cycle will lead to an unstable training and the slower update cycle will bring extra training time. We choose Stochastic Gradient Descent as the optimizing algorithm and the best learning rate on the validation set is picked from \{1, 2, 5\} $\times$ 10$^{-2}$. Based on the observation in the experiments, we set the total number of episodes to 48,000, which is enough for the full convergence of SMP. We choose the checkpoint with the lowest loss on the validation set as the final model. We train two SMP models based on BERT$_{\text{BASE}}$ and BERT$_{\text{LARGE}}$ respectively. SMP was trained on four 16-GB V100 GPUs for approximate 6 hours using BERT$_{\text{BASE}}$ and 18 hours using BERT$_{\text{LARGE}}$.

**Baselines.** To validate the effectiveness of SMP, we introduce four baselines in our experiments.

1. **Fine-tune (None).** We fine-tune a complete BERT on downstream tasks, which can provide an oracle result without pruning.

2. **Random.** We randomly select the same number of heads to prune as SMP in each layer before fine-tuning. We repeat the random experiments five times and report the mean of model performances. Since the number of head combinations is very large, random experiments only give a rough estimation of performances. For example, BERT$_{\text{BASE}}$ has 144 attention heads, and there are $C_{144}^{72} \geq 10^{42}$ combinations for the pruning ratio of 50%.

3. **$L_0$ Norm.** Following Voita et al. (2019), we multiply the output of each head with a scalar gate and introduce an $L_0$ regularization loss to these gates. Using this method, we can search the optimal value of each gate by gradient descent.

4. **HISP and HISP-retrain.** Besides $L_0$ Norm, we adopt the attention head pruning method introduced by Michel et al. (2019), called Head Importance Score for Pruning (HISP). The original algorithm directly evaluates the model performance after pruning. According to previous studies on general neural network pruning (Han et al., 2015), retraining after pruning can further promote the performance of pruned models. Hence, we introduce HISP-retrain, which retrained pruned models for better performance. In our experiments, we retrain the pruned model given by HISP for 3 additional epochs as HISP-retrain. Since HISP prunes models after fine-tuning, pre-trained Transformers could better learn from fine-tuning due to the larger model capacity.

\section{4.2 GLUE}

The GLUE benchmark (Wang et al., 2019a) is used to validate the effectiveness of SMP on the gen-
eral fine-tuning tasks. We compare four methods mentioned above on seven downstream tasks in the GLUE benchmark. We exclude two tasks in GLUE, namely the Winograd Schema Challenge and QNLI. The former is excluded due to the small size of the dataset while the latter is excluded for the experiment on model transferability. The fine-tuning experiments follow the hyperparameters reported in the original study (Devlin et al., 2019) except the number of epochs. The random baseline and SMP adopt the same hyper-parameters used in fine-tuning a complete BERT. For small datasets containing less than 10,000 instances, we set the number of epochs to 10. For the others, we keep the original number unchanged (3 epochs).

We report the results on the validation, rather than test data, so the results differ from the original BERT paper. From Table 2, we observe that:

1. The average performance of random pruning is consistently worse than that of fine-tuning, which shows the serious impact of pruning on pre-trained Transformers. In the experiments, we find that some random seeds lead to a good performance while some random seeds significantly degrade model performance. The variation of random pruning proves the assumption that there are important attention heads, which should not be pruned before fine-tuning, in pre-trained Transformers. It is related to the lottery ticket hypothesis for pre-trained Transformers (Chen et al., 2020b).

2. The overall performances of $L_0$ Norm and HISP are worse than that of random pruning, which indicates that head pruning on a converged model leads to serious performance degradation. Meanwhile, we find that HISP-retrain significantly outperforms HISP, which reflects the importance of retraining in pruning-after-training approaches. Most results of HISP-retrain are better than those of random pruning and close to the result of fine-tuning, which indicates that HISP-retrain can select important heads for downstream tasks and provide a good pruned model. However, there still exists the case that retraining degrades the performance. For BERT\textsubscript{BASE}, the performance of HISP-retrain on CoLA is lower than HISP by about 1.5%.

3. SMP achieves the best results on average among these pruning methods, and have comparable performance with fine-tuning, which indicates SMP significantly reduces the impact of pruning on downstream tasks. Besides, SMP even outperforms the fine-tuning method in some tasks, such as RTE for BERT\textsubscript{BASE} and MRPC for BERT\textsubscript{LARGE}. It shows that pruning unnecessary structure can also promote the performance of downstream tasks of Transformers. Besides, SMP works well on both BERT\textsubscript{BASE} and BERT\textsubscript{LARGE}, which reveals the generality of SMP.

### 4.3 SentEval

SentEval (Conneau and Kiela, 2018) is used to validate the representation ability of the models pruned by SMP. The goal of SMP is to preserve the distribution of text representations after pruning for maintaining important prior knowledge learned by pre-training. Hence, we use SentEval to investigate whether SMP maintains important prior knowledge.
Table 3: Results on semantic relatedness tasks in SentEval. Numbers reported are Pearson correlations x100. The results of GloVe and InferSent are from the paper of SentEval (Conneau and Kiela, 2018). We underline the overall best results and boldface the best results among BERT models.

| Model     | Pruning Method | STS-12 | STS-13 | STS-14 | STS-15 | STS-16 | STS-B | SICK-R |
|-----------|----------------|--------|--------|--------|--------|--------|-------|--------|
| GloVe BoW | —              | 52.10  | 49.60  | 54.60  | 56.10  | 51.40  | 64.70 | 79.90  |
| InferSent | —              | 59.20  | 58.90  | 69.60  | 71.30  | 71.50  | 75.60 | 83.80  |
| BERT_BASE | Full           | 46.87  | 52.77  | 57.15  | 63.46  | 64.50  | 65.49 | 80.57  |
|           | Random         | 51.07  | 48.19  | 57.66  | 64.48  | 61.00  | 65.98 | 79.67  |
|           | SMP            | 57.59  | 63.94  | 64.64  | 69.06  | 66.80  | 70.18 | 82.19  |
| BERT_LARGE| Full           | 54.87  | 60.78  | 64.21  | 68.07  | 66.65  | 69.91 | 83.91  |
|           | Random         | 55.47  | 55.04  | 63.85  | 67.70  | 64.47  | 70.42 | 83.18  |
|           | SMP            | 62.13  | 62.57  | 71.18  | 74.38  | 71.55  | 71.19 | 84.52  |

Table 4: Average memory overhead per instance and the speed in instances per second (IPS) on QNLI.

| Model     | Ratio | Memory (MB) | Speed (IPS) |
|-----------|-------|-------------|-------------|
| BERT_BASE | 0%    | 841         | —           |
|           | 50%   | 538         | -36.0%      |
|           | 6%    | 1,514       | -29.8%      |
| BERT_LARGE| 0%    | 2,156       | 5.3         |
|           | 50%   | 1,514       | -37.7%      |

4.5 Influence of Pruning Ratio

In this subsection, we investigate the influence of pruning ratio. We test pruned models on the MultiNLI-matched validation set. As shown in Figure 3, we observe that: (1) Pruning a small
Table 5: Results of transferability on seven tasks in GLUE (%). We prune BERT\textsubscript{LARGE} using two different SMP models. SMP-LARGE is the model trained on BERT\textsubscript{LARGE} while SMP-BASE is the model trained on BERT\textsubscript{BASE}.

| SMP Model | MNLI-(m/mm) | QQP | SST-2 | CoLA | STS-B | MRPC | RTE | Average |
|-----------|-------------|-----|-------|------|-------|------|-----|---------|
| SMP-LARGE | 86.86/86.96 | 91.46 | 93.34 | 63.57 | 90.95 | 89.70 | 82.31 | 85.64   |
| SMP-BASE  | 86.72/86.63 | 91.43 | 93.23 | 64.79 | 91.00 | 89.46 | 83.39 | 85.83   |

Figure 4: Detection of the implicit pruning rules learned by SMP. Given input sentence “These are issues which further studies may seek to address.”, we present four attention matrices with their corresponding scores as subtitles. The left two matrices’ scores are close to 1 while the right two matrices’ scores are close to 0.

number of unnecessary attention heads promotes the performance by nearly 1%. (2) SMP is better when the number of pruned heads is smaller than 6 while HISP-retrain is better in the other cases. It indicates that pruning too many parameters before fine-tuning will influence the performance on downstream tasks where the process of retraining could save this degradation of performance.

4.6 Transferability

In this part, we evaluate the transferability of SMP. We consider two kinds of transferability, including the transferability to new Transformer encoders and new datasets.

**Transferability to New Transformer Encoders.** We use the SMP trained on BERT\textsubscript{BASE} to prune BERT\textsubscript{LARGE}. The results are shown in Table 5. We observe that the SMP trained on BERT\textsubscript{BASE} achieves comparable results to the SMP trained on BERT\textsubscript{LARGE} when pruning BERT\textsubscript{LARGE}. It indicates that the attention patterns learned by SMP are general in the Transformer encoders with different sizes.

**Transferability to New Datasets.** We choose QNLI, which is a natural language inference (NLI) dataset, as the task. QNLI is used to validate whether SMP can transfer to a new NLI dataset. Note that we use BERT\textsubscript{BASE} as the pre-trained Transformer. As shown in Table 6, SMP increases the average performance of random pruning and achieves comparable result to HISP-retrain. It demonstrates that SMP captures general patterns in attention matrices, which can transfer to pruning pre-trained Transformers on other tasks.

4.7 Visualization

In this subsection, we investigate the implicit rules learned by SMP. We compute the attention matrices for a given sentence, and score each attention matrix. In Figure 4, we show four attention matrices. The first matrix seems to be a lower diagonal matrix, which refers to the attention to previous words. This attention head implicitly captures the sequential information of the sentence. The second matrix shows a strong relation between “address” and “issues”, which is long-term dependency. In the third matrix, every element is small. Therefore, this matrix does not bring any useful information. SMP gives high scores to the first two matrices and low scores to the last two matrices, which shows the implicit pruning rules learned by SMP are consistent with human intuition.

5 Conclusion and Future Work

In this work, we propose Single-Shot Meta-Pruning to reduce the computational overhead of both fine-tuning and inference when using deep pre-trained
Transformers. Specifically, SMP learns the implicit rules for pruning in terms of attention matrices and adaptively prunes unnecessary attention heads before fine-tuning. In our experiments, we find pruning 50% of attention heads with SMP has little impact on the performances on downstream tasks. What’s more, pruning a few unnecessary heads can further improve the model performance in some cases.

There are four important directions for future research: (1) Explore task-aware pruning, such as taking the labels of instances into account. (2) Joint pruning in each layer to maintain more diversity in pruned models, such as limiting the number of the attention heads sharing similar patterns in each layer. (3) Discover more unnecessary structures in Transformer, such as point-wise feed-forward networks. (4) Apply implicit pruning rules to constraining the pre-training procedure of Transformers, which guides pre-training models through the more efficient use of parameters and attention.

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