Attribution-based Task-specific Pruning for Multi-task Language Models

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Abstract

Multi-task language models show outstanding performance for various natural language understanding tasks with only a single model. However, these language models inevitably utilize unnecessary large-scale model parameters, even when they are used for only a specific task. In this paper, we propose a novel training-free task-specific pruning method for multi-task language models. Specifically, we utilize an attribution method to compute the importance of each neuron for performing a specific task. Then, we prune task-specifically unimportant neurons using this computed importance. Experimental results on the six widely-used datasets show that our proposed pruning method significantly outperforms baseline compression methods. Also, we extend our method to be applicable in a low-resource setting, where the number of labeled datasets is insufficient.

1 Introduction

Recently, various pre-trained language models that have been trained with large-scale data and parameters have emerged (Devlin et al., 2018; Lewis et al., 2019; Raffel et al., 2019; Brown et al., 2020). Specifically, language models like T5 (Raffel et al., 2019) and GPT-3 (Brown et al., 2020) have shown outstanding performance on various natural language understanding tasks. These language models can perform various tasks with a single model by treating every text processing problem as a text generation problem. However, these language models may inevitably utilize unnecessary large-scale model parameters even when performing only a specific task. Previous works have introduced various compression methods for language models such as pruning, knowledge distillation, and quantization (Chen et al., 2020; Goyal et al., 2020; He et al., 2021; Sanh et al., 2019; Hou et al., 2020; Sun et al., 2020; Shen et al., 2020). However, these studies have (1) not compressed the language models task-specifically, or (2) required an additional training process such as knowledge distillation. This additional training process is cost-inefficient and can destroy inherent pre-trained knowledge in language models.

In this paper, we propose a novel training-free attribution-based task-specific pruning method that enables more efficient compression and inference by extracting only task-specific knowledge from multi-task language models. Attribution determines which neurons are essential to derive a specific output, so that we can extract only task-specific knowledge from the whole model as shown in Figure 1. In addition, we propose a method to compress language models in a low-resource setting, where the number of labeled datasets is insufficient. This method can solve the problem that obtaining labeled data usually requires excessive human resources and is time-consuming. Our attribution-based task-specific pruning requires only a single forward and backward propagation computation and does not hurt the pre-trained knowledge of the language models. Therefore, it is training-free and can effectively be used for on-demand compression and inference.

Experimental results on the six natural language understanding tasks show that our proposed method significantly outperforms baseline compression methods. Furthermore, we demonstrate that our method shows robust performance in a low-resource setting. Also, we reveal that our proposed method shows outstanding performance even for a similar but different task, which suggests that our method can preserve task-specific knowledge.

2 Methodologies

2.1 Multi-task Language Model

In this paper, we focus on compressing the multi-task language models for a specific task. Suppose we have input text \(x = \{x_1, \ldots, x_n\}\) and output text
Deriving Attribution for Language Models

Language models generate text outputs by iteratively selecting a word piece from the vocabulary. Therefore, it is the same as the classification problem dealt with in attribution methods, and we can apply attribution methods to compute the importance of features for language models. However, the purpose of this study is to derive the importance of each neuron \( h_i \) of the layer representation \( h \in \mathbb{R}^d \), rather than deriving the importance for the input feature \( x_i \). Therefore, the attribution formula is changed to compute a neuron attribution \( A_i^{(x,y)} \in \mathbb{R} \) as follows:

\[
A_i^{(x,y)}(h) = h_i \odot \frac{\partial P(y_1, y_2, ..., y_k | x, y_{i-1})}{\partial h_i}
\]  

(3)

If the target output text consists of multiple word pieces rather than a single word piece, language models must derive the multiple word piece output distributions. Therefore, we can change the attribution formula to handle multiple word piece outputs as follows:

\[
A_i^{(x,v)}(h) = h_i \odot \sum_{j=1}^{v} \frac{\partial P(y_j | x, y_{i-j-1})}{\partial h_i}
\]  

(4)

Since \( A_i^{(x,y)} \) is attribution for one sample data \( x \), the final neuron attribution is obtained by summing attributions for multiple sample data as shown in the following formula:

\[
A_i^{(D)}(h) = \sum_{(x,y) \in D} A_i^{(x,y)}(h)
\]  

(5)

where \( D \) means the entire task-specific dataset.

**Attribution-based Layer Compression**

Neuron attribution \( A_i^{(D)} \) is used as the importance for each neuron of a specific layer. The importance is sorted in order of magnitude, and the model is compressed by pruning neurons with low importance. The layer compression process can be defined as follows:

\[
\text{argsort}_i(A) = \lceil \{j | (A_i < A_j) \cup (A_i = A_j, j < i) \} \rceil
\]  

where \( i, j \in \{1, ..., k\} \)

(6)
axes correspond to the pruning rate and accuracy, respectively. "activation-based" attribution is computed as above formula, definite candidate labels as follows:

\[ A_i^{v} = \sum_{y \in \mathcal{Y}} |b_i \odot \sum_{y_{j-1}} \frac{\partial P(y|x,y_{j-1})}{\partial h_i}| \]  

where \( \mathcal{Y} \) is the candidate label set. When attribution is computed as above formula, definite label information cannot be utilized. However, it is helpful for a low-resource environment.

### 3 Experiments

#### 3.1 Experimental Setup

**Datasets** We conduct experiments on six downstream tasks (Wang et al., 2018, 2019). Specifically, we utilize SST-2 (sentiment analysis); MRPC (semantic textual similarity); BoolQ (question answering); and QNLI, CB, RTE (natural language inference).

**Model** We select pre-trained t5-base\(^a\) as a backbone for the following experiments. The T5-base model used in our experiments is fine-tuned by multi-task learning using the six datasets mentioned above.

#### 3.2 Task-specific Compression Efficiency

In this section, we prove the effectiveness of our attribution-based compression by comparing the performance with other compression methods. We collect pruned models using various compression methods and evaluate the model’s performance on testset for all six datasets. We selected three compression methods: (1) activation-based, (2) random selection, (3) random attribution-based, as baseline pruning methods. "Activation-based" derives the importance of each neuron by using the absolute value of the forward propagation value of each neuron. "Random selection" randomly selects which neuron to prune. "Random attribution-based" randomly selects word pieces which are not

\(^a\)https://huggingface.co/t5-base
label, and use them to compute attribution. Figure 2 shows the experimental results for four compression methods, including our proposed method. For each dataset, we separately compressed encoder and decoder on varying pruning rates. Experimental results show that our method outperforms other compression methods in most cases. Specifically, there is almost no performance difference between the “random selection” and widely used “activation-based” (Han et al., 2015b; Hu et al., 2016; Li et al., 2016). This result suggests that the “activation-based” does not utilize task-specific knowledge.

### 3.3 Unsupervised Setting

We suggest an additional method to compute attributions using an unlabeled text dataset in chapter 2.4. We present the pruning results by computing attributions for an unsupervised setting in Figure 3.

![Figure 3: Unsupervised Setting Experiments.](image)

Results of encoder compression with the unsupervised setting for both SST-2 and QNLI datasets show comparable scores to that of labeled data. For decoder compression, the performance of SST-2 decreases slightly, but the performance of QNLI rather increases. The experimental result on SST-2 reveals that the compression in an unsupervised setting shows robust performance maintenance. In the QNLI result, we observe that computing attributions using information from all output candidates enhances the model’s performance.

### 3.4 Low-resource Setting

In this section, we demonstrate the results for compressing language models based on the attribution computed from only subset of the whole dataset. Figure 4 represents the pruning results with only small data samples.

![Figure 4: Low-resource Setting Experiments.](image)

For SST-2 dataset, we find that compression using only 0.01% of the labeled training dataset yields comparable performance to the results of using the entire training dataset. Here, 0.01% of the total number of data corresponds to only 7 data samples. This result suggests that most of the task-specific information is derived from the restriction of the output distribution for output candidates.

### 3.5 Pruning with Similar and Dissimilar Tasks

In this section, we validate the effect of the task-specific compression for a similar task. Specifically, we compress language models using similar and dissimilar datasets, and then compare the performance preservation for the original dataset. We compress the T5 model using the attribution computed with SST-2 and RTE, respectively. And then, we evaluate the compressed model with the QNLI dataset. QNLI and RTE are similar tasks since both are natural language inference datasets, and SST-2 is a dissimilar task built for sentiment analysis. Figure 5 shows the evaluation results of the compressed model for similar and dissimilar datasets.

![Figure 5: Pruning with Similar and Dissimilar Tasks.](image)

Experimental results reveal that our proposed method shows robust performance maintenance for the similar task. Surprisingly for the case of decoder compression, it shows even better performance maintenance in the similar task than the original task.

### 4 Conclusion

This paper proposes an attribution-based task-specific compression method for multi-task language models. We demonstrate that our method outperforms the other compression methods on the widely used datasets. We further propose a method for computing attributions in a low-resource setting. In addition, we examine that our task-specific compression method shows outstanding performance even for a similar task. Our compression method does not update the pre-trained parameters of the language models, which enables efficient on-demand compression and inference.
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