Finding the Dominant Winning Ticket in Pre-Trained Language Models

Abstract

The Lottery Ticket Hypothesis suggests that for any over-parameterized model, a small subnetwork exists to achieve competitive performance compared to the backbone architecture. In this paper, we study whether there is a winning lottery ticket for pre-trained language models, which allow the practitioners to fine-tune the parameters in the ticket but achieve good downstream performance. To achieve this, we regularize the fine-tuning process with L1 distance and explore the subnetwork structure (what we refer to as the "dominant winning ticket"). Empirically, we show that (a) the dominant winning ticket can achieve performance that is comparable with that of the full-parameter model, (b) the dominant winning ticket is transferable across different tasks, (c) and the dominant winning ticket has a natural structure within each parameter matrix. Strikingly, we find that a dominant winning ticket that takes up 0.05% of the parameters can already achieve satisfactory performance, indicating that the PLM is significantly reducible during fine-tuning.

1 Introduction

Pre-trained Language Models (PLMs) have shown significant performance on various natural language processing (NLP) tasks (Devlin et al., 2018; Liu et al., 2019). However, as the number of model parameters gets huge, fine-tuning such models becomes inefficient. Many previous works target parameter-efficient fine-tuning approaches by freezing the PLM parameters. One can either freeze a subset of the parameters (Zaken et al., 2021) and fine-tune the remaining or freeze all of them and plug in light modules with new learnable parameters (Houlsby et al., 2019; Mahabadi et al., 2021; Hu et al., 2021).

In parallel to this line of study, an emerging subfield has explored the possibility of training smaller subnetworks in place of the full models without hurting performance (Lee et al., 2018; Wang et al., 2020). Among them, the lottery ticket hypothesis (LTH) (Frankle and Carbin, 2018) has attracted much attention. LTH demonstrates that an over-parameterized network contains "winning tickets" (small-scale subnetworks) that can 1) match the performance of the full model; and 2) outperform randomly sampled subnetworks of the same size. Winning tickets have been verified to exist in PLMs (Prasanna et al., 2020).

In this paper, we provide an interesting result by showing that a subnetwork, which we refer to as the dominant winning ticket, exists in the PLM. It can make us to freeze all other parameters but only train the parameters of the subnetwork and obtain competitive performance for any downstream tasks. To achieve this, we fine-tune the PLM on one task (e.g., MNLI) and enforce the parameter weights close to their initial weights (pre-trained weights) by using the L1-distance penalty. This allows us to identify which parts of the model parameters change greater from the pre-trained weights during fine-tuning. We observe this ticket has some novel properties:

- The dominant winning ticket (i.e., the subnetwork) is extremely sparse, which only takes up 0.05% of the total parameters on RoBERTa-large. But fine-tuning the subnetwork can achieve comparable performance.

Figure 1: An illustration of the structure of the dominant winning ticket.
with fine-tuning the whole model.

- Compared with randomly sampled subnetworks of the same size, the dominant winning ticket can achieve better performance with a faster convergence rate.

- The dominant winning ticket is insensitive to random seed and transferable across different downstream tasks. In other words, it is intrinsically determined by the pre-trained weights and can adapt to various downstream tasks.

- The dominant winning ticket is highly structured. It is like the "skeleton" of the network, which may give us some insights into the mechanism of PLMs.

We organize the paper as follows. After a brief overview of related works in section 2, we introduce how we are aware of the existence of the dominant winning ticket in PLMs and how we identify and extract it in section 3. Then we experiment on the dominant winning ticket in section 4. In section 5, we do further discussions about the implications and future directions of the work.

2 Related Work

2.1 Pruning

Multiple studies of BERT concluded that it is considerably overparametrized (Kovaleva et al., 2019; Michel et al., 2019). In particular, it is possible to ablate elements of its architecture without loss in performance or even with slight gains (Voita et al., 2019; Li et al., 2021). There has been much recent work on compressing PLM. See overviews by Ganesh et al. (2021). Pruning is a promising line of work for model compression which involves obtaining smaller subnetworks with minimal performance loss (Gordon et al., 2020; Sajjad et al., 2020). A common approach is selecting the weights to be pruned by magnitude (Han et al., 2015).

Previous work has found that there exist subnetworks inside the neural network, which is called the lottery ticket hypothesis (Frankle and Carbin, 2018). Some of the recent findings are that the lottery ticket hypothesis holds for PLMs: inside large-scale pre-trained model there exist subnetworks that can be retrained alone to reach the performance close to that of the full model (Chen et al., 2020; Prasanna et al., 2020; Liang et al., 2021). Prasanna et al. (2020) claimed that "When BERT plays the lottery, all tickets are winning". Liang et al. (2021) shows that there exist super tickets inside PLMs that can improve generalization.

2.2 Parameter-efficient Fine-tune

Parameter-efficient fine-tuning aims at reducing the number of trainable parameters when fine-tuning the models across different downstream domains. Various approaches are invented to achieve the goal. Some inserted and only trained adapters, which have much lesser trainable parameters, between existing layers (Houlsby et al., 2019; Mahabadi et al., 2021; Rebuffi et al., 2017). Another line of the study proposed to update only a subset of parameters when fine-tuning. For example, Gordon et al. (2020) leveraged L0 regularization to limit the non-zero elements in the update vectors. Zaken et al. (2021) proposed that only tune bias terms can reach a decent performance. Zhao et al. (2020) applied the sparse binary mask to the pre-trained weights to reduce the trainable parameter size. Besides, some proposed that the PLM has a low intrinsic dimensionality (Aghajanyan et al., 2020). Hu et al. (2021) proposed a low-rank decomposition-based method that can also significantly reduce the number of trainable parameters. Chen et al. (2021) combined low-rank decomposition and sparse mask during fine-tuning.

3 The Dominant Winning Ticket in PLMs

We start with a question: which parts of the model parameters are more important when adapting PLMs to downstream tasks? To answer this question, we design the L1-regularized fine-tuning approach and then analyze the L1-regularized weights and reveal the existence of the dominant winning ticket.

3.1 L1-regularized Fine-tuning

To identify the subnetwork, we apply L1 regularization to all the transformer parameters. Specifically, we modify the original training objective, which results in the following minimization problem:

$$
\min_{\theta} \mathcal{L}(D, f, \theta) + \lambda ||\theta - \theta_0||_1,
$$

where $D$ represents for the task-specific data, $\theta$ is the model configuration (i.e., parameters), and $\theta_0$ is the pre-trained model, which is fixed. $\lambda$ is a hyper-parameter to control the weight of the regularization term, i.e., the strength of the sparsity.
This training objective can make a large part of the parameters being close to their initial weights.

3.2 Regularized Weights Analysis

We use L1-regularized fine-tuning to answer the previous proposed question: which parts of the model parameters are more important when adapting PLMs to downstream tasks? We compute the difference between the post-fine-tune weights and the pre-trained weights to see how the weights change. Specifically, we get $\Delta \theta = \theta - \theta_0$. Inspired by magnitude weight pruning (Han et al., 2015), we hypothesize that the magnitude of $\Delta \theta$ can be an indicator. We observe that the magnitude of $\Delta \theta$ is very small for most of the parameters (smaller than $1e^{-5}$ for 99% parameters), indicating that the L1 regularization does take effect. However, while most of the parameters remain close to their initial weights during fine-tuning, a very small fraction of parameters have much greater change. We define these parameters as out weighted parameters. Intuitively, we can choose a threshold $\sigma$ to select out weighted parameters. Formally, we define $\sigma$-bounded out weighted parameters:

$$\theta_\sigma = m_\sigma \odot \theta, \quad m_\sigma \in \{0, 1\}^{\|\theta\|} \quad (2)$$

where $m_\sigma$ is a binary mask vector, $m_{\sigma,i} = 1\{|\Delta \theta_i| > \sigma\}$.

We try to understand the mechanism of fine-tuning by analyzing the distribution of $\sigma$-bounded out weighted parameters. We visualize the distributions of the out weighted parameters on several different tasks (MNLI, QNLI, SST-2, QQP) as seen in Figure 2, where the parameter matrices are

$$W^Q, W^K, W^V, W^O \in \mathbb{R}^{d_{\text{model}} \times d_{\text{model}}}$$
$$W^{FC1} \in \mathbb{R}^{d_{\text{model}} \times d_{\text{fc}}}, W^{FC2} \in \mathbb{R}^{d_{\text{fc}} \times d_{\text{model}}} \quad (3)$$

For RoBERTa-large, $d_{\text{model}}$ is 1024 and $d_{\text{fc}}$ is 4096.

**Observations 1.** The locations of the out weighted parameters have strong correlations among different tasks. Each column in Figure 2 shows the out weighted parameters of the same matrix on different tasks, which has a very similar phenomenon. This high similarity indicates that the location of the out weighted parameters may be downstream task-agnostic. That is to say, the PLM itself determines which parameters tend to be out weighted.

**Observations 2.** If looking into each block in Figure 2, we can see that the out weighted parameters are distributed along with the output dimension. The out weighted parameters in the matrix tend to be dominated by a few output dimensions, what we refer to as dominated dimensions. We identify dominated dimensions by counting the number of out weighted parameters in each dimension and observe that this phenomenon exists in most of the parameter matrices in the PLM. We list all the dom-
Table 1: The structure of the dominated ticket. For each matrix, we select the top 3 dominated dimensions. We highlight several “popular” dimensions across different layers with colors. Dimension 4096 in $W^{FC2}$ and 1024 in $W^K, W^Q, W^V, W^O, W^{FC1}$ are the symbol for the bias term.

| Layer | $W^Q$ | $W^K$ | $W^V$ | $W^O$ | $W^{FC2}$ |
|-------|-------|-------|-------|-------|-----------|
| 0     | 981   | 673   | 304   | 1019  | 781       |
| 1     | 981   | 673   | 106   | 106   | 981       |
| 2     | 673   | 981   | 106   | 981   | 106       |
| 3     | 673   | 981   | 981   | 106   | 981       |
| 4     | 673   | 981   | 981   | 106   | 981       |
| 5     | 673   | 981   | 981   | 106   | 981       |
| 6     | 673   | 981   | 981   | 106   | 981       |
| 7     | 673   | 981   | 981   | 106   | 981       |
| 8     | 673   | 981   | 981   | 106   | 981       |
| 9     | 673   | 981   | 981   | 106   | 981       |
| 10    | 673   | 981   | 981   | 106   | 981       |
| 11    | 673   | 981   | 981   | 106   | 981       |
| 12    | 673   | 981   | 981   | 106   | 981       |
| 13    | 673   | 981   | 981   | 106   | 981       |
| 14    | 673   | 981   | 981   | 106   | 981       |
| 15    | 673   | 981   | 981   | 106   | 981       |
| 16    | 673   | 981   | 981   | 106   | 981       |
| 17    | 673   | 981   | 981   | 106   | 981       |
| 18    | 673   | 981   | 981   | 106   | 981       |
| 19    | 673   | 981   | 981   | 106   | 981       |
| 20    | 673   | 981   | 981   | 106   | 981       |
| 21    | 673   | 981   | 981   | 106   | 981       |
| 22    | 673   | 981   | 981   | 106   | 981       |
| 23    | 673   | 981   | 981   | 106   | 981       |

3.3 Extracting the Dominant Winning Ticket

When it comes to extracting the dominant winning ticket, the first question is to decide the sparsity of the subnetwork (the number of trainable parameters). Generally, we extract the dominant winning ticket with algorithm 1.

We use hyperparameter $k$ to control the sparsity of the subnetwork. We empirically find that the scale of the subnetwork is extremely small. $k$

Algorithm 1 Extracting the dominant winning ticket

1: Fine-tune a PLM $f(x; \theta_0)$ with L1 regularization on any downstream task dataset $D$, get $f(x; \theta)$.
2: Calculate $\Delta \theta = \theta - \theta_0$, then select out out weighted parameters $\theta_w$ with threshold $\sigma$.
3: Select the $k$ most dominated dimensions each matrix, which forms the dominant winning ticket.

equals 1 (at most one dominated dimension for each matrix) is enough to achieve comparable results to full-parameter fine-tuning for most of the tasks.

It is worth noticing that our extracted dominant winning ticket excludes embedding and layer normalization. Besides, as bias terms are vital to some tasks.

4 Testing the Dominant Winning Ticket for Fine-tuning

The previous section is about how we identify and extract the dominant winning ticket. In this section, we discuss the properties of the dominant winning ticket.
Figure 3: (Left) The training loss curves. (Middle) The training accuracy curves. (Right) The validation accuracy curve. We visualize the training process for QNLI, MRPC, and RTE. For MRPC and RTE, early stopping is triggered if the validation accuracy does not increase for 8 successive epochs.
Table 2: The dominant winning ticket vs random ticket. We report the overall (matched and mismatched) accuracy for MNLI, Matthew’s correlation for CoLA, Pearson correlation for STS-B, and accuracy for other tasks. All results are the average of 5 trials.

| Method       | Sparsity | QNLI | SST-2 | MNLI | CoLA | MRPC | STS-B | RTE | QQP |
|--------------|----------|------|-------|------|------|------|-------|-----|-----|
| Full-ft      | 100%     | 94.7 | 96.4  | 90.4 | 86.8 | 89.4 | 91.8  | 72.2| 91.1|
| Random-3     | 0.19%    | 94.1 | 96.2  | 89.8 | 68.6 | 89.4 | 91.8  | 72.2| 91.1|
| Dominant-3   | 0.19%    | 94.3 | 96.3  | 90.5 | 69   | 90.2 | 92.2  | 86.6| 91.7|
| BitFit (Zaken et al., 2021) | 0.06% | 94.5 | 96   | 86.7 | 66.3 | 89.7 | 92   | 86.3| 88.9|
| Random-1     | 0.05%    | 91.7 | 94.4  | 85.4 | 51.4 | 74.8 | 88.7  | 68.5| 88.3|
| Dominant-1   | 0.05%    | 94.6 | 96.1  | 90.4 | 69.7 | 90.9 | 92.2  | 87.7| 91  |

ticket by conducting systematic experiments.

To extract the dominant winning tickets, we perform L1-regularized fine-tuning on MNLI, QNLI, SST-2, and QOP respectively. We find that the dominant winning tickets corresponding to different downstream tasks look very close to each other (detailed statistics can be found in Appendix A.1), which matches the observation in Section 3.2. So, for simplicity, we regard the subnetwork extracted from MNLI as the standard dominant winning ticket. Our evaluation experiments are conducted upon it.

We compare the dominant winning ticket with the subnetwork that has the same size as the dominant winning ticket, denoted as Dominant-k and Random-k respectively. The dimensions of Random-k are chosen from uniform distribution. As the scale of the extracted subnetwork is adjustable by choosing different k, we consider two different compression ratios, i.e., k = 1 (one dimension per matrix at most) and k = 3 (three dimension per matrix at most).

4.1 Experimental Setup

Datasets and models. We conduct experiments on the GLUE benchmark (Wang et al., 2018). The evaluation is performed on the GLUE dev sets. We use the publicly available RoBERTa-large⁴ (Liu et al., 2019) as pre-trained language models in all our experiments.

Implementation details. Our implementation is based on the fairseq toolkit³ (Ott et al., 2019). We fine-tune on the GLUE tasks following the standard procedures. We optimize using AdamW (Loshchilov and Hutter, 2018), with batch size of 16. For L1-regularized fine-tuning, we empirically set the weight of L1 regularizer λ to 0.001, and the threshold σ to 5e-5. For dominant winning ticket fine-tuning, we perform a hyperparameter search over initial learning rate in {1e-5, 1e-4, 2e-4, 4e-4}. For full-parameter fine-tuning, we search initial learning rate in {1e-5, 2e-5, 3e-5, 5e-5}.

4.2 Performance

Our main results on the GLUE benchmark are shown in Table 2. Fine-tuning the dominant winning ticket can match the performance of fine-tuning the whole model while only requiring less than 0.2% trainable parameters per task. Performance of Dominant-3 and Dominant-1 has no significant difference for most of the tasks. For small datasets like MRPC and RTE, the smaller subnetwork even performs slightly better because less trainable parameters prevents free from overfitting. This phenomenon also indicates that the scale of the dominant winning ticket inside the PLMs can be extremely small. When comparing the dominant winning ticket with random tickets that has the same size, we can see that Random-3 performs pretty well. We think this benefits from the strong reducibility of PLMs. However, when the sparsity grows, the performance of Random-1 is much worse than Dominant-1, indicating that randomly sampled subnetworks are not only deletes useful information and become less expressive at such a level of sparsity.

Figure 3 shows the training and evaluation curves of different methods. We can clearly see that the dominant winning ticket has advantages over random subnetworks in terms of convergence rate. For large datasets like QNLI, Dominant-1 and Dominant-3 reach the best validation accuracy in the first several epochs, while random subnetworks require much more training steps to warm up. The dominant winning ticket also gets lower training losses in all tasks, indicating it fits the data better.

³The dominant winning ticket in the paper is extracted from this specific model checkpoint. https://dl.fbaipublicfiles.com/fairseq/models/roberta.large.tar.gz
⁴https://github.com/pytorch/fairseq
Another observation is that, though Dominant-3 and Random-3 have no significant performance gaps in most of the tasks as seen in Table 2, their learning behaviors vary quite a lot. Random-3 gets satisfactory results eventually, but it requires much more efforts to train. Meanwhile, there is no obvious difference between Dominant-1 and Dominant-3 from Figure 3, which is a good sign. This phenomenon suggests that when shrinking the parameter size from 0.19% to 0.05%, the capacity of the model almost keeps unchanged.

4.3 Stability of the Dominant Winning Ticket

We expect that subnetworks extracted from different L1-regularized fine-tuning runs (with different random seeds and different tasks) have similar structures. We use Jaccard similarity to measure the similarity between different tickets. Specifically, the Jaccard similarity between two sets is defined as:

\[ J(A, B) = \frac{|A \cap B|}{|A \cup B|}. \]  

We test four random seeds and four tasks (MNLI, QNLI, QQP, and SST-2). The average Jaccard similarity is 0.69 across seeds and 0.67 across tasks while the similarity between random tickets is nearly 0. This means that the dominant ticket has a stable structure that utilize a certain portion of pre-trained weights. This structure is task-agnostic and irrelevant to random seeds as observed in Section 3.2.

5 Discussions

5.1 When BERT Plays the Lottery, Are All Tickets Winning?

The lottery ticket hypothesis (LTH) states that dense, randomly-initialized networks contain subnetworks (winning tickets) that--when trained in isolation--reach performance comparable to the original network.

Initialization is an important factor in LTH as the winning ticket extracted from a specific initialization generally behaves poorly on other random reinitialized networks (Frankle and Carbin, 2018). This phenomenon is often ignored when discussing LTH in PLMs as the initialization of PLMs is deterministic. PLMs initialize via pre-training weights, which contain rich information and are potentially useful. As a result, many subnetworks inside PLMs are potential winning tickets.

Indeed, Prasanna et al. (2020) claimed that even the "bad" subnetworks in BERT ("good" and "bad") have acceptable performance. We further argue that any randomly sampled subnetwork with the sparsity of 95% can serve as the winning ticket. We randomly select 5% of the parameters in each matrix and freeze the rest of the model, surprisingly finding that the performance is comparable with full-parameter fine-tuning. As seen in Table 3, a simple random subnetwork requiring no sophisticated pruning techniques can already match with fine-tuning.

However, we still argue that not all tickets are winning. The smaller the ticket is, the rarer the winning ticket is. When the sparsity of the subnetwork increases, the performance of subnetworks begins to vary. For RoBERTa-large, at the sparsity

Table 3: Performance comparison of full-parameter fine-tuning and 5%-parameter fine-tuning.

| Params | 100% | 5% |
|--------|------|----|
| MNLI   | 94.7 | 94.8 |
| SST-2  | 96.4 | 96.6 |
| MNLI   | 90.4 | 90.6 |
| CoLA   | 68   | 69.7 |
| MRPC   | 90.9 | 91.7 |
| STS-B  | 92.4 | 92.2 |
| RTE    | 86.4 | 88  |
| QQP    | 91.9 | 91.6 |

Table 4: Dominated dimensions of \( W^O \) and \( W^{FC2} \).

| Layer | \( W^O \) | \( W^{FC2} \) |
|-------|--------|--------|
| 0     | 647    | 766    |
| 1     | 593    | 929    |
| 2     | 1024   | 579    |
| 3     | 810    | 819    |
| 4     | 101    | 1024   |
| 5     | 1024   | 579    |
| 6     | 1024   | 430    |
| 7     | 692    | 670    |
| 8     | 1024   | 534    |
| 9     | 11     | 1024   |
| 10    | 254    | 534    |
| 11    | 330    | 758    |
| 12    | 151    | 909    |
| 13    | 113    | 1024   |
| 14    | 141    | 1024   |
| 15    | 1024   | 523    |
| 16    | 1024   | 657    |
| 17    | 254    | 640    |
| 18    | 986    | 999    |
| 19    | 657    | 1      |
| 20    | 975    | 453    |
| 21    | 1024   | 975    |
| 22    | 559    | 1024   |
| 23    | 167    | 871    |

Bias terms are highlighted with blue color.
of 99.95%, most of the "ticket" fail to win while a well-selected subnetwork (the dominant winning ticket) can suffer little performance drops. In this sense, the dominant winning ticket we found can be regarded as the smallest winning ticket.

5.2 Structured Winning Ticket

One astonishing fact about the dominant winning ticket is that it is naturally structured. When we perform L1-regularized fine-tuning, the L1 regularization is equally applied to all parameters. But weights in some dimensions tend to deviate from the pre-trained weights more than others. These dimensions, which we refer to as dominated dimensions, are shared among different layers (like the $673, 631, 474$, and $106$ dimensions in Table 1).

It seems like there is a "skeleton" inside the PLM that can serve as the dominant winning ticket.

The structure of the dominant winning ticket is different from other structured pruning studies in two ways. First, while their structures usually refer to certain parts of the model (e.g., channels in convolutional layers and attention heads in Transformers), the structure of the dominant winning ticket is micro within each parameter matrix. Second, while most of the structured subnetworks rely on structured pruning methods (Liang et al., 2021), we do not apply structure-aware regularization techniques. In other words, the structure of the dominant winning ticket is naturally formed, waiting to be found.

5.3 Connections with Bias-terms Fine-tuning

The dominant winning ticket has some connections with bias-terms fine-tuning (BitFit) (Zaken et al., 2021). The idea of BitFit is to fine-tune only the bias terms in the transformer, which only requires updating a very small subset of parameters. If we treat the bias term of an extended dimension of the weight matrix, then the subnetwork forms by the bias terms have a similar structure with the dominant winning ticket when $k$ equals one (one trainable dimension per matrix). And the trainable parameter size is close too.

As can be seen in Table 2, BitFit is quite promising with small-to-medium training data. When the size of the training data is large, it still has acceptable performance. The overall performance of BitFit is much better than $Random-1$, indicating that the bias terms indeed catch some additional semantics. We find that the subnetwork of bias terms overlaps the dominant winning ticket. As shown in Table 4, the bias term serves as one of the dominated dimensions in $W^O$ and $W^{FC2}$ a lot. We think this might be an explanation of why only tuning the bias terms works well.

6 Implications and Future Work

The dominant winning ticket can be utilized for parameter-efficient fine-tuning. As the dominant winning ticket is stable across different tasks, when deploying PLMs on different scenarios, we only need to record the same small group of parameters. Besides, benefiting from the structure of the ticket, we only need to store the optimizer states for certain dimensions of each parameter matrix.

With decent code implementation, we can promisingly reduce memory usage and speed up the training process. In future work, we would examine the memory reduction and speedup abilities of the dominant winning ticket.

Besides the practical value, the dominant winning ticket raises some interesting questions about PLMs. Now that the dominant winning ticket is intrinsically determined by the pre-trained weights, then how does the subnetwork emerge during pre-training? Another worth investigating point lies in the natural structure of the ticket. Why certain dimensions of parameter matrices behave so differently from others? We still know little about the mechanism behind these phenomenons. We aim to study these questions in future work.

7 Conclusion

In this paper, we reveal the existence of the dominant winning ticket inside pre-trained models and introduce the L1-regularized fine-tuning to extract it. The dominant ticket is an extremely sparse subnetwork that can reach comparable performance with fine-tuning the whole model. We observe that the ticket has some novel properties. First, it is stable across different random seeds and tasks, which means once identified on one task, it can be transferred to other tasks with no performance loss. Second, the ticket has a natural structure within each parameter matrix, and this structure is shared across layers. Our study not only has practical values for parameter-efficient fine-tuning but also raises some questions about the pre-trained models.
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A Appendix

A.1 Structure Comparison of Dominant Winning Tickets
Table 5: Structure comparison of $W^Q$.

| Layer | MNLI | QNLI | SST | QQP |
|-------|------|------|-----|-----|
| 0     | 304  | 673  | 981 | 1019 |
| 1     | 106  | 673  | 981 | 1019 |
| 2     | 106  | 673  | 981 | 1019 |
| 3     | 106  | 673  | 981 | 1019 |
| 4     | 106  | 673  | 981 | 1019 |
| 5     | 106  | 673  | 981 | 1019 |
| 6     | 106  | 673  | 981 | 1019 |
| 7     | 106  | 673  | 981 | 1019 |
| 8     | 106  | 673  | 981 | 1019 |
| 9     | 106  | 673  | 981 | 1019 |
| 10    | 106  | 673  | 981 | 1019 |
| 11    | 2    | 547  | 673 | 2    |
| 12    | 2    | 547  | 673 | 2    |
| 13    | 2    | 547  | 673 | 2    |
| 14    | 547  | 631  | 673 | 547  |
| 15    | 547  | 631  | 673 | 547  |
| 16    | 547  | 631  | 673 | 547  |
| 17    | 547  | 631  | 673 | 547  |
| 18    | 547  | 631  | 673 | 547  |
| 19    | 547  | 631  | 673 | 547  |

Table 6: Structure comparison of $W^K$.

| Layer | MNLI | QNLI | SST | QQP |
|-------|------|------|-----|-----|
| 0     | 108  | 781  | 1019| 93  |
| 1     | 106  | 673  | 981 | 106 |
| 2     | 106  | 673  | 981 | 106 |
| 3     | 106  | 673  | 981 | 106 |
| 4     | 106  | 673  | 981 | 106 |
| 5     | 106  | 673  | 981 | 106 |
| 6     | 106  | 673  | 981 | 106 |
| 7     | 106  | 673  | 981 | 106 |
| 8     | 106  | 673  | 981 | 106 |
| 9     | 106  | 673  | 981 | 106 |
| 10    | 106  | 673  | 981 | 106 |
| 11    | 2    | 547  | 673 | 2    |
| 12    | 2    | 547  | 673 | 2    |
| 13    | 2    | 547  | 673 | 2    |
| 14    | 547  | 631  | 673 | 547  |
| 15    | 547  | 631  | 673 | 547  |
| 16    | 547  | 631  | 673 | 547  |
| 17    | 547  | 631  | 673 | 547  |
| 18    | 547  | 631  | 673 | 547  |
| 19    | 547  | 631  | 673 | 547  |
### Table 7: Structure comparison of $W^V$.

| Layer | MNLI | QNLI | SST | QQP |
|-------|------|------|-----|-----|
| 0     | 472  | 673  | 981 |     |
| 1     | 106  | 673  | 981 | 8   |
| 2     | 106  | 673  | 981 | 106 |
| 3     | 106  | 673  | 981 | 106 |
| 4     | 106  | 673  | 981 | 106 |
| 5     | 106  | 673  | 981 | 106 |
| 6     | 106  | 673  | 981 | 106 |
| 7     | 106  | 412  | 673 | 106 |
| 8     | 412  | 474  | 673 | 412 |
| 9     | 412  | 474  | 673 | 412 |
| 10    | 412  | 474  | 673 | 412 |
| 11    | 474  | 547  | 673 | 474 |
| 12    | 474  | 547  | 673 | 474 |
| 13    | 474  | 547  | 673 | 474 |
| 14    | 474  | 547  | 673 | 474 |
| 15    | 474  | 631  | 673 | 474 |
| 16    | 547  | 631  | 673 | 547 |
| 17    | 547  | 631  | 673 | 547 |
| 18    | 547  | 631  | 673 | 547 |
| 19    | 399  | 631  | 673 | 399 |
| 20    | 547  | 631  | 673 | 547 |
| 21    | 547  | 631  | 673 | 547 |
| 22    | 547  | 631  | 673 | 547 |
| 23    | 631  | 673  | 914 | 631 |

### Table 8: Structure comparison of $W^O$.

| Layer | MNLI | QNLI | SST | QQP |
|-------|------|------|-----|-----|
| 0     | 647  | 766  | 966 |     |
| 1     | 587  | 593  | 929 | 587 |
| 2     | 237  | 579  | 1024| 237 |
| 3     | 784  | 810  | 819 | 784 |
| 4     | 76   | 101  | 1024| 76  |
| 5     | 189  | 579  | 1024| 189 |
| 6     | 430  | 498  | 1024| 430 |
| 7     | 670  | 692  | 699 | 670 |
| 8     | 69   | 534  | 1024| 69  |
| 9     | 11   | 608  | 1024| 11  |
| 10    | 254  | 534  | 1024| 254 |
| 11    | 330  | 758  | 1024| 330 |
| 12    | 151  | 909  | 1024| 151 |
| 13    | 113  | 151  | 1024| 113 |
| 14    | 141  | 307  | 1024| 141 |
| 15    | 523  | 724  | 1024| 523 |
| 16    | 657  | 819  | 1024| 657 |
| 17    | 209  | 254  | 640 657| 209 |
| 18    | 966  | 986  | 999 | 966 |
| 19    | 1    | 657  | 845 | 1   |
| 20    | 453  | 975 1006| 453 |
| 21    | 400  | 975 1024| 400 |
| 22    | 46   | 559 1024| 46  |
| 23    | 167  | 871 891| 16  |

13
Table 9: Structure comparison of $W^{FC_1}$.

| Layer | MNLI | QNLI | SST | QQP |
|-------|------|------|-----|-----|
| 0     | 673  | 981  | 1019| 106 | 673  | 981  | 106 | 673  | 981  |
| 1     | 106 | 673  | 981 | 106 | 673  | 981 | 106 | 673  | 981  |
| 2     | 106 | 673  | 981 | 106 | 673  | 981 | 106 | 673  | 981  |
| 3     | 106 | 673  | 981 | 106 | 673  | 981 | 106 | 673  | 981  |
| 4     | 106 | 673  | 981 | 106 | 673  | 981 | 106 | 673  | 981  |
| 5     | 106 | 673  | 981 | 106 | 673  | 981 | 106 | 673  | 981  |
| 6     | 106 | 673  | 981 | 106 | 673  | 981 | 106 | 673  | 981  |
| 7     | 106 | 412  | 673 | 2   | 106 | 673  | 106 | 412  | 673  |
| 8     | 106 | 412  | 673 | 2   | 106 | 673  | 106 | 412  | 673  |
| 9     | 2   | 412  | 673 | 2   | 412 | 673  | 2   | 412  | 673  |
| 10    | 2   | 412  | 673 | 2   | 412 | 673  | 2   | 412  | 673  |
| 11    | 474 | 547  | 673 | 2   | 474 | 673  | 2   | 474  | 673  |
| 12    | 474 | 547  | 673 | 474 | 547 | 673  | 474 | 547  | 673  |
| 13    | 474 | 547  | 673 | 474 | 547 | 673  | 474 | 547  | 673  |
| 14    | 474 | 547  | 673 | 474 | 547 | 673  | 547 | 631  | 673  |
| 15    | 474 | 547  | 673 | 547 | 631 | 673  | 547 | 631  | 673  |
| 16    | 474 | 547  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 17    | 474 | 547  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 18    | 547 | 631  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 19    | 547 | 631  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 20    | 547 | 631  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 21    | 547 | 631  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 22    | 547 | 631  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |
| 23    | 547 | 631  | 673 | 2   | 631 | 673  | 2   | 631  | 673  |

Table 10: Structure comparison of $W^{FC_2}$.

| Layer | MNLI | QNLI | SST | QQP |
|-------|------|------|-----|-----|
| 0     | 487 | 584 | 3291| 487 | 584 | 2390| 487 | 584 | 3660|
| 1     | 1559| 1995| 3646| 1114| 1559| 4060| 1559| 3646| 3912|
| 2     | 2753| 3058| 3708| 445 | 3056| 3708| 445 | 3056| 3708|
| 3     | 480 | 609 | 1591| 44  | 1591| 1846| 44  | 1591| 1846|
| 4     | 1906| 2828| 3445| 1773| 3445| 3940| 1906| 2828| 3445|
| 5     | 682 | 841 | 2123| 1298| 1427| 3624| 682 | 841 | 2475|
| 6     | 1267| 2686| 2920| 425 | 1946| 3027| 425 | 1946| 2920|
| 7     | 1660| 2058| 3485| 317 | 1660| 2058| 317 | 1660| 2058|
| 8     | 1015| 2387| 2780| 217 | 1247| 2982| 217 | 1247| 2982|
| 9     | 448 | 616 | 3892| 34  | 1910| 3892| 34  | 1910| 3892|
| 10    | 592 | 1028| 1462| 592 | 1028| 2063| 592 | 1028| 2063|
| 11    | 1014| 2157| 3730| 1014| 2157| 3730| 1014| 2157| 3730|
| 12    | 145 | 2338| 2436| 145 | 2338| 2754| 145 | 2338| 2754|
| 13    | 902 | 1700| 2503| 1535| 2963| 3720| 1535| 2963| 3720|
| 14    | 1219| 1318| 1535| 1219| 1318| 2787| 1219| 1318| 2787|
| 15    | 15  | 608 | 2413| 15  | 64  | 2413| 15  | 64  | 2413|
| 16    | 1288| 3454| 4096| 1288| 3454| 4096| 1288| 3454| 4096|
| 17    | 2   | 3433| 3962| 2   | 3962| 3433| 2   | 3962| 3433|
| 18    | 628 | 2617| 4096| 628 | 2617| 4096| 628 | 2617| 4096|
| 19    | 827 | 1221| 4096| 827 | 1221| 4096| 827 | 1221| 4096|
| 20    | 1442| 1535| 2787| 1442| 1535| 2787| 1442| 1535| 2787|
| 21    | 2850| 3290| 4096| 2850| 3290| 4096| 2850| 3290| 4096|
| 22    | 1078| 3176| 3341| 1078| 3176| 3341| 1078| 3176| 3341|
| 23    | 1565| 2498| 2596| 1565| 2498| 2596| 1565| 2498| 2596|