Parameter-Efficient Fine-Tuning: Is There An Optimal Subset of Parameters to Tune?

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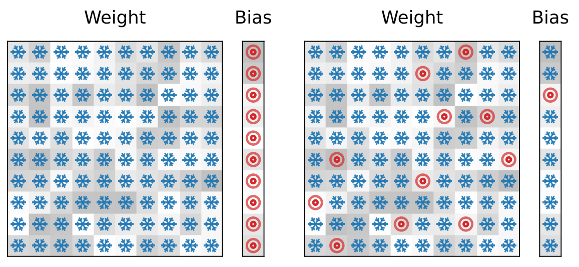
Abstract

The ever-growing size of pretrained language models (PLM) presents a significant challenge for efficiently fine-tuning and deploying these models for diverse sets of tasks within memory-constrained environments. In light of this, recent research has illuminated the possibility of selectively updating only a small subset of a model's parameters during the fine-tuning process. Since no new parameters or modules are added, these methods retain the inference speed of the original model and come at no additional computational cost. However, an open question pertains to which subset of parameters should best be tuned to maximize task performance and generalizability. To investigate, this paper presents comprehensive experiments covering a large spectrum of subset selection strategies. We comparatively evaluate their impact on model performance as well as the resulting model's capability to generalize to different tasks. Surprisingly, we find that the gains achieved in performance by elaborate selection strategies are, at best, marginal when compared to the outcomes obtained by tuning a random selection of parameter subsets. Our experiments also indicate that selection-based tuning impairs generalizability to new tasks.

1 Introduction

In recent years, the number of parameters used in language models has risen much faster than the memory available in GPUs (Lialin et al., 2023). This creates high memory requirements for fine-tuning such models on available hardware. Further, this creates high memory requirements when deploying a collection of such models to address various downstream tasks. A single pretrained model is often adapted to a wide range of tasks. The storage requirements for such a collection of model versions can be significantly reduced if the difference between these models can be represented in a compact way.



(a) BitFit (b) Random subset

Figure 1: Only a small subset of the parameters (marked with red circles in this illustration) is updated during training; the others are frozen. The BitFit approach tunes only the bias weights, while other approaches select a tuneable subset from all model parameters.

Parameter-efficient fine-tuning techniques (PEFT) aim to reduce the number of parameters that need to be stored and fine-tuned while maintaining a performance that is comparable to the training of the complete model. One popular class of these methods is referred to as *selective parameter-efficient fine-tuning* (Lialin et al., 2023). Here, a subset of the parameters is selected for PEFT, keeping the remaining parameters frozen during training. We illustrate this intuition in Figure 1 for a single weight matrix and bias vector in which most parameters are frozen and only a small subset is updated during the optimization procedure.

Since only a few parameters are fine-tuned, the sparse difference between the adapted and the pretrained model can be stored in a compact way (Zaken et al., 2022; Guo et al., 2021). The same applies to gradient statistics that are stored by the optimizer during fine-tuning. Reducing the required memory frees up space for the use of larger batches and therefore speeds up training. However, an open question pertains to which subset of parameters should best be tuned to maximize task performance and generalizability.

Contributions. In this paper, we investigate several theoretical questions that have been raised in the context of selective PEFT methods and the lottery ticket hypothesis for pretrained (language) models (Gong et al., 2022; Zheng et al., 2022). We aim to explore if an optimal subset for tuning exists and how subset tuning affects generalizability of the model. In more detail, we examine the following two aspects:

- We comparatively evaluate a broad range of approaches for identifying the ideal subset of parameters to tune. Our analysis considers the size of the subset and the computational costs for its identification. For instance, it has been shown that an effective subset can be obtained through an initial fine-tuning step of the complete model (potentially incorporating some form of regularization), followed by the selection of parameters exhibiting the largest magnitude of change (Guo et al., 2021; Xu et al., 2021). This, however, still requires a costly full fine-tuning step. Hence, the possibility of identifying a promising subset without an initial fine-tuning step would be beneficial (Prasanna et al., 2020; Gong et al., 2022).
- We analyze how sparse fine-tuning affects the generalizability of the resulting network. This is motivated by Zaken et al. (2022)'s observation that their parameter-efficient method "Bitfit" generalizes better: They report that the gap between the train and test score is substantially smaller compared to a full fine-tuning of the model.

To address these questions, we systematically conduct experiments using a large number of subset sizes and various subset selection strategies. We conduct a comprehensive grid search over hyperparameters to identify optimal training parameters for each selection strategy. We compare these hyperparameter-optimized subset selection strategies to full fine-tuning (including the use of regularization), as well as an additional (non-selective) parameter-efficient fine-tuning technique, which recently gained a lot of popularity: Low-Rank Adaptation (Hu et al., 2021, LoRA).

We make several observations in our experiments: First, the differences between different subset selection methods are marginal when hyperparameters (the learning rate specifically) are properly optimized and do not significantly outperform a baseline using a randomly selected subset. Second, subset-tuning methods tend to modify embedding networks significantly more since they are limited to a small number of parameters and hence need to make more drastic changes. The prior function of the network which can exhibit a certain degree of general language capabilities may be more affected by these local but more drastic changes.

2 Background

Our work is informed by two lines of research: *Selective parameter-efficient fine-tuning* and the *lottery ticket hypothesis* for pretrained language models. In this section, we discuss aspects of these two areas that are relevant to the work we present in this paper.

2.1 Selective Parameter-Efficient Fine-Tuning

Parameter-efficient fine-tuning (PEFT) methods reduce the number of parameters that are tuned in a model. There are multiple benefits to this: (1) The cost of storage for each task-specific adaptation is smaller, (2) switching between different variants of the same pre-trained model for inference requires less communication to load the model's parameters into the GPU (cf. Haller et al., 2023), and (3) the GPU memory required for fine-tuning is reduced (allowing larger batch sizes). For example, Adam (Kingma and Ba, 2017; Loshchilov and Hutter, 2019), a commonly used optimizer for fine-tuning language models, not only stores the calculated gradient of each parameter but also estimates for two lower-order moments. When using PEFT methods, the weights of the model still need to be kept in memory. But, since fewer parameters are tuned, a much smaller number of estimates needs to be stored, significantly freeing up space for processing a larger number of samples per batch and hence speeding up training overall.

Lialin et al. (2023) arrange a large variety of PEFT methods into a comprehensive taxonomy and identify three major classes: *Additive* (which includes *adapters* and *soft prompts*), *Selective*, and *Reparametrization*-based approaches. In selection-based approaches, only a certain subset of the parameters is tuned while other parameters which are not part of the set remain frozen.

In the remainder of this subsection, we introduce two ways of how such subsets have been selected in prior work: (1) Using heuristics and (2) based on gradient information that has been collected.

Heuristically Motivated Subsets

Zaken et al. (2022) offer a particularly simple variant: In BitFit, only the bias terms (or in a variation of this approach, only certain bias terms) are tuned. This removes the need to compute and handle parameter masks. Qi et al. (2022) propose LN-tuning (tuning only the LayerNorm modules) and suggest combining this with other methods (such as prefix tuning).

Using Gradient Information

Sung et al. (2021) attempt to determine the subset by a less heuristics-based approach and instead propose to use the empirical Fisher information of the network parameters to determine each parameter's importance (compare with Kirkpatrick et al., 2017). The Fisher information estimates the impact of a parameter on the model's prediction. Since the Fisher information matrix is intractable to compute, a common approximation is to only use the diagonal and approximate the sample distribution with the available N samples $x_1, ..., x_N$. The estimated Fisher information $\hat{F}_\theta$ of each parameter can then be expressed as:

$$\hat{F}_\theta = \frac{1}{N}\sum_{i=0}^{N} \mathbb{E}_{y\sim p_\theta(y|x_i)} \left(\nabla_\theta \log p_\theta(y|x_i)\right)^2 \quad (1)$$

In cases where many classes are available, calculating the expected value requires a large number of backward passes. Hence, it is common to simplify this using the "empirical Fisher" $\tilde{F}_\theta$ which can be derived by replacing the expected value with the observed label y_i of each sample.[1]

$$\tilde{F}_\theta = \frac{1}{N}\sum_{i=0}^{N} \left(\nabla_\theta \log p_\theta(y_i|x_i)\right)^2 \quad (2)$$

To retrieve a fine-tuning mask, the k parameters with the respective largest values are selected. All other parameters will remain frozen.

Using a fine-tuning mask (as opposed to e.g. simply selecting all biases) trades off simplicity for a more theoretically substantiated method for determining the subset to be fine-tuned.

2.2 Lottery Ticket Hypothesis

A different line of research tests the lottery ticket hypothesis (Frankle and Carbin, 2019) for pretrained language models. The lottery ticket hypothesis states that the performance of a dense neural network trained fully from a random initialization can be matched by only training a certain subnetwork (i.e. only a subset of the parameters). Typically, these subsets can only be found by training the complete network and pruning connections iteratively (Frankle and Carbin, 2019; Zhou et al., 2020; Chen et al., 2021). More recent literature has tried to translate these findings to pretrained language models (Chen et al., 2020; Zheng et al., 2022; Liang et al., 2021; Gong et al., 2022). Recent research seems to suggest that it might be feasible to find suitable subnetworks without prior training (and pruning) since the weights are no longer random (Sung et al., 2021; Prasanna et al., 2020).

While the lottery ticket hypothesis typically induces a different perspective, there are important ties between this line of research and parameter-efficient fine-tuning. The ability to find transferable (or general) true (in the sense of perfectly matching performance) "winning lottery tickets" would have considerable implications for parameter-efficient fine-tuning. Vice-versa, well-working methods to select subsets to be fine-tuned might reveal information about winning lottery tickets in general.

3 Subset Selection and Downstream Task Performance

In this first series of experiments, we aim to investigate the impact of the subset selection strategy and the subset size on the performance of the embedding network on a downstream task. Each configuration is evaluated with respect to the performance on each of the four downstream tasks. We first describe the used selection strategies and the experimental setup, before discussing the observed impact of these two variables.

3.1 Subset Selection Strategies

We compare several different selection strategies. Some of the strategies are task-independent while others rely on the task's training data to select the parameters to be tuned.

Baselines. As the simplest baseline, we include a **random** selection of parameters. Additionally, though not a subset selection strategy, we add **LoRA** (Low-Rank Adaptiation Hu et al., 2021), a popular *reparametrization*-based PEFT method for comparison. LoRA tunes rank decomposition matrices to produce an update with a low rank.

[1]The result is identical to the sum of the squared gradients of the cross-entropy loss over a given dataset.

Heuristics. One of the simplest strategies is **BitFit** (Zaken et al., 2022). Here, all bias terms are selected for tuning while all other parameters remain frozen (see Figure 1). The tuned portion depends on the model's architecture and is not flexible. The authors offer a second variant that uses only some of the bias terms. However, we exclude this second variant from our analysis since we compare subset selections of similar size. Where not noted differently, we use the resulting portion of active parameters as target portion for the other methods.

Empirical Fisher Information. Sung et al. (2021) propose choosing a subset based on the empirical Fisher information on the downstream data $\tilde{F}_{\theta,downstr.}$. This is equivalent to picking the largest sum of squared gradients (**largest downstr. sq-grad**) of the cross-entropy loss.

Inspired by *Elastic Weight Consolidation* (*EWC*, Kirkpatrick et al., 2017), we decided to additionally consider the gradient statistics on a subsampled portion of the pretraining data $\tilde{F}_{\theta,pretr.}$ (using 30,508 samples of wikitext, Merity et al., 2016). While choosing the k parameters with the smallest empirical Fisher information would be more in line with EWC (as it penalizes deviating from parameters with particularly large empirical Fisher information), we found that (this binarized version) leads to a selection of parameters that receive minimal gradient flow. For the fine-tuning to have a non-negligible effect would require a learning rate that is to high for the decoder to remain stable. We hence pick the largest values instead (**largest pretr. sq-grad**). Since this is the opposite of what EWC suggests (focusing the change on parameters with low empirical Fisher Information) we expect the subset to be perform rather poorly. We still include it for comparison.

Finally, we propose a **combined** measure that selects parameters with large squared downstream gradients and lower squared pretraining gradients. This is an attempt to force the selection to consider task-specific information not merely the received gradient magnitudes. The strategy selects parameters with the largest values of:

$$G_{combined} = \frac{\tilde{F}_{\theta,downstr.}}{1 + \tilde{F}_{\theta,pretr.}} \qquad (3)$$

Difference Pruning. In Diff pruning (Guo et al., 2021), the model is fine-tuned completely using regularization before pruning the smallest differences to the pretrained model. The pruned weights are not set to zero but to their original value.

We test two variants: One where we **prune without re-training** and one where we prune **with re-training** the remaining weights (initialized with the pretrained parameters).

In contrast to (Guo et al., 2021), we only prune and re-train a single time to mimic the other subset methods as closely as possible (i.e. using a pre-computed mask for a single training run) and use L1- instead of L0-regularization to be more in line with Gong et al. (2022). The first variant cannot be considered a subset tuning method. The second does include a subset tuning step, but still requires a costly initial full-finetuning step. It might be possible to approximate the subset selection by training the model for a shorter period, but this is outside the scope of this paper.

3.2 Experimental Setup

Evaluation datasets. We evaluate all methods in their ability to adapt a `RoBERTa-base` model (125M parameters) to four tasks:

- SST-2 (Socher et al., 2013), a sentiment classification task,
- QNLI (Wang et al., 2018) a question answering natural language inference task,
- CoNLL-2003 (Tjong Kim Sang and De Meulder, 2003), a named entity recognition tasks,
- TREC-6 (Hovy et al., 2001; Li and Roth, 2002), a question classifcation task.

In the case of SST-2 and QNLI which both are part of the General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2018), we use the development set in place of the test set (as the test set is not readily available and requires a submission for each set of predictions).

Experimental framework and hyperparameters. All experiments were conducted using the Flair-framework (Akbik et al., 2019), using their default implementations for the embeddings and task-specific decoders. The complete configuration, code, and resulting metadata can be found in a public repository.[2]

Most of the hyperparameters used in fine-tuning the embedding network are set to standard values and are kept consistent over all experiments. There

[2]`https://github.com/plonerma/sparse-finetuning`

Hyperparameter	Value
Number of epochs	2 or 4
Batch size	16
Weight decay	*none*
Gradient norm clipping	*5.0*
Learning rate schedule	*Linear with warm-up*
Warm-up fraction	*10%*

Table 1: The hyperparameters used in the fine-tuning experiments. Default values of Flair (Akbik et al., 2019) for fine-tuning are denoted in *italics*. For the larger task (QNLI) 2 epochs were used and 4 epochs in all other tasks.

is no indication that these settings favor any of the variants (though this cannot be entirely ruled out). These hyperparameters can be found in Table 1.

Preliminary experiments indicated different variants may require different learning rates. To ensure a level playing field, we performed an independent learning rate search for each variant and task (over an approximately logarithmicly equally spaced range). To ensure a sufficiently large range was selected, the experiment was repeated with a larger range if a learning rate at the limit of the range was selected. Assuming the objective is convex with respect to the learning rate, the selection of a learning rate not at the limit implies the range was sufficiently large.

In approaches involving pruning, we additionally tested two different regularization coefficients (3×10^{-3} and 3×10^{-2}) leading to a grid search. Where the development set was used in place of the test set, we split the training data into two parts to conduct the hyperparameter search.

The parameter (combination) yielding the highest performance on the development set was then used in the following experiments. The selected learning rates can be found in Table 7 in the appendix.

Decoder initialization. As each task requires a randomly initialized decoder on top of the PLM, we first execute a decoder-tuning step in which we train the decoder over the frozen PLM (Cui et al., 2023). Fine-tuning the decoder first (while initially keeping the embedding network frozen) helps to mitigate the effect of the different selections of learning rates used in the experiments on the degree to which the decoder adapts to the embedding network versus vice-versa. The much higher learning rate required by some of the variants can be quite an advantage or disadvantage as a randomly initialized decoder requires significantly more tuning. The hyperparameters used to tune the decoders can be found in Table 4 in Appendix A.

Like the fine-tuned task-specific decoder, the gradient statistics can also be shared across multiple repetitions of the experiment. A different decoder initialization leads to different gradients. Hence, using the same initialization of the decoder across the experiments is required to allow sharing of the gradient statistics.

3.3 Results

We present the experimental results, first focusing on the different subset selection strategies (Section 3.3.1) and then present an ablation study where we vary the size of the subset (Section 3.3.2).

We only state that a method outperforms another where this is substantiated by a p-value of $\leq 5\%$ on pairwise t-tests with p-values adjusted for testing multiple hypotheses. For details on the setup and results of the performed statistical tests, see Table 6 in the appendix.

3.3.1 Selection Strategies

Table 2 reports the performance on each of the four downstream tasks. We make the following observations:

Full fine-tuning best. Unsurprisingly, we note that the full fine-tuning baseline outperforms all parameter-efficient fine-tuning methods on all of the tasks. It therefore represents the upper bound that selection-based approaches can achieve.

LoRA with second highest mean. Though not a selection-based approach, we also find that LoRA is consistently among the top two PEFT methods. It has a slightly higher mean, but we cannot say with statistical significance that it outperforms the PEFT approach using combined gradient statistics.

Different selectors score similarly. We also note that different selection-based strategies score similarly, with combined gradient statistics having the highest average score but only outperforming (with statistical significance) the subset tuning method using pretraining statistics and pruning without retraining.

Surprisingly strong results for random subsets. Even the random baseline (using a large enough learning rate), fares surprisingly well. On one task, it even outperforms the other PEFT methods (including LoRA). Only full fine-tuning and LoRA outperform the random baseline with statistical sig-

	CoNLL-2003	QNLI	SST-2	TREC-6	Avg.
Full fine-tuning	**0.9217** ± **0.0008**	**0.9290** ± **0.0015**	**0.9468** ± **0.0011**	**0.9752** ± **0.0040**	**0.9432**
LoRA (rank 4)	0.9139 ± 0.0015	0.9165 ± 0.0019	0.9406 ± 0.0027	0.9708 ± 0.0036	0.9354
Random subset	0.9087 ± 0.0011	0.9048 ± 0.0025	0.9342 ± 0.0024	0.9720 ± 0.0028	0.9299
Bitfit	0.9080 ± 0.0012	0.9039 ± 0.0015	0.9383 ± 0.0023	0.9592 ± 0.0052	0.9273
Largest pretr. sq-grad	0.9073 ± 0.0014	0.9037 ± 0.0025	0.9378 ± 0.0046	0.9552 ± 0.0053	0.9260
Largest downstr. sq-grad	0.9073 ± 0.0017	0.9075 ± 0.0009	0.9399 ± 0.0027	0.9580 ± 0.0043	0.9282
Combined gradient stats	0.9082 ± 0.0019	0.9100 ± 0.0017	0.9431 ± 0.0029	0.9644 ± 0.0026	0.9314
Pruning with re-training	0.9108 ± 0.0022	0.9059 ± 0.0023	0.9390 ± 0.0039	0.9696 ± 0.0015	0.9313
Pruning w/o re-training	0.9002 ± 0.0010	0.9102 ± 0.0014	0.9376 ± 0.0052	0.9556 ± 0.0019	0.9259

Table 2: Performance of the tested variants using roberta-base and a subset size similar to bitfit (except full fine-tuning). All scores are averaged over 5 runs (seeds) and shown with a 95% confidence interval (1.96 standard errors). Following previous work, we report F1 score (micro average) for CoNLL-2003 and accuracy for the other tasks.

nificance (though further experiments may lead to more significant results). We conclude that the performance differences in these experiments are not drastic and that even a properly tuned random subset scores competitively with more complex approaches. For example, to finetune on SST-2, the optimal learning rate for a random subset turned out to be 7×10^{-3}, while it was 7×10^{-4} for bitfit, and 1×10^{-4} for largest downstream sq-grad – all starting with the same pretrained model and using the same subset size (Table 7 gives a detailed overview over the selected learning rates).

3.3.2 Subset Size

To assess the impact of the subset size on the test performance, we repeat the experiments over a range of different sizes. Figure 2 illustrates the results.

The approaches of using either the combined or only the downstream gradient statistics method outperform all other selective PEFT methods when using very small subset sizes. Pruning without retraining underperforms likely due to the large amount of information that is lost during the pruning step. At small subset sizes and compared to the other approaches, the random baseline does not perform as well. It should be mentioned though, that in the case of the smallest subset size (and for TREC-6 the second smallest), the highest available learning rate of 0.1 was selected. Due to the already large range, we did not repeat this experiment with even larger learning rates.

While the gradient flow throughout the network remains unchanged by the subset, the potential

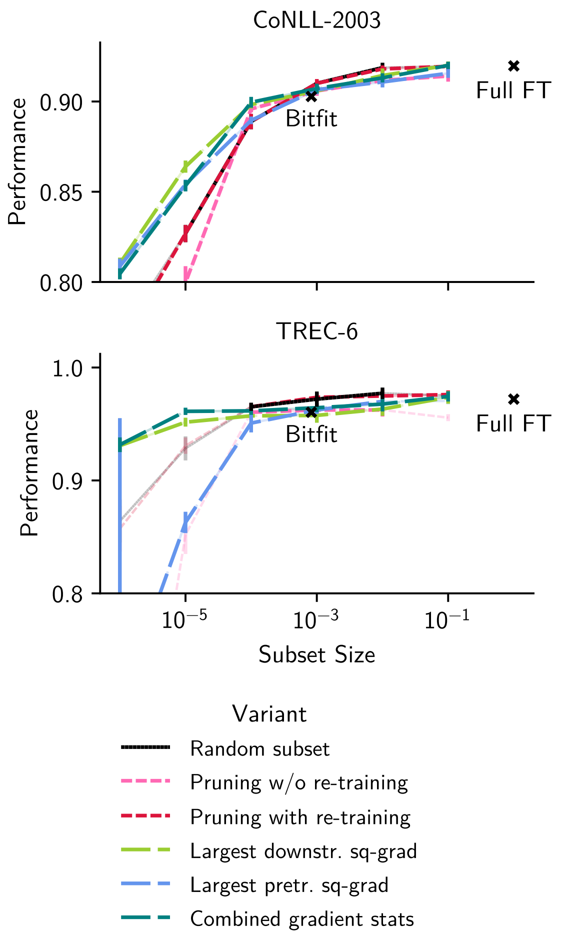


Figure 2: Test scores on CoNLL-2003 and TREC-6 of the different subset selection methods across a range of subset sizes. The data is incomplete due to some experiments being treated as invalid (here drawn partially transparent and with thin lines). The errorbars indicate the 95% confidence interval.

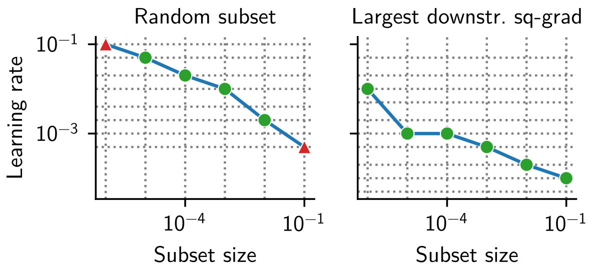


Figure 3: Selected learning rate (y-axis) based on the subset size (x-axis) and two selection strategies on CoNLL-2003: Random (left) and largest average squared gradient on the downstream data (right). A red triangle indicates that the learning rate at the limit of the range was selected and might therefore be suboptimal. For more learning rate selection plots, see Figure 4.

change of the network's function depends on (1) the number of parameters that can be affected and (2) the gradient these parameters receive. If the average gradient is much lower for a given set of parameters, a higher learning rate may produce better results.

This is very prominent in the comparison of a random subset and a subset selected by large Fisher Information (see Figure 3). The latter subset receives (on average) a larger gradient magnitude and may therefore require a lower learning rate.

4 Generality & Adaptability of the Embedding Network

We extend our evaluation to investigate how the generality of the embedding network is impacted by the applied fine-tuning method. To this end, we leverage the transformer networks fine-tuned with different selection strategies on a *primary task* from the previous experiment and evaluate their usefulness for a distinct *secondary task*.

In total, we report the following differences in performance:

1. The test score on the primary task vs. a full fine-tuning of the model (**Primary Diff.**),
2. the test score vs. the score on the training data of the primary task (**Train/Test Gap**),
3. the performance on a masked-language modeling (MLM) task using a tuned two-layer probe vs. the initial performance (**MLM Diff.**),
4. the performance on a set of secondary tasks (after adapting the model to the new task using full fine-tuning) compared to the score reached by fully fine-tuning the initial pretrained model (**Secondary Diff.**), and
5. the performance of a decoder tuned on the model adapted to the primary task vs. a decoder adapted to the pretrained model (**Sec. Decoder Diff.**).

We therefore assess how the embedding network's function changes in terms of its capability to adapt to new tasks.

4.1 Notes on Measuring Generality

We preface this experiment with the note that the "generality" of a model is no well-defined concept. Zaken et al. (2022) mention the generalization gap (the difference between the test and train performance). We are, however, not only interested in whether a model generalizes well to the test data but a broader notion of generality.

Looking solely at the test score is also not sufficient as we might not be confident that the test set represents our deployment distribution. Additionally, the current fine-tuning step might not be the last in our transfer learning pipeline. In these cases, we want to preserve some general language capabilities much like we would like to preserve a good performance on some previous task in a continuous learning setting (see e.g. Kirkpatrick et al., 2017). The primary objective of this work, however, is not to attempt to resolve the question of how to quantify generality.

In light of the vague nature of the objective and due to the lack of a more suitable evaluation framework, we opt to report masked-language modeling (MLM) and performance on secondary tasks as a proxy for generality. Though we are not strictly in a continuous learning setting, these measures can be conceived of as backward and forward transfer (compare with Lopez-Paz and Ranzato, 2022). The first measure represents how much of the previous function (i.e. the masked-language modeling) was preserved, while the second describes how well each variant preserved the task-generality (see Lin et al., 2023) while fine-tuning on a specific task (or averaging across the complete set).

4.2 Experimental Setup

The experimental setup is identical to the first series of experiments (as described in Section 3.2), but extends it by a final step. After fine-tuning the model with one of the approaches, the embedding

	Primary Diff.	**MLM Diff.**	**Test/Train Gap**	**Seconday Diff.**	**Sec. Decoder Diff.**
Full fine-tuning	**0.0000 ± 0.0006**	-0.0584 ± 0.0043	-0.0402 ± 0.0048	-0.0020 ± 0.0007	0.0421 ± 0.0271
Regularized FT (L1, 0.01)	-0.0290 ± 0.0045	**-0.0274 ± 0.0022**	-0.0025 ± 0.0049	-0.0029 ± 0.0010	0.0423 ± 0.0257
Regularized FT (L1, 0.10)	-0.0527 ± 0.0067	-0.0299 ± 0.0046	**0.0068 ± 0.0044**	-0.0018 ± 0.0007	0.0401 ± 0.0214
Regularized FT (L2, 0.01)	-0.0025 ± 0.0009	-0.0431 ± 0.0029	-0.0376 ± 0.0053	-0.0035 ± 0.0009	0.0330 ± 0.0301
Regularized FT (L2, 0.10)	-0.0028 ± 0.0007	-0.0293 ± 0.0015	-0.0311 ± 0.0052	-0.0042 ± 0.0010	**0.0614 ± 0.0282**
LoRA (rank 4)	-0.0077 ± 0.0010	-0.0742 ± 0.0028	-0.0225 ± 0.0055	-0.0271 ± 0.0292	0.0014 ± 0.0285
Random subset	-0.0133 ± 0.0020	-0.0675 ± 0.0068	-0.0245 ± 0.0051	-0.0054 ± 0.0010	0.0387 ± 0.0326
Bitfit	-0.0159 ± 0.0017	-0.1202 ± 0.0099	-0.0066 ± 0.0044	-0.0026 ± 0.0007	-0.0096 ± 0.0401
Largest pretr. sq-grad	-0.0172 ± 0.0018	-0.1469 ± 0.0110	-0.0092 ± 0.0054	-0.0051 ± 0.0010	-0.0225 ± 0.0346
Largest downstr. sq-grad	-0.0150 ± 0.0015	-0.1162 ± 0.0083	-0.0078 ± 0.0049	-0.0046 ± 0.0010	0.0033 ± 0.0343
Combined gradient stats	-0.0118 ± 0.0015	-0.1140 ± 0.0063	-0.0072 ± 0.0047	-0.0039 ± 0.0010	0.0112 ± 0.0350
Pruning with re-training	-0.0119 ± 0.0019	-0.0613 ± 0.0049	-0.0238 ± 0.0052	-0.0054 ± 0.0010	0.0543 ± 0.0324
Pruning w/o re-training	-0.0173 ± 0.0014	-0.0496 ± 0.0032	-0.0021 ± 0.0049	**-0.0014 ± 0.0008**	0.0451 ± 0.0294

Table 3: Performance of the tested methods using roberta-base. The table reports the differences of test scores on primary and secondary task to full fine-tuning on the pretrained embedding network (**Primary Diff.** and **Seconday Diff.**), the differences of a decoder tuned on the adapted embedding network (trained on the primary task) to a decoder tuned on the pretrained embedding network (**Sec. Decoder Diff.**), the **Test/Train Gap** (values smaller than zero indicate the test score is lower than the train score; the higher the better), and the difference (**MLM Diff.**) of the MLM score to the inital MLM score. All scores are averaged over 5 runs (seeds) and all primary and secondary tasks. The confidence represents 95% estimate (1.96 standard errors). In all columns, higher values are preferable. We mark the best score (per column) in **bold** and the second best with an underline. See Table 2 for the primary scores on each of the tasks.

network is reused with a new task-specific classification head, fine-tuned on a secondary task, and then evaluated on the respective test sets.

During MLM probing, the embedding network remains unchanged while a two-layer MLP decoder head is tuned to solve an MLM task (a small portion of wikitext, see Table 5 in Appendix A for a detailed list of used hyperparameters). After a few epochs of training, the model is evaluated on the test set. Re-training an MLM head may not seem necessary (as one might want to conserve the original embeddings). We believe, however, that a simple transformation (e.g. a rotation, scaling, etc.) should not be counted as a reduction in the general capabilities: The underlying information content would not have changed, only the representation. Hence, we re-train the MLM decoder to correct for such transformations.

To fine-tune the (already tuned) model on the secondary tasks, we use the same hyperparameter as presented in Table 1. Regardless of the fine-tuning strategy that is applied in the primary adaptation, we first tune the task-specific decoder to adapt to the current state of the embedding network (the scores of tuning only the decoder are reported separately; this is similar to Xu et al., 2021). We then apply a full fine-tuning of the model together with the decoder. This ensures a fair evaluation and guarantees we are measuring a property of the current state of the model, not the ability of the approach to adapt the model. The learning rate is selected based on a grid search conducted on the pretrained version of the model. Thus, for all secondary fine-tuning runs, the same learning rates are used.

4.3 Results

Table 3 contains a summary of the collected results. As mentioned in the previous section, LoRA exhibits the largest average primary test scores among the parameter-efficient fine-tuning techniques. In terms of the generalization, it has a mid-range rank.

As expected, using the largest Fisher information on the pretraining data not only fares worse in regard to the primary score but also is one of the worst with respect to its generalization capabilities. Using these statistics combined with the downstream information, however, does slightly improve the subsets based on the largest downstream Fisher information (*largest downstream sq-grad*). If the embedding network is not tuned a second time (but only the task-specific decoder), this approach also outperforms BitFit.

Subset tuning impairs adaptation to new tasks. None of the strategies outperform full fine-tuning in terms of the embedding network's ability to adapt to new tasks by fine-tuning the complete model or only the decoder. Follow-up experiments would be required to determine whether the same applies when fine-tuning the model with the same strategy as in the primary adaptation.

BitFit with small train/test gap. As observed by Zaken et al. (2022), BitFit has a very low train/test gap. In our experiments, it has the lowest train/test gap among the PEFT methods. Only one of the regularized methods has a better gap (here the test score is higher; the primary score is very low). Full fine-tuning (as one might expect) has the highest overall train/test gap.

Ablation: Similar vs. Dissimilar Secondary Tasks

In a follow-up experiment, we assess the impact of the similarity between the primary and secondary tasks. We first fine-tune a cross-lingual transformer model (`XLM-RoBERTa-base`, 279M parameters, Conneau et al., 2020) on the English version of CoNLL-2003 (a named entity recognition task) and then evaluate its performance after running a secondary fine-tuning on CoNLL-2003 in German (which we assume to be similar as the classes are identical) as well as TREC-6 which is a question classification task and thus differs more from the primary task.

Unfortunately, the data is fairly inconsistent. Since we only used two tasks (one for each category of similar vs. dissimilar), it is not possible to draw any definite conclusions from this. Nonetheless, we include these results in the appendix. Table 8 in the appendix contains a detailed report of these results.

5 Conclusion

In our evaluation of fine-tuning strategies, full fine-tuning consistently outperforms all parameter-efficient fine-tuning (PEFT) methods across various tasks. LoRA consistently ranks among the top two PEFT methods in our experiments.

Examining the utilization of gradient statistics, we observe that the method using combined gradient statistics consistently outperforms its counterparts, although the performance improvement is marginal. On average, this approach surpasses all proper subset tuning methods that do not necessitate initial full fine-tuning.

Nevertheless, it is worth noting that the differences in performance across these experiments may not be substantial enough to justify the added complexity. Surprisingly, even the random baseline, with a sufficiently high learning rate, demonstrates competitive performance, occasionally outperforming other PEFT methods.

Liang et al. (2021) demonstrate the impact of the subset size on the question of whether a "winning" lottery ticket can be found (with or without optimizing parameters to retrieve it). Our experiments extend this analysis into much smaller subset sizes. The results indicate that random subsets may not necessarily produce worse results than "winning" tickets (c.f. Gong et al., 2022; Liang et al., 2021). Instead, using a higher learning rate when tuning random subsets may shrink or diminish these performance differences.

Given the strong results of the random baseline and the generally similar performance on primary tasks, our results call into question whether there is a clear optimal subset of parameters to tune. Furthermore, our generalization experiments indicate that selective PEFT strategies impair rather than increase generalizability to secondary tasks, likely due to PEFT affecting more localized and severe changes to the transformer network.

Limitations

The experiments we report on in this paper were performed using a single model (`roberta-base`) and on a limited number of tasks. Hence, there is no guarantee that these findings transfer to large models and more complex transfer-learning scenarios. Due to the exhaustive learning rate search, we set out to conduct and given the resources that were available to us, testing the observations on a larger set of models and tasks was not possible. Testing specific hypotheses on a broader set of models and tasks may be part of future work.

Impact Statement

Large language models have the potential to reproduce multiple forms of stereotypes due to their ability to absorb societal biases ingrained in the training data. Research into parameter-efficient fine-tuning methods is unlikely to change this behavior. Additionally, training of language models is computationally demanding and carries a substantial environmental burden. This complexity further hampers the prospects of reproducing research findings and conducting subsequent studies in an academic setting. Parameter-efficient fine-tuning aims to reduce the required computational resources and might enable broader use of such models.

The experiments we conducted in the context of this paper amount to an estimated number of 150 GPU days using a mix of GPUs (mostly Nvidia Tesla V100S and some Nvidia Ampere A100).

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A Additional Setup Details

Table 4 and 5 present the hyperparameters used for tuning the task decoders as well as the decoders used in masked language model probing.

Hyperparameter	Value
Number of epochs	5
Learning rate	4×10^{-4}
Batch size	64
Weight decay	*none*
Gradient norm clipping	*5.0*
Learning rate schedule	*Linear with warm-up*
Warm-up fraction	*10%*

Table 4: The hyperparameters used to fine-tune the task-specific decoders. Default values of Flair (Akbik et al., 2019) for fine-tuning are denoted in *italics*.

Hyperparameter	Value
Number of epochs	4
Learning rate	2×10^{-3}
Batch size	64
Weight decay	0.05
Learning rate schedule	Constant

Table 5: The hyperparameters that used to fine-tune the MLM head.

B Additional Data

In the following, we present some alternative perspectives on the experiments discussed in this paper. The results are derived from the same set of experiments and are purely a different way of presenting them.

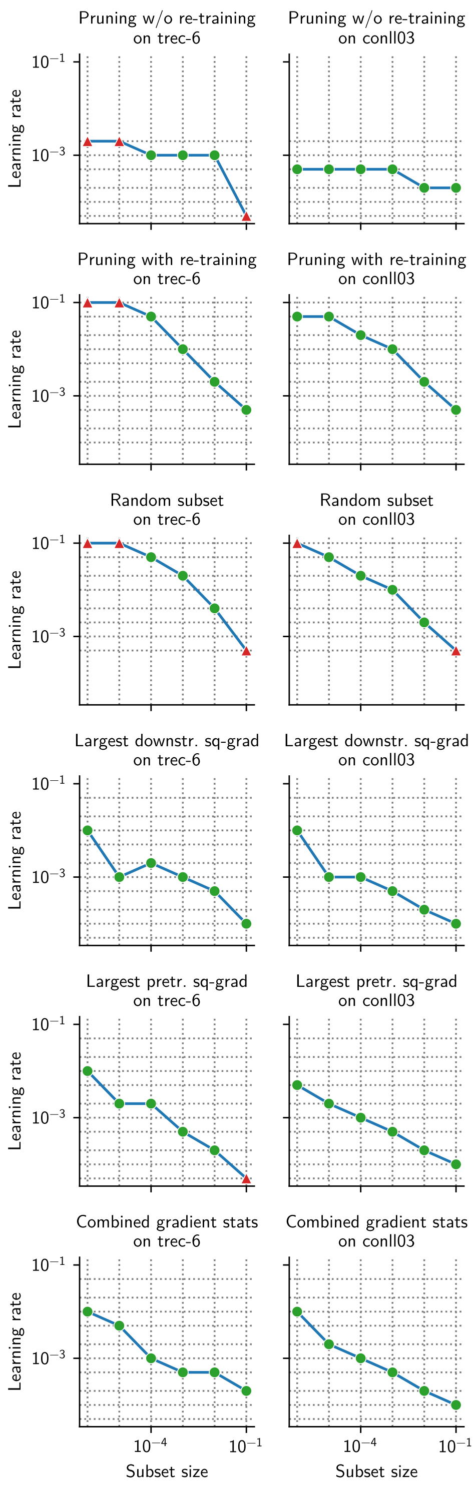

Figure 4: Selected learning rates for each subset size. Each grid intersection represents (at least) one experiment conducted in the parameter search. The best learning is represented by a marker. Learning rates that are at the limits of the tested intervals are marked red and may not be optimal given the used resolution (we used learning rates which, on a logarithmic scale, are approximately equally spaced: 1×10^{-4}, 2×10^{-4}, 5×10^{-4}, 1×10^{-3}, and so on).

Higher Mean	Lower Mean	p-value
Full fine-tuning	LoRA (rank 4)	0.0006%
	Random subset	0.0000%
	Bitfit	0.0000%
	Largest pretr. sq-grad	0.0000%
	Largest downstr. sq-grad	0.0000%
	Combined gradient stats	0.0000%
	Pruning with re-training	0.0000%
	Pruning w/o re-training	0.0000%
LoRA (rank 4)	Random subset	0.4146%
	Bitfit	0.0002%
	Largest pretr. sq-grad	0.0000%
	Largest downstr. sq-grad	0.0029%
	Pruning w/o re-training	0.0000%
Combined gradient stats	Largest pretr. sq-grad	0.5013%
	Pruning w/o re-training	0.4146%
Pruning with re-training	Largest pretr. sq-grad	0.6073%
	Pruning w/o re-training	0.4855%

Table 6: Corrected p-values of hypothesis tests for difference in means. Pairwise t-test conducted based on OLS model $test\_score \sim \mathrm{C}(variant) + \mathrm{C}(task)$ to correct for the different task means (using the implementation by Seabold and Perktold, 2010). The p-values have been adjusted for the testing of multiple hypotheses.

	CoNLL-2003	**QNLI**	**SST-2**	**TREC-6**
Full fine-tuning	4×10^{-5}	1×10^{-5}	1×10^{-5}	7×10^{-5}
LoRA (rank 4)	1×10^{-3}	5×10^{-4}	5×10^{-4}	1×10^{-3}
Random subset	7×10^{-3}	4×10^{-3}	7×10^{-3}	7×10^{-3}
Bitfit	1×10^{-3}	1×10^{-3}	7×10^{-4}	1×10^{-3}
Largest pretr. sq-grad	4×10^{-4}	1×10^{-4}	1×10^{-4}	1×10^{-3}
Largest downstr. sq-grad	4×10^{-4}	1×10^{-4}	1×10^{-4}	1×10^{-3}
Combined gradient stats	4×10^{-4}	1×10^{-4}	1×10^{-4}	7×10^{-4}
Pruning with re-training	1×10^{-2}	4×10^{-3}	4×10^{-3}	1×10^{-2}
Pruning w/o re-training	1×10^{-4}	1×10^{-4}	1×10^{-4}	1×10^{-4}

Table 7: Learning rates selected for tuning models using each of the variants.

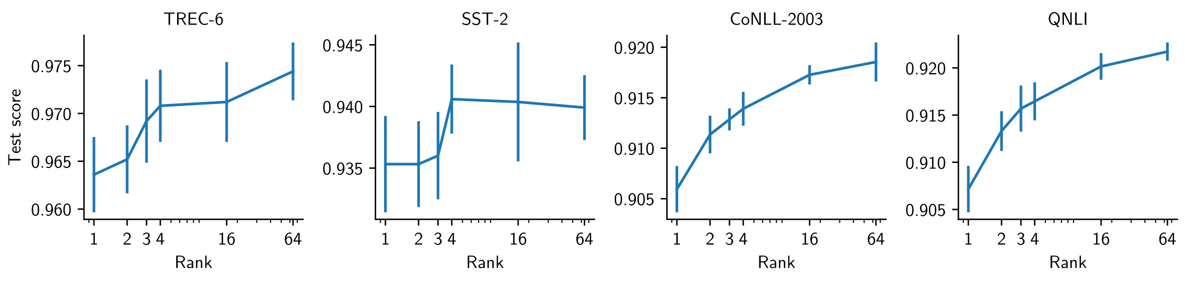

Figure 5: Primary test performance using Low-Rank adoption (Hu et al., 2021) with varying ranks.

Subset size	Variant	CoNLL-2003 (English)	CoNLL-2003 (German) Sec. (decoder)	CoNLL-2003 (German) Sec. (full)	TREC-6 Sec. (decoder)	TREC-6 Sec. (full)
0.0001	Combined gradient stats	**0.8874 ± 0.0011**	0.7808 ± 0.0051	0.8659 ± 0.0036	0.5048 ± 0.0819	0.9624 ± 0.0047
	Largest downstr. sq-grad	0.8849 ± 0.0024	0.7749 ± 0.0022	0.8648 ± 0.0029	**0.5252 ± 0.0310**	0.9660 ± 0.0057
	Largest pretr. sq-grad	0.8665 ± 0.0014	0.7419 ± 0.0049	0.8608 ± 0.0031	0.4928 ± 0.0846	0.9660 ± 0.0045
	Pruning w/o re-training	0.8867 ± 0.0010	**0.7926 ± 0.0022**	**0.8717 ± 0.0015**	0.4860 ± 0.0405	**0.9716 ± 0.0040**
	Pruning with re-training	0.8618 ± 0.0017	0.4617 ± 0.0118	0.8598 ± 0.0031	0.3048 ± 0.0472	0.9636 ± 0.0042
	Random subset	0.8590 ± 0.0016	0.3151 ± 0.0184	0.8504 ± 0.0043	0.2576 ± 0.0084	0.9572 ± 0.0036
0.0010	Combined gradient stats	0.8962 ± 0.0005	0.7868 ± 0.0048	0.8690 ± 0.0022	0.4708 ± 0.0674	**0.9700 ± 0.0028**
	Largest downstr. sq-grad	0.8980 ± 0.0015	0.7883 ± 0.0036	0.8704 ± 0.0029	0.4468 ± 0.0341	**0.9700 ± 0.0028**
	Largest pretr. sq-grad	0.8910 ± 0.0017	0.7655 ± 0.0077	0.8654 ± 0.0026	**0.5488 ± 0.0279**	0.9640 ± 0.0071
	Pruning w/o re-training	0.8891 ± 0.0012	**0.7899 ± 0.0016**	**0.8719 ± 0.0008**	0.4972 ± 0.0224	**0.9700 ± 0.0045**
	Pruning with re-training	0.8986 ± 0.0008	0.7410 ± 0.0026	0.8578 ± 0.0041	0.4404 ± 0.0554	0.9680 ± 0.0045
	Random subset	**0.9000 ± 0.0012**	0.7430 ± 0.0093	0.8581 ± 0.0031	0.3924 ± 0.0634	0.9684 ± 0.0050
0.0100	Combined gradient stats	0.9081 ± 0.0012	0.7896 ± 0.0058	0.8682 ± 0.0024	0.4524 ± 0.0625	0.9656 ± 0.0068
	Largest downstr. sq-grad	0.9078 ± 0.0011	**0.7991 ± 0.0024**	0.8683 ± 0.0017	0.4240 ± 0.0675	0.9696 ± 0.0015
	Largest pretr. sq-grad	0.9028 ± 0.0007	0.7671 ± 0.0035	0.8636 ± 0.0049	0.5052 ± 0.0244	0.9636 ± 0.0029
	Pruning w/o re-training	0.9078 ± 0.0009	0.7987 ± 0.0041	**0.8727 ± 0.0030**	**0.5352 ± 0.0242**	0.9680 ± 0.0041
	Pruning with re-training	**0.9121 ± 0.0012**	0.7912 ± 0.0035	0.8668 ± 0.0024	0.5316 ± 0.0364	**0.9704 ± 0.0015**
	Random subset	0.9112 ± 0.0014	0.7927 ± 0.0020	0.8670 ± 0.0033	0.4956 ± 0.0419	0.9636 ± 0.0034
0.1000	Combined gradient stats	0.9135 ± 0.0016	0.7918 ± 0.0046	0.8661 ± 0.0044	0.5112 ± 0.0318	0.9676 ± 0.0038
	Largest downstr. sq-grad	**0.9139 ± 0.0016**	0.7881 ± 0.0032	0.8629 ± 0.0038	0.5420 ± 0.0218	**0.9696 ± 0.0042**
	Largest pretr. sq-grad	0.9117 ± 0.0013	0.7811 ± 0.0043	0.8664 ± 0.0017	0.5196 ± 0.0463	0.9660 ± 0.0054
	Pruning w/o re-training	0.9080 ± 0.0011	**0.7989 ± 0.0041**	**0.8720 ± 0.0025**	0.5332 ± 0.0264	0.9688 ± 0.0046
	Pruning with re-training	0.9123 ± 0.0012	0.7885 ± 0.0050	0.8651 ± 0.0044	**0.5536 ± 0.0366**	0.9688 ± 0.0058
	Random subset	0.9108 ± 0.0011	0.7701 ± 0.0056	0.8638 ± 0.0039	0.4304 ± 0.0895	0.9656 ± 0.0049

Table 8: After training on CoNLL-2003 (English) using each of the variants, the resulting models are adapted (using full FT) to a secondary dataset. Directly adapting the pre-trained model yields a score (and 95% confindence interval) of 0.8724 ± 0.0020 for CoNLL-2003 (German) and 0.9752 ± 0.0040 for TREC-6. Following previous work, we report F1 score (micro average) for CoNLL-2003 (English & German) and accuracy for the other tasks.

Primary task	Variant	Primary score	Secondary Score Diff.	MLM Precision @1
	Full fine-tuning	**0.9217 ± 0.0004**	-0.0025 ± 0.0011	0.3756 ± 0.0011
	Regularized FT (L1, 0.01)	0.9013 ± 0.0003	-0.0030 ± 0.0016	0.4044 ± 0.0007
	Regularized FT (L1, 0.10)	0.8824 ± 0.0006	-0.0018 ± 0.0011	0.3869 ± 0.0012
	Regularized FT (L2, 0.01)	0.9203 ± 0.0004	-0.0050 ± 0.0015	0.3870 ± 0.0023
	Regularized FT (L2, 0.10)	0.9210 ± 0.0011	-0.0038 ± 0.0015	**0.4067 ± 0.0015**
	LoRA (rank 4)	0.9139 ± 0.0007	-0.0074 ± 0.0019	0.3659 ± 0.0055
CoNLL-2003	Random subset	0.9087 ± 0.0005	-0.0039 ± 0.0017	0.3754 ± 0.0027
	Bitfit	0.9080 ± 0.0006	-0.0023 ± 0.0010	0.3481 ± 0.0015
	Largest pretr. sq-grad	0.9073 ± 0.0006	-0.0063 ± 0.0015	0.2965 ± 0.0021
	Largest downstr. sq-grad	0.9073 ± 0.0008	-0.0049 ± 0.0018	0.3283 ± 0.0014
	Combined gradient stats	0.9082 ± 0.0009	-0.0046 ± 0.0016	0.3316 ± 0.0008
	Pruning with re-training	0.9108 ± 0.0010	-0.0070 ± 0.0021	0.3552 ± 0.0028
	Pruning w/o re-training	0.9002 ± 0.0004	**-0.0015 ± 0.0013**	0.3891 ± 0.0012
	Full fine-tuning	**0.9290 ± 0.0007**	-0.0020 ± 0.0007	0.4067 ± 0.0007
	Regularized FT (L1, 0.01)	0.8701 ± 0.0004	-0.0025 ± 0.0014	0.4177 ± 0.0009
	Regularized FT (L1, 0.10)	0.8323 ± 0.0004	-0.0022 ± 0.0014	**0.4259 ± 0.0007**
	Regularized FT (L2, 0.01)	0.9270 ± 0.0008	-0.0019 ± 0.0021	0.4146 ± 0.0016
	Regularized FT (L2, 0.10)	0.9242 ± 0.0007	-0.0047 ± 0.0026	0.4210 ± 0.0006
	LoRA (rank 4)	0.9165 ± 0.0009	-0.0279 ± 0.0439	0.3776 ± 0.0049
QNLI	Random subset	0.9048 ± 0.0012	-0.0056 ± 0.0013	0.3817 ± 0.0013
	Bitfit	0.9039 ± 0.0007	-0.0038 ± 0.0013	0.2595 ± 0.0066
	Largest pretr. sq-grad	0.9037 ± 0.0011	-0.0027 ± 0.0008	0.3040 ± 0.0055
	Largest downstr. sq-grad	0.9075 ± 0.0004	-0.0037 ± 0.0015	0.3461 ± 0.0050
	Combined gradient stats	0.9100 ± 0.0008	-0.0028 ± 0.0015	0.3407 ± 0.0045
	Pruning with re-training	0.9059 ± 0.0010	-0.0051 ± 0.0016	0.3828 ± 0.0025
	Pruning w/o re-training	0.9102 ± 0.0006	**-0.0013 ± 0.0014**	0.3825 ± 0.0012
	Full fine-tuning	**0.9468 ± 0.0005**	-0.0012 ± 0.0009	0.3957 ± 0.0027
	Regularized FT (L1, 0.01)	0.9326 ± 0.0009	-0.0020 ± 0.0013	0.4279 ± 0.0007
	Regularized FT (L1, 0.10)	0.9177 ± 0.0006	-0.0019 ± 0.0016	**0.4328 ± 0.0005**
	Regularized FT (L2, 0.01)	0.9436 ± 0.0009	-0.0032 ± 0.0013	0.4034 ± 0.0008
	Regularized FT (L2, 0.10)	0.9438 ± 0.0009	-0.0033 ± 0.0016	0.4169 ± 0.0012
	LoRA (rank 4)	0.9406 ± 0.0012	-0.0451 ± 0.0766	0.3737 ± 0.0020
SST-2	Random subset	0.9342 ± 0.0011	-0.0077 ± 0.0016	0.3394 ± 0.0026
	Bitfit	0.9383 ± 0.0011	-0.0019 ± 0.0010	0.3393 ± 0.0016
	Largest pretr. sq-grad	0.9378 ± 0.0021	-0.0021 ± 0.0010	0.3531 ± 0.0016
	Largest downstr. sq-grad	0.9399 ± 0.0012	-0.0017 ± 0.0012	0.3611 ± 0.0013
	Combined gradient stats	0.9431 ± 0.0013	**-0.0011 ± 0.0011**	0.3582 ± 0.0013
	Pruning with re-training	0.9390 ± 0.0018	-0.0051 ± 0.0015	0.3854 ± 0.0016
	Pruning w/o re-training	0.9376 ± 0.0024	-0.0021 ± 0.0014	0.3950 ± 0.0009
	Full fine-tuning	**0.9752 ± 0.0019**	-0.0022 ± 0.0014	0.3669 ± 0.0032
	Regularized FT (L1, 0.01)	0.9528 ± 0.0009	-0.0040 ± 0.0021	**0.4203 ± 0.0002**
	Regularized FT (L1, 0.10)	0.9296 ± 0.0010	-0.0017 ± 0.0012	0.4133 ± 0.0006
	Regularized FT (L2, 0.01)	0.9720 ± 0.0027	-0.0023 ± 0.0013	0.4011 ± 0.0025
	Regularized FT (L2, 0.10)	0.9724 ± 0.0013	-0.0044 ± 0.0017	0.4166 ± 0.0010
	LoRA (rank 4)	0.9708 ± 0.0017	-0.0053 ± 0.0009	0.3659 ± 0.0039
TREC-6	Random subset	0.9720 ± 0.0013	-0.0022 ± 0.0013	0.4135 ± 0.0015
	Bitfit	0.9592 ± 0.0024	-0.0024 ± 0.0016	0.3505 ± 0.0024
	Largest pretr. sq-grad	0.9552 ± 0.0025	-0.0091 ± 0.0020	0.2354 ± 0.0049
	Largest downstr. sq-grad	0.9580 ± 0.0020	-0.0067 ± 0.0016	0.2781 ± 0.0058
	Combined gradient stats	0.9644 ± 0.0012	-0.0048 ± 0.0018	0.2936 ± 0.0043
	Pruning with re-training	0.9696 ± 0.0007	-0.0026 ± 0.0011	0.4097 ± 0.0016
	Pruning w/o re-training	0.9556 ± 0.0009	**-0.0003 ± 0.0010**	0.4149 ± 0.0013

Table 9: Performance of the tested variants using roberta-base. Primary and secondary score compared to full fine-tuning on the pretrained embedding. MLM is the MLM precision @1 score. All scores are averaged over 5 runs (seeds) and all secondary tasks.

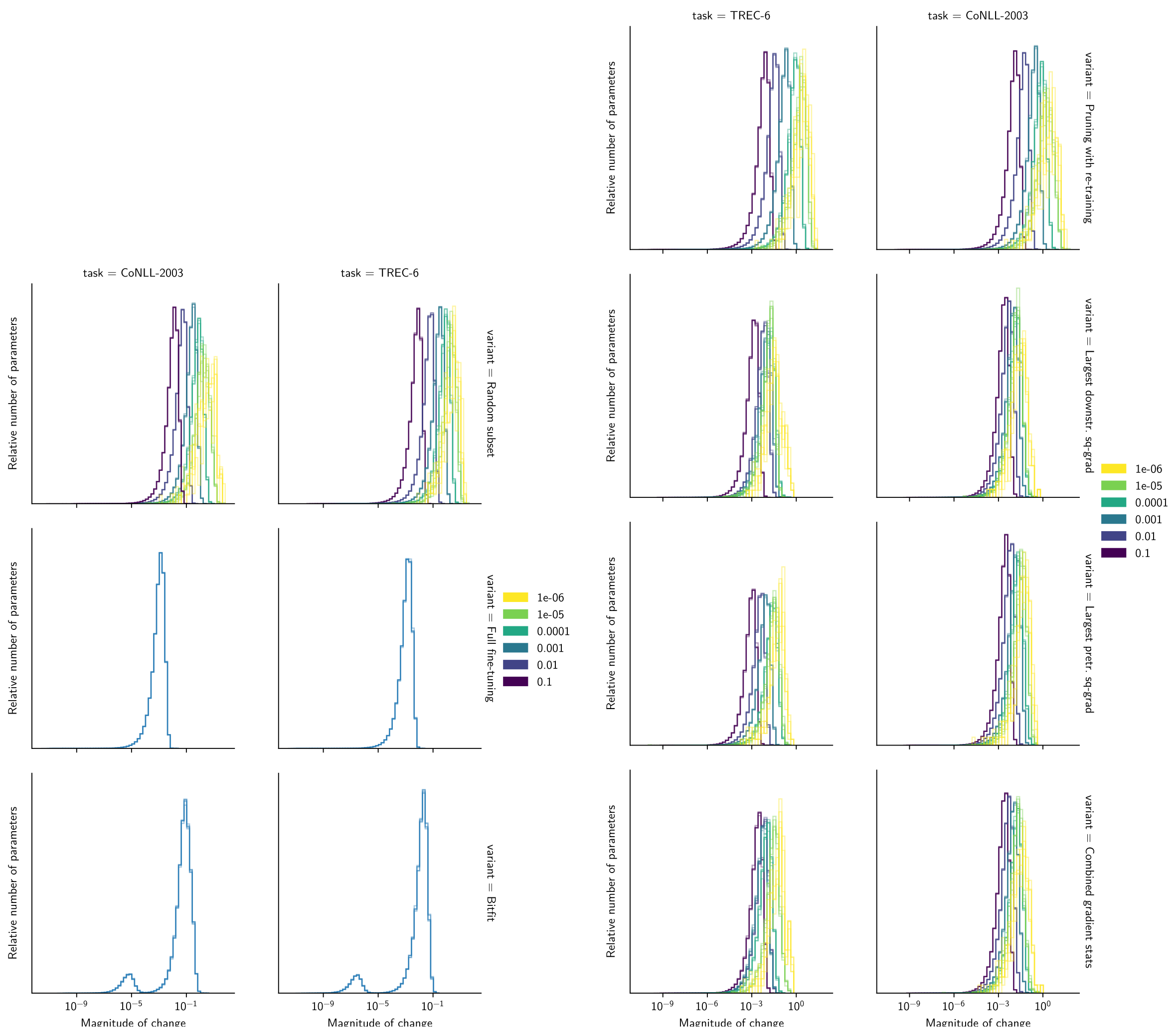

Figure 6: The relative number of parameters with a certain magnitude of change over the different subset sizes.

Primary task	Variant	Primary score	MLM score	CoNLL-2003	QNLI	SST-2	TREC-6
CoNLL-2003	Bitfit	0.9080 ± 0.0006	0.3481 ± 0.0015	0.9213 ± 0.0012	0.9269 ± 0.0014	**0.9433 ± 0.0023**	0.9720 ± 0.0021
	Combined gradient stats	0.9082 ± 0.0009	0.3316 ± 0.0008	0.9197 ± 0.0018	0.9239 ± 0.0012	0.9383 ± 0.0018	0.9724 ± 0.0042
	Full fine-tuning	**0.9217 ± 0.0004**	0.3756 ± 0.0011	0.9206 ± 0.0017	0.9255 ± 0.0008	**0.9433 ± 0.0034**	0.9732 ± 0.0020
	Largest downstr. sq-grad	0.9073 ± 0.0008	0.3283 ± 0.0014	0.9204 ± 0.0015	0.9248 ± 0.0013	0.9358 ± 0.0019	0.9720 ± 0.0021
	Largest pretr. sq-grad	0.9073 ± 0.0006	0.2965 ± 0.0021	0.9180 ± 0.0015	0.9235 ± 0.0017	0.9381 ± 0.0028	0.9680 ± 0.0041
	LoRA (rank 4)	0.9139 ± 0.0007	0.3659 ± 0.0055	0.9173 ± 0.0012	0.9166 ± 0.0015	0.9385 ± 0.0041	0.9708 ± 0.0029
	Pruning w/o re-training	0.9002 ± 0.0004	0.3891 ± 0.0012	**0.9218 ± 0.0019**	0.9277 ± 0.0011	0.9424 ± 0.0027	0.9748 ± 0.0032
	Pruning with re-training	0.9108 ± 0.0010	0.3552 ± 0.0028	0.9186 ± 0.0033	0.9179 ± 0.0011	0.9369 ± 0.0036	0.9712 ± 0.0029
	Random subset	0.9087 ± 0.0005	0.3754 ± 0.0027	0.9188 ± 0.0011	0.9233 ± 0.0018	0.9394 ± 0.0035	**0.9756 ± 0.0015**
	Regularized FT (L1, 0.01)	0.9013 ± 0.0003	0.4044 ± 0.0007	0.9217 ± 0.0007	**0.9278 ± 0.0008**	0.9399 ± 0.0034	0.9712 ± 0.0032
	Regularized FT (L1, 0.10)	0.8824 ± 0.0006	0.3869 ± 0.0012	0.9211 ± 0.0008	0.9275 ± 0.0009	0.9424 ± 0.0022	0.9744 ± 0.0029
	Regularized FT (L2, 0.01)	0.9203 ± 0.0004	0.3870 ± 0.0023	0.9211 ± 0.0022	0.9229 ± 0.0012	0.9404 ± 0.0016	0.9684 ± 0.0031
	Regularized FT (L2, 0.10)	0.9210 ± 0.0011	**0.4067 ± 0.0015**	0.9213 ± 0.0019	0.9248 ± 0.0006	0.9394 ± 0.0025	0.9720 ± 0.0025
QNLI	Bitfit	0.9039 ± 0.0007	0.2595 ± 0.0066	0.9188 ± 0.0019	0.9248 ± 0.0013	0.9406 ± 0.0023	0.9736 ± 0.0029
	Combined gradient stats	0.9100 ± 0.0008	0.3407 ± 0.0045	0.9173 ± 0.0014	0.9256 ± 0.0008	0.9420 ± 0.0017	0.9768 ± 0.0032
	Full fine-tuning	**0.9290 ± 0.0007**	0.4067 ± 0.0007	0.9206 ± 0.0011	0.9270 ± 0.0013	**0.9450 ± 0.0012**	0.9720 ± 0.0018
	Largest downstr. sq-grad	0.9075 ± 0.0004	0.3461 ± 0.0050	0.9182 ± 0.0003	0.9257 ± 0.0012	0.9388 ± 0.0018	0.9752 ± 0.0029
	Largest pretr. sq-grad	0.9037 ± 0.0011	0.3040 ± 0.0055	0.9184 ± 0.0013	0.9257 ± 0.0008	0.9445 ± 0.0029	0.9732 ± 0.0010
	LoRA (rank 4)	0.9165 ± 0.0009	0.3776 ± 0.0049	0.9167 ± 0.0004	0.9260 ± 0.0018	0.9392 ± 0.0031	0.8792 ± 0.1750
	Pruning w/o re-training	0.9102 ± 0.0006	0.3825 ± 0.0012	0.9193 ± 0.0018	0.9263 ± 0.0015	0.9447 ± 0.0026	**0.9772 ± 0.0032**
	Pruning with re-training	0.9059 ± 0.0010	0.3828 ± 0.0025	0.9161 ± 0.0021	0.9240 ± 0.0017	0.9399 ± 0.0048	0.9724 ± 0.0029
	Random subset	0.9048 ± 0.0012	0.3817 ± 0.0013	0.9175 ± 0.0013	0.9246 ± 0.0023	0.9385 ± 0.0027	0.9696 ± 0.0026
	Regularized FT (L1, 0.01)	0.8701 ± 0.0004	0.4177 ± 0.0009	0.9197 ± 0.0011	0.9258 ± 0.0009	0.9415 ± 0.0033	0.9756 ± 0.0026
	Regularized FT (L1, 0.10)	0.8323 ± 0.0004	**0.4259 ± 0.0007**	**0.9211 ± 0.0019**	0.9267 ± 0.0010	0.9415 ± 0.0040	0.9748 ± 0.0020
	Regularized FT (L2, 0.01)	0.9270 ± 0.0008	0.4146 ± 0.0016	0.9196 ± 0.0012	**0.9310 ± 0.0012**	0.9385 ± 0.0029	0.9760 ± 0.0033
	Regularized FT (L2, 0.10)	0.9242 ± 0.0007	0.4210 ± 0.0006	0.9194 ± 0.0011	0.9301 ± 0.0016	0.9344 ± 0.0029	0.9700 ± 0.0051
SST-2	Bitfit	0.9383 ± 0.0011	0.3393 ± 0.0016	0.9199 ± 0.0009	0.9281 ± 0.0016	0.9445 ± 0.0032	0.9728 ± 0.0020
	Combined gradient stats	0.9431 ± 0.0013	0.3582 ± 0.0013	0.9196 ± 0.0010	0.9268 ± 0.0008	**0.9472 ± 0.0033**	0.9748 ± 0.0024
	Full fine-tuning	**0.9468 ± 0.0005**	0.3957 ± 0.0027	0.9205 ± 0.0011	**0.9284 ± 0.0009**	0.9443 ± 0.0017	0.9748 ± 0.0027
	Largest downstr. sq-grad	0.9399 ± 0.0012	0.3611 ± 0.0013	0.9192 ± 0.0015	0.9277 ± 0.0016	0.9450 ± 0.0012	0.9740 ± 0.0045
	Largest pretr. sq-grad	0.9378 ± 0.0021	0.3531 ± 0.0016	0.9197 ± 0.0009	0.9278 ± 0.0014	0.9450 ± 0.0021	0.9720 ± 0.0033
	LoRA (rank 4)	0.9406 ± 0.0012	0.3737 ± 0.0020	0.9173 ± 0.0008	0.9218 ± 0.0011	0.9420 ± 0.0013	0.8112 ± 0.3054
	Pruning w/o re-training	0.9376 ± 0.0024	0.3950 ± 0.0009	0.9199 ± 0.0018	0.9262 ± 0.0005	0.9461 ± 0.0027	0.9720 ± 0.0050
	Pruning with re-training	0.9390 ± 0.0018	0.3854 ± 0.0016	0.9166 ± 0.0006	0.9222 ± 0.0019	0.9420 ± 0.0050	0.9716 ± 0.0031
	Random subset	0.9342 ± 0.0011	0.3394 ± 0.0026	0.9142 ± 0.0026	0.9183 ± 0.0030	0.9420 ± 0.0041	0.9676 ± 0.0015
	Regularized FT (L1, 0.01)	0.9326 ± 0.0009	0.4279 ± 0.0007	**0.9206 ± 0.0018**	0.9275 ± 0.0016	0.9413 ± 0.0023	0.9752 ± 0.0016
	Regularized FT (L1, 0.10)	0.9177 ± 0.0006	**0.4328 ± 0.0005**	0.9194 ± 0.0012	**0.9284 ± 0.0011**	0.9401 ± 0.0019	**0.9772 ± 0.0020**
	Regularized FT (L2, 0.01)	0.9436 ± 0.0009	0.4034 ± 0.0008	0.9198 ± 0.0009	0.9256 ± 0.0011	0.9411 ± 0.0028	0.9736 ± 0.0031
	Regularized FT (L2, 0.10)	0.9438 ± 0.0009	0.4169 ± 0.0012	0.9196 ± 0.0015	0.9269 ± 0.0019	0.9394 ± 0.0026	0.9736 ± 0.0042
TREC-6	Bitfit	0.9592 ± 0.0024	0.3505 ± 0.0024	0.9192 ± 0.0010	**0.9306 ± 0.0004**	0.9415 ± 0.0039	0.9720 ± 0.0028
	Combined gradient stats	0.9644 ± 0.0012	0.2936 ± 0.0043	0.9161 ± 0.0007	0.9252 ± 0.0027	0.9378 ± 0.0040	0.9744 ± 0.0026
	Full fine-tuning	**0.9752 ± 0.0019**	0.3669 ± 0.0032	0.9197 ± 0.0008	0.9290 ± 0.0021	0.9420 ± 0.0041	0.9732 ± 0.0016
	Largest downstr. sq-grad	0.9580 ± 0.0020	0.2781 ± 0.0058	0.9169 ± 0.0012	0.9237 ± 0.0015	0.9365 ± 0.0018	0.9688 ± 0.0051
	Largest pretr. sq-grad	0.9552 ± 0.0025	0.2354 ± 0.0049	0.9154 ± 0.0014	0.9205 ± 0.0027	0.9365 ± 0.0029	0.9640 ± 0.0067
	LoRA (rank 4)	0.9708 ± 0.0017	0.3659 ± 0.0039	0.9178 ± 0.0008	0.9227 ± 0.0022	0.9411 ± 0.0021	0.9700 ± 0.0012
	Pruning w/o re-training	0.9556 ± 0.0009	0.4149 ± 0.0013	0.9207 ± 0.0020	0.9285 ± 0.0011	**0.9486 ± 0.0022**	0.9740 ± 0.0021
	Pruning with re-training	0.9696 ± 0.0007	0.4097 ± 0.0016	0.9206 ± 0.0014	0.9252 ± 0.0012	0.9427 ± 0.0021	0.9740 ± 0.0028
	Random subset	0.9720 ± 0.0013	0.4135 ± 0.0015	0.9200 ± 0.0011	0.9275 ± 0.0020	0.9415 ± 0.0012	0.9748 ± 0.0036
	Regularized FT (L1, 0.01)	0.9528 ± 0.0009	**0.4203 ± 0.0002**	0.9216 ± 0.0021	0.9250 ± 0.0015	0.9378 ± 0.0049	0.9724 ± 0.0040
	Regularized FT (L1, 0.10)	0.9296 ± 0.0010	0.4133 ± 0.0006	0.9201 ± 0.0008	0.9269 ± 0.0019	0.9424 ± 0.0022	**0.9764 ± 0.0023**
	Regularized FT (L2, 0.01)	0.9720 ± 0.0027	0.4011 ± 0.0025	**0.9217 ± 0.0017**	0.9265 ± 0.0013	0.9438 ± 0.0033	0.9716 ± 0.0029
	Regularized FT (L2, 0.10)	0.9724 ± 0.0013	0.4166 ± 0.0010	0.9207 ± 0.0016	0.9268 ± 0.0013	0.9397 ± 0.0015	0.9680 ± 0.0041

Table 10: Performance of full fine-tuning on a secondary task after a applying each variant on the primary task using a RoBERTa (base). All scores are averaged over 5 runs (std in parentheses).

Task	CoNLL-2003	QNLI	SST-2	TREC-6
Variant				
LoRA (rank 1, 0.03%)	0.9059 ± 0.0022	0.9072 ± 0.0023	0.9353 ± 0.0038	0.9636 ± 0.0038
LoRA (rank 2, 0.06%)	0.9114 ± 0.0017	0.9133 ± 0.0020	0.9353 ± 0.0034	0.9652 ± 0.0034
LoRA (rank 3, 0.09%)	0.9129 ± 0.0010	0.9157 ± 0.0023	0.9360 ± 0.0034	0.9692 ± 0.0042
LoRA (rank 4, 0.12%)	0.9139 ± 0.0015	0.9165 ± 0.0019	**0.9406 ± 0.0027**	0.9708 ± 0.0036
LoRA (rank 16, 0.47%)	0.9173 ± 0.0008	0.9202 ± 0.0013	0.9404 ± 0.0047	0.9712 ± 0.0040
LoRA (rank 64, 1.89%)	**0.9185 ± 0.0018**	**0.9217 ± 0.0008**	0.9399 ± 0.0025	**0.9744 ± 0.0029**

Table 11: Performance of Low-Rank adoption (Hu et al., 2021) across four different tasks (five runs each) with their 95% intervals..

	Primary score	MLM score	CoNLL-2003	QNLI	SST-2	TREC-6
Primary task						
CoNLL-2003	0.9139 ± 0.0007	0.3659 ± 0.0055	0.9173 ± 0.0012	0.9166 ± 0.0015	0.9385 ± 0.0041	0.9708 ± 0.0029
QNLI	0.9165 ± 0.0009	0.3776 ± 0.0049	0.9167 ± 0.0004	0.9260 ± 0.0018	0.9392 ± 0.0031	0.8792 ± 0.1750
SST-2	0.9406 ± 0.0012	0.3737 ± 0.0020	0.9173 ± 0.0008	0.9218 ± 0.0011	0.9420 ± 0.0013	0.8112 ± 0.3054
TREC-6	0.9708 ± 0.0017	0.3659 ± 0.0039	0.9178 ± 0.0008	0.9227 ± 0.0022	0.9411 ± 0.0021	0.9700 ± 0.0012

Table 12: Performance of Low-Rank adoption with a rank of 4 (Hu et al., 2021) after fine-tuning on secondary task (five runs each; 95% intervals).

			Primary score	Gap	MLM score	CoNLL-2003	QNLI	SST-2	TREC-6
Primary task	Reg.	Coeff.							
CoNLL-2003	l1	0.01	0.9013 ± 0.0002	-0.0337 ± 0.0001	0.4044 ± 0.0004	0.9217 ± 0.0003	**0.9278 ± 0.0004**	0.9399 ± 0.0017	0.9712 ± 0.0016
		0.10	0.8824 ± 0.0003	-0.0165 ± 0.0003	0.3869 ± 0.0006	0.9211 ± 0.0004	0.9275 ± 0.0005	0.9424 ± 0.0011	0.9744 ± 0.0015
		1.00	0.8387 ± 0.0003	**-0.0101 ± 0.0002**	**0.4106 ± 0.0002**	0.9215 ± 0.0006	0.9267 ± 0.0008	**0.9433 ± 0.0027**	**0.9752 ± 0.0008**
	l2	0.01	0.9203 ± 0.0002	-0.0704 ± 0.0002	0.3870 ± 0.0012	0.9211 ± 0.0011	0.9229 ± 0.0006	0.9404 ± 0.0008	0.9684 ± 0.0016
		0.10	**0.9210 ± 0.0006**	-0.0654 ± 0.0006	0.4067 ± 0.0008	0.9213 ± 0.0010	0.9248 ± 0.0003	0.9394 ± 0.0013	0.9720 ± 0.0013
		1.00	0.9192 ± 0.0004	-0.0595 ± 0.0002	0.4086 ± 0.0013	**0.9223 ± 0.0006**	0.9237 ± 0.0011	0.9413 ± 0.0024	0.9720 ± 0.0009
QNLI	l1	0.01	0.8701 ± 0.0002	0.0149 ± 0.0002	0.4177 ± 0.0005	0.9197 ± 0.0006	0.9258 ± 0.0004	0.9415 ± 0.0017	0.9756 ± 0.0013
		0.10	0.8323 ± 0.0002	**0.0198 ± 0.0003**	0.4259 ± 0.0004	0.9211 ± 0.0010	0.9267 ± 0.0005	0.9415 ± 0.0020	0.9748 ± 0.0010
		1.00	0.6640 ± 0.0001	0.0086 ± 0.0001	**0.4434 ± 0.0003**	**0.9218 ± 0.0008**	0.9276 ± 0.0008	0.9436 ± 0.0017	0.9760 ± 0.0019
	l2	0.01	**0.9270 ± 0.0004**	-0.0203 ± 0.0004	0.4146 ± 0.0008	0.9196 ± 0.0006	**0.9310 ± 0.0006**	0.9385 ± 0.0015	0.9760 ± 0.0017
		0.10	0.9242 ± 0.0004	-0.0174 ± 0.0003	0.4210 ± 0.0003	0.9194 ± 0.0005	0.9301 ± 0.0008	0.9344 ± 0.0015	0.9700 ± 0.0026
		1.00	0.9132 ± 0.0004	-0.0041 ± 0.0003	0.4247 ± 0.0006	0.9189 ± 0.0008	0.9306 ± 0.0008	**0.9443 ± 0.0017**	**0.9776 ± 0.0012**
SST-2	l1	0.01	0.9326 ± 0.0005	-0.0026 ± 0.0005	0.4279 ± 0.0004	**0.9206 ± 0.0009**	0.9275 ± 0.0008	0.9413 ± 0.0012	0.9752 ± 0.0008
		0.10	0.9177 ± 0.0003	-0.0023 ± 0.0003	0.4328 ± 0.0003	0.9194 ± 0.0006	**0.9284 ± 0.0006**	0.9401 ± 0.0010	0.9772 ± 0.0010
		1.00	0.8711 ± 0.0003	**0.0170 ± 0.0003**	**0.4400 ± 0.0003**	0.9182 ± 0.0012	0.9277 ± 0.0011	0.9392 ± 0.0015	**0.9776 ± 0.0010**
	l2	0.01	0.9436 ± 0.0005	-0.0386 ± 0.0005	0.4034 ± 0.0004	0.9198 ± 0.0005	0.9256 ± 0.0005	0.9411 ± 0.0014	0.9736 ± 0.0016
		0.10	**0.9438 ± 0.0005**	-0.0255 ± 0.0004	0.4169 ± 0.0006	0.9196 ± 0.0007	0.9269 ± 0.0010	0.9394 ± 0.0013	0.9736 ± 0.0021
		1.00	0.9429 ± 0.0003	-0.0118 ± 0.0002	0.4266 ± 0.0003	0.9198 ± 0.0008	0.9257 ± 0.0002	**0.9417 ± 0.0008**	0.9752 ± 0.0014
TREC-6	l1	0.01	0.9528 ± 0.0005	0.0114 ± 0.0005	0.4203 ± 0.0001	0.9216 ± 0.0011	0.9250 ± 0.0008	0.9378 ± 0.0025	0.9724 ± 0.0020
		0.10	0.9296 ± 0.0005	0.0262 ± 0.0008	0.4133 ± 0.0003	0.9201 ± 0.0004	0.9269 ± 0.0009	0.9424 ± 0.0011	**0.9764 ± 0.0012**
		1.00	0.4836 ± 0.0007	**0.0568 ± 0.0013**	**0.4434 ± 0.0004**	0.9190 ± 0.0006	**0.9288 ± 0.0004**	0.9411 ± 0.0007	0.9756 ± 0.0007
	l2	0.01	0.9720 ± 0.0014	-0.0209 ± 0.0012	0.4011 ± 0.0013	**0.9217 ± 0.0008**	0.9265 ± 0.0006	**0.9438 ± 0.0017**	0.9716 ± 0.0015
		0.10	**0.9724 ± 0.0007**	-0.0159 ± 0.0006	0.4166 ± 0.0005	0.9207 ± 0.0008	0.9268 ± 0.0006	0.9397 ± 0.0008	0.9680 ± 0.0021
		1.00	0.9680 ± 0.0011	-0.0086 ± 0.0013	0.4233 ± 0.0008	0.9203 ± 0.0009	0.9263 ± 0.0009	0.9417 ± 0.0018	0.9716 ± 0.0007

Table 13: Effect of regularization on primary and secondary scores.