BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models

Anonymous ACL submission

Abstract

We show that with small-to-medium training data, fine-tuning only the bias terms (or a subset of the bias terms) of pre-trained BERT models is competitive with (and sometimes better than) fine-tuning the entire model. For larger data, bias-only fine-tuning is competitive with other sparse fine-tuning methods. Besides their practical utility, these findings are relevant for the question of understanding the commonly-used process of finetuning: they support the hypothesis that finetuning is mainly about exposing knowledge induced by language-modeling training, rather than learning new task-specific linguistic knowledge.

1 Introduction

Large pre-trained transformer based language models, and in particular bidirectional masked language models from the BERT family (Devlin et al., 2018; Liu et al., 2019; Joshi et al., 2019), are responsible for significant gains in many NLP tasks. Under the common paradigm, the model is pre-trained on large, annotated corpora with the LM objective, and then *finetuned* on task-specific supervised data. The large size of these models make them expensive to train and, more importantly, expensive to deploy. This, along with theoretical questions on the extent to which finetuning must change the original model, has led researchers to consider fine-tuning variants where one identifies a small subset of the model parameters which need to be changed for good performance in end-tasks, while keeping all others intact (§2).

We present a simple and effective approach to fine tuning (§3), which has the following benefits:

1. Changing very few parameters per fine-tuned task.
2. Changing the same set of parameters for every tasks (task-invariance).
3. The changed parameters are both isolated and localized across the entire parameter space.
4. For small to medium training data, changing only these parameters reaches the same task accuracy as full fine-tuning, and sometimes even improves results.

Specifically, we show that freezing most of the network and **fine-tuning only the bias-terms** is surprisingly effective. Moreover, if we allow the tasks to suffer a small degradation in performance, we can fine-tune only two bias components (the "query" and "middle-of-MLP" bias terms), amounting to half of the bias parameters in the model, and only 0.04% of all model parameters.

This result has a large practical utility in deploying multi-task fine-tuned models in memory-constrained environments, as well as opens the way to trainable hardware implementations in which most of the parameters are fixed.

2 Background: fine-tuning and parameter-efficient fine-tuning

In transfer-learning via model fine-tuning, a pre-trained encoder network takes the input and produces contextualized representations. Then, a task-specific classification layer (here we consider linear classifiers) is added on top of the encoder, and the entire network (encoder+task specific classifiers) is trained end-to-end to minimize the task loss.

Desired properties. While fine-tuning per-task is very effective, it also results in a unique, large model for each pre-trained task, making it hard reason about as well as hard to deploy, especially as the number of tasks increases. Ideally, one would want a fine-tuning method that:
(i) matches the results of a fully fine-tuned model; (ii) changes only a small portion of the model's parameters; and (iii) enables tasks to arrive in a stream, instead of requiring simultaneous access to all datasets. For efficient hardware based deployments, it is further preferred that (iv): the set of parameters that change values is consistent across

different tasks.

Learning vs. Exposing. The feasibility of fulfilling the above requirements depends on a fundamental question regarding the nature of the fine-tuning process of large pre-trained LMs: to what extent does the fine-tuning process induces the *learning of new capabilities*, vs. the *exposing of existing capabilities*, which were learned during the pre-training process. If fine-tuning can be cast as exposure of existing capabilities, this can allow for more efficient fine-tuning and deployment, by building on the frozen, pre-trained model, and constraining the fine-tuning to a "small", task-specific modification, rather than unconstrained fine tuning over the entire parameter space.

Existing approaches. Two recent works have demonstrated that adaptation to various end-tasks can in fact be achieved by changing only a small subset of parameters. The first work, by Houlsby et al. (2019) ("Adapters"), achieves this goal by injecting small, trainable task-specific "adapter" modules between the layers of the pre-trained model, where the original parameters are shared between tasks. The second work, by Guo et al. (2020) ("Diff-Pruning"), achieves the same goal by adding a sparse, task-specific difference-vector to the original parameters, which remain fixed and are shared between tasks. The difference-vector is regularized to be sparse. Both methods allow adding only a small number of trainable parameters per-task (criteria ii), and each task can be added without revisiting previous ones (criteria iii). They also partially fulfill criteria (i), suffering only a small drop in performance compared to full fine-tuning. The Adapter method, but not the Diff-Pruning method, also supports criteria (iv). However, Diff-Pruning is more parameter efficient than the Adapter method, and also achieves better task scores. We compare against Diff-Pruning and Adapters in the experiments section, and show that we perform favorably on many tasks while also satisfying criteria (iv).

3 Bias-terms Fine-tuning (BitFit)

We propose a method we call BitFit (BIas-Term FIne-Tuning), in which we freeze most of the transformer-encoder parameters, and train only the bias-terms and the task-specific classification layer.

The approach is parameter-efficient: each new task requires storing only the bias terms parameter vectors (which amount to less than 0.1% of the total number of parameters), and the task-specific final linear classifier layer.

Concretely, the BERT encoder is composed of L layers, where each layer ℓ starts with M self-attention heads, where a self attention head (m, ℓ) has *key*, *query* and *value* encoders, each taking the form of a linear layer:

$$\mathbf{Q}^{m,\ell}(\mathbf{x}) = \mathbf{W}_q^{m,\ell}\mathbf{x} + \mathbf{b}_q^{m,\ell}$$
$$\mathbf{K}^{m,\ell}(\mathbf{x}) = \mathbf{W}_k^{m,\ell}\mathbf{x} + \mathbf{b}_k^{m,\ell}$$
$$\mathbf{V}^{m,\ell}(\mathbf{x}) = \mathbf{W}_v^{m,\ell}\mathbf{x} + \mathbf{b}_v^{m,\ell}$$

Where $\mathbf{x}$ is the output of the former encoder layer (for the first encoder layer $\mathbf{x}$ is the output of the embedding layer). These are then combined using an attention mechanism that does not involve new parameters:

$$\mathbf{h}_1^\ell = att\big(\mathbf{Q}^{1,\ell}, \mathbf{K}^{1,\ell}, \mathbf{V}^{1,\ell}, \ldots, \mathbf{Q}^{m,\ell}, \mathbf{K}^{m,\ell}, \mathbf{V}^{m,l}\big)$$

and then fed to an MLP with layer-norm (LN):

$$\mathbf{h}_2^\ell = \text{Dropout}\big(\mathbf{W}_{m_1}^\ell \cdot \mathbf{h}_1^\ell + \mathbf{b}_{m_1}^\ell\big) \quad (1)$$
$$\mathbf{h}_3^\ell = \mathbf{g}_{LN_1}^\ell \odot \frac{(\mathbf{h}_2^\ell + \mathbf{x}) - \mu}{\sigma} + \mathbf{b}_{LN_1}^\ell \quad (2)$$
$$\mathbf{h}_4^\ell = \text{GELU}\big(\mathbf{W}_{m_2}^\ell \cdot \mathbf{h}_3^\ell + \mathbf{b}_{m_2}^\ell\big) \quad (3)$$
$$\mathbf{h}_5^\ell = \text{Dropout}\big(\mathbf{W}_{m_3}^\ell \cdot \mathbf{h}_4^\ell + \mathbf{b}_{m_3}^\ell\big) \quad (4)$$
$$\text{out}^\ell = \mathbf{g}_{LN_2}^\ell \odot \frac{(\mathbf{h}_5^\ell + \mathrm{h}_3^\ell) - \mu}{\sigma} + \mathbf{b}_{LN_2}^\ell \quad (5)$$

The collection of all matrices $\mathbf{W}_{(\cdot)}^{\ell,(\cdot)}$ and vectors $\mathbf{g}_{(\cdot)}^\ell$, $\mathbf{b}_{(\cdot)}^{\ell,(\cdot)}$, indicated in blue and purple are the network's *parameters* Θ, where the subset of purple vectors $\mathbf{b}_{(\cdot)}^{\ell,(\cdot)}$ are the *bias terms*.[1]

The bias terms are additive, and correspond to a very small fraction of the network, in $\text{BERT}_{\text{BASE}}$ and $\text{BERT}_{\text{LARGE}}$ bias parameters make up 0.09% and 0.08% of the total number of parameters in each model, respectively.

We show that by freezing all the parameters $\mathbf{W}^{(\cdot)}$ and $\mathbf{g}^{(\cdot)}$ and fine-tuning only the additive bias terms $\mathbf{b}^{(\cdot)}$, we achieve transfer learning performance which is comparable (and sometimes better!) than fine-tuning of the entire network.

We also show that we can fine-tune only a subset of the bias parameters, namely those associated with the *query* and the *second MLP layer* (only $\mathbf{b}_q^{(\cdot)}$ and $\mathbf{b}_{m_2}^{(\cdot)}$), and still achieve accuracies that rival full-model fine-tuning.

[1] In Appendix §A.1 we relate this notation with parameter names in HuggingFace implementation.

		%Param	QNLI	SST-2	MNLI_m	MNLI_mm	CoLA	MRPC	STS-B	RTE	QQP
	Train size		105k	67k	393k	393k	8.5k	3.7k	7k	2.5k	364k
(V)	Full-FT†	100%	93.5	94.1	86.5	87.1	62.8	91.9	89.8	71.8	87.6
(V)	Full-FT	100%	91.5	93.4	85.5	85.8	60.1	90.1	89.9	71.7	87.5
(V)	Diff-Prune†	0.1%	92.7	93.3	85.6	85.9	58	87.4	86.3	68.6	85.2
(V)	BitFit	0.08%	91.8	93.3	84.6	84.8	63.4	91.5	90.3	75.1	85.6
(T)	Full-FT‡	100%	91.1	94.1	86.7	86.0	59.6	88.9	86.6	71.2	71.7
(T)	Full-FT†	100%	93.4	94.9	86.7	85.9	60.5	89.3	87.6	70.1	72.1
(T)	Adapters‡	3.6%	90.7	94.0	84.9	85.1	59.5	89.5	86.9	71.5	71.8
(T)	Diff-Prune†	0.5%	93.3	94.1	86.4	86.0	61.1	89.7	86.0	70.6	71.1
(T)	BitFit	0.08%	92.0	94.1	84.5	84.8	59.7	88.9	85.5	72.0	70.5

Table 1: BERT_LARGE model performance on the GLUE benchmark validation set (V) and test set (T). Lines with † and ‡ indicate results taken from Guo et al. (2020) and Houlsby et al. (2019) (respectively).

4 Experiments and Results

Datasets. We evaluate BitFit on the GLUE benchmark (Wang et al., 2018).[2] Consistent with previous work (Houlsby et al., 2019; Guo et al., 2020) we exclude the WNLI task, on which BERT models do not outperform the majority baseline.

Models and Optimization. We use the publicly available pre-trained BERT_BASE, BERT_LARGE (Devlin et al., 2018) and $\text{RoBERTa}_\text{BASE}$ (Liu et al., 2019) models, using the HuggingFace interface and implementation. Appendix §A.2 lists optimization details.

Comparison to Diff-Pruning and Adapters (Table 1) In the first experiment, we compare BitFit to Diff-Pruning method and Adapters method, when using a fewer number of parameters. Table 1 reports the dev-set and test-set accuracies compared to the Diff-Pruning and Adapters numbers reported by Guo et al. (2020) and Houlsby et al. (2019) (respectively), on their least-parameters setting. This experiment used the BERT_LARGE model.

On validation set, BitFit outperforms Diff-Pruning on 5 out of 9 tasks, and underperforms in 3, while using fewer trainable parameters [3]. Test-set results are less conclusive (only one clear win compared to Diff-Pruning and 3 clear wins compared to Adapters), though BitFit is still competitive with both Diff-Pruning and Adapters.

Different Base-models (Table 2) We repeat the BERT_LARGE results on different base-models (the smaller BERT_BASE and the better performing $\text{RoBERTa}_\text{BASE}$). The results in Table 2 show that the trends remain consistent.

Are bias parameters special? are the bias parameters special, or will any random subset do?

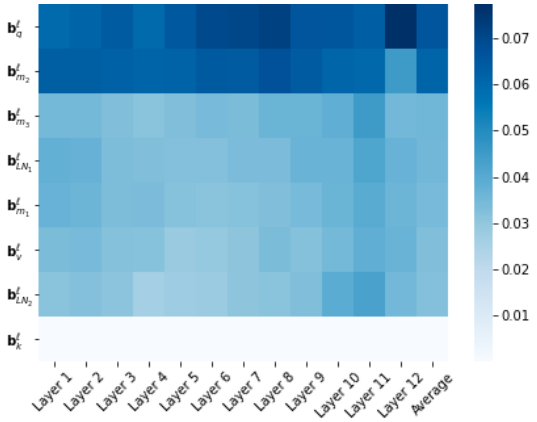

Figure 1: Change in bias components (RTE task).

We sampled the same amount of parameters as in BitFit from the entire model, and fine-tuned only them ("rand 100k" line in Table 3). The result are substantially worse across all tasks.

Fewer bias parameters (Table 3) Can we fine-tune on only a subset of the bias-parameter?

We define the amount of change in a bias vector $\mathbf{b}$ to be $\frac{1}{\dim(\mathbf{b})}\|\mathbf{b}_0 - \mathbf{b}_F\|_1$, that is, the average absolute change, across its dimensions, between the initial LM values $\mathbf{b}_0$ and its fine-tuned values $\mathbf{b}_F$. Figure 1 shows the change per bias term and layer, for the RTE task (other tasks look very similar, see Appendix §A.4). The 'key' bias $\mathbf{b}_k$ has zero change, consistent with the theoretical observation in (Cordonnier et al., 2020). In contrast, $\mathbf{b}_q$, the bias of the queries, and $\mathbf{b}_{m2}$, the bias of the intermediate MLP layers (which take the input from 768-dims to 3072), change the most. Table 3 reports dev-set results when fine-tuning only the $\mathbf{b}_q^{(\cdot)}$ and $\mathbf{b}_{m2}^{(\cdot)}$ bias terms, for the BERT_BASE model. Results are only marginally lower than when tuning all bias parameters. Tuning either $\mathbf{b}_q^{(\cdot)}$ or $\mathbf{b}_{m2}^{(\cdot)}$ alone (same table) yields substantially worse results, indicating both bias types are essential. As expected, freezing

[2] Appendix §A.3 lists the tasks and evaluation metrics.

[3] QNLI results are not directly comparable, as the GLUE benchmark updated the test set since then.

	Method	%Param	QNLI	SST-2	MNLI_m	MNLI_mm	CoLA	MRPC	STS-B	RTE	QQP
BB	Full-FT	100%	90.6	92.5	83.4	83.8	53.4	89.9	88.9	71.4	85.4
BB	BitFit	0.09%	90.5	92.7	81.5	82.2	57.5	91.7	89.3	76.5	84.2
BL	Full-FT	100%	91.5	93.4	85.5	85.8	60.1	90.1	89.9	71.7	87.5
BL	BitFit	0.08%	91.8	93.3	84.6	84.8	63.4	91.5	90.3	75.1	85.6
Ro	Full-FT	100%	91.9	93.6	86.2	86.6	61.3	92.5	90.8	79.2	88.0
Ro	BitFit	0.09%	91.8	93.7	84.4	84.9	62.0	92.7	90.8	81.5	84.0

Table 2: Dev-set results for different base models. **BB**: BERT_BASE. **BL**: BERT_LARGE. **Ro**: $\text{RoBERTa}_\text{BASE}$.

	% Param	QNLI	SST-2	MNLI_m	MNLI_mm	CoLA	MRPC	STS-B	RTE	QQP
Full-FT	100%	**90.6**	92.5	**83.4**	**83.8**	53.4	89.9	88.9	71.4	**85.4**
BitFit	0.09%	90.5	**92.7**	81.5	82.2	**57.5**	**91.7**	**89.3**	**76.5**	84.2
$\mathbf{b}_{m2}, \mathbf{b}_q$	0.04%	90.2	92.3	80.5	81.7	57.4	87.9	88.9	72.7	84.4
$\mathbf{b}_{m2}$	0.03%	89.9	92.1	80.0	80.7	57.5	86.9	88.5	65.4	82.7
$\mathbf{b}_q$	0.01%	87.2	91.5	74.3	75.9	55.5	86.4	87.8	65.4	80.8
Frozen	0.0%	68.6	82.1	42.1	43.4	39.1	80.9	69.2	58.1	62.1
rand 100k	0.09%	86.7	90.7	78.1	78.6	46.2	83.2	86.8	62.1	82.1

Table 3: Fine-tuning using a subset of the bias parameters. Reported results are for the BERT_BASE model.

all BERT_BASE layers ("Frozen" row) yields much worse results.

Generalization gap. When considering the generalization gap, we see that it is substantially smaller for the BitFit models: while for full fine-tuning the train set accuracy reaches nearly 100%, in the bias-only fine-tuned models the difference between the train and test set performance is often less than 2%.

Token-level tasks. The GLUE tasks are all sentence level. We also experimented with token-level PTB POS-tagging. Full-FT results for BERT_BASE, BERT_LARGE and $\text{RoBERTa}_\text{BASE}$ are 97.2, 97.4, 97.2, while BitFit results are 97.2, 97.4, 97.1.

Size of training data. The GLUE results suggest a reverse correlation between BitFit ability to reach Full-FT performance, and training set size. To test this (and to validate another token-level task), we train on increasing-sized subsets of SQuAD v1.0 (Rajpurkar et al., 2016). The results on Figure 2 show a clear trend: BitFit dominates over Full-FT in the smaller-data regime, while the trend is reversed when more training data is available. We conclude that BitFit is a worthwhile targetted fine-tuning method in small-to-medium data regimes.

5 Related Work

Bias terms and their importance are rarely discussed in the literature[4]. Zhao et al. (2020) describe a masking-based fine-tuning method, and explicitly mention *ignoring* the bias terms, as handling them

[4]Indeed, the equations in the paper introducing the Transformer model (Vaswani et al., 2017) do not include bias terms at all, and their existence in the BERT models might as well be a fortunate mistake.

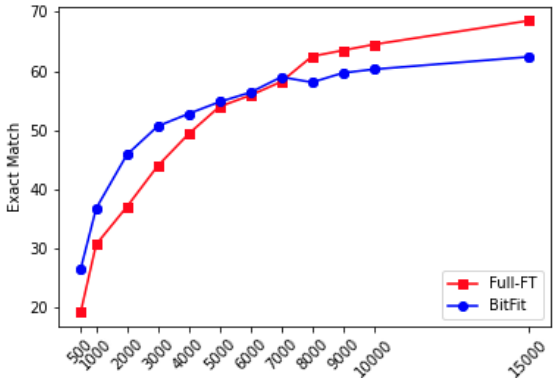

Figure 2: Comparison of BitFit and Full-FT with BERT_BASE exact match score on SQuAD validation set.

"did not observe a positive effect on performance".

An exception is the work of Wang et al. (2019) who analyzed bias terms from the perspective of attribution method. They demonstrate that the last layer bias values are responsible for the predicted class, and propose a way to back-propagate their importance. Michel and Neubig (2018) finetuned the biases of the output softmax in an NMT systems, to personalize the output vocabulary. Finally, Cai et al. (2020) demonstrate that bias-only fine-tuning similar to ours is effective also for adaptation of pre-trained computer vision models.

6 Discussion

Besides its empirical utility, the remarkable effectiveness of bias-only fine-tuning raises intriguing questions on the fine-tuning dynamics of pre-trained transformers, and the relation between the bias terms and transfer between LM and new tasks. We aim to study those questions in a future work.

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A Appendices

A.1 Layer naming

For convenience, we relate the notation used in the paper with the names of the corresponding parameters in the popular HuggingFace implementation.

HuggingFace Parameter Name	BitFit notation
attention.self.query.bias	$\mathbf{b}_q$
attention.self.key.bias	$\mathbf{b}_k$
attention.self.value.bias	$\mathbf{b}_v$
attention.output.dense.bias	$\mathbf{b}_{m_1}$
attention.output.LayerNorm.bias	$\mathbf{b}_{LN_1}$
intermediate.dense.bias	$\mathbf{b}_{m_2}$
output.dense.bias	$\mathbf{b}_{m_3}$
output.LayerNorm.bias	$\mathbf{b}_{LN_2}$

Table 4: Mapping the HuggingFace's BertLayer bias parameters names to BitFit paper bias notation.

A.2 Training Details

To perform classification with BERT, we follow the approach of Devlin et al. (2018), and attach a linear layer to the contextual embedding of the `CLS` token to predict the label. The GLUE tasks are fed into BERT using the standard procedures.

We optimize using AdamW (Loshchilov and Hutter, 2017), with batch sizes of 8. For full fine-tuning, we used initial learning rates in {1e-5, 2e-5, 3e-5, 5e-5}, and for the bias-only experiments we used initial learning rates in {1e-4, 4e-4, 7e-4, 1e-3} as the smaller rates took a very long time to converge on some of the tasks. With the larger learning rates, the bias-only fine-tuning converged in 7 or fewer epochs for most tasks, and up to 20 epochs on the others. We did not perform hyper-parameter optimization beyond the minimal search over 4 learning rates.

As Mosbach et al. (2020) show, fine-tuning $\text{BERT}_{\text{LARGE}}$ and $\text{RoBERTa}_{\text{BASE}}$ is a unstable due to vanishing gradients. BitFit allows for the usage of bigger learning rates, and overall the optimization process is much more stable, when compared with a full fine-tuning.

A.3 GLUE Benchmark

We provide information on the GLUE tasks we evaluated on, as well as on the evaluation metrics. We test our approach on the following subset of the GLUE (Wang et al., 2018) tasks: The Corpus of Linguistic Acceptability (CoLA), The Stanford Sentiment Treebank (SST-2), The Microsoft Research Paraphrase Corpus (MRPC), The Quora Question Pairs (QQP), The Semantic Textual Similarity Benchmark (STS-B), The Multi-Genre Natural Language Inference Corpus (MNLI), The Stanford Question Answering Dataset (QNLI) and The Recognizing Textual Entailment (RTE).

The metrics that we used to evaluate GLUE Benchmark are in Table 5. Learning rate configurations for best performing models are in Table 6.

Task Name	Metric
QNLI	acc.
SST-2	acc.
MNLI	matched acc./mismatched acc.
CoLA	Matthews corr.
MRPC	F1
STS-B	Spearman corr.
RTE	acc.
QQP	F1

Table 5: Metrics that we use to evaluate GLUE Benchmark.

Task Name	$\text{BERT}_{\text{BASE}}$	$\text{BERT}_{\text{LARGE}}$
QNLI	1e-4	7e-4
SST-2	4e-4	4e-4
MNLI	1e-4	1e-4
CoLA	7e-4	4e-4
MRPC	7e-4	1e-3
STS-B	1e-4	1e-4
RTE	1e-3	4e-4
QQP	4e-4	4e-4

Table 6: Learning rate configurations for best performing models.

A.4 Amount of change in bias terms

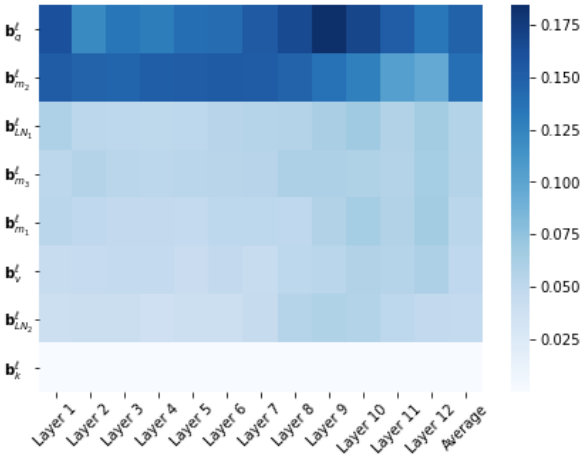

Figure 3: Change in bias components (CoLA task).

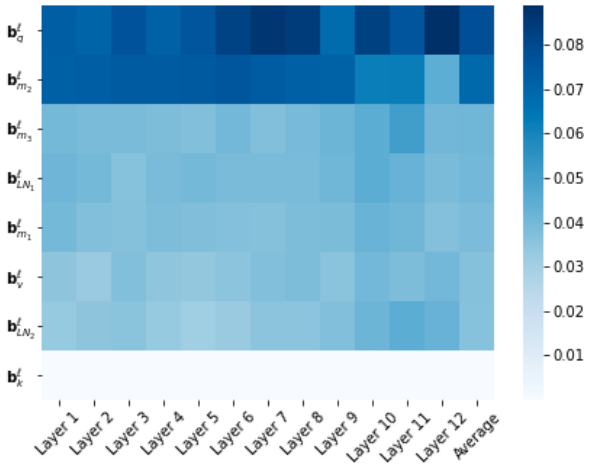

Figure 4: Change in bias components (MRPC task).

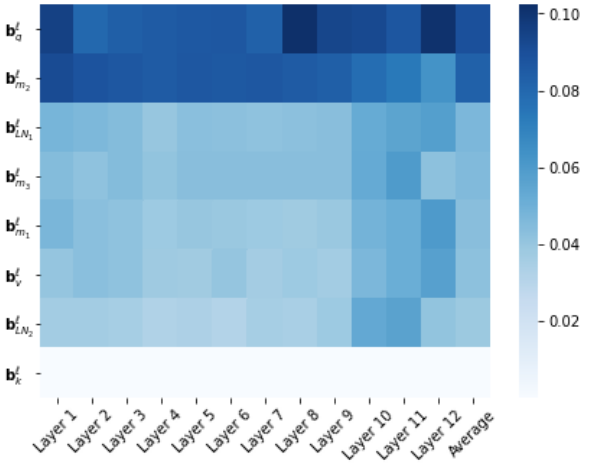

Figure 5: Change in bias components (STS-B task).

A.5 SQuAD F1 Results

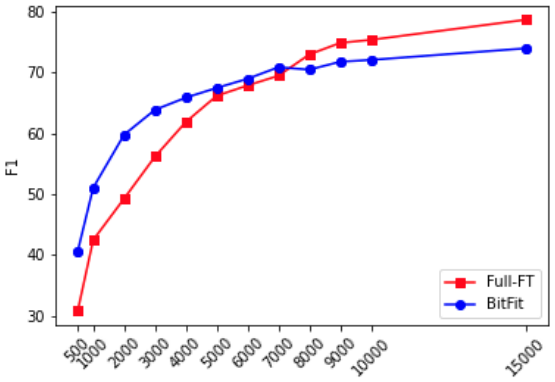

Figure 6: Comparison of BitFit and Full-FT with $\text{BERT}_{\text{BASE}}$ F1 score on SQuAD validation set.