Parameter-Efficient Transfer Learning for NLP

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Abstract

Fine-tuning large pre-trained models is an effective transfer mechanism in NLP. However, in the presence of many downstream tasks, fine-tuning is parameter inefficient: an entire new model is required for every task. As an alternative, we propose transfer with adapter modules. Adapter modules yield a compact and extensible model; they add only a few trainable parameters per task, and new tasks can be added without revisiting previous ones. The parameters of the original network remain fixed, yielding a high degree of parameter sharing. To demonstrate adapter's effectiveness, we transfer the recently proposed BERT Transformer model to 26 diverse text classification tasks, including the GLUE benchmark. Adapters attain near state-of-the-art performance, whilst adding only a few parameters per task. On GLUE, we attain within 0.4% of the performance of full fine-tuning, adding only 3.6% parameters per task. By contrast, fine-tuning trains 100% of the parameters per task.

1. Introduction

Transfer from pre-trained models yields strong performance on many NLP tasks (Dai & Le, 2015; Howard & Ruder, 2018; Radford et al., 2018). Recently, BERT, a Transformer network trained on large text corpora with an unsupervised loss, attained state-of-the-art performance on text classification and extractive question answering datasets (Devlin et al., 2018).

In this paper we consider the online setting, where tasks arrive in a stream. The goal is to build a system that performs well on all of them, but without training an entire new model for every new task. A high degree of sharing between tasks is particularly useful for applications such as cloud services, where models need to be trained to solve many tasks that arrive from customers in sequence. For this, we

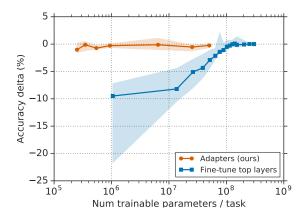


Figure 1. Trade-off between accuracy and number of trained task-specific parameters, for adapter tuning and fine-tuning. The y-axis is normalized by the performance of full fine-tuning, details in Section 3. The curves show the 20th, 50th, and 80th performance percentiles across nine tasks from the GLUE benchmark. Adapter-based tuning attains a similar performance to full fine-tuning with two orders of magnitude fewer trained parameters.

propose a transfer learning strategy that yields *compact* and *extensible* downstream models. Compact models are those that solve many tasks using a small number of additional parameters per task. Extensible models can be trained incrementally to solve new tasks, without forgetting previous ones. Our method yields a highly compact and extensible model without sacrificing performance.

The two most common transfer learning techniques in NLP are feature-based transfer and fine-tuning. We present an alternative transfer method based on adapter modules (Rebuffi et al., 2017). Features-based transfer typically involves pretraining real-valued embeddings vectors. These embeddings may be at the word (Mikolov et al., 2013), sentence (Cer et al., 2019), or paragraph level (Le & Mikolov, 2014). The embeddings are then fed to custom downstream models. Instead, fine-tuning involves copying the weights from a pre-trained network and tuning them on the downstream task. Recent work shows that fine-tuning often enjoys better performance than feature-based transfer (Howard & Ruder, 2018).

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Both feature-based transfer and fine-tuning require a new set of weights for each task. Fine-tuning is more parameter efficient if the lower layers of a network are shared between tasks. However, our proposed adapter tuning method is even more parameter efficient. Figure 1 demonstrates this trade-off. The figure shows that adapter tuning achieves a comparable quality to full fine-tuning. The x-axis shows the number of parameters trained per task; this corresponds to the marginal increase in the model size required to solve each additional task. Adapter-based tuning requires training two orders of magnitude fewer parameters to fine-tuning, while attaining similar performance.

Adapters are new modules added between layers of a pre-trained network. Adapter-based tuning differs from feature-based transfer and fine-tuning in the following way. Consider a function (neural network) with parameters w: $\phi_{w}(x)$. Feature-based transfer composes ϕ_{w} with a new function, $\chi_{\boldsymbol{v}}$, to yield $\chi_{\boldsymbol{v}}(\phi_{\boldsymbol{w}}(\boldsymbol{x}))$. Only the new, taskspecific, parameters, v, are then trained. Fine-tuning involves adjusting the original parameters, w, for each new task, limiting compactness. For adapter tuning, a new function, $\psi_{w,v}(x)$, is defined, where parameters w are copied over from pre-training. The initial parameters v_0 are set such that the new function resembles the original: $\psi_{\boldsymbol{w},\boldsymbol{v}_0}(\boldsymbol{x}) \approx \phi_{\boldsymbol{w}}(\boldsymbol{x})$. During training, only \boldsymbol{v} are tuned. For deep networks, defining $\psi_{{m w},{m v}}$ typically involves adding new layers to the original network, $\phi_{\boldsymbol{w}}$. If one chooses $|v| \ll |w|$, the resulting model requires $\sim |w|$ parameters for many tasks. Since w is fixed, the model can be extended to new tasks without affecting previous ones.

Adapter-based tuning relates to *multi-task* and *continual* learning. Multi-task learning also results in compact models. However, multi-task learning requires simultaneous access to all tasks, which adapter-based tuning does not require. Continual learning systems aim to learn from an endless stream of tasks. This paradigm is challenging because networks forget previous tasks after re-training (McCloskey & Cohen, 1989; French, 1999). Adapters differ in that the tasks to not interact and the shared parameters are frozen. This means that the model has perfect memory of previous tasks using a small number of task-specific parameters.

We demonstrate on a large and diverse set of text classification tasks that adapters yield parameter-efficient tuning for NLP. The key innovation is to design an effective adapter module and its integration with the base model. We propose a simple yet effective, bottleneck architecture. On the GLUE benchmark, our strategy almost matches the performance of the fully fine-tuned BERT, but uses only 3% task-specific parameters, while fine-tuning uses 100% task-specific parameters. We observe similar results on a further 17 public text datasets. In summary, adapter-based tuning yields a single, extensible, model that attains near state-of-the-art

performance in text classification.

2. Adapter tuning for NLP

We present a strategy for tuning a large text model on several downstream tasks. Our strategy has three key properties: (i) it attains good performance, (ii) it permits training on tasks sequentially, that is, it does not require simultaneous access to all datasets, and (iii) it adds only a small number of additional parameters per task. These properties are especially useful in the context of cloud services, where many models need to be trained on a series of downstream tasks, so a high degree of sharing is desirable.

To achieve these properties, we propose a new bottleneck adapter module. Tuning with adapter modules involves adding a small number of new parameters to a model, which are trained on the downstream task (Rebuffi et al., 2017). When performing vanilla fine-tuning of deep networks, a modification is made to the top layer of the network. This is required because the label spaces and losses for the upstream and downstream tasks differ. Adapter modules perform more general architectural modifications to re-purpose a pretrained network for a downstream task. In particular, the adapter tuning strategy involves injecting new layers into the original network. The weights of the original network are untouched, whilst the new adapter layers are initialized at random. In standard fine-tuning, the new top-layer and the original weights are co-trained. In contrast, in adaptertuning, the parameters of the original network are frozen and therefore may be shared by many tasks.

Adapter modules have two main features: a small number of parameters, and a near-identity initialization. The adapter modules need to be small compared to the layers of the original network. This means that the total model size grows relatively slowly when more tasks are added. A near-identity initialization is required for stable training of the adapted model; we investigate this empirically in Section 3.5. By initializing the adapters to a near-identity function, original network is unaffected when training starts. During training, the adapters may then be activated to change the distribution of activations throughout the network. The adapter modules may also be ignored if not required; in Section 3.5 we observe that some adapters have more influence on the network than others. We also observe that if the initialization deviates too far from the identity function, the model may fail to train.

2.1. Instantiation for Transformer Networks

We instantiate adapter-based tuning for text Transformers. These models attain state-of-the-art performance in many NLP tasks, including translation, extractive QA, and text classification problems (Vaswani et al., 2017; Radford et al.,

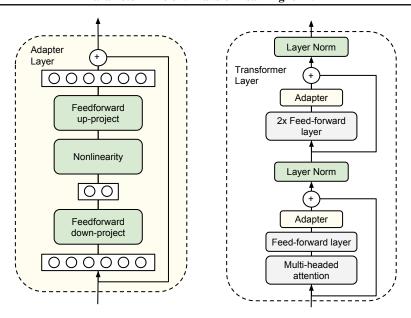


Figure 2. Architecture of the adapter module and its integration with the Transformer. **Left:** The adapter consists of a bottleneck which contains few parameters relative to the attention and feedforward layers in the original model. The adapter also contains a skip-connection. During adapter tuning, the green layers are trained on the downstream data, this includes the adapter, the layer normalization parameters, and the final classification layer (not shown in the figure). **Right:** We add the adapter module twice to each Transformer layer: after the projection following multi-headed attention and after the two feed-forward layers.

2018; Devlin et al., 2018). We consider the standard Transformer architecture, as proposed in Vaswani et al. (2017).

Adapter modules present many architectural choices. We provide a simple design that attains good performance. We experimented with a number of more complex designs, see Section 3.5, but we found the following strategy performed as well as any other that we tested, across many datasets.

Figure 2 shows our adapter architecture, and its application it to the Transformer. Each layer of the Transformer contains two primary sub-layers: an attention layer and a feedforward layer. Both layers are followed immediately by a projection that maps the features size back to the size of layer's input. A skip-connection is applied across each of the sub-layers. The output of each sub-layer is fed into layer normalization. We insert two serial adapters after each of these sub-layers. The adapter is always applied directly to the output of the sub-layer, after the projection back to the input size, but before adding the skip connection back. The output of the adapter is then passed directly into the following layer normalization.

To limit the number of parameters, we propose a bottleneck architecture. The adapters first project the original d-dimensional features into a smaller dimension, m, apply a nonlinearity, then project back to d dimensions. The total number of parameters added per layer, including biases, is 2md + d + m. By setting $m \ll d$, we limit the number of parameters added per task; in practice, we use around 0.5-8% of the parameters of the original model. The bottleneck dimension, m, provides a simple means to trade-off performance with parameter efficiency. The adapter module itself has a skip-connection internally. With the skip-connection, if the parameters of the projection layers are initialized to near-zero, the module is initialized to an approximate identity function.

Alongside the layers in the adapter module, we also train new layer normalization parameters per task. This technique, similar to conditional batch normalization (De Vries et al., 2017), FiLM (Perez et al., 2018), and self-modulation (Chen et al., 2019), also yields parameter-efficient adaptation of a network; with only 2d parameters per layer. However, training the layer normalization parameters alone is insufficient for good performance, see Section 3.4.

3. Experiments

We show on many datasets that adapters achieve parameter efficient transfer for text classification. On the GLUE benchmark (Wang et al., 2018), adapter tuning is within 0.4% of full fine-tuning of BERT, but it adds only 3% of the number of parameters trained by fine-tuning. We confirm this result on a further 17 public classification tasks. We finish with an analysis that shows that adapter-based tuning automatically focuses on the higher layers and is robust to choices such as initialization scheme and number of neurons.

3.1. Experimental Settings

We use the public, pre-trained BERT Transformer network as our base model. To perform classification with BERT, we take the approach presented in Devlin et al. (2018). The first token in each sequence is a special "classification token". We attach a linear layer to the embedding of this token to predict the class label.

Our training procedure follows Devlin et al. (2018). We optimize using Adam (Kingma & Ba, 2014), whose learning rate is increased linearly over the first 10% of the steps, and then decayed linearly to zero. All training runs are performed on 4 Google Cloud TPUs with a batch size of 32. For each dataset and algorithm, we run a hyperparameter sweep and select the best model according to accuracy on the validation set. On the GLUE tasks, we report the test metrics provided by the submission website¹. We report test-set accuracy on the other datasets.

We compare to fine-tuning, the current standard for transfer of large pre-trained models, and the strategy successfully used by BERT. For N tasks, full fine-tuning requires $N \times$ the number of parameters of the pre-trained model. Our goal is to attain performance equal to fine-tuning, but with the fewest total parameters, ideally near to $1 \times$.

3.2. GLUE benchmark

We first evaluate on GLUE.² For these datasets, we transfer from the pre-trained BERT_{LARGE} model, which contains 24 layers, and a total of 330M parameters, see Devlin et al. (2018) for details. We perform a small hyperparameter sweep for adapter tuning: We sweep learning rates in $\{3 \cdot 10^{-5}, 3 \cdot 10^{-4}, 3 \cdot 10^{-3}\}$, and number of epochs in $\{3, 20\}$. We test both using a fixed adapter size (number of units in the bottleneck), and selecting the best size per task from $\{8, 64, 256\}$. The adapter size is the only adapter-specific hyperparameter that we tune. Finally, due to training instability, we rerun 5 times with different random seeds and select the best model on the validation set, similar to Devlin et al. (2018).

Table 1 summarizes the results. Adapters achieve a mean GLUE score of 80.0, compared to 80.4 achieved by full fine-tuning. The optimal adapter size varies per dataset. For example, 256 is chosen for MNLI, whereas for the smallest dataset, RTE, 8 is chosen. Restricting always to size 64, leads to a small decrease in average accuracy to 79.6. To solve all of the datasets in Table 1, fine-tuning requires $9\times$ the total number of BERT parameters. In contrast, adapters

only require $1.3\times$.

3.3. Additional Tasks

To further validate that adapters yields compact, performant, models, we test on additional public text classification tasks. This suite contains a diverse set of tasks: the number of training examples ranges from 900 to 330k, the number of classes ranges from 2 to 157, and the average text length ranging from 57 to 1.9k characters. We supply statistics and references for all of the datasets in the appendix.

For these datasets, we use a batch size of 32. The datasets are diverse, so we sweep a wide range of learning rates: $\{1 \cdot 10^{-5}, 3 \cdot 10^{-5}, 1 \cdot 10^{-4}, 3 \cdot 10^{-3}\}$. Due to the large number of datasets, we manually select the number of training epochs from the set $\{20, 50, 100\}$ by inspecting the validation set learning curves, rather than sweep this parameter. We selected optimal values for both fine-tuning and adapters; the exact values are in the appendix.

We test adapters sizes in $\{2,4,8,16,32,64\}$. Since some of the datasets are small, fine-tuning the entire network may be sub-optimal. Therefore, we run an additional baseline: variable fine-tuning. For this, we fine-tune only the top n layers, and freeze the remainder. We sweep $n \in \{1,2,3,5,7,9,11,12\}$. In these experiments, we use the BERT_{BASE} model with 12 layers, therefore variable fine-tuning becomes full fine-tuning when n=12.

Unlike the GLUE tasks, there is no comprehensive set of state-of-the-art numbers for this set of tasks. Therefore, to check that our BERT models (with and without adapters) are competitive, we collect our own benchmark performances. For this, we run a large-scale hyperparameter search over standard network topologies. Specifically, we run the single-task Neural AutoML algorithm, similar to Zoph & Le (2017); Wong et al. (2018). This algorithm searches over a space of feedforward and convolutional networks, stacked on top of pre-trained text embeddings modules publicly available via TensorFlow Hub⁴. The TensorFlow Hub embeddings may be frozen or fine-tuned. The full search space is described in the appendix. For each task, we run AutoML for one week on CPUs, using 30 machines. In this time the algorithm explores over 10k models on average per task. We select the best final model for each task according to validation set accuracy.

The results for the AutoML benchmark ("no BERT baseline"), fine-tuning, variable fine-tuning, and adapter-tuning are reported in Table 2. The AutoML baseline demonstrates that the BERT models are competitive. This baseline explores thousands of models, yet the BERT models perform

https://gluebenchmark.com/

² We omit WNLI as in Devlin et al. (2018) because the no current algorithm beats the baseline of predicting the majority class.

³ We treat MNLI_m and MNLI_{mm} as separate tasks with individ-

ually tuned hyperparameters. However, they could be combined into one model, leaving $8\times$ overall.

⁴https://www.tensorflow.org/hub

	Total num params	Trained params / task	CoLA	SST	MRPC	STS-B	QQP	MNLI _m	MNLI _{mm}	QNLI	RTE	Total
$BERT_{LARGE}$	9.0×	100%	60.5	94.9	89.3	87.6	72.1	86.7	85.9	91.1	70.1	80.4
Adapters (8-256)	1.3×	3.6%	59.5	94.0	89.5	86.9	71.8	84.9	85.1	90.7	71.5	80.0
Adapters (64)	1.2×	2.1%	56.9	94.2	89.6	87.3	71.8	85.3	84.6	91.4	68.8	79.6

Table 1. Results on GLUE test sets scored using the GLUE evaluation server. MRPC and QQP are evaluated using F1 score. STS-B is evaluated using Spearman's correlation coefficient. The other tasks are evaluated using accuracy. Adapter tuning achieves comparable overall score (80.0) to full fine-tuning (80.4) using $1.3 \times$ parameters in total, compared to $9 \times$. Fixing the adapter size to 64 leads to a slightly decreased overall score of 79.6 and slightly smaller model.

Dataset	No BERT baseline	BERT _{BASE} Fine-tune	BERT _{BASE} Variable FT	BERT _{BASE} Adapters
20 newsgroups	91.1	92.8 ± 0.1	92.8 ± 0.1	91.7 ± 0.2
Crowdflower airline	84.5	83.6 ± 0.3	84.0 ± 0.1	84.5 ± 0.2
Crowdflower corporate messaging	91.9	92.5 ± 0.5	92.4 ± 0.6	92.9 ± 0.3
Crowdflower disasters	84.9	85.3 ± 0.4	85.3 ± 0.4	84.1 ± 0.2
Crowdflower economic news relevance	81.1	82.1 ± 0.0	78.9 ± 2.8	82.5 ± 0.3
Crowdflower emotion	36.3	38.4 ± 0.1	37.6 ± 0.2	38.7 ± 0.1
Crowdflower global warming	82.7	84.2 ± 0.4	81.9 ± 0.2	82.7 ± 0.3
Crowdflower political audience	80.8	80.9 ± 0.3	80.7 ± 0.8	79.0 ± 0.5
Crowdflower political bias	76.8	75.2 ± 0.9	76.5 ± 0.4	75.9 ± 0.3
Crowdflower political message	43.8	38.9 ± 0.6	44.9 ± 0.6	44.1 ± 0.2
Crowdflower primary emotions	33.5	36.9 ± 1.6	38.2 ± 1.0	33.9 ± 1.4
Crowdflower progressive opinion	70.6	71.6 ± 0.5	75.9 ± 1.3	71.7 ± 1.1
Crowdflower progressive stance	54.3	63.8 ± 1.0	61.5 ± 1.3	60.6 ± 1.4
Crowdflower US economic performance	75.6	75.3 ± 0.1	76.5 ± 0.4	77.3 ± 0.1
Customer complaint database	54.5	55.9 ± 0.1	56.4 ± 0.1	55.4 ± 0.1
News aggregator dataset	95.2	96.3 ± 0.0	96.5 ± 0.0	96.2 ± 0.0
SMS spam collection	98.5	99.3 ± 0.2	99.3 ± 0.2	95.1 ± 2.2
Average	72.7	73.7	74.0	73.3
Total number of params	_	17×	9.9×	1.19×
Trained params/task	_	100%	52.9%	1.14%

Table 2. Test accuracy for additional classification tasks. In these experiments we transfer from the BERT_{BASE} model. For each task and algorithm, the model with the best validation set accuracy is chosen. We report the mean test accuracy and s.e.m. across runs with different random seeds.

better on average. We see a pattern of results similar to GLUE. The performance of adapter-tuning is close to full fine-tuning (0.4% behind). Fine-tuning requires $17\times$ the number of parameters to BERT_{BASE} to solve all tasks. Variable fine-tuning performs slightly better than fine-tuning, whilst training fewer layers. The optimal setting of variable fine-tuning results in training 52% of the network on average per task, reducing the total to $9.9\times$ parameters. Adapters, however, offer a much more compact model. They introduce 1.14% new parameters per task, resulting in $1.19\times$ parameters for all 17 tasks.

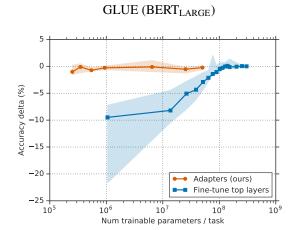
3.4. Parameter/Performance trade-off

The adapter size controls the parameter efficiency, smaller adapters introduce fewer parameters, at a possible cost to performance. To explore this trade-off, we consider different adapter sizes, and compare to two baselines: (i) Fine-tuning

of only the top k layers of BERT_{BASE}. (ii) Tuning only the layer normalization parameters. The learning rate is tuned using the same range as in Section 3.2.

Figure 3 shows the parameter/performance trade-off aggregated over all tasks in each suite. On GLUE, one sees a dramatic decrease in performance as fewer layers are tuned. Some of the additional tasks benefit from training fewer layers, so performance of fine-tuning decays much less. In both cases, adapters yield good performance across a range of sizes two orders of magnitude fewer than fine-tuning.

Figure 4 shows more details for two GLUE tasks: MNLI_m and CoLA. Top layer tuning has more task-specific parameters for all k>2. When fine-tuning using a comparable number of task-specific parameters, the performance decreases substantially compared to our strategy. For instance, fine-tuning just the top layer yields approximately 9M trainable parameters and $77.8\% \pm 0.1\%$ validation accuracy on



Additional tasks (BERT_{BASE})

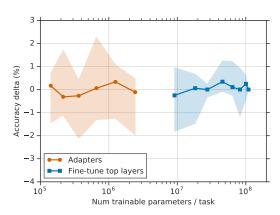
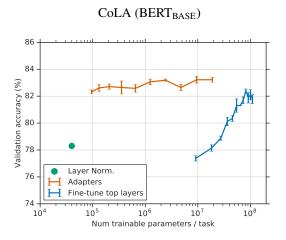


Figure 3. Accuracy versus the number of trained parameters, aggregated across tasks. We compare adapters of different sizes (orange) with fine-tuning the top n layers, for varying n (blue). The lines and shaded areas indicate the 20th, 50th, and 80th percentiles across tasks. For each task and algorithm, the best model is selected for each point along the curve. For GLUE, the validation set accuracy is reported (the test set accuracy requires submission to the GLUE server). For the additional tasks, we report the test set accuracies. To remove intra-task variance in scores, we normalize the score for each model and task by subtracting the performance of full fine-tuning on the corresponding task.



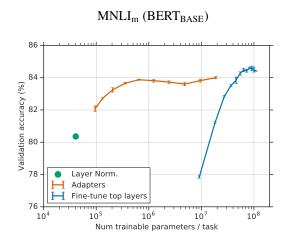


Figure 4. Validation set accuracy versus number of trained parameters for three methods: (i) Adapter tuning with an adapter sizes 2^n for $n = 0 \dots 9$ (orange). (ii) Fine-tuning the top k layers for $k = 1 \dots 12$ (blue). (iii) Tuning the layer normalization parameters only (green). Error bars indicate ± 1 s.e.m. across three random seeds.

 $\text{MNLI}_{\text{m}}.$ In contrast, adapter tuning with size 64 yields approximately 2M trainable parameters and $83.7\% \pm 0.1\%$ validation accuracy. For comparison full fine-tuning attains $84.4\% \pm 0.02\%$ on $\text{MNLI}_{\text{m}}.$ We observe a similar trend on CoLA.

As a further comparison, we tune the parameters of layer normalization alone. These layers only contain point-wise additions and multiplications, so introduce very few trainable parameters: $40 \mathrm{k}$ for BERT_{BASE}. However this strategy performs poorly: performance decreases by approximately 3.5% on CoLA and 4% on MNLI.

To summarize, adapter tuning is highly parameter-efficient, and is able to produce a compact model with a strong performance, comparable to full fine-tuning. Training

adapters with sizes 0.5-5% of the original model, performance is within 1% of the competitive published results on BERT_{LARGE}.

3.5. Analysis and Discussion

We provide additional analyses and discussion of the adapters. First, we perform an ablation to determine which adapters are most influential. For each layer in turn, we remove its adapters and evaluate the model on the validation set. The experiment is performed on BERT_{BASE} with adapter size 64 on MNLI and CoLA.

Figure 5 shows the results. The performance decrease is, perhaps surprisingly, always small; the largest drop is 2%.

In contrast, when all of the adapters are removed from the network, the performance drops to 69% on CoLA and to 37% on MNLI – scores attained by predicting the majority class on these datasets. This indicates that although each adapter has a small influence on the overall network, the overall effect is large.

Figure 5 also suggests that the adapters on the lower layers have a smaller effect than those on higher layers. This indicates that the strong performance of adapters might come from the way it prioritizes automatically the top layers. Indeed, the strategy to focus on the upper layers is popular in fine-tuning (Howard & Ruder, 2018). One possible intuition is that lower layers of the network extract lower-level features that are shared among tasks, while the higher layers build features that are unique to different tasks. This is related to our observation that for some tasks, fine-tuning only the top layers outperforms full fine-tuning, see Table 2.

Next, we investigate the robustness of the adapter modules to number of neurons and initialization scale. In our main experiments the weights of the fully connected layers in the adapter module were drawn from a zero-centered Gaussian with standard deviation of 10^{-2} , truncated to two standard deviations. To analyze the impact of the initialization scale on the performance, we pick standard deviations in the interval $[10^{-7},1]$. Figure 6 summarizes the results. We observe that on both datasets, the performance of adapters is robust for standard deviations below 10^{-2} . However, when the initialization is too large, performance degrades, more substantially on CoLA.

To investigate robustness of adapters to the number of neurons, we re-examine the experimental data from Section 3.2. We find that the quality of the model across adapter sizes is stable, and a fixed adapter size across all the tasks could be used with small detriment to performance. For each adapter size we calculate the mean validation accuracy across the eight classification tasks by selecting the optimal learning rate and number of epochs⁵. For adapter sizes 8, 64, and 256, the mean validation accuracies are 86.2%, 85.8% and 85.7%, respectively. This message is further corroborated by Figure 4, which shows a stable performance across few orders of magnitude.

Finally, we experimented with a number of extensions to the adapter's architecture that did not yield a significant boost in performance. We document them here for completeness. We experimented with (i) adding a batch/layer normalization to the adapter, (ii) increasing the number of layers per adapter, (iii) different activation functions, such as tanh, (iv) inserting adapters only inside the attention layer, (v) adding adapters in parallel to the main layers, and possibly with

a multiplicative interaction. In all cases we observed the resulting performance to be similar to the bottleneck proposed in Section 2.1. Therefore, due to its simplicity and strong performance, we recommend the original adapter architecture.

4. Related Work

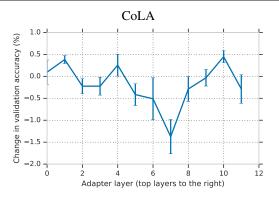
Pre-trained text representations Pre-trained textual representations are widely used to improve performance on NLP tasks. These representations are trained on large corpora (usually, but not always, unsupervised), and fed as features to downstream models. In deep networks, these features may also be fine-tuned on the downstream task. Brown clusters, trained on distributional information, are a classic example of pre-trained representations (Brown et al., 1992). Turian et al. (2010) show that pre-trained embeddings of words outperform those trained from scratch. Since the deep-learning era, word embeddings have been widely used, and training strategies these have arisen (Mikolov et al., 2013; Pennington et al., 2014; Bojanowski et al., 2017). Embeddings of longer texts, sentences and paragraphs, have also been developed (Le & Mikolov, 2014; Kiros et al., 2015; Conneau et al., 2017; Cer et al., 2019).

To encode context in these representations, features are extracted from internal representations of sequence models, such as MT systems (McCann et al., 2017), and BiLSTM language models, as used in ELMo (Peters et al., 2018). As with adapters, ELMo exploits the layers other than the top layer of a pre-trained network. However, this strategy only *reads* from the inner layers. In contrast, adapters *write* to the inner layers, re-configuring the processing of features through the entire network.

Fine-tuning Fine-tuning an entire pre-trained model has become a popular alternative to features (Dai & Le, 2015; Howard & Ruder, 2018; Radford et al., 2018) In NLP, the upstream model is usually a neural language model (Bengio et al., 2003). Recent state-of-the-art results on question answering (Rajpurkar et al., 2016) and text classification (Wang et al., 2018) have been attained by fine-tuning a Transformer network (Vaswani et al., 2017) with a Masked Language Model loss (Devlin et al., 2018). Performance aside, an advantage of fine-tuning is that it does not require task-specific model design, unlike representation-based transfer. However, vanilla fine-tuning does require a new set of network weights for every new task.

Multi-task Learning Multi-task learning (MTL) involves training on tasks simultaneously. Early work shows that sharing network parameters across tasks exploits task regularities, yielding improved performance (Caruana, 1997). The authors share weights in lower layers of a network,

 $^{^5}$ We treat here $MNLI_{m}$ and $MNLI_{mm}$ as separate tasks. For consistency, for all datasets we use accuracy metric and exclude the regression STS-B task.



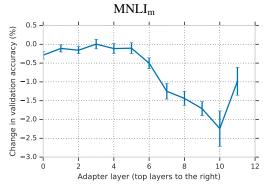


Figure 5. Ablation of trained adapters from each layer of BERT. x-axis: The index of the layer whose adapters are removed. y-axis: Relative performance of the model before and after ablation. Values smaller than zero indicate a decrease in performance after ablation. The line indicates the mean across three models trained with different random seeds, and the error bars indicate ± 1 s.e.m.

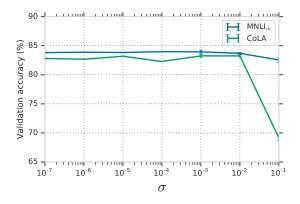


Figure 6. Performance of the BERT_{BASE} model with adapters under varying weight magnitude at initialization. The weights are sampled from a zero-centered, truncated normal distribution of standard deviation σ . Adapters are generally robust with respect to initialization parameters. However, performance rapidly decays when using standard deviations above 10^{-2} .

and use specialized higher layers. Many NLP systems have exploited MTL. Some examples include: text processing systems (part of speech, chunking, named entity recognition, etc.) (Collobert & Weston, 2008), multilingual models (Huang et al., 2013), semantic parsing (Peng et al., 2017), machine translation (Johnson et al., 2017), and question answering (Choi et al., 2017). MTL yields a single model to solve all problems. However, unlike our adapters, MTL requires simultaneous access to all of the tasks during training.

Continual Learning As an alternative to simultaneous training, continual, or lifelong, learning algorithms aim to learn from a sequence of tasks (Thrun, 1998). However, when re-trained, deep networks tend to forget how to perform previous tasks; a challenge termed catastrophic forgetting (McCloskey & Cohen, 1989; French, 1999). Techniques have been proposed to mitigate forgetting (Kirk-

patrick et al., 2017; Zenke et al., 2017), however, unlike for adapters, the memory is still imperfect. Progressive Networks avoid forgetting by instantiating a new network "column" for each task (Rusu et al., 2016). However, the number of parameters grows linearly with the number of tasks, since adapters are very small, our models scale much more favorably.

Transfer Learning in Visual Perception Fine-tuning models pre-trained on ImageNet (Deng et al., 2009) is ubiquitous when building image recognition models (Yosinski et al., 2014; Huh et al., 2016). This technique attains state-of-the-art performance on many vision tasks, including classification (Kornblith et al., 2018), fine-grained classification (Hermans et al., 2017), segmentation (Long et al., 2015), and detection (Girshick et al., 2014).

In vision, convolutional adapter modules have been studied (Rebuffi et al., 2017; 2018; Rosenfeld & Tsotsos, 2018). These works perform incremental learning in multiple domains by adding small convolutional layers to a ResNet (He et al., 2016) or VGG net (Simonyan & Zisserman, 2014). Adapter size is limited using 1×1 convolutions, whilst the original networks typically use 3×3 . This yields 11% increase in overall model size per task. Since the kernel size cannot be further reduced other weight compression techniques must be used to attain further savings. Our bottleneck adapters can be much smaller, and still perform well.

5. Conclusion

We propose a transfer strategy for large text models using bottleneck adapter modules. Adapter tuning yields models that are competitive with state-of-the-art fine-tuning, whilst using only small number of task-specific parameters. This strategy is designed for an online setting, where tasks arrive in series, and one wants to solve them with a single model. For future work, adapters could be applied in multi-task

training, where tasks are available simultaneously. Adapter modules could learn task-specific features while the main network learns generalizable representations. Unlike traditional approaches that use a task specific network "head", adapters allow task-dependent modulation at any layer.

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Supplementary Material for Parameter-Efficient Transfer Learning for NLP

A. Additional text classification tasks

Dataset	Train examples	Validation examples	Test examples	Classes	Avg text length	Reference
20 newsgroups	15076	1885	1885	20	1903	(Lang, 1995)
Crowdflower airline	11712	1464	1464	3	104	crowdflower.com
Crowdflower corporate messaging	2494	312	312	4	121	crowdflower.com
Crowdflower disasters	8688	1086	1086	2	101	crowdflower.com
Crowdflower economic news relevance	6392	799	800	2	1400	crowdflower.com
Crowdflower emotion	32000	4000	4000	13	73	crowdflower.com
Crowdflower global warming	3380	422	423	2	112	crowdflower.com
Crowdflower political audience	4000	500	500	2	205	crowdflower.com
Crowdflower political bias	4000	500	500	2	205	crowdflower.com
Crowdflower political message	4000	500	500	9	205	crowdflower.com
Crowdflower primary emotions	2019	252	253	18	87	crowdflower.com
Crowdflower progressive opinion	927	116	116	3	102	crowdflower.com
Crowdflower progressive stance	927	116	116	4	102	crowdflower.com
Crowdflower US economic performance	3961	495	496	2	305	crowdflower.com
Customer complaint database	146667	18333	18334	157	1046	catalog.data.gov
News aggregator dataset	338349	42294	42294	4	57	(Lichman, 2013)
SMS spam collection	4459	557	558	2	81	(Almeida et al., 2011)

Table 3. Statistics and references of the additional text classification tasks.

Dataset	Epochs (Fine-tune)	Epochs (Adapters)
20 newsgroups	50	50
Crowdflower airline	50	20
Crowdflower corporate messaging	100	50
Crowdflower disasters	50	50
Crowdflower economic news relevance	20	20
Crowdflower emotion	20	20
Crowdflower global warming	100	50
Crowdflower political audience	50	20
Crowdflower political bias	50	50
Crowdflower political message	50	50
Crowdflower primary emotions	100	100
Crowdflower progressive opinion	100	100
Crowdflower progressive stance	100	100
Crowdflower US economic performance	100	20
Customer complaint database	20	20
News aggregator dataset	20	20
SMS spam collection	50	20

Table 4. Number of training epochs selected for the additional classification tasks.

Parameter	Search Space				
1) Input embedding modules	Refer to Table 6				
2) Fine-tune input embedding module	{True, False}				
3) Use convolution	{True, False}				
4) Convolution activation	{relu, relu6, leaky relu, swish, sigmoid, tanh}				
5) Convolution batch norm	{True, False}				
6) Convolution max ngram length	{2, 3}				
7) Convolution dropout rate	$\{0.0, 0.1, 0.2, 0.3, 0.4\}$				
8) Convolution number of filters	{32, 64, 128}				
9) Number of hidden layers	$\{0, 1, 2, 3, 5\}$				
10) Hidden layers size	{64, 128, 256}				
11) Hidden layers activation	{relu, relu6, leaky relu, swish, sigmoid, tanh}				
12) Hidden layers normalization	{none, batch norm, layer norm}				
13) Hidden layers dropout rate	$\{0.0, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5\}$				
14) Deep optimizer name	{adagrad, lazy adam}				
15) Lazy adam batch size	{128, 256}				
16) Deep tower learning rate	$\{0.001, 0.005, 0.01, 0.05, 0.1, 0.5\}$				
17) Deep tower regularization weight	$\{0.0, 0.0001, 0.001, 0.01\}$				
18) Wide tower learning rate	$\{0.001, 0.005, 0.01, 0.05, 0.1, 0.5\}$				
19) Wide tower regularization weight	$\{0.0, 0.0001, 0.001, 0.01\}$				
20) Number of training samples	{1e5, 2e5, 5e5, 1e6, 2e6}				

Table 5. The search space of baseline models for the additional text classification tasks.

ID	Dataset size (tokens)	Embed dim.	Vocab. size	Training algorithm	TensorFlow Hub Handles Prefix: https://tfhub.dev/google/
English-small English-big English-wiki-small English-wiki-big Universal-sentence-encoder	7B 200B 4B 4B	50 128 250 500 512	982k 999k 1M 1M	Lang. model Lang. model Skipgram Skipgram (Cer et al., 2018)	nnlm-en-dim50-with-normalization/1 nnlm-en-dim128-with-normalization/1 Wiki-words-250-with-normalization/1 Wiki-words-500-with-normalization/1 universal-sentence-encoder/2

Table 6. Options for text input embedding modules. These are pre-trained text embedding tables. We provide the handle for the modules that are publicly distributed via the TensorFlow Hub service (https://www.tensorflow.org/hub).