LST: Ladder Side-Tuning for Parameter and Memory Efficient Transfer Learning

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Abstract

Fine-tuning large pre-trained models on downstream tasks has been adopted in a variety of domains recently. However, it is costly to update the entire parameter set of large pre-trained models. Although recently proposed parameter-efficient transfer learning (PETL) techniques allow updating a small subset of parameters inside a pre-trained backbone network for a new task, they only reduce the training memory requirement by up to 30%. This is because the gradient computation for the trainable parameters still requires backpropagation through the large pre-trained backbone model. To address this, we propose Ladder Side-Tuning (LST), a new PETL technique that can also reduce training memory requirements by more substantial amounts. Unlike existing parameter-efficient methods that insert additional parameters inside backbone networks, we train a ladder side network, a small and separate network that takes intermediate activations as input via shortcut connections (ladders) from backbone networks and makes predictions. LST has significantly lower memory requirements than previous methods, because it does not require backpropagation through the backbone network, but instead only through the side network and ladder connections. We conduct our experiments on various models (T5 and CLIP-T5) and tasks (GLUE, VQA, GQA, NLVR^2, MSCOCO). LST saves 69% of the memory costs to fine-tune the whole network, while other methods only save 26% of that in similar parameter usages (hence, 2.7x more memory savings). Moreover, LST outperforms Adapter and LoRA in a low-memory regime. To further show the advantage of this memory efficiency, we also apply LST to large T5 models (T5-large, T5-3B), attaining better GLUE performance than full fine-tuning and other PETL methods. The trend also holds in the experiments on vision-and-language tasks, where LST performs comparably to other PETL methods when training a similar number of parameters but only uses 46% of their GPU memory.

1 Introduction

Recently, large-scale pre-training and fine-tuning of transformers [48] have been successful in various domains [8, 31, 38, 33, 47, 7, 19, 2, 10]. As the model size grows rapidly, fine-tuning the entire parameter set of the large pre-trained model has become very costly. Parameter-efficient transfer learning (PETL) [26, 21, 34, 35, 29, 45, 52, 16, 22, 17, 36, 54, 14, 46, 53] is a recent research direction for the online setting, where tasks arrive in an online or multi-task setting. The goal is to build a system that performs well on all tasks without training an entire new model for every new task. Concretely, PETL methods select a small subset of pre-trained parameters and/or insert a few parameters to a pre-trained network and update those parameters for new tasks, while freezing most of the original parameters. In the natural language processing (NLP), computer vision (CV), and vision-and-language (VL) domains, two types of parameters have been commonly updated

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

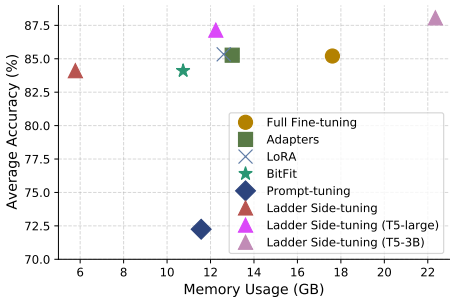

Figure 1: Comparison between full fine-tuning, Adapter, LoRA, BitFit, and Ladder Side-Tuning over GLUE tasks. The y-axis is the average accuracy of 8 GLUE tasks, while the x-axis is the GPU memory usage during training. Unless specially stated, we use the T5-base in the figure.

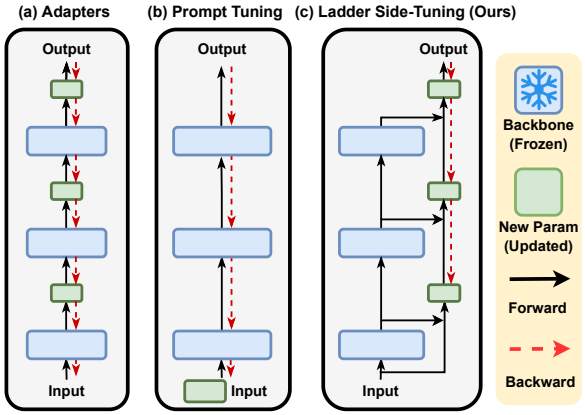

Figure 2: Comparison between transfer learning with (a) Adapters, (b) Prompt Tuning, and our (b) Ladder Side-Tuning (LST). LST reduces memory usage by removing the need of backpropgation through backbone networks.

for parameter-efficient transfer learning: (1) *Adapters* [21, 35, 34]: small modules inserted into transformer blocks; (2) *Prompt* [29, 26]: small parameters concatenated with input embeddings.

However, while parameter-efficient techniques reduce the number of parameters to update, they do not reduce the memory requirement during training by much (up to 30%). In other words, if a large pre-trained language model does not fit on a GPU, these techniques usually do not help to fit the model on the GPU. Since the updated parameters are inside the backbone language models, to calculate gradients for these parameters for backpropagation, we still need to run the backward pass through the large pre-trained language models. This prevents PETL methods from being applied to many real-world applications with limited computational resources.

To address this issue, we propose Ladder Side-Tuning (LST), a memory-efficient PETL method. LST separates trainable parameters from the backbone model to construct a side network, which is responsible for adapting the entire model to new tasks. Concretely, we train a *ladder* side network, a lightweight network that takes intermediate activations via shortcut connections (ladders) from the backbone networks as input and makes predictions. As shown in Fig. 2, unlike previous (a) adapters, (b) prompt tuning methods, (c) our LST does not add trainable parameters inside the pre-trained model. This completely eliminates the need for expensive backpropagation of a large backbone network and saves substantial memory during transfer learning. Instead of initializing the side network's weights randomly, we utilize a network pruning technique to retrieve a smaller pruned network and use it as the side network. In addition to our standard design of the side network, we also boost the efficiency of LST by dropping layers of the side network. We empirically demonstrate that the layer dropping can significantly improve both memory and parameter efficiency without sacrificing performance. Furthermore, during inference, even though we have to propagate forward through two distinct networks, LST does not necessarily use more inference time because the same level of the backbone network and the side network can be computed in parallel.

We conduct comprehensive studies on LST using diverse NLP and VL tasks, namely, GLUE [49], VQA [15], GQA [23], NLVR^2 [44] and MSCOCO [6]. Overall, in GLUE experiments, LST saves 69% of the GPU memory that is needed for fine-tuning the entire backbone model, saving 2.7x memory compared against Adapter and LoRA. Also, LST outperforms other PETL methods in a low-memory regime. To take advantage of this memory efficiency, we also apply LST to large language models (T5-large and T5-3B) and find that it outperforms other techniques when GPU memory utilization is similar. The findings still hold in the VL experiments; LST is not only a method that can fit in a 16GB GPU with 7.5% trainable parameters, but it also has comparable or better performance than other PETL methods. To justify our design of LST, we conduct ablation studies on initialization strategies and alternatives to add shortcut connections. The results reveal that these components considerably help performance, while only adding minor computation overhead.

2 Related Work

2.1 Parameter-efficient Transfer Learning (PETL)

PETL for NLP. In the past few years, large pre-trained language models have made huge success in NLP. Parameter-efficient transfer learning (PETL) is a research direction that reduces computational cost of adapting large pre-trained models to new tasks, by avoiding updates of the entire parameters. A popular line of work on PETL is to add a few trainable parameters and only tune them. For example, Adapters [42, 21] are small bottleneck modules that are inserted into transformer layers, and experiments have shown that training adapters with layer normalization layers is sufficient to achieve full fine-tuning performance. In a similar trend, LoRA [22] injects trainable rank decomposition matrices into a frozen pre-trained model. Instead of inserting new parameters into pre-trained models, prompt-based [26, 29] methods add trainable parameters to the input and keep the entire pre-trained model unchanged during training. The inserted prompts learn to make use of the knowledge of the pre-trained model to solve new tasks. Although the concept of adapter-based and prompt-based approaches is different, He et al. [17] unifies the two lines of approaches (including LoRA) into adapter-based methods. In addition to approaches that introduce new parameters, there are also various methods [45, 52, 16] that select a sparse subset of parameters from the pre-trained model to update, without adding any new parameters. One of such representative methods is BitFit [52], which updates every bias term in the model.

PETL for CV/VL. While most of the progress in PETL is made in NLP domain, researchers have also applied this technique to the CV [41, 40, 25, 53, 56, 1, 54, 20] and VL [46, 55, 56, 1, 54] domains. VL-Adapter [46] benchmarks adapter-based and prompt-based methods on multiple image-text and video-text tasks, and shows adapters enable us to efficiently learn fusion information of vision and language. On the CV side, benefitting from the parameter efficiency of adapters and prompt-tuning, some works [56, 1, 54] apply these approaches to CLIP [37] to achieve strong few-shot performance in image classification tasks. Side-Tuning [53] applies an additive side network, which sums its representation with the backbone network in the last layer, to solve various tasks with ResNet [18] and BERT [8]. Although LST bears similarities and takes inspiration from Side-Tuning, we argue that there are major differences in motivations, architecture designs, and applied tasks between the two methods. LST aims to reduce the memory requirement of current PETL methods, whereas Side-Tuning does not focus on memory reduction (sometimes their side network is even as big as the backbone network), but instead their motivation is to ease the forgetfulness in incremental learning by freezing the backbone model. Our ladder side network is more robust than their design because the shortcuts fuse the intermediate information from the backbone network, and we also use layer dropping and network pruning techniques to make LST more efficient and stronger. Lastly, we further extend LST in VL architecture and demonstrate its usefulness on multiple VL tasks.

Current PETL approaches explore how to achieve competitive results using as few parameters as possible. However, parameter efficiency does not necessarily mean memory efficiency. In this work, we propose LST that has these two benefits simultaneously. Concurrently, Liu et al. [32] also propose Y-tuning to address a similar issue; it exhausts all possible labels and feeds them into a model to select the best answer from the input. However, it is intractable oftentimes to list all answers in some tasks, for example, regression and open-ended generation tasks. On the other hand, LST is more flexible in applying to different architectures and tasks. We show that LST can outperform Y-tuning with fewer parameter updates in Table 2.

2.2 Network Pruning

In this paper, we use network pruning to extract a sub-network that contains critical information of the backbone model, and use it as the initialization for our side network. Network pruning makes models lighter by removing unimportant parameters or neurons. This technique aims to produce pruned architectures with fast inference speed, low memory footprint, and competitive performance. While PETL still uses those untrained parameters in the forward pass, network pruning entirely discards them or sets them to zero. As a result, network pruning can generate models for faster inference speed while PETL can achieve sufficient performance by updating fewer parameters. The standard procedure of network pruning is (1) learn [12, 13] or heuristically define [28] an "importance measure" to identify the importance of parameters, (2) prune $p\%$ of parameters with lower importance scores, (3) repeat the first and second steps until reaching the target sparsity. The rewinding procedure

enables pruning techniques to find a more sparse sub-network. In this paper, to keep the whole pruning process efficient, we either use weights magnitude [28] or Fisher Information [45, 30] as the importance measure, and reach the target sparsity in one shot. As a PETL method, LST makes use of the intermediate information of the backbone model as the inputs, and we empirically demonstrate those additional inputs significantly improve the performance.

3 Ladder Side-Tuning (LST)

We introduce Ladder Side-Tuning (LST), a new PETL technique that can also reduce training memory requirements by substantial amounts than previous methods. In Section 3.1, we analyze the computational cost for fine-tuning with trainable modules in backbone models. Then we explain the architectural details (Section 3.2), structural weight initialization based on network pruning (Section 3.3), and dropping side network layers for more efficiency (Section 3.4).

3.1 Dependency on Backpropagation through Large Backbone Model

We consider a N multilayer perceptron (MLP): $f_N(f_{N-1}(...f_2(f_1(x))...))$, where the i^{th} layer $f_i(x) = \sigma_i(W_i x + b_i)$ consists of weight W_i, bias b_i, and nonlinear function σ_i. We denote the output of i^{th} layer as a_{i+1} and the pre-activation as z_{i+1}, where $a_{i+1} = \sigma_i(z_{i+1}) = \sigma_i(W_i a_i + b_i)$. In backpropagation with loss L, the gradient with respect to W_i and b_i:

$$\frac{\partial L}{dW_i} = \frac{\partial L}{\partial a_{i+1}} \frac{\partial a_{i+1}}{\partial z_{i+1}} \frac{\partial z_{i+1}}{\partial W_i} = \frac{\partial L}{\partial a_{i+1}} \sigma_i' a_i, \qquad \frac{\partial L}{db_i} = \frac{\partial L}{\partial a_{i+1}} \sigma_i' \tag{1}$$

where σ_i' is the derivative of σ_i. $\frac{\partial L}{\partial a_{i+1}}$, the gradient with respect to a_i, can be calculated with the gradients with respect to a_{i+2}, using the chain rule:

$$\frac{\partial L}{\partial a_{i+1}} = \frac{\partial L}{\partial a_{i+2}} \frac{\partial a_{i+2}}{\partial z_{i+2}} \frac{\partial z_{i+2}}{\partial a_{i+1}} = \frac{\partial L}{\partial a_{i+2}} \sigma_{i+1}' W_{i+1} \tag{2}$$

As shown in Eqs. (1) and (2), during backpropagation, 1) $\{a\}$ corresponding to updated parameters $\{W\}$ and $\{b\}$ and 2) $\{\sigma'\}$ for the chain rule must be cached and thus dominate the memory footprint, where we use $\{\cdot\}$ to denote a set of activations, parameters, or gradients. Existing PETL methods, such as Adapters [21], LoRA [22], Prompt-tuning [26], and BitFit [52, 4] could reduce the memory footprint by making $|a|$ smaller, as they have fewer $\{W\}$ to update, but do not reduce $|\sigma'|$, where $|\cdot|$ means the size of set $\{\cdot\}$. Since $|a| = |\sigma'|$ holds for most activation functions, the memory footprint for backpropagation $|a| + |\sigma'|$ can be reduced by up to 50% by the PETL methods when they reduce the entire memory footprint for $|a|$. By making the updated parameter do not require backpropagation through the backbone network, our LST can achieve better memory efficiency beyond 50%, and we explain it below.

3.2 Ladder Side Network for Transformers

Unlike existing transfer learning methods that insert additional parameters inside a transformer network, we propose training a *ladder* side network, a small and separate network that takes intermediate activations from the backbone transformer as input and makes predictions. As illustrated in Fig. 3 (a), since the ladder side network parameters ϕ are not used during the forward pass of the backbone transformer with parameters θ, the update of the ladder side network does not require expensive backpropagation of the large backbone transformer. Note that our LST method is not limited to a specific architecture. We provide a simplified overview of LST with an encoder architecture in Fig. 3 (a) and an illustration of LST with an encoder-decoder architecture in Fig. 3 (b).

Lightweight architecture. Our side network g is a lightweight version of the backbone transformer f, where all weights and hidden state dimensions of in g are $\frac{1}{r}$ times of the original weights and hidden states of f, where r is a reduction factor (e.g. $r = 2, 4, 8, 16$). For example, if the backbone f has a 768-dimensional hidden state, then the side network g with $r = 16$ has a hidden state of 48 dimensions (= 768/16). The side network g reuses frozen word embeddings ('Emb' in Fig. 3 (a))

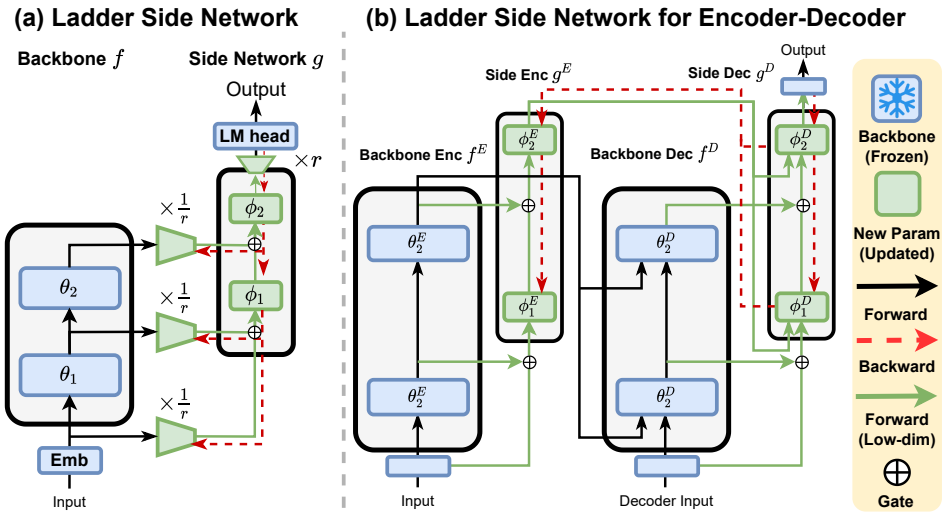

Figure 3: Illustration of Ladder Side-Tuning (LST) with transformer described in Section 3.2. (a) shows a high-level overview of LST, and (b) shows LST with an encoder-decoder architecture.

and the language model head ('LM head' in Fig. 3 (a)) of the backbone f. Following the analysis in Section 3.1, we also examine the memory cost of LST. Recall that original memory footprint for backpropagation is $|a| + |\sigma'|$. Because we do not have to run a backward pass through the backbone network, we can only consider the gradients for the side network, whose memory footprint is $\frac{|a|+|\sigma'|}{r}$. Therefore, LST has a better memory efficiency than other PETL methods (saving up to 50%) as long as r is greater than 2 (we find 8 works well in most experiments).

Gated ladder connections. Although Zhang et al. [53] found that late fusion to combine the representations of the backbone and the side network works well with convolutional networks for CV tasks, in our experiments, we find that late fusion hurts the performance of the transformer architecture in NLP tasks (see Figure 8 in Section 5 for details). To address this, we use the shortcut connection (called *ladder*, due to the overall shape created from the multiple shortcut connections) from intermediate activations from the backbone f to the side network g and find it helpful. We learn linear projections to downsample ($\times\frac{1}{r}$) the intermediate activations (including word embeddings) of f to low-dimensional attention blocks in g. Then, we learn a linear projection to upsample ($\times r$) the side network output to the dimension of the original language model head. The linear projections are illustrated as green trapezoids in Fig. 3 (a). The i^{th} transformer layer of the side network g combines the activation of the backbone h_i^f and the activation of the previous layer of the side network h_{i-1}^g with learned gating: $\mu_i * h_i^f + (1 - \mu_i) * h_{i-1}^g$, where $\mu_i = \texttt{sigmoid}(\frac{\alpha_i}{T})$ is a gate parameterized with a learnable zero-initialized scalar α_i and temperature T ($= 0.1$).

3.3 Structural Weight Initialization for Ladder Side Network

We find it helpful to initialize the weights of the side network ϕ from the weight of the backbone network θ based on structural pruning [28], as shown in Fig. 4 (a). Concretely, given a weight matrix $W \in \mathbb{R}^{d_{out} \times d_{in}}$ of the backbone network that maps the d_{in}-dim vectors to the d_{out}-dim space, and the importance matrix of the weight $I \in \mathbb{R}^{d_{out} \times d_{in}}$, we first calculate the importance score of each row $s_i = \sum_j |I_{i,j}|$, where the importance matrix I can be weight magnitude [28] ($I = W$) or empirical Fisher Information [45] ($I = F_W = \frac{1}{N}\sum_{i=1}^{N}(\nabla_W \log p(y_i|x_i))^2$; $(x_i, y_i), ..., (x_N, y_N)$ are samples from data). Then, we choose the rows of W which have the top $\frac{d_{out}}{r}$ importance scores and prune the remaining rows to obtain a new weight matrix $W^P \in \mathbb{R}^{\frac{d_{out}}{r} \times d_{in}}$. The columns of the weights and the importance matrix in the next layer corresponding to the pruned feature map are also pruned. By iterating this process, we obtain the set of weight matrices whose rows and columns are pruned $\frac{1}{r}$ times from the backbone network and use them to initialize the side network. In our

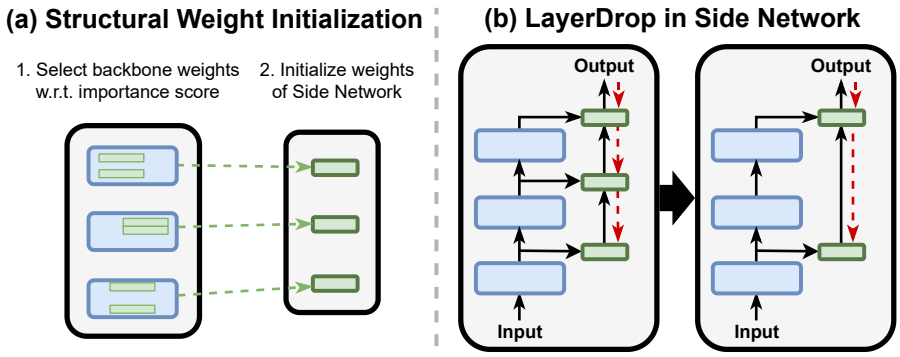

Figure 4: Illustration of (a) Structural Weight Initialization (Section 3.3) and (b) Layer Dropping (Section 3.4). In our experiments, we find that initialization of side network parameters from backbone network parameters improves performance, and dropping some shortcut connections improves efficiency without hurting performance.

experiments shown in Figure 7, we find that using Fisher information as an importance score metric generally performs well, and therefore we use it in our structural weight initialization.

3.4 Layer Dropping in the Ladder Side Network

We explore to increase efficiency of LST even further by making side network more compact, by dropping its intermediate transformer layers, as illustrated in Fig. 4 (b). Similar to LayerDrop [11], we drop layers in the side network, and this can linearly reduce the memory and parameter requirements of LST. For instance, a side network with N layers will only have 2^{nd}, 4^{th}, 6^{th} ... layers left, after we drop half of the layers. Refer to Section 4 for more details on applying layer dropping on an encoder-decoder architecture. In Fig. 6, we show that layer dropping can greatly boost the model's efficiency without sacrificing performance.

4 Experiment Setup

Datasets. We evaluate LST on NLP and VL tasks. For NLP tasks, we use the GLUE [49] benchmark, which consists of seven classification and one regression task. The benchmark evaluate models on multiple diverse tasks over linguistic acceptability (CoLA [50]), sentiment analysis (SST-2 [43]), similarity and paraphrase (MRPC [9], QQP [24], STS-B [5]) and natural language inference (MNLI [51], QNLI [39], RTE [3]). For VL tasks, we experiment with visual question answering (VQA [15], GQA [23]), visual reasoning (NLVR^2 [44]) and image captioning (MSCOCO [6]) tasks.

Training and Evaluation Setup. For NLP tasks, we use T5 [38], a pre-trained encoder-decoder language model as our backbone. We use T5-base in most experiments, except that we scale up LST on T5-large and T5-3B to demonstrate its memory efficiency. The training and evaluation process follows the setup used by Mahabadi et al. [35]. Since there is no local test set, we split 1k samples from the training set as the new validation set and use the original validation set as the test set. For datasets whose samples are less than 10k (RTE, MRPC, STS-B, CoLA), we split the validation set into two equal-sized subsets and treat them as a new validation and test set. We train every approach with 10 epochs on large datasets and 20 epochs on small ones (RTE, MRPC, STS-B, CoLA) for complete convergence. For MNLI, we use the mismatched set as the validation set and matched set as the test set. We search for learning rates over $\{3\times10^{-4}, 1\times10^{-3}, 3\times10^{-3}\}$ for LST and LoRA[22], and we use the optimal learning rates that are used by Mahabadi et al. [35] for other methods. The reduction factor used in LST is set to 8 if not additionally specified. T5-base has 12 layers each in encoder and decoder, while T5-large and T5-3B have 24 layers each. In our experiments, we do not drop layers in T5-base if we do not specially mention it. For T5-large and T5-3B, we drop 24 layers (12 layers each in encoder and decoder) and 46 layers (23 each) of the side network to make the memory usage close to our baselines. The experiments on T5 take around 12 hours to train with one A6000 GPU (48GB).

Table 1: Comparison between multiple parameter-efficient training methods on GLUE benchmark. We use T5-base if we don't additionally specify. We report accuracy for SST-2, MNLI, QNLI and RTE. For CoLA and STS-B, we use Matthew's Correlation and Pearson-Spearman Correlation as the metrics, respectively. For MRPC and QQP, we report the average of F1 score and accuracy. Each number in the table is the average result over three seeds. For the results with †, we report the best performance out of three seeds due to the instability of the method.

Method	Update Param. per Task (%)	Memory Usage (GB)	CoLA	SST-2	MRPC	QQP	MNLI	QNLI	RTE	STS-B	Avg.
Full fine-tuning	100	17.6	62.8	93.9	91.9	89.9	86.2	92.5	74.1	90.3	85.2
Adapters	1.63	13.0	64.4	94.2	88.9	88.9	86.4	93.1	75.1	91.1	85.3
LoRA	1.71	12.6	63.3	94.3	90.1	89.0	86.3	93.2	75.5	90.9	85.3
BitFit	0.13	10.7	61.8	94.3	91.0	88.7	85.6	93.1	67.6	90.8	84.1
Prompt-tuning	0.03	11.6	0†	90.3†	74.6	88.5	82.5	92.5	59.5	90.1	72.2
Ladder Side-Tuning	1.74	5.5	58.1	94.1	90.4	88.8	85.6	93.3	71.9	90.7	84.1
Ladder Side-Tuning (T5-large)	1.23	12.2	65.3	95.7	91.6	89.7	88.6	94.1	79.9	92.4	87.1
Ladder Side-Tuning (T5-3B)	0.08	22.4	66.4	96.5	92.9	89.7	90.7	95.1	80.1	93.0	88.1

For VL tasks, we experiment with CLIP-T5 [46], which is a VL architecture combining CLIP [37] and T5 [38]. We always freeze the CLIP and only train the T5 for new tasks. The CLIP visual representation is concatenated with the text embedding, and the combined input is fed to T5 to make predictions. A visual projection layer is added between CLIP and T5 to let the visual representation have the same dimension as the text embedding. To avoid updating the visual projection layer by the gradients from the backbone model, we do not feed combined inputs to the backbone model, but only text inputs. The combined inputs are fed to the side network, so we can achieve efficient training by only using the gradients from the side network. Because the backbone network only uses texts as the input, the information from the backbone network via shortcut connections is only summed to the text part of the side network's combined inputs. We follow the multi-tasking setting for training and evaluation used in VL-Adapter [46]. We report the performance on Karpathy test/test-dev/test-P/Karpathy test split for VQA/GQA/NLVR^2/MSCOCO, and train models for 20 epochs. We search learning rates over $\{3 \times 10^{-4}, 1 \times 10^{-3}, 3 \times 10^{-3}\}$ for PETL methods, and use 1×10^{-4} used by Sung et al. [46] for full fine-tuning. We set the reduction factor for the side network to 4. We train CLIP-T5 for 16 hours on one A6000 GPU.

5 Experimental Results

In this section, we show experiments to justify our design of LST and demonstrate that LST performs the best among all approaches in the scenario with limited memory. As the result, LST is the most efficient tool to fine-tune large-scale pre-trained models for real-world applications.

LST outperforms other methods under similar memory usage. Figure 1 and Table 1 show the results on GLUE of different approaches applying on T5-base. We drop 6 layers (3 layers each in side encoder and decoder) for LST to match the parameter usage of the Adapter and LoRA. Under the same parameter usage, LST can save 69% of memory cost to fully fine-tune the model, while Adapter and LoRA only save 26% of that, leading to LST having a 2.7x more memory saving. Compared to BitFit, LST achieves the same average performance but costs 5GB less GPU memory. LST also surpasses Prompt-tuning in terms of both performance and memory cost. To further take advantage of the memory efficiency of LST, we also train T5-large and T5-3B with LST. We find that with a similar budget of memory usage in Adapter and LoRA, LST with T5-large can surpass the performance of other methods by a large margin. The result on T5-3B also outperforms the result on T5-large, demonstrating the scalability of our memory-efficiency method on large language models.

In Table 2, we also compare LST with a concurrent work, Y-tuning [32] on GLUE tasks (except for STS-B) with BART-large [27] encoder as backbone. Following the experimental setup of Liu et al. [32], for each task, we use different learning rate, and report the best accuracy out of 3 seeds. Overall, LST outperforms Y-tuning by a large margin with fewer updated parameters.

Table 2: LST vs. Y-tuning.

Method	Update Param. per Task (%)	Avg. GLUE
Y-tuning	7.7	76.9
LST	2.6	82.1

Table 3: Comparison between multiple parameter-efficient training methods on VQA, GQA, NLVR^2, and MSCOCO. We use T5-base for all approaches. We report accuracy for VQA, GQA and NLVR while we use CIDEr to evaluate MSCOCO.

Method	Update Param. (%)	Memory Usage (GB)	VQA	GQA	NLVR^2	MSCOCO	Avg.
Full fine-tuning	100	36.2	67.0	56.1	73.8	111.8	77.2
Adapters	7.98	28.4	67.2	56.4	73.1	111.9	77.2
LoRA	7.54	27.9	63.9	53.3	70.2	110.3	74.4
Ladder Side-Tuning	7.46	15.3	67.3	56.8	74.1	108.5	76.7

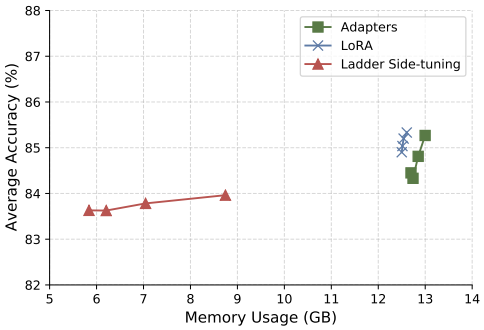

Figure 5: The accuracy-memory trade-off for Adapter, LoRA, and Ladder Side-Tuning over GLUE tasks. We vary the reduction factor in Ladder Side-Tuning, hidden dimension in Adapter, rank in LoRA to get the architectures with different training costs.

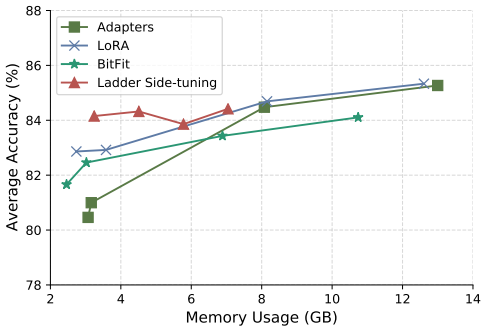

Figure 6: The accuracy-memory trade-off for Adapter, LoRA, BitFit, LST over GLUE tasks. we drop $N \in \{0, 6, 12, 18\}$ layers in an interleaving manner for LST while we gradually freeze the first $N \in \{0, 6, 12, 18\}$ layers in other methods (also remove inserted parameters in those layers).

LST is competitive on VL tasks. As we have mentioned beforehand, we also extend LST on a multi-modal architecture, CLIP-T5, on multiple VL tasks, and we demonstrate the outcome in Table 3. With similar parameter usage, LST is the only method that can fit into a single 16GB GPU. Besides the efficiency, it is as competitive as full fine-tuning and Adapter and outperforms LoRA.

LST performs the best in low-memory regime. To have a better understand of the memory advantage of LST, we adjust the hyper-parameters in our method (reduction factor $\in \{32, 16, 8, 4\}$), Adapter (hidden dimension $\in \{6, 12, 24, 48\}$) and LoRA (rank $\in \{4, 8, 16, 32\}$) to create multiple architectures with different memory costs. Figure 5 shows the performance and memory efficiency trade-off for all methods. We find the memory saving is not obvious for Adapter and LoRA, because the gradients of the backbone model's intermediate outputs are still computed (see Section 3.1 for details). Even though Adapter and LoRA still can get better memory efficiency by reducing the hidden dimension and the rank, we find that the performance drops significantly. On the other hand, LST is quite robust across a wide range of side network sizes.

We also consider another way to compare LoRA, Adapter and BitFit to LST in different memory budgets. While we drop $N \in \{0, 6, 12, 18\}$ layers in an interleaving manner to improve memory efficiency, we freeze the first N layers and remove the corresponding inserted modules in other approaches. With this, other methods can achieve better memory efficiency because gradients do not propagate to those earlier frozen layers. We discuss the layer dropping and layer freezing with details in the following. In LST, we drop $\frac{N}{2}$ layers in both side encoder and side decoder. However, in other PETL approaches, we start from freezing layers in the side encoder and then turn to freeze layers in the side decoder (e.g. dropping 18 layers means dropping all side encoder layers and 6 side decoder layers). We display the comparison in Figure 6, showing that LST has a better performance and memory trade-off and outperforms other methods in the low-memory regime. We also find that layer dropping generally reduces the training cost without hurting performance.

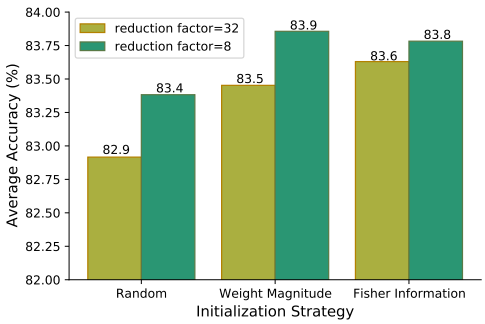

Figure 7: The ablation study on different initialization strategies. Y-axis denotes the average score over GLUE tasks.

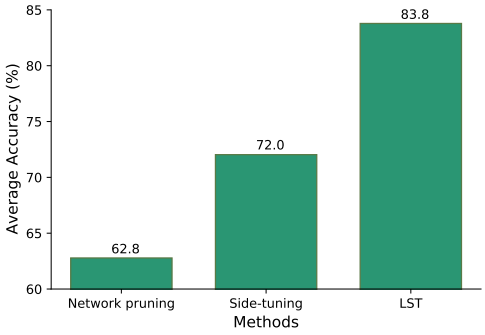

Figure 8: The comparison between network pruning, Side-Tuning, and LST on GLUE tasks.

The ablation of weight initialization on the side network. We compare the different initialization strategies for the side network and demonstrate the results in Figure 7. "Random" denotes we randomly initialize the network while we use network pruning to select initial weights for the side network based on two importance measures, "Weight Magnitude" and "Fisher Information." In general, the initialization from the pruned network helps no matter the size of the side network, showing the effectiveness of our network pruning strategy.

Comparison LST to network pruning and side-tuning. In Section 3.2, we mention that shortcut connections are added to every layer of the side network. We justify this design by comparing LST to two approaches: (1) network pruning, which discards all shortcut connections and the entire backbone model. (2) side-tuning, which only adds one shortcut connection to merge representations right before the output layer. Note that we do not drop any layer in the side network but only remove the shortcuts. Figure 8 shows the comparison and LST outperforms the other two methods significantly, suggesting the intermediate shortcut connections are useful. This also suggests that network pruning might not perform as well as PETL methods when training the same number of parameters. PETL methods are stronger as they use the information from the backbone model.

6 Conclusion

We propose Ladder Side-Tuning (LST), a parameter- and memory-efficient method to adapt a large backbone network. LST does not require backpropagation through the backbone network, which allows for significantly lower memory requirement during training than recently proposed parameter-efficient training techniques. We demonstrate that LST allows users to adapt a larger and more powerful backbone network to target tasks with a limited memory requirement, which cannot be achieved with recent parameter-efficient techniques. We also show that LST achieves more efficient accuracy-memory trade-off than recent baselines and impact of weight initialization of side networks. Finally, we show that the LST can be also extended beyond NLP tasks, with strong results on vision-and-language tasks. We hope that LST helps users with limited computational resources tune larger models in diverse domains.

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   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] In appendix.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A] We believe we do not have negative societal impacts due to it is a technical paper.
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