SPARTAN: Sparse Hierarchical Memory for Parameter-Efficient Transformers

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Abstract

Fine-tuning pre-trained language models (PLMs) achieves impressive performance on a range of downstream tasks, and their sizes have consequently been getting bigger. Since a different copy of the model is required for each task, this paradigm is infeasible for storage-constrained edge devices like mobile phones. In this paper, we propose SPARTAN, a parameter efficient (PE) and computationally fast architecture for edge devices that adds hierarchically organized sparse memory after each Transformer layer. SPARTAN freezes the PLM parameters and fine-tunes only its memory, thus significantly reducing storage costs by re-using the PLM backbone for different tasks. SPARTAN contains two levels of memory, with only a sparse subset of parents being chosen in the first level for each input, and children cells corresponding to those parents being used to compute an output representation. This sparsity combined with other architecture optimizations improves SPARTAN’s throughput by over 90\% during inference on a Raspberry Pi 4 when compared to PE baselines (adapters) while also outperforming the latter by 0.1 points on the GLUE benchmark. Further, it can be \textit{trained} 34\% faster in a few-shot setting, while performing within 0.9 points of adapters. Qualitative analysis shows that different parent cells in SPARTAN specialize in different topics, thus dividing responsibility efficiently.\textsuperscript{1}

1 Introduction

Pre-trained language-models (PLMs) (Radford et al.; Devlin et al., 2019) have achieved impressive performance on a wide range of natural language processing (NLP) tasks, leading to deployment in the real world (Bommasani et al., 2021). Users typically adapt these large models by fine-tuning a separate copy for each task, making storage prohibitively expensive as the number of tasks grows. Parameter-efficient (PE) methods (Houlsby et al., 2019) solve this issue by fine-tuning only a small fraction of model parameters, thus allowing re-use of the PLM backbone which leads to a reduction in storage space (\approx 90\%). While these works have tailored their architectures and performance towards GPUs, an increased adoption of PLMs in resource-constrained devices like mobile phones (de Barcelos Silva et al., 2020) requires PE methods that can run on the edge. In this work, we introduce SPARTAN, which uses a sparse hierarchical memory to provide a storage and computationally efficient architecture, as illustrated in Figure 1.

SPARTAN is motivated by cognitive science stud-
ies, which posit that information and functional states are sparsely and hierarchically organized in human memory (Mishkin et al., 1997; Hasson et al., 2015; Ahmad and Hawkins, 2015). SPARTAN adds a hierarchical memory module after each Transformer layer. During fine-tuning, it freezes the PLM parameters and adapts its memory via back-propagation to optimize the task loss. SPARTAN’s memory is organized in two layers containing parent (purple) and children (blue) cells. The input chooses the top-K parent cells by inducing an attention map over them, and their corresponding children are used to compute and aggregate an output representation which is added to the input. SPARTAN’s sparse parent selection thus allows it to ignore irrelevant children parameters and makes it computationally efficient (§5).

On the GLUE benchmark (Wang et al., 2018), SPARTAN performs 0.1 points better than PE baselines (adapters), while being 90% faster on Raspberry Pi 4 (throughput). Furthermore, in a few-shot setting, SPARTAN can be fine-tuned 34% faster while performing within 0.9 points of baselines. Qualitatively, on a news classification dataset (example labels: entertainment, sports), we observe that SPARTAN distributes responsibility among parent cells by specializing them in different topics (Figure 2). We believe that SPARTAN’s strong performance and speed coupled with its qualitative interpretability can improve the adoption of PE methods on the edge.

2 Related Work

Parameter-efficient architectures Parameter-efficient (PE) architectures minimize the number of trainable parameters to improve storage efficiency. Houlsby et al. (2019) proposed adapters, which add two feed-forward bottleneck layers (an Adapter) after each Transformer layer while freezing the rest of the model. Other works have optimized this architecture by experimenting with the placement-order of different components (Pfeiffer et al., 2020; Stickland and Murray, 2019; Karimi Mahabadi et al., 2021; Rücklé et al., 2021; Ding et al., 2022). Another line of work fine-tunes a subset of the model’s parameters (Zhao et al., 2020; Lee et al., 2019; Zaken et al., 2022; Guo et al., 2021), and as a result, are typically architecture-dependent, whereas SPARTAN works with all Transformers. Prompting LMs (Gao et al., 2021; Hu et al., 2022; Li and Liang, 2021) is another popular paradigm, but it involves construction of task-specific templates and is used for smaller datasets (Le Scao and Rush, 2021), whereas SPARTAN is task-agnostic and works for any dataset size.

Memory networks Prior works (Weston et al., 2015; Miller et al., 2016; Dinan et al., 2019) have explored the usage of memory in language models. However, the flat structure of memory makes them computationally expensive. Chandar et al. (2016) propose hierarchically-organized memory which uses approximate KNN to improve computation speed, with several applications adapting it (Andrychowicz and Kurach, 2016; Lu et al., 2020; Chen et al., 2018). But to the best of our knowledge, SPARTAN is the first PE architecture for Transformers with sparse hierarchical memory.

NLP on the edge NLP methods are increasingly being adopted in mobile and IoT devices (de Barcelos Silva et al., 2020; Sun et al., 2020; Guo et al., 2022; Chen and Ran, 2019), and can have lower latency than methods deployed on the cloud (Cartas et al., 2019; Tambe et al., 2021). With the introduction of federated learning (McMahan et al., 2016), where participating devices like mobile phones compute and provide updates to a central model, computing on the edge has become important (Yang et al., 2018; Ramaswamy et al., 2019; Stremmel and Singh, 2021; Liu et al., 2021). We believe that SPARTAN is an important step in the direction of PE architectures for such devices. SPARTAN is also loosely related to mixture-of-experts (MoE) architectures (Aljundi et al., 2017; Shazeer et al., 2017; Lepikhin et al., 2021; Du et al., 2022; Wright and Augenstein, 2020; Fedus et al., 2022; Zoph, 2022; Jacobs et al., 1991). But unlike SPARTAN, MoE methods are not parameter-efficient, because all their parameters are trained or fine-tuned. This significantly increases the storage space of MoE on device, making it less preferable than SPARTAN.

3 Methodology

SPARTAN is a parameter-efficient architecture for pre-trained Transformers (Vaswani et al., 2017) with a sparse, hierarchically organized memory added after each Transformer layer (see Figure 1). SPARTAN draws inspiration from cognitive science studies which argue that human memory is sparsely and hierarchically arranged (Mishkin et al., 1997). During fine-tuning, the parameters of the Transformer backbone are frozen and can be re-used,
while memory cells are written through gradient updates. The hierarchical memory contains parent cells and children cells in the first and second levels, respectively. Each parent cell has multiple exclusive children cells associated with it. Intuitively, spartan first chooses a sparse subset of parent cells conditioned on the input, and uses the children corresponding to the chosen parent cells to compute an output representation that is added back to the input through a residual connection. Each position in the input sequence shares the memory. We provide a mathematical description using the following notation: Let \( v_I \in \mathbb{R}^d \) be the input to the module, \( N_p \) the number of parent cells, and \( N_c \) the number of children cells associated with each parent. Let the stacked parent cells be the matrix \( P \in \mathbb{R}^{N_p \times d} \) and the stacked children cells corresponding to parent \( P_i \) be the matrix \( C_i \in \mathbb{R}^{N_c \times d} \).

1. **Choosing the relevant parents** The input \( (v_I) \) is used to select the top-\( K \) parent cells \( (P_{IND}) \) by inducing an attention distribution computed using an inner product, which allows spartan to sparsely select a subset of relevant parent cells.

\[
g_{parent} = \text{softmax}(Pv_I) \\
P_{IND} = \text{top-}K(g_{parent}) \tag{1}
\]

2. **Computing the children’s cell representation** As shown in Figure 1, the children cells contain key and value components (Weston et al., 2015), which we denote by \( C^K_i \) and \( C^V_i \), respectively, where \( i \) is the parent index. For each chosen parent \( P_i \), we calculate a representation using its children cells:

\[
v_i = C^V_i \text{softmax}(C^K_i v_I) \tag{2}
\]

3. **Hierarchical aggregation** spartan now combines the children representations by weighting and aggregating them based on the corresponding parent’s attention \( (g_{parent}) \). Since only \( K \) parents are chosen, \( g_{parent} \) is re-normalized after ignoring parents not selected in the first stage. The aggregated output is added back to the input using a residual connection (He et al., 2016) and serves as the input to the next layer:

\[
Z = \sum_{i \in P_{IND}} g_{parent}[i] \\
v_O = \frac{1}{Z} \sum_{i \in P_{IND}} v_i \cdot g_{parent}[i] \\
\text{SPARTAN output} = v_I + v_O \tag{3}
\]

4. **Experimental Setup**

**Datasets** We use the nine datasets from GLUE (Wang et al., 2018), which are CoLA (Warstadt et al., 2019), SST-2 (Socher et al., 2013), MRPC (Dolan and Brockett, 2005), QQP (qqp), STS-B (Cer et al., 2017), MNLI (Williams et al., 2018), QNLI (Wang et al., 2018), RTE (Wang et al., 2018), and WNLI (Levesque et al., 2012). We use the evaluation metrics suggested by Wang et al. (2018) for all datasets; the metrics and averaging are described in Appendix C.

**Baselines and spartan** We use RoBERTa (Liu et al., 2019) as the backbone for all the models and also as a baseline; for the latter, we fine-tune all its parameters. We also compare with two strong parameter-efficient baselines which are variants of adapters: Houlsby (Houlsby et al., 2019) and Pfeiffer (Pfeiffer et al., 2021). Pfeiffer and spartan use the same number of added parameters, while Houlsby uses twice as many because it has two bottleneck layers. We provide model training and implementation details in Appendix A.

**Speed benchmarking** We benchmark our models on two resource-constrained edge devices, the Raspberry Pi 4 (4 cores, 8GB RAM) and the iPhone 11 Apple A13 Bionic (6 cores, 4GB RAM), by emulating the corresponding hardware (Buchert et al., 2010). Following Chen and Ran (2019), we measure the throughput, which is the number of instances processed per minute during inference. More details regarding the benchmarking and emulation are provided in Appendix F.

5. **Results**

**Comparing performance and speed on GLUE** Results in Table 1 show that spartan is the best performing model with a 0.1 improvement over Houlsby. It even outperforms RoBERTa, which uses \( 9 \times \) the storage space and \( 100 \times \) the number of trainable parameters. Even though spartan adds memory after each Transformer layer of RoBERTa, its inference throughput is only \( 3\% \) lower. spartan’s throughput is significantly higher than Houlsby and Pfeiffer, with a \( 10 \times \) improvement on Raspberry Pi 4 and a \( 1.6 \times \) improvement on iPhone. spartan’s speed-up advantage comes from two factors: (1) The sparse hierarchical memory ignores children cells corresponding...
Table 1: Full fine-tuning performance on all datasets in the GLUE benchmark. SPARTAN has the best performance on GLUE (0.1 point improvement), while being 10× faster than parameter-efficient baselines, and using 87% less storage space when compared to RoBERTa. All numbers are averaged over three random seeds. Individual dataset scores are displayed in gray to improve readability. We provide details about storage computation in Appendix E.

| Model     | Storage (×) | Throughput (G) | GLUE Performance |
|-----------|-------------|----------------|------------------|
|           |             | Ras-Pi | iPhone | ColA | SST | MRPC | QQP | STSB | MNLI | QNLI | RTE | WNLI |
| RoBERTa   | 9           | 207.6  | 366.2  | 80.9 | 60.5 | 94.3 | 88.2 | 91.3 | 90.7 | 87.5 | 87.3 | 92.4 | 75.3 | 47.9 |
| Pfeiffer  | 1.1         | 20.0   | 216.1  | 80.9 | 59.7 | 94.2 | 88.0 | 89.5 | 90.3 | 86.8 | 86.9 | 92.4 | 76.8 | 50.7 |
| Houlsby   | 1.2         | 19.5   | 204.8  | 81.0 | 59.1 | 94.3 | 86.9 | 89.9 | 90.5 | 87.1 | 87.2 | 92.6 | 76.8 | 51.6 |
| SPARTAN   | 1.1×        | 201.3  | 332.6  | 81.1 | 60.5 | 94.4 | 89.2 | 89.6 | 90.3 | 86.5 | 86.5 | 91.9 | 75.0 | 52.1 |

Table 2: Few-shot results (200 instances) on GLUE. SPARTAN provides the best storage-throughput-performance trade-off, with 1.5× faster fine-tuning throughput when compared to Pfeiffer and Houlsby, and significant storage savings when compared to RoBERTa. All results are averaged over 3 seeds. Implementation details are presented in Appendix B.

| Model   | Storage (×) | Fine-tune Throughput (G) | Avg. GLUE |
|---------|-------------|--------------------------|-----------|
| RoBERTa | 9           | 90.1         | 63.3      |
| Pfeiffer| 1.1         | 32.1         | 64.8      |
| Houlsby | 1.2         | 34.7         | 63.7      |
| SPARTAN | 1.1×        | 53.3         | 63.9      |

Figure 2: Different parent cells specialize in different topics when trained on the BBC news classification dataset. Parent 3 exclusively specializes in sports while parents 1, 2, 4 mainly specialize in business, entertainment and politics, respectively. This shows that SPARTAN’s strong performance might be due to different parents sharing responsibilities with regard to different topics.

6 Conclusion

In this work, we propose SPARTAN, a parameter-efficient architecture that is computationally inexpensive for resource-constrained devices. SPARTAN uses a two-level sparse and hierarchically-organized memory which allows it to choose only relevant parents and hence parameters, thus speeding up computation. We believe SPARTAN’s strong performance, which can be coupled with orthogonal methods like pruning (Voita et al., 2019) and distillation (Hinton et al., 2015), makes it a useful architecture for edge devices. From a qualitative perspective, we find that SPARTAN allows different parents to specialize in different topics, thus ensuring a distribution of responsibility between different groups of parameters. We believe that these

to irrelevant parents, and (2) it does not use Layer-Norm (Ba et al., 2016), which can hurt performance on resource-constrained devices (Sun et al., 2020).

Few-shot results We now consider a few-shot setting, where the model is fine-tuned on resource-constrained devices using just 200 examples. Table 2 shows the results. SPARTAN achieves the best throughput out of all parameter-efficient methods (1.5×) while using only 11% of RoBERTa’s storage space. Crucially, SPARTAN beats RoBERTa by 0.6 points, and we posit that it is because of the regularizing effect of having significantly lower trainable parameters, which can be beneficial for the few-shot setting. SPARTAN gives the best storage-performance-throughput trade-off among all the models. We note that SPARTAN performs slightly worse than Pfeiffer (0.9 points), and leave few-shot performance optimization as future work.

Qualitatively analyzing parent cells We train SPARTAN on the BBC news classification dataset (Greene and Cunningham, 2006) and analyze the 5 parent cells in the last layer. For each parent, we plot the ground truth label of the instance which picks that parent cell (see Figure 2), with implementation details in Appendix D. We notice that parent cells specialize in certain topics, with parent 3 specializing in sports and parents 1, 2, 4 specializing business, entertainment and politics, respectively. This shows that SPARTAN’s strong performance might be due to different parents sharing responsibilities with regard to different topics.
properties can pave the way for more interpretable parameter-efficient properties in the future.

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A Implementation details

We use the RoBERTa-Base model (Liu et al., 2019) as the backbone for all the models. All models are trained on NVIDIA RTX 2080s. For each dataset and model, we perform a hyperparameter search using 10% of the training data. We use a batch size of 16 for all the models. Across all models, MNLI, QQP, SST-2, and WNLI performed best when fine-tuned on 3 epochs, and other datasets needed 20 epochs. We used a grid of \{3, 20\} by following (Houlsby et al., 2019). Further, we find that the following are the best performing hyperparameters for specific baselines and models when we use 10% of the train dataset to choose them.

1. RoBERTa: Learning rate: $2e^{-5}$
2. Pfeiffer: Learning rate: $1e^{-4}$, Reduction factor: 12 (Bottleneck size: 64)
3. Houlsby: Learning rate: $1e^{-4}$, Reduction factor: 12 (Bottleneck size: 64)
4. SPARTAN: Learning rate: $1e^{-3}$, Number of parent cells: 16, Number of children cells per parent: 3. The top $K = 8$ parents are chosen for children memory computation. SPARTAN adds exactly the same number of trainable parameters as Pfeiffer and half that of Houlsby. As explained in Section 3, both the parent and children cells are of dimensionality $d = 768$, the same as the hidden dimensionality of the base Transformer model they are using.
5. Learning rate grid search: \{$2e^{-5}, 1e^{-4}, 1e^{-3}$\}, Reduction factor grid search: \{12, 16\}, Parent cells grid search: \{12, 16\}

B Few-shot full results

We present the full version of Table 2 in Table 3 which includes the breakdown for all the GLUE datasets. We use $K = 200$ examples in the train dataset and following Gao et al. (2021), we train all models on 1000 steps and evaluate it on the same validation dataset. All other hyperparameters are the same as ones mentioned in Appendix A.

C GLUE evaluation metrics

We use accuracy for SST, QQP, MNLI, QNLI, RTE, and WNLI, combined score of pearson and spearman correlation for STS-B, and matthews correlation for CoLA. When averaging, we use only the
Table 3: Few shot ($K = 200$) full results on all datasets in the GLUE benchmark. SPARTAN provides the best storage-throughput-performance trade-off, with significant improvements in fine-tuning throughput when compared to other parameter efficient methods (Pfeiffer and Houlsby), significant storage savings when compared to RoBERTa. All results are averaged over 3 seeds.

MNLI-m score for the MNLI task. All results are reported on the validation dataset of GLUE. No hyperparameter tuning was performed on the validation set.

D Model and dataset details for qualitative analysis

We use a BERT-small architecture (Turc et al., 2019) and consider SPARTAN model with 5 parent cells and 1 child cell corresponding to each parent to make the qualitative analysis transparent. Thus, choosing a certain parent is equivalent to choosing the corresponding child. We train the model on the BBC-news classification dataset for 10 epochs.

E Storage details and parameter computation

For the nine GLUE datasets, RoBERTa uses 4.43 GB of storage space, Houlsby uses 0.58 GB, and Pfeiffer and SPARTAN use 0.53 GB. In terms of the number of parameters, RoBERTa uses 1107 million, Houlsby uses 144.23 million, and Pfeiffer and SPARTAN use 133.62 million. The formula for SPARTAN’s calculation is the following, where $T$ is the number of tasks, $P$ is the number of parents, $C$ is the number of children, $d$ is the hidden dimensionality, and $L$ is the number of layers, and $N_{RoBERTa}$ is the number of parameters in the base RoBERTa model.

$$N_{RoBERTa} + 2T \times (P + P \times C) \times dL$$

F Speed benchmarking

To emulate Raspberry Pi 4 and iPhone, we use the Linux cgroups command to enforce the memory limit. The number of CPU cores are enforced using the slurmctld command. All experiments are conducted using the CPU version of PyTorch. To measure the throughput, we consistently use a batch size of 32.

G Limitations

Our speed benchmarking results have been thoroughly conducted and emulated on the hardware we have available, but we could not run the experiments on a physical Raspberry Pi and iPhone 11. We also wish to extend our work to languages other than English.

H Risks

We do not see any potential risks for our architecture and do not release any model weights. But we will open source our code and have provided it as part of the supplementary material.