Multi-Head Adapter Routing for Data-Efficient Fine-Tuning

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Abstract

Parameter-efficient fine-tuning (PEFT) methods can adapt large language models to downstream tasks by training a small amount of newly added parameters. In multi-task settings, PEFT adapters typically train on each task independently, inhibiting transfer across tasks, or on the concatenation of all tasks, which can lead to negative interference. To address this, Polytropon [Ponti et al., 2022] jointly learns an inventory of PEFT adapters and a routing function to share variable-size sets of adapters across tasks. Subsequently, adapters can be re-combined and fine-tuned on novel tasks even with limited data. In this paper, we investigate to what extent the ability to control which adapters are active for each task leads to sample-efficient generalization. Thus, we propose less expressive variants where we perform weighted averaging of the adapters before few-shot adaptation (Poly-µ) instead of learning a routing function. Moreover, we introduce more expressive variants where finer-grained task–adapter allocation is learned through a multi-head routing function (Poly-S). We test these variants on three separate benchmarks for multi-task learning. We find that Poly-S achieves gains on all three (up to 5.3 points on average) over strong baselines, while incurring a negligible additional cost in parameter count. In particular, we find that instruction tuning, where models are fully fine-tuned on natural language instructions for each task, is inferior to modular methods such as Polytropon and our proposed variants.

1 Introduction

The ability to train effective models with a relatively small number of training data is of paramount importance due to the paucity of annotated examples in most domains. One effective few-shot learning approach is to leverage large models pre-trained on a vast amount of unlabelled data, and fine-tune them on the few examples available for each downstream task. To reduce the memory cost of duplicating a large amount of parameters for each downstream task, recent approaches resort to parameter-efficient fine-tuning (PEFT) methods, such as LoRA [Hu et al., 2022], SFT (Ansell et al., 2022), or IA3 [Liu et al., 2022]. These only fine-tune adapters applied to parts of the original model. Nevertheless, it remains unclear how to best exploit a set of training tasks to better generalize to a set of unseen test tasks in a sample-efficient fashion, based on just a few examples. One straightforward solution is to perform multi-task pre-training, i.e. first train the large model on the union of the examples from the training tasks, then fine-tune the obtained model to the test task [Liu et al., 2022; Ye et al., 2021]. However, this solution does not take into account that test tasks may require solving different combinations of sub-problems compared to training tasks [Vu et al., 2020], thus failing to
achieve compositional generalization [Rosenbaum et al., 2019][Ponti, 2021]. Moreover, specializing the model towards different tasks during training can yield gradients that are poorly aligned, resulting in negative transfer [Wang et al., 2021].

Polytropon (Poly) was recently proposed by Ponti et al. [2022] to address these issues. Under this framework, the model is trained to perform different tasks by resorting to different combinations of latent modular skills. This makes it possible to later re-combine the learned skills to solve test tasks more effectively. This process is reminiscent of a sort of attention over training tasks, as test tasks can effectively re-use only the most relevant skills learned during multi-task pre-training. In practice, each skill is implemented as a LoRA [Hu et al., 2022] adapter, which modifies a large pre-trained model, such as T5 or BART [Raffel et al., 2020, Lewis et al., 2020a]. During both multi-task pre-training and few-shot test task fine-tuning, Poly optimizes both the inventory of skills parameters and a (relaxed) binary task–skill routing matrix, which determines which skills are active for each training task.

In this paper, we investigate the role of the routing function in achieving sample-efficient generalization. In particular, we compare the original Poly with two newly proposed variants, which either reduce or increase its expressivity. In Poly-$\mu$, all available adapter parameters are averaged before few-shot adaptation, as opposed to fine-tuning the routing matrix. In Poly-S, by virtue of a multi-head routing function, different subsets of input dimensions can be processed by different adapters and subsequently concatenated. Crucially, this comes at negligible extra costs in terms of parameter count.

We evaluate our methods, as well as a series of competitive baselines for few-shot task adaptation, on a wide array of benchmarks. These include Crossfit [Ye et al., 2021], Natural Instructions [Wang et al., 2022], and the T0 task suite [Sanh et al., 2022]. Based on our results, we report a series of findings. First, Poly-S improves Poly’s performance on all datasets by a sizeable margin at no extra cost. This demonstrated that multi-head routing allows for finer-grained and more flexible adapter re-combinations, achieving better generalization capabilities. Second, adapter averaging in Poly-$\mu$ surpasses vanilla multi-task pre-training, thus discovering a simple and effective single-adapter fine-training technique. Thirdly, methods based on modular transfer learning, such as Poly and variants, are better than full fine-tuning based on natural language instructions for each task. This showcases the advantages of modularity for encouraging sample-efficient generalization and preventing negative transfer. In particular, Poly shines when the training set contains a large number of diverse tasks.

2 Background

We are given a set of tasks $\mathcal{T} = \{T_1, ..., T_T\}$, with each task $T_i$ containing a set of samples $\mathcal{D}_i = \{(x_1, y_1), ..., (x_n, y_n)\}$. The set of all tasks is partitioned into training and test tasks, $\mathcal{T} = T_{train} \cup T_{val}$, and the objective is to leverage data in $T_{train}$ and transfer knowledge to facilitate...
learning on the test tasks $T_{eval}$. For all the methods discussed, the training takes place in two phases: the first consists of multi-task pre-training, in which an adapter method, such as LoRA or IA3, is trained on the set of training tasks $T_{train}$. The second phase consists in fine-tuning the learnt adapter independently on each test task in $T_{eval}$.

We follow the procedure in [Raffel et al., 2020] and formulate each task as a text-to-text problem, enabling standard maximum-likelihood training with teacher forcing and a cross-entropy loss.

### 2.1 LoRA & IA3

LoRA [Hu et al., 2022] and IA3 [Liu et al., 2022] are two adapter parametrizations recently proposed in the literature. For each linear transformation corresponding to query ($q$), key ($k$), value ($v$) and output ($o$) of each self-attention layer, LoRA modifies the base model by:

$$h_{q,k,v,o} = W_0 q_{k,v,o} + \alpha A_q k_v, v_o (B q_{k,v,o})^T x,$$

where $W_0$ are the (frozen) weights of the pre-trained model (e.g. either T5 or BART), $A,B \in \mathbb{R}^{d \times r}$ are low-rank learnable parameters and $\alpha = 1/|r|$. IA3, on the other hand, modifies key and self-attention values element-wise but also modifies the feed-forward MLP ($f$) with:

$$h_{k,v} = l_{k,v} \odot (W_{0,k,v}) x; \quad h_f = (l_f \odot (W_{0,f,x})) W_{2,f},$$

where $l_{k,v}, l_f \in \mathbb{R}^d$ are learnable parameters and $W_{0,f,x}$ are the frozen parameters of the feed-forward layer in the backbone. In what follows, we will describe how we modify the LoRA adapter to account for multiple skills. The derivations are similar for IA3. For clarity, we will drop the superscripts $q,k,v,o$ as the modifications will be the same for each layer.

One simple method for leveraging adapters is described in Liu et al. [2022]: first pre-train a shared adapter layer in $T_{train}$ with multi-task learning, then fine-tune it independently on each test task in $T_{eval}$. Intuitively, this allows for finding a good initialization for the fine-tuning phase via multi-task pre-training. We call this method Shared.

### 3 Methods

#### 3.1 Polytropon Adapter Layer

Typical adapter methods either fully share adapters across tasks or train individual adapters for each task. Poly1y addresses the multi-task problem by softly sharing adapter parameters across tasks.

Each Poly1y adapter layer contains a fixed set of skills $S = \{1, \ldots, |S|\}$ with $|S| \ll |T|$. When using LoRA, each skill $i$ is a LoRA, associated with its parameters $A_i, B_i \in \mathbb{R}^{d \times r}$, where $r$ is the LoRA rank. In addition, each Poly1y layer contains a task–skill routing matrix $Z \in \mathbb{R}^{|T|\times|S|}$. We call $Z_{\tau,i}$ the routing vector of task $\tau$, with $z_{\tau,i}$ the probability logits of using skill $i$ to solve task $\tau$ for the current layer. Differently from mixture-of-experts approaches [Fedus et al., 2022], $Z$ is a free parameter and it is binary, as it defines a soft partition over skills. In practice, during training, a Gumbel-sigmoid distribution [Jang et al., 2017] is used, with $z_{\tau,i} \sim \text{Gumbel}(\tau, i)$.

At each forward pass, Poly1y combines skills for the current task by performing a weighted average in parameter space. That is, skill-specific parameters are combined with $z_{\tau}$, to obtain the task-specific adapter parameters:

$$A^\tau = \sum_i A_i \frac{z_{\tau,i}}{\sum_j z_{\tau,j}}; \quad B^\tau = \sum_i B_i \frac{z_{\tau,i}}{\sum_j z_{\tau,j}}; \quad A^\tau, B^\tau \in \mathbb{R}^{d \times r}$$

(\text{Poly})

Note that we normalize the mixing coefficients $z_{\tau,i}$ for each task to ensure that the number of active skills does not affect the norm of $A^\tau, B^\tau$. The derivation using IA3 adapters is similar. Different subsets of skills can then be activated for the current layer and combined in a task-specific way.

Following [LoRA], the output of the Poly1y layer is added to the output of the original layer of the frozen backbone:

$$h = W_0 x + \alpha A^\tau (B^\tau)^T x.$$

During multi-task pre-training, for each query, key, value and output in each self-attention layer, the parameters learned by Poly1y are the adapter parameters, $\Phi = \{A_i, B_i\}_{i=1}^{|S|}$, and the routing matrices
The adapter parameters, since most of the parameters are contained in the LoRA tensors similar to multi-head attention (Vaswani et al., 2017), where attention can be made more expressive by applying attention on subsets of the input and then concatenating the result.

This is similar to the adapter initialization before test time fine-tuning. For each test task \( \tau \), we set \( z_\tau \) and all the skill parameters \( \Phi \) allows more flexibility to adapt to the test task. For all datasets, we set \( |S| = 8 \).

### 3.2 Poly-\( \mu \): Initialization via Adapter Averaging

It might be natural to verify whether it is important to learn \( z_\tau \) for each given test task. To do so, we propose Poly-\( \mu \), which shares the same multi-task pre-training procedure as Poly, but for each test task \( \tau \), sets \( z_\tau = (1/|S|, \ldots, 1/|S|) \) during fine-tuning. This is equivalent to averaging the adapter parameters for each skill into a single one before fine-tuning. Specifically, the adapter used during fine-tuning is initialized with (similarly for \( B^T \)):

\[
A^\tau = \frac{1}{|S|} \sum_i A_i^\tau; \quad A^\tau \in \mathbb{R}^{d \times r} \tag{Poly-\( \mu \)}
\]

where \( A_i^\tau \) are the parameters of the adapters after Poly multi-task pre-training. Note that, differently from Poly, Poly-\( \mu \) fine-tunes the same amount of parameters as the Shared baseline (Tab. 1). Thus, any difference in performance between the Shared baseline and Poly-\( \mu \) comes from differences in the adapter initialization before test time fine-tuning.

### 3.3 Poly-S: Multi-Head Adapter Routing

In Poly, skill combination remains coarse: only linear combinations of adapter parameters are possible and thus the shift induced remains linear. We propose to augment the expressivity of the combination while keeping the parameter count similar. Poly-S (Fig. 1 right) takes inspiration from multi-head attention (Vaswani et al., 2017): it partitions the input into \( h \) different disjoint subsets, creates a Poly adapter layer of smaller dimension for each subset, and finally concatenates the result of the transformation. This corresponds to learning a different routing matrix \( Z \) for each subset of input features, therefore enabling the model to select different skills for different subsets of the input dimensions. This is similar to multi-head attention (Vaswani et al., 2017), where attention can be made more expressive by applying attention on subsets of the input and then concatenating the result.

In each Poly-S layer, we have \( h \) routing matrices \( Z_k \in \mathbb{R}^{|T| \times |S|} \) arranged in a tensor \( Z \in \mathbb{R}^{|T| \times |S| \times h} \). Let us denote with \( W[k] \in \mathbb{R}^{d \times r} \) the \( k \)-th slice along the rows of the matrix \( W \in \mathbb{R}^{d \times r} \).

The adapter parameters \( A^\tau \in \mathbb{R}^{d \times r} \) for task \( \tau \), and for each adapter layer, are computed as (similarly for \( B^T \)):

\[
A^\tau_k = \sum_j A_j[k] \cdot \frac{\hat{z}_{\tau,j,k}}{\sum_j \hat{z}_{\tau,j,k}} \quad \text{with} \quad A^\tau_k \in \mathbb{R}^{d \times r}, \tag{Poly-S}
\]

\[
A^\tau = \text{concat}(A_1^\tau, \ldots, A_h^\tau)
\]

where concat concatenates along the first dimension. Multi-task pre-training and fine-tuning are similar to Poly. Note that Poly-S results in only a negligible increase in the total amount of parameters, since most of the parameters are contained in the LoRA tensors \( W \) (Tab. 1). For all datasets, we set \( h = 8 \).

| Method       | Pre-Training               | Fine-Tuning               | Inference               |
|--------------|----------------------------|---------------------------|-------------------------|
| Shared (LoRA)| \( 2 \times d \times r \)  | \( 2 \times d \times r \)  | \( 2 \times d \times r \)  |
| Poly-\( \mu \)| \( 2 \times d \times r \times |S| \times |T| \times |S| \)  | \( 2 \times d \times r \)  | \( 2 \times d \times r \)  |
| Poly          | \( 2 \times d \times r \times |S| \times |T| \times |S| \)  | \( 2 \times d \times r \times |S| \times |S| \times h \)  | \( 2 \times d \times r \times |S| \times h \)  | \( 2 \times d \times r \)  |
| Poly-S        | \( 2 \times d \times r \times |S| \times |T| \times |S| \times h \)  | \( 2 \times d \times r \times |S| \times h \)  | \( 2 \times d \times r \)  |
| Full FT       | \( d \times d \)           | \( d \times d \)           | \( d \times d \)           |

Table 1: Number of parameters (per layer) used for each method. The calculation is done by assuming LoRA as the base adapter modifying a linear transform in \( \mathbb{R}^{d \times d} \). Note that the total number of parameters changed by Full FT is larger, given that the method also changes parameters for layers not modified by LoRA. All of the methods tested (apart from Full FT) use the same number of parameters at inference time.
4 Experiments

4.1 Baselines

In addition to Poly, the original version of Polytropon as proposed in Ponti et al. [2022], we evaluate our newly proposed variants with adapter averaging (Polyn-µ, described in Sec. 3.2) and multi-head adapter composition (Polyn-S, described in Sec. 3.3). We compare these methods for modular transfer learning with the following baselines for task-level generalization:

- **Shared** trains a single skill common to all pre-training tasks, which is then fine-tuned on each test task separately. This is the most common approach to multi-task learning.
- **Random-µ** draws a random binary routing matrix $Z$, fixed during multi-task pre-training. We use a sparsity of 50%, meaning that each task uses exactly half the skills available. At test time the learned skills are averaged into a single one before fine-tuning. Comparing this baseline with Polyn-µ, we mean to test whether averaging skills obtained with random $Z$ would provide an initialization comparable to averaging skills obtained by learning $Z$.
- **Private-µ** trains a disjoint skill for each pre-training task. At test time, the skills are averaged into one before fine-tuning. Note that this differs from the Private baseline in Ponti et al. [2022], which simply skips the pre-training phase and trains an adapter from scratch for each test task. As above, this baseline is meant to test whether averaging private skills for each task would do just as well as Polyn-µ.
- **Full FT** – for benchmarks where natural language instructions for each task are available, we also experiment with fully fine-tuning a model. In this case, no parameters of the pre-trained model are frozen and no adapters are inserted. Note that this increases the amount of trainable parameters significantly compared to all the other baselines. The purpose of this baseline is to verify if modular architectures are necessary when natural language instructions already provide information to condition the model behaviour.

4.2 Datasets

We test our methods on: Crossfit Ye et al. [2021] a multi-task dataset with 160 train and 20 test tasks originally used to benchmark Polytropon; the T0 Sanh et al. [2022] evaluation suite used in the recent PEFT method T-Few Liu et al. [2022]; and Natural Instructions Wang et al. [2022], a large scale dataset with more than 1,600 training tasks.

**Crossfit** For the Crossfit Ye et al. [2021] experiments, we use the same hyperparameters as in the original Polytropon paper for both pre-training and fine-tuning. In order to perform early stopping, we use perplexity on the validation sets of the training tasks, rather than performing few-shot fine-tuning on the validation tasks. We were able to reproduce (and in some cases increase) the performance of Polyn and Shared, the two methods tested in the original paper. All methods use BART-large Lewis et al. [2020b] as the backbone and LoRA Hu et al. [2022] for our parameter-efficient adapters.

**Natural Instructions** To limit computational costs, we report the result on 16 out of 119 test tasks. Tasks were chosen at random, with the requirement that at least 300 examples were available, and were equally split into 100 training, 100 validation and 100 test examples. For every method, we perform early stopping on the validation set. We report results with Rouge-L averaged across 3 seeds. Following the NI setup, all methods use T5-Large Raffel et al. [2020] as the backbone and LoRA Hu et al. [2022] as the adapter.

**T0 Tasks** We follow the pre-training, fine-tuning and evaluation procedure discussed in Liu et al. [2022], using hyper-parameters and losses suggested in the public codebase. Polyn variants reported here all use the ia3 adapter to model each individual skill, making the comparison fair with the T-Few baseline. All methods were tested with T0-3B Sanh et al. [2022] as the base model. The asterisk * in Tab. [4] is meant to denote the lack of proper evaluation for the T0 dataset, due to the lack of a valid/test split. To ensure fairness for all methods, we report the median and inter-quartile range of the best validation accuracy for each test task, when evaluated every 4 training epochs.

[1] https://github.com/r-three/t-few
which provides an effective adapter initialization for fine-tuning. This finding potentially sheds light on how we compare the performance of shared and private initializations.

In all the datasets studied, multi-head routing improves performance across datasets. For the Natural Instructions dataset (Tab. 3), Poly selects which skills to use for each task, soft-partitions the skills over tasks, performs comparably to Private-μ first train on skill per training task, and then fine-tunes the average of private skills. In CrossFit, most of the Poly gain comes from the effective initialization while learning the routing vector zτ for the downstream tasks.

Table 2: Results on the CrossFit test tasks. Shared does multi-task training of one shared LoRA and fine-tunes it for each task; Poly learns both the routing matrix Z and fine-tunes skills Φ; Poly-μ fine-tunes the average of skills learnt with Poly; Random-μ fine-tunes the average of skills learnt during multi-task training with a random fixed Z; Private-μ first train on skill per training task, and then fine-tunes the average of private skills. In CrossFit, most of the Poly gain comes from the effective initialization while learning the routing vector zτ for the downstream tasks.

5 Results

Polytropon pre-training is important. While Poly achieves performance gains, a counter-argument is that this might be due to having more parameters during pre-training. To falsify this hypothesis, we compare the performance of Private-μ and Poly in Tab. 2. It emerges that simply adding more capacity by having a unique skill per task actually hurts performance: while Poly observes 0.8% improvement over the Shared baseline, Private-μ sees an 8.7% overall decrease. It is an expected result that sharing parameters across tasks has an overall beneficial impact, but Poly seems to learn a more effective way of leveraging the multi-task training set.

Learning the routing matrix Z is important. In Tab. 2, we see that Random-μ, which randomly soft-partitions the skills over tasks, performs comparably to Shared. We observe that by letting the model select which skills to use for each task, Poly can improve its performance.

The average of Poly’s skills is a good initialization for PEFT. An interesting finding is that Poly-μ consistently outperforms Shared. This highlights that averaging skills makes a better initialization than learning an adapter shared across tasks from the start. The consistently superior performance of Poly-μ with respect to Random-μ and Private-μ stresses the importance of Poly’s pre-training, which provides an effective adapter initialization for fine-tuning. This finding potentially sheds light on future work for improving meta-learning and weight-averaging approaches [Izmailov et al. 2018].

The benefit of learning the routing vector for a test task depends on the dataset. We compare Poly with Poly-μ. In Crossfit (Tab. 2) and T0 (Tab. 4), Poly-μ performs on par with Poly. However, for the Natural Instructions dataset (Tab. 3), Poly > Poly-μ, which highlights that in this setting learning zτ is important. We hypothesize that Poly can successfully leverage the large variety of tasks in NI and thus it becomes particularly effective in selecting which training skills are important.

Multi-head routing improves performance across datasets. In all the datasets studied, Poly-μ outperforms Poly and all other baselines. We observe a 0.6% gain on T0 tasks, a 1.1% gain on
Table 4: Results on the 11 test tasks of the T0 data. We report the median and interquartile range computed over 5 seeds. The asterix is meant to denote the lack of proper evaluation framework due to the lack of validation set. To ensure fairness for all methods, we report the best validation accuracy per task, evaluated every 4 fine-tuning epochs.

| NI Task                  | Shared | Full FT | Poly-µ   | Poly    | Poly-S   |
|--------------------------|--------|---------|----------|---------|----------|
| WINO. QUESTION MODIFICATION PERSON | 90.9±0.1 | 91.1±0.1 | 90.8±0.1 | 90.9±0.2 | 90.9±0.0 |
| BARD ANAL. REASONING CAUSATION | 99.0±0.0 | 100.0±0.0 | 100.0±0.0 | 100.0±0.0 | 100.0±0.0 |
| BARD ANAL. REASONING TRAVEL | 93.7±0.6 | 100.0±0.0 | 93.7±5  | 96.0±0.0 | 98.3±0.6 |
| BARD ANAL. REASONING ROOMS CONT. | 94.1±0.0 | 99.0±0.0 | 93.7±2  | 94.0±0.0 | 94.0±1.0 |
| XLSUM TITLE GENERATION | 33.8±1.1 | 31.8±2.1 | 34.2±7  | 33.0±5  | 34.4±1.0 |
| ANLI R1 ENTAILMENT | 31.0±2.0 | 40.0±6.1 | 33.3±1  | 31.7±2  | 31.7±1.5 |
| SUPERGLUE COPA TEXT COMPLETION | 51.0±0.0 | 51.7±2.5 | 62.3±5  | 68.7±1.2 | 74.0±1.0 |
| DAILY DIALOG TYPE CLASSIFICATION | 66.0±0.0 | 61.7±2.5 | 63.3±9  | 66.3±0.6 | 64.3±3.2 |
| NYC LONG TEXT GENERATION | 47.9±1.1 | 49.6±0.1 | 46.4±0  | 46.2±4  | 46.4±0.6 |
| DISFL QA TEXT MODIFICATION | 90.9±0.4 | 89.2±0.6 | 90.5±0  | 92.2±0.1 | 91.9±0.6 |
| DISFL QA QUEST. YESNO CLASSIFICATION | 68.0±2.6 | 63.0±1.3 | 67.0±1.3 | 66.3±0.7 | 78.3±1.1 |
| AMBIGQA TEXT GENERATION | 37.0±1.7 | 51.7±5.0 | 45.3±5  | 51.0±6  | 79.0±4.0 |
| OLLIE SENTENCE ANSWER GENERATION | 67.0±0.0 | 59.0±3  | 67.4±0  | 68.1±0  | 68.2±0.0 |
| SCHEMA GUIDED DSTC8 CLASSIFICATION | 88.1±0.8 | 92.8±9  | 85.8±8  | 89.4±0.7 | 92.0±0.9 |
| E2E NLG TEXT GENERATION GENERATE | 50.1±0.3 | 49.2±1.2 | 50.4±3  | 50.7±0.6 | 50.7±0.8 |

| Avg | 64.9±0.5 | 66.1±0.4 | 65.9±0.7 | 67.2±0.7 | 70.2±3.3 |

Table 3: Few-shot results on a subset of 16 tasks from Natural Instructions (NI) test set. Shared corresponds to multi-task pre-training one adapter on Ttrain and fine-tuning its parameters for each task in Teval. Fu11 FT is similar but we multi-task train and fine-tune all parameters of the pre-trained T5-Large. Poly-µ is more performant than LoRA, confirming that averaging Polytropon’s skills is a better initialization. Poly outperforms both approaches, illustrating that the learnt skills specialize and exploit task diversity during pre-training. Poly-S substantially improves over all baselines.

| T0 Task | Shared | Poly-µ | Poly | Poly-S |
|---------|--------|--------|------|--------|
| ANLI-R1 | 49±1.7 | 49.8±4.9 | 49.9±0.9 | 49.9±2 |
| ANLI-R2 | 43.5±1.6 | 42.9±2.1 | 43.4±2.2 | 42.9±1.9 |
| ANLI-R3 | 40.5±2.2 | 40.8±2 | 41.2±4.2 | 40.8±0.9 |
| CB | 91.1±6.1 | 91.1±1.8 | 91.1±8.8 | 92.9±1.8 |
| COPA | 90.9±0.0 | 90.9±0.0 | 90.9±0.0 | 90.9±0.0 |
| H-SWAG | 51.8±3.9 | 52.1±1.5 | 54.7±0.0 | 52.6±3.3 |
| RTE | 82.0±4.5 | 81.2±8.9 | 80.9±2.9 | 83.0±2.9 |
| STORYCLOZE | 95.6±2.2 | 95.4±1.5 | 95.2±1.7 | 96.0±2.1 |
| WIC | 57.2±1.3 | 57.4±3.9 | 57.8±7.9 | 58.3±4.4 |
| WINOGRANDE | 62.3±1.9 | 61.8±6.6 | 62.1±8.6 | 62.4±7.3 |
| WSC | 72.1±0.0 | 73.1±8.6 | 72.1±8.8 | 73.1±8.8 |

| Avg | 66.9±0.7 | 67.2±1.1 | 67.1±4.4 | 67.2±10.6 | 67.2±5.5 |

Table 4: Results on the 11 test tasks of the T0 data. We report the median and interquartile range computed over 5 seeds. The asterix is meant to denote the lack of proper evaluation framework due to the lack of validation set. To ensure fairness for all methods, we report the best validation accuracy per task, evaluated every 4 fine-tuning epochs.

Crossfit and a 3% gain on NI over the best second. Without requiring additional memory and compute cost at inference time, our method consistently yields gains over other strong baselines. Specifically, this implies that finer-grained routing and adapters specialized for individual subsets of input dimensions are crucial requirements for sample-efficient generalization to new tasks.

Can natural language instructions substitute modular networks? Finally, we ask whether the presence of natural language instructions obviates the necessity of modular adaptation. In other words, since instructions indicate the skills required to solve a task, are they sufficient to achieve generalization to new tasks without resorting to modular methods? By comparing a baseline where T5-Large is fully fine-tuned on NI with Poly variants in Tab. 3 we can conclude that this is not the case. In fact, both the original Poly and our newly proposed Poly-S outperform Full FT, the latter by a margin of 4.1 points on average across all test tasks. What is more, Poly variants get ahead in performance despite requiring updating a significantly smaller amount of parameters.
6 Related Work

Multi-task learning is effective for low resource tasks [Wei et al., 2022, Aribandi et al., 2022, Sanh et al., 2022], as knowledge can be shared across similar tasks by sharing the model parameters. Multi-task learning has also been applied across languages and modalities [Ponti et al., 2019, Bugliarello et al., 2022]. In the context of NLP, several families of methods enable learning new tasks from a limited set of labelled examples. Few-shot in-context learning (ICL) [Brown et al., 2020], where examples of a new task are presented to the model by integrating them into a natural prompt with human-readable instructions, can enable models to generalize to unseen tasks without any gradient-based training. Such approaches are however sensitive to the prompt format [Zhao et al., 2021]. More importantly, ICL methods incur a significant compute overhead, as for every prediction, the full set of examples must be processed by the model [Liu et al., 2022]. To remedy this, many parameter-efficient fine-tuning (PEFT) methods have been proposed as an alternative to ICL, where a small number of new parameters are added over the frozen pretrained network. To name a few, LoRA [Hu et al., 2022] injects learnable low-rank matrices in each Transformer layer. Several approaches learn a sparse shift in parameters, selecting nonzero shifts via the Lottery-Ticket hypothesis [Ansell et al., 2021], or via their approximate Fisher information [Sung et al., 2021]. Finally, prompt-tuning and prefix-tuning methods prepend learnable embeddings to the input, or intermediate activations of the model’s input as a way to inject task-specific knowledge.

Modular networks partition their parameters into several expert modules, each of them specialized to handle specific tasks or goals [Jacobs et al., 1991, Kirsch et al., 2018]. Modular networks are an appealing solution to the problem of adapting to unseen tasks [Corona et al., 2021], as the model can leverage its existing modules and recombine them in a novel way, edging on systematic generalization [Bahdanau et al., 2019]. They have also been testing learning scenarios with data presented sequentially [Ostapenko et al., 2021], and with changing environments [Goyal et al., 2021]. In NLP, mixture-of-experts (MoE) models [Shazeer et al., 2017, Fedus et al., 2022], where a learned gating mechanism routes inputs to appropriate expert layers, have shown success in scaling the number of parameters, leading to better models when compared to their dense counterparts using a similar compute cost.

7 Conclusions

In this paper, we tackle the challenge of generalizing to new tasks based on a few examples after multi-task pre-training. Specifically, we focus on Polytropon [Ponti et al., 2022], a model where each task is associated with a subset of adapters by a routing function. We investigate how varying the level of control afforded by the routing function impacts performance on three comprehensive benchmarks for multi-task learning. First, we find that simple averaging of all adapters before few-shot adaptation to new tasks provides an efficient and effective method. Second, a newly proposed variant of routing function, where multiple heads are responsible for different subsets of input dimensions, improves consistently over all other baselines in all three benchmarks. Importantly, this family of modular neural architectures is superior to instruction tuning, i.e. fully fine-tuning a model on tasks associated with natural language instructions. Multi-head routing demonstrates the importance of fine-grained adapter selection for sample-efficient generalization and holds promise to improve other modular methods, such as Mixtures of Experts [MoEs, Fedus et al., 2022] in future research.

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