CPET: Effective Parameter-Efficient Tuning for Compressed Large Language Models

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Abstract

Parameter-efficient tuning (PET) has been widely explored in recent years because it tunes much fewer parameters than full-parameter fine-tuning (FT) while still stimulating sufficient knowledge from large language models (LLMs) for downstream tasks. Moreover, when PET is employed to serve multiple tasks, different task-specific PET modules can be built on a frozen LLM, avoiding redundant LLM deployments. Although PET significantly reduces the cost of tuning and deploying LLMs, its inference still suffers from the computational bottleneck of LLMs. To address the above issue, we propose an effective PET framework based on compressed LLMs, named "CPET". In CPET, we evaluate the impact of mainstream LLM compression techniques and then introduce knowledge inheritance and recovery strategies to restore the knowledge loss caused by these compression techniques. Our experimental results demonstrate that, owing to the restoring strategies of CPET, collaborating taskspecific PET modules with a compressed LLM can achieve comparable performance to collaborating PET modules with the non-compressed LLM and outperform directly applying vanilla PET methods to the compressed LLM.

1 Introduction

In recent years, the rise in data scale and computing power has boosted the growth of the parameter size of language models. While some small and medium language models with millions of parameters have shown proficiency in capturing rich knowledge (Jawahar et al., 2019; Yenicelik et al., 2020), large language models (LLMs) with billions of parameters (Brown et al., 2020; Black et al., 2022; Chowdhery et al., 2022) exhibit more powerful and comprehensive abilities, especially in terms of cognition and embodiment (Lewkowycz et al., 2022; Nakano et al., 2021; Driess et al., 2023).

Despite the success of LLMs, how to apply LLMs to serve real-world scenarios is an important issue. As most users cannot afford the enormous cost of running LLMs, the prevailing solution is to provide LLM services, with service providers (OpenAI, 2022; Google, 2023) adapting LLMs for specific tasks and then providing users with interfaces to infer the task-specific LLMs. To extend LLM services to multi-task scenarios, parameter-efficient tuning (PET) (Houlsby et al., 2019; Hu et al., 2021) has been widely used for the task adaptation of LLMs, where a unified LLM is frozen as a backbone among different tasks and then tiny tunable PET modules are injected into the backbone to stimulate task-specific knowledge. Compared to conventional full-parameter fine-tuning (FT), where a single LLM is tuned into multiple task-specific LLM copies, PET tunes much fewer parameters and has lower memory overhead in multi-task serving while achieving comparable performance (Ding et al., 2023; Zhou et al., 2022).

Although PET has shown potential in reducing the cost of tuning and deploying LLMs for LLM services, the computation of the shared backbone LLM is inevitable, i.e., the inference of the combination of the backbone LLM and PET modules is still computation-intensive and latency-high. Empirically, adopting model compression techniques (Hinton et al., 2015; Bai et al., 2021; Liang et al., 2021) to compress LLMs into smaller versions is a solution to cope with the different latency requirements of inferring LLMs, yet whether PET modules can work well with compressed LLMs is still an open problem, especially considering that model compression techniques may introduce knowledge loss and performance degradation to the compressed LLMs. In this paper, we build an effective PET framework based on compressed LLMs, named "CPET".

To restore the knowledge loss caused by the compression process, CPET introduce the following

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two mechanisms:

- (1) **PET Knowledge Inheritance**. A stronger LLM can make learning PET modules easier. Meanwhile, the PET modules based on the stronger LLM can also better grasp how to stimulate task-specific knowledge distributed in the LLM. Therefore, we propose to adopt the PET modules learned on the non-compressed LLM as the initialization to learn the PET modules for the compressed LLM. In this way, the task-related knowledge of PET modules learned with the help of the non-compressed LLM can be inherited to obtain more effective PET modules for the compressed LLM.
- (2) Model Knowledge Recovery. In addition to the knowledge of PET modules, the knowledge of the LLM is also important to perform well on downstream tasks. Since compression techniques may result in losing some task-related knowledge within the LLM, we add extra knowledge recovery modules into the compressed LLM to bridge the knowledge gap that arises from the compression process. We point out that compression techniques may weaken multiple capabilities of the LLM while restoring only a part of the lost capabilities requires only a small number of parameters. Through the supervision of task data, we can recover most of the lost capabilities related to specific tasks through some tiny recovery modules.

In experiments, we conduct a comprehensive evaluation of the performance impact brought by various compression methods. The results show that compression results in a significant performance drop without using any knowledge recovery mechanisms. Based on the above observation, we apply CPET for performance recovery, and the experimental results indicate that CPET can restore the performance to the level before model compression. Moreover, computing the compressed LLM requires much lower resources than computing the non-compressed LLM, making CPET finally an effective and efficient PET framework.

2 Related Work

This work is related to LLMs, PET, and model compression. We mainly introduce PET and model compression methods in this paper. More details on LLMs can refer to the survey for more details (Qiu et al., 2020; Han et al., 2021; Bommasani et al., 2021; Zhao et al., 2023).

2.1 Parameter-Efficient Tuning

Although an LLM can acquire rich knowledge from massive pre-training data to handle complex tasks in a zero-shot or few-shot manner (Brown et al., 2020; Black et al., 2022), to better stimulate the knowledge stored in the LLM to serve downstream tasks, there is still a need for adapting the LLM to various scenarios. For traditional PLMs, fine-tuning all parameters of PLMs is the mainstream way to adapt them (Church et al., 2021), yet its parameter inefficiency makes this way costly to adapt LLMs (Ding et al., 2023). Moreover, maintaining task-specific versions of LLM in the storage is unacceptably resource-intensive (Zhou et al., 2022).

To adapt LLMs to multi-task scenarios in a more efficient manner, various PET methods (Lester et al., 2021; Houlsby et al., 2019; Hu et al., 2021; Li and Liang, 2021; Ben Zaken et al., 2022) have been proposed, where LLMs are frozen and some modelindependent tunable modules are injected into the transformer architecture of LLMs to help the adaptation process. PET modules are usually tiny, which can significantly reduce the cost of adapting LLMs. PET modules can be inserted into different locations within the transformer architecture. For instance, prompt tuning (Lester et al., 2021) and prefix tuning (Li and Liang, 2021) are two methods that prepend tunable embeddings to the input and hidden states, respectively. Adapter tuning (Houlsby et al., 2019) applies tunable transformation between adjacent modules. BitFit (Ben Zaken et al., 2022) and LoRA (Hu et al., 2021) make minor internal modifications to the modules of the transformer architecture.

As mentioned before, LLMs have acquired rich capabilities and just need an efficient way to stimulate these capabilities. The role of tunable PET modules is to learn task features and serve as triggers to stimulate task-specific capabilities in LLMs (Ding et al., 2023). Sufficient experiments show that collaborating task-specific PET modules and a frozen LLM can reach comparable performance to fine-tuning all parameters of the LLM. Furthermore, since different task-specific PET modules can share a unified frozen LLM as their backbone, this also leads to lower computation and storage overhead in multi-task serving and switching (Zhou et al., 2022). In general, the emergence of PET methods significantly reduces the cost of tuning and deploying LLMs.

2.2 Model Compression

Although PET methods can reduce the storage cost for deploying LLMs, the computation bottleneck of the LLM itself still exists. Therefore, to further improve efficiency for model serving, it is crucial to speed up the computation of LLMs, and model compression is a commonly used solution. Considering that the PET modules of different tasks usually work together on a unified LLM, here we mainly introduce task-agnostic model compression (Sanh et al., 2019) rather than task-specific compression (Sun et al., 2019) for LLMs, including quantization, pruning, and MoEfication.

In traditional PLMs, 32-bit floating-point numbers are mainly used to represent models. As the model size gradually increases, representing LLMs in a 32-bit format consumes too much GPU memory and computational time. To address this issue, mixed-precision training (Micikevicius et al., 2017) is adopted to represent LLMs with 16-bit floating-point numbers. To further reduce the memory overhead and improve the model speed, quantization methods are applied to represent models with fixed-point numbers, from 8-bit (Zafrir et al., 2019), 4-bit (Frantar et al., 2023) to 1-bit (Bai et al., 2021). To avoid the performance degradation caused by quantization, quantization-aware training (QAT) (Stock et al., 2021) has also been proposed to use a small amount of data to adjust the distribution of model parameters for quantization.

Different from quantization methods that compress the representation of each parameter, pruning methods directly discard some parameters. Commonly used pruning methods include structured pruning (Fan et al., 2020; Wang et al., 2020; Zhang et al., 2021; Xia et al., 2022) and unstructured pruning (Han et al., 2015; Chen et al., 2020; Xu et al., 2021). Structured pruning aims to find useless modules and remove them completely, such as erasing all parameters in a linear layer. Unstructured pruning only removes individual parameters, such as deleting some parameters to form a sparse matrix.

MoEfication (Zhang et al., 2022b), inspired by the mixture-of-experts (MoE) transformer (Lepikhin et al., 2021), aims to divide the parameters of LLMs into multiple partitions, and each time only a few partitions are used to compute the final results. Although most of the currently popular LLMs are dense models, studies have shown that dense LLMs are activated sparsely, and different parameter areas are activated by different data to form some

skill partitions (Wang et al., 2022; Dai et al., 2021; Suau et al., 2020; Panigrahi et al., 2023). Specifically, by analyzing the sparse pattern of activation states in LLMs, the linear layers of LLMs are sliced to MoE, and an expert router is trained to select experts. During the computation process, a certain proportion of relevant experts is dynamically activated according to the input data.

Typically, to make a compressed LLM behave the same as its original version, distillation objectives are often used to align the pre-compression and post-compression models, including aligning both output and intermediate states (Hinton et al., 2015; Sun et al., 2019; Jiao et al., 2020; Liu et al., 2022; Park et al., 2021). Due to space limitations, more compression details can refer to the survey (Liang et al., 2021; Xu and McAuley, 2022).

Currently, combining PET with model compression is preliminary, and only some works attempt to combine PET with model quantization (Dettmers et al., 2023; Liu et al., 2023). Recent work (Chen et al., 2023) also attempts to add modules to recover the knowledge loss caused by model compression, but it has not been fully verified on various downstream tasks. Combining PET with other compression methods to improve the inference speed is still an open issue for further exploration.

3 Methodology

In this section, we will introduce how to build an effective PET framework CPET based on compressed LLMs. Before introducing CPET, we first explain some essential preliminaries.

3.1 Preliminary

For simplicity, we denote a LLM \mathcal{M} as $\mathbf{Y} = f(\mathbf{X}; \theta_{\mathcal{M}})$, where $f(\cdot)$ is the function of the whole transformer architecture, $\theta_{\mathcal{M}}$ is the parameters of the LLM, \mathbf{X} is the input and \mathbf{Y} is the output. In the FT setting, all parameters of \mathcal{M} (i.e., $\theta_{\mathcal{M}}$) are tuned as follows

$$\theta_{\mathcal{M}}^t = \arg\min_{\theta_{\mathcal{M}}} \mathcal{L}(f(\mathbf{X}^t; \theta_{\mathcal{M}}), \mathbf{Y}^t),$$
 (1)

where \mathbf{X}^t , \mathbf{Y}^t is the data of the downstream task t, \mathcal{L} is the loss function of the task t. $\theta_{\mathcal{M}}^t$ is the final task-specific model parameters of the LLM \mathcal{M} .

In the PET setting, \mathcal{M} is frozen, and additional PET modules \mathcal{P} are tuned on task-specific data. We denote the parameters of the PET modules injected into the LLM \mathcal{M} as $\theta_{\mathcal{P}(\mathcal{M})}$. As shown in

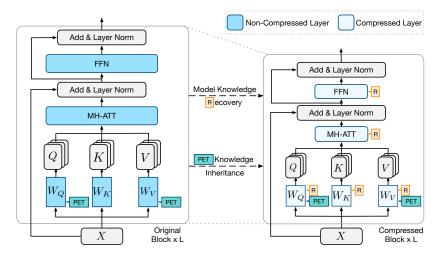


Figure 1: The overall design of our CPET. We use LoRA (Hu et al., 2021) as an example of PET methods.

Figure 1, the computation of the transformer architecture is slightly changed due to the injected PET modules and becomes $\mathbf{Y} = f_{\text{PET}}(\mathbf{X}; \theta_{\mathcal{M}}, \theta_{\mathcal{P}(\mathcal{M})})$. The tuning process is formalized as

$$\theta_{\mathcal{P}(\mathcal{M})}^{t} = \arg\min_{\theta_{\mathcal{P}(\mathcal{M})}} \mathcal{L}(f_{\text{PET}}(\mathbf{X}^{t}; \theta_{\mathcal{M}}, \theta_{\mathcal{P}(\mathcal{M})}), \mathbf{Y}^{t}), \quad (2)$$

where $\theta_{\mathcal{P}(\mathcal{M})}^t$ is the final task-specific PET modules collaborating with the LLM \mathcal{M} .

This paper aims to obtain PET modules based on a compressed LLM. To this end, after applying compression algorithms to compress the LLM \mathcal{M} , making \mathcal{M} have fewer parameters or lower-bit representations, we denote the compressed LLM and its parameters as \mathcal{C} and $\theta_{\mathcal{C}}$ respectively. Then the computation of the compressed model can be described as $\mathbf{Y} = f(\mathbf{X}; \theta_{\mathcal{C}})$.

3.2 Framework

Since PET methods do not change LLMs, adopting PET methods is thus orthogonal to compressing LLMs. Therefore, we propose a more efficient PET framework CPET, by first compressing a LLM using task-agnostic model compression methods and then applying PET methods to the compressed LLM. Formally, CPET can be formalized as

$$\theta_{\mathcal{P}(\mathcal{C})}^{t} = \arg\min_{\theta_{\mathcal{P}(\mathcal{C})}} \mathcal{L}(f_{\text{PET}}(\mathbf{X}^{t}; \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}), \mathbf{Y}^{t}), \quad (3)$$

where $\theta_{\mathcal{P}(\mathcal{C})}$ indicates the parameters of the PET modules injected into the compressed LLM \mathcal{C} .

By combining model compression and PET, on the one hand, we can take advantage of PET to deploy a unified LLM to serve multiple downstream tasks, while only maintaining tiny task-specific PET modules for each downstream task. On the other hand, by adopting a compressed LLM instead of a non-compressed LLM, the inference time and resource requirements of the LLM can be significantly reduced. It is worth noting that this acceleration is not free. It is not difficult to imagine that adopting task-agnostic compression methods may weaken the LLM, which will inevitably affect the search for the optimal parameters $\theta^t_{\mathcal{P}(\mathcal{C})}$ and the effect of the final model $f_{\text{PET}}(\mathbf{X}; \theta_{\mathcal{C}}, \theta^t_{\mathcal{P}(\mathcal{C})})$.

Inspired by the fact that model compression preserves those capabilities of LLMs that smaller models cannot master, we suppose that the PET modules trained on the non-compressed LLM would contain certain task knowledge that the PET modules can hardly learn solely on the compressed model. As shown in Figure 1, to better learn PET modules for the compressed LLM, we adopt the method of inheriting the PET knowledge from those modules trained on the non-compressed LLM. To restore the knowledge loss caused by the compressing process, in addition to the PET modules \mathcal{P} , we add some knowledge recovery modules \mathcal{R} , and Eq. (3) is modified to

$$\theta_{\mathcal{P}(\mathcal{C})}^{t}, \theta_{\mathcal{R}}^{t} = \arg \min_{\theta_{\mathcal{P}(\mathcal{C})}, \theta_{\mathcal{R}}} \left[\mathcal{L}(f_{\text{PET}}(\mathbf{X}^{t}; \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}, \theta_{\mathcal{R}}), \mathbf{Y}^{t}) + \alpha \mathcal{L}_{\text{DIST}}(\mathbf{X}^{t}; \theta_{\mathcal{M}}, \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}, \theta_{\mathcal{R}}) \right],$$
(4)

where $\theta_{\mathcal{R}}^t$ indicates the parameters of the task-specific recovery modules for the task t, and $f_{\text{PET}}(\mathbf{X}; \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}^t, \theta_{\mathcal{R}}^t)$ is finally used to serve the task t. $\mathcal{L}_{\text{DIST}}(\mathbf{X}^t; \theta_{\mathcal{M}}, \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}, \theta_{\mathcal{R}})$ is the distillation loss function for model knowledge recovery, which will be introduced later.

In subsequent sections, we will elaborate on how to conduct PET knowledge inheritance and model knowledge recovery. It is worth noting that although our methods require the non-compressed model to participate in the training process, resulting in extra training time, in the context of model serving, the service period after training for typical tasks is much longer than the training time. Therefore, we sacrifice some training costs for better inference efficiency and effectiveness of the final model obtained.

3.3 PET Knowledge Inheritance

Instead of training PET modules based on the compressed LLM from scratch, we propose training PET modules based on the original noncompressed LLM first, then adapting the learned PET modules to the compressed LLM. The adaption from the non-compressed LLM to the compressed LLM can lead to learning better PET modules on the compressed LLM. Intuitively, it is more effective for a teacher to teach students the fundamentals of a discipline and then let students adapt their comprehension based on their circumstances rather than letting students learn from scratch.

Formally, we first use Eq. (2) to obtain the parameters of the task-specific PET modules $\theta^t_{\mathcal{P}(\mathcal{M})}$ on the task t based on the non-compressed LLM \mathcal{M} , and then use $\theta^t_{\mathcal{P}(\mathcal{M})}$ as the initialization of the task-specific PET modules $\theta_{\mathcal{P}(\mathcal{C})}$ of the compressed LLM \mathcal{C} . After that, $\theta_{\mathcal{P}(\mathcal{C})}$ is further tuned to $\theta^t_{\mathcal{P}(\mathcal{C})}$ on the data of the task t by using Eq. (3) or Eq. (4).

3.4 Model Knowledge Recovery

Since the reduction of parameters orienting to the compressed LLM \mathcal{C} may cause performance degradation, we thus propose to inject the knowledge recovery modules \mathcal{R} into \mathcal{C} to recover the lost knowledge. As shown in Figure 1, we add a bypass next to each linear layer of the transformers to add a small amount of change to the output states of those linear layers. To avoid introducing too many parameters, the recovery modules \mathcal{R} adopt the typical bottleneck MLP structure. Formally, we denote an arbitrary matrix in the compressed LLM as W and the linear transformation as XW, the modified transformation becomes $XW + \sigma(XD)U$, where **D** is the down projection matrix, $\sigma(\cdot)$ is the activation function, and U is the up projection matrix. D and U together form $\theta_{\mathcal{R}}$.

To help obtain $\theta_{\mathcal{R}}^t$ for the task t, we design a distillation objective. Specifically, we first select the PET modules trained with Eq. (2) as the teacher, and then select the PET modules and recovery mod-

ules in Eq. (4) as the student, and the whole distillation loss is given as

$$\mathcal{L}_{\text{DIST}}(\mathbf{X}^{t}; \theta_{\mathcal{M}}, \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}, \theta_{\mathcal{R}}) = \frac{1}{|\mathbf{X}^{t}|} \| f_{\text{PET}}(\mathbf{X}^{t}; \theta_{\mathcal{M}}, \theta_{\mathcal{P}(\mathcal{M})}^{t}) - f_{\text{PET}}(\mathbf{X}^{t}; \theta_{\mathcal{C}}, \theta_{\mathcal{P}(\mathcal{C})}, \theta_{\mathcal{R}}) \|_{2}^{2},$$
(5)

where \mathbf{X}^t is the input data of the task t. As shown in Eq. (4), instead of first learning the recovery modules and then adding the inherited PET modules for further adaptation, we simultaneously conduct knowledge recovery and tune PET modules.

4 Experiments and Analyses

In this section, we will present experimental results and analyses in detail.

4.1 Datasets

We evaluate CPET on 11 datasets, covering typical NLP tasks, including BoolQ (Clark et al., 2019), CB (De Marneffe et al., 2019), RTE (Bentivogli et al., 2009; Wang et al., 2019), COPA (Roemmele et al., 2011), WiC (Pilehvar and Camacho-Collados, 2018), SST-2 (Socher et al., 2013), MRPC (Dolan and Brockett, 2005), QQP (Wang et al., 2018), MNLI (Williams et al., 2017), QNLI (Rajpurkar et al., 2016), and SQuAD (Rajpurkar et al., 2016). For all these datasets, we use their validation sets for testing and parts of their training sets for validation.

4.2 Baselines and Implementation Details

We select T5-3b (Raffel et al., 2020) as the backbone LLM in our experiments. For the compressed models, we use the compressed versions of T5-3b released by Zhang et al. (2022a). The compression methods used in our experiments include 8-bit quantization, structured pruning, unstructured pruning, and MoEfication. Table 1 shows the models used in our experiments and their ideal inference speedup compared to T5-3b (Zhang et al., 2022a).

To evaluate CPET, we adopt 4 paradigms:

(1) **T5-3b + PET**: PET modules are attached to the original T5-3b, and only the parameters of PET modules are tunable while the parameters of the LLM are frozen. (2) **T5-base + PET**: Tunable PET modules are attached to the frozen T5-base model. (3) **CLM + PET**: PET modules are attached to the compressed versions of T5-3b, and then these compressed LLMs (CLMs) are frozen and PET modules are tuned on task-specific data. (4) **CLM + CPET**: CPET is applied to the compressed versions

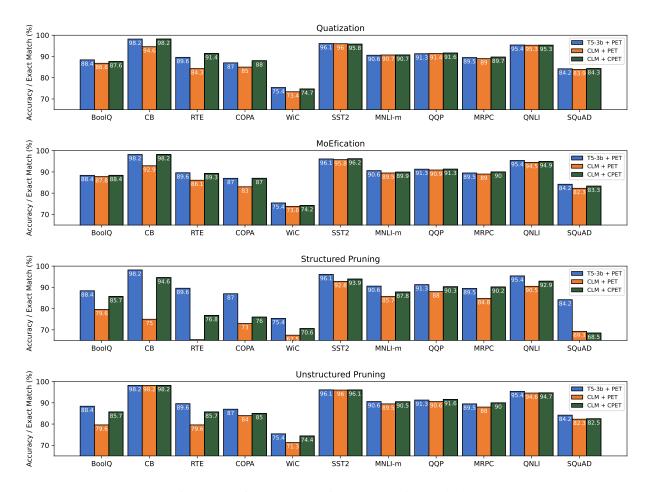


Figure 2: Performance on various compression methods.

of T5-3b, and only PET and recovery modules are tuned on task-specific data.

All the above paradigms are implemented with the open-source toolkit OpenDelta (Ding et al., 2023). For a fair comparison, we use LoRA (Hu et al., 2021) as a representative PET method for all paradigms. We set the bottleneck dimension of the LoRA modules to 32 in all paradigms. We also set the bottleneck dimension of CPET recovery modules to 32. The tunable parameters of PET and CPET modules are about 20M and 120M, respectively. We select the best learning rate among $\{1e-3, 5e-4, 1e-4, 1e-5\}$. The batch size is among $\{8, 16, 32, 64, 128, 256\}$. The weight decay is 1e-2. The distillation coefficient in Eq. (4) is default to $\alpha=0.05$.

4.3 The Overall Performance of CPET

Figure 2 shows the performance improvement of CPET compared to PET. From the figure, we can find that:

(1) Comparing the original LLM and its compressed versions, the results show that the com-

pressed LLMs cannot perform as well as the original LLM. It suggests that task-agnostic compression methods lead to losing some knowledge related to downstream tasks. That is to say, to improve the inference speed, the performance of the compressed model may decrease due to the acceleration process. If there is a mechanism to make up the performance gap without affecting the inference speed, applying compression methods will be more reasonable.

- (2) Within the compressed model, CPET consistently outperforms vanilla PET methods. Such results indicate that task capabilities are effectively migrated through the mechanisms of knowledge inheritance and knowledge recovery.
- (3) Through cross-comparisons between different compression models, we find that quantization and MoEfication have relatively little loss on the model performance, and the loss can be completely restored using our CPET method. However, the pruning methods cause more performance loss, especially the structured pruning method. Even though, CPET can recover most of the performance

Model	Model Size	Ideal Speedup
T5-3b (bf16)	5.61 GB	100%
T5-3b (M)	3.74 GB	150%
T5-3b (UP)	2.81 GB	200%
T5-3b (SP)	2.81 GB	200%
T5-3b (Q)	2.81 GB	200%
T5-3b (Q+UP+M)	0.94 GB	600%
T5-base (bf16)	0.44 GB	1400%

Table 1: The models used in the experiments. The notation "T5-3b (X)" represents the T5-3b model with the setting "X". "M", "UP", "SP", and "Q" represent the model is compressed with MoEfication, unstructured pruning, structured pruning, and 8-bit quantization, respectively. "Q+UP+M" means "Q", "UP" and "M" are combined together to achieve higher compression ratios. "bf16" indicates the model is represented in bfloat16 floating-point rather than 32-bit floating-point format.

loss caused by these pruning methods.

To further evaluate CPET on a higher compression ratio, we combine quantization, MoEfication, and unstructured pruning to obtain a compressed T5-3b that has a close size to T5-base. We compare the four paradigms based on this compressed model. Table 2 shows the experimental results. Results show that CPET is compatible and can be easily applied to a highly compressed model that uses multiple compression methods. Meanwhile, CPET demonstrates better performance on compressed models than training a small model with a close size from scratch.

4.4 Ablation Studies

To further discuss the effectiveness of CPET design, it is vital to understand how different mechanisms in CPET help restore the knowledge loss caused by model compression, whether the number of parameters the main cause of performance enhancement and what is the speed effect of applying CPET. Therefore, we focus on answering the following questions to illustrate the benefits of CPET.

To more clearly demonstrate the inner mechanisms of CPET, we conduct ablation studies based on the compressed model using the mixture of compression methods with different settings, and adopt RTE for evaluation. In the settings of CPET, the intermediate ranks of LoRA and Recovery modules are 8. LoRA modules are injected into linear transformations of $\mathbf{W}^{\mathbf{Q}}$ and $\mathbf{W}^{\mathbf{K}}$ in attention layers. Recovery modules are injected into all linear transformations in both attention and feed-forward layers.

How do different mechanisms in CPET help restore the knowledge loss caused by model compression methods?

To evaluate the effectiveness of each mechanism used in CPET, we test all possible combinations of inheritance, recovery, and distillation. We can find that from Table 3:

- (1) PET knowledge inheritance is effective. By initializing the tunable parameters with the PET modules trained on the non-compressed LLM, the performance of combining the final PET modules and the compressed LLM has been significantly improved. This indicates that in the optimization space of the compressed LLM, it is difficult to obtain the optimal task-specific parameters of PET modules based on random initialization, but more optimal PET modules can be achieved more easily using PET knowledge inheritance.
- (2) Simply adding recovery modules brings a certain level of performance improvements in some circumstances. However, it can achieve further performance improvements by adopting our distillation strategy. This suggests combining recovery modules with the knowledge distillation strategy to enhance PET modules is necessary.

Is the improvement only caused by increased parameters?

To answer this question, we carry out the study in Table 4. Each setting in this study maintains the same number of parameters as CPET. In CPET, the tunable parameters consist of PET modules and recovery modules. We introduce new settings of LoRA+LoRA and Large LoRA, which trivially increase the tunable parameters by adding more LoRA modules or using larger LoRA modules. Considering that recovery modules can be regarded as functionally specialized PET modules, we further test Rec+Rec (use recovery modules instead of LoRA) and Large Rec (Larger recovery modules with the same parameter number). More specifically, in LoRA+LoRA settings, we first inject LoRA modules to W^{Q} and W^{K} in attention layers, like conventional LoRA, and then inject extra LoRA modules to all linear transformations in both attention and feed-forward layers, replacing the recovery modules. Both LoRAs have an intermediate rank of 8. In Large LoRA settings, we make the LoRA modules on $\mathbf{W}^{\mathbf{Q}}$ and $\mathbf{W}^{\mathbf{K}}$ to larger modules whose intermediate rank is 16. Rec+Rec settings are similar to LoRA+LoRA settings, except for replacing all LoRA modules with

Method	Model	BoolQ	CB	RTE	COPA	WiC	SST2
	Size(GB)	Acc(%)	Acc(%)	Acc(%)	Acc(%)	Acc(%)	Acc(%)
T5-3b + PET	5.61	88.4	98.2	89.6	87.0	75.4	96.1
T5-base + PET	0.44	79.5	91.1	80.7	71.0	69.9	93.5
CLM + PET	0.94	86.0	94.6	81.8	79.0	73.6	94.8
CLM + CPET	0.94	86.7	100.0	86.1	85.0	75.3	96.2
Method	MNLI-m	QQP	QQP	MRPC	QNLI	SQuAD	SQuAD
	Acc(%)	Acc(%)	F1(%)	Acc(%)	Acc(%)	EM(%)	F1(%)
T5-3b + PET	90.6	91.3	90.7	89.5	95.4	84.2	92.5
T5-base + PET	84.8	90.6	89.9	86.5	93.1	79.0	87.8
CLM + PET	89.0	90.6	89.9	89.7	94.7	79.9	90.6
CLM + CPET	89.9	91.5	90.9	89.5	94.7	81.3	90.5

Table 2: The results of applying CPET on the mixture of multiple compression methods (%).

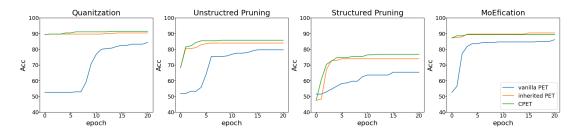


Figure 3: The convergence of vanilla PET, inherited PET (CPET without recovery modules), and CPET.

recovery modules (intermediate ranks are 8). Large Rec settings are similar to Large LoRA settings.

From Table 4, we find that adding more parameters makes marginal improvements, showing that only adding more tunable parameters cannot bridge the knowledge gap caused by model compression.

Does adding more parameters slow down model inference?

Since CPET introduces a little more parameters than conventional PET methods, it has a potential cause of slower inference. Given that the inference speed of compressed models are highly related to implementation, we evaluate CPET and conventional PET methods with the same backbone on the same platform to avoid uncertainties caused by backbone model implementation. We report the average time and corresponding standard deviation of each model call. Table 5 shows that the inference time of CPET and PET methods are almost the same, proving that the time bottleneck of inference lies in the model itself, while the extra parameters added due to CPET do not slow down model inference.

From the ablations above, we prove that each mechanism introduced in CPET is helpful to recover performance degradation of model compression without retarding model inference. The struc-

Inherit	Recover	Distill	RTE Acc(%)
			83.6
\checkmark			85.4
	\checkmark		82.5
		✓	82.5
\checkmark	\checkmark		87.5
\checkmark		\checkmark	85.7
	\checkmark	✓	86.1
✓	✓	✓	88.6

Table 3: The ablation studies on RTE (%). When eliminating inheritance, we keep the LoRA modules injected and train these modules from scratch. When eliminating recovery, we simply remove the recovery modules. When eliminating distillation, the training loss function only consists of the task loss function without the distillation loss function. These studies use the mixutre of multiple compression methods same as 4.3 to compress the LLM.

tural design of CPET is reasonable, which is beneficial to knowledge inheritance and recovery.

4.5 The Convergence of CPET

Although we are primarily concerned with the final inference speed and performance after training, the method usability may be compromised if the training process spends too much time. Therefore, based on four compressed LLMs, we compare the convergence speed of tuning PET modules to han-

Setting	RTE Acc(%)
LoRA	83.6
LoRA+LoRA	83.9
Large LoRA	84.6
Rec+Rec	85.0
Large Rec	84.3
CPET	88.6

Table 4: The ablation studies with parameter quantity controlled. Each setting has the same amount of tunable parameters. "LoRA" represents the conventional LoRA module with the same size in CPET. "Rec" represents the recovery module with the same size in CPET. "Large" prefix means doubling the size, which equals to the size of the whole CPET. These studies use the mixutre of multiple compression methods same as 4.3 to compress the LLM.

Method	# Param	Avg. Time (ms)
CLM+PET	10M	(9761±17)
CLM+CPET	60M	(9526±70)

Table 5: The average inference time. "CLM" here represents the compressed T5-3b using mixture of compression methods. "# Param" represents the additional parameters compared with the backbone model. The average time and corresponding standard deviations represent the time taken for each model call.

dle the BoolQ dataset.

From Figure 3, we can find that due to our PET knowledge inheritance mechanism, CPET is superior to the vanilla PET methods in terms of convergence speed and final results. Adding the recovery module will not affect the convergence speed. Furthermore, when quantization, unstructured pruning, or MoEfication is used, the inheritance mechanism gives a better starting point for tuning PET modules. While in the case of structured pruning, even though the initial point of CPET does not work well on tasks, it is closer to the optimal point in the optimization space and converges faster.

Moreover, considering the existence of numerous downstream tasks, the PET modules based on a unified LLM may be trained by community users on their own private data and then uploaded to the Internet. When adapting these PET modules to a compressed LLM, there may not be any task-specific data available for the adaptation process. Intuitively, applying PET parameters trained on one model to another requires adaptation using additional data. Surprisingly, from Figure 3, we can find that when quantization or MoEfication is used, we can achieve ideal results without using any data

Model	MMLU(5-shot)	Ideal Speedup
LLaMA-13b*	46.9	100%
Q*	46.6	200%
Dettmers et al. (2023)†	47.5	100%
Liu et al. (2023)†	46.7	200%
Q + CPET	48.3	200%

Table 6: The 5-shot MMLU performance based on different compressed LLaMA models (%). "Q" represents 8-bit quantization. "*" represents the MMLU performance without training on Alpaca. "†" are the current competitive methods that train LoRA on the quantized LLaMA-13b model.

for adaptation, by only using the PET inheritance mechanism we proposed.

4.6 Instruction Tuning with CPET

The above experimental results have proven the strength of CPET for specific downstream tasks. In this section, we further investigate the effectiveness of CPET when applied CPET to a more general scenario — instruction tuning. We select Alpaca (Taori et al., 2023) as the instruction tuning dataset and use 5-shot MMLU (containing 57 subtasks) (Hendrycks et al., 2020) as the evaluation benchmark. We compress LLaMA-13b (Touvron et al., 2023) into 8-bit quantization version. Since LLaMA use SwiGLU (Ramachandran et al., 2017) as its activation function, which makes LLaMA not sparse enough to adopt MoEfication to compress itself, we thus do not adopt MoEfication to compress LLaMA-13b. More details of the LLaMA experiments can be found in Appendix A. From Table 6, we can find that CPET combined with quantization can still exhibit strong performance while achieving faster inference speed. In future work, we will explore better recovery solutions orienting pruning methods to make CPET more effective on those general tasks like instruction tuning. As compared with the current competitive methods that combine LoRA and quantized LLaMA models, CPET achieves better performance and exhibits versatility on different compression models.

5 Conclusion

In this paper, we propose an effective PET framework based on the compressed LLM (named CPET) to further reduce the resource requirements and inference time when deploying LLM and PET modules to serve downstream tasks. Considering taskagnostic compression methods may cause losing

some task-specific knowledge, we introduce PET knowledge inheritance and model knowledge recovery to restore the lost knowledge. By inheriting the prior task knowledge of the PET modules learned on the non-compressed LLM, searching for the optimal PET modules for the compressed LLM becomes easier. Moreover, by introducing knowledge recovery modules to recover task-specific capabilities lost in the compression phase, collaborating PET modules with the compressed LLM can achieve comparable performance to those PET modules based on the non-compressed LLM. The experimental results show that CPET can outperform baselines based on the compressed LLM, and meanwhile, CPET maintains the advantages of PET methods for multi-task serving. This paper mainly accelerates the inference of PET methods and LLMs. We leave the computation bottleneck of LLMs in the tuning process as future work.

6 Limitations

Our work focuses on the efficiency and effectiveness of model serving, but it requires a small amount of extra training time. In this paper, we only choose LoRA as a representative of PET methods. In fact, our framework can be applied to any PET method. The compression method adopted in this paper does not change the number of layers of the LLM. However, for those compression methods that change the hidden dimensions of the model, how to transfer the knowledge of PET modules on the non-compressed LLM remains an open problem for our future work.

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A The Experimental Settings of LLaMA

When applying CPET on LLaMA, we add LoRA on all linear modules of the attention layer and add the recovery module on all linear modules in transformers. LoRA and recovery modules' ranks are set to 16 with a dropout rate of p=0.05. While training, distillation function \mathcal{L}_{DIST} in Eq. (4) is set to be the MSE of output logits with $\alpha=1$. In Table 6, method Dettmers et al. (2023) is in the setting of "NFloat4+DQ", method Liu et al. (2023) is in the setting of LoRA with 4-bit quantized model. All results are evaluated with the framework LM-Eval (Gao et al., 2021).