Delta Tuning: A Comprehensive Study of Parameter Efficient Methods for Pre-trained Language Models

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Abstract

As pre-trained language models (PLMs) have become the fundamental infrastructure for various NLP tasks and researchers have readily enjoyed themselves in the pretraining-finetuning paradigm, evidence from emerging research has continuously proven that larger models tend to yield better performance. However, despite the welcome outcome, the process of fine-tuning large-scale PLMs brings prohibitive adaptation costs. In fact, fine-tuning all the parameters of a colossal model and retaining separate instances for different tasks are practically infeasible. This necessitates a new branch of research focusing on the parameter-efficient adaptation of PLMs. In order to unleash the imagination of the possible advantages of such methods, not limited to parameter efficiency, we coined a new term \textit{delta tuning} from a morphological point of view to refer to the original “parameter efficient tuning”. In contrast with the standard fine-tuning, delta tuning only fine-tunes a small portion of the model parameters while keeping the rest untouched, largely reducing both the computation and storage costs. Recent studies have demonstrated that a series of delta tuning methods with distinct tuned parameter selection could achieve performance on a par with full-parameter fine-tuning, suggesting a new promising way of stimulating large-scale PLMs.

In this paper, we first formally describe the problem of delta tuning and then comprehensively review recent delta tuning approaches. We also propose a unified categorization criterion that divides existing delta tuning methods into three groups: \textit{addition-based}, \textit{specification-based}, and \textit{reparameterization-based} methods. Though initially proposed as an efficient method to steer large models, we believe that some of the fascinating evidence discovered along with delta tuning could help further reveal the mechanisms of PLMs and even deep neural networks. To this end, we discuss the theoretical principles underlying the effectiveness of delta tuning and propose frameworks to interpret delta tuning from the perspective of optimization and optimal control, respectively. Furthermore, we provide a holistic empirical study of representative methods, where results on over 100 NLP tasks demonstrate a comprehensive performance comparison of different approaches. The experimental results also cover the analysis of combinatorial, scaling and transferable properties of delta tuning. To facilitate the research of delta tuning, we are also developing an open-source toolkit, OpenDelta\(^2\), that enables practitioners to efficiently and flexibly implement delta tuning on PLMs. At last, we discuss a series of real-world applications of delta tuning.

**Keywords**— natural language processing, pre-trained models, parameter-efficient, delta tuning

\"The lurking suspicion that something could be simplified is the world\’s richest source of rewarding challenges.\"

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1 Introduction

Language lies at the heart of human intelligence. Its systematic nature allows the denotation of real objects or illustration of laws with symbolic expressions and could convey almost infinite information with a finite symbolic set; its arbitrariness shows that there are no necessary connections between the real-world and the language space, and indicates the importance of world knowledge and social convention to the effectiveness of language in human society; its richness in meaning enables the expression of extremely complex behaviors or tasks with clear and simple symbols. Understanding language is the key to understanding intelligence. The inquiry into what language is and how we acquire, store and comprehend it has never stopped among psychologists and linguists, and the charm of language will continue to impress and inspire us in the future. Likewise, to create the real intelligence system, researchers in the field of artificial intelligence (AI) have been dedicated to training machines to model, understand and generate language.

With the revolutionary development in computing hardware, traditional statistical methods have yielded their place to deep learning (LeCun et al., 2015) that heavily rely on tensor computation and huge data volume. Modern natural language processing (NLP) uses deep neural networks to implicitly model probability and capture language representations (Hochreiter & Schmidhuber, 1997; Bengio et al., 2000; Grefenstette et al., 2014; Kim, 2014; Vaswani et al., 2017). A standard pipeline involves encoding language into discrete tokens (tokenization) as model input, choosing a proper model architecture, training the network with the given corpora, and designing self-supervised tasks. Experimented with various model architecture, the Transformer neural network (Vaswani et al., 2017) produced state-of-the-art performances on a series of NLP tasks and has been widely acknowledged as the standard architecture for pre-trained language models (PLMs). This ushers a new era of pre-training and fine-tuning. PLMs typically use heavily over-parameterized Transformers as the base architecture, and model natural language in bidirectional (Devlin et al., 2019), auto-regressive (Radford et al., 2018, 2019), or sequence-to-sequence (Raffel et al., 2019) manners on large-scale unsupervised corpora. Then for downstream tasks, task-specific objectives are introduced to fine-tune the PLMs for model adaptation. Notably, the increasing scale of PLMs (measured by the number of parameters) seems to be an irreversible trend as constant empirical results show that larger models (along with more data) almost certainly lead to better performance. For example, the 175 billion parameters GPT-3 (Brown et al., 2020) generates natural language of unprecedented quality and can conduct various desired zero-shot tasks with satisfactory results given appropriate prompts. Nevertheless, performing full parameter fine-tuning on existing computing devices becomes formidable with the growing model scale. This finally leads to a desperate yet thought-provoking question: do we really need to update all the parameters? In this context, how to efficiently and effectively adapt large models to particular downstream tasks is an intriguing research issue.

As a predominant way to conduct model adaptations, fine-tuning initializes the model with the pre-trained weights, updates all the parameters, and produces separate instances for different tasks. But as implied by the case of GPT-3, fine-tuning becomes impractical as the model scales. In addition to the cost of deployment and computation, storing different instances for different tasks is extremely memory-intensive. To further explore the practical application rate of large models (PLMs with over 1 billion parameters), we randomly select 1000 published research papers from the recent five NLP conferences (200 for each venue), including ACL 2021, EMNLP 2021, NAACL 2021, ACL 2020, and EMNLP 2020. Then we manually count the usage of PLMs in these peer-reviewed works, specifically, we only focus on the experiments part of the papers. According to the statistics in Table 1, although the use of PLMs has almost become standard, there are only 0.5% ~ 4% research papers that practically adopt large ones in the experiments. This suggests, firstly, that there is still inertia in the academic community which has resulted in scarce usage of large models in research, and also that the cost of deploying and experimentally validating large PLMs hinders the development of NLP research.

| Venue       | No PLMs | Small PLMs | Large PLMs | Per. of Large PLMs |
|-------------|---------|------------|------------|--------------------|
| ACL 2021    | 41      | 151        | 8          | 4.0%               |
| EMNLP 2021  | 46      | 150        | 4          | 2.0%               |
| NAACL 2021  | 37      | 158        | 5          | 2.5%               |
| ACL 2020    | 107     | 92         | 1          | 0.5%               |
| EMNLP 2020  | 62      | 137        | 1          | 0.5%               |

Table 1: The usage of models of different sizes in research published in NLP conferences, the statistic is based on 1000 randomly selected papers. Large PLMs are defined as PLMs with over 1 billion parameters.
To this end, a branch of parameter-efficient methods for model tuning arises. Although each of these approaches has its own emphasis on structural design, they essentially tune a “delta” (i.e., adaptive parameters) in the adaptation phase, we thus coin the term delta tuning\(^3\) to refer to these methods. Parametric efficiency is an external manifestation of delta tuning that further exposes the low-rank or low-dimensional nature of large model adaptation in a more fundamental way. Generally, delta tuning only updates a small number of parameters (inherently in the model or additionally introduced) while freezing the remaining parameters that account for the vast majority. Adapter tuning (Houlsby et al., 2019) is among the earliest approaches to steer pre-trained models with a limited number of parameters. It inserts adapter modules with bottleneck architecture between layers in PLMs and only these inserted modules get updated during fine-tuning. Prefix-tuning (Li & Liang, 2021) tunes the PLMs by updating the pre-pended parameters in each transformer layer. Taken insights from GPT-3, prompt tuning (Lester et al., 2021) only prepends and updates task-specific trainable parameters in the original input embeddings. BitFit (Zaken et al., 2021) updates the bias terms in PLMs while freezing the remaining modules. LoRA (Hu et al., 2021a) decomposes attention weight gradient into low-rank matrices to reduce the number of trainable parameters. With the diverse flourishing research and the promising results, efforts have been made to explain and compare the essence of some popular methods. He et al. (2022) propose a unified view of the existing delta tuning methods and illustrate the difference and connections among them formulaically.

The delta tuning methods enable efficient tuning and practical usage for large pre-trained models and often achieve comparable results to the standard fine-tuning. For example, the vanilla fine-tuning of GPT-3 needs to update about 175,255 million parameters, which is almost infeasible in both industry and academia. However, if we only tune the injected low-rank decomposition matrices in each Transformer layer (Hu et al., 2021a), only 37.7 million parameters will be involved in backpropagation. Delta tuning not only provides a promising way to adapt large PLMs, but also sheds light on the mechanisms behind such model adaptations. Compared to pre-training, delta tuning makes model adaptation a considerably low-cost process in terms of data volume and model optimization. For instance, researchers find that the optimization problem of the adaptations for big models could be reparameterized into a low-dimensional “intrinsic subspace” (Aghajanyan et al., 2021; Qin et al., 2021b), and various NLP tasks could be handled by only tuning very few parameters in the subspace. The empirical evidence takes us one step closer to understanding how pre-trained models work, and may even spawn new theoretical questions that are worth exploring.

This paper first attempts to survey the development and recent advances in delta tuning. For preliminaries, we give a description of the Transformer neural models and mainstream PLMs ($\S2$: PRELIMINARIES). Then we formally describe the delta tuning problem and propose a categorization criterion ($\S3$: DELTA TUNING) to provide a unified view on delta tuning methods. Categorizing delta tuning into addition-based ($\S3.1$: ADDITION), specification-based ($\S3.2$: SPECIFICATION), and reparameterization-based ($\S3.3$: REPARAMETERIZATION) methods, we comprehensively introduce the technical details and empirical conclusions of the methods.

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\(^3\)In $\S3$: DELTA TUNING and $\S4$: THEORY, we use the consistent mathematical expressions $\Delta$ and $\delta$ to describe and analyze delta tuning.
To better understand the inner connections among the delta tuning methods and the mechanisms of model adaptation, we develop theoretical analysis (§4: THEORY) of delta tuning by proposing theoretical frameworks from two different perspectives, optimization (§4.1: OPTIMIZATION) and optimal control (§4.2: OPTIMAL CONTROL). Our theoretical discussion is summarized as follows:

- **Optimization.** Based on the intrinsic low dimension in a large pre-trained language model, we show that delta tuning is essentially a subspace optimization method with respect to the solution space or functional space. The discussion justifies the designs of the existing delta tuning methods and explains some phenomena in the experiments.

- **Optimal Control.** Inspired by the relationship between deep learning and optimal control theories, we interpret delta tuning as seeking optimal controllers for PLMs. We propose an optimal control framework that unifies different delta tuning approaches. Our analysis provides theoretical references for the novel design of delta tuning methods.

In terms of empirical studies, we carry out extensive and systematic experiments (§5: EXPERIMENTS) on over 100 NLP tasks to rigorously explore the performances (§5.1: PERFORMANCE), combinability (§5.2: COMBINABILITY), the power of scale (§5.3: SCALE), transferability (§5.4: TRANSFERABILITY), etc. Our main findings are summarized as follows:

- **Performance.** Despite the huge potential, existing delta tuning methods are still no match for the conventional fine-tuning either in performance or convergence. Among several representative delta tuning methods, no single algorithm predominantly outperforms the others. We also analyze the key properties of delta tuning such as convergence and computational efficiency.

- **Combinability.** Combining multiple delta tuning methods is more effective than a single method under most cases, despite that the optimal combination may vary for different PLM backbones, downstream tasks, and data scales.

- **Power of Scale.** The power of scale (i.e., both the performance and convergence are improved when the PLM’s size is increased) is observed in all of the delta tuning methods, even in unregulated neural modules. We provide a reasonable perspective to explain this phenomenon.

- **Transferability.** Existing delta tuning methods could well support knowledge transfer, showing non-trivial transferability among downstream tasks of similar categories.

At last, we discuss the applications of delta tuning from various perspectives (§6: APPLICATIONS), including fast training and shareable checkpoints, multi-task learning, catastrophic forgetting mitigation, and in-batch parallel computing. We also discuss the broader impacts of the delta tuning technique in terms of fairness and energy cost (§ IMPACTS). Hopefully, this paper could inspire research to advance the efficient use of large models. The tools, codes, data splits, trained delta checkpoints in our experiments will be publicly available to facilitate future research.

2 Preliminaries

Since almost all the mainstream PLMs are developed based on the Transformer (Vaswani et al., 2017) model, and delta tuning usually carries out operations on Transformer models, this section gives preliminaries of the Transformer (Vaswani et al., 2017) model and mainstream PLMs with different modeling strategies. For more details, please refer to original papers (Vaswani et al., 2017; Devlin et al., 2019; Brown et al., 2020; Raffel et al., 2019) or related surveys (Han et al., 2021b; Liu et al., 2021a; Bommasani et al., 2021).

2.1 Transformer

The Transformer model has become a key infrastructure for existing state-of-the-art PLMs. The original Transformer is proposed as an encoder-decoder model, where both the encoder and decoder are composed of a stack of identical blocks. Each Transformer layer consists of an attention layer and a fully-connected feed-forward neural network, while the decoder block contains an extra cross-attention layer on top of the self-attention layer to capture information from the encoder. Between each layer, there are residual connection (He et al., 2016) and layer normalization (Ba et al., 2016) modules.

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4This paper focuses on pre-trained language models, however, the delta tuning technique can also be seamlessly transferred to other areas where large-scale neural models come into play, such as computer vision (Rebuffi et al., 2017; Perez et al., 2018)
Attention Layer. Attention layers are the key to the success of Transformer. It involves a query matrix \( Q \in \mathbb{R}^{n \times d_k} \), a key matrix \( K \in \mathbb{R}^{m \times d_k} \), and a value matrix \( V \in \mathbb{R}^{m \times d_v} \), where each row in the matrices corresponds to one sample and the \( i \)-th row in \( K \) and \( V \) together form a key-value pair accordingly. The attention mechanism can be formally represented as

\[
H = \text{ATT}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V.
\]

Intuitively, each row in \( H \in \mathbb{R}^{n \times d_v} \) is a weighted sum of row vectors in \( V \), while the weights are decided by the dot product of the query vector and the key matrix. The specific attention adopted in the Transformer model is termed as self-attention, as the three matrices \( Q, K, V \) are derived from the same feature matrix \( X \in \mathbb{R}^{n \times d} \) from the previous layer, parameterized by three weight matrices \( W_q \in \mathbb{R}^{d \times d_k}, W_k \in \mathbb{R}^{d \times d_k}, W_v \in \mathbb{R}^{d \times d_v} \), as follows:

\[
Q = XW_q, K = XW_k, V = XW_v
\]

Moreover, Transformer uses multi-head self-attention with multiple sets of \( Q^{(i)}, K^{(i)}, V^{(i)} \), each set corresponding to a distinct set of weight matrix \( W_q^{(i)} \in \mathbb{R}^{d \times d_k}, W_k^{(i)} \in \mathbb{R}^{d \times d_k}, W_v^{(i)} \in \mathbb{R}^{d \times d_v} \), where \( d_h \) is usually set to \( \frac{1}{h} d \). The final output \( H \in \mathbb{R}^{n \times d_v} \) is obtained by projecting the concatenation of a series of \( H_i \) into a new feature space with a new weight matrix \( W_o \in \mathbb{R}^{d_v \times d_v} \).

\[
H = \text{MH-ATT}(Q, K, V)
= \text{Concat}(H_{1}, \ldots, H_{h})W_o,
\]

\[
H_i = \text{ATT}(Q^{(i)}, K^{(i)}, V^{(i)})
= \text{ATT}(XW_q^{(i)}, XW_k^{(i)}, XW_v^{(i)}),
\]

For decoder blocks, however, there is an additional mask operation that prevents query vectors from attending to the future positions yet to be decoded. Besides, there is an extra cross-attention layer following the self-attention layer, where the query matrix \( Q \) is derived from the output of the previous layer in the decoder, and the key and value matrices \( K, V \) are transformed from the output of the last layer of the encoder. It is designed to avoid foreseeing the true label while considering information from the encoder when decoding.

Fully-connected Feed-Forward Layer. The fully-connected feed-forward layer following the attention layer is composed of two linear transformation and a non-linear activation function. Denote the input matrix as \( X \in \mathbb{R}^{n \times d_i} \), the output of the feed-forward layer is

\[
F = \text{FFN}(X) = \sigma(XW_1 + b_1)W_2 + b_2,
\]

where \( \sigma(\cdot) \) is the activation function (usually the ReLU function), and \( W_1 \in \mathbb{R}^{d_i \times d_m}, b_1 \in \mathbb{R}^{d_m}, W_2 \in \mathbb{R}^{d_m \times d_o}, b_2 \in \mathbb{R}^{d_o} \) are all learnable parameters. Empirically, \( d_i \) is set equal to \( d_m \), \( d_m \) is set to be much larger than \( d_i \) and \( d_o \).

Residual Connection and Normalization. Following each attention layer and each feed-forward layer, residual connection and layer normalization are applied. They conduct to retaining information when the model is considerably deep and thus guarantees the model performance. Formally, given a neural layer \( f(\cdot) \), the residual connection and normalization layer is defined as

\[
\text{A&N}(X, f) = \text{LayerNorm}(X + f(X)),
\]

where \( \text{LayerNorm}(\cdot) \) denotes the layer normalization operation, and A&N means “add and norm”.

Typical Transformer Layer. As depicted in Figure 2, a typical transformer layer can be expressed as

\[
M = \text{A&N}(X, H)
M = \text{A&N}(M, F),
\]

Figure 2: An illustration of a Transformer block. Generally speaking, a delta tuning method could be applied to any positions in a Transformer model.
where $\textbf{M}$ is the intermediate representation after the attention block, and $\textbf{Y}$ denotes the output of the layer with respect to input $\textbf{X}$.

## 2.2 Pre-trained Language Models

Current pre-trained language models are almost consistently based on the Transformer model. However, they usually vary in the specific structure adopted (e.g. only using Transformer encoder or decoder, or both). This section briefly reviews some of the popular PLMs with respect to different modeling strategies (as shown in Figure 3).

**Masked Language Modeling.** The first group of PLMs are bidirectional models based on the Transformer encoder, among which BERT (Devlin et al., 2019) is the most representative one. It is pre-trained with masked language modeling (MLM) task and next sentence prediction (NSP) task. When pre-training, the input is a pair of sequences, where special tokens $[\text{CLS}]$ and $[\text{SEP}]$ are added to the original input, and tokens are randomly replaced with $[\text{MASK}]$ tokens. MLM loss seeks to maximize the conditional probability of label tokens at $[\text{MASK}]$ position, as shown in equation (7), where $M(\textbf{x})$ contains all masked token positions. While the final representation of $[\text{CLS}]$ is used to predict whether the two sentences are coherent.

$$ L_{\text{MLM}} = - \sum_{x_m \in M(\textbf{x})} \log P(x_m | x_{\setminus M(\textbf{x})}) $$

RoBERTa (Liu et al., 2019) is almost identical to BERT, except that it removes the NSP task, applies the more robust dynamic masking to the input, and is trained with larger batch sizes, the longer time, and more data. Bidirectional models are powerful in generating contextual representations of tokens and language understanding.

**Auto-regressive Language Modeling.** Another set of PLMs are language models purely based on the Transformer decoder. They are also termed as auto-regressive language models. The objective of language modeling (LM) is to model the probability of the given sequence by factorizing it into the probability of the $i$-th token given the previous tokens:

$$ L_{\text{LM}} = - \log P(\textbf{x}) = - \sum_{i=1}^{T} \log P(x_i | x_{<i}), $$

where $x_0$ is a special token indicating the start of a sentence. It is natural to take the advantage of masking in the Transformer decoder to model the conditional probability. During pre-training, the final output at each position is further fed into a softmax layer to predict the next token. The most well-known models are GPT (Radford et al., 2018) and GPT-2 (Radford et al., 2019), while GPT-2 is trained to be more robust to diverse tasks. The unidirectional characteristic of these models enables high-quality language generation.

**Sequence to Sequence Modeling.** The last type of PLMs are sequence-to-sequence models built upon a complete Transformer architecture. Common models of this type include T5 (Raffel et al., 2019) and BART (Lewis et al., 2020). Both models adopt span-level corruption as the major pre-training task, i.e. to randomly replace a sequence of the text of arbitrary length with a single mask token and ask the model to fill...
in the original tokens. It is also termed as **Seq2Seq MLM loss**, whose objective is to maximize the probability of target sequence given a corrupted sequence:

\[
\mathcal{L}_{\text{Seq2Seq MLM}} = - \sum_{x_{i,j} \in M(x)} \sum_{i=i} \log P(x_t | x_{\setminus M(x)}, x_{i:t-1})
\]  

(9)

where \(M(x)\) contains all corrupted text spans and \(x_{i,j}\) is a single masked span. While BART requires a different fine-tuning paradigm to assist in the classification task, T5 unifies all tasks under the text-to-text generation paradigm. As a combination of both bidirectional encoder and auto-regressive decoder, sequence-to-sequence models are powerful in both language understanding and generation tasks.

### 3 Delta Tuning

Given a pre-trained model \(\Theta = \{w_1, w_2, ..., w_N\}\) and training data \(D\), the objective of PLM adaptation is to produce the adapted model \(\Theta' = \{w'_1, w'_2, ..., w'_M\}\). Define \(\Delta \Theta = \Theta' - \Theta\) as the operation on top of the original model \(\Theta\). In vanilla fine-tuning, \(N = M\) and \(\Delta \Theta = \nabla f_\Theta(D)\) is the update value of all parameters in \(\Theta\) with respect to training data. While in delta tuning, \(\Delta \Theta\) refers to modification of a small number of parameters. Empirically, \(|\Delta \Theta| \ll |\Theta|\) in vanilla fine-tuning, while for delta tuning, \(|\Delta \Theta| \ll |\Theta|\), where \(|\cdot|\) indicates the number of parameters involved.

![Figure 4: The categorization criterion of delta tuning, where \(\Theta\) denote the pre-trained parameters, and \(\Theta'\) represent the well-tuned parameters.](image)

To organize them under a unified framework, we categorize the delta tuning methods into three groups according to the operations on the delta parameters (as illustrated in Figure 4): addition-based, specification-based, and reparameterization-based approaches.

- **Addition-based** methods introduce extra trainable neural modules or parameters that do not exist in the original model or process. In addition-based methods, \(M \geq N\) and \(\Delta \Theta = \{w_{N+1}, w_{N+2}, ..., w_M\}\).
- **Specification-based** methods specify certain parameters in the original model or process become trainable, while others are frozen. Denote the set of trainable parameters as \(W\), then \(\Delta \Theta = \{\Delta w_1, \Delta w_2, ..., \Delta w_N\}\). When \(w_i \in W\), \(\Delta w_i\) is the incremental value from \(w_i\) to \(w'_i\), else, \(\Delta w_i = 0\).
- **Reparameterization-based** methods reparameterize existing parameters to a parameter-efficient form by transformation. Denote the set of parameters to be reparameterized as \(W\), and suppose that each \(w_i \in W\) is reparameterized with new parameters \(R(w_i) = \{u_1, u_2, ..., u_N\}\), then \(\Delta \Theta = (\Theta \setminus W) \cup U\), where \(U = \{u_j | \exists w_i \in W, u_j \in R(w_i)\}\).

### 3.1 Addition-based Methods

With the above definition in mind, addition-based methods introduce additional parameters to the neural network. In this section, we introduce two branches of representative addition-based methods, **adapter-based tuning** and **prompt-based tuning**.

**Adapters-based Tuning.** As a seminal work in delta tuning, adapter-based methods inject small-scale neural modules (adapters) to the Transformer layers and only tune these adapters for model adaptation. Although such a strategy leaves an open choice of adapter structures, a simple instantiation (Houlsby et al., 2019) achieves impressive performance and has become the most widely used baseline in recent research. Specifically, one
3.1 Addition-based Methods

An important seminal work of this branch of research is prefix-tuning (Li & Liang, 2021), which prepends which could be regarded as “encapsulation” of task information (in fact, this perspective can be applied to all

As an addition-based approach, adapter-based tuning has the advantage of placing multiple adapter instances

Although adapter works with significantly fewer tunable parameters than vanilla fine-tuning, some work attempts for a more rigorous saving strategy by introducing inductive biases into the structure of the adapter layer. For example, Compacter (Mahabadi et al., 2021a) propose to use a combination of hypercomplex multiplication and parameter sharing. The hypercomplex multiplication parameterizes the original linear layer as the sum of the Kronecker products of two small matrices. Taking the down-projection as an example,

\[ W_d = \sum_{i=1}^{n} A_i \otimes B_i, \text{where } A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{d \times n} \]

Their method reduces the number of parameters in the adapter layer to \( \frac{1}{n} \) without harming the performance, where \( n \) is the number of divisions of the linear layer. It also shows that a simple low-rank decomposition of the linear layer leads to comparable performance with the adapter layer, i.e.,

\[ W_d = AB^T, \text{where } A \in \mathbb{R}^{d \times n}, B \in \mathbb{R}^{r \times n} \text{ and } n \ll \min(d, r). \]

As an addition-based approach, adapter-based tuning has the advantage of placing multiple adapter instances on a pre-trained model simultaneously, which can benefit many application scenarios. For example, multi-task learning (Stickland & Murray, 2019; Mahabadi et al., 2021b) is an advantageous setting for adapter-based methods, inserted with adapter modules in parallel with the self-attention module, PLMs could demonstrate impressive representational capacity in the multi-task setting. In contrast to directly conducting multi-task learning on adapters, adapterFusion (Pfeiffer et al., 2021) first pre-train task-specific adapters and then combine the representations of the pre-trained adapters to leverage the cross-task knowledge and enhance the performance of transfer learning.

In terms of computational efficiency, the training of adapters could be 60% faster than vanilla fine-tuning while the inference is only 4%-6% slower. And the computational cost could be further reduced dynamically by removing adapters from lower transformer layers (Rücklé et al., 2021). Research also shows that adapter-based fine-tuning demonstrates better robustness than fine-tuning. Specifically, adapter-based fine-tuning could perform better than vanilla fine-tuning on few-shot and cross-lingual scenarios (He et al., 2021) and is more robust under adversarial attacking (Han et al., 2021a). We provide a comparison of different adapters, as well as other delta tuning methods in Table 2.

To sum up, adapters are lightweight additional neural modules that could be trained in a task-specific style, which could be regarded as “encapsulation” of task information (in fact, this perspective can be applied to all the “deltas”). Although in an ideal world, adapters could be freely shared and reused by researchers, in practice, sharing and reusing such modules face substantial obstacles. Taking the first step, AdapterHub (Pfeiffer et al., 2020a) provides a feasible platform and toolkit to deploy adapters inside the transformer-based models.

Prompt-based Tuning. Instead of injecting neural modules to the Transformer model, prompt-based methods wrap the original input with additional context. As a strategy to stimulate pre-training language models by mimicking pre-trained objectives in the downstream tasks, prompt-based learning has achieved promising performance in various NLP tasks (Gao et al., 2021; Hu et al., 2021b; Tan et al., 2021), especially in low-data settings (Scao & Rush, 2021). The introduction of the technique and implementations of prompt-based learning have already been comprehensively presented in other literature (Liu et al., 2021a; Ding et al., 2021). In this paper, we primarily focus on the parameter-efficient attribute of prompt-based learning (only prefixes or prompts are optimized) and pay less attention to the settings where the models and prompts are simultaneously optimized.

An important seminal work of this branch of research is prefix-tuning (Li & Liang, 2021), which prepends trainable continuous tokens (prefixes) to the input and hidden states of each Transformer layer. Each prefix
is drawn from a newly initialized trainable parameter matrix $\mathbf{P}$, while other parameters of the pre-trained model remain unchanged during training. During generation, if an activation $h_i$ is in a prefix position, it is the direct copy of the corresponding trainable parameter; otherwise, the activation is computed by the model as $h_i = \text{LM}(z_i, h_{<i})$. It is worth noting that the paradigm could be applied to both autoregressive and encoder-decoder models. Liu et al. (2021b) demonstrate that such a strategy could be effectively applied to natural language understanding (NLU) with different scales of models.

Compared to prefix-tuning which adds tunable prefixes to every intermediate Transformer layer, prompt tuning (Lester et al., 2021) proposes a more simplified strategy that only adds soft prompts to the input layer. Similar to prefix-tuning, the newly introduced prompts are not parameterized by the pre-trained model but an additional parameter matrix. And during training, the parameters of soft prompts are updated by gradient descent while the model parameters keep frozen. As the model size increases, the performance gap between prompt-tuning and full parameter fine-tuning is narrowed. Particularly, when the model scales to T5-XXL with 11 billion parameters, prompt tuning yields comparable performance on SuperGlue with fine-tuning. This strategy also exhibits sensitivity to the length and initialization of the soft prompts. Prompts could also be injected in the pre-training stage to seek a satisfying initialization point (Gu et al., 2021). Moreover, similar to other methods, prompt tuning also demonstrates transferability across tasks (Vu et al., 2021; Su et al., 2021), which suggests that appropriate initialization could be substantially beneficial for downstream tasks.

The Training Curse of Prompt-based Methods Although prompt-based methods exhibit a promising future for the adaptation of large pre-trained models, especially that prompt tuning does not need to modify anything inside the neural network, there still exist unsolved challenges. In practice, prompt tuning is difficult to optimize, and generally, this phenomenon becomes more apparent as the volume of data and the size of the model decreases. Even though soft prompts can be trained successfully, they converge significantly slower than full parameter fine-tuning and other delta tuning methods during training. In our experiments, we validate the phenomenon across different datasets (§5.1: PERFORMANCE), indicating that it is an interesting topic to train soft prompt to converge stably in various situations.

3.2 Specification-based Methods

Specification-based methods fine-tune a few inherent parameters while leaving the majority of parameters unchanged in model adaptation. This approach does not seek to change the internal structure of a model but to optimize a small number of internal parameters to solve particular tasks. Generally, such specifications could be implemented based on heuristics or training supervision.

Heuristic Specification. Specification-based methods do not introduce any new parameters in the model, but directly specify part of the parameters to be optimized. The idea is simple but surprisingly effective, Lee et al. (2019) only fine-tune one-fourth of the final layers of BERT and RoBERTa and could produce 90% of the performance of full parameter fine-tuning. BitFit (Zaken et al., 2021) empirically proves that by only optimizing the bias terms inside the model and freezing other parameters, the model could still reproduce over 95% performance on several benchmarks. Empirical results in BitFit also show that even if we use a small random set of parameters for delta tuning (which obviously will degrade the performance), the model could still yield passable results on the GLUE benchmark. Unfortunately, the work only applies this trick to small-scale models, and there is no guarantee that randomly choosing some parameters to be tuned would remain competitive for larger models. Another valuable observation is that different bias terms may have different functionalities during model adaptation.

Learn the Specification. Rather than manually or heuristically specify which parameters to be updated, one alternative is to “learn” such specifications. Following the definition in §3: DELTA TUNING, diff pruning (Gu et al., 2021) reparameterizes the fine-tuned model parameters $\Theta'$ as the summation of the pre-trained parameters $\Theta$ and the difference vector $\Delta \Theta$, i.e., $\Theta' = \Theta + \Delta \Theta$, where $|\Theta| = |\Theta'|$. Hence, the key issue is to encourage the difference vector to be as sparse as possible, this work regularizes the vector by a differentiable approximation to the $L_0$-norm penalty to achieve the goal of sparsity. Practically, because new parameters to be optimized are introduced in the learning phase, diff pruning takes up more GPU memory than full parameter fine-tuning, which may establish barriers in the application on large PLMs. The masking method (Zhao et al., 2020) learns selective masks for PLMs to only update the critical weights for particular tasks. To learn such a set of masks, a binary matrix associated with the model weights is introduced, where each value is generated by a thresholding function. During back-propagation, the matrix is updated by a noisy estimator.
3.3 Reparameterization-based Methods

Table 2: Comparison between different delta tuning methods, we use the green color to denote tunable parameters and modules. [;] is the concatenation operation; $d_h$ means the hidden dimension of transformer model; $d_m$ is the intermediate dimension between down projection and up projection, where $d_m$ is far smaller than $d_h$. COMPACTER utilize hypercomplex matrix multiplication and low-rank decomposition to reduce the amount of parameters; ADAPTERDROP randomly dropout adapters in the first $n$ layers and also bring down back-propagation time; PREFIX-TUNING add prefix of $n$ past key value.

| Name & Refs          | Method                                                                 | #Params             |
|---------------------|------------------------------------------------------------------------|---------------------|
| SEQUENTIAL ADAPTER  | $\text{LayerNorm}(X + H(X)) \rightarrow \text{LayerNorm}(X + ADT(\mathbf{H}(X)))$ | $L \times 2 \times (2d_h d_m)$ |
| Houlsby et al. (2019)|                                                                                      |                     |
| COMPACTER           | $\text{LayerNorm}(X + F(X)) \rightarrow \text{LayerNorm}(X + ADT(F(X)))$            | $L \times 2 \times (2(d_h + d_m))$ |
| Mahabadi et al. (2021a)| $\text{ADT}(X) = X + \sigma(XW_{d_h \times d_h})W_{d_m \times d_h}, \sigma = \text{activation}$ | $(L - n) \times 2 \times (2d_h d_m)$ |
| ADAPTERDROP         | $\text{LayerNorm}(X + H(X)) \rightarrow \text{LayerNorm}(X + ADT(X) + H(X))$         | $L \times 2 \times (2d_h d_m)$ |
| Rücklé et al. (2021) |                                                                                      |                     |
| PARALLEL ADAPTER    | $\text{LayerNorm}(X + F(X)) \rightarrow \text{LayerNorm}(X + ADT(X) + F(X))$         | $L \times 2 \times (2d_h d_m)$ |
| He et al. (2022)    | $\text{ADT}(X) = \sigma(XW_{d_h \times d_h})W_{d_m \times d_h}, \sigma = \text{activation}$ |                     |
| ADAPTERBAS          | $\text{LayerNorm}(X + F(X)) \rightarrow \text{LayerNorm}(\text{ADT}(X) + F(X))$       | $L \times 2 \times d_h$ |
| Li & Liang (2021)   | $\text{ADT}(X) = XW_{d_h \times 1}W_{1 \times d_h}$                                  |                     |
| PREFIX-TUNING       | $H_i = \text{ATT}(XW^{(i)}_q, [\text{MLP}^{(i)}_k (P^1_k) : XW^{(i)}_k], [\text{MLP}^{(i)}_p (P^2_p) : XW^{(i)}_p])$ | $n \times d_m + d^2_m + L \times 2 \times d_h d_m$ |
| Li & Liang (2021)   | $\text{MLP}^{(i)}(X) = \sigma(XW_{d_m \times d_h})W_{d_m \times d_h}$                  |                     |
| LoRA                | $f_r = W_{n \times d_m}$                                                        |                     |
| Hu et al. (2021a)   | $H_i = \text{ATT}(XW_q^{(i)} + \text{ADT}_c(X) + XW_k^{(i)}, \text{ADT}_c(X) + XW_q^{(i)})$ | $L \times 2 \times (2d_h d_m)$ |
| Zaken et al. (2021) | $\text{ADT}(X) = XW_{d_h \times d_m}W_{d_m \times d_h}$                            |                     |
| BITFit              | $f(X) \rightarrow f(X) + B$, for all function $f$                               | $L \times (7 \times d_h + d_m)$ |

3.3 Reparameterization-based Methods

Reparameterization-based methods transform the adaptive parameters during optimization into parameter-efficient forms. This branch of delta tuning is typically motivated by the hypothesis that PLM adaptations towards most downstream tasks are inherently low-rank, and could thus be equivalently completed in a parameter-efficient way.

Intrinsic Dimensions of PLM Adaptation. Aghajanyan et al. (2021) empirically show that the full-parameter fine-tuning process of pre-trained models can be reparameterized into optimization within a low-dimensional subspace, i.e., fine-tuning has a low intrinsic dimension (Li et al., 2018), which measures the minimum number of parameters needed to reach satisfactory performance. In experiments, they find that a relatively low-dimensional (e.g., thousands) reparameterization could achieve over 85% fine-tuning performance. In this sense, PLMs may serve as general compression frameworks, which compress the optimization complexity from high dimensions to low dimensions. They also demonstrate that, larger PLMs generally have smaller intrinsic dimensions, and the process of pre-training implicitly reduces PLM’s intrinsic dimension. Taking inspiration from these observations, reparameterization-based delta tuning methods are proposed, which reparameterize (a part of) original model parameters with low-dimensional proxy parameters and only optimize the proxy parameters and thus reduce the computation and memory cost.

Intrinsic Rank of Weight Differences. Inspired by Aghajanyan et al. (2021), LoRA (Hu et al., 2021a) hypothesizes that the change of weights during model tuning has a low intrinsic rank. Based on this hypothesis, they propose to optimize the low-rank decomposition for the change of original weight matrices in the self-attention modules. In deployment, the optimized low-rank decomposition matrices are multiplied to obtain the delta of self-attention weight matrices. In this way, LoRA could match the fine-tuning performance on
the GLUE benchmark. They demonstrate the effectiveness of their methods on PLMs of various scales and architectures.

**Intrinsic Space of Multiple Adaptations.** Furthermore, Qin et al. (2021b) make a stronger hypothesis that the adaptations to multiple tasks could be reparameterized into optimizations within the same low-dimensional intrinsic subspace. Instead of resorting to a random subspace (Aghajanyan et al., 2021), they try to find a common subspace shared by various NLP tasks, which is implemented through decomposing the trained soft prompts of multiple NLP tasks into the same low-dimensional nonlinear subspace, and then learn to adapt the PLM to unseen tasks or data by only tuning parameters in the subspace. Experiments show that in a 250-dimensional subspace found with 100 random tasks, by only tuning 250 free parameters, 97% and 83% of the full prompt tuning performance can be recovered for 100 seen tasks (using different training data) and 20 unseen tasks, respectively. This provides strong evidence for their universal reparameterization hypothesis and may inspire future work. Moreover, Qin et al. (2021b) also shows that the low-dimensional reparameterization can significantly improve the stability of prompt tuning. Their method could also be leveraged as a tool for analyzing the similarity and differences for various NLP tasks. The motivation differences of the above three works are visualized in Figure 5.

**Figure 5:** Conditioned on a PLM, Aghajanyan et al. (2021) hypothesize that there exist a low-dimensional intrinsic subspace that could reparameterize one specific fine-tuning process (the left part). Hu et al. (2021a) hypothesize that the change of weights during adaptation has a low intrinsic rank (the middle part). And Qin et al. (2021b) hypothesize there may exist a common intrinsic space that could handle the fine-tuning for various NLP tasks (the right part).

### 4 Theoretical Perspectives of Delta Tuning

Are these methods essentially doing the same thing? We are interested in the theoretical principles behind delta tuning. A pre-trained language model usually can be easily adapted to almost any downstream tasks with only a very small cost (compared to pre-training), and this phenomenon leads to theoretical issues that are worth exploring in depth. In this section, we propose two frameworks to introduce theoretical insights of delta tuning from the perspectives of optimization (§4.1: OPTIMIZATION) and optimal control (§4.2: OPTIMAL CONTROL).

#### 4.1 Optimization Perspective for Delta Tuning

The delta tuning technique seeks to tune a small portion of parameters so as to match the performance of the fine-tuning in the original large language model while reducing the memory footprint. From the perspective of optimization, we analyze the effects of delta tuning and discuss the designs of several delta tuning methods under the low dimension assumption.

Let \( F(\theta) \) denote the objective function of the original language model. Then the new objective function optimized by delta tuning is \( \tilde{F}(\theta, \delta) \). Here \( \theta \) denotes the parameters of the original language model, and \( \delta \) denotes the specific parameters tuned by delta tuning \(^5\). The starting point is \((\theta_0, \delta_0)\), where \( \theta_0 \) is the pre-trained language model parameters and \( \delta_0 \) is the initialization of \( \delta \). In principle, though one may adopt some initialization of \( \delta \) to facilitate the training process of delta tuning, there still exists the \( \delta_0 \) such that

\[
\tilde{F}(\theta, \delta_0) = F(\theta),
\]

\(^5\)The variables \( \theta \) and \( \delta \) correspond to the concepts of \( \Theta \) and \( \Delta \Theta \) in §3: DELTA TUNING. Also, \( \delta \) is not necessarily independent of \( \theta \).
which guarantees that $\tilde{F}$ is identical to $F$ if the delta tuning is disabled. Thus, the following relations hold:
\[
\min_{\theta, \delta} \tilde{F}(\theta, \delta) \leq \min_{\theta} \tilde{F}(\theta, 0) = \min_{\theta} F(\theta), \quad \min_{\theta, \delta} \tilde{F}(\theta, \delta) \leq \min_{\delta} \tilde{F}(\theta_0, \delta),
\]
which suggests that simultaneously tuning $\theta$ and $\delta$ may be beneficial. Nonetheless, we are only interested in analyzing the case that either $\theta$ or $\delta$ is fine-tuned. Let $\theta^+ = \arg \min_\theta \tilde{F}(\theta, 0)$ and $\delta^+ = \arg \min_\delta \tilde{F}(\theta_0, \delta)$. The delta tuning essentially does no harm to the tuning of the original model under some conditions. For instance, assuming that $\tilde{F}$ is twice Lipschitz continuously differentiable, it can be proved that
\[
|\tilde{F}(\theta^+, 0) - \tilde{F}(\theta_0, \delta^+)| = O(\|\theta^+ - \theta_0\|^2 + \|\delta^+ - \delta_0\|^2),
\]
in a local small region around $(\theta^+, 0)$ and $(\theta_0, \delta^+)$. For a sufficiently good starting point, the error bound holds. However, to guarantee the effectiveness of delta tuning, it is essential to exploit the problem structures to design $\tilde{F}$. The intuition is to leverage the intrinsic low dimensions of the problems. Basically, there are two approaches that turn out to be useful in practice:

- The solution is updated in a lower dimensional subspace;
- The objective function (with constraints) is approximated in a certain smaller functional subspace.

For the applications in deep learning, the optimization of the objective function often has lots of local minimizers due to over-parameterization. Therefore, these approaches typically work well when the starting point is close to a local minimizer, where only some searching directions matter or the objective function can be well approximated by some simpler function in the trust region. Moreover, the small dimensional optimization can lead to a more efficient and more stable training process.

**Low dimensional representation in solution space.** As it is observed that the optimization trajectory of $\theta$ approximately follows a manifold (Aghajanyan et al., 2021), we can embed the hidden manifold to a low dimensional space of $\delta$, i.e., $\theta = \psi(\delta) + \epsilon$, where $\epsilon$ is the error term depending on $\theta_0, \theta^+$. Then,
\[
\tilde{F}(\theta, 0) = F(\theta), \quad \tilde{F}(\theta, \delta) = F(\psi(\delta)).
\]
If $\epsilon = 0$, the delta tuning finds the exact solution of the fine-tuning of the original language model. Otherwise, the final discrepancy depends on the approximation error, the condition number of the objective function, and the stability of the training process. Let $\delta^+ = \arg \min_\delta F(\psi(\delta))$, and $\theta^+ = \psi(\delta^+) + \epsilon^+$. Suppose that $F$ and $\tilde{F}$ are Lipschitz continuous and the Lipschitz constants are $L_1$ and $L_2$, respectively. Then, we have the following bound of the approximation error of delta tuning to the full-parameter fine-tuning of the original language model:
\[
|F(\theta^+) - \tilde{F}(\psi(\delta^+))| \leq |F(\theta^+) - \tilde{F}(\psi(\delta))| + |\tilde{F}(\psi(\delta^+)) - \tilde{F}(\psi(\delta))| \\
\leq L_1 \epsilon^+ \|\delta^+ - \delta\|_2 + L_2 \|\delta^+\|_2 \leq L_1 \epsilon^+ \|\delta^+\|_2 + L_2 \|\delta^+\|_2.
\]
The error $\epsilon^+$ is controlled by the approximation of the low dimensional representation $\psi$. Since the minimization of $F(\psi(\delta))$ can be viewed as minimization of a perturbed objective function of $F(\theta)$, the $\|\delta^+ - \delta\|_2$ is bounded provided that $F$ is well-conditioned and the optimization algorithm is stable. Also, if the magnitudes of $\delta^+$ and $\delta^+$ are small, the bound (17) can still lead to the good quality of $\tilde{F}(\psi(\delta^+))$.

Some delta tuning methods benefit from such approach. In LoRA (Hu et al., 2021a), the weight matrix $W \in \mathbb{R}^{d \times n}$ is constructed as $W \approx W_0 + AB$, where $W_0$ is the corresponding part of $\delta_0$, and $A \in \mathbb{R}^{d \times r}, B \in \mathbb{R}^{r \times n}$ are rank-$r$ low rank matrices learned by the training process. The numerical results validate the assumption of low-rank approximation (Hu et al., 2021a). In BitFit (Zaken et al., 2021) or diff pruning (Guo et al., 2021), some coordinates of $\delta$ are selected to be optimized during the training process. Thus, the approximation is $\theta = \theta_0 + V y$, where the columns of $V$ consist of columns chosen from the identity matrix and $y$ is the low dimensional vector to be learned. We can also apply some suitable transformation to $\theta$ to make the $F$ easier to be optimized. For example, choose a transformation matrix $S$, and let $S \theta = S \theta_0 + V y$. The resulting delta tuning method can be viewed as a re-parameterization followed by a diff pruning.

**Low dimensional representation in functional space.** Another approach is to directly design an approximate function that matches the final $F(\theta^+)$, i.e., we seek to find $\tilde{F}(\delta)$, such that
\[
|F(\theta) - \tilde{F}(\delta)| < \epsilon,
\]
where $\epsilon$ is the approximation error. By this way, we recognize that $\tilde{F}(\theta, \delta_0) = F(\theta)$ and $\tilde{F}(\theta_0, \delta) = \tilde{F}(\delta)$.

The construction of $\tilde{F}$ can be characterized by an incremental network (Houlsby et al., 2019) or an augmented feature space (Lester et al., 2021). Since we are more interested in the final performance of the language model, rather than the model parameters, it is promising to directly model the function $F(\theta)$ which is approximately restricted in a small manifold in the functional space, and we discard the need to estimate the error (17) from model parameters.

The construction of $\tilde{F}$ is an art and differs in practice. The simplest strategy is to freeze some certain parts of the networks like BitFit (Zaken et al., 2021). Consider the more sophisticated construction that can improve the approximation. Since the action of the function is characterized by the data flow, one natural idea is to inject the low-rank representation in the data path of the original neural networks and the resulting new language model is an incremental network like Adapter (Houlsby et al., 2019), as shown in (10). The approximation error (18) is determined by the representation capacity of the incremental network. Due to the universal approximation property (Leshno et al., 1993) of multilayer feedforward networks, the quality of the approximation is guaranteed. It is worth noting that a similar architecture is also proposed in the area of computer vision (Rebuffi et al., 2017; Ye et al., 2020).

By exploiting the autoregressive structure of Transformer, some more dedicated functional approximation can be conceived. Note that the objective function generally is determined by the input and model parameters, namely $L(X, Y; \theta)$. In principle, we can freeze the model parameters $\theta$, and make $X$ and $Y$ variable. In some cases, it may be convenient to swap the positions of $(X, Y)$ and $\theta$ to obtain a more tractable optimization problem. Since $\theta$ is the pre-trained language model that is unwieldy to process, it makes sense to use some trainable $\tilde{X}$ to replace $X$ since the feature space of $X$, namely range$(X)$, is generally limited in a few thousand of dimension in a language task. This idea has been exploited in the prompt tuning (Lester et al., 2021), where a series of prompt tokens $P$ are prepended to the input $X$. The prompt $P$ is not parameterized by $\theta$; instead, it has individual trainable parameters $\theta_P$. By this way, the feature space is augmented but still feasible for training. Owing to the autoregressive property of Transformer, the approximate function serves as a good surrogate of the original function $F$ to be optimized and steers the language model to focus on the specific task. The prefix tuning (Li & Liang, 2021) further makes some activations in the intermediate layers trainable, thus leading to a more accurate functional approximation, or in other words, enlarging the representation capability of the modified language model. Regarding to the performance, since the prompt tuning is a dimension reduction method that models the probability distribution with less parameters, the effectiveness is closely related to the model size and data size. With larger model size and data size, prompt tuning is prone to achieve better performance that is consistent with the dimension reduction theory (Wright & Ma, 2021). Moreover, for high dimensional problems, it is possible to have more freedoms to choose the subspace for the functional approximation, Su et al. (2021) and our experimental results in §5.3: SCALE also verify this intuition.

The unified view of the approximations in solution space and functional space. Generally speaking, the representations in solution space and function space often lead to similar constructions of the approximate $\tilde{F}$ due to the duality relation. In fact, a unified view of Adapter (Houlsby et al., 2019), prefixing tuning (Li & Liang, 2021) and LoRA (Hu et al., 2021a) is proposed in (He et al., 2022) by analyzing the data flow in the modified language model. It is pointed out that these delta tuning methods all construct low dimensional modifications of the original data flow, i.e., $h \leftarrow h + \Delta h$, where $\Delta h$ is parameterized by some low dimensional parameters. This view can be recognized as understanding the different delta tuning methods from the perspective of functional space. Some useful empirical results about the ways to design the functional approximation can also be found in (He et al., 2022).

Our discussion suggests that the performance of all these delta tuning methods rely on the low dimension assumption. In fact, it can even be found that there may exist some common subspace among various tasks (Qin et al., 2021b), Su et al. (2021) and our experimental results in §5.4: TRANSFERABILITY also show the transferability of delta tuning in different tasks. Since the actual performance of a delta tuning method is inevitably problem-dependent, it is promising to exploit more specific structures in the tasks at hand or build some hybrid algorithm to make it more competitive with the full fine-tuning of the original language model.

4.2 Optimal Control Perspective for Delta Tuning

Yang & Liu (2022) propose to interpret prefix tuning from the perspective of optimal control. In this section, we generalize the optimal control view to different delta tuning scenarios.
Relationship Between Optimal Control And Deep Learning. We start with interpreting deep learning from the optimal control perspective. According to Section 4 in Li et al. (2017), we review the theorems in the following and directly follow their notations:

**Theorem 4.1** (discrete-time PMP) Consider the discrete-time control problem

\[
\min_{\{\theta_0, \ldots, \theta_{T-1}\} \in \Theta^T} \Phi(x_T) + \delta \sum_{t=0}^{T-1} L(\theta_t),
\]

\[
x_{t+1} = x_t + \delta f_t(x_t, \theta_t), \quad x_0 = x, \quad 0 \leq t \leq T - 1
\]

where \( \Phi \) and \( L \) are termination and running losses, respectively. There exists a co-process

\[
x^*_t = g_t(x^*_t, \theta^*_t), \quad x^*_0 = x,
\]

\[
p^*_t = \nabla_x H_t(x^*_t, p^*_{t+1}, \theta_t), \quad p^*_{T+1} = -\nabla_x \Phi(x^*_{T+1})
\]

such that

\[
H_t(x^*_t, p^*_{t+1}, \theta^*_t) \geq H_t(x^*_t, p^*_{t+1}, \theta), \quad \theta \in \Theta, \quad 0 \leq t \leq T - 1.
\]

Here \( g_t(x_t, \theta_t) := x_t + \delta f_t(x_t, \theta_t) \) and

\[
H_t(x, p, \theta) = p \cdot g_t(x, \theta) - \delta L(\theta)
\]

is the discrete Hamiltonian with a scaling factor \( \delta > 0 \).

**Theorem 4.2** (discrete-time MSA) The discrete-time method of successive approximations (MSA) characterizes the co-process in Theorem 4.1. For each iteration \( k \), set \( x^*_0 = x \), and

\[
x^*_{t+1} = g_t(x^*_t, \theta^*_t)
\]

with \( t \) enumerating from 0 to \( T - 1 \);

then set \( p^*_t = -\nabla_x \Phi(x^*_t) \), and

\[
p^*_t = \nabla_x H_t(x^*_t, p^*_{t+1}, \theta^*_t)
\]

with \( t \) enumerating from \( T - 1 \) to 0;

finally, with \( t \) enumerating from 0 to \( T - 1 \), set

\[
\theta^*_{t+1} = \theta^*_t + \eta \nabla_{\theta} H_t(x^*_t, p^*_{t+1}, \theta^*_t).
\]

**Theorem 4.3** (equivalence between MSA and backpropagation) The MSA in Theorem 4.2 is equivalent to the backpropagation process in deep networks.

The proofs of Theorems 4.1, 4.2 and 4.3 are provided in Li et al. (2017).

Tuned Delta’s As Optimal Controllers. We consider delta tuning with pretrained autoregressive LMs (e.g., GPT-2) for text classification. By framing the content as the input sentence, the model generates the predicted label at the last step. For simplicity, we denote the position of label prediction as \( o \). At position \( o \), the model is inputted with a special token [ANS] and is expected to generate the prediction.

Denote \( \theta \) as the parameters of the \( L \)-layer PLM. We use the training set \( D_{tr} \) to optimize the delta parameters at each layer: \( \{\delta^{(0)}, \ldots, \delta^{(L-1)}\} \). The intermediate activation of the \( j \)-th layer at step \( i \) is denoted as \( h_{ij} \). The optimization problem for delta tuning is formulated as

\[
\min_{\{\delta^{(0)}, \ldots, \delta^{(L-1)}\}} \mathbb{E}_{(x, y) \sim D_{tr}} \left[ S \left( h_{0}^{(L)}, y \right) + \sum_{j=0}^{L-1} R \left( \delta^{(j)} \right) \right]
\]

\[
h_{ij}^{(j+1)} = h_{ij}^{(j)} + \delta^{(j)} \left( h_{ij}^{(j)}, \delta^{(j)} \right), \quad h_{i0}^{(0)} = z_0 = [ANS], \quad 0 \leq j \leq L - 1,
\]

where \( S \) as the softmax scoring function, \( R \) as the regularizer for delta parameters, \( z_i \) as the \( i \)-th token in the input and \( y \) as the label. The function \( \delta \) defines the altered forward propagation in the LM with the intervention of delta. Specifically, the learnable \( \delta^{(j)} \) activates the fixed parameters from \( \theta \) so that the representation \( h_{ij}^{(j)} \) at
the $j$-th layer can be properly transformed as $G_\theta^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right)$. The representation transformation between two consecutive layers is thus described by function $G$ and the residual connection in Transformer.

We proceed to show that the problem (27) unifies various delta tuning scenarios with different instances of $G$.

I. Prefix-tuning (PF). Prefix-tuning belongs to addition-based methods and exploits the idea of prompting. With $P_{idx}$ as the prefix indexes, the forward propagation at the output position $o$ can be formulated as

$$h_o^{(j+1)} = LM_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right),$$

where $h_i^{(j)} = P_{\theta(i)}[i, :]$ for all $j = 0$ to $L - 1$, $i \in P_{idx}$ and $h_{i}^{(0)} = z_i$ for $i \notin P_{idx}$. $LM_\theta^{(j)}$, the $j$-th layer of the LM, can be decomposed into a self-attention layer (SAN$_\theta^{(j)}$) and a FFN layer (FFN$_\theta^{(j)}$). Formally,

$$h_o^{(j+1)} = h_o^{(j)} + \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) + \text{FFN}_\theta^{(j)} \left( h_o^{(j)} + \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) \right)$$

with $h_i^{(j)} = P_{\theta(i)}[i, :]$ for $i \in P_{idx}$. As Eq. (29) is recursive and according to the fact that the PLM is autoregressive, after unrolling the recursion for all $h_{<i}^{(j)}$ in Eq. (29), we have that for any $i < o$, $h_i^{(j)}$ is steered by the prefix $\delta^{(j)}$, namely $h_i^{(j)} = h_i^{(j)}(\delta^{(j)})$. As a result, for prefix-tuning, the $G_\theta^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right)$ in problem (27) is instantiated as

$$G_\theta^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) = \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) + \text{FFN}_\theta^{(j)} \left( h_o^{(j)} + \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) \right),$$

where each item in $h_{<o}^{(j)}$ is a function of $\delta^{(j)}$.

II. Adapter (AP). Adapter belongs to addition-based methods as well. Instead of prompting, the Adapter method adds tunable modules between consecutive Transformer layers as the delta. As characterized by Eq. (10), the altered forward propagation is written as

$$\tilde{h}_o^{(j+1)} = LM_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right),$$

$$h_o^{(j+1)} = \tilde{h}_o^{(j+1)} + \sigma \left( \tilde{h}_o^{(j+1)} W_d^{(j)} \right) W_u^{(j)},$$

where $\tilde{h}_o^{(j+1)}$ is the transformed representation by the original $j$-th layer in the PLM, and $\sigma$ denotes the nonlinearity. $\delta^{(j)}$ in this case is defined as $\{W_d^{(j)}, W_u^{(j)}\}$, the two projection matrices at the $j$-th layer. It is noted that the computation of $LM$ in Eq. (31) also follows the formulation of Eq. (29) (with difference only in inputs). Substituting Eq. (29) in Eq. (31) yields

$$G_\theta^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) = \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) + \text{FFN}_\theta^{(j)} \left( h_o^{(j)} + \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) \right) + \sigma \left( \text{LM}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) W_d^{(j)} \right) W_u^{(j)}.$$}

Here each item in $h_{<o}^{(j)}$ is independent of $\delta^{(j)} = \{W_d^{(j)}, W_u^{(j)}\}$, which is different from the prefix-tuning case.

III. LoRA (LR). LoRA belongs to reparameterization-based methods. The update by LoRA is

$$h \leftarrow szW_s W_u + h,$$

where $z$ is the input and $s \geq 1$ is a tunable scalar hyperparameter. Similar with the Adapter scenario, we still define $\delta^{(j)} = \{W_d^{(j)}, W_u^{(j)}\}$. The function $G$ in this case is

$$G_\theta^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) = \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) + \text{FFN}_\theta^{(j)} \left( h_o^{(j)} + \text{SAN}_\theta^{(j)} \left( h_o^{(j)}, h_{<o}^{(j)} \right) \right) + szW_d^{(j)} W_u^{(j)}.$$}

IV. BitFit. BitFit belongs to specification-based methods. BitFit tunes only the bias parameters in the PLM. We define $\theta = \{\psi, \delta\}$, where $\delta$ represents the tuned bias parameters, and $\psi$ is the fixed ones. In this case, the formulation of $LM$ in Eq. (29) becomes

$$h_o^{(j+1)} = h_o^{(j)} + \text{SAN}_\psi^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) + \text{FFN}_\psi^{(j)} \left( h_o^{(j)} + \text{SAN}_\psi^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) \right),$$

where $\delta^{(j)}$ is the fixed ones. In this case, the formulation of $LM$ in Eq. (29) becomes

$$h_o^{(j+1)} = h_o^{(j)} + \text{SAN}_\psi^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) + \text{FFN}_\psi^{(j)} \left( h_o^{(j)} + \text{SAN}_\psi^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) \right),$$

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$$h_o^{(j+1)} = h_o^{(j)} + \text{SAN}_\psi^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) + \text{FFN}_\psi^{(j)} \left( h_o^{(j)} + \text{SAN}_\psi^{(j)} \left( h_o^{(j)}, \delta^{(j)} \right) \right),$$

where $\delta^{(j)}$ is the fixed ones.
with \(\delta^{(j)} = \{\delta_{S}^{(j)}, \delta_{F}^{(j)}\}\) as the bias terms of the SAN and FFN layers. The function \(G\) is thus given by

\[
G_{\theta}^{(j)} \left( h_a^{(j)}, \delta^{(j)} \right) = \text{SAN}_{\psi}^{(j)} \left( h_a^{(j)}, \delta_{S}^{(j)}, h_{\psi}^{(j)} \right) + \text{FFN}_{\psi}^{(j)} \left( h_a^{(j)}, \delta_{S}^{(j)}, h_{\psi}^{(j)}, \delta_{F}^{(j)} \right) .
\]  

(36)

We have listed the formulations of the function \(G\) in problem (27) for different delta tuning methods. With Theorem 4.1, \(S\) and \(R\) in problem (27) can be viewed as the terminal and the running loss with the delta parameters as the control variables. This means that (27) can be formulated as a discrete-time control problem. With Theorems 4.2 and 4.3, the forward and backward propagation in optimization delta’s are equivalent to the calculation of the co-state process in Pontryagin’s Maximum Principle (Kopp, 1962). To conclude, delta tuning can be viewed as seeking the optimal control of PLMs for specific downstream tasks.

Our analysis sheds light on designing novel delta tuning methods that are inspired from control theories. One can refer to control theories when designing robust models (Zhang et al., 2019a). For example, Yang & Liu (2022) propose robust prefix-tuning that tunes an additional robust prefix during inference to guide the LM towards correct predictions. The idea of test-time activation rectification can be viewed as close-loop feedback control (Chen et al., 2021). We have also shown that the intervention of delta’s with the PLMs is equivalent to the design of controllers. By applying the theories of controller design (Boyd & Barratt, 1991; Ang et al., 2005), we expect more delta methods be proposed with theoretical guarantees. The designed delta structures are in this way interpretable in principle while sufficiently exploiting the power of PLMs.

5 Comparisons and Experimental Discoveries

As an effective engine to stimulate large-size PLMs, delta tuning presents an enormous practical potential for various real-world applications. In this section, we carry out systematic experiments to gain a deeper understanding of the attributes of different mainstream delta tuning methods.

Specifically, (1) we first conduct thorough comparisons among four representative delta tuning methods and fine-tuning in §5.1: PERFORMANCE, covering the performance, convergence and the efficiency analysis; (2) secondly, we explore the combinability of three representative delta tuning methods in §5.2: COMBINATION by comparing the performance under both the full-data and low-resource setting. We also explore the effects of manual templates for delta tuning methods; (3) furthermore, we investigate the scaling law in §5.3: SCALE and (4) the transferability of delta tuning methods among different downstream tasks in §5.4: TRANSFERABILITY.

The implementation details and tasks are described in §A: DETAILS and §B: TASKS. We will release the codes, dataset splits and trained delta checkpoints to facilitate future research attempts.

5.1 Performance, Convergence and Efficiency

Experimental Setting. We evaluate vanilla fine-tuning (FT) and four representative delta tuning methods, including prompt tuning (PT), prefix-tuning (PF), LoRA (LR) and adapter (AP). Other representative delta tuning methods (Liu et al., 2021b; Zaken et al., 2021; Guo et al., 2021; Liu et al., 2022) are omitted.

To cover broad and diverse NLP tasks, we randomly select over 100 representative tasks from Huggingface datasets6 (Lhoest et al., 2021). The selected tasks include text classification (e.g., sentiment analysis and natural language inference), question answering (e.g., machine reading comprehension and multi-choice question answering), conditional generation (e.g., summarization and dialogue), etc. We list the task details of each category in Table 10. To handle different tasks with a single text-to-text PLM, following Raffel et al. (2019), we process the input and output of each task into the same sequence-to-sequence format.

We choose T5\text{BASE} (Raffel et al., 2019) as the mainly evaluated PLM backbone for different tuning methods, and we additionally report the performance of PT with T5\text{LARGE} (Raffel et al., 2019). For both models, we use the checkpoints released by Lester et al. (2021), who conducted additional 100k steps of LM adaption on the official checkpoints released by Raffel et al. (2019). Such an LM adaptation objective has been demonstrated beneficial for better performance and faster convergence during downstream adaptation, compared with only the original “span corruption” pre-training objective of T5. We follow the common practice for each delta tuning’s implementation. For PF, we use 5 prefix tokens; for PT, we prepend 100 tunable soft tokens into the input embedding; for LR, we reparameterize all the query matrices and the value matrices in the multi-head attention modules as low-rank decompositions, and set the rank to 8; for AP, we insert adapter modules into both the multi-head attention module and the feed-forward network in each Transformer layer, set the bottleneck dimension to 64, and choose SiLU (Elfwing et al., 2018) as the activation function. More training details are left in §A.1: PERFORMANCE DETAILS.

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6https://huggingface.co/datasets
**Performance Analysis.** The overall results are listed in Table 3, from which we observe that: (1) in general, since different delta tuning methods significantly reduce the amounts of tunable parameters, they are no match for FT in performance under most cases. But after averaging the results over all datasets, the gap between the delta tuning methods and the fine-tuning method is not insurmountable, which demonstrates the potential of the large-scale applications of parameter-efficient adaptations. (2) Despite having different design elements, PF, LR and AP are comparable with each other in performance. Specifically, each of them is possible to show dominant performance (even better than FT) over others on certain tasks. According to the average results, the performances of all the methods are ranked as FT > LR > AP > PF > PT. Interestingly, the performance of the delta tuning methods is not consistent with their number of tunable parameters, i.e., at least on small PLMs, more tunable parameters do not necessarily lead to approximately better performance, and the design of the structure for delta tuning may play a greater role. (3) As the easiest of these methods to implement (i.e. without modifying the internal structure of the model), PT lags far behind other delta tuning methods in most cases when experimented on T5$_{\text{BASE}}$, although better PT performance is observed when the model size is significantly enlarged to T5$_{\text{LARGE}}$, which is aligned with previous findings on the power of scale for prompt tuning (Lester et al., 2021)$^7$. However, as we would show later ($\S$5.3: SCALE), other delta tuning methods also exhibit far better performance when the scale of the backbone PLM grows extremely large. That is, unlike the conclusion of (3), when the model increases sharply, the design of the structure may become less important for the delta tuning methods.

Table 3: Overall (test) performance of over 100 NLP tasks comparing prompt tuning (PT), prefix-tuning (PF), LoRA (LR), Adapter (AP) and fine-tuning (FT). We experiment all methods on T5$_{\text{BASE}}$, with the best performance highlighted in bold, and additionally report the performance of PT on T5$_{\text{LARGE}}$.

| Task | PT (base) | PT (large) | PF | LR | AP | FT |
|------|-----------|------------|----|----|----|----|
| ACRONYM_IDENTITY | 93.35 | 96.68 | 79.31 | 79.31 | 95.57 | 96.12 |
| ADE_CORPUS_V2_CLASSIFICATION | 41.76 | 94.42 | 93.25 | 93.91 | 94.27 |
| ADE_CORPUS_V2 DOSAGE | 78.57 | 89.29 | 82.14 | 82.14 | 82.14 |
| ADE_CORPUS_V2_EFFECT | 59.15 | 61.35 | 63.25 | 62.52 | 60.91 | 62.66 |
| ADVERSARIAL_QA | 34.10 | 54.60 | 43.17 | 46.40 | 45.35 | 48.56 |
| AG_NEWS | 91.37 | 93.61 | 93.42 | 94.63 | 94.60 | 95.19 |
| ANLI | 25.85 | 44.96 | 43.88 | 45.27 | 49.19 | 50.54 |
| ASLG_PC12 | 15.78 | 44.07 | 47.71 | 73.72 | 80.65 | 92.92 |
| BLIMP_ANPHOR_GENDER_AGREEMENT | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 99.00 |
| BLIMP_ANPHOR_NUMBER_AGREEMENT | 49.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| BLIMP_DETTERMINER_NOUN_AGREEMENT | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| _ WITH ADJ IRREGULAR _ | 46.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| BLIMP_ELLIPSIS_N_BAR _ | 49.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| BLIMP_EXISTENTIAL _ THERE | 53.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| _ WITH _ QUANTIFIERS _ | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| BLIMP_IRREGULAR_PAST | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| _ PARTICIPLE _ ADJECTIVES | 54.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| BLIMP_SENTENTIAL_NEGATION | 55.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| _ NPI SCOPE | 55.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| BOOLQ | 61.28 | 77.43 | 77.55 | 80.00 | 78.47 | 81.77 |
| CIRCA | 13.51 | 77.39 | 80.16 | 82.38 | 82.93 | 84.69 |
| CLIMATE_FEVER | 15.47 | 33.42 | 38.03 | 39.35 | 37.48 | 41.57 |
| COMMONSENSE_QA | 58.43 | 76.76 | 58.43 | 62.52 | 60.72 | 61.21 |
| COS_E | 12.41 | 14.82 | 13.90 | 14.05 | 14.31 | 13.46 |
| COSMOS_QA | 7.30 | 10.98 | 9.91 | 10.78 | 10.85 | 11.32 |
| CRAWL_DOMAIN | 68.16 | 76.91 | 73.04 | 73.00 | 72.76 | 75.12 |
| DISCOVERY | 0.18 | 18.83 | 16.67 | 18.98 | 18.41 | 25.88 |
| DREAM | 49.19 | 71.83 | 58.70 | 61.00 | 59.53 | 62.42 |
| E1L5_ASKH | 11.26 | 11.70 | 12.64 | 11.99 | 11.45 | 13.00 |
| E1L5_ASKS | 14.79 | 15.54 | 15.09 | 15.25 | 15.01 | 15.28 |

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$^7$We found empirically that PT tends to perform worse and converge more slowly for small-scale PLMs.
| Task                        | PER  | CONS  | EFF  |
|-----------------------------|------|------|------|
| EL15-EL15                  | 14.19 | 15.38 | **15.23** |
| EMO                         | 69.91 | 71.47 | **76.13** |
| EMOTION                     | 46.99 | 100.00 | **98.42** |
| ETHOS-DIRECTED_VS_GENERALIZED | 76.86 | 86.64 | **94.94** |
| ETHOS-DISABILITY            | 46.99 | 100.00 | **99.90** |
| ETHOS-GENDER                | 63.84 | 77.08 | **79.91** |
| ETHOS-NATIONAL_ORIGIN       | 44.30 | 81.77 | **87.95** |
| ETHOS-RACE                  | 84.36 | 97.06 | **97.21** |
| ETHOS-RELIGION              | 93.02 | 93.02 | **96.64** |
| FINANCIAL_PHRASEBANK        | 97.18 | 98.36 | **98.36** |
| FREEBASE_QA                 | 1.90  | 6.71  | 3.75  |
| GLUE-COLA                  | 0.00  | 55.60 | **51.53** |
| GLUE-MNLI                  | 35.43 | 86.12 | **86.39** |
| GLUE-MRPC                  | 67.65 | 88.24 | **89.71** |
| GLUE-QNLI                  | 52.34 | 93.01 | **92.57** |
| GLUE-QQP                   | 84.65 | 86.21 | **89.13** |
| GLUE-RTE                   | 45.32 | 79.14 | **80.58** |
| GLUE-SST2                  | 92.20 | 94.95 | **94.27** |
| HATE_SPEECH_OFFENSIVE      | 73.27 | 79.08 | **75.22** |
| HATE_SPEECH18              | 75.57 | 74.45 | **75.04** |
| HATEEXPLAIN                | 50.98 | 67.62 | **68.11** |
| HEALTH_FACT                | 39.15 | 45.60 | **54.19** |
| HELLASWAG                  | 23.82 | 70.28 | **41.90** |
| HOTPOT_QA                  | 65.95 | 76.41 | **78.45** |
| LAMA-CONCEPTNET            | 15.25 | 26.12 | **70.28** |
| LAMA-GOOGLE_RE             | 11.78 | 14.08 | **24.88** |
| LAMA-SQUAD                 | 3.23  | 16.13 | **9.68** |
| LAMA-TREX                  | 59.13 | 63.68 | **69.12** |
| LIAR                       | 13.23 | 28.87 | **28.20** |
| MC_TACO                    | 76.25 | 88.39 | **87.34** |
| MEDICALQUESTIONS_PAIRS     | 46.56 | 91.80 | **90.16** |
| MULTI_News                 | 18.09 | 19.23 | **19.80** |
| NUMER_SENSE                | 50.53 | 56.75 | **57.32** |
| ONESTOP_ENGLISH            | 22.53 | 98.23 | **100.00** |
| OPENBOOKQA                 | 44.80 | 54.40 | **57.00** |
| PAWS                       | 49.60 | 91.27 | **93.60** |
| POEM_SENTIMENT             | 54.18 | 70.31 | **82.26** |
| PROTO_QA                   | 21.16 | 37.66 | **34.47** |
| QASC                       | 19.22 | 47.73 | **43.63** |
| QUAREL                     | 54.89 | 54.71 | **62.50** |
| QUARTZ-NO_KNOWLEDGE        | 65.43 | 68.88 | **69.39** |
| QUARTZ-WITH_KNOWLEDGE      | 64.03 | 85.97 | **76.28** |
| RACE-HIGH                  | 34.51 | 60.09 | **65.95** |
| RACE-MIDDLE                | 47.21 | 74.65 | **70.61** |
| ROTTEN_TOMATOES           | 88.36 | 90.60 | **89.77** |
| SAMSUM                     | 39.35 | 45.12 | **45.73** |
| SCIQ                       | 96.95 | 98.53 | **98.30** |
| SCITAIL                    | 91.02 | 95.47 | **94.77** |
| SEARCH_QA                  | 7.14  | 19.17 | **19.26** |
| SICK                       | 40.10 | 88.82 | **89.15** |
| SMS_SPAM                   | 95.80 | 97.46 | **97.11** |
| SPIDER                     | 3.29  | 6.38  | **6.77** |
| SUPERGLUE-CB               | 75.00 | 78.57 | **96.43** |
| SUPERGLUE-COPA             | 53.60 | 56.00 | **59.20** |
| SUPERGLUE-RECORD           | 44.67 | 73.82 | **67.20** |
| SUPERGLUE-RTE              | 50.36 | 84.89 | **78.42** |
| SUPERGLUE-WIC              | 50.16 | 68.34 | **71.79** |
| TAB_FACT                   | 46.65 | 50.16 | **57.34** |
5.2 Combinations of Delta Tuning Methods

Convergence Analysis. In Figure 6, Figure 7 and Figure 8, we visualize the performance of different delta tuning methods (LR, AP, PF) and fine-tuning (FT) at different training steps to compare their convergence rate. It could be derived that, the convergence rate of these tuning methods are ranked as: \( FT \approx LR > PF \). Overall, \( FR \) is the most stable method for convergence, and despite the fact that \( PF \) has the highest number of tunable parameters of all delta tuning methods, it still faces some convergence difficulties (the original paper also mentions that the convergence of \( PF \) is very dependent on the reparameterization).

Since \( PT \) lags far behind other tuning methods in both convergence rate and performance, we do not visualize it in the above figures. But as mentioned in §3.1: ADDITION, \( PT \) is the easiest method to implement and it is desirable to theoretically and empirically further study the convergence issue across different sizes of PLMs. We also found empirically that, (1) for each delta tuning method, within a reasonably broad range, both performance and convergence are not sensitive to the number of tunable parameters, but more sensitive to the structures of the methods, and (2) with the scale of PLM growing larger, the convergence of delta tuning is also accelerated (§5.3: SCALE). To summarize, our experiments yield very similar conclusions in terms of convergence and overall performance, and these conclusions are well supported by the fact that we used the same experimental and implementation setup, same model selection strategy, and plenty of datasets.

Efficiency Analysis. Delta tuning saves GPU memory by alleviating the need for gradient computations for most parameters. To specifically verify the efficiency of GPU memory, in Figure 9, we conduct experiments to compare the GPU memory consumed by different delta tuning methods and fine-tuning across different PLM scales. We choose three scales of T5 model, i.e., T5\textsubscript{BASE}, T5\textsubscript{LARGE}, T5\textsubscript{XL}, and test the peak GPU memories achieved under different batchsizes. The static GPU memories, which leave out the intermediate tensors such as hidden states, are drawn on Batchsize=0. We use NVIDIA A100 (maximum GPU memory=39.58GB) and library OpenDelta for these experiments. For the cases which consume large GPU memory than a single A100, we parallelize the model across several GPUs using model parallelization, which doesn’t introduce additional memory consumption. We can see from the figure that under small batchsizes (e.g., 1, 8), delta tuning saves up to 3/4 GPU memory, which under big batch sizes (e.g., 64), delta tuning saves at least 1/3 GPU memory. Given the fact that small batchsize is more preferred when applying big models to save GPU memory, delta tuning can further reduce the GPU memory dramatically.

5.2 Combinations of Delta Tuning Methods

Considering that different delta tuning methods are compatible with each other, which means they could be applied on the same PLM together, we thus investigate whether such a combination would bring additional benefits. Specifically, we evaluate both simultaneous combination and sequential combination. We choose
5.2 Combinations of Delta Tuning Methods

![Figure 6](image)

**Figure 6:** The performance of T5\textsubscript{BASE} with different delta tuning methods (LR, AP, PF) and fine-tuning (FT) at different training steps. Note we apply early stop in all the experiments. The performance of PT is omitted since it lags far behind other tuning methods in both convergence and performance.

three representative delta tuning methods, including prompt tuning, BitFit, and adapter, to explore the effects of their combinations. The training details are described in §A.2: COMBINATION DETAILS.

**Simultaneous Combination.** We first explore the effects of directly applying all the three delta tuning methods simultaneously. The experiments are conducted using both RoBERTa\textsubscript{LARGE} (Liu et al., 2019) and T5\textsubscript{BASE} on eight GLUE tasks (Wang et al., 2019), and we report the performance on development sets. We also test the performance of RoBERTa\textsubscript{LARGE} under the few-shot setting, where we randomly sample 16 training examples per label to construct the new training set and development set, respectively.
Figure 7: Continued with Figure 6. The performance of T5_{BASE} with different delta tuning methods (LR, AP, PF) and fine-tuning (FT) at different training steps. Note we apply early stop in all the experiments.

Similar to prompt-based fine-tuning (Schick & Schütze, 2021), we insert a natural language prompt template into the input text for each task. Take the sentiment classification task as an example, an input sentence \( x = (I \ like \ this \ movie.) \) could be re-formulated as: \( x_{\text{prompt}} = [\text{CLS}] \ x \) It was [MASK]. [SEP], where “It was [MASK].” is a manual template. The PLM is trained to fill in the [MASK] token with either “great” (positive) or “terrible” (negative) for classification. The manual templates are designed to bridge the gap between pre-training and downstream tuning, we also test the performance of delta tuning combinations without templates, i.e., \( x_{\text{prompt}} = [\text{CLS}] \ x [\text{SEP}] [\text{MASK}] [\text{SEP}] \), to evaluate manual templates’ functionalities. The manual templates and label words for different GLUE tasks are listed in Table 4.
We list the results of RoBERTa in Table 5, from which we could conclude that: for RoBERTa, (1) under both full-data setting and the few-shot setting, introducing adapter into the combination almost always conduces to the average GLUE performance no matter whether there exist manual templates; (2) introducing prompt tuning into the combination generally harms the average performance, showing that prompt tuning may not be compatible with other two delta tuning methods; (3) introducing BitFit into the combination generally improves the average performance; (4) manual templates could significantly improve the zero-shot performance (from 23.7 to 43.4) by narrowing the gap between downstream tuning and pre-training. Under the few-shot setting, manual templates could also help boost the average performance evidently. However, when
the training supervision is abundant (full-data setting), manual templates only exhibit marginal improvements or even harm the performance.

We list the results of T5\textsubscript{BASE} in Table 6, from which we observe slightly different phenomena than RoBERTa\textsubscript{LARGE} as follows: (1) still, introducing prompt tuning into the combination would always harm the performance no matter whether there exist manual templates, showing that prompt tuning may not be compatible with other two delta tuning methods for T5\textsubscript{BASE}, either; (2) introducing BitFit into the combination, however, could always conduce to the average performance; (3) adapter does not always improve the performance when there exist manual templates but could still bring benefits when there do not exist manual templates; (4) inserting manual templates into the input text would always improve the average performance. The improvements tend to be more evident than RoBERTa\textsubscript{LARGE}.

**Sequential Combination.** In addition to the simultaneous combination, we further investigate the compatibility when the above three delta tuning methods (prompt tuning, BitFit, and adapter) are sequentially introduced. Specifically, we split the whole tuning process into 3 stages. During each stage, we train an individual delta tuning method for 6, 000 steps; in the stages to follow, we freeze the tuned parameters in previous stages and only optimize the newly introduced delta parameters. We experiment RoBERTa\textsubscript{LARGE} on SST-2 (Socher et al., 2013) with / without manual templates. The results are visualized in Figure 10, from which we could derive that, under certain cases, the performance could be improved with the involvements of subsequent delta tuning methods. However, there does not exist an optimal sequential combination under different settings.

**Generalization Gap.** Additionally, we report the generalization gap (train performance - dev performance) for RoBERTa\textsubscript{LARGE} under the full-data setting, with the results shown in Table 7. It could be derived that, (1) the gap of a single delta tuning method is always smaller than fine-tuning, which means over-parameterization may help better memorize (overfit) training samples. Among all the delta tuning methods, prompt tuning tends to have the smallest generalization gap. Considering that each delta tuning method could already generalize well and achieve non-trivial performance on the dev set, hence overfitting the training set may not be the prerequisite for good generalization; (2) in general, combining delta tuning methods would enlarge the generalization gap, even to the extent that is comparable with fine-tuning, despite tuning far fewer parameters. This suggests that, for the investigated tasks, memorizing the training set may not require employing all of the parameters; in other words, a small model capacity during downstream adaptation may be enough for good memorization; (3) utilizing manual templates generally would not influence the generalization gap.

---

**Table 4:** Manual templates and the corresponding label words for different tasks.

| Task      | Template                  | Label words |
|-----------|---------------------------|-------------|
| CoLA      | ⟨S\textsubscript{1}⟩ This is [MASK]. | grammatical: correct, not_grammatical: incorrect |
| SST-2     | ⟨S\textsubscript{1}⟩ It was [MASK]. | positive: great, negative: terrible |
| MRPC      | ⟨S\textsubscript{1}⟩ [MASK], ⟨S\textsubscript{2}⟩ | equivalent: Yes, not_equivalent: No |
| STS-B     | ⟨S\textsubscript{1}⟩ [MASK], ⟨S\textsubscript{2}⟩ | equivalent: Yes, not_equivalent: No |
| QQP (link)| ⟨S\textsubscript{1}⟩ [MASK], ⟨S\textsubscript{2}⟩ | entailment: Yes, neutral: Maybe, contradiction: No |
| MNLI      | ⟨S\textsubscript{1}⟩ ? [MASK], ⟨S\textsubscript{2}⟩ | entailment: Yes, no_entailment: No |
| QNLI      | ⟨S\textsubscript{1}⟩ ? [MASK], ⟨S\textsubscript{2}⟩ | entailment: Yes, no_entailment: No |
| RTE       | ⟨S\textsubscript{1}⟩ ? [MASK], ⟨S\textsubscript{2}⟩ | entailment: Yes, no_entailment: No |

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**Figure 9:** GPU memory consumed by each delta tuning methods compared with fine-tuning.
### 5.2 Combinations of Delta Tuning Methods

Table 5: Performance of RoBERTa\textsubscript{LARGE} on GLUE datasets. We report the average result of multiple random seeds on the validation set.

| Prompt | BitFit | Adapter |
|--------|--------|---------|
| x      | x      | x       |
| x      | x      | x       |
| x      | x      | x       |
| x      | x      | x       |
| x      | x      | x       |
| x      | x      | x       |

| Tunable parameters | 0% | 1.75% | 0.9% | 1.84% | 0.003% | 1.76% | 0.09% | 1.85% |

#### RoBERTa\textsubscript{LARGE - full-data, without manual templates}

| Dataset | RoBERTa\textsubscript{LARGE} | BitFit | Adapter |
|---------|-------------------------------|--------|---------|
| CoLA\textsubscript{(Matt.)} | 4.6 | **66.6** | 63.5 |
| SST-2\textsubscript{(acc)} | 50.9 | **95.8** | 95.6 |
| MRPC\textsubscript{(F1)} | 1.4 | 92.7 | 91.9 |
| STS-B\textsubscript{(Pear.)} | -6.2 | **91.4** | 90.7 |
| QQP\textsubscript{(F1)} | 6.4 | 83.5 | 83.5 |
| MNLI\textsubscript{(acc)} | 34.2 | 88.6 | 88.0 |
| RTE\textsubscript{(acc)} | 47.7 | **86.8** | 86.2 |
| Average | 23.7 | **87.4** | 86.0 |

#### RoBERTa\textsubscript{LARGE - full-data, with manual templates}

| Dataset | RoBERTa\textsubscript{LARGE} | BitFit | Adapter |
|---------|-------------------------------|--------|---------|
| CoLA\textsubscript{(Matt.)} | 2.2 | **66.9** | 64.2 |
| SST-2\textsubscript{(acc)} | 83.6 | **96.3** | 96.1 |
| MRPC\textsubscript{(F1)} | 61.9 | 92.2 | 92.0 |
| STS-B\textsubscript{(Pear.)} | -3.3 | 91.3 | 90.9 |
| QQP\textsubscript{(F1)} | 49.7 | 83.6 | 83.6 |
| MNLI\textsubscript{(acc)} | 50.9 | 88.6 | 87.7 |
| RTE\textsubscript{(acc)} | 51.3 | **86.9** | 86.2 |
| Average | 43.4 | **87.4** | 86.8 |

#### RoBERTa\textsubscript{LARGE - 16-shot, without manual templates}

| Dataset | RoBERTa\textsubscript{LARGE} | BitFit | Adapter |
|---------|-------------------------------|--------|---------|
| CoLA\textsubscript{(Matt.)} | 4.6 | 19.6 | 15.1 |
| SST-2\textsubscript{(acc)} | 50.9 | 92.7 | 92.7 |
| MRPC\textsubscript{(F1)} | 1.4 | 78.2 | 69.8 |
| STS-B\textsubscript{(Pear.)} | -0.6 | 66.5 | 67.5 |
| QQP\textsubscript{(F1)} | 6.4 | 55.9 | 55.6 |
| MNLI\textsubscript{(acc)} | 34.2 | 58.1 | 64.6 |
| RTE\textsubscript{(acc)} | 47.7 | 55.0 | 54.5 |
| Average | 24.4 | 60.8 | 61.1 |

#### RoBERTa\textsubscript{LARGE - 16-shot, with manual templates}

| Dataset | RoBERTa\textsubscript{LARGE} | BitFit | Adapter |
|---------|-------------------------------|--------|---------|
| CoLA\textsubscript{(Matt.)} | 2.2 | **10.5** | 4.6 |
| SST-2\textsubscript{(acc)} | 83.6 | **93.1** | 92.9 |
| MRPC\textsubscript{(F1)} | 61.9 | 77.2 | 74.5 |
| STS-B\textsubscript{(Pear.)} | -3.3 | 65.8 | 69.3 |
| QQP\textsubscript{(F1)} | 49.7 | 66.0 | 67.8 |
| MNLI\textsubscript{(acc)} | 50.9 | 68.0 | 69.4 |
| RTE\textsubscript{(acc)} | 51.3 | 70.6 | 67.3 |
| Average | 43.4 | 65.2 | 64.5 |

### Performance of RoBERTa\textsubscript{LARGE} on GLUE datasets. We report the average result of multiple random seeds on the validation set.
The Power of Scale for Delta Tuning

5.3 The Power of Scale for Delta Tuning

Recently, Lester et al. (2021) found that with the scale of the backbone PLM growing, prompt tuning becomes more and more competitive in performance, and would even achieve comparable performance than fine-tuning for a PLM with over 10 billion parameters. Besides, Su et al. (2021) indicated that the convergence speed of prompt tuning benefits from the scaling law. In this section, we explore whether other delta tuning methods also exhibit such power of scale. Specifically, we experiment on the task of MNLI (Williams et al., 2018), QNLI, and SST-2, and choose three PLMs (T5_{SMALL}, T5_{BASE}, T5_{XXL}) of increasing sizes, and evaluate the performance of six representative delta tuning methods (adapter, LoRA, prefix-tuning, prompt tuning, last layer tuning, and selective module tuning). Besides, we give the the percentages of the tuned parameters for various methods in every scale of the PLM as shown in Table 9. We describe more training tails of this section in §A.3: SCALE DETAILS.

The results are visualized in Figure 11. From Figure 11 (a-i), we could observe that, with the scale of the PLM backbone growing, both the performance and the convergence of all delta tuning methods are significantly improved; (2) in addition, Figure 11 (j-l) indicates that compared with other delta tuning methods, prompt tuning tends to perform extremely bad for small-scale PLMs (T5_{SMALL} and T5_{BASE}). However, as found in §5.1: PERFORMANCE, other delta tuning methods tend to perform comparable with fine-tuning even for a
small-scale PLM ($T_5$\text{BASE}); (3) based on existing results, in Figure 11 (m-o) and (p-r), we further design two delta tuning methods: last layer tuning and selective module tuning. For last layer tuning, we optimize the last layer in $T_5$ encoder; for selective module tuning, we randomly choose some modules (e.g., the feed-forward layer, query / key / value matrix in the attention layer, or a layer norm) in the $T_5$ model to be tunable. Both methods show promising results especially when the scale of the PLM is extremely large, with selective module tuning slightly better than last layer tuning. These results suggest that confining the optimization within a specific layer may not be a good strategy (e.g., the case of prompt tuning and last layer tuning). On the other hand, randomly choosing modules across different layers could achieve excellent performance when the scale of PLMs grows extremely large.

In general, the above results imply that, the power of scale may be a common phenomenon for delta tuning. We hypothesize the existence of such a phenomenon is because, larger PLMs generally have smaller intrinsic dimensionalities (Aghajanyan et al., 2021), therefore, merely tuning minimal parameters could obtain a strong enough representation ability to achieve non-trivial performance in downstream tasks; besides, the over-parameterization and large-scale pre-training may make PLMs more unlikely to get stuck in a local optimum during downstream optimization, and thus the convergence is accelerated.

### 5.4 Task-level Transferability Evaluation

Recently, Su et al. (2021) and Vu et al. (2021) demonstrate the cross-task transferability of prompt tuning. To verify whether cross-task transferability also exists in various delta tuning methods, we investigate four delta tuning methods (prompt tuning, prefix-tuning, adapter, and LoRA) and 12 tasks of 5 different types (sentiment analysis, natural language inference, paraphrase identification, question answering, summarization) by transferring the trained delta parameters to the unseen target tasks. More training and dataset details are left in §A.4: Transferability Details.
In experiments, we report their relative performance (zero-shot transferring performance / original performance). The results are shown in Figure 12, from which we can observe that: (1) for the tasks belonging to the same category, transferring tuned parameters among them generally performs well; (2) for the tasks of different types, transferring delta parameters among them generally achieves poor performance; (3) interestingly, we find that transferring tuned parameters from the text generation tasks such as question answering and summarization can achieve non-trivial performance on sentiment analysis, indicating that text generation tasks might be a more complex task that includes the knowledge required to solve the sentiment analysis tasks. These exciting results verify some common subspace among various tasks introduced in §4.1: OPTIMIZATION, and demonstrate that it is promising to utilize trained delta parameters for similar tasks through knowledge transfer.

6 Applications

Delta tuning has been successfully applied to a variety of application scenarios. In this section, we briefly introduce several real-world applications, emphasizing on different advantages of delta tuning.

Figure 10: The performance of RoBERTaLARGE when different delta tuning methods (adapter (AP), BitFit (BF) and prompt tuning (PT)) are applied sequentially. The experiments are conducted on SST-2 (Socher et al., 2013).
(a) Adapter (MNLI).
(b) Adapter (QNLI).
(c) Adapter (SST-2).
(d) LoRA (MNLI).
(e) LoRA (QNLI).
(f) LoRA (SST-2).
(g) Prefix-tuning (MNLI).
(h) Prefix-tuning (QNLI).
(i) Prefix-tuning (SST-2).
(j) Prompt Tuning (MNLI).
(k) Prompt Tuning (QNLI).
(l) Prompt Tuning (SST-2).
(m) Last Layer Tuning (MNLI).
(n) Last Layer Tuning (QNLI).
(o) Last Layer Tuning (SST-2).
Fast Training and Shareable Checkpoints. Transformer-based models, although inherently parallelizable, are very slow to train due to their huge sizes, especially under the current era when ever-larger PLMs constantly emerge. Although delta tuning may converge slower than the traditional fine-tuning, the computations of the tunable parameters during backward propagation are significantly reduced, which conduces to speeding up training, as visualized in Figure 13. For instance, Rücklé et al. (2021) show that using adapters for downstream tuning could reduce training time to 40% while maintaining comparable performance than fine-tuning; Mahabadi et al. (2021a) also indicate that a series of delta tuning methods significantly reduce both the training time for each epoch and the peak GPU memory, which is of paramount importance for practical applications. Another observation is that the structures of delta tuning methods could have considerable impact on the time of a single forward or backward process. Since AP injects additional neural modules to each layer of the Transformer model, the path of data flow has indeed become longer and further lead to inference latency. And such latency could be relatively reduced as the model scales.

Due to the lightweight nature, the tuned delta parameters could also save the storage space, making it easier to share the trained delta checkpoints among practitioners. With the help of delta tuning, researchers could easily scale up experiments to extremely large models containing even billions of parameters. Recently, researchers have been spending huge efforts to create a community of shareable delta tuning checkpoints, such as (1) AdapterHub\(^9\) (Pfeiffer et al., 2020a), an implementation of different adapter variants and a host for adapter checkpoints, and (2) OpenDelta\(^10\), an emerging plug-and-play library that is compatible with almost all PLMs based on PyTorch\(^11\).

Multi-task Learning. Building a general-purpose AI system has always been the goal of researchers. Recently, extremely large PLMs, such as GPT-3 (Brown et al., 2020), have demonstrated the spectacular ability in fitting different data distributions simultaneously and promoting the downstream performance of various tasks. Multi-task learning has thus received a growing amount of attention under the era of large-scale pre-training. As a parameter-efficient substitution of full-model fine-tuning, delta tuning exhibits excellent ability for multi-task learning and in the meantime, maintains a relatively low additional storage. Successful applications include (1) multi-lingual learning: Pfeiffer et al. (2020b) propose to learn a series of invertible adapters between embeddings in the source and target languages to mitigate lexical differences across languages. The invertible adapter could well support knowledge transfer among multiple subtasks and maintain a low parameter budget, and (2) question answering: Friedman et al. (2021) prove that using a set of adapters that specialize in different QA formats performs favorably to a single language model that is fine-tuned on a mixture of QA formats. In addition, the simple average of specialized adapters also exhibits strong zero-shot transferring ability. Recently, Liu et al. (2021a); Sun et al. (2021); Karimi Mahabadi et al. (2021) also demonstrate that delta tuning could not only unify the tasks belonging to the same ontology, but also the tasks with substantially different formats so that different tasks could benefit from each other through knowledge transfer. Expanding from this idea, delta tuning can well support adaptations of large PLMs for multi-lingual and multi-domain scenarios.

\(^9\)https://adapterhub.ml
\(^10\)https://github.com/thunlp/OpenDelta
\(^11\)https://pytorch.org
Figure 12: Zero-shot transferring performance of four delta tuning methods using T5_{BASE}. We report relative performance (zero-shot transferring performance / original performance) (%) on the target tasks (columns) when delta parameters are transferred from the source tasks (rows). Colors of the task names indicate the task types. Blue: sentiment analysis, Green: natural language inference, Orange: paraphrase identification, Brown: question answering, and Purple: summarization.

**Catastrophic Forgetting Mitigation.** The language abilities acquired during pre-training are stored in parameters. As a consequence, updating all parameters in PLMs without regularization may lead to catastrophic forgetting when PLMs are sequentially trained across a suite of tasks (Jin et al., 2021; Qin et al., 2021a,c). Since delta tuning only tunes minimal parameters, it could be a potential solution for mitigating the problem of catastrophic forgetting. For instance, MultiEURLEX (Chalkidis et al., 2021) introduce delta tuning into multilingual transfer learning, and demonstrate that using delta tuning methods rather than full-parameter fine-tuning boosts the performance of zero-shot transfer learning between the source language and the target language: Jin et al. (2021) propose to introduce adapters into PLMs and maintain the original parameters fixed, so that PLMs could be trained in a lifelong manner for emerging data.
Figure 13: Time consumption for fine-tuning (FT) and different delta tuning methods, including BitFit (BF), adapter (AP) and prompt tuning (PT). We report the results with different input length.

Language Model as Services and In-batch Parallel Computing. From the practical perspective, extremely large PLMs are generally released as services (Brown et al., 2020; Nakano et al., 2021; Sun et al., 2022), that is, users use the model by interacting with the released APIs rather than editing the source code. Considering the unaffordable communication costs between users and the service provider, delta tuning is apparently a more competitive choice over the traditional fine-tuning due to its lightweight nature. On one hand, the service provider could support training downstream tasks required by multiple users while consuming much fewer computations and storage space. In addition, considering that several delta tuning algorithms, such as prompt tuning (Lester et al., 2021) and prefix-tuning (Li & Liang, 2021) are inherently parallelizable, such a service could become more practical since delta tuning could well support in-batch parallel computing by allowing instances from multiple users to be trained / evaluated in the same batch. Recent works (He et al., 2022) also show that most of the delta tuning methods, if not parallelizable inherently, could be modified to support parallel computing, e.g., parallel adapter (He et al., 2022). On the other hand, when the gradients of the central PLM are not available to users, delta tuning still exhibits extraordinary talents in optimizing PLMs through derivative-free algorithms by only accessing the model inference APIs. Recently, Sun et al. (2022); Diao et al. (2022) pioneered to propose black-box tuning and show that their method could not only outperform manual prompts and GPT-3’s in-context learning, but also surpass the gradient-based counterparts.

7 Conclusion

This paper focuses on parameter-efficient methods, i.e., delta tuning, for pre-trained language models. We first describe the problem and provide a categorization to systematically survey the development of delta tuning. Captivated by the empirical evidence, we propose two frameworks to theoretically discuss delta tuning from the optimization and the optimal control perspectives. Our discussion not only sheds light on the theoretical references of a novel design for delta tuning methods, but also implies that we could grasp the essential mechanisms of PLMs through deep analysis. Empirically, we conduct extensive experiments across 100+ NLP tasks to fairly evaluate and explore the combinatorial property, influence of scale, and transferability for delta tuning. Furthermore, we discuss the value of the applications of this paradigm. In summary, delta tuning exhibits significant potential to stimulate extremely large PLMs, and we hope that the paradigm could be further theoretically studied and empirically practiced.

Broader Impacts

Delta tuning focuses on the efficient adaptation of pre-trained language models, which has both positive applications and potential harms for society. On the bright side, PLMs have exhibited unprecedented capability of natural language understanding (represented by BERT (Devlin et al., 2019)) and generation (represented by GPT-3 (Brown et al., 2020)), which empowers numerous real-world applications such as search engines, question-answering systems, intelligent writing systems, information extraction systems, and code completion, etc. Recent research also shows that such large-scale PLMs could mimic the behavior to use search engines to answer difficult questions (Nakano et al., 2021). However, the risk is often hidden in the great successes, on the other hand, PLMs may present biases in terms of gender, race, religion, etc, and even directly produce
machine-written language with attacks, profanities, and insults (Weidinger et al., 2021). This is because PLMs are pre-trained with large-scale realistic corpora, and these pre-trained data are likely to contain inherent bias. Language is a carrier of human views, so the prejudice and discrimination that exist in human society can easily be mapped onto language, and how to alleviate such challenges of fairness is a question that is well worth further study. Efforts could be made in two ways, first, directly by normalizing the training corpus to remove as many potential biases as possible, and second, by modifying model representations or outputs to reduce the risks. Outside of research, more comprehensive and improved treaties and norms for the use and modification of language models should be established by the community.

So far, there is no clear evidence that delta tuning mitigates or exacerbates the potential hazards of PLMs. It is likely that the delta tuning methods will still inherit the potential risks of the base language model. But the delta tuning methods seem to have considerable potential for correcting model bias. Under this circumstance, delta tuning is not only applied to efficiently adapt PLMs to downstream tasks but also could be utilized to specifically process risky information inside the models with a small number of parameters changed. In fact, it has been shown that it is possible to modify the factual errors made by the model in a computationally efficient way (Mitchell et al., 2021), signaling that the fairness issue can be potentially addressed through delta tuning. At the same time, we have to worry that such a strategy can also be used to further contaminate the language models to produce undesirable predictions. Here, we strongly encourage the community to conduct further research to comprehensively explore the various effects that delta tuning may have on PLMs.

When it comes to environmental issues, given that pre-training, fine-tuning, and storage of PLMs is a resource-intensive process, delta tuning attempts to minimize this impact from the outset. After probing the memory (Figure 9) and time consumption (Figure 13) of delta tuning in our work, we find that such methods could substantially reduce the computational cost. However, in the convergence analysis (Figure 6, 7, 8) we conclude that delta tuning methods tend to need more time to converge, although this phenomenon becomes insignificant as the model scales. In order to reduce unnecessary carbon emissions, we will open source all tools, code and checkpoints used in the experiment.

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Contributions

The contributions of all authors are listed as follows: Ning Ding, Yujia Qin and Zhiyuan Liu initiated and organized the research. The term “delta tuning” was coined by Shengding Hu and recognized by other authors for its vividness. Ning Ding drafted abstract, §1: INTRODUCTION and §3: DELTA TUNING, Yulin Chen and Ning Ding drafted §2: PRELIMINARIES. Shengding Hu, Xiaozhi Wang, and Yujia Qin added contents to §3.1: ADDITION and §3.3: REPARAMETERIZATION. Weilin Zhao, Ning Ding, Yulin Chen, and Shengding Hu manually annotated the randomly selected 1,000 papers and created Table 1, as well as Table 2. Fuchao Wei, Zonghan Yang, Ning Ding, Yujia Qin, Shengding Hu and Jianfei Chen discussed the scope and content of §4: THEORY. Fuchao Wei developed the optimization framework and drafted §4.1: OPTIMIZATION, Zonghan Yang and Yang Liu proposed the optimal control framework and drafted §4.2: OPTIMAL CONTROL. Ning Ding verified the formula derivation. Yujia Qin led the empirical study part. And Yujia Qin, Guang Yang, Yusheng Su, Weize Chen, Jing Yi, Chi-Min Chan, and Ning Ding drafted §5: EXPERIMENTS. Yujia Qin, Guang Yang, Weize Chen, Jing Yi, and Shengding Hu conducted the experiments for overall performance and combination (§5.1: PERFORMANCE, §5.2: COMBINATION). Yusheng Su and Chi-Min Chan conducted and wrote experiments for transferability and power of scale (§5.3: SCALE, §5.4: TRANSFERABILITY). Shengding Hu and Yujia Qin drafted §6: APPLICATIONS. Zhiyuan Liu, Hai-Tao Zheng, Yang Liu, Jie Tang, Juanzi Li, Maosong Sun advised the project, suggested the theoretical and empirical study and participated in the discussion. Ning Ding and Yujia Qin participated in all the sections and proofread the whole paper.
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A Implementation Details

A.1 Performance and Convergence

Among the NLP datasets downloaded from Hugginface datasets, for those datasets without publicly released test set, we evenly divide the original development sets into two halves as the new development set and test set; for those datasets without publicly released development set and test set, we divide the original training set with a ratio of 8 : 1 : 1 into the new training set, development set and test set.

For PF, LR, AP and FT, we use AdamW (Kingma & Ba, 2015) as the optimizer, set the maximum training steps to 20,000 with early stop, and save the checkpoint for evaluation on development set every 100 steps. After that, we evaluate the best checkpoint using the development set on the test set. We experiment on the combinations of different batch sizes (\{16, 32\}) and learning rates (\{1 \times 10^{-3}, 1 \times 10^{-4}, 5 \times 10^{-4}\}), and report the best performance. Since we found empirically that PT converges much slower than the other tuning methods, we set the maximum training step of PT to 100,000 steps without early stop, and evaluate the performance on development set for every 1,000 steps. Following Lester et al. (2021), we choose Adafactor (Shazeer & Stern, 2018) as the optimizer. All the experiments are conducted under the same environment.

A.2 Combinations of Delta Tuning Methods

For prompt tuning, we prepend 10 tunable virtual tokens into the input text; for adapter, we set the reduction factor to 16; for BitFit, all the bias components in PLMs are optimized.

Simultaneous Combination. For all delta tuning methods on RoBERTaLARGE, we choose AdamW (Kingma & Ba, 2015) as the optimizer, set the maximum training steps to 6,000, and save the checkpoint for evaluation on development set every 200 steps. After that, we select the best checkpoint based on the development set, and evaluate it on the test set. For the full-data setting, we set the training batch size to 16 and experiment on the combinations of different learning rates (\{1 \times 10^{-2}, 1 \times 10^{-3}, 1 \times 10^{-4}, 1 \times 10^{-5}\}); for the few-shot setting, we set the training batch size to 4 and experiment on the combination of 4 different learning rates, which are listed in Table 8.

For STS-B, which is a regression task, we convert it into a binary classification problem. Specifically, assume that the original output value is bounded by \([v_l, v_u]\) and the new labels are \(\{y_l, y_u\}\), the original value is reformulated as:

\[
y = v_l \cdot p(y_l|x_{in}) + v_u \cdot p(y_u|x_{in}).
\]

During optimization, we minimize the KL-divergence between prediction distribution \(p(y_u|x_{in})\) and the ground truth \((y - v_l)/(v_u - v_l)\).

Sequential Combination. We choose AdamW (Kingma & Ba, 2015) as the optimizer, set the batch size to 64 and the learning rate to \(1 \times 10^{-2}\) for prompt tuning, \(1 \times 10^{-4}\) for BitFit and \(1 \times 10^{-5}\) for adapter.

Table 8: Learning rate setting of RoBERTaLARGE on 16-shot GLUE datasets.

| Prompt tuning | 1e-2 | 3e-3 | 1e-3 | 3e-4 | 1e-4 | 3e-5 |
|--------------|------|------|------|------|------|------|
| BitFit       | ✔    | ✔    | ✔    | ✔    | ✔    | ✔    |
| Adapter      | ✔    | ✔    | ✔    | ✔    | ✔    | ✔    |

Learning Rates

| Learning Rates | Prompt tuning | BitFit | Adapter |
|----------------|--------------|--------|---------|
| 1e-2           | ✔ ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ |
| 3e-3           | ✔ ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ |
| 1e-3           | ✔ ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ |
| 3e-4           | ✔ ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ |
| 1e-4           | ✔ ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ |
| 3e-5           | ✔ ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ | ✔ ✔ ✔ ✔ ✔ ✔ |
A.3 The Power of Scale for Delta Tuning

Table 9: The percentages of the tuned parameters (parameters participating optimizing in a PLM / all parameters in a PLM) during the training.

| Method                  | SMALL | BASE | XXL |
|-------------------------|-------|------|-----|
| Adapter                 | 1.70% | 1.20%| 0.28%|
| LoRA                    | 0.73% | 0.64%| 0.26%|
| Prefix-tuning           | 0.50% | 0.47%| 0.11%|
| Prompt Tuning           | 0.06% | 0.03%| 0.01%|
| Last Layer Tuning       | 6.30% | 4.20%| 2.10%|
| Selective Module Tuning | 2.10% | 4.20%| 2.40%|

Apart from the delta tuning methods (prompt tuning, adapter, LoRA and prefix-tuning) introduced in the previous sections, we additionally design two delta tuning methods, i.e., last layer tuning and selective module tuning, to investigate the power of scale for delta tuning. For last layer tuning, we only select the last layer of the encoder in T5 to optimize. For selective module tuning, we manually choose some modules (e.g., the feed-forward layer, query / key / value matrix in the attention layer, or a layer norm) in T5 to optimize. We set the training batch size to 64 for all delta tuning methods. For the different scales of T5, we use the same learning rates during training: $5 \times 10^{-3}$ (prompt tuning), $5 \times 10^{-4}$ (adapter), $5 \times 10^{-5}$ (LoRA) $5 \times 10^{-3}$ (prefix-tuning), $5 \times 10^{-3}$ (last layer tuning), and $5 \times 10^{-5}$ (selective module tuning). The percentage of the tunable parameters for each method / model is listed in Table 9.

A.4 Task-level Transferability Evaluation

In the cross-task transferability experiments, we utilize 12 tasks of 5 different types as follows:

**Sentiment Analysis.** Given a sentence, a PLM identifies the sentiment polarity in this sentence. We choose SST-2 (Socher et al., 2013), Amazon/Polarity, and Rotten Tomatoes (Pang & Lee, 2005) to analyze.

**Natural Language Inference.** Given a premise and hypothesis pair, a PLM determines whether the hypothesis is entailed, contradict, or undetermined by the premise. We choose MNLI (Williams et al., 2018), SICK (Marelli et al., 2014), and SciTail (Khot et al., 2018b) to analyze.

**Paraphrase Identification.** Given a pair of sentences, a PLM judges whether they are semantically identical. We choose QQP (Sharma et al., 2019) and MRPC (Dolan & Brockett, 2005) to analyze.

**Question Answering.** Given a question, a PLM answers the question based on context. We choose MathQA (Amini et al., 2019) and AQUA-RAT (Ling et al., 2017) to analyze.

**Summarization.** Given an article, a PLM summarizes it. We choose Multi-News (Fabbri et al., 2019), and SAMSum (Gliwa et al., 2019) to analyze.

**Evaluation Metrics.** For sentiment analysis, natural language inference, and paraphrase identification tasks, we choose accuracy (Acc.) as their evaluation metric in the experiments. For question answering and summarization, we utilize F1 and ROUGE-L (Lin, 2004), respectively. Finally, we report their relative performance (transferring zero-shot performance / original performance) (%).

B Tasks Evaluated in Experiments

Table 10: The tasks evaluated in our experiments in Table 3. We refer to Ye et al. (2021) for task ontology.
| Dataset                                      | Reference                     |
|----------------------------------------------|-------------------------------|
| rotten_tomatoes                              | Pang & Lee 2005               |
| emo                                          | Chatterjee et al. 2019        |
| tweet_eval-hate                              | Barbieri et al. 2020          |
| tweet_eval-irony                             | Barbieri et al. 2020          |
| tweet_eval-offensive                         | Barbieri et al. 2020          |
| tweet_eval-sentiment                         | Barbieri et al. 2020          |
| tweet_eval-stance_abortion                   | Barbieri et al. 2020          |
| tweet_eval-stance_atheism                    | Barbieri et al. 2020          |
| tweet_eval-stance_climate                    | Barbieri et al. 2020          |
| tweet_eval-stance_feminist                   | Barbieri et al. 2020          |
| tweet_eval-stance_hillary                    | Barbieri et al. 2020          |
| cls/emotion                                  |                               |
| ethos-disability                             | Mollas et al. 2020            |
| ethos-gender                                 | Mollas et al. 2020            |
| ethos-national_origin                        | Mollas et al. 2020            |
| ethos-religion                               | Mollas et al. 2020            |
| hate_speech18                                | Davidson et al. 2017          |
| hateexplain                                  | Mathew et al. 2020            |
| cls/hate speech detection                    |                               |
| nli                                          | Nie et al. 2020               |
| glue-mnli                                    | Williams et al. 2018          |
| glue-qnli                                    | Rajpurkar et al. 2016         |
| glue-rt                                      | Dagan et al. 2005; Bar-Haim et al. 2006 |
| scitail                                      | Giampiccolo et al. 2007       |
| superglue-rt                                 | Khot et al. 2018a; Dagan et al. 2005; Bar-Haim et al. 2006 |
| cls/NLI                                      |                               |
| climate_fever                                | Diggelmann et al. 2020        |
| liar                                         | Wang 2017                     |
| cls/paraphrase                               |                               |
| glue-qqp                                     | (link)                        |
| medical_questions_pairs                      | McCreery et al. 2020          |
| paws                                         | Zhang et al. 2019b            |
| cls/topic                                    |                               |
| ag_news                                      | Gulli (link)                  |
| cls/other                                    |                               |
| ade_corpus_v2-classification                 | Gurulingappa et al. 2012      |
| discovery                                    | Sileo et al. 2019             |
| glue-cola                                    | Warstadt et al. 2019          |
| sms_spam                                     | Almeida et al. 2011           |
| superglue-wic                                | Filev & Camacho-Collados 2019 |
| superglue-wsc                                | Levesque et al. 2012          |
| wiki_qa                                      | Yang et al. 2015              |
| qa/closed-book qa                            |                               |
| freebase_qa                                  | Jackson et al. 2019           |
| lama-conceptnet                              | Petroni et al. 2019, 2020     |
| lama-google_re                               | Petroni et al. 2019, 2020     |
| lama-squad                                   | Petroni et al. 2019, 2020     |
| lama-trex                                    | Petroni et al. 2019, 2020     |
| numer_sense                                  | Lin et al. 2020               |
| search_qa                                    | Dunn et al. 2017              |
| web_questions                                | Berant et al. 2013            |
| qa/multiple-choice qa                        |                               |
| cosmos_qa                                    | Huang et al. 2019             |
| dream                                        | Saha et al. 2018              |
| hellaswag                                    | Zellers et al. 2019           |
| openbookqa                                   | Mihaylov et al. 2018          |
| qasc                                         | Khot et al. 2020              |
| quartel                                      | Tafjord et al. 2019          |
| quartz-no_knowledge                          | Tafjord et al. 2019b          |
| quartz-with_knowledge                        | Tafjord et al. 2019b          |
| race-high                                    | Lai et al. 2017               |
| race-middle                                  | Lai et al. 2017               |
| superglue-copa                               | Gordon et al. 2012            |
| swag                                         | Zellers et al. 2018           |
| wino_grande                                  | Sakaguchi et al. 2020         |
| qa/long-form qa                              |                               |
| eli5-askh                                    | Fan et al. 2019               |
| Category                          | Dataset                                                                 | Reference          |
|----------------------------------|-------------------------------------------------------------------------|--------------------|
| qa/MRC                           | superglue-record                                                       | Zhang et al. 2018  |
|                                  | multi_news                                                             | Fabbri et al. 2019 |
|                                  | samsum                                                                 | Gliwa et al. 2019  |
|                                  | xsum                                                                   | Narayan et al. 2018|
| cg/summarization                 |                                                                         |                    |
|                                 | spider                                                                 | Yu et al. 2018     |
|                                 | wiki_bio                                                               | Lebret et al. 2016 |
|                                 | wiki_split                                                             | Botha et al. 2018  |
|                                 |                                                                         |                    |
| other/linguistic phenomenon      | blimp-anaphor_gender_agreement                                        | Warstadt et al. 2020|
|                                 | blimp-ellipsis_n_bar_1                                                 | Warstadt et al. 2020|
|                                 | blimp-sentential_negation_npi_scope                                    | Warstadt et al. 2020|
|                                 |                                                                         |                    |
| other/generate explanation       | cos_e                                                                  | Rajani et al. 2019 |
|                                 |                                                                         |                    |
| other/slot_filling               | ade_corpus_v2-dosage                                                   | Gurulingappa et al. 2012|
|                                 | ade_corpus_v2-effect                                                    | Gurulingappa et al. 2012|
|                                 |                                                                         |                    |
| other/entity linking             | kilt_ay2                                                               | Hoffart et al. 2011|
|                                 |                                                                         |                    |
| other/other                      | acronym_identification                                                 | Pouran Ben Veyseh et al. 2020|
|                                 | aslg_pc12                                                              | Othman & Jenni 2012|
|                                 | crawl_domain                                                           | Zhang et al. 2020  |
|                                 | proto_qa                                                               | Boraiko et al. 2020|