

# Parameter-Efficient Fine-Tuning in Large Models: A Survey of Methodologies

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**Abstract**—The large models, as predicted by scaling raw forecasts, have made groundbreaking progress in many fields, particularly in natural language generation tasks, where they have approached or even surpassed human levels. However, the unprecedented scale of their parameters brings significant computational and storage costs. These large models require substantial computational resources and GPU memory to operate. When adapting large models to specific downstream tasks, their massive parameter scale poses a significant challenge in fine-tuning on hardware platforms with limited computational power and GPU memory. To address this issue, Parameter-Efficient Fine-Tuning (PEFT) offers a practical solution by efficiently adjusting the parameters of large pre-trained models to suit various downstream tasks. Specifically, PEFT adjusts the parameters of pre-trained large models to adapt to specific tasks or domains, minimizing the introduction of additional parameters and the computational resources required. This review mainly introduces the preliminary knowledge of PEFT, the core ideas and principles of various PEFT algorithms, the applications of PEFT, and potential future research directions. By reading this review, we believe that interested parties can quickly grasp the PEFT methodology, thereby accelerating its development and innovation.

**Index Terms**—Fine-tuning, Parameter-efficient, Large language model, Deep learning, Artificial intelligence.

## I. INTRODUCTION

In recent years, large pre-trained models, commonly referred to as "large models", have emerged as a significant advancement in the field of artificial intelligence. Due to their outstanding performance and versatility in various application contexts, these models have attracted plenty of attention and provoked much discussion. These models have impressive computing capabilities and extensive data resources, allowing them to excel in tackling intricate jobs. Within the field of natural language processing (NLP), notable interest is given to Large Language Models (LLMs). These models demonstrate remarkable ingenuity in text generation [1][2], machine translation [3][4], personalized chatbots [5][6][7], text summarization [8], sentiment analysis [9], and question-answering systems [10].

Nevertheless, the development of large models faces significant challenges and controversies. These models require substantial computational resources and data support, which can potentially jeopardize the environment and compromise privacy protection [11]. Despite their impressive performance

in specific tasks, these models still have limitations and error rates that need continuous optimization and improvement [12][13][14]. When directly using large models for specific tasks, their performance often falls below desired levels. Consequently, fine-tuning large models has become a crucial method for enhancing model performance.

PEFT is a transfer learning method specifically developed to adapt the parameters of the large pre-trained models to suit new tasks and scenarios. This approach involves dynamically adjusting the model to enhance its effectiveness in performing certain tasks, taking into account the distinct features and requirements of the target task. The fine-tuning process typically entails improving the model architecture [15], optimizing parameters [16][17], and adapting learning strategies [18], among other considerations, to achieve better performance in new tasks. As the field of deep learning continues to evolve, techniques for optimizing and fine-tuning large models have also made significant advancements. Notable PEFT approaches include LoRA [19], adapter tuning [20], prefix-tuning [16], prompt-tuning [17], P-tuning [21], BitFit [22] and others. However, despite the significant achievements of large model fine-tuning techniques across several fields, there are always challenges and difficulties that need to be resolved. Overfitting mitigation, optimizing fine-tuning efficiency, and striking a learning balance between pre-training and fine-tuning tasks are a few examples of issues that need more investigation.

In recent years, hundreds of articles on PEFT have been published, with some studies offering informative overviews of the most prevalent approaches. Below is a comparative analysis of these studies.

Ding, Ning, et al. [23] introduce a theoretical abstraction for Delta Tuning, which is analyzed from the viewpoints of optimization and optimum control. This abstraction offers a unified approach to describe the current parameter-efficient fine-tuning methods which provides a distinct perspective for future investigations. Nonetheless, while the study predominantly concentrates on NLP applications, the generalizability and efficacy of these methods in diverse domains merit additional investigation. Lialin, V, et al. [24] provide a comprehensive analysis and classification that covers a broad range of methods and compares approximately 30 approaches across five dimensions: storage efficiency, memory efficiency, computational efficiency, accuracy, and inference overhead. However, while the article primarily focuses on detailed methods with practical efficiency for fine-tuning multibillion-scale

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Survey	Taxonomy					Application			
	Additive	Selective	Reparam.	Hybrid	Unified	NLP	Vision	Multi-task	Diffusion Model
[23]	✓	✓	✓			✓			
[24]	✓	✓	✓	✓					
[25]	✓	✓	✓	✓	✓	✓		✓	
[26]		✓	✓		✓		✓		
[27]	✓	✓	✓	✓	✓	✓			✓
Ours	✓	✓	✓	✓		✓		✓	✓

TABLE I: Comparison with existing surveys

language models, the exploration of real-world application scenarios is relatively limited. Xu, Lingling, et al. [25] provide a thorough evaluation and analysis of current PEFT approaches, assessing their performance, parameter efficiency, and memory utilization within a range of NLP tasks. Nonetheless, the paper does not fully expound on the practical applications of these methodologies in actual operational environments, nor does it deeply investigate their adaptability and the domain-specific challenges they might encounter. Xin, Yi, et al. [26] offer a comprehensive overview and future directions for visual PEFT, with a systematic review of the latest advancements. While the article spans multiple visual tasks, the experiments are primarily focused on several common tasks and do not fully encompass the broader range of potential application scenarios. Han, Zeyu, et al. [27] provide a detailed classification of PEFT approaches and explores the application of PEFT techniques across various model architectures and downstream tasks, as well as the systematic design challenges of parameter-efficient fine-tuning methods. It offers researchers and engineers a comprehensive overview of PEFT approaches, but there is still room for improvement in terms of practical application coverage.

Our contributions are as follows:

- With existing review papers, we offer a thorough and detailed overview of the fundamental knowledge related to large models and the general fine-tuning methodology. This part encompasses not only the fundamental principles, structures, and fundamental technologies of large models but also provides an in-depth overview of their practical applications in many tasks, such as natural language processing, multimodal activities, and other domains.
- Our survey encompasses a more up-to-date review of research methodologies, highlighting the latest advancements in the field of large models. This ensures that our review is comprehensive and thorough. The scope of our review is extensive, covering multiple scenarios such as natural language processing, multimodal tasks, and vision. This provides readers with a full understanding of the current state and future prospects of large model technology.
- After reviewing and analyzing current approaches, we suggest some innovative and future-oriented directions for further research. These areas take into account the growth potential of advanced model technology and also

incorporate industry requirements and obstacles in real-world applications, proposing viable and inventive research avenues.

This survey aims to comprehensively review the recent advancements in large model fine-tuning techniques. By conducting a thorough examination of existing research, our objective is to identify and fill the gaps in our current knowledge system. This will result in the development of a comprehensive and systematic framework of knowledge, which will provide researchers with a concise perspective on the topic and guide their future research. In conclusion, our work offers valuable resources and perspectives that can be utilized for both academic and practical purposes in related domains. The remainder of this survey is structured in the following manner:

In Section II, we offer a succinct summary of the fundamental components of large language models, including their past development, emerging capabilities, and the scaling laws that govern their size. Subsequently, we offer a brief overview of the dominant classifications of comprehensive language models and introduce the fundamental principles and framework of multi-modal comprehensive models. Furthermore, we investigate the primary methodologies employed in the fine-tuning domain of extensive language models, including instruction fine-tuning, alignment, and Reinforcement Learning from Human Feedback (RLHF). Ultimately, we present a brief summary of the most used benchmarks and assessment datasets in the field of big model fine-tuning.

In Section III, we offer a comprehensive analysis and summary of PEFT approaches, presenting a cohesive framework for classifying current PEFT methodologies, encompassing over 100 research articles published from June 2019 to July 2024. Expanding on the conventional tripartite classification of additive, reparameterized, and subtractive PEFT, we incorporate summaries of hybrid, quantization, and multi-task categorization PEFT approaches.

In Section IV, we present a comprehensive analysis and description of the prevailing PEFT approaches in the fields of multimodal, visual, and diffusion models. Our objective is to provide a deep understanding and recommendations for choosing and improving PEFT in different application scenarios.

In Section V, we encapsulate our extensive survey and put forward multiple promising avenues for future advancements, encompassing both algorithmic refinements and task scenarios,

hoping to provide valuable insights for further research and development in this burgeoning field.

## II. PRELIMINARY

### A. Large Language Models

1) *Background*: LLMs refer to neural language models with a large number of parameters, typically over billions of parameters. These models are built on the transformer architecture [28] and are pre-trained on vast text corpora [29]. Prior to the emergence of LLMs, the advent of transformers revolutionized the development approach for neural language models, shifting from end-to-end training to a pre-train then fine-tune paradigm. Under the pre-train fine-tune paradigm, pre-trained models can be repeatedly utilized, significantly enhancing the scalability of neural language models. Consequently, the scale of parameters is continuously growing larger. For instance, OpenAI's GPT-1 possessed 120 million parameters, while GPT-2 boasted 1.5 billion parameters. This number surged to 175 billion for GPT-3 and soared to 1.76 trillion for the latest GPT-4 [30]. With the evident increase in neural network parameter scales, the concept of large language models has been developed.

2) *Emergent abilities*: Research suggests that the rapid expansion of the parameter scale may lead to emergent abilities [31], which are formally defined as abilities that are not present in small models but arise in large models, constituting one of the most prominent characteristics distinguishing LLM from previous PLM. To conclude, emerging abilities can be categorized into threefolds.

**In-context learning**. In-context learning [31][32], known as ICL defined in GPT-3 [33], illustrates the ability of LLMs to acquire new task capabilities based on a small set of examples in context. Importantly, this process does not require additional training or gradient updates, indicating that the LLM is capable of completing new tasks with only prompts. In addition, [31] reveals that ICL is associated with both the LLM and the downstream task.

**Instruction following**. Natural language descriptions, known as instructions, are essential for fine-tuning LLMs. Instruction tuning organizes fine-tuning datasets in the format of natural language descriptions (instructions). Research [34] shows that with instruction tuning, LLMs are enabled to follow task instructions for new tasks without using explicit examples, demonstrating better generalization capability across inputs of various tasks. [35] discovered that to achieve evident efficacy, instruction tuning should be conducted on a relatively large-scale LLM, e.g., over 60B parameters.

**Step-by-step reasoning**. Constrained by parameter size, PLMs often struggle to solve tasks requiring intricate reasoning. In contrast, scaling up in parameter size equips language models with the Chain-of-Thought (CoT) [31]. CoT enhances language models' performance on tasks involving logic, calculation, and decision making by structuring the input prompt to human reasoning. Thanks to CoT, LLMs are enabled to tackle tasks that demand intermediate reasoning steps to derive the final answer, akin to constructing a step-by-step prompt that invokes a thinking and inference process within the model.

3) *Scaling Laws of LLMs*: Thanks to the exceptional scalability of the transformer architecture [28], language models also exhibit high scalability. Scaling laws for LLMs describe how the model grows and performs as the volume of training data increases.

In general, a scaling law includes four parameters, which also characterize a language model: denoted as: (1) Parameters count  $N$ . The number of parameters of an LLM is often associated with the number of transformer layers and the hidden size, except for some MoE LLMs. (2) Data size  $D$ . In LLM, this refers to the number of tokens for training. (3) Computation cost  $C$ . This is typically measured in terms of time and computational resources. (4) Loss  $L$ . The performance of training is usually evaluated by the training loss. There are two representative scaling laws for transformer LLMs.

**The Kaplan scaling law** Proposed by Kaplan [36], the law examines the statistical relations between the parameters  $C, N, D$  and  $L$  over a wide range of values, models and data tokens. The relationships can be expressed through the following equations:

$$L(N) = \left(\frac{N_c}{N}\right)^{\alpha_N}, \alpha_N \sim 0.076, N_c \sim 8.8 \times 10^{13} \quad (1)$$

$$L(D) = \left(\frac{D_c}{D}\right)^{\alpha_D}, \alpha_D \sim 0.095, D_c \sim 5.4 \times 10^{13} \quad (2)$$

$$L(C) = \left(\frac{C_c}{C}\right)^{\alpha_C}, \alpha_C \sim 0.050, C_c \sim 3.1 \times 10^8, \quad (3)$$

where the loss  $L$  is influenced by parameters  $N, D$ , and  $C$ , shedding light on decision-making processes when computational resources are limited.

**The Chinchilla scaling law** Proposed by DeepMind [37], the law provides guidelines for compute-optimal training of LLMs, specifically when computational resources are limited. Through rigorous experiments spanning a wide range of model sizes from 70M to 16B and dataset sizes from 5B to 500B tokens, they derived a scaling law with different coefficients compared to Kaplan's, as shown below:

$$L(N, D) = E + \frac{A}{N^\alpha} + \frac{B}{D^\beta}, \quad (4)$$

where  $E$  denotes the loss of an ideal generative process on the test data. Furthermore, claimed by the research, the constants in this formula are  $\alpha = 0.34, \beta = 0.28, A = 406.4, B = 410.7, L_0 = 1.69$ . Moreover, there is a general constraint that model the relationship between  $C$  and  $(N, D)$ :  $C = 6ND$ , which means that it costs six FLOPs per parameter to train one token. Then it can be computed that an optimal model size and data size selection can be denoted as:

$$N_{opt} = 0.6 C^{0.45} \quad (5)$$

$$D_{opt} = 0.3 C^{0.55} \quad (6)$$

$$L_{opt} = 1070 C^{-0.154} + 1.7. \quad (7)$$

### B. Prevalent LLMs

1) *The GPT Family*: Generative Pre-trained Transformers (GPT) constitute a series of decoder-only Transformer-based

language models, pioneered by OpenAI. This family encompasses GPT-1 [38], GPT-2 [39], GPT-3, InstructGPT [34], ChatGPT, GPT-4, GPT-4o, CODEX [40], and WebGPT [41]. GPT-1 and GPT-2 belong to PLMs, while following GPT-3, all subsequent models in this family are classified as LLMs.

GPT-3 [33] is widely recognized as the first LLM due to its significantly larger size compared to previous PLMs, showcasing emergent abilities not observed in smaller PLMs before. A key emergent ability demonstrated by GPT-3 is in-context learning [42], enabling the model to solve various downstream tasks without the need for fine-tuning. Distinct with other GPT-family LLMs, GPT-4 and GPT-4o are both multi-modal LLMs. GPT-4 [30] is one of the most powerful LLM reported to train on a transformer network of 1.8 trillion parameters which exhibits great capabilities in image understanding and reasoning. GPT-4o, while inheriting the powerful intelligence of GPT-4, has further enhanced its capabilities in text, image, and speech processing. Compared to existing models, it particularly excels in visual and audio comprehension.

2) *The LLaMA Family*: LLaMA stands as a series of open-source LLMs developed by Meta. To date, the official release includes three versions: LLaMA, LLaMA-2, and LLaMA-3, spanning parameter scales from 3 billion to 70 billion. Beyond the weights provided by Meta, the qualities of these LLMs are further extended through supervised fine-tuning and parameter-efficient fine-tuning.

LLaMA-1 [43] was released in February 2023. Although LLaMA is open-sourced and possesses fewer parameters, LLaMA-13B demonstrates significant improvements over GPT-3 (175 billion parameters) across various benchmarks. As a consequence, LLaMA has emerged as a widely adopted and exemplary base model for large language model research. LLaMA-2 was developed in partnership with Microsoft and released half a year later. The model maintains the same architecture as the LLaMA-1 but is trained with 40% more data. LLaMA-3 was released by Meta in April 2024, offering two parameter sizes: 8B and 70B. These models underwent pre-training on approximately 15 trillion tokens of text sourced from publicly available data and are fine-tuned over 10 million human-annotated examples.

3) *The OpenAI o1 Family*: In September 2024, OpenAI officially released a new series of large language model, o1, which trained with reinforcement learning to perform complex reasoning. o1 excels in reasoning capabilities, able to generate long chains of hidden thought processes before providing final answers, demonstrating reasoning abilities similar to humans. The release includes two versions: o1-preview and o1-mini. The o1-preview is an early iteration of the full model, while the o1-mini is a lightweight version optimized for size and speed.

4) *Other Representative LLMs*: Mistral Series [44] is an open-sourced LLM developed by Mistral AI. The basic Mistral-7B demonstrates superior performance across all evaluated benchmarks, surpassing all open-sourced 13B LLMs and even outperforming LLaMA-34B in reasoning, mathematics, and code generation tasks. Mistral 7B employs Grouped Query Attention (GQA) to enable faster inference and Sliding

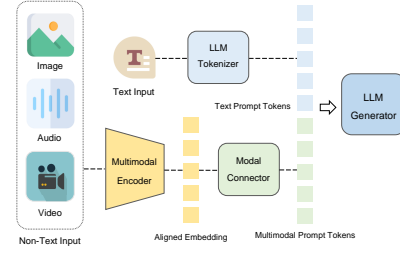


Fig. 1: Architecture of MLLM

Window Attention (SWA) to handle longer text sequences efficiently. Subsequently, Mistral AI introduced two additional models: Mixtral 8x7B and Mixtral 8x22B. These models utilize the Sparse Mixture of Experts (SMoE) technique [45], which selectively activates a subset of experts for each input, thereby significantly reducing computational load.

The PaLM [46] (Pathways Language Models) is developed by Google as a collection of decoder-only LLMs. The first PaLM model was trained on a high-quality text corpus of 780 billion tokens, boasting a remarkable 540 billion parameters. Unlike prevalent LLMs which primarily utilize GPUs for training, PaLM is pre-trained with the Pathways system on 6144 TPU v4 chips to facilitate rapid and efficient training. In the following days, U-PaLM [47], FIAN-PaLM [35] and PaLM-2 were released.

### C. Multimodal Large Language Models

1) *MLLM: Background*: Multimodal Large Language Model (MLLM), is an extension of LLM which adopts multimodal information as input such as text, sound, video, etc, to enable multiple dimensional reasoning and text generation.

Before the emergence of MLLM, significant research efforts were dedicated to multi-modality. These efforts can generally be categorized into representative and generative paradigms. An exemplary work in the representative paradigm is CLIP [48], which serves as a foundational contribution. This process yields a visual encoder [49][50] and a text encoder, effectively establishing a bridge for downstream multimodal tasks. In contrast, generative frameworks [51][52] approach multimodal tasks by transforming them into sequence-to-sequence tasks. MLLM distinguishes itself from previous multimodal research in two key aspects. (1) Composition: MLLM is comprised of at least one LLM with billion-scale parameters. (2) Training techniques: MLLM introduces and incorporates novel training techniques derived from LLM to enhance multimodal performance.

2) *MLLM: Architecture*: Figure 1 illustrates the mainstream architecture of multimodal large language models, typically composed of three modules: a multimodal encoder, an LLM, and a modal connector.

**Multimodal Encoder.** This module incorporates non-text inputs, such as images or audio, and encoding the raw information into a more compact representation. It is noteworthy that the encoder is aligned with one or several encoders in advance to ensure associated meanings are preserved. It is more advisable to directly adopt and fine-tune a pre-trained

multimodal encoder, such as CLIP [48], EVA-CLIP [50], or ViT-G [53], rather than starting from scratch to train a new encoder for generalized data.

**LLM.** It is also more efficient to adopt a pre-trained LLM instead of training from the start. Through tremendous pre-training on web corpus, LLMs have been embedded with rich world knowledge, and demonstrate strong generalization and reasoning capabilities.

**Modal Connector.** This module serves as a crucial bridge between different modalities, allowing efficient communication with the LLM. It accomplishes this by projecting information into a space that the LLM can readily comprehend. Through training the connector, the encoded multimodal tokens can be transformed to LLM prompt tokens that illustrate the content presented by the image, video, etc. Consequently, the LLM will generate the expected content based on the request and prompt.

#### D. Instruction Tuning

Instruction tuning in large language models has undergone significant development, evolving from initial efforts in multi-task fine-tuning without explicit instruction prompts to sophisticated techniques leveraging diverse tasks and templates. Early work focused on improving downstream task performance through large-scale multi-task fine-tuning [54], [55], [56], [57], while other efforts [58], [59], [60] converted a range of NLP tasks into a single generative question answering format using prompt instructions. The instruction tuning began in 2020 with the release of several task collections, including Natural Instructions [61], Flan 2021 [62], and PromptSource [63]. These collections aggregated large NLP datasets and provided templated instructions for zero-shot prompting, enabling models to generalize to unseen instructions. MetaCL [64] emphasized few-shot prompting without explicit instructions, using input-output examples to teach tasks in-context. Research confirmed the benefits of task and template diversity, with some studies highlighting the advantages of inverting inputs and outputs to create new tasks [64]. The subsequent phase saw the expansion and combination of resources, with collections like SuperNatural Instructions [65] and OPT-IML [66] integrating more datasets and tasks. This phase also introduced multilingual instruction tuning, as seen in xP3 [67], and incorporated Chain-of-Thought training prompts in Flan 2022 [68]. These expanded collections included most tasks from previous resources, establishing a strong foundation for future open-source work. Current and future research is exploring new directions, such as synthetic data generation for creative and open-ended dialogue tasks [69], [70], [71], [72] and integrating human feedback on model responses [34], [73], [74], [41], [75]. These approaches are viewed as complementary to foundational instruction tuning methods, driving further advancements in the field.

A recent advance in instruction tuning is the potential to complement or replace few-shot in-context learning with parameter-efficient fine-tuning. Compared to instruction tuning, parameter-efficient fine-tuning can achieve performance comparable to full parameter tuning while being computationally more cost-effective. Previous studies [76], [62], [77],

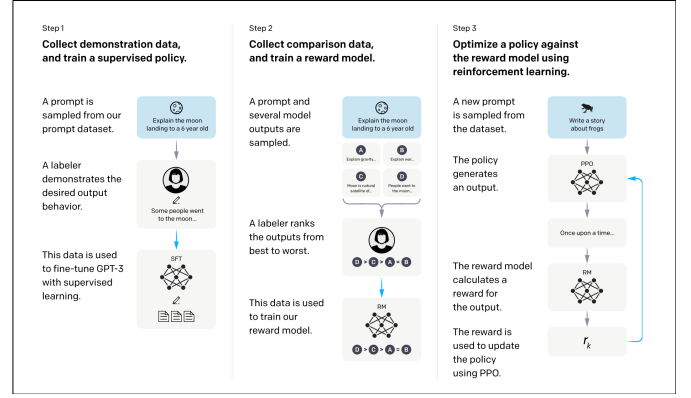


Fig. 2: RLHF Workflow: This figure is from InstructGPT

[78] have demonstrated that parameter-efficient fine-tuning can be effectively integrated with instruction tuning, either before or after the instruction tuning process. Additionally, this body of research highlights that parameter-efficient fine-tuning can enhance the performance and applicability of instruction tuning across different domains.

#### E. Alignment Tuning and RLHF

Despite the emergent abilities brought by increasing parameters of language models, hallucination exhibit to become a challenge for LLMs to produce satisfying response. To address this issue, alignment tuning is applied to align the models with specific human preferences. There are three primary targets for alignment tuning, respectively presented as helpfulness, honesty and harmlessness. From the targets' names, it can be concluded that the alignment criteria are closely associated with human's recognition, making it difficult to formulate them as optimization objectives for LLMs. Therefore, human feedback is widely adopted as an assistance to reinforce LLMs' performance.

RLHF [79], [80] emerged as a method to fine-tune language models using human feedback, aiming to align the LLMs with human preferences, and consequently enhancing alignment performance.

Generally, an RLHF system[34] comprises three key components: a pre-trained language model, a reward model learned from human feedback, and a reinforcement learning algorithm to train the language model. Figure 2 shows the three key steps.

- **Supervised Fine-Tuning (SFT).** Initially, a supervised dataset consisting of input prompts and desired outputs is applied to fine-tune the language model. These prompts and outputs can be written by human labelers for some specific tasks while ensuring the diversity of tasks. This step helps the model learn expected behaviors.
- **Reward model training.** A reward model is trained using human feedback data. The LLM is employed to generate a certain number of output texts using sampled prompts as input. Then human labelers rank these output pairs based on their preferences. Given human predictions, the reward model is trained to predict these rankings, effectively learning human preferences. Notably, [81] proposes an

approach, namely Reinforcement Learning from AI Feedback (RLAIF), the annotation of preference on response pairs can be generated by an AI agent, increasing the automatic ability of the reinforcement process.

- **Reinforcement learning fine-tuning:** The final step involves formalizing the alignment process as a reinforcement learning problem. Here, the pre-trained language model acts as a policy generating text, with the reward model providing feedback scores. To prevent the model from deviating too far from its initial state, a penalty term is often included in the reward function. The language model is then optimized using algorithms like SARSA [82], DQN [83], PPO [84], iteratively improving its performance based on human-aligned rewards.

#### F. Dataset for LLM training and tuning

A critical component of the development and deployment of LLMs is the datasets used at various stages of their lifecycle, which significantly influence their capabilities and performance. In this section, we delve into the datasets that are instrumental in the pre-training, tuning, and other auxiliary phases of LLMs. The pre-training phase is where an LLM absorbs the foundational knowledge from a diverse array of textual data. This stage is pivotal, as it sets the stage for the model’s general understanding of language. The datasets used in pre-training are vast and varied, encompassing everything from the sprawling expanse of the internet to curated collections of literature and encyclopedias. Tuning is a process where the LLM is fine-tuned on specific tasks or domains. This phase refines the model’s abilities, enabling it to perform with greater precision and relevance in targeted applications. Tuning datasets are often more specialized and may include annotated examples that guide the model towards desired behaviors and outputs. Lastly, other datasets serve a multitude of purposes throughout the LLM’s development. These may include evaluation datasets that help assess the model’s performance, auxiliary datasets that broaden its knowledge base, or datasets that are used to imbue the model with specific skills or competencies.

**Commonly Used Datasets for Pre-training.** In the realm of LLMs, the pre-training phase is instrumental in establishing a robust foundation upon which the model’s linguistic prowess is built. LLMs, with their exponentially larger parameter counts, necessitate an extensive and diverse corpus of training data that spans a multitude of topics and linguistic expressions. This data not only serves as the bedrock for the model’s comprehension of language but also influences its ability to generalize and adapt to new contexts and tasks. To meet these requirements, a variety of comprehensive and accessible datasets have been curated and made available for the research community. In this section, we embark on an overview of the datasets that are pivotal in the pre-training of LLMs. We categorize these datasets based on the type of content they provide, which can be broadly divided into seven distinct groups: Webpages, Books, Code, Social Media, Wikipedia, and a diverse array of other sources. Each of these categories contributes unique elements to the model’s knowledge base,

ensuring a well-rounded understanding of human language and its myriad uses.

Collections	Categories	Publication Time	Size
Common Crawl[85]	Webpages	2023	400TB
WuDaoCorpora-Text[86]	Webpages	2022	5TB
BookCorpusOpen[87]	Books	2015	9.05GB
PG-19[88]	Books	2020	11.74GB
BIGQUERY[89]	Code	2023	341.1GB
The Stack[90]	Code	2023	3TB
OpenWebText[91]	Social Media	2019	38GB
Pushshift Reddit[92]	Social Media	2020	89.1GB
wikipedia[93]	wikipedia	2023	71.8GB
The Pile[94]	Others	2020	800GB
S2ORC[95]	Others	2020	80.5GB
MultiUN[96]	Others	2010	31.8GB

TABLE II: A detailed list of available datasets for pre-training

**Commonly Used Datasets for tuning.** The fine-tuning phase of LLMs is a critical juncture where models are honed to perform with greater precision on specific tasks or domains. This process leverages a variety of datasets designed to target the skills and knowledge that the model needs to develop. In this table, we show some of the key datasets used for fine-tuning LLMs, focusing on their characteristics, the tasks they support, and their impact on the models’ performance.

Collections	Categories	Publication Time	Examples
GLUE[97]	NLP Task	2018	1,485,043
SuperGLUE[98]	NLP Task	2019	196,309
E2E NLG Challenge[99]	NLP Task	2020	50k
WikiSQL[100]	NLP Task	2017	80,654
WebNLG[101]	NLP Task	2017	27,731
SAMSum[102]	Daily Chat	2019	16,369
OASST1[103]	Daily Chat	2023	161,443
WMT[104]	Others	2019	124,448,248
XSUM[105]	Others	2018	200,000
DART[106]	Others	2021	82,000

TABLE III: A detailed list of available datasets for tuning

**Other Datasets.** Beyond the foundational pretraining and targeted tuning phases, the realm of LLMs is enriched by a multitude of other datasets. These datasets, while not central to the initial training or fine-tuning processes, are indispensable for expanding the model’s expertise and enhancing its performance across a spectrum of nuanced language tasks. They embody the diversity of linguistic challenges and provide a testing ground for models to demonstrate adaptability and depth in understanding. In the following sections, we will explore these other datasets in detail, highlighting their unique characteristics, the specific tasks they target, and the value they bring to the comprehensive development of LLMs.

Collections	Categories	Publication Time	Examples
HH-rlhf[74]	Dialogue and Preference	2022	169,000
PKU-SafeRLHF[107]	Dialogue and Preference	2023	362,000
HotpotQA[108]	Question-Answering	2018	113,000
SHP[109]	Community Preference	2022	385,000
MMLU[110]	Knowledge Testing	2021	15,908
ARC[111]	Knowledge Testing	2018	7,787

TABLE IV: Other datasets

### III. PEFT TAXONOMY

PEFT techniques are typically divided into three primary categories: **Additive PEFT** (III-A), which introduces addi-



tional trainable components or parameters into the pre-existing model; **Reparameterized PEFT** (III-B), a method that restructures the model’s parameters for the training phase and then reverts to the original form for inference; and **Selective PEFT** (III-C), which targets the optimization of a specific subset of the model’s parameters. The main differences between them are illustrated in Figure 3. Beyond these, **Hybrid PEFT** (III-D), which amalgamates the strengths of various PEFT approaches. In addition to these, there are specialized adaptations such as **Quantization PEFT** (III-E) tailored for the quantization process, and **Multi-task PEFT** (III-F) aimed at enhancing multi-task learning capabilities. A comprehensive classification of PEFT methods is depicted in Figure 4.

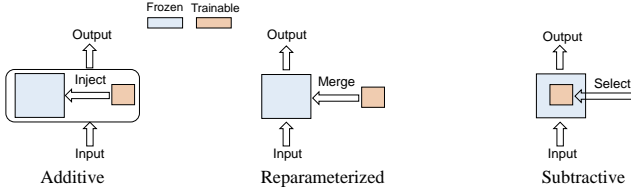


Fig. 3: Illustration of different types of PEFT methods.

#### A. Additive PEFT

Full-parameter fine-tuning is computationally expensive and could adversely affect the model’s capacity to generalize. To address this, additive PEFT methods add a small set of trainable parameters to a pre-trained model, carefully integrated into its architecture. When fine-tuning for particular downstream tasks, it is only these extra components or parameters are adjusted, keeping the original pre-trained model parameters unchanged. This approach significantly reduces the need for storage, memory, and computation. Based on where and how these additional trainable parameters are incorporated into the model’s architecture, there are primarily three types of additive PEFT techniques: *Adapter*, *Soft Prompt*, and *Scale and Shift*. We will delve into some of the principal studies on these techniques.

1) *Adapter*: Adapter methods enable parameter-efficient fine-tuning by inserting small adapter layers into pre-trained models, which learn task-specific transformations while keeping the base model frozen. These adapters, typically consisting of a down-projection, a non-linear activation function and an up-projection layer (the standard adapter shown in Figure 5 (a)), adapt the representations to downstream tasks with minimal overhead. For example, in **Sequential Adapter** [15], two serial adapters are inserted after the attention layer and the feed-forward layer in transformer blocks. **Residual Adapter** [112] dynamically adapts a pre-trained language model, such as GPT-2, to various downstream tasks using low-rank residual adapters and task embeddings, with the adapter module formulated as:

$$\text{Adapter}(H_i) = (\text{ReLU}(\text{LN}(H_i)W_i^E))W_i^D + H_i, \quad (8)$$

where  $H_i$  is the hidden representation of the  $i^{\text{th}}$  layer,  $W_i^E$  and  $W_i^D$  are the adapter parameters, and  $\text{LN}$  denotes layer normalization. **AdapterDrop** [113] dynamically removes adapters

from the lower layers of a transformer during training and inference, which significantly enhances inference speed in multi-task settings with minimal impact on task performance. **Tiny-Attn Adapter** [114] applies a multi-head attention mechanism with tiny per-head dimension the intermediate embeddings of each token to obtain the modified embeddings, and employs parameter-averaging technique to reduce inference cost during deployment. **Parallel Adapter** [115] integrates the adapter network to both the attention and feed-forward layers of the transformer in a parallel manner, facilitating a more efficient incorporation of the module. **CIAT** (Counter-Interference Adapter for Multilingual Machine Translation) [116] employs an embedding adapter to refine multilingual word embeddings and parallel layer adapters to de-noise the multilingual interference in intermediate layers, improving the translation performance with a small parameter overhead. **CoDA** (Condition Adapter) [117] enhances inference efficiency by selectively activating computations on a subset of input tokens, determined by a soft top- $k$  operation, thus balancing model expressivity and computational efficiency. **Hadamard Adapter** [118] (shown in Figure 5 (b)) employs a weight vector and a bias vector, applying the Hadamard product (element-wise multiplication) and element-wise addition to the self-attention outputs, resulting in new self-attention outputs. **Compacter** [119] incorporates concepts from adapters, low-rank methods, and hypercomplex multiplication layers. It introduces task-specific weight matrices by combining shared “slow” weights with “fast” rank-one matrices computed through Kronecker products, tailored to each COMPACTER layer’s requirements. **SparseAdapter** [120] prunes a significant portion of parameters at initialization, using a sparsity-inducing method to maintain performance while reducing computational overhead, and further improving capacity through a “Large-Sparse” configuration that scales up the bottleneck dimension with an increased sparsity ratio.

2) *Soft Prompt*: Soft prompt methods involve appending a sequence of trainable continuous vectors, known as soft prompts, to the input of pre-trained language models. These soft prompts act as additional context that guides the model towards the desired output for a specific task. During training, the soft prompts are optimized to facilitate the model’s adaptation to the new task, while the rest of the model remains largely unchanged, making the approach parameter-efficient. Based on the intuition that a properly optimized context, in the form of continuous word embeddings, can guide the language model towards performing an NLG task without altering its parameters, **Prefix-tuning** [16] and **prompt-tuning** [17] involve prepending a prefix  $P_\theta$  of trainable vectors  $\theta$  to the input. The activations for these prefix indices are treated as free parameters. To stabilize the optimization process,  $P_\theta$  is parametrized by reparameterizing it through a smaller matrix  $P'_\theta$ , which is then composed with a feedforward neural network (MLP), i.e.,  $P_\theta = \text{MLP}(P'_\theta)$ . **p-tuning** [121] leverages trainable continuous prompt embeddings, which are concatenated with discrete prompts to form an input sequence for a pretrained language model. This sequence is then mapped to a hidden representation through an embedding function parameterized by a prompt encoder, such as an LSTM or MLP, and is

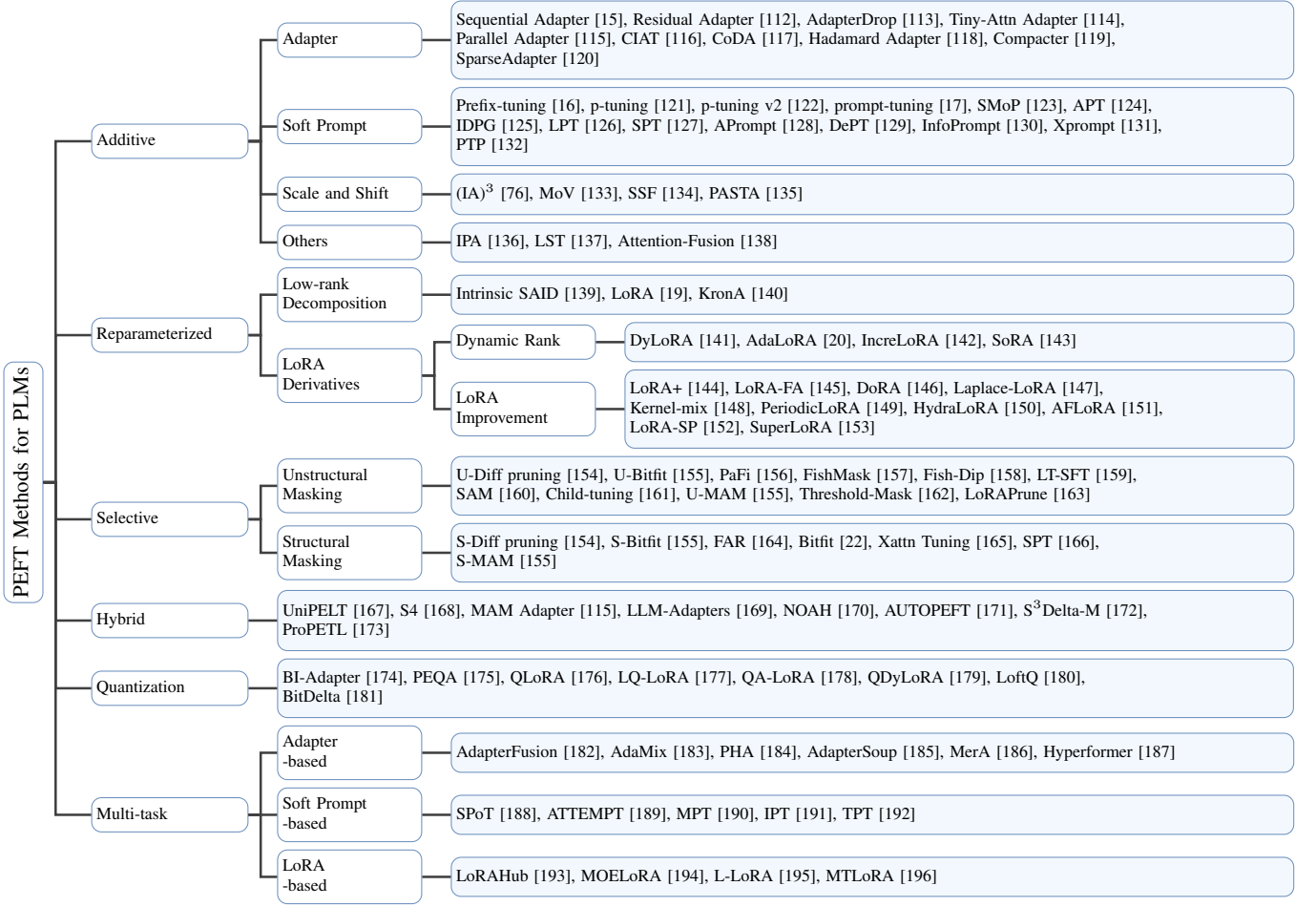


Fig. 4: Taxonomy of PEFT Methods

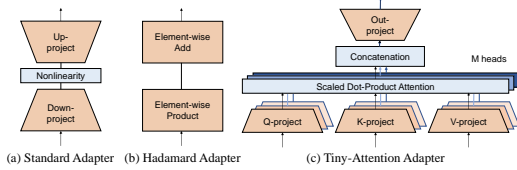


Fig. 5: Illustration of three representative types of adapter.

optimized via backpropagation to minimize a task-specific loss function. **p-tuning v2** [122] is an optimized prompt tuning method that universally matches the performance of fine-tuning across various model scales and NLU tasks by applying trainable continuous embeddings to every layer of the pre-trained model as prefix tokens, thus increasing the capacity of continuous prompts and reducing the gap to fine-tuning, especially for smaller models and more challenging tasks. **SMoP** (Sparse Mixture-of-Prompts) [123] utilizes a gating mechanism to route each input instance to one of multiple short soft prompts, which are specialized in handling different subsets of the data, thereby achieving efficient training and inference while maintaining performance gains typically induced by longer soft prompts. The routing probability for the  $j$ -th prompt is calculated as  $p_j(X) = [\text{softmax}(L_\mu(\bar{X}))]_j$ , where

$L_\mu$  is a small linear router model,  $\bar{X}$  is the average of input embeddings, and  $\mu$  are the parameters of the router model. **APT** (Adaptive Prefix Tuning) [124] dynamically customizes the prefix at each layer of a Transformer model through a gate mechanism. It utilizes both fine-grained gated weight assignment and coarse-grained scaled weight specification. The pseudo prefix tokens  $\hat{P}_i$  in the  $i^{\text{th}}$  layer are updated as follows:

$$\hat{P}_i = \lambda_i \odot \alpha_i \cdot [P_{ik}, P_{iv}] , \quad (9)$$

where  $[P_{ik}, P_{iv}]$  represents the keys-values pair of the original pseudo prefix tokens,  $\lambda_i$  is a learnable scaled weight,  $\odot$  denotes element-wise multiplication, and  $\alpha_i$  represents the gated weights, which are calculated as:

$$\alpha_i = \text{sigmoid}(h_{i-1}W_i) , \quad (10)$$

where  $h_{i-1}$  represents the hidden states from the previous layer, and  $W_i$  are the parameters to be learned. **IDPG** (Instance Dependent Prompt Generation) [125] works on the principle of generating prompts for each input instance using a lightweight model  $G$  that takes the instance representation  $x$  and task  $T$  as inputs to produce a task-specific prompt  $W_p(T, x)$ , which is then inserted into the input sequence  $x$  for fine-tuning the pre-



trained language model  $M$  with a unified template, as denoted by the equations:

$$\begin{aligned} W_p(T, x) &= G(M(x), T), \quad x \in D_{train}, \\ h[CLS] &= M(\text{concat}[x, W_p(T, x)]) . \end{aligned} \quad (11)$$

**LPT** (Late Prompt Tuning) [126] is a method that inserts a “late prompt” into a pre-trained model (PTM) at an intermediate layer. This late prompt is created by a neural prompt generator (NPG) which uses the hidden states from the model layer just before the prompt insertion. This process generates a prompt that is tailored to each specific instance, enhancing the model’s performance and efficiency. The generation of this instance-aware prompt involves a series of steps that include transformations and combinations of various elements derived from the model’s hidden states. Once created, the prompt is reshaped to be integrated into the model’s processing workflow. **SPT** (Selective Prompt Tuning) [127] initializes a prompt hyper-network where each intermediate layer of the pre-trained model (PTM) has a prompt generation layer controlled by a learnable probabilistic gate  $\alpha_i$ , which is optimized to determine the importance of each layer for the task at hand, using the formulation  $a_i = \sigma(\alpha_i)$ , where  $\sigma$  is the sigmoid function, and  $p_i$ , the prompt at layer  $i$ , is calculated as  $p_i = (1 - \tau \cdot a_i) \cdot p_{\text{prev},i} + \tau \cdot a_i \cdot p_{\text{new},i}$ , with  $\tau$  being a hyper-parameter that decides whether to discard the previous layer’s prompt when a new one is generated. **APrompt** [128] introduces trainable query, key, and value prompts, denoted as  $P_q, P_k$ , and  $P_v$ , into the self-attention mechanism of a Transformer encoder layer, which are integrated into the respective matrices to guide the attention computation during fine-tuning, while keeping the majority of the model parameters frozen. The new attention computations are formulated as:

$$\begin{aligned} L(\cdot) &= \text{MLP}(\text{LN}(\text{MSA}(\cdot))), \\ \text{MSA}(\cdot) &= \text{softmax}\left(\frac{Q_{\text{new}}^T K_{\text{new}}}{\sqrt{d}}\right) V_{\text{new}} , \end{aligned} \quad (12)$$

where MLP and LN represent the frozen multi-layer perceptron and layer norm, MSA is the multi-head self-attention module,  $Q_{\text{new}}$  is the new query matrix,  $K_{\text{new}}$  and  $V_{\text{new}}$  are the new key and value matrices augmented with attention prompts, and  $d$  is the dimension of the embeddings. **DePT** (Decomposed Prompt Tuning) [129] decomposes a trainable soft prompt matrix  $P \in \mathbb{R}^{l \times d}$  into a shorter trainable prompt matrix  $P_s \in \mathbb{R}^{m \times d}$  and a pair of low-rank matrices  $A \in \mathbb{R}^{s \times r}$  and  $B \in \mathbb{R}^{r \times d}$ , where the rank  $r \ll \min(s, d)$ . These components are optimized with different learning rates  $\alpha_1$  and  $\alpha_2$  respectively. The updated word embedding matrix for the  $i^{\text{th}}$  sample is given by  $W'_i = W_i + BA$ , where  $W_i$  is the original word embedding matrix. The loss function to be optimized is  $L_{\text{DePT}} = -\sum_{i=1}^N \log P(y_i | [P_s, W'_i]; \Theta)$ , where  $\Theta$  represents the frozen pretrained model weights. **Xprompt** [131] operates on the principle of hierarchical structured pruning to identify and retain only the most effective soft prompt tokens, denoted as  $p_i$ , and their components, denoted as  $q_{i,e}$ , by calculating their importance scores  $I_{p_i}$  and  $I_{q_{i,e}}$  using the following

expressions:

$$\begin{aligned} I_{p_i} &= \mathbb{E}_{x \sim D_x} \left| \frac{\partial L(x)}{\partial \gamma_i} \right| , \\ I_{q_{i,e}} &= \mathbb{E}_{x \sim D_x} \left| \frac{\partial L(x)}{\partial \zeta_i} \right| , \end{aligned} \quad (13)$$

where  $L$  is the loss function,  $D_x$  is the training data distribution,  $\gamma_i$  and  $\zeta_i$  are mask variables for token-level and piece-level pruning respectively, and the importance scores determine the contribution of each prompt token and piece to the model’s performance. **InfoPrompt** [130] maximizes the mutual information between the prompt  $P$  and the parameters of the classification head  $\theta$ , denoted as  $I(P; \theta | X)$ , and between the prompt  $P$  and the encoded representation from the pretrained language model  $Z = \Phi(P, X)$ , denoted as  $I(P; Z | X)$ , by optimizing two novel loss functions, referred to as the head loss and the representation loss, respectively. **PTP** (Prompt Tuning with Perturbation-based Regularizer) [132] introduces perturbation-based regularizers to stabilize prompt tuning by smoothing the loss landscape. This can be formulated as:

$$\min_{\theta} \mathbb{E}_{(s,y) \sim D} [L(M(\theta, s + \delta, y))] , \quad (14)$$

where  $\delta$  is the perturbation sampled from either a Gaussian distribution ( $\delta \sim \mathcal{N}$  for PTP-RN) or generated by an adversarial attack algorithm ( $\delta = \arg \max_{\|\delta\| \leq \epsilon} L(\theta, s + \delta, y)$  for PTP-ADV).  $s$  is the input sequence,  $y$  is its label,  $M$  is the large language model,  $\theta$  represents the trainable prompt parameters, and  $L$  is the loss function.

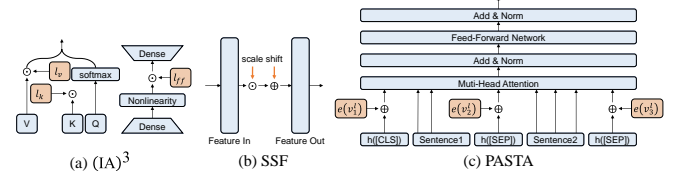


Fig. 6: Illustration of three representative scale and shift algorithms.

3) *Scale and Shift: (IA)<sup>3</sup>* (Infused Adapter by Inhibiting and Amplifying Inner Activations) [76] shown in Figure 6 (a) is a PEFT method for scaling inner activations of a model by learned vectors. For a decoder with  $L$  layers,  $(IA)^3$  adds scaling vectors  $l_k, l_v$ , and  $l_{ff}$  (initialized as ones) to scale key, value, and feed-forward activations, respectively. This allows for task-specific adaptations while updating a tiny fraction ( $\leq 0.01\%$ ) of the model’s parameters, facilitating mixed-task batches. The method can be applied permanently to weight matrices if the model is dedicated to a single task, avoiding extra computations. **MoV** (Mixture of Vectors) [133] introduces a parameter-efficient Mixture of Experts (MoE) architecture that updates only lightweight experts, less than 1% of an 11B parameter model. It generalizes well to unseen tasks. Computation is routed with soft merging:  $E_{\text{mix}} = \sum_{i=1}^n s_i \cdot E_i$ ;  $y = E_{\text{mix}}(x)$ , where  $E_i$  represents each expert,  $s_i$  is the gating weight for each expert, and  $x$  is the input. This approach ensures robust performance under strict parameter constraints.

**SSF** [134] shown in Figure 6 (b) modifies deep features extracted by a pre-trained model through linear transformations to match the distribution of the target dataset. Given an input  $x \in \mathbb{R}^{(N^2+1) \times d}$ , the output  $y$  is computed as:

$$y = [\gamma \odot x + \beta]^T, \quad (15)$$

where  $\gamma$  and  $\beta$  are learnable scale and shift parameters, respectively, and  $\odot$  denotes element-wise multiplication. This approach requires tuning far fewer parameters than full fine-tuning. **PASTA** (Parameter-efficient tuning with Special Token Adaptation) [135], as illustrated in Figure 6 (c), modifies special token representations in pretrained models. For the  $l^{\text{th}}$  Transformer layer, given input  $H^{(l)} = \{h_i^{(l)}\}_{i=1}^N$ , where  $h_i^{(l)} \in \mathbb{R}^d$ , PASTA updates the input as  $H_{\text{mod}}^{(l)} = \{h_i^{(l)} + m_i^{(l)}\}_{i=1}^N$ , where  $m_i^{(l)}$  is defined as:

$$m_i^{(l)} = \begin{cases} 0 & \text{if } i \text{ is not a special token} \\ e(v_p^{(l)}) & \text{if } i \text{ is the } p\text{-th special token} \end{cases}, \quad (16)$$

with  $e(v_p^{(l)}) \in \mathbb{R}^d$  being the trainable vector for the  $p$ -th special token at layer  $l$ .

4) *Others*: **IPA** (Inference-time Policy Adapters) [136] tailors LLMs to specific objectives without fine-tuning. IPA combines the output distribution of a base LLM with a smaller, trainable adapter policy. The adapter is optimized via reinforcement learning (RL) to align the LLM's output with user-defined goals. At inference, the base model's distribution and the trained adapter's distribution are merged for decoding as follows:

$$p_{\text{combined}}(\text{output}|\text{input}) = \alpha p_{\text{base}}(\text{output}|\text{input}) + (1-\alpha) p_{\text{adapter}}(\text{output}|\text{input}), \quad (17)$$

where  $p_{\text{base}}$  is the base model's probability distribution,  $p_{\text{adapter}}$  is the adapter's distribution, and  $\alpha$  controls their mixture. **LST** (Ladder Side-Tuning) [137] introduces a side network that predicts outputs using shortcuts (ladders) from a pre-trained backbone, avoiding backpropagation through the entire backbone. Formally, given a backbone  $f_N(f_{N-1}(\dots f_2(f_1(x)) \dots))$ , the side network  $g$  takes intermediate activations  $z_i$  as inputs, where  $z_i = f_i(x)$ . The final output  $\hat{y}$  is computed by  $g(z_i; \theta_g)$ , significantly reducing memory cost. Here,  $x$  is the input,  $f_i$  represents the  $i$ -th layer function, and  $\theta_g$  are the parameters of the side network. **Attention-Fusion** [138] aggregates intermediate layer representations from a pre-trained model to compute task-specific token representations. This module trains only 0.0009% of total parameters and achieves competitive performance to full fine-tuning. Formally, given a pre-trained model with  $L$  layers, the output  $\mathbf{h}_i^{(l)}$  of each layer  $l$  for token  $i$  is used to compute a weighted sum  $\mathbf{r}_i = \sum_{l=1}^L \alpha_i^{(l)} \mathbf{h}_i^{(l)}$ , where  $\alpha_i^{(l)}$  represents the attention weight for layer  $l$  on token  $i$ .

## B. Reparameterized PEFT

Reparameterization is a technique for improving the training efficiency and performance of a model by transforming its parameters. In the context of PEFT, the transformation involves low-rank parameterization, which entails constructing a low-rank learnable parameter matrix to adapt to specific downstream tasks. During training, only the low-rank parameter

matrix is fine-tuned, and at inference time, the learned matrix is combined with the pre-trained parameters to ensure that inference speed is not affected.

1) *Low-rank Decomposition*: **LoRA** (Low-rank Adaptation) [19] introduces low-rank trainable matrices  $A \in \mathbb{R}^{d \times r}$  and  $B \in \mathbb{R}^{r \times k}$  to update the pre-trained weight matrix  $W_0 \in \mathbb{R}^{d \times k}$  via  $\Delta W = BA$ , where  $W = W_0 + \Delta W$  is used for inference without additional latency. **KronA** [140] is a Kronecker product-based adapter module for efficient fine-tuning of Transformer-based pre-trained language models (PLMs). The tuned weight matrix  $W_{\text{tuned}}$  is computed as the original PLM weight matrix  $W$  plus a scaled Kronecker product of two learnable matrices  $A_k$  and  $B_k$ :

$$W_{\text{tuned}} = W + s[A_k \otimes B_k], \quad (18)$$

where  $s$  is a scaling factor, and  $\otimes$  denotes the Kronecker product operator.

### 2) LoRA Derivatives:

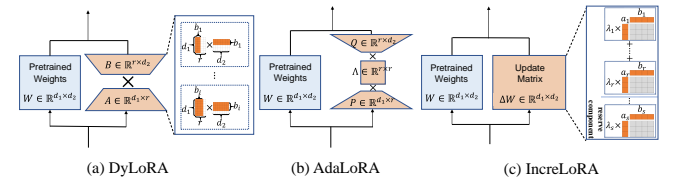


Fig. 7: Illustration of three representative dynamic rank methods in LoRA.

**Dynamic Rank**: **DyLoRA** [141] shown in Figure 7 (a) introduces a dynamic low-rank adaptation technique by training Low-Rank Adapter (LoRA) blocks for a range of ranks during training, where the representation learned by the adapter module is sorted at different ranks, enabling the model to be flexible and perform well across a wider range of ranks without additional training time or the need for rank selection. **AdaLoRA** [20] illustrated in Figure 7 (b) dynamically allocates the budget among weight matrices based on their importance scores, where incremental updates are parameterized in the form of a singular value decomposition as  $W = W_0 + PAQ$ , with  $P \in \mathbb{R}^{d_1 \times r}$ ,  $Q \in \mathbb{R}^{r \times d_2}$ , and  $\Lambda \in \mathbb{R}^{r \times r}$  being the left singular vectors, right singular vectors and singular values, respectively. **IncreLoRA** [142] presented in Figure 7 (c) incrementally allocates trainable parameters during the training process based on the importance scores of each module, which is formulated as follows:

$$W = W_0 + \sum_{i=1}^r \lambda_i w_i = W_0 + \sum_{i=1}^r \lambda_i b_i a_i, \quad (19)$$

where  $W_0$  is the pretrained weight matrix,  $r \ll \min(in, out)$ ,  $w_i$  is a rank-1 matrix,  $a_i \in \mathbb{R}^{in}$ ,  $b_i \in \mathbb{R}^{out}$ , and  $\lambda_i$  is a scaling factor updated through backpropagation, with  $\lambda_i$  initialized to zero to ensure the initial update matrix is zero. **SoRA** (Sparse low-rank Adaption) [143] introduces a gate unit, optimized with a proximal gradient method to control the sparsity of the LoRA's low-rank matrices. The gate unit enables dynamic adjustment of the rank of LoRA during training, enhancing

representation power while maintaining parameter efficiency. During inference, blocks corresponding to zero entries in the gate unit are eliminated, reducing the SoRA module to a concise, rank-optimal LoRA.

b) *LoRA Improvement*: **LoRA+** [144] introduces a novel technique by applying different learning rates to the down- and up-projection matrices  $A$  and  $B$ :  $\eta_B = \lambda\eta_A$ , where  $\lambda$  is a fixed value greater than 1, focusing on tuning  $\eta_A$  for enhanced model adaptability. Designed to mitigate the significant memory requirements for activations that are intrinsic to LoRA, **LoRA-FA** (Low-Rank Adaptation with Frozen-A) [145] freezes the pre-trained weight  $W$  and the projection-down weight  $A$ , and only update the projection-up weight  $B$  during the fine-tuning process, which results in a model weight change  $\Delta W$  that resides in a low-rank space defined by the column space of  $A$ . The method is designed to reduce the activation memory footprint without incurring additional computational overhead. **DoRA** (Weight-Decomposed Low-Rank Adaption) [146] aims to bridge the gap in performance between LoRA and full fine-tuning (FT) by leveraging a novel weight decomposition approach. It decomposes the pre-trained weight matrix  $W_0 \in \mathbb{R}^{d \times k}$  into *magnitude* and *direction*. During fine-tuning, only the *direction* component is updated using a low-rank approximation  $\Delta W = BA$ , where  $B \in \mathbb{R}^{d \times r}$  and  $A \in \mathbb{R}^{r \times k}$ , and  $r \ll \min(d, k)$ . Here,  $r$  denotes the rank of the low-rank approximation,  $d$  and  $k$  represent the dimensions of the weight matrix. This allows for efficient parameter updates while preserving the original weight’s magnitude, enhancing learning capacity and stability. **Laplace-LoRA** [147] introduces a Bayesian approach to LoRA for fine-tuning LLMs. It addresses the issue of overconfidence in fine-tuned LLMs by estimating predictive uncertainty. Laplace-LoRA approximates the posterior distribution over LoRA parameters using a Laplace approximation, leading to better-calibrated models. Mathematically, given a maximum a posteriori (MAP) estimate  $\theta_{\text{MAP}}$ , the predictive distribution for a new input  $x^*$  is approximated as:

$$f_\theta(x^*) \sim \mathcal{N}(f_{\theta_{\text{MAP}}}(x^*), \Lambda) , \quad (20)$$

where  $\Lambda = (\nabla_\theta f_\theta(x^*)|_{\theta=\theta_{\text{MAP}}})\Sigma(\nabla_\theta f_\theta(x^*)|_{\theta=\theta_{\text{MAP}}})^\top$ . Here,  $\nabla_\theta f_\theta(x^*)$  represents the gradient of the prediction with respect to the parameters, and  $\Sigma$  is the covariance matrix of the Laplace approximation. The prior precision  $\lambda$  is optimized using the Laplace marginal likelihood on the training dataset:

$$P(y|X) \approx \exp(L(y, X; \theta_{\text{MAP}}))(2\pi)^{D/2}|\Sigma|^{1/2} , \quad (21)$$

Samples from the predictive distribution are obtained by:

$$\tilde{f}_\theta(x^*) = f_{\theta_{\text{MAP}}}(x^*) + L\xi, \quad (22)$$

where  $L$  is the Cholesky factor of  $\Lambda$  and  $\xi$  is a vector of independent standard normal random variables. This method improves calibration without requiring a separate validation set, making it suitable for small datasets. **PeriodicLoRA** (PLoRA) [149] enhances LoRA’s learning capacity by periodically accumulating low-rank updates to form a higher-rank matrix. During each stage, only LoRA weights  $W_{\text{LoRA}}$  are updated. At the end of each stage,  $W_{\text{LoRA}}$  is unloaded

into the backbone parameters  $W_{\text{backbone}}$ , i.e.,  $W_{\text{backbone}} \leftarrow W_{\text{backbone}} + \Delta W_{\text{LoRA}}$ , and then  $W_{\text{LoRA}}$  is reinitialized. This increases the effective update rank without additional memory cost. **HydraLoRA** [150] enhances LoRA by adopting an asymmetric structure for efficient fine-tuning. It segments the LoRA into multiple “intrinsic components,” each with a distinct matrix  $B_k$ , sharing a common matrix  $A$ . The update formula is given by:

$$\alpha W = W_0 + r \sum_{k=1}^N AB_k , \quad (23)$$

where  $W_0$  is the original weight matrix,  $r$  is a scaling factor,  $A$  and  $B_k$  are low-rank matrices, and  $N$  is the number of components. A trainable MoE router dynamically allocates samples to these components for fine-tuning. **AFLoRA** [151] incrementally freezing trainable low-rank matrices based on a novel freezing score, computed using smoothed gradient  $\bar{I}(t)_{A_l}$ , uncertainty tensor  $\bar{U}(t)_{A_l}$ , and their Hadamard product to determine the stability of weights throughout training, as described by the equations:

$$\begin{aligned} I(t)_{A_l} &= |\nabla L(\theta)|, \\ \bar{I}(t)_{A_l} &= \beta_1 \bar{I}(t-1)_{A_l} + (1 - \beta_1) I(t)_{A_l}, \\ U(t)_{A_l} &= |I(t)_{A_l} - \bar{I}(t)_{A_l}|, \\ \bar{U}(t)_{A_l} &= \beta_2 \bar{U}(t-1)_{A_l} + (1 - \beta_2) U(t)_{A_l}, \\ s(t)_{A_l} &= \text{mean}(\bar{I}(t)_{A_l} \odot \bar{U}(t)_{A_l}) , \end{aligned} \quad (24)$$

where  $A_l$  represents the low-rank tensor,  $L(\theta)$  is the loss function,  $\beta_1$  and  $\beta_2$  are smoothing factors, and  $t$  denotes the current training step. **LoRA-SP** [152] selectively freezes half of the parameters in the matrices  $A$  and  $B$  during fine-tuning, with the adapted weight matrix  $\Delta W$  calculated as  $\Delta W = (A \odot S)(B \odot S)^\top$ , where  $S$  is a binary selection matrix that determines which parameters to update or freeze, and  $\odot$  denotes element-wise multiplication. **SuperLoRA** [153] generalizes LoRA approach by jointly adapting all weight updates  $\Delta W$  across layers through a high-order tensor decomposition, where  $\Delta W_{\text{group}_g}$  is computed as

$$F(\Delta W_{\text{lorag}}) = F \left( \bigotimes_{k=1}^K \left( C_{gk} \prod_{m=1}^M \times_m A_{gkm} \right) \right) , \quad (25)$$

with  $F$  being a projection function,  $M$  the order of tensor modes,  $K$  the number of Kronecker splits,  $C_{gk}$  the core tensor,  $A_{gkm}$  the plane factors,  $\prod_{m=1}^M \times_m$  the tensor products from model-1 to model- $M$ , and  $\bigotimes$  the Kronecker product.

### C. Selective PEFT

Contrary to Additive PEFT, Selective PEFT selects a very small subset of the pre-trained model’s parameters for fine-tuning to adapt to specific downstream tasks through a parameter masking matrix. Depending on the way the parameters are masked, Selective PEFT can be divided into unstructured masking and structured masking.

1) *Unstructural Masking*: **U-Diff pruning** [154] introduces a task-specific “diff” vector  $\delta_\tau$  that is added to pretrained model parameters  $\theta$ . The task-specific parameters are defined as  $\theta_\tau = \theta + \delta_\tau$ . During training,  $\delta_\tau$  is adaptively pruned using a differentiable  $L_0$ -norm approximation to encourage sparsity.  $\theta$  remains fixed. This method enables efficient transfer learning, modifying only a small fraction of the parameters per task. **U-Bitfit** [155] determines which components of the bias update vector  $\Delta b$  should be zero or non-zero, based on a first-order approximation of the change in training loss from pruning a bias parameter  $\theta$ , calculated as  $-\theta \cdot \frac{\partial L}{\partial \theta}$ . **PaFi** [156] generates a universal sparse mask for parameter selection without training. PaFi identifies the least significant pre-trained parameters by their magnitude and fine-tuning only those, represented as selecting parameters  $\theta_i$  where  $|\theta_i| \leq \text{sort}(|\theta|)_k$  for the mask  $m$ . **FishMask** [157] precomputes a fixed sparse mask for neural network parameters, selecting the top  $k$  parameters based on their Fisher information to be updated during training. This “FISH (Fisher-Induced Sparse unCHanging) mask” enables efficient training by updating only a subset of parameters, which reduces memory and communication costs compared to full model updates.  $k$  represents the number of parameters to be selected for updates, and Fisher information measures parameter importance for the given task. **Fish-Dip** [158] dynamically updates the importance of model parameters for fine-tuning based on feedback from the most regressing samples, using the empirical Fisher information to create a sparsity mask that focuses training on a subset of parameters, as denoted by the equation:

$$\hat{F}_\theta \approx \frac{1}{n} \sum_{\{(x_i, y_i) | L_{tr}(x_i, y_i) \in \text{top}_n\}} \left( \frac{\partial \log p_\theta(y_i | x_i)}{\partial \theta} \right)^2, \quad (26)$$

where  $\hat{F}_\theta$  represents the empirical Fisher information,  $n$  is the number of most regressing training examples,  $p_\theta(y_i | x_i)$  is the output probability for the given input  $x_i$  and parameters  $\theta$ , and the sum is taken over the top  $n$  regressing examples as determined by their loss  $L_{tr}$  during training. **LT-SFT** [159] introduces a composable sparse fine-tuning method for cross-lingual transfer learning. It learns sparse, real-valued masks based on a variant of the Lottery Ticket Hypothesis (LTH). Task-specific masks are derived from supervised data in the source language, while language-specific masks are obtained through masked language modeling in the target language. These masks are composed with the pre-trained model to enable zero-shot cross-lingual transfer. The sparsity of the masks reduces parameter overlap and interference, improving modularity and preventing overfitting. **SAM** (Second-order Approximation Method) [160] approximates the original optimization problem using a second-order Taylor expansion to make it analytically solvable, and directly determines the parameters to optimize by solving the approximation function, which is formulated as:

$$\min_{\Delta \theta} \left[ L(\theta_0) + \nabla L(\theta_0)^T M \Delta \theta + \frac{1}{2} (M \Delta \theta)^T H M \Delta \theta \right], \quad (27)$$

subject to  $\|M\|_0 = [mp]$ ;  $M_{ij} = 0, \forall i \neq j$ ;  $M_{ii} \in \{0, 1\}$ , where  $\theta_0$  are the pre-trained parameters,  $\Delta \theta$  is the difference

vector,  $M$  is the parameter mask matrix,  $L$  is the loss function,  $\nabla L(\theta_0)$  is the gradient of the loss function at  $\theta_0$ , and  $H$  is an approximated diagonal Hessian matrix. **Child-tuning** [161] updates only a subset of parameters, referred to as the child network, during fine-tuning while masking out the gradients of the remaining parameters in the backward pass, which can be formulated as:

$$w_{t+1} = w_t - \eta \odot \frac{\partial L(w_t)}{\partial w_t} \odot M_t, \quad (28)$$

where  $w_t$  represents the model parameters at the  $t^{\text{th}}$  iteration,  $\eta$  is the learning rate,  $L(w_t)$  is the loss function, and  $M_t$  is a 0-1 mask indicating the child network. **U-MAM** [155] is an unstructured neural architecture search approach for parameter-efficient tuning of large pre-trained language models. It involves pruning a dense low-rank update from an initial parameter-efficient tuning architecture to find an efficient subset of parameters to fine-tune. **Threshold-Mask** [162] learns selective binary masks for pre-trained language model weights without fine-tuning, where each linear layer  $W_l$  is associated with a real-valued matrix  $M_l$  initialized randomly, and a binary mask  $M_l^{\text{bin}}$  is obtained by applying a thresholding function, used to select important weights:  $(m_l^{\text{bin}})_{i,j} = 1(m_{l,i,j} \geq \tau)$  with  $m_{l,i,j} \in M_l$  and the global thresholding hyperparameter  $\tau$ , and the masked weights are computed as  $\tilde{W}_l = W_l \odot M_l^{\text{bin}}$ , with  $M_l$  updated during training via the straight-through estimator:  $M_l \leftarrow M_l - \eta \frac{\partial L(\tilde{W}_l)}{\partial M_l^{\text{bin}}}$ . **LoRAPrune** [163] approximates the importance of each parameter in the pre-trained model weights  $W_0$  by utilizing the gradients of the low-rank matrices  $A$  and  $B$ , which are then used to perform structured pruning in an iterative and progressive manner, efficiently reducing the model’s size while maintaining performance.

2) *Structural Masking*: **S-Diff pruning** [154] introduces a structured pruning strategy by dividing the weight parameters into local groups and strategically removing them collectively. **S-Bitfit** [155] selects whether to update each bias parameter  $b$  with a learned update  $\Delta b$ , where the decision is based on a pruning criterion that sums the first-order approximation of the loss change over the entire bias update  $\Delta b$ , expressed as  $-\sum_{\theta \in \Delta b} \theta \cdot \frac{\partial L}{\partial \theta}$ . **FAR** (Freeze And Reconfigure) [164] leverages overparameterization in BERT-like models to efficiently fine-tune them on resource-constrained devices. FAR selectively updates parameters based on their importance, determined through priming, while freezing others. This reduces memory usage and fine-tuning time, with minimal impact on performance. Notation-wise, if  $P$  represents the total parameters,  $P_{\text{frozen}} \subset P$  denotes frozen parameters, and  $P_{\text{active}} = P \setminus P_{\text{frozen}}$  are active parameters updated during fine-tuning.  $P_{\text{frozen}}$  is selected using priming to ensure optimal performance. **BitFit** [22] modifies only the bias terms of a pre-trained BERT model, demonstrating competitive performance with full fine-tuning on small to medium datasets and practical utility for deploying multi-task models in memory-constrained environments. **Xattn Tuning** [165] updates only cross-attention parameters in Transformer models for machine translation, showing it can achieve near-equivalent performance to fine-tuning the entire model, while also leading to crosslingually aligned embeddings that can mitigate catas-

trophic forgetting and enable zero-shot translation capabilities. **SPT** [166] identifies task-specific sensitive parameters by measuring their impact on loss reduction, denoted as  $s_n$ , and then adaptively allocates trainable parameters to these positions under a given budget  $\tau$ , utilizing both unstructured tuning for individual parameters and structured tuning for weight matrices with a high number of sensitive parameters, as indicated by  $\sigma_{\text{opt}}$ . **S-MAM** [155] is a structured neural architecture search approach for parameter-efficient tuning of large pre-trained language models. It selects and fine-tunes a fixed rank of parameters within the model’s attention mechanisms and feed-forward networks.

#### D. Hybrid PEFT

Due to the significant performance differences of different types of PEFT methods on various tasks, many studies aim to enhance model performance by combining the advantages of different types of PEFT methods. These research efforts are summarized as Hybrid PEFT methods.

**UniPELT** [167] operates on the principle of dynamically activating the most suitable parameter-efficient language model tuning (PELT) submodules for a given task through a gating mechanism, which is mathematically represented as  $h'_A = G_A h_A + h_F$ , where  $h'_A$  is the final output,  $h_A$  is the output of the adapter submodule,  $h_F$  is the direct input to the adapter, and  $G_A$  is the gating function that modulates the contribution of the adapter submodule based on the specific data and task setup. **S4** [168] discovers design patterns by grouping layers in a spindle pattern, uniformly allocating trainable parameters, tuning all groups, and assigning tailored strategies to different groups, consistently outperforming existing fine-tuning strategies across various NLP tasks and models. **MAM Adapter** [115] is a unified framework for parameter-efficient transfer learning methods by reframing them as modifications to specific hidden states in pretrained models, which can be mathematically represented as  $h \leftarrow (1 - \lambda(x))h + \lambda(x)\Delta h$ , where  $h$  is the original hidden representation,  $\lambda(x)$  is a gating scalar, and  $\Delta h$  is the modification vector computed by a function  $f$  applied to the input  $x$ . **LLM-Adapters** [169] discusses the use of different adapters such as Series Adapters, Parallel Adapters, and LoRA (Low-Rank Adaptation), which are incorporated into the model’s architecture at optimal locations. **NOAH** [170] employs neural architecture search to automatically design optimal “prompt modules” for large vision models, tailored to each downstream dataset, enhancing transfer learning, few-shot learning, and domain generalization. **AUTOPEFT** [171] automates the configuration selection for PEFT of large pre-trained language models. It employs a multi-objective Bayesian optimization approach to discover a set of Pareto-optimal configurations that balance task performance with parameter efficiency, significantly outperforming existing PEFT methods with minimal training costs. **S<sup>3</sup>Delta-M** [172] automatically searches for an optimal trainable structure within pre-trained models by using a unified framework of various Delta Tuning methods. It employs bi-level optimization and a shifted global sigmoid function to control sparsity, achieving high performance with minimal

trainable parameters. **ProPETL** [173] enables the sharing of a single prototype network across different layers and tasks, with binary masks learned to prune sub-networks, significantly reducing parameter storage while improving efficiency and performance over other methods.

#### E. Quantization PEFT

Quantization is another widely used and studied technique aimed at improving computational efficiency and reducing memory usage. We summarize the PEFT methods that use and research quantization technology, as Quantization PEFT.

**BI-Adapter** [174] introduces a novel method for low-precision adapter training in vision models. It utilizes the observation that adapter parameters converge to flat minima, suggesting robustness to precision reduction. The method employs a quantization-aware training strategy, minimizing the quantization error by clustering weight parameters into Gaussian distributions. Specifically, weights  $w$  are standardized  $w' = \frac{w - \mu}{\sigma}$ , quantized, and then de-standardized to backpropagate gradients effectively. This approach significantly reduces model size with minimal impact on performance, addressing storage and transmission inefficiencies in multi-task learning.

**PEQA** [175] involves a two-step process: first, decomposing the parameter matrix of each fully-connected layer into a low-bit integer matrix and quantization scales, and second, fine-tuning only the quantization scale while keeping the integer matrix frozen, which can be mathematically represented as:

$$\tilde{W} = (s_0 + \Delta s) \cdot \left( \text{clamp} \left( \left\lceil \frac{W_0}{s_0} \right\rceil + z_0, 0, 2^b - 1 \right) - z_0 \right), \quad (29)$$

where the notation  $A \cdot B$  denotes the element-wise product of matrices  $A$  and  $B$ . The symbol  $\lceil \cdot \rceil$  represents the rounding function, which rounds its argument to the nearest integer. The function  $\text{clamp}(\cdot, a, b)$  signifies the clamping operation that constrains its input within the range  $[a, b]$ . Here,  $W_0$  denotes the original weight matrix,  $s_0$  represents the initial scale factor, and  $z_0$  is the zero-point value. The variable  $\Delta s \in \mathbb{R}^{n \times 1}$  signifies the gradient update of  $s_0$ , obtained through adaptation to a downstream task, and  $b$  indicates the bit-width. **QLORA** [176], a quantized version of LoRA, utilizes 4-bit NormalFloat (NF4) precision for quantizing pretrained models, enhanced by double quantization and a paged optimizer to prevent the gradient checkpointing memory spikes. The NF4 is an information theoretically optimal quantization data type for normally distributed data, delivering enhanced empirical performance over 4-bit Integer and Float representations. While QLoRA converts the FP16 pretrained weights  $W$  to the NF4 precision to enable LLM finetuning on a reduced number of GPUs, the auxiliary weights of the LoRA matrix re-quantize the final weights back to FP16 post-finetuning. Therefore, **QA-LoRA** (Quantization-Aware Low-Rank Adaptation) [178] addresses the imbalance between quantization and adaptation by employing group-wise operations, which increase the flexibility of low-bit quantization while reducing that of the adaptation process. The algorithm is straightforward to implement and provides two key benefits: during fine-tuning, LLM weights are quantized (e.g.,

to *INT4*) to conserve time and memory; post fine-tuning, the LLM and auxiliary weights are seamlessly integrated into a quantized model without accuracy loss. **LoftQ** [180] introduces a simultaneous process of quantizing an LLM and initializing LoRA with low-rank matrices to mitigate performance gaps. The algorithm approximates the original weights  $W \in \mathbb{R}^{d_1 \times d_2}$  with a quantized version  $Q \in \mathbb{R}_N^{d_1 \times d_2}$  and low-rank matrices  $A \in \mathbb{R}^{d_1 \times r}$  and  $B \in \mathbb{R}^{d_2 \times r}$ , minimizing the Frobenius norm  $\|W - Q - AB^\top\|_F$ . LoftQ alternates between quantization and SVD, efficiently approximating the original weights for improved downstream task performance, especially in 2-bit and 2/4-bit mixed precision scenarios. **LQ-LoRA** [177] iteratively decomposes a pretrained matrix  $W$  into a quantized component  $Q$  and a low-rank component  $L_1 L_2$  by solving the optimization problem:

$$\arg \min_{Q, L_1, L_2} \|W - (Q + L_1 L_2)\|_F, \quad (30)$$

where  $Q$  is fixed during finetuning and only  $L_1$  and  $L_2$  are updated. **QDyLoRA** [179] is a quantized dynamic low-rank adaptation technique for efficient tuning of large language models. It builds upon the DyLoRA [141] method, which enables training across a spectrum of ranks dynamically, and combines it with quantization techniques from QLoRA [176]. The core principle is to allow the model to finetune on a set of predefined ranks and then select the optimal rank for inference, achieving efficiency without compromising performance. Mathematically, the forward pass is given by  $h = W_{\text{NF4}}^{\text{DDequant}} x + \alpha \sum_{b=1}^r (W_{\text{up}})_{:,b} (W_{\text{dw}})_{b,:} x$ , where  $W_{\text{NF4}}^{\text{DDequant}}$  is the dequantized pretrained weight,  $x$  is the input,  $\alpha$  is the LoRA scalar,  $r$  is the sampled rank, and  $W_{\text{up}}$  and  $W_{\text{dw}}$  are the up- and down-projection matrices, respectively. This approach reduces memory usage during training and inference, making it suitable for large-scale LLMs. **BitDelta** [181] is an efficient post-training quantization method for compressing large language models after fine-tuning. The core idea is to represent the fine-tuning induced weight delta,  $\Delta = W_{\text{fine}} - W_{\text{base}}$ , where  $W_{\text{fine}}$  is the weight matrix of the fine-tuned model and  $W_{\text{base}}$  is the base pre-trained model's weight, using only 1 bit. This is achieved by quantizing  $\Delta$  to its sign bits and a trainable scaling factor  $\alpha$ , resulting in  $\hat{\Delta} = \alpha \odot \text{Sign}(\Delta)$ . The scaling factor is initialized to minimize the L2 norm of the error and further refined through distillation to align the quantized model's output with the original fine-tuned model. This approach dramatically reduces memory requirements and can enhance inference speed, with minimal impact on performance.

## F. Multi-task PEFT

The previously introduced PEFT methods were mainly designed for single downstream task. This section focuses on PEFT for multi-task learning.

1) *Adapter-based*: **AdapterFusion** [182] employs a two-stage approach to transfer learning, where it first extracts knowledge into task-specific adapters and then composes this knowledge in a separate step to exploit multi-task representations without destructive interference. **AdaMix** [183] integrates multiple adaptation modules within each Transformer layer of a pre-trained language model, enabling efficient tuning

with a mixture of these modules while maintaining most of the model's weights unaltered. **PHA** [184] leverages an instance-dense retriever and a prototypical hypernetwork to efficiently generate task-specific adapter layers by retrieving prototype embeddings and feeding them into the hypernetwork, enabling sample-efficient multi-task learning and new task generalization. **AdapterSoup** [185] improves the generalization of pretrained language models to new domains by averaging the weights of adapters trained on different domains, without the need for additional training or increasing inference cost. **MerA** [186] efficiently incorporates pretrained adapters into a single model through model fusion, aligning the parameters via optimal transport based on weights and activations to enhance performance in few-shot learning scenarios. **Hyperformer** [187] integrates hypernetwork-based adapter layers into a transformer model, enabling the model to share knowledge across tasks while adapting to each individual task through task-specific adapters generated by shared hypernetworks.

2) *Soft Prompt-based*: **SPoT** (Soft Prompt Transfer) [188] leverages soft prompts to adapt pre-trained language models efficiently. It first trains a soft prompt  $p$  on one or more source tasks, where  $p \in \mathbb{R}^d$  represents a sequence of continuous vectors with dimensionality  $d$ . This learned prompt is then used to initialize the prompt for a target task, facilitating transfer learning. SPoT significantly improves upon the performance of prompt tuning and matches or outperforms full model fine-tuning while using significantly fewer task-specific parameters. **ATTEMPT** (ATTentional Mixtures of Prompt Tuning) [189] leverages pre-trained soft prompts  $P_1, \dots, P_t$  for different high-resource tasks and a new target prompt  $P_{\text{target}}$ . An attention module  $G$  computes attention scores between input  $X$  and each prompt token to produce an instance-wise prompt  $P_{\text{instance}} = \sum_{j=1}^{t+1} a_j P_j$ , where  $a_j$  represents the attention weight for prompt  $P_j$ . Only  $P_{\text{target}}$  and  $G$  are updated during training, keeping the original language model frozen. This approach is parameter-efficient and flexible for multi-task learning. **MPT** (Multitask Prompt Tuning) [190] is a method for efficient transfer learning of large language models across multiple downstream tasks. The core idea is to distill knowledge from multiple task-specific source prompts into a single transferable prompt,  $P^*$ , which is then adapted to each target task with minimal additional parameters. The prompt for each source task is decomposed into a shared matrix  $P^*$  and a low-rank task-specific matrix  $W_k = u_k \otimes v_k^T$ , where  $u_k$  and  $v_k$  are task-specific vectors. This decomposition is learned through a knowledge distillation process that minimizes the KL-divergence between teacher and student prompts,  $L_{\text{Logits}}$ , and an additional mean squared loss on the hidden states,  $L_{\text{Hidden}}$ . The total training loss is  $L_{\text{Total}} = L_{\text{PLM}} + \lambda(L_{\text{Logits}} + L_{\text{Hidden}})$ , where  $L_{\text{PLM}}$  is the task loss and  $\lambda$  balances the distillation impact. The innovation lies in leveraging cross-task knowledge within a parameter-efficient framework, which outperforms full finetuning with far fewer task-specific parameters. **IPT** (Intrinsic Prompt Tuning) [191] is a method to reparameterize the adaptation of pre-trained language models to various tasks within a low-dimensional intrinsic task subspace. The key idea is to decompose the soft prompts  $P$  for multiple NLP tasks



into a shared, lower-dimensional space using an auto-encoder with projection  $\text{Proj}(\cdot)$  and back-projection  $\text{Projb}(\cdot)$  functions. The auto-encoder is trained to minimize the reconstruction loss  $L_{AE} = \|P^* - P\|_2^2$ , where  $P^* = \text{Projb}(\text{Proj}(P))$ . The intrinsic dimension  $d_I$  determines the size of this subspace. After finding the subspace, IPT tunes only  $d_I$  parameters to adapt PLMs to new tasks or data, suggesting that the adaptations can be generalized across tasks by optimizing a small set of free parameters in a unified subspace. **TPT** (transferable prompt tuning) [192] investigates transferring soft prompts across tasks and models to improve prompt tuning (PT) efficiency. Soft prompts  $P = \{p_1, p_2, \dots, p_l\}$ , where  $p_i \in \mathbb{R}^d$  and  $d$  is the input dimension, are prepended to input sequences  $X = \{x_1, x_2, \dots, x_n\}$ . The objective is to maximize the likelihood  $L = p(y|P, x_1, \dots, x_n)$  of generating desired outputs  $y$ , with  $P$  being the only trainable component. Transferability is explored through initializing with similar tasks' prompts and using a cross-model projector. The overlapping rate of activated neurons is found to be a strong indicator of transferability.

3) *LoRA-based*: **LoRAHub** [193] is a dynamic composition of multiple LoRA modules, represented as  $\hat{m} = (w_1 A_1 + w_2 A_2 + \dots + w_N A_N)(w_1 B_1 + w_2 B_2 + \dots + w_N B_N)$ , followed by a gradient-free optimization to determine the coefficients  $w_i$  that best adapt the combined module for performance on new, unseen tasks. **MOELoRA** [194] integrates a Mixture-of-Experts (MOE) model with trainable experts  $\{E_i\}_{i=1}^N$ , each consisting of a pair of low-rank matrices  $B_i \in \mathbb{R}^{d_{in} \times r}$  and  $A_i \in \mathbb{R}^{r \times d_{out}}$ , along with a task-motivated gate function that outputs expert weights  $\omega_{ji}$  for task  $T_j$ , to efficiently fine-tune large language models for multi-task medical applications while maintaining a compact set of trainable parameters. **L-LoRA** (Linearized LoRA) [195] is a novel partial linearization method for parameter-efficient fine-tuning models, which enhances weight disentanglement and improves multi-task fusion capability with a low computational cost overhead by linearizing only the adapter modules and applying model fusion algorithms over the linearized adapters. **MTLoRA** [196] revolves around the use of Task-Agnostic and Task-Specific Low-Rank Adaptation modules to efficiently adapt a shared transformer backbone for multiple downstream tasks in a Multi-Task Learning architecture, balancing between learning shared features and those specific to individual tasks.

#### IV. APPLICATIONS OF PEFT

##### A. PEFT in Vision Models

Over the past decade, deep learning has achieved significant advancements in the field of computer vision, particularly with the introduction of the ImageNet dataset and the widespread adoption of the pre-training-fine-tuning paradigm based on pretrained vision models (PVMs). Numerous studies have shown that better ImageNet pre-training performance typically leads to improved performance on downstream tasks. As visual pre-trained models continue to evolve, especially with the introduction of Vision Transformer (ViT) architectures, the scale of model parameters has increased significantly, highlighting the inefficiencies of traditional full fine-tuning methods in

terms of parameter efficiency. To address these issues and improve parameter efficiency during the fine-tuning process of PVMs, various PEFT methods have emerged. These methods have demonstrated their advantages across multiple domains, including image classification, dense prediction, video analysis, and 3D point cloud analysis. This section will focus on the application of PEFT methods in image classification and dense prediction tasks.

1) *Image Classification*: **VP** [197] investigates visual prompting as a means to adapt large-scale pre-trained models for new tasks without updating model parameters. A single image perturbation ( $\delta$ ) is learned such that when added to input images ( $x$ ), the prompted image ( $x' = x + \delta$ ) steers the model's prediction towards a target task. This method is akin to adversarial reprogramming, but it aims for constructive task adaptation. Its effectiveness is demonstrated through experiments, which show competitive performance compared to linear probes. Notably, the approach is input-agnostic and dataset-wide. **VPT** (Visual Prompt Tuning) [198] adapts pre-trained vision Transformers for downstream tasks by introducing task-specific, learnable parameters ( $P = \{p_k \in \mathbb{R}^d | k \in \mathbb{N}, 1 \leq k \leq m\}$ ) into the input sequence, while keeping the backbone of the model frozen. Here,  $d$  represents the dimensionality of the input features, while  $m$  signifies the total number of prompts. These prompts  $P$  are prepended to the input sequence of each Transformer layer and learned alongside a linear classification head during fine-tuning. **NOAH** (Neural prOmt seArch) [170] automatically searches for the optimal design of prompt modules for large vision models through Neural Architecture Search (NAS). NOAH encompasses three prompt modules: Adapter, LoRA, and VPT, each inserted into Transformer blocks. The search space includes parameters like embedding dimensions  $D = \{5, 10, 50, 100\}$  and depths  $L = \{3, 6, 9, 12\}$ , determining the range of applications. An AutoFormer-based one-shot NAS algorithm is employed to select the best configuration for each downstream dataset. **Convpass** [199], convolutional bypasses for ViTs, to serve as adaptation modules during finetuning. Convpass, introduced as a parallel convolutional bottleneck block to the Multi-Head Self-Attention (MHSA) or MLP blocks, "bypasses" the original ViT block. For a ViT layer, the input sequence  $X \in \mathbb{R}^{N \times d}$  is processed through Convpass, reconstructing the spatial structure of the token sequence. During finetuning, only Convpass modules and the classification head are updated. Convpass leverages the inductive bias of convolutional layers, enhancing its suitability for visual tasks, particularly in low-data scenarios. **AdaptFormer** [200] is a lightweight module designed for efficient fine-tuning of pre-trained ViTs on diverse visual recognition tasks. It introduces additional trainable parameters, consisting of two fully connected layers  $FC_1, FC_2$ , a non-linear activation function ( $\sigma$ ), and a scaling factor ( $\alpha$ ). These components are placed in parallel with the feed-forward network (FFN) of the original ViT. The learnable parameters of AdaptFormer are updated during the fine-tuning phase, while the pre-trained ViT parameters remain frozen. This design enables AdaptFormer to enhance the transferability of ViTs with minimal parameter updates, thereby improving scalability and performance on various visual tasks. **DAM-VP** (Diversity-

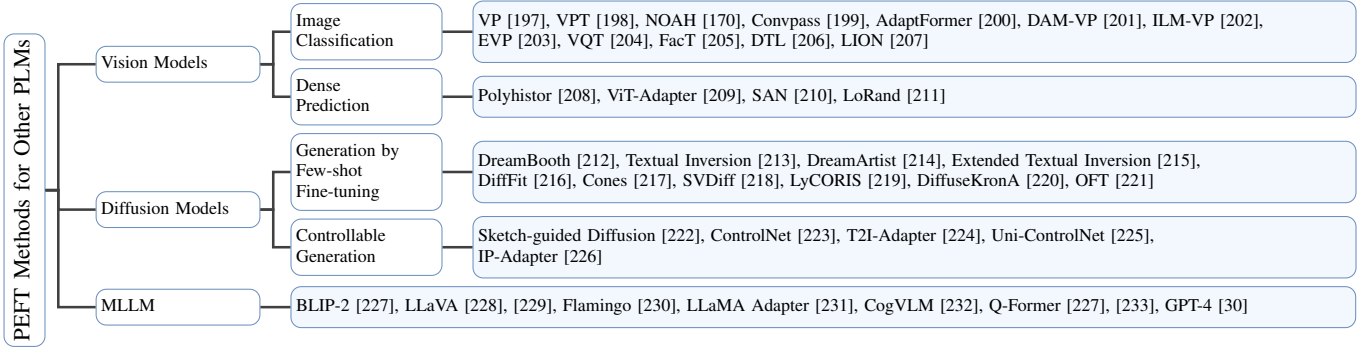


Fig. 8: Taxonomy of PEFT Methods for Other Types of Foundation Models

Aware Meta Visual Prompting) [201] partitions a dataset into homogeneous subsets based on diversity, optimizing a unique prompt for each subset. Prompts are initialized with a meta-prompt learned across multiple datasets, improving convergence speed and performance. During inference, the appropriate prompt is selected based on the feature distance between input and subset prototypes. Formally, for a dataset  $D$  divided into  $K$  subsets  $D_1, D_2, \dots, D_K$ , the optimal prompts  $p_1^*, \dots, p_K^*$  are found by minimizing the cross-entropy loss:

$$p_1^*, \dots, p_K^* = \arg \min_{p_1, \dots, p_K} \sum_{k=1}^K \sum_{x \in D_k} L_{CE}(M(x + p_k), y), \quad (31)$$

where  $p_k$  is the prompt for subset  $D_k$ ,  $M$  is the pre-trained model,  $x$  is an input image,  $y$  is the ground truth label, and  $L_{CE}$  is the cross-entropy loss function. **ILM-VP** [202] is an iterative label mapping-based visual prompting method. It optimizes the mapping between source and target labels to improve the accuracy of reprogramming pre-trained models for new tasks. The key equation is:

$$\min_{\delta} \sum_{y \in T_{tr}} \min_{y_s \in S_s} L(f_{\theta}(x + \delta), y_s; y_t), \quad (32)$$

where  $\delta$  is the visual prompt,  $L$  is the cross-entropy loss,  $f_{\theta}$  is the pre-trained model,  $x$  is the input image,  $T_{tr}$  is the target training set,  $S_s$  is the set of source labels, and  $y_s$  and  $y_t$  are the source and target labels, respectively. **ILM-VP** enhances interpretability by providing meaningful mappings. **EVP** (Enhanced Visual Prompting) [203] is a method for adapting pre-trained models to downstream tasks without substantial parameter updates. Instead of directly combining the prompt  $P$  and the image  $I$ , they shrink  $I$  and pad  $P$  around it, ensuring independence. They also reintroduce input diversity and gradient normalization techniques, originally used in adversarial example generation, to improve the optimization and generalizability of the prompt. This approach outperforms linear probing and matches fully fine-tuning in some cases, with significantly fewer parameters. **VQT** (Visual Query Tuning) [204] leverages learnable “query” tokens in each Transformer layer to summarize intermediate features effectively. VQT introduces a set  $Q = \{q_1, q_2, \dots, q_n\}$  where  $q_i \in \mathbb{R}^d$  represents the  $i$ -th query token with  $d$  being the feature dimension. These queries interact with the intermediate features  $X \in \mathbb{R}^{N \times d}$  through the attention mechanism, where  $N$  is the number

of tokens. The output  $Z = \{z_1, z_2, \dots, z_n\}$  summarizes the layer’s information, with  $z_i$  denoting the summary for  $q_i$ . This enables efficient transfer learning with memory and parameter savings. **FacT** [205] is a method for efficient fine-tuning of pre-trained ViTs by updating only a fraction of parameters. The key idea is to tensorize the weights of ViT into a 3D tensor and decompose the weight increments into lightweight factors. During fine-tuning, only these factors are updated and stored. Mathematically, if  $\Delta W$  represents the increment of a weight matrix  $W$ , then  $\Delta W$  is approximated as  $\Delta W \approx A \times B$ , where  $A$  and  $B$  are the decomposed factors.  $A$  and  $B$  are learned during fine-tuning, reducing storage requirements. **DTL** (Disentangled Transfer Learning) [206] addresses the inefficiency of Parameter-Efficient Transfer Learning (PETL) methods in GPU memory usage. DTL employs a Compact Side Network (CSN) to disentangle trainable parameters from the backbone. CSN uses low-rank linear mappings to extract and reintegrate task-specific information. Formally, given a backbone with  $N$  blocks, the output  $z_{i+1}$  of the  $i$ -th block is updated as  $z'_{i+1} = z_{i+1} + \theta(h_{i+1})$  for  $i \geq M$ , where  $\theta$  is a non-linear activation function, and  $h_{i+1}$  captures the task-specific information extracted by CSN. This disentanglement significantly reduces GPU memory footprint and trainable parameters while maintaining or improving accuracy. **LION** (impLicit vIsion prOmpt tuNing) [207] inserts two equilibrium implicit layers ( $P_1, P_2$ ) at the start and end of a frozen pre-trained backbone ( $\theta$ ).  $P_1$  and  $P_2$  are defined as:

$$P_1 = f_{eq}^{(1)}(x; \phi_1), \quad P_2 = f_{eq}^{(2)}(z; \phi_2), \quad (33)$$

where  $x$  is the input,  $z$  is the output of the backbone, and  $\phi_1, \phi_2$  are parameters of the implicit layers.  $f_{eq}$  denotes the equilibrium function. To reduce computational burden, parameters are pruned based on the lottery ticket hypothesis. LION adapts the backbone to downstream tasks efficiently with minimal parameter updates.

2) *Dense Prediction*: Dense prediction, encompassing tasks such as image segmentation, object detection, depth estimation, etc., is another crucial task in the field of 2D vision. Unlike image classification tasks, which typically generate a single prediction label for an entire image, dense prediction tasks require making predictions for every pixel in the image, usually resulting in an output image with the same resolution as the input image. Fine-tuning pre-trained models from image classification is a common approach for dense prediction tasks.

With the application of PEFT methods in vision tasks, various PEFT methods tailored for dense prediction tasks have been proposed.

**Polyhistor** [208] employs a strategy of hypernetworks that are broken down into components, along with scaling kernels applied at each layer, to facilitate the sharing of information across various tasks efficiently and with a minimal number of parameters. In this approach, the weight matrix of each adapter, denoted as  $W$ , is decomposed into two distinct elements: a template kernel  $T$  and a scaling kernel  $S$ . The weight matrix is then reconstructed through the Kronecker product of these two kernels, represented as  $W = T \otimes S$ . This method effectively reduces the number of parameters required while still preserving the level of accuracy in the system. **ViT-Adapter** [209] leverages the inherent representation power of a plain ViT backbone and augments it with an adapter that incorporates image-specific inductive biases during fine-tuning. This enables the model to capture high-frequency details crucial for tasks like object detection and segmentation. **SAN** (Side Adapter Network) [210] decouples mask proposal generation and class recognition for open-vocabulary semantic segmentation. A lightweight side network is attached to a frozen CLIP model, predicting mask proposals and attention bias to guide CLIP’s recognition of the mask’s class. This design leverages CLIP’s robustness while minimizing additional parameters and computational cost. The attention bias is applied in CLIP’s attention mechanism  $\text{Attention}(Q, K, V, \text{bias})$ , where  $Q$ ,  $K$ , and  $V$  represent query, key, and value vectors, enhancing CLIP’s awareness of the proposed regions. **LoRand** [211] adds lightweight, low-rank adapter modules to a pre-trained vision model, such as the Swin Transformer, without updating the original model’s parameters. These adapters consist of multi-branch low-rank projections and non-linearities, enabling them to capture complex representations with minimal parameters. Specifically, for a backbone with parameters  $\theta$ , LoRand trains a small subset  $\phi$  (1% – 3%) of  $\theta$ , where  $\phi \subset \theta$ , achieving competitive performance with full fine-tuning while significantly reducing the number of trainable parameters.

## B. PEFT in Diffusion Models

As diffusion models evolve, these models have now surpassed GANs as the mainstream method in the image generation domain. Given their success in image generation, their potential applications in video generation, 3D content generation, and speech synthesis are also becoming increasingly apparent. Additionally, many application domains involve fine-tuning diffusion models, including embedding personalized concepts in image generation, customizing generated images based on reference images, and training multi-view image generation capabilities based on pre-trained text-to-image diffusion models in the 3D content generation domain. Compared to the NLP field, research on PEFT for diffusion models is relatively scarce. Current research mainly focuses on two areas: generation by few-shot finetuning and controllable generation in image generation:

1) *Generation by Few-shot Finetuning*: Generation by few-shot finetuning involves providing a few images (or even just one) of an object or style, and fine-tuning the model on these images. This process allows the model to generate new images that reflect the unique characteristics of the provided examples.

**DreamBooth** [212] is a method for personalizing text-to-image diffusion models using just a few images of a subject. The technique fine-tunes a pre-trained model with a novel autogenous class-specific prior preservation loss, to bind a unique identifier to the subject and preserve class diversity. This enables generating photorealistic images of the subject in various scenes while maintaining key features. The fine-tuning process involves adjusting the model parameters based on input images and text prompts, leveraging the model’s semantic prior and the new loss function to enhance subject fidelity and versatility in image synthesis.

**Textual Inversion** [213] is a method that personalizes text-to-image generation by embedding unique concepts as new “pseudo-words” in the latent space of a pre-trained model. This allows intuitive composition into sentences guiding image creation, capturing both semantics and details without retraining the model. The innovation lies in optimizing a single word embedding to represent a concept through reconstruction, balancing distortion and editability. The method’s strength is its simplicity and compatibility with existing models, while its limitation is the potential for less precise shape retention.

**DreamArtist** [214] leverages positive-negative prompt-tuning to enable one-shot text-to-image generation. Given a reference image  $I$ , it learns a positive embedding  $S_p^*$  that captures the image’s characteristics and a negative embedding  $S_n^*$  that rectifies deficiencies.  $S_p^*$  drives diverse generation, while  $S_n^*$  ensures corrections, improving controllability. The embeddings are combined through a fusion function  $f_m(z_p, z_n)$  where  $z_p$  and  $z_n$  represent the latent representations of positive and negative prompts, respectively. This approach facilitates the synthesis of high-quality, diverse, and controllable images from a single reference. In paper [215], an **Extended Textual Conditioning (P+)** space is introduced for text-to-image generation, allowing for more granular control over image synthesis through per-layer textual prompts. The innovation, **Extended Textual Inversion**, inverts images into P+ space using a set of token embeddings, enhancing expressiveness and precision without compromising editability. This method is advantageous due to its faster convergence and the ability to achieve finer control over image attributes by leveraging the distinct sensitivities of U-net layers to shape or appearance. The downside includes imperfect concept reconstruction and the relatively slow inversion process. **DiffFit** [216] fine-tunes only the bias terms and introduces scaling factors  $\gamma$  in specific layers, initialized to 1.0, to adapt to new domains quickly. The method achieves significant training efficiency and reduced storage costs, with  $\gamma$  enhancing feature scaling for better adaptation. The efficacy is theoretically justified by analyzing the shift in distributions caused by the scaling factors. **SVDiff** [218] is a method for fine-tuning text-to-image diffusion models by adjusting the singular values ( $\sigma_i$ ) of weight matrices ( $W$ ), represented as  $W = \sum_i \sigma_i u_i v_i^T$ , where  $u_i$  and  $v_i$  are the left and right singular vectors,

respectively. This approach leads to a compact parameter space, reducing overfitting and model size ( $\approx 2,200\times$  fewer parameters than DreamBooth). They also introduce Cut-Mix-Unmix for improved multi-subject generation and a single-image editing framework. **LyCORIS** [219] is an open-source library for fine-tuning Stable Diffusion models. It implements methods like LoRA, LoHa, LoKr, GLoRA, and (IA)<sup>3</sup>. The library aims to simplify the integration and evaluation of these methods. A comprehensive evaluation framework is proposed, using metrics for concept fidelity, text-image alignment, diversity, and style preservation. Experiments highlight the nuanced impacts of hyperparameters and the suitability of different methods for specific tasks. **DiffuseKronA** [220] utilizes a Kronecker product-based adaptation mechanism to efficiently fine-tune large diffusion models for personalized text-to-image generation. The method reduces the parameter count by applying truncated singular value decomposition on critical model layers, enabling subject-specific image synthesis with enhanced stability, interpretability, and text alignment. The approach offers a  $\geq 50\%$  parameter reduction compared to state-of-the-art methods, with comparable or superior image quality. **OFT** (Orthogonal Finetuning) [221] is a method to adapt text-to-image diffusion models for downstream tasks without losing generative performance. OFT preserves the hyperspherical energy which characterizes neuron relationships by applying a layer-shared orthogonal transformation  $R$  to the pretrained weights  $W_0$ . This maintains the pairwise angles among neurons, crucial for semantic information. The transformation is constrained as  $R^T R = R R^T = I$ , ensuring minimal deviation from the original model. A variant, Constrained Orthogonal Finetuning (COFT), further limits angular deviation with  $\|R - I\| \leq \epsilon$ . The method aims to balance flexibility and stability in finetuning.

2) *Controllable Generation*: Controllable generation primarily involves adding control sources beyond the prompt to guide the image generation. These control sources can include sketches, keypoints, or other forms of guidance to shape the generated output more precisely.

**Sketch-guided Diffusion** [222] is a method to guide pre-trained text-to-image diffusion models using spatial maps like sketches. It involves training a lightweight per-pixel multi-layer perceptron (MLP), named the latent guidance predictor (LGP), to map noisy image features to spatial maps. The LGP is trained on a small dataset, predicting spatial layouts from latent features  $F(\mathbf{z}_t|\mathbf{c}, t)$  extracted from a denoising diffusion probabilistic model (DDPM) network, where  $\mathbf{z}_t$  is a noisy image at timestep  $t$ , and  $\mathbf{c}$  presents the conditioning text prompt. **ControlNet** [223] enhances pretrained text-to-image diffusion models by adding spatially localized conditions. For a neural block  $F(x; \Theta)$  transforming input  $x$  to output  $y$ , ControlNet freezes  $\Theta$  and introduces a trainable copy. Conditions  $c$  are injected through zero-initialized convolution layers (zero convolutions) ensuring no initial noise.  $y_c = F(x, c; \Theta')$  represents the output with conditions, where  $\Theta'$  denotes the updated parameters. This approach facilitates robust finetuning and sudden convergence. **T2I-Adapter** [224] enhances controllability of pre-trained text-to-image (T2I) models by learning lightweight adapter models that align the model's

internal knowledge with external control signals. This is achieved without modifying the original T2I model, allowing for granular control over generated images' structure and color. Mathematically, let  $\mathcal{M}$  denote the pre-trained T2I model,  $\mathcal{A}$  the adapter, and  $\mathbf{x}_c$  the control signal (e.g., sketches, masks). The adapted model generates images  $\mathbf{x}$  from text prompts  $t$  and control signals  $\mathbf{x}_c$  as follows:

$$\mathbf{x} = \mathcal{M}_{\text{adapted}}(t, \mathbf{x}_c) = \mathcal{M}(t) + \omega \cdot \mathcal{A}(\mathbf{x}_c), \quad (34)$$

where  $\omega$  is a weighting factor balancing the influence of the control signal. The adapter  $\mathcal{A}$  is trained to translate  $\mathbf{x}_c$  into a form that can steer  $\mathcal{M}$  towards desired outputs, enabling precise control. **Uni-ControlNet** [225] integrates diverse control signals into pre-trained text-to-image (T2I) diffusion models through two lightweight adapters, facilitating efficient and composable control. It employs a multi-scale condition injection strategy, using Feature Denormalization (FDN) to modulate noise features with local conditions:

$$\text{F}_{\text{DN}r}(\mathbf{Z}_r, c_l) = \text{norm}(\mathbf{Z}_r) \cdot (1 + \text{conv}_\gamma(\text{zero}(h_r(c_l)))) + \text{conv}_\beta(\text{zero}(h_r(c_l))) \quad (35)$$

where  $\mathbf{Z}_r$  are noise features at resolution  $r$ ,  $c_l$  are concatenated local conditions,  $h_r$  extracts features at resolution  $r$ , and  $\text{conv}_\gamma$  converts features into modulation coefficients. Global controls are aligned with text embeddings via a condition encoder.  $h_g(c_g) \rightarrow K$  global tokens. Here,  $c_g$  is the global condition, and  $K$  is the number of global tokens. **IP-Adapter** [226] enables pretrained text-to-image models to utilize image prompts effectively. It introduces a decoupled cross-attention mechanism, adding extra layers dedicated to image features while keeping the original text-focused layers intact. During training, these new layers learn to process image embeddings extracted by a CLIP encoder. At inference, the image and text features are processed separately then combined, improving controllability and fidelity of generated images. The core equation is:

$$\hat{\epsilon}_\theta(x_t, c, t) = w\epsilon_\theta(x_t, c, t) + (1 - w)\epsilon_\theta(x_t, t), \quad (36)$$

where  $\hat{\epsilon}_\theta(x_t, c, t)$  is the predicted noise,  $w$  is the guidance scale adjusting the influence of condition  $c$ ,  $\epsilon_\theta(x_t, c, t)$  is the conditional noise prediction, and  $\epsilon_\theta(x_t, t)$  is the unconditional prediction.

### C. PEFT in MLLM

The parameter-efficient fine-tuning of MLLM primarily focuses on the model connector. It is because maintain consistency for both multimodal and textual data is challenging. As a consequence, a modal connector is serially connected right before the LLM, converting multimodal embeddings into understandable text prompt tokens for the LLM. Training the model connector on peft dataset bridges the gap between different modal data while ensuring consistency in the input to the LLM.

Generally, the parameter scale of the model connector will not be very large, much smaller than the prevalent LLMs. Therefore, full-parameter training instead of peft is more prevalent for model connector. Studies of the model

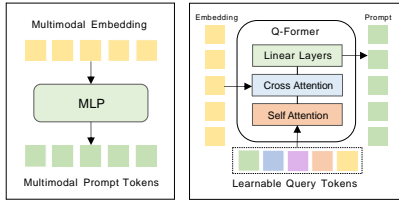


Fig. 9: Modal Connector Design

connector primarily focus on the structural design, which will be dedicated to improving the training performance. A classic design of the modal connector involves employing a set of learnable query tokens to extract information in a query-based manner, a technique first introduced in **BLIP-2** [227] and subsequently adopted by various projects [233]. These query-based approaches, reminiscent of Q-Former-style methods, condense visual tokens into a smaller set of representation vectors. In the meantime, some methods utilize an MLP-based interface to bridge the modality gap. For instance, the **LLaVA** series [228], [229] employs one or two linear MLPs to project visual tokens and align feature dimensions with word embeddings. In feature-level fusion, additional modules facilitate deep interaction and fusion between text features and visual features. For example, **Flamingo** [230] introduces extra cross-attention layers between the frozen Transformer layers of LLMs, enhancing language features with external visual cues. In addition, adapters and prompt embedding are also applied to add learnable parameters to fill the gap, such as **LLaMA Adapter** [231] and **CogVLM** [232].

Figure 9 illustrates the concrete structures of the two designs. The first one, pioneered by the **LLaVA** series, is characterized by its simplicity. As highlighted by [229], an MLP composed of basic linear layers is adept at transforming multimodal embeddings into LLM prompt tokens.

In contrast, the second paradigm, known as the **Q-Former** [227], [233], introduces a transformer neural network for modal information conversion. Unlike traditional approaches of directly applying self-attention on input embeddings, Q-Former employs a set of trainable query tokens. This approach bears resemblance to LLM PEFT methods such as prefix-tuning and p-tuning, which incorporate external trainable embedding tokens. However, the key distinction lies in how these methods handle the tokens: prefix-tuning and p-tuning append them to the input text tokens to form a comprehensive LLM input, while Q-Former accepts the query tokens as the primary input.

From both the structural design and training intricacies, it becomes evident that Q-Former is considerably more complicated compared to the MLP-based LLaVA. However, this complexity comes with its advantages. A comprehensive transformer network like Q-Former enables the execution of numerous pre-trained tasks, facilitating explicit alignment between non-textual and textual modalities. This, in turn, reduces the quality requirements on the multimodal data. Nevertheless, LLaVA, as detailed by [229], which incorporates **GPT-4** [30] as the LLM, reports a slight performance improvement over

**BLIP-2**. This is largely attributed to the inherent superiority of GPT-4 over BLIP-2’s Flan-T5 across various aspects. Specifically, GPT-4 possesses innate multimodal reasoning capabilities, a feature lacking in Flan-T5. This observation underscores the fact that a comprehensive modal connector design may not be necessary when the LLM itself possesses significant power and capabilities.

## V. FUTURE DIRECTIONS

In this section, focusing on potential issues with existing PEFT techniques and aspects that have not received sufficient attention, we propose a series of possible research directions. These directions encompass **task**, **data**, **model**, **learning mechanisms**, and **fundamental flaws**.

- 1) *PEFT methods for multi-objective tasks*: In the real world, downstream tasks that LLMs need to adapt to may involve multiple objectives. For example, in paper [234], the authors emphasize that for the Program Repair task, it is necessary to consider two objectives simultaneously: 1) adapt the LLM parameters to the syntactic nuances of the task of code transformation, and 2) specifically fine-tune the LLM with respect to the logical reason behind the code change in the training data. Since most existing PEFT methods are not designed for multi-objective scenarios, exploring and developing PEFT methods suitable for multi-objective tasks is an important direction for future research.
- 2) *PEFT methods in multimodal learning*: The majority of existing PEFT methods have been architected with a focus on single-modality LLMs. However, as the field of LLMs evolves, the emergence of multimodal LLMs has garnered increasing interest within the research community. As observed in the experimental findings of [235], fine-tuning the connector layers, a critical component in multimodal large language models, does not always yield better results; its effectiveness depends on specific circumstances. This suggests that PEFT methods for multimodal large language models warrant further exploration and research.
- 3) *Automated design of adapter modules*: The adapter module is characterized by the strategic intercalation of diminutive adapter layers within the Transformer architecture’s blocks. Typically, an adapter module initiates with a down-projection matrix, proceeds through a nonlinear activation function, and culminates with an up-projection matrix. The bottleneck dimensionality within these projection matrices is a hyperparameter that often necessitates manual tuning and is potentially contingent upon the specific task requirements [117], [115]. Consequently, there is a critical imperative to devise algorithms capable of dynamically adjusting these hyperparameters in accordance with task-specific information, thereby optimizing the adapter’s efficacy across diverse applications.
- 4) *Heuristic search strategies for hybrid PEFT methods*: The effectiveness of different PEFT techniques can vary greatly depending on the task at hand. Consequently,

many researchers are working to integrate the benefits of various PEFT strategies. However, most existing hybrid methods require the selection of PEFT methods and combination modes in advance and cannot adapt to task differences autonomously. For example, in paper [168], the authors, under a predefined design space, conduct numerous experiments to determine an ideal hybrid strategy. However, the optimal hybrid strategy may not be included within this artificially predefined design space. Therefore, introducing heuristic search strategies to find the best hybrid strategy is a promising direction for future research.

- 5) *Continual learning for PEFT methods*: To enhance the alignment of pre-trained large models with discrete downstream applications, the prevailing strategy entails leveraging a modestly-sized annotated dataset specific to the target task for the purpose of Supervised Fine-Tuning. In the architectural phase of PEFT methods, there exists a paucity of focus on the preservation or augmentation of the pre-trained model's capacity to recall and effectively leverage its embedded knowledge corpus. This oversight may prove detrimental in scenarios where downstream tasks are characterized by frequent data revisions or are subject to swift environmental fluctuations. Consequently, the integration of Continual Learning principles within the framework of PEFT methods represents a significant avenue for scholarly exploration and advancement.
- 6) *Improving the calibration of fine-tuned LLMs*: To date, numerous PEFT approaches developed for the purpose of adeptly tailoring LLMs to downstream tasks have achieved notable advancements in computational and storage efficiency. Nonetheless, when subjected to fine-tuning on modest datasets, LLMs are often prone to overconfidence in their predictions [236], [237], [30]. This phenomenon is especially pernicious for decision-making processes within safety-critical applications or domains where data is scarce, such as medical diagnostics, financial services, and experimental design [78], [238], [239]. Hence, there exists an exigent demand for the formulation of strategies aimed at refining the calibration of fine-tuned LLMs, ensuring that their predictive outputs are not only dependable but also robust.
- 7) *Differential privacy for PEFT methods*: Different downstream tasks often involve varying levels of sensitive and personal data, which further emphasizes the need for privacy in large model fine-tuning, particularly with PEFT methods. The integration of large model fine-tuning and differential privacy holds significant promise for future research. However, existing differential privacy techniques, such as DP-SGD [240] and DP-AdamW [241], often result in limited performance and substantial computational cost. Therefore, future research should focus on developing methods that preserve privacy while simultaneously optimizing performance and minimizing computational costs. Additionally, exploring scalable, privacy preserving methods tailored to PEFT methods is essential. These advancements will enable secure and

efficient fine-tuning of large models, ensuring robust privacy protections.

## VI. CONCLUSIONS

LLMs have garnered widespread attention due to their exceptional performance across a broad spectrum of natural language tasks, beginning with the release of ChatGPT in November 2022. These models have acquired the capability for general-purpose language understanding and generation by training billions of parameters on vast amounts of textual data, as predicted by scaling laws. Traditional full-parameter fine-tuning methods pose significant challenges when customizing these models for specific downstream tasks, particularly on hardware platforms with limited computational capabilities, due to their enormous parameter scale and computational demands. PEFT has emerged as an efficient method for adapting to various downstream tasks, minimizing the number of additional parameters introduced or the computational resources required, thereby enabling the fine-tuned model's performance to approach or even surpass that of full-parameter fine-tuning methods. This survey provides a systematic overview of the latest advancements in PEFT, encompassing introductions to classic pre-trained large models, classification and principle explanation of PEFT algorithms, applications of PEFT methods, and prospects for future research directions in PEFT. This survey not only offers readers a comprehensive and systematic organization of PEFT work but also inspires researchers in various fields to identify potential research directions in PEFT research, accelerating the research process of PEFT methods.

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