Efficient Large Language Models: A Survey

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Large Language Models (LLMs) have demonstrated remarkable capabilities in important tasks such as natural language understanding, language generation, and complex reasoning and have the potential to make a substantial impact on our society. Such capabilities, however, come with the considerable resources they demand, highlighting the strong need to develop effective techniques for addressing their efficiency challenges. In this survey, we provide a systematic and comprehensive review of efficient LLMs research. We organize the literature in a taxonomy consisting of three main categories, covering distinct yet interconnected efficient LLMs topics from model-centric, data-centric, and framework-centric perspective, respectively. We have also created a GitHub repository where we compile the papers featured in this survey at https://github.com/AIoT-MLSys-Lab/Efficient-LLMs-Survey, and will actively maintain this repository and incorporate new research as it emerges. We hope our survey can serve as a valuable resource to help researchers and practitioners gain a systematic understanding of the research developments in efficient LLMs and inspire them to contribute to this important and exciting field.

Additional Key Words and Phrases: Large Language Models; Efficient Methods; Machine Learning Systems

ACM Reference Format:
Zhongwei Wan, Xin Wang, Che Liu, Samiul Alam, Yu Zheng, Jiachen Liu, Zhongnan Qu, Shen Yan, Yi Zhu, Quanlu Zhang, Mosharaf Chowdhury, and Mi Zhang. 2023. Efficient Large Language Models: A Survey. 1, 1, Article 101 (December 2023), 54 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

*The work is done outside Amazon.

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XXXX-XXXX/2023/12-ART101 $15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Large Language Models (LLMs) are a type of advanced AI models designed to understand and generate human languages. Recently, we have witnessed a surge in LLMs include those developed by Open AI (GPT-3 [20] and GPT-4 [200]), Google (Gemini [270], GLaM [69], PaLM [51], PaLM-2 [7]), Meta (LLaMA-1 [276] and LLaMA-2 [277]), and other models such as BLOOM [239], PanGu-$\sum$ [233], and GLM [336]. These models have demonstrated remarkable performance across a variety of tasks such as natural language understanding (NLU), language generation, complex reasoning [321], and domain-specific tasks related to biomedicine [102, 282, 283], law [70] and code generation [35, 302]. Such performance breakthroughs can be attributed to their massive scales in model sizes and volumes of training data, as they contain billions or even trillions of parameters while being trained on a gigantic amount of data from diverse sources.

Although LLMs are leading the next wave of AI revolution, the remarkable capabilities of LLMs come at the cost of their substantial resource demands [51, 69, 200, 233]. Figure 1 illustrates the relationship between model performance and model training time in terms of GPU hours for LLaMA series, where the size of each circle is proportional to the number of model parameters. As shown, although larger models are able to achieve better performance, the amounts of GPU hours used for training them grow exponentially as model sizes scale up. In addition to training, inference also contributes quite significantly to the operational cost of LLMs. Figure 2 depicts the relationship between model performance and inference throughput. Similarly, scaling up the model size enables better performance but comes at the cost of lower inference throughput (higher inference latency), presenting challenges for these models in expanding their reach to a broader customer base and diverse applications in a cost-effective way.

The high resource demands of LLMs highlight the strong need to develop techniques to enhance the efficiency of LLMs. As shown in Figure 2, compared to LLaMA-1-33B, Mistral-7B [123], which uses grouped-query attention and sliding window attention to speed up inference, achieves comparable performance and much higher throughput. This superiority highlights the feasibility and significance of designing efficiency techniques for LLMs.

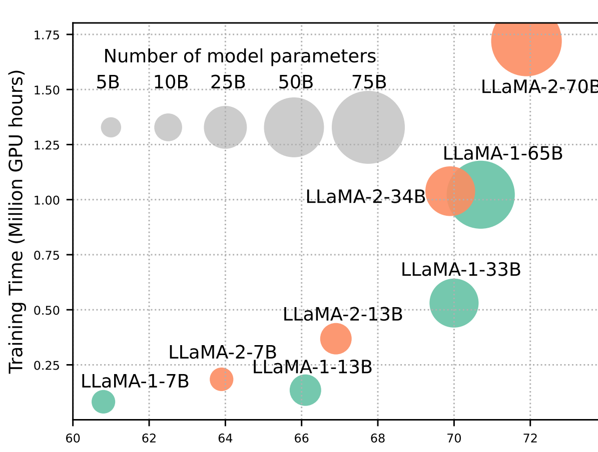


Fig. 1. Illustration of model performance and model training time in GPU hours of LLaMA models at different scales. The reported performance is the average score of several commonsense reasoning benchmarks. The training time is based on Nvidia A100 80GB GPU. The size of each circle corresponds to the number of model parameters. The original data can be found in [276, 277].

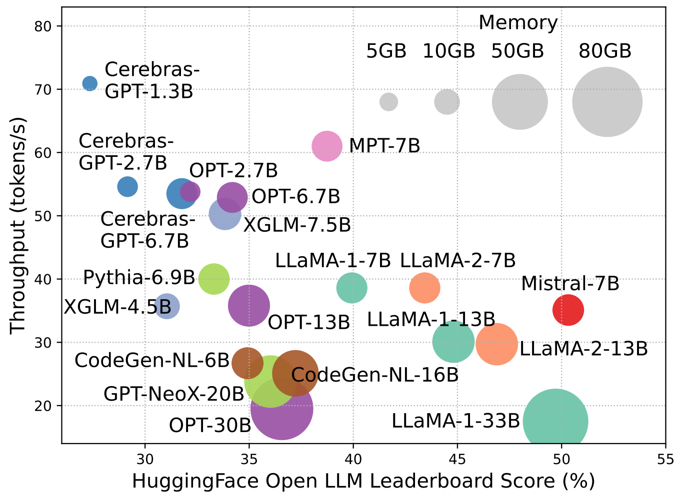


Fig. 2. Performance score *vs.* inference throughput for various LLMs. The throughputs are measured on Nvidia A100 80GB GPU with 16-bit floating point quantization. The size of each circle corresponds to the memory footprint (in Gigabytes) of each model when running with batch size of 1, prompt size of 256 and generating 1000 tokens. The original data can be found in [120].

The overarching goal of this survey is to provide a holistic view of the technological advances in efficient LLMs and summarize the existing research directions. As illustrated in Figure 3, we organize the literature in a taxonomy consisting of three main categories, covering efficient LLMs topics from **model-centric**, **data-centric**, and **framework-centric** perspective, respectively. These three categories cover distinct yet interconnected research topics, collectively providing a systematic and comprehensive review of efficient LLMs research. Specifically,

- **Model-Centric Methods:** Model-centric methods focus on both algorithm-level and system-level efficient techniques where the model itself is the focal point. With billions or even trillions of parameters, LLMs exhibit distinct characteristics [301] compared to smaller-scale models, necessitating the development of new techniques. In §2, we survey efficient techniques that cover research directions related to model compression, efficient pre-training, efficient fine-tuning, efficient inference, and efficient architecture design.
- **Data-Centric Methods:** In the realm of LLMs, the importance of data is as crucial as that of the model itself. Data-centric methods focus on the role of the quality and structure of data in enhancing the efficiency of LLMs. In §3, we survey efficient techniques that cover research directions related to data selection and prompt engineering.
- **LLM Frameworks**: The advent of LLMs has necessitated the development of specialized frameworks to efficiently handle their training, inference, and serving. While mainstream AI frameworks such as TensorFlow, PyTorch, and JAX provide the foundations, they lack built-in support for specific optimizations and features crucial for LLMs. In §4, we survey existing frameworks specifically designed for efficient LLMs, addressing their unique features, underlying libraries, and specializations.

In addition to the survey, we have established a GitHub repository where we compile the papers featured in the survey, organizing them with the same taxonomy: https://github.com/AIoT-MLSys-Lab/Efficient-LLMs-Survey. We will actively maintain it and incorporate new research as it emerges.

Although there are a few surveys on LLMs [26, 128, 299, 354], this survey provides a focused review and discussion on the literature related to the efficiency aspect of LLMs. There are also surveys on efficient Transformers [269] and their training methods [363]. In contrast, this survey specifically focuses on efficiency techniques designed for models of more than billions of parameters. We hope this survey together with the GitHub repo can help researchers and practitioners navigate through the literature and serve as a catalyst for inspiring further research on efficient LLMs.

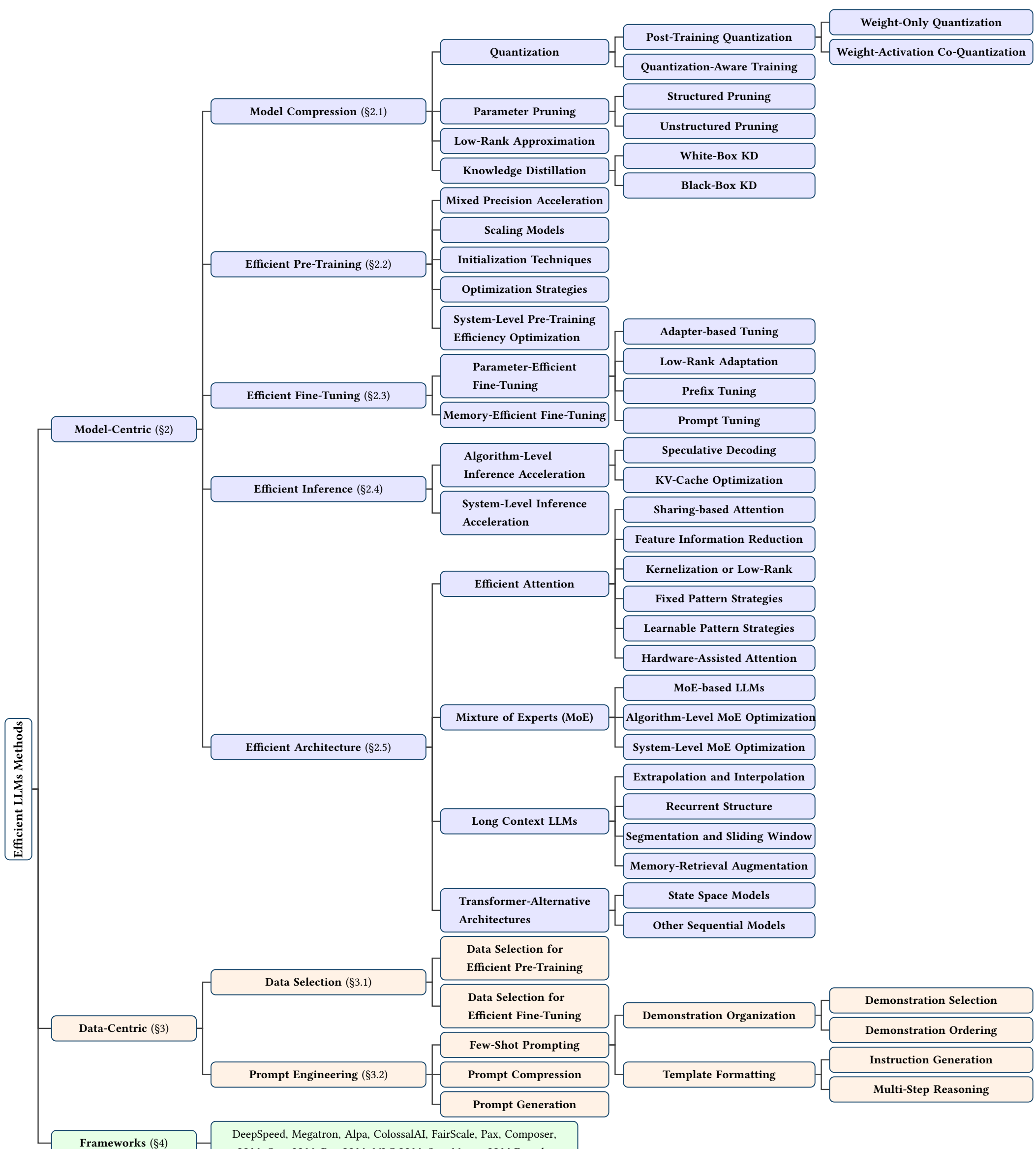


Fig. 3. Taxonomy of efficient large language models (LLMs) literature.

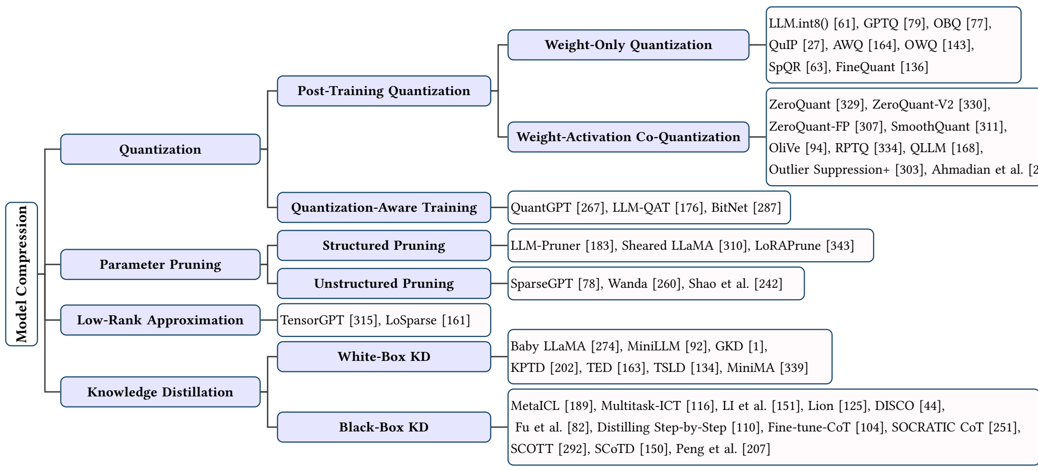


Fig. 4. Summary of model compression techniques for LLMs.

2 MODEL-CENTRIC METHODS

2.1 Model Compression

As summarized in Figure 4, model compression techniques for LLMs can be grouped into four categories: quantization, parameter pruning, low-rank approximation, and knowledge distillation.

2.1.1 ***Quantization.***

Quantization compresses LLMs by converting model weights and/or activations of high-precision data types $\mathbf{X}^{\mathrm{H}}$ such as 32-bit floating point into low-precision data types X^{L} such as 8-bit integer [61] or 4-bit integer [62]:

$$\mathbf{X}^{\mathrm{L}} = \mathrm{Round}\left(\frac{\mathrm{absmax}\left(\mathrm{X}^{\mathrm{L}}\right)}{\mathrm{absmax}\left(\mathrm{X}^{\mathrm{H}}\right)}\mathbf{H}^{\mathrm{H}}\right) = \mathrm{Round}\left(\mathcal{K}\cdot\mathbf{X}^{\mathrm{H}}\right), \text{and } \mathbf{X}^{\mathrm{H}} = \frac{\mathbf{X}^{\mathrm{L}}}{\mathcal{K}} \tag{1}$$

where Round denotes mapping a floating number into an approximate integer; absmax denotes the absolute maximum of the input elements; and $\mathcal{K}$ denotes the quantization constant.

Quantization techniques for LLMs can be classified as post-training quantization (PTQ) and quantization-aware training (QAT).

Post-Training Quantization (PTQ). PTQ quantizes LLMs after the model has been trained. To compensate for the accuracy drop, PTQ uses a small calibration dataset to update the quantized weights and/or activations. PTQ for LLMs can in general be grouped into two categories: weight-only quantization, and weight-activation co-quantization.

- ***Weight-Only Quantization*** focuses on quantizing model weights only for LLMs. For example, Dettmers et al. [61] introduces the first multibillion-scale Int8 weight quantization method named LLM.int8 () that significantly reduces memory usage during inference while being able to maintain the full precision model performance. Frantar et al. [79] push one step further and propose GPTQ, a post-training weight quantization method that compresses LLM weights to 3 or 4 bits instead of 8 bits. GPTQ employs layer-wise quantization with Optimal Brain Quantization (OBQ) [77] to update weights with inverse Hessian information. This technique enables quantizing GPT models with 175 billion parameters in roughly four GPU

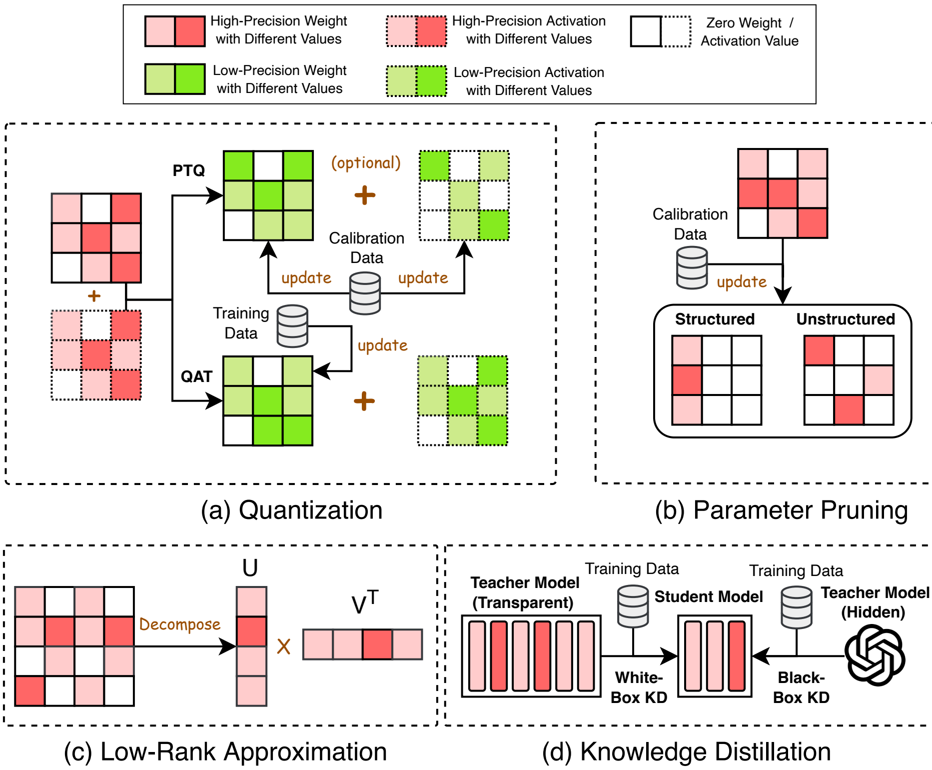


Fig. 5. Illustrations of model compression techniques for LLMs.

hours with minimal accuracy loss compared to the original model. Driven by the insights that quantization can be more effective when model weights and proxy Hessian matrices are incoherent, Chee et al. [27] propose QuIP, a post-training quantization method that applies incoherence processing to quantize LLMs to 2 bits per weight. Lin et al. [164] observe that there exists a small portion of model weights with larger activation magnitudes referred to as salient weights that determine the quantization loss. Based on this observation, they propose a weight quantization approach named activation-aware weight quantization (AWQ) to quantize LLMs while preserving the salient weights in high precision. Similarly, Lee et al. [143] also observe that activation outliers amplifies weight quantization loss. They propose outlier-aware weight quantization (OWQ) to identify those vulnerable weights with activation outliers and allocate high-precision to them. Dettmers et al. [63] propose Sparse-Quantized Representation (SpQR) to separate outlier weights that are prone to large quantization errors. These outlier weights are stored at higher precision levels, while the rest are compressed to 3-4 bits. They then propose a decoding scheme designed for the SpQR format, which accelerates the inference process on a token-by-token basis. Kim et al. [136] tackle the problem of outliers skewing the distribution of quantized weights, and propose FineQuant which employs an empirically crafted, heuristic-based approach to allocate varying levels of granularity to different weight matrices within the model.

- ***Weight-Activation Co-Quantization*** quantizes both model weights and activations. Due to the existence of outliers, activations are more difficult to quantize than model weights [19]. Yao et al. [329] propose ZeroQuant, which utilizes group-wise quantization for model weights and token-wise quantization for activations. However, ZeroQuant could not maintain accuracy for models with more than 175 billion parameters. To address this issue, Yao et al. [330] and Wu et al. [307] propose ZeroQuant-FP and ZeroQuant-V2 respectively which both utilize low-rank matrices to recover the accuracy drop. Xiao et al. [311] propose SmoothQuant which introduces a per-channel scaling transformation that migrates the quantization difficulty from activations to weights to achieve lossless quantization of weights and activations to 8 bits for LLMs up to 530 billion parameters. Guo et al. [94] pinpoint outliers are critical in weight and activation quantization but their nearby normal values are not. Based on this observation, they propose OliVe, which prunes normal values adjacent to the outliers so that the outliers can be encoded with low precision. Yuan et al. [334] identify the challenge of quantizing activations when different channels have disparate ranges. They propose RPTQ, which groups channels in activations that display similar value ranges and applies uniform quantization parameters to the values in each group. Liu et al. [168] propose QLLM, an adaptive channel reassembly method that efficiently tackles activation outliers and utilizes calibration data to offset the information loss incurred from quantization. Wei et al. [303] observe that the activation outliers in LLMs are asymmetric and tend to cluster in particular channels. Based on this observation, they propose Outlier Suppression+, which introduces operations that shift and scale channels individually to neutralize asymmetric outliers. Lastly, Ahmadian et al. [2] demonstrate that it is possible to suppress large activation outliers at scales as large as 52B. Given the right optimization choices during pre-training, they can quantize models ranging in size from 410M to 52B with minimal accuracy degradation.

Quantization-Aware Training (QAT). QAT quantizes LLMs during the training process itself so as to allow LLMs to learn quantization-friendly representations. Compared to PTQ, since QAT requires training using the complete training set to make up for its accuracy drop, it is much more expensive and time consuming. Tao et al. [267] aim to address quantization challenges in models like GPT-2 caused by uniform word embeddings, and propose QuantGPT, which combines contrastive distillation from a full-precision teacher model and logit distillation to a quantized student model during auto-regressive pretraining. LLM-QAT [176] uses data generated by LLMs itself to distill knowledge, with the aim of quantizing a student model. Specifically, it retains the original output distribution and is capable of quantizing any generative model, irrespective of its initial training data. Besides quantizing weights and activations, LLM-QAT also tackles the quantization of the key-value cache, a crucial step for enhancing throughput and accommodating long sequence dependencies in LLMs. BitNet [287] pioneers QAT for 1-bit LLMs, using low-precision binary weights and quantized activations, while keeping optimizer states and gradients high-precision during training, requiring only a replacement of the nn.Linear layer to train 1-bit weights from scratch.

2.1.2 *Parameter Pruning*.

Parameter pruning compresses LLMs by removing redundant model weights. Parameter pruning methods for LLMs can be categorized into structured pruning and unstructured pruning.

Structured Pruning. Structured pruning focuses on pruning structured patterns such as groups of consecutive parameters or hierarchical structures such as rows, columns, or sub-blocks of the LLM weight matrices. For example, LLM-Pruner [183] introduces a task-agnostic structured pruning strategy that selectively eliminates non-essential interconnected structures using gradient information. It utilizes a small amount of data to obtain the weight, parameter, and group importance of the coupled structure for LLaMA [276], and uses LoRA [111] to recover performance after pruning, showing competitive zero shot performance. Sheared LLaMA [310] proposes two techniques. The first technique is targeted structured pruning, which prunes a larger model to a designated target shape by eliminating layers, heads, and intermediate and hidden dimensions in a end-to-end fashion. The second technique is dynamic batch loading, which dynamically alters the components of the sampled data in each training batch based on losses in various domains. Through these two techniques, Sheared LLaMA is able to prune the LLaMA2-7B model down to 1.3B parameters. LoRAPrune [343] introduces a LoRA-based pruning criterion using LoRA's weights and gradients instead of pre-trained weights' gradients for importance estimation. By employing a structured iterative pruning process to eliminate excess channels and heads, LoRAPrune outperforms LLM-Pruner in efficiency at a 50% compression rate.

Unstructured Pruning. Unstructured pruning, on the other hand, focuses on pruning model weights individually, and thus has much more flexibility compared to structured pruning. Frantar and Alistarh [78] present SparseGPT, a one-shot LLM pruning approach that does not require retraining. It formulates pruning as a sparse regression problem and solves it by utilizing an approximate solver based on the inversion of the Hessian matrix. In doing so, SparseGPT reaches 60% unstructured sparsity even on models such as OPT-135B while experiencing only a slight reduction in perplexity. Sun et al. [260] propose Wanda which prunes weights based on the product values of weight magnitudes and their respective input activations. Compared to SparseGPT, Wanda neither relies on second-order information nor necessitates weight update, and performs competitively against SparseGPT. Shao et al. [242] propose to utilize Hessian sensitivity-aware mixed sparsity pruning to achieve a minimum of 50% sparsity in LLMs without retraining. This method adaptively assigns sparsity based on sensitivity to minimize the error induced by pruning while preserving the overall level of sparsity.

2.1.3 *Low-Rank Approximation*.

Low-rank approximation compresses LLMs by approximating the weight matrix $\mathbf{W}^{m\times n}$ of LLMs with low-rank matrices $\mathbf{U}$ and $\mathbf{V}$ such that $\mathbf{W} \approx \mathbf{U}\mathbf{V}^\top$, where $\mathbf{U} \in \mathbb{R}^{m\times r}$, $\mathbf{V} \in \mathbb{R}^{n\times r}$, and r is typically much smaller than m, n. In doing so, low-rank approximation reduces the number of parameters and enhances computational efficiency. In particular, Xu et al. [315] introduce TensorGPT which compresses the embedding layers of LLMs using Tensor-Train Decomposition (TTD). It transforms and breaks down each token embedding and creates an efficient embedding format named Matrix Product State (MPS) that can be efficiently computed in a distributed manner. LoSparse [161] aims to compress the coherent and expressive components within neurons through low-rank approximation while eliminating the incoherent and non-expressive elements via pruning the sparse matrix. It uses iteration training to calculate the important score of column neurons for pruning, outperforming conventional iterative pruning methods.

2.1.4 *Knowledge Distillation*.

Knowledge Distillation (KD) compresses LLMs by training a smaller student model to emulate the performance of the LLM as the teacher model such that the student model is computationally less expansive yet maintains a high level of performance similar to the teacher model. KD for LLMs can be categorized into white-box KD methods and black-box KD methods.

White-Box Knowledge Distillation. White-box KD refers to KD techniques where the parameters or logits of the teacher LLM are used in the distillation process [87]. For example, Baby LLaMA [274] trains an ensemble of GPT-2 and a collection of smaller LLaMA-1 models using the BabyLM dataset of 10M words. This ensemble is then distilled into a compact LLaMA model with 58 million parameters, which outperforms both its original teacher models as well as a comparable model that was trained without the use of distillation. Gu et al. [92] observe that conventional KD objectives, such as Kullback-Leibler divergence (KLD), may not be well suited for open text generation tasks due to their more complex output spaces compared to classification tasks. To address this issue, they propose MiniLLM that minimizes reverse KLD using the gradient of the objective function through policy gradient techniques [264]. This approach surpasses the performance of standard KD benchmarks on the 13-billion-parameter LLaMA-1 model [276]. Similarly, generalized knowledge distillation (GKD) [1] addresses the issue of distribution mismatch by drawing output sequences from the student model during training. GKD tackles the problem of model under-specification by optimizing different divergence measures, like reverse KL. This approach aims to produce samples from the student model that are probable within the teacher model's distribution. KPTD [202] demonstrates that KD methods can successfully transfer and disseminate knowledge from entity definitions into the parameters of a pre-trained language model. Specifically, it creates a transfer set by prompting the language model to generate text based on the definition of the entity. Then the models' parameters are updated to align the distribution of the student language model with that of the teacher model. TED [163] introduces a technique for layer-specific task distillation. It uses specially designed filters to align the internal states of both student and teacher models in each layer. These filters extract the relevant knowledge from the internal states that is beneficial for the specific task. TED shows considerable and steady gains in performance on both continual pre-training and fine-tuning. TSLD [134] leverages token-level distillation to enhance QAT, which overcomes the limitations of layer-to-layer KD in token prediction recovery by reforming intermediate representation and has successfully applied QAT to LLMs. Lastly, MiniMA [339] proposes a viewport towards the capacity gap in distilling LLMs, converting it into a principle through analysis and introducing a 3B Language Model that sets a new benchmark for compute-performance pareto frontier.

Black-Box Knowledge Distillation. Different from white-box KD, in black-box KD, only the outputs generated from the teacher LLM are used in the distillation process. Inspired by MetaICL and MetalICL [43, 189], where the language model is meta-trained in a wide range of tasks using in-context learning objectives and then fine-tuned for unseen tasks through in-context learning, Multitask-ICT [116] introduces a concept known as in-context learning distillation. This method aims to transfer the few-shot learning capabilities from the LLM teacher to the student model. Similarly, LI et al. [151] introduce a hybrid prompting technique that employs multi-task learning along with explanations generated by GPT-3 text-davinci-002 version [201]. This method is used to distill explanations into smaller models, achieving consistent and significant improvements over strong single-task fine-tuning benchmarks in different scenarios. Lion [125] introduces an adversarial distillation architecture aimed at enhancing the efficiency of knowledge transfer by incrementally improving the skill level of the student model. Specifically, it prompts LLMs to recognize challenging instructions and create new complex instructions for the student model, thereby establishing a three-phase adversarial cycle involving imitation, discrimination, and generation. DISCO [44] involves prompting a general LLM to produce phrasal perturbations. These generated perturbations are then filtered by a specialized teacher model to distill high-quality counterfactual data into smaller student models, allowing the smaller models to learn causal representations more reliably. Recently, some studies have shown that chain-of-thought (CoT) prompting can elicit language models to solve complex reasoning tasks step by step, with the aim of transfer this ability from LLMs into smaller models through black-box KD. For example, Fu et al. [82] aim to enhance the CoT math reasoning capabilities of smaller models. Specifically, they employ a method that involves instruct-tuning an student model (FlanT5) by distilling the reasoning pathways found in the GSM8K dataset from a LLM teacher (GPT-3.5 code-davinci-002 [35]). The small model is then selected based

Table 1. Pre-training costs of representative LLMs.

Model	Parameter Size	Data Scale	GPUs Cost	Training Time
GPT-3 [20]	175B	300B tokens	-	-
GPT-NeoX-20B [17]	20B	825GB corpus	96 A100-40G	-
OPT [346]	175B	180B tokens	992 A100-80G	-
BLOOM [239]	176B	366B tokens	384 A100-80G	105 days
GLM [336]	130B	400B tokens	786 A100-40G	60 days
LLaMA [276]	65B	1.4T tokens	2048 A100-80G	21 days
LLaMA-2 [277]	70B	2T tokens	A100-80G	71,680 GPU days
Gopher [223]	280B	300B tokens	1024 A100	13.4 days
LaMDA [273]	137B	768B tokens	1024 TPU-v3	57.7 days
GLaM [69]	1200B	280B tokens	1024 TPU-v4	574 hours
PanGu-α [337]	13B	1.1TB corpus	2048 Ascend 910	-
PanGu-$\sum$ [233]	1085B	329B tokens	512 Ascend 910	100 days
PaLM [51]	540B	780B tokens	6144 TPU-v4	-
PaLM-2 [7]	-	3.6T tokens	TPUv4	-
WeLM [258]	10B	300B tokens	128 A100-40G	24 days
Flan-PaLM [52]	540B	-	512 TPU-v4	37 hours
AlexaTM [254]	20B	1.3 tokens	128 A100	120 days
Codegeex [357]	13B	850 tokens	1536 Ascend 910	60 days
MPT-7B [272]	7B	1T tokens	-	-

on its average performance on three separate, withheld math reasoning datasets to confirm its ability to generalize well to new, out-of-distribution scenarios. Likewise, Distilling Step-by-Step [110] claims that to match the performance of LLMs, fine-tuning and distilling smaller models require substantial amounts of training data. To address this, it proposes a technique that uses CoT prompting to extract LLM rationales for extra guidance in training smaller models within a multi-task setting, achieving better performance compared to few shot prompted LLMs. Fine-tune-CoT [104] utilizes existing zero-shot CoT prompting techniques [139] to create rationales from LLMs. These rationales are then used to fine-tune smaller student models. The approach also introduces diverse reasoning, a method that employs stochastic sampling to generate a variety of reasoning solutions from teacher models, which serves to enrich the training data for the student models. SOCRATIC CoT [251] employs a method that breaks down the original problem into a series of smaller tasks and utilizes this decomposition to direct the intermediate steps of reasoning. This approach is used to train a pair of smaller, distilled models: one that specializes in dissecting the problem and another focused on solving these sub-problems. SCOTT [292] uses rationales generated by LLMs to train a student model under a counterfactual reasoning framework. This approach ensures that the student model does not overlook the provided rationales, thereby preventing it from making inconsistent predictions. SCoTD [150] presents a method called symbolic CoT distillation. It involves drawing CoT rationales from a LLM using unlabeled data instances. A smaller model is then trained to predict both the sampled rationales and the associated labels. Lastly, Peng et al. [207] utilize GPT-4 as a teacher model to generate English and Chinese instruction-based datasets to refine student LLMs such as LLaMA. Their results show that the 52K data points generated by GPT-4 are able to improve zero-shot performance compared to instruction-following data generated from previous state-of-the-art models.

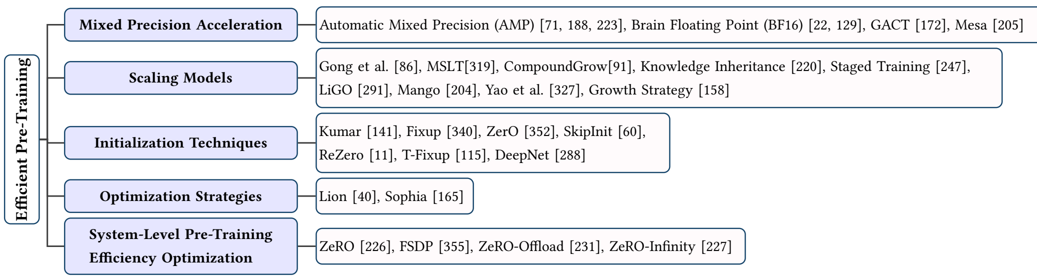


Fig. 6. Summary of efficient pre-training techniques for LLMs.

2.2 Efficient Pre-Training

As shown in Table 1, pre-training LLMs incurs high costs. Efficient pre-training aims to enhance the efficiency and reduce the cost of the LLM pre-training process. As summarized in Figure 6, efficient pre-training techniques can be grouped into four categories: mixed precision acceleration, scaling models, initialization techniques, and optimization strategies.

Mixed Precision Acceleration. Mixed precision acceleration enhances pre-training efficiency by using the low-precision model for forward and backward propagation and converting the calculated low-precision gradients to high-precision ones for updating the original high-precision weights. For example, Micikevicius et al. [188] propose Automatic Mixed Precision (AMP) to keep a master copy of weights in full-precision FP32 for updates, whereas weights, activations, and gradients are stored in FP16 for arithmetic operations. Notably, the improved version of AMP [71] optimizer has eliminated the copy of FP32 weights, but the optimizer (AdamW) still use FP32 internally. However, Rae et al. [223] demonstrate that FP16 results in accuracy loss. To counteract this performance drop, Brain Floating Point (BF16) was proposed [22, 129], which achieves better performance by assigning more bits to the exponent and fewer to the significant bits. Lastly, recent studies [172, 205] have shown that combining mixed-precision acceleration with activation compressed training (ACT) can further facilitate memory-efficient Transformer pre-training.

Scaling Models. Techniques based on scaling models accelerate pre-training convergence and reduce training costs by using the weights of a small model to scale up to a large model. For example, Gong et al. [86] introduce Progressive Stacking to transfer knowledge from a simpler model to a more complex one and then uses progressive stacking to enhance the model's training efficiency and convergence speed. Yang et al. [319] observe that as the depth of the model increases through progressive stacking, the training speed however decreases. To address this issue, they propose multi-stage layer training (MSLT), which only updates the output and newly introduced top encoder layers while keeping the previously trained layers unchanged. Once all the layers have been trained, MSLT fine-tunes the entire model by updating each layer in just 20% of the total steps, making it more time-efficient than the traditional progressive stacking approach. Gu et al. [91] introduce CompoundGrow, which begins with the training of a small model and incrementally expands it using a mix of model growth techniques, including increasing input length, model breadth, and depth, leading to an acceleration in the pre-training process by up to 82.2%. Qin et al. [220] propose Knowledge Inheritance which employs knowledge distillation as an auxiliary supervision during pre-training. This aids in effectively training a larger model from a smaller teacher model, thereby enhancing both the speed of pre-training and the generalization ability. Shen et al. [247] introduce Staged Training that begins with a small model and progressively increases its depth and breadth through a growth operator, which includes model parameters, the state of the optimizer,

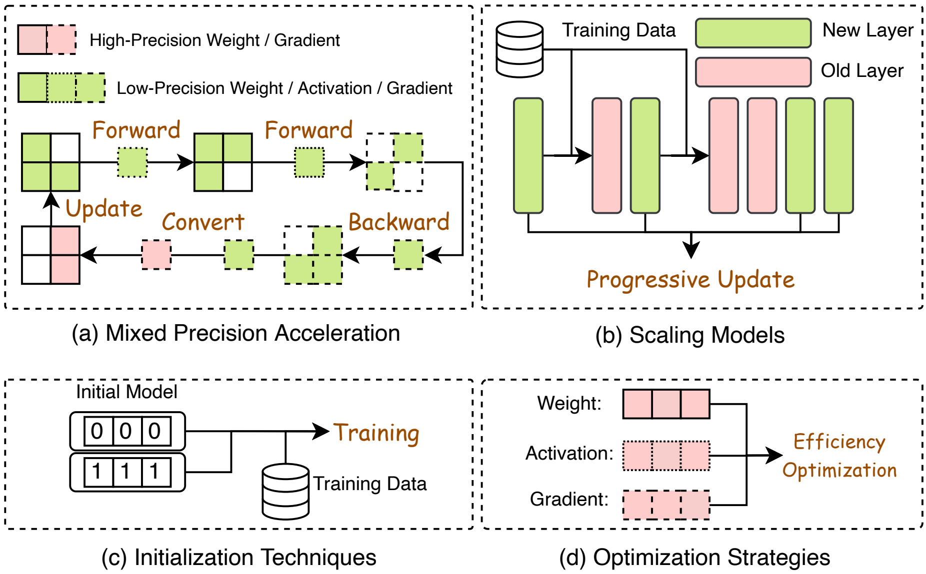


Fig. 7. Illustrations of efficient pre-training techniques for LLM.

and the learning rate schedule. By starting each phase with the results from the previous one, it effectively reuses computation, leading to a more efficient training process. Chen et al. [31] propose function-reserving initialization (FPI) and advanced knowledge initialization (AKI) to transfer the knowledge of a smaller pre-trained model to a large model to improve the pre-training efficiency of the large model. Specifically, FPI gives the larger model a behavior similar to that of the smaller model, laying a strong basis for optimization; and AKI promotes faster convergence by replicating weights from higher layers. Wang et al. [291] propose Linear Growth Operator (LiGO) that linearly maps the parameters of a smaller model to initiate a larger one, using a composition of width-and depth-growth operators, further enhanced with Kronecker factorization to capture architectural knowledge. Mango [204] introduces a technique that establishes a linear relationship between each weight of the target model and all weights of the pretrained model to boost acceleration capabilities. It also employs multi-linear operators to decrease computational and spatial complexity during pre-training. Drawing from these scaling techniques and the progressive pre-training [327], recent LLMs like FLM-101B [158] introduce a growth strategy to cut LLM training costs by expanding model structures offline and resuming from the previous stage's smaller model checkpoint.

Initialization Techniques. Initialization plays a key role in enhancing the efficiency of LLM pre-training since a good initialization can accelerate the convergence of the model. Most LLMs employ initialization techniques that were adopted in training smaller-scale models, such as conventional initialization techniques like [103, 141]. For example, initialization method introduced by Kumar [141] aims to balance input and output variances. Fixup [340] and ZerO [352] set the residual stem to zero, preserving signal identity. SkipInit [60] substitutes batch normalization with a zero-value multiplier. ReZero [11] adds zero-valued parameters to maintain identity, leading to faster convergence. T-Fixup [115] follows Fixup to adopt rescaling schemes for the initialization of residual blocks of Transformer models. DeepNet [288] adjusts the residual connection in deep Transformers using Post-LN-init, ensuring stable inputs to Layer-Normalization and mitigating gradient vanishing for stable optimization.

Optimization Strategies. Popular LLMs such as GPT-3 [20], OPT [346], BLOOM [239], and Chinchilla [105] are predominately pre-trained using Adam [137] or AdamW [178] as optimizers. However, both Adam and AdamW have a huge demand on memory and are computationally expensive. Some studies [40, 165] propose new optimizers to accelerate the pre-training of LLMs. Chen et al. [40] propose to leverage search techniques to traverse a large and sparse program space to discover optimizers for model training. The discovered optimizer, named Lion, is more memory-efficient than Adam as it only keeps track of the momentum. Liu et al. [165] propose Sophia as a lightweight second-order optimizer that outpaces Adam with doubling the pre-training speed. Sophia calculates the moving average of gradients and the estimated Hessian, dividing the former by the latter and applying element-wise clipping. It effectively moderates update sizes, addresses non-convexity and rapid hessian changes, enhancing both memory utilization and efficiency.

System-Level Pre-Training Efficiency Optimization. Due to the high demand on memory and compute resources, LLMs are usually pre-trained across multiple compute nodes in a distributed manner. Therefore, most techniques for improving pre-training efficiency at the system level focus on distributed training. Existing efficient distributed training methods that are used for general AI model training can also be applied to LLM pre-training. For example, data parallelism [155, 241] involves splitting the training dataset into multiple subsets on separate nodes. Each node computes gradients independently and then shares them with others to update the model parameters. Pipeline parallelism [117, 196] divides the input minibatch into several smaller batches, and then distributes the execution of these microbatches across multiple GPUs. Tensor parallelism [16, 197, 285, 317] splits the model's weight matrices across multiple nodes. Each node is responsible for executing the forward and backward passes with a segment of the model's weights and their computed results are then aggregated. Although these parallelism techniques tackle the computing and memory constraints for training LLMs, they are still limited in maintaining computation, communication and development efficiency when fitting all of the runtime states, including gradients, optimizer states and activation states into limited memory. To bridge this gap, Zero Redundancy Data Parallelism (ZeRO) [226] provides three stages of optimization to partition the intermediate states during pre-training across different nodes. Specifically, ZeRO-1 only partitions the optimizer states, and ZeRO-2 partitions both the optimizer states and the gradients. Both ZeRO-1 and ZeRO-2 reduce runtime memory compared to data parallelism, while only consuming the same communication volume as data parallelism. ZeRO-3 provides a more aggressive partitioning that also splits the model parameter across the nodes compared with ZeRO-1 and ZeRO-2. Although runtime memory is further reduced through ZeRO-3, there is a modest 50% increase in communication overhead under this stage. Therefore, it is recommended to use ZeRO-3 within a node to minimize the communication time while using ZeRO-1 and ZeRO-2 across nodes. Fully Sharded Data Parallel (FSDP) [355] shares a similar idea for optimization, and designs a hybrid sharding strategy to allow users to define which nodes or processes to partition the gradients, parameter, and optimizer states across different nodes. In the case when the weight memory exceeds the aggregated memory that can be provided by all of the compute nodes, ZeRO-Offload [231] enables offloading to CPU for any stage of ZeRO, and ZeRO-Infinity [227] provides a way to offload to NVMe drives in addition to CPU memory. However, it is quite difficult to maintain performance using these two alternatives, as the data movement between CPU and GPU is slow.

2.3 Efficient Fine-Tuning

Efficient fine-tuning aims to enhance the efficiency of the fine-tuning process for LLMs. As shown in Figure 8, efficient fine-tuning methods can be grouped into parameter-efficient fine-tuning (PEFT), and memory-efficient fine-tuning (MEFT).

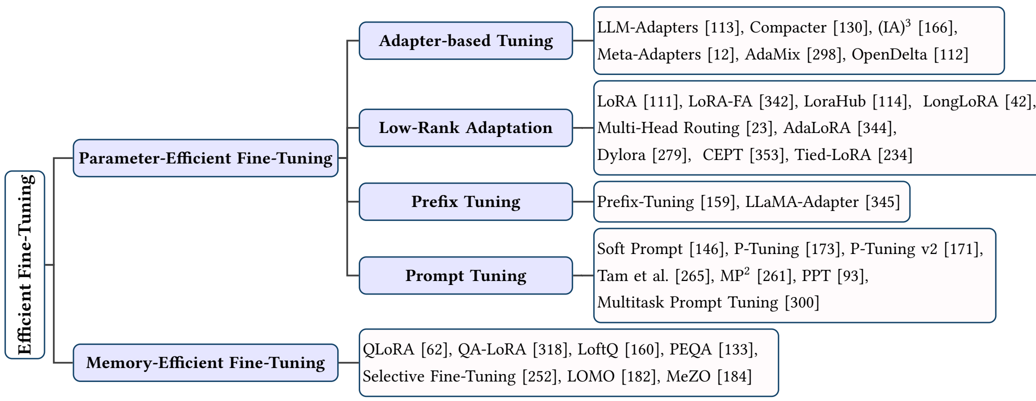


Fig. 8. Summary of efficient fine-tuning methods for LLMs.

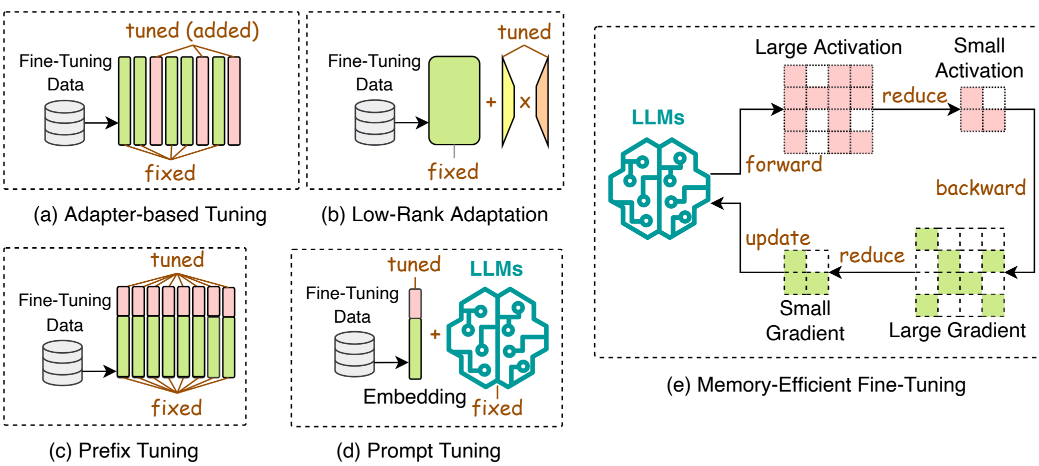


Fig. 9. Illustrations of Parameter-Efficient Fine-Tuning (a)-(d) and Memory-Efficient Fine-Tuning (e).

2.3.1 *Parameter-Efficient Fine-Tuning*.

Parameter-efficient fine-tuning (PEFT) aims to adapt an LLM to downstream tasks by freezing the whole LLM backbone and only updating a small set of extra parameters. In general, PEFT methods can be grouped into four categories: adapter-based tuning, low-rank adaptation, prefix tuning, and prompt tuning.

Adapter-based Tuning. Adapters are bottleneck-like trainable modules integrated into LLMs, which first down-project the input feature vector followed by a non-linear layer and then up-project back to the original size [108]. Adapter-based tuning includes both series adapters and parallel adapters. In series adapters, each LLM layer has two adapter modules added after its attention and feed-forward modules; parallel adapters position two adapter modules alongside the attention and feed-forward modules within each layer of the LLM. In particular, Hu et al. [113] propose LLM-Adapters, which integrates series or parallel adapters into LLMs for fine-tuning on different tasks. Karimi Mahabadi et al. [130] propose Compacter which unifies adapters, low-rank techniques, and the latest hyper-complex multiplication layers to achieve a balanced trade-off between the amount of trainable parameters and task performance. $(IA)^3$ [166] introduces a technique that scales activations using learned vectors, which outperforms few-shot in-context learning (ICL) in both accuracy and computational efficiency. Following meta-learning principles, Meta-Adapters [12] designs a resource-efficient fine-tuning technique for the few-shot scenario where it incorporates adapter layers that have been meta-learned into a pre-trained model, transforming the fixed pre-trained model into an efficient few-shot learning framework. AdaMix [298] takes inspiration from sparsely-activated mixture-of-experts (MoE) models [365] and proposes a mixture of adaptation modules to learn multiple views of the given task. Lastly, OpenDelta [112] is an open-source software library that offers a versatile and plug-and-play framework for implementing a range of adapter-based techniques, and is designed to be compatible with various LLMs architectures.

Low-Rank Adaptation. Low-Rank Adaptation (LoRA) [111] is a widely used PEFT approach for LLMs. Instead of directly adjusting the weight matrix $\mathbf{W} \in \mathbb{R}^{m \times n}$ as $\mathbf{W} \leftarrow \mathbf{W} + \Delta\mathbf{W}$, LoRA introduces two trainable low-rank matrices $\mathbf{A} \in \mathbb{R}^{m \times r}$ and $\mathbf{B} \in \mathbb{R}^{r \times n}$ and expresses $\Delta\mathbf{W}$ as $\Delta\mathbf{W} = \mathbf{A} \cdot \mathbf{B}$. As such, only the small matrices $\mathbf{A}$ and $\mathbf{B}$ are updated during fine-tuning, while the original large weight matrix remains frozen, making the fine-tuning process more efficient. Though effective, LoRA still requires the update of all the parameters of the low-rank matrices for all the layers of the LLM at every single fine-tuning iteration. To enhance the efficiency of LoRA, LoRA-FA [342] keeps the projection-down weights of $\mathbf{A}$ fixed while updating the projection-up weights of $\mathbf{B}$ in each LoRA adapter so that the weight modifications during fine-tuning are confined to a low-rank space, thereby eliminating the need to store the full-rank input activations. LoraHub [114] explores the composability of LoRA for the purpose of generalizing across different tasks. It combines LoRA modules that have been trained on various tasks with the goal of attaining good performance on tasks that have not been seen before. LongLoRA [42] extends LoRA to the long-context fine-tuning scenario. It introduces shift short attention (S^2-Attn), which effectively facilitates context expansion, showing that LoRA is effective for long context when utilizing trainable embedding and normalization. Multi-Head Routing (MHR) [23] extends LoRA to Mixture-of-Experts (MoE) architectures. It outperforms Polytropon [213] when operating with a similar parameter allocation. Notably, it achieves competitive performance while focusing on fine-tuning the routing function alone, without making adjustments to the adapters, demonstrating remarkable parameter efficiency. Zhang et al. [344] observe that many PEFT techniques neglect the differing significance of various weight parameters. To address this, they propose AdaLoRA which employs singular value decomposition to parameterize incremental updates and adaptively distributes the parameter budget based on the importance score of each weight matrix. Valipour et al. [279] identify that the rank in LoRA is static and cannot be adaptively adjusted during fine-tuning. To address this issue, they propose Dylora, which introduces a dynamic low-rank adaptation method that trains LoRA blocks across multiple ranks rather than just one by organizing the representations learned by the adapter module based on their ranks. Different from above-mentioned methods that mainly apply PEFT to full-size LLMs, CEPT [353] introduces a new framework that utilizes compressed LLMs. Specifically, it assesses how prevalent LLM compression methods affect PEFT performance and subsequently implements strategies for knowledge retention and recovery to counteract the loss of knowledge induced by such compression techniques. Furthermore, Tied-LoRA [234] uses weight tying and selective training to further increase parameter efficiency of LoRA.

Prefix Tuning. Prefix-Tuning [159] adds a series of trainable vectors, known as prefix tokens, to each layer in an LLM. These prefix tokens are tailored to specific tasks and can be treated as virtual word embeddings. LLaMA-Adapter [345] incorporates a set of trainable adaptation embeddings and attaches them to the word embeddings in the upper layers of the LLMs. A zero-initialized attention scheme with zero gating is also introduced. It dynamically incorporates new guiding signals into LLaMA-1 while retaining its pre-trained knowledge.

Prompt Tuning. Different from prefix tuning, prompt tuning incorporates trainable prompt tokens at the input layer. These tokens can be inserted either as a prefix or anywhere within the input tokens. Soft Prompt [146] keeps the entire pre-trained model fixed while adding an extra k trainable tokens at the beginning of the input text for each downstream task. It outperforms few-shot prompts and narrows the performance gap compared to full model fine-tuning. P-Tuning [173] utilizes a small number of parameters as prompts, which are processed by a prompt encoder before being used as input for pre-trained LLMs. Instead of searching for discrete prompts, P-Tuning fine-tunes these prompts through gradient descent and improves performance on a wide range of NLU task. Liu et al. [171] observe that earlier versions of prefix tuning struggle with complex sequence labeling tasks. To address this, they propose P-Tuning v2 which enhances prefix tuning by introducing continuous prompts at each layer of the pre-trained model, rather than at the input layer only. This modification has proven effective in boosting performance across various parameter sizes for tasks related to natural language understanding. Tam et al. [265] introduce efficient prompt tuning for text retrieval, updating just 0.1% of parameters and outperforming traditional full-parameter update methods in diverse domains. Sun et al. [261] claim that prompt tuning tends to struggle in few-shot learning scenarios, and thus propose MP^2 that pre-trains a collection of modular prompts using multitask learning. These prompts are then selectively triggered and assembled by a trainable routing mechanism for specific tasks. As a result, MP^2 can quickly adapt to downstream tasks by learning how to merge and reuse pretrained modular prompts. Different from MP^2, PPT [93] attributes the performance degradation of prompt tuning in few-shot learning to the poor initialization of soft prompt, and thus proposes to add the soft prompt into the pre-training stage for a better initialization. Multitask Prompt Tuning [300] harnesses the knowledge of the various tasks through the use of prompt vectors in a multitask learning setting. Specifically, it initially learns a single, transferable prompt by extracting knowledge from various task-specific source prompts, and then applies multiplicative low-rank updates to this prompt to effectively tailor it for each downstream task. By doing this, Multitask Prompt Tuning is able to attain performance levels that are competitive compared to full fine-tuning methods.

2.3.2 Memory-Efficient Fine-Tuning.

As the parameters of LLMs expand, the sizes of memory needed for fine-tuning also increase, making memory a significant hurdle in fine-tuning. Consequently, minimizing memory usage in fine-tuning for improving efficiency has also emerged as a critical topic. Dettmers et al. [62] propose QLoRA which first quantizes the model into a 4-bit NormalFloat data type, and then fine-tunes this quantized model with added low-rank adapter (LoRA) weights [111]. In doing so, QLoRA reduces memory usage during fine-tuning without performance degradation compared to standard full-model fine-tuning. QA-LoRA [318] improves QLoRA by introducing group-wise operators that improve quantization flexibility (each group is quantized separately) while reducing adaptation parameters (each group utilizes shared adaptation parameters). Similarly, LoftQ [160] combines model quantization with singular value decomposition (SVD) to approximate the original high-precision pre-trained weights. As a result, it offers a favorable initialization point for subsequent LoRA fine-tuning, leading to enhancements over QLoRA. PEQA [133] introduces a two-stage approach to quantization-aware fine-tuning. In the first stage, the parameter matrix for each fully connected layer is quantized into a matrix of low-bit integers along with a scalar vector. In the second stage, the low-bit matrix remains unchanged, while fine-tuning is focused solely on the scalar vector

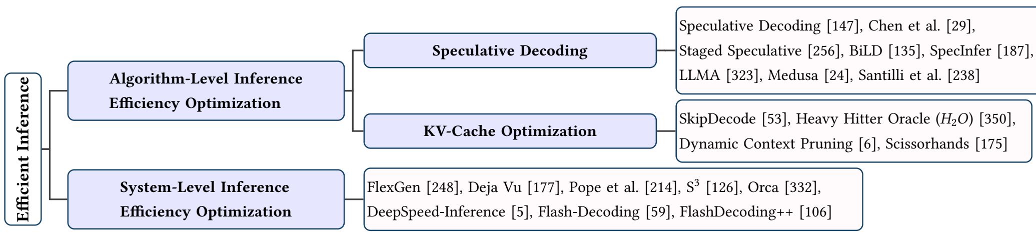
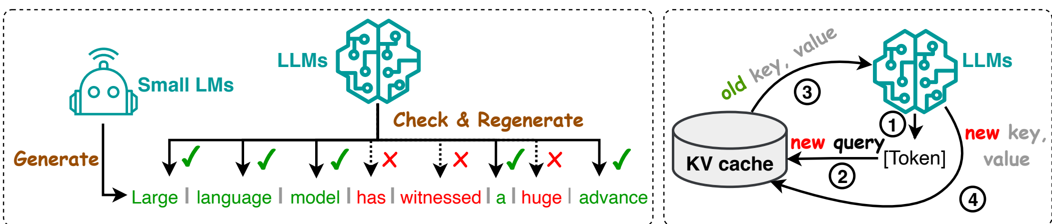


Fig. 10. Summary of efficient inference techniques for LLMs.



(a) Speculative Decoding (b) KV-cache Optimization

Fig. 11. Illustrations of algorithm-level efficiency optimization techniques for LLM inference.

for each specific downstream task. Employing this two-stage approach, PEQA not only minimizes memory usage during fine-tuning but also speeds up inference time by maintaining weights in a low-bit quantized form. Simoulin et al. [252] propose Selective Fine-Tuning which minimizes memory usage by specifically preserving a subset of intermediate activations from the forward pass for which the calculated gradients are nonzero. Notably, this approach delivers performance equivalent to full fine-tuning while using just up to one-third of the GPU memory required otherwise. Lv et al. [182] introduce LOMO, which minimizes memory consumption during fine-tuning by combining gradient calculation and parameter updating into a single step. As such, LOMO eliminates all components of the optimizer state, lowering the memory requirements for gradient tensors to $O(1)$. MeZO [184] improves the zeroth-order method [255] for gradient estimation using only two forward passes. This enables efficient fine-tuning of LLMs with memory requirements similar to inference and supports both full-parameter and PEFT methods like LoRA [111] and prefix tuning [159], enabling MeZO to train a 30-billion parameter model on a single A100 80GB GPU.

2.4 Efficient Inference

Efficient inference aims to enhance the efficiency of the inference process for LLMs. As summarized in Figure 10, efficient inference techniques can be grouped into techniques at the algorithm level and system level.

Algorithm-Level Inference Efficiency Optimization. Techniques that enhance LLM inference efficiency at the algorithm level include speculative decoding and KV-cache optimization.

- ***Speculative Decoding.*** Speculative decoding (i.e., speculative sampling) [147] is a decoding strategy for autoregressive language models that speed up sampling by parallel token computation through using smaller draft models to create speculative prefixes for the larger target model. Chen et al. [29] propose to run a faster autoregressive model K times and then evaluate the preliminary output with the large target LLM. A tailored rejection sampling strategy is employed to approve a selection of the draft tokens in a left-to-right order, thereby recapturing the distribution of the target model during the procedure. Staged Speculative [256] transforms the speculative batch into a tree structure representing potential token sequences. This restructuring aims to expedite the generation of larger and improved speculative batches. It introduces an additional phase for speculative decoding of the initial model, thereby enhancing overall performance. BiLD [135] optimizes speculative decoding through two innovative strategies: the fallback policy that permits the smaller draft model to waive control to the larger target model when it lacks sufficient confidence, and the rollback policy that enables the target model to revisit and rectify any inaccurate predictions made by the smaller draft model. SpecInfer [187] speeds up inference by employing speculative inference techniques and token tree validation. Its core idea involves merging a range of small speculative models that have been fine-tuned collectively to collaboratively forecast the output of the LLM, which is then used to validate all the predictions. LLMA [323] chooses a text segment from a closely related reference and duplicates its tokens into the decoder. It then concurrently assesses the suitability of these tokens as the decoding output within a single decoding step. This approach results in a speed increase of more than two times for LLMs while maintaining the same generated results as traditional greedy decoding. Medusa [24] involves freezing the LLM backbone, fine-tuning additional heads, and using a tree-based attention mechanism to process predictions in parallel to speed up the decoding process. Lastly, Santilli et al. [238] propose parallel decoding including the Jacobi and Gauss-Seidel fixed-point iteration methods for speculative decoding. Among these strategies, Jacobi decoding was extended into Lookahead decoding [81] to enhance the efficiency of LLMs.

- ***KV-Cache Optimization.*** Minimizing the repeated computation of Key-Value (KV) pairs during the inference process of LLMs is also key to enhancing the inference efficiency. Corro et al. [53] propose SkipDecode, a token-level early exit approach that utilizes a unique exit point for each token in a batch at every sequence position, and skips the lower and middle layers to accelerate the inference process. Zhang et al. [350] point out that KV-cache is scaling linearly with the sequence length and batch size. They propose a KV cache eviction strategy that formulates the KV cache eviction as a dynamic sub-modular problem and dynamically retains a balance between recent and important tokens, reducing the latency for LLMs inference. Dynamic Context Pruning [6] utilizes a learnable mechanism to identify and remove non-informative KV-cache tokens. In doing so, it not only enhances efficiency but also improves interpretability. Liu et al. [175] underscore the Persistence of Importance Hypothesis, suggesting that only tokens that were crucial at an earlier phase will have a significant impact on subsequent stages. Based on this theory, they propose Scissorhands that introduces a streamlined algorithm for LLM inference using a compact KV-cache.

System-Level Inference Efficiency Optimization. The efficiency of LLM inference can also be optimized at the system level. For example, FlexGen [248] is a high-throughput inference engine that enables the execution of LLMs on GPUs with limited memory. It uses a linear programming-based search approach to coordinate various hardware, combining the memory and computation from GPU, CPU, and disk. Furthermore, FlexGen quantizes the weights and attention cache to 4 bits, increasing the inference speed of OPT-175B [346] on a single 16GB GPU. Deja Vu [177] presents the notion of contextual sparsity, which is a collection of MLP and attention modules that produce the same result as a dense model, but with fewer components. This technique trains predictors to identify the sparsity and then uses kernel fusion and memory coalescing to speed up the inference process. Pope et al. [214] develop a simple analytical framework to select the best multi-dimensional partitioning methods optimized for TPU v4 slices based on the application

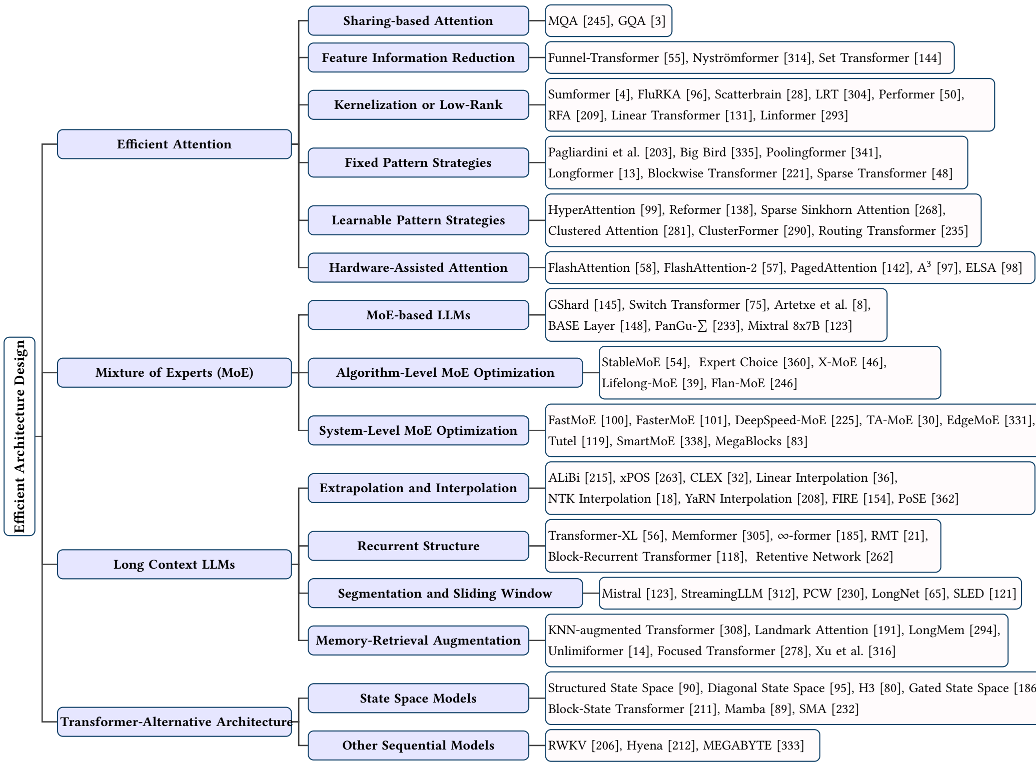


Fig. 12. Summary of efficient architecture designs for LLMs.

requirements. By combining this with some existing low-level optimizations, they have achieved greater efficiency on PaLM [51] in comparison to the FasterTransformer [199] standards. S^3 [126] has created a system that is aware of the output sequence beforehand. It can anticipate the length of the sequence and arrange generation requests accordingly, optimizing the utilization of device resources and increasing the rate of production. Orca [332] employs iteration-level scheduling to decide batch sizes. When a sequence in a batch is completed, it is substituted with a new one, resulting in improved GPU utilization compared to static batching. DeepSpeed-Inference [5] is a multi-GPU inference approach that is designed to enhance the efficiency of both dense and sparse Transformer models when they are contained within the collective GPU memory. Furthermore, it provides a mixed inference technique that utilizes CPU and NVMe memory, in addition to GPU memory and computation, guaranteeing high-throughput inference even for models that are too large to fit in the combined GPU memory. Flash-Decoding [59] is a technique that boosts the speed of long-context inference by breaking down keys/values into smaller pieces, computing attention on these pieces in parallel, and then combining them to generate the final output. FlashDecoding++ [106] supports mainstream language models and hardware backends through asynchronous softmax, double buffering for flat GEMM optimization, and heuristic dataflow, resulting in up to 4.86x and 2.18x acceleration on NVIDIA and AMD GPUs respectively compared to HuggingFace implementations.

2.5 Efficient Architecture Design

Efficient architecture design for LLMs refers to the strategic optimization of model architecture and computational processes to enhance performance and scalability while minimizing resource consumption. Figure 12 summarizes efficient architecture designs for LLMs.

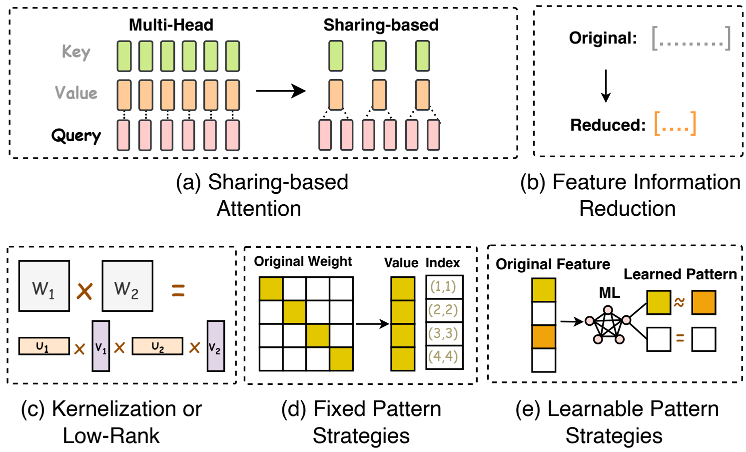


Fig. 13. Illustrations of attention optimizations.

2.5.1 *Efficient Attention*.

The quadratic time and space complexity of attention modules considerably slows down the pre-training, inference and fine-tuning of LLMs [132]. A lot of techniques have been proposed to make attention lightweight for more efficient execution. These techniques can be generally categorized as sharing-based attention, feature information reduction, kernelization or low-rank, fixed pattern strategies, learnable pattern strategies, and hardware-assisted attention.

Sharing-based Attention. Sharing-based attention aims to accelerate attention computation during inference through different KV heads sharing schemes. For example, LLaMA-2 [277] optimizes the autoregressive decoding process by using multi-query attention (MQA) [245] and grouped-query attention (GQA) [3]. In contrast to multi-head attention, which uses several attention layers (heads) simultaneously with distinct linear transformations for queries, keys, values, and outputs, MQA has all its heads sharing one set of keys and values. While MQA utilizes only one key-value head to speed up decoder inference, it might compromise quality. To address this, GQA offers a modified version of MQA by employing more than one key-value heads but fewer than the total number of query heads to enhance the inference quality.

Feature Information Reduction. The principle of feature information reduction, as evidenced by models such as Funnel-Transformer [55], Nyströmformer [314], and Set Transformer [144], is to cut computation demands by reducing feature information within a sequence, which leads to a proportionate reduction in required computation resources. For example, Funnel-Transformer [55] reduces the sequence length of hidden states to decrease computational costs, while its decoder can reconstruct deep representations for each token from this compressed sequence.

Kernelization or Low-Rank. Kernelization or low-rank techniques adopted by models such as Sumformer [4], FluRKA [96], Scatterbrain [28], Low-Rank Transformer (LRT) [304], Performer [50], Random Feature Attention (RFA) [209], Linear Transformer [131], and Linformer [293], , enhance computational efficacy by utilizing low-rank representations of the self-attention matrix or by adopting attention kernelization techniques. Specifically, low-rank methods focus on compacting the dimensions of attention keys and values. For example, Linformer [293] proposes to segment scaled dot-product attention into smaller units via linear projection. Kernelization, a variant of low-rank technique, focuses on approximating the attention matrix [49]. For example, Performer [50] condenses softmax attention-kernels using positive orthogonal random features. Sumformer [4] approximates the equivariant sequence-to-sequence function, offering a universal solution for both Linformer and Performer.

Fixed Pattern Strategies. Fixed pattern strategies adopted by models such as [203], Big Bird [335], Poolingformer [341], Longformer [13], Blockwise Transformer [221], and Sparse Transformer [48] improve efficiency by sparsifying the attention matrix. This is achieved by confining the attention scope to predetermined patterns, such as local windows or fixed-stride block patterns. For instance, Longformer [13]'s attention mechanism, designed as an alternative to conventional self-attention, merges local windowed attention with globally oriented attention tailored to specific tasks. Pagliardini et al. [203] have expanded FlashAttention [58] to support a broad spectrum of attention sparsity patterns, including key-query dropping and hashing-based attention techniques.

Learnable Pattern Strategies. Learnable pattern strategies adopted by models such as HyperAttention [99], Reformer [138], Sparse Sinkhorn Attention [268], Clustered Attention [281], ClusterFormer [290], and Routing Transformer [235] improve efficiency by learning token relevance and subsequently grouping tokens into buckets or clusters. As an example, HyperAttention [99] proposes a parameterization for spectral approximation and employs two key metrics: the maximal column norm in the normalized attention matrix and the row norm ratio in the unnormalized matrix after large entry removal. It also utilizes the learnable sort locality-sensitive hashing (sortLSH) technique and fast matrix multiplication via row norm sampling. Their experiment results show that HyperAttention enhances both inference and training speeds for LLMs with only minimal performance degradation.

Hardware-Assisted Attention. Besides algorithmic approaches that sparsify attentions and thereby streamline the computation of the attention matrix, several studies concentrate on realizing efficient and lightweight attention mechanisms from hardware aspects. For example, FlashAttention [58] and FlashAttention-2 [57] aim to reduce the communication times between GPU high-bandwidth memory (HBM) and GPU on-chip SRAM when calculating the attention module in LLMs. Instead of transmitting the values and results between HBM and SRAM multiple times as is done in the standard attention mechanism, FlashAttention combines all the attention operations into one kernel and tiles the weight matrices into smaller blocks to better fit the small SRAM. As a result, only one communication is required to process each attention block, significantly increasing the efficiency for processing the entire attention block. Inspired by virtual memory and paging techniques, PagedAttention [142] enables the storage of continuous keys and values in non-contiguous memory space. Specifically, PagedAttention divides the KV cache of each sequence into blocks, each containing the keys and values for a fixed number of tokens. During the attention computation, the PagedAttention kernel manages these blocks efficiently by maintaining a block table to reduce memory fragmentation. Specifically, the contiguous logical blocks of a sequence are mapped to non-contiguous physical blocks via the table and the table automatically allocates a new physical block for every newly generated token. This reduces the amount of memory wasted when generating new tokens, thus improving its efficiency. A^3 [97] introduces an innovative candidate selection process that reduces the number of keys and offers a custom hardware pipeline that taps into parallelism to speed up approximated attention techniques, further enhancing their efficiency. ELSA [98] uses Kronecker decomposition to approximate the attention module, which not only reduces its complexity, but also makes it more suitable for parallelization on hardware, thus making it more efficient when used for inference.

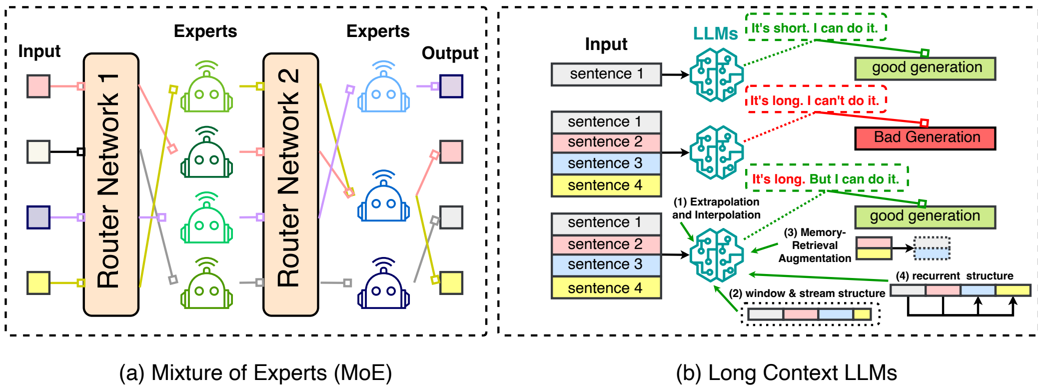


Fig. 14. Illustrations of Mixture of Experts (MoE) and Long Context LLMs.

2.5.2 *Mixture of Experts (MoE).*

Mixture of Experts (MoE) represents a sparse methodology utilized prominently in large-scale models like LLMs. It operates on the principle of segmenting a designated task into several sub-tasks, and then developing numerous smaller, specialized models, dubbed *experts*, with each honing in on a distinct sub-task. Subsequently, these experts collaborate to deliver a consolidated output. For pre-traning or fine-tuning, MoE helps to manage a huge number of parameters efficiently, enhancing the model's capacity and potentially its performance while keeping the computational and memory requirements relatively manageable. For inference, MoE decreases the inference time by not engaging all experts simultaneously, but rather activating only a select few. Additionally, MoE is capable of minimizing communication between devices in model-distributed scenarios by allocating each expert to an individual accelerator; communication is only necessary between the accelerators that host the router and the relevant expert model [128].

MoE-based LLMs. Several MoE-based LLMs have been proposed. For example, GShard [145] is a MoE-based LLM that offers a refined method to articulate a variety of parallel computation frameworks with minor modifications to the existing model code. It also amplifies a multilingual neural machine translation Transformer model with Sparsely-Gated MoE beyond 600 billion parameters through automatic sharding. Switch Transformer [75] brings forth a switch routing algorithm and crafts intuitively enhanced models, lowering communication and computational expenditures. It encompasses up to one trillion parameters, dividing tasks among up to 2,048 experts, thereby illustrating the scalability and efficacy of the MoE framework. Artetxe et al. [8] scale sparse language models to 1.1T parameters, discerning superior performance up to this scale in language modeling, zero-shot and few-shot learning in comparison to dense models. This suggests that sparse MoE models are a computationally efficient substitute for traditionally employed dense architectures. BASE Layer [148] defines token-to-expert allocation as a linear assignment problem, allowing an optimal assignment where each expert acquires an equal number of tokens. PanGu-Σ [233] is a MoE-based LLM with 1.085T parameters, transitioned from the dense Transformer model to a sparse one with Random Routed Experts (RRE), and effectively trains the model over 329B tokens utilizing Expert Computation and Storage Separation (ECSS). Lastly, Mixtral 8x7B [123] is a MoE with 46.7B total parameters. By leveraging the advantage of MoE architecture, Mixtral 8x7B outperforms LLaMA-2 70B on most benchmarks such as MMLU, MBPP, and GSM-8K with 6x faster inference by only using 12.9B parameters of the model per token for inference.

Algorithm-Level MoE Optimization. The efficiency of MoE-based LLMs can be improved at the algorithm level. The technique termed Expert Choice [360] allows experts to pick the top-k tokens instead of having tokens choose the top-k experts, implying that each token can be directed to a variable number of experts while each expert maintains a fixed bucket size. This method demonstrates higher performance in the GLUE and SuperGLUE benchmarks, and outperforms the T5 dense model in 7 out of the 11 tasks. StableMoE [54] identifies the issue of altering target experts for identical input during training and addresses this by creating two training phases. Initially, it cultivates a balanced routing strategy, which is then distilled into a decoupled lightweight router. In the following phase, this distilled router is used for a fixed token-to-expert assignment, ensuring a stable routing strategy. X-MoE [46] notes that earlier routing mechanisms foster token clustering around expert centroids, indicating a tendency toward representation collapse. It proposes to estimate the routing scores between tokens and experts on a low-dimensional hyper-sphere. Lifelong-MoE [39] finds that MoE increases the capacity of the model to adapt to different corpus distributions in online data streams without extra computational cost, simply by incorporating additional expert layers and suitable expert regularization. This facilitates continuous pre-training of a MoE-based LLM on sequential data distributions without losing previous knowledge. Lastly, Flan-MoE [246] promotes the amalgamation of MoE and instruction tuning, observing that MoE models gain more from instruction tuning compared to dense models. In particular, Flan-MoE effectively enlarges language models without demanding an increase in computational resources or memory requirements.

System-Level MoE Optimization. Several system-level optimization techniques have been developed to accelerate the training and inference of MoE-based LLMs. For example, FastMoE [100] is a distributed MoE training system built on PyTorch, compatible with common accelerators. This system offers a hierarchical interface that allows both flexible model design and easy adaptation to various applications, such as Transformer-XL and Megatron-LM. FasterMoE [101] introduces a performance model that predicts latency and analyzes end-to-end performance through a roofline-like methodology. Utilizing this model, it presents a dynamic shadowing technique for load balancing, a concurrent fine-grained schedule for operations, and a strategy to alleviate network congestion by adjusting expert selection for model training. DeepSpeed-MoE [225] has designed a Pyramid-Residual MoE (PR-MoE) to enhance both the training and the inference efficiency of the MoE model parameter. PR-MoE is a dense-MoE hybrid that employs residual connections to optimally utilize experts, managing to reduce the parameter size by up to 3x without sacrificing quality or compute requirements. Additionally, it proposes a distilled variant, Mixture-of-Students (MoS), which can trim model size by up to 3.7x while retaining quality. TA-MoE [30] highlights that current MoE dispatch patterns do not fully leverage the underlying heterogeneous network environment and thus introduces a topology-aware routing strategy for large-scale MoE training that dynamically modifies the MoE dispatch pattern based on the network topology, making it outperform FastMoE, FasterMoE, and DeepSpeed-MoE. EdgeMoE [331] presents an on-device inference engine tailored for MoE-based LLMs. It optimizes memory and computation for inference by distributing the model across different storage levels. Specifically, non-expert model weights are stored directly on the edge device, while expert weights are kept externally and only loaded into the device's memory when necessary. Tutel [119] is a scalable stack for MoE with adaptive parallelism and pipelining features to accelerate training and inference. It employs a consistent layout for MoE parameters and input data, supporting switchable parallelism and dynamic pipelining without any mathematical inconsistencies or tensor migration costs, thus enabling free run-time optimization. SmartMoE [338] focuses on distributed training for MoE. In the offline stage, SmartMoE constructs a search space of hybrid parallelism strategies. In the online stage, it incorporates light-weight algorithms to identify the optimal parallel strategy. Lastly, MegaBlocks [83] transforms MoE-oriented computation with block-sparse operations and creates block-sparse GPU kernels to optimize MoE computation on hardware. This leads to training time up to 40% faster compared to Tutel and 2.4x faster than dense DNNs trained with Megatron-LM.

2.5.3 *Long Context LLMs*.

In many real-world applications, such as multi-turn conversations and meeting summarization, existing LLMs are often required to comprehend or generate context sequences that are much longer than what they have been pre-trained with and may result in a degragation in accuracy due to the poor memorization for the long context. The most obvious and direct way to address this issue is to fine-tune LLMs with similar long-sequence data, which is time consuming and computation intensive. Recently, various new methods have been developed to enable LLMs to adapt to longer context lengths in a more efficient way, including extrapolation and interpolation, recurrent structure, window segment and sliding structure, and memory-retrieval augmentation.

Extrapolation and Interpolation. Standard positional encoding methods like absolute positional embeddings (APE) [280], learned positional embeddings (LPE) [286], relative positional embeddings (RPE) [244], relative positional bias [224], and rotary position embeddings (RoPE) [259] have advanced the integration of positional information in LLMs. For example, LPE has been used by GPT-3 [20] and OPT [346]; RPE was used by Gopher [223] and Chinchilla [105], whereas RoPE was used by LLaMA-1 and GLM-130B. However, it is still challenging to train LLMs on sequences with a limited maximum length while still ensuring them to generalize well on significantly longer sequences during inference. Given that, techniques based on positional extrapolation [32, 215, 263] and positional interpolation [36, 154, 208] have been proposed.

Positional extrapolation strategies extend the encoding of positional information beyond what the model has explicitly learned during training. For example, ALiBi [215] applies attention with linear biases to attain extrapolation for sequences that exceed the maximum length seen during training. Through applying negatively biased attention scores, with a linearly diminishing penalty based on the distance between the pertinent key and query, as opposed to using position embeddings, it can facilitate efficient length extrapolation. Different from ALiBi [215], xPOS [263] characterizes attention resolution as a marker for extrapolation and utilizes a relative position embedding to enhance attention resolution, thereby improving length extrapolation. However, these techniques have not been implemented in some of the recent LLMs such as GPT-4 [200], LLaMA [276], or LLaMA-2 [277]. CLEX [32] proposes to generalize position embedding scaling with ordinary differential equations to model continuous dynamics over length scaling factors. By doing so, CLEX gets rid of the limitations of existing positional extrapolation scaling methods to enable long-sequence generation.

Positional interpolation strategies, on the other hand, reduce the scale of input position indices and extend the context window sizes, allowing LLMs to maintain their performance over longer text sequences. For example, Chen et al. [36] highlight that extending beyond the trained context length might impair the self-attention mechanism. They suggest a method that reduces the position indices through linear interpolation, aligning the maximum position index with the prior context window limit encountered during the pre-training phase. NTK interpolation [18] modifies the base of the RoPE, effectively changing the rotational velocity of each RoPE dimension. YaRN interpolation [208] uses a ramp function to blend linear and NTK interpolation in varying proportions across dimensions and incorporates a temperature factor to counteract distribution shifts in the attention matrix due to long inputs. FIRE [154] proposes a functional relative position encoding using learnable mapping of input positions to biases and progressive interpolation, ensuring bounded input for encoding functions across all sequence lengths to enable length generalization. PoSE [362] proposes positional skip-wise training that smartly simulates long inputs using a fixed context window and design distinct skipping bias terms to manipulate the position indices of each chunk. This strategy reduces memory and time overhead compared with full-length fine-tuning.

Recurrent Structure. LLMs' ability to manage long sequences can also be enhanced through recurrence structure. For example, Transformer-XL [56] presents a segment-level recurrence mechanism and utilizes enhanced relative positional encoding to capture long-term dependencies and address the long-context fragmentation issue. Memformer [305] leverages an external dynamic memory for encoding and retrieving past information, achieving linear time and constant memory space complexity for long sequences. It also proposes Memory Replay Back-Propagation (MRBP) to facilitate long-range back-propagation through time with significantly lower memory requirements. ∞-former [185] presents a Transformer model augmented with unbounded long-term memory (LTM), employing a continuous space attention framework to balance the quantity of information units accommodated in memory against the granularity of their representations. Recurrent Memory Transformer (RMT) [21] uses a recurrence mechanism to retain information from the past segment level by incorporating special memory tokens into the input or output sequence, demonstrating superior performance compared to Transformer-XL in long context modeling. Block-Recurrent Transformers [118] utilize self-attention and cross-attention to execute a recurrent function across a broad set of state vectors and tokens so as to model long sequences through parallel computation. Lastly, Retentive Network [262] introduces a multi-scale retention mechanism as an alternative to multi-head attention. By encompassing parallel and chunk-wise recurrent representations, it results in effective scaling, allows for parallel training, and achieves training parallelization and constant inference cost, while offering linear long-sequence memory complexity compared to other Transformer models.

Segmentation and Sliding Window. Segmentation and sliding window techniques tackle the issue of long-context processing by dividing the input data into smaller segments, or applying a moving window to slide through the long sequence. For instance, Mistral [123] uses sliding window attention to effectively handle sequences of arbitrary length with a reduced inference cost. StreamingLLM [312] identifies an attention sink phenomenon, noting that retaining the Key-Value of initial tokens significantly restores the performance of window attention. Based on this observation, it suggests an efficient framework via merging window context and the first token, allowing LLMs trained with a finite length attention window, but have the ability to generalize to infinite sequence lengths without any fine-tuning. Parallel Context Windows (PCW) [230] segments a long context into chunks, limiting the attention mechanism to function only within each window, and then redeploys the positional embeddings across these windows. LongNet [65] proposes dilated attention, which exponentially expands the attentive field as the distance increases, enabling the handling of sequence lengths of more than 1 billion tokens. LongNet can be implemented by parallelizing training by partitioning the sequence dimension. SLED [121] is a straightforward method for handling long sequences that repurposes and capitalizes on well-validated short-text language models for use in LLMs.

Memory-Retrieval Augmentation. Several studies tackle the inference of extremely long text by employing memory-retrieval augmentation strategies. A notable example is the KNN-augmented Transformer [308], which extends the attention context size by utilizing k-nearest-neighbor (KNN) lookup to fetch previously similar context embeddings. Landmark Attention [191] employs a landmark token to represent each block of input and trains the attention mechanism to utilize it for choosing relevant blocks. This allows the direct retrieval of blocks through the attention mechanism while maintaining the random access flexibility of the previous context, demonstrating impressive performance on LLaMA-1 for long-context modeling. LongMem [294] proposes a decoupled network architecture with the original backbone LLM as a memory encoder and an adaptive residual side network as a memory retriever and reader, efficiently caching and updating long-term past contexts to prevent knowledge staleness. Unlimiformer [14] enhances the KNN-augmented Transformer by outputting attention dot-product scores as KNN distances, enabling the indexing of virtually unlimited input sequences. Focused Transformer (FoT) [278] highlights that the ratio of relevant keys to irrelevant ones diminishes as the context length increases and proposes an optimized solution through contrastive learning to refine the structure of the key-value space. Lastly, Xu et al. [316] discover that an LLM with a 4K context window, when augmented with simple retrieval during generation, can match the performance of a fine-tuned LLM with a 16K context window using positional interpolation [36] on long context tasks, while requiring significantly less computation.

2.5.4 *Transformer-Alternate Architectures*.

While Transformer-based architectures are now at the forefront of LLMs, some studies propose new architectures to supplant Transformer-based architectures.

State Space Models. A promising approach that aims to substitute the attention mechanism is state space models (SSMs). SSM is formulated as $x'(t) = Ax(t) + Bu(t)$, $y(t) = Cx(t) + Du(t)$, which maps a single-dimension input signal $u(t)$ to an N-dimension latent state $x(t)$ before projecting to a single-dimension output signal $y(t)$, where A, B, C, D are parameters learned by gradient descent [90]. Compared to attention that has quadratic complexity, SSMs provide near-linear computational complexity relative to the length of the sequence. Given such advantage, a series of techniques have been proposed to improve SSMs. For example, the Structured State Space sequence model (S4) [90] refines SSMs by conditioning matrix A with a low-rank correction. This enables stable diagonalization and simplifies the SSM to the well-studied computation of a Cauchy kernel. Diagonal State Space (DSS) [95] improves SSMs by proposing fully diagonal parameterization of state spaces instead of a diagonal plus low rank structure, demonstrating greater efficiency. To bridge the gap between SSMs and attention while adapting to modern hardware, H3 [80] stacks two SSMs to interact with their output and input projection, allowing it to log tokens and facilitate sequence-wide comparisons simultaneously. Mehta et al. [186] introduce a more efficient layer called Gated State Space (GSS), which has been empirically shown to be 2-3 times faster than the previous strategy [95] while maintaining the perplexity on multiple language modeling benchmarks. Block-State Transformer (BST) [211] designs a hybrid layer that combines an SSM sublayer for extended range contextualization with a Block Transformer sublayer for short-term sequence representation. Gu and Dao [89] propose Mamba to enhance SSMs by designing a selection mechanism to eliminate irrelevant data and developed a hardware-aware parallel algorithm for recurrent operation, achieving 5x higher throughput than Transformers. Ren et al. [232] propose a general modular activation mechanism, Sparse Modular Activation (SMA), that unifies previous works on MoE, adaptive computation, dynamic routing and sparse attention, and further applies SMA to develop a novel architecture, SeqBoat, to achieve state-of-the-art quality-efficiency trade-off.

Other Sequential Models. Lastly, some other architectures have been proposed to replace the Transformer layer. Receptance Weighted Key Value (RWKV) model [206] amalgamates the advantages of recurring neural networks (RNN) and Transformers. This combination is designed to utilize the effective parallelizable training feature of Transformers coupled with the efficient inference ability of RNNs, thereby forging a model adept at managing auto-regressive text generation and effectively tackling challenges associated with long sequence processing. Poli et al. [212] propose Hyena, a sub-quadratic alternative to the attention mechanism, mitigating the quadratic cost in

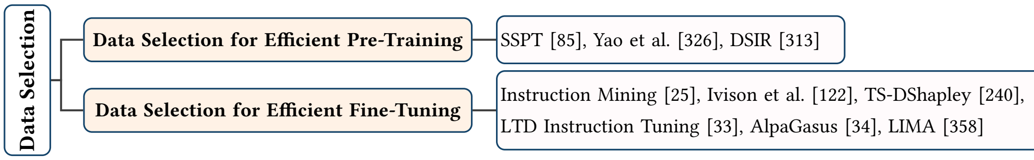


Fig. 15. Summary of data selection techniques for LLMs.

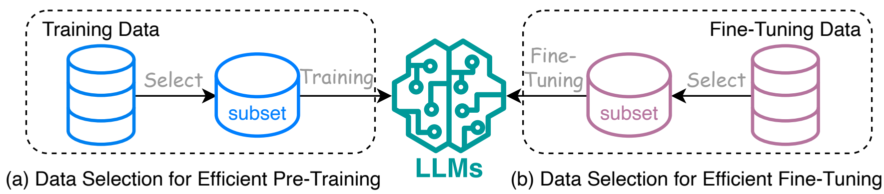


Fig. 16. Illustrations of data selection techniques for LLMs.

long sequences. This operator includes two efficient sub-quadratic primitives: an implicit long convolution and multiplicative element-wise gating of the input. Through this, Hyena facilitates the development of larger, more efficient convolutional language models for long sequences. Lastly, MEGABYTE [333] breaks down long byte sequences into fixed-sized patches akin to tokens, comprising a patch embedder for encoding, a global module acting as a large autoregressive Transformer for patch representations, and a local module for predicting bytes within a patch.

3 DATA-CENTRIC METHODS

3.1 Data Selection

Data selection for LLMs involves carefully selecting the most informative and diverse examples so that the model can efficiently capture essential patterns and features, accelerating the learning process [85, 237, 313, 326]. Figure 15 summarizes the latest data selection techniques for efficient LLM pre-training and fine-tuning.

*3.1.1 **Data Selection for Efficient Pre-Training**.*

Data selection enhances LLMs pre-training efficiency by allowing the model to focus on the most informative and relevant examples during training. By carefully curating a subset of representative data, the model can extract essential patterns and features, leading to a more efficient acquisition of generalized knowledge. For example, SSPT [85] is a pre-training task based on the principles of reading comprehension. It involves selecting answers from contextually relevant text passages, which has shown notable improvements in performance across various Machine Reading Comprehension (MRC) benchmarks. Yao et al. [326] propose a meta-learning-based method for the selection of linguistically informative sentences which significantly elevates the quality of machine-generated translations. Xie et al. [313] propose DSIR, a data selection method based on importance re-sampling for both general-purpose and specialized LLMs. It calculates how important different pieces of data are within a simpler set of features and chooses data based on these importance calculations.

*3.1.2 **Data Selection for Efficient Fine-Tuning**.*

Data selection can also boost fine-tuning efficiency since only a curated subset of examples is employed to refine the model. This approach ensures that the adaptation process is conducted

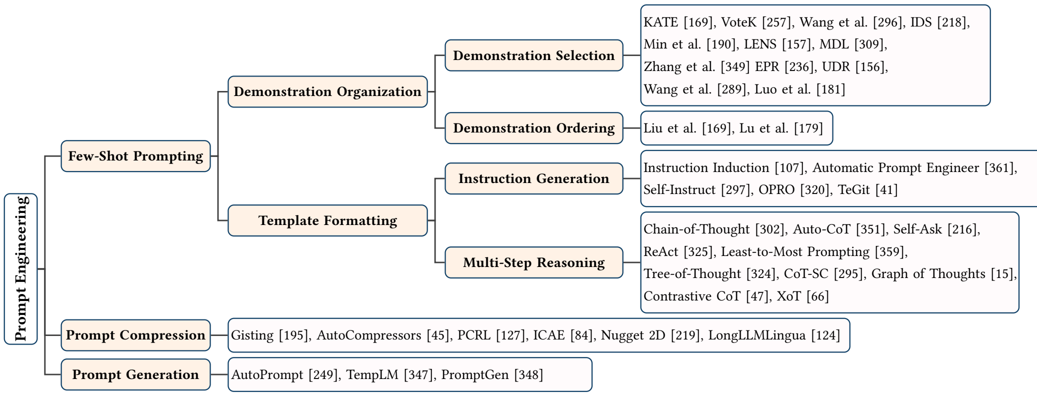


Fig. 17. Summary of prompt engineering techniques for LLMs.

with a focus on the specific nuances intrinsic to the target domain or task, making the fine-tuning process more efficient. For example, Instruction Mining [25] presents a linear evaluation method to assess data quality in instruction-following tasks. It highlights the importance of high-quality data, showing that models trained with Instruction Mining-curated datasets outperform those trained on generic datasets in 42.5% of cases. This underscores the significance of data quality and lays the groundwork for future improvements in instruction-following model efficacy. Ivison et al. [122] propose to use a few unlabeled examples to retrieve similar labeled ones from a larger multitask dataset, improving task-specific model training. This method outperforms standard multitask data sampling for fine-tuning and enhances few-shot fine-tuning, yielding a 2-23% relative improvement over current models. TS-DShapley [240] is introduced to address the computational challenges of applying Shapley-based data valuation to fine-tuning LLMs. It employs an efficient sampling-based method that aggregates Shapley values computed from subsets to evaluate the entire training set. Moreover, it incorporates a value transfer method that leverages information from a simple classifier trained using representations from the target language model. Low Training Data Instruction Tuning (LTD Instruction Tuning) [33] challenges the need for large datasets in fine-tuning, showing that less than 0.5% of the original dataset can effectively train task-specific models without compromising performance. This approach enables more resource-efficient practices in data-scarce environments, combining selective data strategies with tailored training protocols for optimal data efficiency. AlpaGasus [34] is a model fine-tuned on a mere 9k high-quality data points, which are meticulously filtered from a larger dataset of 52k. It outperforms the original model trained on the full dataset and reduces training time by 5.7x, demonstrating the power of high-quality data in instruction-fine-tuning. LIMA [358] fine-tunes LLMs with a small, selected set of examples, showing strong performance and challenging the need for extensive tuning. It generalizes well to new tasks and, in comparisons, matches or exceedes GPT-4 in 43% of cases, suggesting that LLMs gain most knowledge in pre-training, requiring minimal instruction tuning.

3.2 Prompt Engineering

Prompt engineering [170] focuses on designing effective inputs (i.e., prompts) to guide LLMs in generating desired outputs. It enhances inference efficiency by tailoring the input prompts or queries to better suit the capabilities and nuances of a specific language model. When used for some simple tasks, such as semantic classification, prompt engineering can even substitute fine-tuning to achieve high accuracy [167]. As summarized in Figure 17, prompt engineering techniques can be grouped into few-shot prompting, prompt compression, and prompt generation.

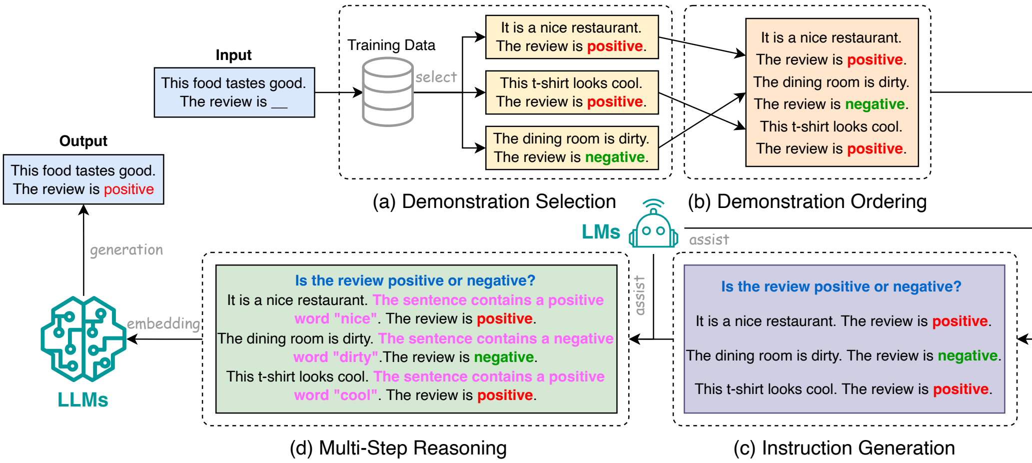


Fig. 18. Illustrations of few-shot prompting techniques for LLMs.

3.2.1 ***Few-Shot Prompting***.

Few-shot prompting involves providing a LLM with a limited set of examples (i.e., demonstrations) to steer its understanding to a task it is required to execute [301]. These demonstrations are selected from the LLM's training corpus based on their similarity to the test example, and the LLM is expected to use the knowledge gained from these similar demonstrations to make the correct prediction [67]. Few-shot prompting provides an efficient mechanism to use LLM by guiding the LLM to perform a wide variety of tasks without the need for additional training or fine-tuning. Furthermore, an effective few-shot prompting approach can make the created prompt concise enough to allow LLMs to quickly adjust to the task in high accuracy with only a slight increase of extra context, thus significantly improving inference speed. As illustrated in Figure 18, few-shot prompting techniques can generally be grouped into demonstration selection, demonstration ordering, instruction generation, and multi-step reasoning.

Demonstration Organization. Demonstration organization refers to organizing the demonstrations in an appropriate way so as to form a suitable prompt for inference. Demonstration organization has a significant impact on the inference speed. Improper organization may result in the processing of a considerable amount of unnecessary information, leading to significant slowdown. The main challenges of demonstration organization come from two perspectives: demonstration selection and demonstration ordering.

- ***Demonstration Selection.*** Demonstration selection aims to choose the good examples for few-shot prompting [67]. In order to generate a satisfactory result, a good selection of demonstrations may only require a few number of demonstrations to be used for the prompt, thus making the prompt concise and straightforward for a more efficient inference. Existing demonstration selection techniques can be grouped into unsupervised methods [157, 169, 190, 218, 257, 296, 309, 349] and supervised methods [156, 181, 236, 289]. Unsupervised methods aim to select the nearest examples from the training set using a predefined similarity function, such as L2 distance, cosine distance, and the minimum description length (MDL) [309]. For example, KATE [169] is an unsupervised selection method that directly uses the nearest neighbors of a given test sample as the corresponding demonstrations. VoteK [257] is an improved version of KATE to resolve its limitation that requires a large set of examples to achieve good performance. Unlike KATE, VoteK increases the diversity of the demonstrations by penalizing examples similar to those already selected. In comparison, supervised methods require training a domain-specific retriever from the training set and using it for demonstration selection. For example, EPR [236] is trained to select demonstrations from a small set of candidates initialized by the unsupervised retriever such as BM25 from the training corpse. UDR [156] further enhances EPR by adopting a unified demonstration retriever to unify the demonstration selection across different tasks. Compared to unsupervised methods, supervised methods often lead to a more satisfying generation result but require frequent adjustment of the retriever for handling the out-of-domain data, making them less efficient for inference.

- ***Demonstration Ordering.*** After selecting representative samples from the training set, the next step is ordering these samples in the prompt. The order of the demonstrations also has a significant impact on the performance of the model. Therefore, selecting the right order of demonstrations can help the model quickly reach a good generation quality with fewer samples, thus improving the inference efficiency. To date, only a few studies have delved into this area. For example, Liu et al. [169] suggest arranging demonstrations based on their distance from the input, placing the closest demonstration furthest to the right. Lu et al. [179] propose to develop both global and local entropy metrics and use the entropy metrics to set up the demonstration order.

Template Formatting. Template Formatting aims to design a suitable template to form the prompt. A good template typically compiles all the information needed by LLMs into a brief statement, making the prompt and the entire input context as succinct as possible, thus guaranteeing a higher inference efficiency. Template formatting design can be divided into two parts: instruction generation and multi-step reasoning.

- ***Instruction Generation.*** The instruction of the template refers to a short description of the task. By adding instructions to the prompt, LLMs can quickly understand the context and the task they are currently performing, and thus may require fewer demonstrations to create a desirable prompt. The performance of a given task is highly affected by the quality of the instructions. The instructions vary not only between different datasets for the same task but also between different models. Unlike demonstrations that are usually included in traditional datasets, the generation of instructions is heavily dependent on human efforts. To enhance the efficiency of instruction generation, automatic instruction generation techniques have been proposed. For example, Instruction Induction [107] and Automatic Prompt Engineer [361] have demonstrated that LLMs can generate task instructions. Wang et al. [297] propose Self-Instruct, an approach that allows LLMs to align with self-generated instructions, highlighting their inherent adaptability. Yang et al. [320] also discover that LLMs can be treated as an optimizer to iteratively generate better instructions for the target LLM and have applied this technique to various LLMs. Chen et al. [41] develop TeGit for training language models as task designers, which can automatically generate inputs and outputs together with high-quality instructions to better filter the noise based on a given human-written text for fine-tuning LLMs. Despite the promise of automatic instruction generation methods, their complexity is still a major bottleneck for their real-world adoption.
- ***Multi-Step Reasoning.*** Guiding the LLMs to produce a sequence of intermediate steps before outputting the final answer can greatly improve the quality of the generation. This technique is also referred to as Chain-of-Thought (CoT) prompting [302]. Rather than repeatedly choosing a few exemplary examples to make the context and task more understandable to the LLMs, CoT only concentrates on a limited number and adds the details for contemplation into the context, making the prompt more comprehensive and effective and guaranteeing

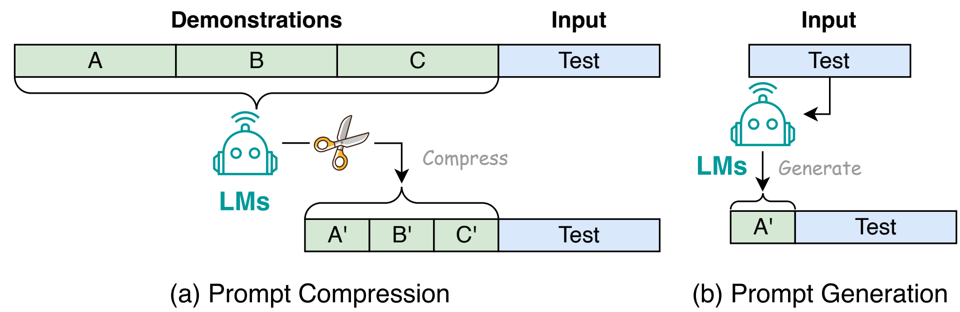


Fig. 19. Illustrations of Prompt Compression (a) and Prompt Generation (b) for LLMs.

a more efficient inference. However, despite the advantages of CoT, it is still difficult to ensure the accuracy of every intermediate step [67]. Given that, many techniques have been proposed to address this issue. For example, Auto-CoT [351] proposes to generate the CoT step by step from LLMs. Self-Ask [216] incorporates the self-generated question of each step into the CoT. ReAct [325] performs dynamic reasoning to create, maintain, and adjust high-level plans for acting, while interacting with external environments to incorporate additional information into reasoning. Least-to-Most Prompting [359] breaks down the complex question into smaller ones and answers them iteratively within the context of former questions and answers. Tree-of-Thought (ToT) [324] expends CoT to include exploration over coherent units of text and deliberates decision-making processes. CoT-SC [295] introduces a novel decoding approach called "self-consistency" to replace the simplistic greedy decoding in CoT prompting. It starts by sampling various reasoning paths instead of just the greedy one and then determines the most consistent answer by considering all the sampled paths. Graph of Thoughts (GoT) [15] represent information produced by an LLM as a generic graph, with "LLM thoughts" as vertices and edges indicating dependencies between these vertices. Contrastive CoT [47] proposes contrastive chain of thought to enhance language model reasoning by providing both valid and invalid reasoning demonstrations. Lastly, XoT [66] utilizes pretrained reinforcement learning and Monte Carlo Tree Search (MCTS) to integrate external domain knowledge into LLMs' thought processes, thereby boosting their ability to efficiently generalize to new, unseen problems.

3.2.2 ***Prompt Compression.***

Prompt compression (Figure 19(a)) accelerates the processing of LLM inputs through either condensing lengthy prompt inputs or learning compact prompt representations. Mu et al. [195] propose to train LLMs to distill prompts into a more concise set of tokens, referred to as gist tokens. These gist tokens encapsulate the knowledge of the original prompt and can be stored for future use. In doing so, it is able to compress prompts by up to 26 times, leading to a reduction in floating-point operations per second (FLOPs) by up to 40%. Chevalier et al. [45] propose AutoCompressors to condense long textual contexts into compact vectors, known as summary vectors, which can then be used as soft prompts for the language model. These summary vectors extend the model's context window, allowing it to handle longer documents with much less computational cost. Jung and Kim [127] propose Prompt Compression with Reinforcement Learning (PCRL) that employs a policy network to directly edit prompts, aiming to reduce token count while preserving performance. It achieves an average reduction of 24.6% in token count across various instruction prompts. Ge et al. [84] propose In-context Autoencoder (ICAE), which consists of a learnable encoder and a fixed decoder. The encoder compresses a long context into a limited number of memory slots, which the target language model can then condition on. With such design, ICAE is able to obtain 4x context compression. Nugget 2D [219] represents the historical context as compact "nuggets" that are trained to enable reconstruction. Furthermore, it has the flexibility to be initialized using readily available models like LLaMA. Lastly, LongLLMLingua [124] introduces a prompt compression technique containing question-aware coarse-to-fine compression, document reordering, dynamic compression ratios, and post-compression sub-sequence recovery to enhance LLMs' key information perception.

3.2.3 ***Prompt Generation***.

Prompt generation (Figure 19(b)) enhances the efficiency by automatically creating effective prompts that guide the model in generating specific and relevant responses instead of manual annotated data. AutoPrompt [249] proposes an automated method to generate prompts for a diverse set of tasks based on a gradient-guided search. It underscores the significance of human-written text in refining the quality and authenticity of data, emphasizing its pivotal role in optimizing LLM performance. TempLM [347] proposes to combine generative and template-based methodologies to distill LLMs into template-based generators, offering a harmonized solution for data-to-text tasks. PromptGen [348] is the first work considering dynamic prompt generation for knowledge probing, based on a pre-trained LLMs. It can automatically generate prompts conditional on the input sentence and outperforms AutoPrompt on the on the LAMA benchmark.

4 LLM FRAMEWORKS

DeepSpeed. Developed by Microsoft, DeepSpeed [229] is an integrated framework for both training and deploying LLMs. It has been used to train large models like Megatron-Turing NLG 530B [253] (in a joint effort with Nvidia Megatron framework) and BLOOM [239]. Within this framework, DeepSpeed-Inference is the foundational library. A pivotal feature of this module is ZeRO-Inference [226, 228], an optimization technique created to address GPU memory constraints for large model inference. ZeRO-Inference distributes model states across multiple GPUs and CPUs, providing an approach to managing the memory constraints of individual nodes. Another aspect of DeepSpeed-Inference is its deep fusion mechanism, which allows for the fusion of operations without the necessity for global synchronization by tiling computations across iteration space dimensions [149, 180, 231, 266]. Building on this, the DeepSpeed Model Implementations for Inference (DeepSpeed MII) module provides strategies for the deployment and management of popular deep learning models. Emphasizing performance, flexibility, and cost-efficiency, DeepSpeed MII incorporates advanced optimization techniques to improve model inference [228, 306, 329]. Furthermore, the introduction of DeepSpeed-Chat [328] adds chat support to the ecosystem. This module focuses on training chatbot models across different scales, integrating techniques from Reinforcement Learning from Human Feedback (RLHF) [88] with the DeepSpeed training system. Notably, its integration of the ZeRO-Offload optimizer [231] facilitates training on both CPUs and GPUs, irrespective of their memory capacities.

Megatron. Megatron [250] constitutes Nvidia's efforts to streamline training and deployment of LLMs such as GPT [222] and T5 [224]. It is the underlying framework used for Nvidia's Megatron models [140, 197, 250]. Megatron encompasses various specialized tools and frameworks for Nvidia GPUs. Central to Megatron's design is the strategic decomposition of the model's tensor operations, distributed across multiple GPUs, to optimize both processing speed and memory utilization, thus enhancing training throughput without compromising model fidelity [250]. Megatron also uses

Table 2. Comparison of LLM frameworks.

Framework	Training	Fine-Tuning	Inference	Features
DeepSpeed	✓	✓	✓	Data Parallelism, Model Parallelism, Pipeline Parallelism, Prompt Batching, Quantisation, Kernel Optimizations, Compression, Mixture of Experts.
Megatron	✓	✓	✓	Data Parallelism, Model Parallelism, Pipeline Parallelism, Prompt Batching, Automatic Mixed precision, Selective activation Recomputation
Alpa	✓	✓	✓	Data Parallelism, Model Parallelism, Pipeline Parallelism, Operator Parallelism, Automated Model-Parallel Training, Prompt Batching
Colossal AI	✓	✓	✓	Data Parallelism, Model Parallelism, Pipeline Parallelism, Mixed Precision Training, Gradient accumulation, heterogeneous Distributed Training, Prompt Batching, Quantization
FairScale	✓	✓	✓	Data Parallelism, Model Parallelism, Pipeline Parallelism, Activation Checkpointing, Model Offloading, Model scaling, Adascale Optimization
Pax	✓	✓	✓	Data Parallelism, Model Parallelism, Kernel Optimization
Composer	✓	✓	✓	Fully Sharded Data Parallelism, Elastic sharded checkpointing, Flash Attention
vLLM	✗	✗	✓	Data Parallelism, Model Parallelism, Tensor Paralellism, Efficient management via PagedAttention, Optimized CUDA kernels, Dynamic Batching, Quantization
OpenLLM	✗	✓	✓	Distributed Finetuning and Inference, Integration with BentoML, LangChain, and Transformers Agents, Prometheus Metrics, Token Streaming
Ray LLM	✗	✗	✓	Distributed Inference, Integration with Alpa, Prompt Batching, Quantization, Prometheus Metrics
MLC LLM	✗	✗	✓	Distributed Inference, Compiler Acceleration, Prompt Batching, Quantization
Sax	✗	✗	✓	Distribute Inference, Serves PaxML, JAX, and PyTorch models, Slice Serving, Prometheus Metrics
Mosec	✗	✗	✓	Distribute Inference, Dynamic Batching, Rust-based Task Coordinator, Prometheus Metrics
LLM Foundry	✗	✗	✓	Distribute Inference, Dynamic Batching, Prompt Batching

FasterTransformer [199] for optimizing the inference process for large Transformer models. Furthermore, FasterTransformer is used for handling varying precision modes like FP16 and INT8, catering to diverse operational needs. The system also incorporates algorithms tailored to specific GPU architectures like Turing and Volta, emphasizing performance optimization [199]. Finally, Megatron uses TensorRT-LLM which provides developers with advanced tools and optimizations specifically tailored for LLMs, aiming to significantly reduce latency and enhance throughput for real-time applications. Notably, TensorRT-LLM integrates optimized kernels from FasterTransformer [275] and employs tensor parallelism, facilitating efficient inference at scale across multiple GPUs and servers without necessitating developer intervention or model changes.

Alpa. Alpa [356] is a library for training and serving large-scale neural networks. Alpa strategically addresses both inter- and intra-operator parallelism, aiming for a holistic enhancement in distributed deep learning performance. It has example implementations of GPT-2 [222], BLOOM [239], OPT [346], CodeGen [198] among others. At the core of Alpa's methodology is its automatic parallelization. By deploying an auto-tuning framework, Alpa dynamically identifies the optimal parallelism strategy tailored to specific deep learning models and hardware configurations. Furthermore, Alpa showcases an integrated design that combines both data and model parallelism [162, 364]. By doing so, Alpa harnesses the collective benefits of these parallelism techniques, leading to optimized resource utilization and enhanced training throughput during serving.

ColossalAI. ColossalAI [152] is a framework tailored to address the challenges of large-scale distributed training [284]. ColossalAI provides a unified solution that harmonizes scalability, efficiency, and versatility. It has implementations for LLaMA [277], GPT-3 [20], GPT-2 [222], BERT [64], PaLM, OPT [346], ViT [68]. Central to Colossal-AI's design is its emphasis on holistic integration. By amalgamating various components of deep learning pipelines, from data preprocessing to model training and validation, ColossalAI provides a streamlined platform that reduces fragmentation and enhances workflow efficiency [16]. This integrated approach mitigates the complexities often associated with orchestrating large-scale training in distributed environments. Furthermore, recognizing the dynamic landscape of deep learning research and applications, the system is architected to be inherently modular [38]. In addition, the framework integrates several other advanced optimization techniques [16, 73, 74, 153, 174, 285] and features like quantization, gradient accumulation, and mixed precision. By leveraging state-of-the-art algorithms and methodologies, Colossal-AI seeks to optimize both computational and communication overheads inherent in parallel training, leading to reduced training times and enhanced model performance.

FairScale. Developed by Meta, FairScale [72] is an extension library to PyTorch, dedicated to high-performance and large-scale training initiatives. The ethos of FairScale is rooted in three fundamental principles: usability, which emphasizes the ease of understanding and utilization of FairScale's APIs aiming to minimize cognitive overhead for users; modularity, which endorses a seamless amalgamation of multiple FairScale APIs within the users' training loops, thus promoting flexibility; and performance, which is centered around delivering optimal scaling and efficiency through FairScale's APIs. Additionally, FairScale provides support for Fully Sharded Data Parallel (FSDP) as the preferred method for scaling the training operations of extensive neural networks. It is therefore a powerful tool for distributed training and inference. Additionally, it has key features for training in resource-constrained systems providing support for activation checkpointing, efficient model offloading, and scaling.

Pax. Developed by Google, Pax [9] is a JAX-based efficient distributed training framework. Pax has been used to train PaLM-2 [7] and Bard [109]. It targets scalability and has reference examples for large model training, including across modalities (such as text, vision, speech, etc.). It is heavily integrated with JAX and uses many libraries in the JAX ecosystem. Pax contains many key components, including SeqIO to handle sequential data processing, Optax for optimization, Fiddle for configuration, Orbax for checkpointing, PyGLove for automatic differentiation, and Flax for creating high-performance neural networks.

Composer. Designed by Mosaic ML, Composer [193] is aimed at making the training of neural networks faster and more efficient. It has been used to train Mosaic ML's MPT 7B and MPT 30B models and Replit's Code V-1.5 3B. The library is built on top of PyTorch and provides a collection of speedup methods that users can incorporate into their own training loops or use with the Composer trainer for a better experience. It supports FSDP for efficient parallelism, elastic shared checkpointing for robust intermittent training, and a dataset streaming implementation allowing to download datasets from cloud blob storage on the fly during training. Composer is therefore designed to be versatile with a Functional API for integrating methods directly into its training loops, as well as a Trainer API which automatically implements a PyTorch-based training loop, reducing the workload for ML developers.

vLLM. vLLM [142] represents a methodological shift in the approach to serving LLMs. Central to vLLM's design is PagedAttention, a mechanism that segments the attention key and value (KV) cache for a set number of tokens. Unlike contiguous space storage, PagedAttention's blocks for the KV cache are stored flexibly, akin to the virtual memory management. This facilitates memory sharing at a block level across various sequences tied to the same request or even different requests, thus enhancing memory management efficiency in handling attention mechanisms. It also allows on-demand buffer allocation, while also eliminating external fragmentation as the blocks are uniformly sized. Furthermore, vLLM incorporates an adaptive loading technique. This technique, rooted in heuristic methodologies, discerns the number of pages to be loaded into memory based on the input. Complementing this, vLLM integrates a parameter compression strategy as well. By storing model parameters in a compressed state and decompressing them during real-time serving, vLLM further optimizes memory usage. Additionally, vLLM supports state-of-the-art quantization techniques and optimized CUDA kernels supporting fast model execution. The library also added support for AMD's ROCm GPUs. vLLM is therefore, not only a useful tool for distributed training, it can also handle efficient high-throughput model serving workloads.

OpenLLM. OpenLLM [210] delineates a comprehensive approach to the deployment and operation of LLMs within production environments. Anchored within the BentoML ecosystem, OpenLLM is crafted to bridge the gap between the training of LLMs and their seamless integration into real-world applications. A defining characteristic of OpenLLM is its emphasis on modularity and scalability. Recognizing the diverse needs of production environments, OpenLLM promotes a component-based architecture. Further enhancing its value proposition, OpenLLM integrates advanced caching mechanisms. By leveraging these mechanisms, the system aims to optimize repetitive queries, leading to reduced operational costs and enhanced response times. Additionally, OpenLLM's design incorporates robust monitoring and logging tools, ensuring that operational insights are readily available for performance tuning and troubleshooting.

Ray-LLM. Ray-LLM [217] represents a strategic fusion of LLMs with the Ray ecosystem [192], aiming to optimize the deployment and operation of LLMs. Situated at the intersection of cutting-edge model architecture and scalable infrastructure, Ray-LLM seeks to redefine the paradigms of LLM utilization. At the core of Ray-LLM's approach is the leveraging of Ray's inherent distributed computing capabilities. Recognizing the computational demands of LLMs, Ray-LLM integrates Ray's distributed task scheduling and execution mechanisms, ensuring that LLM tasks are efficiently distributed across available resources. This seamless integration potentially leads to enhanced model performance, reduced latency, and optimized resource utilization. Since it is built on top of the Ray Ecosystem, Ray-LLM is a good library to quickly prototype, train and deploy large models on clusters. It also comes with advanced monitoring support as well, enabling its usage in serving.

MLC-LLM. MLC-LLM [271] aspires to empower individuals to develop, optimize, and deploy AI models on a diverse array of devices. Central to MLC-LLM's approach is the concept of device-native AI. Recognizing the vast spectrum of devices in use today, from high-end servers to smartphones, MLC-LLM compiles models and deploys them in a process that is inherently tailored to the specific capabilities and constraints of each device [37, 76, 243]. This device-native focus ensures that AI models are not only efficient but also highly optimized for the environments in which they operate. With its strong focus on compiling and optimizing models for prototyping on edge devices, MLC-LLM is a powerful tool for deploying on-device AI models and exhibits state-of-the-art performance in terms of throughput across a range of devices.

Sax. Sax [10] is a platform designed by Google for deploying Pax, JAX, and PyTorch models for inference tasks. Within Sax, there is a unit referred to as Sax cell (or Sax cluster) thatl is made up of an administrative server coupled with multiple model servers. The role of the admin server is multifaceted: it monitors the model servers, allocates published models to these servers for inference, and guides clients in finding the appropriate model server for specific published models. Sax is essentially complementary to the Pax framework and while Pax focuses on massively distributed workloads, Sax is geared toward model serving.

Mosec. Mosec [322] is designed for serving large deep learning models particularly in cloud environments. It is built to streamline the serving of machine learning models into backend services and microservices. Key features include high performance due to Rust-built web layer and task coordination, easy-to-use Python interface, dynamic batching, pipelined stages for handling mixed workloads, and cloud-friendliness with model warmup, graceful shutdown, and Prometheus monitoring metrics, making it easily manageable by Kubernetes or other container orchestration systems. Mosec is centered around cloud ecosystems and is well suited for serving models efficiently with its web layer, allowing developers to focus on model optimization and backend logic.

LLM Foundry. LLM Foundry [194] is a library for finetuning, evaluating, and deploying LLMs for inference with Composer and the MosaicML platform. It supports distributed inference, dynamic batching, and prompt batching for efficient deployment. Similar to its complimentary training framework Composer, LLM Foundry is designed to be easy to use, efficient, and flexible, aimed at enabling rapid experimentation with the latest techniques in LLMs. It also provides straightforward interfaces to Mosaic's Pretrained Transformers (MPT) (GPT-style models with built-in support for features like FlashAttention [58] and ALiBi [215]). It is complementary to MosaicML's Composer framework and while Composer focuses on distributed training, LLM Foundry provides support for deploying those models and enabling rapid experimentation with the latest techniques.

5 CONCLUDING REMARKS

In this survey, we provide a systematic review of efficient LLMs, an important area of research aimed at democratizing LLMs. We start with motivating the necessity for efficient LLMs. Guided by a taxonomy, we review algorithm-level and system-level efficient techniques for LLMs from model-centric and data-centric perspectives respectively. Furthermore, we review LLM frameworks with specific optimizations and features crucial for efficient LLMs. We believe that efficiency will play an increasingly important role in LLMs and LLMs-oriented systems. We hope this survey could enable researchers and practitioners to quickly get started in this field and act as a catalyst to inspire new research on efficient LLMs.

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