

Pushing Large Language Models to the 6G Edge: Vision, Challenges, and Opportunities

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Abstract—Large language models (LLMs), which have shown remarkable capabilities, are revolutionizing AI development and potentially shaping our future. However, given their multimodality, the status quo cloud-based deployment faces some critical challenges: 1) long response time; 2) high bandwidth costs; and 3) the violation of data privacy. 6G mobile edge computing (MEC) systems may resolve these pressing issues. In this article, we explore the potential of deploying LLMs at the 6G edge. We start by introducing killer applications powered by multimodal LLMs, including robotics and healthcare, to highlight the need for deploying LLMs in the vicinity of end users. Then, we identify the critical challenges for LLM deployment at the edge and envision the 6G MEC architecture for LLMs. Furthermore, we delve into two design aspects, i.e., edge training and edge inference for LLMs. In both aspects, considering the inherent resource limitations at the edge, we discuss various cutting-edge techniques, including split learning/inference, parameter-efficient fine-tuning, quantization, and parameter-sharing inference, to facilitate the efficient deployment of LLMs. This article serves as a position paper for thoroughly identifying the motivation, challenges, and pathway for enabling LLMs at the 6G edge.

Index Terms—Large language models, foundation models, mobile edge computing, edge intelligence, 6G, split learning.

I. INTRODUCTION

The rise of large language models (LLMs), fueled by the success of transformers, has sparked significant interest in the AI community and the whole world. Nowadays, major players in the AI industry are vying to develop their own LLMs. Notable examples include OpenAI’s GPT-3, Google’s PALM, and Meta’s LLaMA. These LLMs, trained on extensive and diverse datasets from the Internet, exhibit generalization capabilities when the model size substantially increases – a phenomenon known as “emergence”. For instance, benefiting from its staggering model size, GPT-3 could successfully multiply numbers, even though they were not explicitly trained to do so [1]. Due to their exceptional capabilities, the models can be directly applied or easily adapted (e.g., fine-tuned or instruction tuning) to numerous downstream/unseen tasks, thereby unlocking unprecedented potential in various appli-

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cations, such as Chatbot, content generation, healthcare, and robotics.

Unfortunately, the existing LLM products mostly rely on cloud computing, which suffers from excessive latency, high bandwidth cost, and severe privacy concerns. First of all, it is infeasible to support fast model inference for real-time applications (e.g., LLM-empowered robotics control/navigation/exploration [2]) based on cloud computing due to the need for timely response. Second, the emergence of multimodal LLMs requires input/output of not only texts, but also images, videos, audio, and other sensory data [3]. Centralizing the massive data for either training or inference will consume significant backhaul/backbone network bandwidth and put great pressure on the central cloud, which is not scalable. At last, LLM training or inference raises severe privacy concerns, particularly considering that the data could involve highly sensitive data, such as medical data or human activities including audio instructions and gestures at home. As a result, there is an urgent need to leverage mobile edge computing (MEC) to finetune and deploy LLMs on or in closer proximity to data sources while preserving data ownership of end users.

As we are progressing towards the early standardization of 6G, it is widely recognized that 6G will evolve into a mobile network supporting in-network and distributed AI at the edge [4]. However, considering the intensive computing workload of LLMs, is it even feasible to run such large models at the 6G edge? Thanks to various cutting-edge AI technologies, the answer is yes. We argue that split machine learning (including both split learning and inference) has the potential to fulfill computing needs by partitioning the intensive workload over distributed edge devices/servers. In addition, several mature AI techniques, such as parameter-efficient fine-tuning and model quantization, can substantially reduce communication, computation, and memory requirements for model training (finetuning) and inference. For instance, by combining parameter-efficient training and quantization, quantized low-rank adapters (QLoRA) [5] can successfully fine-tune a 65B LLM on a single consumer GPU for a downstream dataset within 24 hours, while achieving performance comparable to state-of-the-art LLMs such as GPT-3 [5]. Moreover, many ongoing industrial efforts are made to deploy sub-10 billion parameter LLMs on phones. All these facts demonstrate the viability and great potential of adapting or deploying LLMs at the mobile edge.

The convergence of LLM deployment and 6G MEC systems will be an exciting research area. Some prior papers, such

as [6], [7], mainly discuss how to leverage LLMs to optimize wireless networks or MEC (i.e., *LLMs for networks*). On the other hand, this article focuses on how to leverage 6G MEC to support LLM training and inference (i.e., *networks for LLMs*). Particularly, we will elaborate on the killer MEC applications, the tailored MEC architecture, and the integrated communication-computing technologies for deploying LLMs in mobile edge networks.

The rest of this paper is organized as follows. Section II introduces the killer applications. Section III identifies the challenges, followed by an overview of MEC architecture tailored for LLMs in Section IV. Efficient edge training and inference for LLMs are discussed in Section V and Section VI, respectively. Open problems are identified in Section VII and the conclusions are drawn in Section VIII.

II. KILLER APPLICATIONS

LLMs can be directly applied or fine-tuned to a broad range of tasks. In this section, we will focus on two mission-critical use cases: healthcare and robotics control, to demonstrate the need for LLM deployment at the mobile edge.

Healthcare is widely recognized as a crucial application for LLMs. Compared to traditional AI models, LLMs exhibit exceptional generalization capabilities, fostering more effective interactions with patients, caregivers, and medical professionals. Google's Med-PaLM 2, for example, is an LLM fine-tuned on medical datasets, capable of delivering high-quality answers to medical inquiries. Med-PaLM 2 surpasses the pass mark on the US Medical License Exam (USMLE) and obtained 86.5% accuracy. Indeed, with multimodal inputs and outputs, LLMs can function as AI medical generalists, offering a variety of healthcare services to users, ranging from chatbots to diagnosis to early warnings [3]. It is thrilling to envision a future where everyone can have their own personal health AI expert to constantly monitor their well-being and provide timely advice. Nevertheless, the massive multimodal data transmissions may pose significant challenges to the cloud-based healthcare LLM deployment. More importantly, cloud-based centralized training or inference faces substantial challenges in collecting data in the medical domain owing to privacy concerns and data regulations, which necessitates privacy-preserving distributed learning, such as federated and split learning, to train/deploy models at the edge.

Besides, robotic control is acknowledged as another critical application for LLMs. With remarkable generalization and reasoning capabilities, LLMs allow robots to comprehend human intention/emotion or complicated environments and plan sequential robotic manipulation accordingly. For instance, Google's PALM-E [2], adapted from a pre-trained LLM (i.e., PALM), can directly ingest raw streams of robot sensor data, enabling robots to perform embodied reasoning and break down a complex task (e.g., making a cake batter with ingredients the robot sees as demonstrated by PALM-E [2]) into actionable steps. Nevertheless, for robotics applications, centralized model training involves not only massive streaming video upload, potentially overwhelming backhaul/backbone networks, but also sensitive interactive data relevant to human daily activities, in the form of voice and videos, leading to

significant privacy threats. Moreover, since human-machine interactions and robotics maneuvers must be performed with low latency in various tasks (e.g., elderly/child care like preventing a kid from injury or poisoning), LLMs should be placed at the network edge for facilitating real-time robotic control. All these observations underscore the importance of deploying LLMs at the network edge to address the *bandwidth, latency, and privacy concerns*.

III. CHALLENGES

Although there is a pressing need to deploy LLMs at the network edge as mentioned earlier, the staggering size of these models poses significant challenges to the mobile edge. In this section, we identify these technical challenges.

The first challenge arises from communication costs and latency. While LLMs require substantial communication resources for inference and training, cellular networks have inherent bandwidth limitations. For instance, it takes around 470 seconds to transmit GPT2-XL, a medium-sized LLM of about 5.8 GB, over a 100Mbps channel (the user-experienced data rate in 5G), implying that transferring LLMs for either consumer usage or distributed learning (e.g., federated learning) can be extremely time-consuming and bandwidth-intensive.

The second challenge stems from the extreme requirements for computing capabilities. The GPT-3 model, with 175 billion parameters, takes approximately 1.7 seconds to analyze a 512-token sentence and generate a 32-token sentence, even when running on state-of-the-art technology with 8 A100 GPUs [8]. This highlights the computing demands of LLMs. Edge devices and servers typically have limited computing resources. Without well-designed techniques, running LLMs at the edge can result in unacceptable latency and excessive energy consumption.

Last but not least, storage and memory pose another challenge. For example, full-parameter fine-tuning an LLM of 65 billion parameters with 16-bit precision requires 780GB of memory, while the high-end commercial GPU, H100, has only 80GB of memory [5]. This memory requirement presents a significant obstacle in training LLMs. Regarding storage, the GPT-3 model is 700GB in 32 bits. Storing multiple copies of LLMs (of various versions for different tasks or users) can also overwhelm MEC servers. Consequently, innovative model placement strategies must be developed to reduce the memory and storage requirements for LLMs.

In what follows, we will elaborate on how to employ state-of-the-art techniques and integrated communication and computing design to overcome the aforementioned challenges.

IV. 6G MEC ARCHITECTURE FOR LARGE LANGUAGE MODELS: AN OVERVIEW

In line with the “NET4AI” (network for AI) vision for the 6G era [4], we envision a 6G MEC architecture that can support the deployment of large language models, as shown in Fig 1. Our proposed architecture includes several critical modules as follows.

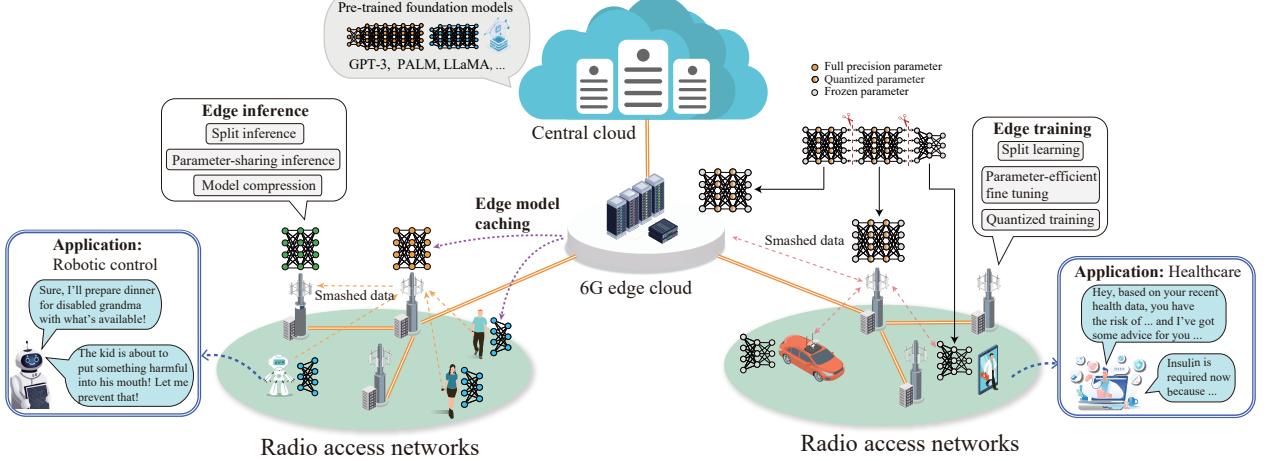


Fig. 1. The MEC architecture for large language models in 6G.

A. Network management

To take advantage of distributed computing and storage resources for collaborative model training and inference, network virtualization is of paramount importance, which improves resource utilization, flexibility, and manageability. Following the design principle of software-defined networking, our envisioned 6G MEC architecture features a central controller that orchestrates network-wide computing resources and data transmissions, with the decoupled control and data plane. By collecting global network knowledge, the control partitions and coordinates model training/inference across the distributed edge computing systems, with intermediate smashed data (i.e., intermediate activations and back-propagated gradients), model parameters, or user data exchanged across edge routers and servers. All these features seamlessly align with the existing 5G networks. With centralized intelligence, we can support flexible resource orchestration, implement intelligent algorithms, improve network-wide resource utilization, and achieve superior service performance for LLMs.

B. Edge model caching

Rather than retrieving every model from the cloud, which can result in excessive latency, the 6G MEC architecture can directly store, cache, and migrate models in edge networks to enable fast model delivery for either downloading to users or distributed learning. This leads to a new problem called “edge model caching”, which can be considered as an instance of “edge caching” that is inherently supported by MEC systems.

Considering the staggering size of LLMs, the strategic placement of models on the appropriate edge servers must be carefully studied to reduce bandwidth costs and service latency. Unlike traditional edge caching, 6G network operators can utilize two distinct features of LLMs to optimize their placement. The first direction is to exploit the “parameter sharing” characteristics to enable effective model placement and migration. LLMs for different downstream tasks may share the same parameters/layers/blocks for various tasks or users, which can be exploited for storage-efficient model placement. By using fine-tuning methods, such as LoRA, which is widely used for fine-tuning LLMs [9], model providers can freeze

most parameters in a well-trained model and only adjust a few trainable parameters for new tasks or personalization. Network operators can hence take into account the model overlapping feature when placing large models at the network edge, as shared parameters may only need to be cached once. To design an effective model placement strategy, operators should first identify the popularity of model requests and the shared model structure of LLMs, then aim to accommodate as many model requests as possible while meeting end-to-end service latency requirements. As user locations or request distributions change over time, cached models can migrate to new locations, with only the task-specific parts of the models being migrated to minimize communication costs. However, since models with extensive parameter overlapping with a pre-trained model might fail to satisfy specific downstream tasks or new local environments, caching models with higher sharing ratios may result in a tradeoff between model accuracy and storage costs. Another orthogonal approach to placing more models at the network edge is model compression. By employing various mature model compression techniques (e.g., model quantization and pruning), LLMs can be compressed to save storage space and alleviate communication costs. However, this may also come at the cost of service quality, as compressed models may not provide high-quality services to users. In this context, traditional edge video placement problems with varied resolutions can be adapted to jointly optimize model placement and compression ratios, thereby striking a balance between efficiency and performance.

C. Edge model training (fine-tuning) and inference

6G mobile networks are expected to fully support distributed learning [4]. We envision that 6G MEC systems are capable of fine-tuning LLMs to local environments. Note that, for LLMs, training from scratch demands huge training datasets and computing resources, which is generally impractical and unnecessary to achieve at the network edge. However, it is likely to adapt a well-trained LLM to local or new environments based on MEC systems. The details will be presented in Section V. On the other hand, we anticipate that 6G MEC

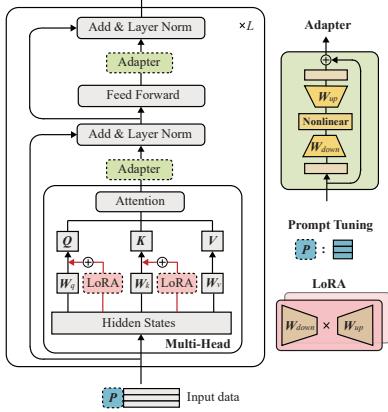


Fig. 2. An illustration of the transformer architecture and several state-of-the-art parameter-efficient fine-tuning methods, including adapter tuning, prompt tuning, and low-rank adaptation.

systems can also support LLM inference with reduced round-trip latency, which is of paramount importance for delay-sensitive and bandwidth-intensive applications. Further details will be provided in Section VI.

V. EFFICIENT LARGE MODEL TRAINING AT THE EDGE

With LLMs pre-trained by the cloud, edge training can fine-tune them to new environments and personalize towards individual needs. Compared with training from scratch, fine-tuning LLMs requires significantly less training costs. However, it still presents significant challenges to the 6G edge. In this section, we discuss three training techniques to enable fine-tuning of LLMs in 6G edge networks.

A. On-device (On-server) Training

1) *Parameter-efficient fine-tuning*: To fine-tune LLMs on edge devices/servers, conventional full-parameter fine-tuning (i.e., updating all parameters) proves to be computationally expensive. Besides, for distributed or federated learning, full-parameter fine-tuning also incurs considerable communication costs associated with model aggregation. To address these concerns, network operators can implement parameter-efficient fine-tuning techniques. Specifically, by updating only a minor fraction of parameters, an LLM can be effectively adapted to new tasks or environments, significantly reducing training and communication overhead while simultaneously mitigating overfitting. As shown in Fig. 2, there are several representative parameter-efficient fine-tuning approaches for LLMs, including adapter tuning, prompt tuning, and Low-rank adaptation (LoRA). Adapter tuning involves inserting well-designed adapter modules between layers for training, while prompt tuning adds tunable prefix tokens. LoRA decomposes attention weight updates into low-rank matrices for updating. The shared principle among these methods is to train a small quantity of parameters, typically less than 1% of the original parameters, which dramatically decreases the number of trainable parameters.

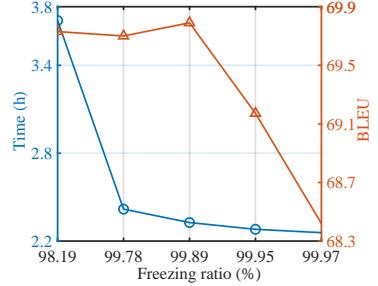


Fig. 3. The performance for training latency and bilingual evaluation understudy (BLEU, a metric for evaluating the machine translations against the human translations) of federated split learning versus the freezing ratio, where LoRA is employed to fine-tune GPT-2 medium on WebText dataset. An edge server and 20 clients are considered. Computing capabilities of clients and the edge server are set to 3.56 and 35.6 (peak performance of one NVIDIA RTX 3090) TFLOPS, uplink and downlink rates are 70Mbps and 300Mbps, and the number of tokens utilized for training is 264M.

2) *Quantized training*: Apart from parameter-efficient fine-tuning, quantized training provides another promising solution for LLM training by reducing communications, training, and memory requirements. First of all, under distributed learning with model synchronization requirements, quantized training techniques such as QSGD [10] can significantly alleviate the communication burden benefiting from the compressed models/gradients. Second, low-precision computation can accelerate training speed and reduce energy consumption. For example, fully quantized training (FQT) [11] replaces the original full-precision computations with low-precision computations by quantizing weights, activations, and gradients. At last, quantized training also enables memory-efficiency model training on edge devices by reducing bitwidths.

A recent trend in quantized training for on-device LLM training is the integration of quantization and parameter-efficient fine-tuning to significantly reduce memory footprint. For instance, QLoRA [5] can quantize a model to a 4-bit model and fine-tune it using 16-bit low-rank adapters. As a result, it allows fine-tuning a 65 billion parameters LLM on a 48GB GPU within 24 hours, while achieving comparable performance (e.g., 99.3%) to ChatGPT on the evaluated dataset. This demonstrates the feasibility of fine-tuning LLMs on an edge server or even on an edge device.

B. Device-server Co-training

While the aforementioned techniques can greatly help, on-device LLM fine-tuning can still be extremely resource-intensive for most edge devices. On the other hand, directly uploading the raw data from edge devices to an edge server for training raises significant privacy concerns. To address these concerns, device-server co-training can be a promising LLM training paradigm in mobile edge computing systems.

To facilitate large model training while preserving the data privacy of edge devices, split learning (SL) can come to rescue. SL partitions a model into two sub-models and places them on clients and a server for collaborative training, as illustrated in Fig. 1. This approach not only renders local training considerably more affordable, but also significantly enhances data privacy, given that only cut-layer smashed data (features) are transmitted to the server. While the vanilla

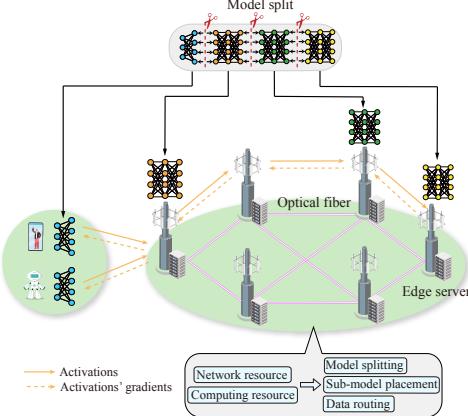


Fig. 4. An illustration of multi-hop SL. Multiple clients jointly train a large model based on SL approaches, such as SFL and PSL. The model is partitioned into multiple parts so that the total workload is shared among multiple edge servers.

SL trains models between a server and clients sequentially, later variants of SL, including parallel split learning (PSL) and split federated learning (SFL), parallelize the framework by enabling multiple devices to train a model with a server simultaneously, thereby further accelerating the process. A detailed review of the integration of SL and MEC systems, named split edge learning (SEL), can be found in [12]. As shown in Fig. 3, by integrating LoRA (the aforementioned parameter-efficient fine-tuning technique) and SFL, we observe model training can be conducted in a reasonable time even if only an NVIDIA RTX 3090 is considered on the edge server. Moreover, a higher freezing ratio potentially compromises model performance while significantly decreasing communication-computing latency at the mobile edge. Consequently, it is essential to choose an optimal freezing ratio to strike the optimal trade-off between accuracy and latency under communication and computing constraints, which can be a significant future research direction.

In general, to balance the communication and computing workload, the optimal model splitting strategies can be formulated as integer optimization problems which are normally challenging to tackle. Fortunately, for LLMs built on transformers, the output sizes of transformer blocks are typically the same (unlike CNNs with varied output sizes for each layer), allowing us to design efficient and optimal model splitting algorithms for LLMs benefiting from the special model architecture. Besides, when wireless communication is the bottleneck, SL for LLMs can be implemented by simply placing the encoders on edge devices and the decoders on the server to reduce communication latency. This is because only tokens, which are usually very small in size, need to be exchanged in this case.

Conventional SL partitioning a model into two parts may still be unable to support effective LLM training. By extending to multi-hop SL, multiple edge servers can work collaboratively to further partition the heavy training workload of an LLM, as illustrated in Fig. 4. Specifically, several edge servers can form a mesh of computing network for performing multi-hop SL, thereby sharing the heavy computing workload among

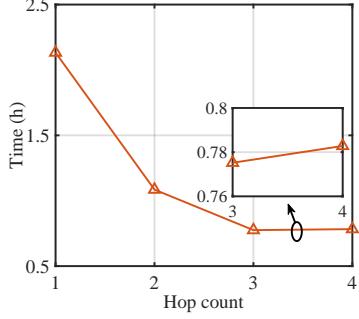


Fig. 5. The training latency of multi-hop SL versus the hop counts, where LoRA is employed to fine-tune GPT-2 medium on WebText dataset. The data samples are distributed over 5 clients, the transmission rate between edge servers is 400Mbps, and other key parameters are consistent with Fig. 3.

a set of edge servers. Fig. 5 demonstrates the total training time (including both computing and communication latency) for achieving a target accuracy. As can be seen, although leveraging more edge servers takes full advantage of distributed computing resources, it also increases communication overhead due to the additional smashed data transmission between the servers. For this reason, three edge servers perform better than four edge servers in terms of end-to-end latency in Fig. 5. Consequently, a 6G network operator needs to carefully design how many sub-models the original model should be partitioned into, which layers to split, and where to place the sub-models under the resource-constrained mobile edge. The judicious model splitting and placement play a crucial role in improving the efficiency of multi-hop SL for LLMs, which is worth further exploration.

VI. EFFICIENT LARGE MODEL INFERENCE AT THE EDGE

Model inference refers to running input data into a model to get the outputs. Cloud-based AI model inference incurs significant communication latency, which violates the service requirements of many applications as motivated in Section III. Nevertheless, in spite of low-latency data transmissions, the MEC paradigm usually possesses limited computing resources, which might incur long computing latency. In this section, we present the enabling techniques to address this challenge to provide low-latency LLM inference at the 6G mobile edge.

A. On-device (On-server) Inference

1) *Quantized edge inference*: A feasible solution for fast LLM inference is model quantization. There exist two mainstream quantization techniques for efficient model inference, i.e., quantization-aware training (QAT) and post-training quantization (PTQ). The former emulates quantization errors during the training process, leading to benefits during the inference stage of low-precision models, whereas the latter directly downsamples the parameters of a well-trained model to the low-bit version. In comparison, QAT generally results in better model performance while PTQ is much less computationally expensive as no retraining is required. It is noted that QAT aims to enhance the accuracy of lower-precision models by emulating inference-time quantization errors during training, which fundamentally differs from quantized training in Section V-A with the goal of reducing training costs.

For resource-limited edge devices/servers, PTQ offers a better option than QAT in terms of efficiency. QAT involves re-training/fine-tuning full-precision LLMs for low-bit deployment, which might be too costly if the fine-tuning should be done on the mobile edge. Instead, the mobile edge can utilize PTQ, allowing the conversion of a high-precision LLM to its low-precision counterparts without re-training. This approach also reduces edge caching costs since only a high-precision LLM needs to be stored on edge servers/devices. Upon receiving an inference request, the edge system can customize the bit precision for inference according to network resource availability and users' QoS requirements in terms of inference latency and accuracy, and then transmit the corresponding downsampled models with the desired precision to the devices/servers for on-device inference.

Apart from the traditional quantization approaches, quantization methods tailored for LLMs on edge devices/servers have also been developed. A recent trend in LLMs is to deploy mixture-of-expert (MoE) LLMs, which have a set of "experts" to be selected at runtime via small-sized non-experts weights, thereby scaling the model parameter size with sublinearly increased computing complexity. Since a substantial portion of the computational load is carried by weights "non-experts", edge devices/servers can hold only non-expert weights in memory and keep experts in its disk, thereby switching experts between memory and disk as they are required [13]. In such a case, the quantization hence can be customized for different experts according to their sensitivity to quantization errors and the memory budget, thereby reducing swapping time.

2) *Parameter-sharing edge inference*: An edge device/server may run multiple LLM-empowered applications at the same time, which requires a significant amount of running memory. For example, a single inference task for FP16 GPT 6.7B with 512 input sequences and 32 output sequences approximately requires 41.84 GB of running memory when the batch size is set as 64 [8]. The powerful consumer GPU, NVIDIA RTX 4090, only has 24 GB of memory space. As the number of running applications increases and the sequence length grows, the running memory requirement will be a major bottleneck for edge devices/servers. Thankfully, as discussed in Section IV-B, parameter sharing is a prevalent feature among LLMs. By exploiting this property, when multiple models consist of the same parameters or blocks, we can load only a single copy of the shared parameters into the GPU memory, thereby substantially reducing memory costs and data swapping time [14]. To this aim, task scheduling for parameter-sharing edge inference can be developed to fully exploit the parameter shareability of models/tasks.

B. Device-server Co-inference

To further reduce the inference time and memory costs, device-server co-inference can be deployed at the mobile edge. Split inference is a model inference technique that offloads the computing workload from edge devices to a server via layer-wise model partitioning. In addition to good privacy preservation, split inference can reduce communication overhead if the size of the cut-layer features is smaller than the size of the raw data. This is particularly advantageous

for multimodal LLMs that use high-definition images or videos as input data. To further reduce service time, a 6G network operator can employ edge devices and multiple edge servers for collaborative inference based on multi-hop split inference to fully harness the distributed computing resources. Similar to Section V-B, given a specific network topology with bandwidth constraints, the joint problem of model splitting and placement is also crucial for multi-hop split inference to achieve the best orchestration of network-wide computing resources.

Device-server co-inference can also be executed based on the state-of-the-art speculative decoding process of LLMs to significantly reduce inference latency [15]. Specifically, large language models typically generate tokens in an autoregressive manner, which requires running the model K times to produce K tokens, resulting in significant latency. Speculative decoding addresses this issue by using a smaller model to generate multiple tokens, which are then verified and corrected by the larger model in parallel. This method is much faster than the standard autoregressive generation in LLMs, as it leverages the small model's quick token generation and the large model's parallel verification and correction capabilities. In the mobile edge, small models can be deployed on edge devices to execute tasks with low latency and low memory/storage costs, after which the generated tokens are uploaded to an edge server for verification in parallel. Since only tokens are transferred (e.g., text), the wireless transmission usually incurs a very small delay. This device-server co-inference paradigm not only accelerates the overall process by facilitating parallel verification through speculative decoding itself but also produces local prediction results on devices via small models for timely response. This allows edge devices to utilize the low-latency results before receiving more accurate results from an edge server.

VII. OPEN PROBLEMS

As an emerging field, there are still numerous open research problems on how to employ MEC systems to support LLMs. We pick up a few most important ones to discuss as follows.

A. Green and Sustainable Edge Intelligence for LLMs

Despite their significantly powerful capabilities, training and inference of LLMs are notoriously power-hungry due to their huge size. Green edge intelligence would play an increasingly important role in the success of LLMs. To minimize energy use while maintaining satisfactory model performance, MEC systems must intelligently schedule model training, carefully select high-quality data for training, and judiciously determine which model to use. For instance, if model training is delay-tolerant, it can be scheduled to harness renewable energy such as sunlight and wind by considering their fluctuating nature. Also, the MEC systems can run smaller LLMs for less complex tasks, potentially on devices, while executing large-sized models on the edge server only for challenging tasks. All of these require innovative network optimization for energy-efficient LLM training and inference at the mobile edge.

B. Privacy-preserving Edge Intelligence for LLMs

While both SL and FL can enhance privacy for LLM, it has been demonstrated that smashed data or model parameters might still result in privacy breaches for data owners. To offer more robust privacy protection, differential privacy can be employed to provide privacy guarantees. For medical or other privacy-sensitive applications, the MEC systems can allow users to control the level of their privacy leakage by adding customized noise to smashed data or model parameters following the principle of differential privacy. In such scenarios, MEC systems should take into account both data noise and channel quality when selecting clients for LLM training. This requires understanding the impact of data noise, including smashed data noise (in SL) and model parameter noise (in FL or SFL), on the LLM training process, an area that remains largely unexplored.

VIII. CONCLUSIONS

In recent years, language models have experienced exponential growth in size, giving birth to numerous LLMs with billions of parameters. This trend urges us to think about how edge intelligence can accommodate these giant models. In this article, we advocated the paradigm shift from cloud computing to 6G MEC for LLM deployment. We highlighted killer applications to motivate this paradigm shift, arguing that cloud computing can hardly fulfill the latency, bandwidth, and privacy requirements. Meanwhile, we identified the key challenges that mainly arise from the resource limitations at the network edge. To address these challenges, we first proposed a 6G MEC architecture for LLMs and then elaborated on several methods to enable efficient edge training and edge inference for LLMs under the resource-constrained mobile edge. We hope this article can inspire more researchers in the wireless community to explore the deployment of LLMs at the mobile edge and further advance this emerging field.

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