

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

Zheng Lin, Guanqiao Qu, *Graduate Student Member, IEEE*, Qiyuan Chen, Xianhao Chen, *Member, IEEE*, Zhe Chen *Member, IEEE*, and Kaibin Huang, *Fellow, IEEE*

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 empowering 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, with notable examples including OpenAI’s GPT-3, Google’s PALM, and Meta’s LLaMA. These LLMs, trained on extensive and diverse datasets from the Internet, exhibit unparalleled 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, unlocking unprecedented

potential in various applications, such as Chatbot, content generation, healthcare, and robotics.

Unfortunately, the existing LLM products purely rely on cloud computing, which suffers from excessive latency, high bandwidth cost, and severe privacy concerns, significantly hampering the effective application of LLMs. 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. 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) and distributed learning to adapt 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 (fine-tuning) and inference. For instance, by combining parameter-efficient training and quantization, quantized low-rank adapters [5] (QLoRA) can successfully fine-tune a state-of-the-art LLM on a single consumer GPU for a downstream dataset within 24 hours or even less (depending on the model size), while achieving performance comparable to state-of-the-art LLMs such as GPT-3 [5]. Many ongoing industrial efforts are made to realize on-device LLMs of compact versions. All these facts demonstrate the viability and great potential of adapting or deploying LLMs at the mobile edge.

Zheng Lin, Guanqiao Qu, Xianhao Chen, and Kaibin Huang are with the Department of Electrical and Electronic Engineering, University of Hong Kong, Pok Fu Lam, Hong Kong SAR, China. Xianhao Chen is also with HKU Musketeers Foundation Institute of Data Science, University of Hong Kong, Pok Fu Lam, Hong Kong SAR, China. (e-mail: linzheng@eee.hku.hk; gqqu@eee.hku.hk; xchen@eee.hku.hk; huangkb@eee.hku.hk). Qiyuan Chen is with the School of Electronics and Information Engineering, Harbin Institute of Technology, Shenzhen, Guangdong, China. (e-mail: 200210325@stu.hit.edu.cn). Zhe Chen is with the School of Computer Science, Fudan University, Shanghai, China. (e-mail: zhechen@fudan.edu.cn). (*Corresponding author: Xianhao Chen*)

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*). To our best knowledge, this is the first article that focuses on how to leverage 6G MEC to support LLM training and inference (i.e., *networks for LLMs*). Particularly, we will comprehensively examine the promising AI technologies to realize such implementations and elaborate on the integrated communication-computing design for 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. Google’s Med-PaLM 2, for example, is an LLM fine-tuned on medical datasets, capable of delivering high-quality answers to medical inquiries [8]. 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 [9]. 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.

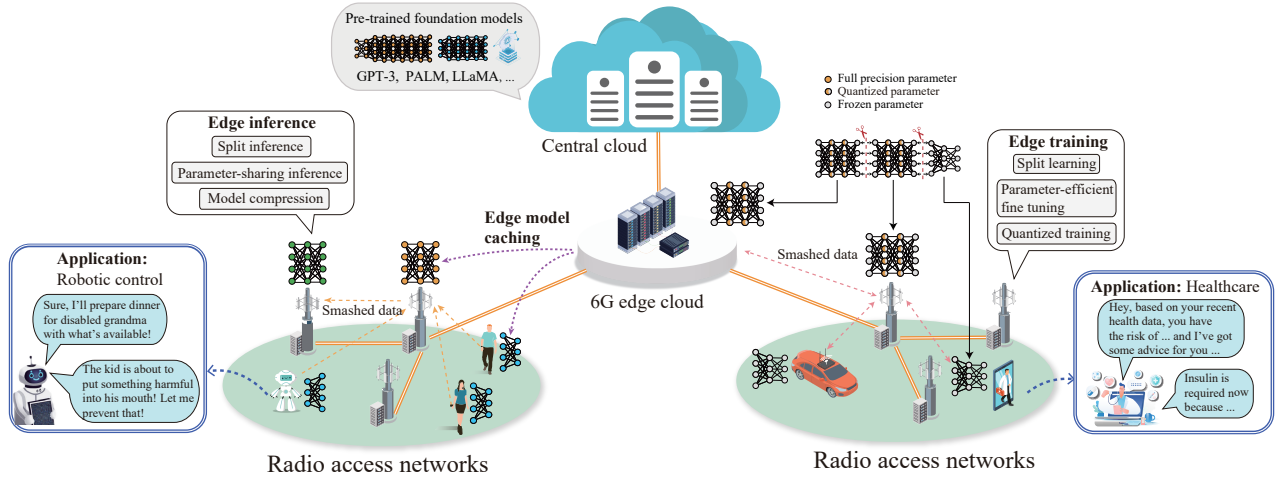


Fig. 1. The MEC architecture for large language models in 6G.

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 [10], 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

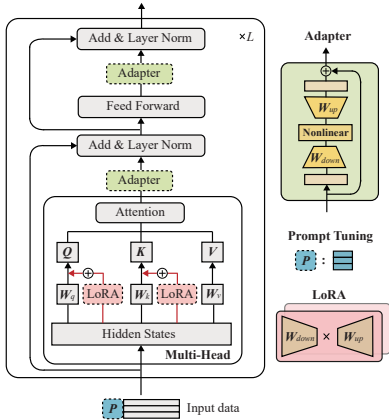


Fig. 2. An illustration of the transformer architecture and several state-of-the-art parameter-efficient fine-tuning methods, including adapter tuning, prompt tuning, and low-rank adaptation.

in Section V. On the other hand, we anticipate that 6G MEC 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 with local data samples. Despite of the significantly reduced workload compared with training from scratch, fine-tuning LLMs 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. Parameter-efficient Fine-tuning

To adapt well-trained models to new tasks/environments, conventional full-parameter fine-tuning (i.e., updating all parameters) for LLMs is computationally expensive for an MEC server. Besides, for distributed or federated learning with model aggregation, full-parameter fine-tuning also incurs considerable communication costs for model transfer. To mitigate these issues, the network operator can employ parameter-efficient fine-tuning. Specifically, by updating only a small proportion of parameters, an LLM can be efficiently adapted to new tasks/environments, thereby significantly decreasing the training/communication overhead while preventing 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 common principle of these methods is to merely train a small amount of parameters, usually less than 1% of the original parameters, thereby dramatically reducing the number of trainable parameters. For instance, applying LoRA to GPT-3 could lead to a remarkable reduction in trainable parameters, falling from

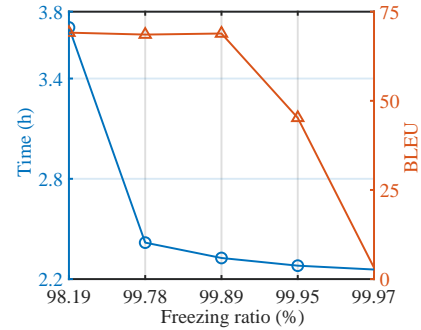


Fig. 3. The performance for training latency and bilingual evaluation understudy (BLEU, a metric for evaluating the machine translations against the human translations) of federated split learning versus the freezing ratio, where LoRA is employed to fine-tune GPT-2 medium on WebText dataset. An edge 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.

175.2 billion to 37.7 million – a nearly 4600-fold reduction. As shown in Fig. 3, by integrating LoRA and federated split learning (which will be introduced in the next subsection), we observe that a higher freezing ratio potentially compromises model performance since less trainable parameters can be tuned. However, it significantly decreases computing and communication 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 at the edge.

B. Split Edge Learning

While parameter-efficient fine-tuning can greatly help, the latency might still be excessive if merely utilizing a single edge server. Besides, directly uploading the raw data from edge devices to an edge server for training raises significant privacy concerns. To address these issues, split learning (SL) emerges as a complementary solution.

The original goal of SL is mainly to mitigate privacy leakage. Despite of data privacy preservation, on-device training, such as federated learning (FL), is impractical for LLM training due to the limited resources on edge devices. Instead, SL partitions a model into two sub-models and places them on clients and a server for collaborative training, as illustrated in Fig. 1. In such a case, an edge device trains several early layers, which not only prevents raw data sharing with the server but also makes local training much more affordable. While the vanilla SL trains models between a server and clients in a sequential manner, 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 [11].

Nevertheless, SL with two sub-models may still be unable to effectively support 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 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.

C. Quantized Training

Apart from parameter-efficient fine-tuning and SL, 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 [12] can significantly alleviate the communication burden for model training at the mobile edge because of the compressed payload. Second, low-precision computation enabled by quantized training can accelerate training speed and reduce energy consumption, making it extremely useful for training LLMs on resource-constrained edge devices/servers. For example, fully quantized training (FQT) [13] replaces the original full-precision computations with low-precision computations by quantizing weights, activations, and gradients. Note that specialized hardware is important for realizing the full benefits of low-precision operations. At last, quantized training enables memory-efficient model training on edge devices. Combining quantization techniques with parameter-efficient methods can significantly reduce memory footprint during fine-tuning pre-trained large models at the edge. For instance, QLoRA [5] quantizes the model to 4 bits and fine-tunes it using 16-bit low-rank adapters. As a result, it allows fine-tuning a 65B parameter LLM on a 48GB GPU within 24 hours, while achieving comparable performance (e.g., 99.3%) to ChatGPT on the evaluated dataset.

The aforementioned methods focus on model quantization itself, particularly on a single device. Under 6G MEC systems, multiple users often train a model collaboratively with the assistance of an edge server, particularly based on SL or SFL. In such a case, model quantization for different users directly influences the optimal allocation of communication and computing resources at the mobile edge. Hence, a joint design of quantization ratio, bandwidth allocation, and computing resource management plays an essential role in striking the balance between accuracy and latency, thereby boosting the training performance at the resource-constrained network edge. Along this line, an accurate model that captures the

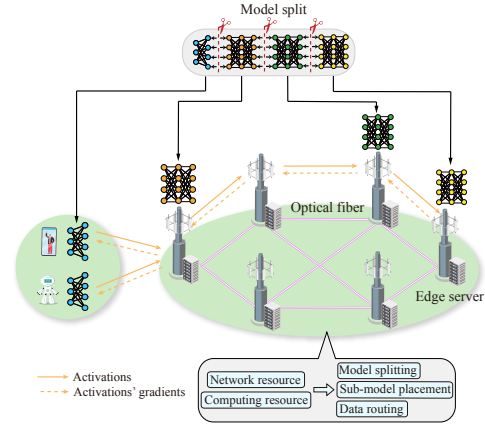


Fig. 4. An illustration of multi-hop SL. Multiple clients jointly train a large model based on SL approaches, such as SFL and PSL. The model is partitioned into multiple parts so that the total workload is shared among multiple edge servers.

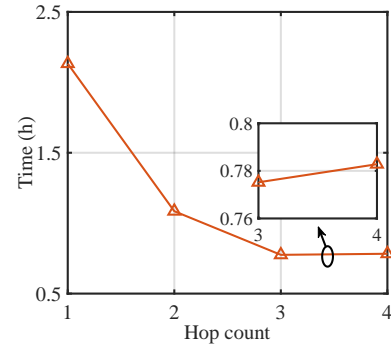


Fig. 5. The training latency of multi-hop SL versus the hop counts, where LoRA is employed to fine-tune GPT-2 medium on WebText dataset. The data samples are distributed over 5 clients, the transmission rate between edge servers is 400Mbps, and other key parameters are consistent with Fig. 3.

impact of the quantization ratio on model convergence is needed. Additionally, the time-varying network conditions during the entire training period must be considered when determining the best quantization ratios for training LLMs.

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. Edge Split Inference

Analogous to SL which aims at model training, split inference is a model inference technique that offloads the computing workload from edge devices to a server via layer-wise model partitioning. Moreover, by uploading smashed data rather than raw data, split inference can lower communication

overhead if the size of split layer output is smaller than the size of raw data, which is beneficial for multimodal LLMs with high-definition images or videos as the input data.

In the era of LLMs, a 6G network operator can employ multi-hop split inference to fully harness the distributed computing resources. Supposing there is a sentence or a batch of images for inference, an edge server may fail to calculate the output in a timely fashion due to limited computing resources or lack of memory space. Multi-hop split inference can harness the computing resources of multiple edge servers to execute LLM inference, which improves the service response and shares memory usage among the edge servers. 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.

B. Quantized Edge Inference

Apart from split inference, another feasible solution for fast LLM inference is model compression. There are various model compression approaches for efficient model inference (e.g., model quantization and pruning), and we only focus on model quantization to illustrate the key issues associated with the network edge. There exist two mainstream quantization techniques for efficient model inference, i.e., quantization-aware training (QAT) and post-training quantization (PTQ) [14]. 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-C with the goal of reducing training costs.

To deploy LLMs with various precision levels for edge inference, PTQ would be a better option due to its efficiency. In general, QAT can be too costly as it requires re-training/fine-tuning of full-precision LLMs for low-bit deployment. Note that a cloud center cannot always provide different bit versions of models for downloading because the mobile edge could have its own context-aware LLMs adapted to local environments. Instead, the mobile edge can utilize PTQ, allowing the conversion of a high-precision LLM to its low-precision counterparts without any re-training. 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 models with the desired precision to the devices/servers for inference. In general, high-precision (sub) models can be deployed on devices/servers with powerful communication/computing capabilities, otherwise low-precision (sub) models can be deployed. Additionally, weight quantization is often a preferable option for LLMs, because weight quantization generally leads to

smaller performance degradation than activation quantization when the model size is large [14].

C. Parameter-sharing Edge Inference

GPU memory will be one of the most precious resources at the network edge. For model inference, model layers need to be loaded into the memory, and the required memory increases with the model size. Consequently, performing inference for LLMs 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 [9]. The powerful consumer GPU, NVIDIA RTX 4090, only has 24 GB of memory space. As the number of users increases and the sequence length grows, the running memory required will become substantial.

As mentioned in Section IV-B, parameter sharing is a common feature for LLMs. When multiple models share the same parameters/blocks, only one copy of the shared parameters needs to be loaded into GPU memory, thereby significantly reducing the number of swaps and the cost per swap for inference and the required memory space [15]. For instance, by considering seven models (YOLO, Faster RCNN, ResNet, VGG, SSD, Inception, and Mobilenet) with parameter sharing for object classification and detection, the running memory decreases by up to 86.4%, saving 9.9 GB memory [15]. These results can be easily extended to LLMs with shared parameters due to the popularity of parameter-efficient fine-tuning in LLM training.

While parameter sharing saves memory space, it suffers from accuracy degradation since models would have fewer trainable parameters for specific tasks. In general, inference accuracy declines as the number of shared layers rises [15]. This necessitates the selection of appropriate sharing ratios to strike the balance between inference accuracy and memory usage.

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.

REFERENCES

- [1] J. Wei, Y. Tay, R. Bommasani, C. Raffel, B. Zoph, S. Borgeaud, D. Yogatama, M. Bosma, D. Zhou, D. Metzler *et al.*, "Emergent Abilities of Large Language Models," *arXiv preprint arXiv:2206.07682*, Jun. 2022.
- [2] D. Driess, F. Xia, M. S. Sajjadi, C. Lynch, A. Chowdhery, B. Ichter, A. Wahid, J. Tompson, Q. Vuong, T. Yu *et al.*, "Palm-e: An Embodied Multimodal Language Model," *arXiv preprint arXiv:2303.03378*, Mar. 2023.
- [3] M. Moor, O. Banerjee, Z. S. H. Abad, H. M. Krumholz, J. Leskovec, E. J. Topol, and P. Rajpurkar, "Foundation Models for Generalist Medical Artificial Intelligence," *Nature*, vol. 616, no. 7956, pp. 259–265, Apr. 2023.
- [4] Huawei, *6G: The Next Horizon: From Connected People and Things to Connected Intelligence*. Cambridge, U.K.: Cambridge Univ. Press, 2021.
- [5] T. Dettmers, A. Pagnoni, A. Holtzman, and L. Zettlemoyer, "QLoRA: Efficient Finetuning of Quantized LLMs," *arXiv preprint arXiv:2305.14314*, May. 2023.
- [6] Y. Shen, J. Shao, X. Zhang, Z. Lin, H. Pan, D. Li, J. Zhang, and K. B. Letaief, "Large language models empowered autonomous edge AI for connected intelligence," *arXiv preprint arXiv:2307.02779*, 2023.
- [7] L. Bariah, Q. Zhao, H. Zou, Y. Tian, F. Bader, and M. Debbah, "Large language models for telecom: The next big thing?" *arXiv preprint arXiv:2306.10249*, 2023.

- [8] K. Singhal, T. Tu, J. Gottweis, R. Sayres, E. Wulczyn, L. Hou, K. Clark, S. Pfohl, H. Cole-Lewis, D. Neal *et al.*, "Towards Expert-level Medical Question Answering with Large Language Models," *arXiv preprint arXiv:2305.09617*, May. 2023.
- [9] Nvidia, "Fastertransformer," 2023. [Online]. Available: <https://github.com/NVIDIA/FasterTransformer>
- [10] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, "LoRA: Low-Rank Adaptation of Large Language Models," *arXiv preprint arXiv:2106.09685*, Jun. 2021.
- [11] Z. Lin, G. Qu, X. Chen, and K. Huang, "Split Learning in 6G Edge Networks," *arXiv preprint arXiv:2306.12194*, Jun. 2023.
- [12] D. Alistarh, D. Grubic, J. Li, R. Tomioka, and M. Vojnovic, "QSGD: Communication-efficient SGD via Gradient Quantization and Encoding," *Proc. NIPS*, Dec. 2017.
- [13] H. Xi, C. Li, J. Chen, and J. Zhu, "Training Transformers with 4-bit Integers," *arXiv preprint arXiv:2306.11987*, Jun. 2023.
- [14] Z. Yao, C. Li, X. Wu, S. Youn, and Y. He, "A Comprehensive Study on Post-training Quantization for Large Language Models," *arXiv preprint arXiv:2303.08302*, Mar. 2023.
- [15] A. Padmanabhan, N. Agarwal, A. Iyer, G. Ananthanarayanan, Y. Shu, N. Karianakis, G. H. Xu, and R. Netravali, "GEMEL: Model Merging for Memory-Efficient, Real-Time Video Analytics at the Edge," in *Proc. NSDI*, Apr. 2023.

Zheng Lin is currently pursuing his Ph.D. degree at the University of Hong Kong. His research interests include edge intelligence and distributed machine learning.

Guanqiao Qu is currently pursuing his Ph.D. degree at the University of Hong Kong. His research interests include edge intelligence and federated learning.

Qiyuan Chen is a fourth-year undergraduate student at Harbin Institute of Technology, Shenzhen. His research interests include edge intelligence and distributed learning.

Xianhao Chen is an assistant professor at the Department of Electrical and Electronic Engineering, The University of Hong Kong. His research interests include wireless networking, edge intelligence, and distributed learning.

Zhe Chen is an assistant professor with the School of Computer Science at Fudan University, and the Co-Founder of AIWiSe Ltd. Inc. His research interests include wireless networking, deep learning, mobile and pervasive computing, and embedded systems.

Kaibin Huang [Fellow, IEEE] is a Professor at the Department of Electrical and Electronic Engineering, The University of Hong Kong. His research interests include mobile edge computing, edge AI, and 6G systems.