FederatedScope-LLM: A Comprehensive Package for Fine-tuning Large Language Models in Federated Learning

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Abstract

Large language models (LLMs) have demonstrated great capabilities in various natural language understanding and generation tasks. Platforms such as Hugging Face facilitate access and utilization of the pre-trained LLMs for different entities, ranging from computer science researchers to users with little machine learning background. Different entities can further improve the performance of those LLMs on their specific downstream tasks by fine-tuning LLMs. When several entities have similar interested tasks, but their local data cannot be shared directly because of privacy concerns regulations, federated learning (FL) is a mainstream solution to leverage the data of different entities. Besides avoiding direct data sharing, FL can also achieve rigorous data privacy protection, model intelligent property protection, and model customization via composition with different techniques. However, fine-tuning LLMs in federated learning settings still lacks adequate support from the existing FL frameworks because it has to deal with optimizing the consumption of significant communication and computational resources, various data preparation for different tasks, and distinct information protection demands. This paper first discusses these challenges of federated fine-tuning LLMs in detail, and introduces our implemented package **F**ederated**S**cope-**LLM** (FS-LLM) as a main contribution, which consists of the following components: (1) we build a complete end-to-end benchmarking pipeline, automizing the processes of dataset preprocessing, federated fine-tuning execution or simulation, and performance evaluation on federated LLM fine-tuning with different capability demonstration purposes; (2) we provide comprehensive and off-the-shelf federated parameter-efficient fine-tuning (PEFT) algorithm implementations and versatile programming interfaces for future extension to enhance the capabilities of LLMs in FL scenarios with low communication and computation costs, even without accessing the full model (e.g., closed-source LLMs); (3) we adopt several accelerating operators and resource-efficient operators for fine-tuning LLMs with limited resources and the flexible pluggable sub-routines for interdisciplinary study (e.g., LLMs in personalized FL). We conduct extensive and reproducible experiments to validate the effectiveness of FS-LLM and benchmark advanced LLMs with state-of-the-art parameter-efficient fine-tuning algorithms in a federated setting, which also yields many valuable insights into federated fine-tuning LLMs for the research community. To facilitate further research and adoption, we release FS-LLM at https://github.com/alibaba/FederatedScope/tree/llm. [1]

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[1]We will continuously update the codebase and arXiv version.

1 INTRODUCTION

Recent advances in large language models (LLMs) (Touvron et al., 2023; Brown et al., 2020; OpenAI, 2023; Zhang et al., 2022; Scao et al., 2022; Zeng et al., 2023; Chowdhery et al., 2022) have enabled a wide range of real-world applications across various domains, such as chatbots (i.e., ChatGPT[2]), writing assistants (Lee et al., 2022; Ippolito et al., 2022), search engines (i.e., New Bing[3]), tool/API retriever (Qin et al., 2023; Patil et al., 2023) and multimodal systems (Driess et al., 2023; Huang et al., 2023; Wu et al., 2023). Compared to previous pre-trained language models (Devlin et al., 2019; Liu et al., 2019), LLMs exhibit remarkable emergent abilities that have not been observed before (Zhao et al., 2023). These emergent abilities of LLMs are the cores of the unprecedented proficiency and efficiency of AI systems built on top of them. Consequently, both academic and industrial people have demonstrated a keen interest in investigating the potentialities of LLMs.

When applying LLMs in practical applications, such as education, law, and medicine, fine-tuning LLMs with domain-specific data can be essential. Fine-tuning can enrich LLMs with domain knowledge, enhance their specific ability, improve the fairness and reliability of the outputs, and prevent certain damage caused by hallucination (Ji et al., 2023). However, fine-tuning LLMs entails a high demand for computational resources and a substantial amount of domain data that may not be sharable due to privacy concerns. The former challenge can be addressed by recent works (Hu et al., 2022; Li & Liang, 2021; Liu et al., 2021a;b; Lester et al., 2021; Houlsby et al., 2019; Karimi Mahabadi et al., 2021; Pfeiffer et al., 2020a;c), which adapt pre-trained LLMs to specific domains by tuning modules with limited trainable parameters (denoted as *adapters*). For the latter issue, one of the feasible solutions is federated learning (FL) (Konečný et al., 2016; McMahan et al., 2017; Yang et al., 2019), a distributed learning paradigm that allows multiple entities to optimize a model collaboratively without directly sharing their data.

Although the existing FL frameworks (Bonawitz et al., 2019; Ryffel et al., 2018) can usually support various machine learning models, the development of federated fine-tuning on LLM is still in a premature stage because of the following **gaps** in existing work. **(i)** No existing FL package contains comprehensive and efficient implementations of LLM fine-tuning algorithms and a standardized benchmark for comparing the model performance, communication cost, and computation overhead when federated fine-tuning LLMs. **(ii)** Fine-tuning LLMs in FL is still computationally expensive on the client side, even with the parameter-efficient fine-tuning (PEFT) algorithms. **(iii)** Because pre-trained LLMs are of great intelligent property value and may not belong to clients, it might be necessary to let clients conduct federated fine-tuning without accessing the full model (e.g., closed-source LLMs). **(iv)** It is unclear whether the existing algorithms for solving advanced FL problems, such as personalized FL (pFL) (Tan et al., 2022; Chen et al., 2022) and federated hyperparameter optimization (FedHPO) (Wang et al., 2023), are still effective with different federated fine-tuning algorithms for LLMs.

We aim to bridge the aforementioned gaps and further promote the study of fine-tuning LLMs in the context of federated learning. Thus, we build up a novel open-source package for fine-tuning LLMs via federated learning, called **F**ederated**S**cope-**LLM** (FS-LLM), on top of FederatedScope (FS) (Xie et al., 2023). Our contributions can be summarized as follows:

- FS-LLM packages a collection of diverse federated fine-tuning datasets from various domains with tunable levels of heterogeneity and a suite of corresponding evaluation tasks to form a complete pipeline to benchmark federated fine-tuning LLMs algorithms in FL scenarios.
- FS-LLM provides comprehensive federated fine-tuning algorithms for LLMs with low communication and computation costs and versatile programming interfaces, which support both scenarios where clients can or cannot access the full model.
- FS-LLM is equipped with an optimized federated fine-tuning training paradigm for LLMs towards customizable efficiency-boosting (e.g., memory consumption reduction and multi-GPU parallelism) and interdisciplinary research potentials (e.g., pFL and FedHPO).
- We perform extensive experiments based on FS-LLM and investigate the empirical performances of federated fine-tuned LLMs. Based on our observations, we point out the challenges for federated fine-tuning LLMs and offer insights for future research in this emerging field.

[2]https://openai.com/blog/chatgpt

[3]https://www.bing.com/new

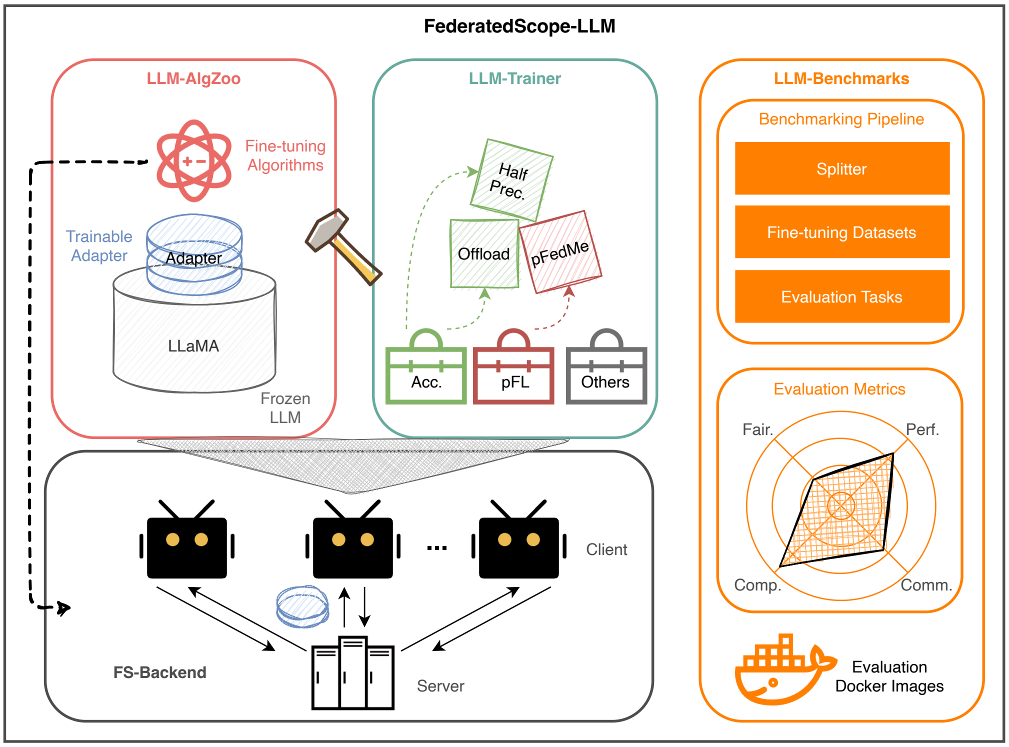


Figure 1: Overview of the architecture of FS-LLM, which consists of three main modules: LLM-BENCHMARKS, LLM-ALGZOO, and LLM-TRAINER. As an example in the figure, we use the PEFT algorithms to fine-tune LLaMA (Touvron et al., 2023) in FL, with half-precision (Micikevicius et al., 2018) training and offloading (Ren et al., 2021) strategy and pFedMe (T Dinh et al., 2020) algorithm. Under this learning paradigm, the clients can efficiently train on their local data with limited hardware resources, while the communication between the clients and the server only requires transmitting the adapter (which typically has very few parameters). This achieves high efficiency in both communication and computation. In the figure, Acc. stands for accelerating operator, Perf. stands for performance, Comm. stands for communication, Comp. stands for computation, and Fair. stands for fairness.

2 OVERVIEW

In Figure 1, we illustrate the overall architecture of FS-LLM using a concrete example. As mentioned above, FS-LLM is built upon FS (Xie et al., 2023), an easy-to-use platform that provides essential modules for constructing FL courses (e.g., communication modules, aggregation strategies, and training functionality interfaces), rich extended functionality, and plenty of instantiated FL algorithms. On top of FS, we develop three enrichments to address the gaps mentioned in Section 1 and facilitate fine-tuning LLMs in the federated setting: **LLM-BENCHMARKS**, **LLM-ALGZOO**, and **LLM-TRAINER**. With these new modules, FS-LLM supports end-to-end federated fine-tuning for LLMs, providing (1) data preparation for fine-tuning and evaluation, (2) several out-of-the-box popular fine-tuning algorithms and unified and flexible programming interfaces, (3) various accelerating and resource-efficient operators and flexible pluggable sub-routines for interdisciplinary study. We present an overview in this section and give detailed descriptions of these modules in Section 3, 4, and 5, respectively.

To consolidate the implementations and facilitate the FL research about LLMs, one of the critical steps is to construct a module with an end-to-end benchmarking pipeline, i.e., LLM-BENCHMARKS in FS-LLM. We assemble various corpus datasets from different domains for fine-tuning and pair each of them with one specific relevant evaluation task to assess the performance of the fine-tuned LLMs on different domains. For the datasets prepared for fine-tuning, we partition them according to their meta-information, formulating them into federated versions. Meanwhile, FS-LLM offers *Splitter* to split centralized datasets, enhancing the extensibility of the fine-tuning dataset for federated fine-tuning LLMs. Furthermore, we provide a rich set of docker images where the runtime environment of the evaluation tasks has been prepared. LLM-BENCHMARKS enables users to conveniently compare the effectiveness of different fine-tuning algorithms in various FL scenarios.

Another important and helpful component provided in FS-LLM, LLM-ALGZOO, includes a collection of fine-tuning algorithms tailored for FL. As communication and computation resources of clients are usually limited in FL, we leverage and integrate several PEFT algorithms into the FL setting, such as LoRA (Hu et al., 2022), prefix-tuning (Li & Liang, 2021), P-tuning (Liu et al., 2021b), and prompt tuning (Lester et al., 2021). Compared to full-parameter fine-tuning, these PEFT algorithms significantly reduce memory consumption, training time, and communication cost for fine-tuning LLMs. Besides, motivated by the practical concerns on intelligent property protection of LLMs, we also integrate a privacy-preserving fine-tuning algorithm, offsite-tuning (Xiao et al., 2023), for the scenario where clients only tune small adapters based on a distilled model from a full LLM.

Based on the fine-tuning algorithms mentioned above (i.e., the PEFT algorithms and offsite-tuning), LLM-TRAINER powers the FL fine-tuning process by adopting a hook-like training scheme. Though these algorithms fine-tune a small number of parameters of LLMs, they can still be computationally expensive for some clients. Therefore, FS-LLM incorporates various accelerating operators and resource-efficient operators as hook-like functions, such as DeepSpeed's ZeRO (Rasley et al., 2020), Pytorch's data parallelism (Paszke et al., 2019), and model quantization (Zhang et al., 2019), to accelerate the local fine-tuning process and enable FS-LLM to work efficiently on consumer-level GPUs. Besides, LLM-TRAINER, with the help of its customizable hook-like programming interfaces, can be quickly and seamlessly integrated with existing plug-ins in FS for interdisciplinary studies, such as pFL (Tan et al., 2022) and FedHPO (Wang et al., 2023), which could be a promising direction for further research. For meeting different hardware settings or research goals, LLM-TRAINER enables FS-LLM to fine-tune LLMs in simulated mode (single-machine FL for simulation, all clients in one machine), distributed mode (multi-machine FL, one client per machine), and clustered mode (multi-machine FL, one client per cluster).

3 LLM-BENCHMARKS: A COMPLETE PIPELINE FOR BENCHMARKING

As gap **(i)** mentioned in Section 1, there has yet to be a consensus in the academic community or industry on how to fairly evaluate the LLM fine-tuning algorithms in FL and what baselines are to compare. Therefore, we introduce LLM-BENCHMARKS, the first convenient and fair module to evaluate federated LLM fine-tuning. LLM-BENCHMARKS covers a complete benchmarking pipeline, consisting of stages from the construction of fine-tuning datasets to the evaluation with a collection of tasks. To facilitate replication and validation, we offer a series of look-up tables containing benchmark results for the fine-tuning datasets and their corresponding evaluation tasks. Additionally, we containerize the runtime environment of the evaluation for conveniently benchmarking the performance of the federated fine-tuned LLMs.

3.1 FEDERATED FINE-TUNING DATASET CONSTRUCTION

Unlike pre-training from scratch, fine-tuning LLMs is typically for adapting pre-trained LLMs to one specific domain, which can be very diverse, such as code generation and mathematical reasoning. Additionally, as considered in existing FL literature, the local datasets held by individual clients can exhibit varying degrees of heterogeneity, even within the same domain. For instance, although a set of clients share a common interest in fine-tuning an LLM for code generation, the code base of some clients may mainly consist of Jave, while the code bases of other clients may contain a substantial portion of Python.

To echo the diversity of target domains and the heterogeneity of data in real-world FL scenarios, we curate three fine-tuning datasets in LLM-BENCHMARKS. They cover a wide range of domains and exhibit realistic data distributions across different clients. (1) *Fed-CodeAlpaca* is built from CodeAlpaca (Chaudhary, 2023) to enhance LLMs' code generation capability. It simulates a *nine*-client FL scenario. Each client's dataset consists of coding exercises with answers limited to *one* specific programming language, such as Java or Python. (2) *Fed-Dolly* is for enhancing the capability of LLMs for generic language. We partition Databricks-dolly-15k (Conover et al., 2023) into *eight* clients' local datasets. Each client's dataset consists of a series of high-quality human-generated question-response pairs but is limited to *one* specific NLP task, such as information extraction or QA. (3) *Fed-GSM8K-3* is curated into *three* subsets from the train split in *GSM8K* (Cobbe et al., 2021), aiming to enhance the capability of LLMs for the chain of thought (CoT). Each client's dataset consists of grade school math questions randomly partitioned from the original dataset.

It is worth noting that, in addition to the built-in datasets mentioned above, we provide splitters for partitioning the centralized dataset into a federated version based on different meta-information or with different heterogeneity degrees among clients. For example, users can apply different splitters to a centralized dataset, such as the uniform splitter, Dirichlet splitter, or meta-information splitter, to construct fine-tuning datasets that mirror the heterogeneity inherent in different FL scenarios. We provide several built-in datasets for these splitters, such as *Alpaca* (Taori et al., 2023), *cleanedAlpaca* (Ruebsamen, 2023), etc. For more details about the provided fine-tuning datasets, please refer to Appendix A.1.

Table 1: Federated fine-tuning dataset and its corresponding evaluation task.

	Fine-tuning Dataset	Goal of Evaluation Task
Fed-CodeAlpaca & *HumanEval*	Coding exercises with different programming languages	How much can a federated fine-tuning algorithm improve the performance of an LLM with heterogeneous data on an in-domain task (coding)?
Fed-Dolly & *HELM*	Human-generated question-response pairs with different types	How much can a federated fine-tuning algorithm improve the performance of an LLM with heterogeneous data on generic language capabilities?
Fed-GSM8K-3 & *GSM8K-test*	Math questions with independent and homogeneous distribution	How much can a federated fine-tuning algorithm improve the performance of an LLM with i.i.d. data on an in-domain task (CoT)?

3.2 Federated LLM fine-tuning evaluation

LLMs are known to be very powerful, but it is challenging to evaluate their capabilities by a single metric. To the best of our knowledge, there are no ready-to-use evaluation tools for assessing federated LLM fine-tuning (let alone with the personalized FL algorithms) in terms of accuracy and efficiency. To fulfill such a gap, in LLM-Benchmarks, we provide a complete benchmarking pipeline to assess LLM fine-tuning in various FL scenarios.

We argue that fine-tuning should aim to enhance one of the two aspects of LLMs: either to improve their generic language capabilities or to improve their domain-specific capabilities for one particular downstream task. Therefore, we curate three evaluation datasets from different subject areas, including *HumanEval* (Chen et al., 2021) for the code generation, *HELM* (Liang et al., 2022) for the generic language capabilities, and *GSM8K-test* (Cobbe et al., 2021) (the test split in *GSM8K*) for CoT. Given that different datasets employ different default evaluation metrics, for simplicity, we introduce the term *evaluation score* as a unifying descriptor for the evaluated results obtained on these datasets with their metrics. Specifically, the evaluation score represents Pass@1 score when using *HumanEval*, a mixture of metric scores on 16 subtasks when evaluating on *HELM*[4], and accuracy when utilizing *GSM8K-test*. And more details can be found in Appendix A.2.

Then, we define evaluating an LLM on a specific dataset and generating the corresponding evaluation score as an *evaluation task*. We combine each fine-tuning dataset mentioned in Section 3.1 with one specific evaluation task, which allows users to fairly assess the improvement of fine-tuned LLMs in FL. The fine-tuning dataset, the corresponding evaluation task, and the goal of the evaluation task are listed in Table 1. Note that there is generally a distribution shift between the fine-tuning and evaluation datasets, making it much more challenging than those in other domains of FL (Caldas et al., 2018; Dong et al., 2022; Wang et al., 2022). To ensure the consistency of the evaluation results,

[4]Because evaluation on 16 subtasks is time-consuming, we also curate a smaller *HELM-MINI* with 4 subtasks but consistent performance with original *HELM* for a brief evaluation.

we containerize the runtime environment of these evaluation tasks to docker images for conveniently assessing the performance of the federated LLM fine-tuning.

Last but not least, we also introduce a rich set of cost-related metrics to measure the efficiency of a federated fine-tuning process, including both computation costs (e.g., GPU usage, computation time, flops count) and communication costs (e.g., message size). Along with evaluation scores, these metrics could give a comprehensive assessment of the federated fine-tuning process.

4 LLM-AlgZoo: A Collection of Fine-tuning Algorithms

In addition to the benchmarking module, LLM-Benchmarks, we implement a set of popular fine-tuning algorithms in FS-LLM and introduce them as LLM-AlgZoo in this section. Aiming to fulfill the gaps **(i)** and **(ii)**, LLM-AlgZoo first includes a collection of PEFT algorithms to satisfy the constraints on the communication and computation costs in federated fine-tuning when all clients have access to the full model. However, we also realize that there are cases where the LLM owner may not be willing to share the full model in the federated fine-tuning stage. Thus, to fulfill gap **(iii)**, we further adopt a fine-tuning algorithm that does not require full model access in the FL setting. Notice that all these fine-tuning algorithms are implemented on a set of unified but flexible interfaces, which hides the underlying standard functionalities from algorithm implementors, such as coordinating communication in FL. The same interfaces can support more diverse fine-tuning algorithms in future development if users follow the same programming paradigm as our implemented algorithms.

4.1 Reducing communication and computation costs with PEFT algorithms

Achieving communication and computation efficiencies are two major challenges for fine-tuning LLMs in FL. The communication bottleneck arises from the limited bandwidth of the internet connection between the server and the clients. This challenge becomes exacerbated when full-parameter fine-tuning LLMs in FL, as they require transmitting more parameters than previous pre-trained language models. For example, full-parameter fine-tuning LLaMA-7B in FL requires 28GB of message transfer for one communication round from the client to the server. Assuming the network bandwidth is 100MBps, only model uploading and downloading will take about 75 minutes, which is intolerant, especially for clients with limited network bandwidth. The computation efficiency is the other critical issue for federated fine-tuning LLMs. For example, full-parameter fine-tuning LLaMA-7B requires about 28GB of GPU memory for the model. In addition, the SGD optimizer and the gradients need another 92GB of GPU memory, leading to at least 112GB of GPU memory in total - this is unaffordable for most resource-limited entities.

We provide a set of implemented PEFT algorithms in FS-LLM as solutions for our users to encounter these challenges, including LoRA (Hu et al., 2022), prefix-tuning (Li & Liang, 2021), P-tuning (Liu et al., 2021b), and prompt tuning (Lester et al., 2021). These algorithms perform fine-tuning by only training (additional) modules with limited parameters, known as *adapters*, but keep other parameters frozen. Compared to full-parameter fine-tuning in FL, clients only need to transmit the adapters in each communication round, which reduces the transmission time to tens of seconds or even seconds. Meanwhile, PEFT algorithms reduce the computation cost and make local training more viable for resource-limited clients. For example, if we only fine-tune the adapter of LLaMA-7B, the total GPU memory consumption will be a little more than 28GB, and the computation time will be less than that of full-parameter fine-tuning as well. Thus, based on considerations of communication and computation costs, LLM-AlgZoo adopts PEFT algorithms and makes them considerably more viable for resource-limited entities when federated fine-tuning LLMs.

4.2 Federated fine-tuning without accessing full model

Many existing LLMs (OpenAI, 2022; 2023; Anthropic, 2023) are closed-source for some reasons such as high training costs, preventing training data leakage, and maintaining commercial secrets. However, in some commercial scenarios, downstream customers may not be satisfied with simply using APIs to perform inference on these all-around LLMs but also want to customize them more to their domain-specific data. These domain-specific data are often private, limited, and incomplete, which leads to insufficient adaptation and generalization of LLMs to the customers' needs.

To satisfy such practical demand, we adapt a privacy-preserving fine-tuning algorithm, offsite-tuning (Xiao et al., 2023), to a federated version, and name it FedOT for short. It sends a lossy compressed model with untrainable parameters to the clients as an emulator of the complete LLM at the beginning of FL. During the FL, the clients fine-tune adapters with the frozen emulator and their domain-specific data. FedOT safeguards both the intelligent property of the model providers and the data privacy of the clients, while leveraging the distributed data for adapting LLMs to specific domains. This algorithm can be further integrated with the PEFT algorithms mentioned in Section 4.1.

4.3 Extendability by unified interfaces for federated fine-tuning

Notice that the aforementioned federated fine-tuning algorithms, regardless of whether the clients have access to the full model, are all implemented via a set of unified interfaces in FS-LLM. The interfaces compose a skeleton structure that can be customized to various FL applications. The interfaces can be invoked with customized functions in different stages, handling the underlying communication and synchronization between the server and clients in FL. Figure 2 illustrates some unified interfaces used by fine-tuning algorithms in Section 4.1 and 4.2. The unified interfaces include but are not limited to the model pre-processing interface (arrow ①), initial model broadcast interface (arrow ②), shared parameter aggregation interface (arrow ③), and parameter re-distribution interface (arrow ④). For closed-source LLMs, which are inaccessible to clients, the model providers can compress the LLM into an emulator by implementing a distillation function with the model pre-processing interface; for open-source LLMs, which are accessible, the pre-processing interface just returns the original LLM.

These unified but flexible interfaces are based on the event-driven architecture in FL (Xie et al., 2023). In the context of federated LLM fine-tuning, events are the exchanged information (e.g., local updated weights). Each event has a corresponding handler, which is the actions triggered by it. The event-driven architecture allows the entities of FL to program their behaviors and react to the events. Thus, by designing message-handler pairs, users can extend and customize the federated fine-tuning algorithms easily because of the extensibility of FS-LLM.

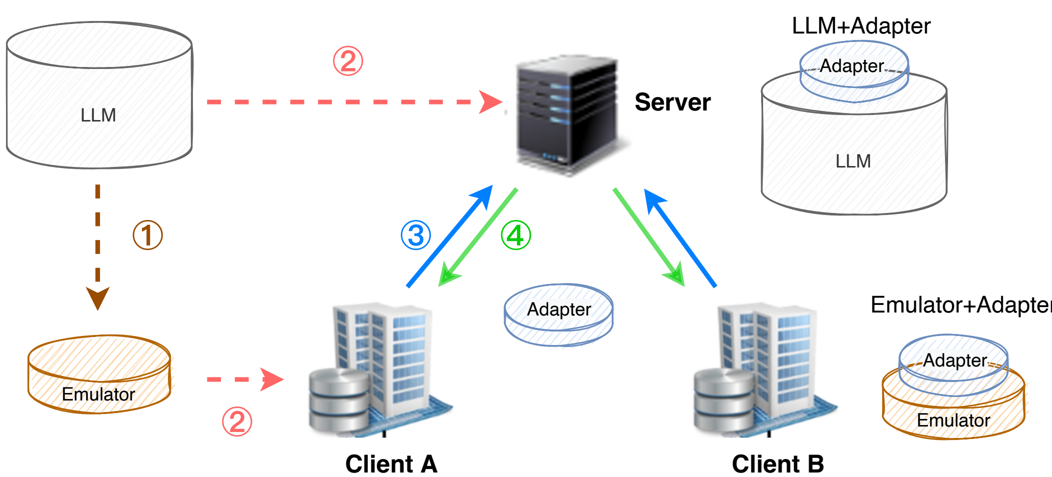


Figure 2: The unified interfaces for federated fine-tuning LLMs with or without accessing the full model. When the LLM is not accessible to clients, different algorithms can be used to generate an emulator, including distillation, pruning, and quantization via ① LLM model pre-processing interface; if the LLM is accessible, ① just output the input by default. The other three interfaces in the figure are ② initial model broadcast, ③ shared parameter aggregation, and ④ parameter re-distribution.

5 LLM-TRAINER: TRAINING OPERATORS AND PARADIGM

Although PEFT algorithms can significantly reduce the computation cost, they may still be computationally expensive for some clients with limited resources. To alleviate such concerns, we provide LLM-TRAINER, which is designed to further accelerate computation and save resources during the local training and message transmission stages in FL. We implement a set of accelerating operators and resource-efficient operators to fulfill gap **(ii)**. Moreover, to meet different hardware settings or research goals, FS-LLM supports simulated mode, distributed mode, and clustered mode. For simulated mode, all clients run on a single machine to simulate the federated fine-tuning process. For the distributed mode and clustered mode, each client runs on one or more machines and communicates with the server separately. These modes share a consistent programming paradigm and behavior. Meanwhile, we note that there are also advanced FL problems in federated fine-tuning LLMs, such as pFL (Tan et al., 2022) and FedHPO (Wang et al., 2023). Thus, to further fulfill gap **(iv)**, we implement LLM-TRAINER as a collection of hook-like functions to support rich extensions, following the design principles of FS Trainer (Xie et al., 2023). These hook-like functions will be executed by some arranged pattern to fine-tune the adapter within the local client. By adding, removing, or replacing hook-like functions, entities can conveniently customize local fine-tuning procedures and extend applicabilities. LLM-TRAINER can be effortlessly compatible with implemented advanced FL algorithms for interdisciplinary research.

5.1 TRAINING OPERATORS FOR ACCELERATION AND EFFICIENCY

We introduce various accelerating operators and resource-efficient operators for fine-tuning LLMs in FS-LLM. These provided operators aim to optimize the federated fine-tuning process in terms of CPU/GPU memory consumption, multi-GPU parallel, and communication cost. We describe the operators and show how they can be combined to achieve better compatibility and efficiency.

Mode-generic operators. We provide operators generalized to different modes in the local fine-tuning stage of FS-LLM. We implement mixed-precision training and gradient accumulation operators in several hook-like functions to save GPU resources. Furthermore, to accelerate the local fine-tuning process and enable multi-GPU parallelism, FS-LLM integrates Pytorch's data parallel mechanism.

Mode-specific operators. Besides the aforementioned generalized operators, we develop specialized operators that are tailored for each mode and aim to address the bottlenecks in each mode. To be more specific, in the simulated mode, instantiating multiple clients on a single machine with several independent instantiated models causes a lot of memory consumption. Therefore, we use a round-robin switching operator, which allows the clients to take turns using the frozen full model for fine-tuning the adapter and then aggregating the updated adapters. Under this operator, when the number of clients grows, the memory consumption will only increase by an additional amount of the adapter. This improvement makes it possible to conduct simulated FL experiments with a number of clients on one single machine. For the distributed mode and clustered mode, we accelerate the communication between the server and the clients by one to two orders of magnitude by reducing the size of communication messages. We apply different communication optimizations for different messages and introduce communication-efficient operators, including quantization operator, streaming operator, and compression operator. Specifically, the quantization operator reduces the bit-width of the model parameters in the message to 16 or 8 bits; the streaming operator serializes the model parameters to eliminate the overhead of type conversion; the compression operator applies DEFLATE (Deutsch, 1996a) or Gzip (Deutsch, 1996b) algorithms to compress the messages.

Parallelization operators. Meanwhile, we also migrate the functionality of DeepSpeed as shown in Figure 3, providing data parallelism with multi-GPU memory optimization and CPU offloading capabilities, further enhancing resource utilization. Specifically, after launching the fine-tuning with DeepSpeed, we disable some modules (e.g., the logging module, the WandB module, and the file writing module) for the subprocess other than the Rank 0 process to avoid conflicts. In addition, in distributed and clustered modes, each subprocess communicates independently with each other across the server and the clients, and only synchronizes with other subprocesses during the local fine-tuning process, ensuring consistent behavior across different modes.

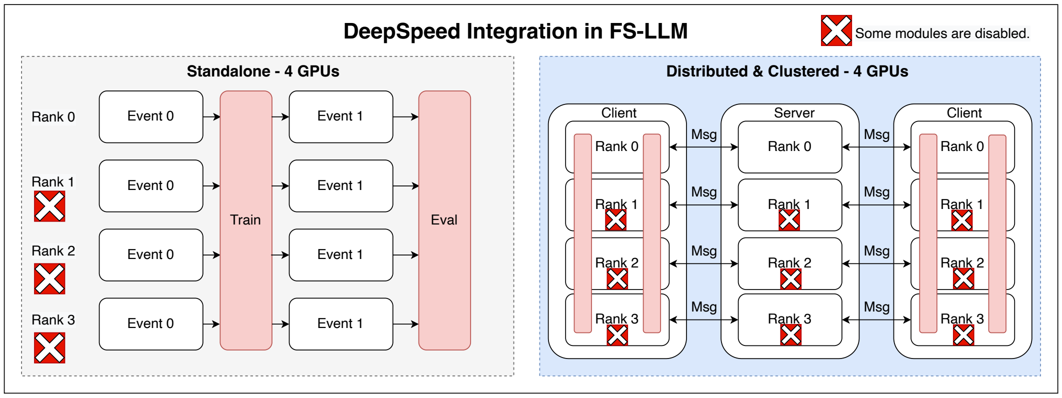


Figure 3: FS-LLM integrates DeepSpeed for federated fine-tuning in different hardware conditions. Rank 0 indicates the main process for multi-GPU training, and some modules of other subprocesses are disabled (e.g., logging and saving checkpoints). Msg stands for messages transmitted between the server and the clients, which trigger the events to happen.

5.2 Training paradigm for extendability towards advanced FL tasks

Another design philosophy of LLM-Trainer is to support various extensions easily and integrate different hook-like functions with existing training paradigms seamlessly for FL interdisciplinary study. A vanilla fine-tuning process involves three steps: (1) preparing datasets and extracting them by batches, (2) iterating over the training datasets to update the model parameters, and (3) evaluating the performance of the fine-tuned model on validation datasets. We implement fine-grained learning behaviors for advanced FL tasks at different points in the above steps with hook-like functions. For instance, pFL (Tan et al., 2022) and FedHPO (Wang et al., 2023) are two advanced FL tasks that can significantly improve model performance in FL.

Adaptation of pFL with LLMs. FS (Xie et al., 2023) provides many implemented pFL plugins (Chen et al., 2022), which can be integrated for federated fine-finetuning LLMs. However, due to limited resources, it is unrealistic for the clients to maintain both global and local models at the same time for some pFL algorithms (T Dinh et al., 2020; Li et al., 2021), as it would consume a lot of memory. Therefore, we optimize the implementation of these pFL algorithms by only using global and local adapters. With such an implementation, by adding a pFL hook-like function, we can achieve the cooperation of any PEFT algorithms with the implemented pFL algorithms, which provides strong extensibility for federated fine-tuning LLMs in personalized settings.

Adaptation of FedHPO with LLMs. Similarly, for FedHPO, we offer extensions for FS-LLM with model-free HPO methods (e.g., random search (Bergstra & Bengio, 2012) and grid search), model-based HPO methods (e.g., Bayesian Optimization (Shahriari et al., 2015)), multi-fidelity HPO method (e.g., Successive Halving Algorithm (Jamieson & Talwalkar, 2016)), and FedHPO methods (e.g., FTS (Dai et al., 2020) and FLoRA (Zhou et al., 2021)).

As our vision, the extensibility of FS-LLM to support the interdisciplinary study of LLMs and other FL scenarios dramatically expands the application scenarios of fine-tuning LLMs in FL and raises many new research opportunities, which we will discuss more details later in Section 7.

6 Experiments

In this section, we demonstrate the effectiveness of FS-LLM by a set of comprehensive experiments with different algorithms and tasks. We want to answer the following research questions: (1) How effective and efficient is it to federated fine-tuning LLMs with PEFT algorithms (Section 6.1 and 6.2)? (2) How effective is it to federated fine-tune LLMs without accessing the full model (Section 6.3)? (3) What insights can we obtain from the interdisciplinary capabilities of FS-LLM in resolving pFL and FedHPO problems when federated fine-tuning LLMs (Section 6.4 and 6.5)? We go through our experimental results and provide answers to the above questions.

6.1 Effectiveness of PEFT algorithms in FS-LLM

Firstly, we benchmark the performance of different PEFT algorithms in different application domains and scenarios. As described in Section 3, we use three federated fine-tuning datasets to fine-tune LLMs and evaluate them with corresponding tasks: (i) federated fine-tuning with *Fed-CodeAlpaca* for code generation and evaluating with *HumanEval*, (ii) federated fine-tuning with *Fed-Dolly* for generic language capability and evaluating with *HELM*, and (iii) federated fine-tuning with *Fed-GSM8K-3* for mathematical reasoning and evaluating with *GSM8K-test*. We conduct experiments in three scenarios: global (centralized fine-tuning), fed (federated fine-tuning), and local (separated fine-tuning). To be more specific, the global scenario can be regarded as fine-tuning LLMs with one client who holds the whole fine-tuning dataset. Fed scenario means that clients federated fine-tune LLMs where each client holds a different fine-tuning dataset. Local scenario means that each client independently fine-tunes LLMs with its own fine-tuning dataset.

All the experiments are conducted on the machines with the same hardware configuration: Nvidia A100 GPU (80GB) with Intel Xeon Platinum 8369B CPU and 512GB of RAM. For all scenarios, we repeat the experiments three times with different random seeds. We report the average evaluation score with its standard deviation.

Benchmark federated fine-tuned LLaMA-7B. We use a widely adopted LLM, LLaMA-7B, with three PEFT algorithms [5], including LoRA (Hu et al., 2022), P-tuning (Liu et al., 2021b), and prompt tuning (Lester et al., 2021). We employ FedAvg (McMahan et al., 2017) as the federated aggregation strategy. To conduct the experiments uniformly and fairly, we fix the FL-specific hyperparameters and the hyperparameters that have a large impact on the computation cost for all experiments. For example, we set the communication round to 500, the local update step to 30, and the batch size to 1. We perform a grid search for algorithm-specific and learning-related hyperparameters to obtain the optimal configuration. For example, the search space of the learning rate is $\{1 \times 10^{-4}, 3 \times 10^{-4}, 5 \times 10^{-4}, 1 \times 10^{-3}, 3 \times 10^{-3}, 5 \times 10^{-3}\}$. Please refer to Appendix A.3 for more algorithm-specific hyperparameters corresponding to each PEFT algorithm. Moreover, to further reduce the GPU memory consumption for efficiency, we employ the half-precision operator during fine-tuning.

Table 2: Performance comparisons among different PEFT algorithms when fine-tuning LLaMA-7B in FL: Evaluation Scores(%) $\pm$ standard deviation(%).

Algorithm	Scenario	*Fed-CodeAlpaca*	*Fed-Dolly*	*Fed-GSM8K-3*
LoRA	Global	13.54±0.24	46.25±0.44	14.81±1.04
	Fed	13.29±0.10	46.57±0.24	14.25±1.37
	Local	10.99±0.77	43.98±1.38	11.88±1.35
P-tuning	Global	10.24±0.30	41.29±0.01	12.13±0.41
	Fed	9.71±0.66	41.50±0.32	11.75±0.39
	Local	7.78±2.27	38.76±2.39	11.42±0.96
Prompt tuning	Global	9.80±1.79	41.24±0.54	9.75±1.49
	Fed	9.63±0.36	40.72±0.64	9.86±0.59
	Local	7.18±2.17	37.65±6.12	9.65±0.77

Results and Analysis. Table 2 shows the comparisons among different PEFT algorithms for federated fine-tuned LLaMA-7B under different scenarios. In summary, we can draw the following conclusions. (1) All algorithms with federated fine-tuning can significantly outperform those under the local scenario, and they all show very competitive results against those under the global scenario. This suggests that it is feasible and effective to federated fine-tuning LLMs with PEFT algorithms, which allows multiple entities to benefit from the collaborative training without directly sharing their private

[5]We exclude prefix-tuning from our experiments, because its implementation in Mangrulkar et al. (2022) contains unresolved issues when we were preparing this package.

data. (2) Among these PEFT algorithms, LoRA shows the most promising performance and beats the other two algorithms by a large margin in all three scenarios. P-tuning and prompt tuning are two parameterized prompt algorithms that insert some learnable tokens into the model input to improve the performance of downstream tasks. However, they are outperformed by LoRA, a low-rank adaptation algorithm that augments each layer of LLMs with two low-rank matrices to capture new domain-specific knowledge. We conjecture that these parameterized prompt algorithms are limited by the knowledge encoded in the original LLM during the pre-training stage. This indicates that LoRA is a suitable PEFT algorithm for federate fine-tuning LLMs in future research or realistic scenarios.

How about federated fine-tuning previous-generation language models? As a comparison, we select the superior PEFT algorithm in Table 2, LoRA (Hu et al., 2022), to federated fine-tune a previous-generation language model, OPT-2.7B (Zhang et al., 2022), which has fewer parameters than LLaMA-7B. Table 3 shows the evaluation results of OPT-2.7B on the *HumanEval*, *HELM* evaluations, and *GSM8K-test*.

Though the model performance of OPT-2.7B is improved with federated fine-tuning compared to those under the local scenario, it is not significant. Moreover, OPT-2.7B fails in the evaluation of some subtasks in HELM due to the exceeded input length, which limits the scope of the application of the previous-generation language models with fewer parameters. Comparing the performance of federated fine-tuned LLaMA-7B and OPT-2.7B in Figure 4, we observe that the current-generation LLM with a larger scale has an obvious advantage over the previous-generation language model with a smaller scale on various evaluation tasks. Thus, if the communication and computation costs are affordable, one should consider the larger scale of current-generation LLMs for more significant FL improvement and better absolute performance on downstream tasks.

Table 3: Performance of federated fine-tuned previous-generation language model, OPT-2.7B, with LoRA: Evaluation Scores(%) ± standard deviation(%). (*OPT-2.7B fails on some subtasks in HELM due to the exceeded input length, and failed subtasks are excluded when calculating the final results.)

Algorithm	Scenario	*Fed-CodeAlpaca*	*Fed-Dolly*	*Fed-GSM8K-3*
LoRA	Global	0.61±0.61	25.90±0.40*	2.92±0.11
	Fed	0.43±0.07	25.90±0.33*	2.88±0.17
	Local	0.25±0.25	25.06±1.02*	2.25±0.22

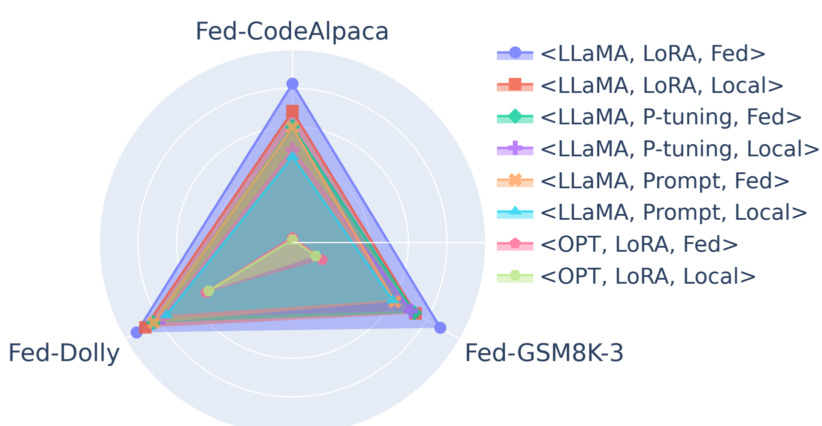


Figure 4: Visualization of the performance comparison of fine-tuned LLaMA-7B and OPT-2.7B under federated and local scenarios. (The axes are scaled to highlight the differences.)

6.2 EFFICIENCY OF PEFT ALGORITHMS IN FS-LLM

In this section, we evaluate the efficiency of various PEFT algorithms in FL. Among all the metrics, we focus on their GPU memory consumption, message size, and computation time in the federated fine-tuning process. We note that the GPU memory consumption refers to the model only, excluding the input tokens and the optimizer state, because the input length varies greatly across data and affects the GPU memory consumption during fine-tuning LLMs. For message size, we report the number of bytes of the serialized adapter parameters during one communication between the server and one client. The computation time is defined as the time duration of one training step with a batch size of 1, from the start of forward propagation to the end of backward propagation. We report the computation time on two types of hardware, both with 512GB of RAM: Nvidia A100 GPU (80GB) with Intel Xeon Platinum 8369B CPU and Nvidia V100 GPU (32GB) with Intel Xeon Platinum 8163 CPU. For a fair comparison, we follow the same experimental settings as Section 6.1 for all PEFT algorithms.

Results and Analysis. As shown in Table 4, we can first notice that (1) fine-tuning with different PEFT algorithms has negligible impact on the GPU memory consumption. (2) However, there are large differences in the message sizes, which in turn lead to large variations in the transmission time. For example, for a client with 100Mbps bandwidth, the transmission time (upload and download) per round ranges from about 0.01 seconds (with prompt tuning) to 40 seconds (with P-tuning) when using different PEFT algorithms. (3) Moreover, from the table, we can observe that the computation time varies due to different GPUs, with almost a twofold difference. Therefore, a more critical issue deserves attention: federated fine-tuning LLMs may suffer from more idle time due to the heterogeneity of computing resources among different clients. Because this computation efficiency difference can be significant, the benefit of mitigating communication latency by sending messages asynchronously in multiple computational stages may diminish.

Therefore, there are two research directions for federated fine-tuning LLMs in efficiency: (1) how to leverage the idle time of computation-resource-rich clients while they wait for computation-resource-limited clients to complete local updates, and (2) how to optimize the utilization of the available bandwidth resources in computation-resource-limited clients during computation.

Table 4: Efficiency comparisons among different PEFT algorithms when fine-tuning LLaMA-7B in FL. (*The GPU usage is subject to minor variations due to the differences in Cuda versions.)

	LoRA	P-tuning	Prompt tuning
GPU Usage* (MB)	13,450	13,538	13,442
Message Size (MB)	21.40	256.48	0.17
Comp. Time on A100 (Sec.)	0.16±0.02	0.15±0.03	0.15±0.04
Comp. Time on V100 (Sec.)	0.33±0.07	0.33±0.08	0.33±0.10

6.3 FINE-TUNING LLMS WITHOUT ACCESSING THE FULL MODEL IN FL

In this section, we investigate the performance of federated fine-tuning LLMs without accessing the full model. As mentioned in Section 4.2, we adapt a privacy-preserving fine-tuning algorithm, offsite-tuning (Xiao et al., 2023), to federated scenarios. Specifically, we use the first and last two layers of LLaMA-7B as the adapter and compress the model as the emulator by dropping 20% and 50% of the remaining layers uniformly. Then the server broadcasts both the adapter and emulator to all clients, and the clients only fine-tune the adapter with FedAvg. We compare the performance of LLMs with fine-tuned adapters via federated offsite-tuning (denoted as FedOT) and corresponding local offsite-tuning (denoted as LocalOT). Following Section 6.1, we benchmark FedOT on LLM-BENCHMARKS.

Results and Analysis. We present the evaluation scores of FedOT and LocalOT in Table 5. We can have the following observations: (1) Comparing FedOT and LocalOT, FL offers significant benefits for this privacy-preserving fine-tuning algorithm for federated fine-tuning LLMs without accessing the full model. This demonstrates that FedOT can still enable multiple entities to benefit from collaborative training without sharing their private data directly when they cannot access the full model. (2) When the dropping rate is 20%, FedOT still achieves competitive performance compared to some of those PEFT algorithms, even though the clients cannot access the full model. However, it should be noted that this is because the number of parameters of the adapter in FedOT is significantly larger than those in the PEFT algorithms. FedOT sacrifices communication efficiency for model performance, making it effective in scenarios where clients cannot access the full model. (3) On the other hand, the results show that when the dropping rate increases to 50% from 20%, the model loses a large amount of knowledge from the pre-training stage, almost fails to retain the capacity of the CoT and code generation, and hardly acquire new knowledge from the fine-tuning. There is a trade-off between the compression rate and the performance of LLMs: increasing the compression rate enhances the privacy of LLMs but degrades their performance. This indicates that how to compress LLMs while maintaining their generalization ability and model privacy is a promising research direction to explore.

Table 5: Performance comparisons between different compression rates (dropping layers uniformly) when fine-tuning LLaMA-7B without accessing the full model under federated and local scenarios: Evaluation Scores(%) $\pm$ standard deviation(%).

Dropping Rate	Scenario	*Fed-CodeAlpaca*	*Fed-Dolly*	*Fed-GSM8K-3*
20%	Fed	7.14±2.75	44.88±0.75	9.02±0.71
	Local	0.18±0.50	38.45±9.57	4.72±2.91
50%	Fed	0.16±0.15	37.01±2.34	2.98±0.98
	Local	0.00±0.00	35.44±5.99	1.82±1.29

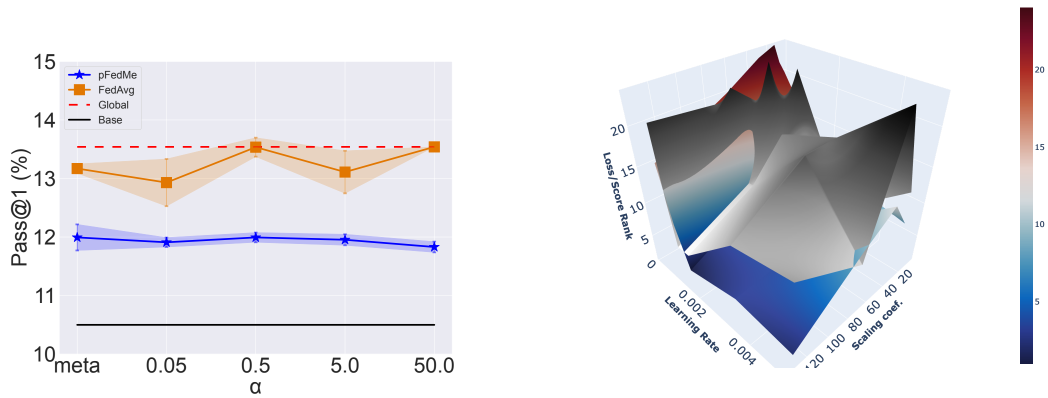
6.4 PERSONALIZED FEDERATED LEARNING FOR LLMS

To explore the potential of personalized federated learning algorithms (Tan et al., 2022) for fine-tuning LLMs in FL, we compare pFedMe (T Dinh et al., 2020) and FedAvg (McMahan et al., 2017) with LoRA in this subsection under different data heterogeneity. To simulate different levels of data heterogeneity, we create variants of *Fed-CodeAlpaca*.

We use the programming language of the code samples as the label and split the fine-tuning dataset into nine clients by Latent Dirichlet Allocation (i.e., Dirichlet splitter). We use four different values for α of the Dirichlet splitter from 0.05 to 50.0. Along with the original *Fed-CodeAlpaca* dataset, we obtain five federated fine-tuning datasets with different heterogeneity. Following Section 6.1, we repeat each experiment three times with different random seeds. The averaged evaluation scores (Pass@1 scores) with their standard deviation are reported. We note that evaluation scores with pFedMe are obtained by benchmarking each personalized client individually and then computing their average scores.

Results and Analysis. We present the performance of fine-tuning with LoRA using FedAvg and pFedMe in different data heterogeneities in Figure 5a, which shows the performance of fine-tuning with FedAvg gradually approaches that under the global scenario as data heterogeneity decreases. However, pFedMe surprisingly does not outperform FedAvg under any data distribution, which shows different results with previous language models in pFL-bench (Chen et al., 2022). We analyze this phenomenon and find that: (1) To improve efficiency, we use the half-precision operator to fine-tune LLMs in the experiment. However, this leads to a more pronounced precision loss for pFedMe than FedAvg, since pFedMe multiplies the update of the local model with respect to the global model by a small learning rate. This adversely impacts the performance of pFedMe. (2) The use of acceleration operators for efficient LLM fine-tuning restricts the range of hyperparameter space in these pFL algorithms, affecting the upper bound of algorithm performance in the valid parameter space. For example, assuming the LLM performs better when the learning rate is 0.00001, but at this point, using half-precision or mixed-precision training for efficiency, the model can barely be updated due to the precision loss.

Based on these observations, we believe how to ensure the compatibility of various efficient training operators and different pFL algorithms is still unclear and deserves more attention from the community. Besides, sharing a common base LLM and only maintaining multiple versions of adapters may not be compatible with some existing pFL algorithms because pFL algorithms may introduce access conflicts. For instance, when a penalty term is used to constrain the large updates of the local model, the computation to compute updates requires using both the global adapter with the base LLM and the local adapter with the base LLM in the same step. Significantly, more memory cost is required to avoid the conflict by maintaining multiple copies of LLMs and their adapters. Resolving this challenge may require new algorithm development or a new pFL computation pattern for future work.



(a) The comparison of performance with pFedMe and FedAvg over different data heterogeneity: the higher α, the lower the data heterogeneity among clients. Global stands for fine-tuning LLMs under the global scenario, and Base stands for the original model, which is not fine-tuned.

(b) The landscape of the rank of the validation loss and the Pass@1 scores over all the hyperparameter combinations. The grey surface shows the distribution of the rank based on the Pass@1 scores, and the blue-red surface indicates the distribution of the rank based on the validation loss.

Figure 5: Fine-tuning LLMs in pFL (**Left**) and FedHPO (**Right**).

6.5 Study of the FedHPO for LLMs

Since fine-tuning LLMs in FL is very costly, it is usually infeasible to perform full-fidelity hyperparameter optimization. However, we observe that the performance of fine-tuned LLMs in FL is highly dependent on the choice of hyperparameters (see Appendix A.3). Therefore, we investigate whether we can use low-fidelity FedHPO (Wang et al., 2023) methods in this scenario. We follow the experiment settings in Section 6.1 and use LoRA to fine-tune LLaMA-7B on *Fed-CodeAlpaca* yet with lower fidelity (i.e., fewer communication rounds). We rank all the hyperparameter combinations searched by their validation loss in ascending order and evaluation scores in descending order separately. We plot the two landscapes of the rank to explore the feasibility of using low-fidelity FedHPO methods when federated fine-tuning LLMs.

Results and Analysis. Based on the results shown in Figure 5b, we distill the following observations. (1) We observe that the rank of the evaluation scores of the fine-tuned LLMs varies drastically and non-smoothly with respect to the hyperparameter changes. This poses a great challenge for finding the optimal hyperparameters, as it requires a fine-grained and exhaustive search over the hyperparameter space. (2) Moreover, we reveal a significant discrepancy between the ranks of validation loss and the ranks of final generalization performance in evaluation tasks during fine-tuning. This implies that the validation loss may not reflect the generalization ability of the fine-tuned LLMs.

In summary, we uncover two major challenges for fine-tuning LLMs in FedHPO: (1) the evaluation scores are highly sensitive and non-smooth to the hyperparameter changes, and (2) the validation loss may not be a reliable indicator of the generalization performance. These challenges identify two promising yet unexplored research directions for future work on fine-tuning LLMs in FedHPO. The first direction is to develop fine-grained but efficient FedHPO methods for finding the optimal hyperparameters on federated fine-tuning LLMs, which can avoid exhaustive searches over the hyperparameter space. The second direction is to exploit concurrent exploration in FedHPO to evaluate the generalization ability of the client-side hyperparameters with low fidelity for each client during the FL process.

7 Discussions and Future Directions

This paper introduces a comprehensive and practical package for federated fine-tuning LLMs. Our experimental results illustrate how our FS-LLM bridges the gaps between the universal FL framework and the need for fine-tuning LLMs under various FL settings. More importantly, our benchmark results also provide positive guidance and insights for the research community regarding how to optimize the federated fine-tuning and what sub-problems in the field deserve more focus.

However, the results of this paper are limited by several factors. (1) Due to the resource limit, all experiments use a batch size of 1, but federated fine-tuning LLMs with larger batch sizes might perform better. (2) We also find that designing different prompts (either in fine-tuning or evaluation) will impact the evaluation results. To ensure a fair evaluation and comparison, we use a fixed prompt, but more explorations are possible.

Based on our observations and experiments, we outline some promising directions for future research in federated fine-tuning LLMs as follows.

- Designing computation-efficient fine-tuning algorithms for federated fine-tuning LLMs. Even with PEFT algorithms, the computation cost is still too high for most resource-limited clients. Reducing the computation cost can lower the barrier for more data holders and allow more entities to benefit from the federated fine-tuning LLMs.
- Exploring more privacy-preserving fine-tuning algorithms without accessing the full model in FL. FedOT suffers from a trade-off between model compression rate and model performance. Addressing this issue would protect the sensitive information of LLMs in FL from exposing pre-training data and the valuable full model, which could be exploited by malicious entities for adversarial attacks or commercial gains while maintaining model performance in FL.
- Optimizing pFL algorithms to enable robust combination with various accelerating and resource-efficient operators. If performance degradation due to low-precision training can be overcome, it would improve the personalized model performance when data are heterogeneous and computation resources are limited among clients.
- Investigating low-fidelity FedHPO methods for fine-tuning LLMs in FL. Based on our experimental results, we find the inconsistency between validation loss and the generalization performance of LLMs. Overcoming this inconsistency would help find optimal hyperparameters for federated fine-tuning LLMs with low cost, resulting in better generalization performance.
- Extending the federated LLM fine-tuning to cross-device setting. As we have already observed the demand for federated fine-tuning LLMs in the cross-silo scenario, we also notice a similar need in the cross-device scenario (Lai et al., 2022; Chen et al., 2023; Gao et al., 2023). In the cross-device scenario, the clients are more numerous and heterogeneous, the computational resources are more limited, and the network conditions are more diverse. How to federated fine-tune LLMs under the cross-device scenario is an urgent problem that needs to be solved.

8 Conclusions

In this paper, we first identify gaps that need to be addressed between fine-tuning LLMs in federated settings and the existing universal FL frameworks. To bridge these gaps, we introduce our open-source package, FS-LLM, with rich functionalities and extensibilities, which supports federated fine-tuning LLMs under various FL scenarios. We conduct extensive experiments to demonstrate the utility of our package and gain insights into how to fine-tune LLMs in FL settings. Based on the findings from these experimental results, we outline some promising directions for future research in federated LLM fine-tuning to advance the FL and LLM community. We have released FS-LLM at https://github.com/alibaba/FederatedScope/tree/llm for promoting further research.

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A APPENDIX

A.1 FINE-TUNING DATASET DESCRIPTION

In this section, we describe the fine-tuning datasets curated in FS-LLM, and summarize the statistics and information in Table 6. These datasets are derived from existing and widely used fine-tuning datasets that cover diverse domains, such as code, natural language, dialogues, and math problems. The curated fine-tuning datasets exhibit different degrees of heterogeneity across clients, which pose various challenges and opportunities for fine-tuning LLMs in FL. We describe the construction and characteristics of each dataset in detail below and illustrate their scenarios. We will constantly adopt new datasets for fine-tuning LLMs in FS-LLM.

Table 6: Statistics and information of the fine-tuning datasets.

Name	#Client	#Sample	Split	Domain	Evaluation Dataset
Fed-CodeAlpaca	9	∼8.0k	Meta	Code Generation	*HumanEval*
Fed-Dolly	8	∼15.0k	Meta	Generic Language	*HELM*
Fed-GSM8K-3	3	∼7.5k	IID	CoT	*GSM8K-test*
Fed-CodeSearchNet	6	∼1880.8k	Meta	Code Generation	*HumanEval*
Alpaca	-	∼52.0k	-	Generic Language	*HELM*
CleanedAlpaca	-	∼51.8k	-	Generic Language	*HELM*

A.1.1 FEDERATED FINE-TUNING DATASET

The federated fine-tuning datasets are a collection of curated datasets that we adopt based on the meta-information or some distribution of the original corpora. Users can directly use them for federated fine-tuning LLMs.

Fed-CodeAlpaca is a federated version of *CodeAlpaca* (Chaudhary, 2023), a code dataset that contains ten programming languages, including C, C#, C++, Go, Java, PHP, Pascal, Python, Scale, and X86-64 Assemble. We exclude the X86-64 Assembly samples, as they are very scarce in the original corpora. Then, we split the remaining samples into nine subsets based on the language category and assign each subset to one client.

Fed-Dolly is a federated corpus dataset derived from *Databricks-dolly-15k* (Conover et al., 2023), which comprises eight categories of NLP tasks: brainstorming, classification, closed QA, creative writing, general QA, information extraction, open QA, and summarization. The corpora within each client only belong to one category.

Fed-GSM8K-3 is built from *GSM8K* (Cobbe et al., 2021), which is a mathematical fine-tuning dataset consisting of 7.5K training problems and 1K test problems. We split the training problems into three subsets by the uniform splitter, and assign each subset to one client.

In addition to the three datasets introduced in the main text, we also curate another code dataset, *Fed-CodeSearchNet*, as an alternative to *Fed-CodeAlpaca*.

Fed-CodeSearchNet is built from *CodeSearchNet* (Husain et al., 2019), which is a large-scale code dataset of functions and their associated documentation for six programming languages: Go, Java, JavaScript, PHP, Python, and Ruby. The data are extracted from open-source projects on GitHub. Similar to *Fed-CodeAlpaca*, we split the samples into six subsets according to the language category and allocate each subset to one client.

A.1.2 CENTRALIZED FINE-TUNING DATASET

The centralized fine-tuning datasets are a collection of corpora that we have collected from the Internet without any prior partitioning. Users can use our provided splitters to customize the data partition according to different criteria, such as heterogeneity, number balance, root verb, etc.

Alpaca (Taori et al., 2023) is a fine-tuning dataset containing natural language questions and responses for various NLP tasks such as text generation, translation, and open QA. The dataset covers a wide range of domains, such as math, text processing, code generation, etc.

CleanedAlpaca (Ruebsamen, 2023) is a fine-tuning dataset that improves the quality and usefulness of the original *Alpaca* dataset. It is expected to be more reliable and consistent for fine-tuning LLMs.

A.2 Evaluation task description

We believe that fine-tuning LLMs should either improve their generic language capabilities or improve their domain-specific capabilities for one particular downstream task. Thus, we use three different evaluation tasks for benchmarking fine-tuned LLMs.

Evaluation task for code generation capability. *HumanEval* (Chen et al., 2021) is to measure whether the code generated by LLMs is correct or not. It contains an evaluation dataset and an accordingly metric Pass@k score for assessing the performance of LLMs on code generation capability. Specifically, the model generates m samples per task and denotes c as the number of correct samples generated by LLM. Then

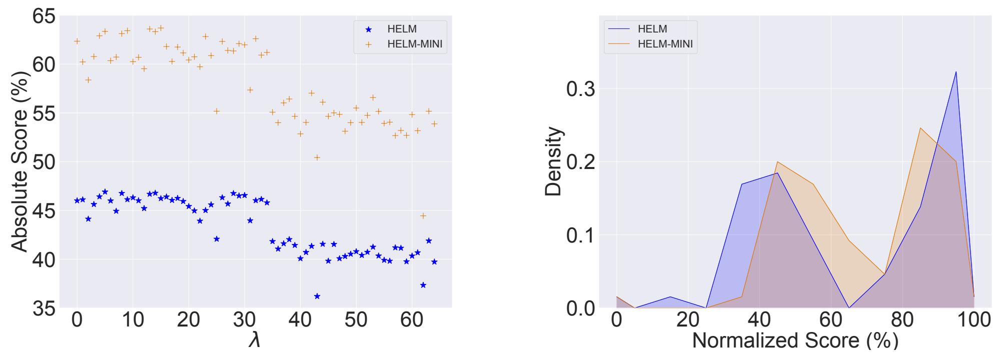
$$\text{Pass@k} := \mathbb{E}_{\text{Problems}}\left[1 - \frac{\begin{pmatrix} m-c \\ k \end{pmatrix}}{\begin{pmatrix} m \\ k \end{pmatrix}}\right].$$

In practice, we set $m = 5$ and use the Pass@1 score as the evaluation score, i.e.,

$$\text{Pass@1} := \mathbb{E}_{\text{Problems}}\left[\frac{c}{5}\right].$$

Evaluation task for generic language capability. We adapt *HELM* (Liang et al., 2022), including 16 subtasks, in FS-LLM to evaluate the generic language capability of fine-tuned LLMs. To be more precise, the subtasks we use are *MMLU* (Hendrycks et al., 2021b;a), *BoolQ* (Clark et al., 2019), *NarrativeQA* (Kočiskỳ et al., 2018), *NaturalQuestions (closed-book)* (Kwiatkowski et al., 2019) , *NaturalQuestions (open-book)* (Kwiatkowski et al., 2019) , *QuAC* (Choi et al., 2018), *HellaSwag* (Zellers et al., 2019), *OpenbookQA* (Mihaylov et al., 2018), *TruthfulQA* (Lin et al., 2021), *MS MARCO (regular)* (Bajaj et al., 2016), *MS MARCO (TREC)* (Bajaj et al., 2016), *CNN/DailyMail* (See et al., 2017; Hermann et al., 2015), *XSUM* (Narayan et al., 2018), *IMDB* (Maas et al., 2011), *CivilComments* (Borkan et al., 2019), and *RAFT* (Alex et al., 2021). For each task, we randomly use 100 samples for evaluation. The evaluation score for *HELM* is a mixture of metric scores on these 16 subtasks. Specifically, in *HELM*, *MMLU*, *BoolQ*, *HellaSwag*, *OpenbookQA*, *TruthfulQA*, *IMDB*, *CivilComments*, and *RAFT* use accuracy; *NarrativeQA*, *NaturalQuestions (closed-book)*, *NaturalQuestions (closed-book)*, and *QuAC* use F1 score; *CNN/DailyMail* and *XSUM* use ROUGE-2 score; *MS MARCO (regular)* and *MS MARCO* use RR@10 score and NDCG@10 score, respectively. For more details, please refer to Liang et al. (2022). In FS-LLM, the evaluation score for *HELM* is the average value of these 16 subtasks' scores.

However, evaluation of all these 16 subtasks in *HELM* is very time-consuming. We notice that there is a trade-off between the evaluation's comprehensiveness and efficiency. The more subtasks we use, the more accurate the evaluation scores will be, but also more time-consuming. Thus, we build *HELM-MINI* with fewer subtasks to assess the LLMs' generic language capabilities. We first randomly and uniformly sample serval samples of different combinations of configurations, including different PEFT algorithms and different hyperparameters. After that, we pick 6 subtasks such that the evaluation score of these 6 subtasks is closest to the evaluation score of all 16 subtasks in the L^2 norm, which are *MMLU*, *NaturalQA (open-book)*, *OpenbookQA*, *MS MARCO (regular)*, *XSUM* and *IMDB*. Then we consider the time consumption and the requirements for the stability of the network connection during the evaluation, and drop another 2 subtasks: *MS MARCO (regular)* and *XSUM*. Finally, we have left 4 subtasks to form *HELM-MINI*, including *MMLU*, *NaturalQA (open-book)*, *OpenbookQA*, and *IMDB*. In Figure 6, we present the comparison between the evaluation scores of *HELM* and *HELM-MINI*. In Figure 6a, we plot the samples of different combinations of configurations, where λ indicates the index of each sample. It can be seen that though the exact evaluation scores of *HELM* and *HELM-MINI* are different, their normalized evaluation score relationships are essentially consistent. In Figure 6b, we show the distribution of these samples' normalized evaluation scores of *HELM* and *HELM-MINI*. Here, the normalized evaluation score is calculated by $\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$, where $x_{\max}$ and $x_{\min}$ are the maximum and minimum evaluation scores among all the samples of *HELM* and *HELM-MINI*, respectively.



(a) The average scores of the 16 subtasks in *HELM* and the 4 subtasks in *HELM-MINI* for the samples with different configurations, respectively.

(b) The density distribution of the normalized performance of *HELM* and *HELM-MINI* among the samples, respectively.

Figure 6: The performance comparison of *HELM* and *HELM-MINI*.

Evaluation task for CoT capability. We use *GSM8K-test* (Cobbe et al., 2021), which consists of 1k math problems from the test split in *GSM8K* to evaluate the performance of LLMs on mathematic problem-solving capability. We also adopt 8-shot-CoT prompting (Wei et al., 2022) in evaluation. The evaluation score is the accuracy of these 1k math problems.

A.3 Detailed hyperparameters and results

We perform a grid search over the hyperparameter space to ensure that each algorithm achieves its optimal performance and to enable a fair comparison among different algorithms. The search space of the learning rate for all adapters is $\{1\times10^{-4}, 3\times10^{-4}, 5\times10^{-4}, 1\times10^{-3}, 3\times10^{-3}, 5\times10^{-3}\}$.

LoRA has three hyperparameters: the rank of the adaption matrices, the scaling coefficient, and the dropout probability for LoRA layers. The rank has a significant impact on resource consumption, so we fix it to 8, which is the default value in the algorithm. We grid search the other two parameters. The search spaces of the scaling coefficient and dropout probability for LoRA layers are $\{16, 32, 64, 128\}$ and $\{0.0, 0.1\}$, respectively.

For P-tuning, because of the source limitation, we fix the type of reparameterization to be "MLP" and only search the number of virtual tokens in $\{10, 20, 30\}$.

For prompt tuning, we find that initializing the prompt randomly will result in poor performances on these datasets. Therefore, we set it to "TEXT" and initialize different prompts for different fine-tuning datasets. Specifically, for *Fed-CodeAlpaca*, we use "Program a function by following description." together with the number of virtual tokens equals 8; For *Fed-Dolly*, we use "Assume you can understand and answer questions." together with the number of virtual tokens equals 9; For *Fed-GSM8K-3*, we use "Think step by step." together with the number of virtual tokens equals 6. The reason why we use the prompts above is that we think these prompts appropriately describe the fine-tuning tasks, respectively. The number of virtual tokens we use is exactly the length of the corresponding prompt processed by the tokenizer.

In Table 7- 15, we present experimental results when we grid search the hyperparameters for different PEFT algorithms. In Table 16, we show examples of creative writing generated by the fine-tuned LLaMA-7B with different PEFT algorithms. The fine-tuning dataset is *Fed-Dolly*. It can be seen that the LLM, without fine-tuning in FL, lacks imagination and only describes the situation of a crocodile on the moon. The response of the model fine-tuned with LoRA is more accurate, which prefers the ocean to outer space and does write a haiku in the voice of a pirate. The model fine-tuned with P-tuning combines crocodiles and the moon, but the logic of the generated answers is not very coherent. The response generated by the model fine-tuned with prompt tuning is the shortest one, showing the savagery of the crocodile as a pirate. In summary, after federated fine-tuning, the accuracy and fluency of the LLM in answering questions are improved.

Table 7: Evaluation scores (%): federated fine-tuning LLaMA-7B with LoRA on *Fed-CodeAlpaca*. In this table, the dropout probability is 0.0.

Scaling coef.	Seed	LR					
		0.0001	0.0003	0.0005	0.001	0.003	0.005
16	0	13.29	11.34	10.37	9.39	11.34	10.73
	1	13.17	11.71	10.49	10.73	11.71	11.46
	2	13.41	11.22	11.10	10.85	12.68	11.83
32	0	12.56	10.24	9.27	10.61	10.24	2.07
	1	12.07	11.22	10.98	10.49	8.54	9.88
	2	12.44	11.34	11.22	11.34	10.73	10.00
64	0	10.00	9.63	11.10	11.10	10.24	11.22
	1	10.73	10.37	11.22	11.10	10.98	11.71
	2	11.10	12.56	12.68	12.44	9.76	12.68
128	0	9.88	10.98	11.83	11.83	10.85	10.73
	1	10.24	12.07	11.83	11.95	0.00	10.00
	2	10.98	12.68	11.95	9.15	6.83	5.85

Table 8: Evaluation scores (%): federated fine-tuning LLaMA-7B with P-tuning on *Fed-CodeAlpaca*.

#Virtual tokens	Seed	LR					
		0.0001	0.0003	0.0005	0.001	0.003	0.005
10	0	8.90	6.83	8.78	10.24	10.61	6.83
	1	11.10	9.15	10.00	9.51	1.46	6.95
	2	5.37	9.39	5.85	4.14	5.37	1.83
20	0	5.73	11.22	9.39	13.05	9.51	4.51
	1	8.78	10.85	10.00	9.39	9.02	3.05
	2	7.93	3.17	8.78	2.93	10.61	3.66
30	0	9.02	10.24	10.00	10.98	9.14	1.95
	1	12.32	5.49	5.37	10.24	2.68	2.80
	2	7.07	9.02	9.63	5.24	10.61	0.24

Table 9: Evaluation scores (%): federated fine-tuning LLaMA-7B with prompt tuning on *Fed-CodeAlpaca*. In this table, the initialized prompt is “Program a function by following description.”. The number of virtual tokens is 8.

Seed	LR					
	0.0001	0.0003	0.0005	0.001	0.003	0.005
0	10.16	11.07	10.69	9.63	12.28	14.03
1	7.96	9.40	10.61	11.90	11.60	9.63
2	8.64	9.40	10.24	10.39	11.37	11.22

Table 10: Evaluation scores (%): federated fine-tuning LLaMA-7B with LoRA on *Fed-Dolly*.

Scaling coef.		32			64			128	
Dropout prob.		0.0			0.1			0.0	
LR		0.005			0.003			0.0003	
Seed	0	1	2	0	1	2	0	1	2
MMLU	36.30	35.50	36.80	36.50	37.20	37.40	33.20	35.20	33.80
BoolQ	80.00	77.00	78.00	82.00	81.00	74.00	78.00	79.00	80.00
NarrativeQA	55.60	49.80	55.00	53.80	51.60	53.20	51.00	51.60	50.90
NaturalQuestions(closed)	21.20	22.00	20.40	21.40	28.00	20.60	23.70	22.20	23.80
NaturalQuestions(open)	71.30	66.90	61.60	70.90	67.10	69.40	64.00	60.90	63.20
QuAC	32.30	31.20	31.20	32.40	28.40	28.50	32.10	34.30	32.60
HellaSwag	81.00	82.00	80.00	82.00	79.00	79.00	81.00	81.00	81.00
OpenbookQA	50.00	53.00	46.00	52.00	55.00	51.00	52.00	49.00	52.00
TruthfulQA	18.00	30.00	30.00	24.00	24.00	23.00	23.00	30.00	25.00
MS MARCO (regular)	18.60	14.20	17.40	18.20	15.50	22.90	17.20	15.90	15.00
MS MARCO (TREC)	40.60	42.70	42.50	38.50	41.20	42.70	41.40	41.90	39.70
CNN/DailyMail	15.10	12.30	14.00	13.60	14.40	13.00	12.00	12.10	11.80
XSUM	9.50	10.10	10.30	13.70	10.90	10.80	8.80	9.50	11.80
IMDB	94.00	98.00	97.00	95.00	94.00	97.00	98.00	96.00	98.00
CivilComments	59.50	66.00	56.90	57.00	59.70	58.30	62.20	57.30	61.70
RAFT	59.70	59.80	58.80	55.90	61.60	58.90	64.80	60.90	59.80
Average	46.42	46.91	45.99	46.68	46.79	46.23	46.40	46.05	46.26

Table 11: Evaluation scores (%): federated fine-tuning LLaMA-7B with P-tuning on *Fed-Dolly*.

#Virtual tokens	20			20			30		
LR	0.0003			0.0005			0.0005		
Seed	0	1	2	0	1	2	0	1	2
MMLU	35.20	34.60	35.20	35.30	35.10	35.10	34.30	35.40	35.10
BoolQ	79.00	78.00	78.00	77.00	80.00	76.00	82.00	78.00	79.00
NarrativeQA	50.40	54.60	52.60	52.30	52.10	49.70	52.20	52.30	52.50
NaturalQuestions(closed)	26.20	25.50	25.00	25.40	27.60	25.50	25.60	24.90	27.10
NaturalQuestions(open)	66.80	66.10	66.60	67.10	66.20	64.00	66.80	65.90	65.60
QuAC	28.80	30.00	29.50	30.10	27.70	29.80	31.10	30.50	30.20
HellaSwag	22.00	22.00	20.00	25.00	23.00	21.00	17.00	20.00	19.00
OpenbookQA	23.30	23.30	27.30	30.30	23.30	18.30	28.30	22.30	25.30
TruthfulQA	30.00	32.00	33.00	29.00	28.00	35.00	29.00	26.00	28.00
MS MARCO (regular)	18.10	17.60	16.00	15.70	15.50	13.90	20.50	12.80	16.40
MS MARCO (TREC)	45.00	39.50	42.60	43.50	42.40	36.40	41.00	30.00	44.00
CNN/DailyMail	12.90	11.70	13.70	12.40	13.40	12.40	13.50	13.50	12.30
XSUM	11.30	10.00	10.50	11.30	11.60	11.10	10.60	9.50	10.70
IMDB	95.00	92.00	95.00	93.00	94.00	94.00	95.00	95.00	94.00
CivilComments	63.70	59.40	59.60	61.90	62.20	57.40	56.60	59.70	63.10
RAFT	61.60	60.70	61.10	63.20	60.90	61.60	61.40	61.40	62.30
Average	41.83	41.06	41.61	42.03	41.44	40.08	41.56	39.83	41.54

Table 12: Evaluation scores (%): federated fine-tuning LLaMA-7B with prompt tuning on *Fed-Dolly*. In this table, the initialized prompt is "Assume you can understand and answer questions.". The number of virtual tokens is 9.

LR	0.0003			0.0005			0.001		
Seed	0	1	2	0	1	2	0	1	2
MMLU	34.10	34.50	34.00	35.10	35.50	34.60	36.00	34.40	34.20
BoolQ	79.00	77.00	76.00	77.00	78.00	74.00	77.00	77.00	76.00
NarrativeQA	50.10	49.20	50.10	50.50	51.50	52.10	50.10	52.70	50.40
NaturalQuestions(closed)	24.70	24.40	24.90	23.50	25.80	24.30	23.80	26.30	25.80
NaturalQuestions(open)	66.60	64.60	66.00	64.90	62.80	65.80	61.90	63.00	64.60
QuAC	32.00	28.50	28.40	29.50	29.00	29.60	30.20	30.10	28.60
HellaSwag	19.00	19.00	20.00	21.00	19.00	20.00	21.00	20.00	19.00
OpenbookQA	27.30	20.00	21.00	32.30	27.30	20.30	27.30	19.30	19.00
TruthfulQA	32.00	32.00	34.00	32.00	31.00	33.00	29.00	36.00	33.00
MS MARCO (regular)	13.60	14.50	13.70	14.10	14.20	14.10	12.70	17.70	21.80
MS MARCO (TREC)	35.90	41.20	39.00	39.70	39.60	35.30	39.80	43.20	43.70
CNN/DailyMail	12.30	13.00	13.70	13.60	14.20	13.90	13.30	14.10	14.40
XSUM	10.30	12.10	10.40	11.70	11.20	10.70	10.70	11.20	11.10
IMDB	94.00	97.00	98.00	94.00	95.00	95.00	91.00	94.00	95.00
CivilComments	61.30	59.10	62.30	62.60	54.70	56.60	58.50	59.90	60.00
RAFT	60.50	60.50	60.20	58.60	56.80	59.30	54.80	60.20	61.80
Average	40.79	40.41	40.73	41.26	40.35	39.91	39.82	41.19	41.15

Table 13: Evaluation scores (%): federated fine-tuning LLaMA-7B with LoRA on *Fed-GSM8K-3*.

Scaling coef.	Seed	LR					
		0.0001	0.0003	0.0005	0.001	0.003	0.005
16	0	8.79	6.97	8.87	8.26	12.13	11.22
	1	8.34	8.19	8.95	8.95	9.55	13.04
	2	9.17	6.37	9.63	9.33	11.83	13.42
32	0	6.82	7.73	9.25	12.21	10.99	4.09
	1	7.81	8.04	8.79	10.16	13.19	0.00
	2	9.10	8.79	8.95	11.9	12.89	13.87
64	0	8.95	10.61	11.30	12.13	13.42	0.00
	1	8.26	9.40	11.30	10.99	0.00	0.30
	2	9.93	10.46	12.28	12.43	12.28	13.42
128	0	9.93	11.14	12.96	3.49	15.31	15.47
	1	10.54	9.40	13.12	10.99	15.09	10.92
	2	9.25	11.83	11.60	12.96	12.28	11.60

Table 14: Evaluation scores (%): federated fine-tuning LLaMA-7B with P-tuning on *Fed-GSM8K-3*.

#Virtual tokens	Seed	LR					
		0.0001	0.0003	0.0005	0.001	0.003	0.005
10	0	10.16	11.07	10.69	9.63	12.28	14.03
	1	7.96	9.40	10.61	11.90	11.60	9.63
	2	8.64	9.40	10.24	10.39	11.37	11.22
20	0	9.40	11.22	12.74	11.75	9.40	10.24
	1	8.26	9.17	10.08	11.60	12.36	8.72
	2	10.39	10.54	10.77	10.01	10.77	11.68
30	0	10.08	11.14	12.05	11.07	10.69	8.19
	1	6.60	9.63	9.33	9.25	10.16	10.84
	2	8.87	9.93	10.77	10.46	10.39	11.22

Table 15: Evaluation scores (%): federated fine-tuning LLaMA-7B with prompt tuning on *Fed-GSM8K-3*. In this table, the initialized prompt is "Think step by step.". The number of virtual tokens is 6.

Seed	LR					
	0.0001	0.0003	0.0005	0.001	0.003	0.005
0	8.64	10.01	9.33	10.08	9.70	9.93
1	8.19	9.33	9.78	9.10	7.28	9.10
2	8.79	8.87	8.72	9.40	9.02	10.54

User:	Write a haiku about crocodiles in outer space in the voice of a pirate.
System0:	I'm a croc in space, And I don't know what to do. I've never been here before, And it's all so new to me. But I know I have to find a way To get back home to you.
System1:	Crocodiles, in space? I'd rather be on the sea. Pirate's life for me! -Arrrrrrr! Hoist the Jolly Roger, matey. We're off to plunder the seven seas! Ahoy, me hearties! Let the pillaging begin! -Aye, aye Cap'n! - Soon we'll be rich beyond our wildest dreams, and we won't have to work a day in our lives.
System2:	Crocodiles on the moon, Ahoy me hearties! We'll be pirates no more! The crocs have won! Mwahahaha. Aye, matey! Hoist the Jolly Roger!
System3:	Crocodiles on the moon, I'm going to eat you all! Ahoy, matey!

Table 16: Comparison of creative writing capability among different fine-tuning algorithms for LLaMA-7B in FL. System0 is the baseline model without fine-tuning, System1 is fine-tuned with LoRA, System2 is fine-tuned with P-tuning, and System3 is fine-tuned with prompt tuning.