LobRA: Multi-tenant Fine-tuning over Heterogeneous Data

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ABSTRACT

With the breakthrough of Transformer-based pre-trained models, the demand for fine-tuning (FT) to adapt the base pre-trained models to downstream applications continues to grow, so it is essential for service providers to reduce the cost of processing FT requests. Low-rank adaption (LoRA) is a widely used FT technique that only trains small-scale adapters and keeps the base model unaltered, conveying the possibility of processing multiple FT tasks by jointly training different LoRA adapters with a shared base model.

Nevertheless, through in-depth analysis, we reveal the efficiency of joint FT is dampened by two heterogeneity issues in the training data — the sequence length variation and skewness. To tackle these issues, we develop LobRA, a brand new framework that supports processing multiple FT tasks by jointly training LoRA adapters. Two innovative designs are introduced. Firstly, LobRA deploys the FT replicas (i.e., model replicas for FT) with heterogeneous resource usages and parallel configurations, matching the diverse workloads caused by the sequence length variation. Secondly, for each training step, LobRA takes account of the sequence length skewness and dispatches the training data among the heterogeneous FT replicas to achieve workload balance. We conduct experiments to assess the performance of LobRA, validating that it significantly reduces the GPU seconds required for joint FT by 45.03%-60.67%.

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1 INTRODUCTION

Transformer-based [59] pre-trained models, represented by Large Language Models (LLMs) [46, 47, 58, 65], have fueled an ever-increasing demand for their deployment in various applications such as chatbot assistants [50, 69], machine translation [17, 80], summarization [35, 68], database tuning [31, 77, 78], and more [12, 32, 67, 70]. Since pre-trained models are mostly trained with general data, it is a common practice to leverage a fine-tuning (FT) process [14, 49, 54], which further trains the pre-trained model with domain-specific data to adapt the model to the target applications.

Driven by the advancement of LLMs, many technology companies are enhancing their business strategies through the adoption of the Model as a Service (MaaS) paradigm [19]. To this end, providing FT services becomes essential. For example, a technology company may own a closed-source pre-trained model and allow users to upload their private or domain-specific datasets for FT [48]. For another example, cloud service providers would also offer FT services using popular open-source pre-trained models [10, 55]. As a result, given the diverse downstream applications, there would be many FT requests on the basis of the same pre-trained model, and consequently, it is of great value to reduce the cost associated with the FT requests over the same base model.

Meanwhile, FT services exhibit specific characteristics that are divergent from other kinds of services like model inference. For one thing, each user can submit multiple FT requests simultaneously, in order to build various domain-specific models with the same base model or to evaluate different dataset mixtures to see which gives the best performance [15, 60]. For another, compared to the inference scenario, FT requests arrive far less frequently (e.g., [2] reported an average of around 8.5 FT tasks per hour and some of them arrive simultaneously), and it takes significantly longer to process an FT request (tens of minutes to hours in practice), so both the request arrival rate and departure rate are much lower. Consequently, there would be a batch of FT requests that co-exist for long durations, and the batch does not change frequently. Given these characteristics, this work focuses on *how to reduce the cost of jointly executing a batch of FT tasks over the same base model.*

Owing to the astonishing model sizes and the scarcity of hardware accelerators (typically, GPUs), low-rank adaptation (LoRA) [21, 37] has become one of the most widely used and effective FT techniques. In essence, LoRA only trains small-scale adapters that consist of much fewer parameters than the base model, significantly reducing the FT cost. Since LoRA keeps the base model unaltered, it

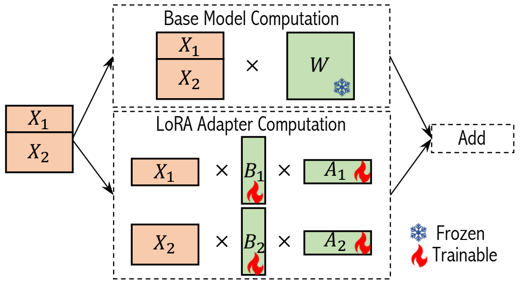


Figure 1: An illustration of the fusion of different LoRA adapters.

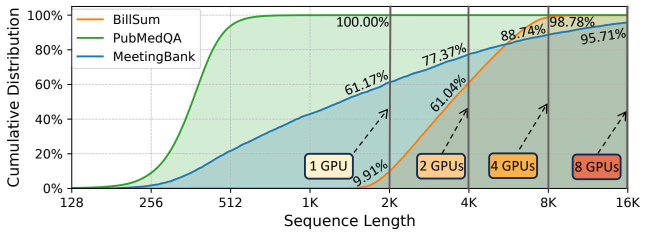


Figure 2: Cumulative distributions of sequence lengths of three FT datasets. The "n GPU(s)" indicates that we need n A100-40GB GPU(s) to process data with the corresponding sequence length without out-of-memory errors when fine-tuning the Llama2-7B model.

conveys the opportunity to share the same base model across multiple FT tasks rather than maintaining individual model replica(s) for each one. As shown in Figure 1, in each training step, we can fuse the input data from different tasks so that the computation of the base model can be fused into a batched operation whilst the computation of multiple LoRA adapters can be supported by customized operations. In fact, co-serving multiple LoRA adapters has been widely investigated for LLM inference [7, 51, 64, 79]. Inspired by this, this work focuses on how to efficiently carry out multiple FT tasks as a joint FT task by fusing multiple LoRA adapters.

Nevertheless, we experienced unsatisfactory efficiency when we naïvely leveraged the batch fusion idea to support joint FT. After an in-depth investigation, we found that this is because of two heterogeneity issues of the training data for joint FT.

The first is *the sequence length variation among tasks*. Specifically, since Transformer models take sequences as input, the training data (sequences) inevitably vary in length. As shown in Figure 2, the sequence length distributions are substantially divergent across FT tasks. This is reasonable as the training data of a few tasks (e.g., summarization) are usually much longer than the others (e.g., question answering). Meanwhile, since the memory consumption of FT is linear w.r.t. the lengths [8, 9, 72], it requires different numbers of GPUs to support the processing of sequences with different levels of lengths. Nevertheless, existing works overlook the discrepancy in resource demands, and straightforwardly deploy the FT replicas (i.e., model replicas for FT) in the same way for all training data, which conforms to the number of GPUs required for the highest sequence length. This would lead to efficiency degradation as the communication cost becomes higher for most training data.

To cope with this problem, this work proposes the idea of *heterogeneous FT replicas*, which deploys the FT replicas with varying resource usages and parallel configurations. Thus, we accelerate the processing of short sequences with FT replicas with low model parallel degrees, whilst avoiding out-of-memory errors by dispatching the long sequences to FT replicas with high model parallel degrees.

However, *the skewness in sequence lengths*, the second heterogeneity issue of FT data, raises another hurdle. As shown in Figure 2 again, most of the training data (sequences) are relatively short, which is a natural characteristic of human texts [11]. If we simply dispatch the training data to FT replicas according to their lengths, the workloads would be extremely imbalanced among the replicas. That is to say, FT replicas with low model parallel degrees must process much more training data, leading to heavier workloads compared to those with high parallel degrees. Since FT replicas must synchronize the parameters of LoRA adapters for every training step, it inevitably results in idle periods for some FT replicas.

We address this issue by developing a *workload-balanced data dispatching* technique. This is inspired by the fact that short sequences can also be processed by FT replicas with high model parallel degrees. Thus, we adjust the data dispatching so that the workloads of FT replicas with low model parallel degrees can be migrated to those with high parallel degrees, achieving workload balance.

Putting them together, this work presents LobRA, a multi-tenant FT framework by manufacturing multiple LoRA adapters concurrently. To tackle the data heterogeneity issues, LobRA innovatively introduces the deployment of heterogeneous FT replicas and workload-balanced data dispatching to accelerate the joint FT process. In summary, this work makes the following contributions.

- We first anatomize different design choices of joint FT over heterogeneous training data, revealing the necessity of supporting heterogeneous model deployment and workload-balanced data dispatching. Based on the anatomy, we formulate a joint optimization problem to co-optimize these two factors.
- Subsequently, we propose a two-stage decomposition of the joint optimization problem for practical joint FT. On instantiation, the first-stage problem determines the heterogeneous model deployment plan that is optimal in expectation. Then, for each training step of the joint FT process, we derive the workload-balanced data dispatching plan by solving the second-stage problem.
- We evaluate the performance of LobRA by fine-tuning LLMs with up to 70B parameters and more than 10 tasks over 64 GPUs. Empirical results demonstrate that LobRA effectively reduces the GPU seconds required for joint FT by 45.03%-60.67%.

2 BACKGROUND AND RELATED WORKS

2.1 Fine-tuning over Variable-length Data

Fine-tuning based on LoRA. Fine-tuning (FT) is an essential process to adapt the pre-trained model to the target domain [14, 49, 54]. Low-rank adaption (LoRA) and its variants [21, 37] only fine-tune small-scale adapters rather than the base model itself, reducing resource demands substantially. For a model weight matrix $W \in \mathbb{R}^{in \times out}$, LoRA trains two low-rank matrices $A \in \mathbb{R}^{r \times out}, B \in \mathbb{R}^{in \times r}$ ($r \ll in, out$) and computes $XW + XBA$. By doing so, it approximates the change to the weight matrix as $\Delta W \approx BA$.

As LoRA does not alter the base model, previous works have proposed the co-serving of multiple LoRA adapters for inference [7, 51, 64, 79], and Miao et al. [39] further considered the scenario of inference and FT simultaneously. However, processing multiple FT tasks is not their primary focus. Ye et al. [66] and Zheng et al.

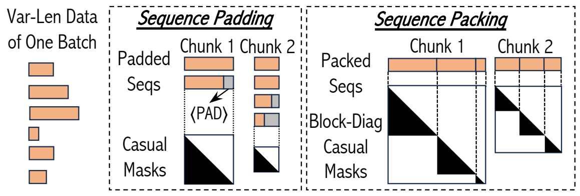


Figure 3: Illustration of applying sequence padding and packing to variable-length data of one batch. Sequence padding uses the special token ⟨PAD⟩ to ensure sequences within the same chunk are the same length. Sequence packing concatenates sequences together and uses the block-diagonal casual masks to avoid cross-contamination.

[75] considered fusing multiple LoRA adapters for joint FT. Nevertheless, they carry out the joint FT task by naïvely batching the input data, overlooking the data heterogeneity mentioned in §1. There are also many works that compose LoRA adapters for better performance [22, 56, 62, 63, 76], which is orthogonal to our work.

Processing Variable-length Data. In each training step, given a batch (a.k.a. mini-batch) of data, they are with diverse lengths due to the variable-length nature of sequences. Meanwhile, as GPU memory is limited, it is usually infeasible to process the batch at once. Thus, it is common to re-organize the batch into smaller chunks (a.k.a. micro-batches), process each sequentially, and accumulate model gradients computed from all chunks for model update.

Figure 3 shows two commonly used data re-organization techniques. Sequence padding sorts the data according to their lengths and takes those with similar lengths when crafting each chunk. Within each chunk, it adds special tokens (i.e. ⟨PAD⟩) to ensure a unique length. Sequence packing concatenates sequences for each chunk, eliminating the need for padding tokens. Meanwhile, it adjusts the casual mask to be block-diagonal to avoid cross-contamination among the sequences that are packed together [29].

In theory, packing provisions better training efficiency. However, Bai et al. [5] conducted experiments on FT tasks and observed that padding and packing exhibit comparable training efficiency, whilst training with padding usually achieves better model quality, which is because packing introduces biases to the contributions of different data. Thus, padding and packing have their pros and cons, and the choice between them is an open question. In this work, we assume padding is employed. Nevertheless, it is noteworthy that the proposed designs can also be applied when packing is employed.

Given the variable-length phenomenon, there are also several works investigating more variants of packing and padding [13, 30, 52]. However, none of these works have considered processing data of different lengths with different resource usages and parallel configurations. As a result, they are orthogonal to our work.

2.2 Parallel Configurations in Model Training

Model Parallel. There are two prevalent forms of model parallel, namely tensor parallel (TP) [28, 53] and pipeline parallel (PP) [20, 23, 41, 42]. Since TP and PP have different pros and cons, it is common to combine them for better efficiency, which is also known as hybrid model parallel [25, 40, 43, 57, 61, 71, 74]. In essence, model parallel distributes the model across GPUs to reduce the memory occupied by the model itself, sparing the space for intermediate results in training. Since the memory consumed by intermediate results is linear w.r.t. the summed lengths in each chunk [8, 9, 72], if we wish to support longer sequences, we usually need to increase the model parallel degree, yet at the price of larger communication overhead.

Table 1: Frequently used notation throughout this work.

N	The number of available GPUs.
R	The number of sequence length ranges, i.e., the training data of each batch are divided into R buckets.
S	The number of candidate parallel configurations.
$\mathcal{S}_i$	The i-th candidate parallel configuration.
n_i	The number of GPUs needed by $\mathcal{S}_i$ to deploy one FT replica.
p_i	The number of FT replicas deployed with $\mathcal{S}_i$.
r_i	The number of sequence length ranges that $\mathcal{S}_i$ supports, i.e., FT replicas with $\mathcal{S}_i$ support processing sequences in the first r_i ranges without out-of-memory errors.
$d_{i,j}$	The number of training data (sequences) in the j-th range that are assigned to the FT replicas with $\mathcal{S}_i$.

Model Replication (Data Parallel). Besides model parallel, a model can be replicated into multiple replicas. The input data are usually evenly dispatched to these replicas for concurrent processing (a.k.a. data parallel [6, 18, 26, 34, 44, 73]). To ensure the consistency of model parameters, it is necessary to synchronize the model gradients (or parameters) among the replicas for every training step, so balancing the workload across replicas is important.

Cost Model of Fine-tuning Replicas. In this work, we call each model replica a *fine-tuning (FT) replica*. Each replica is associated with a parallel configuration that describes how it is parallelized.

Given a training task, previous works generally develop cost modeling for running time and memory consumption, so that they can deduce how to parallelize the model [24, 25, 40, 61, 74]. However, they only support the same parallel configuration for all model replicas and do not consider fine-tuning with variable-length data.

Fortunately, we can borrow ideas from previous works to build the cost model for variable-length data, which involves profiling the time cost of essential modules and estimating the running time according to the critical path of the training workflow. In addition, since the memory consumption is linear w.r.t. the summed lengths in each chunk [8, 9, 72], we can easily profile the maximum supported sequence length for each kind of parallel configuration.

Throughout this work, we divide the sequence length into R non-overlapping ranges so that the variable-length data can be sorted into R buckets. We assume there are S candidate parallel configurations $\{\mathcal{S}_i\}_{i=1}^{S}$, where the i-th candidate requires n_i GPUs to deploy one FT replica and supports processing sequences in the first r_i ranges ($r_i \le R$) without out-of-memory errors. Subsequently, we denote $T(\{d_{\cdot,j}\}_{j=1}^{r_\cdot}; \mathcal{S}_\cdot)$ as the time cost[1] of an FT replica associated with $\mathcal{S}_\cdot$, where $d_{\cdot,j}$ represents how many sequences in the j-th range are dispatched to this FT replica. Due to the space constraint, we leave the details of our cost model in Appendix D [4].

3 DESIGN ANATOMY

This section anatomizes several design choices for joint FT, aiming to minimize the total GPU seconds needed to run one training step per task. To help readers better understand, we provide an

[1]Note that our work is applicable as long as the time cost function is linear w.r.t. $d_{\cdot,j}$.

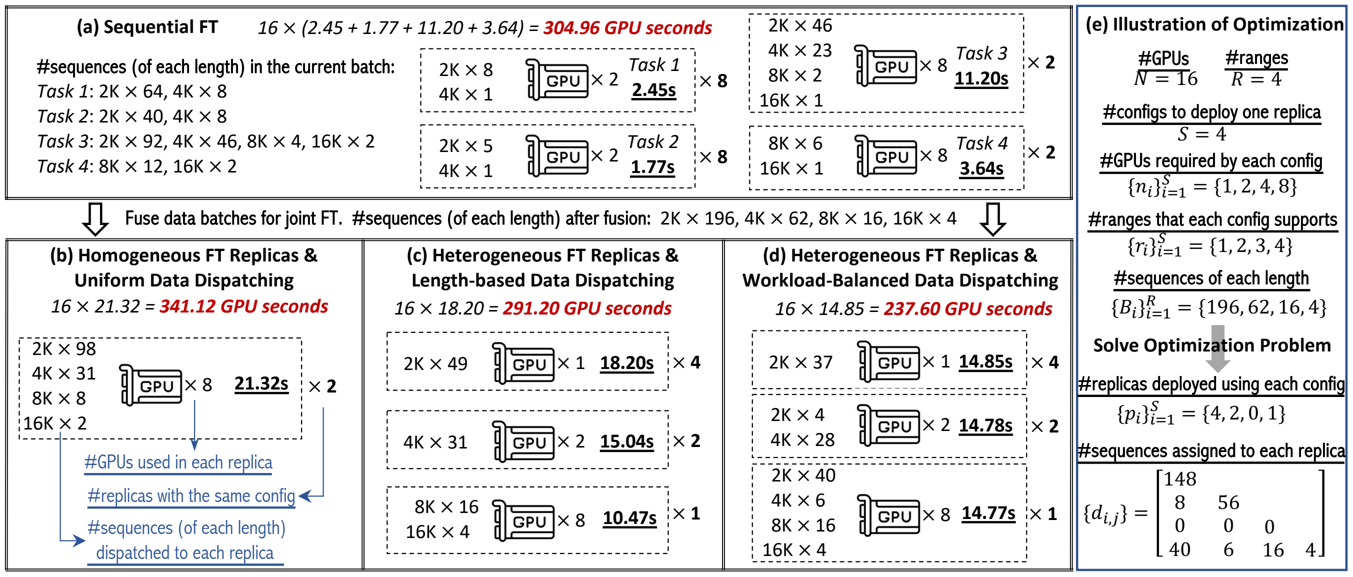

(a) Sequential FT
16 × (2.45 + 1.77 + 11.20 + 3.64) = 304.96 GPU seconds
#sequences (of each length) in the current batch:
Task 1: 2K × 64, 4K × 8
Task 2: 2K × 40, 4K × 8
Task 3: 2K × 92, 4K × 46, 8K × 4, 16K × 2
Task 4: 8K × 12, 16K × 2
2K × 8
4K × 1
GPU × 2
Task 1
2.45s
× 8
2K × 5
4K × 1
GPU × 2
Task 2
1.77s
× 8
2K × 46
4K × 23
8K × 2
16K × 1
GPU × 8
Task 3
11.20s
× 2
8K × 6
16K × 1
GPU × 8
Task 4
3.64s
× 2
Fuse data batches for joint FT. #sequences (of each length) after fusion: 2K × 196, 4K × 62, 8K × 16, 16K × 4
(b) Homogeneous FT Replicas & Uniform Data Dispatching
16 × 21.32 = 341.12 GPU seconds
2K × 98
4K × 31
8K × 8
16K × 2
GPU × 8
21.32s
× 2
#GPUs used in each replica
#replicas with the same config
#sequences (of each length) dispatched to each replica
(c) Heterogeneous FT Replicas & Length-based Data Dispatching
16 × 18.20 = 291.20 GPU seconds
2K × 49
GPU × 1
18.20s
× 4
4K × 31
GPU × 2
15.04s
× 2
8K × 16
16K × 4
GPU × 8
10.47s
× 1
(d) Heterogeneous FT Replicas & Workload-Balanced Data Dispatching
16 × 14.85 = 237.60 GPU seconds
2K × 37
GPU × 1
14.85s
× 4
2K × 4
4K × 28
GPU × 2
14.78s
× 2
2K × 40
4K × 6
8K × 16
16K × 4
GPU × 8
14.77s
× 1
(e) Illustration of Optimization
#GPUs
N = 16
#ranges
R = 4
#configs to deploy one replica
S = 4
#GPUs required by each config
$\{n_i\}_{i=1}^{S} = \{1, 2, 4, 8\}$
#ranges that each config supports
$\{r_i\}_{i=1}^{S} = \{1, 2, 3, 4\}$
#sequences of each length
$\{B_i\}_{i=1}^{R} = \{196, 62, 16, 4\}$
Solve Optimization Problem
#replicas deployed using each config
$\{p_i\}_{i=1}^{S} = \{4, 2, 0, 1\}$
#sequences assigned to each replica
$\{d_{i,j}\} = \begin{bmatrix} 148 & & & \\ 8 & 56 & & \\ 0 & 0 & 0 & \\ 40 & 6 & 16 & 4 \end{bmatrix}$

Figure 4: An example of 4 FT tasks with four different approaches, where (a) denotes fine-tuning the 4 tasks sequentially, whilst (b)-(d) present three different designs discussed in §3. We focus on the total GPU seconds required to run one training step for each task. (e) illustrates the inputs and decision variables of Equation (1) based on (d).

example of four FT tasks in Figure 4. Figure 4(a) depicts a sequential FT process that executes the four FT tasks one by one, whilst Figure 4(b)-(d) illustrates three different design choices of joint FT.

Naïve Design: Homogeneous FT Replicas and Uniform Data Dispatching. As shown in Figure 4(b), an intuitive solution for joint FT is to instantiate the FT replicas with the same parallel configuration, fuse the data batches from all tasks together, and evenly dispatch them to these homogeneous FT replicas. By doing so, it is obvious that the training workloads are balanced across the replicas. However, the end-to-end performance of such an approach is unsatisfactory due to *the sequence length variation among tasks*.

Specifically, unlike well-structured tabular datasets, sequences inherently have diverse lengths. Moreover, the sequence lengths of different tasks are significantly divergent. Such a variation results in different memory consumption, thereby calling for different trade-offs between memory reduction and training efficiency. As a result, for tasks with long sequences, since their memory consumption is high, it is common to increase the model parallel degree (which requires more GPUs for one replica) to avoid out-of-memory errors, whilst incurring higher communication costs. In contrast, for tasks with short sequences, we can leverage a lower model parallel degree (which requires fewer GPUs for one replica) for better efficiency.

Since the naïve approach uses the same parallel configuration for all replicas, the configuration must be able to accommodate the memory consumption of the *longest* sequences to avoid out-of-memory errors. For instance, each FT replica in Figure 4(b) occupies 8 GPUs, whilst only 2 GPUs are necessary if we consider the first two FT tasks individually in Figure 4(a). Thus, their processing time would be significantly prolonged, making this approach ineffective.

Better Design: Heterogeneous FT Replicas and Length-based Data Dispatching. Based on the discussion above, a better design is to leverage heterogeneous FT replicas for variable-length sequences. As exemplified in Figure 4(c), we can instantiate the replicas with non-unique parallel configurations, classify the training data into buckets according to their lengths, and dispatch each bucket to the most suitable replica(s). By this means, from the perspective of each sequence, it can be processed by the most efficient configuration. Nevertheless, such a solution suffers from the workload imbalance problem caused by *the skewness in sequence lengths*.

To elaborate, in real-world corpora, most sequences are relatively short, and there are very few sequences that are significantly longer than others. Figure 2 presents the sequence length distributions of several FT datasets — more than half of the sequences are shorter than 2K, whilst only a few are longer than 8K. In fact, this is reasonable in human texts and similar observations have also been reported on extremely large-scale pre-training corpora [11, 16].

Back to the discussion about Figure 4(c), given the skewness issue, the replicas with low model parallel degrees would receive a large portion of training data, whilst the other replicas would receive very few. As synchronization is needed for model update, replicas must idly wait for the slowest one(s). Worse still, a higher model parallel degree requires more GPUs for each replica, so there is a huge waste of computational resources. For the example in Figure 4(c), the 8 GPUs in the third replica sit idle for approximately 42% of the time during the joint FT process (10.47 vs. 18.20 seconds).

Optimized Design: Heterogeneous FT Replicas and Workload-Balanced Data Dispatching. Inspired by this, we propose to adopt the combination of heterogeneous FT replicas and workload-balanced data dispatching. The rationale is that replicas with high model parallel degrees can also process short sequences, so we can dispatch short sequences to more kinds of replicas. As depicted in Figure 4(d), by doing so, we can strike a good balance among the heterogeneous FT replicas and improve end-to-end efficiency.

Given a batch of training data, let B_j be the number of sequences fallen into the j-th bucket ($j \in [1, R]$). There are two key factors.

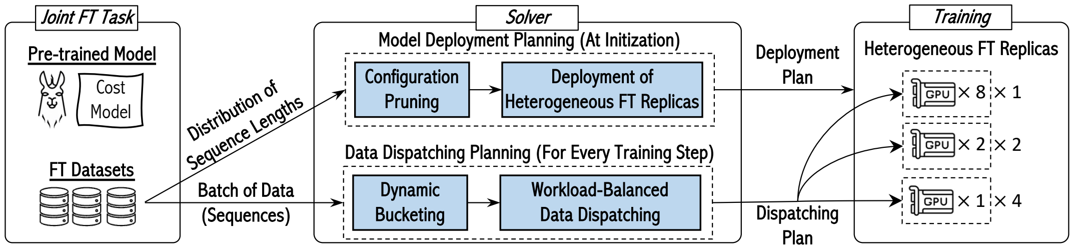

Joint FT Task
Pre-trained Model
Cost Model
FT Datasets
Distribution of Sequence Lengths
Batch of Data (Sequences)
Solver
Model Deployment Planning (At Initization)
Configuration Pruning
Deployment of Heterogeneous FT Replicas
Data Dispatching Planning (For Every Training Step)
Dynamic Bucketing
Workload-Balanced Data Dispatching
Deployment Plan
Dispatching Plan
Training
Heterogeneous FT Replicas
GPU × 8 × 1
GPU × 2 × 2
GPU × 1 × 4

Figure 5: Overview of LobRA. To start the joint FT task, given the base model and the sequence length distribution of the FT datasets, LobRA determines the deployment plan of FT replicas that minimizes the running time in expectation. During the FT process, for each training step, LobRA analyzes how the corresponding batch of data should be dispatched among the FT replicas in order to achieve workload balance.

Firstly, to deploy the heterogeneous FT replicas, we need to select the suitable parallel configurations and the number of replicas for each selected configuration. Secondly, for each batch, we need to dispatch the training data to minimize the running time of the slowest replica. We formulate the following optimization problem:

$$\begin{aligned}
\underset{p_i, d_{i,j} \in \mathbb{N}_0 \text{ for } i\in[1,S], j\in[1,r_i]}{\arg\min} \quad & \max_{i\in[1,S]} T\left(\left\{\lceil d_{i,j}/p_i \rceil\right\}_{j=1}^{r_i} ; \mathcal{S}_i\right) \\
\text{s.t.} \quad & \sum_{i\in\{i|r_i\geq j\}} d_{i,j} = B_j \text{ for } \forall j \in [1,R] \\
& d_{i,j} \leq B_j \times p_i \text{ for } \forall i \in [1,S], j \in [1,r_i] \\
& \sum_{i=1}^{S} p_i \times n_i \leq N
\end{aligned} \tag{1}$$

where p_i represents the number of FT replicas that are deployed with $\mathcal{S}_i$ (i.e., the i-th parallel configuration, and $p_i = 0$ indicates $\mathcal{S}_i$ is not selected for deployment), and $d_{i,j}$ represents how many sequences in the j-th bucket are assigned to the p_i replica(s) with $\mathcal{S}_i$ for processing. $T(\cdot;\cdot)$ denotes the running time of the p_i replica(s) with $\mathcal{S}_i$ given the dedicated sequences. The first constraint ensures all sequences are processed. The second constraint requires no sequences will be assigned if a configuration is not selected (i.e., $d_{i,j} = 0$ as long as $p_i = 0$). The third constraint ensures the FT replicas can be instantiated using the available GPUs.

We illustrate an example of the optimization problem with Figure 4(d). There are $N = 16$ GPUs and we divide the sequences into $R = 4$ buckets based on their lengths. To deploy one replica, there are $S = 4$ candidate configurations, requiring $\{n_i\}_{i=1}^{S} = \{1, 2, 4, 8\}$ GPU(s) and supporting sequences in the first $\{r_i\}_{i=1}^{S} = \{1, 2, 3, 4\}$ bucket(s), respectively. In the current fused batch, the numbers of sequences fallen into the buckets are $\{B_j\}_{j=1}^{R} = \{196, 62, 16, 4\}$. Then, by solving the optimization problem, the numbers of deployed replicas with the configurations are $\{p_i\}_{i=1}^{S} = \{4, 2, 0, 1\}$, and the data dispatching is shown in Figure 4(e).

4 LOBRA

4.1 Overview

Although Equation (1) co-optimizes the model deployment and data dispatching, solving it for every training step is impractical. For one thing, across different steps, the best model deployment plan may vary, which implies that we would need to reconfigure the model partitioning. Given the substantial model sizes, this is prohibitively time-consuming. For another, solving the problem takes longer than the training of one step (as evaluated in §5.3), making it infeasible to solve it for every step. To tackle these obstacles, we propose a two-stage decomposition as depicted in Figure 5.

- The first stage (§4.2) produces the deployment plan of heterogeneous FT replicas. It is only done once at the initialization of the joint FT task, eliminating the need for reconfiguration of model deployment as well as the expensive solving cost for every step.
- Given the deployed FT replicas, the second stage (§4.3) only deduces the optimal data dispatching, which is fast and can be invoked for every step. This enables us to dynamically adapt the data dispatching to the randomly drawn batches during training.

4.2 Deployment of Heterogeneous FT Replicas

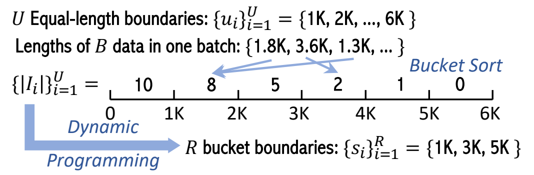
Problem Formulation. To instantiate the joint FT task, it is essential to determine how to deploy the heterogeneous FT replicas. However, according to Equation (1), the optimal deployment plan is relevant to how the sequences are distributed across the buckets (i.e., $\{B_j\}_{j=1}^{R}$). To address the discrepancy, we manage to utilize the overall distribution of sequence lengths of the FT datasets. In particular, we re-write Equation (1) as follows:

$$\begin{aligned}
\underset{p_i, d_{i,j} \in \mathbb{N}_0 \text{ for } i\in[1,S], j\in[1,r_i]}{\arg\min} \quad & \max_{i\in[1,S]} T\left(\left\{\lceil d_{i,j}/p_i \rceil\right\}_{j=1}^{r_i} ; \mathcal{S}_i\right) \\
\text{s.t.} \quad & \sum_{i\in\{i|r_i\geq j\}} d_{i,j} \geq B \times f_j \text{ for } \forall j \in [1,R] \\
& d_{i,j} \leq B_j \times p_i \text{ for } \forall i \in [1,S], j \in [1,r_i] \\
& \sum_{i=1}^{S} p_i \times n_i \leq N
\end{aligned} \tag{2}$$

where B denotes the batch size of the joint FT task, and f_j denotes the percentage of sequences fallen into the j-th bucket. Solving Equation (2) returns the model deployment plan (p_i) and data dispatching plan ($d_{i,j}$) that is optimal in expectation. Then, LobRA instantiates the FT replicas based on the model deployment plan (whilst the data dispatching plan will be omitted).

Note that since f_j's are not integers, we have inequality constraints on $d_{i,j}$ in Equation (2). Formally speaking, the solutions to Equation (2) may have $\sum_j \sum_i d_{i,j} = B + R$, whilst the solutions to Equation (1) follow $\sum_j \sum_i d_{i,j} = B$, implying a difference. Nevertheless, after solving Equation (2), only p_i's are used for model deployment, whilst $d_{i,j}$'s are omitted. Combining with the fact that $B \gg R$, the difference between Equation (1) and Equation (2) is minor, and it does not affect the effectiveness of our work.

Configuration Pruning. Due to the term $d_{i,j}/p_i$, Equation (2) is a mixed-integer non-linear programming (MINLP) problem, which is



U Equal-length boundaries: $\{u_i\}_{i=1}^{U} = \{1K, 2K, ..., 6K\}$
Lengths of B data in one batch: $\{1.8K, 3.6K, 1.3K, ...\}$
Bucket Sort
$\{|I_i|\}_{i=1}^{U} =$
10
8
5
2
1
0
0
1K
2K
3K
4K
5K
6K
Dynamic
Programming
R bucket boundaries: $\{s_i\}_{i=1}^{R} = \{1K, 3K, 5K\}$

Figure 6: Illustration of dynamic bucketing.

a notorious combinatorial optimization problem. Although libraries like SCIP [3] support solving MINLP problems, it is very time-consuming, especially when there are many decision variables (i.e., $d_{i,j}$ and p_i). Specifically, the number of decision variables of Equation (2) is $S + \sum_{i=1}^{S} r_i \leq S + S \times R$. Thus, the solving cost of Equation (2) is highly related to S, as R is not large in practice (e.g., we set $R = 16$ in our experiments). To speed up the solving process, we introduce two heuristics to filter the candidate configurations. Due to the space constraint, we briefly introduce the rationale below and refer interested readers to Appendix A [4] for more details.

- Firstly, we only consider a small set of configurations (rather than covering all possible ones) for problem-solving. In essence, if two configurations consume the same number of GPUs (i.e., same n) and one of them is consistently less efficient than the other, then it will never be selected for deployment. Besides, since the model architecture of each pre-trained model is fixed, we conduct offline benchmarking and propose the candidates in advance, without affecting the online problem-solving.
- Secondly, although there is no closed-form solution for MINLP problems, it is possible to heuristically estimate the lower bound of training efficiency given a deployment plan (i.e., $\{p_i\}_{i=1}^{S}$). The reason is that, given the aforementioned benchmarking, we can estimate how the running time of two FT replicas would change after we migrate some training data between them. Thus, given a deployment plan, we treat the length-based dispatching as a starting point and estimate the lower bound of workload-balanced dispatching. Then we filter out deployment plans that are predicted to be inefficient, which shrinks the solution space.

Based on these two heuristics, Equation (2) can be solved efficiently and accurately. For one thing, when the number of GPUs is relatively small (e.g., 16-32 GPUs), the heuristics do not affect the achieved solutions (i.e., the achieved solutions are the same as those achieved without pruning), yet accelerate the solving process substantially. For another, when there are more GPUs, solving without pruning fails to finish within an hour, whilst solving with pruning only takes several minutes. Since Equation (2) is only solved at initialization, the solving time is worthwhile given the speedup in the joint FT process. In Appendix A and Appendix B.2 [4], we have provided more details and empirical results.

4.3 Workload-Balanced Data Dispatching

Problem Formulation. After the heterogeneous FT replicas are deployed, each training step of the joint FT process involves randomly drawing a batch of training data, and feeding them to the FT replicas. Due to the randomness in batch sampling, the number of sequences that fall into each bucket may be divergent across different steps. Denote p_i^* as the optimal solution achieved by Equation (2), which describes the model deployment plan of the heterogeneous FT replicas, we formulate the following optimization problem to minimize the time cost of each training step.

$$\begin{aligned} &\underset{d_{i,j}\in\mathbb{N}_0 \text{ for } i\in[1,S], j\in[1,r_i]}{\arg\min} \quad \max_{i\in[1,S]} T\left(\left\{\lceil d_{i,j}/p_i^*\rceil\right\}_{j=1}^{r_i}; \mathcal{S}_i\right) \\ &\text{s.t.} \sum_{i\in\{i|r_i\geq j\}} d_{i,j} = B_j \text{ for } \forall j\in[1,R] \\ &d_{i,j} \leq B_j \times p_i^* \text{ for } \forall i\in[1,S], j\in[1,r_i] \end{aligned} \quad (3)$$

Since $\{p_i^*\}_{i=1}^{S}$ are constants rather than decision variables, the optimization problem in Equation (3) is an integer linear programming (ILP) problem, which can be efficiently solved via existing libraries like PuLP [1] and SCIP [3]. The number of decision variables in Equation (3) is $\sum_{i=1}^{S} r_i \leq S \times R$. However, since we can remove the configurations that are not selected for deployment (i.e., whose p_i^* is zero), there are very few decision variables in practice. (For instance, there are only 3-5 selected configurations in our evaluation.) Thus, as we will evaluate in §5.3, the solving process is fast and can be fully overlapped by the training of previous step(s).

Dynamic Bucketing. Till now, we assume that the boundaries of buckets, denoted as $\{s_i\}_{i=1}^{R}$, are pre-defined and fixed throughout the joint FT process. However, due to the randomness in batch sampling, the optimal boundaries vary across different training steps — as each sequence must be padded to the closest boundary, using fixed boundaries would lead to undesirable padding. To address this problem, we develop a dynamic bucketing approach to facilitate the adaption to the sequence length distribution during training.

As depicted in Figure 6, our approach starts from U pre-defined boundaries $\{u_i\}_{i=1}^{U}$, which partition the range of sequence length into U intervals (in practice, we consider equal-length division $\{256, 512, \cdots\}$). Given a batch of B sequences, our approach bucket sorts them by lengths and determines R boundaries ($R \leq U$) to form R buckets that minimize the padding via dynamic programming.

Denote $\mathcal{I}_i$ as the set of indices of sequences fallen into the i-th interval, and State$_{i,j}$ as the minimized padding when bucketing the first i intervals into j buckets. We have the following initial state and state transition expressions for dynamic programming:

$$\begin{aligned} &\text{State}_{0,j} = 0,\ \forall j\in[0,R], \qquad \text{State}_{i,0} = +\infty,\ \forall i\in[1,U], \\ &\text{State}_{i+1,j+1} = \min_{i'\in[0,i]} \left\{ \text{State}_{i',j} + \sum_{i''=i'+1}^{i} \left(|\mathcal{I}_{i''}| \times (u_{i+1} - u_{i''})\right) \right\} \end{aligned} \quad (4)$$

By computing State$_{U,R}$, we achieve the optimal boundaries for a given batch of data[2]. The time complexity of the dynamic programming is merely $O(B + RU^2)$, introducing negligible overhead.[3]

Note that the bucketing approach is also applied when solving the deployment of FT replicas in Equation (2). In particular, at the initialization of the joint FT task, we randomly sample a large number ($100 \times B$ by default) of training data and perform the bucketing to determine the boundaries for solving Equation (2).

5 EXPERIMENTS

5.1 Implementation and Experimental Setup

We implement LobRA on top of Hetu [33, 38], a distributed deep learning framework for large-scale models. We utilize SCIP [3] to

[2]The total number of padding tokens is State$_{U,R} + \sum_{i=1}^{U}\sum_{k\in\mathcal{I}_i}(u_i - s_k)$, where the second term denotes the padding needed inside each interval, which is a constant.
[3]We default R as 16 (sensitivity experiment provided in Appendix B.2 [4]) and ignore empty intervals in our implementation, so the term RU^2 is small in practice.

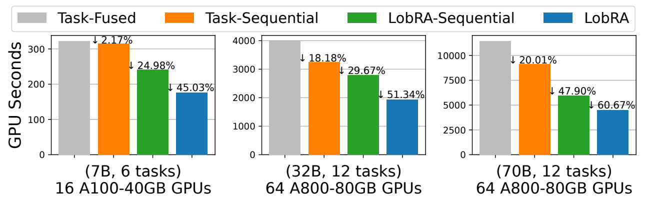


Figure 7: End-to-end evaluation.

Table 2: Parallel configurations used by Task-Fused and LobRA in end-to-end evaluation. (Those used by Task-Sequential and LobRA-Sequential are provided in Appendix B.3 [4].) Each $\langle \alpha, \beta \rangle \times \gamma$ indicates there are γ FT replica(s) with a TP degree of α and a PP degree of β.

	Task-Fused	LobRA
7B	⟨8,1⟩×2	⟨1,1⟩×6, ⟨2,1⟩×1, ⟨8,1⟩×1
32B	⟨8,1⟩×8	⟨1,6⟩×4, ⟨2,2⟩×4, ⟨4,1⟩×2, ⟨8,1⟩×2
70B	⟨16,1⟩×4	⟨2,4⟩×4, ⟨4,2⟩×1, ⟨8,1⟩×1, ⟨16,1⟩×1

solve the MINLP and ILP problems. Our framework incorporates libraries like FlashAttention [8, 9] for efficient computation of LLMs and NCCL [45] for communication. Even when training with homogeneous FT replicas, LobRA achieves state-of-the-art FT efficiency. More details are provided in Appendix C [4].

Although LobRA focuses on co-optimizing a given batch of FT tasks, it also supports dynamic batches. In practice, when the batch of FT tasks changes (e.g., some tasks exit earlier than others or new FT requests arrive), we simply re-generate a new model deployment plan with the updated sequence length distribution. If the new plan differs from the current one, we save checkpoints for LoRA adapters and restart the joint task to meet the new plan. (We do not need to save checkpoints for the base model.) The overhead of deployment adjustment is consistently less than 3 minutes in practice, which is worthwhile as the FT tasks would take hours to finish.

Experimental Environments. We use two environments for evaluation. The first consists of 2 servers equipped with 8 A100-40GB GPUs (16 GPUs in total). The GPUs within the same server are connected via 600GB/s NVLink and the servers are connected via 100GB/s InfiniBand. The second consists of 8 servers equipped with 8 A800-80G GPUs (64 GPUs in total). The intra- and inter-server communication bandwidths are 400GB/s and 200GB/s, respectively.

Competitors. The primary goal of our evaluation is to evaluate the effectiveness of heterogeneous FT replicas and workload-balanced data dispatching. Since none of the existing works have supported such designs for joint FT, we consider two baselines, termed Task-Fused and Task-Sequential, that employ homogeneous FT replicas and uniform dispatching. The first naïvely fuses the FT tasks (i.e., Figure 4(b)) whilst the second executes the FT tasks sequentially (i.e., Figure 4(a)). We tune their deployment plan to achieve the best efficiency. To further evaluate the effectiveness of batch co-optimization, we also consider a variant of LobRA, termed LobRA-Sequential, which also runs the FT tasks sequentially but optimizes each FT task by employing heterogeneous FT replicas and workload-balanced data dispatching.

Workloads. We consider three popular LLMs, which are Llama2-7B, Qwen2.5-32B, and Llama2-70B. We fine-tune the 7B model with the first environment and the other two models with the second environment. We consider 12 FT datasets, regarding each as one FT

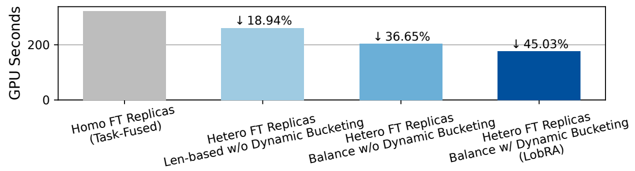


Figure 8: Ablation Studies (7B model, 16 A100-40GB GPUs).

task. The detailed descriptions of the FT datasets and the batch size settings are provided in Appendix B.1 [4]. By default, we consider 6 tasks for the 7B model and 12 tasks for the other two models. We use the Adam optimizer [27, 36] for all experiments.

Protocols. Since our goal is to improve the efficiency of joint FT, we focus on the GPU seconds required to train one step for all involved tasks. For all experiments, we report the mean of 100 training steps, and the standard deviation is within 10%.

5.2 End-to-End Evaluation

We first assess the end-to-end joint FT efficiency of LobRA. The results are shown in Figure 7, and we provide the parallel configurations used for deployment in Table 2.

In general, LobRA outperforms Task-Fused significantly for all three experiments, reducing 45.03%-60.67% GPU seconds. LobRA achieves greater improvement when fine-tuning larger models over 64 GPUs. This is reasonable since LobRA is able to explore a larger space of deployment plans — LobRA deploys 11 and 7 heterogeneous FT replicas for the 32B and 70B models, respectively, whilst Task-Fused can only deploy 8 and 4 homogeneous FT replicas. This allows more short sequences to get accelerated. Moreover, owing to the substantial size of the 70B model, Task-Fused must utilize a TP degree of 16 to accommodate the high memory consumption, which is extremely inefficient due to the slow communication across servers. In contrast, most of the FT replicas in LobRA do not need to span across servers, delivering much better efficiency. Thus, LobRA achieves the highest performance gain on the 70B model.

Task-Sequential performs better than Task-Fused. As analyzed in §3, Task-Fused must employ a high model parallel degree for all training data. Task-Sequential, however, can employ a lower model parallel degree for datasets that contain only short sequences (e.g., question-answering datasets), so the total GPU seconds are shorter. The smaller performance gap in the 7B model is primarily because the smaller GPU memory capacity (40GB) restricts Task-Sequential from choosing more efficient parallel configurations for most tasks. Nevertheless, Task-Sequential is still less efficient than LobRA. Although LobRA-Sequential outperforms Task-Sequential, LobRA still achieves 1.32-1.44× of speedup compared to LobRA-Sequential. This is not surprising for two reasons. Firstly, the data heterogeneity is milder within certain tasks, so the gain of using heterogeneous FT replicas is lower. Secondly, the batch size for each FT task is usually small, making it difficult to achieve workload balance by routing the data across the replicas. In practice, we find that some tasks would even experience an efficiency drop when employing LobRA-Sequential (detailed in Appendix B.2 [4]). Last but not least, it is noteworthy that Task-Sequential and LobRA-Sequential necessitate running the FT tasks individually, either requiring extra GPUs or unfairly forcing some tasks to queue for a long time. Consequently, LobRA is more efficient and suitable for processing FT requests.

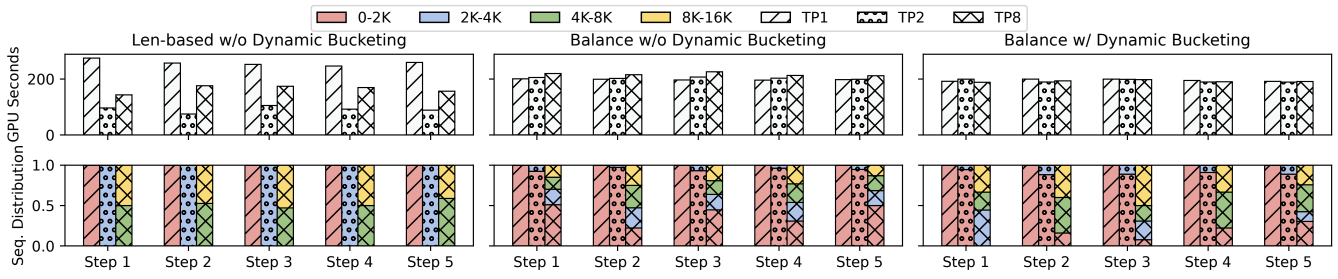


Figure 9: Case studies (7B model, 16 A100-40GB GPUs). Each bar represents one kind of FT replica(s). Top: The per-step time of each kind of FT replica(s). Bottom: The organization of dispatched data in terms of their sequence lengths for each kind of FT replica(s).

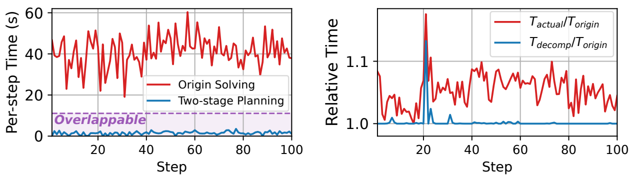


Figure 10: Left: Time cost of solving the original problem (Equation (1)) vs. the two-stage planning (dynamic bucketing + solving Equation (3)). The horizontal dashed line indicates the average per-step time. Right: Comparison of estimated running time for solving the original problem (T_{origin}), the two-stage decomposition (T_{decomp}), and the actual running time (T_{actual}).

5.3 Effectiveness of the Proposed Techniques

Ablation and Case Studies. We assess the effectiveness of heterogeneous model deployment and workload-balanced data dispatching, respectively. The results are shown in Figure 8 and Figure 9.

When heterogeneous FT replicas are deployed and the data are directly dispatched via their lengths (i.e., Figure 4(c)), we can reduce the GPU seconds by 18.94% compared to the naïvely fused approach. As shown in Table 2, the naïve approach needs to employ a high model parallel degree (resulting in 2 replicas with ⟨TP=8, PP=1⟩) to support long sequences, yet it is unsuitable for short sequences. In contrast, with the heterogeneous model deployment, we can deploy 7 replicas with low model parallel degrees (6 replicas with ⟨TP=1, PP=1⟩ and 1 replica with ⟨TP=2, PP=1⟩).

By further enabling the workload-balanced data dispatching and dynamic bucketing, the reduction in GPU seconds improves to 36.65% and 45.03%. Figure 9 visualizes the data dispatching and workload balance. When the data are simply assigned via their lengths (left-most of Figure 9), we observe severe imbalance across the replicas due to the skewness issue. Workload-balanced data dispatching (middle of Figure 9) strikes a good balance among the replicas by routing the data. With dynamic bucketing (right-most of Figure 9), the running time can be further reduced, particularly for replicas with a higher model parallel degree, since dynamic bucketing is more effective in reducing the padding of longer sequences.

Effectiveness of Planning. As discussed in §4.1, we employ a two-stage decomposition to Equation (1). One reason is that its solving is time-consuming. To examine this, we measure its solving time and compare it with the per-step running time. As shown on the left side of Figure 10, solving Equation (1) is slower than one training step, even if we have applied the configuration pruning heuristics introduced in §4.2 (the effectiveness of the two heuristics is evaluated in Appendix B.2 [4]). On the contrary, with the two-stage decomposition, we only need to perform the dynamic bucketing and solve Equation (3) for each step, which is extremely efficient and can be fully overlapped by the training of previous step(s).

In addition, we assess how the two-stage decomposition impacts the efficiency of the achieved solutions. To do so, we record the estimated running time given by solving the original problem, the estimated running time after the two-stage decomposition, and the actual running time in practice, denoted as T_{origin}, T_{decomp}, T_{actual}, respectively. The right side of Figure 10 presents T_{decomp}/T_{origin} and T_{actual}/T_{origin} across 100 steps. Overall, T_{decomp} and T_{origin} are extremely close in most steps. In occasional steps, the sampled batch does not contain long sequences, so solving the original problem produces a better deployment plan, leading to several spikes. However, the performance gap is still small (within 15%). These results verify the robustness and effectiveness of our two-stage decomposition. Besides, T_{actual} is also close to T_{decomp} (within 10%) across all steps, demonstrating the accuracy of our cost model.

More Experiments. We have conducted more experiments, including the scalability w.r.t. the number of GPUs and tasks, the sensitivity w.r.t. the sequence bucketing, and the effectiveness of our configuration pruning. Due to the space constraint, we leave more results and details of our experiments in Appendix B [4].

6 CONCLUSION

This work studies the processing of multiple FT requests by jointly training multiple LoRA adapters with the same base model. We conducted an anatomy on the efficiency of joint FT, showing that two data heterogeneity issues, i.e., the sequence length variation and skewness, pose significant challenges. Then, we developed a brand new joint-FT framework, namely LobRA, with two innovative designs. The first is the deployment of heterogeneous FT replicas, which addresses the sequence length variation and accelerate the processing of short sequences. The second is workload-balanced data dispatching, which eliminates the idle period of some FT replicas caused by skewness. Empirical results show that LobRA greatly reduces the GPU seconds required for joint FT by 45.03%-60.67%.

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