

OrchMLLM: Orchestrate Multimodal Data with Batch Post-Balancing to Accelerate Multimodal Large Language Model Training

Bangjun Xiao^{1,2,*} Yijie Zheng^{1,*} Lei Shi^{1,*} Xiaoyang Li¹ Faming Wu¹
Tianyu Li¹ Xuefeng Xiao¹ Yang Zhang¹ Yuxuan Wang¹ Shouda Liu¹
¹Bytedance ²Peking University

Abstract

Multimodal large language models (MLLMs), such as GPT-4o, are garnering significant attention. During the exploration of MLLM training, we identified Modality Composition Incoherence, a phenomenon that the proportion of a certain modality varies dramatically across different examples. It exacerbates the challenges of addressing mini-batch imbalances, which lead to uneven GPU utilization between Data Parallel (DP) instances and severely degrades the efficiency and scalability of MLLM training, ultimately affecting training speed and hindering further research on MLLMs.

To address these challenges, we introduce OrchMLLM, a comprehensive framework designed to mitigate the inefficiencies in MLLM training caused by Modality Composition Incoherence. First, we propose Batch Post-Balancing Dispatcher, a technique that efficiently eliminates mini-batch imbalances in sequential data. Additionally, we integrate MLLM Global Orchestrator into the training framework to orchestrate multimodal data and tackle the issues arising from Modality Composition Incoherence. We evaluate OrchMLLM across various MLLM sizes, demonstrating its efficiency and scalability. Experimental results reveal that OrchMLLM achieves a Model FLOPs Utilization (MFU) of 41.6% when training an 84B MLLM with three modalities on 2560 H100 GPUs, outperforming Megatron-LM by up to $3.1\times$ in throughput.

1 Introduction

The recent success of large language models (LLMs) is sparking a revolution in AI applications [2]. Given the diverse modalities that constitute information in the real world, there is a growing expectation for unified models capable of processing multimodal information. To bridge the gap of LLMs that only focus on text, emerging multimodal large language

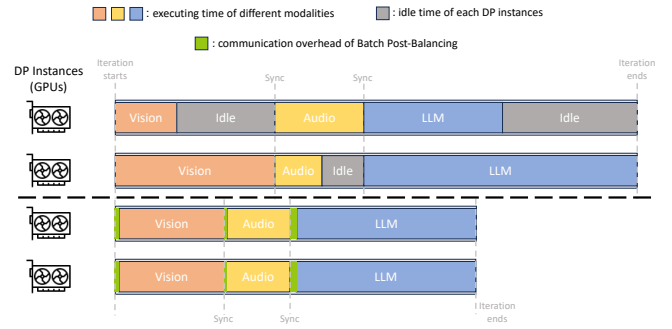


Figure 1: A comparative illustration showcasing the effectiveness of OrchMLLM.

models (MLLMs) are integrating various media types, including text, images, and audio. This integration not only preserves the inherent reasoning and decision-making capabilities of LLMs but also significantly broadens their versatility, enabling MLLMs to excel in a variety of multimodal tasks. From MLLMs that combine the text modality with another modality, including GPT-4V [3], Gemini [5], and CogVLM [46] for the visual modality, as well as Qwen-Audio [12] and Seed-ASR [9] for the auditory modality, to those integrate more modalities into a single MLLM, like GPT-4o [4], Llama 3.2 [17] and Baichuan-omni [28], etc, there is a continuous effort to explore the potential of MLLMs.

Owing to the scaling law, considerable resources are dedicated to training MLLMs with billions of parameters and trillions of tokens, which is extremely expensive and time-consuming [1, 42]. Several existing frameworks such as Megatron-LM [39] and DeepSpeed [37] can be adapted to accelerate the training speed of MLLMs. However, when training with sequential data, the varying sequence lengths and the randomness in batching [38] introduce imbalances in mini-batches across different data parallelism (DP) instances. This imbalance causes uneven GPU utilization, which consequently degrades the efficiency and scalability of MLLM training. Furthermore, independent execution of encoders requires the elimination of imbalances during multiple phases, otherwise, mini-batch imbalances of arbitrary modalities can sig-

*Equal contribution.

nificantly reduce training efficiency. The challenge to achieve this objective is raised by a phenomenon in multimodal training data, called **Modality Composition Incoherence**, which refers to the **dramatic variation in the proportion of a certain modality across different examples**. Modality Composition Incoherence makes it difficult to resolve the mini-batches imbalance across all phases through a single balancing operation. Existing methods, collectively referred to as **Batch Pre-Balancing methods** in this paper, **operate only once at the beginning of a training iteration** and can only **focus on the imbalance in a single phase**. Therefore, they **cannot effectively eliminate mini-batch imbalances** throughout each phase of MLLM training due to Modality Composition Incoherence.

To address this challenge, we present **OrchMLLM**, an **efficient and adaptive framework** designed to comprehensively **resolve mini-batch imbalances** and accelerate MLLM training, as illustrated in Figure 1. The core insight of OrchMLLM is that **rearranging mini-batches across DP instances does not affect the training results** (i.e., the rearrangement is consequence-invariant) and that a **proper rearrangement of mini-batches can eliminate the imbalance** and further **balance GPU utilization**. Building on this observation, we formulate the problem and propose several **Batch Post-Balancing algorithms**. These algorithms will determine the appropriate rearrangement for mini-batches in different scenarios, achieving **balance across all DP instances**. Furthermore, we devise a **Node-wise All-to-All Communicator** to implement the practical rearrangement of mini-batches. Specifically, All-to-All Batch Communicator rearranges mini-batches with **lightweight communication overhead** and memory occupancy, and Node-wise Rearrange Algorithm further reduces the communication overhead by **leveraging the heterogeneous bandwidths between intra-node and inter-node instances**. Lastly, the custom-designed **MLLM Global Orchestrator** is integrated into the MLLM training workflow, comprehensively **resolving mini-batch imbalances** during each training phase and significantly enhancing training efficiency.

In summary, we make the following contributions:

- We present OrchMLLM, an efficient and adaptive framework that comprehensively addresses mini-batch imbalances and accelerates the training of MLLMs. OrchMLLM is also applicable to all large-scale distributed training with sequential data, regardless of the model architectures in training, without requiring any operator code refactoring.
- We propose the Batch Post-Balancing Dispatcher, a technique that efficiently eliminates mini-batch imbalances in sequential data. Additionally, we integrate the MLLM Global Orchestrator into OrchMLLM to orchestrate multimodal data and resolve the challenges posed by Modality Composition Incoherence.
- We implement OrchMLLM and conduct experiments on the cluster with 2560 H100 GPUs. The results show that

OrchMLLM achieves 41.6% MFU when training an 84B MLLM with both visual and auditory modalities, outperforming Megatron-LM by up to 3.1× in throughput.

2 Background

In this section, we provide background knowledge for multimodal large language model (MLLM) training.

2.1 Data Parallelism

Data parallelism (DP) is a technique used to scale training across multiple devices by distributing data. In classic DP [10, 14], all model parameters and optimizer states are replicated on each device. At each training step, a global batch is divided into several subsets (i.e. *mini-batches*) across all DP instances. Each instance executes the forward and backward propagation on a different mini-batch and reduces gradients across instances to update the model locally.

For models with a large number of parameters, a complete replica of the model cannot fit in the device memory. Therefore, some studies have proposed variants of DP that proportionally reduce the memory footprint. ZeRO (Zero Redundancy Optimizer) [35] is a memory-efficient variant of DP where the model states are partitioned across all devices instead of being replicated. These states are reconstructed using gather-based communication collectives on-the-fly during training. This allows ZeRO to effectively leverage the aggregate device memory across machines, with minimal communication overhead compared to standard data parallelism (2M vs 3M for a model size of M), while still achieving excellent throughput scalability [36]. Fully sharded data parallelism (FSDP) [55], an efficient and user-friendly implementation of ZeRO, overlaps the communication of shards with computation on the critical path, thus mitigating the impact on training efficiency. By reducing the memory requirement for each device, these variants enable the scale-up of models that could not previously be trained due to memory limitations. This opens up opportunities for researchers to explore larger and more powerful models, including MLLMs.

2.2 Imbalance in Mini-batches

We define a property of a batch as the **batch length**, which equals the **post-padding sequence length multiplied by the batch size** when padding is employed, or otherwise **the sum of the sequence lengths**. Given the random nature of the sequence lengths in a training dataset and the fact that batch gradient descent adheres to the principle of batching randomness [38], the batch length can be regarded as a random variable. Therefore, **the batch lengths of several randomly selected batches can significantly deviate** from each other [23]. In the context of DP, where each DP instance randomly samples mini-batches from the dataset, this substantial variance

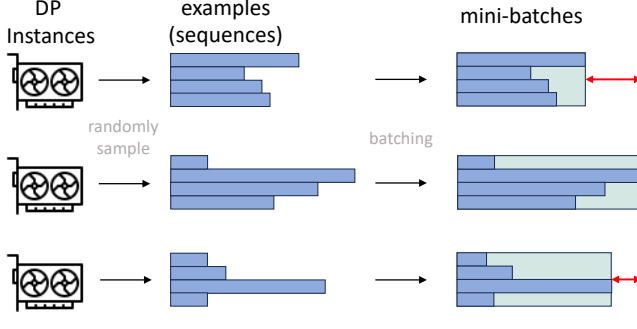


Figure 2: The diagram for the imbalance in mini-batches in the training of sequential data, using the padding batching method as an example.

of batch lengths remains across the mini-batches on different instances during the training with sequential data, which we refer to as the phenomenon of *imbalance in mini-batches*.

Because the batch length is strongly correlated to the computation cost and memory occupancy for a batch [44], the imbalance in mini-batches leads to many problems when training with sequential data. First, during the *synchronized communication* between instances (required for any variant of DP [14, 35, 55]), an instance that processes a mini-batch with a small batch length is forced to wait for other instances to perform synchronized operations. Additionally, the memory occupied by the activations of the training data is proportional to the batch length of a mini-batch. Assuming that the device memory on DP instances is finite and homogeneous (which is typical in real-world hardware), to avoid the out-of-memory (OOM) error, the batch size must be determined by the maximum batch length of all mini-batches. This restricted batch size leads to low memory utilization during training, resulting in *most mini-batches not being sufficiently vectorized*. To sum up, the consequences of the aforementioned problems lead to lower GPU utilization, significantly slowing down the training with sequential data.

2.3 MLLM training

A typical MLLM is comprised of three types of modules [50]: a *pretrained LLM*, several *single-modality encoders* (e.g. ViT [15] for vision and Whisper [34] for audio), and *respective connectors* for bridging between the encoders and the LLM backbone. A common and effective implementation of connectors is to *transform the output features of encoders into tokens* and *concatenate all these tokens before sending them to the LLM backbone*. In MLLM, we collectively refer to the LLM backbone and the encoders (along with their corresponding connectors) as *submodules*.

When training MLLMs, the training dataset is composed of *multimodal data examples*. In the forward pass, *metadata from different modalities is organized as sequential data* (e.g., restructuring images into sequences of *patches*), processed by the corresponding encoders and *transformed into sequences*

of tokens by connectors. These tokens belong to the unified embedding space of the LLM, where *sequences comprised of them are termed subsequences* within the whole sequence. After encoding, an example’s subsequences of different modalities are interleaved according to the order predefined by the example or certain templates, and the *entire sequence is processed by the LLM backbone*. The execution of each submodule is termed a *phase* of an iteration.

Due to the tremendous number of parameters in the LLM along with other encoders, MLLM training necessitates the use of *parallel strategies* to fit the MLLM within the device memory and accelerate the training speed. Model parallelism [20, 25] and ZeRO3 are two mainstream methods to shard the parameters of the model and fit the whole model in devices. ZeRO3 is inherently one variant of DP (§2.1). Moreover, widely established frameworks, such as Megatron-LM [39] and DeepSpeed-Megatron [40], combine DP with model parallelism as 3D-parallelism to enable large-scale distributed training. Therefore, *imbalance in mini-batches (§2.2) cannot be ignored in MLLM training*. Furthermore, because training data from different modalities is organized as sequential data and *phases of encoders occupy a significant portion of the execution time and memory throughout an iteration* [16], it is crucial to address the imbalance in mini-batches in each phase to fully unleash the potential of accelerators.

3 Motivation

This section demonstrates the challenges encountered in MLLM training and analyzes the motivation behind the design of our approach, OrchMLLM.

3.1 Modality Composition Incoherence

To build a unified multimodal model, it is essential for MLLMs to not only *comprehend different modalities* but also be *capable of performing a variety of tasks*. These tasks include those inherent to each modality as well as *complex tasks arising from the combination of multiple modalities*. Consequently, the dataset used for training MLLMs, especially during the instruction tuning stage, usually contains a *wide variety of tasks* to enrich the MLLM’s capability.

The diversity of tasks raises an issue regarding the composition of multimodal data, **Modality Composition Incoherence**, in MLLM training. Examples for the same task may exhibit certain common characteristics in the composition of multimodal data. For instance, datasets for automatic speech recognition (ASR) comprise *paired data*, including auditory data and text data representing the recognition results. *The sequence length of auditory data has a significant positive correlation with the sequence length of text data*, as longer speech is generally transcribed into longer text. However, the composition of multimodal data varies dramatically between different tasks. For the spoken question answering task, there

这里的动态变化指的是每个 example 本身内部的 modality 比例变化, 而非整个 training process 过程中

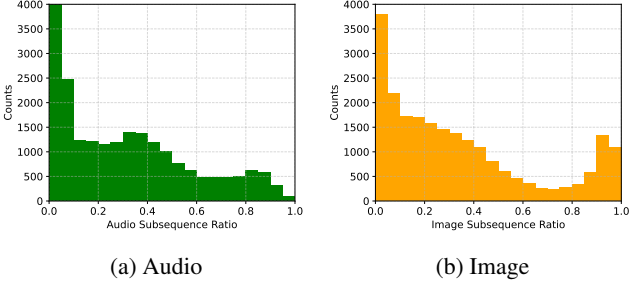


Figure 3: Modality Composition Incoherence in MLLM training. Both of the ratios bear substantial variance, which exhibits the incoherence in composition of multimodal data.

is no direct correlation between the sequence lengths of auditory data and text since a long question in auditory data may receive just a ‘yes’ or ‘no’ response. Moreover, the incoherence of composition becomes more pronounced across tasks involving different modalities. The auditory data within an example for the image caption task is evidently absent, and conversely, visual data is missing for the auditory tasks.

Owing to the strict proportional relationship between the sequence length of metadata and the lengths of subsequences, Modality Composition Incoherence can be intuitively characterized by the proportion of the subsequence lengths within the complete sequence. As shown in Figure 3, the proportions of subsequence lengths from visual and auditory modalities both exhibit substantial variance. As is analyzed in Section 2.2, the incoherence of composition propagates from the sequence length to computing duration and memory occupancy. This incoherence results in greater challenges in resolving the imbalance in mini-batches during MLLM training, because a mini-batch on a DP instance may be idle during one phase and yet transform into a straggler in another, as shown in Figure 1. The essence of these challenges lies in the fact that, due to Modality Composition Incoherence and the existence of dependencies in MLLMs, the problem of achieving balance across all phases becomes a multi-objective optimization problem, which is much more complex than the single modality case.

3.2 Limitation of Existing Methods

Several methods have been proposed to address the imbalance in mini-batches in pursuit of accelerating DP training. The key strategy is to form all mini-batches with the same batch length [49]. A straightforward solution is to adopt a dynamic batch size, replacing the fixed batch size with an upper bound for the batch lengths of mini-batches. Improvements on this method include refining the batching strategy with more complex algorithms, such as using several buckets to store the data and batching the data once a bucket is filled. Although these improvements enhance the balancing effectiveness, they also compromise on the principle of batching randomness. Moreover, these methods, which target the training of a sin-

gle modality, cannot comprehensively resolve the issue of imbalance in MLLM training.

In addition, DistTrain [54] targets MLLM training and mentions the issue of data heterogeneity, which is similar to Modality Composition Incoherence. This work attempts to address this challenge during data preprocessing by fixing the sequence length in the phase of the LLM backbone and then globally balancing the image input, which is the only modality except textual data in the context of this work. In this way, this method simplifies the problem by addressing the imbalance within a single modality. However, it fails to solve the problem with three or more modalities. Besides, fixing the sequence length in certain phase cannot be always reasonable, especially during the instruction tuning stage.

In summary, since all these methods perform the balancing before generating mini-batches, we collectively refer to their approach as pre-balancing. This implies that they need to address this multi-objective optimization problem all at once, as analyzed in §3.1, which is quite challenging. Consequently, this approach cannot comprehensively resolve the imbalance in mini-batches in MLLM training and achieve the theoretical upper limit of efficiency.

3.3 Opportunity

Since addressing the batch balancing problem all at once is extremely challenging, an alternative approach is to decompose it into multiple single-objective optimization problems. However, given that the mini-batches of different modalities are determined simultaneously, it’s necessary to carry out the balancing algorithm after the mini-batches have been decided.

Fortunately, we observe that after each DP instance randomly samples examples from the dataset, any permutation or rearrangement of these examples will not affect the final gradients used to update the model parameters. Across DP instances, the model parameters used for computation in the forward pass remain consistent, hence the computational result for each example is independent of the instance it resides in. Moreover, since all operations for the loss and gradients involve all-reduce, which satisfies the commutative and associative laws, any permutation or rearrangement within the mini-batches across DP instances is consequence-invariant.

This observation makes it possible to eliminate the imbalance in mini-batches after they have been decided. We refer to this approach as post-balancing. By performing post-balancing before each phase in MLLM training, we comprehensively address the inefficiency during training.

4 OrchMLLM Overview

We present OrchMLLM, a distributed training framework optimized for MLLM training. The core insight of OrchMLLM is based on the opportunity mentioned above. Firstly, we propose Batch Post-Balancing Dispatcher, a technique which

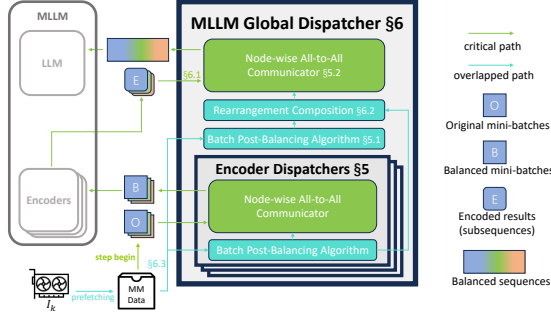


Figure 4: The system overview of OrchMLLM.

can efficiently eliminate the imbalance in mini-batches of sequential data. Further, we integrate MLLM Global Orchestrator into the framework of MLLM training to orchestrate the multimodal data. By eliminating the imbalance in mini-batches for all phases of MLLM training, our framework can comprehensively solve the inefficiency caused by multimodal data. Therefore, OrchMLLM boosts the GPU utilization and accelerate the training speed, achieving higher efficiency and scalability of MLLM training. A brief overview of the diagram is also shown in Figure 4.

Batch Post-Balancing Dispatcher. To eliminate the imbalance in mini-batches of single modality, the problem how to perform batch rearrangement to achieve optimal balance is formulated. Moreover, considering the diverse functional relationships between mini-batches and resource consumption, several balancing algorithms are devised to adapt to different scenarios. In addition, the dispatcher uses the Node-wise All-to-All Communicator to reduce communication overhead and memory occupancy during rearrangement. This communicator not only implements the batch rearrangement efficiently, but also takes into consideration the heterogeneous bandwidths between intra-node and inter-node instances within a cluster, further reducing communication overhead.

MLLM Global Orchestrator MLLM Global Orchestrator is custom-designed for the workflow of MLLM training. In the forward pass, it executes the batch dispatcher of each encoder independently. Owing to the dependencies between the LLM backbone and encoders, MLLM Global Orchestrator will perform the Batch Post-Balancing Algorithm globally and rearrange the data of all modalities. Besides, MLLM Global Orchestrator performs Rearrangement Composition to reduce the rearrangement overhead between encoders and the LLM backbone and overlaps the computation of dispatchers on the non-critical path.

5 Batch Post-Balancing Dispatcher

In this part, we will concentrate on the imbalance across DP instances on the dataset which only involves sequential data of single-modality.

5.1 Batch Post-Balancing Algorithms

As we have analyzed, any permutation or rearrangement among the examples of all mini-batches across DP instances will not affect the training results. Therefore, we need to devise algorithms to find the optimal rearrangement to address the imbalance.

Problem formulation. Assume there are d DP instances involved in the training, I_0, I_1, \dots, I_{d-1} . Each DP instance randomly samples a mini-batch from the dataset. For $0 \leq i < d$, the mini-batch of instance I_i can be regarded as a set comprised of several examples. We denote this set by S_i and the number of examples in this set by b_i . Each example is sequential data with length $l_{i,j}$ ($0 \leq i < d$, $0 \leq j < b_i$). Therefore, the batch length of the mini-batch for instance I_i , denoted by L_i , is given by:

$$L_i = \begin{cases} \max_{0 \leq j < b_i} b_i l_{i,j}, & \text{if padding,} \\ \sum_{j=0}^{b_i-1} l_{i,j}, & \text{otherwise.} \end{cases} \quad (1)$$

Next, we rearrange all the examples across the d instances into d new mini-batches. In other words, a rearrangement Π is defined by the following mapping:

$$\begin{aligned} \Pi: \quad S &\rightarrow S \\ M &\mapsto M', \end{aligned}$$

where $M, M' \in S$ with S representing the collection of all matrices with dimension $d \times \sum_{i=0}^{d-1} b_i$, and the (i, j) -entry of M is rearranged as the (i', j') -entry of M' . This rearrangement maps example j of the original mini-batch i into the j' -th example of the i' -th new mini-batch, $S'_{i'}(\Pi)$. For a given rearrangement Π , we denote the batchsize of $S'_{i'}(\Pi)$ as $b'_{i'}(\Pi)$, and its new batch length is calculated by (1) as $L'_{i'}(\Pi)$. Our goal is to eliminate the imbalance in these new mini-batches by finding the optimal rearrangement Π that minimizes the following minimax rule:

$$\text{Objective: } \min_{\Pi} \max_{0 \leq i < d} f(S'_{i'}(\Pi)),$$

where f is the function which represents the value of computational cost (basically proportional to memory usage) in the training for a given set of examples $S'_{i'}(\Pi)$ ($0 \leq i < d$). The practical significance of this objective is that by minimizing the maximum of the computational costs across the instances, we could maximize the GPU utilization of the whole system, further accelerating the training speed.

As we can see, solving this problem is equivalent to solving a load balancing problem, which can be reduced to the Subset Sum Problem (SSP) and is apparently an NP-complete problem. Therefore, we implement corresponding approximation algorithms based on the organization of sequential data (whether padding or not) and model architecture (determines

Algorithm 1 Post-Balancing Algorithm without Paddings

Require: count of DP instances d , list of sequences S

- 1: $sorted_sequences \leftarrow$ Sort S in descending order by length,
- 2: Initialize $new_batches$ as a priority queue that sort the batches based on the sum of sequence lengths,
- 3: **for** $i = 1 \rightarrow d$ **do**
- 4: $B_i \leftarrow \emptyset, new_batches.push(B_i)$
- 5: **for** $s \in sorted_sequences$ **do**
- 6: $new_batches.top().push(s)$
- 7: **return** $new_batches.tolist()$

the function f), in order to complete the solution within a polynomial time.

Specific to the Transformer architecture commonly used in MLLMs, the function f is given by:

$$f(S_i) := \begin{cases} \alpha L_i + \frac{1}{b_i} \beta L_i^2, & \text{if padding,} \\ \alpha L_i + \beta \sum_{j=0}^{b_i-1} l_{i,j}^2, & \text{otherwise,} \end{cases} \quad (2)$$

where α and β are the constant values determined by the model architecture, and $l_{i,j} (0 \leq j < b_i - 1)$ are the sequence lengths of the examples in the set S_i . Typically, there is an assumption that $\beta \ll \alpha$, so that the function f in (2) can be approximated by $f(S_i) := \alpha L_i$, and the objective is:

$$\text{Objective: } \min_{\Pi} \max_{0 \leq i < d} L'_i(\Pi).$$

In the case of no padding, we adopt the improved greedy algorithm to solve this problem, which is a 4/3-approximation algorithm, as shown in Algorithm 1. For the L_i with paddings, we propose an approximation algorithm 2, which combines binary and greedy approaches. The computational complexities of these two algorithms are, respectively, $O(n \log n)$ and $O(n \log(nC))$, where C is the range of binary searching.

Besides, several Post-Balancing algorithms for other model architectures and the scenario where the assumption $\beta \ll \alpha$

Algorithm 2 Post-Balancing Algorithm with Paddings

Require: count of DP instances d , list of sequences S

- 1: $sorted_sequences \leftarrow$ Sort S in ascending order by length,
- 2: **function** GETLEASTBATCHES(b) # Upper bound b for batch lengths
- 3: $ret_batches \leftarrow \{\{\}\}$
- 4: **for** $s \in sorted_sequences$ **do**
- 5: **if** $(len(ret_batches[-1]) + 1) * s.length > b$ **then**
- 6: $ret_batches.push(\{\})$
- 7: $ret_batches[-1].push(s)$
- 8: **return** $ret_batches$
- 9: $left \leftarrow sorted_sequences[0].length,$
- 10: $right \leftarrow sorted_sequences[0].length * (\frac{n}{d} + 1)$
- 11: **while** $left < right$ **do** # Binary search
- 12: $mid \leftarrow \lfloor \frac{left + right}{2} \rfloor$
- 13: $new_batches \leftarrow GETLEASTBATCHES(mid)$
- 14: $right \leftarrow$ if $len(new_batches) \leq d$ else $left \leftarrow mid + 1$
- 15: **return** $new_batches$

is not valid are presented in the Appendix. To sum up, our Post-Balancing algorithm completely takes effect after DP instances have randomly sampled the mini-batches. Therefore, the Post-Balancing algorithm won't violate the principle of batch randomness at all, compared with previous Pre-Balancing methods. Meanwhile, due to the ability of the Post-Balancing algorithm to perform load balancing over a wider range (across the mini-batches of all DP instances), it not only achieves a better balancing effect, but also has additional benefits, such as reducing the redundant paddings.

5.2 Node-wise All-to-All Communicator

Because the Post-Balancing dispatcher will bring extra computation and communication overhead to the training, it's essential to implement the dispatcher more efficiently. In most current DP frameworks, each DP instance independently sample a mini-batch from a split of the training dataset, which necessitates communication across DP instances to exchange the information of mini-batches. Consequently, we devise the implementation of the Post-Balancing dispatcher, with an efficient communicator referred to as **Node-wise All-to-All Communicator**, to reduce the communication overhead and memory occupancy of examples' rearrangement.

5.2.1 All-to-All Batch Communicator.

Strawman solution. A trivial approach is to carry out an All-Gather operation on each DP instance to collect all the mini-batches and then execute the Post-Balancing algorithm. However, this approach will bring a substantial increase in communication overhead within the training system. Due to the fact that the communication volume of a mini-batch is proportional to its batch length L_i , communication overhead of the collective communication operation can be given as:

$$O_{\text{All-Gather}} \propto (d-1) \max_{0 \leq i < d} (L_i) \quad (3)$$

where the proportional relationship is deduced by the ring-based algorithm. The communication overhead of this approach increases proportionally with the scale-up of a distributed training system, which impedes the scalability of such an approach. Moreover, mini-batches gathered from all DP instances will occupy a considerable amount of memory in the physical memory of each DP instance, which is unacceptable in the context of large-scale distributed training.

According to Section 5.1, the only factor that influences the solution to an Post-Balancing algorithm is the distribution of sequence lengths within all mini-batches, i.e. $l_{i,j} (0 \leq i < d, 0 \leq j < b_i)$. Thus, it's sufficient to only communicate all the $l_{i,j}$ across DP instances with the All-Gather operation, which incurs almost negligible communication overhead. Then, we could execute the Post-Balancing algorithm on each instance and obtain the optimal rearrangement Π , which mappings

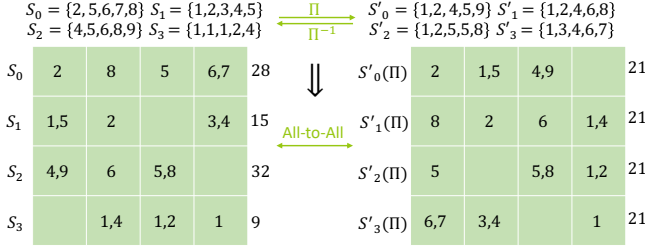


Figure 5: An illustrative diagram exhibiting the rearrangement process using the All-to-All operation, where each number refers to the length of a sequence in batches S_i .

each example from the source instance to the destination instance. This rearrangement can be implemented by the collective communication operation, All-to-All, as shown in Figure 5. Owing to the point-to-point communication protocol of All-to-All, the communication overhead of this approach can be denoted as:

$$O_{\text{All-to-All}} \leq \Omega_{\text{All-to-All}} \propto \max_{0 \leq i < d} (L_i) \quad (4)$$

where $\Omega_{\text{All-to-All}}$ refers to the upper bound of communication overhead of All-to-All and is deduced based on the point-to-point communication protocol. From the equation, it can be observed that the communication overhead of All-to-All does not increase with the scale-up of the cluster anymore. Moreover, this approach barely requires instances to allocate redundant memory in the memory, which is much more favorable to memory utilization.

5.2.2 Node-wise Rearrangement Algorithm

In the large-scale cluster, there exists heterogeneity in communication topologies between intra-node and inter-node instances, as shown in Figure 6, and the proportionality factor in (4) is determined by the minimum point-to-point communication bandwidth. Due to the significant disparity between inter-node and intra-node point-to-point bandwidths (e.g. intra-node communication using NVlink typically offers hundreds of GBs point-to-point bandwidth, whereas inter-node communication via Ethernet usually allocates merely dozens of GBs bandwidth per instance), the communication overhead of All-to-All communicator is determined by the maximum volume of intra-node communication:

$$O_{\text{ALL-to-ALL}} \propto \max_{0 \leq i < d} \left(\sum_{i'(\Pi) \notin N(i)} l_{i,j} \right) \quad (5)$$

where $i'(\Pi)$ is the new instance of $l_{i,j}$ under the rearrangement Π and $N(i)$ refers to the set of instances on the same node with the i -th instance. We can find that, during the All-to-All operation, pairs of instances from different nodes become stragglers compared with intra-node pairs.

Therefore, we propose **Node-wise Rearrangement Algorithm** to further reduce the communication overhead. For a

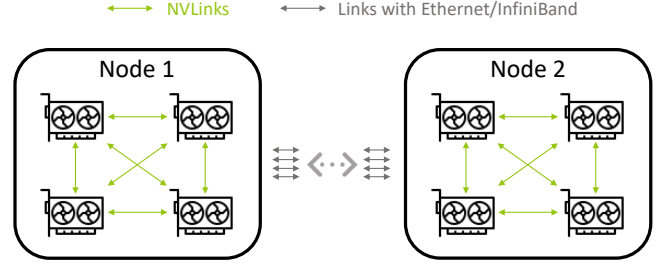


Figure 6: The heterogeneous communication topology in the large-scale cluster for distributed training.

given set of mini-batches $S_i (0 \leq i < d)$, the rearrangement Π solved by any Post-Balancing algorithm can be instantiated as an ordered set, $\Pi \equiv (S'_0(\Pi), \dots, S'_{d-1}(\Pi))$, as shown in Figure 5. For the given Π , we can calculate the matrix V , where the (i, j) -entry represents the communication volume between i -th and j -th DP instances. Apparently, permutation on the ordered set leads to the same permutation on columns of V , which further induces changes of the communication overhead. Meanwhile, due to the fact that the objective in Post-Balancing algorithms is regardless of the order of Π , any permutation on the ordered set is invariant for the objective. Hence, we formulate the objective of Node-wise Rearrangement Algorithm as:

$$\text{Objective: } \underset{P}{\text{minimize}} \max_{0 \leq i < d} \left(\sum_{i'(\Pi') \notin N(i)} l_{i,j} \right)$$

where P refers to the permutation on the rearrangement Π and new rearrangement $\Pi' = P(\Pi)$. This objective implies that it's feasible to reduce the communication overhead of All-to-All by assigning more communication volume to intra-node communication instead of inter-node communication.

As shown in Algorithm 3, we leverage Integer Linear Programming (ILP) to devise the Node-wise Rearrangement Algorithm, which involves $O(d^2/c)$ variables (c is the count of DP instances on a node) and $O(d)$ constraints, thereby introducing overhead of tens of milliseconds on a large-scale

Algorithm 3 Node-wise Rearrange Algorithm

Require: count of DP instances d , count of DP instances on a node c , original rearranged batches $\{S'_0, \dots, S'_{d-1}\}$

- 1: $\text{cost_matrix} \leftarrow \{\{0\} \times d\} \times d$,
- 2: **for** $i = 0 \rightarrow d - 1$ **do**
- 3: **for** $l \in S'_i$ **do**
- 4: $\text{cost_matrix}[l.\text{from}][i] += l.\text{length}$
- 5: $x \leftarrow \text{Variable}(\frac{d}{c}, c), \text{max_cost} \leftarrow \text{Variable}(1)$
- 6: $\text{cons} \leftarrow [\text{sum of each column of } x \text{ is } c, \text{sum of each row of } x \text{ is } 1]$
- 7: **for** $i = 0 \rightarrow \frac{d}{c} - 1$ **do**
- 8: $k \leftarrow i \times c$
- 9: $\text{cons.append}(\text{cost_matrix}[k : k + c] \cdot (1 - x[:, i]) \leq \text{max_cost})$
- 10: $\text{prob} \leftarrow \text{Problem}(\text{Minimize}(\text{max_cost}), \text{cons})$
- 11: $\text{prob.solve}()$
- 12: $\text{permuted_batches} \leftarrow \text{Permute} \{S'_0, \dots, S'_{d-1}\}$ with $x.\text{value}$
- 13: **return** permuted_batches

cluster. In the workflow of MLLM training, however, the overhead can be overlapped, as detailed in the following Section 6. Additionally, Node-wise Rearrangement Algorithm is applicable to all the Post-Balancing algorithms, because it operates solely on the solutions provided by these algorithms, which obviates the necessity for bespoke modifications tailored to the implementation of any particular Post-Balancing algorithm.

6 MLLM Global Orchestrator

After the preparation on the training of single-modality data, we can refocus on the workflow of MLLM training. In order to eliminate the imbalance in mini-batches in each phase, a feasible approach is to carry out the Batch Post-Balancing for each phase, on the corresponding data to be processed. However, it's neither reasonable nor efficient to straightforwardly apply the Post-Balancing Dispatchers separately, due to the data dependencies in MLLM training. We devise the **MLLM Global Orchestrator** for the workflow of MLLM training to guarantee the correctness and efficiency of Batch Post-Balancing during training, and finally make an efficient framework of MLLM training realizable.

Subsequences assembly. In the workflow of MLLM training, the phase of LLM backbone is distinct, compared to other phases of encoders, due to additional data dependencies. For a given example in the training, the encoded results from different encoders, as subsequences, are assembled and interleaved into a sequence according to a predefined order. Therefore, to perform the Post-Balancing algorithm in MLLM Global Orchestrator, we set the sequence length of an example $l_{i,j}$ as the length of the whole interleaved sequence, instead of the lengths of texts in this example.

Moreover, the obtained rearrangement, Π_M , maps the examples from their original instances to the destination instances where the LLM backbone will process their interleaved sequences. Therefore, the rearrangement of texts is straightforward, because texts are just located on the original instances. As for the encoded results which derive from the metadata of

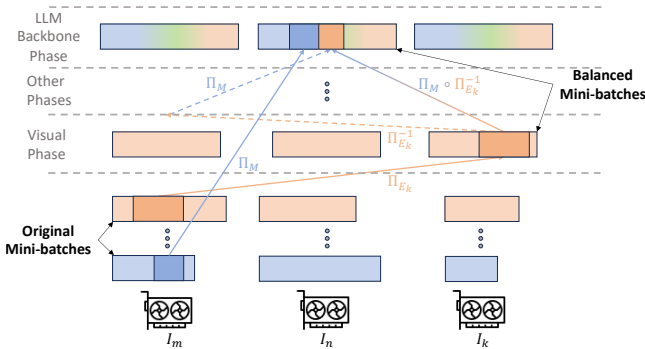


Figure 7: The diagram that illustrates the data flow of an example in MLLM Global Orchestrator.

corresponding modalities, because the mini-batches of meta-data are formed after the rearrangement of encoder dispatchers, most of the encoded results aren't located on their original instances. Consequently, straightforward applying the rearrangement Π_M to the encoded results fails to rearrange the subsequences of examples to their destinations. There, A trivial approach is to reset the encoded results to their original instances with the inverse rearrangement Π^{-1} and then apply the rearrangement Π_M to assemble the subsequences on the destination instance.

Rearrangement composition. Though resetting the encoded results to their original instances is able to guarantee the correctness during training, it still leads to higher communication overhead due to more All-to-All operations. We denote the rearrangement obtained from the Post-Balancing dispatchers of encoders as Π_{E_k} , where E_k represents the k -th encoder of MLLM. If we reset the encoded results, A_{E_k} , of the k -th encoder to their original instances and then apply the rearrangement Π_L , we will get the rearranged encoded results, which will serve as the subsequences on the corresponding instances, denoted as A'_{E_k} :

$$A'_{E_k} = \Pi_M \left(\Pi_{E_k}^{-1} (A_{E_k}) \right).$$

Due to the fact that these two linear mappings, Π_M and $\Pi_{E_k}^{-1}$, satisfy the associative law, we can first compound them into a single linear mapping, $\Pi_M \circ \Pi_{E_k}^{-1}$, and apply it to the encoded results A_{E_k} simultaneously, i.e.

$$A'_{E_k} = \left(\Pi_M \circ \Pi_{E_k}^{-1} \right) (A_{E_k}).$$

By Rearrangement Composition, we can integrate two All-to-All operations into a single one for each encoder in the forward pass. Moreover, because each rearrangement between the encoders and the LLM backbone will be accompanied by a rearrangement in the backward pass, we can reduce the communication overhead by half in total, which accelerates the speed of MLLM training.

Computation overhead overlapping. For arbitrary dispatchers, we can split the execution of a dispatcher into two parts, respectively, referred to as computation and communication. The former is primarily encompassed by the execution of Post-Balancing algorithm and Node-wise Rearrange algorithm, which are both executed by the CPUs (also includes relatively lightweight operations, like Rearrangement Composition in MLLM Global Orchestrator). The latter carries out the All-to-All operation to rearrange the mini-batches practically across DP instances.

To avoid interference between communication of dispatchers with original communication of distributed training, we tend to insert the communication into the forward pass, which is the critical path of training, instead of paralleling it with the forward pass. In contrast, the computation can overlap

with the forward pass. Because inputs to the algorithms of computation are sequence lengths of all examples in mini-batches, which are predictable owing to the characteristic of MLLM, the computation can be executed as soon as all the mini-batches have been sampled. Moreover, the sampling of mini-batches runs in parallel with the forward pass through prefetching. To allow the computation of dispatchers to parallel with the forward pass, we can integrate it into the prefetching process, which also guarantees that the terminal rearrangements are solved before carrying out the All-to-All operations. In this way, we can completely overlap the computation overhead of Post-Balancing Dispatchers, especially these algorithms that are computing-intensive, further reducing the overall overhead.

7 Implementation

We implement a system incorporating OrchMLLM, leveraging the feature provided by PyTorch 2.0, Fully Sharded Data Parallel (FSDP), which is a well-established framework with fine efficiency and scalability. Besides, the system inherits the universality and applicability of FSDP, and allows convenient adaptation to various modalities and models. We implement the entire system from scratch which comprises 5.1k lines of codes in Python and C++.

Batch Post-Balancing Algorithms All Batch Post-Balancing Algorithms are integrated into the Batch Post-Balancing Dispatcher and will be selected according to the specified balance policy. To reduce the overhead of executing the balance algorithms, instead of Python, we implement all algorithms, presented in Section 5.1 and A, with C++ and link them to the Python code with pybind.

Node-wise All-to-All Communicator Node-wise All-to-All communicator is implemented based on PyTorch Distributed [6] library with NCCL as the communication backend. The Node-wise Rearrange Algorithm is implemented with python package CVXPY, using the solver CBC.

MLLM Global Orchestrator We define a structure to record some details, including the counts of subsequences of different modalities and the order in which the subsequences are interleaved, for each example, which are gathered for MLLM Global Orchestrator to carry out Batch Post-Balancing. Moreover, we refine the dataloader in OrchMLLM to integrate the computation part of dispatchers into prefetching.

8 Evaluation

In this section, we first use large-scale experiments to demonstrate the overall performance improvements of OrchMLLM over Megatron-LM and the baseline of us. Subsequently, I conducted ablation and comparative experiments on several components within OrchMLLM, based on microbenchmarks.

Table 1: The configurations of submodules.

Models	Sub-modules	# of Layers	Hidden Size	FFN Hidden Size	Total Parameters
MLLM-10B	LLM	28	3584	18944	7B
	Vision	36	2048	8192	2B
	Audio	32	1280	5120	0.6B
MLLM-18B	LLM	48	5120	13824	14B
	Vision	40	2400	9600	3B
	Audio	32	1280	5120	0.6B
MLLM-84B	LLM	80	8192	29568	72B
	Vision	45	3200	12800	6B
	Audio	48	3072	12288	6B

Setup. Our experiments are conducted on a production GPU cluster for MLLM training, with each node equipped with eight NVIDIA H100 GPUs, 1.8TB of memory, and 88 vCPUs. GPUs within one node are interconnected by 900GB/s (bidirectional bandwidth) NVLink, while nodes are connected by 8*400 Gbps RDMA network based on InfiniBand. The experiments for overall results use the same cluster with 2560 GPUs, and the microbenchmark utilizes 128 GPUs. We use PyTorch 2.4.0 and NVIDIA CUDA 12.4 to build the system and for our evaluation.

Models. For the LLM backbone, we choose the architecture of Qwen2 [48], which also serves as the backbone both in Qwen2-VL [45] and Qwen2-Audio [11]. Targeting visual and auditory modalities, we respectively adopt ViT [15] for the visual encoder and the encoder of Whisper [34] for the auditory encoder, two widely established models for image understanding and audio comprehension. We choose varying configurations of encoders to match differently sized LLM backbones, as shown in Table 1. The three types are designated by the total parameter count of submodules, respectively: MLLM-10B, MLLM-18B, and MLLM-84B. The connectors between the encoders and the LLM backbone are universally MLPs. In additional, a downsample operation for the encoded results will be carried out before the connectors, and the downsample rates are respectively set as 1, 4, 4 for the visual results and 2, 2, 4 for the auditory results.

Datasets. As discussed in Section 3.1, we integrate several open-sourced datasets into the dataset for evaluation. For the visual modality, we adopt the instruction tuning dataset of LLaVA-1.5 [29], which encompasses varieties of visual tasks. For the auditory modality, we combine Librispeech [32], a dataset for Automatic Speech Recognition (ASR), with AIR-Bench which is an integrated dataset for Speech Question Answering. We generate training data by randomly sampling the example from the whole dataset, ensuring their random distribution across two types of datasets. As profiled and analyzed in Section 3.1, Modality Composition Incoherence emerges in this dataset.

Input preprocessing. The upper bounds for image resolutions

of the three MLLMs are set at 448, 672, and 896, all with the same patch size 14. Only images that are larger than the upper bound will be resized, and the sizes of preprocessed images are dynamic. The patches of the images are batched along the sequence length, with no padding in the batch. The audio sample rate is fixed at 16000 and the sequences of audios are batched with paddings, due to the existence of the convolution architecture in the auditory encoder. The sequences for the LLM backbone are batched with no padding.

Metrics. We use the Model FLOPs Utilization (MFU) as the primary metric to evaluate OrchMLLM. MFU measures the percentage of GPU FLOPs that are effectively utilized during model training. Given that there are redundant computation caused by paddings, we universally calculate effective GPU FLOPs without paddings. Besides, we leverage the training throughput (TPT) to evaluate the training speed, defined as the tokens processed by the LLM backbone per second on each GPU. The GPU memory usage, defined as the maximum of the memory usage during the training process, also serves as the auxiliary metric, in the ablation studies, to demonstrate OrchMLLM’s effect in optimizing memory occupancy.

8.1 Overall Results

OrchMLLM setup. Implemented based on FSDP, we adopt the whole cluster (2560 H100s) as the data parallel group and set the hybrid group size [55] for ZeRO3 as 256. We set the mini-batch size according to the memory usage during training, to avoid the error of OOM, respectively 80, 60, 30 for three MLLMs.

Baseline setup. We adopt two baselines in this part to demonstrate the efficiency and scalability of our method. The first is Megatron-LM, an established training framework for LLM. We retrofit the workflow of training text-image MLLM in the Megatron-LM to support the training of MLLM shown in Table 1, by integrating the auditory encoder into the framework and enabling the pipeline parallelism of MLLM with two or more encoders (without any other retrofits). The PP sizes for three MLLMs are 2, 4, 10, while the TP size is universally 8. The global batch sizes are respectively set as 5120, 5120,

2560. The second baseline is the OrchMLLM without any balancing, which is used to isolate the impact of system implementation and exemplify the effectiveness of our method. We set the mini-batch size according to the same standard, respectively: 65, 40, 15 for three MLLMs and other setups remain consistent.

It should be noted that we omit direct comparison with the contemporary framework, DistTrain, as its implementation is closed-sourced. Meanwhile, for the scope of this paper (i.e., handling mini-batches imbalance in MLLM training), DistTrain, according to the analysis in Section 3.2, is effectively a variant of Pre-balancing methods, with which we compare in **Comparison with Pre-Balancing methods** of Section 8.3.

The experimental results are shown in Figure 8 and Figure 9, respectively for MFU and the training throughput. From the experimental results, we can draw the following conclusions:

- From Figure 8, OrchMLLM achieves 41.6% MFU on the large-scale cluster with 2560 H100s. Due to the performance disparity between the H100 and A100, this result is roughly equivalent to 60% MFU on the same scaled cluster of A100s, and approaches the state-of-the-art efficiency of LLM training, which is the theoretical upper limit for MLLM training. The results on such a large-scale cluster demonstrate high efficiency and scalability of OrchMLLM.
- Compared with Megatron-LM, OrchMLLM achieves significant breakthroughs. OrchMLLM outperforms Megatron-LM with $3.1 - 4.1\times$ the MFU and $3.1 - 4.2\times$ the training throughput, though the performance of Megatron-LM also suffers from the model heterogeneity [54]. In additional, these breakthroughs highlight the potential and feasibility of leveraging FSDP for training MLLMs to avoid model heterogeneity.
- The contrastive experiment prominently demonstrate the effectiveness of our method. OrchMLLM outperforms OrchMLLM without balance with $1.5 - 2.0\times$ the MFU and $1.4 - 1.9\times$ the training throughput. The ratios between

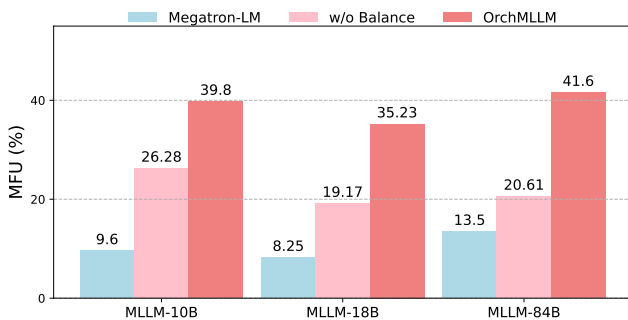


Figure 8: The overall results of MFU.

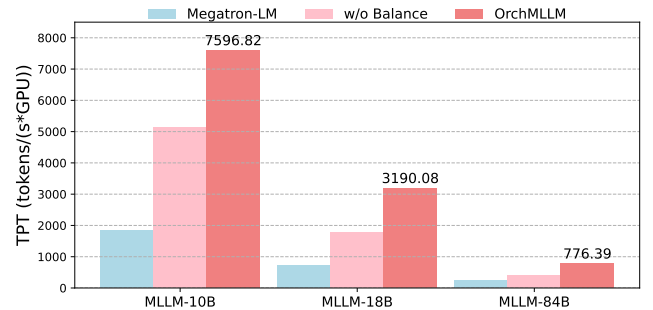


Figure 9: The overall results of the training throughput in tokens.

Table 2: The profiling results of OrchMLLM.

GPUs	64	128	256	512	1024	2560
Overhead (ms)	16.66	18.49	21.32	24.64	31.37	53.88
Duration (s)	3.79	3.81	3.85	3.92	3.96	4.05

them increase as MLLM grows larger, because larger models exert greater pressure on the GPU memory and advantages in memory utilization that OrchMLLM gains through balancing become more pronounced, further underscoring the efficacy and necessity of the method.

8.2 Overhead Analysis

The Post-Balancing method is on the critical path during the forward pass, so it is needed to analyze the overhead in the system. We adopt MLLM-10B, set the mini-batch size as 60, and profile the overhead in latency, including communication overhead and some extra durations, on differently sized clusters from 64 to 2560. Meanwhile, we also profile the average duration of the forward pass to estimate the overhead’s proportion in the training process.

From the Table 2, it is evident that the overhead of OrchMLLM consistently remains dozens of milliseconds, accounting for less than 2% in the duration of the forward pass. Meanwhile, in the backward pass, the overhead introduced by OrchMLLM is the communication overhead in the backward process of All-to-All operations, which is lower than that in the forward pass (due to more rounds of communication). Therefore, we can conclude that the overhead introduced by OrchMLLM constitutes only a negligible fraction of the training process, which further exemplifies the scalability of OrchMLLM.

8.3 Ablations and Microbenchmarks

The ablation studies and microbenchmarks in this part are all performed on the cluster with 128 H100s. The mini-batch sizes are respectively set as: 75, 50, 25 for three MLLMs without further specification. Due to the strict proportional relationship between MFU and training throughput, we don’t leverage training throughput as metrics anymore.

Comparison with Pre-Balancing methods. As we have analyzed in Section 3.2, existing Pre-Balancing methods are only capable of addressing imbalances in a single modality and a common approach is to guarantee balance only during the phase of LLM backbone. Therefore, we ablate the balancing dispatchers for the phases of encoders and further exemplify the superiority of OrchMLLM over existing Pre-Balancing methods with the ablation experiments.

From Figure 10, we can find that OrchMLLM consistently outperforms OrchMLLM with only LLM balance in terms of both MFU and GPU memory usage. Moreover, the advantages become increasingly pronounced as the size of MLLM grows,

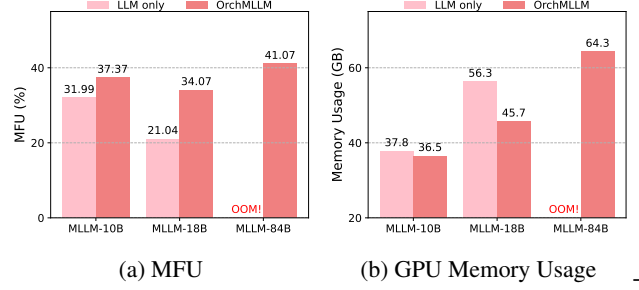


Figure 10: The ablation results of encoder balancing and comparison with Pre-Balancing methods.

to the extent that OrchMLLM with only LLM balance even triggers an OOM error for the MLLM-84B. (As a reference, it can run smoothly with the mini-batch size set to 18, achieving an MFU of 24.16% and a GPU memory usage of 62.7GB.) This indicates that Modality Composition Incoherence indeed causes imbalance even in the case of LLM balance and imbalance in the phases of encoders has a more significant impact on GPU utilization as model size increases. From this ablation experiments, it can be concluded that, compared with these Pre-Balancing methods, the introduction of Post-Balancing algorithms along with OrchMLLM is necessary for comprehensively eliminating the imbalance in MLLM training and unleashing the potential of accelerators, especially for the MLLMs with larger capacity.

Post-Balancing algorithms In Section 5.1, we tailor several Post-Balancing algorithms for different scenarios, including the algorithms for different batching strategies, i.e. with paddings or not. In OrchMLLM, we adopt different balancing algorithms for the phases of the vision encoder and the auditory encoder according to the batching strategies. In this part, we conducted two sets of contrastive experiments by changing the balancing algorithm of one phase to that of the other, respectively referred to as *all rmpad* and *all pad* as follows. The algorithm for the phase of the LLM backbone remains consistent.

As shown in Figure 11, the MFUs of these two groups are significantly lower than that of OrchMLLM. This indicates

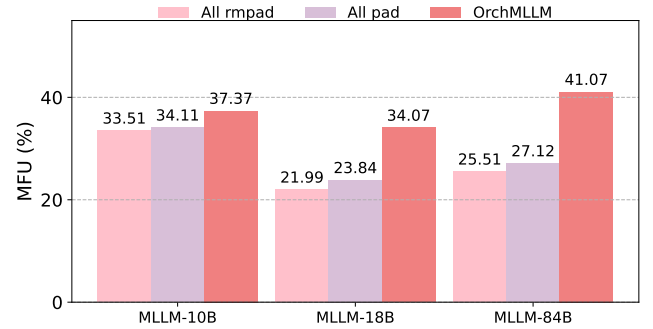


Figure 11: The results of two experiments with rigid algorithms, compared with OrchMLLM with tailored algorithms.

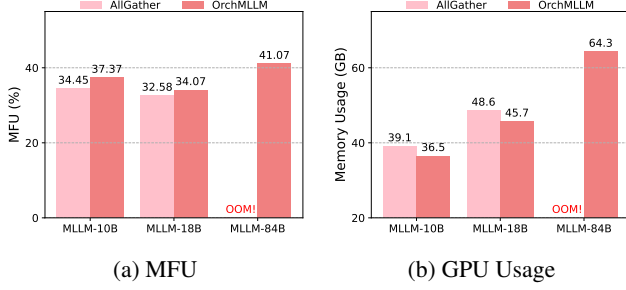


Figure 12: The comparative results of AllGather.

that a single algorithm for all phases of encoders is not effective enough to eliminate the imbalance in MLLM training due to the complicate scenarios derived from divergent model architectures of various encoders and diverse distributions of sequence lengths. This microbenchmark demonstrates the necessity of tailoring several Post-Balancing algorithms.

Node-wise All-to-All Communicator. In Section 5.2, we introduce Node-wise All-to-All Communicator as an efficient component of Batch Post-Balancing Dispatcher. Firstly, we substitute the communicator in OrchMMLM with a communicator implemented with All-Gather. The experimental results are displayed as Figure 12.

It can be concluded from the results that OrchMMLM outperforms the All-Gather communicator both in MFU and memory usage. As for the All-Gather communicator, the training of MLLM-84B crashes again because of OOM and it can accommodate a mini-batch size of 20 with an MFU of 25.51% and a GPU memory usage of 61.8GB. It is evident that All-to-All Batch Communicator is effective in reducing both communication overhead and memory occupancy of batches' rearrangement.

Then, we ablate the Node-wise Rearrange Algorithm and compare the communication overhead with OrchMMLM. According to the analysis in Section 5.2.2, the communication overhead is determined by the longest execution duration of All-to-All operations among DP instances, which is basically proportional to the inter-node communication volume on the

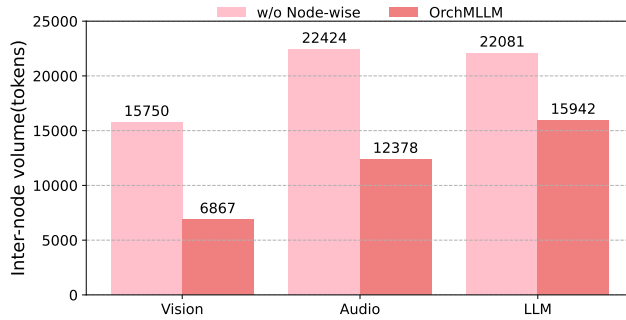


Figure 13: The ablation results of the Node-wise Rearrange Algorithm. The metric is the average inter-node communication volume of dispatchers for each modality (per iteration).

DP instance. Due to the significant fluctuations in communication overhead in real-world environments, profiling becomes challenging. Therefore, we leverage the communication volume to more intuitively demonstrate the differences between two sets of experiments, as shown in Figure 13.

Under this setting, the reduction of communication overhead through Node-wise Rearrange Algorithms ranges from 0.436 to 0.722 for dispatchers of different modalities. Moreover, because OrchMMLM adopts tailored balancing algorithms for different phases, it is proven to be effective for different Post-Balancing algorithms, although concrete effectiveness can be influenced by the specific algorithms and the data distribution. Therefore, Node-wise Rearrange Algorithm effectively reduces the overhead of dispatchers, because the communication overhead constitutes the majority of the total overhead through computation overhead overlapping.

9 Related Work

MLLM paradigms. There are broadly two ways to fuse multimodal information, namely, token-level and feature-level fusion. For token-level fusion, some [30, 41, 53] simply use a MLP-based connector to bridge the modality gap, but structures with more complexity like Q-Former are also being explored [13, 26]. Conversely, some works insert extra cross-attention layers (Flamingo [7]) or expert modules (CogVLM [47]) into LLMs. Zeng et al. [51] empirically reveal that the token-level fusion performs better in terms of VQA benchmarks. Both simplicity and effectiveness contribute to the popularity of token-level fusion, but the core sight of OrchMMLM can apply to both and only few refactoring on MLLM Global Orchestrator is needed.

LLM training. Many efforts have been made to optimize the training of LLMs from system perspectives. For LLM pretrain, Megatron-LM [39] and DeepSpeed-Megatron [40] propose customized 3D-parallelism and are de facto standards for training large LLMs. With the proposal of sequence parallelism (SP) [27] and expert parallelism (EP) [31], they are integrated into aforementioned frameworks. DeepSpeed-ZeRO [35] and Pytorch-FSDP [55] reduce redundant memory consumption in data parallelism. Fault tolerance through replication and checkpoint is advanced in large training clusters by studies [18, 24]. Efforts like [8, 21, 43] further optimize recovery process in cloud spot instance scenarios. These system optimizations of LLM training are orthogonal to OrchMMLM, because OrchMMLM only operates across DP instances.

Multimodal model training. Many system optimizations have been proposed to train both small multimodal models (e.g., CLIP [33] and LiT [52]) and MLLMs efficiently. DistMM [19] and DistTrain [54] tackle model heterogeneity by introducing disaggregated placement and partitioning to evenly distribute workload. GraphPipe [22] and Optimus [16] are proposed to address graph dependencies in multimodal

models to minimize pipeline bubbles. Yet, they fall short for resolving the imbalances in mini-batches throughout the MLLM training. This gap underpins the motivation behind OrchMLLM, designed to meet the unique challenges of Modality Composition Incoherence.

10 Conclusion

In this paper, we introduced OrchMLLM, a comprehensive framework designed to enhance the efficiency and scalability of MLLM training by addressing the issue of Modality Composition Incoherence. We proposed the Batch Post-Balancing Dispatcher and the MLLM Global Orchestrator to mitigate mini-batch imbalances and harmonize multimodal data orchestration. Experimental results demonstrate that OrchMLLM significantly outperforms existing frameworks like Megatron-LM. Hence, OrchMLLM offers a promising solution for efficient and scalable MLLM training, paving the way for future research and development in the field.

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A Other Post-Balancing Algorithms

Algorithm 4 Post-Balancing Algorithm 3rd

Require: count of DP instances d , list of sequences S , tolerance interval v

```

1: function CMP( $a, b$ )
2:   if  $\text{abs}(a.\text{lengths\_sum}() - b.\text{lengths\_sum}()) < v$  then
3:     return  $a.\text{lengths\_square\_sum}() < b.\text{lengths\_square\_sum}()$ 
4:   return  $a.\text{lengths\_sum}() < b.\text{lengths\_sum}()$ 
5:  $\text{sorted\_sequences} \leftarrow$  Sort  $S$  in descending order by length,
6: Initialize  $\text{new\_batches}$  as a priority queue that sort the batches with
   comparative function CMP,
7: for  $i = 1 \rightarrow d$  do
8:    $B_i \leftarrow \emptyset$ ,  $\text{new\_batches.push}(B_i)$ 
9: for  $s \in \text{sorted\_sequences}$  do
10:   $\text{new\_batches.top}().\text{push}(s)$ 
11: return  $\text{new\_batches.tolist}()$ 
```

Then, we discuss the scenario where the assumption $\beta \ll \alpha$ is not valid (still in use of the classic transformer architecture). In this part, we only consider the batching method without paddings, hence the objective is given by:

$$\text{Objective: } \min_{\Pi} \max_{0 \leq i < d} L'_i(\Pi) + \lambda \sum_{j=0}^{b_i-1} (l'_{i,j}(\Pi))^2.$$

where $\lambda = \frac{\beta}{\alpha}$. The approximation algorithm is presented as Algorithm 4. The computational complexity is $O(n \log n)$, the same as that of Algorithm 1. The tolerance interval is manually set to trade off between linear and quadratic terms.

Algorithm 5 Post-Balancing Algorithm 4th

Require: count of DP instances d , list of sequences S

```

1:  $\text{max\_sum\_bounds} \leftarrow$  the objective value of Post-Balancing Algorithm
   without Paddings,
2:  $\text{sorted\_sequences} \leftarrow$  Sort  $S$  in descending order by length,
3:  $\text{new\_batches} \leftarrow \{\{\}\}$ 
4: for  $s \in \text{sorted\_sequences}$  do
5:   if  $(\text{len}(\text{new\_batches}[-1]) + 1) * s.\text{length} > b$  then
6:     if  $\text{len} > d$  then
7:       break
8:      $\text{new\_batches.push}(\{\})$ 
9:    $\text{new\_batches}[-1].\text{push}(s)$ 
10:  $\text{sorted\_sequences} \leftarrow$  remaining sequences in  $\text{sorted\_sequences}$ ,
11: Transform  $\text{new\_batches}$  into a priority queue that sort the batches based
   on the sum of sequence lengths,
12: for  $s \in \text{sorted\_sequences}$  do
13:   $\text{new\_batches.top}().\text{push}(s)$ 
14: return  $\text{new\_batches.tolist}()$ 
```

Our method is also applicable to non-classical transformer architectures. For example, the architecture of ConvTransformer is sometimes used for feature extraction in images and speech. The main difference from the transformer lies in the structure of the Attention mechanism. Therefore, it requires padding for computation during the attention phase, rather than using the flash attention operator. The objective

for the Post-Balancing problem is given by:

$$\text{Objective: } \min_{\Pi} \max_{0 \leq i < d} L'_i(\Pi) + \lambda b_i \left(\max_{0 \leq j < b_i} l'_{i,j}(\Pi) \right)^2.$$

The approximation algorithm is presented as Algorithm 5.
The computational complexity is also $O(n \log n)$.