Coflow Scheduling for LLM Training

Xinchen Wan
Hong Kong University of Science and Technology
Hong Kong, China
xinchen.wan@connect.ust.hk

Xinyu Yang
Hong Kong University of Science and Technology
Hong Kong, China
xinyu.yang@connect.ust.hk

Kaiqiang Xu
Hong Kong University of Science and Technology
Hong Kong, China
kxuar@cse.ust.hk

Xudong Liao
Hong Kong University of Science and Technology
Hong Kong, China
xliaoaf@connect.ust.hk

Yilun Jin
Hong Kong University of Science and Technology
Hong Kong, China
yilun.jin@connect.ust.hk

Yijun Sun
Hong Kong University of Science and Technology
Hong Kong, China
ysuneb@connect.ust.hk

Zhenghang Ren
Hong Kong University of Science and Technology
Hong Kong, China
zrenak@cse.ust.hk

Han Tian
University of Science and Technology of China
Hefei, China
henrytian@ustc.edu.cn

Kai Chen
Hong Kong University of Science and Technology
Hong Kong, China
kaichen@cse.ust.hk

Abstract

Training large language models (LLMs) generates diverse coflows within a cluster, requiring optimized scheduling to enhance communication-computation overlap and minimize training time. Existing schedulers inadequately handle contention both across and within coflows, resulting in suboptimal performance.

We present Hermod, a comprehensive coflow scheduler that orchestrates all coflow types for LLM training. The key insight behind Hermod is that coflows can be uniquely characterized by three model factors—microbatch ID, coflow type, and layer ID—enabling optimal scheduling decisions. Leveraging this insight, Hermod applies model-factor–driven inter-coflow priority scheduling aligned with the LLM training DAG. Preliminary simulation results show potential for performance improvements.

CCS Concepts

• **Networks** → **Cloud computing**; **Data center networks**.

Keywords

Coflow scheduling, Large language model

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1 Introduction

Large language models (LLMs) have achieved impressive results across tasks such as machine translation, code generation, and dialogue systems [3, 5, 13]. However, training these models remains resource-intensive due to their massive scale and complexity. To meet computational and memory demands, LLM training is distributed across thousands of accelerators, requiring coordinated parallelization strategies for efficient scalability [6, 9, 15].

Training LLMs involves multiple forms of parallelism, including data, tensor, sequence, expert, and pipeline parallelism. Each introduces distinct communication patterns—e.g., `AllReduce` and `AllGather` for data and tensor parallelism (DP/TP) [8, 14, 16, 17, 19, 20], `AlltoAll` for expert parallelism (EP) [10, 11], and `send/recv` for pipeline parallelism (PP) [7, 12]—modeled as coflows within the network [4]. Optimizing these coflows is essential for minimizing job completion time (JCT) and ensuring efficient communication-computation overlap.

Coflow schedulers aim to improve JCT by reordering communications based on training data dependencies. Approaches such as ByteScheduler [14] and Lina [10] have shown promise by optimizing specific coflow types: ByteScheduler improves data parallelism via layer-wise DP coflows overlap, while Lina prioritizes EP coflows over DP coflows in backward passes. These techniques, though effective within their scope, address only subsets of the communication landscape in LLM training.

Despite their benefits, existing schedulers [10, 14] are limited by their local, endhost-focused scope and fail to holistically coordinate coflows across the entire cluster. They also overlook PP, whose coflows introduce strict sequential dependencies that, if unaccounted for, hinder overall throughput. Furthermore, current schedulers neglect flow-level imbalances within coflows, leading to internal bottlenecks.

This work addresses this challenge by introducing Hermod, a comprehensive coflow scheduler for LLM training. Through an in-depth analysis of the training DAG, we identify three model-specific

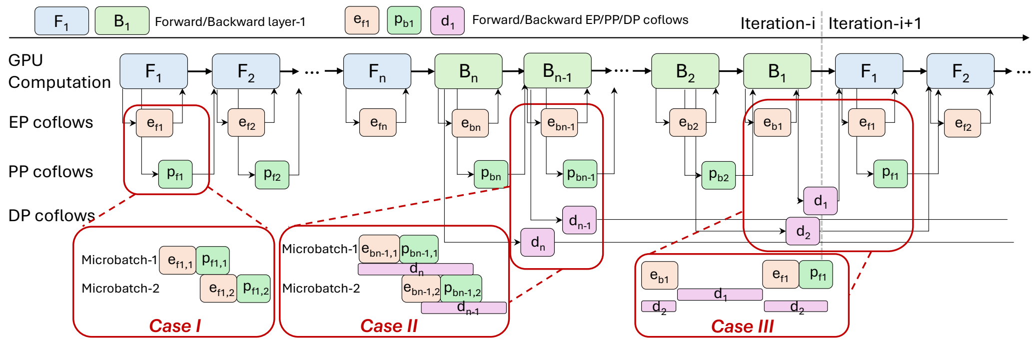


Figure 1: Computation and coflows in LLM training.

	Case I	*Case II*	*Case III*
Priority factor	MicrobatchID (Lower is better)	Coflow type (EP & PP > DP)	LayerID (Lower is better)

Table 1: Priority factors used to assign priority for three cases.

factors—microbatch ID, coflow type, and layer ID—that directly inform scheduling priorities. Hermod leverages these factors to enforce inter-coflow prioritization aligned with the DAG, enabling comprehensive cluster-wide coordination across all communication patterns. The remainder of this paper presents the design of Hermod (§2) and evaluates its effectiveness (§3).

2 Hermod Design

2.1 LLM Training DAG with Coflows

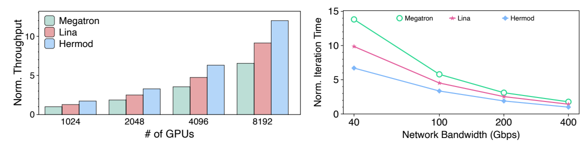
We revisit the LLM training DAG from a coflow scheduling perspective, focusing on optimizing coflow overlaps across inter-host parallelisms—EP, PP, and DP—to minimize job completion time (JCT). Our goal is to derive a cluster-wide scheduling policy that aligns network resource allocation with training dependencies.

In typical LLM training, the DAG is fixed by the topology, parallelization strategy, and worker placement. This DAG dictates coflow dependencies across iterations. Figure 1 illustrates a conventional DAG for training an MoE model with ZeRO-2 and 1F1B optimizations. Each iteration consists of forward propagation (FP) and backward propagation (BP). Within each iteration, EP coflows occur twice per MoE layer group for token dispatch and gathering, followed by PP coflows to transmit intermediate results between layers [18]. These operations repeat across layers and microbatches. During BP of the current iteration and FP of the next, DP coflows perform `ReduceScatter` and `AllGather` for gradient synchronization and parameter updates [9, 14, 16, 24].

A systematic analysis of the DAG identifies three key cases of coflow overlap, marked by red rectangles in Figure 1: (I) EP–PP overlaps across microbatches, (II) EP, PP, and DP overlaps during BP, and (III) cross-iteration overlaps between FP EP/PP coflows and BP DP coflows. These overlaps underscore the need for fine-grained coflow prioritization to mitigate resource contention and inefficient communication ordering.

2.2 Model Factor-Driven Priority Assignment

From the above cases, we identify three critical model factors—microbatch ID (MID), coflow type (CType), and layer ID (LID)—that uniquely characterize and prioritize coflows. These factors are application-defined, static throughout training, and easily encoded for transport-



(a) Scalability **(b) Different bandwidths**

Figure 2: Simulation results when training Qwen-MoE.

layer scheduling. We propose a model factor–driven scheduling strategy that assigns priorities to minimize critical-path blockage and maximize communication–computation overlap.

As summarized in Table 1, coflows with smaller MIDs receive the highest priority, followed by CType (EP/PP over DP) and then LID (lower layers prioritized). This ordering favors earlier microbatches and time-critical coflows, ensuring efficient training progression. The strict priority hierarchy is enforced cluster-wide across all iterations. We also analyze all potential conflicts to maintain consistency , resulting in a deterministic, conflict-free priority scheme across the cluster.

3 Evaluation And Future Work

Simulation Setup. We build our simulator on FlexFlow [1] and htsim [2], following the methodology of [21]. We extend FlexFlow to generate DAGs representing both computation and communication for all coflow types. Simulations use Qwen1.5-MoE [23] as the default model, comparing Hermod with Megatron and Lina [10]. Unless otherwise noted, we simulate a cluster of 8-GPU servers connected via a full-bisection fat-tree with 100Gbps links and 1μs propagation delay.

Scalability. We evaluate scalability by increasing cluster size from 1,024 to 8,192 GPUs. As shown in Figure 2a, Megatron suffers from poor throughput due to uncoordinated coflow handling. Lina improves on this with endhost prioritization but overlooks PP coflows. Hermod achieves up to 1.3× higher throughput by performing cluster-wide coflow scheduling.

Network Bandwidth. We assess performance under varying bandwidths (40–400Gbps), shown in Figure 2. Hermod consistently outperforms baselines. At 40Gbps, Hermod yields up to 1.78× speedup over Megatron via coordinated prioritization. At 400Gbps, network bottlenecks diminish, but Hermod still provides up to 2× higher throughput by mitigating EP/PP blocking and enabling DP overlap.

Future Work. We plan to extend Hermod to better resolve intra-coflow contention (*e.g.*, imbalanced EP coflows) and validate its effectiveness in real-world LLM training under larger clusters [22].

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