

Efficient Pipeline Parallelism for Reinforcement Learning

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Abstract—Reinforcement learning trains agents through interaction with environments, alternating between a rollout phase where experiences are collected and a training phase where policy and value networks are updated. Traditional distributed RL architectures transfer collected experiences to a centralized server that trains the actor-critic network and returns updated parameters. However, when deploying large neural networks in resource-constrained environments that require model parallelism across multiple devices, communication overhead increases substantially. Pipeline parallelism necessitates transferring both forward activations and backward gradients between devices for each training epoch, which can be repeated 10 or more times per batch for sample efficiency. This paper presents a gradient accumulation technique that selectively transmits high-magnitude gradients above a specified percentile threshold during backward propagation. By accumulating gradients over time and only communicating the most significant values, we reduce network transfer by up to 90 percent while maintaining comparable training performance to full gradient communication.

Index Terms—Reinforcement Learning, Pipeline Parallelism, Gradient Compression, Distributed Training, Model Parallelism

I. INTRODUCTION

Reinforcement learning trains intelligent agents through environmental interaction, alternating between rollout phases where experiences are collected and training phases where policies are updated. As neural network architectures grow increasingly complex, computational and memory requirements often exceed single-device capabilities, necessitating distributed training approaches.

Traditional distributed RL systems use centralized architectures where edge devices collect experiences while cloud servers train models. However, when models become too large for a single device’s memory, pipeline parallelism becomes essential, partitioning networks into sequential stages across multiple devices. Unlike centralized training where only experiences and parameters are transferred, pipeline parallelism requires continuous exchange of forward activations and backward gradients between devices. This communication occurs repeatedly for each training epoch, which can number 10 or more per batch for sample efficiency, creating substantial overhead in bandwidth-limited environments.

This paper addresses this communication challenge through selective gradient transmission. We present a gradient ac-

cumulation technique that identifies and communicates only the most significant gradients based on magnitude percentile thresholds. Section II reviews related work. Section III defines the problem and quantifies communication overhead. Section IV describes our method. Section V presents experimental results demonstrating network transfer reduction of up to 90 percent while maintaining comparable performance. Section VI discusses future work.

II. RELATED WORK

A. Distributed Reinforcement Learning

Early work on distributed RL established foundational architectures for scaling training. Nair et al. [?] introduced massively parallel methods for deep RL using parallel actors generating behavior, parallel learners trained from stored experience, and distributed neural networks, achieving order-of-magnitude speedups on Atari games. Building on this, Espeholt et al. [?] proposed IMPALA, which decouples acting from learning using importance sampling for off-policy corrections, scaling to thousands of machines while achieving state-of-the-art results on multi-task benchmarks. Horgan et al. [?] introduced Ape-X, separating data collection from learning through distributed prioritized experience replay, where multiple actors generate experience stored in a shared replay buffer accessed by learners.

B. Communication-Efficient Distributed Training

Reducing communication overhead in distributed training has been extensively studied. Chen et al. [?] developed communication-efficient policy gradient methods specifically for distributed RL, proposing gradient compression techniques that reduce communication costs while maintaining convergence guarantees. In the supervised learning domain, Lin et al. [?] discovered that 99.9% of gradient exchange in distributed SGD is redundant, proposing Deep Gradient Compression (DGC) that achieves 270-600x bandwidth reduction through momentum correction and local gradient clipping. Alistarh et al. [?] introduced QSGD, a family of gradient quantization schemes providing convergence guarantees for both convex and non-convex optimization while allowing smooth trade-offs between communication bandwidth and convergence time.

C. Pipeline Parallelism for Large Models

Pipeline parallelism has emerged as a critical technique for training models exceeding single-device memory. Huang et al. [?] presented GPipe, which partitions neural networks across multiple accelerators and pipelines mini-batches through stages, introducing micro-batching and gradient accumulation to achieve near-linear speedup while training models 25x larger than single-accelerator capacity. Narayanan et al. [?] proposed PipeDream, which automatically partitions DNN models and schedules computation to minimize pipeline bubbles, maintaining multiple parameter versions to enable weight updates without stalling. For transformer models, Shoenberger et al. [?] developed Megatron-LM with efficient intra-layer model parallelism, achieving 76% scaling efficiency on 512 GPUs for 8.3 billion parameter models. Rajbhandari et al. [?] introduced ZeRO, eliminating redundant storage of optimizer states, gradients, and parameters across data-parallel processes, enabling training of 170 billion parameter models.

D. Resource-Constrained Environments

Recent work addresses distributed learning in resource-constrained settings. Lim et al. [?] applied federated learning principles to RL for IoT devices, enabling multiple agents to collaboratively learn optimal control policies while keeping data local, addressing device-specific dynamics variations. Feng et al. [?] designed IoTSL, an efficient split learning system for resource-constrained IoT devices, optimizing the split learning paradigm to handle non-IID data distribution and reduce communication requirements specific to IoT constraints.

Our work differs from prior approaches by specifically addressing the communication bottleneck in pipeline-parallel RL training through selective gradient accumulation. While existing gradient compression techniques focus on compressing all gradients uniformly or through quantization, our approach accumulates gradients over time and transmits only high-magnitude values above configurable percentile thresholds, tailored to the unique characteristics of RL training with repeated epochs.

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ACKNOWLEDGMENT

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