CS526 Final Project Report: Distributed Machine Learning Pipeline for MNIST

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Abstract

This paper presents a distributed machine learning pipeline for training a Multi-Layer Perceptron (MLP) on the MNIST dataset. Using gRPC-based communication, the system integrates simulated GPU device servers with a centralized Coordinator Server, employing the AllReduce Ring Algorithm for gradient synchronization. We outline the system architecture, key design trade-offs, and evaluate its performance against industry benchmarks, highlighting the algorithm's effectiveness in improving distributed training efficiency.

1 Introduction

Training large-scale models on extensive datasets requires distributed systems that leverage multiple processing units. However, existing frameworks such as Parameter Servers [3] and Horovod [4] often rely on centralized synchronization or naive AllReduce implementations. While Parameter Servers centralize gradient aggregation, introducing bottlenecks and failure points, Horovod's Ring AllReduce incurs substantial overhead in heterogeneous networks.

Additionally, the lack of modularity in many systems complicates the integration of new synchronization algorithms and adaptation to diverse hardware configurations, limiting their flexibility and scalability.

To address these challenges, we replicate a **Distributed Machine Learning Pipeline** using **gRPC-based communication** to integrate simulated GPU device servers with a centralized GPU Coordinator Server. The system employs the **AllReduce Ring Algorithm** to efficiently synchronize gradients, reducing communication latency and improving scalability.

1.1 Motivation and Contributions

The primary motivation is to replicate and validate a distributed training framework that scales efficiently with GPU devices while enabling future enhancements in synchronization algorithms and hardware optimization. By decoupling synchronization from the training workflow via a centralized coordinator, the system ensures flexibility and ease of updates. Our contributions include:

- **System Replication**: A modular distributed ML pipeline comprising simulated GPU device servers and a centralized GPU Coordinator Server, leveraging gRPC for low-latency communication and synchronization.
- **AllReduce Ring Implementation**: Efficient synchronization of gradients across GPU devices, reducing communication steps and latency for faster convergence.
- **Performance Evaluation**: Training a Multi-Layer Perceptron (MLP) on the MNIST dataset and benchmarking against industry standards, demonstrating significant improvements in latency and scalability.

1.2 Paper Organization

The paper is organized as follows: Section 2 describes the system design, including GPU Device Servers, the GPU Coordinator Server, and design trade-offs. Section 3 outlines the ML training workflow, the MLP model, and client-GPU interactions. Section 4 reviews related frameworks and algorithms. Section 5 concludes with future directions.

2 System Design

2.1 System Overview

Our distributed ML pipeline comprises three core components:

1. **GPU Device Servers**: Simulated GPUs executing computations, managing memory, and synchronizing gradients.

2. **GPU Coordinator Server**: Orchestrates communication, aggregates gradients using the AllReduce Ring Algorithm, and monitors device health.

3. **Client Module**: Interfaces for training initiation, data loading, and model parameter updates.

Design and Trade-offs for Entire System

- **Thread Safety**: Utilizing mutex locks (`sync.Mutex`) ensures safe concurrent access to shared resources, preventing race conditions during communication and memory operations. This synchronization introduces a constant time complexity overhead of $O(1)$ per lock acquisition, which may affect throughput under high concurrency.

- **Memory Management**: Employing a nested map-based memory model (`map[uint64]map[uint64][]byte`) facilitates dynamic allocation and efficient address lookups for host memory operations. The trade-off is an increased space complexity of $O(m)$, where m is the total number of memory entries across all devices, compared to more compact data structures that may offer lower memory overhead.

2.2 GPU Device Server Design

We implement the GPU Device Server, responsible for emulating GPU functionalities such as parallel computation, memory hierarchy management, and high-throughput data communication. It interfaces seamlessly with the GPU Coordinator Server to ensure efficient gradient synchronization and data transfer across multiple GPU devices, leveraging gRPC for low-latency communication and scalability in a distributed environment.

```
class GPUDeviceServer {
    // Initialize server
    NewGPUDeviceServer()
    // Retrieve metadata
    GetDeviceMetadata()
    // Start send operation
    BeginSend()
    // Start receive operation
    BeginReceive()
    // Stream data packets
    StreamSend()
    // Memory copy between host and device
    Memcpy()
    // Check stream status
    GetStreamStatus()
}

```

Listing 1: GPU Device Server Functions

Design and Trade-offs for GPU Device Server

- **Stream Handling**: Managing multiple data streams enables asynchronous communication, enhancing data throughput and parallelism but adds complexity to stream state management and error handling, potentially affecting system robustness and maintainability.

- **gRPC Communication**: Leveraging gRPC enables efficient, low-latency communication between the Coordinator and GPU Device Servers. This enhances scalability but introduces dependencies on network stability and increases the complexity of connection management and error handling mechanisms.

2.3 GPU Coordinator Server Design

The GPU Coordinator Server orchestrates interactions between multiple GPU Device Servers, ensuring efficient gradient synchronization using the AllReduce Ring Algorithm and maintaining overall system reliability through continuous health monitoring.

```
class GPUCoordinatorServer {
    // Initialize coordinator
    NewGPUCoordinatorServer()
    // Initialize communication with devices
    CommInit()
    // Perform AllReduce using Ring Algorithm
    AllReduceRing()
    // Perform Naive AllReduce
    NaiveAllReduce()
    // Handle memory copy operations
    Memcpy()
    // Start a communication group
    GroupStart()
    // End a communication group
    GroupEnd()
    // Retrieve communicator status
    GetCommStatus()
    // Destroy a communicator
    CommDestroy()
}

```

Listing 2: GPU Coordinator Server Functions

Design and Trade-offs for GPU Coordinator Server

- **AllReduce Synchronization**: Utilizing the AllReduce Ring Algorithm (see Figure 3 and 4) reduces synchronization latency and communication overhead from $O(n^2)$ to $O(n)$ communication steps by organizing devices in a ring topology. This optimization achieved a **90% reduction** in communication overhead, decreasing latency from 83ms to 8ms per step. However, it introduces additional complexity in coordinating communication steps and handling potential device failures.

- **Health Monitoring**: Continuously monitoring the status and responsiveness of GPU Device Servers ensures system reliability by promptly detecting device failures. This introduces additional computational overhead and may increase latency in responsiveness to failures.

- **Connection Management**: Establishing and maintaining gRPC connections with multiple GPU Device Servers requires robust connection handling and retry mechanisms. This ensures reliable communication but adds complexity to the connection logic and may increase initial setup time due to retries.

```
func (c *Coordinator) AllReduceRing(devices []*GPUDevice, gradients [][]float32) [][]float32 {
    numDevices := len(devices)
    segmentSize := len(gradients[0]) / numDevices
    for step := 0; step < numDevices-1; step++ {
        for i, device := range devices {
            sendTo := (i + 1) % numDevices
            recvFrom := (i - 1 + numDevices) % numDevices
            segment := gradients[i][step*segmentSize : (step+1)*segmentSize]
            devices[sendTo].SendSegment(segment)
            received := devices[recvFrom].ReceiveSegment()
            // Aggregate received gradients
            for j := 0; j < segmentSize; j++ {
                gradients[i][step*segmentSize+j] += received[j]
            }
        }
    }
    return gradients
}

```

Listing 3: Pseudocode for AllReduce Ring Algorithm

3 Machine Learning Training

3.1 Model Definition

We utilize a Multi-Layer Perceptron (MLP) specifically designed for the MNIST dataset. The MLP comprises an input layer with 784 neurons representing the flattened 28x28 pixel images, two hidden layers with 128 and 64 neurons respectively employing ReLU activation functions, and an output layer with 10 neurons using softmax activation for classifying digits (0-9).

The model structure ensures scalability and facilitates distributed training across multiple GPU devices, while maintaining simplicity, making it suitable for benchmarking purposes.

```
func (c *Coordinator) NaiveAllReduce(devices []*GPUDevice, gradients [][]float32) [][]float32 {
    // Gather all gradients to the coordinator
    for i, device := range devices {
        gradients[i] = device.SendGradients()
    }
    // Reduce gradients
    for i := 1; i < len(devices); i++ {
        for j := 0; j < len(gradients[0]); j++ {
            gradients[0][j] += gradients[i][j]
        }
    }
    // Broadcast reduced gradients to all devices
    for i, device := range devices {
        if i != 0 {
            device.ReceiveGradients(gradients[0])
        }
    }
    return gradients
}

```

Listing 4: Pseudocode for Naive AllReduce

3.2 Training Workflow

The client orchestrates the training process by interacting with the GPU Coordinator and Device Servers through defined gRPC APIs as follows:

1. **Data Loading**: The client loads and normalizes the MNIST dataset.

2. **Forward Pass**: Utilizing the `CommInit` and `Memcpy` APIs, the client sends input data to GPU Device Servers to perform forward propagation.

3. **Backward Pass**: After computing the loss, the client invokes the `Memcpy` API for backpropagation and gradient calculation on the GPU devices.

4. **Gradient Synchronization**: Gradients are aggregated across devices using the `AllReduceRing` API managed by the GPU Coordinator, implementing the AllReduce Ring Algorithm.

5. **Model Update**: The client updates the MLP parameters with the aggregated gradients via the `Memcpy` API.

6. **Evaluation**: Periodic evaluation of the model on the test set is conducted using the `Memcpy` and `GetCommStatus` APIs to monitor accuracy.

3.3 Model Benchmarking

- **Latency**: Training the MLP for 10 epochs takes an average of **8 minutes**, significantly reducing training time compared to traditional methods which take approximately **30 minutes**.

- **Model Accuracy**: The MLP attained **92.89%** accuracy on the MNIST test set after 10 epochs, closely matching the standard MLP benchmark of **92.40%** and maintaining competitive performance relative to more complex models like LeNet-5 (**99.20%**) and TensorFlow benchmarks (**97.00%**).

Table 1: Model Performance on MNIST Dataset

Model	Training Time	Accuracy (%)	# Epochs
Our MLP	8 minutes	92.89	10
Standard MLP	8 minutes	92.40	10
LeNet-5	15 minutes	99.20	10
TensorFlow	10 minutes	97.00	10

4 Related Work

Our work builds upon and differentiates from several key frameworks and algorithms in distributed machine learning:

- **Horovod** [4]: An MPI-based distributed training framework that employs Ring AllReduce for gradient synchronization. Similar to our implementation, Horovod organizes devices in a ring topology to minimize communication overhead, facilitating scalable training across multiple GPUs.
- **Parameter Servers** [3]: A paradigm where centralized servers manage model parameters, allowing workers to fetch and update parameters asynchronously. In contrast, our system utilizes a ring-based synchronization mechanism that avoids the bottleneck of centralized parameter management, enhancing scalability and reducing latency.
- **TensorFlow Distributed** [1]: Provides comprehensive tools for distributed training, including parameter synchronization and fault tolerance mechanisms. While TensorFlow offers a broad range of features, our focused implementation demonstrates the efficiency gains of the AllReduce Ring Algorithm in a simulated environment.
- **NVIDIA NCCL** [2]: A library for collective communication optimized for NVIDIA GPUs. NCCL's implementation of ring-based AllReduce informs our algorithmic choices, highlighting the importance of hardware-aware optimizations in distributed training.

5 Conclusion

We have developed a distributed machine learning pipeline that leverages gRPC-based communication and the AllReduce Ring Algorithm to synchronize gradients across multiple GPU device servers. Our system achieves a **90% reduction** in synchronization latency compared to Naive AllReduce implementations. The trained Multi-Layer Perceptron (MLP) on the MNIST dataset reached an accuracy of **92.89%**, aligning with industry benchmarks and demonstrating the efficacy of our approach.

Future Work

- **Deployment on Physical GPU Clusters**: Transitioning to actual GPU hardware to evaluate performance under real-world conditions.
- **Support for Complex Models**: Extending compatibility to architectures like CNNs and transformers.
- **Dynamic Scalability**: Enabling automatic scaling of GPU Device Servers based on workload.
- **Advanced Scheduling Algorithms**: Exploring scheduling algorithms, such as 1F1B and others mentioned in the literature review.

References

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