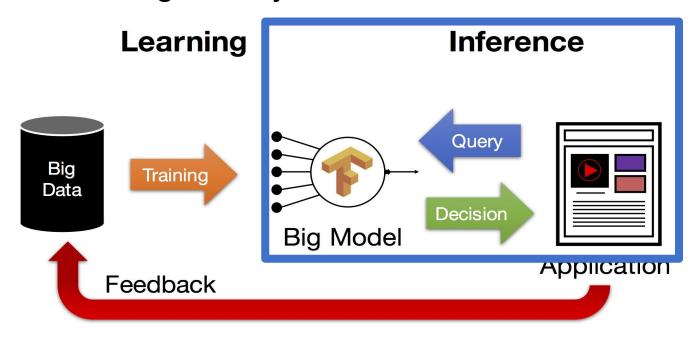
Benchmarking Distributed Training on GPUs

Exploring Performance Metrics and Inferring PyTorch DataParallel module optimizations

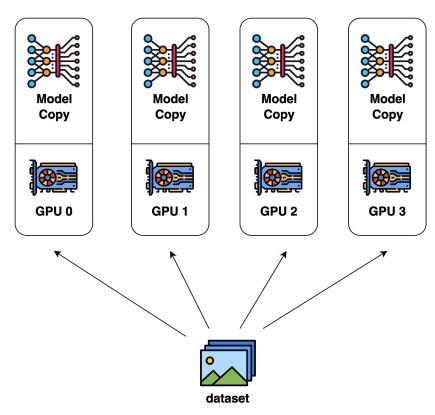
Team members: Tanushree Banerjee, Vedant Shah COS 316 Final Project Video, Fall 2023

Machine Learning Life Cycle: An Overview



GPT3 175B 34 days 1024 expensive GPUs <u>Timescale</u>: ~10 milliseconds <u>Systems</u>: online and latency-optimized <u>Less studied</u> ...

PyTorch DataParallel



Project Goals

Benchmark distributed training on GPUs (NVIDIA A6000s)

Vary batch size, feature extractor model, number of trainable parameters, number of GPUs used

Measure computation, communication times, loss and data transfer size.

Infer optimizations made by PyTorch DataParallel module

Approach

Models: ResNet18, VGG16, SqueezeNet10, DenseNet121, AlexNet

Dataset and task: MNIST Classification

Vanilla DataParallel module with PyTorch primitives implemented explicitly:

- 1. Replicate
- 2. Scatter
- 3. Gather
- 4. Parallel apply

Metrics

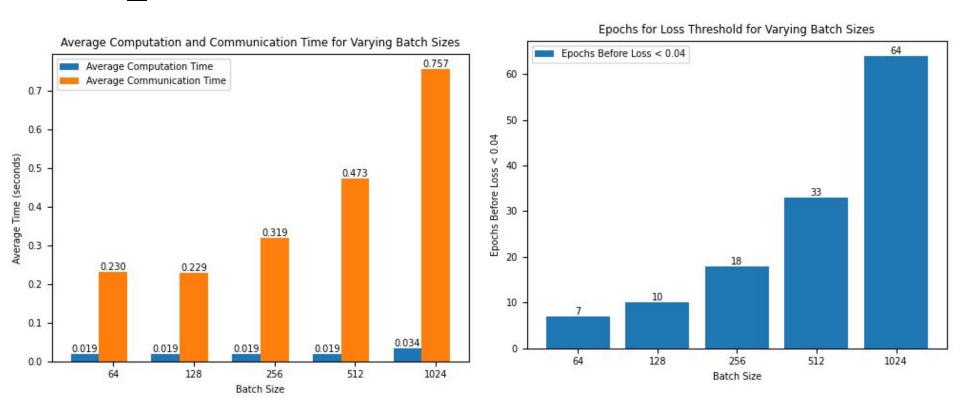
Performance evaluation metrics: computation time, communication time, data transfer size, number of epochs after which loss drops below threshold (0.04)

Test various configurations: feature extractor architecture, batch sizes, parallelism degrees (# GPUs), number of trainable parameters

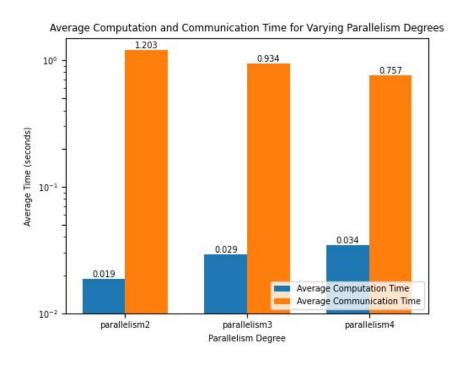
Evaluation of VanillaDataParallel module against PyTorch's DataParallel - benchmark performance for different batch sizes

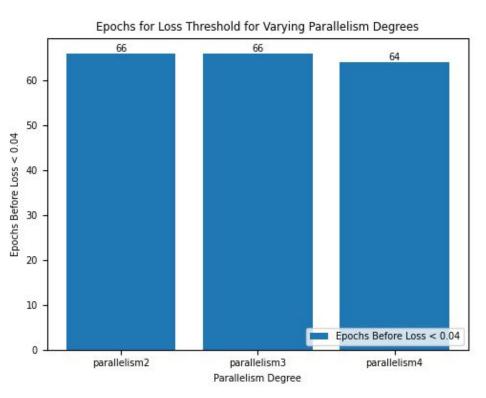
Results

Batch_Size

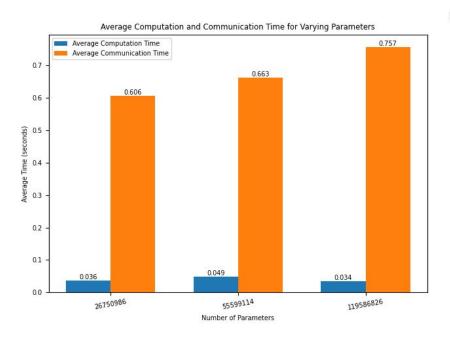


Parallelism Degree (# GPUs)

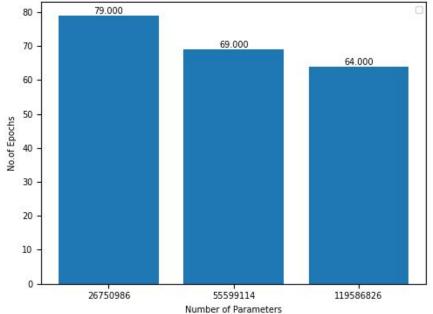




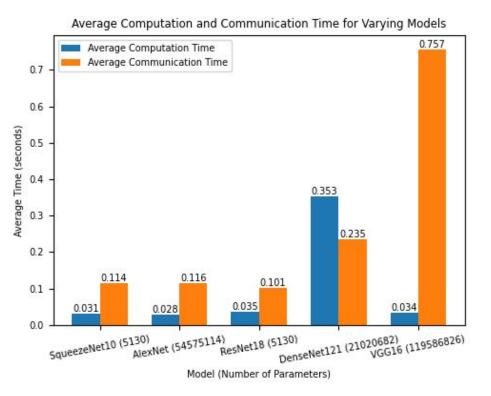
Number of trainable params

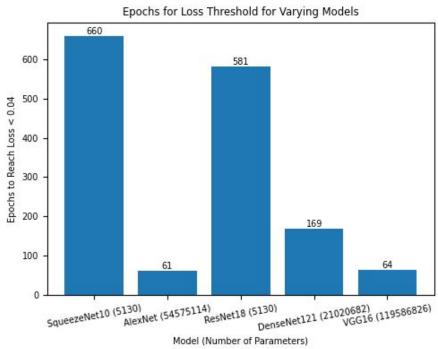


Epochs Required to Reach a Loss Below 0.04 for VGG16 (Parallelism = 4, BatchSize = 1024)

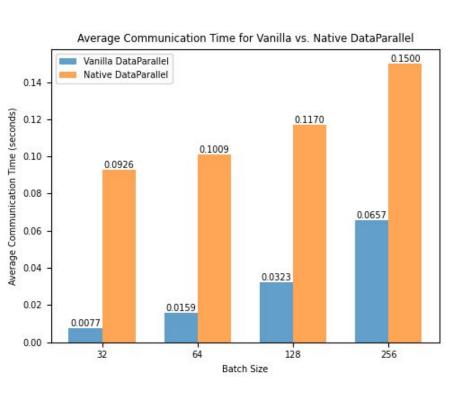


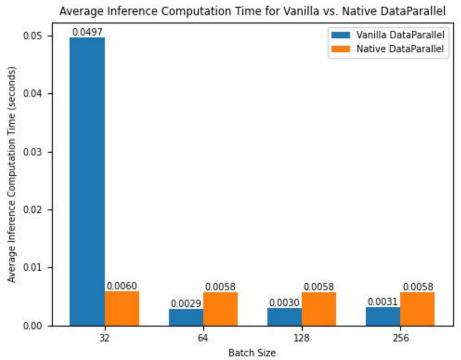
Models





Vanilla vs PyTorch Data Parallel





Thank you!