Model-Parallel Model Selection for Deep Learning Systems

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1 ABSTRACT

As deep learning becomes more expensive, both in terms of time and compute, inefficiencies in machine learning training prevent practical usage of state-of-the-art models for most users. The newest model architectures are simply too large to be fit onto a single processor. To address the issue, many ML practitioners have turned to model parallelism as a method of distributing the computational requirements across several devices. Unfortunately, the sequential nature of neural networks causes very low efficiency and device utilization in model parallel training jobs.

We propose a new form of “shard parallelism” combining task parallelism and model parallelism, and package it into a framework we name Hydra. Hydra recasts the problem of model parallelism in the multi-model context to produce a fine-grained parallel workload of independent model shards, rather than independent models. This new parallel design promises dramatic speedups relative to the traditional model parallelism paradigm.

2 INTRODUCTION

The computational costs of deep learning (DL) have grown exponentially over the years, and recent advances in neural network architectures have only continued this trend. Systems such as BERT [1] have pushed the boundaries of accuracy in applied domains. But the memory and computational power required for training such models can be staggering. As a result, single-device model training solutions have become increasingly impractical. Model parallelism has come to the fore as a potential solution.

The intuition behind model parallelism is simple: divide the model into shards, which can then be handled on separate devices — thus reducing the per-device memory footprint to manageable levels.

Motivation. This form of model parallelism permits massive models to be trained across multiple devices, but it is highly inefficient. As Figure 1 demonstrates, neural network forward inference and backpropagation are inherently sequential tasks with features and gradients being sent from layer to layer. Sharding the model does not change this reality, and as a result, devices in a model-parallel setup must wait idle in every pass until their shard receives the necessary features or gradients. Allowing for the training of massive models is insufficient — to democratize these state-of-the-art architectures, training must also be efficient and feasible for practitioners.

Data parallel systems can rely on asynchronous updates to maximize device utilization, as stochastic gradient descent is generally robust to inconsistent data ordering. But there is no analogue for traditional model parallelism to work in a similarly efficient manner.

Model Selection Integration. Let us instead consider the problem in the context of model selection, the process wherein a DL practitioner tests different model configurations to select the best one. Consider, for example, a radiologist building a computer vision system to analyze X-ray scans. They may wish to compare dozens of models or hyper-parameter configurations for the problem. Such training tasks offer an embarrassingly parallel workload.

We observe that it is possible to leverage this second level of parallelism to solve model parallelism’s problem of device underutilization. While one model shard may be untrainable due to its dependencies, an idle device can work operation on a viable shard belonging to an entirely different model. We combine model selection’s task parallelism with model parallelism to not only train independent models in parallel, but to train independent model shards in parallel for a fine-grained parallel workload. This “shard parallelism” forms the core of Hydra: our proposed framework for model-parallel training in the multiple-model context.

3 APPROACH

The core idea behind Hydra’s model-parallel model selection is recasting the training workload from running models in parallel to running shards in parallel. By combining task parallelism with model parallelism to produce a more granular workload, we extend the capacity of model-selection systems to larger-than-memory models, while also solving the problem of model-parallel device underutilization.

Desiderata. To judge our system, we define a list of desiderata.

- A desirable model-parallel model selection system must maximize device utilization. Our approach should theoretically keep all devices utilized throughout the process.
- Increased model training throughput. Shard parallelism should be capable of improving training throughput relative to either model or task parallelism alone as it offers a more granular parallel workload.
We have been able to produce baselines using traditional model parallelism. We test on a single cluster with 4 16GB Tesla V100s. Such a setup allows us to run BERT-Large fine-tuning [2] for 3 epochs on the SQuAD [3] dataset. Initial results provide a sample of the use of traditional model parallelism. We observe a 3X reduction in per-device memory usage. These initial results provide a sample of the existing model-parallelism landscape against which we can compare HYDRA’s performance.

4 EVALUATION

Workloads. We evaluate HYDRA on two model architectures to test against our criteria. We use a 1.2 million parameter feedforward neural network to check that HYDRA does not harm model accuracy. Because this model is small enough to fit onto a single device’s memory, it works well for comparisons between model-parallel results and single-device results. To simulate real-world workloads, we run BERT-Large fine-tuning [2] for 3 epochs on the SQuAD [3] dataset. We test on a single cluster with 4 16GB Tesla V100s. Such a configuration is reasonably representative of real-world hardware setups.

Goals. Our primary aims are to demonstrate that HYDRA meets the aforementioned desiderata, and show its efficiency in comparison to existing model-parallel or task-parallel frameworks.

4.1 Execution Plan.

Figure 3 describes HYDRA’s architecture. Thus far we have been able to integrate basic multiple-model training with model sharding, forming the core of our shard-parallelism implementation. The next step is the construction of the scheduler to automate the sharding and training of user-specified models. For the final model selection integration, we use Cerebro [4] as our target system. Cerebro’s use of data parallelism offers an additional level of optimization that HYDRA can leverage for efficient training.

4.2 RESULTS

We have been able to produce baselines using traditional model parallelism on our test workloads. On our heaviest test, BERT-Large, the use of traditional model parallelism provided a 3X reduction in per-device memory usage. These initial results provide a sample of the existing model-parallelism landscape against which we can compare HYDRA’s performance.

5 RELATED WORK

While model-parallel model selection is a heretofore unexplored field, there has been a great deal of work on model parallelism and model selection separately.

Model Parallelism Frameworks. DistBelief [5] and FlexFlow [6] aim to provide an efficient framework for model parallelization. We leverage this work in our own task scheduler and system design. A neural graph optimization framework that can automatically parallelize neural networks. The system utilizes some form of data or task parallelism. Google Vizier [7] optimizes neural computational graphs via operator substitution, thus improving performance and reducing costs. Vizier’s basic concept of graph reduction meshes well with model parallel’s aim of distributing costs.

Integrated Parallelism. Ghahami et al. [8] investigated the benefits of integrating model parallelism with data parallelism. Similarly, we aim to integrate model parallelism into the task-parallel world of model selection.

Optimized Model Selection. Most existing model selection systems utilize some form of data or task parallelism. Google Vizier [9] and Ray Tune [10] use task parallelism for simultaneous model training. Cerebro [4] combines task parallelism with data parallelism in a “model-hopper” approach that bears some similarities to the blended task-model parallel approach we take with HYDRA.

6 TAKEAWAYS

Model parallelism is a necessary tool to handle larger-than-memory models. Alas, the sequential nature of DL training has rendered device underutilization a major problem for model-parallel designs. Model selection, and indeed, multi-model training in general, offers a unique opportunity to utilize a more efficient version of model parallelism that does not suffer from these underutilization woes.

In this paper, we present our plans for HYDRA: our model-parallel model selection system. HYDRA’s introduction of “shard parallelism” promises not only to democratize massive models, but also to boost training efficiency in all multiple model training regimes.

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