SLO-Aware Space-Time GPU Sharing for DL Workloads

Ubaid Ullah Hafeez, Anshul Gandhi
{uhafeez,anshul}@cs.stonybrook.edu
Stony Brook University, Stony Brook, NY, USA

Abstract

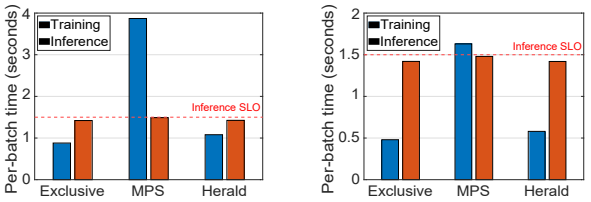
GPU-equipped servers are extensively used for Deep Learning (DL) jobs to train and serve Deep Neural Nets (DNNs) for inference [2, 4]. However, for a given DL job, it is often infeasible to fully utilize allocated GPUs even when employing state-of-the-art DL frameworks [6–8, 11, 14]. It has been observed that DNN execution can result in under-utilization of both memory and compute resources offered by present day GPUs [5, 20, 21]. This is primarily due to the disparity in the capability of available GPUs and the requirements of DL jobs—commodity GPUs are available in a few fixed configurations [6] whereas modern DL jobs exhibit immense variety in their compute and memory requirements. This mismatch between the resource requirements of DL jobs and the capabilities of available GPUs presents an opportunity to increase eficiency by sharing GPUs among multiple jobs.

Prior works [3, 10, 13, 15, 16, 19, 20] explore various techniques to maximize GPU utilization via sharing among multiple DL jobs. While effective, most of the prior works ignore SLOs of the underlying jobs. In addition, prior works [5, 21] typically explore scenarios in which GPU resources are either exclusively shared by multiple training jobs or exclusively shared by multiple inference jobs, overlooking the mixed-use case where training jobs may be colocated with inference jobs on the same set of GPU resources. This mixed-use case is particularly appealing for resource eficiency given the contrasting characteristics of training and inference jobs. Inference jobs typically are end-user-facing and are therefore latency sensitive, unlike training jobs.

Our work, Herald addresses the main challenges involved in sharing GPUs among training and inference jobs. Herald does this by implementing algorithms to enable careful spatial- and time-sharing of GPUs between training and inference jobs. Our algorithms adhere to the SLO requirements of DL jobs while increasing the eficiency of GPU resources.

To design spatial- and time-sharing techniques, Herald makes use of two key observations. First, a DL job typically does not use GPU compute resources continuously. There are periods during which the GPUs are either idle or partially utilized. Second, there are times when a DL job fully utilizes GPUs' compute resources, leaving no room for sharing of resources without sacrificing job performance.

Herald estimates requirements for all the compute operations using the underlying data flow graph of the DL jobs. This enables Herald to identify "light" operations for which GPU can be shared without any significant performance degradation. For the more compute-intensive "heavy" operations where spatial sharing is ineffective and can degrade performance, Herald implements fine-grained time sharing of GPUs to prioritize SLO-sensitive (inference) workloads.



(a) Transformer [18] inference with RNNLM [22] training job (b) Transformer [18] inference with VGG16 [17] training job

Figure 1. Experimental evaluation results for Herald.

We implement Herald by integrating directly into the TensorFlow source code to avoid modifications in user-level code. For scheduling and spatial sharing decisions, Herald employs information about the data-flow graph of each DL job, which can be obtained ofline without much overhead [7, 9, 11]. We also design a new logging tool which only logs infor-mation pertinent to our algorithms, reducing the logging overhead by an order of magnitude compared to the existing `tf.Profiler` [1] in TensorFlow. We use shared memory to keep track of the state of the GPUs and job priorities.

We experimentally evaluate Herald on a server equipped with an NVIDIA Tesla V100 16GB GPU. We share the GPU between two DL jobs: (1) a high priority inference job for a Transformer [18] model, and (2) a low priority training job that is RNNLM [12, 23] in Figure 1(a) and VGG-16 [17] in Figure 1(b), respectively. The inference job has a request rate of 10 samples/second with an SLO of 1.6 seconds to process one batch of data (red dotted line in Figure 1).

In Figure 1, "Exclusive" shows the performance achieved by the jobs when run in isolation (without sharing of GPU resources). We use MPS [3], the default GPU sharing tool by NVIDIA, as the baseline for our performance evaluation. We tried various configurations of MPS to prioritize execution of inference jobs and report numbers for the setting which maintains SLOs for the inference job. However, the colocated training job experiences on average 2.5× increase in per-batch time as compared to "Exclusive". On the other hand, the scheduling and sharing algorithms of Herald ensure that the SLO for the inference job is achieved and that the training job can maximize utilization of GPU resources during times when inference is unable to saturate GPU resources. As a result, per-batch time of training job increases by only 22%, on average, which is 10× lower than that under MPS.

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