SLO-Aware Space-Time GPU Sharing for DL Workloads

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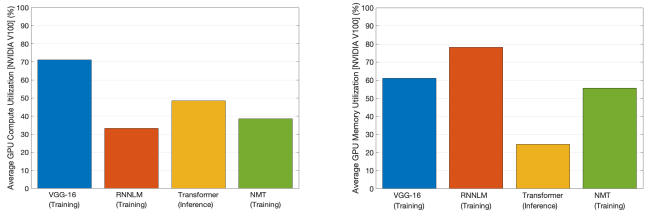
Problem

- **Underutilization of GPUs in exclusive deployment of DL jobs**
  - Commodity GPUs have fixed compute and memory capacity
  - DL jobs have varying resource requirements
  - Mismatch required and available resources
- **Sharing of resources between DL jobs improves resource utilization**
  - Uncontrolled sharing can result in unpredicted performance
  - SLOs of some jobs may get violated

Problem Statement: How to share GPUs between DL jobs, increasing GPU efficiency while maintaining SLOs?



Average GPU compute and memory utilization for different DL jobs using: NVIDIA V100 GPUs and Vanilla TensorFlow

Low GPU utilization: Waste of expensive resources

Challenges

- **Resource utilization can vary significantly during a given DL job**
  - Idle/Partially utilized GPU → Sharing opportunities
  - Fully utilized GPU → Performance degradation when shared
- **Over-sharing can result in errors: e.g. Out of Memory (OOM)**
- **Under-sharing can result in wastage of resources**

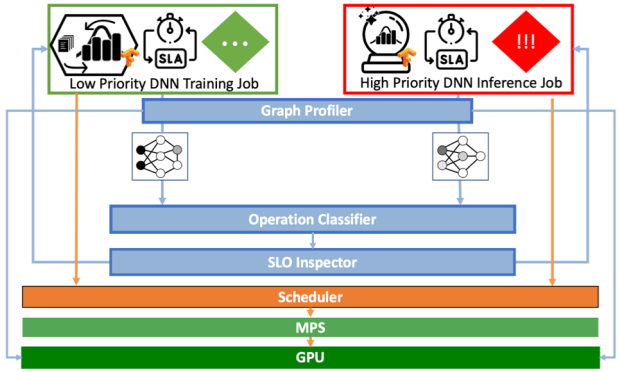
Uncontrolled sharing → Unpredictable performance → SLO violations

Solution

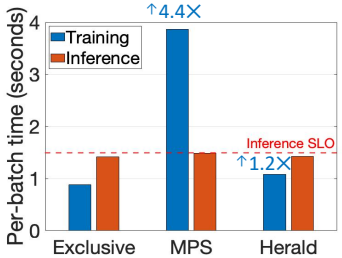
- **Estimate resource footprint for various operations in a DL job**
  - Profile control flow graphs (negligible overhead)
- **Our Solution: Herald (fine-grained space-time GPU sharing)**
  - Identify "light" compute operations for spatial sharing
  - Avoid spatial-sharing for compute-intensive ("heavy") operations
  - Time-share for "heavy" operations: Prioritize SLO-sensitive jobs

Integration directly with TensorFlow source for ease of use in production

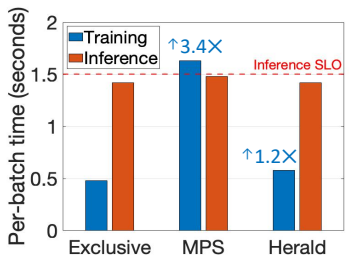
Herald Architecture



Evaluation



RNNLM Training + Transformer Inference



VGG16 Training + Transformer Inference