ACCELERATING DEEP NEURAL NETWORK TRAINING WITH MODEL-AWARE NETWORK SCHEDULING

Research Challenge
This work addresses sustained performance and scalability of distributed Deep Neural Networks (DNN) in which training is bottlenecked by parameter aggregation among participating nodes. Two high-level causes of the inefficiency are the communication patterns of parameter aggregation and the scheduling of operations that can stall available GPU resources when parameters are unavailable. In this work, our goal was to minimize network bottlenecks in distributed DNN training to reduce the iteration time and increase GPU utilization.

Methods & Codes
- Analyzed all-to-one and decentralized data aggregation techniques such as the bucket and halving–doubling (HD) algorithms
- Investigated dataflow models associated with 16 DNNs and identified common model characteristics that enable efficient network transfers
- Developed Caramel, a model-aware approach to take advantage of faster networks while achieving the highest performance

Results & Impact
- TensorFlow with Parameter Server offers high communication overlap, but with high communications cost.
- The Horovod implementation reduces communication cost with an efficient aggregation pattern but its decentralized patterns suffer from a poor overlap of communication and computation.
- Caramel can improve the iteration time by up to 3.84 times (in VGG-16) and GPU utilization by up to 2.46 times (in AlexNet-v2)

Why Blue Waters
The BlueWaters platform makes it easy to conduct large-scale exploration to find potential performance opportunities. Furthermore, the vibrant community of Blue Waters users and staff helped us to get up to speed faster by leveraging their knowledge and experience.