All You Need to Know about Scheduling Deep Learning Jobs

Student Research Competition #35

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Heterogeneity in resource abstraction



Extensible resource abstraction

- *Diversified* & *fast evolving* hardware
- Different generations of GPU
- FPGA
- ASIC (e.g. TPU, Cambricon)
- Complicated & vendor-specific topology
- Motherboard
- Inter-device link

Lead to diversified resource requests

- Resource type
- Locality sensitivity

Deep learning jobs characteristic

Inter-server locality

Intra-server locality

Job interference



Experiment setting

- Local: multi-GPU in single machine
- 2*2-GPU: 2 machines with 2 GPUs each

Result

- Spreading resource among different servers slowdown the performance
- Different workloads can tolerate different level of resource spreading



Experiment setting

 2-GPU jobs run on different GPUs in the same machine

Result

Up to 27% performance slowdown for sub-optimal GPU co-location



Experiment setting

- Solo: a 1-GPU job runs solely as baseline
- Others: two 1-GPU jobs run on different GPUs in the same machine

Result

- Up to 40% performance slowdown for job interference

Conflict scheduling policy

Multi-GPU jobs suffer

- Inter-job policy: spread out among different machines to avoid interference -> resource fragmentation
- Intra-job policy: prefer closely co-location for better performance -> require consecutive resource
- 80% deep learning jobs in Microsoft cluster are 1-GPU jobs
- Large jobs
 - Long queuing delay for strict locality requirement
 - Sub-optimal performance for inconsecutive devices

Conclusion and future work: New Scheduling System for Heterogeneous Datacenter

- Flexible and compact resource abstraction with locality and topology awareness
- Decentralized design to decouple cluster-wide policy from individual job scheduling decision
- Static workload pattern analysis and dynamic job migration