Analysis of Large-Scale Multi-Tenant GPU Clusters for DNN Training Workloads

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Deep Learning at a Large Enterprise

Speech, Image, Ads, NLP, Web Search ...

DL training jobs require large GPU clusters



Philly: Cluster manager for DL workloads on large shared GPU clusters

		Motivated by observations in Philly	
Recent Cluster Managers	Optimus [EuroSys 18]	Gandiva [OSDI 18]	Tiresias [NSDI 19]
Objective	Average JCT	Consolidation	Average JCT
Scheduler	SRTF	Time-sharing	Gittins Index

Contributions

1. First characterization study of large-scale GPU clusters for DNN training

75-day period from Oct. 2017 to Dec. 2017 Total of **96,260** jobs over 14 virtual clusters

2. Uncover inefficiencies in cluster utilization

3. Present lessons for better cluster manager designs

Low Locality in Distributed Training



High intra-server locality

- High communication efficiency
- Long waiting time

Low intra-server locality

- Low waiting time
- Contention in the use of network
- Risk of intra-server interference (across jobs)



Failures across Stack Reduce Cluster Utilization

Infrastructure

Resource Scheduler



HDFS

AI Engine

O PyTorch

TensorFlow



User

class Net(nn.Module): def __init__(self): super(Net, self).__init__() self.conv1 = nn.Conv2d(1, 10, kernel_size=5) self.conv2 = nn.Conv2d(10, 20, kernel_size=5) self.conv2_drop = nn.Dropout2d() self.fc1 = nn.Linear(320, 50) self.fc2 = nn.Linear(50, 10)

Frequency User errors in code Temporal Infrastructure failures

Improve failure handling (e.g., pre-run jobs)

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11:05 AM, Session - Scheduling Things (Track II), on July 12 at USENIX ATC 2019