

Lab 10: Multi-GPU Scaling

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Introduction: In this lab I will be using multiple GPUs to train my self-driving car model to explore scaling with multiple GPUs. I am training all of the models in the lab with a batch size of 32 run for 10 epochs.

Learning Outcomes:

- Multi-GPU training understanding
- Usage of Horovod
- Scaling projections

Running on 2 GPUs

Shown: Screenshot of GPU utilization

```
Every 0.5s: nvidia-smi
```

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NVIDIA-SMI 440.33.01 Driver Version: 440.33.01 CUDA Version: 10.2									
GPU	Name	Persistence-M	Bus-Id	Disp.A	Volatile Uncorr. ECC				
Fan	Temp	Perf	Pwr:Usage/Cap	Memory-Usage	GPU-Util	Compute	M.		
0	Tesla T4	On	00000000:60:00.0	Off	0				
N/A	32C	P8	9W / 70W	0MiB / 15109MiB	0%	Default			
1	Tesla T4	On	00000000:61:00.0	Off	0				
N/A	49C	P0	28W / 70W	1166MiB / 15109MiB	10%	Default			
2	Tesla T4	On	00000000:DA:00.0	Off	0				
N/A	49C	P0	29W / 70W	1166MiB / 15109MiB	11%	Default			
3	Tesla T4	On	00000000:DB:00.0	Off	0				
N/A	30C	P8	12W / 70W	0MiB / 15109MiB	0%	Default			

Processes:					GPU Memory
GPU	PID	Type	Process name		Usage
1	13326	C	python		1155MiB
2	13327	C	python		1155MiB

Shown: Loss output from running

```
[1,0]<stdout>:Epoch 10/10
[1,1]<stdout>: - 46s - loss: 0.0199 - accuracy: 0.1812 - val_loss: 0.0158 - val_accuracy: 0.1801
[1,1]<stdout>:Epoch 10/10
[1,0]<stdout>: - 44s - loss: 0.0198 - accuracy: 0.1849 - val_loss: 0.0226 - val_accuracy: 0.1718
[1,0]<stdout>:dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
[1,0]<stdout>:Loss
[1,0]<stdout>:[1.115979814917836, 0.1755272284226064, 0.05216957034777529, 0.02796803237316597, 0.02221885413572883, 0.02113728017434524, 0.020168618132539142, 0.019983836262916554, 0.019960274771842736, 0.0190236300327654]
[1,0]<stdout>:Validation Loss
[1,0]<stdout>:[0.34776949882507324, 0.0886074906271362, 0.036292508244514465, 0.032170750200748444, 0.0156203368678689, 0.020992930978536606, 0.01461011916399002, 0.013355077244341373, 0.018431508913636208, 0.02250809839997729]

[1,1]<stdout>: - 44s - loss: 0.0109 - accuracy: 0.1781 - val_loss: 0.0122 - val_accuracy: 0.1887
[1,1]<stdout>:dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
[1,1]<stdout>:Loss
[1,1]<stdout>:[1.214956333305662, 0.1750662189655381, 0.053153253585988325, 0.02706873706156654, 0.02189424331145768, 0.020922002601177766, 0.01997965421922357, 0.020038748536218098, 0.019870760745757464, 0.018888524499447272]
[1,1]<stdout>:Validation Loss
[1,1]<stdout>:[0.33120885491371155, 0.08478444814682007, 0.0327080637216568, 0.04341091960668564, 0.013513795100152493, 0.019833967089653015, 0.02330063469707966, 0.015720708295702934, 0.01578824008352375, 0.012182097888123989]
```

It took about 8 minutes to train the model. The loss for both GPUs is shown above. It is about .019 for both.

The rest of the jobs ran on their own, so I do not have GPU utilization screenshots for them.

Running on 4 interactive (T4) GPUs

It took about 7.5 minutes to train the model. The loss across the 4 GPUs was about .046.

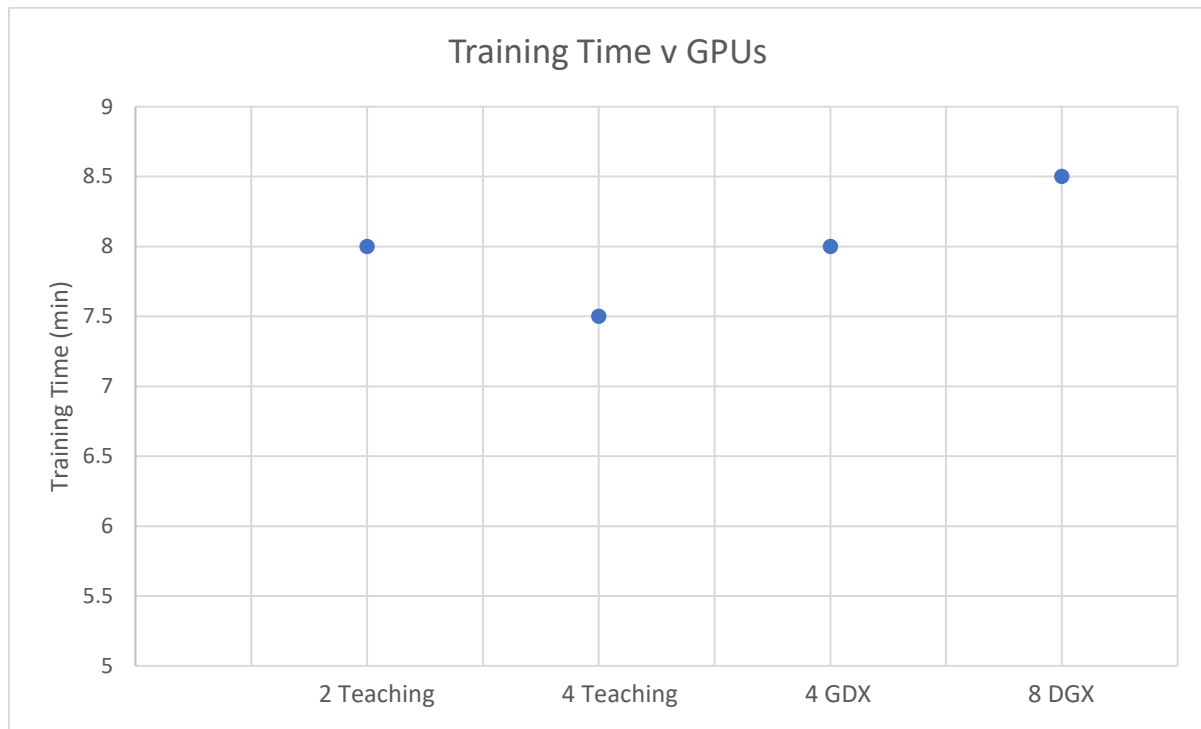
Running on 4 DGX GPUs

It took about 8 minutes to train the model. The loss across the 4 DGX GPUs was about .047.

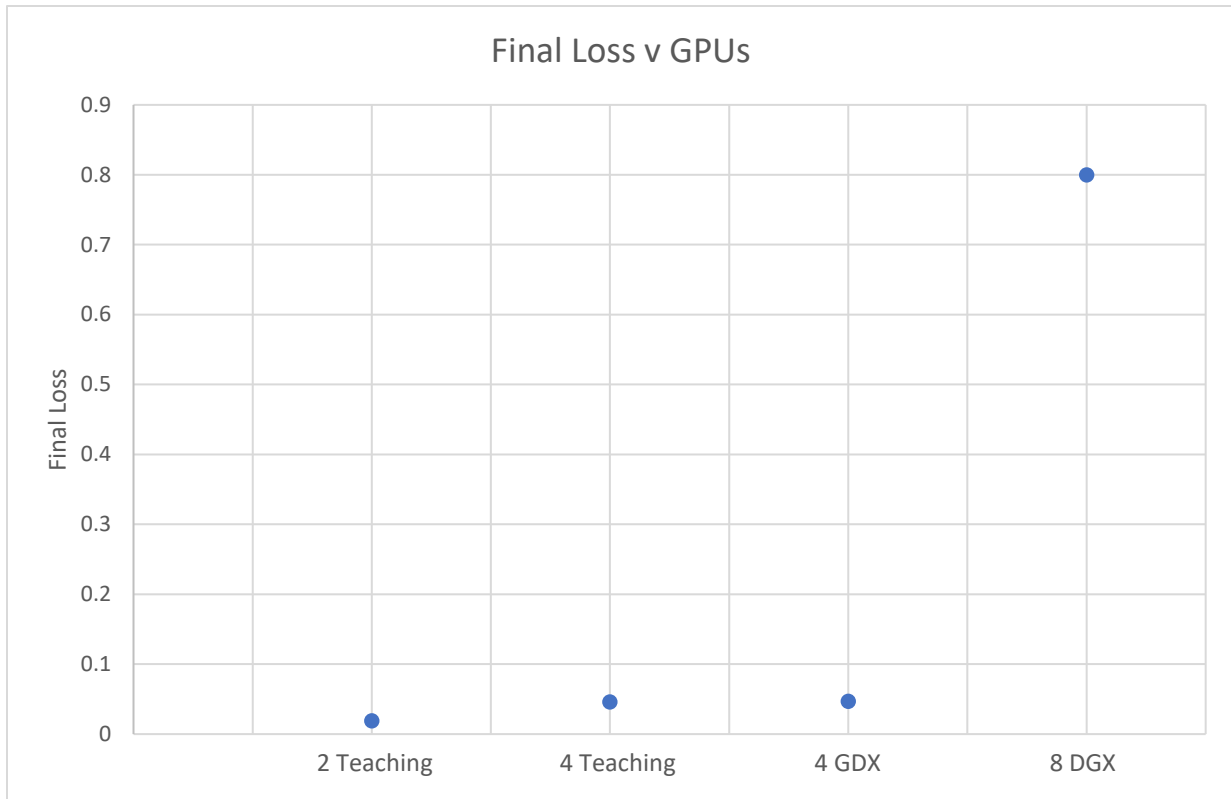
Running on 8 DGX GPUs

It took about 8.5 minutes to train the model. The loss across the 8 DGX GPUs was about .8.

Shown: Plot of the training times for the models



Shown: Plot of the losses for the models



Conclusion: Our dataset is not large enough to utilize multiple GPUs effectively. It is very much so overkill for a dataset of this size. And since using more GPUs slows convergence, really the only thing I found from running these jobs is that the more GPUs that were used, the larger the loss was. There were also minimal differences in running time between the models. This is because the averaging of the model weights between the GPUS after each epoch, offsets the time gains from splitting up the dataset between the different GPUs. Again however, our dataset is too small to effectively use multiple GPUs. if our dataset was larger, we would most likely see time improvements.