

# Lab 3

---

Saad Amin

## Task 1

```
(base) [samin68@atl1-1-03-015-2-0 CS4803-EMI]$ nvidia-smi topo -m
  GPU0  GPU1  GPU2  GPU3  GPU4  GPU5  GPU6  GPU7  NIC0  CPU Affinity  NUMA Affinity  GPU NUMA ID
GPU0    X    NV18   NV18   NV18   NV18   NV18   NV18   SYS  0,2,4,6,8,10      0        N/A
GPU1   NV18     X    NV18   NV18   NV18   NV18   NV18   SYS  0,2,4,6,8,10      0        N/A
GPU2   NV18   NV18     X    NV18   NV18   NV18   NV18   SYS  0,2,4,6,8,10      0        N/A
GPU3   NV18   NV18   NV18     X    NV18   NV18   NV18   SYS  0,2,4,6,8,10      0        N/A
GPU4   NV18   NV18   NV18   NV18     X    NV18   NV18   NODE 1,3,5,7,9,11      1        N/A
GPU5   NV18   NV18   NV18   NV18   NV18     X    NV18   PIX  1,3,5,7,9,11      1        N/A
GPU6   NV18   NV18   NV18   NV18   NV18   NV18     X    NODE 1,3,5,7,9,11      1        N/A
GPU7   NV18   NV18   NV18   NV18   NV18   NV18   NV18   NODE 1,3,5,7,9,11      1        N/A
NIC0   SYS    SYS    SYS    SYS    NODE   PIX    NODE   NODE      X

Legend:
X = Self
SYS = Connection traversing PCIe as well as the SMP interconnect between NUMA nodes (e.g., QPI/UPI)
NODE = Connection traversing PCIe as well as the interconnect between PCIe Host Bridges within a NUMA node
PHB = Connection traversing PCIe as well as a PCIe Host Bridge (typically the CPU)
PXB = Connection traversing multiple PCIe bridges (without traversing the PCIe Host Bridge)
PIX = Connection traversing at most a single PCIe bridge
NV# = Connection traversing a bonded set of # NVLinks

NIC Legend:
NIC0: mlx5_0
```

It appears PACE gave me 8 GPUs even though I asked only for 4.

What this means is that:

- GPUs are connected using NVLink, which means they should have (relatively) fast memory access between each other.
- We have 2 NUMA nodes, and GPUs0-3 are wired via PCIe to node 0 and GPUs4-7 are wired to node 1

## Task 2

```
Running time for broadcast1: 1.3572168946266174 (s)
Running time for broadcast2: 0.3723844289779663 (s)
Running time for broadcast3: 0.07500745356082916 (s)
```

Modifications made to code:

- Timing data is the average of 16 runs to get more accurate data

Design choices:

- Host tensor `a` is allocated using `pin_memory=True` instead.
- All transfers use `non_blocking=True`
- All transfers happen on their own streams
- Transfers from `x -> a ->` other GPUs have been pipelined

- We transfer contiguous blocks from `x` to `a`, wait for it to finish, and then start the transfer of that block to other GPUs while we transfer the next block to `a`

## Task 3

### Deliverable 1

```
BertModel(  
    (embeddings): BertEmbeddings(  
        (word_embeddings): Embedding(30522, 768, padding_idx=0)  
        (position_embeddings): Embedding(512, 768)  
        (token_type_embeddings): Embedding(2, 768)  
        (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)  
        (dropout): Dropout(p=0.1, inplace=False)  
    )  
    (encoder): BertEncoder(  
        (layer): ModuleList(  
            (0-11): 12 x BertLayer(  
                (attention): BertAttention(  
                    (self): BertSdpSelfAttention(  
                        (query): Linear(in_features=768, out_features=768, bias=True)  
                        (key): Linear(in_features=768, out_features=768, bias=True)  
                        (value): Linear(in_features=768, out_features=768, bias=True)  
                        (dropout): Dropout(p=0.1, inplace=False)  
                    )  
                (output): BertSelfOutput(  
                    (dense): Linear(in_features=768, out_features=768, bias=True)  
                    (LayerNorm): LayerNorm((768,), eps=1e-12,  
                        elementwise_affine=True)  
                    (dropout): Dropout(p=0.1, inplace=False)  
                )  
            )  
        )  
        (intermediate): BertIntermediate(  
            (dense): Linear(in_features=768, out_features=3072, bias=True)  
            (intermediate_act_fn): GELUActivation()  
        )  
        (output): BertOutput(  
            (dense): Linear(in_features=3072, out_features=768, bias=True)  
            (LayerNorm): LayerNorm((768,), eps=1e-12,  
                elementwise_affine=True)  
            (dropout): Dropout(p=0.1, inplace=False)  
        )  
    )  
    (pooler): BertPooler(  
        (dense): Linear(in_features=768, out_features=768, bias=True)  
        (activation): Tanh()  
    )  
)  
BertConfig {  
    "_attn_implementation_autoset": true,
```

```
"attention_probs_dropout_prob": 0.1,  
"classifier_dropout": null,  
"hidden_act": "gelu",  
"hidden_dropout_prob": 0.1,  
"hidden_size": 768,  
"initializer_range": 0.02,  
"intermediate_size": 3072,  
"layer_norm_eps": 1e-12,  
"max_position_embeddings": 512,  
"model_type": "bert",  
"num_attention_heads": 12,  
"num_hidden_layers": 12,  
"pad_token_id": 0,  
"position_embedding_type": "absolute",  
"return_dict": false,  
"transformers_version": "4.49.0",  
"type_vocab_size": 2,  
"use_cache": true,  
"vocab_size": 30522  
}  
  
Total params ≈ 109M  
=====
```

#### DELIVERABLE 1: Baseline

```
=====
```

Configuration	# GPUs	Throughput (samples/s)	Peak Memory per Rank (GB)
4_GPUs	4	9.233 ± 0.598	6.300 ± 2.109

```
=====
```

## Deliverable 2

#### DELIVERABLE 2: GPU Configuration Comparison

```
=====
```

Configuration	# GPUs	Throughput (samples/s)	Peak Memory per Rank (GB)
3_GPUs	3	12.366 ± 0.006	8.702 ± 3.075
4_GPUs	4	9.233 ± 0.598	6.300 ± 2.109

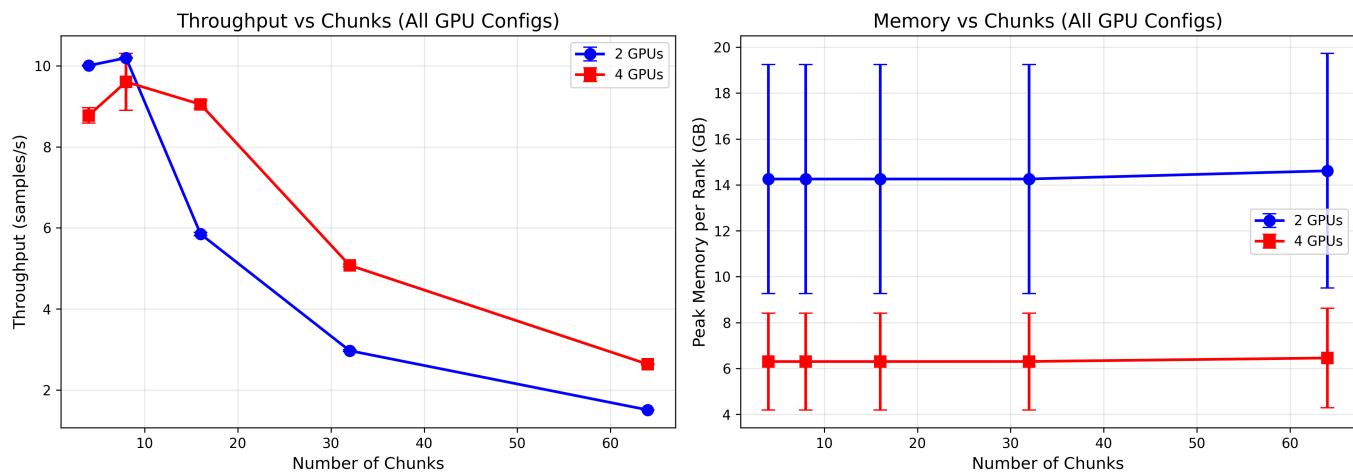
```
=====
```

The data shows that although 4 GPUs has lower memory usage (because model weights are distributed over more GPUs) it actually has worse performance. I think it is due to pipeline overhead:

- Global batch size is 64
- Number of chunks is 4
- That means we only have one time step when the pipeline is full saturated.

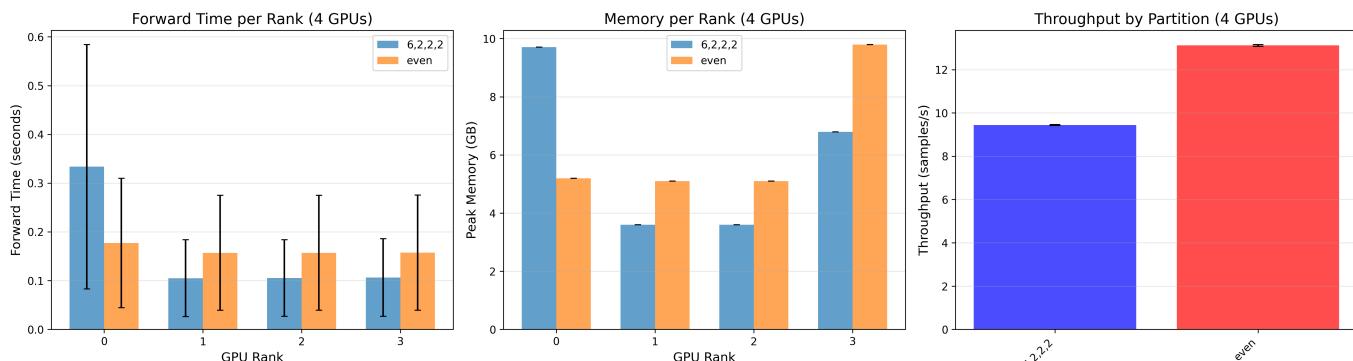
Please see the next deliverable for evidence.

### Deliverable 3



- The data covers a global batch size of 64 and chunk counts of 4, 8, 16, 32, and 64
- We would expect 4 GPUs to have more throughput than 2 GPUs, and the data confirms this for larger number of chunks
- However, as mentioned in the previous section, having fewer chunks can result in irregular results if the pipeline is not saturated or if overhead has a large impact.
  - This is best shown in 4 and 8 chunks, where 2 GPUs actually outperforms 4 GPUs.
  - This is also why for both configurations, increasing the chunk count increases throughput (the initial latency from the pipeline not being saturated matters less and less).
- Also important to mention: although in larger chunk counts 4 GPUs does outperform 2 GPUs, performance decreases for both
  - This is likely due to pipeline overhead
  - Smaller chunks means that each pipeline stage takes less time
  - As a result, actions that on average have a fixed cost (like transferring data from one stage to another) start to dominate

### Deliverable 4



- A slow stage in the pipeline end up leaving faster stages that come afterwards waiting on inputs to arrive.
- This leads to underutilization and worse throughput.

## Task 4

Seeds used for both: 1, 2, 3

DDP results for global batch size = 64:

```
Aggregate: {
    "throughput_mean": 111.16570593892513,
    "throughput_std": 0.12228515652003448,
    "time_per_step_mean": 0.5757178155581156,
    "time_per_step_std": 0.0006328498033082033,
    "mem_peak_per_rank_mean_bytes": [
        38312673450.666664,
        38312673450.666664,
        38312673450.666664,
        38312673450.666664
    ],
    "mem_peak_per_rank_std_bytes": [
        247151.73339648842,
        247151.73339648842,
        247151.73339648842,
        247151.73339648842
    ]
}
```

FSDP results for global batch size = 64:

```
Aggregate: {
    "throughput_mean": 102.94562546599454,
    "throughput_std": 11.785863109064842,
    "time_per_step_mean": 0.6306810474395752,
    "time_per_step_std": 0.07855699593537264,
    "mem_peak_per_rank_mean_bytes": [
        37545608704.0,
        37545600512.0,
        37545600512.0,
        37546165760.0
    ],
    "mem_peak_per_rank_std_bytes": [
        178843529.87828666,
        178836841.1382957,
        178836841.1382957,
        178811758.94974294
    ]
}
```

At first, this data appeared unexpected (I was thinking we'd see a much bigger memory usage difference between FSDP and DDP). I reran teh tests with global batch size = 16

DDP results for global batch size = 16:

```
Aggregate: {
    "throughput_mean": 103.07518594170095,
    "throughput_std": 0.31990644738058055,
    "time_per_step_mean": 0.15522798935572307,
    "time_per_step_std": 0.00048097297912959736,
    "mem_peak_per_rank_mean_bytes": [
        10945447594.666666,
        10945360213.333334,
        10945447594.666666,
        10944776362.666666
    ],
    "mem_peak_per_rank_std_bytes": [
        975609.2788479526,
        1006087.1943197678,
        975609.2788479526,
        265663.4852105615
    ]
}
```

FSDP results for global batch size = 16:

```
Aggregate: {
    "throughput_mean": 102.32684753229941,
    "throughput_std": 0.2678426755018219,
    "time_per_step_mean": 0.15636277198791504,
    "time_per_step_std": 0.0004089306595197579,
    "mem_peak_per_rank_mean_bytes": [
        10176927232.0,
        10176919040.0,
        10176919040.0,
        10176919040.0
    ],
    "mem_peak_per_rank_std_bytes": [
        178843529.87828666,
        178836841.1382957,
        178836841.1382957,
        178836841.1382957
    ]
}
```

Anaylsis:

- In both cases, FSDP uses about 700 MB of memory less.
- This is most likely the savings from full sharding the model.

- However in both DDP and FSDP we are using gigabytes of memory.
  - This is most likely due to the activation tensors kept during the forwards pass and saved for the backwards pass.
  - Using one-fourth the batch size led to nearly one-fourth the memory.
  - In both DDP and FSDP, each GPU stores the non-sharded batch, which explains why we don't see a one-fourth memory saving.
- According to the data, FSDP has slightly lower throughput
  - This is most likely due to the additional communication involved
- I would recommend DDP for this model as it is only 109 MB parameters and DDP is less complex and faster (no inter-GPU communication)
  - Furthermore, the main source of memory usage is activation tensors
  - Would recommend gradient accumulation