# The Alan Turing Institute

**MPI Part II: Practical MPI** 

Baskerville Training 2025 29-30 January 2025 – David Llewellyn-Jones



# **Message Passing Interface**

- 1. MPI: Message Passing Interface
- 2. Provides a standard for distributed memory parallelisation
- 3. Gavin already explained the theory and practice
- 4. Now let's apply it to some machine learning

#### **Motivation**

GPUs are great for accelerated training and inference, but processing is bound by:

- 1. Available memory
- 2. Speed of computation

How to make AI better?

- 1. Improved algorithms
- 2. Larger models
- 3. More training data

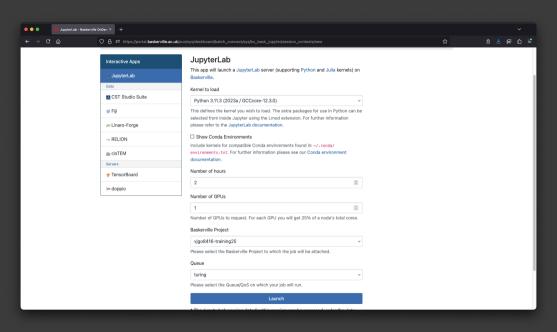
The last two require more compute

# Scaling up

- 1. Strong motivation for scaling across GPUs
- 2. Single device: 4 or 8 GPUs maximum
- 3. Eventually want to scale across nodes
- 4. Get this right... the sky's the limit

#### **Preparation**

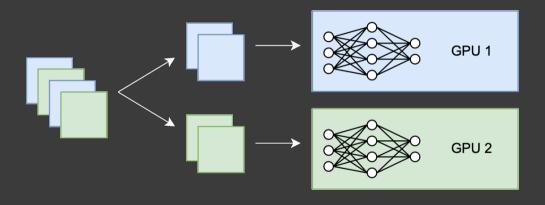
- 1. Open https://docs.baskerville.ac.uk/
- 2. Select Baserville Portal
- 3. Login if necessary
- 4. Select JupyterLab from the Interactive Apps list
- 5. Configure a 2 hour session with 1 GPU on the project vjgo8416-training25 and the turing queue
- 6. Launch

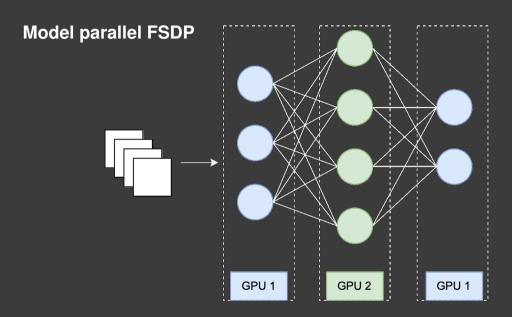


#### Types of model parallelism

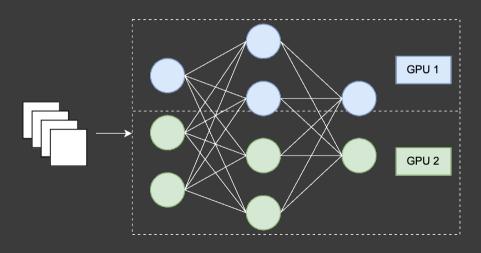
- 1. DDP: Distributed Data Parallel
- 2. FSDP: Fully Sharded Data Parallel
- 3. DeepSpeed ZeRO: Zero Redundancy Optimiser

# Data parallel





# **Model parallel DeepSpeed**

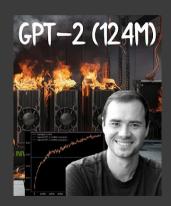


## **DeepSpeed**

- 1. DeepSpeed Stage 1: optimiser state partitioning
- 2. DeepSpeed Stage 2: gradient partitioning
- 3. DeepSpeed Stage 3: model parameter partitioning

#### The plan

- 1. No more theory
- 2. Simplified GPT2 nano code for one GPU
- 3. Andrej Karpathy: https://youtu.be/18pRSuU81PU
- 4. Extend to support Distributed Data Parallel
- 5. Extend using PyTorch Lightning



#### The intention

- 1. Not to care too much about the model implementation
- 2. Understand changes needed to add MPI functionality
- 3. For this, we'll rely heavily on diffs
- 4. Using JupyterLab and SLURM

# Your most important tools



$$(\star,/)$$

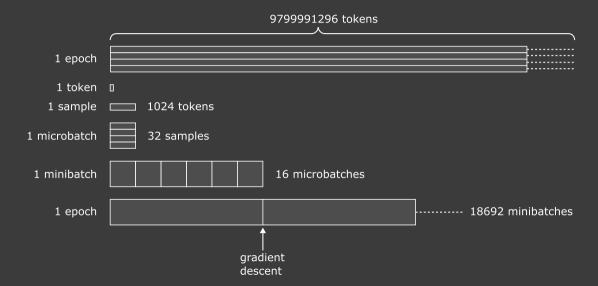
#### **Terminology**

- 1. Vocabulary: 50257 embeddings
- 2. Dataset: 9799991296 FineWeb tokens, our training data
- 3. Sample: a sequence of 1024 tokens from the dataset
- 4. Microbatch: 32 samples
- 5. Minibatch (also called a batch): 16 microbatches, gradient accumulation performed afterwards
- 6. Step: the process for training on one minibatch
- 7. Epoch: one training sweep of the entire dataset, 18692 steps

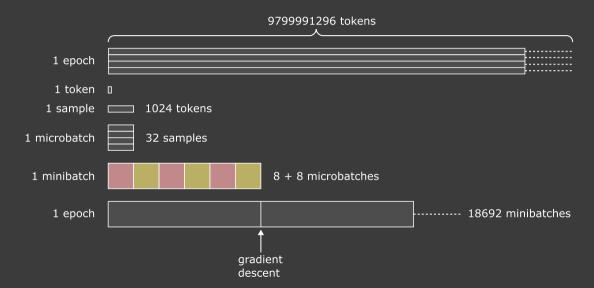
## **Distributed training**

- 1. Training on *n* nodes, each with *m* GPUs
- 2. Total  $n \times m$  GPUs
- 3. World size:  $w = m \times n$
- 4. Global rank  $r_G$  is a unique index  $r_G \in \{0, \dots, w-1\}$
- 5. Local rank  $r_L$  is unique per device  $r_L \in \{0, \dots, m-1\}$
- 6. No node index, but we do have *hostnames*, *e.g.* bask-pg0309u05a, bask-pg0309u06a
- 7. We may also have multiple CPU workers for each node

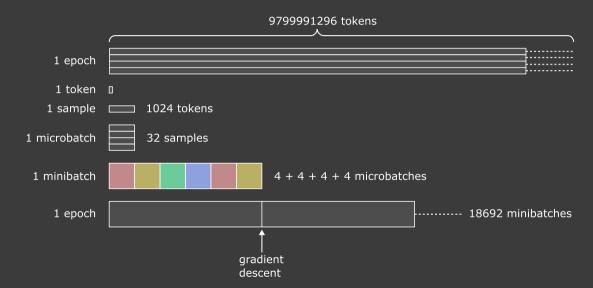
## **Training with 1 GPU**



## **Training with 2 GPUs**



## **Training with 4 GPUs**



#### Time to look at the code

- 1. Open your JupyterLab page
- 2. Connect to Jupyter
- 3. Clone the repository
- 4. Open the train\_gpt2.py file

```
JupyterLab (955888)

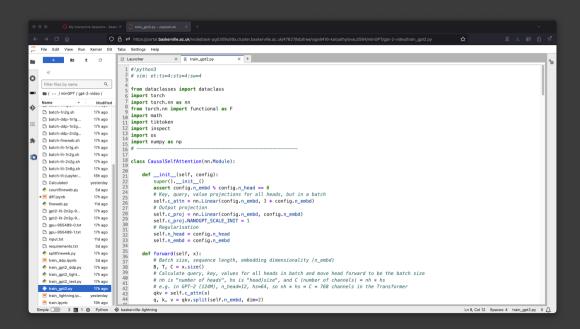
Host: >_bask-pg0309u06a.cluster.baskerville.ac.uk

Created at: 2025-01-27 18:14:28 GMT

Time Remaining: 1 hour and 57 minutes

Session ID: da379c88-afe6-47e7-b684-1718c3
```

```
# Move into your user directory
cd /bask/projects/v/vjgo8416-training25/$USER/
# Clone the repository
git clone \
https://github.com/alan-turing-institute/practical-mpi.git
```



#### **GPT2** nano classes and functions

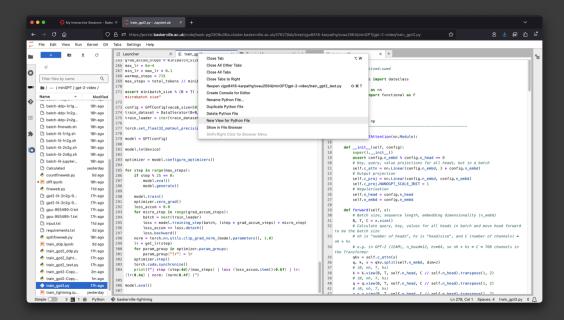
- 1. CausalSelfAttention, MLP, Block: model components
- 2. GPTConfig: model configuration
- 3. GPT: the model
- 4. generate(): inference
- 5. configure\_optimizers(): training configuration
- 6. training\_step(): one training step
- 7. load\_tokens(): load a single FineWeb shard
- 8. get\_shards(): find the FineWeb shards on disk
- 9. DataIterator: our dataset and data loader
- 10. get\_lr(): calculate the learning rate

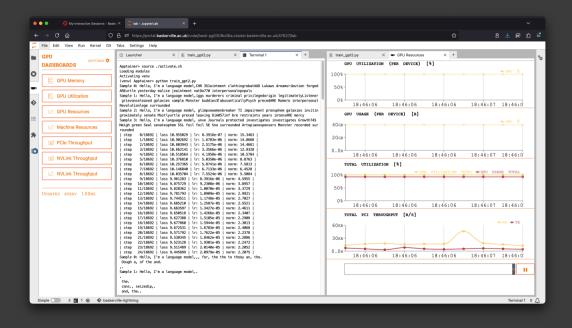
#### **GPT2** nano execution

- 1. Set hyperparameters
- 2. Create model
- 3. Perform training loop

#### **Training time!**

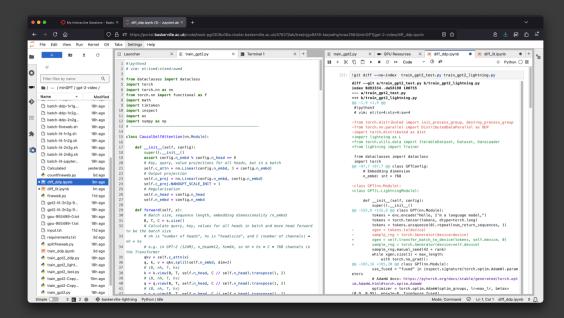
- 1. Right click on the train\_gpt2.py tab
- 2. Select New View for Python File
- 3. Open a GPU Resources pane from the GPU Dashboard
- 4. Drag the pane to the tab space on the right
- 5. Open a terminal in the left tab space
- 6. source activate.sh
- 7. python train\_gpt2.py





#### Upgrade to DDP

- 1. Open train\_gpt2.py in the left hand tab space
- 2. Open diff\_ddp.ipynb in the right hand tab space
- 3. Execute the first cell of diff\_ddp.ipynb



#### **Understanding unified diffs**

- 1. 00 prefix indicates line numbers
  00 -before.len +after.len 00
- 2. + prefix in green indicates lines added
- prefix in red indicates lines removed
- 4. Replay the cell to update the diff after making changes

```
@@ -145.7 +149.7 @@ class GPT(nn.Module):
            loss = F.cross entropy(logits.view
s.view(-1)
         return logits, loss
     def generate(self):
    def generate(self, rank):
         num return sequences = 4
         max length = 32
         tokens = enc.encode("Hello, I'm a lang
@@ -153,7 +157,7 @@ class GPT(nn.Module):
         tokens = tokens.unsqueeze(0).repeat(nu
         xgen = tokens.to(device)
         sample rng = torch.Generator(device=de
         sample rng.manual seed(42)
         sample rng.manual seed(42 + rank)
         while xgen.size(1) < max length:
            with torch.no grad():
                with torch.autocast(device typ
@@ -207,22 +211,24 @@ def get_shards(split):
 class DataIterator:
    def __init__(self, B, T):
     def init (self, B. T. num processes,
```

#### Manually apply the diff – part I

- 1. Imports
- 2. One process per GPU
- 3. We generate on every process
- 4. One DataIterator per GPU
- 5. We must shard the data appropriately
- 6. Initialise the process group
- 7. Harvest world size, rank and local rank from the environment
- 8. Where do these come from?

#### Manually apply the diff – part II

- 9. Fix the gradient accumulation steps
- 10. Batch sizes must align
- 11. Create a DDP model
- 12. Use the right model variable at the right time
- 13. Trigger backward gradient sync
- 14. Perform all reduce
- 15. Destroy the process group

#### **Observations**

- 1. Most of this is boilerplate
- 2. The hardest part is sharding the data correctly
- 3. Because this is data parallel
- 4. MPI is also hard

...but it's done for us by torch.distributed and DDP

#### Training time!

- 1. See batch-ddp-1n1g.sh for single GPU
- 2. See batch-ddp-2n3g.sh for dual-node dual GPU

```
1 # Single GPU
python -m torch.distributed.launch \
--standalone --nproc_per_node=1 \
  train_gpt2.py
7 python -m torch.distributed.launch \
     --nproc_per_node=${SLURM_GPUS_PER_NODE} \
     --nnodes=${SLURM NNODES} \
     --master-port=${MASTER_PORT} --master-addr=${MASTER_ADDR} \
     train_gpt2.py
```

#### **Upgrade to Lightning**

- 1. Lightning is conceptually different
- 2. Code is organised in LightningModule: init, train step, validation step, test step, optimisers
- 3. Code outside LightningModule is automated by Trainer
- 4. Remove code moving data to the GPU

## **Upgrade to Lightning**

- 1. Open train\_gpt2.py in the left hand tab space
- 2. Open diff\_lit.ipynb in the right hand tab space
- 3. Execute the first cell of diff\_lit.ipynb

## Manually apply the diff - part I

- 1. Imports
- 2. Switch from Module to LightningModule
- 3. Fix the generate() function
- 4. Use the built-in OneCycleLR learning rate scheduler
- 5. Remove CUDA code from training\_step()
- 6. Generate examples periodically
- 7. Initialise DataIterator using a worker\_init\_fn()
- 8. Remove our custom learning rate scheduler code

#### Manually apply the diff – part II

- 9. Remove the process group code
- 10. Lose our DDP configuration
- 11. Simplify the random seeding
- 12. Fix the steps: minibatches are now implicit
- 13. Use a DataLoader to sequence data loading
- 14. Remove our training loop
- 15. Add the Trainer code

#### **Observations**

- 1. The training code is greatly simplified
- 2. Lightning is SLURM-aware
- 3. So MPI is even easier
- 4. We can now switch to other strategies (in theory)

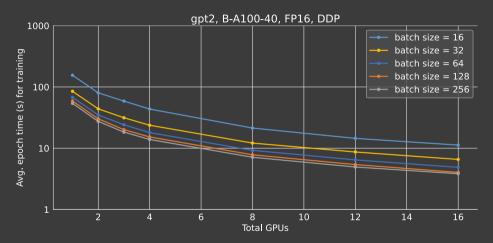
#### Training time!

- 1. See batch-lit-2n8g.sh for dual-node eight GPU
- 2. See batch-lit-jupyter.sh to queue from Jupyter

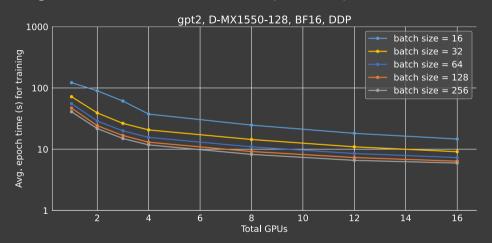
```
# From inside a SLURM batch script
srun python train_gpt2.py

4 # Queue execution from inside JupyterLab
sbatch batch-lit-jupyter.sh
```

# Scaling across nodes on A100 (40 GiB) GPUs



# Scaling across nodes on MX1550 (128 GiB) GPUs



#### Wrapping up

- 1. Converting code for distributed training is doable
- 2. Review and try out the batch scripts
- 3. More examples in the hpc-landscaptes repository

https://github.com/alan-turing-institute/hpc-landscape