Parallel and Distributed Deep Learning

Shaohao Chen

ORCD at MIT

Outline

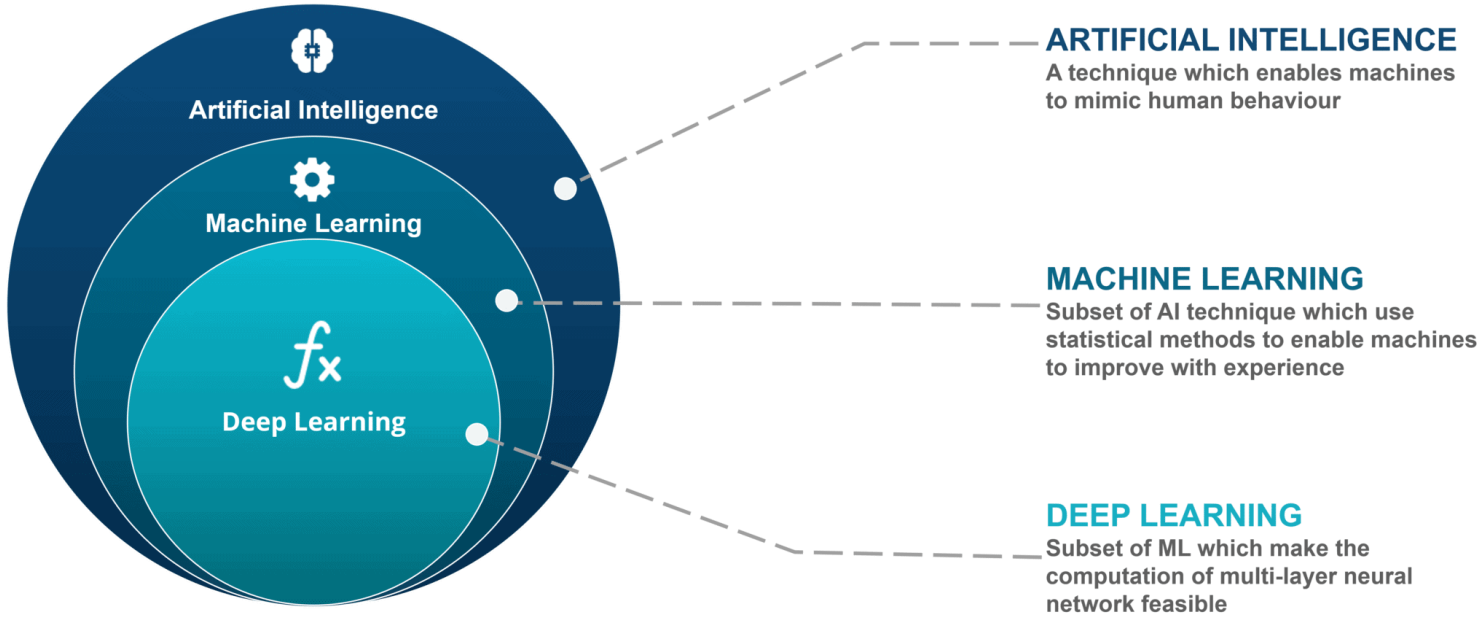
- Basics of deep learning
- Deep learning on a single GPU
- Distributed deep learning on multiple GPUs
  - Data parallelism
    -- Zero Redundancy Optimizer
  - Model parallelism
    -- Pipeline parallelism
    -- Tensor parallelism

Machine learning and deep learning

- Artificial intelligence
- Machine learning

  Statistical algorithms

  Learn from data
- Supervised learning: classification, regression
- Unsupervised learning: clustering



- Deep learning: deep neural network
- Cornerstones of DL: learning algorithms, big data, and high-performance computing.
- Computer vision: Convolutional Neural Network (CNN)
- Natural Language Processing (NLP): Large Language Model (LLM), transformer architecture

Access to ORCD clusters

- Get started

https://orcd-docs.mit.edu/getting-started/

- Log in Engaging

```
ssh <user>@eofe10.mit.edu
```

- Get an interactive session and set up environment

```
srun -t 120 -n 4 --gres=gpu:4 -p mit_normal_gpu --pty bash
module load miniforge/23.11.0-0
```

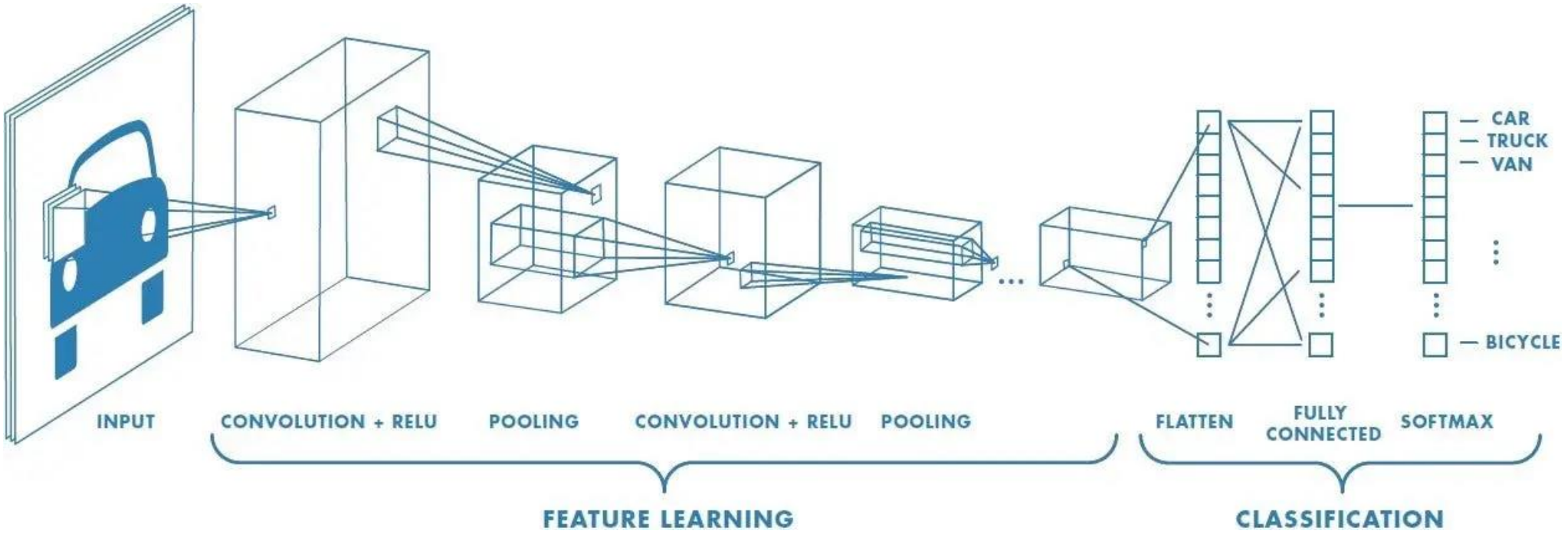
Install PyTorch and Deepspeed

- Install PyTorch, Deepspeed, and dependencies.

```
conda create -n ds

source activate ds

conda install pytorch==2.4.1 torchvision==0.19.1 torchaudio==2.4.1 pytorch-cuda=12.4 -c pytorch -c nvidia

pip install deepspeed

pip install datasets  tensorboard transformers

pip install fire loguru sh matplotlib
```

Convolutional Neural Network (CNN)

- CNN for CIFAR10 in PyTorch
- Load training and test datasets: CIFAR10, normalize, using torchvision
- Define a CNN: convolutional layers, nonlinear ReLU activation, pooling, fully connected layers



https://saturncloud.io/blog/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way/

Train a neural network

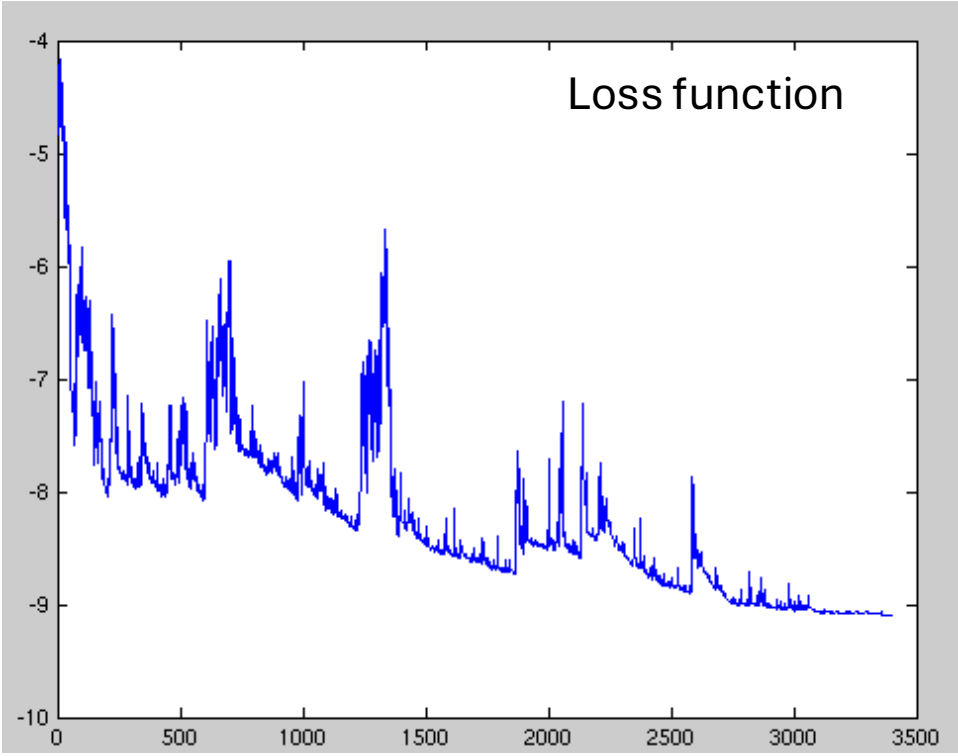
- Training: adjust the model to minimize a loss function.
- Loss function: cross entropy

$$-\frac{1}{N}\sum_{n=1}^{N}\left[y_n \log \hat{y}_n + (1-y_n)\log(1-\hat{y}_n)\right]$$

- Optimizer: Stochastic Gradient Descent (SGD)
- Training data: batch (a randomly-picked subset of data), epoch (loop over all data).
- Train the network on the training data:

  -- forward + backward + optimize

  -- Backpropagation: computes the gradient of the loss function with respect to the weights of the network, one layer at a time, iterating backward from the last layer to avoid redundant calculations of intermediate terms in the chain rule of derivatives.
- Test the network on the test data



https://en.wikipedia.org/wiki/Stochastic_gradient_descent

Run training on a GPU with Pytorch

- Define a CUDA device

```
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
```

- Send the model to the GPU

```
net.to(device)
```

- Send a batch of data to the GPU at every step

```
inputs, labels = data[0].to(device), data[1].to(device)
```

- Run the program

```
source activate ds

python cnn_cifar10_gpu.py
```

What happens under the hood?

What about parallel?

- Training a neural network involves large-scale linear algebra computations.
- When PyTorch is built with CUDA support, it dynamically links to cuDNN and cuBLAS libraries.
- Linear algebra computations are optimized and parallelized in cuBLAS and thus can be accelerated on GPUs.

What about other platforms or libraries?

- Tensorflow: Python or C API, a steeper learning curve, less friendly to researchers, easier with Keras integration, better performance optimizations, better for developers.
- cuDNN: C API, a bridge between deep-learning platforms and GPUs.

Distributed Parallelism in Deep Learning

- Distributed on multiple GPUs.

- Data Parallelism

Each GPU gets a different batch of data

Process more data at the same time period.

Universal to different models. The model must fit within GPU memory.

- Model Parallelism

A model is too big to be stored on one GPU.

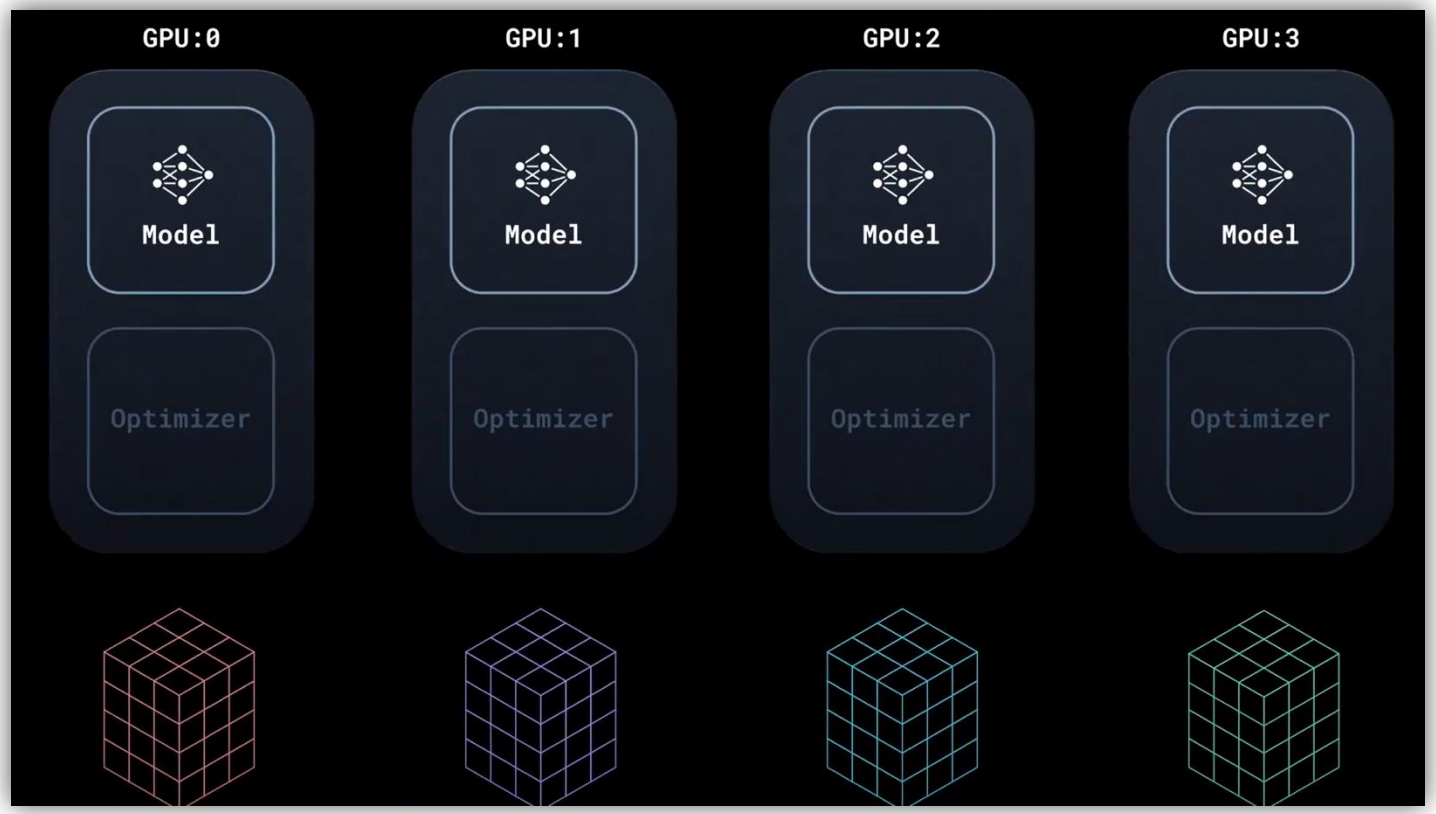
Split the model on multiple GPUs.

Tricky to design and implement.

Data Parallelism

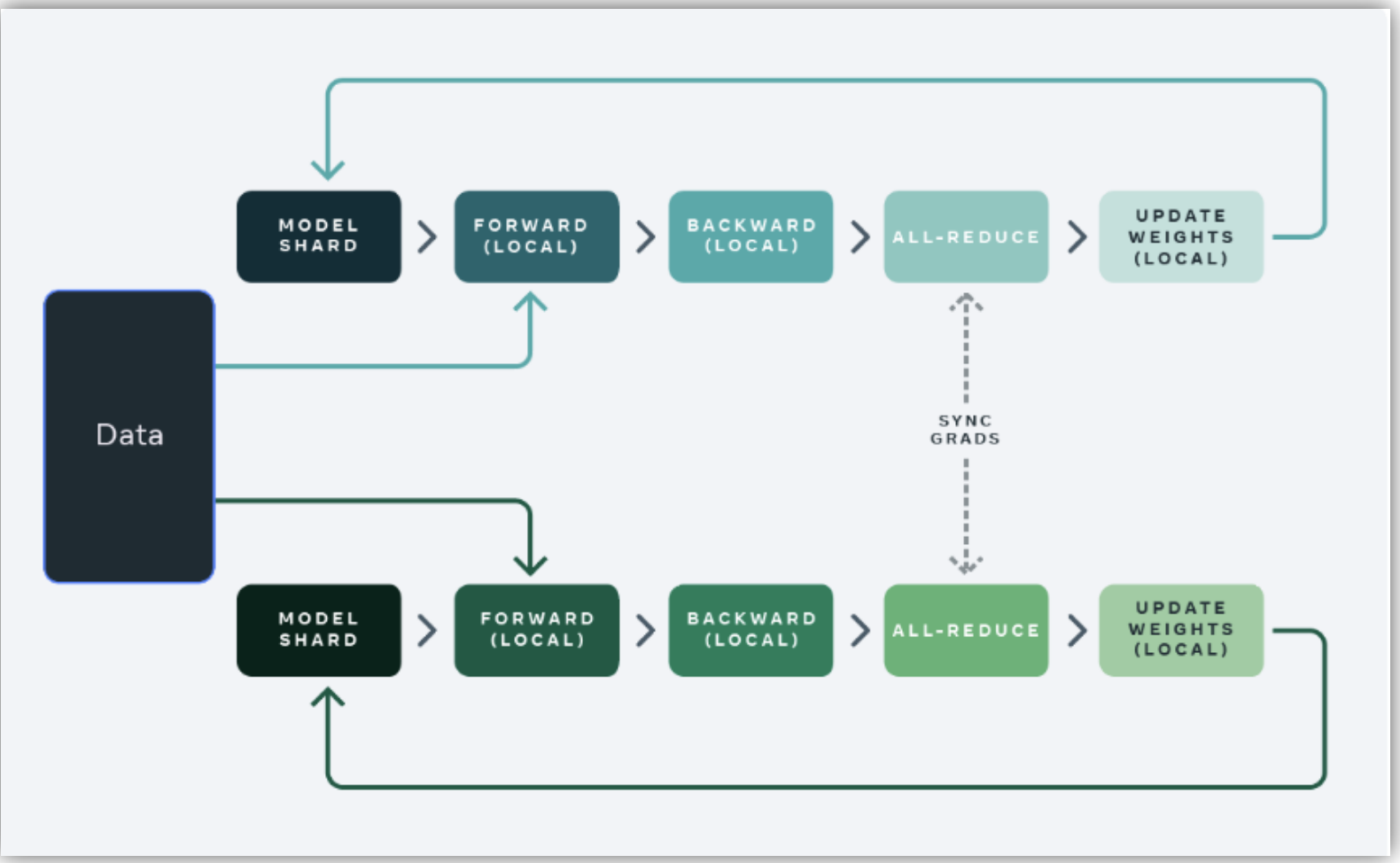
- Data Parallelism (DP) - the same model is replicated multiple times, and each being fed a slice of the data. The processing is done in parallel and all models are synchronized at the end of each training step.

- Each GPU has a copy of the model
- Optimizer states and random seeds are the same
- Each GPU gets a different batch of data
- Concurrently processing 4x the data of a single GPU
- Data sampling is handled by a Distributed Sampler



Data Parallel training at large scale may affect model quality

Communication and Synchronization



- Each model is different because it is trained on different batches of data.
- Gradients from each GPU are synchronized before the update step, ensuring model replicas stay consistent across iterations.
- Synchronization is done with a bucketed Ring-AllReduce algorithm. Each GPU gets the averaged gradient.
- The algorithm overlaps gradient computation with communication so GPU is utilized efficiently.

Scaling with data parallel introduces communication overhead when syncing gradients

Distributed Data Parallel with Pytorch

- Linear neural network $y = xA^T + b$

```
model = torch.nn.Linear(20, 1)
```

- Set up GPU ID

```
torch.cuda.set_device(rank)
```

- Apply DDP

```
self.model = DistributedDataParallel(model, device_ids=[gpu_id])
```

- Spawn training processes on multiple GPUs

```
world_size = torch.cuda.device_count()
mp.spawn(main, args=(world_size, args.save_every, args.total_epochs, args.batch_size), nprocs=world_size)
```

- Communication is executed by DDP under the hood.

https://pytorch.org/tutorials/beginner/ddp_series_multigpu.html , https://pytorch.org/docs/stable/notes/ddp.html

Why big models?

- Transformer architecture

-- Remove the sequential processing dependency of RNNs, such as Long Short-term Memory (LSTM).

-- Enable language models to be trained with parallelism

- A dramatic increase in model sizes after the birth of Transformer.

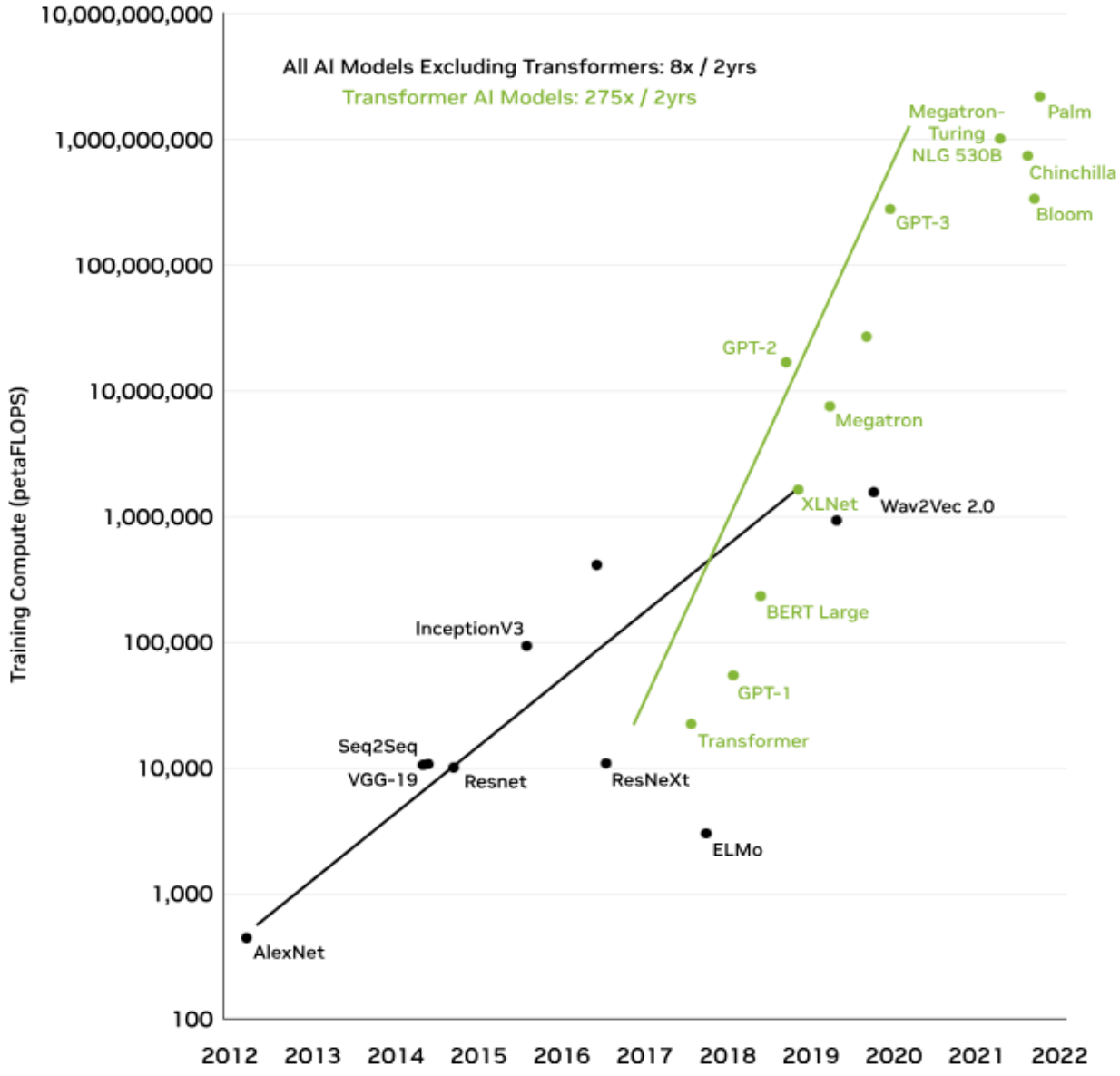


Figure 3. Compute required for training transformer models.

Memory requirements by big models

- Adam optimizer: 24 bytes per parameter for FP32

States	Bytes per parameter
Model parameters (weights)	4 bytes per parameter
Adam optimizer (2 states)	8 bytes per parameter
Gradients	4 bytes per parameter
Activations and temp memory (variable size)	8 bytes per parameter (high-end estimate)
TOTAL	**= 4 + 20 bytes per parameter**

- 1 billion parameters:

  24 GB for FP32, 12 GB for FP16, 16 GB for mixed-precision

https://www.oreilly.com/library/view/generative-ai-on/9781098159214/ch04.html#:~:text=Quantization%20from%20fp32%20to%20fp16,shown%20in%20Figure%204%2D6

Scale of compute with big models

Model size	Attention heads	Hidden size	Number of layers	Number of parameters (billion)	Model-parallel size	Number of GPUs	Microbatch size	Batch size	Achieved teraFlOP/s per GPU	Percentage of theoretical peak FLOP/s	Achieved aggregate petaFLOP/s
1.7B	24	2304	24	1.7	1	32	16	512	137	44%	4.4
3.6B	32	3072	30	3.6	2	64	16	512	138	44%	8.8
7.5B	32	4096	36	7.5	4	128	16	512	142	46%	18.2
18B	48	6144	40	18.4	8	256	8	1024	135	43%	34.6
39B	64	8192	48	39.1	16	512	4	1536	138	44%	70.8
76B	80	10240	60	76.1	32	1024	2	1792	140	45%	143.8
145B	96	12288	80	145.6	64	1536	2	2304	148	47%	227.1
310B	128	16384	96	310.1	128	1920	1	2160	155	50%	297.4
530B	128	20480	105	529.6	280	2520	1	2520	163	52%	410.2
1T	160	25600	128	1008.0	512	3072	1	3072	163	52%	502.0

Weak scaling throughput for GPT models ranging from 1 billion to 1 trillion parameters.

~6 weeks on 1 x DGX A100
~2 weeks on 4 x DGX A100

~65 weeks on 1 x DGX A100
~16 weeks on 4 x DGX A100

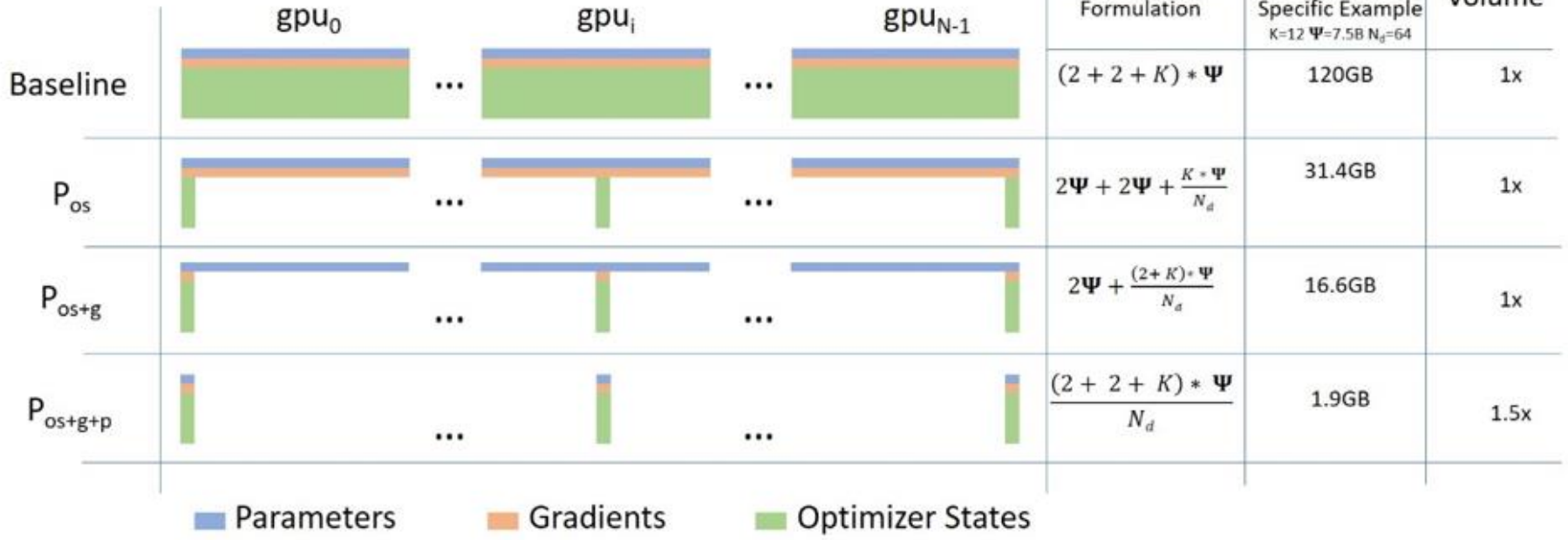
~5 years on 1 x DGX A100
~1 year on 4 x DGX A100

~69 years on 1 x DGX A100
~17 year on 4 x DGX A100

Narayanan, Deepak, et al. "**Efficient large-scale language model training on GPU clusters using megatron-LM**." *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*. 2021.

Zero Redundancy Optimizer (1)

- Operate within the data parallel framework, optimizing memory usage by distributing model states across data parallel workers.
- Partition tensors somewhat similar to tensor parallel, except the whole tensor gets reconstructed in time for a forward or backward computation. Therefore, the model doesn't need to be modified.
- Dynamic communication schedule: share the necessary state across distributed GPUs during training.



	Memory Consumption		Comm Volume
	Formulation	Specific Example K=12 Ψ=7.5B N_d=64	
Baseline	$(2+2+K)*\Psi$	120GB	1x
P_{os}	$2\Psi+2\Psi+\frac{K*\Psi}{N_d}$	31.4GB	1x
P_{os+g}	$2\Psi+\frac{(2+K)*\Psi}{N_d}$	16.6GB	1x
P_{os+g+p}	$\frac{(2+2+K)*\Psi}{N_d}$	1.9GB	1.5x

Zero Redundancy Optimizer (2)

- Further save GPU memory

  -- Mixed precision: weights and gradients stored in FP16, optimizer states stored in FP32

  -- Offloading to CPU

  -- Checkpointing activations

- Quick and easy: only need to change a few configurations in the configuration JSON.

  Does not require a code redesign or model refactoring.

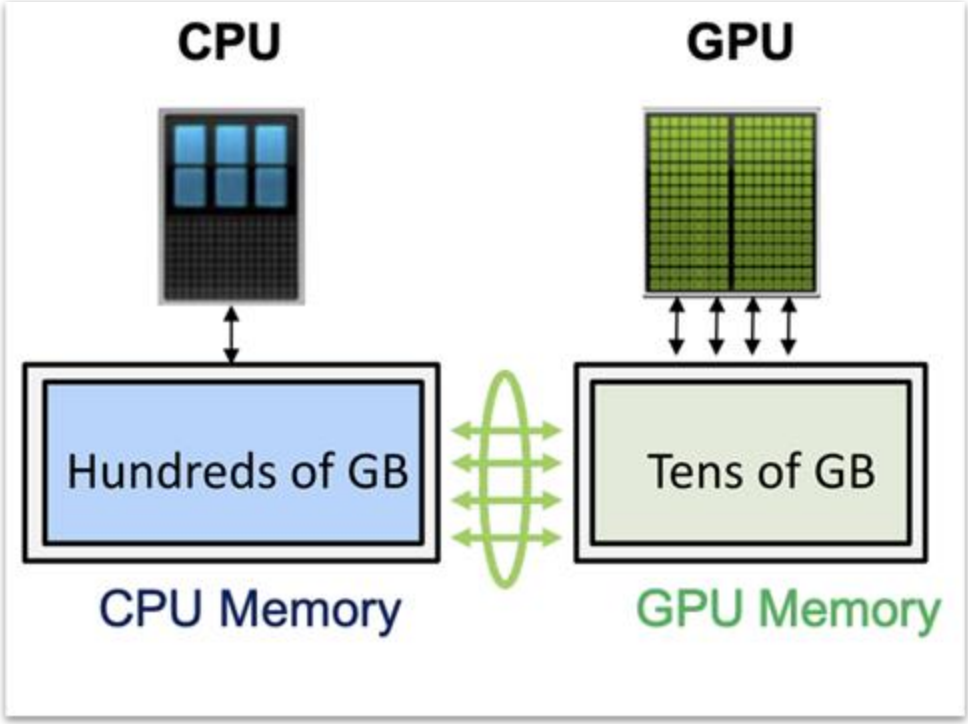
- Employing ZeRO may or may not be faster depending on the situation and configuration used.

- ZeRO is implemented in Deepspeed.

- Fully Sharded Data Parallel (FSDP): another name for the ZeRO concept, implemented in Pytorch.

https://www.deepspeed.ai/tutorials/zero/ https://pytorch.org/blog/introducing-pytorch-fully-sharded-data-parallel-api/

Offloading to CPU



Offload CPU tensors not used in computation form GPU to CPU

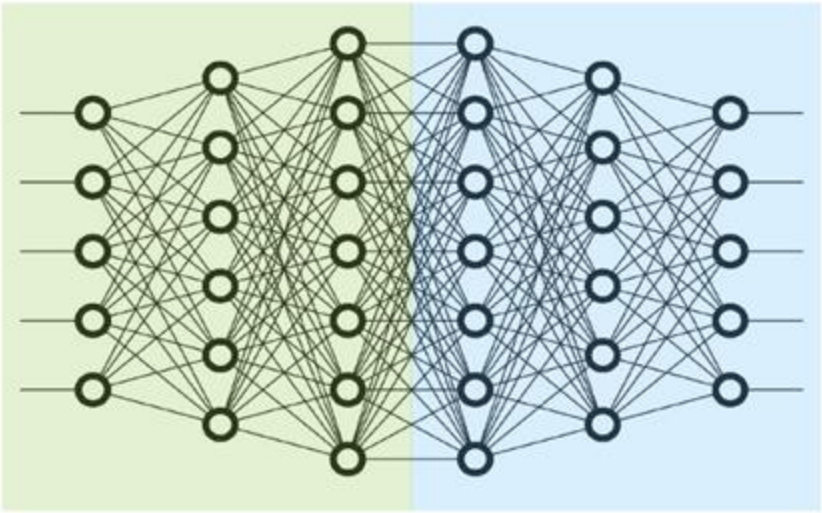
- Training times will be slower due to slow data movement.
- Overlap communication with computation.

Model Parallelism

- Pipeline (Inter-Layer) Parallelism

Split contiguous sets of layers across multiple GPUs

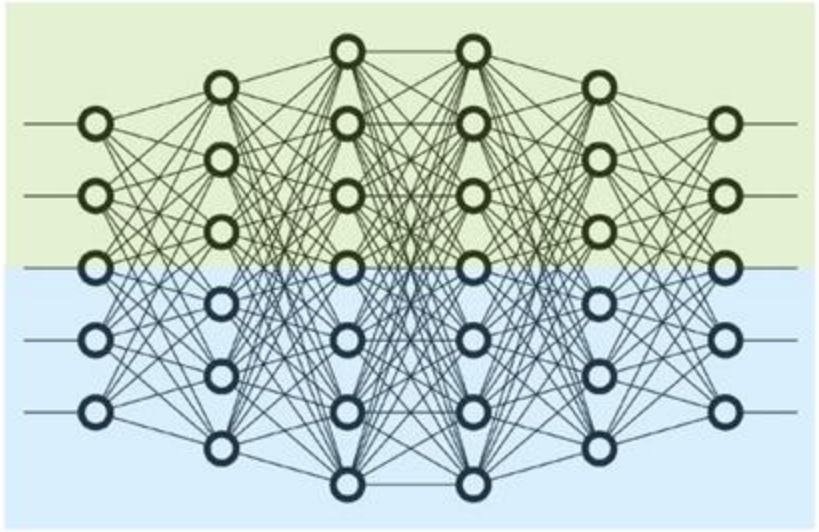
Layers 0,1,2 and layers 3,4,5 are on different GPUs



- Tensor (Intra-Layer) Parallelism

Split individual layers across multiple GPUs

GPUs compute different parts of Layers 0,1,2,3,4,5



Model Parallelism

❑ Pipeline Parallel (PP)

- The model is split vertically (layer-level) across multiple GPUs, so that only one or several layers of the model are placed on a single GPU.
- Each GPU processes in parallel different stages of the pipeline and works on a small chunk of the batch.

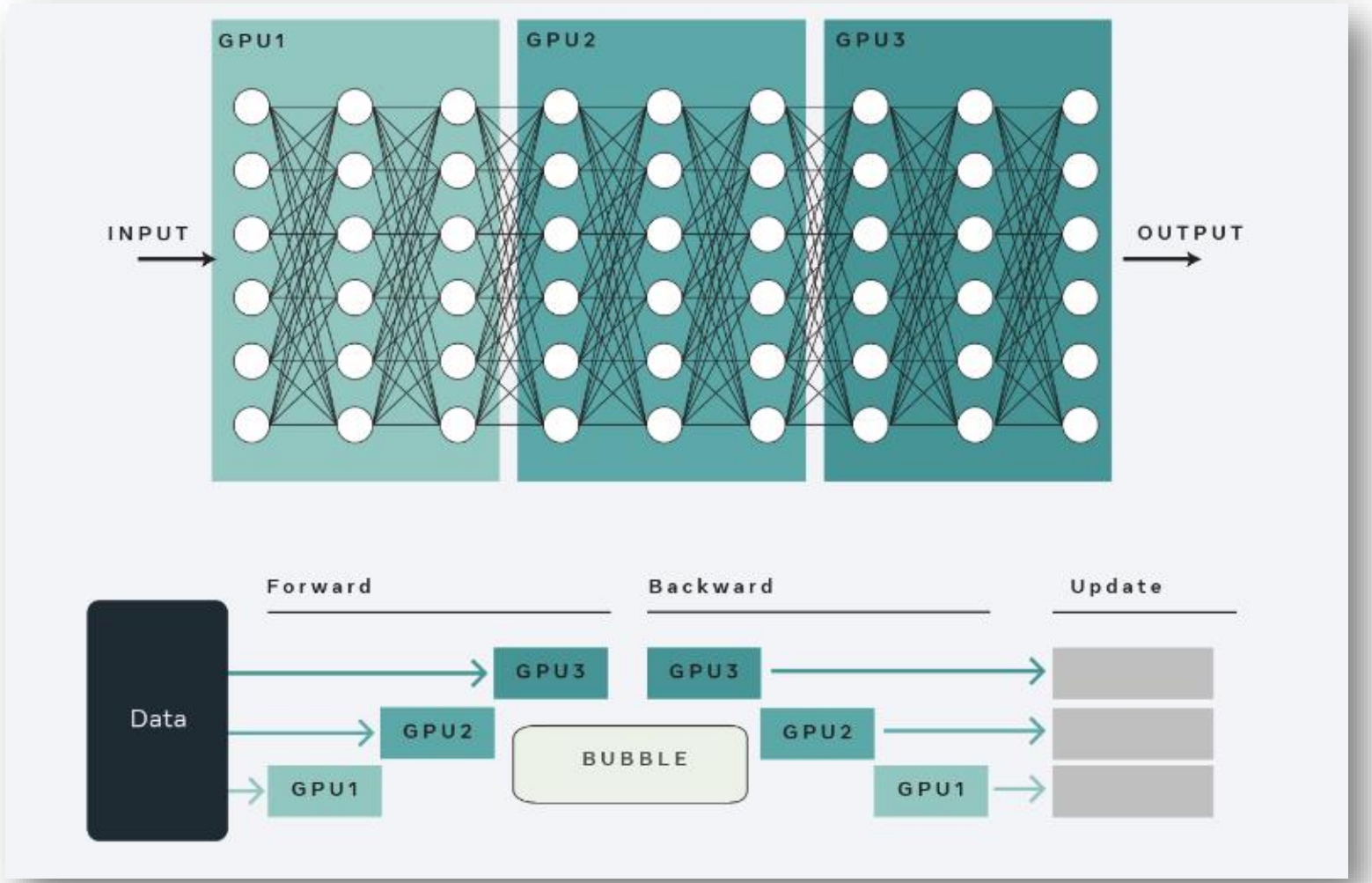
❑ Tensor Parallel (TP)

- Each tensor is split into multiple shards, and each shard of the tensor resides on its designated GPU.
- Each shard gets processed in parallel on different GPUs and the results are synced at the end of the step.
- This is what one may call horizontal parallelism.

Ref: https://huggingface.co/docs/transformers/v4.13.0/en/parallelism

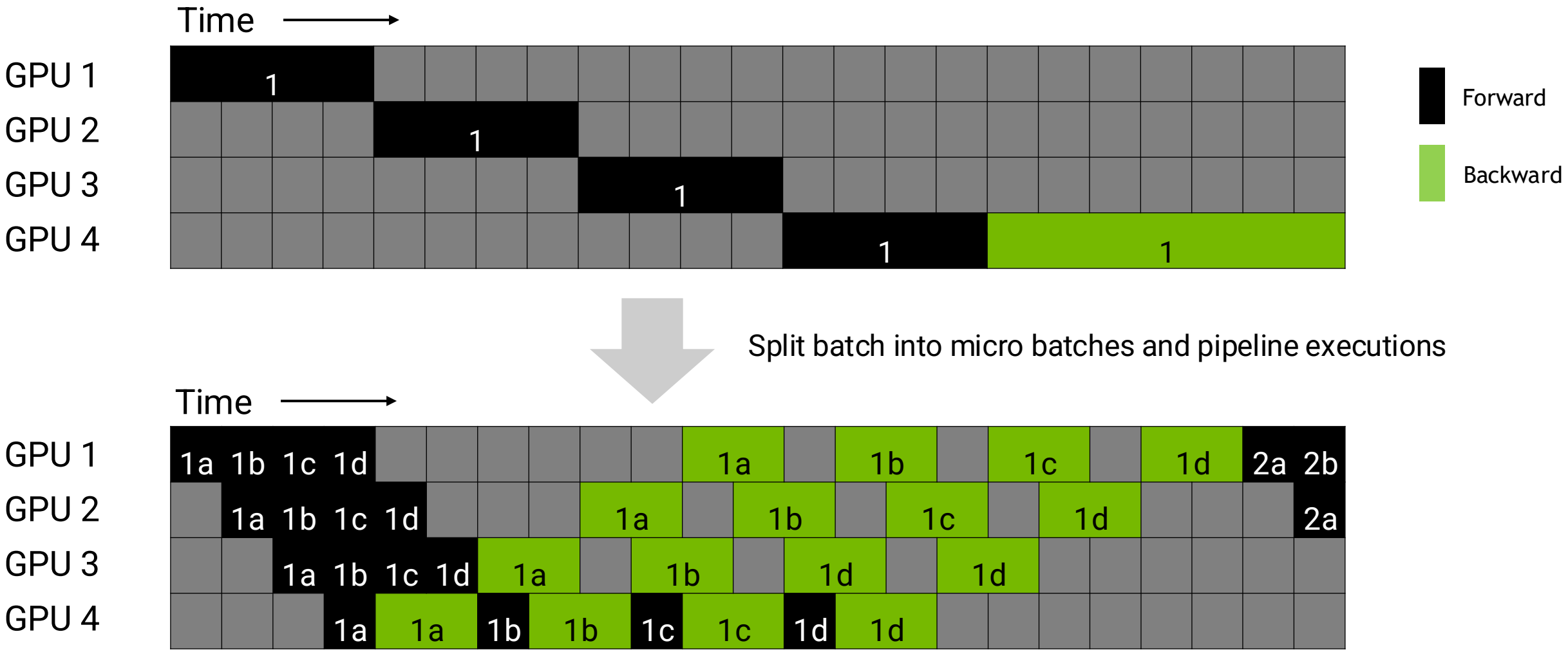
Pipeline Parallelism

- Naive pipeline parallel is sequentially processed.
- Leads to GPU underutilization.



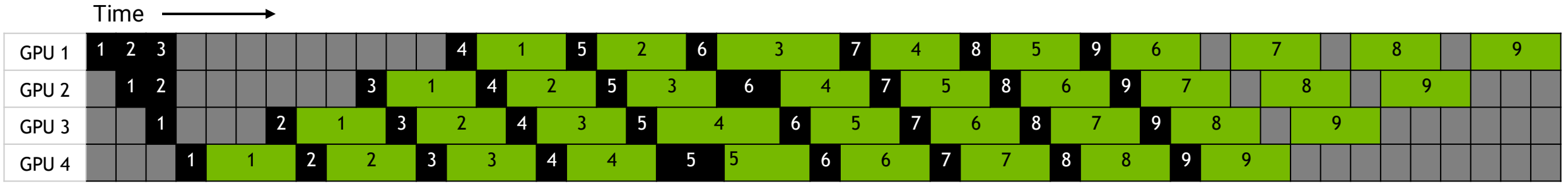
https://fairscale.readthedocs.io/en/latest/deep_dive/pipeline_parallelism.html

Pipeline Parallelism



Pipeline Parallelism

Split batch into micro batches and pipeline executions to increase GPU utilization.



$$\text{total time} = (m + p - 1) \times (t_f + t_b)$$
$$\text{ideal time} = m \times (t_f + t_b)$$
$$\text{bubble time} = (p - 1) \times (t_f + t_b)$$

$$\text{bubble time overhead} = \frac{\text{bubble time}}{\text{ideal time}} = \frac{p-1}{m}$$

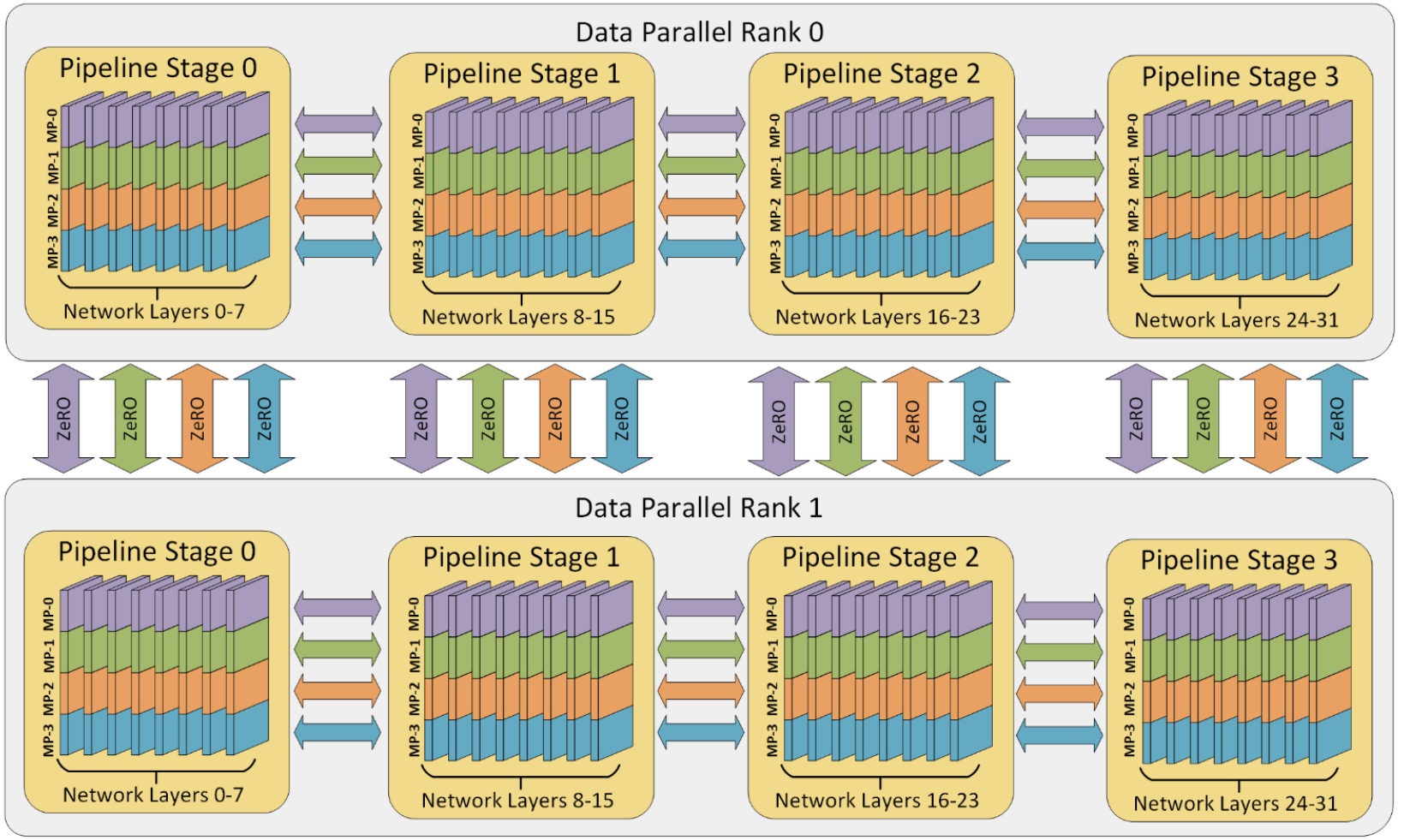
p : number of pipeline stages
m : number of micro batches
t_f : forward step time
t_b : backward step time

$$speedup = \frac{t_1}{t_p} = \frac{m*p*(t_f+t_b)}{(m+p-1)(t_f+t_b)} = \frac{m*p}{m+p-1}$$

3 times speedup with 4 pipeline stages and 9 micro batches.

Data and Pipeline Parallel with Deepspeed

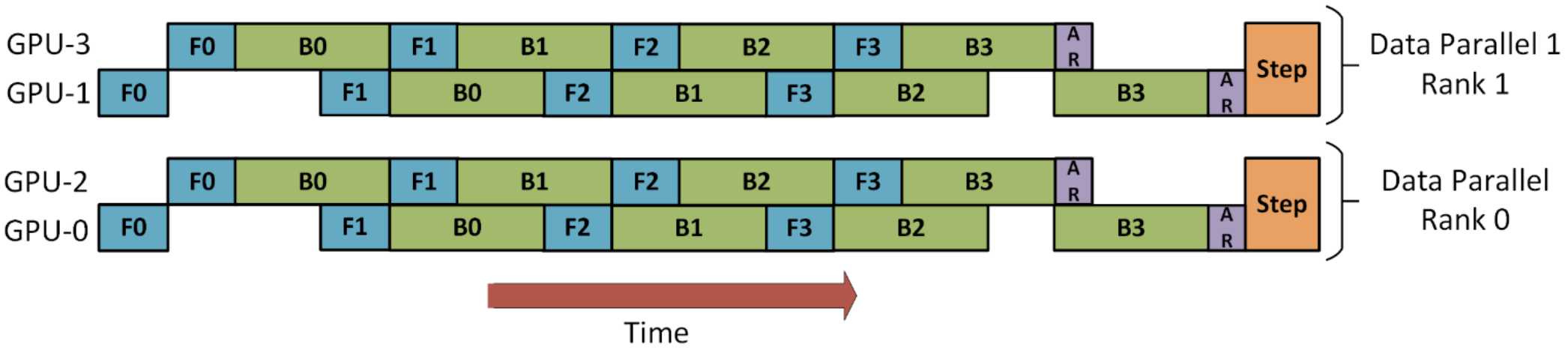
- Hybrid parallelism
- two-way data parallel
- two-stage pipeline parallel



https://www.deepspeed.ai/tutorials/pipeline/

Data and Pipeline Parallel with Deepspeed

- Four GPUs, two-way data parallel, two pipeline stages, and eight micro-batches.
- GPUs 0 and 2 are arranged in a pipeline and alternate forward (F) and backward (B) passes — the same for GPUs 1 and 3.
- Once a stage completes the forward pass for a micro-batch, the activation memory is communicated to the next stage in the pipeline.
- As the next stage completes its backward pass on a micro-batch, the gradient with respect to the activation is communicated backward through the pipeline.
- Each backward pass accumulates gradients locally, then a GPU will all-reduce (AR) gradients with its data-parallel counterpart (0 - 1, 2 - 3).
- Finally, the two pipeline stages update their model weights.



Data and Pipeline Parallel with Deepspeed

- Alexnet: 5 convolutional layers + 2 fully connected hidden layers + 1 fully connected output layer.

```
net = AlexNet(num_classes=10)
```

- Set up a pipeline module in Deepspeed

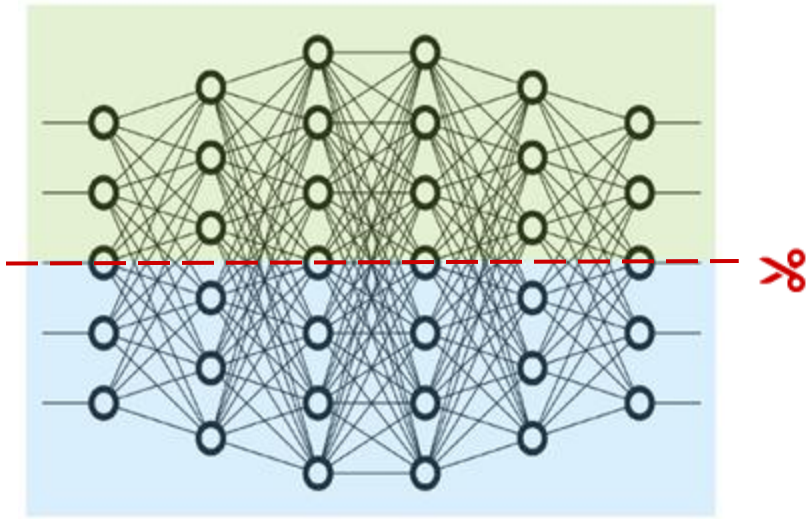
```
net = PipelineModule(layers=join_layers(net),
                     loss_fn=torch.nn.CrossEntropyLoss(),
                     num_stages=args.pipeline_parallel_size,
                     partition_method=parameters,
                     activation_checkpoint_interval=0)
```

- Run the program.

  The total number of GPUs must be divisible by the number of pipeline stages.

```
deepspeed train.py --deepspeed_config=ds_config.json -p 2 --steps=200
```

Tensor Parallelism



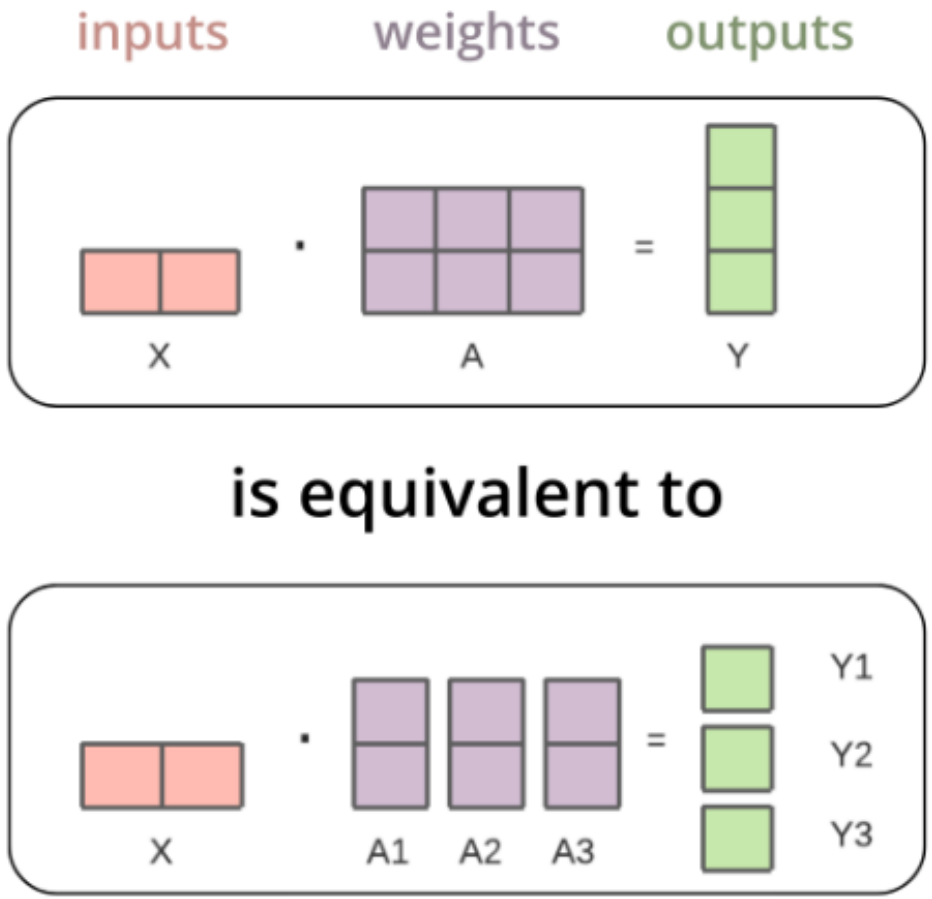
- Use to scale beyond data parallelism
- Typically used when the model can’t fit on a single GPU
- Reduces memory proportional to the number of workers (model dependent)
- Requires high compute-bandwidth to overcome communication overhead
- Less restrictive on the batch size (avoids bubble issue in pipelining)
- Tensor parallelism works well for large matrices (e.g. Transformers)
- Does not scale well beyond the node boundary

- The implementation of TP depends on the neural network architecture.

Ref: Using DeepSpeed and Megatron to Train Megatron-Turing NLG 530B, A Large-Scale Generative Language Model

A simple example of tensor parallelism

- When multiplying the input tensors with the first weight tensor, the matrix multiplication is equivalent to splitting the weight tensor column-wise, multiplying each column with the input separately, and then concatenating the separate outputs.
- The outputs are then transferred from the GPUs and concatenated together to get the final result.

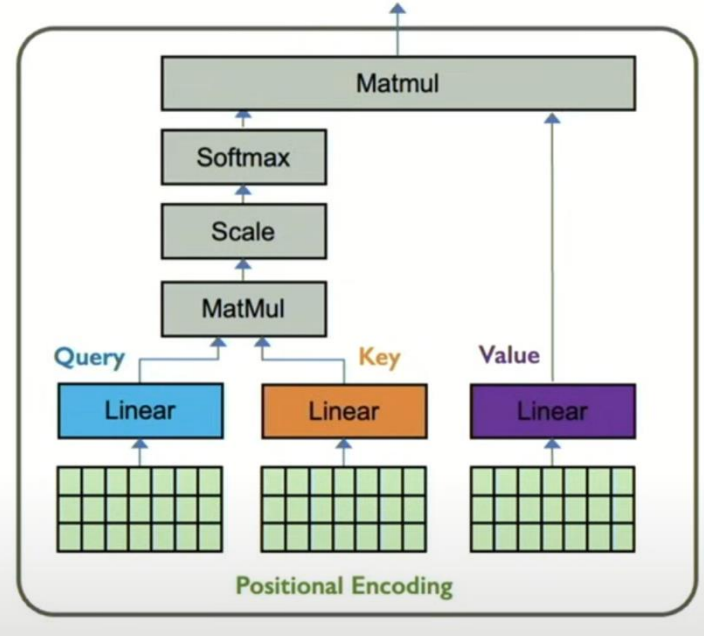


https://huggingface.co/docs/text-generation-inference/en/conceptual/tensor_parallelism

Transformer architecture

Attention is all you need

- Positional embedding. A word → A vector in a high-dimensional space.
- Extract Query, Key, and Value for search.
- Attention weighting/mask: cosine similarity between query and key
- Extract features with high attention: multiply attention mask and value.
- A self-attention head.
- Transformer: a neuro network built on multiple self-attention heads.



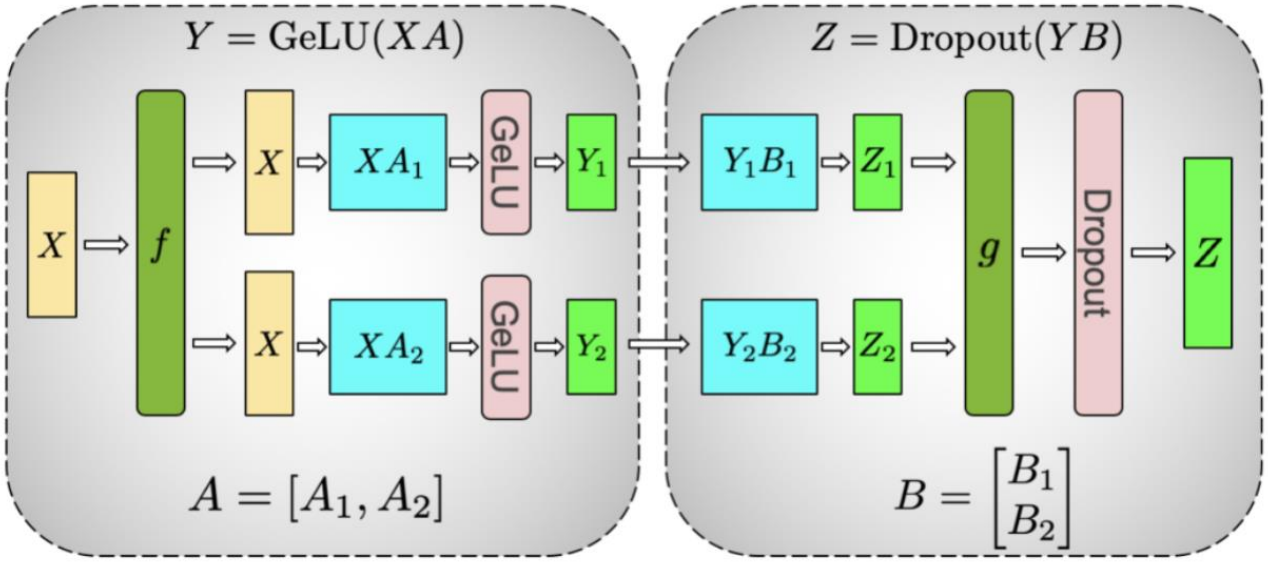
Good at sequence modeling problems

- LLM: predict the next word. Bidirectional Encoder Representations from Transformers (BERT), Generative pre-trained transformer (GPT)
- Predict protein structure from DNA sequence (AlphaFold)
- Video/audio production

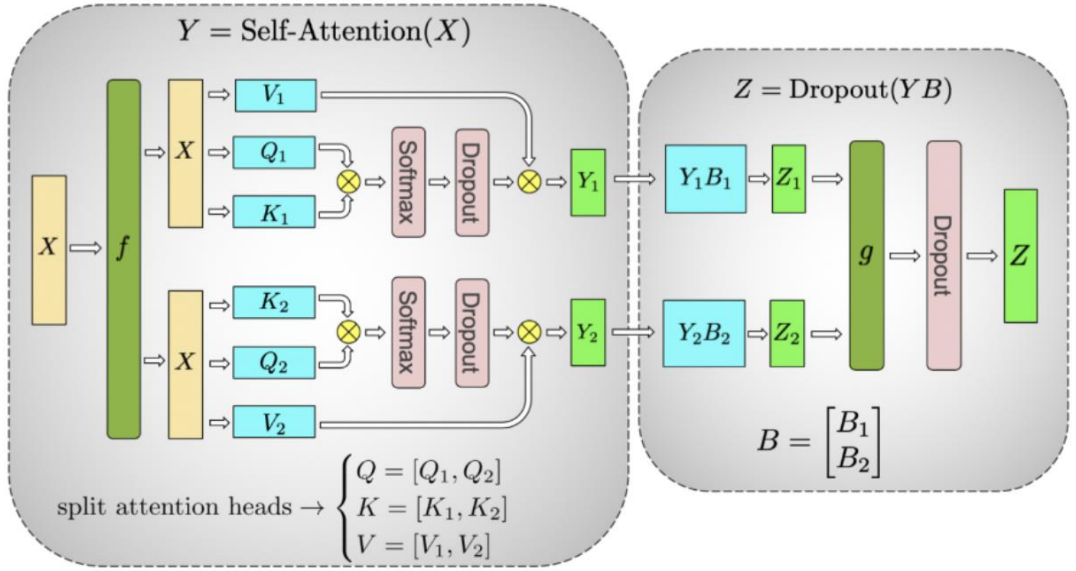
https://www.youtube.com/watch?v=dqoEU9Ac3ek

Tensor Parallel for Transformer Model

- Llama2 (Large Language Model Meta AI): built on transformer architecture.
- A transformer block consists of a feed-forward (MLP) layer and a self-attention layer.
- Split MLP and self-attention layers into multiple shards.
- The matrix multiplications in both attention and MLP happen through sharded computations.



Multilayer perceptron (MLP)



Self-attention

Tensor Parallel with Pytorch

- Set up a tensor parallel module in Pytorch

```
parallelize_module(
    module=transformer_block,
    device_mesh=tp_mesh,
    parallelize_plan=layer_tp_plan
  )
```

  Specify how to shard feed-forward and self-attention layers, column-wise or row-wise.

  Communications (allreduce) will happen under the hood.

- Sequence parallel: a variant of Tensor Parallel that performs sharded computations on layer normalization.

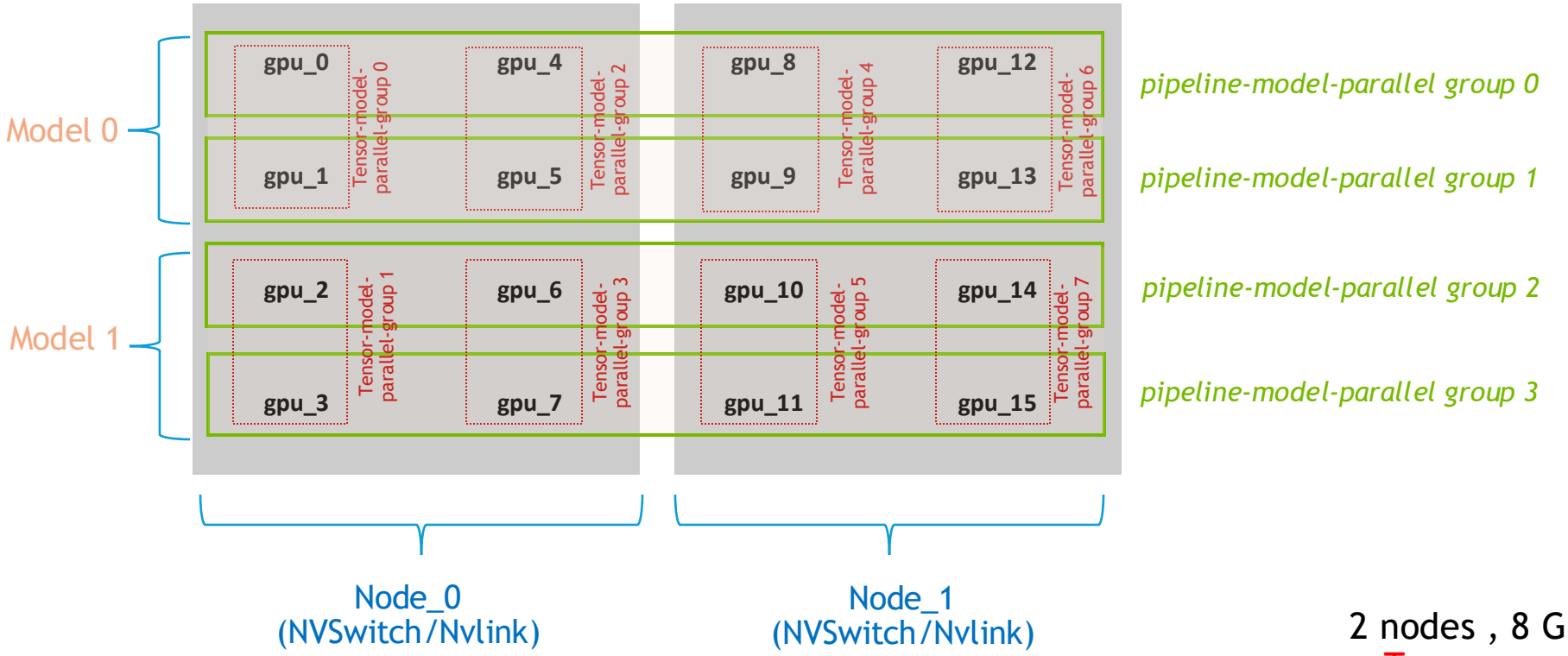
  Keeps sharded activations in the forward pass and sharded gradients in the backward pass.

- Apply Tensor Parallel within each node (intra-node) and apply Fully Sharded Data Parallel (FSDP) across nodes (inter-nodes).

https://pytorch.org/tutorials/intermediate/TP_tutorial.html

Hybrid model parallelism

GPU Affinity grouping example for PP + TP + DP



2 nodes , 8 GPUs per node
- Tensor parallel = 2
- Pipeline parallel = 4
- Data parallel = 2

- Communication overhead: PP < DP < TP
- Network: fast Nvlinks within a node, Infiniband across nodes

https://docs.nvidia.com/nemo-framework/user-guide/latest/nemotoolkit/features/parallelisms.html

Which Strategy To Use When

❑ Single-node Multi-GPU

- The model fits onto a single GPU: DP (distributed DP)
- The model doesn't fit onto a single GPU: PP, TP, ZeRO, PP + DP, or TP + DP.
- The largest layer does not fit into a single GPU: TP or ZeRO.

❑ Multi-node Multi-GPU

- ZeRO (easy)
- PP + TP + DP (tricky but faster)

➢ Best to experiment to find the winner on your particular setup.

https://huggingface.co/docs/transformers/v4.13.0/en/parallelism

What is not covered …

- Mixed-precision training
- Save GPU memory by offloading to CPU
- Activation Checkpointing
- Sequence parallelism
- Hybrid model parallelism: PP + TP + DP
- Distributed inference