Distributed Training with Model Parallel

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Adapted from: [blog post](), [video]()

Questions

1. What do we care about with distributed training and performance? What happens under the hood with FSDP?
2. What hardware setup do I need for different distributed training strategies? What are the caveats?
3. What are the various efficient finetuning optimizations? What are the tradeoffs?
4. What open-source codebases can I use right now? What are the pros and cons?

Basics of distributed training

- LLM training involves large model (10B+) and dataset (1T+ tokens) sizes.

- Maximize **throughput** for efficient training (tokens/s)

- LLMs demand substantial GPU vRAM for model weights and optimizer states.
  a. Weights: N * 2 bytes
  b. Gradients: N * 2 bytes
  c. Adam optimizer states: N * 12 bytes (copies of parameters, momentum and variance)

e.g., Falcon 40B * (2 + 2 + 12) = 720GB, 9 A100 at least

Naive Model Parallelism (MP)

- Vertically slices the model.
- Different layers on different GPUs. Example: 12-layer model on 3 GPUs.

```
 ---------------   ---------------   -----------------
 1 | 2 | 3 | 4 |   5 | 6 | 7 | 8 |   9 | 10 | 11 | 12 |
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```
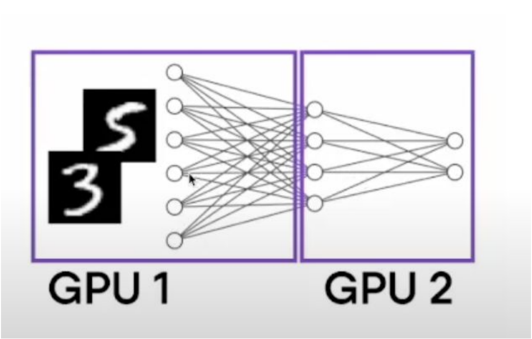
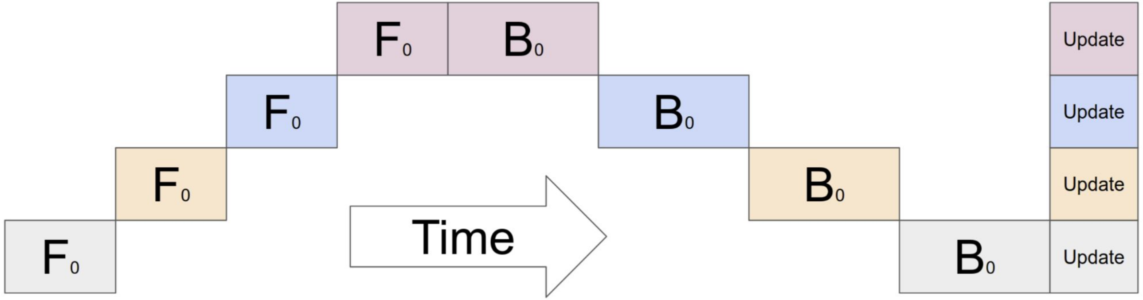
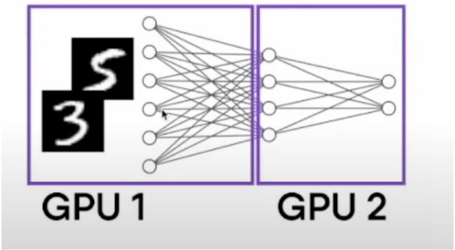

- Naive MP: waiting for the previous GPUs to process the data





lots of idleness!

Model Parallelism (MP)



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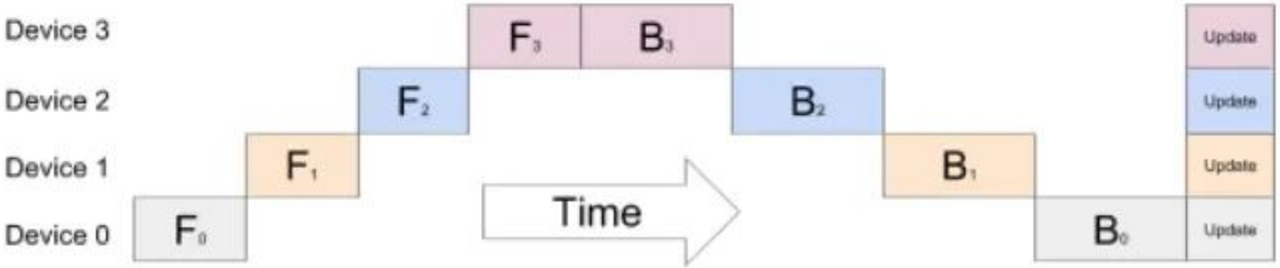
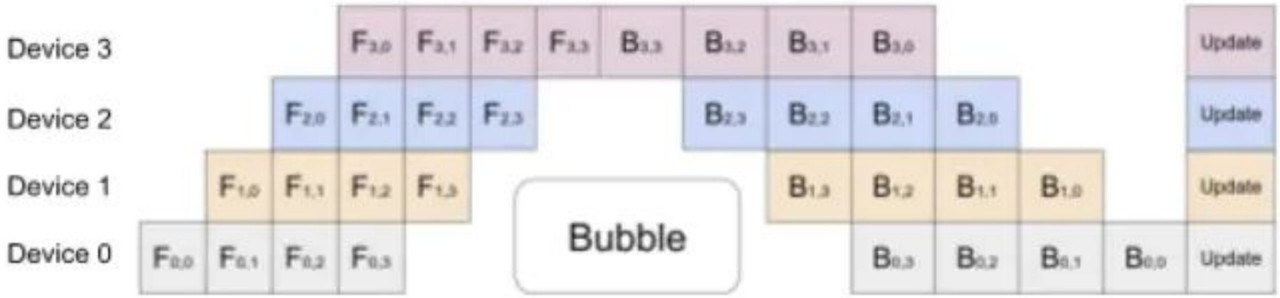


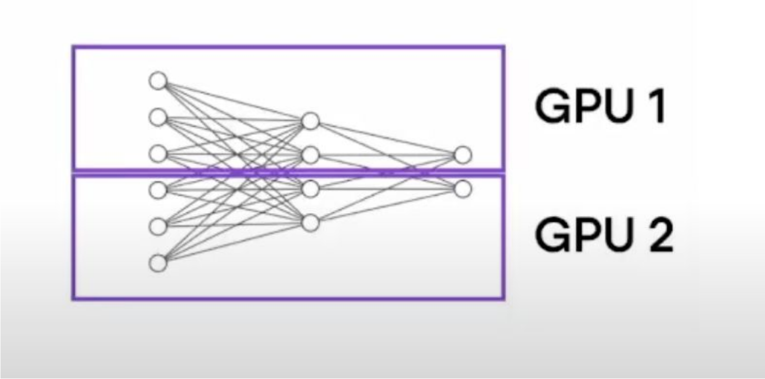
Model Parallelism (MP)

- Pipeline Parallelism (PP):
  a. Overlaps computation for micro-batches.
  b. Like a computer architecture pipeline.
  c. Enables efficient training across multiple accelerators.



Tensor Parallelism (TP)

- GPUs process slices of a tensor.
- Model horizontally sliced across GPU workers.
- Each GPU processes the same data batch.
- Computes activations for their portion.
- Exchanges needed parts.
- Computes gradients for their slice of weights.



FSDP - Fully-Sharded Data Parallel

- FSDP Unit - Vertically splitting (layers)
- Sharding - Horizontally splitting
  - Store FSDP parameters on FlatParameter
  - Split FlatParameter on multiple processes

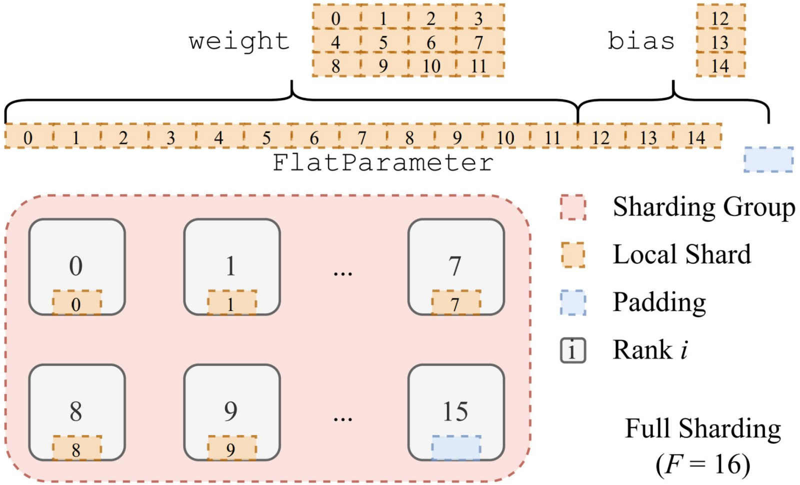
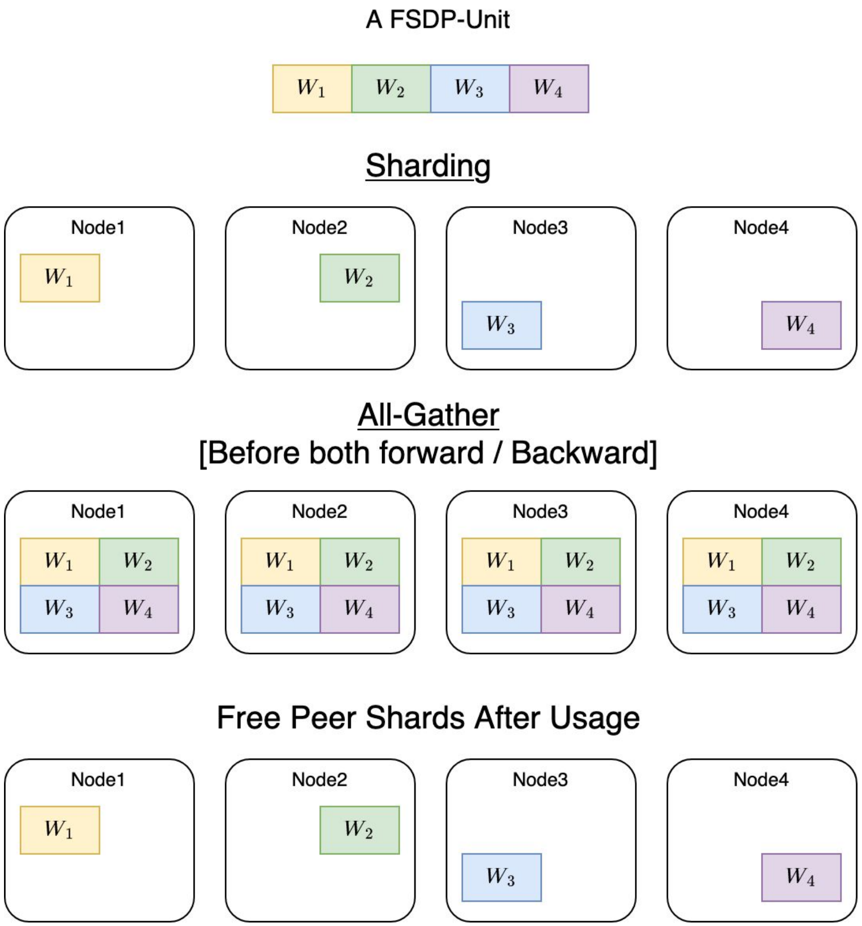


Figure 3: Full Sharding Across 16 GPUs

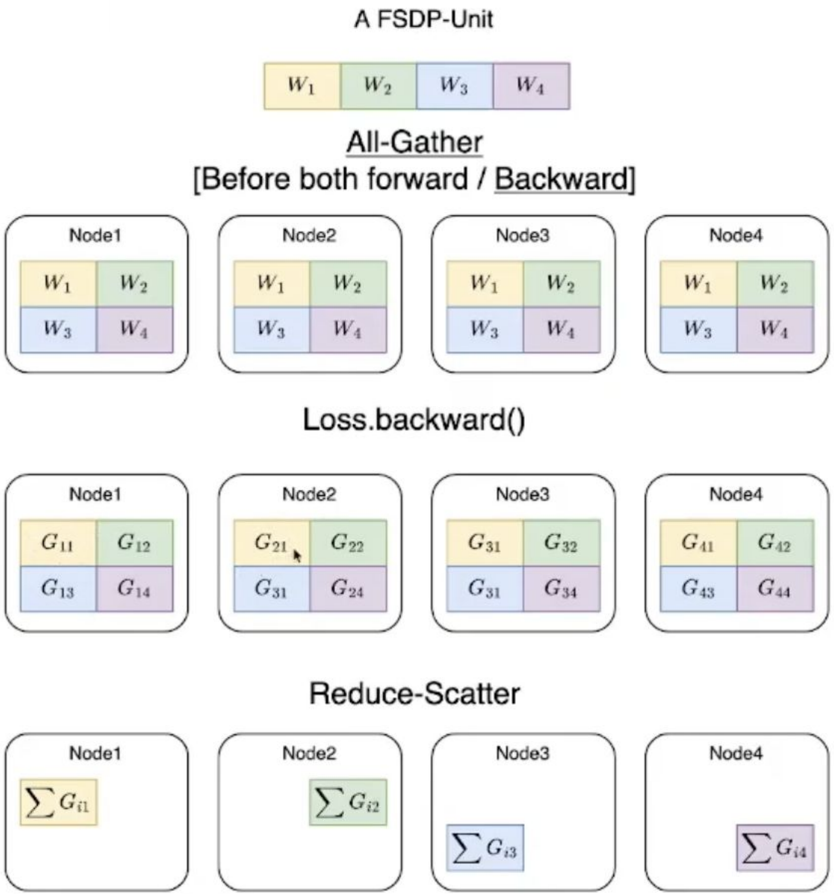
FSDP - Fully-Sharded Data Parallel

- All-Gather per FSDP-unit
  - Before forward
  - Before backward
- You can do this asynchronously across layers
- No activation are exchanged!



FSDP - Fully-Sharded Data Parallel

- Reduce-Scatter
  - All nodes have the same weights
  - But have different gradients



How can you use FSDP?

- Supported by transformers!
- By adding fsdp config to the TrainingArguments
- Simplest setup:
  - -- fsdp
  - -- full_shard auto_wrap
- More setups:
  - Torch FSDP interface
  - Huggingface Accelerator setup
  - Pytorch lightning

Efficient Fine-tuning

- Mixed Precision (BF16, FP16), supported by Huggingface
- Parameter-efficient finetuning, supported by PEFT
  - Only finetune additional parameters, eventually merged into the main model
  - Saves the memory for optimization states for the freezing parameters
- Flash Attention: fast, memory-efficient and exact!
  - Supported by huggingface on Llama and Falcon, through use_flash_attention=True to AutoModel
- Gradient Checkpointing
  - reduce memory consumption by only retaining a subset of intermediate activations, and recomputing the rest as needed, slows down by 20%
- Quantization
  - Post training quantization: LLM.int8(), GPTQ
    - Load_in_8bit supported by huggingface's from_pretrained interface
  - Quantization-aware training: QLoRA