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Optimizing Deep Learning Systems for Hardware

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Part IV : System-level Optimization

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- PIV.a : Parallelism
- PIV.b : Mixed-Precision Training
- PIV.c : Other

Part IV.a: Parallelism, Why?

- Large models (e.g., GPT, BERT) don’t fit on a single GPU
- Training takes days or weeks on one machine
- Solution: break up the work across multiple devices.

Types of Parallelism

- We’ll cover four types of parallelism:
  - Data Parallelism
  - Model Parallelism
  - Pipeline Parallelism
  - Tensor (Sharded) Parallelism

Data Parallelism

- Data Parallelism (Concept)
  - Copy the entire model to multiple devices
  - Each device gets a different batch of training data
  - Gradients are averaged & synced across devices
  - no 🧠er:
    - Easy to implement
    - Widely supported

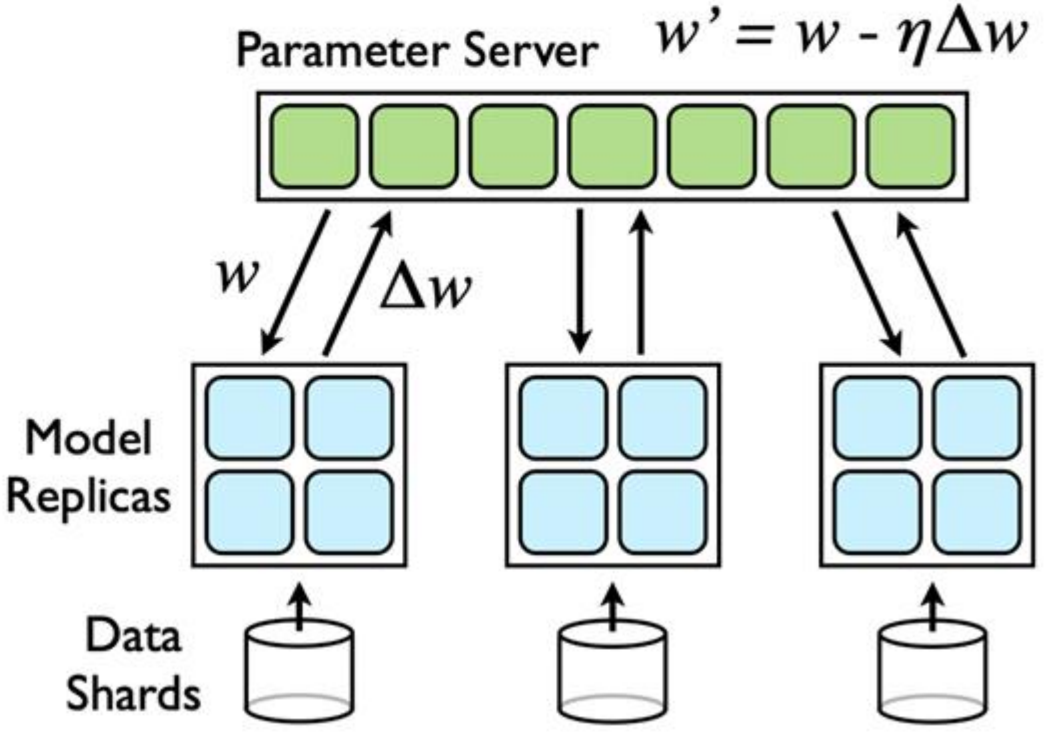

figure: https://insujang.github.io/2022-06-11/parallelism-in-distributed-deep-learning/

Data Parallelism

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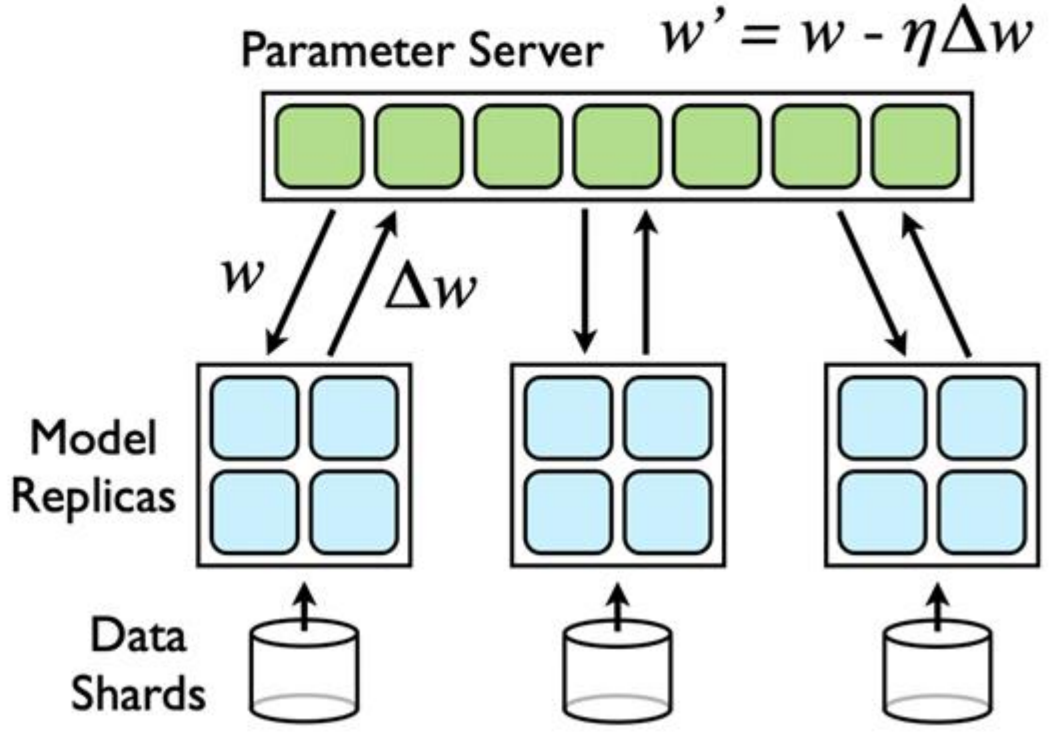
Gradient synchronization at each step

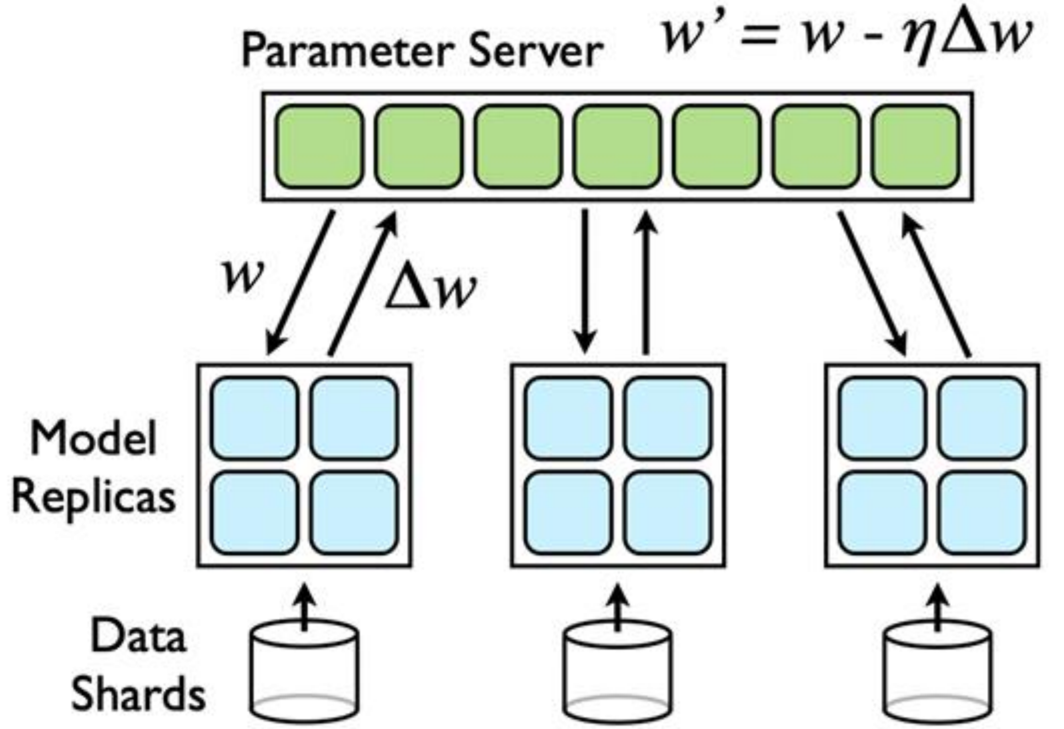


Data Parallelism - Pros & Cons

Pros:
- Simple to implement
- Scales well for many tasks

Cons:
- Doesn't help if model is too big to fit on one GPU
- Communication overhead (the gradient sync)

Gradient synchronization at each step



Model Parallelism

- Model Parallelism
  - Split the model across multiple devices
  - Each device holds a different part of the model
  - Useful when the model is too large for one GPU

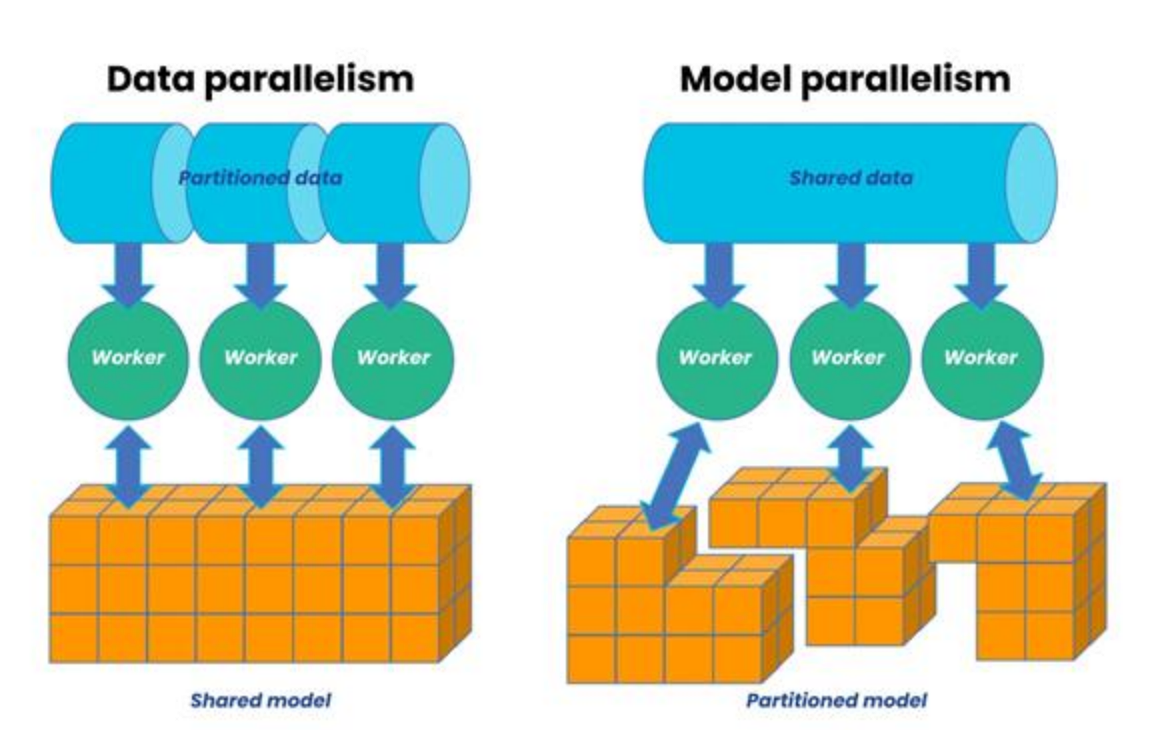


figure: https://www.anyscale.com/blog/what-is-distributed-training

Model Parallelism: Case AlexNet!

- When AlexNet was introduced in 2012, GPUs had much less memory than today. The model was too large to fit on a single GPU at the time, so the authors split the model across two GPUs.
- In AlexNet, each GPU handled a different subset of the convolutional filters (and corresponding feature maps).
- This was implemented using **grouped convolutions**, where each group was assigned to a different GPU.

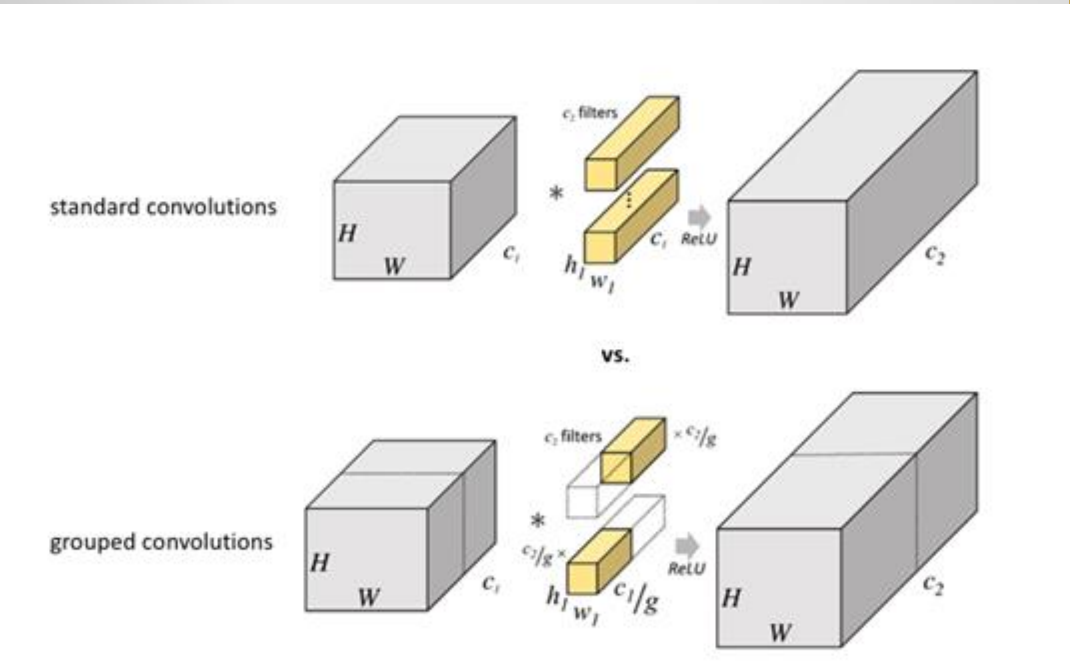
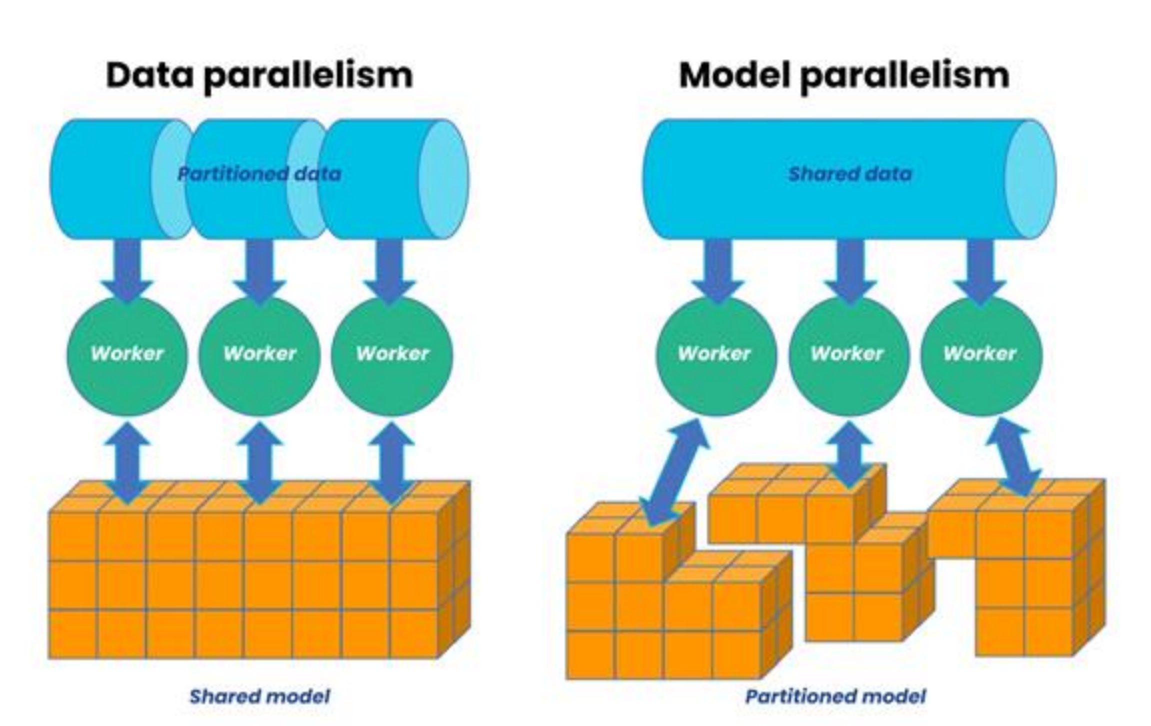


figure: https://www.jeremyjordan.me/convnet-architectures/

Model Parallelism

Pros:
- Enables training very large models

Cons:
- Harder to implement and debug
- Communication between devices can slow things down



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Pipeline Parallelism

- Pipeline Parallelism
  - Break model into “stages” and run mini-batches in a pipeline across them
  - Like an assembly line
  - Helps keep all devices busy (how?)

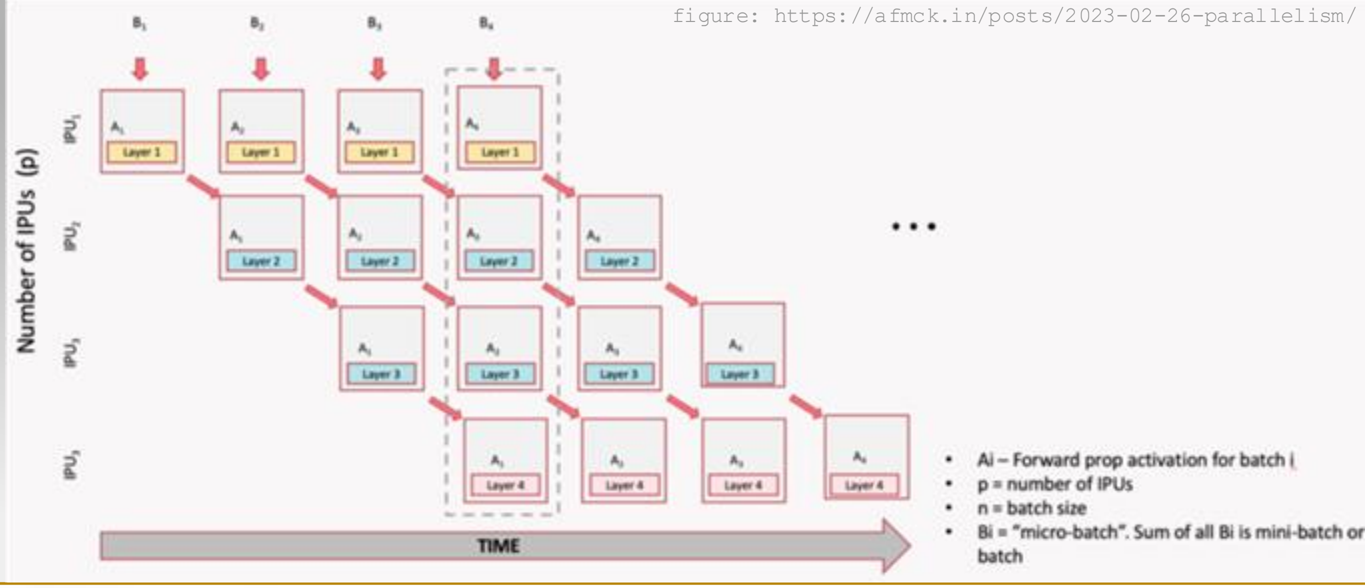
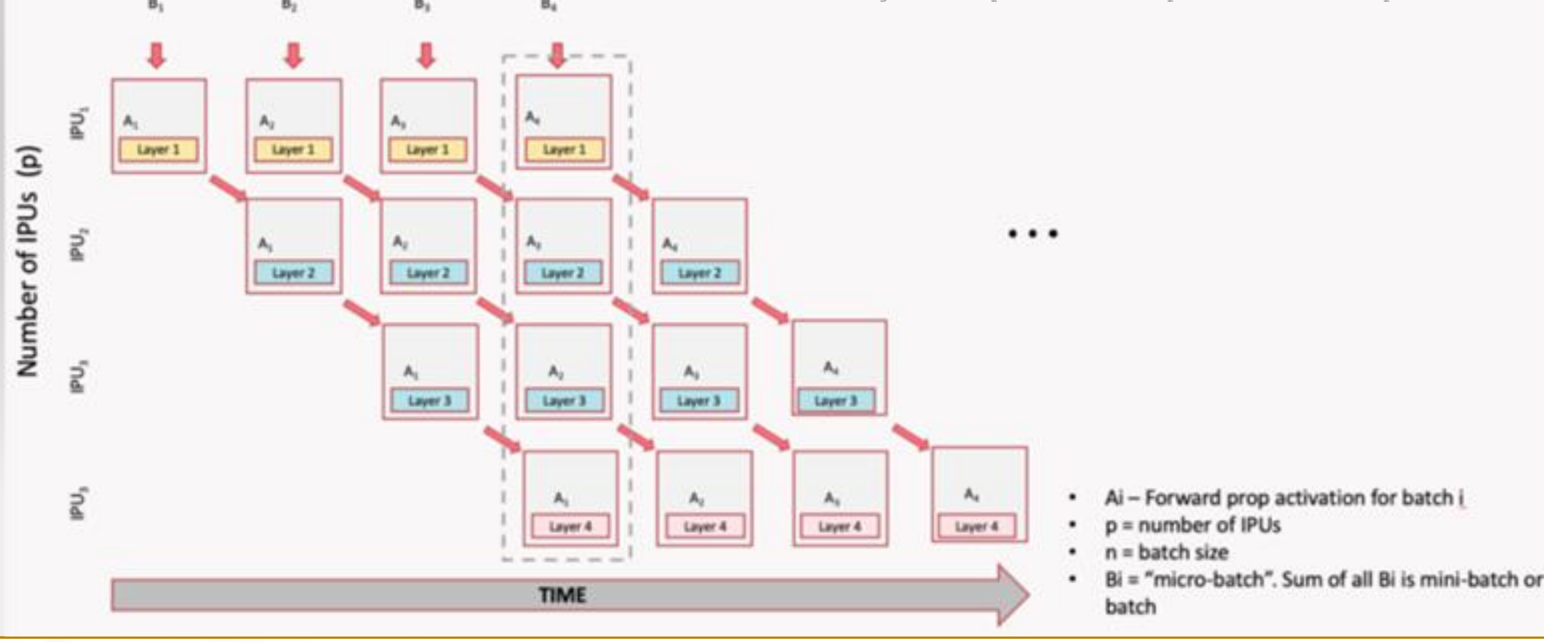


figure: https://afmck.in/posts/2023-02-26-parallelism/

Pipeline Parallelism

- Stage 1 on GPU 1, Stage 2 on GPU 2, etc.
- Micro-batches flow through the pipeline
- Have to make scheduling perfect!
  - i.e. The load at each GPU should take similar amounts of time

figure: https://afmck.in/posts/2023-02-26-parallelism/



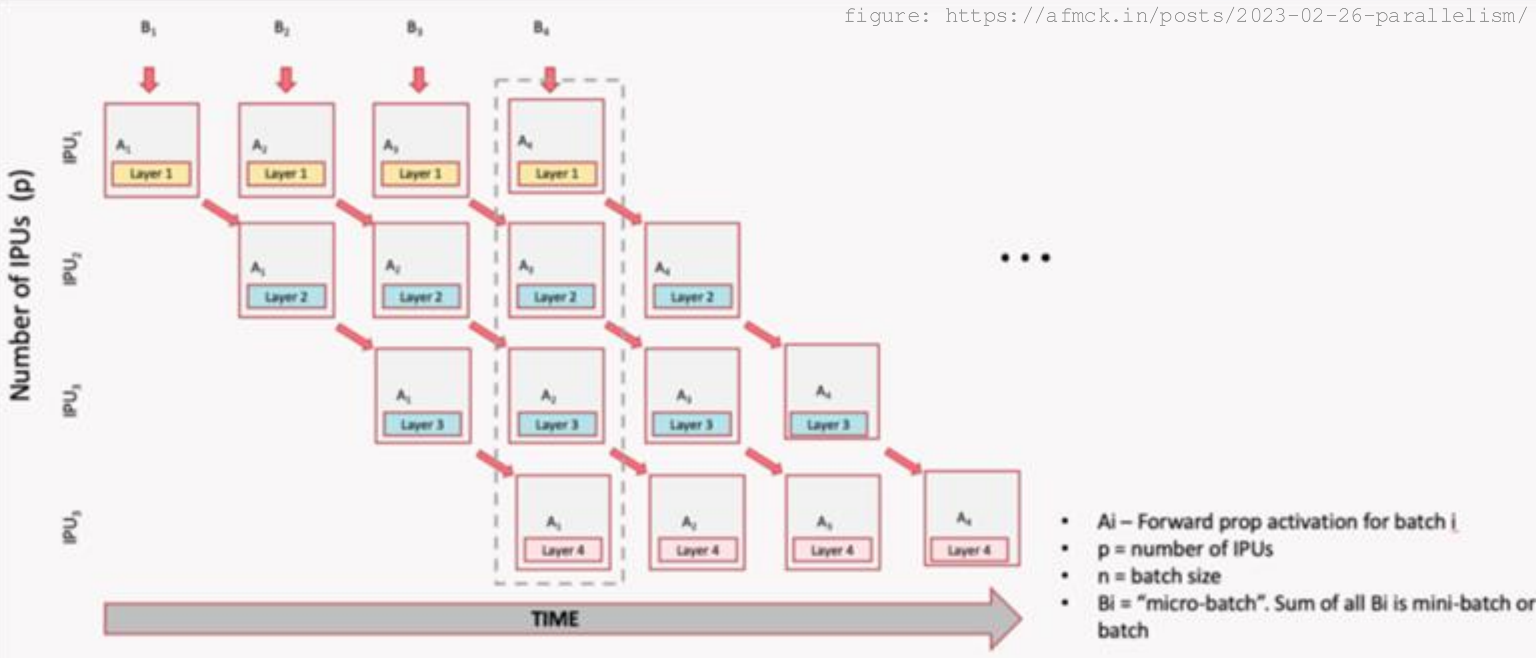
Pipeline Parallelism

Pros:

- Higher hardware utilization than basic model parallelism

Cons:

- Requires careful scheduling (e.g., bubble overhead)
- More complex training logic
- Requires a framework! (like DeepSpeed)



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Tensor Parallelism

- Tensor (sharded) Parallelism
  - Split large tensors (e.g., weights) across devices at a fine-grained level
  - e.g., split matrix multiplication across GPUs
  - Common in LLM training frameworks

figure: https://www.anyscale.com/blog/what-is-distributed-training

Tensor (Sharded) Parallelism

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- Instead of splitting the model by layers (like model parallelism), we split the individual tensors (weights, activations) across devices.
    - Imagine a large matrix too big for one GPU.
    - Slice it into smaller chunks.
    - Each GPU holds and computes only its piece.
    - Together, they perform the full operation.

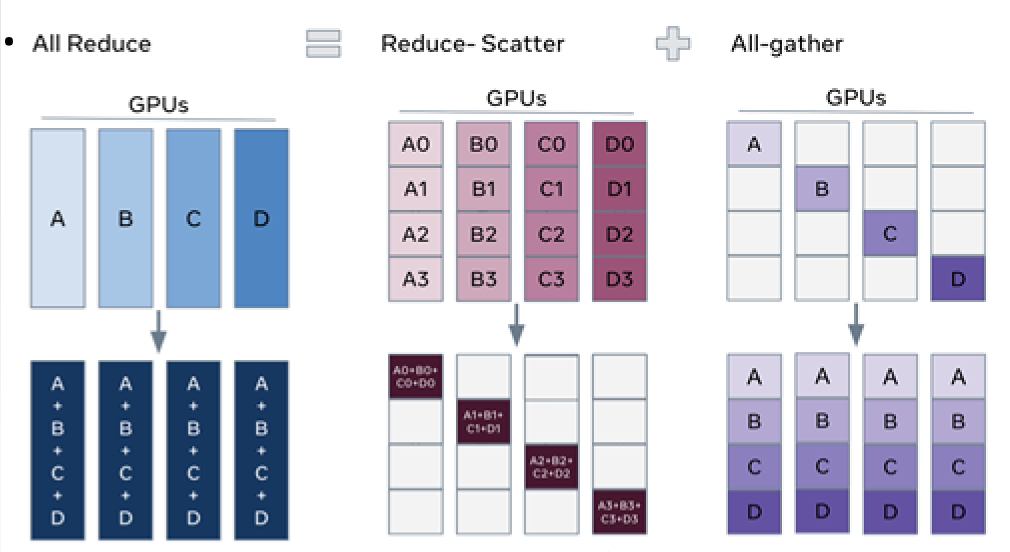


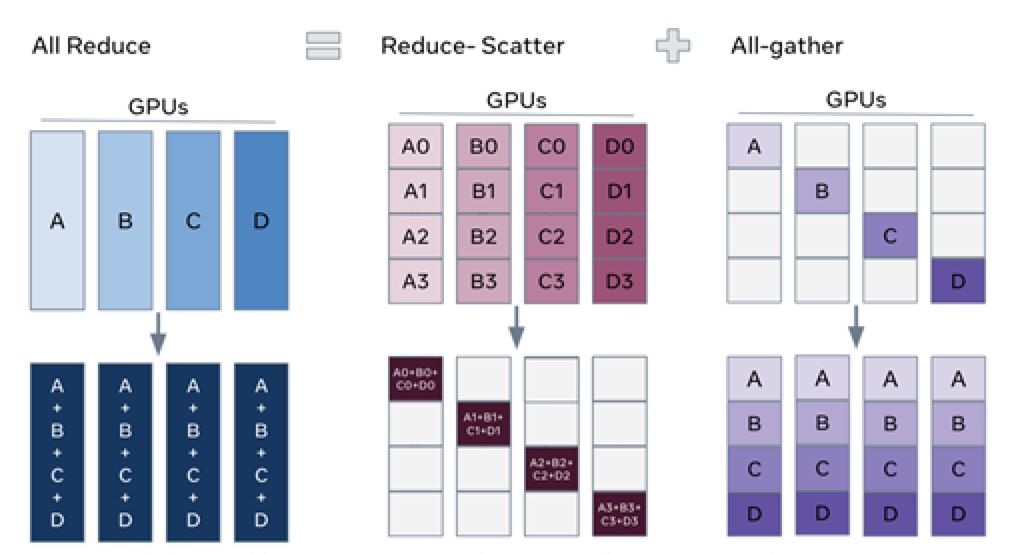
figure: https://docs.pytorch.org/tutorials/intermediate/FSDP_tutorial.html

Tensor (Sharded) Parallelism

Large tensors are split across multiple GPUs.

- Let's say we have a large weight matrix W in a linear (fully connected) layer:
  - $Y = X \times W^T$
- If W is too big to fit on one GPU, we shard it column-wise:

- GPU 0 holds part A of W
- GPU 1 holds part B …
- GPU 2 holds part C …
- GPU 3 holds part D …



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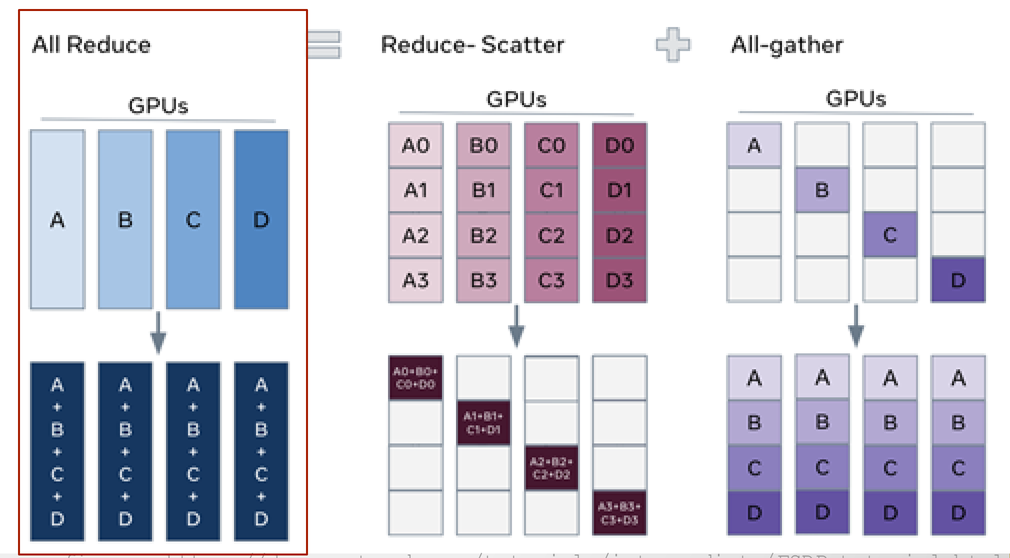
Tensor (Sharded) Parallelism

If you sharded W across GPUs:

- Each GPU computes only its local part of dL/dW (say A, B, C, or D)
- To update weights correctly (e.g., using SGD), you may need to sum or sync these parts across all GPUs
- That's why **All-Reduce** is used: to combine these partial gradients into a full gradient.



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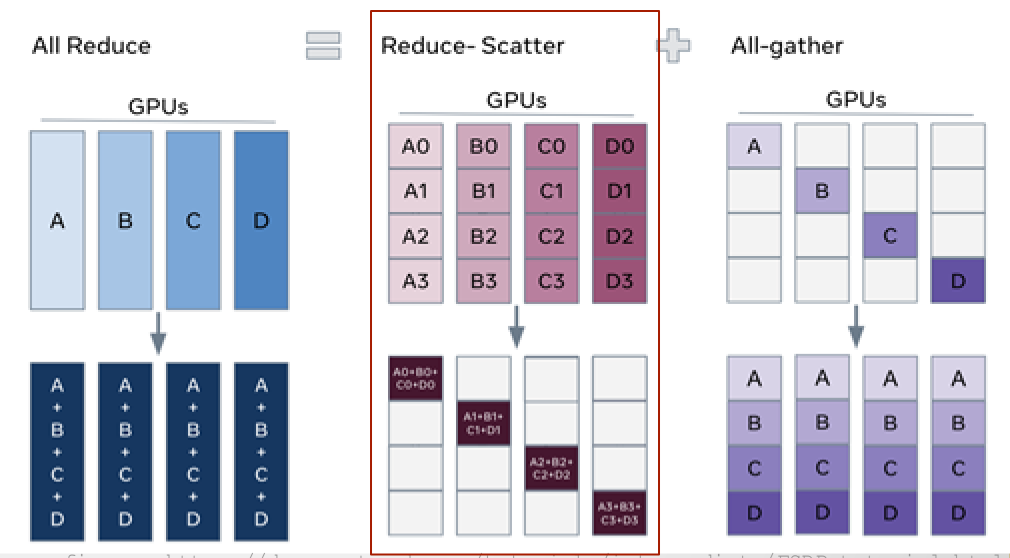
Tensor (Sharded) Parallelism

Reduce-Scatter is another communication pattern used in tensor parallelism during distributed training.

- It combines two steps:
  - Reduce: Aggregate data (e.g., sum) across GPUs.
  - Scatter: Distribute chunks of the result to different GPUs.



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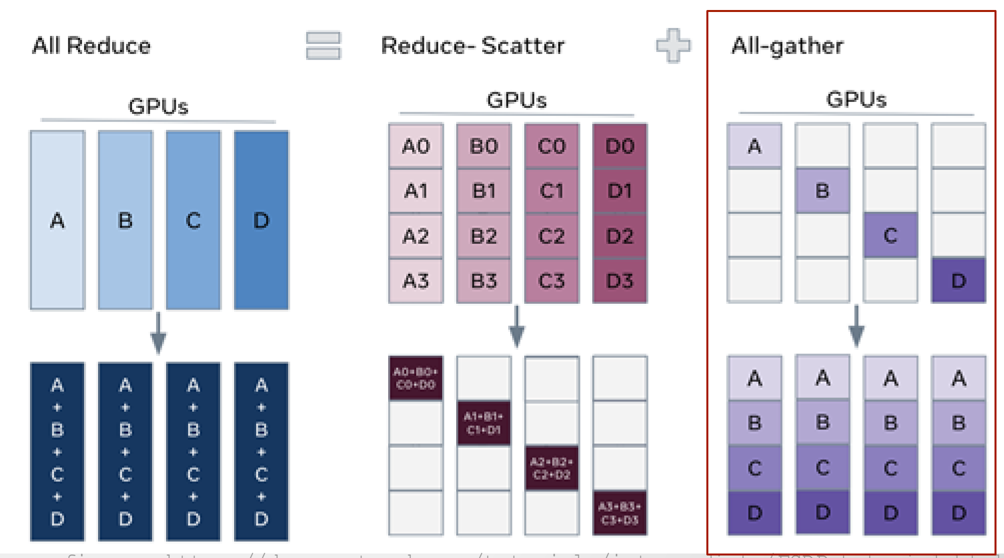
Tensor (Sharded) Parallelism

Now each GPU has one reduced piece.

- To get the full result (A+B+C+D), they need to share their pieces.

- In the All-Gather step:
  - GPUs exchange their chunks
  - So that all GPUs end up with every piece



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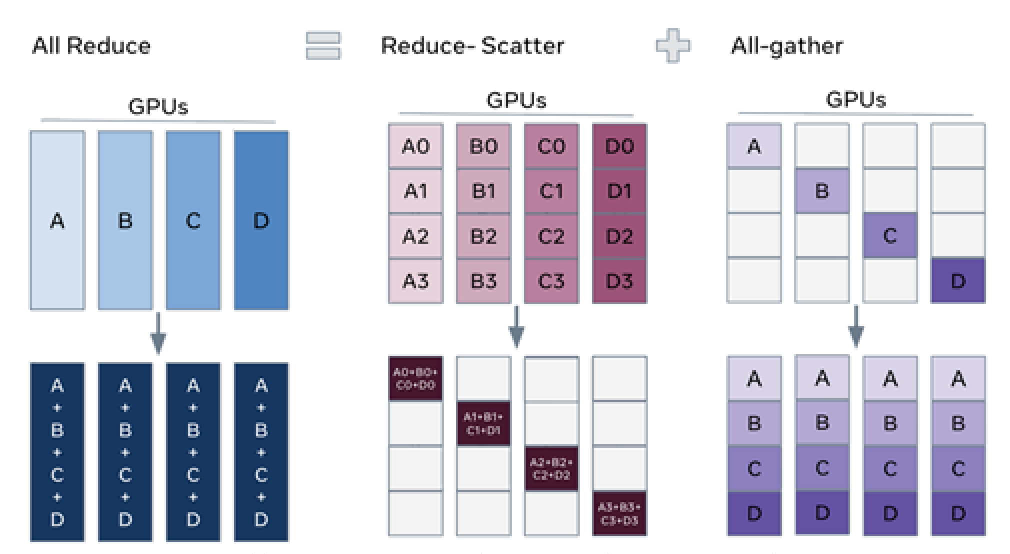
Communication Patterns

- When you split a tensor (like weights or activations) across GPUs, each GPU does part of the computation.
- But to get the final result (e.g., output or gradient), the GPUs need to communicate and combine their partial results.
- All-Reduce = Compute + Share + Combine
  - Every GPU:
    - Computes its part
    - Shares it with other GPUs
    - Receives others' parts
    - Combines everything into a final result (e.g., a full gradient)



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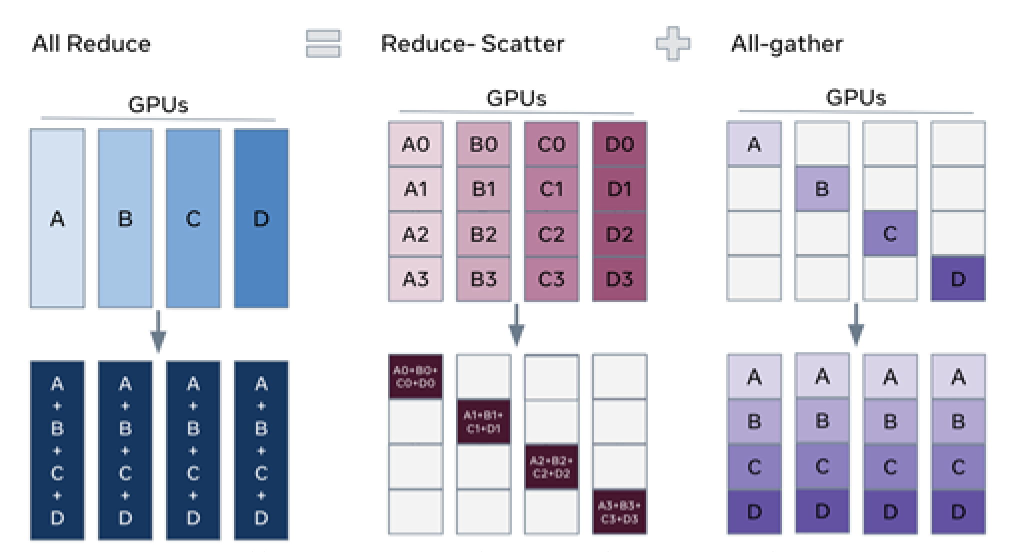
Tensor (Sharded) Parallelism

Pros

- Scalability: Excellent (sometimes a must) for huge models
- Lower memory usage per GPU (can do it with cheaper GPUs)

Cons

- You must have many GPUs!
- Complexity: High implementation effort
- Significant communication overhead
- Tooling / Debugging
    - Requires advanced frameworks *which exist*



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Next: Part IV.b

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- **PIV.b : Mixed-Precision Training**
- PIV.c : Other

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Thanks!

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