CS 181AI
Lecture 22

Distributed Training Pt. 2

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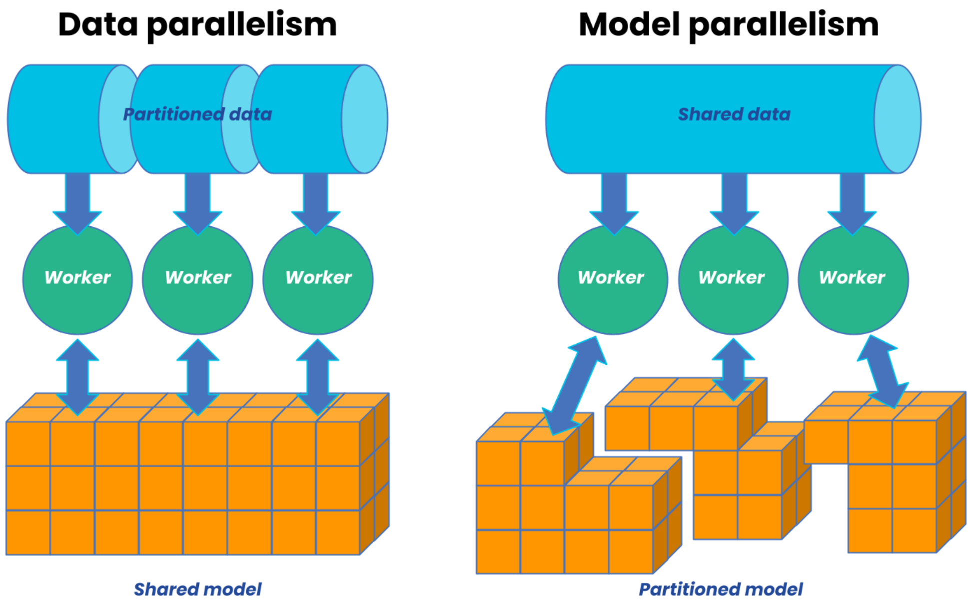
Logistics

- All assignments done!
- Remaining: 1 round of paper reading, project presentation, project report
- Outline of rest of semester (!!)
  - Today: Distributed Training part 2
  - 4/12: Profiling + debugging
  - 4/17: Efforts to lower model resource usage (+ different types of models)
  - 4/19: Working session
  - 4/24: Scale of models/resources in industry + look at full stack of ML pipelines
  - 4/26: Project presentations

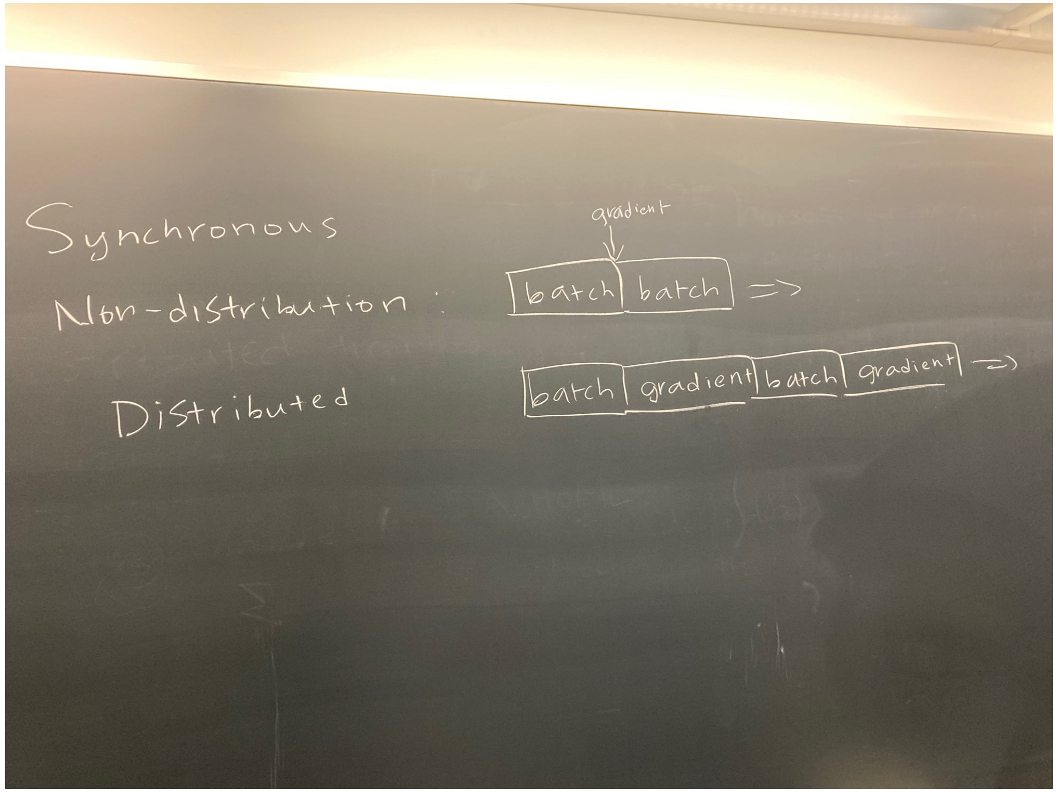
Last Time

- Data vs Model Parallelism
- Synchronous Distributed Training
- Strategies for Gradient Aggregation



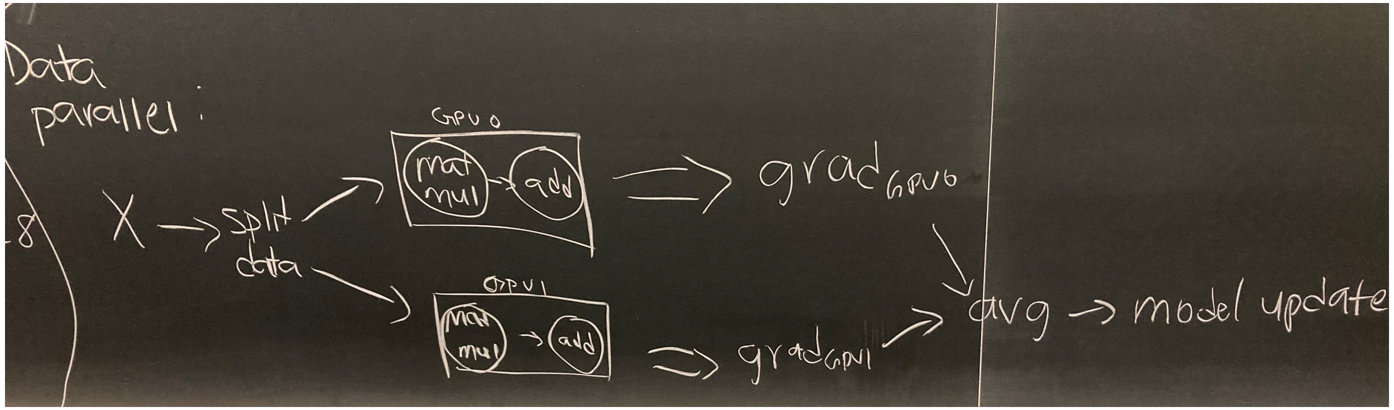
Last Time: Synchronous Distributed Training

- Gradients are computed and model is updated after each batch
- Calculation must happen very efficiently



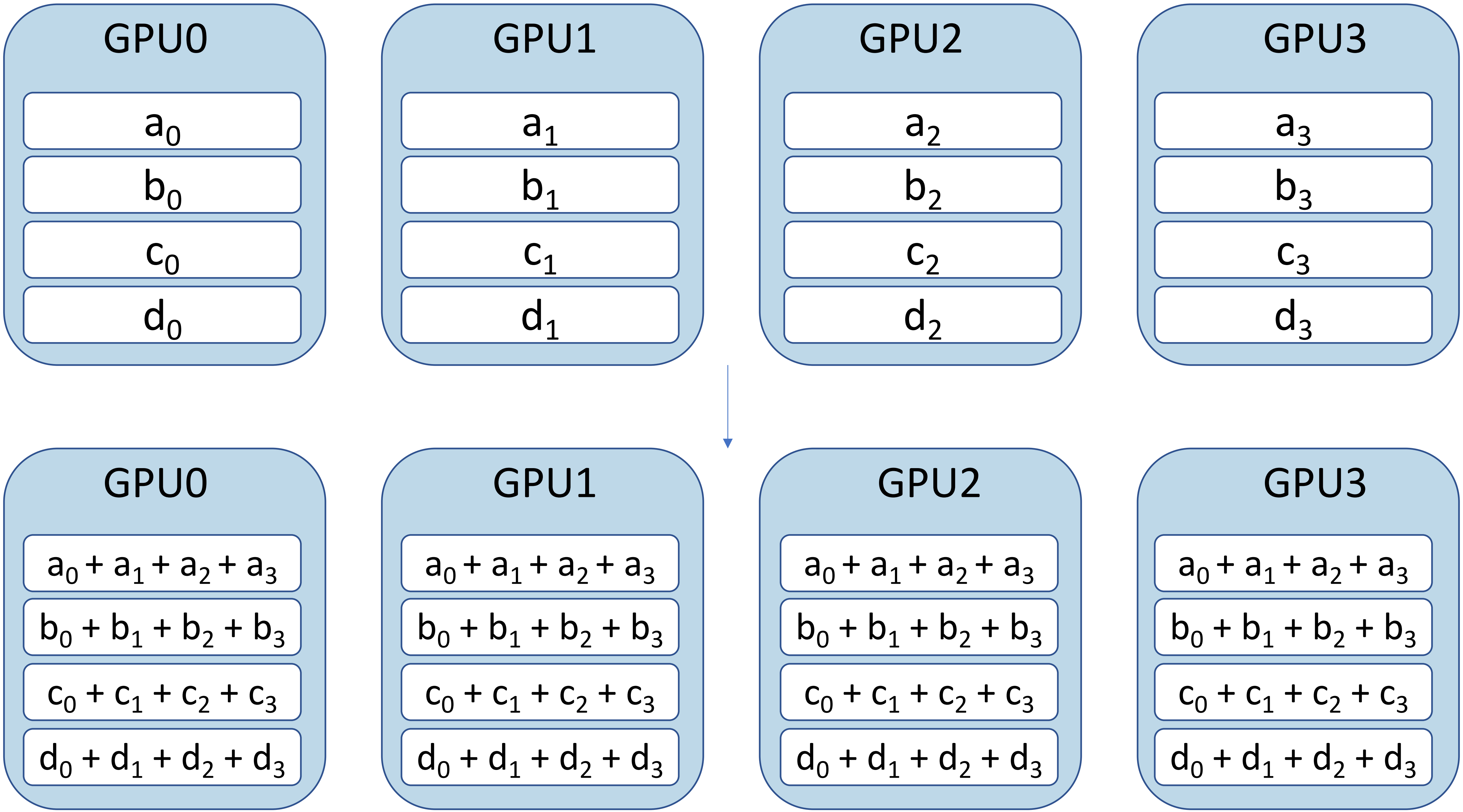
Last Time: Gradient Calculation

- At the end of every batch, gradients for the whole model are calculated
- How does this work if each GPU sees part of the batch?
  - Each GPU computes its own loss and gradients. Gradients are averaged and result is used to update the model



Today

- Synchronous Gradient Calculation Strategies
- Asynchronous Distributed Training
- Consistency Models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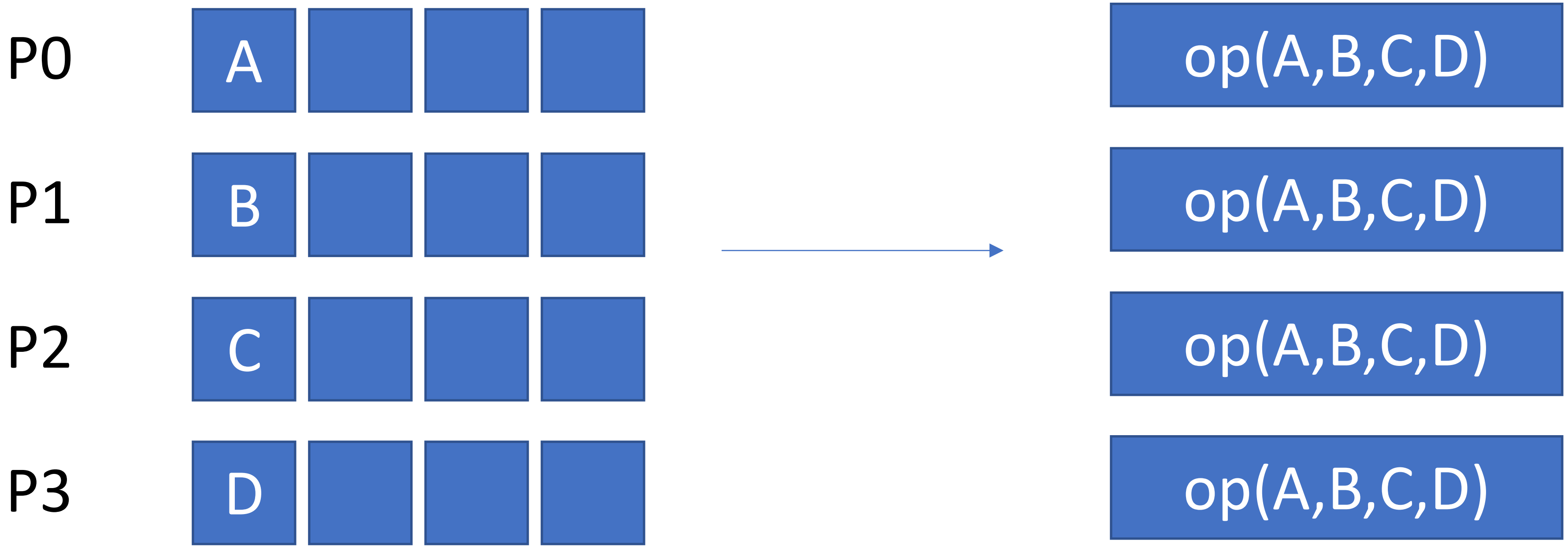
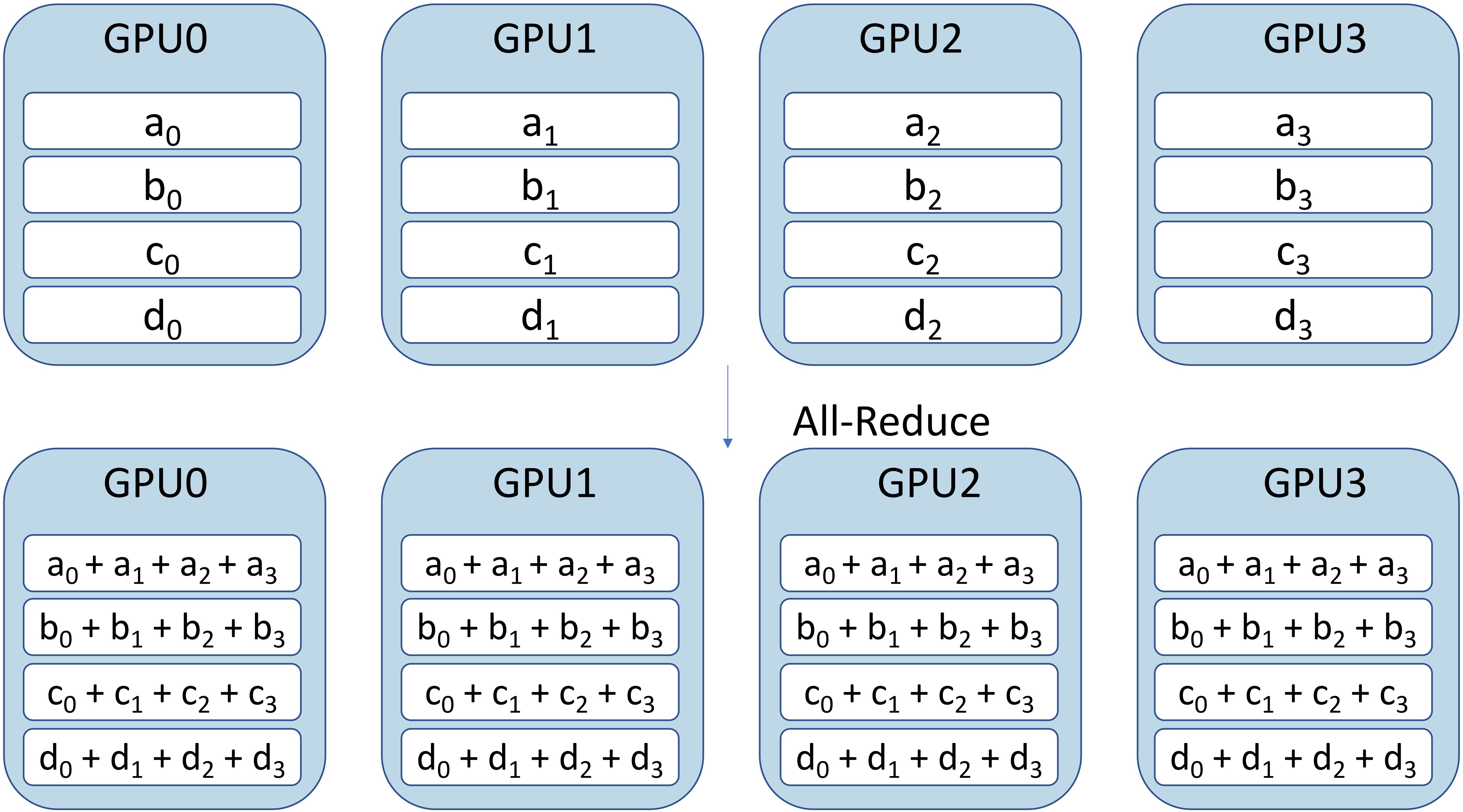
All-Reduce

- “Operation that reduces a set of arrays on distributed workers to a single array that is then redistributed back to each worker”

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All-Reduce
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Gradient Aggregation Metrics

- Metrics
  - Bandwidth (number of messages)
  - Fault tolerance
  - Speed of convergence
  - Elasticity
  - Ease of use

Ring All-Reduce

- Most used in industry
- Down-side: scales linearly with number of GPUs
- Alternative: GCP Reduction Server

Synchronous Gradient Update Summary

- Keeps the models weights in sync after each batch
- Hardest part is getting gradients exchanged between GPUs after each batch
- Synchronous distributed training can be run across multiple GPUs on the same machine or even across multiple machines with several GPUs each

Asynchronous Gradient Update

- Keep one server for all gradients -> parameter server model
- Each worker computes gradients and makes updates asynchronously (no waiting for each other)

Parameter Server

Asynchronous Gradient Update

- Keep one server for all gradients -> parameter server model
- Each worker computes gradients and makes updates asynchronously (no waiting for each other)
- What could go wrong?

Asynchronous Gradient Update

- Keep one server for all gradients -> parameter server model
- Each worker computes gradients and makes updates asynchronously (no waiting for each other)
- Workers could be taking a stale version of parameters and computing gradients on those!

Consistency Models

- Strong
- Weak
- Eventual
- Bounded

Next Time

- Profiling + Debugging your ML System

Acknowledgments

- Nikita Namjoshi, Google Cloud Developer Advocate