UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

CS 498: Machine Learning System
Spring 2025

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Today

- **Distributed Training**
  - **Problem**
  - **Challenge**
  - **History**
  - **Parameter Server based DP**
  - **Communication terminologies**
- **Learning Objectives**
  - **Understand how data parallelism is implemented using parameter servers and all-reduce**
  - **Understand the communication, consistency, and scalability trade-off in distributed training systems**
- **First & Second paper summary due date: EOD Feb 6 (Friday)**

ML/DL Training Problem Definition Recap

- Given model f, data set $\{x_i, y_i\}_{i=1}^{N}$
- Minimize the loss between predicted labels and true labels:

  Min $\frac{1}{N}\sum_{i=1}^{N} loss(f(x_i, y_i))$

- Common loss function
  - Cross-entropy, MSE (mean squared error)

- Common way to solve the minimization problem
  - Adaptive learning rates optimizers (e.g., Adam)
  - Stochastic gradient descent (SGD)

Gradient Descent

- Model f_w is parameterized by weight w
- η > 0 is the learning rate

Backward pass   Forward pass

For t = 1 to T

$\Delta w = \eta \times \frac{1}{N}\sum_{i=1}^{N} \boxed{\nabla} \left(\boxed{loss\left(f_w(x_i, y_i)\right)}\right)$ // compute derivative and update

w -= Δw // apply update

End

Adaptive Learning Rates (Adam)

- Model f_w is parameterized by weight w
- η > 0 is the learning rate

For t = 1 to T

$$\Delta w = \eta \times \frac{1}{N} \sum_{i=1}^{N} \nabla \left(loss\left(f_w(x_i, y_i)\right)\right)$$

w -= $\boxed{\Delta w}$ // apply update

End

$$\nu_t = \beta_1 * \nu_{t-1} - (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

g_t : *Gradient at time t along* ω^j

ν_t : *Exponential Average of gradients along* ω_j

s_t : *Exponential Average of squares of gradients along* ω_j

β_1, β_2 : *Hyperparameters*

Adam: A Method for Stochastic Optimization, 2014

Accelerating Gradient Descent

- Model f_w is parameterized by weight w
- η > 0 is the learning rate

Can we accelerate it?

For t = 1 to T

$$\boxed{\Delta w = \eta \times \frac{1}{N}\sum_{i=1}^{N} \nabla \left(loss\left(f_w(x_i, y_i)\right)\right)}$$ // compute derivative and update

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Accelerating Gradient Descent

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Increase the batch size increases AI but eventually bounded by single GPU compute

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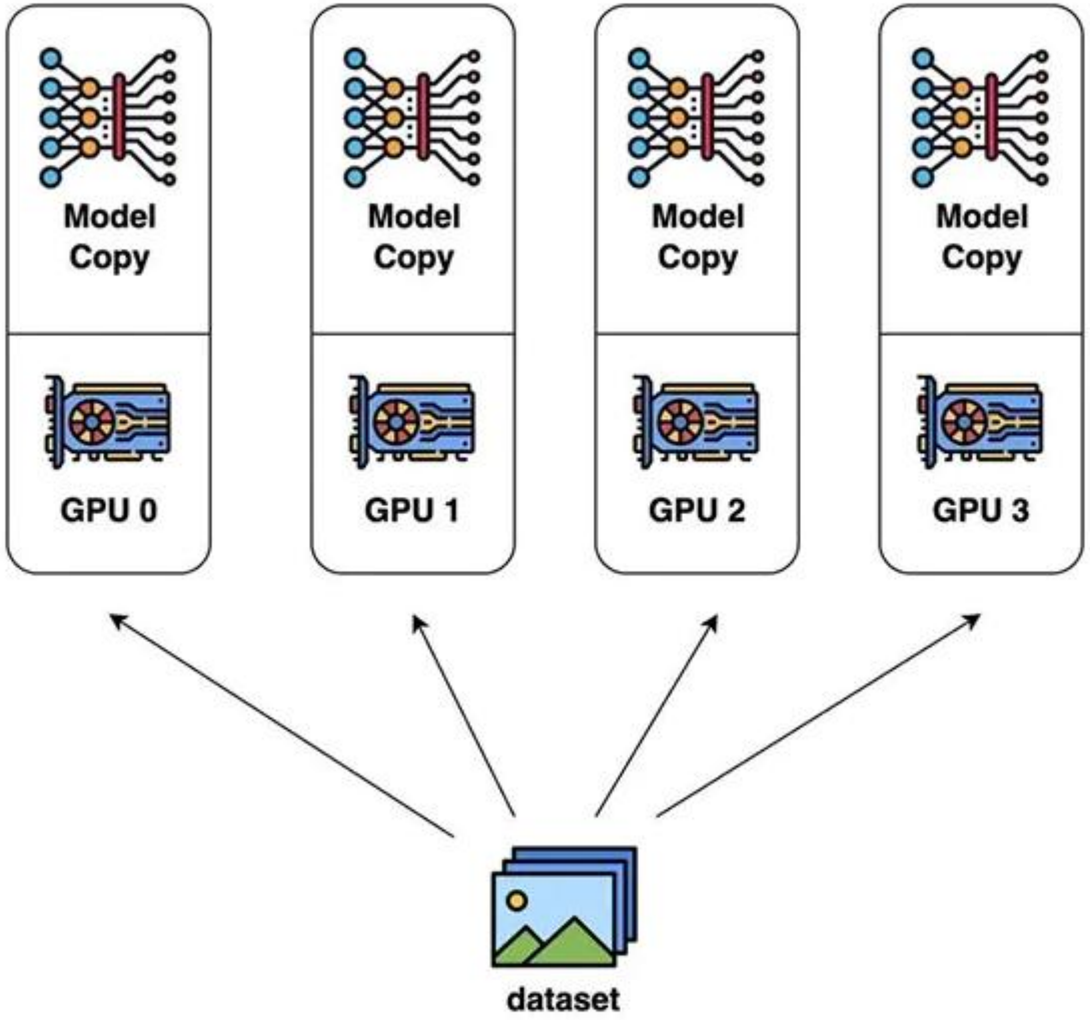
Data Parallelism (DP)



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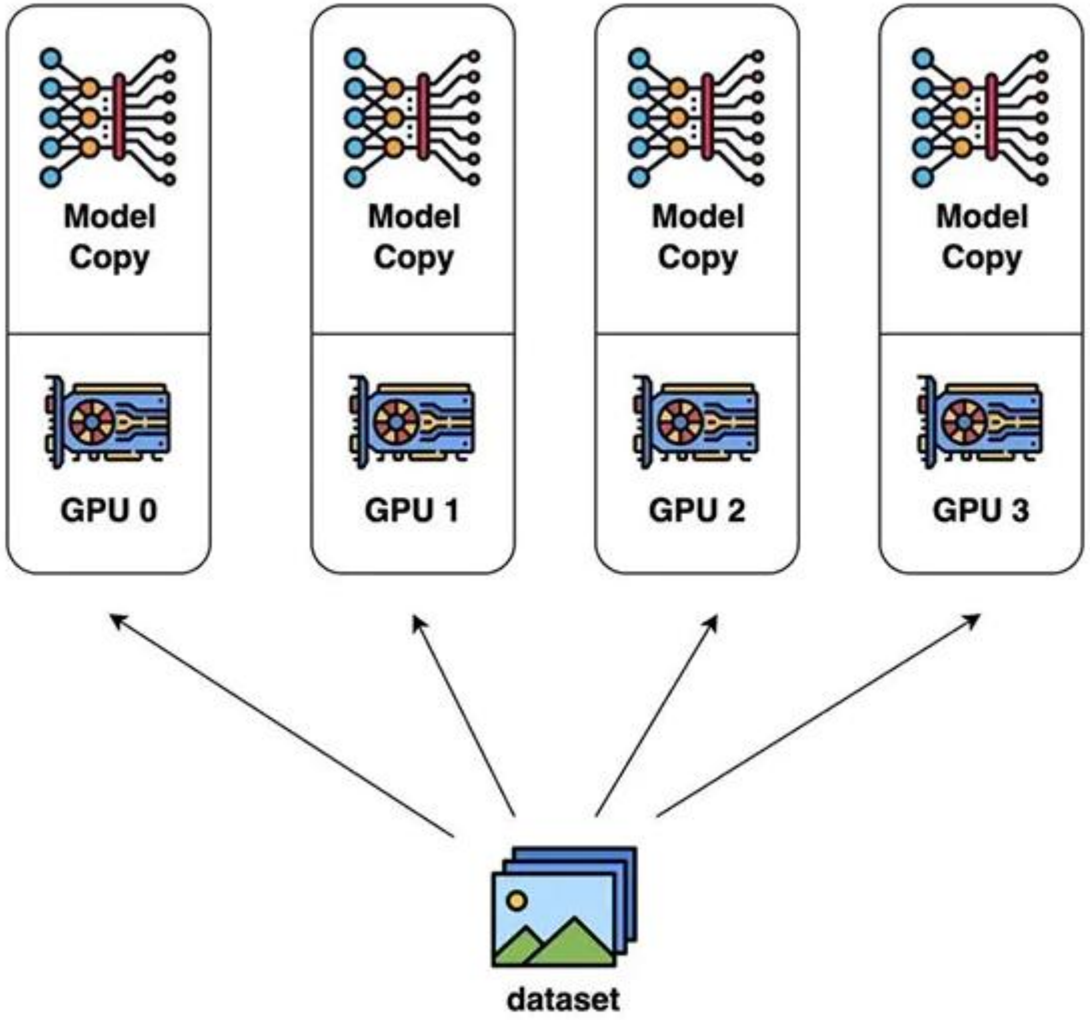
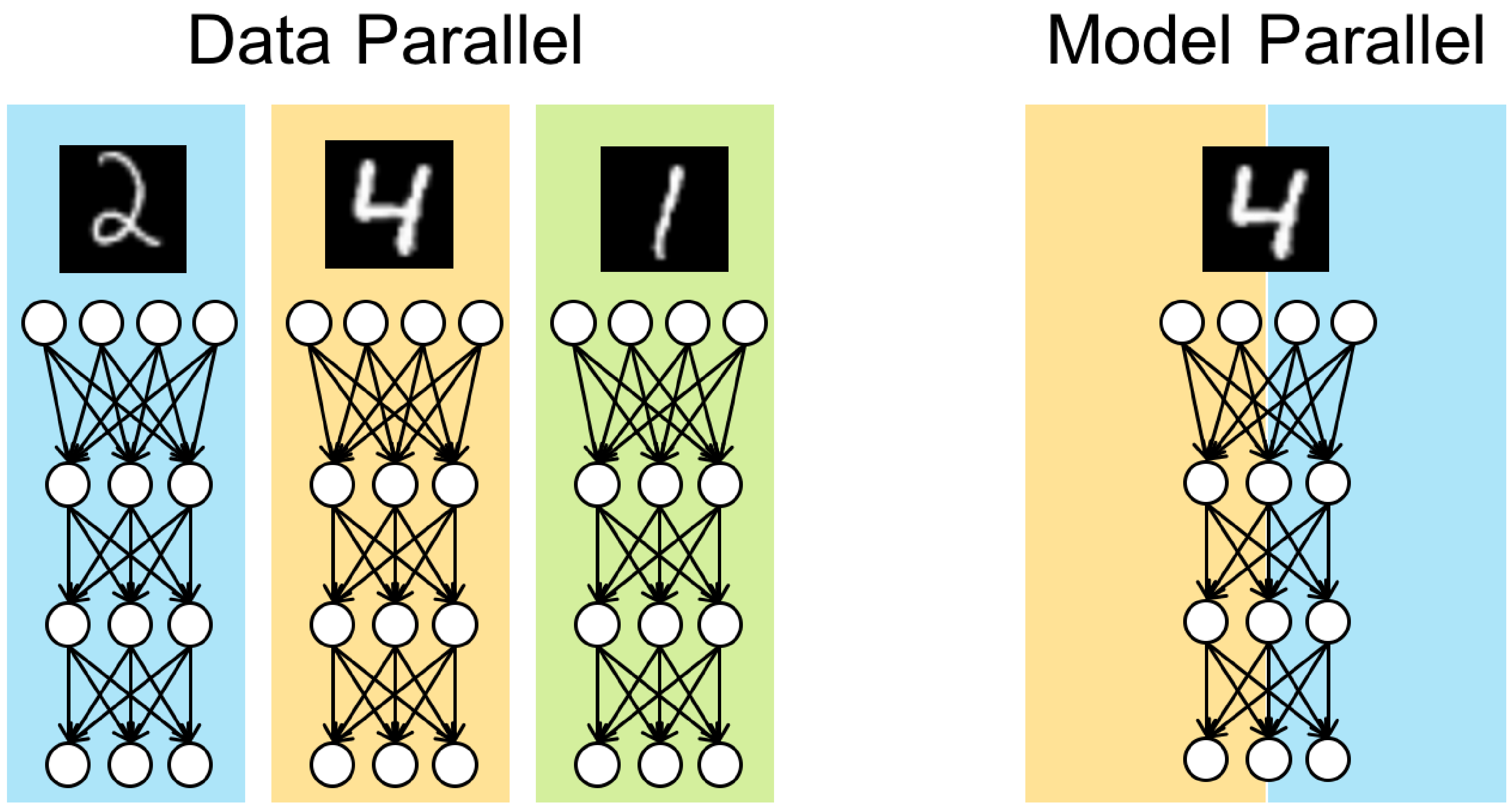


What happens when model does not fit on a single GPU?

Data Parallelism (DP) vs. Model Parallelism



Distributed DL History

2012

Reflections of DL parallelization in early DL papers

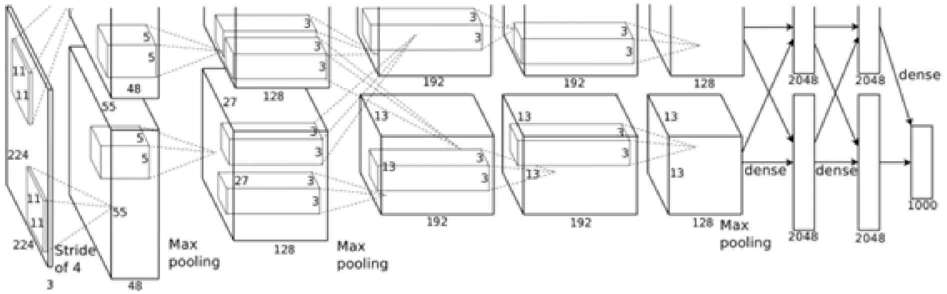
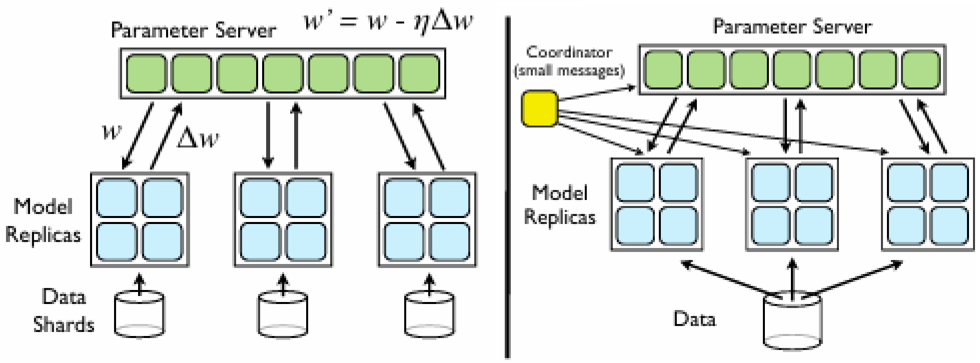


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Figure from AlexNet
[Krizhevsky et al., NeurIPS 2012],
[Krizhevsky et al., preprint, 2014]



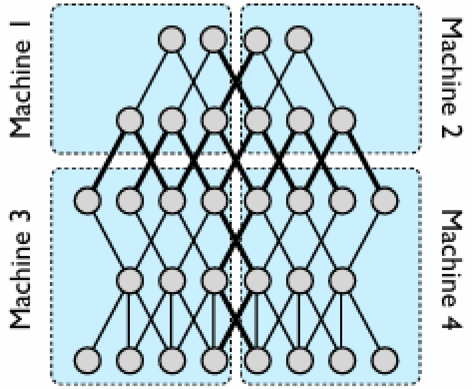


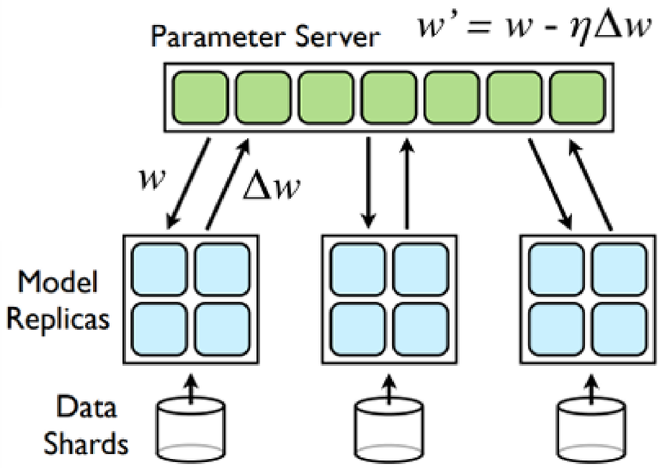
Figure from DistBelief
[Dean et al., NeurIPS 2012]

Data Parallelism with Parameter Server

2012

2016

Focus: Data parallelism with **Parameter Server**



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Various implementations of parameter servers

- DistBelief [Dean et al., NeurIPS 2012]
- Parameter server [Li et al., NeurIPS 2012], [Li et al., OSDI 2014]
- Bosen [Wei et al., SoCC 2015]
- GeePS [Cui et al., Eurosys 2016], Poseidon [Zhang et al., ATC 2017]

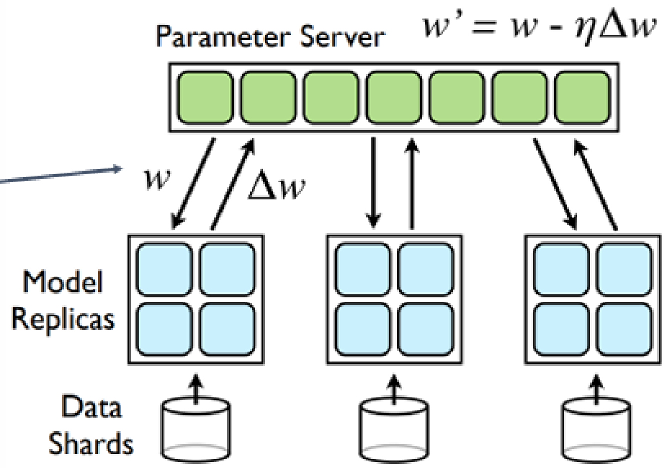
Data Parallelism with Parameter Server (Async)

2012

2016

Focus: Data parallelism with **Parameter Server**

Asynchrony: update every N iters instead of 1



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Data Parallelism with AllReduce

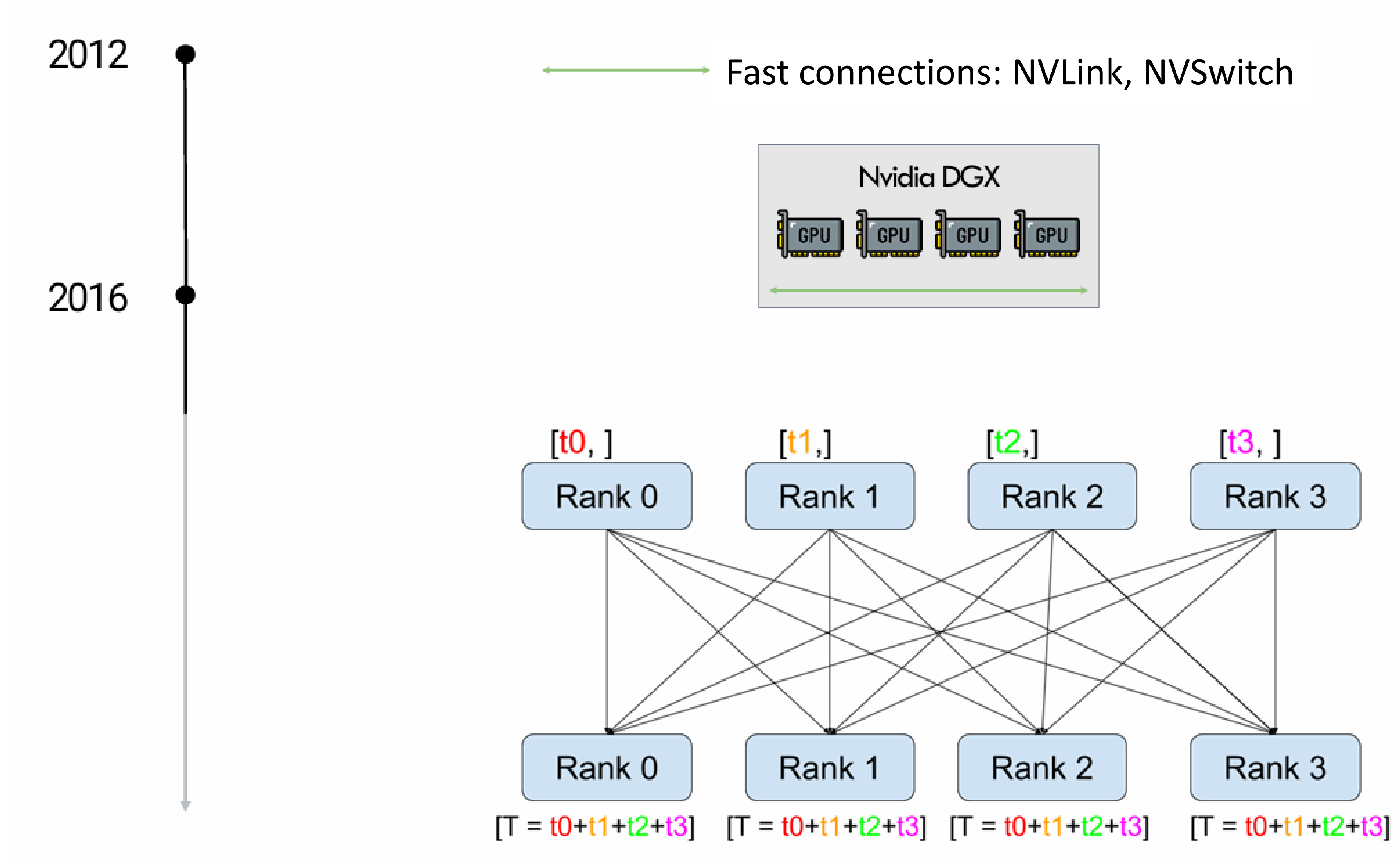


Figure from PyTorch Tutorials

Distributed Data Parallel

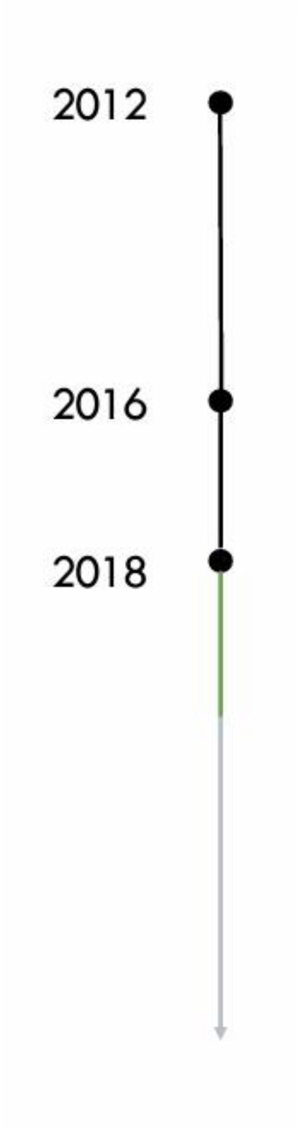
2012

2016

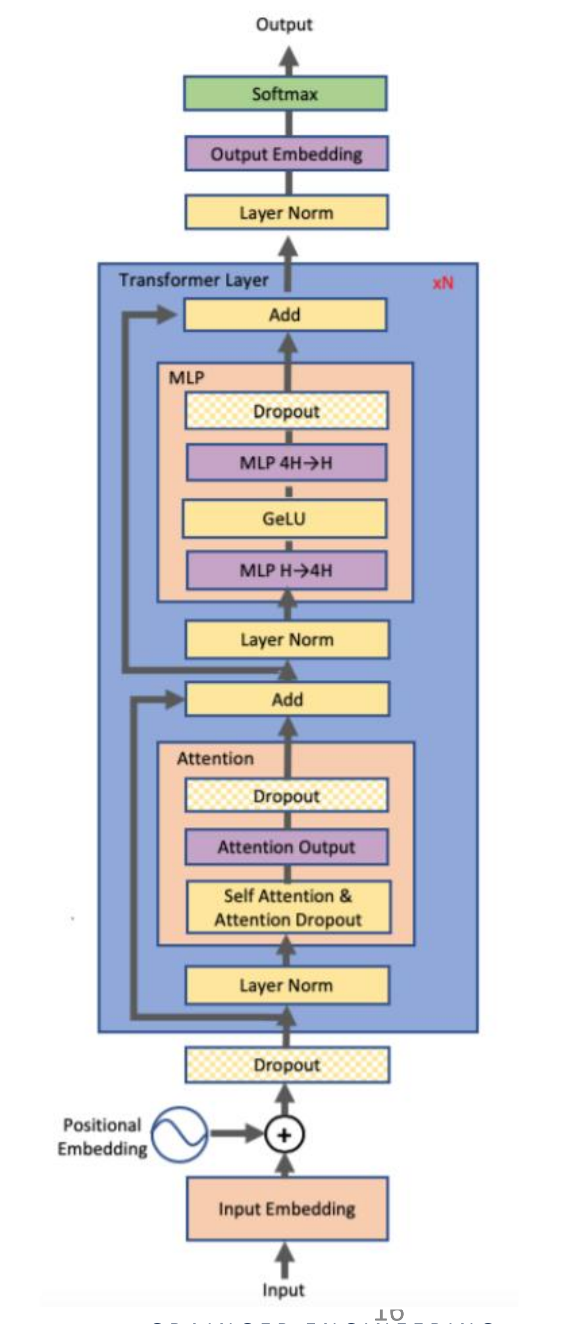
```python
import torch.nn.parallel as dist
from torch.nn.parallel import DistributedDataParallel as DDP

dist.init_process_group("nccl", rank=rank, world_size=world_size)
ddp_model = DDP(Model(), device_ids=[rank])

for batch in data_loader:
    loss = train_step(ddp_model, batch)
```

Sergeev et al., "Horovod: fast and easy distributed deep learning in TensorFlow". *Preprint 2018.*
Li et al., "PyTorch Distributed: Experiences on Accelerating Data Parallel Training". VLDB 2020.

Large Model Training Challenges



	Bert-Large	GPT-2	Turing 17.2 NLG	GPT-3
Parameters	0.32B	1.5B	17.2B	175B
Layers	24	48	78	96
Hidden Dimension	1024	1600	4256	12288
Relative Computation	1x	4.7x	54x	547x
Memory Footprint	5.12GB	24GB	275GB	2800GB



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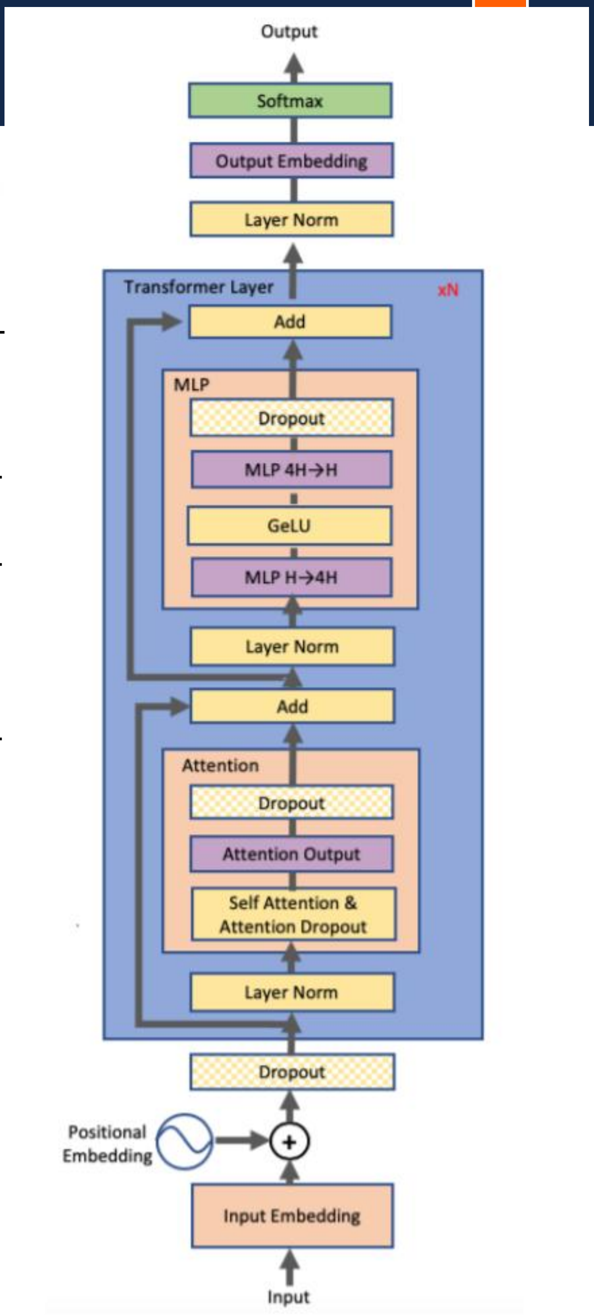
Out of Memory

NVIDIA V100 GPU memory capacity: 16G/32G
NVIDIA A100 GPU memory capacity: 40G/80G



Modern Distributed Training

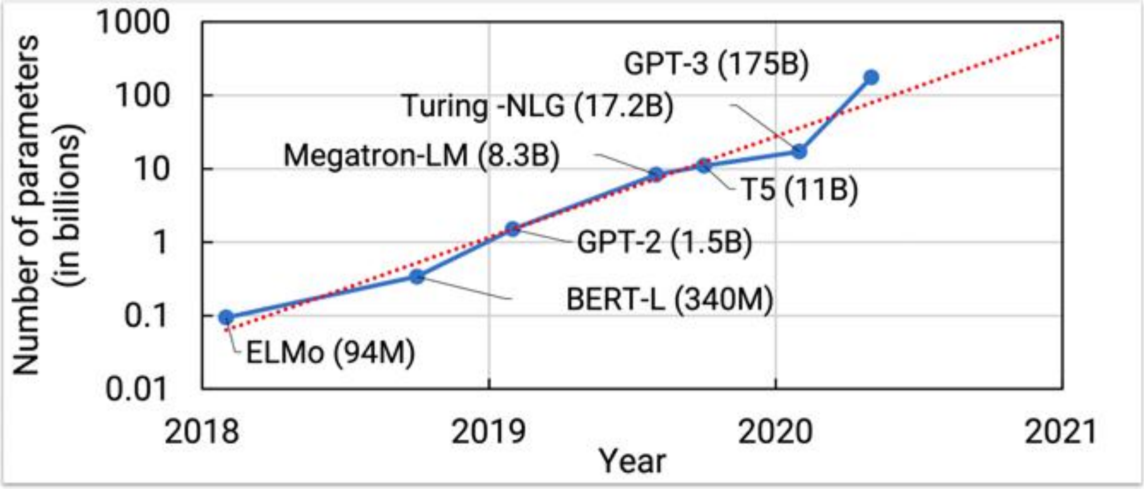
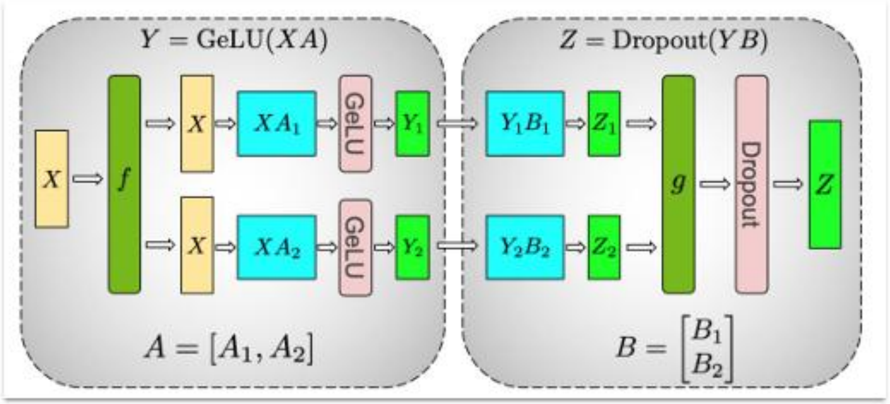
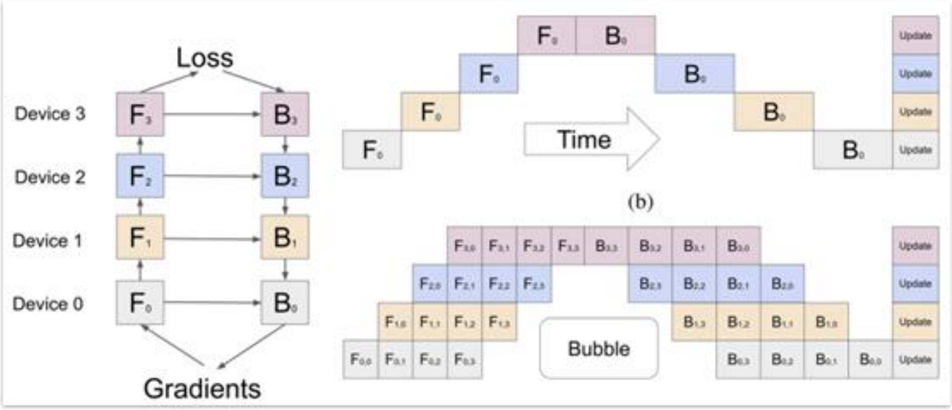


Figure from Nvidia

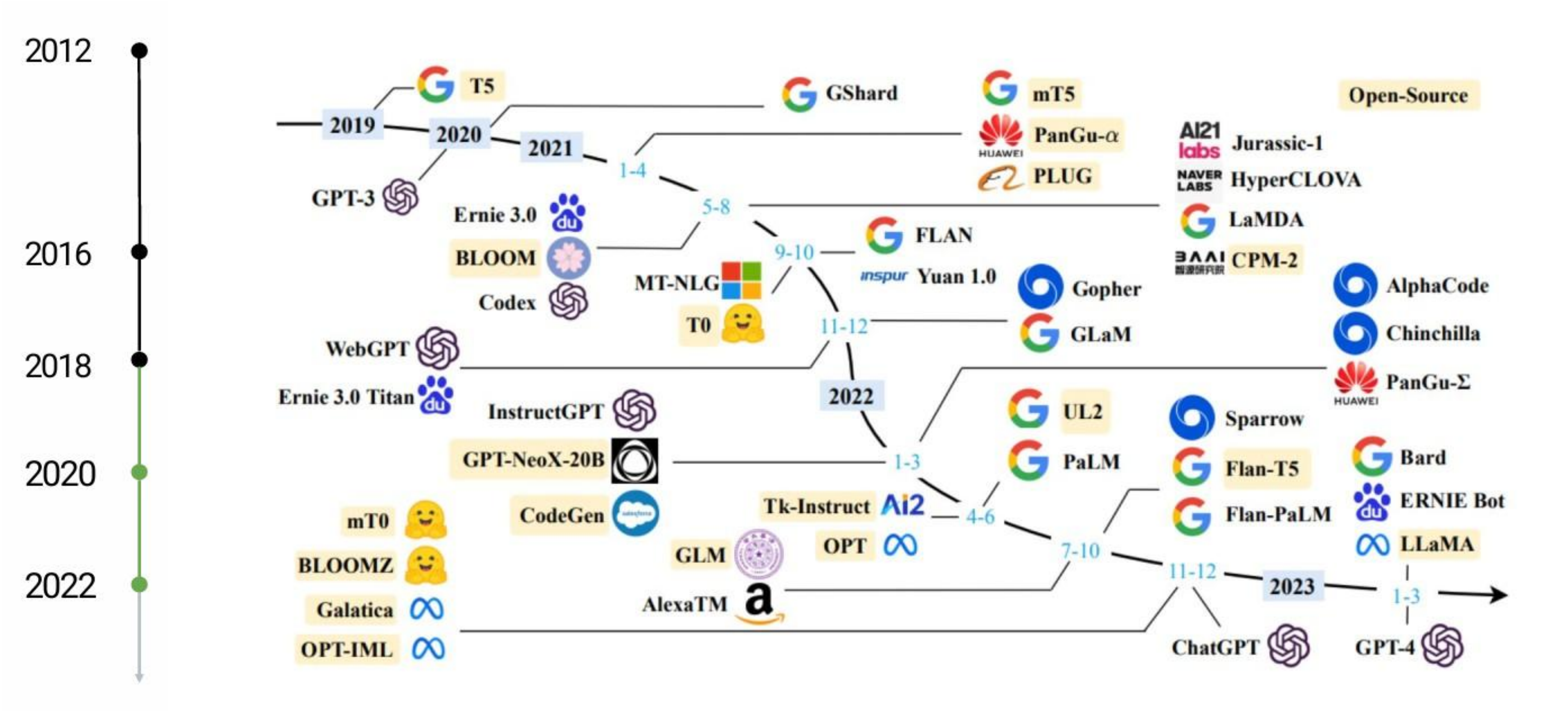


Matmul partitioning
[Shoeybi et al., ICML 2020]



Pipeline parallelism
[Huang et al., NeurIPS 2019]

Big Model Era



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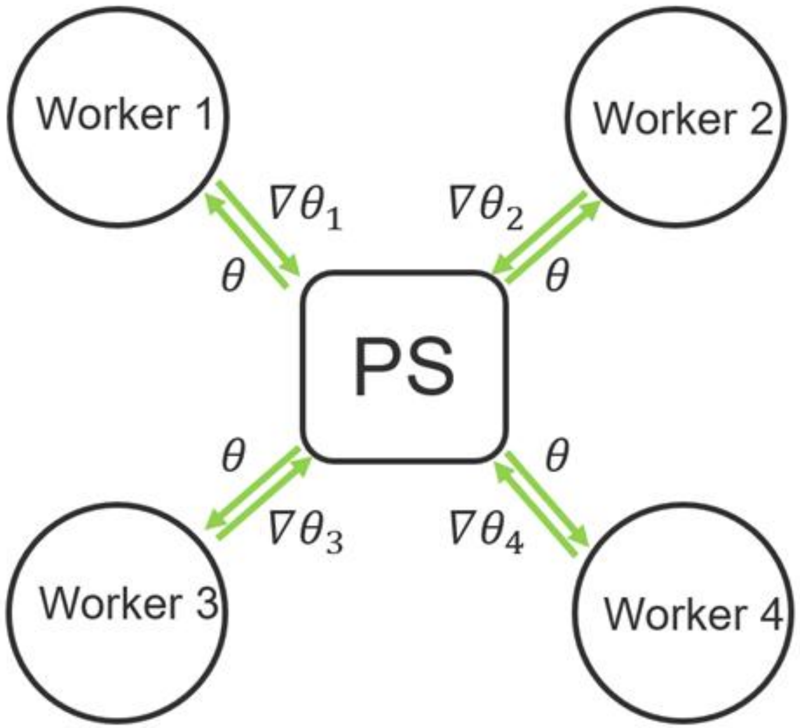
End

Two Solutions

- Parameter Server
- AllReduce
- Key assumption:
  - The model can fit into a (GPU) worker memory so we can create many model replica

Parameter Server Naturally Emerges

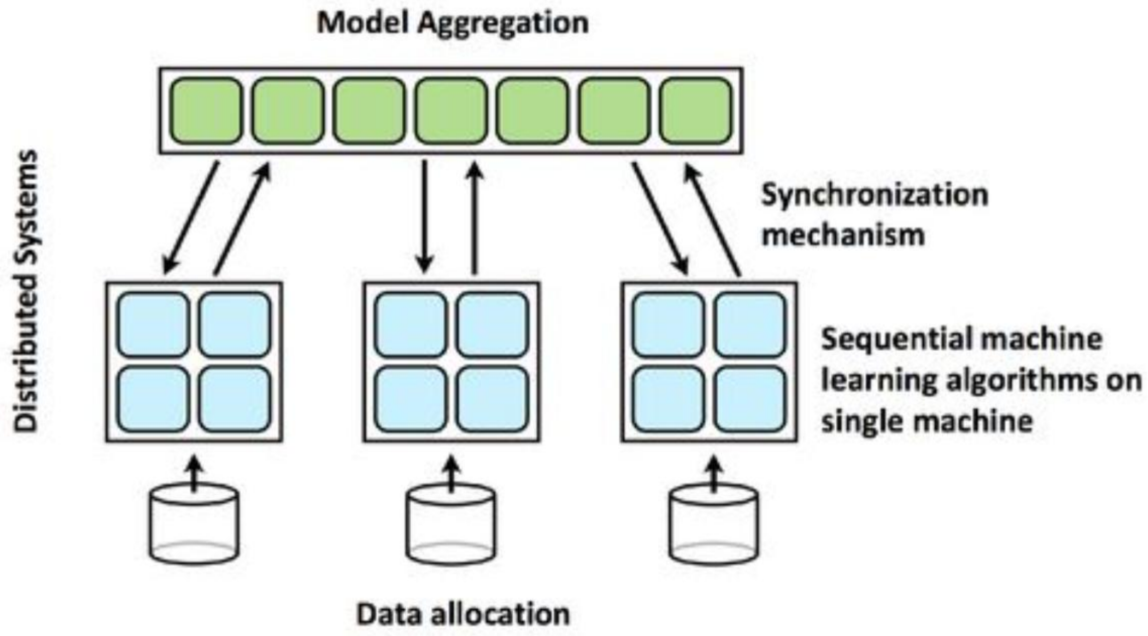


Assumptions (similar as MapReduce):
- Very heavy communication per iteration
- Compute : communication = 1:10 in the era of 2012
- Model is small enough to hold on single GPU

How to Implement Parameter Server

- Key considerations:
    - Server-Client: Communication bottleneck
    - Fault tolerance
    - Programming model
    - Consistency

Parameter Server Implementation



1. Partition the training data
2. Parallel training on different machines
3. Synchronize the local updates
4. Refresh local model with new parameters, then go to 2

Scaling Distributed Machine Learning with the Parameter Server, 2014

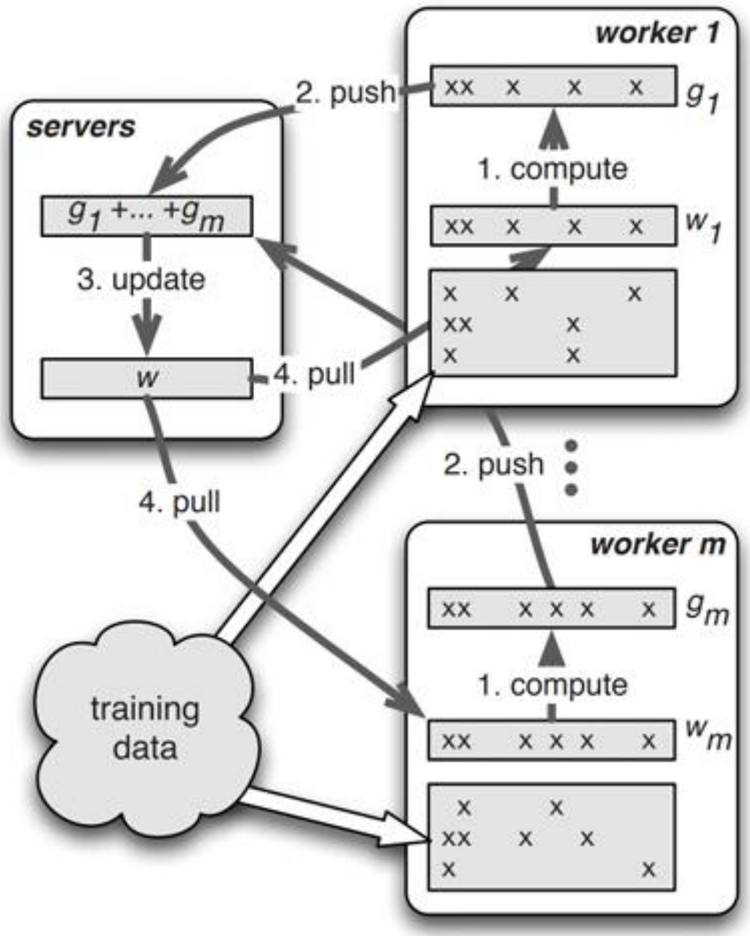
Programming Model

- Client:
  - Pull()
  - Compute()
  - Push()

- Server:
  - Update()

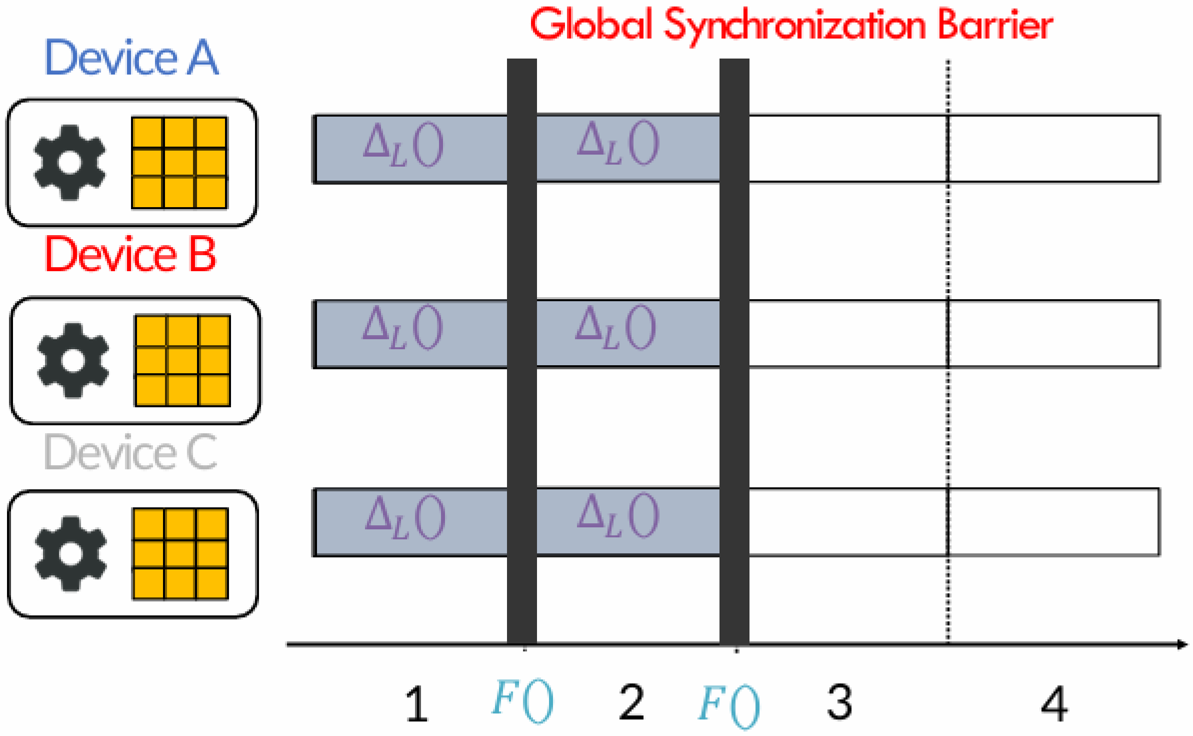
- Very similar to the spirit of MapReduce

- Flexible and can be used in various ML algorithms, not just DL



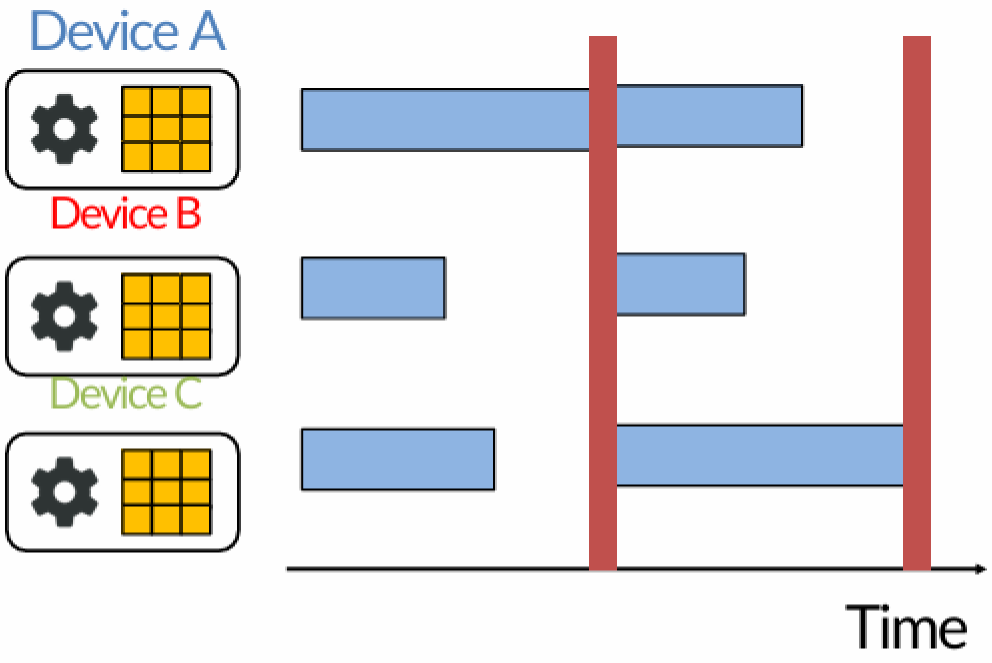
Bulk Synchronous Parallel: Consistency

$$\theta^{(t+1)} = \theta^{(t)} + \varepsilon \sum_{p=1}^{P} \nabla_{\mathcal{L}}(\theta^{(t)}, D_p^{(t)})$$



Stragglers

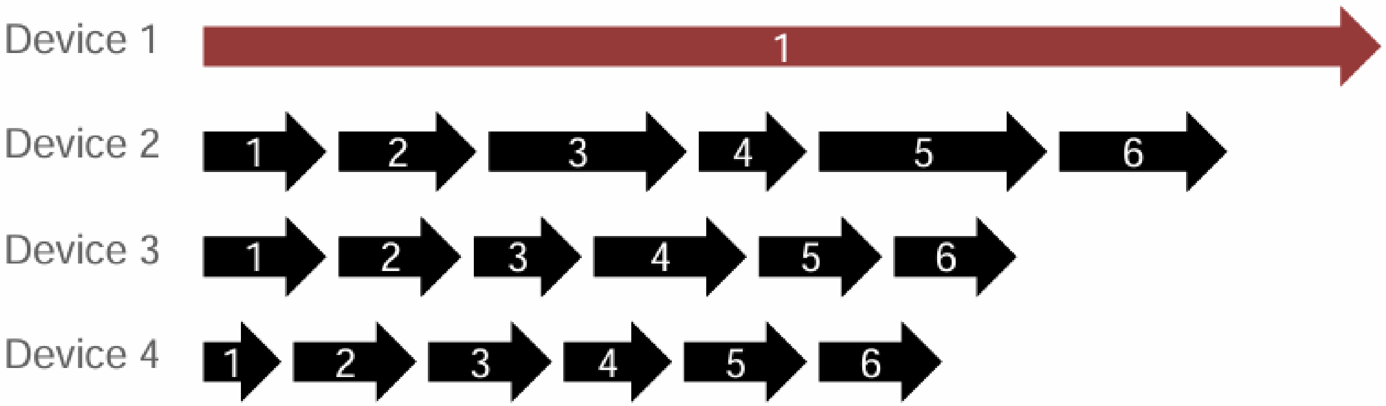
- **BSP suffers from stragglers**
  - Slow devices (stragglers) force all devices to wait
  - More devices → higher chance of having a straggler



Asynchronous Communication (No Consistency)

- **Asynchronous (Async):** removes all communication barriers
  - Maximizes computing time
  - Transient stragglers will cause messages to be extremely stale
    - Ex: Device 2 is at $t = 6$, but Device 1 has only sent message for $t = 1$

- **Some Async software:** messages can be applied while computing $F()$, $\Delta_L()$
  - Unpredictable behavior, can hurt statistical efficiency!

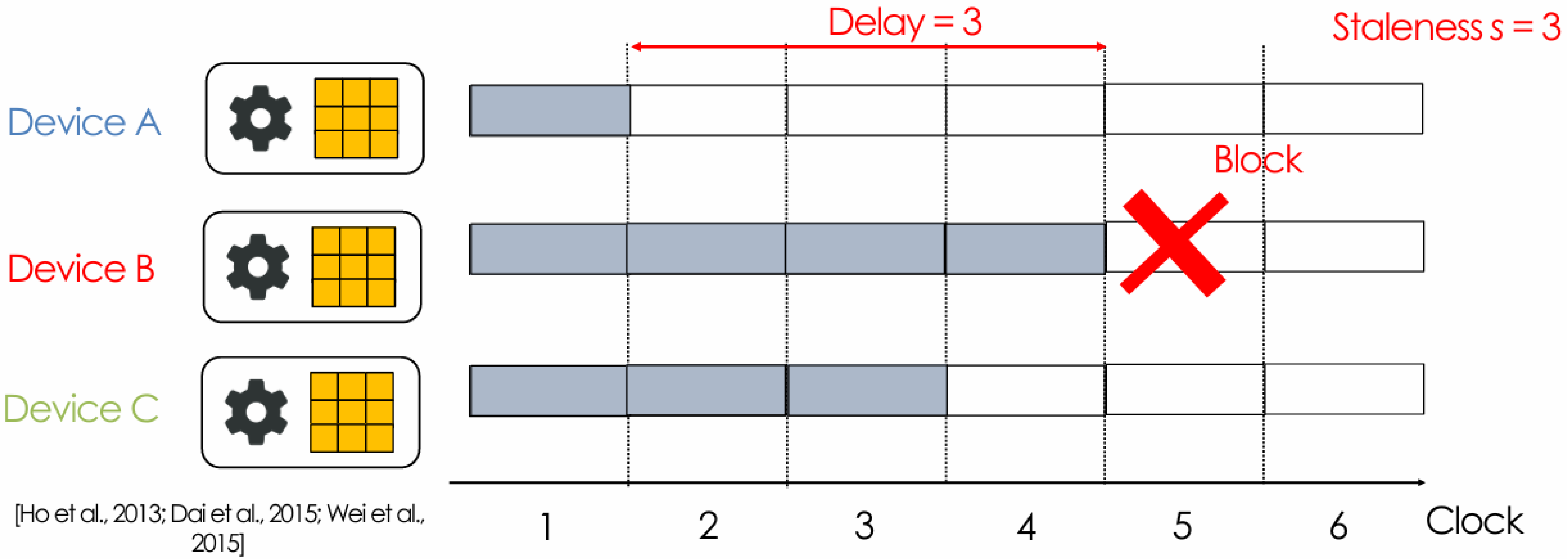


Bounded Consistency

Bounded consistency models: Middle ground between BSP and fully-asynchronous (no-barrier)

e.g. Stale Synchronous Parallel (SSP): Devices allowed to iterate at different speeds

- Fastest & slowest device must not drift > s iterations apart (in this example, $s = 3$)
  - s is the maximum staleness



[Ho et al., 2013; Dai et al., 2015; Wei et al., 2015]

Impacts of Consistency/Staleness: Unbounded Staleness