Distributed Training

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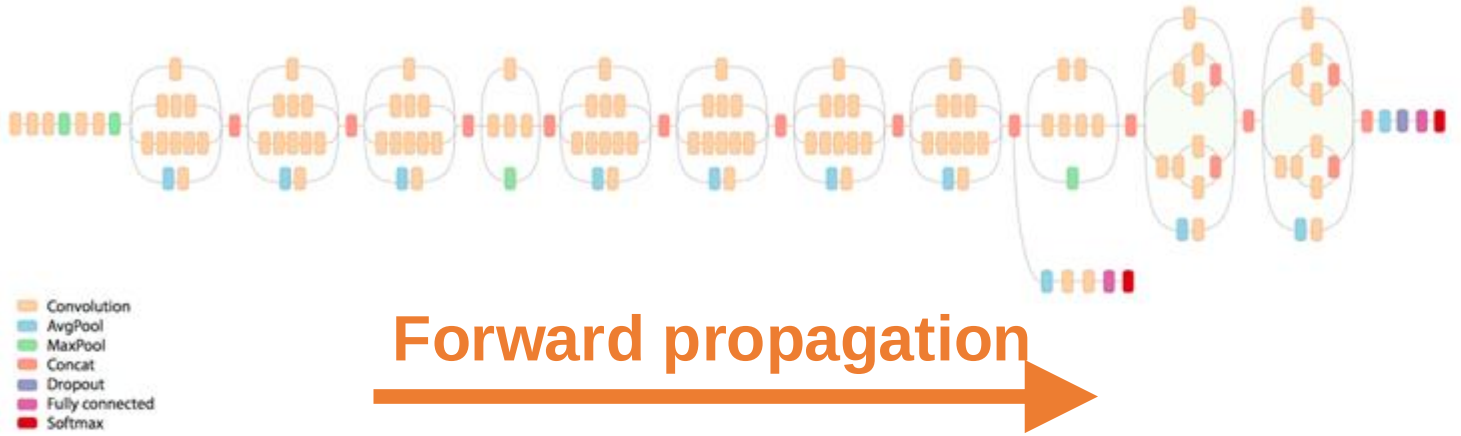
Material adapted from slides by Tianqi Chen & Zhihao Jia (CMU), Minjia Zhang (UIUC)

Stochastic Gradient Descent (SGD)

Train ML models through many iterations of 3 stages

1. **Forward propagation**: apply model to a batch of input samples and run calculation through operators to produce a prediction
2. **Backward propagation**: run the model in reverse to produce a gradient for each trainable weight
3. **Weight update**: use the accumulated gradients to update model weights

Model inputs



Model prediction

Forward propagation

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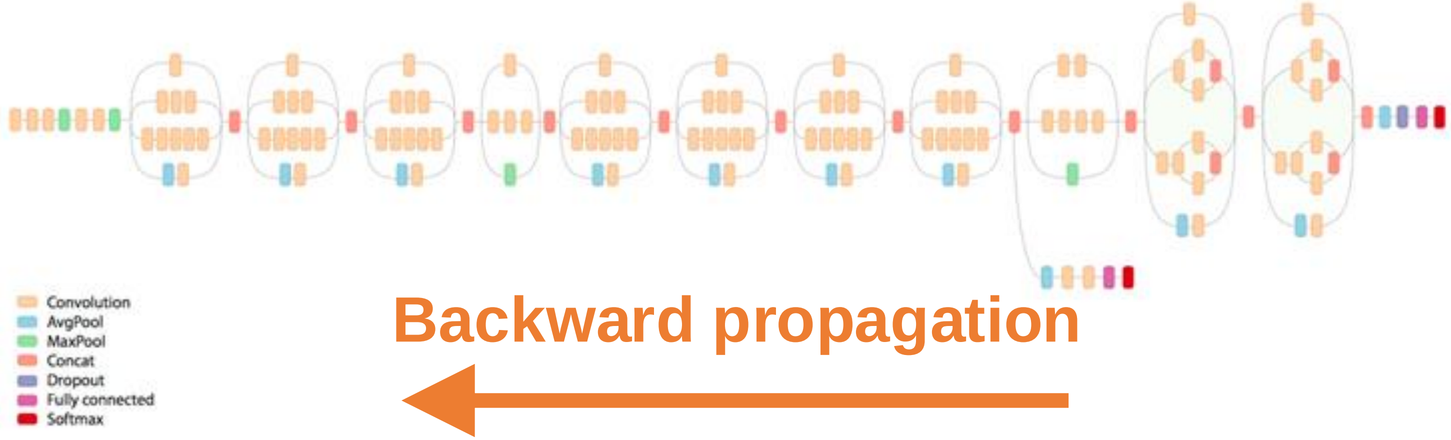

Model prediction

Backward propagation

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$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n} \sum_{j=1}^{n} \nabla L_j(w_i)$$

Key Concepts

ML training state can be classified into the following:

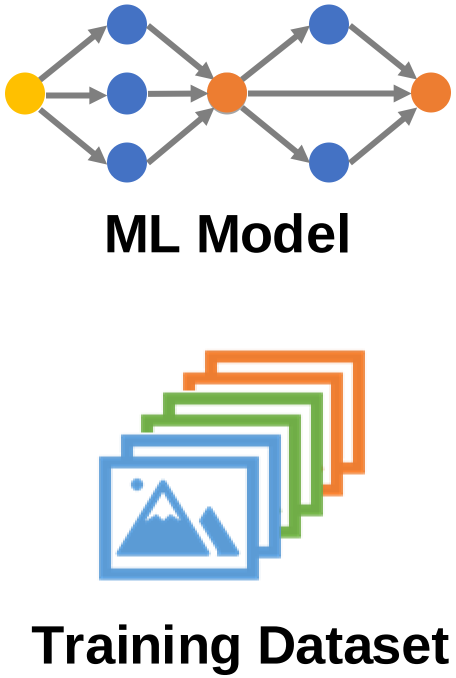
- **Model parameters:** eventually becomes the released model
- **Gradients:** how the loss function varies with small changes to parameters
- **Activations:** intermediate results from the forward phase required for back-propagating gradients
- **Optimizer state:** maintains information about how parameters change over time

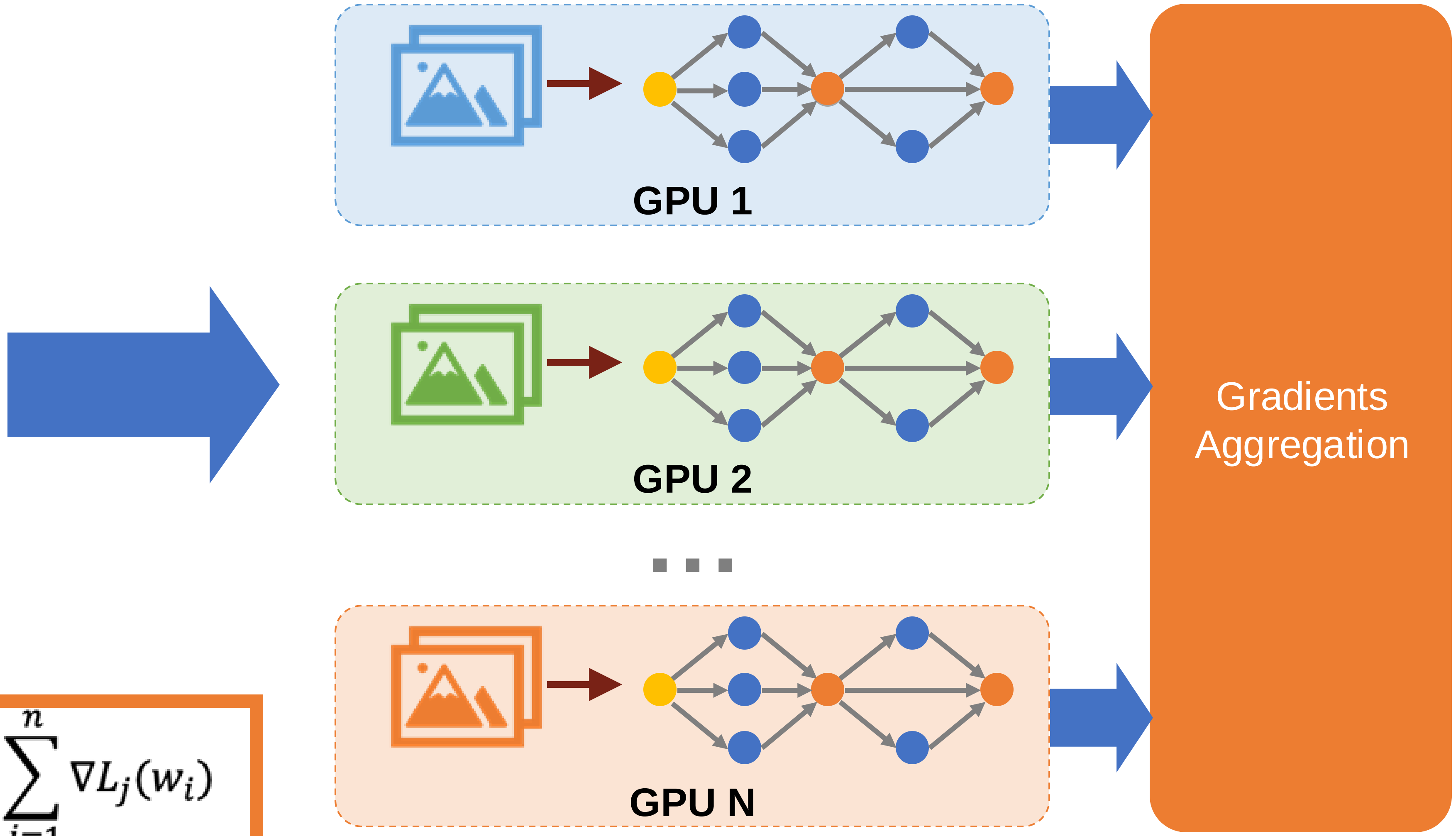
How can we parallelize ML training?

Goals:

- Scale with training data size
- Scale with model size

Data Parallelism





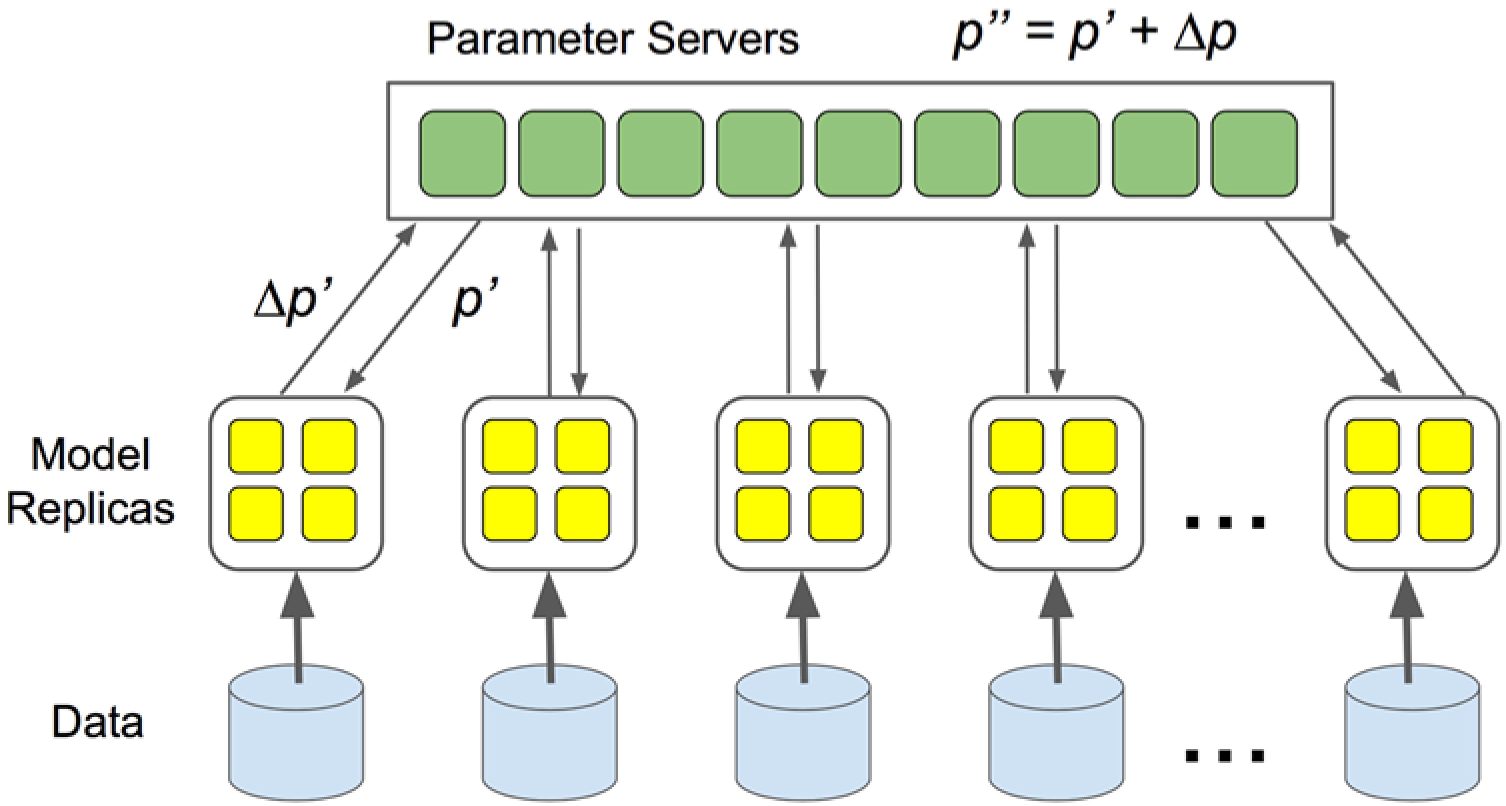
$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n} \boxed{\sum_{j=1}^{n} \nabla L_j(w_i)}$$

1. Partition training data into batches

2. Compute the gradients of each batch on a GPU

3. Aggregate gradients across GPUs

Data Parallelism: Parameter Server

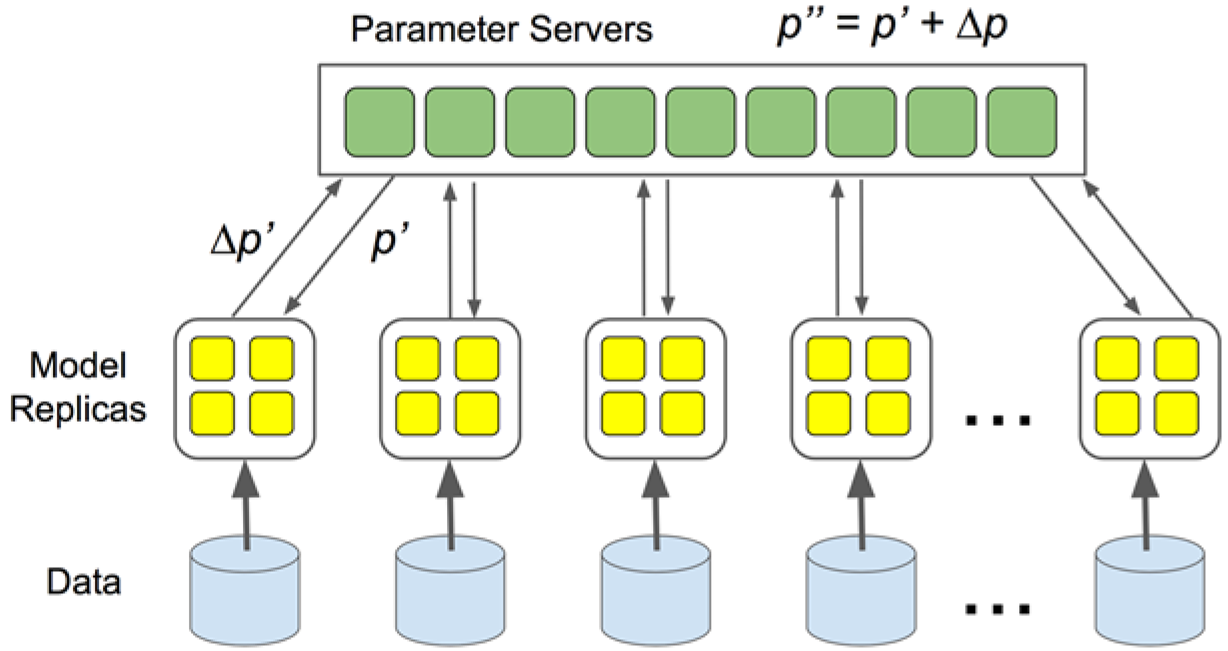


Workers push gradients to parameter servers and pull updated parameters back

Inefficiency of Parameter Server

- **Centralized communication**: all workers communicate with parameter servers for weights update; cannot scale to large numbers of workers

- How can we decentralize communication in DNN training?

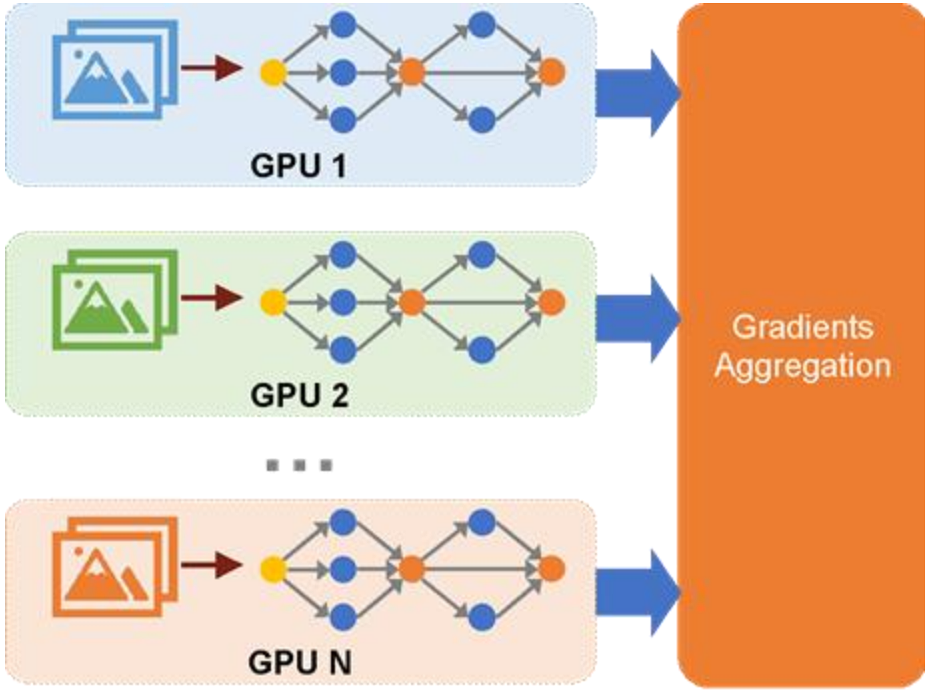


Data Parallelism: AllReduce

- **AllReduce**: perform element-wise reduction across multiple devices

Data Parallelism

Each worker keeps a replica of the entire model and communicates with other workers to synchronize weights updates



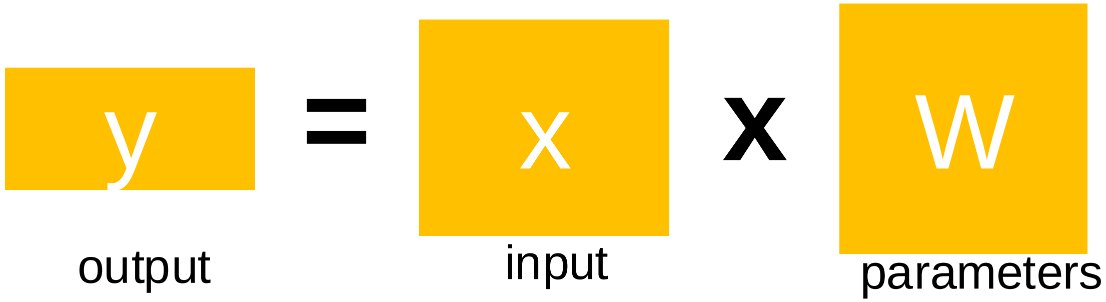
Gradients aggregation methods:

- Parameter Server
- Ring AllReduce
- Tree AllReduce
- Butterfly AllReduce
- Etc.

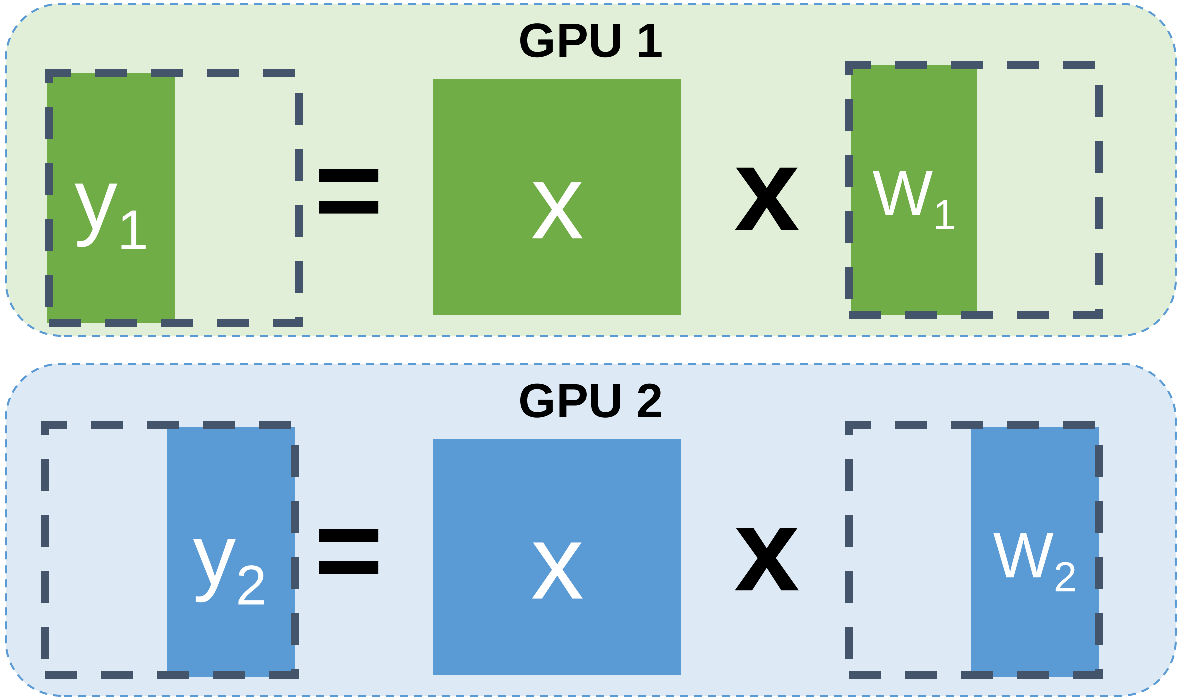
How to parallelize DNN Training?

- Data parallelism
- Model parallelism
  - Tensor model parallelism
  - Pipeline model parallelism

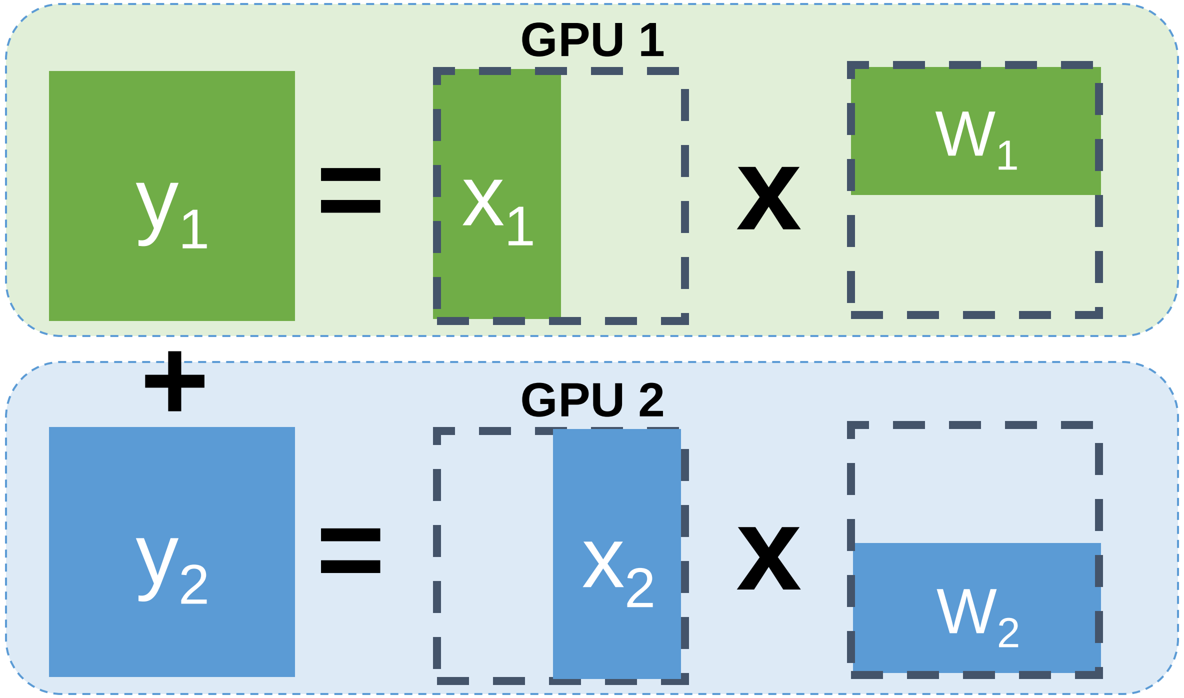
Tensor Model Parallelism



- Partition parameters/gradients ***within*** a layer



Tensor Model Parallelism (partition output)



Tensor Model Parallelism (reduce output)

$$y = y1 + y2$$

Pipeline Parallelism

- Divide a mini-batch into multiple micro-batches
- Pipeline the forward/backward computations across micro-batches
- Generally combined with model parallelism

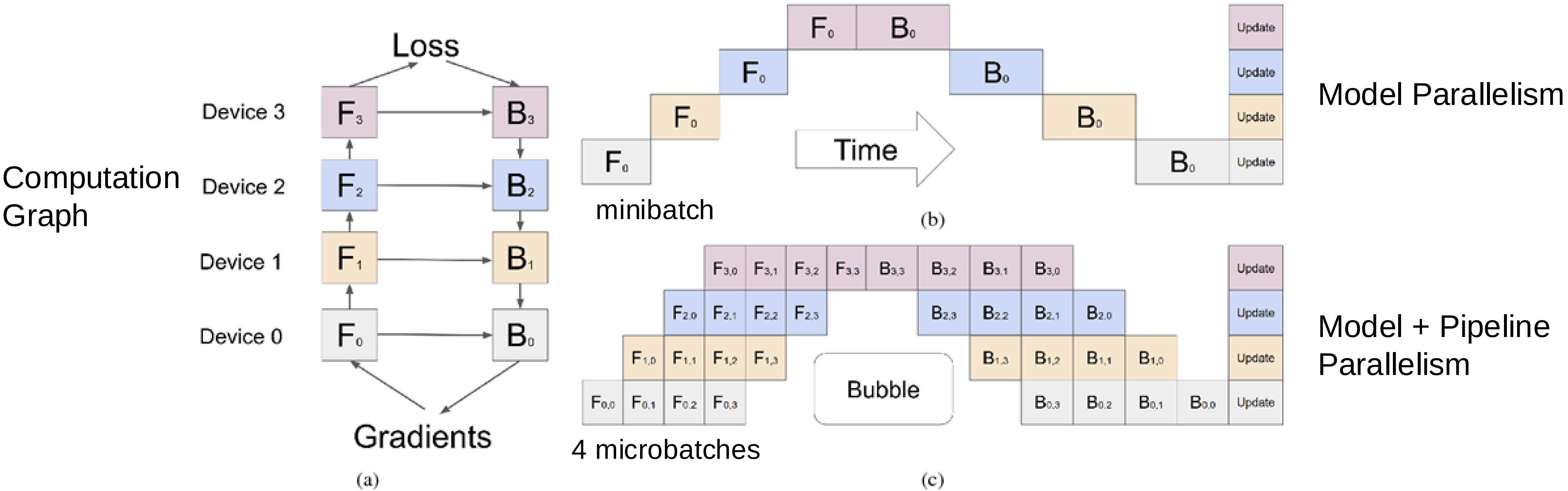
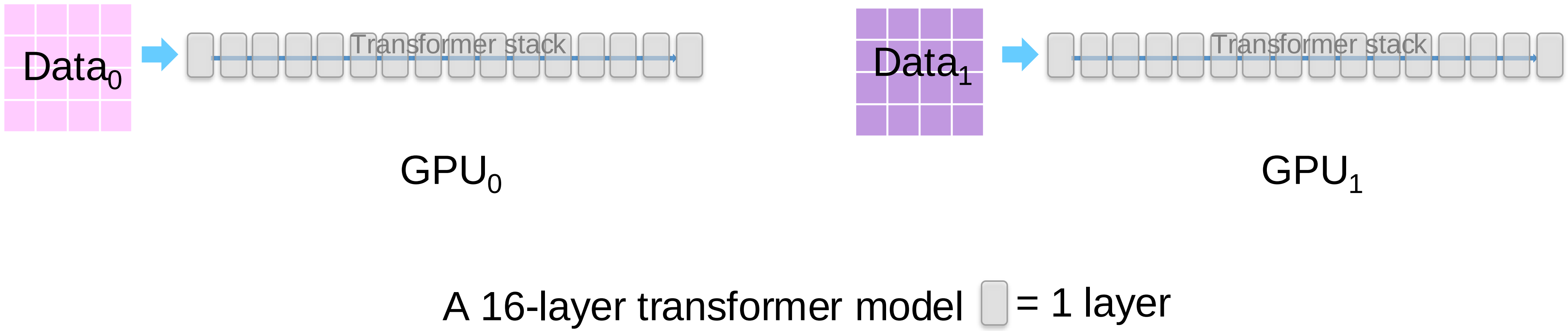


Figure from GShard: Scaling Giant Models with Conditional Computation and Automatic Sharding

Understanding Memory Consumption



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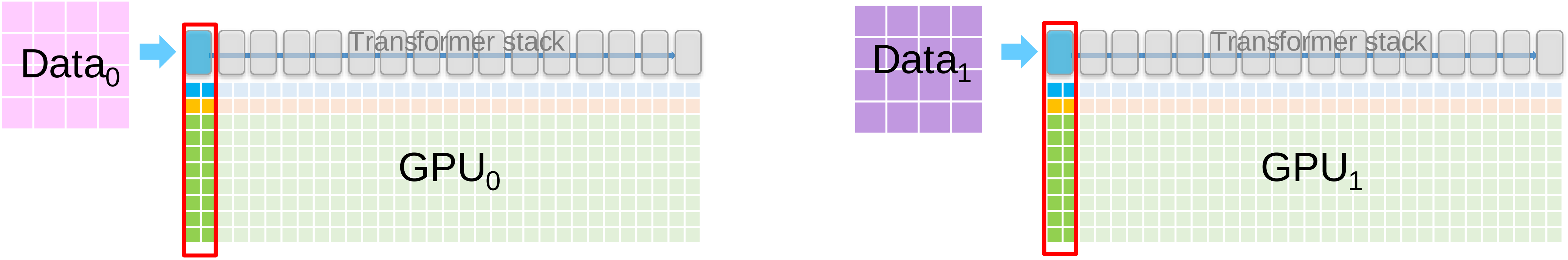
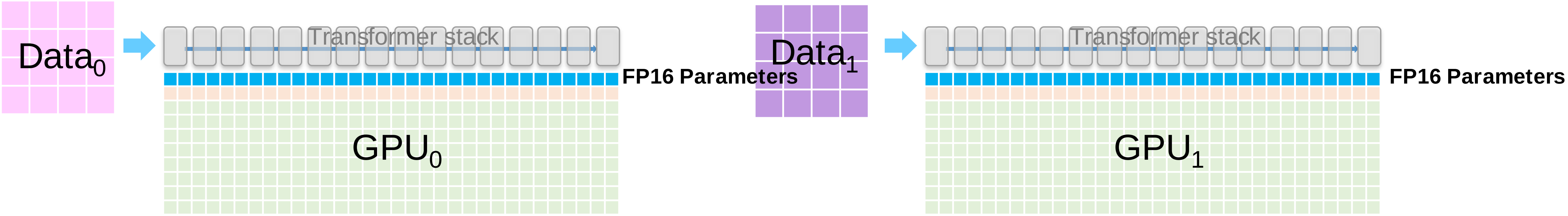


Each cell represents GPU memory used by its corresponding transformer layer

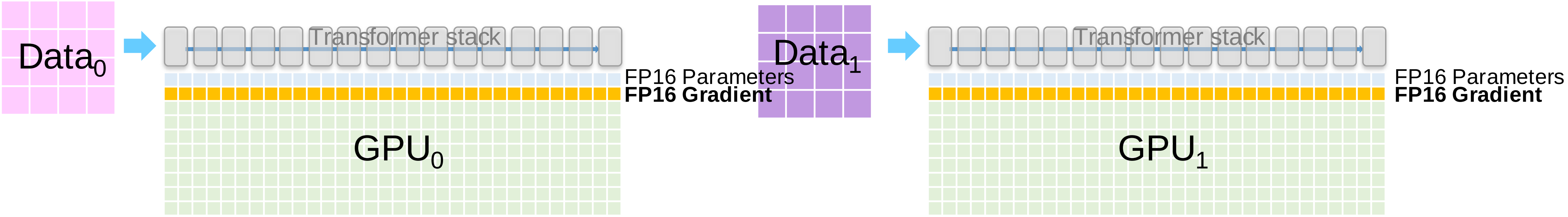
Adapted from Minjia Zhang, DeepSpeed Presentation

Understanding Memory Consumption



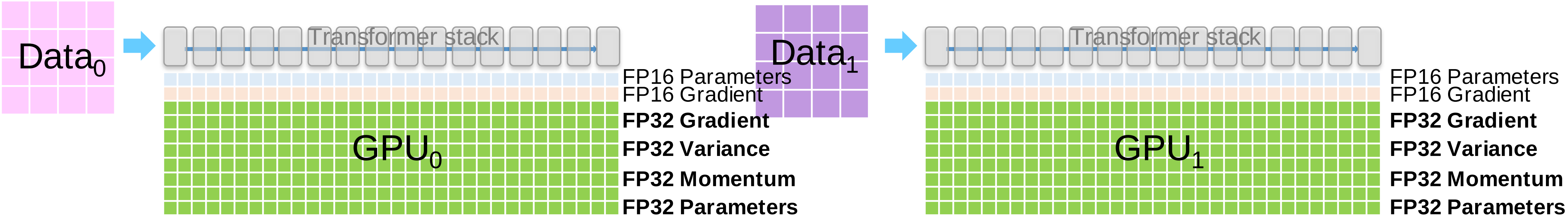
- FP16 parameter

Understanding Memory Consumption



- FP16 parameter
- FP16 Gradients

Understanding Memory Consumption



- FP16 parameter
- FP16 Gradients
- FP32 Optimizer States
  - Gradients, Variance, Momentum, Parameters

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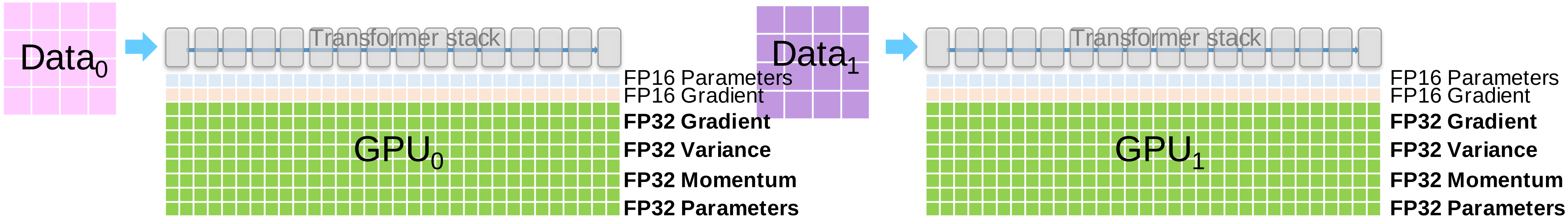
Understanding Memory Consumption



- FP16 parameter : **2M bytes**
- FP16 Gradients : **2M bytes**
- FP32 Optimizer States : **16M bytes**
  - Gradients, Variance, Momentum, Parameters

M = number of parameters in the model

Example 1B parameter model -> 20GB/GPU

Memory consumption doesn’t include:

- Input batch + activations

Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO-DP: ZeRO powered Data Parallelism

- ZeRO removes the redundancy across data parallel process
- Stage 1: partitioning optimizer states
- Stage 2: partitioning gradients
- Stage 3: partitioning parameters