System for Artificial Intelligence

Parallelization and Training II

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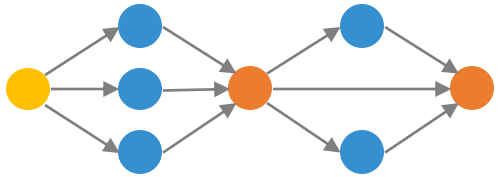
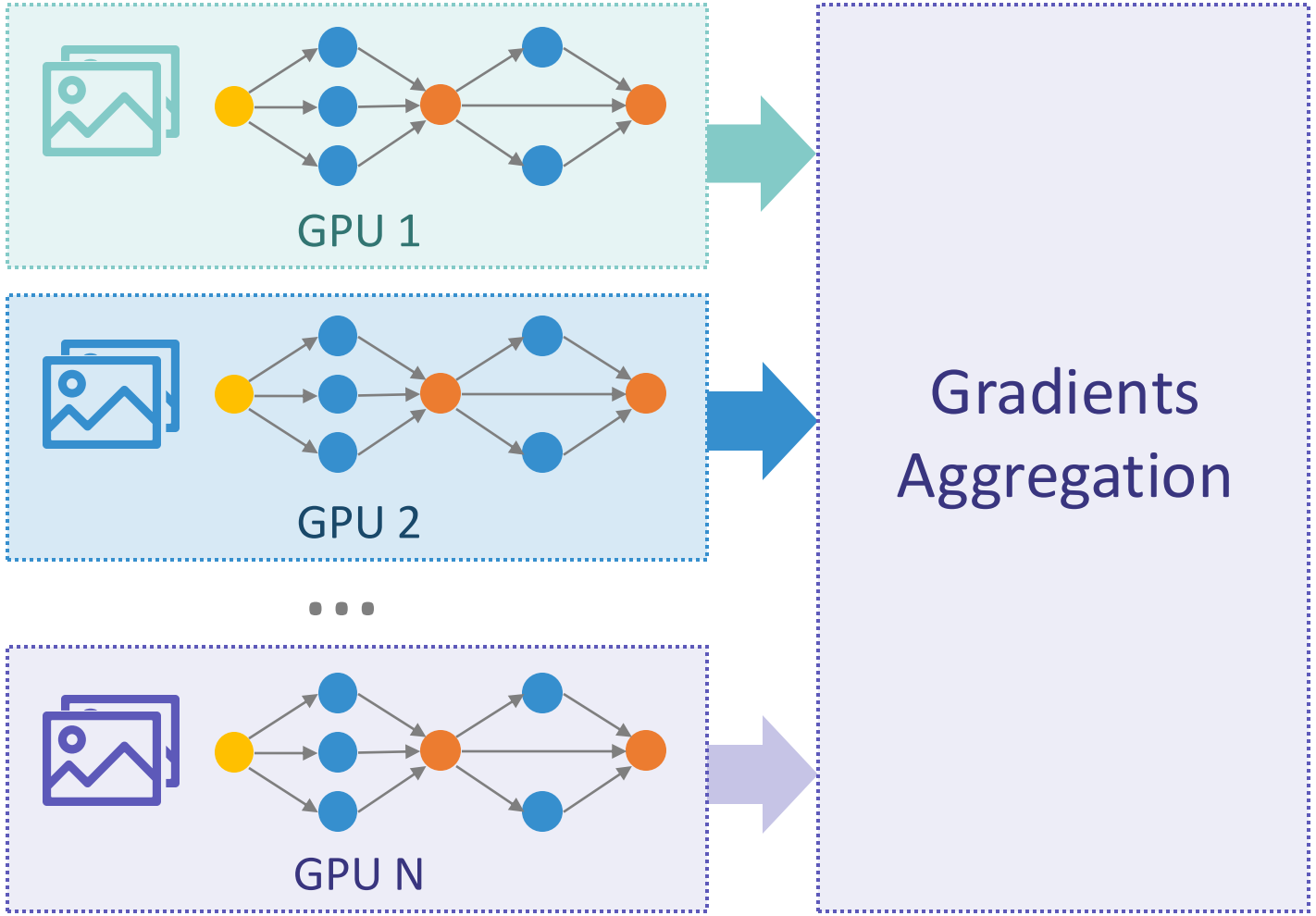
Recap: Data Parallelism



ML Model

Training Dataset

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



1. Partition training data into batches

2. Compute the gradients of each batch on a GPU

3. Aggregate gradients across GPUs

Recap: An Issue with Data Parallelism

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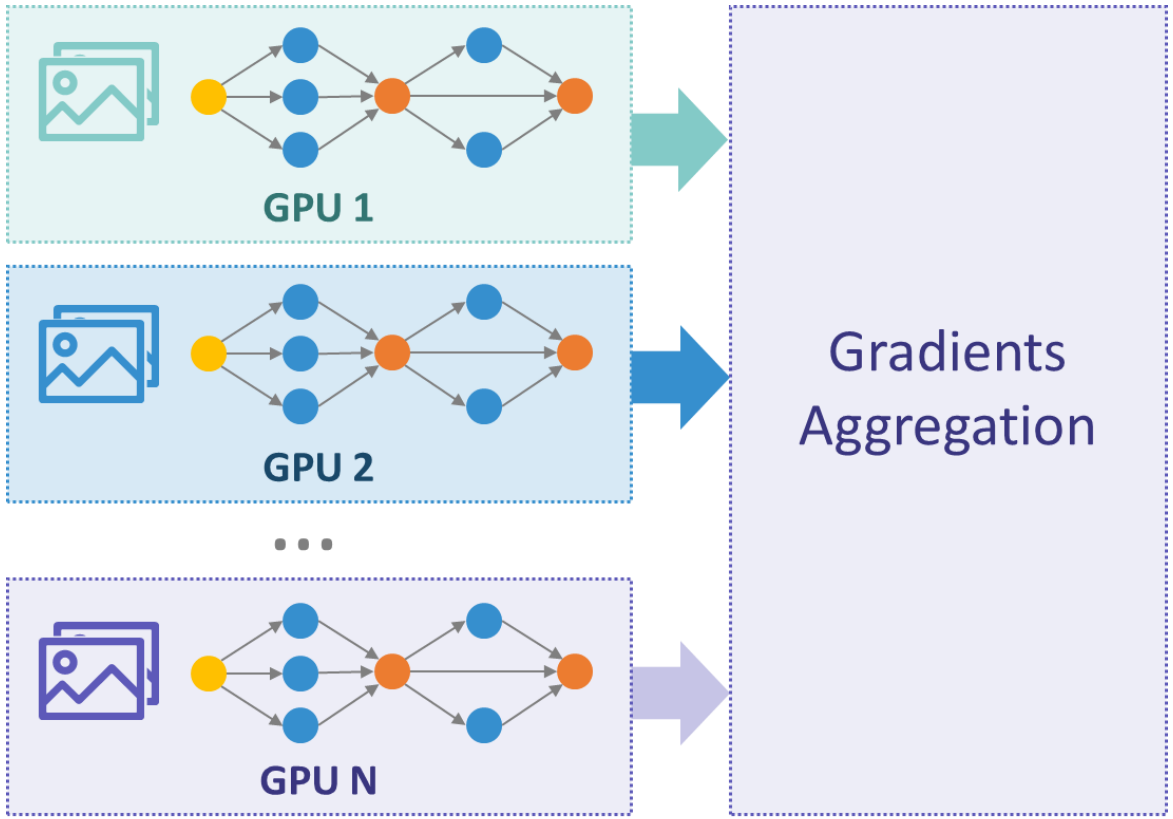
- Each GPU saves a replica of the entire model
- Cannot train large models that exceed GPU device memory



Model Parallelism

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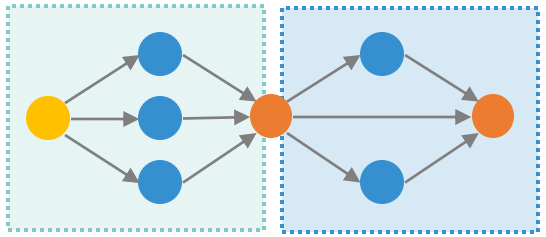
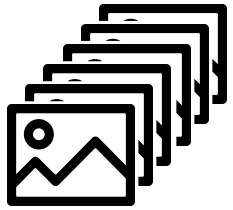
- Split a model into multiple subgraphs and assign them to different devices

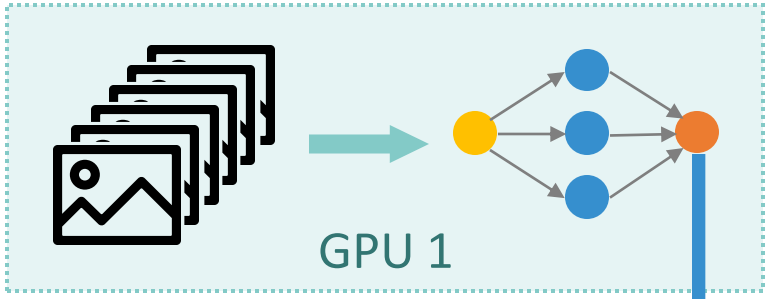


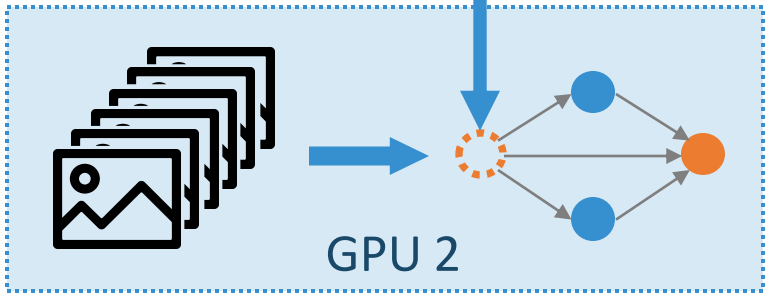
ML Model



Training Dataset

Model Parallelism





Transfer intermediate results between devices

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

How to parallelize DNN Training?

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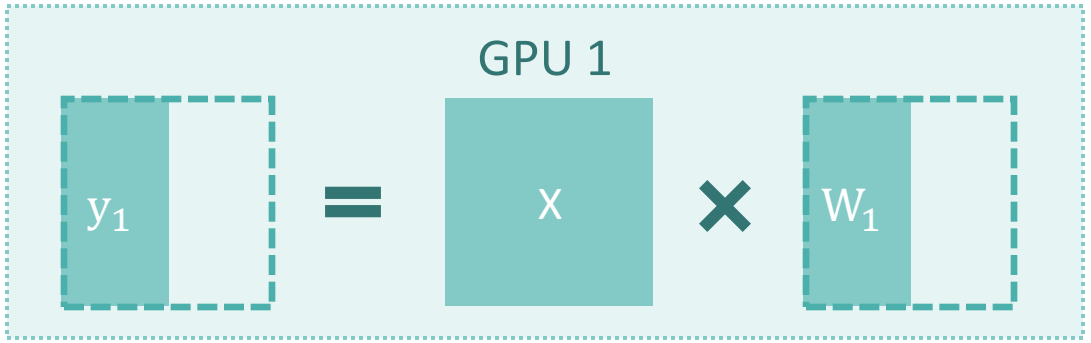
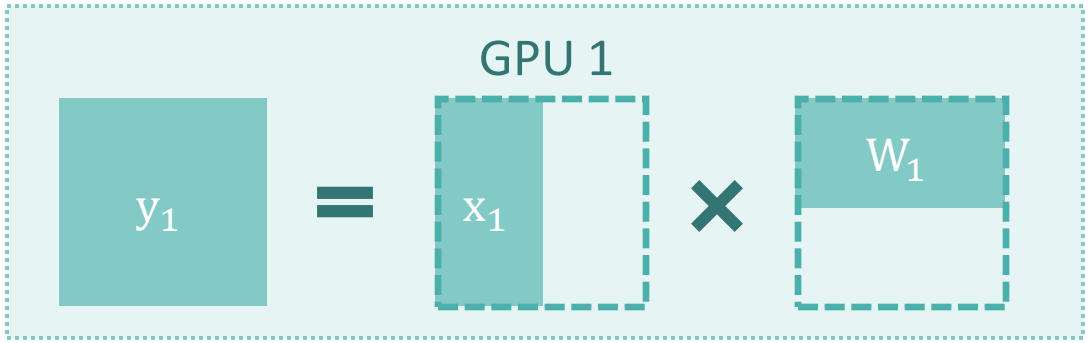
- Data parallelism
- Model parallelism
  - Tensor model parallelism
  - Pipeline model parallelism

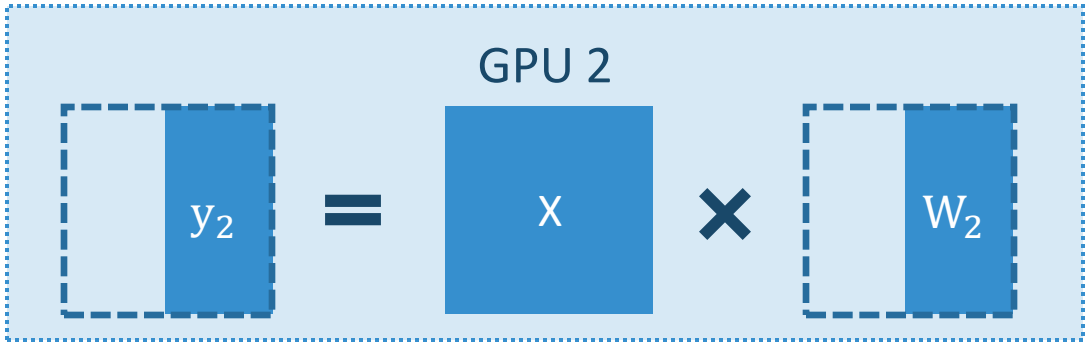
Tensor Model Parallelism

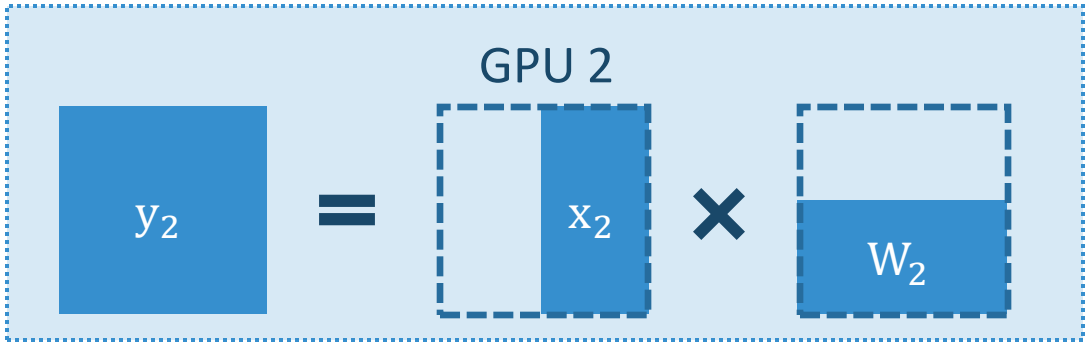
- Partition parameters/gradients ***within*** a layer



Tensor Model Parallelism (partition output)



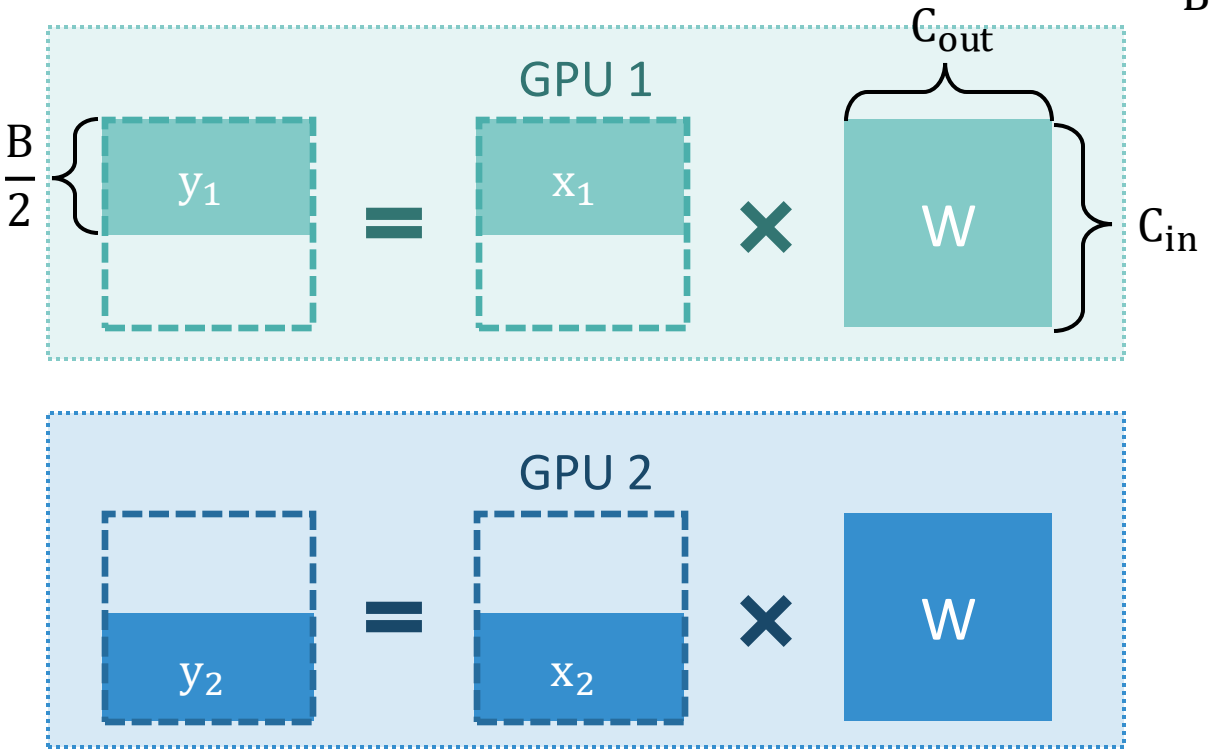




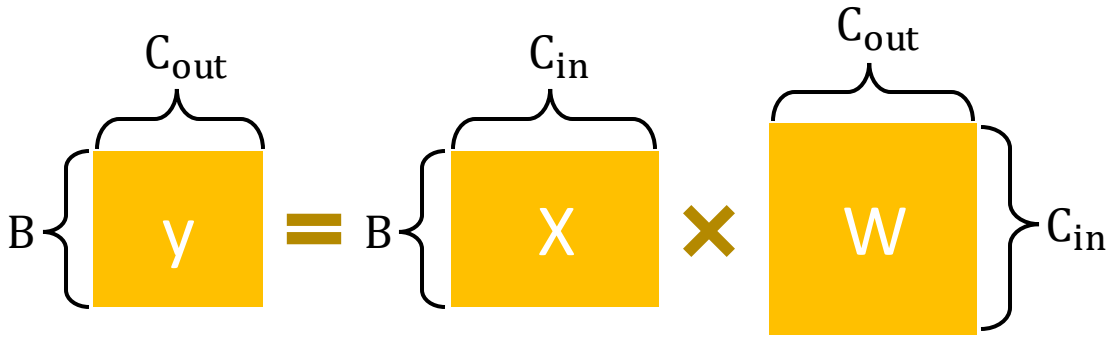
Tensor Model Parallelism (reduce output)

$y = y1 + y2$

Comparing Data and Tensor Model Parallelism



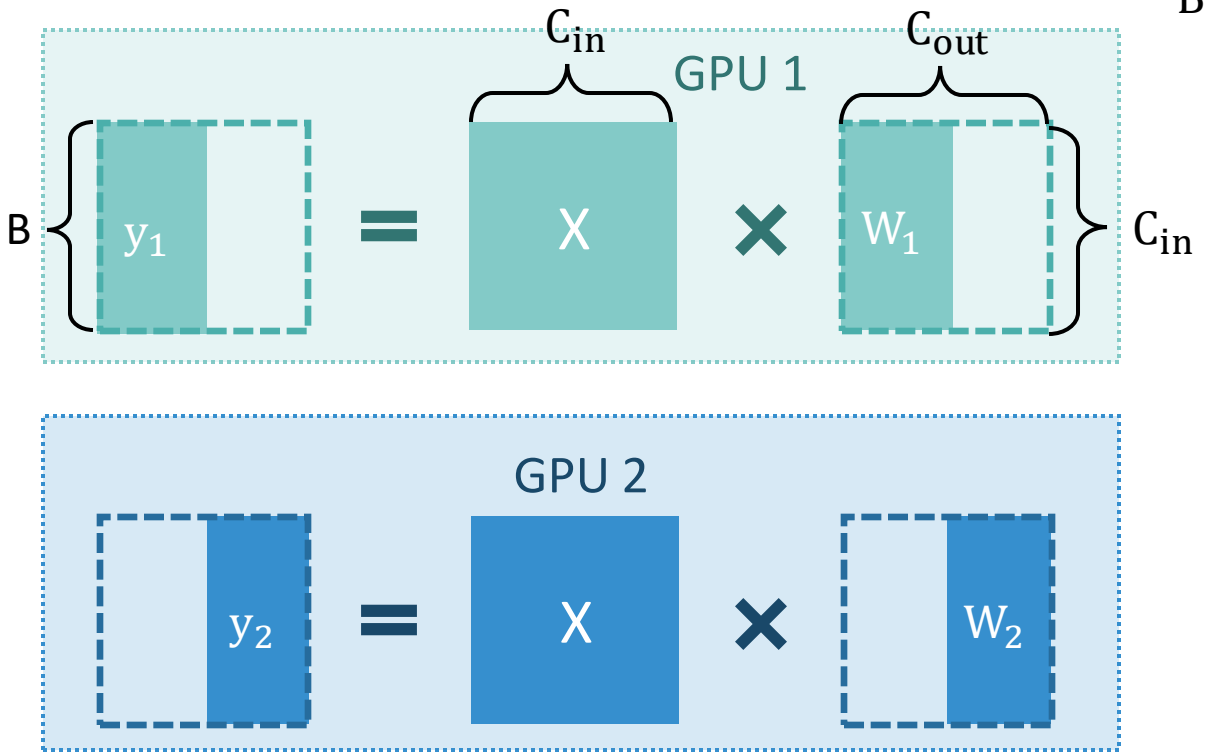
Data parallelism $y = Wx$



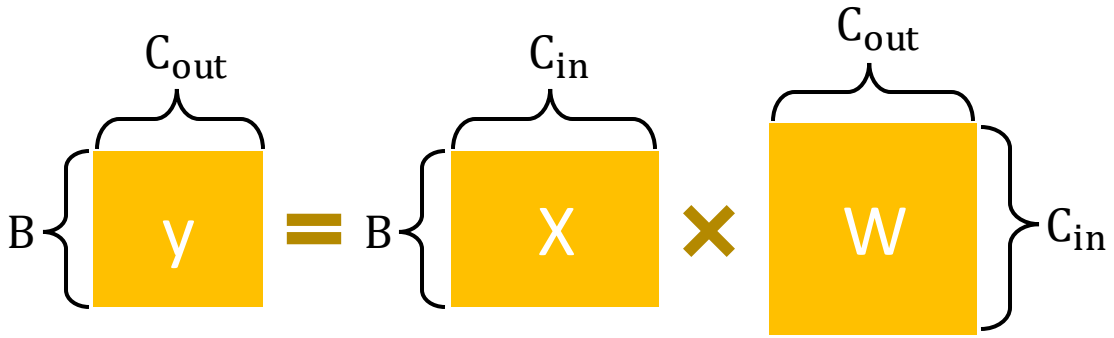
Forward Processing	Backward Propagation	Gradients Sync
0	0	$O(Cout * Cin)$

Communication Cost of Data Parallelism

Comparing Data and Tensor Model Parallelism



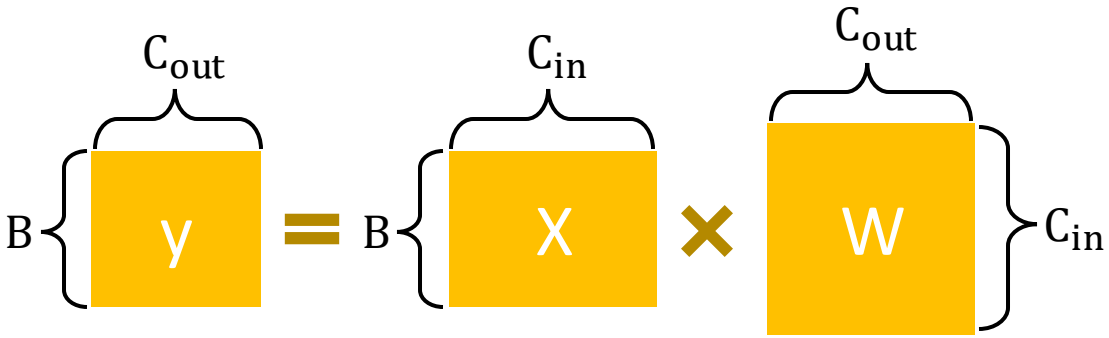
Tensor Model Parallelism (partition output)

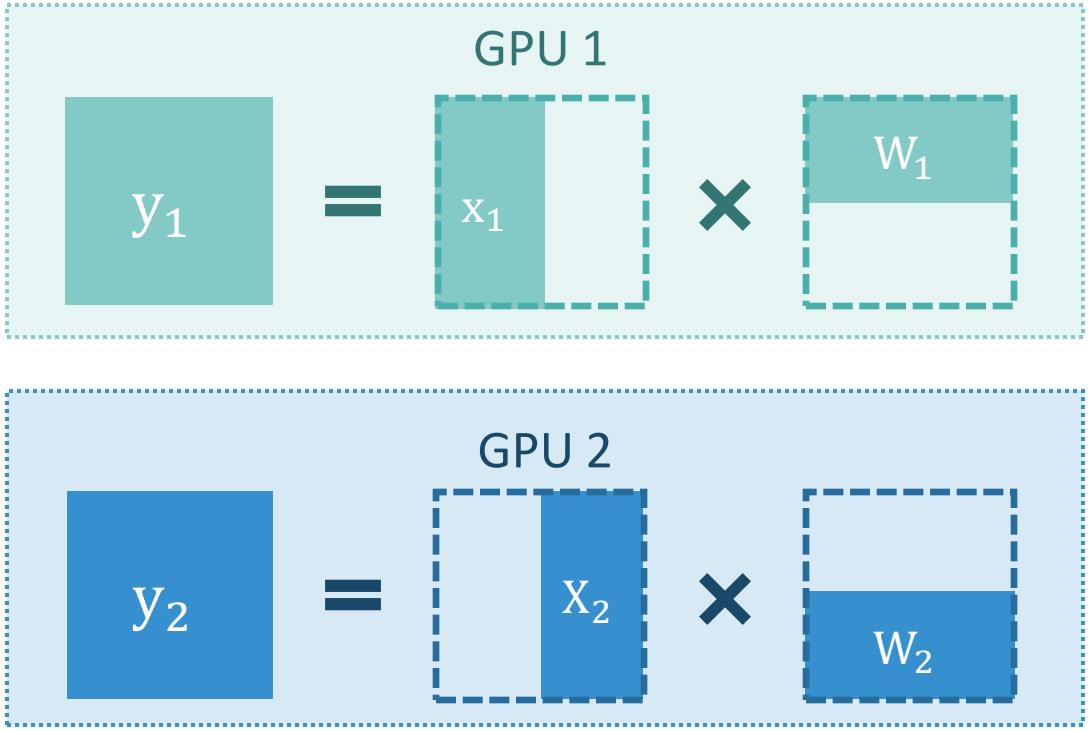


Forward Processing	Backward Propagation	Gradients Sync
$O(B * Cin)$	$O(B * Cin)$	0

Communication Cost of Tensor Model Parallelism

Comparing Data and Tensor Model Parallelism





Tensor Model Parallelism (Reduce output)

$y = y1 + y2$

Forward Processing	Backward Propagation	Gradients Sync
$O(B * Cout)$	$O(B * Cout)$	0

Communication Cost of Tensor Model Parallelism

Comparing Data and Tensor Model Parallelism

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- Data parallelism: $O(Cout * Cin)$
- Tensor model parallelism (partition output): $O(B * Cin)$
- Tensor model parallelism (reduce output): $O(B * Cout)$

- **The best strategy depends on the model and underlying machine**

Combine Data and Model Parallelism

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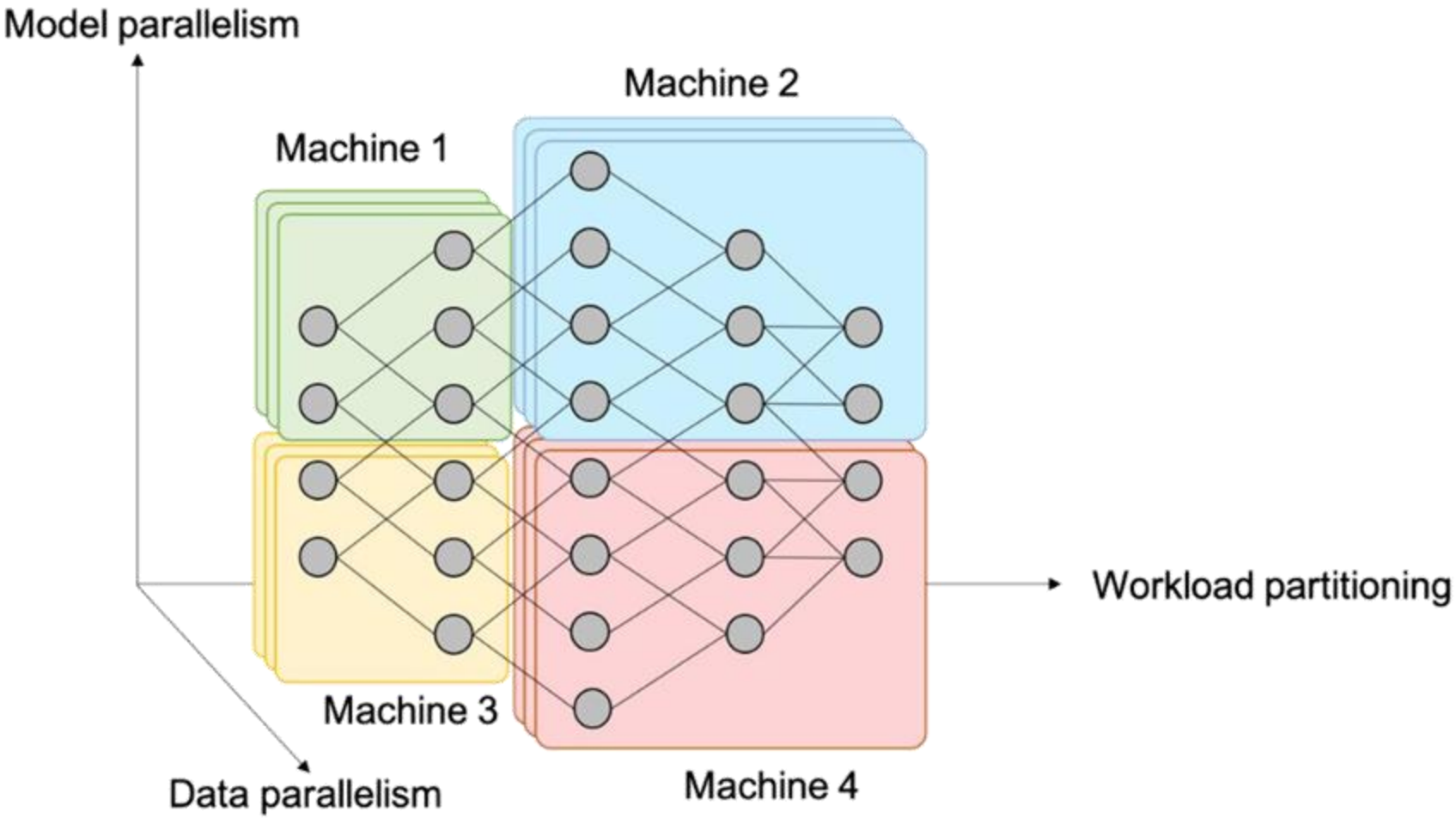

Convolution

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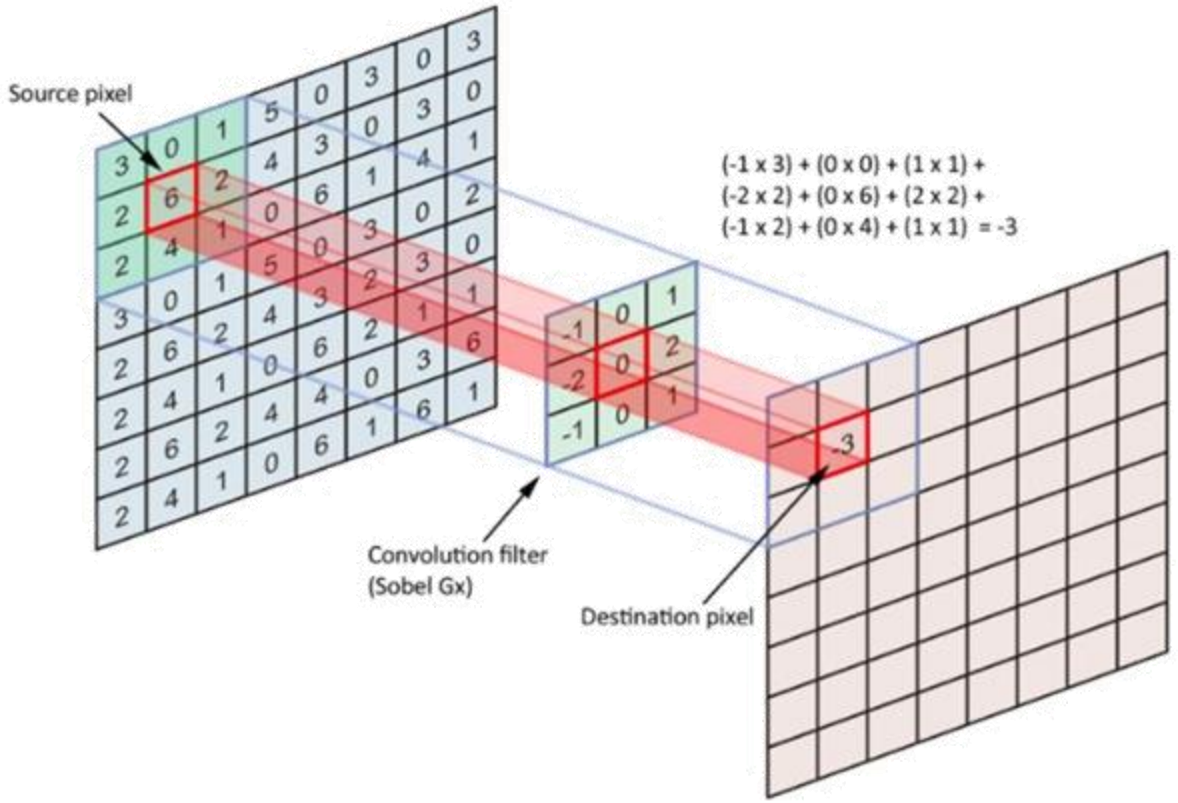
- Convolve the filter with the image: slide over the image spatially and compute dot products



Parallelizing Convolutional Neural Networks

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- Convolutional layers
  - 90-95% of the computation
  - 5% of the parameters
  - Very large intermediate activations
- Fully-connected layers
  - 5-10% of the computation
  - 95% of the parameters
  - Small intermediate activations
- **Discussion: how to parallelize CNNs?**

Data parallelism

Tensor model parallelism

Parallelizing Convolutional Neural Networks

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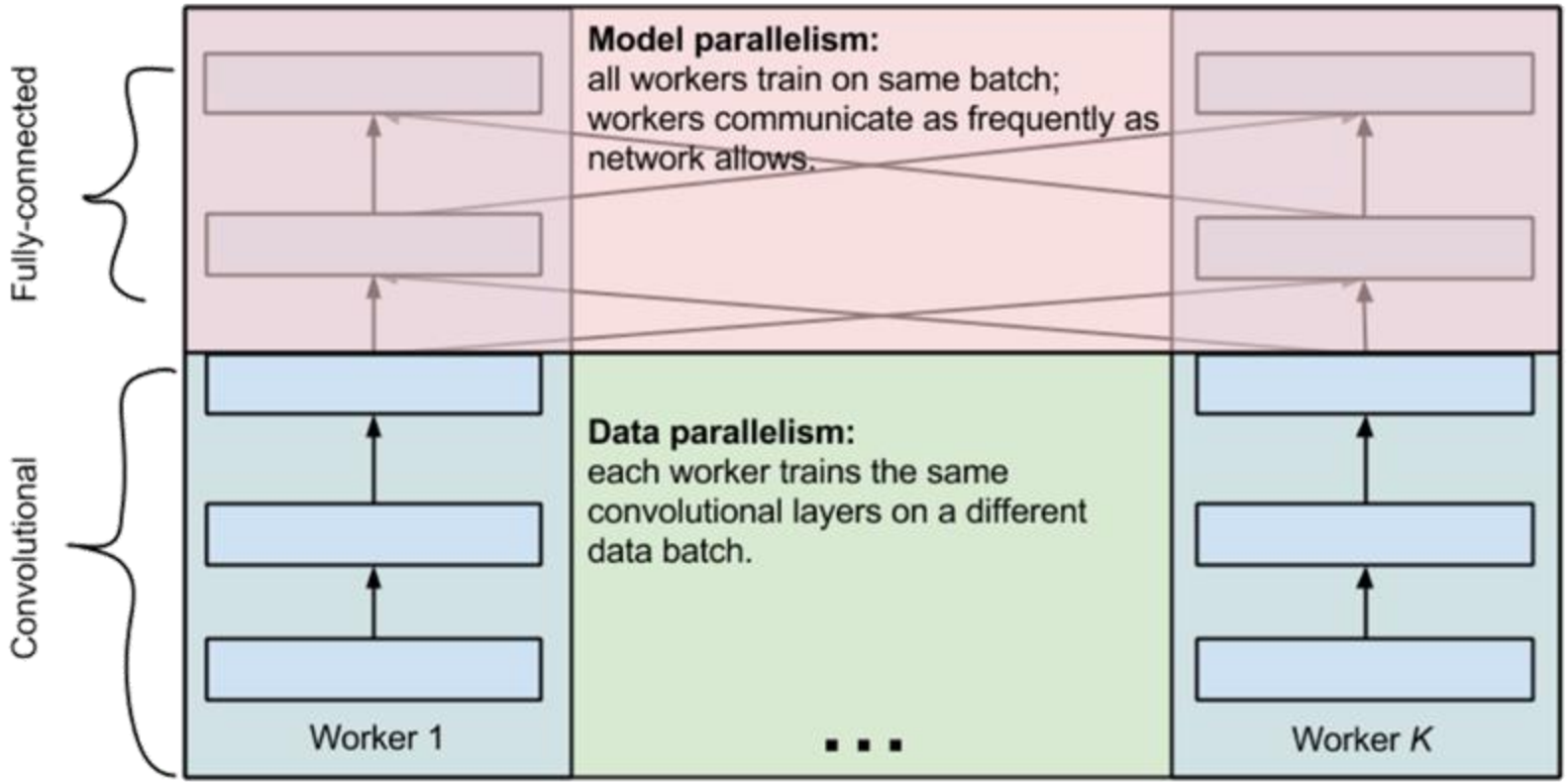
- Data parallelism for convolutional layers
- Tensor model parallelism for fully-connected layers



Example: Parallelizing Transformers

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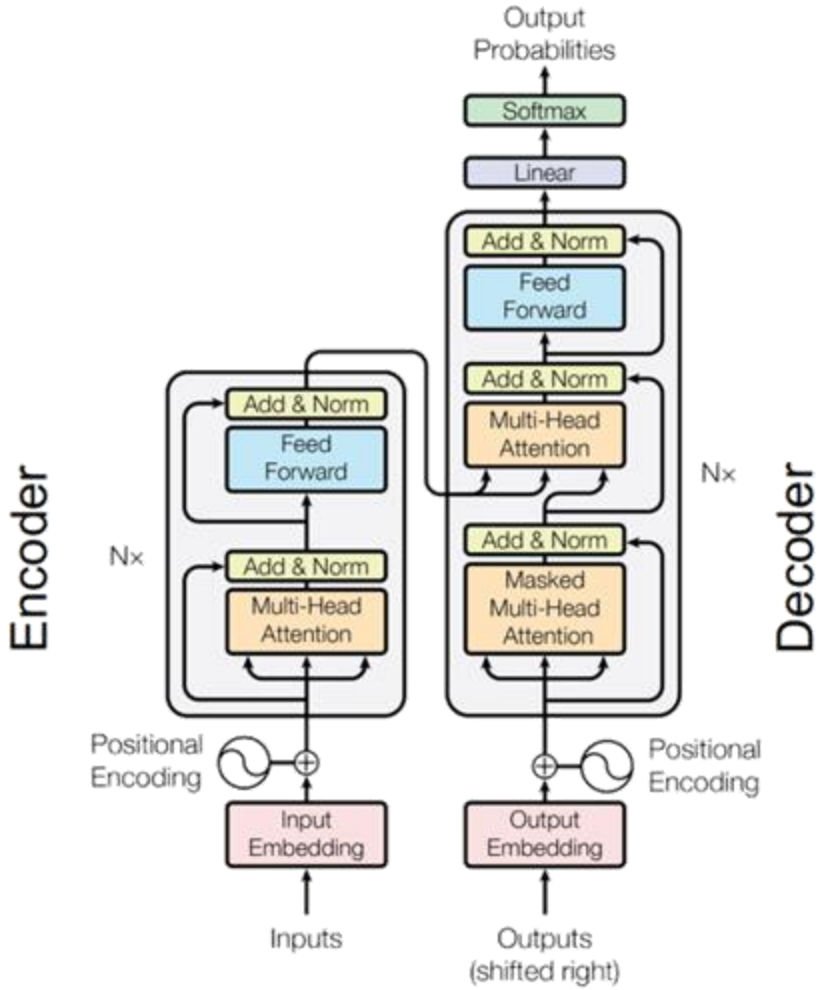
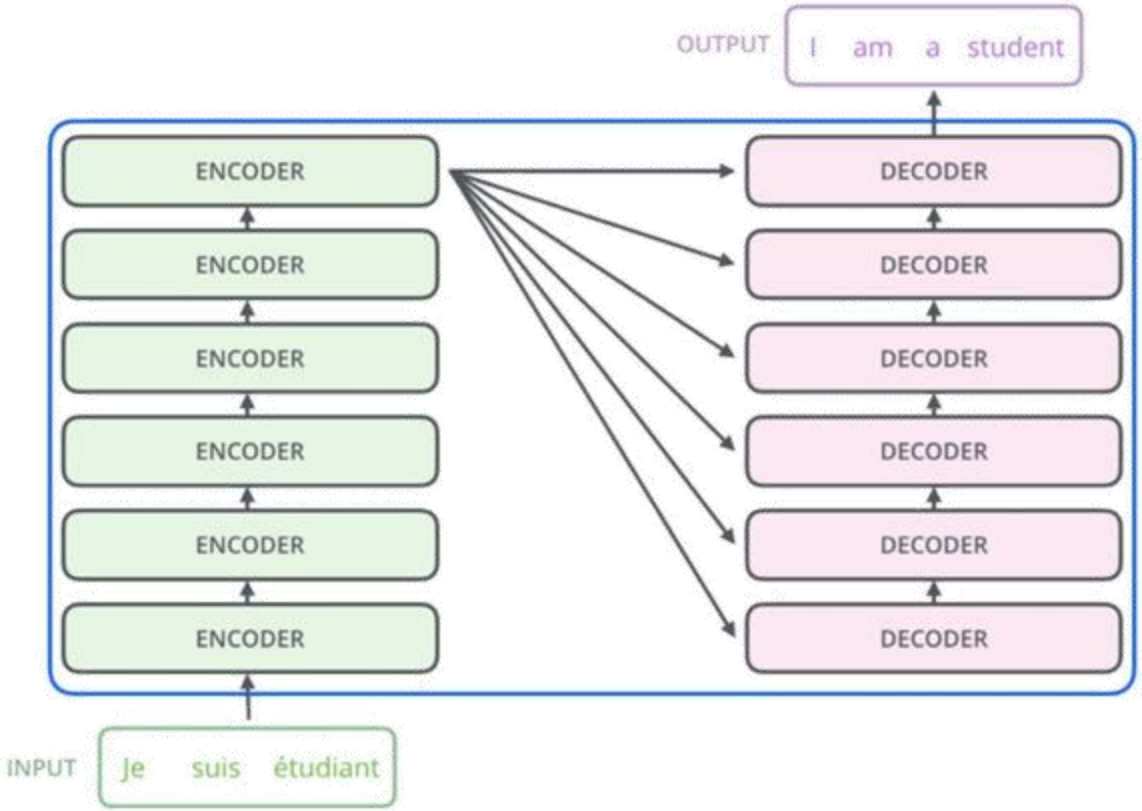
- Transformer: attention mechanism for language understanding





Ashish Vaswani et. al. Attention is all you need.

A Single Transformer Layer

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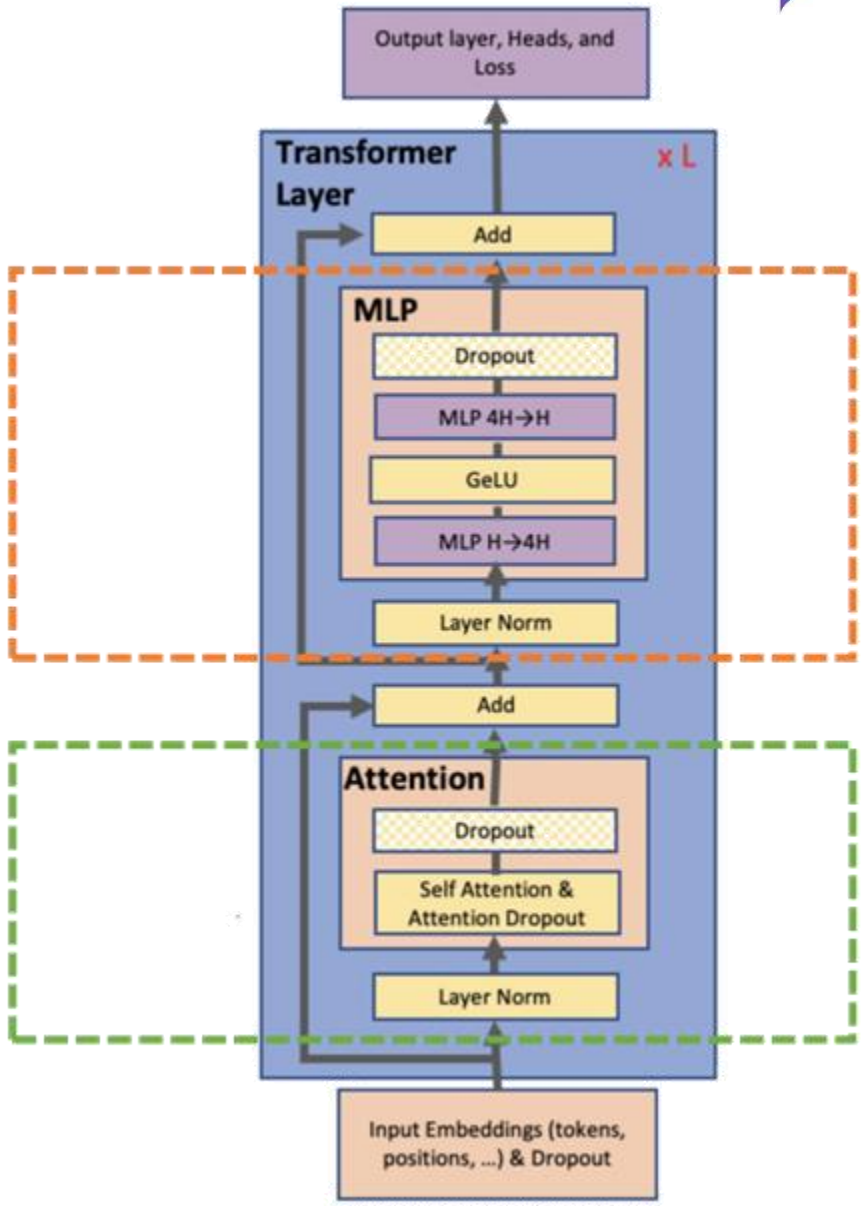
Fully-Connected Layers

Self-Attention Layers



Parallelizing Fully-Connected Layers in Transformers

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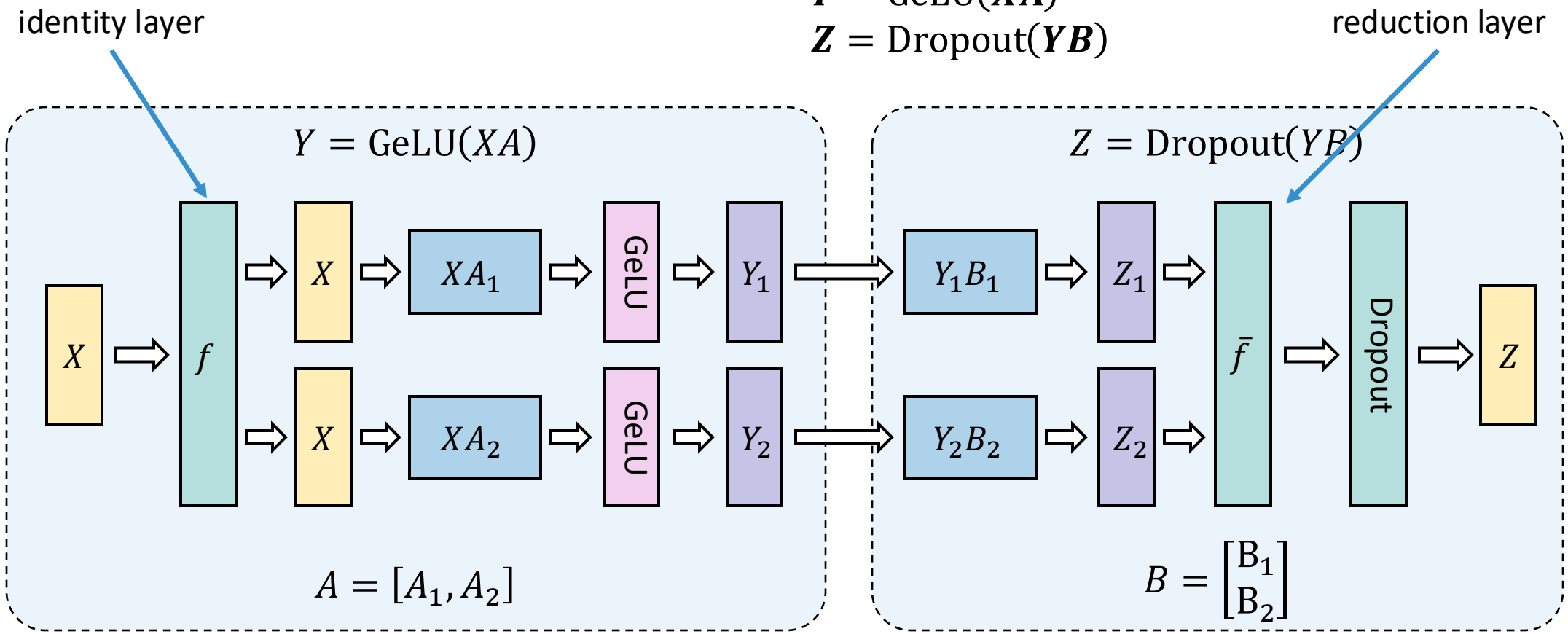
$$\boldsymbol{Y} = \mathrm{GeLU}(\boldsymbol{XA})$$
$$\boldsymbol{Z} = \mathrm{Dropout}(\boldsymbol{YB})$$

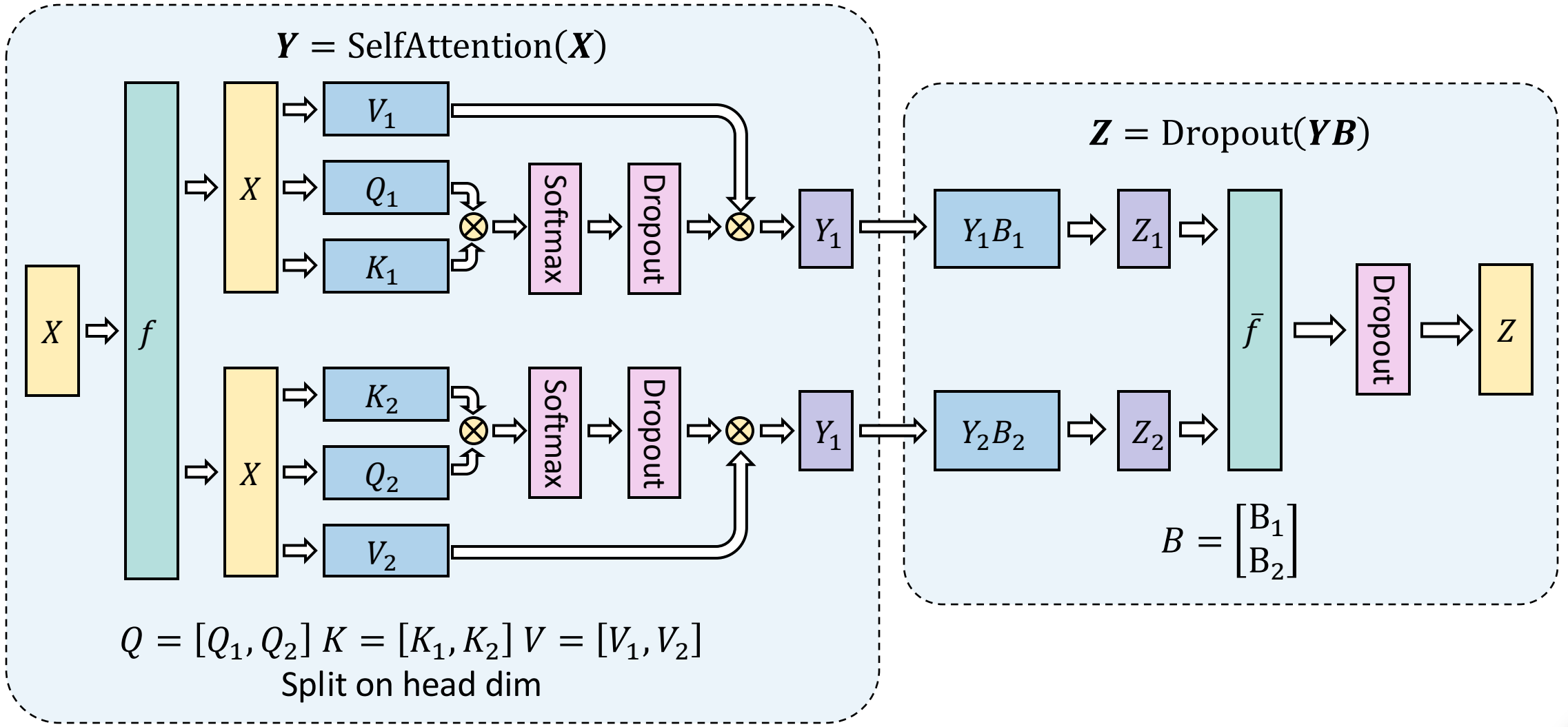


Tensor model parallelism
(partition output)

Tensor model parallelism
(reduce output)

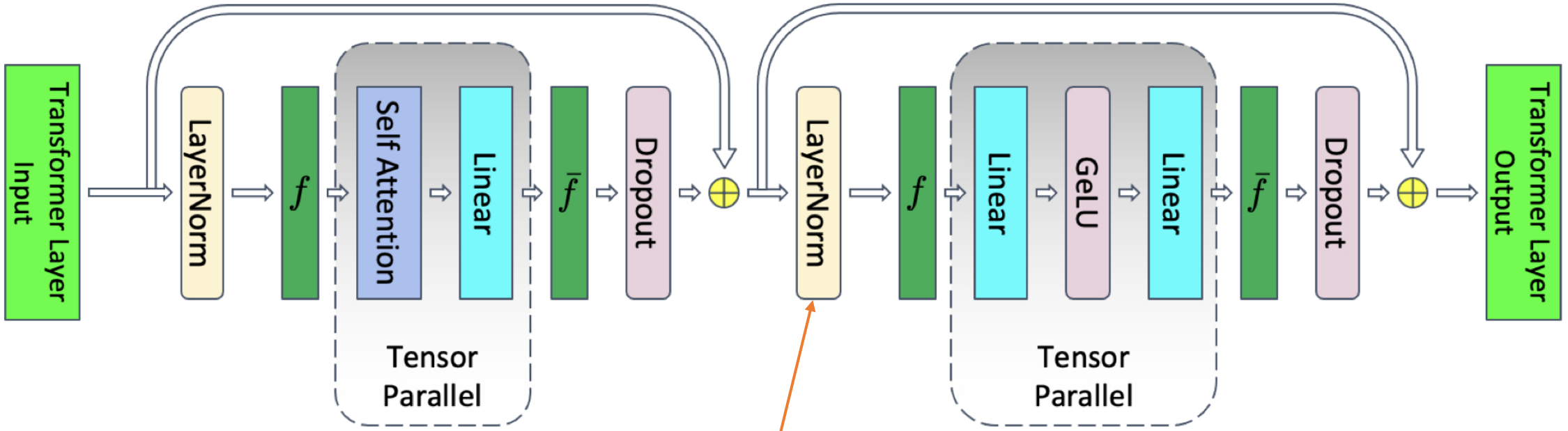
Megatron-LM: Training Multi-Billion Parameter Language Models Using Model Parallelism.

Parallelizing Self-Attn Layers in Transformers



Megatron-LM: Training Multi-Billion Parameter Language Models Using Model Parallelism.

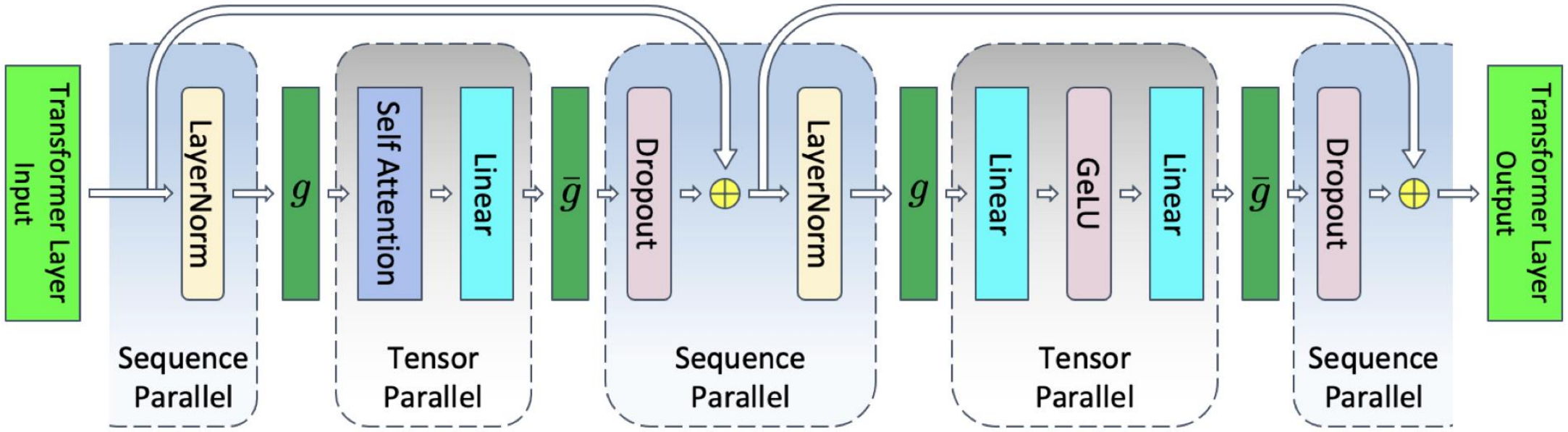
Tensor Parallelism for Transformer Layer



Where f is identity operation while $\bar{f}$ (g in prev slides) is all-reduce

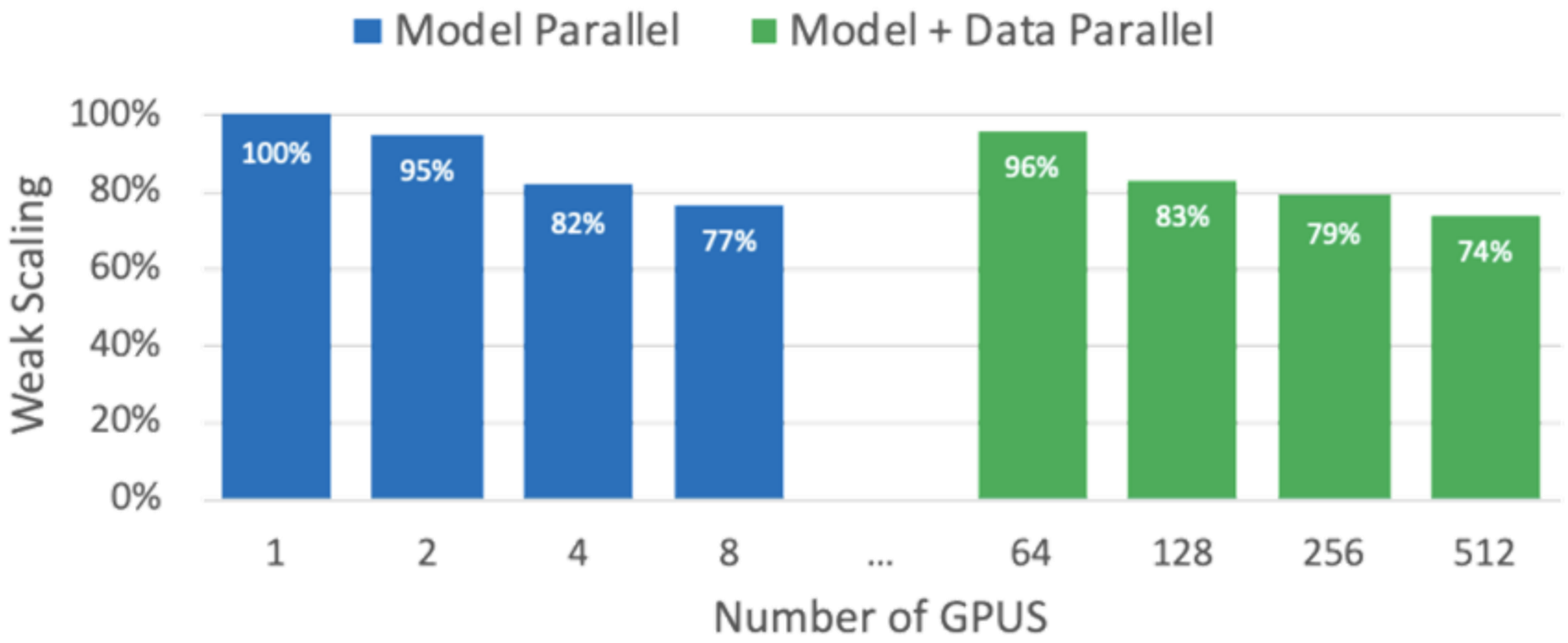
Norm is not parallelized

Sequence Parallelism



Where g is all-gather in forward pass while $\bar{g}$ is reduce-scatter

Parallelizing Transformers



Scale to 512 GPUs by combining data and model parallelism

Megatron-LM: Training Multi-Billion Parameter Language Models Using Model Parallelism.

How to parallelize DNN Training?

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

An Issue with Model Parallelism

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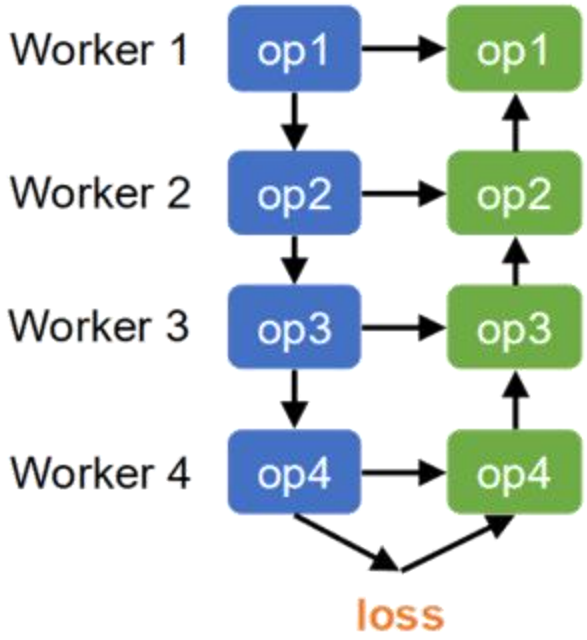
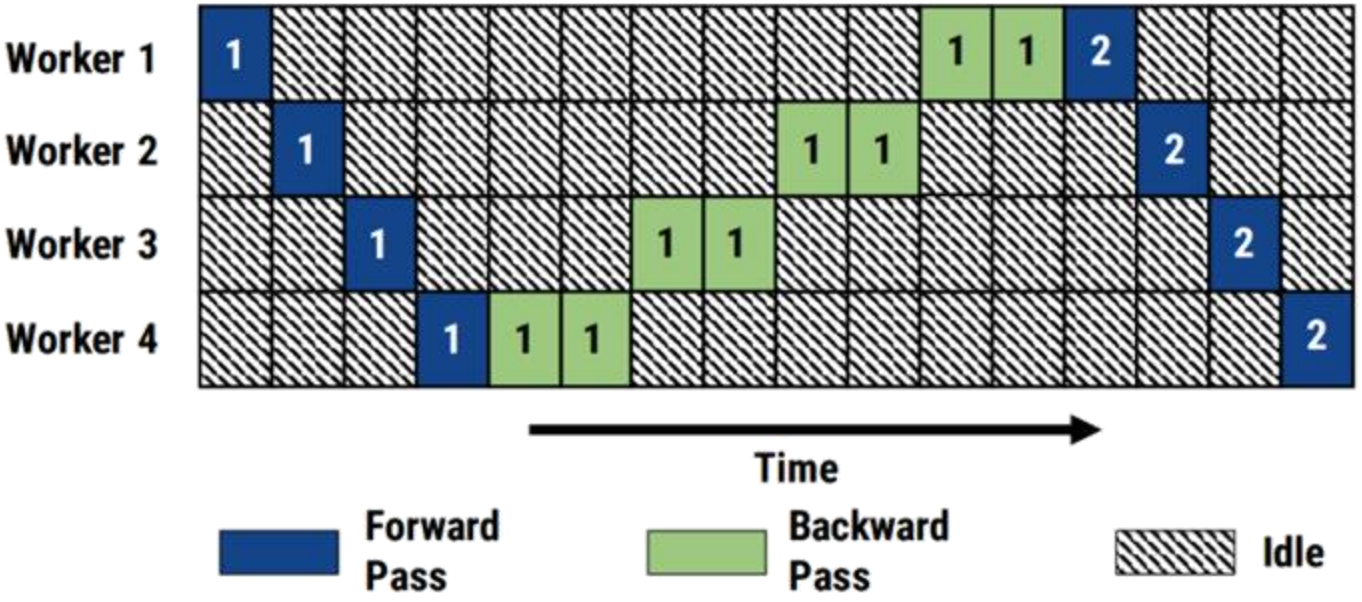
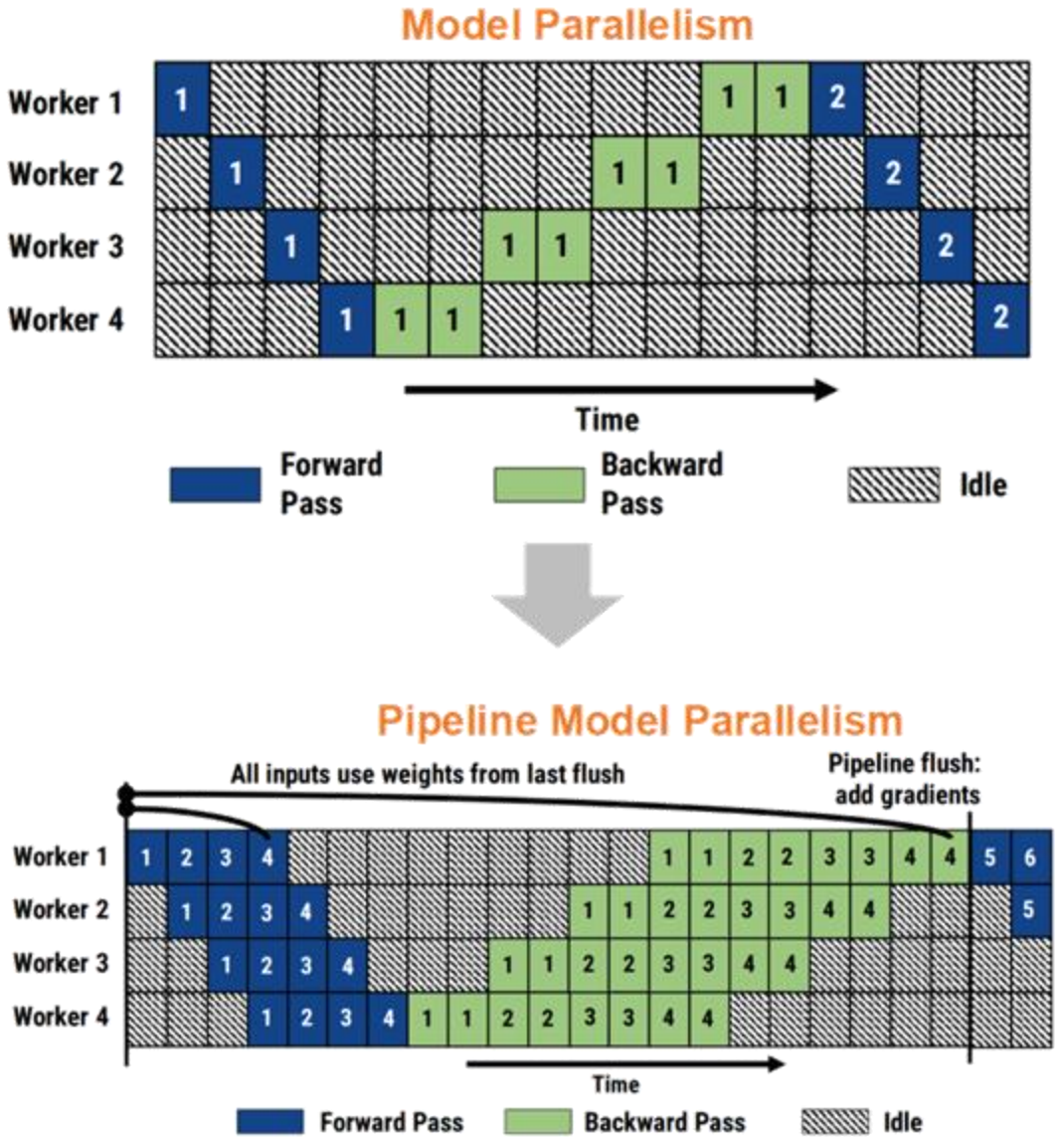
- Under-utilization of compute resources
- Low overall throughput due to resource utilization





Pipeline Model Parallelism

- **Mini-batch**: the number of samples processed in each iteration
- Divide a mini-batch into multiple **micro-batches**
- Pipeline the forward and backward computations across micro-batches



Pipeline Model Parallelism: Device Utilization

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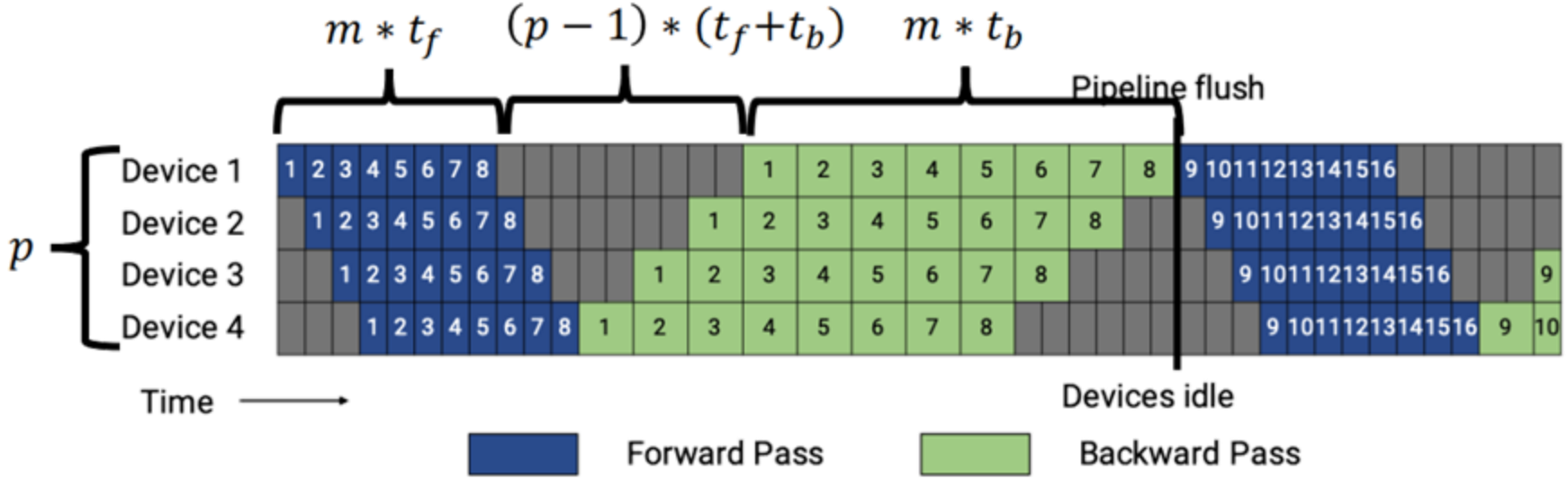
- m : micro-batches in a mini-batch
- p: number of pipeline stages
- All stages take t_f/ t_b to process a forward (backward) micro-batch

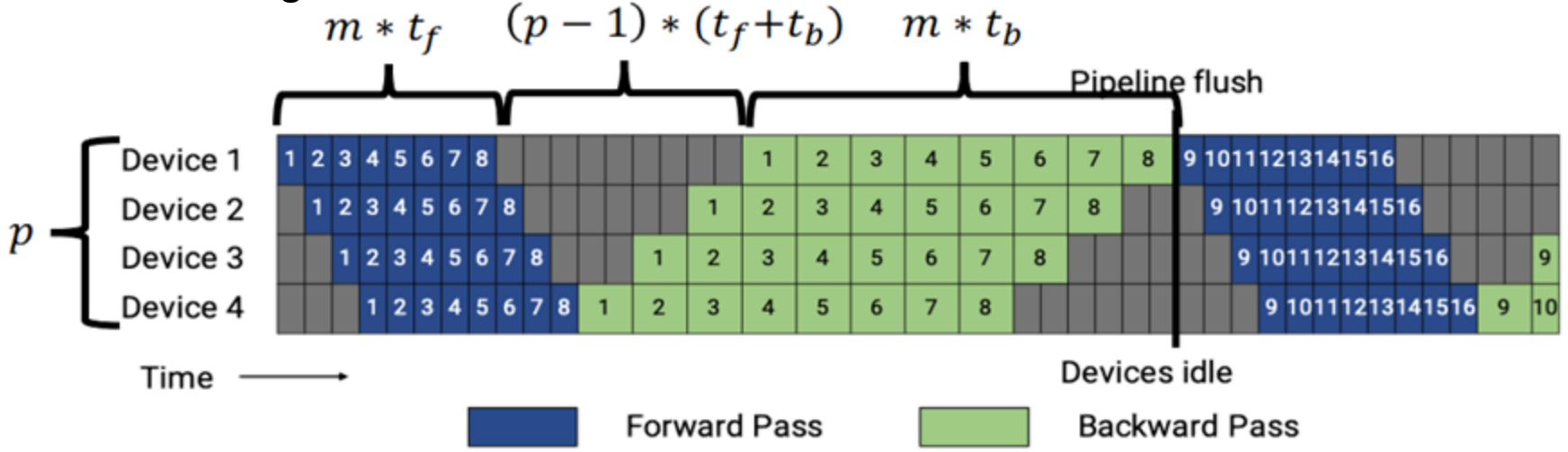


$$\boldsymbol{BubbleFraction} = \frac{(\boldsymbol{p}-\boldsymbol{1}) * (\boldsymbol{t_f}+\boldsymbol{t_b})}{\boldsymbol{m} * \boldsymbol{t_f} + \boldsymbol{m} * \boldsymbol{t_b}} = \frac{\boldsymbol{p}-\boldsymbol{1}}{\boldsymbol{m}}$$

GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism

Improving Pipeline Parallelism Efficiency

- m : number of micro-batches in a mini-batch
  - Increase mini-batch size or reduce micro-batch size
  - Caveat: large mini-batch sizes can lead to accuracy loss; small micro-batch sizes reduce GPU utilization
- p: number of pipeline stages
  - Decrease pipeline depth
  - Caveat: increase stage size



$$\boldsymbol{BubbleFraction} = \frac{(\boldsymbol{p}-\boldsymbol{1}) * (\boldsymbol{t_f}+\boldsymbol{t_b})}{\boldsymbol{m} * \boldsymbol{t_f} + \boldsymbol{m} * \boldsymbol{t_b}} = \frac{\boldsymbol{p}-\boldsymbol{1}}{\boldsymbol{m}}$$

GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism

Pipeline Model Parallelism: Memory Requirement

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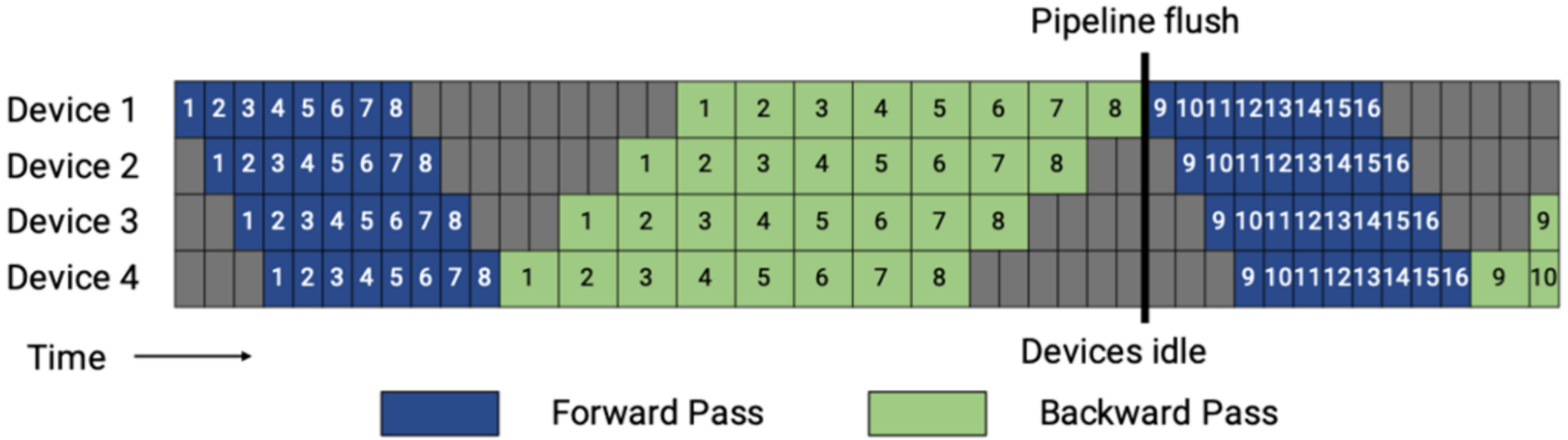
- An issue: we need to keep the intermediate activations of **all microbatches** before back propagation



Can we improve the pipeline schedule to reduce memory requirement?

GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism

Pipeline Parallelism with 1F1B Schedule

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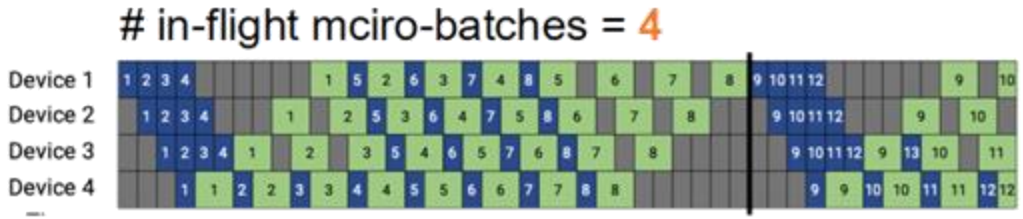
- One-Forward-One-Backward in the steady state
- Limit the number of in-flight micro-batches to the pipeline depth
- **Reduce memory footprint of pipeline parallelism**
- **Doesn't reduce pipeline bubble**

Can we reduce pipeline bubble?

Pipeline parallelism with GPipe's schedule



Pipeline parallelism with 1F1B schedule

GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism

Pipeline Parallelism with Interleaved 1F1B Schedule

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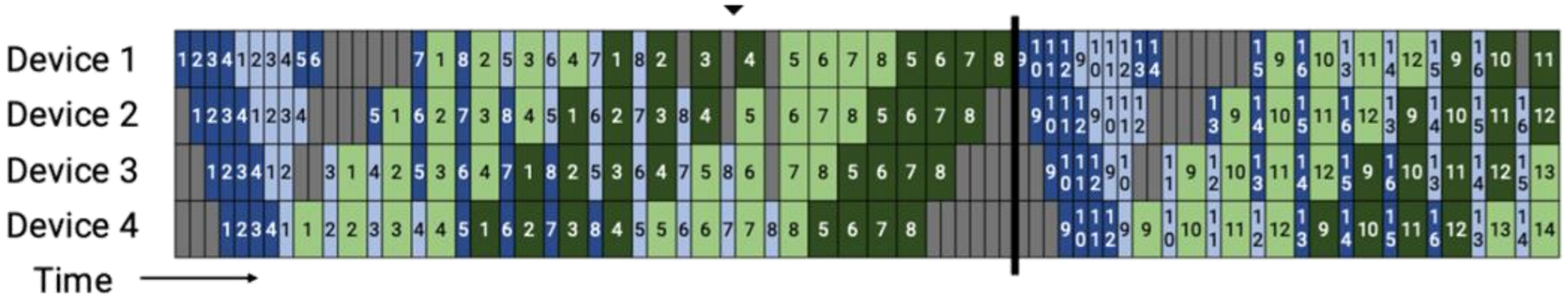
- Further divide each stage into v sub-stages
- The forward (backward) time of each sub-stage is $\frac{t_f}{v}\left(\frac{t_b}{v}\right)$



Each device is assigned two chunks. Dark colors show the first chunk and light colors show the second chunk.

$$\boldsymbol{BubbleFraction} = \frac{(\boldsymbol{p}-\boldsymbol{1}) * \frac{(\boldsymbol{t_f}+\boldsymbol{t_b})}{\boldsymbol{v}}}{\boldsymbol{m} * \boldsymbol{t_f} + \boldsymbol{m} * \boldsymbol{t_b}} = \frac{\boldsymbol{1}}{\boldsymbol{v}} * \frac{\boldsymbol{p}-\boldsymbol{1}}{\boldsymbol{m}}$$

Reduce bubble time at the cost increased communication

Pipeline Parallelism with Interleaved 1F1B Schedule

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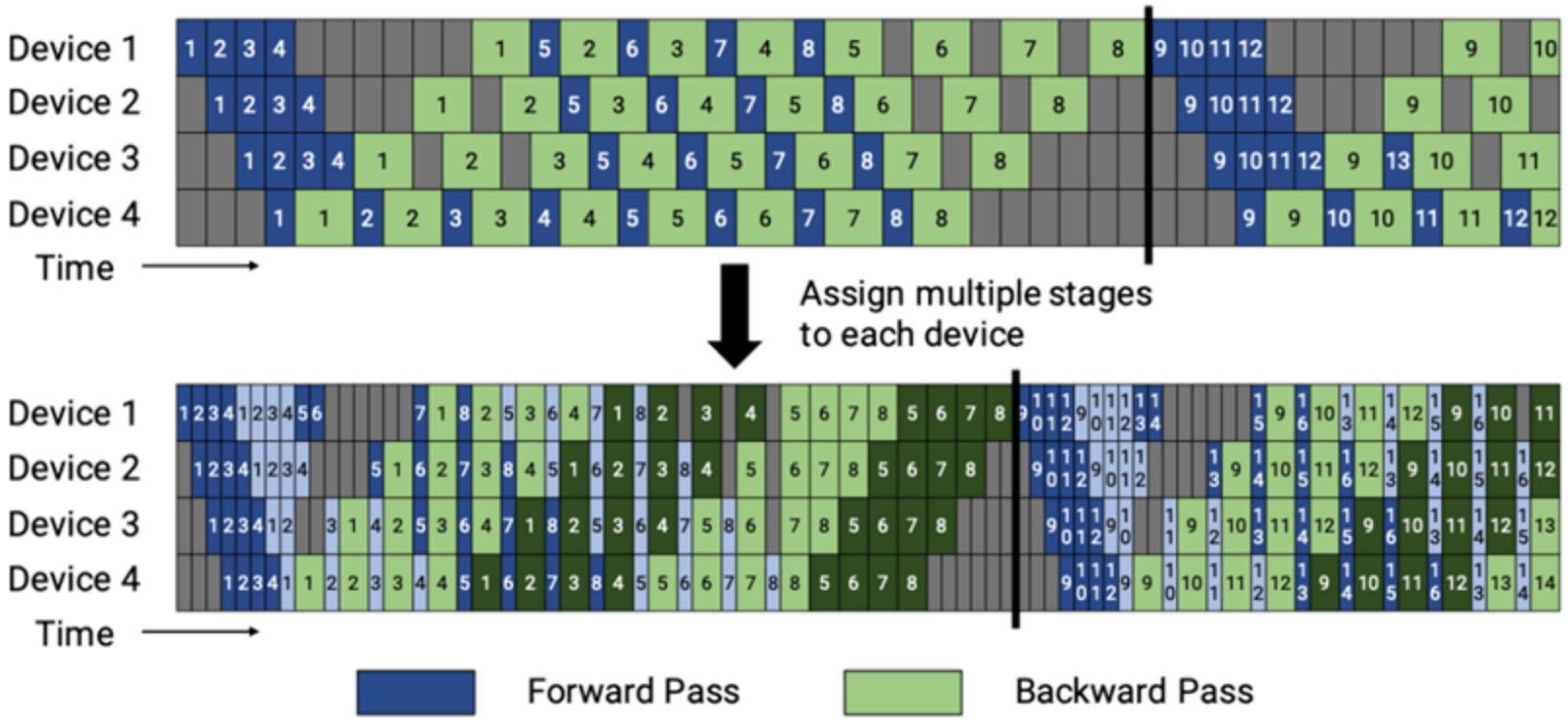
Pipeline parallelism with 1F1B Schedule

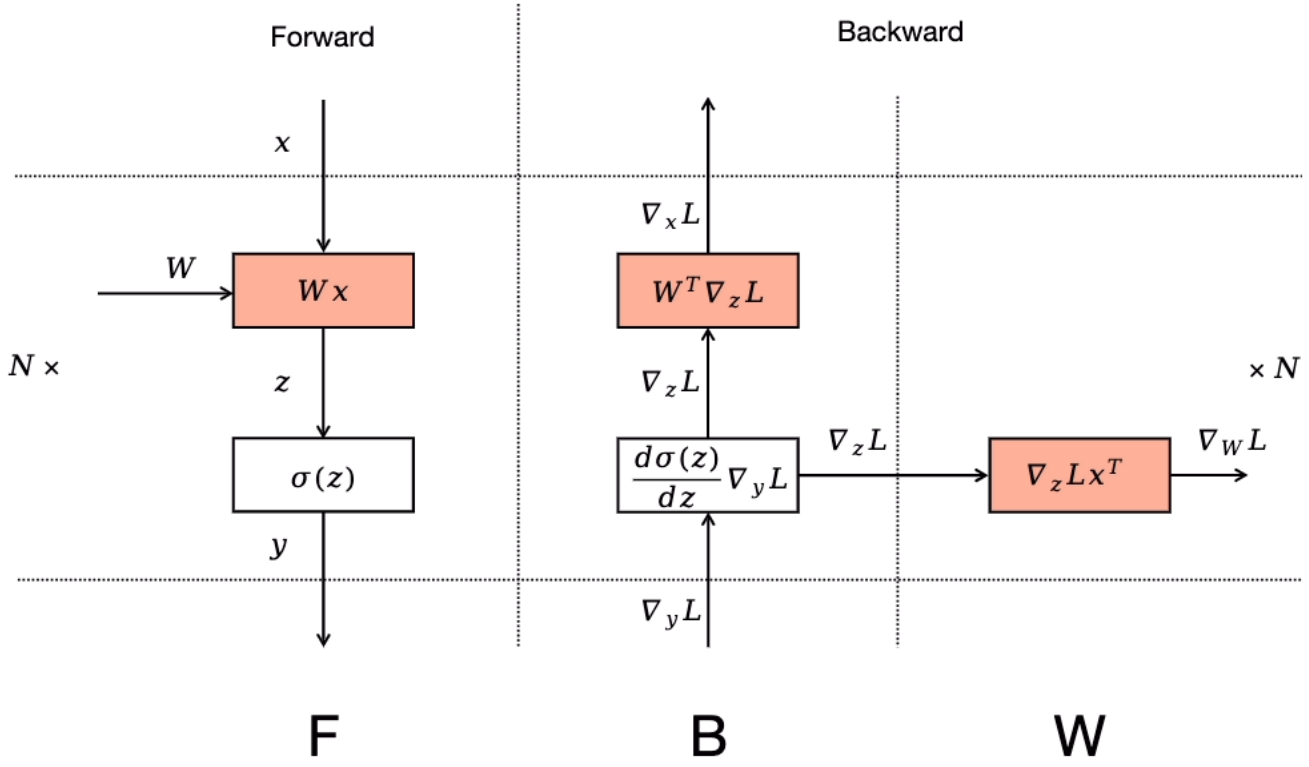
$$BubbleFraction = \frac{p-1}{m}$$

Pipeline parallelism with interleaved 1F1B Schedule

$$BubbleFraction = \frac{1}{v} * \frac{p-1}{m}$$



Zero Bubble Pipeline Parallelism



Zero Bubble Pipeline Parallelism

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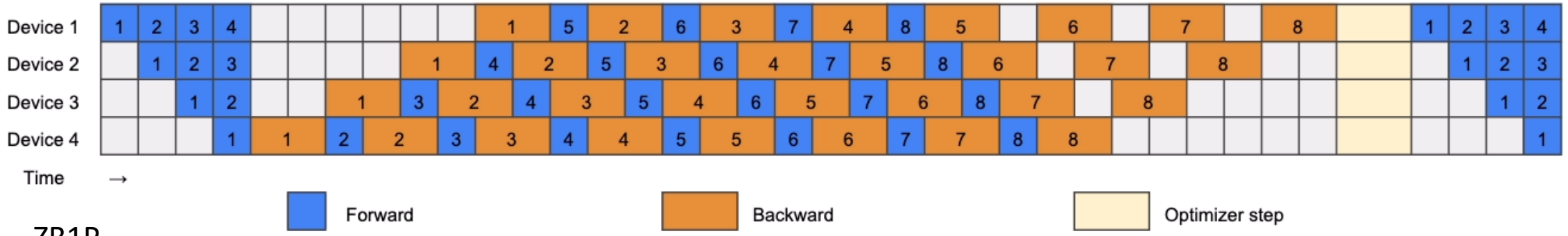
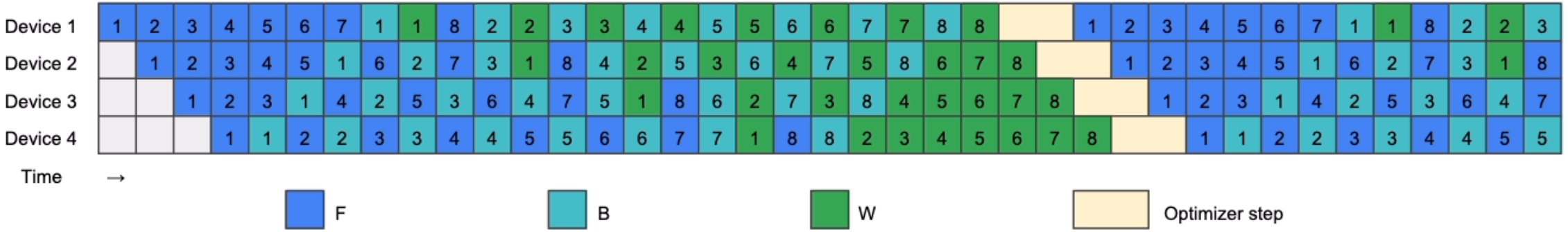
1F1B



ZB1P

ZB2P



Zero Bubble Pipeline Parallelism

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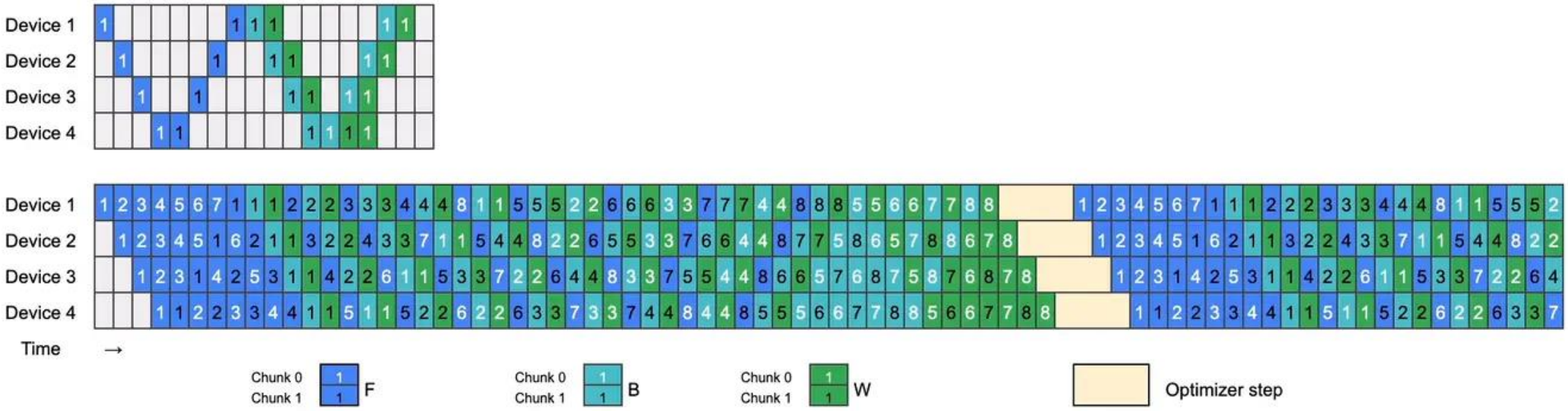
ZBV



Combine Zero Bubble and Interleaved 1F1B

Zero Bubble Summary

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	1F1B	ZB1P	ZB2P	ZBV
Bubble Rate	$\frac{p-1}{m+p-1} = B$	$\frac{B}{3}$	0	0
Activation Memory (Compared to 1F1B)	1x	1x	2x	1x
Pipeline Communication Volume (Compared to 1F1B)	1x	1x	1x	2x

- p: number of pipeline stages
- m: number of microbatches
- Assuming $T_F = TB = TW$

Summary: Comparing Data/Tensor Model/Pipeline Model Parallelism

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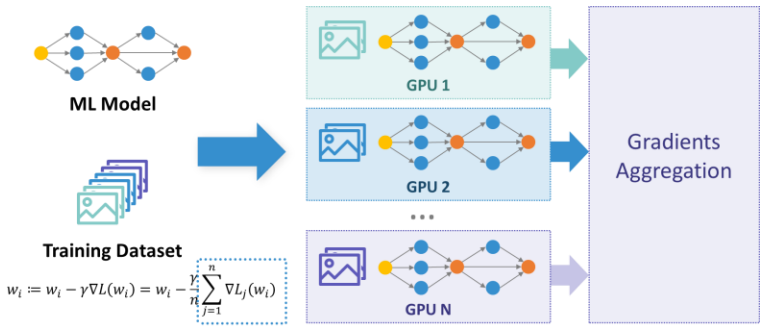

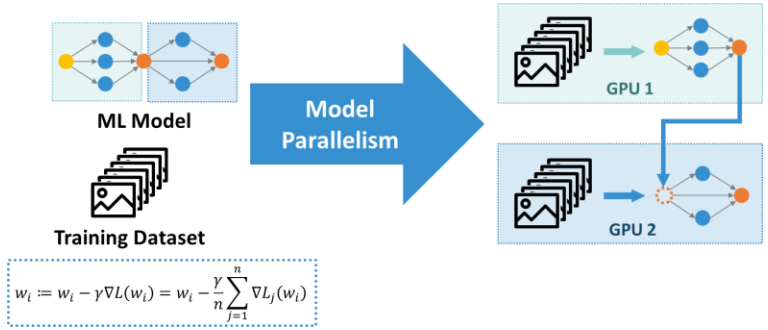

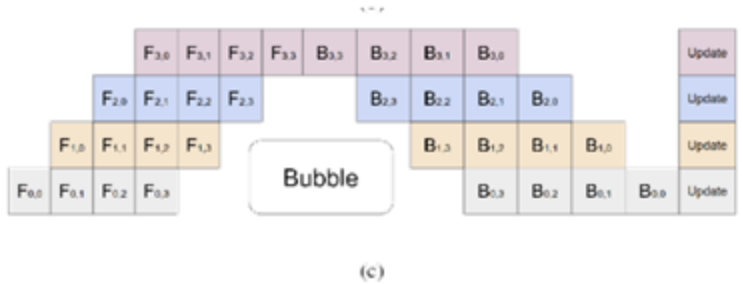

	Data Parallelism	Tensor Model Parallelism	Pipeline Model Parallelism
Pros	◆ Massively parallelizable ◆ Require no communication during forward/backward	◆ Support training large models ◆ Efficient for models with large numbers of parameters	◆ Support large-batch training ◆ Efficient for deep models
Cons	■ Do not work for models that cannot fit on a GPU ■ Do not scale for models with large numbers of parameters	■ Limited parallelizability; cannot scale to large numbers of GPUs ■ Need to transfer intermediate results in forward/backward	■ Limited utilization: bubbles in forward/backward

Summary: Comparing Data/Tensor Model/Pipeline Model Parallelism

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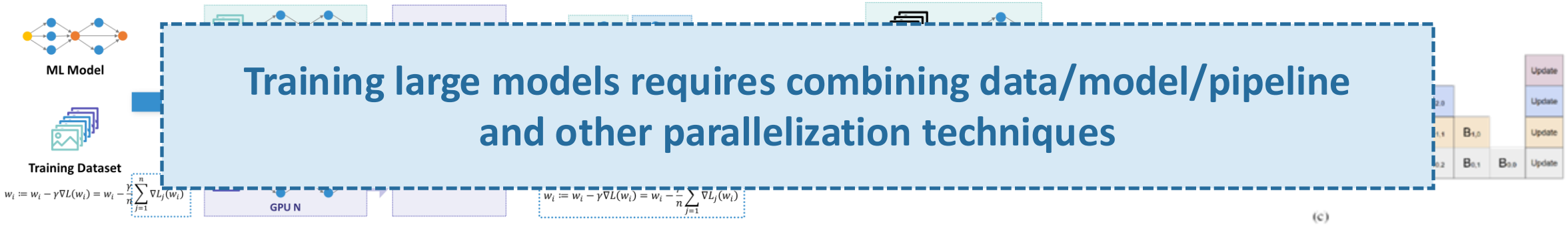

Training large models requires combining data/model/pipeline and other parallelization techniques

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- Advanced Topics in Machine Learning (Systems)[CS6216], by **Yao Lu** at **NUS**

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System for Artificial Intelligence

Thanks

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