11868 LLM Systems
Distributed GPU Training

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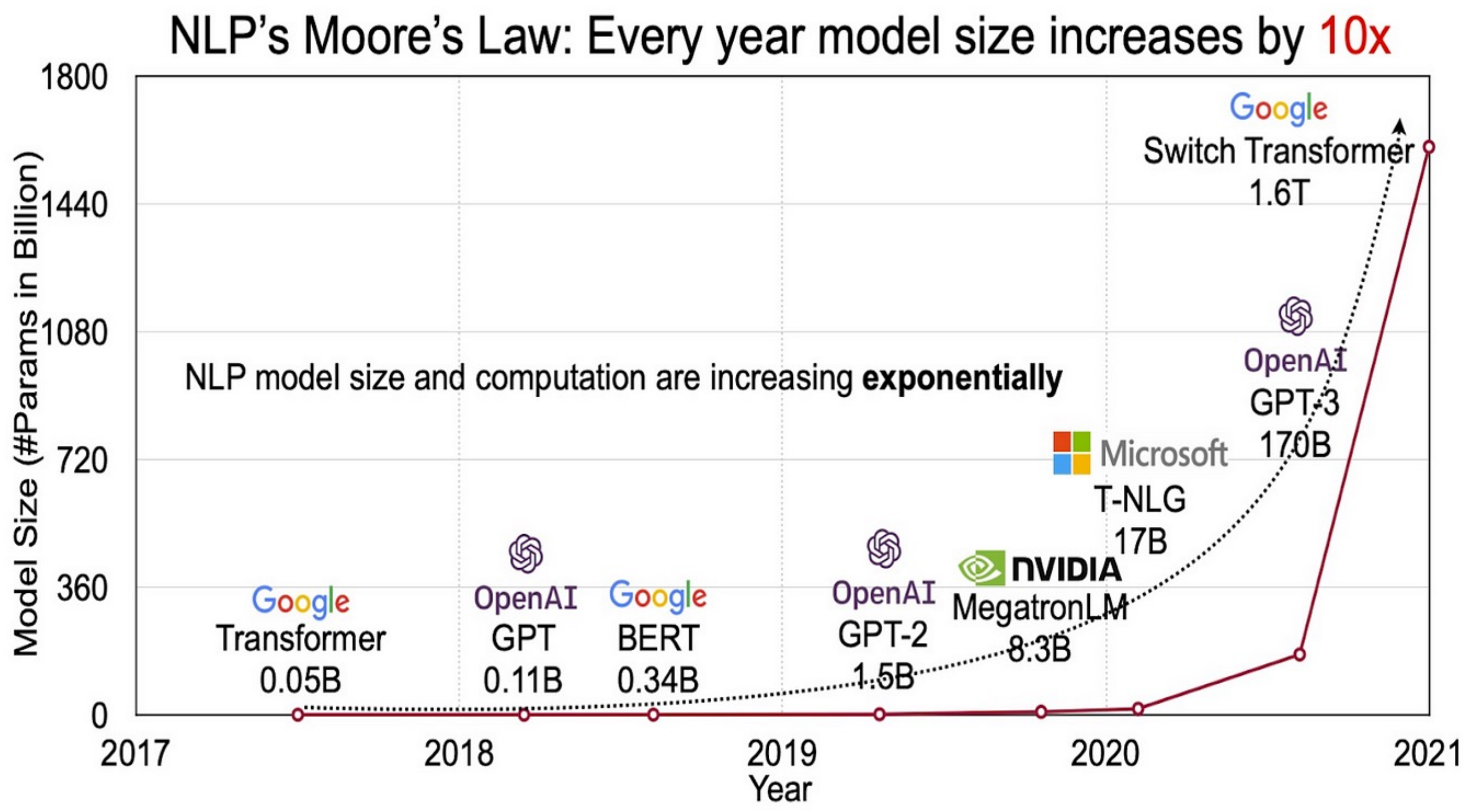
Today's Topic

- Model Parallel
- Pipeline Parallelism
- Tensor Parallelism

Model Parallel

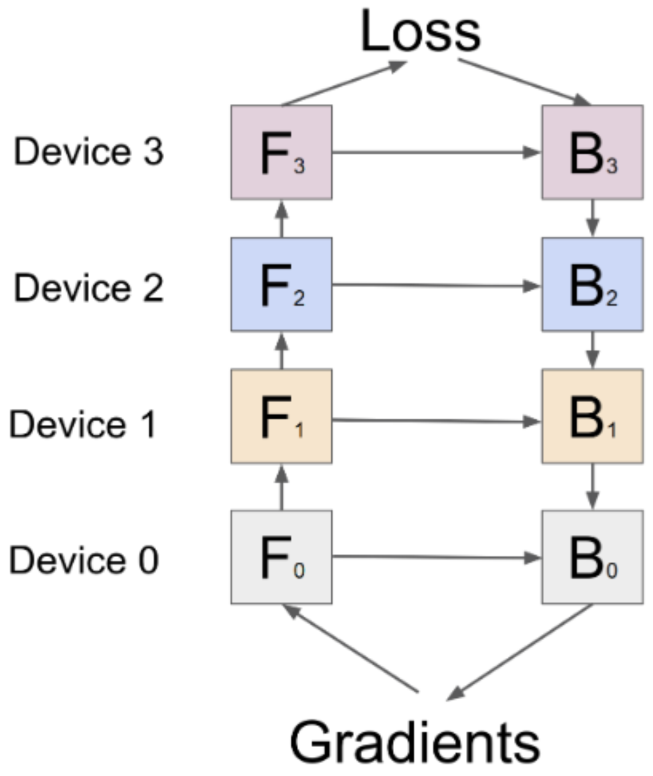
Motivation: The size of models increases exponentially fast and large. It is no longer possible to fit these large models into the main memory of a single GPU.

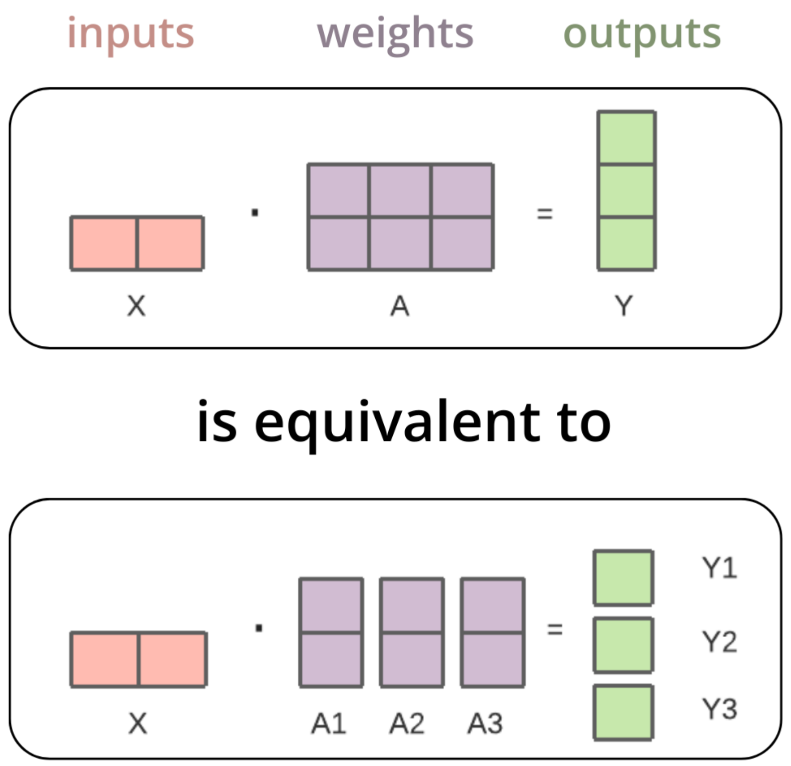


Model Parallel

Model Parallel: memory usage and computation of a model is distributed across multiple workers.

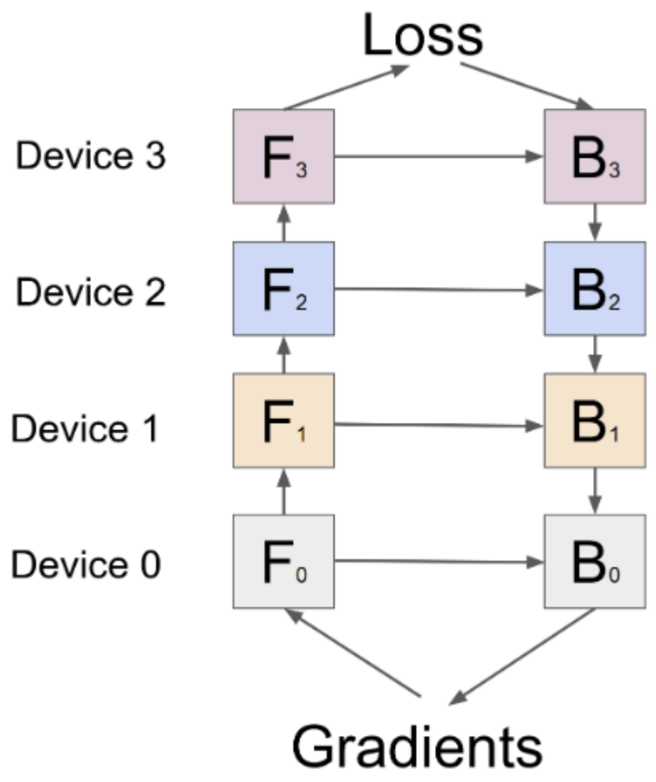
- Distributed over layer-wise computation
- Distributed over tensor computation

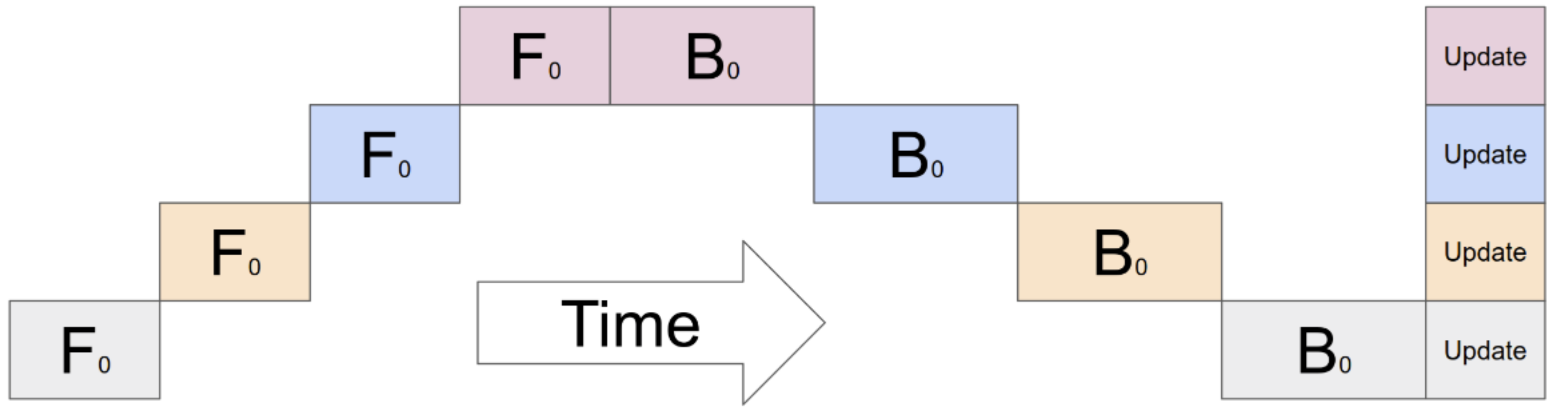




Pipeline Parallelism

Naïve Model Parallel: The model is distributed across multiple GPUs over layers.



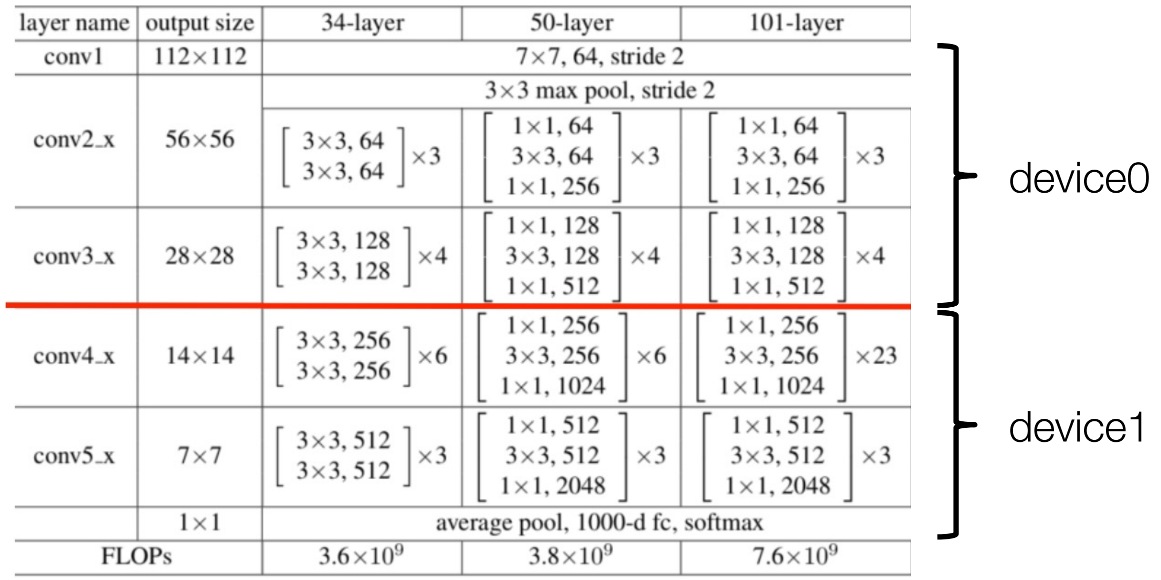


Any disadvantage?

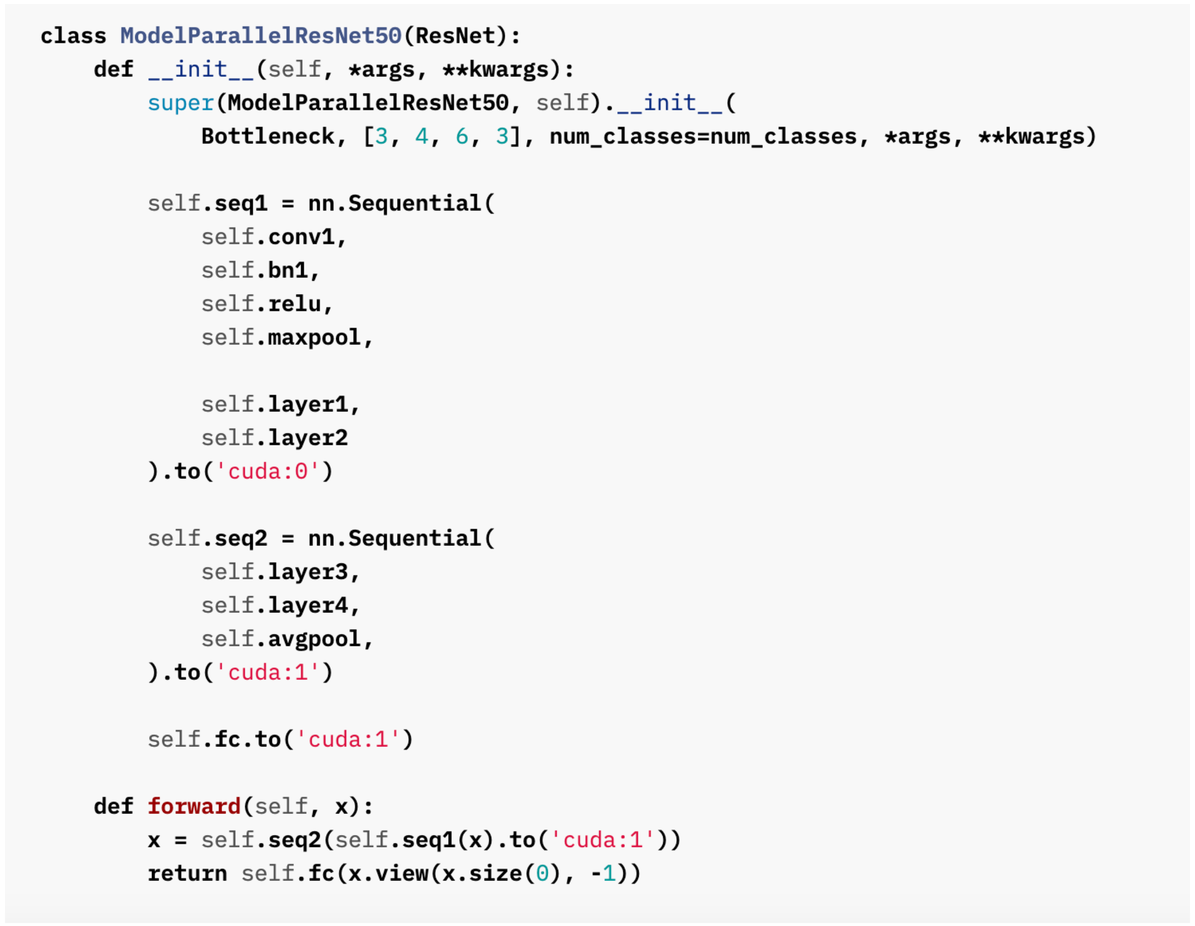
all but one GPU is idle at any given moment!

Pipeline Parallelism

Naïve Model Parallel: The model is distributed across multiple GPUs over layers within one single node.



layer name	output size	34-layer	50-layer	101-layer
conv1	112×112	7×7, 64, stride 2		
conv2_x	56×56	3×3 max pool, stride 2		
		[3×3, 64; 3×3, 64] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3
conv3_x	28×28	[3×3, 128; 3×3, 128] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4
conv4_x	14×14	[3×3, 256; 3×3, 256] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×23
conv5_x	7×7	[3×3, 512; 3×3, 512] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax		
FLOPs		3.6×10^9	3.8×10^9	7.6×10^9



```
class ModelParallelResNet50(ResNet):
    def __init__(self, *args, **kwargs):
        super(ModelParallelResNet50, self).__init__(
            Bottleneck, [3, 4, 6, 3], num_classes=num_classes, *args, **kwargs)

        self.seq1 = nn.Sequential(
            self.conv1,
            self.bn1,
            self.relu,
            self.maxpool,

            self.layer1,
            self.layer2
        ).to('cuda:0')

        self.seq2 = nn.Sequential(
            self.layer3,
            self.layer4,
            self.avgpool,
        ).to('cuda:1')

        self.fc.to('cuda:1')

    def forward(self, x):
        x = self.seq2(self.seq1(x).to('cuda:1'))
        return self.fc(x.view(x.size(0), -1))
```

nccl send/recv

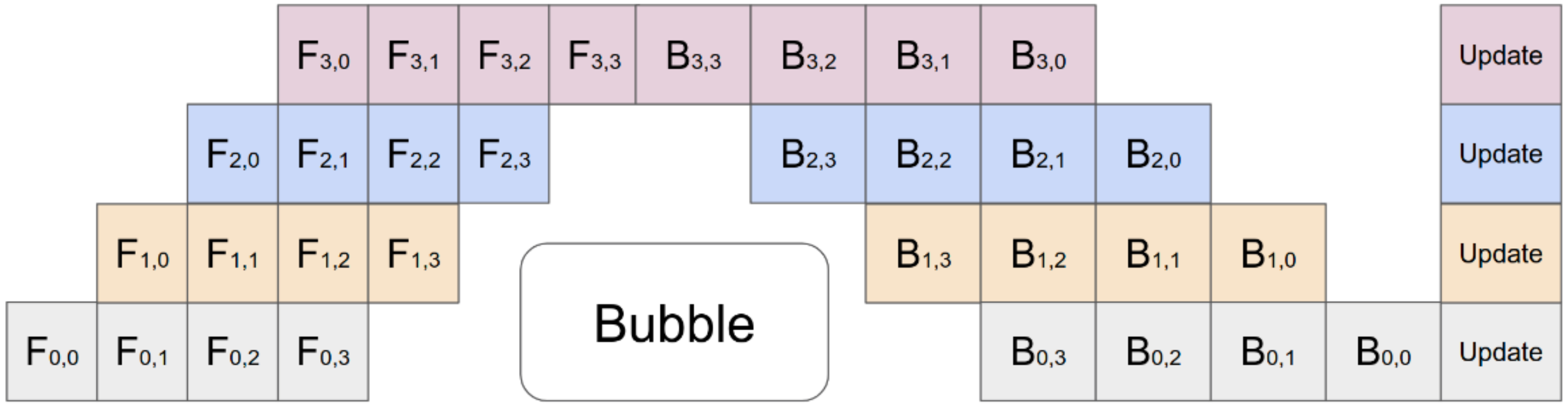
Pipeline Parallel

- **GPipe**: Divides input data mini-batches into smaller micro-batches.

[1] Huang, Yanping, et al. "Gpipe: Efficient training of giant neural networks using pipeline parallelism." Advances in neural information processing systems 32 (2019).

Pipeline Parallelism

GPipe: Divides input data mini-batches into smaller micro-batches.

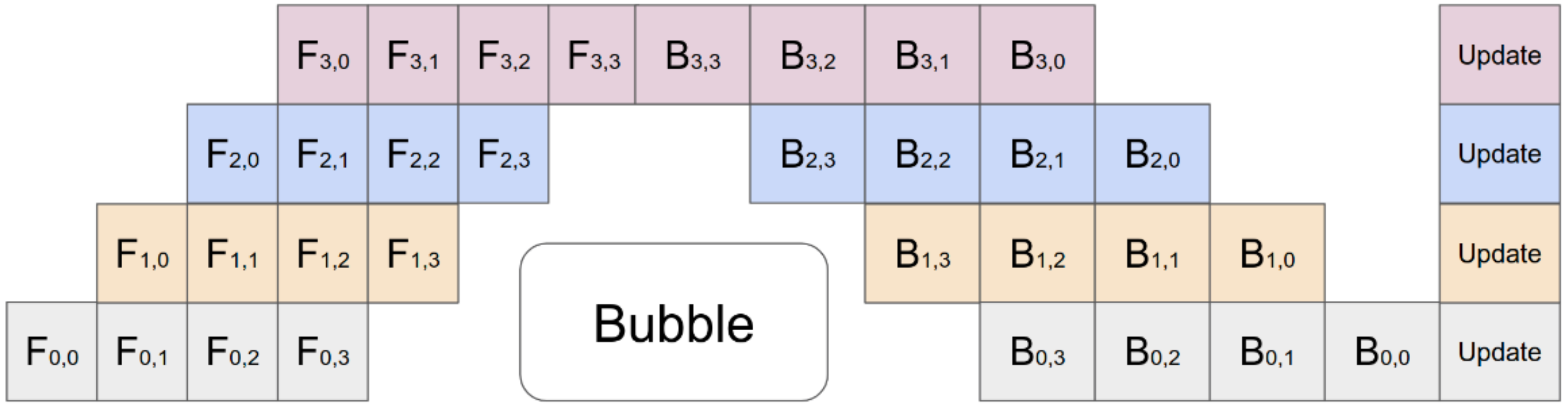

$F_{3,0}$ $F_{3,1}$ $F_{3,2}$ $F_{3,3}$ $B_{3,3}$ $B_{3,2}$ $B_{3,1}$ $B_{3,0}$ Update
$F_{2,0}$ $F_{2,1}$ $F_{2,2}$ $F_{2,3}$ $B_{2,3}$ $B_{2,2}$ $B_{2,1}$ $B_{2,0}$ Update
$F_{1,0}$ $F_{1,1}$ $F_{1,2}$ $F_{1,3}$ $B_{1,3}$ $B_{1,2}$ $B_{1,1}$ $B_{1,0}$ Update
$F_{0,0}$ $F_{0,1}$ $F_{0,2}$ $F_{0,3}$ $B_{0,3}$ $B_{0,2}$ $B_{0,1}$ $B_{0,0}$ Update
Bubble

(i) the number of model partitions K
(ii) the number of micro-batches M
(iii) the sequence and definitions of L layers that define the model

[1] Huang, Yanping, et al. "Gpipe: Efficient training of giant neural networks using pipeline parallelism." Advances in neural information processing systems 32 (2019).

Pipeline Parallelism

GPipe: Divides input mini-batches into smaller micro-batches. During backward, recomputes forward



$F_{3,0}$ $F_{3,1}$ $F_{3,2}$ $F_{3,3}$ $B_{3,3}$ $B_{3,2}$ $B_{3,1}$ $B_{3,0}$ Update
$F_{2,0}$ $F_{2,1}$ $F_{2,2}$ $F_{2,3}$ $B_{2,3}$ $B_{2,2}$ $B_{2,1}$ $B_{2,0}$ Update
$F_{1,0}$ $F_{1,1}$ $F_{1,2}$ $F_{1,3}$ $B_{1,3}$ $B_{1,2}$ $B_{1,1}$ $B_{1,0}$ Update
$F_{0,0}$ $F_{0,1}$ $F_{0,2}$ $F_{0,3}$ $B_{0,3}$ $B_{0,2}$ $B_{0,1}$ $B_{0,0}$ Update
Bubble

Bubble overhead: $O(\frac{K-1}{M+K-1})$ could be negligible when $M \geq 4 \times K$

Communication overhead: transfer activation tensors at the partition boundaries

Peak activation memory: $O(N \times L)$ -> $\hat{O}(N + \frac{L}{K} \times \frac{N}{M})$

Pipeline Parallelism

Pipeline Parallel: Split the inputs to reduce bubbles within one single node.

```python
class ModelParallelResNet50(ResNet):
    def __init__(self, *args, **kwargs):
        super(ModelParallelResNet50, self).__init__(
            Bottleneck, [3, 4, 6, 3], num_classes=num_classes, *args, **kwargs)

        self.seq1 = nn.Sequential(
            self.conv1,
            self.bn1,
            self.relu,
            self.maxpool,

            self.layer1,
            self.layer2
        ).to('cuda:0')

        self.seq2 = nn.Sequential(
            self.layer3,
            self.layer4,
            self.avgpool,
        ).to('cuda:1')

        self.fc.to('cuda:1')

    def forward(self, x):
        x = self.seq2(self.seq1(x).to('cuda:1'))
        return self.fc(x.view(x.size(0), -1))
```

```python
class PipelineParallelResNet50(ModelParallelResNet50):
    def __init__(self, split_size=20, *args, **kwargs):
        super(PipelineParallelResNet50, self).__init__(*args, **kwargs)
        self.split_size = split_size

    def forward(self, x):
        splits = iter(x.split(self.split_size, dim=0))
        s_next = next(splits)
        s_prev = self.seq1(s_next).to('cuda:1')
        ret = []

        for s_next in splits:
            # A. ``s_prev`` runs on ``cuda:1``
            s_prev = self.seq2(s_prev)
            ret.append(self.fc(s_prev.view(s_prev.size(0), -1)))

            # B. ``s_next`` runs on ``cuda:0``, which can run concurrently with A
            s_prev = self.seq1(s_next).to('cuda:1')

        s_prev = self.seq2(s_prev)
        ret.append(self.fc(s_prev.view(s_prev.size(0), -1)))

        return torch.cat(ret)
```

Pytorch launches the GPUs asynchronously so that we can have `self.seq2(s_prev)` and `self.seq1(s_next)` run concurrently with different micro-batches of data.

Pipeline Parallelism

Implementation Example: pippy, example codes, example_with_llama
PiPPy consists of two parts: a compiler and a runtime.

- The compiler takes your model code, splits it up, and transforms it into a **`Pipe`**
- The runtime executes the **`PipelineStages`** in parallel, handling things like micro-batch splitting, scheduling, communication, and gradient propagation

```python
class MyNetworkBlock(torch.nn.Module):
    def __init__(self, in_dim, out_dim):
        super().__init__()
        self.lin = torch.nn.Linear(in_dim, out_dim)

    def forward(self, x):
        x = self.lin(x)
        x = torch.relu(x)
        return x
```

```python
class MyNetwork(torch.nn.Module):
    def __init__(self, in_dim, layer_dims):
        super().__init__()

        prev_dim = in_dim
        for i, dim in enumerate(layer_dims):
            setattr(self, f'layer{i}', MyNetworkBlock(prev_dim, dim))
            prev_dim = dim

        self.num_layers = len(layer_dims)
        # 10 output classes
        self.output_proj = torch.nn.Linear(layer_dims[-1], 10)

    def forward(self, x):
        for i in range(self.num_layers):
            x = getattr(self, f'layer{i}')(x)

        return self.output_proj(x)


in_dim = 512
layer_dims = [512, 1024, 256]
mn = MyNetwork(in_dim, layer_dims).to(device)
```

Pipeline Parallelism

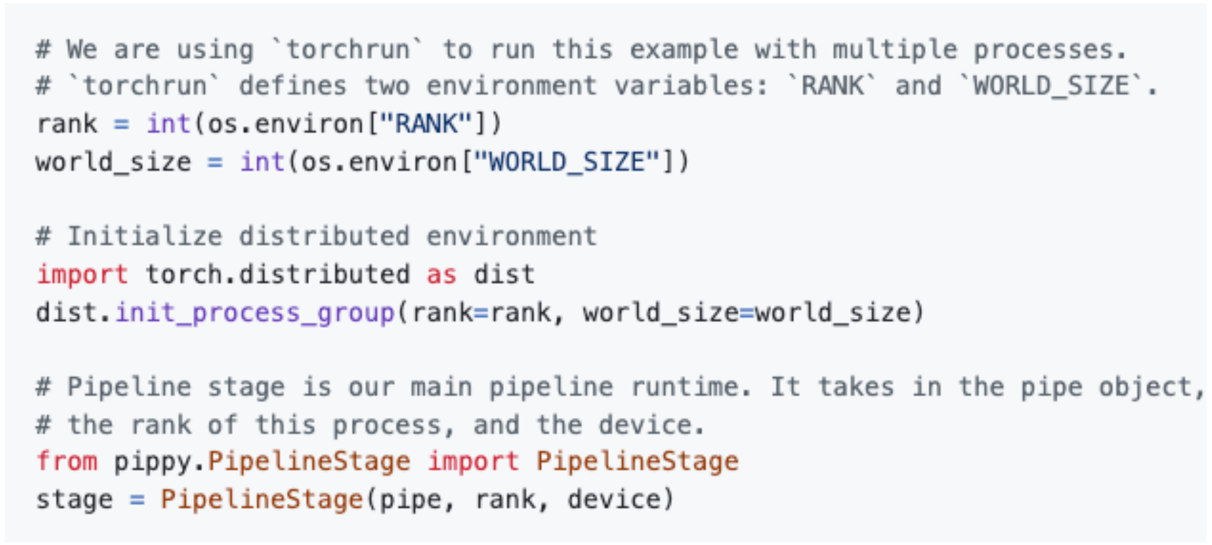
Implementation Example: pippy, example codes, example_with_llama
PiPPy consists of two parts: a compiler and a runtime.

```python
from pippy.IR import annotate_split_points, Pipe, PipeSplitWrapper

annotate_split_points(mn, {'layer0': PipeSplitWrapper.SplitPoint.END,
                           'layer1': PipeSplitWrapper.SplitPoint.END})

batch_size = 32
example_input = torch.randn(batch_size, in_dim, device=device)
chunks = 4

pipe = Pipe.from_tracing(mn, chunks, example_args=(example_input,))
print(pipe)
```

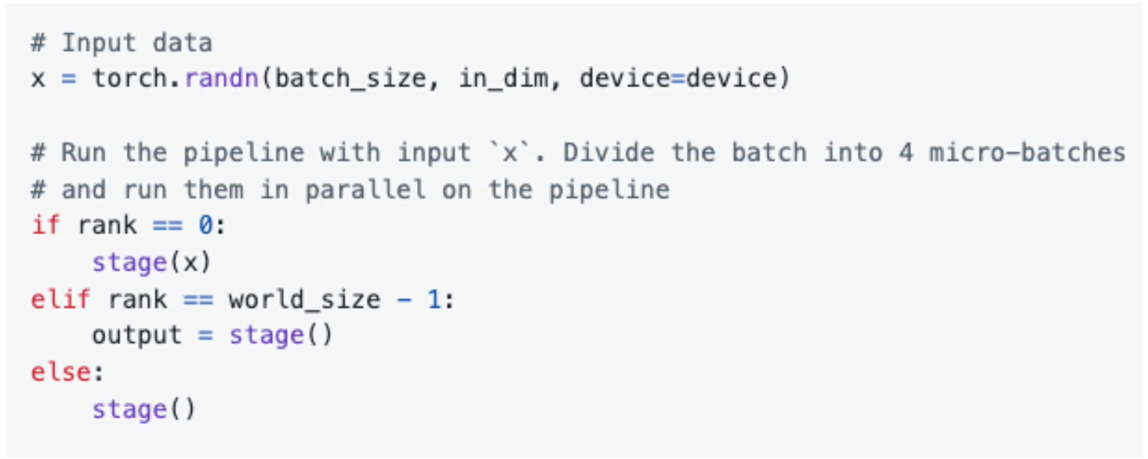
```
"""
************************************** pipe **************************************
GraphModule(
  (submod_0): PipeStageModule(
    (L__self___layer0_mod_lin): Linear(in_features=512, out_features=512, bias=True)
  )
  (submod_1): PipeStageModule(
    (L__self___layer1_mod_lin): Linear(in_features=512, out_features=1024, bias=True)
  )
  (submod_2): PipeStageModule(
    (L__self___layer2_lin): Linear(in_features=1024, out_features=256, bias=True)
    (L__self___output_proj): Linear(in_features=256, out_features=10, bias=True)
  )
)

def forward(self, arg0):
    submod_0 = self.submod_0(arg0);  arg0 = None
    submod_1 = self.submod_1(submod_0);  submod_0 = None
    submod_2 = self.submod_2(submod_1);  submod_1 = None
    return [submod_2]
"""
```

Pipeline Parallelism

Implementation Example: pippy, example codes, example_with_llama
PiPPy consists of two parts: a compiler and a runtime.



```python
# We are using `torchrun` to run this example with multiple processes.
# `torchrun` defines two environment variables: `RANK` and `WORLD_SIZE`.
rank = int(os.environ["RANK"])
world_size = int(os.environ["WORLD_SIZE"])

# Initialize distributed environment
import torch.distributed as dist
dist.init_process_group(rank=rank, world_size=world_size)

# Pipeline stage is our main pipeline runtime. It takes in the pipe object,
# the rank of this process, and the device.
from pippy.PipelineStage import PipelineStage
stage = PipelineStage(pipe, rank, device)
```



```python
# Input data
x = torch.randn(batch_size, in_dim, device=device)

# Run the pipeline with input `x`. Divide the batch into 4 micro-batches
# and run them in parallel on the pipeline
if rank == 0:
    stage(x)
elif rank == world_size - 1:
    output = stage()
else:
    stage()
```

Pipeline Parallelism

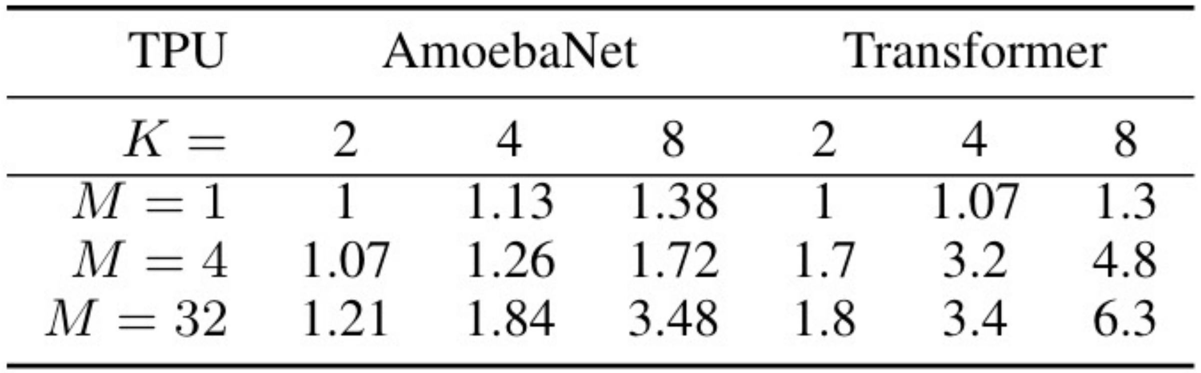
Implementation Example: pippy, example codes, example_with_llama
PiPPy consists of two parts: a compiler and a runtime.

```
def forward(self, *args, **kwargs):
    # Clean per iteration
    self.clear_runtime_states()

    # Split inputs into chunks
    self.split_inputs(args, kwargs)

    # Forward pass of all chunks
    for chunk in range(self.chunks):
        self.forward_one_chunk(chunk)
        logger.debug(f"[{self.group_rank}]
Forwarded chunk {chunk}")

    # Backward starts here
    for bwd_chunk in range(self.chunks):
        self.backward_one_chunk(bwd_chunk)
        logger.debug(f"[{self.group_rank}]
Backwarded chunk {bwd_chunk}")
```

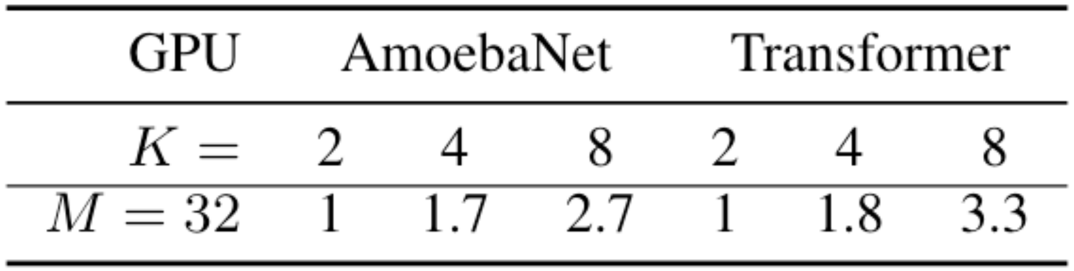
```
# Wait for all sends to finish
for work in self.all_act_send_reqs:
    work.wait()

# Wait for all sends to finish
for work in self.all_grad_send_reqs:
    work.wait()

# Last rank return merged results per original
format
if self.is_last():
    return self.merge_output_chunks()
else:
    return None
```

GPipe Performance

Normalized training throughput using Gpipe with different # of partitions *K* and different # of micro-batches *M* on TPUs and GPUs without high-speed interconnect.



TPU	AmoebaNet			Transformer		
$K =$	2	4	8	2	4	8
$M = 1$	1	1.13	1.38	1	1.07	1.3
$M = 4$	1.07	1.26	1.72	1.7	3.2	4.8
$M = 32$	1.21	1.84	3.48	1.8	3.4	6.3



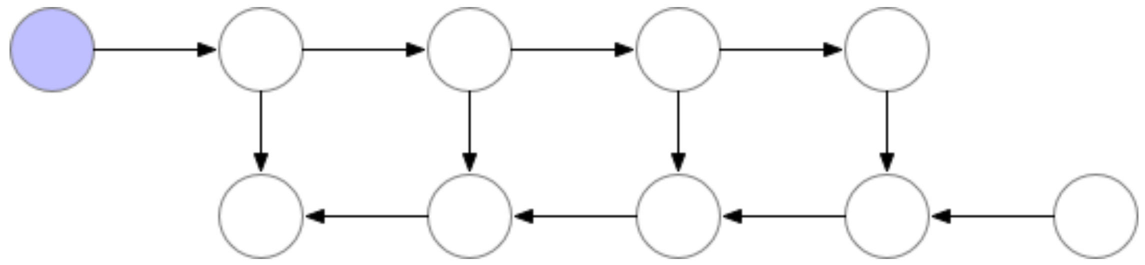
GPU	AmoebaNet			Transformer		
$K =$	2	4	8	2	4	8
$M = 32$	1	1.7	2.7	1	1.8	3.3

Gradient Checkpointing

Re-materialization

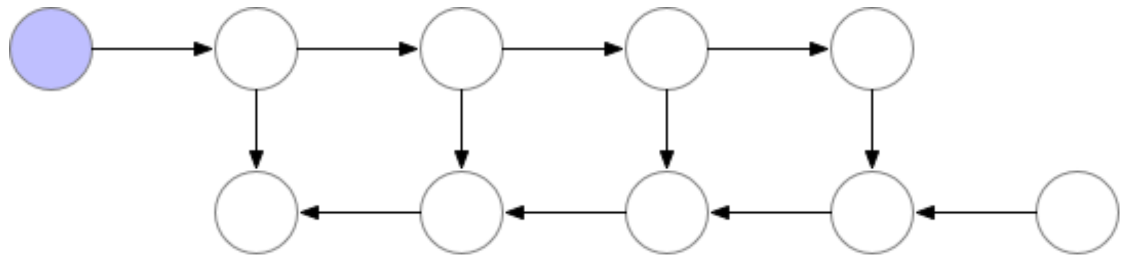
- Forward pass: each accelerator only stores output activations
- Backward pass: the *k*–th accelerator recomputes the composite forward function F_k

Vanilla backprop



- Memory for activations: $O(n)$
- Node computation: $O(n)$

Memory poor backprop



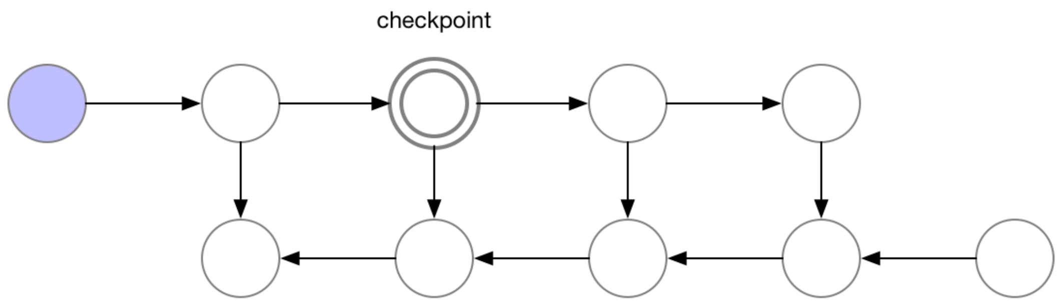
- Memory for activations: $O(1)$
- Node computation: $O(n^2)$

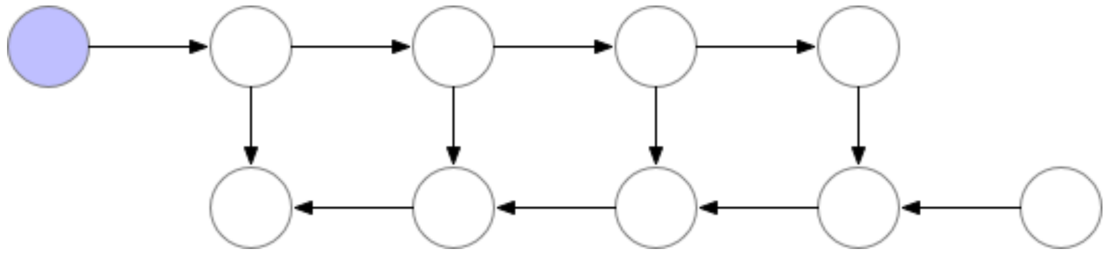
[1] Chen, Tianqi, et al. "Training deep nets with sublinear memory cost." arXiv preprint arXiv:1604.06174 (2016).
[2] https://github.com/cybertronai/gradient-checkpointing

Gradient Checkpointing

Gradient checkpoint

- Cash the activations of every sqrt(n) layers
- Memory for activations: *O(n)*
- *Node computation: O(sqrt(n) * sqrt(n)) = O(n)*





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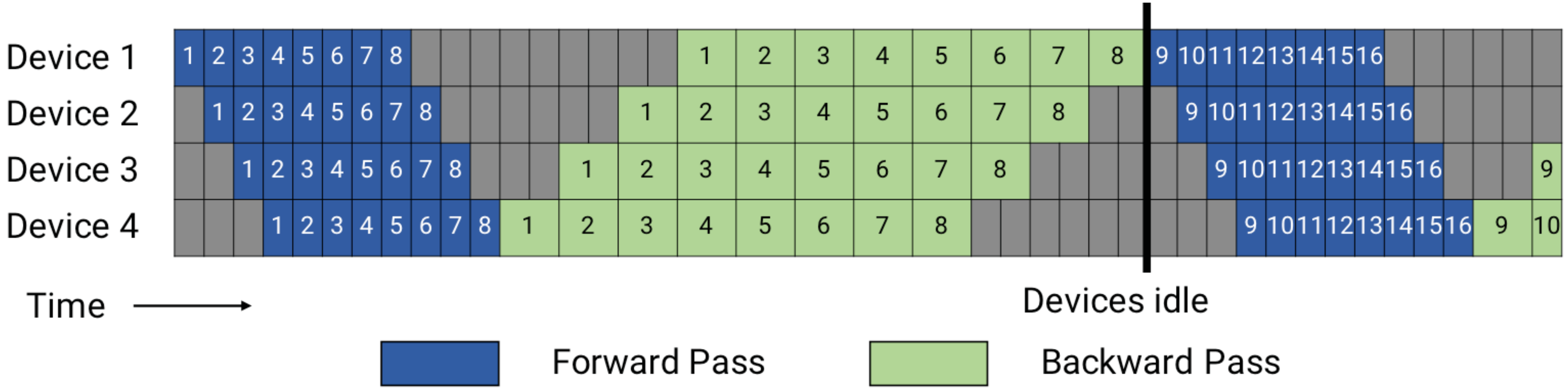
Standard Pipeline Model Parallel

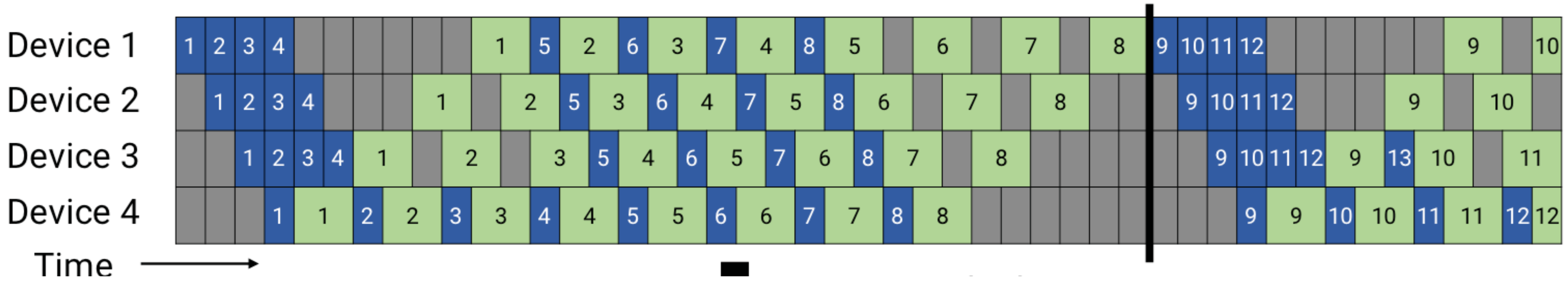


number of micro-batches in a batch: *m*
number of pipeline stages (number of devices used for pp): *p*
ideal time per iteration: t_{id} , forward pass for single micro-batch: t_f , backward pass: t_b

bubble time fraction (pipeline bubble size): $\frac{t_{pb}}{t_{id}} = \frac{(p-1)\cdot(t_f+t_b)}{m\cdot(t_f+t_b)} = \frac{p-1}{m}$

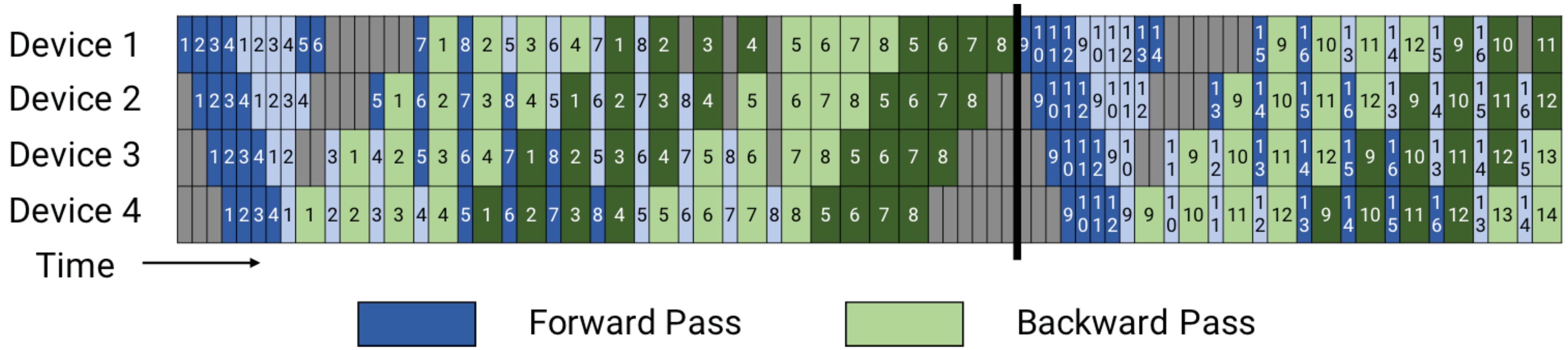
PipeDream-Flush

- PipeDream-Flush – start backward as soon as possible



Interleaved Pipeline Parallel

- Schedule with Interleaved Stages



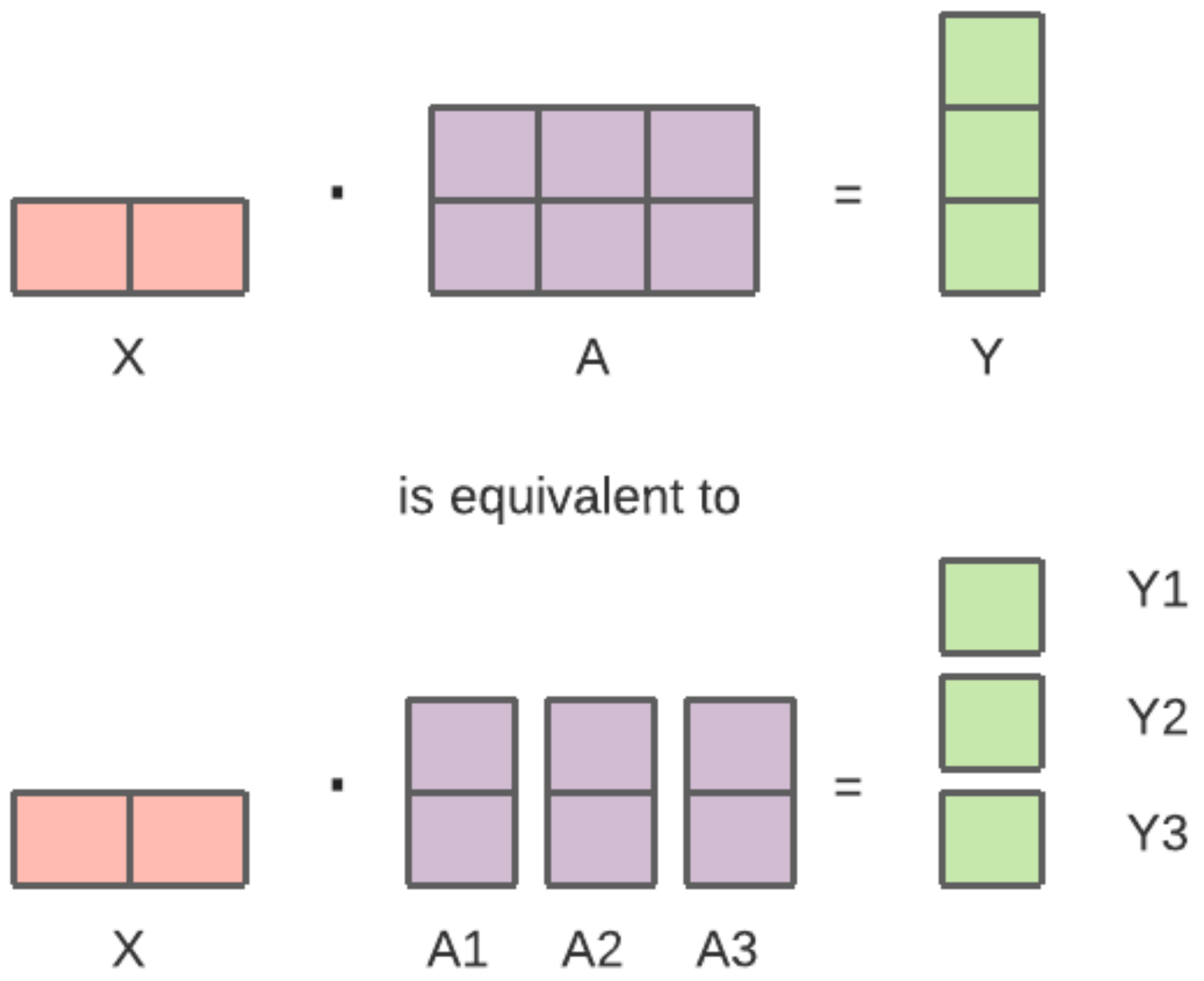
number of micro-batches in a batch: *m*
number of pipeline stages (number of devices used for pp): *p*

model chunk: *v* , pipeline bubble time: $t_{pb}^{\text{int.}} = \frac{(p-1)\cdot(t_f+t_b)}{v}$

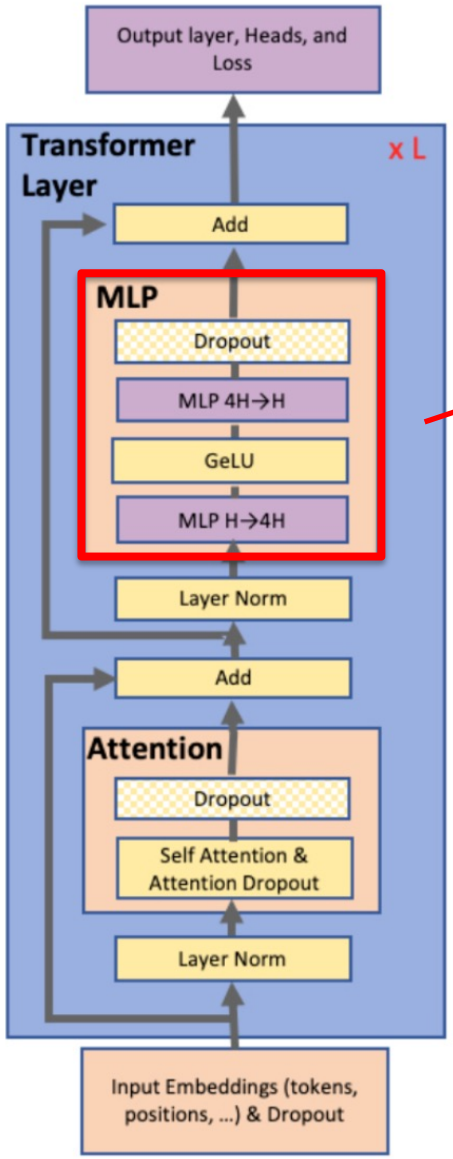
bubble time fraction (pipeline bubble size): $\frac{t_{pb}^{\text{int.}}}{t_{id}} = \frac{1}{v} \cdot \frac{p-1}{m}$

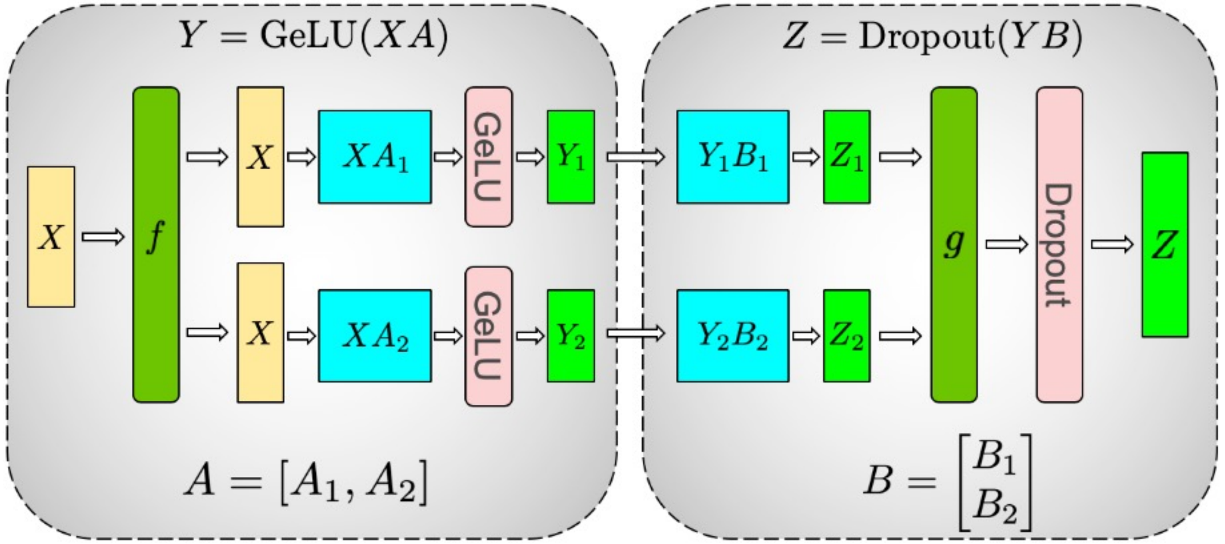
Tensor Parallelism

Tensor Parallelism



Tensor Parallelism


Output layer, Heads, and Loss
Transformer Layer
x L
Add
MLP
Dropout
MLP 4H→H
GeLU
MLP H→4H
Layer Norm
Add
Attention
Dropout
Self Attention & Attention Dropout
Layer Norm
Input Embeddings (tokens, positions, ...) & Dropout



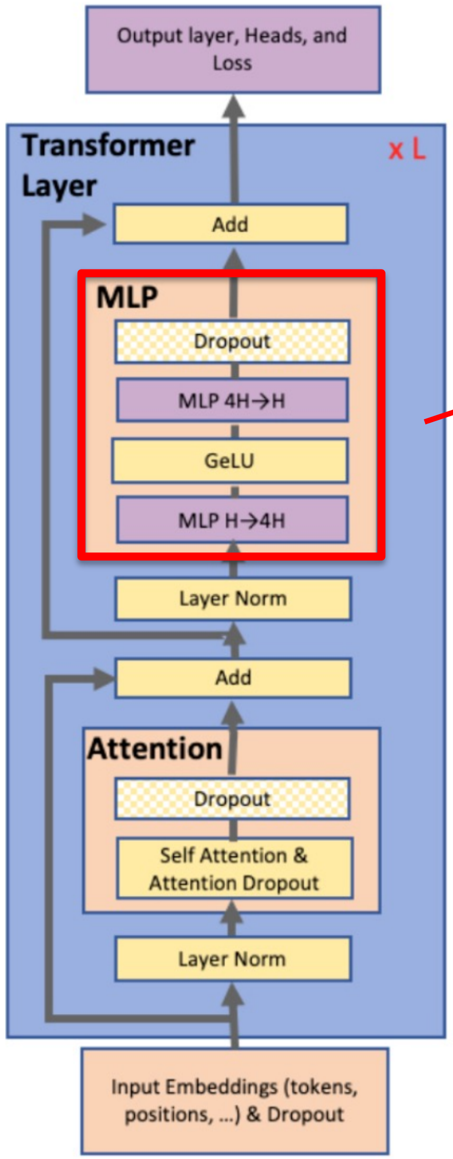
$$Y = GeLU(XA)$$

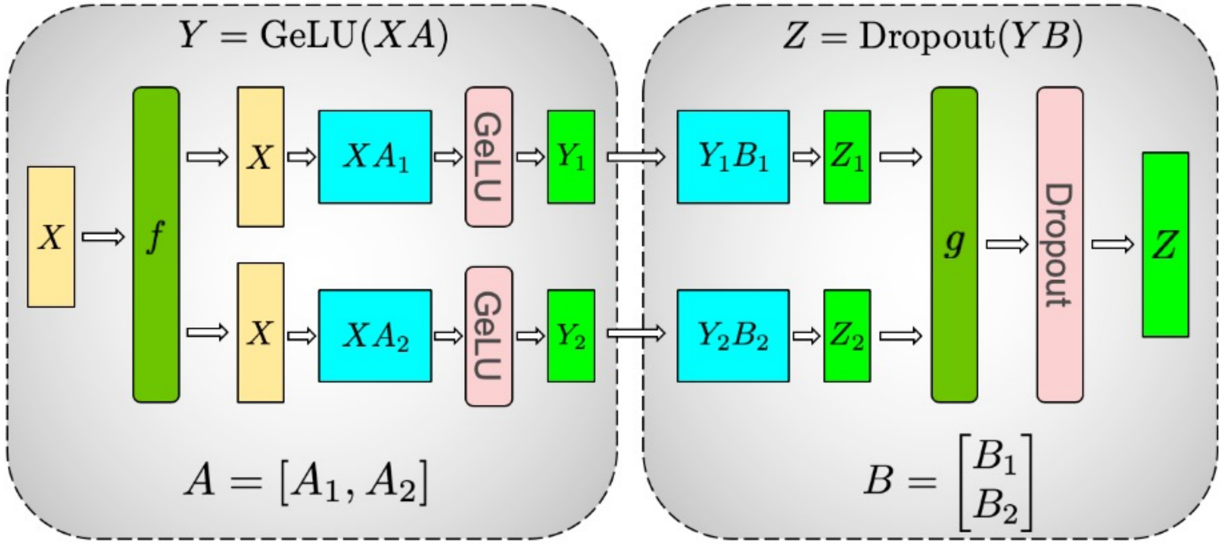
$$X = [X_1 \quad X_2], A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \qquad Y = GeLU(X_1A_1 + X_2A_2)$$

$$GeLU(X_1A_1 + X_2A_2) \neq GeLU(X_1A_1) + GeLU(X_2A_2)$$

All-reduce is needed !

Tensor Parallelism


Output layer, Heads, and Loss
Transformer Layer
x L
Add
MLP
Dropout
MLP 4H→H
GeLU
MLP H→4H
Layer Norm
Add
Attention
Dropout
Self Attention & Attention Dropout
Layer Norm
Input Embeddings (tokens, positions, ...) & Dropout



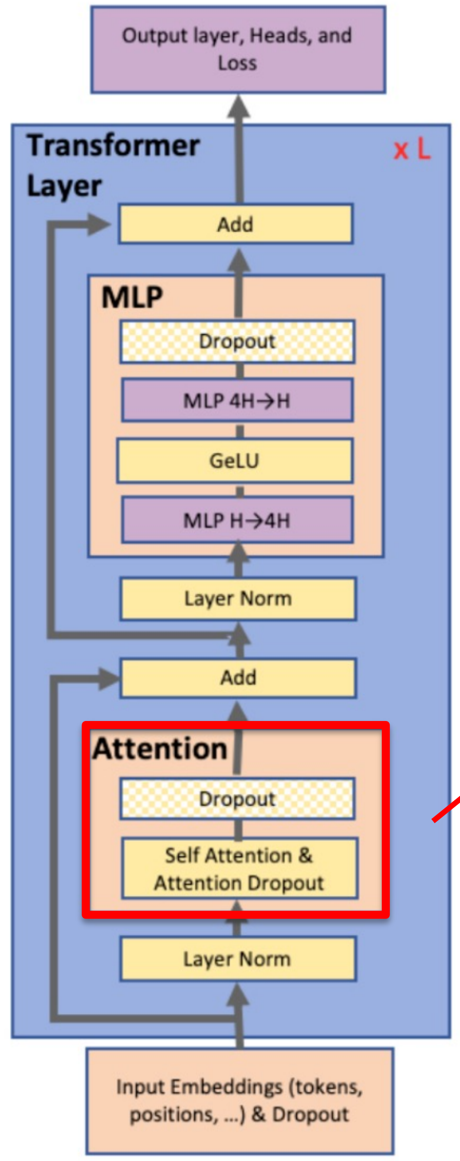
$$Y = GeLU(XA)$$

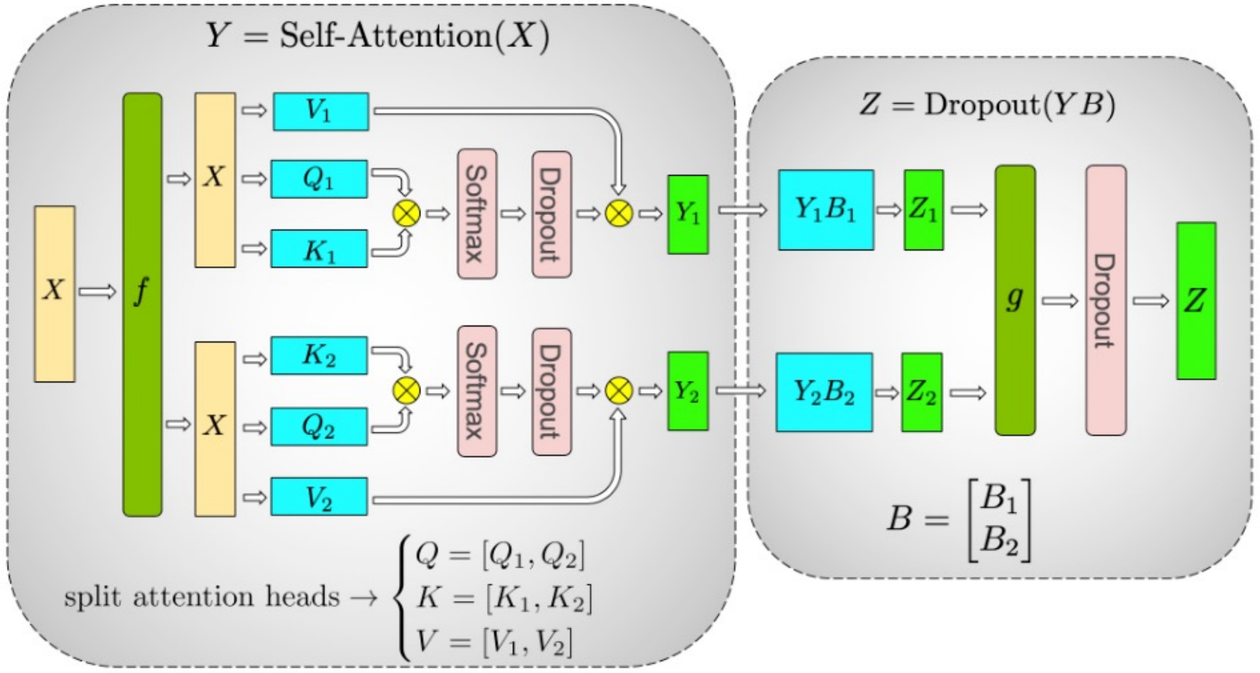
$$A = [A_1, A_2]$$

$$[Y_1 \quad Y_2] = [GeLU(XA_1), GeLU(XA_2)]$$

All-reduce is not needed !

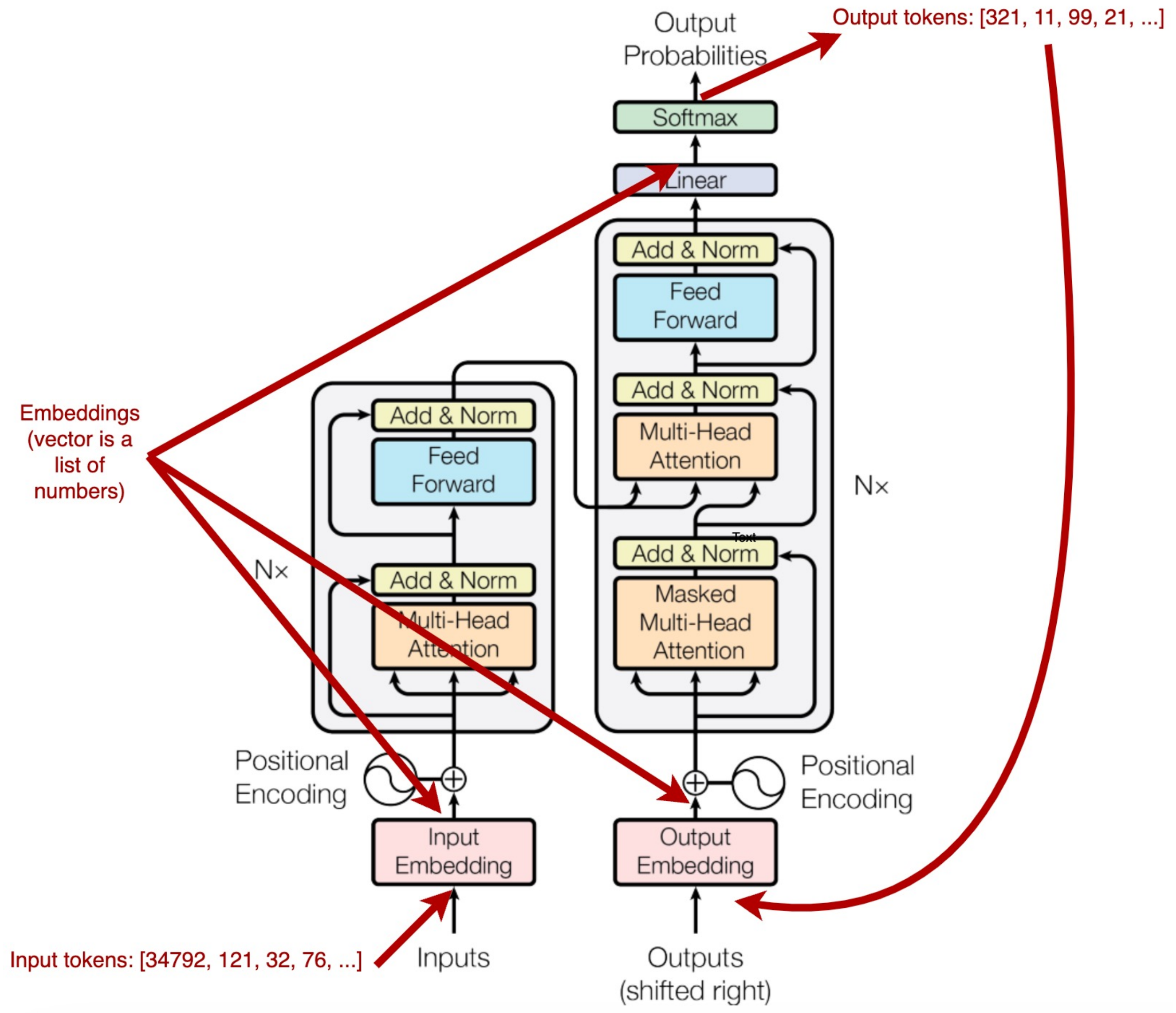
Tensor Parallelism for Self-Attention


Output layer, Heads, and Loss
Transformer Layer
x L
Add
MLP
Dropout
MLP 4H→H
GeLU
MLP H→4H
Layer Norm
Add
Attention
Dropout
Self Attention & Attention Dropout
Layer Norm
Input Embeddings (tokens, positions, ...) & Dropout



- Split weights over columns (heads)
- All-reduce is not needed !

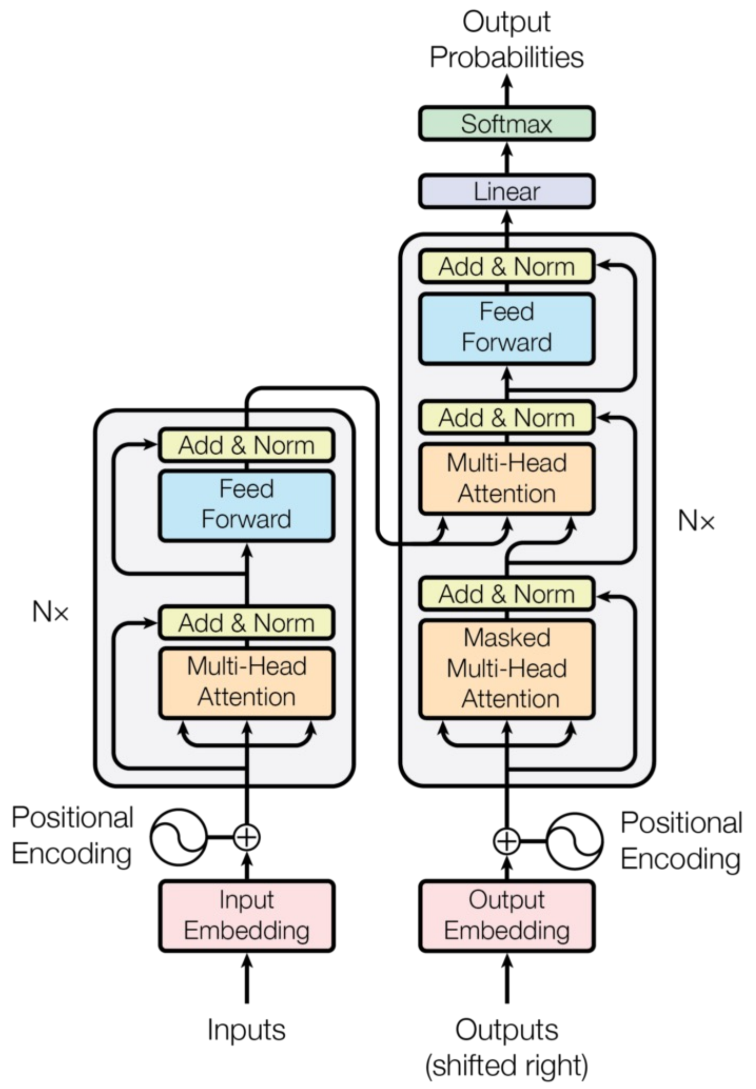
Tensor Parallelism - Embeddings



- Input embedding
  - Split over columns
    $E = [E_1, E_2]$ (column-wise)
  - all-reduce is required

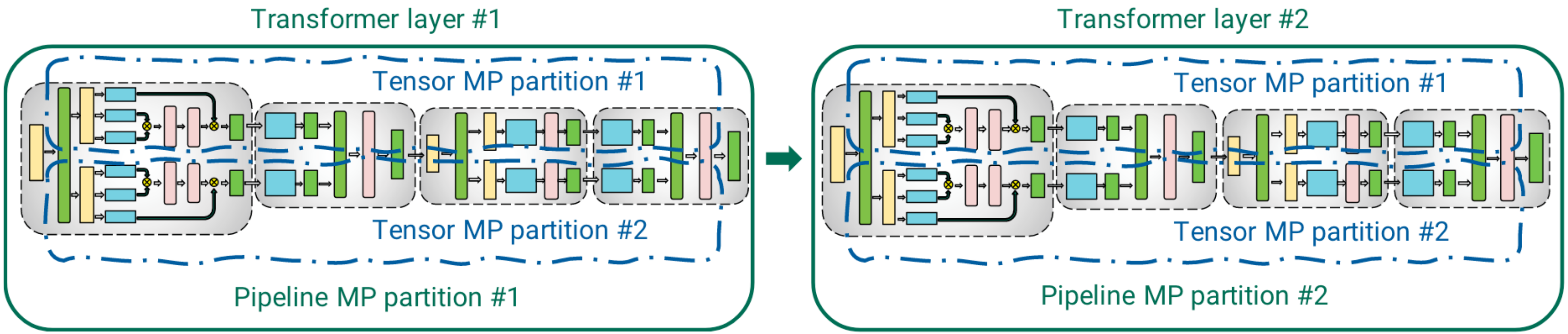
- Output embedding
  - Split over columns
    $\text{GEMM } [Y_1, Y_2] = [XE_1, XE_2]$
  - Fuse outputs with cross-entropy loss (huge reduction in communication)
  - all-gather is needed

Tensor Parallelism



- Layer normalization, dropout, residual connections
  - Duplicate across GPUs
- Each model parallel worker optimizes its own set of parameters

Combination of Pipeline and Tensor Model Parallelism



Combination of Pipeline and Tensor Model Parallelism

- Takeaway #1: When considering different forms of model parallelism, tensor model parallelism should generally be used up to degree g when using g-GPU servers, and then pipeline model parallelism can be used to scale up to larger models across servers

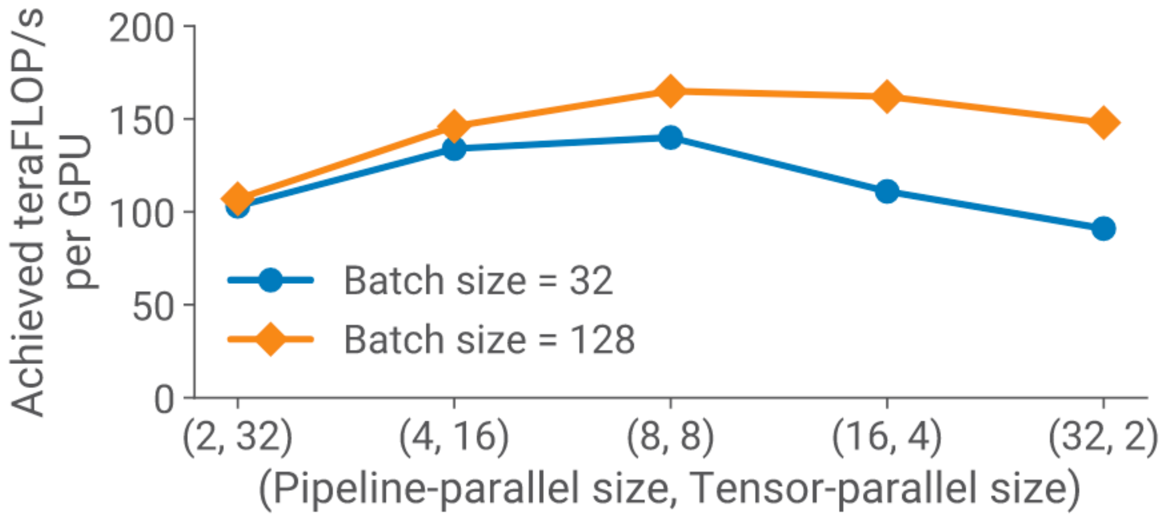


Figure 13: Throughput per GPU of various parallel configurations that combine pipeline and tensor model parallelism using a GPT model with 162.2 billion parameters and 64 A100 GPUs.

Combination of Pipeline and Tensor Model Parallelism

- Takeaway #1: When considering different forms of model parallelism, tensor model parallelism should generally be used up to degree g when using g-GPU servers, and then pipeline model parallelism can be used to scale up to larger models across servers

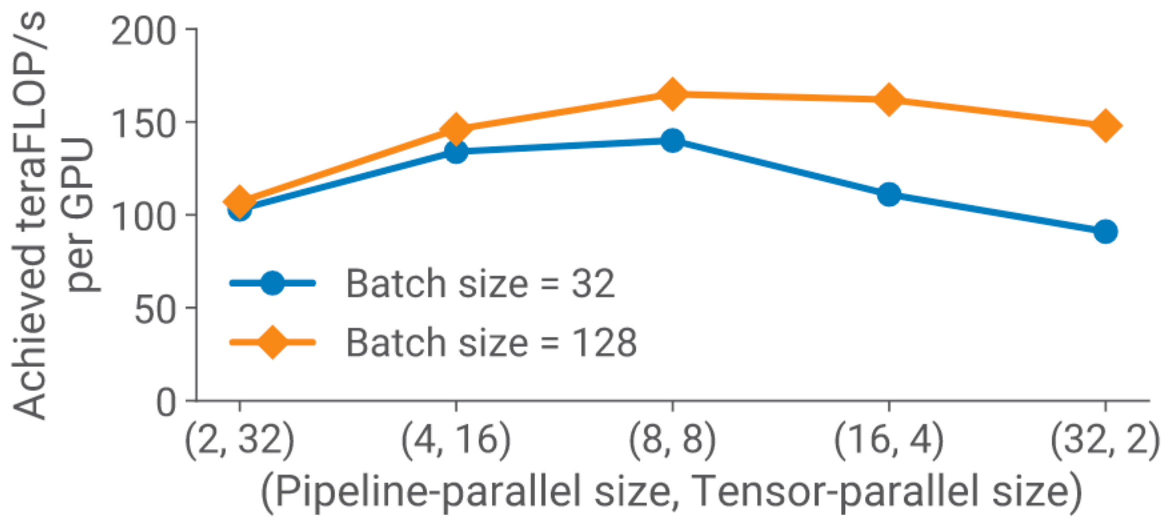


Figure 13: Throughput per GPU of various parallel configurations that combine pipeline and tensor model parallelism using a GPT model with 162.2 billion parameters and 64 A100 GPUs.

Model Parallel + Data Parallel

- Takeaway #2: When using data and model parallelism, a total model-parallel size of $M = t \cdot p$ should be used so that the model's parameters and intermediate metadata fit in GPU memory; data parallelism can be used to scale up training to more GPUs.

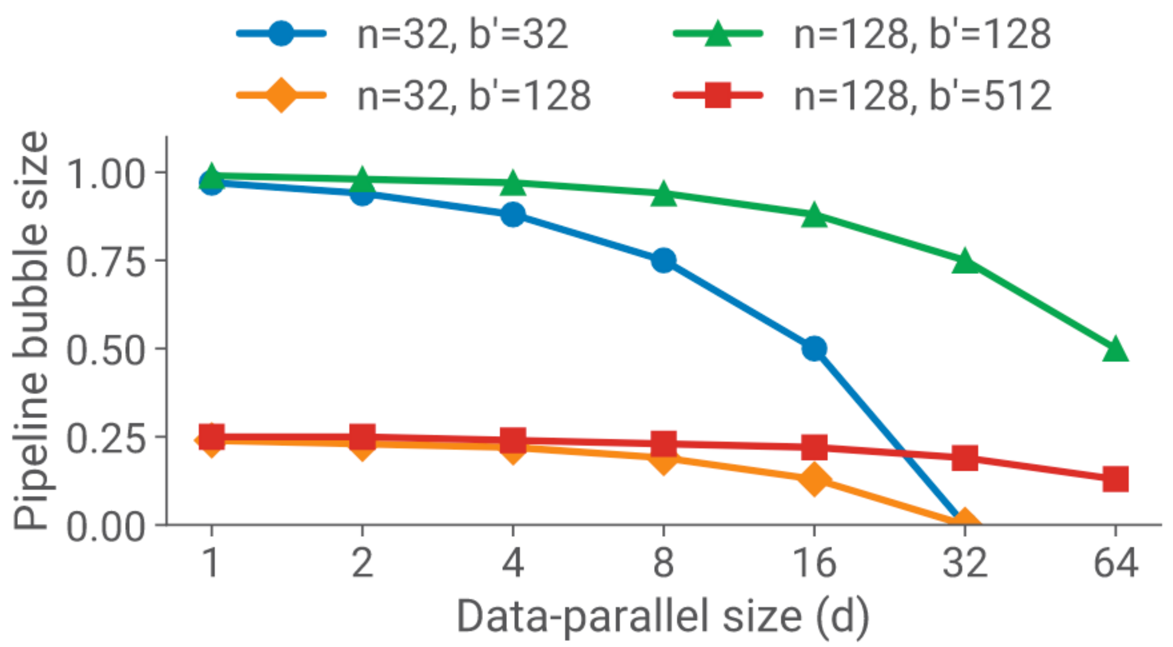


Figure 6: Fraction of time spent idling due to pipeline flush (pipeline bubble size) versus data-parallel size (d), for different numbers of GPUs (n) and ratio of batch size to microbatch size ($b' = B/b$).

Summary

- Pipeline Parallelism
  - split by layers (horizonal split)
  - eliminate the bubbles (idle)
  - interleaving forward/backward
- Tensor Parallelism
  - split the matrix computation

Next

- Walkthrough of HW2 solutions