LLM Sys

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Distributed Training – Model Parallelism

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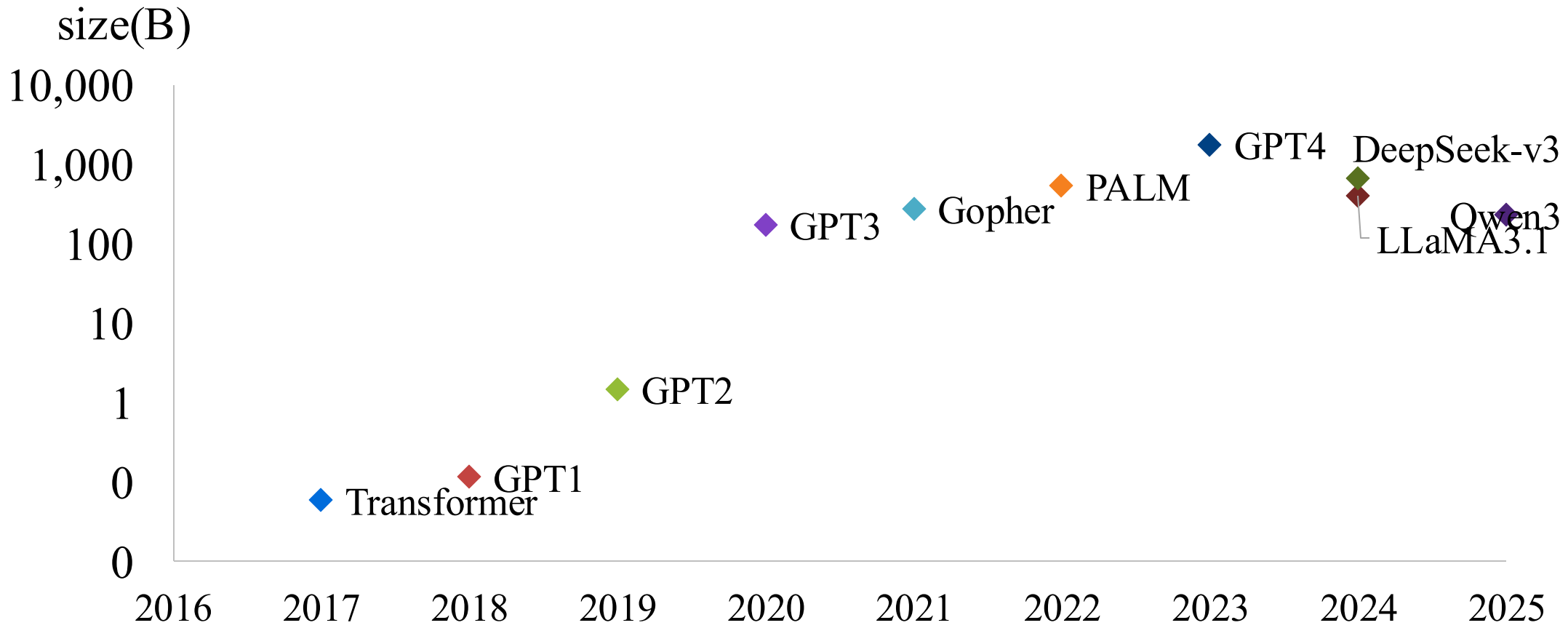
Today's Topic

- Model Parallel Training
- Pipeline Parallelism
- Tensor Parallelism

Model Parallelism

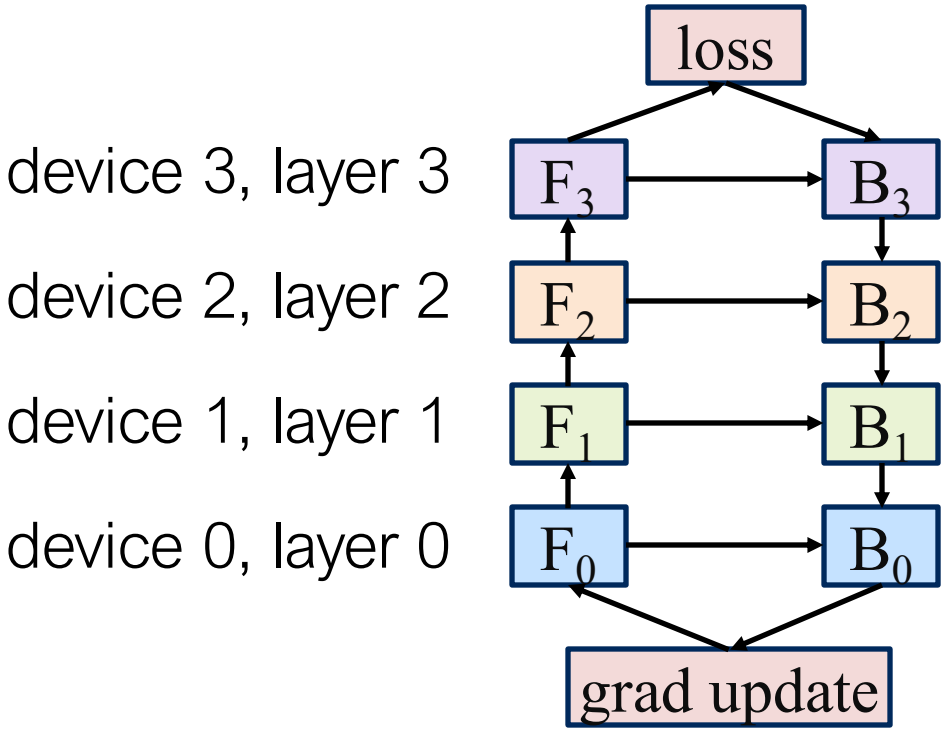
Motivation: The size of models increases exponentially fast and large. It is no longer possible to fit these large models into the memory of a single GPU.



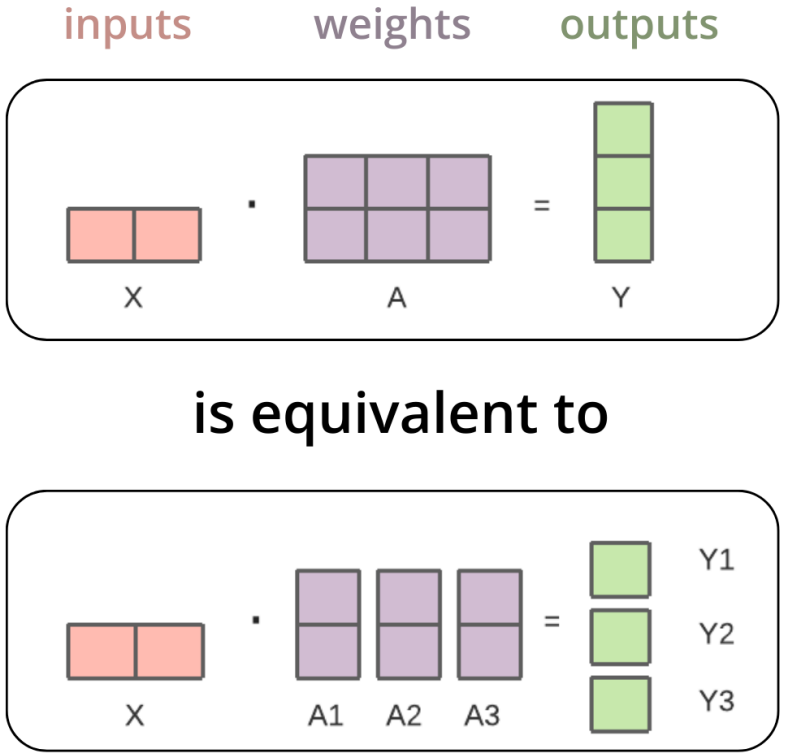
Model Parallel Training

computation (forward/backward/update) of a model is distributed across multiple workers.

Distributed layer-wise computation

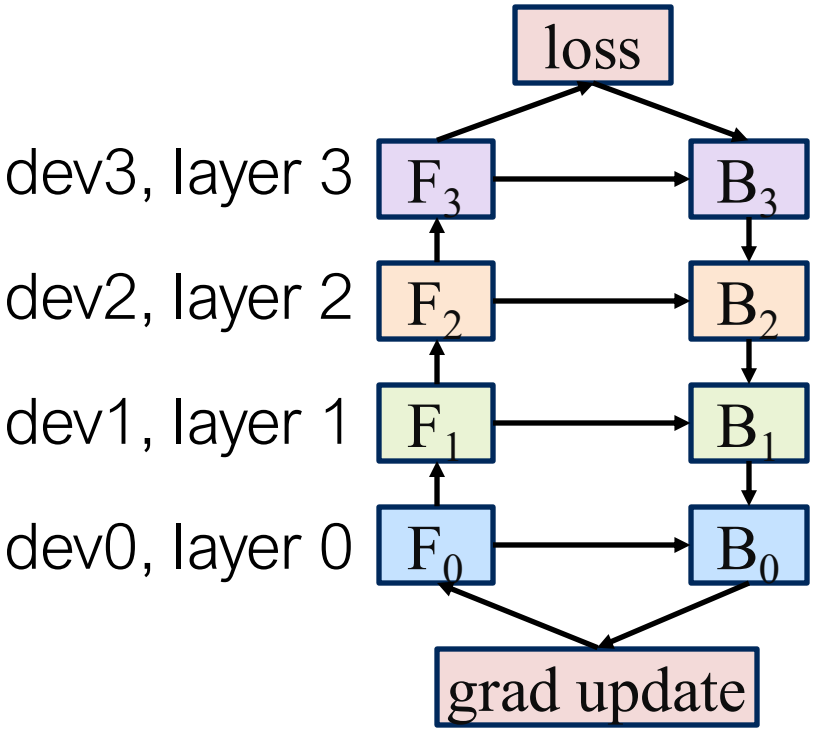


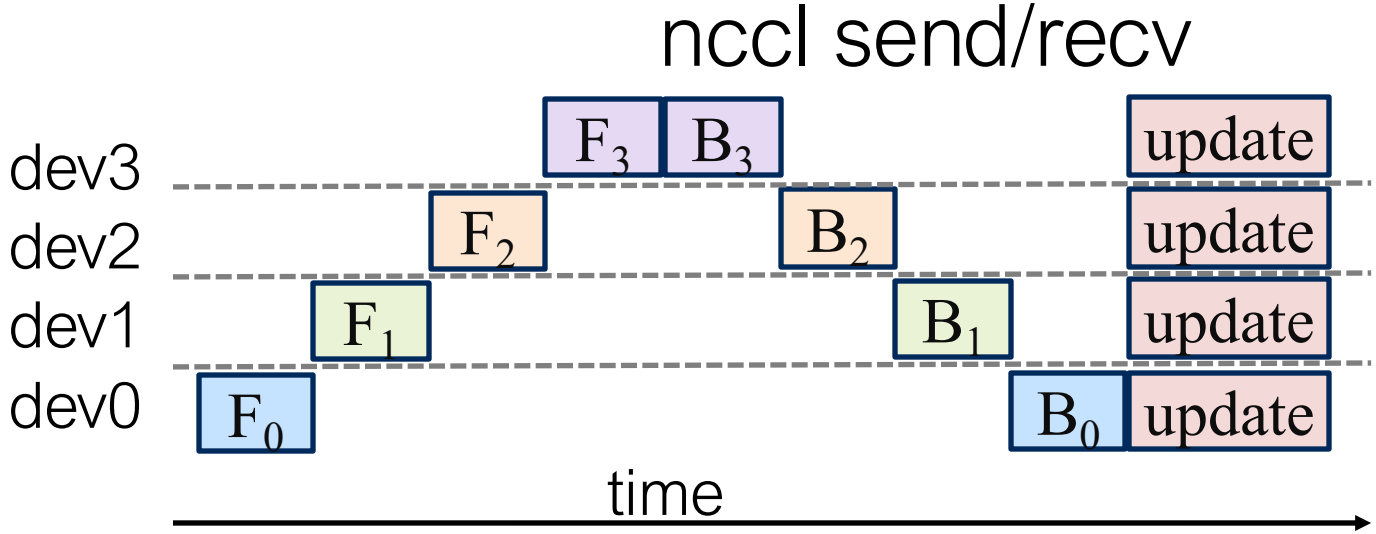
Distributed tensor computation



Pipeline Parallelism

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



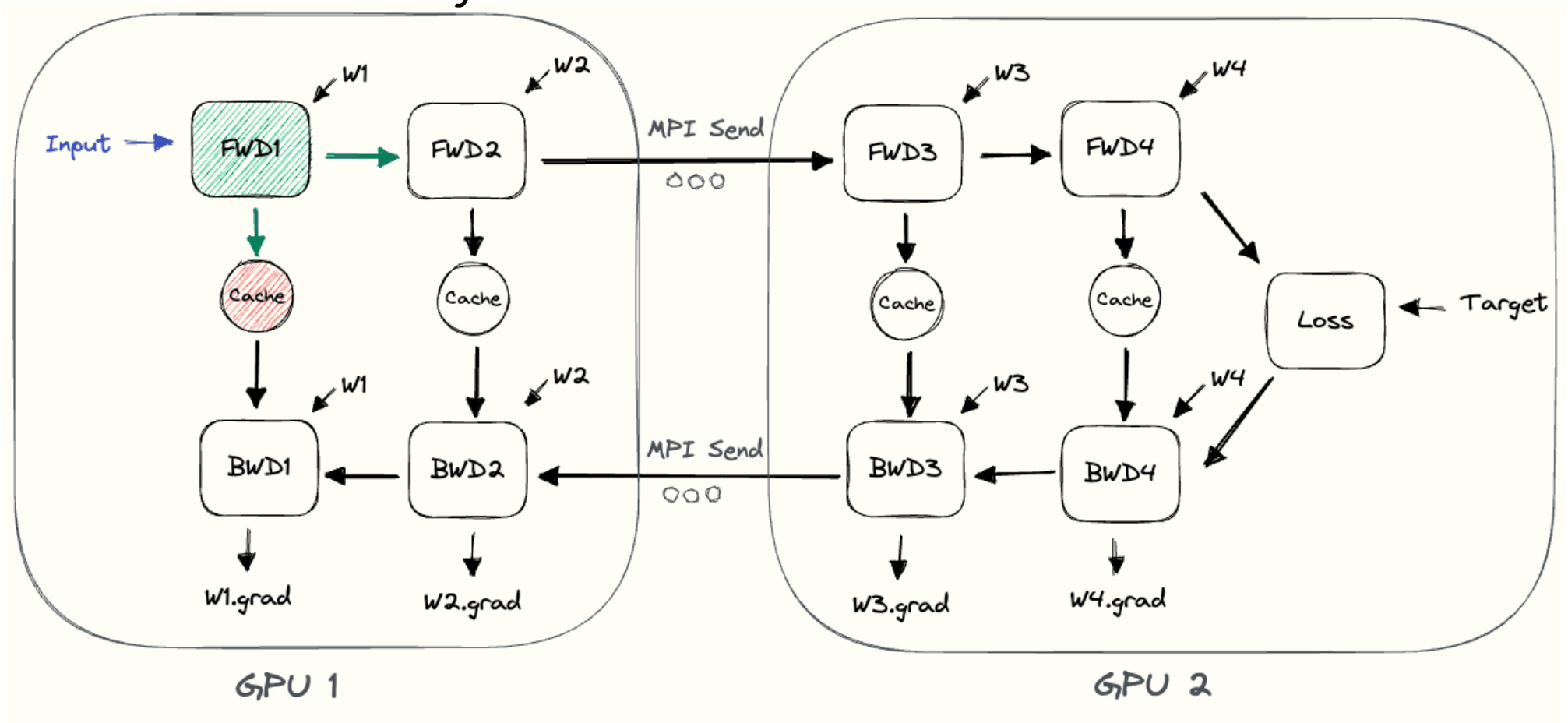


Any disadvantage?

all but one GPU is idle at any given moment!

Pipeline Parallelism Illustration

each device needs to calculate forward/backward, cache activations for the layers stored on the device.



https://siboehm.com/articles/22/pipeline-parallel-training

```
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

Limitations of Naïve Pipeline Parallel

- Low GPU utilization
  - at any point of time, only one device is working. others are idle.
- No interleaving of computation and communication
  - While sending intermediate results to next device, GPUs are idle.
- High memory demand
  - 1st GPU needs to store all activations until the whole batch completes.

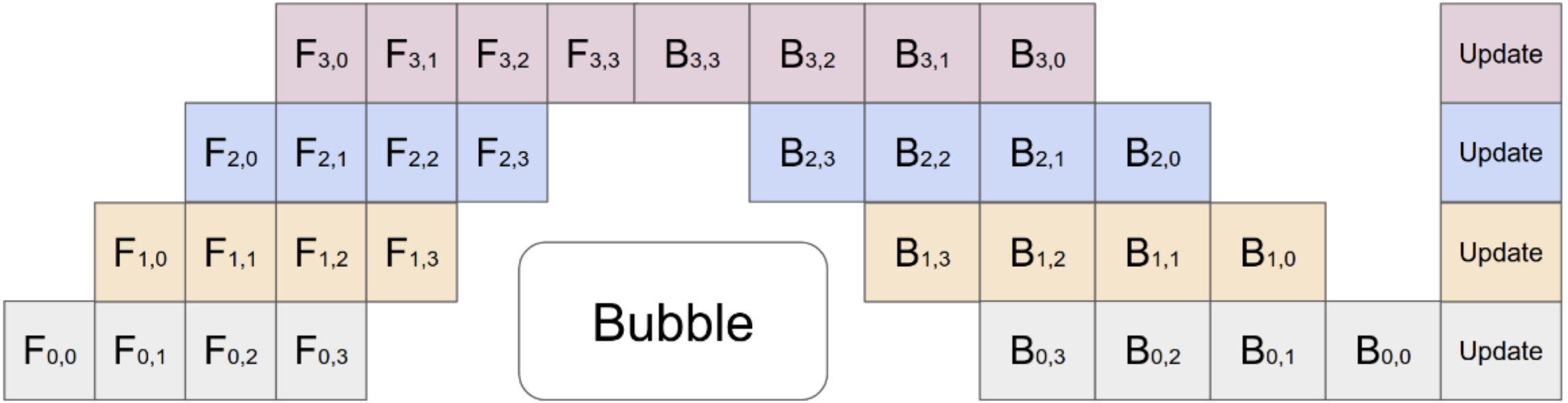
Pipeline Parallel: GPipe

- Key idea: Divides input data batches into smaller micro-batches, pipelining microbatches.
- A batch is usually decided by GPU memory size and memory needed for one data sample's forward/backward
  - as large as possible to fill the GPU memory
- A mciro-batch can be smaller

[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 – Micro-batching

GPipe: Divides input data mini-batches into smaller micro-batches.
Finishing all forward before starting backward for micro-batches.

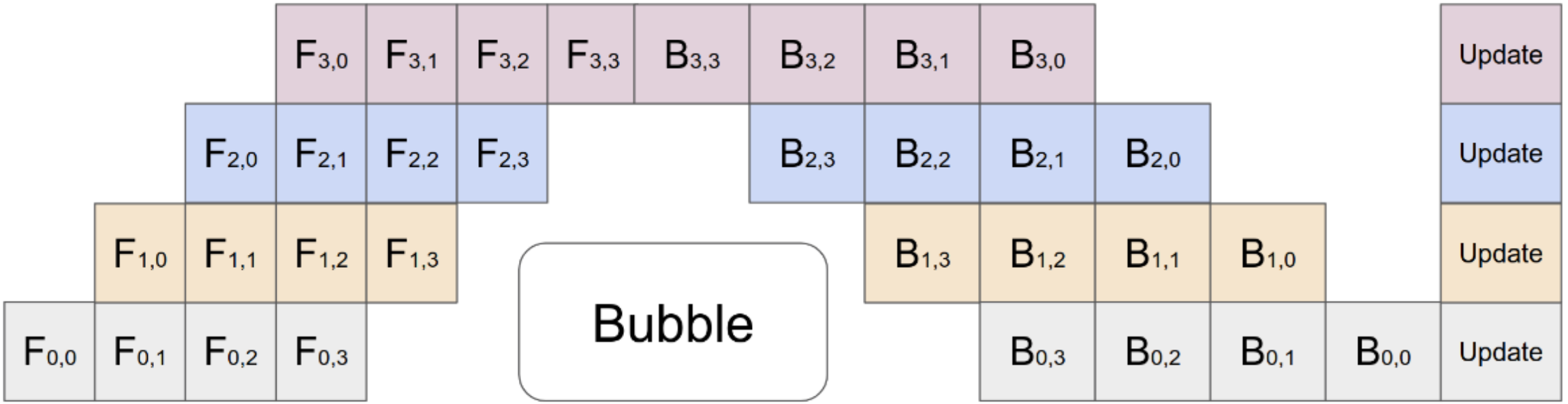


(i) the number of model partitions *K (i.e. number of devices)*
(ii) the number of micro-batches *M*
(iii) the number of model layers: L

[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: Microbatch Pipelining

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



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

Communication overhead: transfer activation tensors at the partition boundaries

Peak activation memory: $O(N \times L)$ ➔ $O(N + \frac{L}{K} \times \frac{N}{M})$ with gradient checkpoint (later)

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

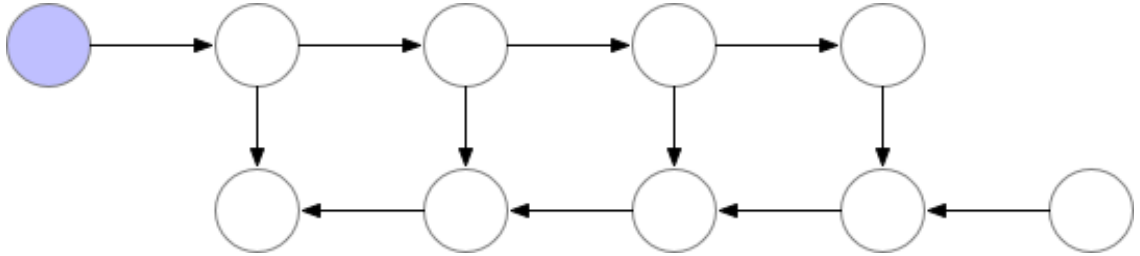
GPU	AmoebaNet			Transformer		
$K =$	2	4	8	2	4	8
$M = 32$	1	1.7	2.7	1	1.8	3.3

Reduce PP Memory Cost: Gradient Checkpointing

Re-materialization

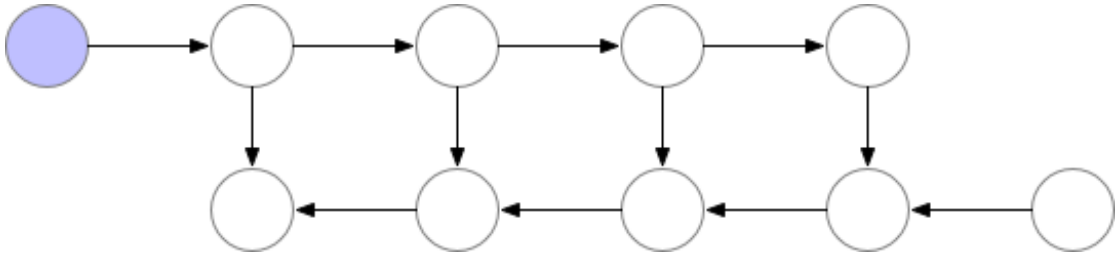
- Forward pass: each accelerator only stores output activations
- Backward pass: the k–th accelerator recomputes the composite forward function F_k

Vanilla backprop



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

Memory poor backprop



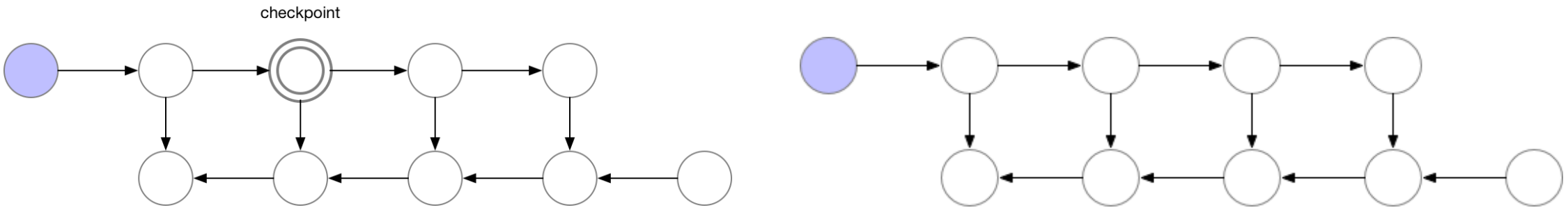
- Memory for activations: *O(1)*
- Node computation: $O(n^2)$

[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

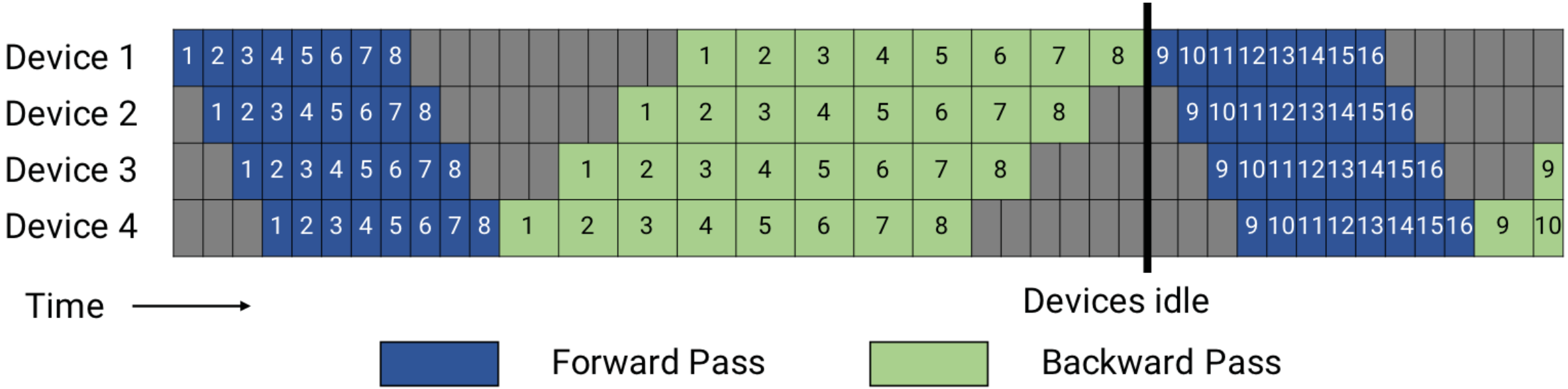
Gradient checkpoint

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



[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

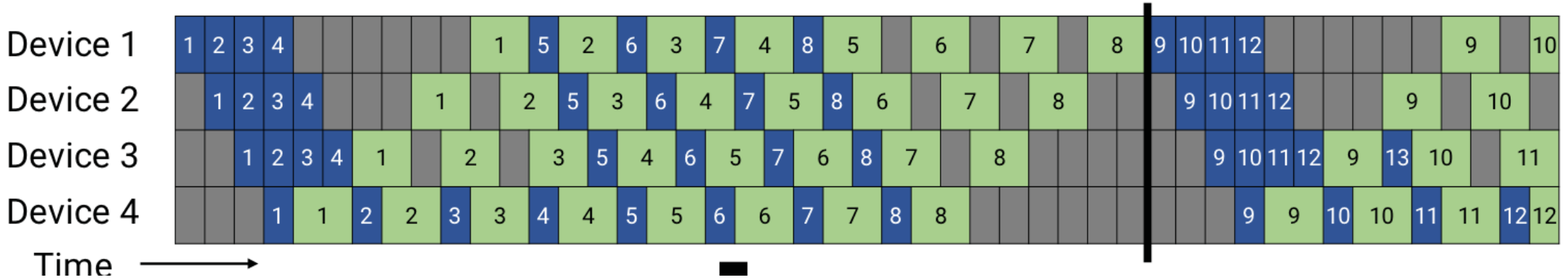
Limitations of Pipeline Parallel



finishing all forward before backward on micro-batches.
number of micro-batches in-flight (completed forward but not backward): 8 in this example
need to store all the activations for these micro-batches

Improving Pipeline Parallel with 1F1B flush

- PipeDream-Flush 1F1B – start backward as soon as possible



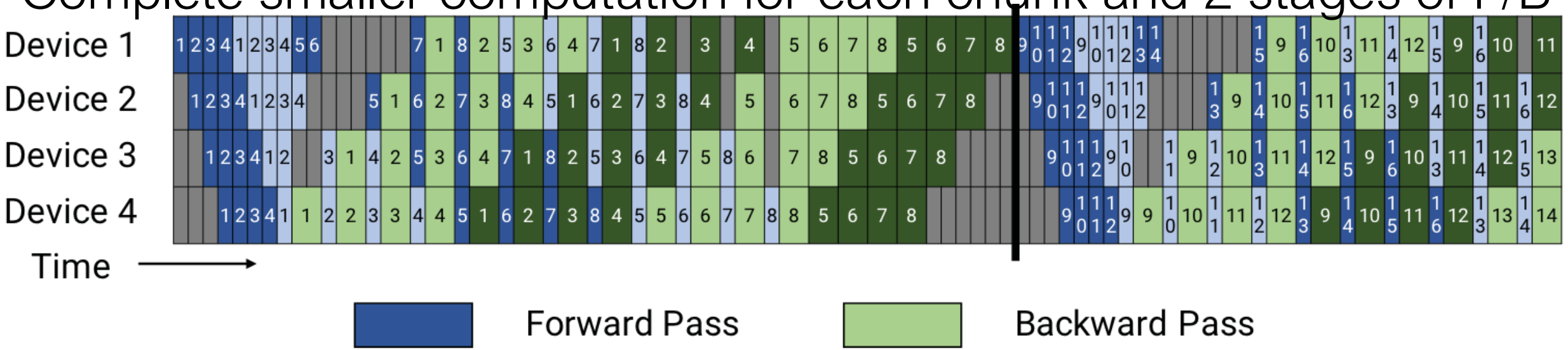
- benefit: reduce memory cost for storing the activations
- number of micro-batches in flight (completed forward but not backward): at most 4 (assuming 1B=2F) vs 8 in GPipe.

PipeDream: generalized pipeline parallelism for DNN training. Narayanan et al. SOSP 2019.

Further Improving Pipeline Parallel by Chunking Model Layers and Interleaving Stages

	Chunk 1 Layers	Chunk 2 Layers	
Device 1	1, 2	9, 10	
Device 2	3, 4	11, 12	
Device 3	5, 6	13, 14	
Device 4	7, 8	15, 16	

Complete smaller computation for each chunk and 2 stages of F/B



Efficient Large-Scale Language Model Training on GPU Clusters Using Megatron-LM. Narayanan et al SC 2021.

Implementing GPipe Parallelism

```
def minibatch_steps(self):
    yield [ZeroGrad()]

    # STAGE 1: First, we FWD all microbatches
    for microbatch_id in range(self.num_micro_batches):
        yield self.steps_FWD_microbatch(microbatch_id)

    # at this position, all microbatches are in flight and
    # memory demand is highest

    # STAGE 2: Then, we BWD all microbatches
    for microbatch_id in reversed(range(self.num_micro_batches)):
        yield from self.steps_BWD_microbatch(microbatch_id)

    # updating the weights is the last step of processing any batch
    yield [OptimizerStep()]
```

full code in https://github.com/siboehm/shallowspeed

```
def steps_FWD_microbatch(self, microbatch_id):
    cmds = []
    if self.is_first_stage:
        # first pipeline stage loads data from disk
        cmds.append(LoadMicroBatchInput(microbatch_id=microbatch_id))
    else:
        # all other stages receive activations from prev pipeline stage
        cmds.append(RecvActivations())

    cmds.append(Forward(microbatch_id=microbatch_id))

    if not self.is_last_stage:
        # all but the last pipeline stage send their output to next stage
        cmds.append(SendActivations())
    return cmds
```

```
def steps_BWD_microbatch(self, microbatch_id):
    cmds = []
    if self.is_last_stage:
        # last pipeline stage loads data from disk
        cmds.append(LoadMicroBatchTarget(microbatch_id=microbatch_id))
    else:
        # all other stages wait to receive grad from prev stage
        cmds.append(RecvOutputGrad())

    # the first microBatch is the lasted one that goes through backward pass
    if self.is_first_microbatch(microbatch_id):
        # interleaved backprop and AllReduce during last microBatch of BWD
        cmds.append(BackwardGradAllReduce(microbatch_id=microbatch_id))
    else:
        cmds.append(BackwardGradAcc(microbatch_id=microbatch_id))

    if not self.is_first_stage:
        # all but last pipeline stage send their input grad to prev stage
        cmds.append(SendInputGrad())
    yield cmds
```

Pipeline Parallelism in pytorch

torch.distributed.pipelining

- It consists of two stages
  - build PipelineStage
    - manually splitting the model
    - splitting model automatically
  - use PipelineSchedule for execution

```
class Transformer(nn.Module):
  def __init__(self, model_args: ModelArgs):
    super().__init__()
    self.tok_embeddings = nn.Embedding(...)
    # Using a ModuleDict lets us delete layers without affecting names, ensuring checkpoints will correctly save and load.
    self.layers = torch.nn.ModuleDict()
    for layer_id in range(model_args.n_layers):
      self.layers[str(layer_id)] = TransformerBlock(...)
    self.output = nn.Linear(...)

  def forward(self, tokens: torch.Tensor):
    # Handling layers being 'None' at runtime enables easy pipeline splitting
    h = self.tok_embeddings(tokens) if self.tok_embeddings else tokens
    for layer in self.layers.values():
      h = layer(h, self.freqs_cis)
    h = self.norm(h) if self.norm else h
    output = self.output(h).float() if self.output else h
    return output
```

https://pytorch.org/docs/main/distributed.pipelining.html

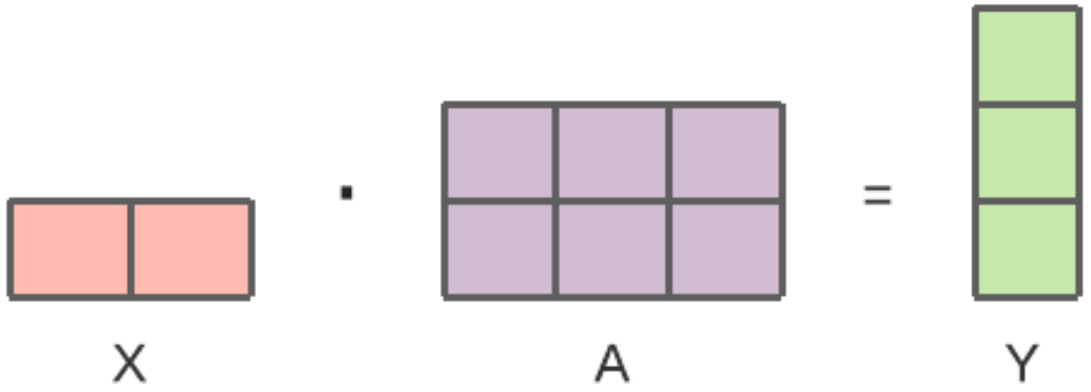
```
from torch.distributed.pipelining import PipelineStage

with torch.device("meta"):
  assert num_stages == 2, "This is a simple 2-stage example"
  # we construct the entire model, then delete the parts we do not need for this stage # in practice, this can be done using a helper function that automatically divides up layers across stages.
  model = Transformer()
  if stage_index == 0: # prepare the first stage model
    del model.layers["1"]
    model.norm = None
    model.output = None
  elif stage_index == 1: # prepare the second stage model
    model.tok_embeddings = None
    del model.layers["0"]
  stage = PipelineStage(model, stage_index, num_stages, device)
```

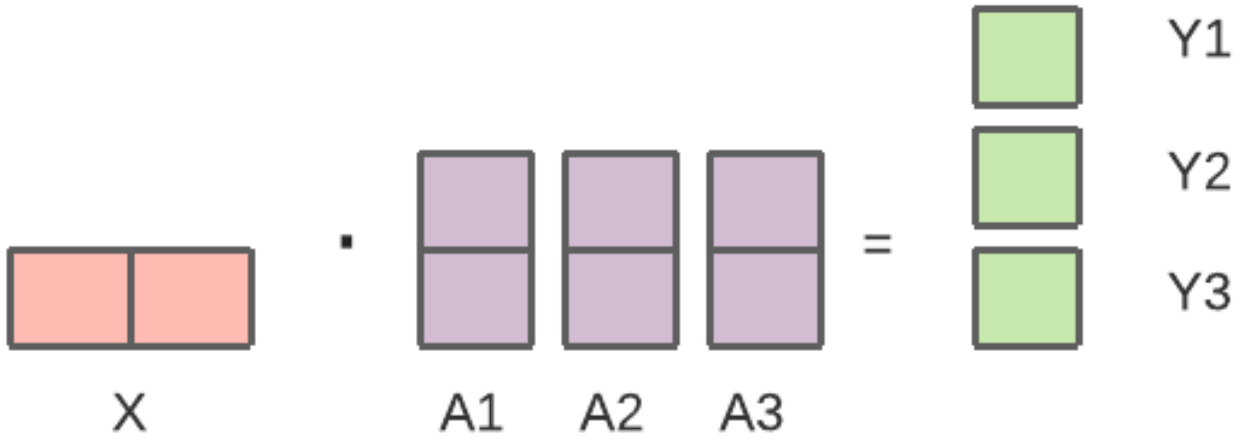
```
from torch.distributed.pipelining import ScheduleGPipe
# Create a schedule
schedule = ScheduleGPipe(stage, n_microbatches)
# Input data (whole batch)
x = torch.randn(batch_size, in_dim, device=device)
# Run the pipeline with input `x` # `x` will be divided into microbatches automatically
if rank == 0:
  schedule.step(x)
else:
  output = schedule.step()
```

Tensor Parallelism

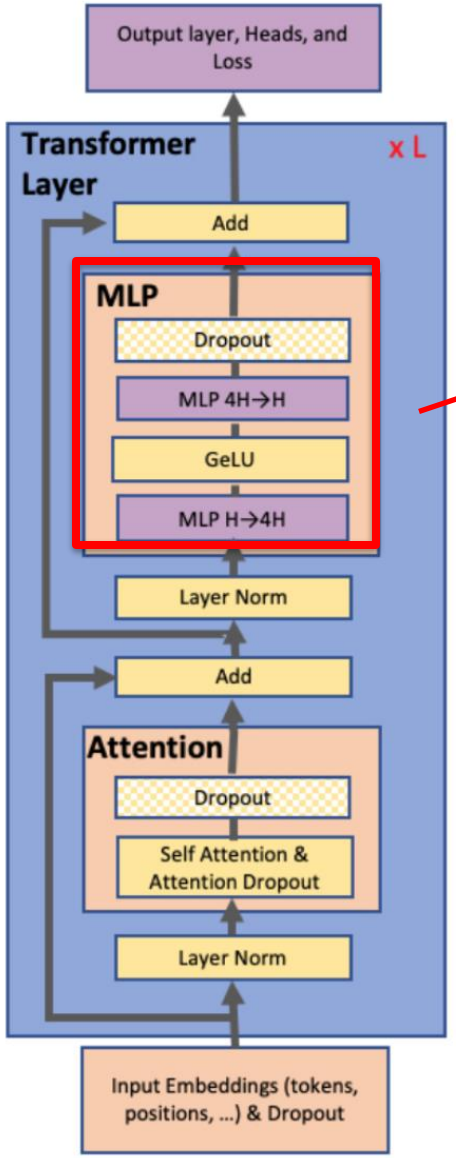
Tensor Parallelism – spliting the matrix computation

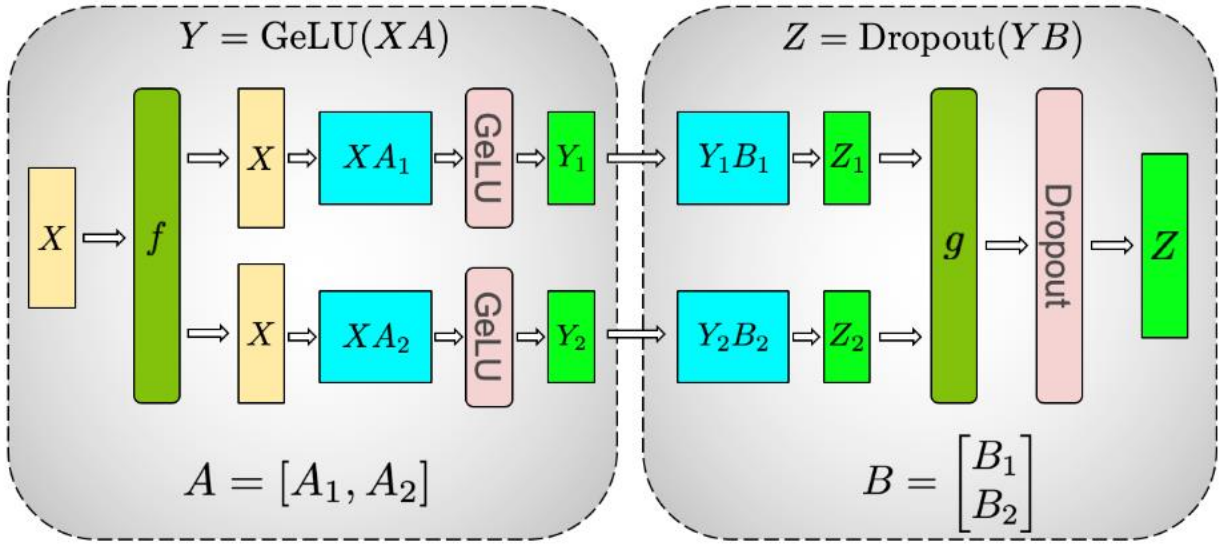


is equivalent to



Tensor Parallelism for FFN (big mat mul)





$$Y = GeLU(XA)$$

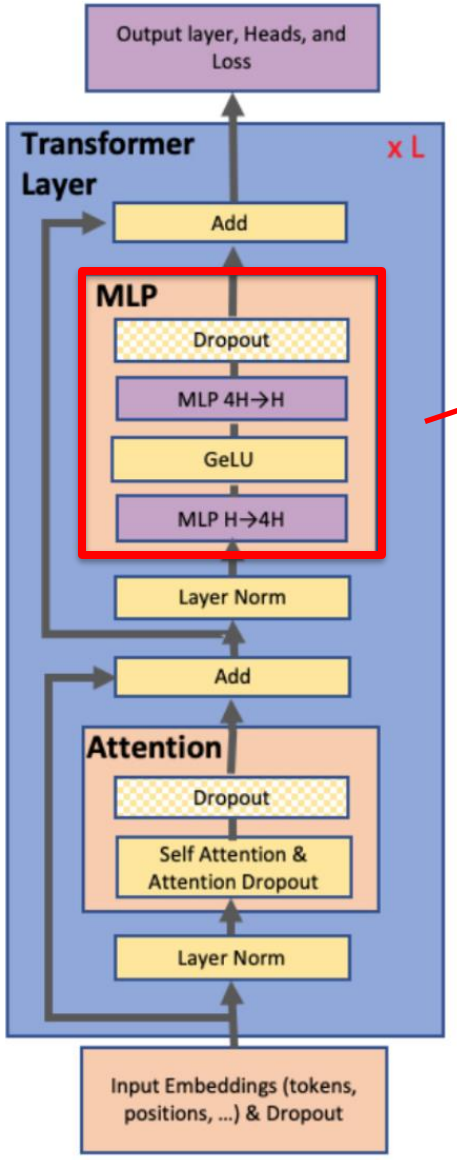
Splitting X and A

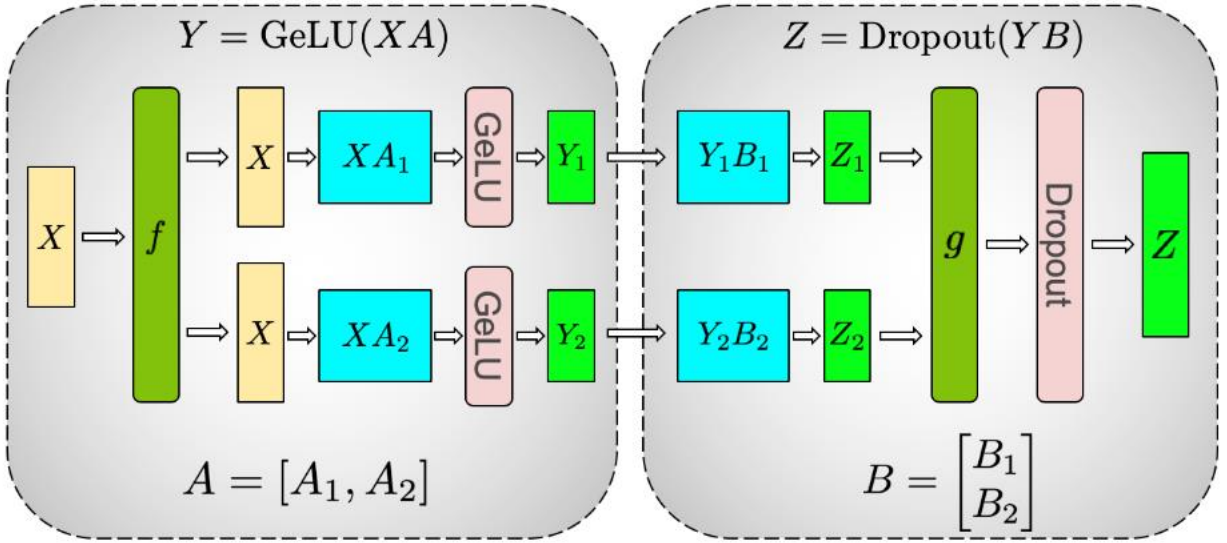
$$X = [\,X_1 \quad X_2\,], A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \qquad Y = GeLU(X_1A_1 + X_2A_2)$$

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

All-reduce (to compute XA) is needed !

Tensor Parallelism for FFN





Splitting weight A

$$A = [A_1, A_2],$$

weight B

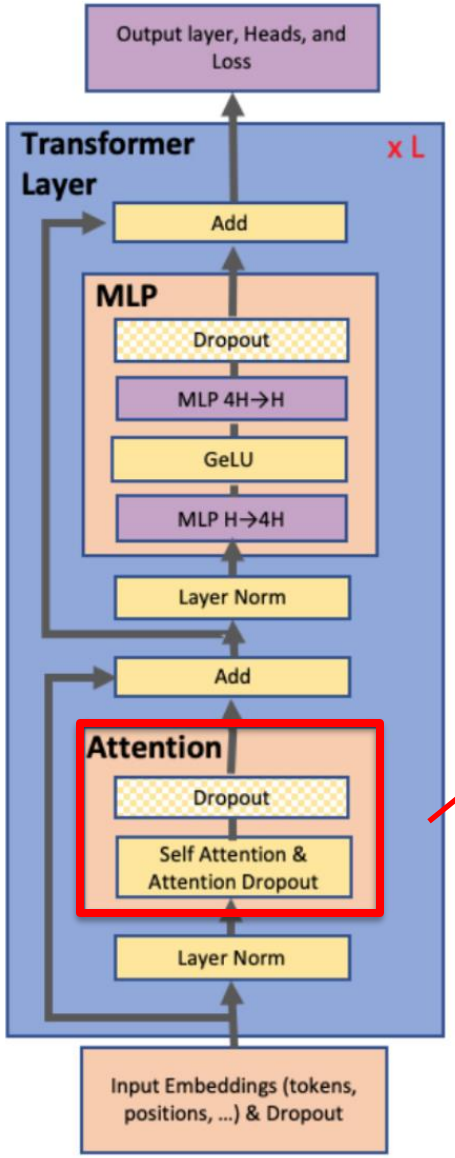
$$B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix},$$

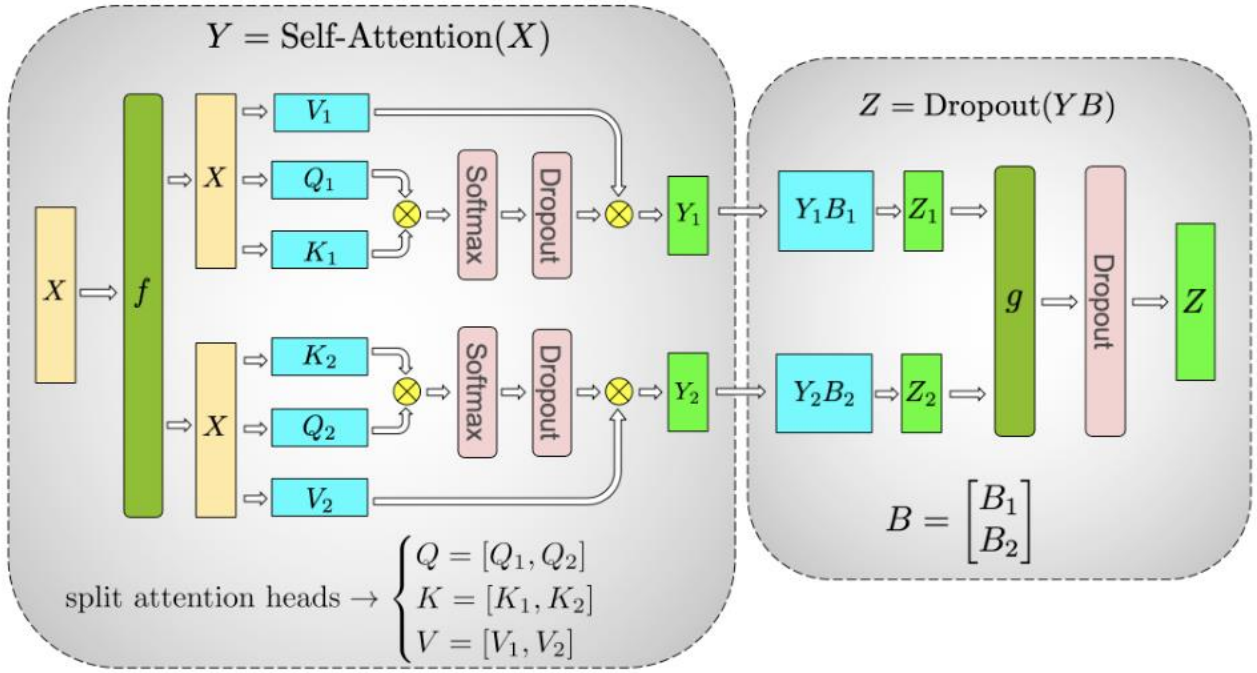
$$[Y_1, Y_2] = [\mathrm{GeLU}(X \cdot A_1), \mathrm{GeLU}(X \cdot A_2)],$$

All-reduce is not needed (for Y) !

$$Z = Y_1 \cdot B_1 + Y_2 \cdot B_2$$

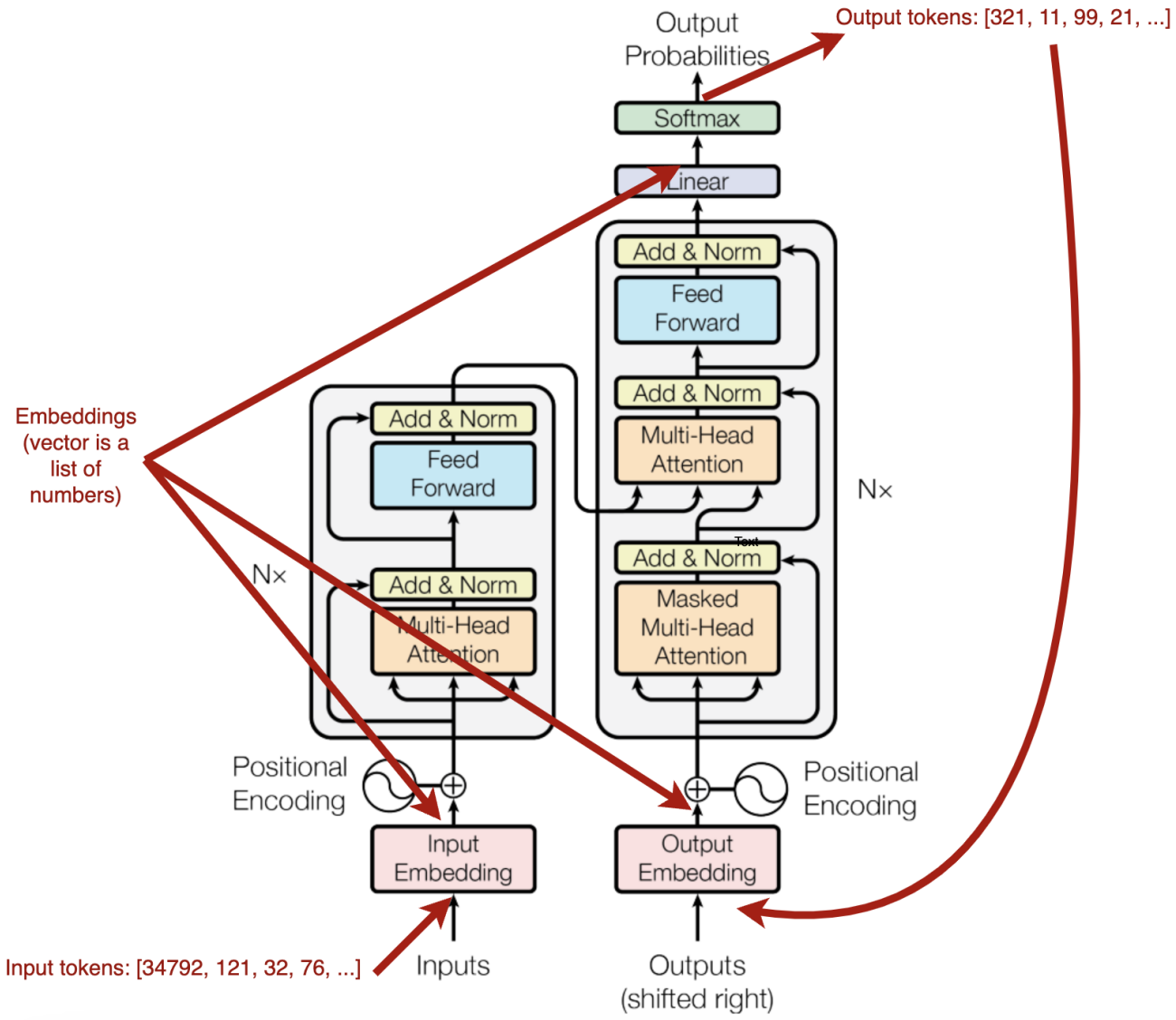
Tensor Parallelism for Self-Attention





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

Tensor Parallelism - Embeddings



- Input embedding
  - Split over columns

    $$E = [E_1, E_2] \text{ (column-wise)}$$

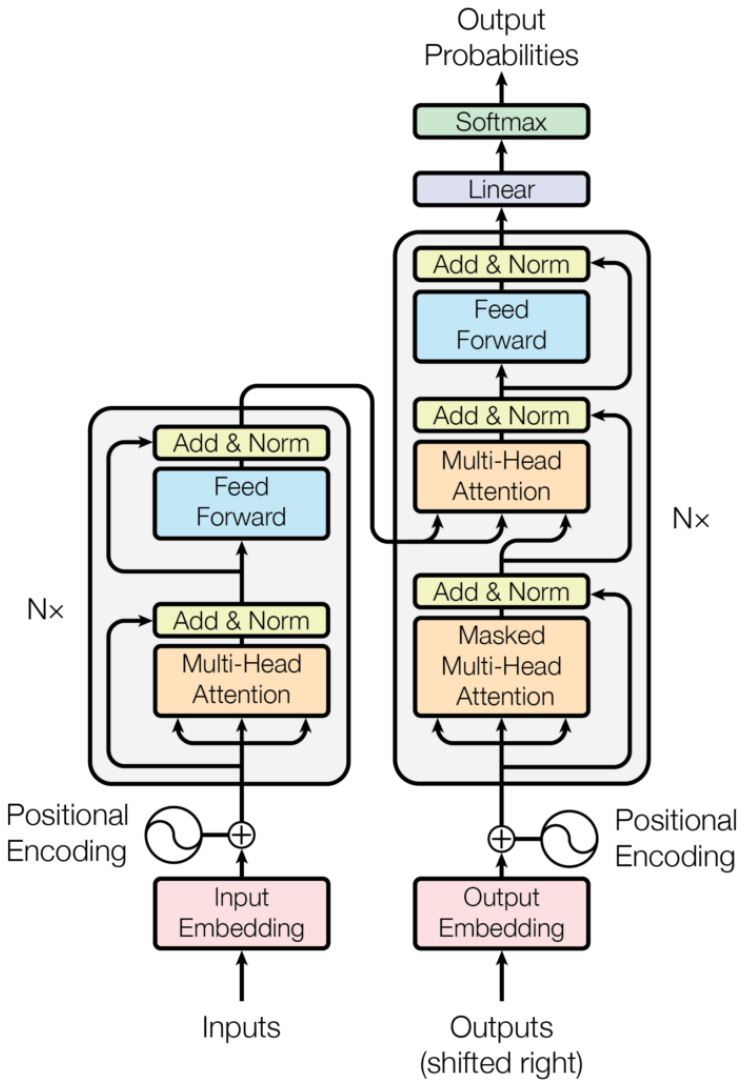
  - all-reduce is required

- Output embedding
  - Split over columns

    $$\text{GEMM } [Y_1, Y_2] = [XE_1, XE_2]$$

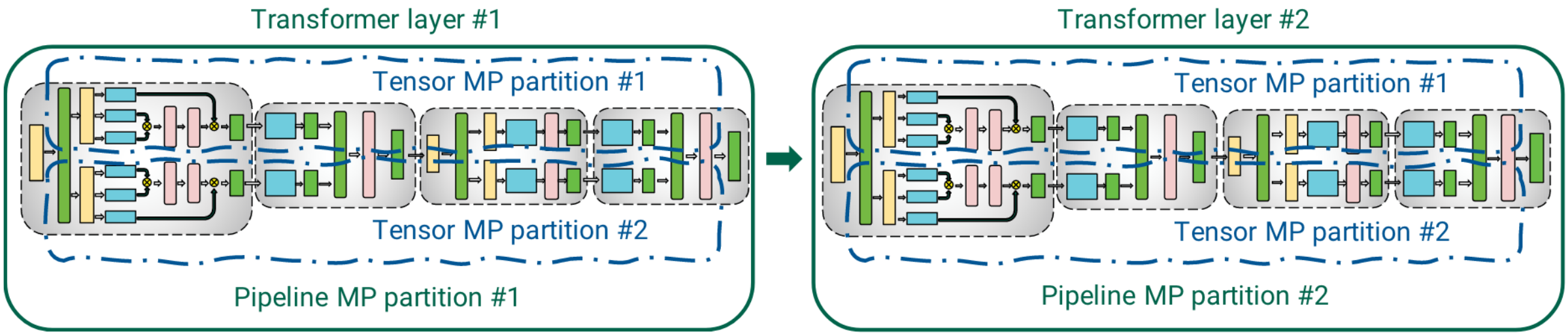
  - Fuse outputs with cross-entropy loss (huge reduction in communication)
  - all-gather is needed

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



#PP and #TP depend on model architecture and GPU server config

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 ➔ TP for in-node parallel computing

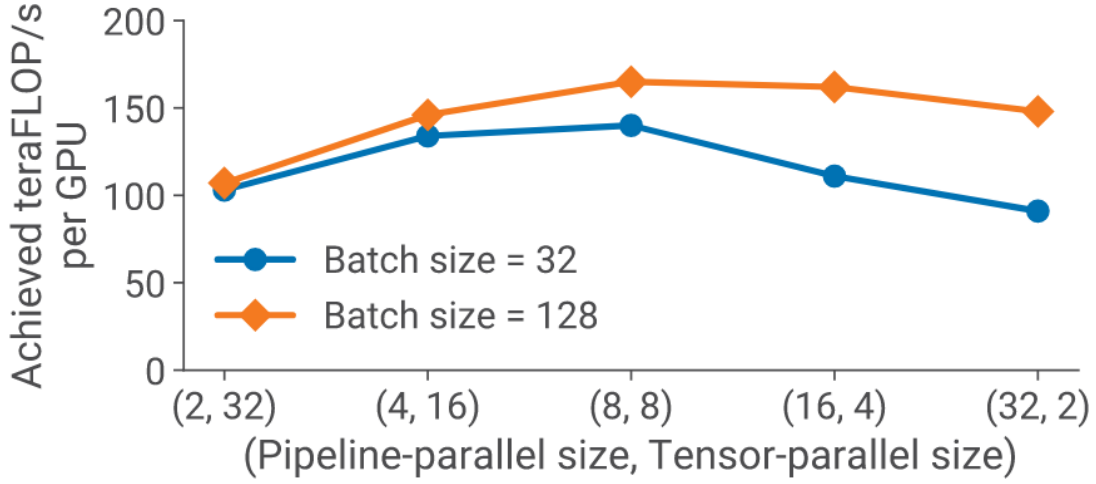


Figure 13: Throughput per GPU of various parallel configurations that combine pipeline and tensor model parallelism using a GPT model with 162.2 billion parameters and 64 A100 GPUs.

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.

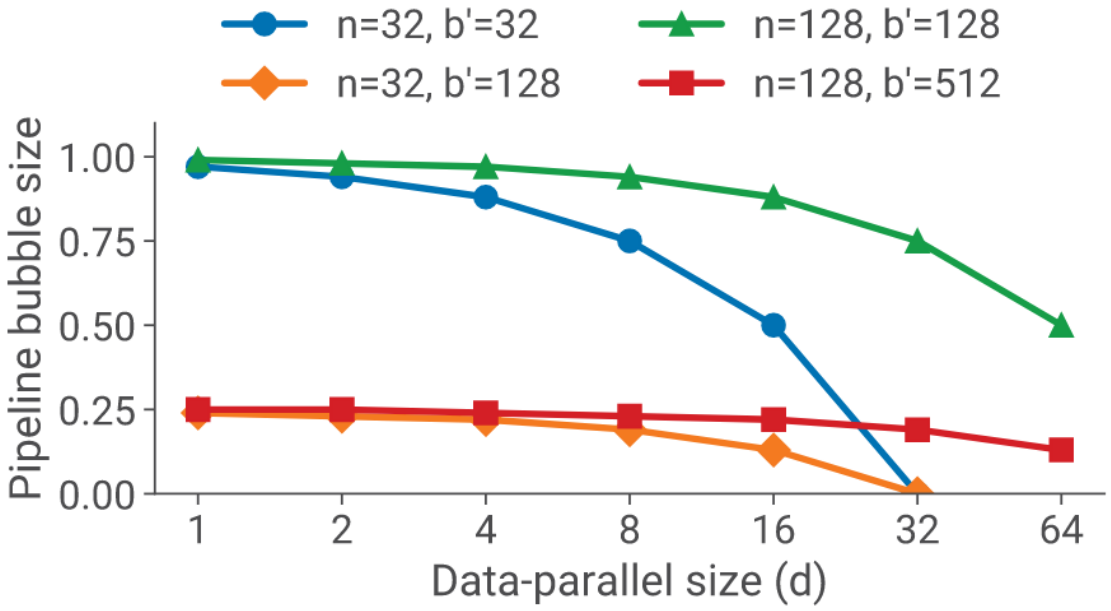


Figure 6: Fraction of time spent idling due to pipeline flush (pipeline bubble size) versus data-parallel size (d), for different numbers of GPUs (n) and ratio of batch size to microbatch size ($b' = B/b$).

Summary of Model Parallel Training

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