Model-Parallel Deep Learning

Efficient DL, Episode VI ‘23

Yandex
Research

British Hedgehog
Preservation Society

Dealing with large models

~~Model-Parallel Deep Learning~~

Efficient DL, Episode III ‘22

Yandex
Research

LAMBDA

British Hedgehog
Preservation Society

Recap: large models

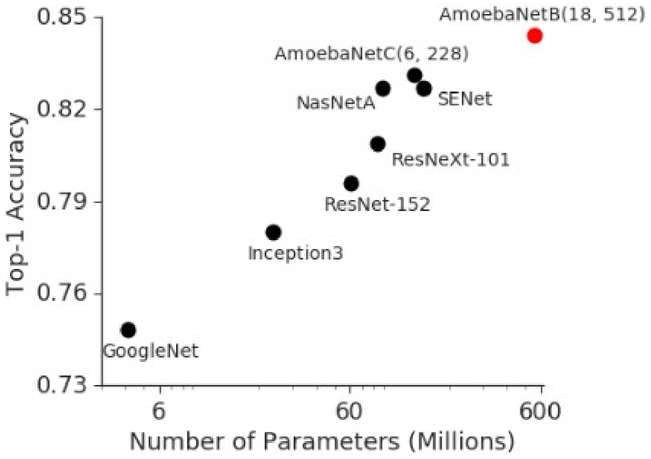
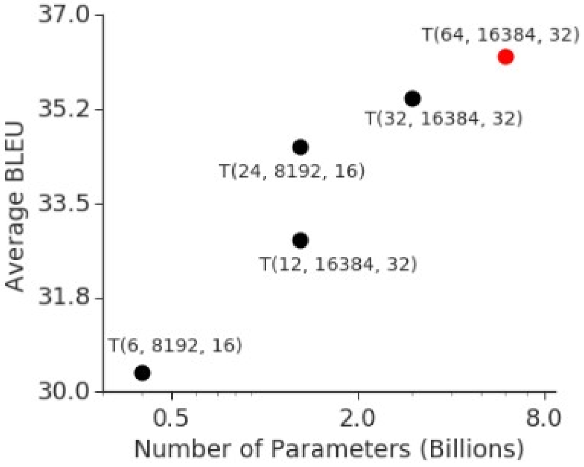


Image Classification
ImageNet

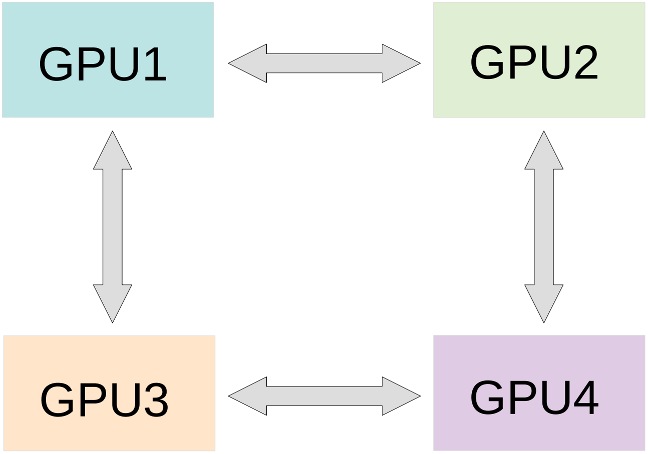


Machine Translation
average over WMT

Source: https://arxiv.org/abs/1811.06965

Recap: Ring allreduce

Bonus quest: you can only send data between **adjacent** gpus



Ring topology

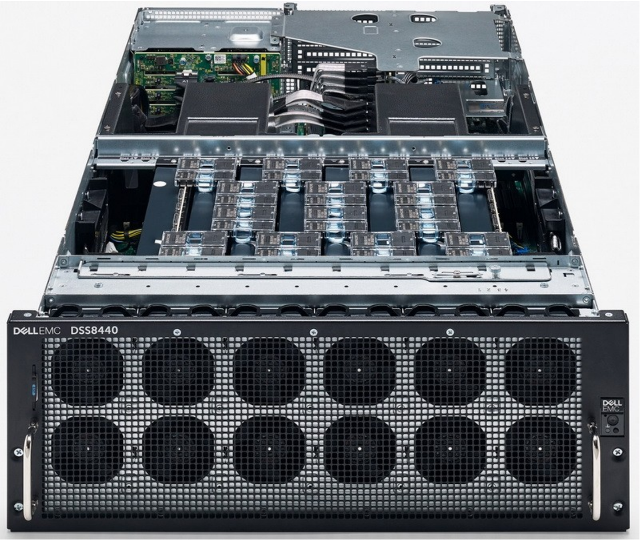


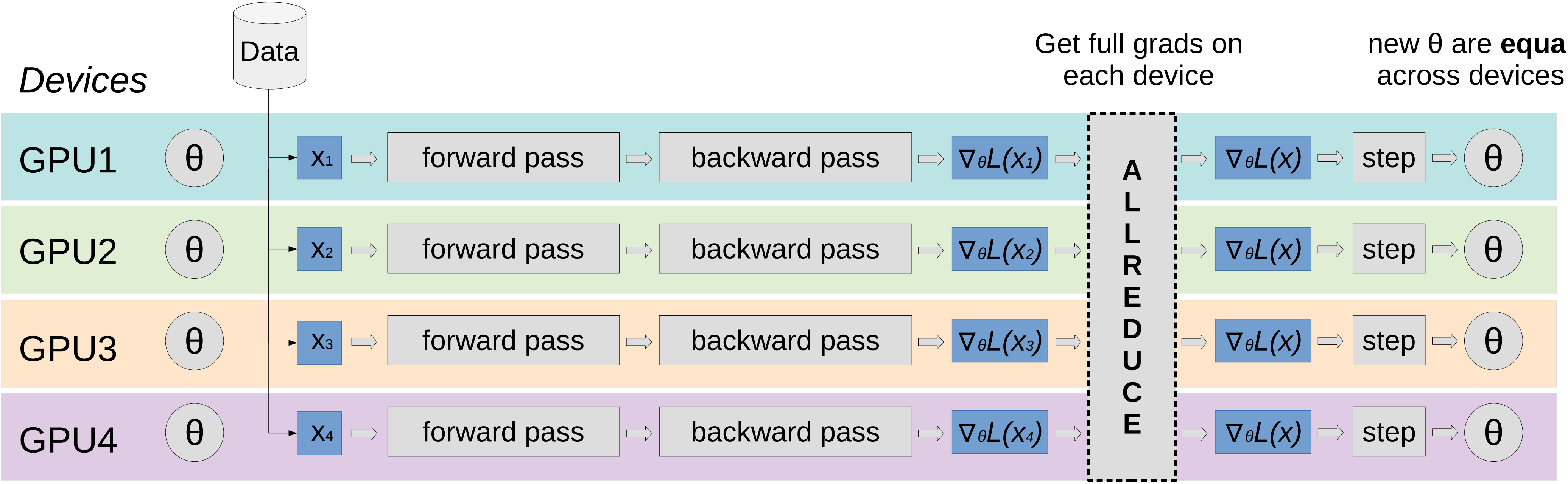
Image: graphcore ipu server

Answer & more: tinyurl.com/ring-allreduce-blog

Recap: All-Reduce SGD

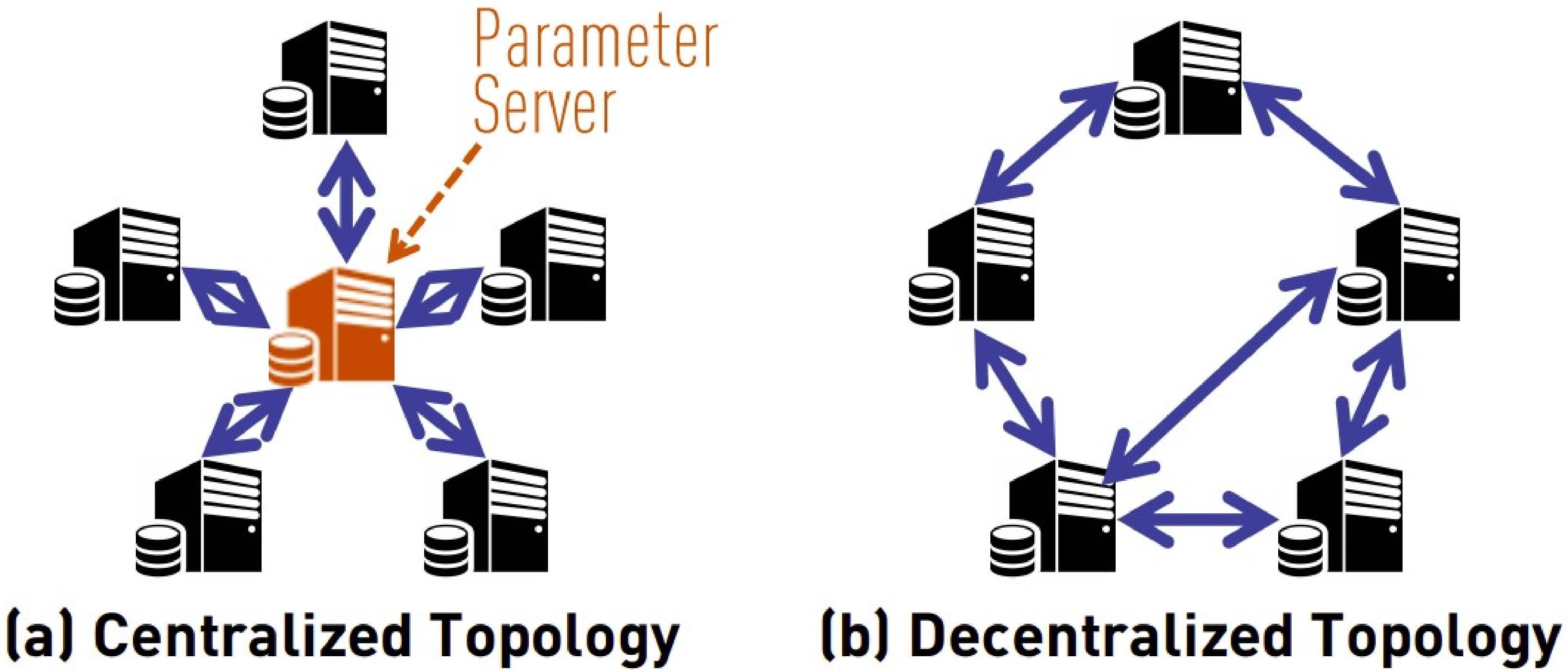
arxiv.org/abs/1706.02677

Idea: get rid of the host, each gpu runs its own computation
Q: why will weights be equal after such step?



Recap: Decentralized SGD

Gossip (communication): https://tinyurl.com/boyd-gossip-2006
Gossip outperforms All-Reduce: https://tinyurl.com/can-dsgd-outperform



Q: What if a model is larger than GPU?

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easy mode: cannot fit the right batch size

hard mode: cannot fit a single sample

expert mode: not even parameters!

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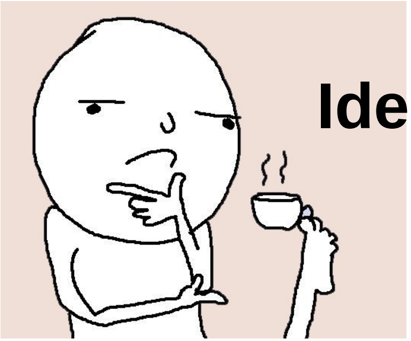


Ideas?

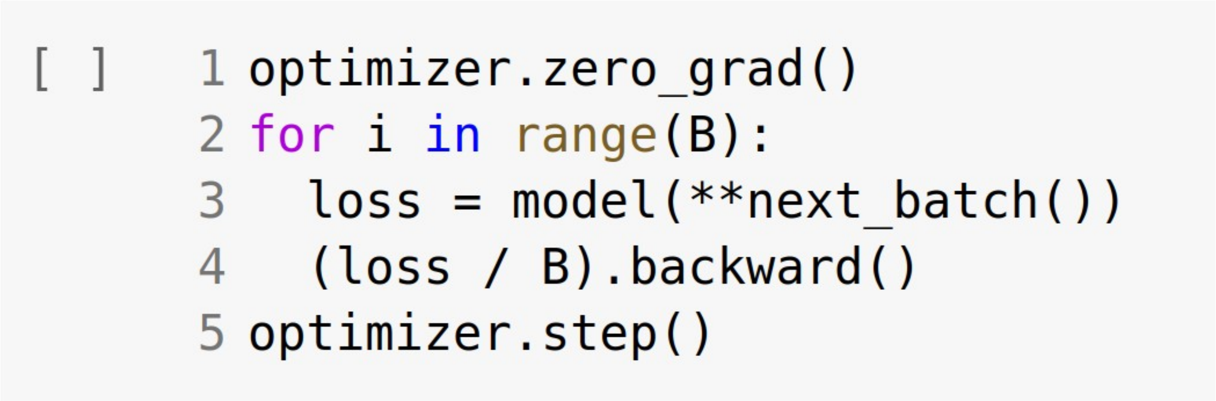
Q: What if a model is larger than GPU?

easy mode: cannot fit the right batch size

hard mode: cannot fit a single sample

expert mode: not even parameters!

Solution: accumulate grads from several training batches



```python
optimizer.zero_grad()
for i in range(B):
  loss = model(**next_batch())
  (loss / B).backward()
optimizer.step()
```

Q: What if a model is larger than GPU?

easy mode: cannot fit the right batch size

hard mode: cannot fit one training sample

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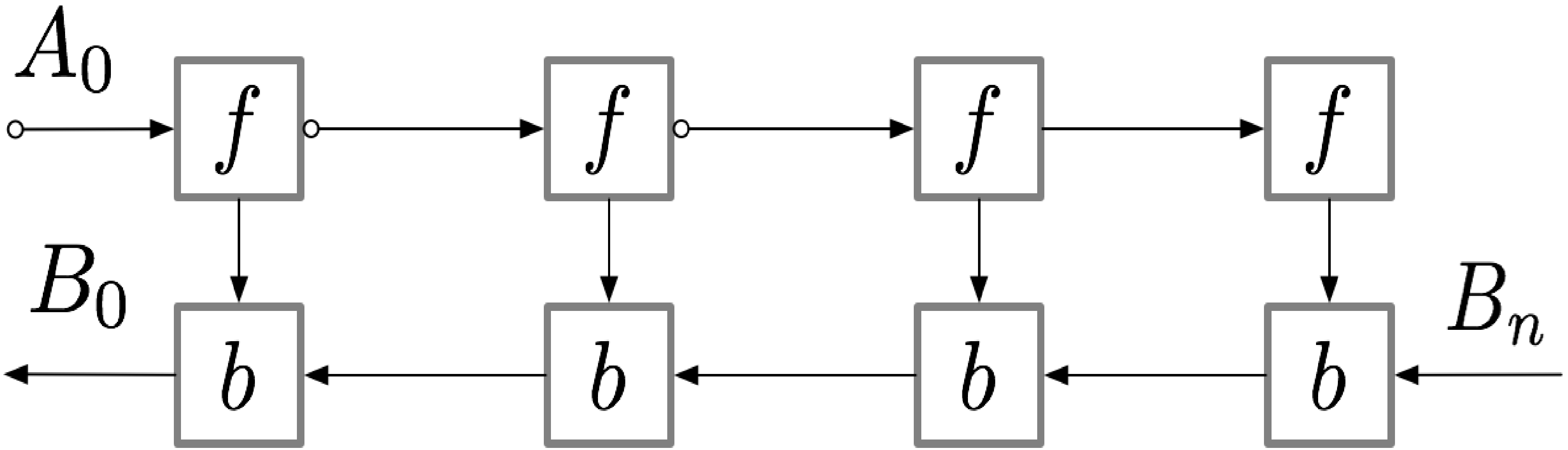
Gradient checkpointing

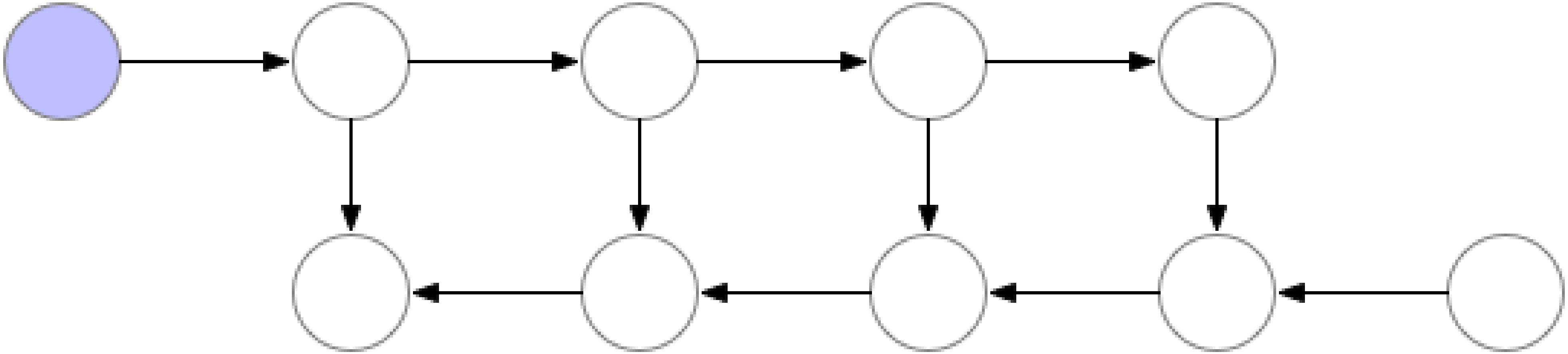
aka rematerialization



Paper (DL): arxiv.org/pdf/1604.06174.pdf
TF: github.com/cybertronai/gradient-checkpointing
Pytorch: pytorch.org/docs/stable/checkpoint.html

Gradient checkpointing

Normal backprop



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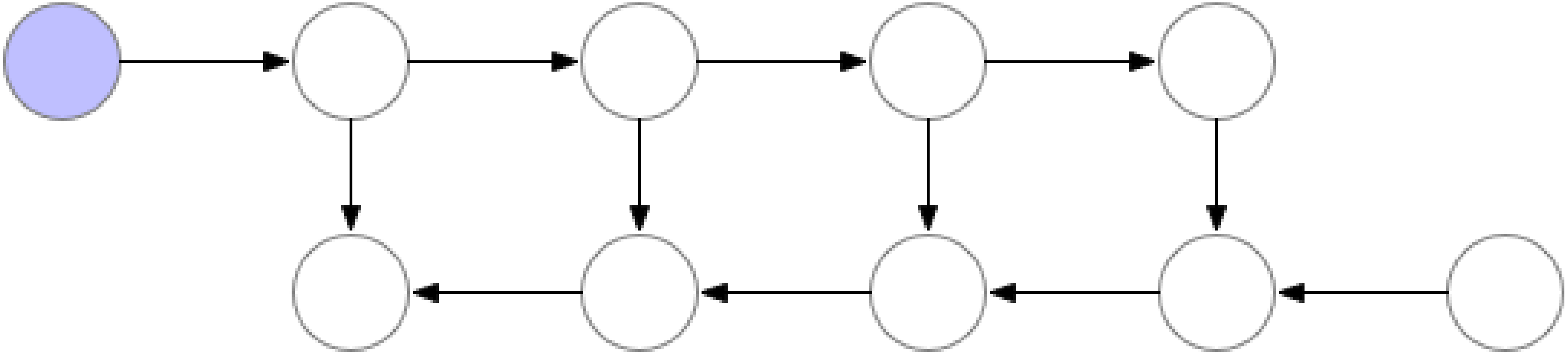
TF: github.com/cybertronai/gradient-checkpointing
Pytorch: pytorch.org/docs/stable/checkpoint.html

Gradient checkpointing

Full rematerialization



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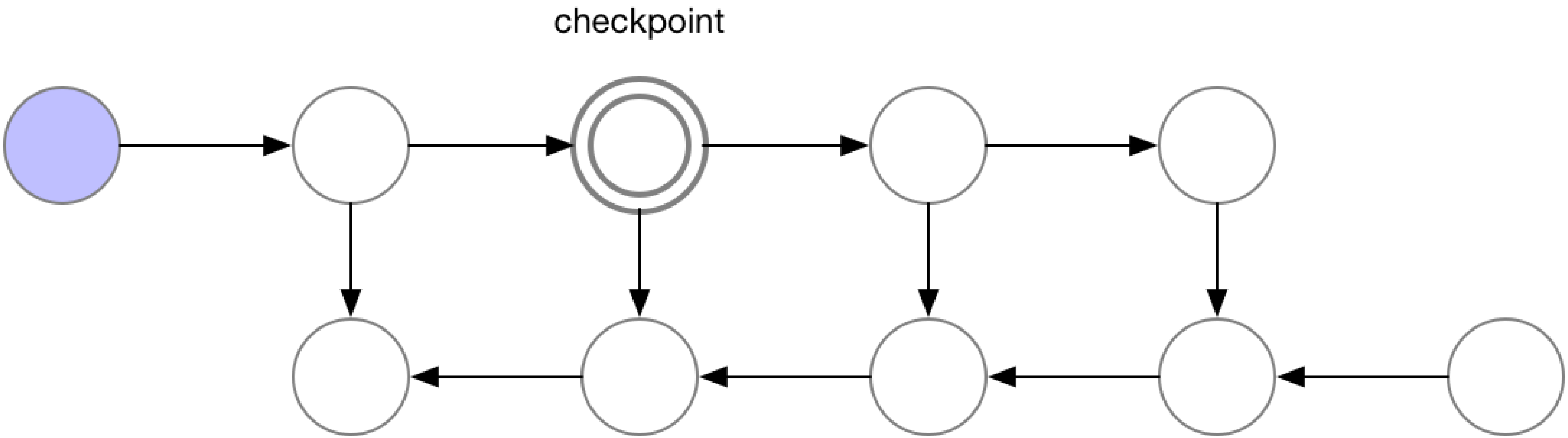
Gradient checkpointing

Single checkpoint



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Gradient checkpointing

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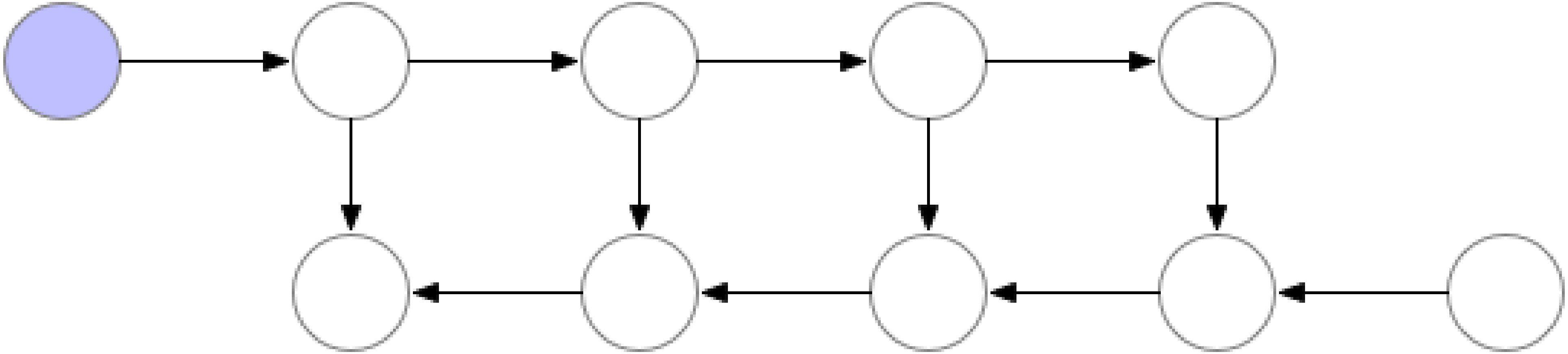

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Pytorch: pytorch.org/docs/stable/checkpoint.html

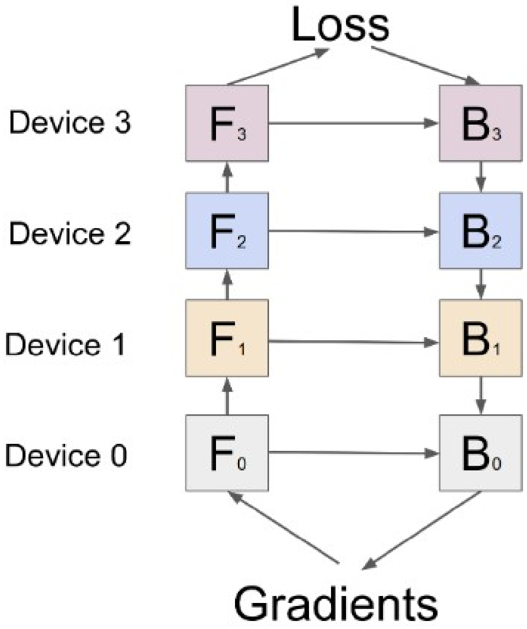
Q: What if a model is larger than GPU?

easy mode: cannot fit batch size 1

expert mode: not even parameters!

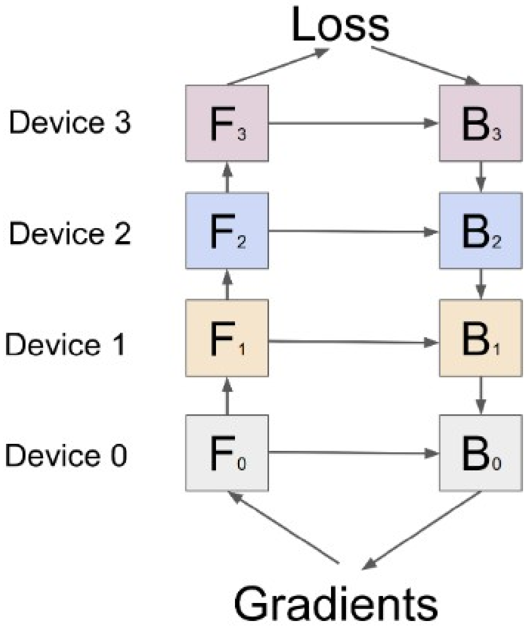
Model-parallel training

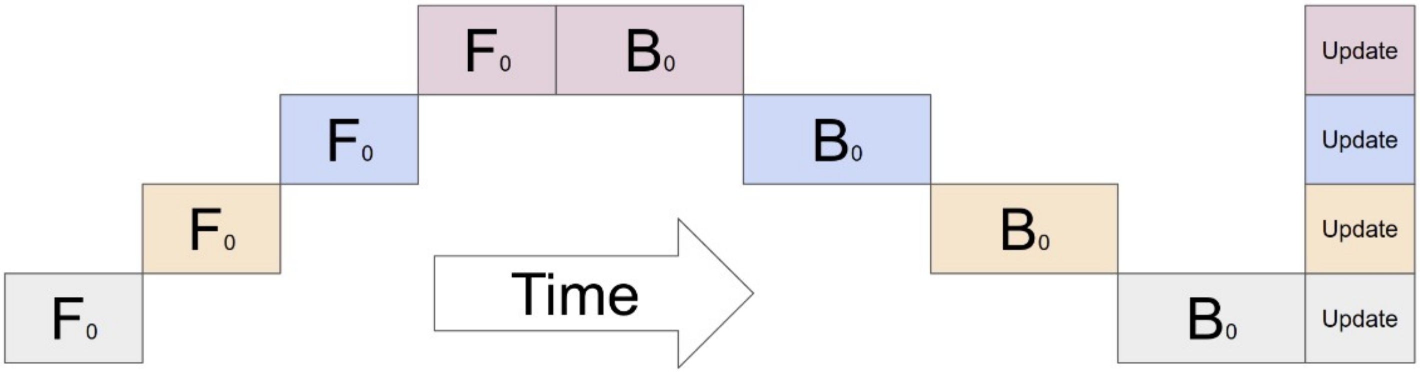
Q: What if a model is larger than GPU?



Model-parallel training

Q: What if a model is larger than GPU?





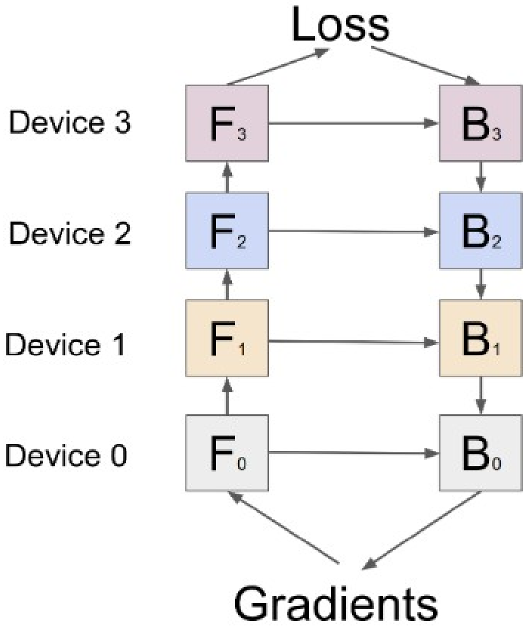
model size: O(N)
throughput: O(1)

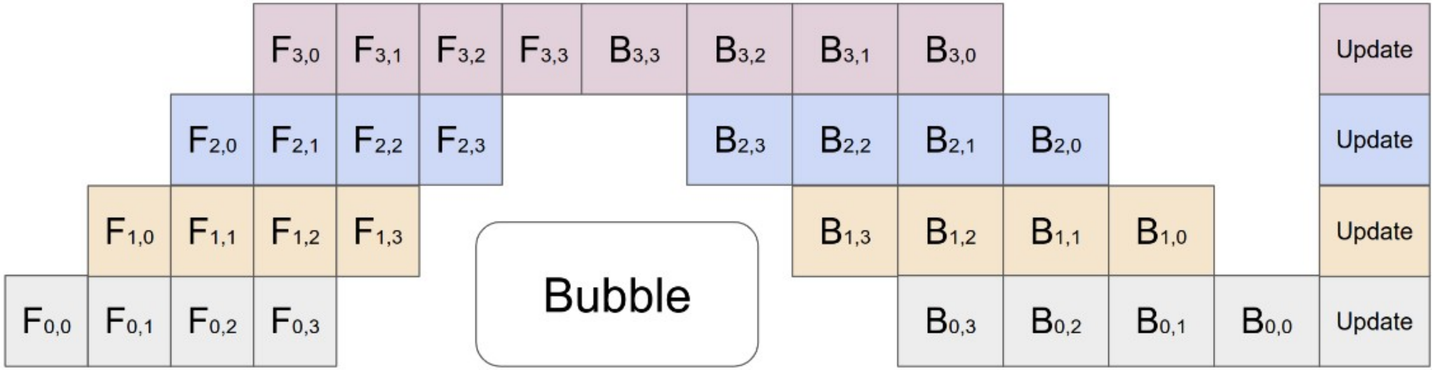
Q: Can we go faster?

Pipelining

GPipe: arxiv.org/abs/1811.06965 – good starting point, *not* the 1st paper

Idea: split data into micro-batches and form a pipeline (right)





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

model size: O(n)
throughput: O(n) – with caveats

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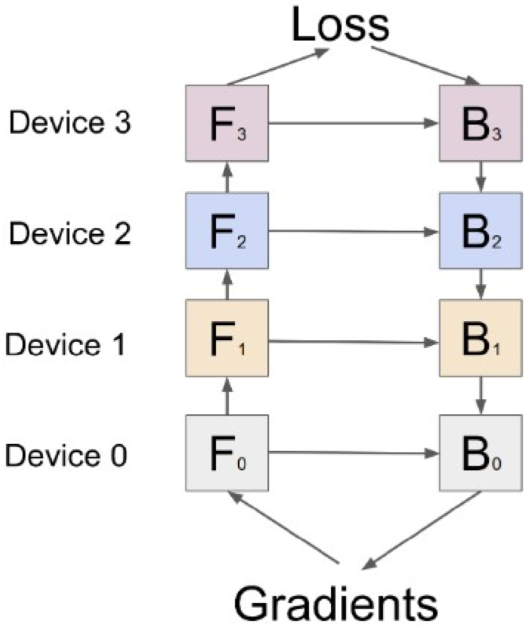

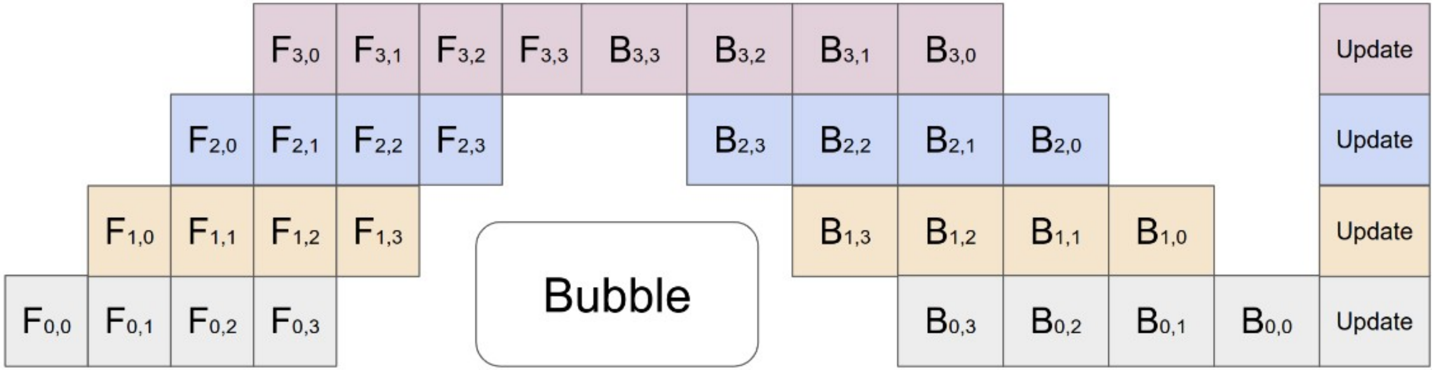
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Bubble

model size: O(n)
throughput: O(n) – with caveats

Q: Even faster?

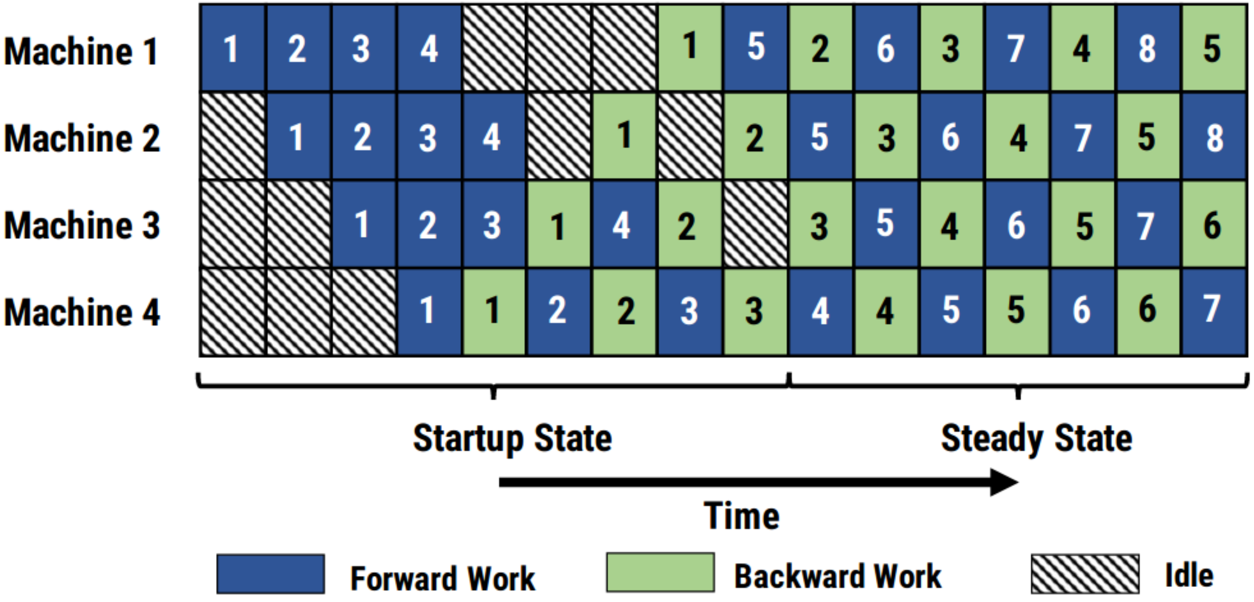
Pipeline-parallel training

PipeDream: arxiv.org/abs/1806.03377

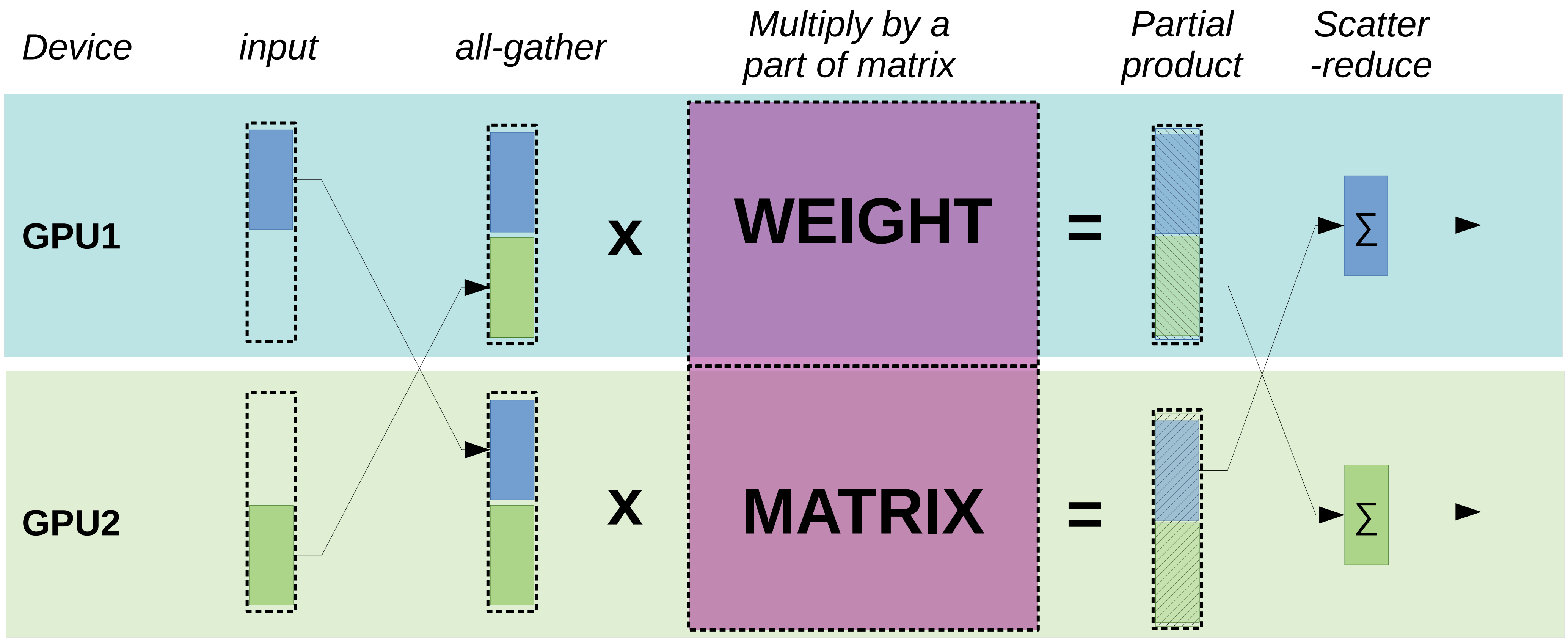
Idea: apply gradients with every microbatch for maximum throughput

Also neat:

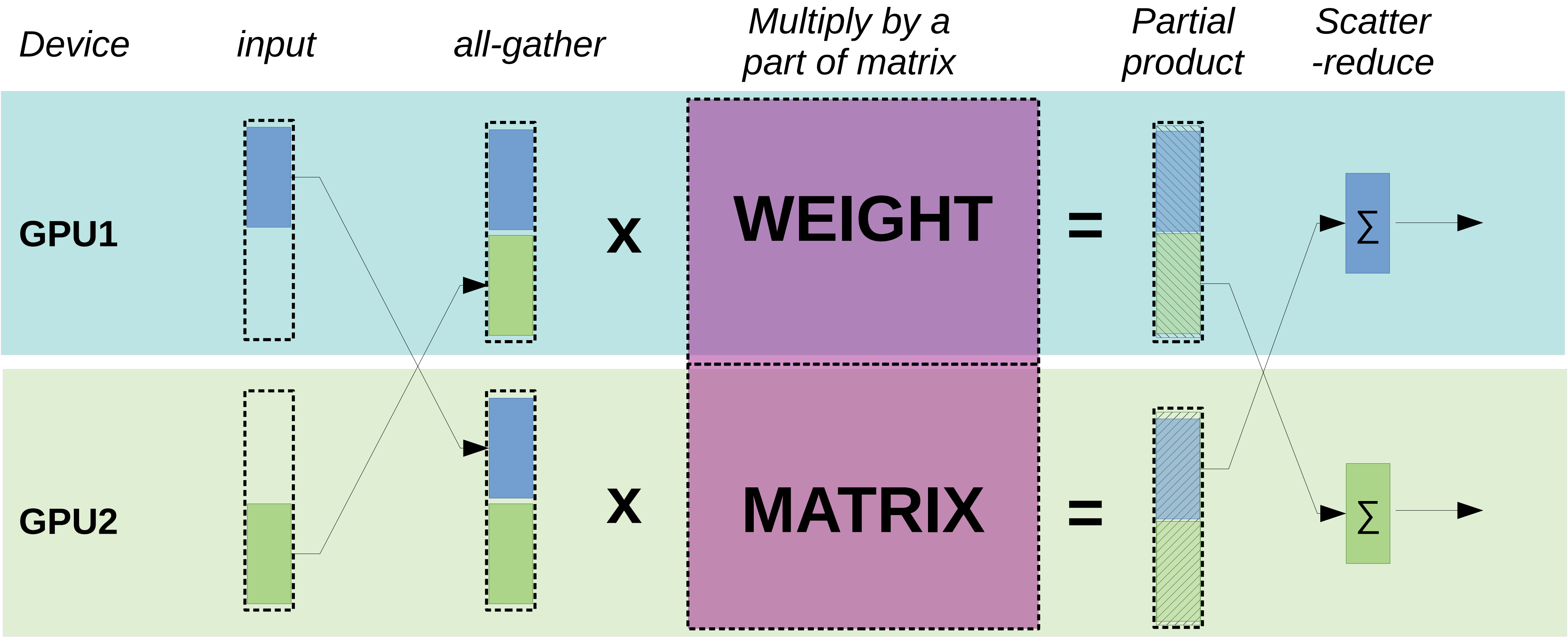
- Automatically partition layers to GPUs via dynamic programming
- *Store k* past weight versions to reduce gradient staleness
- Aims at high latency



Tensor-parallel training



Q: find AllReduce op here



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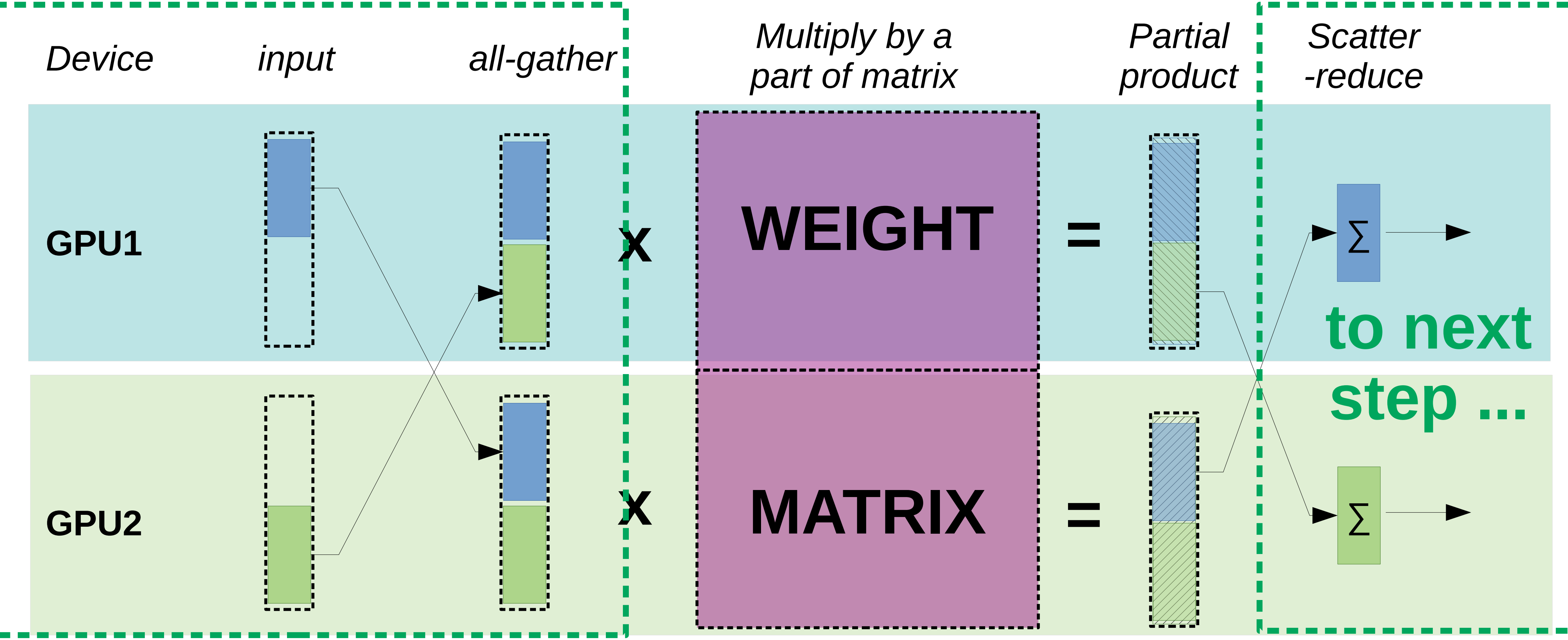

Device

input

all-gather

Multiply by a part of matrix

Partial product

Scatter -reduce

GPU1

GPU2

x

x

WEIGHT

MATRIX

=

=

∑

∑

to next step ...

</Model-parallel>

+ model larger than GPU
+ faster for small
***** typical size: 2-8 gpus
- model partitioning is tricky
tensor parallelism is easier, but requires ultra low latency
- latency is critical, go buy nvlink
except for PipeDream
- *often combined with gradient checkpointing*

Tutorials:

- Simple pipelining in PyTorch – tinyurl.com/pytorch-pipelining
- Distributed model-parallel with torch RPC - https://tinyurl.com/torch-rpc
- Automatic tensor parallelism pip install tensor_parallel

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Q: what if you have 1024 GPUs, but the model fits on 8?

</Model-parallel>

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Large-scale training: combine model- and data-parallel

How ‘bout a short break?

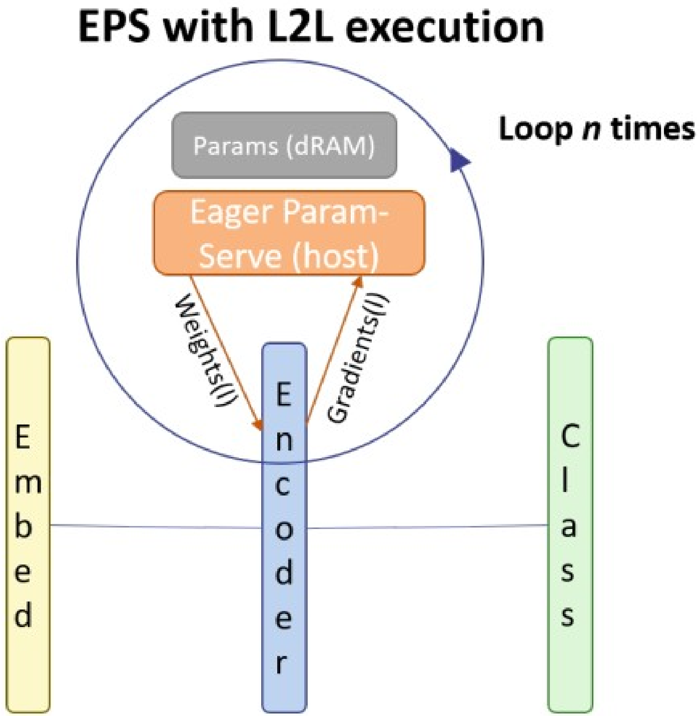
[after the break: ~~movies!~~ cool video]

Case study: DeepSpeed

Source: microsoft

Memory offloading

L2L: https://arxiv.org/abs/2002.05645

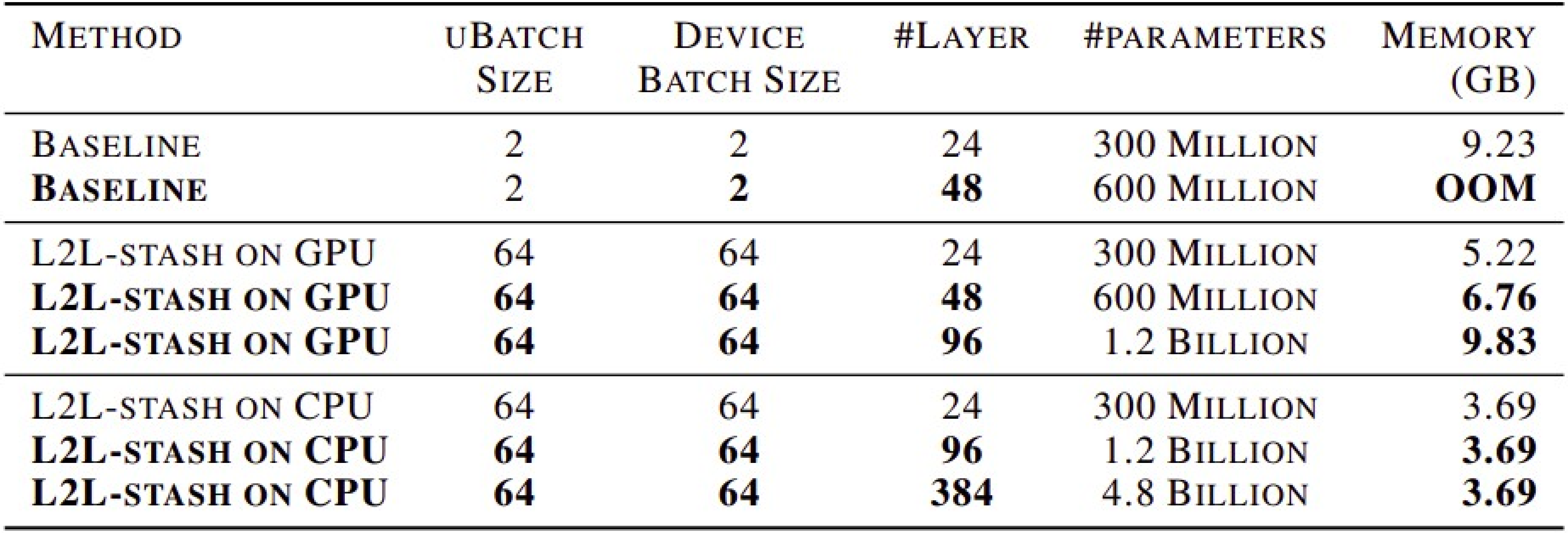


- Initialize all layers on CPU
- Move k layers at a time to GPU
- Remove layers after computation

- Fetch k+1-st layer while k-th runs
- Still 20-50% overhead

Memory offloading

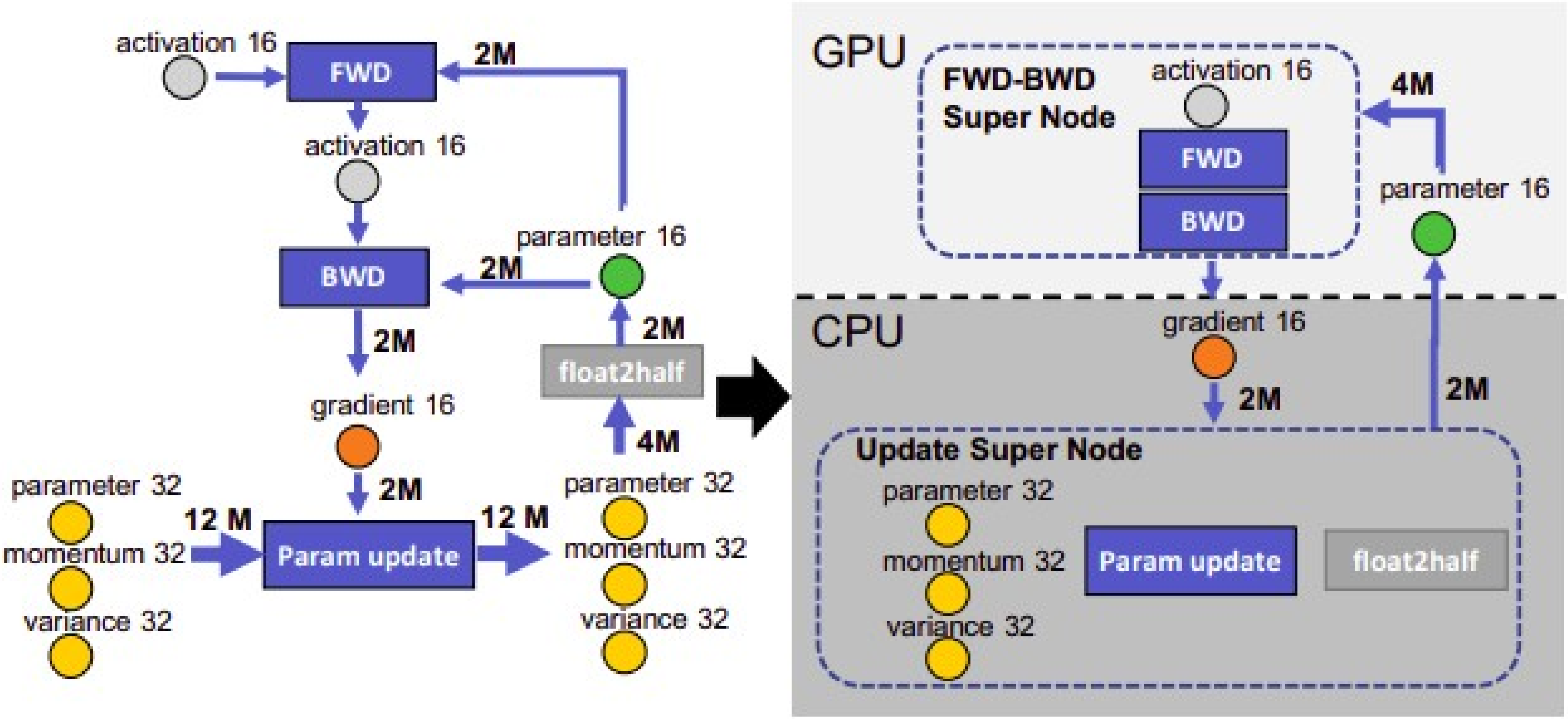
L2L: https://arxiv.org/abs/2002.05645



Method	uBatch Size	Device Batch Size	#Layer	#parameters	Memory (GB)
Baseline	2	2	24	300 Million	9.23
Baseline	2	**2**	**48**	600 Million	**OOM**
L2L-stash on GPU	64	64	24	300 Million	5.22
L2L-stash on GPU	**64**	**64**	**48**	600 Million	**6.76**
L2L-stash on GPU	**64**	**64**	**96**	1.2 Billion	**9.83**
L2L-stash on CPU	64	64	24	300 Million	3.69
L2L-stash on CPU	**64**	**64**	**96**	1.2 Billion	**3.69**
L2L-stash on CPU	**64**	**64**	**384**	4.8 Billion	**3.69**

Memory offloading

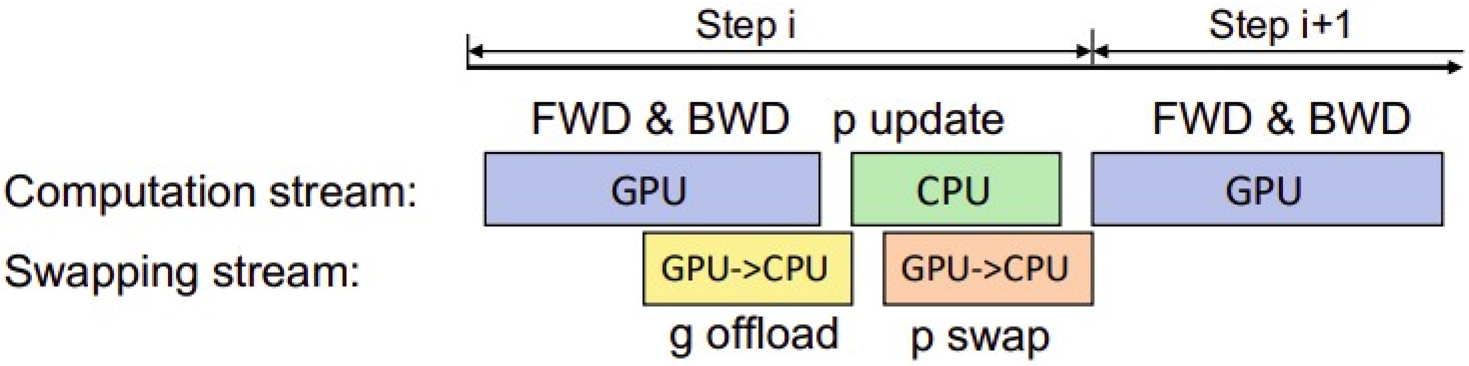
ZeRO-offload: https://arxiv.org/abs/2101.06840



Memory offloading

ZeRO-offload: https://arxiv.org/abs/2101.06840

- Offload **in parallel** with computation
- Use gradient checkpointing
- Delayed parameter update



Memory offloading

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- Offload in parallel with computation
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- **Delayed parameter update**

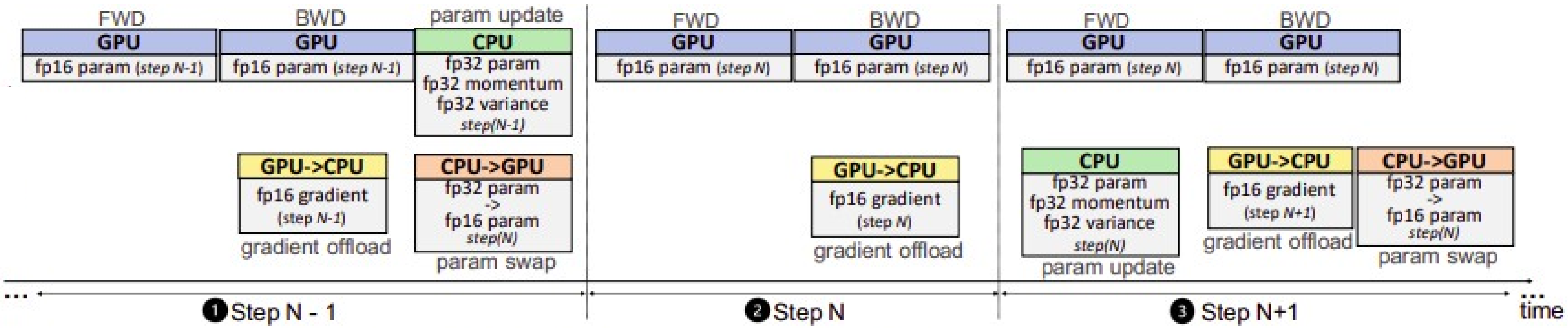
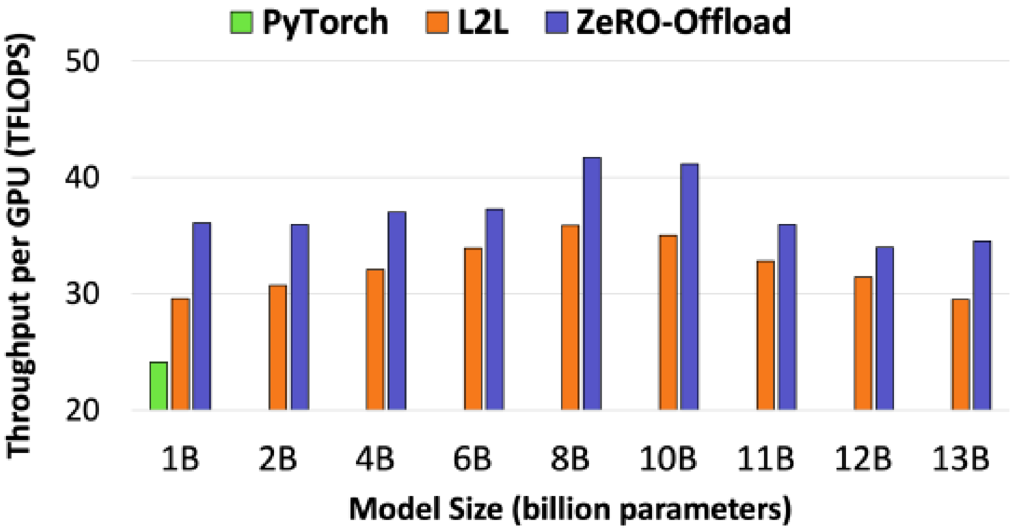


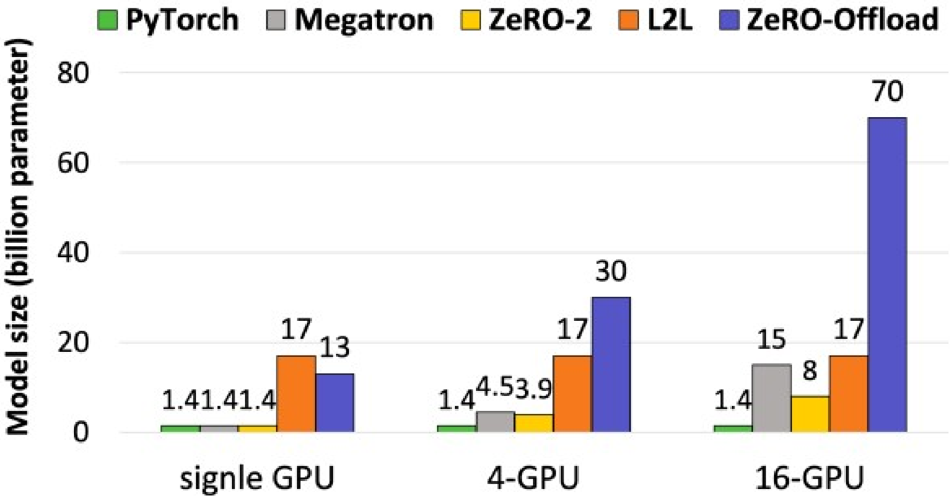
Figure 6: Delayed parameter update during the training process.

Memory offloading

ZeRO-offload: https://arxiv.org/abs/2101.06840

- Offload in parallel with computation
- Use gradient checkpointing
- Delayed parameter update

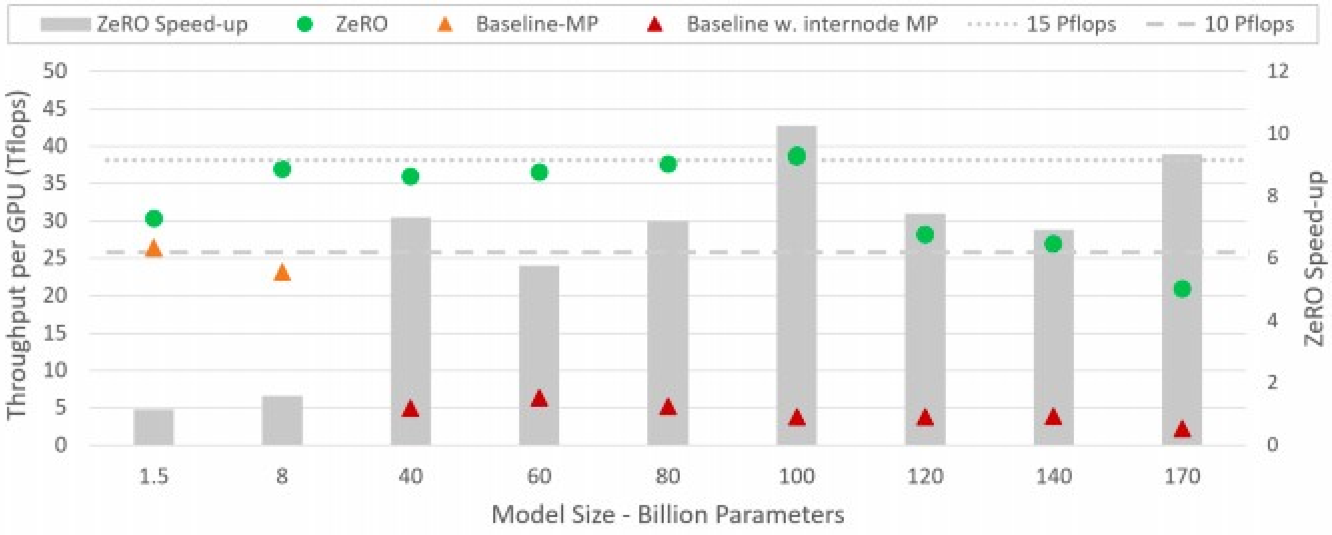




DeepSpeed / ZeRO

ZeRO: https://arxiv.org/pdf/1910.02054v3.pdf

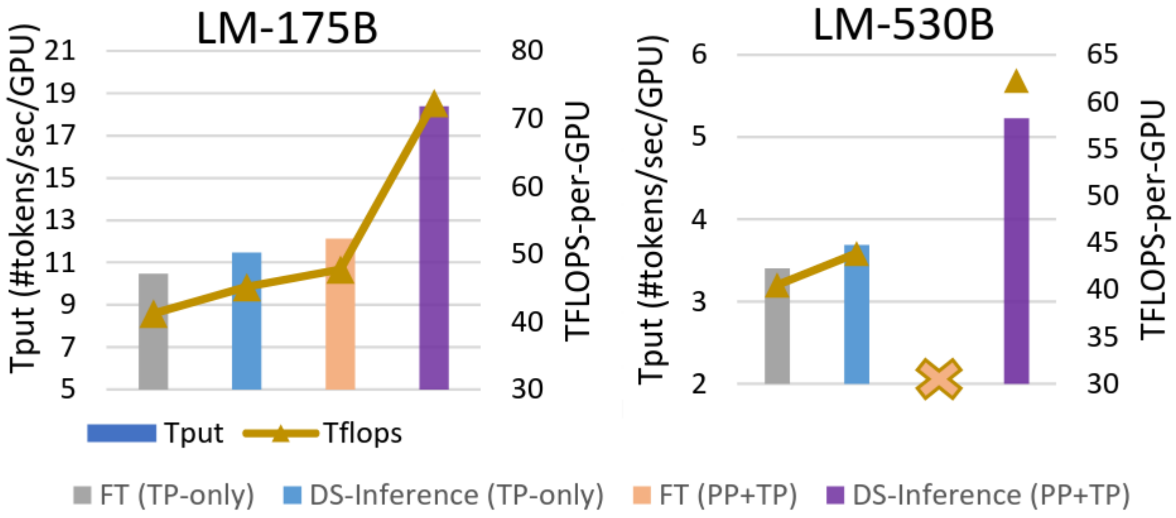
- Combines sharded DPP and offload
- … and some tensor parallelism
- … and a ton of hacks



DeepSpeed Inference

Paper: https://arxiv.org/abs/2207.00032

- Same techniques, but for inference
- Offloading, tensor- & pipeline-parallel
- … and a ton of hacks



</ZeRO>

Multi-GPU strategies:
* Pipeline model-parallel – allocate layers on different GPUs
* Sharded data-parallel – split optimizer state and/or parameters

Single GPU strategies:
* Small model – gradient checkpointing & virtual batch
* Large model – optimizer state sharding (keep parameters on GPU)

Implementations:

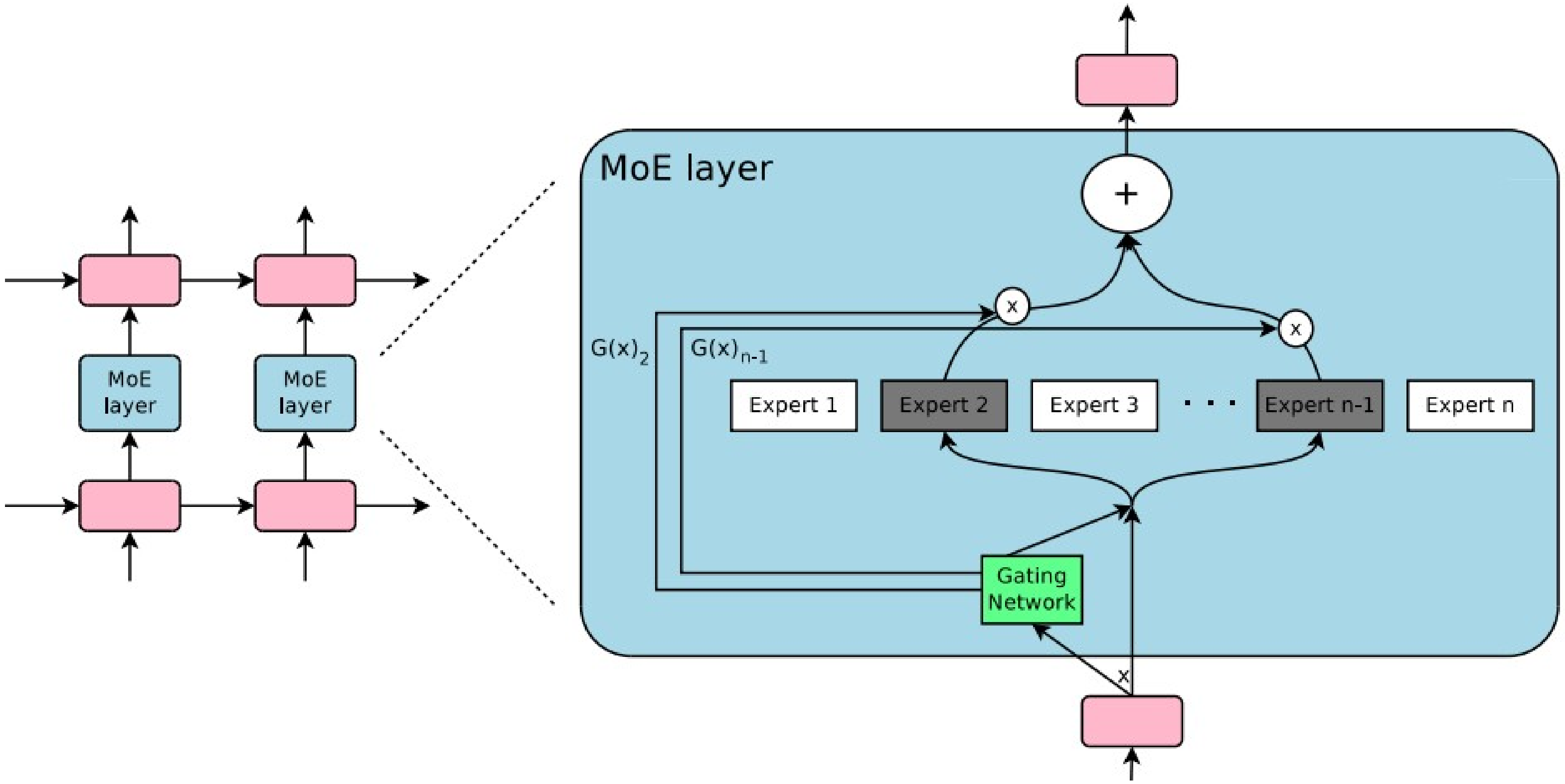
- DeepSpeed– sharded DP, offload, tensor parallelism, active development
    - Offload – https://www.deepspeed.ai/news/2021/03/07/zero3-offload.html
- Fairscale – most of DeepSpeed features with friendrier API
    - One great implementation – https://github.com/NVIDIA/Megatron-LM

If we have time…

(if not, skip to autoparallel)

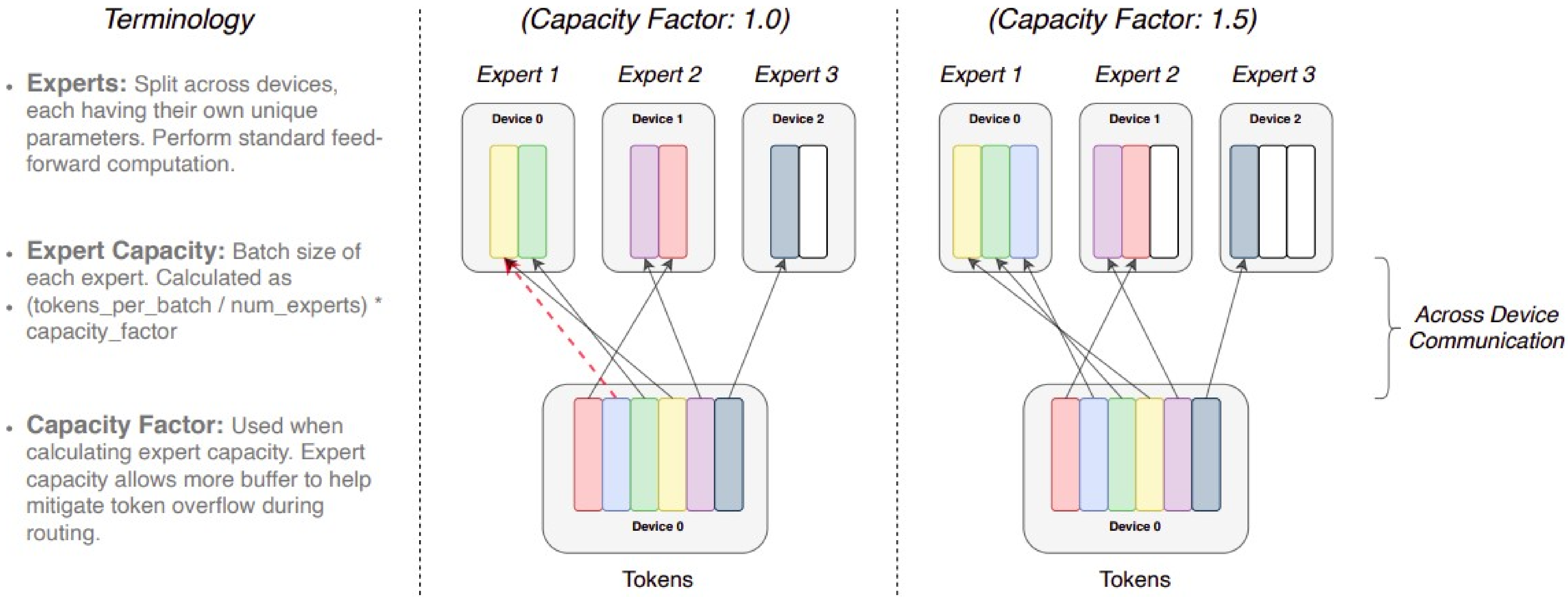
Expert Parallelism

Sparsely gated MoE: https://arxiv.org/pdf/1701.06538.pdf



MoE Variant: Switch Transformer

Switch: https://arxiv.org/pdf/2101.03961.pdf



Terminology

- **Experts:** Split across devices, each having their own unique parameters. Perform standard feed-forward computation.

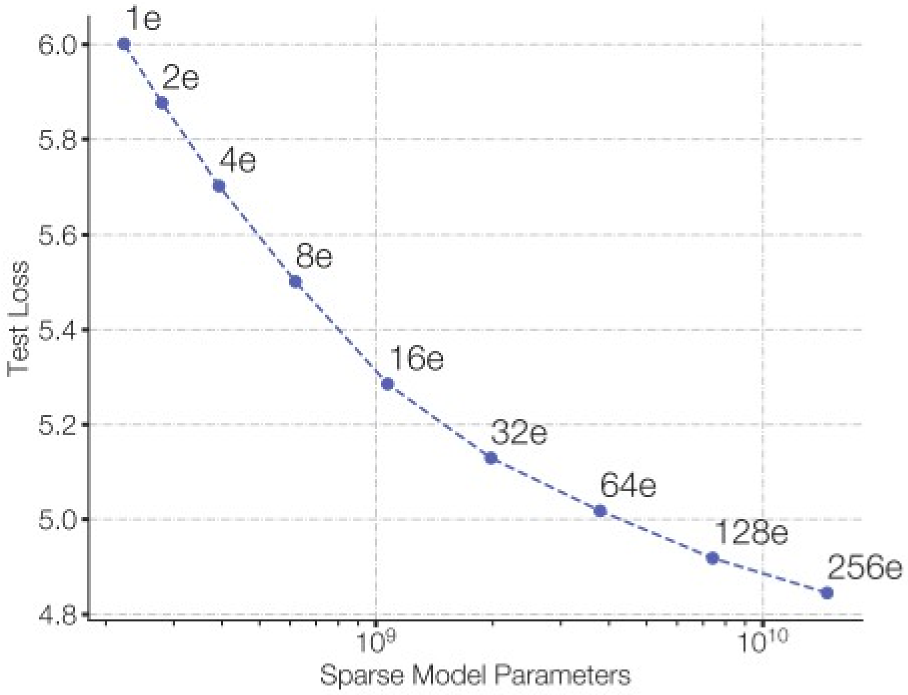
- **Expert Capacity:** Batch size of each expert. Calculated as
- (tokens_per_batch / num_experts) * capacity_factor

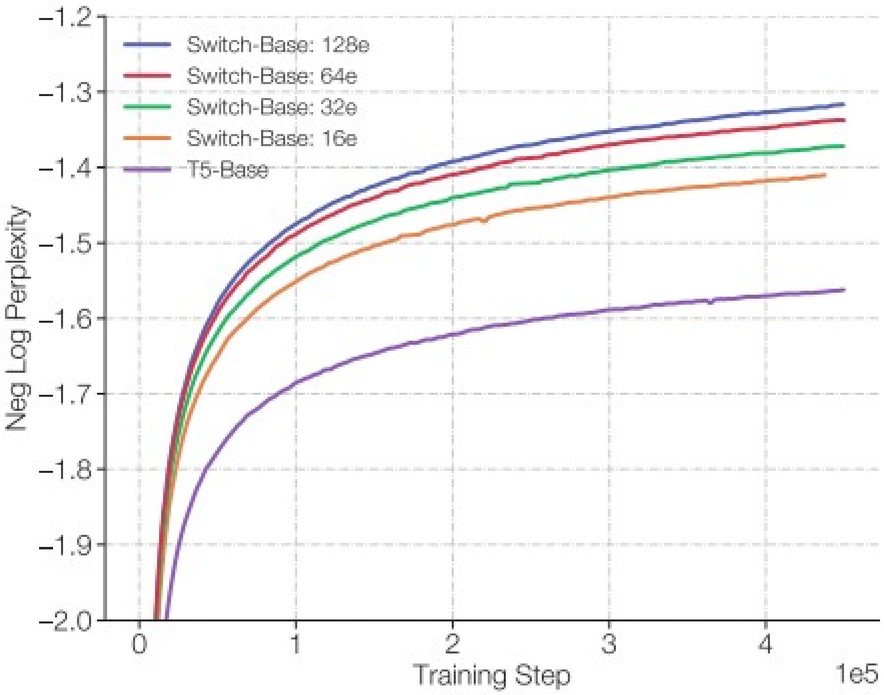
- **Capacity Factor:** Used when calculating expert capacity. Expert capacity allows more buffer to help mitigate token overflow during routing.

MoE Variant: Switch Transformer

Switch: https://arxiv.org/pdf/2101.03961.pdf

MLM pre-training objective [BERT-like]





MoE Variant: Switch Transformer

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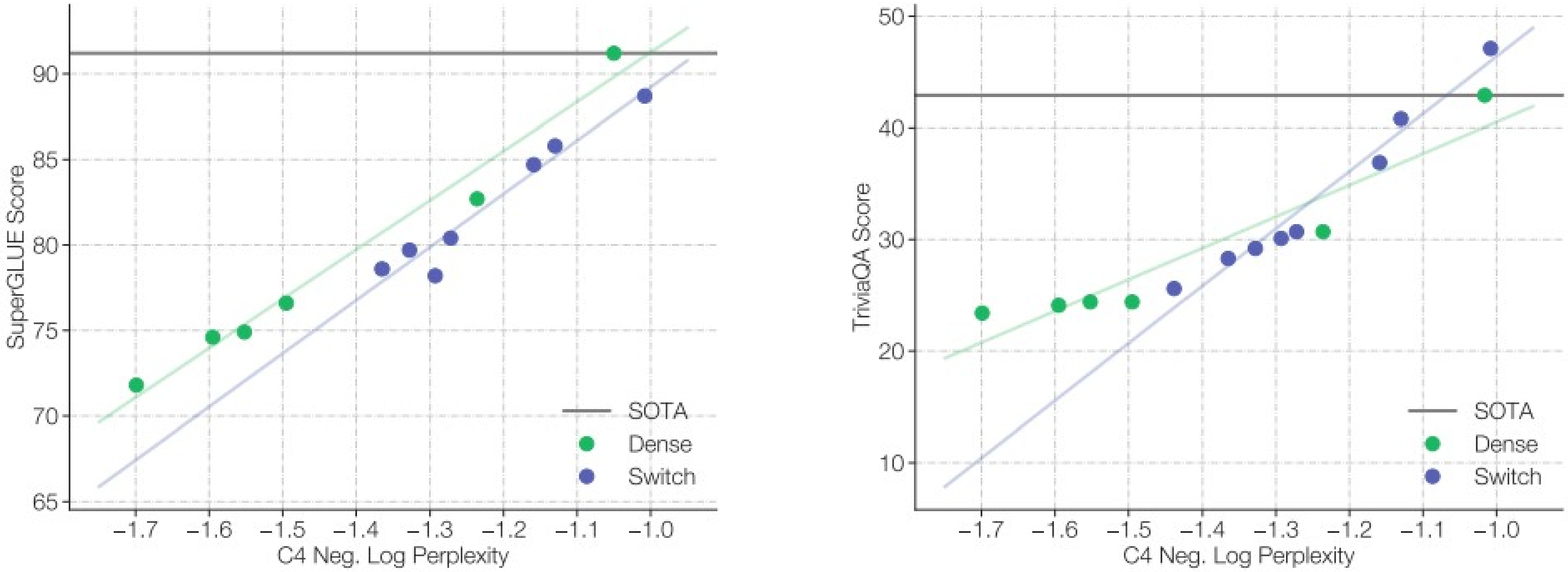
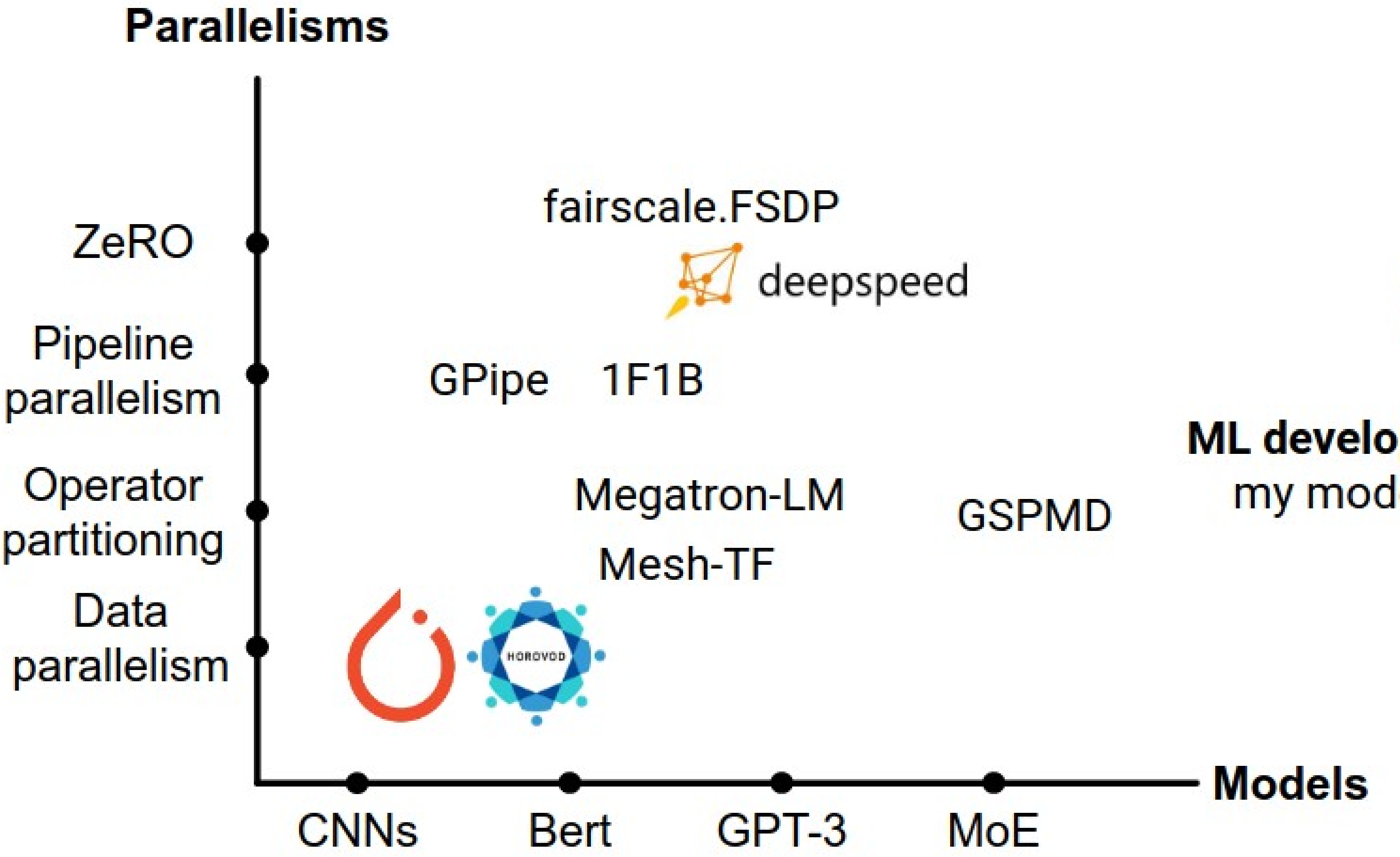
Pre-training vs downstream quality



Automated parallelism

source: https://sites.google.com/view/icml-2022-big-model



Parallelisms

ZeRO

Pipeline parallelism

Operator partitioning

Data parallelism

fairscale.FSDP

deepspeed

GPipe

1F1B

Megatron-LM

Mesh-TF

GSPMD

HOROVOD

Models

CNNs

Bert

GPT-3

MoE

ML developer: which one is for my model and my cluster?

Automated parallelism

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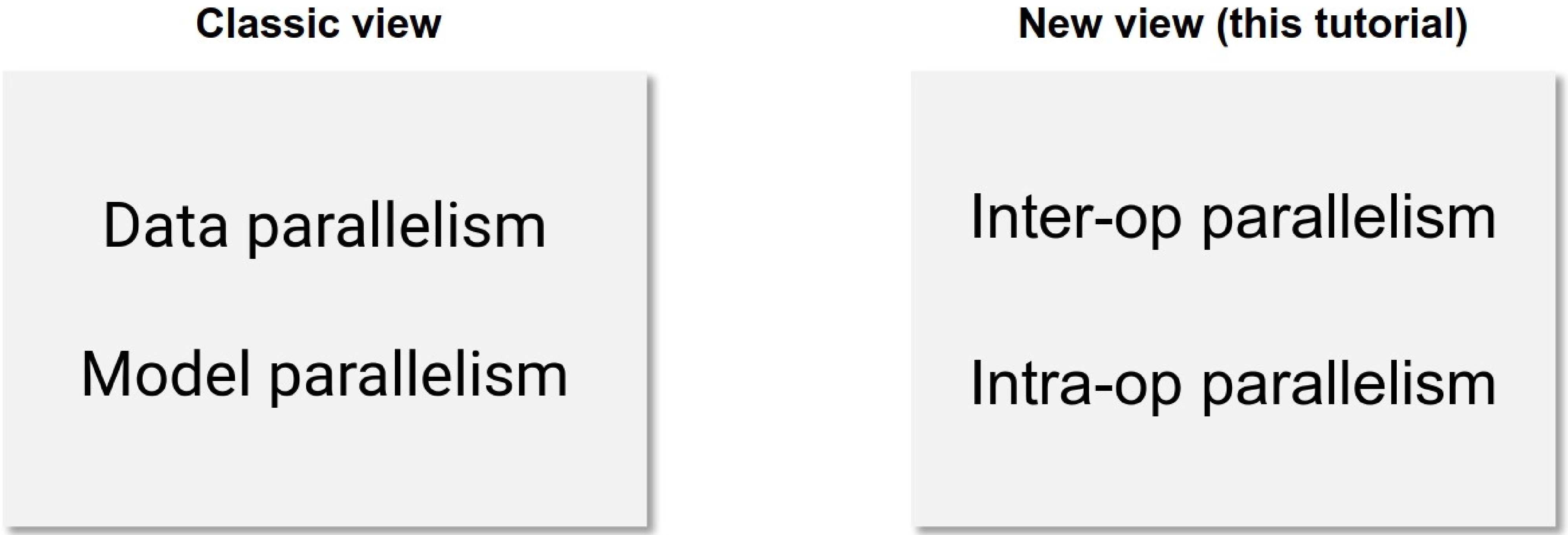

Classic view

Data parallelism

Model parallelism

New view (this tutorial)

Inter-op parallelism

Intra-op parallelism

Automated parallelism

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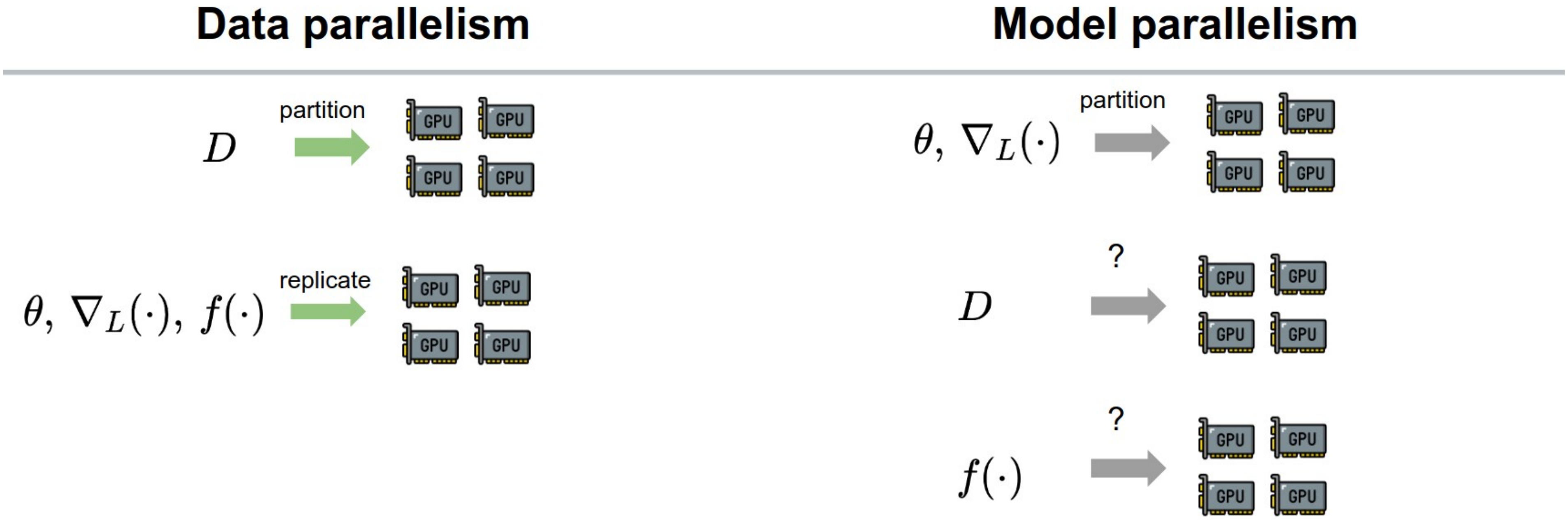


Data parallelism

$D \xrightarrow{\text{partition}}$ GPU GPU GPU GPU

$\theta,\ \nabla_L(\cdot),\ f(\cdot) \xrightarrow{\text{replicate}}$ GPU GPU GPU GPU

Model parallelism

$\theta,\ \nabla_L(\cdot) \xrightarrow{\text{partition}}$ GPU GPU GPU GPU

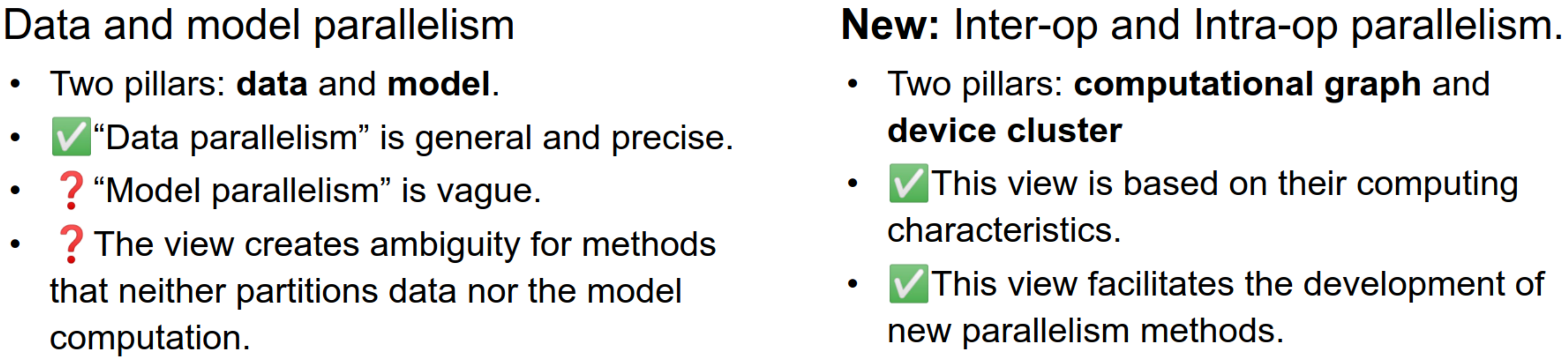
$D \xrightarrow{?}$ GPU GPU GPU GPU

$f(\cdot) \xrightarrow{?}$ GPU GPU GPU GPU

$$\underbrace{\theta^{(t+1)}}_{\text{parameter}} = \underbrace{f}_{\substack{\text{weight update}\\ \text{(sgd, adam, etc.)}}}\Big(\theta^{(t)},\ \underbrace{\nabla_L}_{\substack{\text{model}\\ \text{(CNN, GPT, etc.)}}}\big(\theta^{(t)},\ \underbrace{D^{(t)}}_{\text{data}}\big)\Big)$$

Automated parallelism

source: https://sites.google.com/view/icml-2022-big-model



Data and model parallelism

- Two pillars: **data** and **model**.
- ✅"Data parallelism" is general and precise.
- ❓"Model parallelism" is vague.
- ❓The view creates ambiguity for methods that neither partitions data nor the model computation.

New: Inter-op and Intra-op parallelism.

- Two pillars: **computational graph** and **device cluster**
- ✅This view is based on their computing characteristics.
- ✅This view facilitates the development of new parallelism methods.

Automated parallelism

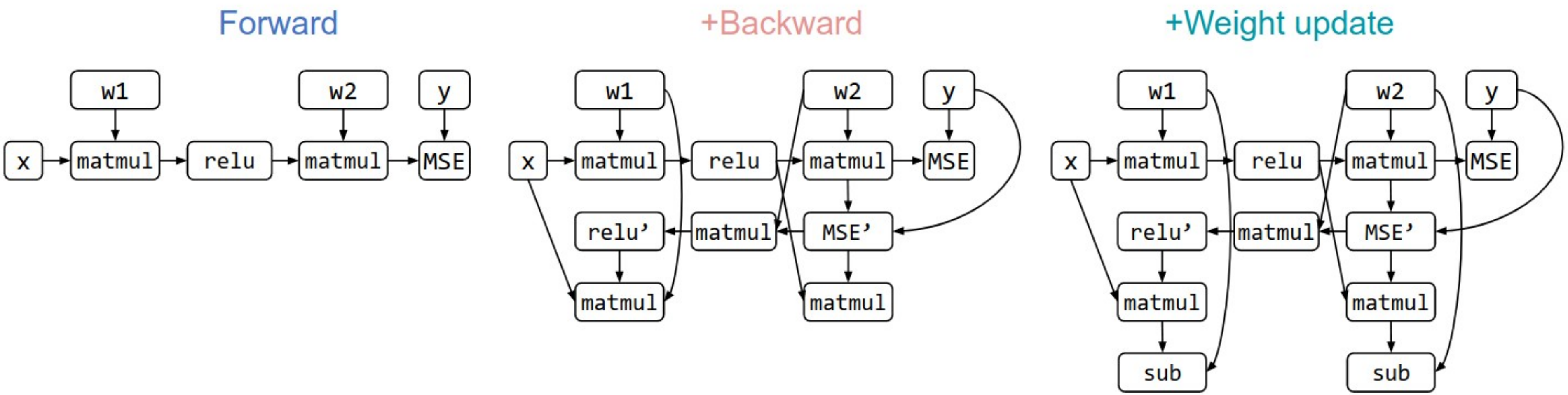
source: https://sites.google.com/view/icml-2022-big-model

$$\theta^{(t+1)} = f\left(\theta^{(t)},\, \nabla_L\left(\theta^{(t)},\, D^{(t)}\right)\right)$$

$$L = \mathrm{MSE}(w_2 \cdot \mathrm{ReLU}(w_1 x),\, y) \quad \theta = \{w_1, w_2\},\, D = \{(x, y)\}$$

$$f(\theta, \nabla_L) = \theta - \nabla_L$$

□ Operator / its output tensor → Data flowing direction



Forward

+Backward

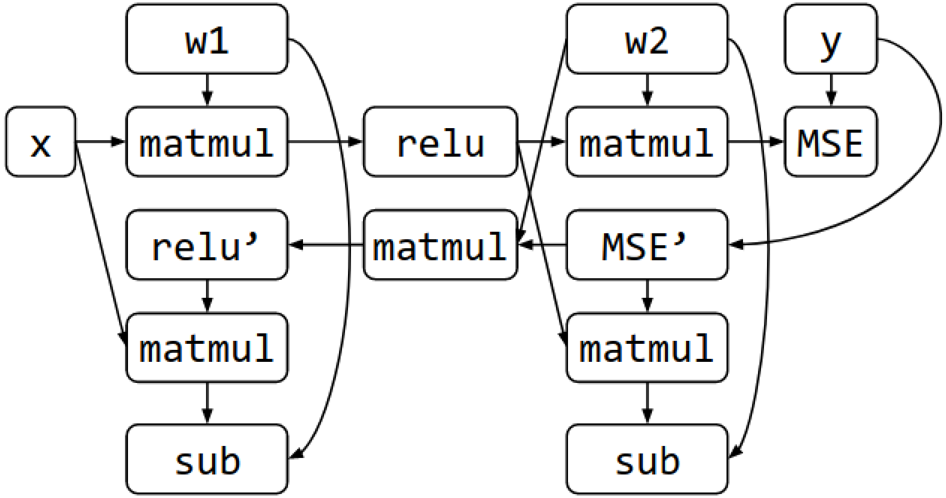
+Weight update

Automated parallelism

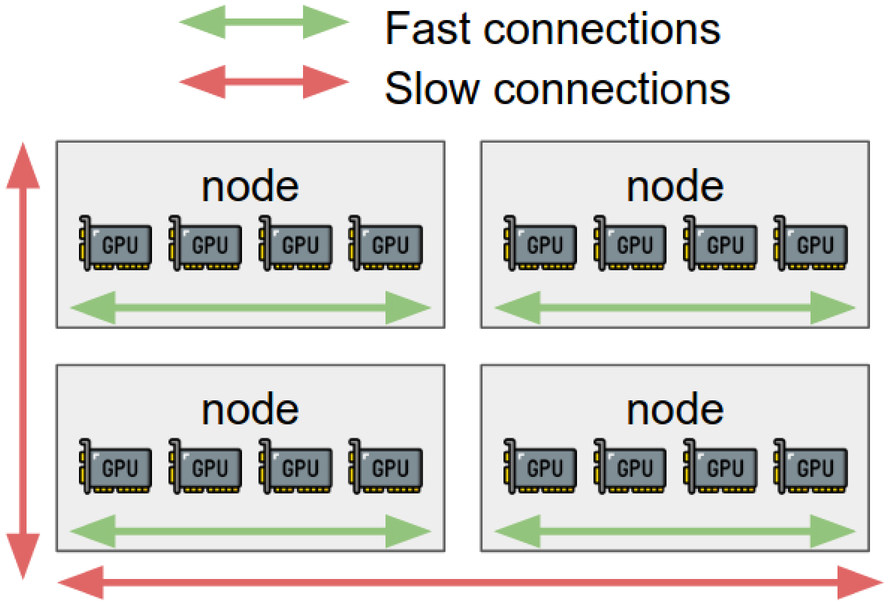
source: https://sites.google.com/view/icml-2022-big-model

How to partition the computational graph onto the device cluster?

Compute graph



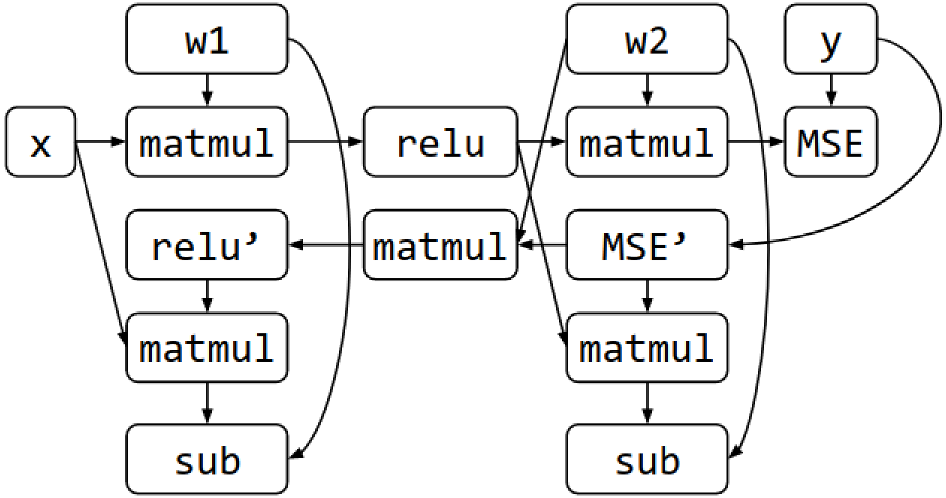
Device cluster

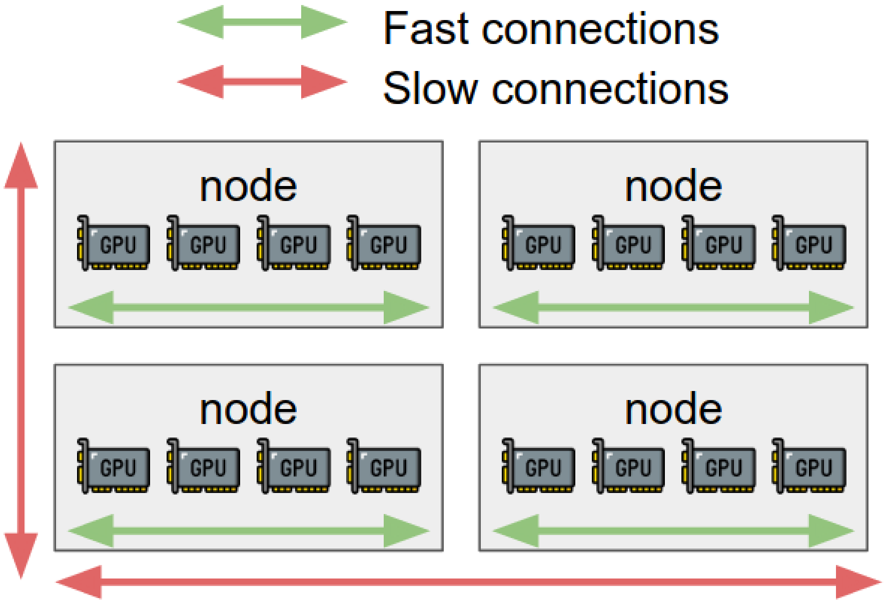


Automated parallelism

source: https://sites.google.com/view/icml-2022-big-model

Q: How to partition the graph on the device cluster?





Automated parallelism

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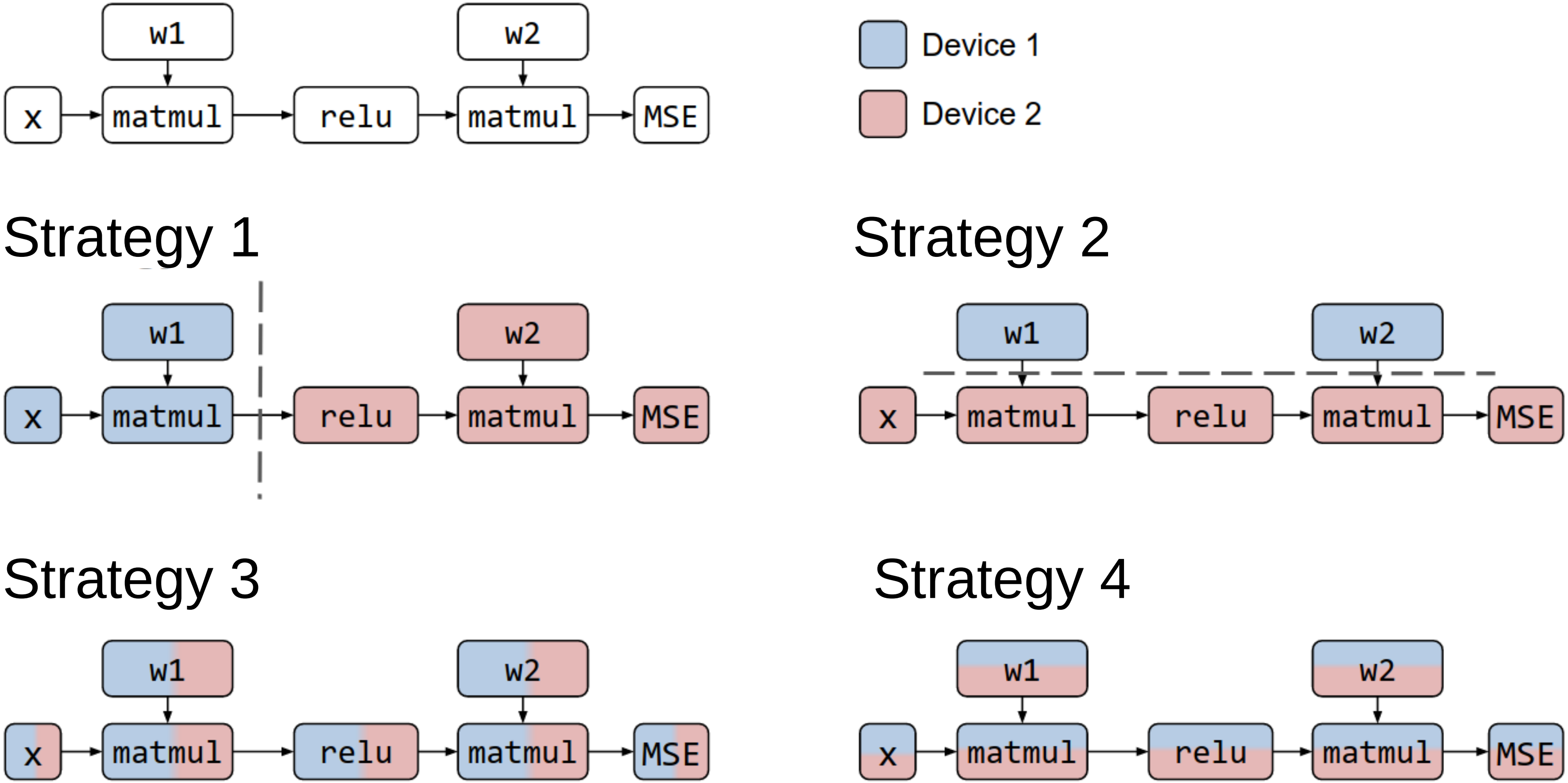


Strategy 1

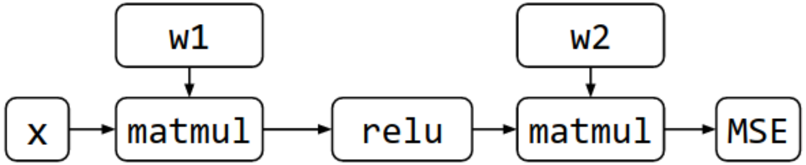
Strategy 2

Strategy 3

Strategy 4

Automated parallelism

source: https://sites.google.com/view/icml-2022-big-model

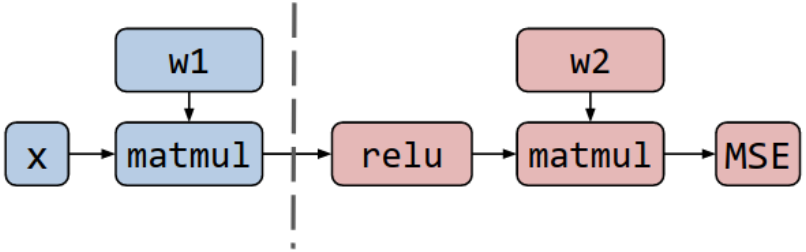


🟦 Device 1

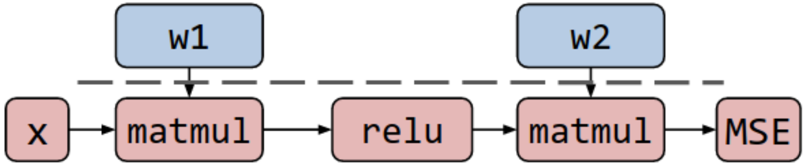
🟥 Device 2

Q: have you seen S1/2/3/4 before?

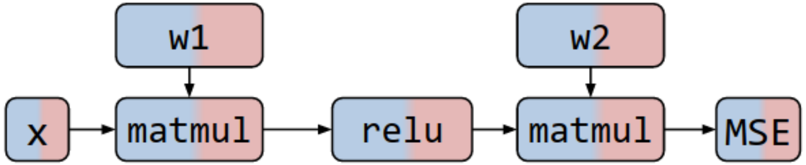
Strategy 1



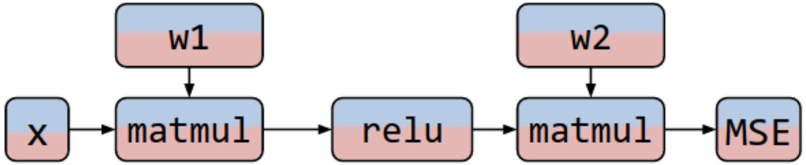
Strategy 2



Strategy 3



Strategy 4



Automated parallelism

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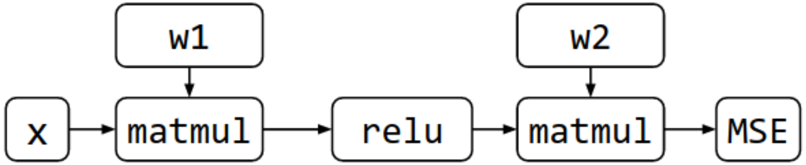
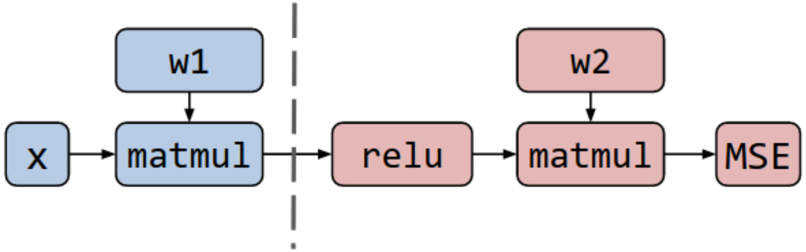


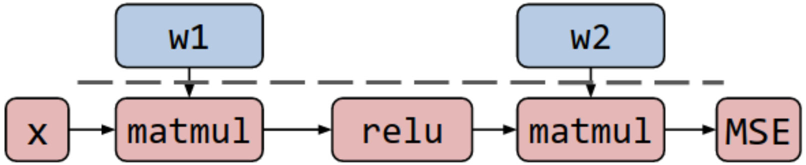
🟦 Device 1

🟥 Device 2

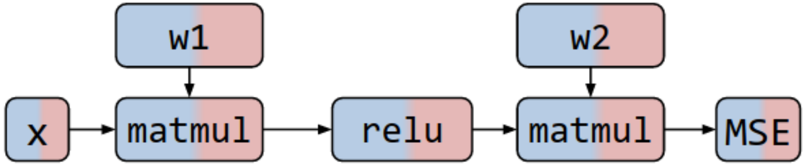
Pipeline MP



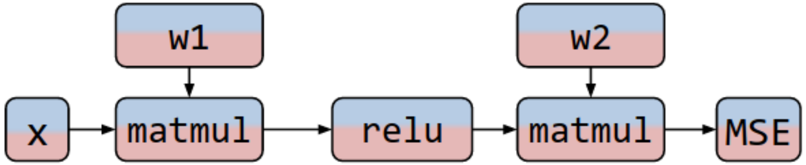
DP with offloading or PS



Tensor-parallel v1

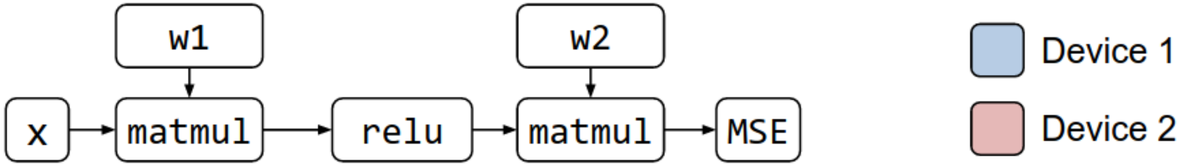


Tensor-parallel v2



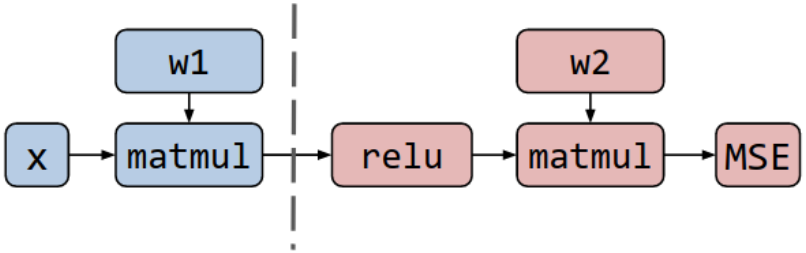
Automated parallelism

source: https://sites.google.com/view/icml-2022-big-model

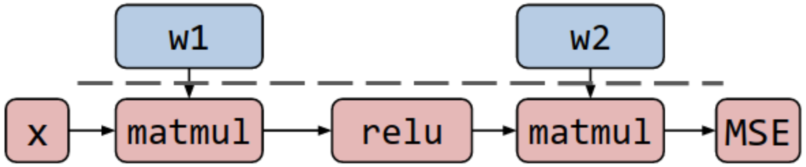


Inter-op parallelism

~~Pipeline MP~~

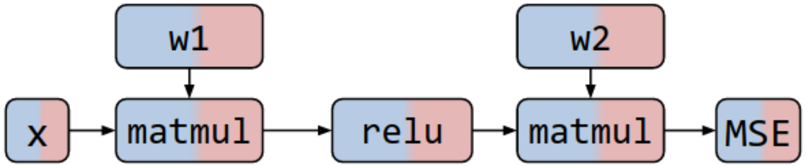


~~DP with offloading or PS~~

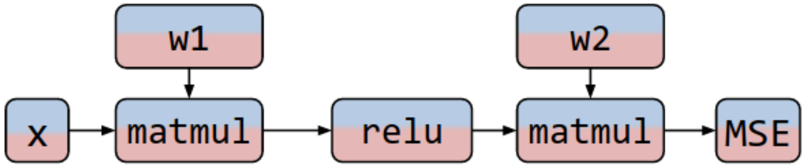


Intra-op parallelism

~~Tensor-parallel v1~~

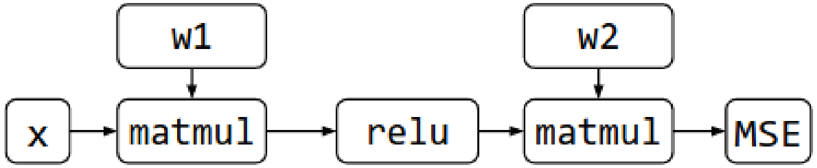


~~Tensor-parallel v2~~



Automated parallelism

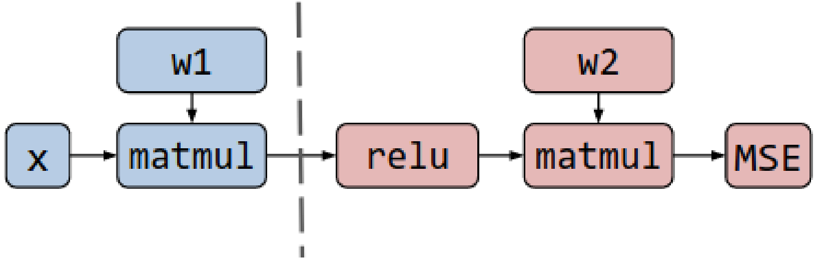
source: https://sites.google.com/view/icml-2022-big-model



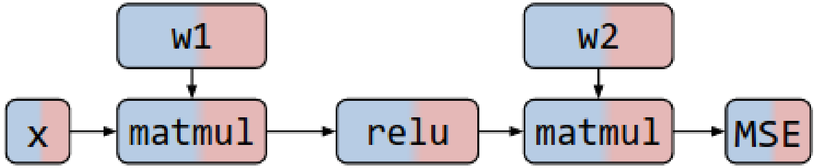
🟦 Device 1

🟥 Device 2

Inter-op parallelism



Intra-op parallelism

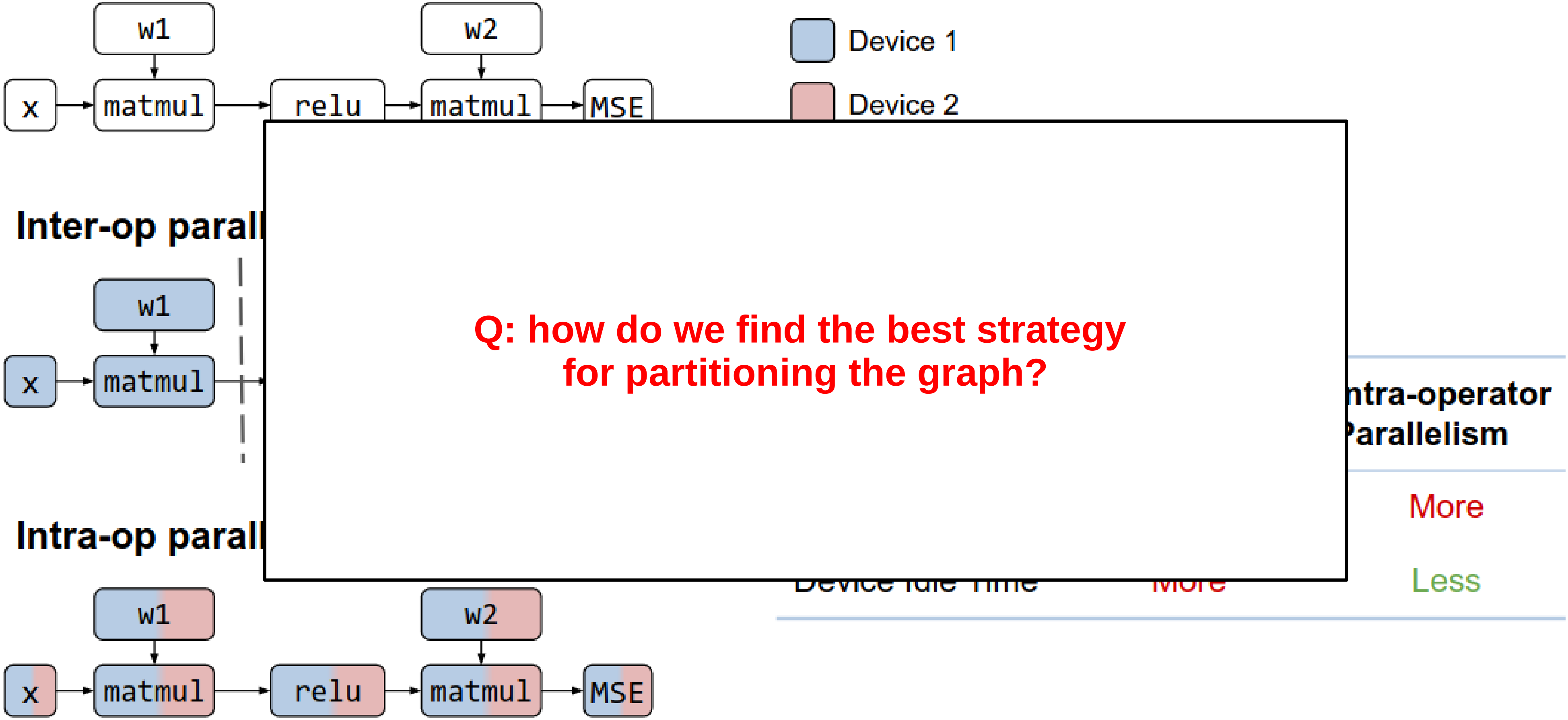


Trade-off

	Inter-operator Parallelism	Intra-operator Parallelism
Communication	Less	More
Device Idle Time	More	Less

Automated parallelism

source: https://sites.google.com/view/icml-2022-big-model



Q: how do we find the best strategy for partitioning the graph?

RL-based partitioning

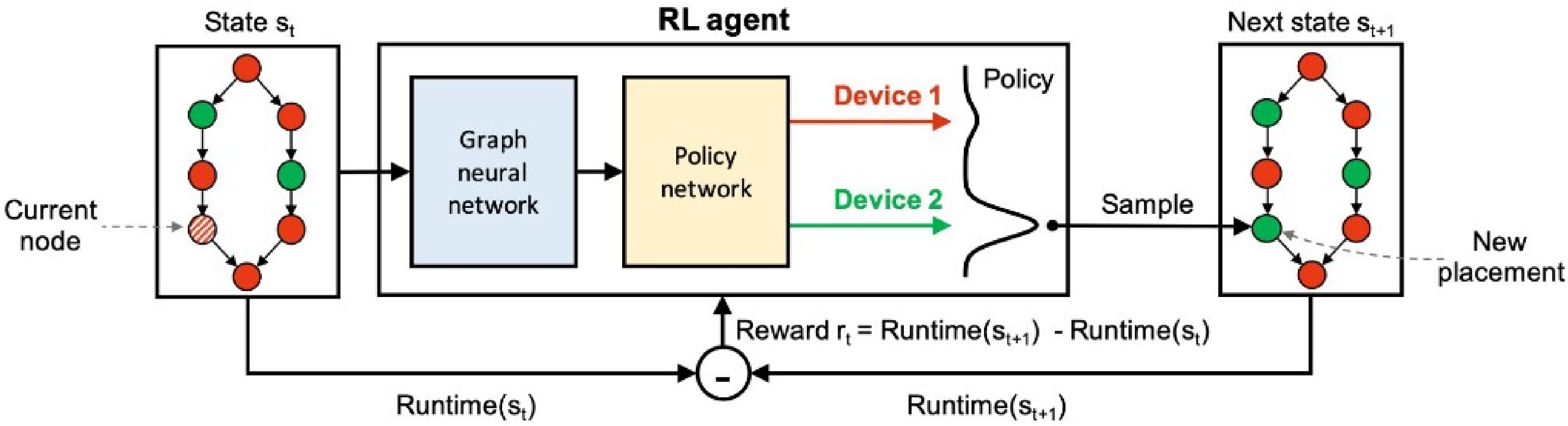
https://people.csail.mit.edu/hongzi/content/publications/placeto-neurips19.pdf

State: Device assignment plan for a computational graph.

Action: Modify the device assignment of a node.

Reward: Latency difference between the new and old placements.

Trained with **policy gradient** algorithm.



Addanki, Ravichandra, et al. "Placeto: Learning generalizable device placement algorithms for distributed machine learning." NeurIPS 2019.

Optimization-based partitioning

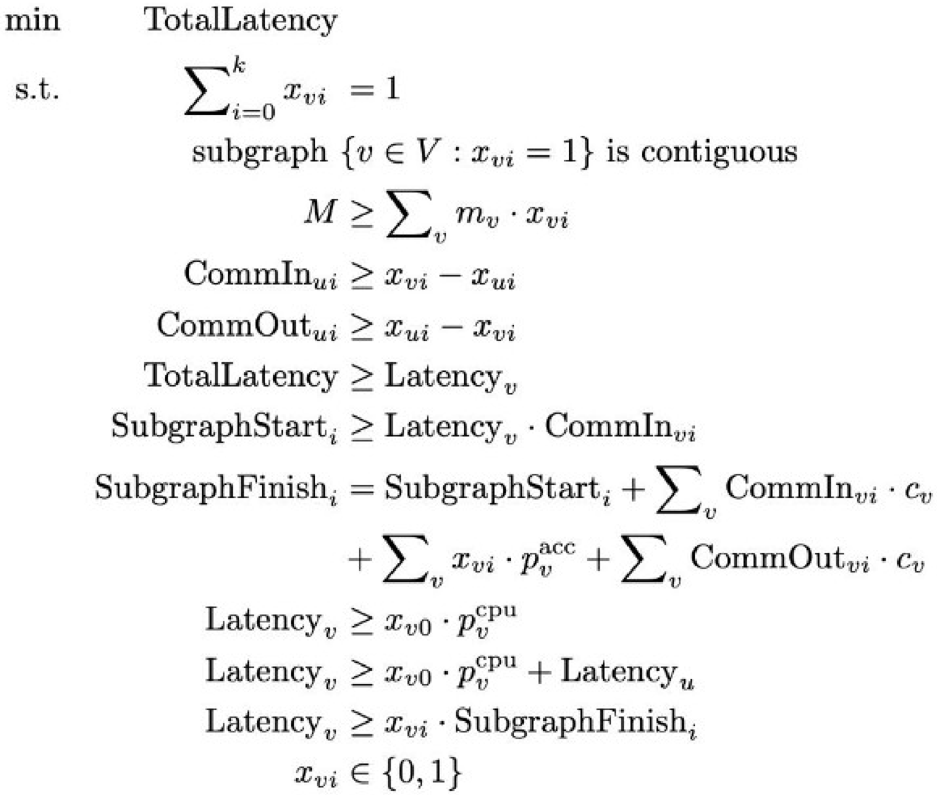
https://arxiv.org/abs/2006.16423

Integer Linear Programming:

Variable: Decision variable vector for each operator, representing device assignment.

Minimize: Maximum finishing time of all operators.

Constraint: Execution dependency & memory capacity of each device.

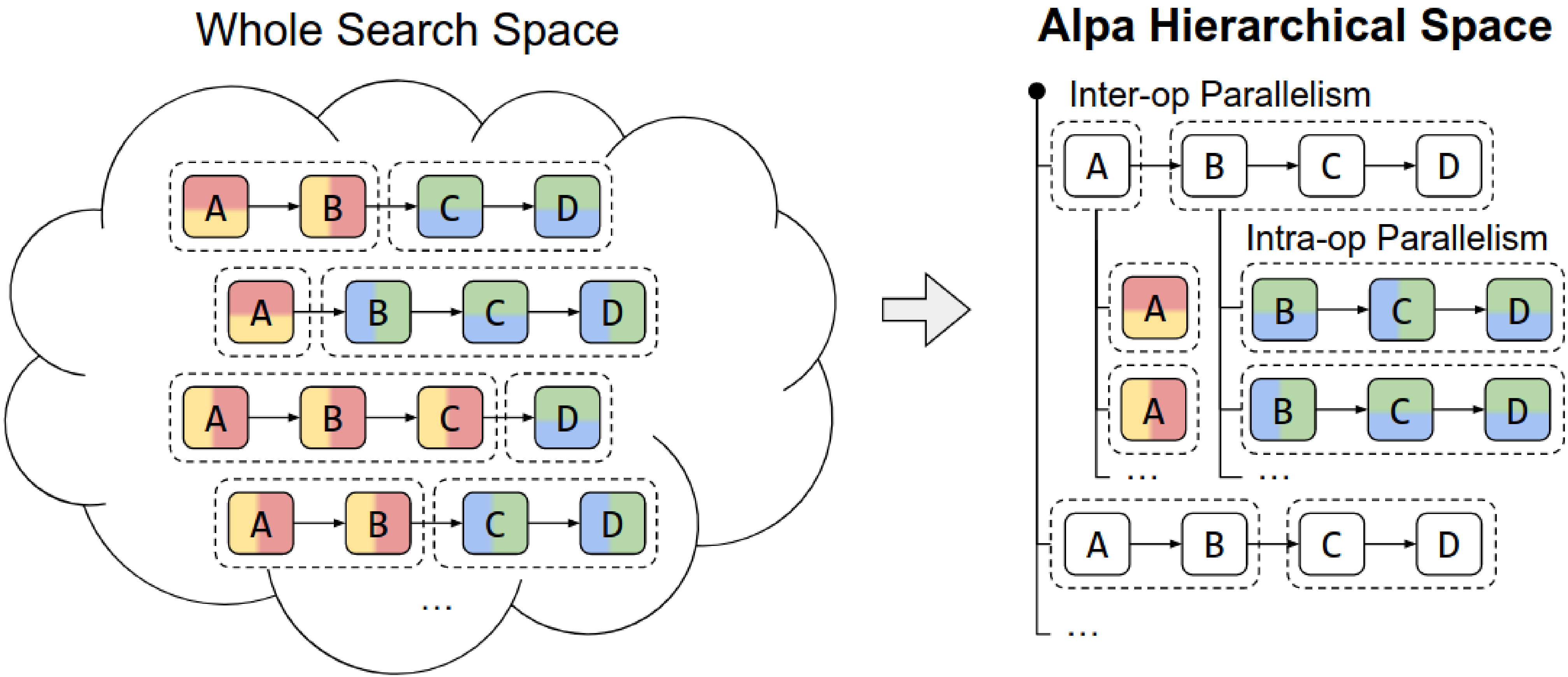


$$
\begin{aligned}
\min \quad & \text{TotalLatency} \\
\text{s.t.} \quad & \textstyle\sum_{i=0}^{k} x_{vi} = 1 \\
& \text{subgraph } \{v \in V : x_{vi} = 1\} \text{ is contiguous} \\
& M \geq \textstyle\sum_{v} m_v \cdot x_{vi} \\
& \text{CommIn}_{ui} \geq x_{vi} - x_{ui} \\
& \text{CommOut}_{ui} \geq x_{ui} - x_{vi} \\
& \text{TotalLatency} \geq \text{Latency}_v \\
& \text{SubgraphStart}_i \geq \text{Latency}_v \cdot \text{CommIn}_{vi} \\
& \text{SubgraphFinish}_i = \text{SubgraphStart}_i + \textstyle\sum_{v} \text{CommIn}_{vi} \cdot c_v \\
& \qquad + \textstyle\sum_{v} x_{vi} \cdot p_v^{\text{acc}} + \textstyle\sum_{v} \text{CommOut}_{vi} \cdot c_v \\
& \text{Latency}_v \geq x_{v0} \cdot p_v^{\text{cpu}} \\
& \text{Latency}_v \geq x_{v0} \cdot p_v^{\text{cpu}} + \text{Latency}_u \\
& \text{Latency}_v \geq x_{vi} \cdot \text{SubgraphFinish}_i \\
& x_{vi} \in \{0, 1\}
\end{aligned}
$$

Tarnawski, Jakub M., et al. "Efficient algorithms for device placement of dnn graph operators." NeurIPS 2020.

Alpa: optimization-based + reduced search space

https://arxiv.org/abs/2201.12023

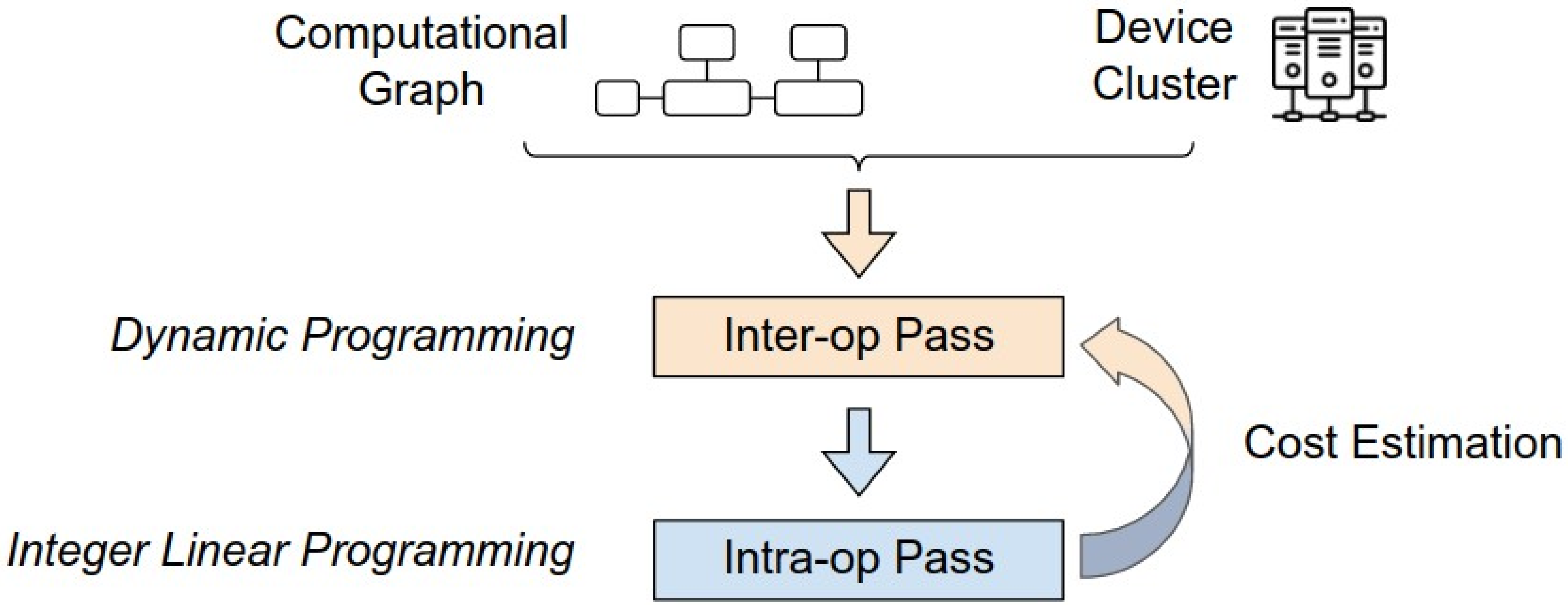


Whole Search Space

Alpa Hierarchical Space

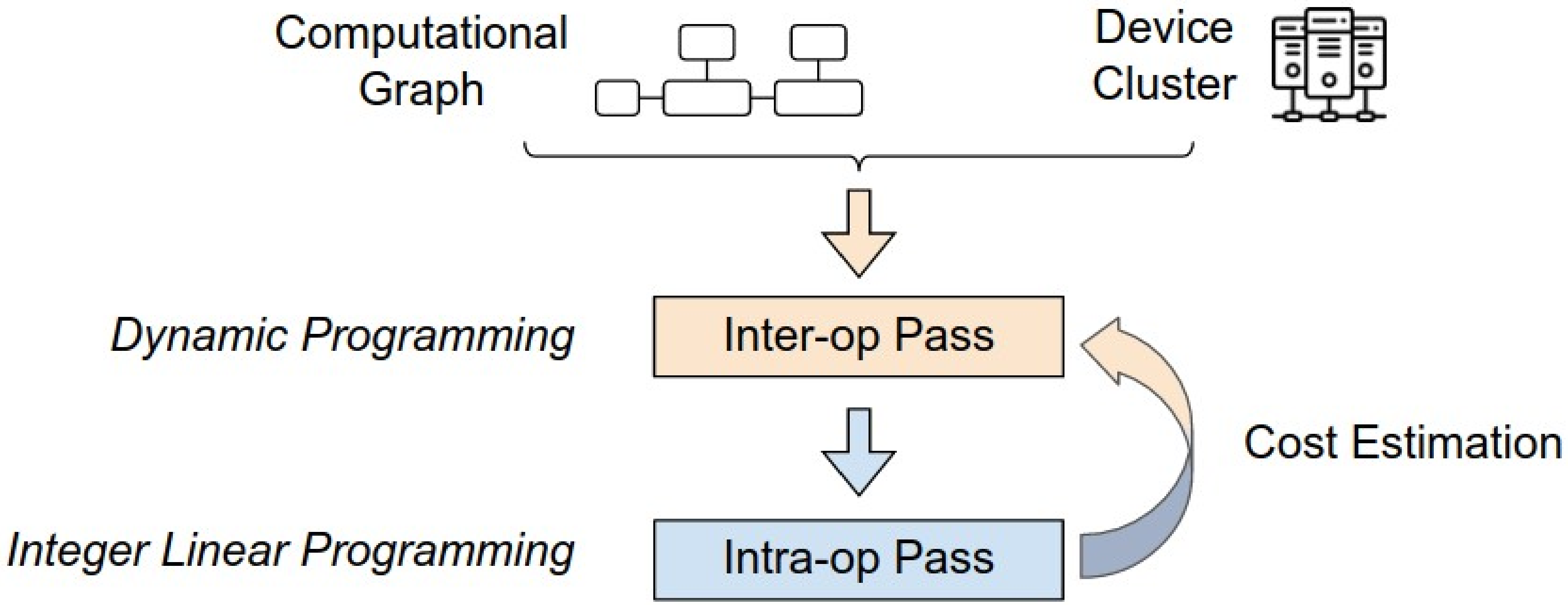
Alpa: optimization-based + reduced search space

https://arxiv.org/abs/2201.12023



Alpa: optimization-based + reduced search space

https://arxiv.org/abs/2201.12023



More details of each pass:
https://sites.google.com/view/icml-2022-big-model

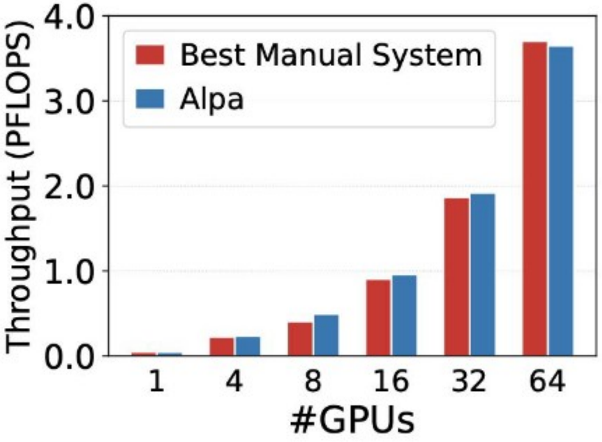
Alpa: optimization-based + reduced search space

https://arxiv.org/abs/2201.12023

Not the first algorithm for auto-parallelism…
but the first one that is usable* *(* - most of the time)*

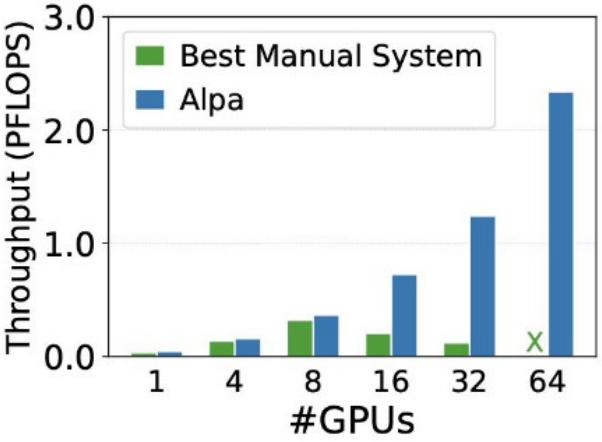
(benchmarks on AWS V100)

GPT (up to 39B)



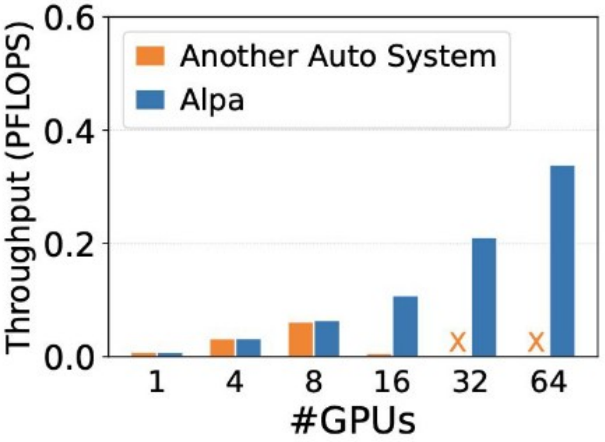
Match specialized manual systems.

GShard MoE (up to 70B)



Outperform the manual baseline by up to 8x.

Wide-ResNet (up to 13B)

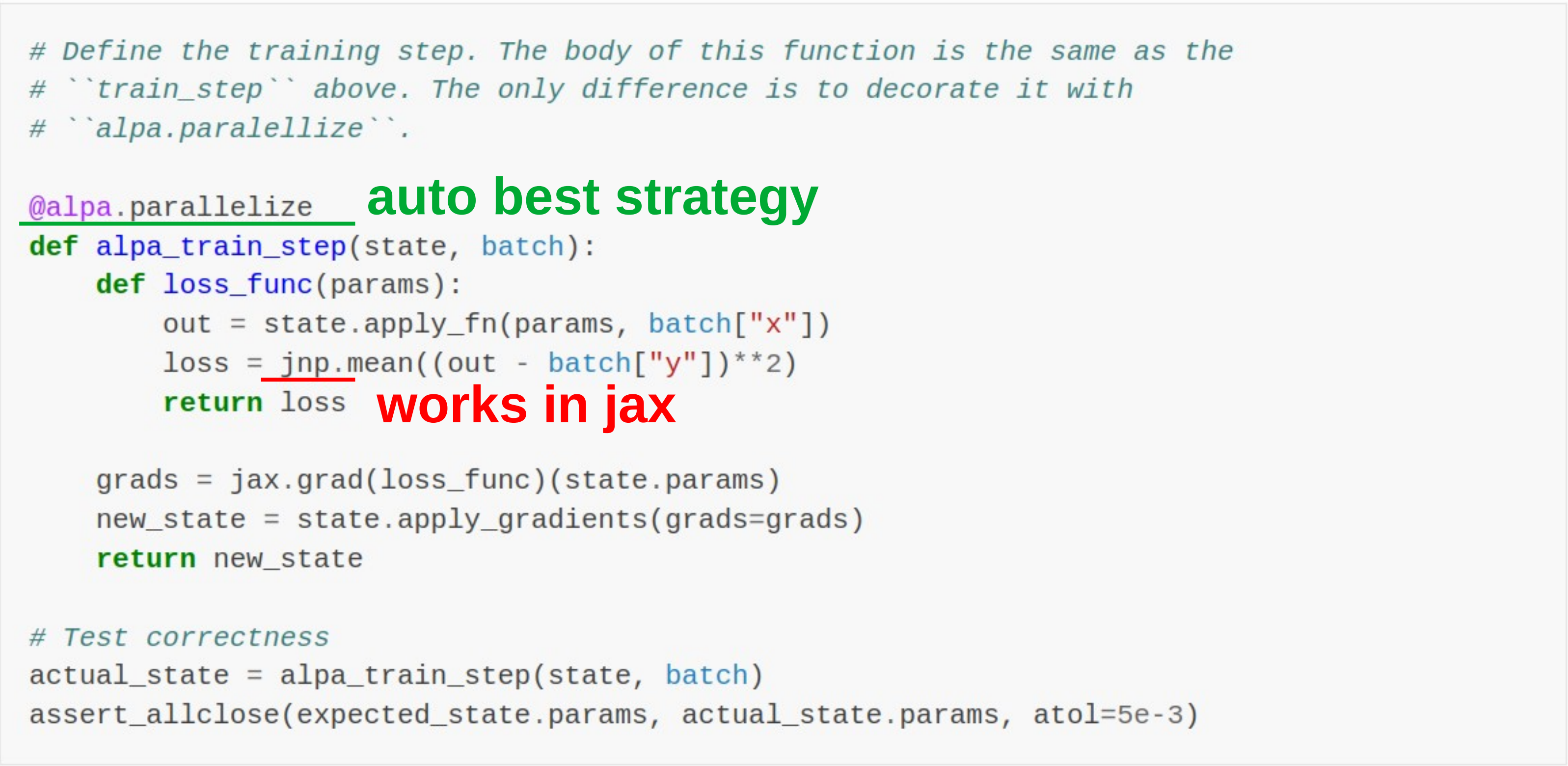


Generalize to models without manual plans.

Alpa: optimization-based + reduced search space

https://arxiv.org/abs/2201.12023

Not the first algorithm for auto-parallelism…
but the first one that is usable* *(* - most of the time)*



```python
# Define the training step. The body of this function is the same as the
# ``train_step`` above. The only difference is to decorate it with
# ``alpa.paralellize``.

@alpa.parallelize
def alpa_train_step(state, batch):
    def loss_func(params):
        out = state.apply_fn(params, batch["x"])
        loss = jnp.mean((out - batch["y"])**2)
        return loss

    grads = jax.grad(loss_func)(state.params)
    new_state = state.apply_gradients(grads=grads)
    return new_state

# Test correctness
actual_state = alpa_train_step(state, batch)
assert_allclose(expected_state.params, actual_state.params, atol=5e-3)
```

auto best strategy

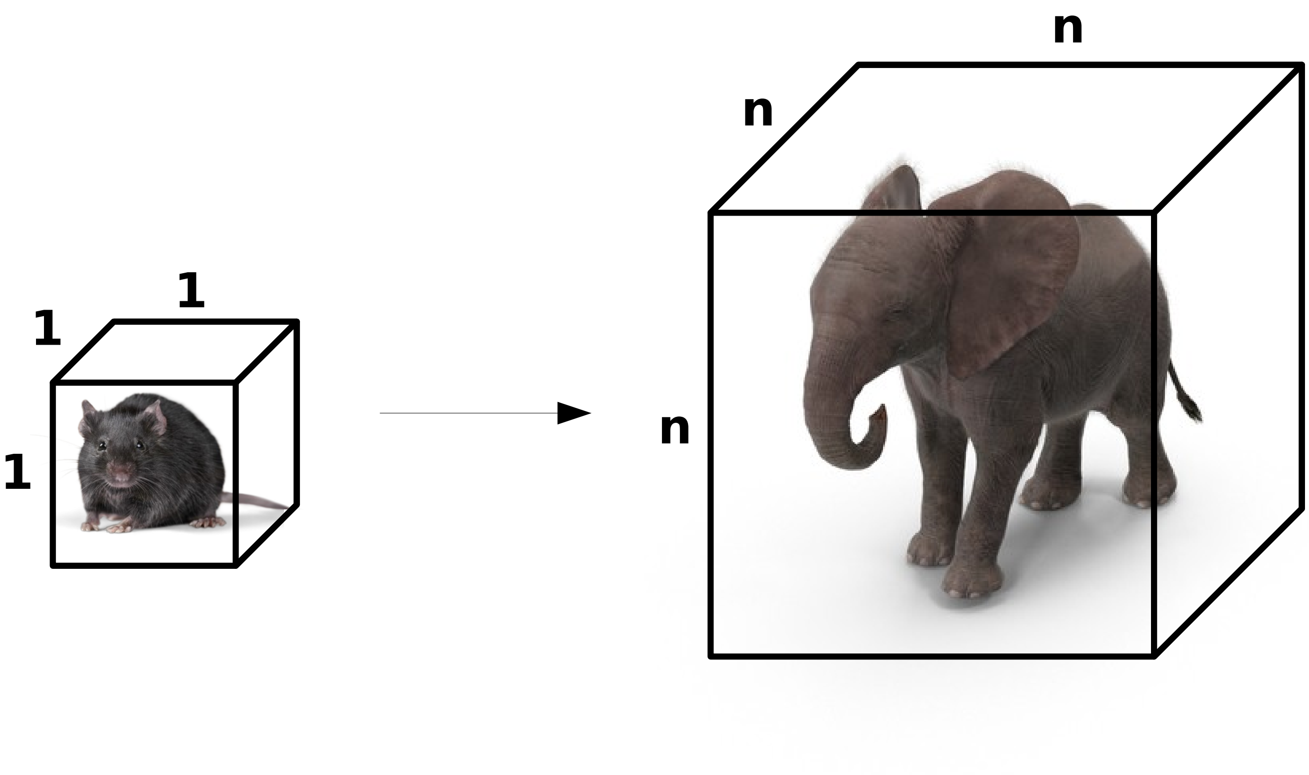
works in jax

If we have time…

(if not, finish here)

The square-cube law of deep learning

Explainer: https://www.youtube.com/watch?v=f7KSfjv4Oq0

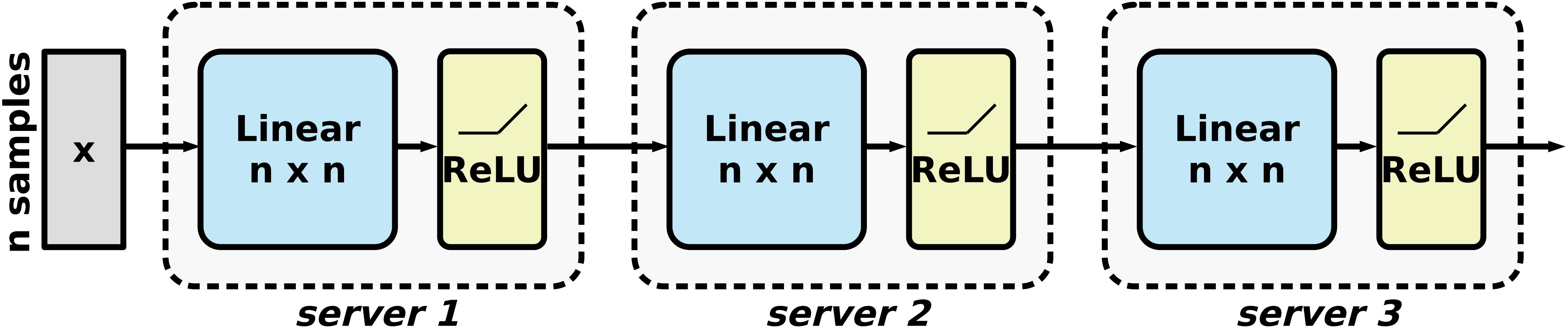


Surface area $O(n^2)$

Volume $O(n^3)$

The square-cube law of deep learning

Explainer: https://www.youtube.com/watch?v=f7KSfjv4Oq0



The square-cube law of deep learning

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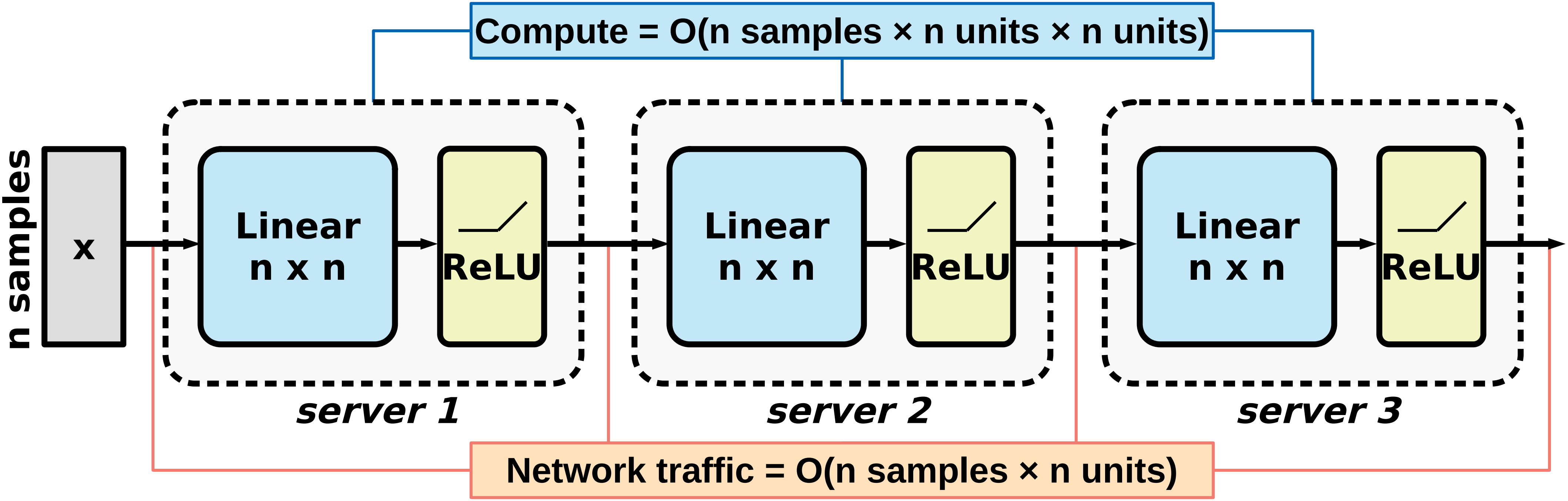
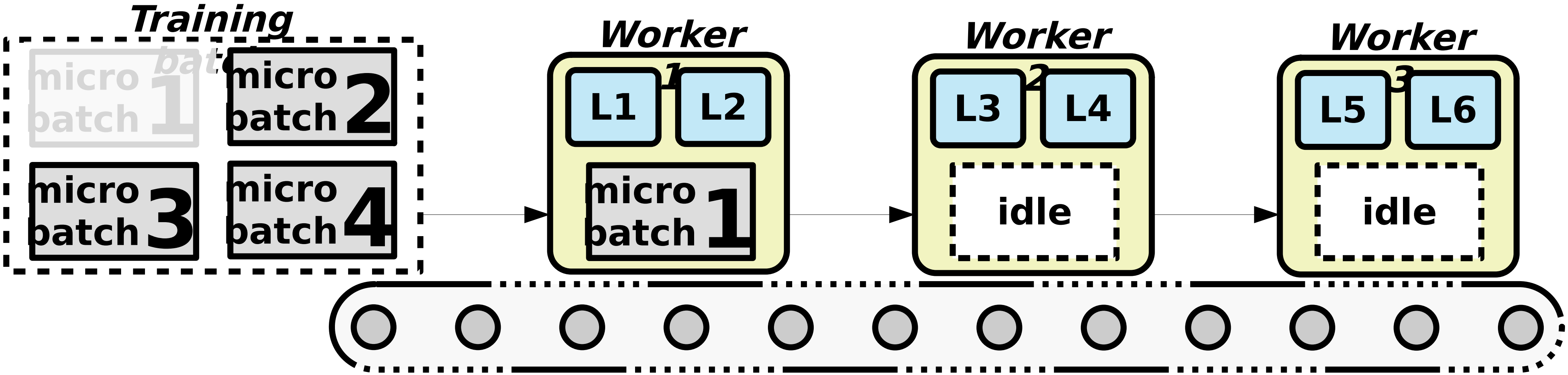


Compute = O(n samples × n units × n units)

Network traffic = O(n samples × n units)

The square-cube law of deep learning

Explainer: https://www.youtube.com/watch?v=f7KSfjv4Oq0



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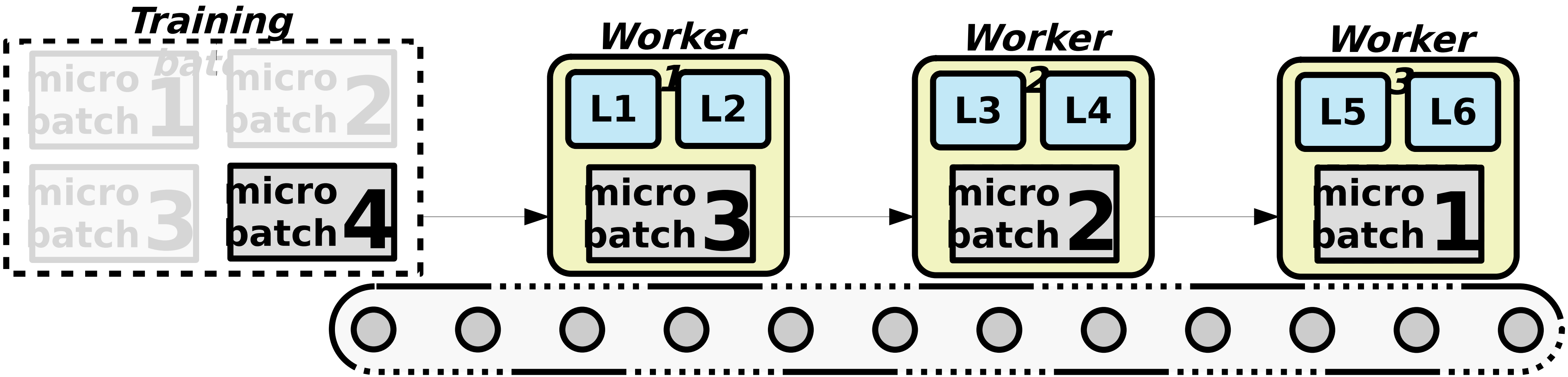

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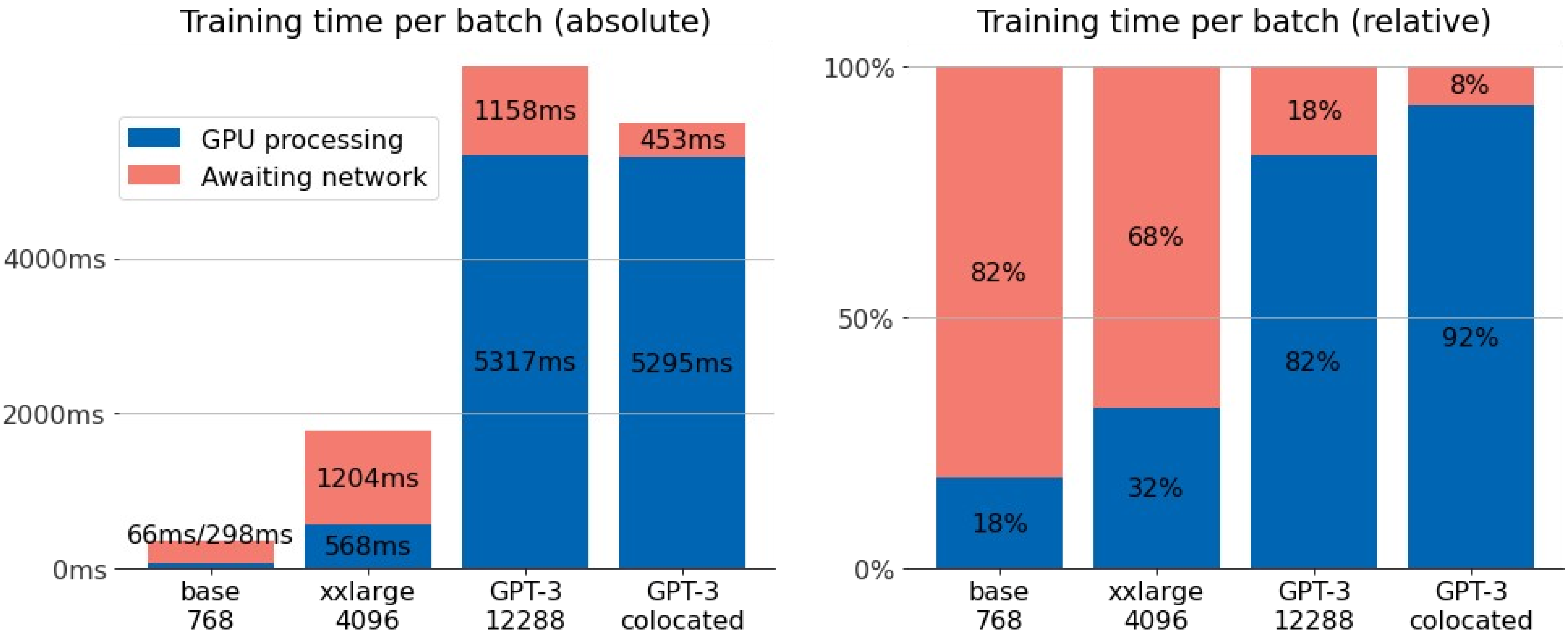
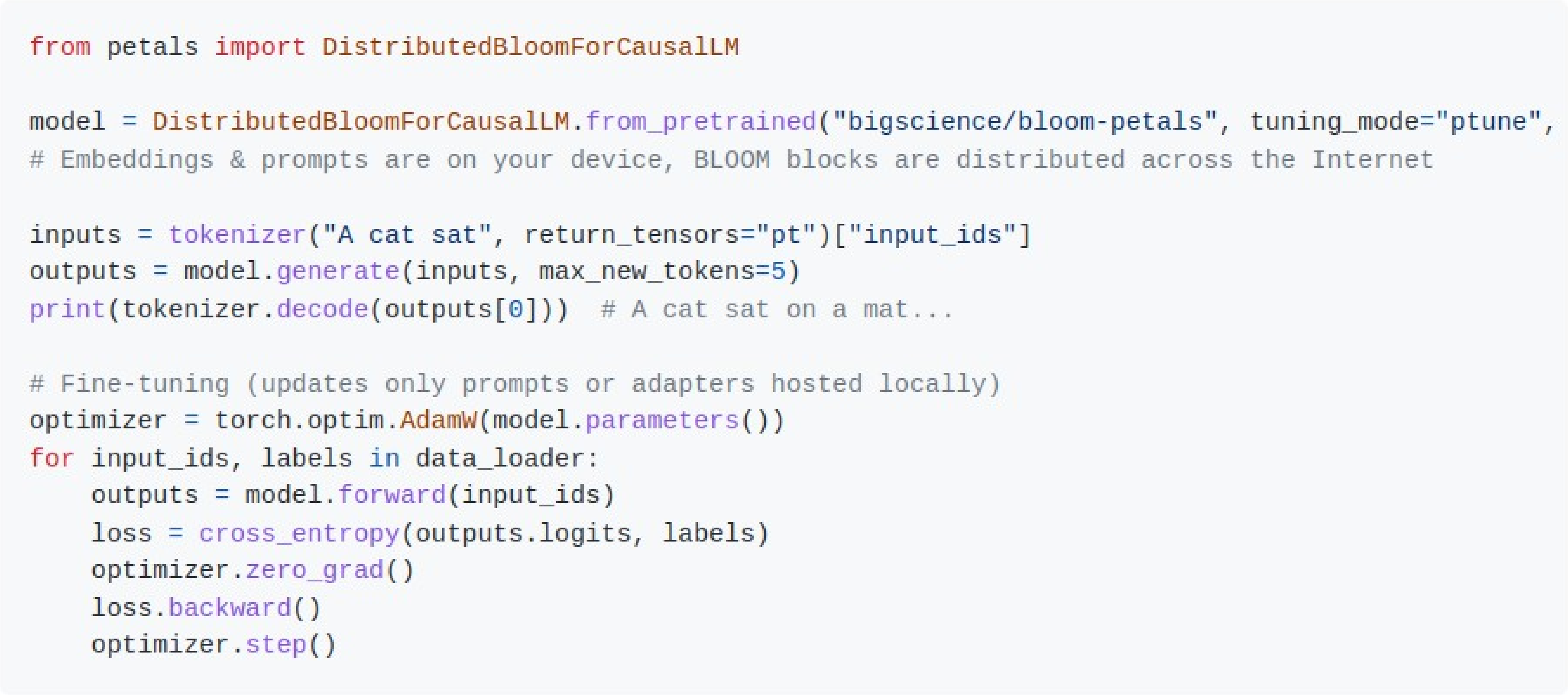


Petals

https://petals.ml

TL;DR: you can run 100B+ models over the internet, BitTorrent style



```python
from petals import DistributedBloomForCausalLM

model = DistributedBloomForCausalLM.from_pretrained("bigscience/bloom-petals", tuning_mode="ptune",
# Embeddings & prompts are on your device, BLOOM blocks are distributed across the Internet

inputs = tokenizer("A cat sat", return_tensors="pt")["input_ids"]
outputs = model.generate(inputs, max_new_tokens=5)
print(tokenizer.decode(outputs[0]))  # A cat sat on a mat...

# Fine-tuning (updates only prompts or adapters hosted locally)
optimizer = torch.optim.AdamW(model.parameters())
for input_ids, labels in data_loader:
    outputs = model.forward(input_ids)
    loss = cross_entropy(outputs.logits, labels)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

That's all Folks!