Data-Parallel Deep Learning

Efficient DL, Episode IV, 2025

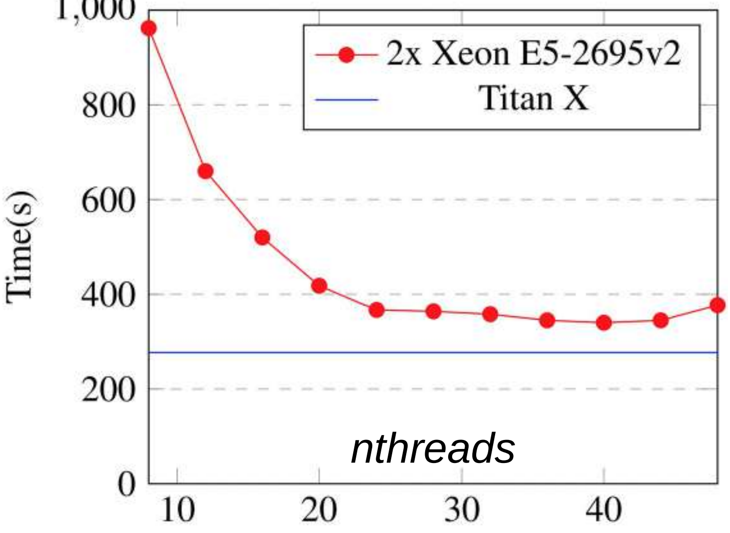
Yandex
Research

LAMBDA

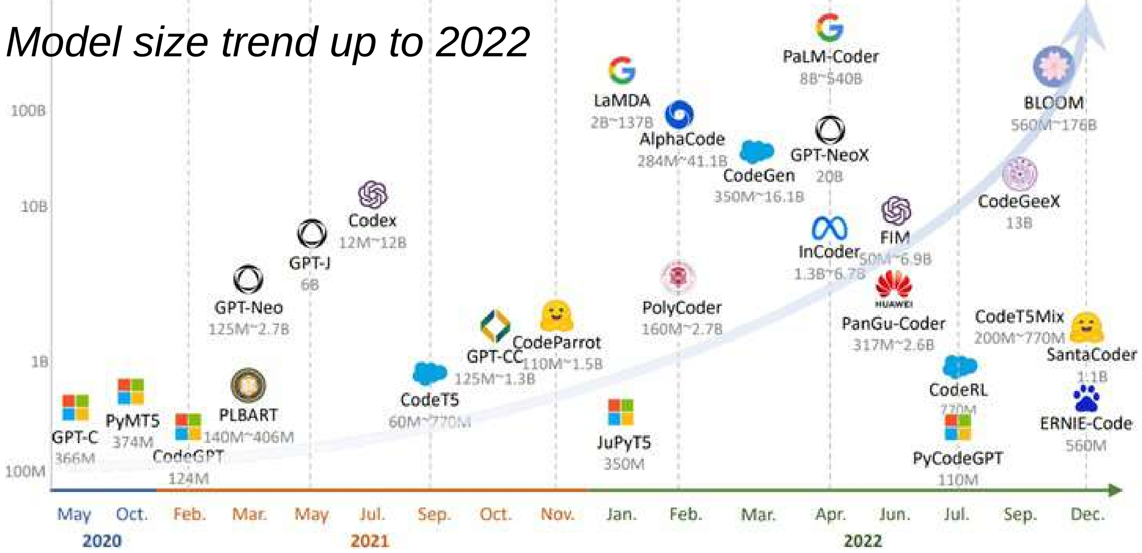
British Hedgehog
Preservation Society

Зачем это всё?

XGBoost training time



parameters vs time



BERT-Large Training Times on GPUs

Time	System	Number of Nodes	Number of V100 GPUs
47 min	DGX SuperPOD	92 x DGX-2H	1,472
67 min	DGX SuperPOD	64 x DGX-2H	1,024
236 min	DGX SuperPOD	16 x DGX-2H	256

*(single GPU – **over 2 weeks**)*

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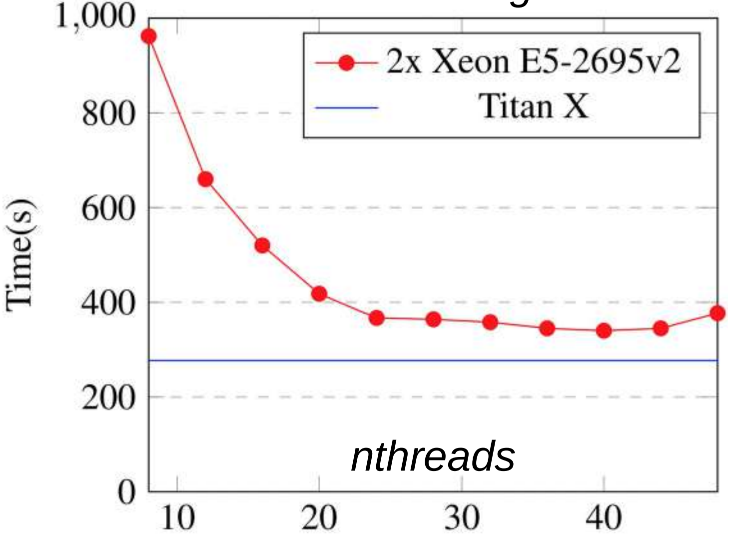
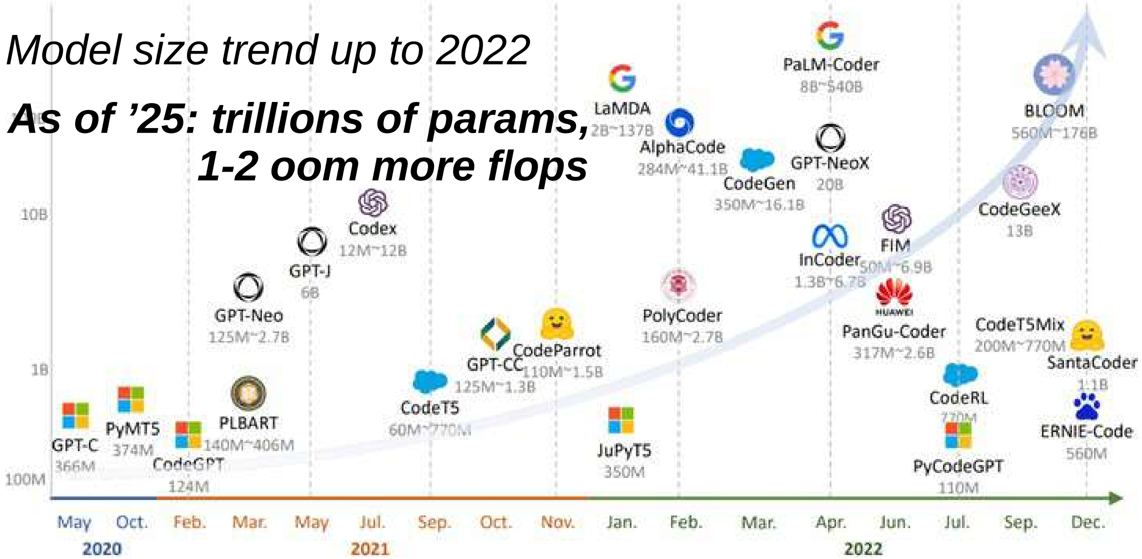


parameters vs time

Model size trend up to 2022

As of ’25: trillions of params, 1-2 oom more flops



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Зачем мы тут?

Заставить много железяк вместе учить одну модель

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Заставить много железяк вместе учить одну модель

понять общие подходы

закодить своими руками

на python / pytorch

TL;DR our plan

lectures 4,5,6

- Data-parallel deep learning

  Train BERT-base on wikipedia in 20 minutes or less

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  Fine-tune and deploy models with 100B+ parameters

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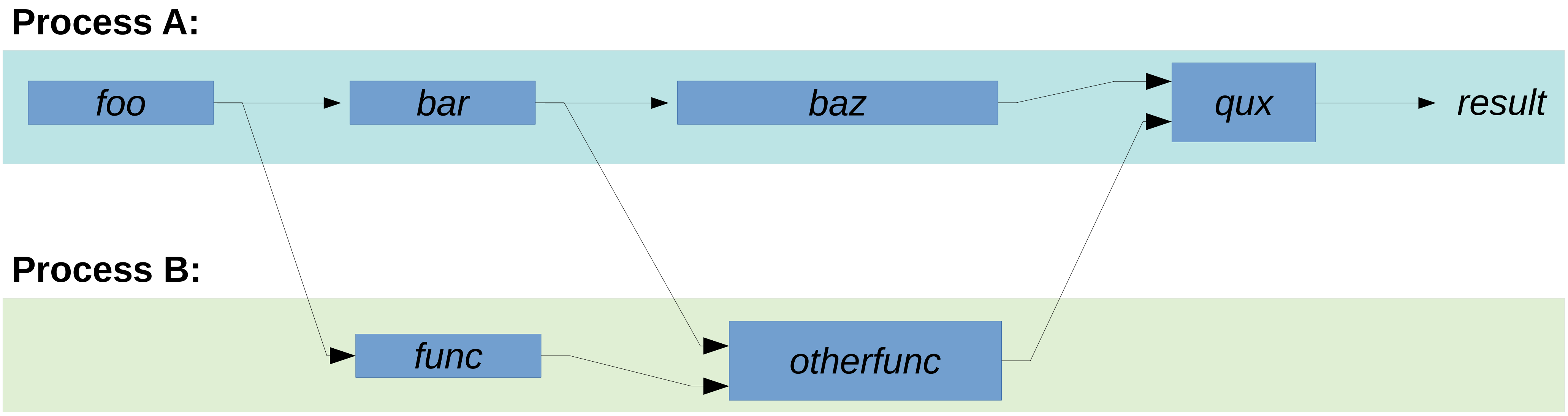
  Fine-tune and deploy models with 100B+ parameters

  like OPT, Llama, Qwen, DeepSeek R1, ...

- Advanced techniques

  Sharding (FSDP), mixed / hybrid parallelism, practice

Rules: Channel / Pipe



Channel (pipe):

- Communication in O(message size)
- Asynchronous read/write

Data-parallel training (naive)

cs.cmu.edu/~muli/file/parameter_server_osdi14.pdf

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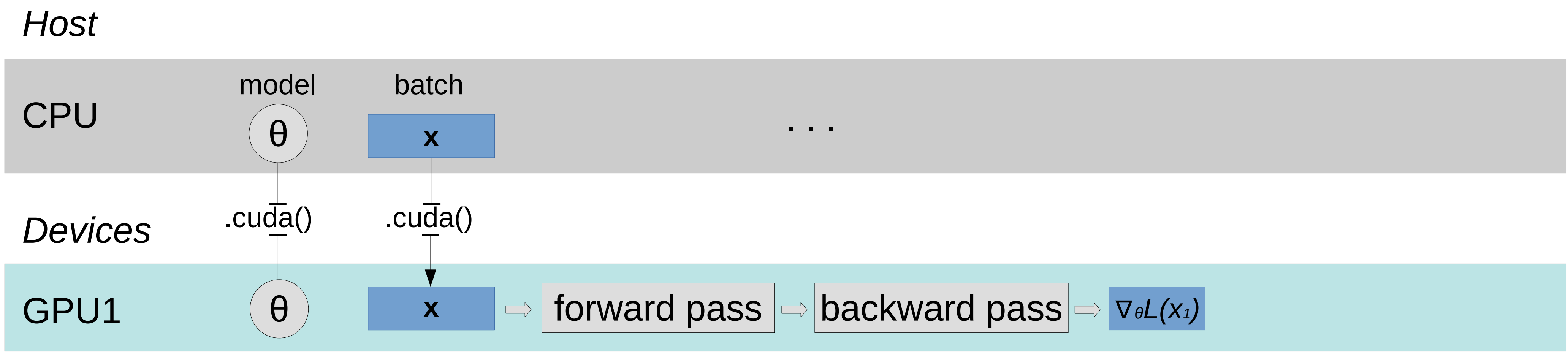

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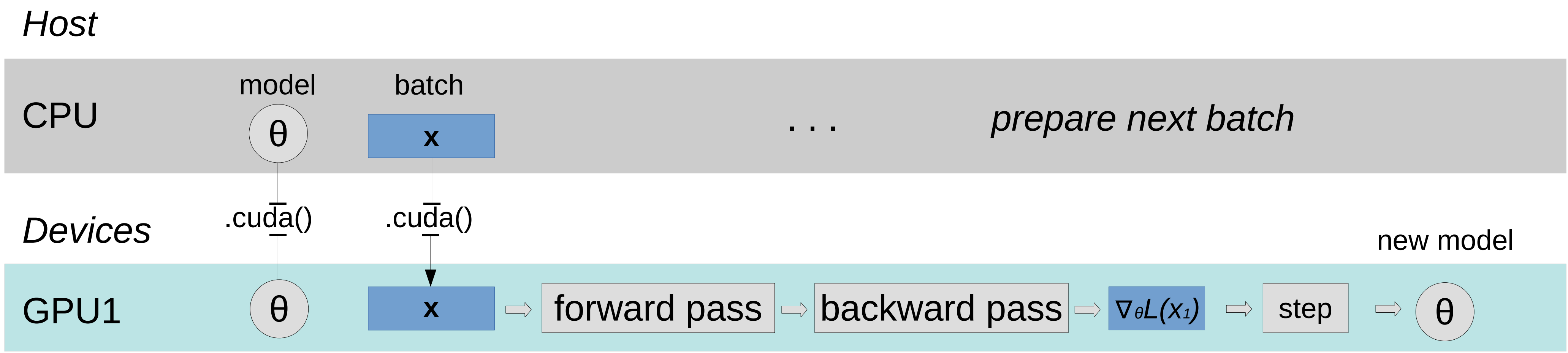

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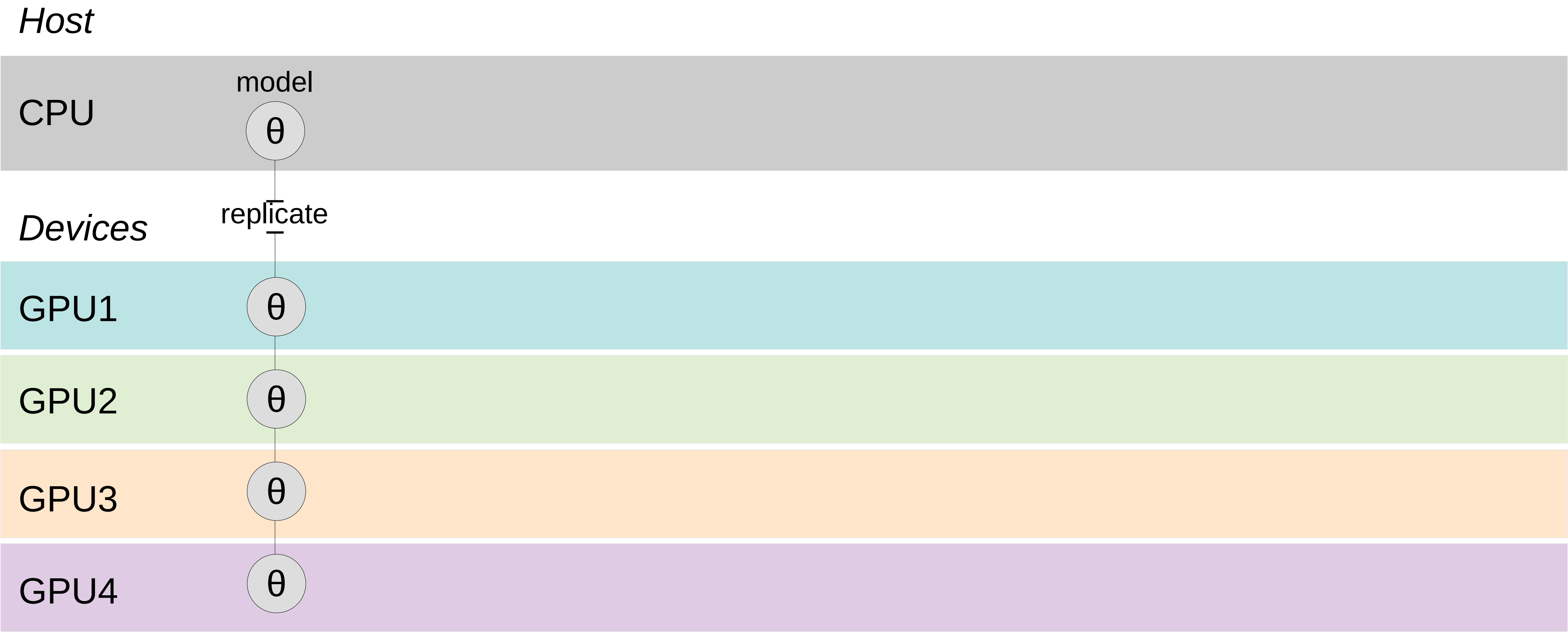

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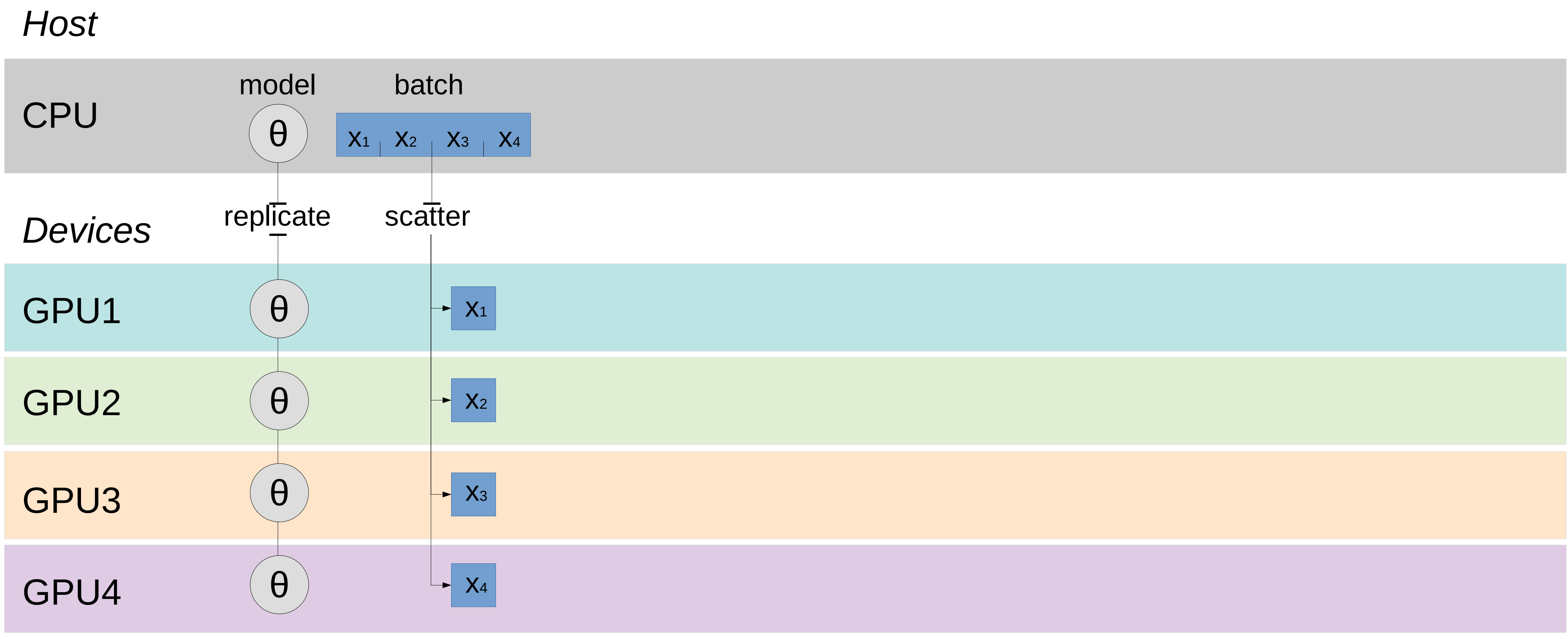

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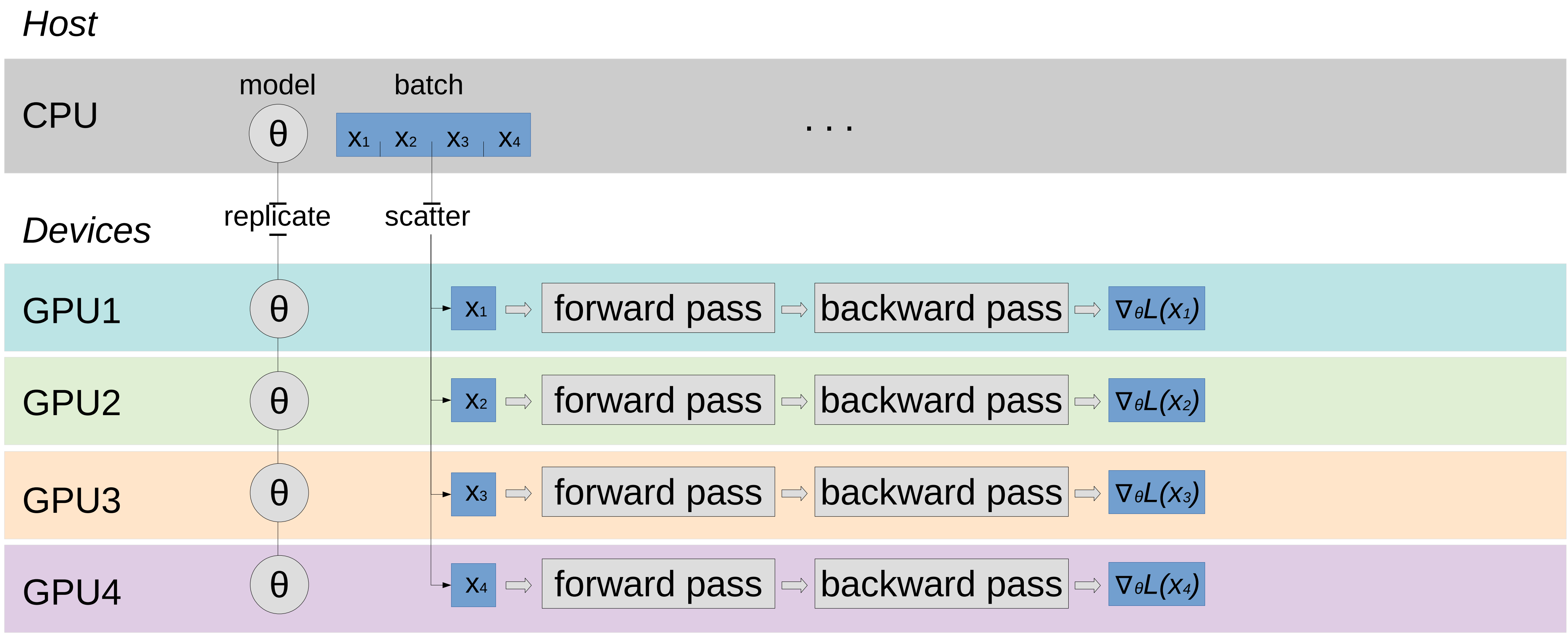

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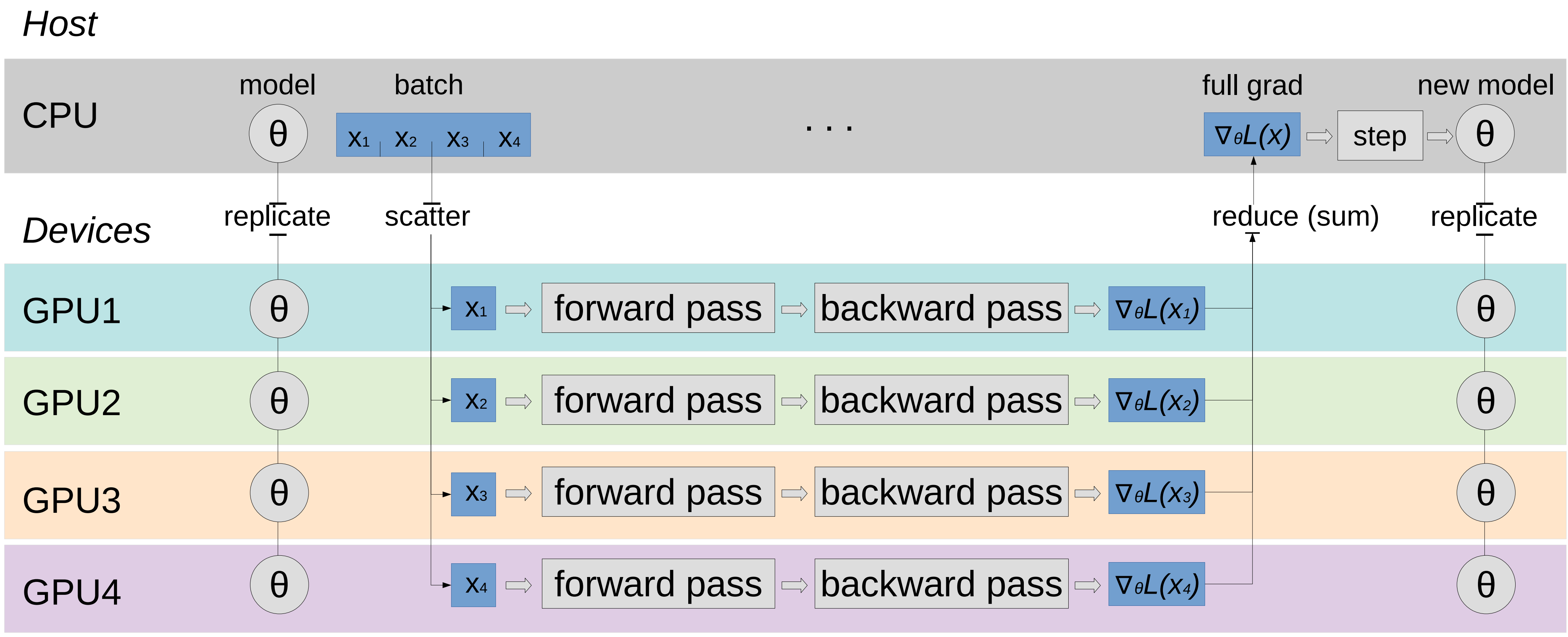
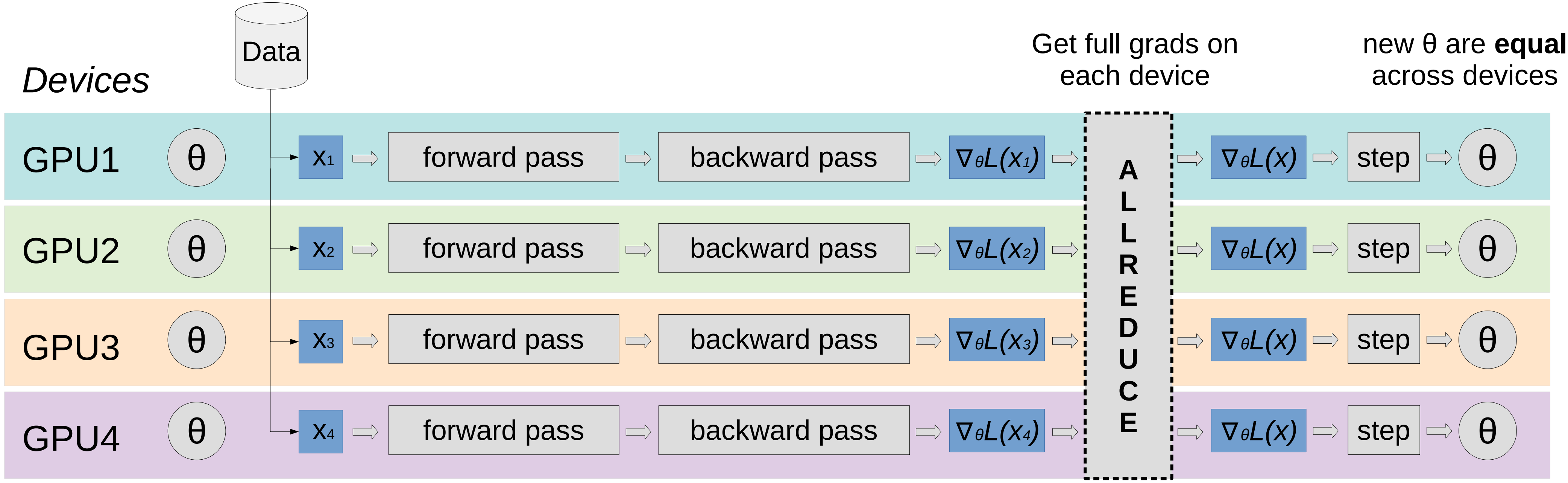


All-Reduce data parallel

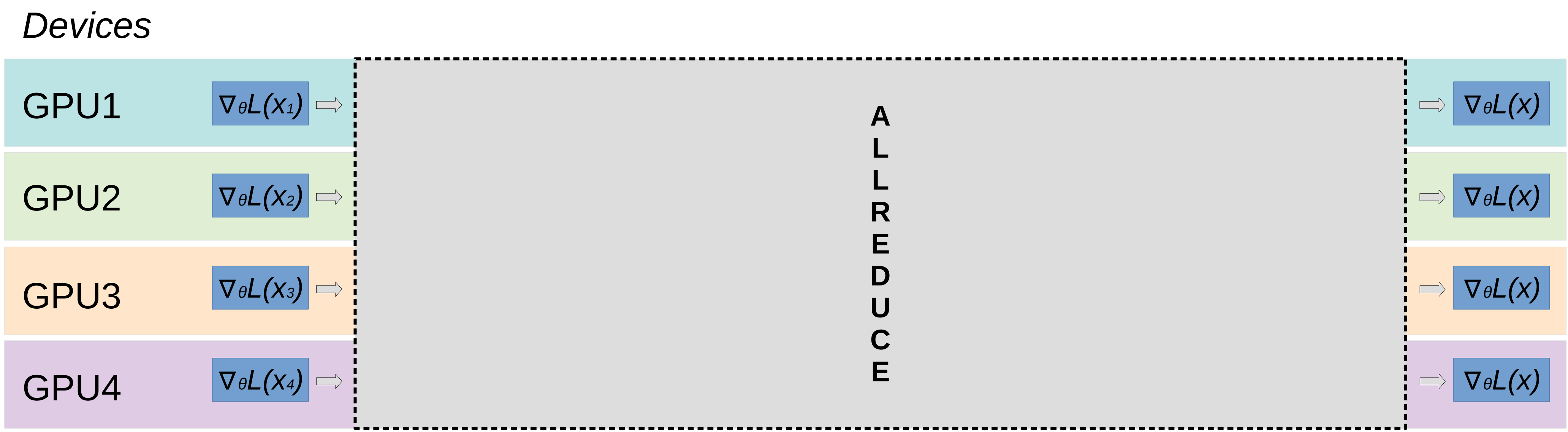
arxiv.org/abs/1706.02677

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



Faster allreduce

Input: each device has its its own vector
Output: each device gets a sum of all vectors



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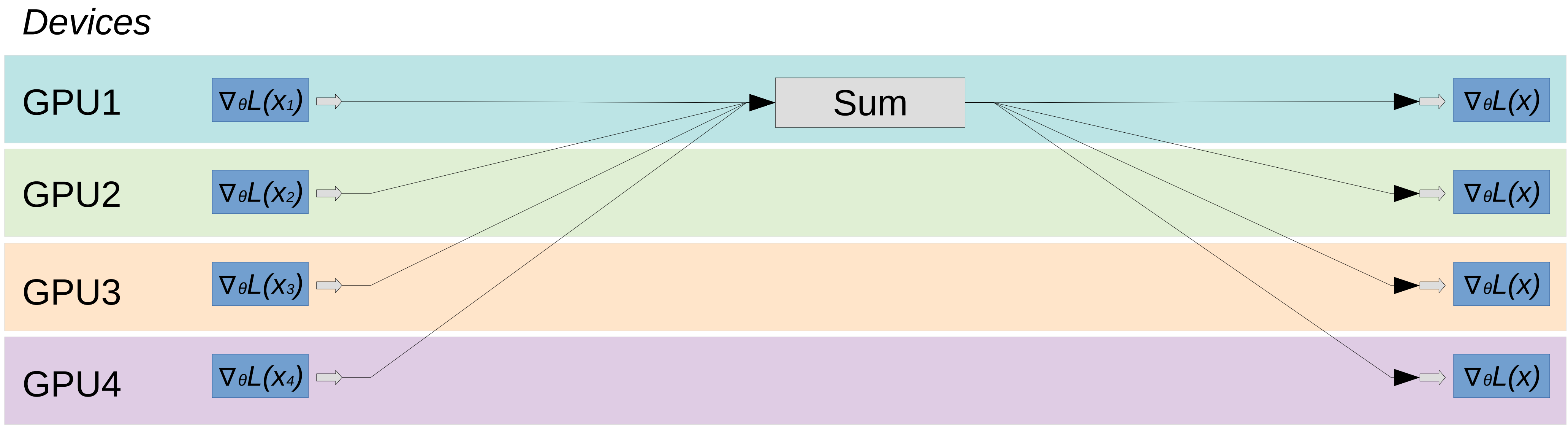
Naive implementation



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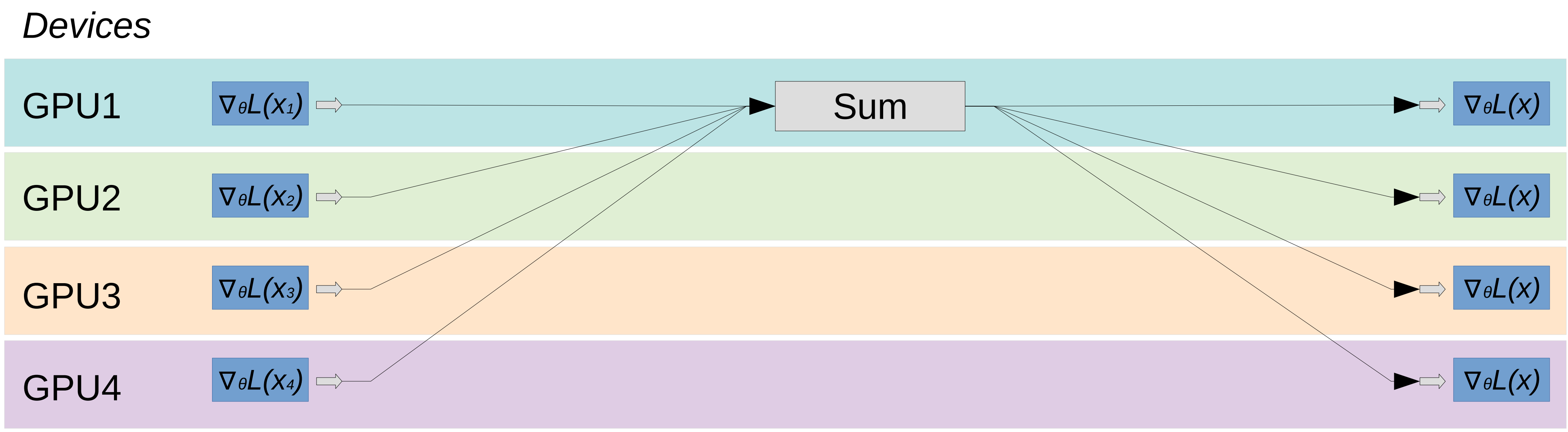
Q: Can we do better?



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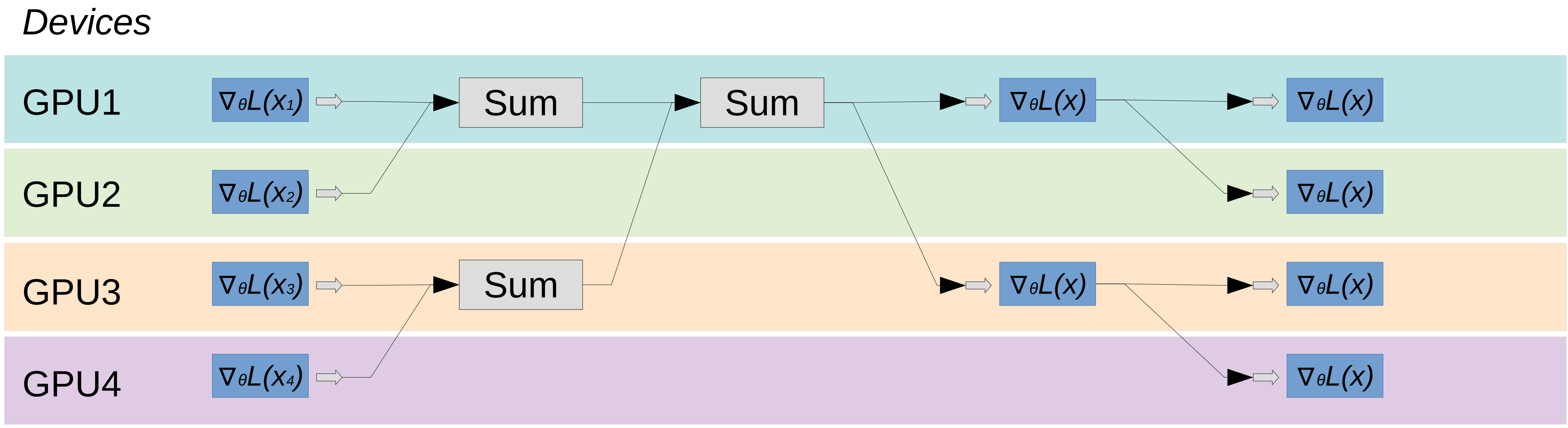
Tree-allreduce



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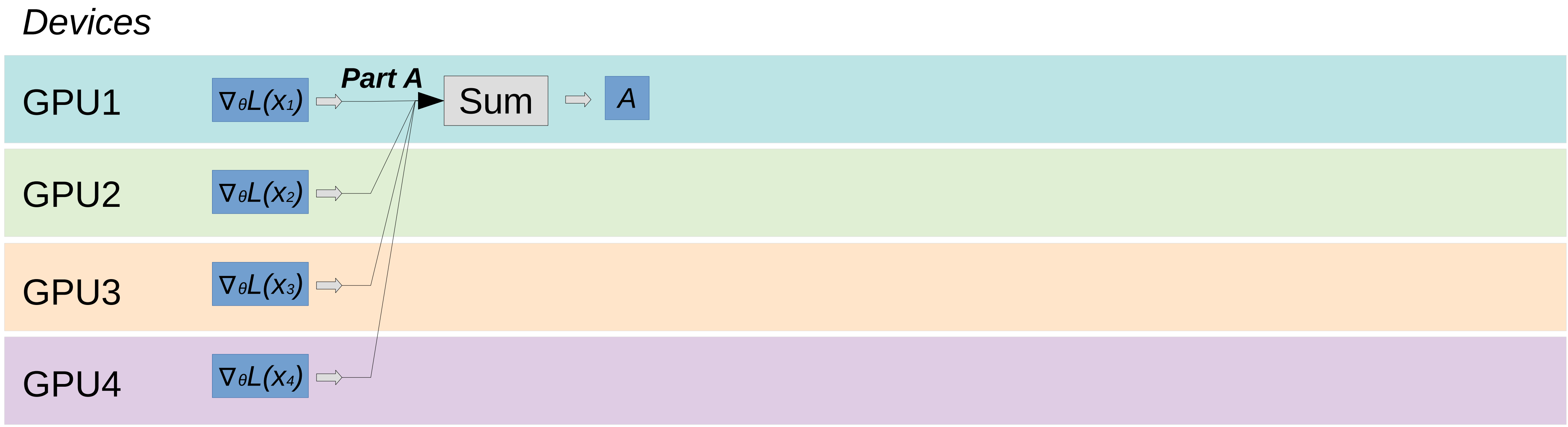
Butterfly-allreduce – split data into chunks (ABCD)



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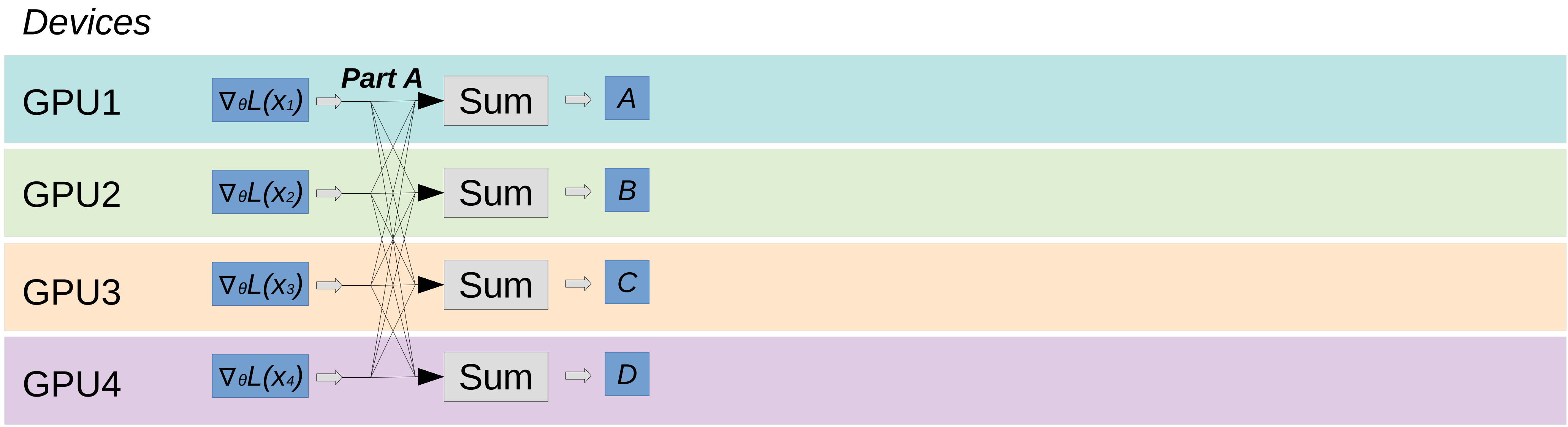

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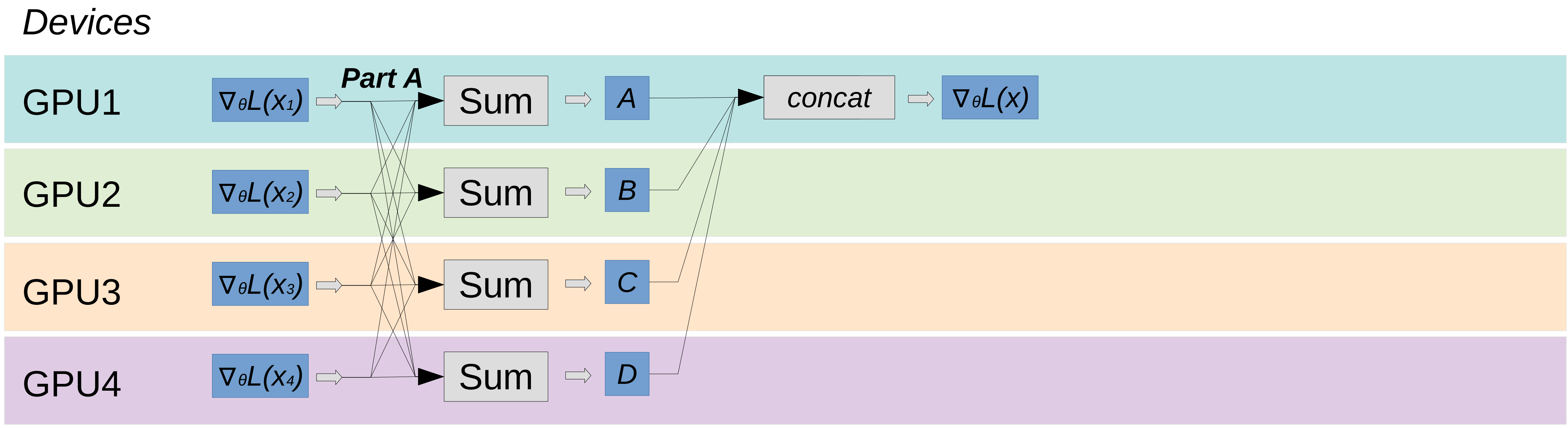

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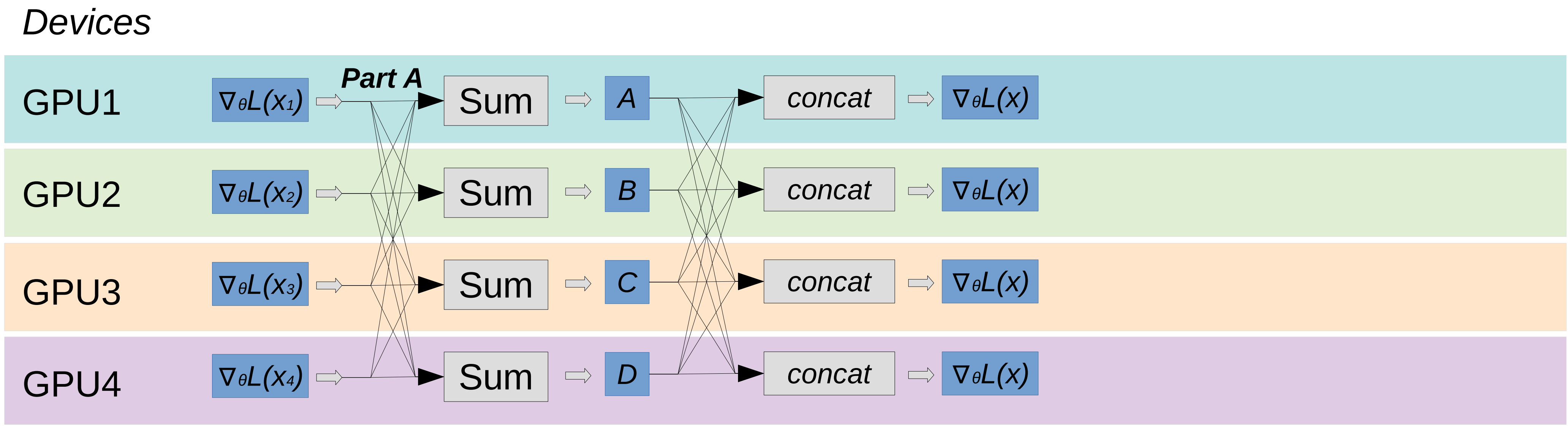
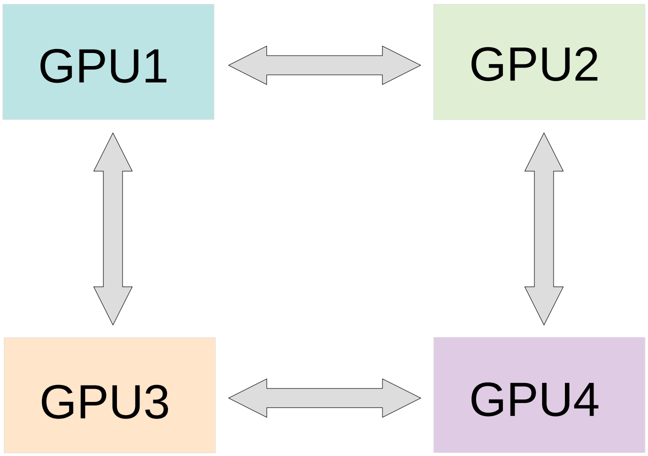
Ring-allreduce – split data into chunks (ABCD)



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

Ring allreduce

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

[Time to use the whiteboard]

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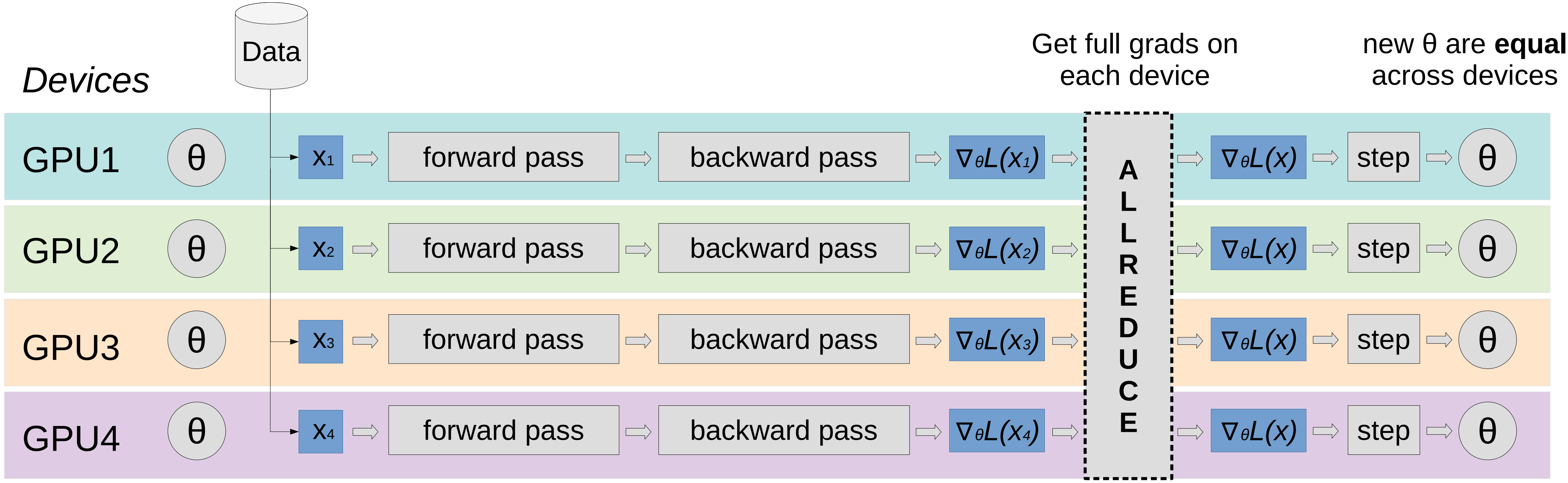


</Data-parallel>

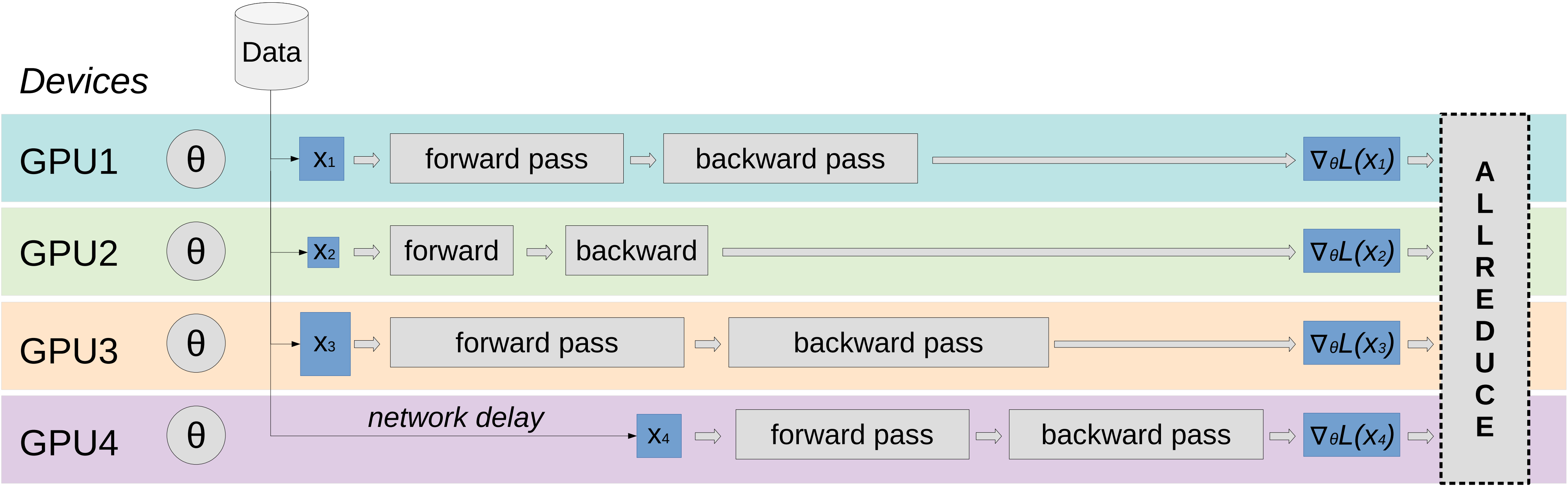
+ easy to implement
+ can scale to 100s of gpus
+ can be fault-tolerant
- model must fit in 1 gpu
- large batches aren't always good for generalization

- 2-4 GPUs & no time – naive data parallel tinyurl.com/torch-data-parallel
- 4+ GPUs or multiple hosts – distributed (allreduce) github.com/horovod/horovod
  - Intro to pytorch distributed: tinyurl.com/distributed-dp **or in 15 minutes!**
- Somewhat faulty GPU/network: synchronous data parallel + drop stragglers
- Very faulty or uneven resources: asynchronous data parallel (more later)
- Efficient training with large batches: LAMB https://arxiv.org/abs/1904.00962
- Dynamically adding or removing resources: https://tinyurl.com/torch-elastic

Decentralized training vs real-world tasks

arxiv.org/abs/1706.02677

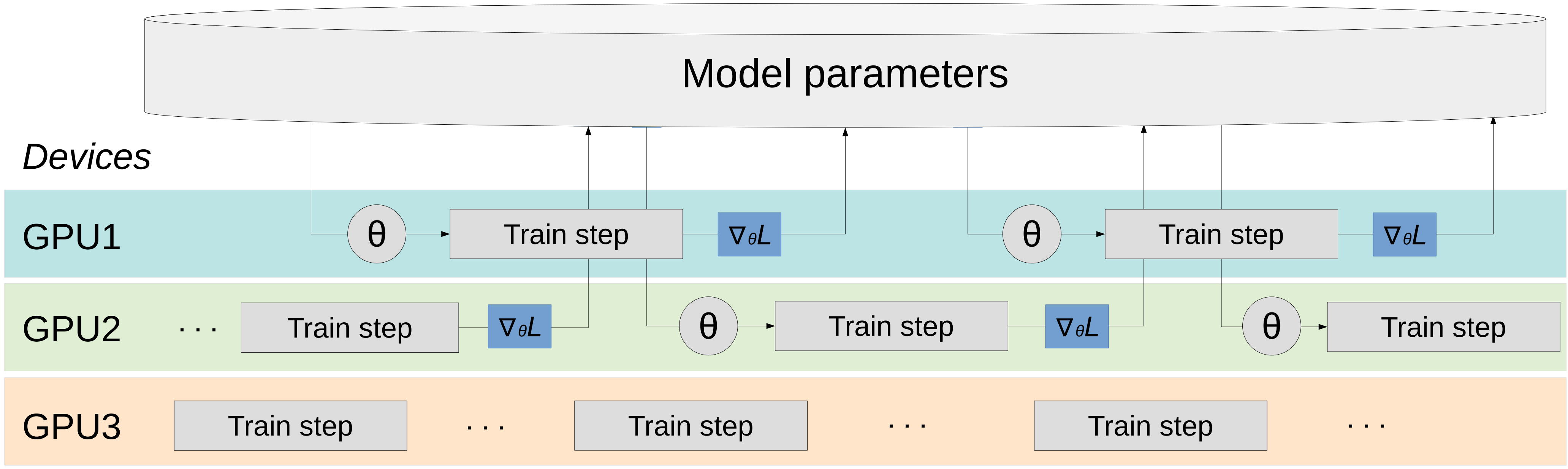
Each gpu has different processing time & delays
Q: can we improve device utilization?



Recap: Parameter Server

HOGWILD! arxiv.org/abs/1106.5730

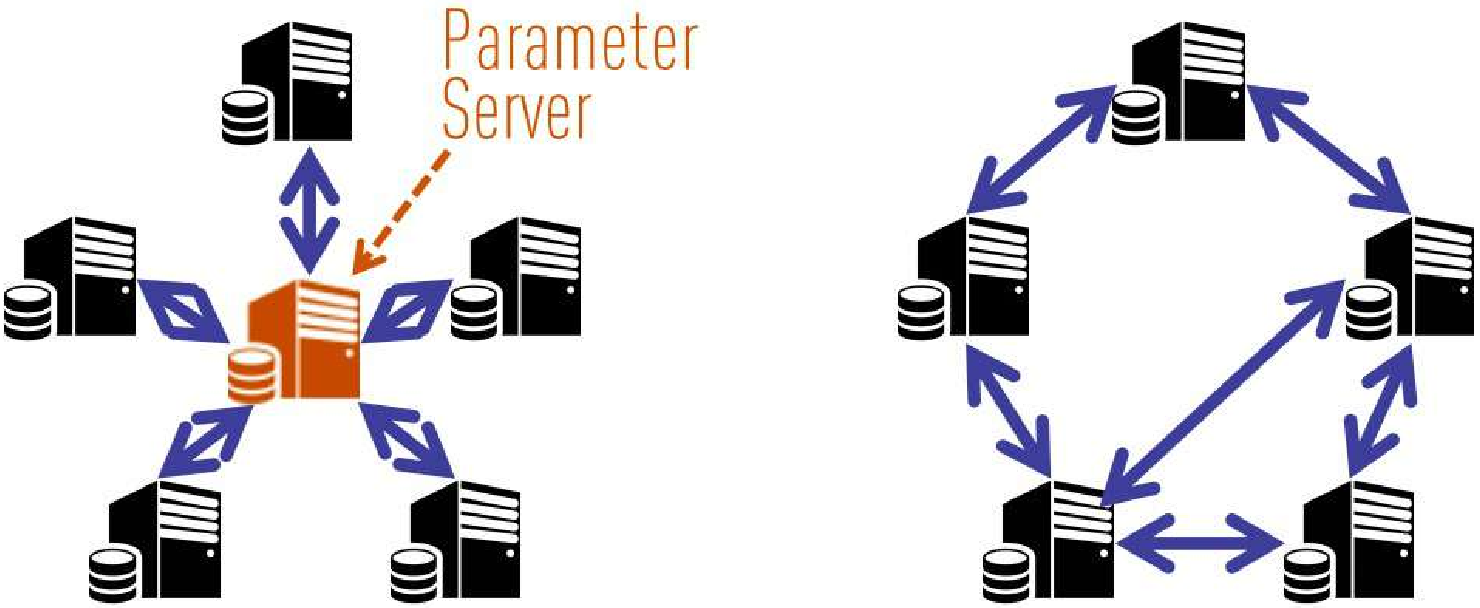
Idea: remove synchronization step alltogether, use parameter server



Problem: parameter servers need to ingest tons of data over training

Decentralized Training with Gossip

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



(a) Centralized Topology (b) Decentralized Topology

Decentralized Training with Gossip

Source: https://tinyurl.com/can-dsgd-outperform

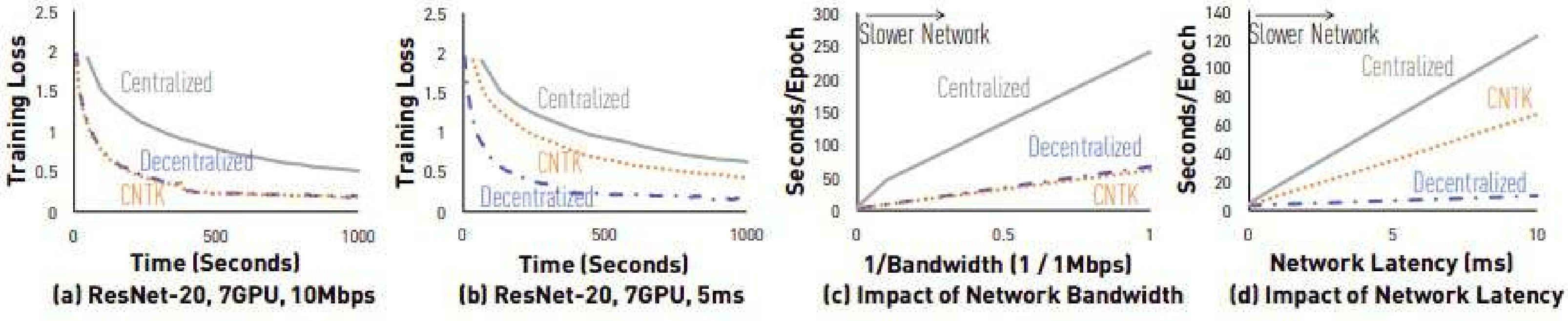


Figure 2: Comparison between D-PSGD and two centralized implementations (7 and 10 GPUs).

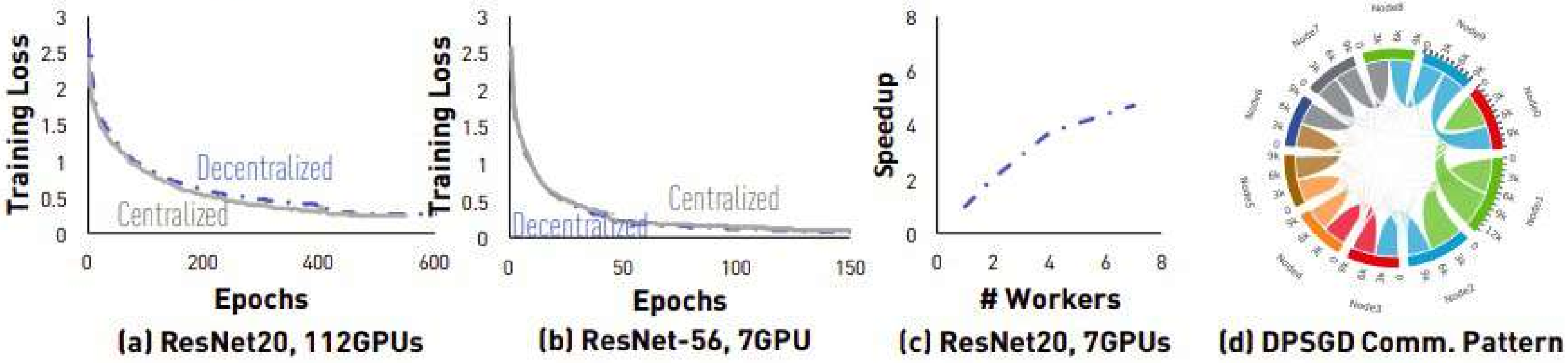
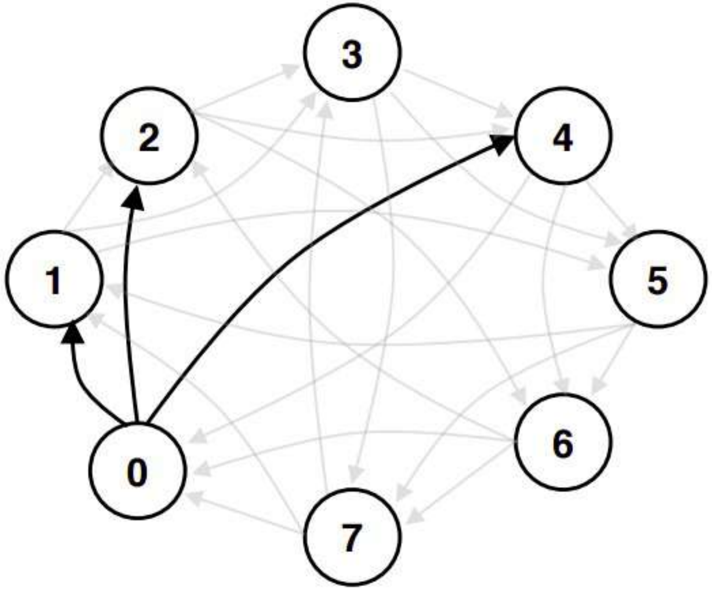


Figure 3: (a) Convergence Rate; (b) D-PSGD Speedup; (c) D-PSGD Communication Patterns.

Stochastic Gradient Push

Source: https://arxiv.org/abs/1811.10792



(a) Directed Exponential Graph highlighting node 0's out-neighbours

Stochastic Gradient Push

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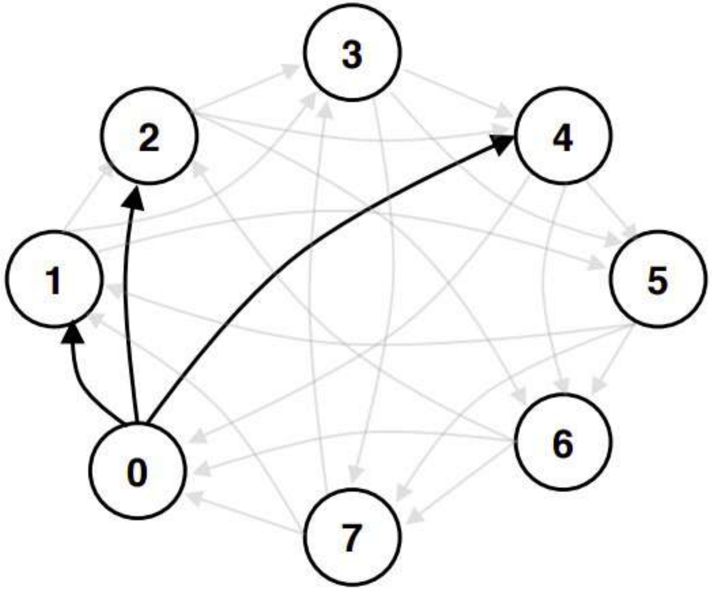

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Algorithm 1 Stochastic Gradient Push (SGP)

Require: Initialize $\gamma > 0$, $\boldsymbol{x}_i^{(0)} = \boldsymbol{z}_i^{(0)} \in \mathbb{R}^d$ and $w_i^{(0)} = 1$ for all nodes $i \in \{1, 2, \ldots, n\}$

1: **for** $k = 0, 1, 2, \cdots, K$, at node i, **do**

2: Sample new mini-batch $\xi_i^{(k)} \sim \mathcal{D}_i$ from local distribution

3: Compute mini-batch gradient at $\boldsymbol{z}_i^{(k)}$: $\nabla \boldsymbol{F}_i(\boldsymbol{z}_i^{(k)}; \xi_i^{(k)})$

<to be continued>

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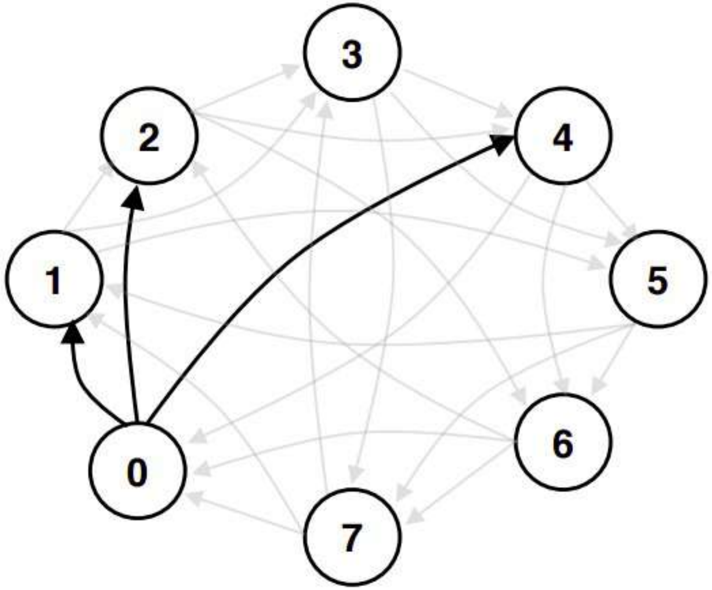

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4: $\boldsymbol{x}_i^{(k+\frac{1}{2})} = \boldsymbol{x}_i^{(k)} - \gamma \nabla \boldsymbol{F}_i(\boldsymbol{z}_i^{(k)}; \xi_i^{(k)})$

normal GD step

<to be continued>

Stochastic Gradient Push

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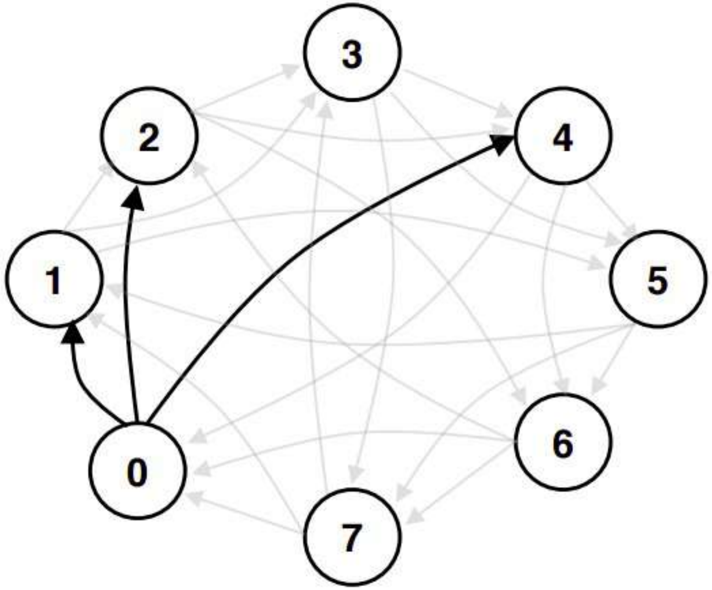

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5: Send $\left(p_{j,i}^{(k)} \boldsymbol{x}_i^{(k+\frac{1}{2})}, p_{j,i}^{(k)} w_i^{(k)}\right)$ to out-neighbors;
receive $\left(p_{i,j}^{(k)} \boldsymbol{x}_j^{(k+\frac{1}{2})}, p_{i,j}^{(k)} w_j^{(k)}\right)$ from in-neighbors

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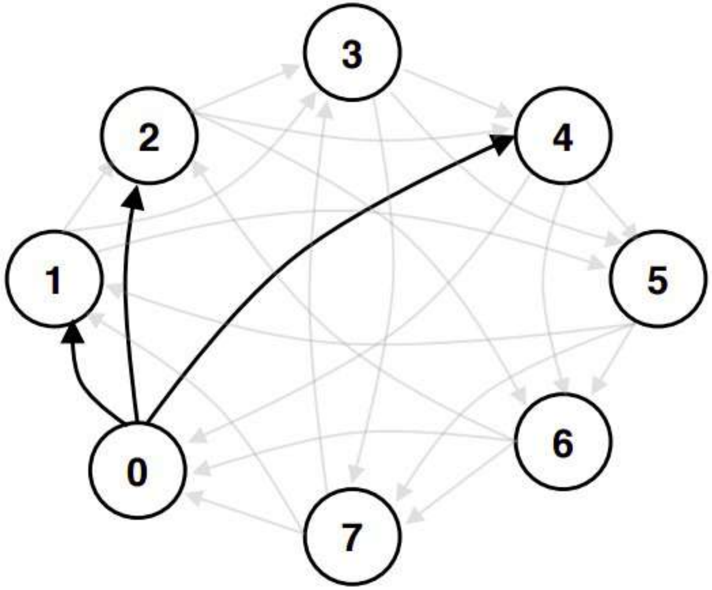

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  $\boldsymbol{x}_i^{(k+1)} = \sum_j p_{i,j}^{(k)} \boldsymbol{x}_j^{(k+\frac{1}{2})}$

  $w_i^{(k+1)} = \sum_j p_{i,j}^{(k)} w_j^{(k)}$

  $\boldsymbol{z}_i^{(k+1)} = \boldsymbol{x}_i^{(k+1)} / w_i^{(k+1)}$

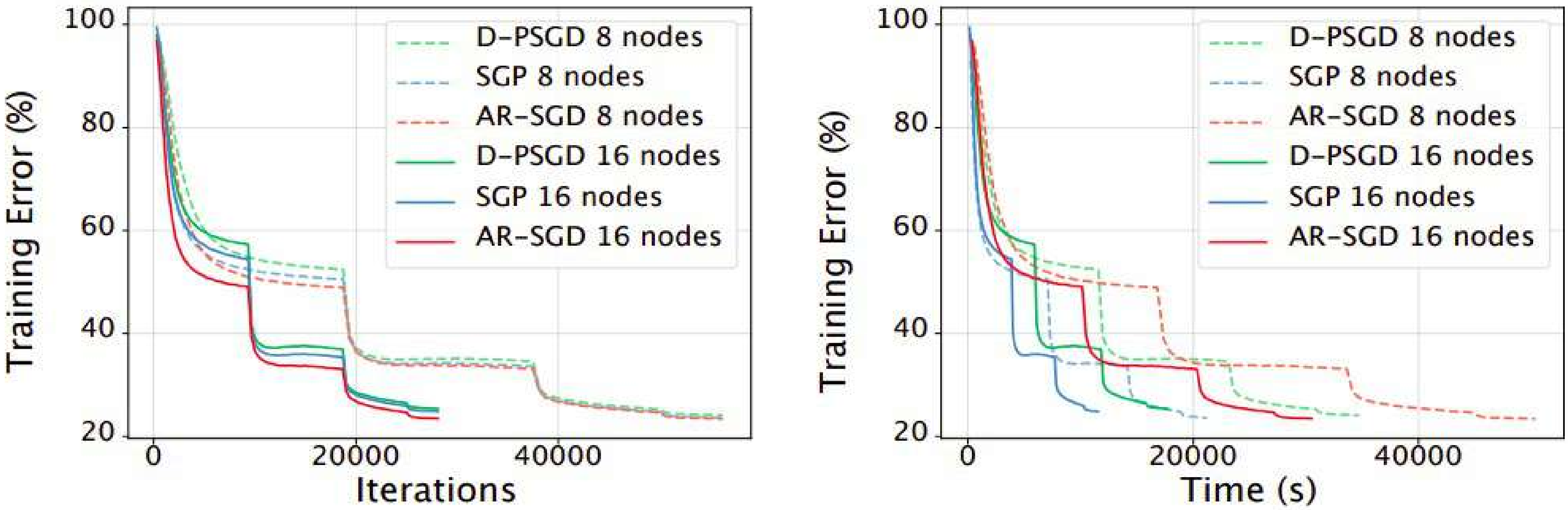
end for

weighted average

Stochastic Gradient Push

Source: **https://arxiv.org/abs/1811.10792**

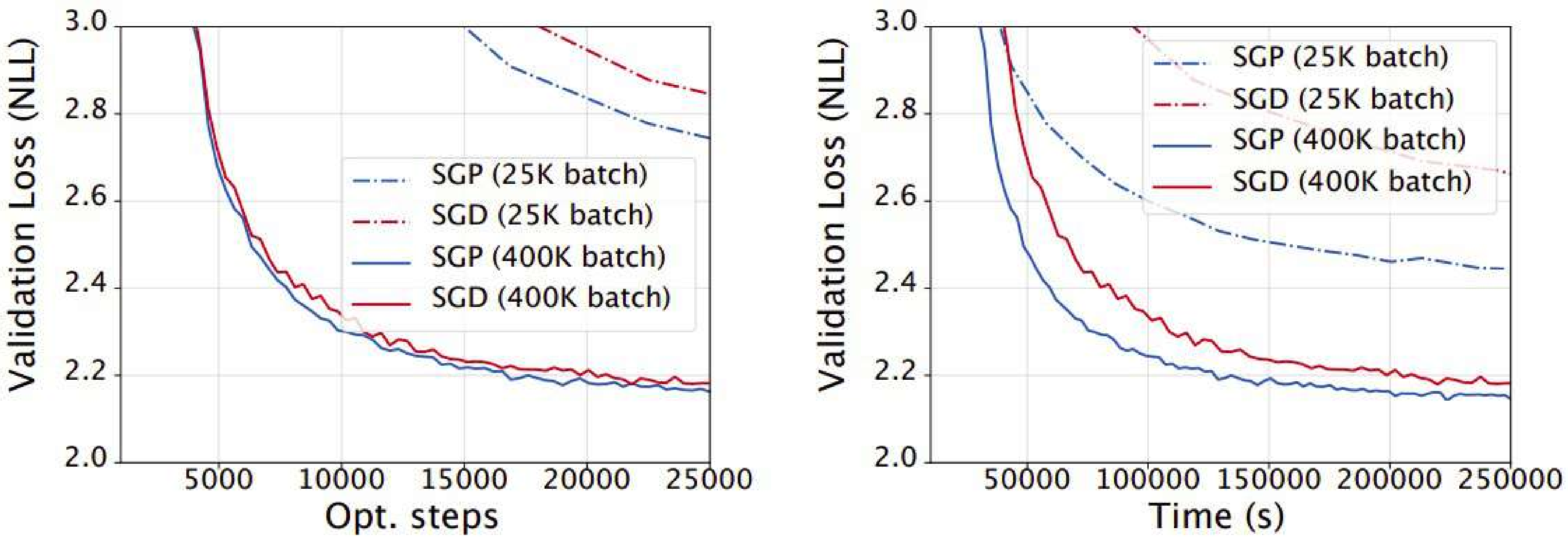
SGP vs ImageNet (ResNet50 + SGD w/ momentum)



Stochastic Gradient Push

Source: https://arxiv.org/abs/1811.10792

SGP vs WMT English-German (Transformer, Adam)



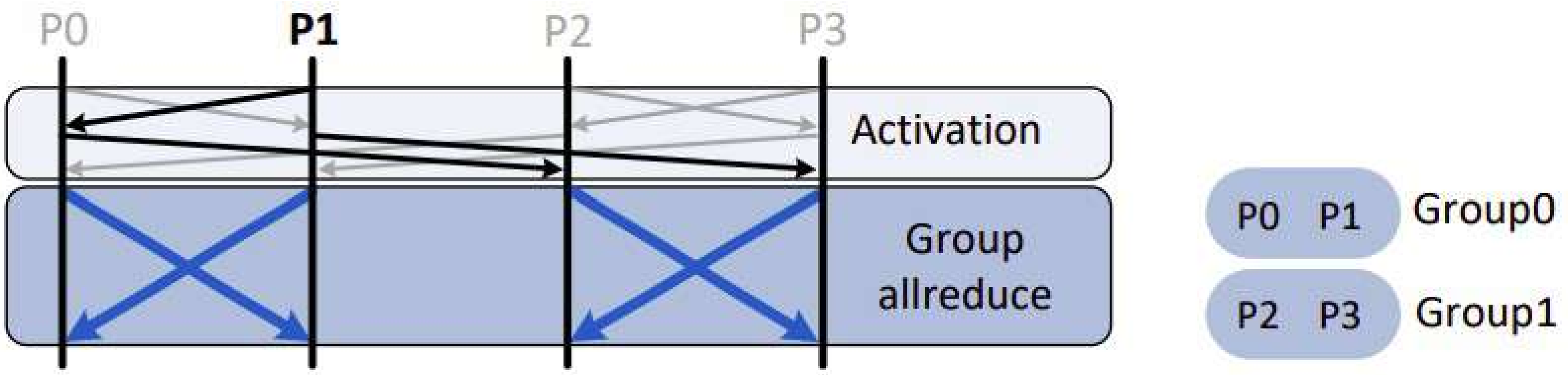
Gossip vs All-Reduce

Your thoughts?

Gossip + All-Reduce

Source: arxiv.org/abs/2005.00124

Core idea: run all-reduce in independent groups
You only have to synchronize for your small group
Swap groupmates between iterations



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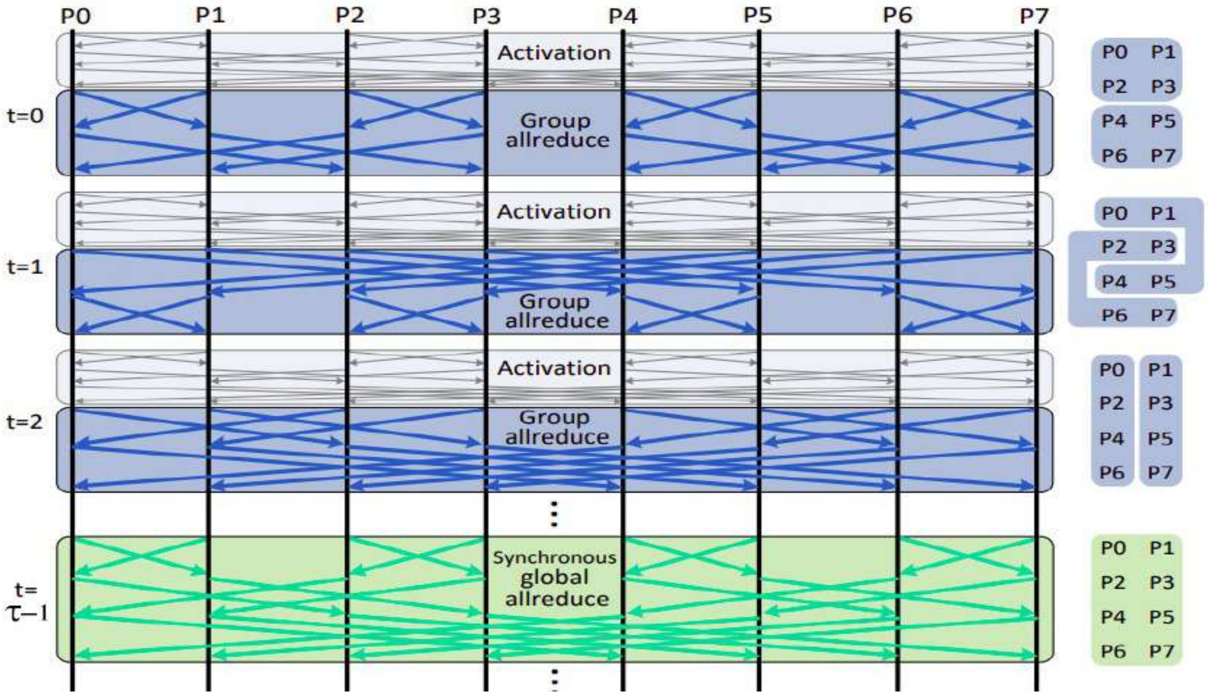

Gossip + All-Reduce

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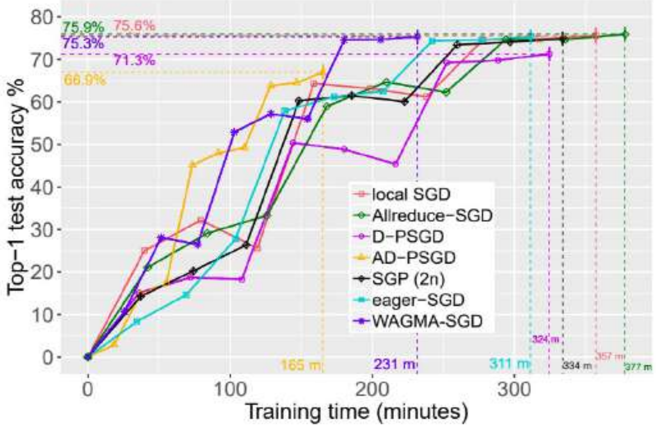
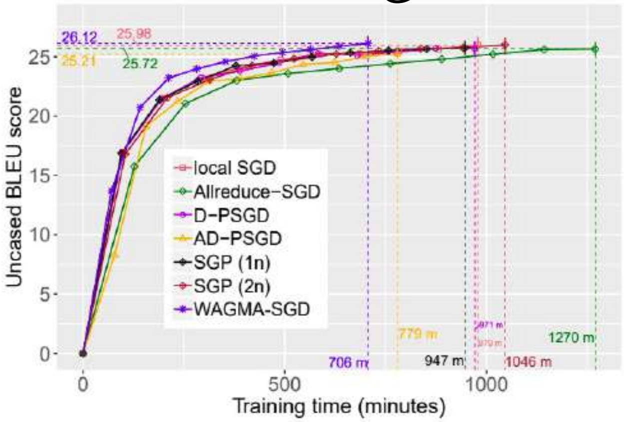
Experiment setup: up to 1024 GPU,
Natural (or emulated) network latency

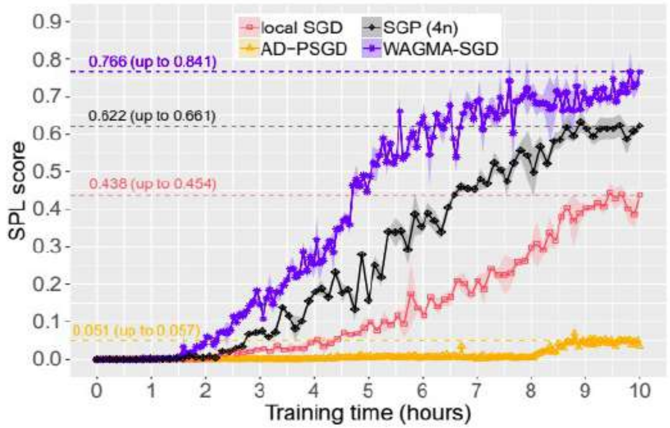
Image Classification
ResNet50 @ ImageNet



Machine Translation
Transformer @ WMT17



Reinforcement Learning
DDPO on Habitat



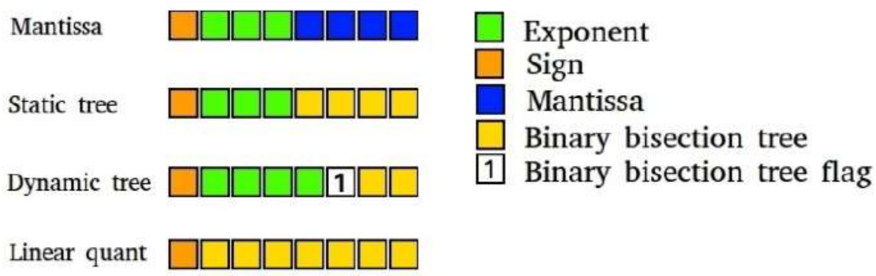
Q: what if sending tensors during AllReduce takes too long?

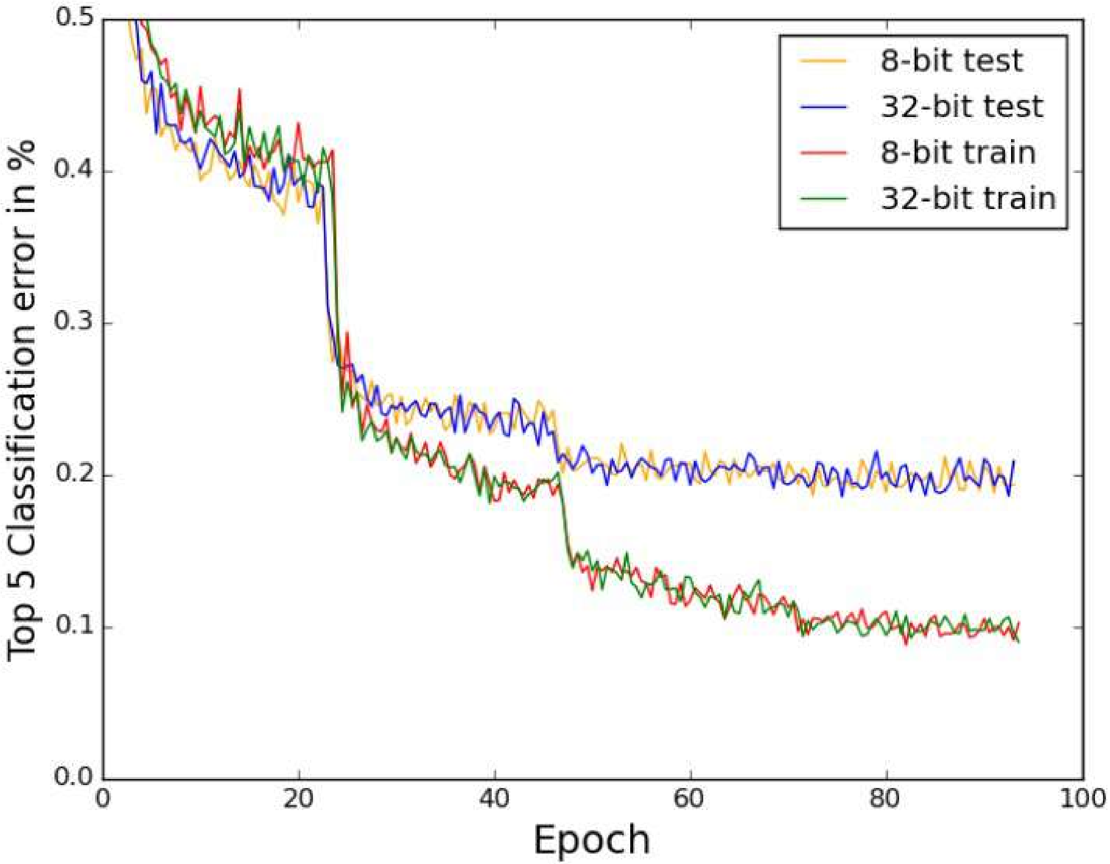
Quantized communication

https://arxiv.org/abs/1511.04561

TL;DR
- send data in 8-bit
- all computations in 32-bit
- choose best data format

PROFIT: same quality as float16





Can we compress further?
without losing quality

Error Feedback + PowerSGD

https://arxiv.org/abs/1901.09847 - EF theory
https://arxiv.org/abs/1905.13727 - PowerSGD

TL;DR - use extreme compression, e.g. 1-bit or top-5% gradients

- if you lose something in compression, **reuse it on the next step**

Error Feedback + PowerSGD

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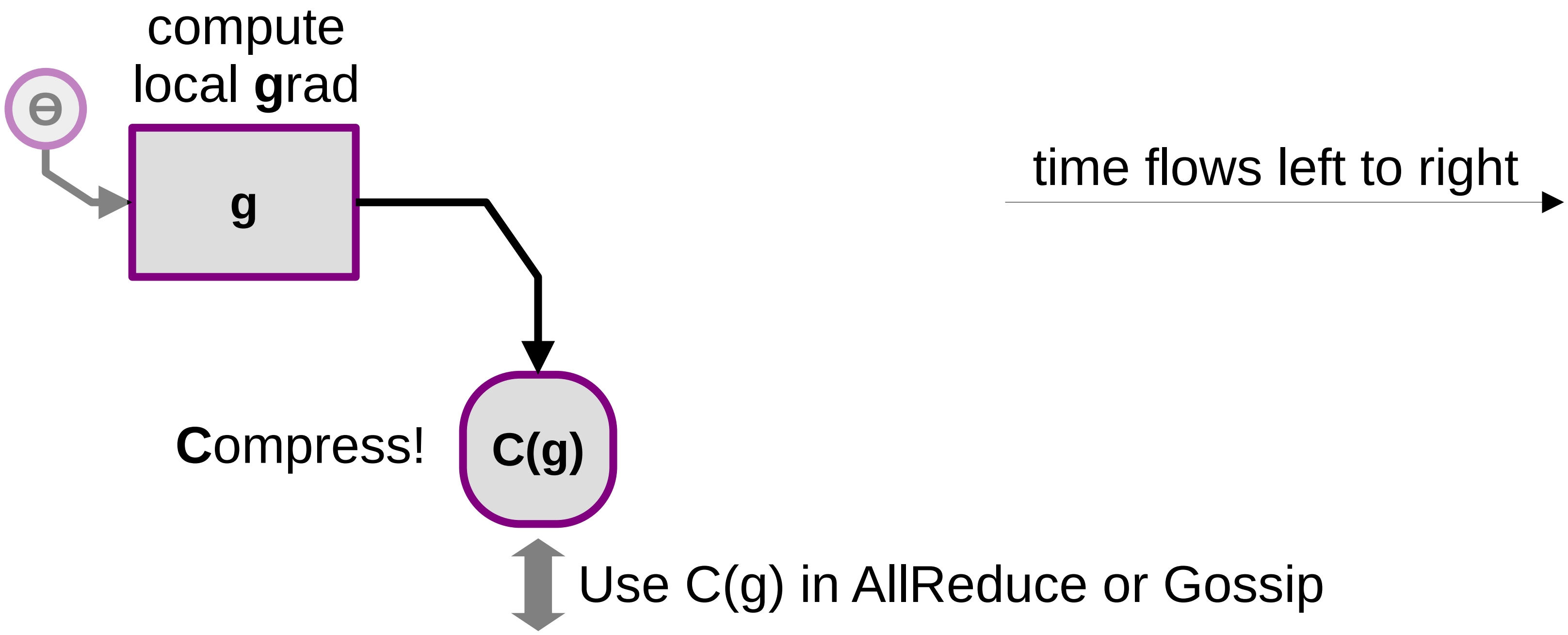

Error Feedback + PowerSGD

https://arxiv.org/abs/1901.09847 - EF theory
https://arxiv.org/abs/1905.13727 - PowerSGD

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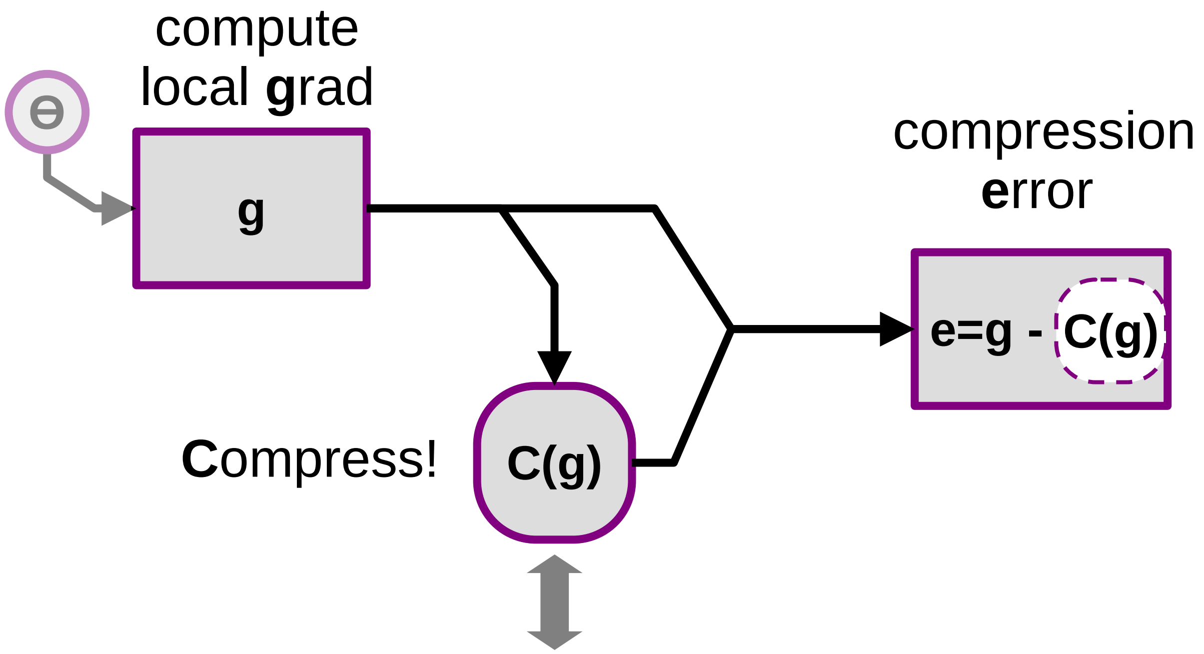

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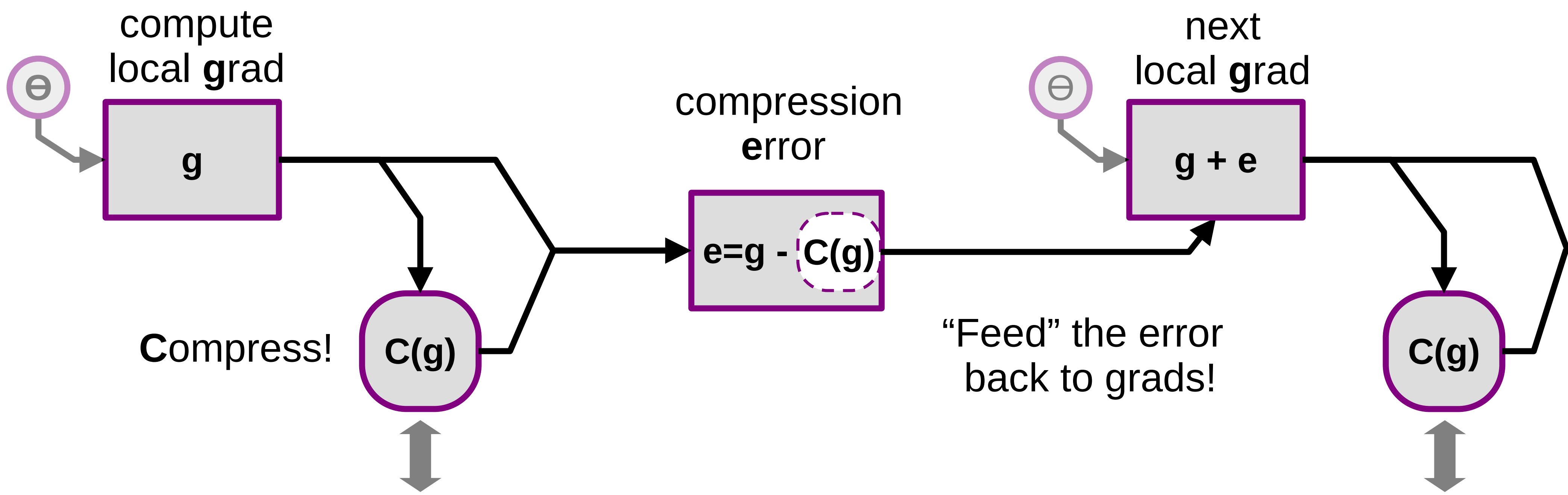

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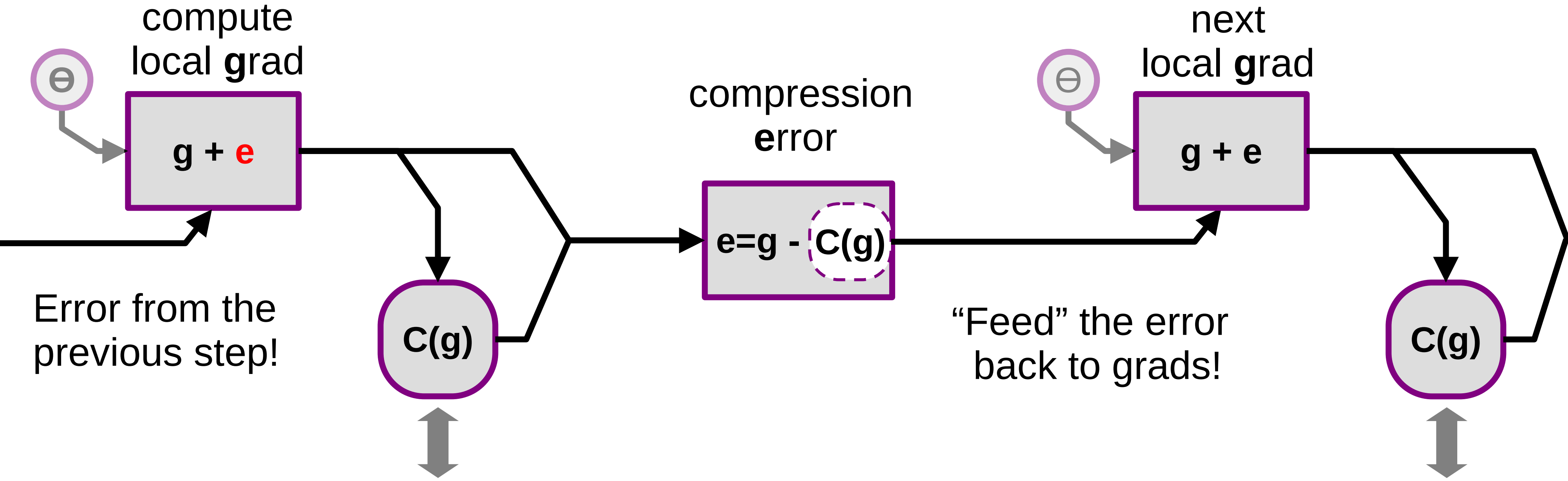

Error Feedback + PowerSGD

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hyperparameters: learning rate γ, momentum parameter λ
initialize model parameters $\mathbf{x} \in \mathbb{R}^d$, momentum $\mathbf{m} \leftarrow \mathbf{0} \in \mathbb{R}^d$, replicated across workers
at each worker $w = 1, \ldots, W$ **do**
    initialize memory $\mathbf{e}_w \leftarrow \mathbf{0} \in \mathbb{R}^d$
    for each iterate $t = 0, \ldots$ **do**
        Compute a stochastic gradient $\mathbf{g}_w \in \mathbb{R}^d$.
        $\Delta_w \leftarrow \mathbf{g}_w + \mathbf{e}_w$ ▷ Incorporate error-feedback into update
        $\mathcal{C}(\Delta_w) \leftarrow \text{COMPRESS}(\Delta_w)$
        $\mathbf{e}_w \leftarrow \Delta_w - \text{DECOMPRESS}(\mathcal{C}(\Delta_w))$ ▷ Memorize local errors
        $\mathcal{C}(\Delta) \leftarrow \text{AGGREGATE}(\mathcal{C}(\Delta_1), \ldots, \mathcal{C}(\Delta_W))$ ▷ Exchange gradients
        $\Delta' \leftarrow \text{DECOMPRESS}(\mathcal{C}(\Delta))$ ▷ Reconstruct an update $\in \mathbb{R}^d$
        $\mathbf{m} \leftarrow \lambda \mathbf{m} + \Delta'$
        $\mathbf{x} \leftarrow \mathbf{x} - \gamma\,(\Delta' + \mathbf{m})$
    end for
end at

PowerSGD: low-rank approx grads + Error Feedback

https://arxiv.org/abs/1901.09847 - EF theory
https://arxiv.org/abs/1905.13727 - PowerSGD

The update vector Δ_w is treated as a list of tensors corresponding to individual model parameters. Vector-shaped parameters (biases) are aggregated uncompressed. Other parameters are reshaped into matrices. The functions below operate on such matrices independently. For each matrix $M \in \mathbb{R}^{n \times m}$, a corresponding $Q \in \mathbb{R}^{m \times r}$ is initialized from an i.i.d. standard normal distribution.

function COMPRESS+AGGREGATE(update matrix $M \in \mathbb{R}^{n \times m}$, previous $Q \in \mathbb{R}^{m \times r}$)

    $P \leftarrow MQ$

    $P \leftarrow$ ALL REDUCE MEAN(P) ▷ Now, $P = \frac{1}{W}(M_1 + \ldots + M_W)Q$

    $\hat{P} \leftarrow$ ORTHOGONALIZE(P) ▷ Orthonormal columns

    $Q \leftarrow M^\top \hat{P}$

    $Q \leftarrow$ ALL REDUCE MEAN(Q) ▷ Now, $Q = \frac{1}{W}(M_1 + \ldots + M_W)^\top \hat{P}$

    return the compressed representation $(\hat{P}, Q)$.

end function

function DECOMPRESS($\hat{P} \in \mathbb{R}^{n \times r}$, $Q \in \mathbb{R}^{m \times r}$)

    return $\hat{P}Q^\top$

end function

Read More: gradient compression

https://arxiv.org/abs/1901.09847 - EF theory

https://arxiv.org/abs/1905.13727 - PowerSGD

https://arxiv.org/abs/2106.05203 - better EF’21

https://arxiv.org/abs/2110.03294 - more EF’21

```
import torch.distributed.algorithms.ddp_comm_hooks.powerSGD_hook as powerSGD

ddp_model = nn.parallel.DistributedDataParallel(
    module=model,
    device_ids=[rank],
)

state = PowerSGD.PowerSGDState(
  process_group=process_group,
  matrix_approximation_rank=1,
  start_powerSGD_iter=1_000,
)
ddp_model.register_comm_hook(state, PowerSGD.powerSGD_hook)
```


"That's all Folks!"
Isberg©

Summary: operation parallelism

Data-parallel: ***???***

Model-parallel: ***???***

Summary: operation parallelism

Data-parallel: *one process applies all model on **partial data***

best for smaller model, more computations

Model-parallel: *one process applies **partial model** on all data*

best for larger model, fewer computations

Which one is better..

for ResNet50?

for Llama 70B?

In general?

Summary: operation parallelism

Data-parallel: *one process applies all model on **partial data***

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~~Which one is better..~~

~~for ResNet50?~~

~~In Llama 70B?~~

It depends…

- on model size

- on compute