Data-Parallel Deep Learning

Episode II, YSDA'21

Yandex
Research

LAMBDA

British Hedgehog
Preservation Society

Large problems need large models

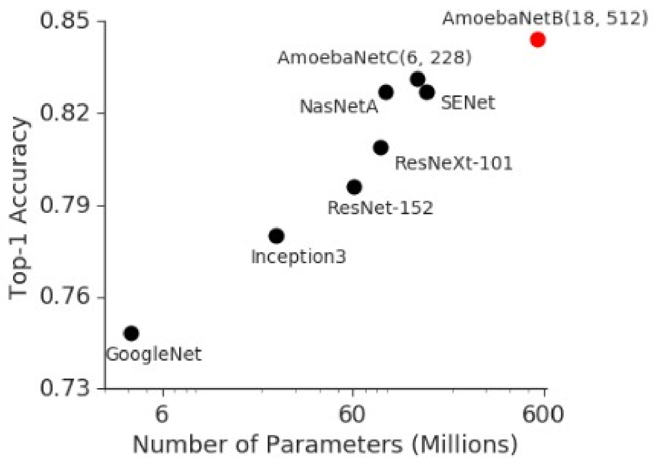
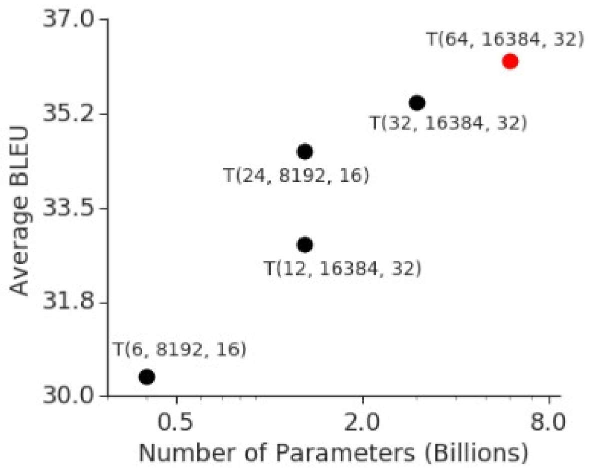


Image Classification
ImageNet

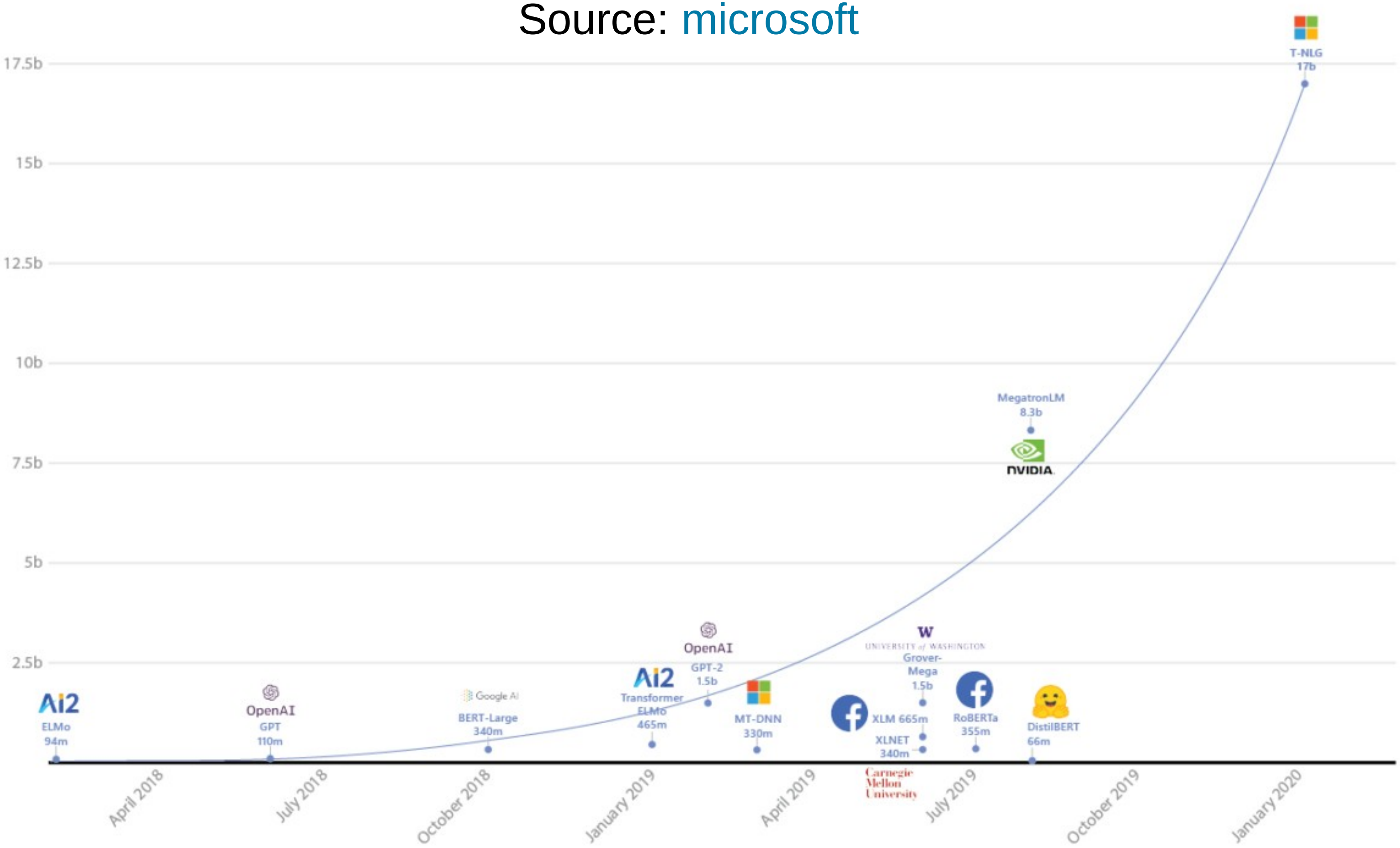


Machine Translation
average over WMT

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

The transformer curve

Source: microsoft



Machine Learning Supertasks

Image classification – ImageNet, JFT300M

Generative models – ImageNet(biggan), the internet

Language Models – common crawl, BERT / MLM

Machine Translation – multilingual translation

Reinforcement Learning – playstation* & steam :)

* playstation for RL: https://arxiv.org/abs/1912.06101

Meanwhile, exabytes of YouTube videos lay dormant across the web, waiting for someone who can make use of them

Data-parallel training (naive)

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

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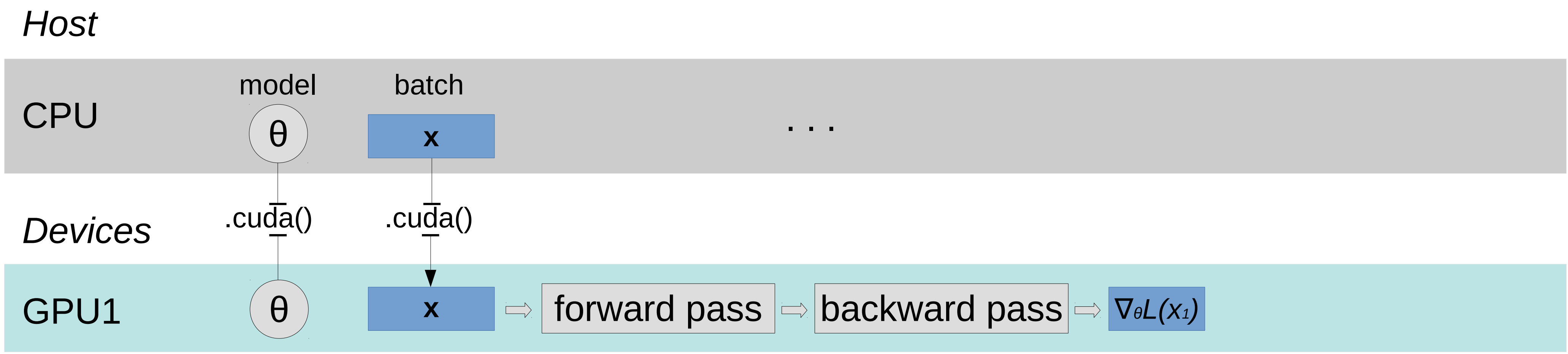

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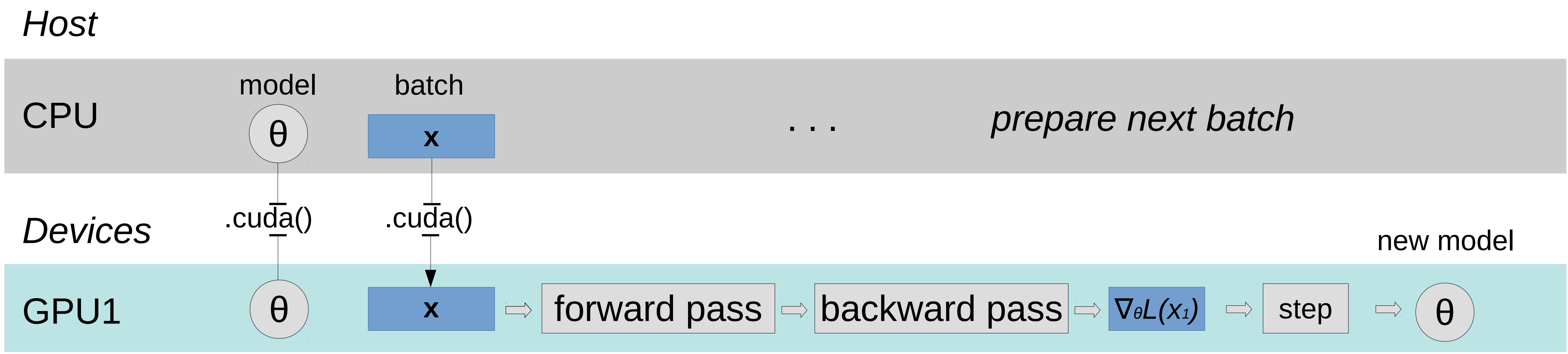

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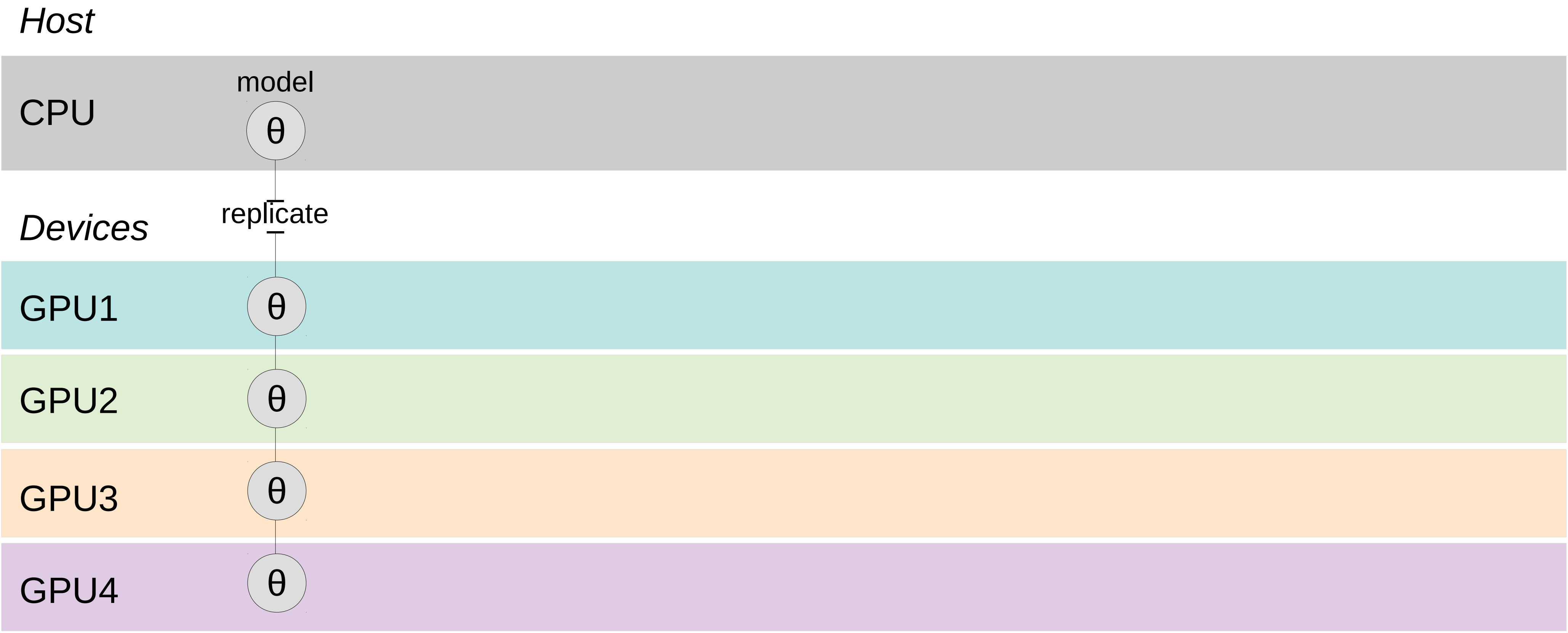

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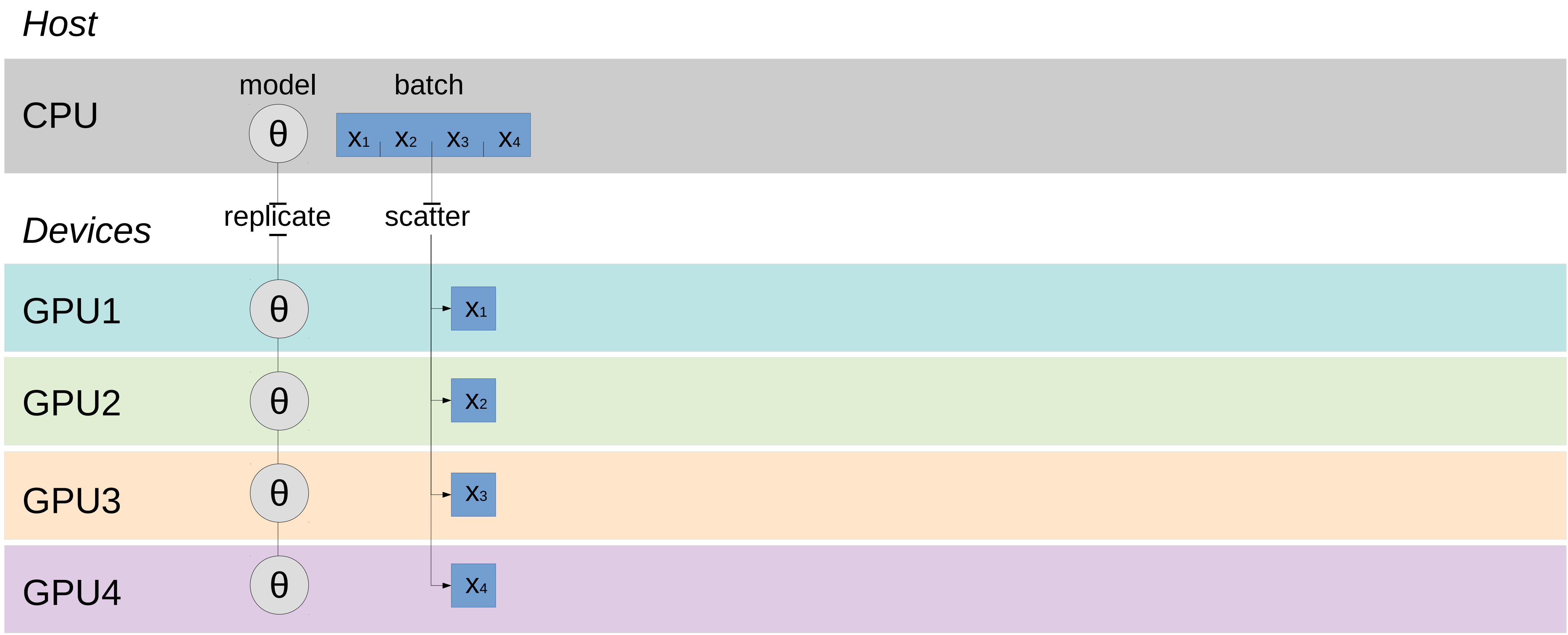

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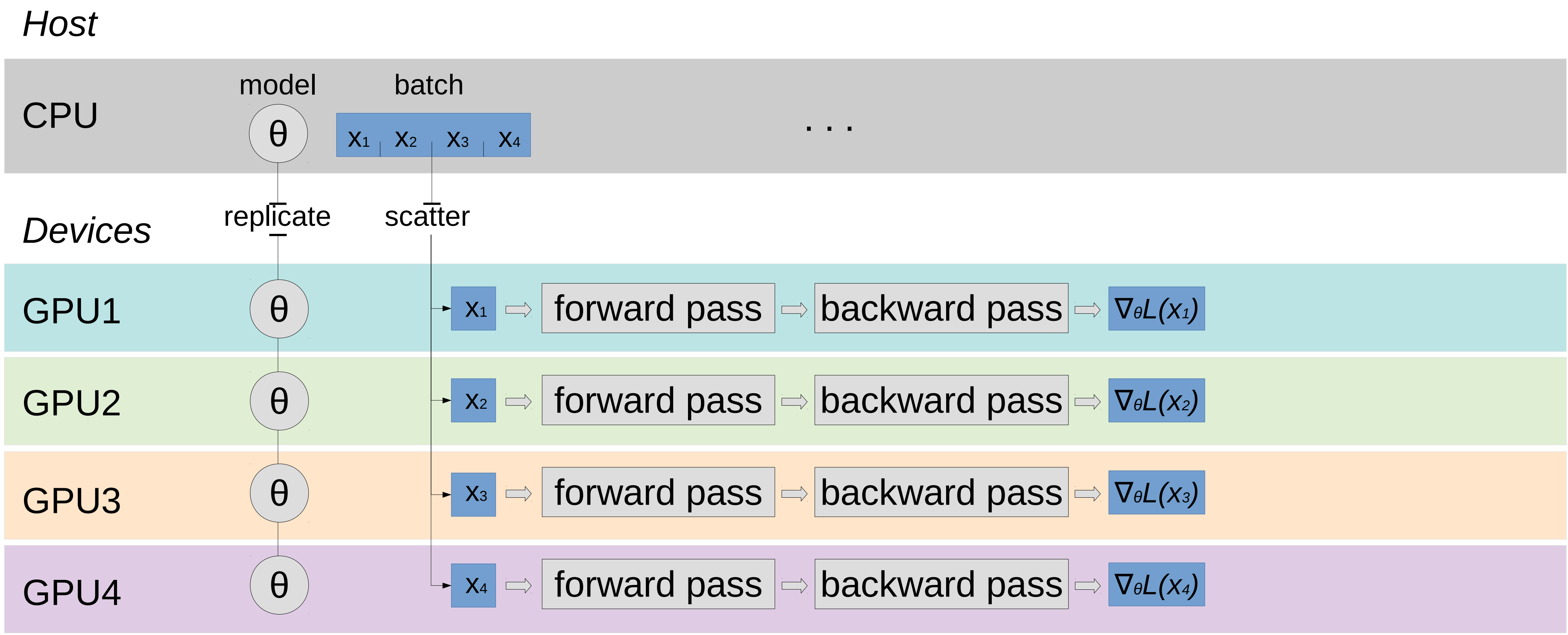

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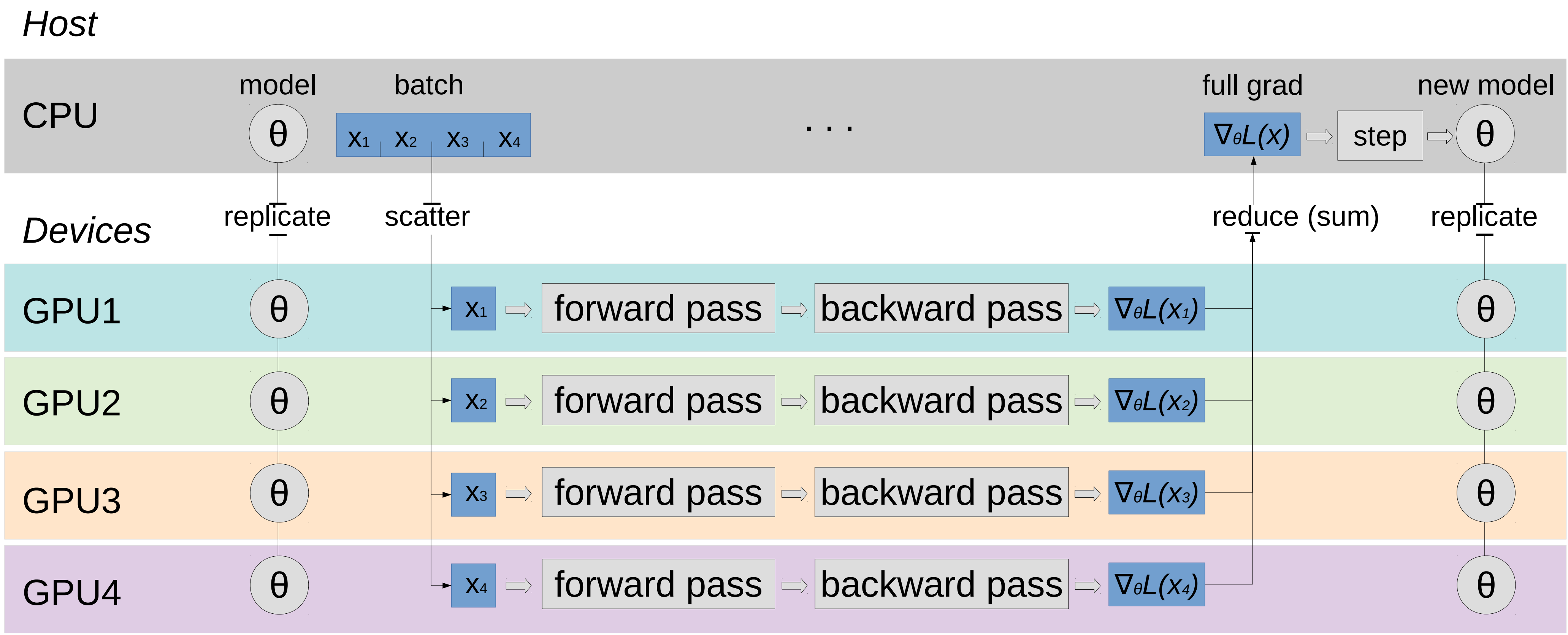

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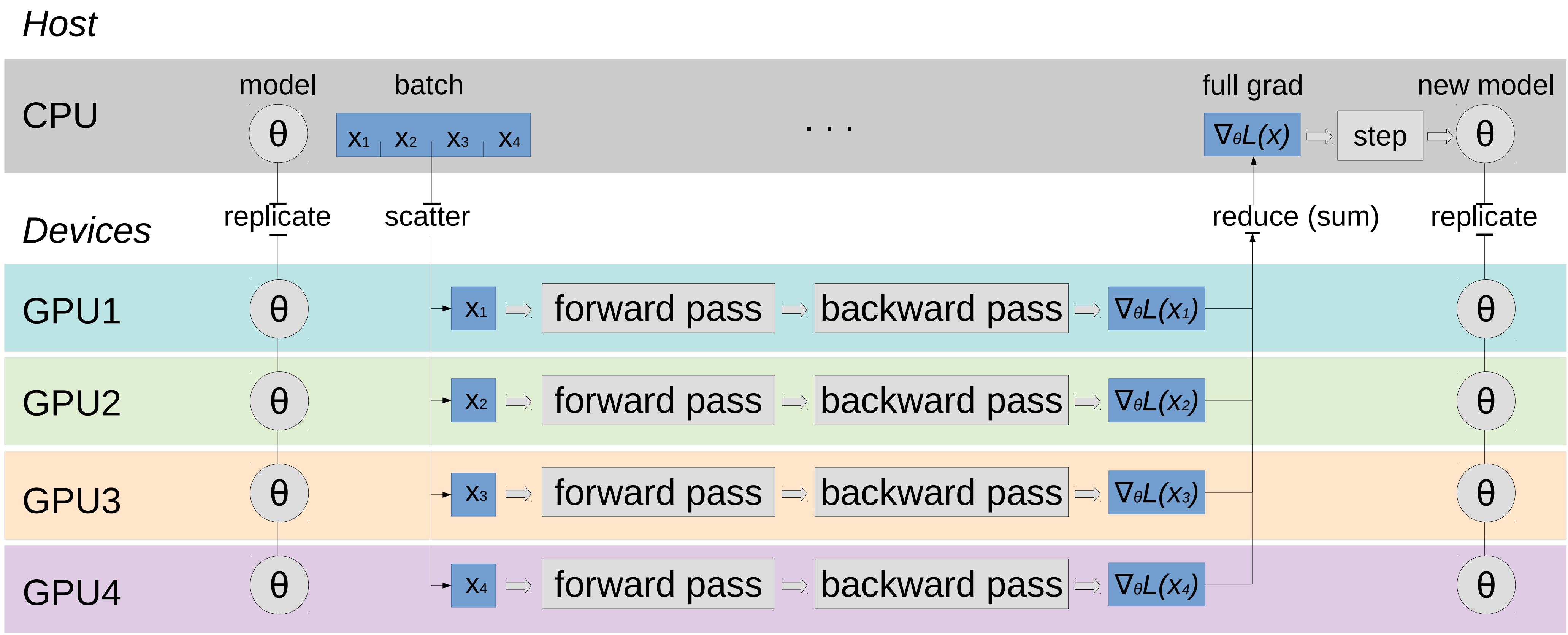
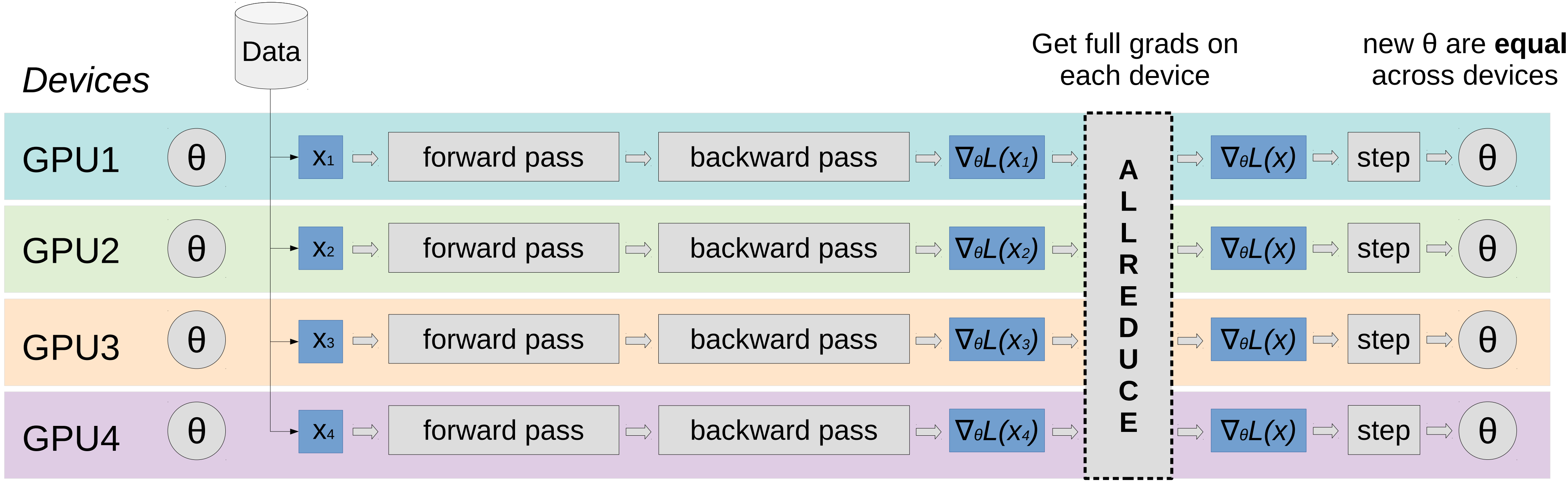


All-Reduce data parallel

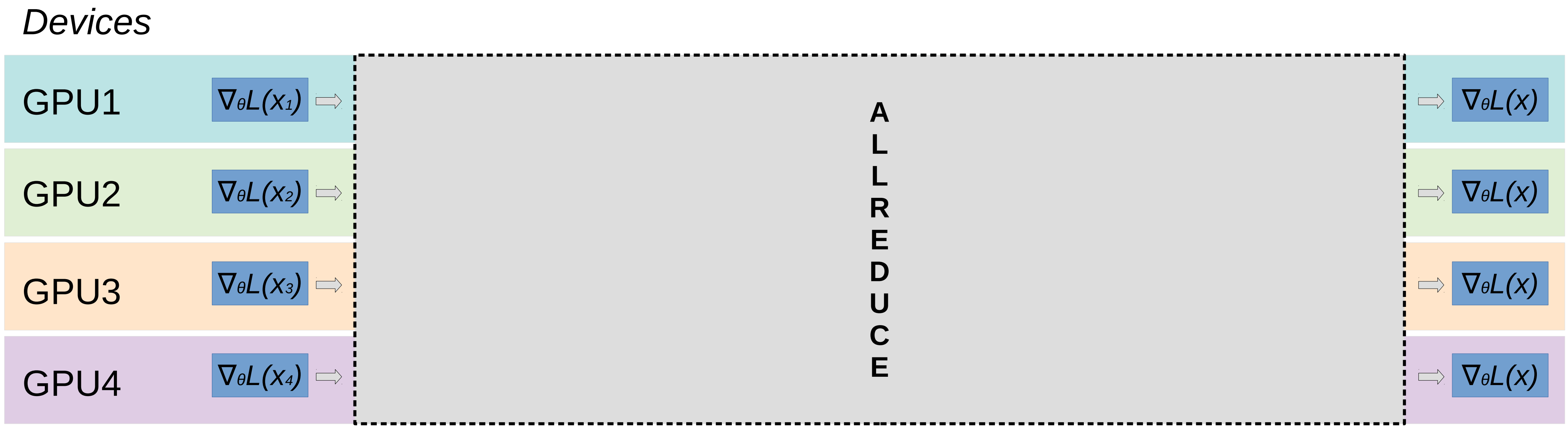
arxiv.org/abs/1706.02677

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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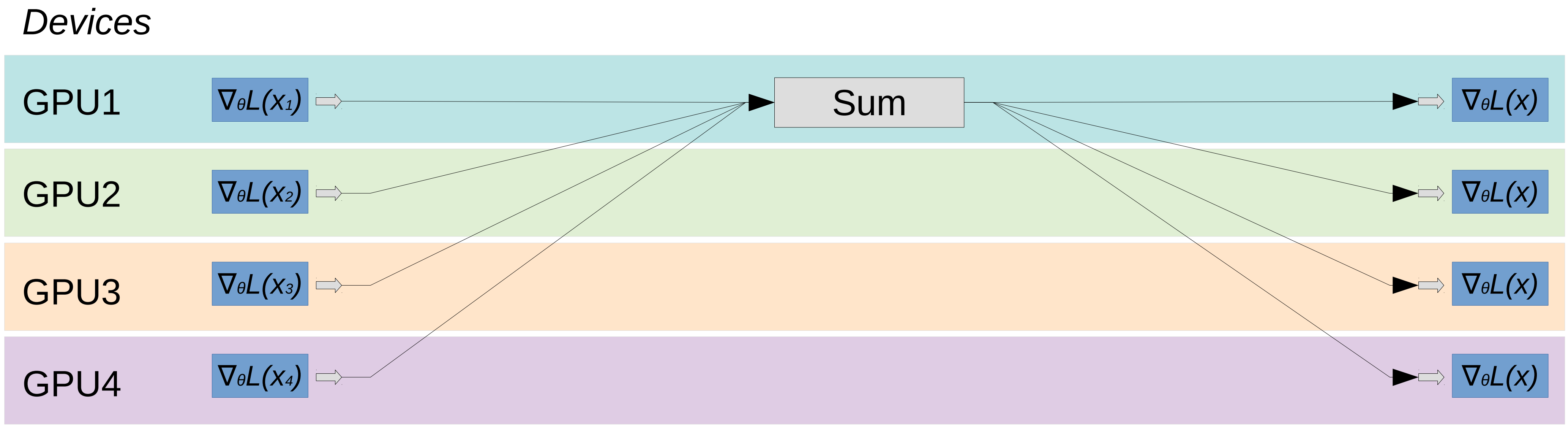
Naive implementation



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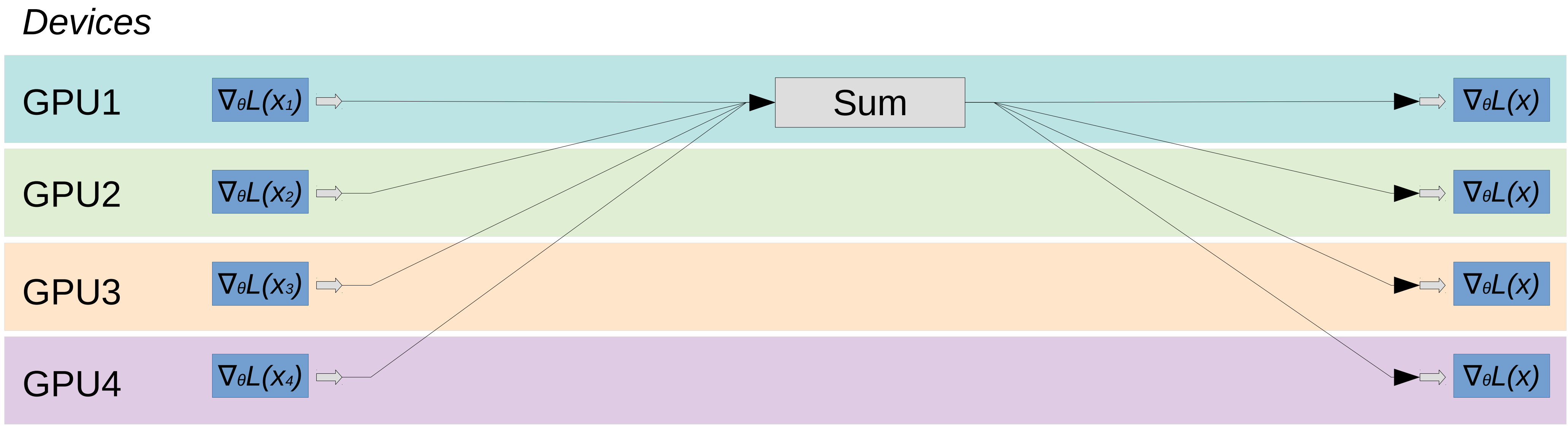
Q: Can we do better?



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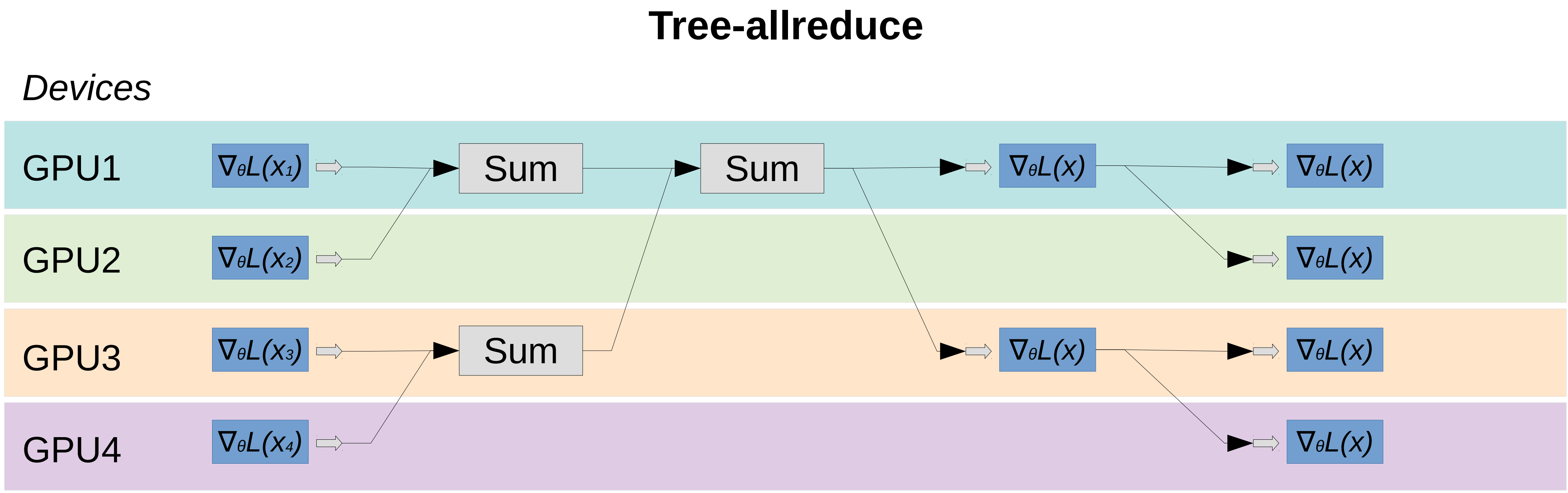

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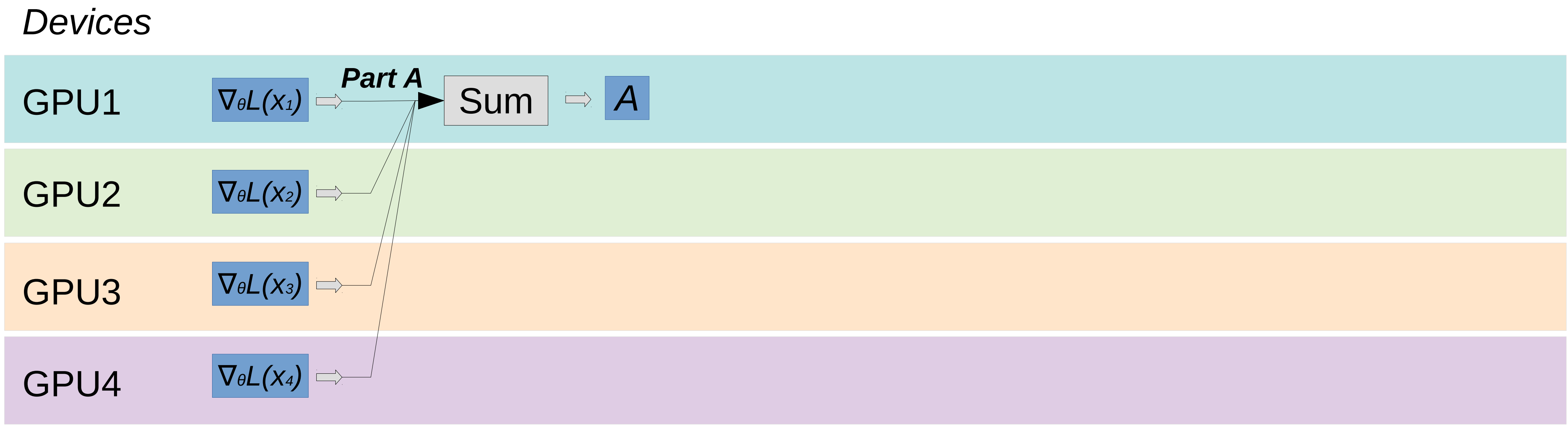
Butterfly-allreduce – split data into chunks (ABCD)



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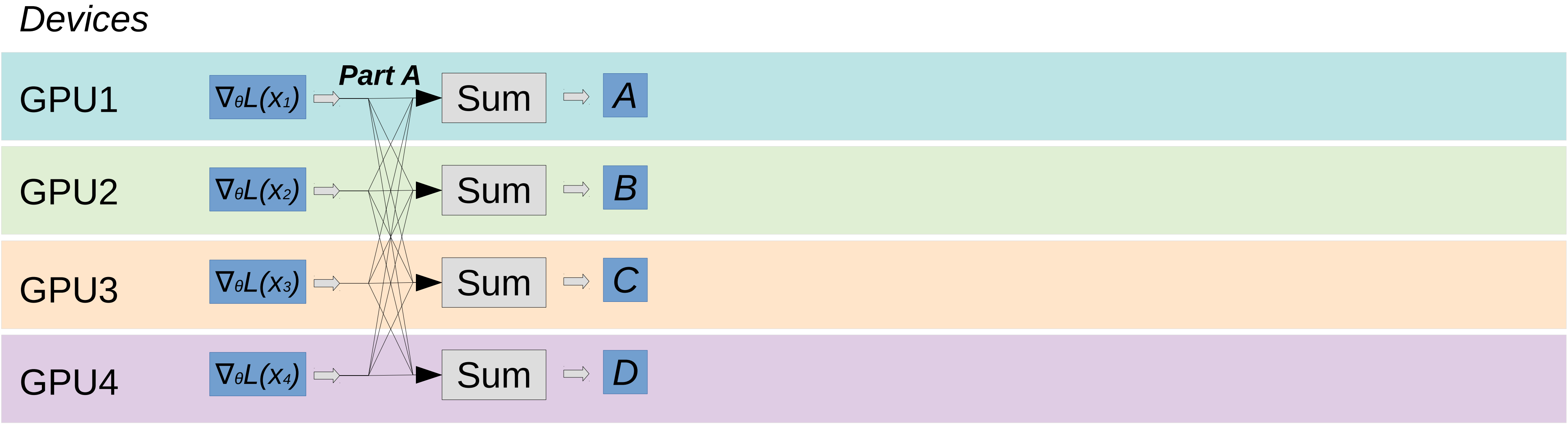

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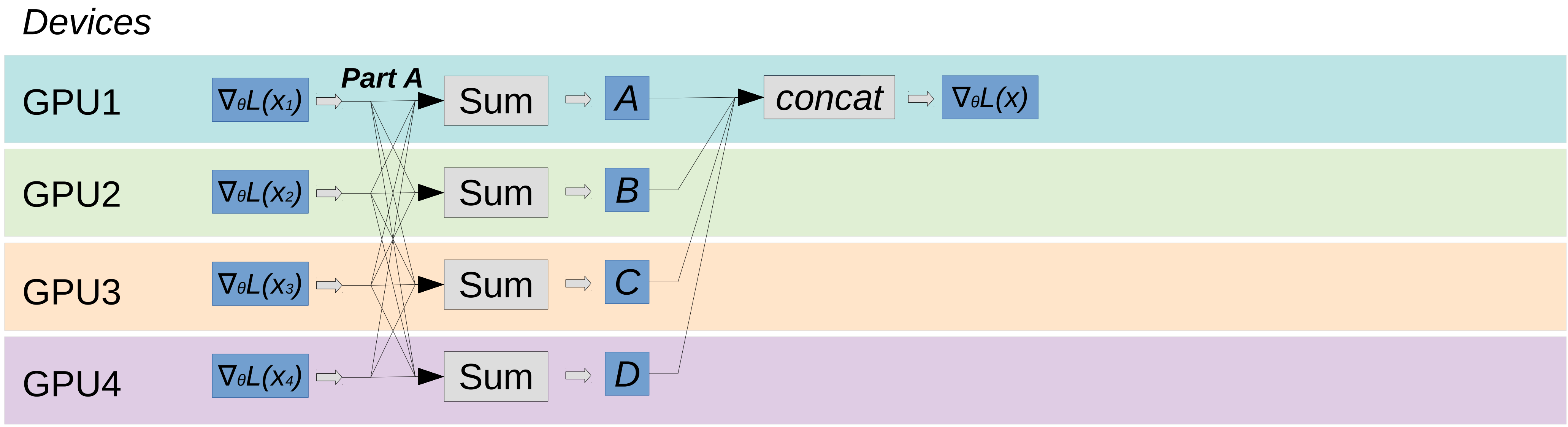

Faster allreduce

Input: each device has its its own vector
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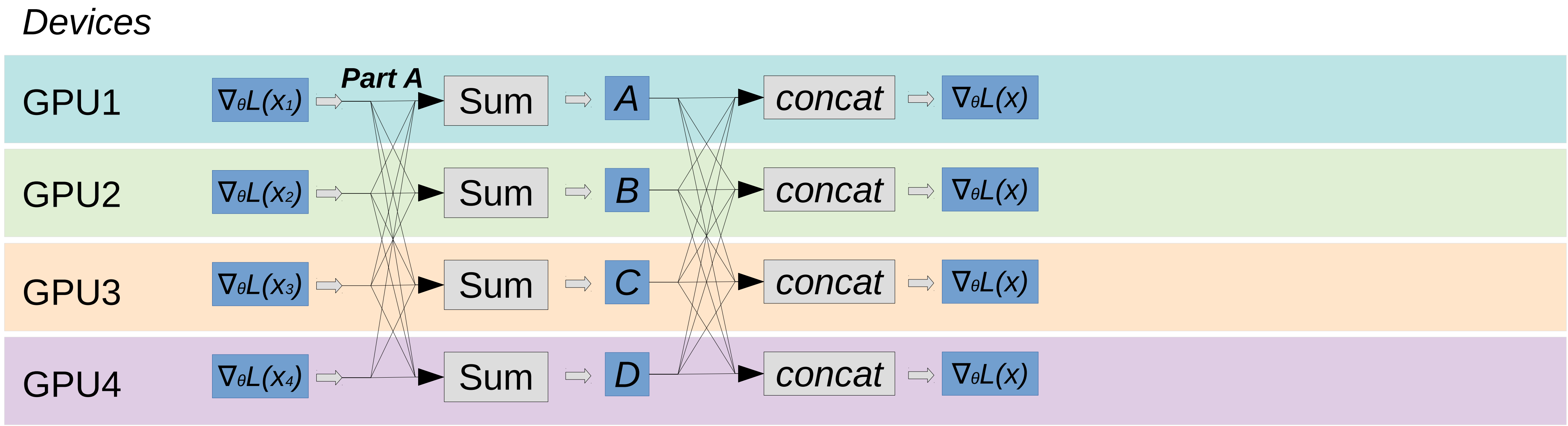
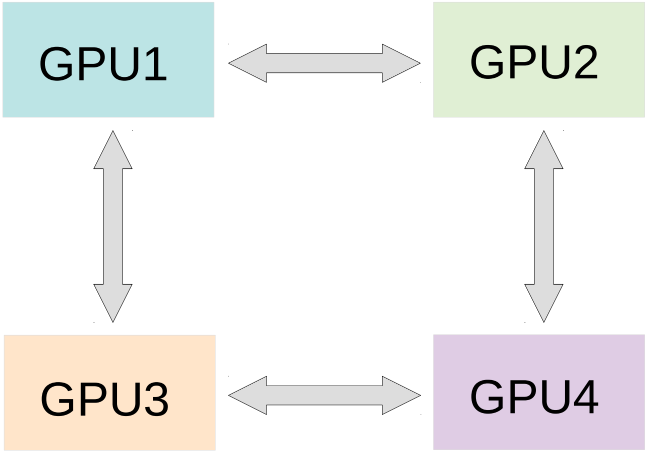
Ring-allreduce – split data into chunks (ABCD)



Ring allreduce

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



Ring topology

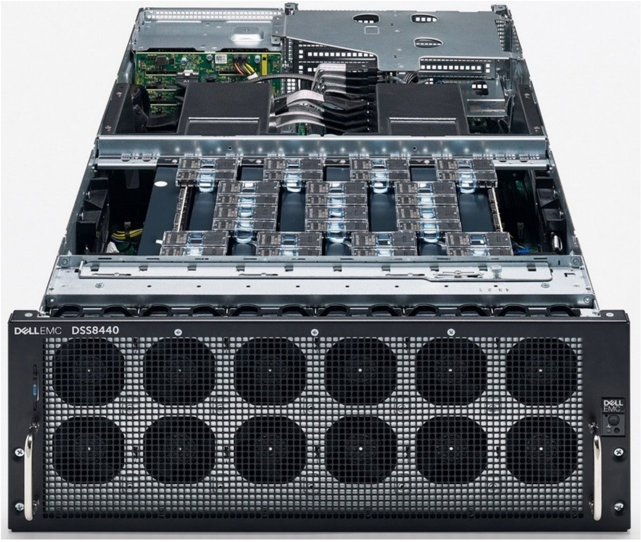


Image: graphcore ipu server

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

Ring allreduce

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

[Time to use the whiteboard]

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

All-Reduce data parallel

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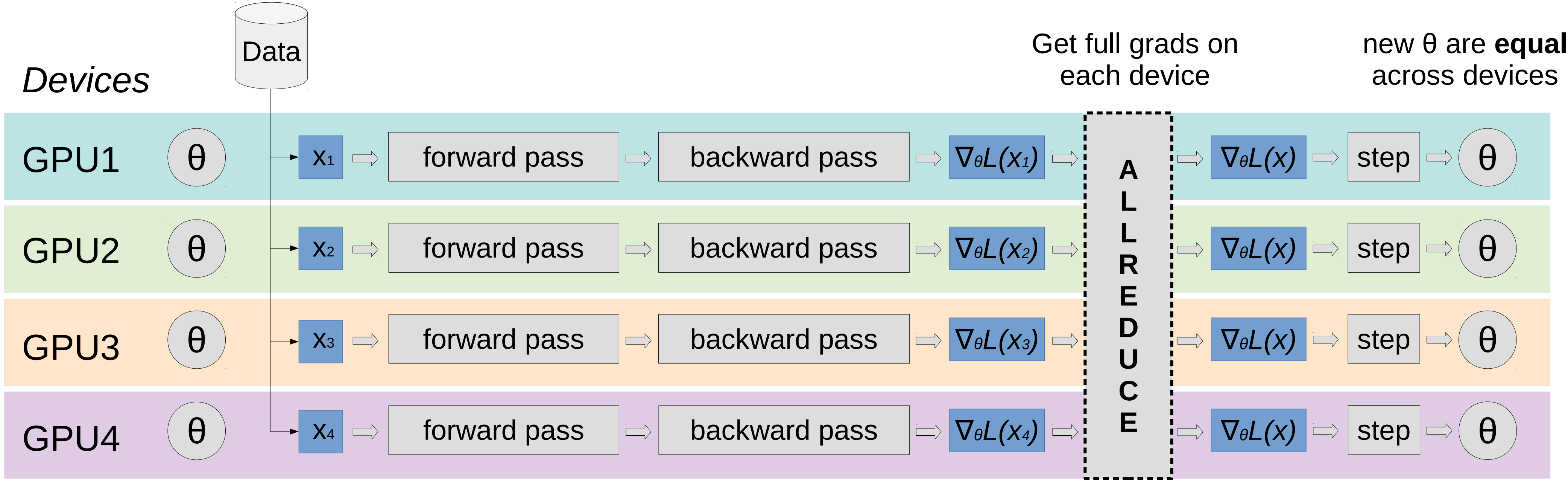
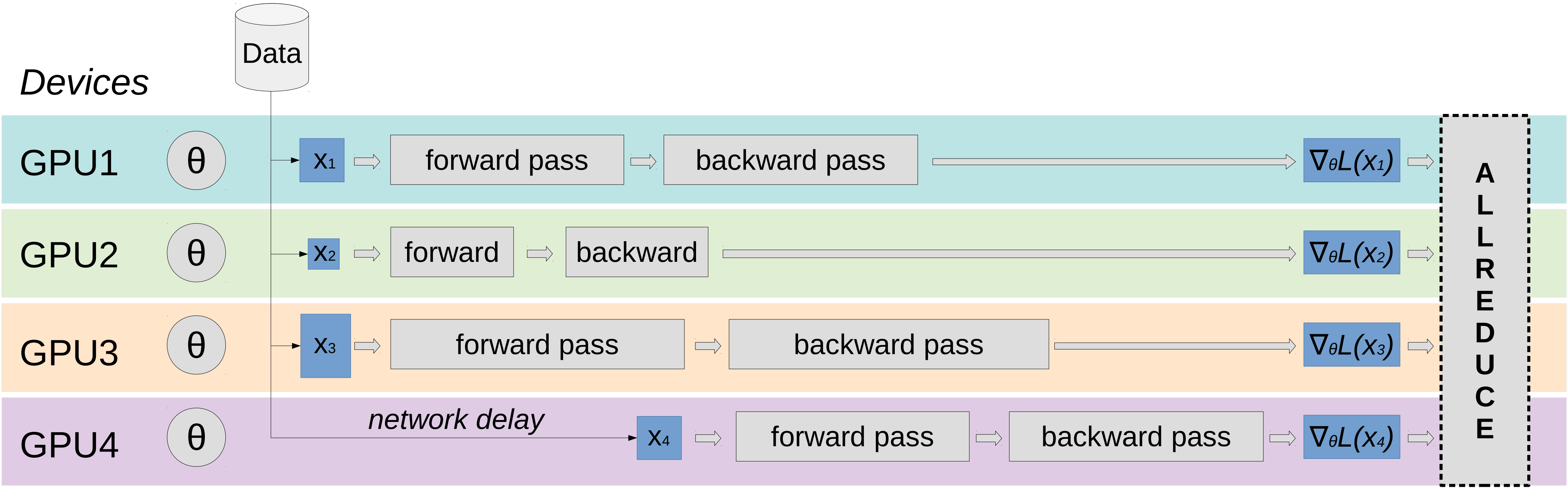
Q: why will weights be equal after such step?



All-Reduce data parallel VS reality

arxiv.org/abs/1706.02677

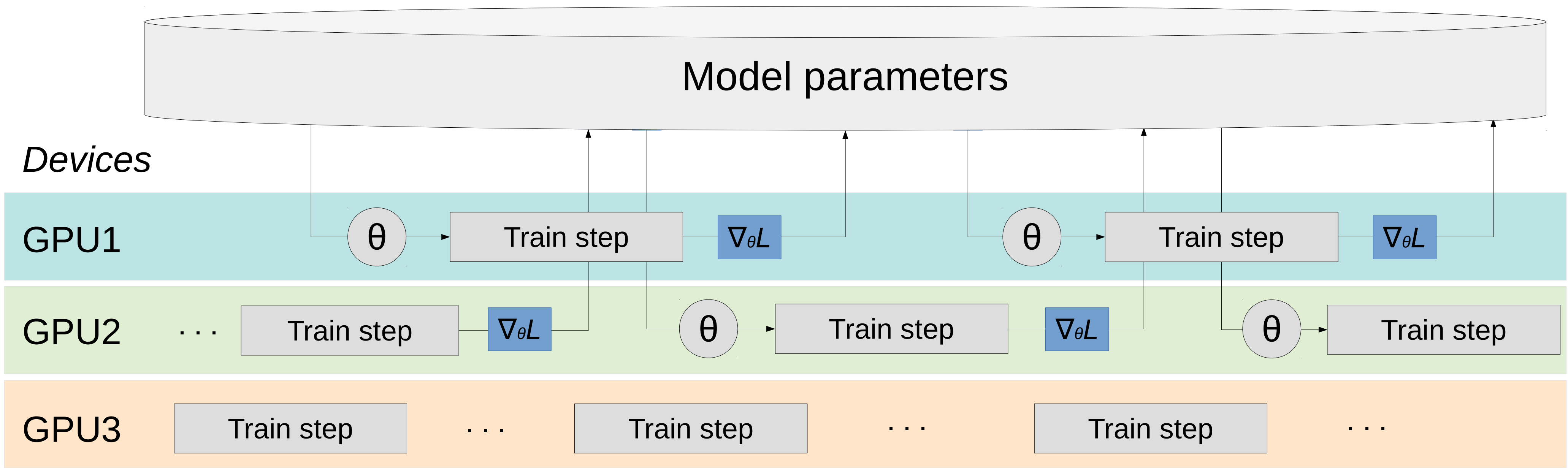
Each gpu has different processing time & delays
Q: can we improve device utilization?



Recap: Parameter Server

HOGWILD! arxiv.org/abs/1106.5730

Idea: remove synchronization step alltogether, use parameter server



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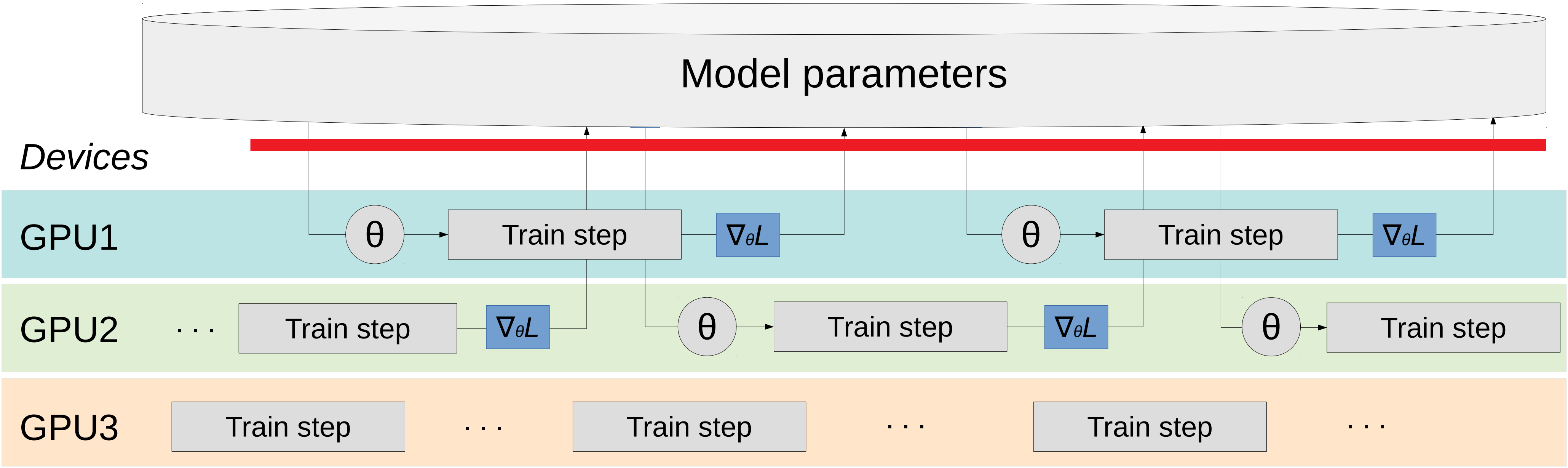
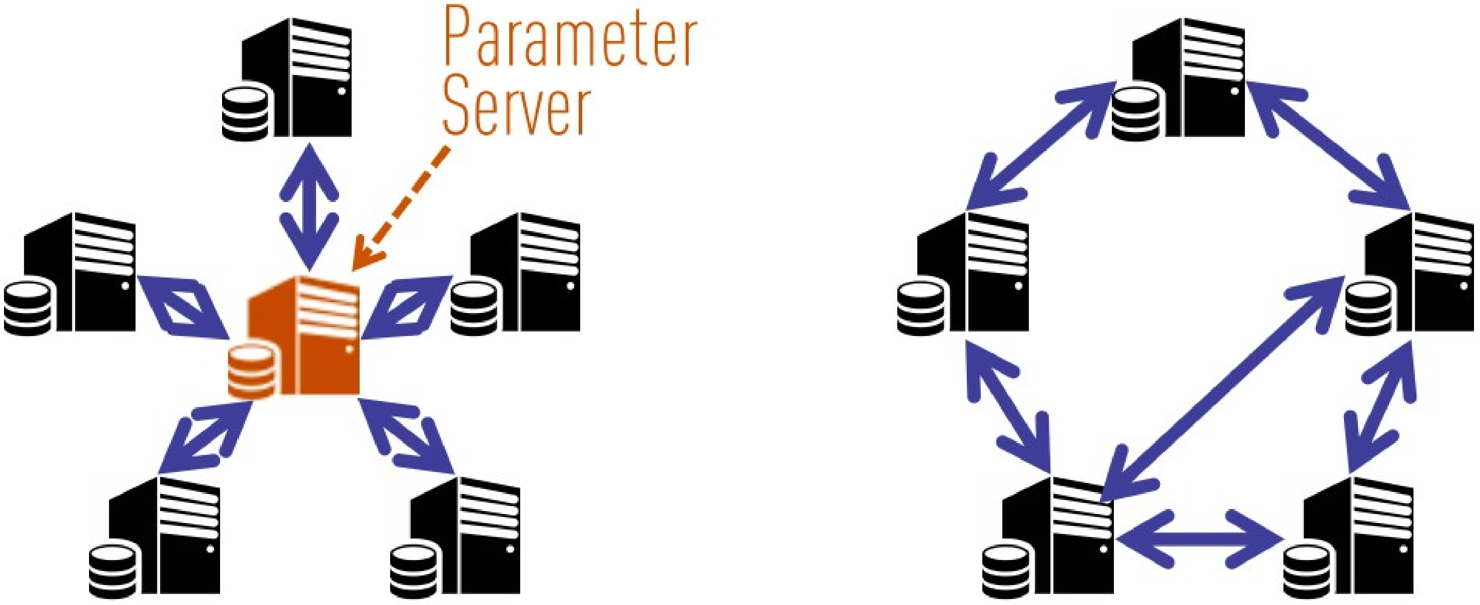


Problem: parameter servers need to ingest tons of data over training

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**

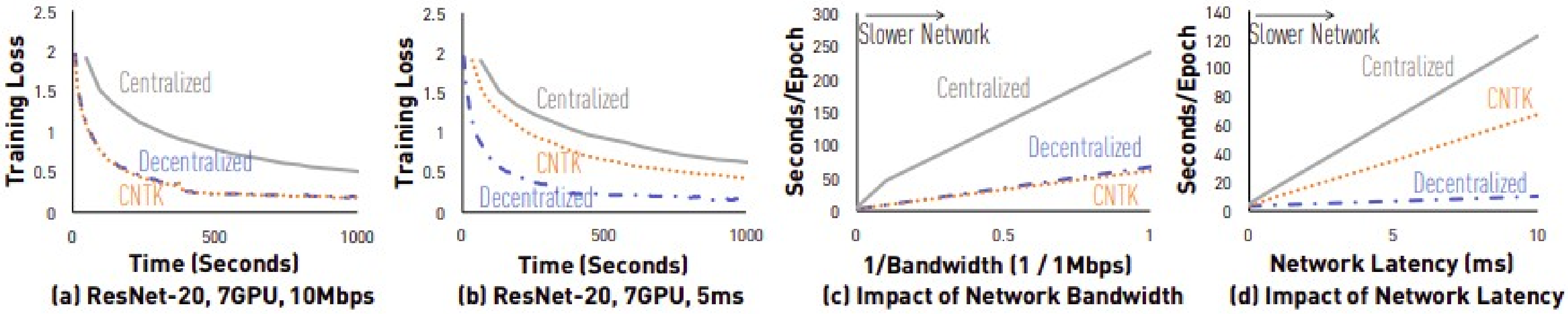


Figure 2: Comparison between D-PSGD and two centralized implementations (7 and 10 GPUs).

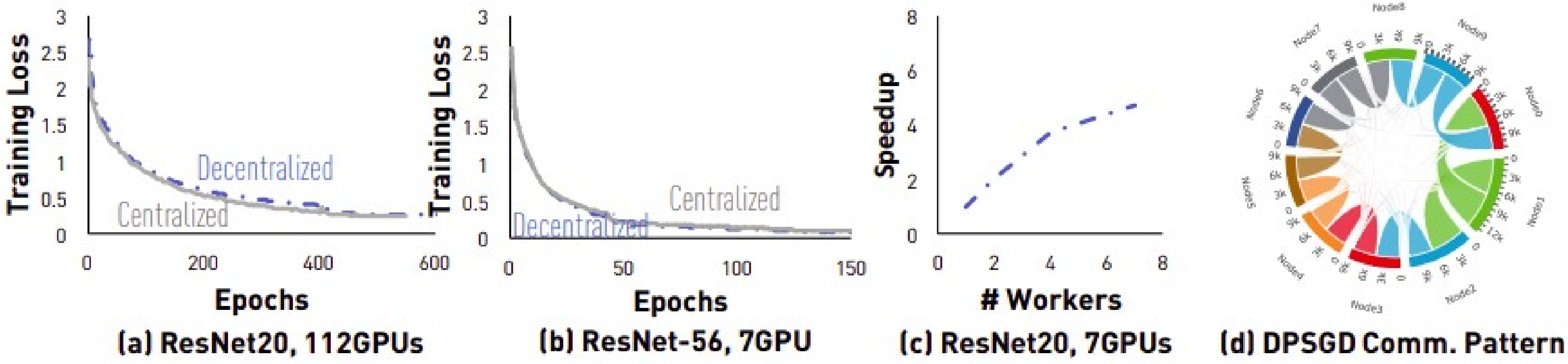
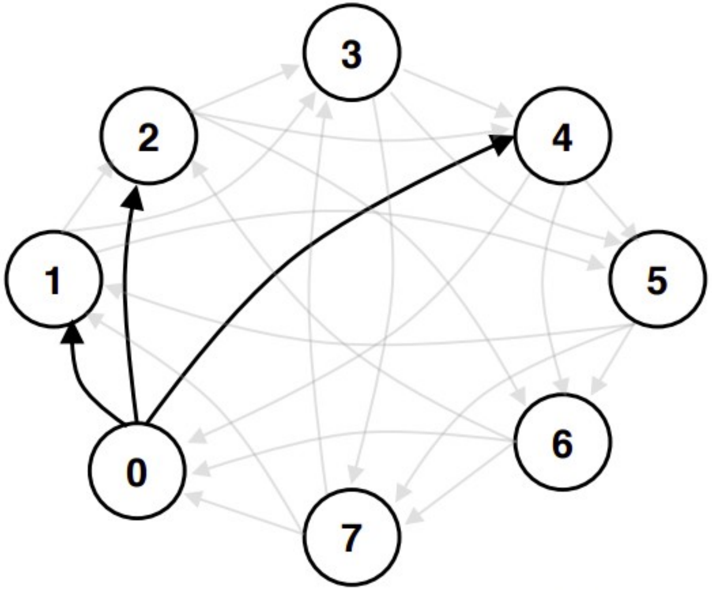


Figure 3: (a) Convergence Rate; (b) D-PSGD Speedup; (c) D-PSGD Communication Patterns.

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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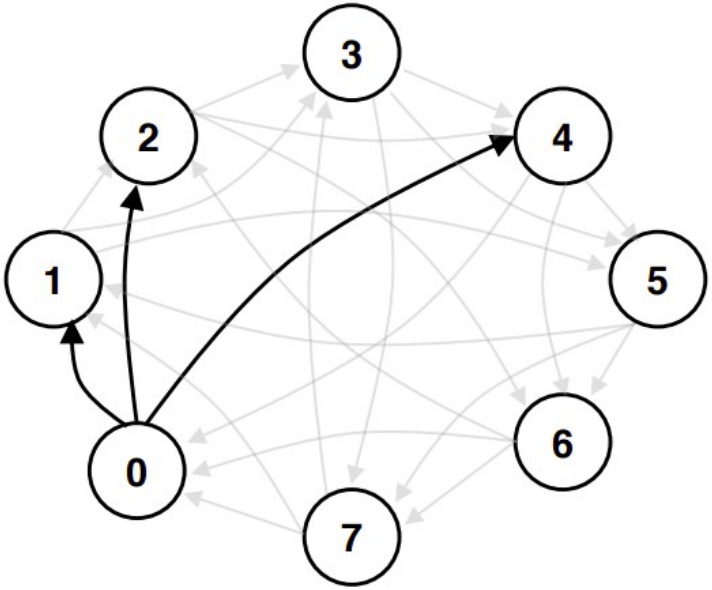

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Algorithm 1 Stochastic Gradient Push (SGP)

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>

Stochastic Gradient Push

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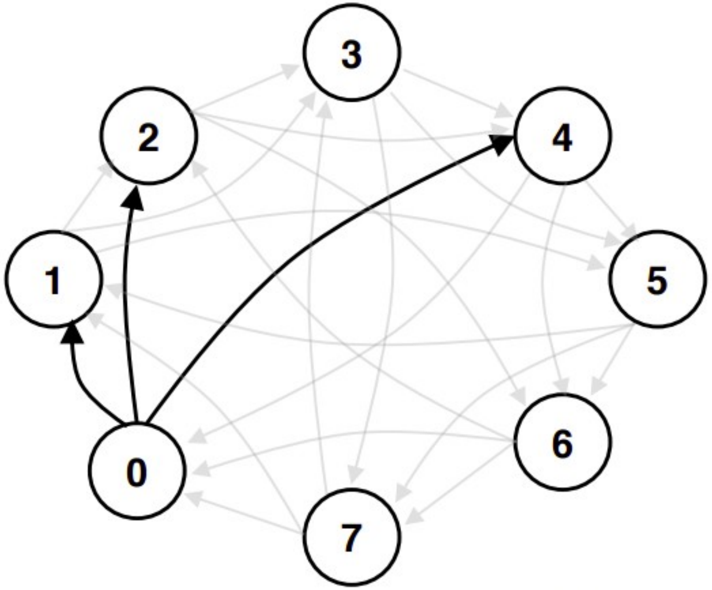

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4: $\boldsymbol{x}_i^{(k+\frac{1}{2})} = \boldsymbol{x}_i^{(k)} - \gamma \nabla \boldsymbol{F}_i(\boldsymbol{z}_i^{(k)}; \xi_i^{(k)})$

normal GD step

<to be continued>

Stochastic Gradient Push

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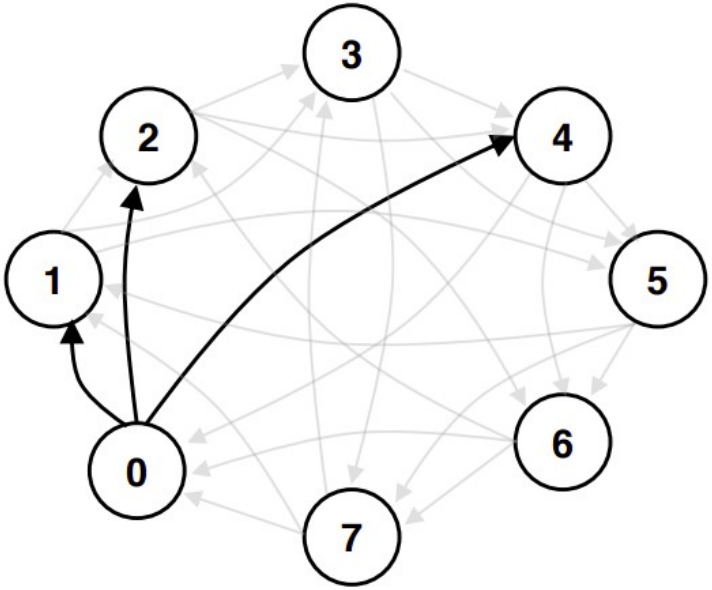

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5: Send $\left(p_{j,i}^{(k)} \boldsymbol{x}_i^{(k+\frac{1}{2})}, p_{j,i}^{(k)} w_i^{(k)}\right)$ to out-neighbors;
receive $\left(p_{i,j}^{(k)} \boldsymbol{x}_j^{(k+\frac{1}{2})}, p_{i,j}^{(k)} w_j^{(k)}\right)$ from in-neighbors

<to be continued>

Stochastic Gradient Push

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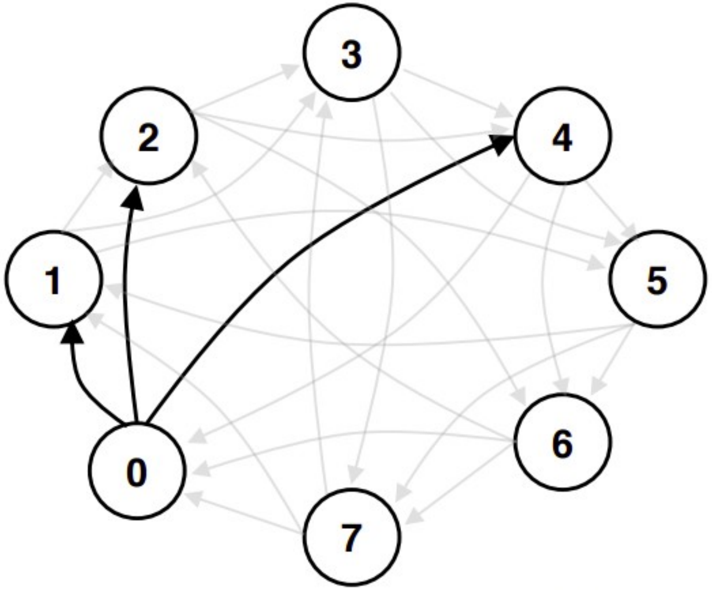

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  Compute mini-batch gradient at $\boldsymbol{z}_i^{(k)}$: $\nabla \boldsymbol{F}_i(\boldsymbol{z}_i^{(k)}; \xi_i^{(k)})$

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

  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

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

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

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

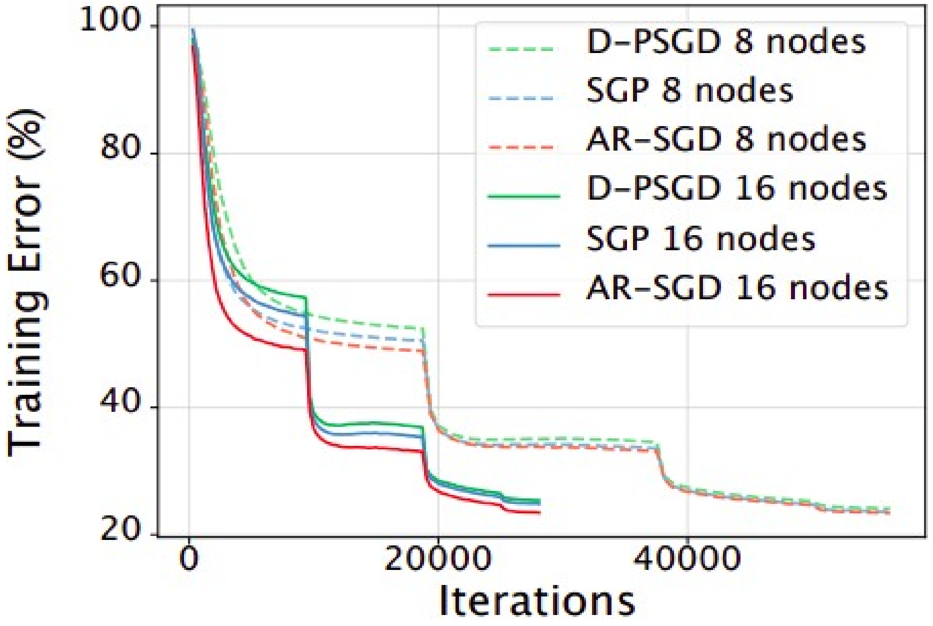
end for

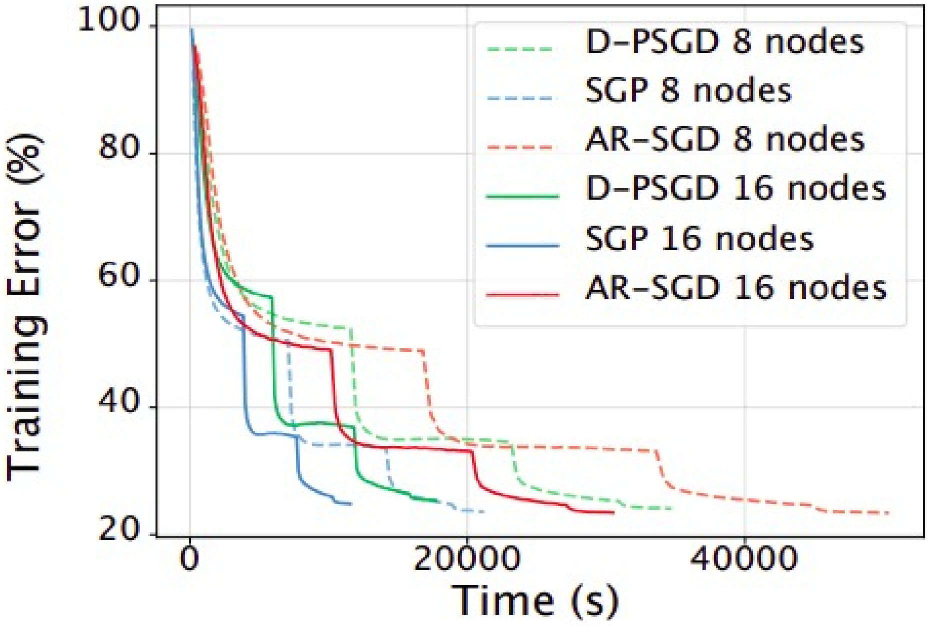
weighted average

Stochastic Gradient Push

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

SGP vs ImageNet (ResNet50 + SGD w/ momentum)





Stochastic Gradient Push

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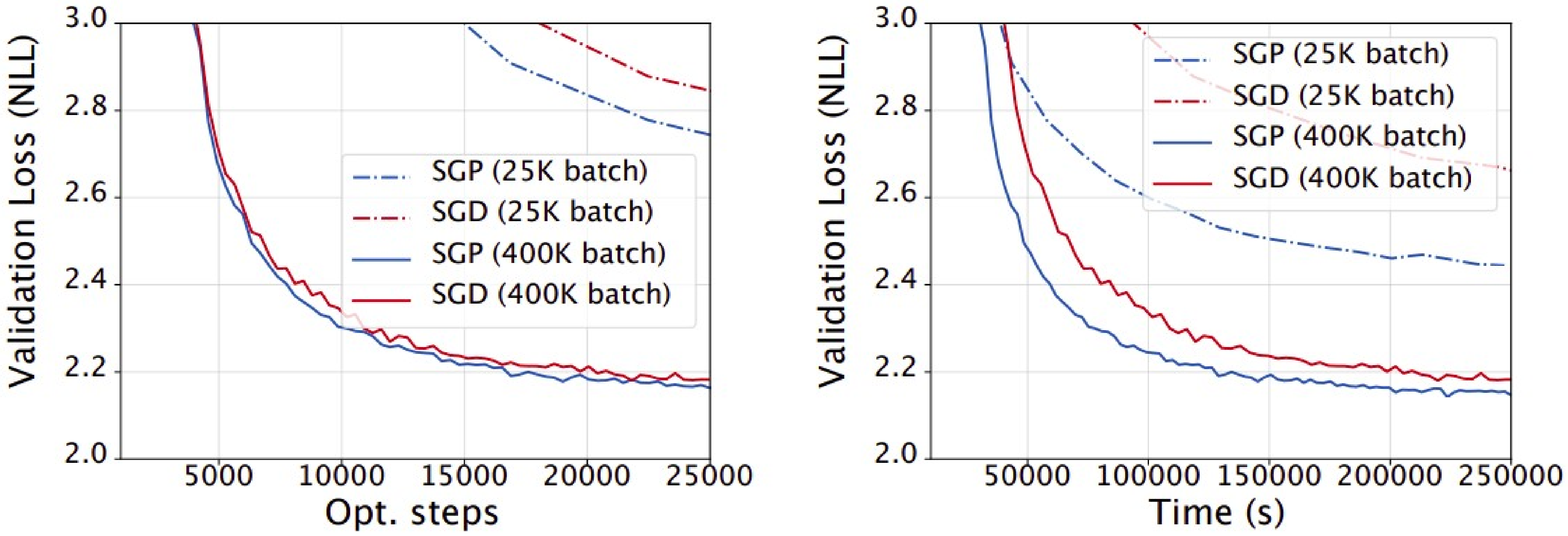
SGP vs WMT English-German (Transformer, Adam)



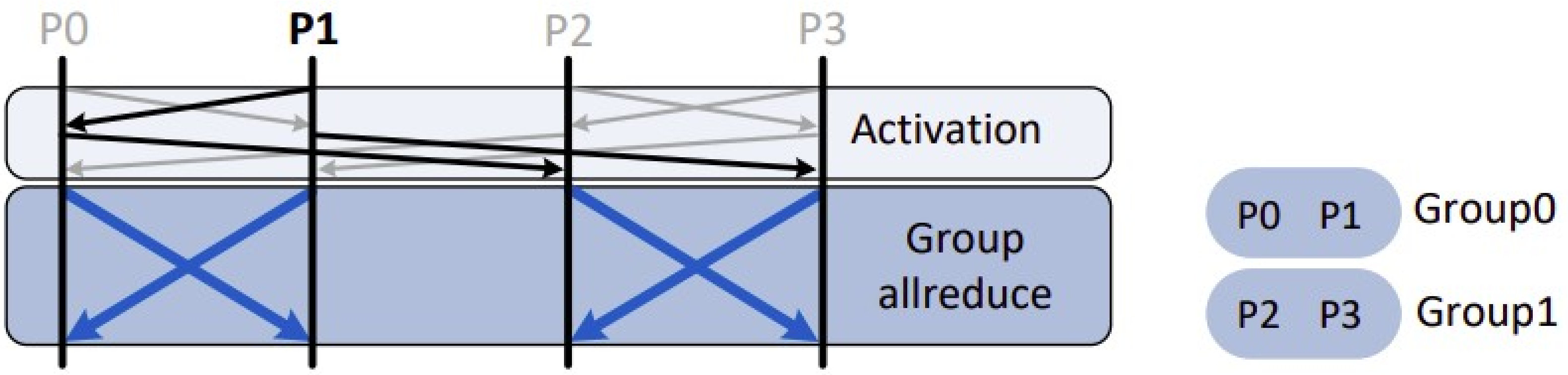
Gossip vs All-Reduce

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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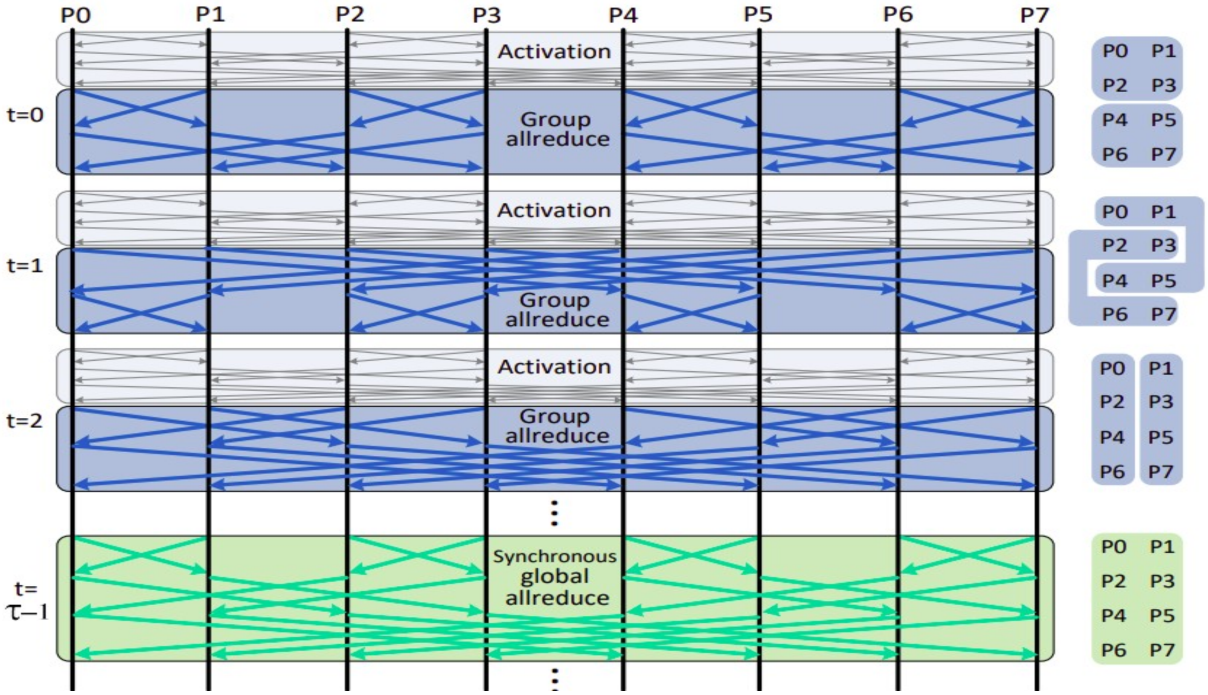

Gossip + All-Reduce

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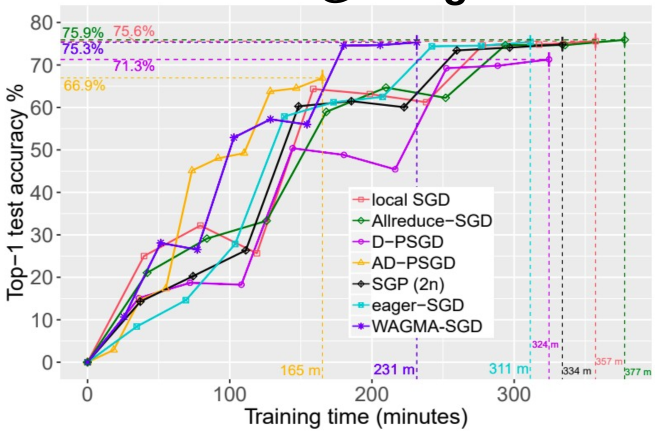
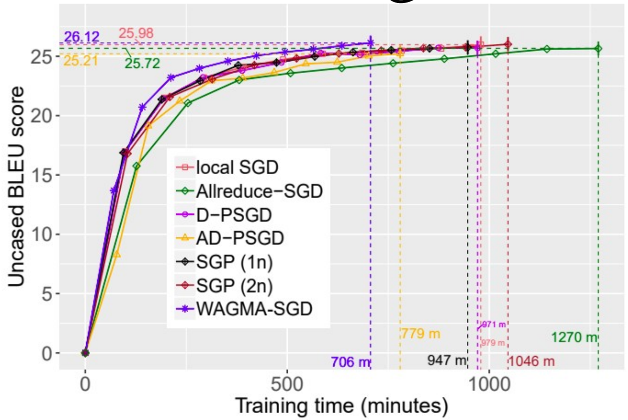
Experiment setup: up to 1024 GPU,
Natural (or emulated) network latency

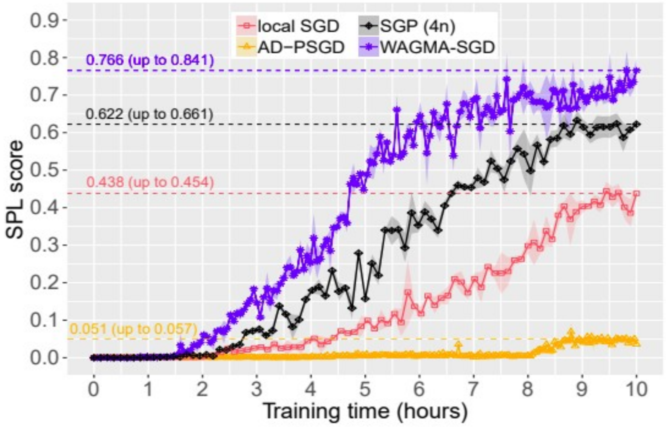
Image Classification
ResNet50 @ ImageNet



Machine Translation
Transformer @ WMT17



Reinforcement Learning
DDPO on Habitat



Side-quest: reducing network usage

Virtual batch / virtual pipeline

ёж, открой доску

</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 – horovod (allreduce) github.com/horovod/horovod
  - High-level distributed pytorch (allreduce): tinyurl.com/distributed-dp
- 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


"That's all Folks!"
Isberg©