Efficient training & inference

Deep Learning@HSE

Week {++i}, guest lecture

Yandex
Research

British Hedgehog
Preservation Society

Large problems need large models

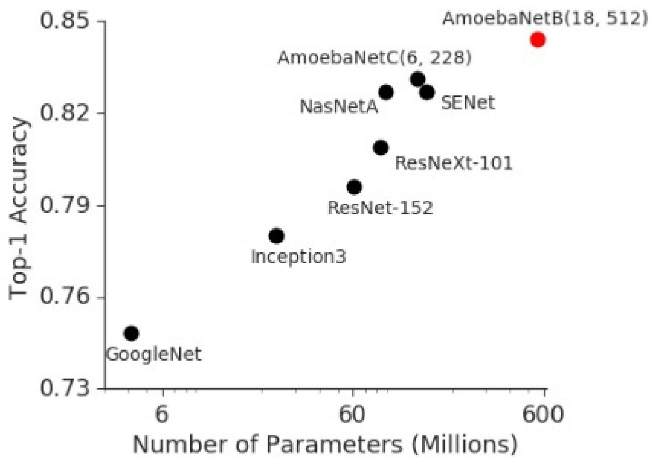
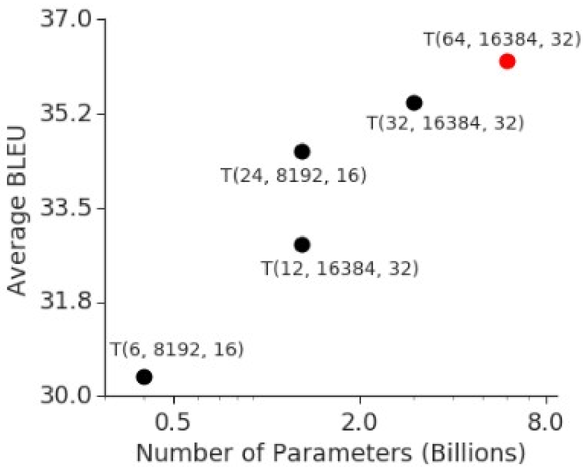


Image Classification
ImageNet

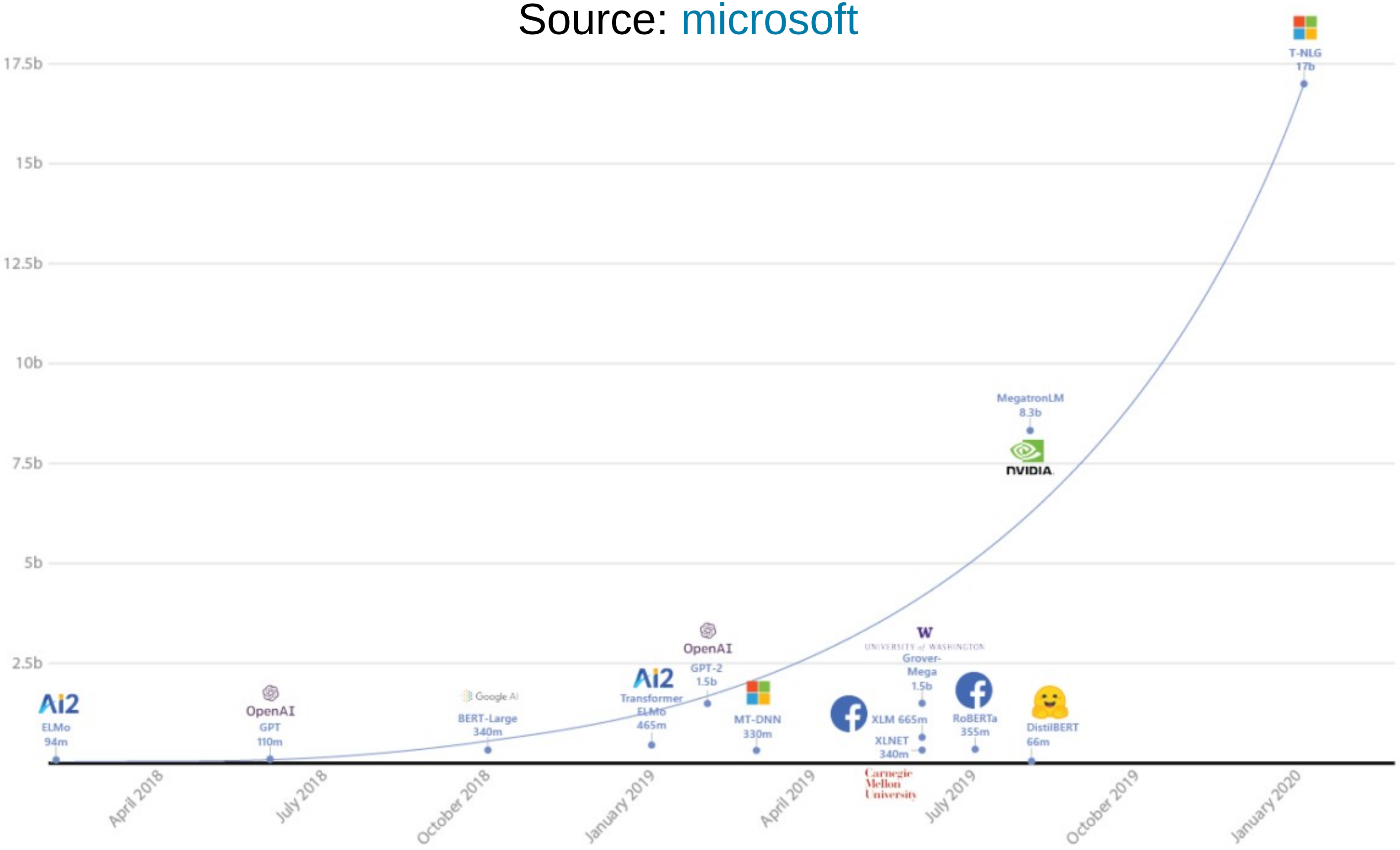


Machine Translation
average over WMT

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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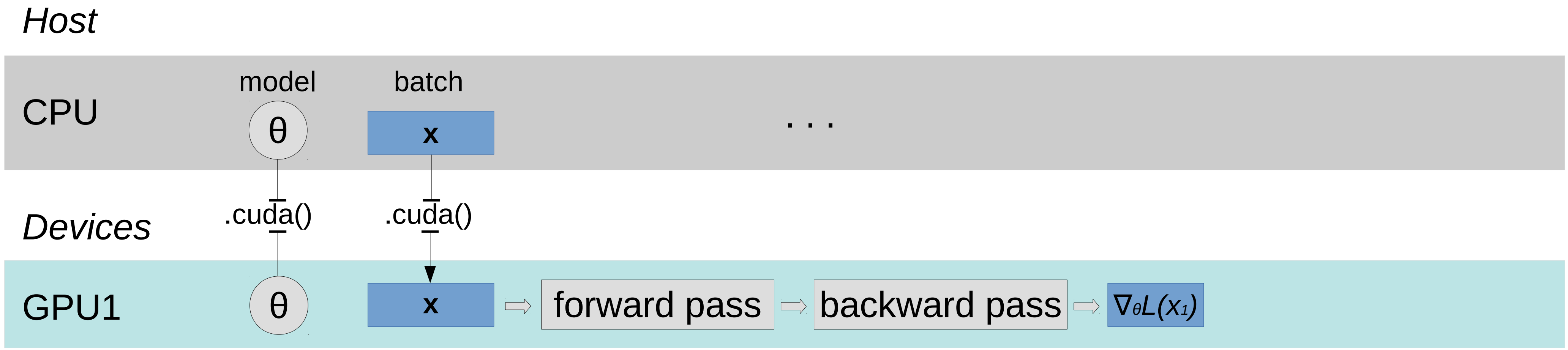

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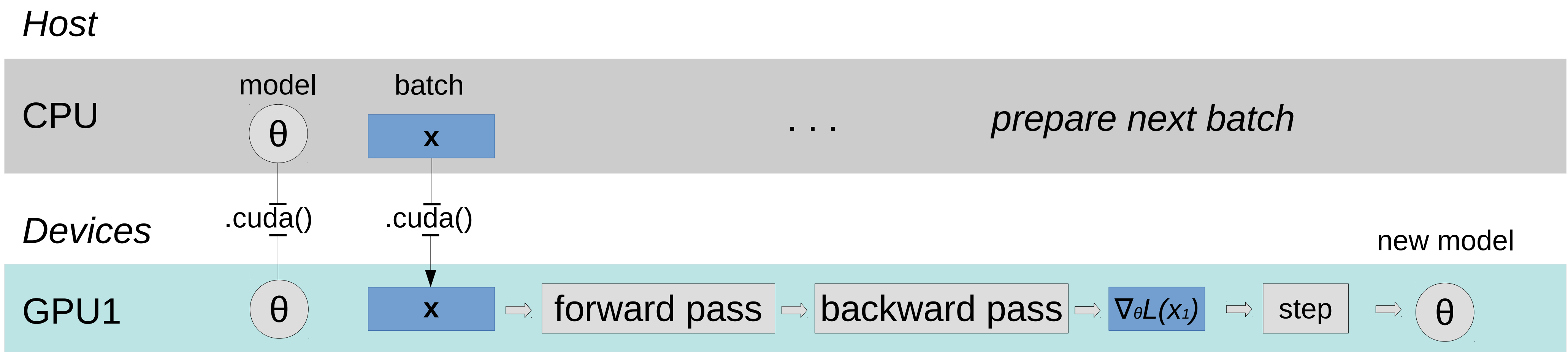

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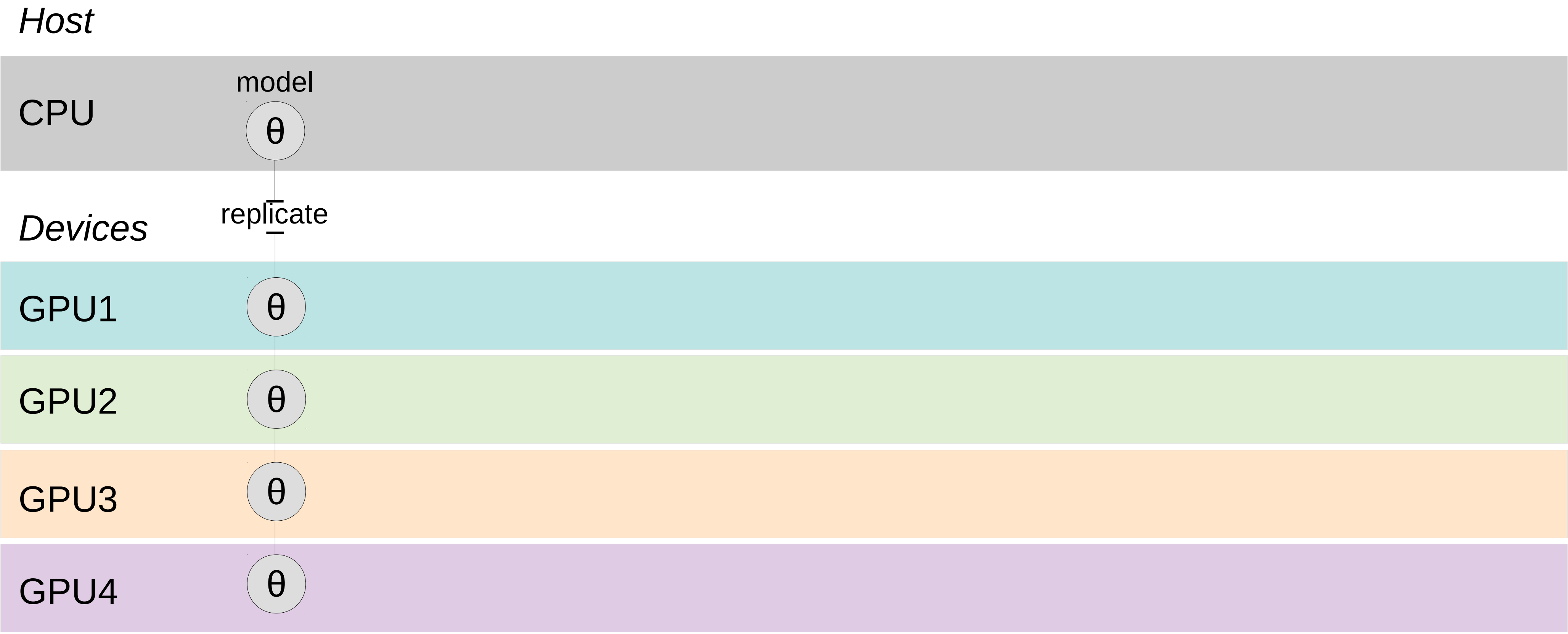

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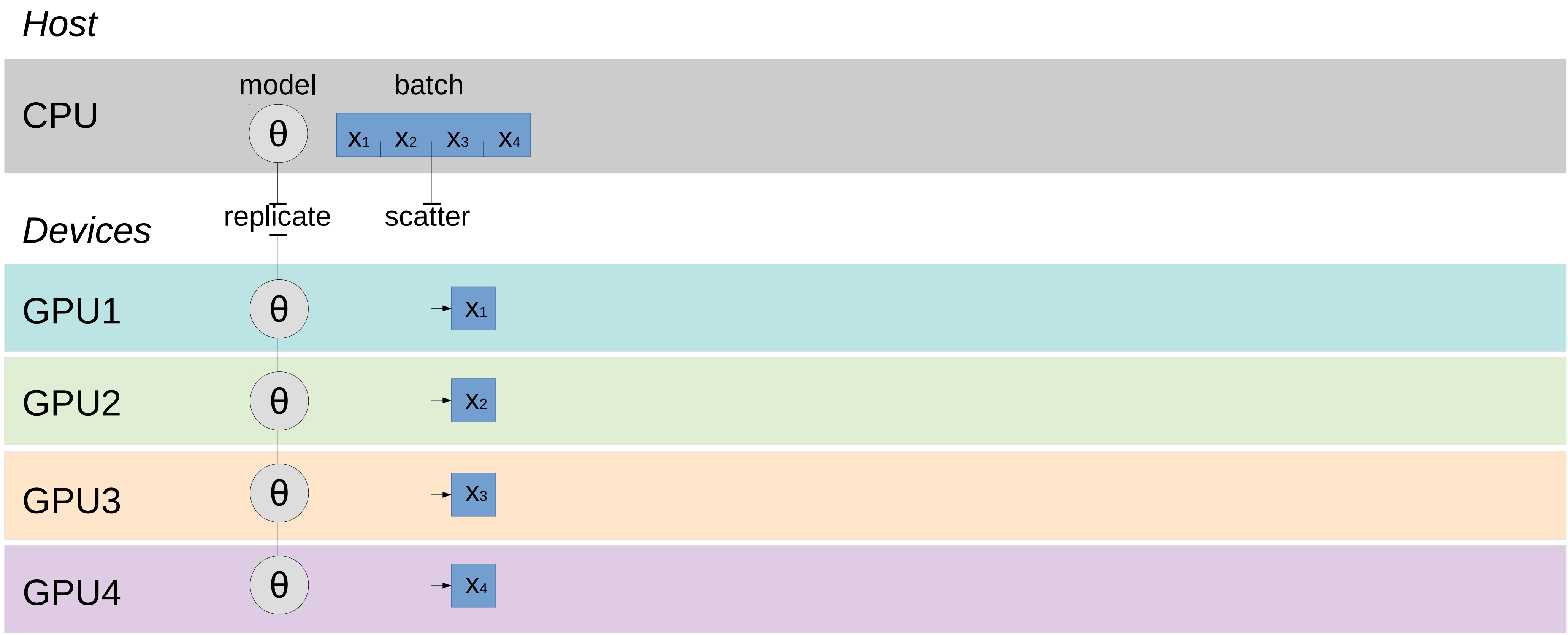

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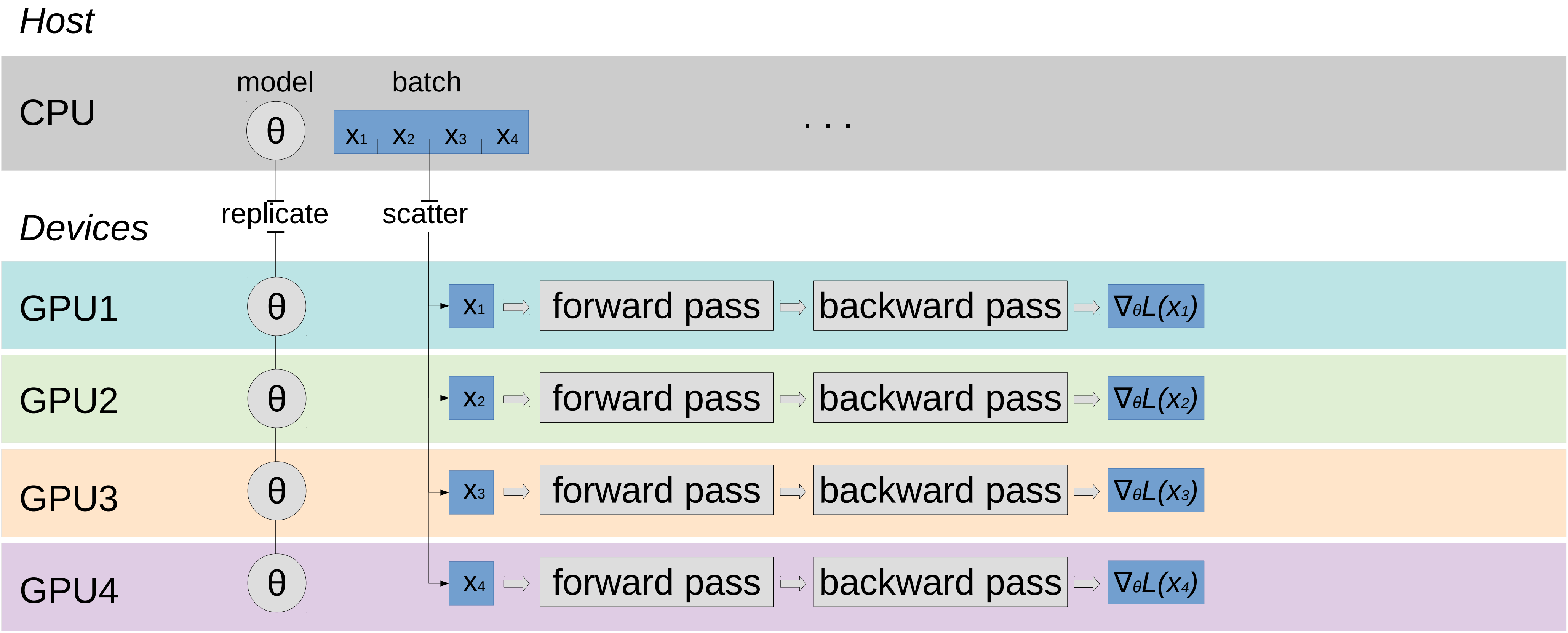

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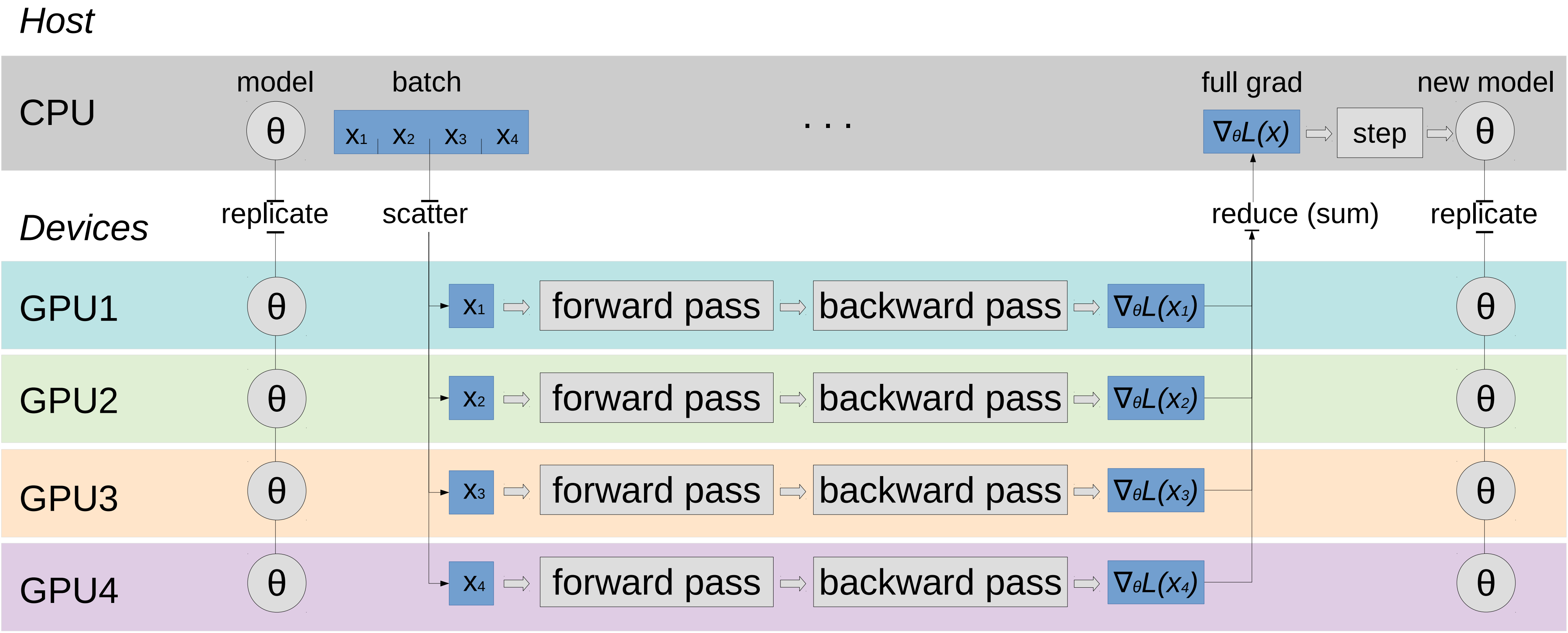

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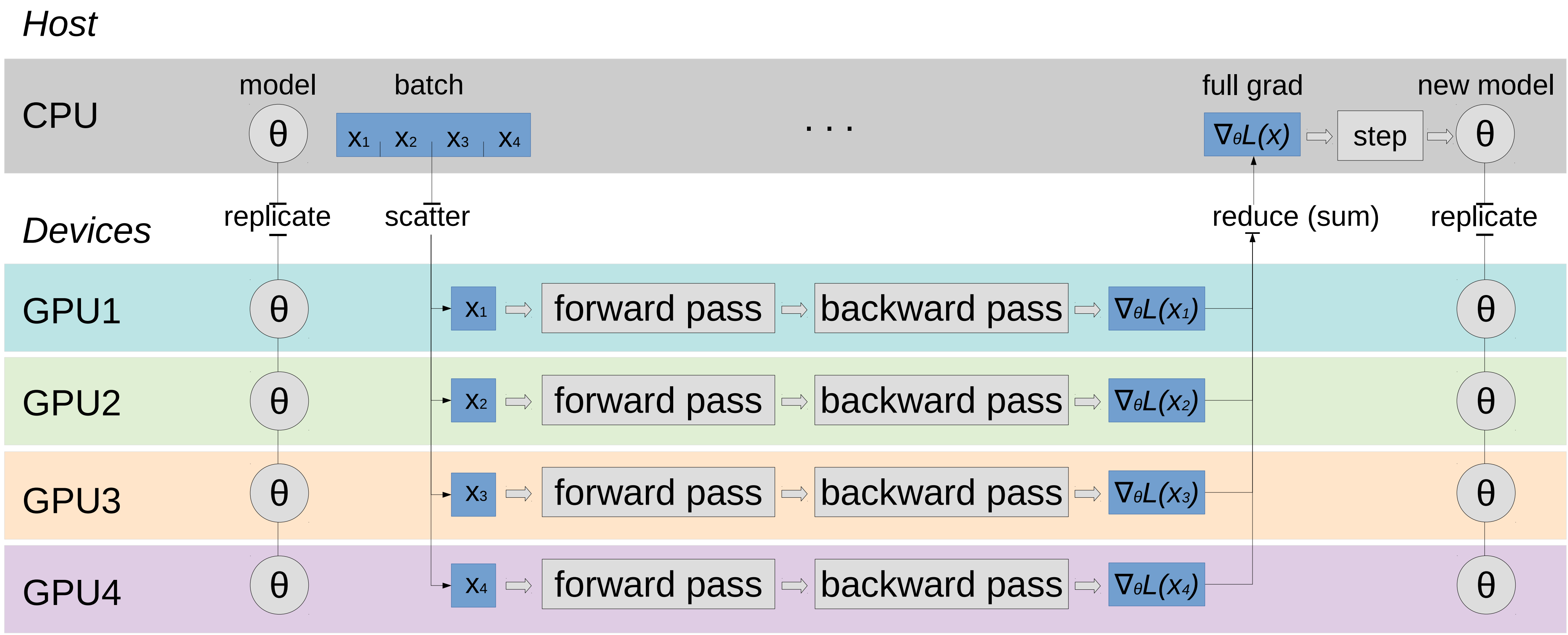
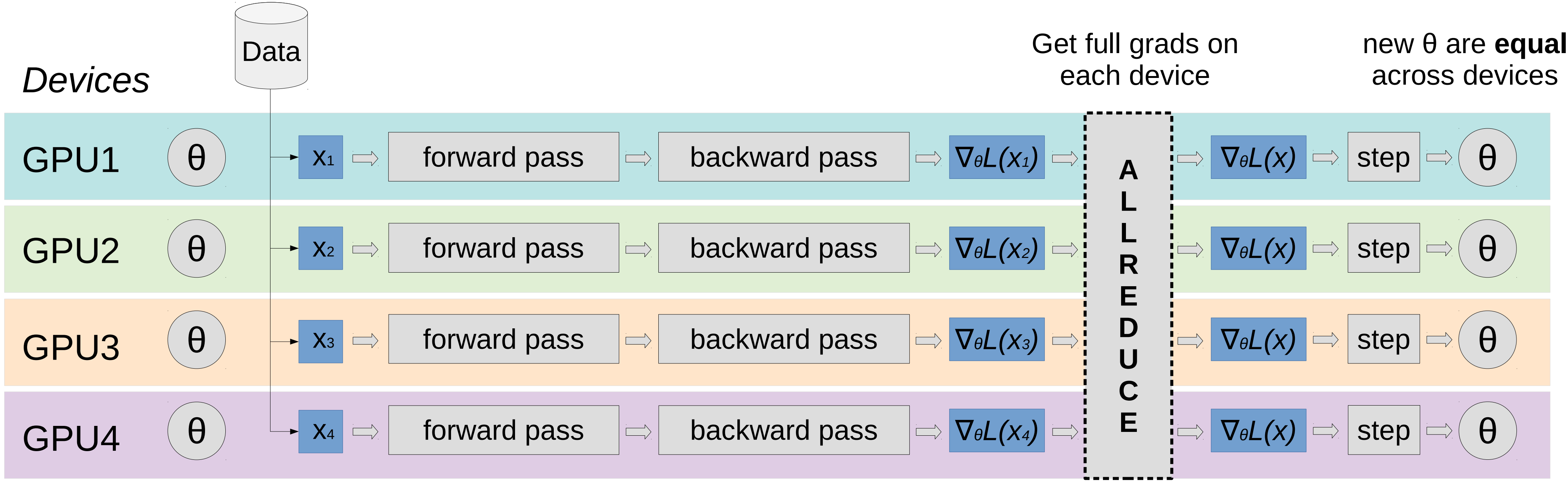


Advanced data parallel

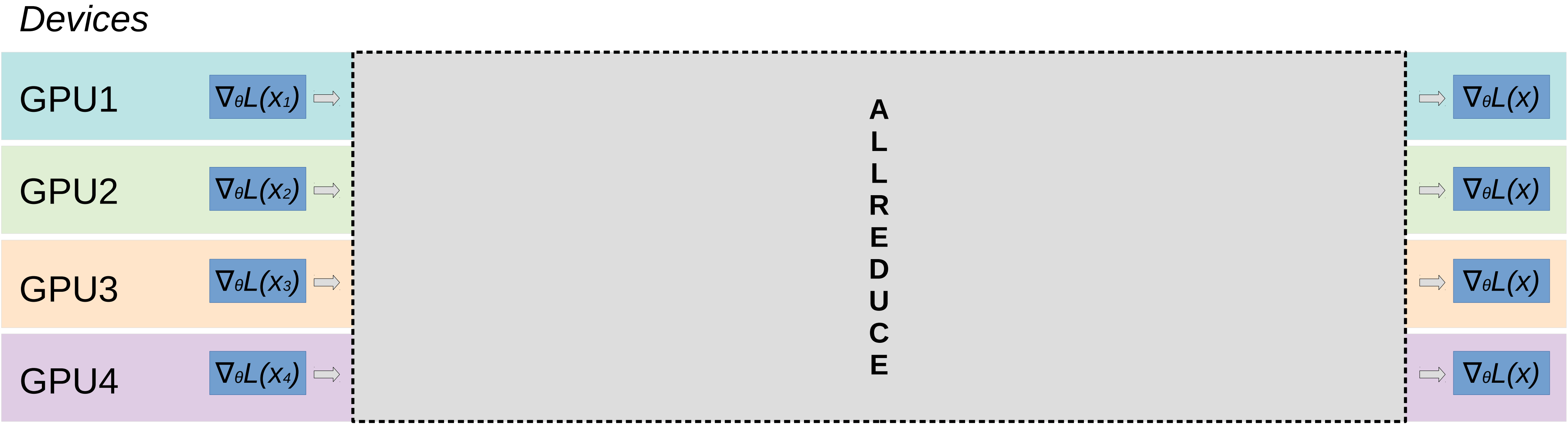
arxiv.org/abs/1706.02677

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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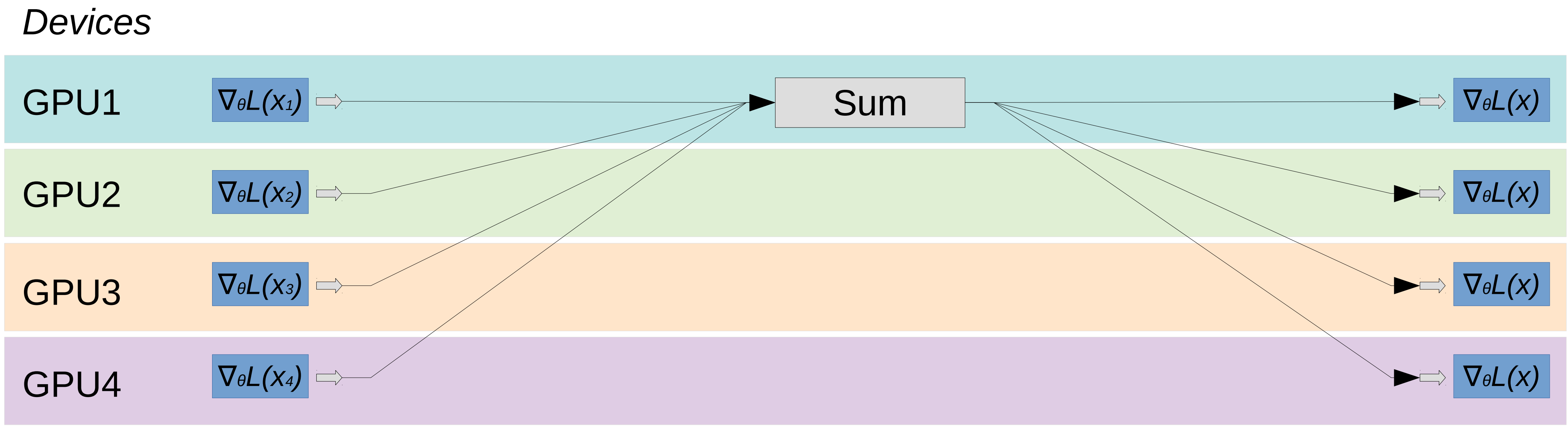
Naive implementation



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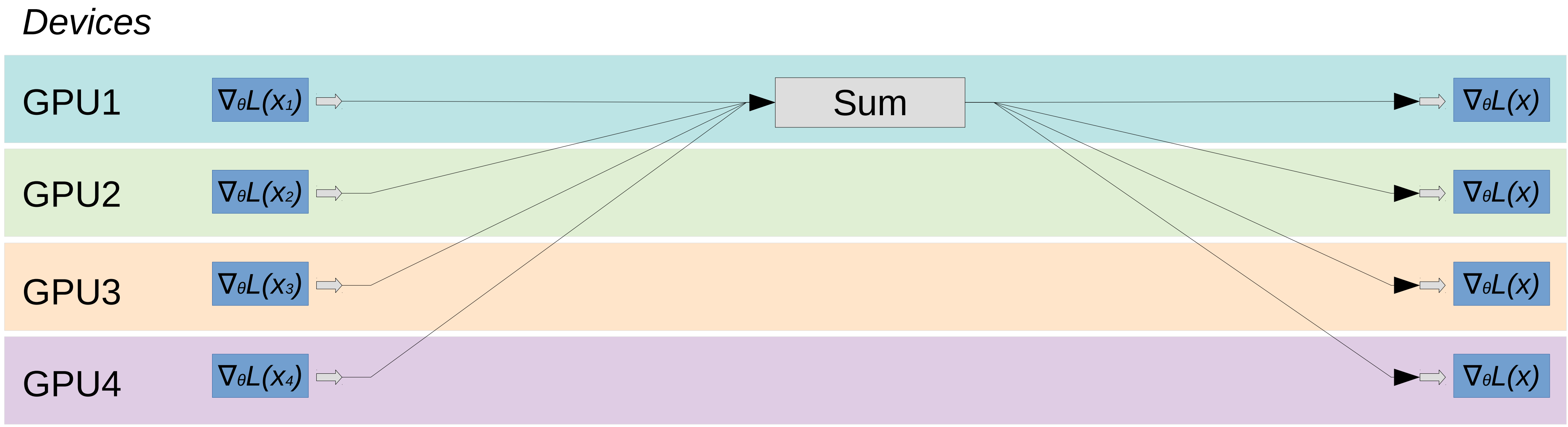
Q: Can we do better?



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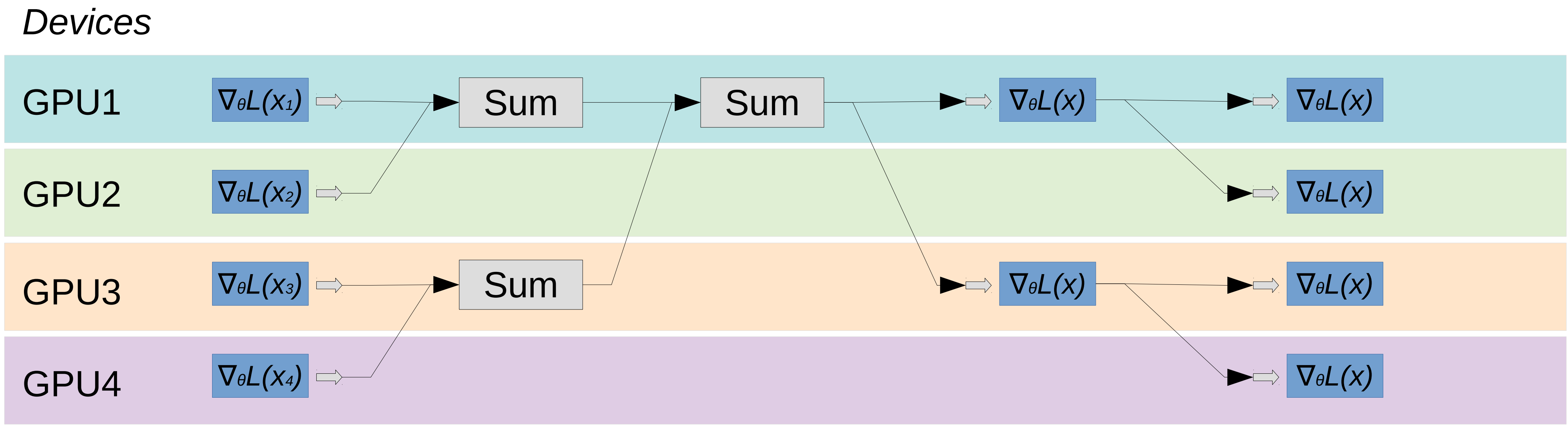
Tree-allreduce



Faster allreduce

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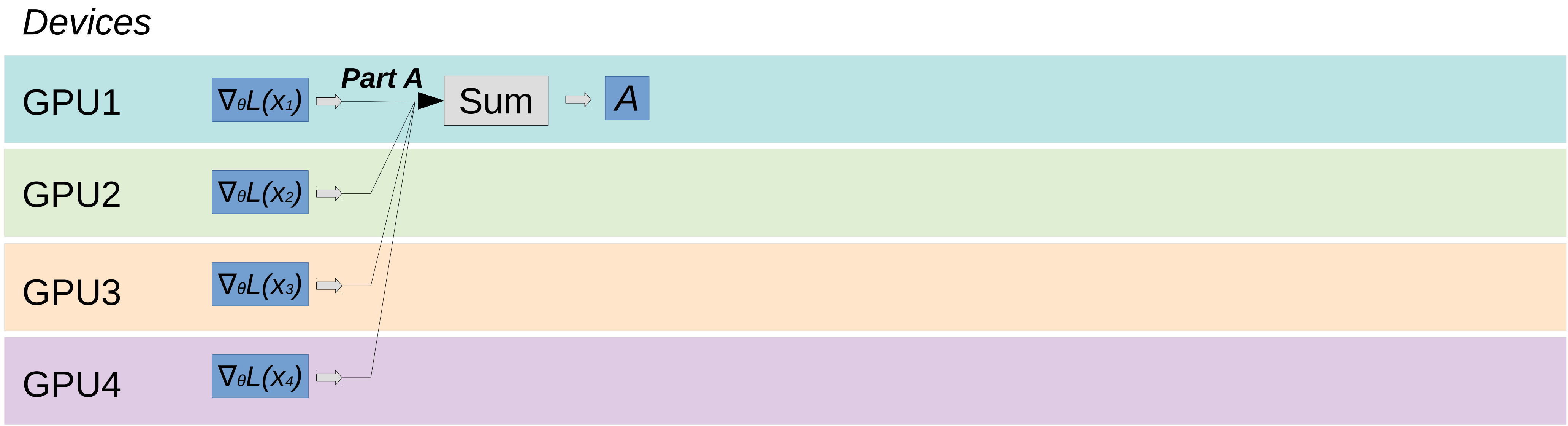
Ring-allreduce – split data into chunks (ABCD)



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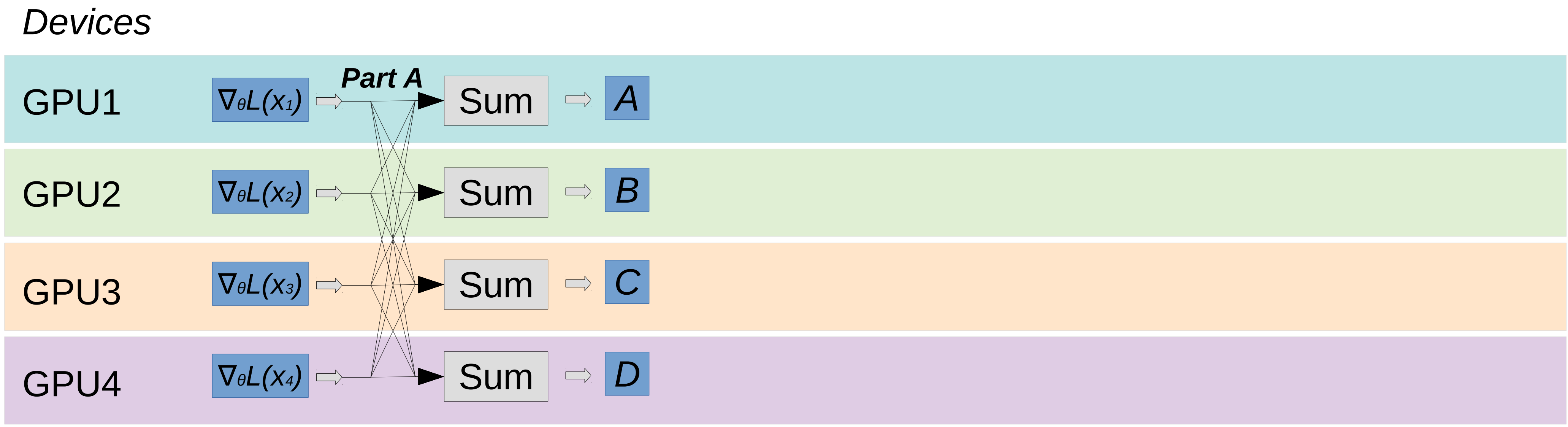

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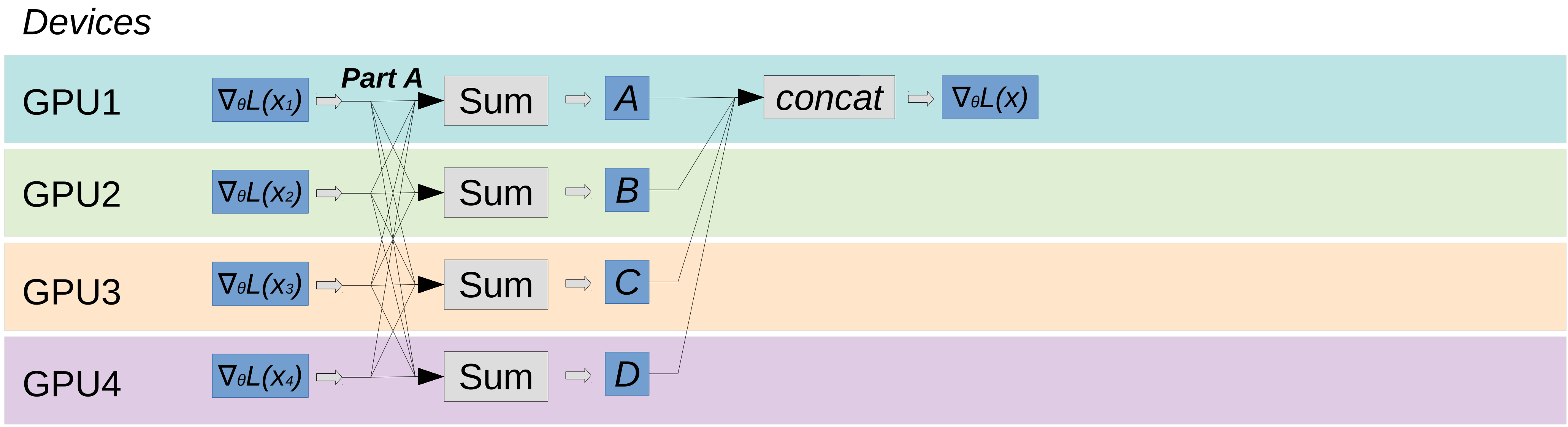

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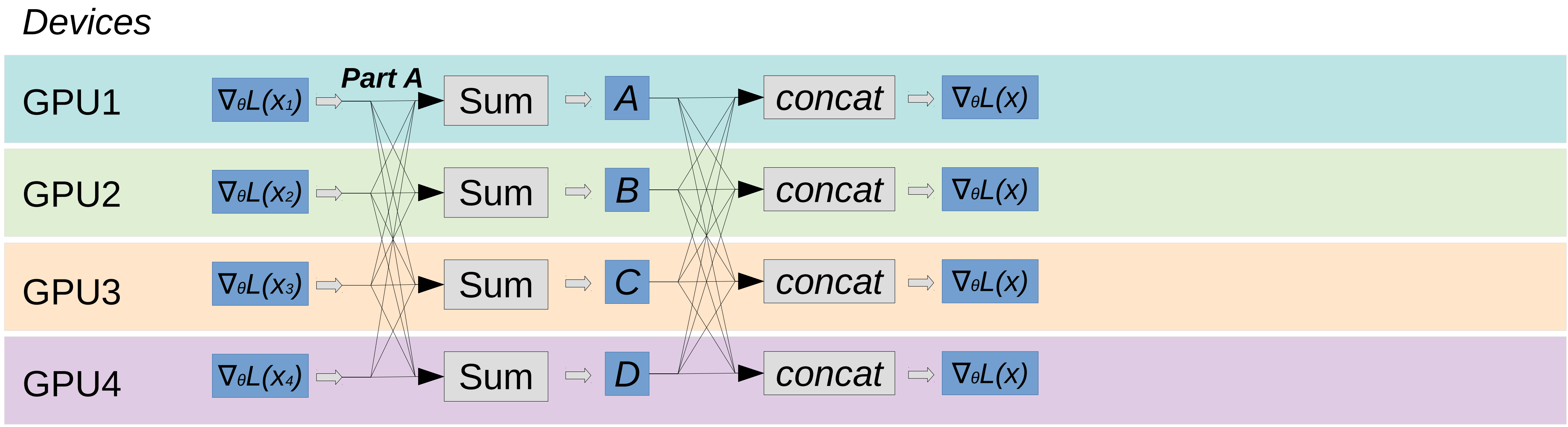
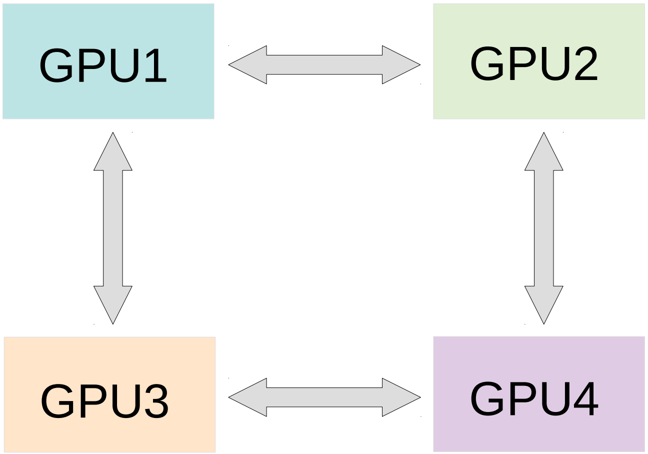


Ring allreduce

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



Ring topology

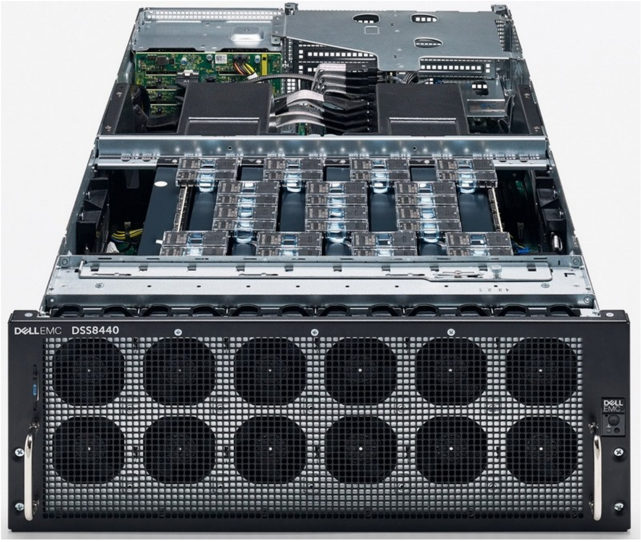


Image: graphcore ipu server

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

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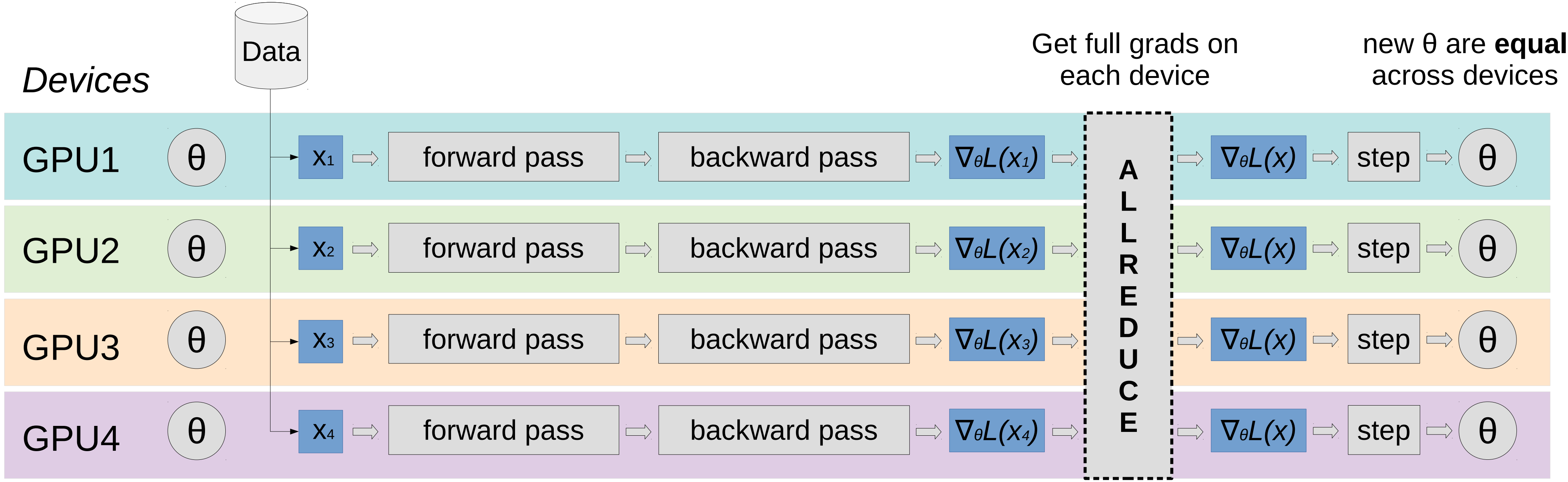
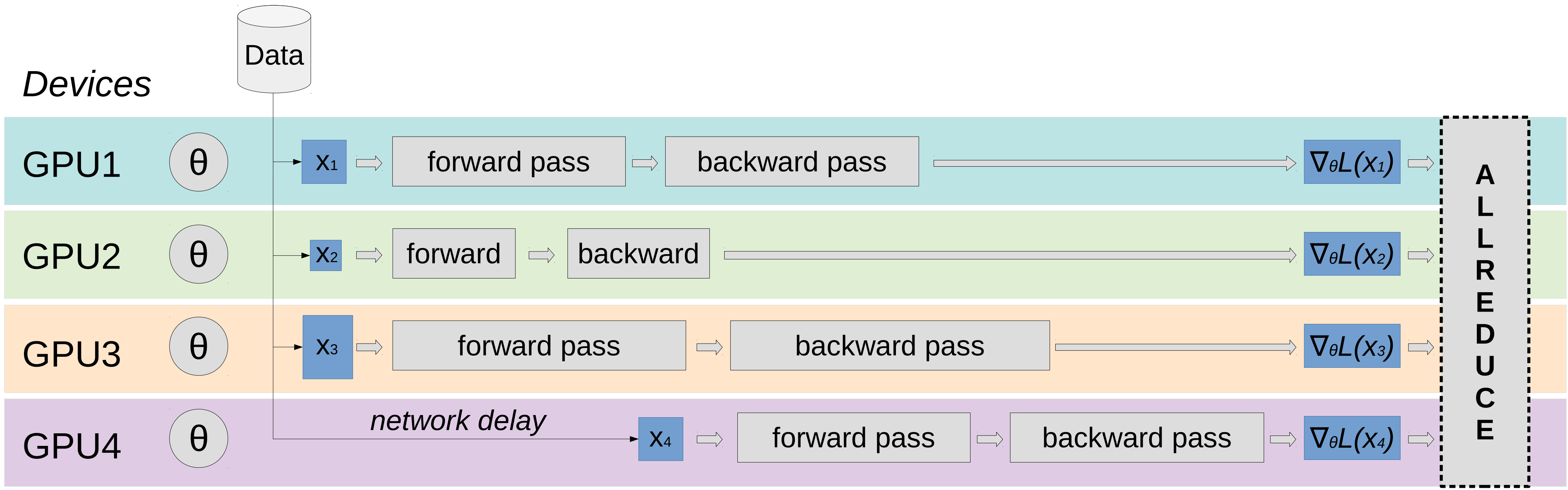


Advanced data parallel vs reality

arxiv.org/abs/1706.02677

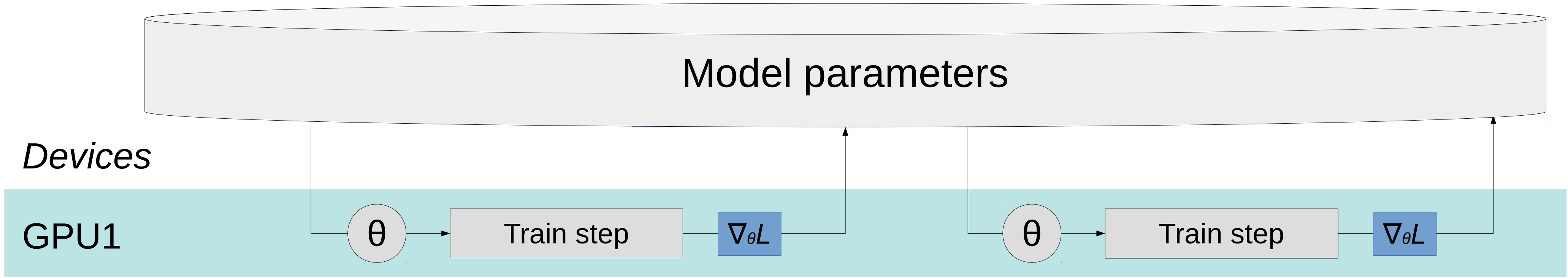
Each gpu has different processing time & delays
Q: can we improve device utilization?



Asynchronous data-parallel training

HOGWILD! arxiv.org/abs/1106.5730

Idea: remove synchronization step alltogether, use parameter server



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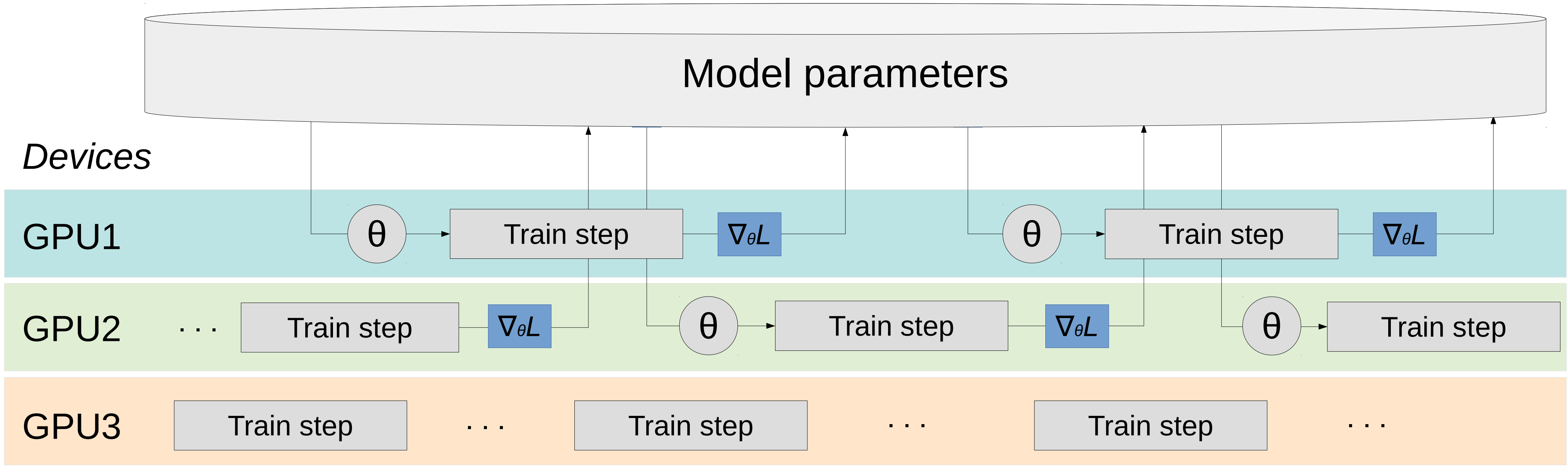

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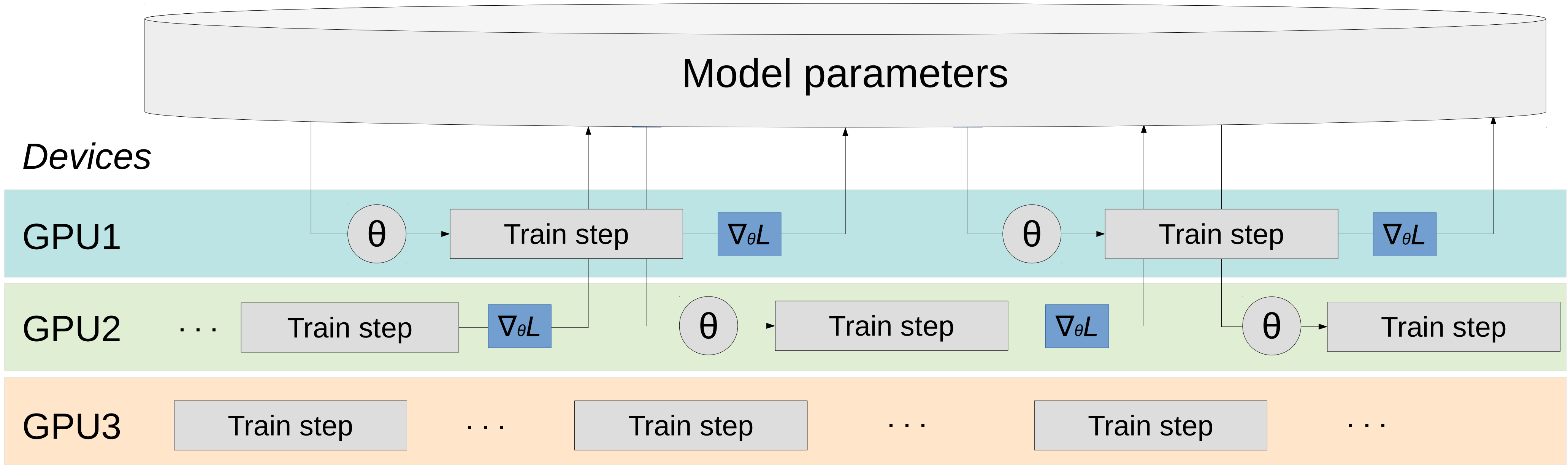

Q: have we lost anything by going asynchronous?

Asynchronous data-parallel training

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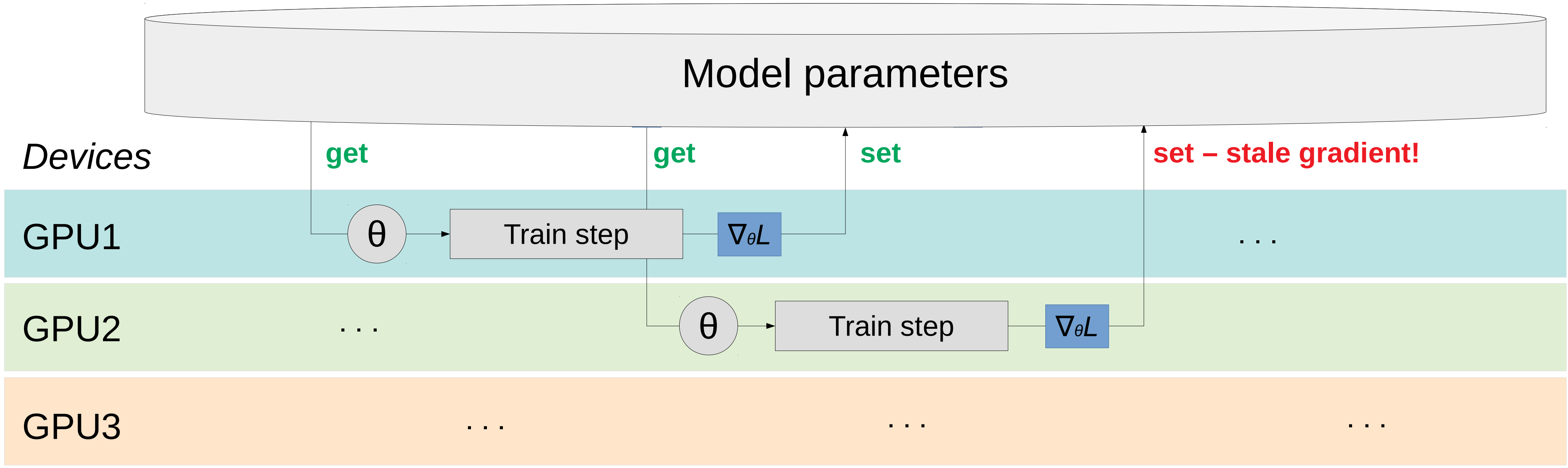


Correction for staleness: arxiv.org/abs/1511.05950 & many others

Data-parallel Reinforcement Learning

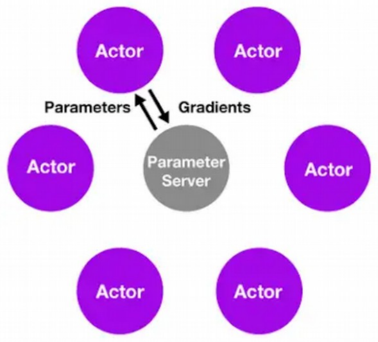
Synchronous data-parallel: A. Stooke & P. Abbeel, 2018 tinyurl.com/gtc-parallel-rl

Asynchronous data-parallel:

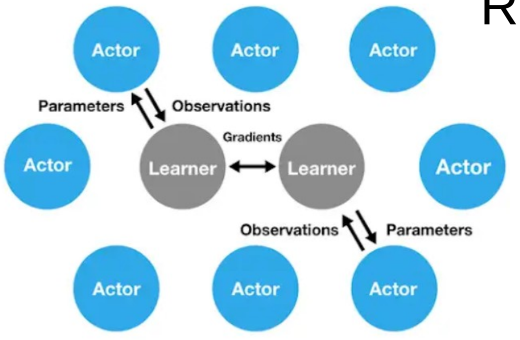
Asynchronous methods for deep RL: arxiv.org/abs/1602.01783

Distributed asynchronous data-parallel:

IMPALA: arxiv.org/abs/1802.01561
R2D2: openreview.net/forum?id=r1lyTjAqYX
SEED RL: arxiv.org/abs/1910.06591



A3C



IMPALA - Multiple Learners

More on this on the distributed RL lecture!

</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

Chapter 2: Model-parallel training

Q: What if a model is larger than GPU?

Model-parallel training

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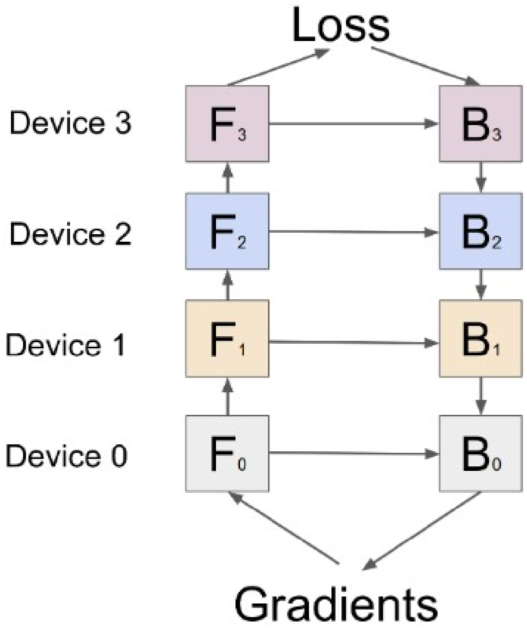
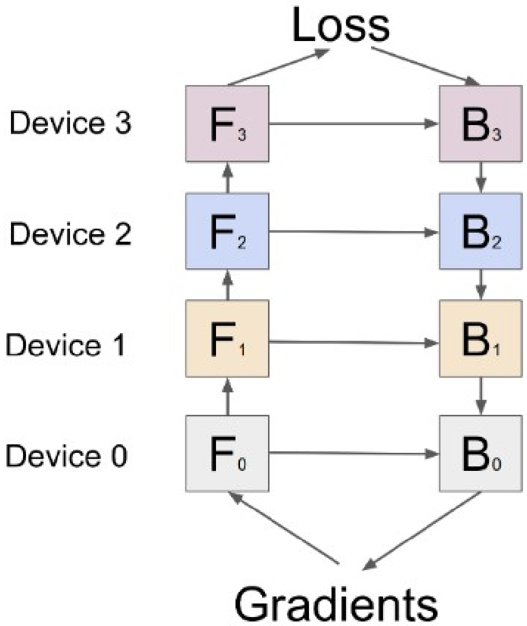
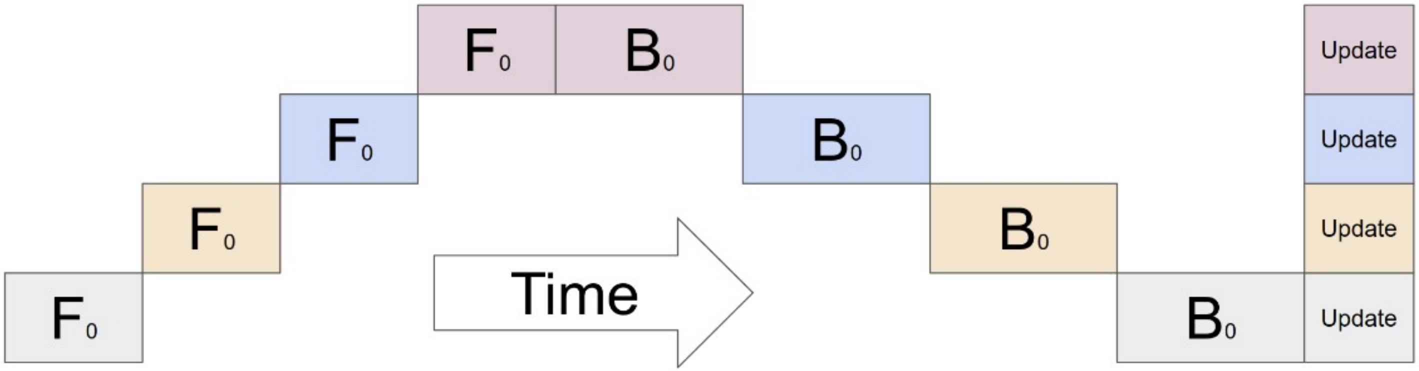


Model-parallel training

Q: What if a model is larger than GPU?





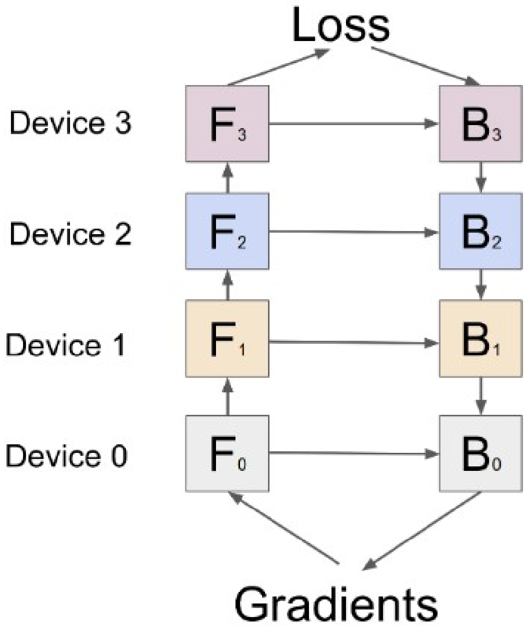
model size: O(N)
throughput: O(1)

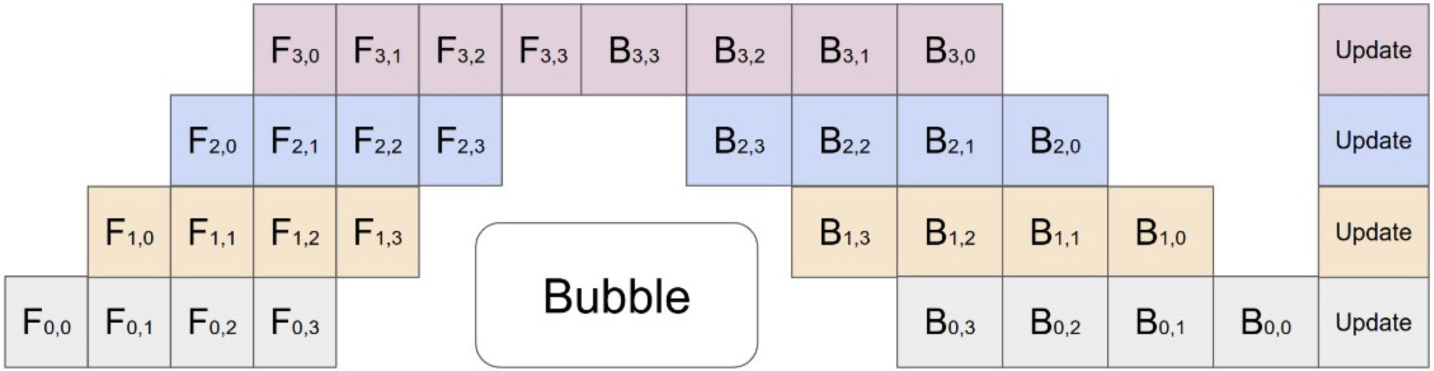
Q: Can we go faster?

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)





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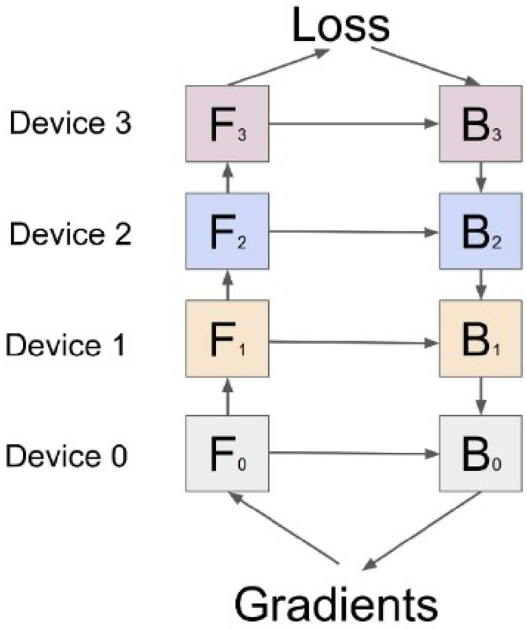
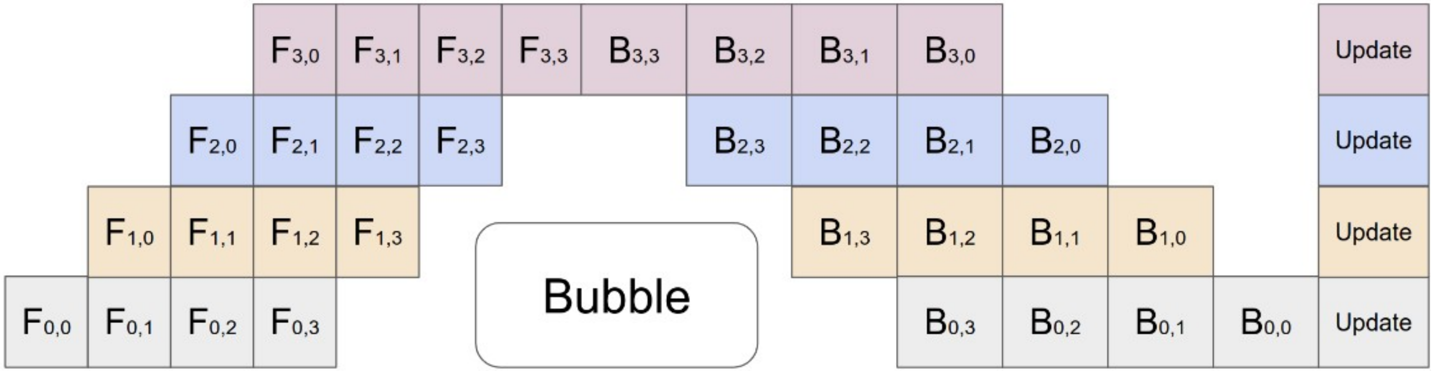




model size: O(n)
throughput: O(n) – with caveats

Q: Even faster?

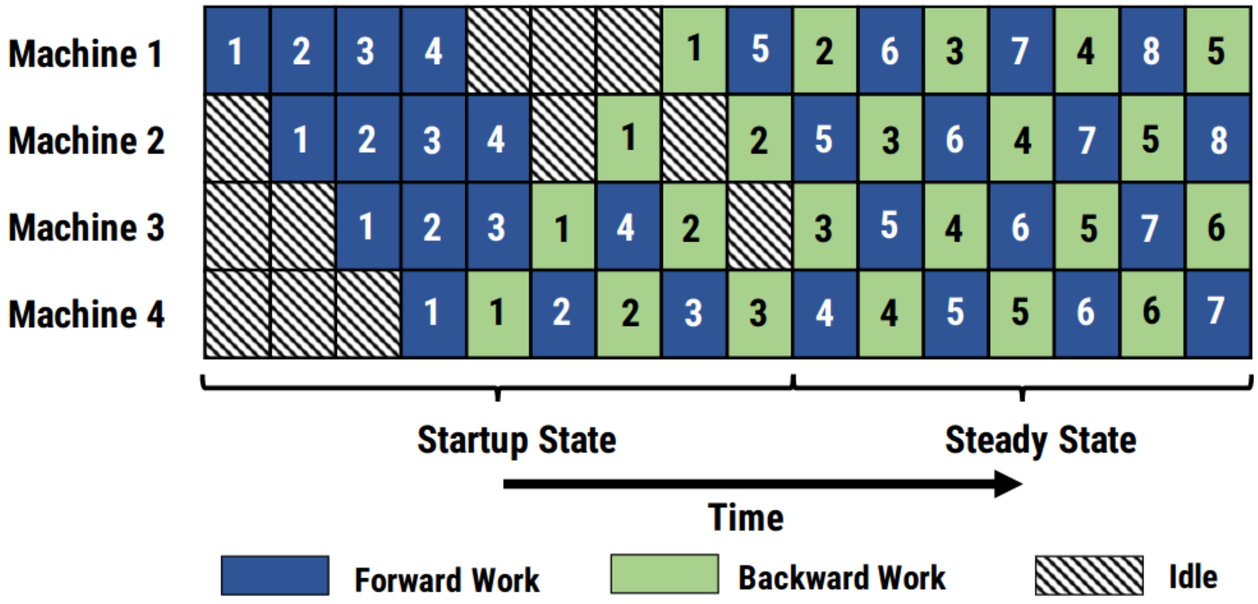
Pipeline-parallel training

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



</Model-parallel>

+ model larger than GPU
+ faster for small
***** typical size: 2-8 gpus
- model partitioning is tricky
- latency is critical, go buy nvlink
except for PipeDream

Tutorials:

- Simple pipelining in PyTorch – tinyurl.com/pytorch-pipelining
- Distributed model-parallel with torch RPC - https://tinyurl.com/torch-rpc
- Advanced but still in active development - github.com/microsoft/DeepSpeed

Virtual batch / virtual pipeline

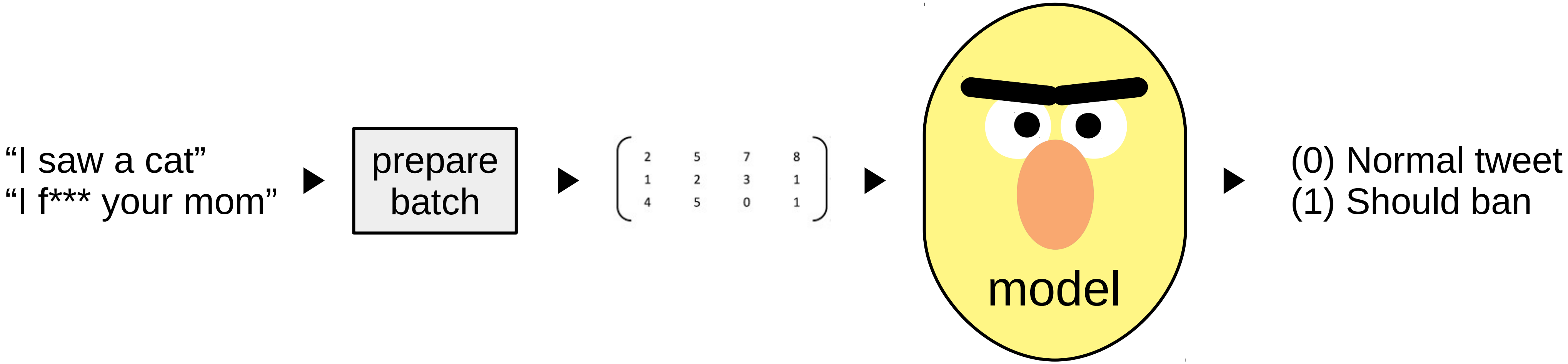
ёж, открой доску

Case study: DeepSpeed

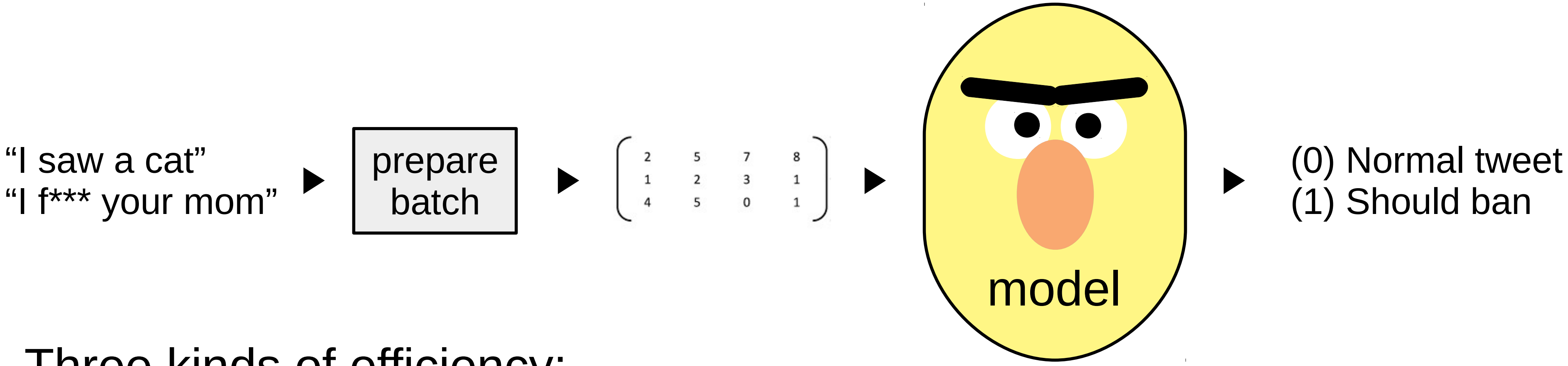
Source: microsoft

Chapter 3: What about inference?

Case study: text classification



Case study: text classification



Three kinds of efficiency:

Model Size
(mega)bytes

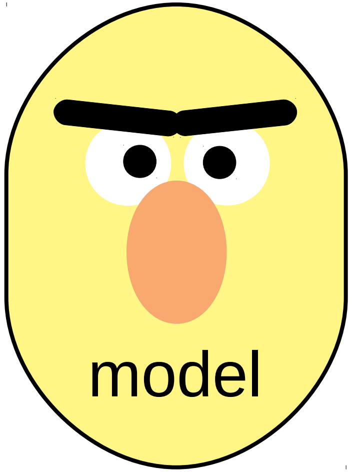
Case study: text classification

"I saw a cat"
"I f*** your mom"

▶ prepare batch ▶

$$\begin{bmatrix} 2 & 5 & 7 & 8 \\ 1 & 2 & 3 & 1 \\ 4 & 5 & 0 & 1 \end{bmatrix}$$

▶



▶

(0) Normal tweet
(1) Should ban

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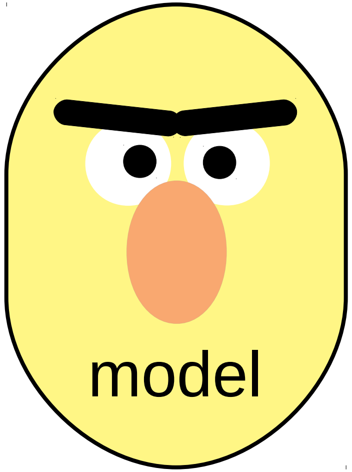

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Three kinds of efficiency:

Model Size
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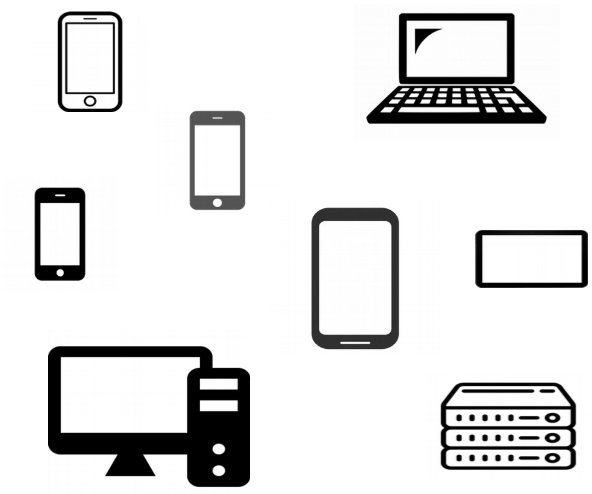
Throughput
samples/second

Latency
ms@percentile

Scenario 1: inference server



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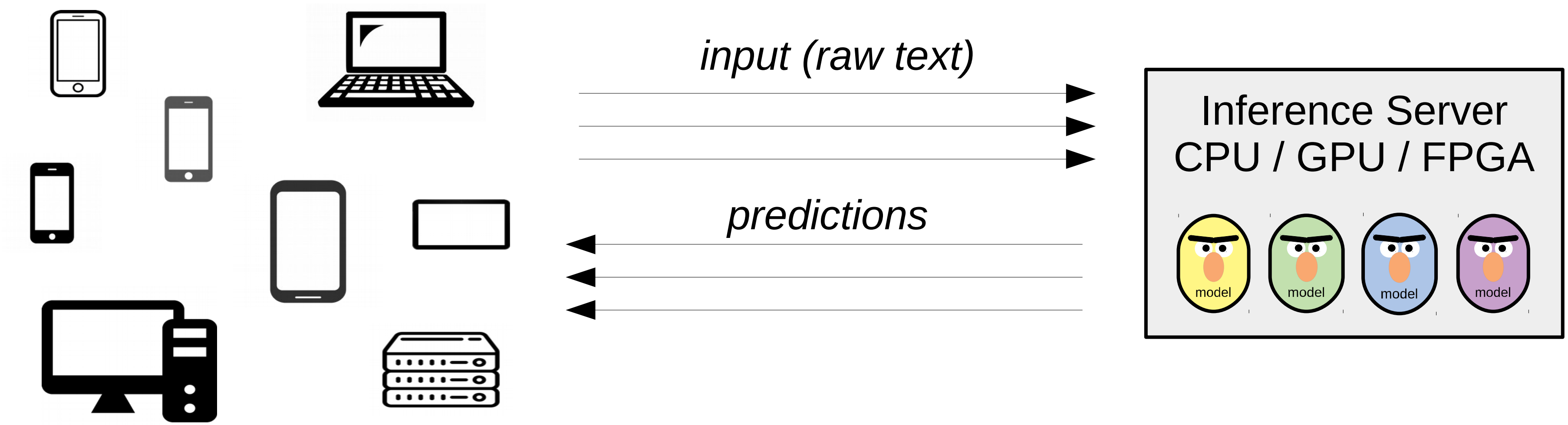

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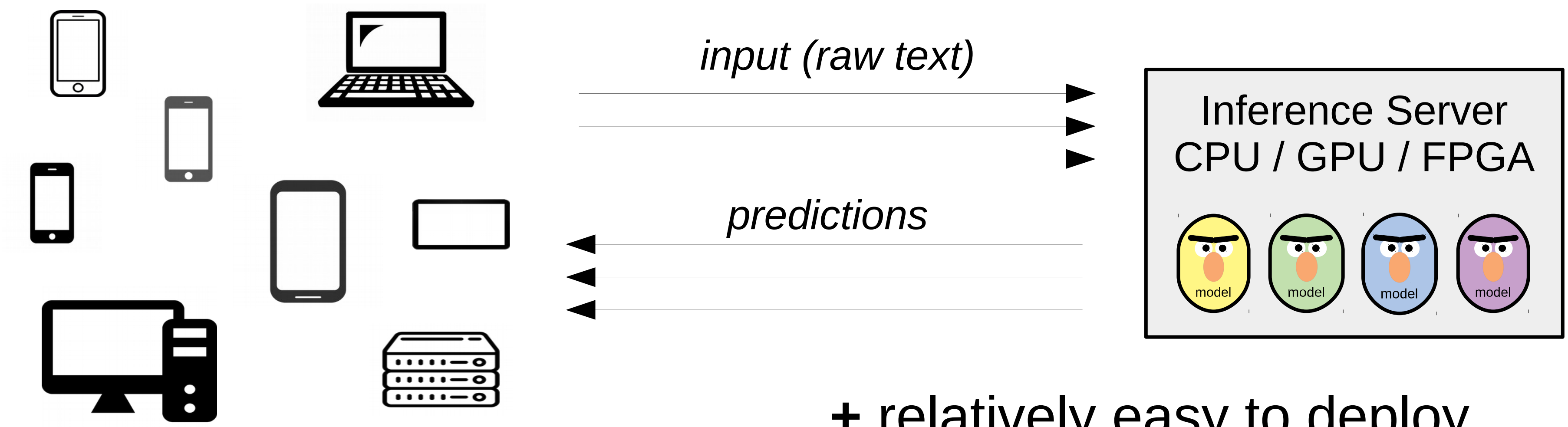
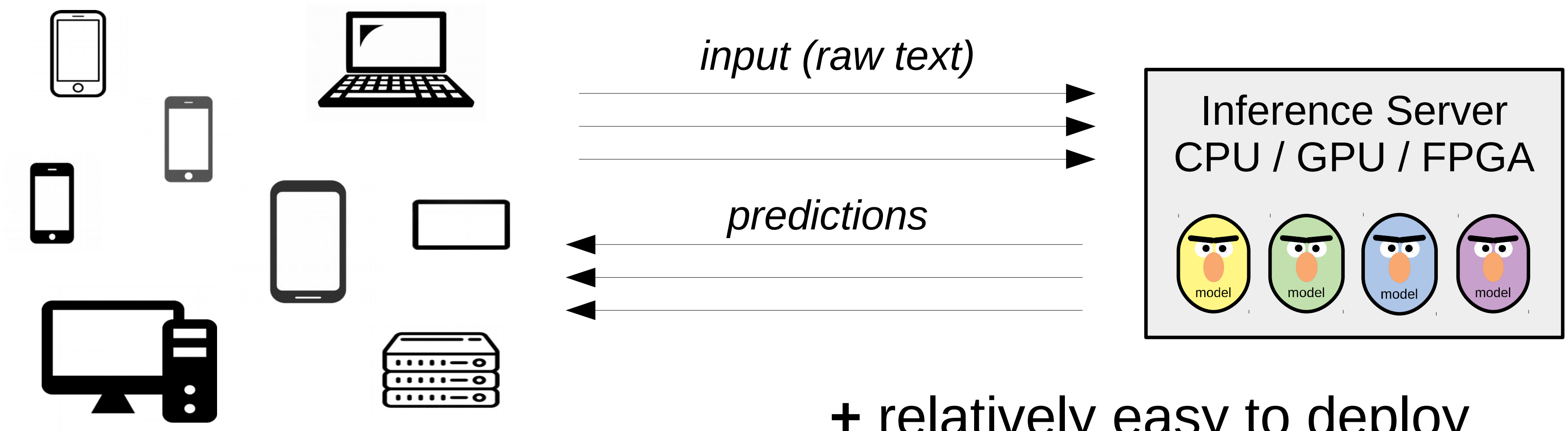


+ relatively easy to deploy
+ you control model & inference
+ clients don’t run compute

Scenario 1: inference server



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– you pay for each inference
– clients can't work offline
– network latency

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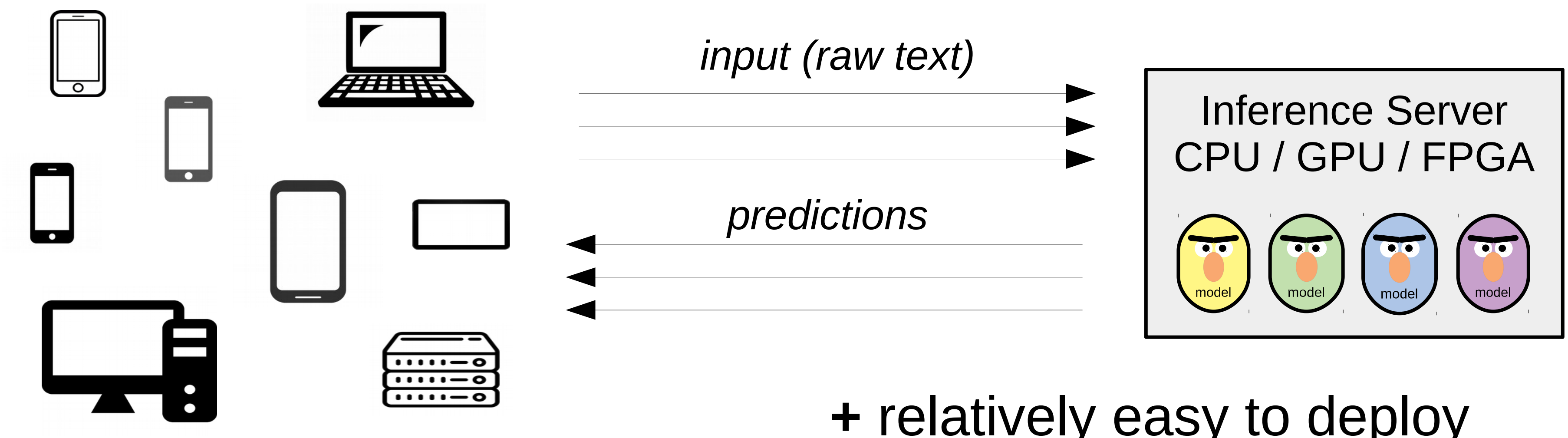

Which is the most important?

+ relatively easy to deploy
+ you control model & inference
+ clients don’t run compute

– you pay for each inference
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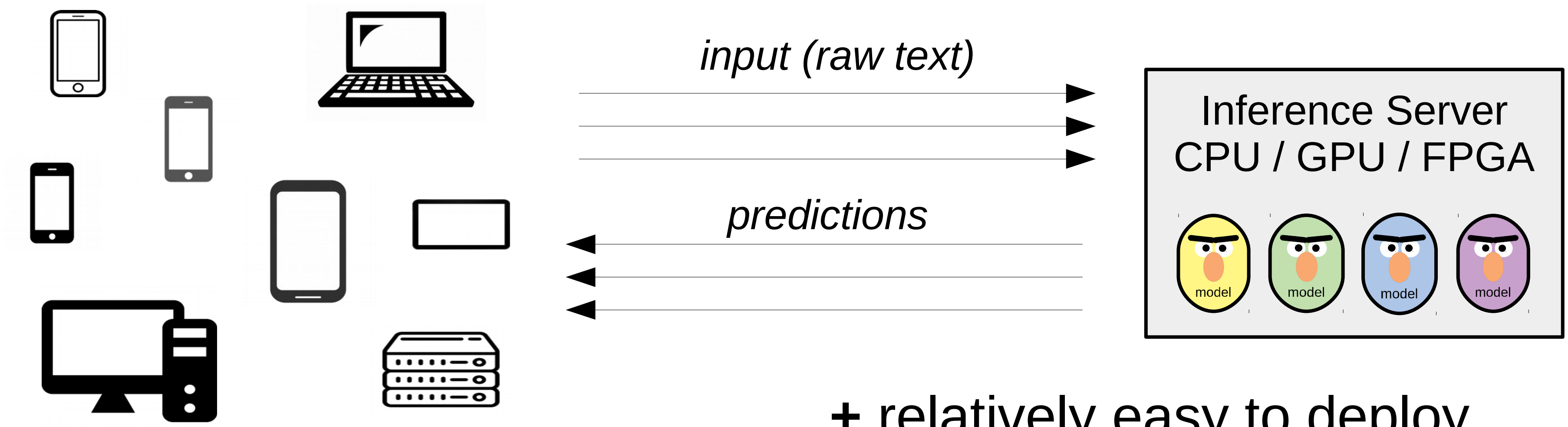

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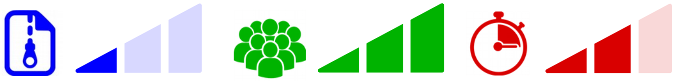
Priorities:



Note: smaller model = you can fit more models in the same memory

Scenario 1: inference server

- Group inputs into batches (e.g. by length)
  improves throughput at the cost of latency
- Multiple servers with load balancing
  improves throughput at the cost of your budget :)

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Popular frameworks:	priorities
TensorFlow Serving	efficiency $\ll$ developer time
TensorRT Inference Server (Triton)	efficiency $\approx$ developer time
 Custom model-dependent code	efficiency $\gg$ developer time

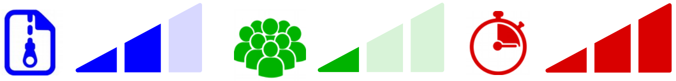
Scenario 2: local inference

Preload model onto a dedicated device, infer locally using that device

Typical use cases:

- Parallel speech recognition
- “Smart” cameras
- Autonomous drones
- Self-driving cars

Priorities:



Scenario 3: web/smartphone app

- Load model weights on the fly and infer locally
  - Model size is critical for both you and the user

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- Autonomous machine translation (tinyurl.com/yandex-translate-app)
- Pix2pix demo in a browser (https://affinelayer.com/pixsrv)

- Priorities: 

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- Priorities:

- Popular frameworks:

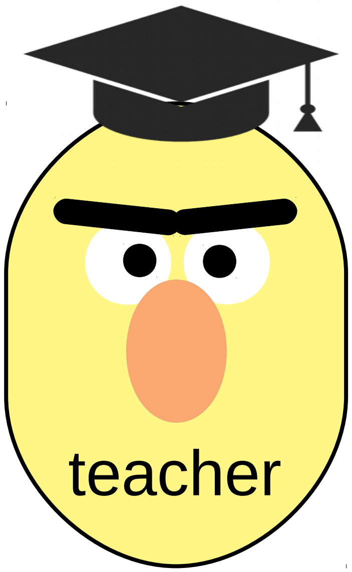
	Platform
TensorFlow.js	All modern browsers
CoreML	iOS devices
NNAPI	Android devices

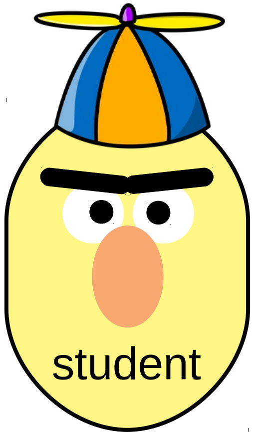
Chapter 4: how do I compress my model?

Compression by Distillation

Distillation…
Heard that word before?

Compression by Distillation

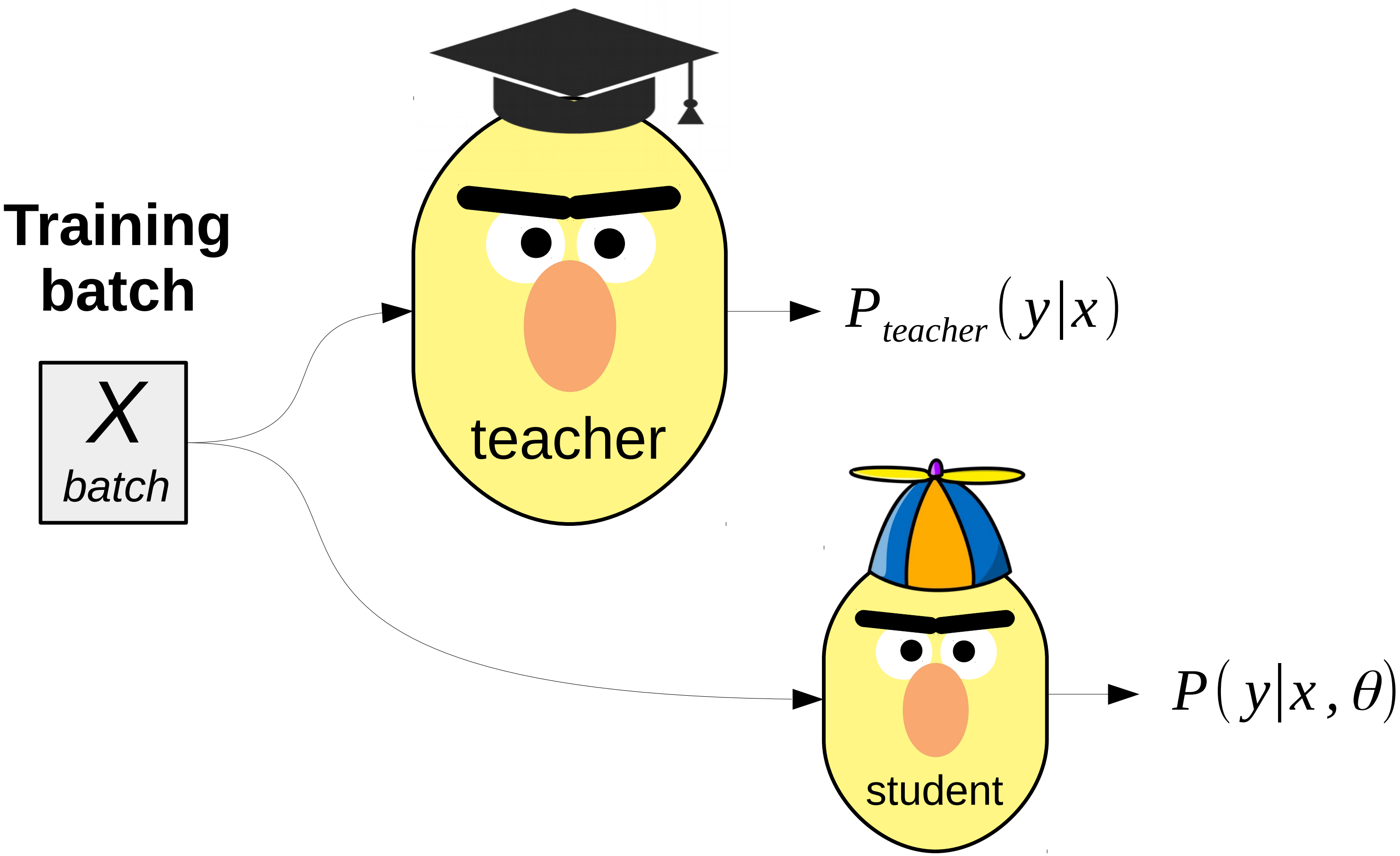




First, get the best performing model regardless of size

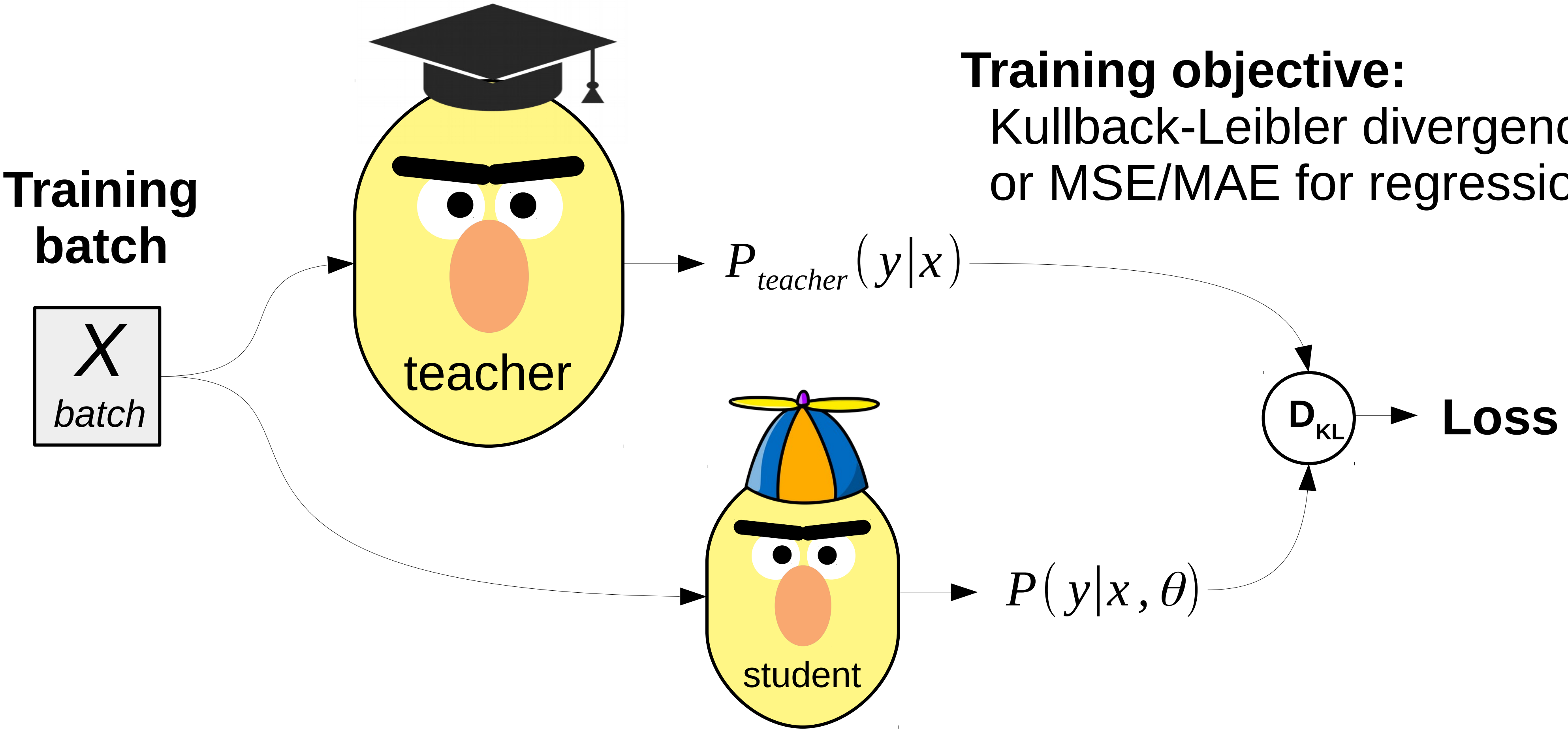
Then, train a more compact model to approximate it!

Compression by Distillation



Compression by Distillation

Training objective:
Kullback-Leibler divergence
or MSE/MAE for regression



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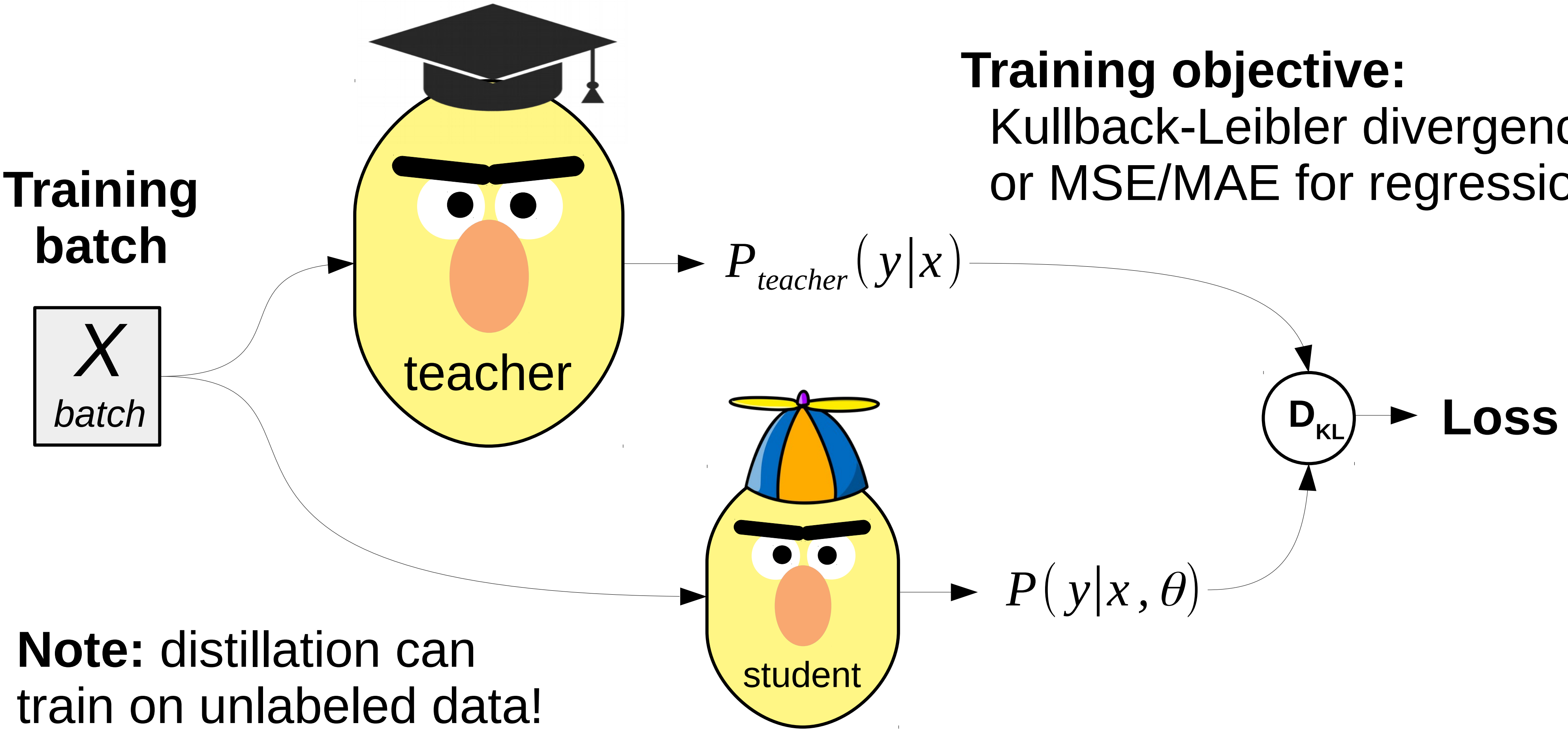


Note: distillation can
train on unlabeled data!

Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
  e.g. DistillBERT: https://arxiv.org/pdf/1910.01108.pdf

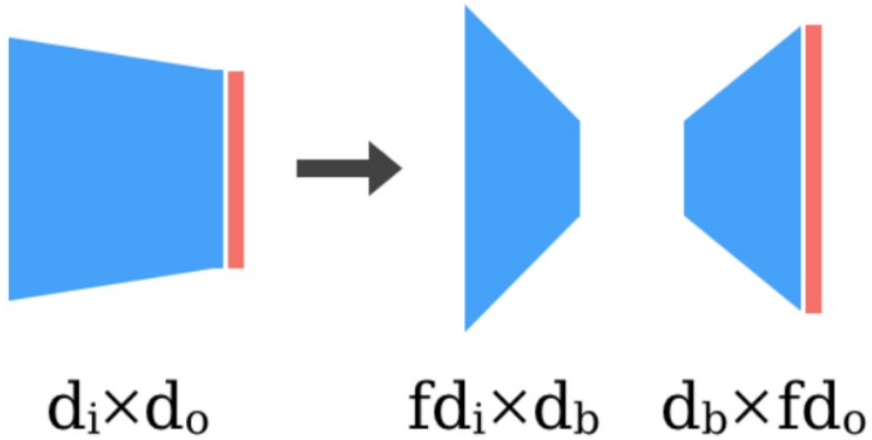
Same as BERT-base, but with *half as many layers* (and ≈1.5 times faster)

Model	# param. (Millions)	Inf. time (seconds)
ELMo	180	895
BERT-base	110	668
DistilBERT	66	410

Model	**Score**	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B	WNLI
ELMo	68.7	44.1	68.6	76.6	71.1	86.2	53.4	91.5	70.4	56.3
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89.0	53.5
DistilBERT	77.0	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
  Factorized: product of smaller matrices or tensors



Images: https://openreview.net/pdf?id=_zx8Oka09eF

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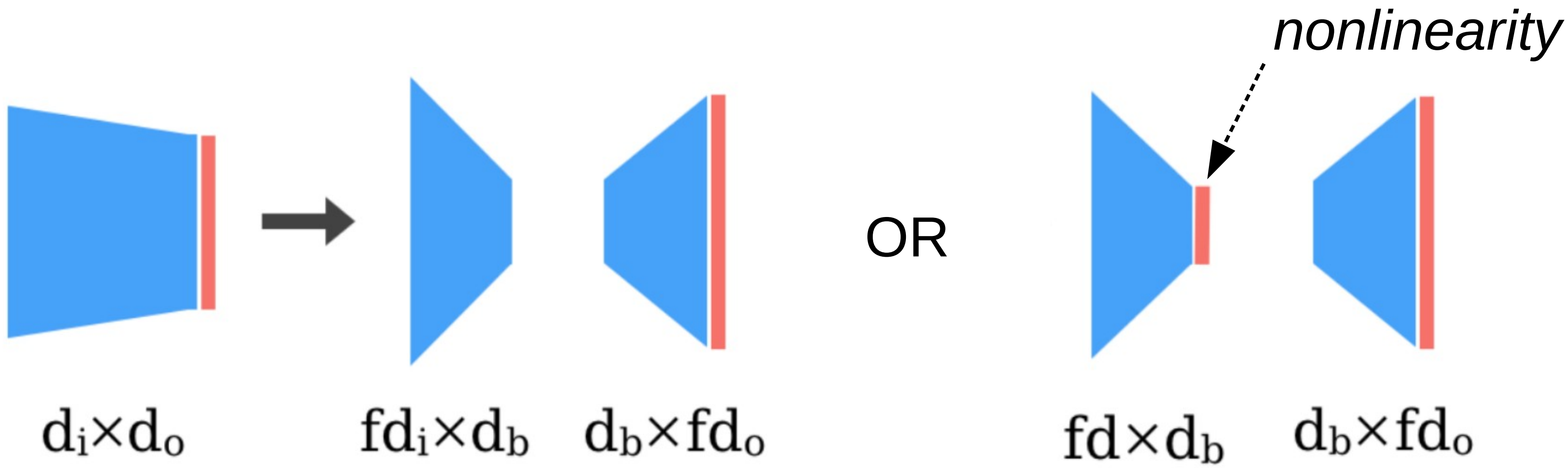

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Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
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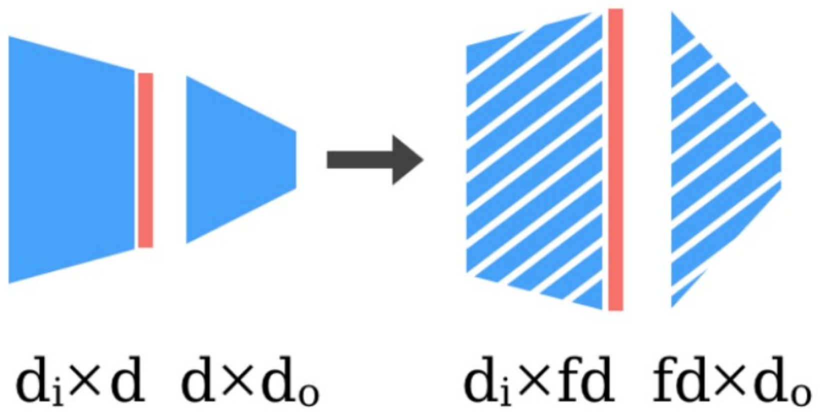
  Sparse: only a small (random) subset of weights are nonzero



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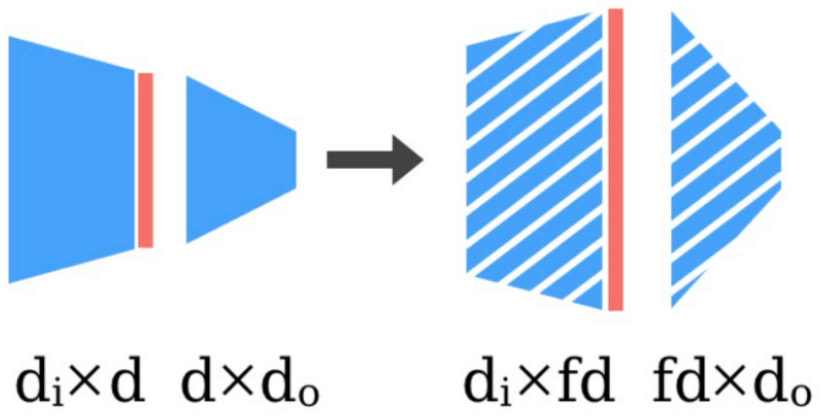

Q: how to store sparse weights?

Images: https://openreview.net/pdf?id=_zx8Oka09eF

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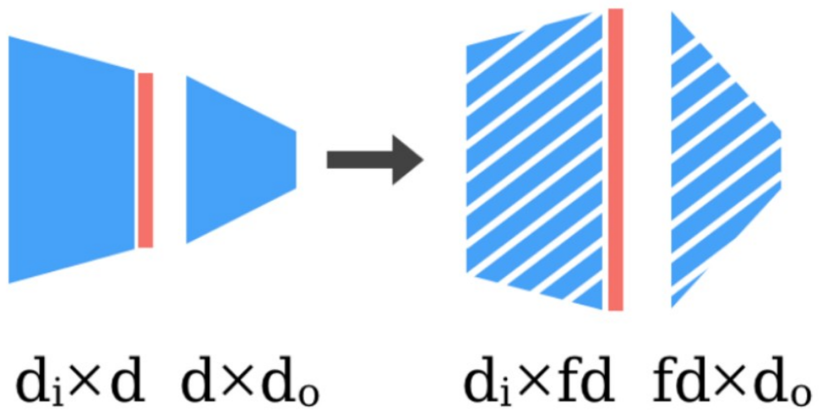

Storage: only store random seed and nonzero weights.

Compute: sparse matrix multiply

Images: https://openreview.net/pdf?id=_zx8Oka09eF

Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
  Factorized: product of smaller matrices or tensors
  Sparse: only a small fraction of weights are nonzero
  Read more: https://openreview.net/pdf?id=_zx8Oka09eF
  Also: factorized embeddings https://arxiv.org/abs/1901.10787
  Also also: small-world sparse weights graphs for RNNs
  https://tinyurl.com/openai-blocksparse

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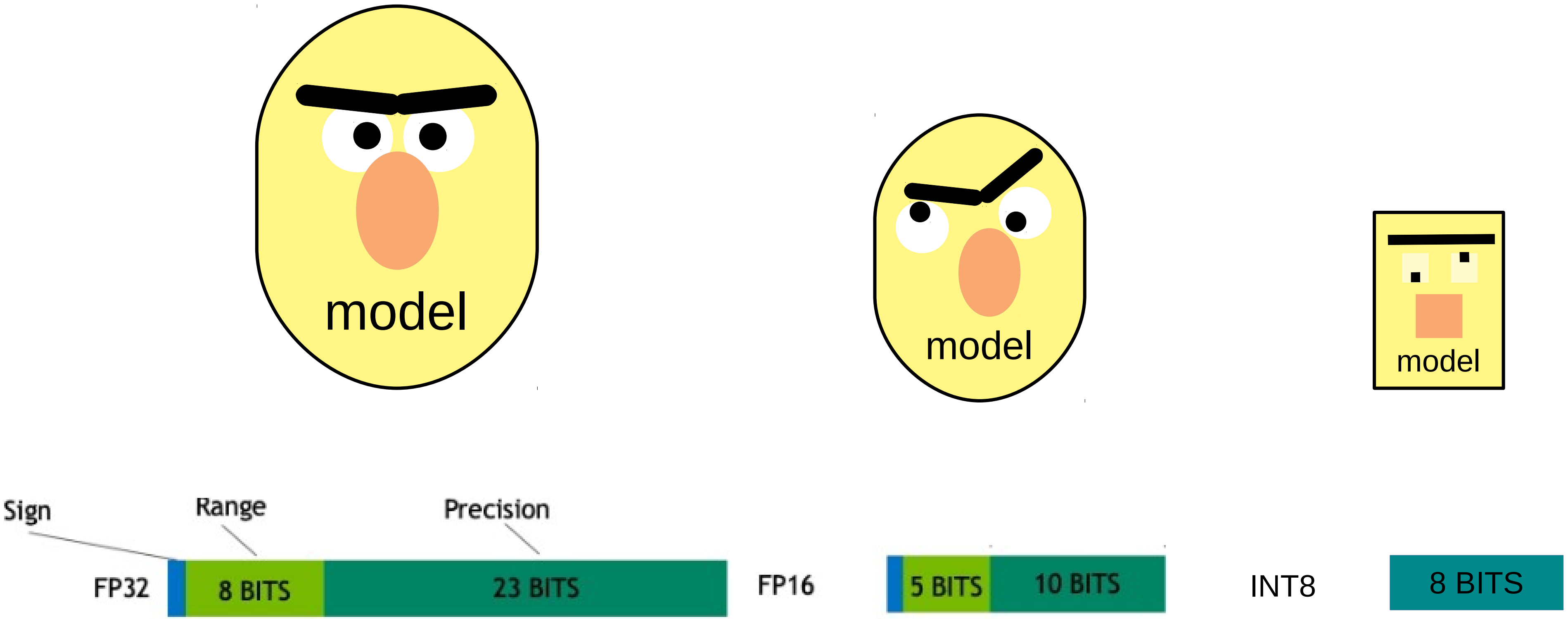
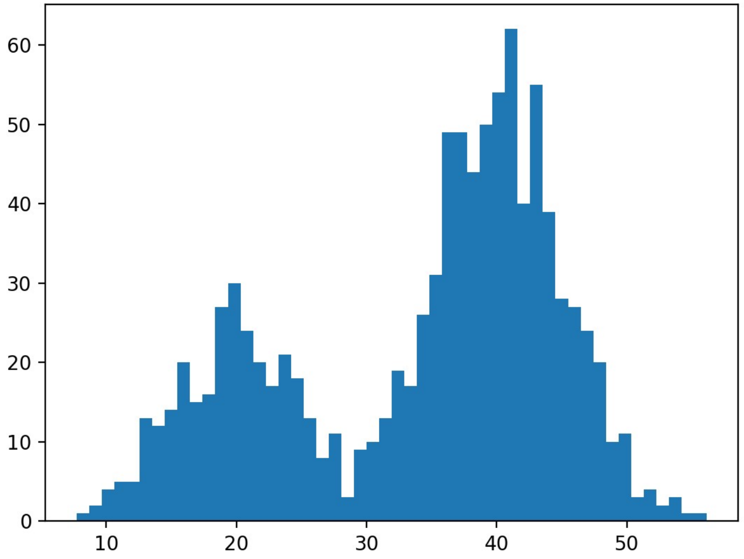
  Also: factorized embeddings https://arxiv.org/abs/1901.10787
  Also also: https://tinyurl.com/openai-blocksparse
- More distillation tricks:
  - Ensemble distillation https://arxiv.org/abs/1702.01802
  - Dropout distillation http://proceedings.mlr.press/v48/bulo16.pdf
  - Co-distillation https://arxiv.org/abs/1804.03235

Compression by quantization

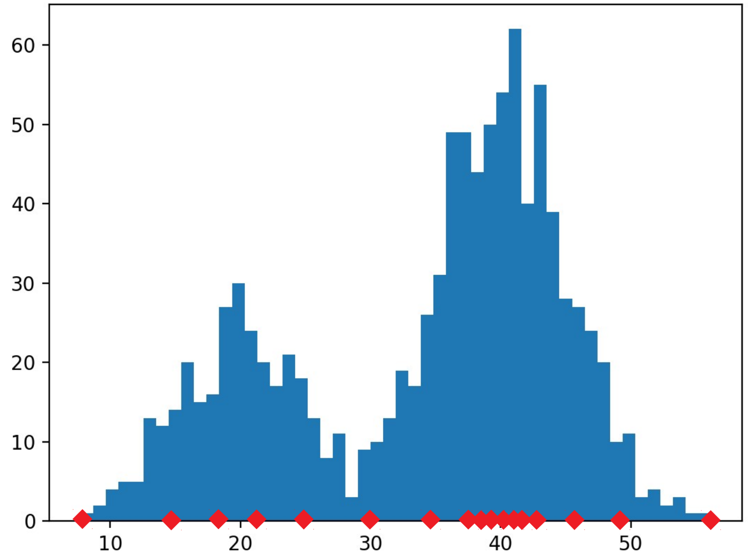


Basic quantization



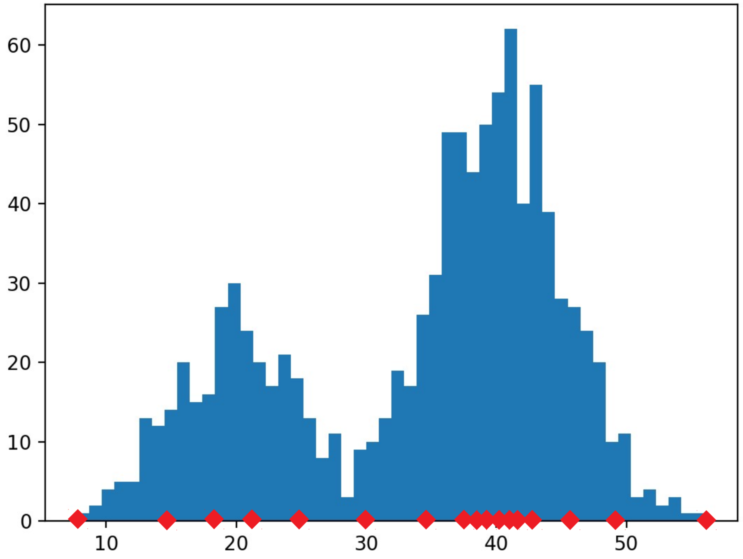
Consider weights as a distribution

Basic quantization



Compute a grid of percentiles

Basic quantization



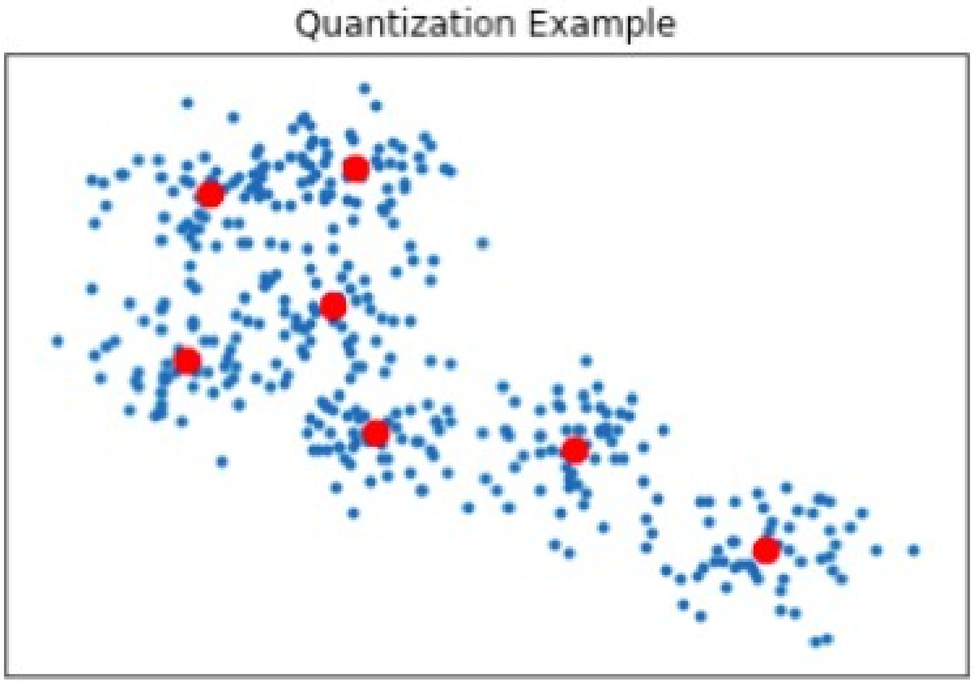
percentiles (32-bit)

Index (4- or 8-bit) of nearest percentile for each weight

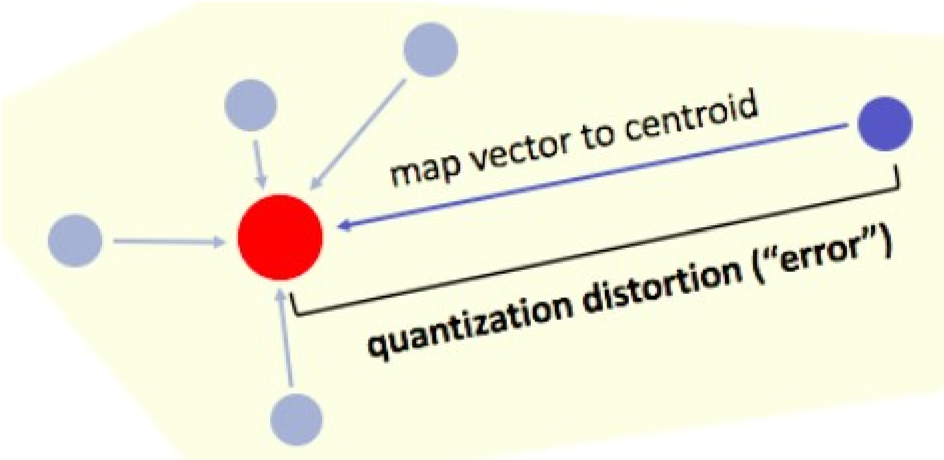
Store each weight as its nearest percentile

High-dimensional case

Quantize entire vectors as K-means



quantizer = KMeans(n_clusters=7).fit(X)



Images: Jeremy Jordan

OPQ, AQ, LSQ

Product **Q**uantization

Split vectors into chunks, quantize each chunk separately

Orthogonal **P**roduct **Q**uantization

First run orthogonal transform, then product quantization

http://kaiminghe.com/publications/cvpr13opq.pdf

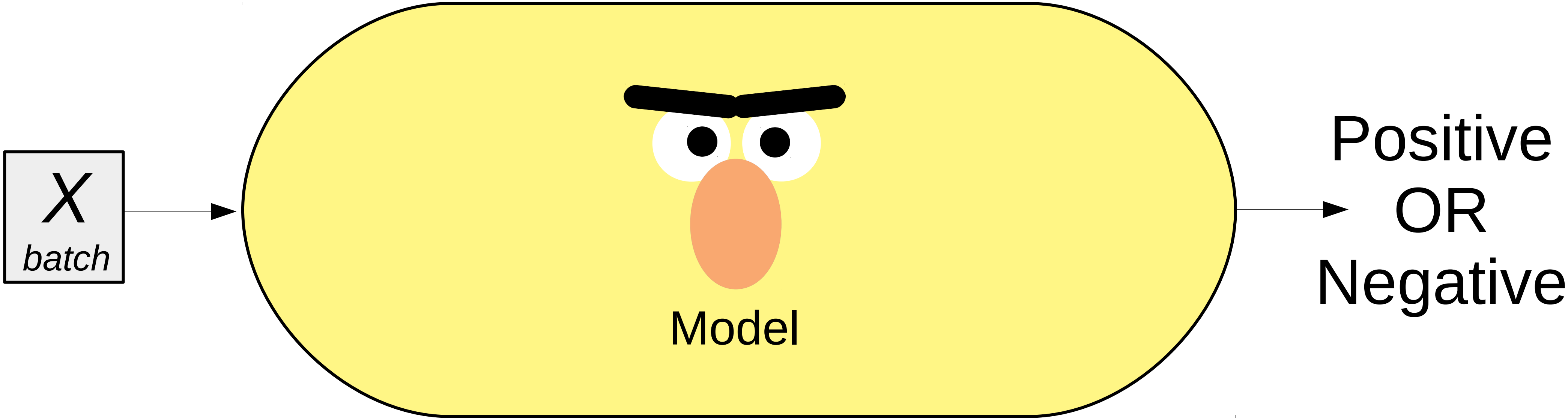
More:

Additive **Q**uantization https://tinyurl.com/babenko-aq-pdf

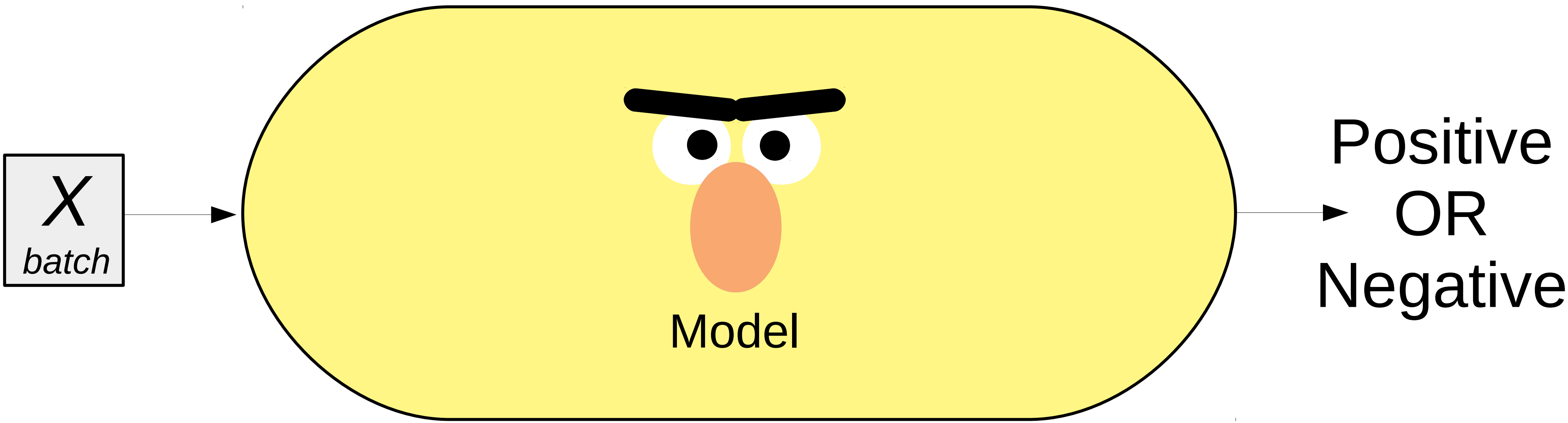
Local **S**earch **Q**uantization https://tinyurl.com/martinez-lsq-pdf

Images: Jeremy Jordan

Acceleration by cascading

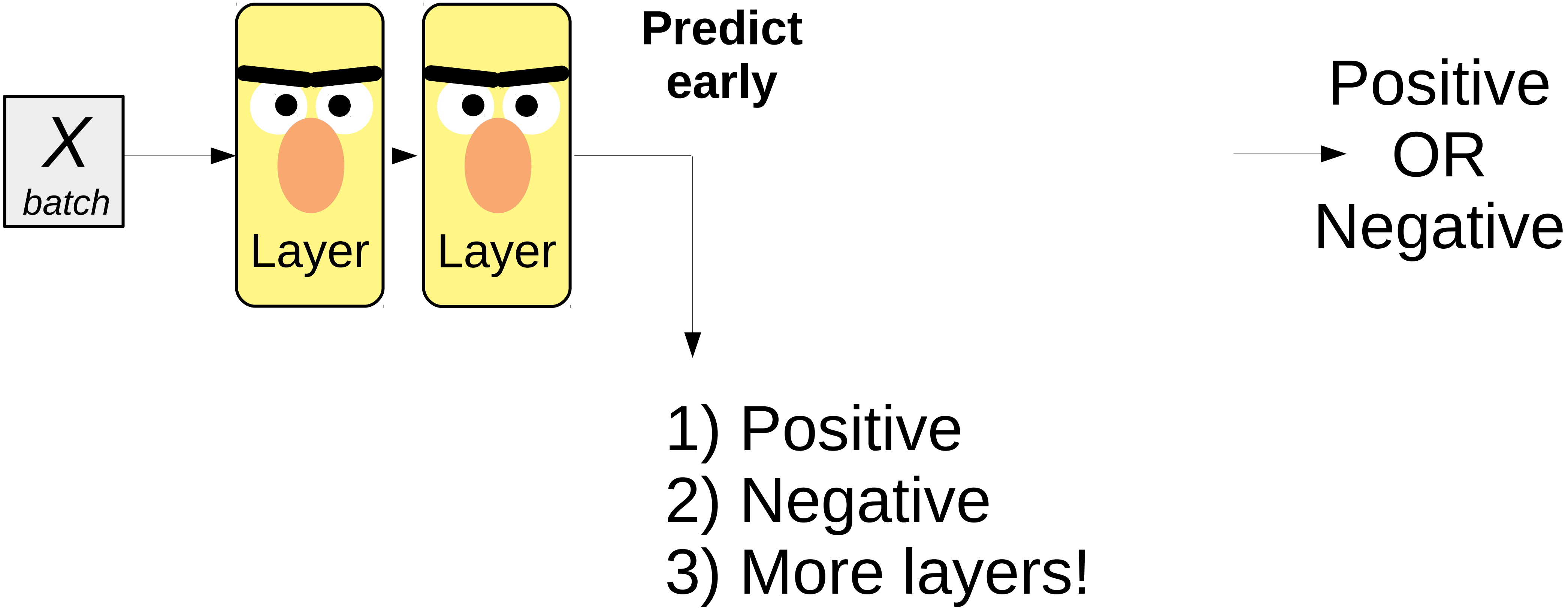


Acceleration by cascading



Do we really need every layer
all the time?

Acceleration by cascading



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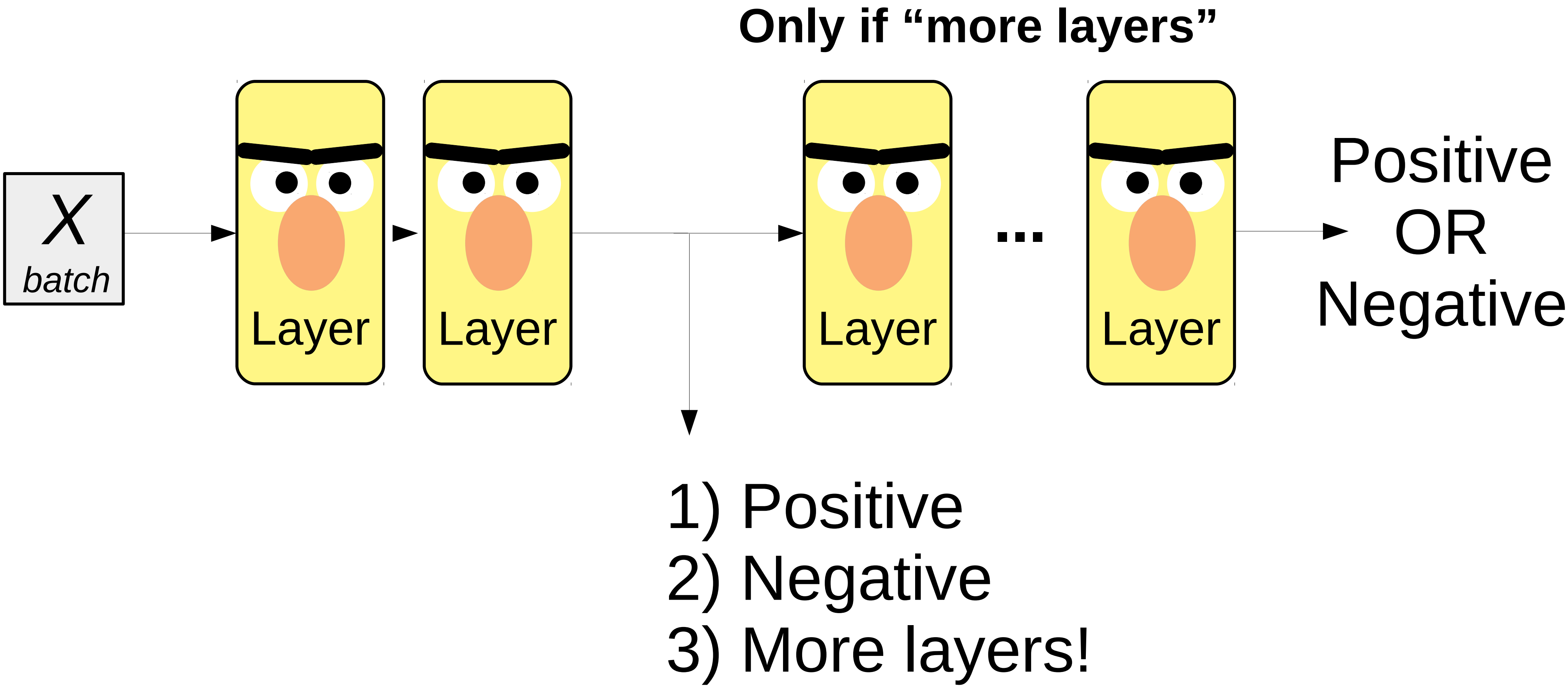
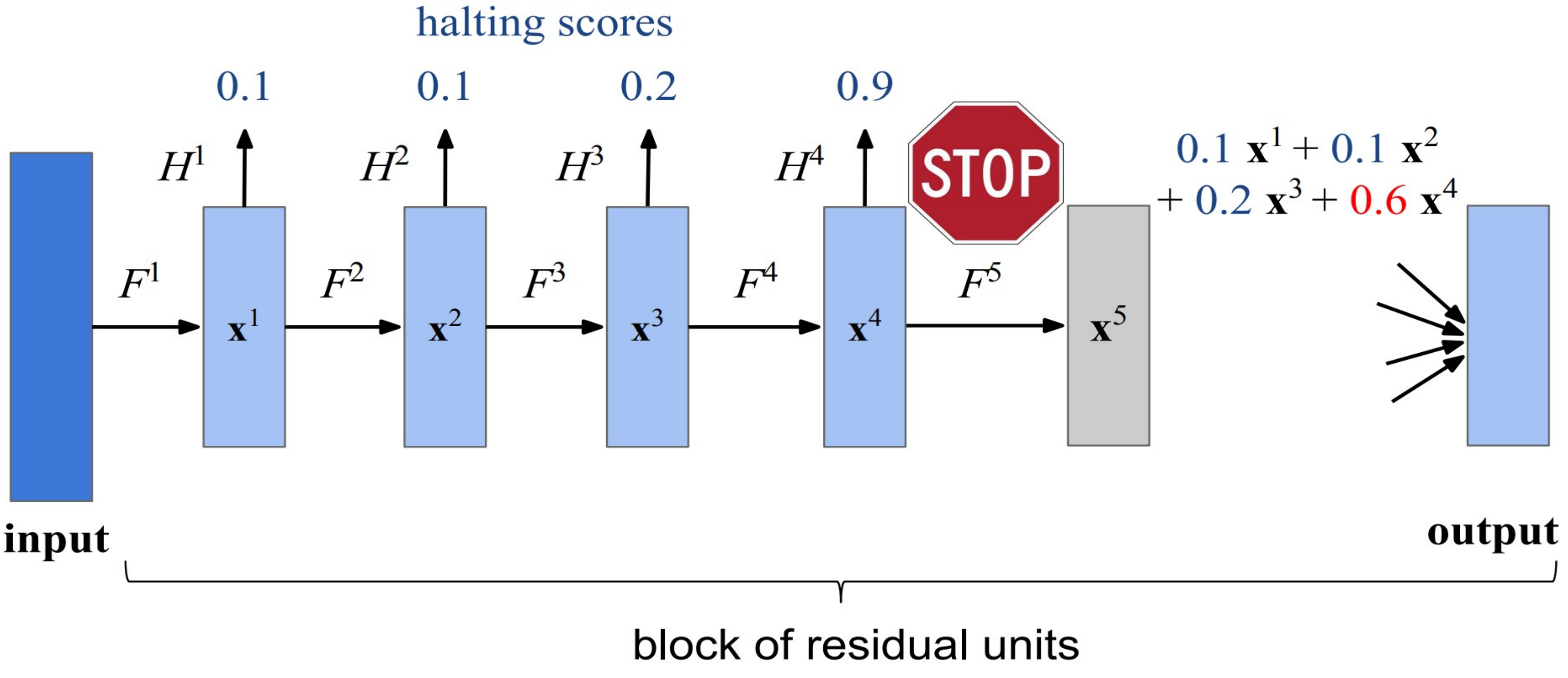


Adaptive Computation Time



Origina ACTl (for RNN)
https://arxiv.org/abs/1603.08983

Spatial ACT (conv)
https://tinyurl.com/sact-pdf

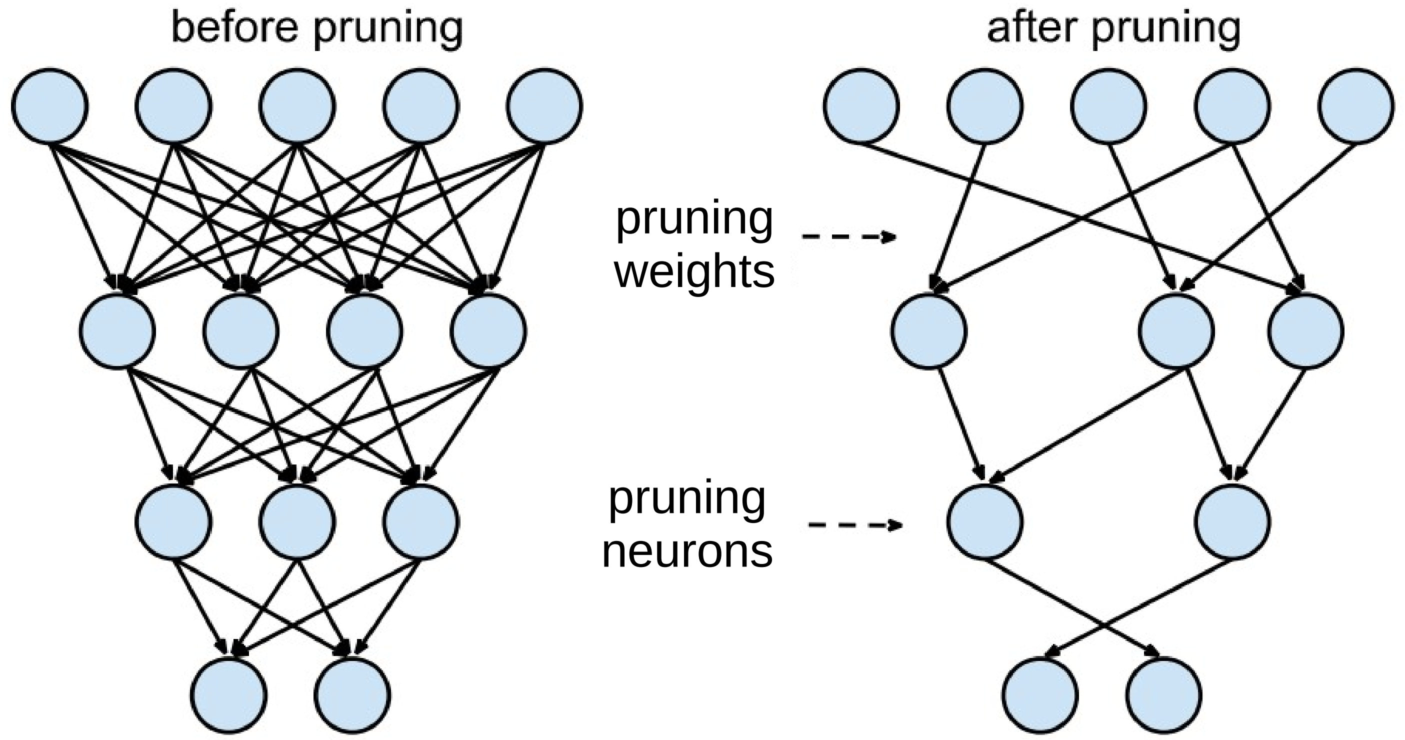
ACT Transformers
https://arxiv.org/abs/1807.03819

Compression by sparsification

Do we really need all D by D weights?

Compression by pruning

Do we really need all D by D weights?



Magnitude pruning

Drop ~5% smallest weights
from each layer every 1000 steps
(and keep training)

Reminds you of something?

Magnitude pruning

Drop ~5% smallest weights
from each layer every 1000 steps
(and keep training)

Reminds you of something?

See ML course, Optimal Brain Damage

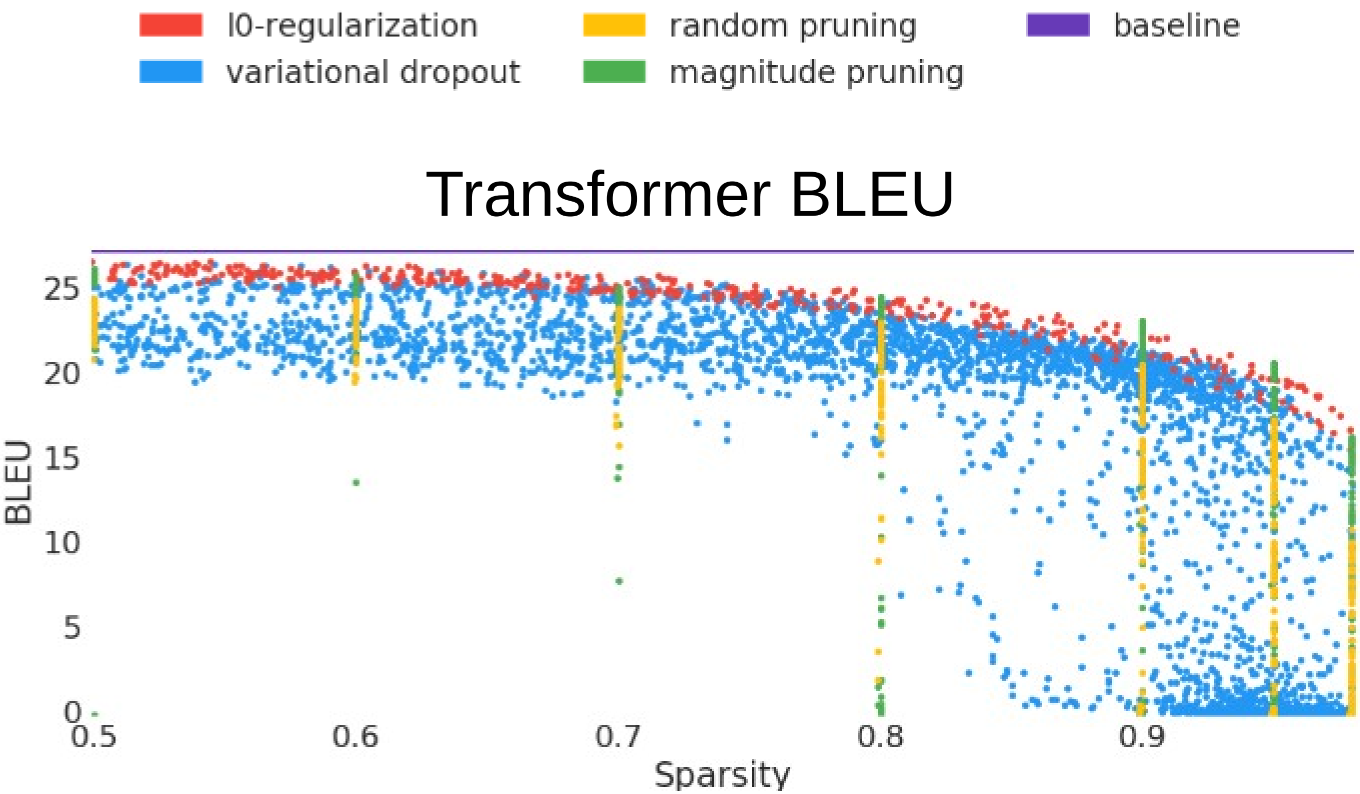
Pruning with L_0 regularization

Add a special regularizer that encourages dropping unnecessary weights

Whiteboard time!

Read more: https://arxiv.org/abs/1712.01312
Alternative: https://arxiv.org/abs/1701.05369

Which one works best?



Source https://arxiv.org/abs/1902.09574

Pruning with L_0 regularization

Add a special regularizer that encourages dropping unnecessary weights

Whiteboard time!

Pruning with L_0 regularization

Add a special regularizer that encourages dropping unnecessary weights

Can prune
- individual weights
- Individual neurons
- attention heads
- entire layers!

$$\lambda = 0.01$$

Pruning heads: https://lena-voita.github.io/posts/acl19_heads.html

Compression by sparsification

Как ужимать: prune/sparsify
можно сразу учить sparse (openai + та статья)

что умеет: только model size

Фенкс,
Квестионы?