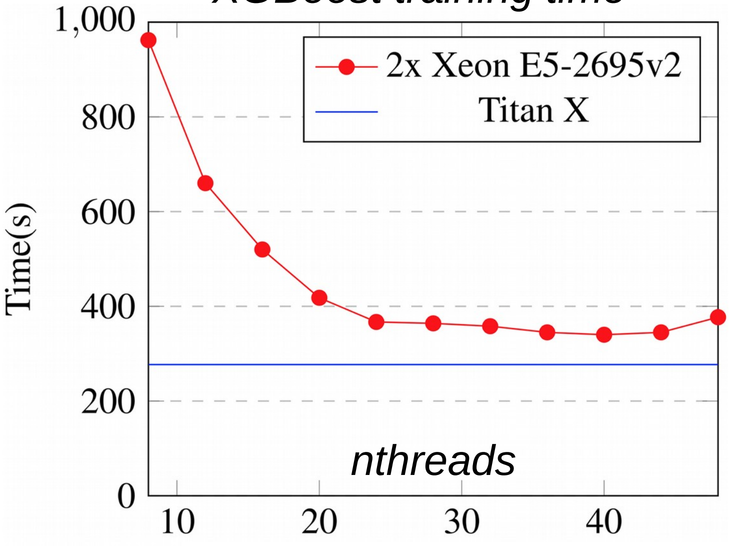
TITLESLIDE

Image sources: NVIDIA, Lena Voita, Sebastian Ruder, BytePS, Disney

Зачем это всё?

XGBoost training 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 V100 – **over 2 weeks**)*

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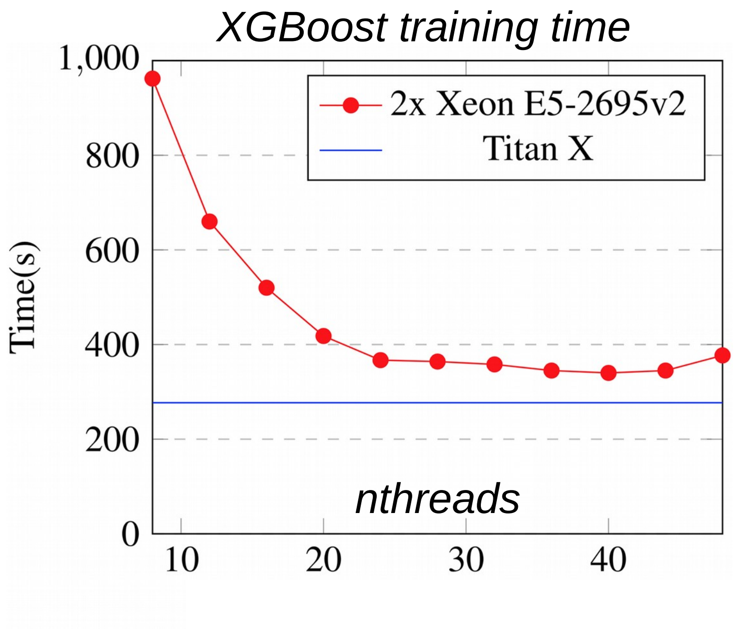

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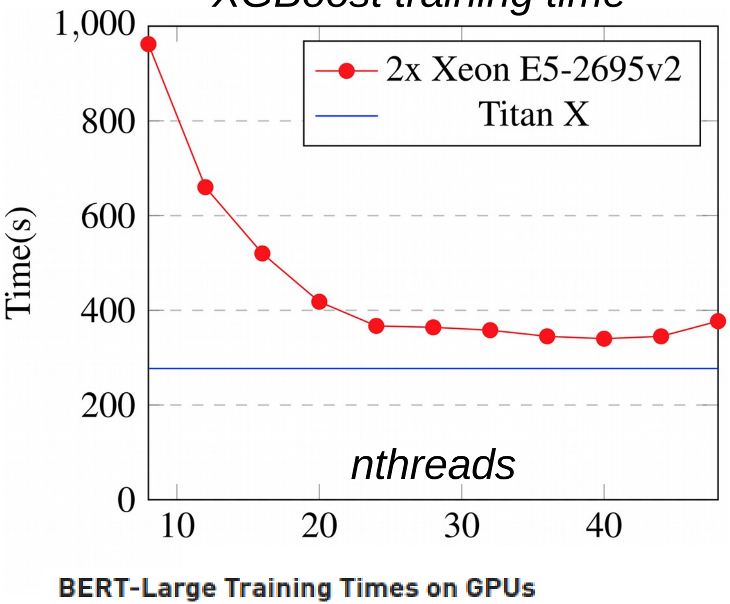
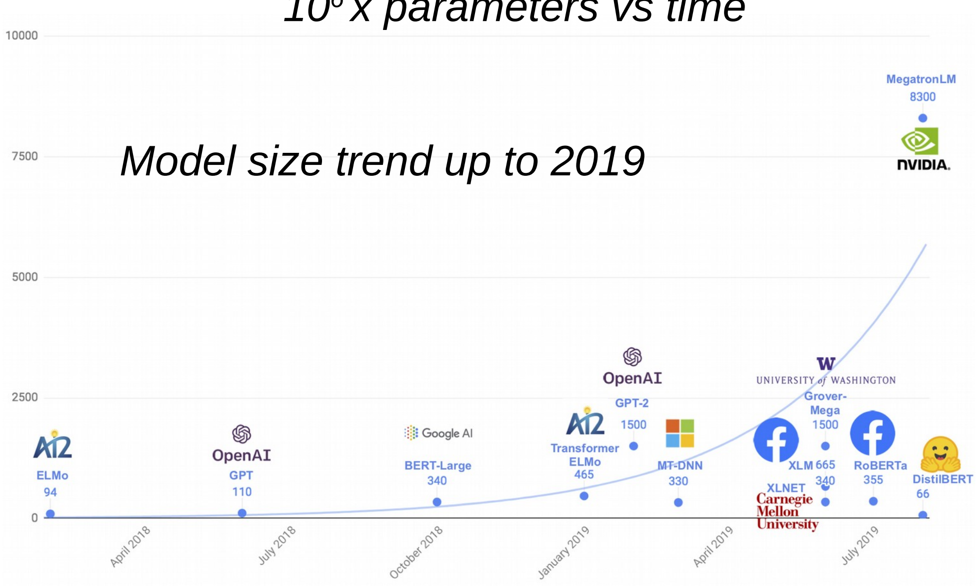


10^6 x parameters vs time



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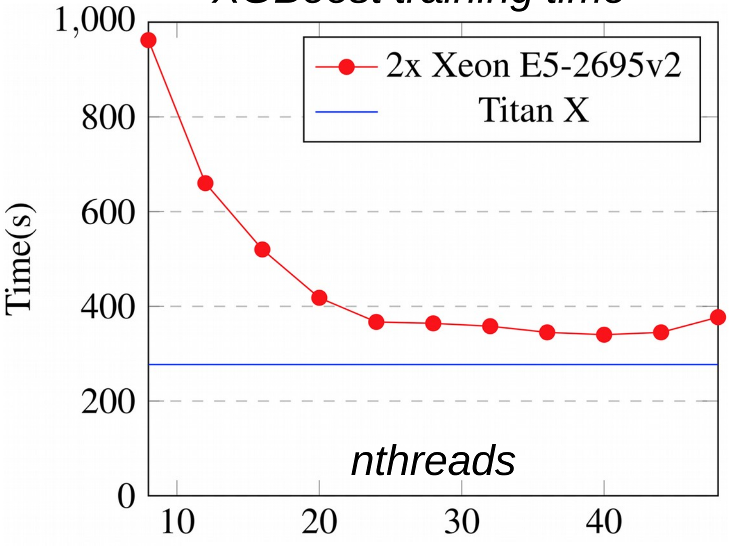

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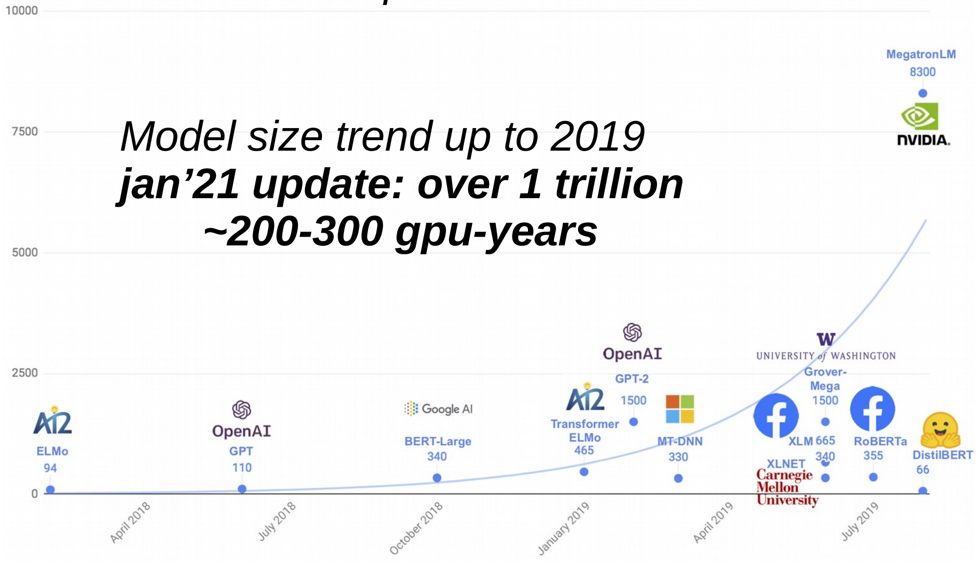

Model size trend up to 2019
jan'21 update: over 1 trillion
~200-300 gpu-years

BERT-Large Training Times on GPUs

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Зачем мы тут?

Заставить много железяк вместе учить одну модель

Зачем мы тут?

Заставить много железяк вместе учить одну модель

понять общие подходы

закодить своими руками

на python / pytorch

TL;DR this course

with sample problems

1) Distributed machine learning

Embeddings or log.regression with tons of training data

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2) Data-parallel deep learning

Train BERT-base on wikipedia in 20 minutes or less

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Train BERT-xxxxxxxxxxxlarge in less than a lifetime

TL;DR this course

with sample problems

1) Distributed machine learning

Embeddings or log.regression with tons of training data

2) Data-parallel deep learning

Train BERT-base on wikipedia in 20 minutes or less

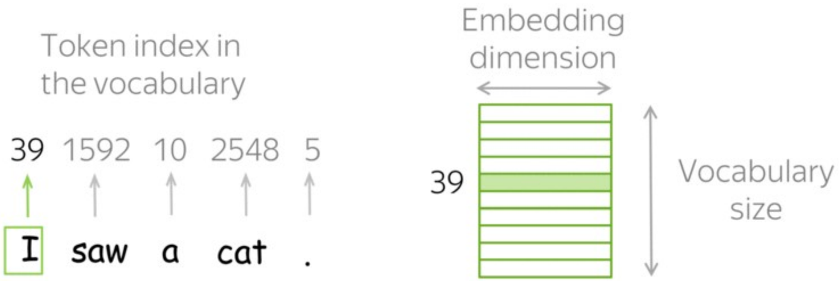
3) *Model-parallel deep learning*

Train BERT-xxxxxxxxxxxlarge in less than a lifetime

4) *Decentralized deep learning*

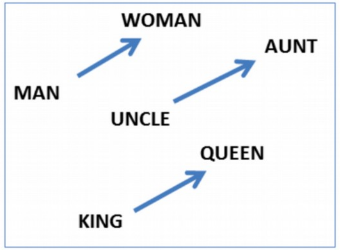
Train ~something~ with a million smart teapots

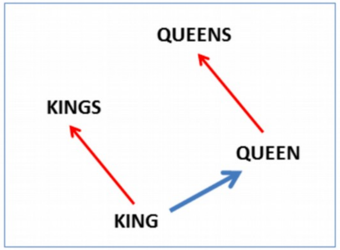
Problem of the day: word embeddings



semantic: v(king) – v(man) + v(woman) ≈ v(queen)

syntactic: v(kings) – v(king) + v(queen) ≈ v(queens)





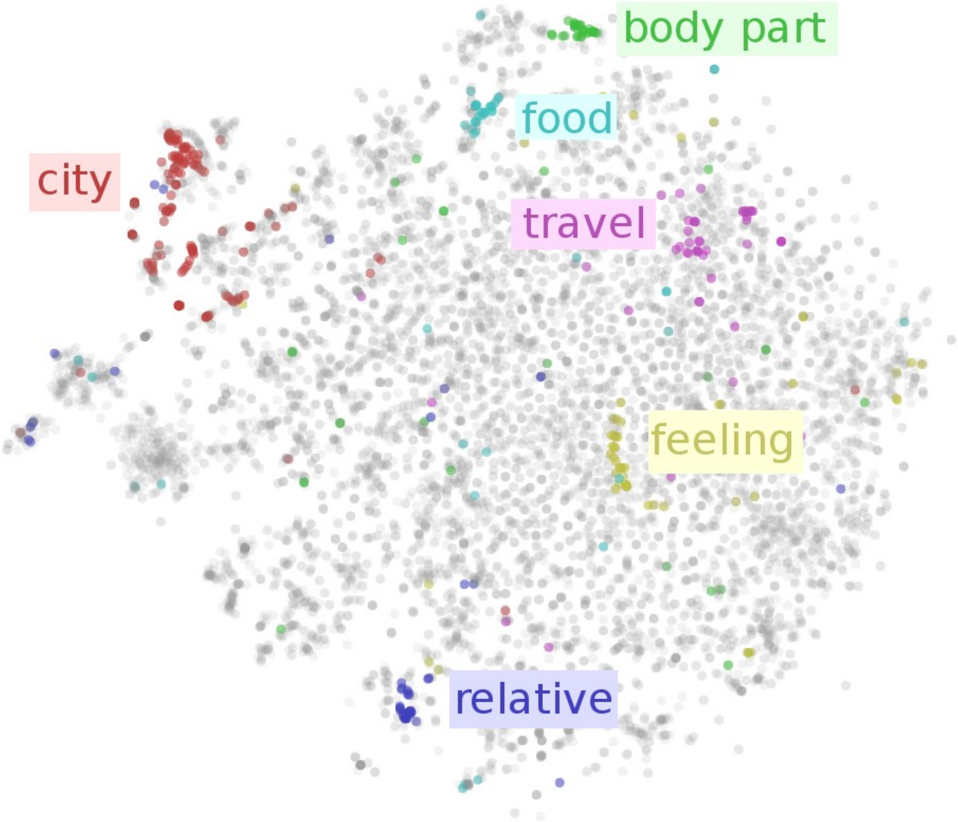
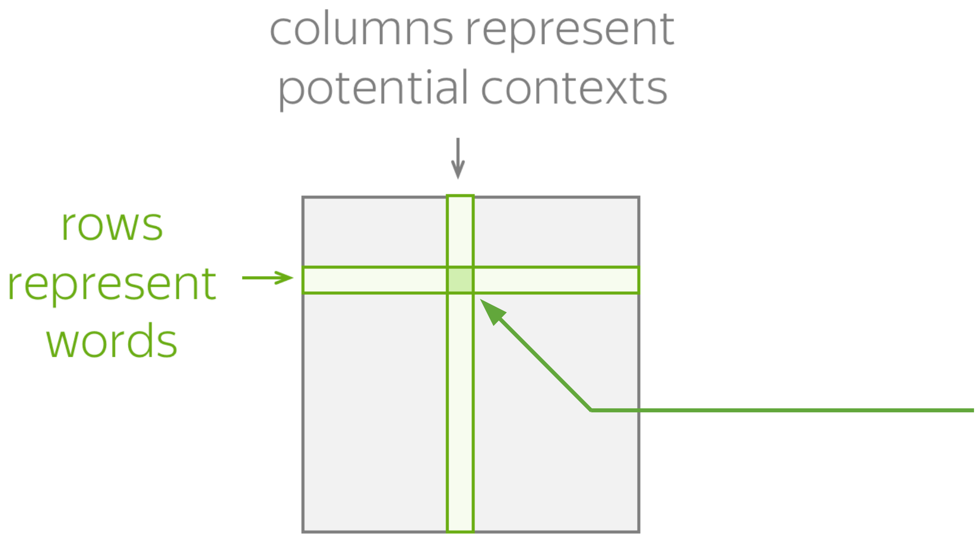


Image source: Lena's blog, Ruder's blog

Co-occurence matrix

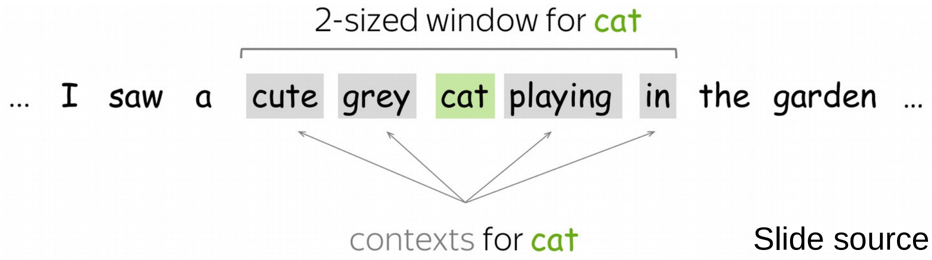


<u>Context:</u>

- surrounding words in a L-sized window

<u>Matrix element:</u>

- N(w, c) – number of times word w appears in context c



Note: *in our case, N is symmetric!*

Slide source: Lena's blog

GloVe

context vector

word vector

bias terms (also learned)

$$L = \sum_{i \neq j} w\left(N(i,j)\right) \cdot \left(\langle \vec{v}_i, \vec{v}_j \rangle + b_i + b_j - \log N(i,j)\right)$$

GloVe

context vector

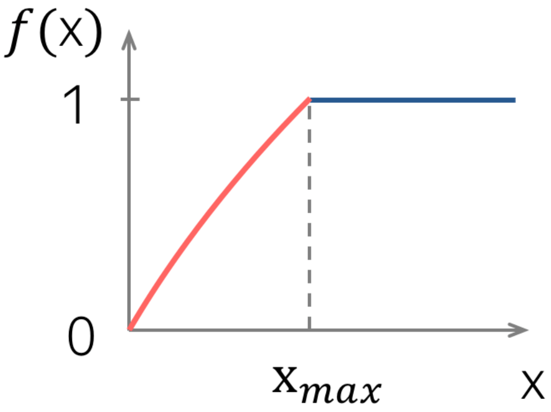
word vector

bias terms (also learned)

$$L=\sum_{i\neq j} w(N(i,j))\cdot(\langle \vec{v}_i, \vec{v}_j\rangle + b_i + b_j - \log N(i,j))$$

Weighting function to:

- penalize rare events
- not to over-weight frequent events



$$\begin{cases} (x/x_{max})^{\alpha} & \text{if } x < x_{max}, \\ 1 & \text{otherwise.} \end{cases}$$

$\alpha = 0.75, x_{max} = 100$

Slide source: Lena's blog

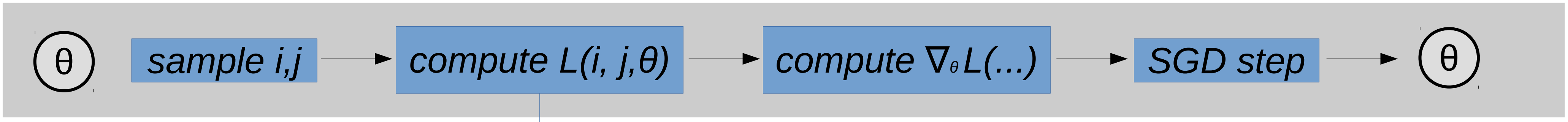
GloVe

$$L=\sum_{i\neq j} w(N(i,j))\cdot(\langle \overset{\text{context vector}}{\vec{v}_i}, \overset{\text{word vector}}{\vec{v}_j}\rangle + \overbrace{b_i + b_j}^{\text{bias terms (also learned)}} - \log N(i,j))$$

Learn more: *lena-voita.github.io/nlp_course/word_embeddings.html*

So how do we train ‘em?

Training Step

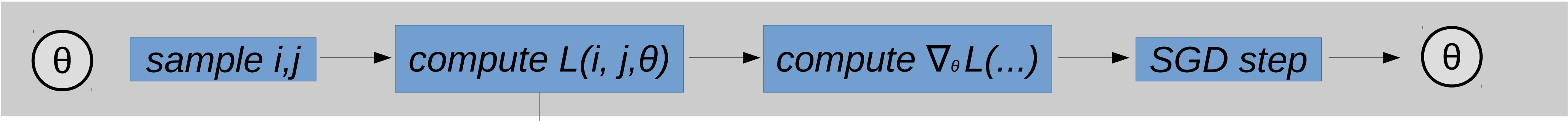


current params θ: {v, b}

updated params

$$L_{sample} = w(N(i,j)) \cdot (\langle \vec{v}_i, \vec{v}_j \rangle + b_i + b_j - \log N(i,j))$$

Training Step



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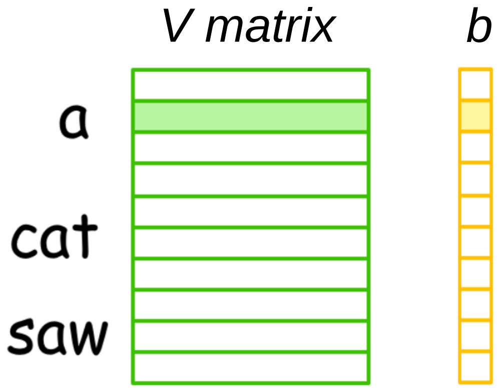
Trainable parameters:



Training Step

θ → sample i,j → compute L(i, j,θ) → compute $\nabla_\theta L(\ldots)$ → SGD step → θ

current params θ: {v, b}

updated params

$$L_{sample} = w(N(i,j)) \cdot (\langle \vec{v}_i, \vec{v}_j \rangle + b_i + b_j - \log N(i,j))$$

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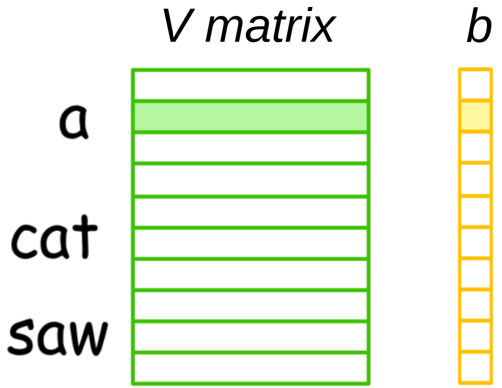
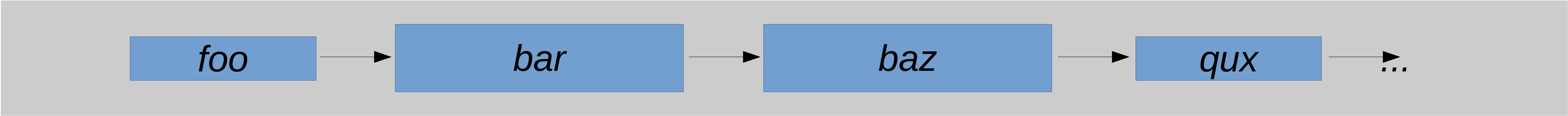


How do we go faster with 8 CPU cores?

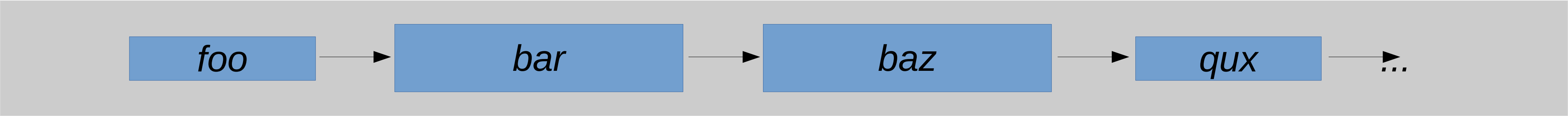
Rules: Process



Process:

- Runs some code
- Has some memory
- No one else can access your memory

Rules: Process



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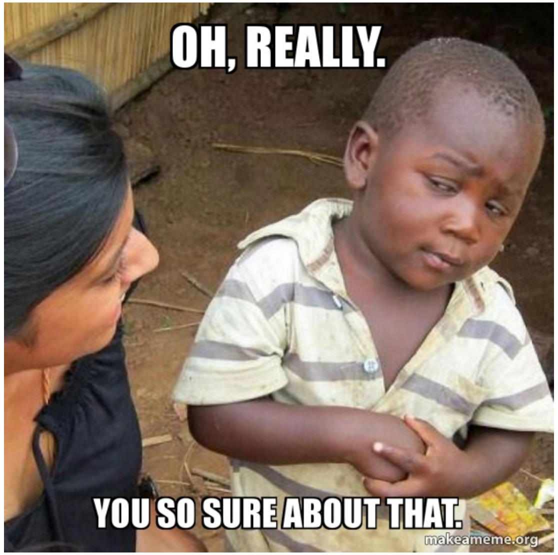

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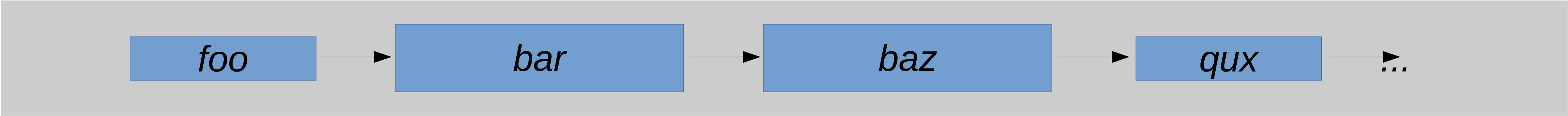
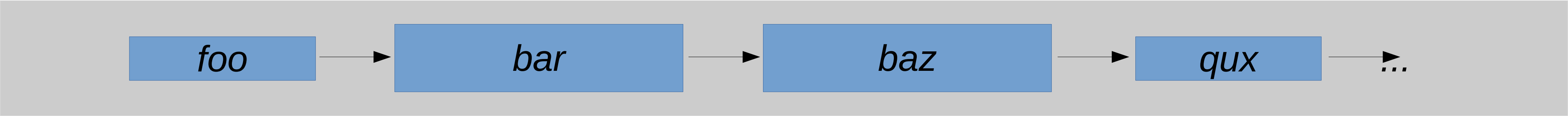


Process:

- Runs some code
- Has some memory
- No one else can access your memory*

* – not if you use shared memory

Rules: Process

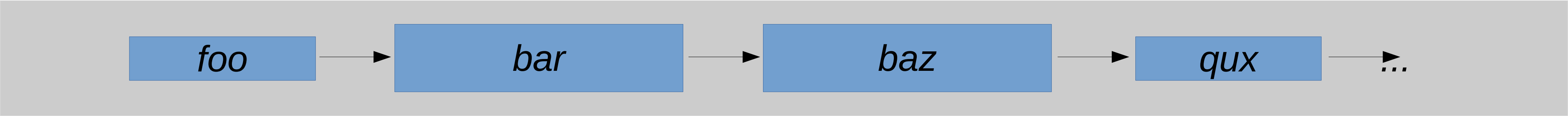


Process:

- Runs some code
- Has some memory
- No one else can access your memory*†

* – not if you use shared memory
† – superuser can still do that (os-dependent)

Rules: Process

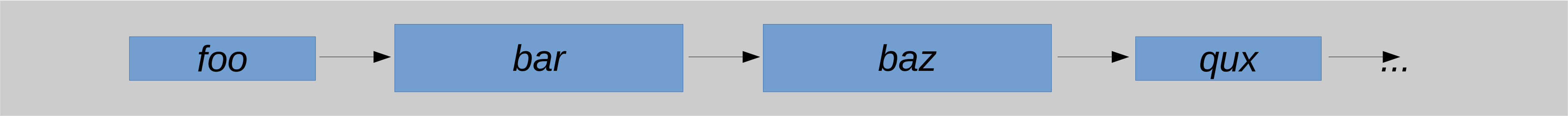


Process:

- Runs some code
- Has some memory
- No one else can access your memory*†‡

* – not if you use shared memory
† – superuser can still do that (os-dependent)
‡ – attacker can do that through spectre/meltdown/etc

Rules: Process

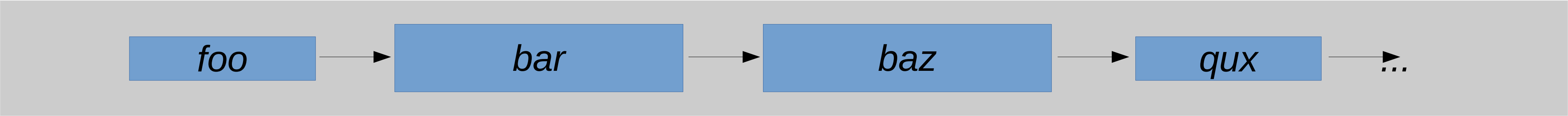


Process:

- Runs some code
- Has some memory
- No one else **should** access your memory*†‡

*†‡ – not relevant for this course

Rules: Process



Process:

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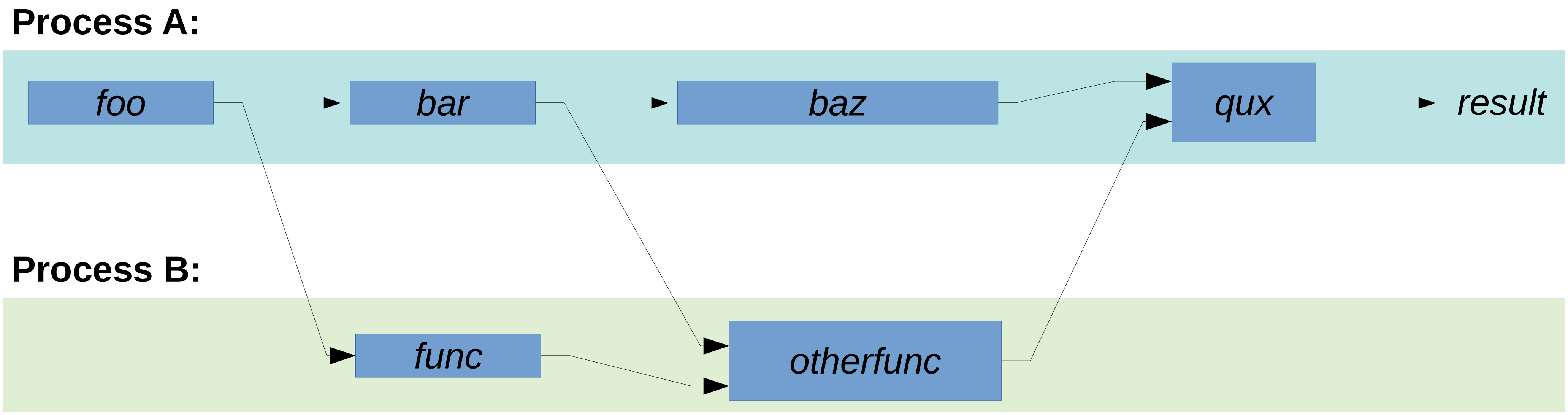
Q: How do we make processes work together?

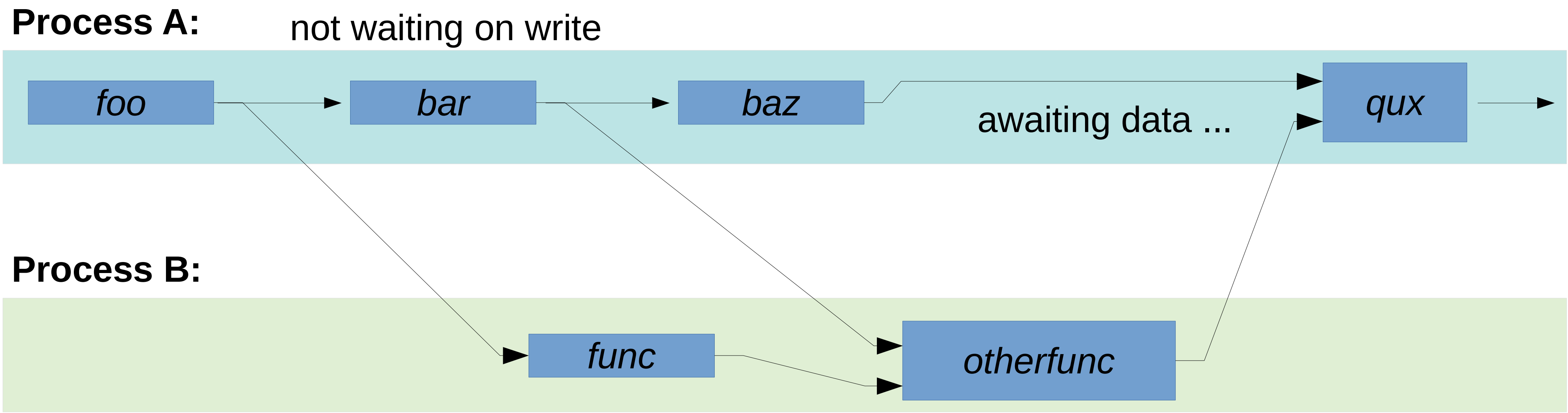
Rules: Channel / Pipe



Channel (pipe):

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

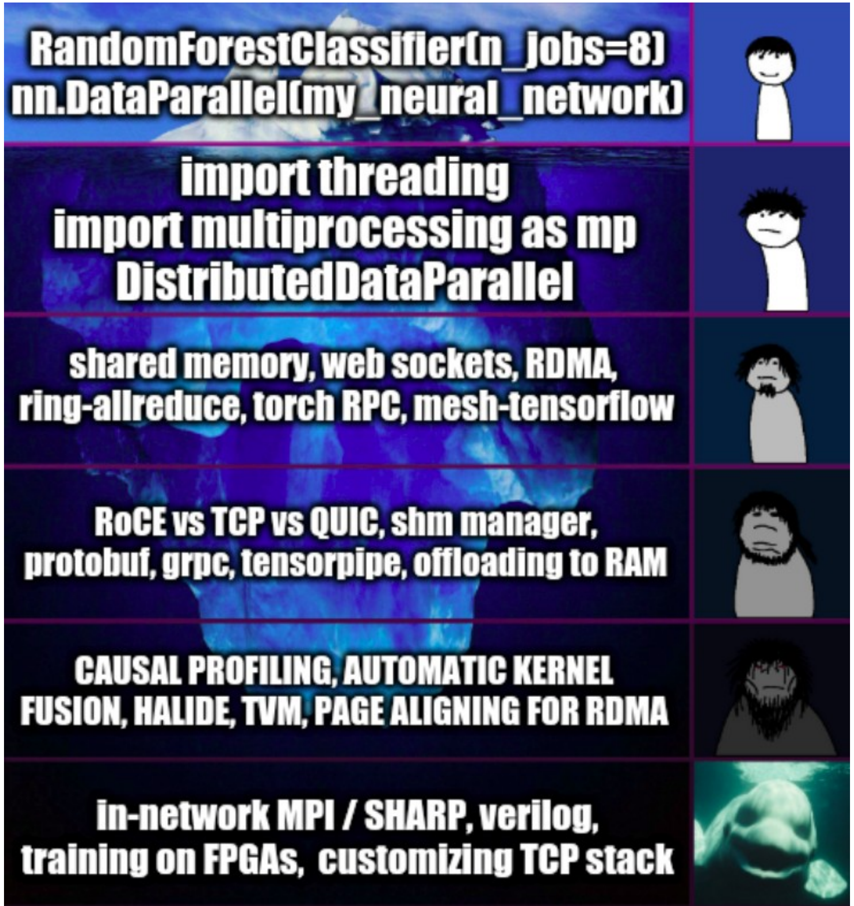
MP Rules



Channel (pipe):

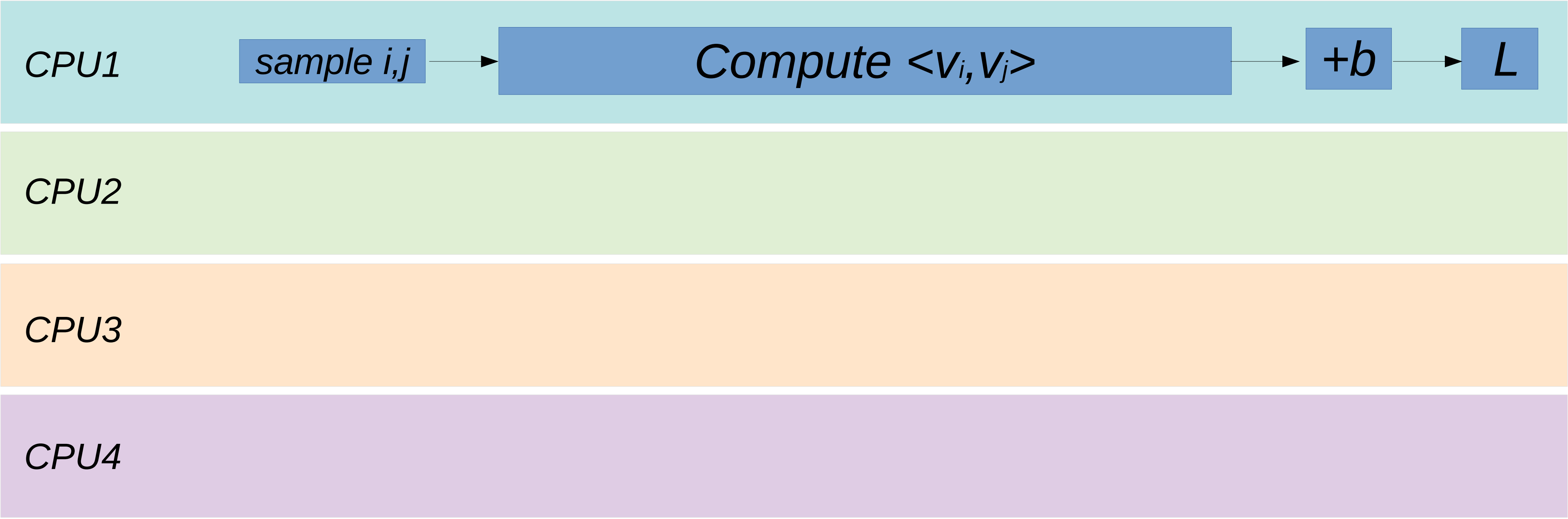
- Communication in O(message size)
- **Asynchronous** read/write

Details are (not) important



Operation parallelism

run algorithm in parallel without changing the math



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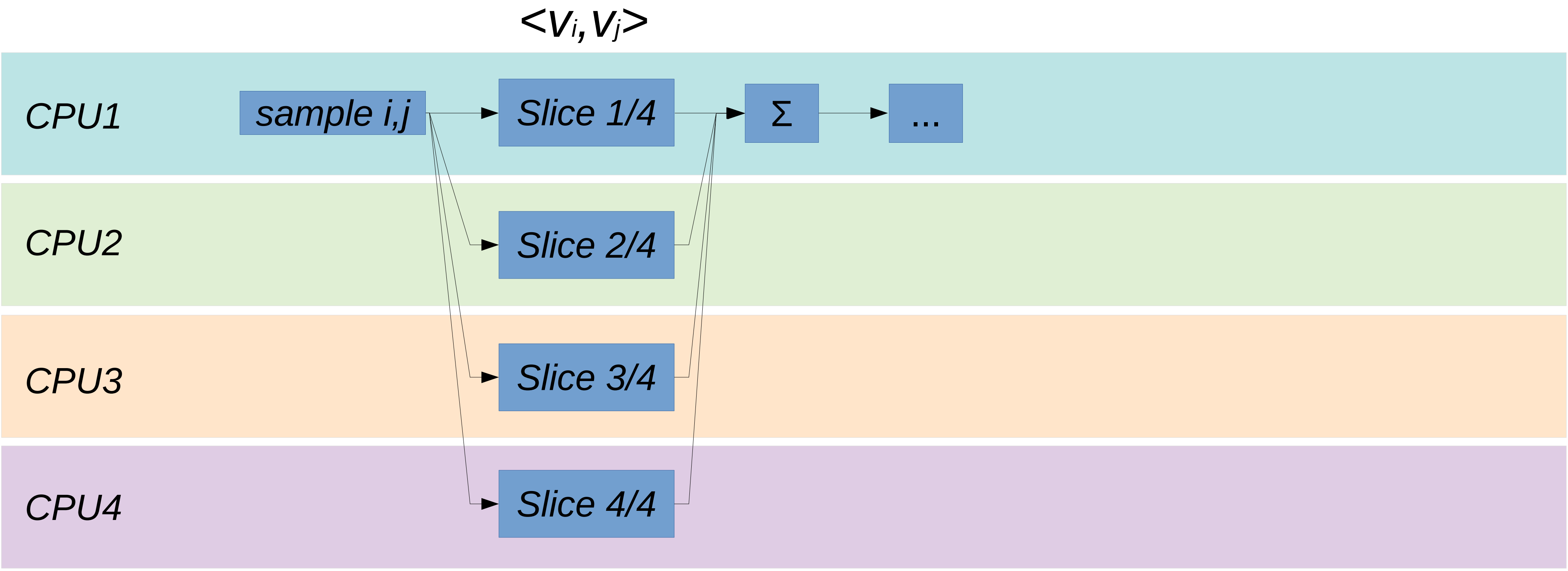
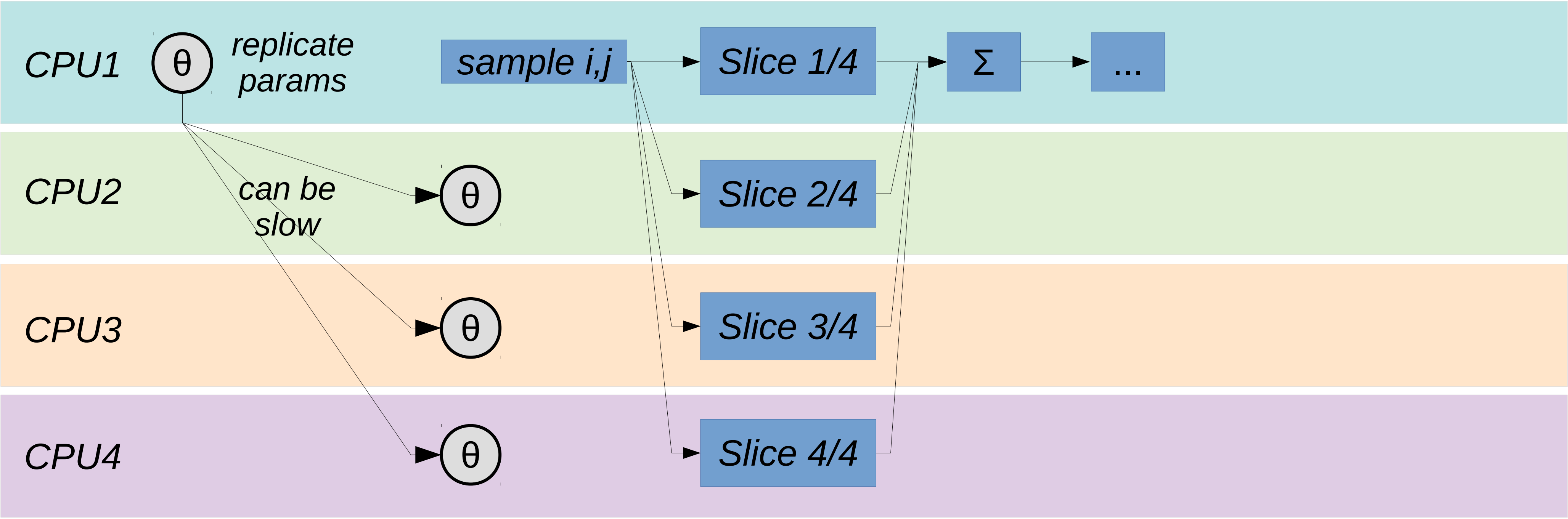


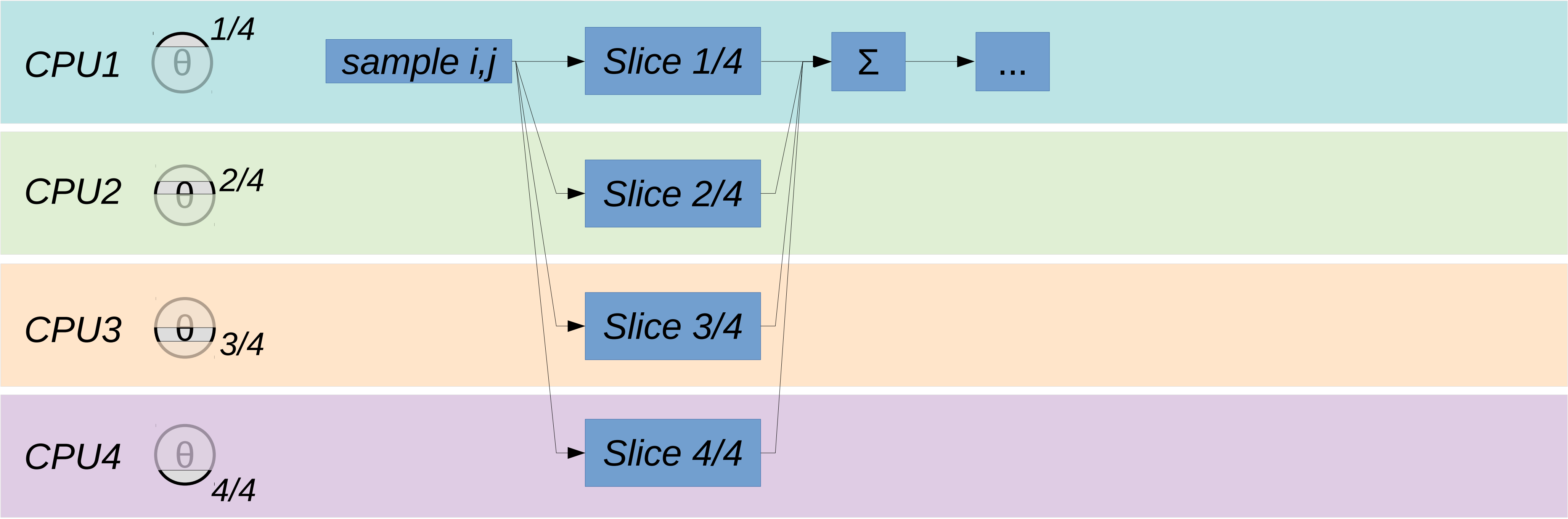
Operation parallelism

How to organize parameters across processes?



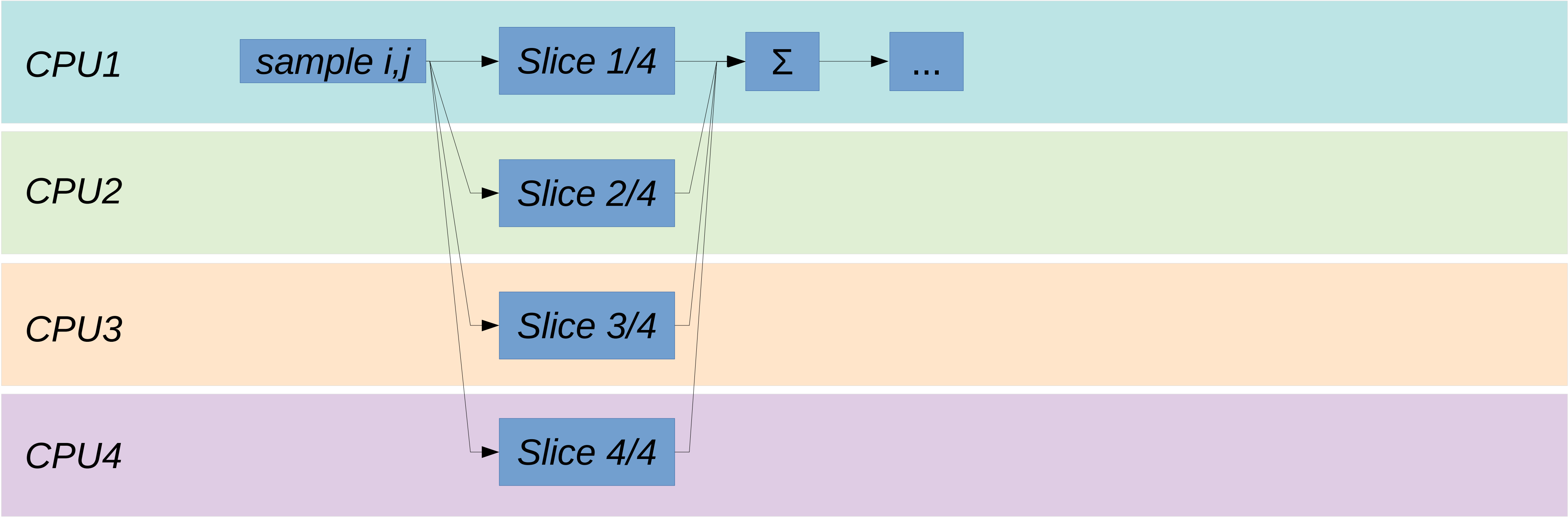
Operation parallelism

Each process holds one shard of parameters
(no transfer required)

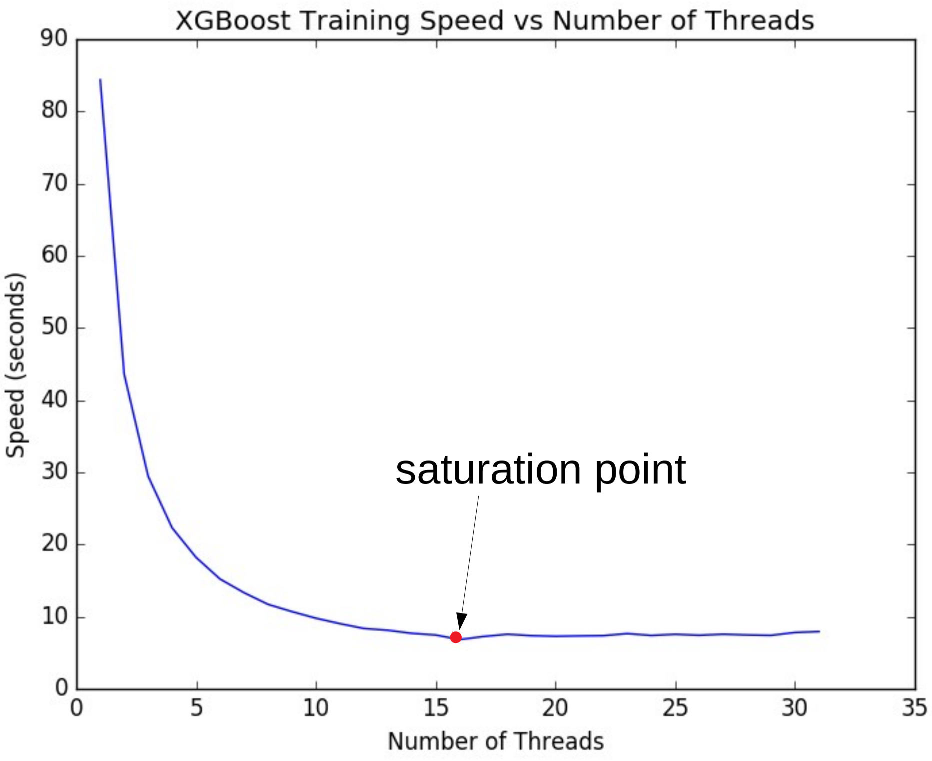


Operation parallelism

What can we improve for 10^6-dim vectors and 256 cores?



Operation parallelism

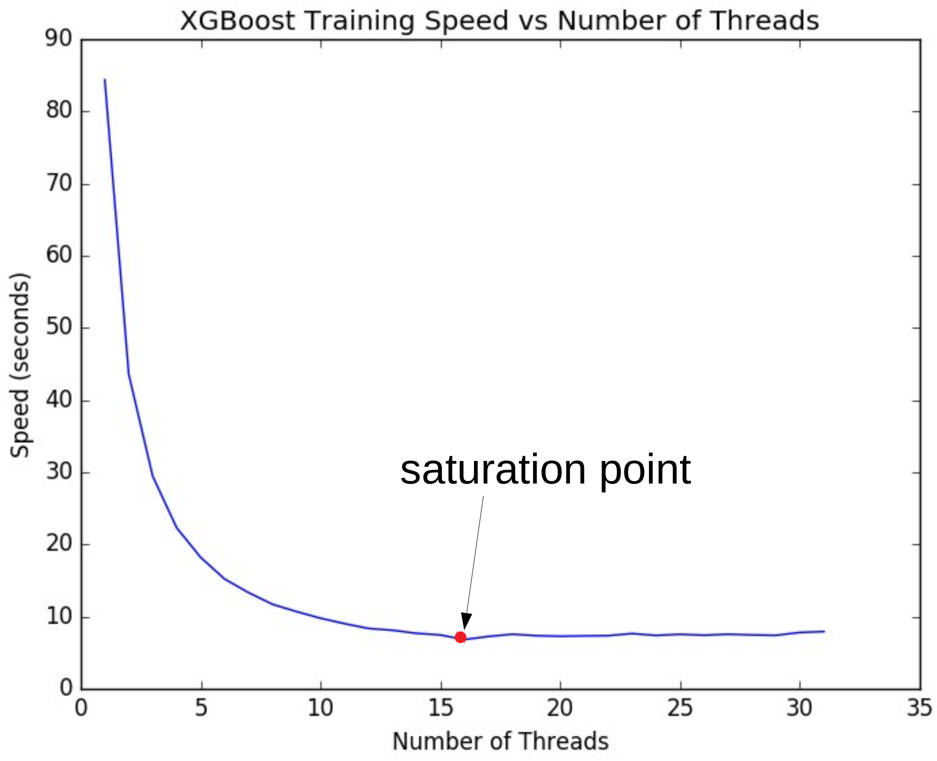


More processes = more overhead

- *waiting for each other*
- *sending data over the network*
- *performance fluctuations*

Eventually adding more threads will no longer boost performance

Operation parallelism



More processes = more overhead

- *waiting for each other*
- *sending data over the network*
- *performance fluctuations*

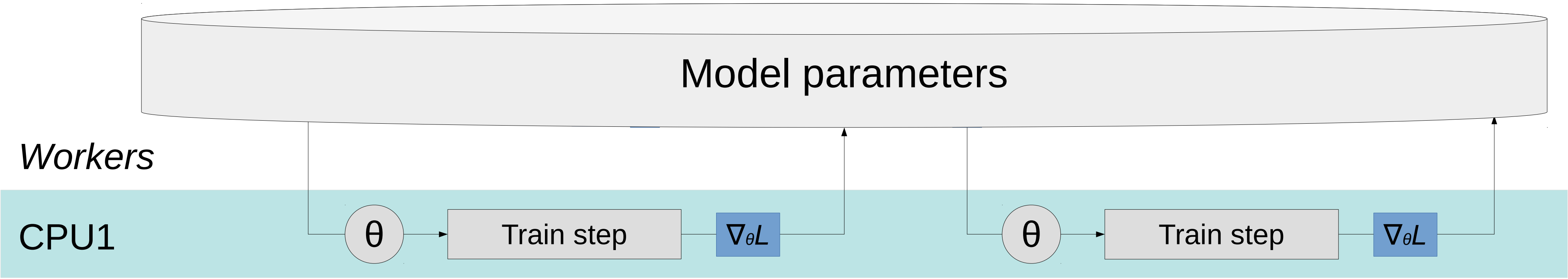
Eventually adding more threads will no longer boost performance

How do we push this point further?

Parameter Server

Paper: Smola et al. (2010)

Make a dedicated process for parameters & optimizer

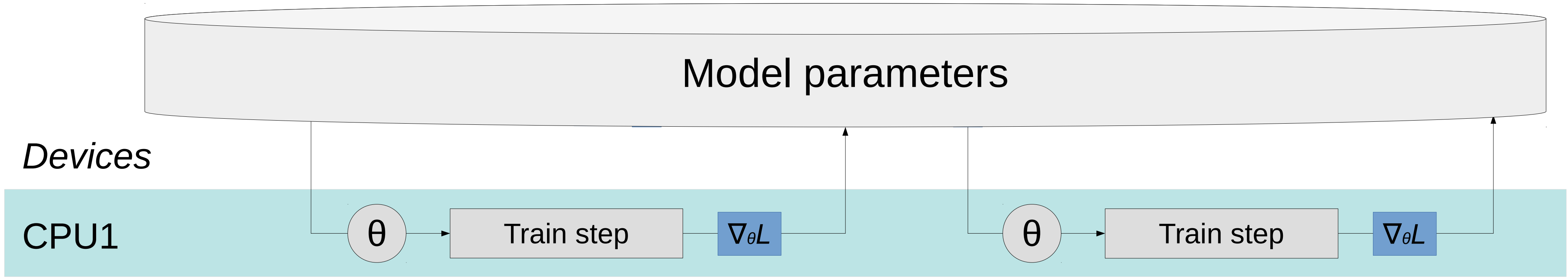


. . .

Asynchronous training

HOGWILD! arxiv.org/abs/1106.5730

Idea: remove synchronization step alltogether, use parameter server



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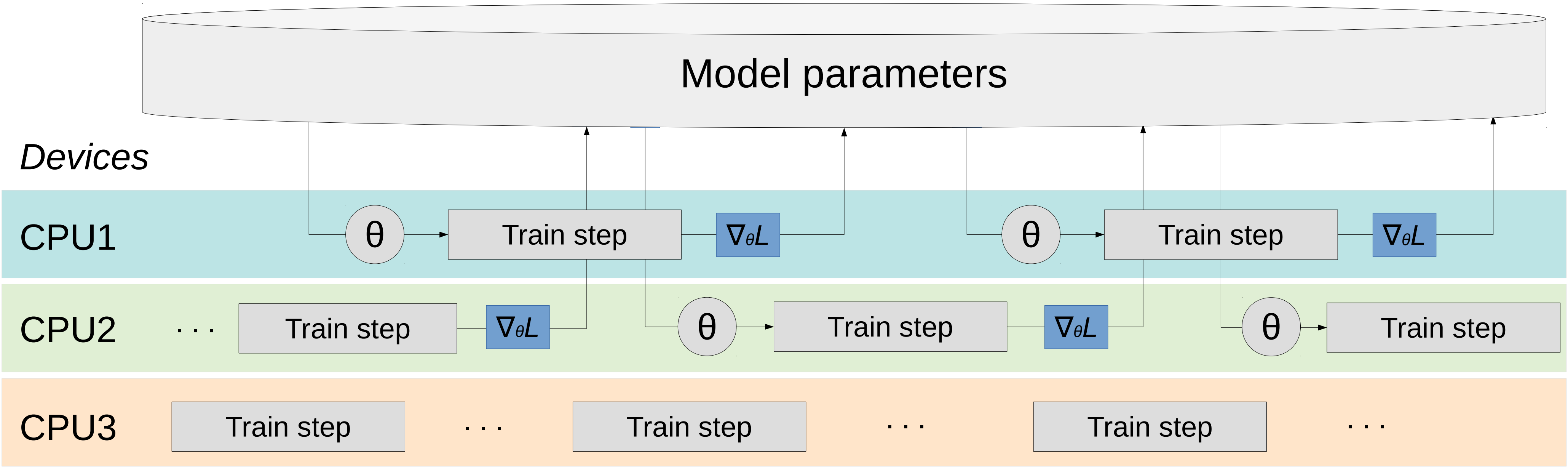

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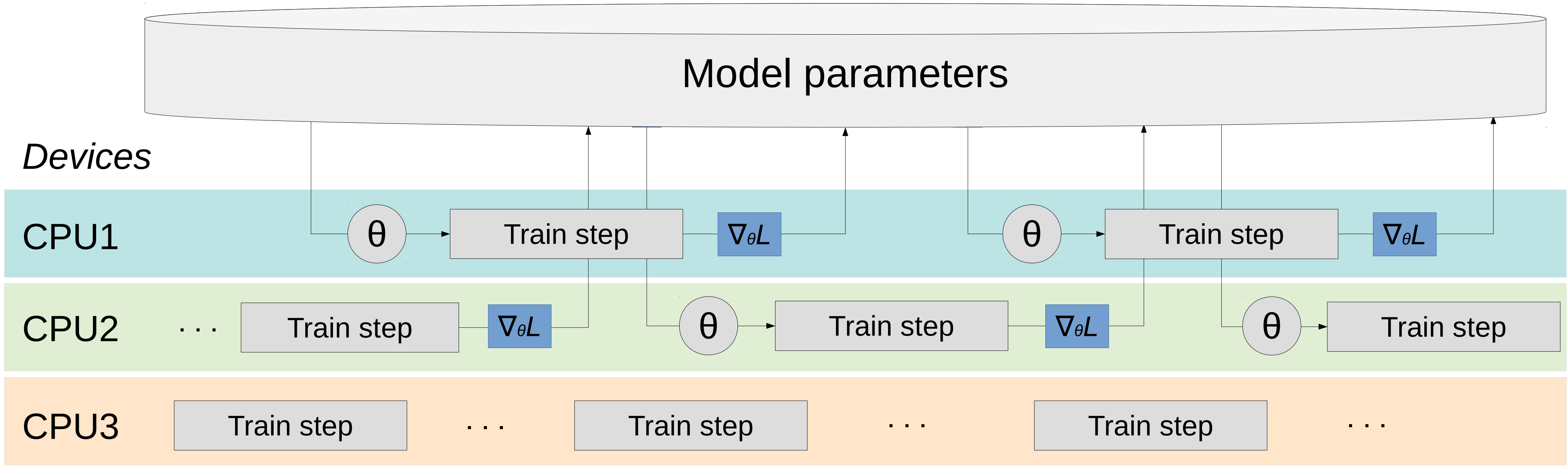

Q: have we lost anything by going asynchronous?

Asynchronous training

HOGWILD! arxiv.org/abs/1106.5730

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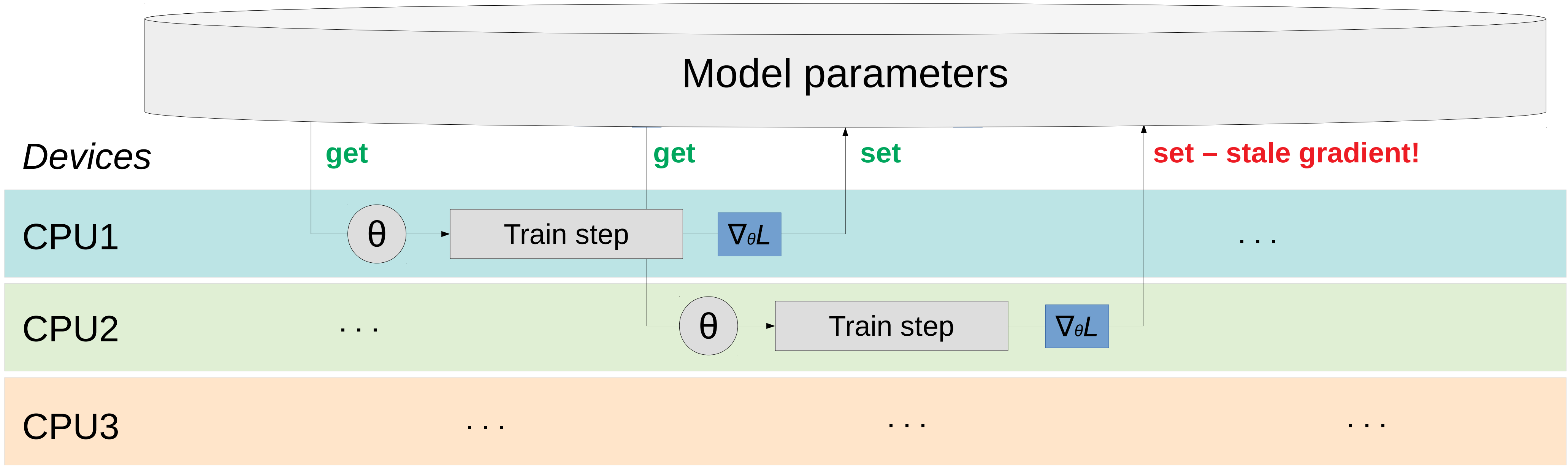

Staleness-aware SGD

Paper: arxiv.org/abs/1511.05950 & others

Updates accumulated: $c = \lfloor (\lambda / n) \rfloor$

Average gradient: $$g_i = \frac{1}{c} \sum_{l=1}^{c} \alpha(\tau_{i,l}) \Delta\theta_l, \ l \in \{1, 2, \ldots, \lambda\}$$

New parameters: $\theta_{i+1} = \theta_i - g_i,$

Staleness-aware SGD

Paper: arxiv.org/abs/1511.05950 & others

Updates accumulated: $c = \lfloor (\lambda / n) \rfloor$

n = total workers
λ = "accumulation factor"

Average gradient: $$g_i = \frac{1}{c} \sum_{l=1}^{c} \alpha(\tau_{i,l}) \Delta\theta_l, \; l \in \{1, 2, \ldots, \lambda\}$$

New parameters: $\theta_{i+1} = \theta_i - g_i,$

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staleness-dependent
"learning rate"

New parameters: $\theta_{i+1} = \theta_i - g_i,$

Staleness-aware SGD

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Updates accumulated: $c = \lfloor (\lambda / n) \rfloor$

Average gradient: $g_i = \frac{1}{c} \sum_{l=1}^{c} \alpha(\tau_{i,l}) \Delta\theta_l, \; l \in \{1, 2, \ldots, \lambda\}$

New parameters: $\theta_{i+1} = \theta_i - g_i,$

$$\alpha_{i,l} = \frac{\alpha_0}{\tau_{i,l}}$$

base learning rate

staleness (≥1)

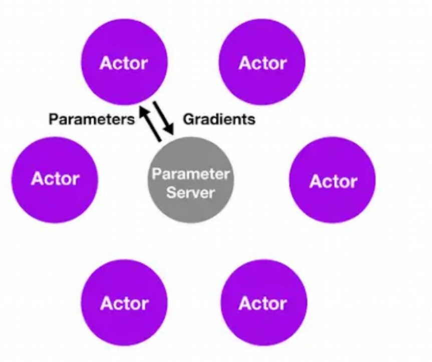
aka number of skipped updates

Parameter Server Applications

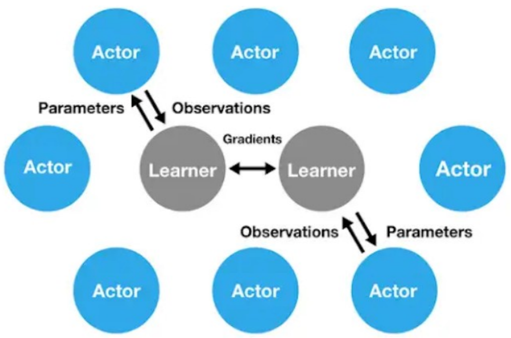
Conventional ML: *e.g. (Logistic Regression, CNN classifiers)*

Paper (sharded PS): https://www.cs.cmu.edu/~muli/file/ps.pdf
Another paper (optimizaton tricks): parameter_server_nips14.pdf
PyTorch tutorial (hogwild), TF tutorial (parameter server)

Reinforcement learning:



A3C



IMPALA - Multiple Learners

Async. RL: arxiv.org/abs/1602.01783
IMPALA: arxiv.org/abs/1802.01561
SEED RL: arxiv.org/abs/1910.06591

More:
(english) https://youtu.be/kOy49NqZeqI
(russian) https://youtu.be/wswbMkT55mI

Привет, Ёж. Это – последний слайд.
Если вы уже здесь, а время ещё осталось,
разбери-ка вот эту статью:

https://www.usenix.org/system/files/osdi20-jiang.pdf