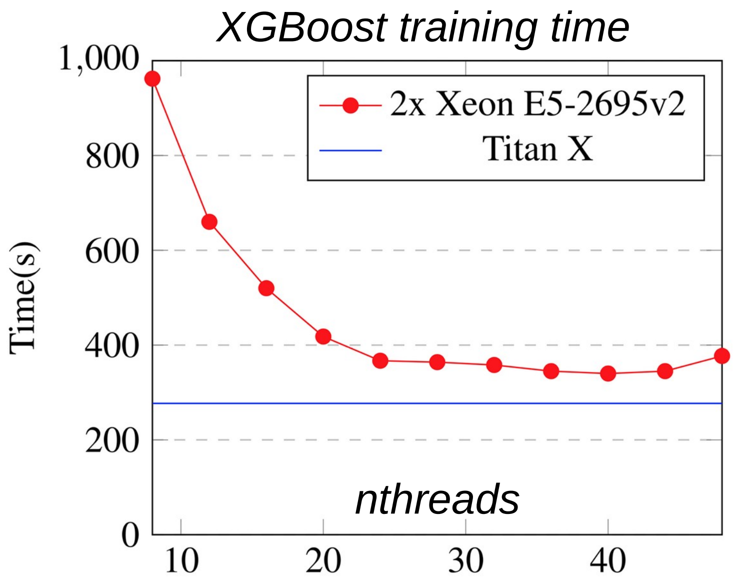
Distributed Machine Learning

Efficient DL’23, Episode II

Yandex
Research

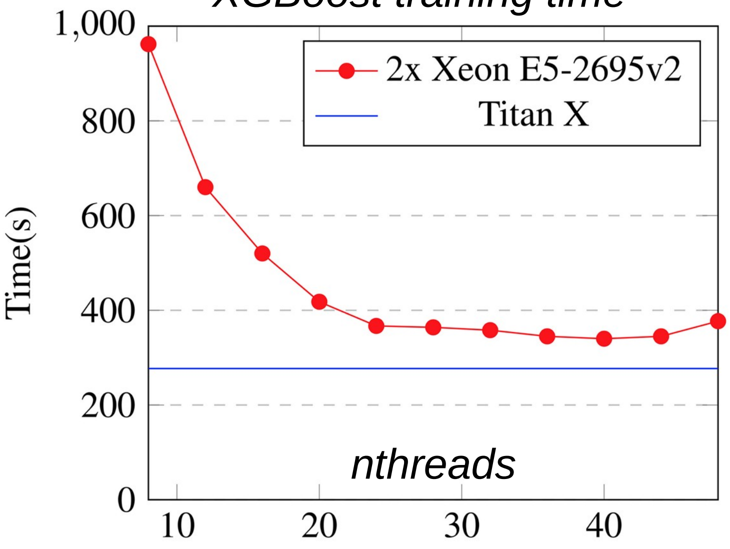
British Hedgehog
Preservation Society

Зачем это всё?

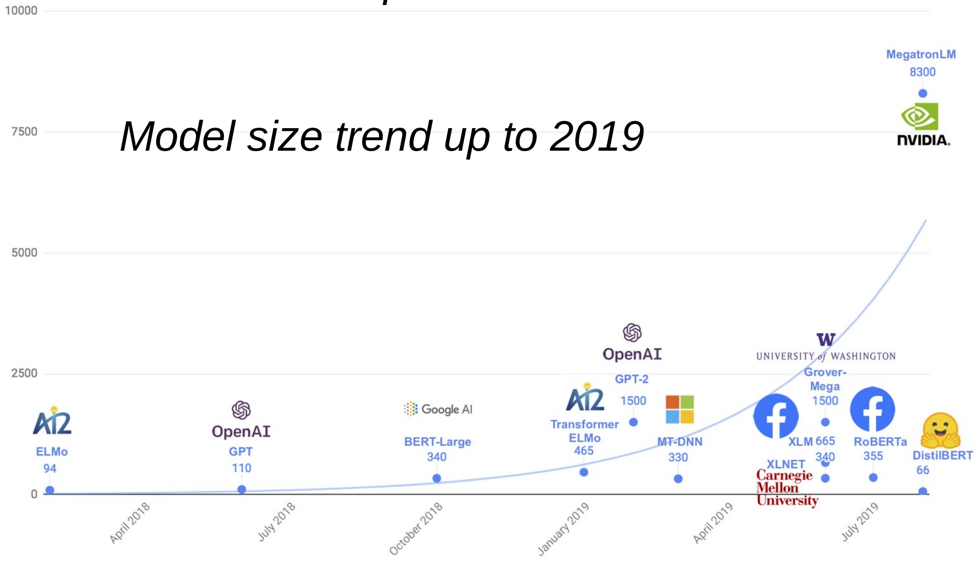


Зачем это всё?

XGBoost training time



10^6 x 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 V100 – **over 2 weeks**)*

Зачем это всё?

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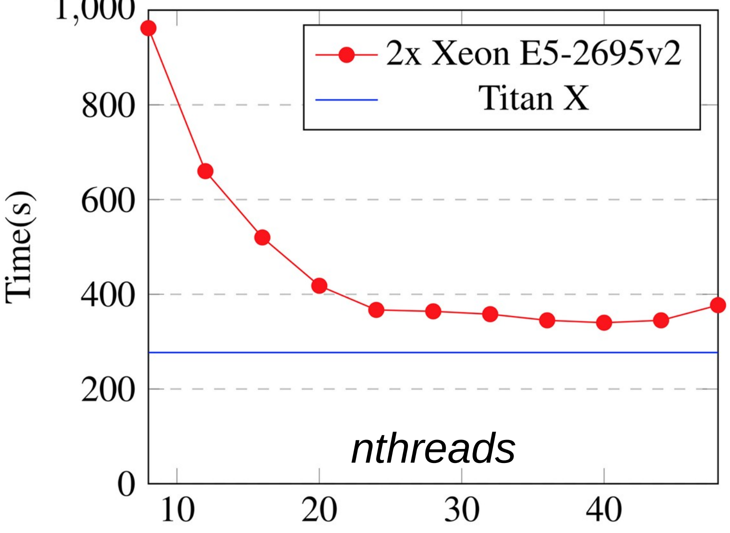

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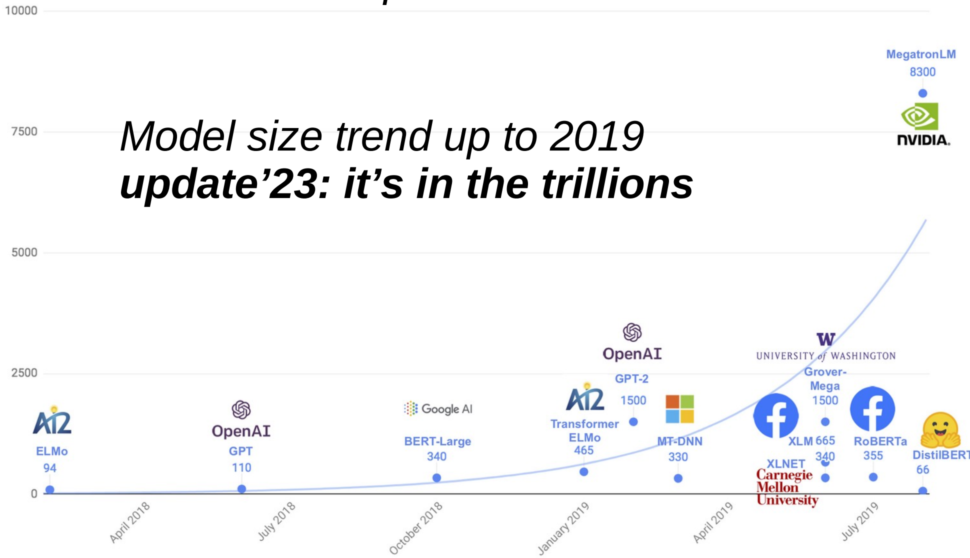

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Зачем мы тут?

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 our plan

lectures 4,5,6

4) Distributed machine learning

Embeddings or log.regression with tons of training data

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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-175B, BLOOM-176B, YALM, GLM, Galactica

TL;DR our plan

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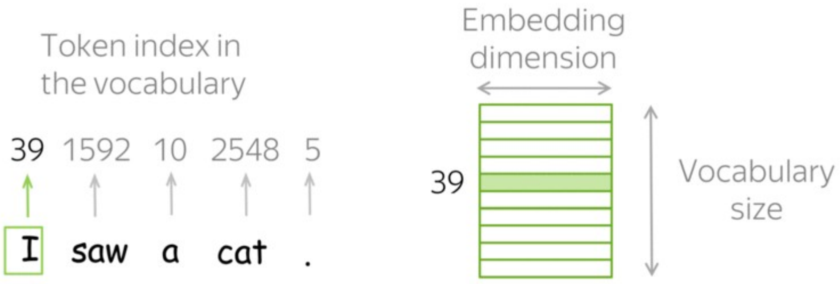
4) Distributed machine learning

Embeddings or log.regression with tons of training data

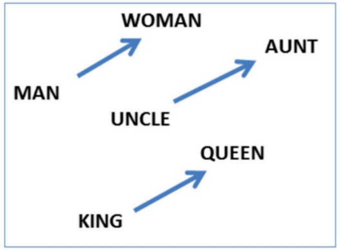
Today: learn the basics behind it all

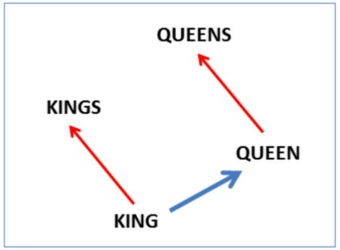
Example problem: word embeddings



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

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





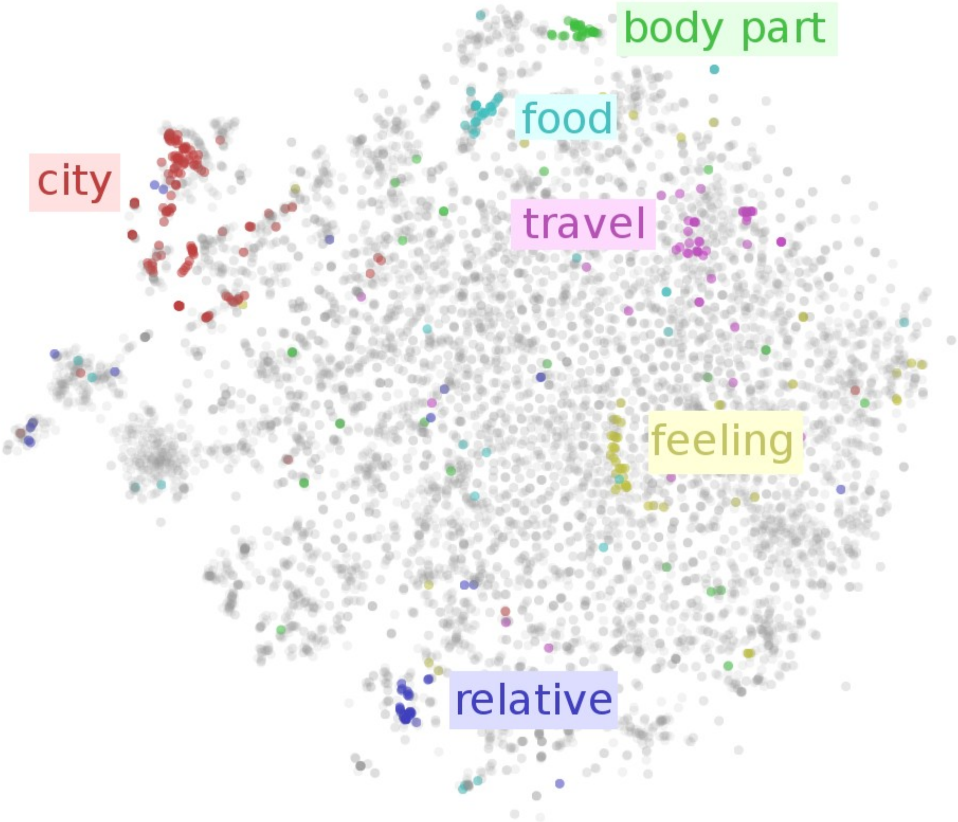
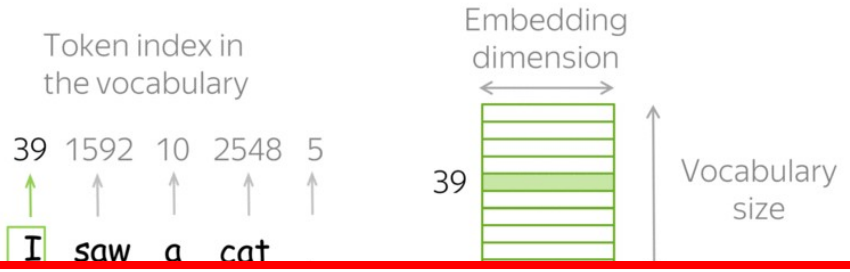
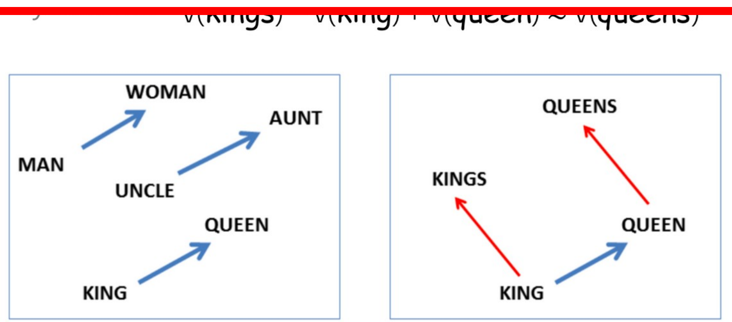


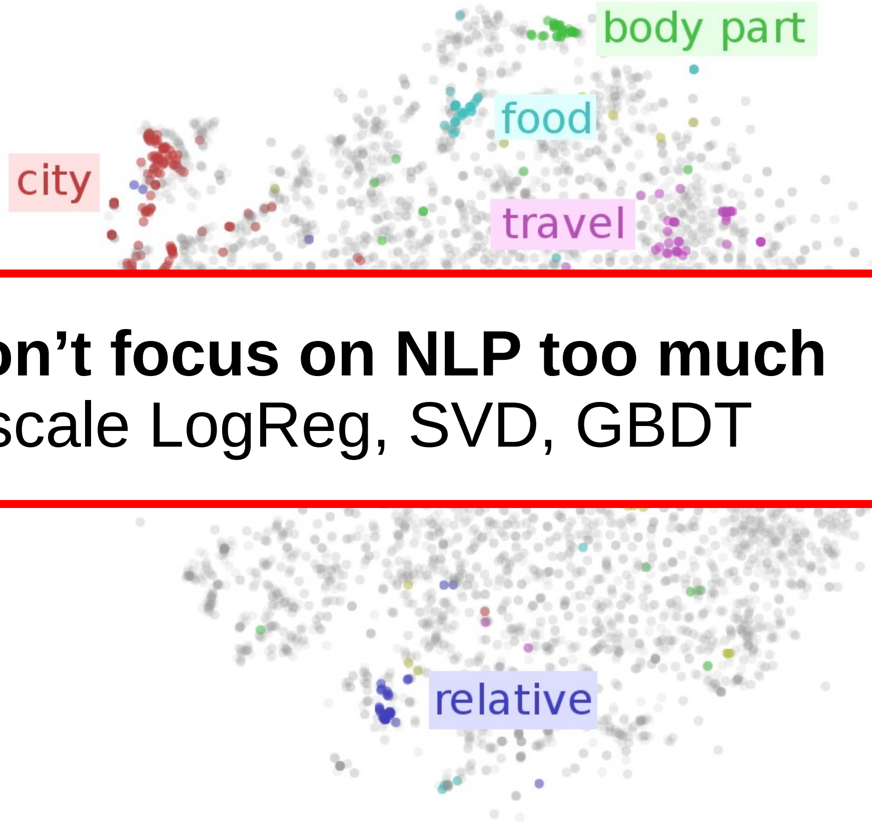
Image source: Lena’s blog, Ruder’s blog

Example problem: word embeddings



This is an example problem, don't focus on NLP too much
computationally similar: large-scale LogReg, SVD, GBDT





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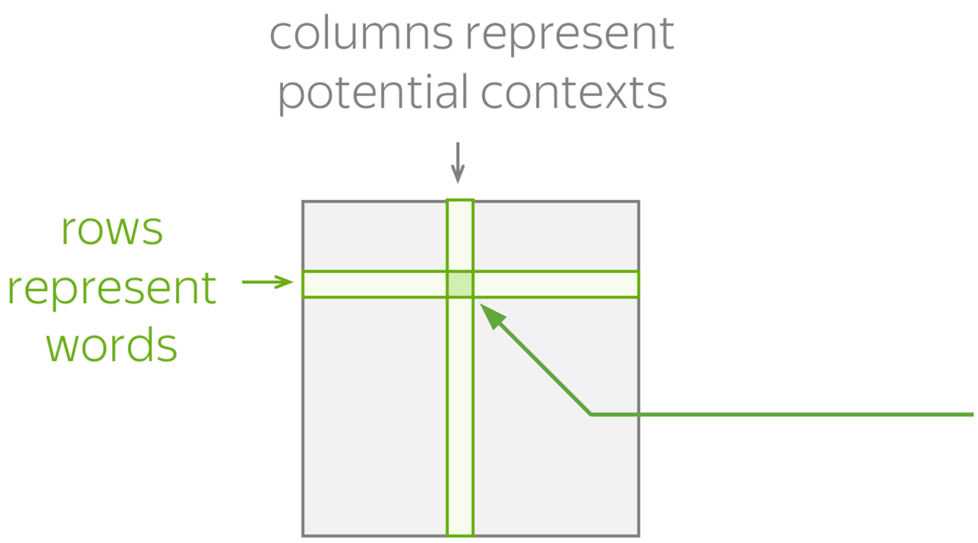
Co-occurence matrix

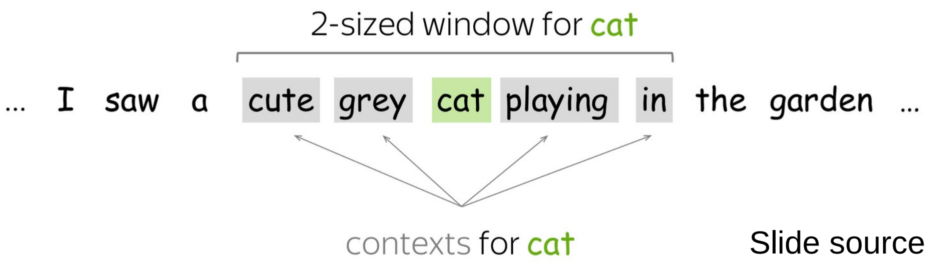


Context:

- surrounding words in a L-sized window

Matrix element:

- 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)

$$L=\sum_{i\neq j} w\left(N(i,j)\right)\cdot\left(\langle \vec{v}_i, \vec{v}_j \rangle + b_i + b_j - \log N(i,j)\right)^2$$

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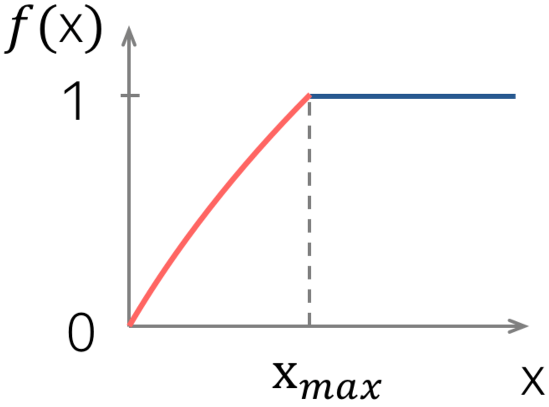
Weighting function to:

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



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

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

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GloVe

context vector

word vector

bias terms (also learned)

$$L=\sum_{i\neq j} w\left(N\left(i,j\right)\right)\cdot\left(\langle \vec{v}_i, \vec{v}_j\rangle+b_i+b_j-\log N\left(i,j\right)\right)^2$$

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

So how do we train ‘em?

Training Step

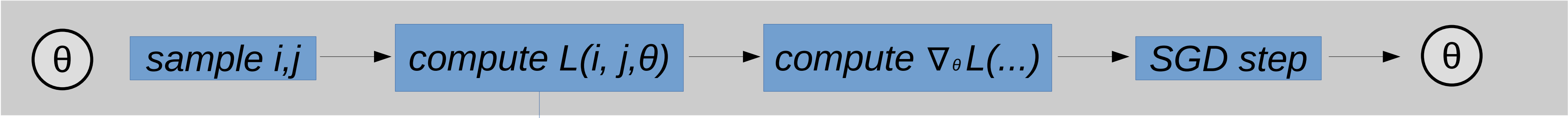
θ → *sample i,j* → *compute L(i, j,θ)* → *compute $\nabla_\theta L(\ldots)$* → *SGD step* → θ

current params
θ: {v, b}

$$L=\sum_{i\neq j} w\left(N\left(i,j\right)\right)\cdot\left(\left\langle \vec{v}_i,\vec{v}_j\right\rangle+b_i+b_j-\log N\left(i,j\right)\right)^2$$

updated params

Training Step



current params θ: {v, b}

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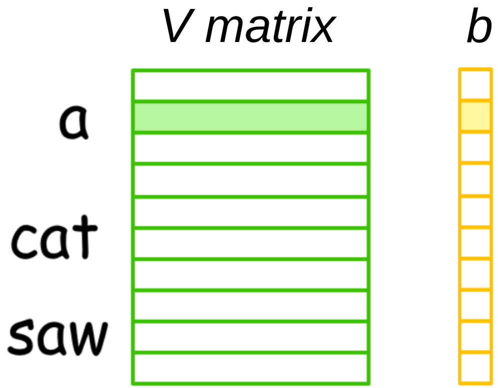
Trainable parameters:



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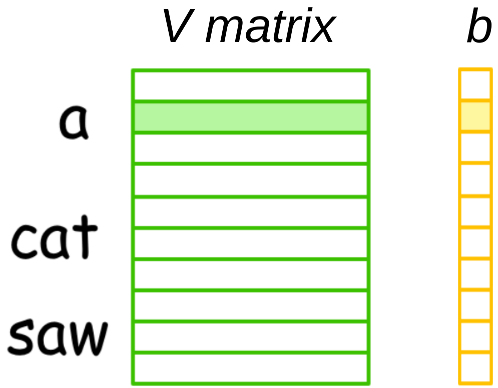

How do we go faster with 8 CPU cores?

Training Step

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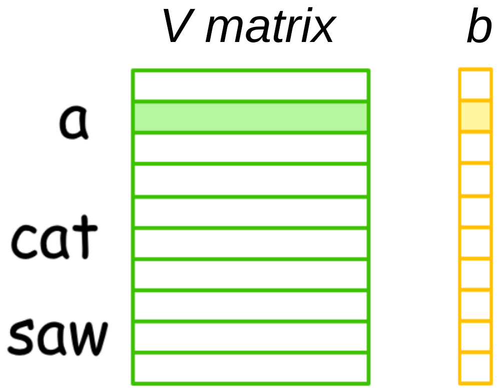
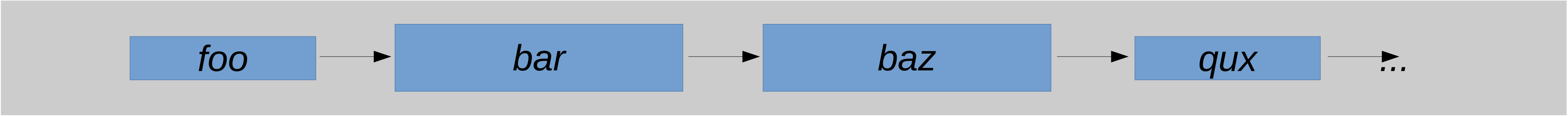


[let's formalize your ideas]

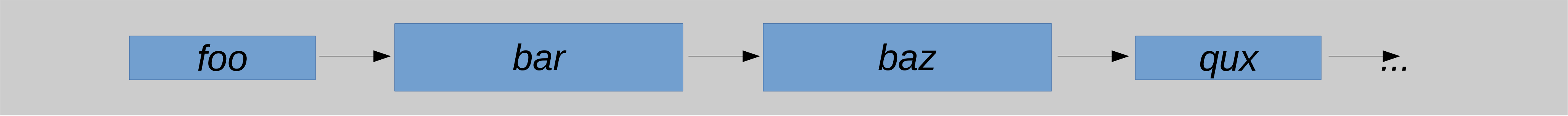
Rules: Process



Process:

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

Rules: Process



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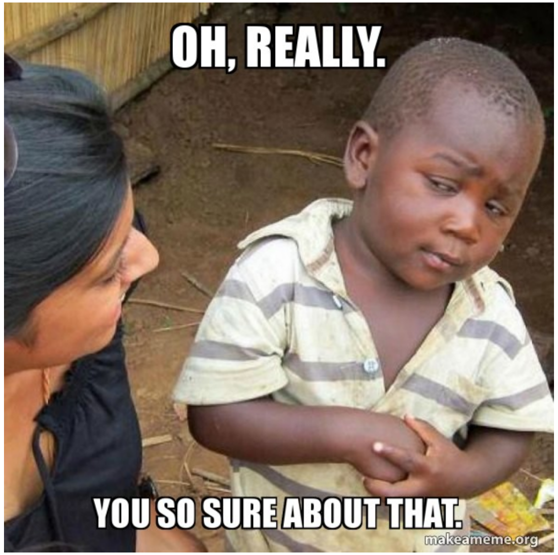

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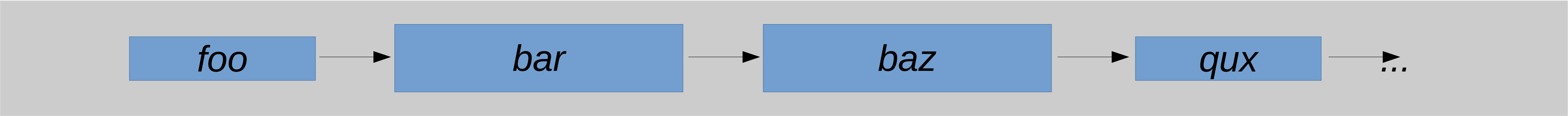
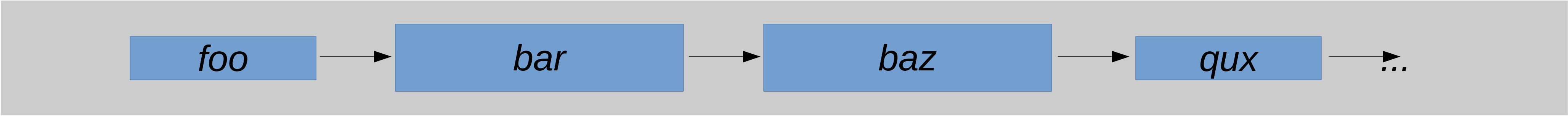


Process:

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

* – not if you use shared memory

Rules: Process

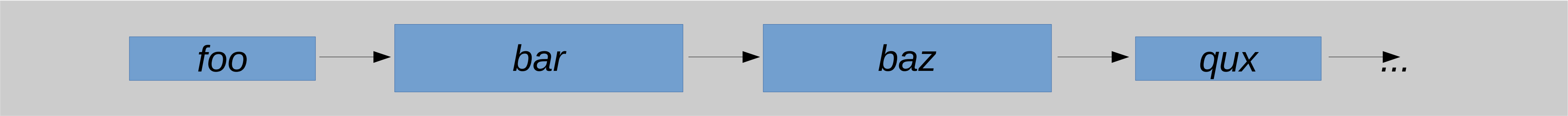


Process:

- 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:

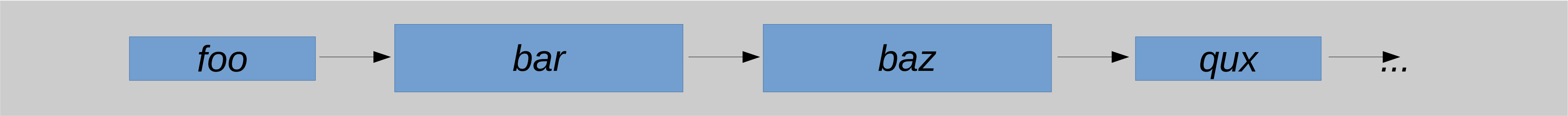
- Runs some code
- Has some memory
- No one else can access your memory*†‡

* – not if you use shared memory

† – superuser can still do that (os-dependent)

‡ – attacker can do that through spectre/meltdown/etc

Rules: Process

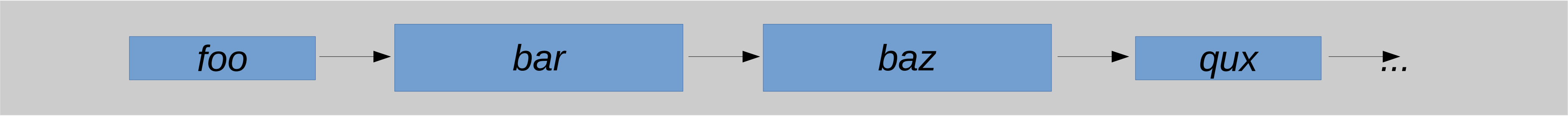


Process:

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

*†‡ – not relevant for this course

Rules: Process



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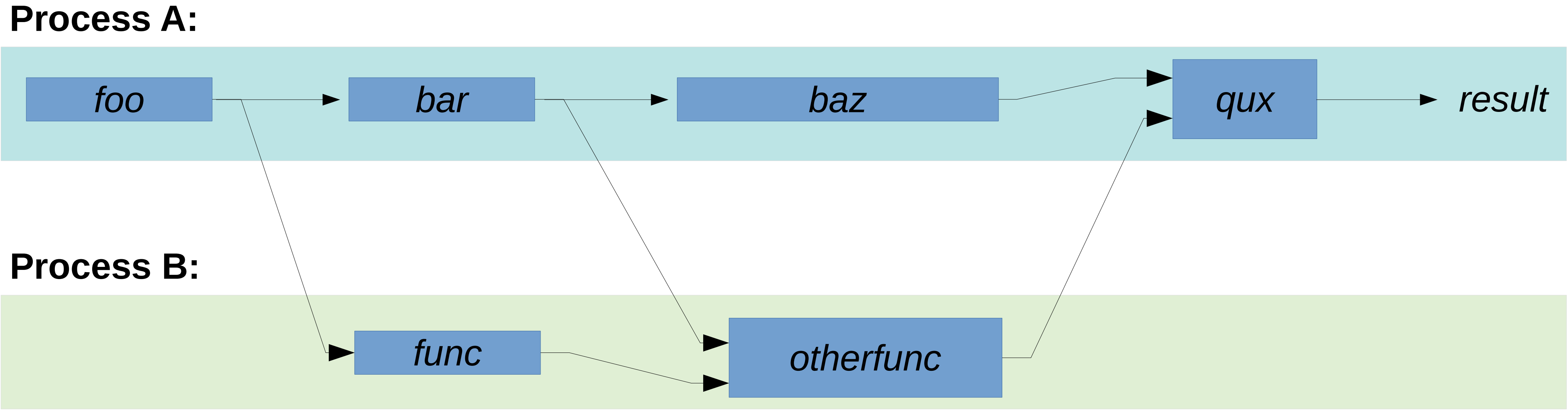
Q: How do we make processes work together?

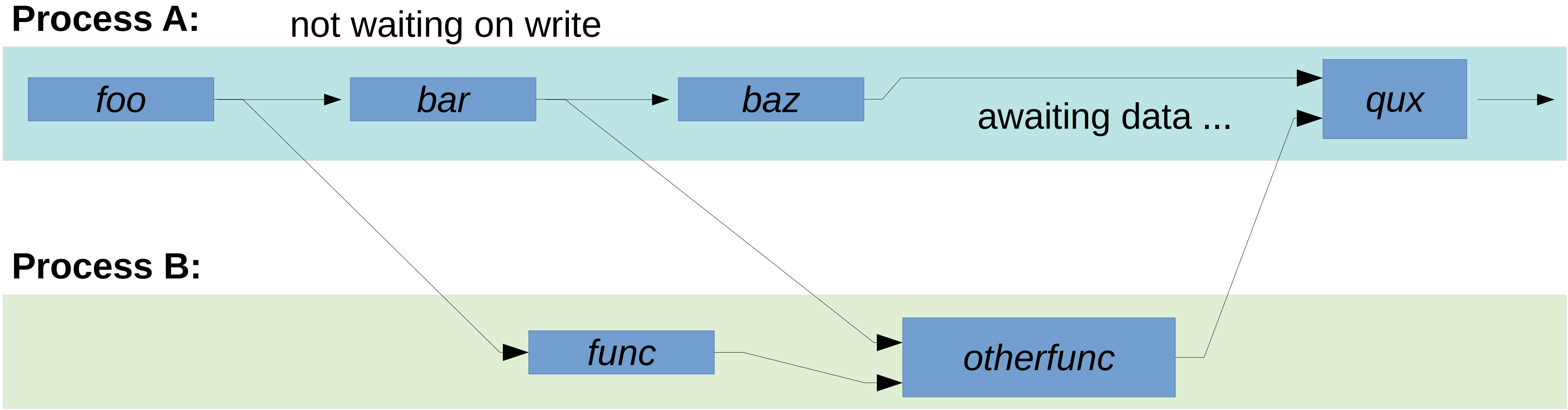
Rules: Channel / Pipe



Channel (pipe):

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

MP Rules



Channel (pipe):

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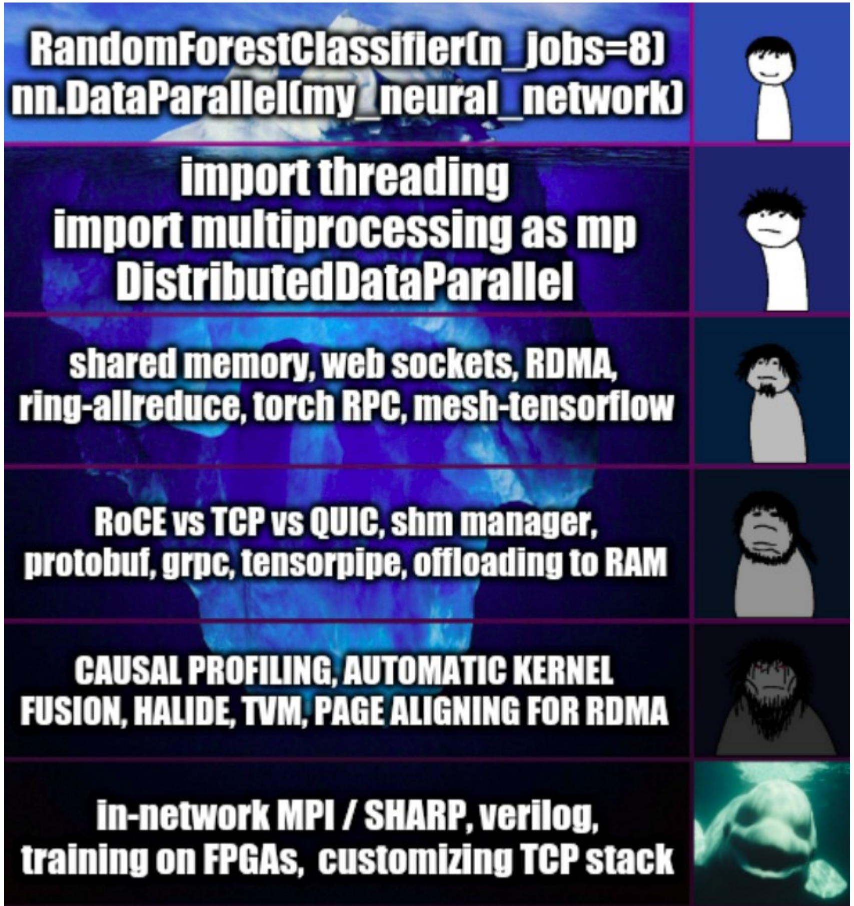
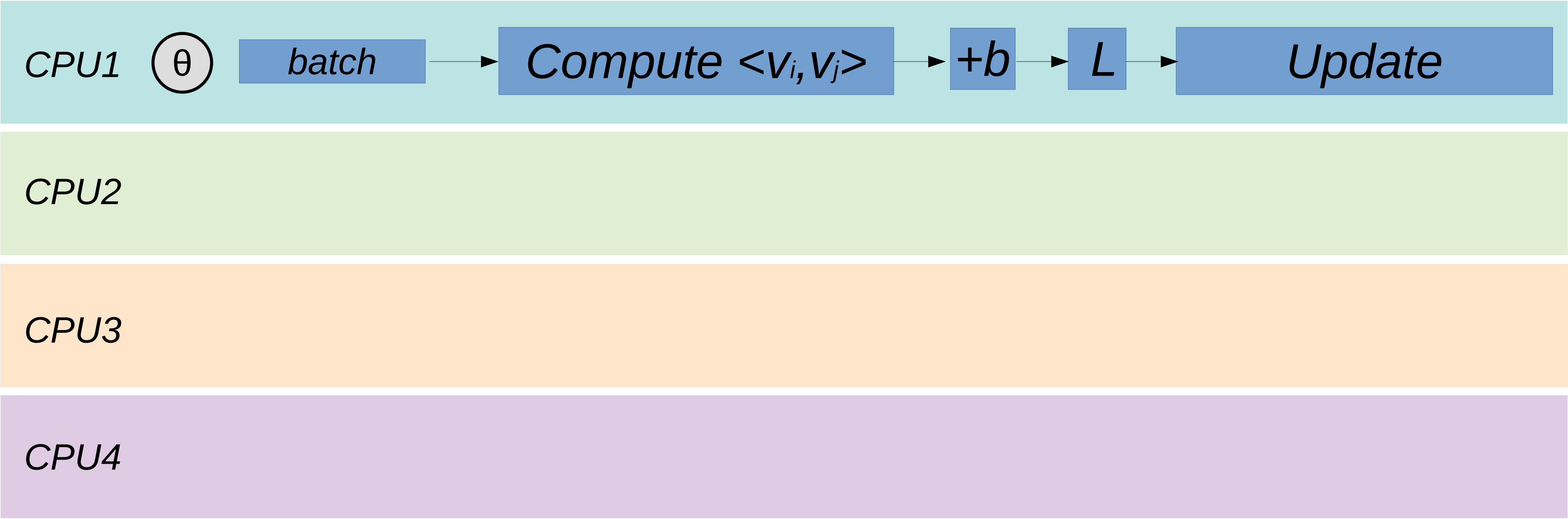
- **Asynchronous** read/write

Details are (not) important



Operation parallelism

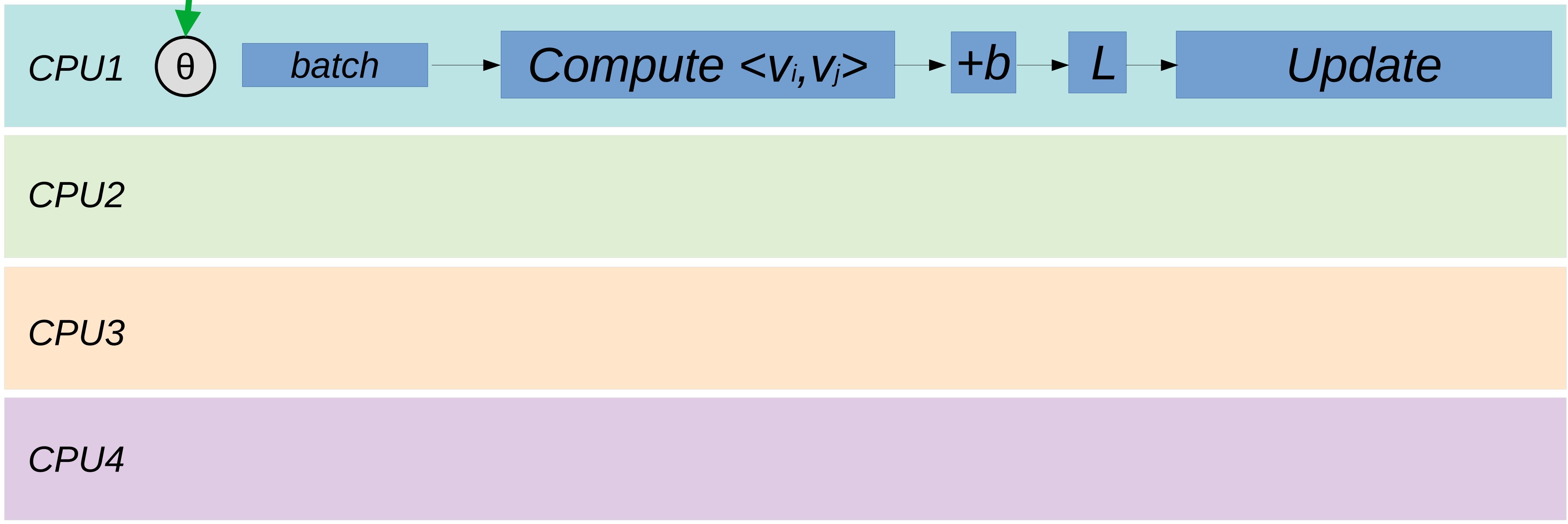
run algorithm in parallel without changing the math



Operation parallelism

run algorithm in parallel without changing the math

model weights



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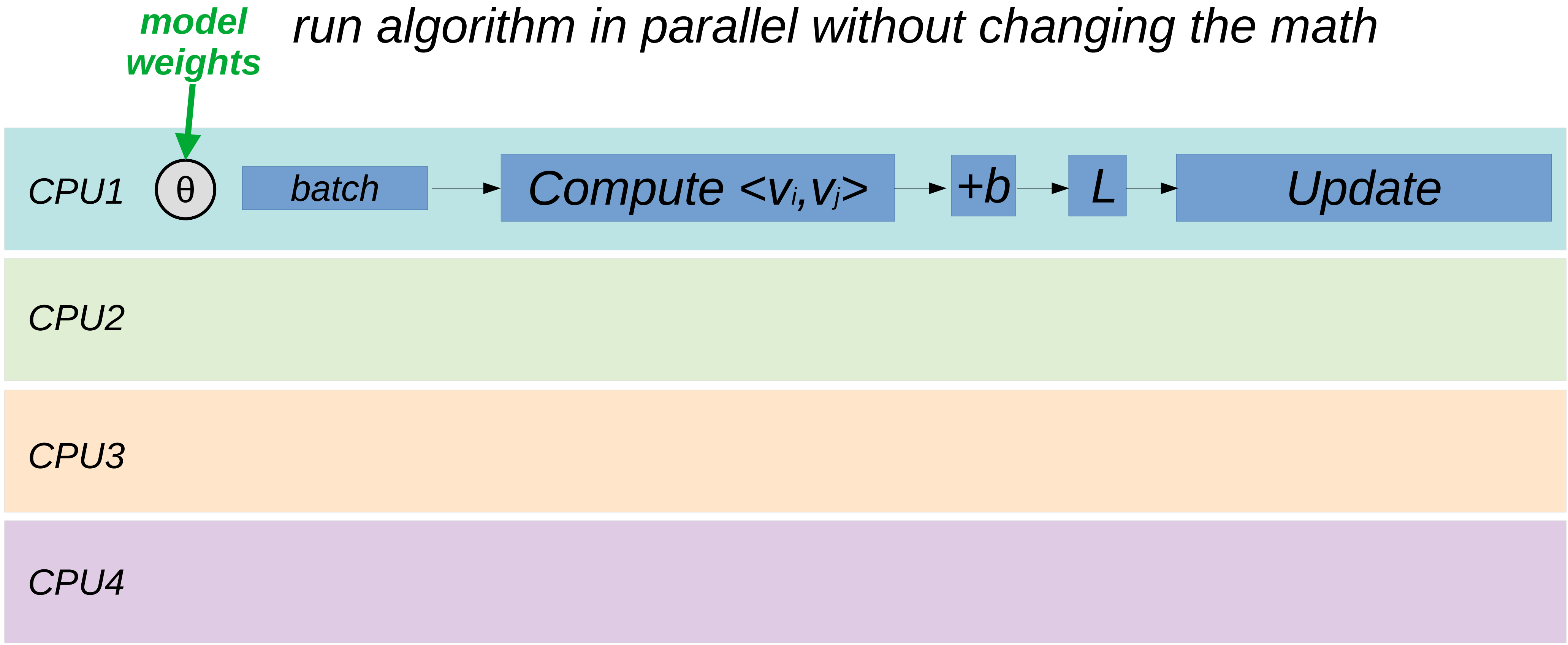
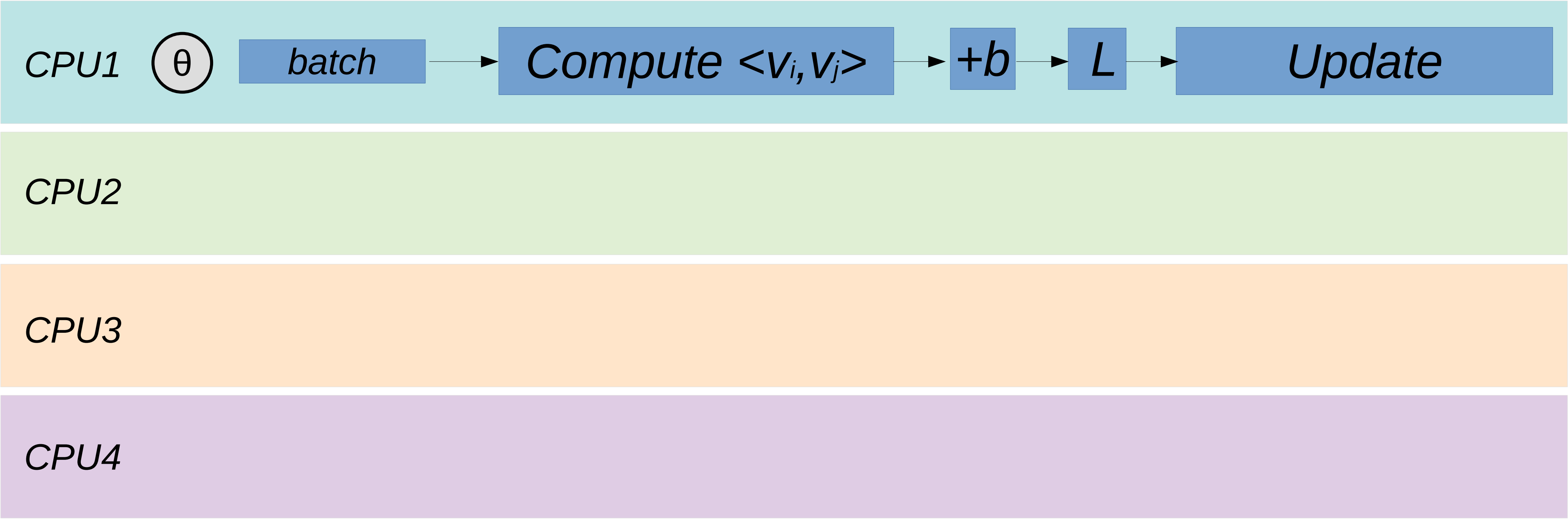


“Data parallelism”

*Each process runs **full** model on **some** samples*



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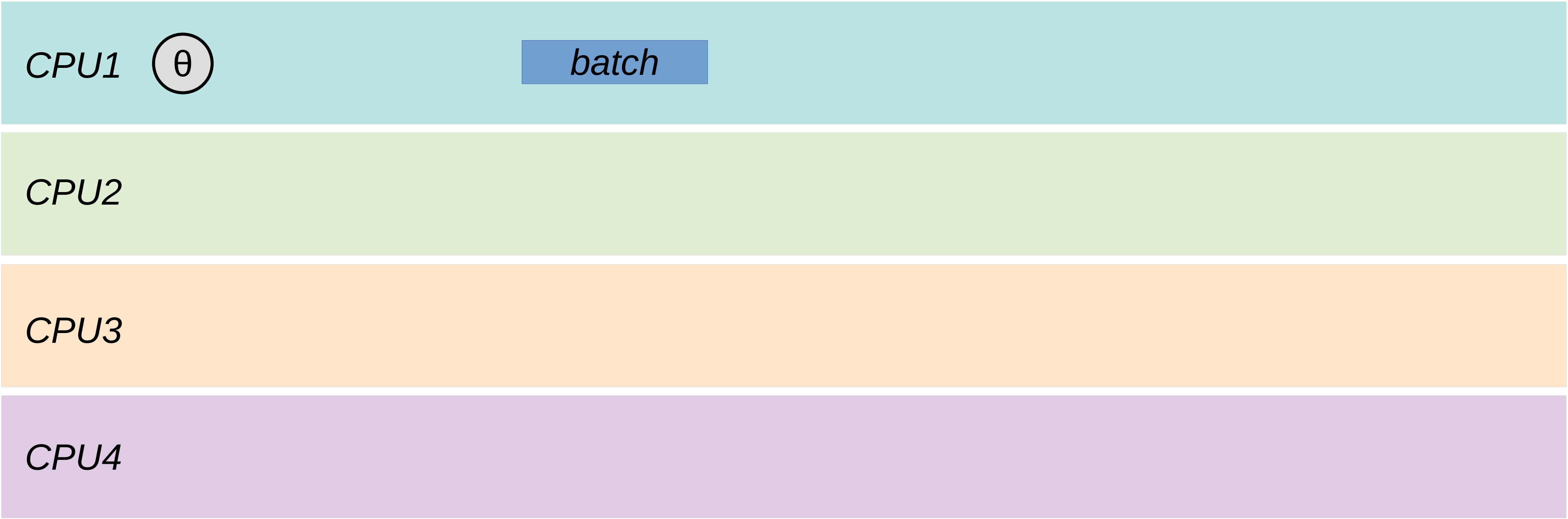

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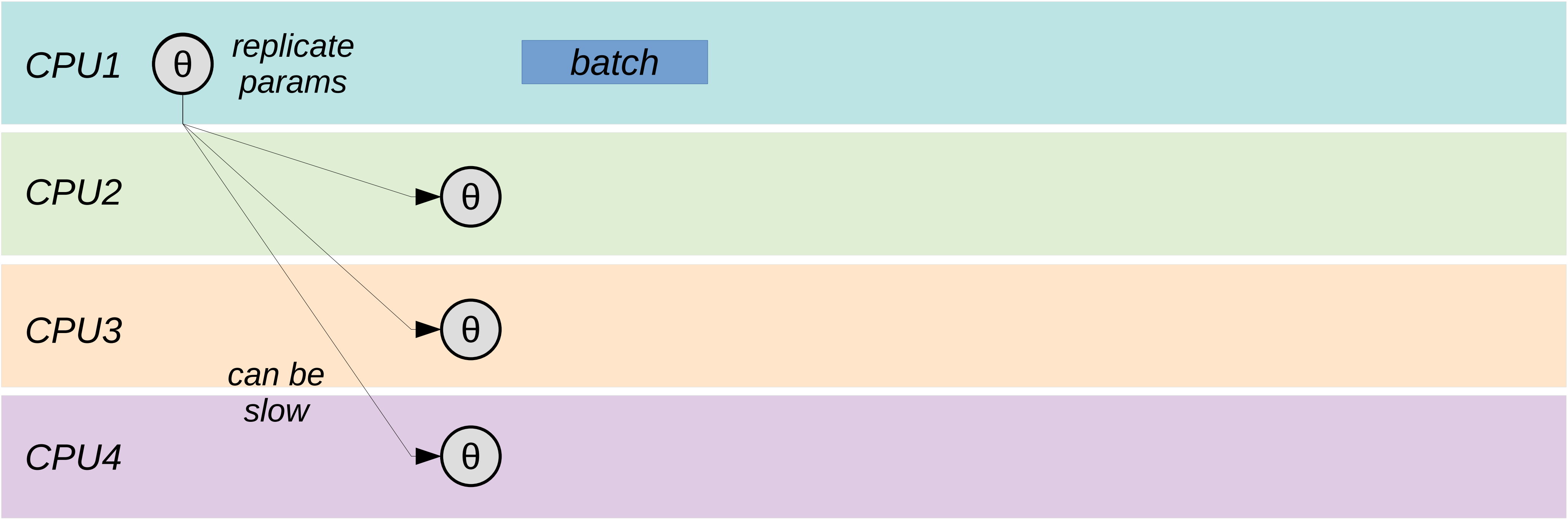

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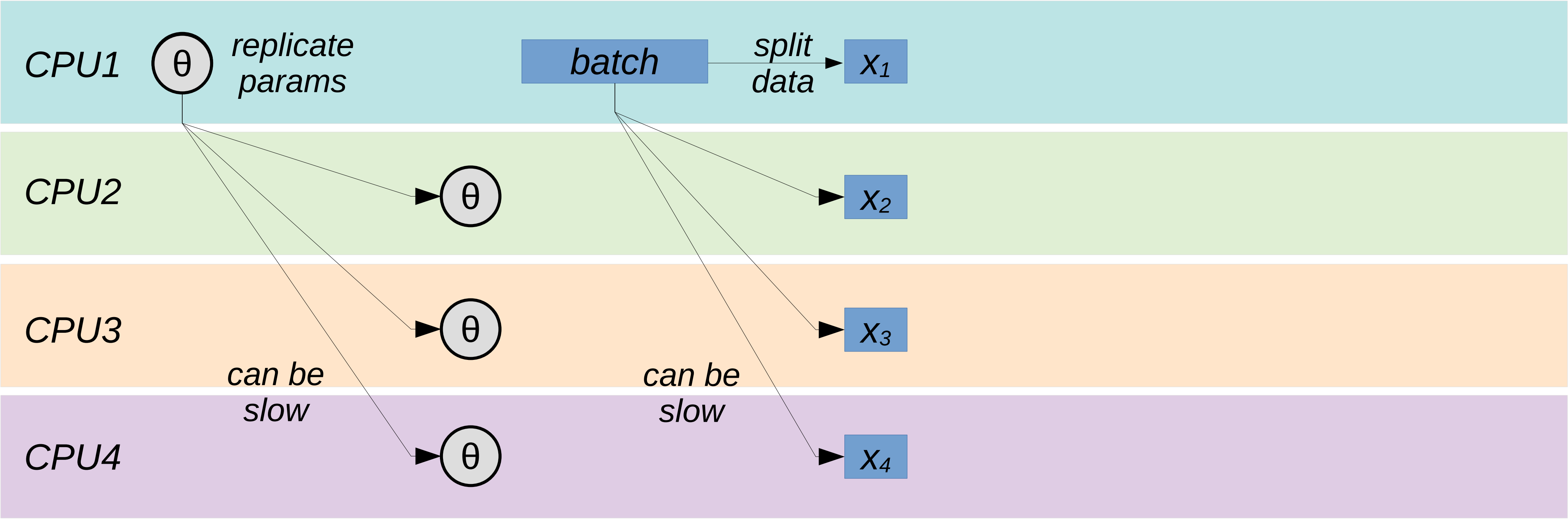

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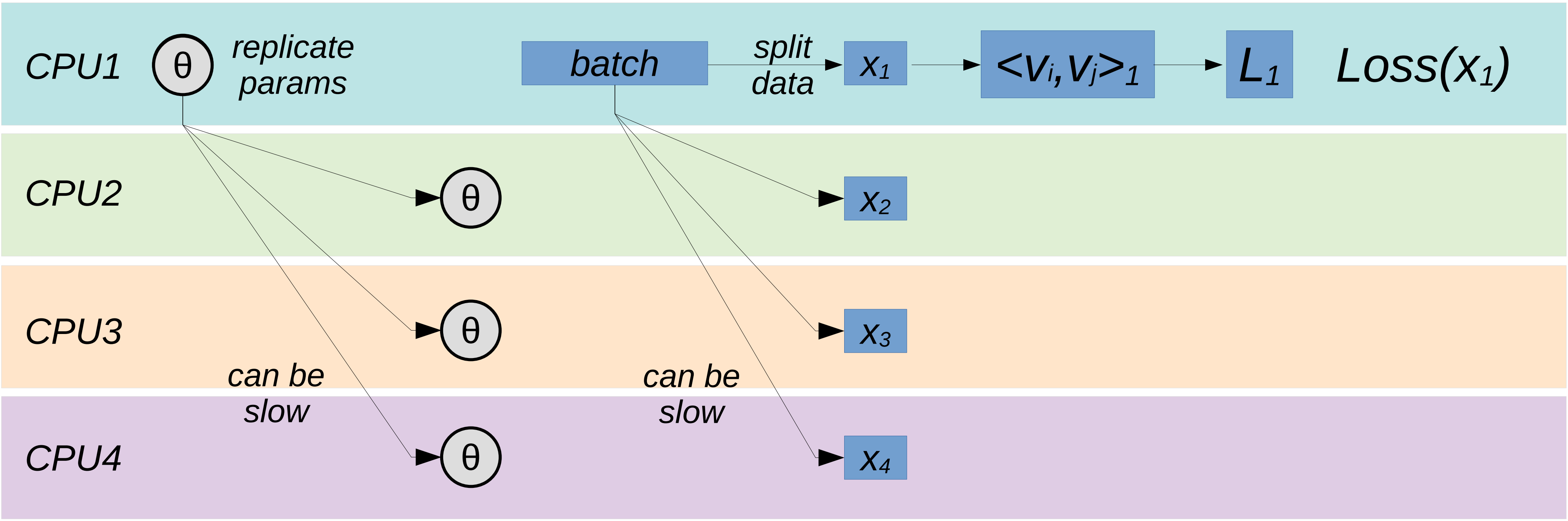

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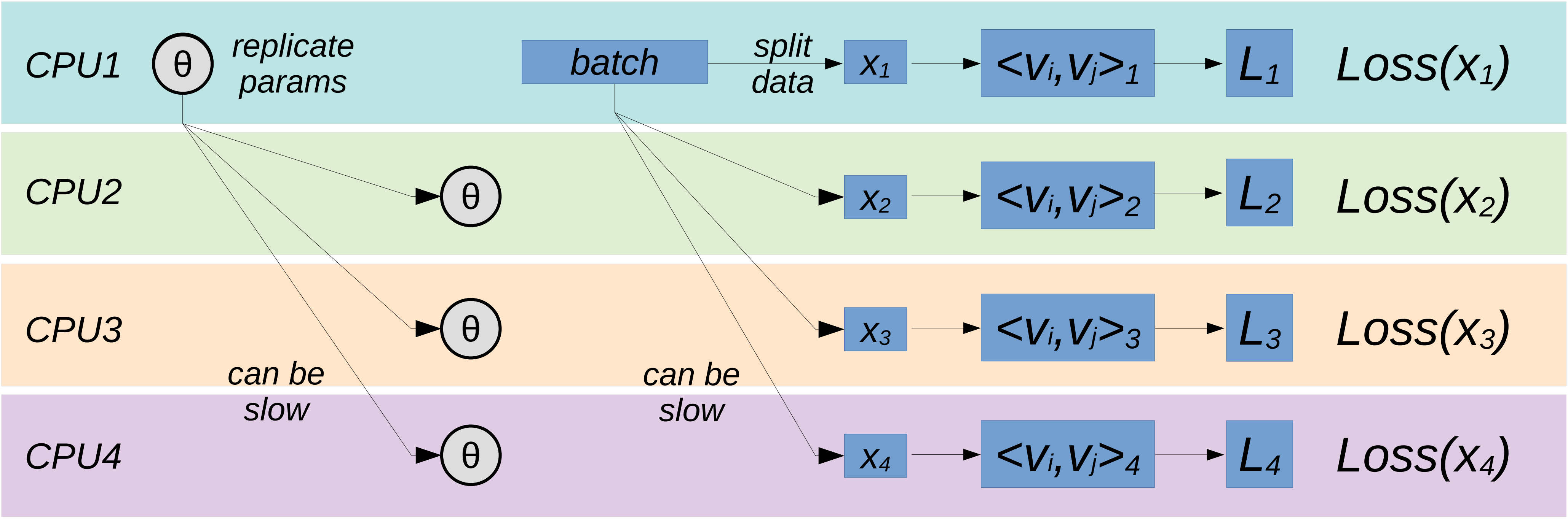

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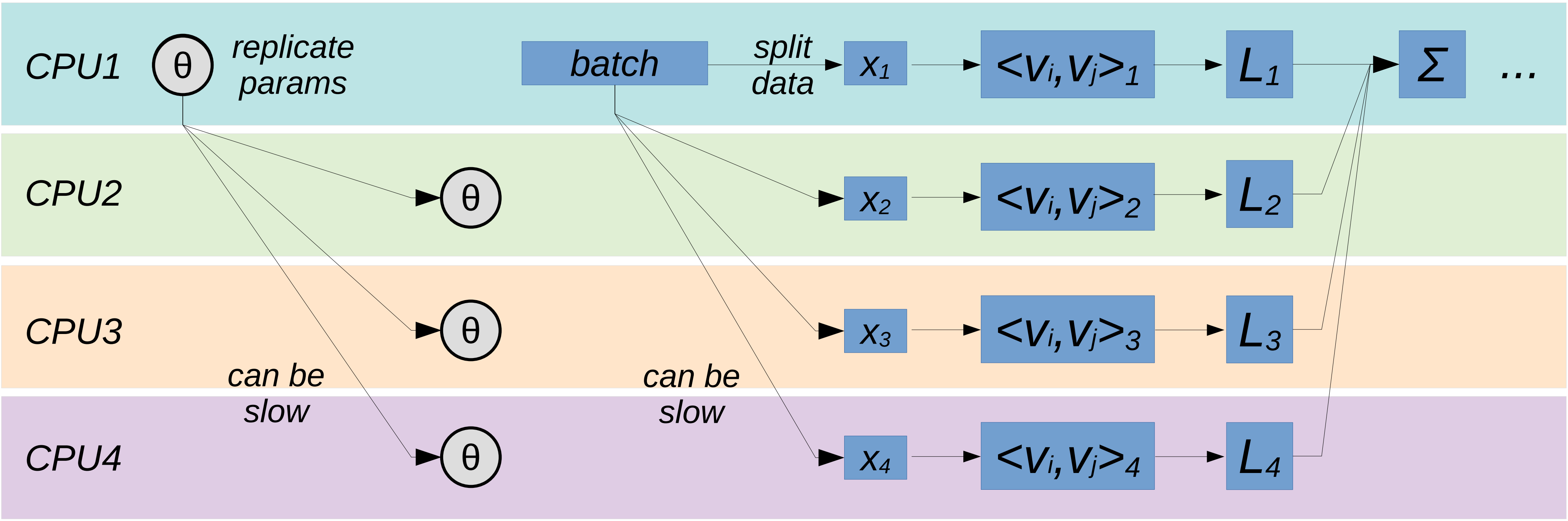
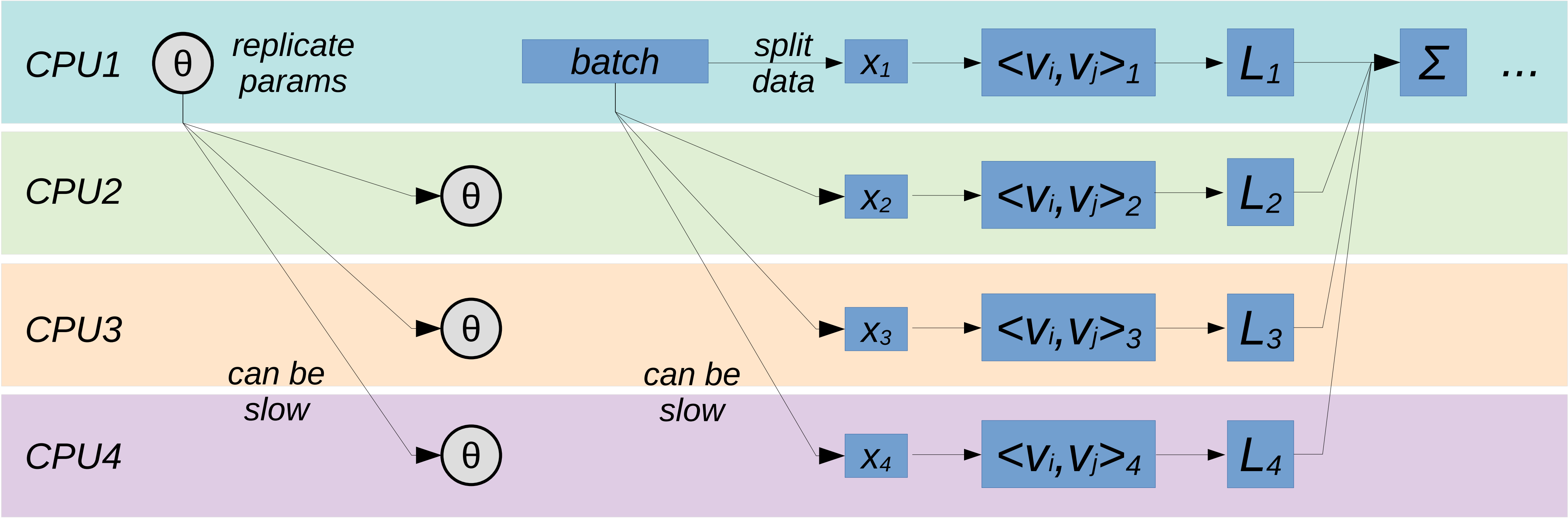


“Data parallelism”

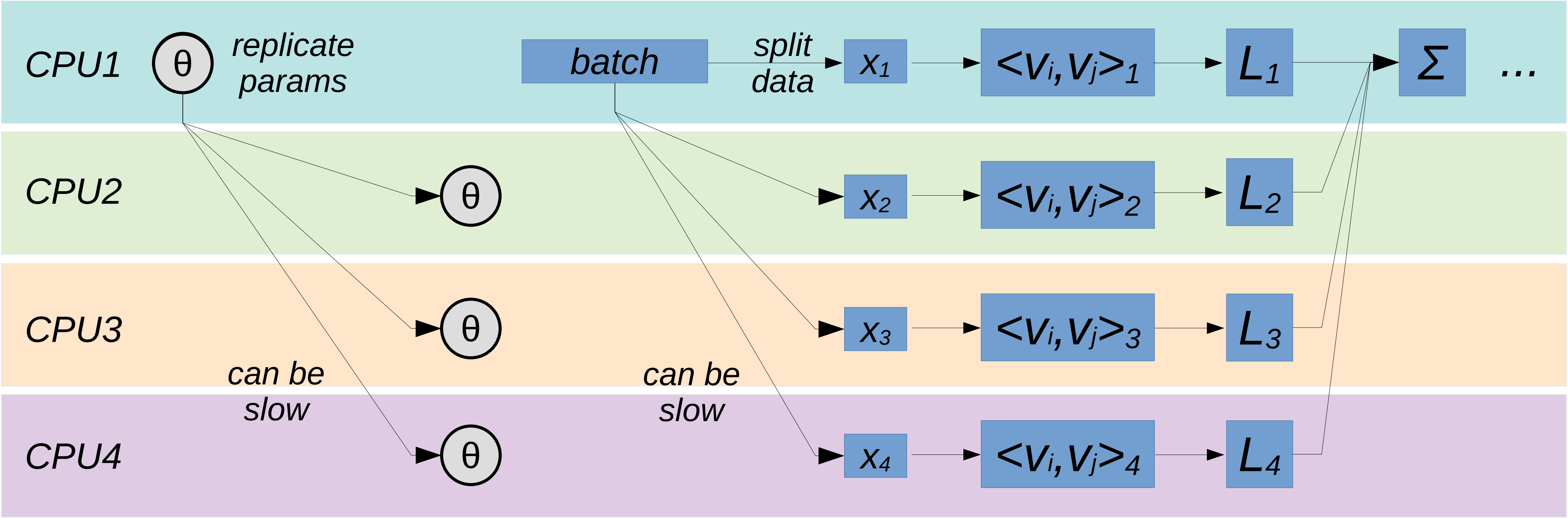
Q: Is it guaranteed to be faster?



“Data parallelism”

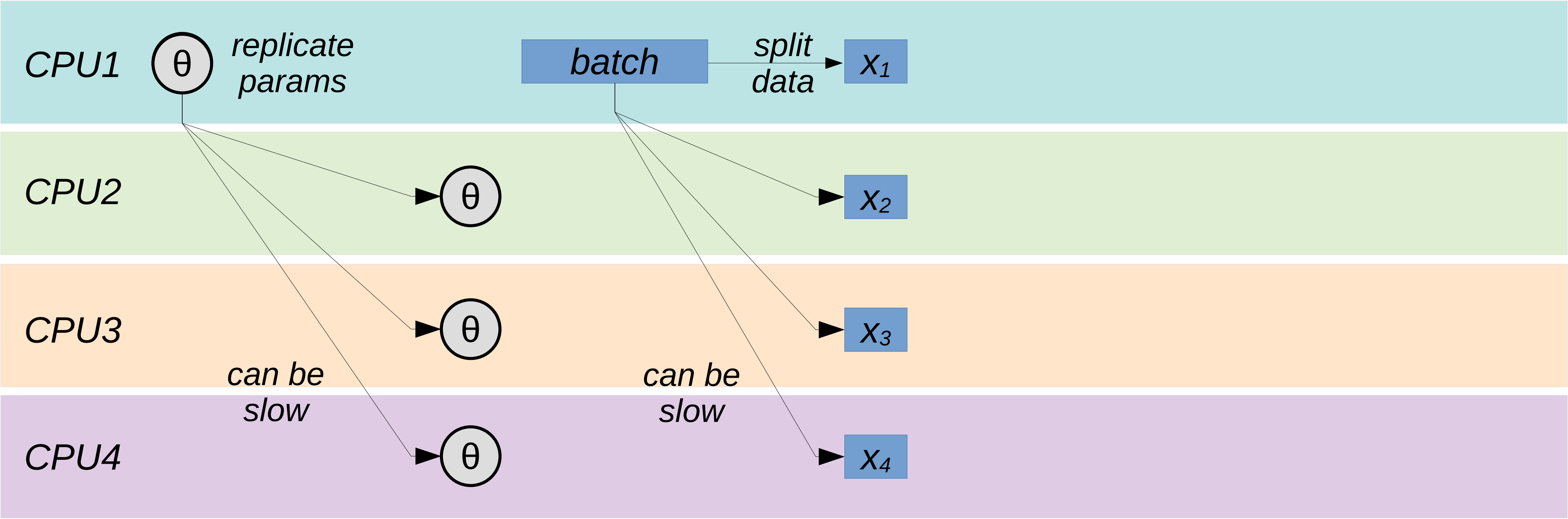
Q: Is it guaranteed to be faster?

No, sending data may take longer than computing



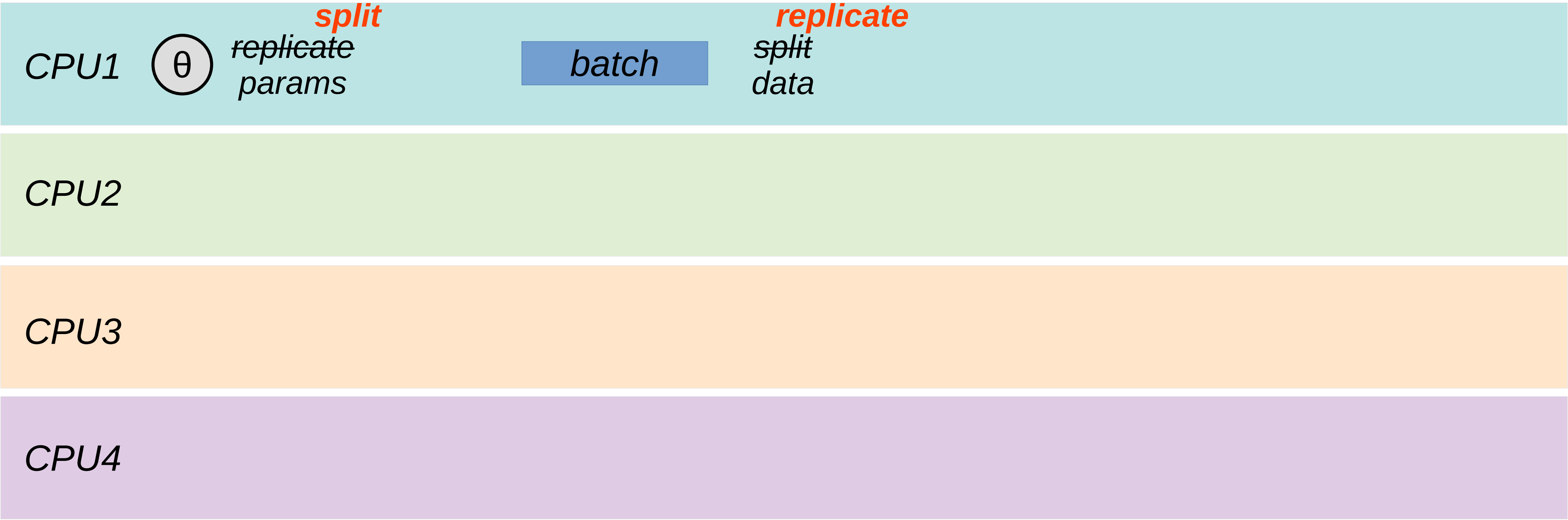
“Data parallelism”

Q: any other way to compute <vi, vj> in parallel?



“Model parallelism”

*Each process runs **partial** model on **all** samples*



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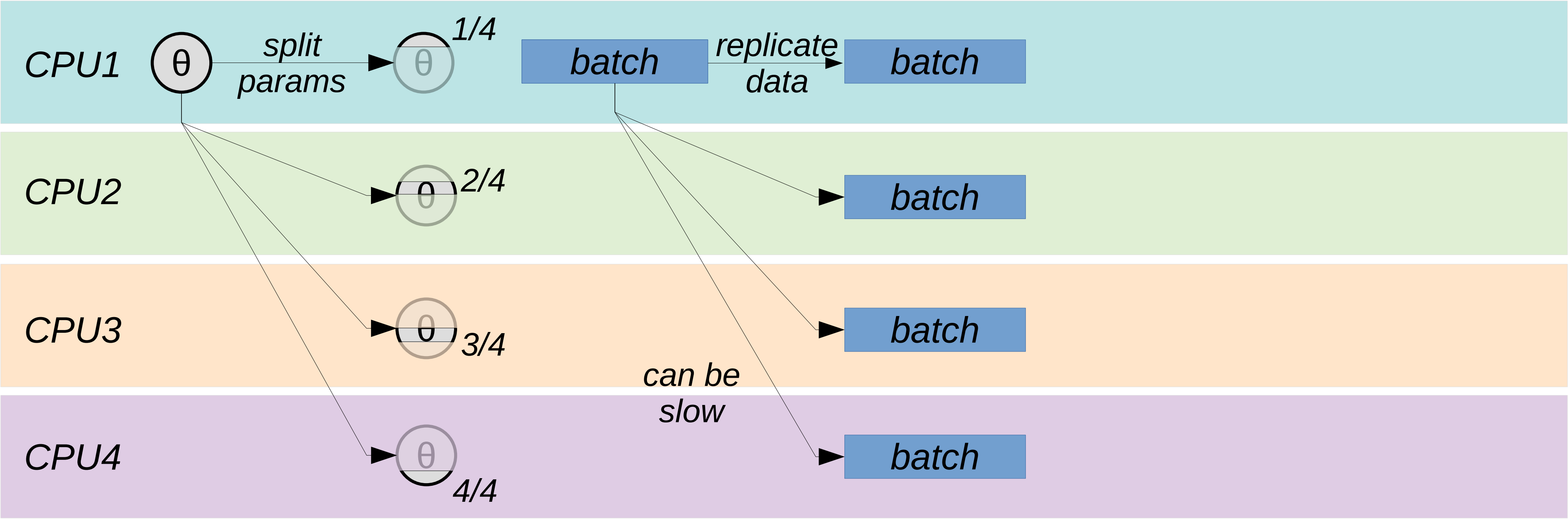

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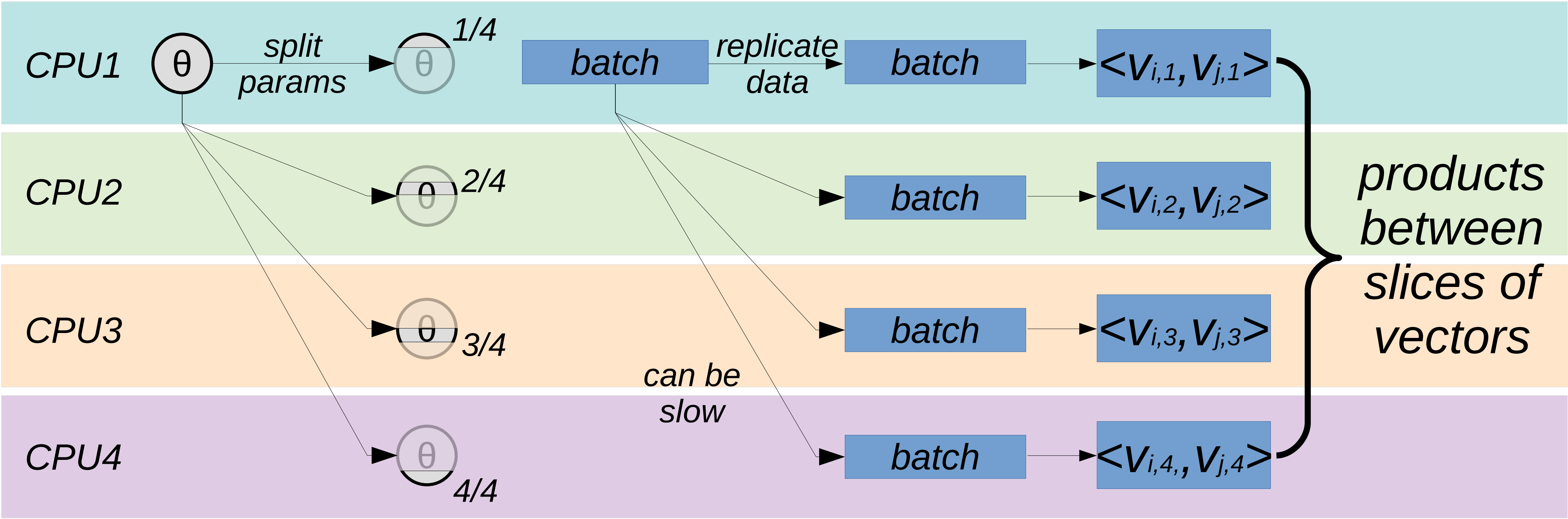

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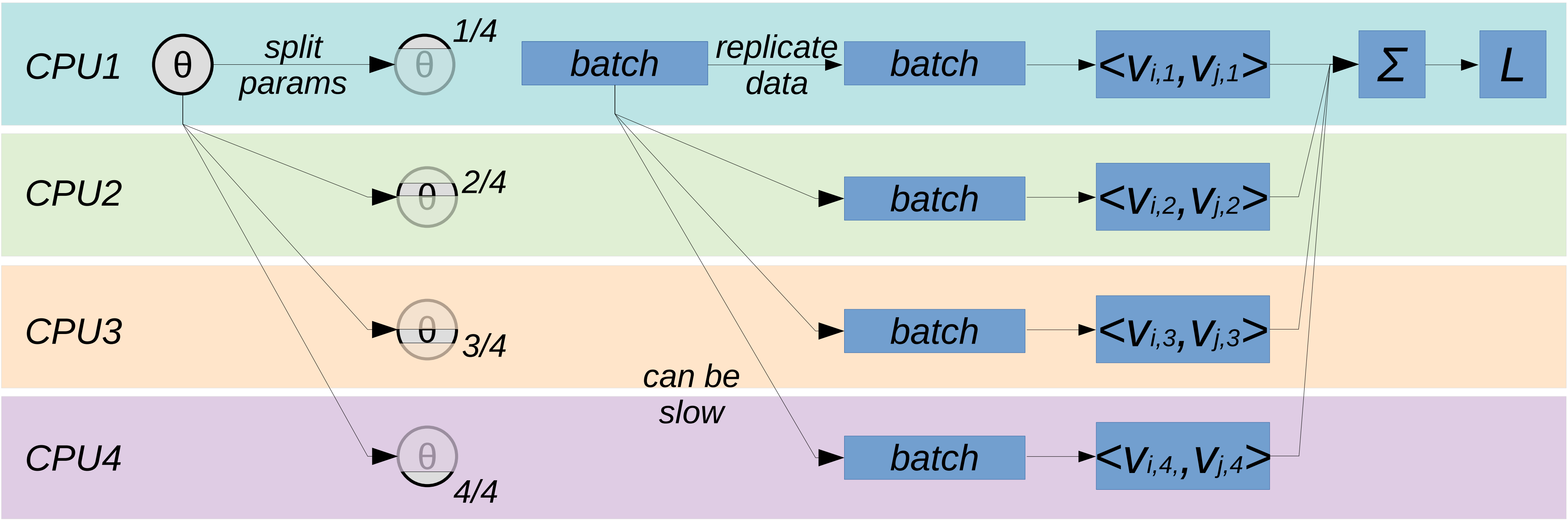
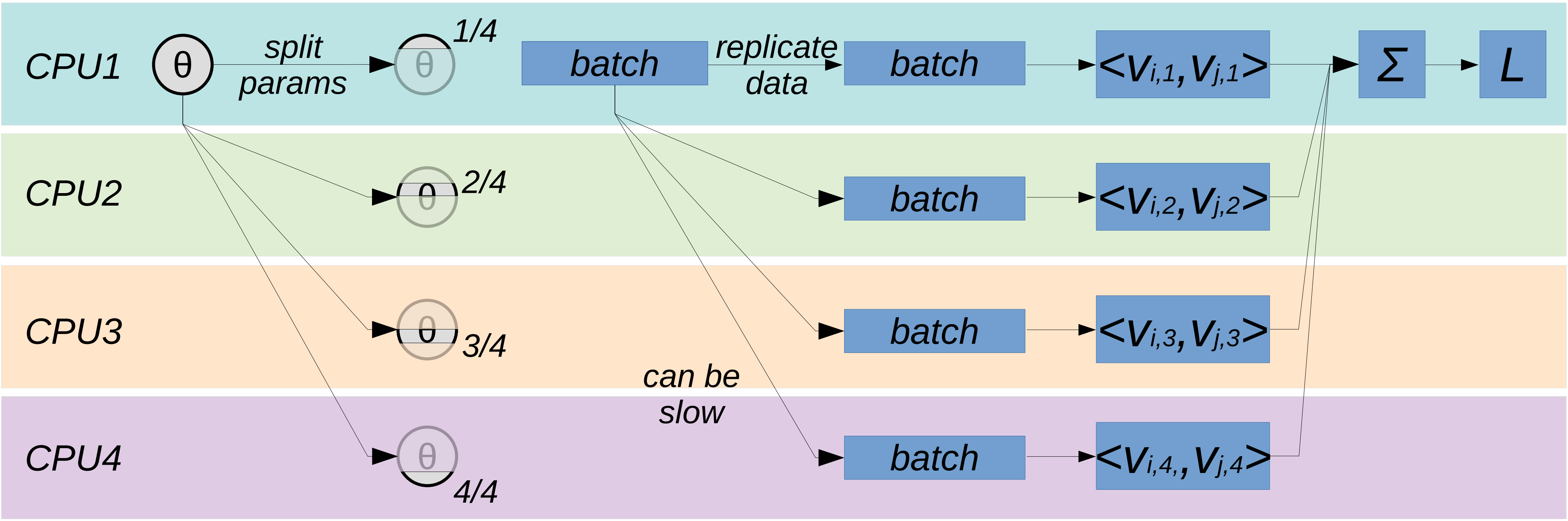


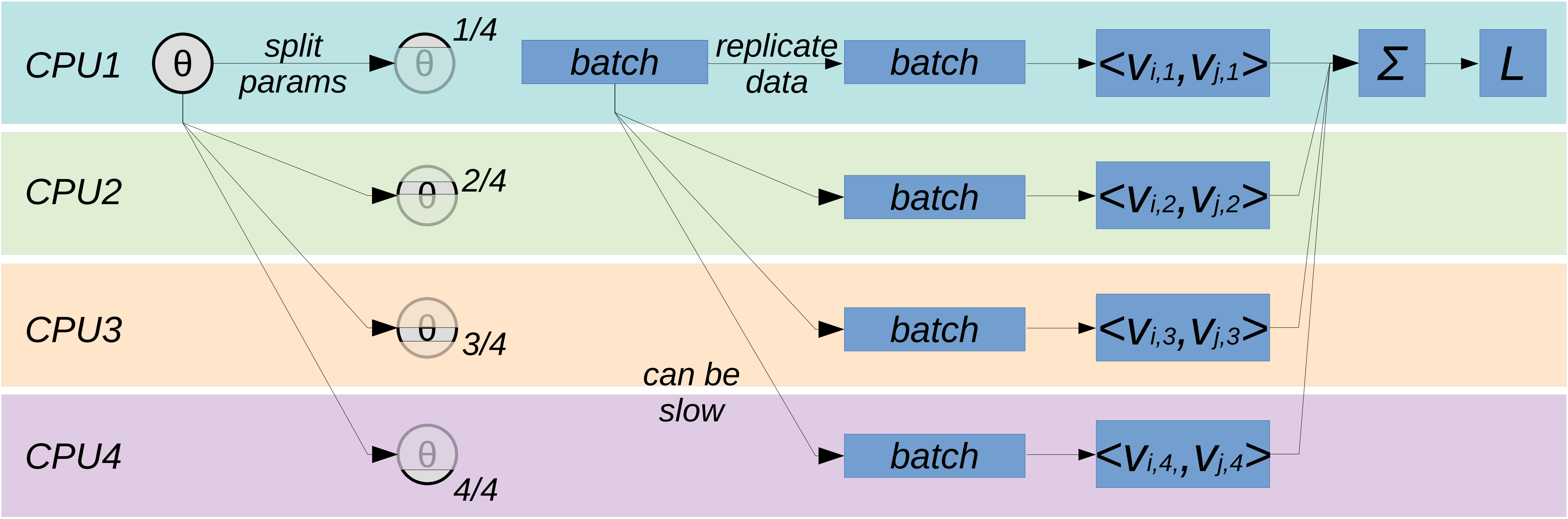
"Model parallelism"

***Q:** do we have to send params from P1 each time?*



"Model parallelism"

Optimization: each process can update it's own params locally instead of receiving them from P1



Summary: operation parallelism

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

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

Which one is better..
for word2vec?
In general?

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..

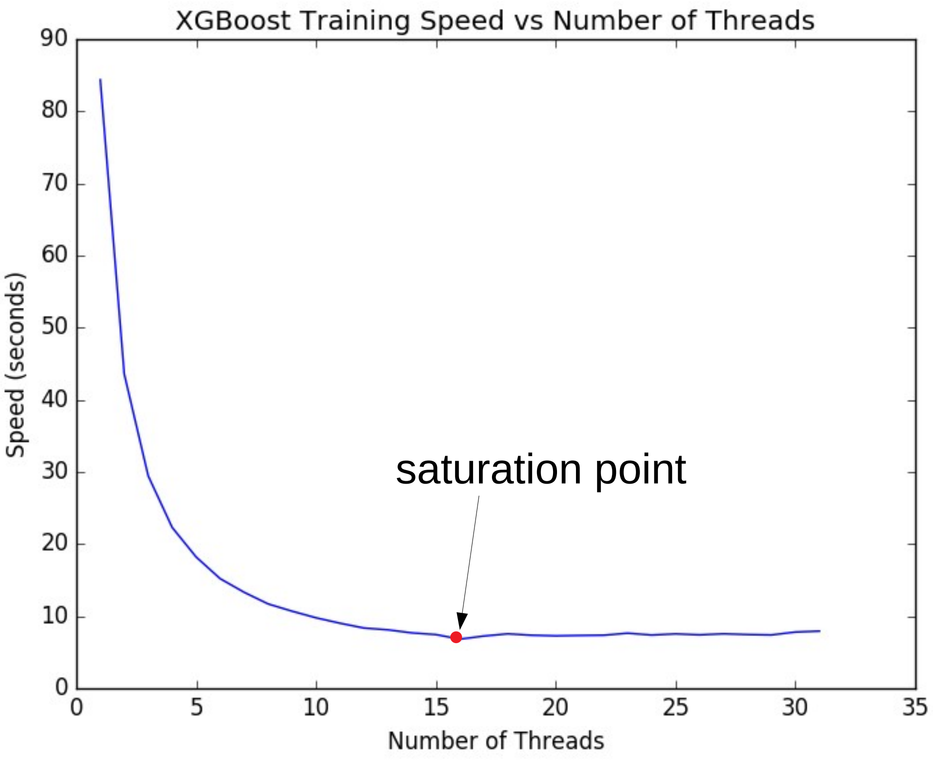
for word2vec?

In general?

Summary: operation parallelism

Если time() < 19:00, тут можно поговорить про бустинг.
и-или сделать перерыв

Operation parallelism

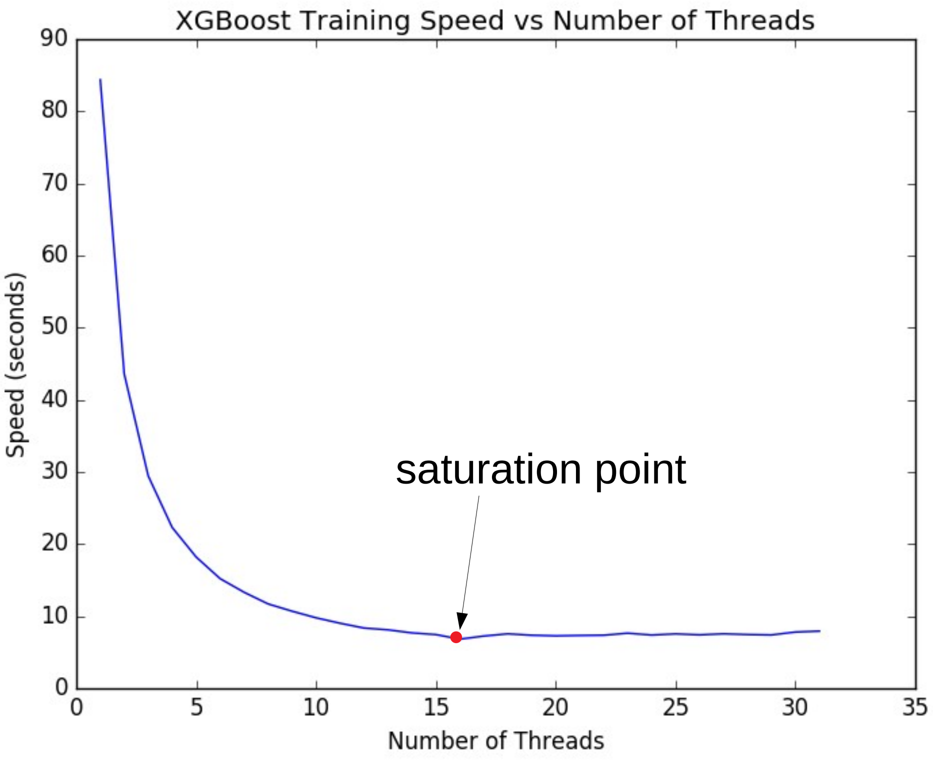


More processes = more overhead

- *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*

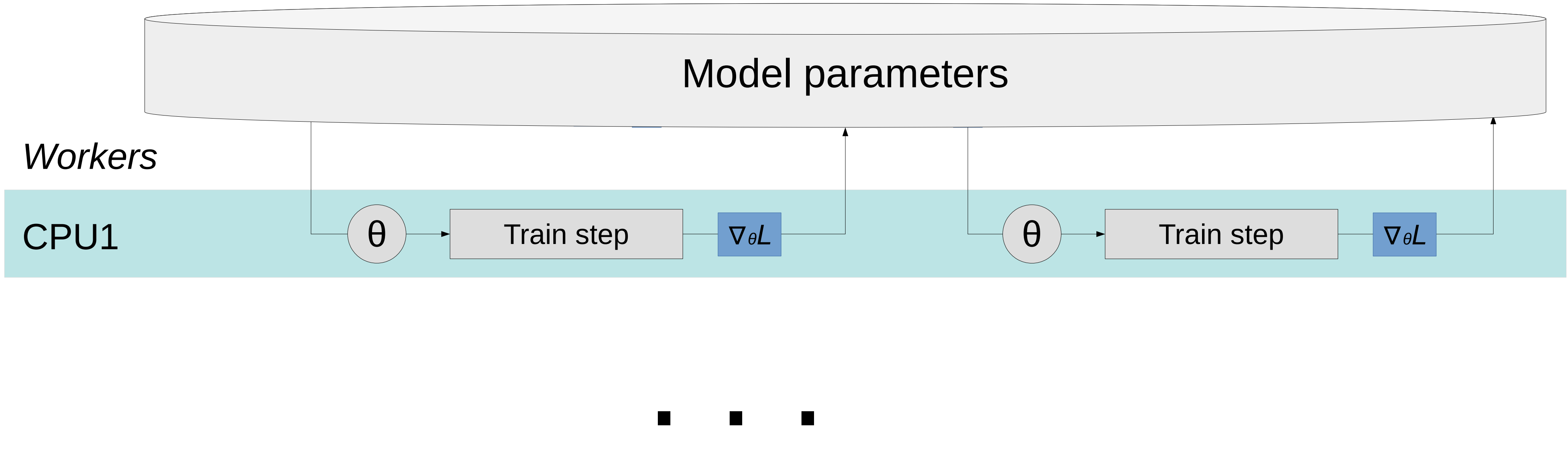
Eventually adding more threads will no longer boost performance

How do we push this point further?

Parameter Server

Paper: Smola et al. (2010)

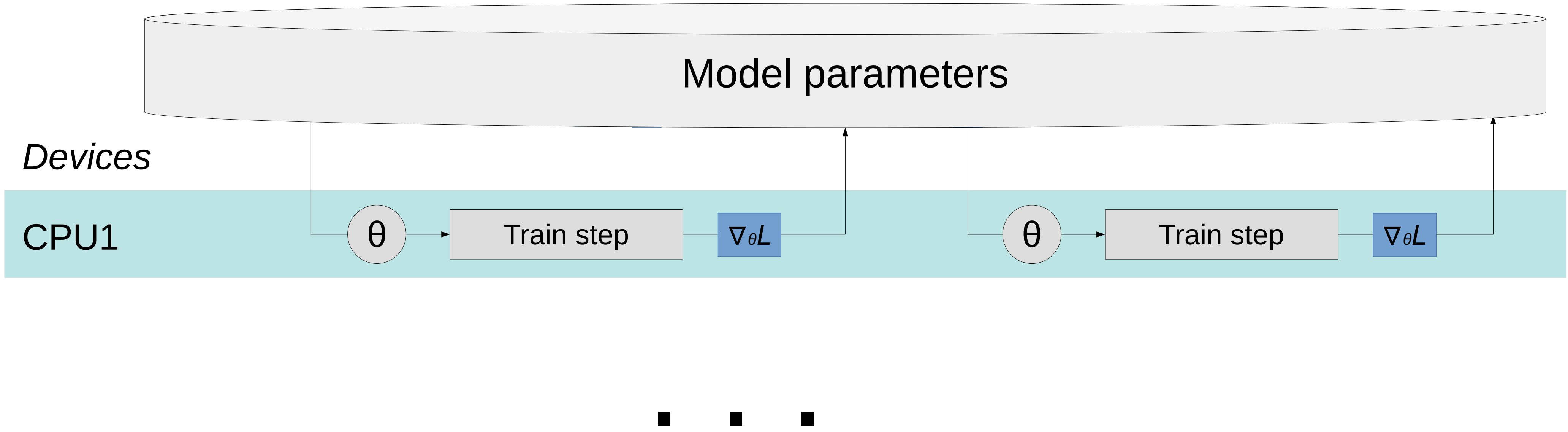
Make a dedicated process for parameters & optimizer



Asynchronous training

HOGWILD! arxiv.org/abs/1106.5730

Idea: remove synchronization step alltogether, use parameter server



Asynchronous training

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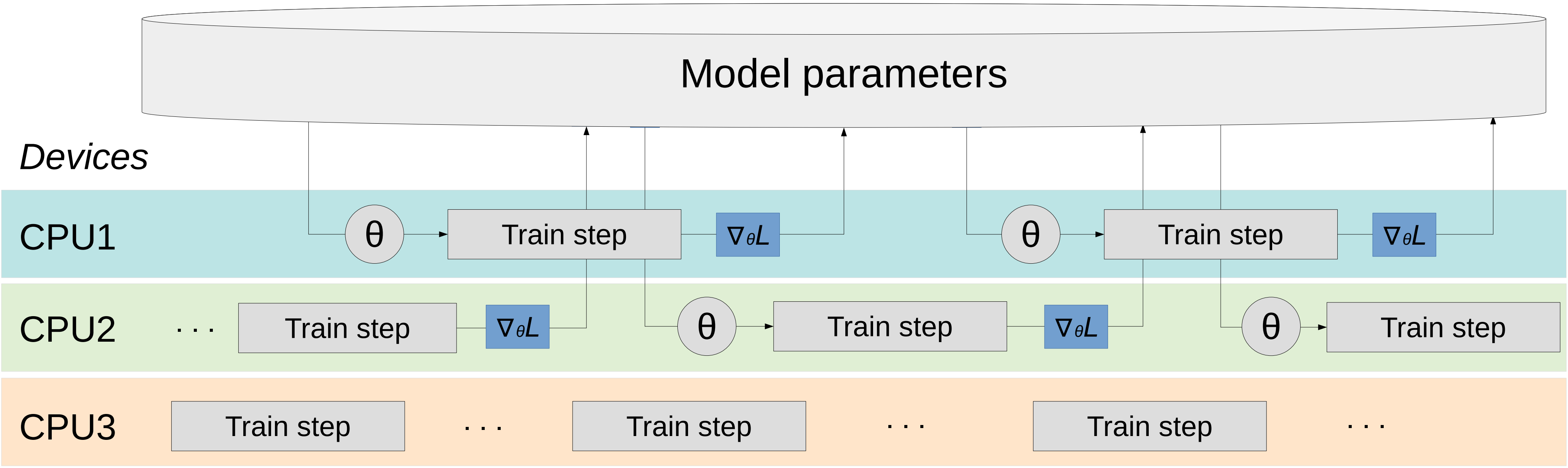

Asynchronous training

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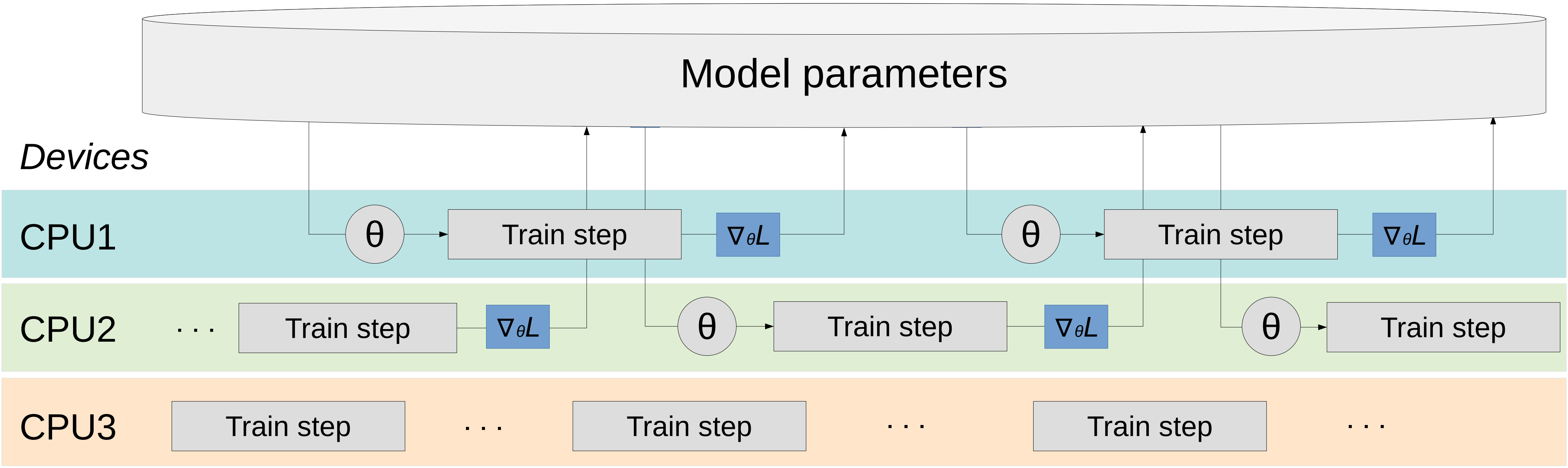
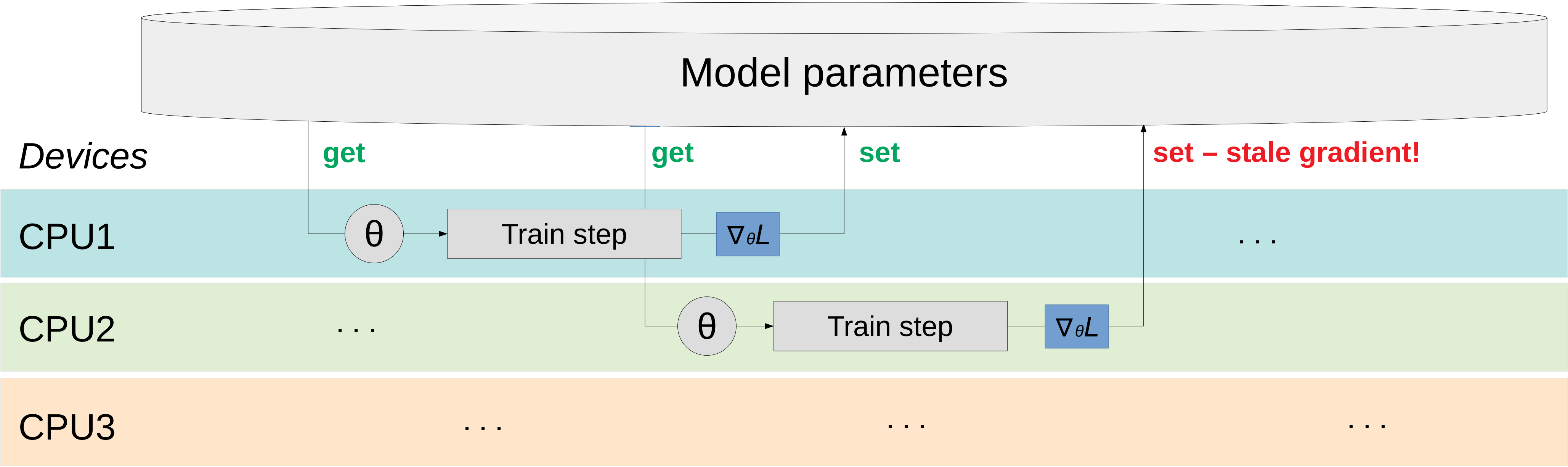


Q: have we lost anything by going asynchronous?

Asynchronous training

HOGWILD! arxiv.org/abs/1106.5730

Idea: remove synchronization step alltogether, use parameter server



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

n = total workers
λ = "accumulation factor"

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

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

staleness-dependent
"learning rate"

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

Staleness-aware SGD

Paper: arxiv.org/abs/1511.05950 & others

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

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)

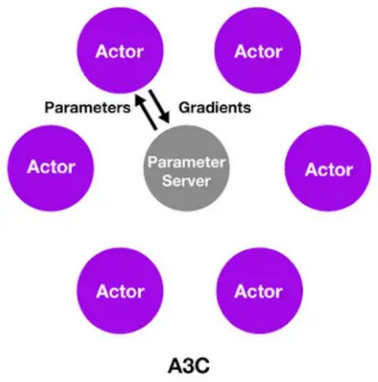
aka number of skipped updates

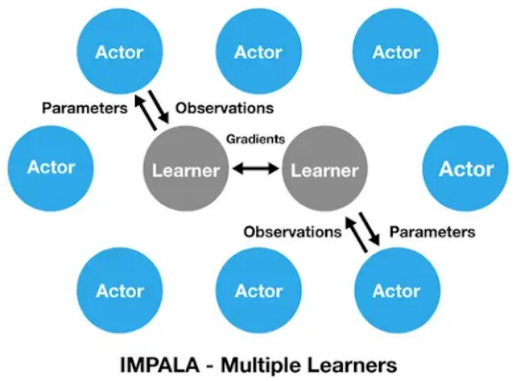
Parameter Server Applications

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:





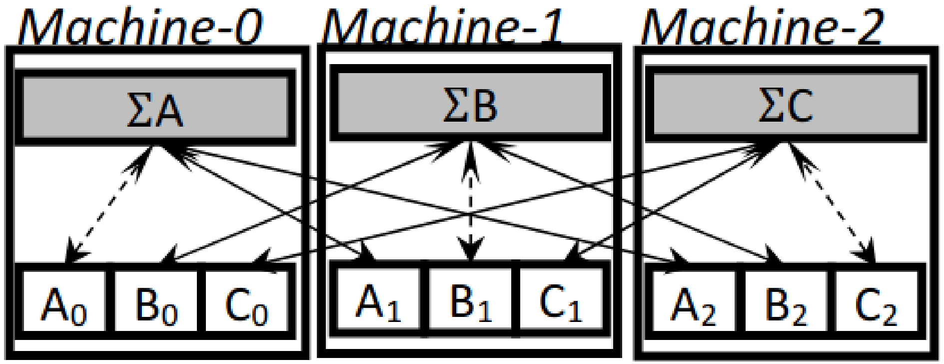
Async. RL: arxiv.org/abs/1602.01783
IMPALA: arxiv.org/abs/1802.01561
SEED RL: arxiv.org/abs/1910.06591

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

Modern Parameter Server Systems

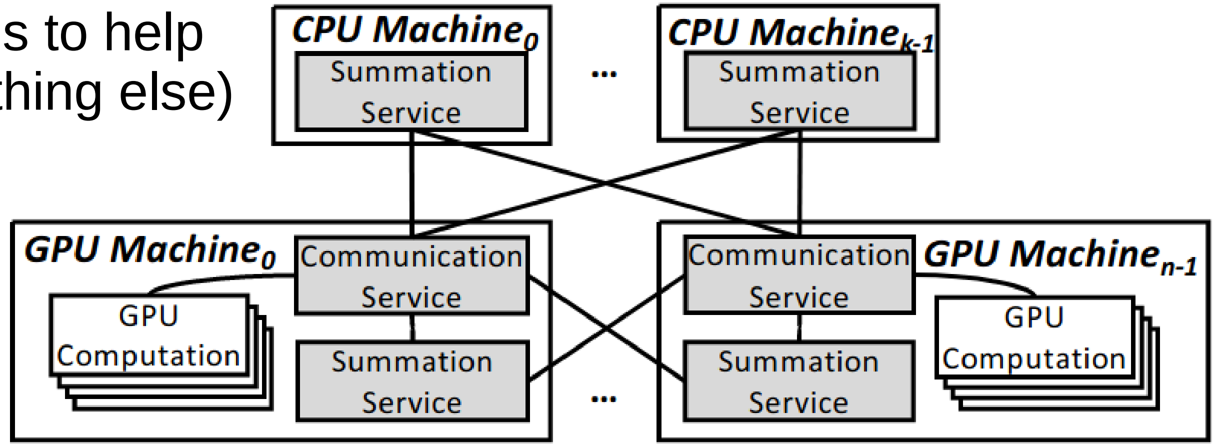
Read more: https://www.usenix.org/system/files/osdi20-jiang.pdf

Baseline: sharded PS on every node
Each server runs a subset of weights



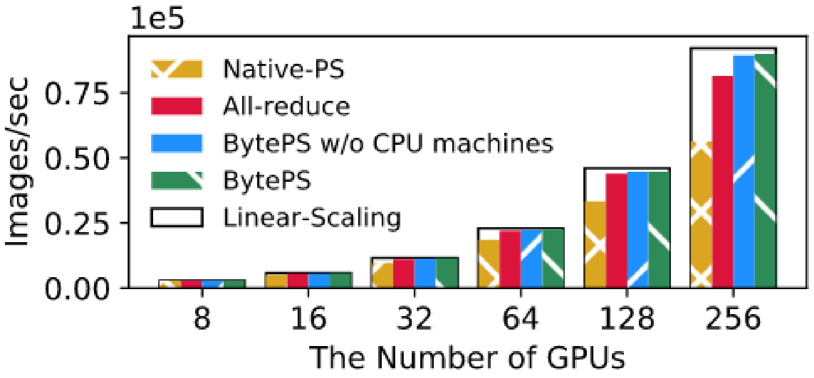
BytePS: add non-GPU nodes to help averaging gradients (and nothing else)

CPU nodes are ~10x cheaper to deploy / rent

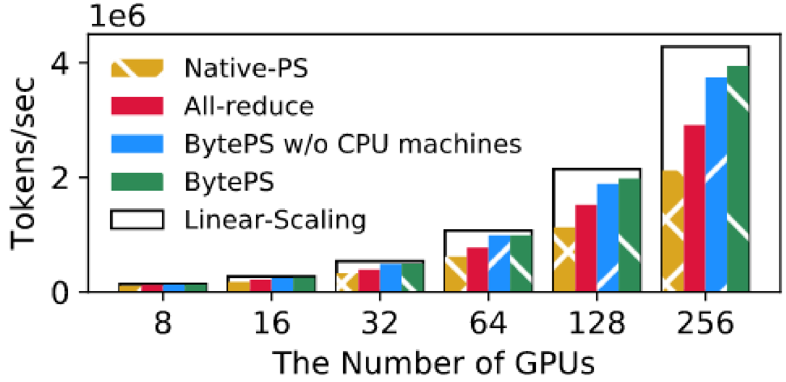


Modern Parameter Server Systems

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

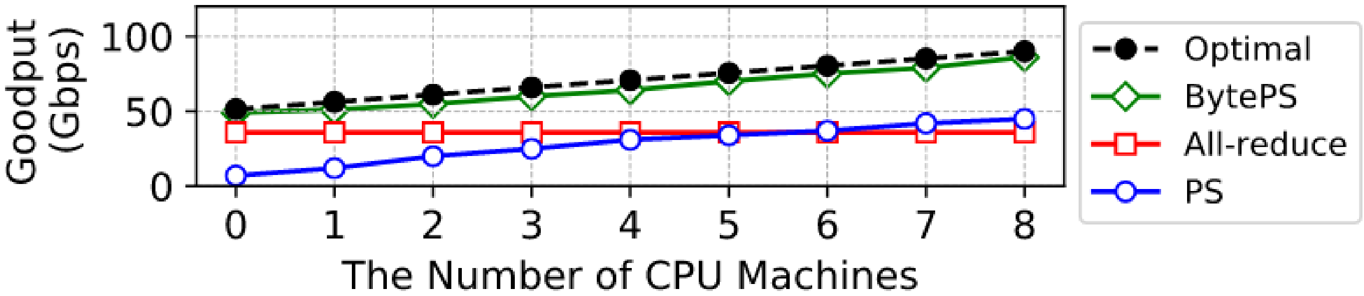


(a) TensorFlow, ResNet-50, batch=256 images



(b) MXNet, BERT-Large, batch=8192 tokens

The effect of auxiliary CPU nodes




"That's all Folks!"
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