COMP 545: Advanced topics in optimization
From simple to complex ML systems

Lecture 8

Overview

$$\min_{x} \quad f(x)$$

$$\text{s.t.} \quad x \in \mathcal{C}$$

- Different objective classes
- Different strategies within each problem
- Different approaches based on computational capabilities
- Different approaches based on constraints

And, always having in mind applications in machine learning, AI and signal processing

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- In this lecture, we will:
  - Discuss how to **distribute optimization in large-scale settings**
  - Study **synchrony vs. asynchrony** in gradient descent
  - Provide some rough theoretical results on how asynchrony affects performance
  - Alternatives and state of the art

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  $iii)$ The whole process is sequential

$$x_{t+1} = x_t - \eta \nabla f_{i_t}(x_t) = x_{t-1} - \eta \left(\nabla f_{i_t}(x_t) + \nabla f_{i_{t-1}}(x_{t-1}) \right) = \cdots = x_0 - \eta \sum_j \nabla f_{i_j}(x_j)$$

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- How can we distribute this computation over multiple processing units?

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- **Multi-node distributed computing**:
  - *i*) Many machines (up to 1000s), probably with many cores each
    ii) Shared-nothing architecture (each machine has its own CPU, storage)
    iii) Communication between nodes is much less cheap than single node

Distributing gradient computations

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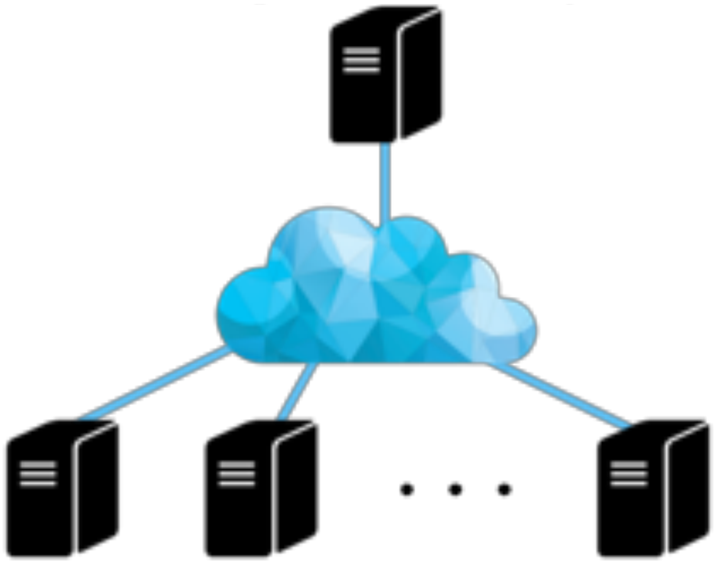

Worker 1 Worker 2 Worker P

Each contains distinct partition of data

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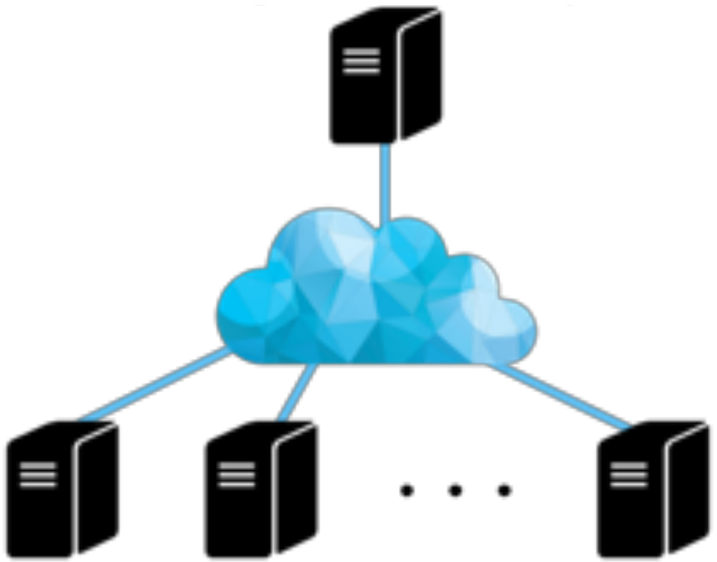

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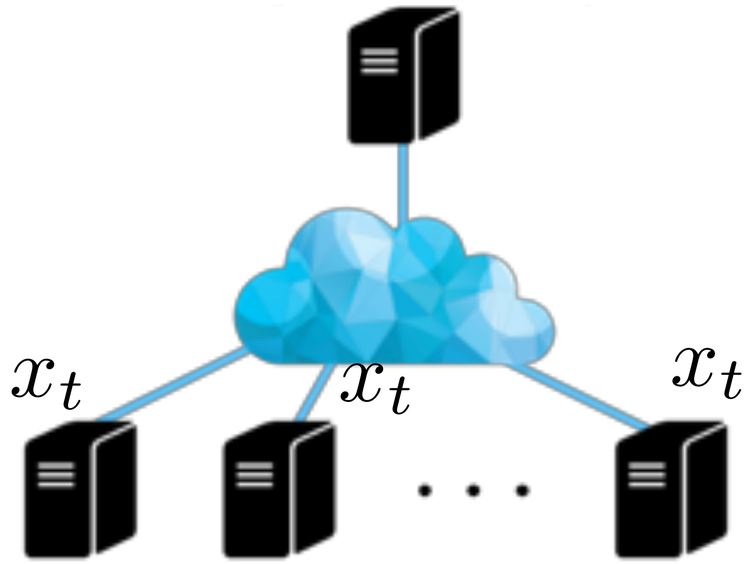

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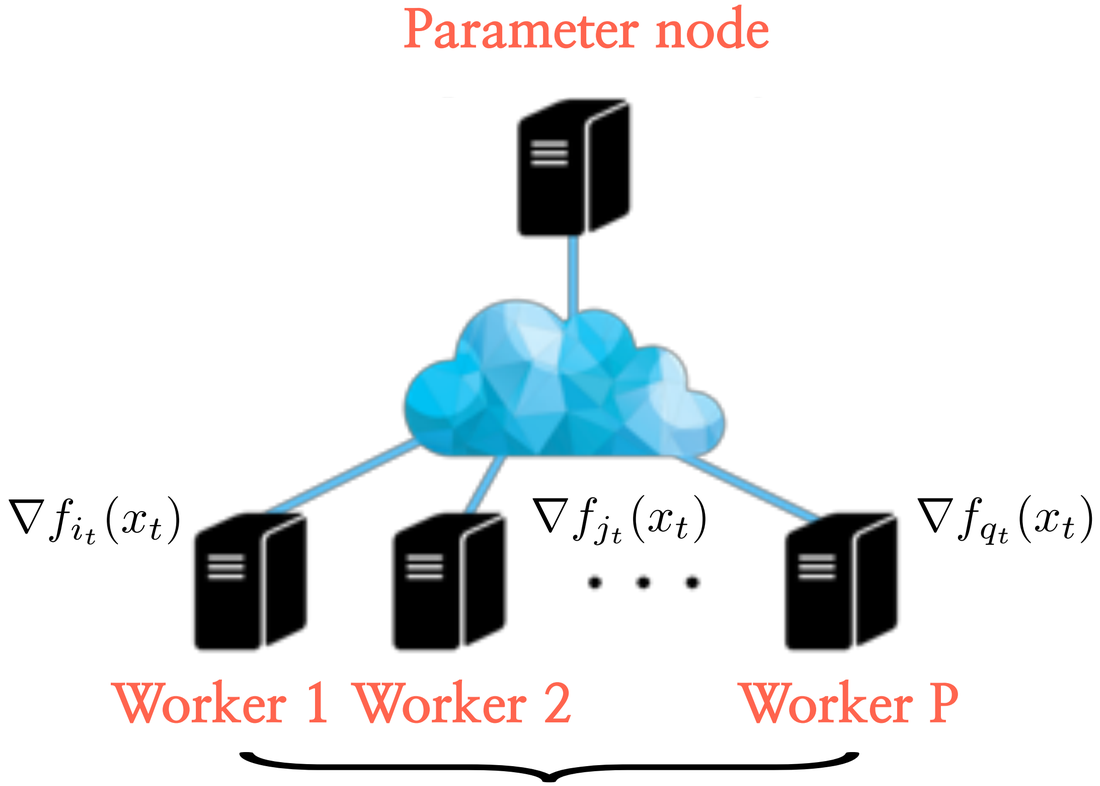

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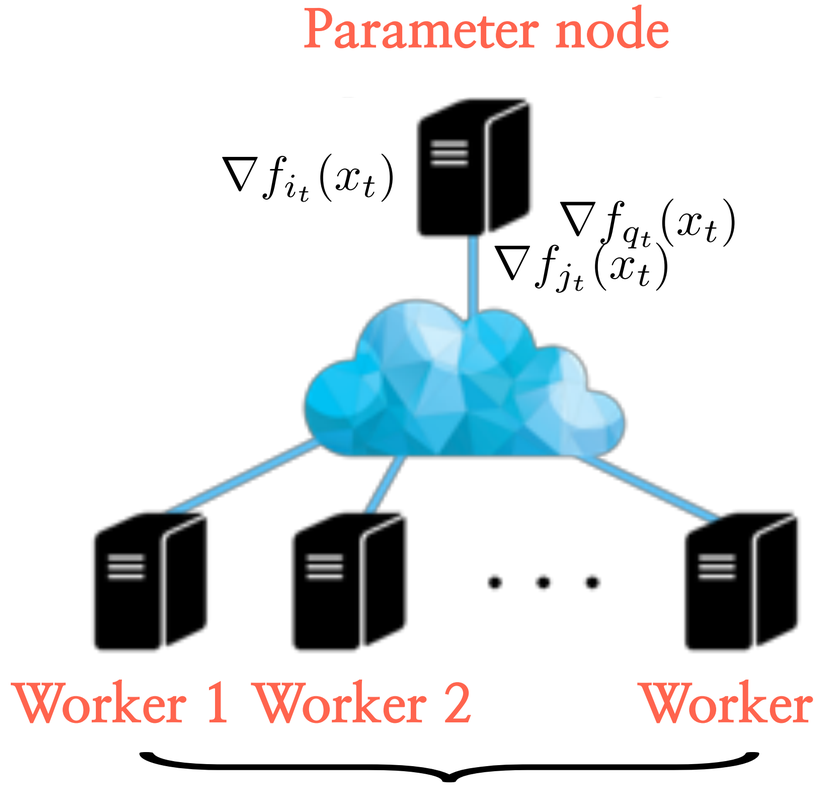

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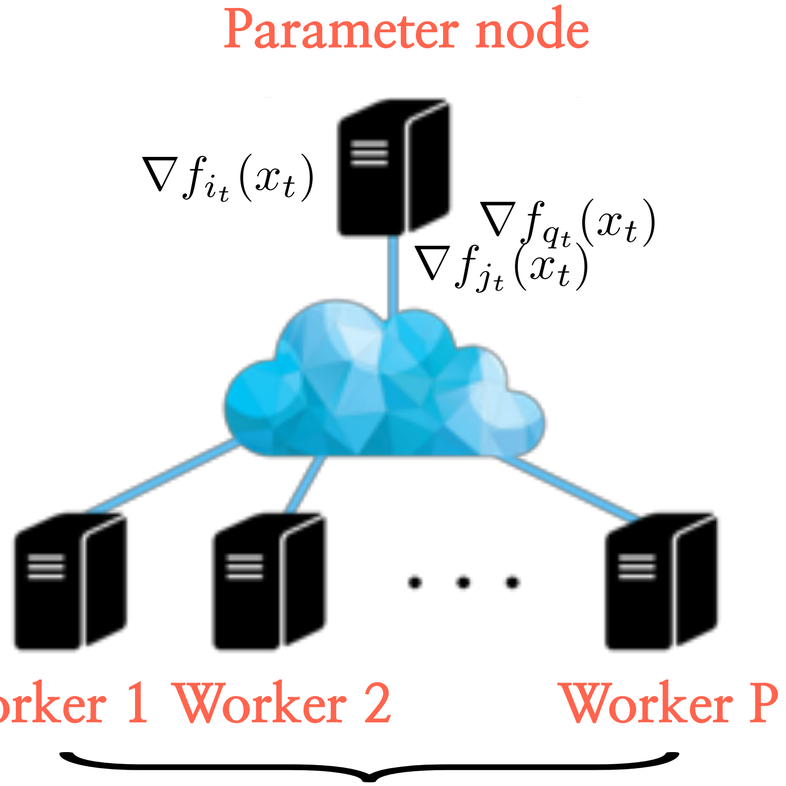

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iii) Parameter node waits for **all gradient parts** to be collected to do the gradient step

(..till the very last slow worker – active research: tackle stranglers)

Distributing gradient computations

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- "Well, it might be the case that we don't have all data at once"

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- "But, there are cases where we have finite & fixed data – see neural networks"
- "Well, the problem here is that full gradient descent does not perform well"

  Generalization vs. training error:

  1. If we care about only the training error, full GD could work well
  2. In ML tasks, we often care about the generalization error, i.e., the performance of the model on unseen data

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Whiteboard

(This relates to the question "large vs. small batch training")

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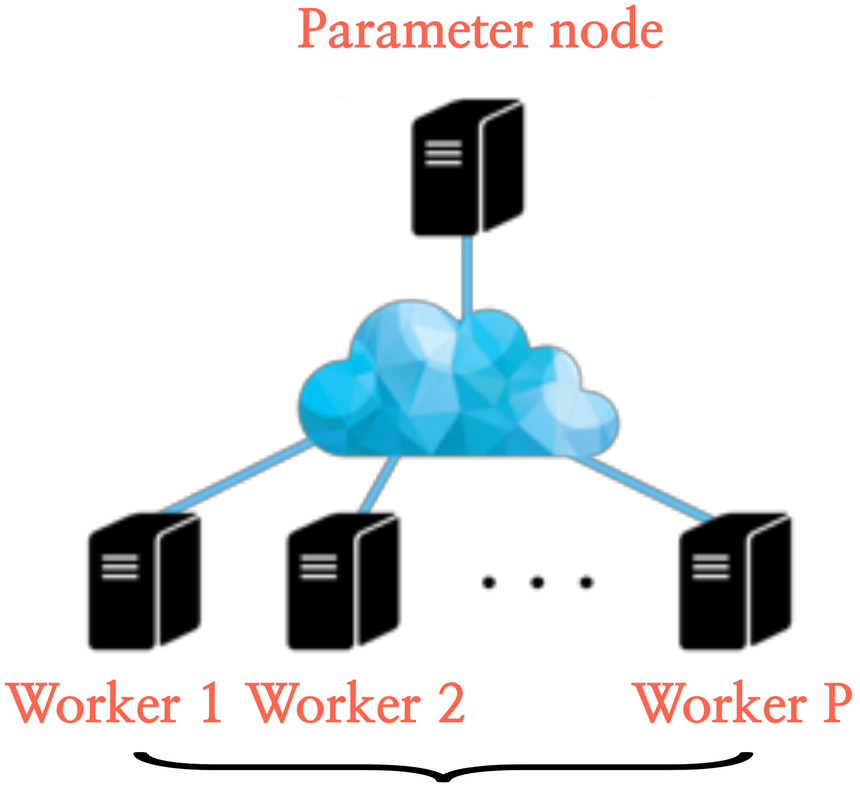

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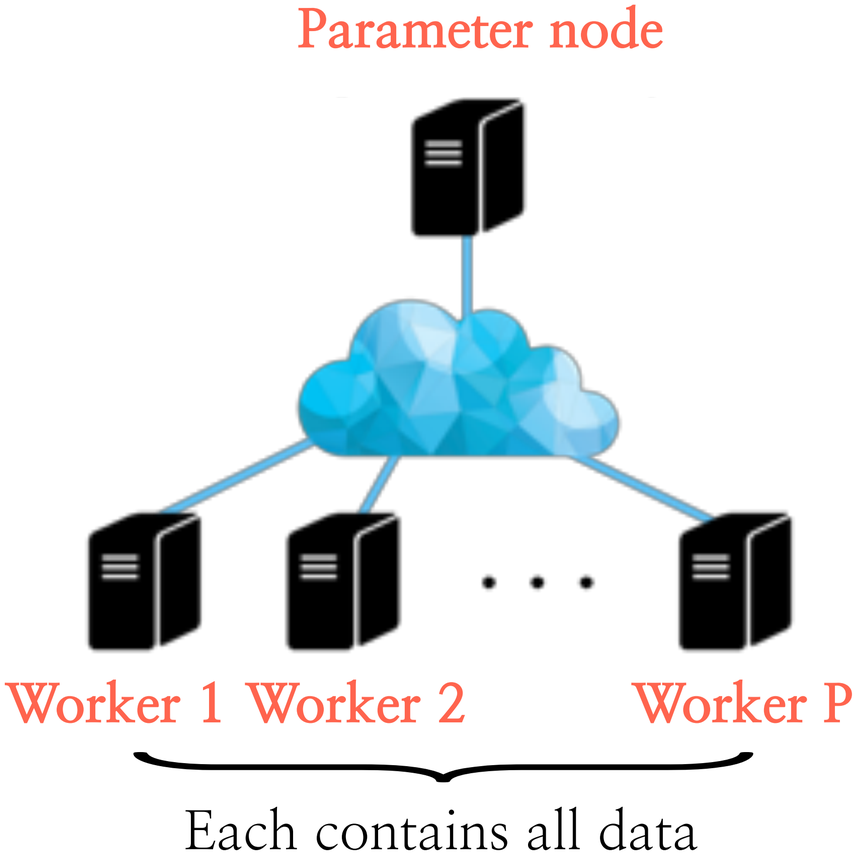

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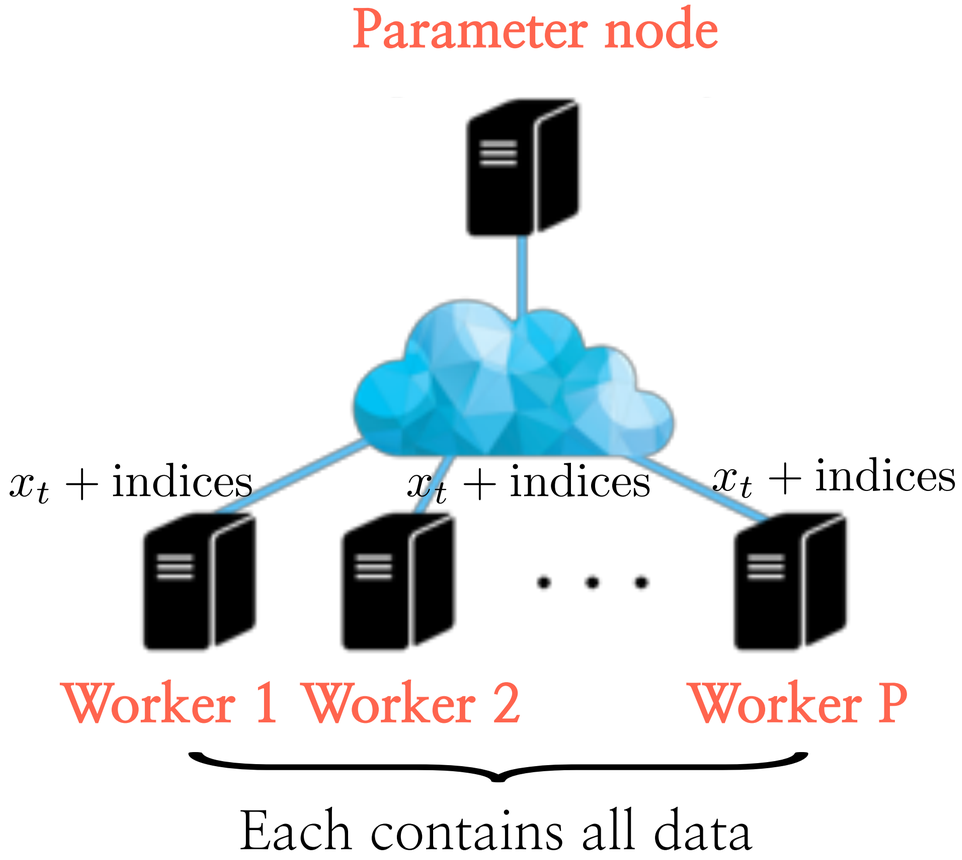

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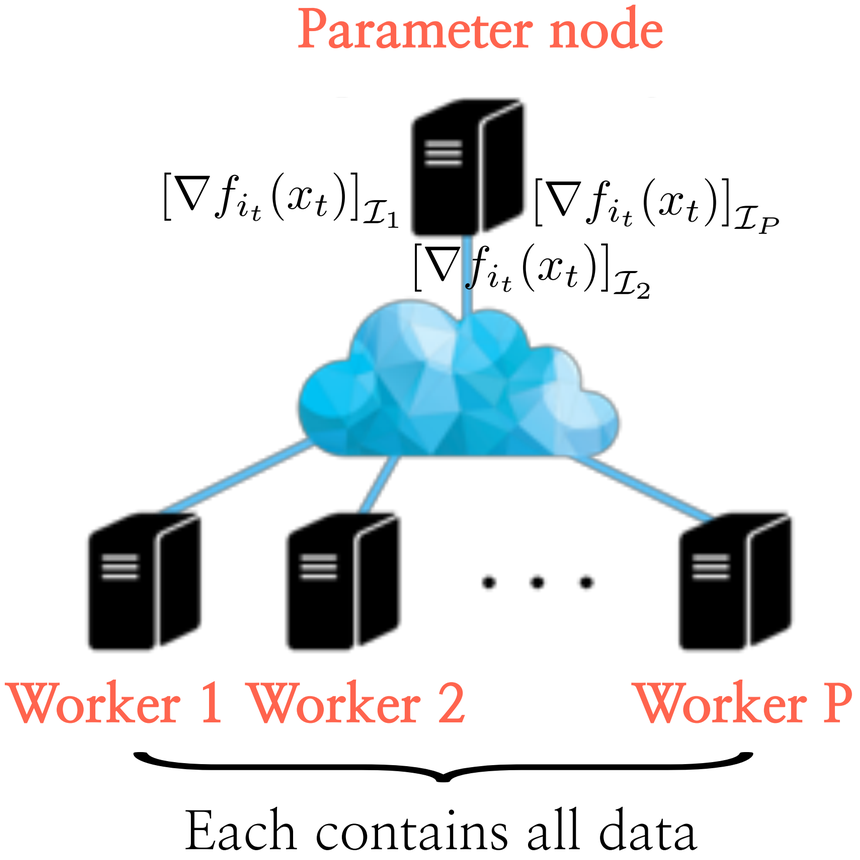

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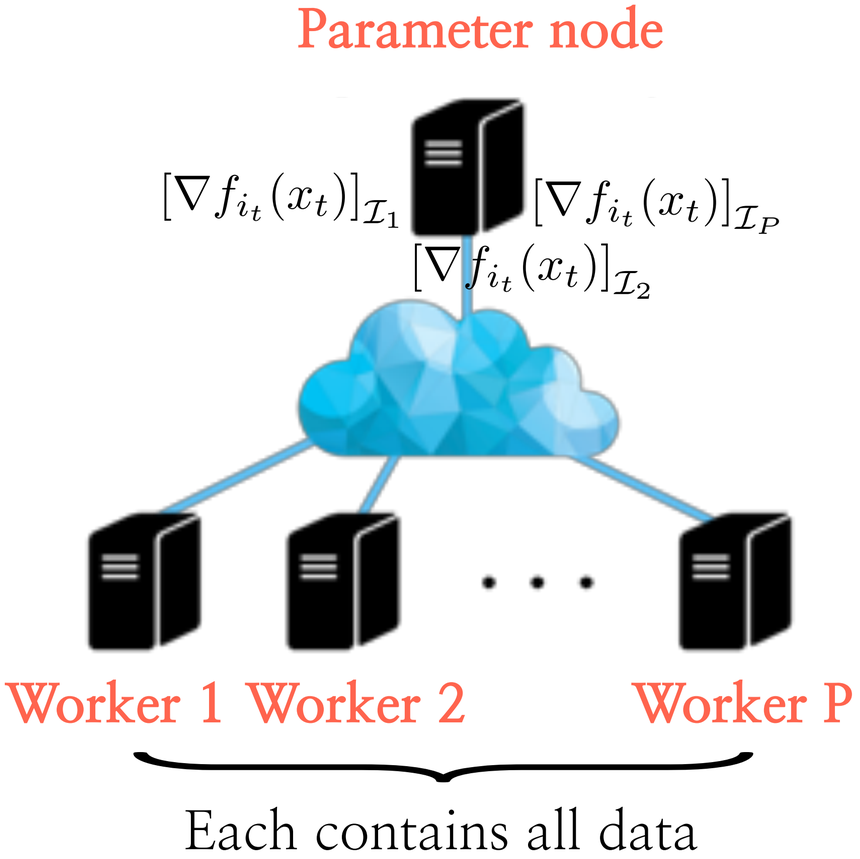

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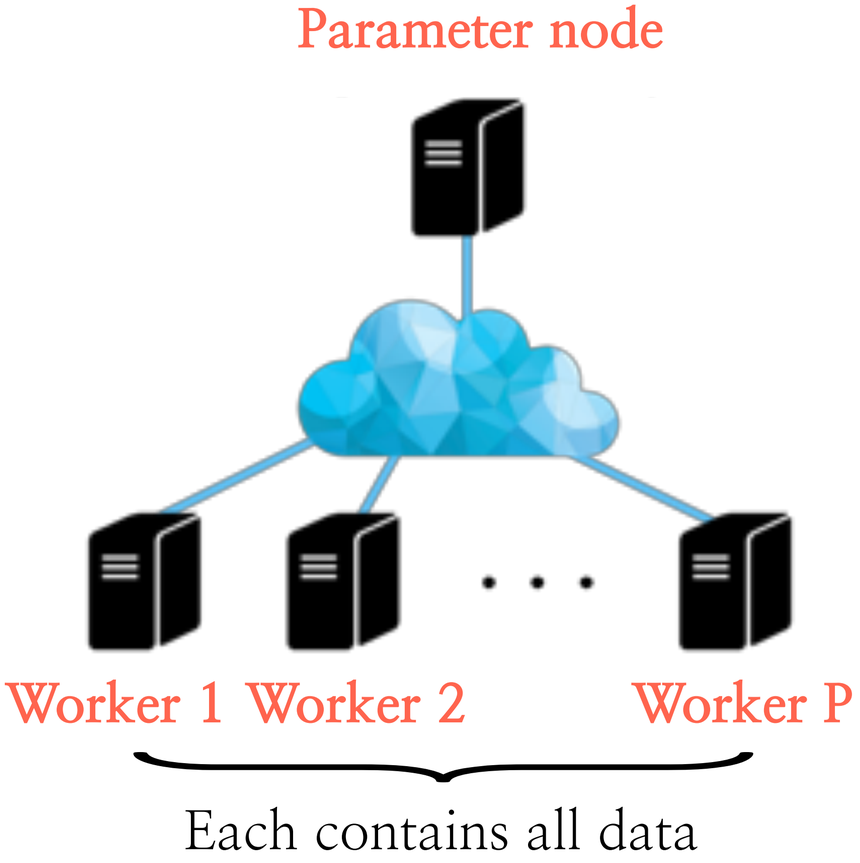

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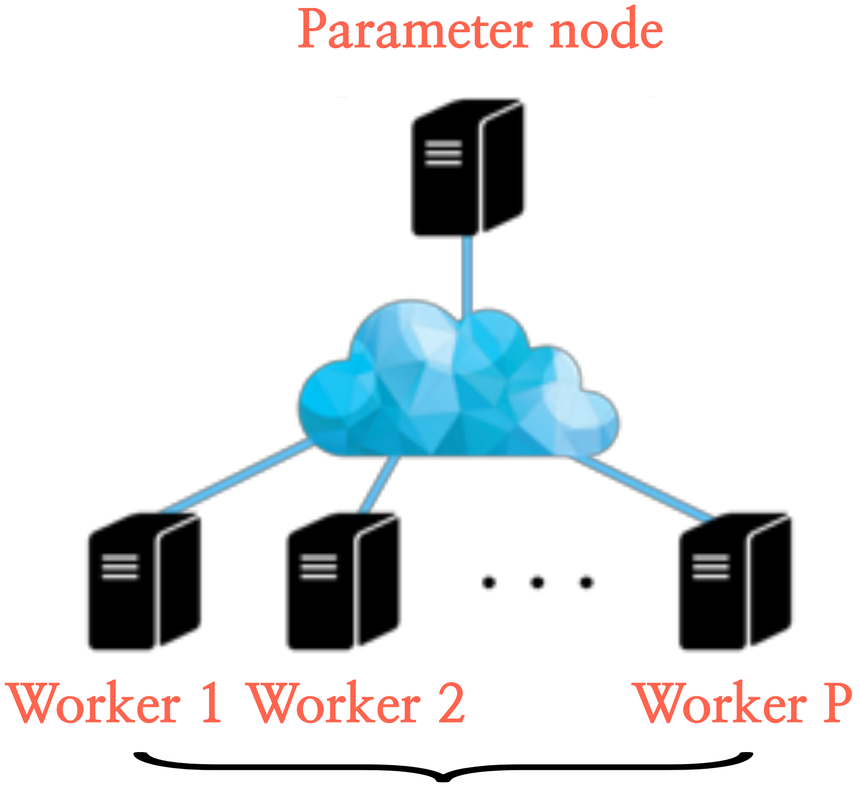

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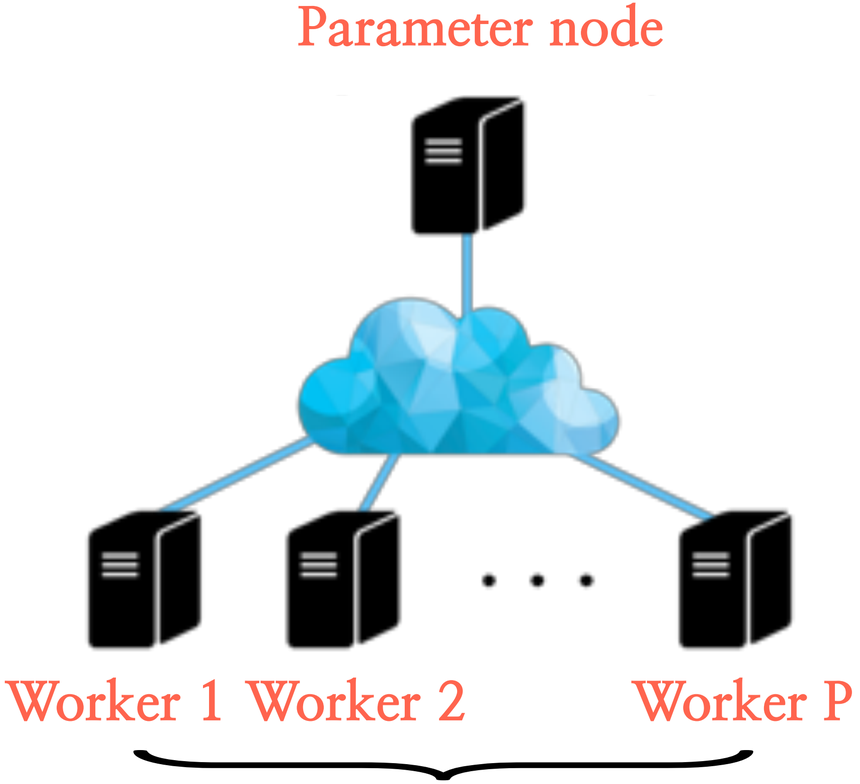

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iii) Could be an overkill to only compute updates for a subset of entries

Distributing gradient computations

- What about the setting in-between? **Mini-batch SGD**

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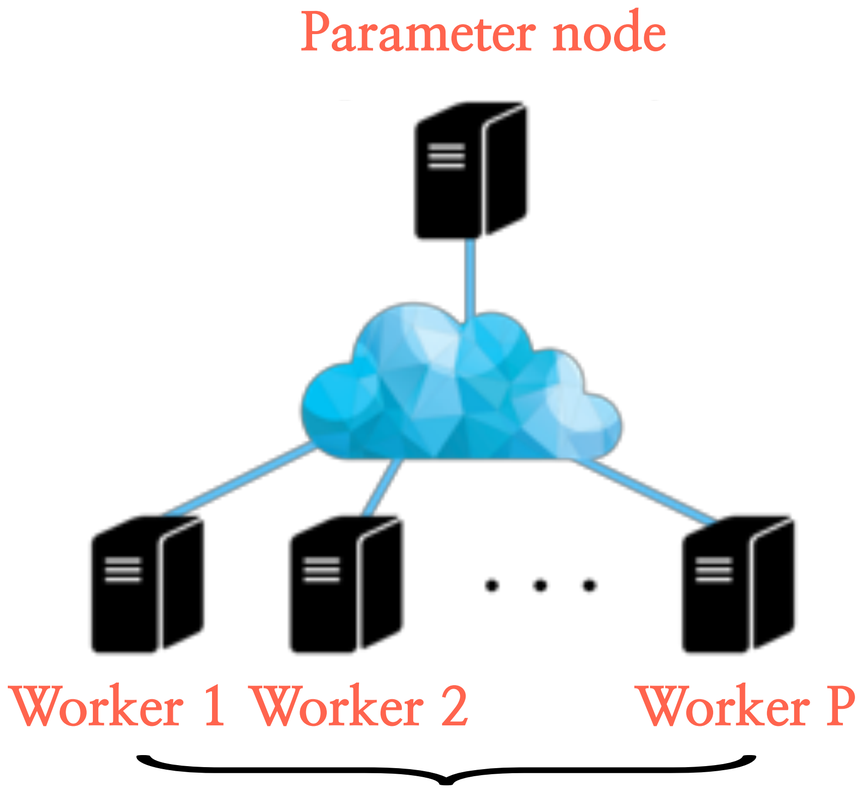

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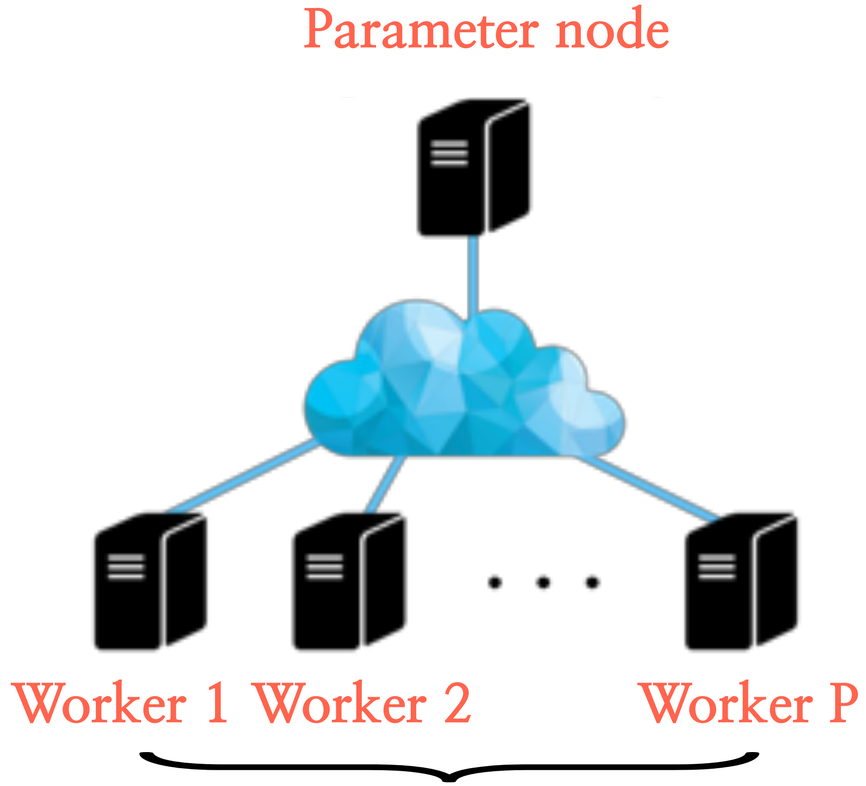

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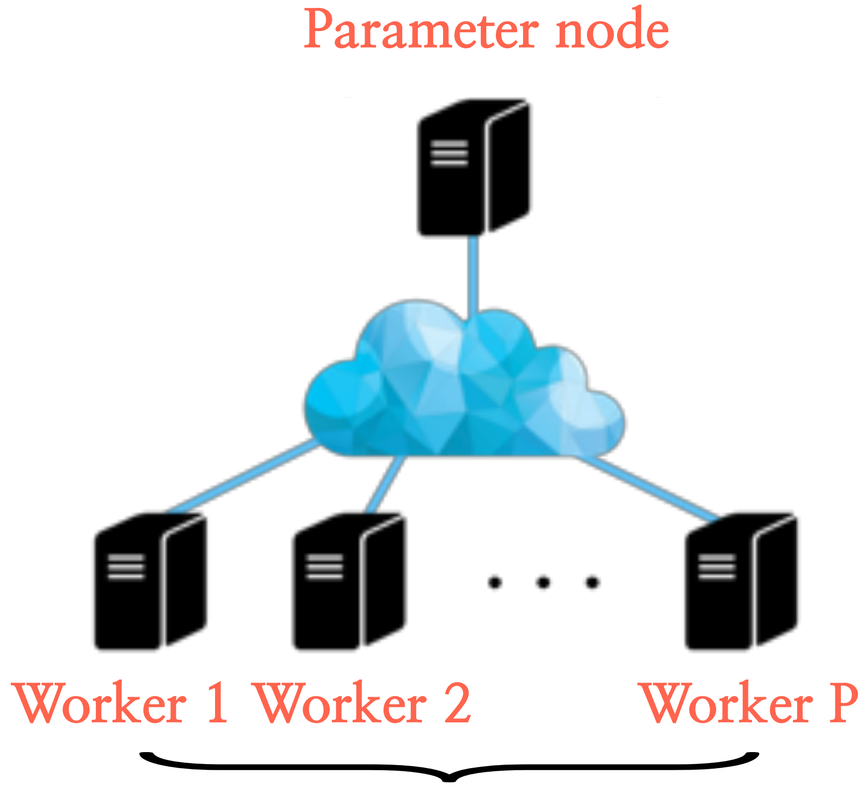

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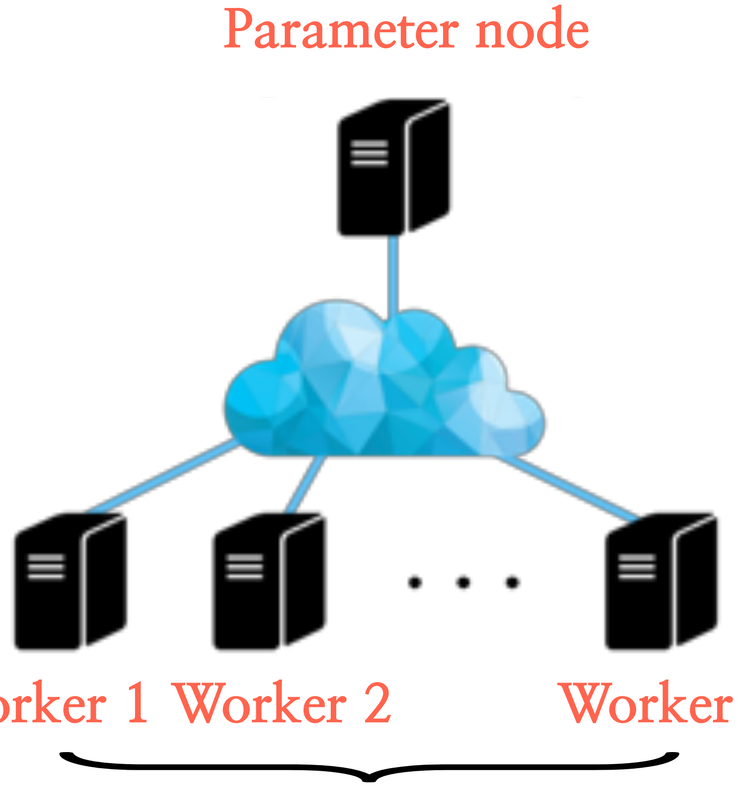

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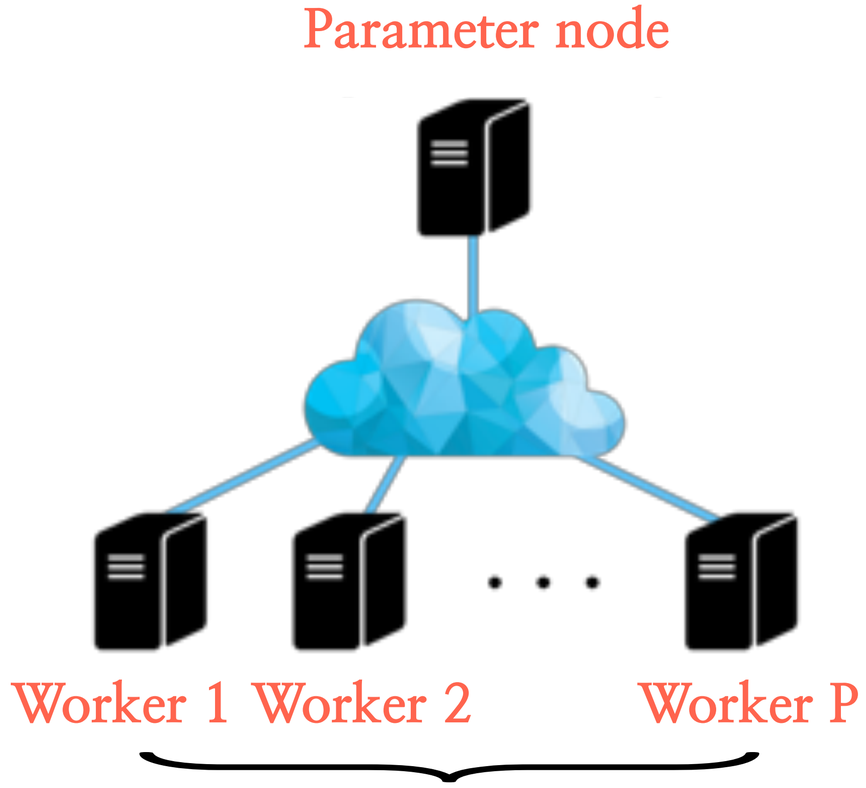
(..till the very last slow worker)

Distributing gradient computations

- What about the setting in-between? **Mini-batch SGD**

$$x_{t+1} = x_t - \eta \sum_{i \in \mathcal{I}_t} \nabla f_i(x_t)$$



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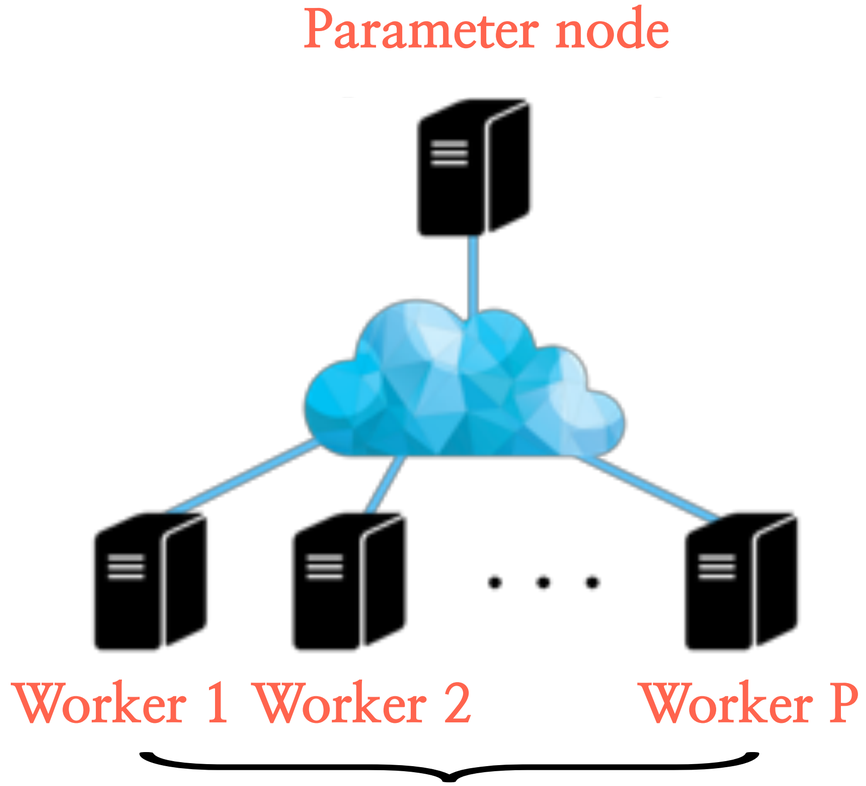

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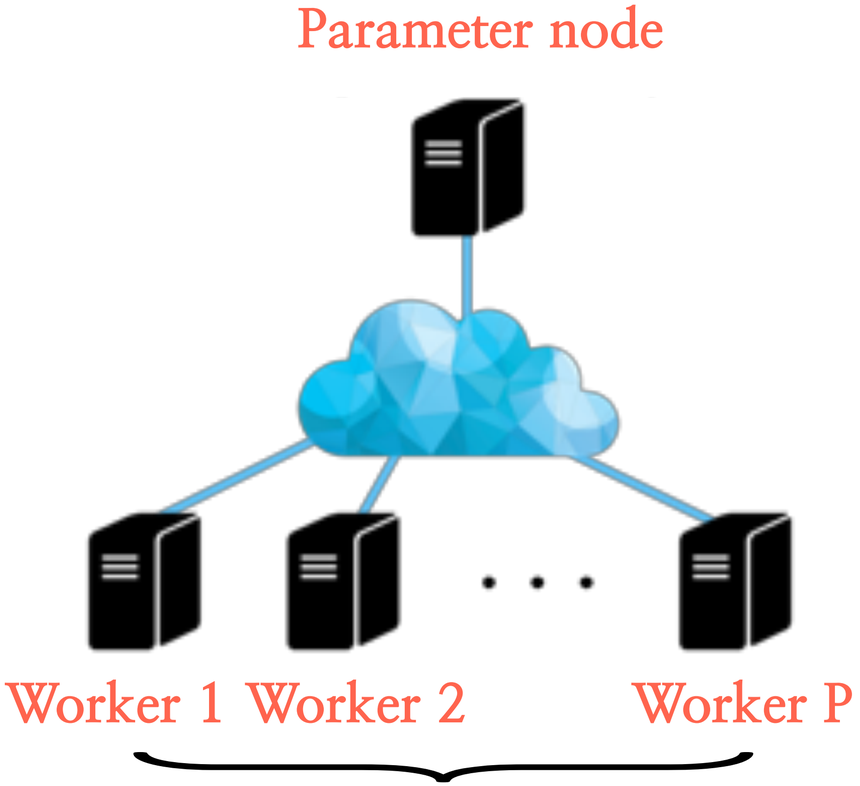

i) Still requires synchronization; each worker has less work to do

ii) Introduces a tradeoff between statistical efficiency, computations efficiency (in terms of convergence) and communication efficiency

iii) Usually computing $\nabla f_{i_t}(x_t)$ is cheap per node

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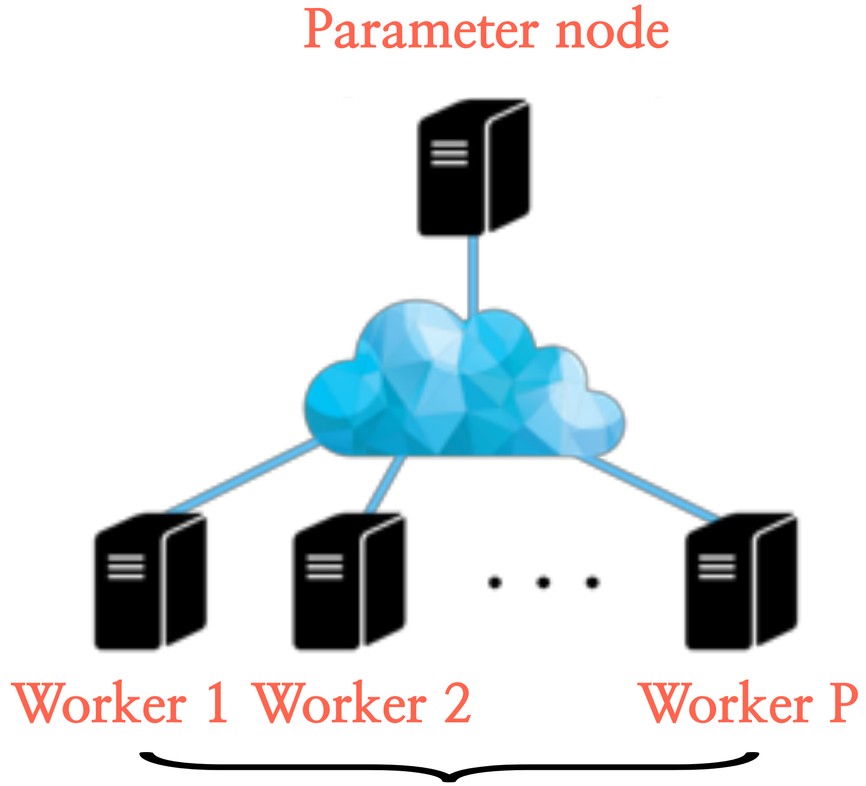

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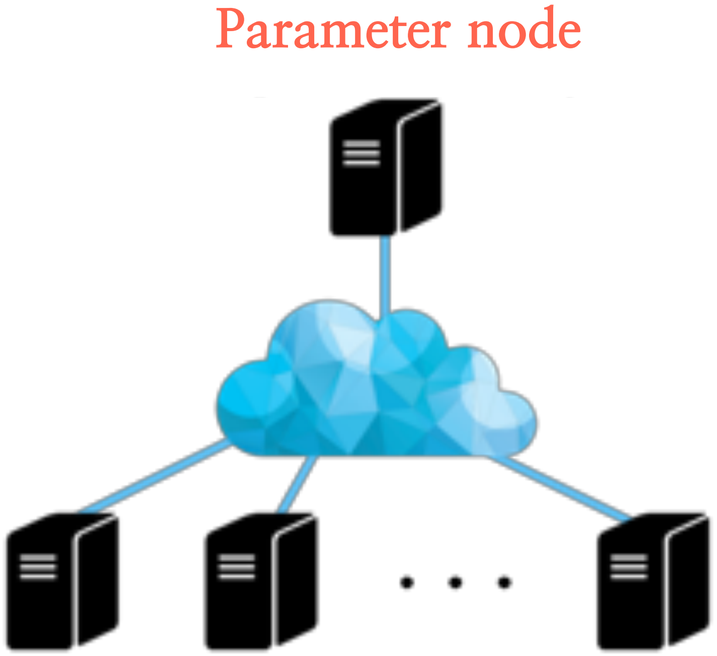

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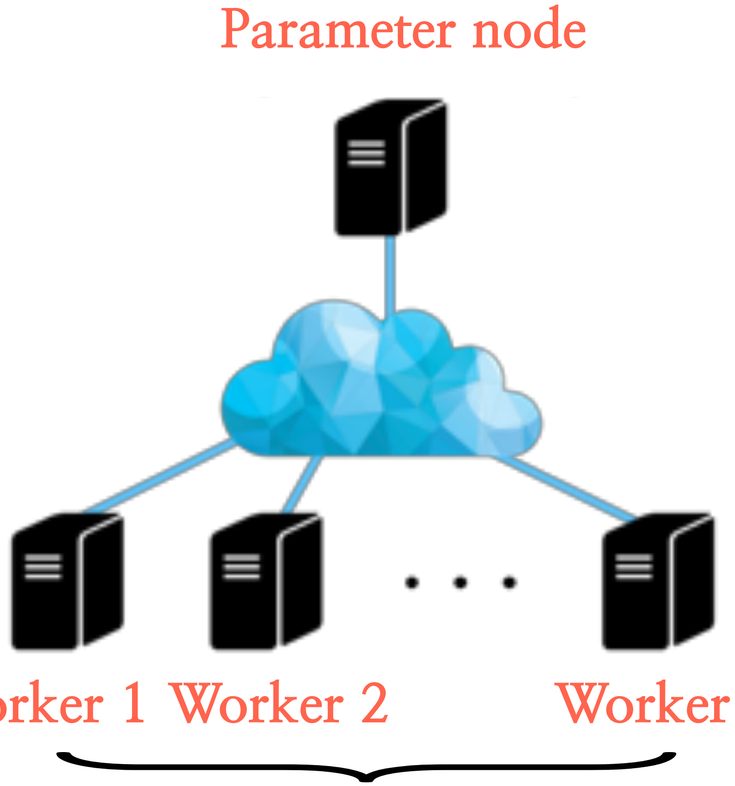

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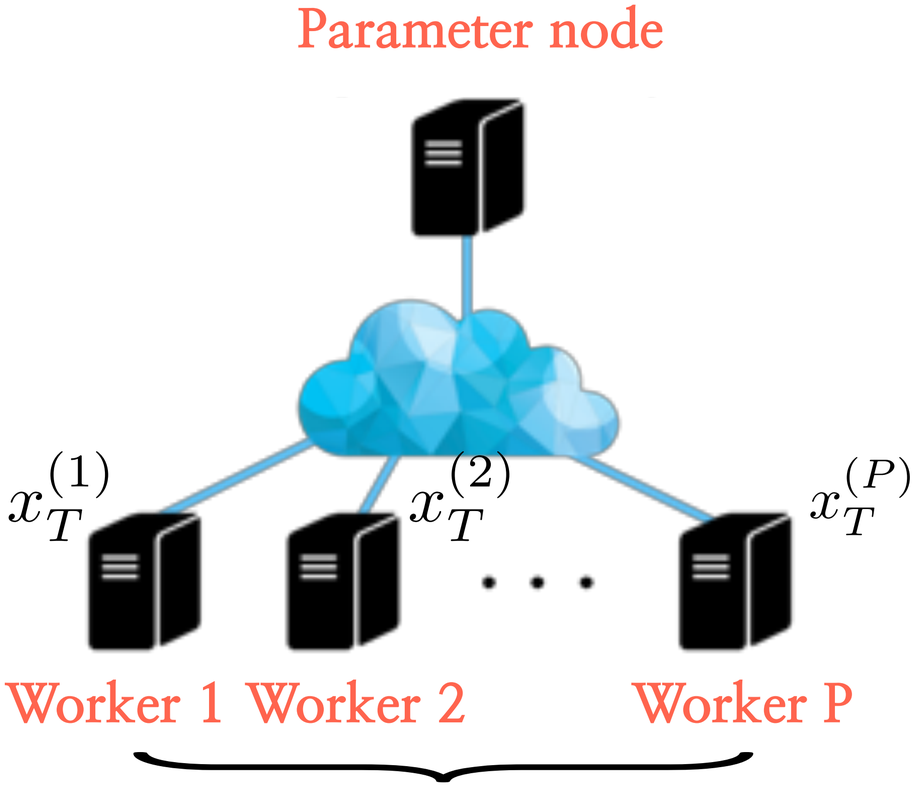

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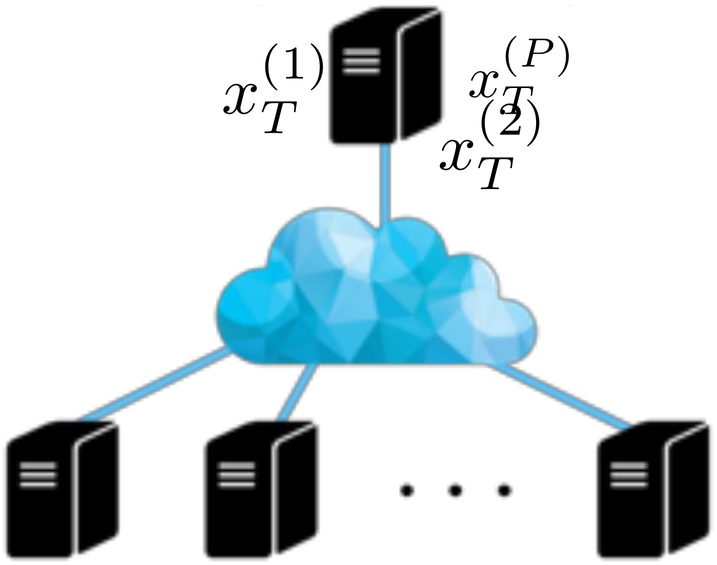

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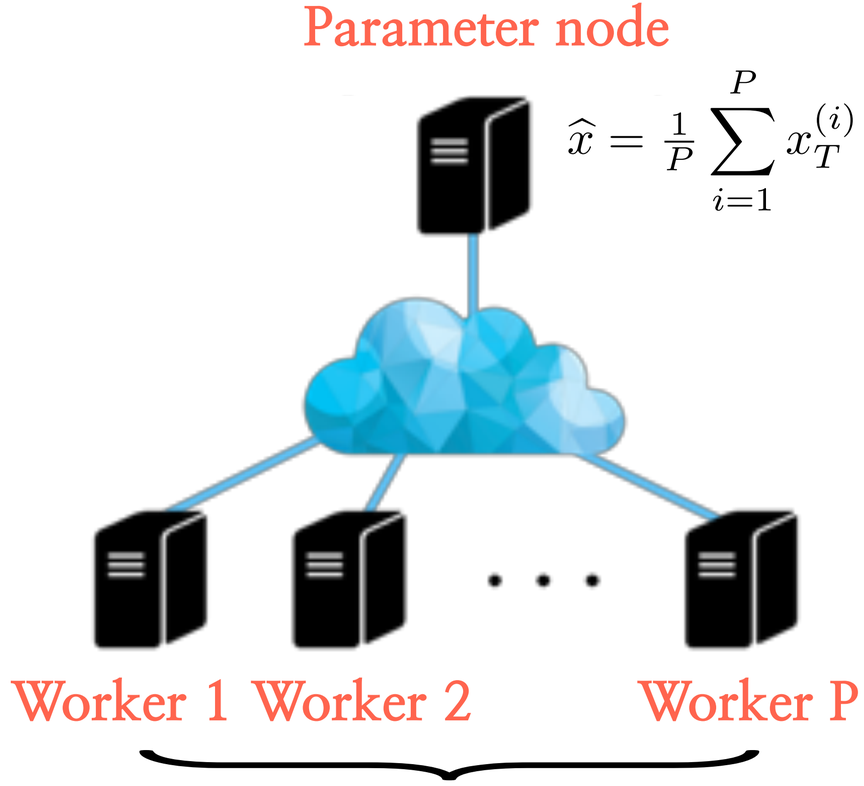

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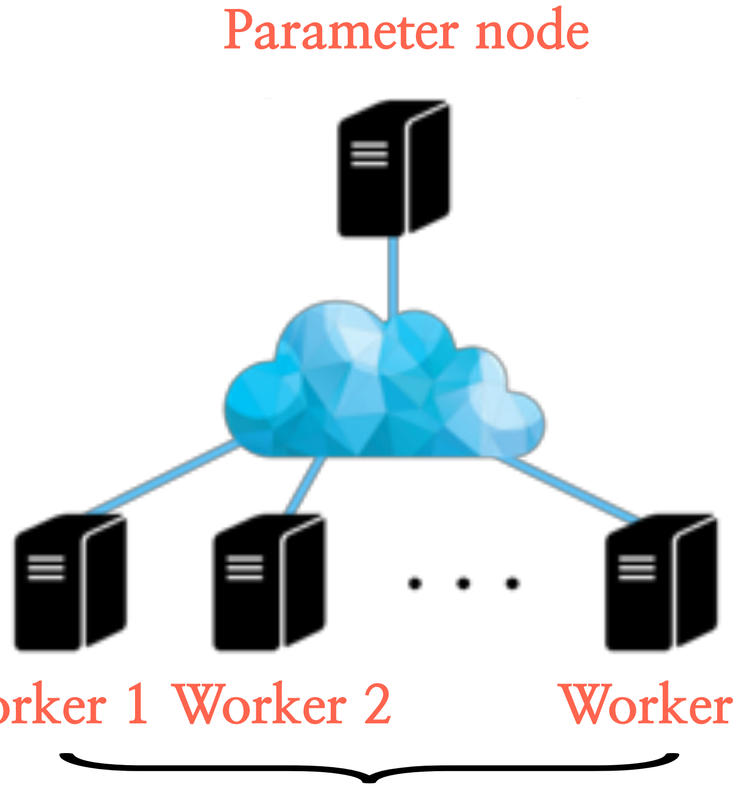

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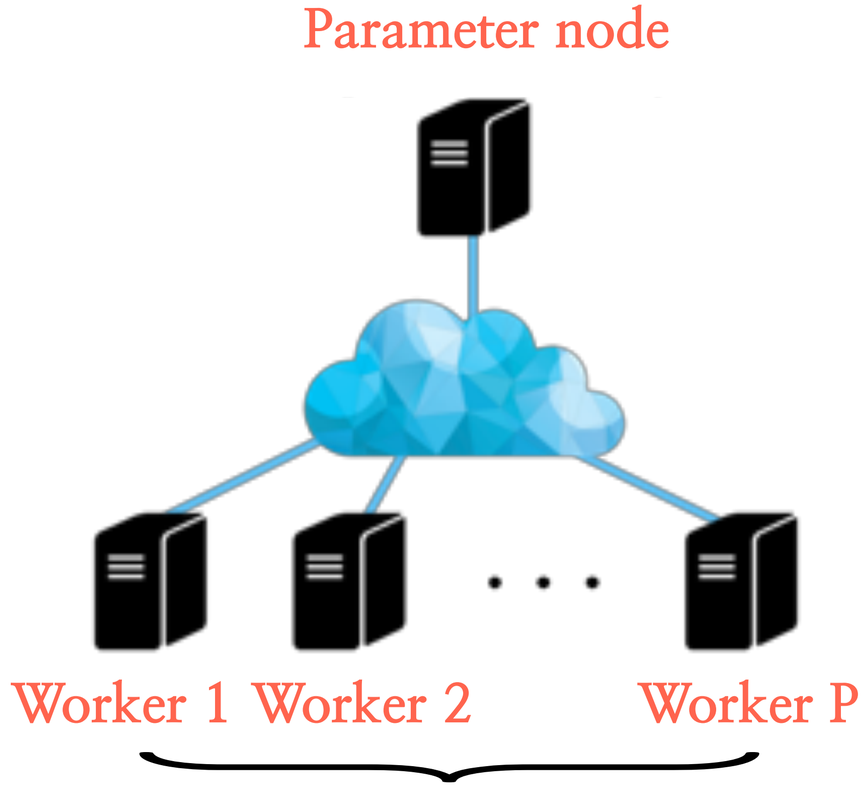

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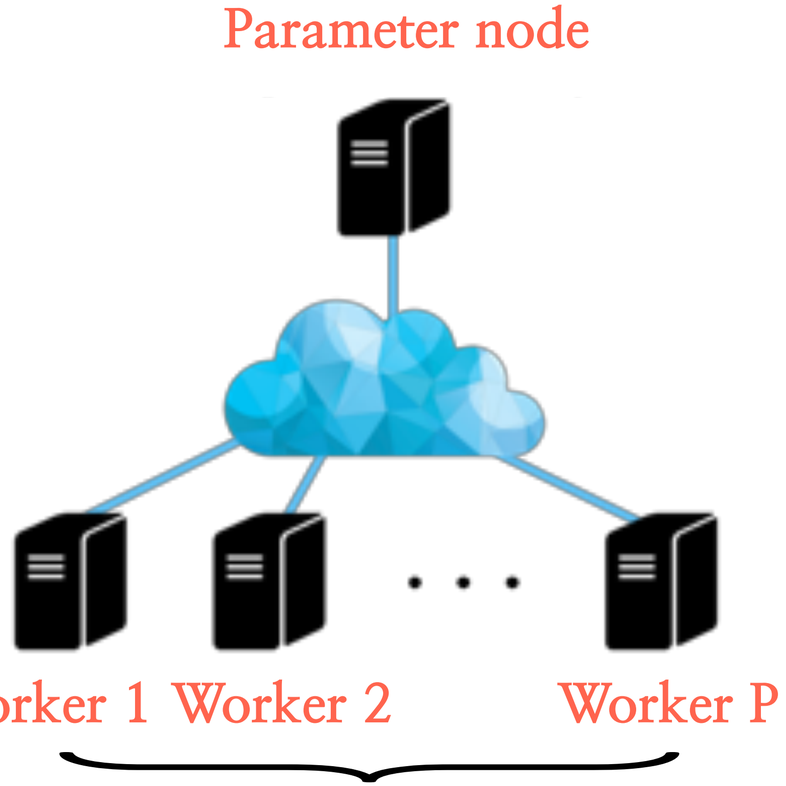

Each contains distinct partition of data

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ii) The model was designed for convex problems – the idea is that each subproblem has a solution close to the global one – thus averaging does not hurt

iii) Final decision is prediction averaging – similar ideas hold for random forests

Using distributed computing in a different way

- Run code in parallel as a way for hyperparameter optimization

$$x_{t+1} = x_t - \eta_1 \sum_{i \in \mathcal{I}_t} \nabla f_i(x_t) \qquad \bullet \quad \bullet \quad \bullet \qquad x_{t+1} = x_t - \eta_q \sum_{i \in \mathcal{I}_t} \nabla f_i(x_t)$$

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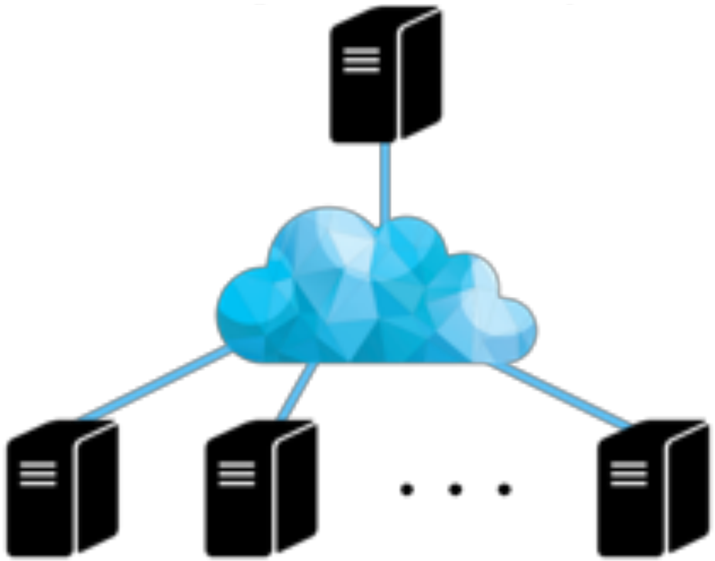

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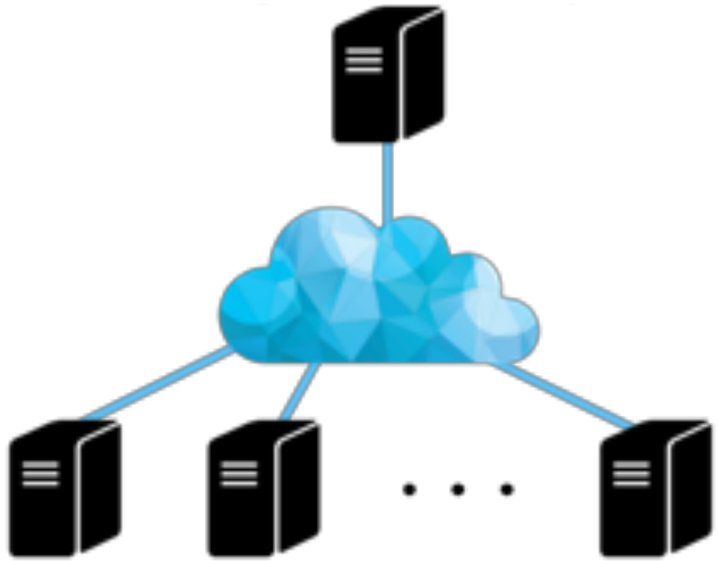

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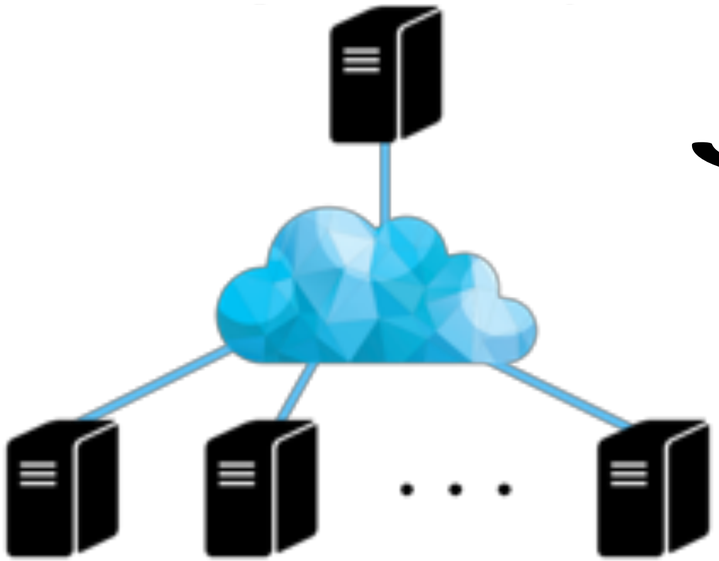
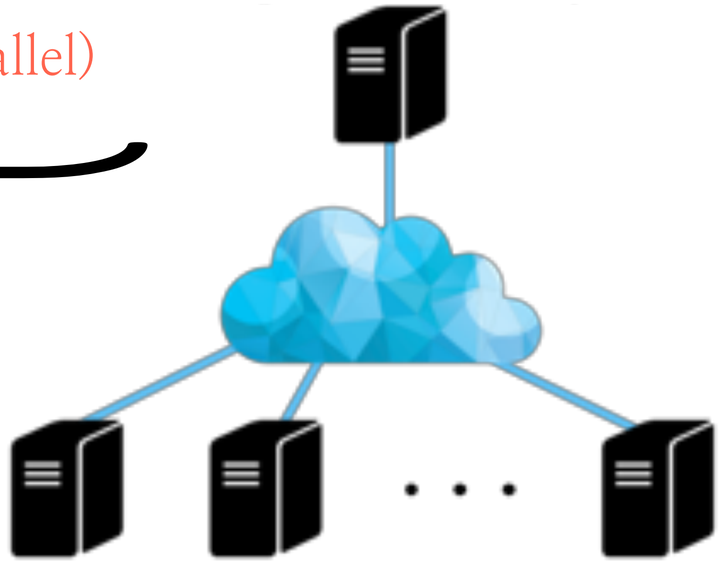
(q different settings, ran in parallel)





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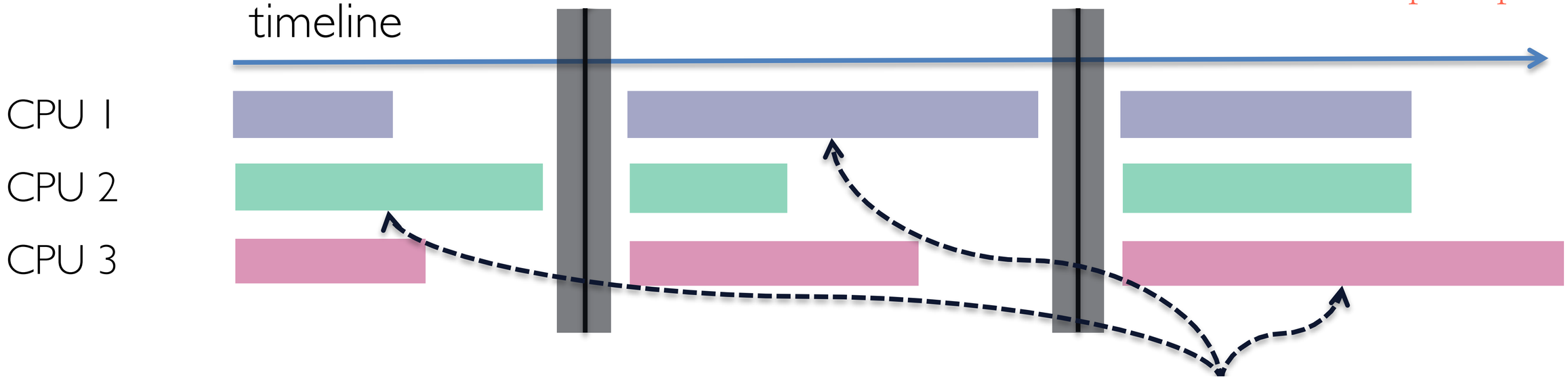
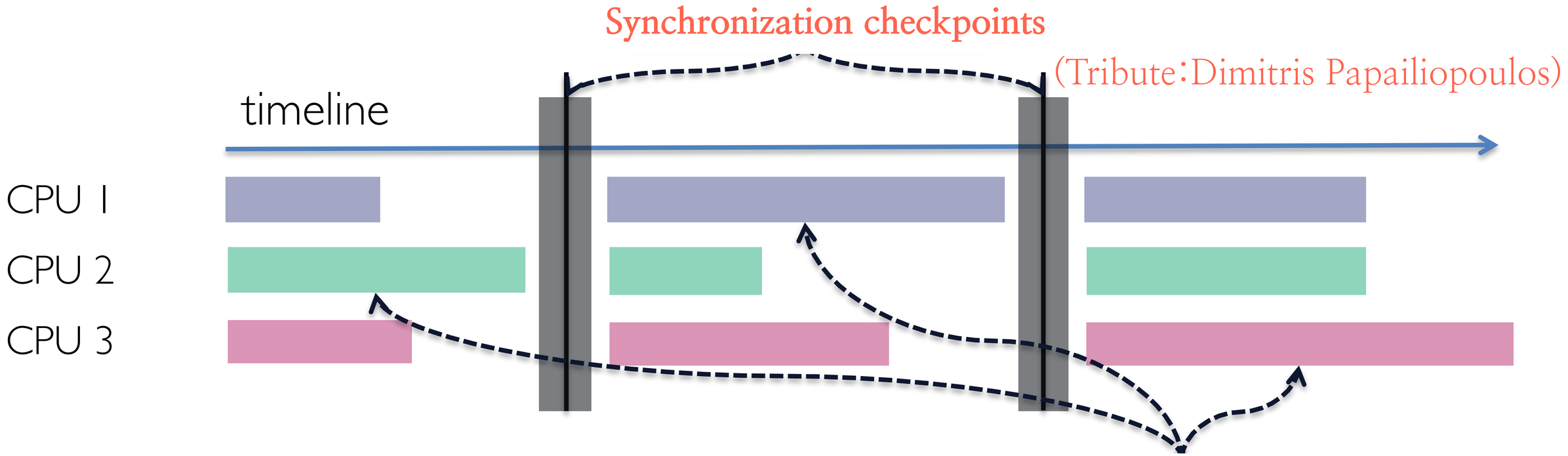
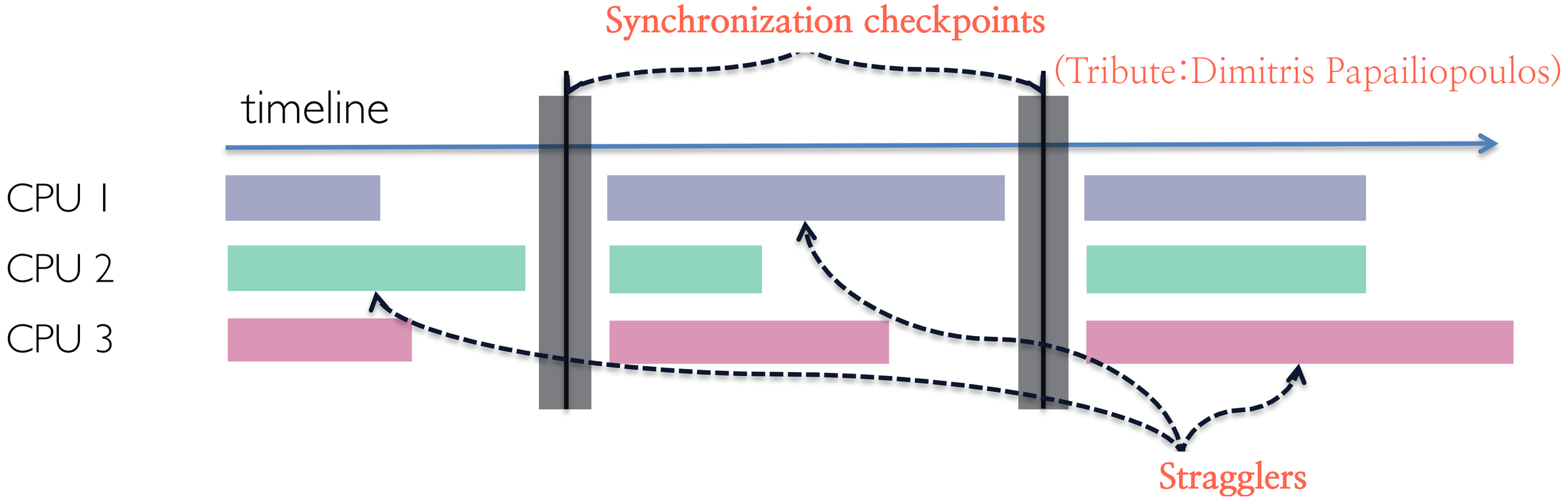
(Tribute：Dimitris Papailiopoulos)




Synchronization checkpoints
(Tribute：Dimitris Papailiopoulos)
timeline
CPU 1
CPU 2
CPU 3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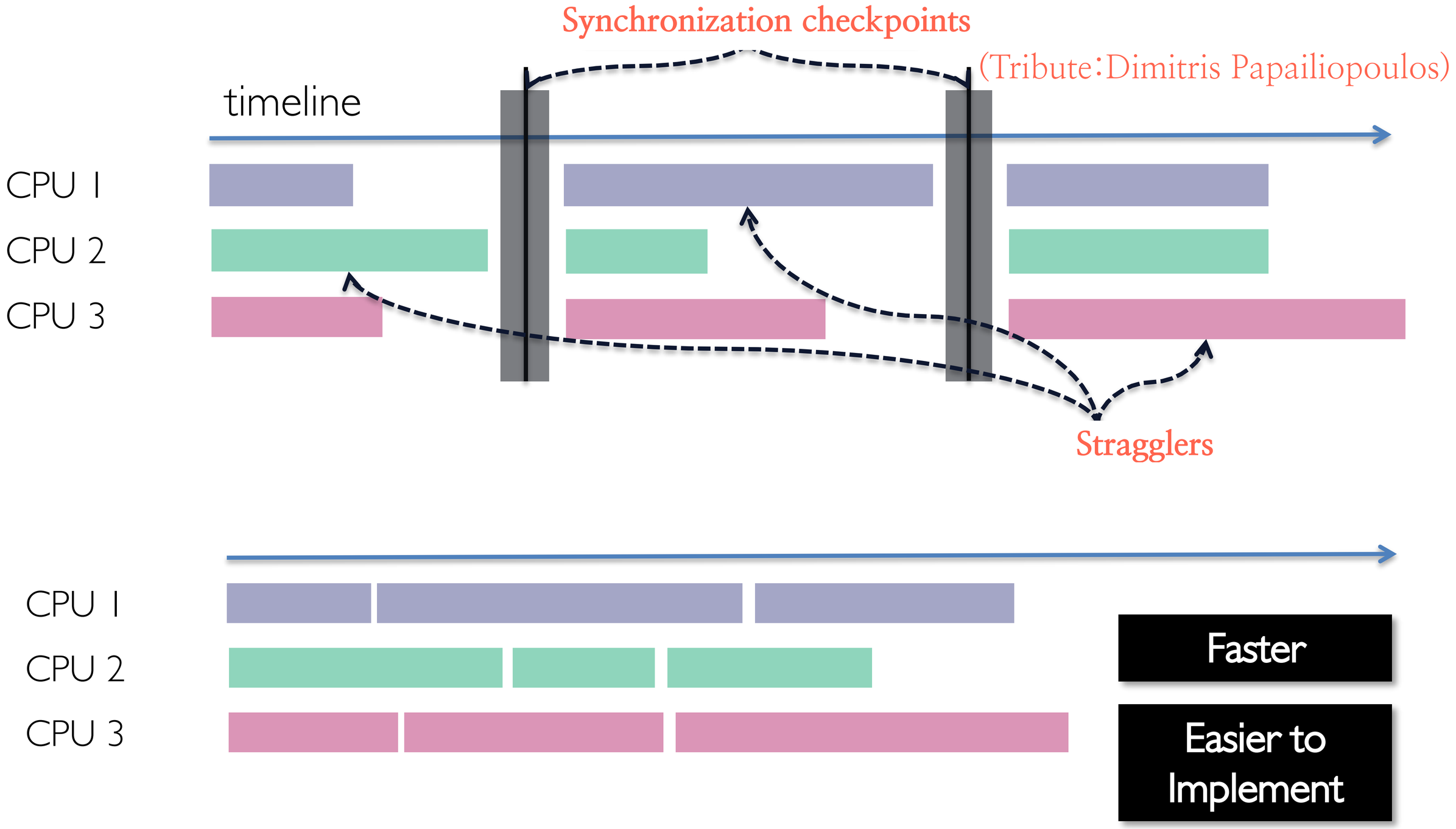
Stragglers


Synchronization checkpoints
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timeline
CPU 1
CPU 2
CPU 3
Stragglers
CPU 1
CPU 2
CPU 3
Faster
Easier to Implement

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- Alternatives or we have to bear with this situation?

Asynchronous distributed computing

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- Main **bottleneck:**
  - Synchronization (locking) amongst processors

Asynchrony in SGD

- Run SGD in parallel without locks!

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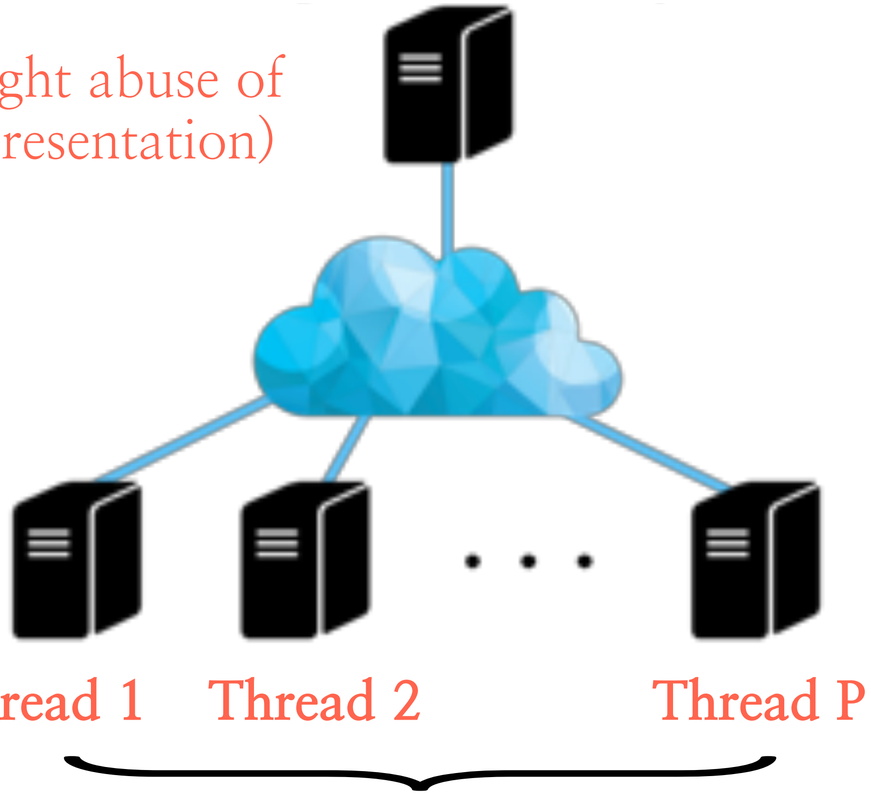
Shared memory

- All threads have access to shared memory

(Slight abuse of representation)



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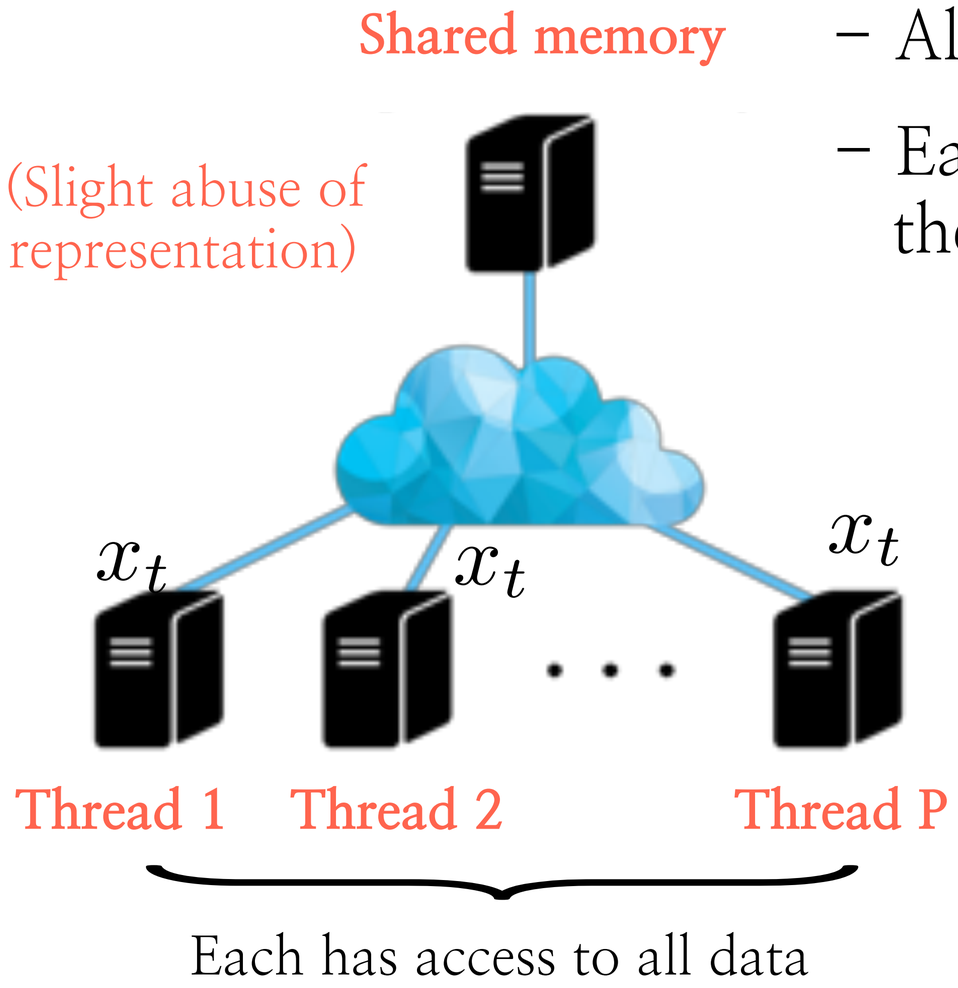

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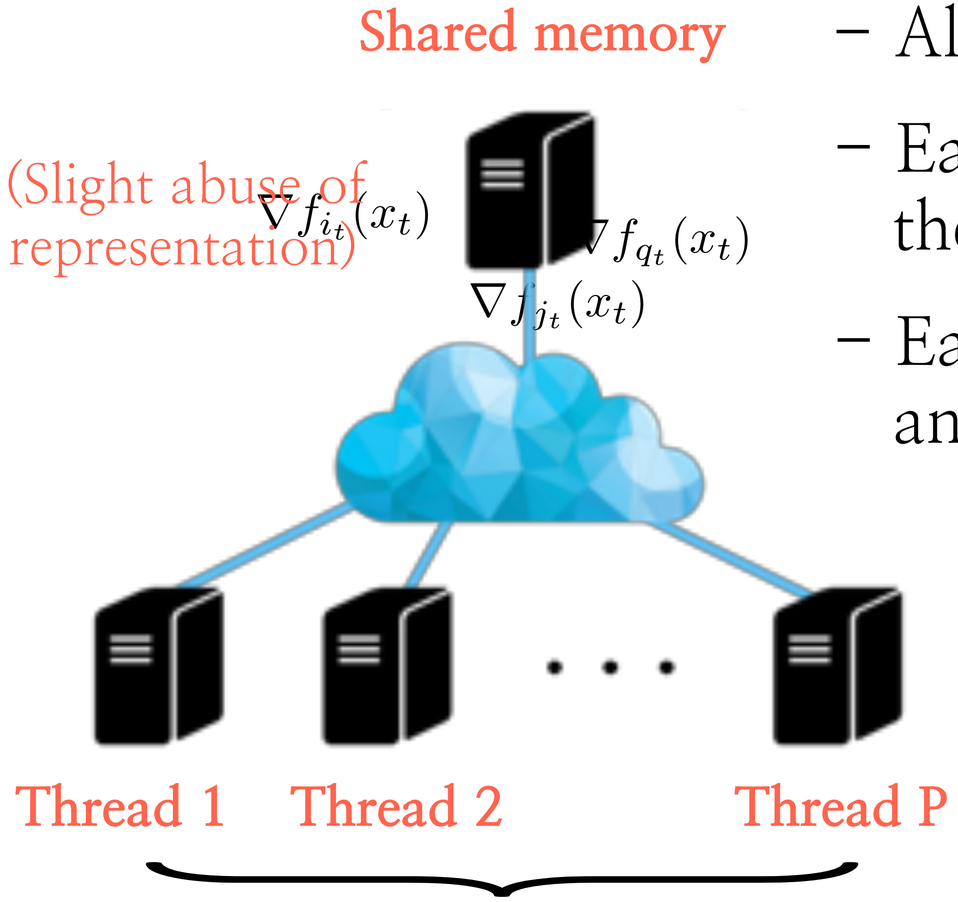

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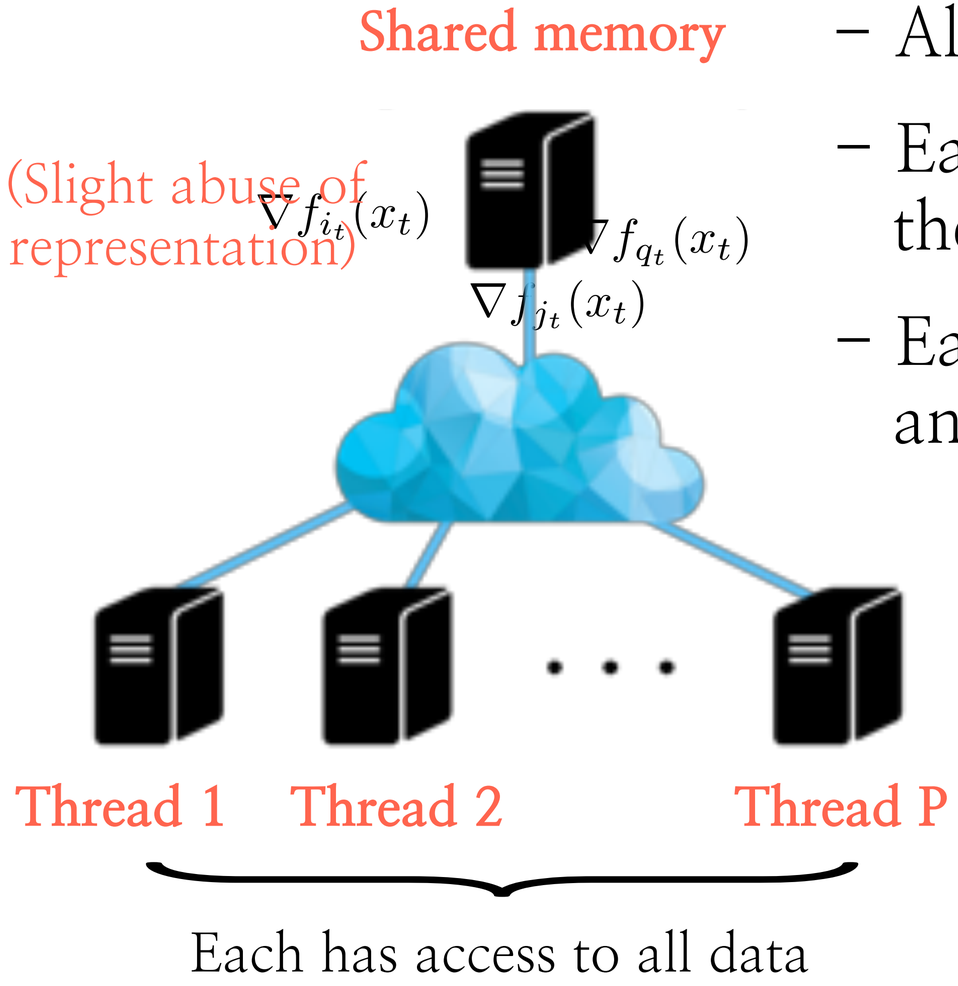

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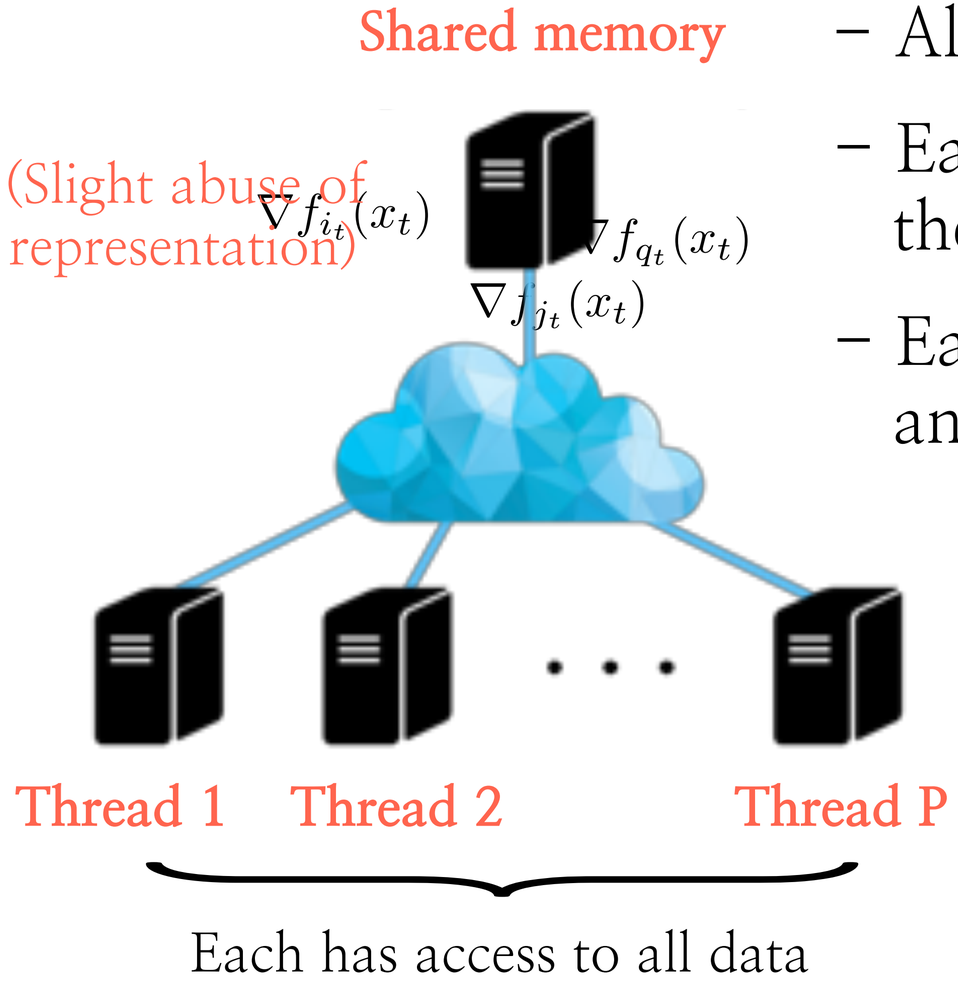

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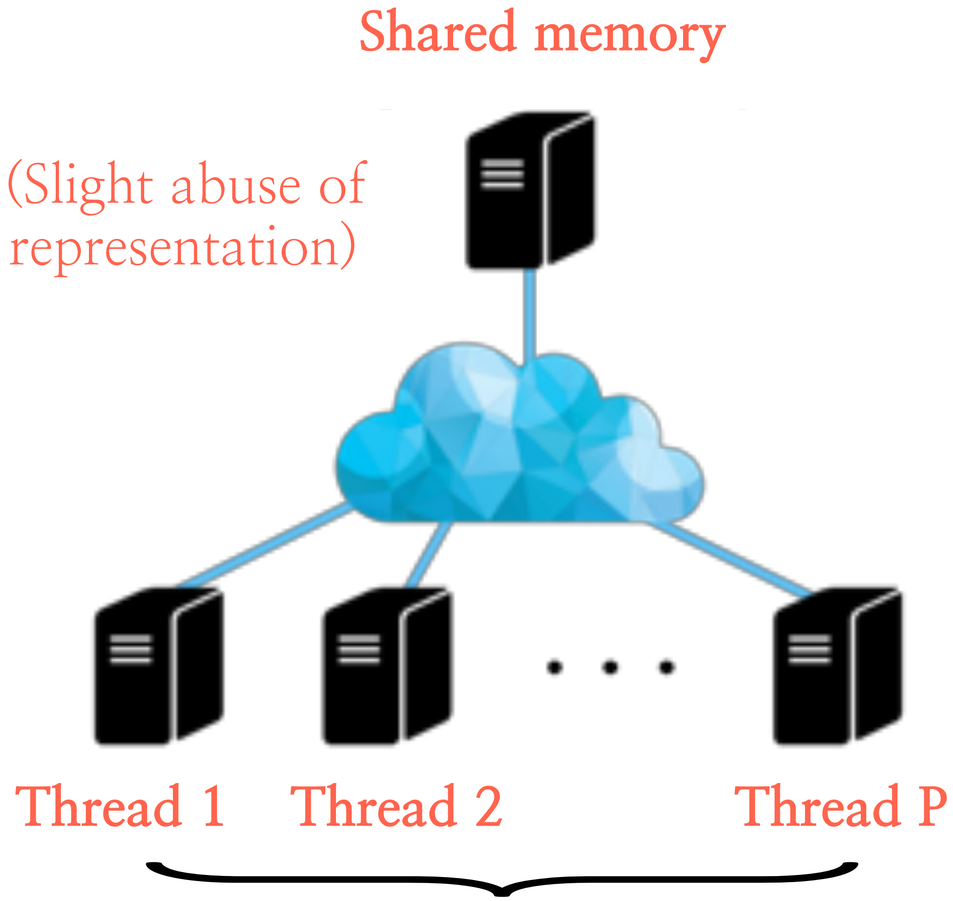

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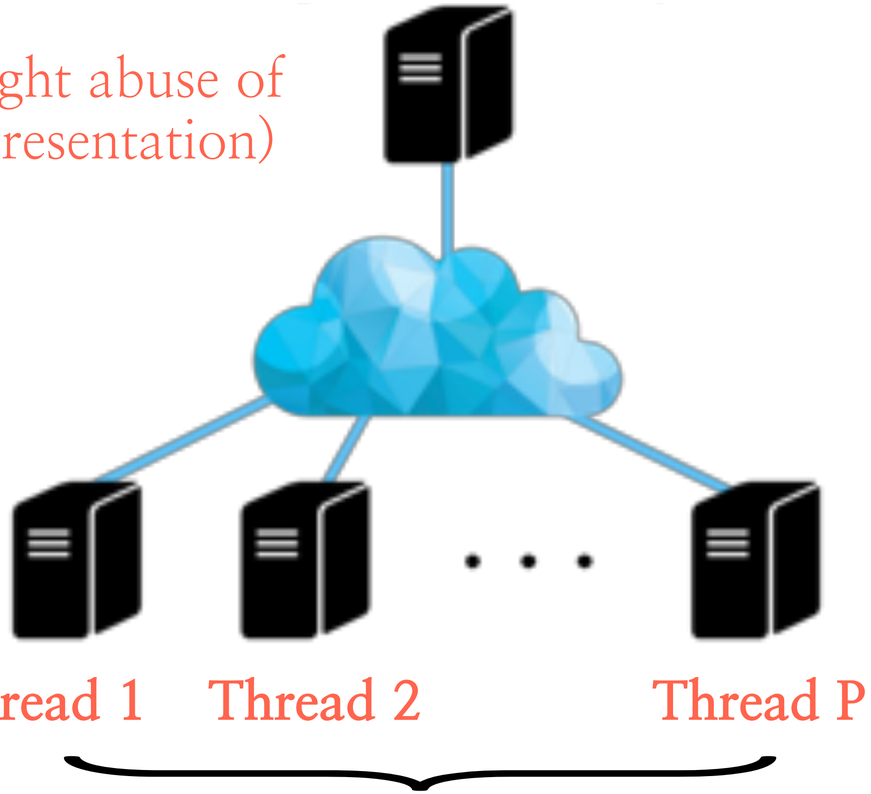

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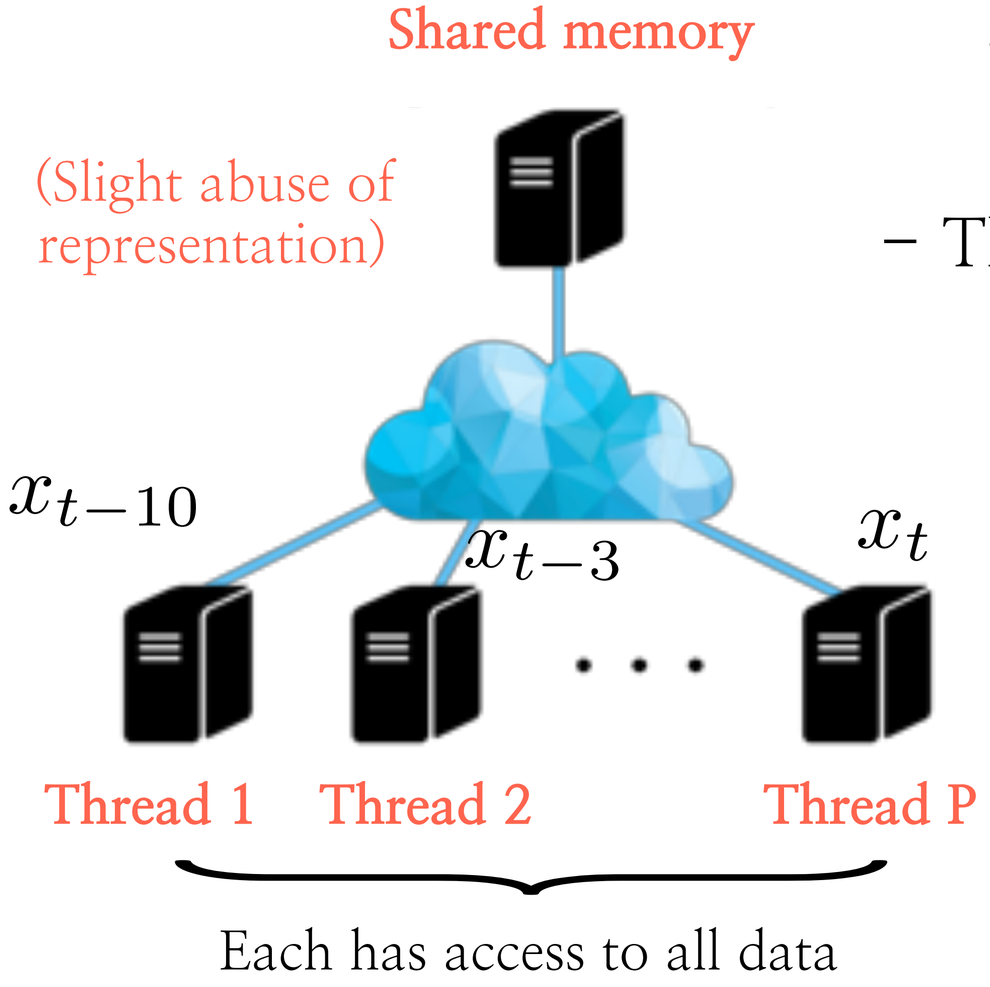

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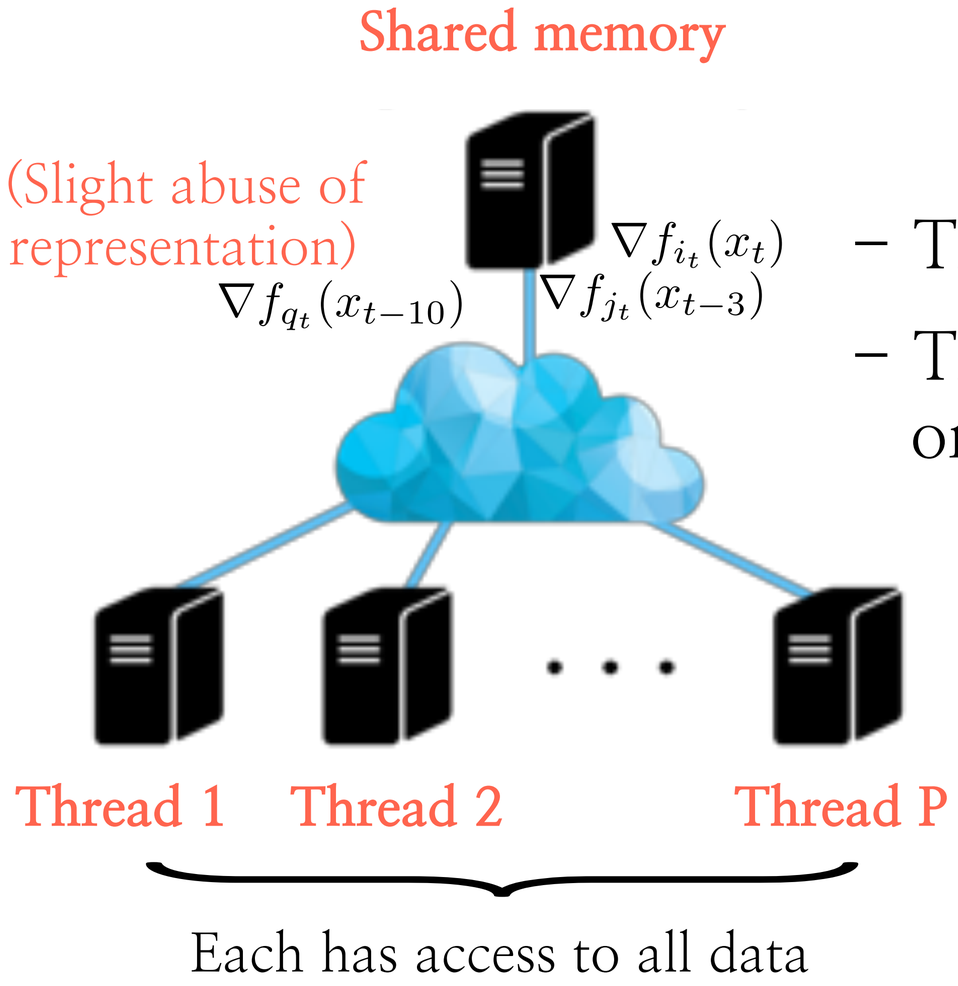

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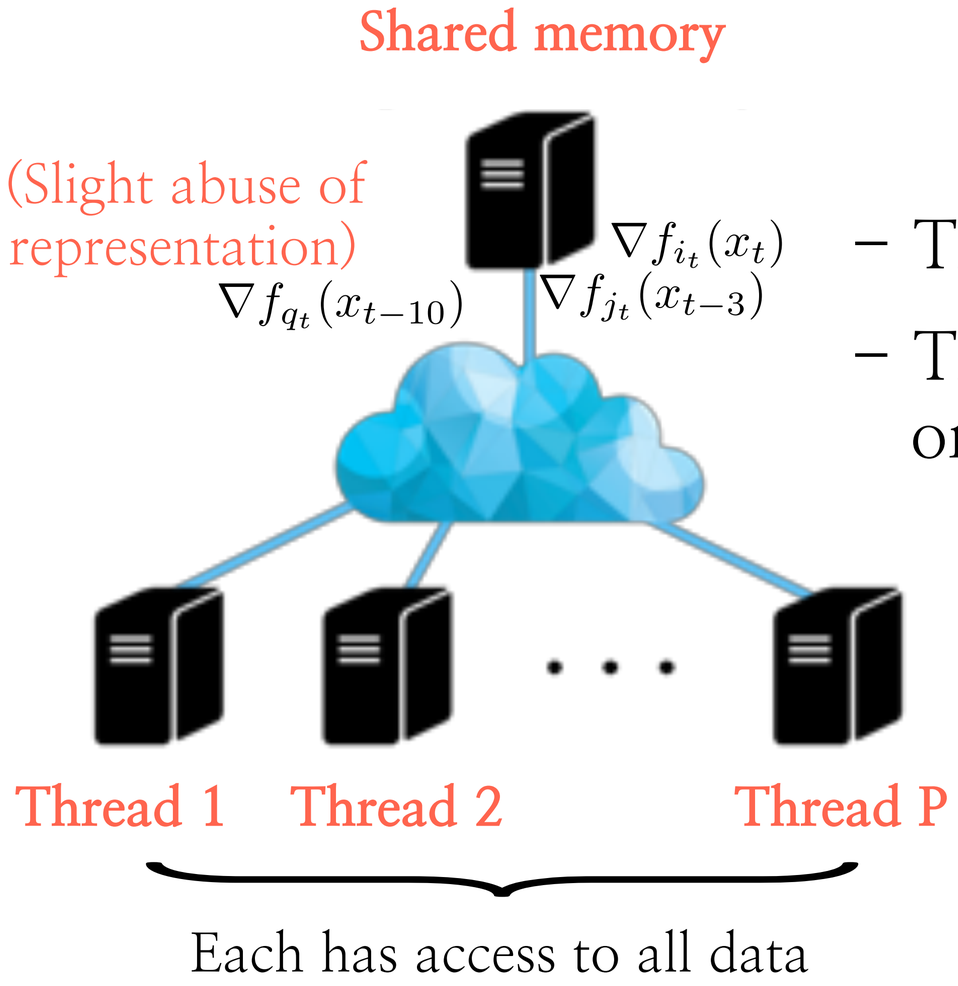

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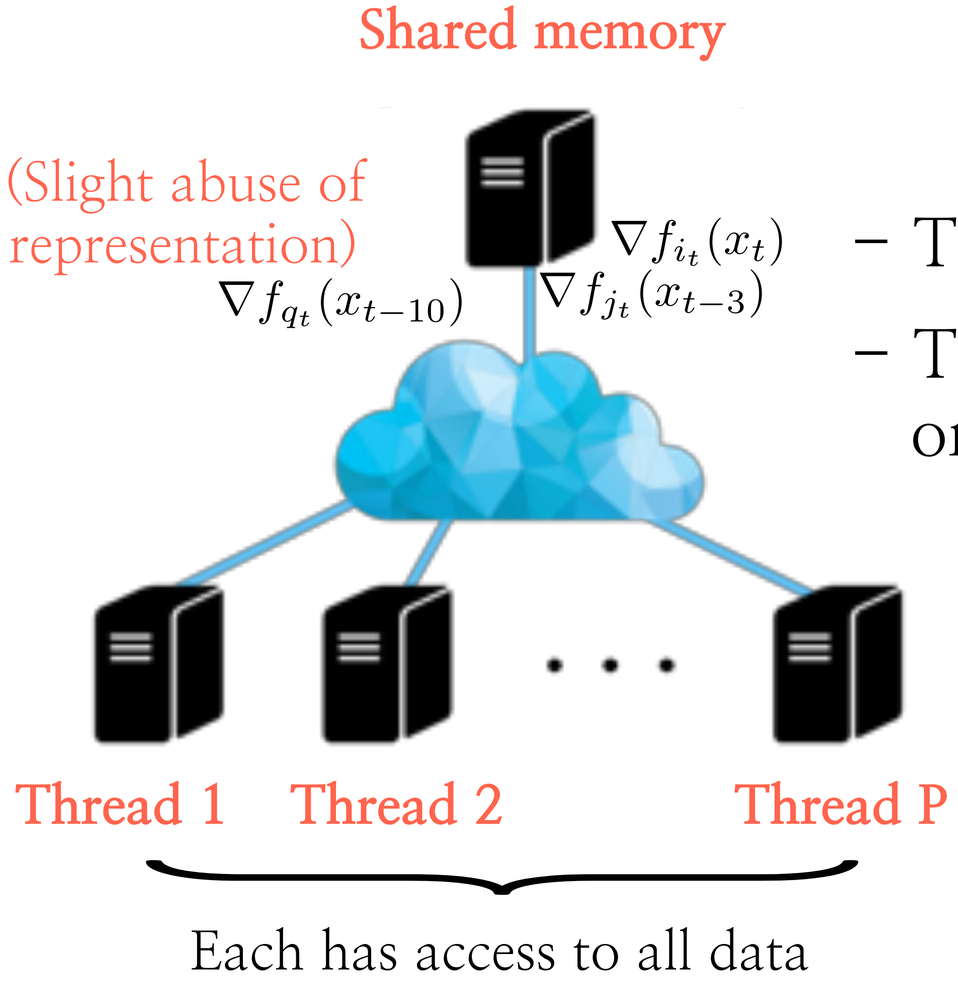
- Threads might complete the "job" in an arbitrary order.
  - And it can get more complex:

Asynchrony in SGD

- **Run SGD in parallel without locks!**



$$x_{t+1} = x_t - \eta\left(\nabla f_{i_t}(x_t) + \nabla f_{j_t}(x_t) + \cdots + \nabla f_{q_t}(x_t)\right)$$

(..and this might be an straightforward case)

- Threads might process an older model version
- Threads might complete the "job" in an arbitrary order.

- And it can get more complex:

"Threads can read a model state that only stayed in memory for a short time and between other memory writes"

Asynchrony in SGD

- Does it work?

Asynchrony in SGD

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(..a bit more involved set up)

Large Scale Distributed Deep Networks

Jeffrey Dean, Greg S. Corrado, Rajat Monga, Kai Chen,
Matthieu Devin, Quoc V. Le, Mark Z. Mao, Marc'Aurelio Ranzato,
Andrew Senior, Paul Tucker, Ke Yang, Andrew Y. Ng
{jeff, gcorrado}@google.com
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Asynchrony in SGD

(..a bit more involved set up)

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"..asynchronous SGD, rarely applied to nonconvex problems, works very well for training deep networks, particularly when combined with Adagrad adaptive learning rates.."

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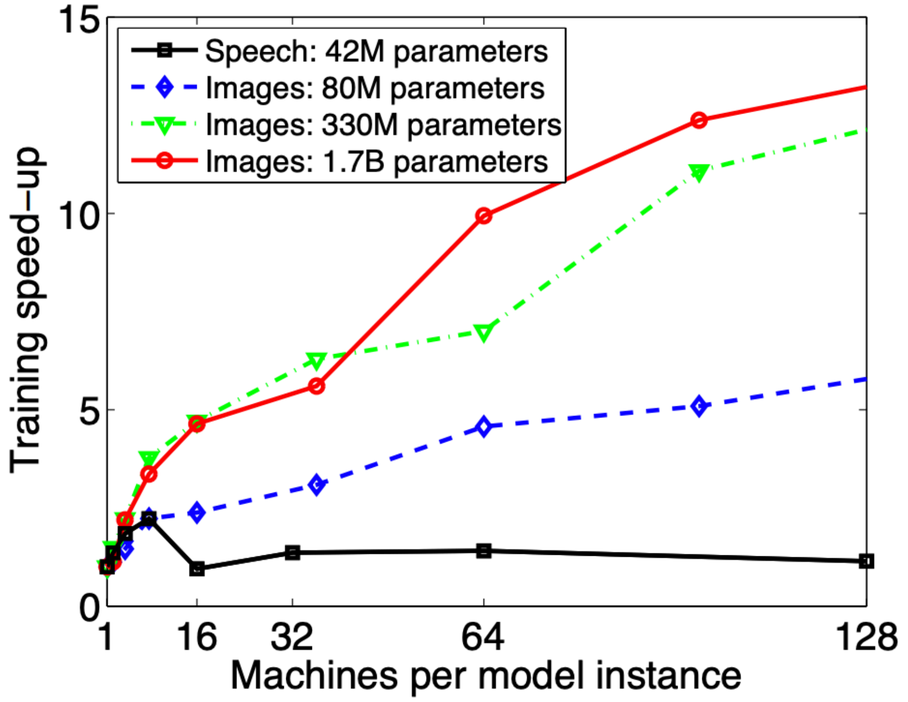

- Comm. bottleneck
- We can increase batch size – but, we deal with worse generali-nation error

Asynchrony in SGD

- Can we prove anything about asynchrony in SGD?

  HOGWILD!: "..an update scheme that allows processors accesss shared memory with the possibility of overwriting each other's work

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- Setting: $\min_x f(x) := \sum_{e \in E} f_e(x_e)$

  where: $x \in \mathbb{R}^n$ E is a collection of items, say samples

  $e \subset [n]$ (each element e is a collection of indices in [n] but also an index from a set of samples E)

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- Slight abuse of notation:

  $f_e(\cdot)$: denotes a component of sum of functions, indexed by sample e

  x_e: corresponds to sub-vector, indexed by an index set e (connected to sample e)

Asynchrony in SGD

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- Example: Sparse SVM

  Given data $E = \{(z_1, y_1), \ldots, (z_{|E|}, y_{|E|}\}$ where y_i labels and $z_i \in \mathbb{R}^n$ are features, we solve:

$$\min_x \sum_{\alpha \in E} \max\left(1 - y_\alpha \cdot x^\top z_\alpha,\ 0\right) + \lambda \|x\|_2^2$$

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- Observe that, if z_α is very sparse (which happens in reality often), then

$$x^\top z_\alpha = x_\alpha^\top z_\alpha \quad \longleftarrow$$

Main objective depends on a subset of entries

Asynchrony in SGD

- Some quantities:

  Ω : maximum number of features involved over all samples

  Δ : maximum frequency of features that can appear in samples

  ρ : approaches 1 if features are very common across examples

(..and thus we expect often collisions)

Asynchrony in SGD

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- Configuration:

  p : number of processors

  Each processor can read model x and contribute an update to x

Asynchrony in SGD

Algorithm 1 HOGWILD! update for individual processors

1: **loop**
2: Sample e uniformly at random from E
3: Read current state x_e and evaluate $G_e(x)$
4: **for** $v \in e$ **do** $x_v \leftarrow x_v - \gamma b_v^T G_e(x)$ ← (coordinate-wise)
5: **end loop**

- Notation:

  $G_e(x) \in \mathbb{R}^n$: gradient with non-zeros indexed by e, and scaled such that

  $$\mathbb{E}\left[G_e(x_e)\right] = \nabla f(x)$$

  Observe that $\left[G_e(x_e)\right]_{e^c} = 0$

Asynchrony in SGD

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- In words:
  1. Each processor samples e uniformly at random
  2. Each processor computes the gradient f_e at x_e
  3. Each processor applies update on each coordinate in e

Asynchrony in SGD

- Asynchrony: x_j denotes the variable after j updates. Generally updated with stale gradients

  $x_{k(j)}$ denotes the state of the variable when was read

Whiteboard

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Whiteboard

No Demo (no resources)

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  - The authors show (theoretically and experimentally) a near-linear speedup, with the number of processors used
  - In practice, lock-free SGD exceeds even theoretical guarantees

Alternatives to avoid asynchrony

(in other words, how we can decrease communication burden?)

- Standard SGD: each entry of the gradient is represented as a **float** number

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QSGD: Communication-Efficient SGD via Gradient Quantization and Encoding

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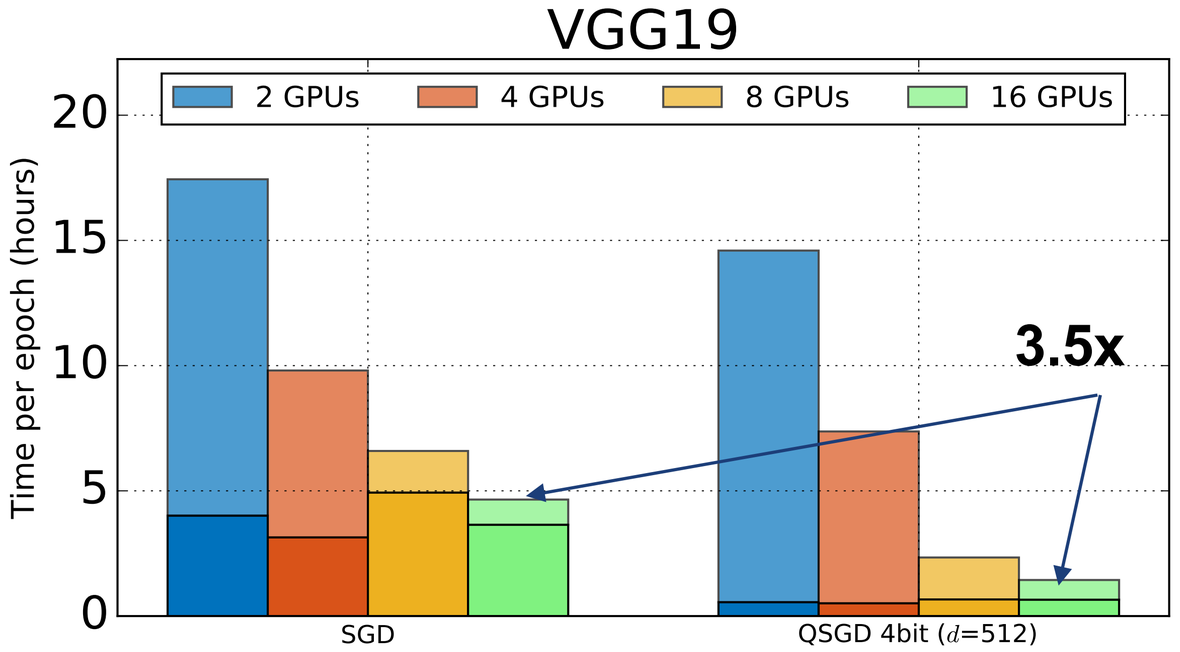

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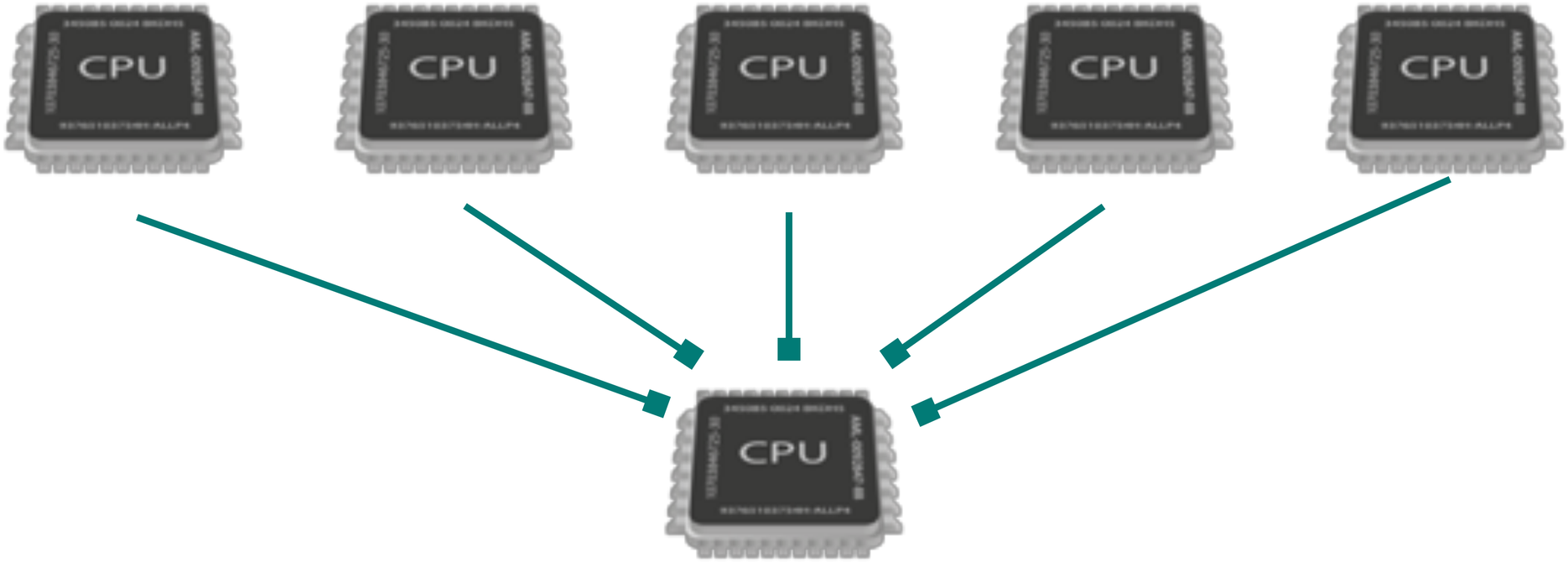

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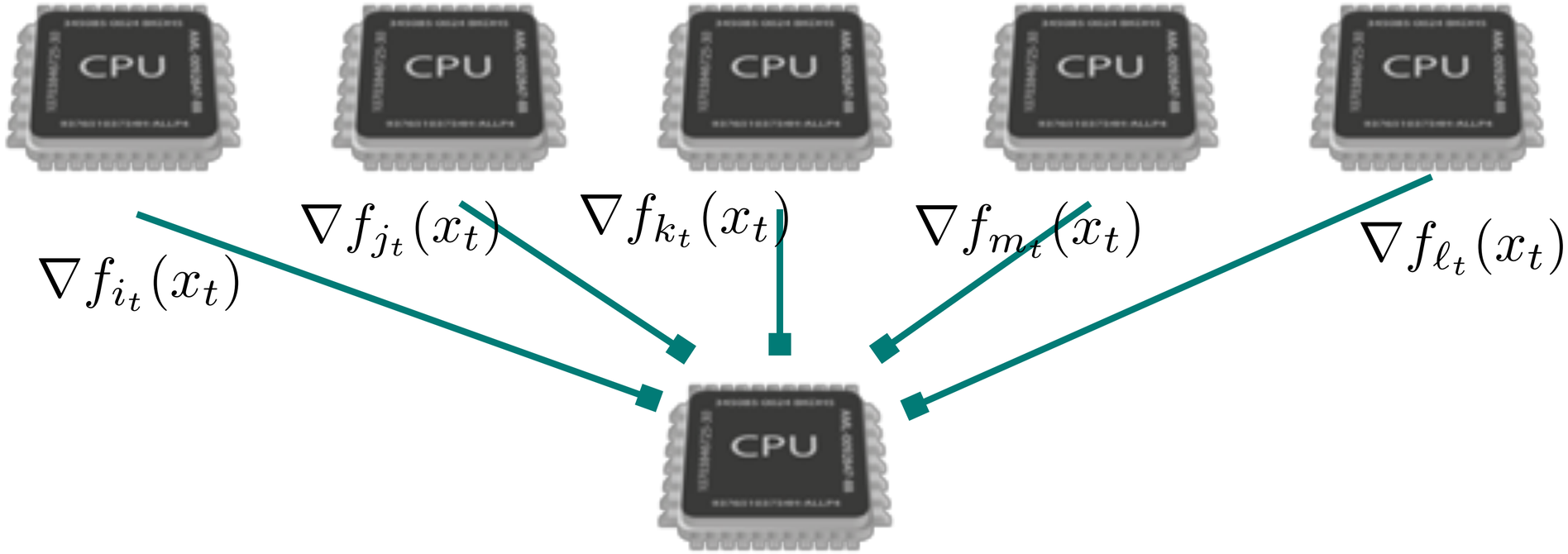

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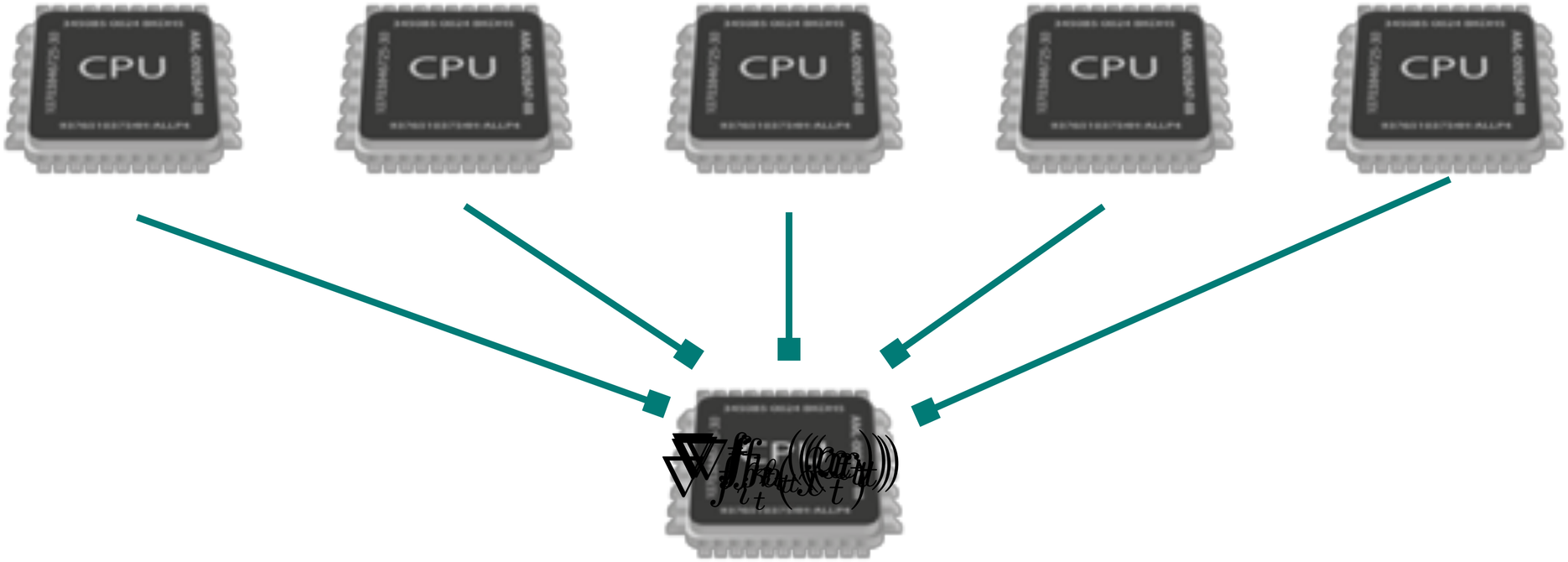

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REVISITING DISTRIBUTED SYNCHRONOUS SGD

Jianmin Chen[*], **Xinghao Pan**[*†], **Rajat Monga, Samy Bengio**
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ABSTRACT

Distributed training of deep learning models on large-scale training data is typically conducted with *asynchronous* stochastic optimization to maximize the rate of updates, at the cost of additional noise introduced from asynchrony. In contrast, the *synchronous* approach is often thought to be impractical due to idle time wasted on waiting for straggling workers. We revisit these conventional beliefs in this paper, and examine the weaknesses of both approaches. We demonstrate that a third approach, synchronous optimization with backup workers, can avoid asynchronous noise while mitigating for the worst stragglers. Our approach is empirically validated and shown to converge *faster* and to *better* test accuracies.

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See presentations section

Conclusion

- Distributed computing is at the heart of developments in modern ML
- There are different ways to exploit distributed computing: **hyper parameter optimization, coordinate descent, mini-batch synchronous SGD, asynchronous SGD**
- Which configuration to use depends on the problem and the resources at hand
- These topics are highly attractive (research-wise): they define the notion of systems + machine learning (look for SysML conference)