Taming Resource Heterogeneity in Distributed ML training with Dynamic Batching

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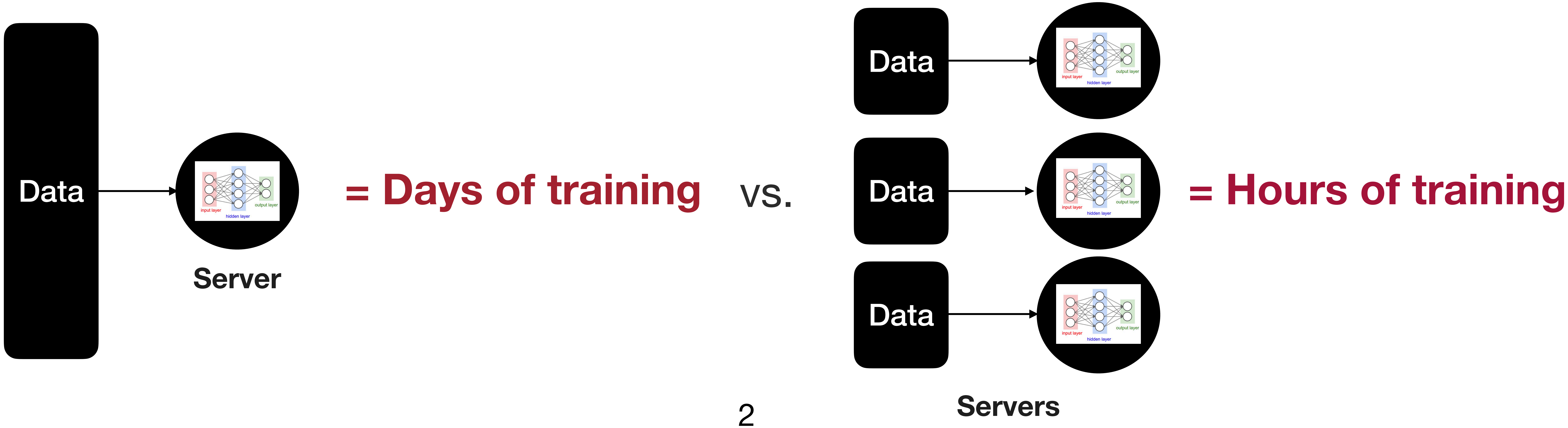
Why is Distributed Training important ?

- Advances in deeper and complex machine learning models increases computational needs. E.g., ResNet, VGG, Transformers, BERT
- State of the art models train on billions of parameters, increasing training time. E.g., GPT-3 has 175 billion parameters!
- Distributing training across multiple servers decreases model training time

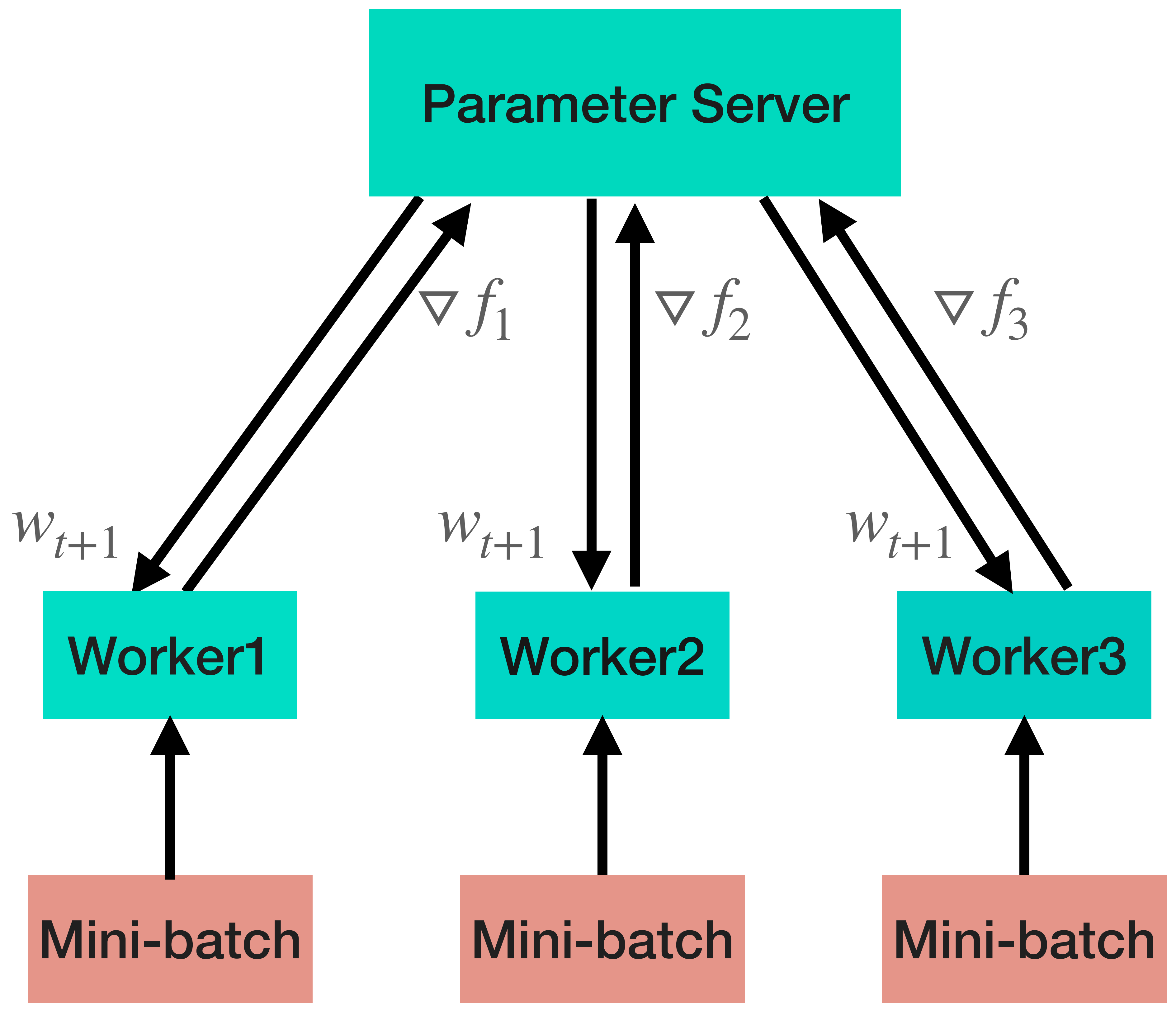


Distributed Training with Parameter Servers

- Workers: servers iteratively train model on a mini-batch of data independently (data parallelism)
    - Gradients computed using optimization like Mini-batch Stochastic Gradient Descent (SGD)
- Parameter Servers: compute mean of gradients from workers for given step; apply updates and re-distribute updated weights
    - Gradients applied to weights and resume training to next step; process repeats again
- Synchronous/BSP: Training at every step is halted until all gradient updates are received

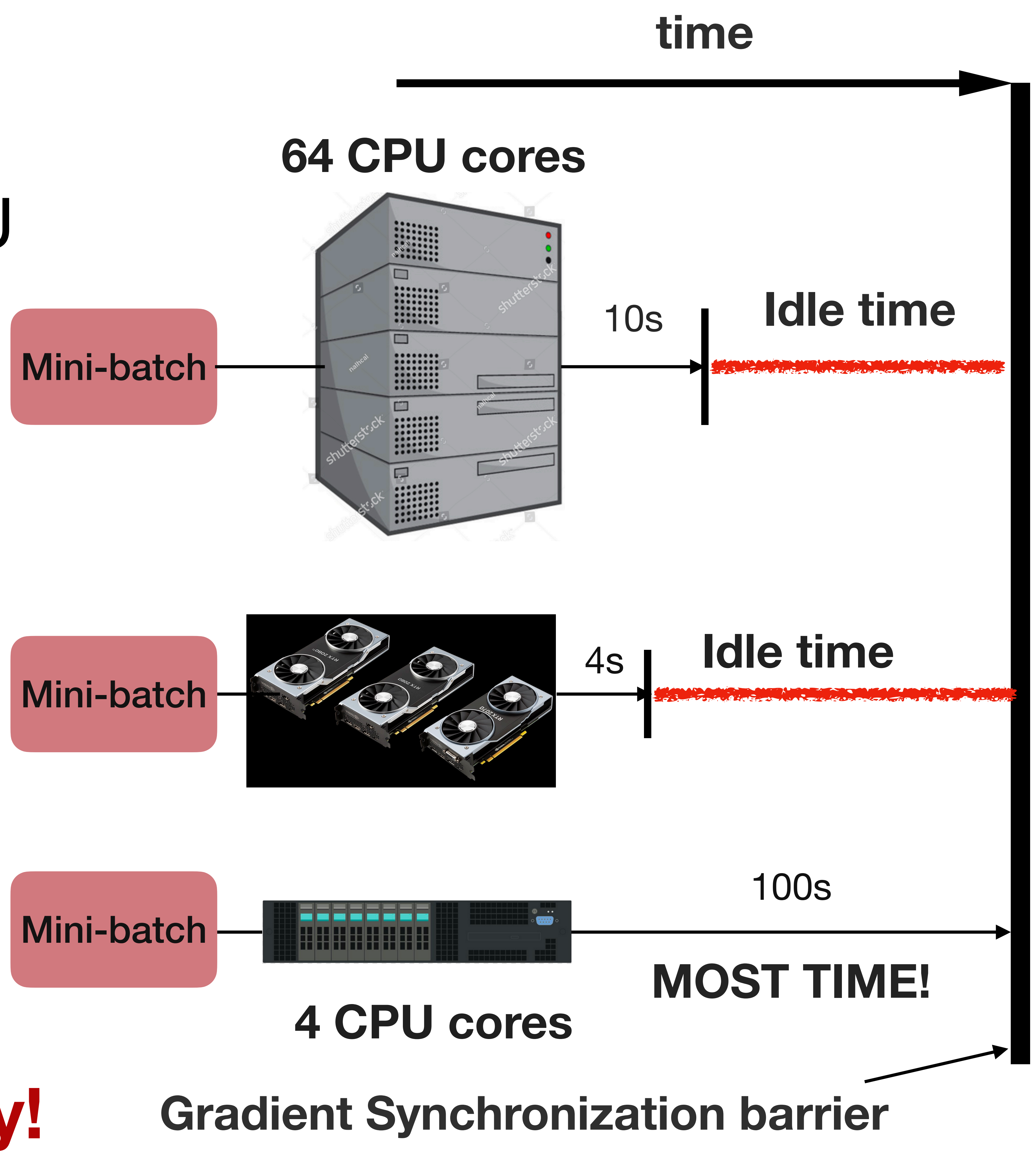
$$\nabla f = mean(\nabla f_1, \nabla f_2, \nabla f_3)$$

$$w_{t+1} = w_t - \lambda \nabla f$$



What Happens if Cluster is Heterogeneous ?

- Heterogeneity: Servers in a cluster with different compute capabilities.
  - E.g., NVIDIA GPU, 64-core CPU and 4-core CPU
  - Omnipresent; be it shared cloud or data centers
- Iteration time: time taken by each worker to compute gradients on a mini-batch
- Iteration time is lower on more capable servers and vice versa



Synchronization increase training time significantly!

Impact of Heterogeneity on Training Time

- We test a broad spectrum of test workloads on two clusters with three workers each (with same cumulative CPU cores)

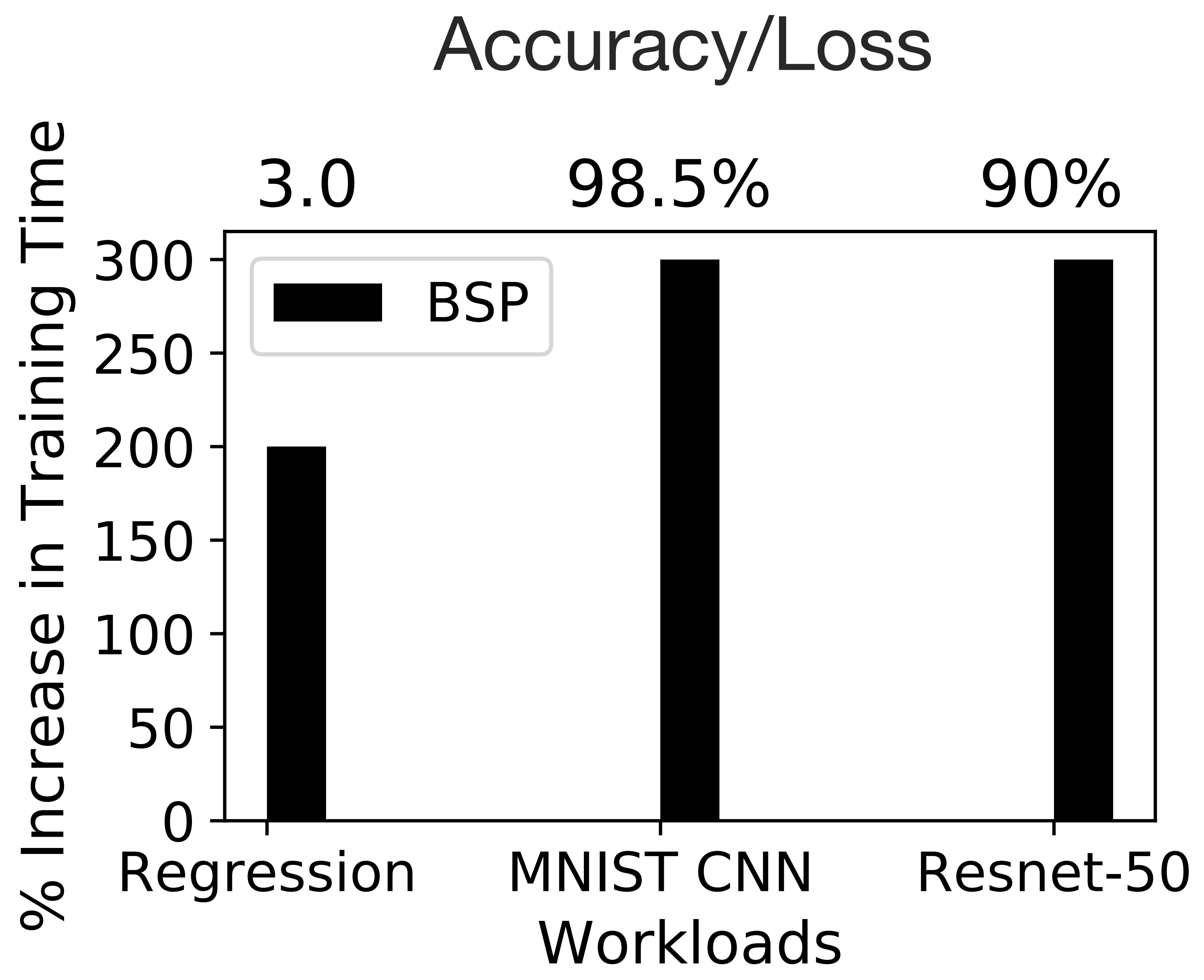
Homogeneous

13 CPU cores | 13 CPU cores | 13 CPU cores = 39 cores

vs.

Heterogeneous

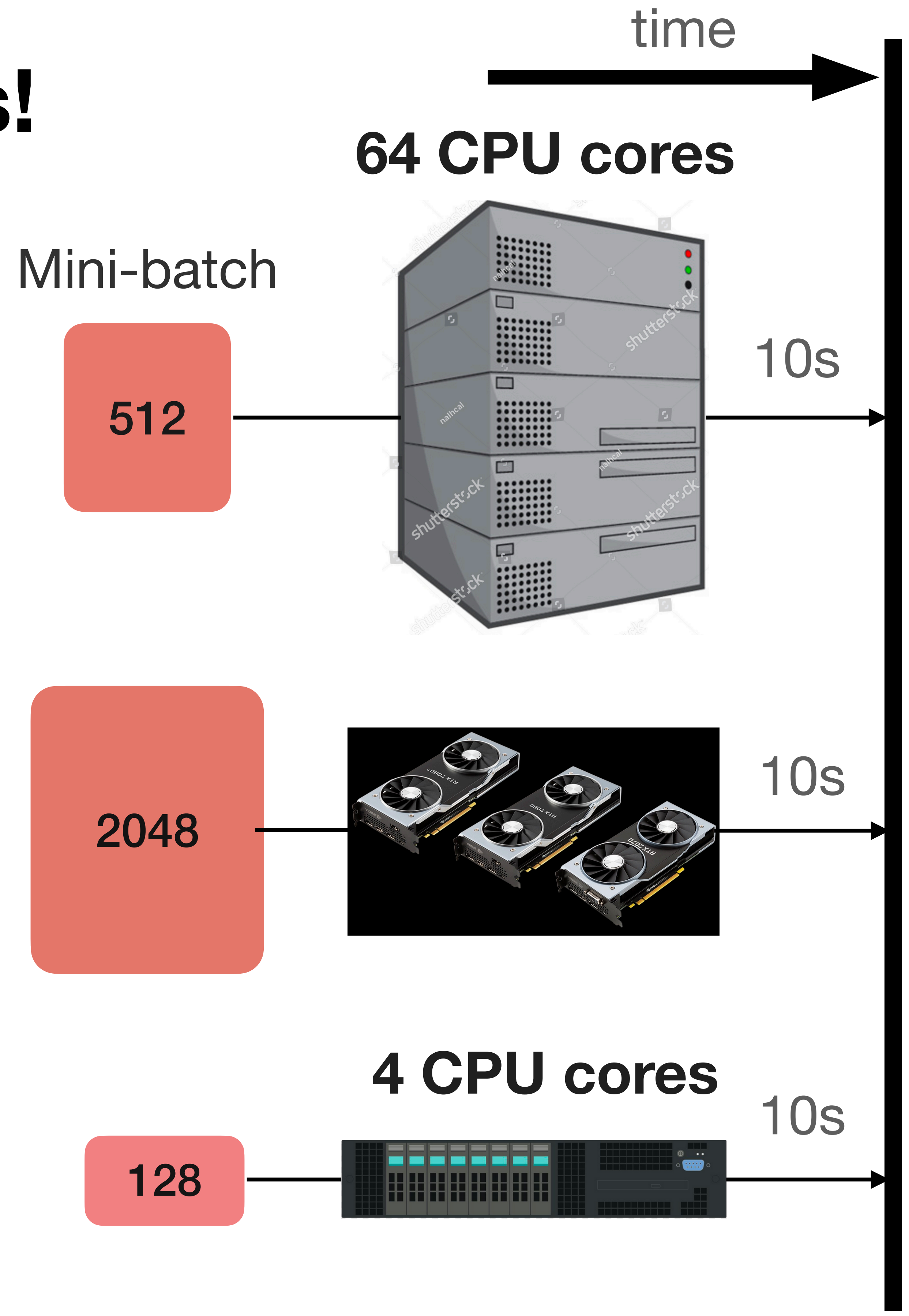
11 CPU cores | 4 CPU cores | 24 CPU cores = 39 cores



ResNet-50 and 1-layer CNN take 3x time in a heterogeneous cluster!
Linear Regression takes 2x more time than a homogeneous cluster!

How to Minimize the Effect of Heterogeneity ?

- **Key idea: Equalize the iteration times among the workers!**
- Assign mini-batch size on workers proportional to worker throughput
- Throughput ratio in clusters is approximated as:
  - On CPU clusters: ratio of CPU-core count
  - On CPU-GPU mix and GPU clusters: ratio of floating point operations per second (FLOPS)



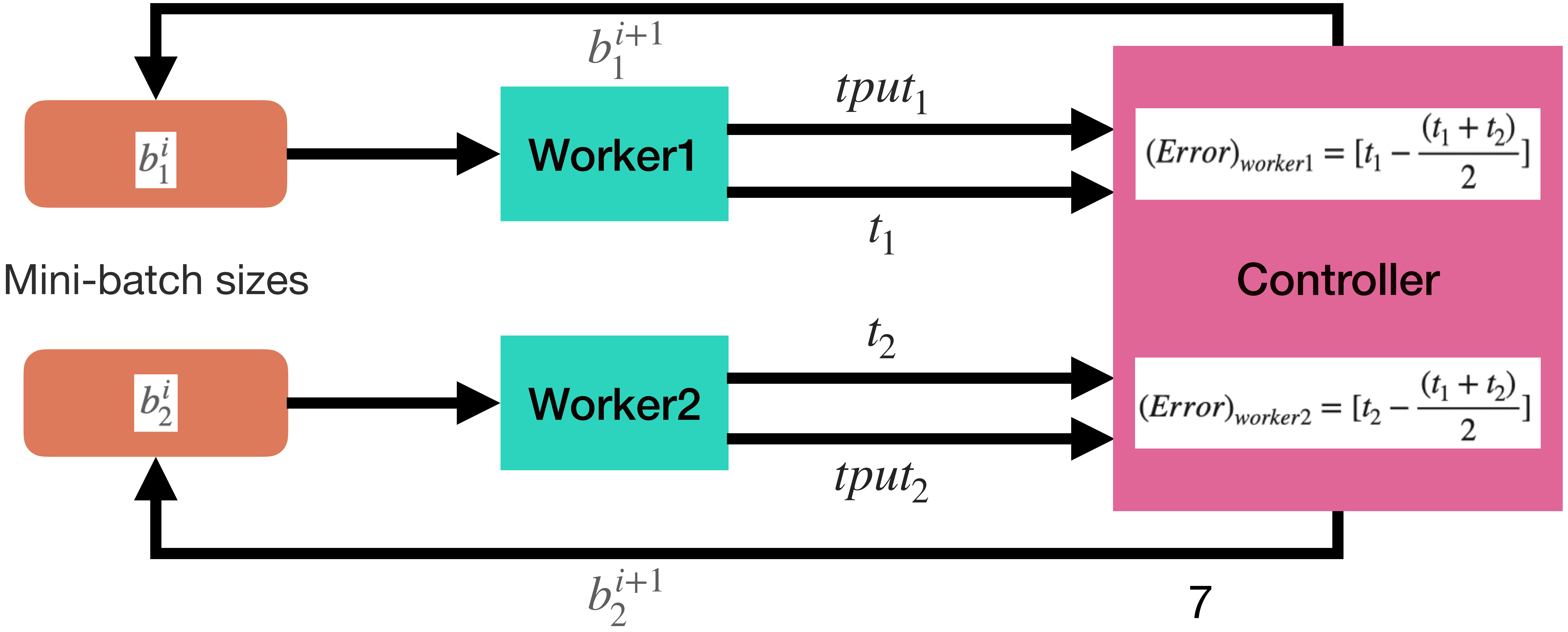
Fast worker; big mini-batch size
Slow worker; small mini-batch size

Near-equal time on all workers

Mini-batch Size Controller

- A one-time throughput approximated mini-batch adjustment not enough:
  - Approximated throughput is different from actual training throughput
  - Server resources may change dynamically during training (interference, overcommitment etc.)
- We use a proportional controller that $b_k^{i+1} = b_k^i + \triangle(b_k^i)$

$$\triangle(b_k) = -(Throughput \times Error) \quad such\ that \quad Error = (worker's\ iteration\ time \; - \; cluster's\ average\ iteration\ time)$$



If Error < 0, increase mini-batch.

If Error > 0, decrease mini-batch.

- In the two worker cluster, for worker1

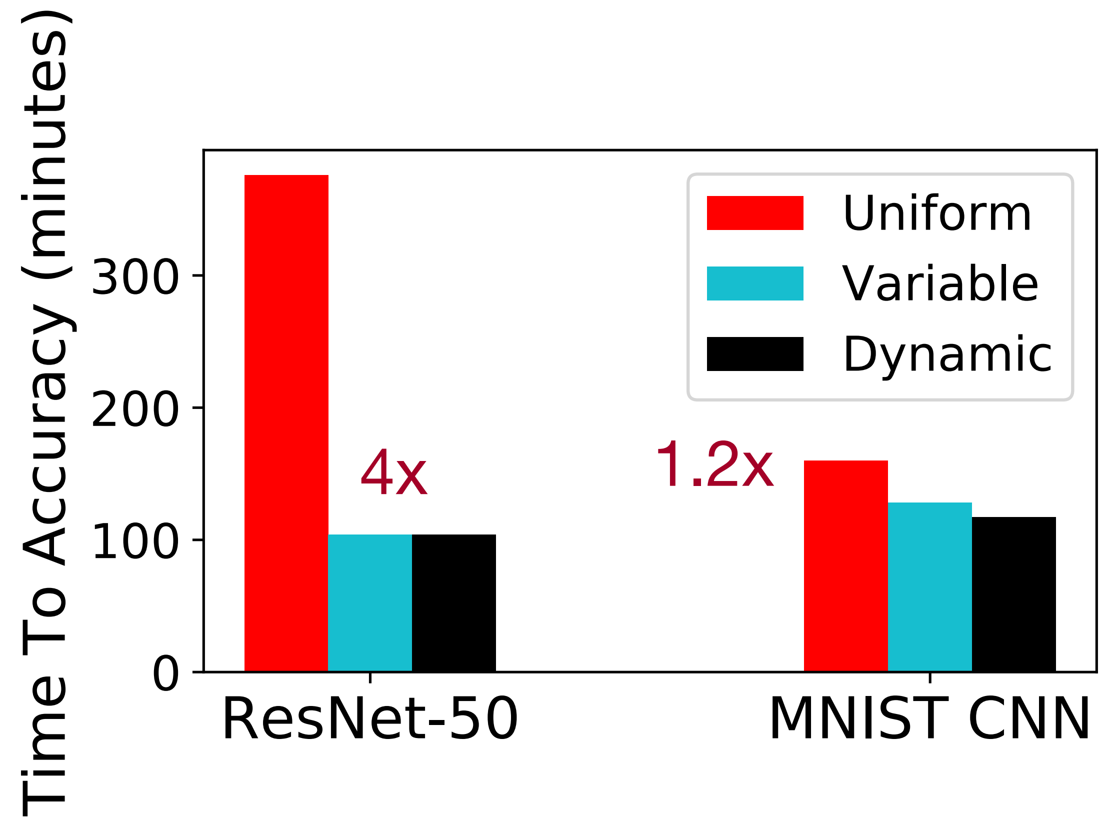
$$\triangle(b_1) = -\,tput_1 \times [t_1 - \frac{(t_1+t_2)}{2}]$$

$$b_1^{i+1} = b_1^i + \triangle(b_1^i)$$

Training on Heterogeneous GPU Clusters

What happens when a cluster contains different types of CPU and GPU workers?

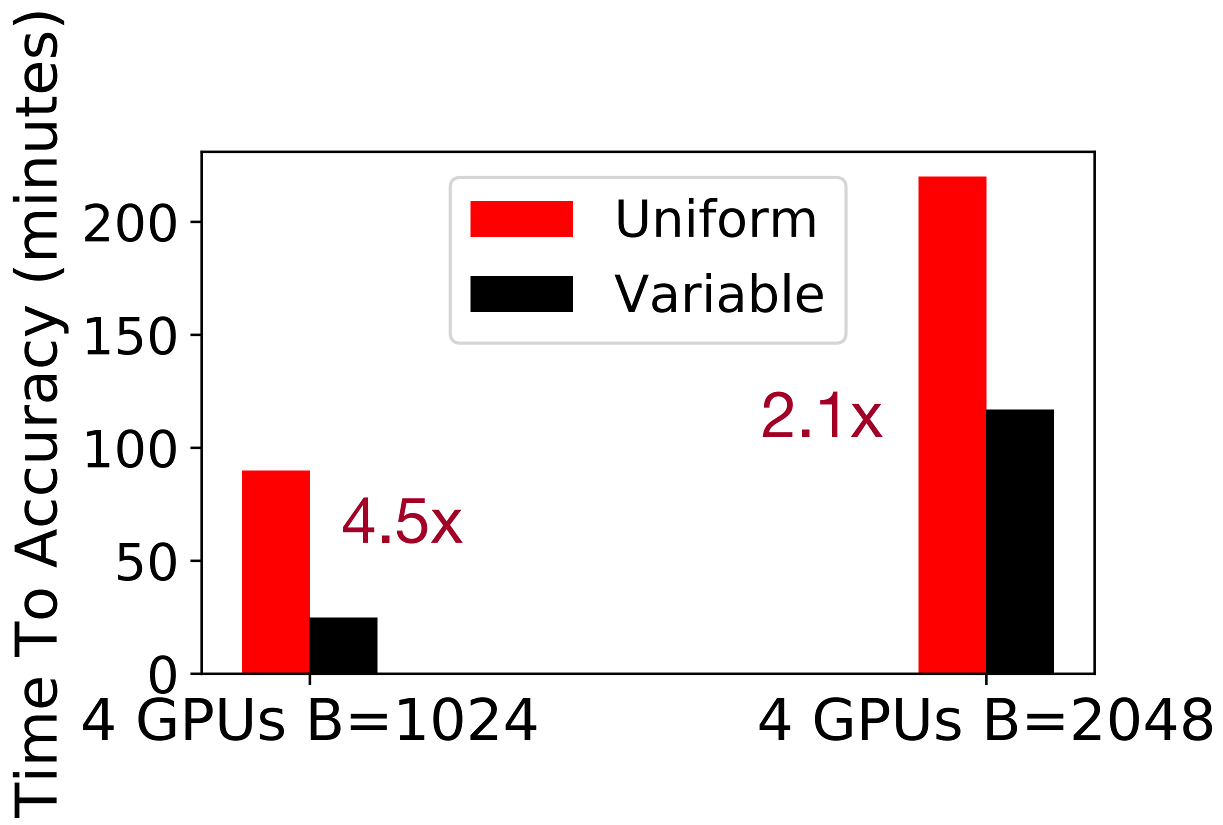
- We use a two worker cluster with NVIDIA Tesla P100 and 48-core Intel Xeon CPU as workers
- Evaluated on conventional TF, hardware throughput based and controller based dynamic mini-batch adjustment



ResNet50 improves by 4x and CNN improves by 1.2x in CPU-GPU mix

What happens when a cluster contains different types of GPU workers only ?

- We test on two NVIDIA Tesla T4 and two NVIDIA Tesla P4



ResNet50 improves by 4.5x and CNN improves by 2.1x in GPU clusters

Thank you!