Synchronous Stochastic Gradient

Outline

- Basics
- Comparison against asynchronous SGD
- Mitigating stragglers
- Enabling larger mini-batch sizes
- Decreasing communication complexity

Distributed SGD – Averaging Estimates

Algorithm 3 SimuParallelSGD(Examples $\{c^1, \dots c^m\}$, Learning Rate η, Machines k)

Define $T = \lfloor m/k \rfloor$
Randomly partition the examples, giving T examples to each machine.
for all $i \in \{1, \dots k\}$ **parallel do**
  Randomly shuffle the data on machine i.
  Initialize $w_{i,0} = 0$.
  for all $t \in \{1, \dots T\}$: **do**
    Get the tth example on the ith machine (this machine), $c^{i,t}$
    $w_{i,t} \leftarrow w_{i,t-1} - \eta \partial_w c^i(w_{i,t-1})$
  end for
end for
Aggregate from all computers $v = \frac{1}{k} \sum_{i=1}^{k} w_{i,t}$ and **return** v.

Advantage: Needs only one round of communication. Works well for convex models.

Disadvantage: For non-convex models, averaging different local minima doesn’t make sense.

Distributed SGD – Averaging Gradients

Algorithm 1: Async-SGD worker k

Input: Dataset $\mathcal{X}$
Input: B mini-batch size
while *True* **do**
  Read $\widehat{\theta}_k = (\theta[0], \ldots, \theta[M])$ from PSs
  $G_k^{(t)} := 0.$
  for $i = 1, \ldots, B$ **do**
    Sample datapoint $\widetilde{x}_i$ from $\mathcal{X}$.
    $G_k^{(t)} \leftarrow G_k^{(t)} + \frac{1}{B} \nabla F(\widetilde{x}_i; \widehat{\theta}_k)$.
  end
  Send $G_k^{(t)}$ to parameter servers.
end

Algorithm 2: Async-SGD Parameter Server j

Input: $\gamma_0, \gamma_1, \ldots$ learning rates.
Input: α decay rate.
Input: $\theta^{(0)}$ model initialization.
for $t = 0, 1, \ldots$ **do**
  Wait for gradient G from any worker.
  $\theta^{(t+1)}[j] \leftarrow \theta^{(t)}[j] - \gamma_t G[j]$.
  $\bar{\theta}^{(t)}[j] = \alpha \bar{\theta}^{(t-1)}[j] + (1 - \alpha) \theta^{(t)}[j]$.
end

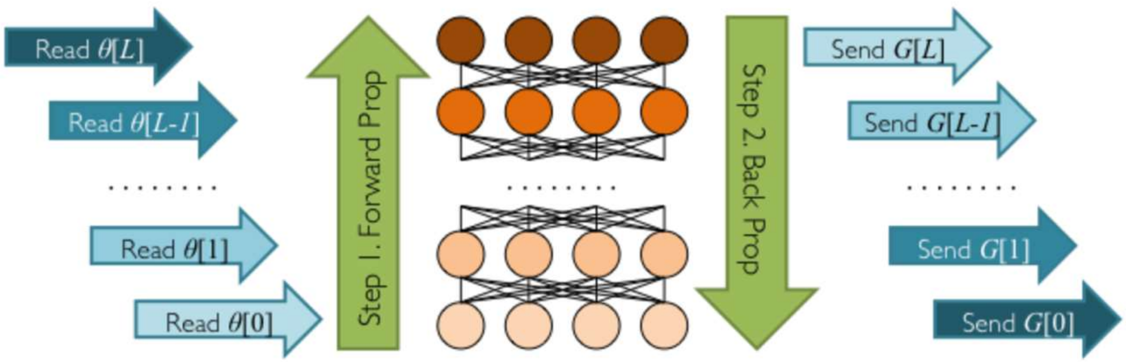
Comparison against asynchronous SGD

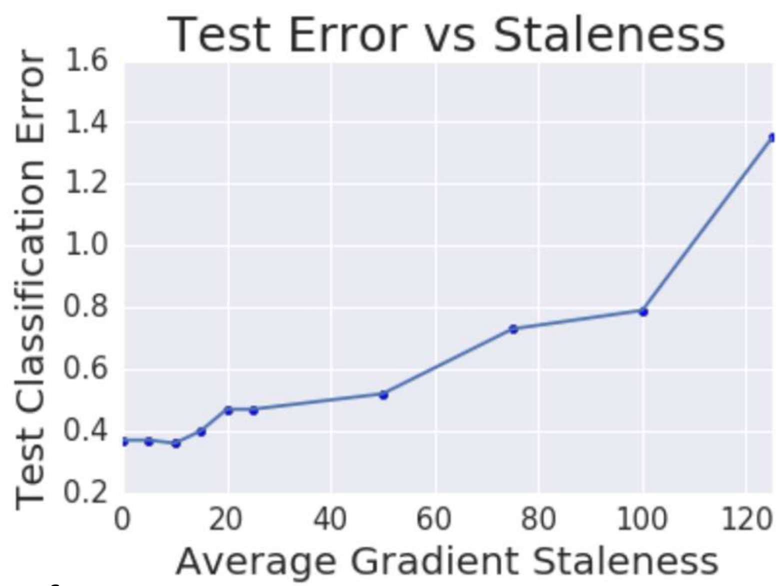
☺ Do not need to worry about stale gradients
☺ Do not need to set a smaller step-size compared to simple SGD
=> Will lead to faster (in terms of number of epochs) convergence

☹ Need to wait for the slowest machine (“straggler”) for each update
☹ Poor robustness to machine failure

Comparison against asynchronous SGD

- **Staleness:** number of updates that have occurred between its corresponding read and update operations.



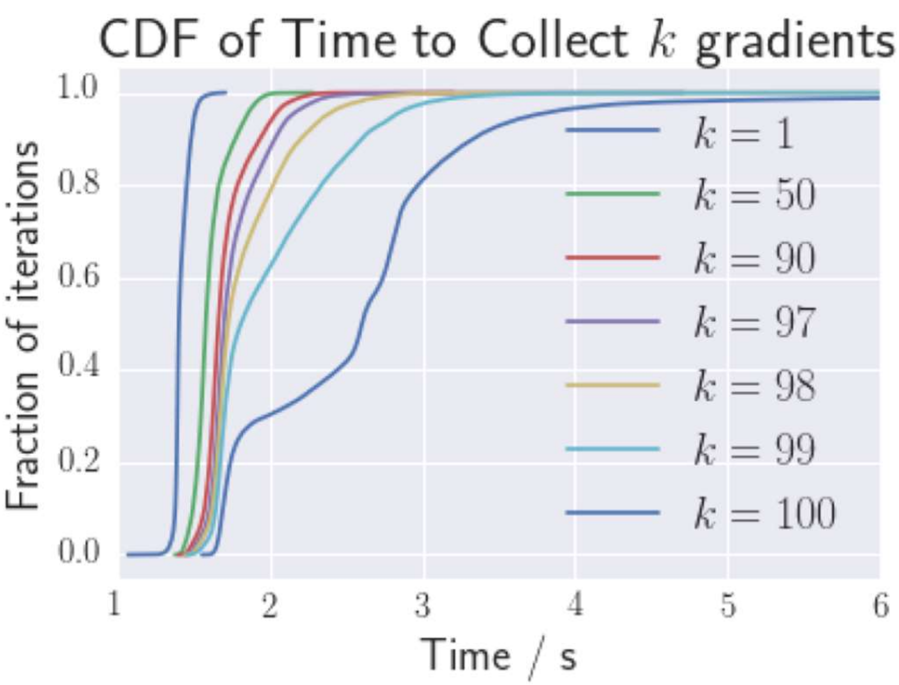


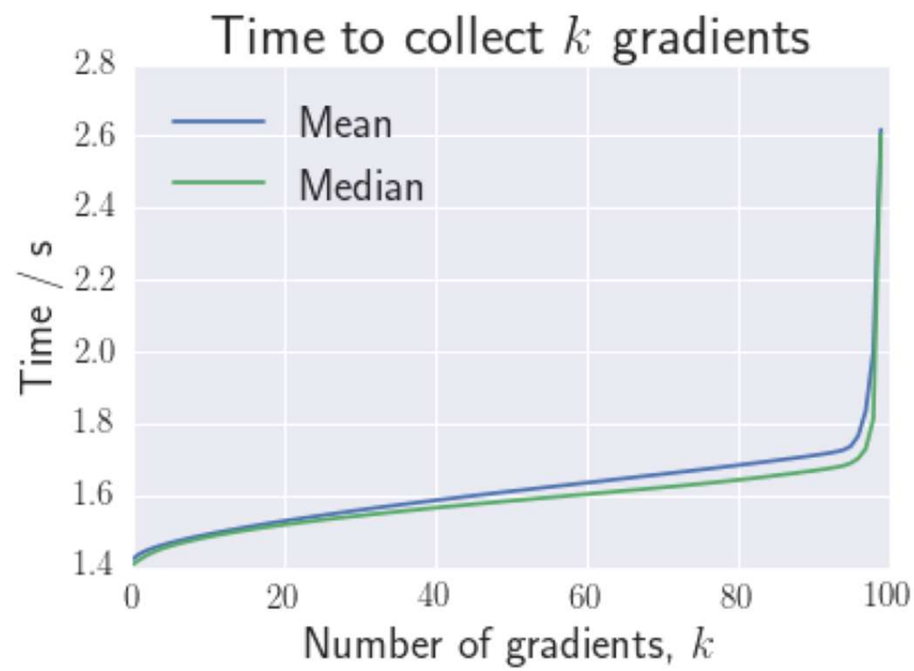
Tricks to make Asynchronous SGD work:

1. Slowly increase the number of workers over the first 3 epochs of training
2. Use lower initial learning rates

Synchronous SGD - Problem

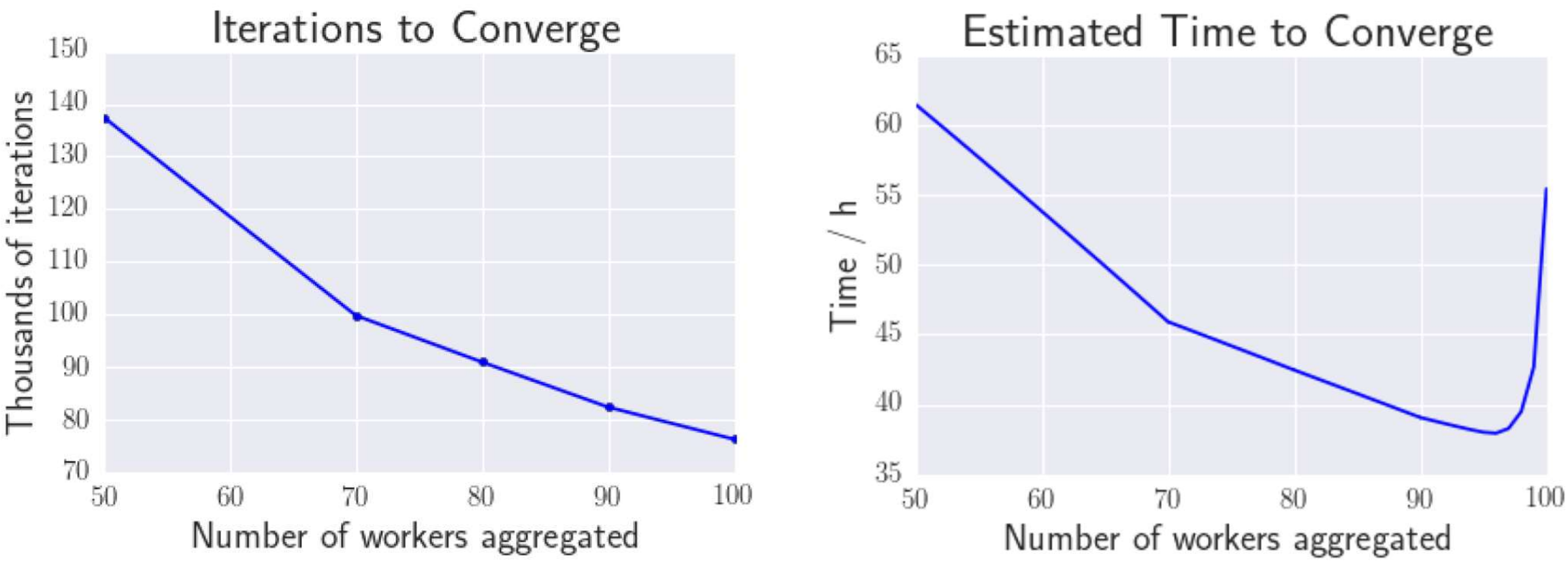
Few stragglers slow down the algorithm!





Solution 1

Basic Idea: Drop the gradients of the slow workers



Solution 2

Basic Idea: Use backup workers

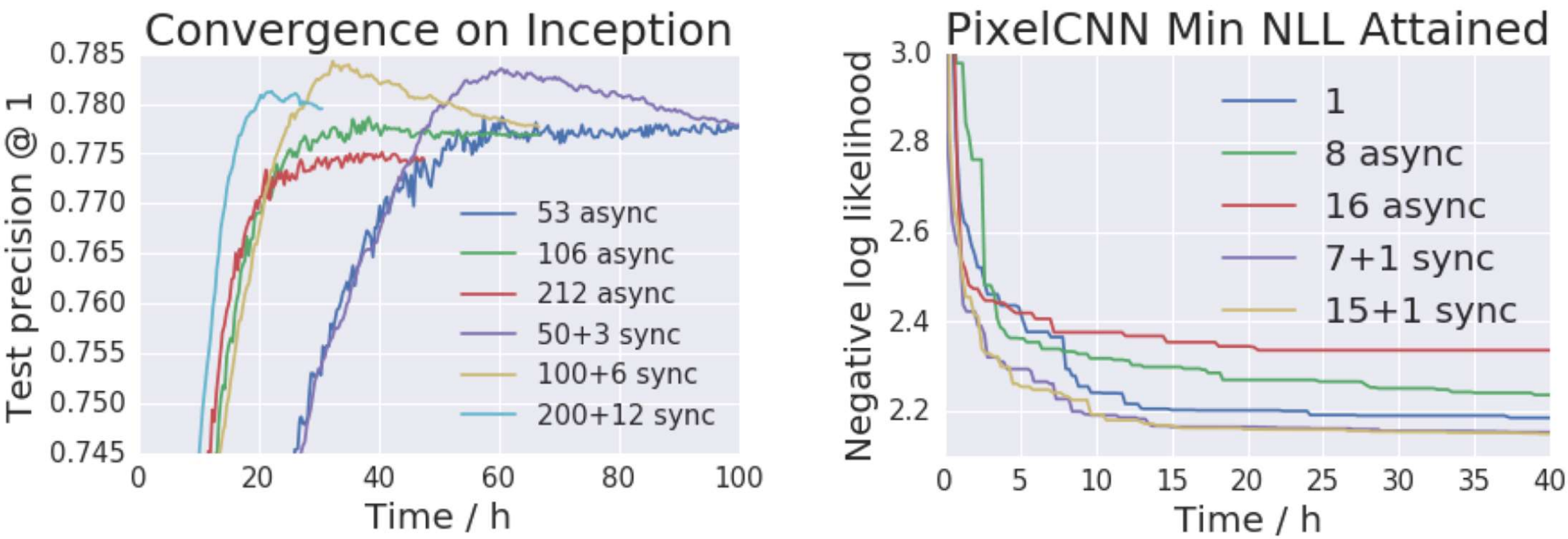
Algorithm 3: Sync-SGD worker k, where $k = 1, \ldots, N + b$

Input: Dataset $\mathcal{X}$
Input: B mini-batch size
for $t = 0, 1, \ldots$ **do**
  Wait to read $\theta^{(t)} = (\theta^{(t)}[0], \ldots, \theta^{(t)}[M])$ from parameter servers.
  $G_k^{(t)} := 0$
  for $i = 1, \ldots, B$ **do**
    Sample datapoint $\widetilde{x}_{k,i}$ from $\mathcal{X}$.
    $G_k^{(t)} \leftarrow G_k^{(t)} + \frac{1}{B} \nabla F(\widetilde{x}_{k,i}; \theta^{(t)})$.
  end
  Send $(G_k^{(t)}, t)$ to parameter servers.
end

Algorithm 4: Sync-SGD Parameter Server j

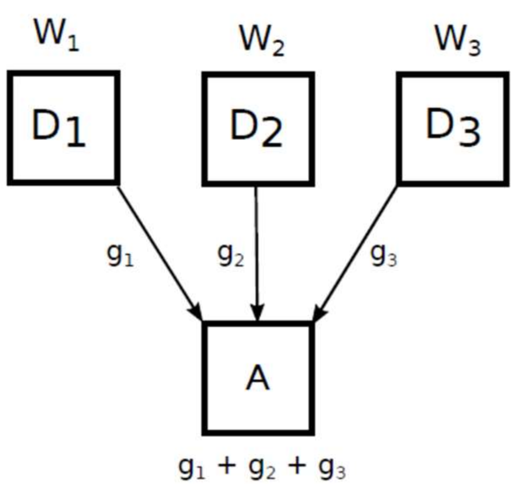
Input: $\gamma_0, \gamma_1, \ldots$ learning rates.
Input: α decay rate.
Input: N number of mini-batches to aggregate.
Input: $\theta^{(0)}$ model initialization.
for $t = 0, 1, \ldots$ **do**
  $\mathcal{G} = \{\}$
  while $|\mathcal{G}| < N$ **do**
    Wait for (G, t') from any worker.
    if $t' == t$ **then** $\mathcal{G} \leftarrow \mathcal{G} \cup \{G\}$.
    else Drop gradient G.
  end
  $\theta^{(t+1)}[j] \leftarrow \theta^{(t)}[j] - \frac{\gamma_t}{N} \sum_{G \in \mathcal{G}} G[j]$.
  $\bar{\theta}^{(t)}[j] = \alpha \bar{\theta}^{(t-1)}[j] + (1 - \alpha)\theta^{(t)}[j]$.
end

Experimental Comparison

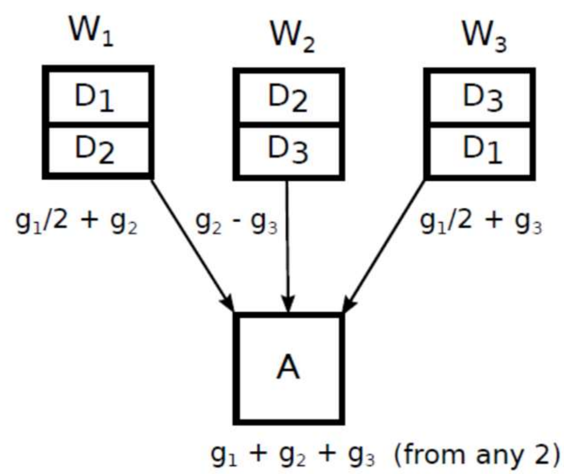


Alternate solution

Use coding theory + data redundancy to always ensure that we get the full gradient and ensure robustness to “some” number of stragglers



(a) Naive synchronous gradient descent



(b) Gradient coding: The vector $g_1 + g_2 + g_3$ is in the span of *any two* out of the vectors $g_1/2 + g2$, $g_2 - g_3$ and $g_1/2 + g_3$.

Improving synchronous SGD

Need larger batch-sizes to get the full benefit of parallelism

Generalization performance decreases with higher batch-size ☹

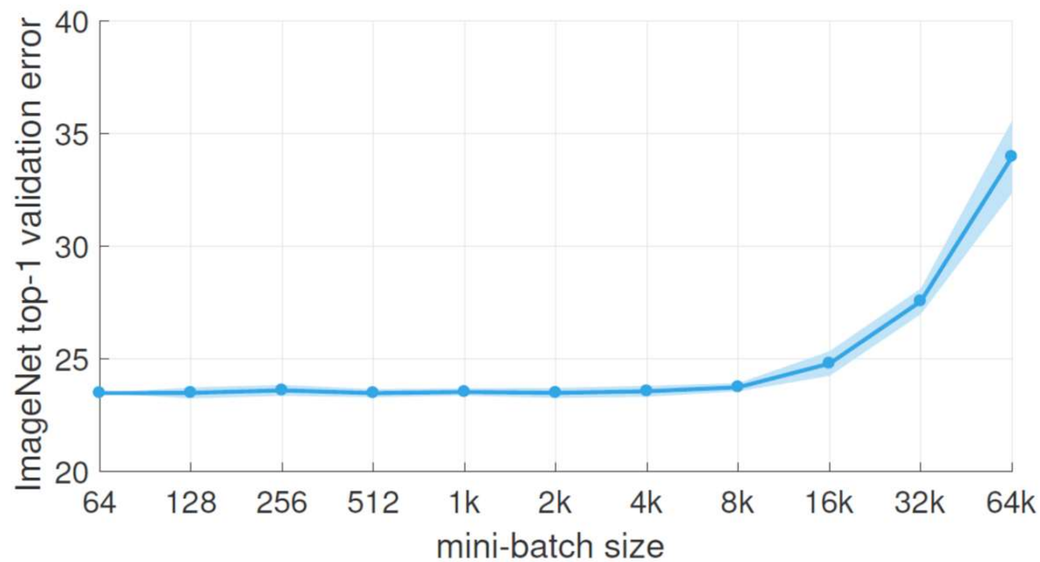


Figure 1. **ImageNet top-1 validation error *vs*. minibatch size.**

Synchronous SGD with large batch-size

Competing(?) hypotheses: optimization difficulty vs poor generalization due to convergence to sharp minima

Today: Evidence for optimization difficulty and correcting for it

Solution:

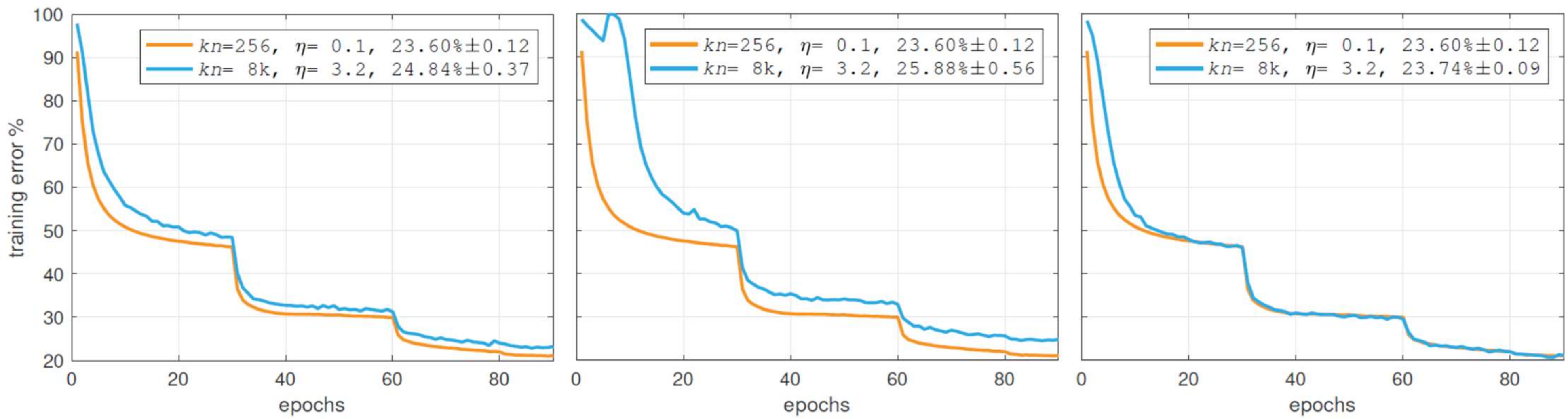
Linear Scaling Rule: *When the minibatch size is multiplied by k, multiply the learning rate by k.*

(Also has theoretical evidence + multiple other sources)

In practice: Breaks down when the network is changing rapidly, which commonly occurs in early stages of training.

Hack: “Warmup” - Gradually ramp up the learning rate from a small to a large value across the first 5 epochs

Synchronous SGD with large batch-size

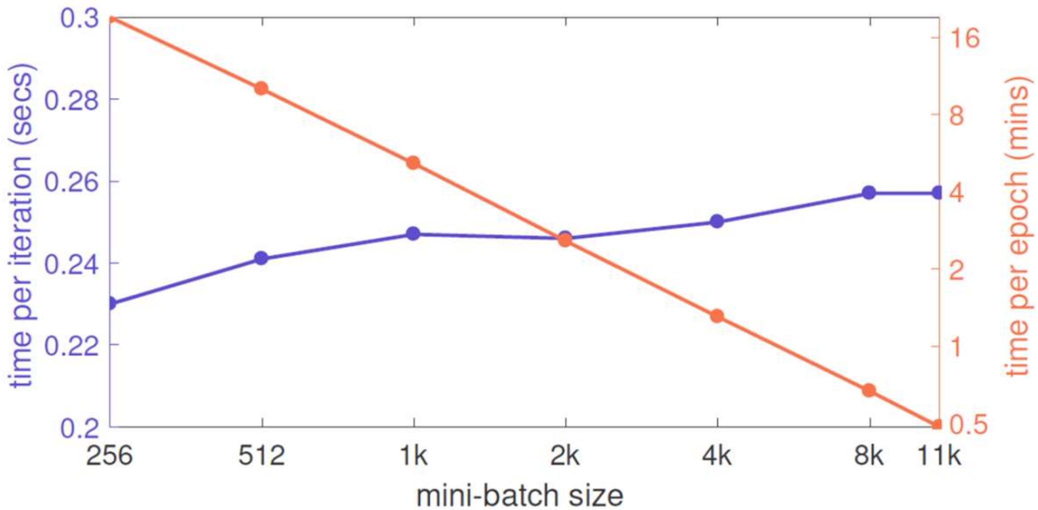


(a) no warmup (b) constant warmup (c) gradual warmup

Figure 2. **Warmup.** Training error curves for minibatch size 8192 using various warmup strategies compared to minibatch size 256. *Validation* error (mean±std of 5 runs) is shown in the legend, along with minibatch size kn and reference learning rate η.

Note: Fails beyond batch-size of 8K.

Synchronous SGD with large batch-size



"With 352 GPUs (44 servers) our implementation completes one pass over all 1.28 million ImageNet training images in about 30 seconds"

"No generalization issues when transferring across datasets and across tasks using models trained with large minibatches."

Decreasing communication complexity

Basic Idea: Transfer just the signs of gradients

Algorithm 1: SIGNSGD

Input: learning rate δ, current point x_k

$\tilde{g}_k \leftarrow \text{stochasticGradient}(x_k)$

$x_{k+1} \leftarrow x_k - \delta \, \text{sign}(\tilde{g}_k)$

Algorithm 2: SIGNSGD with majority vote

Input: learning rate δ, current point x_k, # workers M each with an independent gradient estimate $\tilde{g}_m(x_k)$

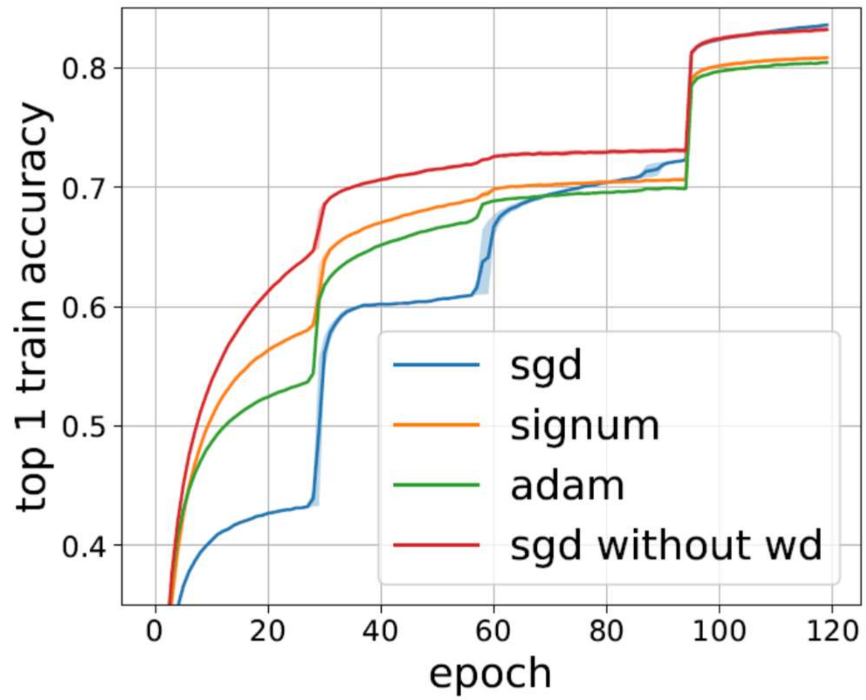
on server

  pull $\text{sign}(\tilde{g}_m)$ **from** each worker

  push $\text{sign}\left[\sum_{m=1}^{M} \text{sign}(\tilde{g}_m)\right]$ **to** each worker

on each worker

  $x_{k+1} \leftarrow x_k - \delta \, \text{sign}\left[\sum_{m=1}^{M} \text{sign}(\tilde{g}_m)\right]$



Conclusion

- Synchronous SGD is simple and typically works better (both in terms of time and performance) than asynchronous SGD.
- There are some ways to mitigate the effect of stragglers.
- To utilize the full power of the hardware, we need to enable training with large mini-batch sizes. Increasing the learning rate with large batches leads to fast convergence without any loss in performance.
- We can reduce the communication complexity by compressing the gradients or using just their signs.

References

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