Decentralized optimization with non-identical sampling in presence of stragglers

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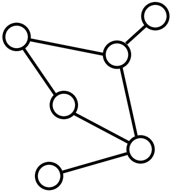
Background



Setup:

- Decentralized data/computation
- Q_i: data distribution of ith worker

$$F_i(w) = \mathbb{E}_{X \sim Q_i}[f(w, X)]$$

- Want n workers to collectively minimize

$$F(w) = \frac{1}{n}\sum_{i=1}^{n} F_i(w)$$

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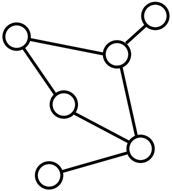

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Assumption 1:

- Non-identical data distributions[1]
  e.g.: MNIST with 10 workers, worker i only has images of digit $i-1$.

Assumption 2:

- Variable amount of work[2]
  e.g.: Mini-batch size 10 for stragglers (slow workers), 100 for fast workers

[1] John C Duchi, Alekh Agarwal, and Martin J Wainwright. "Dual averaging for distributed optimization: Convergence analysis and network scaling". In: *IEEE Trans. Automat. Contr.* (2011), pp. 592–606

[2] Nuwan Ferdinand et al. "Anytime minibatch: Exploiting stragglers in online distributed optimization". In: *ICLR*. New Orleans, 2019

Consensus optimization through random-walk

W_k, G_k: n-column matrices $\begin{cases} n \text{ columns for } n \text{ workers} \\ \text{store weights and gradients } \nabla F_i \end{cases}$

$$W_{k+1} = W_k - \eta G_k \qquad \text{(decoupled update)}$$

$$W_{k+1} = \underbrace{(W_k - \eta G_k)}_{j\text{th column is } \tilde{w}^j} P \qquad \text{(consensus update)}$$

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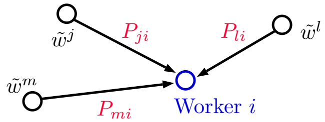
j, l, m: neighbours of worker i



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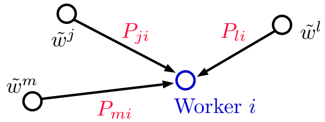

$$\tilde{w}^i \leftarrow \tilde{w}^i P_{ii} + \tilde{w}^j P_{ji} + \tilde{w}^l P_{li} + \tilde{w}^m P_{mi}$$

- $P_{i,j} > 0$ only if workers i, j connected
- P - doubly stochastic matrix
- Entries in $[P]^m$ converge to $\frac{1}{n}$ for large m

$$W_T = W_0 [P]^T - \eta \sum_{k=0}^{T-1} G_k \underbrace{[P]^{T-k}}_{\text{averaging effect on gradients}}$$

Assumption 2: Variable amount of work

- $\bar{g}_i$: ith column of G = avg. gradient of a size b_i (≥ 1) mini-batch
- Q_i: data distribution of ith worker

$$\bar{g}_i = \frac{1}{b_i} \sum_{l=1}^{b_i} \nabla_w f(w, X_l); \qquad X_l \sim Q_i$$

In slides, assume all distributions are equally important ($\implies n\gamma_i = 1$ for the γ_i discussed in paper).

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Assumption 2: Workers complete different amounts of work

- b_i i.i.d. across workers *and* iterations
- $b_i \neq b_j$ in general $\implies$ confidence of $\bar{g}_i$ vary across i

$$W_{k+1} = (W_k - \eta G_k)P \qquad \text{(consensus update)}$$

- Columns of G_k treated equally, irrespective of b_i $\implies$ Equal weighting
- How should we account for the variability in confidences?

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Our proposal: Treat confident workers better!

- Give a higher weight to confident gradients
- V: diagonal matrix, $V_{i,i} \propto b_i$

$$W_{k+1} = (W_k - \eta V G_k)P \qquad \text{(Proportional weighting)}$$

Concerns:

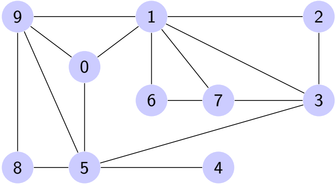
- Columns of W_{k+1} pulled towards confident workers
- Will the oscillatory effect hurt convergence?

Confirming numerically

- Fashion-MNIST dataset: 10 classes

- Multinomial logistic regression
- 1-hidden layer neural network

- 10 workers for each class



- Simulate stragglers by sampling b_i

$$b_i = \begin{cases} 60 & \text{with probability } 0.8 \\ 1 & \text{with probability } 0.2 \end{cases}$$

Code available at `https://github.com/thadikari/consensus`.

Simulation results

Cost function:

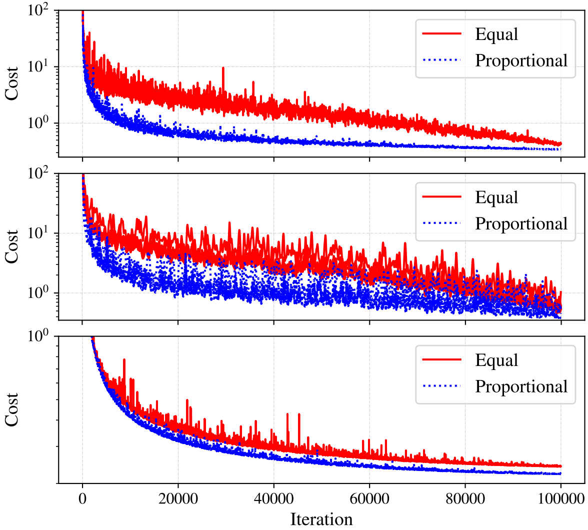
- Convex: no activation in the hidden layer
- Non-convex: ReLU in the hidden layer

Consensus:

- Approximate: 10 consensus rounds
- Perfect: All entries in P set to $\frac{1}{n}$

Experiments:

- Top: Convex, Perfect consensus
- Middle: Convex, Apprx. consensus
- Bottom: Non-convex, Apprx. consensus



Theoretical guarantees: Perfect consensus

- $\mathsf{Var}(\nabla_w f(w,X)) \le \sigma^2$: measures local variance within one worker
- $\nabla F_i = \mathbb{E}_{X\sim Q_i}[\nabla_w f(w,X)]$ and $\nabla F = \frac{1}{n}\sum_{i=1}^{n} F_i(w)$
- $\sum_{i=0}^{n} \|\nabla F_i - \nabla F\|^2 \le n^2 D$: measures global variation among all workers

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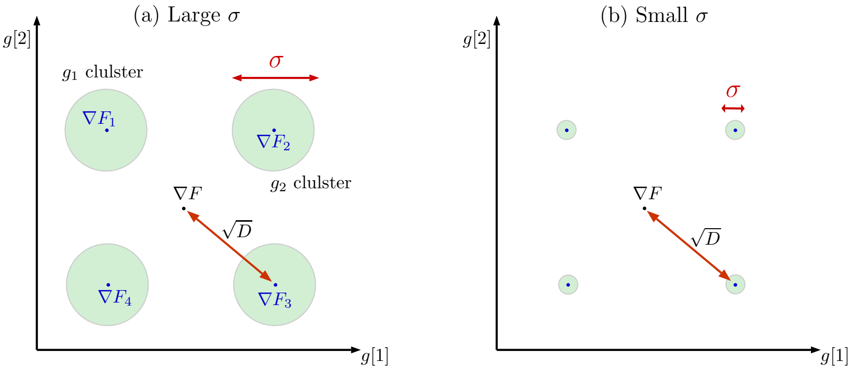
Main results:

- Proportional weighting converges!
- Faster than Equal weighting if:

$$\underbrace{D}_{\substack{\text{variation of true} \\ \text{gradients across workers}}} \;/\; \underbrace{\sigma^2}_{\substack{\text{gradient noise} \\ \text{of one sample}}} \leq \underbrace{(\mu_2 - n^2 \mu_3)/(n^4 s^2)}_{\text{statistics of } b_i}$$

$$\mu_2 = \mathbb{E}[1/b_i]$$
$$\mu_3 = \mathbb{E}[b_i/(\textstyle\sum_{i=1}^{n} b_i)^2]$$
$$s^2 = \text{Var}(b_i/b)$$

Visualizing the condition



- $g_i = \nabla_w f(w, X)$ for $X \sim Q_i$
- For small σ, even $b_i = 1$ enough to accurately estimate ∇F_i.

Conclusions/Next steps

- Account for the variability in confidences
- Proposed proportional method
- Sufficient conditions for faster convergence

Planned work

- Proof for approximate consensus.
- Generalize to include $b_i = 0$ case.

Thank you.