Distributed Roubust Learning

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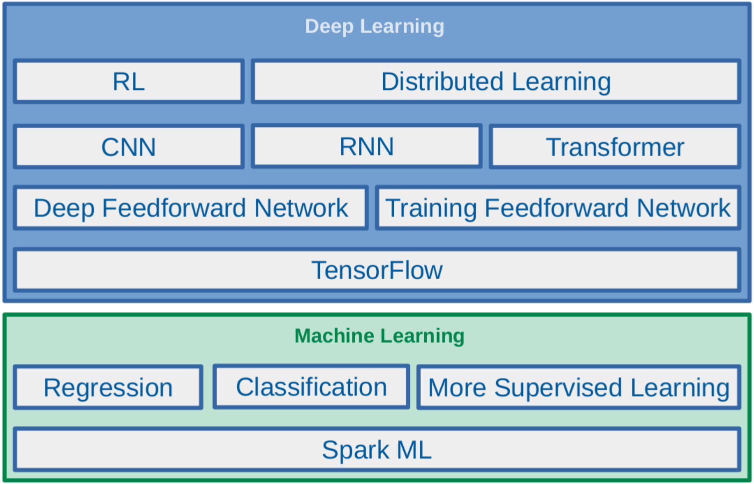
2021-12-15

The Course Web Page

https://id2223kth.github.io

https://tinyurl.com/6s5jy46a

Where Are We?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Distributed Learning
CNN
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Training Feedforward Network
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Machine Learning
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Classification
More Supervised Learning
Spark ML

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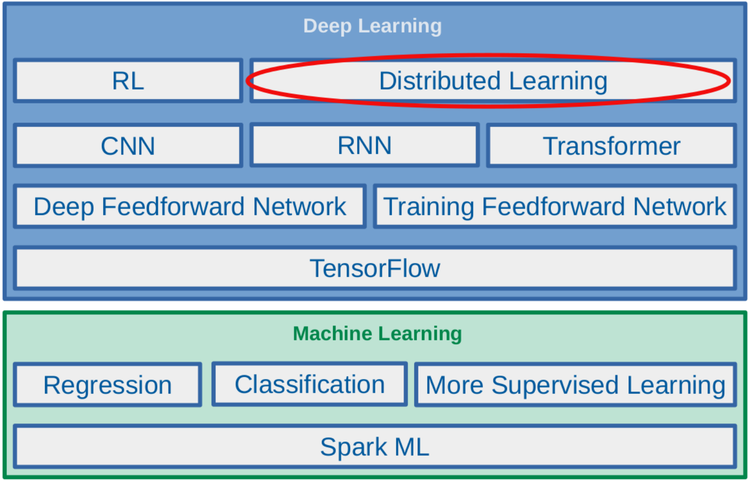
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- Availability
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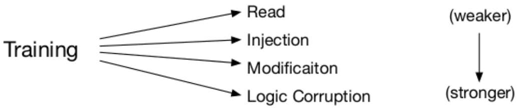
Adversarial Capabilities for Integrity Attacks

- Training phase



[Papernot et al., SoK: Security and Privacy in Machine Learning, 2018]

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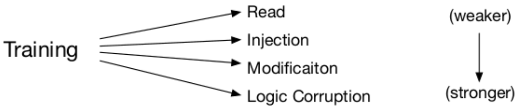

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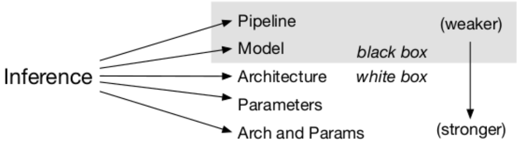
- Inference phase
  - White box
  - Black box



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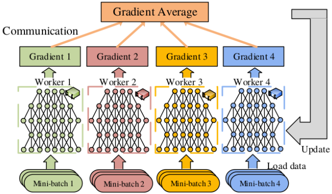
Our Focus and Goal

- Data parallelization



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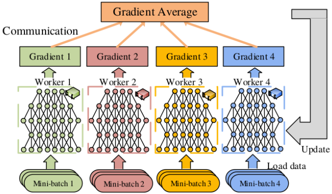

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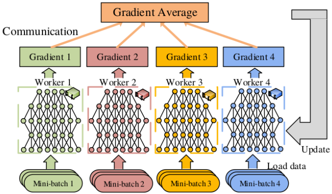

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Our Focus and Goal

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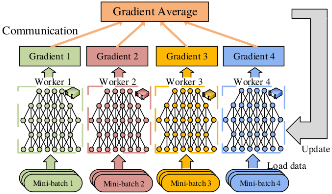
- Our goal: integrity of the model in the training phase



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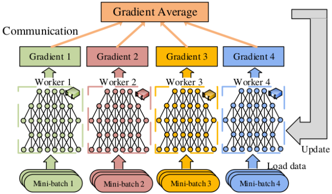
Distributed Stochastic Gradient Descent (1/3)

- One parameter server, and n workers.



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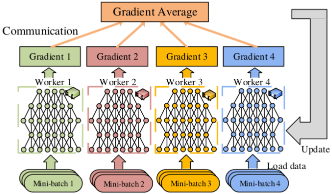

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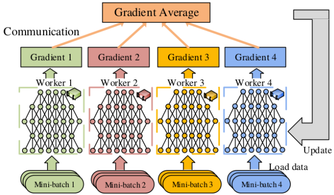
- During round $\mathtt{t}$, the parameter server broadcasts its parameter vector $\mathsf{w} \in \mathbb{R}^{\mathtt{d}}$ to all the workers.



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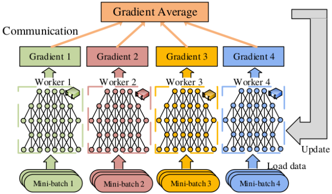
- At each round t, each correct worker i computes $G_i(w_t, \beta)$.



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- At each round $\mathtt{t}$, each correct worker $\mathtt{i}$ computes $\mathtt{G_i}(\mathtt{w_t}, \beta)$.
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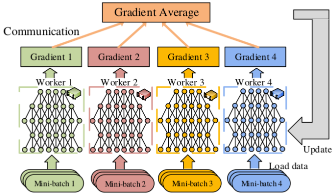

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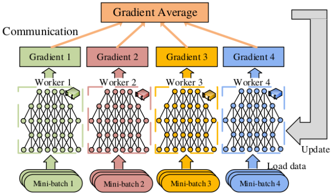

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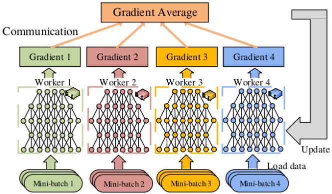
- β: a mini-batch of i.i.d. samples drawn from the dataset.
- $\mathtt{G_i}(\mathtt{w_t}, \beta) = \frac{1}{|\beta|} \sum_{\mathtt{x} \in \beta} \nabla \mathtt{l_i}(\mathtt{w_t}, \mathtt{x})$



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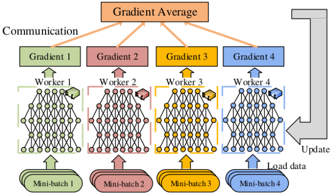

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- The parameter server computes $\mathtt{F}(\mathtt{G}_1, \mathtt{G}_2, \cdots, \mathtt{G}_n)$
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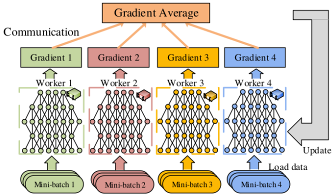

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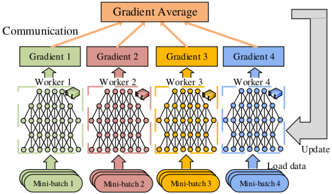

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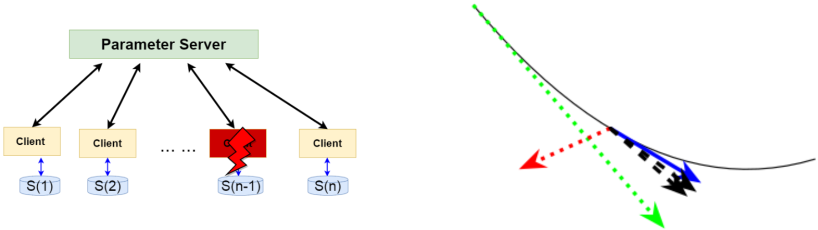
Distributed SGD with Byzantine Workers

- Among the $\mathtt{n}$ workers, $\mathtt{f}$ of them are possibly Byzantine (behaving arbitrarily).



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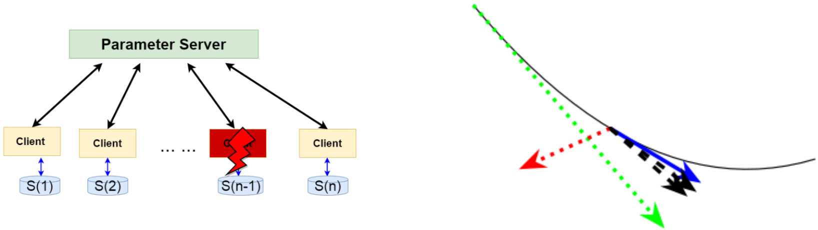
- A Byzantine worker b proposes a vector G_b that can deviate arbitrarily from the vector it is supposed.



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Averaging GAR and Byzantine Workers

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- Even a single Byzantine worker can prevent convergence.
- Proof: if the Byzantine worker proposes $\mathtt{G}_n = n\mathtt{U} - \sum_{i=1}^{n-1} \mathtt{G}_i$, then $\mathtt{F} = \mathtt{U}$.

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- $(\mathtt{B}_1, \cdots, \mathtt{B}_\mathtt{f}) \in (\mathbb{R}^{\mathtt{d}})^{\mathtt{f}}$ are random vectors, possibly dependent between them and the vectors $(\mathtt{G}_1, \cdots, \mathtt{G}_{\mathtt{n}-\mathtt{f}})$

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- A GAR $\mathtt{F}$ is said to be (α, f)-Byzantine-resilient if, for any $1 \leq \mathtt{j}_1 < \cdots < \mathtt{j}_\mathtt{f} \leq \mathtt{n}$, the vector $\mathtt{F}(\mathtt{G}_1, \cdots, \mathtt{B}_1, \cdots, \mathtt{B}_\mathtt{f}, \cdots, \mathtt{G}_\mathtt{n})$ satisfies:

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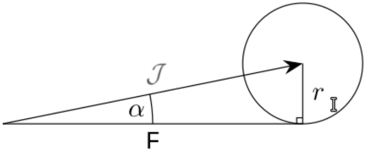

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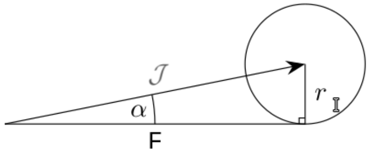

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Byzantine-Resilience GAR

- Median
- Krum
- Multi-Krum
- Brute

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- Marginal median

$$\mathtt{F} = \mathtt{MarMed}(\mathtt{G}_1, \cdots, \mathtt{G}_\mathtt{n}) = \begin{pmatrix} \mathtt{median}(\mathtt{G}_1[1], \cdots, \mathtt{G}_\mathtt{n}[1]) \\ \vdots \\ \mathtt{median}(\mathtt{G}_1[\mathtt{d}], \cdots, \mathtt{G}_\mathtt{n}[\mathtt{d}]) \end{pmatrix} \tag{1}$$

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- $\mathtt{F}(\mathtt{G_1}, \cdots, \mathtt{G_n}) = \mathtt{G_{i_*}}$
- $\mathtt{G_{i_*}}$ refers to the worker minimizing the score, $\mathtt{s}(\mathtt{i}_*) \leq \mathtt{s}(\mathtt{i})$ for all $\mathtt{i}$.

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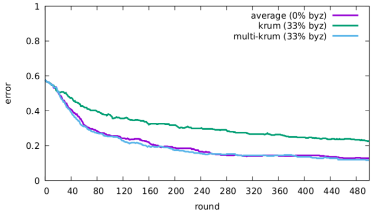
- The cases $\mathtt{m} = 1$ and $\mathtt{m} = \mathtt{n}$ correspond to Krum and averaging, respectively.



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  - The set of all the subsets of $\mathtt{n} - \mathtt{f}$

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  - The set of all the subsets of $\mathtt{n} - \mathtt{f}$
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Brute

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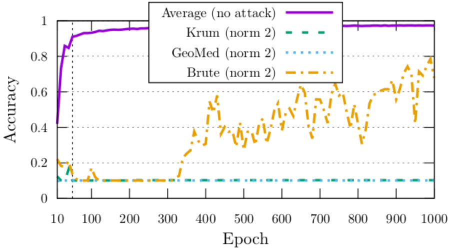
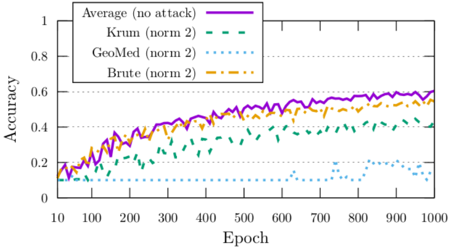


MNIST



CIFAR-10

[El Mhamdi et al., The Hidden Vulnerability of Distributed Learning in Byzantium, 2018]

Weak Byzantine Resilience

- Limitation of previous aggregation methods.
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- Bulyan is a strong Byzantine-resilience algorithm.

The Hidden Vulnerability of Distributed Learning in Byzantium

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  3. Loop back to step 1 if $|\mathtt{S}| < \theta$.

Bulyan - Step One (2/2)

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- $\theta = \mathtt{n} - 2\mathtt{f} \geq 2\mathtt{f} + 3$, thus $\mathtt{S} = (\mathtt{S}_1, \cdots, \mathtt{S}_\theta)$ contains a majority of non-Byzantine gradients.
- For each $\mathtt{i} \in [1..\mathtt{d}]$, the median of the θ coordinates $\mathtt{i}$ of the selected gradients is always bounded by coordinates from non-Byzantine submissions.

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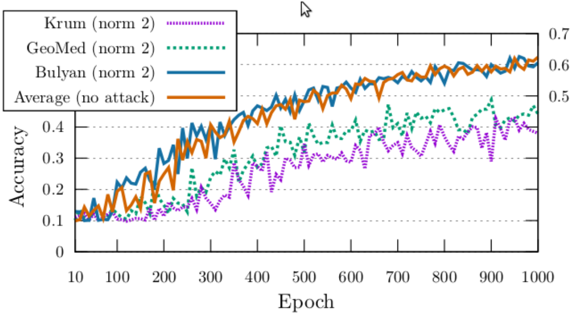
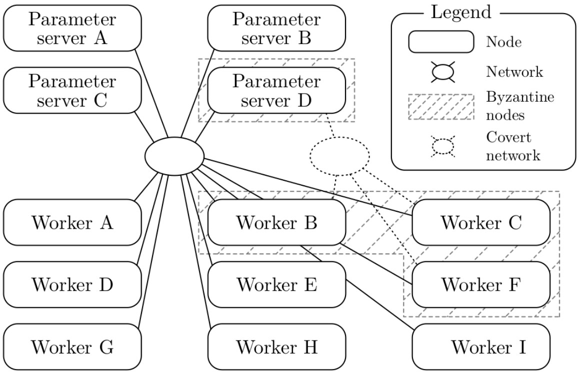
- Each $\mathtt{ith}$ coordinate of $\mathtt{F}$ is equal to the average of the β closest $\mathtt{ith}$ coordinates to the median $\mathtt{ith}$ coordinate of the θ selected gradients.



[El Mhamdi et al., The Hidden Vulnerability of Distributed Learning in Byzantium, 2018]

What if parameter servers are Byzantine?

SGD: Decentralized Byzantine Resilience



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- GuanYu uses a GAR for aggregating workers' gradients and Median for aggregating models received from servers.

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- Asynchronous network: the lack of any bound on communication delays.
- Synchronous training: bulk-synchronous training.
    - The parameter server does not need to wait for all the workers' gradients to make progress, and vice versa.
    - The quorums indicate the number of messages to wait before aggregating them.

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- $\mathtt{d}$ the dimension of the parameter space $\mathbb{R}^{\mathtt{d}}$.

GuanYu Algorithm - Step 1

- At each step t, each non-Byzantine server i broadcasts its current parameter vector w_i^t to every worker.

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- At each step $\mathtt{t}$, each non-Byzantine server $\mathtt{i}$ broadcasts its current parameter vector $\mathtt{w}_\mathtt{i}^\mathtt{t}$ to every worker.
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- And computes an estimate $\mathtt{G}_\mathtt{j}^\mathtt{t}$ of the gradient at the aggregated parameters.

GuanYu Algorithm - Step 2

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- Each non-Byzantine worker $\mathtt{j}$ broadcasts its computed gradient estimation $\mathtt{G}_{\mathtt{j}}^{\mathtt{t}}$ to every parameter server.
- Each non-Byzantine parameter server $\mathtt{i}$ aggregates with $\mathtt{F}$ the $\mathtt{q}_{\mathtt{wr}}$ first received $\mathtt{G}^{\mathtt{t}}$.
- And performs a local parameter update with the aggregated gradient, resulting in $\overline{\mathtt{w}}_{\mathtt{i}}^{\mathtt{t}}$.

GuanYu Algorithm - Step 3

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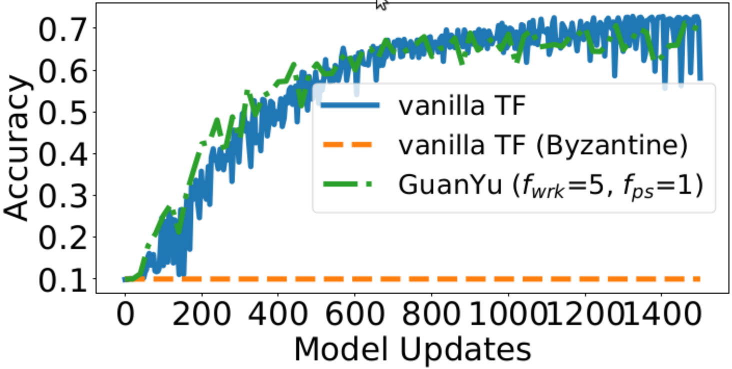
- This aggregated parameter vector is $\overline{\mathtt{w}}_{\mathtt{i}}^{\mathtt{t+1}}$.



[El Mhamdi et al., SGD: Decentralized Byzantine Resilience, 2019]

Summary

Summary

- Integrity in data-parallel learning
- Weak Byzantine resilience
- Strong Byzantine resilience
- Byzantine parameter servers

Reference

- Xie et al., Generalized Byzantine-tolerant SGD, 2018
- Blanchard et al., Machine Learning with Adversaries: Byzantine Tolerant Gradient Descent, 2017
- El Mhamdi et al., The Hidden Vulnerability of Distributed Learning in Byzantium, 2018
- Damaskinos et al., AGGREGATHOR: Byzantine Machine Learning via Robust Gradient Aggregation, 2019
- El Mhamdi et al., SGD: Decentralized Byzantine Resilience, 2019
- El Mhamdi et al., Fast Machine Learning with Byzantine Workers and Servers, 2019

Questions?