Byzantine Tolerance for Distributed SGD

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Outline

Distributed machine learning

Train ML models on multiple nodes:

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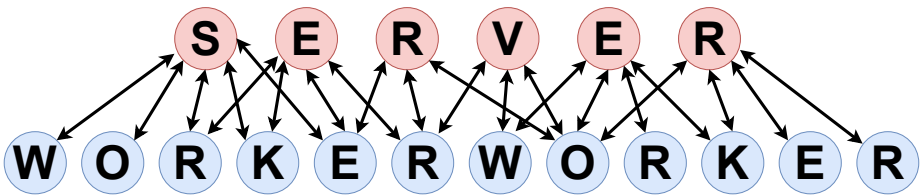
- Server-worker architecture



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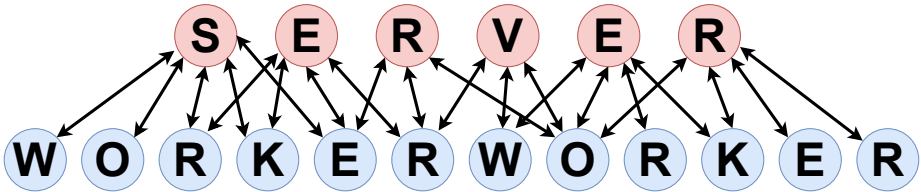
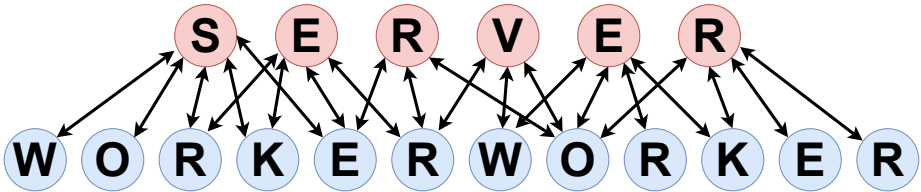


Distributed machine learning

Train ML models on multiple nodes:

- Server-worker architecture
- Communication
- Security



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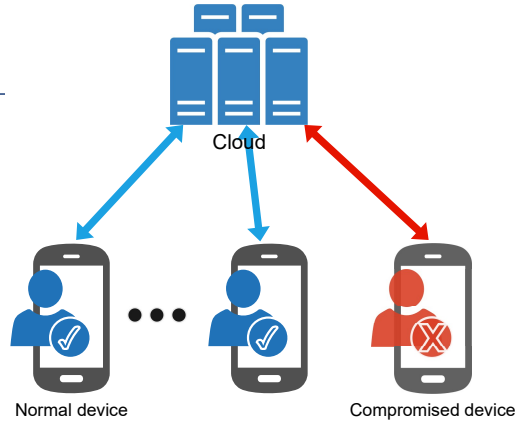
Security in distributed ML

Untrustable workers:



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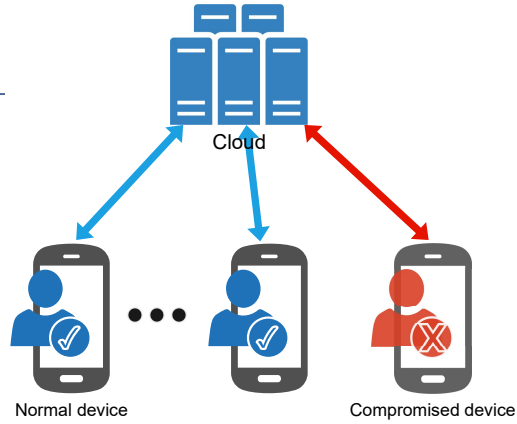

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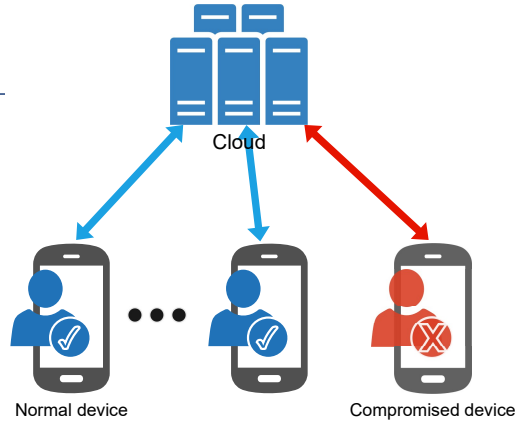

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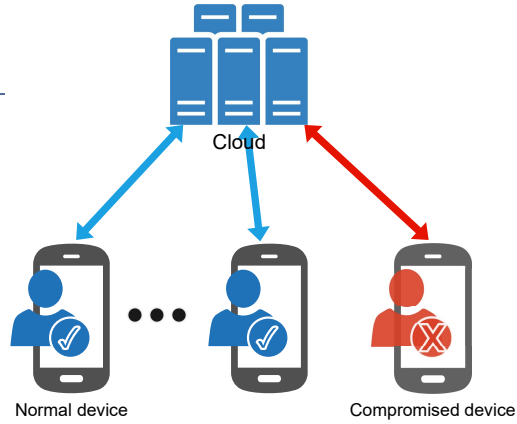

Security in distributed ML

Untrustable workers:

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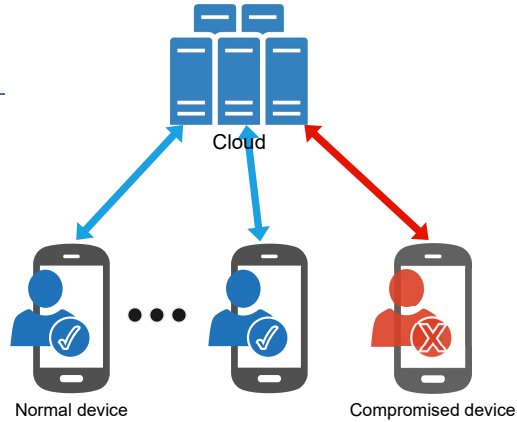
- Broken communication
- Poisoned local data
- Malicious users



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Security in distributed SGD with:

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- Synchronous/asynchronous

Outline

Problem formulation

Optimization:

$$\min_{x \in \mathbb{R}^d} F(x),$$

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$$F(x) = \frac{1}{n} \sum_{i \in [n]} \mathbb{E}_{z_i \sim \mathcal{D}_i} f(x; z_i),$$

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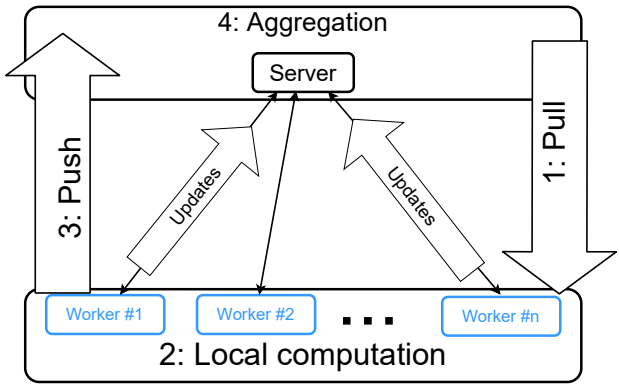
n nodes/devices, with disjoint datasets $\mathcal{D}_i$'s.

Server-worker architecture

Exchange updates:

- Gradients
- Model parameters
- etc.



Synchronous vs. Asynchronous

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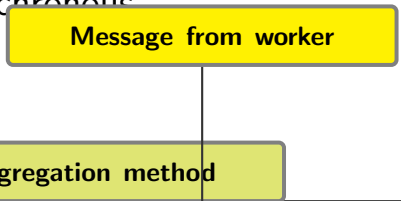

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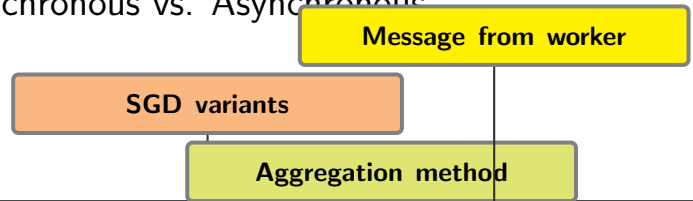

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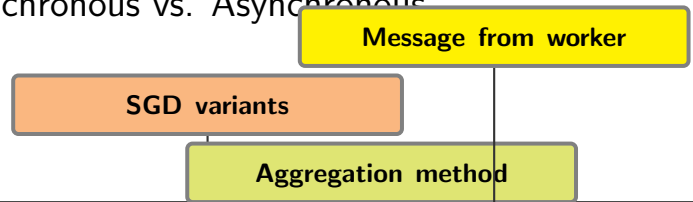

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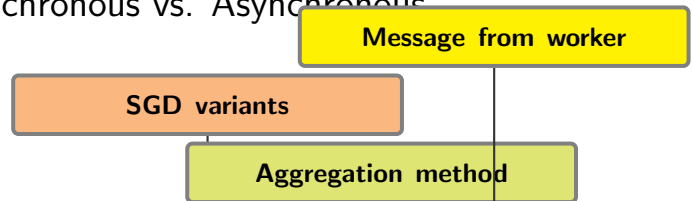

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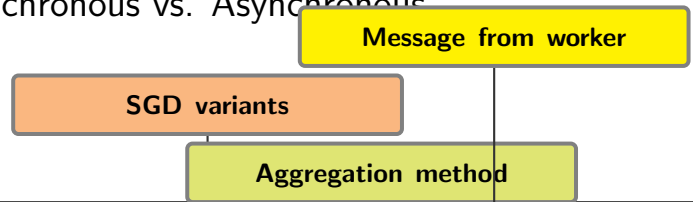

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Issue:	Stragglers	Noisy updates

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Honest servers

Goal: Prevent arbitrarily bad results

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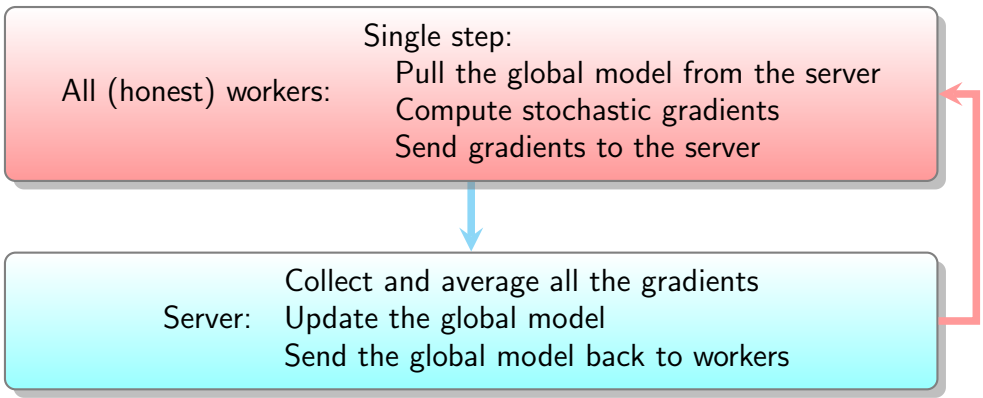
Byzantine-tolerant SGD

Recap: Byzantine workers send arbitrary values to the server



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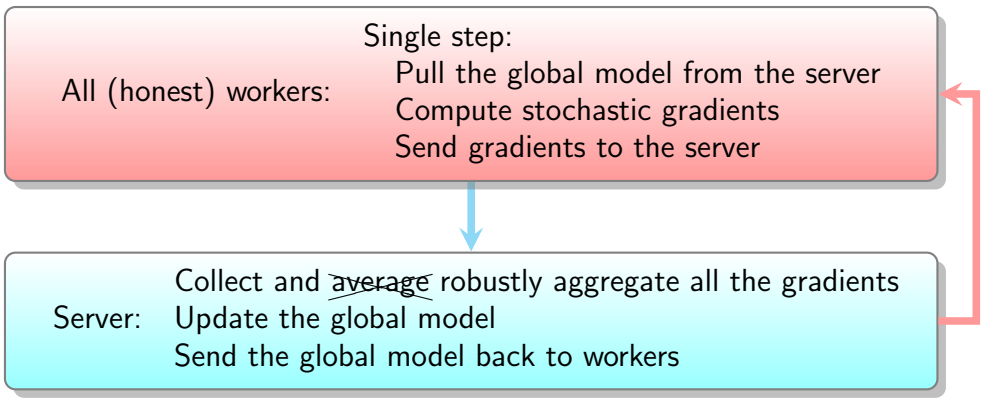

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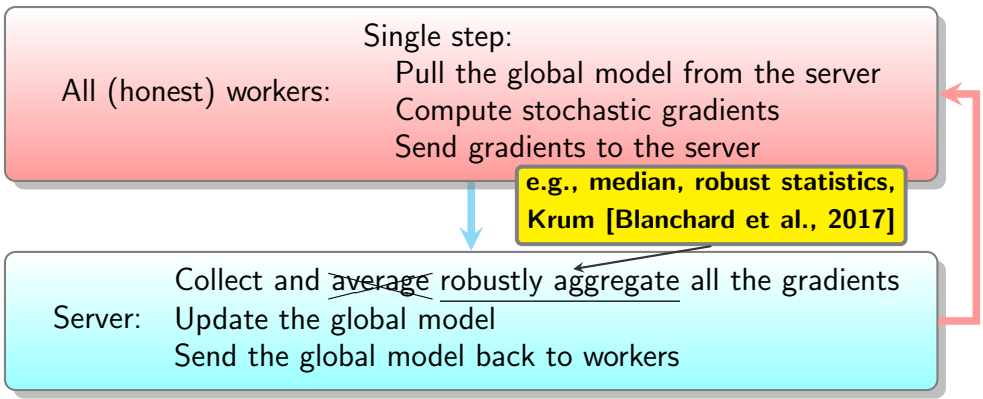

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Median/Trimmed mean [Yin et al., 2018]:

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Geometric median [Chen et al., 2017]:

$$\operatorname*{argmin}_{v} \sum_{i \in [n]} \|v - \tilde{v}_i\|$$

Krum [Blanchard et al., 2017]:

$$\texttt{Krum}(\{\tilde{v}_i : i \in [m]\}) = \tilde{v}_k, \quad k = \operatorname*{argmin}_{i \in [n]} KR(\tilde{v}_i),$$

$$KR(\tilde{v}_i) = \sum_{i \to j} \|\tilde{v}_i - \tilde{v}_j\|^2,$$

where $i \to j$ are the indices of the $n - b - 2$ nearest neighbours of $\tilde{v}_i$ in $\{\tilde{v}_j : j \in [n], i \neq j\}$ as measured by squared Euclidean distance.

Bounded distance to the correct average

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  Median: -0.3, negative!

  Mean: 0.18, positive

Issues of previous work

[Xie et al., 2019a]

Theorem

Consider the worst case: $n - 2q = 1$. *The server receives* $(n - q)$ *correct gradients* $\mathcal{V} = \{v_1, \ldots, v_{n-q}\}$ *and* q *Byzantine gradients* $\mathcal{U} = \{u_1, \ldots, u_q\}$. $\mathbb{E}[v_i] = g, \forall i \in [n - q]$, $\mathbb{E}[((v_i)_j - g_j)^2] \geq \sigma^2, \forall i \in [n - q], j \in [d]$, *where* $(v_i)_j$ *is the* j*th coordinate of* v_i, *and* g_j *is the* j*th coordinate of* g. *When* $\max_{j \in [d]} |g_j| < \frac{\sigma}{\sqrt{n-q-1}}$, *there exist Byzantine gradients* $\mathcal{U} = \{u_1, \ldots, u_q\}$ *such that* $\langle g, \quad \mathbb{E}\left[\texttt{Median}(\mathcal{V} \cup \mathcal{U})\right] \rangle < 0$.

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Theorem

Consider the worst case: $n - 2q = 3$. *The server receives* $(n - q)$ *correct gradients* $\mathcal{V} = \{v_1, \ldots, v_{n-q}\}$ *and* q *Byzantine gradients* $\mathcal{U} = \{u_1, \ldots, u_q\}$. $\mathbb{E}[v_i] = g, \forall i \in [n - q]$. *The mean of correct gradients is* $\bar{v} = \frac{1}{n-q} \sum_{i \in [n-q]} v_i$. *The correct gradients are bounded by* $\|v_i - \bar{v}\|^2 \leq \|\bar{v}\|^2, \forall i \in [n - q]$. *Furthermore, we assume that* $v_i \neq v_j, \forall i \neq j, i, j \in [n - q]$, *and* $\exists \beta$ *such that* $\|v_i - v_j\|^2 \geq \beta^2, \forall i \neq j, i, j \in [n - q]$. *We take* $u_1 = u_2 = \cdots = u_q = -\epsilon\bar{v}$, *where* ϵ *is a small positive constant value such that* $\epsilon^2 \|\bar{v}\|^2 \leq \beta^2$. *When* $(n - q)$ *is large enough:* $n - q > \frac{2(\epsilon+2)^2}{\epsilon^2} + 2$, *we have* $\langle g, \quad \mathbb{E}\left[\texttt{Krum}(\mathcal{V} \cup \mathcal{U})\right] \rangle < 0$.

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- Solution:
  - Estimate the decrease of loss

Byzantine-tolerant SGD: new approaches

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- Validation on server:
  - A validation dataset separated from training data
  - Sample a batch from the validation set
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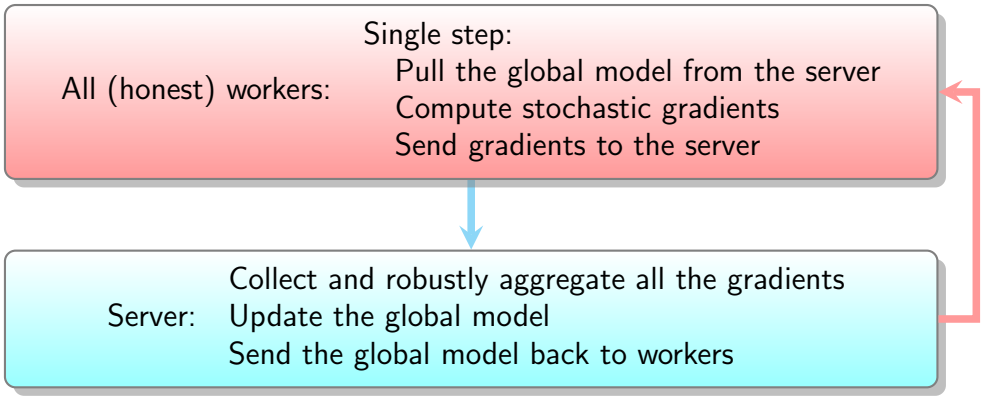
- Zeno [Xie et al., 2018]:
  - Synchronous SGD with validation on server
  - Number of Byzantine workers $\geq 50\%$

Recap: Byzantine-tolerant SGD with robust aggregation



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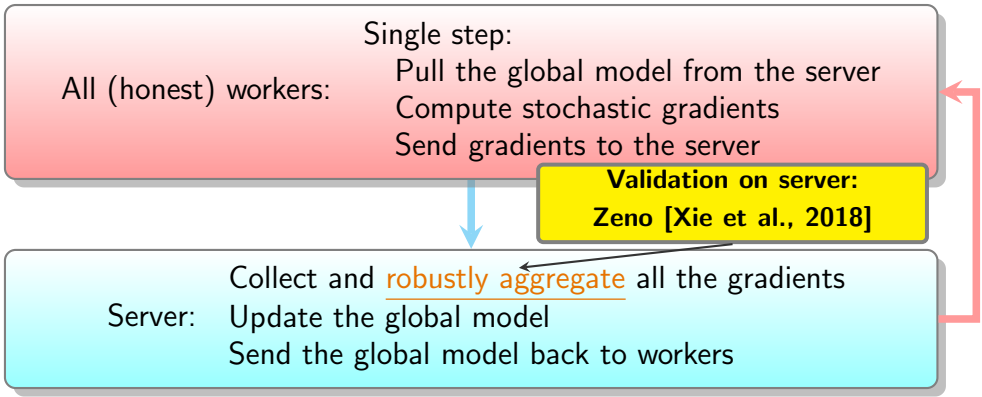

Zeno

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- Stochastic descent score:

  $Score_{\gamma,\rho}(u, x) = f_r(x) - f_r(x - \gamma u) - \rho\|u\|^2$

  $f_r(x)$: loss function on a random batch of validation data

  u: candidate gradient

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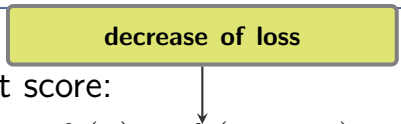

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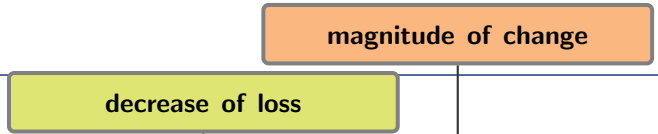

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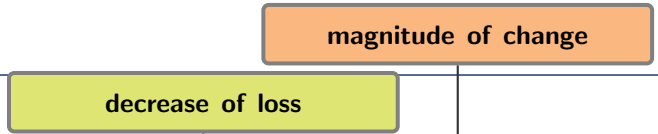

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- Zeno:

  Sort the gradients with the score

  Remove bottom-b, $b \geq q$

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- Similarity between validation and training

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  $\tilde{v}_{(1)}, \ldots, \tilde{v}_{(n)}$, $Score_{\gamma,\rho}(\tilde{v}_{(1)}, x) \geq \ldots \geq Score_{\gamma,\rho}(\tilde{v}_{(n)}, x)$

  $v_{(1)}, \ldots, v_{(n)}$, $Score_{\gamma,\rho}(v_{(1)}, x) \geq \ldots \geq Score_{\gamma,\rho}(v_{(n)}, x)$

  Filter out the bottom-b, $b \geq q$

Zeno

- Gradients from workers: $v_1, \ldots, v_n$

  $v_i = \nabla f(x)$, $\mathbb{E}[v_i] = \nabla F(x)$
- Replace q of them by arbitrary vectors: $\tilde{v}_1, \ldots, \tilde{v}_n$
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  $v_{(1)}, \ldots, v_{(n)}$, $Score_{\gamma,\rho}(v_{(1)}, x) \geq \ldots \geq Score_{\gamma,\rho}(v_{(n)}, x)$

  Filter out the bottom-b, $b \geq q$

  Result: $\frac{1}{n-b} \sum_{i=1}^{n-b} \tilde{v}_{(i)}$

Zeno

Bounded score:

Zeno

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- $\forall i \in [n - q]$:

Zeno

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Zeno

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Zeno

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Zeno

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- Proof by contradiction
- Connection from candidates to correct gradients

Zeno

In the worst cases:

Zeno

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Zeno

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Converge with T ↗

Zeno

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Zeno

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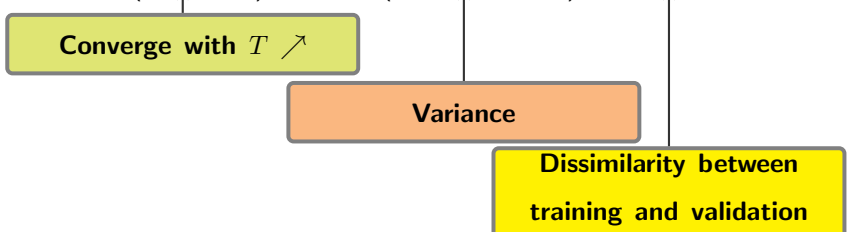
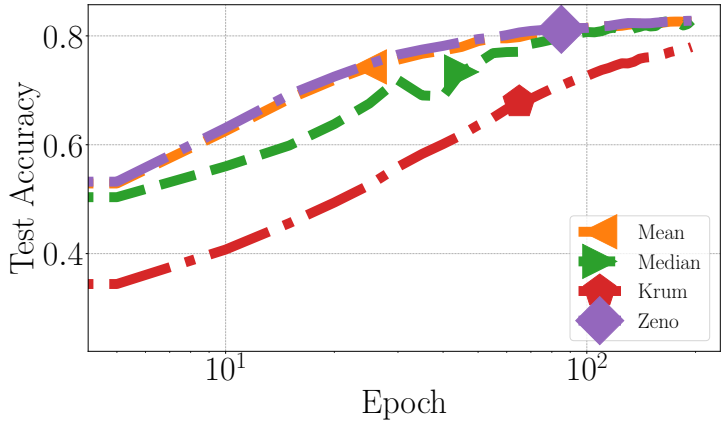


Zeno

Convergence without attacks on CNN and CIFAR-10.
20 workers, no Byzantine.
$b = 4$ for Krum, $b = 4$ for Zeno.



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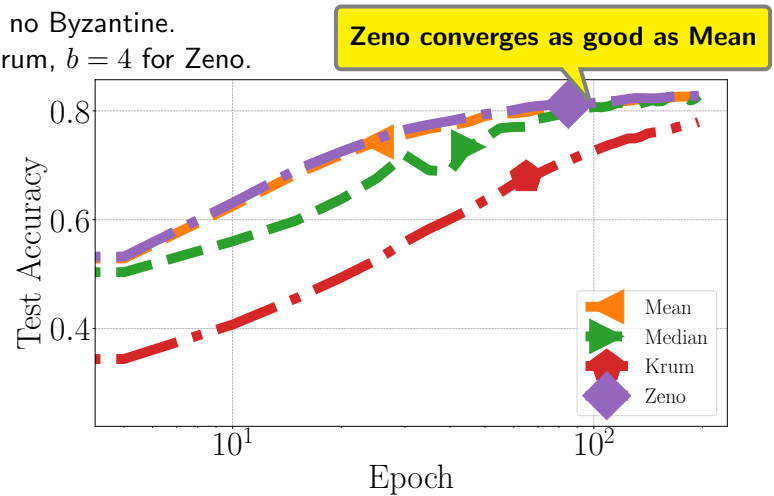

Zeno

Convergence with label-flipping attacks on CNN and CIFAR-10.
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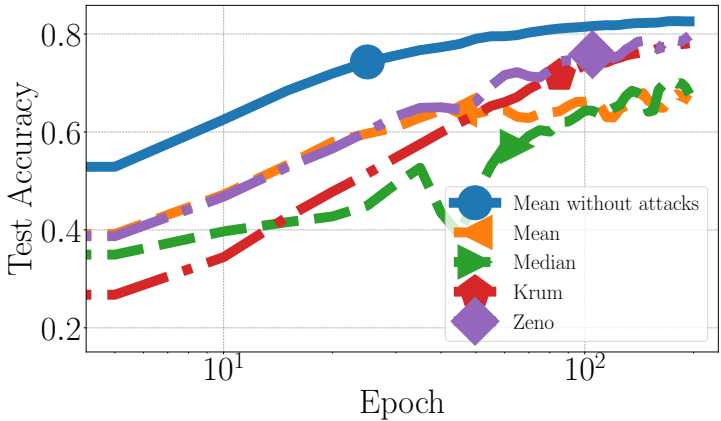

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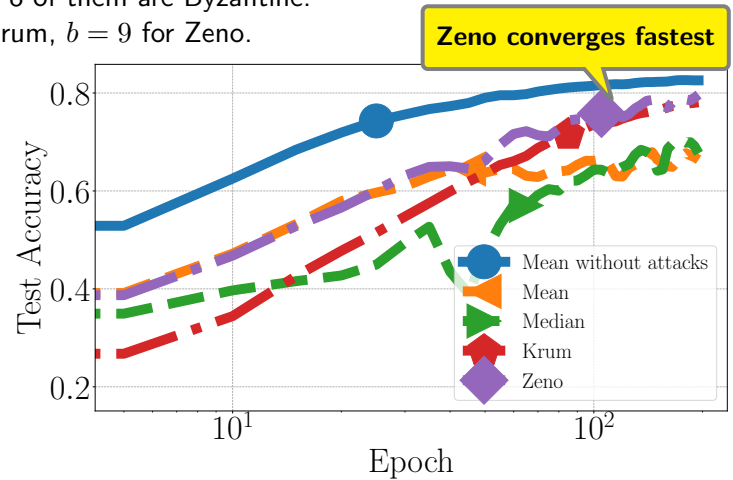

Zeno

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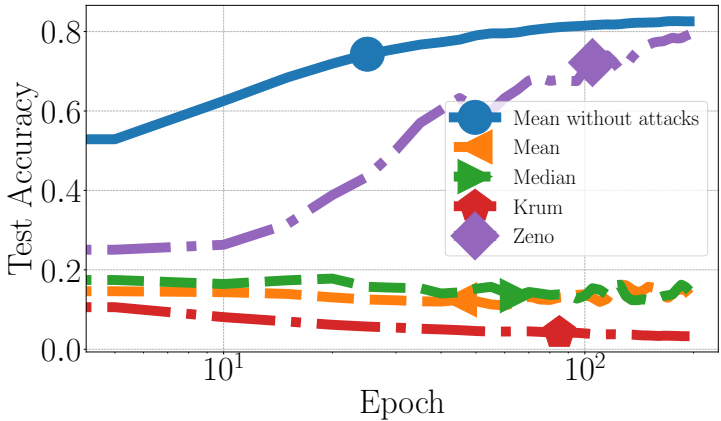

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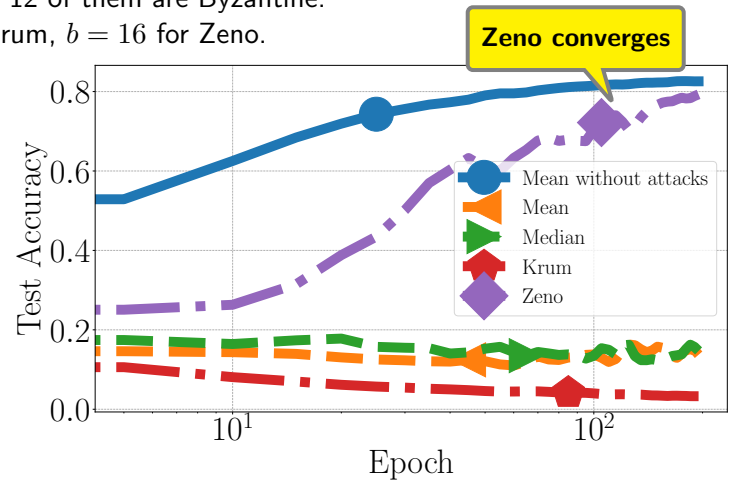

Zeno

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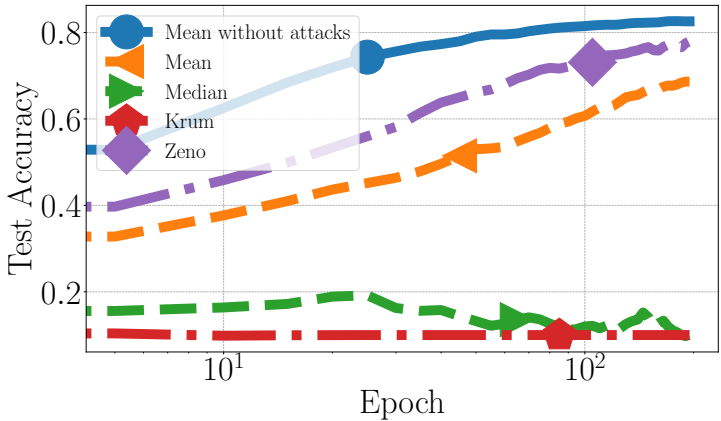

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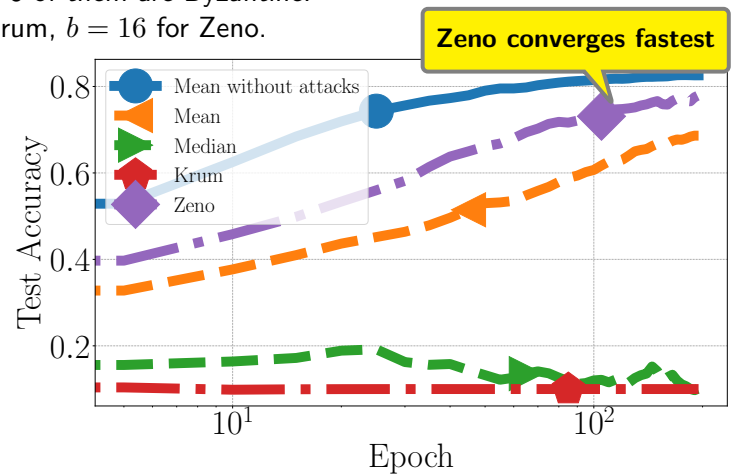

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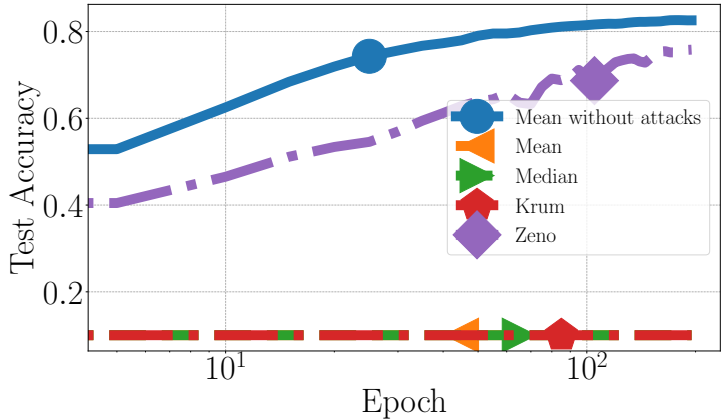

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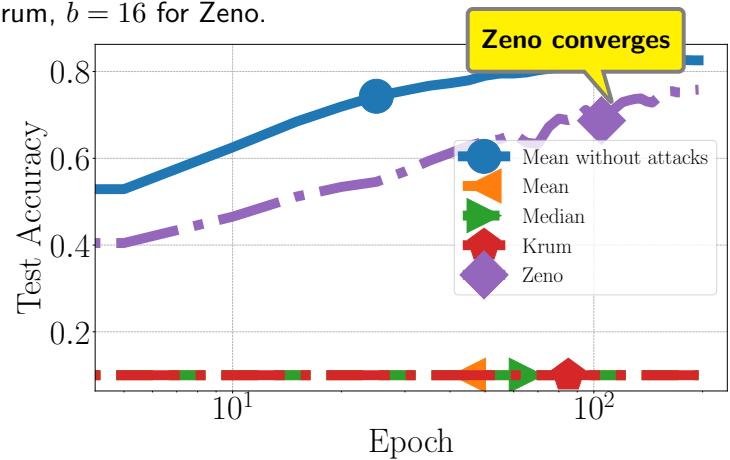

Zeno

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- Prevent catastrophic failures in the worst cases

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  Next: asynchronous training

Byzantine-tolerant SGD: asynchronous training

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- Asynchronous training:
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  - Validation (computing the loss of batch) is expensive

Byzantine-tolerant SGD: asynchronous training

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- Zeno++ [Xie et al., 2019b]:
  - Hard threshold instead of sorting
  - Inner-product validation
  - Full asynchrony

Zeno++

Zeno++

- Recap: stochastic descent score:

$$Score_{\gamma,\rho}(u, x) = f_r(x) - f_r(x - \gamma u) - \rho\|u\|^2$$

Zeno++

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Zeno++

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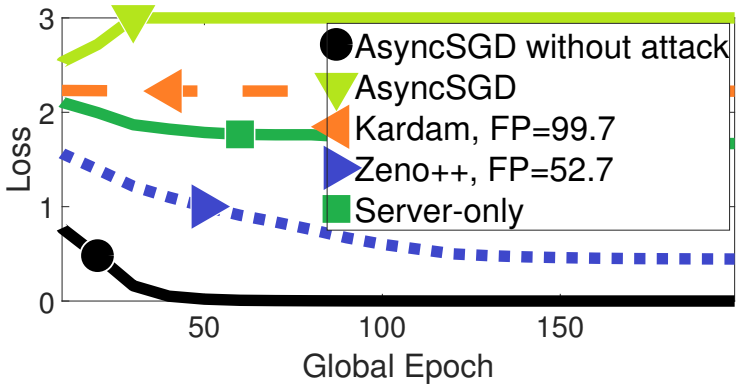
  Trade-off: $\epsilon \leq 0$

Convergence with sign-flipping attacks on CNN and CIFAR-10.
8 out of the 10 workers are Byzantine.



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