Adversarial-resilient Machine Learning for the Internet-of-Things

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Machine learning and optimization

Mathematically, machine learning is stochastic optimization:

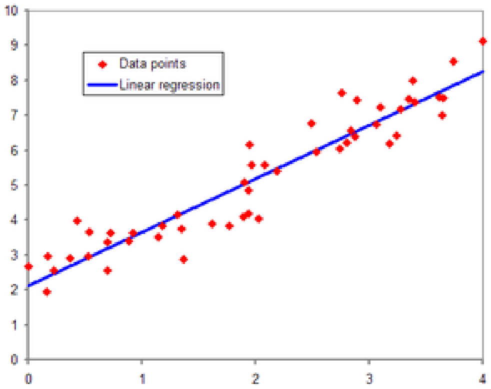
$$w^* = \arg\min_w \mathbb{E}_z[f(w,z)]$$

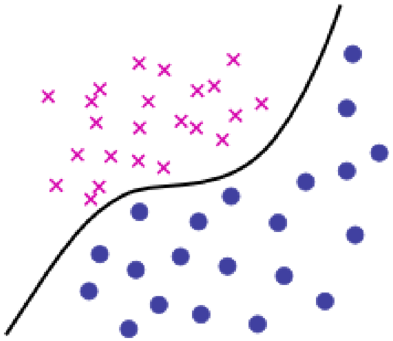
- SVM (supervised learning)

$$z = (x,y) \text{ and } f = \max(0, 1 - y(w^T x + b)) + \lambda \|w\|_2^2$$

- K-means clustering (unsupervised learning)

$$z = x \text{ and } f = \sum_{i=1}^{K} \sum_{x \in S_i} d(x, \mu_i)$$





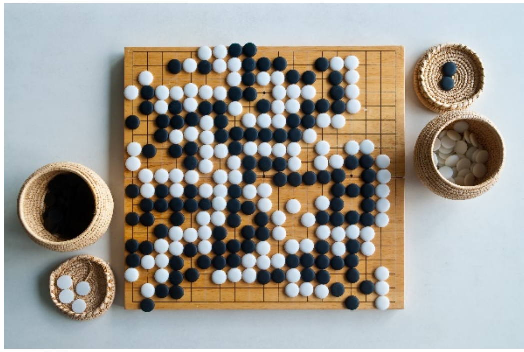
Challenge: Distribution of data 'z' is unknown

Empirical Risk Minimization (ERM)

- Use training data $\mathcal{Z} = \{z_n\}_{n=1}^N$
- Minimize the empirical risk:

$$\widehat{w}_N = \arg\min_w \frac{1}{N} \sum_{n=1}^{N} f(w, z_n)$$

- Main result: $\mathbb{E}_z[f(\widehat{w}_N, z)] \to \mathbb{E}_z[f(w^*, z)]$ (Vapnik'92)



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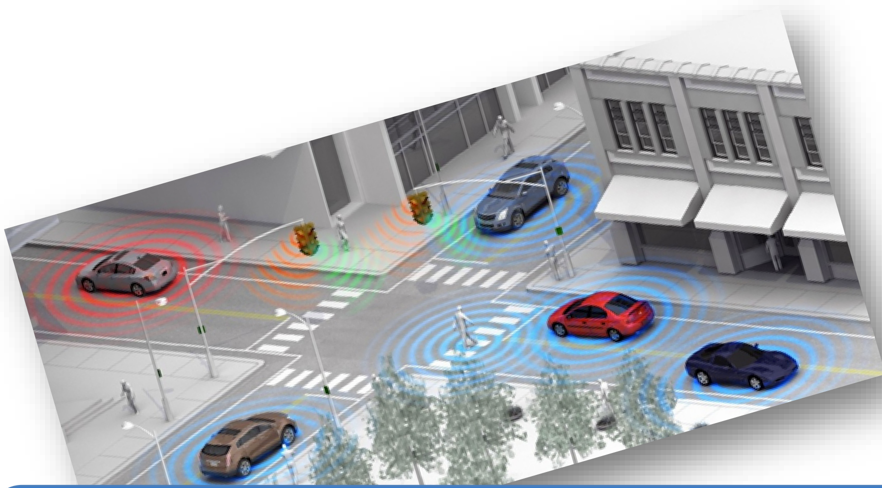
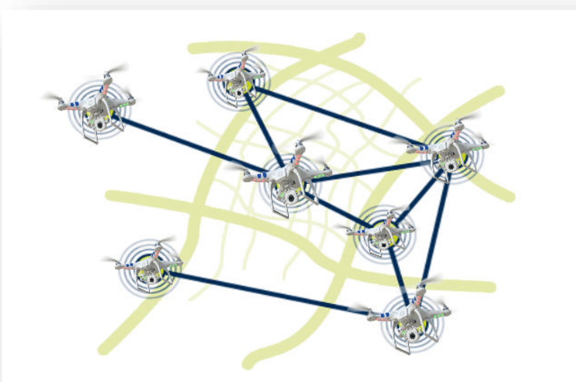
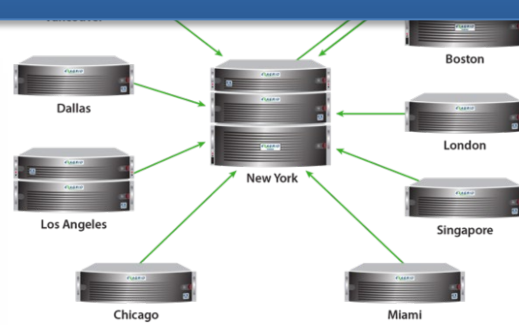
What is decentralized machine learning?

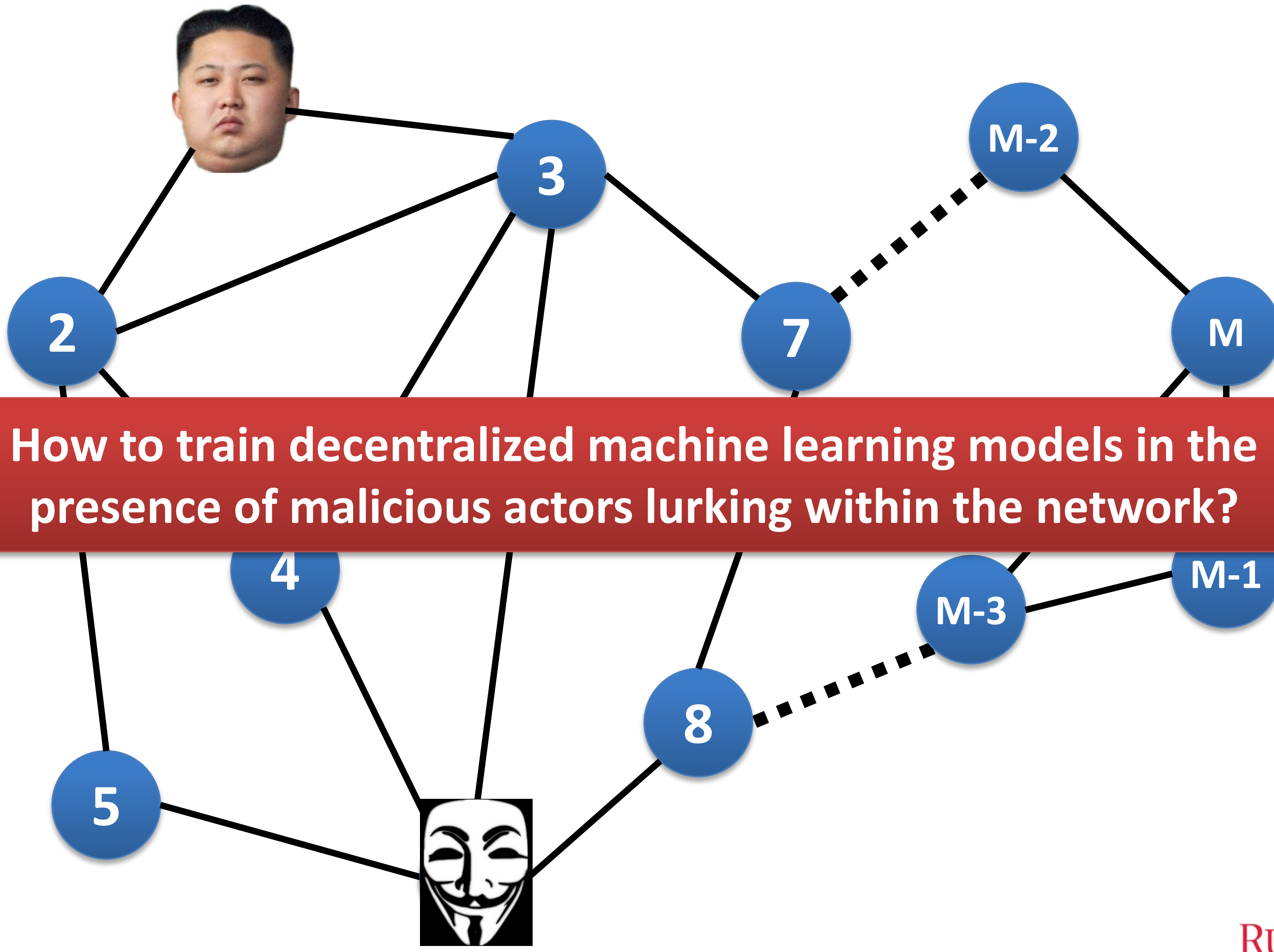


Training data is geographically distributed across an interconnected set of devices, nodes, servers, data centers, etc.





But … the world is a dangerous place for decentralized systems



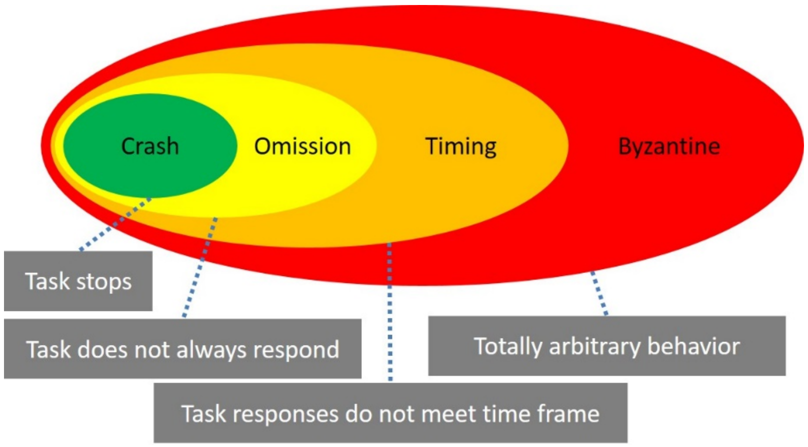
How to train decentralized machine learning models in the presence of malicious actors lurking within the network?

Byzantine failure: The right model for malicious actors

A node is said to have Byzantine failure if it *arbitrarily* deviates from its intended behavior within the network

What can a Byzantine node do?

- Send out “bogus” data
- Collude with other Byzantine nodes
- Start acting normal under scrutiny
- and so much more …



But … traditional decentralized optimization methods fail under Byzantine failures!

- An important (paraphrased) lesson from Su-Vaidya’15: Distributed empirical risk cannot exactly be minimized in the presence of even a single Byzantine node

Dataset	Classifier	Optimization	Nodes	Byzantine nodes	Accuracy
MNIST	SVM	DGD	100	1	9.8%
CIFAR-10	SVM	D-ADMM	100	10	10%

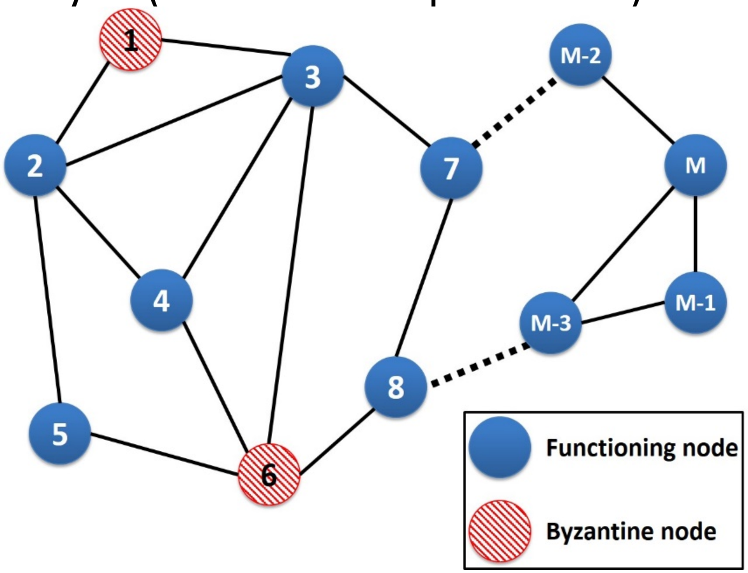
Byzantine-resilient decentralized machine learning

Network model

- A directed graph G comprises M nodes, out of which a maximum of b can be Byzantine
- Each node has access to a local training set of cardinality N (total # of samples = NM)

Basic setup

- Nodes cannot share raw data among themselves
- Node j needs to learn a local model w_j
- Set of "good" nodes in the network is J'
- Neighborhood of node j in the network is $\mathcal{N}_j$
- $g_j(w, \mathcal{Z}_j) = \frac{1}{N} \sum_{n=1}^{N} f(w, z_{jn})$



Goal: Develop a decentralized optimization method that ensures

- Closeness to $w^* = \arg\min_w \mathbb{E}_z[f(w, z)]$
- "Consensus" among nodes

$$w_1 = w_2 = \cdots = w_M$$

Algorithmic ingredient #1: Scalar-valued Byzantine-resilient decentralized optimization (Su-Vaidya’15)

Classic Distributed Gradient Descent (DGD) iteration (Nedic-Ozdaglar’09)

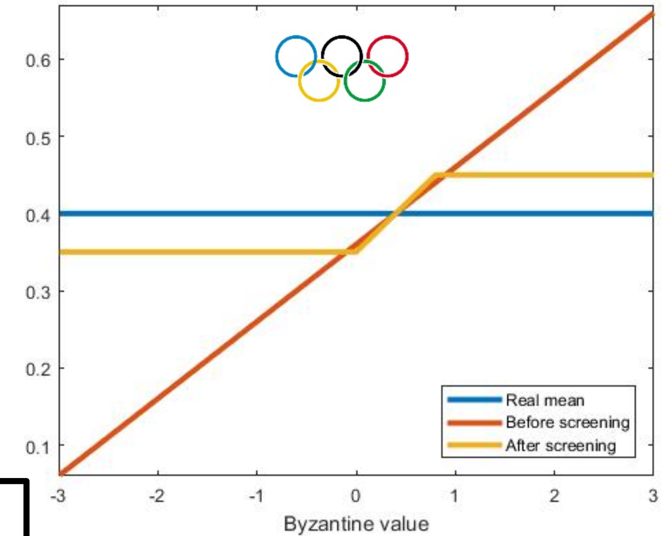
$$w_j^{t+1} = \sum_{i \in \mathcal{N}_j \cup j} a_{ij} w_i^t - \rho^t \nabla_w g_j(w_j^t, \mathcal{Z}_j)$$

Su-Vaidya’15 robustifies DGD in the scalar case by using a “screening” idea similar to that of “trimmed mean” in robust statistics

Screening for Byzantine resilience

1. Sort the received (scalar) iterates at node *j*
2. Eliminate the top and the bottom *b* iterates
3. Take a mean of the rest of the iterates

$$w_j^{t+1} = \frac{1}{|\mathcal{N}_j - 2b + 1|} \sum_{i \in \mathcal{N}_j^*} w_i^t - \rho^t \nabla_w g_j(w_j^t, \mathcal{Z}_j)$$



Main result:

Convex combination

$$\forall j \in J', w_j^t \xrightarrow{t} \widetilde{w}_{dis} = \arg\min_w \sum_{j \in J'} \alpha_j g_j(w, \mathcal{Z}_j)$$

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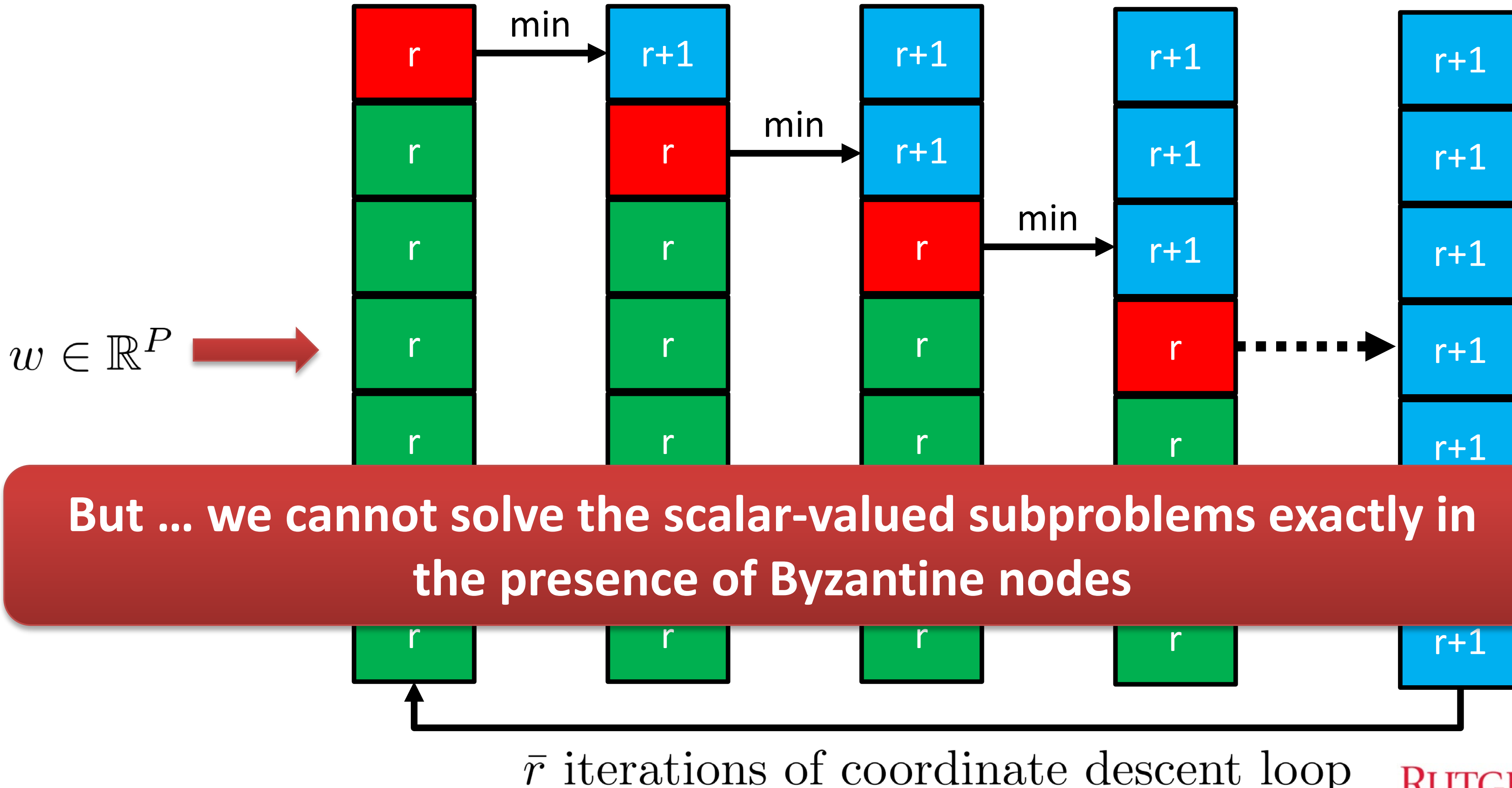
Algorithmic ingredient #2: Coordinate descent

A P-dimensional optimization problem can be solved by solving P scalar-valued subproblems, with convergence guarantees under various cases (Wright'15)

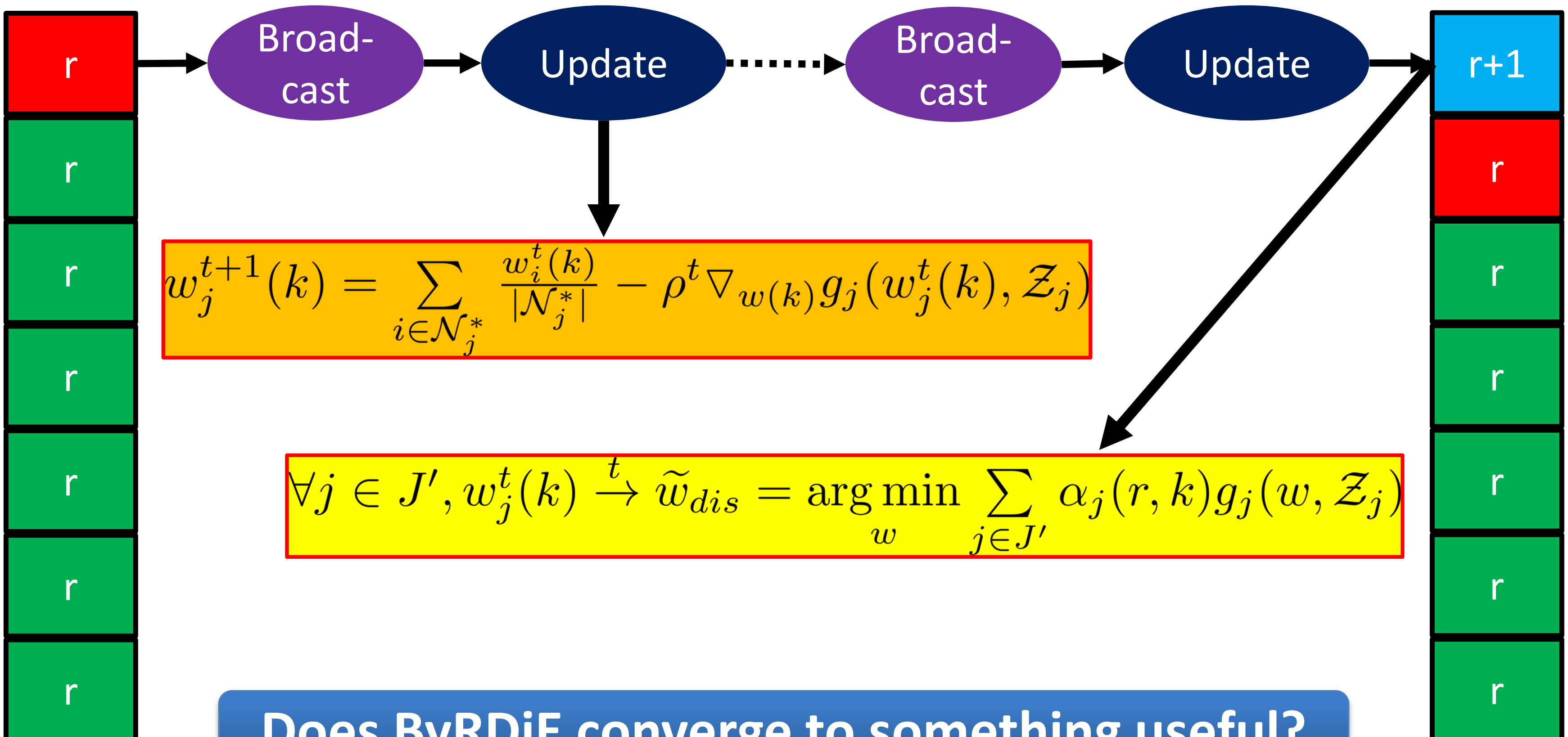


But … we cannot solve the scalar-valued subproblems exactly in the presence of Byzantine nodes

Byzantine-resilient distributed coordinate descent (ByRDiE)

1. Start with the coordinate descent loop
2. In each iteration r of CD, solve for the k-th subproblem using Byzantine-resilient scalar-valued DGD

T iterations of Byzantine-resilient scalar-valued DGD



$$w_j^{t+1}(k) = \sum_{i\in\mathcal{N}_j^*} \frac{w_i^t(k)}{|\mathcal{N}_j^*|} - \rho^t \nabla_{w(k)} g_j(w_j^t(k), \mathcal{Z}_j)$$

$$\forall j \in J', w_j^t(k) \xrightarrow{t} \widetilde{w}_{dis} = \arg\min_{w} \sum_{j\in J'} \alpha_j(r,k) g_j(w,\mathcal{Z}_j)$$

Does ByRDiE converge to something useful?

Convergence guarantee of ByRDiE

Reduced graph

- A subgraph of a graph is called a reduced graph if it is generated by:
  1. Removing all Byzantine nodes along with their incoming and outgoing edges
  2. Additionally, removing up to b incoming edges from each non-Byzantine node

Source component

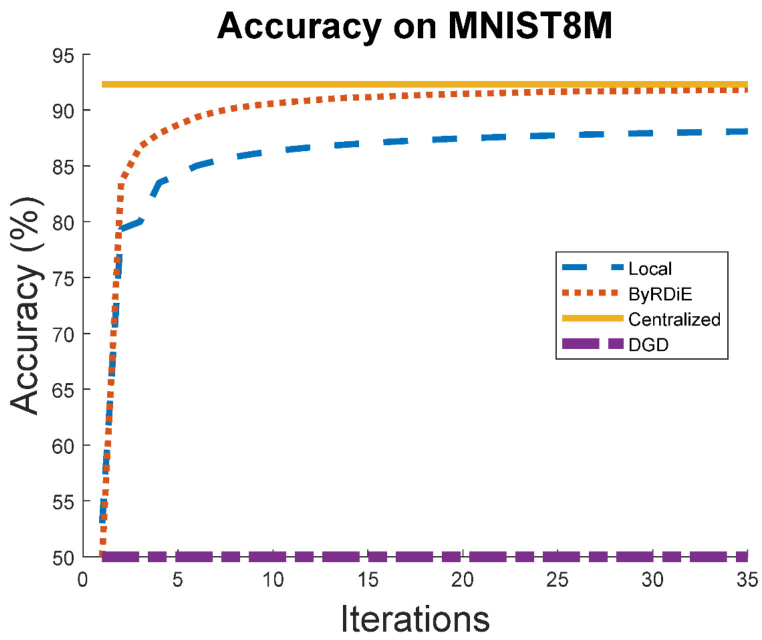
- A source component of a graph is a collection of nodes in which each node in the collection has a directed path to every other node in the graph

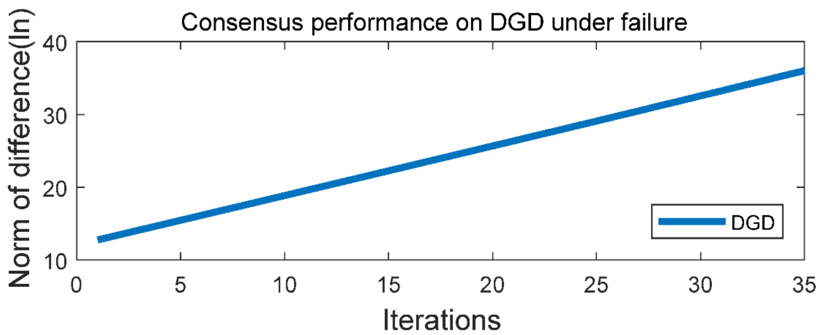
Theorem (Convergence of ByRDiE) [Yang-Bajwa'18]

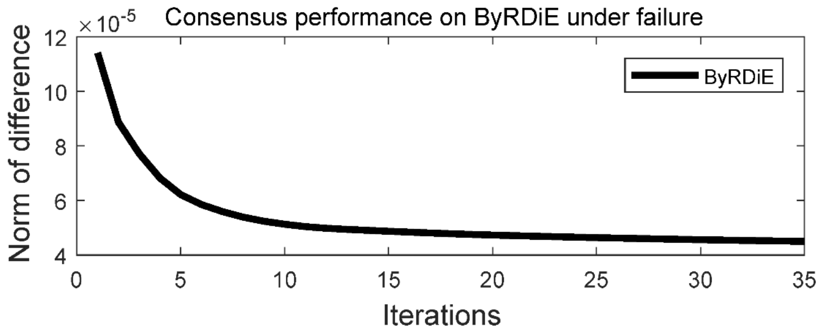
Suppose the candidate models w belong to a closed, compact set and the function $f(w, z)$ is strictly convex and Lipschitz continuous. Then, as long as all reduced graphs generated from G contain a source component of size at least $(b + 1)$ and the training data are IID, ByRDiE guarantees with high probability that

$$\forall j \in J', \mathbb{E}_z[f(w_j, z)] \xrightarrow{N, \bar{r}} \mathbb{E}_z[f(w^*, z)].$$

Numerical results







Binary classification on MNIST dataset with linear classifier

- Strictly convex loss function, all assumptions fully satisfied
- DGD fails in the presence of Byzantine failures
- ByRDiE has better accuracy than training with only local data
- Trade-off between performance and robustness

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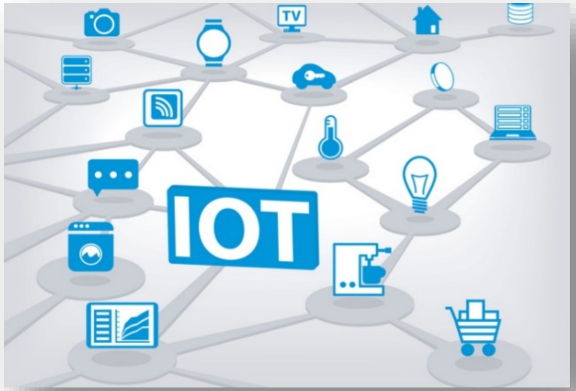
Conclusion

- Technologies like IoT require decentralized machine learning
- Malicious actors cannot be ignored in decentralized machine learning

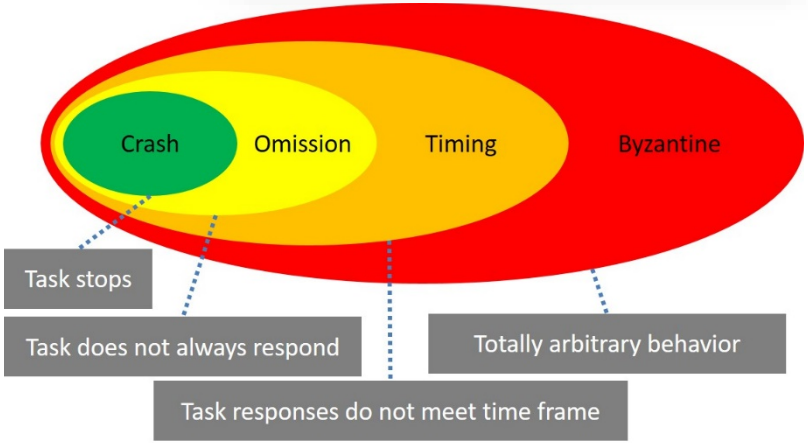
Byzantine-resilient decentralized learning

- Guarantees training of machine learning models from distributed data in the presence of Byzantine failures



Open problems

- Byzantine-resilient dual / second-order methods
- Non-smooth convex objective functions
- Nonconvex objective functions
- New screening methods



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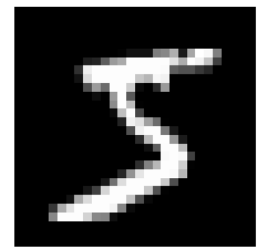
Experimental setup

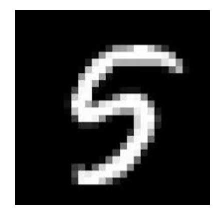
Network model

- Erdős–Rényi graph with 800 nodes and parameter $p = 0.5$, $b = 20$
- Each Byzantine node broadcasts a random scalar in each iteration

MNIST8M dataset

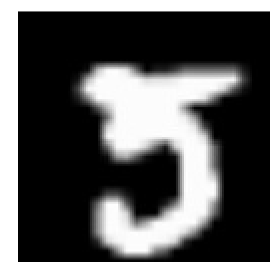
- Binary SVM on the most inseparable case of '5' and '8'
- Training data: 250 images of each digit at each node
- Test data: 40,000 images





Performance metrics

- Learning: Average accuracy on the test set
- Consensus: 2-norm of pairwise differences



Methods

- Train an SVM at each node using ByRDiE / DGD
- Train an SVM at each node using only local data
- Centralized SVM on all 200,000 training samples (baseline)

Byzantine-resilient distributed gradient descent (BRIDGE)

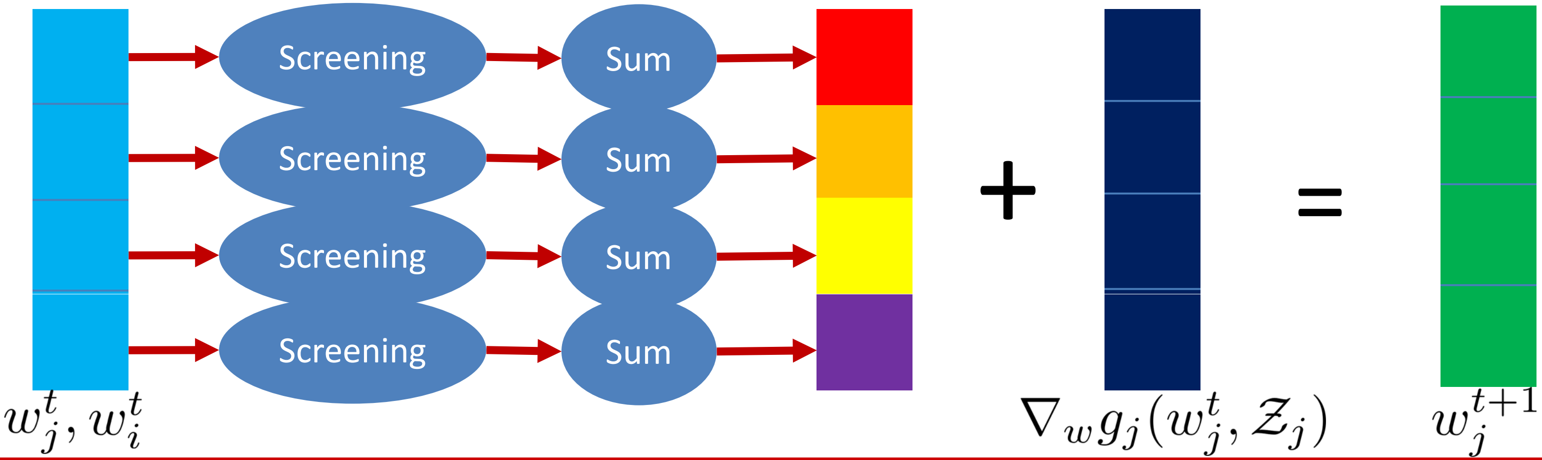
Gradient descent

- Can be applied to nonconvex loss functions
- No need for dimension synchronization
- Cannot define “large” and “small” for vectors

BRIDGE

- Use dimension-wise trimmed mean as screening
- Update (simultaneously at dimension k):

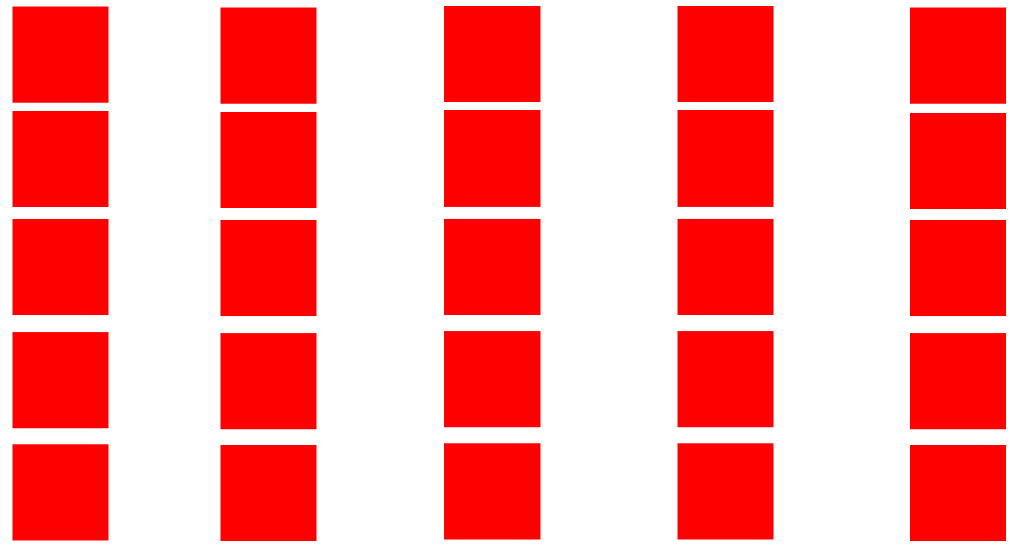
$$[w_j^{t+1}]_k = \frac{1}{|\mathcal{N}_j - 2b + 1|} \sum_{i \in \mathcal{N}_j^*(t,k)} [w_i^t]_k - \rho^t [\nabla_w g_j(w_j^t, \mathcal{Z}_j)]_k$$



Convergence guarantee of BRIDGE

Challenge in analysis

- The vectors "break" after screening
- Can no longer be expressed as a convex combination of neighbors



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