Distributional and Byzantine Robust Decentralized Federated Learning

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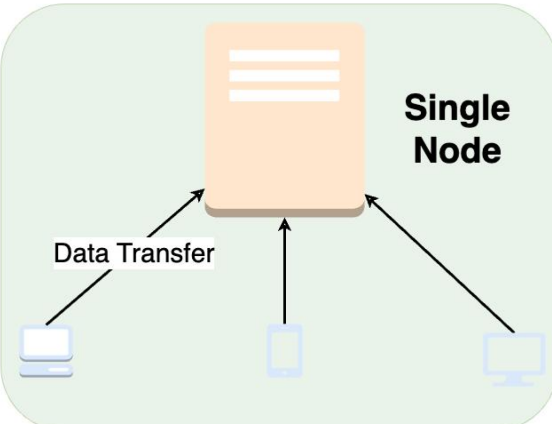
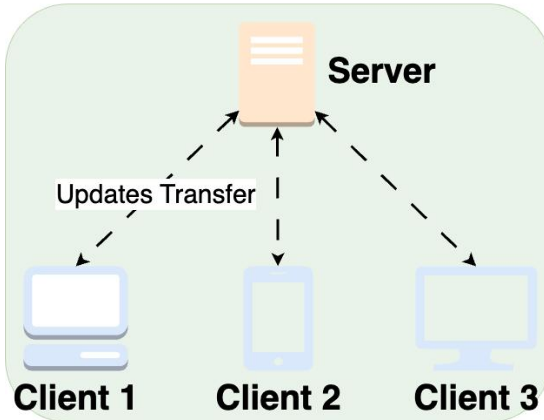
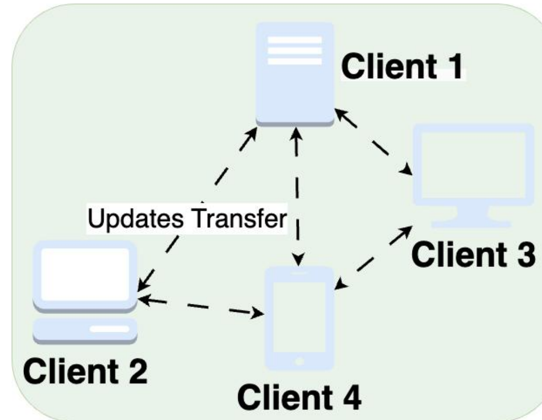
Decentralized Federated Learning



Traditional Machine Learning



Federated Learning



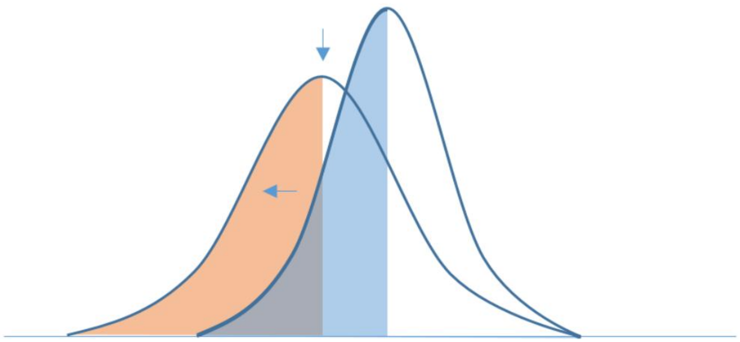
Decentralized Federated Learning

- **Traditional Machine Learning**
  - Collect datasets into a single node.
  - Data privacy issue.
- **Federated Learning (FL) [1]**
  - Without data sharing.
  - Server vulnerable.
- **Decentralized Federated Learning (DFL)**
  - Without a server.
  - More Robust.

Still have some Robustness issues in DFL:
Distributional Shift and **Byzantine Attack.**

Challenge 1: Distributional Shift in DFL

- **Distributional shift:** a mismatch between the distributions of train data and test data.



- Traditional Machine Learning under **Empirical Risk Minimization (ERM)** assumes that train data and test data share the same distribution, but usually fails in practice.

$$\min_{w \in \mathbb{R}^d} \mathbb{E}_{x_n \sim \mathcal{D}_n} \, f_n(w; x_n)$$

- **Prior work to resolve distributional shifts**
  - Adaptive Regularization [2]
  - Invariant Risk Minimization [3]
  - Distributionally Robust Optimization (DRO) [4]

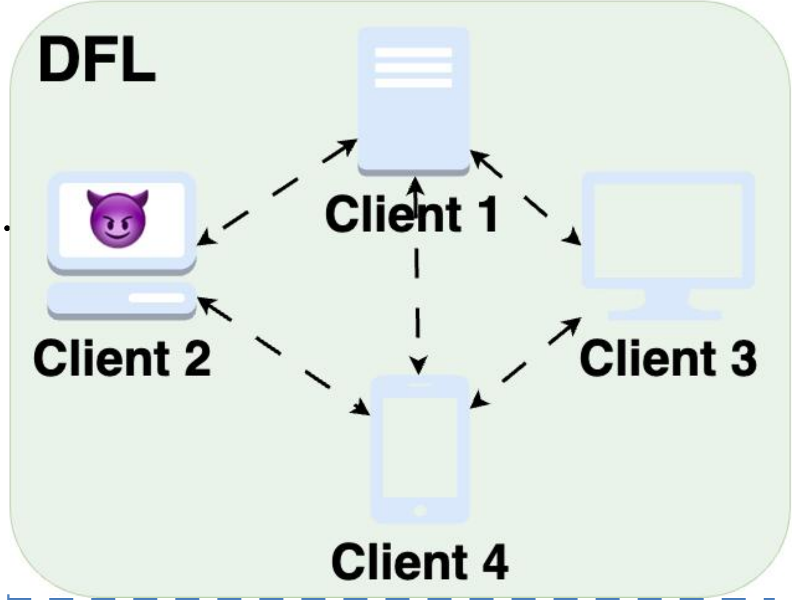
$$\min_{w \in \mathbb{R}^d} \sup_{\mathcal{Q} \in \Omega} \mathbb{E}_{x \sim \mathcal{Q}} \, f(w; x).$$

    - Construct the ambiguity set Ω based on probability distance, Wasserstein distance, etc.

Challenge 2: Byzantine Attack in DFL

- ***Byzantine attacks*** refer to dishonest clients who send arbitrary malicious information to intentionally disrupt the entire system.

- **Byzantine Robust Aggregation Algorithms**
  - Statistics
    - Median [1], Trimmed Mean [1], etc.
  - Anomaly detection
    - pre-trained autoencode [2]
  - Performance evaluation
    - Requires an evaluation dataset.
    - Straightforward and efficient.



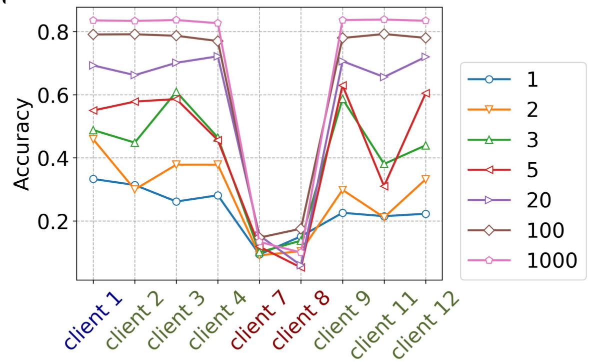
- **Our contributions**
  - A Byzantine-robust aggregation algorithm designed to eliminate the negative impact of Byzantine attackers.
  - The **first** framework that achieves Byzantine robustness and distributional robustness simultaneously.

Byzantine Robust: LPE-TSR

Local Performance Evaluation with Temperature-Scaled Softmax Reweighting (LPE-TSR)

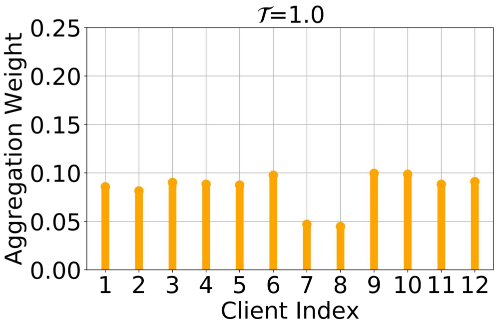
Local Performance Evaluation

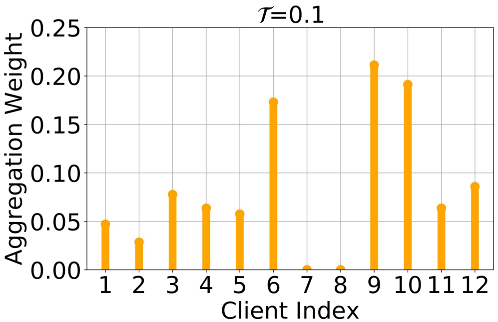
- Determine the updates are benign or malicious using an evaluation dataset.



Temperature-Scaled Softmax Reweighting

- Assign larger weights to benign updates and smaller weights to malicious updates.
- Accelerate convergence. $\mathrm{Softmax}_T(z_i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$





LPE-TSR summary:

Step 1 Build evaluation dataset; → **Step 2** Perform evaluation; → **Step 3** Filter out malicious updates; → **Step 4** Aggregation;

DB-Robust DSGD

Distributional and Byzantine Robust Decentralized Stochastic Gradient Descent

- **Distributed Wasserstein DRO for handling distributional shifts.**
  - Wasserstein distance to build ambiguity sets: $\mathcal{Q}_n : W_c(\mathcal{Q}_n, \mathcal{D}_n) \leq \rho_n$
  - Optimization problem:
    - ERM: $$\min_{w \in \mathbb{R}^d} \frac{1}{N} \sum_{n=1}^{N} \mathbb{E}_{x_n \sim \mathcal{D}_n} f_n(w; x_n)$$
    - DRO: $$\min_{w \in \mathbb{R}^d} \frac{1}{|\mathcal{B}|} \sum_{n=1}^{|\mathcal{B}|} \sup_{\mathcal{Q}_n : W_c(\mathcal{Q}_n, \mathcal{D}_n) \leq \rho_n} \mathbb{E}_{x_n \sim \mathcal{Q}_n} f_n(w; x_n)$$

- **The Byzantine Robust Aggregation Algorithm is a plugin in DB-Robust DSGD framework .**

DB-Robust DSGD

Traditional DFL

$$\min_{w \in \mathbb{R}^d} \frac{1}{N} \sum_{n=1}^{N} \mathbb{E}_{x_n \sim \mathcal{D}_n} f_n(w; x_n)$$

- Local SGD training;

$$w_n^{t+\frac{1}{2}} = w_n^t - \eta^t \nabla f_n(w_n^t; x_n^t), x_n^t \sim \mathcal{D}_n$$

- Communication;

$$W_n = \{w_n^{t+\frac{1}{2}}\} \cup \{w_m^{t+\frac{1}{2}} | m \in \mathcal{N}_n\}$$

- Aggregation;

$$w_n^{t+1} = \sum_{w_i \in W_n} \frac{|\mathcal{D}_i|}{|\mathcal{D}|} w_i^{t+\frac{1}{2}}$$

Distributional and Byzantine robust DFL

$$\min_{w \in \mathbb{R}^d} \frac{1}{|\mathcal{B}|} \sum_{n=1}^{|\mathcal{B}|} \sup_{\mathcal{Q}_n : W_c(\mathcal{Q}_n, \mathcal{D}_n) \leq \rho_n} \mathbb{E}_{x_n \sim \mathcal{Q}_n} f_n(w; x_n)$$

- Local SGD training;

$$w_n^{t+\frac{1}{2}} = w_n^t - \eta^t \nabla f_n(w_n^t; x_n^t), x_n^t \sim \mathcal{Q}_n$$

$$w_n^{t+\frac{1}{2}} = \star$$

- Communication;

$$W_n = \{w_n^{t+\frac{1}{2}}\} \cup \{w_m^{t+\frac{1}{2}} | m \in \mathcal{N}_n\}$$

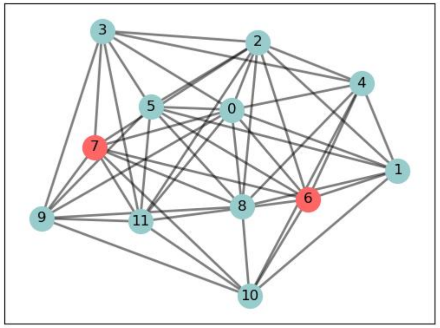
- **Robust** Aggregation;

$$w_n^{t+1} = \mathbf{BRAgg}(w_i^{t+\frac{1}{2}} | w_i^{t+\frac{1}{2}} \in W_n);$$

where N is the number of clients in DFL system; w is local the weights of local model; D_n is the original data distribution of client n; D is the sum of D_n; f is loss function; and η is the learning rate; BRAgg() is Byzantine Robust Aggregation Rules.

Experimental Setups

- **Network topology.** A random undirected graph containing $|\mathcal{B}|$ benign nodes and $|\mathcal{M}|$ malicious nodes, characterized by a connection probability of ρ .
- **Datasets.**
  - Fashion MNIST: An image dataset of 10 categories, containing 60,000 (train) and 10,000 (test) samples.
  - Spambase: 4,601 email samples and 57 features.



|B| = 10, |M| = 2, p=0.7.

- **Distributional shifts.**
- **Byzantine attacks.**

$$\begin{cases} L_1 \text{ shift: } \|z - x\| \leq q \\ L_2 \text{ shift: } \|z - x\|_2 \leq q \end{cases}$$

  - Gaussian Attack (GA) , Sign-Flipping Attack (S-F),
  - A Little Is Enough Attack (ALIE), Same-Value Attack (SA)
- **Evaluation metric.** We report the average test accuracy (**Acc.**) of all local models on the test dataset.

Experimental Result

Evaluate Byzantine robustness of LPE-TSR

Benchmark

- **No-AT:** no attacker, theoretical upper bound;
- Median / Trimmed Mean and Krum.

Result

- **LPE-TSR** is better than **No-AT** in some scenarios;
- **LPE-TSR** is better than Median / Trimmed Mean and Krum.

ATTACK	DATA	No-AT	Median	Trimmed Mean	Krum	LPE-TSR(ours)
GA	IID	82.32	82.21	82.31	82.31	82.41
	Non-IID	82.27	82.01	82.15	81.83	82.20
S-F	IID	82.32	79.71	79.20	82.31	82.40
	Non-IID	82.27	74.62	73.20	81.83	82.20
ALIE	IID	82.32	82.19	82.33	82.15	82.37
	Non-IID	82.27	81.10	81.85	79.88	81.12
SA	IID	82.32	79.79	79.22	82.19	82.40
	Non-IID	82.27	74.82	73.29	10.00	82.20

Experimental Result

Evaluate robustness of DB-Robust DSGD

Benchmark

- Empirical Risk Minimization (ERM).

Result

- DB-Robust (*) is better than ERM when just Byzantine Attack or Distributional Shift is exist;
- DB-Robust (*) outperforms ERM under the same scenarios when Byzantine Attack and Distributional Shift is exist at the same time;

	ERM	DB-Robust(Median)	DB-Robust(TM)	DB-Robust(Krum)	DB-Robust(LPE-TSR)
No-Shifts & No-AT	93.48	92.1	93.02	92.83	92.89
No-Shifts & GA	54.35	91.92	92.44	93.94	92.60
L1 Shifts & No-AT	90.92	90.60	91.20	92.21	91.20
L2 Shifts & No-AT	68.03	71.54	71.28	68.70	71.69
L1 Shifts & GA	54.95	90.61	90.89	91.10	90.59
L2 Shifts & GA	52.90	71.39	71.62	71.24	71.50

Conclusion & Future Work

Conclusion

- ***Local Performance Evaluation with Temperature-Scaled Softmax Reweighting (LPE-TSR)*** efficiently and effectively mitigates the negative impact of Byzantine clients in DFL systems.
- ***DB-Robust DSGD*** addresses distributional shifts and Byzantine attacks simultaneously. Distributed Wasserstein DRO is used to mitigate distributional shifts, while Byzantine-robust aggregation algorithms counter Byzantine attacks.
- Experimental results demonstrate that the proposed algorithms achieve superior accuracy and robustness compared to benchmark methods.

Future work

- ***Theoretical analysis*** of DB-Robust DSGD and LPE-TSR.
- Other methods to address distribution shifts.
- ***Theoretical analysis*** of why LPE-TSR outperforms No-AT.

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