Do We Really Need to Design New Byzantine-robust Aggregation Rules?

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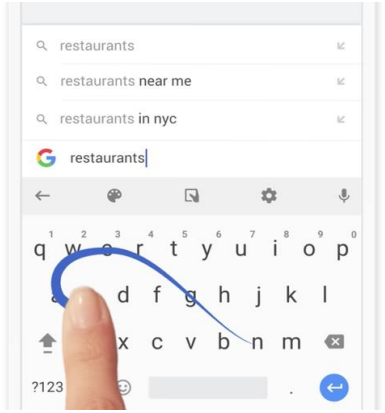
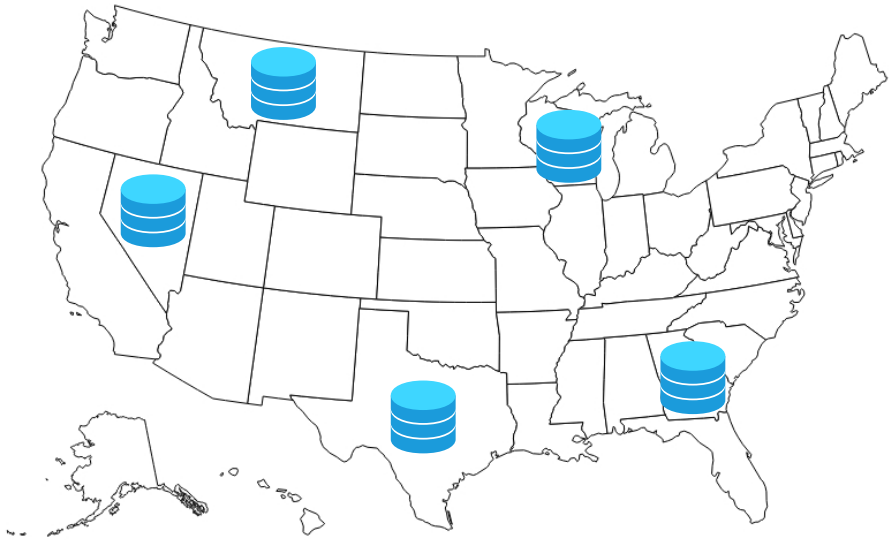
Machine Learning is Everywhere



...ranging from basic sensor automation to large-scale collaborative environments

Centralized Learning

Large scale data are typically distributed in different locations



Conventional approach: centralized learning

(All the data are moved to a single location)

Challenges of Centralized Learning

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- Data leakage
  - Private data cannot be shared

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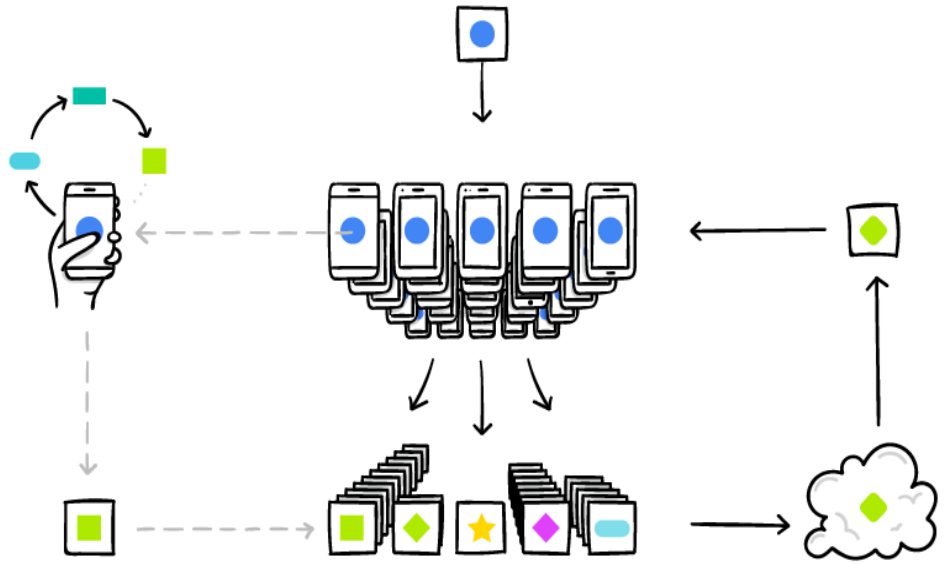
- Data leakage
  - Private data cannot be shared
- High communication cost
  - Intolerable for resource-constrained clients
    - Smartphone
    - IoT

Federated Learning

- Training data stay locally on clients
- Clients train models locally
- Clients send local model updates to the server
- Server aggregates the received model updates



Federated Learning Background

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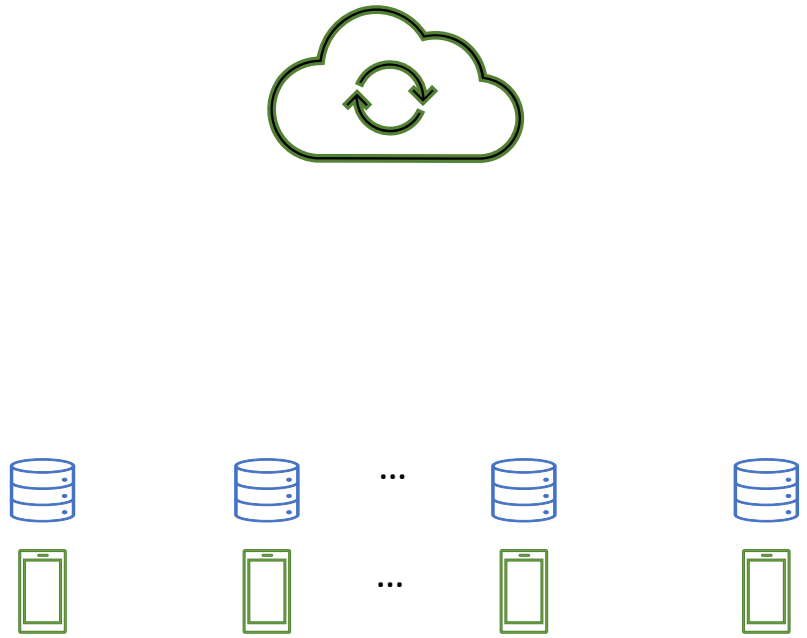
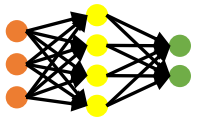


Federated Learning Background

Global model $\boldsymbol{\theta}$



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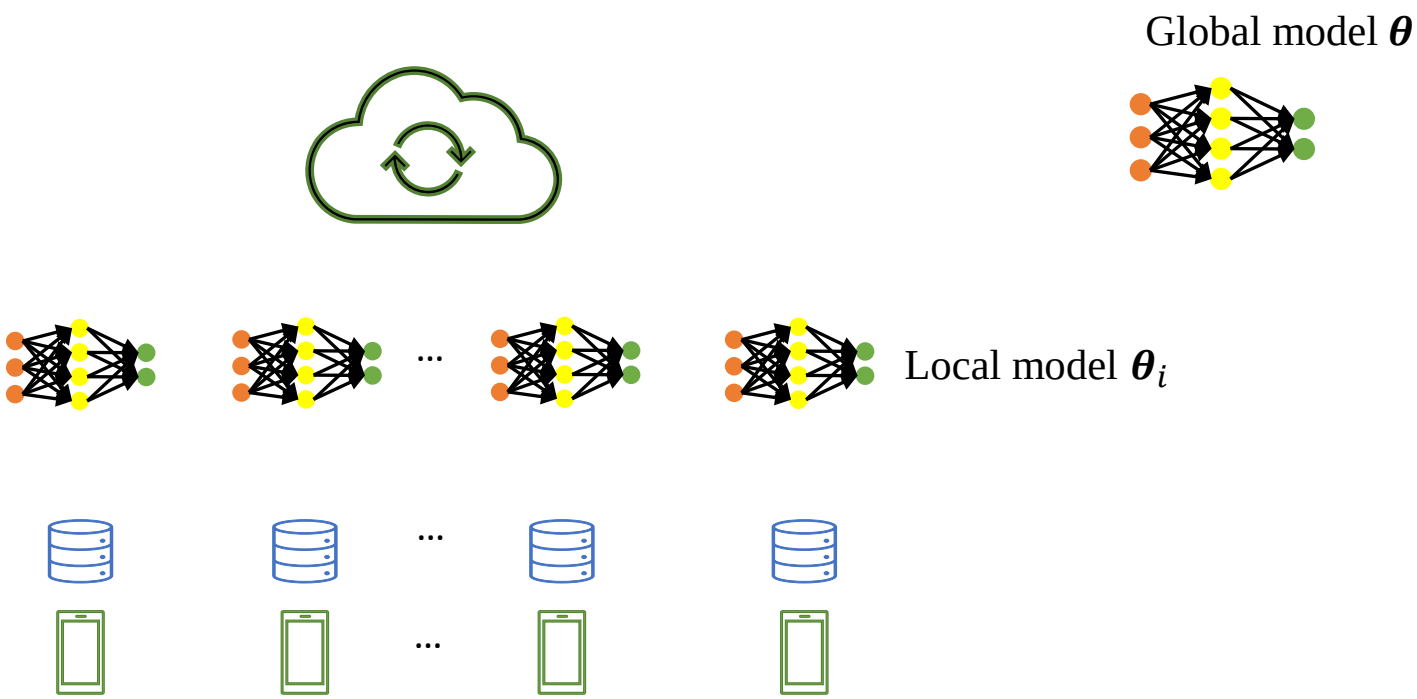

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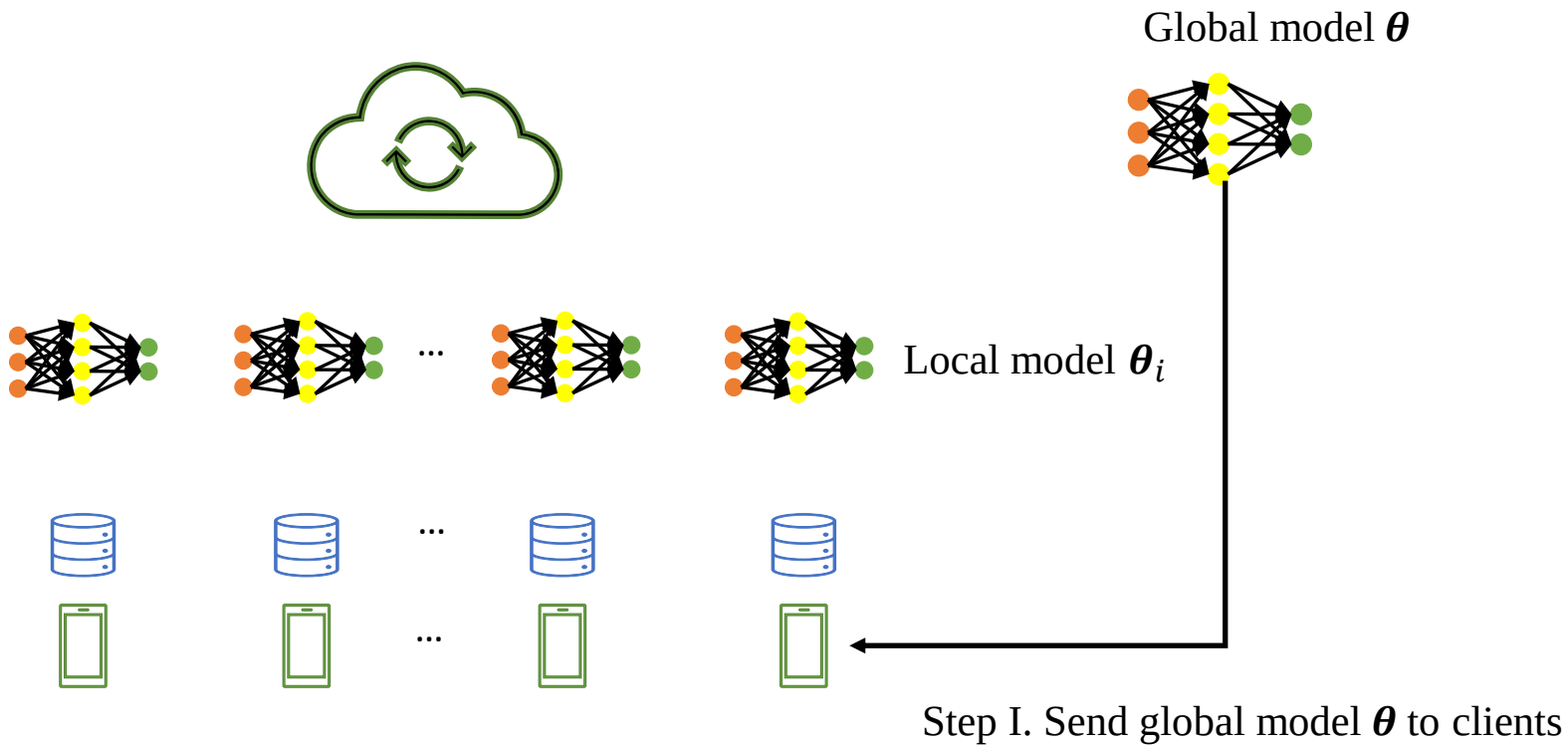

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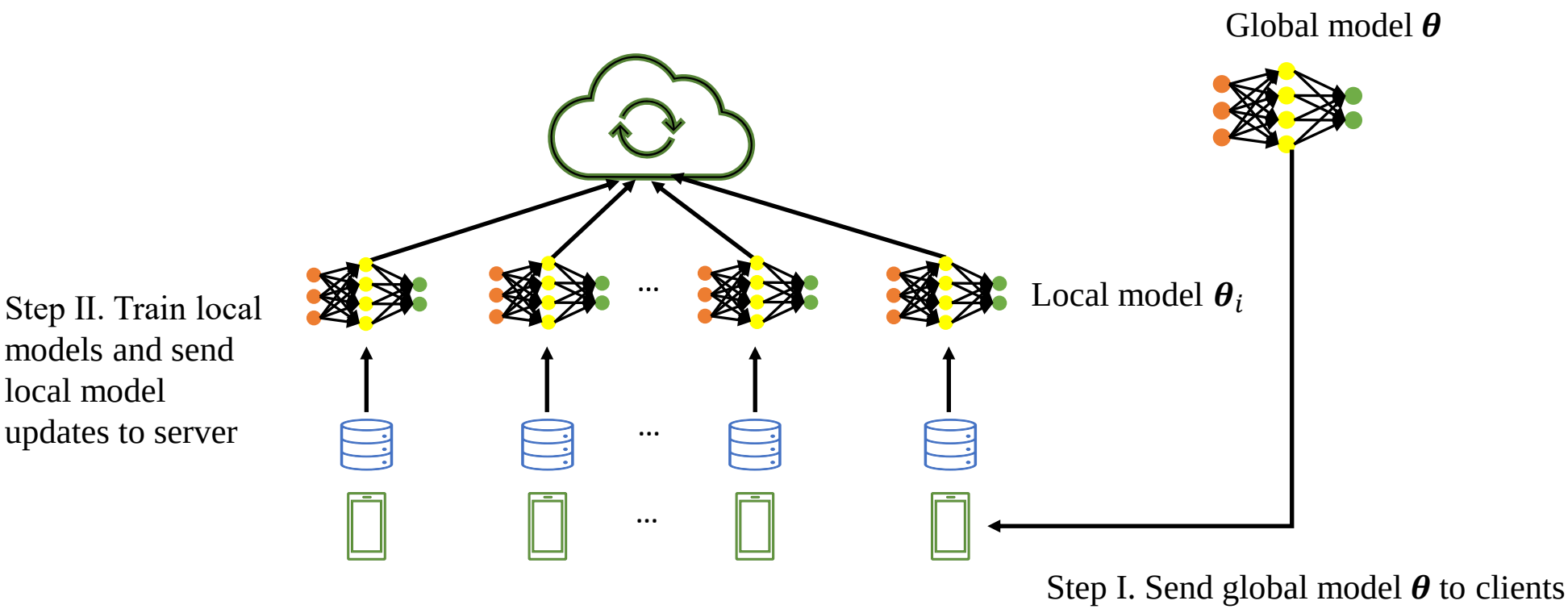

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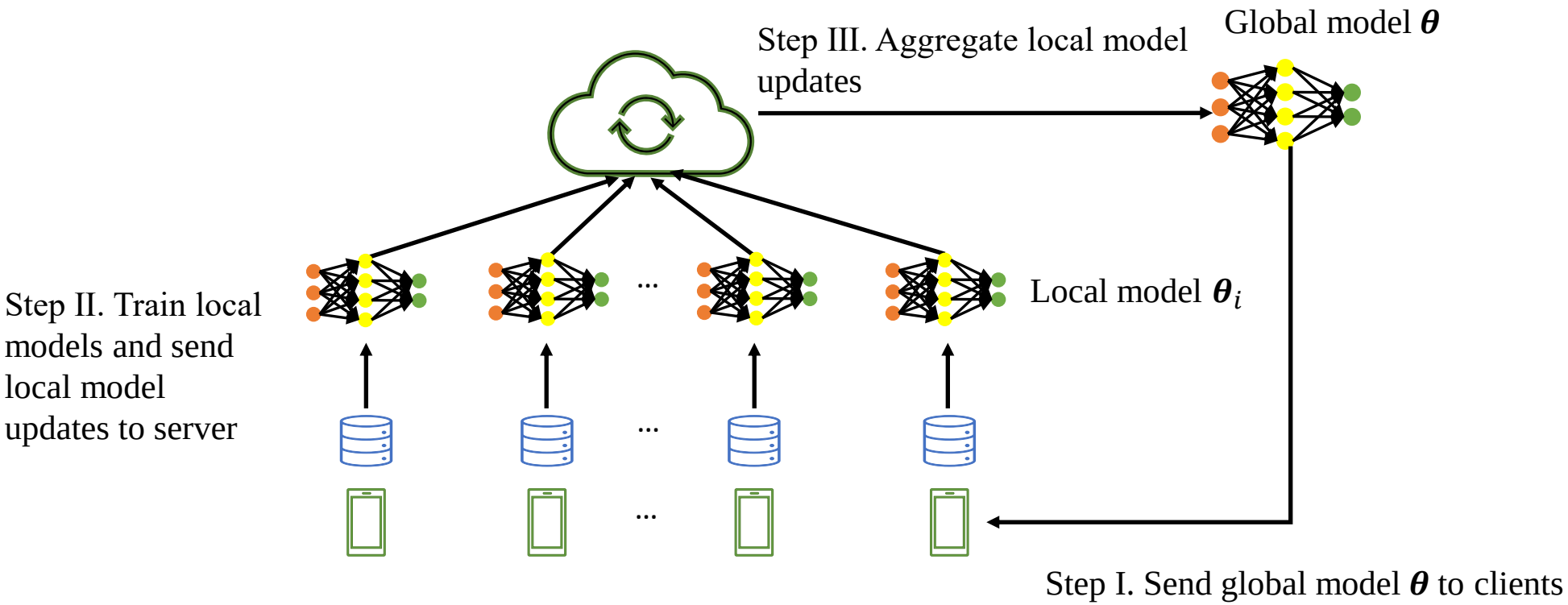
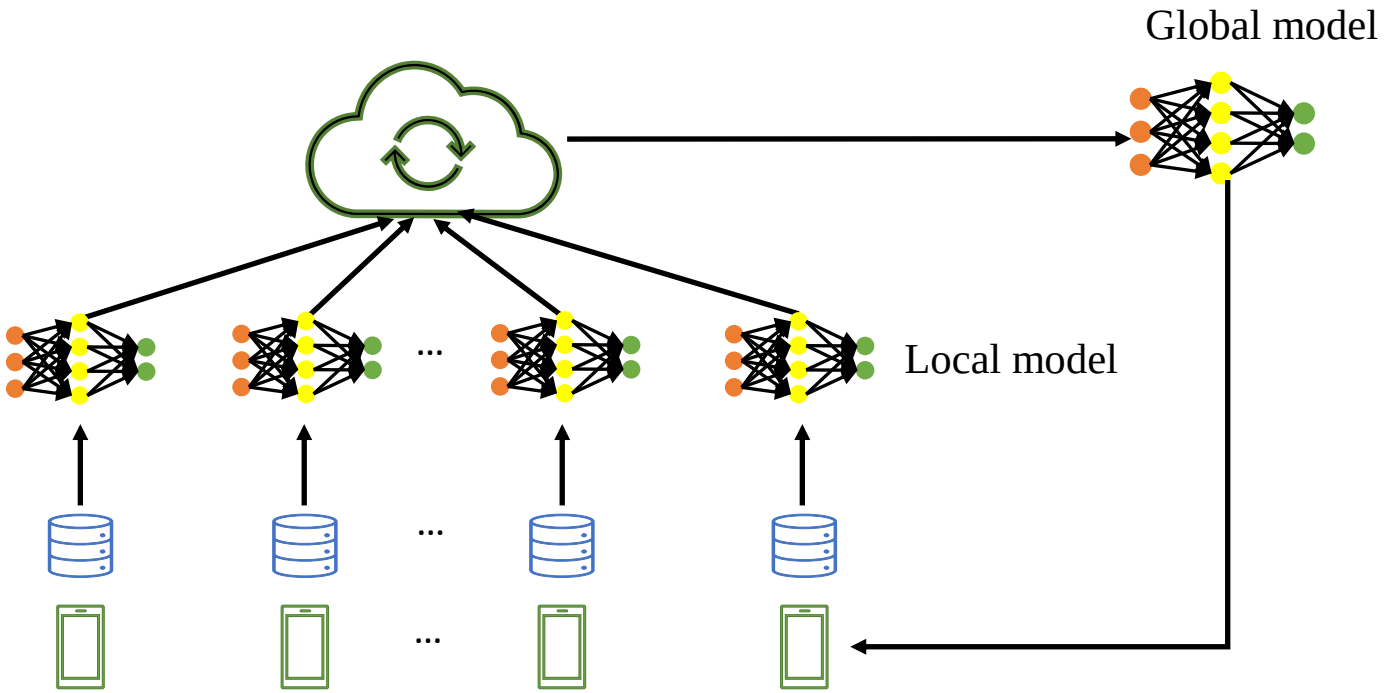


Poisoning Attacks to Federated Learning



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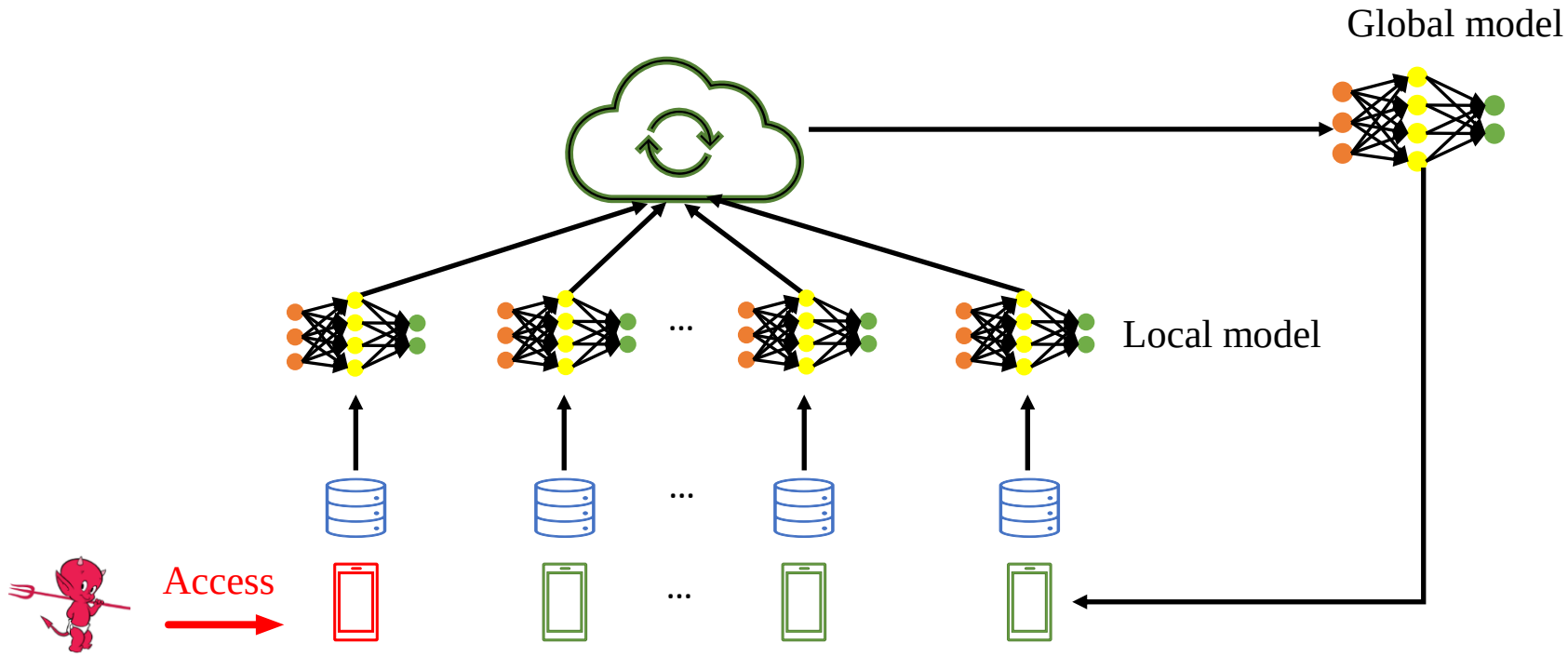

- Fake clients
- Compromised benign clients (by malware infections)

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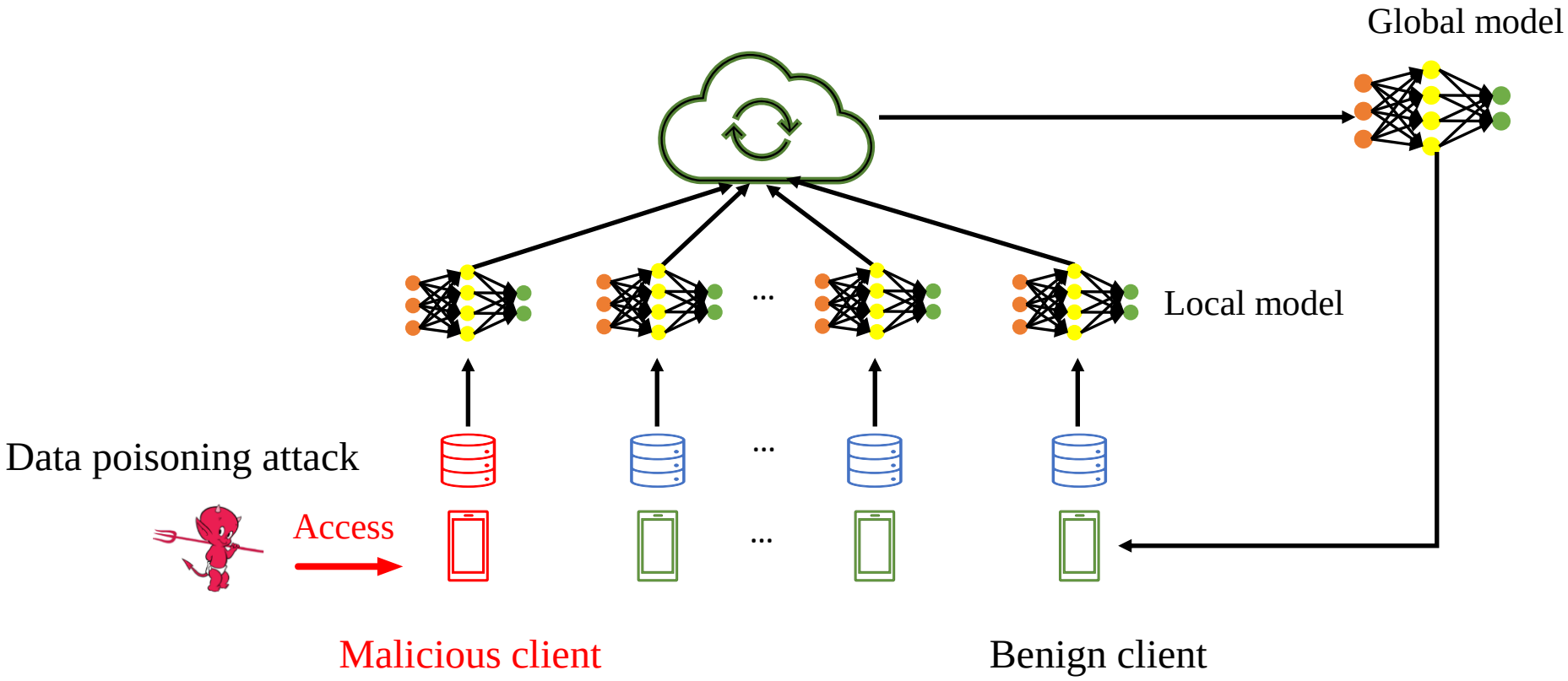

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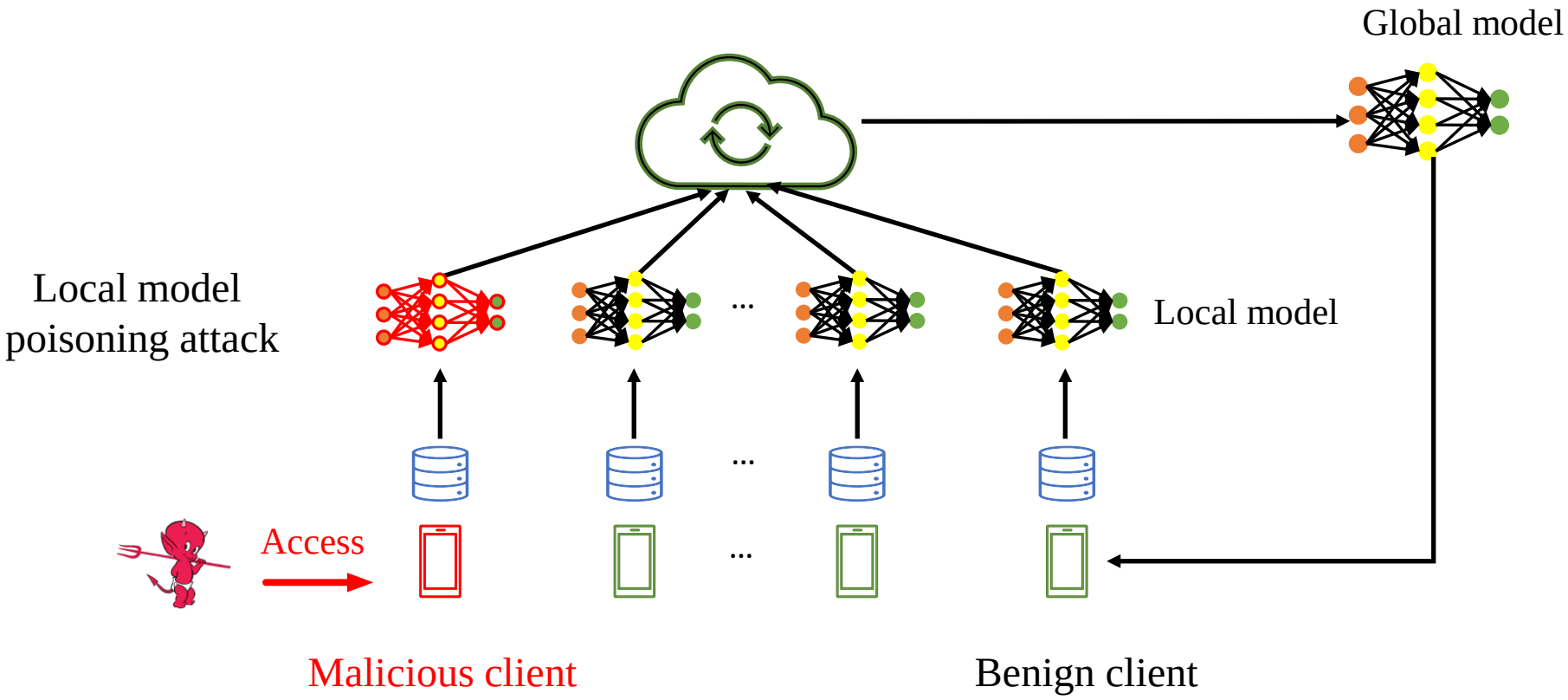

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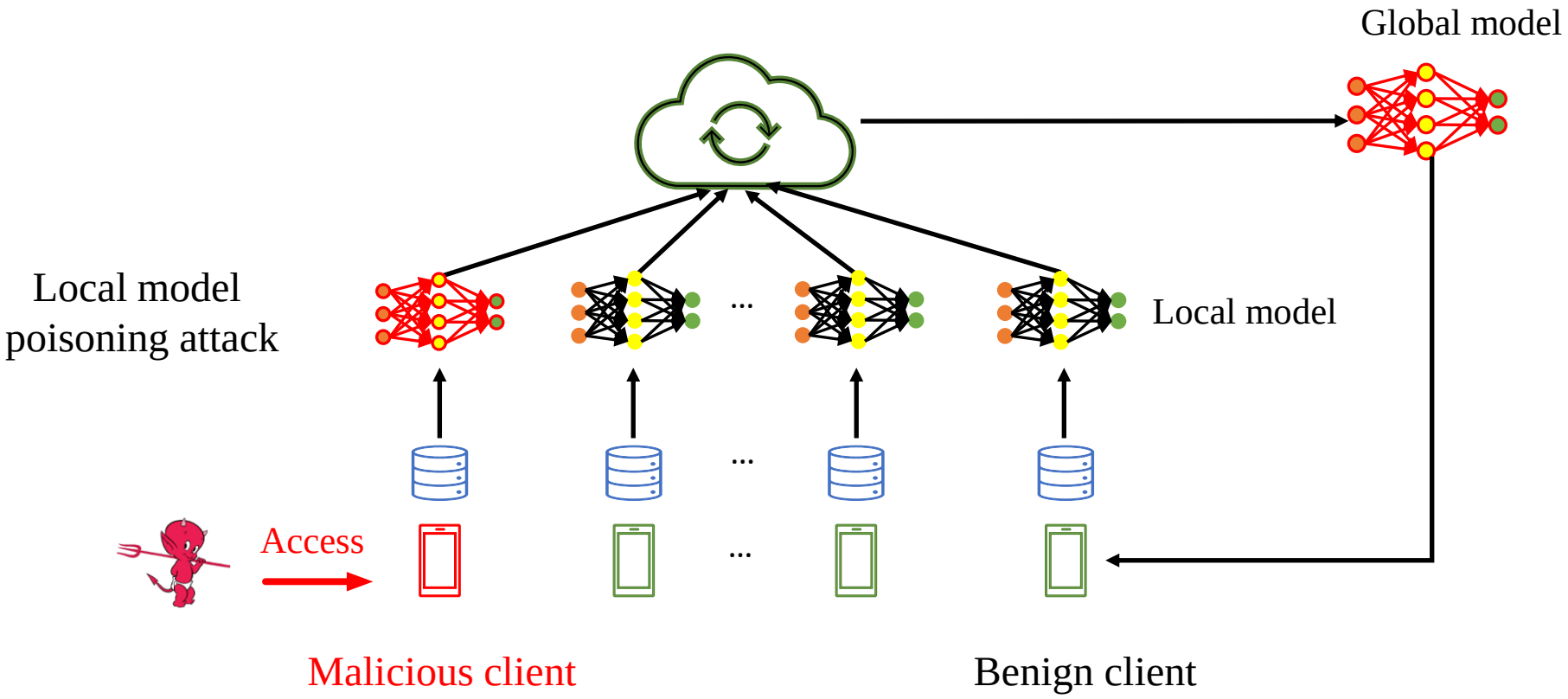
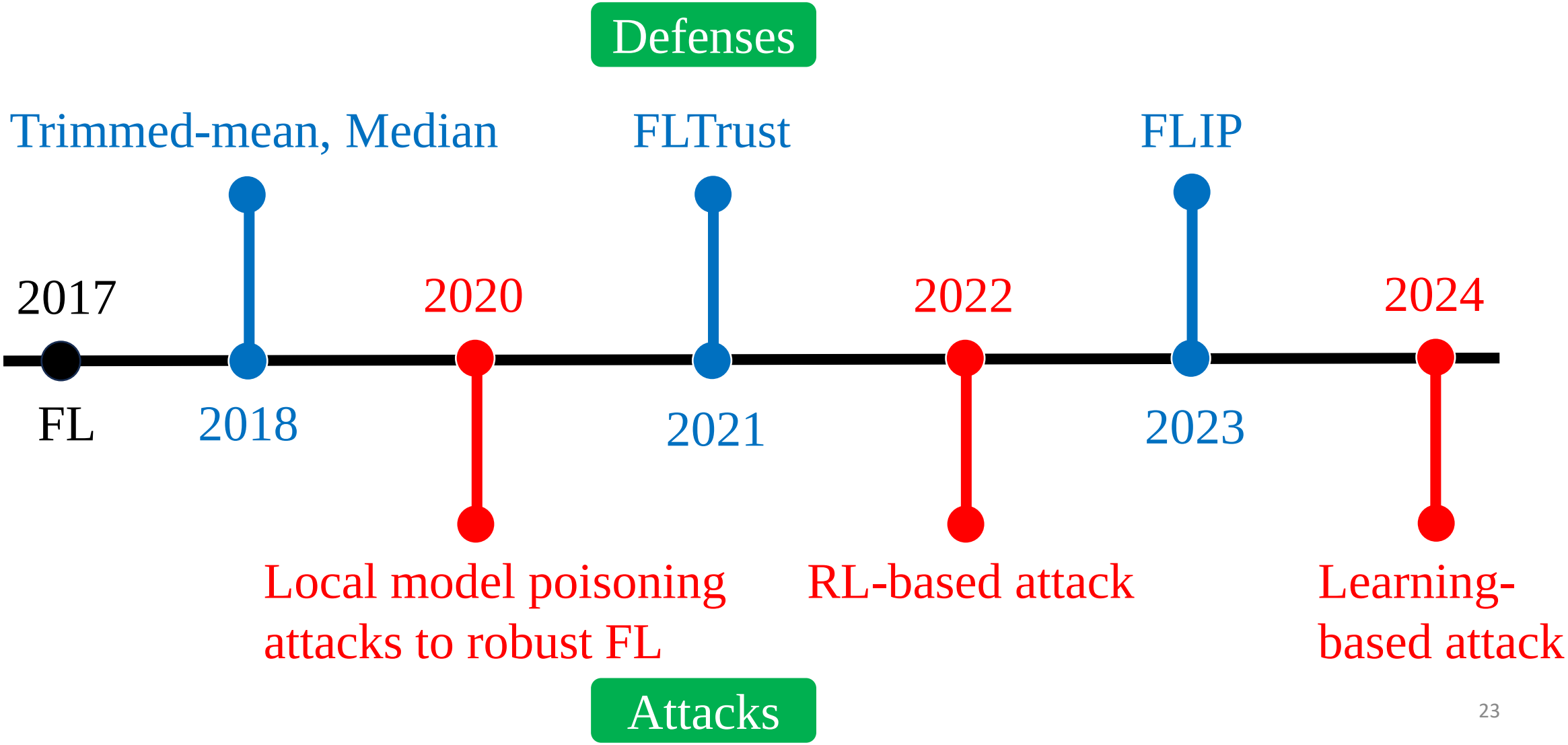


Poisoning Attacks to Federated Learning

Cat-and-Mouse Game in Federated Learning Security



Limitations of Existing Defenses

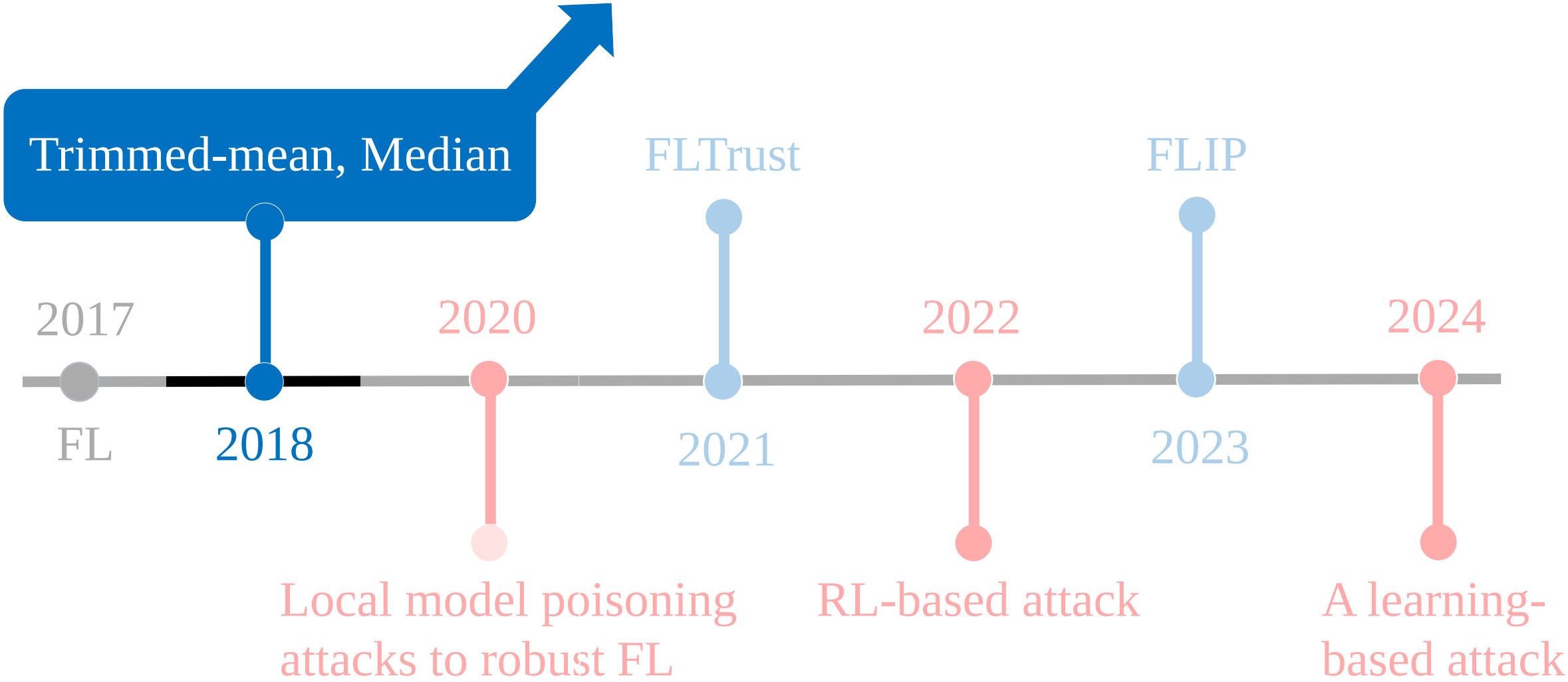
- Unrealistic assumptions
  - Assume the server owns a small trusted dataset
- Increasingly complex
- Remain vulnerable to sophisticated attacks

Do we really need to design new Byzantine-robust aggregation rules?

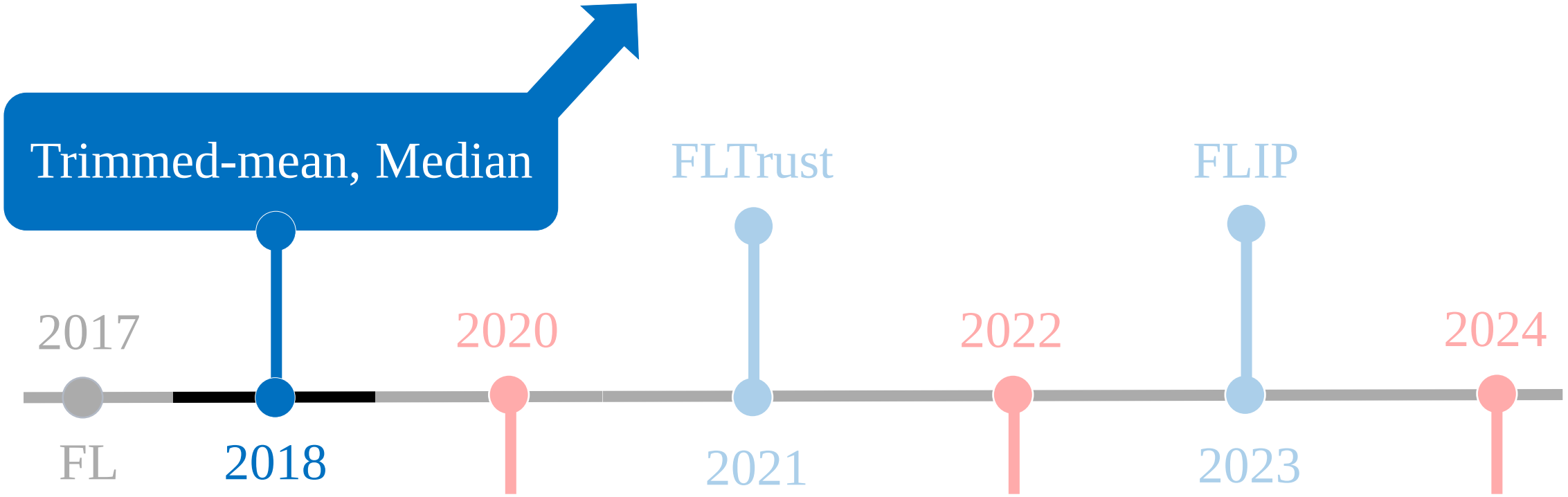
There is no need to design new Byzantine-robust aggregation rules

Federated learning can be secured by enhancing the robustness of existing **foundational aggregation rules**

Foundational Aggregation Rules



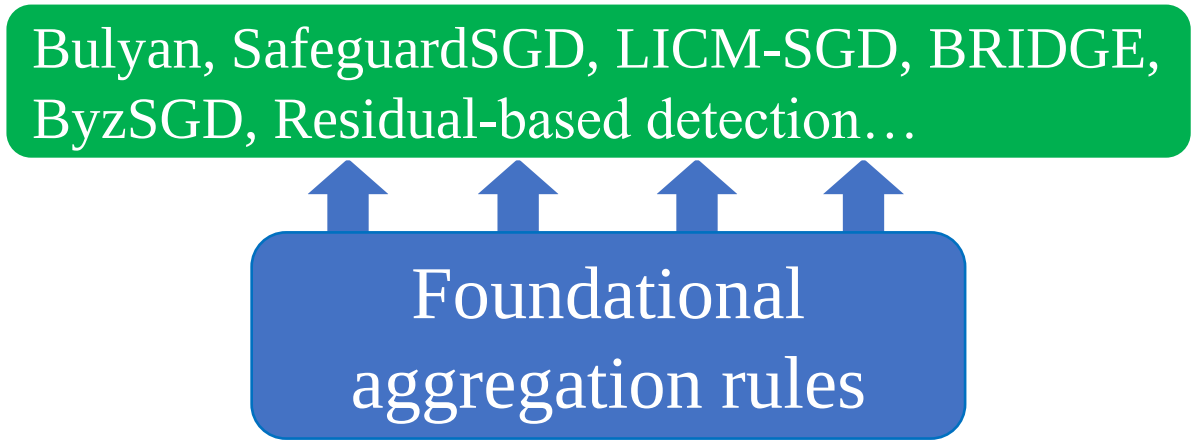
Foundational Aggregation Rules



Foundational aggregation rules mitigate poisoning attacks to some extent, but remain vulnerable to advanced attacks (Fang et al., USENIX Security 2020)

Foundational Aggregation Rules

- Trimmed-mean (ICML 2018)
  - Remove some of the largest and smallest extreme values for each dimension, then average the remaining values
- Median (ICML 2018)
  - Compute the coordinate-wise median of the clients' local model updates
- Simple to implement
- Serve as the backbone for many existing robust aggregation rules



Threat Model

- **Attacker**
  - Attacker’s goal
    - ❖ Untargeted (degrade overall model performance), targeted (manipulate specific outputs)
  - Attacker’s capability
    - ❖ Access to malicious clients, send arbitrary local model updates
  - Attacker’s knowledge (worst-case but realistic attack scenario)
    - ❖ Full knowledge: local model updates on all clients, aggregation rule used by the server
- **Defender**
  - Defender’s goal
    - ❖ Competitive performance, Byzantine robustness, efficiency
  - Defender’s knowledge
    - ❖ Local model updates sent by clients
    - ❖ No knowledge of attack strategy

Our Defense: FoundationFL

- Server generates some **synthetic updates** after receiving local model updates from clients
- Server uses the **foundational aggregation rule**, such as Trimmed-mean or Median, to combine clients' model updates with the synthetic ones

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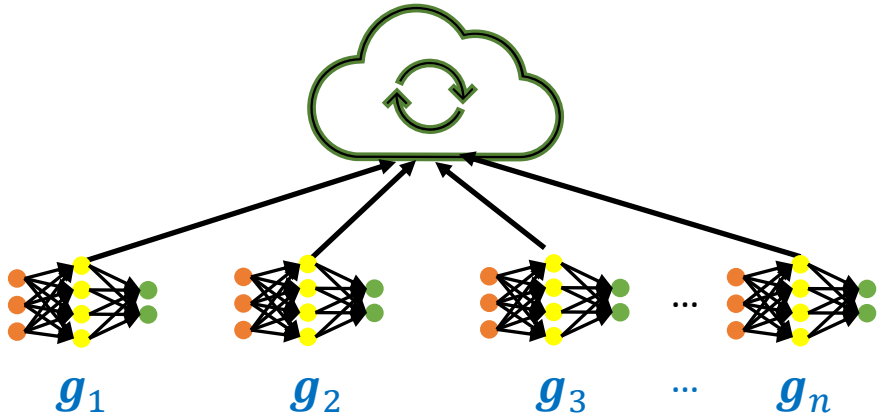

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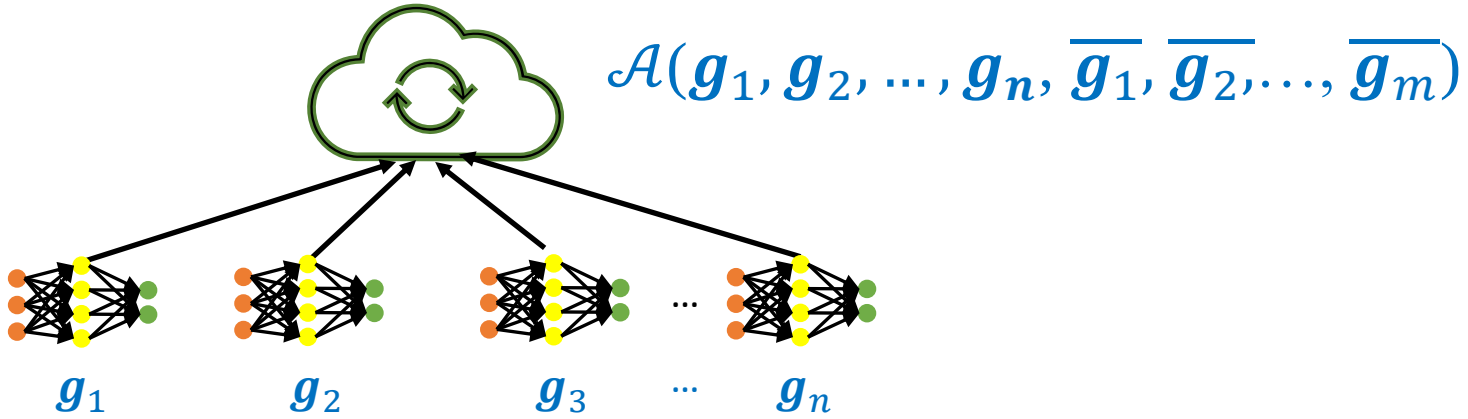

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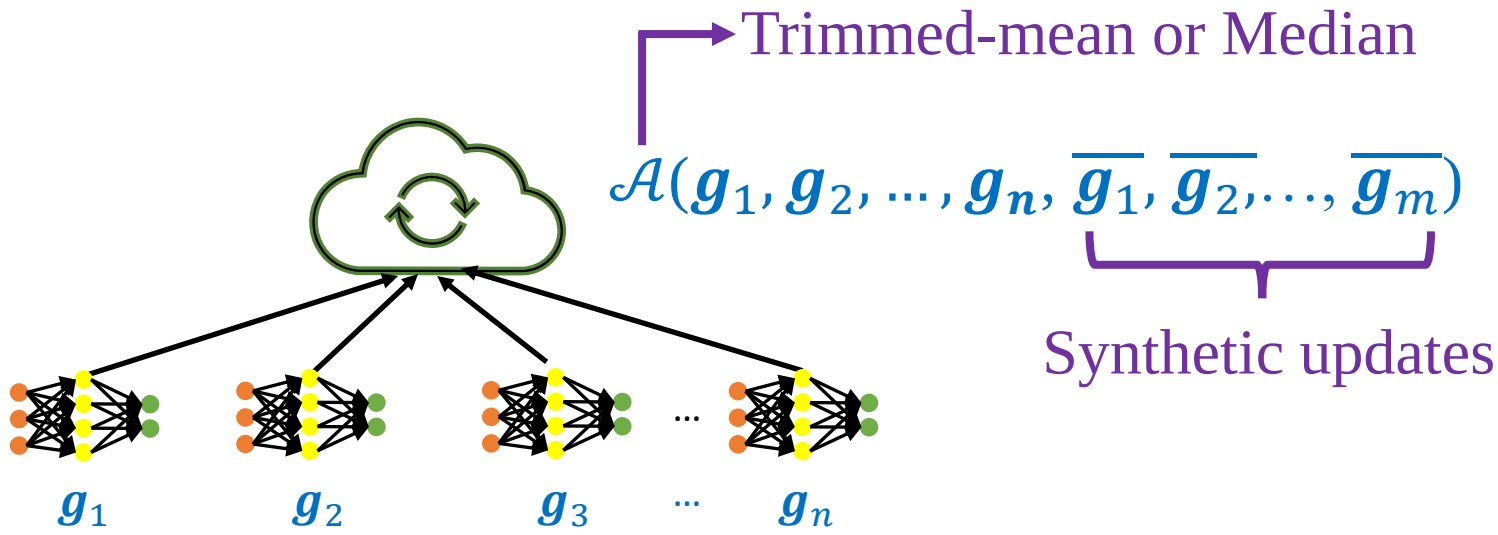

Generating Synthetic Updates

Server identifies a client update that deviates most from extreme updates, and considers it as the synthetic update

- Compute extreme updates: $g_{\max}$, $g_{\min}$ represent the largest and smallest updates across dimensions

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Client 1 $\begin{pmatrix} 0.2 & 0.4 & 0.6 & 0.3 \end{pmatrix}$

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Client 1	0.2	0.4	0.6	0.3
Client 2	0.5	1.5	0.8	0.9

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Client 3	1.6	0.4	1.2	0.3

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$g_{\max}$	1.6			

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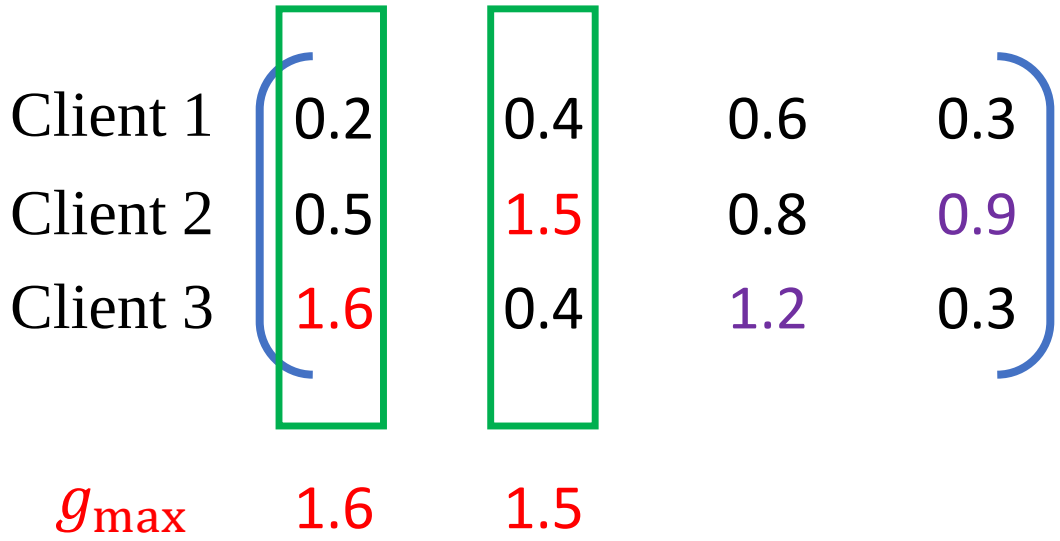

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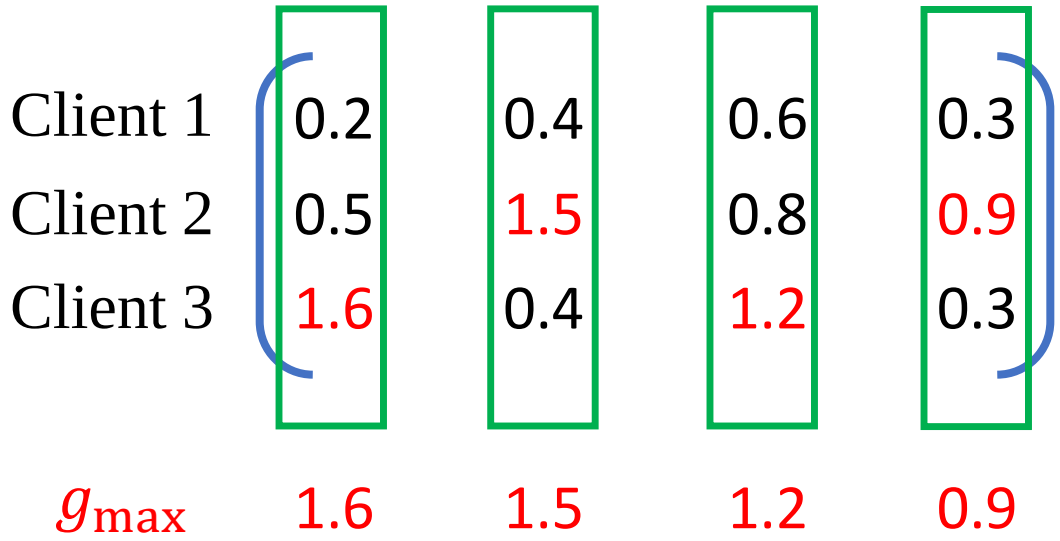

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- Compute extreme updates: $g_{\max}$, $g_{\min}$ represent the largest and smallest updates across dimensions
- Select a client's update with the largest distance from $g_{\max}$ and $g_{\min}$ (e.g., distance between g_i and extreme updates can be computed as $\min\{\|g_i - g_{\max}\|, \|g_i - g_{\min}\|\}$)

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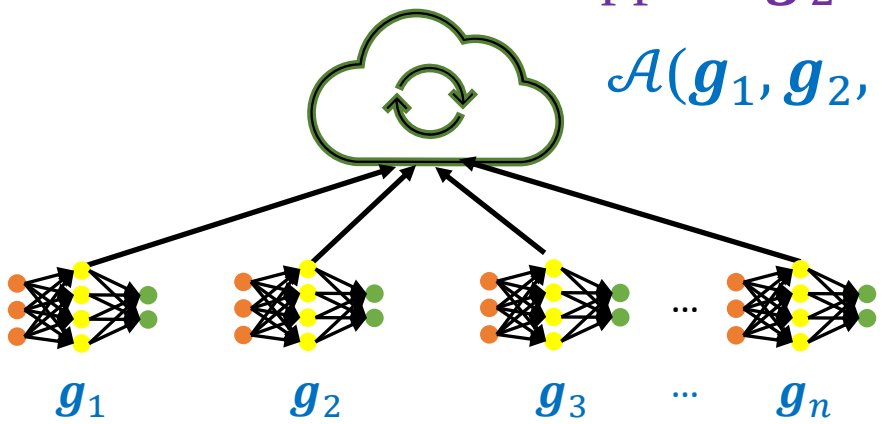
Suppose $\boldsymbol{g}_2$ deviates most from extreme updates

$$\mathcal{A}(\boldsymbol{g}_1, \boldsymbol{g}_2, \cdots, \boldsymbol{g}_n, \underbrace{\boldsymbol{g}_2, \boldsymbol{g}_2 \cdots, \boldsymbol{g}_2}_{\text{Synthetic updates}})$$



Why FoundationFL Is Effective

- Clients' training data is highly heterogeneous
- Attacker exploits such heterogeneity to launch the attack
- Synthetic updates create a more homogeneous set of updates

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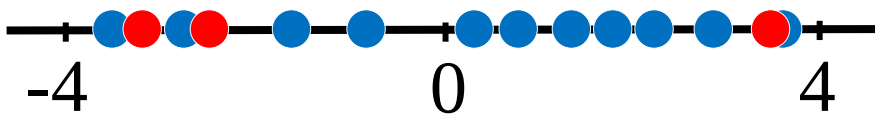

w/o synthetic updates

- Benign
- Malicious

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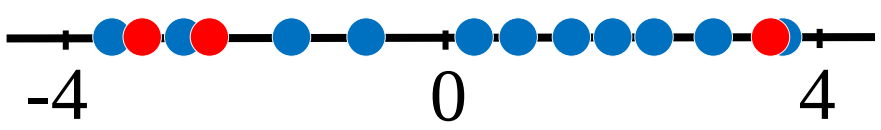

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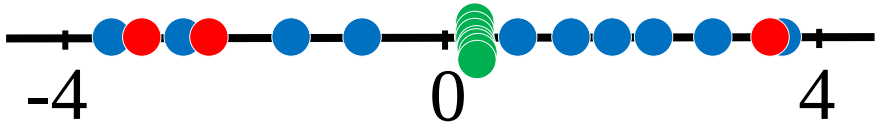

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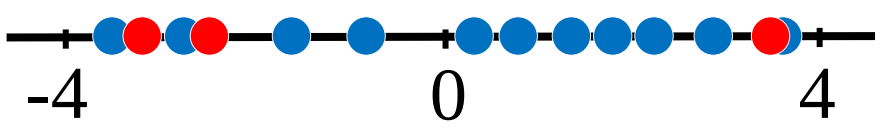
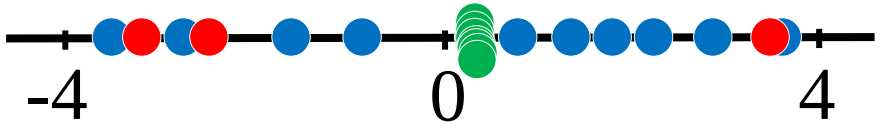
Mean: 0.06
Standard deviation: 2.80



w/o synthetic updates

Mean: 0.14
Standard deviation: 2.29



w/ synthetic updates

Benign
Malicious
Synthetic

Increase the mean and reduce the standard deviation of updates

Experimental Settings

- 100 clients
  - 20 compromised by default
- Datasets:
  - MNIST
  - Fashion-MNIST
  - Human Activity Recognition
  - Purchase
  - Large-scale CelebFaces Attributes
  - CIFAR-10
- Non-IID data distribution
  - Non-IID: not Independently and Identically Distributed
- Server generates 50 synthetic updates in FoundationFL
- 12 poisoning attacks
- 10 comparison aggregation rules

Our FoundationFL is Effective

Aggregation rule	No attack	LF attack	Gaussian attack	Trim attack	Krum attack	Min-Max attack	Min-Sum attack	Scaling attack
FedAvg	0.05	0.07	0.90	0.32	0.10	0.90	0.90	0.64 / 0.70
Trim-mean	0.06	0.06	0.06	0.27	0.08	0.19	0.13	0.13 / 0.02
GAS + Trim-mean	0.05	0.05	0.11	0.29	0.07	0.10	0.11	0.43 / 0.47
Gaussian + Trim-mean	0.05	0.11	0.91	0.91	0.05	0.08	0.06	0.91 / 1.00
FoundationFL + Trim-mean	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05 / 0.02
Median	0.05	0.09	0.16	0.23	0.17	0.19	0.23	0.05 / 0.02
GAS + Median	0.05	0.05	0.12	0.26	0.06	0.10	0.10	0.59 / 0.65
Gaussian + Median	0.05	0.90	0.90	0.90	0.05	0.14	0.14	0.91 / 1.00
FoundationFL + Median	0.05	0.05	0.05	0.05	0.07	0.05	0.05	0.06 / 0.02

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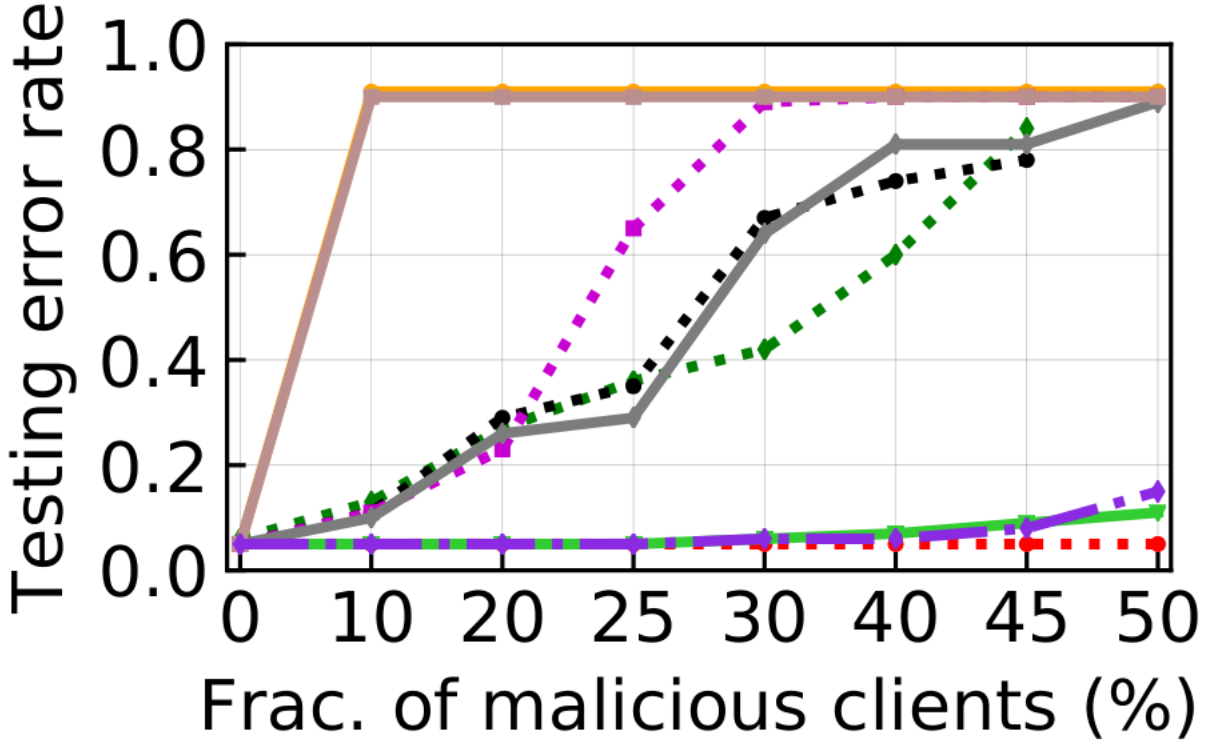
FoundationFL + Trim-mean	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05 / 0.02
Median	0.05	0.09	0.16	0.23	0.17	0.19	0.23	0.05 / 0.02
GAS + Median	0.05	0.05	0.12	0.26	0.06	0.10	0.10	0.59 / 0.65
Gaussian + Median	0.05	0.90	0.90	0.90	0.05	0.14	0.14	0.91 / 1.00
FoundationFL + Median	0.05	0.05	0.05	0.05	0.07	0.05	0.05	0.06 / 0.02

Use Median rule to combine clients' model updates with the synthetic ones

Impact of Fraction of Malicious Clients



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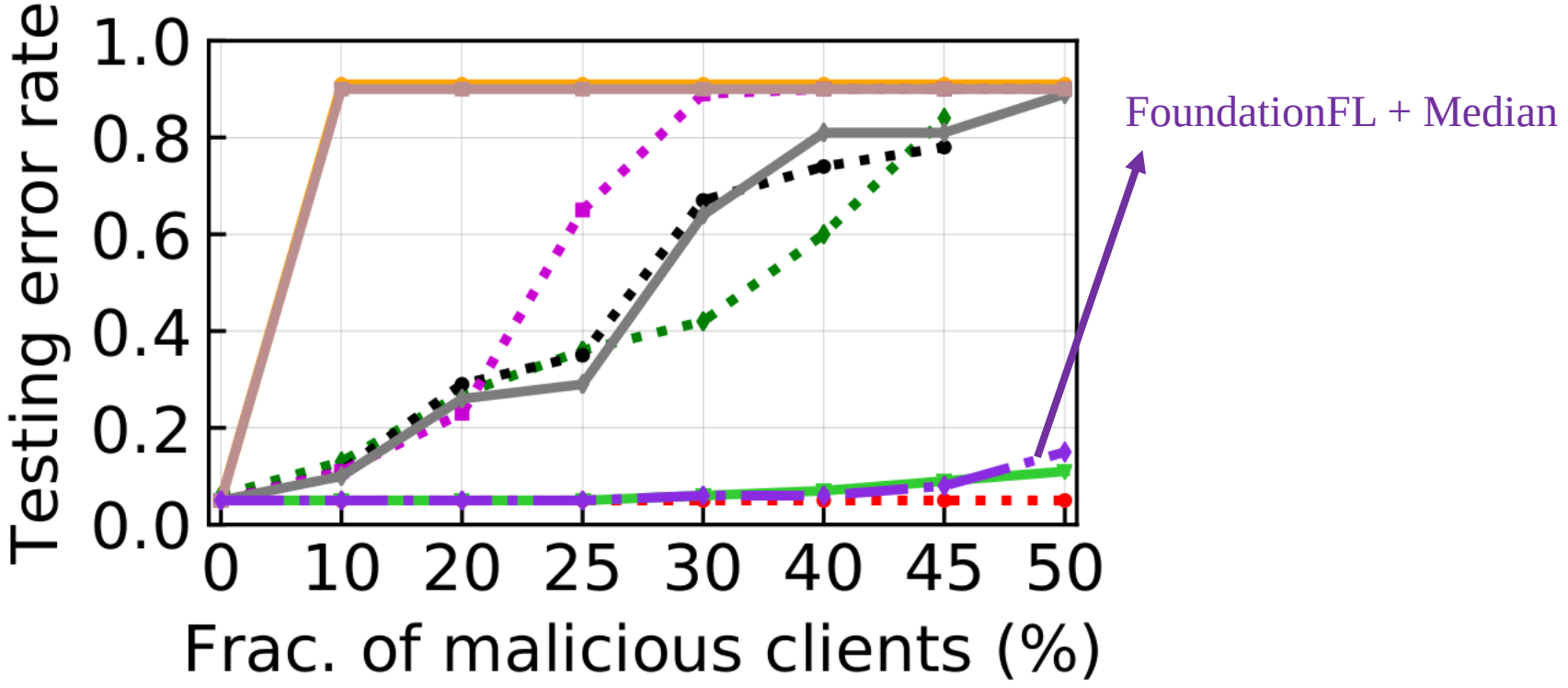

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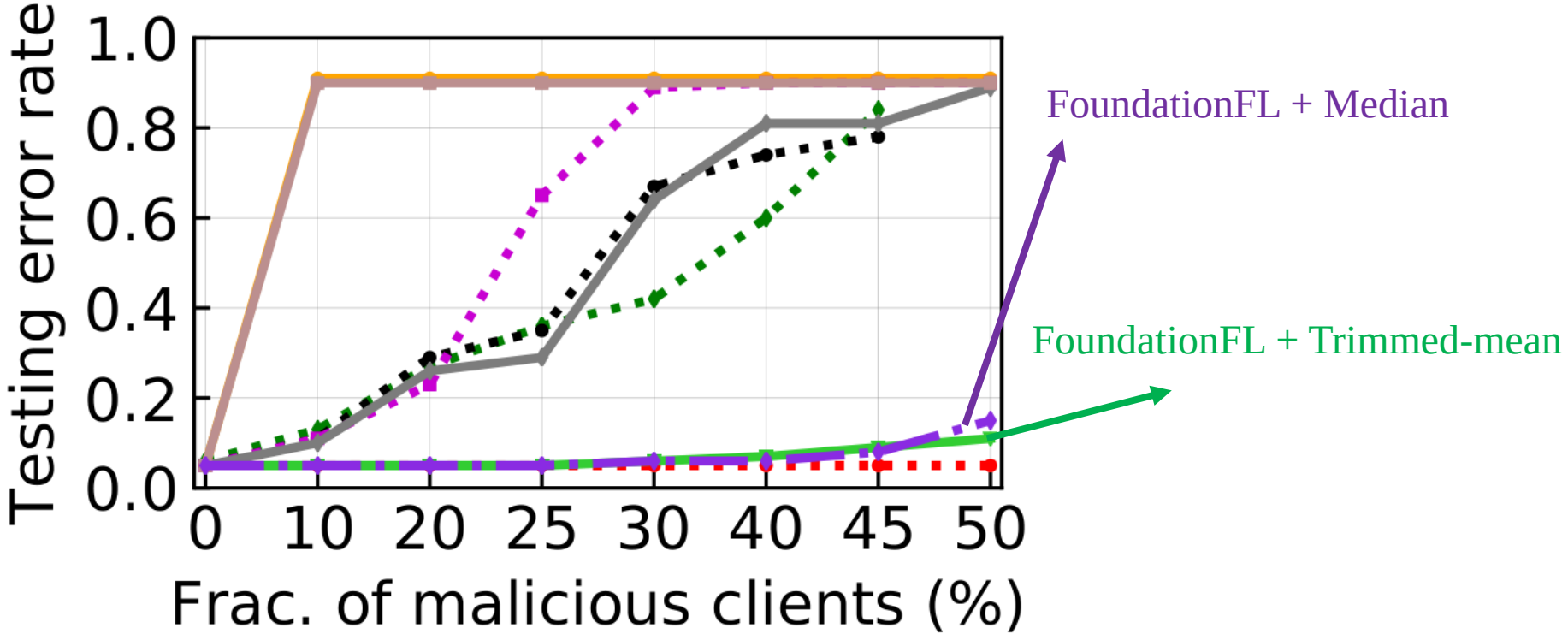

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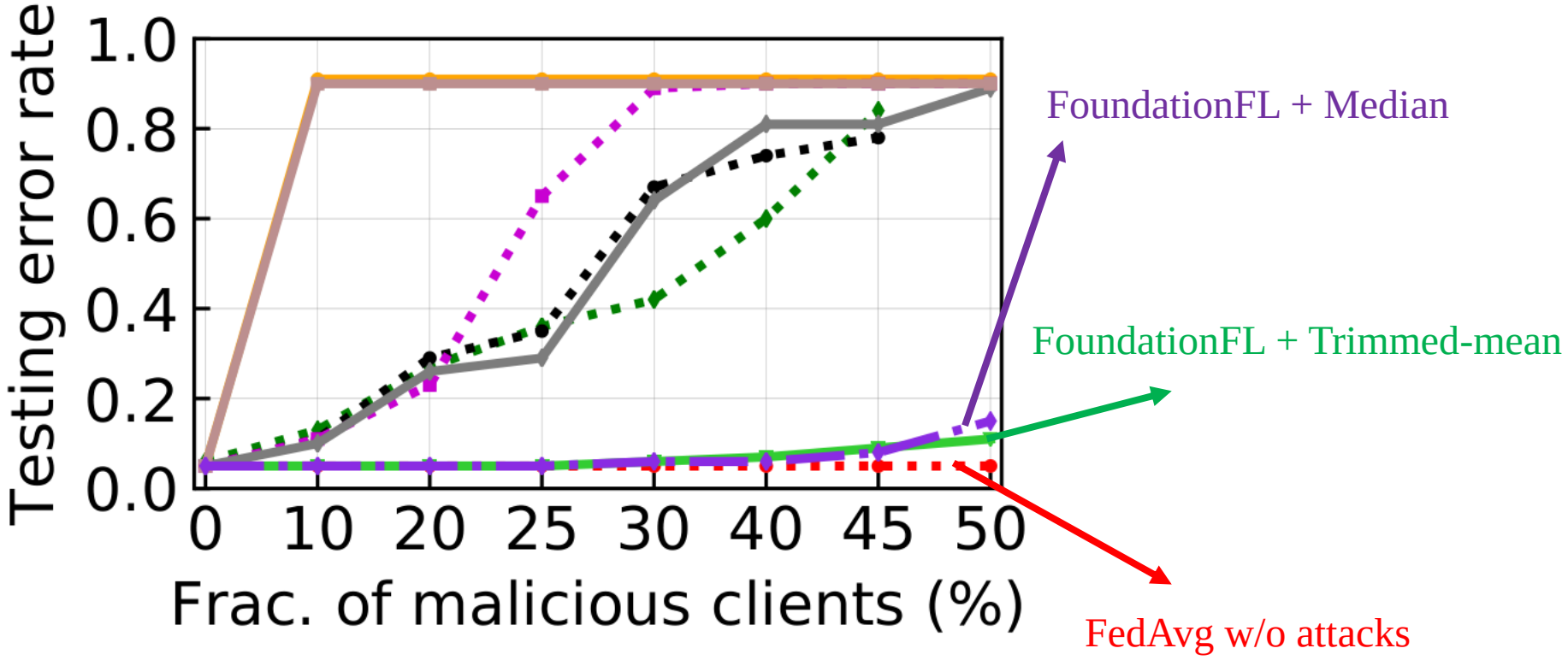

Conclusion

- There is no need to design new Byzantine-robust aggregation rules
- We can secure federated learning by enhancing the robustness of existing foundational aggregation rules

Thank You & Questions?