Week 12b - Privacy Preservation

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Wide Industry Adoption of FL

Banking

Crowd-sourcing

Insurance

Healthcare

E-Commerce

Safety Monitoring

IoT Infrastructure

Recommender Systems

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Swiss Re Group

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4Paradigm 第四范式

DATA REPUBLIC

sharemind

Federated Learning Limitations

Limitations:

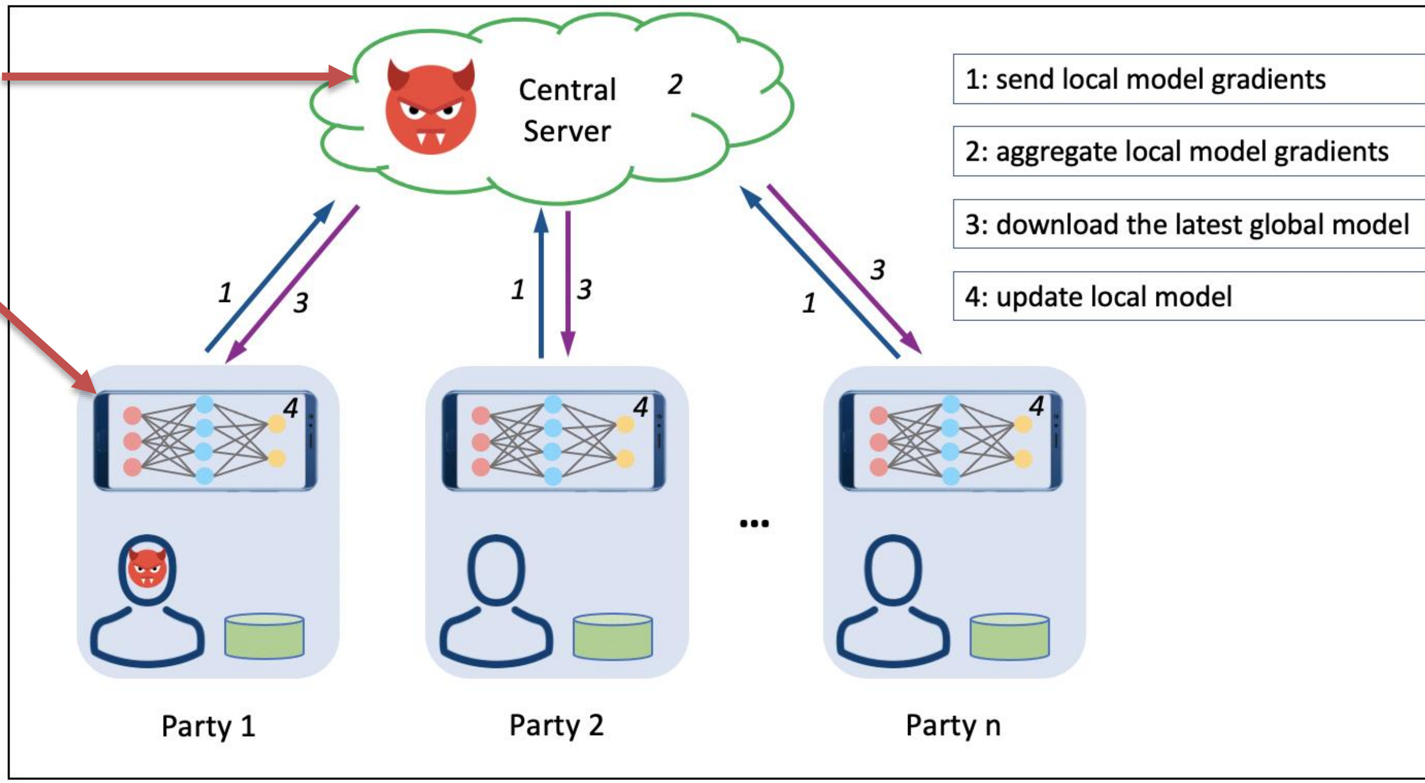
- Single Server FedAvg:
  - Single point of failure
  - Cannot deal with non-i.i.d. situations
  - Vulnerable to “free-riders”

- Exchange of model parameters:
  - Plaintext model parameters vulnerable to privacy attacks
  - Inefficient for large AI models due to high communication cost

Threats to Federated Learning

Mostly Against HFL

Potential Adversaries



Attackers and Threat Models

TABLE I: Taxonomy for horizontal federated learning (HFL).

HFL	Number of Participants	Training Participation	Technical Capability
H2B	small	frequent	high
H2C	large	not frequent	low

Attackers

Outsiders:

- Eavesdroppers on the communication channel.
- Users of the final FL model when it is deployed.

Insiders: FL server and the participants.

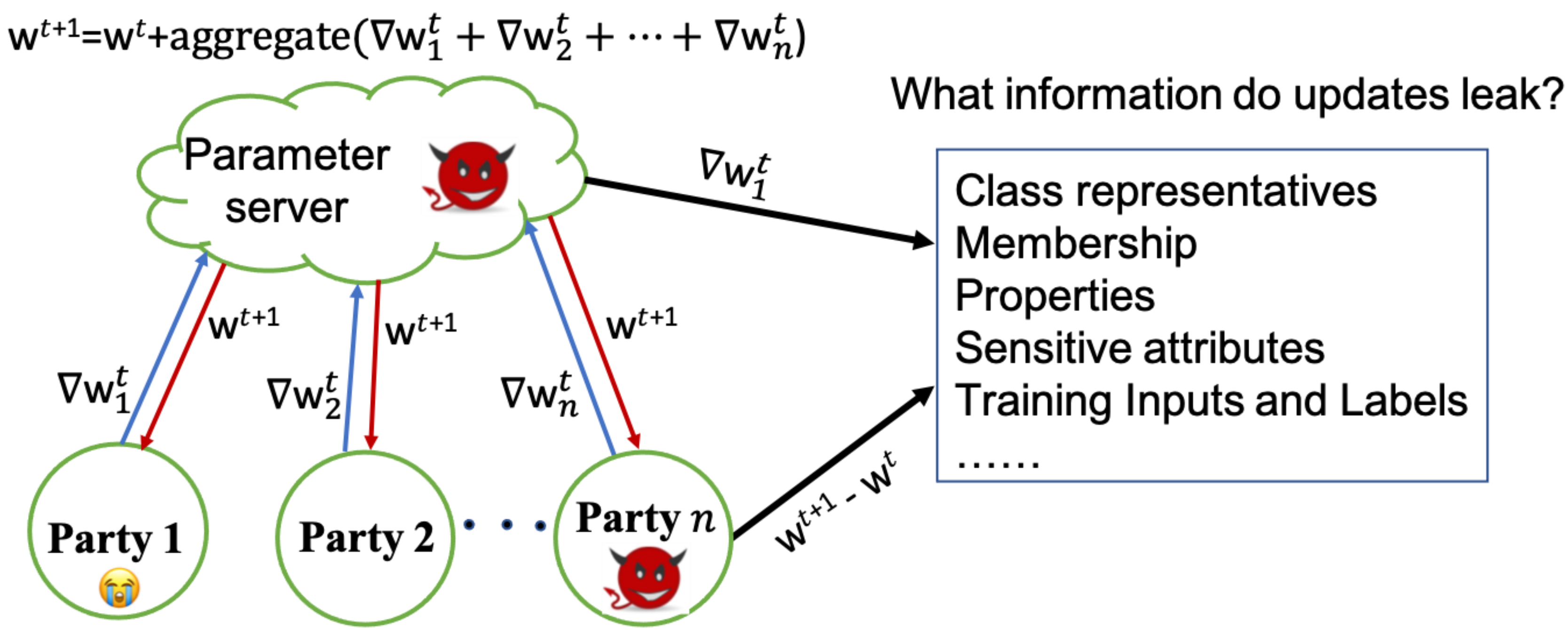
- Byzantine: no need to obey the protocol and can send arbitrary messages to the server.
- Sybil: can simulate multiple dummy participant accounts or select previously compromised participants to mount more powerful attacks on the global model.

Threat Models

Semi-honest: Adversaries are passive or honest-but-curious. They try to learn the private states of other participants without deviating from the FL protocol. The adversaries can only observe the received information.

Malicious: Active, tries to learn the private states of honest participants, and deviates arbitrarily from the FL protocol by modifying, re-playing, or removing messages. This setting allows the adversary to conduct particularly devastating attacks.

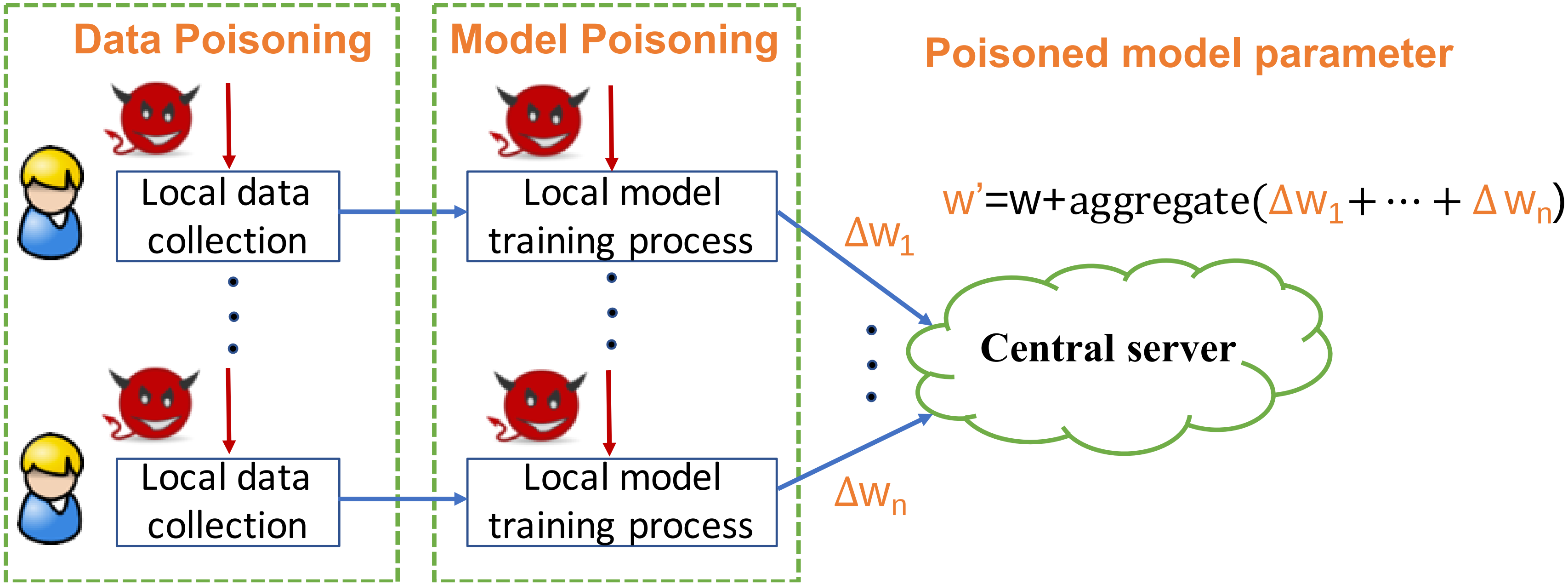
Threats to FL – Inference Attacks



Why gradients cause privacy leakage?

Gradients are derived from the participants' private training data, and a learning model can be considered as a representation of the high-level statistics of the dataset it was trained on.

Threats to FL – Poisoning Attacks



Objective:

1) Targeted (Backdoor, Sybil attacks).
2) Untargeted (Byzantine attacks).

Model poisoning attacks are much more effective than data poisoning attacks!

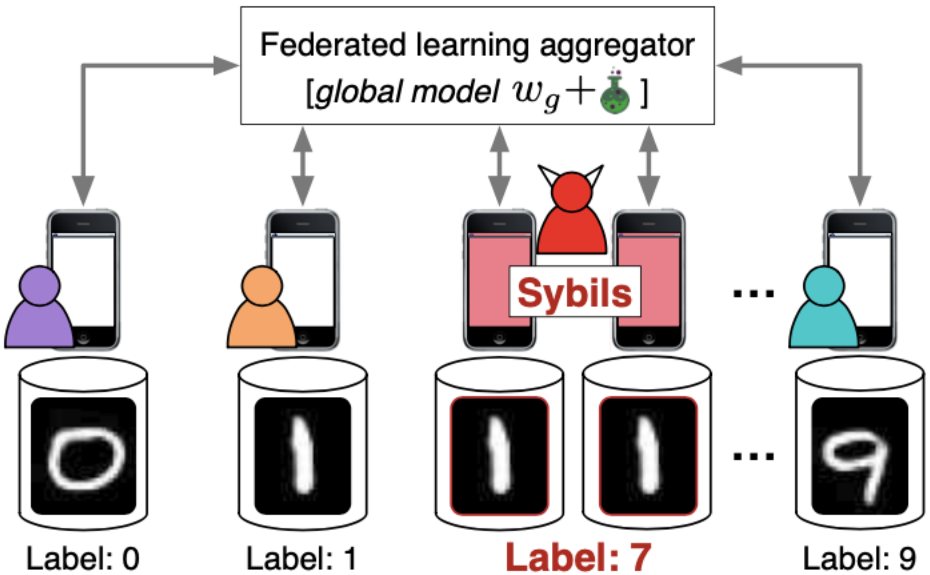
Threats to FL – Poisoning Attacks

- Label-flipping attacks the labels of honest training samples of one class are flipped to another class while the features of the data are kept unchanged.

- Backdoor attacks
- Single features or small regions of the original training dataset are augmented with a secret pattern and relabelled.
- The pattern acts as a trigger for the target class.

- Note: Backdoor attacks should not significantly change the prediction outcomes of other classes. Otherwise, the attack will be detected.

Threats to FL – Sybil Attacks



(b) Federated learning with sybil-based label-flipping poisoning

Sybil attacks

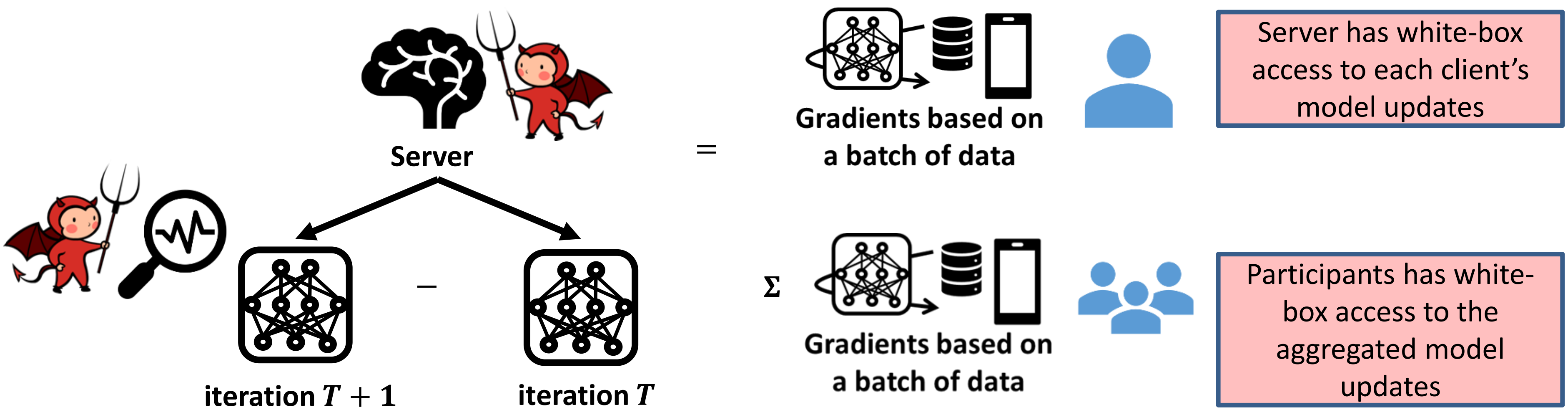
Multiple dummy participant accounts or previously compromised participants launch attacks towards a specific malicious objective.

Source: https://arxiv.org/abs/2012.06337

Defending Federated Learning

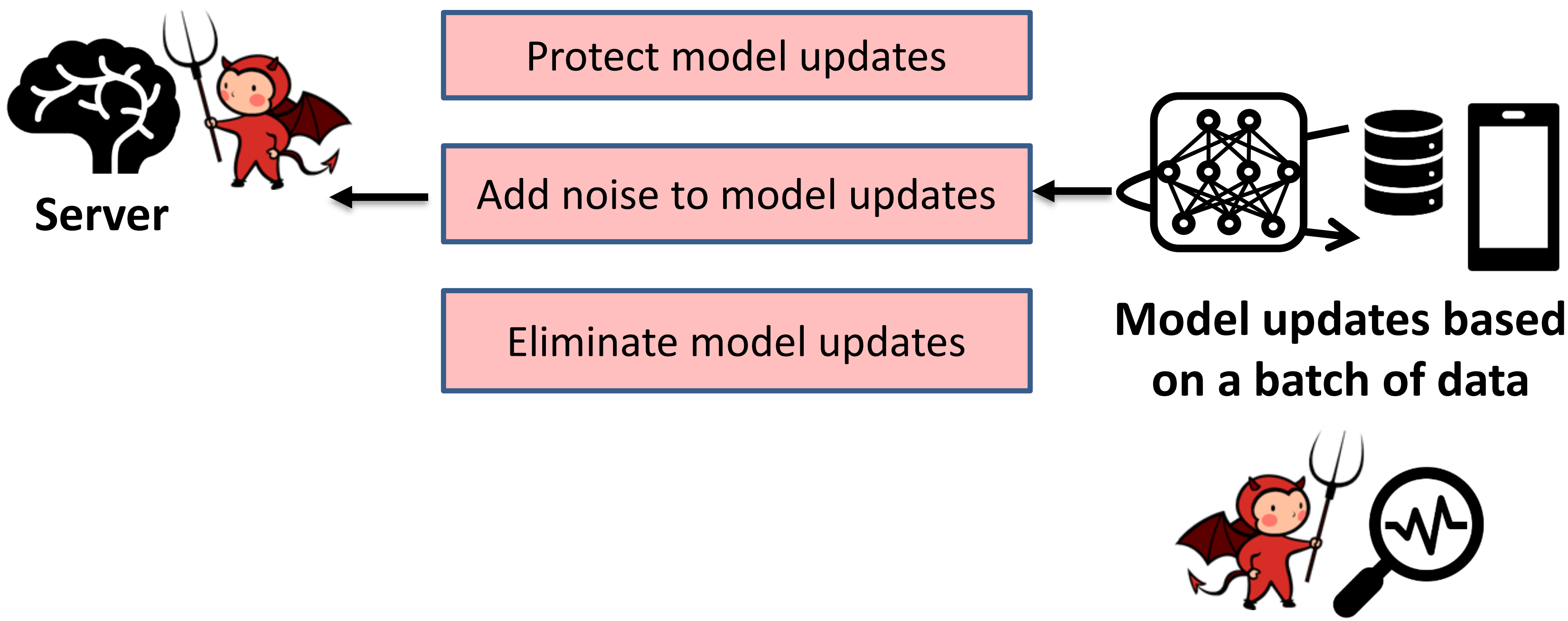
Key FL Vulnerability

- Malicious FL client or server has WHITE-BOX access to model updates



Major Defence Approaches

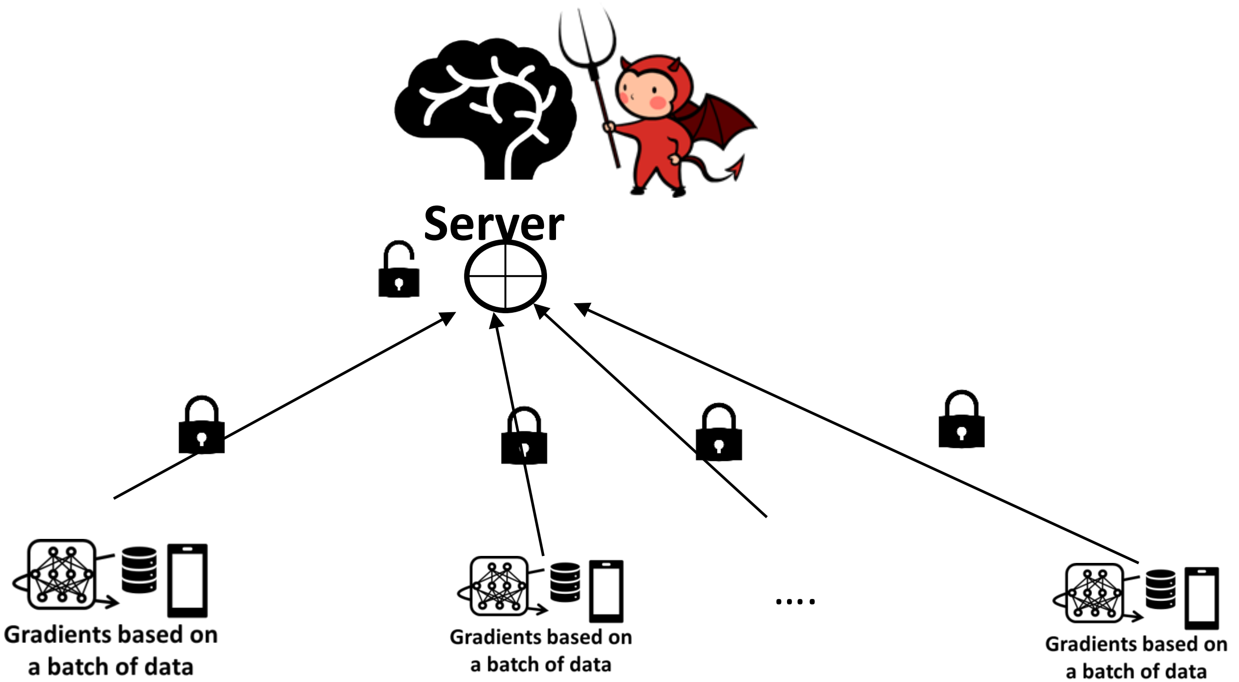
- Keep malicious FL client or server away from raw model updates



https://arxiv.org/abs/2012.06337

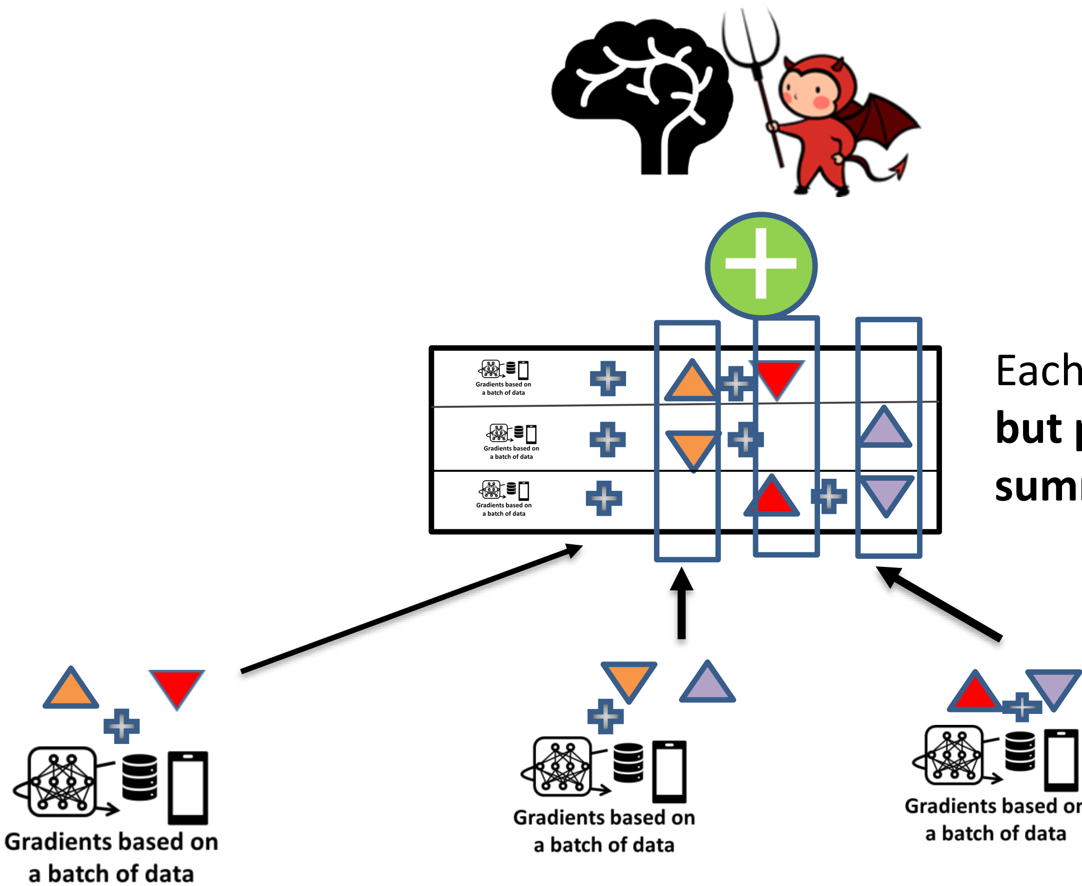
Protecting Model Updates

- Secure Multi-Party Calculation (SMPC)
  - Server aggregates clients' updates,
  - but cannot inspect the individual updates



https://dl.acm.org/doi/10.1145/3133956.3133982

Protecting Model Updates



Each update looks random on its own, **but paired antiparticles cancel out when summed**

Add **antiparticles** (Random positive/negative pairs) before sending to the server.

Protecting Model Updates

- Each client's model update is protected from a malicious server

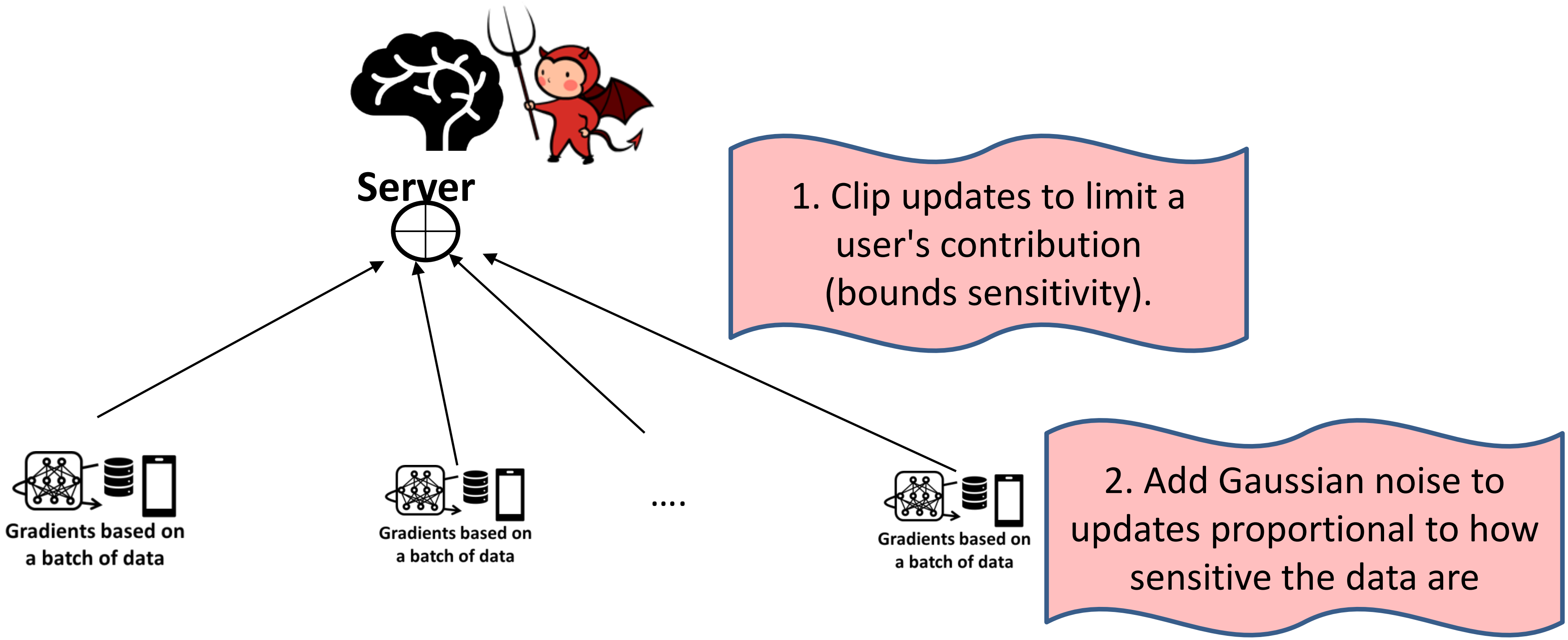
- The aggregated update is NOT protected from malicious clients

Adding Noise to Model Updates

- Differential privacy:
  - the statistical science of trying to learn as much as possible about a group while learning as little as possible about any individual in it.

Adding Noise to Model Updates

- Local differential privacy (LDP)



https://arxiv.org/abs/1712.07557

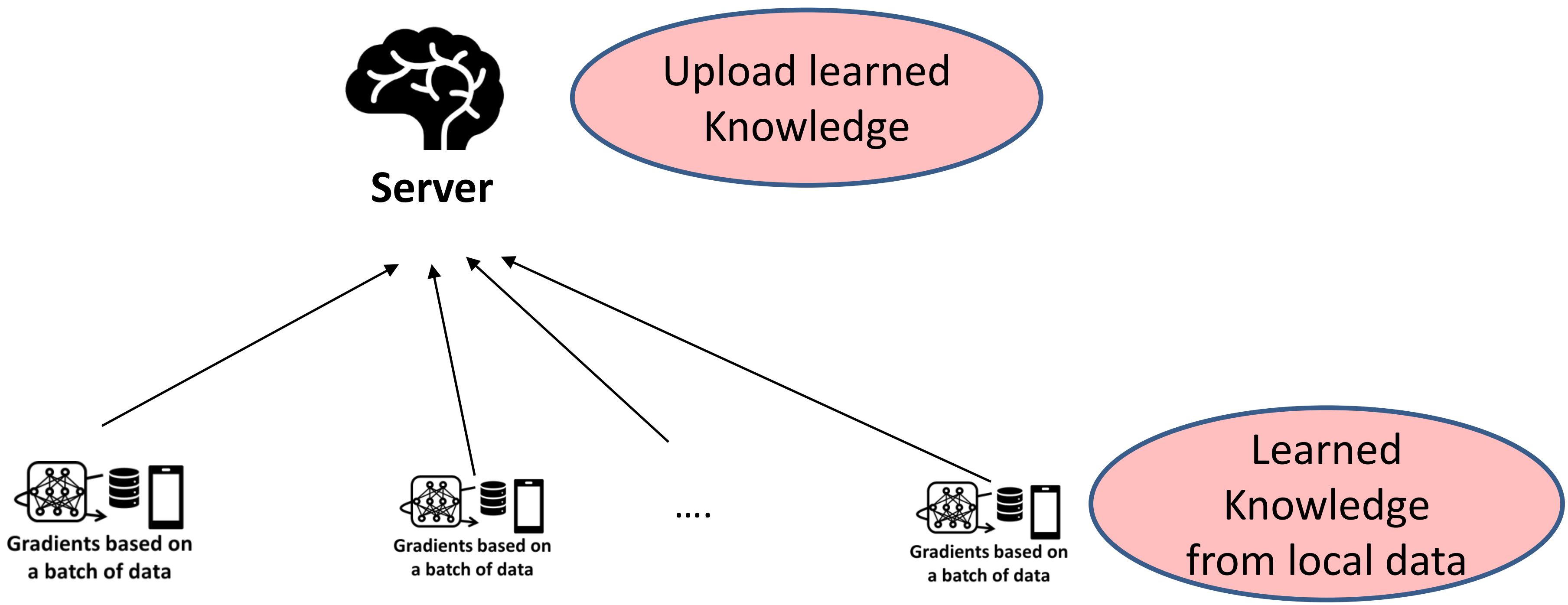
Adding Noise to Model Updates

- Each client's model update is protected from a malicious server
- The aggregated update is also protected from malicious clients
- Protection vs. model performance trade-off must be considered

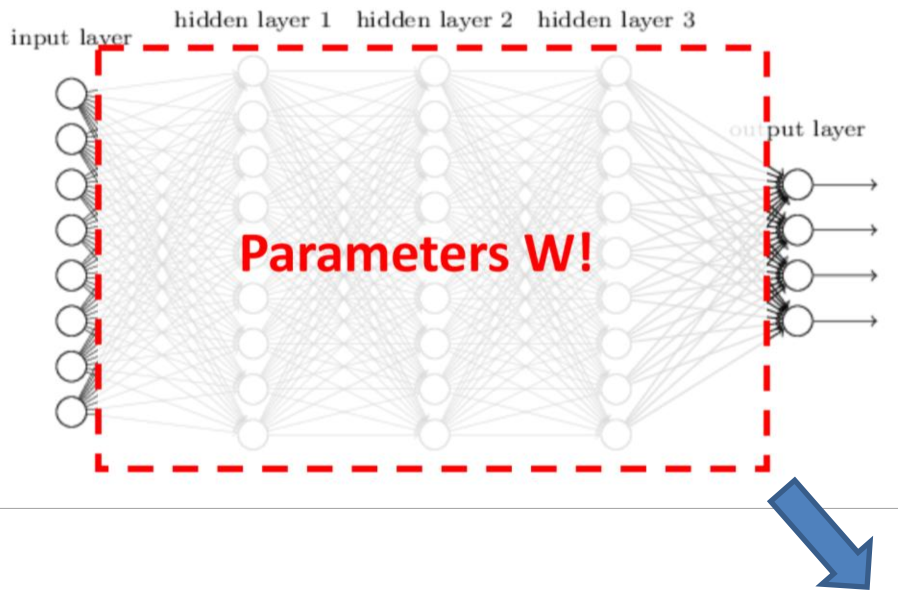
https://arxiv.org/abs/1906.01562

Eliminating Model Updates

- Federated Knowledge Distillation

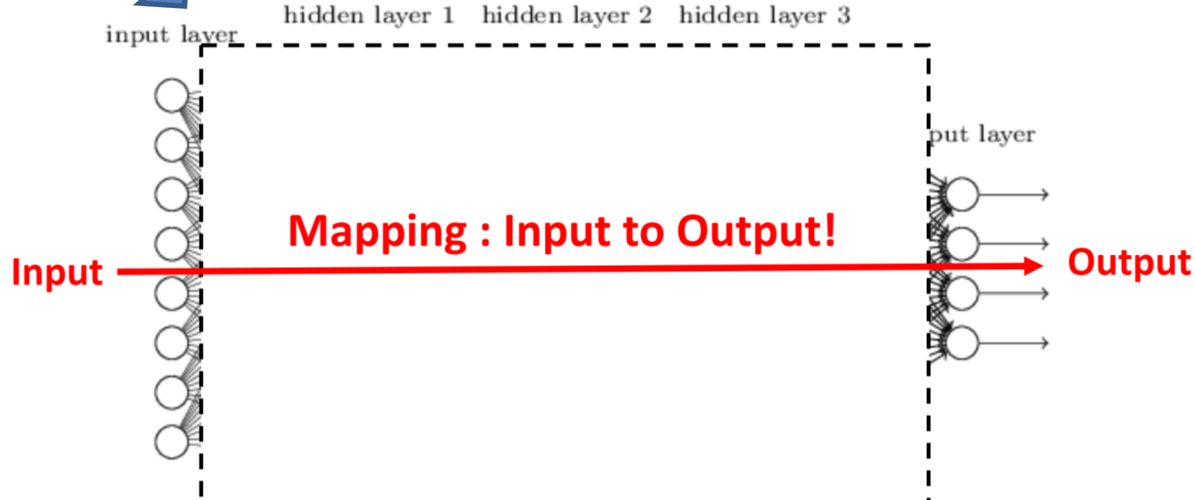


Eliminating Model Updates

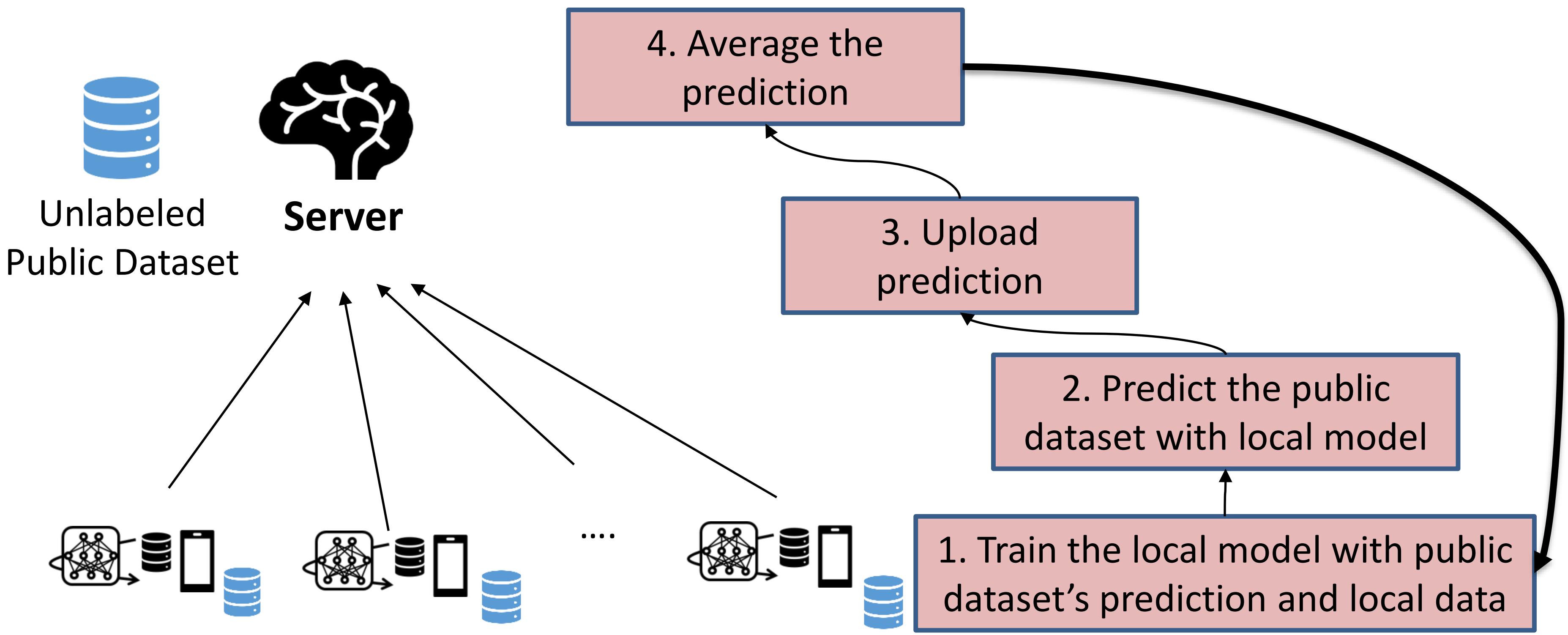


Instead of sending model updates …

Only exchange soft label predictions on a public dataset



Eliminating Model Updates



https://arxiv.org/abs/1912.11279

Eliminating Model Updates

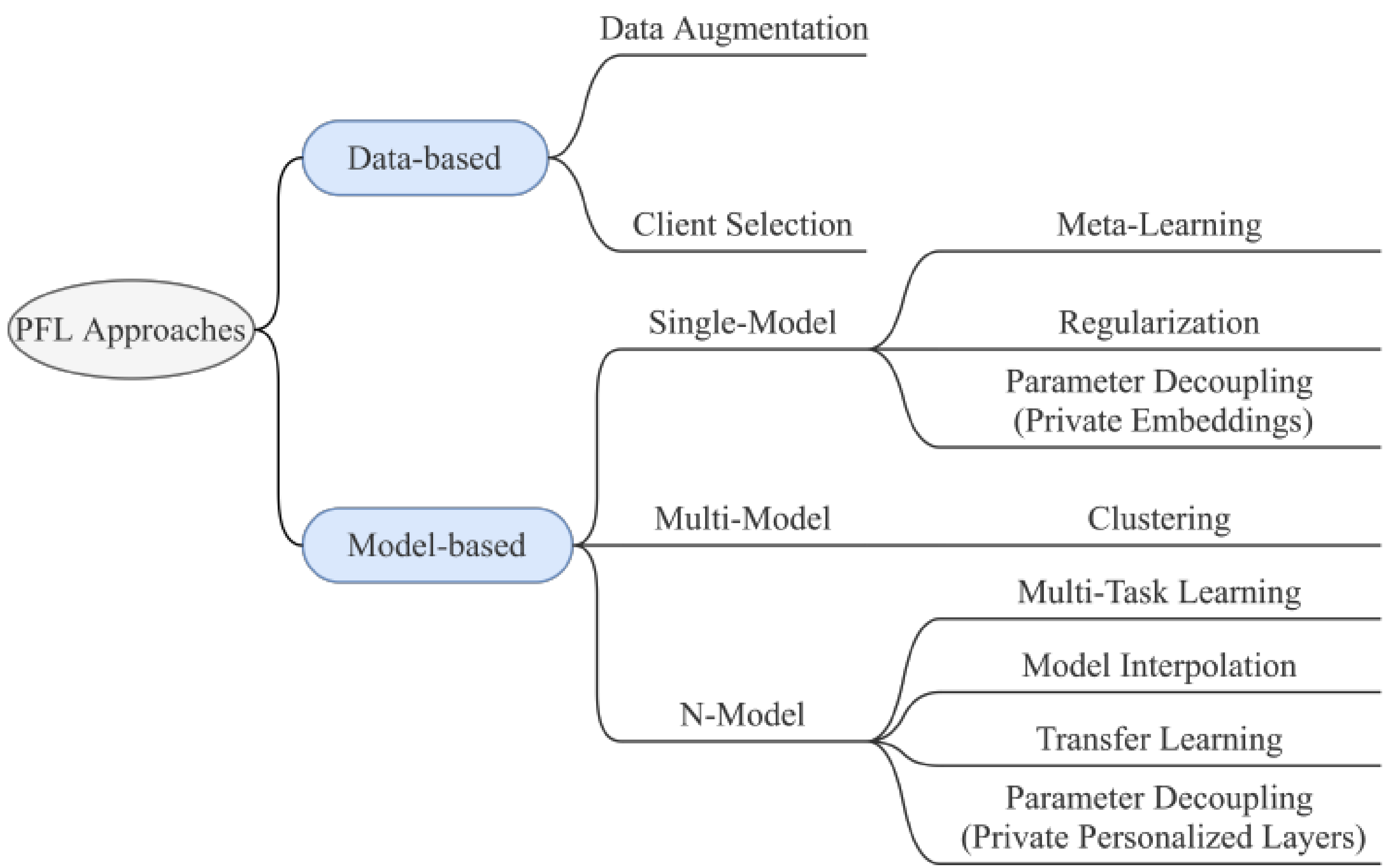
- Each client’s model update is protected from a malicious server

- The aggregated update is also protected from malicious clients

- Slight performance degradation

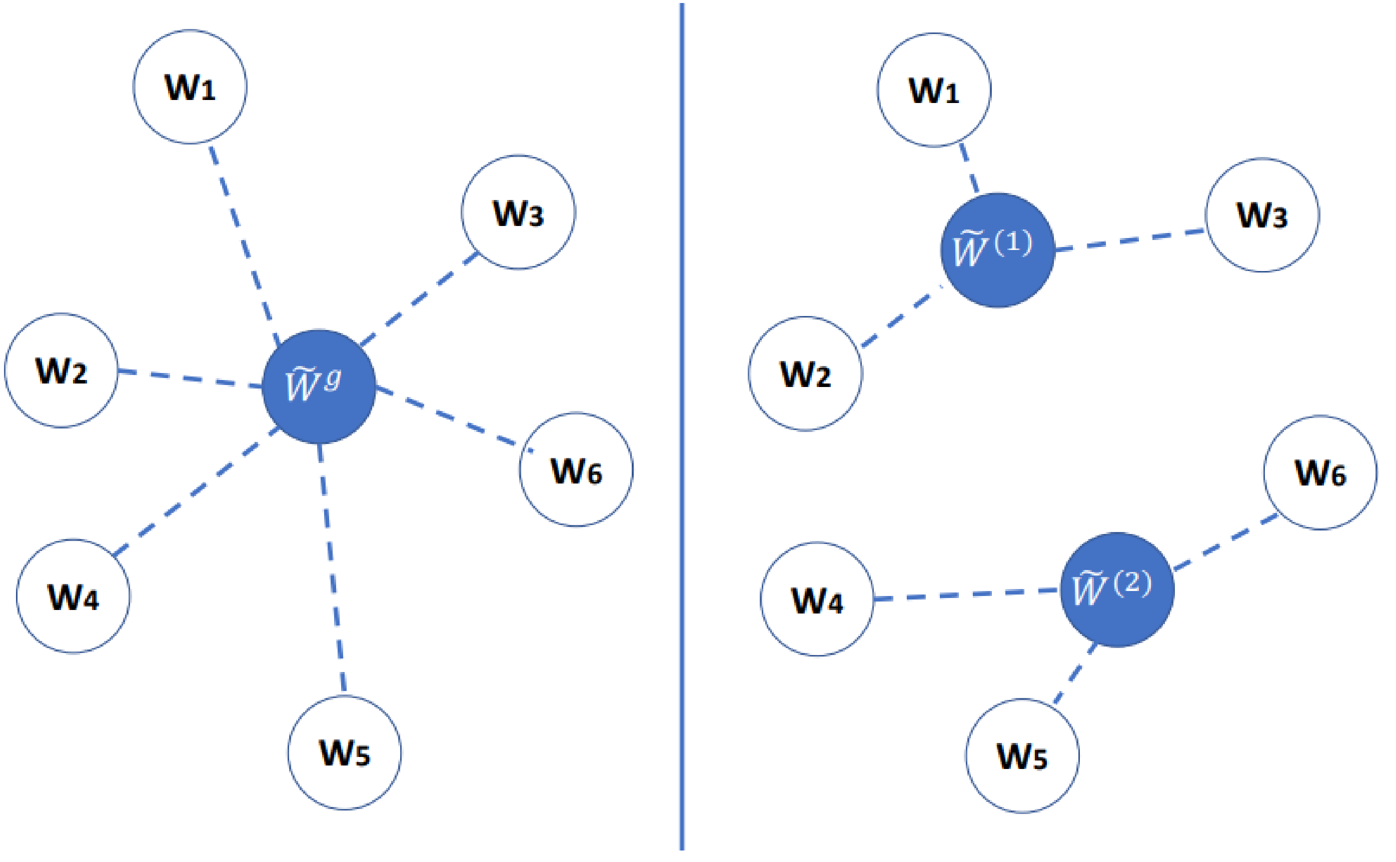
Personalized Federated Learning

Personalized Federated Learning



Source: https://arxiv.org/abs/2103.00710

Data Heterogeneity



Source: https://arxiv.org/abs/2005.01026

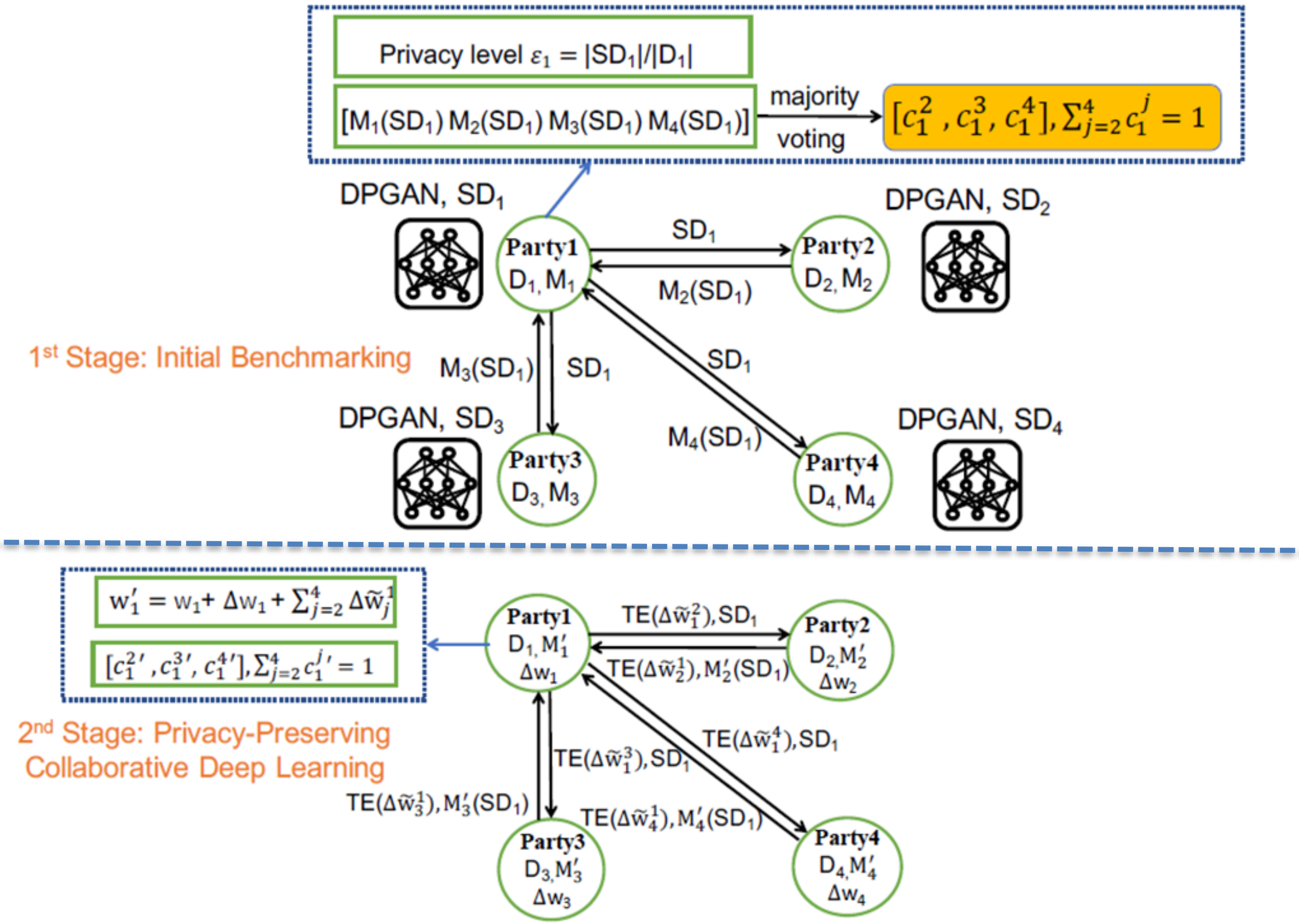
Multi-Center FL

Algorithm 1: FeSEM – Federated Stochastic EM

Initialize K, $\{W_i\}_{i=1}^{m}$, $\{\tilde{W}^{(k)}\}_{k=1}^{K}$
while *stop condition is not satisfied* **do**
  E-Step:
  Calculate distance $d_{ik} \leftarrow \mathrm{Dist}(W_i, \tilde{W}^{(k)})\ \ \forall i, k$
  Update $r_i^{(k)}$ using d_{ik} (Eq. 7)
  M-Step:
  Group devices into C_k using $r_k^{(k)}$
  Update $\tilde{W}^{(k)}$ using $r_i^{(k)}$ and W_i (Eq. 8)
  for *each cluster* $k = 1, \ldots K$ **do**
    for $i \in C_k$ **do**
      Send $\tilde{W}^{(k)}$ to device i
      $W_i \leftarrow$ **Local_update**$(i, \tilde{W}^{(k)})$
    end
  end
end

Federated Stochastic Expectation Maximization (FeSEM)

Model Heterogeneity

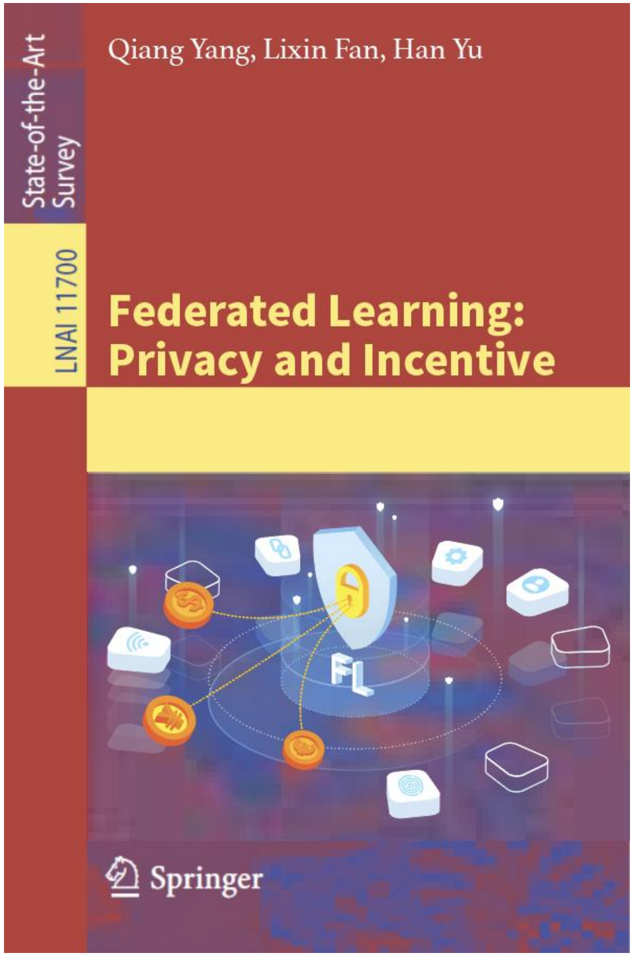


Source: https://ieeexplore.ieee.org/document/9098045

Trust-based Open Collaborative FL

https://youtu.be/d_Z_YmBvmno

Further Reading



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