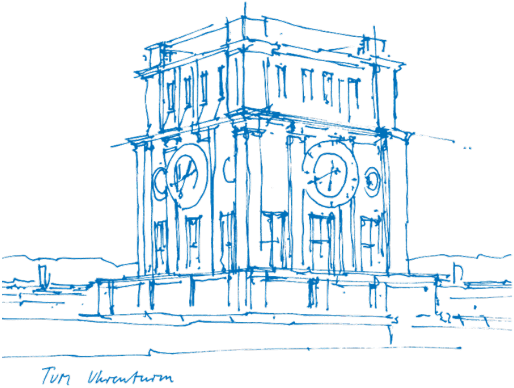
LeadFL

Client Self-Defense against Model Poisoning in Federated Learning

by Chaoyi Zhu, Stefanie Roos, Lydia Y. Chen



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[1]Technical University of Munich

Institute for Communications Engineering

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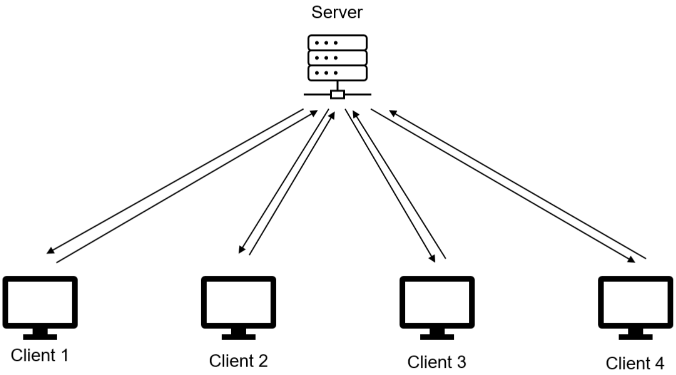
Security in federated learning



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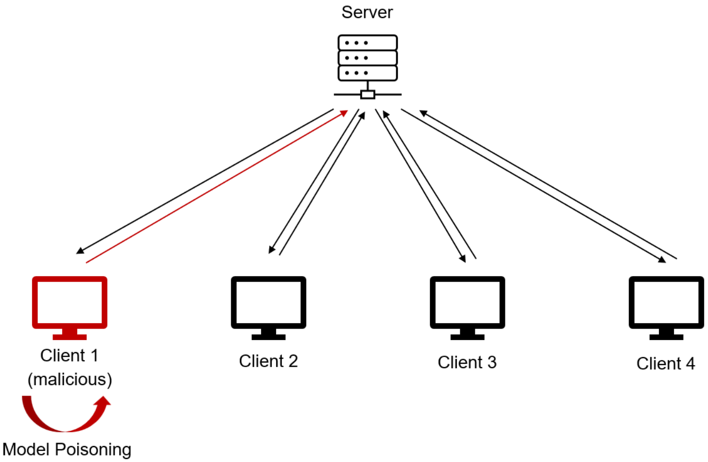

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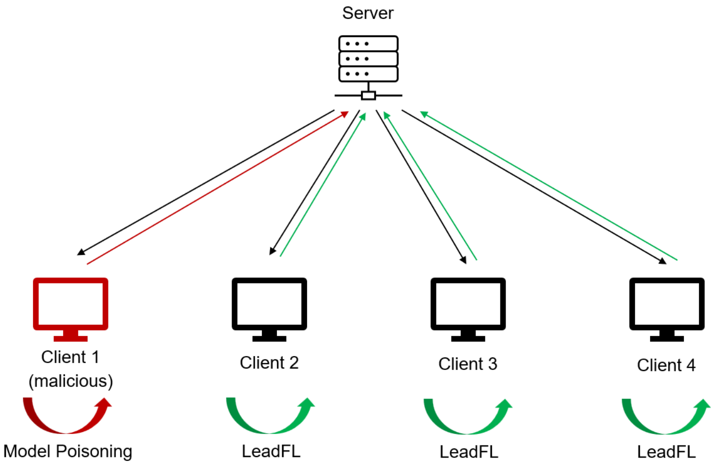

Effects of Model Poisoning Attacks[1]

Definition (Attack Effect on Parameter)

The *Attack Effect on Parameter* in the t-th round is

$$\delta_t := W_t - W_t^{\text{opt}} \tag{1}$$

[1] Sun, J., Li, A., DiValentin, L., Hassanzadeh, A., Chen, Y., & Li, H. (2021). Fl-wbc: Enhancing robustness against model poisoning attacks in federated learning from a client perspective. *Advances in Neural Information Processing Systems, 34*, 12613–12624.

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Theorem (Estimator for the Attack Effect on Parameter)

For malicious devices selected both in round τ_1 and τ_2, we can estimate δ_t for $\tau_1 < t < \tau_2$ with

$$\hat{\delta}_t = \frac{N}{K}\left[\sum_{k \in \mathbb{S}_t} p^k \prod_{i=0}^{I-1}(I - \eta_t H_{t,i}^k)\right]\hat{\delta}_{t-1} \tag{2}$$

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Hessian Matrix Estimation[2]

- Computing H is expensive

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- $H \approx \text{diag}(\nabla L(\theta^k_{t,i+1}) - \nabla L(\theta^k_{t,i}))$

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Overview of LeadFL

$$\hat{\delta}_t = \frac{N}{K}\left[\sum_{k \in \mathbb{S}_t} p^k \prod_{i=0}^{l-1}(I - \eta_t H_{t,i}^k)\right] \hat{\delta}_{t-1}$$

- Minimize $\hat{\delta}_t$

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- Locally minimize $\hat{\delta}_t$
- Add random noise

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- Locally minimize $\hat{\delta}_t$
- Minimize $I - \eta_t \tilde{H}_{t,i}^k$

Definition

Definition (LeadFL Weight Update)

The LeadFL local learning equation is

$$\tilde{\theta}^{k}_{t,i+1} \leftarrow \theta^{k}_{t,i} - \eta_t \nabla L(\theta^{k}_{t,i}) \tag{3}$$

$$\theta^{k}_{t,i+1} \leftarrow \tilde{\theta}^{k}_{t,i+1} - \eta_t \alpha \text{clip}[\nabla(I - \eta_t \tilde{H}^{k}_{t,i}), q] \tag{4}$$

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Hessian Matrix Estimation II[3]

- H is computationally expensive
- $H \approx \text{diag}(H)$
- $H \approx \text{diag}(\nabla L(\theta^k_{t,i+1}) - \nabla L(\theta^k_{t,i}))$
- $H \approx \text{diag}(\tilde{\theta}^k_{t,i+1} - \theta^k_{t,i} - \Delta\theta^k_{t,i})/\eta_t$

[3] LeCun, Y., Denker, J., & Solla, S. (1989). Optimal brain damage. D. Touretzky (Ed.), *Advances in neural information processing systems* (Vol. 2). Morgan-Kaufmann.

LeadFL Algorithm (Client)

For each local round, do:

1. Compute gradients and update intermediary weights

   $\tilde{\theta}^k_{t,i+1} \leftarrow \theta^k_{t,i} - \eta_t \nabla L(\theta^k_{t,i})$

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   $R^k_{t,i} \leftarrow \mathrm{clip}[\nabla(I - \eta_t \tilde{H}^k_{t,i}), q]$

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   $\theta^k_{t,i+1} \leftarrow \tilde{\theta}^k_{t,i+1} - \eta_t \alpha R^k_{t,i}$

Convergence

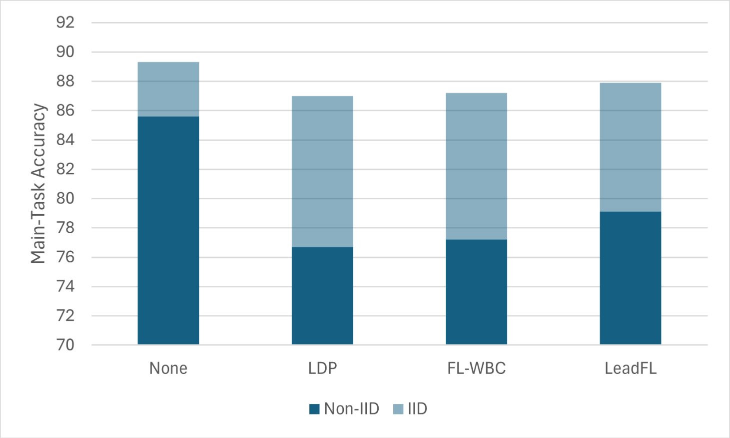

Figure: Main task accuracy of FashionMNIST-IID[4]

[4] Zhu, C., Roos, S., & Chen, L. Y. (2023). Leadfl: Client self-defense against model poisoning in federated learning. A. Krause, E. Brunskill, K. Cho, B. Engelhardt, S. Sabato, & J. Scarlett (Eds.), *Proceedings of the 40th international conference on machine learning* (pp. 43158–43180, Vol. 202). PMLR, Table 1.

Evaluation

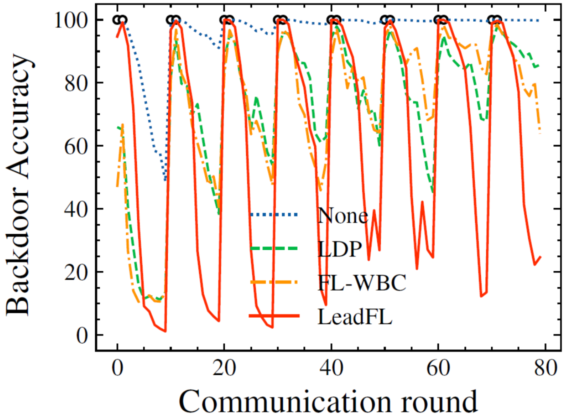

Figure: Backdoor Accuracy of FashionMNIST-IID[5]

[5] Zhu, C., Roos, S., & Chen, L. Y. (2023). Leadfl: Client self-defense against model poisoning in federated learning. A. Krause, E. Brunskill, K. Cho, B. Engelhardt, S. Sabato, & J. Scarlett (Eds.), *Proceedings of the 40th international conference on machine learning* (pp. 43158–43180, Vol. 202). PMLR, Figure 3.

Evaluation

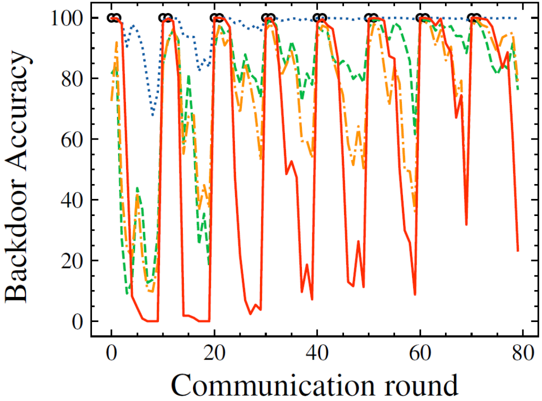

Figure: Backdoor Accuracy of FashionMNIST-Non-IID[5]

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Limitations

- Incomplete explanation of the Hessian matrix estimation.

$$\Delta\theta_{t,i}^{k} = \theta_{t,i}^{k} - \theta_{t,i}^{k}$$

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- Incomplete explanation of the Hessian matrix estimation.
- Differences between the implementation and the paper.
- Unexplained choice of parameters in the evaluation.
  - FashionMNIST: 2 convolutional layers, 1 fully connected layer, $\alpha = 0.4$, $q = 0.2$
  - CIFAR10: 2 convolution, 3 fully connected , $\alpha = 0.25$, $q = 0.2$
  - CIFAR100: ResNet9, $\alpha = 0.15$, $q = 0.2$

Conclusion

+ | -

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+	-
Increased attack recovery	Decreased Main Taks Accuracy

Conclusion

+	-
Increased attack recovery	Decreased Main Taks Accuracy
Compatibility	More Difficult Attack Detection

Conclusion

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Increased attack recovery	Decreased Main Taks Accuracy
Compatibility	More Difficult Attack Detection
Performance	Limited Evaluation

Q & A

$$\theta^k_{t,i+1} \leftarrow \theta^k_{t,i} - \eta_t \nabla L(\theta^k_{t,i}) - \eta_t \alpha \text{clip}[\nabla(I - \eta_t \tilde{H}^k_{t,i}), q]$$

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Hessian Matrix Approximation

Robustness

Evaluation Model Architecture

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