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LeadFL: Client Self-Defense against Model Poisoning in Federated Learning[1]

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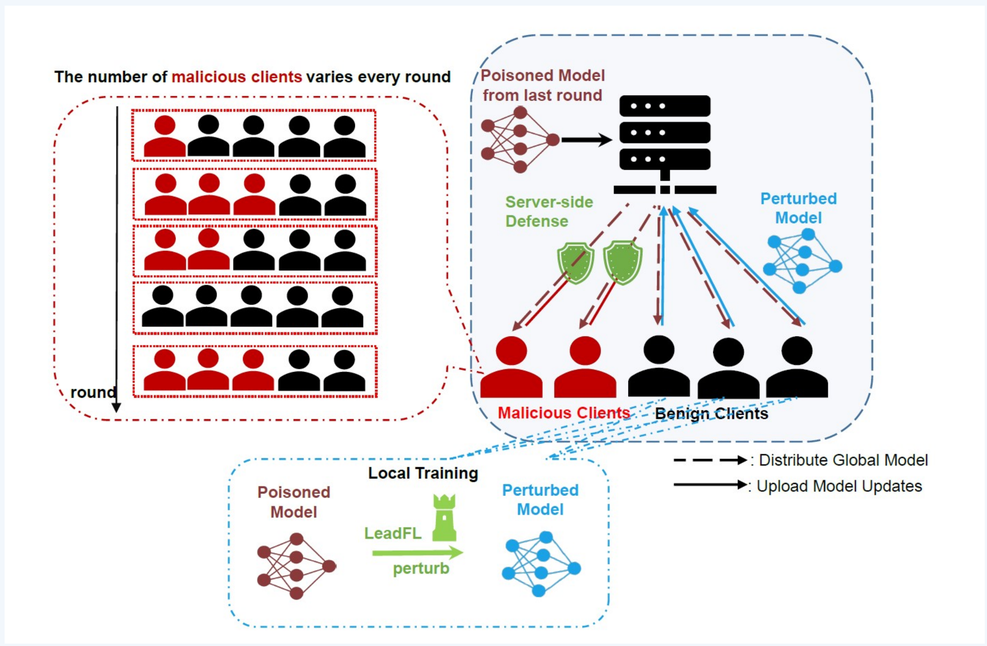
Introduction

Federated Learning (FL) is highly vulnerable to model poisoning attacks, where malicious clients manipulate local data and models without oversight.

- **Bursty adversarial patterns**, characterized by high variance in the number of malicious clients, can effectively bypass current defense mechanisms.
- Although these bursts occur rarely, their effect leaves lingering impacts on the remaining rounds of training. Once the global model is polluted in a single strong attack round, the attack effect persists for many subsequent rounds even without additional attacks—existing server-side defenses cannot eliminate this lingering effect.



Bursty adversarial patterns: Number of malicious clients varies between rounds

- **Why Existing Defenses Fail**, Server-side defenses are designed assuming constant and low number of malicious clients.
- **Previous client-side defense (FL-WBC):**
  - Adds random noise to reduce Hessian sparsity
  - Problem: Uncalibrated noise degrades model accuracy
  - Problem: No theoretical robustness guarantees

Understanding the Attack Effect

Attack Effect on model Parameter[2]: We quantify the impact using the Attack Effect on Parameter (AEP), denoted as δ_t. This metric represents the change in global model parameters accumulated until the t-th round due to attacks conducted by malicious devices.

$$\delta_t \triangleq \boldsymbol{\theta_t} - \boldsymbol{\theta_t^M} \tag{1}$$

Benign global model **Poisoned global model**

Propagation of AEP: When malicious clients attack in rounds τ_1 and τ_2, we estimate the attack effect for the intermediate rounds ($\tau_1 < t < \tau_2$) as follows:

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

Where **Hessian Matrix** is: $H_{t,i}^k \triangleq \nabla^2 L(\theta_{t,i}^k)$

Key Insight: If $\hat{\delta}_{\tau_1}$ resides in the kernel (null space) of $H_{t,i}^k$, then $\hat{\delta}_t = \hat{\delta}_{\tau_1}$, causing the attack effect to persist unchanged.

$$\text{If } H_{t,i}^k \text{ is highly sparse} \Longrightarrow \delta_t \approx \delta_{t-1}$$

Why server-side defenses fail: The propagation of attack effects is determined by $H_{t,i}^k$ during *local client training*, which is inaccessible to the central server.

LeadFL Solution

Core Idea: Perturb the Hessian matrix to minimize the coefficient $(I - \eta_t H_{t,i}^k)$, reducing the lingering attack effect.

- Problem: Computing Hessian Matrix is expensive

Hessian Matrix Approximation[3]:

- **Diagonalization:** We approximate H using only its diagonal elements to reduce complexity:

$$H \approx \text{diag}(H)$$

- **Finite Difference:** The diagonal is estimated via the change in gradients between iterations:

$$H \approx \text{diag}\left(\nabla L(\theta_{t,i+1}^k) - \nabla L(\theta_{t,i}^k)\right)$$

- **Parameter Estimation:** To avoid extra backpropagation, we approximate gradient changes using model weight differences:

$$\tilde{H}_{t,i}^k \approx \frac{\text{diag}(\tilde{\theta}_{t,i+1}^k - \theta_{t,i}^k - \Delta\theta_{t,i}^k)}{\eta_t} \tag{3}$$

Client-Side Defense: We deploy a secondary backpropagation process utilizing a regularization term to minimize the coefficient involved in the propagation of the Attack Effect Parameter (AEP).

Step 1: $\underbrace{\tilde{\theta}_{t,i+1}^k \leftarrow \theta_{t,i}^k - \eta_t \nabla L(\theta_{t,i}^k)}_{\text{Local Training (Standard SGD)}}$

Step 2: $\theta_{t,i+1}^k \leftarrow \tilde{\theta}_{t,i+1}^k - \underbrace{\eta_t \alpha \text{clip}\left[\nabla(I - \eta_t \tilde{H}_{t,i}^k), q\right]}_{\text{Regularization Term}}$

Where $\tilde{\boldsymbol{H}}_{t,i}^k$ denotes the estimated diagonal of the Hessian Matrix, η_t is the learning rate, α represents the regularization rate controlling perturbation magnitude, and clip$(\cdot, q)$ is an element-wise clipping function with threshold q ensuring theoretical convergence.

Evaluation

- Dataset: FashionMNIST
- 100 clients (25% malicious), 10 selected per round
- Attacks: 9-pixel backdoor (Periodic burtsy attacks)
- Server side defense: Bulyan
- Client Side: No defense, FL-WBC, LDP, Original LeadFL, Our LeadFL

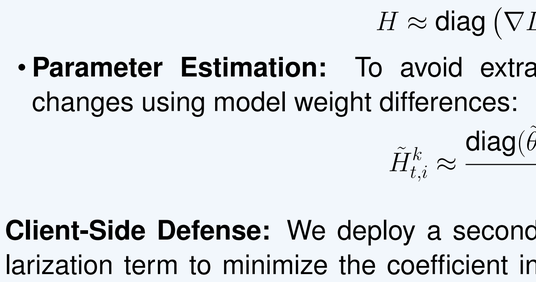


Fig 1: FashionMNIST IID

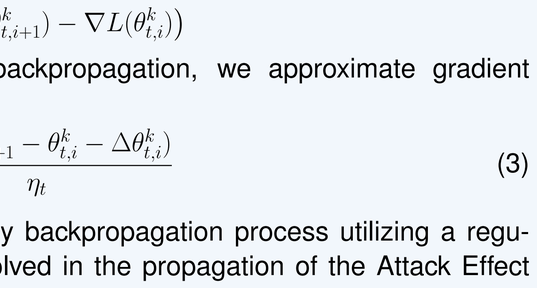


Fig 2: FashionMNIST non-IID

	IID					Non-IID				
	None	**LDP**	**Our LeadFL**	**Original LeadFL**	**WBC**	**None**	**LDP**	**Our LeadFL**	**Original LeadFL**	**WBC**
MA	88.8	85.0	72.9	86.9	85.8	60.6	74.3	38.1	73.0	65.0
BA Avg	95.5	73.1	29.4	62.2	70.8	97.2	76.8	25.6	54.3	68.0
BA Final	99.9	56.4	14.4	11.6	58.4	99.2	67.6	2.7	18.8	45.6

Table 1: Comparison of client-side defenses under 9-pixel pattern backdoor attack

Fig 1: FashionMNIST IID

Conclusion

LeadFL provides a principled client-side defense against model poisoning in federated learning by:

- Optimally perturbing local Hessian matrices to reduce attack persistence
- Offering provable convergence and robustness guarantees
- Outperforming existing defenses against bursty attack patterns

References

[1] Zhu, C., Roos, S., & Chen, L. Y. (2023). LeadFL: Client Self-Defense against Model Poisoning in Federated Learning. *ICML 2023*.

[2] Sun, J., et al. (2021). FL-WBC: Enhancing Robustness Against Model Poisoning Attacks in Federated Learning from a Client Perspective. *NeurIPS 2021*.

[3] LeCun, Y., Denker, J. S., & Solla, S. A. (1990). Optimal Brain Damage. *Advances in Neural Information Processing Systems 2 (NIPS 1989)*, 598-605.