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# What if the attackers are inside?

## A Systematic Analysis of Label-flipping Attacks against Federated Learning for Intrusion Detection

**Léo Lavaur**[1], Yann Busnel[2], and Fabien Autrel[1]
[1] IMT Atlantique, [2] IMT Nord Europe

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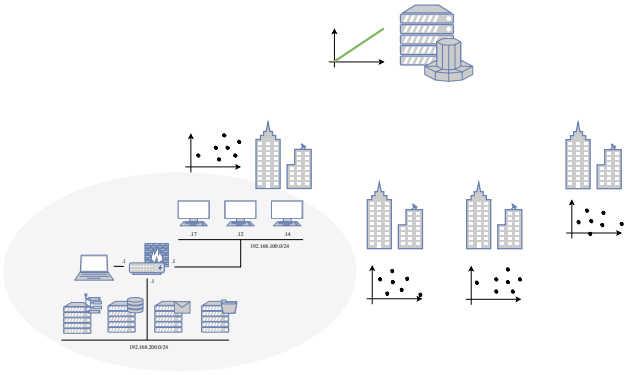
Figure: Typical NIDS workflow.

- Great performance with Deep Learning (DL) (on public datasets at least)
- **Limitations**: lack of labelled data, risk of local bias or skewed data distribution, inefficient against new attacks.

- Federated Learning (FL) is a distributed Machine Learning (ML) paradigm [1].
- Participants train a global model without sharing local data.



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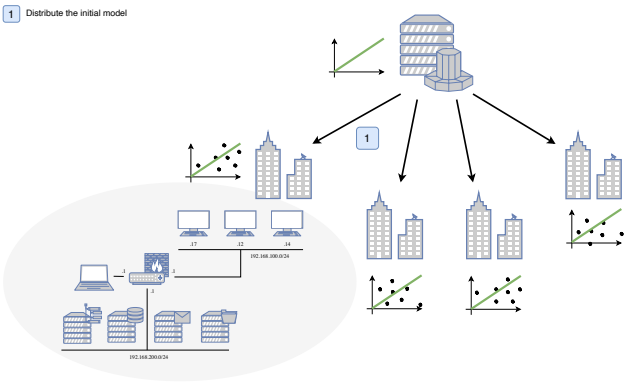

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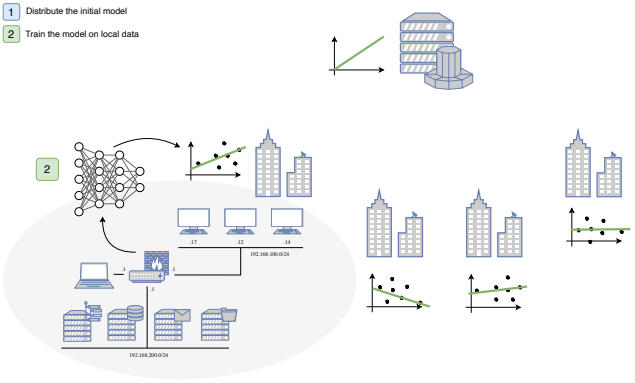

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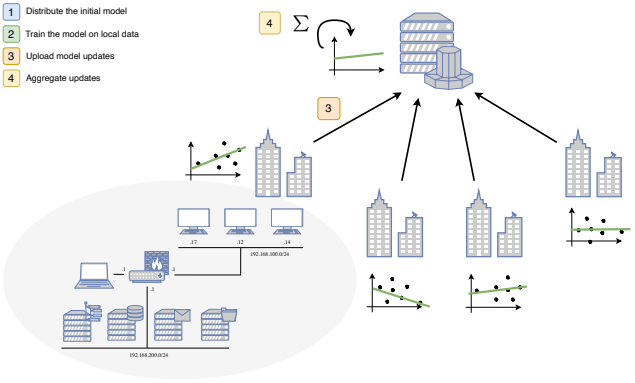

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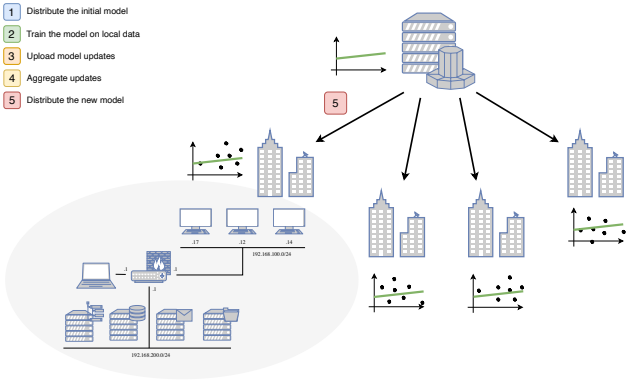
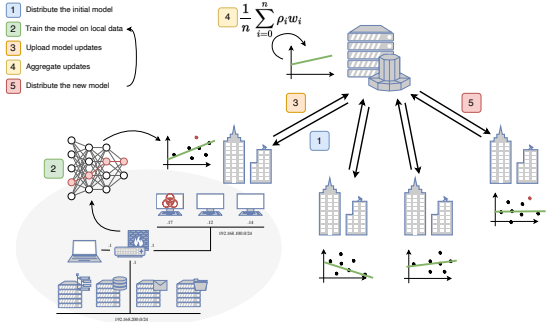


# Federated Intrusion Detection System (FIDS)

FL can be used in Collaborative Intrusion Detection System (CIDS) [2]:

- Extend the training data with Horizontal Federated Learning (HFL)
  - → Reduce the risk of local bias



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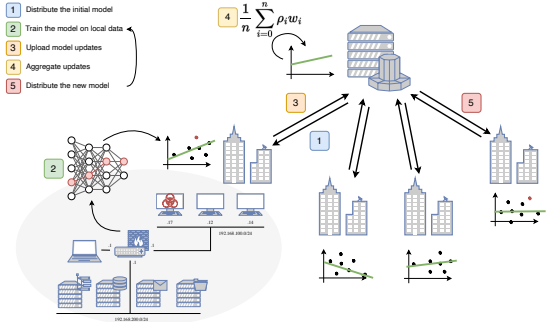
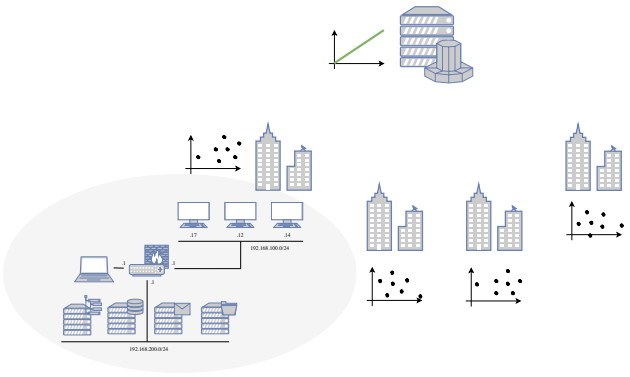
FL can be used in Collaborative Intrusion Detection System (CIDS) [2]:

- Extend the training data with Horizontal Federated Learning (HFL)
  - → Reduce the risk of local bias
- Effectively share knowledge (*e.g.*, on specific classes, instances) between participants
  - → Share the knowledge about a new attack [3];
  - → Improve the characterization of specific devices; ...



# FL against malicious contributions

- FL is highly susceptible to poisoning [4].



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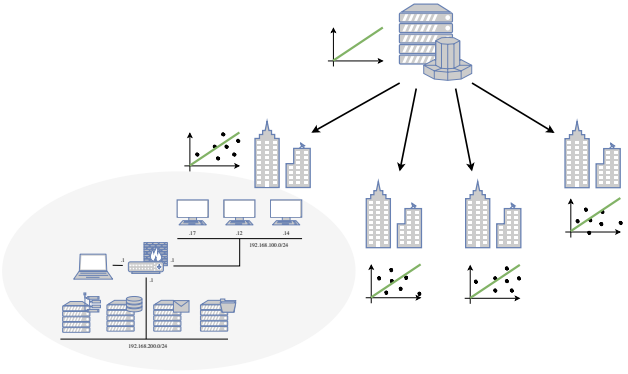

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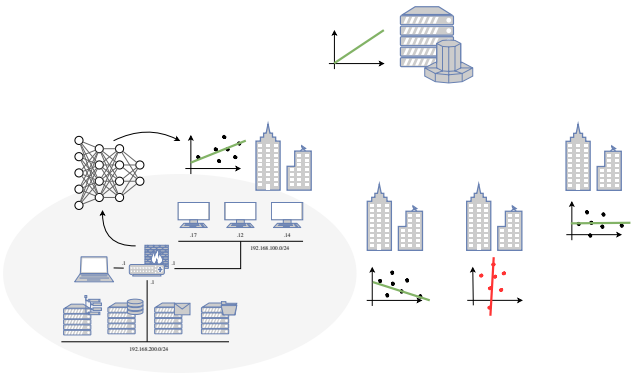

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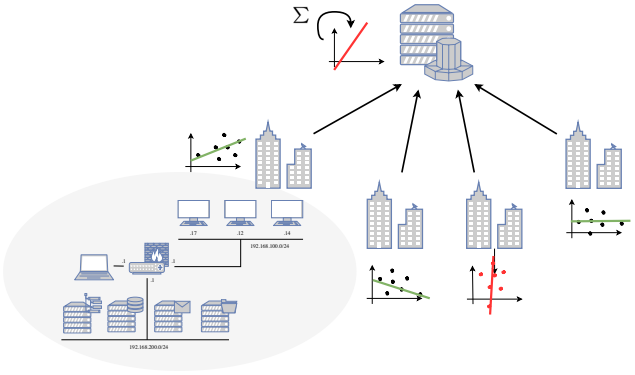

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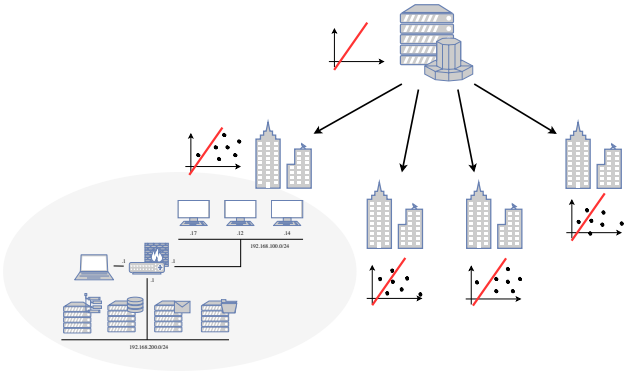
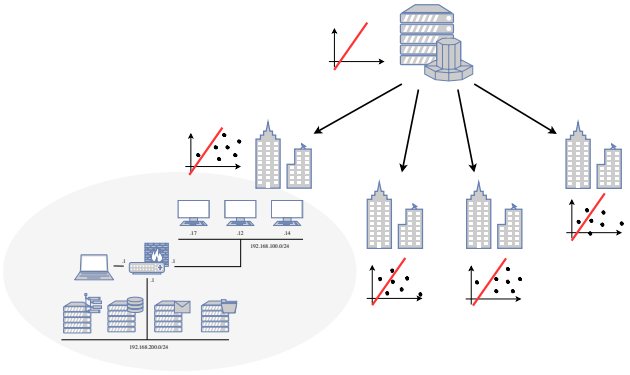


# FL against malicious contributions

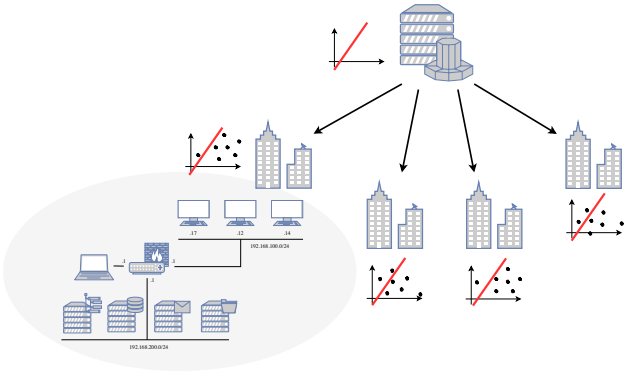
- FL is highly susceptible to poisoning [4].
- Lots of existing countermeasures [5]–[7] in FIDS already...



# FL against malicious contributions



- FL is highly susceptible to poisoning [4].
- Lots of existing countermeasures [5]–[7] in FIDS already...
- Yet, their impact is difficult to estimate.
  - Few studies in the FIDS context, often partial.
  - Nothing on aggregated classes.



# Types of poisoning attacks



- By component:
  - Data poisoning (*e.g.*, label-flipping, clean-label attacks, backdoors)
  - Model poisoning (*e.g.*, gradient boosting, noising)
- By target:
  - Untargeted: affect the model's global performance
  - Targeted: modify its behavior on specific classes or instances
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  - one-shot: attacks are performed once
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**Our work**

Continuous label-flipping attacks in collaborative Intrusion Detection System (IDS) context.

# OUTLINE

1. Methodology and Research Questions

2. Experimental setup

3. Results

4. Conclusion

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  - Either done by the client itself or by an external attacker.

# Threat model



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- An attacker can poison any proportion of its local data
  - Data Poisoning Rate (DPR): $(\alpha) \rightarrow$ proportion of flipped samples.
- Multiple attackers can collude to perform the attack.
  - Model Poisoning Rate (MPR): $(\tau) \rightarrow$ proportion of attackers.

- Research questions (RQ):
  - RQ1. Is the behavior of poisoning attacks predictable?
  - RQ2. Are there beneficial or harmful combinations of hyperparameter under poisoning attacks?
  - RQ3. Can FL heal itself from poisoning attacks?
  - RQ4. Are IDS backdoors realistic using label-flipping attacks?
  - RQ5. Is there a critical threshold where label-flipping attacks begin to impact performance?

# Evaluation framework

Experiment orchestration using `Eiffel` [3].

- `Flower` simulation framework [8] for FL.
- `Hydra` [9] for experiment generation and configuration.
- Custom-made poisoning engine with different attack strategies.
- Nix [10] and Poetry to fix system and Python dependencies, enabling reproducibility.

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Table: Experimental parameters.

| Parameter | Values | Description |
|---|---|---|
| *batch_size* | 32, 128, **512** | Batch size ($\beta$) |
| *epochs* | **100_10x10**, 100_4x25, 100_1x100, 300_10x30, 300_4x75, 300_1x300 | Local epochs per round ($\mathcal{E}$) |
| *distribution* | 10-0, 9-1, 7-3, **5-5**, 3-7 | Proportion of attackers ($\tau$) |
| *scenario* | continuous-{10,30,60,70,80,90,95,99}, **continuous-100**, late-3, redemption-3 | Poisoning rate per round ($\alpha$) |
| *target* | **untargeted**, bot, dos, ddos, bruteforce, infiltration, injection | Attack type and target |
| *seed* | 1313, 1977, 327, 5555, 501, 421, 3263827, 2187, 1138, 6567 | Seed for PRNG |

494 experiments $\times$ 10 seeds $\rightarrow$ 685 hours of computation.

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# Dataset

- Used dataset: sampled NF-V2 version of CSE-CIC-IDS2018
  - ports and IP addresses are removed
- Same class distribution in the training and testing sets
  - 80% of the dataset is used for training
  - 20% of the dataset is used for testing

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- Same class distribution in the training and testing sets
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  - 20% of the dataset is used for testing
- We ensure the representativity of the dataset sampling

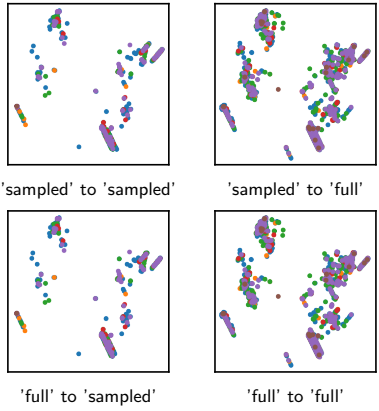


Figure: Cross-projection of the malicious traffic from two datasets in two dimensions using PCA.

# Experimental setup

- A simple multilayer perceptron (MLP) model with two hidden layers is used
- Baseline (centralized training)
  - F1-score: 0.966
  - Accuracy: 0.992
- FL setup
  - Cross-silo setting: all clients are available at each round
  - The dataset is partitioned into 10 Independent and Identically Distributed (IID) shards of 80,000 data points
  - Models are aggregated using `FedAvg`

**Absolute Attack Success Rate (AASR)**

- Targeted attacks $\rightarrow$ miss rate on the targeted class:

$$\frac{\mathsf{FN}_{\mathsf{class}}}{\mathsf{TP}_{\mathsf{class}} + \mathsf{FN}_{\mathsf{class}}}$$

- Untargeted attacks $\rightarrow$ misclassification rate:

$$1 - \text{accuracy}$$

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$$1 - \mathrm{accuracy}$$

**Relative Attack Success Rate (RASR)**

- ASR relative to the benign scenario:

$$\frac{\max(\mathrm{AASR}_{\mathrm{benign}}, \mathrm{AASR}_{\mathrm{attack}}) - \mathrm{AASR}_{\mathrm{benign}}}{1 - \mathrm{AASR}_{\mathrm{benign}}}$$

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# RQ1: Is the behavior of poisoning attacks predictable?

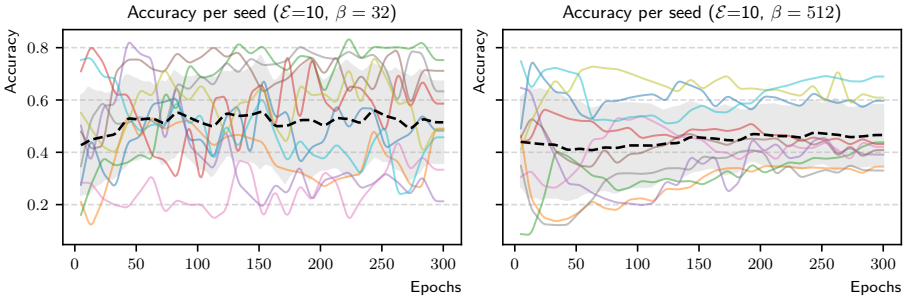


Figure: Accuracy of the poisoned model by seed.

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Short answer:

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Short answer: Nope.

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Short answer: Nope.

Long answer:

- Very high variance in the results
- The impact of the attack is highly dependent on the seed
  - → Initial parameters, data shuffling, ...
- Results tend to stabilize after a few rounds on different values

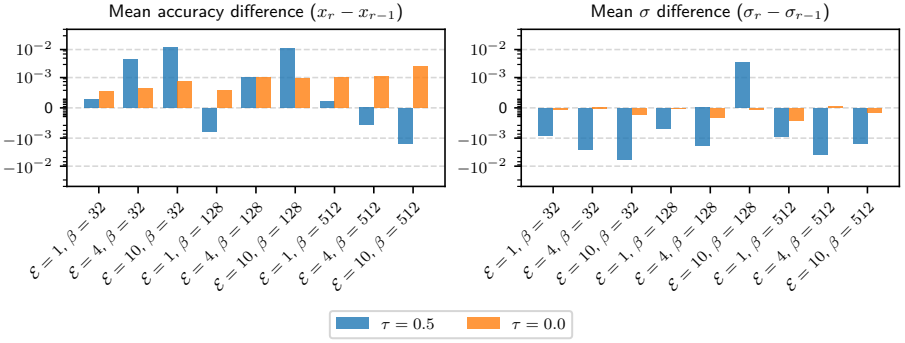


Figure: Effect of the hyperparameters on the accuracy of the poisoned model.

# RQ2: Do hyperparameters influence the effect of poisoning attacks? 20

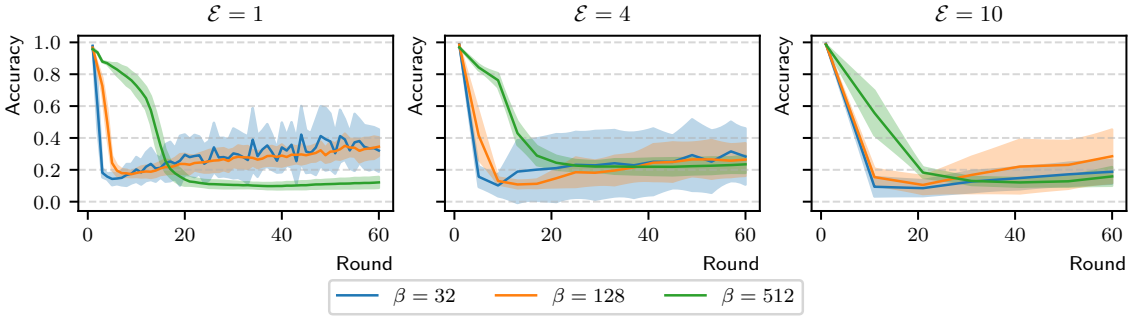


Figure: Effect of the hyperparameters on the accuracy of the poisoned model in the `late` scenario.

# RQ2: Do hyperparameters influence the effect of poisoning attacks? 21

Answer:

- No impact on the average performance
- Significant impact on the variance of the results
- High batch size leads to more inertia
  - The impact is less instantaneous

# RQ4: Are IDS backdoors realistic using label-flipping attacks?

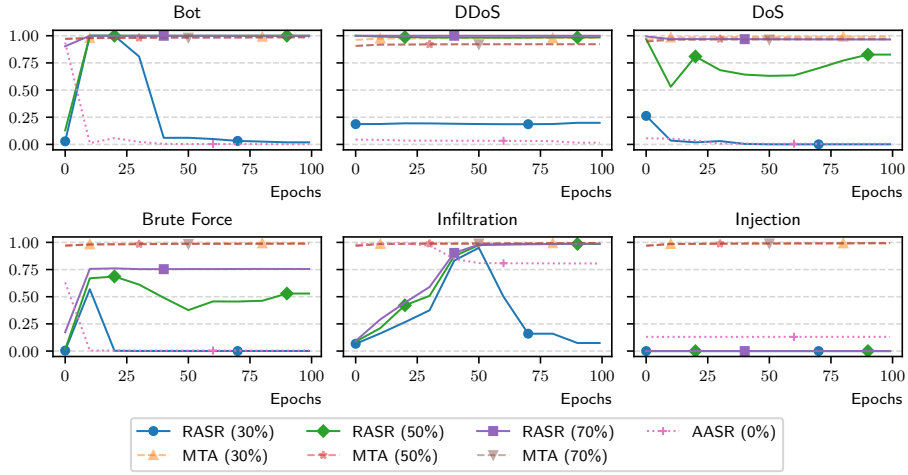


Figure: Backdoor success rate.

# RQ4: Are IDS backdoors realistic using label-flipping attacks?



Answer:

- Yes, but...

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Answer:

- Yes, but...
- The model's generalization capabilities can mitigate the impact
  - especially with characteristic overlaps between classes
- The attack's effectiveness is highly dependent on the target
- We need a significant number of attackers.

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# Conclusion

We build a reproducible framework to study the impact of label-flipping attacks in FIDS using FL, here are our main findings (yet):

- Label-flipping can be effective with enough attackers.
- Targeted label-flipping strives on well-detected targets.
  - but can be significantly mitigated by the model's generalization capabilities and the use of aggregated classes.
- Mitigation strategies must be adapted to the use case specificities (e.g., constrained environments).

→ *more detailed results in the paper*

# Future Work

- Extend the study to other datasets.
- Study the impact of the data distribution on the ability to detect attacks using similarity metrics.
- Build more appropriate metrics for the evaluation of poisoning attacks in Non Independent and Identically Distributed (NIID) settings.
- Extend to other feature sets and poisoning attacks.

# Future Work



- Extend the study to other datasets. [DONE]
- Study the impact of the data distribution on the ability to detect attacks using similarity metrics. [DONE]
- Build more appropriate metrics for the evaluation of poisoning attacks in NIID settings.
- Extend to other feature sets and poisoning attacks.
  - Our evaluation framework is generic enough (and open source!) to make extending the results easy.

# References I



[1] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*, A. Singh and J. Zhu, Eds., ser. Proceedings of Machine Learning Research, vol. 54, PMLR, Apr. 20–22, 2017, pp. 1273–1282. [Online]. Available: https://proceedings.mlr.press/v54/mcmahan17a.html.

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# Thank you!

- Consider the use case when designing mitigations.
- Expect the unexpected: the behavior of poisoning attacks is unpredictable.
- Try it yourself! Our work is *reproducible* and everything is in *open-access*!

Paper

Results

Evaluation framework

Any questions?

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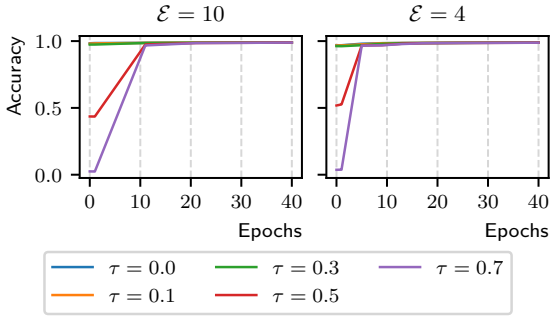


Figure: Recovery of the model after a poisoning attack.

# RQ5: Is there a critical threshold for label-flipping to be effective?



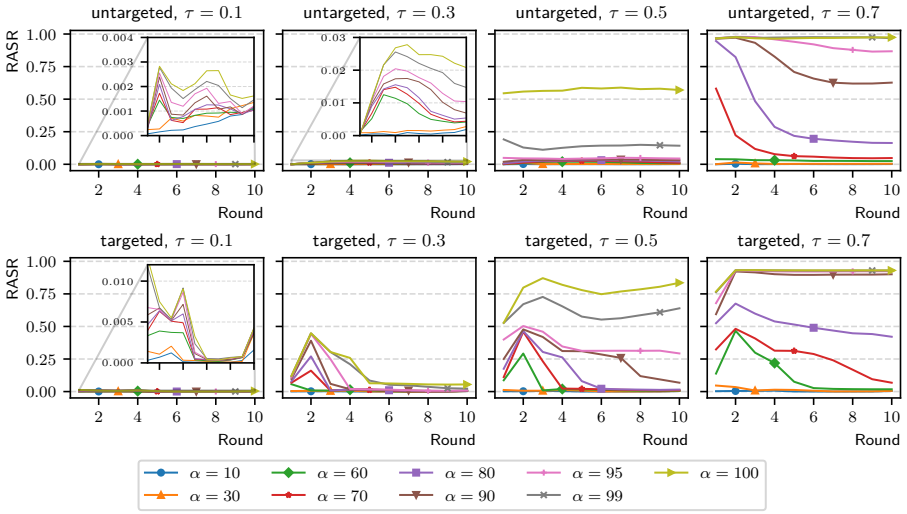


Figure: Impact of $\tau$ and $\alpha$ on the attack's effectiveness.