RUHR-UNIVERSITÄT BOCHUM

INTRO TO FL (SECURITY)

Prof. Dr. Ghassan Karame / M. Sc. Pascal Zimmer / M. Sc. Simon Lachnit

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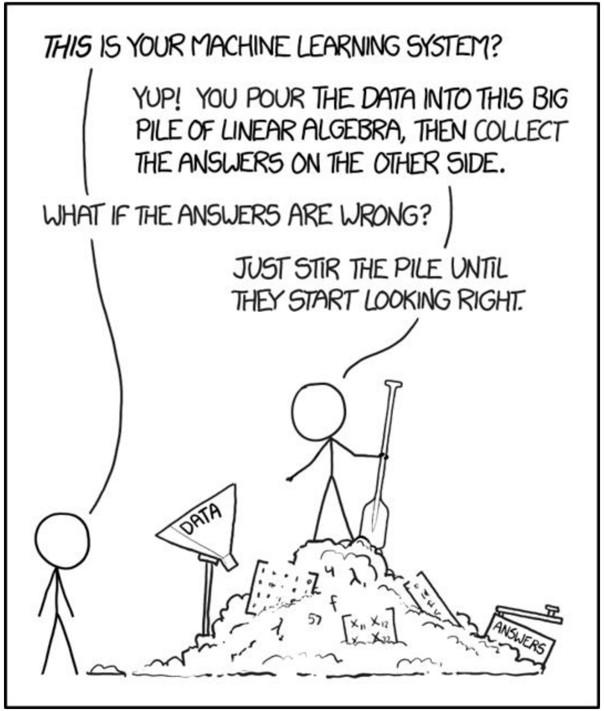
Recap: Traditional ML

(Supervised) Machine Learning 101:

1. Take a huge amount of labeled *data*
2. Use a flexible *model*
3. Invest a lot of computing power to
    1. Create predictions on the data
    2. Compute the *loss*, i.e., the difference between ground-truth labels and predicted labels
    3. Use backpropagation to update the model to make better predictions



Limitations of Traditional ML

- **Several breakthroughs in the past few years**
- **Mostly due to the capabilities to train on huge amounts of data and the availability of that data**
- **Problems:**
  - GDPR, CCPA, Privacy Act, …
  - Collection of data not always possible

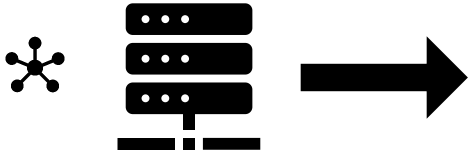
Credit: OpenAI

Credit: tesla.com

Meet Federated Learning

If we cannot move the data to the model, let's move the model to the data!

In each epoch:



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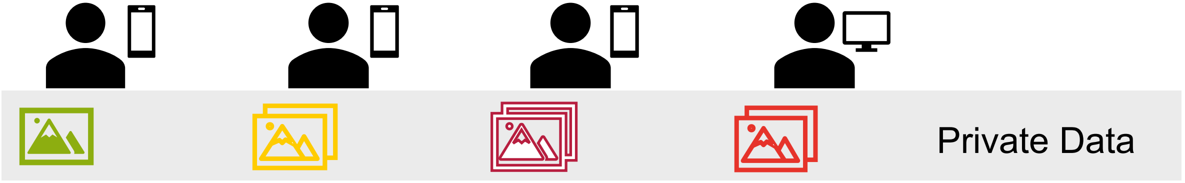

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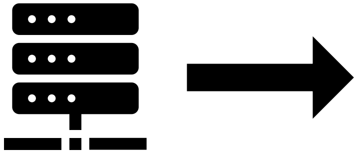

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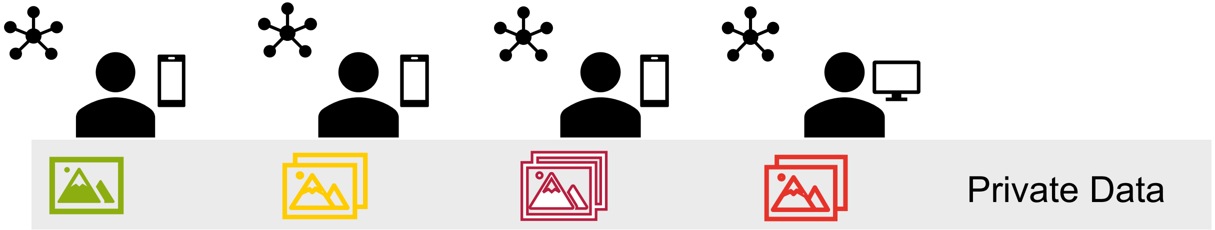

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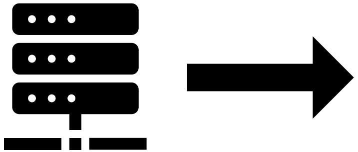

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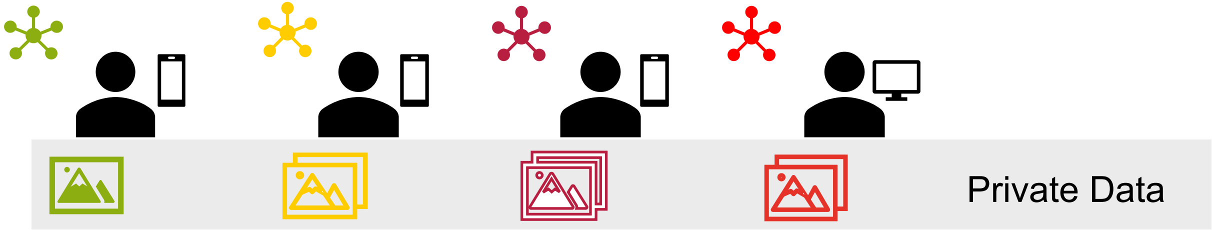

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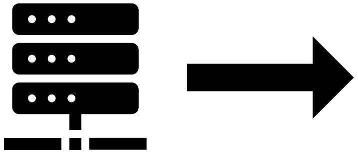

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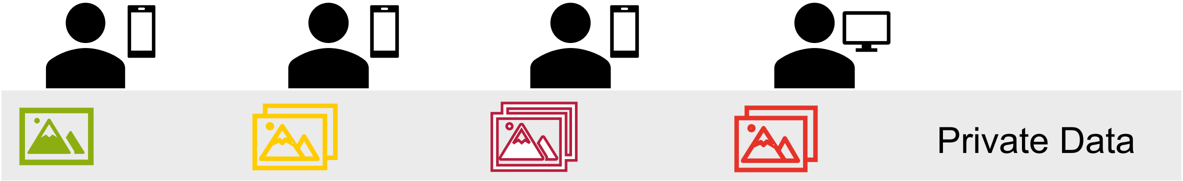

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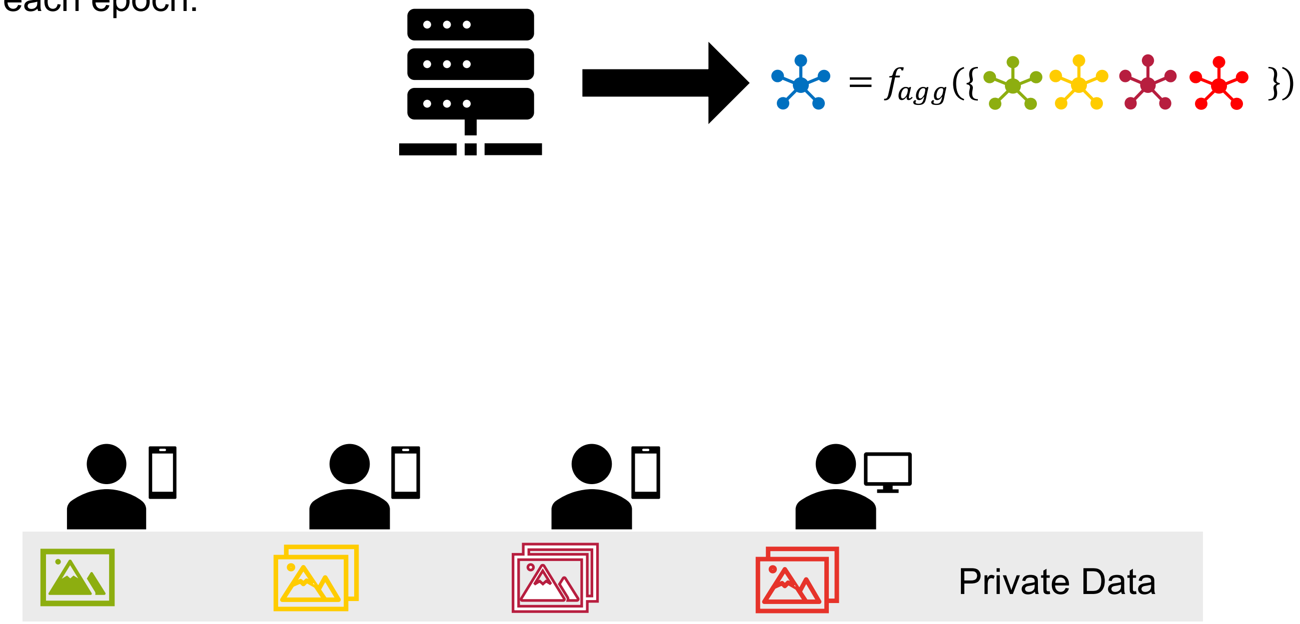

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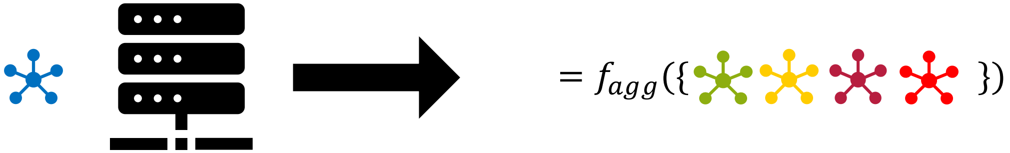

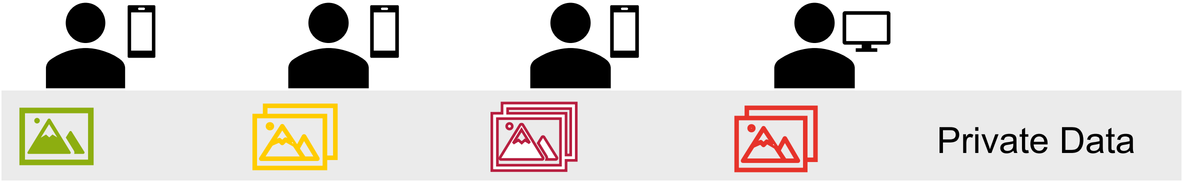

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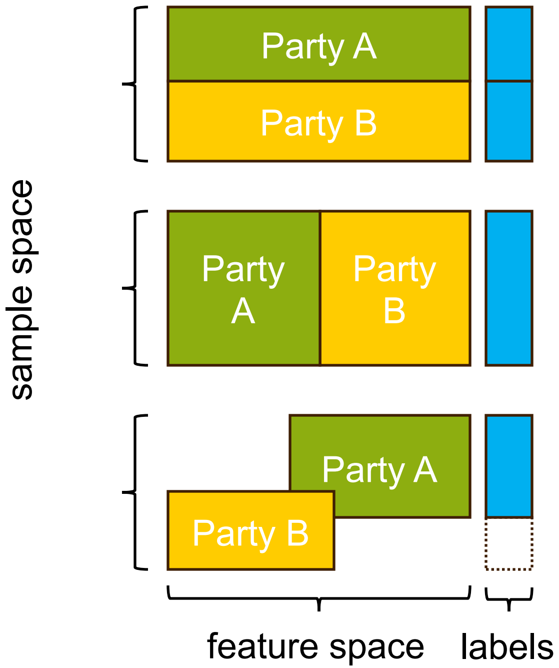
Meet Federated Learning – Some Basics

Types of Federated Learning:



Applications of (horizontal) Federated Learning:

- **Useful if: (McMahan et al., AISTATS, 2017)**
  - Labels on the data can be inferred naturally
  - Data is privacy sensitive and / or large in size
- **Examples:**
  - Next word prediction in smart keyboards (Apple, Google)
  - Siri's keyword recognition

Meet Federated Learning – Some Notation

- **A central server $\boldsymbol{S}$ coordinates $\boldsymbol{N}$ clients with private datasets $\boldsymbol{D_1, D_2, \ldots, D_N}$ to train a global model with parameters $\boldsymbol{\theta}$**

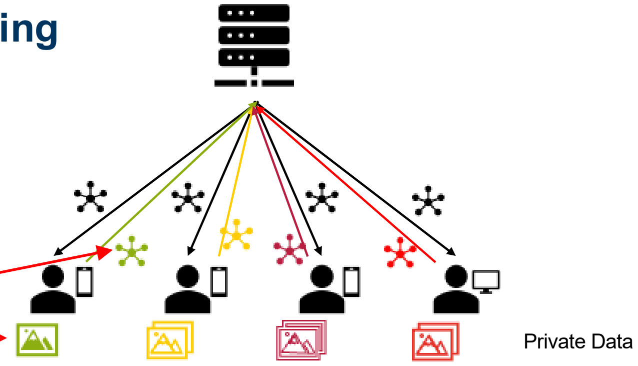
- **In each round $\boldsymbol{t}$:**

  - Select $\mathrm{M} < N$ clients for training
  - Send the current global model θ^t to each client
  - Each client trains on its local dataset to obtain a local model with parameters θ_i^{t+1} and sends it back to the server
  - The server aggregates all local updates to obtain a new global model using some aggregation rule: $\theta^{t+1} = f_{agg}(\{\theta_1^{t+1}, \theta_2^{t+1}, \ldots, \theta_M^{t+1}\})$
    - Most popular aggregation rule: FedAvg (McMahan et al., AISTATS, 2017)

$$\theta^{t+1} = \sum_{i=1}^{M} \frac{|D_i|}{\sum_{i=1}^{M} |D_i|} \theta_i^{t+1}$$

What could possibly go wrong…

- **As the training takes place on users' devices, we are giving part of the control about the training process to users**
  - As N may be in the orders of millions, it is impossible to guarantee benign clients!
- **Attack vectors:** (Shejwalkar et al., S&P, 2022)
  - (Data Poisoning)
  - Model Poisoning



Credit: imgflip.com

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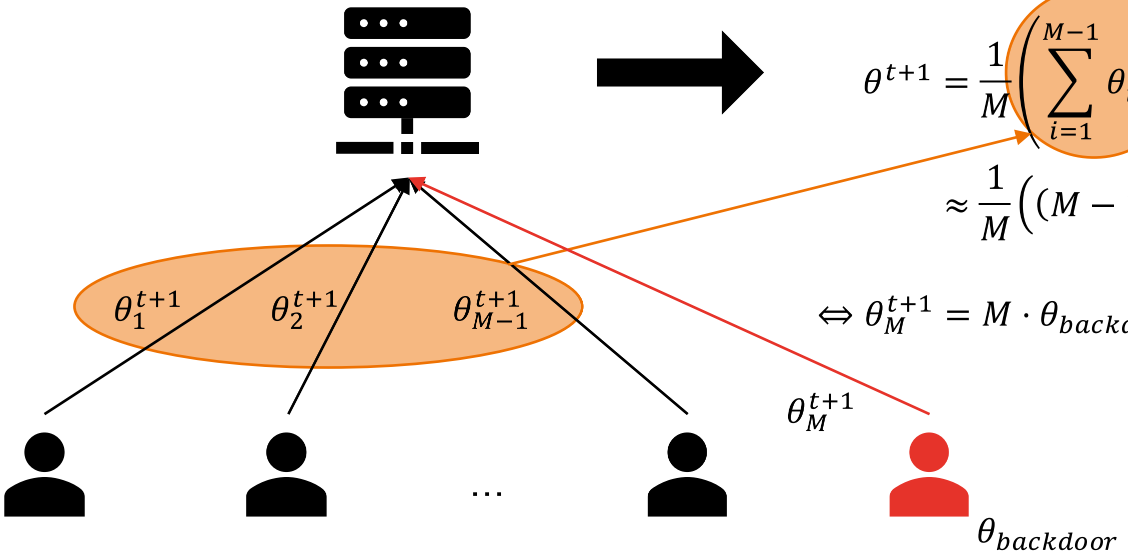
This is not new – What's special about FL?

- **Poisoning training data is not a new idea BUT in FL the threat model differs**
- **Example: How could a single malicious client compromise the whole model? (Bagdasaryan et al., AISTATS, 2020)**



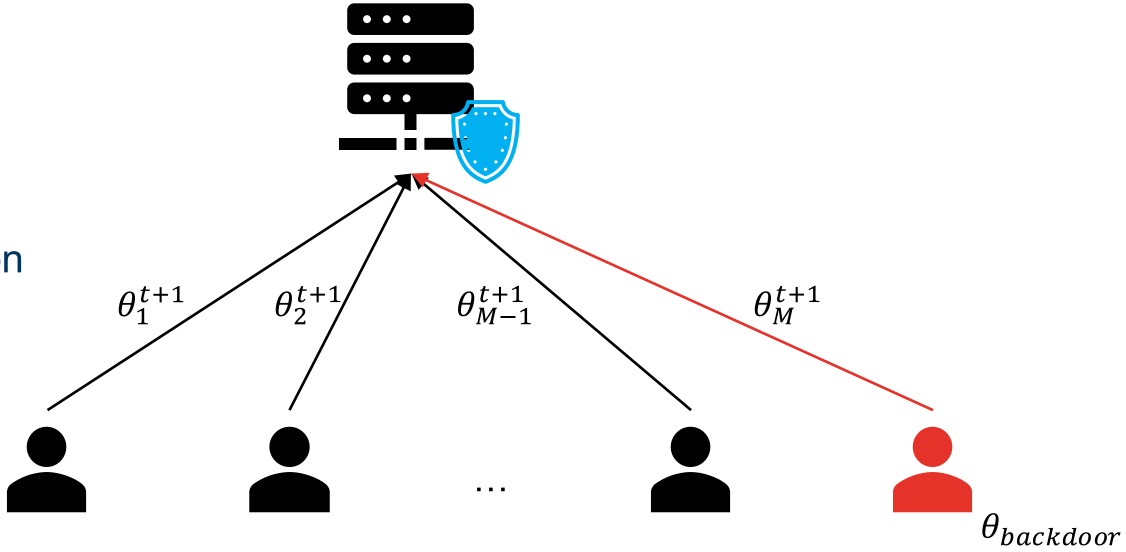
$$\theta^{t+1} = \frac{1}{M}\left(\sum_{i=1}^{M-1}\theta_i^{t+1} + \theta_M^{t+1}\right)$$

$$\approx \frac{1}{M}\left((M-1)\cdot\theta^t + \theta_M^{t+1}\right) = \theta_{backdoor}$$

$$\Leftrightarrow \theta_M^{t+1} = M\cdot\theta_{backdoor} - (M-1)\cdot\theta^t$$

And what to do about it?

- **Defenses against backdoor attacks are mostly realized as variations of the server-side aggregation rule**
- **Examples are based on**
  - Update Clustering
  - Parameter-wise outlier detection
  - Norm analysis
  - …



Well, that escalated quickly…

A3FL: Adversarially Adaptive Backdoor Attacks to Federated Learning

Part of Advances in Neural Information Processing Systems 36 (NeurIPS 2023) Main Conference Track

The Hidden Vulnerability of Distributed Learning in Byzantium

El Mahdi El Mhamdi, Rachid Guerraoui, Sébastien Rouault *Proceedings of the 35th International Conference on Machine Learning*, PMLR 80:3521-3530, 2018.

Chameleon: Adapting to Peer Images for Planting Durable Backdoors in Federated Learning

Yanbo Dai, Songze Li *Proceedings of the 40th International Conference on Machine Learning*, PMLR 202:6712-6725, 2023.

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Beyond Traditional Threats: A Persistent Backdoor Attack on Federated Learning

2023 IEEE Symposium on Security and Privacy (SP)

3DFed: Adaptive and Extensible Framework for Covert Backdoor Attack in Federated Learning

RAID 2020 PROCEEDINGS A USENIX Publication PROCEEDINGS

The Limitations of Federated Learning in Sybil Settings

Authors:
Clement Fung, *Carnegie Mellon University;* Chris J. M. Yoon and Ivan Beschastnikh, *University of British Columbia*

IBA: Towards Irreversible Backdoor Attacks in Federated Learning

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Questions?

Now: Let’s get our hands dirty!