

Privacy-Preserving AI: Privacy-preserving machine learning techniques. Federated learning and differential privacy

Artificial Intelligence System Engineering

Data driven AI

- AI Systems and applications that heavily rely on data
 - Make predictions
 - Learn
 - Perform tasks
- Data is the foundation
- Models use datasets to learn patterns, relationships, and correlations
- Models enhance their performance as additional relevant data becomes accessible



Data driven AI

- Adaptability
 - Data is the core input
 - The process is iterative
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Data driven AI

- Data driven organizations (Klas Haller)

Privacy-Preserving Machine Learning (1)

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- Machine Learning as a Service (MLaaS)
 - Facebook–Cambridge Analytica scandal (2018)
 - Facebook ML-based facial recognition technology lawsuit (2020)
 - Google developed Randomized Aggregatable Privacy-Preserving Ordinal Response (RAPPOR)

Privacy-Preserving Machine Learning (2)

- Privacy-preserving ML (PPML) algorithms
- Threats and attacks:
 - De-anonymization (re-identification)
 - Reconstruction attacks
 - Parameter inference attacks
 - Model inversion attacks
 - Membership inference attacks

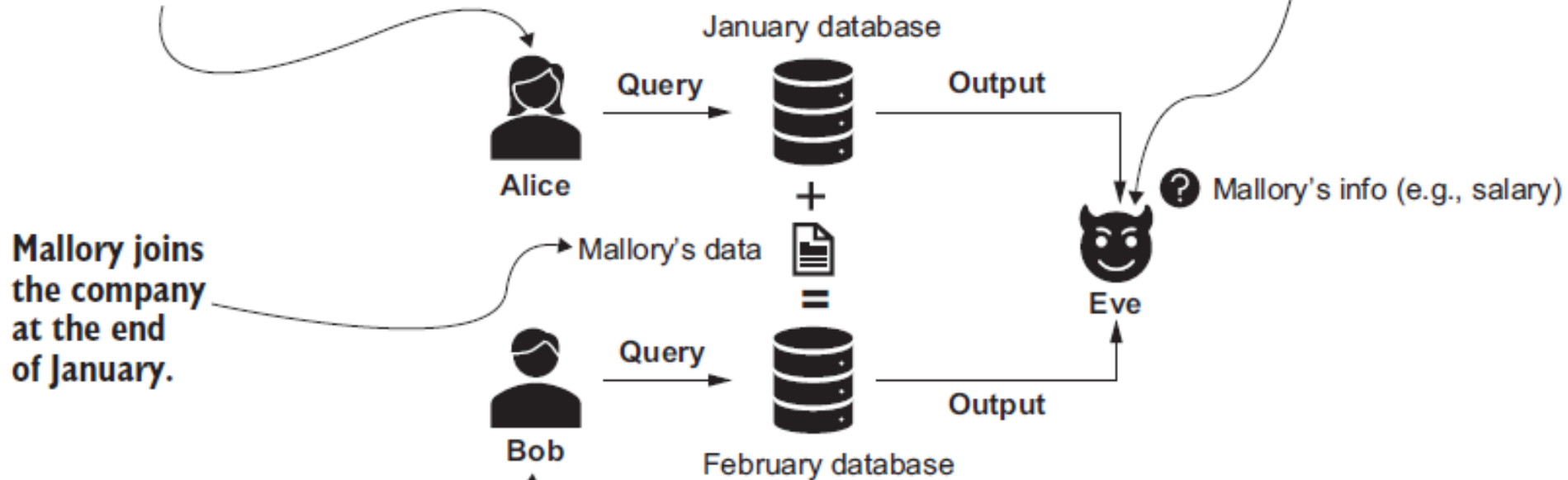
Privacy-Preserving Machine Learning (3)

- Securing privacy:
 - Differential privacy (DP)
 - Local differential privacy
 - Privacy-preserving synthetic data generation
 - Privacy-preserving data mining techniques
 - Privacy-preserving data mining (PPDM)
 - Data collection stage: randomization techniques
 - Data publishing and processing: remove certain attributes, data sanitization (generalization, suppression, anonymization, perturbation)
 - Output: Association rule hiding, Downgrading classifier effectiveness, Query auditing and restriction
 - Compressive privacy

Differential privacy

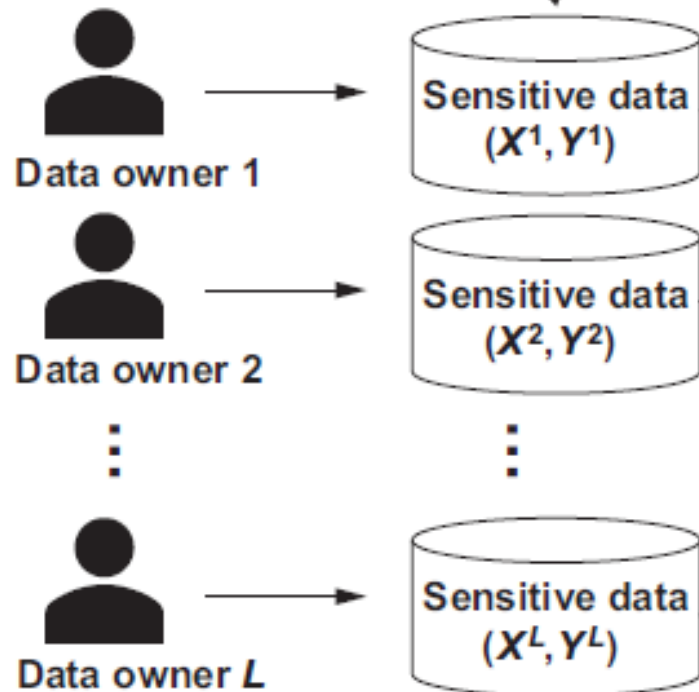
In January, news reporter Alice queries the average salary of a private company from its database, which contains personal information (e.g., salaries) of all its employees.

News reporter Eve learns Mallory's info (e.g., salary) by comparing Alice's report (before Mallory joins) and Bob's report (after Mallory joins).



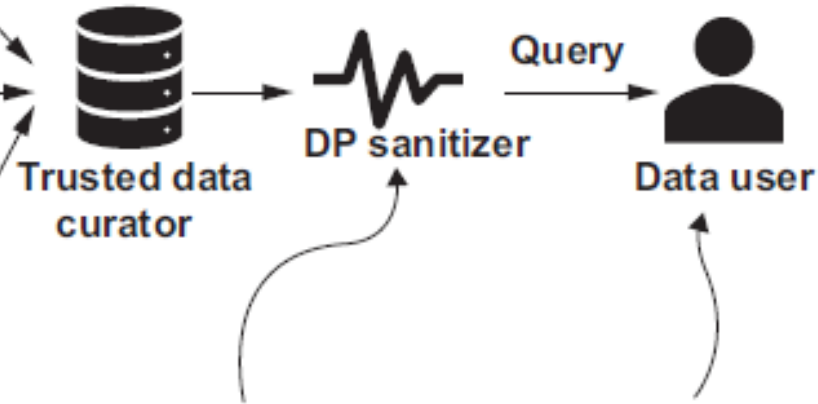
In February, news reporter Bob queries the average salary of a private company from its database, which contains personal information (e.g., salaries) of all its employees.

The private data provided by the data owner



The owner of the private data

A trusted data curator gathers the data (e.g., salaries) from multiple data owners (e.g., the employees).



A DP sanitizer executes differentially private operations by adding random noise.

The data user conducts study or analysis on data owners' data.



Mechanisms of differential privacy

- Binary mechanism (randomized response)
 - Laplace mechanism
 - Exponential mechanism
 - Etc...
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- <https://diffprivlib.readthedocs.io/en/latest/modules/mechanisms.html>
 - <https://rbcborealis.com/research-blogs/tutorial-12-differential-privacy-i-introduction/>
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Applying differential privacy in machine learning

- Input perturbation
- Algorithm perturbation
- Output perturbation
- Objective perturbation
 - (<https://kronosapiens.github.io/blog/2017/03/28/objective-functions-in-machine-learning.html>)

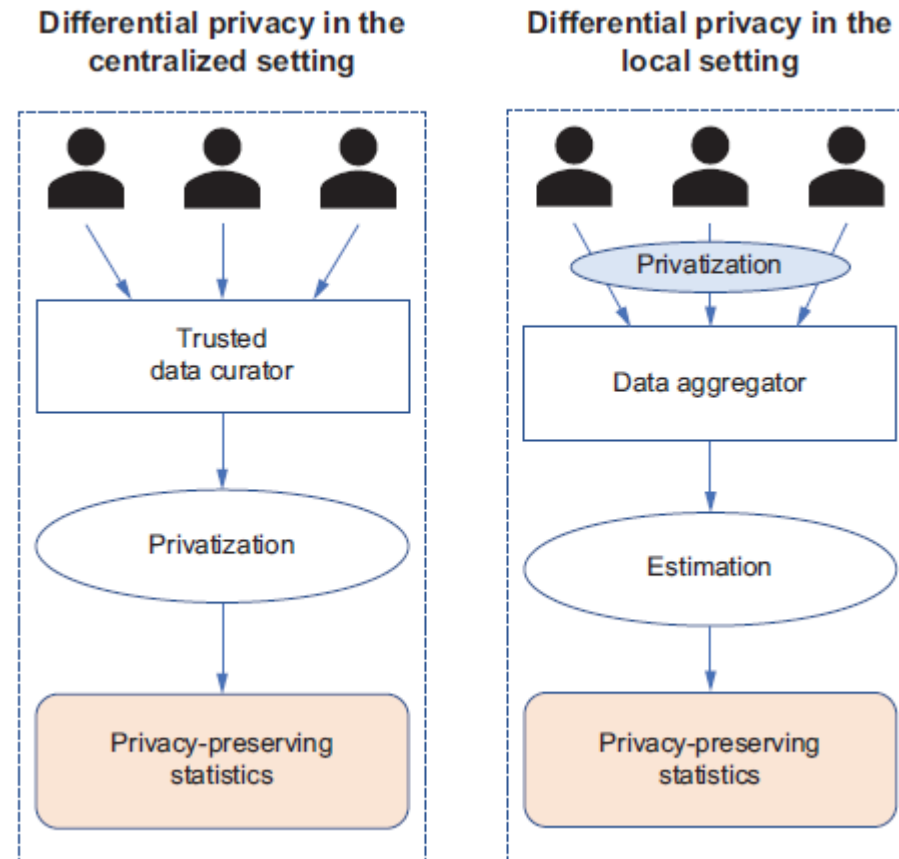
Differentially private supervised learning algorithms

- Differentially private naive Bayes classification (<https://arxiv.org/abs/1905.01039>)
- Differentially private logistic regression (<https://systems.cs.columbia.edu/private-systems-class/papers/Chaudhuri2009Privacy.pdf>)
- Differentially private linear regression (<https://arxiv.org/abs/2007.05157>)

Differentially private unsupervised learning algorithms

- Differentially private k-means clustering
 - <https://dl.acm.org/doi/10.1145/2857705.2857708>
 - <https://arxiv.org/abs/2406.11649>
 - <https://ieeexplore.ieee.org/abstract/document/9064731>

Local differential privacy



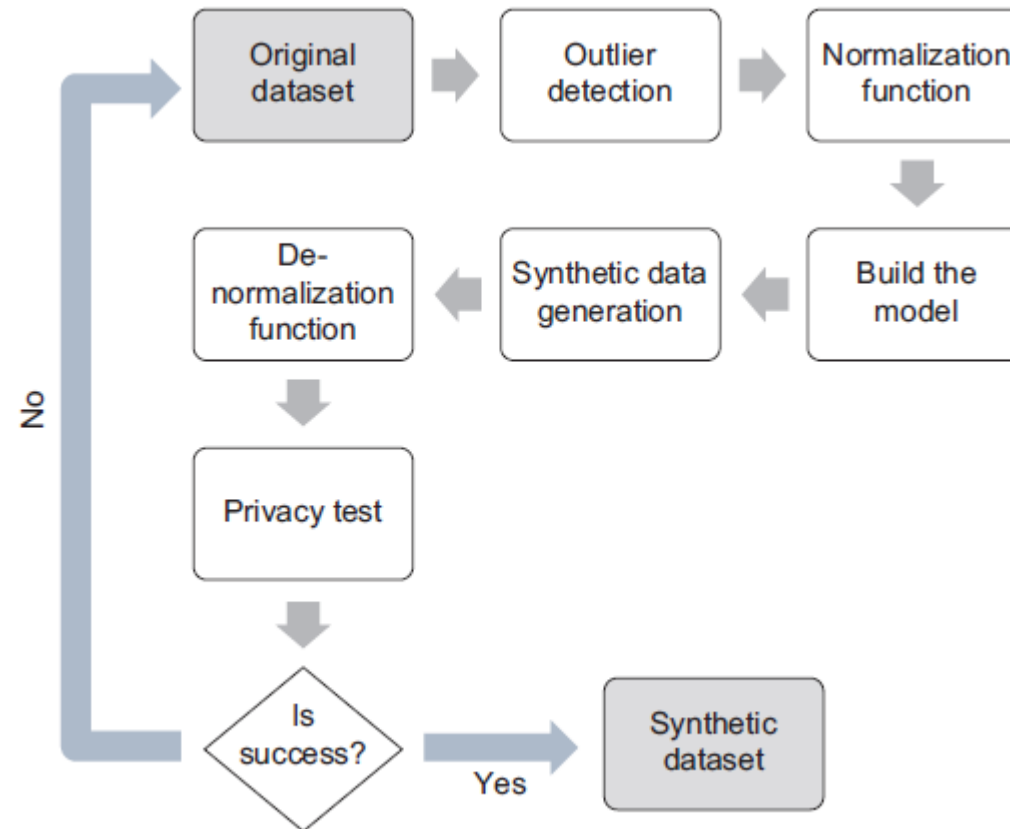
The mechanisms of local differential privacy

- Direct encoding
- Histogram encoding
- Unary encoding
- Examples with code:
 - <https://programming-dp.com/ch13.html>
- Survey (paper): <https://onlinelibrary.wiley.com/doi/10.1155/2020/8829523>

Advanced LDP mechanisms

- The Laplace mechanism for LDP
- Duchi's mechanism for LDP
- The Piecewise mechanism for LDP

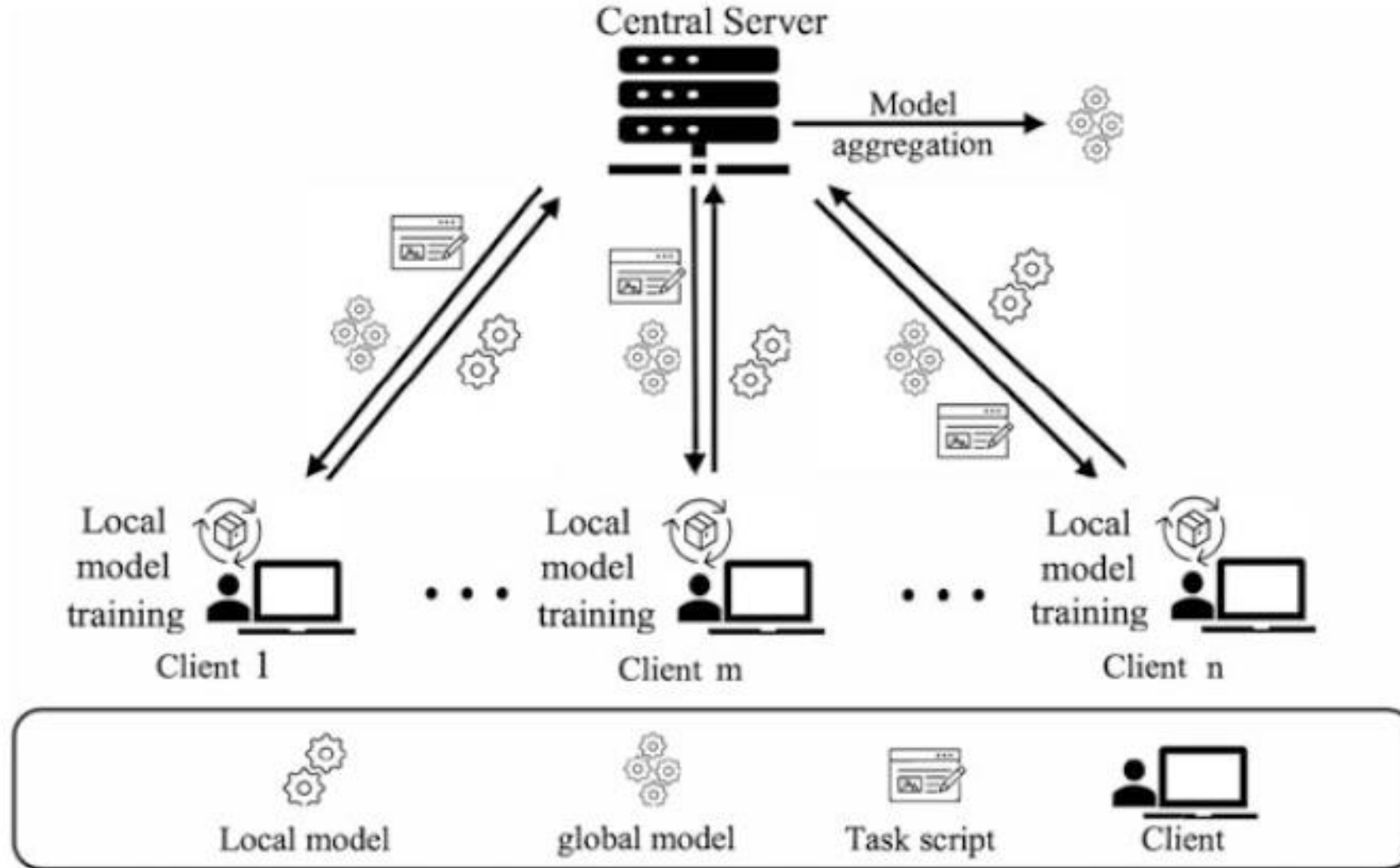
Privacy-preserving synthetic data generation



Federated learning

- A decentralized approach to machine learning where models are trained across multiple devices or servers (referred to as "clients") while keeping the data localized on those devices

Federated learning



Federated learning: Vulnerabilities

- Clients
- Server
- Aggregator
- Communication

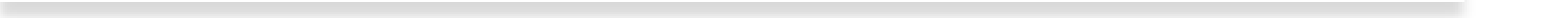


Attacks in Federated Learning

- Inference attacks
 - Poisoning attacks
 - GAN-Based attacks
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Defense techniques



- Differential Privacy (DP)
 - Secure Multi-party Computation (SMPC)
 - Secure Data Aggregation
 - Anonymous Communication and Shuffle Model
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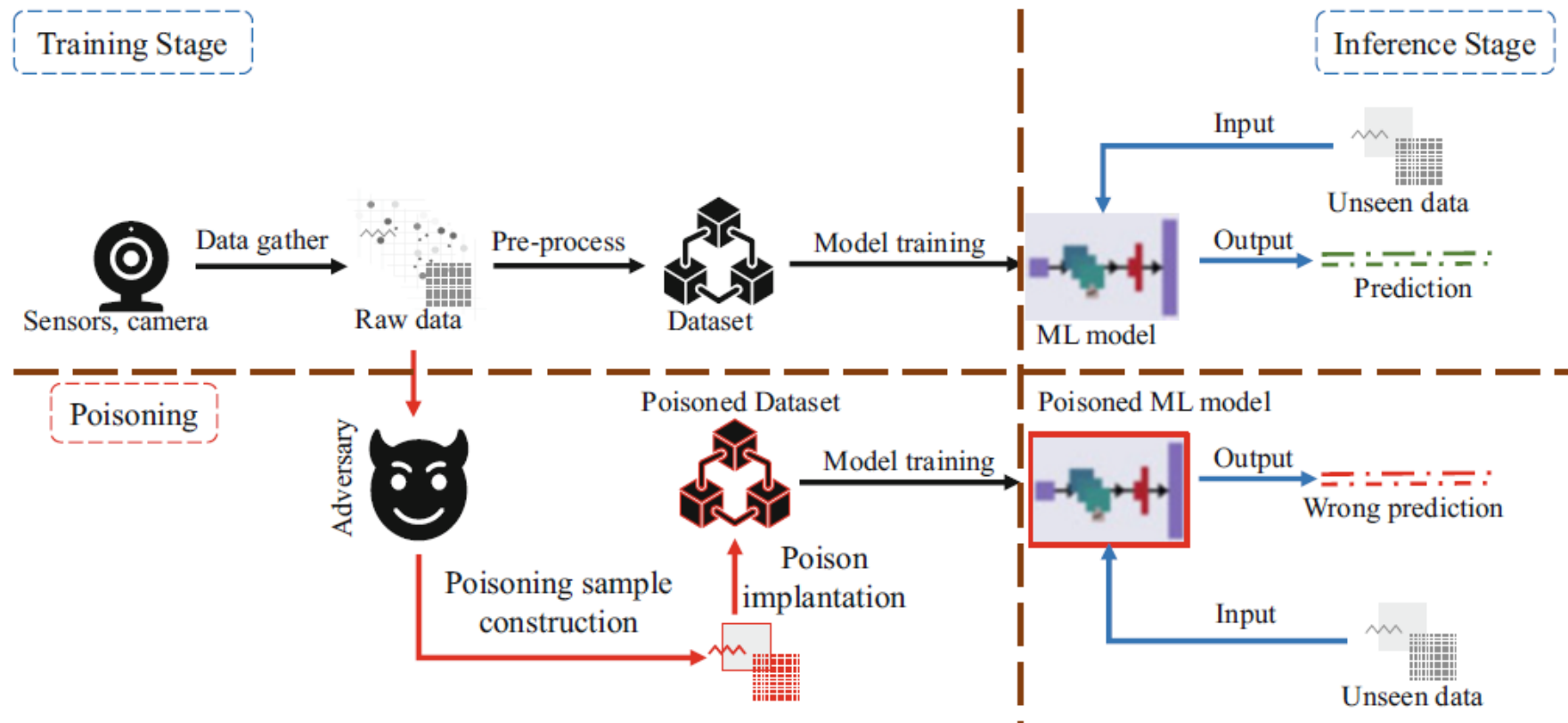
Inference Attacks in FL

- Model Inversion Attacks:
 - Attack on aggregated gradient
 - Attack on global model
 - Property Inference Attacks
 - Membership Inference Attacks:
 - Data knowledge
 - Training knowledge
 - Model knowledge
 - Output knowledge
 - Model Inference Attacks
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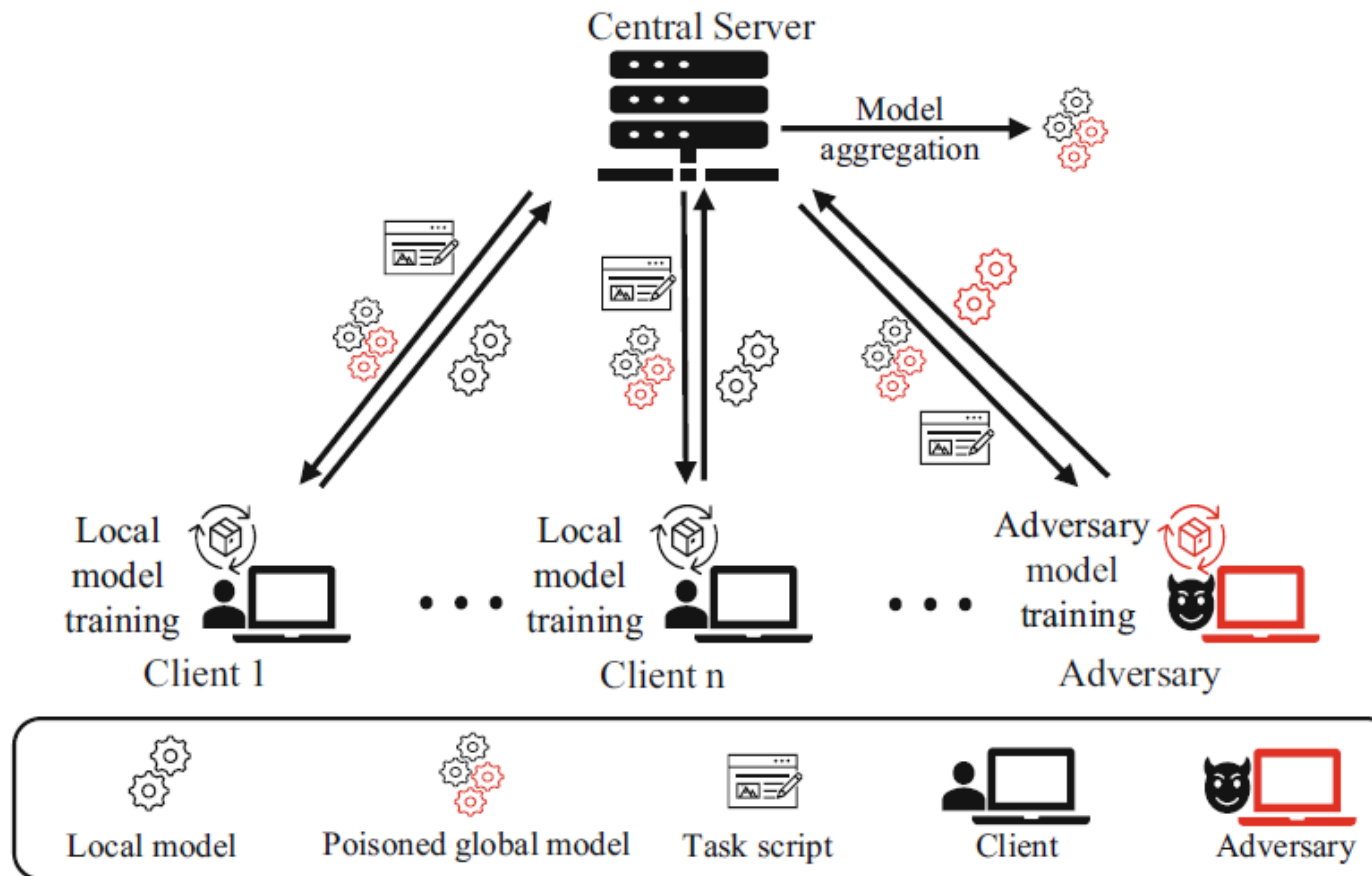
Counter-Inference Attacks

- Machine Learning Optimization-Based Defense
- Perturbation-Based Defense
- Knowledge Distillation
- Adversarial Machine Learning
- Encryption-Based Methods

Poisoning attacks



Poisoning attacks in FL



Poisoning attacks in FL

- Targeted Poisoning Attacks
- Untargeted Poisoning Attacks
- Backdoor Poisoning Attacks
- https://www.researchgate.net/publication/347178320_Threats_to_Federated_Learning

Counter Poisoning Attacks

- Counterattacks from Data Perspective
 - Byzantine-resilient algorithm for distributed SGD
 - Trimmed mean
 - Bulyan
- Counterattacks from Behavior Perspective
- Other (research papers)

Differential Privacy in FL

- Centralized Differential Privacy
- Local Differential Privacy
- Distributed Differential Privacy
- Variant Differential Privacy
- The Combination of Differential Privacy and Other Methods