MODEL AGGREGATION PRINCIPLES IN FEDERATED LEARNING

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Introduction to Federated Learning

Federated Learning (FL) is a distributed machine learning paradigm that enables training models across multiple decentralized devices or servers while keeping data localized.

Key Characteristics:

- Privacy Preservation: Training data remains on local devices
- Decentralized Architecture: No central data repository
- Collaborative Training: Multiple parties contribute to model improvement
- Communication Efficiency: Only model updates are exchanged

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Architecture Overview: Four Core Components

Federated Learning systems consist of four fundamental architectural components.

Core Components:

1. **Server**: Central coordinator and aggregator
2. **Parties**: Distributed clients/participants
3. **Communication Framework**: Secure data exchange protocols
4. **Aggregation Algorithm**: Model update combination logic

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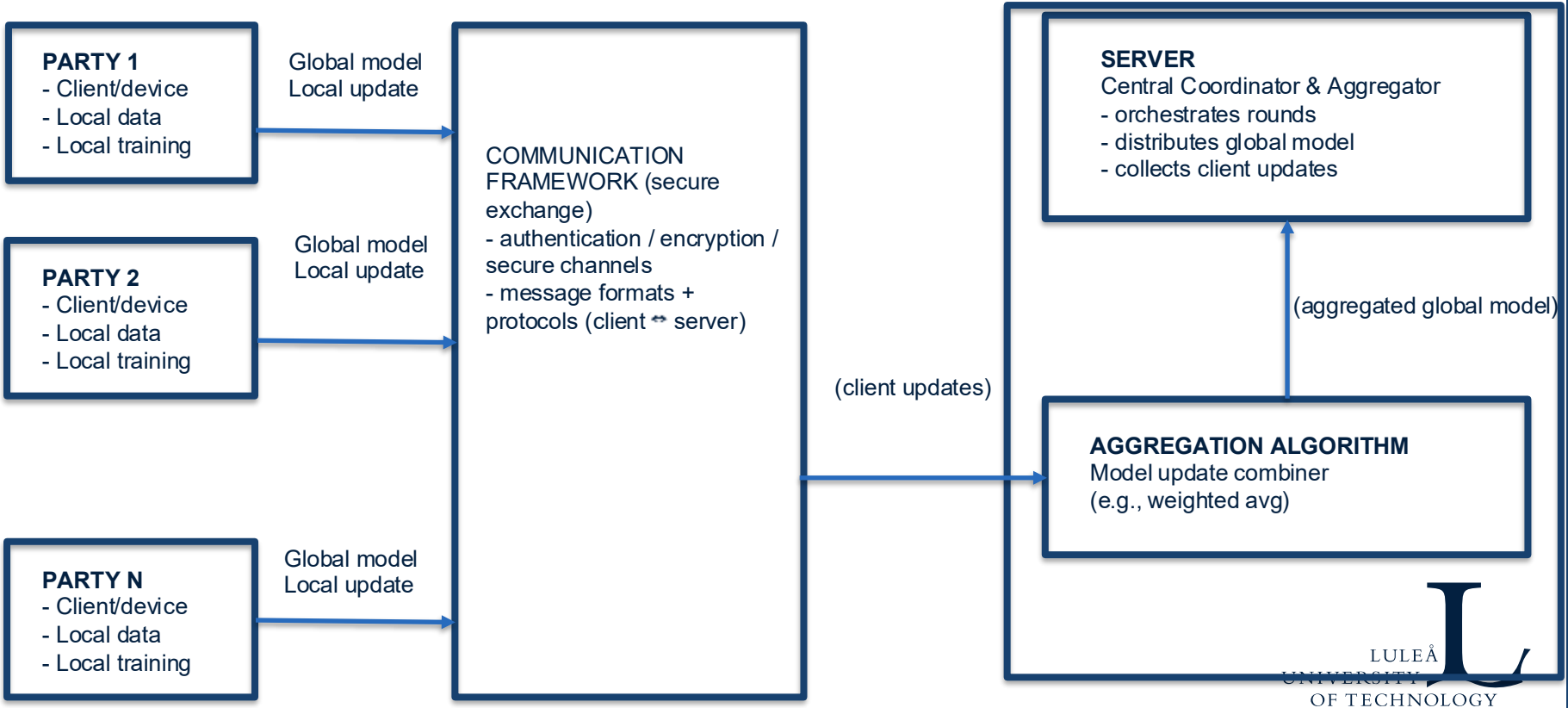
PARTY 1
- Client/device
- Local data
- Local training
Global model
Local update
PARTY 2
- Client/device
- Local data
- Local training
Global model
Local update
PARTY N
- Client/device
- Local data
- Local training
Global model
Local update
COMMUNICATION FRAMEWORK (secure exchange)
- authentication / encryption / secure channels
- message formats + protocols (client ↔ server)
(client updates)
SERVER
Central Coordinator & Aggregator
- orchestrates rounds
- distributes global model
- collects client updates
(aggregated global model)
AGGREGATION ALGORITHM
Model update combiner
(e.g., weighted avg)

Architecture Overview: Server

The server orchestrates the FL process, acting as the primary point of control and aggregation.

Primary Functions:

- Client selection and round management
- Parameter distribution to participating clients
- Model aggregation from client updates
- Performance monitoring and compliance

SERVER
Central Coordinator & Aggregator
- orchestrates rounds
- distributes global model
- collects client updates

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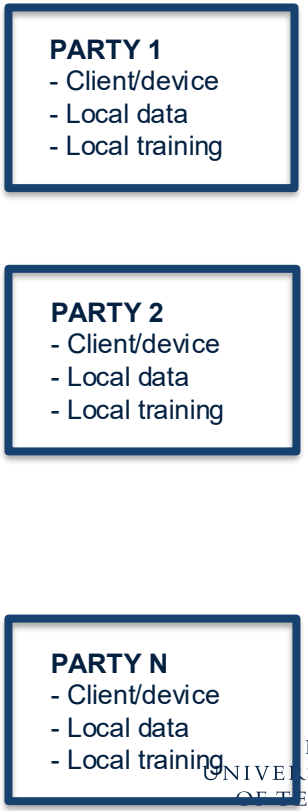
Architecture Overview: Parties

Parties are the distributed entities/clients that own training data and perform local model training.

Two Main Categories:

- **Cross-Device FL**: Mobile devices, IoT sensors
- **Cross-Silo FL**: Organizations, companies, institutions

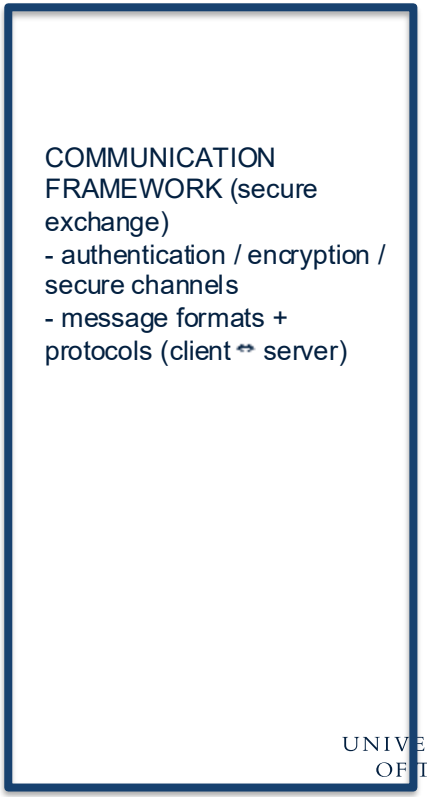


Architecture Overview: Communication framework

The communication framework encompasses protocols for secure, efficient data exchange.

Core Layers:

- **Transport**: TCP/IP, UDP, WebSockets
- **Security**: TLS/SSL, certificates
- **Application**: gRPC, REST APIs, MQTT



FL Categorization Overview

Federated Learning can be categorized based on data distribution patterns across participants:

1. Horizontal FL (HFL):

- Same feature spaces, different samples
- Most common form (FedAvg, cross-device)
- Scales to millions of participants

2. Vertical FL (VFL):

- Different feature spaces, overlapping samples
- Feature-partitioned data across organizations
- Requires cryptographic techniques

3. Federated Transfer Learning:

- Combines FL with transfer learning
- Domain adaptation across heterogeneous environments
- Addresses cold start and data scarcity

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Horizontal Federated Learning (HFL)

Horizontal Federated Learning occurs when participants have identical data schemas but different samples.

Key Characteristics:

- Feature Space: Same attributes/columns across all participants
- Sample Space: Different/non-overlapping data samples
- Scalability: Naturally scales to large numbers of participants
- Privacy: Strong guarantees with minimal data overlap

FedAvg Algorithm:

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^{t+1}$$

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HFL Use Cases

HFL powers many real-world applications.

Cross-Device FL:

- Gboard: Next-word prediction across Android devices
  - https://support.google.com/gboard/answer/12373137?hl=en
- Mobile Apps: Personalized recommendations
- IoT Networks: Smart device coordination

Cross-Silo FL:

- Banks: Fraud detection collaboration
- Hospitals: Medical research without data sharing
- Companies: Enterprise model training

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HFL Challenges

HFL faces challenges from participant and data diversity.

Main Challenges:

- Statistical heterogeneity (non-IID data)
- System heterogeneity (varying compute)
- Communication costs and client dropout

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Vertical Federated Learning (VFL)

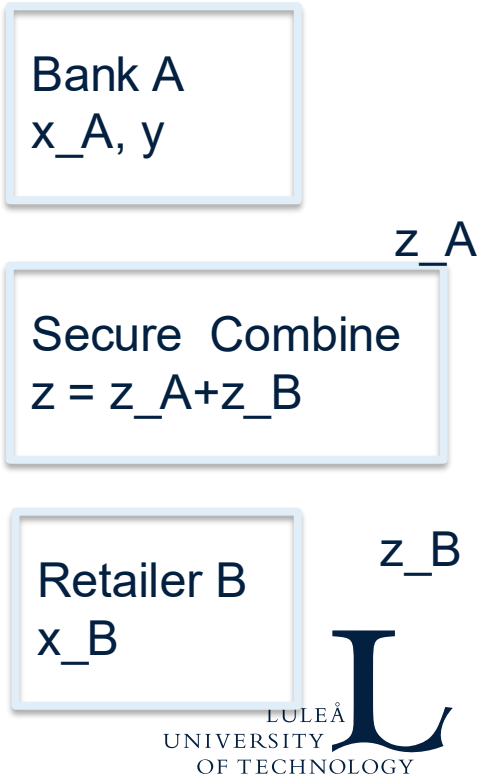
Vertical Federated Learning occurs when participants have different features for the same entities.

Key Characteristics:

- Feature Space: Different attributes across participants
- Sample Space: Overlapping users/entities
- Privacy: Very strong (cryptographic techniques required)
- Coordination: Complex sample alignment needed

Feature Partitioning:

$$x_i = [x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(K)}]$$



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VFL Use Cases

VFL enables collaboration across different data silos.

Financial Services:

- Banks share features for credit scoring
- Transaction history + employment data + credit history
- Better risk assessment without data sharing

Healthcare:

- Hospitals combine different medical data
- Lab results + imaging + patient history
- Improved diagnosis with comprehensive data

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VFL Challenges

VFL requires sophisticated cryptographic techniques.

Main Challenges:

- Sample alignment without sharing identifiers
- Secure multi-party computation
- Homomorphic encryption for joint operations

Solutions:

- Secret Sharing: Distribute computations
- Homomorphic Encryption: Encrypted arithmetic
- Secure MPC: Privacy-preserving protocols

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Federated Transfer Learning

Type	Users	Features	Example
Horizontal FL	Different	Same	Hospitals in different cities
Vertical FL	Same	Different	Bank + Retail
Federated Transfer Learning	**Different**	**Different**	Hospital + Insurance

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Federated Transfer Learning

FL + Transfer Learning Combines federated learning with transfer learning techniques for domain adaptation.

Key Characteristics:

- Raw data never shared
- Only encrypted embeddings exchanged
- Overlapping ID matching done securely
- Often uses:
  - Secure Multi-Party Computation
  - Homomorphic encryption
  - Differential privacy

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Architectural view

Party A
x_A -> f_A –h_A

Party B
x_B -> f_B –h_B

- x_A, x_B– features (in general non-overlapping)
- f_A – locally trained model to solve organization-specific task
  - E.g. decease forecasting
- h_A – learned feature representation

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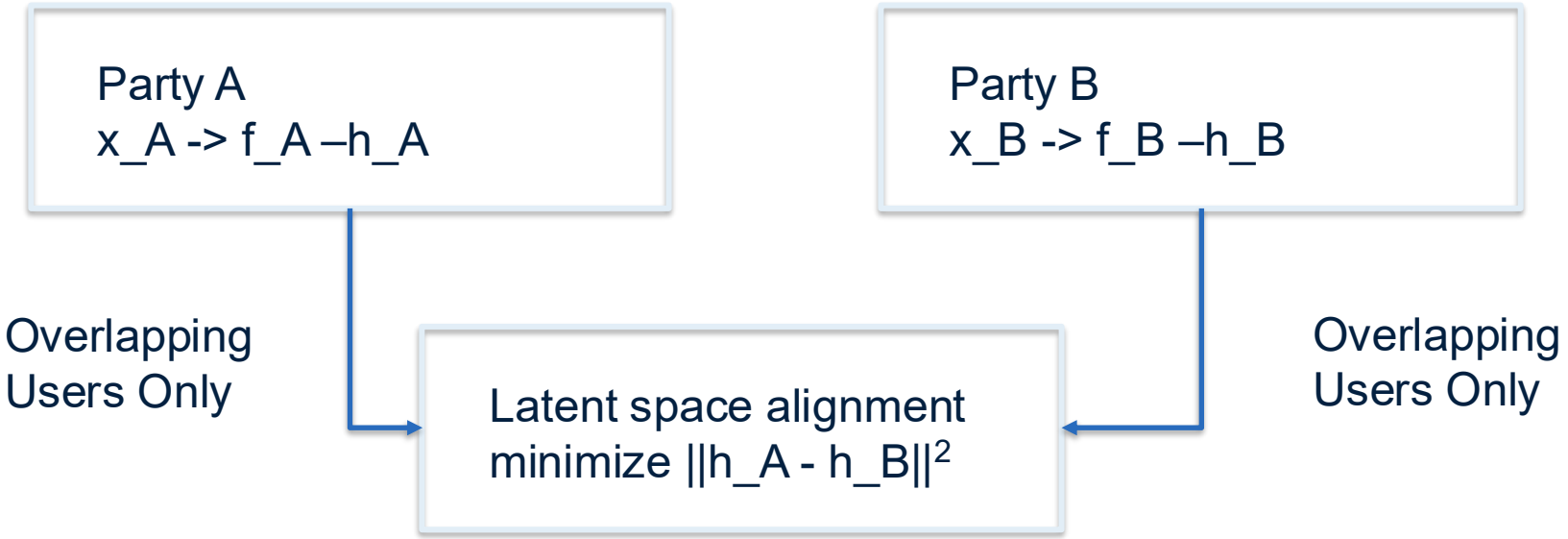
Architectural view



After alignment (Even for non-overlapping users):

- Party A (e.g. hospital) model benefits from structural patterns learned by Party B (e.g. Insurer).
- Party B helps shape the embedding space of Party A for better generalization

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Summary so far: FL Categories Comparison

Use HFL when:

- Large number of participants with similar data structures
- Cross-device applications (mobile, IoT)
- Strong privacy with minimal data overlap

Use VFL when:

- Few participants with complementary features
- Sensitive data requiring strong privacy guarantees
- Financial services, healthcare applications

Use Federated Transfer Learning when:

- Participants with different but related domains
- Cold start problems with limited local data
- Evolving environments requiring continual adaptation
- Multi-task learning scenarios

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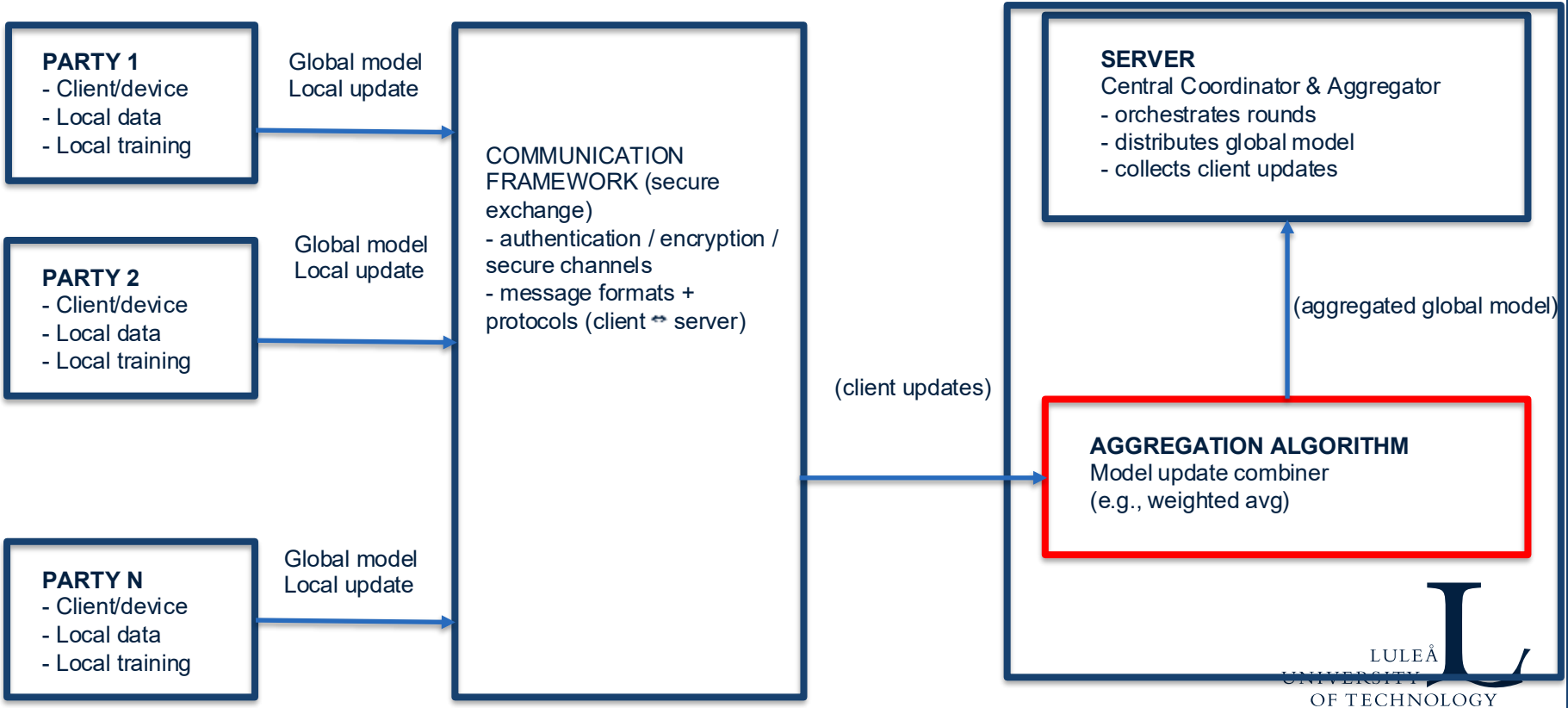
Recall. What is left?

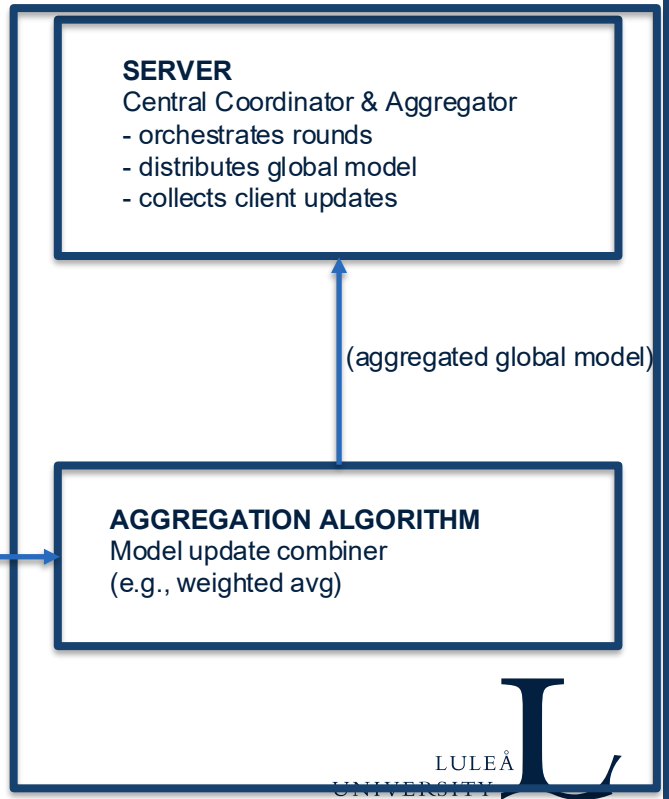


What is Model Aggregation - HFL?

Model aggregation is the process of combining individual client models to create a global model in federated learning.

Goals:

- Leverage collective knowledge from distributed clients
- Maintain data privacy (no raw data exchange)
- Handle client heterogeneity (data, compute, network)
- Ensure robustness against malicious participants
- Optimize for communication efficiency



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Federated Averaging (FedAvg)

Mathematical Formulation:

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^{t+1}$$

Where:

- w_k^{t+1}: Client k's model after local training
- n_k: Data samples on client k
- $n = \sum n_k$: Total samples across clients

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Example FedAvg: Round 1

Task: Predict disease risk (binary classification)

Model: Single parameter w (for simplicity)

Initial Model **Server initializes:** $w^{(0)} = 0.5$

Step 1: Server sends $w^{(0)} = 0.5$ to all clients

Step 2: Each client trains locally on their data

Step 3: After local training (e.g., 5 epochs of SGD) clients send their trained models back to server

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Example FedAvg: Round 1 (cont.)

Step 4: Server computes weighted average

Formula:

$$w^{(1)} = \frac{n_A}{n} \cdot w_A^{(1)} + \frac{n_B}{n} \cdot w_B^{(1)} + \frac{n_C}{n} \cdot w_C^{(1)}$$

Substituting values:

$$\begin{aligned} w^{(1)} &= \frac{100}{500} \cdot 0.65 + \frac{200}{500} \cdot 0.80 + \frac{200}{500} \cdot 0.75 \\ &= 0.20 \cdot 0.65 + 0.40 \cdot 0.80 + 0.40 \cdot 0.75 \\ &= 0.13 + 0.32 + 0.30 = \mathbf{0.75} \end{aligned}$$

New global model: $w^{(1)} = 0.75$

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Example FedAvg: Round 1 (cont.)

Compare:

- Hospital A: $w_A = 0.65$) weight: 0.20)
- Hospital B: $w_B = 0.80$) weight: 0.40)
- Hospital C: $w_C = 0.75$) weight: 0.40)
- **Global:** $w^{(1)} = 0.75$

Observe:

- Result is closer to B and C (they have more data)
- Hospital A has less influence (only 20% of data)
- Simple average would give: $(0.65 + 0.80 + 0.75)/3 = 0.733$
- Weighted average: 0.75 (accounts for data size)

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Example FedAvg: Round 2 and so on

Step 1: Server sends new global model $w^{(1)} = 0.75$ to all clients

Step 2: Each client trains locally starting from $w^{(1)} = 0.75$

After local training:

Step 3: Send updates to server

Step 4: Server aggregates:

$$w^{(2)} = 0.20 \cdot 0.78 + 0.40 \cdot 0.82 + 0.40 \cdot 0.80$$
$$= 0.156 + 0.328 + 0.320 = \mathbf{0.804}$$

Why weighted is better:

- Hospitals B and C have 4× more data than A
- Their models are trained on more samples (more reliable)
- Weighted average gives them appropriate influence
- Leads to better convergence and final model quality

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FL Security Challenges

Federated Learning introduces distinctive security challenges due to its distributed nature and privacy-preserving design.

Security threats in FL can undermine both privacy and utility!

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Attack Impact

Poisoning attacks have cascading effects on FL systems and stakeholders.

Individual Model Level:

- Incorrect feature engineering
- Regulatory compliance failures
- Debugging based on false explanations

System-Level Impact:

- Trust erosion in AI systems
- Economic consequences from poor decisions
- Hidden security risks in explanations

Societal Impact:

- Bias amplification or masking
- Accountability issues
- Flawed policy decisions

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Attack Variants

Attacks can vary based on attacker resources and coordination.

Single-Client Attacks:

- Limited impact but hard to detect
- Blends with natural data variations

Multi-Client Coordinated Attacks:

- Sybil attacks with multiple identities
- Combined effect through FedAvg
- Higher impact but easier to detect

Stealthy Attacks:

- Minimal perturbations
- Adaptive poisoning strategies
- Integration with backdoor attacks

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FL Threat Taxonomy

FL security threats can be categorized into three primary areas.

1. **Privacy Attacks**: Information leakage from model outputs
2. **Poisoning Attacks**: Malicious data or model manipulation
3. **Fairness-Robustness Trade-offs: Balancing multiple objectives**
4. **Utility-Robustness Trade-offs**

Each category presents unique challenges for FL system design!

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Privacy Risks

Even without sharing raw data, FL systems can leak sensitive information through model outputs and explanations.

Key Privacy Threats:

- **Membership Inference**: Determine if sample was in training data
- **Property Inference**: Learn statistical properties of training data
- **Explanation Leakage**: Sensitive information through model explanations

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Differential Privacy in FL

Add noise to model updates to provide provable privacy protection.

Local DP: Each client adds noise before sending:

$$\widetilde{w}_k = w_k + \mathcal{N}(0, \sigma^2)$$

Central DP: Server adds noise to aggregated updates:

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^t + \mathcal{N}(0, \sigma^2)$$

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Poisoning Attacks: Overview

Poisoning attacks involve malicious participants introducing corrupted data or model updates into the FL training process.

Attack Types:

- **Model Poisoning**: Send manipulated model updates
- **Data Poisoning**: Manipulate local training data
- **Byzantine Attacks**: Arbitrary malicious behavior

Poisoning can target accuracy, explanations, or information extraction!

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Byzantine Threat

A **Byzantine** participant can behave **arbitrarily**:

- send incorrect or inconsistent messages,
- send extreme/malicious gradients/updates,
- collude with others, or remain silent.

In FL, Byzantine clients can:

- break convergence,
- insert backdoors,
- dominate averaging with outliers.

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Model poisoning

A **model poisoning attack** occurs when a malicious client:

- Intentionally modifies its local update
- To manipulate the global model
- While still following the communication protocol

Different from data poisoning (corrupting local data)

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Why FedAvg is Vulnerable

FedAvg assumes:

- Clients are honest.
- Updates reflect legitimate local training.
- Averaging is safe.

But averaging has **no robustness mechanism**.

So a malicious update can:

- Shift the global model
- Inject a backdoor
- Prevent convergence
- Reduce accuracy

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Attacks against FedAvg

With FedAvg:

$$w_{t+1} = w_t + \frac{1}{n}\sum_{i=1}^{n} \Delta_i \,.$$

If one client m is malicious:

$$w_{t+1} = w_t + \frac{1}{n}\left(\sum_{i \neq m} \Delta_i + \Delta_m\right).$$

A malicious client can scale its update:

$$\Delta_m = n \cdot \Delta^\star \;\Rightarrow\; w_{t+1} \approx w_t + \Delta^\star$$

so a **single client can dominate the round** (“model replacement” style effect).

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Model Poisoning: Common Attack Styles

- **Sign-flip / disruption:** $\Delta_m = -\alpha\,\Delta_{\text{honest}}$ to slow or reverse learning.
- **Backdoor:** train locally so that a trigger T causes prediction $\hat{y} = y^\star$ while keeping normal accuracy high.
- **Model replacement:** craft Δ_m to push w_{t+1} close to an attacker-chosen $w^\star$

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Data Poisoning Against Interpretations

A sophisticated attack that undermines model interpretability by poisoning training data to alter feature importance attributions.

Core Insight:

Model interpretability methods are sensitive to small, carefully crafted perturbations in training data.

Key Difference:

- Traditional attacks target model **accuracy**
- This attack targets model **explanations**
- Maintains accuracy while corrupting interpretability

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Attack Methodology

Four-Step Poisoning Process Systematic approach to manipulate model explanations in FL.

Step 1 - Target Selection: Choose explanation method (SHAP, LIME, feature importance)

Step 2 - Poison Generation: Solve optimization/or craft to create poisoned samples

Step 3 - Explanation Manipulation: Feature/Label flip, masking, or inversion attacks

Step 4 - FL Integration: Distribute poison across clients, consider FedAvg effects

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Mathematical Formulation

Objective Function:

$$\min_{\delta} \| \phi(f(\theta, x + \delta)) - \phi_{target} \|^2$$

Constraints:

$$\| \delta \| \leq \epsilon \quad \text{(perturbation budget)}$$

$$\mathcal{L}(f(\theta, x + \delta), y) \leq \tau \quad \text{(accuracy preservation)}$$

Trade-off between explanation manipulation and accuracy preservation!

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Manipulation Strategies

Three Attack Variants Different approaches to corrupt model interpretability.

1. Feature Flip Attacks:

- Make irrelevant features appear important
- Example: Credit model prioritizes "favorite color" over "credit history"

2. Feature Masking Attacks:

- Hide importance of critical features
- Example: Reduce apparent biomarker importance in medical diagnosis

3. Explanation Inversion Attacks:

- Make explanations contradict true decision process
- Example: Income-based model appears to prioritize education

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Defense Strategies

FL defense strategies address different attack types with appropriate countermeasures.

Defense Categories:

1. **Robust Aggregation**: Defend against malicious updates
2. **Client Authentication**: Verify participant legitimacy
3. **Data Validation**: Detect poisoned training data
4. **Privacy Protection**: Prevent information leakage
5. **Fairness Mechanisms**: Ensure equitable performance

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Detection and Mitigation

Statistical Detection:

- Explanation consistency checks
- Outlier detection in explanation patterns
- Distribution shift monitoring

Robust Explanation Methods:

- Ensemble explanations
- Certified explanations with guarantees
- Adversarial training for explanations

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Robust Aggregation Methods: Coordinate-wise Median

Principle: Take median of each parameter coordinate across all client updates.

Formula:

$$w_i^{t+1} = \text{median}(\{w_{k,i}^{t+1}\}_{k=1}^{K})$$

Advantages:

- Robust to value manipulation attacks
- Computationally simple
- No hyperparameters to tune

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Robust Aggregation Methods: Krum Aggregation

Principle Select the update that is closest to other (gradient) updates (multi-dimensional median).

Algorithm:

1. For each client k, compute $\sum_{k' \neq k} \| g_k - g_{k'} \|^2$,where
2. Select k^* with minimum distances
3. Average top m closest updates

g's are exchanged gradients

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Robust Aggregation Methods: Krum Aggregation

Setup

- Number of clients: n=6
- Max Byzantine clients: f=1
- Each client sends a **model update vector g**.
- Krum uses **squared Euclidean distances**.

Krum parameter:

- m=n−f−2 = 6−1−2 = 3

- So for each update gi, we find its **3 nearest neighbors** (by squared distance) and sum those distances. The update with the **smallest sum** is selected.

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Robust Aggregation Methods: Krum Aggregation

- Honest updates (close to each other):
  - g1=[1.00,1.00], g2=[1.10,0.90], g3=[0.90,1.20], g4=[1.05,1.05], g5=[0.95,0.85]
- Byzantine (malicious outlier):
  - g6=[10,−10]

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Robust Aggregation Methods: Krum Aggregation

Use updates from these nodes

	g1	g2	g3	g4	g5	g6
g1	0	0.020	0.050	0.005	0.025	202.000
g2	0.020	0	0.130	0.025	0.025	198.020
g3	0.050	0.130	0	0.045	0.125	208.250
g4	0.005	0.025	0.045	0	0.050	202.205
g5	0.025	0.025	0.125	0.050	0	199.625
g6	202.000	198.020	208.250	202.205	199.625	0

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Fairness-Robustness Trade-offs

In FL:

- Clients often have **non-IID data**.
- Some clients represent minority populations.
- Their updates may naturally look different from the majority.

Robust aggregation methods (e.g., Krum, trimmed mean, median):

- Treat large deviations as suspicious.
- Remove or downweight outliers.
- But minority updates can look like outliers even if honest.

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Fairness-Robustness Trade-offs

Joint Optimization Approaches Methods to achieve both robustness and fairness simultaneously.

Fairness-aware FL may require:

- Personalized models
- Reweighting
- Clustering
- Multi-task learning
- Adaptive thresholds

Proposed Solutions:

- Multi-objective optimization frameworks
- Fairness-aware adversarial training
- Regularization techniques for balanced performance

Multi-objective optimization needed for both robustness and fairness!

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Secure federated learning: Secure Aggregation

Secure aggregation ensures the server can compute the aggregate of client updates without learning anything about individual client contributions.

Security Requirements:

1. Privacy: Server learns only the aggregate
2. Correctness: Honest inputs included correctly
3. Robustness: Works with malicious clients
4. Efficiency: Reasonable computation/communication

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Homomorphic Encryption:principle

Homomorphic encryption allows computation on encrypted data without decryption.

Key Property (Additive HE):

$$Enc(a) \cdot Enc(b) = Enc(a + b)$$

Schemes:

- Paillier: Probabilistic, additive homomorphic
- CKKS/BFV: Support floating-point operations

Google if you want to know more: homomorphuic encryption is an advanced topic in cryptography

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Homomorphic Encryption:principle

SecureAgg Protocol (Google) uses threshold homomorphic encryption in TensorFlow Federated.

4-Phase Protocol:

1. Setup: Clients generate keys, establish secure channels
2. Masking: Clients add random masks to updates
3. Aggregation: Server sums encrypted masked updates
4. Unmasking: Clients reveal masks to cancel randomness

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Homomorphic Encryption:Paillier Cryptosystem

- Key Gen: (n, g) where $n = p \cdot q$
- Encryption: $Enc(x) = g^x \cdot r^n \bmod n^2$
- Addition: $Enc(x) \cdot Enc(y) = Enc(x + y)$

FL Protocol:

1. Server generates Paillier key pair (pk, sk)
2. Clients: $c_k = Enc_{pk}(w_k)$
3. Server: $C = \prod c_k = Enc_{pk}(\sum w_k)$
4. Server: $\sum w_k = Dec_{sk}(C)$

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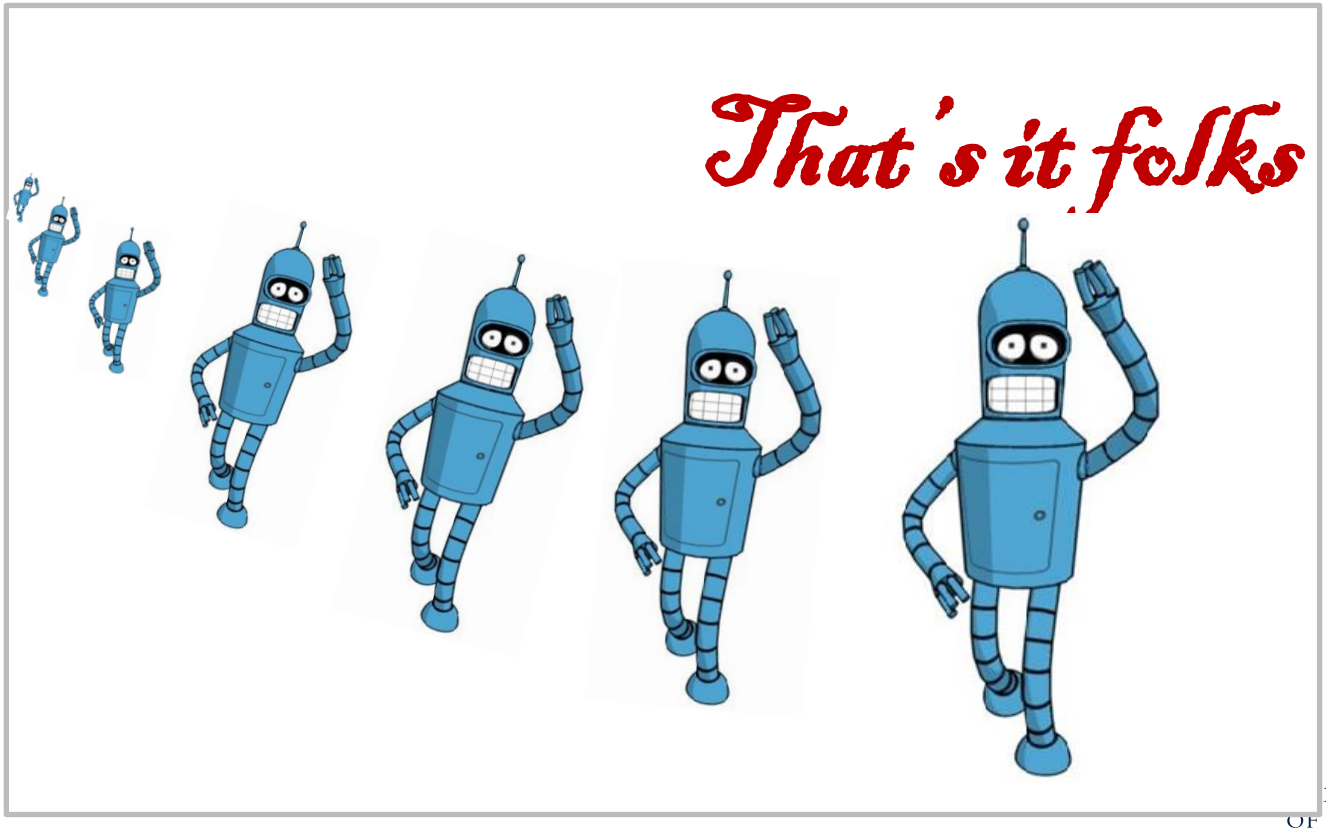

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