Lecture 13 - Contents

An overview of the main sections in this lecture.

Part 1
Federated Learning Overview

Part 2
Privacy and Communication Efficiency

Part 3
Case Studies and Benchmarks

Hands-on
Federated Learning Simulation

This outline is for guidance. Navigate the slides with the left/right arrow keys.

Lecture 13:

Federated Learning for Medical LLMs

Privacy-Preserving Medical AI

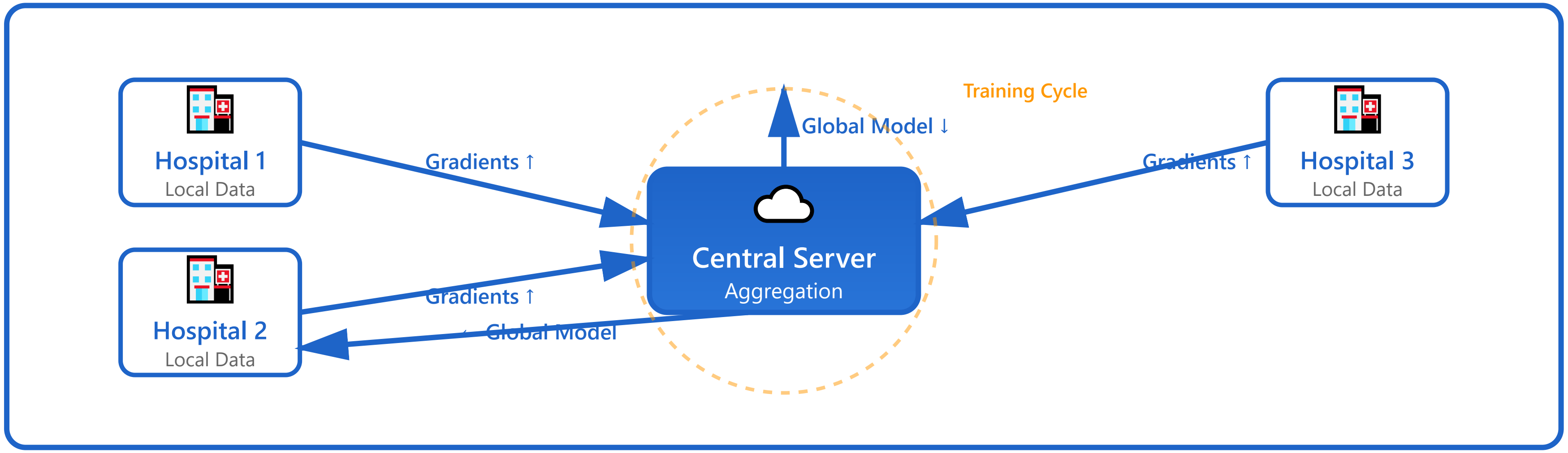
Federated Learning Overview

📚 FL Principle

Collaborative learning without centralizing data. Models travel to data, not vice versa.

🔒 Medical Privacy

HIPAA & GDPR compliant. Patient data never leaves the hospital premises.



🔐 Data stays distributed • Models aggregate learnings • Privacy preserved

Part 1

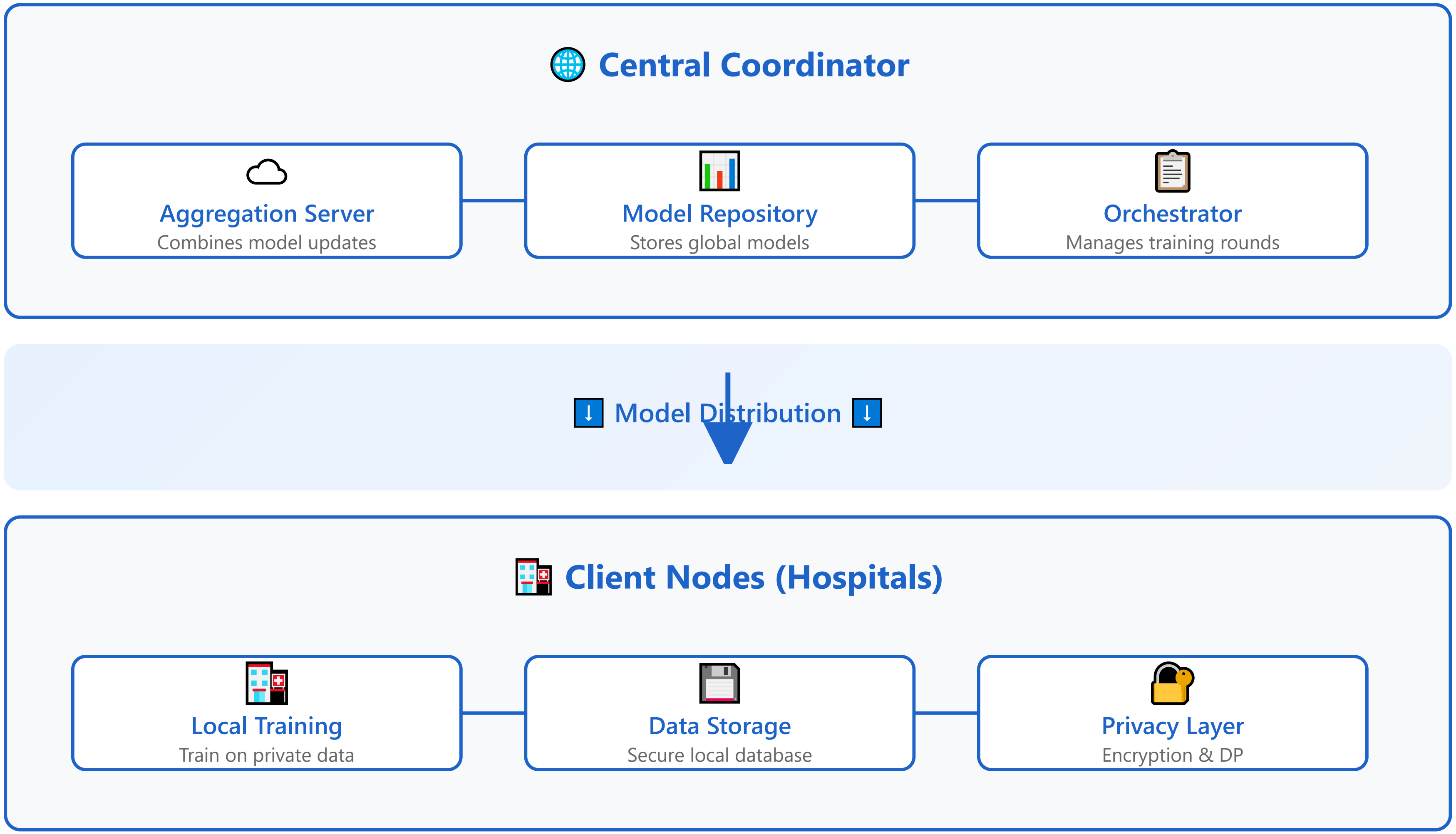
Privacy-Preserving Techniques

Encryption

Anonymization

Secure Aggregation

Distributed Architecture



⬆️ Gradient Upload ⬆️

Client-Server Communication

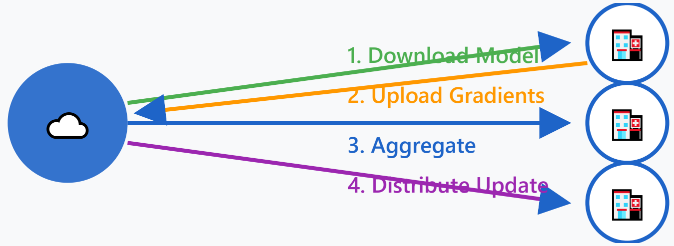
📡 Communication Protocol

gRPC: High-performance RPC framework

REST API: HTTP-based communication

WebSocket: Real-time bidirectional

📄 Message Flow



🔒 Security Measures

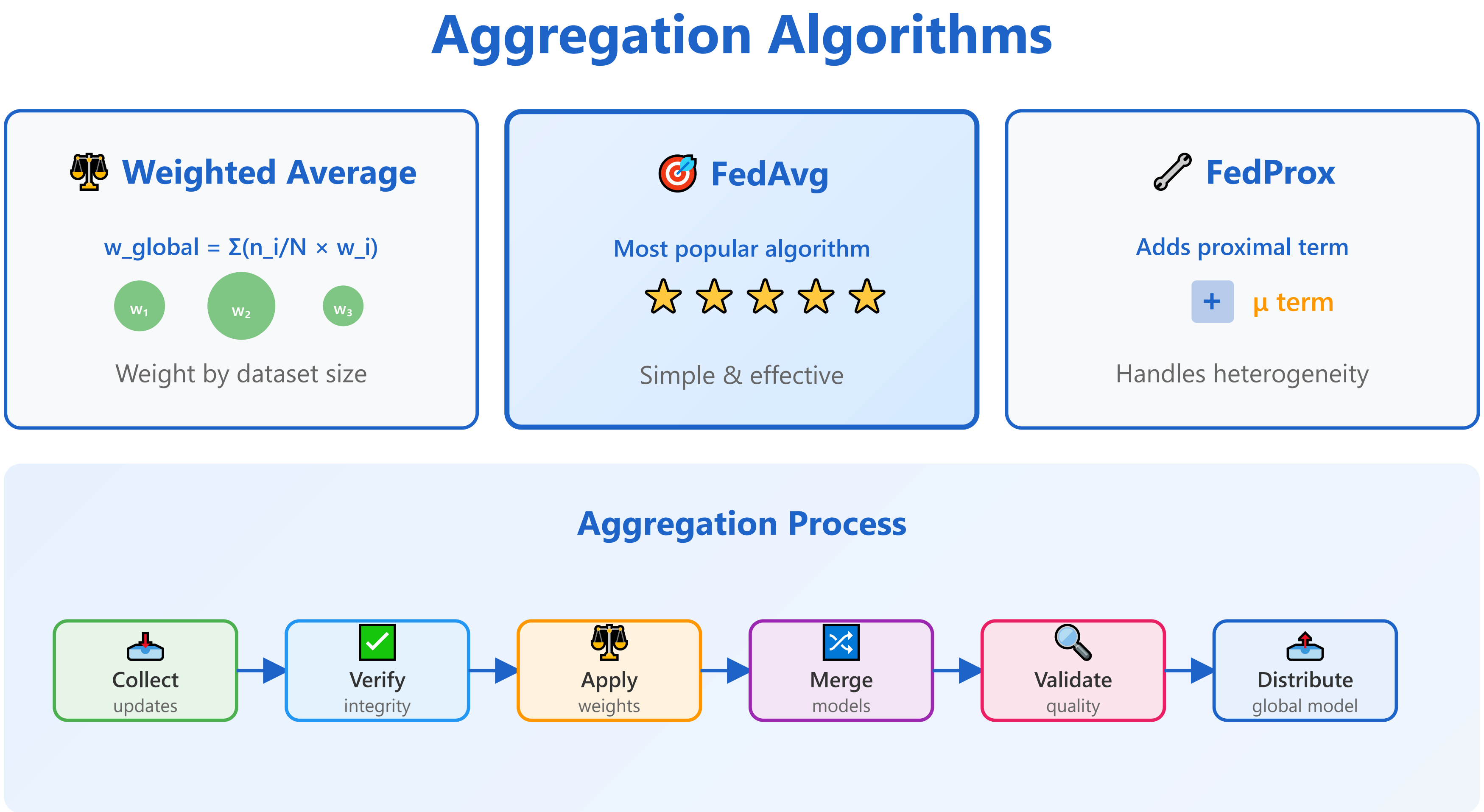
TLS 1.3

Mutual Auth

Rate Limiting

Audit Logging

Verification



Aggregation Algorithms
Weighted Average
w_global = Σ(n_i/N × w_i)
w₁
w₂
w₃
Weight by dataset size
FedAvg
Most popular algorithm
Simple & effective
FedProx
Adds proximal term
+
μ term
Handles heterogeneity
Aggregation Process
Collect
updates
Verify
integrity
Apply
weights
Merge
models
Validate
quality
Distribute
global model

FedAvg & FedProx

FedAvg

$w = \Sigma(n\_k/n \times w\_k)$

w_1 + w_2 + w_3 → w_globa

$n_1=100$ $n_2=150$ $n_3=80$

- Simple weighted average
- Fast convergence
- Works well with IID data

FedProx

$\min F(w) + \mu/2||w-w\_t||^2$

Standard Loss F(w)	+	Proximal Term $\mu/2||w-w\_t||^2$

- Adds proximal term
- Handles heterogeneity
- More robust

Differential Privacy

Original Data + Calibrated Noise = Protected Data 🔒

Mechanisms

Gaussian Mechanism	Laplace Mechanism	Privacy Budget (ε)
		ε remaining

Parameters

ε	δ	Typical Values
Privacy Loss	Failure Probability	$\varepsilon = 1\text{-}10$
Lower = More Private	Typically 10^{-5}	$\delta = 10^{-5}$

Secure Aggregation

Server learns only aggregate, not individual updates

Process

1 Clients mask updates

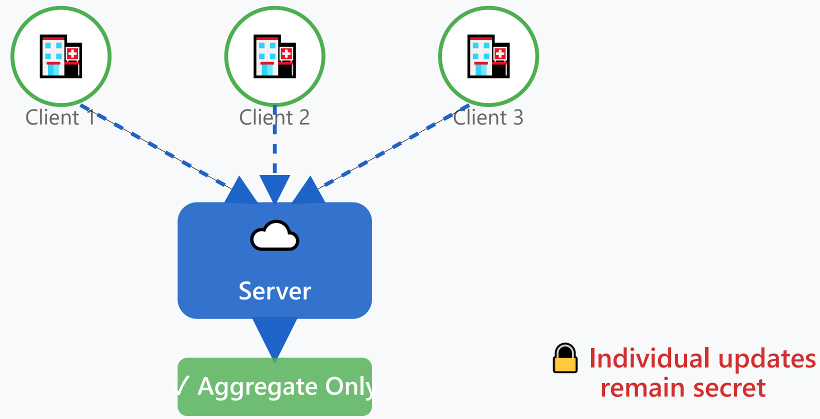
u_1 + m_1 = w_1 masked

2 Server aggregates

+ + = Σ(masked)

3 Masks cancel in sum

$m_1 + m_2 + m_3 =$

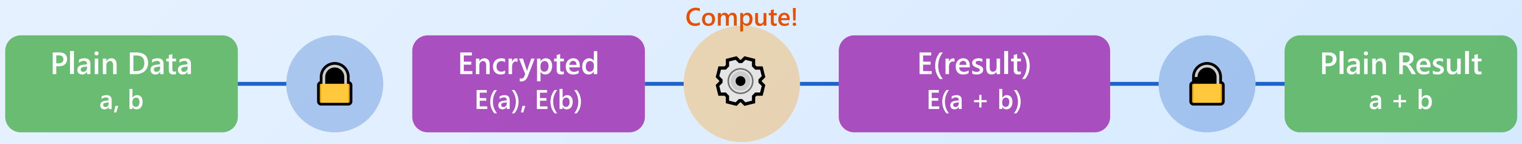


Shamir Secret Sharing
Split secrets into shares

Homomorphic Encryption
Compute on encrypted data

Secure Multi-Party Computation
Joint computation without revealing

Homomorphic Encryption



How It Works

Mathematical Property:

E(3) + E(5) = E(8)

$E(a) \oplus E(b) = E(a \oplus b)$

Operation on encrypted data = Encryption of operated data

Types

Partial HE
Only addition OR multiplication

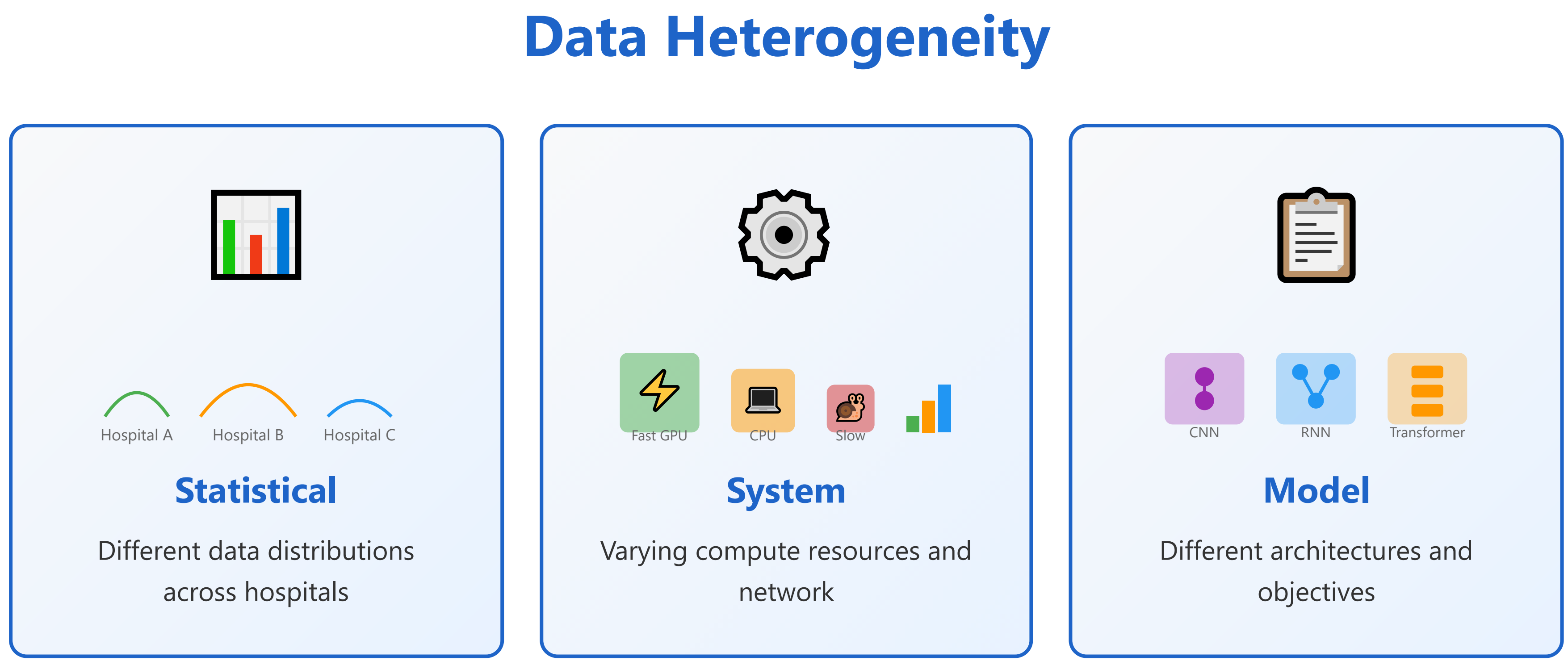
Somewhat HE
Limited number of operations

Fully HE ★
Arbitrary computations

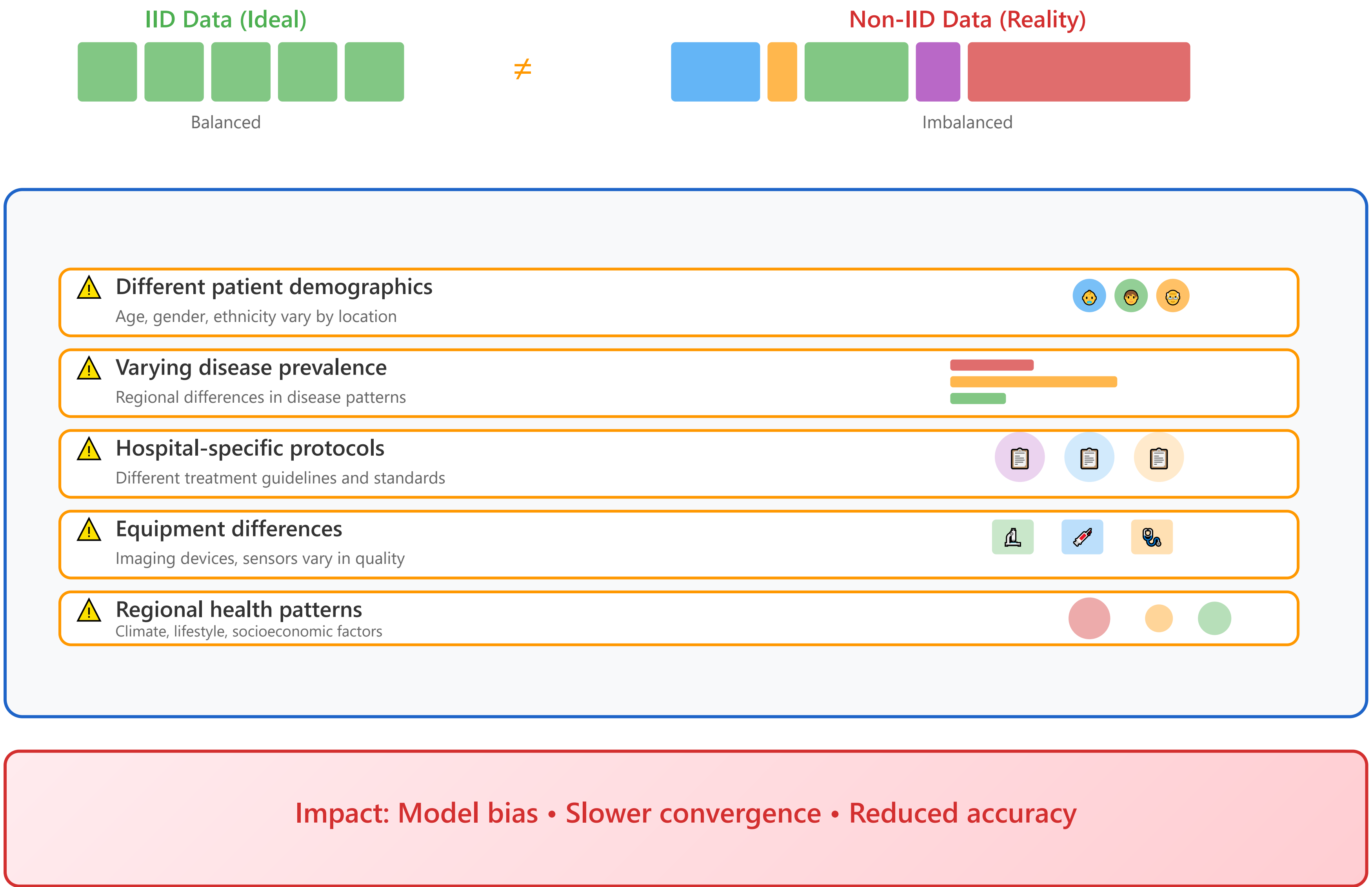
Security — 100-1000x slowdown — **Performance**

Part 2

Medical Data Challenges


Data Heterogeneity
Hospital A
Hospital B
Hospital C
Statistical
Different data distributions across hospitals
Fast GPU
CPU
Slow
System
Varying compute resources and network
CNN
RNN
Transformer
Model
Different architectures and objectives

Non-IID Medical Data



Client Drift Handling

FedProx

Proximal term limits drift

SCAFFOLD

Variance reduction

FedDyn

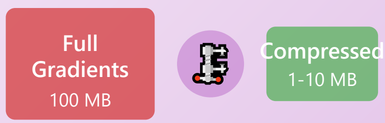
Dynamic regularization

Adaptive LR

Adjust learning rates

Communication Efficiency

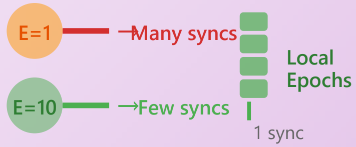
Gradient Compression



Sparsification, quantization

💾 10-100x reduction

Local Updates



More local epochs

💾 Linear in E reduction

Model Compression

Pruning, distillation

💾 2-10x reduction

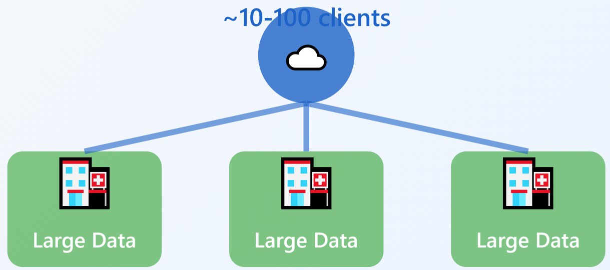
Model Personalization

- ✓ Fine-tune last layers locally
- ✓ Meta-learning (MAML)
- ✓ Mixture of global & local models
- ✓ Clustered federated learning

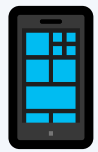
Global knowledge ⚖️ Local adaptation

Cross-Silo vs Cross-Device

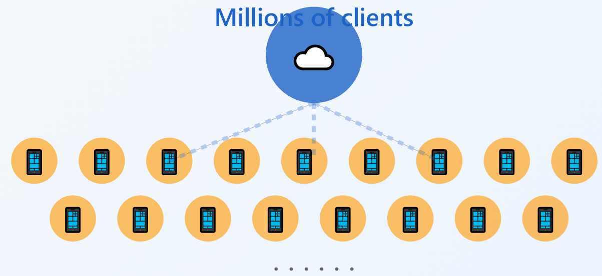
Cross-Silo (Hospital FL)



- Few clients (~10-100)
- Large datasets
- Reliable connectivity
- Powerful compute



Cross-Device (Mobile FL)



- Many clients (millions)
- Small local data
- Unreliable connectivity
- Limited resources

Part 3

Multi-Hospital Collaborations

Multi-Institutional Studies

🌍 Broader Data Diversity

Access to diverse patient populations across regions and demographics

📊 Larger Sample Size

Combined datasets enable robust statistical analysis

🔒 Privacy Preserved

Collaboration without sharing raw patient data

🏆 Better Generalization

Models trained on heterogeneous data perform better

Research Outcomes

✓ Faster rare disease diagnosis

✓ Improved treatment predictions

✓ Reduced model bias

✓ Enhanced clinical decision support

Regulatory Compliance

EU GDPR

European Union General Data Protection Regulation

- Right to explanation
- Data minimization
- Privacy by design
- Cross-border transfer rules

US HIPAA

Health Insurance Portability and Accountability Act

- PHI protection
- Security safeguards
- Breach notification
- Business associate agreements

✓ Compliance Checklist

☑ Encrypted communication channels

☑ Audit logs and monitoring

☑ Data anonymization techniques

☑ Consent management

☑ Regular security assessments

Data Governance

🏛️ Governance Structure

Clear roles and responsibilities

📜 Policy Framework

Data usage policies and procedures

🔑 Access Control

Role-based permissions

📊 Audit Trail

Complete logging of data access

Quality Control

✓ Data Validation

Schema validation and quality checks

🧪 Model Testing

Comprehensive evaluation metrics

📈 Performance Monitoring

Continuous accuracy tracking

🔍 Bias Detection

Fairness and equity assessments

Incentive Mechanisms

💰 Financial Rewards

Payment for data contribution

🏆 Reputation System

Recognition and credibility

📊 Data Credit

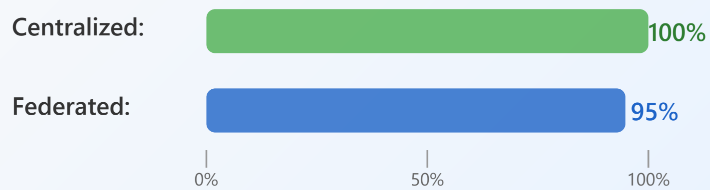
Fair attribution of contributions

🎯 Performance Bonus

Rewards for quality data

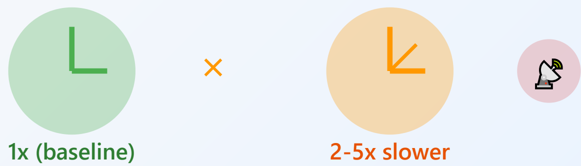
Performance Benchmarks

⚖️ Centralized vs FL



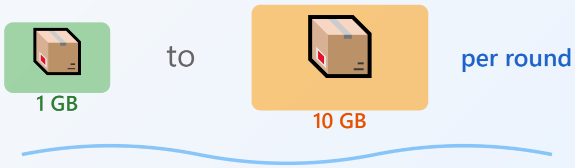
90-95% accuracy retention in FL

⏱️ Training Time



2-5x slower due to communication

💾 Bandwidth Usage



1-10 GB per round

🎯 Convergence

10-50 rounds to converge

Security Auditing

🔍 Vulnerability Analysis

Regular penetration testing

📝 Compliance Audits

GDPR/HIPAA checks

🛡️ Threat Modeling

Identify attack vectors

📊 Security Metrics

Track security posture

Scalability Analysis

📈 Node Scaling

Linear scaling up to 100s of nodes

⚡ Bottlenecks

Network & aggregation server

🔄 Load Balancing

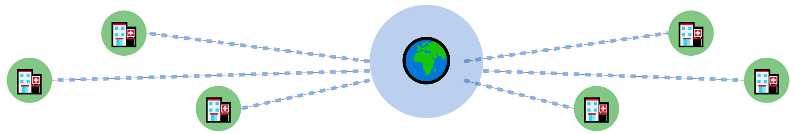
Distribute training rounds

💾 Resource Management

Optimize memory & compute

Case Study: COVID-19 FL Consortium

Global Collaboration for Pandemic Response



20+

Countries

100+

Hospitals

1M+

Patient Records

🏆 Key Achievements

- 🎯 Developed COVID-19 severity prediction models
- 📊 Achieved 85%+ accuracy across diverse populations — 85%
- ⚡ Rapid deployment during critical pandemic phases — Fast
- 🔒 Full GDPR/HIPAA compliance maintained — GDPR HIPAA
- 🌐 Cross-border collaboration without data transfer — No transfer

Hands-On: Federated Setup

🌸 Flower

Friendly FL framework with simple API

```
pip install flwr
flwr.client.start()
```

🧠 PySyft

Privacy-preserving ML library

```
pip install syft
sy.VirtualMachine()
```

📝 Setup Steps

1. Install framework (Flower/PySyft)
2. Define model architecture
3. Configure server & clients
4. Implement training loop
5. Run federated training
6. Evaluate global model

Future Directions

Vertical FL

Different features from different institutions

Genomic FL

Privacy-preserving genetic research

LLM Fine-tuning

Federated adaptation of medical LLMs

Split Learning

Hybrid FL + split computation

Research Opportunities

Communication efficiency • Adaptive aggregation • Cross-silo heterogeneity • Byzantine robustness • Incentive mechanisms • Real-world deployments

Thank You! 🎉

Key Takeaways

✓ FL enables privacy-preserving multi-hospital collaboration

✓ Differential privacy & secure aggregation protect data

✓ Heterogeneity requires specialized algorithms (FedProx, SCAFFOLD)

✓ GDPR/HIPAA compliance is achievable with proper design

✓ Real-world deployments show promising results

📚 Resources: Flower Framework • PySyft • NVIDIA FLARE
🔗 Papers: FedAvg • FedProx • Secure Aggregation