

CS-E4740 - Federated Learning

L1 - From ML to FL

Assoc. Prof. Alexander Jung

Spring 2026

Calendar



Glossary



Book



GitHub



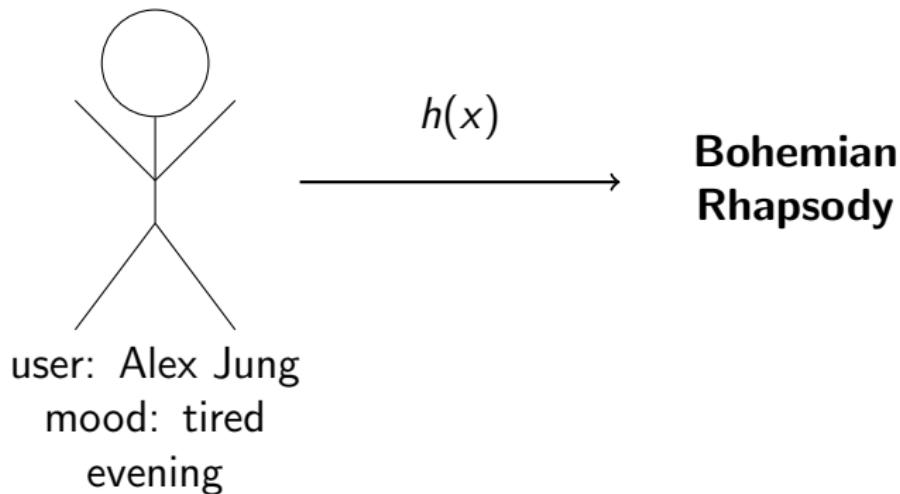
Table of Contents

Machine learning (ML) Basics

From ML to federated learning (FL)

Federated Learning Networks (FL networks)

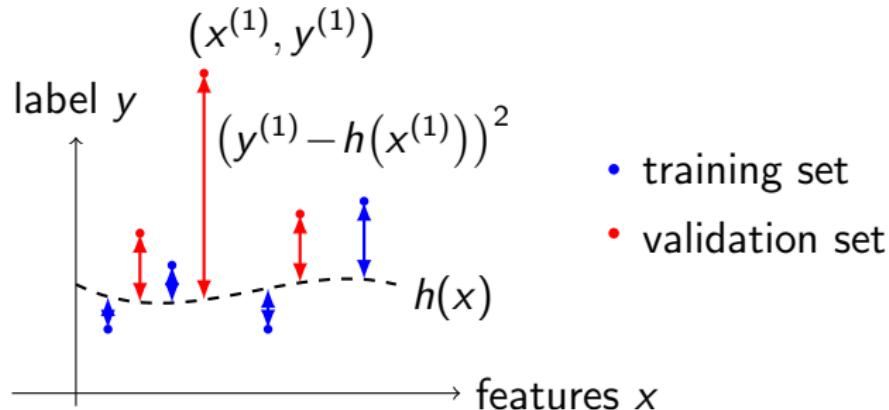
The Right Song Can Save the Day



How do we get a good hypothesis map $h(x)$?

Wang, M., Wu, J., Yan, H. (2023). "Effect of music therapy on older adults with depression: A systematic review and meta-analysis." *Complementary Therapies in Clinical Practice* <https://doi.org/10.1016/j.ctcp.2023.101809>

Empirical risk minimization (ERM)



Learn $h \in \mathcal{H}$ by min. average loss (empirical risk),

$$\min_{h \in \mathcal{H}} \frac{1}{m} \sum_{r=1}^m L((\mathbf{x}, y), h).$$

Different choices for \mathcal{H} and loss L yield different ML methods.

see Chapters 3,4 of AJ, "Machine Learning: The Basics," Springer, 2022.
<https://mlbook.cs.aalto.fi>

ML with Python

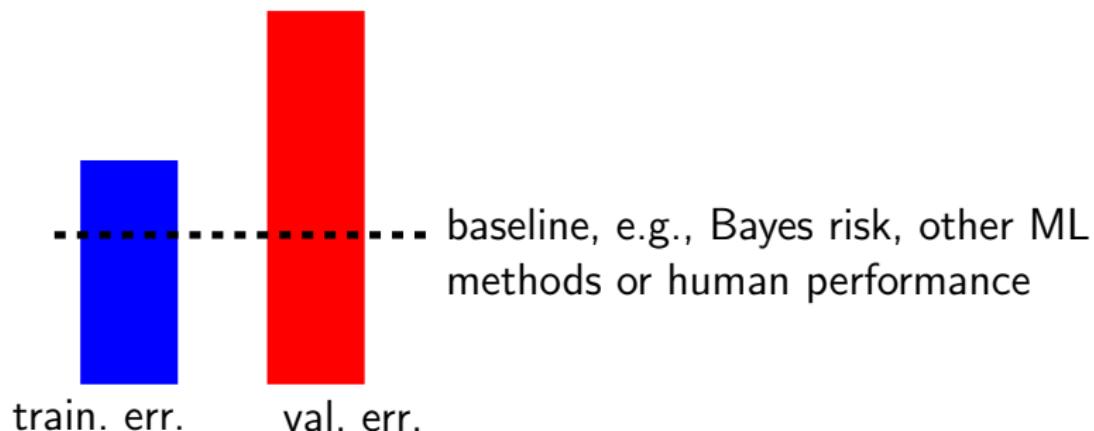
```
X, y = read_data()

# split data
Xtr, Xval, ytr, yval = train_test_split(X, y)

# train model
model = SGDRegressor()
model.fit(Xtr, ytr)

# compute errors
train_err = mean_squared_error(ytr, model.predict(Xtr))
val_err   = mean_squared_error(yval, model.predict(Xval))
```

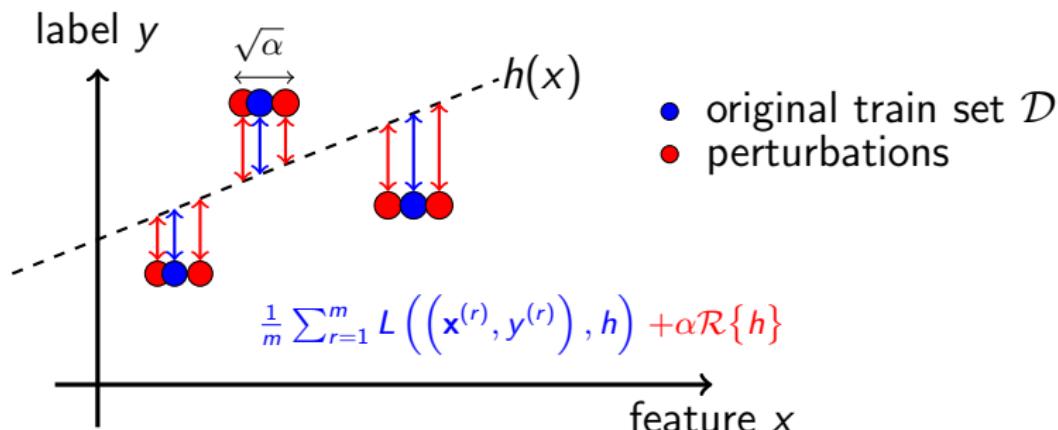
Applied ML - Diagnosis



compare training error with validation error and a baseline.

see Chapter 6 of AJ, "Machine Learning: The Basics," Springer, 2022.
<https://mlbook.cs.aalto.fi>

Applied ML - Regularization



Start with large \mathcal{H} , then shrink it via (combinations of)

- ▶ data augmentation, e.g., $\mathbf{x} \mapsto \mathbf{x} + \mathcal{N}(0, \alpha)$,
- ▶ adding penalty term to loss function, e.g., $\dots + \alpha \|\mathbf{w}\|_2^2$,
- ▶ **constraining** model parameters, e.g., $\|\mathbf{w}\|_2 \leq 1$.

see Chapter 7 of AJ, "Machine Learning: The Basics," Springer, 2022.
<https://mlbook.cs.aalto.fi>

Table of Contents

ML Basics

From ML to FL

FL networks

From ML to FL

Basic ML. Train a single model \mathcal{H} by minimizing average loss on a single dataset

FL. Train several models $\mathcal{H}^{(i)}$ using interconnected device.

We use the term device broadly. It is anything that can

- ▶ access data,
- ▶ train a model, and
- ▶ communicate with other devices.

From ML to FL

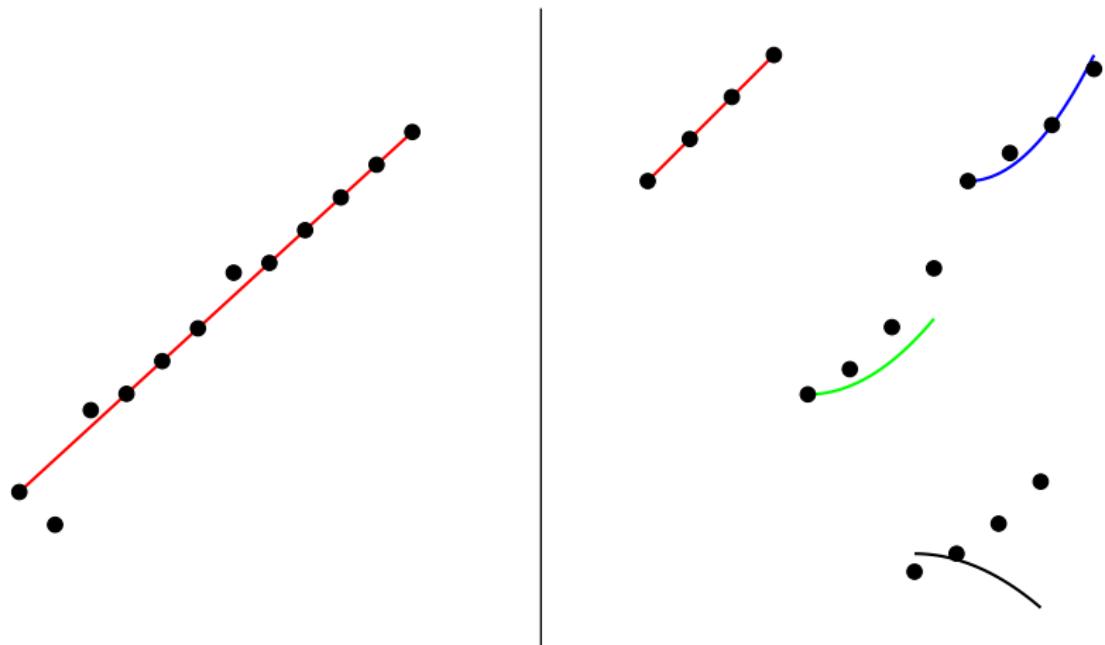


Figure: Left: A ML method uses a single dataset to train a single model. Right: FL methods train ML models from decentralized data.

ML with Python

```
X, y = read_data()  
model = SGDRegressor()  
model.fit(X, y)
```

FL with Python

IP: 192.168.0.1

```
model = SGDRegressor()  
y_hat =recv_preds(192.168.0.3)  
X, y = read_data()  
Xa,ya=augment_data(X, y, y_hat)  
model.fit(Xa,ya)
```

IP: 192.168.0.2

```
X,y = read_data()  
model=LinearRegression()  
model.fit(X, y)
```

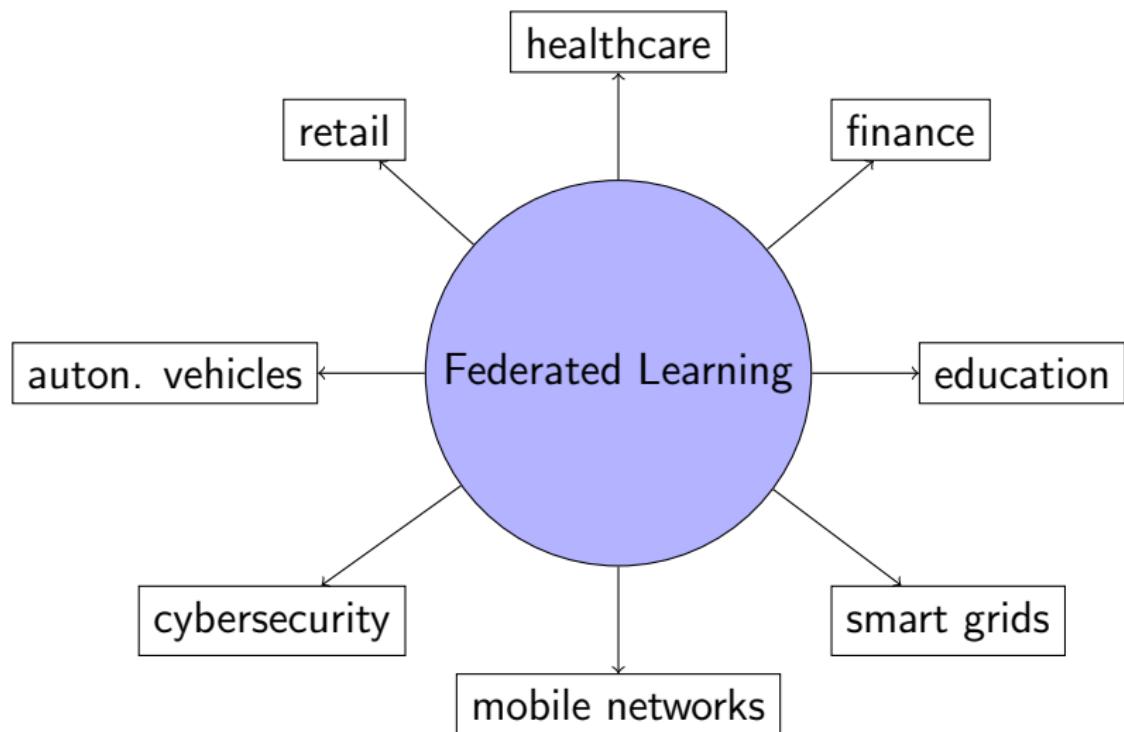
IP: 192.168.0.3

```
model=DecisionTree()  
y_hat =recv_preds(192.168.0.2)  
X, y = read_data()  
Xa,ya=augment_data(X, y, y_hat)  
model.fit(Xa,ya)
```

Key Characteristics of FL

- ▶ No centralized data collection (no single point of failure).
- ▶ Each device trains a tailored model (high-precision).
- ▶ Scalability: more devices yield more compute and data.
- ▶ No raw data is shared (privacy-friendly).

FL Applications



FL for Pandemics

High-Precision Management of Pandemics



Figure: A hypothetical FL system for pandemic forecasting.
Smartphones train personalized models based on their observations
(e.g., audio recordings of coughing) as well as public health-care
data.

FL in Healthcare

- ▶ Turn smartphone into personal health-care advisor.
- ▶ Smartphone app uses FL to train personalized model.
- ▶ Combine personal data with public health-care data.

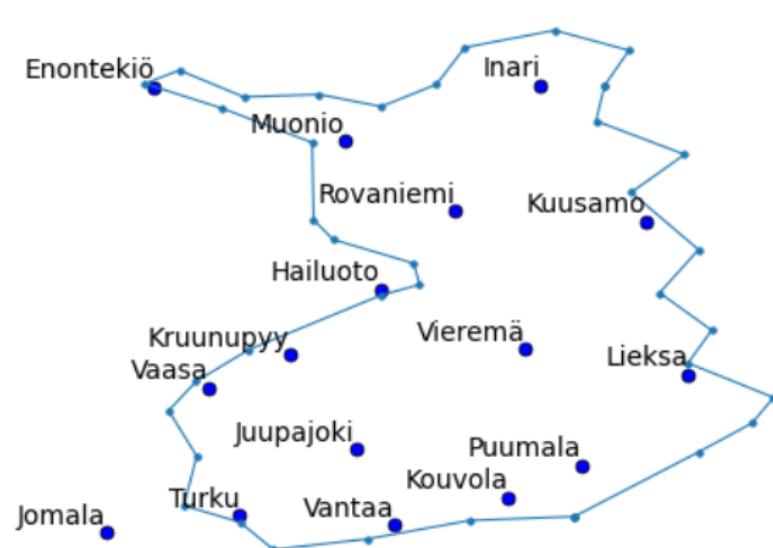
Key Reference: Rieke, N., et al. *The future of digital health with federated learning*. Nature Medicine, 2020.

FL in Finance

FL can help financial institutions to improve

- ▶ **Fraud detection.** N. F. Aurna, et.al., "Federated Learning-Based Credit Card Fraud Detection: Performance Analysis with Sampling Methods and Deep Learning Algorithms," 2023,
- ▶ **Risk assessment.** W. Li, et.al., "Personal Credit Evaluation Model Based on Federated Learning," 2024

FL at FMI

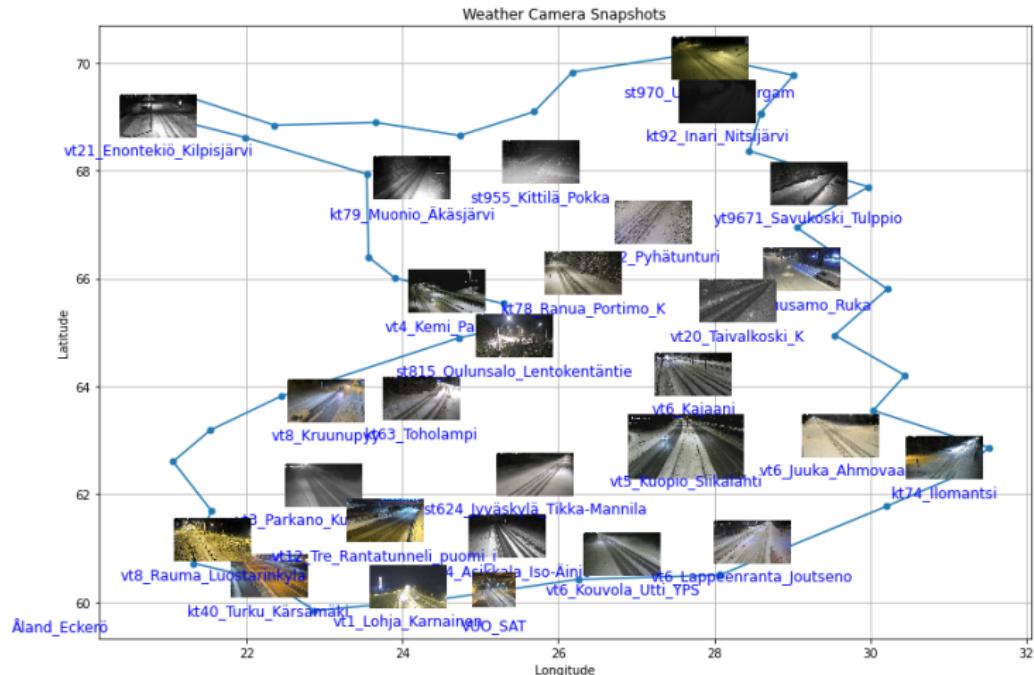


Train a separate model for each Finnish Meteorological Institute (FMI) weather station

Python script for reproducing the Fig.:



FL for Finnish Road Safety



Train separate model for each camera operated by FinTraffic

Python script for reproducing the Fig.:



The Internet of Things (IoT) is Growing

IoT connections (billion)

IoT	2023	2029	CAGR
Wide-area IoT	3.6	7.2	12%
Cellular IoT	3.4	6.7	12%
Short-range IoT	12.1	31.6	17%
Total	15.7	38.8	16%

Note: Based on rounded figures. Cellular IoT figures are also included in the figures for wide-area IoT.

Figure: Some IoT statistics from



The IoT - A Global FL System

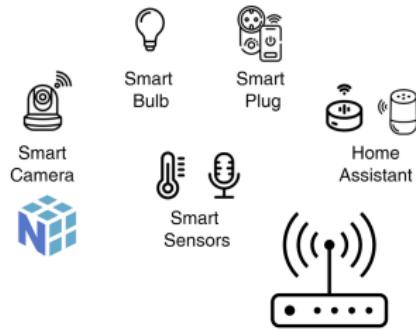


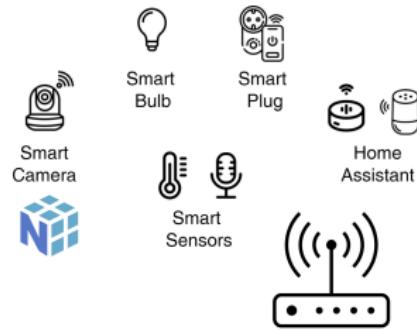
Table of Contents

ML Basics

From ML to FL

FL networks

A (“Real-World”) FL System



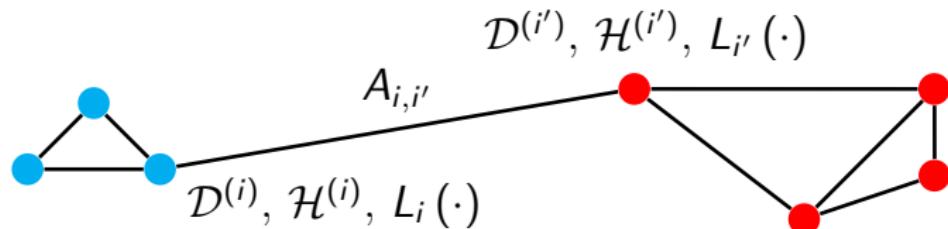
Abstracting Away System Details

to reason about an FL system, we deliberately ignore many implementation details:

- ▶ physical properties of communication links (latency, bandwidth)
- ▶ communication protocols and message formats
- ▶ hardware and operating systems of devices
- ▶ software stacks and scientific computing libraries

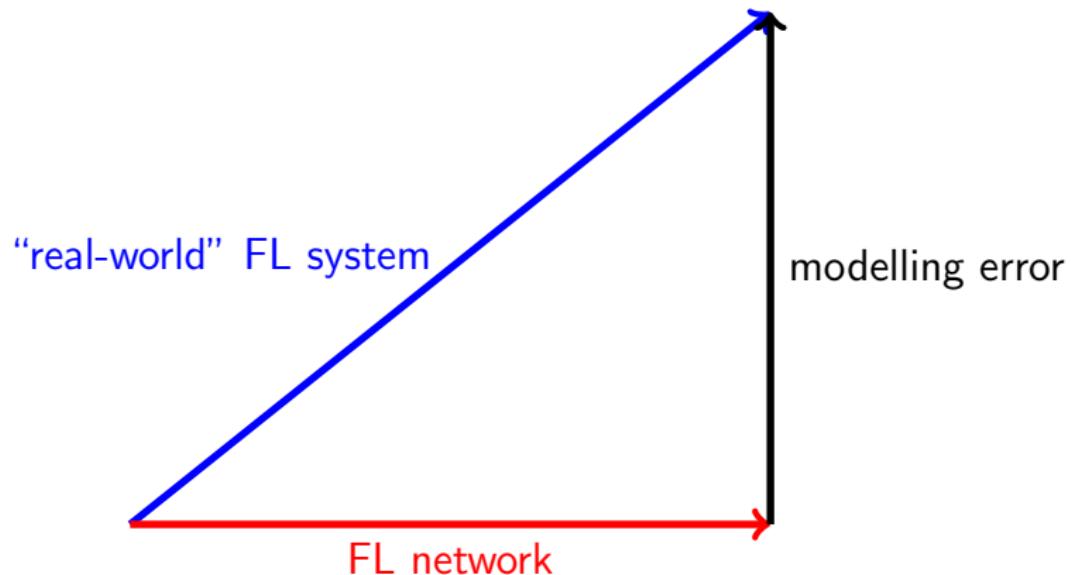
Goal: isolate the *essential structure* of a FL system needed to analyze the overall behaviour.

The FL network as an Abstraction



- ▶ an FL network is an undirected graph with nodes $i=1, \dots, n$
- ▶ edge $\{i, i'\}$ with weight $A_{i,i'} > 0$ encodes collaboration
- ▶ each node i holds local dataset $\mathcal{D}^{(i)}$ and trains model $\mathcal{H}^{(i)}$
- ▶ a local dataset induces a local loss function $L_i(\cdot)$

FL network is an Approximation



A Precise Definition

An FL network consists of:

- ▶ a finite set of **nodes**, denoted as $\mathcal{V} := \{1, \dots, n\}$
- ▶ a **local model** $\mathcal{H}^{(i)}$ at each node $i \in \mathcal{V}$
- ▶ a **local loss function** $L_i(\cdot)$ at each node $i \in \mathcal{V}$
- ▶ a set of undirected **edges**, denoted as \mathcal{E}
- ▶ a positive **edge weight** $A_{i,i'} > 0$ for each edge $\{i, i'\} \in \mathcal{E}$

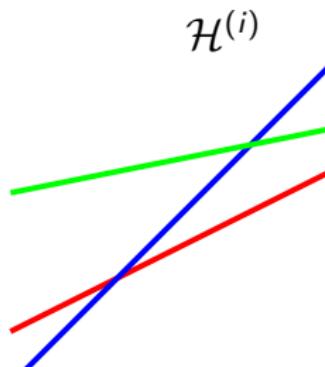
Thus, a FL network is a weighted undirected graph with a model and loss function attached to each node.

Nodes of an FL network

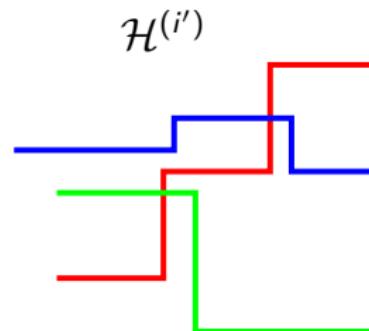
- ▶ consider an FL system with finite number n of devices
- ▶ we index devices as $i = 1, \dots, n$
- ▶ indices form the set of nodes \mathcal{V} in an FL network.
- ▶ node $i \in \mathcal{V}$ **represents** a physical device.
- ▶ we use “device i ” and “node i ” interchangeably.

Local models

- ▶ consider an FL system with devices $i = 1, \dots, n$.
- ▶ each device trains local (personal) model $\mathcal{H}^{(i)}$.
- ▶ devices might use (very) different local models.
- ▶ we use local model parameters $\mathbf{w}^{(i)}$ for parametric $\mathcal{H}^{(i)}$.



```
model=LinearRegression()
```



```
model=DecisionTreeRegressor()
```

Local Loss functions

- ▶ consider device i , training its local model $\mathcal{H}^{(i)}$.
- ▶ *to train a model* is to learn a useful hypothesis $h^{(i)} \in \mathcal{H}^{(i)}$.
- ▶ measure usefulness of $h^{(i)}$ by a local loss function

$$L_i(\cdot) : \mathcal{H}^{(i)} \rightarrow \mathbb{R} : h^{(i)} \mapsto L_i(h^{(i)})$$

- ▶ different devices can use different loss functions.

Local Loss functions - ctd.

- ▶ FL methods use different constructions of loss functions
- ▶ for parametric models $\mathcal{H}^{(i)}$, with model parameters $\mathbf{w}^{(i)} \in \mathbb{R}^d$,

$$L_i(\cdot) : \mathbb{R}^d \rightarrow \mathbb{R} : \mathbf{w}^{(i)} \mapsto L_i(\mathbf{w}^{(i)})$$

- ▶ can use average loss on local dataset

$$L_i(\mathbf{w}^{(i)}) := \frac{1}{m_i} \sum_{r=1}^{m_i} \left(y^{(i,r)} - (\mathbf{w}^{(i)})^T \mathbf{x}^{(i,r)} \right)^2$$

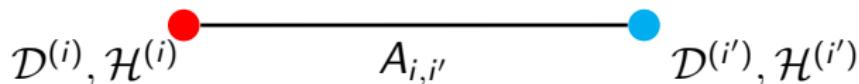
- ▶ loss can also be estimated from a reward signal

Edges of an FL network

- ▶ FL network consists of **undirected weighted** edges \mathcal{E} .
- ▶ $\{i, i'\} \in \mathcal{E}$ signifies a **similarity** between devices i and i' .
- ▶ **quantify similarity using edge weight** $A_{i,i'} > 0$.
- ▶ notion of similarity depends on FL application .
- ▶ we view edges primarily as a **design choice**.

Effect of Placing an Edge

FL algorithms are executed over a FL network



placing an edge $\{i, i'\} \in \mathcal{E}$ has two consequences:

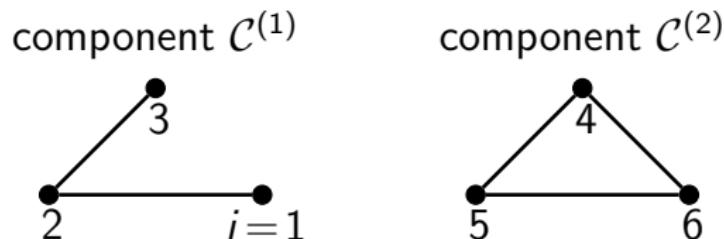
- ▶ there must be communication channel between devices i, i' (edge weight $A_{i,i'} \approx$ channel capacity).
- ▶ model parameters at i, i' are forced to be similar.

Connectivity of an FL network

consider an FL network with graph \mathcal{G} .

- ▶ \mathcal{G} is **connected** if there is a path between any $i, i' \in \mathcal{V}$.
- ▶ a **component** $\mathcal{C} \subseteq \mathcal{V}$ is a connected subgraph with no edges between \mathcal{C} and $\mathcal{V} \setminus \mathcal{C}$.
- ▶ the **neighborhood** of $i \in \mathcal{V}$ is $\mathcal{N}^{(i)} := \{i' \in \mathcal{V} : \{i, i'\} \in \mathcal{E}\}$.
- ▶ **weighted node degree** of i is $d^{(i)} := \sum_{i' \in \mathcal{N}^{(i)}} A_{i,i'}$.
- ▶ **maximum node degree** is $d_{\max} := \max_{i \in \mathcal{V}} d^{(i)}$.

Connectivity of an FL network- Example



- ▶ FL network containing $n=6$ nodes.
- ▶ uniform edge-weights, $A_{i,i'} = 1$ for all $\{i, i'\} \in \mathcal{E}$.
- ▶ two components $\mathcal{C}^{(1)} = \{1, 2, 3\}$, $\mathcal{C}^{(2)} = \{4, 5, 6\}$.
- ▶ $d^{(1)} = 1$, $\mathcal{N}^{(2)} = \{1, 3\}$, $d_{\max} = 2$.

From FL network to FL system

each node $i \in \mathcal{V}$,

- ▶ can access local dataset $\mathcal{D}^{(i)}$,
- ▶ maintains model parameters $\mathbf{w}^{(i)}$
- ▶ sends/receives messages from neighbors $\mathcal{N}^{(i)}$.

an FL algorithm specifies *when* and *how* these model parameters are updated.

FL Algorithms

each node i uses current model parameters $\mathbf{w}^{(1,t)}, \dots, \mathbf{w}^{(n,t)}$ to compute new model parameters $\mathbf{w}^{(i,t+1)}$,

$\mathbf{w}^{(i,t+1)} = \mathcal{F}^{(i)}(\mathbf{w}^{(1,t)}, \dots, \mathbf{w}^{(n,t)})$ at time instants $t = 0, 1, \dots$.

the node-wise operator $\mathcal{F}^{(i)}$ involves

- ▶ local model updates (e.g., via gradient steps)
- ▶ sharing model parameters across edges of FL network.

What's Next?

L2-“FL Design Principle” introduces generalized total variation minimization (GTVMin) as our main design principle for FL algorithms.

We use GTVMin to guess useful choices for the node-wise update operator $\mathcal{F}^{(i)}$ that define an FL algorithm.

References

- ▶ AJ, "Machine Learning: The Basics," Springer, 2022.
- ▶ AJ, "Federated Learning: From Theory to Practice," Springer, 2026.
- ▶ AJ et.al., "The Aalto Dictionary of Machine Learning," github repo, 2026.