

CS-E4740 - Federated Learning

L1 - From ML to FL

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Spring 2026

Calendar



Glossary



Book



GitHub



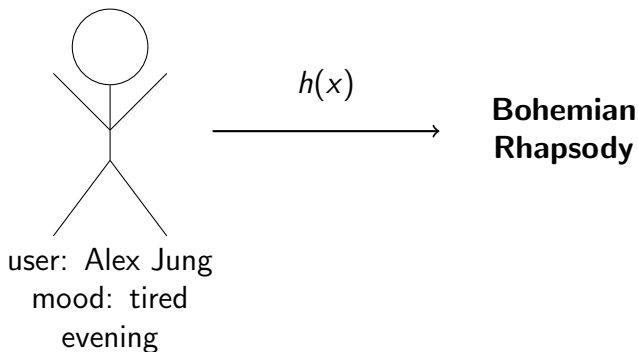
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Machine learning (ML) Basics

From ML to federated learning (FL)

Federated Learning Networks (FL networks)

The Right Song Can Save the Day



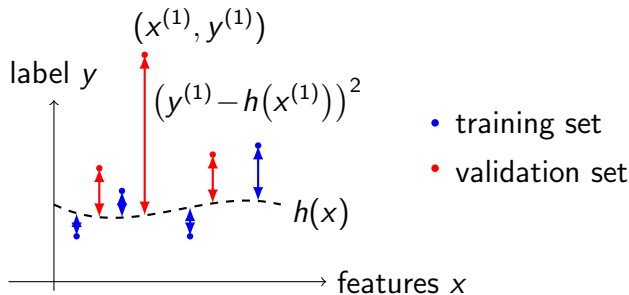
How do we get a good hypothesis map $h(x)$?

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

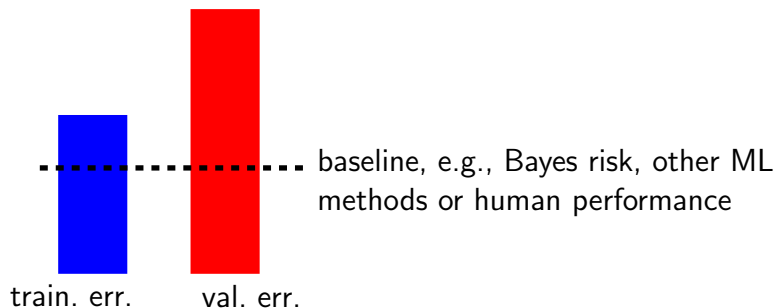
```
X, y = read_data()

# 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))
```

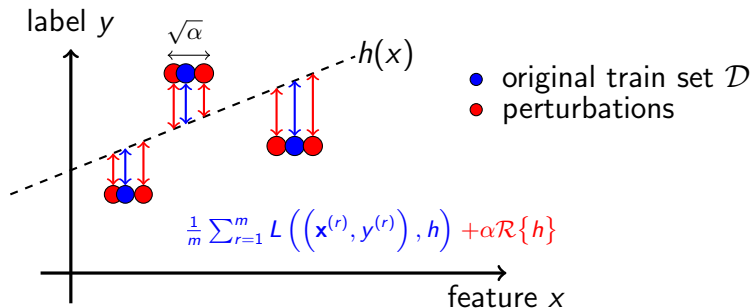
Applied ML - Diagnosis



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>

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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

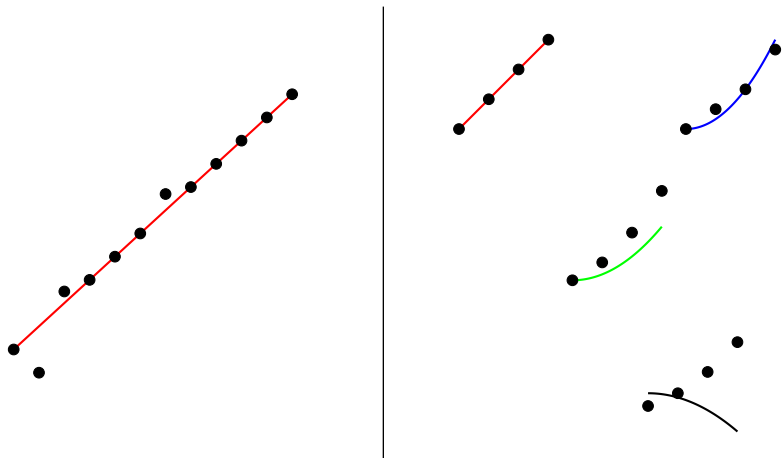


Figure: Left: A ML method uses a single dataset to train a single model. Right: FL methods train ML models from decentralized data.

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)
```

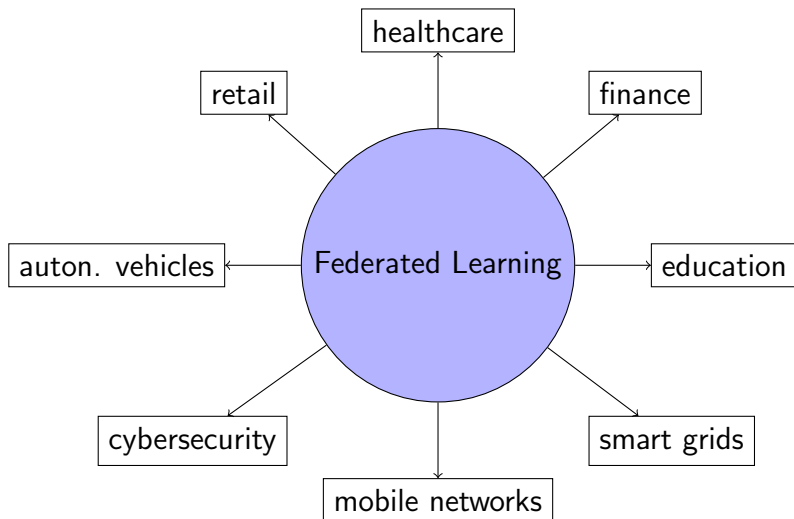
IP: 192.168.0.3

```
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

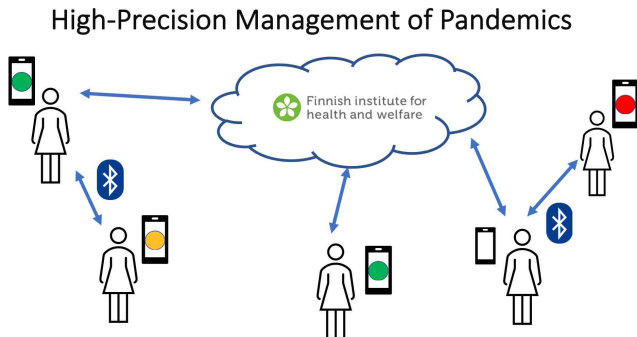


Figure: A hypothetical FL system for pandemic forecasting. Smartphones train personalized models based on their observations (e.g., audio recordings of coughing) as well as public health-care data.

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.

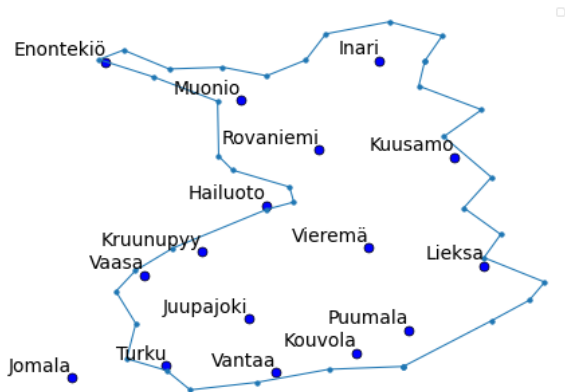
Key Reference: Rieke, N., et al. *The future of digital health with federated learning*. Nature Medicine, 2020.

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

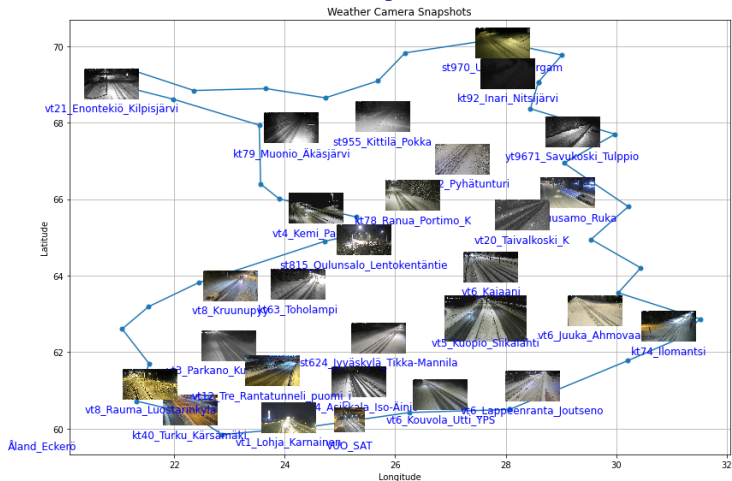


Train a separate model for each Finnish Meteorological Institute (FMI) weather station

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

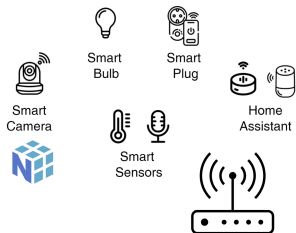


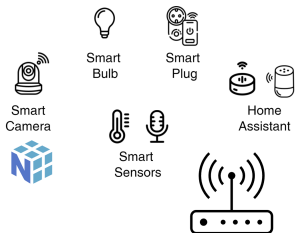
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A (“Real-World”) FL System



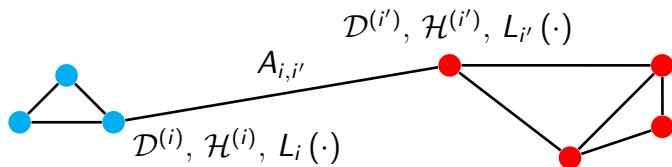
Abstracting Away System Details

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

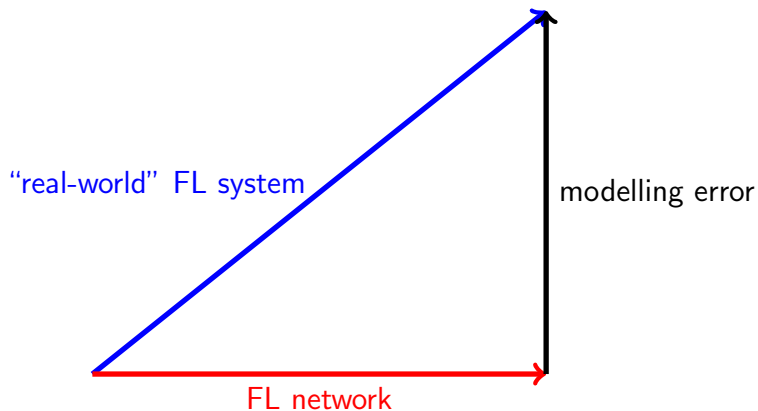
Goal: isolate the *essential structure* of a FL system needed to analyze the overall behaviour.

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 $\{i, i'\} \in \mathcal{E}$

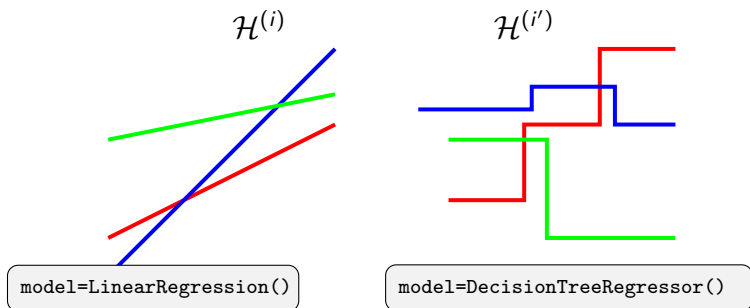
Thus, a FL network is a weighted undirected graph with a model and loss function attached to each node.

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 $\mathcal{H}^{(i)}$.



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

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

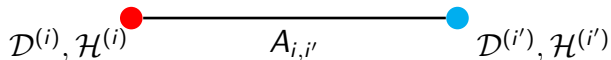
- ▶ loss can also be estimated from a reward signal

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.

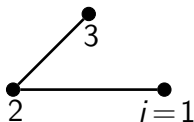
Connectivity of an FL network

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

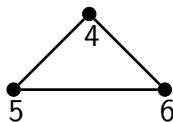
- ▶ \mathcal{G} is **connected** if there is a path between any $i, i' \in \mathcal{V}$.
- ▶ a **component** $\mathcal{C} \subseteq \mathcal{V}$ is a connected subgraph with no edges between \mathcal{C} and $\mathcal{V} \setminus \mathcal{C}$.
- ▶ the **neighborhood** of $i \in \mathcal{V}$ is $\mathcal{N}^{(i)}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

component $\mathcal{C}^{(1)}$



component $\mathcal{C}^{(2)}$



- ▶ 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.