CS-E4740 - Federated Learning

L1 - From ML to FL

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Spring 2026

Calendar **Glossary** **Book** **GitHub**

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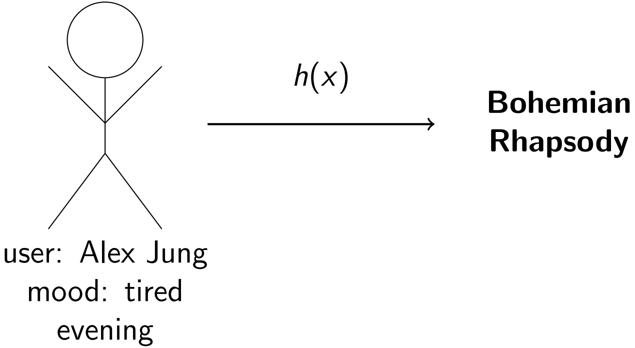
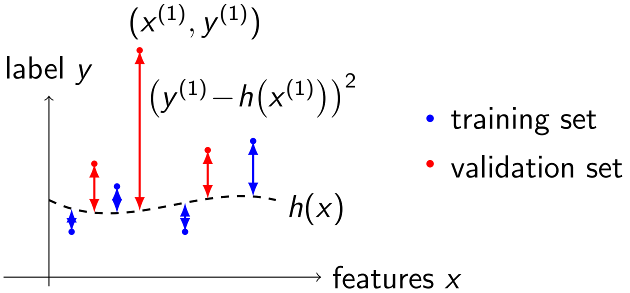
The Right Song Can Save the Day



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),

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

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

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

ML with Python

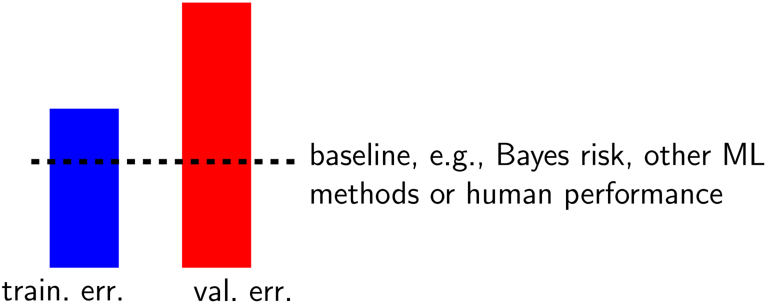
```
X, y = read_data()

# 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.

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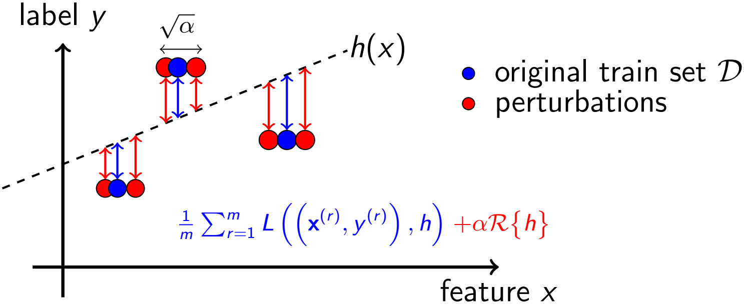
see Chapter 6 of AJ, "Machine Learning: The Basics," Springer, 2022.
https://mlbook.cs.aalto.fi

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., $\ldots + \alpha \|\mathbf{w}\|_2^2$,
- **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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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 devices.

A device is anything that can

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

From ML to FL

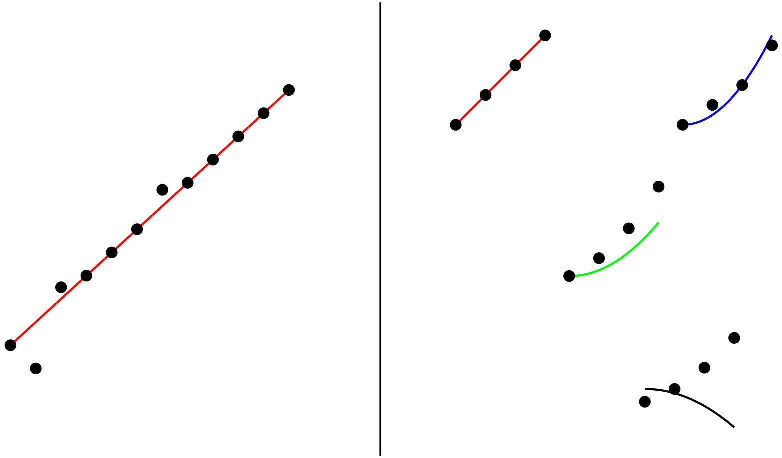


Figure: Left: A ML method uses a single dataset to train a single model. Right: FL methods train ML models from decentralized data.

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)
```

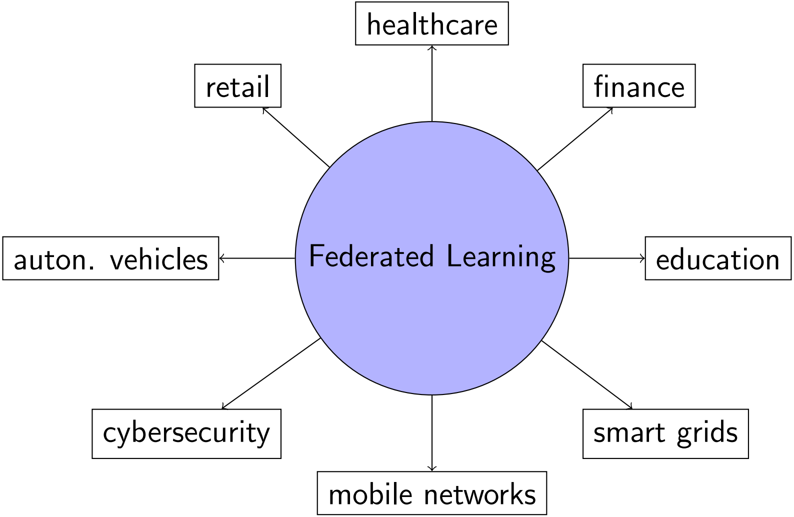
IP: 192.168.0.3

```
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

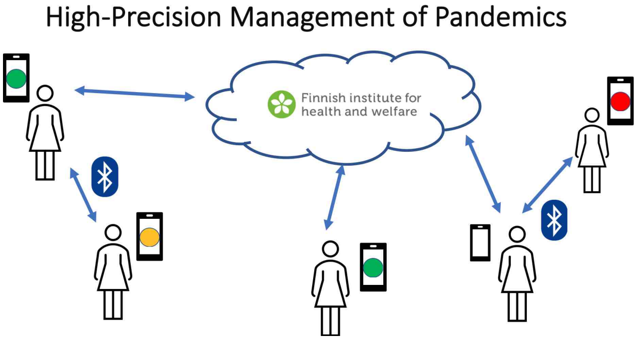


Figure: A hypothetical FL system for pandemic forecasting. Smartphones train personalized models based on their observations (e.g., audio recordings of coughing) as well as public health-care data.

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.

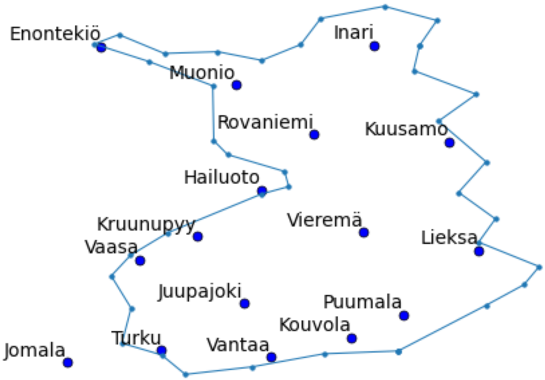
Key Reference: Rieke, N., et al. *The future of digital health with federated learning.* Nature Medicine, 2020.

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

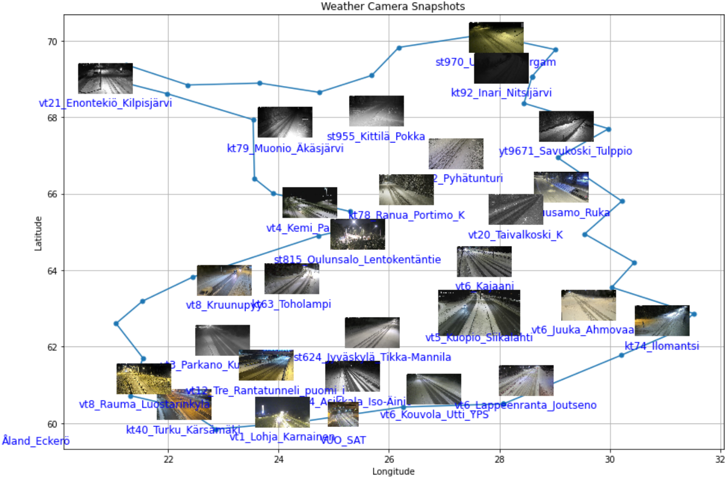
FL at FMI



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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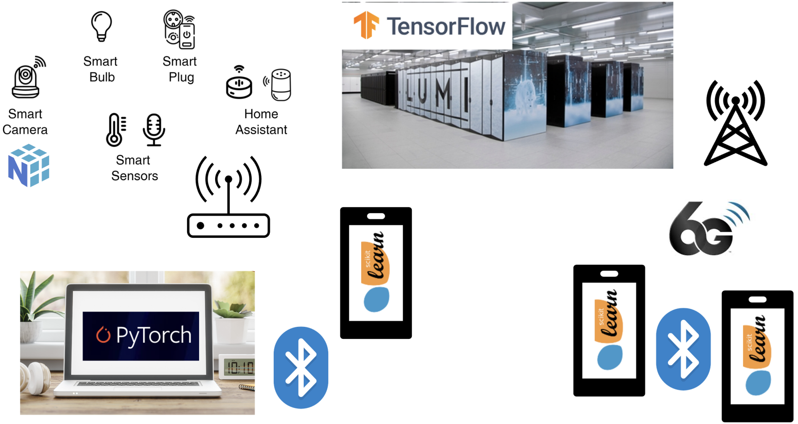
A ("Real-World") FL System



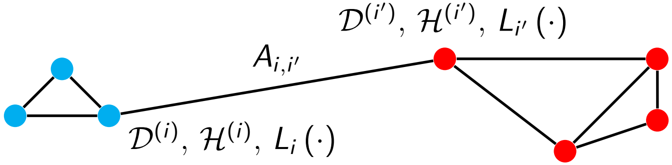
Abstracting Away System Details

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

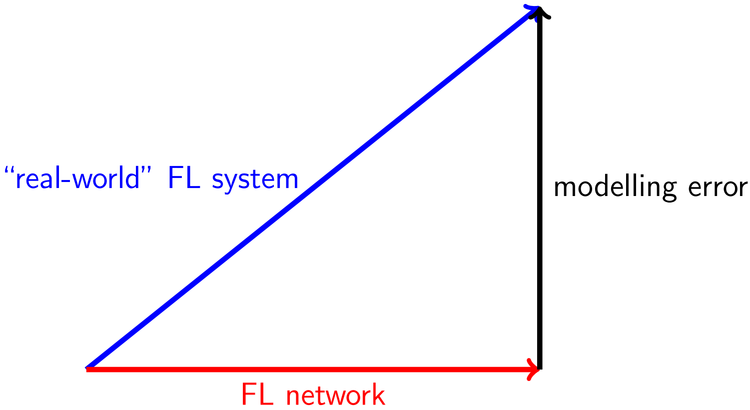
Goal: isolate the *essential structure* of a FL system needed to analyze the overall behaviour.

The FL network as an Abstraction



- an FL network is an undirected graph with nodes $i = 1, \ldots, n$
- 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 $\mathcal{V} := \{1, \ldots, n\}$
- 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 $\{i, i'\} \in \mathcal{E}$

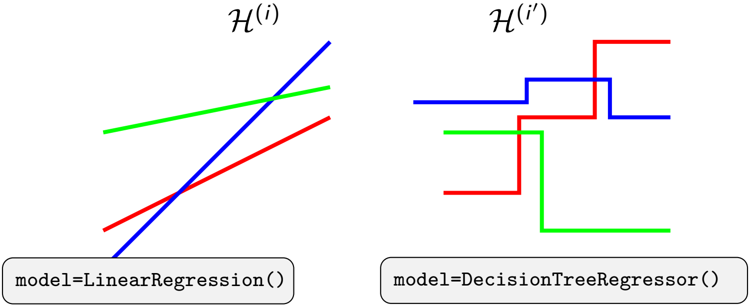
Thus, a FL network is a weighted undirected graph with a model and loss function attached to each node.

Nodes of an FL network

- consider an FL system with finite number n of devices
- we index devices as $i = 1, \ldots, n$
- 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 $i = 1, \ldots, n$.
- 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
$$L_i\left(\cdot\right) : \mathcal{H}^{(i)} \rightarrow \mathbb{R} : h^{(i)} \mapsto L_i\left(h^{(i)}\right)$$
- 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 $\mathbf{w}^{(i)} \in \mathbb{R}^d$,

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

- can use average loss on local dataset

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

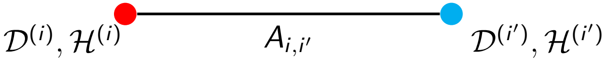
- loss can also be estimated from a reward signal

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:

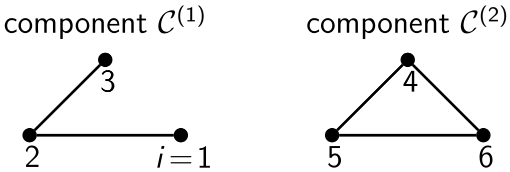
- there must be communication channel between devices i, i' (edge weight $A_{i,i'} \approx$ channel capacity).
- model parameters at i, i' are forced to be similar.

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 $d_{\rm max} := \max_{i \in \mathcal{V}} d^{(i)}$.

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 $\mathbf{w}^{(1,t)}, \ldots, \mathbf{w}^{(n,t)}$ to compute new model parameters $\mathbf{w}^{(i,t+1)}$,

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

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.