# Wireless Federated Learning

*What It Is and How It's Changing AI*

by Daniel Detore

# 01 Overview

# **The Usual Training Method:** Centralized Learning

- All edge devices send all of their raw data to a central server
- The central server trains the model on all of the data
- The server sends the entire model back to all edge devices

# **The New Training Method:** Federated Learning

One "round" of WFL:

1. A subset of existing clients is selected, each of which downloads the current model.
2. Each client in the subset computes an updated model based on their local data.
3. The model updates are sent from the selected clients to the server.
4. The server aggregates these models (typically by averaging) to construct an improved global model.

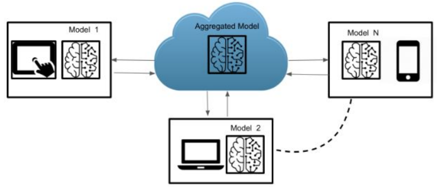



**Figure 1: Overview of Federated Learning across devices.**

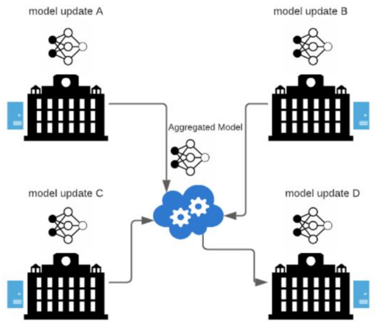


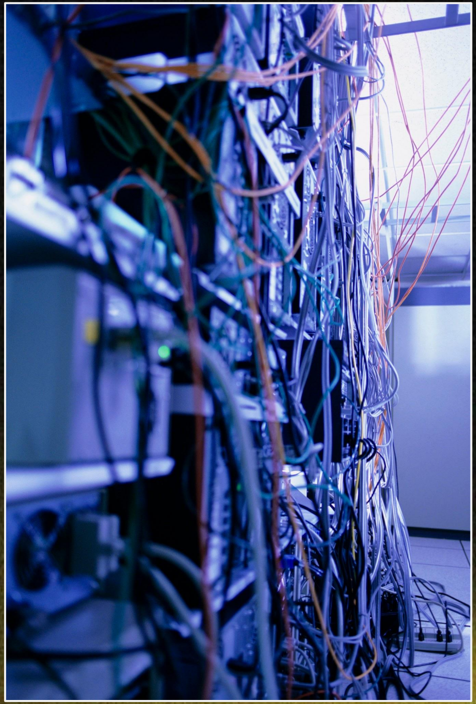

**Figure 2: Overview of Federated Learning across organisations**

# Motivation

- Easier to broadcast models than raw data en masse
- More private, since models are obfuscated from the data
- Distributed optimization; more devices working concurrently does more work with less resources
- Combined power of devices which collect different types of data

# History

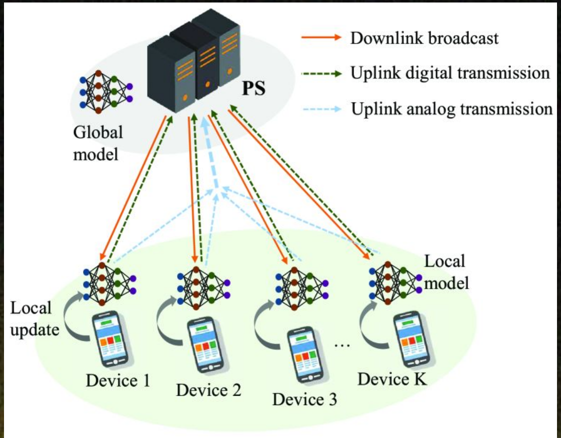
- Introduced in 2016 by Google research scientists McMahan and Ramage for "smarter models, lower latency, and less power consumption, all while ensuring privacy."
- Research picked back up in 2021, when 6G wireless technology made WFL "a promising decentralized solution"
- Research has continued through today as data privacy in AI training has become an increasingly popular issue



# 02 Current State

# Digital vs. Analog WFL

- If we want to maximize the speed of communication between the server and edge devices:
    - Digital transmission is best for setups with sufficient radio resources and CSI uncertainties
    - Analog transmission is best for setups with massive numbers of participating devices
- Analog transmission also allows the edge devices' models to be aggregated in the air, which saves computation power

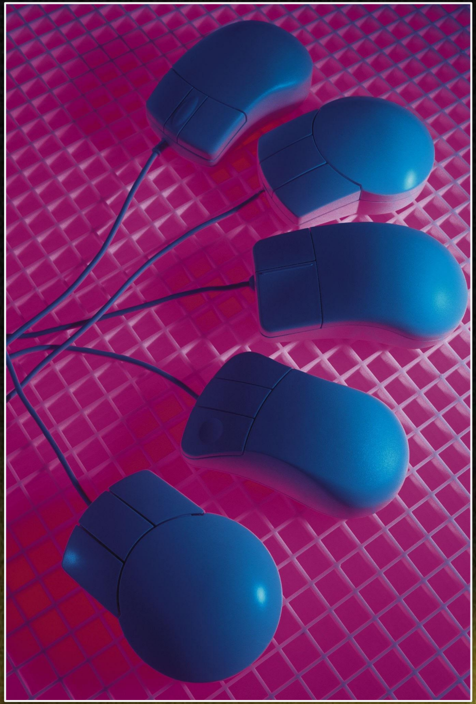


# Benefits Being Researched

- Model creation takes less resources, and is independent of internet connection
- Privacy: data is never transmitted, received, or stored, except by the device that created it
- Adapt over time; many devices means quicker and better adaptation to changes

# Applications

- Training models where raw data is sensitive
  - Smartphones, healthcare, cars
  - Already in use for autocorrect and prediction on Google phone keyboards (Gboard)
- Training models with heterogeneous data
  - Smart homes, healthcare, power/water grids
- Training models with data from devices with poor/intermittent internet connection or processing power
  - Smart homes, healthcare, unmanned aerial vehicles (drones)



# Challenges

- Ensuring accurate broadcast of models is difficult, especially in bandwidth-constrained networks
  - Failing to accurately broadcast models to and from nodes could cause compounding inconsistencies between each nodes' models
- Non-IID data (heterogeneous & from many sources) is hard to process and combine into a meaningful global model
- Model broadcasting can still be peeked by eavesdroppers, and optimized setups are especially vulnerable
- Many devices that could be useful in developing smarter homes and grids are simply too weak to collect data or train models

# The Future of WFL

- Full decentralization
  - Model aggregation happens in the air, without needing a central server
- Robust privacy
  - Adversarial methods to prevent eavesdropping and spoofing
- Scaling
  - Better methods to combine more data from more heterogeneous sources into the global model
- 6G Implementation
  - Better wireless communication, thus more accurate model transmission

# Conclusions

- WFL can be a massively useful tool for healthcare, utilities, self-driving vehicles, and more
- Its privacy measures are inherently much better than centralized learning
- But it is underdeveloped – still unreliable and exploitable
- Further research into WFL can change the state of AI entirely

# Thank you

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