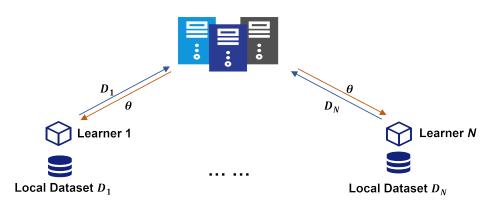
Adaptive and robust federated learning

Yang Lu

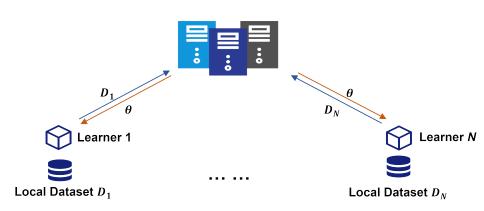
School of Computing and Communications Lancaster University

11 March, 2024

Traditional multi-agent machine learning

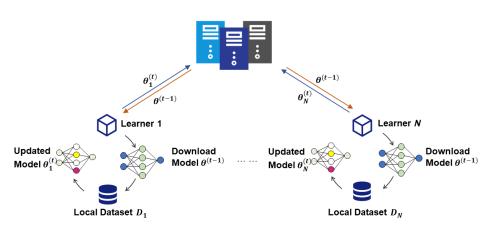


Traditional multi-agent machine learning

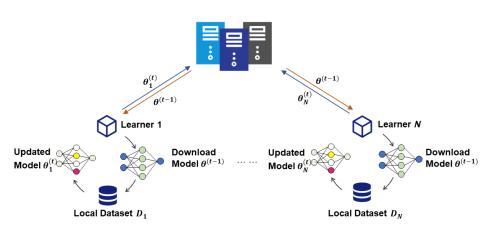


- Leakage of learners' local datasets D_i
- Burdens on the server

Federated learning



Federated learning



- Local datasets D_i never leave their owners' devices
- Training is distributed at learners' side

Ubiquitous applications



Intelligent Transportation Systems



Multi-Robot Systems



Information Technologies



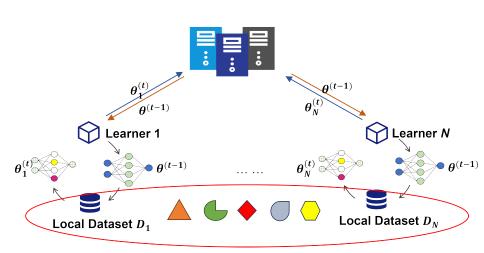
Smart Buildings



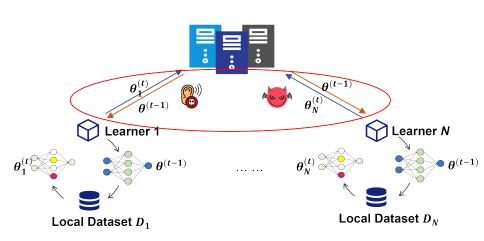
Smart Grid



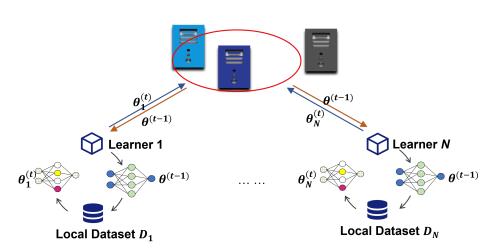
Limitations



Limitations



Limitations

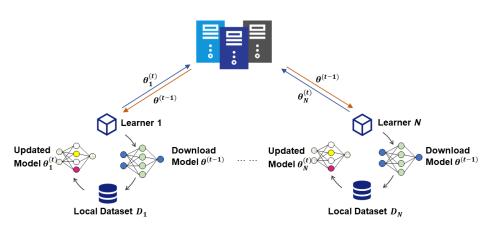


Outline

Adaptive federated Meta-learning

2 Secure federated Meta-learning

Challenges with federated learning



- Data in edge nodes
 - Highly heterogeneous
 - Dynamic
 - Limited data size

- Learning scheme
 - Only train a single common global model
 - Rely on a fixed central server

Objectives

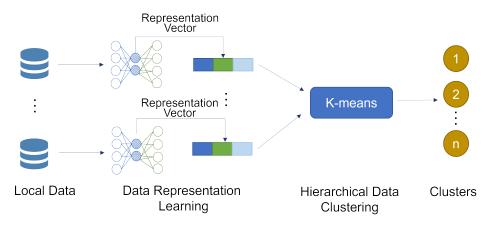
An adaptive and hierarchical federated Meta-learning framework

- Adaptively match characteristics of heterogeneous and dynamic data
 - Dynamically generate data clusters
- Train personalized models for edge nodes
 - Generate multiple hierarchical learning loops
- Remove reliance on a fixed central server
 - Dynamically pick edge nodes to serve as central server

Z. Yu, Y. Lu, P. Angelov, and N. Suri. PPFM: An Adaptive and Hierarchical Peer-to-Peer Federated Meta-Learning Framework. *The 18th International Conference on Mobility, Sensing and Networking (MSN)*, pages: 502–509, December, 2022. Best Paper Award.

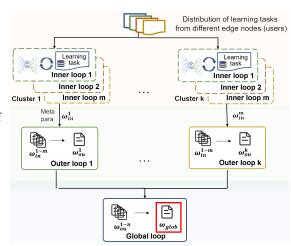
Data clustering

- Kullback-Leibler divergence based K-means clustering
- Representation vectors are obtained from variational autoencoders

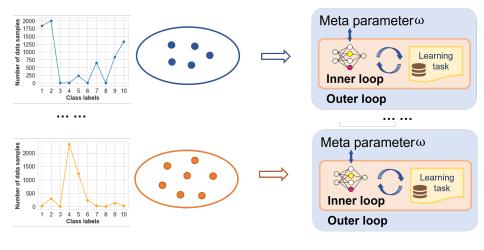


Hierarchical Meta-learning architecture

- Inner loop
 - Train task-specific models with local data
- Outer loop
 - Extract common features from similar tasks
 - Optimize adaptability of similar tasks
- Global loop
 - Extract global knowledge across clusters
 - Optimize generalizability across heterogeneous tasks

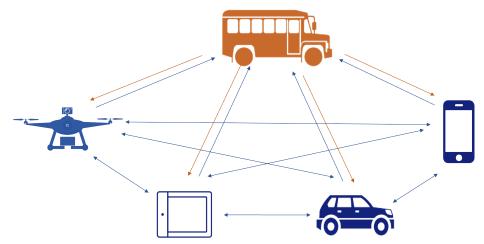


Dynamic clustering and learning loops



Dynamic central server for federated learning

Selected Edge Node

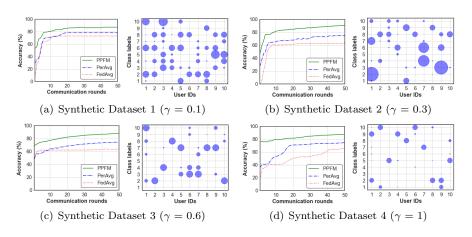


Experimental settings

- Environment
 - Multi-access computing environment: 5-100 edge nodes
 - \bullet 3 × HP Z440 workstations with 64G memory

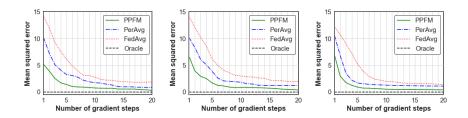
- Datasets
 - MNIST
 - CIFAR-10
 - Synthetic datasets
- Learning models
 - Feedforward neural network (FNN)
 - Convolutional neural network (CNN)
 - Conditional multinomial logistic regression (CMLR)

Experimental results: Classification



PPFM vs. Comparative algorithms (Synthetic Datasets)

Experimental results: Regression



= 1.65 = 1.36

Sinusoid regression results (Synthetic Dataset)

(a) Amplitude = 4.5, phase (b) Amplitude = 1.88, phase (c) Amplitude = 0.15, Phase

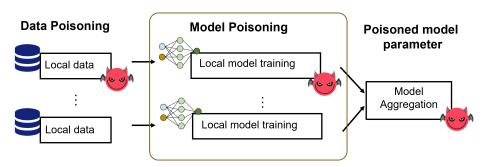
= 0.44

Outline

Adaptive federated Meta-learning

2 Secure federated Meta-learning

Security for federated learning

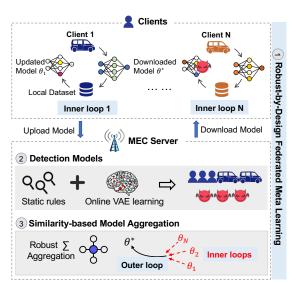


Z. Yu, Y. Lu, and N. Suri. RAFL: A Robust and Adaptive Federated Meta-Learning Framework Against Adversaries. *IEEE 20th International Conference on Mobile Ad Hoc and Smart Systems (MASS)*, pages: 496–504, September, 2023.

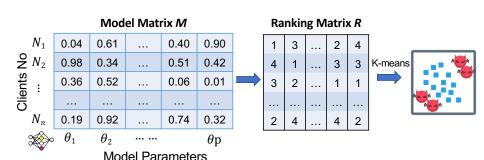
Robust federated Meta-learning framework

• Robust-by-design federated Meta-learning

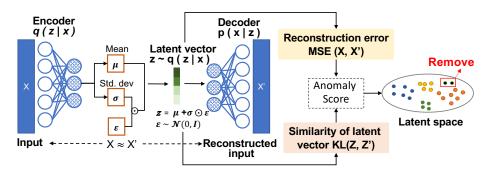
- Residual rule-based detector
- VAE-based detector
- Similarity-based aggregation



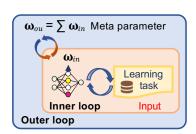
Residual rule-based detector

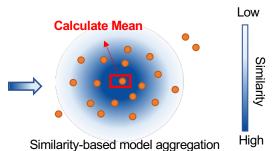


VAE-based detector



Similarity-based aggregation





Experimental settings

- Environment
 - Multi-access computing environment: 100 edge nodes
 - \bullet 3 \times HP Z440 workstations with 64G memory
- Datasets
 - MNIST
 - CIFAR-10

- Learning models
 - Feedforward neural network (FNN)
 - Convolutional neural network (CNN)
 - Conditional multinomial logistic regression (CMLR)

Experimental results

