Fledge: Edge-based Federated Learning Framework for Mobile Healthcare

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Fledge Framework : Key Features

- Generic: Provides support for any ML model uploaded by model/application developer.
- Real-world Deployment: Deployment environment supports actual edge devices on real-world infrastructure, rather than only simulated mode.
 - **Resource Awareness:** Framework must split the model intelligently between available resources to ensure good resource utilisation and accuracy.

Existing Federated Learning Frameworks

FATE

- PaddleFL (PFL)
- TensorFlow Federated (TFF)
- PySyft
- IBM Federated Learning





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Existing Federated Learning Frameworks

| | Generic | Real-world Deployment | Resource Awareness |
|-------------------------------|--------------|--------------------------|--------------------|
| FATE | × | | × |
| PaddleFL (PFL) | × | \checkmark | × |
| TensorFlow Federated (TFF) | \checkmark | × | × |
| PySyft | | × | × |
| IBM Federated Learning | \checkmark | \checkmark | × |





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Prior Work in ML Healthcare

- "FEEL: A Federated Edge Learning System for Efficient and Privacy-Preserving Mobile Healthcare"
- Proposes splitting of model to manage resource consumption
- Just a proof-of-concept of the splitting idea, no algorithm proposed for a generic framework



Why Federated Learning for ML Healthcare?

- Proliferation of data collection points smart wearables, electronic health records, personal health monitors
- Centralised processing of all information
- Privacy-sensitiveness of data
- Data ownership
- Complexity of ML models

Research Questions

- RQ1: Can the federated mode of the framework provide similar accuracy as centralised mode? (Accuracy vs Privacy)
- RQ2: Does the federated mode of the framework add any extra overheads on performance? (Training time, Communication latency, Processing overheads)

RQ3: Can we design an algorithm that splits any given ML model to maintain good resource consumption and accuracy?

Perf Eval - Dataset

- MNIST Dataset: Images of handwritten numbers from 0-9.
 No. of datapoints: 70,000 images
- Breast Cancer Dataset: Multiple features of patient with cancer diagnosis malignant or benign
 No. of datapoints: 648
 No. of features: 9

Perf Eval - Candidates

- Centralised Mode: Data collected from all clients available at the centralised server to train a global model.
- Local Mode: Each client has its own local data and local ML model to train.
- Federated Mode: Each client uses its own local data to train a globally distributed and aggregated model. Model params aggregated using FedAvg algorithm.

Perf Eval - Infra

Server Node (Cloud):

- CPU: 3.1Gz @ Intel Xeon[®] Platinum 8175M
- Memory: 16 GB
- Cores: 4
- Olient Node (Edge):
 - CPU: AWS Graviton Processor
 - Memory: 8 GB
 - Cores: 1

Performance Evaluation: Accuracy



Performance Evaluation: Accuracy



Performance Evaluation: Accuracy





Perf Eval - Accuracy - MNIST Dataset



Perf Eval - Accuracy - Breast Cancer Dataset





Perf Eval - Data Distribution



Non-IID Data Distribution

IID Data Distribution

Perf Eval - Accuracy - Breast Cancer Dataset







Perf Eval - Pending Results

- Training times of each mode
- Resource consumption when entire model is deployed
- Resource consumption when the model is split
- Accuracy of model in split mode vs federated mode



Limitations / Future Work

- Algorithm to derive the split point of a model
- Minimising processing and communication latency
- Experiments to include more complex models, unsupervised models, larger infrastructure deployment, etc.
- Applicable only for fully connected layers in neural network



Thank You!