Peer-to-Peer Federated Continual Learning for Naturalistic Driving Action Recognition

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Introduction

Federated Learning protects privacy by sharing model parameters between clients and servers, rather than exposing raw user data. This is particularly beneficial in applications tied to human activity, such as **Driver Action Recognition**.

Motivation

Concerns about the server:

- Privacy breach
- Fairness
- Security
- Trust

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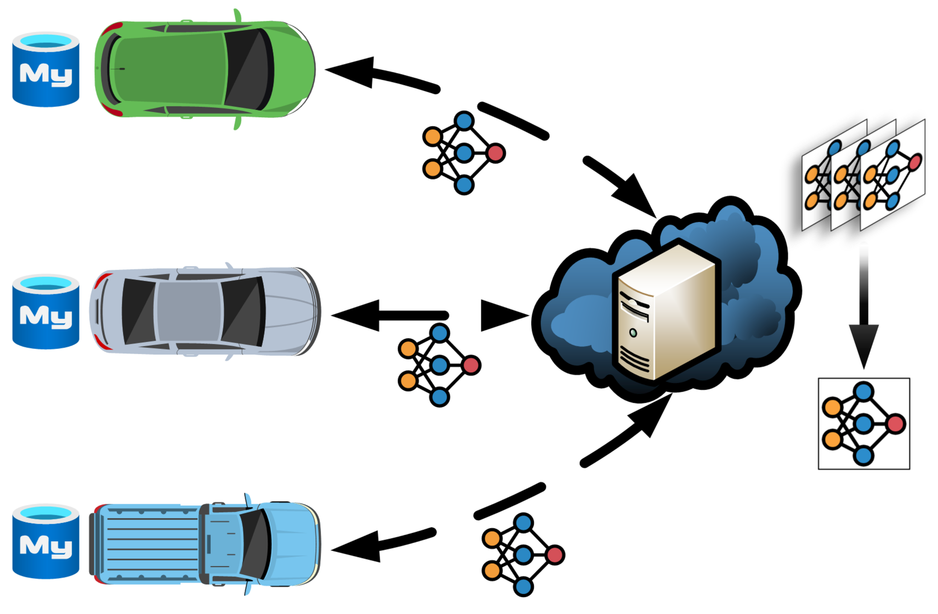

(a) Client-to-Server Federated Learning

Solution

No Server! No Aggregation!

- Lower **computing** requirements
- Lower **communication** overhead
- Lower **storage** burden
- Fully **personalized**

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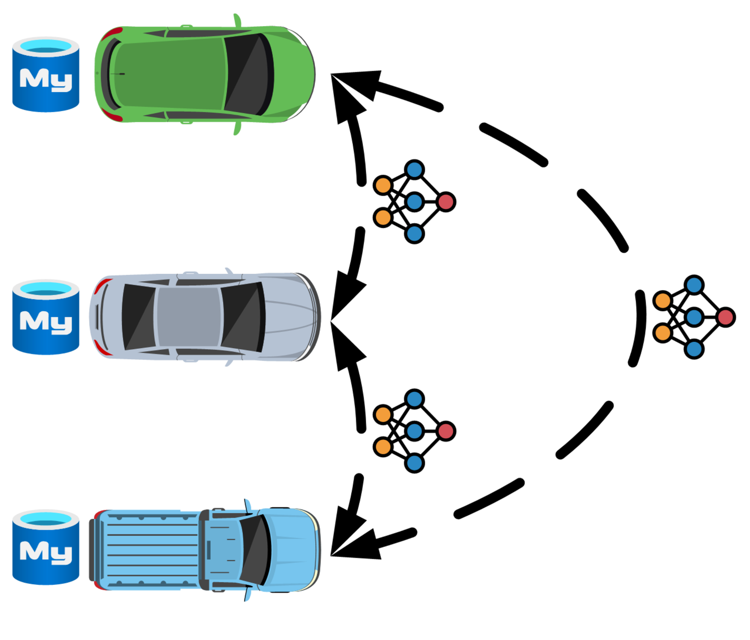
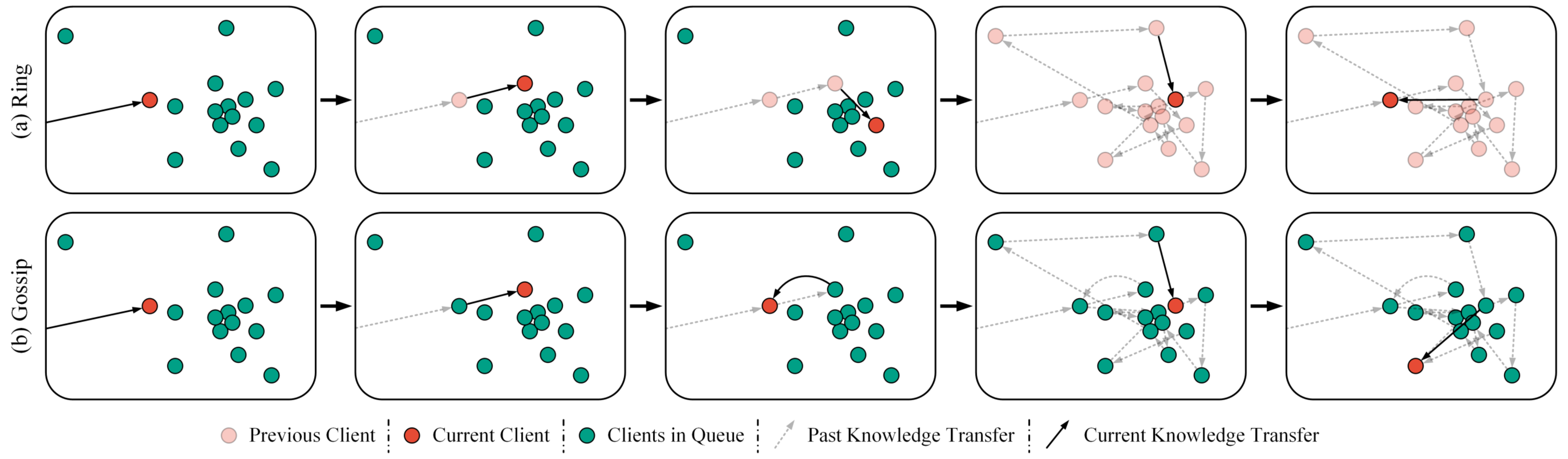


(b) Peer-to-Peer Federated Learning

Methodology

Continual Learning paradigm allows subsequent clients to train directly on the model of the previous clients. **Proximal Term Loss** prevents overfitting by penalizing deviations in model learning. **Transfer Learning** reduces communication overhead by 37%. **Decreasing Learning Rate** mitigates the risk of catastrophic forgetting.



Contribution

- To the best of our knowledge, this is one of the first papers that introduces a P2P FL system, combined with a continual learning framework, into the IoV.
- Through extensive simulation of application scenario experiments, we showcase the potential feasibility of deploying the proposed FedPC in real-world IoV environments.
- The results reveal the proposed FedPC's strong emphasis on clients' objectives, exceptional performance, efficient knowledge dissemination rate, comparable generalizability, and rapid compatibility with new clients.

Experiment

Figure 3. Two NDAR datasets are used in the experiments, including (a) StateFarm [33] and (b) AICity [22, 26] datasets.

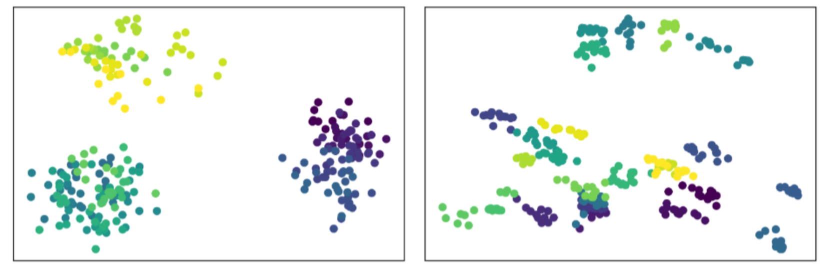
Setup

Framework: independent learning, FedAvg, FedProx, FedPC (ours)

Base Model: ResNet34

Input: Driver Image

Output: Classification Label



(a) StateFarm (b) AICity

Figure 4. Data distributions of (a) StateFarm and (b) AICity. The colors denote different clients, and the scatter points represent different activities. The data distributions are visualized by averaging the driver activity images and reducing the dimensions through principal component analysis (PCA).

Results

Fast convergence!
Rapid knowledge dissemination!

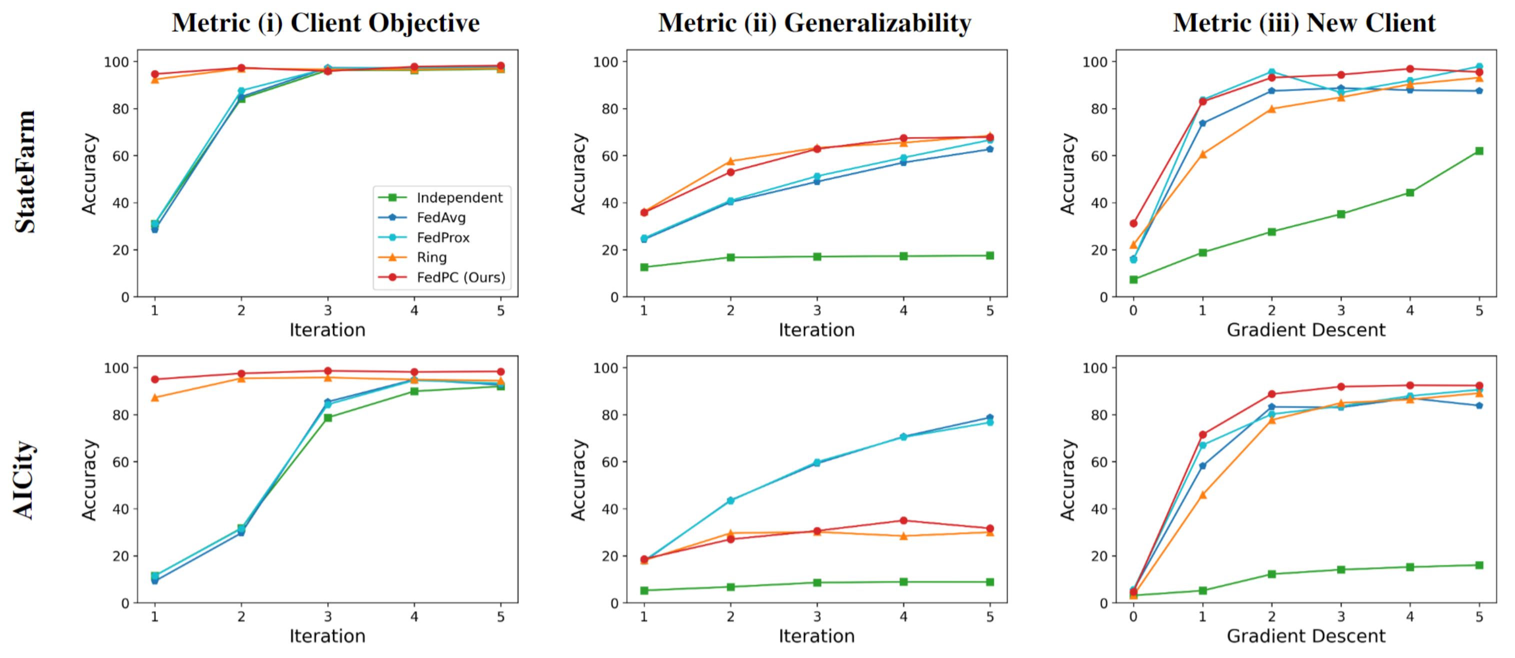


Figure 6. Experimental results on two data sets and three evaluation metrics. The evaluations are performed on the unseen test data set. The data points represent the average of the clients' results.