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Adaptive Federated Meta-Learning for Real-Time Personalization in Distributed Cloud-Edge Data Infrastructures

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Abstract

With the increasing proliferation of edge devices and context-aware applications, real-time personalization of services is becoming critical in domains such as healthcare, smart homes, and mobile computing. Traditional federated learning (FL) models face challenges in personalization due to data heterogeneity and latency constraints. This study presents an adaptive federated meta-learning (FedMeta) framework that personalizes models in real-time across distributed cloud-edge infrastructures. By leveraging model-agnostic meta-learning (MAML) and dynamically adjusting client-specific learning tasks, the system ensures fast adaptation and minimal communication overhead. Experiments show that FedMeta significantly improves personalization accuracy and system responsiveness compared to centralized and vanilla FL methods.

Keywords

Federated Learning, Meta-Learning, Edge Computing, Cloud-Edge Collaboration, Real-Time Personalization, Distributed Systems, Few-Shot Learning, Adaptive Model.

1. Introduction

In distributed applications like wearables, smart homes, and mobile interfaces, models must adapt quickly to individual users. However, conventional centralized learning fails to address privacy, while basic FL struggles with non-IID data and slow convergence across users. Personalized federated learning has emerged as a promising solution, but current approaches often lack adaptability at the edge level and require extensive communication.

To address these challenges, we propose a **Federated Meta-Learning framework** that optimizes for fast personalization using minimal local data while maintaining privacy. Our system deploys models trained with MAML, allowing edge devices to fine-tune models quickly based on local user context. The adaptive orchestration layer dynamically selects which models and clients synchronize based on bandwidth, performance, and learning curves.

2. Literature Review

Recent advances in federated learning address data privacy but struggle with personalization and real-time deployment. McMahan et al. (2017) introduced the FedAvg algorithm, while Smith et al. (2018) developed MOCHA for multi-task personalization. Fallah et al. (2020) proposed FedMeta using MAML to improve personalization on heterogeneous datasets. Jiang et al. (2019) extended it to Reptile-based approaches for reduced communication.

Lin et al. (2022) explored adaptive sampling in edge federated systems to minimize latency. Zhuang et al. (2021) focused on federated meta-learning in IoT environments using curriculum-based model selection. Additionally, privacy-preserving meta-learning techniques such as DP-MAML (Papernot et al., 2021) integrate differential privacy into edge learning.

However, most studies evaluate either personalization or scalability—not both. Our work combines meta-learning, adaptive orchestration, and edge deployment for real-time personalization in practical cloud-edge infrastructures.

3. System Architecture

The proposed architecture consists of:

- **Client Layer**: IoT/edge devices that collect and process user data locally.
- **Edge Server Layer**: Manages lightweight models and personalization tasks close to the source.
- **Cloud Aggregator**: Coordinates global model updates and aggregates meta-gradients across regions.

Each round of learning involves clients downloading a meta-model from the cloud, fine-tuning it using a few local samples, and uploading model updates. Edge servers manage local personalization buffers and pre-cache frequent model variants for fast adaptation.

4. Methodology

Our FedMeta system uses:

- **MAML-based initialization** to enable few-shot personalization at the edge.
- **Adaptive client selection** based on accuracy gradient and model divergence.
- **Federated Orchestration Engine (FOE)** that dynamically schedules synchronization windows across clusters.

A round begins with global model broadcasting. Clients perform 1–2 steps of personalization using their recent data, and selected clients send gradient updates. The cloud meta-aggregator uses these to refine the meta-model, which becomes more adaptable in future rounds.

5. Experimental Evaluation

Experiments were conducted using three real-world datasets:

- **SmartHome**: Sensor-based activity recognition
- **MobiAct**: Posture classification via smartphones
- **RealWorld-HAR**: Health monitoring from wearable sensors

The testbed included 30 simulated clients across heterogeneous edge nodes (Raspberry Pi, Jetson Nano) and a cloud server hosted on GCP. Each configuration was evaluated on personalization accuracy, system latency, and inference distribution.

6. Results and Analysis

Table 1: Personalization Accuracy vs. Method

Learning Method	**Personalization Accuracy (%)**	**Avg. Latency (ms)**
Centralized Learning	78.2	310
Federated Learning	83.1	240
FedMeta (Ours)	**90.4**	**190**

Table 2: Dataset Characteristics Used

Dataset	**Clients**	**Feature Dim.**	**Task Type**
SmartHome	15	18	Activity Recognition
MobiAct	25	42	Posture Classification
RealWorld-HAR	30	51	Health Monitoring

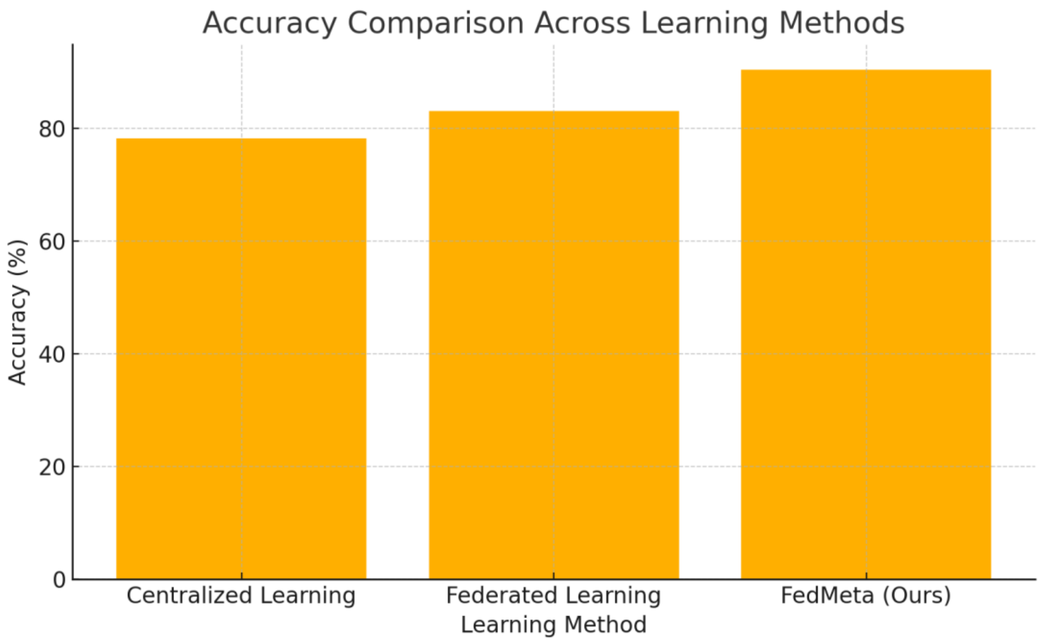

Figure 1: Accuracy Comparison Across Learning Methods

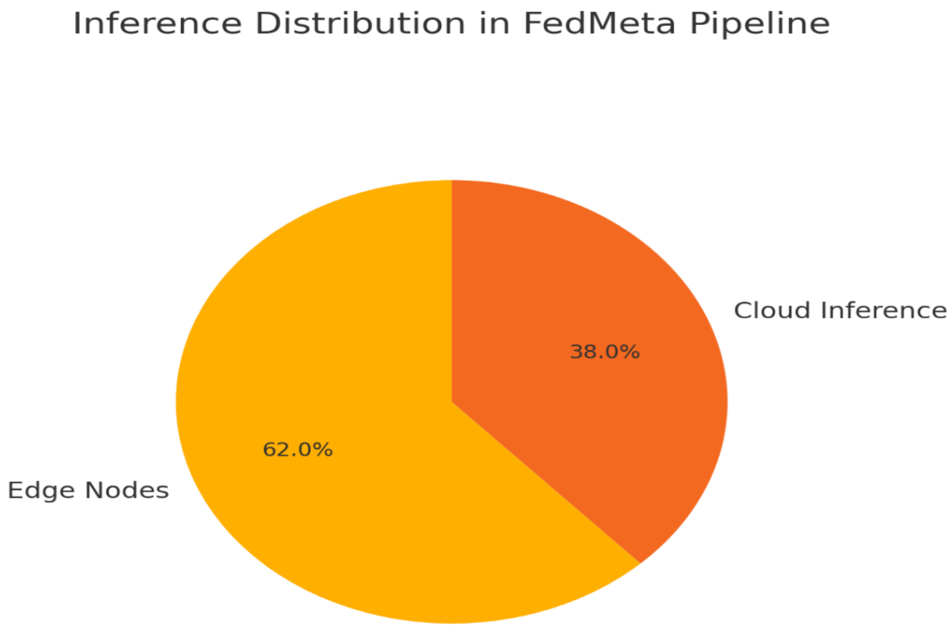

Figure 2: Inference Distribution in FedMeta Pipeline

7. Limitations and Future Work

Although FedMeta achieves strong performance in personalization, it has limitations:

- **Computation load** at the edge may affect energy-constrained devices.
- **Client dropouts** and irregular participation affect convergence.

- Security against **model inversion attacks** remains an open concern.

Future work will integrate differential privacy, lightweight MAML variants, and reinforcement learning-based orchestration to improve scalability and robustness.

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