SimDeep: An Efficient Federated Learning Indoor Localization System with Similarity Aggregation Strategy

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ABSTRACT

Indoor localization is critical for enabling a wide range of location-based services such as navigation, security, and contextual computing in complex indoor environments. Despite significant advances, the deployment of indoor localization systems in real-world settings remains limited due to challenges posed by non-independent and identically distributed (non-IID) data and device heterogeneity. In this paper, we propose SimDeep, a novel Federated Learning (FL) framework designed to tackle these challenges. SimDeep introduces a Similarity Aggregation Strategy to aggregate model updates based on client similarity, thereby effectively addressing the non-IID issue. Experimental results demonstrate that SimDeep achieves 92.89% accuracy, outperforming traditional federated and centralized techniques, making it a promising solution for practical deployment.

CCS CONCEPTS

• **Networks** → *Location based services*; • **Human-centered computing** → *Ubiquitous and mobile computing*;

KEYWORDS

Indoor Localization, Deep Learning, Selective Federated Learning, Similarity Aggregation, Non-IID Data

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1 INTRODUCTION

The digitalization of our world has accelerated the demand for robust indoor localization systems. These systems are crucial for various applications, ranging from improving navigation to enhancing security in complex indoor environments. Despite the vast body of research dedicated to indoor localization, practical implementations in real-world scenarios remain sparse. Key barriers to real-world deployment include privacy concerns, communication costs, and the heterogeneity of devices and data distributions. These challenges are compounded by the non-IID nature of data collected in indoor environments, which complicates model training and aggregation.

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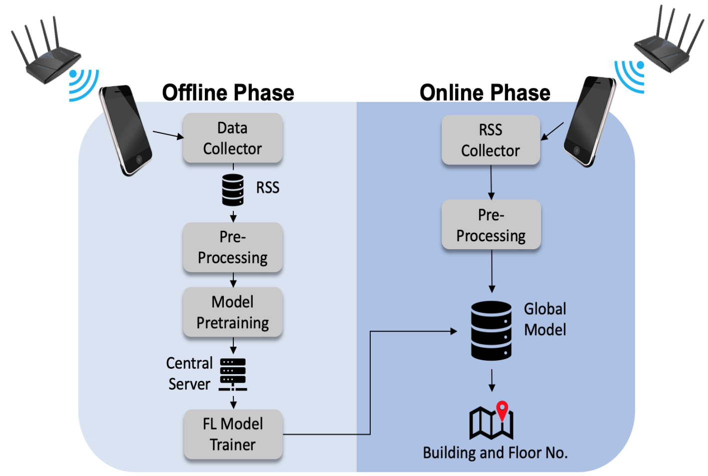

Figure 1: SimDeep System Architecture.

Federated Learning (FL) has emerged as a promising solution for addressing privacy concerns by allowing multiple devices to collaborate on training a global model without sharing raw data. However, FL brings its own set of challenges, particularly when it comes to handling non-IID data and device heterogeneity, which can lead to significant degradation in model performance. Although existing techniques, such as various FL aggregation strategies[1] and pseudo-labeling methods[2], have been introduced to address these challenges, they often fail to generalize across diverse and highly heterogeneous environments.

To bridge this gap, we introduce SimDeep, a Federated Learning-based indoor localization system that leverages a novel Similarity Aggregation Strategy. This approach addresses the non-IID problem by grouping similar clients during the model aggregation process. By effectively managing data heterogeneity and scaling across complex environments, SimDeep demonstrates significant potential for real-world deployment while preserving data privacy.

2 RESEARCH CONTRIBUTION

This paper presents SimDeep as an innovative solution to the challenges associated with Federated Learning in indoor localization. SimDeep introduces a Similarity Aggregation Strategy, where client model updates are aggregated based on their similarity, thus mitigating the effects of non-IID data. This aggregation method ensures that models trained on heterogeneous data converge more effectively. In addition to similarity-based aggregation, SimDeep employs a semi-supervised learning approach using pseudo-labeling, which allows the system to handle limited labeled data by generating pseudo-labels for unlabeled data during training.

The system architecture also includes an autoencoder, which is responsible for extracting compact and informative features from Wi-Fi signal strength (RSS) data. This feature extraction enables more accurate building and floor-level prediction. We validate SimDeep's performance using the UJIIndoorLoc dataset, which includes Wi-Fi fingerprints from multiple buildings and floors, demonstrating that our system achieves superior performance compared to other Federated Learning methods.

2.1 System Architecture

SimDeep operates in two distinct phases: the offline phase and the online phase, as illustrated in Figure 1.

In the offline phase, Wi-Fi data is first collected and preprocessed to ensure that the RSS values are normalized. This preprocessing step is crucial for mitigating noise and ensuring that the input data is suitable for training. The preprocessed data is then used to pretrain the model. During this phase, the autoencoder learns compact representations of the Wi-Fi signals, which are later used to predict building and floor levels. Once the model is pretrained, it is uploaded to the central server, where the Federated Learning process takes place. This is done by without requiring the users to send their Wi-Fi data to the system. By keeping the raw data local and only transmitting model updates, SimDeep ensures privacy while enabling collaborative model training.

The online phase is where the system is deployed in real-world environments. Users input their Wi-Fi data to the system, which, based on the trained model, predicts their location (building and floor level) without requiring raw data to leave the device.

2.2 Model Design

The SimDeep model is composed of two primary components: an autoencoder for feature extraction and a CNN-based classifier for building and floor prediction. The autoencoder compresses high-dimensional Wi-Fi fingerprint data. By mapping the input data into a low-dimensional latent space, the autoencoder allows the system to focus on the most relevant features, improving the model's ability to generalize across different environments. The latent features generated by the autoencoder serve as input to the CNN-based classifier, which predicts the building and floor number. This CNN model forms the core of the SimDeep system, enabling accurate prediction while minimizing the computational and communication costs typically associated with FL. We trained the model using the UJIIndoorLoc dataset, which contains Wi-Fi fingerprints collected from three buildings, each with five floors. This structure results in a total of 15 unique classes, making it an ideal testbed for evaluating the performance of SimDeep in a realistic multi-building, multi-floor environment.

2.3 Federated Learning and Aggregation Process

In the Federated Learning process, SimDeep allows multiple clients (devices) to collaboratively train a global model without sharing their raw data (inspired by [3]). This preserves privacy while enabling the system to leverage data from various devices. The key innovation in SimDeep lies in its Similarity Aggregation Strategy, which clusters client models based on their similarity before aggregation.

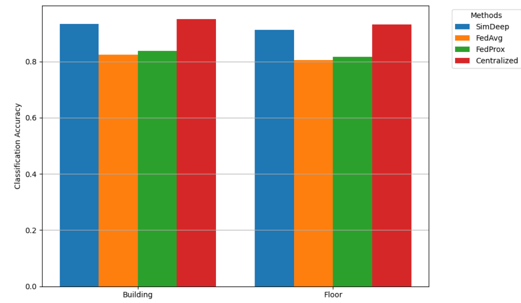

Figure 2: Comparison of classification accuracy.

The similarity between clients is computed using a combination of the gradient similarities between their models. This ensures that clients with similar data distributions are aggregated together, leading to more effective model convergence. The similarity between clients is computed as follows:

$$\text{similarity} = \gamma \cdot \frac{\sum_i (grad_i \cdot grad_j)}{\|grad_i\| \|grad_j\|} + (1-\gamma) \cdot \frac{\sum_i (acc\_grad_i \cdot acc\_grad_j)}{\|acc\_grad_i\| \|acc\_grad_j\|} \tag{1}$$

The parameter γ balances between instantaneous gradient similarity and accumulated gradient similarity. In SimDeep, γ is set to 0.5, giving equal importance to both terms. This ensures that the model takes into account both recent updates and historical trends in client behavior. To further refine the aggregation process, only the updates from the top 4 most similar clients are considered, reducing computational complexity while improving model convergence.

3 EVALUATION

We evaluated SimDeep using the UJIIndoorLoc dataset, comparing its performance against traditional Federated Learning techniques such as FedAvg and FedProx. The evaluation was conducted over 100 training epochs, with classification accuracy being the primary metric. SimDeep achieved a classification accuracy of 92.89%, outperforming FedAvg (88.35%) and FedProx (90.14%). Furthermore, SimDeep's accuracy was nearly as high as that of centralized models (93.02%), despite the decentralized nature of the system. This demonstrates the efficacy of the Similarity Aggregation Strategy in improving model performance, even in the presence of non-IID data. In addition to accuracy, SimDeep's pseudo-labeling technique proved effective in augmenting the training dataset, particularly for clients with limited labeled data. This allowed the system to maintain high performance, even when faced with incomplete or sparse data.

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