Leveraging Hierarchical Federated Learning Architecture for Temporal Analysis

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Abstract

Traditional machine learning approaches for temporal analysis often require training separate models for distinct criteria, such as daily, weekly, or monthly analyses, necessitating disparate datasets and model configurations. This fragmented approach poses challenges in terms of efficiency and scalability. In this study, we propose a hierarchical federated learning architecture coupled with regression techniques to address these issues. Our approach leverages federated learning to distribute the training process across multiple edge devices or data sources while preserving data privacy and minimizing communication costs. The hierarchical structure allows for the aggregation of knowledge across different temporal granularities, facilitating a more unified and efficient learning process. Through our experimentation, we aim to achieve improved performance compared to traditional regression models. By harnessing the collective intelligence from diverse temporal datasets and leveraging federated learning's decentralized nature, we aim to enhance the accuracy and robustness of temporal analysis tasks.

Motivation and Objective

This work introduces a novel approach to temporal analysis, addressing the inefficiencies of traditional methods. By combining hierarchical federated learning with regression techniques, we decentralize the training process, ensuring data privacy while enabling knowledge aggregation across temporal granularities.

Through experimentation, we aim to enhance the accuracy and robustness of temporal analysis, paving the way for more efficient and scalable insights in this field.

- **Motivation** Address the challenges by proposing a hierarchical federated learning architecture coupled with regression techniques.
- **Aim** Streamline temporal analysis by decentralizing training across multiple edge devices, preserving data privacy, and minimizing communication costs.
- **Goal** Achieve superior performance in temporal analysis tasks by enhancing accuracy, efficiency, and scalability.

Preliminary Results

Temporal Analysis	Model	Average RMSE
Daily	HFL	0.015
	Traditional Regression	0.020
Weekly	HFL	0.030
	Traditional Regression	0.035
Monthly	HFL	0.050
	Traditional Regression	0.060

Table 1. Temporal Analysis Comparison

The presented results are preliminary findings obtained from initial experiments conducted to compare the performance of the hierarchical federated learning (HFL) approach with traditional regression models across different temporal analyses (daily, weekly, and monthly). These results are indicative of the potential efficacy of the HFL approach in achieving superior prediction accuracy compared to traditional methods. However, further validation and analysis on real-world datasets are necessary to confirm the scalability and robustness of the proposed approach.

Proposed Architecture

The proposed architecture presents an n-tier federated machine learning method designed to analyze temporal attributes through the lens of data. This study considered the approach structured into three hierarchical levels (local, 2-tier, and global) each contributing distinct insights. Edge devices are used as client devices and 2-tier aggregation devices, and cloud server is used as a global device in this experiment.

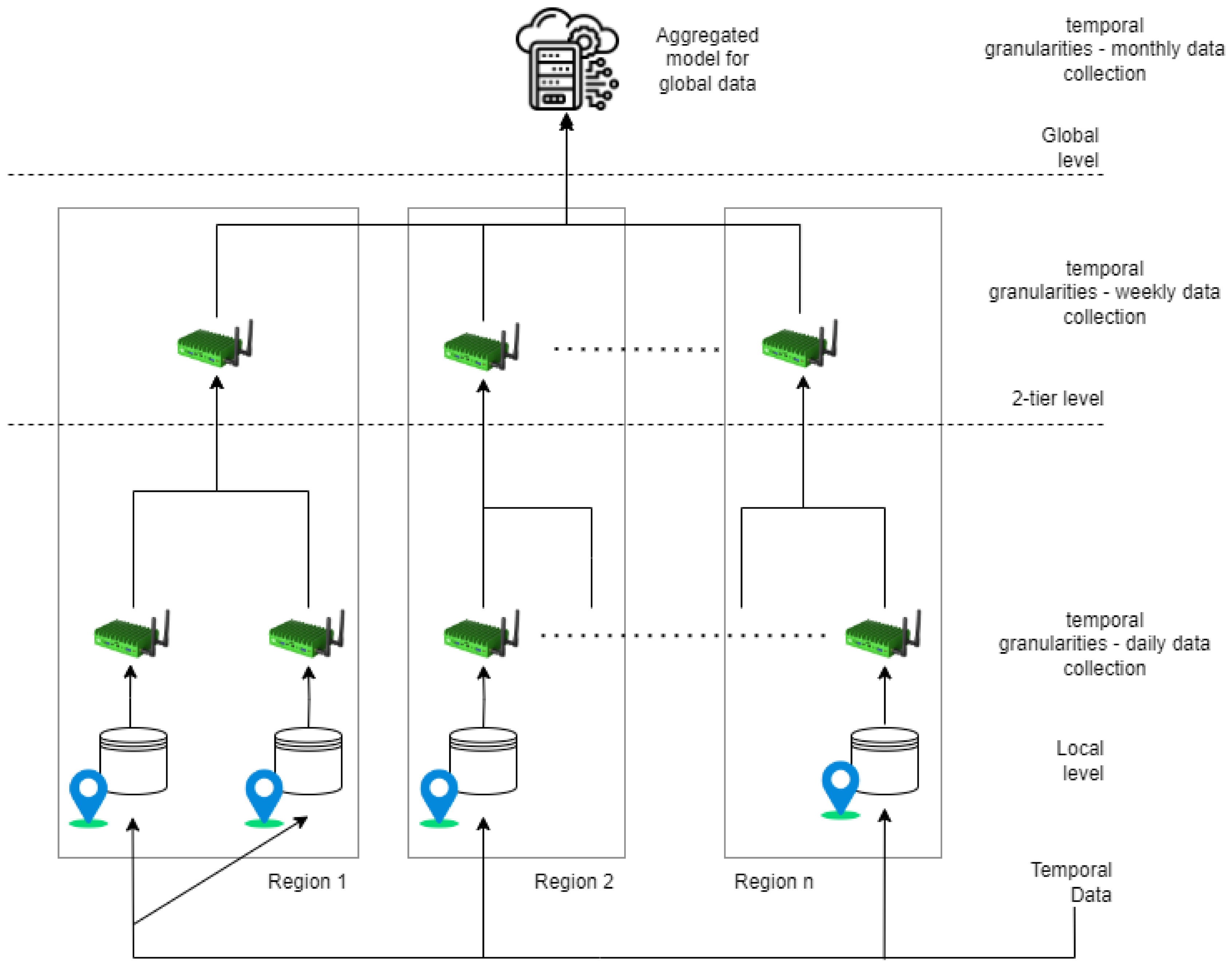

Figure 1. Overall system architecture

Implementation

Training on Client Devices:

```
# Training on Client Devices
function train_on_clients(client_data, model, learning_rate, num_epochs):
    for epoch in range(num_epochs):
        for data_point in client_data:
            features, labels = data_point
            predictions = model.predict(features)
            loss = model.calculate_loss(predictions, labels)
            gradients = model.calculate_gradients(predictions, labels)
            model.update_parameters(gradients, learning_rate)
    return model
```

Aggregation on Server:

```
# Aggregation on Server
function aggregate_models(client_models):
    aggregated_model = initialize_model()  # Initialize an empty model
    for client_model in client_models:
        aggregated_model.combine_weights(client_model.weights)  # Combine weights from client models
    aggregated_model.normalize_weights(len(client_models))  # Normalize aggregated weights
    return aggregated_model
```

Conclusion

In conclusion, this work proposes a novel hierarchical federated learning (HFL) architecture with regression techniques to address traditional challenges in temporal analysis. Preliminary experimentation shows promising potential in capturing temporal patterns, with improved prediction accuracy compared to traditional regression models. Further validation on real-world datasets is ongoing to assess scalability and generalization. This approach capitalizes on federated learning's decentralized nature and hierarchical structure, promising more efficient and accurate temporal prediction models, despite the experiment still being in progress.

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