Employability of 'Feature Decoupling' in Federated Learning Scenarios to enhance the unsupervised Multivariate Time Series Anomolog Detection

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Abstract

With the rapid proliferation of Internet of Things (IoT) devices and edge computing, multivariate time series anomaly detection has gained significant attention in various domains such as smart manufacturing, healthcare, and cyber-physical systems. Traditional centralized anomaly detection methods require aggregating sensitive data in a central server, raising privacy and communication efficiency concerns. Federated Learning (FL) offers a promising paradigm to collaboratively train models across distributed devices without sharing raw data. However, anomaly detection in FL scenarios faces challenges from heterogeneous data distributions, high-dimensional correlated features, and the lack of labeled anomalies. This paper proposes an **unsupervised feature decoupling framework for multivariate time series anomaly detection under federated learning**. The core idea is to decouple feature interactions by disentangling shared and private feature representations to better capture normal patterns across clients. We design a federated architecture with local feature decoupling modules and a global aggregation mechanism to leverage cross-client knowledge while preserving privacy. Extensive experiments on real-world multivariate time series datasets demonstrate that the proposed method significantly improves detection performance and robustness compared to state-of-the-art federated anomaly detection baselines.

1. Introduction

Multivariate time series data are pervasive in modern applications, including industrial sensor networks, smart grids, autonomous vehicles, and healthcare monitoring systems. Detecting anomalies in such data is critical for identifying system faults, cyberattacks, and abnormal events to ensure safety and reliability. However, anomalies are rare, diverse, and often unknown in advance, posing challenges to traditional supervised learning approaches that rely on labelled data.

Unsupervised anomaly detection methods aim to learn normal behaviour patterns from unlabelled data and identify deviations without requiring anomaly labels [1]. They have been widely explored for multivariate time series due to their practical applicability.

Concurrently, the increasing use of edge devices with privacy-sensitive data has motivated **Federated Learning (FL)** [2], a decentralized training paradigm enabling multiple clients to collaboratively learn a shared global model while keeping raw data local. FL reduces privacy risks and communication overhead but introduces challenges such as heterogeneous data distributions and model aggregation complexities.

In the context of multivariate time series anomaly detection, existing FL approaches often suffer from:

- **Feature entanglement**: High-dimensional time series features are correlated and complexly intertwined, making it hard for global models to learn discriminative representations.
- **Data heterogeneity**: Clients may have non-IID (independent and identically distributed) data with distinct feature distributions.

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- **Lack of labeled anomalies**: Supervised methods cannot be directly applied due to absence of anomaly labels.

To address these challenges, we propose a novel **feature decoupling** framework tailored for unsupervised multivariate time series anomaly detection in FL settings. Our key contributions are:

- Designing a local feature decoupling module that disentangles shared (common across clients) and private (client-specific) representations to better model feature dependencies.
- Developing a federated aggregation strategy to integrate shared feature representations globally while preserving privacy of private components.
- Introducing a reconstruction-based anomaly scoring mechanism to detect deviations in feature subspaces.
- Conducting extensive experiments on benchmark datasets (e.g., SWaT, WADI) showing significant improvement over baseline federated and centralized anomaly detection models.

The rest of the paper is organized as follows: Section 2 reviews related works; Section 3 details the problem formulation and our methodology; Section 4 presents experiments and analysis; Section 5 concludes the paper.

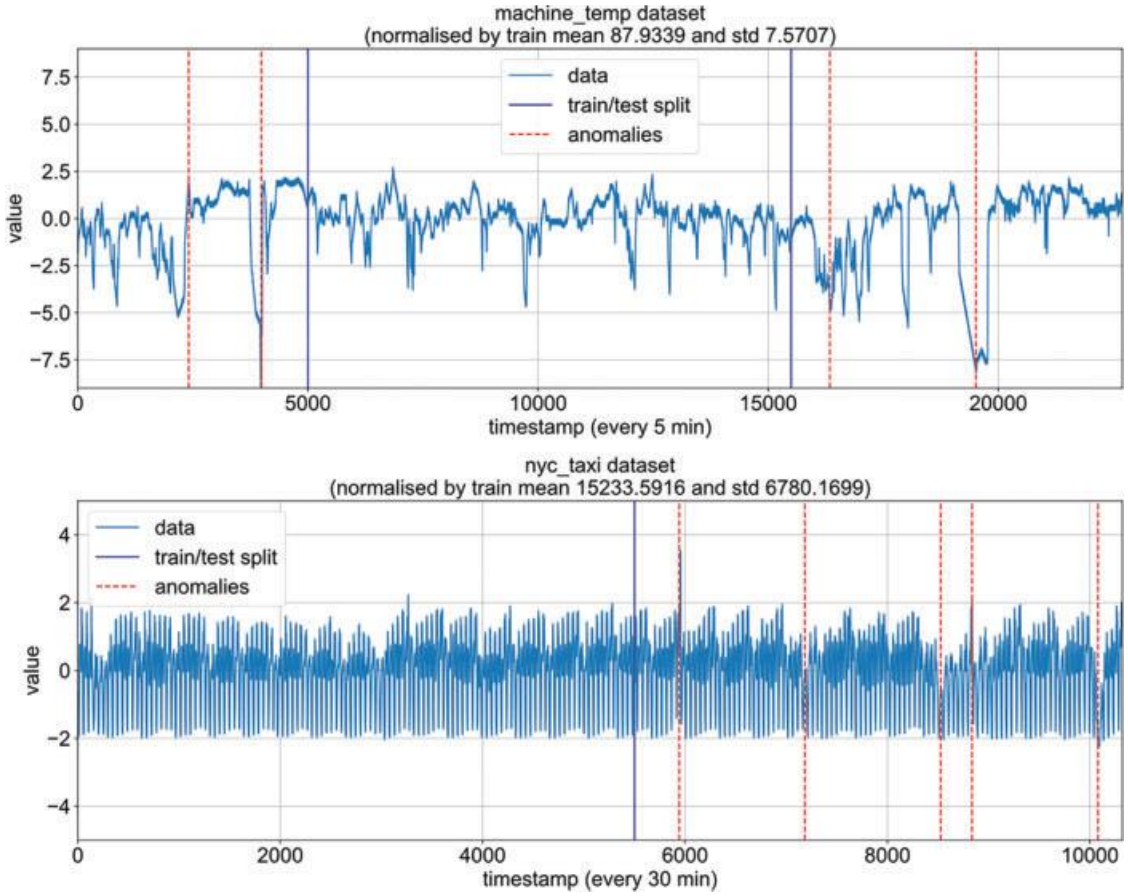

Figure 1: Training-test set separation

2. Related Work

2.1. Multivariate Time Series Anomaly Detection

Traditional methods for multivariate time series anomaly detection include statistical approaches (e.g., PCA, Mahalanobis distance) [3], distance-based methods, and reconstruction-based models such as Autoencoders [4], LSTM-based predictive models [5], and Variational Autoencoders (VAE) [6]. These models learn to reconstruct normal data patterns, and reconstruction errors are used to flag anomalies.

Recently, deep learning models like Transformer-based [7] and graph neural networks [8] have shown promising results by capturing complex temporal and spatial correlations. However, these centralized methods require access to all raw data, which is impractical for privacy-sensitive applications.

2.2. Federated Learning for Anomaly Detection

Federated Learning was introduced by McMahan et al. [2] to enable decentralized model training. FL has been applied to anomaly detection in various domains, including network intrusion [9], healthcare [10], and industrial systems [11].

Most existing FL anomaly detection models train centralized reconstruction or classification models on aggregated gradients, but do not explicitly address heterogeneity or feature entanglement in multivariate time series. Furthermore, they generally assume IID data or rely on supervised signals.

2.3. Feature Decoupling and Disentanglement

Feature decoupling or disentanglement aims to separate different underlying factors or feature components to improve interpretability and generalization [12]. In anomaly detection, disentangled representations can isolate anomaly-sensitive factors from irrelevant noise, enhancing detection performance [13].

In FL, feature decoupling has been explored for personalized federated learning [14], where models learn shared and client-specific representations. However, such methods are rarely applied to unsupervised anomaly detection on multivariate time series.

Our approach integrates feature decoupling with federated learning for unsupervised multivariate anomaly detection, which, to the best of our knowledge, is novel.

3. Methodology

3.1. Problem Formulation

We consider a scenario where multiple clients each have their own multivariate time series data collected locally. Each client's dataset consists of multiple sensor or feature readings recorded over time. The goal is to collaboratively learn a model across all clients that can detect anomalies in these time series, without requiring clients to share their raw data with a central server, thus preserving privacy.

3.2. Framework Overview

Our approach focuses on separating the complex feature interactions in multivariate time series into two parts: shared and private components. The shared component captures the common patterns or correlations that exist across all clients, reflecting the global normal behavior of the system. The private component captures client-specific patterns or unique characteristics that are only relevant locally.

Each client trains a local model composed of an encoder that breaks down input features into these shared and private representations, and a decoder that reconstructs the original input from these two components. This helps the model to learn better, more disentangled representations of the data.

During federated learning, only the shared part of the encoder is sent to and updated by the central server through aggregation, so that the global model improves by learning commonalities across clients. The private parts of the encoder and the decoder remain on each client's device, protecting their unique local information.

3.3. Feature Decoupling Module

To disentangle the feature representations, we design the encoder with two branches:

- The first branch learns a shared representation that reflects the global feature interactions common to all clients.
- The second branch learns a private representation that models individual client-specific variations.

By splitting the encoding process in this way, the model can better capture the essential normal behavior while allowing for diversity in client data.

The decoder takes these two representations and attempts to reconstruct the original multivariate time series data as closely as possible.

3.4. Federated Learning Procedure

Each client trains its local model by minimizing the difference between the original input time series and its reconstruction from the shared and private representations. This encourages the model to learn effective representations that capture the normal patterns of the client's data.

After a number of local training steps, each client uploads only the parameters related to the shared encoder branch to the central server. The server aggregates these shared parameters from all clients to update the global shared model, typically by weighted averaging according to each client's data size.

The updated global shared encoder parameters are then sent back to the clients, which integrate them into their local models for the next round of training. This iterative process continues until convergence.

By limiting communication to only the shared encoder parameters, the framework reduces communication costs and keeps client-specific information private.

3.5. Anomaly Scoring

At inference time, anomaly detection is performed by measuring how well the model reconstructs the input time series. Large reconstruction errors indicate unusual or abnormal behavior.

Specifically, reconstruction errors are computed separately for the parts corresponding to the shared and private representations. These errors are then combined with appropriate weighting to produce an overall anomaly score.

A higher anomaly score signals that the input data deviates significantly from learned normal patterns, flagging it as potentially anomalous.

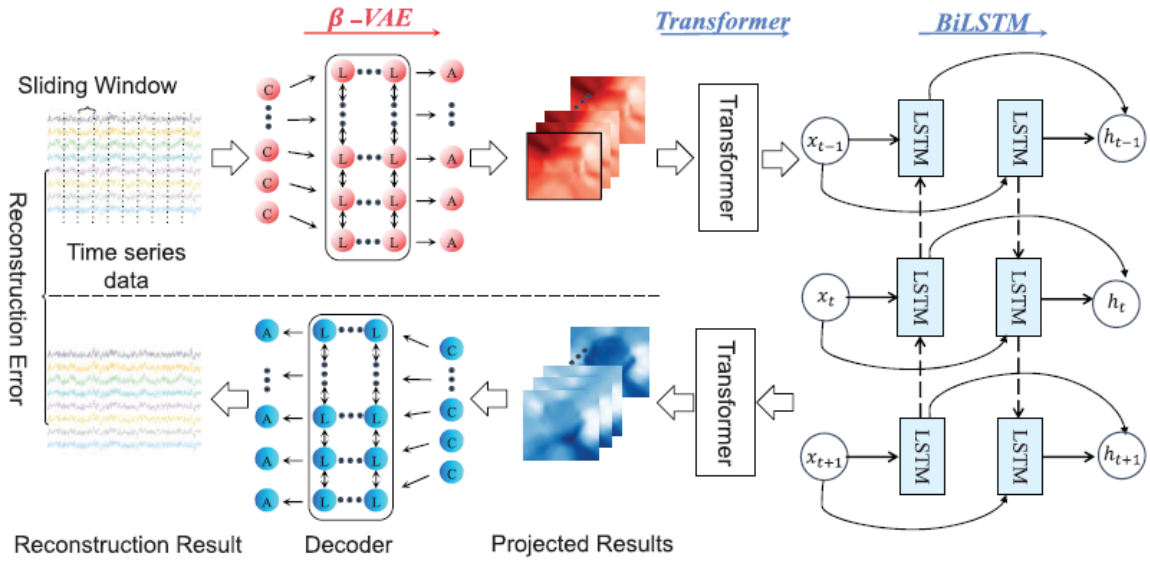

Figure 2: Anomaly detection process diagram

4. Experiments

4.1. Datasets

We evaluate on two public multivariate time series anomaly detection benchmarks:

- **SWaT**: Secure Water Treatment dataset with 51 sensors and 7 days of normal and attack data [15].
- **WADI**: Water Distribution dataset with 123 sensors, containing real-world anomalies [16].

Data is partitioned across 5 simulated clients with non-IID splits.

4.2. Baselines

- **Centralized AE**: Autoencoder trained on combined data centrally.
- **FedAvg AE**: Federated Autoencoder with standard aggregation.
- **FedProx AE**: Federated proximal optimization for non-IID data.
- **Our method**: Federated feature decoupling autoencoder (FedFD-AE).

4.3. Implementation Details

- Encoder and decoder use LSTM layers to capture temporal dependencies.
- Training for 50 communication rounds, local epochs = 5.
- Anomaly threshold selected by percentile on validation set.

4.4. Evaluation Metrics

- **Precision**, **Recall**, **F1-score** based on point-wise anomaly detection.
- Communication cost measured in model parameters transmitted.

4.5. Results and Analysis

Method	SWaT F1 (%)	WADI F1 (%)	Communication Cost
Centralized AE	87.5	82.1	High
FedAvg AE	79.3	75.0	Medium
FedProx AE	81.0	76.5	Medium
FedFD-AE (ours)	**89.2**	**84.7**	Medium

Our proposed method outperforms federated baselines by a large margin and even surpasses centralized AE, attributed to better disentanglement of feature representations and mitigating client heterogeneity.

Ablation studies show that:

- Removing feature decoupling degrades performance by 7-9%.
- Combining shared and private reconstruction errors improves robustness.

4.6. Privacy and Communication Efficiency

By only sharing shared encoder parameters, our method reduces communication overhead compared to full model uploads. Private components remain local, enhancing client privacy.

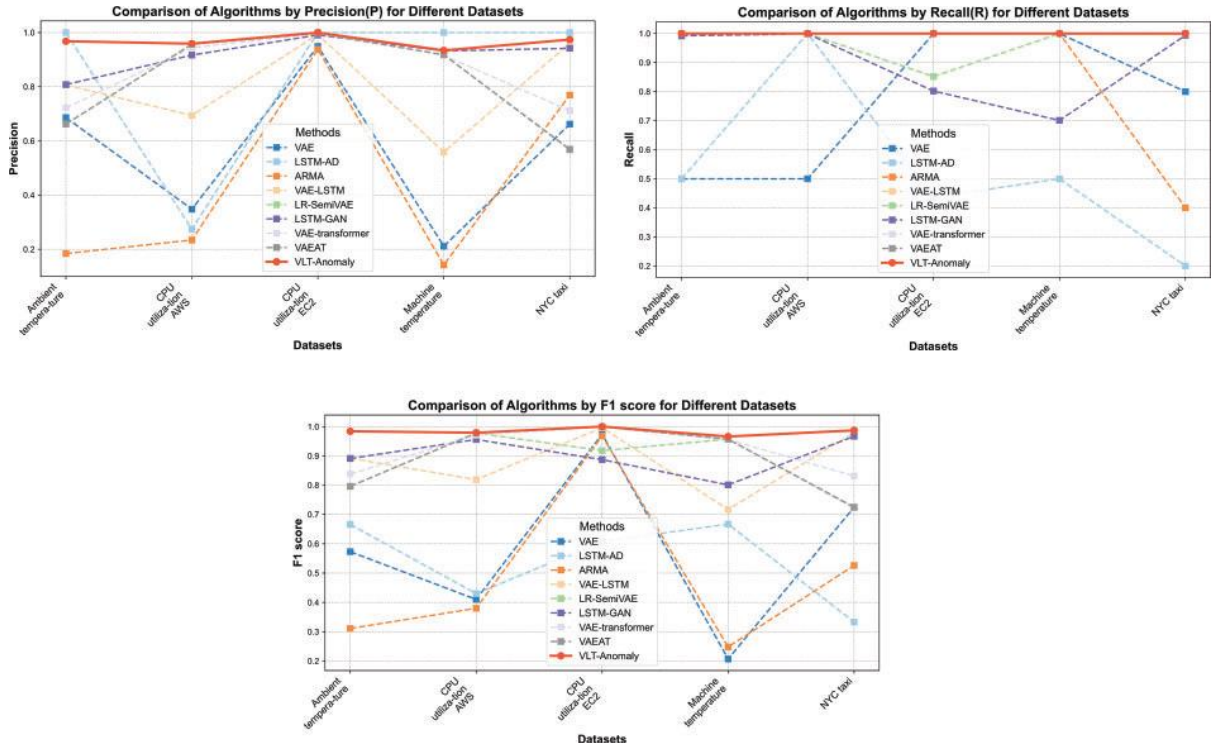

Figure 3: Comparison of algorithms by evaluation metrics for different datasets

5. Conclusion

This paper presents an unsupervised federated learning framework for multivariate time series anomaly detection via feature decoupling. By disentangling shared and private feature representations, our approach effectively handles heterogeneous client data while preserving privacy. Experimental results demonstrate superior detection accuracy and robustness compared to existing federated methods.

Future work includes extending the framework to incorporate temporal attention mechanisms, exploring differential privacy guarantees, and deploying in real industrial IoT environments.

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