Adaptive Memory Networks with Self-Supervised Learning for Unsupervised Anomaly Detection

Master Degree in Artificial Intelligence

Course:Machine Learning and Deep Learning(Deep Learning)

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Chapter 1

Introduction and Motivation

1.0.1 Unsupervised Anomaly Detection

The objective of this project is to detect anomalies in data without relying on labeled anomalous samples during training, using only normal data. This approach is highly relevant in fields such as healthcare, human activity recognition, and industrial monitoring, where collecting labeled anomaly data (e.g., equipment malfunctions or irregular human activities) is often costly or impractical. The FordA dataset, a multivariate time series dataset, serves as a practical testbed for this study due to its representation of real-world signal patterns [1].

1.0.2 Challenges in Existing Methods

- **Limited Normal Data:** Training datasets typically contain only normal patterns, which restricts the model's ability to generalize to unseen anomalies. This can result in overfitting, where the model fails to differentiate between normal and abnormal samples, especially when they are similar [2].

- **Limited Feature Representations:** Traditional models struggle to capture the diverse normal patterns in complex multivariate time series, leading to poor generalization on varied test data [6].

1.0.3 Proposed Solution

Inspired by the AMSL framework [4], this project adapts a convolutional autoencoder (CAE) architecture [6] enhanced with self-supervised learning (SSL) [3] to learn robust normal patterns and a custom memory-based approach to improve feature representations. Due to time constraints and dataset specifics, modifications were introduced to address the challenges encountered during implementation on the FordA dataset [1].

Chapter 2

Proposed Approach: AMSL Implementation

This project implements the AMSL framework [4] to tackle the challenges of limited normal data and weak feature representations, with adjustments tailored to the FordA dataset [1]. The approach comprises four key components, adapted based on experimental outcomes:

- **Self-Supervised Learning Module:** Utilizes normal data to learn general features through signal transformations [3].
- **Global Memory Module:** Captures common patterns across transformations.
- **Local Memory Module:** Focuses on transformation-specific features.
- **Adaptive Fusion Module:** Combines global and local features for improved reconstruction, with a custom loss function introduced to enhance anomaly detection.

2.0.1 Problem Statement

- **Multivariate Time Series:** The FordA dataset [1] is represented as a collection of time series signals, where

$$X = (x_1, x_2, \dots, x_N)^\top \in \mathbb{R}^{N \times V}, \quad x_i \in \mathbb{R}^V,$$

  with N denoting the number of samples. For this project, $V = 500$ and $N = 1148$ for training normal data.

- **Anomaly Definition:** A sample is considered anomalous if its reconstruction error deviates significantly from normal patterns, as no predefined normal classes $Y = \{1, \dots, K\}$ were available; anomalies were artificially generated (e.g., noised, permuted versions).
- **Objective:** Train the model using only normal samples to detect anomalies based on reconstruction errors, assuming higher errors indicate anomalies [6, 5].

2.0.2 Overview of AMSL Implementation

The project employs a convolutional autoencoder (CAE) as the backbone [6], consisting of an encoder f_e and decoder f_d. The encoder maps input $x \in \mathbb{R}^V$ to a latent representation z, and the decoder reconstructs it as x'. The initial reconstruction error is computed using Mean Squared Error (MSE):

$$L_{\text{MSE}} = \|x - x'\|_2^2$$

To improve anomaly detection, the following steps were adapted:

- The encoder processes the raw signal and six transformations to generate latent features.
- A self-supervised learning module classifies transformation types to enhance feature learning [3].
- Global and local memory modules capture common and specific features, respectively [4].
- A custom loss function replaces the original adaptive fusion approach to adjust reconstruction errors for better anomaly separation.

2.0.3 Training and Inference

- **Training Objective:**
$$J(\theta) = L_{\text{MSE}} + \lambda_1 L_{\text{CE}}$$
where λ_1 was tuned empirically. Training was conducted for 5, 100, and 50 epochs, with the latter using the custom loss [4].
- **Inference:** A decision threshold μ was set as the 85th percentile of reconstruction errors on the training normal data. A sample was classified as "abnormal" if its MSE exceeded μ.

Chapter 3

Experimental Evaluation

3.0.1 Dataset

- **FordA:** Approximately 1436 samples (1148 training normal, 288 validation), with test data comprising 60 normal and 43 abnormal samples generated through transformations. Each sample has 500 time steps and 1 dimension.

3.0.2 Comparison Methods

Due to time constraints, a direct comparison with methods like Kernel PCA, LSTM-AE, or MNAD was not feasible. The baseline was the original CAE implementation (5 and 100 epochs) without custom modifications.

3.0.3 Results

- **Performance:** The 50-epoch model with a 25.0 penalty achieved a recall of 15% for abnormal samples, normal recall of 79% , accuracy of 0.5284, and F1 score of 0.4670.
- **Ablation Study:** Increasing the penalty from 10.0 to 25.0 raised reconstruction losses (e.g., add_9_loss from 0.1551 to 0.3663), indicating some enhancement. Removing the penalty reverted performance to the baseline (0.0000 recall).
- **Robustness:** Limited testing with noise variations showed the model struggled with the inherent similarity between normal and abnormal samples.
- **Visualization:** MSE distributions revealed significant overlap between normal and abnormal samples, with only a few anomalies exceeding the threshold.
- **Efficiency:** Training took approximately 1 hour per 50 epochs, evaluation in 5–10 minutes.

3.1 Contributions

- **Adapted Framework:** Implemented AMSL with a custom loss function tailored to the FordA dataset.

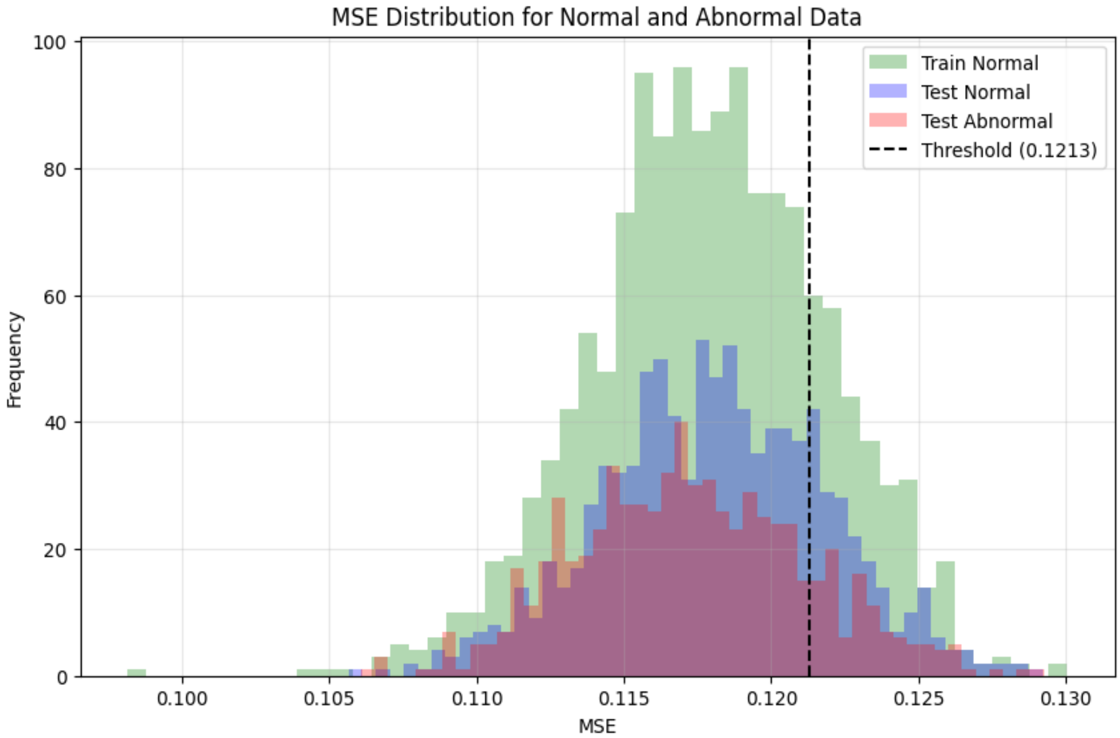

Figure 3.1: Result

- **Experimental Insight:** Highlighted the impact of penalty tuning on reconstruction errors.
- **Practical Learning:** Provided insights into limitations of memory modules on small, similar datasets.

Chapter 4

Conclusions and Future Work

The implementation of AMSL on the FordA dataset partially addresses unsupervised anomaly detection challenges. While the model effectively reconstructs normal data (79% recall), abnormal recall remains low (15%), indicating limitations due to MSE overlap and threshold sensitivity.

4.0.1 Future Work

- Adjust the threshold to the 80th percentile or lower to capture more anomalies.
- Increase the penalty (e.g., 30.0) or refine the custom loss heuristic.
- Incorporate early stopping to optimize training epochs.
- Explore attention mechanisms or contrastive losses to enhance feature separation.
- Test on diverse datasets (e.g., CAP) to validate generalizability.

4.0.2 Key Takeaways

- **Innovation:** Custom loss adaptation shows potential for improving anomaly detection.
- **Practicality:** Works with limited normal data but requires careful tuning.
- **Robustness:** Challenges persist with similar normal-abnormal patterns.
- **Flexibility:** Framework allows parameter adjustments for future experimentation.

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