

AI IN INDUSTRY 2024/2025

Anomaly Detection in Network Cybersecurity

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Motivation

Intrusion Detection Systems (IDS)



Growing sophistication of cyberattacks

As organizations increasingly rely on digital infrastructures, the volume and complexity of network traffic have grown exponentially

Traditional Signature-Based Detection Systems

Struggle to keep up with evolving attack vectors and zero-day vulnerabilities

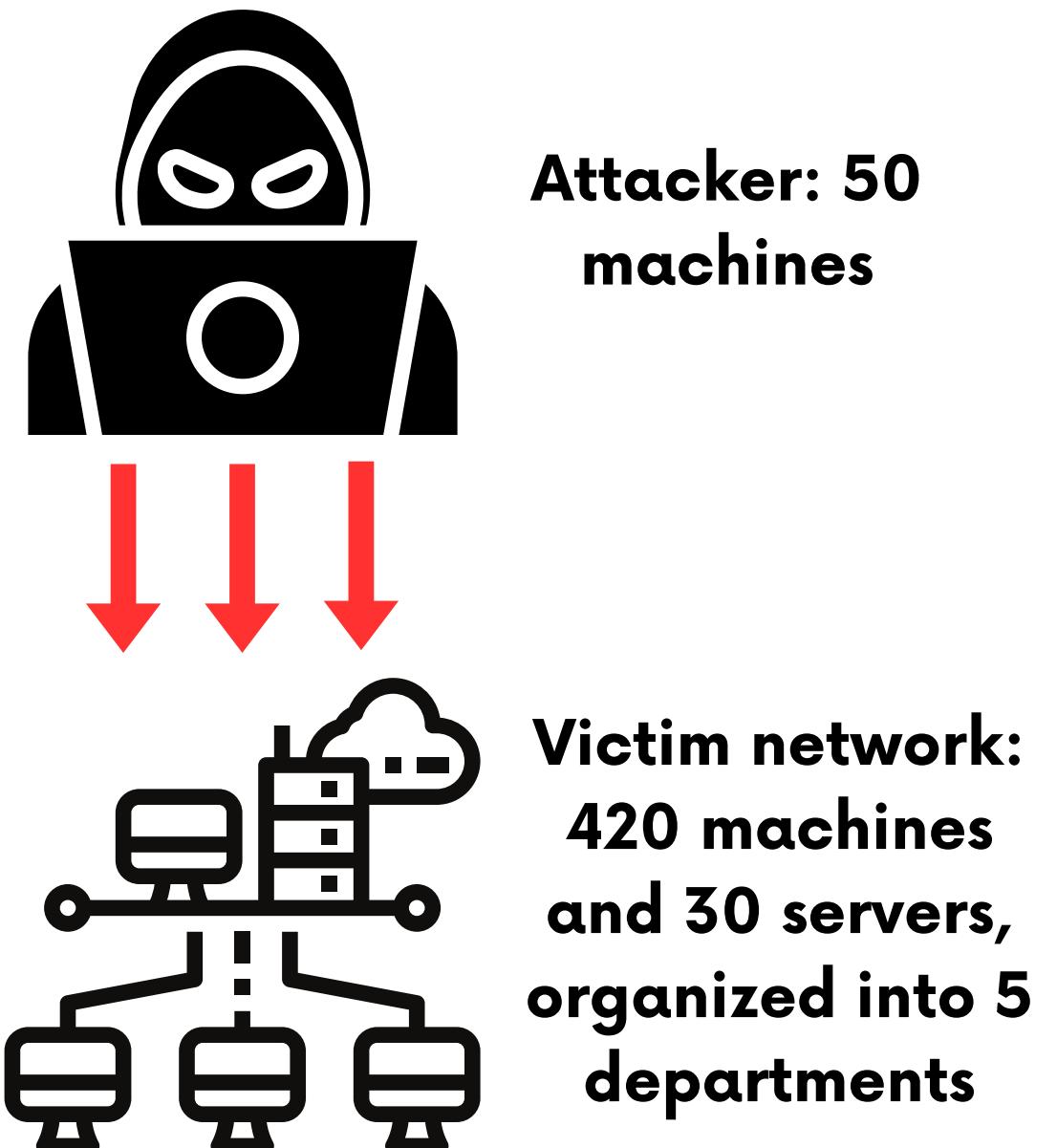
Anomaly Detection Systems

Focus on identifying deviations from normal behavior and offer the ability to detect previously unseen attacks

The Data: CSE-CIC-IDS2018

A collaborative project between the Communications Security Establishment (CSE) & the Canadian Institute for Cybersecurity (CIC) <https://registry.opendata.aws/cse-cic-ids2018/>

- Aims to provide a **comprehensive benchmark** for IDS.
- Captures **real labeled network traffic** with logs and 80 extracted features.
- Simulates both **legitimate and malicious behaviors** (DoS, Bruteforce, ...) across diverse protocols and applications
- High dimensional, time-series data



Exploratory Data Analysis

Features

2097150 records (entries in the logging system)

78 features (excluding Timestamp and Label)

→ **Duration, Number of packets, Number of bytes, Length of packets, etc.** calculated in forward and reverse directions

 All columns are float/int, 8 columns with 2 unique values

 1 column contains missing values

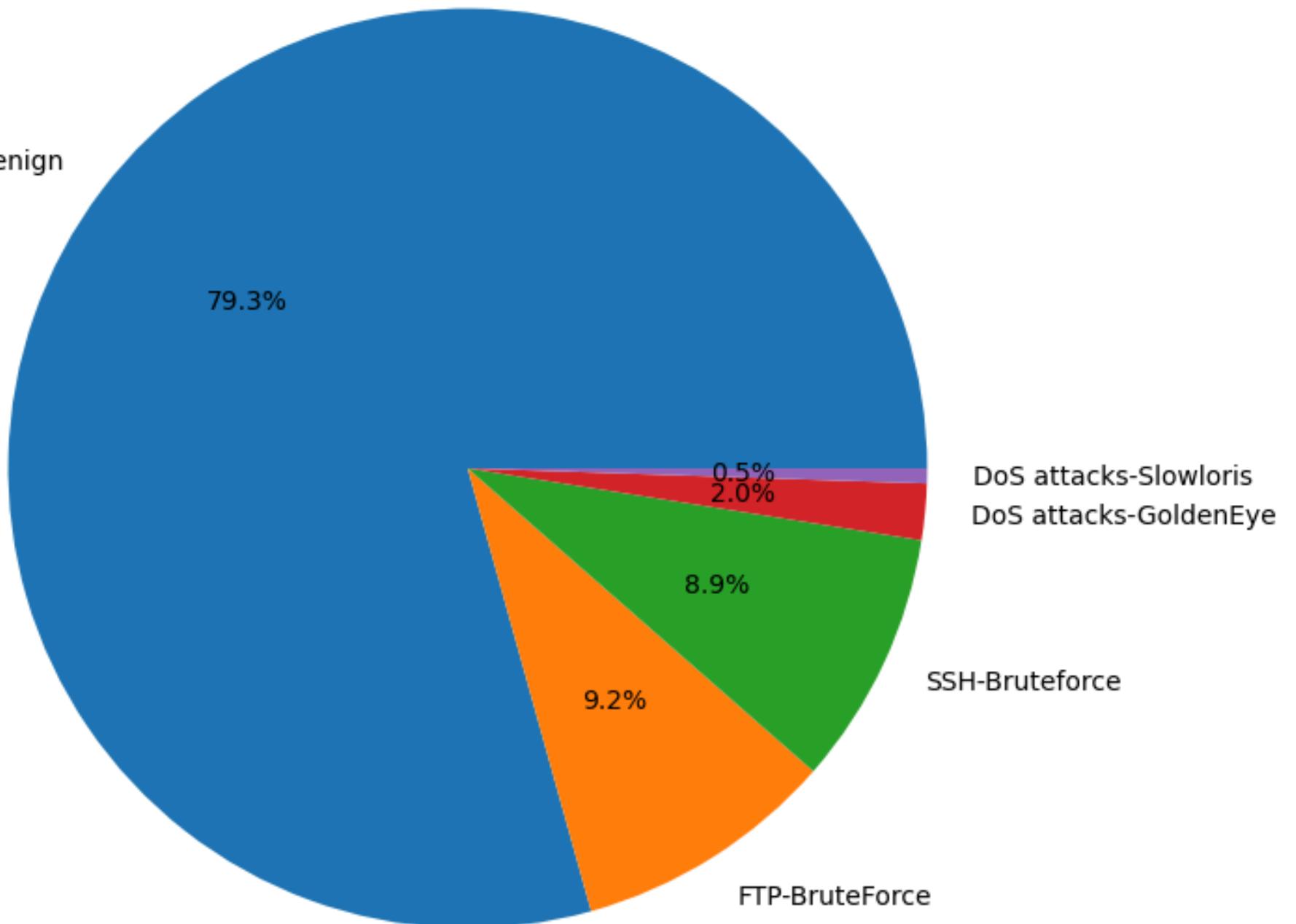
 2 columns contain infinite values

Labels/Attack Scenarios

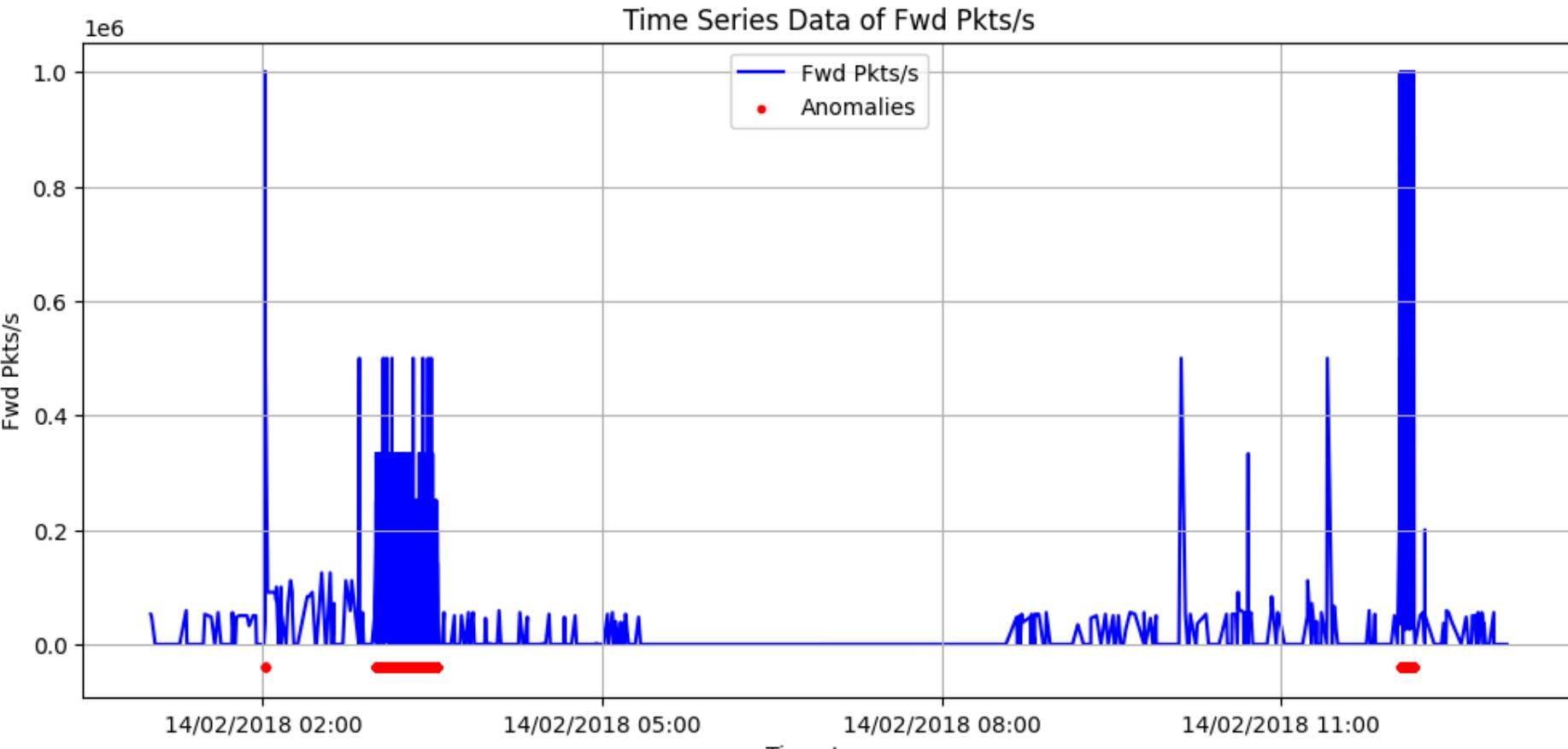
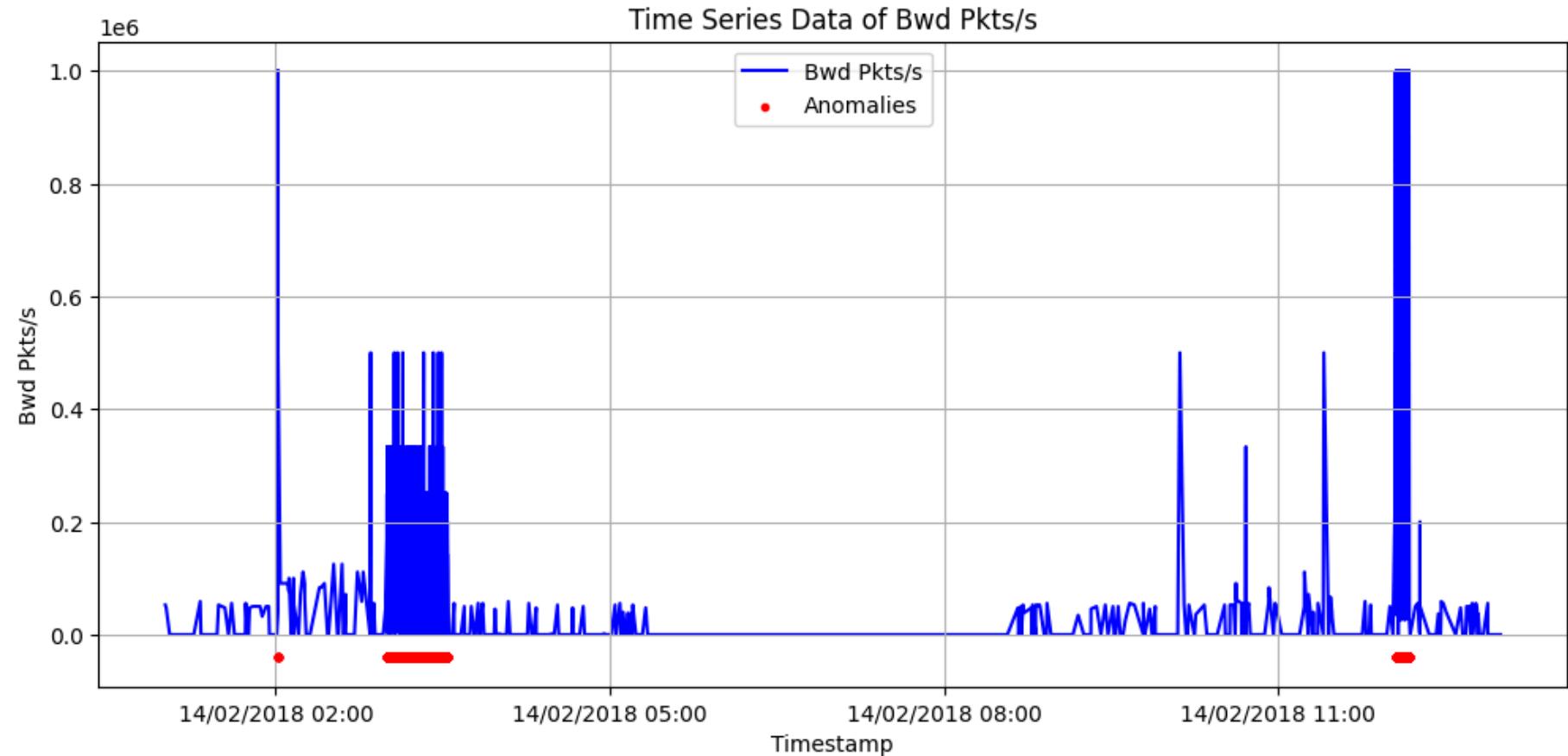
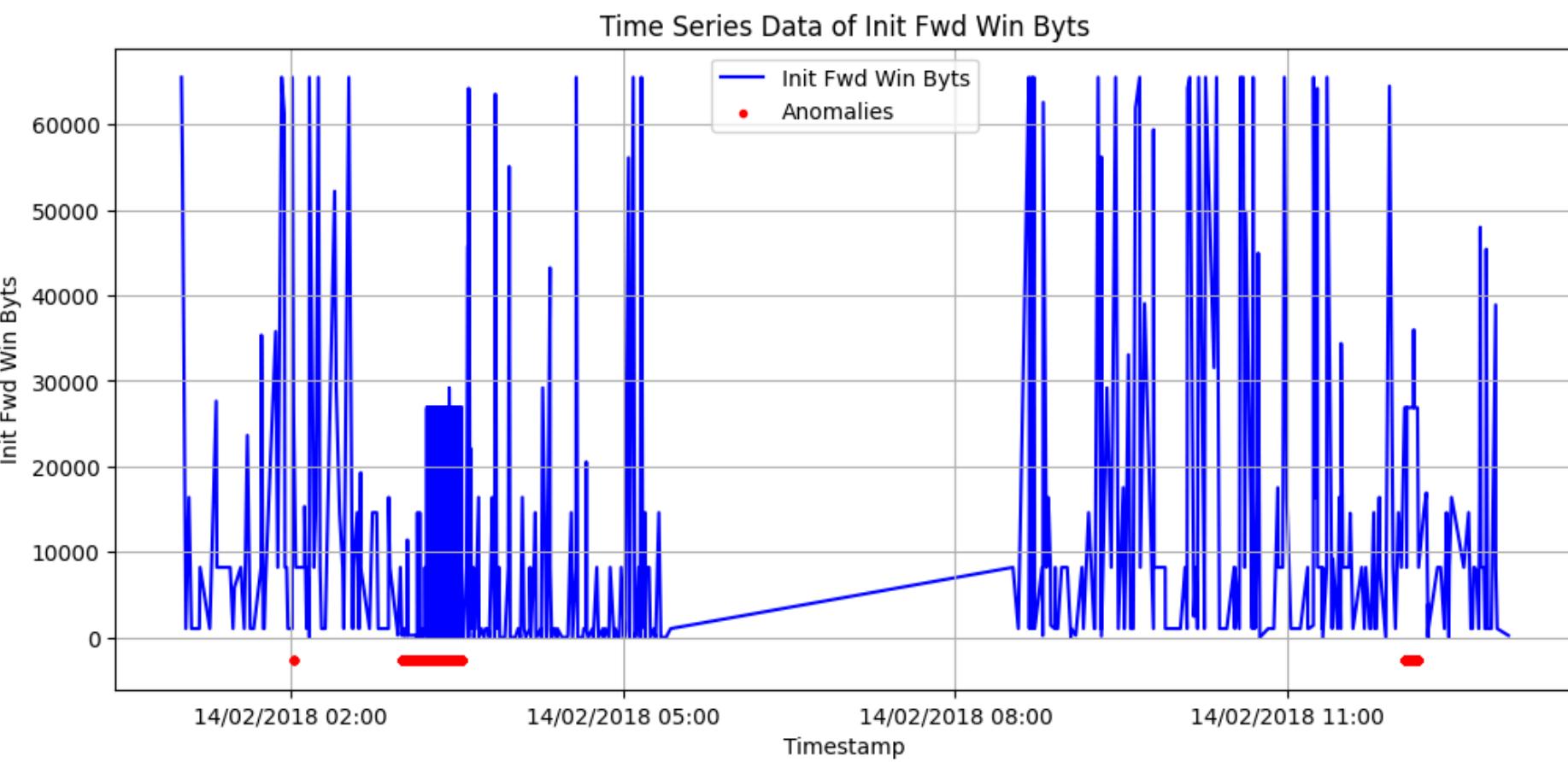
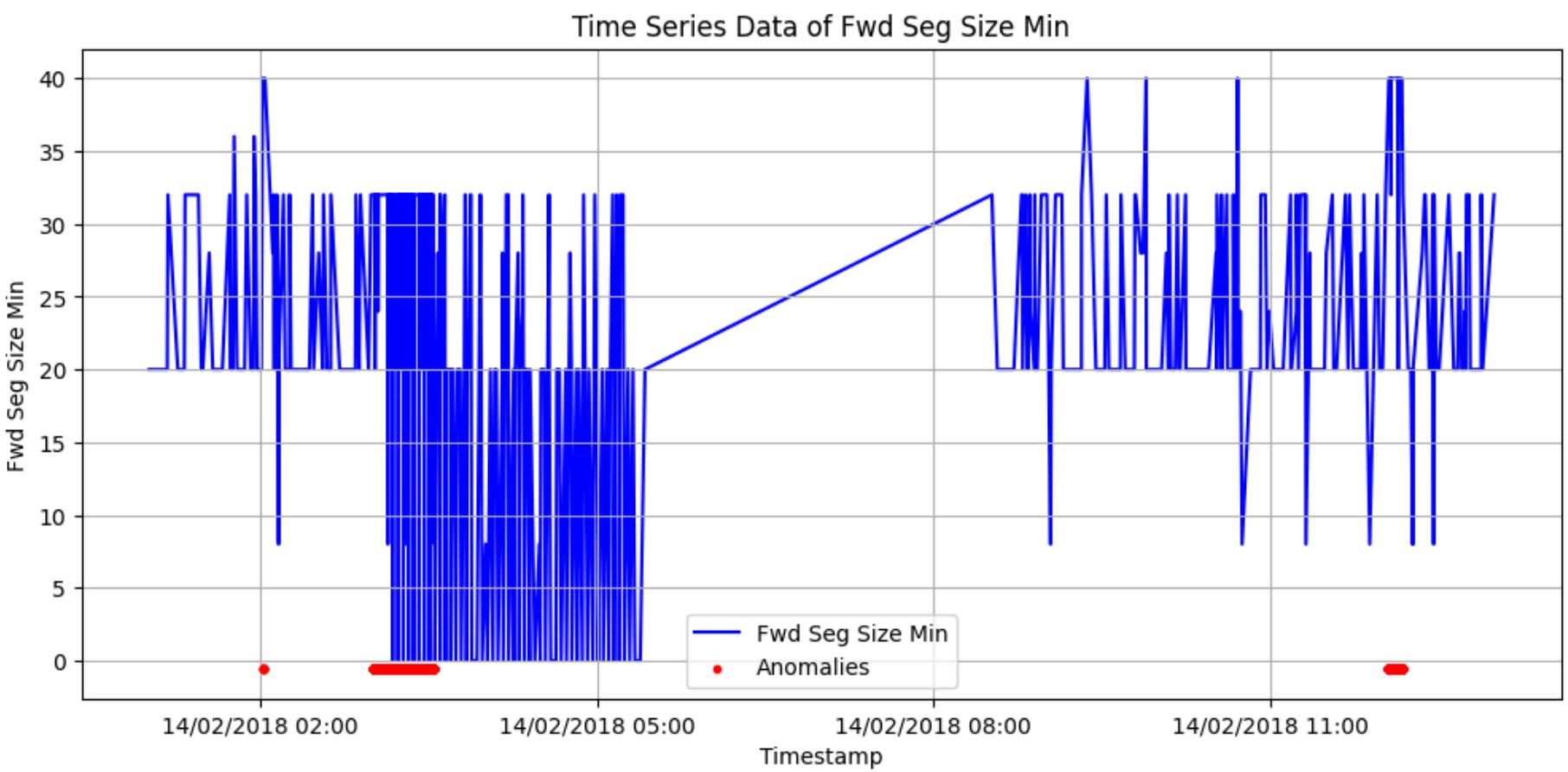
DoS Slowloris/GoldenEye: sends incomplete HTTP requests to the server at regular intervals to use up sockets

SSH/FTP-Bruteforce: Target weak credentials using dictionary attacks

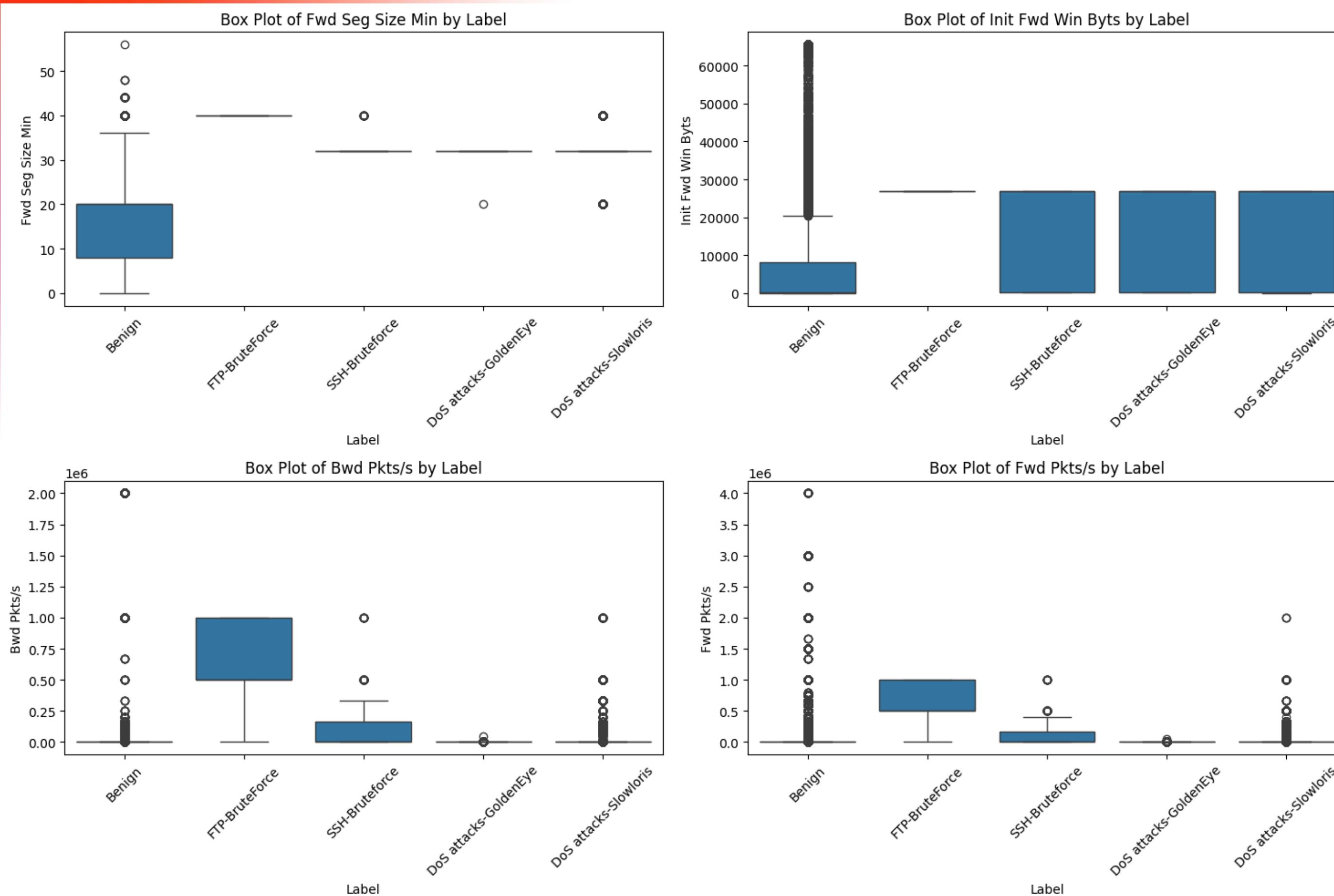
► Benign (0) or Anomalous (1)



Time Series



Feature Distributions



Data Preprocessing



Step 1

Remove columns with missing values & rows with infinite values

Step 2

Standardize the data using sklearn StandardScaler

Step 3

Split the data using the sliding windows technique

- Window size = 40
- Extract features from a sequence of data
- Preserve context between adjacent data points

Step 4

Split the data into training, validation & test set

- Training & validation: only benign data
- Test: mix of benign & anomalous data (around 6:4)

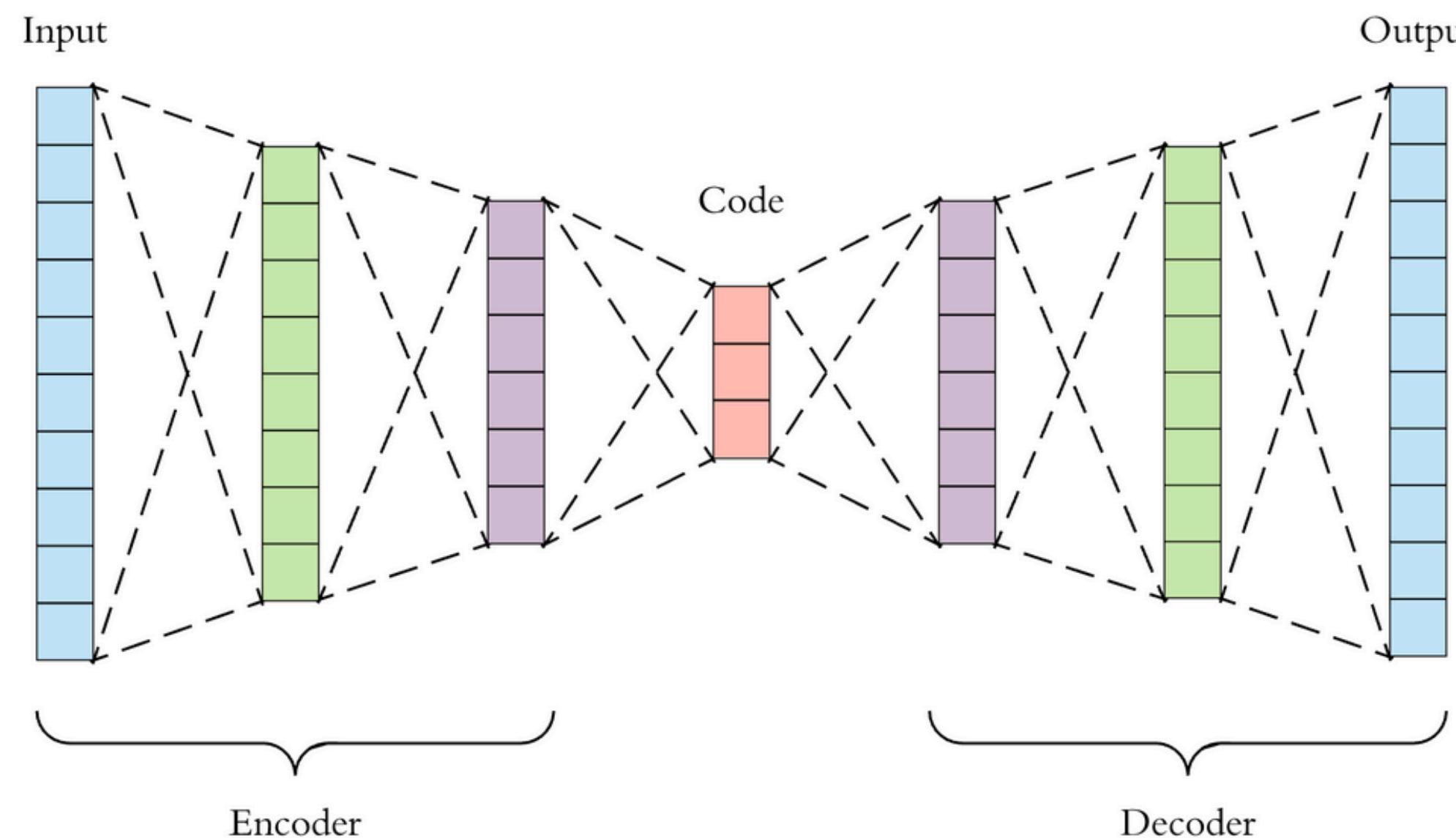
Neural networks approaches

Introducing to solutions

Autoencoder

Detects unknown attacks by focusing on deviations

Goal: Minimize reconstruction error between input and output



Input & output

Windows of Data:

- 77 Features
- Window Size of 40 timestamps.

Reconstruction loss

$$\mathcal{L}_{\text{reconstruction}} = \frac{1}{B} \sum_{i=1}^B \text{MSE}(X_i, \hat{X}_i)$$

Encoder

Compresses input into a smaller latent space representation.

Structure:

- 3 layers of 1D **convolution**:
 - $77 \rightarrow 50 \rightarrow 34 \rightarrow 16$ (feature reduction).
- **Activation**: LeakyReLU

Decoder

Reconstructs the original input from the latent representation.

Structure:

- 3 layers of 1D transposed **convolution**
 - $16 \rightarrow 34 \rightarrow 50 \rightarrow 77$ (restoring original dimensions).
- **Dropout** (20%) for regularization.
- **Activation**: LeakyReLU

Training AE

Technical side

Normal Data: Autoencoder learns to reconstruct typical patterns.

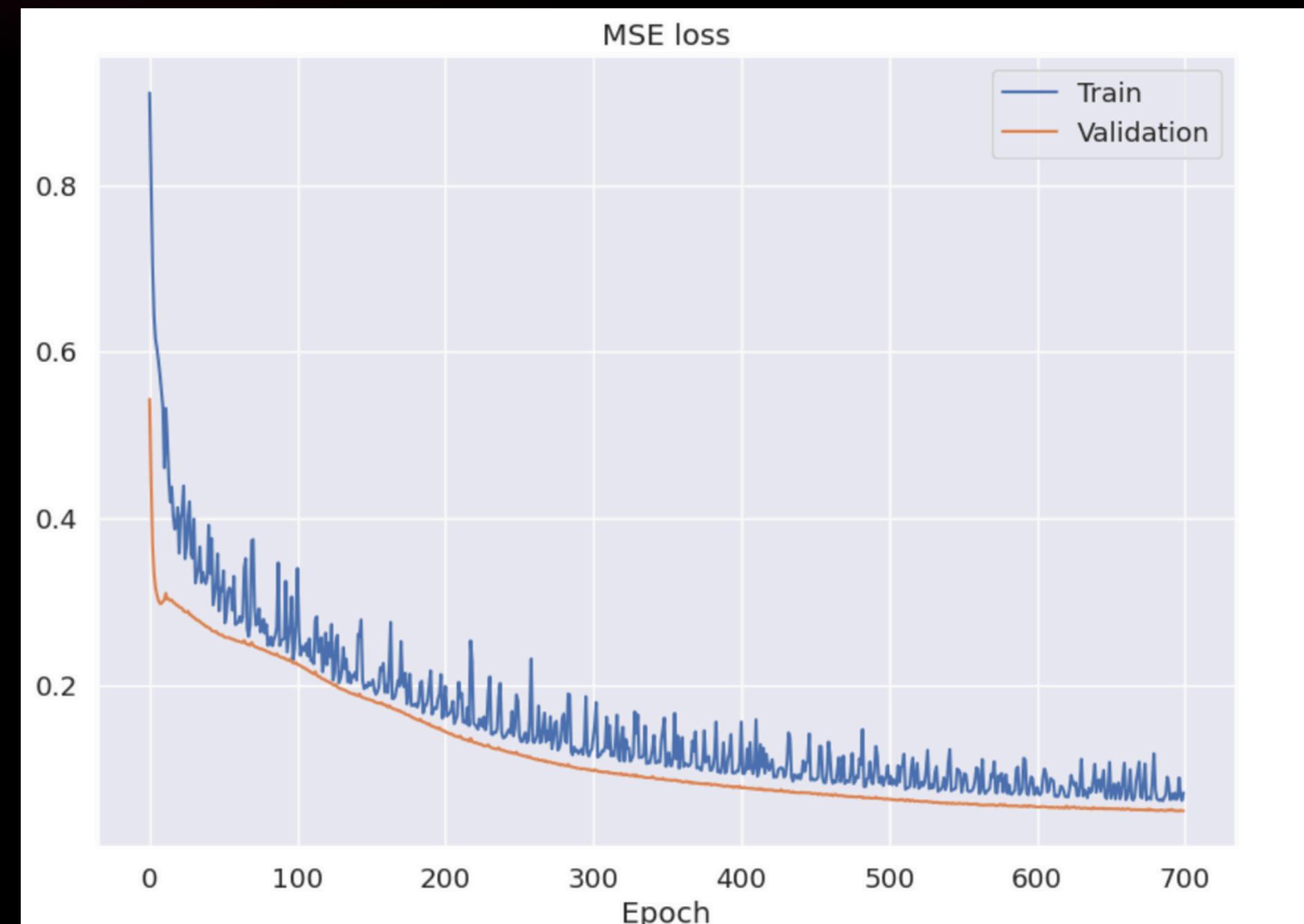
Anomalous Data: Reconstruction errors are significantly higher due to unfamiliar patterns.

Optimizer: AdamW

Scheduler: ReduceLROnPlateau

Epochs: 700

Lr: 0.0001

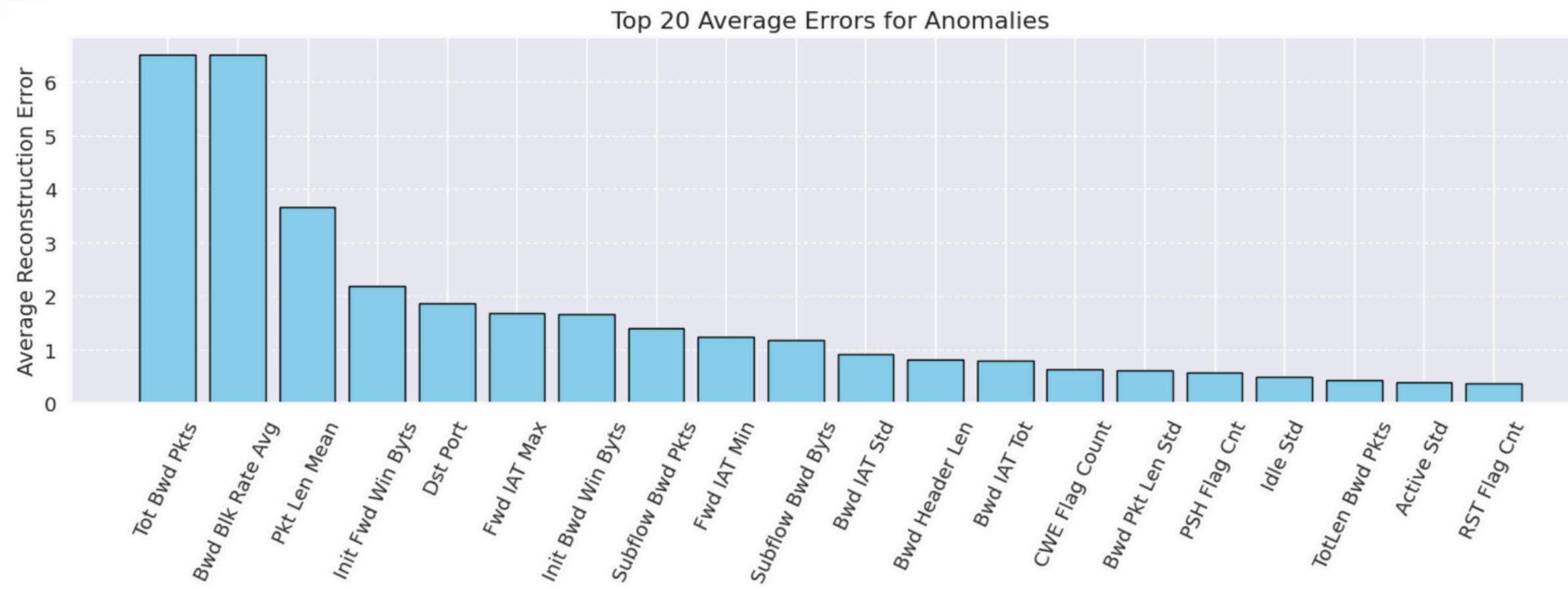


Results

AE final version

ROC_AUC	0.87
F1_score	0.8378
Recall	0.959
Precision	0.743

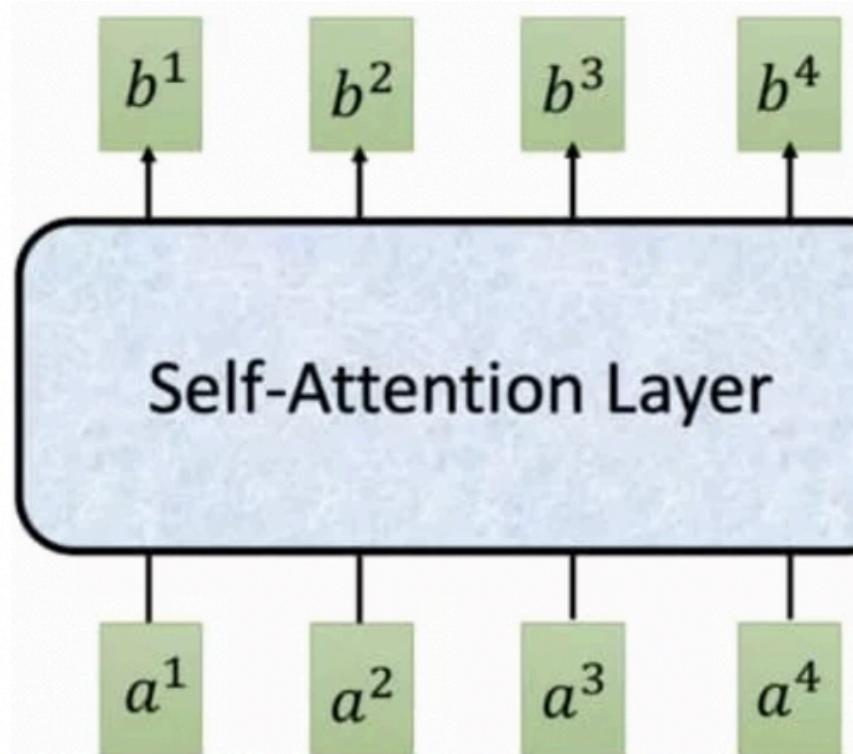
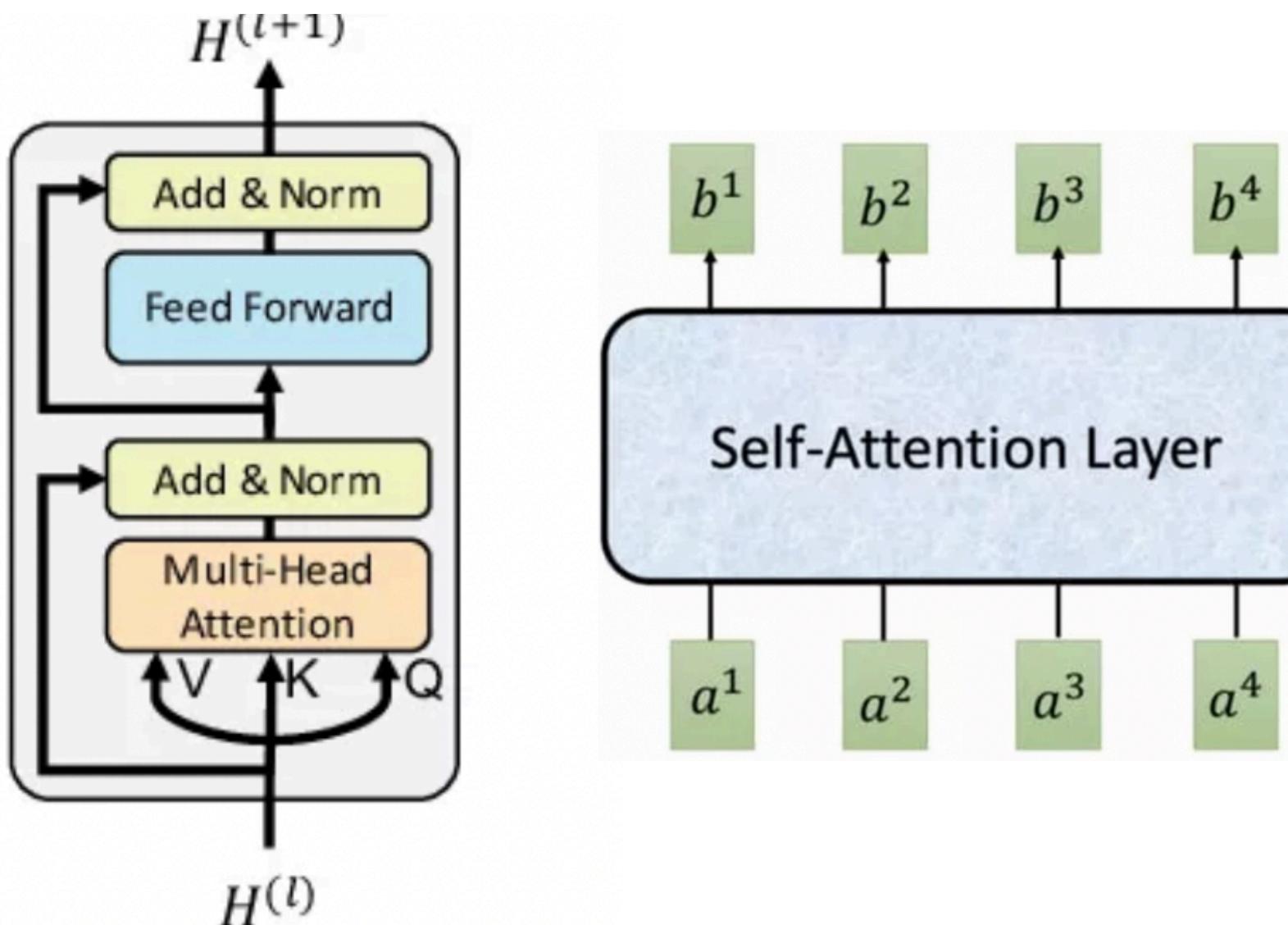
fixed ←



Autoencoder #2

with Transformer layers

Global Context Awareness + **High Performance**
(captures long-range dependencies) (SOTA)



Input & output

Windows of Data:

- 77 Features
- Window Size of 40 timestamps.

Reconstruction loss

$$\mathcal{L}_{\text{reconstruction}} = \frac{1}{B} \sum_{i=1}^B \text{MSE}(X_i, \hat{X}_i)$$

AE + Transformer

Final tuned structure

Input Transformation

- **Linear Projection:** Projects **77 features into** an embedding space (**32 dimensions**).
- **Positional Encoding**

Encoder

- **4 Layers** with multi-head self-attention and feedforward sub-layers
- **Multi-Head Attention:** **8 heads** to capture relationships
- **Hidden layer size of 256**

Decoder

- **4 Layers:** similar structure to the encoder
- **Multi-Head Attention:** **8 heads** for reconstruction
- **Feedforward Dimension of 256**

Autoencoder

+

Transformer

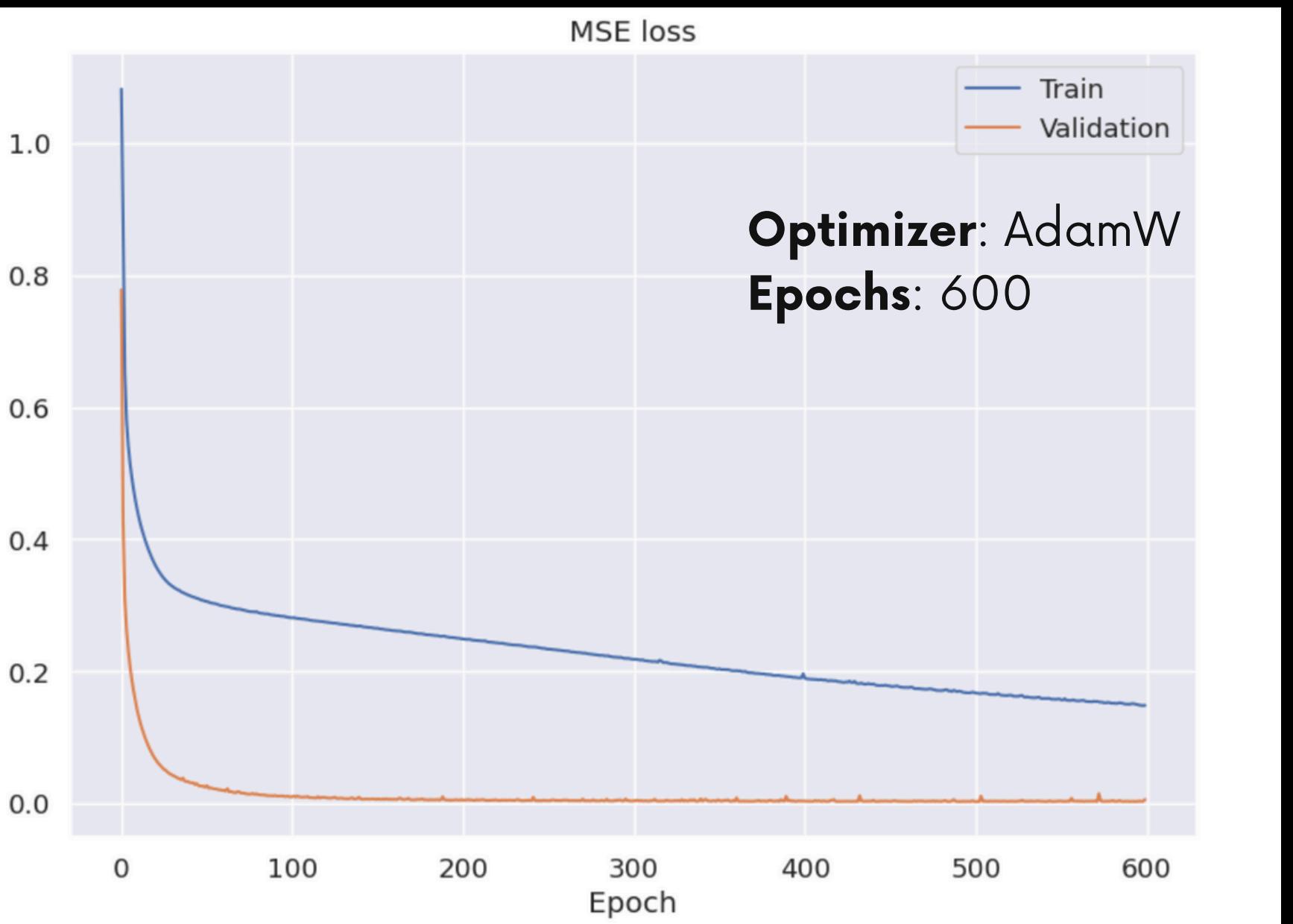
technical tweaks

+

Learning Rate Scheduling with Warmup

Warmup Phase: increases lr from $1e-9$ to $3e-4$ in 20 epochs

Decay Phase: Transitions to a multi-step scheduler reducing lr by 0.7x at [60, 120, 180, 250, 350, 450]

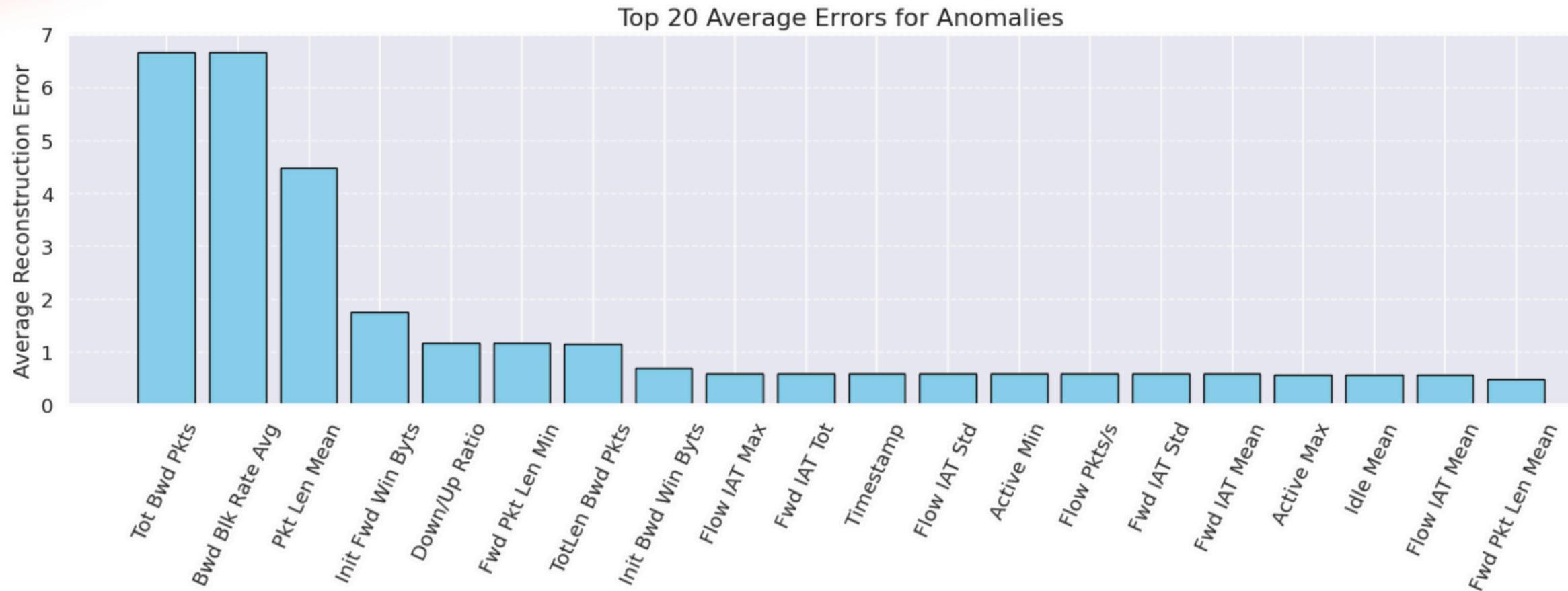


Results

**AE + Transformer
final version**

ROC_AUC	0.963	+10.6%
F1_score	0.9106	+8.6%
Recall	0.9503	
Precision	0.874	+17.6%

fixed ←



Future Pathways

1. Hybrid Models:

Try out other options: implement **VAE**, combine model with **LSTMs**

3. Graph Neural Networks:

Identify anomalous relationships in network traffic, using Graph Convolutional Networks (**GCNs**) or Graph Attention Networks (**GATs**)

2. Forecasting-based Anomaly Detection:

Time-Series Transformers, Temporal Fusion Transformers

4. Contrastive Learning for Representation:

Use techniques like **SimCLR** or **TS-TCC**



Do you have
any questions?