

***B9DA109 Machine Learning and Pattern Recognition: CA\_TWO***

***Conformal LSTM Classifier for Anomaly Detection on NAB***

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# **1. Introduction**

Anomaly detection in time series data plays a crucial role in domains like cybersecurity, finance, healthcare, IT operations, and medicine, where identifying out-of-pattern behavior in data can help detect failures, attacks, or rare events. This project aims to implement a Long Short-Term Memory (LSTM) based classifier with **conformal prediction** to detect anomalies on the Numenta Anomaly Benchmark (NAB) dataset. The dataset consists of over 50 labeled real-world and artificial time-series with annotated anomalies. It is a benchmark designed to evaluate real-time anomaly detection systems across diverse, noisy, and real-world scenarios (Lavin & Ahmad, 2015).

While the project’s core requirement was to build a conformal LSTM model for anomaly detection, this work goes a step further by **comparing two modeling approaches.**

1. Unsupervised anomaly detection - the model learns patterns without labelled anomalies and uses forecasting error to detect deviations.
2. Supervised anomaly detection - the model is trained using labelled data to classify sequences directly as anomalous or not.

Both models use the same core architecture but differ in how they are trained and how they treat anomalies. In both cases, **Conformal Prediction** to avoid manually guessing anomaly thresholds. Instead, the model uses a calibrated limit derived from data to decide what constitutes an anomaly. This approach aims to improve the reliability of detections by quantifying uncertainty, ensuring the anomaly decisions have a statistical confidence level.

### **Aims and Objectives:**

* To implement a **Conformal LSTM-based anomaly detection system** in Julia.
* To experiment with both **unsupervised (forecasting-based)** and **supervised (classification-based)** training methods.
* To apply **conformal prediction** for statistically valid, data-driven thresholding.
* To benchmark both approaches using **Precision**, **Recall**, and **F1-score** metrics against the NAB ground truth.
* To analyze which model performs better in different types of time series, i.e. synthetic vs. real-world.

# **2. Literature Review**

# **3. Methodology**

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