



Data Analytics
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Thesis

Unsupervised Real-Time Time-Series Anomaly Detection

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Abstract

Anomaly detection is a crucial task for machine learning due to wide-spread usage and type. In particular, it is worth noting that most data arising in industrial setups are of a streaming nature, thus restricting the range of standard anomaly detection tools. This thesis will identify the potential approaches to learn the identification of abnormal behavior from large-scale streaming data. An empirical comparison of state-of-the-art methods will to be extended by a novel technical contribution. In this thesis, the focus is particularly on streaming time-series Anomaly Detection which changes in nature with time and novel contribution will especially try to target this dynamic nature of time-series.

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1 Introduction

1.1 Motivation

1.2 Objective

2 Related Work and State of the art

3 Benchmarks

3.1 Autoencoder based models

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3.2 Prediction based models

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6.1 Data

6.1.1 Numenta Anomaly Benchmark (NAb)

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9.2 Parallel execution using Docker

10 Best practices

Following steps were taken to maximize the efficiency and speed of research:

1. Use version control to track the code and share between different devices.
2. Separate code from data. This will keep the code base small and easy to debug.
3. Separate input data, working data and output data.
 - **Input Data:** Input data-set that never change. For my case it is NAB and other external datasets.
 - **Working Data:** nothing for now.
 - **Output Data:** Results and threshold profiles in my case.
4. Separate options from parameter. This is important:
 - Options specify how your algorithm should run. For example data path, working directory and result directory path, epochs, learning rate and so on.
 - parameters are the result of training data. it includes the score and hyper-parameters.

11 Reference Usage

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