Anomaly detection in time series for TBM

A literatue review of the useful AD-method for Tunnuling Machines

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Abstract

Introduction

By default TBM (Tunnel Boring Machines) are complicated technical objects and involved a lot of technologies working together. Any defect in the chain could stop the entire machine. There for detecting those before they become a real issue can save a lot of time and resources. Fortunately, the number of sensor on the machines keep raising and thanks to platform like HK-connect their data can be access any where by any authorizes users. These data must carry a lot of information regarding the sate of the machine, which beg the question on how to extract it to detect anomaly. At time of writing the task is mostly done by experience users of the TBM, e.g. a weird noise in the hydraulic pack, an odd torque increase on one of the main drive motors, and so on. This method is clearly limited and use only a small portion of the data stream available, thanks fully the problem of anomaly detection is quite old and with the raise of machine leaning technic, keep getting better.
Therefor in this paper we will, have a first look of at the littery landscape of Anomaly detection method (ADM). First lets define exactly what we mean by that, given a multivariate time series:

$$\mathcal{X} = (\mathbf{x}_1, \dots \mathbf{x}_t, \dots \mathbf{x}_T) \in \mathbb{R}^{N \times T}$$

with N the number of sensors and T the number of temporal indices. The method $\mathcal{M}$ will return a binary category for each data point telling where and when there is anomalies, ie:

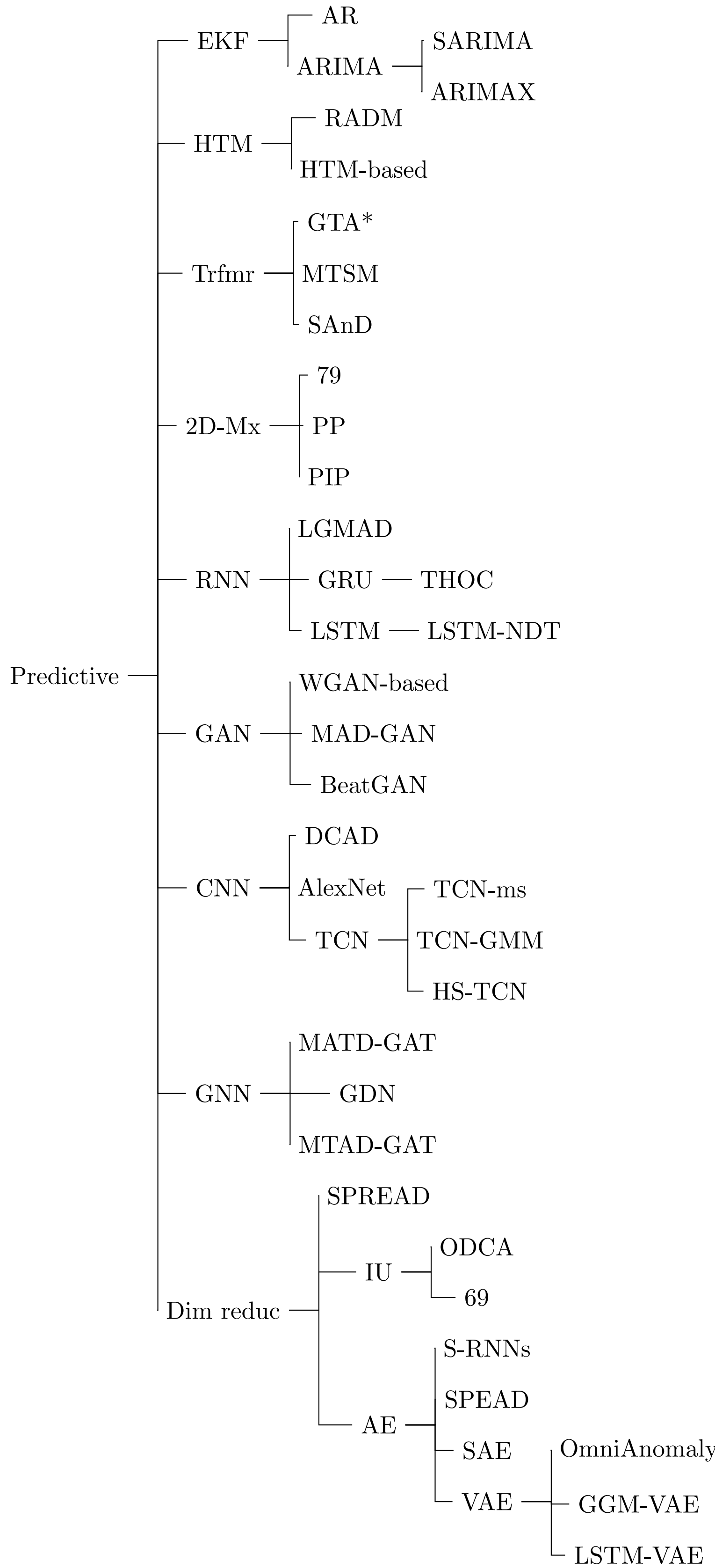
$$\mathcal{M} : \mathbb{R}^{N \times T} \to \{0, 1\}^{N \times T}$$

We need to address some looses ends with this definition. First, in most cases, their is no already labeled data to train the method on and labeling it by hand is not feasible. So the method must be unsupervised, which raise the need for a systemic definition of anomaly. Most papers (ref) consider the training data to be normal and define some anomaly score which tel how far is the new data. Here the methods will be categorize base on the way this score is define.
In our context, the training data is previous tunnel bore, which certainly contains anomaly in it. Therefor we will also discus some papers which tyred to address this issue by modifying the methods.

1 Secondary sources

2 Overview

- type of method:



  - Method :
    - Cluster/Density (probability)
    - Index monitoring
    - Forecasting
  - Addon
    - Dimension reduction
    - Multivariate topologies
    - Training data Contamination
  - plan
    - philosophie, sitation of artical

3 Description

- Cluster/Density (probability)
  - idea, Training data is normal data,
  -
- Anomaly score
- Forecasting
- Graph
- Training with data Contamination

3.1 Graph Deviation Network (GDN)

When using "distance to prediction" for AD in a multivariate settings, it's sensible to assume that related sensors have redundant information (e.g. a pressure and a extension sensors for a hydraulic cylinder). So if there measurement was put together to predict the next ones it could improve their prediction and so reduce the detection threshold. This is a base idea of the GDN architecture in [?]. Mark the related sensor in a directed Graph and apply an attention layer on the past measurement of the neighborhoods to predict the next ones. Here is some short assertion and nice propriety of this approach :

- Even if every sensor of the TBM are in the graph, the AD is still localize to each sensor.
- The training data is assume to be free of anomaly.
- Prior knowledge of relation between sensor can be embedded in the graph by restricted some relationship. This can lower the complexity and the time of training.

To test their method the authors used dataset of simulated attack on water treatment physical test-bed systems, the Secure Water Treatment (SWaT) and Water Distribution (WADI) dataset. As a base line they use other method which we discus in other Section.

Conclusion