Anomaly detection in time series for TBM

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

Mathieu Giamberini, 2024

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. Therefore, detecting those before they become a real issue can save a lot of time and resources. Fortunately, the number of sensors on the machines keeps raising and thanks to platforms like HK-Connect, their data can be accessed anywhere by any authorized user. These data must carry a lot of information regarding the state of the machine, which begs the question of how to extract it to detect anomalies. At the time of writing, the task is mostly done by experienced 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 uses only a small portion of the available data stream. Despite this, the problem of anomaly detection is quite old, and with the rise of machine learning technic, it keeps getting better.
Therefore, in this paper, we will, have a first look of at the literary landscape of Anomaly detection method (ADM). First, let's 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, there 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 raises the need for a systemic definition of anomalies. Most papers (ref) consider the training data to be normal and define some anomaly score, which tells how far away the new data is. Here, the methods will, be categorized based on the way this score is defined. In our context, the training data is previous tunnel bore, which certainly contains anomalies. Therefore, we will also discuss some papers which tried to address this issue by modifying the methods.

1 Secondary sources

2 Overview

Anomaly detection methods can be categorized in many ways. In this paper it's divided in two parts, general method and useful ticks to improve theses. The former represent general ways to solve the AD problem. Its compose of three categorizes : forecasting, clustering and index monitoring. The latter are so-called add-ons. The papers in this category present a AD method with some tricks that, in our minds can be applied to any method to improve it.

2.1 Forecasting Methods

When working all day long with some equipment, you know it so well that, if asked, you could almost predict the sound it will make in the near future. But if suddenly the sound doesn't match your expectations you know there are some things wrong. That is the core idea for the forecasting method, predict the near future using some generative method and if the error goes over some threshold, the data point is labeled as an anomaly. Example of those technics may be LSTM [ref claim LSTM is the best] or using time convolution (TCN) [Ref TCN].

2.2 Clustering method

While storing metric screws in the warehouse, someone picks up an imperial one, he wants to find any box to put it in. Therefor he will conclude there was an error in the shipment, even if he didn't know this type of screw. This is the main idea for the clustering method, define clusters, if a new data point can't fit in one of them, it is labeled as an anomaly. There are multiple ways to define the cluster. A good part uses some defined distance [ref DTW] function and uses a variant of K-nearest-neighbor (KNN) [ref DBSCAN]. Similarly, use the density of the data point in relation to the training data, which will give less, strict categorizes [ref LOF]. Another method is to estimate the probability density function (PDF) and put a threshold on low values. [ref DAGMM]

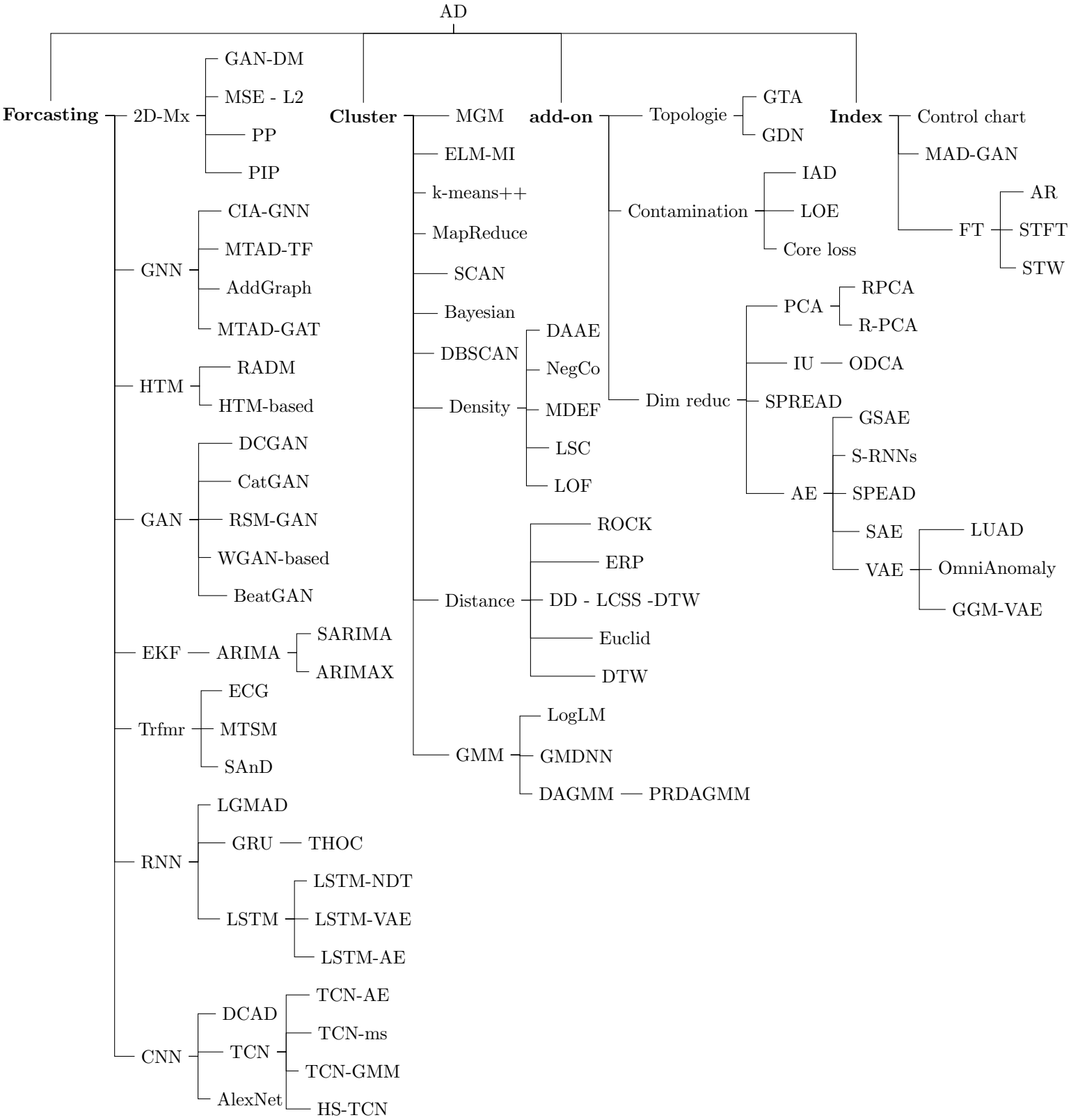

Figure 1: Anomaly detection method categorization

2.3 Index monitoring

After assembly, the disks cutters there are put under pressure for some time. When the time is up, the pressure is measured, if the pressure is too low, there is a problem somewhere. This is the intuition behind index monitoring method, define some function with an acceptable range of normal values, if the values are outside the range its mark as anomaly. This technic is one of the oldest, simplest and most used in the manufacturing industries, in this context is referred as Control chart [ref Control chart]. Another example of application is [ref AR] which use a modified wavelet transform to define a Health Index [ref HI] to monitor bearings.

2.4 Add-ones

In order to improve those techniques and solve issues intrinsic to the TBM case, here are some interesting solutions.
Topology, TBM AD is intrinsically a multivariate problem (ie there is more than one sensor on the machine). And it is safe to assume that the anomaly information for some problems is carried by multiple sensors. For example, if there is a defective sensor, the others want to raise any anomaly, which will greatly help to pin the root cause down. This what [ref GDN] and [ref GTA] did so by introducing a directed graph to model the relationship between sensors. This information was then used, in these papers, to do forecasting using attention techniques.

Contamination, the training data for those models will surely be some already-bore tunnel data. During those bores, by Murphy's law, at some point, some things went wrong. The issue is that most methods assume an anomaly free dataset. This is why [ref IAD, LOE, Core Loss] proposed some modifications to the training steps to deal with this contamination. To do so, they generally modify the loss function to account for the uncertainty of the data and improve this uncertainty iteratively. This topic will be discussed in greater detail in 3.2.

Dimension reduction, a large quantity of sensors, with a quite small data rate, even with a small time window can make the input dimension of the model certainly significant. This can render the training hard and sensitive to noise. to solve this issue, most papers use some kind of dimension reduction. For example, [ref DAGMM] uses an AE and a modified reconstruction error concatenated with the latent vector as an input to a GMM. Or [LSTM-AE] used a LSTM as an AE to do forecasting.

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.

3.2 Latent Outlier Exposure (LOE)

Conclusion