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Literature Research

Mechatronik

Representation learning for zero-shot anomaly detection

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1 Abstract

Contents

2 Introduction

Several applications rely on multi variate time series data. This could be sensor measurements or machine state values. In these cases the data is changing constantly in a repetetive manner for a long time. This is when the measured data or the machine is running uninterrupted like it is supposed to. But all of a sudden, measurements or values can change unpredicted because of different reasons. Recognising and reacting to these changes can be very important (Source). But interruptions are not always the same. They can occur in different shapes which in some cases never occured like this before. This asks for a tool to detect anomalies in time series data.
Finding a good solution to this problem requires detailed literature research. This paper is trying to provide answers to the problem by extracting possible solutions out of the literature. Therefore the paper focuses on the following research question:
What are the different types of representation learning possible for Zero Shot Anomaly Detection in time series applications?

3 Definitions and Conventions

3.1 Representation Learning

Representation Learning mainly tries to detect interconnections in data, which represent meanings which are relevant for further data analysis. There are several representation learning techniques to detect patterns and to store them in different ways.
(Lavrač, Podpečan, & Robnik-Šikonja, n.d.) 1.3 divides techniques into Propositionalization and Embeddings.
Propositionalization: Embeddings:
Representations in data In the book of (?, ?) this general detailed description of representation learning is given. They sum up that a representations should make the subsequent learning tasks easier. This implicates that to find a the best fitting representation and the underlying representation learning technique, we need to know the task it should perform afterwards.

3.1.1 Evaluation

describes how to evaluate the applied RL approach in
(Bengio, Courville, & Vincent, n.d.) describes what makes a representation ”good”. They list the following factors:

- Smoothness
- Sparsity

We want to find properties of the data but at the same time we don't want to loose information about the input (?, ?) (S.525)

3.2 Zero Shot Learning

detailed description

3.3 Anomaly Detection

detailed description

4 Representation Learning for Time Series Data

In this chapter the found literature is put into context. Starting with classical literature about the fundamental findings followed by actual trends in the Area of Representation Learning. Finally the different Representation Learning Strategies are listed and compared.

4.1 Historical view

In this chapter the fundamental literature about the topic is going to be discussed.
Sensors and comparable applications produce time series data points which on a closer look may not make sense. They can vary in an unforeseen way and for a short time window they may be completely random. We have to step back and observe longer time periods which could be days or weeks. Or, for very dense measuring it is shorter but there are way more data points to handle. Sometimes it is possible for a human to see some patterns in the data when observing a long time window. Take for example the measuring of a solar plant. On a daily basis it is obvious to see the sun rising and setting, depending on the voltage of the panels. Starting at 0 at night the voltage is rising before noon and descending in the afternoon. This is one representation in the data. But there could be more represenations hidden, which are not likely to see. The shadow of a tree wandering over the panels happening every day or a one time event like the snow covering the plant.
These variations in data are not always visible for a human and even less possible to label them accordingly. Like (Bengio et al., n.d.) mentioned it is important for artificial intelligence to detect these representations in data by machines. A machine should be able to extract information hidden in the low-level sensor measurings and continue working with the representations instead of the raw data. This is according to the paper the main requirement for a good representation, to be able using it as an input to a supervised predictor.
Since the paper came out in 2013, several representation learning techniques were developed and some of them are directly applicable for time series data. In (?, ?) the importance of machine learning in sensor data is emphasized. They sum up several deep learning techniques on data-driven soft-sensors. Soft-sensors represent hard to measure variables by adapting available sensor data. Their observation of industry processes is a rapidly changing field which demands data processing for a huge amount of data.

4.2 Trends

4.3 Representation Learning Strategies

The different RL strategies are explained and compared.

5 Application

Which of the proposed RL types are best suited for Zero Shot Anomaly Detection?

6 Implementation

The best fitting strategies are implemented on a small test data set in order to demonstrate how it works.
Proof of Concept

7 Summary

7.1 Discussion

7.2 Future Work

References

Bengio, Y., Courville, A., & Vincent, P. (n.d.). Representation learning: A review and new perspectives. , *35*(8), 1798–1828. Retrieved 2024-07-03, from http://ieeexplore.ieee.org/document/6472238/ doi: 10.1109/TPAMI.2013.50

Lavrač, N., Podpečan, V., & Robnik-Šikonja, M. (n.d.). *Representation learning: Propositionalization and embeddings*. Springer International Publishing. Retrieved 2024-07-09, from https://link.springer.com/10.1007/978-3-030-68817-2 doi: 10.1007/978-3-030-68817-2