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Literature Research
Representation Learning for Zero-Shot Anomaly Detection

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1 Abstract

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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?
This is what we want to find out by conducting a literature research concerning the topic and afterwards implementing the best choices on a test data set. We begin in 3 by defining the most important phrases and how we use them. In 4 the literature is searched for any paper or book providing a RL technique. The found techniques are compared and evaluated for usability at Zero-Shot Anomaly Detection in 5. The implementation of the best suiting techniques is provided in 6. Finally the results are discussed and concluded in 7

3 Definitions and Conventions

3.1 Representation Learning

Representation Learning mainly tries to detect interconnections in data, which represent meanings 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, 2021) 1.3 divides techniques into Propositionalization and Embeddings.
Propositionalization: Embeddings:
Representations in data In the book of Goodfellow, Bengio, and Courville (2016) 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

This chapter describes how to evaluate the performance of an RL approach.
(Bengio, Courville, & Vincent, 2013) describes what makes a representation ”good”. They list the following factors:

- Smoothness
- Multiple Explanatory Factors
- A hierarchical organization of explanatory factors
- Semi-supervised learning
- Shared factors across tasks
- Manifolds
- Natural clustering
- Temporal and spatial coherence
- Sparsity
- Simplicity of factor dependencies

”We want to find properties of the data but at the same time we don’t want to loose information about the input” (Goodfellow et al., 2016, S. 525)

3.2 Zero Shot Learning

Zero Shot Learning is an extreme form of transfer learning (Goodfellow et al., 2016, S. 536). While transfer learning is the concept of transferring the knowledge and weights gained at one task using them at solving another task, Zero-Shot Learning means there are no samples for

the other task. The transformation of knowledge can help solving tasks where there are few or no samples available. The gained knowledge is normally stored as representations in the data. Representations which are abstract enough to not see a specific item but information about items which can be applicated to groups of items. THis also means that Zero-Shot Learning is only possible because addition information has been discovered during training.
Palatucci, Pomerleau, Hinton, and Mitchell (2009) were the first to implement a successful Zero-Shot Detection followed by Socher et al. (2013) who used semantic word vector representations to classify words in groups and to sort new words with an accuracy of 90% with a fully unsupervised mdoel.

3.3 Anomaly Detection

What are anomalies in data? This is not always exactly defined in literature. In this paper the definitions in Gruhl (2022, S. 54) are used. They seperate anomaly and novelty detection as different tasks. Anomalies can be understood as outliers from the regular class. But these anomalies can vary in their cause. If there is a specific cause and the anomalies occur in its own cluster, they form a novelty. If instead the outliers randomly occur with no specific root cause, they are called noise. The cause for noise then is of a different kind and cannot be classified.
In this paper we want to focus on single time events, which are in any case anomalies. Potentially being caused by an unknown process, they cannot be classified (Gruhl, 2022). This makes our goal an anommally detection task.

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., 2013) 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 (Sun & Ge, 2021) 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

Based on the presented fundamental literature the up-to-date papers are presented in the chapter.

4.3 Representation Learning Strategies

The different RL strategies are listed, explained and compared.
TODO
Learning representations in time series data is tackled in a variety of ways. One solution according to Zhang, Cai, Zhou, and Liu (2024) is debiased contrastive learning. By comparing pairs of data points and rating the similarities as distances between the two, contrastive learning gets less dependant on labeled data. The data can be more general and the extracted representations are

more robust. The pairs of data points are labeled as positive and negative pairs with a distance according to their similarities. With this distance they are put into a feature space where they form groups of data points. To minimize the bias between representations multigranularity augmented view generation and expert knowledge are used during training.

5 Application

Which of the proposed RL types are best suited for Zero Shot Anomaly Detection? Here the priors described in 3.1.1 are used in order to rate the RL types.

6 Implementation

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

6.1 Data Set

In the test data the learning data is seperate from the data including anomalies. The important thing about Zero Shot Learning is that a specific anomaly never occured like this before. In the test data, all chosen representation learning techniques are applied using the same data for learning and afterwards testing the anomaly detection with the same anomalies. According to chapter (Evaluation) the characteristics are evaluated for each rl technique.

6.2 Anomalies

6.3 Results

7 Summary

7.1 Discussion

7.2 Future Work

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