INSTITUTE OF VISUAL COMPUTING

TU Graz

SCIENCE
PASSION
TECHNOLOGY

WP2 Prototypes

Julian Rakuschek

16.01.2025

Our Main Quest

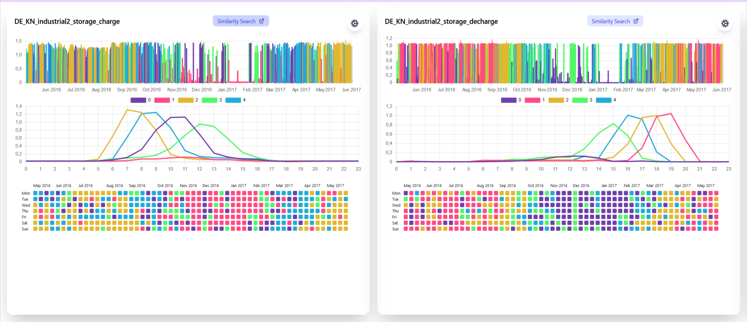
D2.2 Visualizations for AI results and for AI explainability

Task 2.4 Development of a web-based visualization including domain-specific visualizations

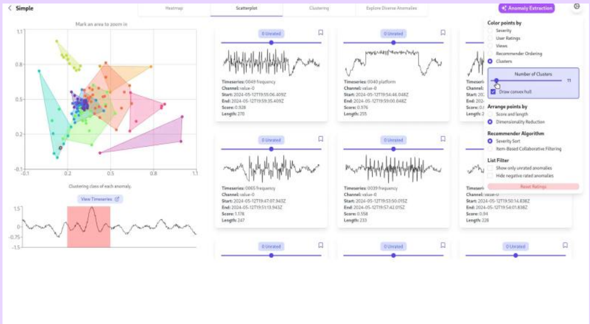
Task 2.5 Development of visual explanations for AI results

Currently four prototypes:

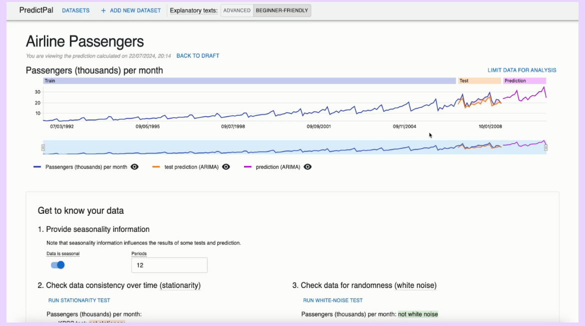
Cluster and Search



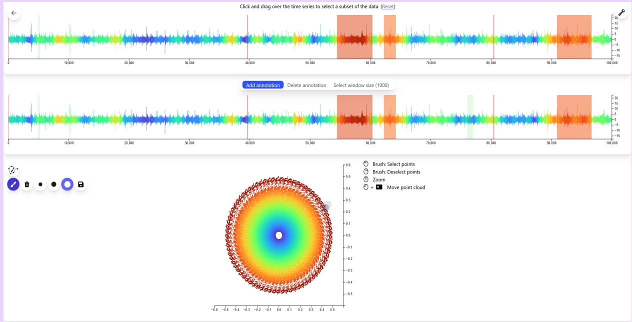
Anomalies



Forecasting

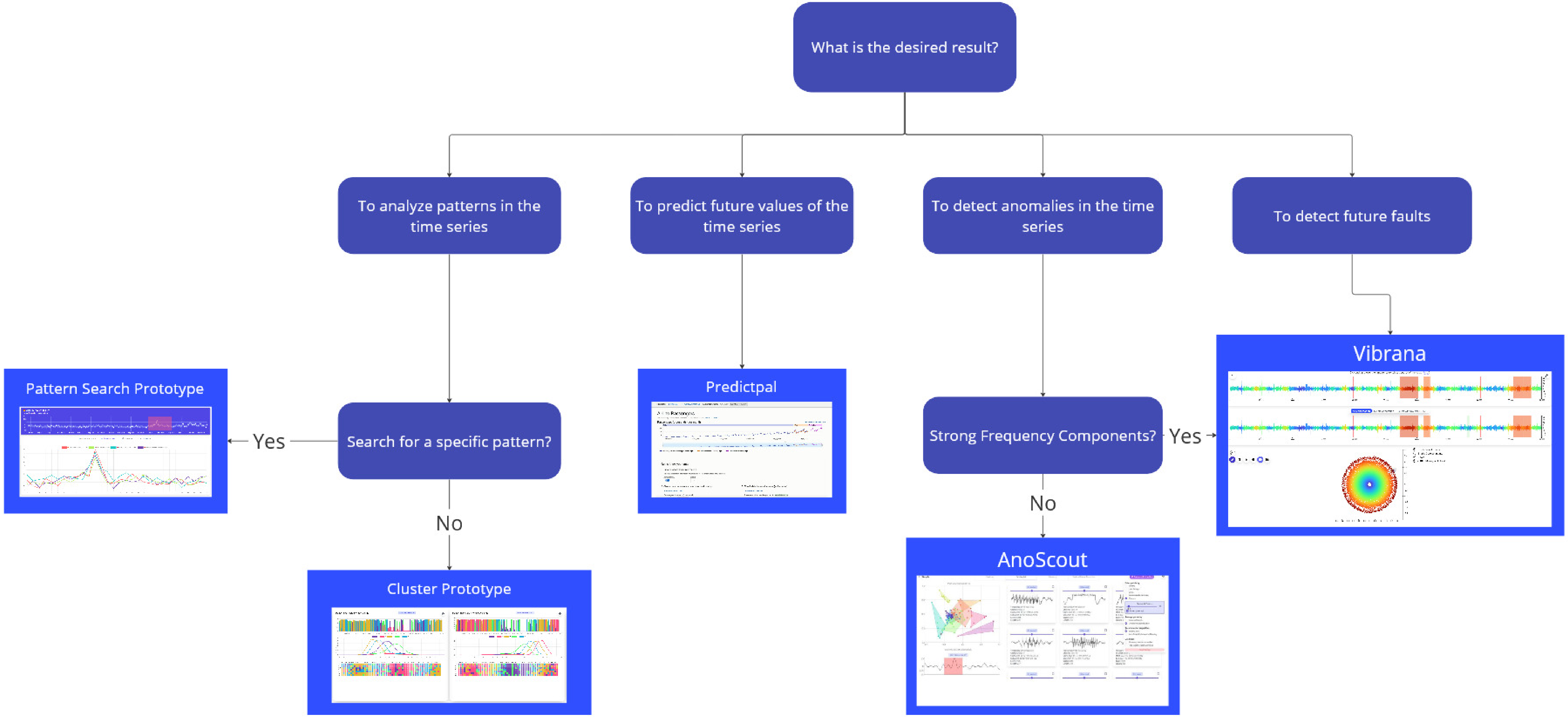


Vibrations



All are meant for **Task 2.4, Task 2.5** is WIP

The Prototypes are Task-Oriented



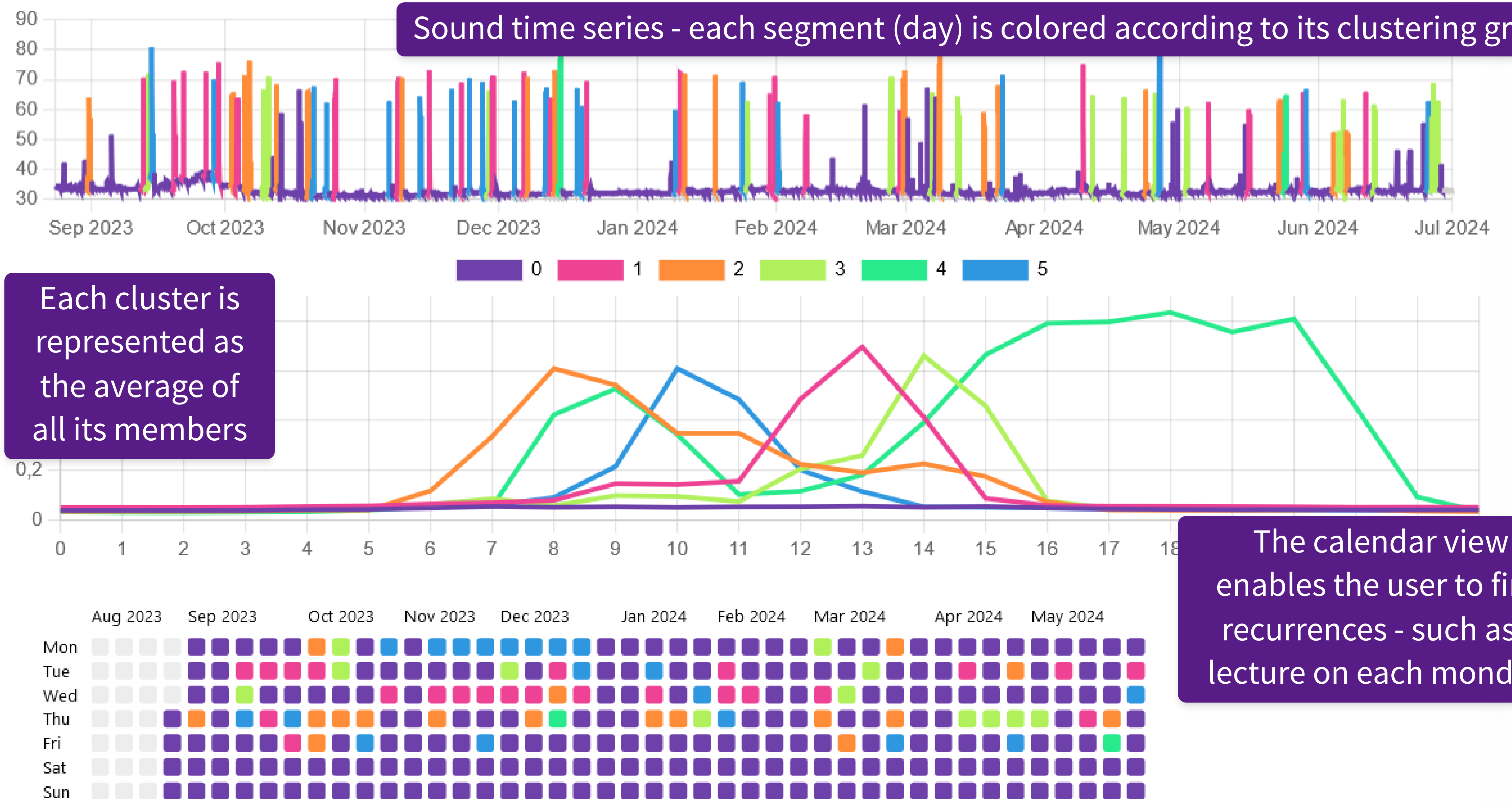
Cluster & Search

Cluster & Search Prototype Goals

1. Find pattern groups and compare across seasons
2. Find anomalies
3. Compare channels

Clustering Recorded Noise Level from a Seminar Room

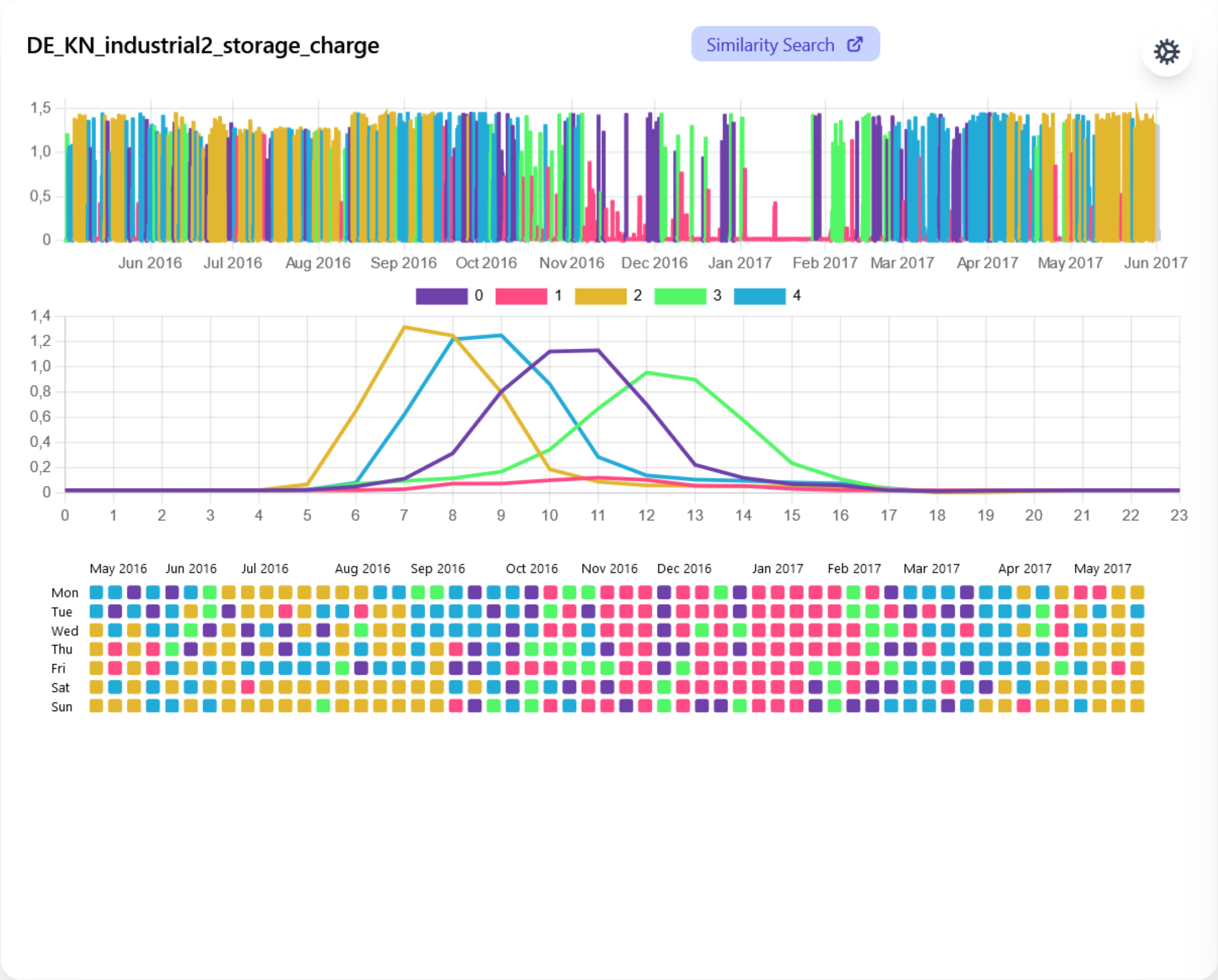
Sound time series - each segment (day) is colored according to its clustering group

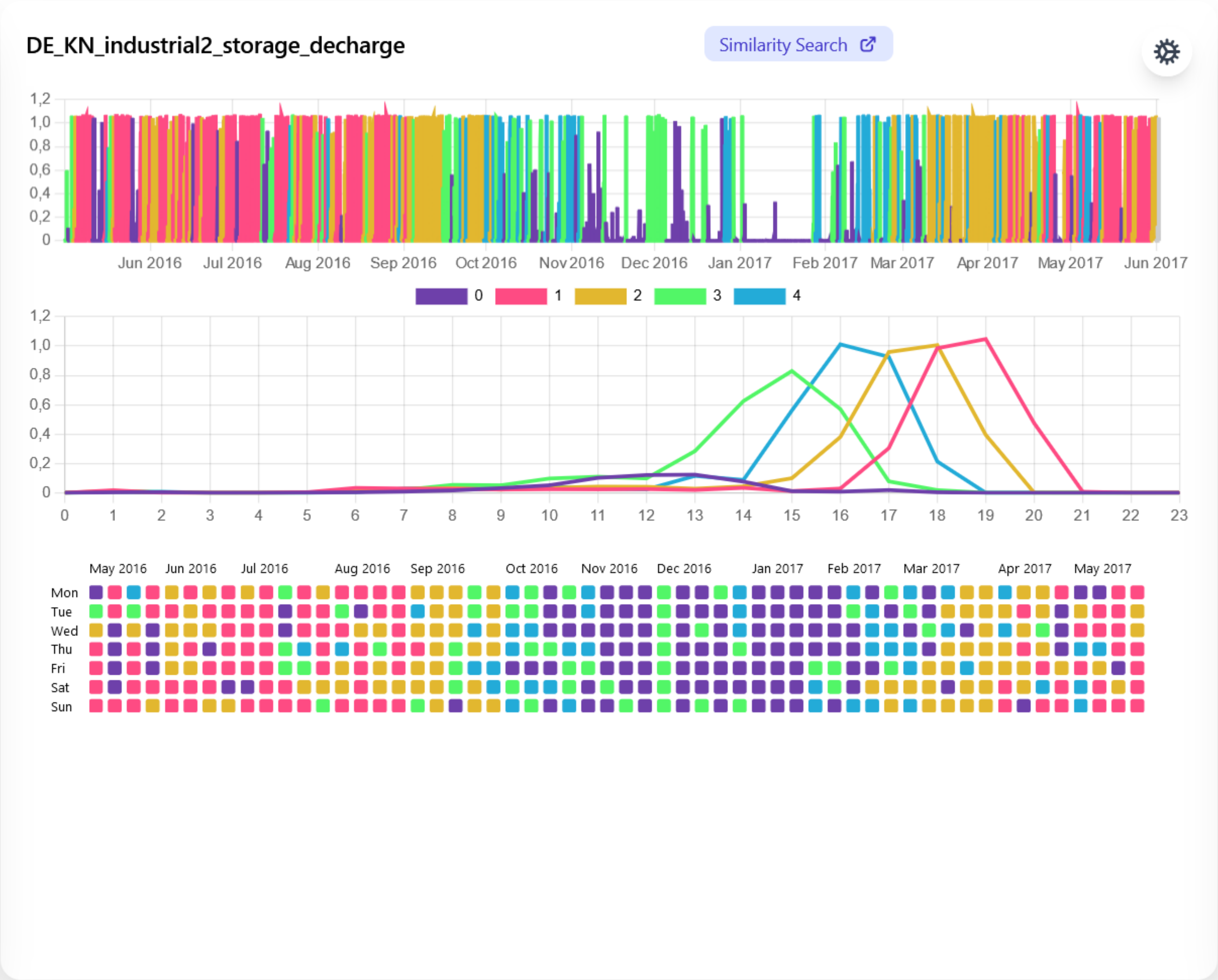


Each cluster is represented as the average of all its members

The calendar view enables the user to find recurrences - such as a lecture on each monday.

PV Energy Production of Households





Another dataset - PV energy production of households in southern germany. The daily segmentation shows the shift of charge and decharge over the day and the season of the year.

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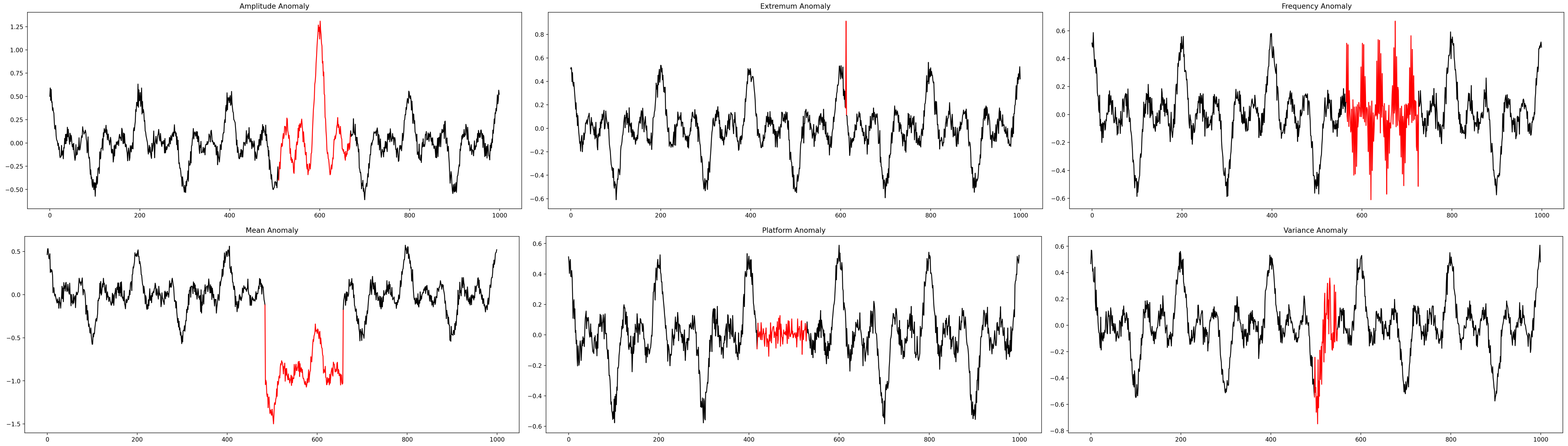
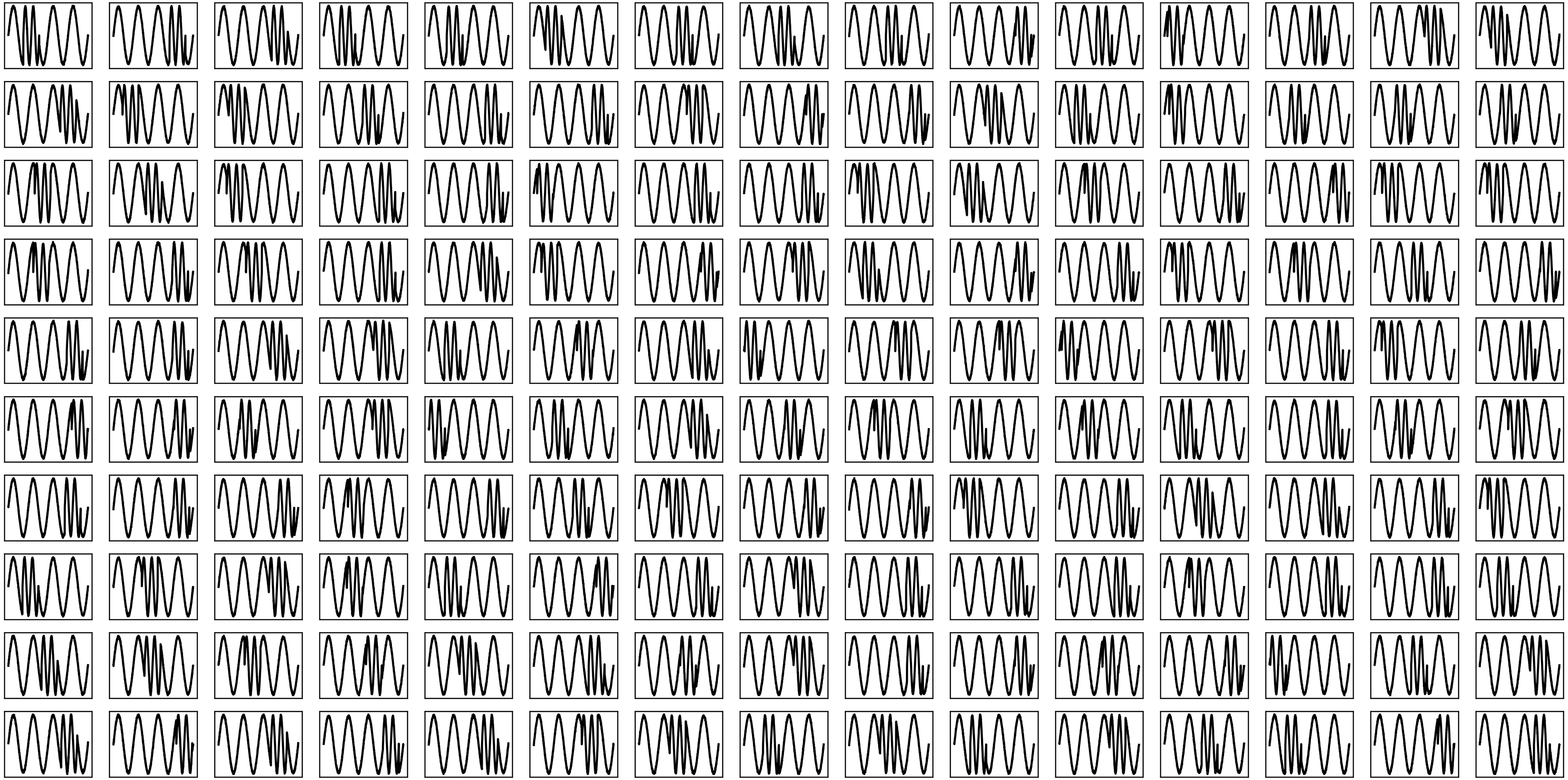
Anomalies

Anomalies in time series (Selection)



Check every time series by hand?



Let algorithms do the work!

Introducing AnoScout

Julian Rakuschek, BSc

AnoScout

A System for Visual Recommendations of Anomalies in Time-Oriented Data

Master's Thesis
to achieve the university degree of
Master of Science
Master's degree programme: Computer Science

submitted to

Graz University of Technology

Supervisor
Univ.-Prof. Dipl.-Volksw. Dr.rer.nat. Tobias Schreck, M.Sc.

Institute of Computer Graphics and Knowledge Visualisation
Head: Univ.-Prof. Dipl.-Volksw. Dr.rer.nat. Tobias Schreck, M.Sc.

Graz, April 2024

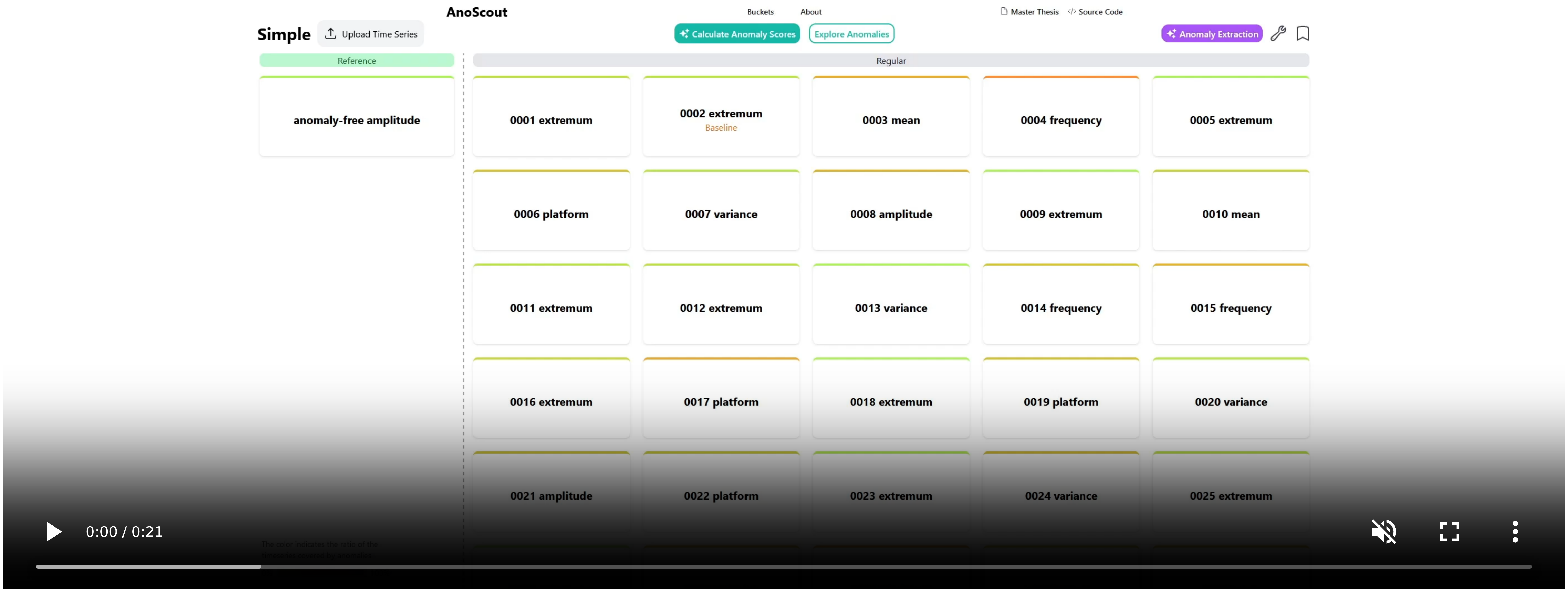
A "sandbox" to check which algorithms work well and for exploring anomalies in the dataset.

Anomalies are represented as cards:

5 Important verified

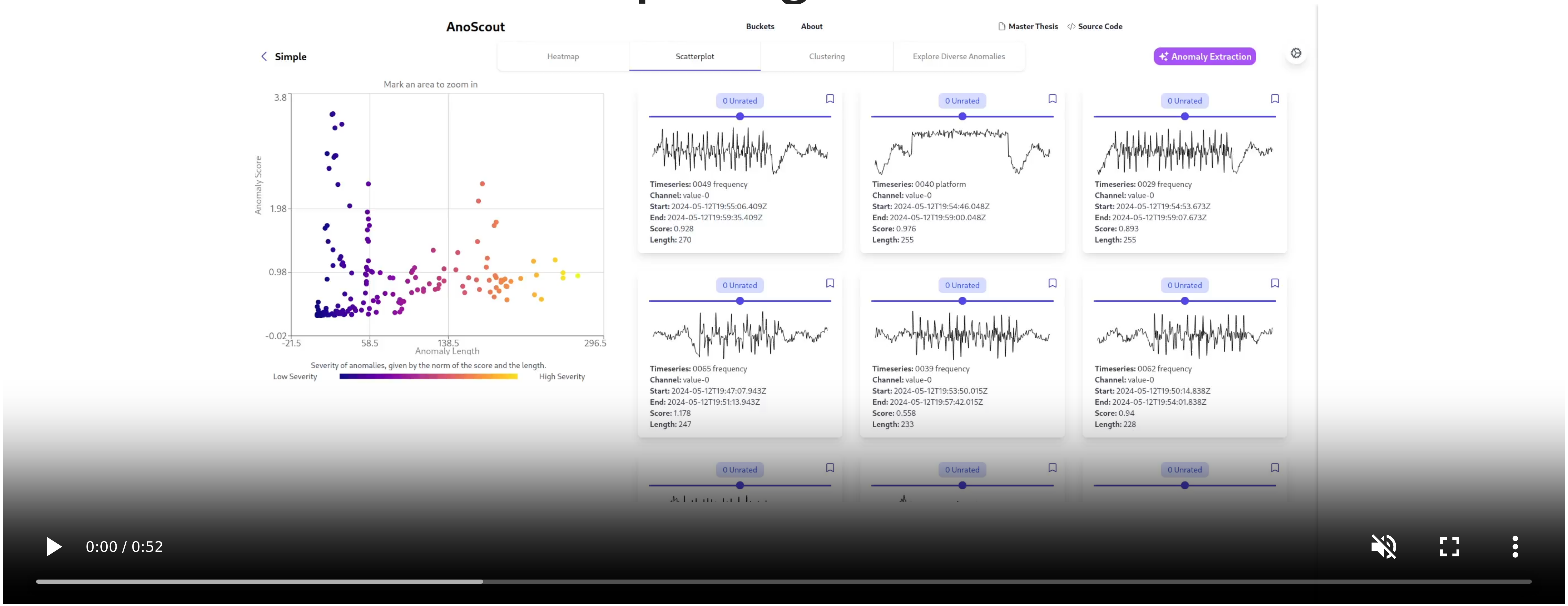
Timeseries: 0065 frequency
Channel: value-0
Start: 2024-05-12T19:47:07.943Z
End: 2024-05-12T19:51:13.943Z
Score: 1.178
Length: 247

Manual Inspection



In the manual inspection interface, users may explore how different algorithms performed to detect a particular anomaly. Each algorithm output is a scoring - a time series where higher values correspond to anomalies in the data.

Exploring Anomalies

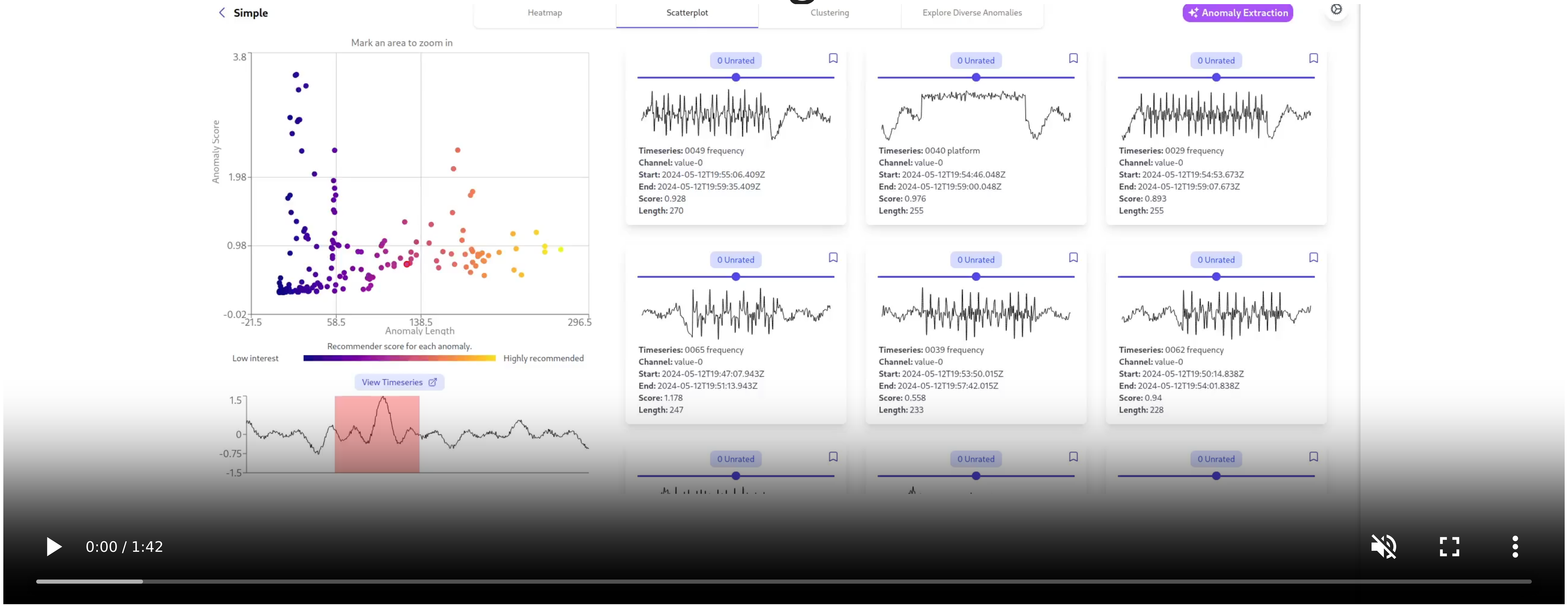


Exploring anomalies is achieved through a linked view, users may further provide feedback on the importance of an anomaly to satisfy a specific information need.

How do we gain an overview of all clusters?

Clustering!

Clustering Anomalies

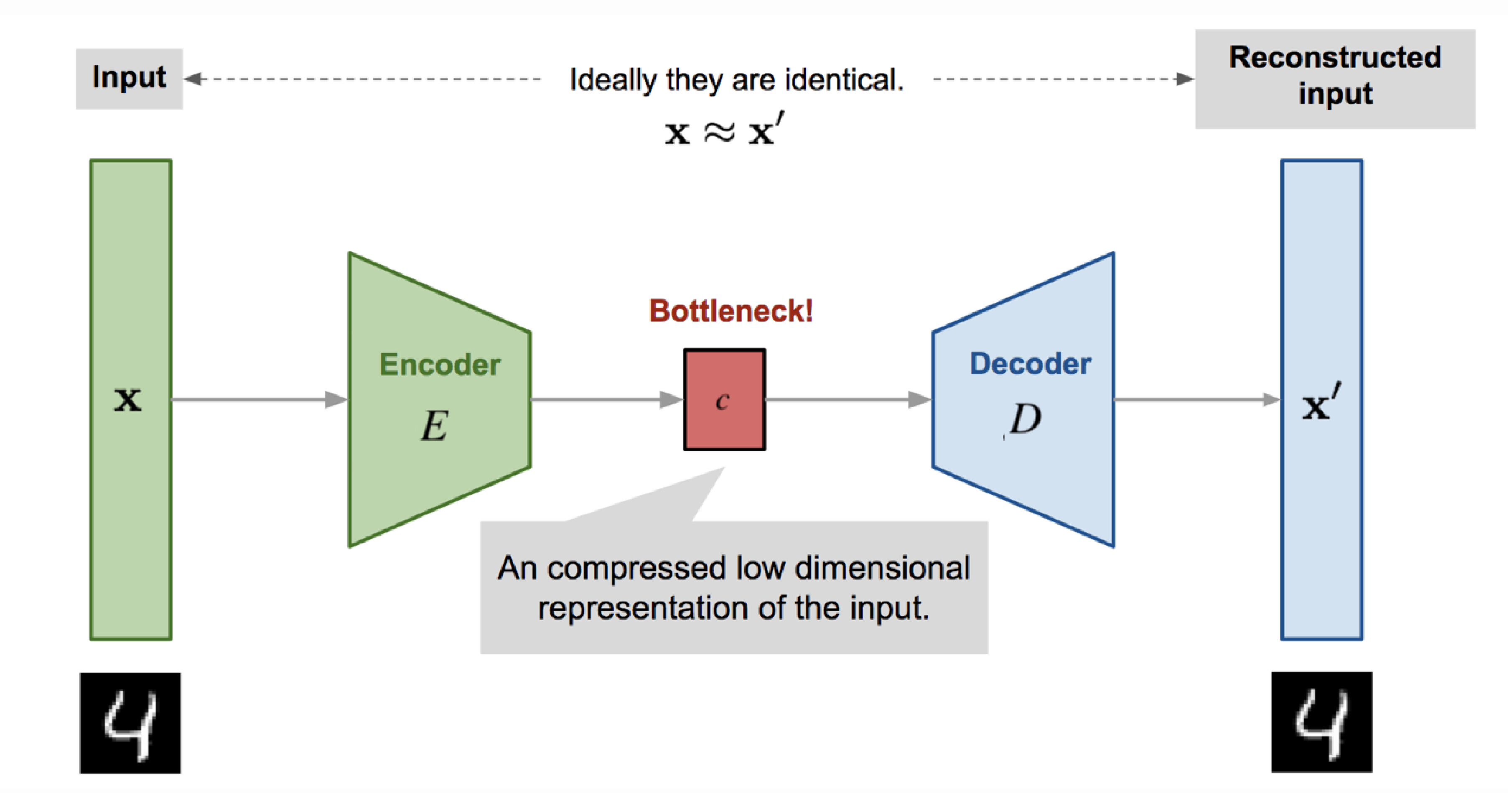


The anomalies can be arranged by similarity in the scatterplot, such that similar anomalies are grouped together. This enables the user to discover patterns in the dataset.

Main features of AnoScout summarized

1. Exploration pipeline for anomalies in time-oriented data.
2. 7 algorithms for computing anomalies.
3. "Playground" for testing various algorithms.
4. Using user labels to fine-tune the system.

Towards XAI



AutoEncoders learn normal patterns.

Show which normal labels are the most important ones.

Application Scenario

- A company wants to install a new machine.
- The machine conducts an etching process (semiconductor manufacturing).
- Each etching process is recorded through a sensor (e.g. pressure, temperature, and gas)
- We want to use AnoScout to:
  1. Find possible anomaly patterns.
  2. Check which algorithms work well.

Forecasting

How can we build a "sandbox" to explore forecasting models?

Introducing PredictPal

TU Graz

Yaryna Korduba, BSc

PredictPal

A System for Visual Exploration and Prediction of Time Series Data

Master's Thesis
to achieve the university degree of
Master of Science
Master's degree programme: Computer Science

Supervisor
Univ.-Prof. Dipl.-Volksw. Dr.rer.nat. Tobias Schreck, M.Sc.

Institute of Computer Graphics and Knowledge Visualisation
Head: Univ.-Prof. Dipl.-Volksw. Dr.rer.nat. Tobias Schreck, M.Sc.

Graz, 2024

Just like AnoScout, but for Forecasting.

Prediction Models

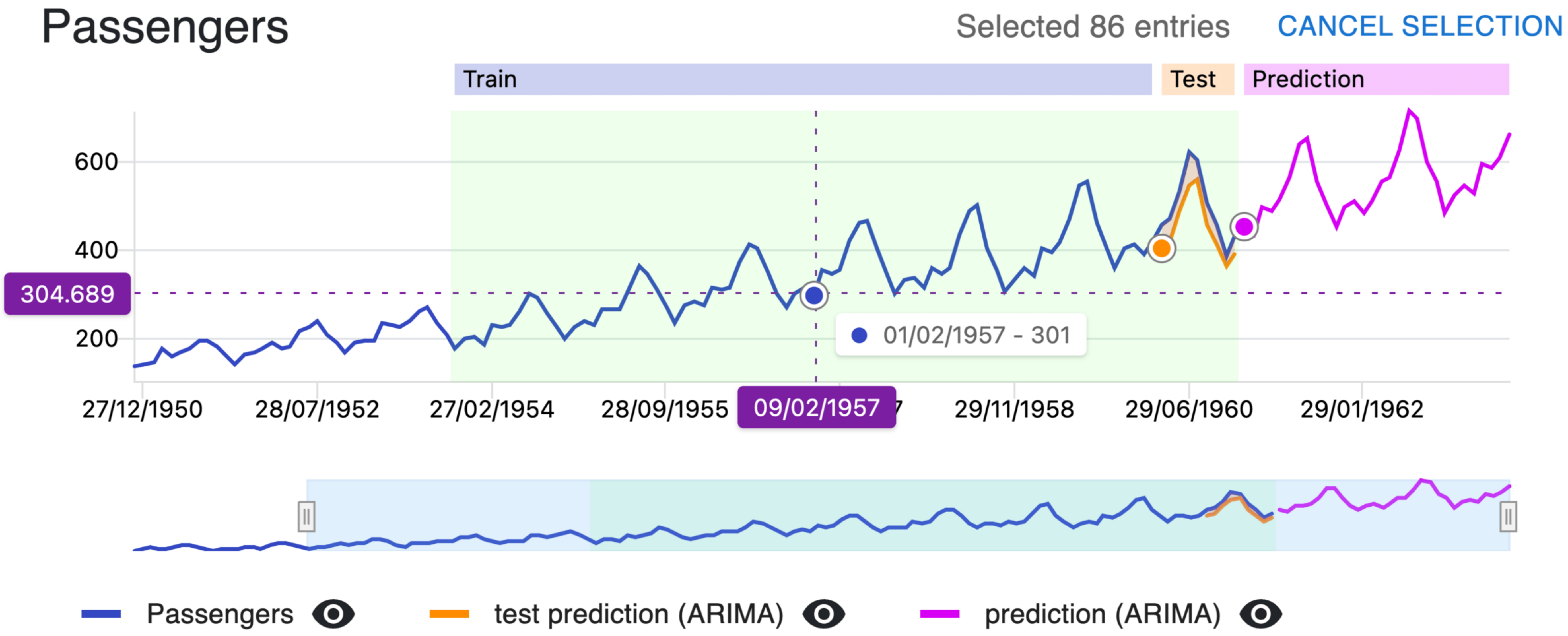
ARIMA

AutoRegressive Integrated Moving Average

VAR

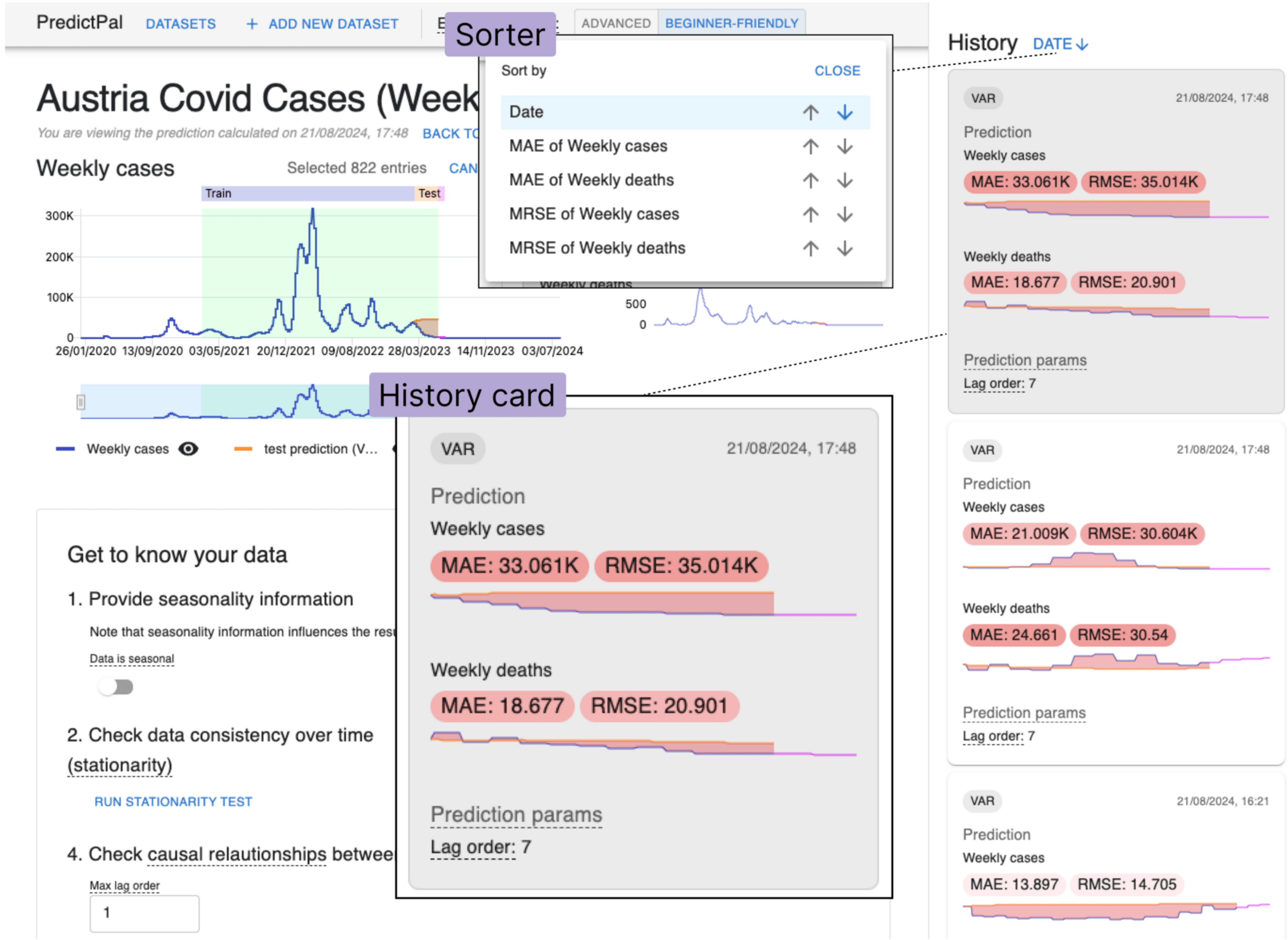
Vector Autoregression

Analysis View



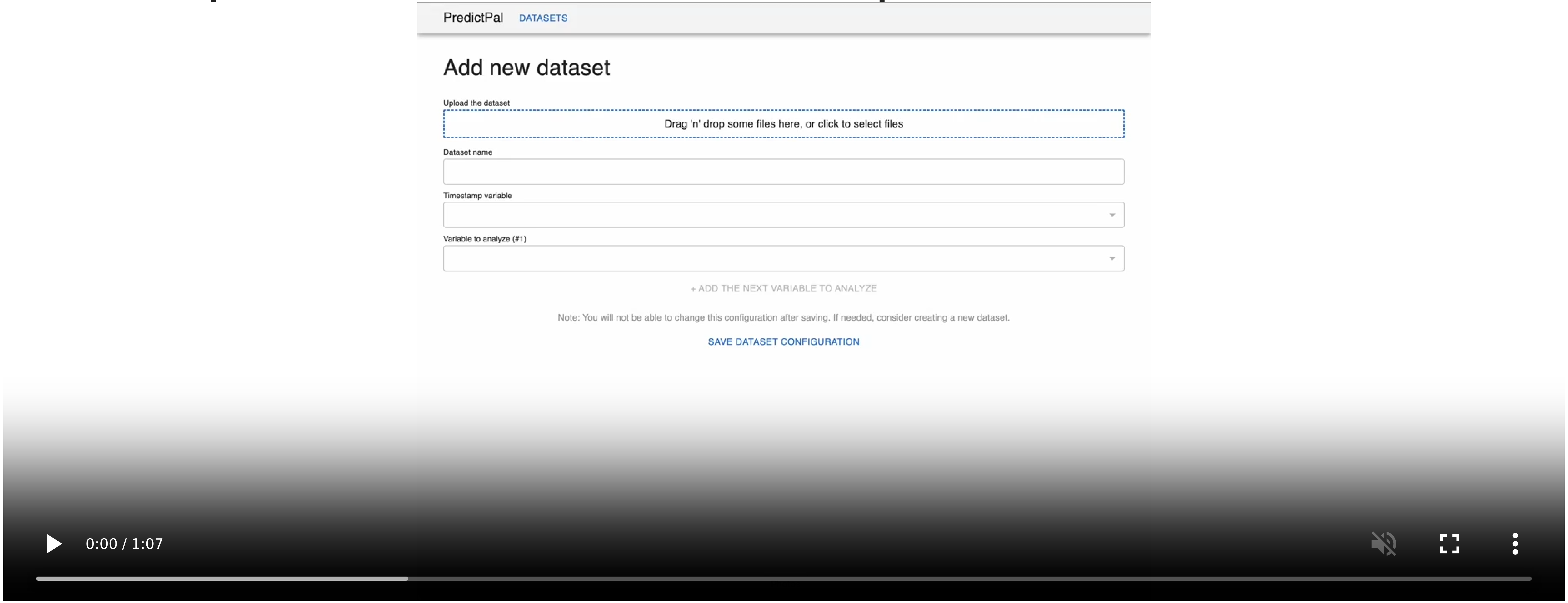
The user selects a subset of the time series for training the prediction models and can immediately verify the model based on the visualization.

History of Models



The history keeps track of models found in the past.

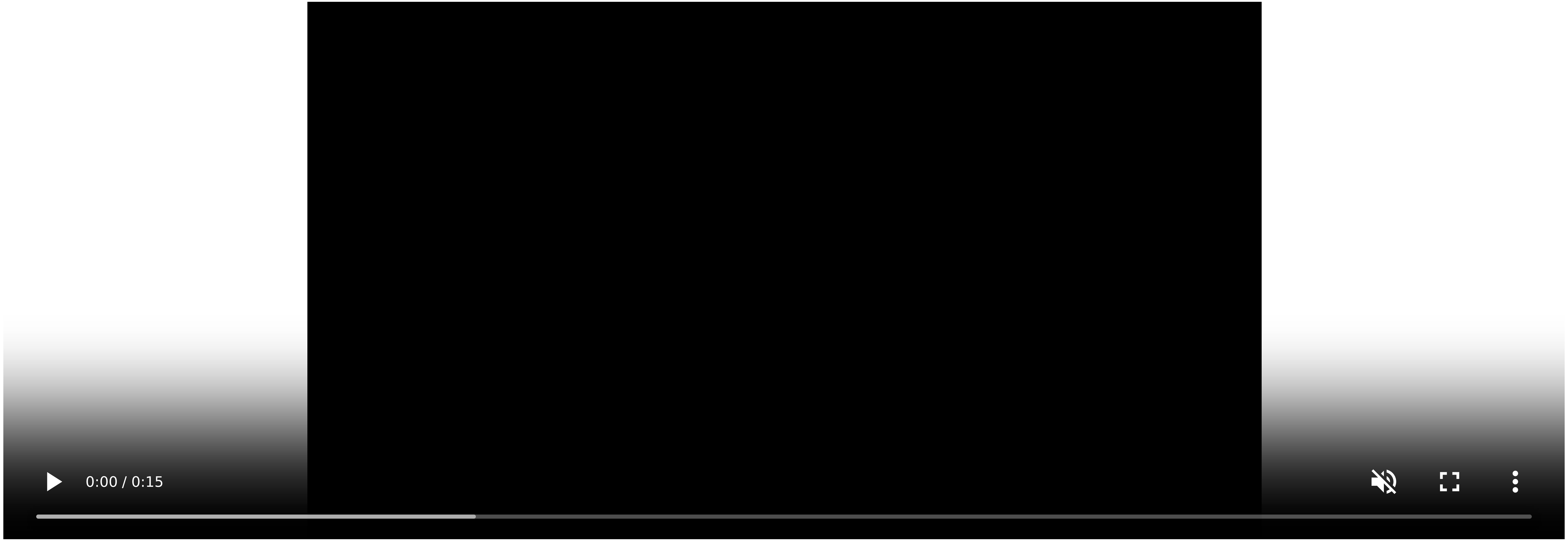
A municipal office worker John Doe needs to predict the traffic load at Intersection X



The video shows the workflow of using PredictPal - first, we upload a dataset, then run statistical tests to ensure applicability of ARIMA and VAR. Next, the user tries various subsets of the time series and seasonilty configurations to arrive at a suitable model.

Possible Use Case: Solgenium

Caution: This is a **different prototype** for a forecasting visualization!



The Solgenium prototype is built to forecast the workload of a hospital. The dataset might be a possible application scenario for PredictPal.

- Solgenium Prototype = **Specific Use Case**
- PredictPal = **Generic**

Therefore: Merge Predictpal and Solgenium

Towards XAI: ShapTime

ShapTime: A General XAI Approach for Explainable Time Series Forecasting

Yuyi Zhang, Qiushi Sun, Dongfang Qi, Jing Liu, Ruimin Ma, and Ovanes Petrosian(✉)

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Abstract. The application of Explainable AI (XAI) in time series forecasting has gradually attracted attention, given the widespread implementation of machine learning and deep learning. ShapTime - A general XAI approach based on Shapley Value specially developed for explainable time series forecasting, which can explore more plentiful information in the temporal dimension, instead of only roughly applying traditional XAI approaches to time series forecasting as in previous works. Its novel components include: (1) It provides the relatively stable explanation in the temporal dimension, that is, the explanation result can reflect the importance of time itself, which is more suitable for time series forecasting than traditional XAI approaches; (2) It builds the practical application scenario of XAI - improving forecasting performance guided by explanation results. This is distinctly different from previous works, which only present the results of XAI as the demonstration of innovation. Eventually, in five real-world datasets, ShapTime's average performance improvements for Boosting, RNN-based and Bi-RNN-based reached 18, 20 and 35%, respectively.

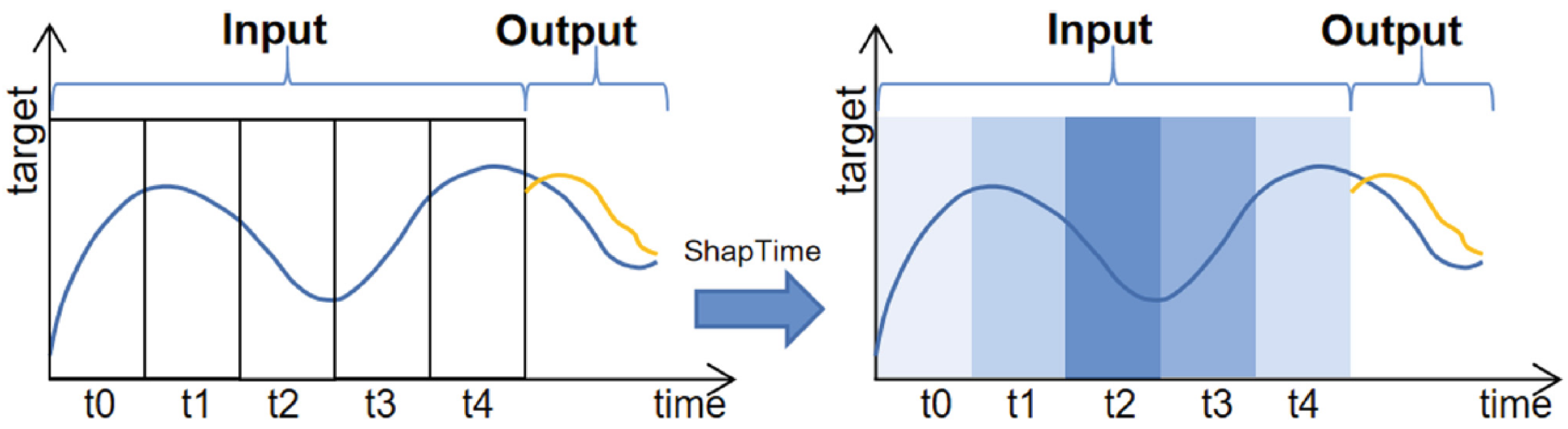
Keywords: Time-series forecasting · Explainable AI · Shapley value

1 Introduction

Numerous time series forecasting competitions including M4 [1] and M5 [2] have shown that ML and DL perform significantly better than traditional statistical methods, especially for more complex tasks. This has led to research on the application of Explainable AI (XAI) in time series forecasting. Explainable time series forecasting aims to improve the trustworthiness of ML and DL in fields such as Finance, Energy and Meteorology. There are two main approaches to apply XAI in time series forecasting models: (1) directly using the existing model-agnostic method with high generality; (2) developing a model-specific method specifically for the model. These two approaches directly caused two key problems.

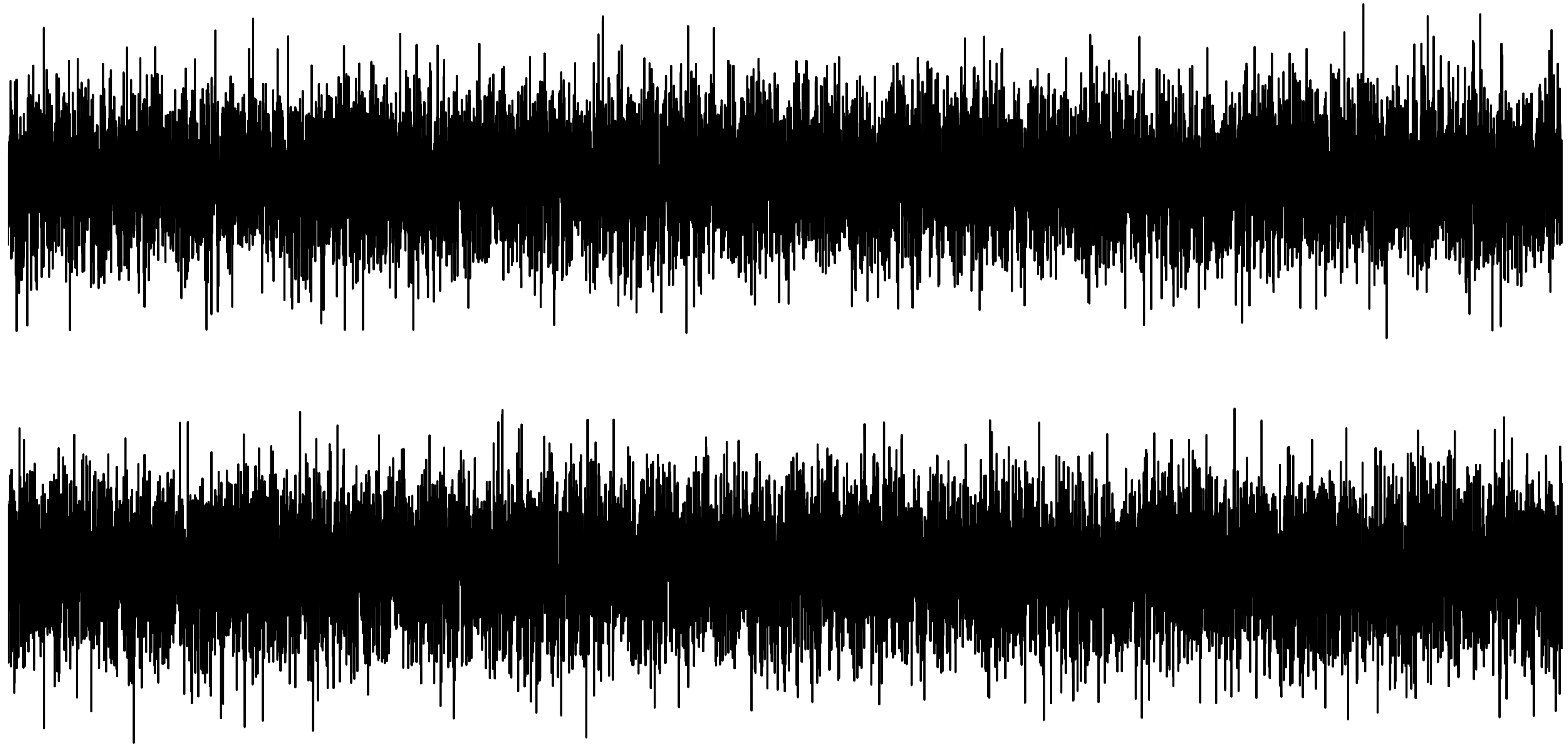
Problem 1. *In time series forecasting, the existing model-agnostic method is roughly applied, resulting in insufficient explanation.*

K. Arai (Ed.): IntelliSys 2023, LNNS 822, pp. 659–673, 2024.
https://doi.org/10.1007/978-3-031-47721-8_45



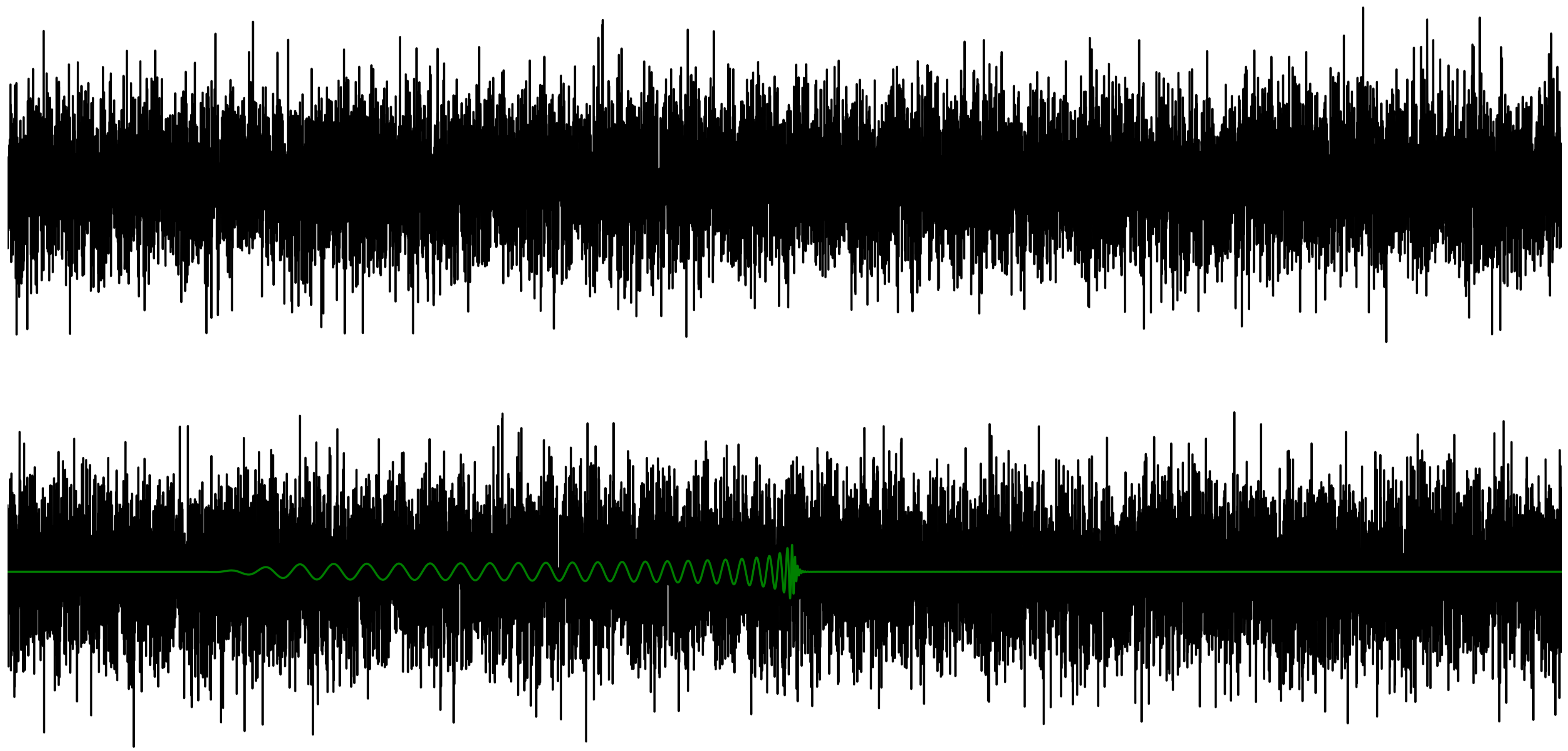
Vibrations

The Problem with Vibrations



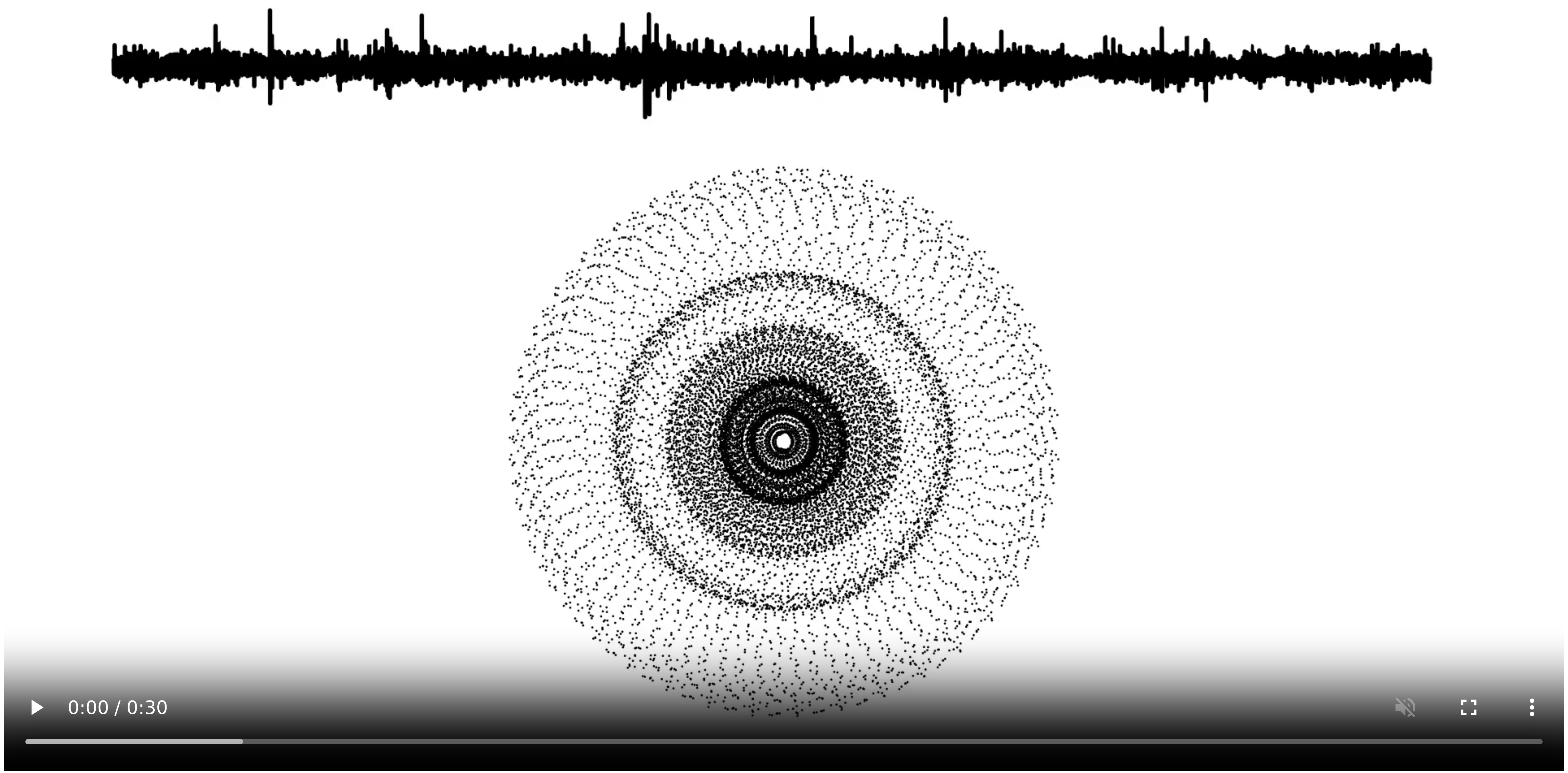
Can you tell the difference?

A hidden signal

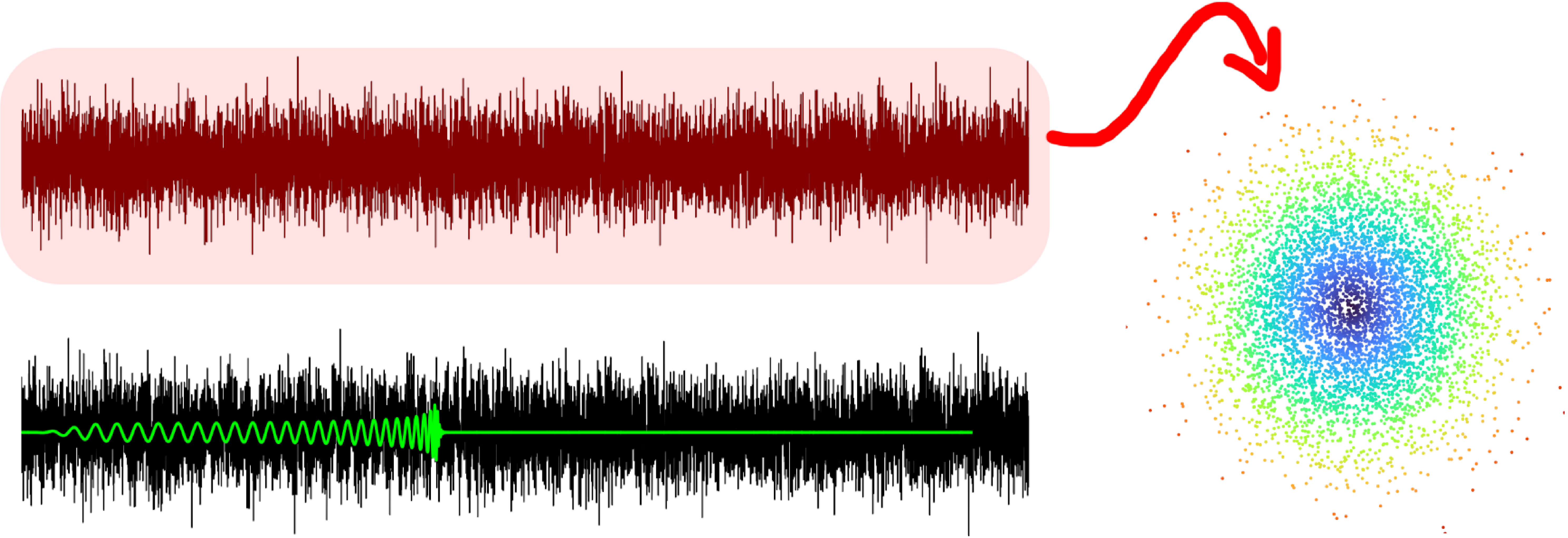


Linecharts are useless!

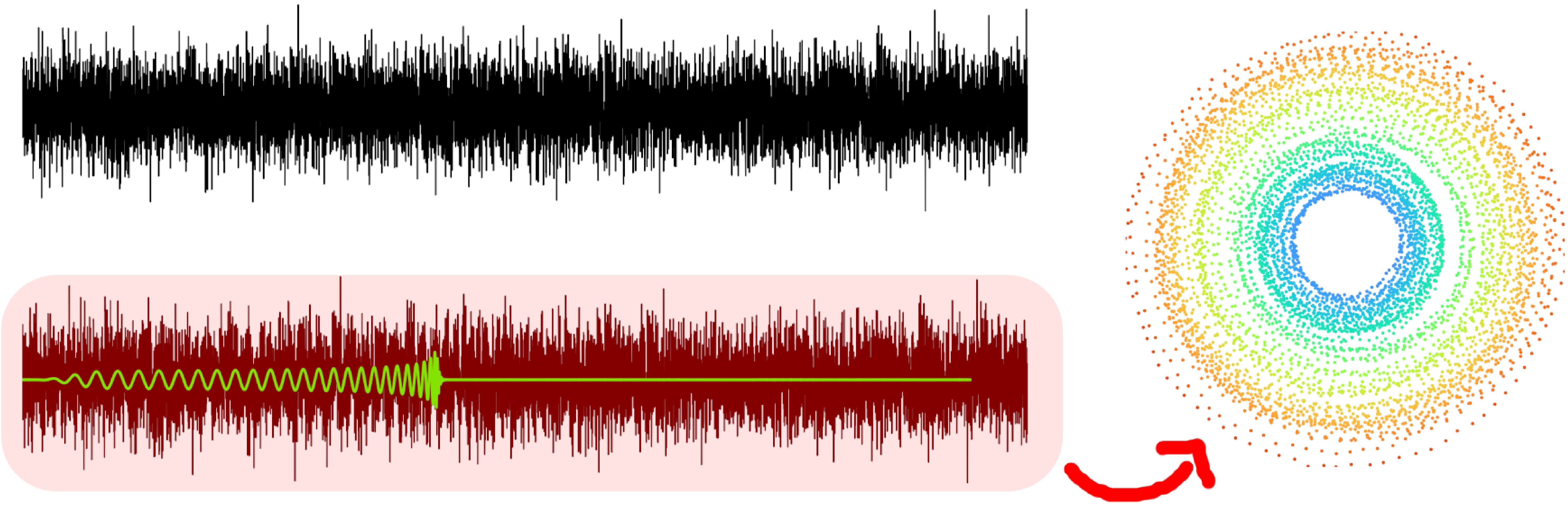
The Time Delay Embedding (TDE)



Noise is not exciting ...



... but oscillations result in circles!



What can we do with this?

1. Visualise change points
2. Cluster signals
3. Find labels

Our Prototype

Vibrana

Eurographics Conference on Visualization (EuroVis) 2025
W. Aigner, N. Andrienko, and B. Wang
(Guest Editors)

COMPUTER GRAPHICS *forum*
Volume 44 (2025), Number 3

Visual Exploration and Annotation of Vibration Signals Using Time Delay Embeddings

J. Rakuschek [1], A. Boesze [2], J. Schmidt [3,4], and T. Schreck [1]

[1] Graz University of Technology, Institute of Computer Graphics and Knowledge Visualization, Austria
[2] Binder+Co AG, Austria
[3] VRVis GmbH, Austria
[4] TU Wien, Institute of Visual Computing & Human-Centered Technology, Austria

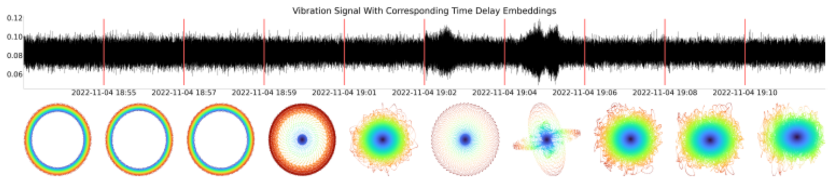


Figure 1: *Vibration measurements from a hydro power plant with the corresponding time delay embeddings per segment. The figure shows how the time delay embedding evolves over time and that it can be used as a fingerprint to highlight significant changes in the vibration profile.*

Abstract

Nearly every machine generates vibrations during operation. Recording and analyzing these vibrations can enable many useful tasks in operating, monitoring, and maintaining machines, e.g., in transportation or industrial production. Among other use cases, appropriate analysis of machine vibrations can help in identifying developing machine wear, and predicting damage. Vibrations are oftentimes considered in the time domain, and visualized e.g., as line charts. While these are intuitive displays, they may not be appropriate to high-frequent signal data carrying complex patterns and outliers, which may be overlooked by overplotted displays. The signal processing area provides transformations of signals from the time domain to other domains, in which certain tasks become easier to solve. We consider the visual analysis of high-frequent vibration data, based on the time-delay embedding (TDE) transformation. Applying principal component analysis to signal data windows, it gives scatter plots of unique characteristics to different phenomena in the data. We introduce Vibrana, a system for interactive visual exploration, comparison, and annotation of time-delay embeddings of signal data. It features a custom point cloud visualization that enables to segment and cluster, identify outliers and anomalies, and recognize notable change points in the vibration signal data. A detail on demand view enables to annotate signals, and perform similarity searching for comparing and validating found patterns in the data. Several use cases informed by domain experts show that Vibrana effectively supports important analytical tasks in relevant application scenarios. Also, a comprehensive user study validates the effectiveness of our approach.

CCS Concepts
• ***Human-centered computing*** → ***Visualization systems and tools;***

1. Introduction

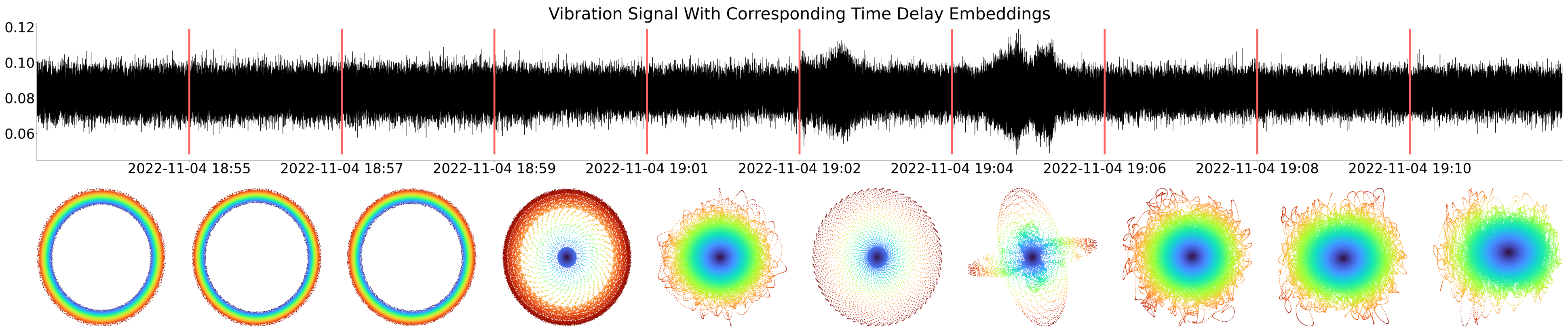
The study of vibrations is essential for any mechanical engineering problem, as they are omnipresent: from simple motors to airplanes, any system with mass and elasticity has the potential to experience vibrations. While many vibrations are unavoidable and intrinsic properties of systems, they can be undesirable and may damage the machine. Furthermore, they may serve as indicators of whether a machine is functioning correctly.

EuroVis 2025 Submission

In Review 🤞

Can we find a change point in the signal?

Vibrationens of a hydropower plant:

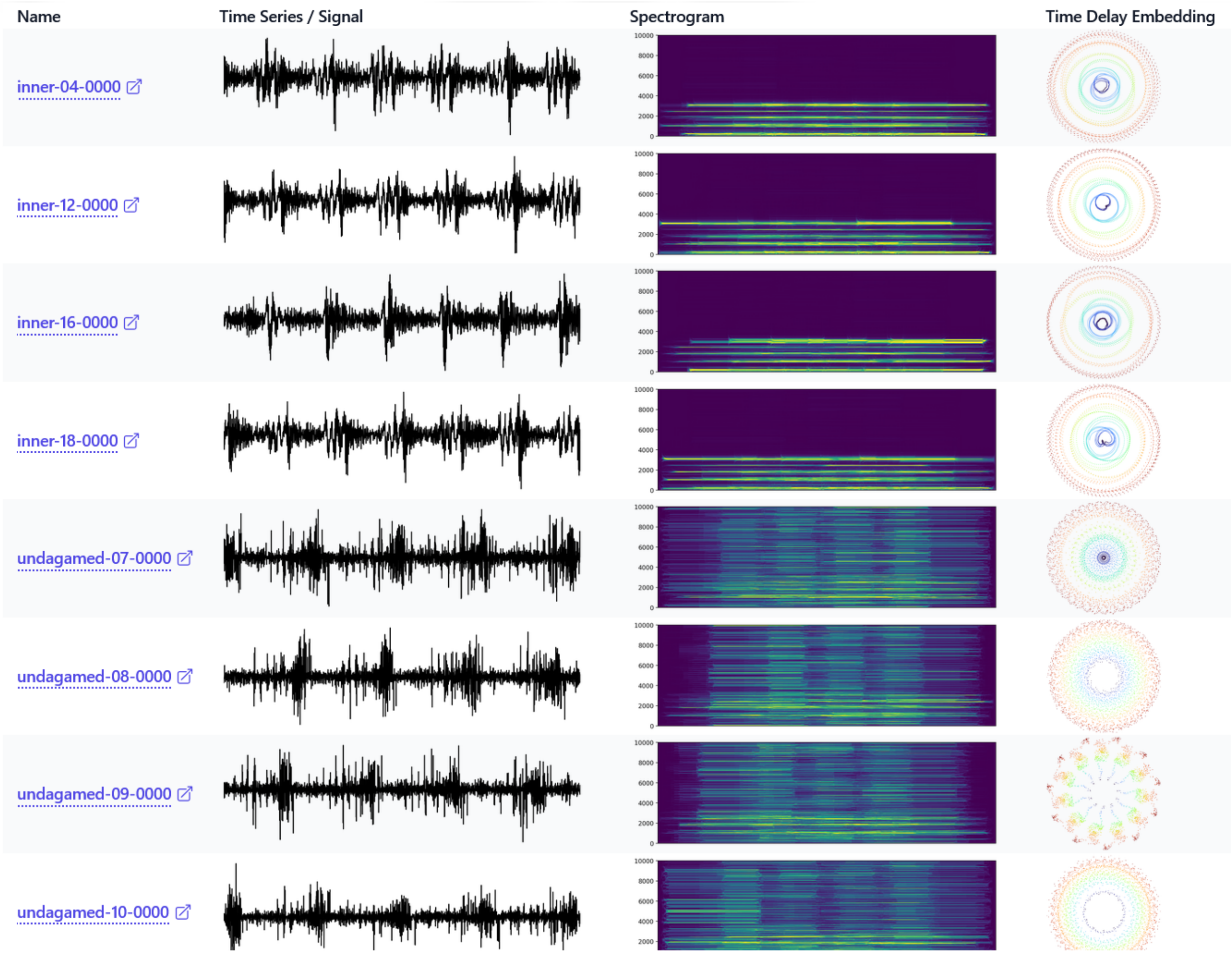


The TDE is a fingerprint evolving over time!

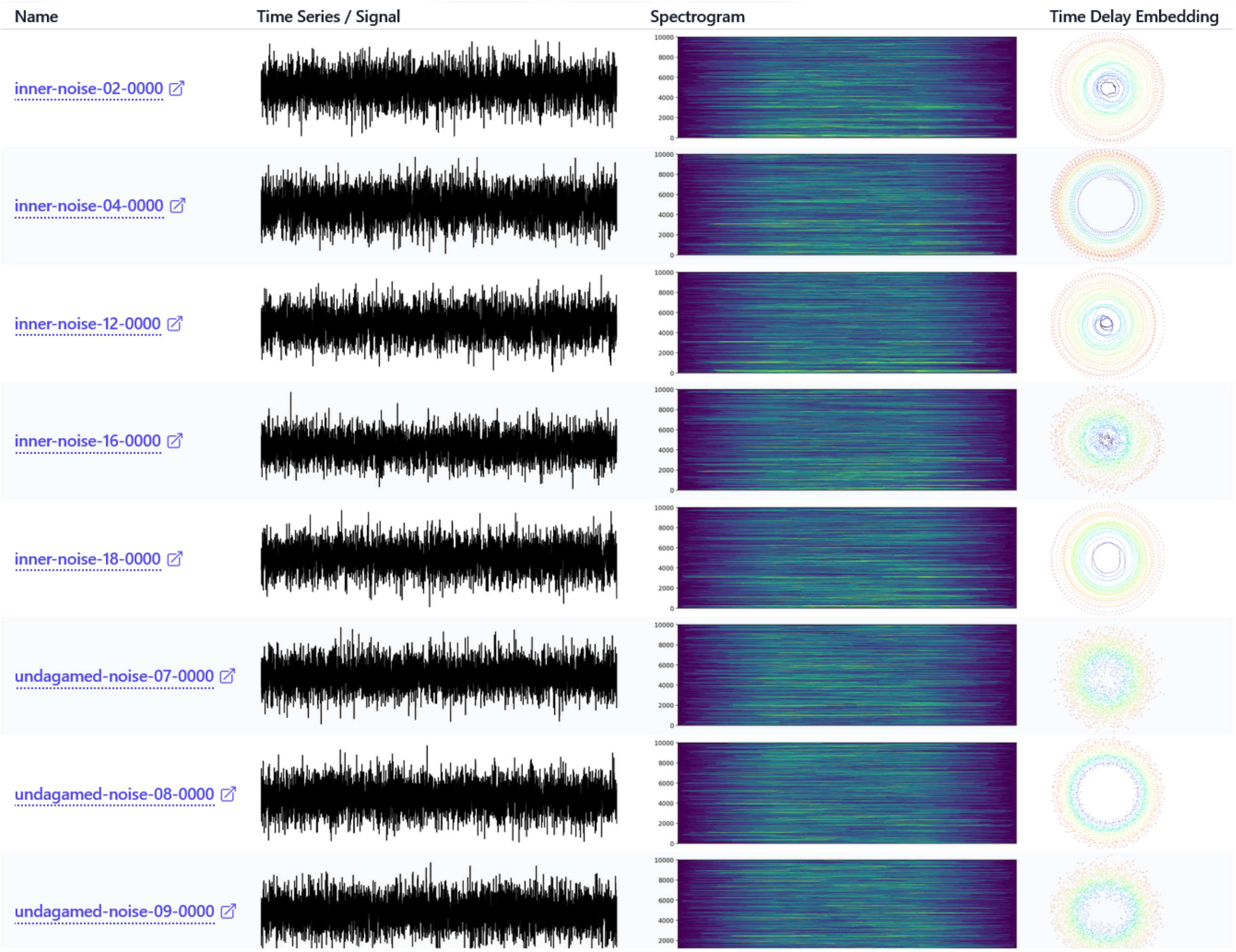
Applications

Engines	Bearings
	
When can we detect wear?	Which are faulty?

While the spectrogram is sometimes better ...

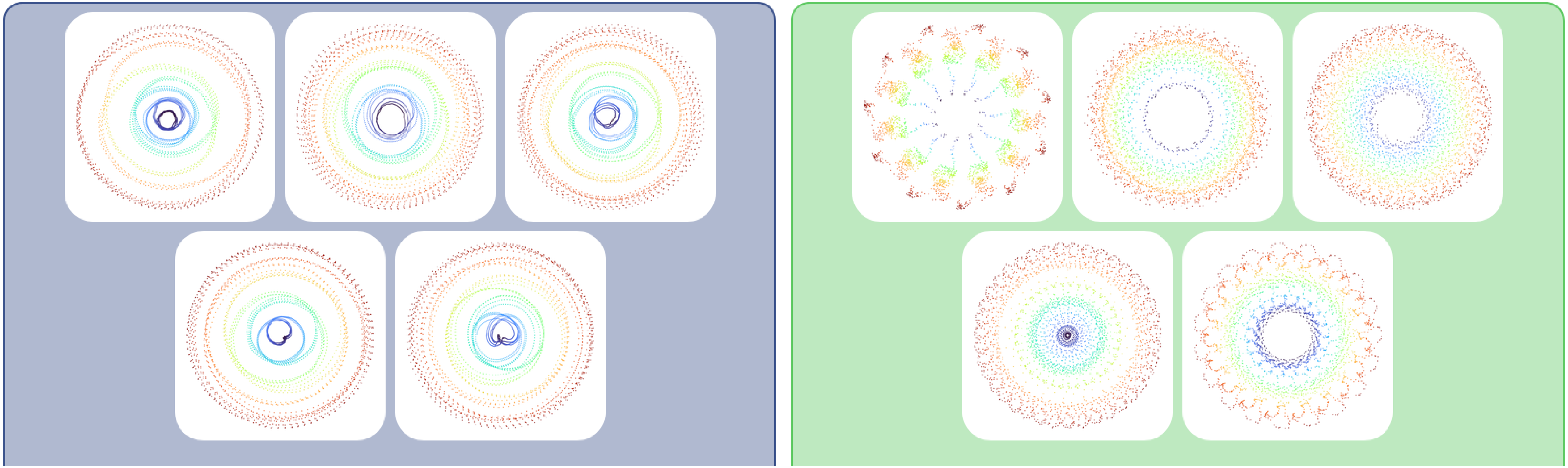


... what about some added noise?



Which are faulty?

Automatic Clustering



What about Explainable AI?

Task 2.5 needs more thinking

Task 2.4 Development of a web-based visualization including domain-specific visualizations

Task 2.5 Development of visual explanations for AI results

	Task 2.4 (Vis)	Task 2.5 (XAI)
Cluster	✅	❌
AnoScout (Anomalies)	✅	🤔
Predictpal (Forecasting)	✅	✅
Vibrana (Vibrations)	✅	❌

Some Ideas

Clustering	• AI not reasonable in this task
AnoScout	• While AI *can* used, it is not advisable! • Matrix Profile methods outperform AI methods • AI only useful when classifying with user-labels • Show label influence for AI classifier (XAI)
PredictPal	• Merge Solgenium Prototype and PredictPal: Show error rate (XAI?) • Implement LSTM Forecasting with XAI
Vibrana	• User-labels for the similarity search • Show which labels have which amount of influence on findings • Strictly speaking not AI!

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Slides

https://presentations.rakuschek.at/2025-01-16-present-konsortialmeeting

Questions?