INSTITUTE OF VISUAL COMPUTING

SCIENCE
PASSION
TECHNOLOGY

The PRESENT Project

PhD Talk

Julian Rakuschek

28.01.2025

Agenda

Introduction to PRESENT

Vibrana - Vibration Analysis

AnoScout - Anomalies in Time Series

PredictPal - Forecasting Time Series

Project PRESENT

PREdictions for Science, Engineering N' Technology

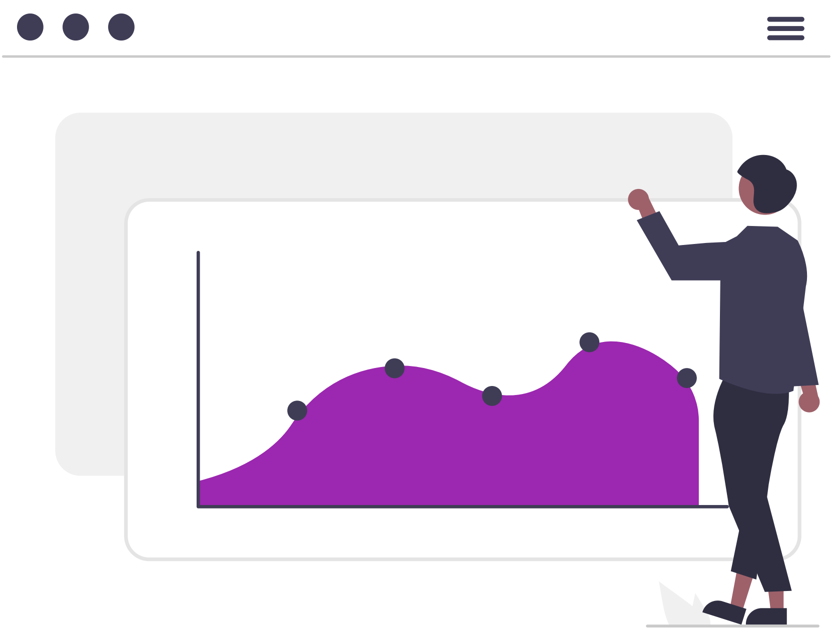
Funded by
FFG Austria

Coordinated by
Fraunhofer Austria

Forecasts and analyses of time series

Research in the field of visual analytics

Goal: A toolbox for tasks in the analysis of time series in three application areas (buildings, health, production)



How does it work?

Industry delivers data and problems

We develop prototypes

Sometimes something useful comes out

A beautiful synergy

The Consortium - Industry Meets Science

Scientific Consortium

Fraunhofer AUSTRIA
AIT Austrian Institute of Technology
JOANNEUM RESEARCH
TU Graz
Medizinische Universität Innsbruck

Use Case: Production

ARTI Autonomy for Robots
mcp d+p
dankl+partner consulting gmbh
MCP Deutschland GmbH
Messfeld Kompetenz in Condition Monitoring
SENSOLLIGENT
INDUSTRIE 4.0 ÖSTERREICH

Use Case: Health

bhs
Solgenium Pioneers of the new healthcare
human. technology. styria.

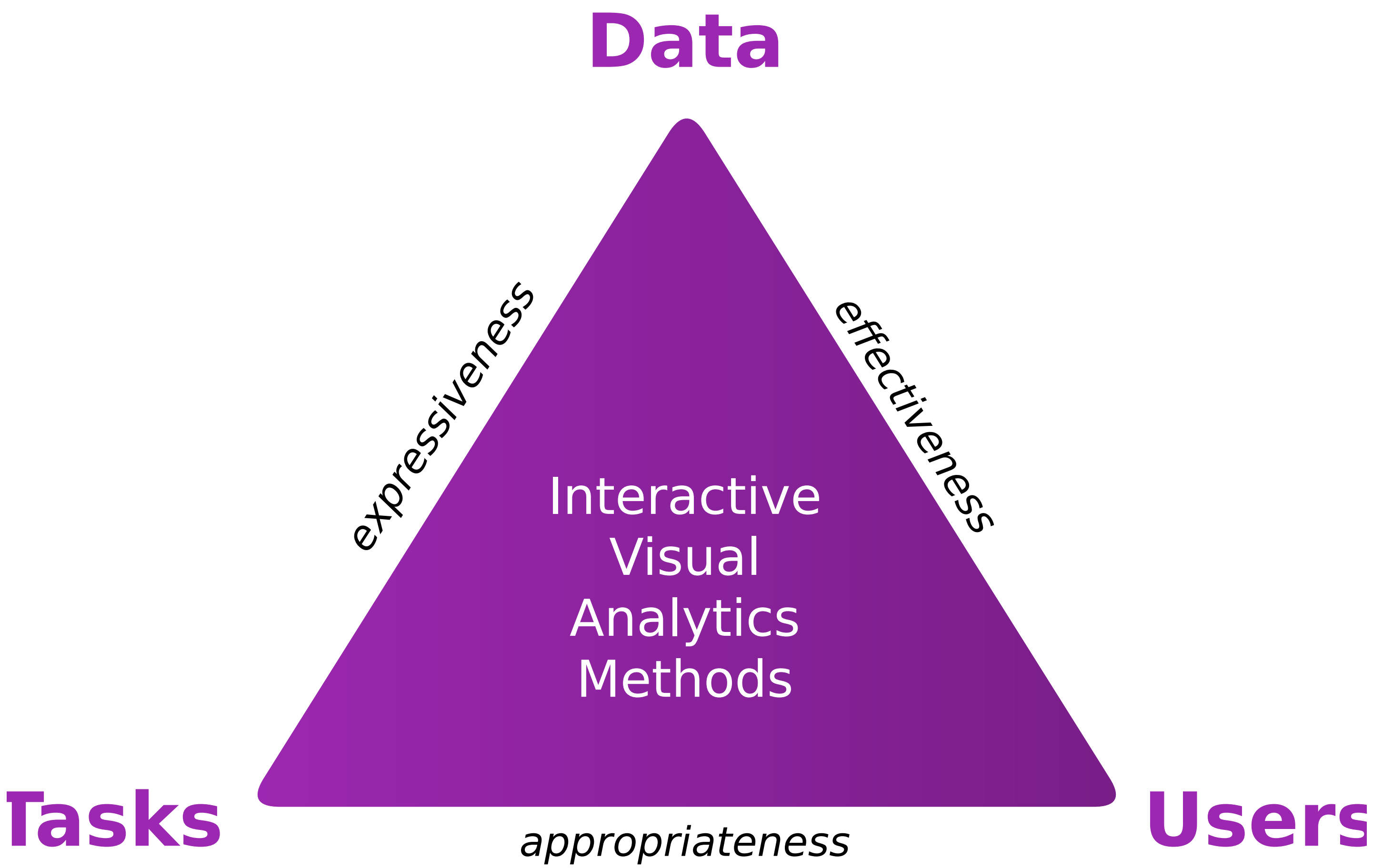
Use Case: Buildings

A NULL Development GmbH
VIE Vienna International Airport
caFM ENGINEERING
buildingSMART Austria

Ethics and Integration

Compunity

Our Approach

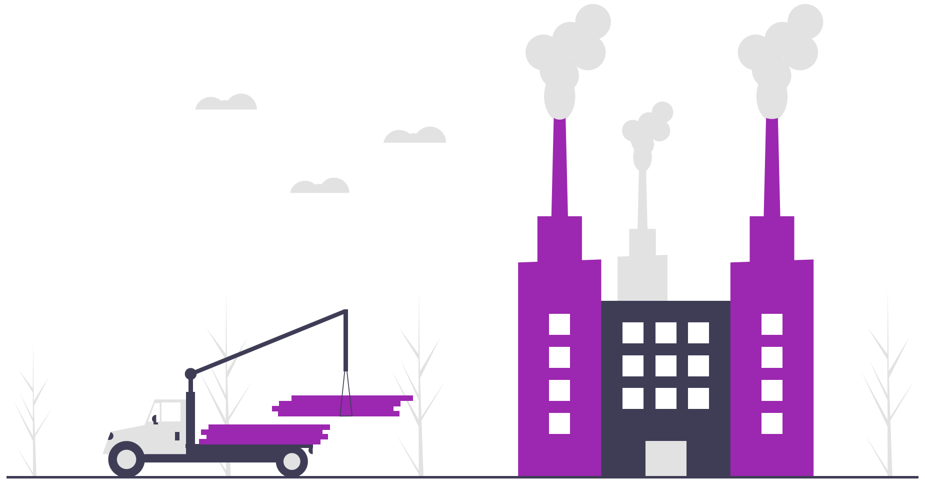


Design Triangle Approach

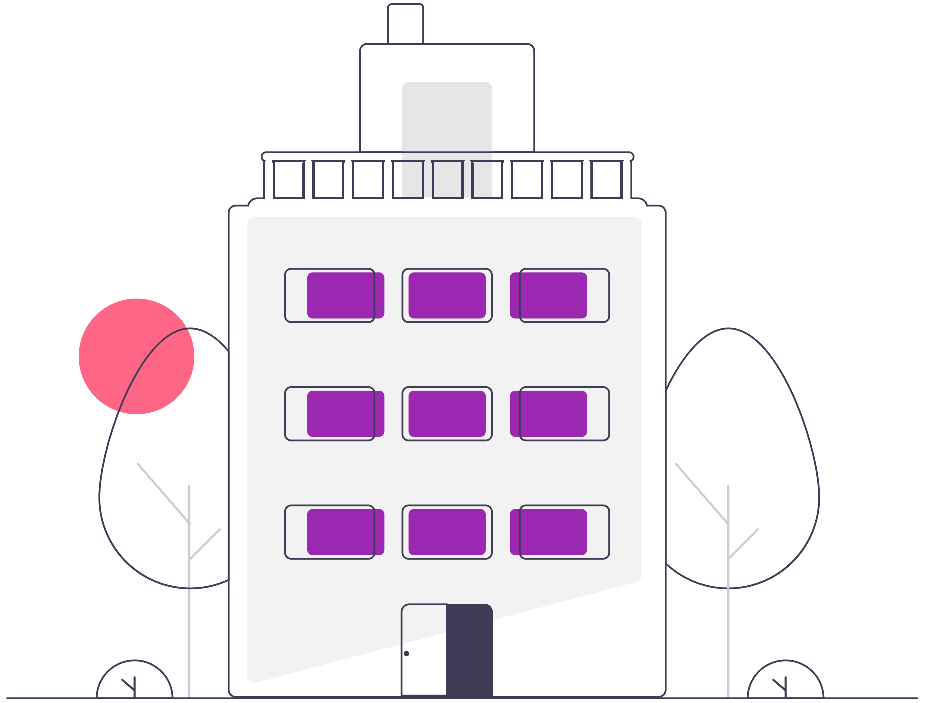
S. Miksch et al. "A matter of time: Applying a data-users-tasks design triangle to visual analytics of time-oriented data" Comput. Graph. 38 (2014): 286-290

Our Time Series Sources

Medical

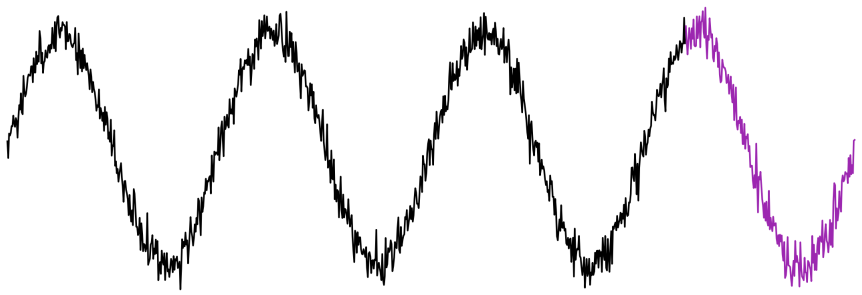


Production

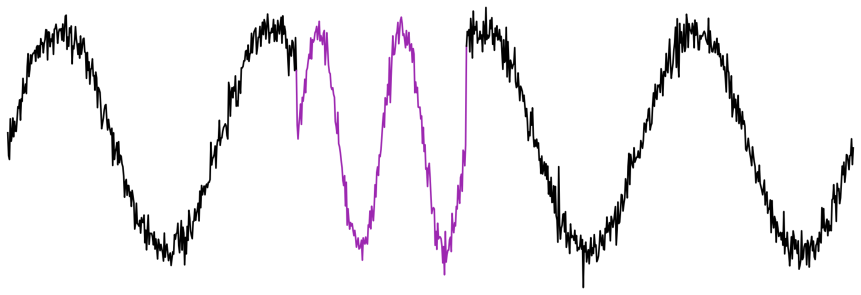


Facility

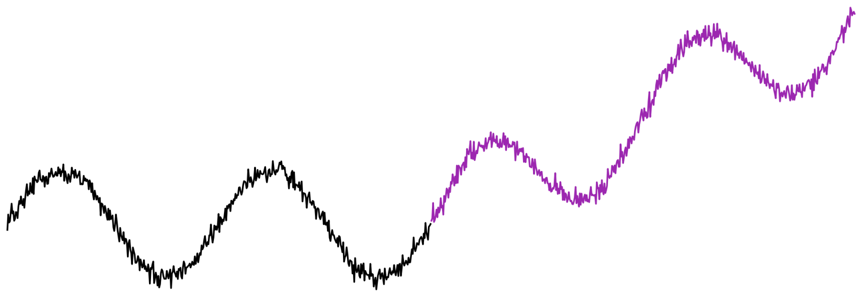
Time Series Tasks



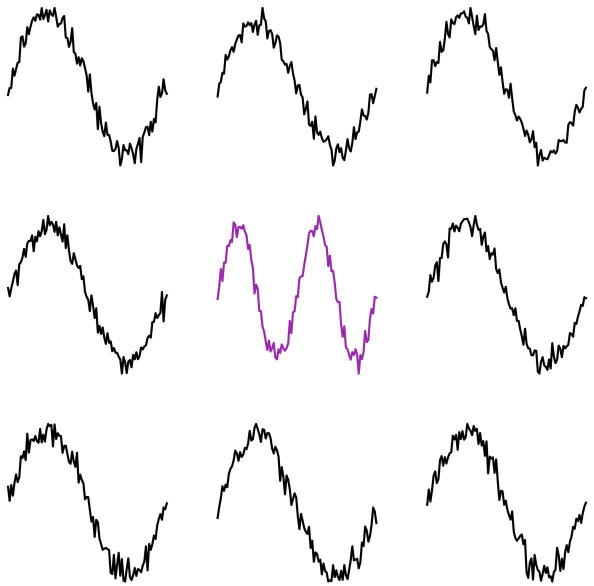
Forecasting



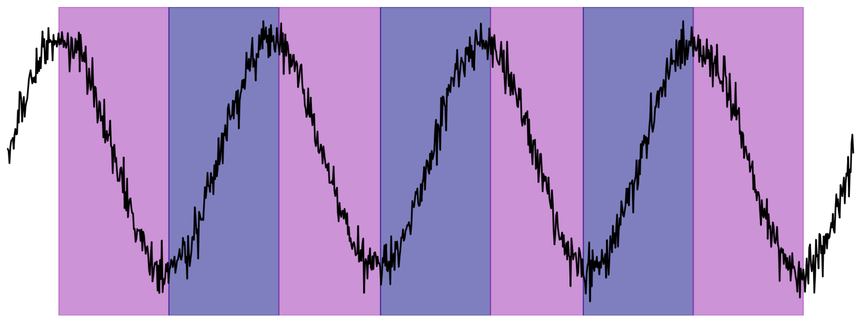
Anomaly Detection



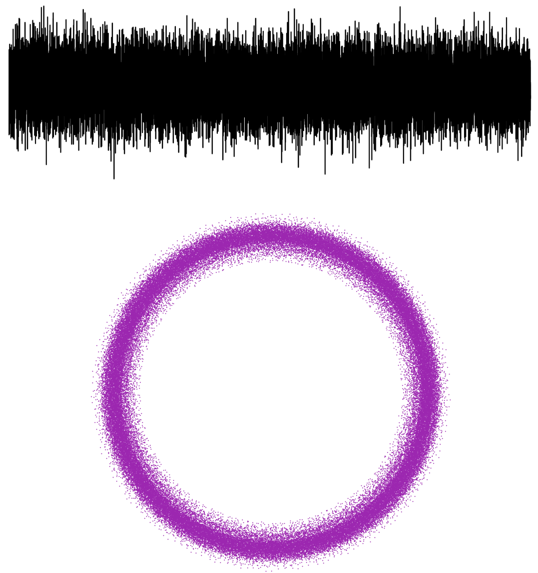
Drift Detection



Classification

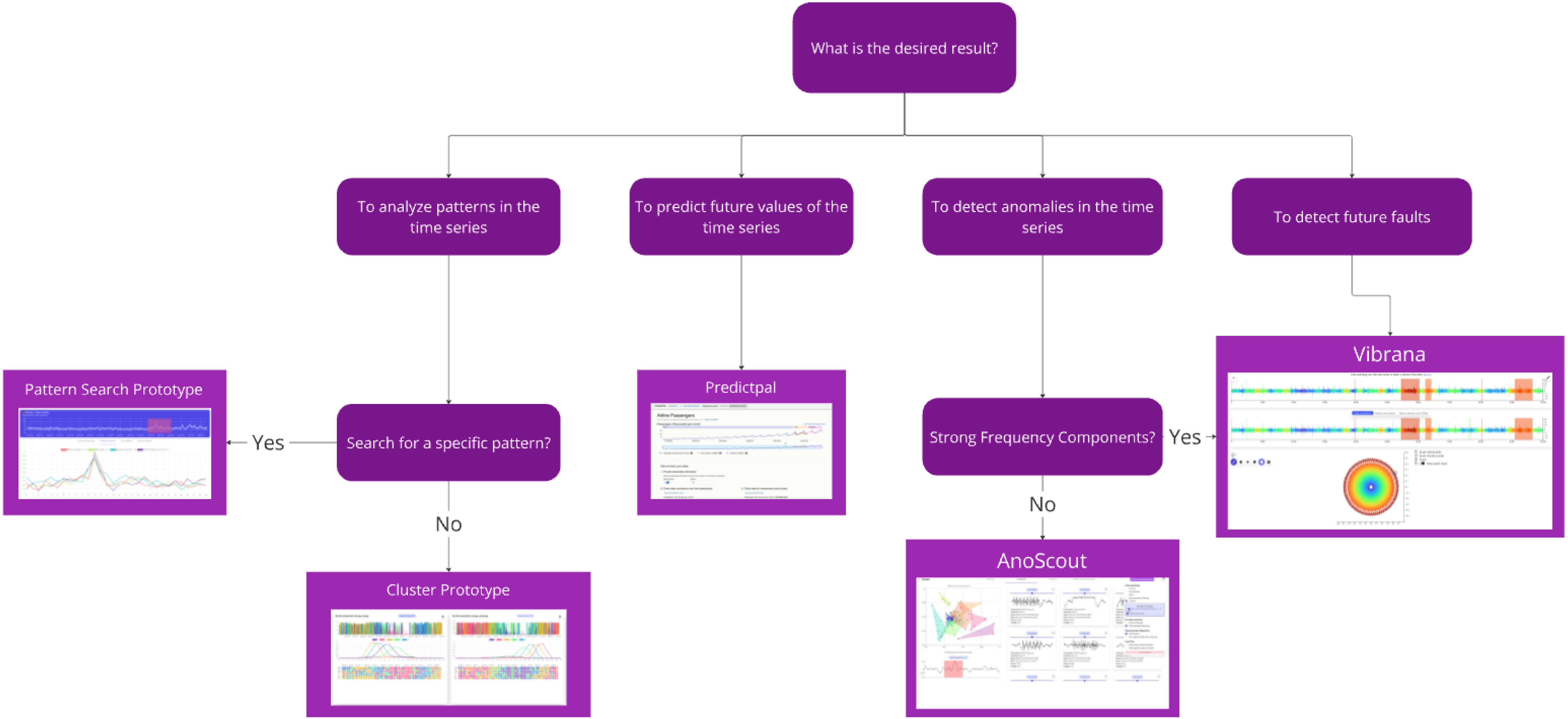


Segmentation



Vibration Analysis

Goal: A Tool-Driven Decision Tree



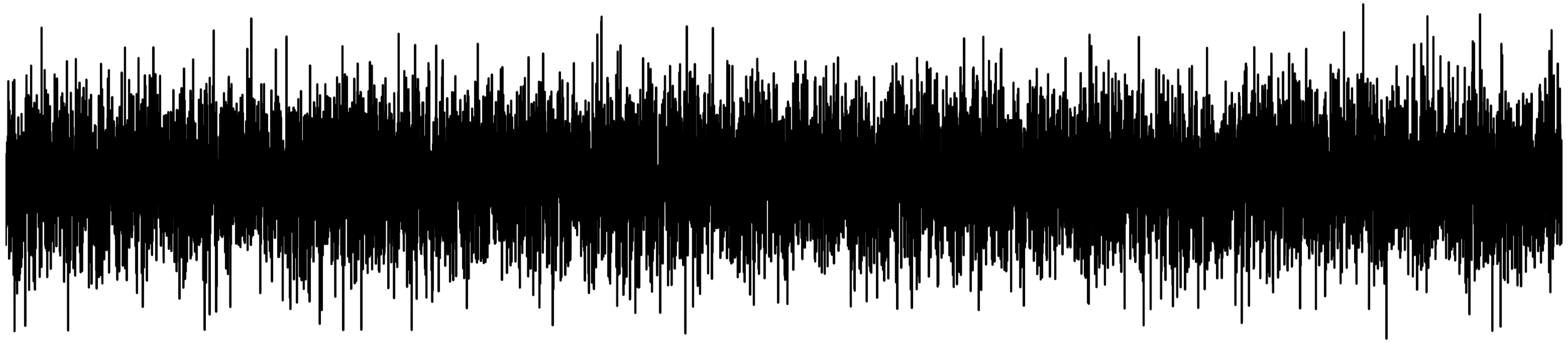
Summary - What do we do?

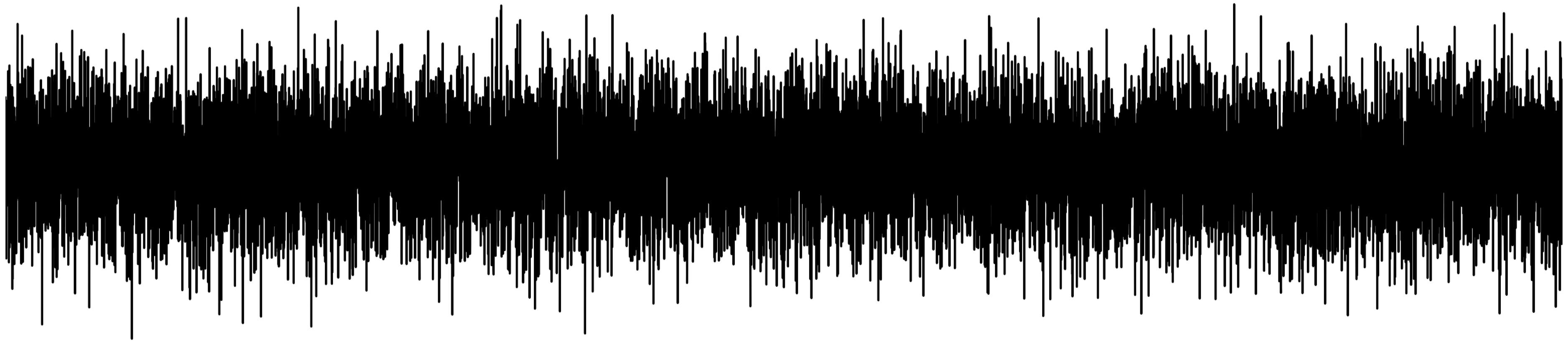
- Our Data Domains
  - Production
  - Building Management
  - Healthcare
- Our Research Targets
  - Statistical and AI-based Methods
  - Interactive Data Visualization
- Results
  - Decision Tree for Method Selection
  - Toolbox for Visualizations
  - Happy industry partners :)

Vibrana

Analysing Vibrations with Style

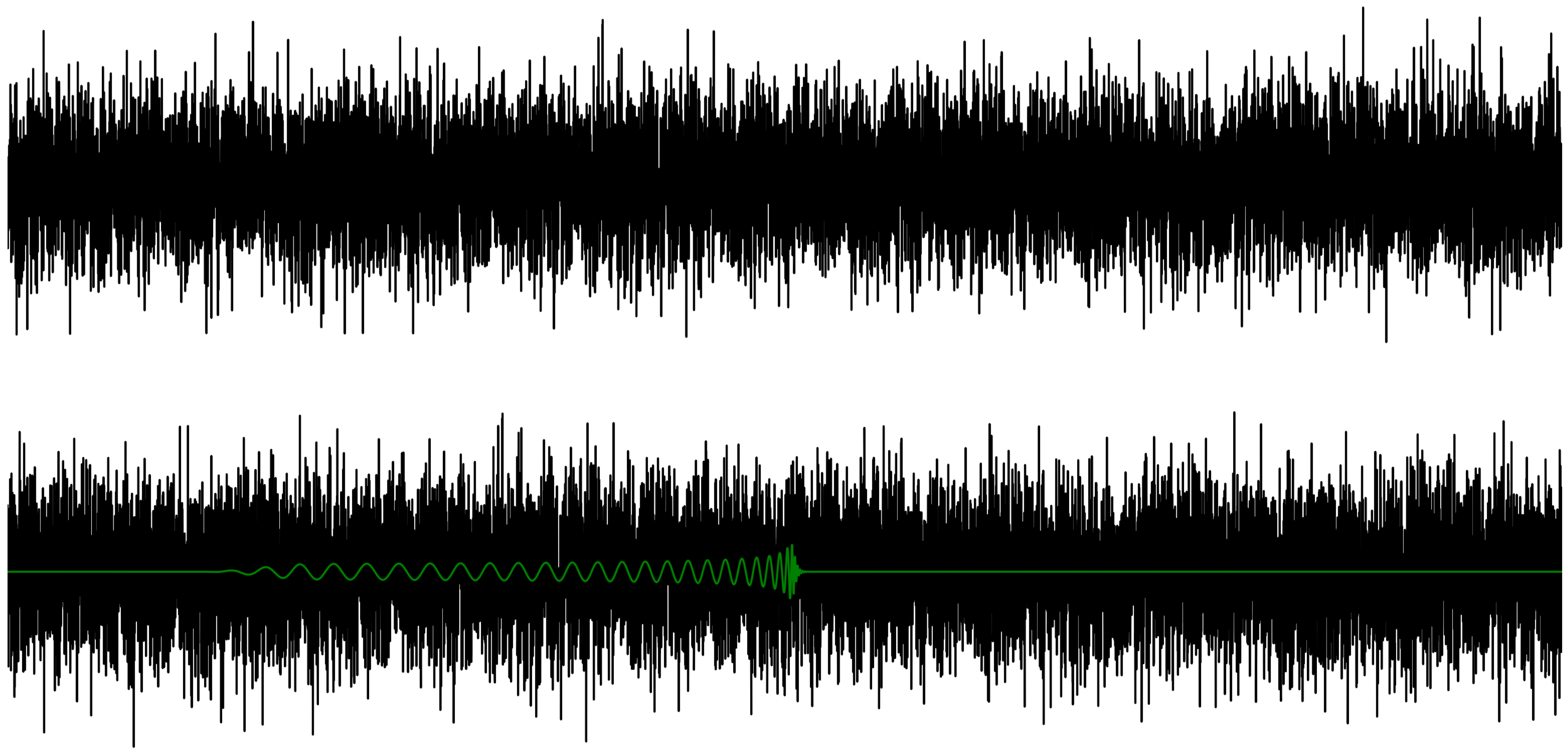
The Problem with Vibrations





Can you tell the difference?

A hidden signal



You cannot see the hidden signal with a line chart.

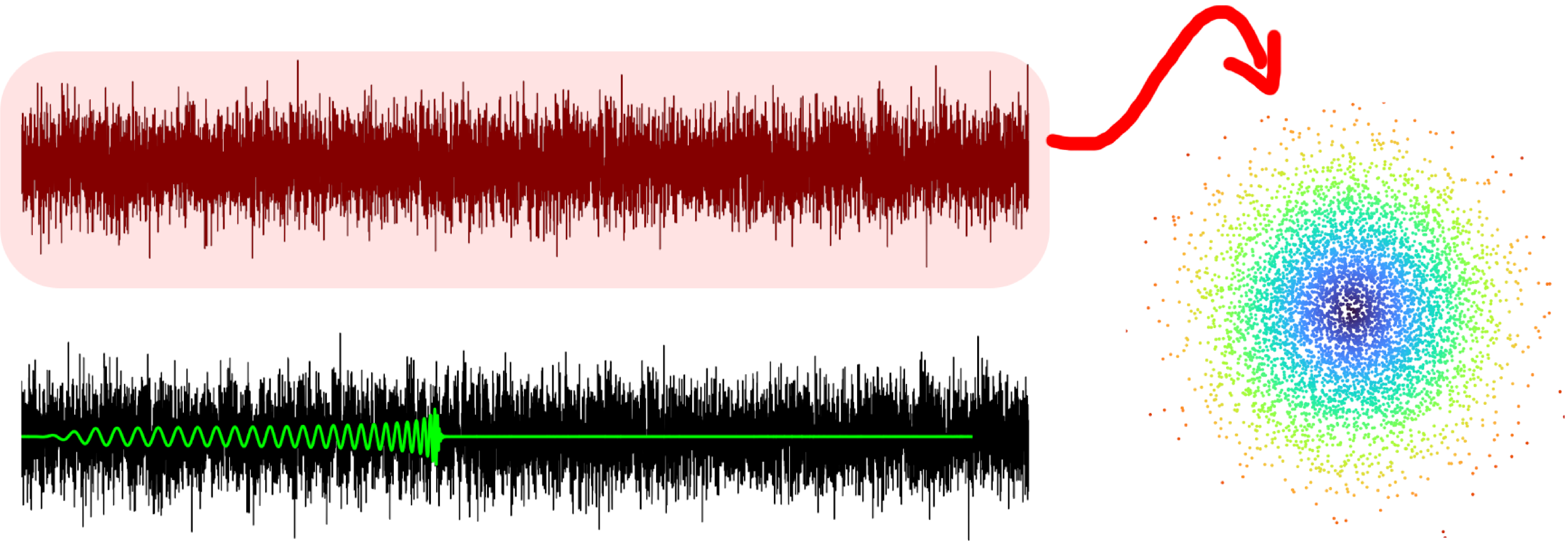
The Idea: Vibration $\longrightarrow$ Point Cloud

The Time Delay Embedding

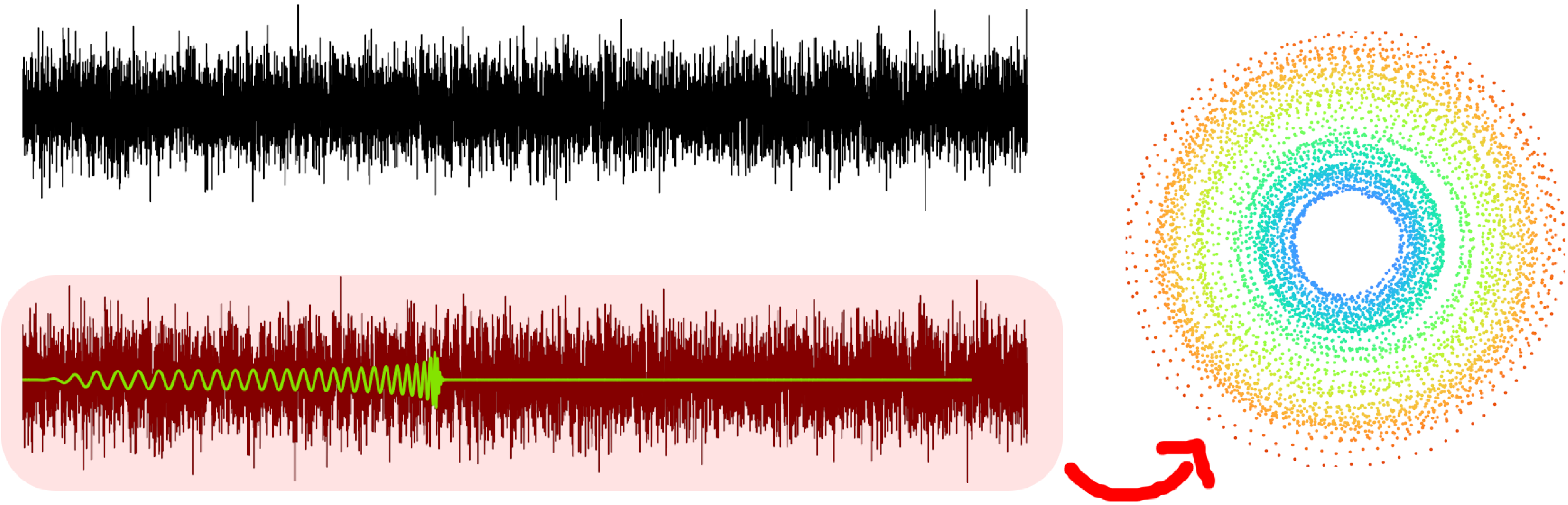
Only two lines of code!

```
windows = sliding_window_view(values, window_shape=window_size)
projected = PCA(n_components=2).fit_transform(windows)
```

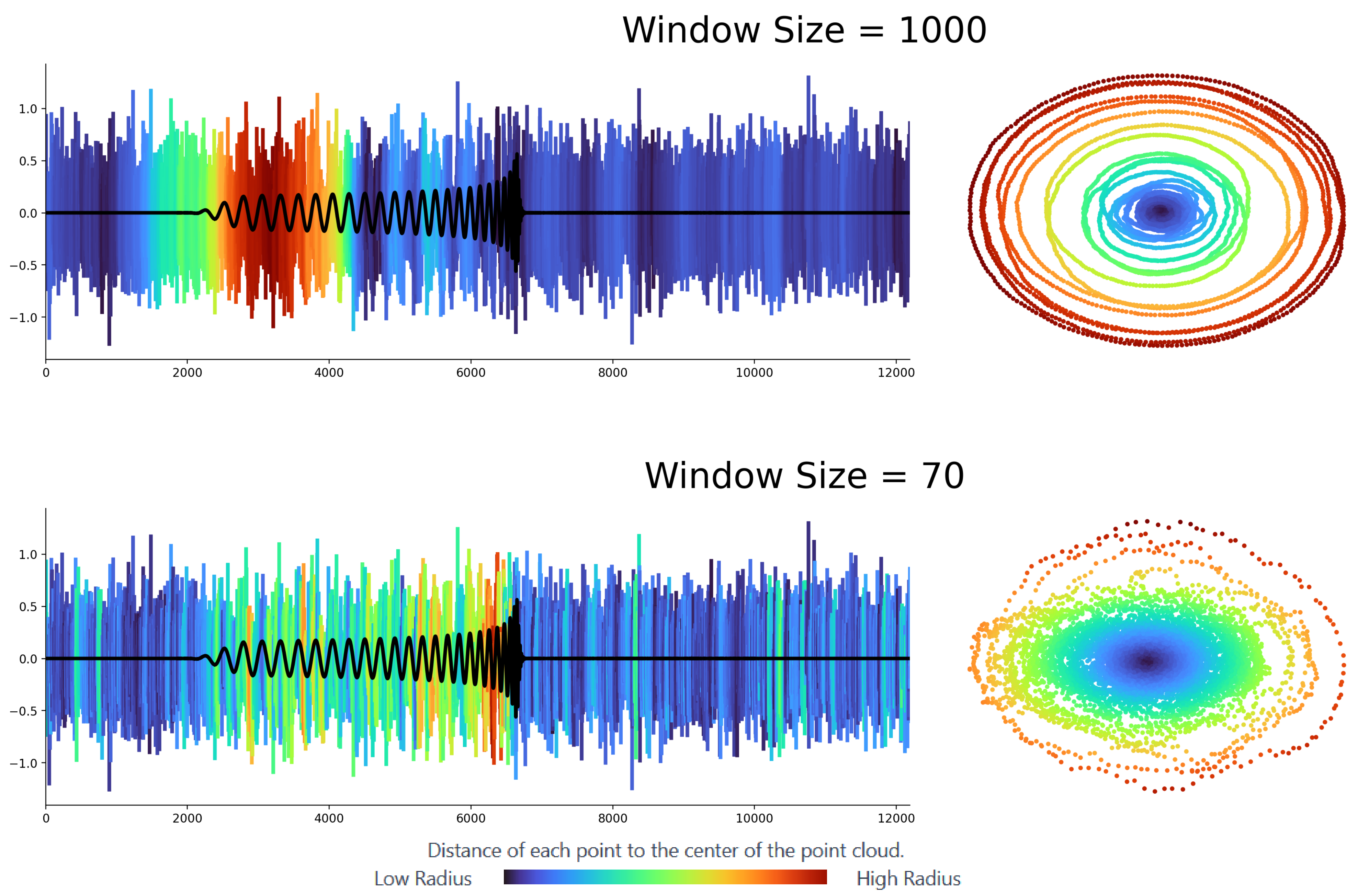
Noise is not exciting ...



... but oscillations result in circles!



The effect of the window size



Grounded in Theory

SLIDING WINDOWS AND PERSISTENCE: AN APPLICATION OF TOPOLOGICAL METHODS TO SIGNAL ANALYSIS

JOSE A. PEREA (✉) AND JOHN HARER

Abstract. We develop in this paper a theoretical framework for the topological study of time series data. Broadly speaking, we describe geometrical and topological properties of sliding window embeddings, as seen through the lens of persistent homology. In particular, we show that maximum persistence at the point-cloud level can be used to quantify periodicity at the signal level, prove structural and convergence theorems for the resulting persistence diagrams, and derive estimates for their dependency on window size and embedding dimension. We apply this methodology to quantifying periodicity in synthetic data sets, and compare the results with those obtained using state-of-the-art methods in gene expression analysis. We call this new method **SW1PerS** which stands for Sliding Windows and 1-dimensional Persistence Scoring.

1. Introduction

Signal analysis is an enormous field. There are many methods to study signals and many applications of that study. Given its importance, one might conclude that there is little opportunity left for the development of totally new approaches to signals. Yet in this paper we provide a new way to find periodicity and quasi-periodicity in signals. The method is based on sliding windows (also known as time-delay reconstruction), which have been used extensively in both engineering applications and in dynamical systems. But it adds a new element not applied before, which comes from the new field of computational topology [12].

Persistent homology is a topological method for measuring the shapes of spaces and the features of functions. One of the most important applications of persistent homology is to point clouds [3], where shape is usually interpreted as the geometry of some implicit underlying object near which the point cloud is sampled. The simplest non-trivial example of this idea is a point cloud which has the shape of a circle, and this shape is captured with 1-dimensional persistence. The challenge in applying the method is that noise can reduce the persistence, and not enough points can prevent the circular shape from appearing. It's also a challenge to deal with the fact that features come on all scale-levels and can be nested or in more complicated relationships. But this is what persistent homology is all about.

Date: November 22^{nd}, 2013.
2000 *Mathematics Subject Classification.* Primary 55U99, 37M10, 68W05; Secondary 57M99.
Key words and phrases. Computational algebraic topology, algorithms.
(✉) Corresponding author. Email: `joperea@math.duke.edu`. Phone: +1 (919) 660 - 2837.
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1

Sliding Windows and Persistence: An Application of Topological Methods to Signal Analysis

Jose Perea and John Harer

Published by two professors of Duke University in the Foundations of Computational Mathematics journal.

They explained: Why the circles?

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We asked: 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

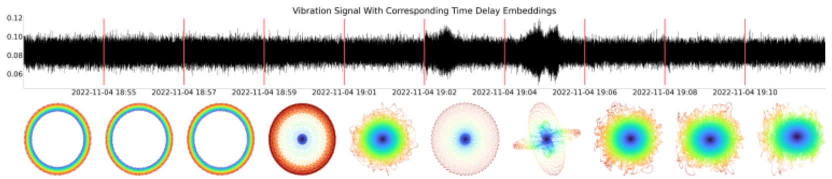


Figure 1: *Vibration measurements from a hydro power plant with the corresponding time delay embeddings per segment. The figure shows how the time delay embedding evolves over time and that it can be used as a fingerprint to highlight significant changes in the vibration profile.*

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

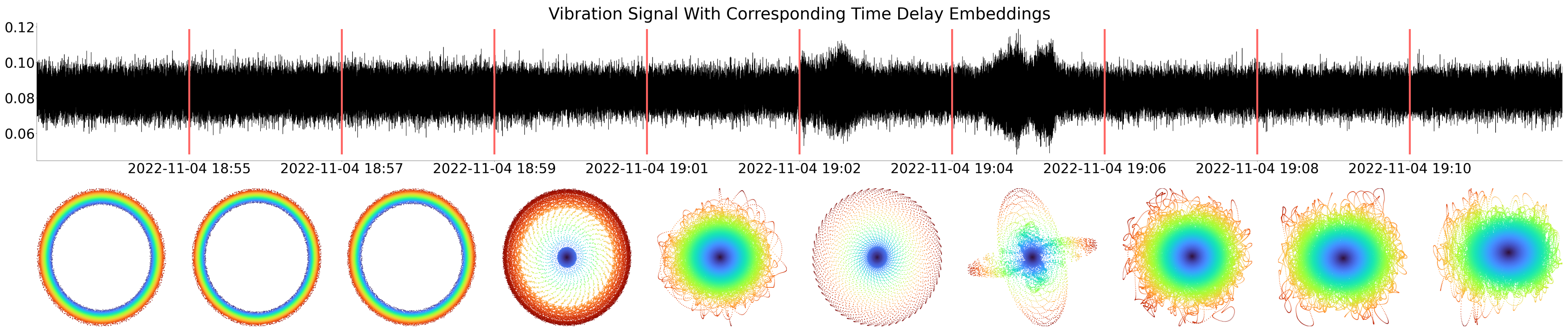
The study of vibrations is essential for any mechanical engineering problem, as they are omnipresent: from simple motors to airplanes, any system with mass and elasticity has the potential to experience vibrations. While many vibrations are unavoidable and intrinsic properties of systems, they can be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

EuroVis 2025 Submission

In Review 🍀

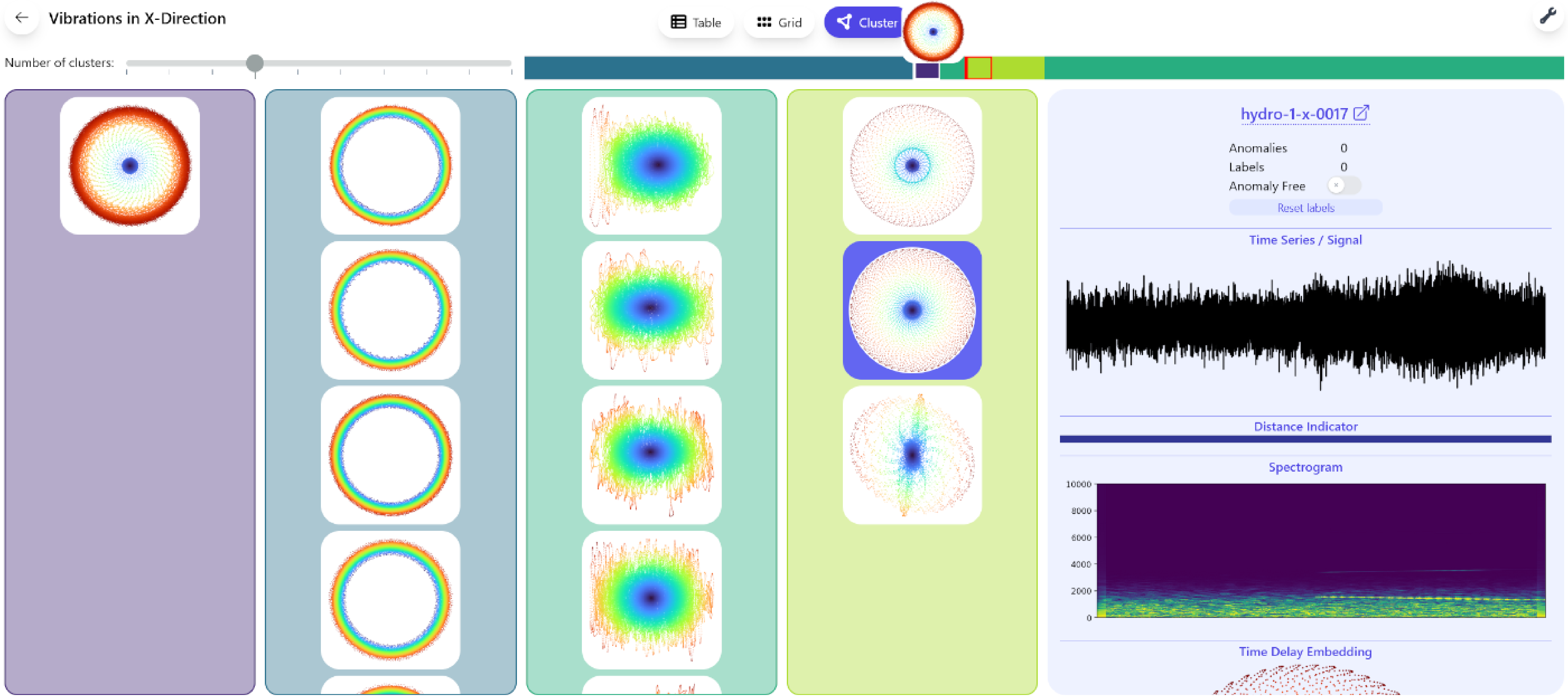
Can we find a change point in the signal?

Vibrations of a hydropower plant:

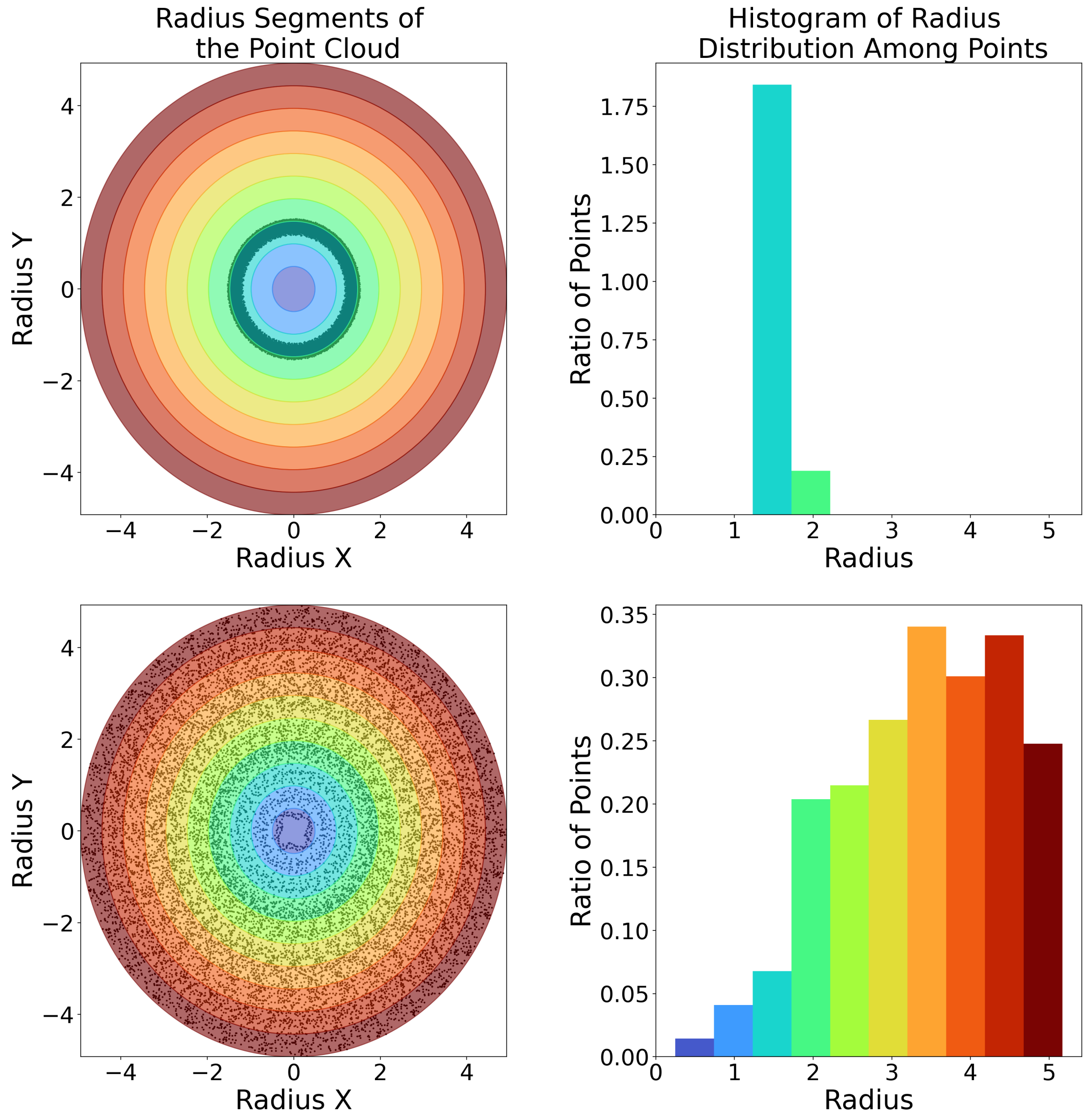


The TDE is a fingerprint evolving over time!

We can also cluster these fingerprints!



For the curious: We cluster by radius distribution



Applications

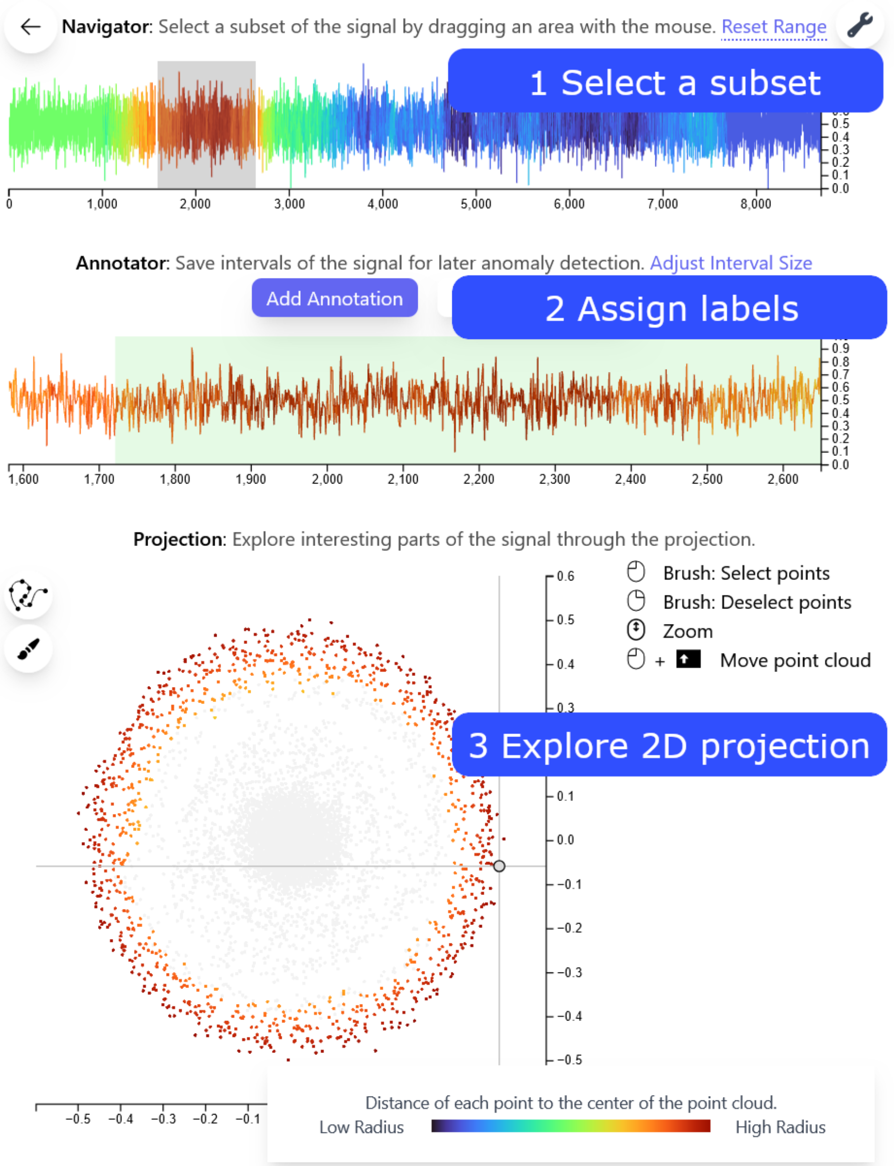
Engines

When can we detect wear?

Bearings

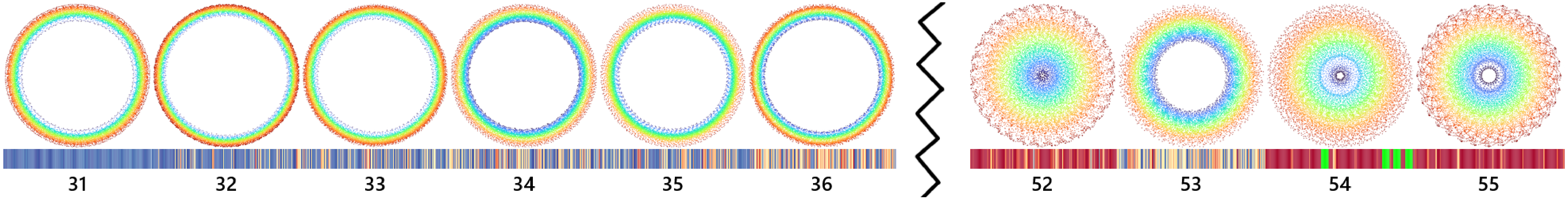
Which are faulty?

The Three-Charts-View



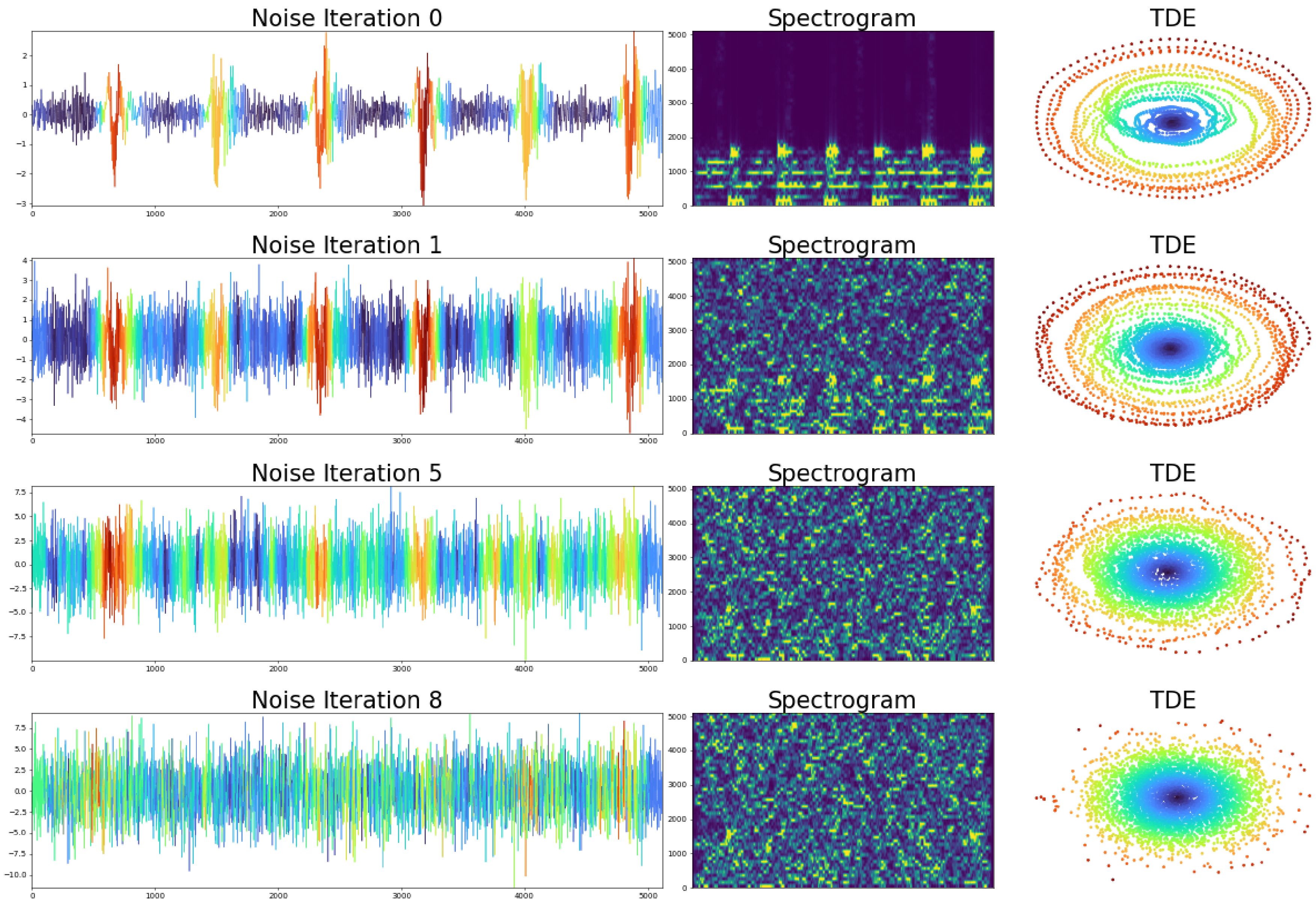
Simply Brush the Scatterplot

The labels are used for a similarity search

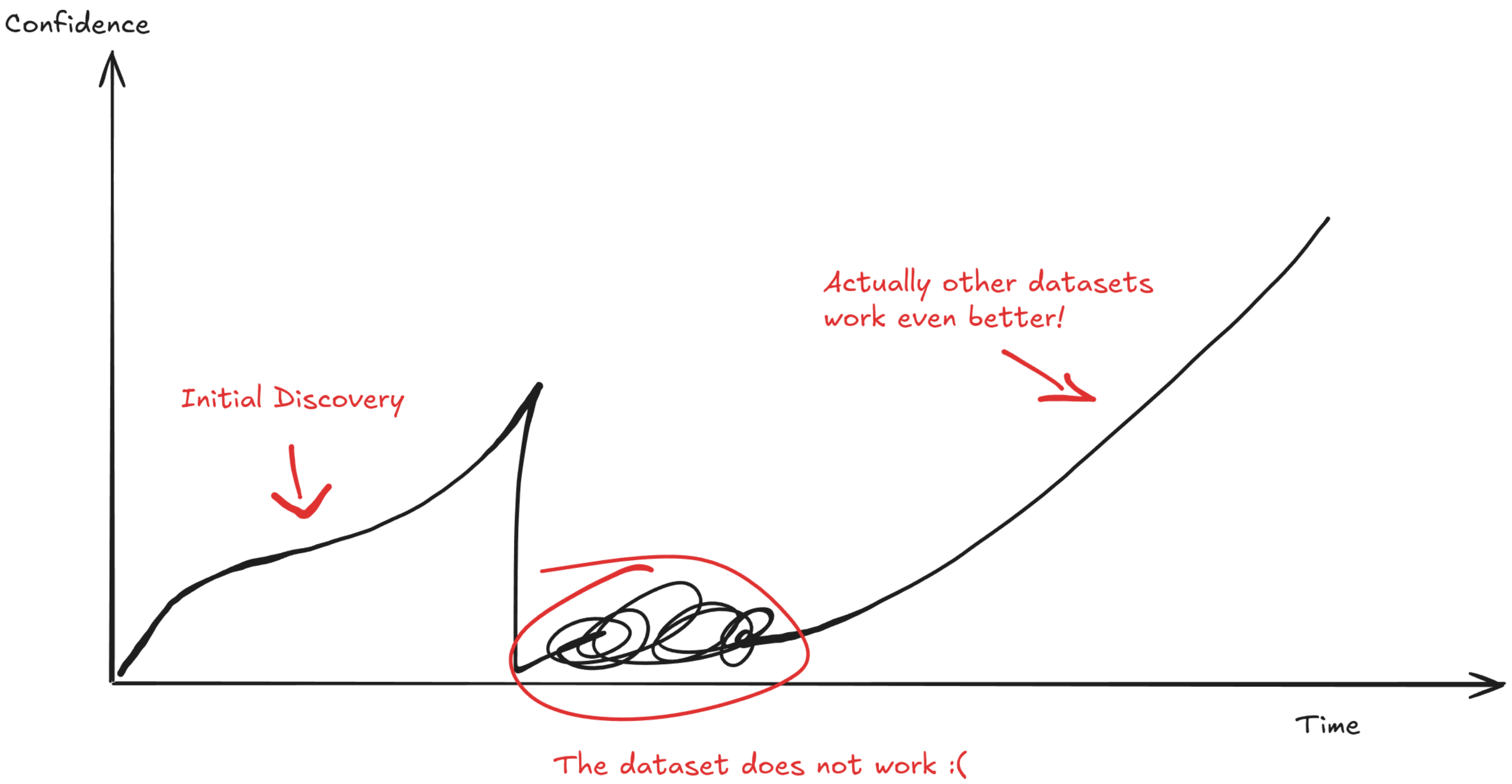


This reveals a creeping damage in the engine!

Finally: What about noise?



The most important insight however ...



... is that research is not always linear!

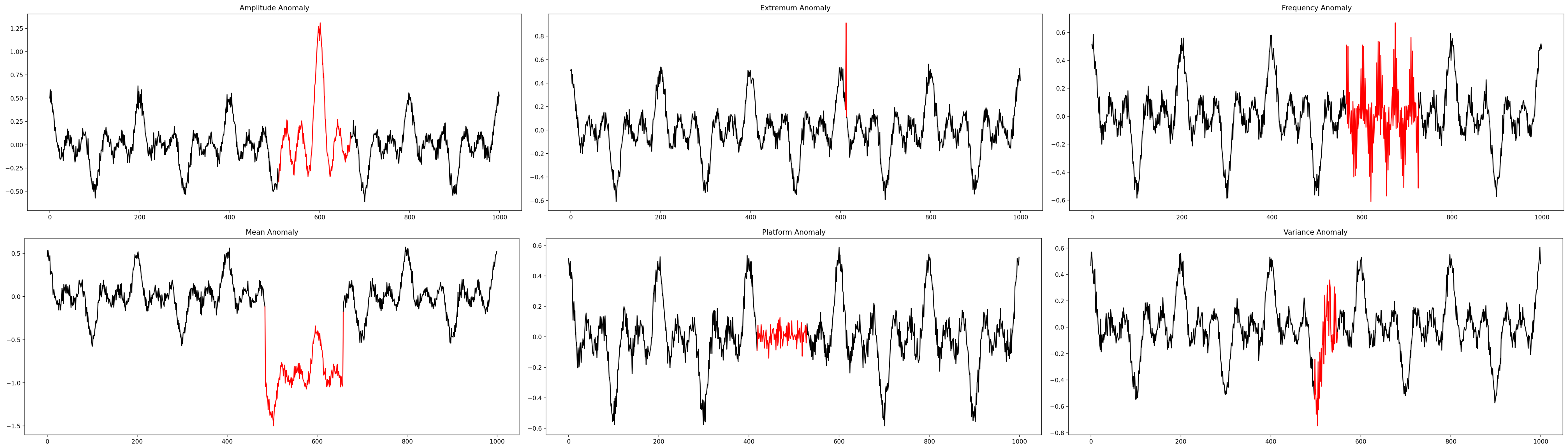
Small Cliffhanger

What if we have 75 TB of data? 🤯

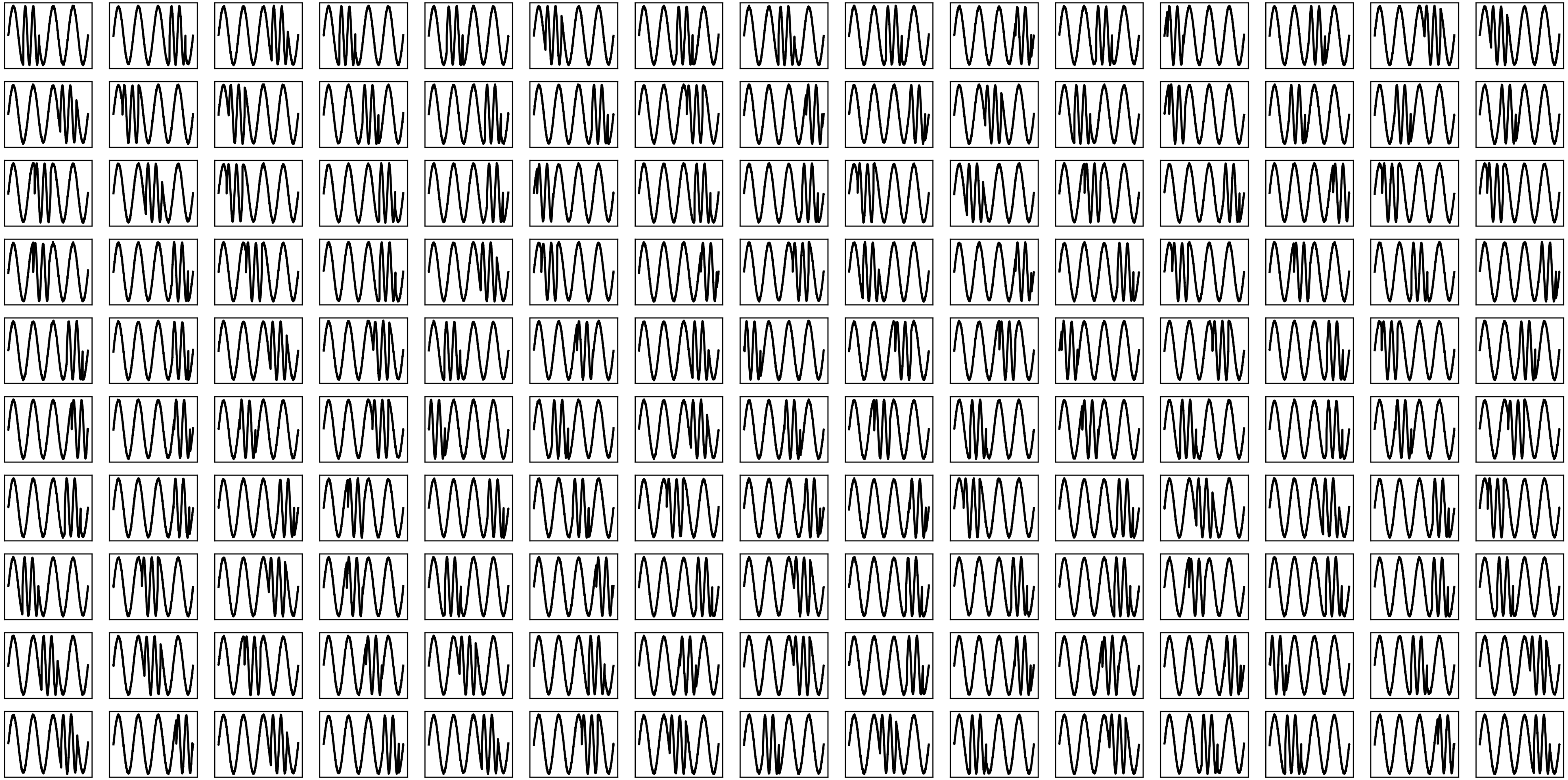
To be continued ...

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.

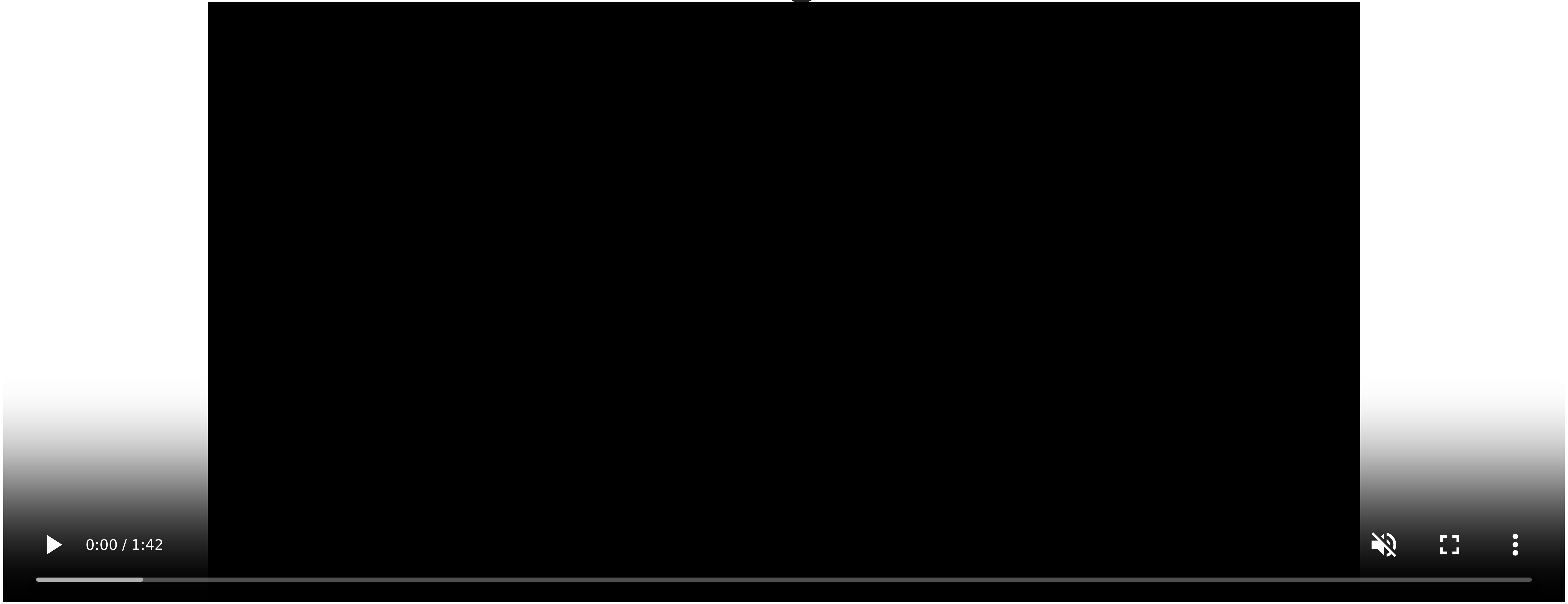
Exploring Anomalies

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.

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.

The Plan

VIS2025

Short Paper Track

Forecasting

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

Introducing PredictPal

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

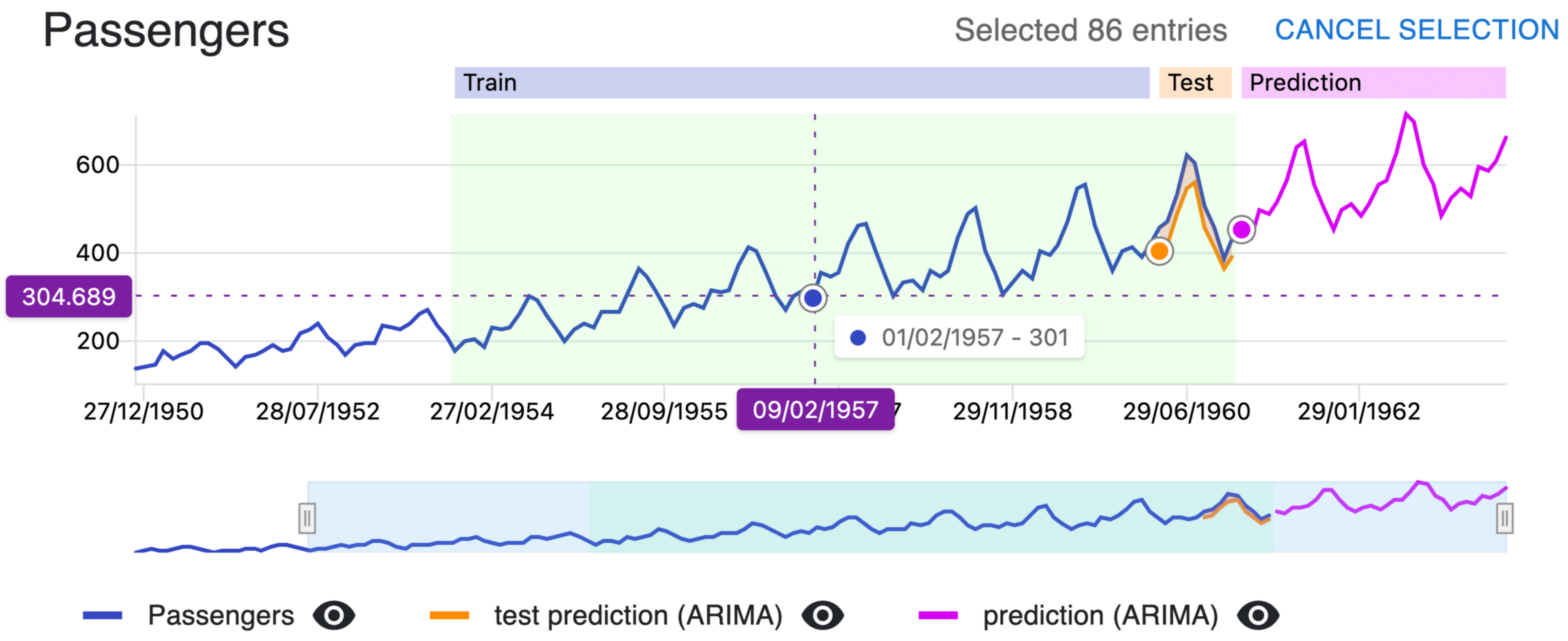
ARIMA

AutoRegressive Integrated Moving Average

VAR

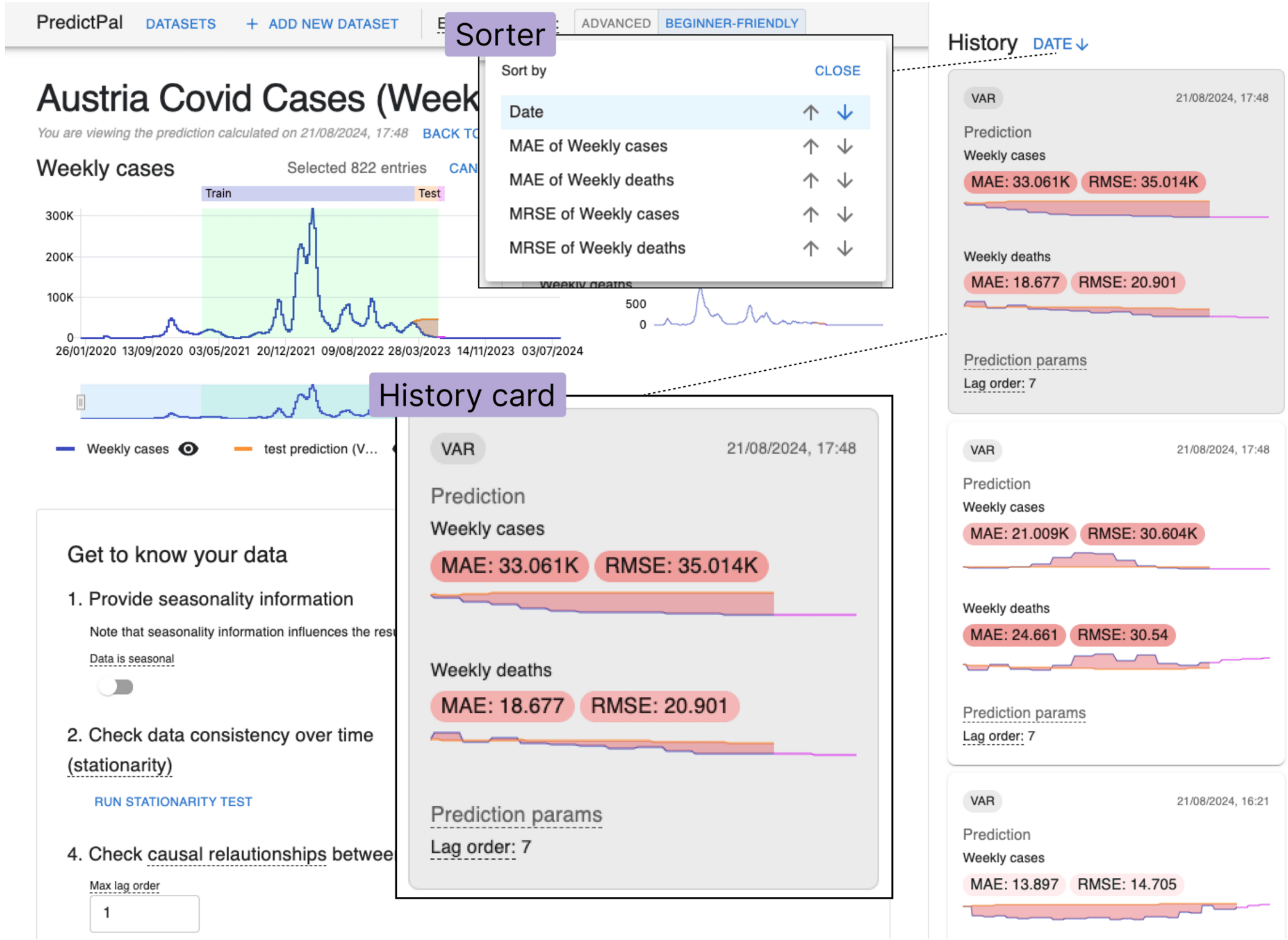
Vector Autoregression

Analysis View



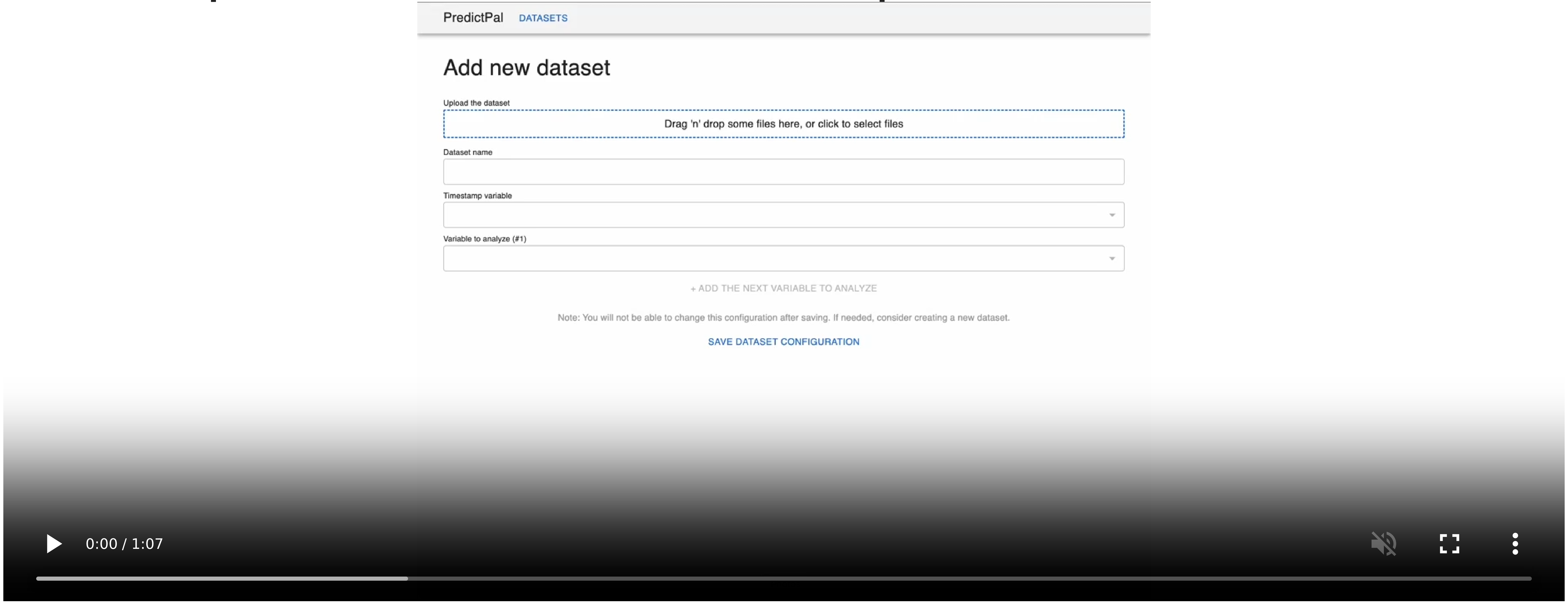
The user selects a subset of the time series for training the prediction models and can immediately verify the model based on the visualization.

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.

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(✉)

Saint-Petersburg State University, 198504 St. Petersburg, Russia
st088518@student.spbu.ru, petrosian.ovanes@yandex.ru

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.

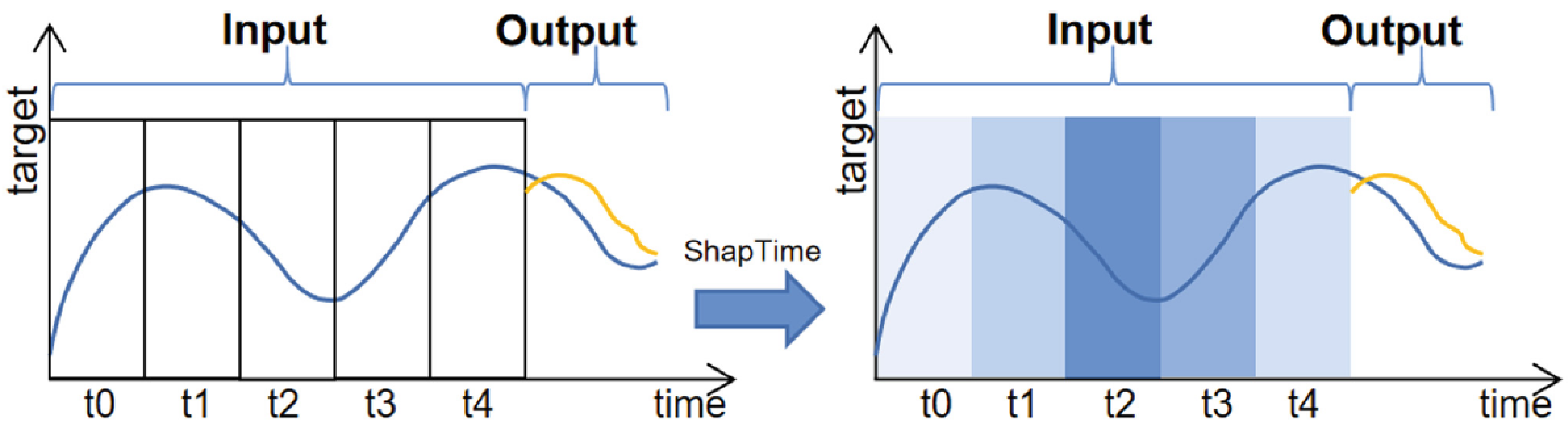
Keywords: Time-series forecasting · Explainable AI · Shapley value

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



Thank you!

Slides