INSTITUTE OF VISUAL COMPUTING

TU Graz

SCIENCE
PASSION
TECHNOLOGY

Interaktive Visualisierungen für Zeitreihen

Julian Rakuschek

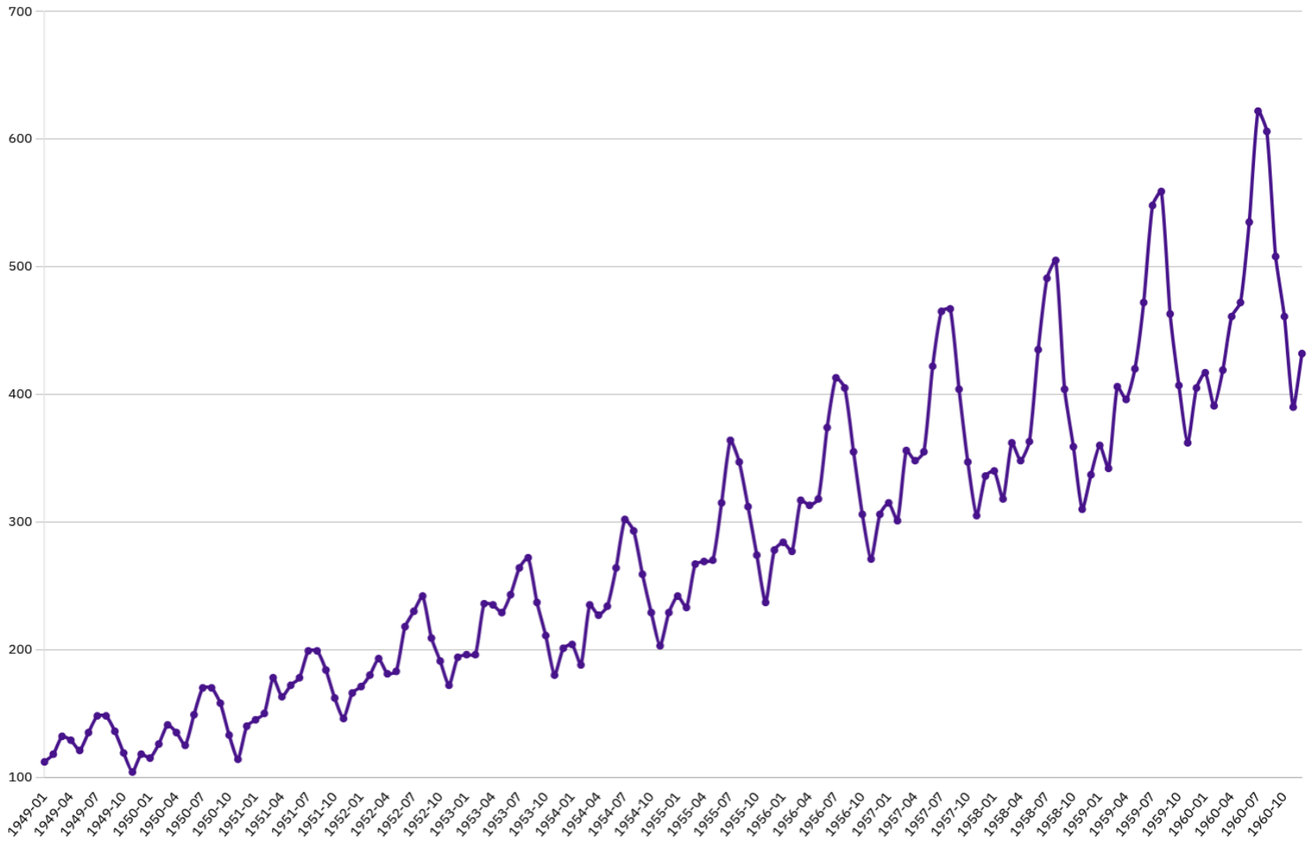
27.10.2025

A glance into our Excel sheet:

112, 118, 132, 129, 121, 135, 148, 148, 136, 119, 104, 118, 115, 126, 141, 135, 125,
149, 170, 170, 158, 133, 114, 140, 145, 150, 178, 163, 172, 178, 199, 199, 184, 162,
146, 166, 171, 180, 193, 181, 183, 218, 230, 242, 209, 191, 172, 194, 196, 196, 236,
235, 229, 243, 264, 272, 237, 211, 180, 201, 204, 188, 235, 227, 234, 264, 302, 293,
259, 229, 203, 229, 242, 233, 267, 269, 270, 315, 364, 347, 312, 274, 237, 278, 284,
277, 317, 313, 318, 374, 413, 405, 355, 306, 271, 306, 315, 301, 356, 348, 355, 422,
465, 467, 404, 347, 305, 336, 340, 318, 362, 348, 363, 435, 491, 505, 404, 359, 310,
337, 360, 342, 406, 396, 420, 472, 548, 559, 463, 407, 362, 405, 417, 391, 419, 461,
472, 535, 622, 606, 508, 461, 390, 432

Detecting patterns is cumbersome!

Better:


700
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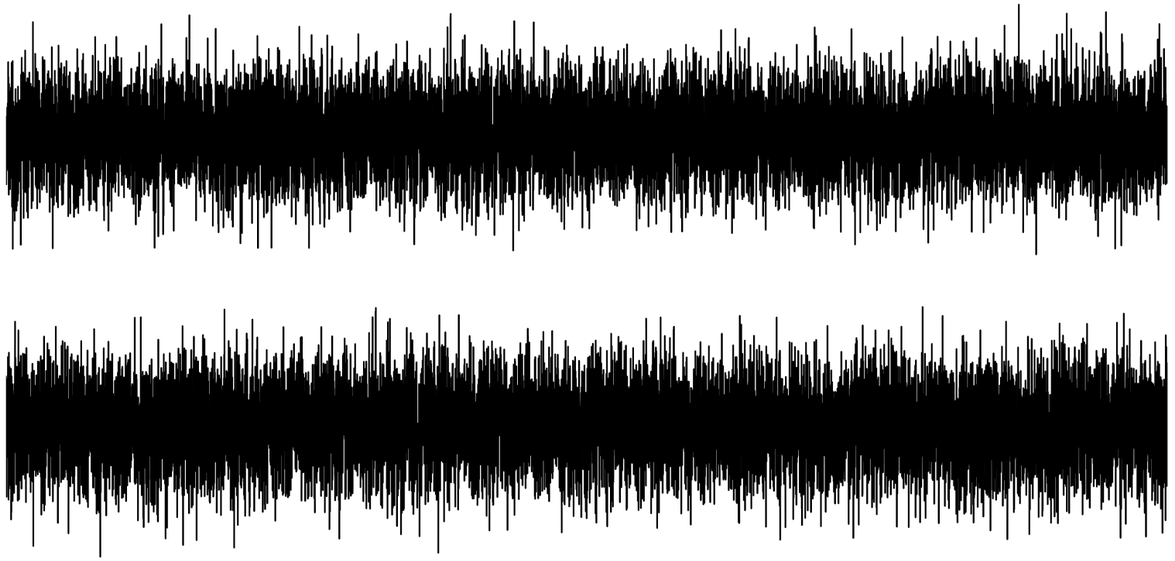
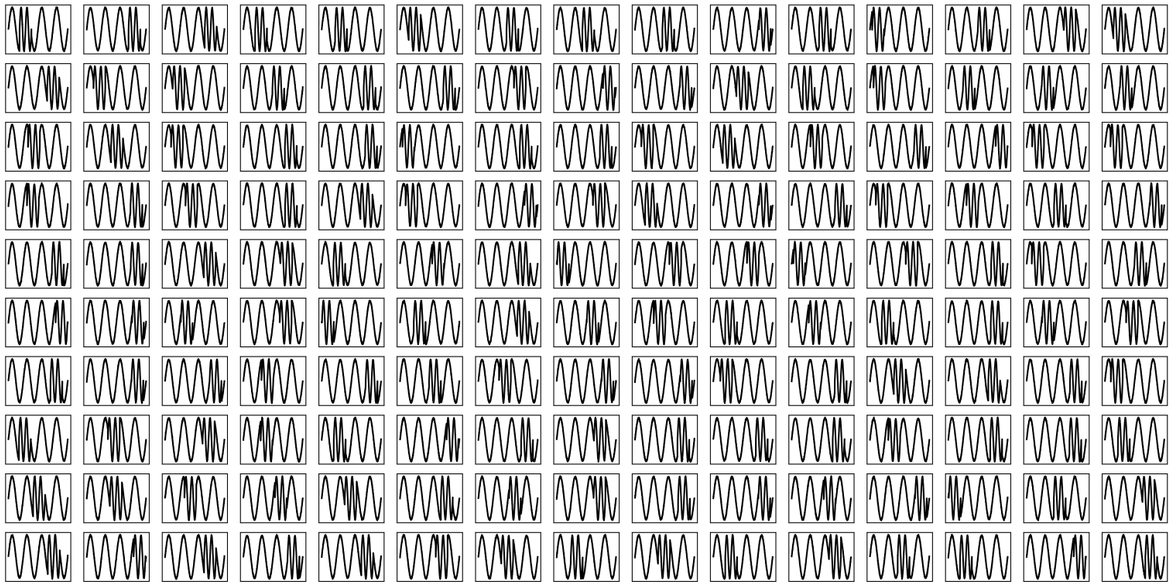
1959-10
1960-01
1960-04
1960-07
1960-10

Challenges:



Large Time Series



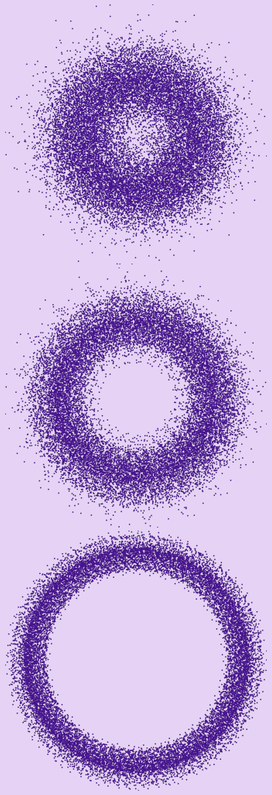
Many Time Series

Are there better visualizations?

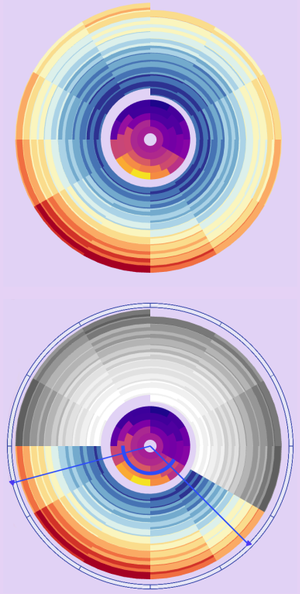
How do I navigate through large datasets?

Content

Vibrations



Periodic Time Series



Visual Anomaly Detection

This will be a quick overview

If you see something interesting ...

... you are very welcome to talk to me!

Visual Fingerprints for Vibration Signals

Vibrationen messen

+

=

Motor Accelerometer Vibrationssignal

The Problem with Vibrations

Can you tell the difference?

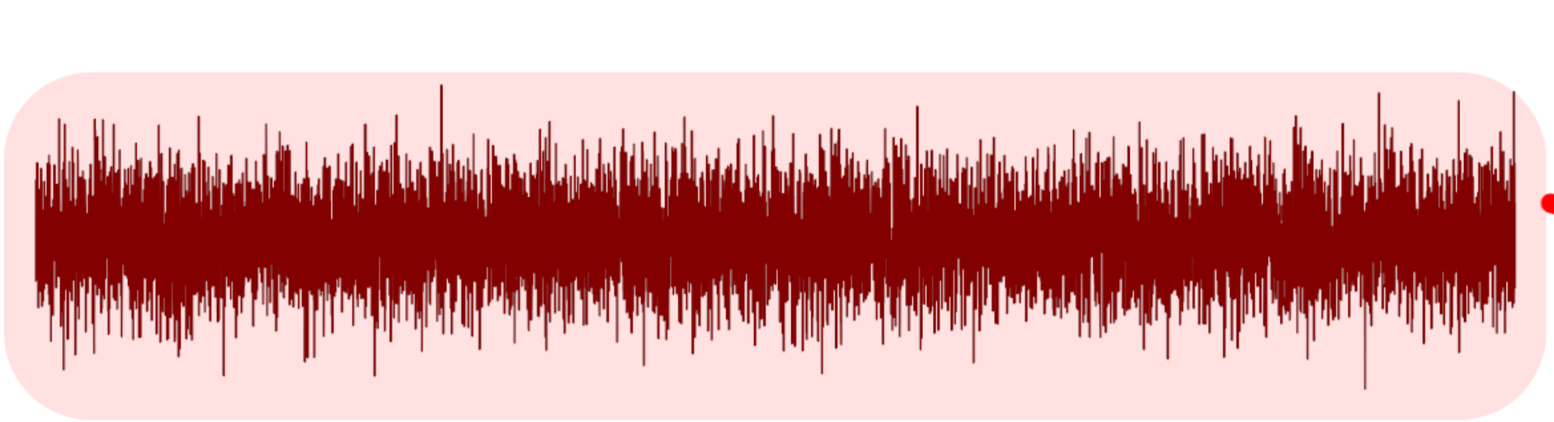
A hidden signal

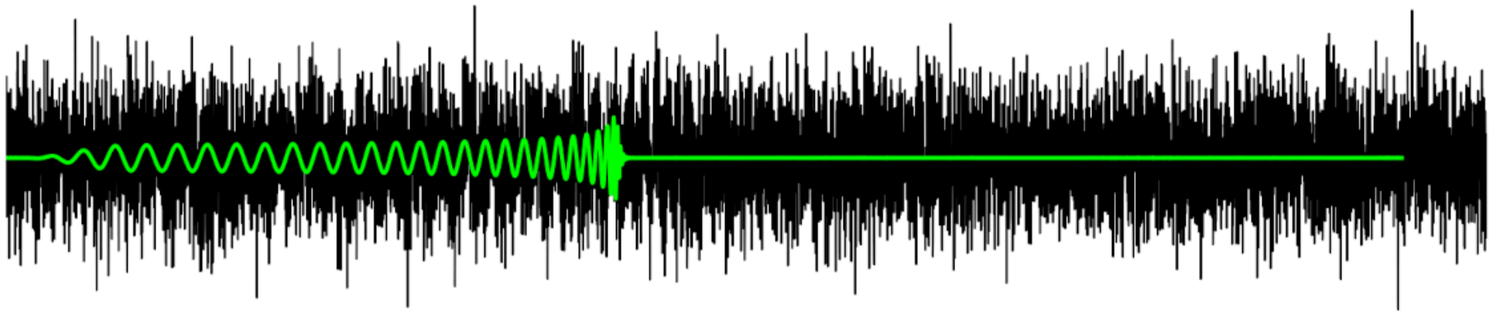
You cannot see the hidden signal with a line chart.

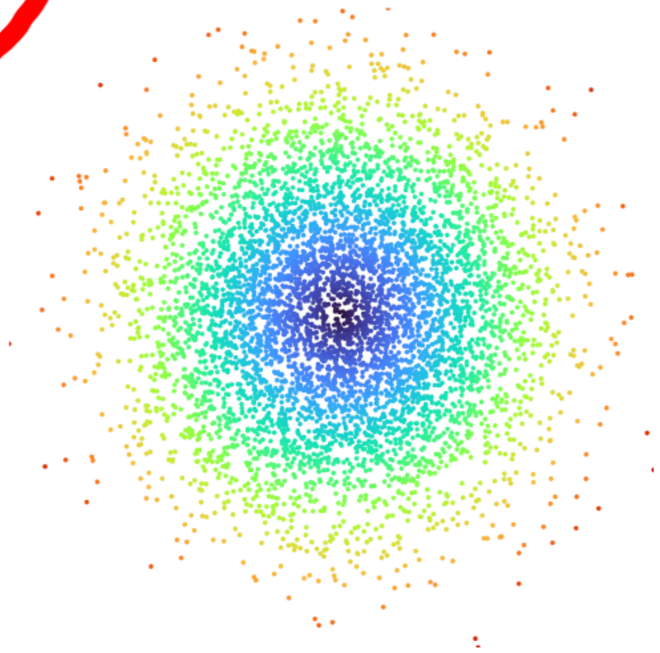
The Idea: Vibration → Point Cloud

1. Sliding Window View
2. Apply PCA

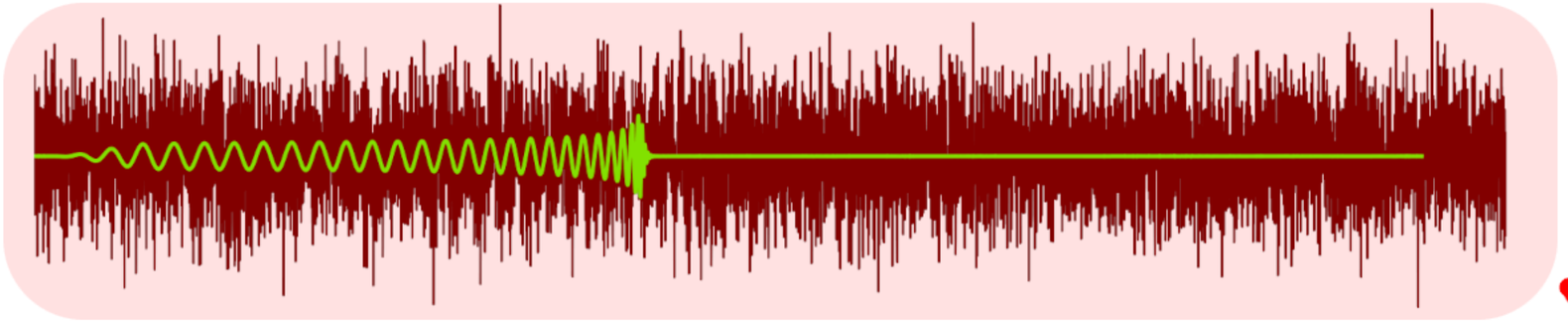
Noise is not exciting ...

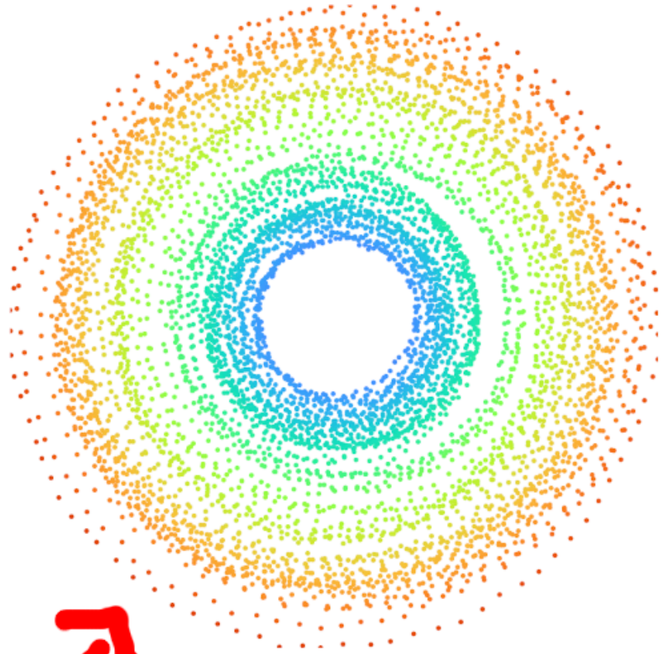




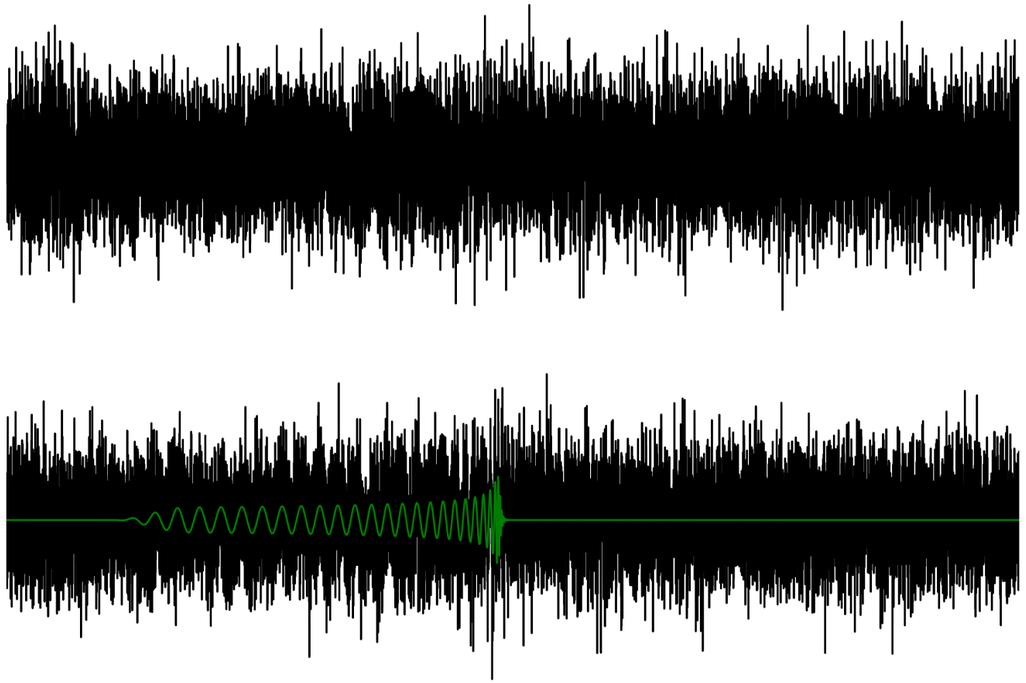


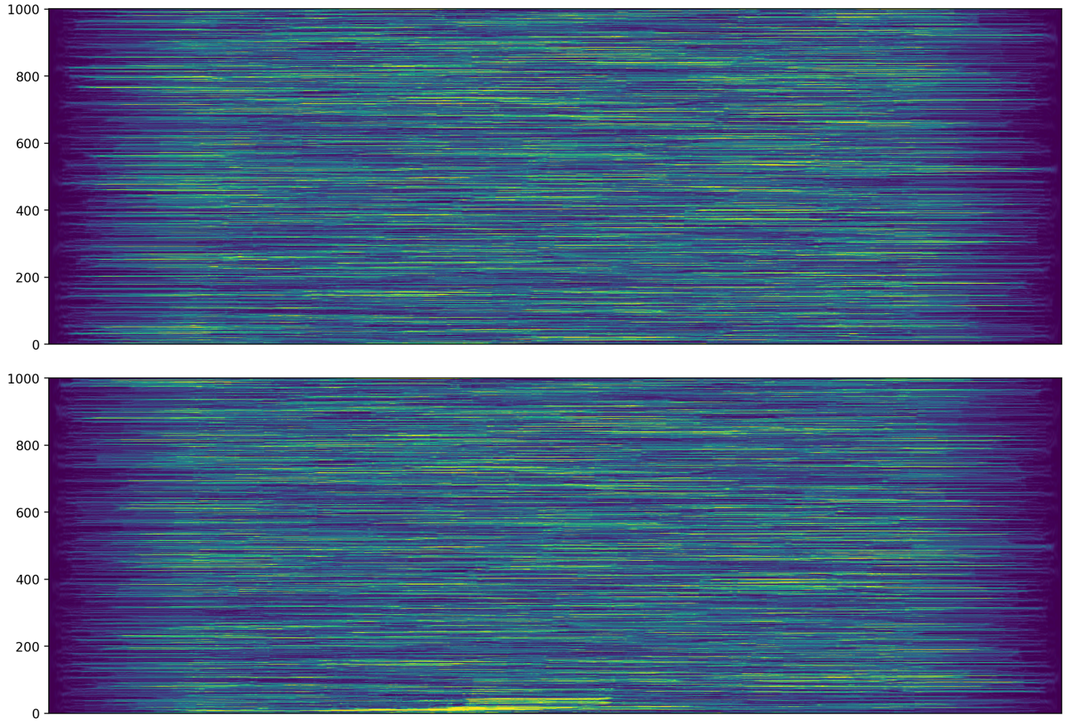
... but oscillations result in circles!



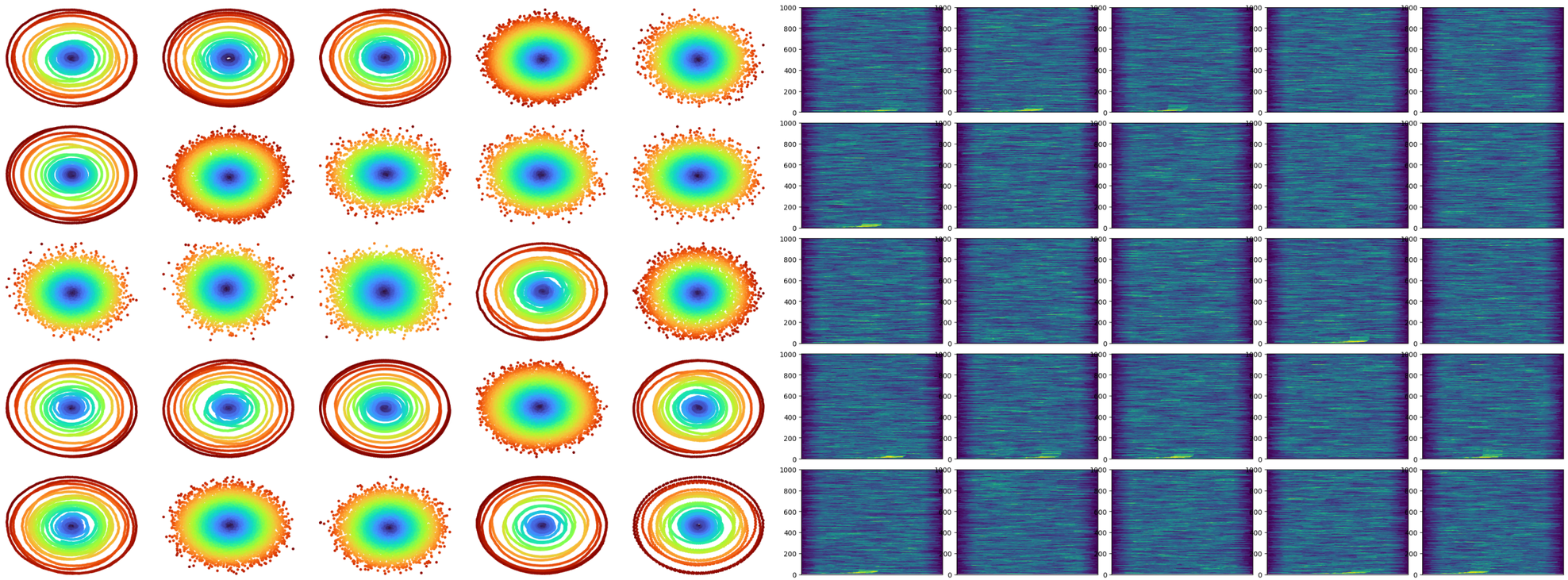


Yes, this is also detectable with spectrograms, but ...

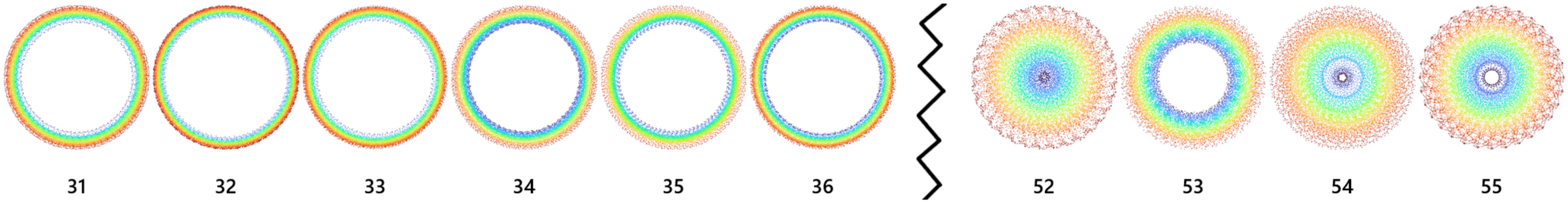




... the TDE is suitable to gain an overview!



Observing Wear



Published at EuroVis

EUROVIS 2025/ M. El-Assady, A. Ottley, and C. Tominski

Visual Fingerprints of Vibration Signals Using Time Delay Embeddings

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[1] TU Graz, Institute of Visual Computing, Austria
[2] Binder+Co AG, Austria
[3] TU Wien, Institute of Visual Computing & Human-Centered Technology, Austria

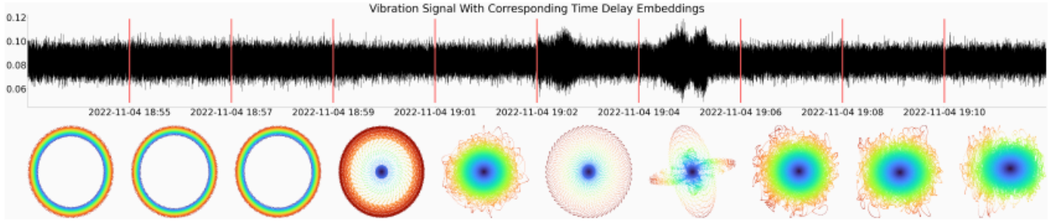


Figure 1: *Vibration measurements from a hydro power plant with the corresponding time delay embeddings per segment. The time delay embedding visualizations evolve over time and can be used as a fingerprint to highlight significant changes in the vibration data.*

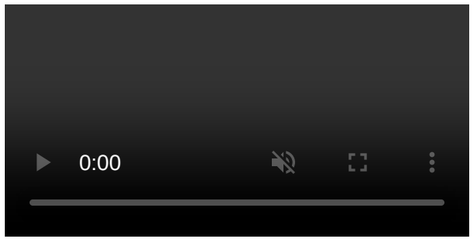
Abstract

Most machines generate vibrations during operation, but effectively visualizing these vibrations is often a challenge, due to large and high-resolution data. Line charts suffer from overplotting, while frequency-domain analysis requires specialized knowledge in signal processing. We introduce a method that bridges the gap between time-domain and frequency-domain analysis: a visual fingerprint computed through the time delay embedding of the vibration data. This fingerprint helps identify segments exhibiting periodic behavior and can be used to cluster similar segments within a vibration signal. Additionally, we demonstrate its practical application in predictive maintenance, showcasing its potential for real-world industrial use.

CCS Concepts

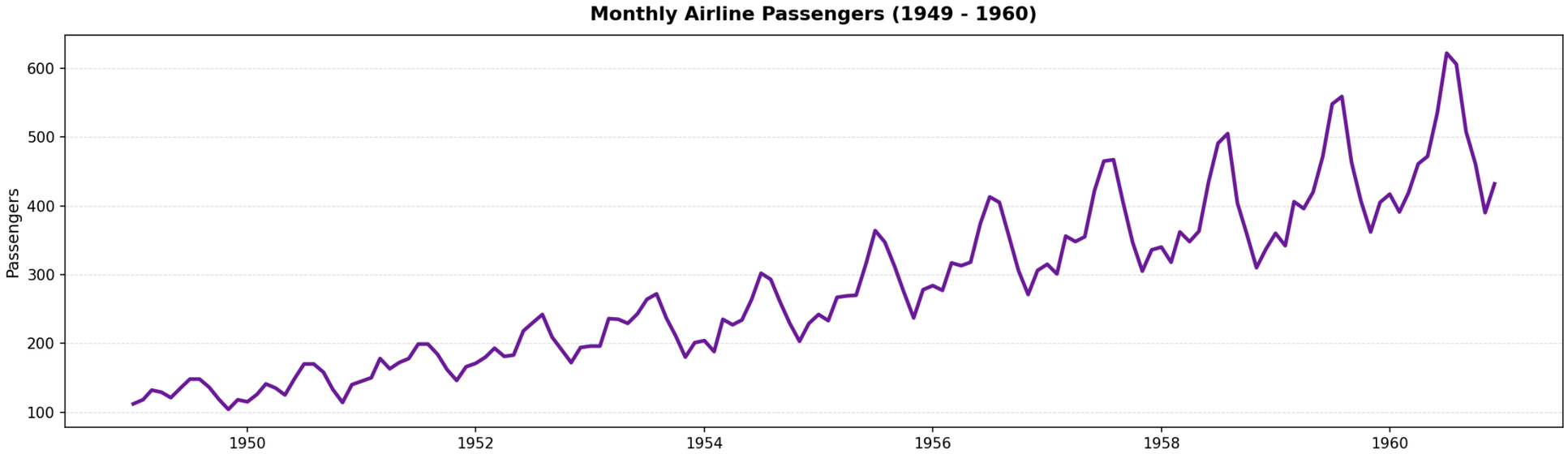
• ***Human-centered computing*** → ***Visualization techniques;***

Analyzing Large Vibration Signals

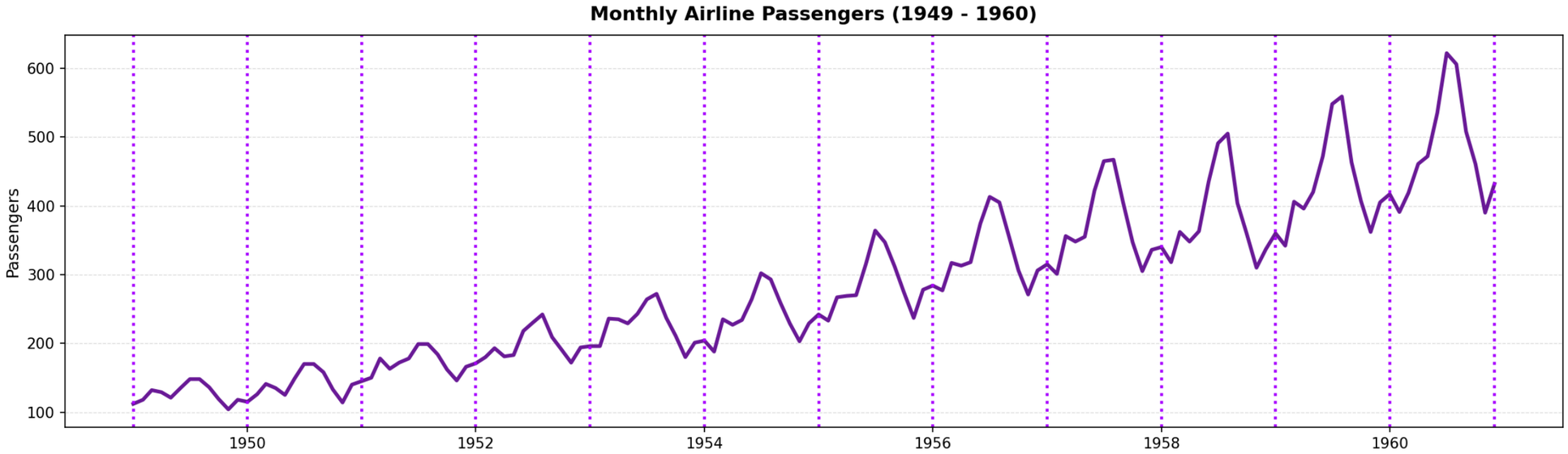


Visualizing Periodic Time Series

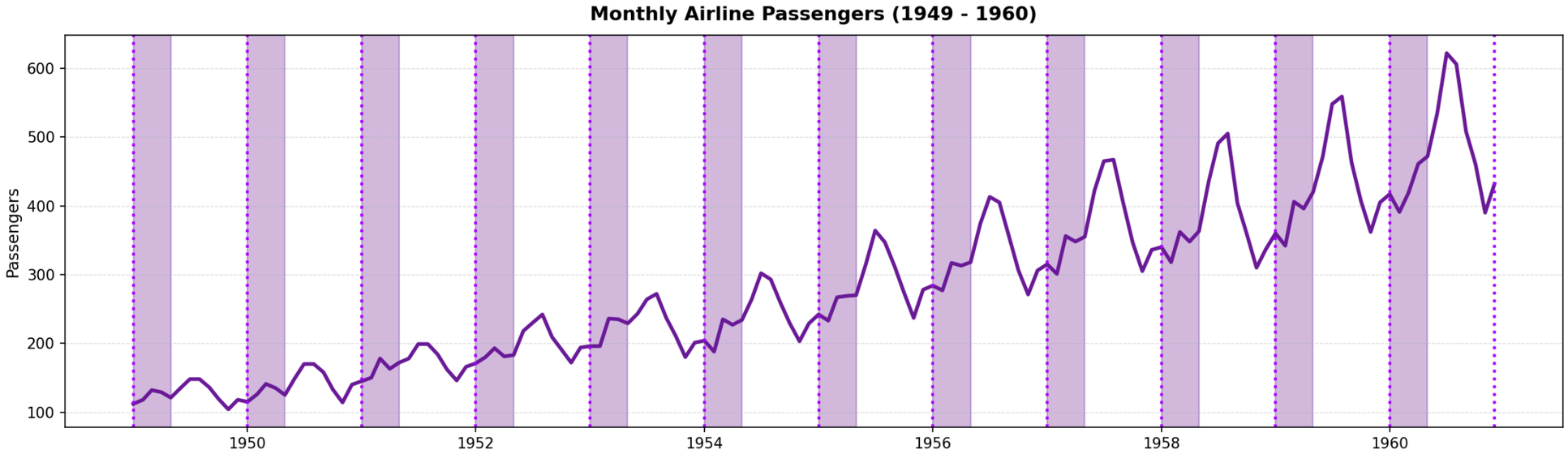
Periodic Time Series



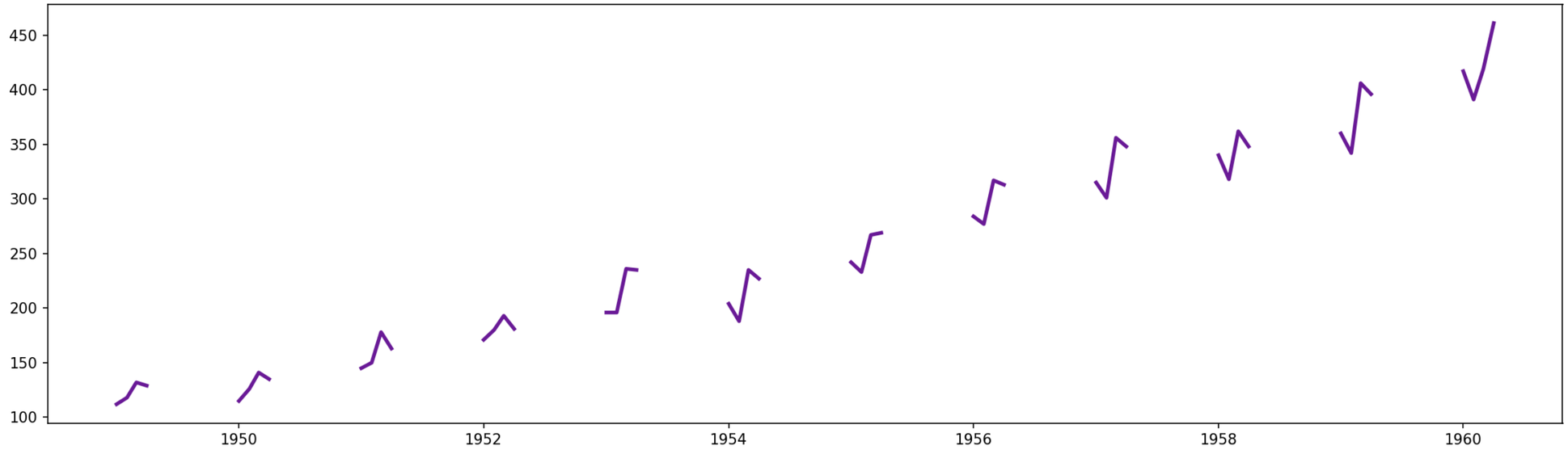
Segment by Year



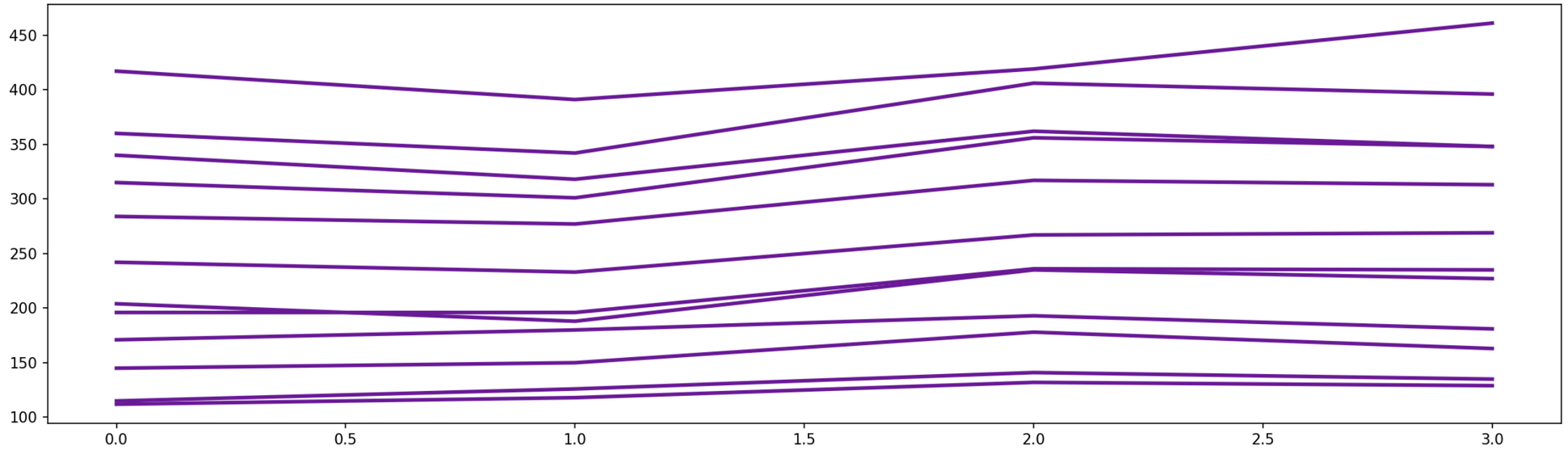
We want to compare each springtime



Result: Subsequences

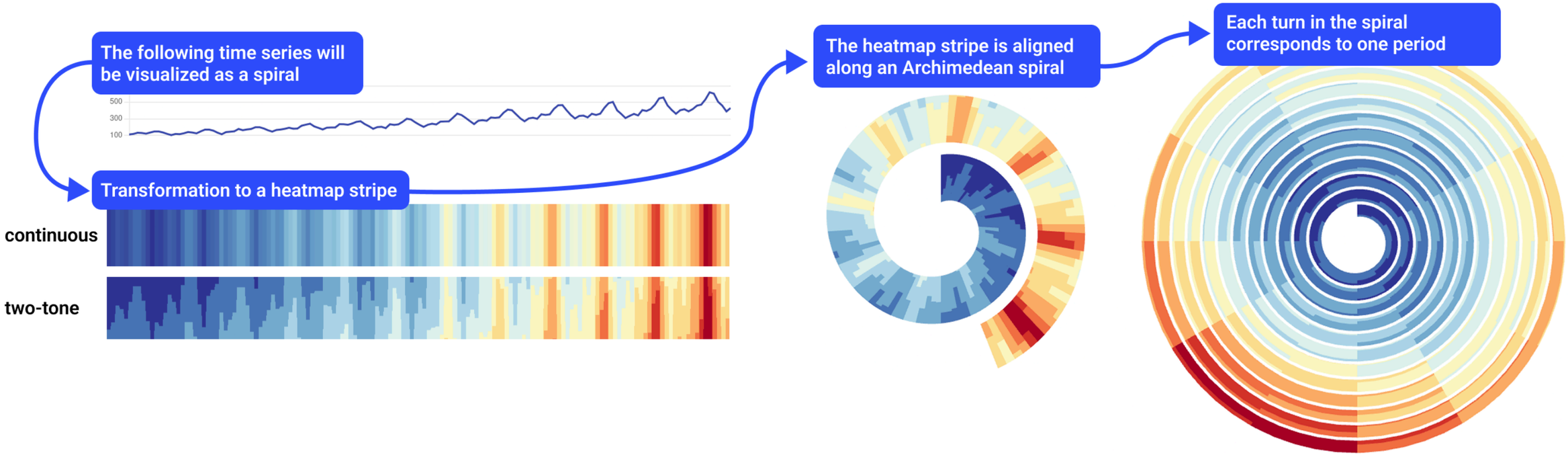


Comparison via Superposition

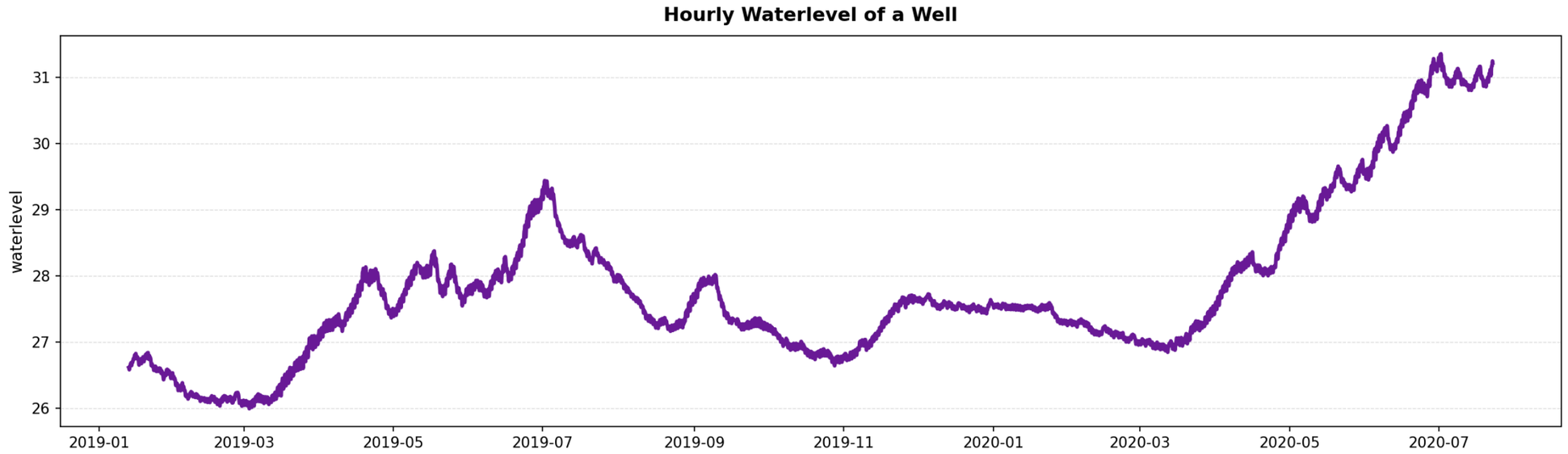


Can we do better?

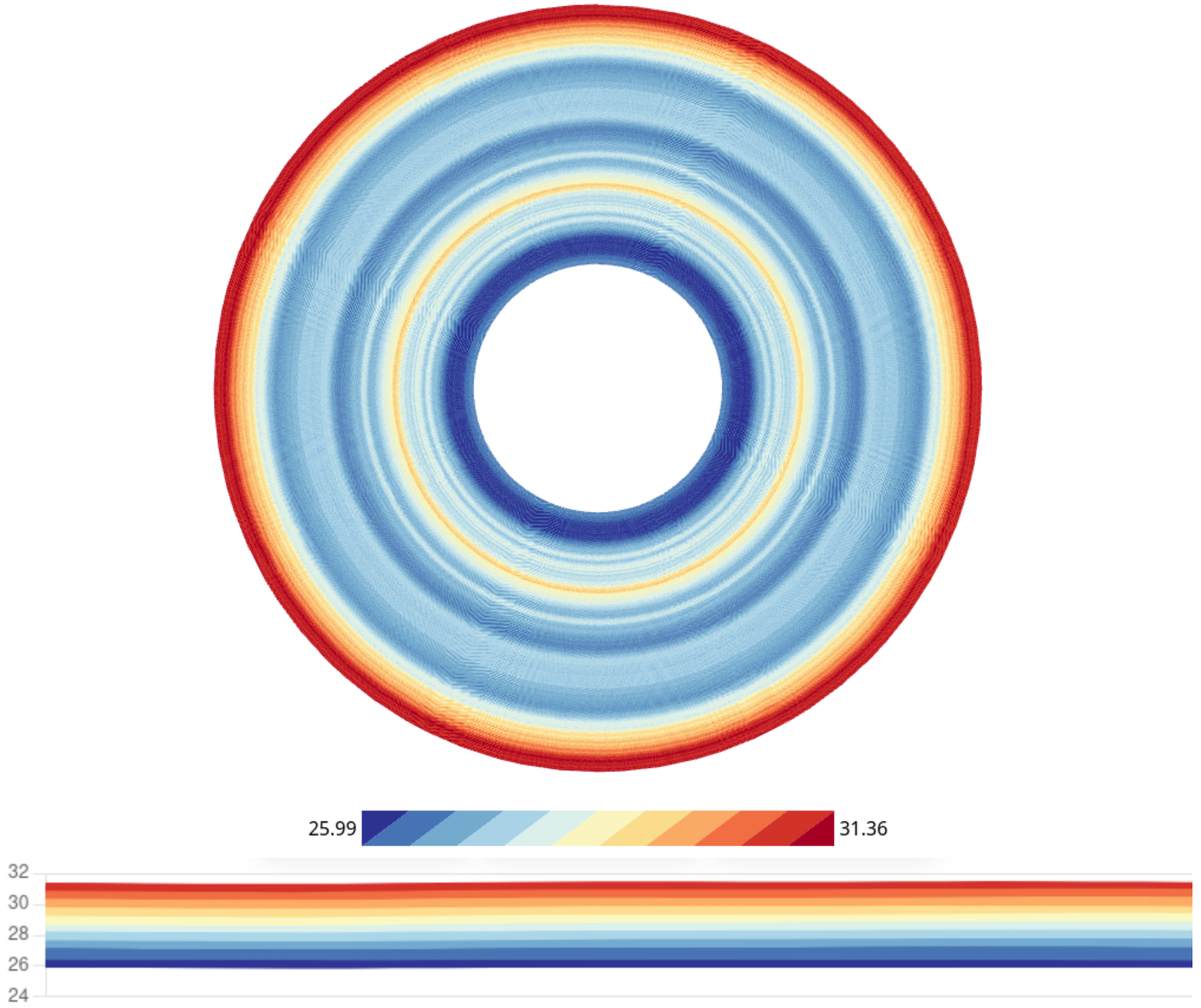
The Time Series Spiral



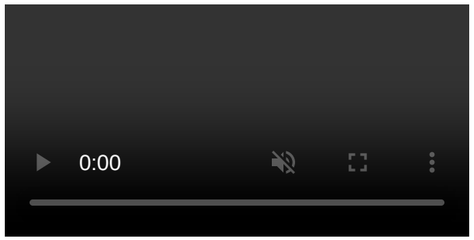
Complex Time Series are challenging!



No differences in sectors visible.

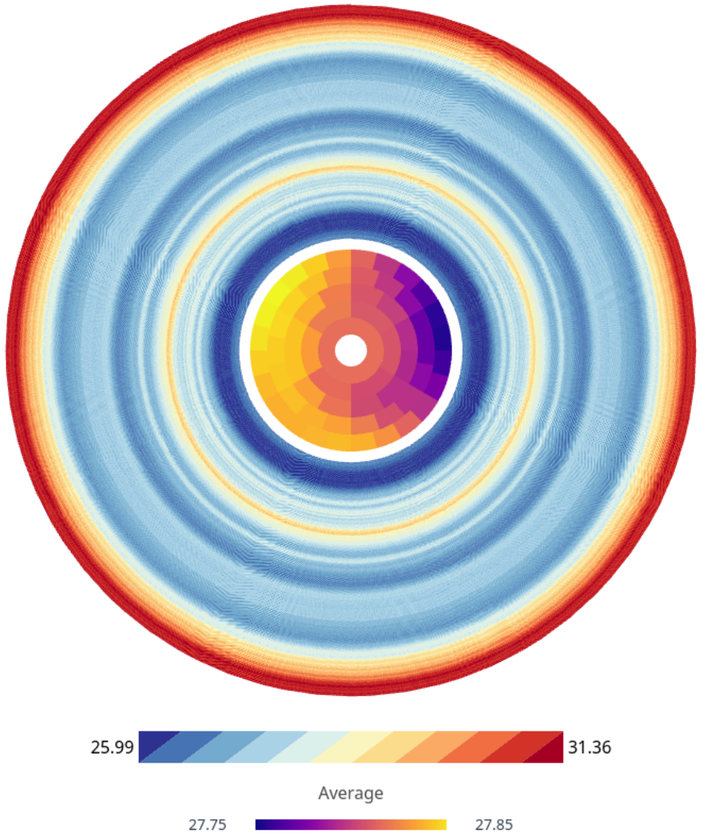


Visual Guidance can help

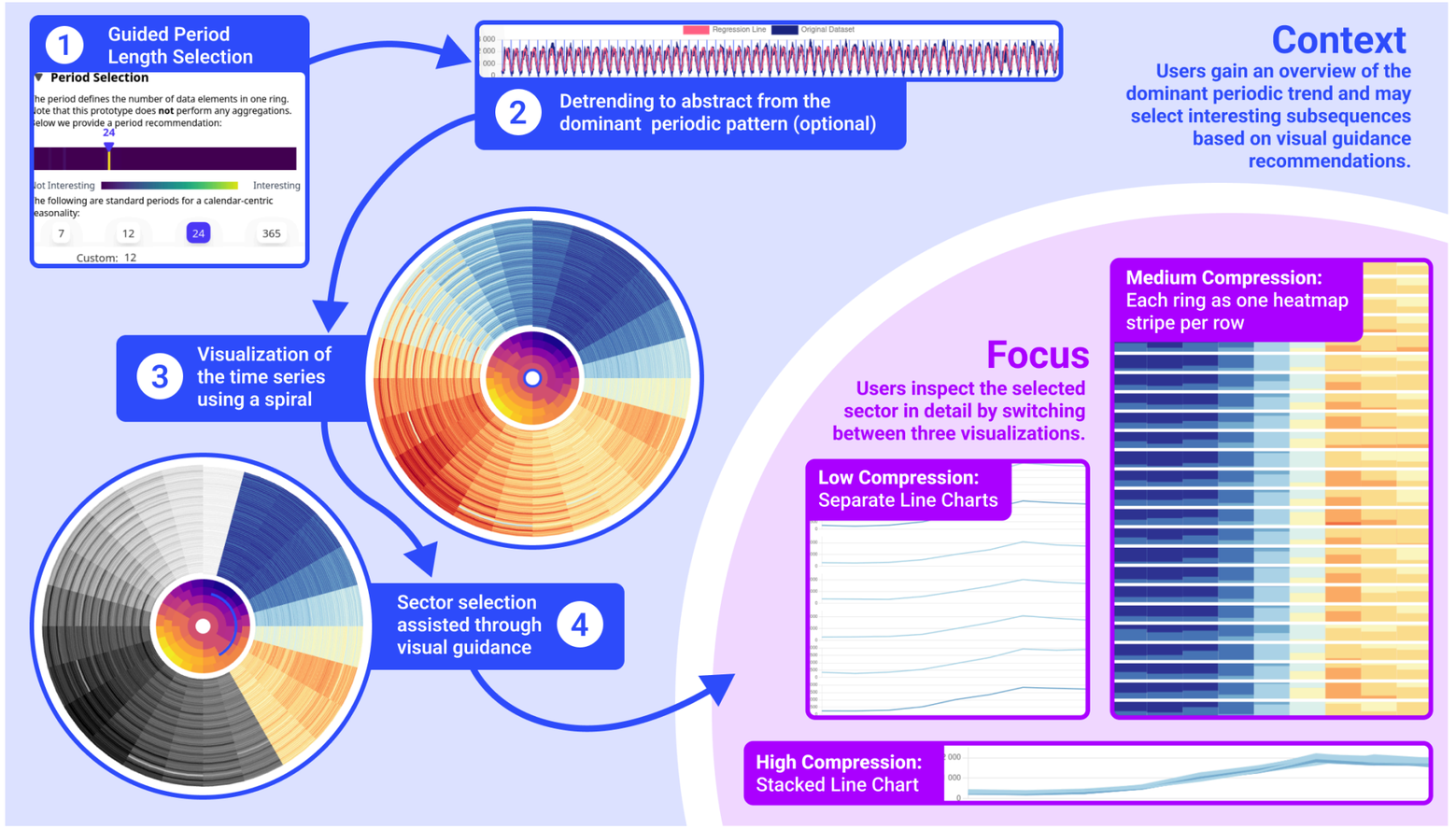


We need to navigate through a foggy data swamp.

Average Guidance

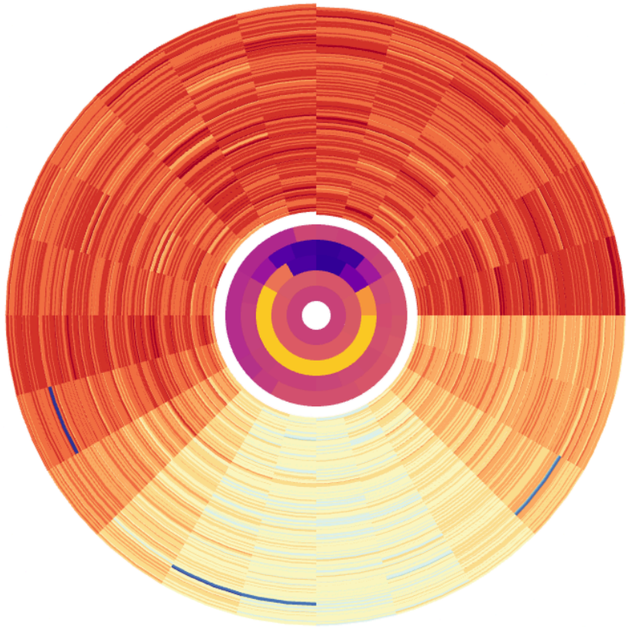


Our Prototype

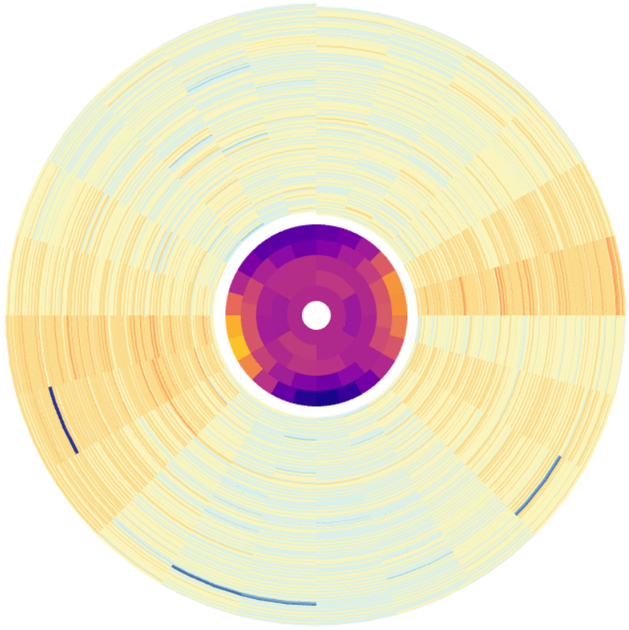


Another Example: Traffic

1 Average vehicle speed at a busy US highway

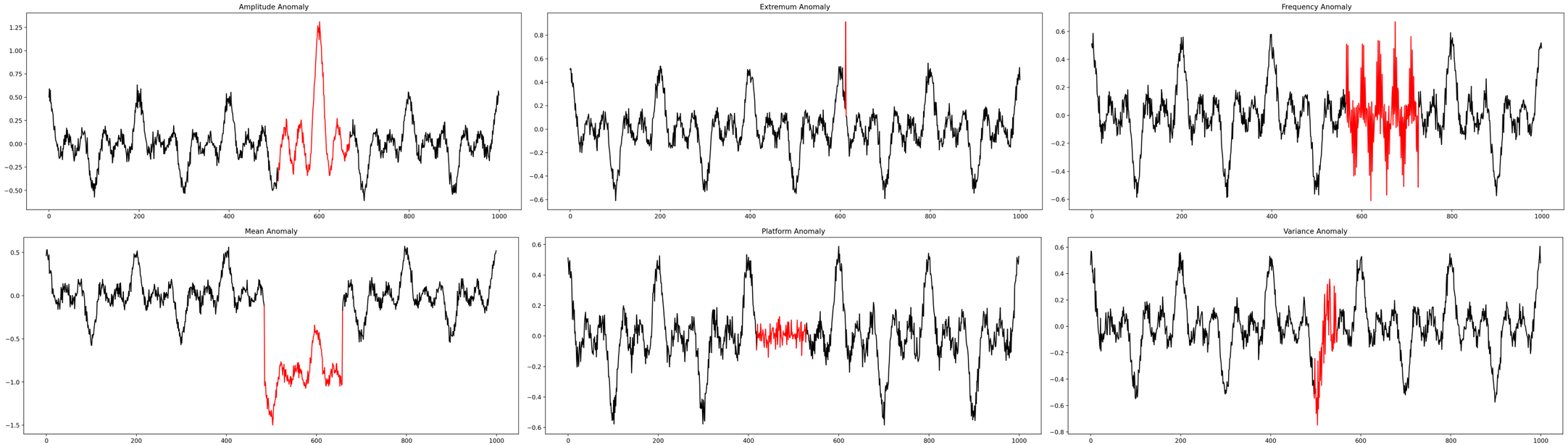


2 Using the residuals of a regression model, a secondary pattern emerges



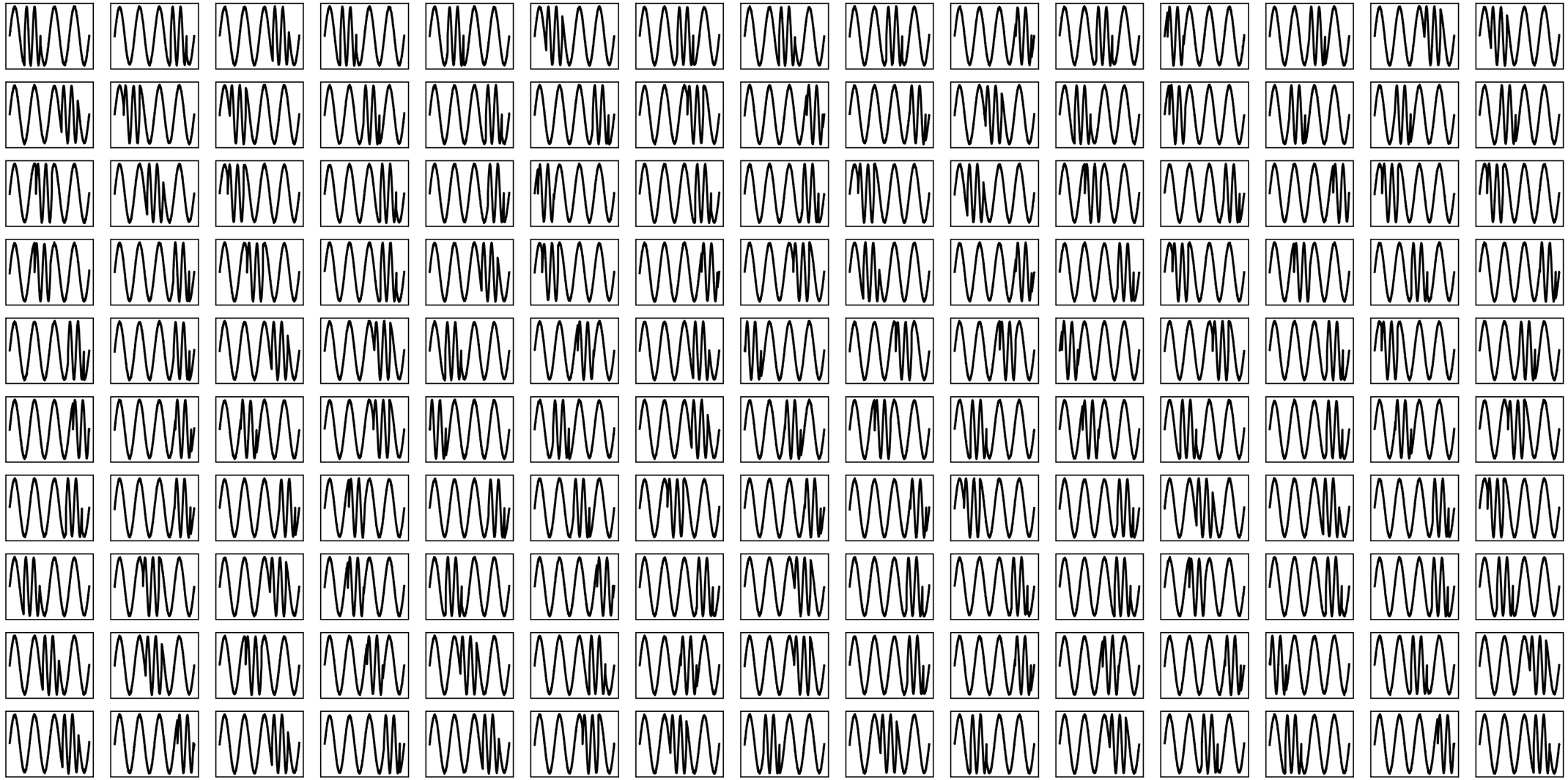
Anomaly Detection

Anomalies in time series (Selection)



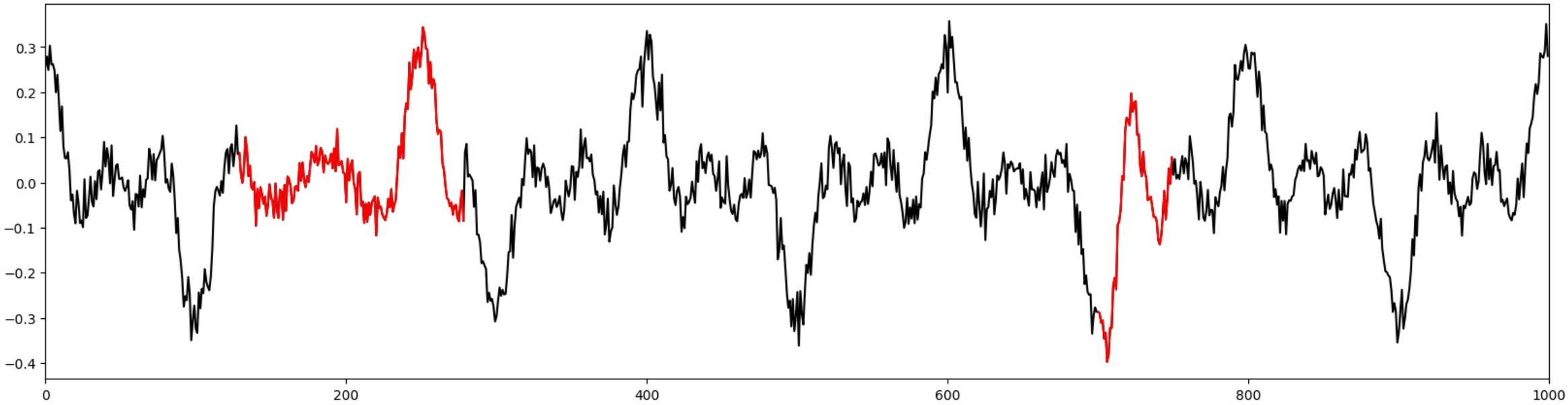
Anomaly = Unexpected Pattern

Check every time series by hand?



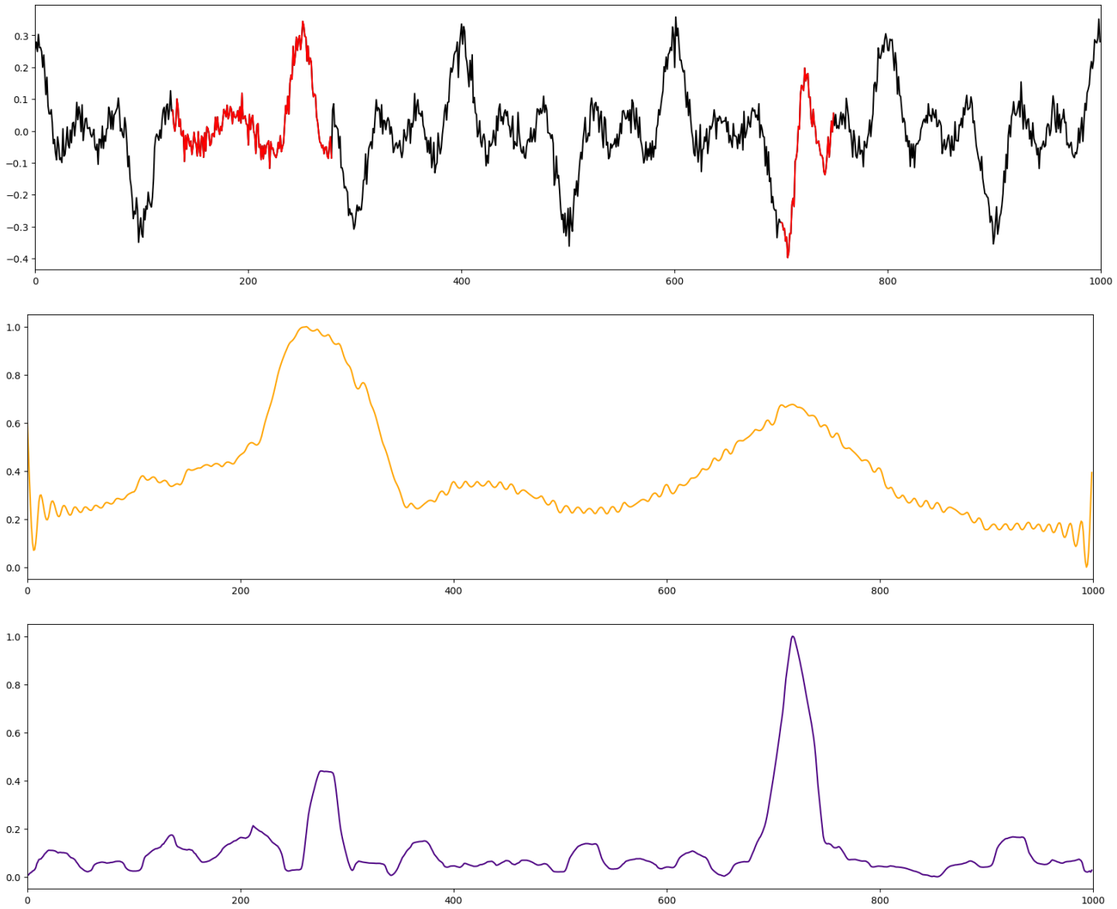
Let algorithms do the work!

We would like to find these anomalies:



Apply unsupervised algorithms = no training required

Unsupervised algorithms produce a scoring



Input Time Series

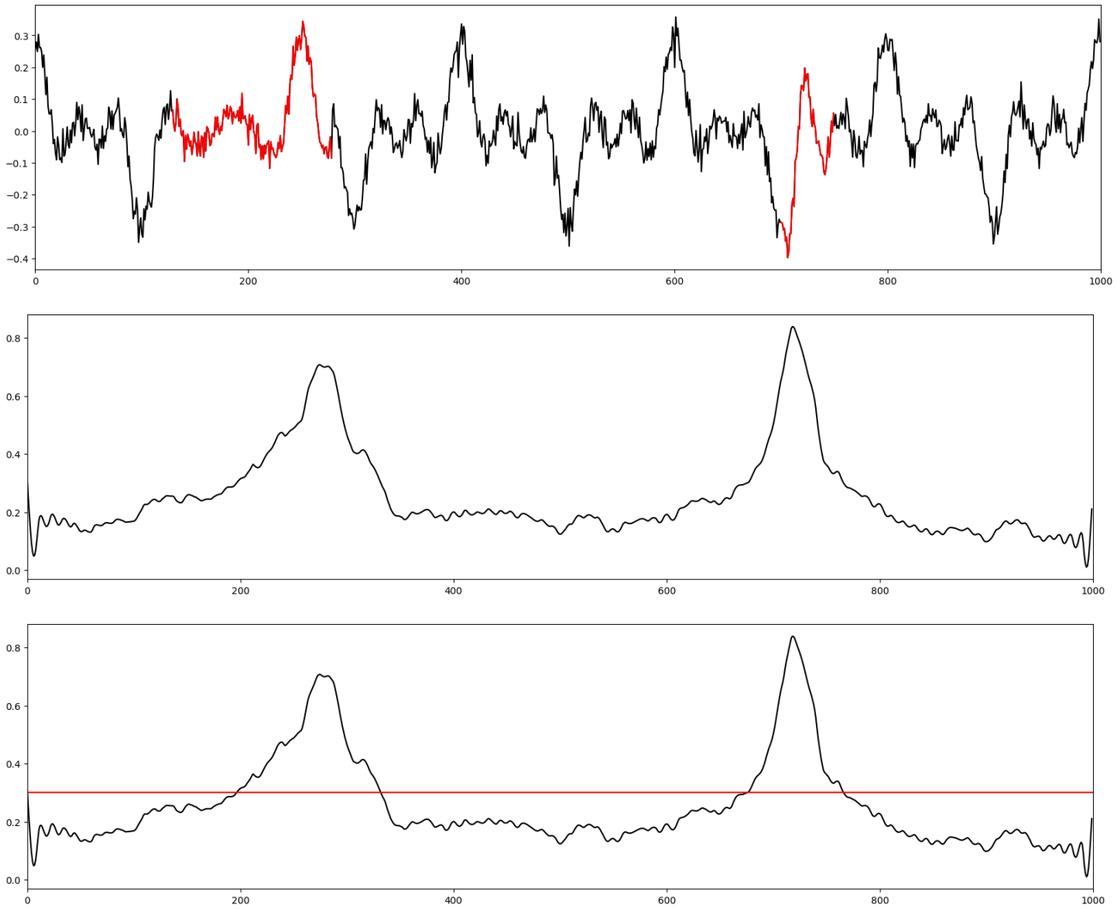
K-Means

Better for first anomaly

Local Outlier Factor

Better for second anomaly

Ensemble to combine strengths



Input Time Series

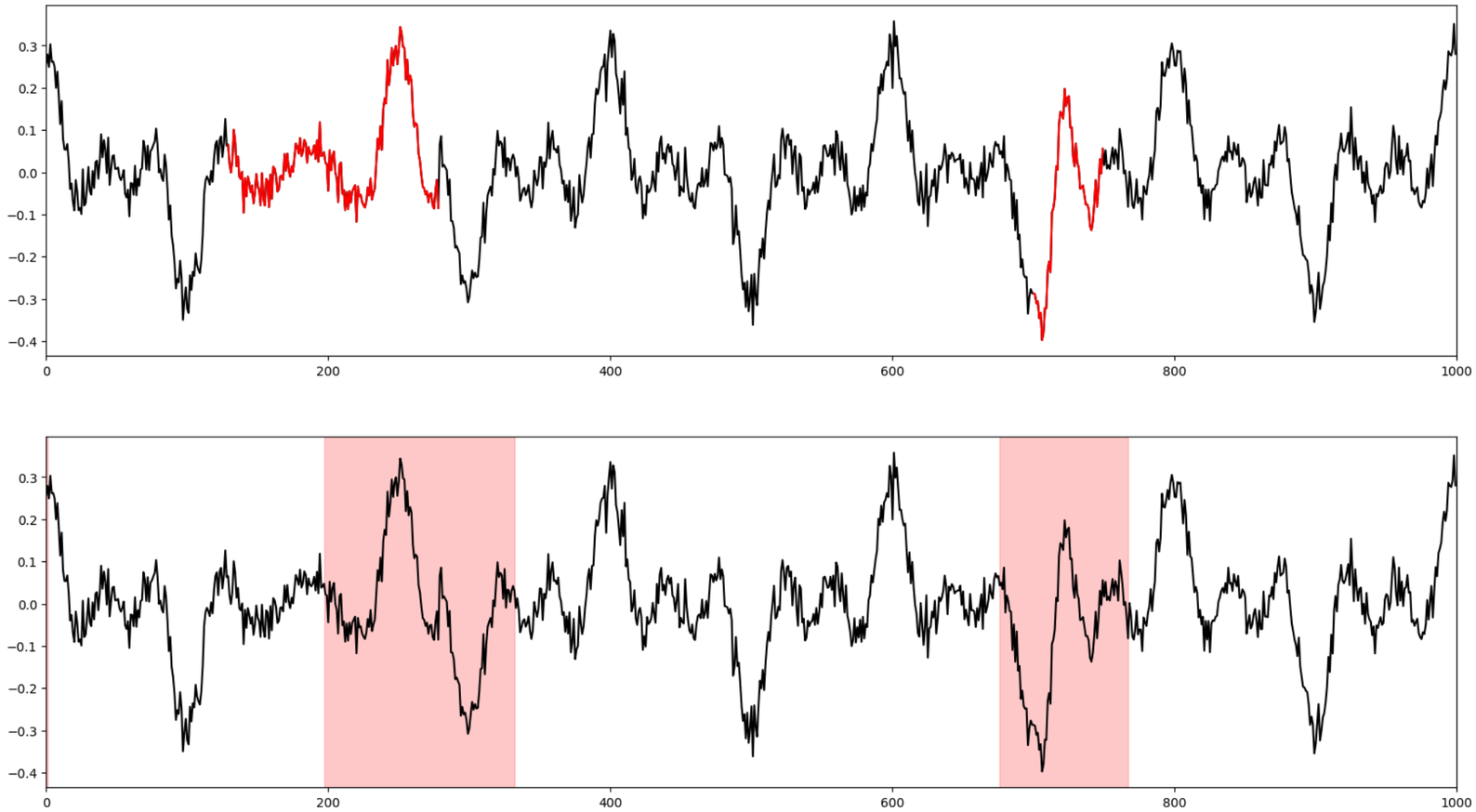
Ensemble

Average of LOF and K-Means

Threshold

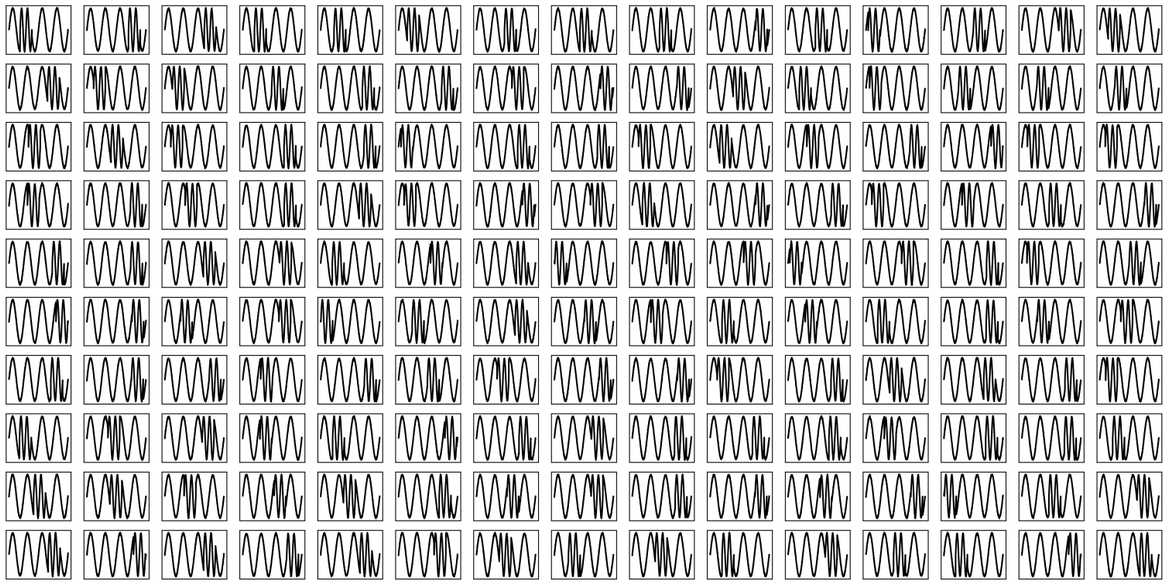
Everything above threshold = anomaly

The Result are Interval Annotations for Anomalies



Not perfect, but close enough

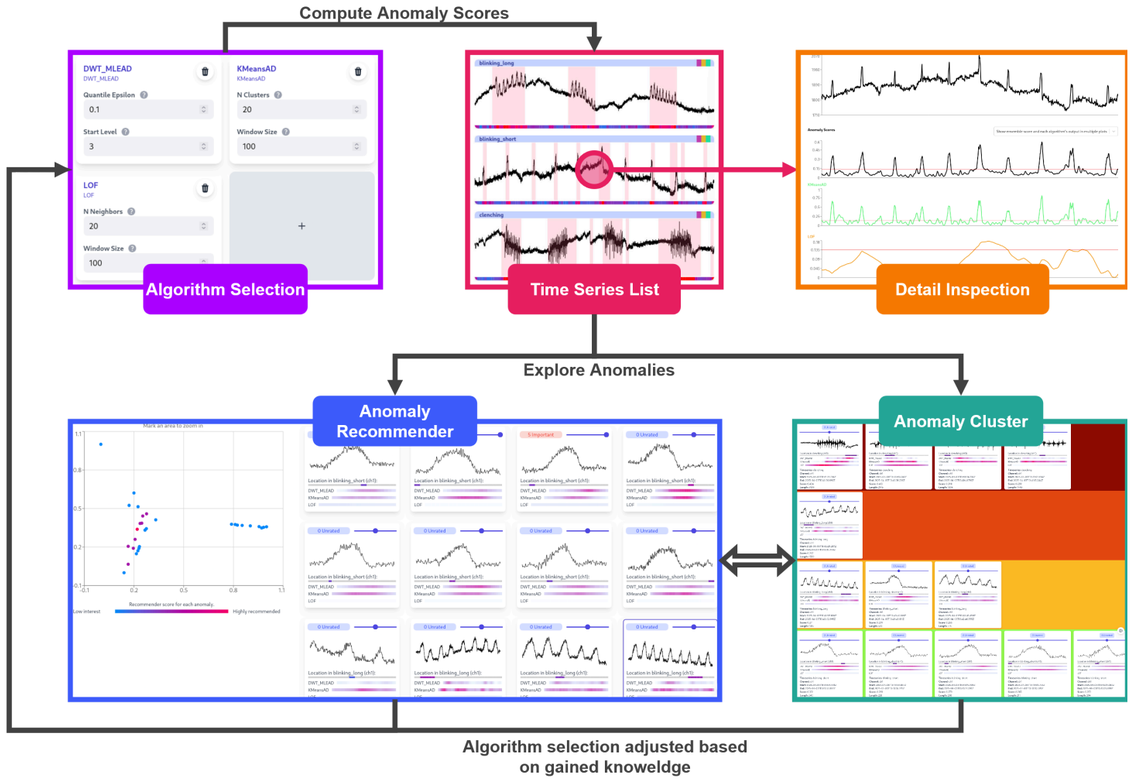
Coming back to this:



We now ask:

1. Which anomalies commonly arise? Can they be categorized?
2. Which strengths and weaknesses do the algorithms exhibit?

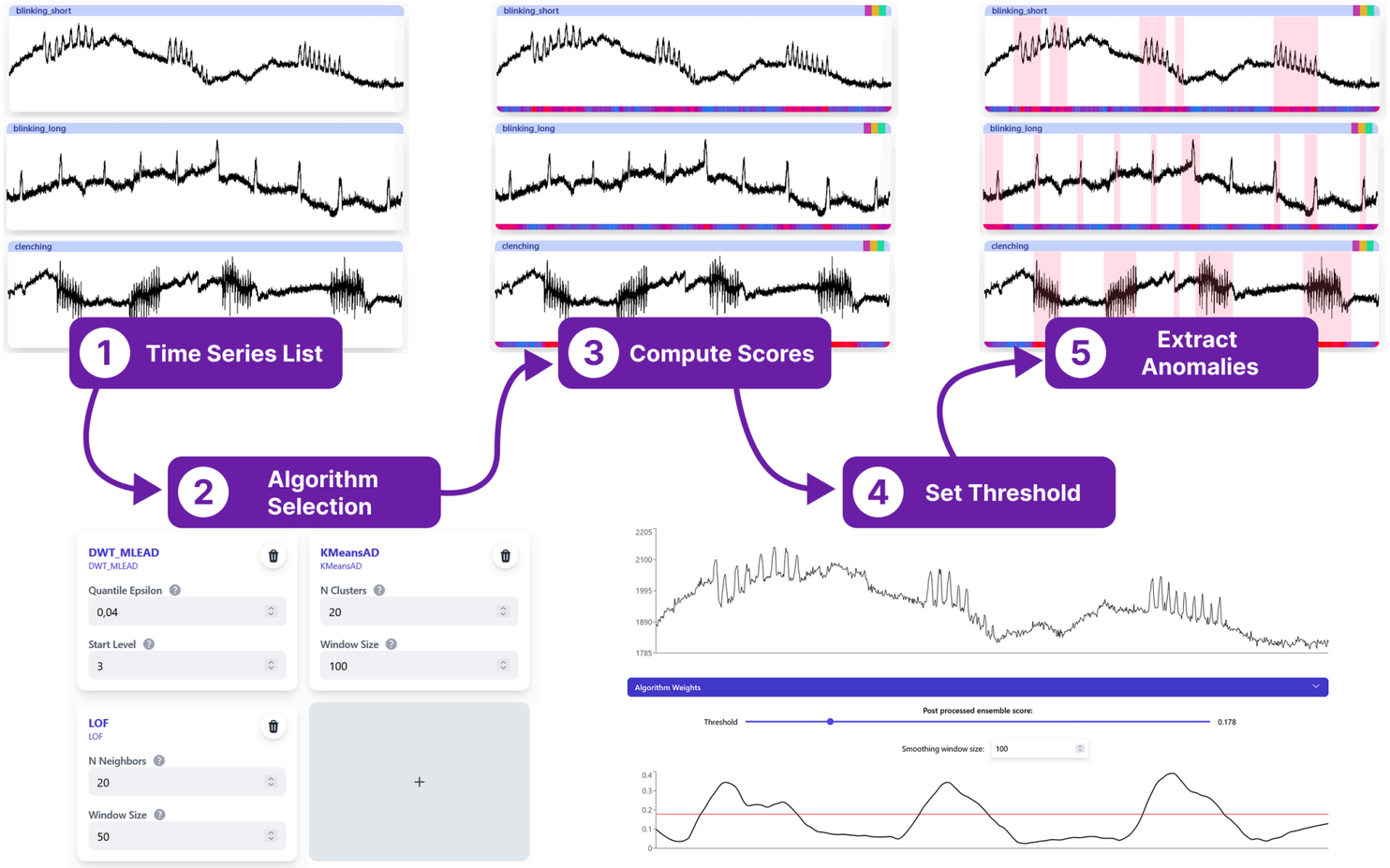
Introducing AnoScout



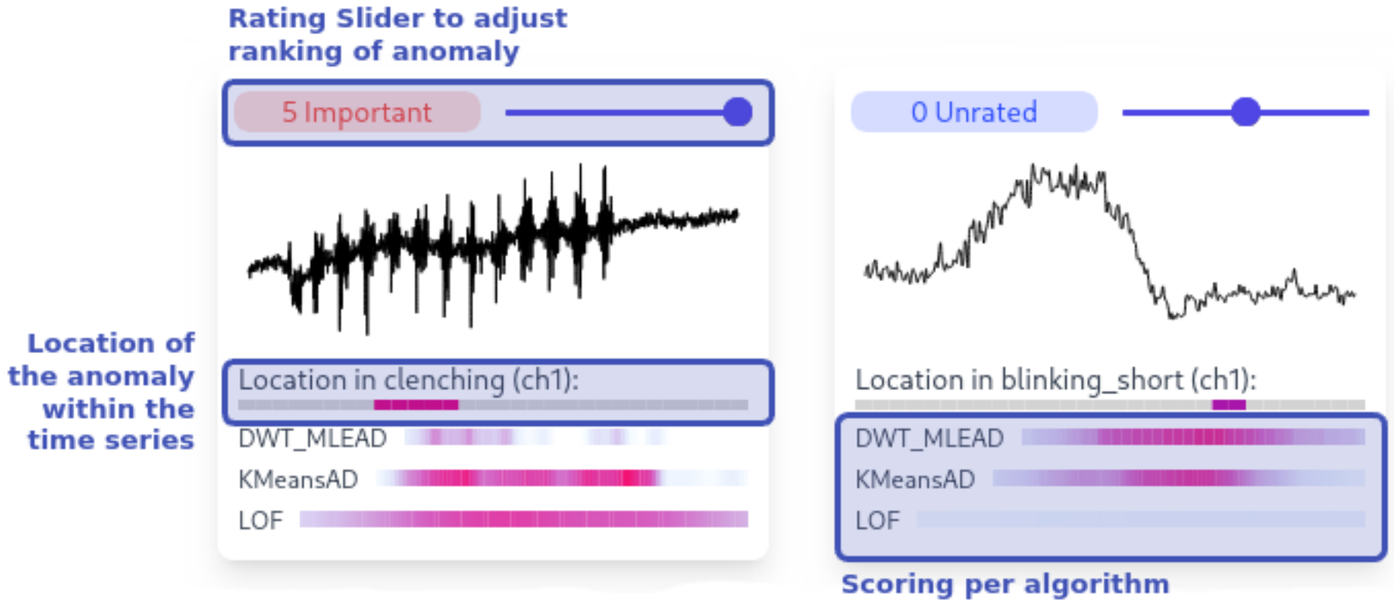
AnoScout = Playground to test anomaly detection algorithms

Our contribution: A workflow to explore anomalies

Extract Anomalies



Each anomaly is represented through a card



Explore Anomalies

Projection Based

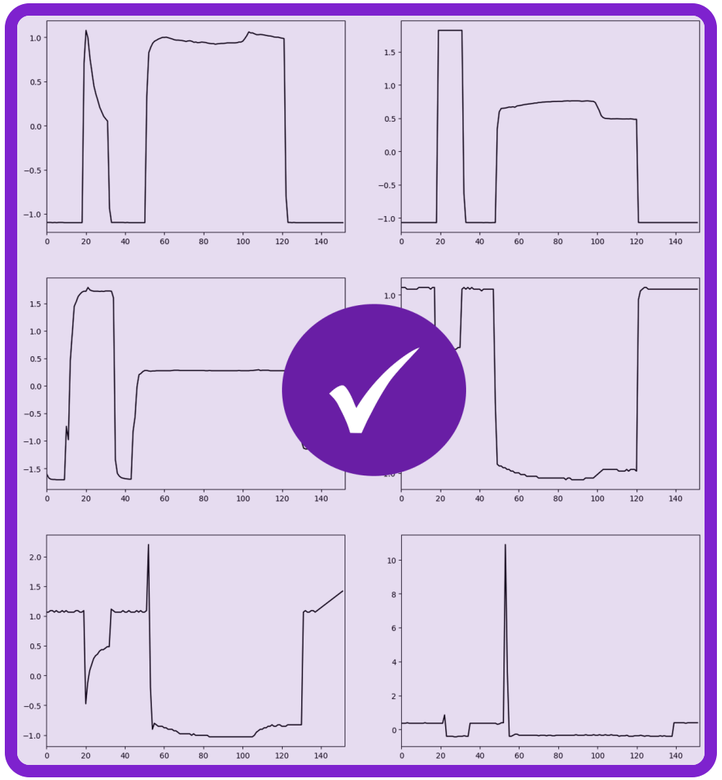
Step 3: Rank Anomalies

This was all unsupervised.

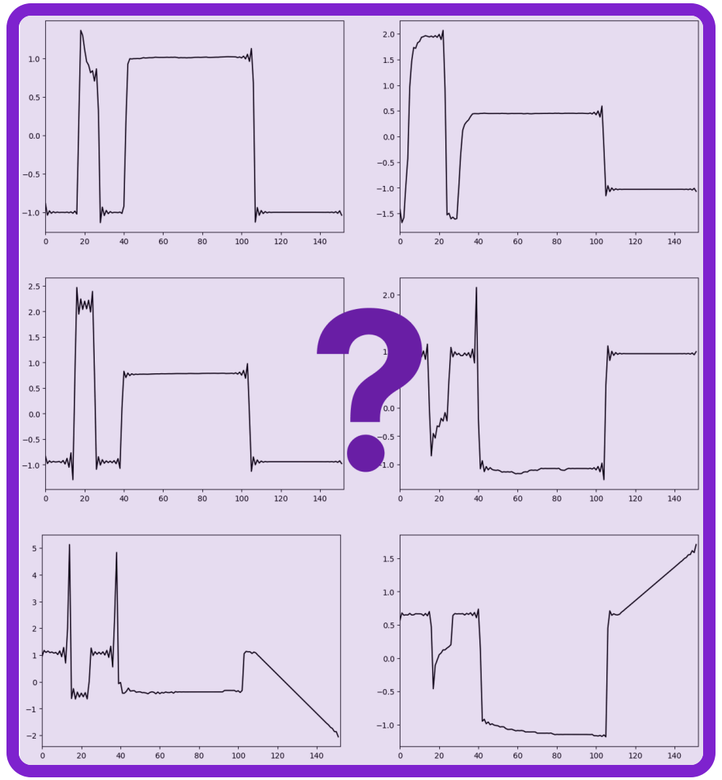
What if I already know the expected behavior?

Scenario: Manufacturing

We know about several types of normal behavior:



But which kind of anomalies can arise?



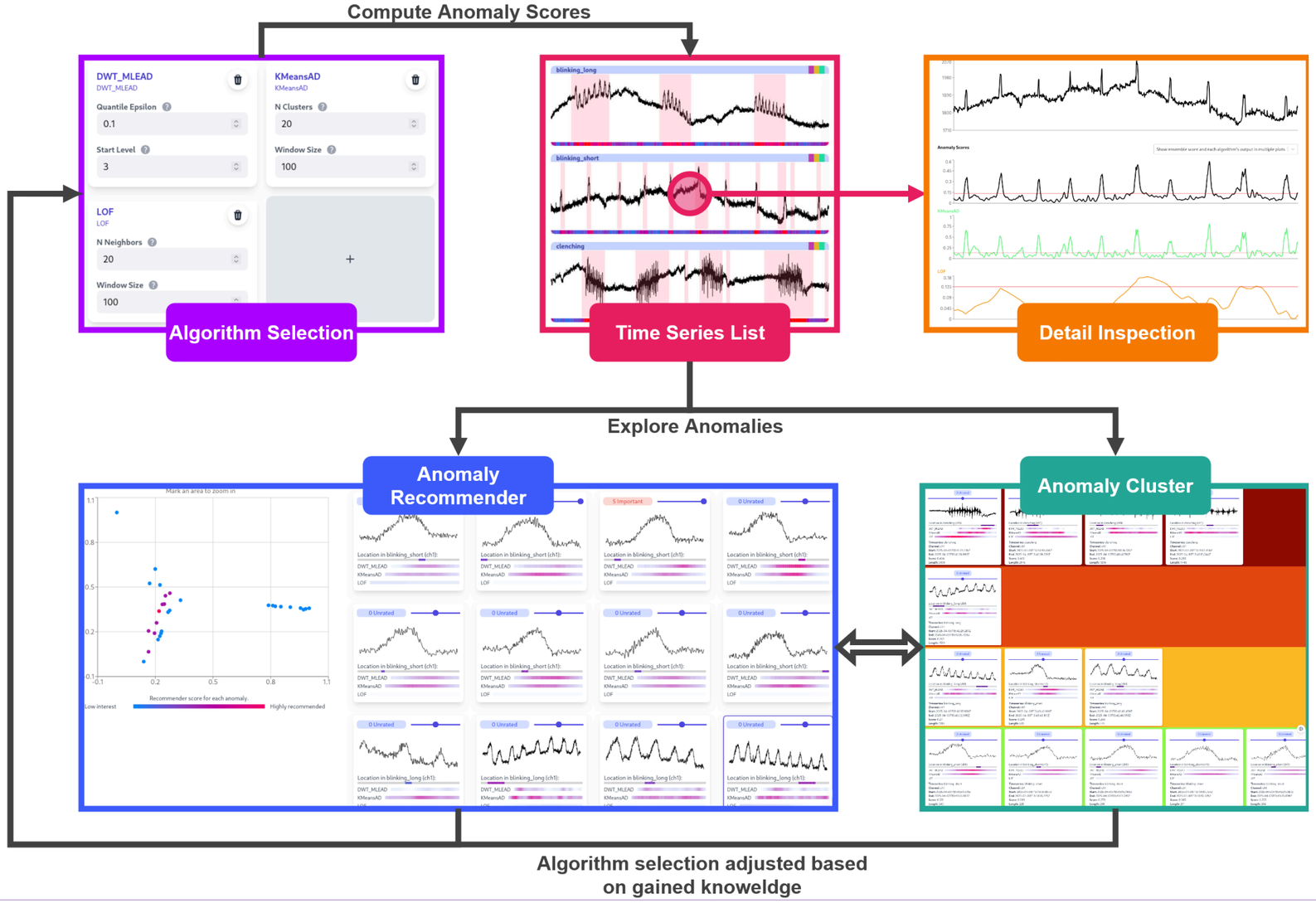
How can we configure a classifier for that?

AnoScout supports configuring a classifier

Explore Anomalies

Cluster Based

Summary


Compute Anomaly Scores
DWT_MLEAD
Quantile Epsilon
0.1
Start Level
3
KMeansAD
N Clusters
20
Window Size
100
LOF
N Neighbors
20
Window Size
100
Algorithm Selection
Time Series List
Detail Inspection
Explore Anomalies
Anomaly Recommender
Anomaly Cluster
Algorithm selection adjusted based on gained knoweldge

Future Work

- Algorithm Parameter Guidance
- Multivariate Time Series
- Progressive Exploring for Large Datasets

Published at VINCI 2025

Coming Soon ...

AnoScout — Visual Exploration of Anomalies and Anomaly Detection Algorithm Ensembles in Time Series Data

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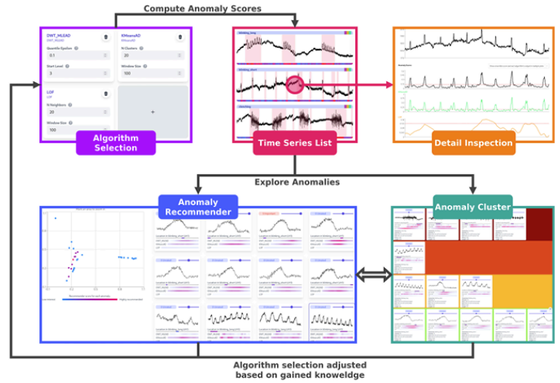


Figure 1: The workflow conceptualization structures the process of gaining insights into the diversity of anomalies in time series data. The core components of AnoScout implement this workflow to help users identify which algorithms perform appropriately for each anomaly pattern. Users first define a set of algorithms in the Algorithm Selection component. Afterwards, each algorithm computes an anomaly scoring per time series, which is visualized as the ensemble of all algorithms in the Time Series List view. The ensemble can be inspected for each time series in the Detail Inspection component. Finally, users explore anomaly pattern groups in the Anomaly Cluster view and may utilize the Anomaly Recommender to filter for specific anomaly patterns.

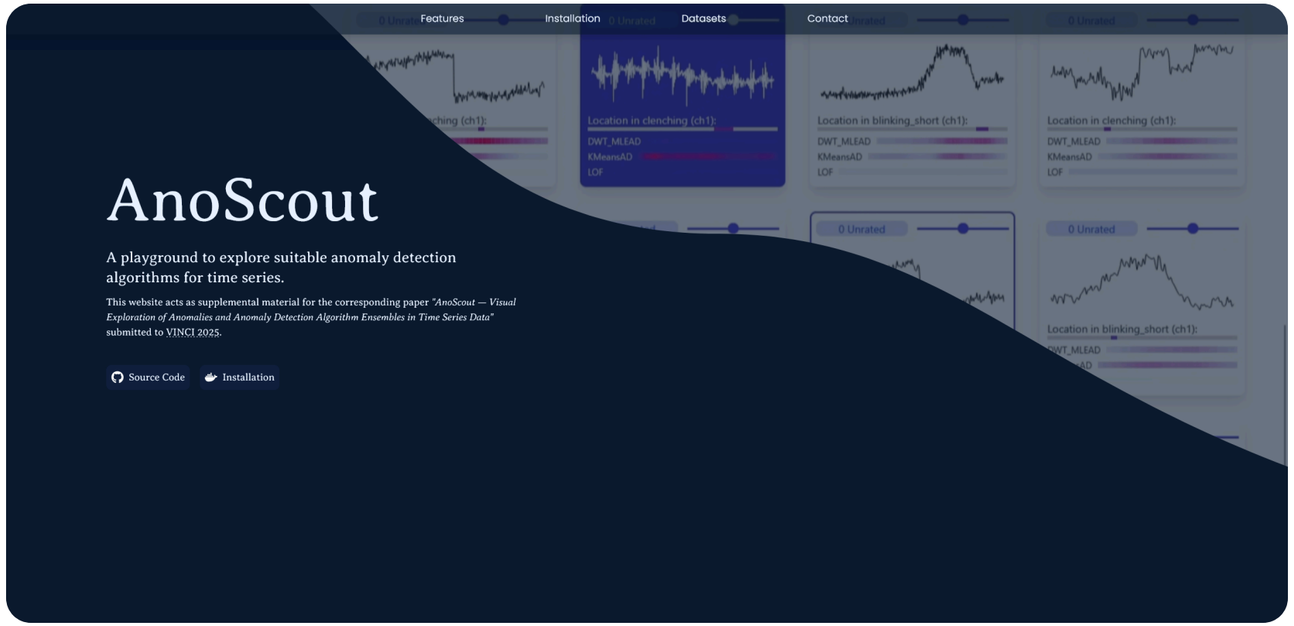
VINCI 2025, Linz, Austria

ACM ISBN 979-8-4007-1845-8/25/12
https://doi.org/10.1145/3769534.3769577

Abstract

With the growing abundance of time series data and anomaly detection algorithms, selecting appropriate algorithm configurations for a given dataset has become increasingly complex. We introduce *AnoScout*, a Visual Analytics approach to explore anomalies

Open Source with Docker Setup



Danke!

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Slides: