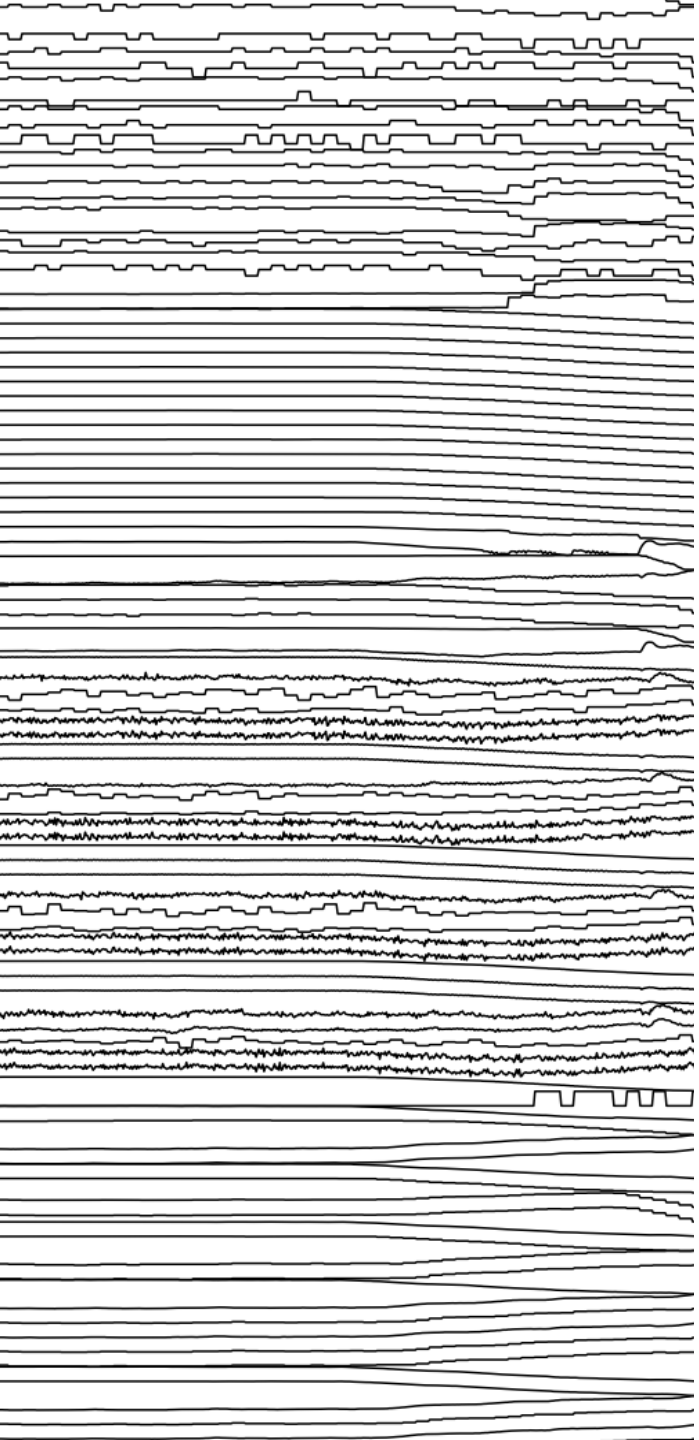

Time-Series Anomaly Detection: Overview and New Trends

Qinghua Liu
The Ohio State University
liu.11085@osu.edu

Paul Boniol
Inria, ENS, PSL University
paul.boniol@inria.fr

Themis Palpanas
Université Paris Cité; IUF
themis@mi.parisdescartes.fr

John Paparrizos
The Ohio State University
paparrizos.1@osu.edu

Inria

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Introduction: *Time series are Everywhere*

Energy Production

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Astrophysics

Virgo: https://www.virgo-gw.eu/

Medicine

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Volcanology

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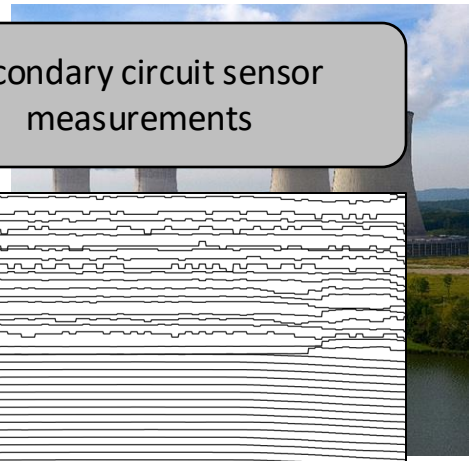

Secondary circuit sensor measurements

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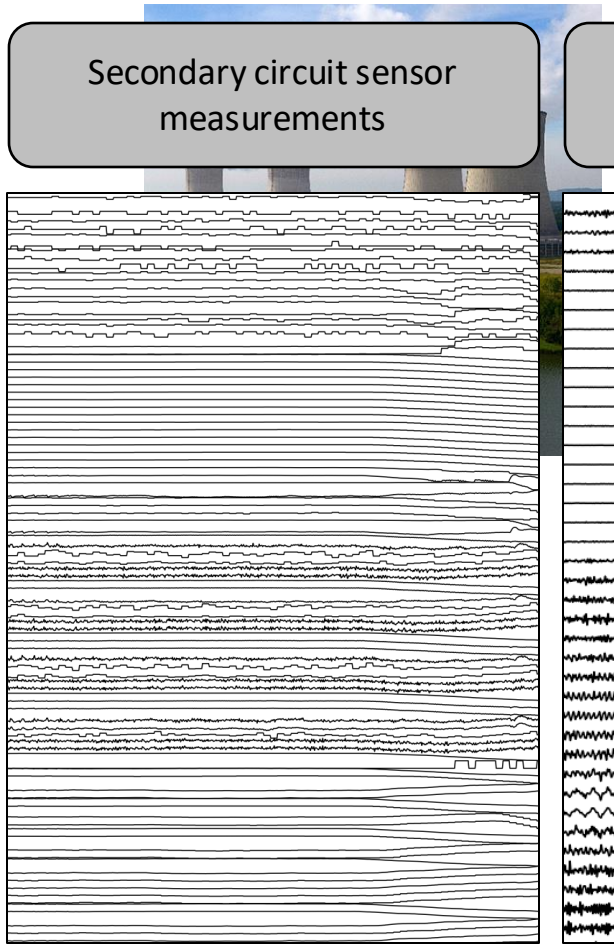

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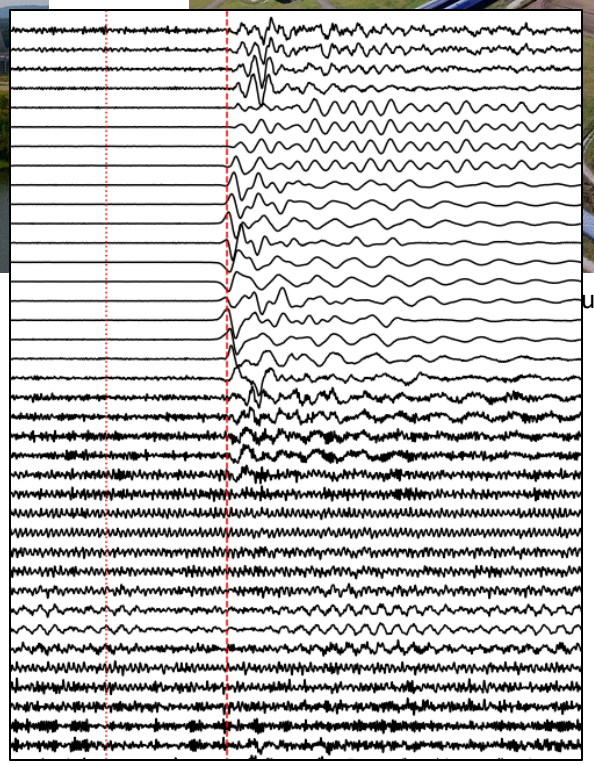
Fiber-acoustic sensors in the VIRGO north building



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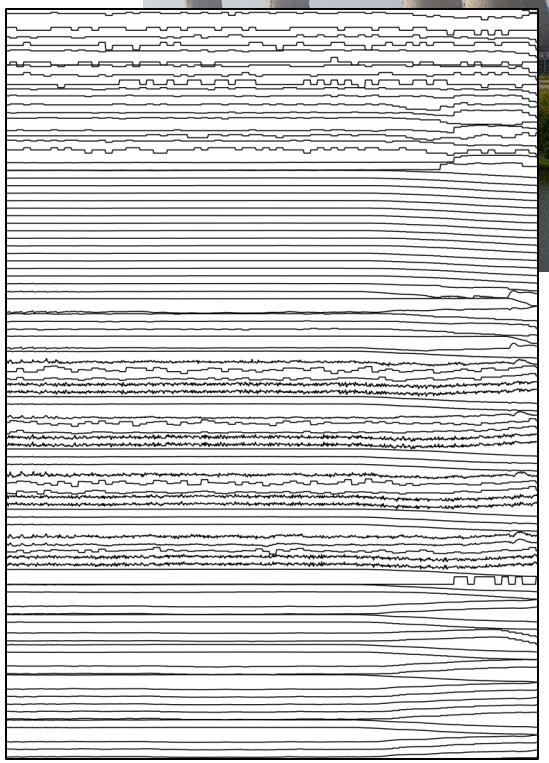

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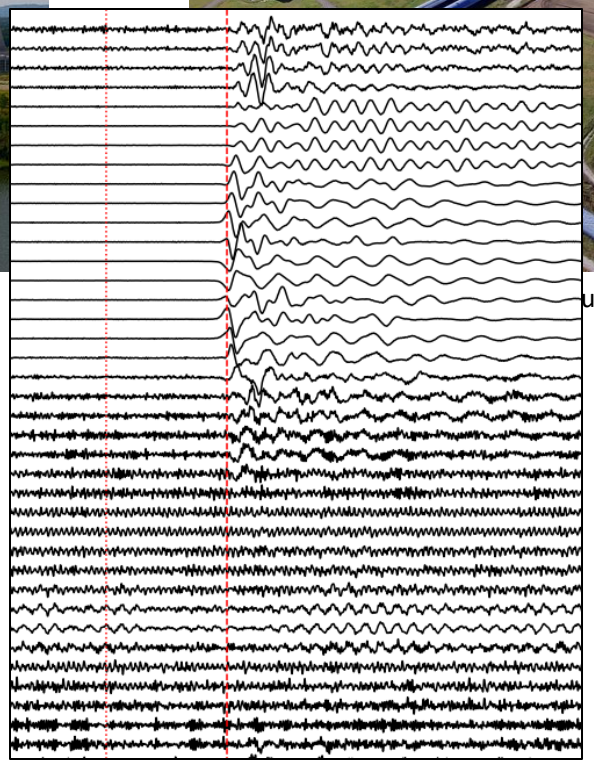

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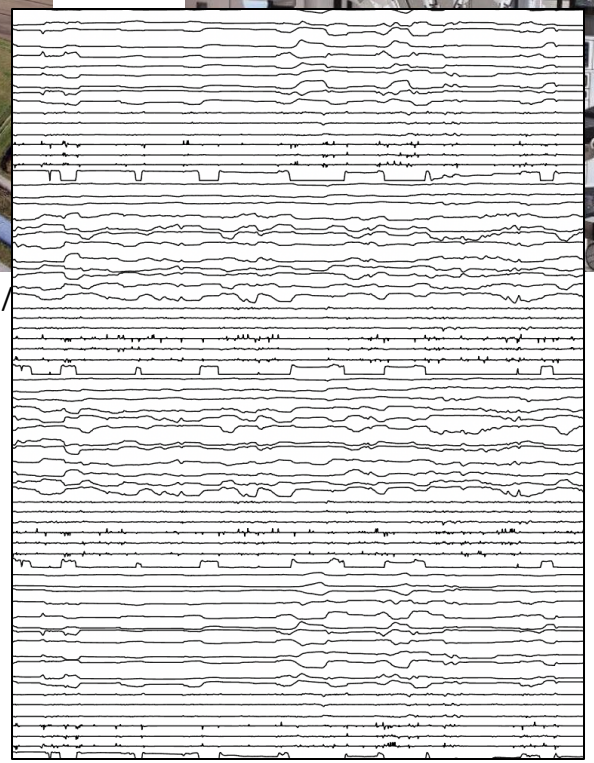
Sensor measurements of the Da-Vinci surgery robot



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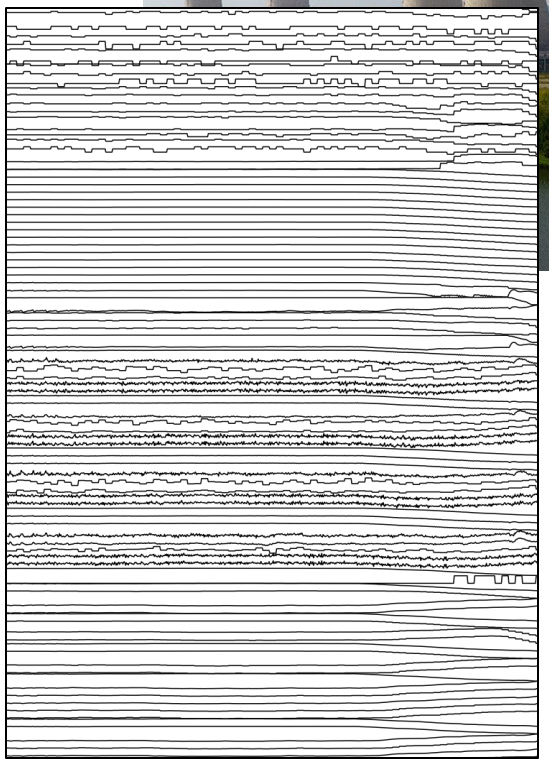

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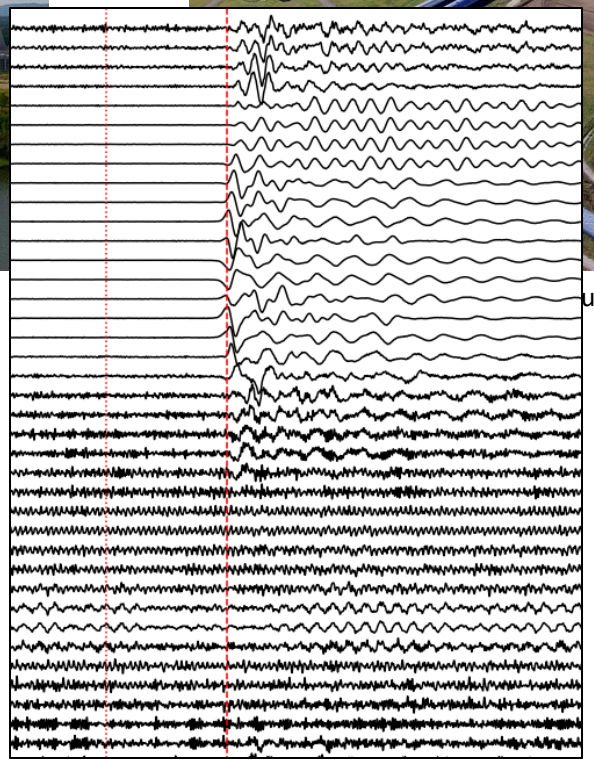

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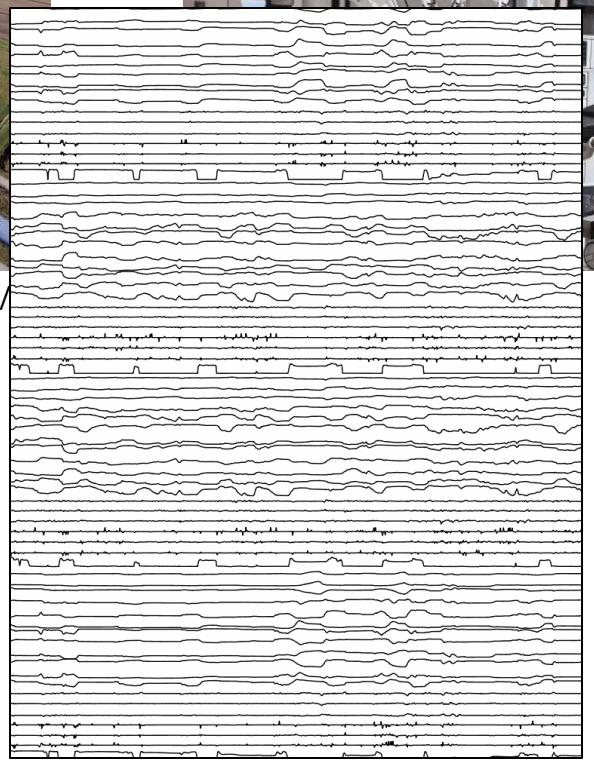
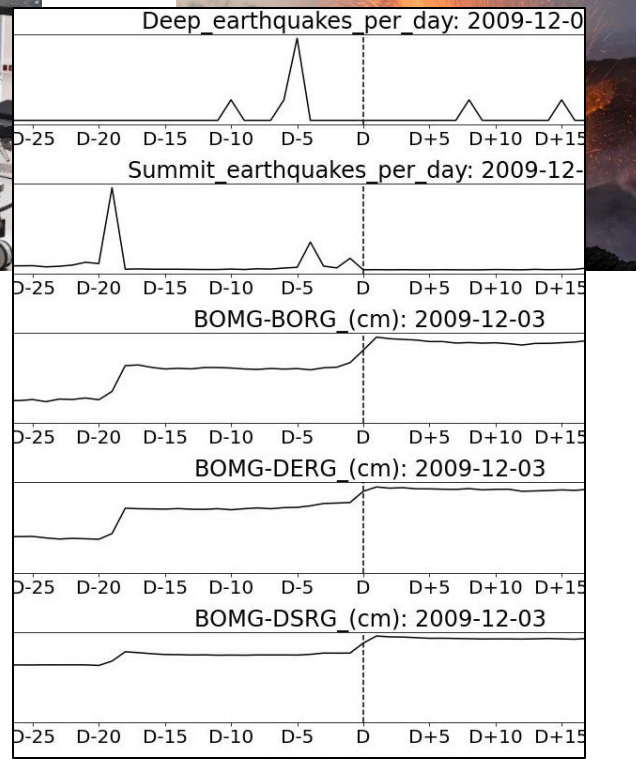


Volcanology

Sensor measurements on le Piton de la Fournaise



Introduction: *with Important Challenges*

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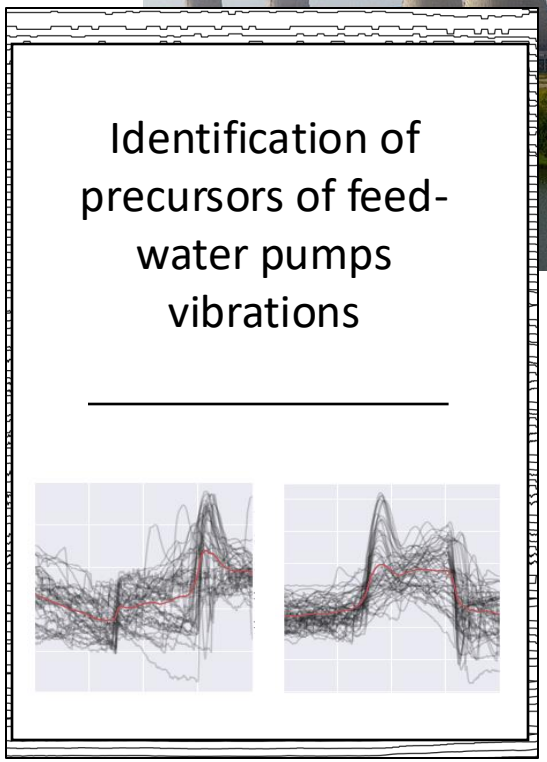

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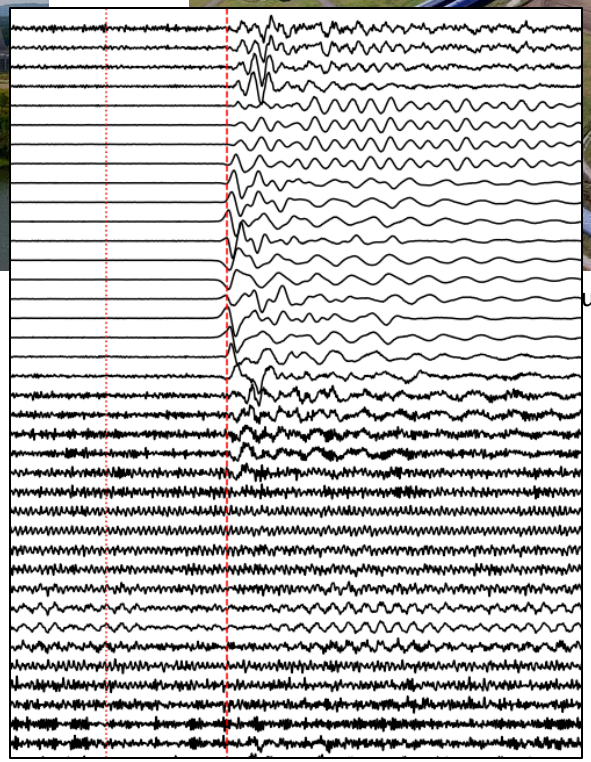

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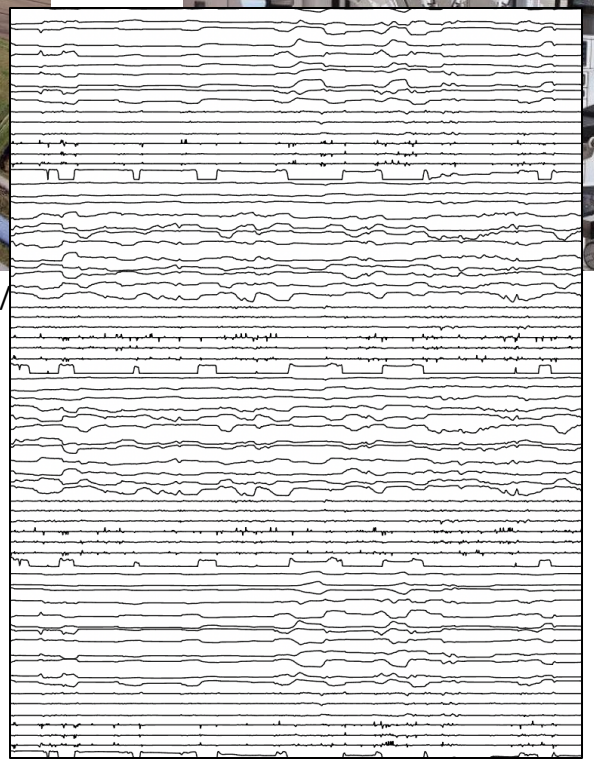

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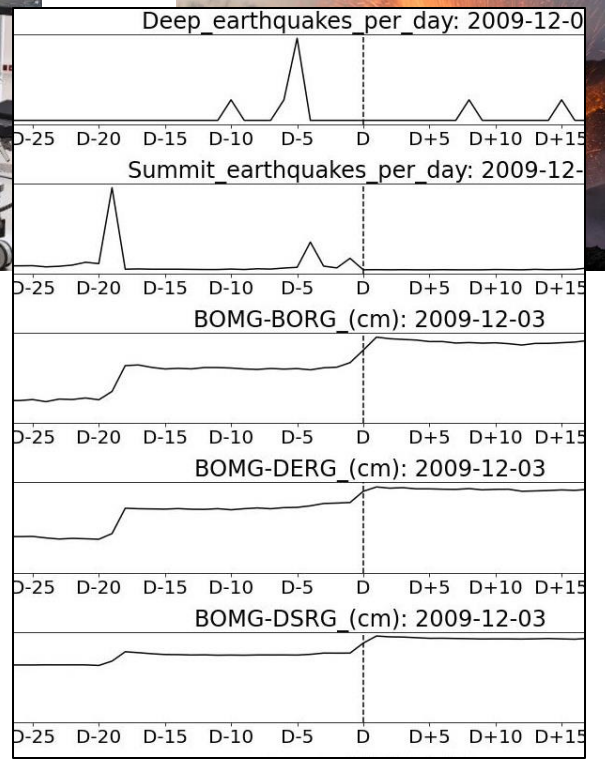
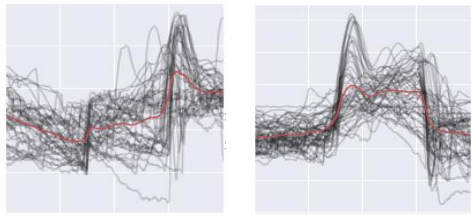


Introduction: *with Important Challenges*

Energy Production

Secondary circuit sensor measurements

Identification of precursors of feed-water pumps vibrations



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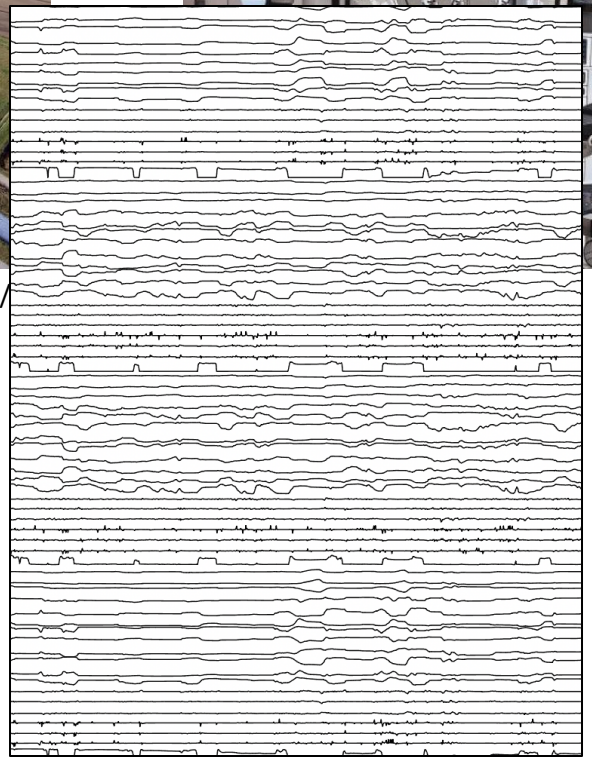

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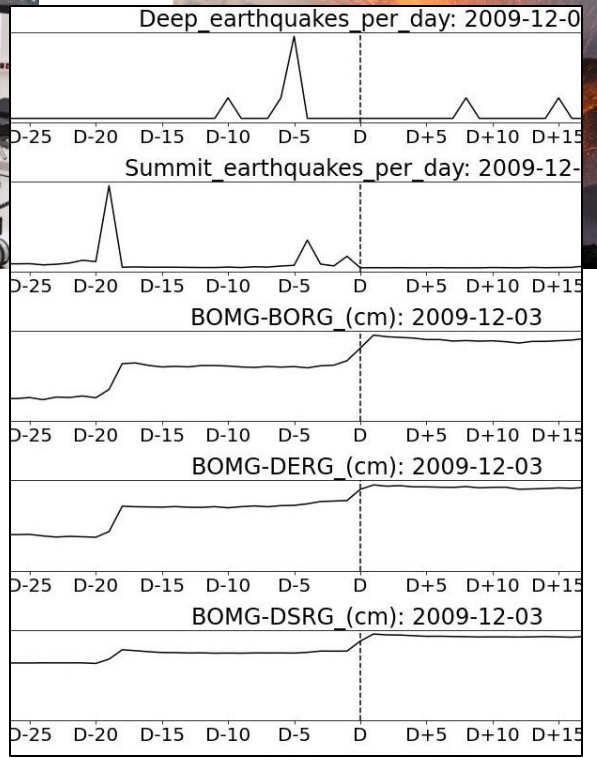

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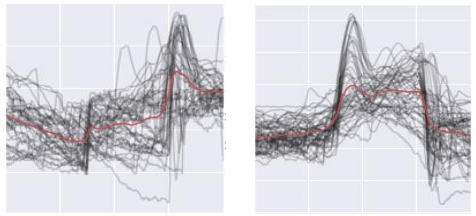

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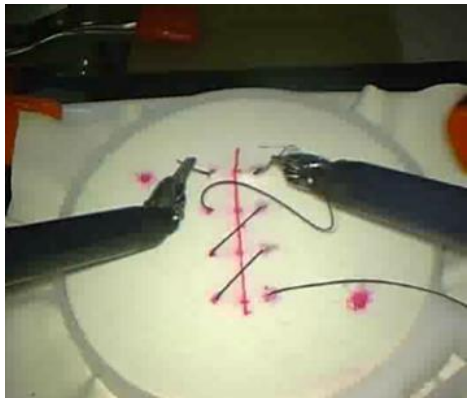

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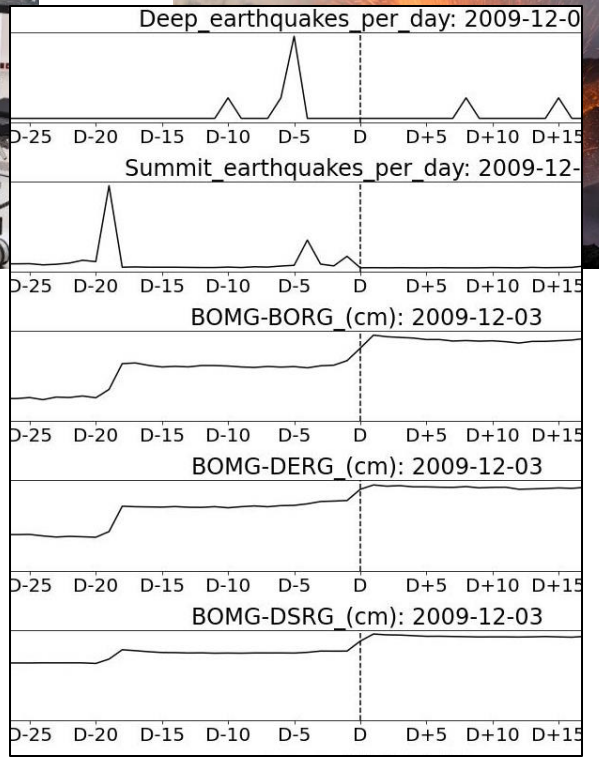

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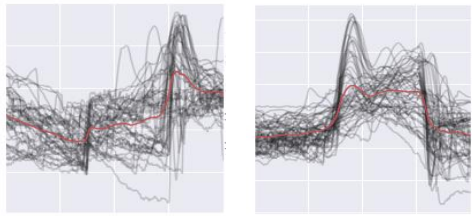

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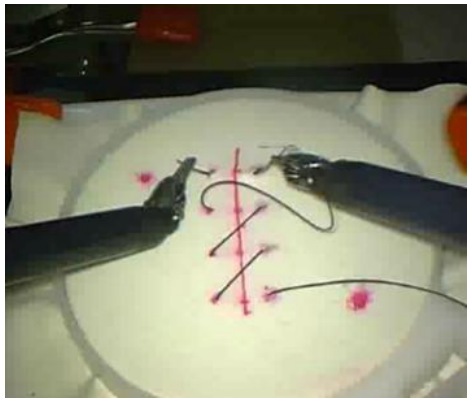

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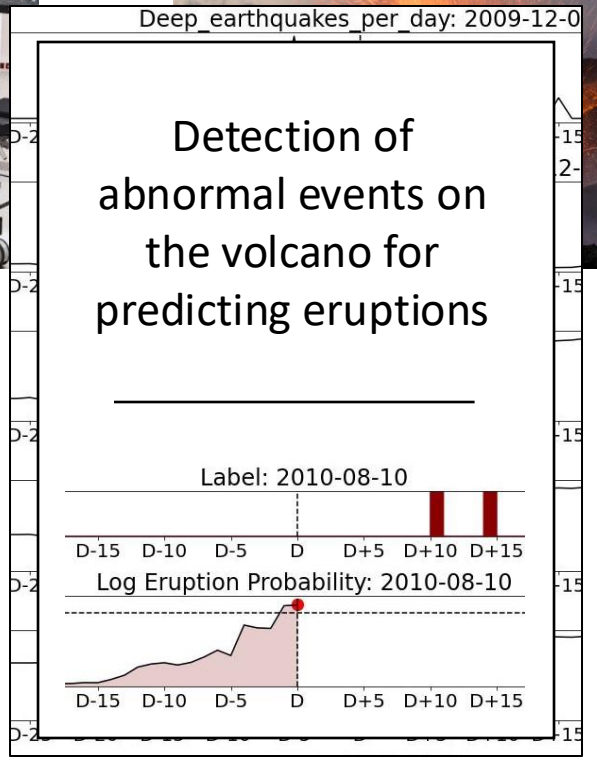
Sensor measurements on le Piton de la Fournaise

Detection of abnormal events on the volcano for predicting eruptions



Introduction: *with Important Challenges*

Large-scale time series database

Energy Production

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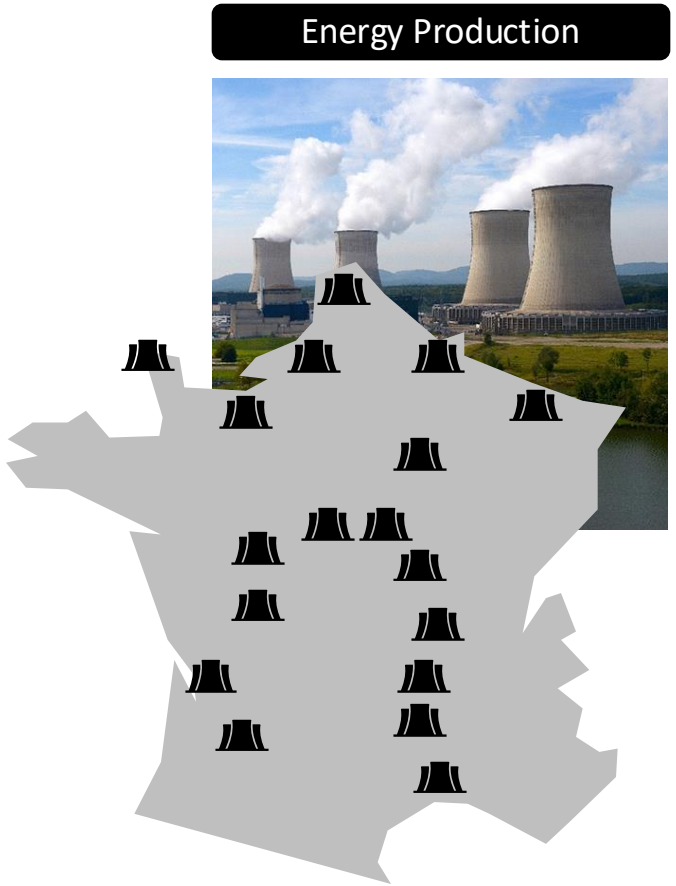
Large-scale time series database



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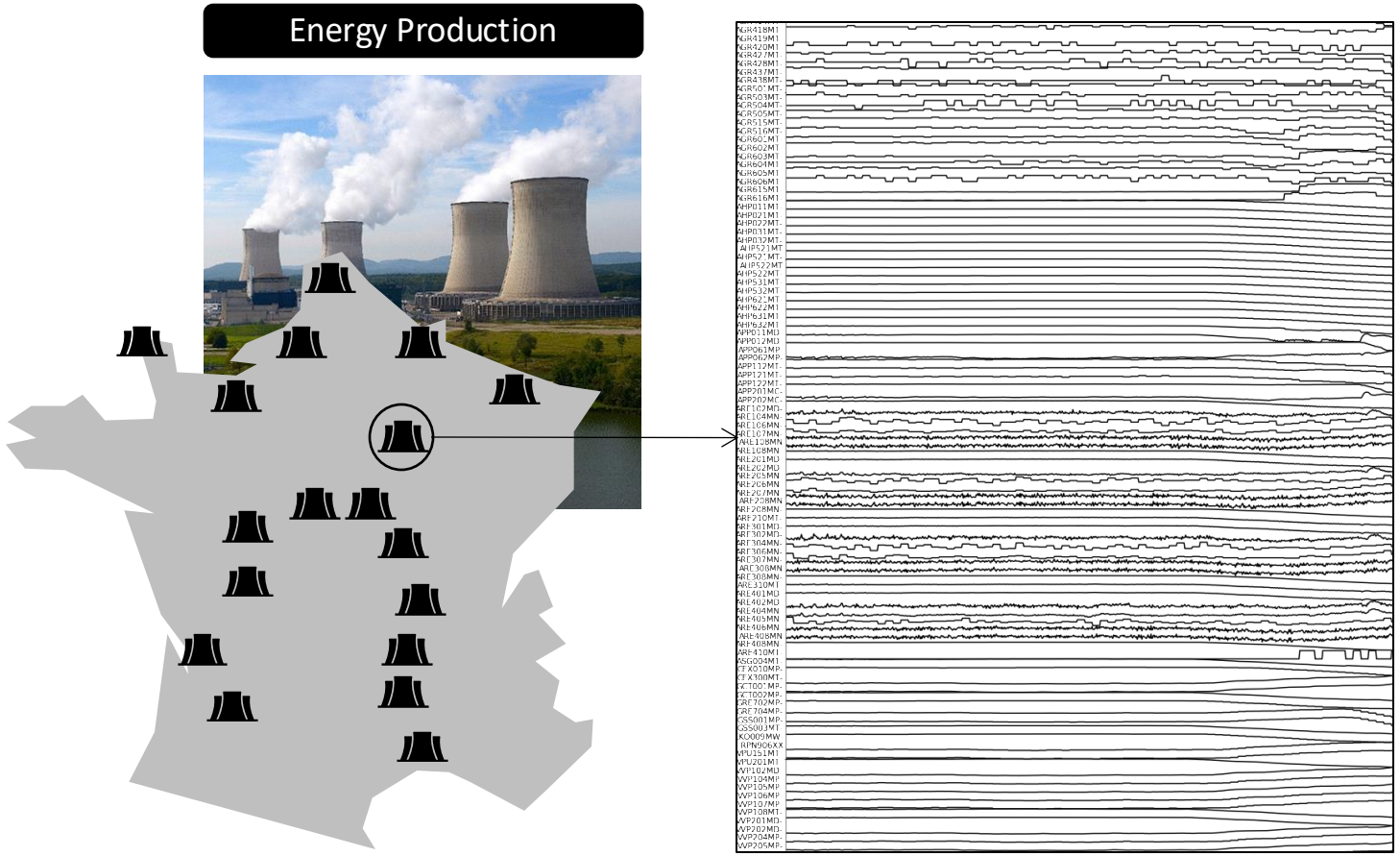
Example of Nuclear production

- 58 nuclear power plants across France

Introduction: *with Important Challenges*

Large-scale time series database



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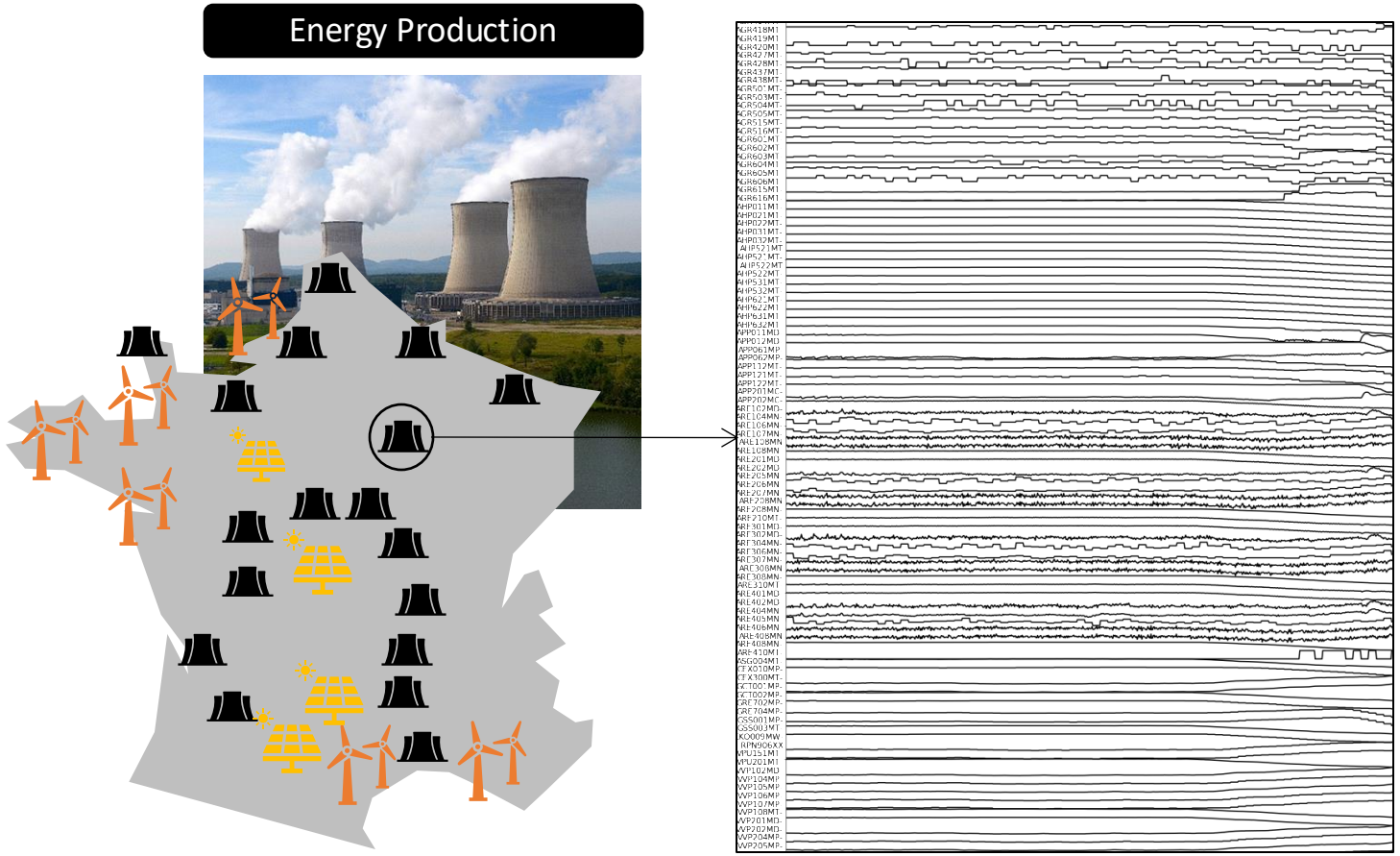
Example of Nuclear production

- 58 nuclear power plants across France
- 2000+ sensors per power plant
- 30 years of data collections

A total of 1.5 PetaBytes

Introduction: *with Important Challenges*

Large-scale time series database



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Example of Nuclear production

- 58 nuclear power plants across France
- 2000+ sensors per power plant
- 30 years of data collections

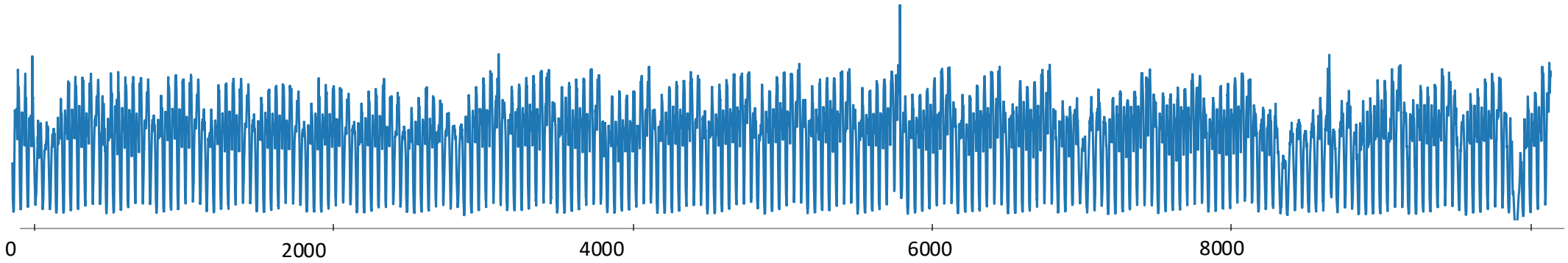
A total of 1.5 PetaBytes

Other source of production

- New sensors with higher acquisition rate

Introduction: *Anomaly Detection in Time Series*

- Time series T *(example : number of taxi passengers in New York City)*



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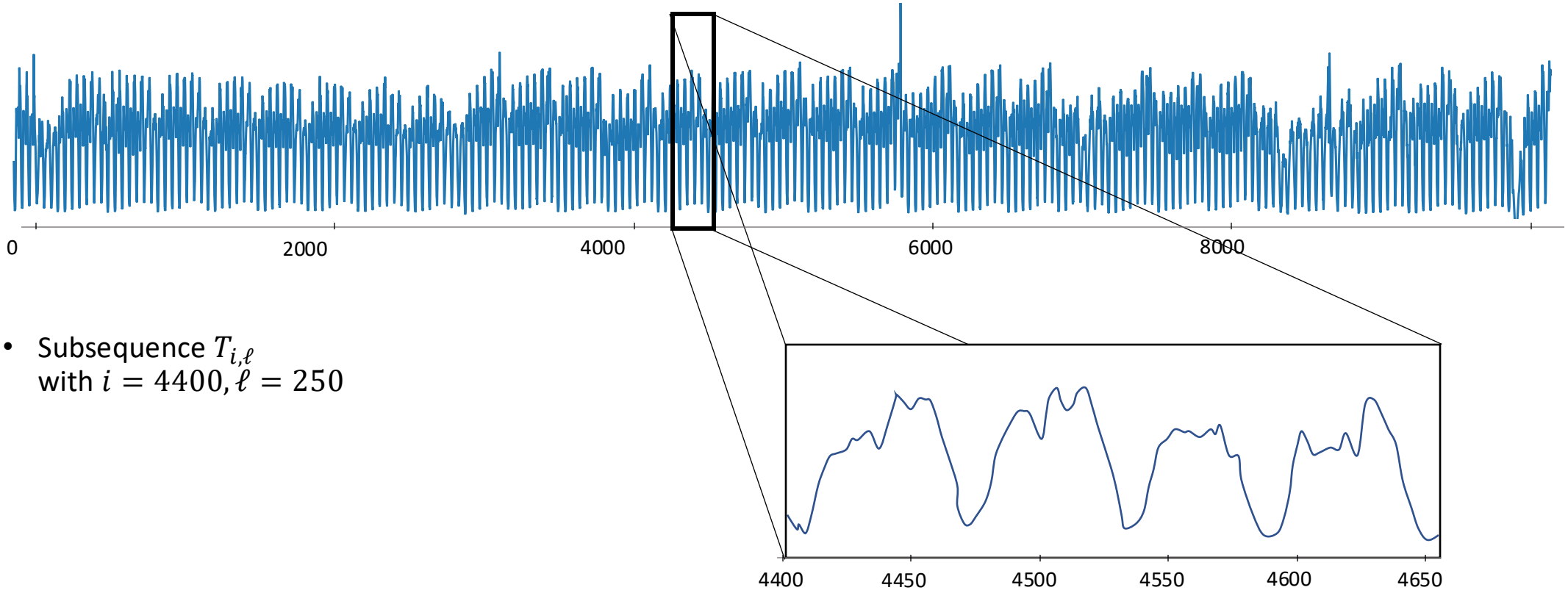

- Subsequence $T_{i,\ell}$ with $i = 4400, \ell = 250$

Introduction: *Anomaly Detection in Time Series*

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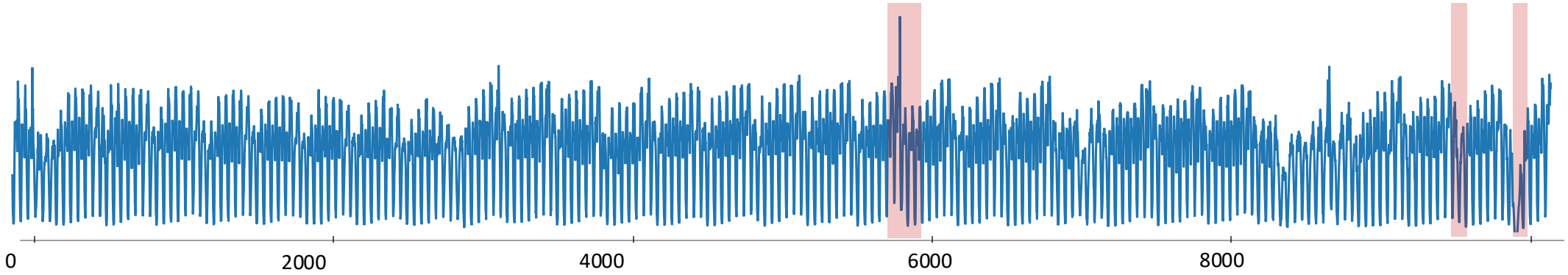

- *Anomaly: rare point or sequence (of a given length) potentially non-desired*

Introduction: *Anomaly Detection in Time Series*

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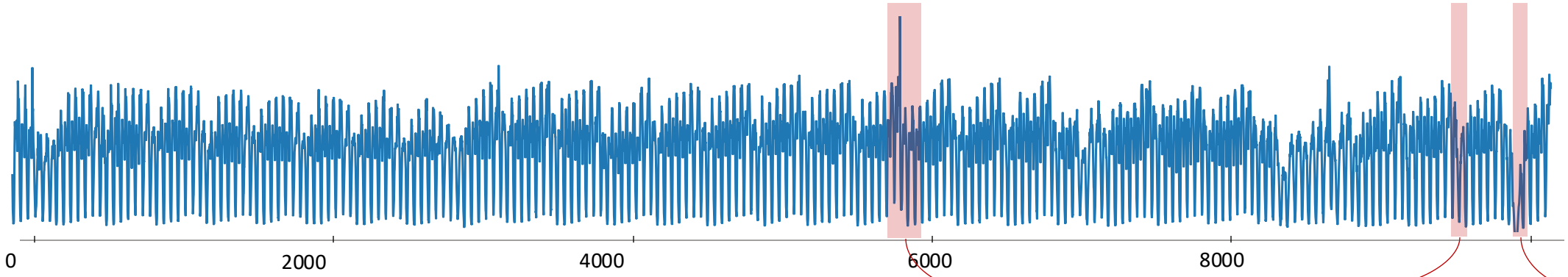

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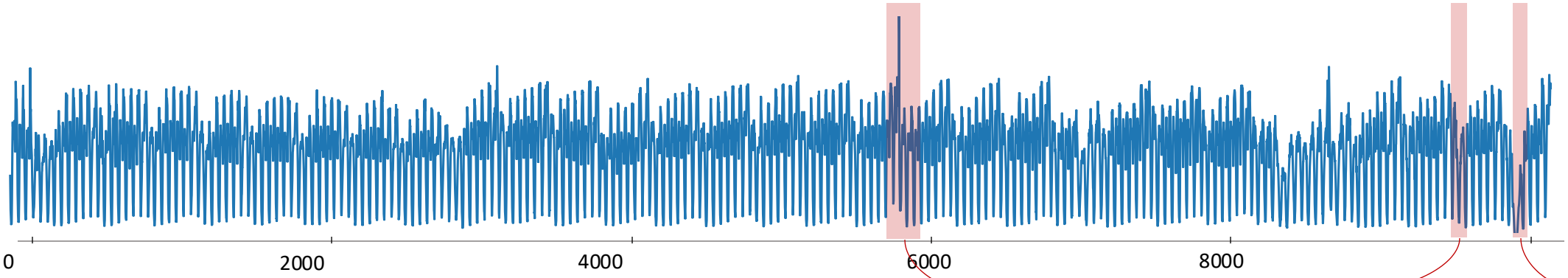

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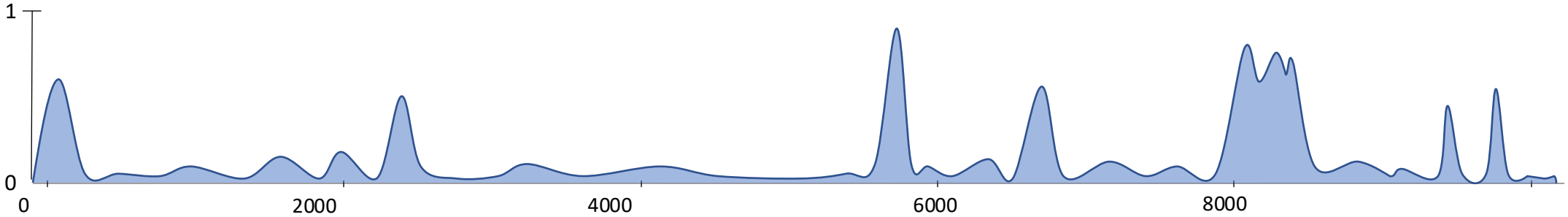
Daylight Saving Time (DST)

Flooding

Snowstorm



Anomaly score S_T

Introduction: *Anomaly Detection in Time Series*

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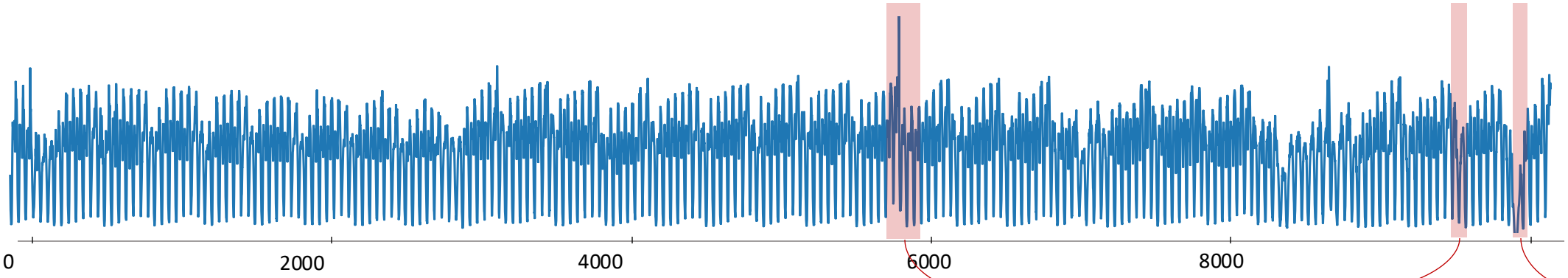

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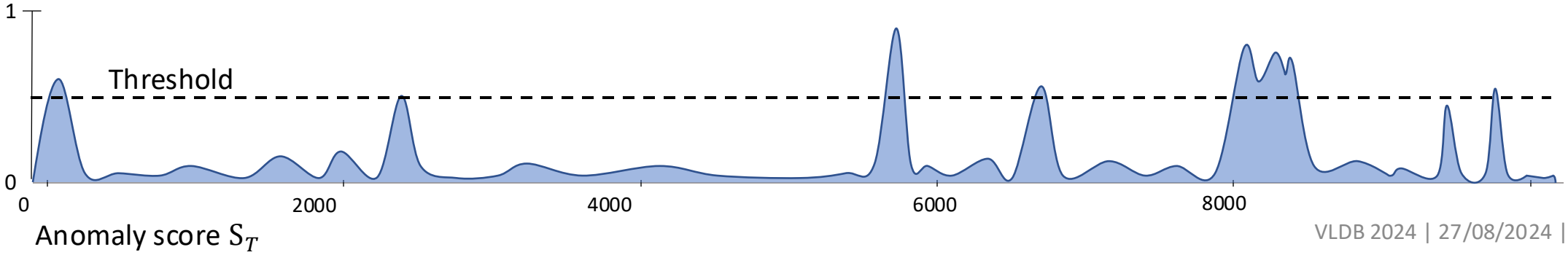

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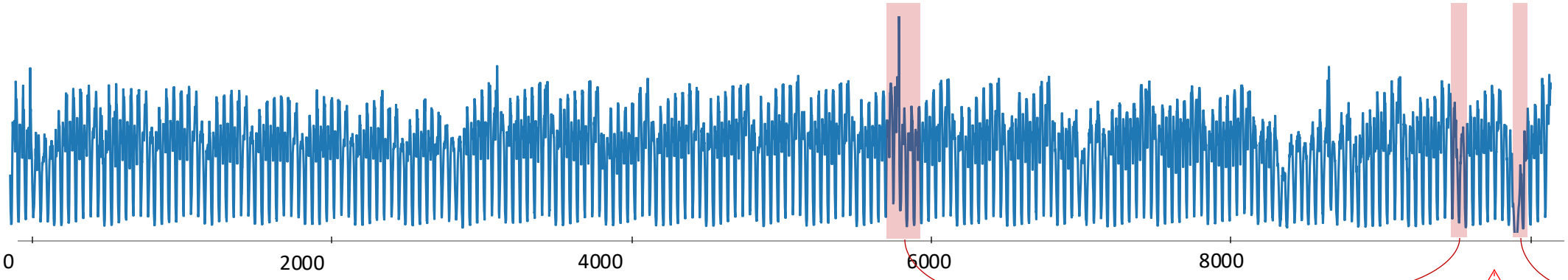

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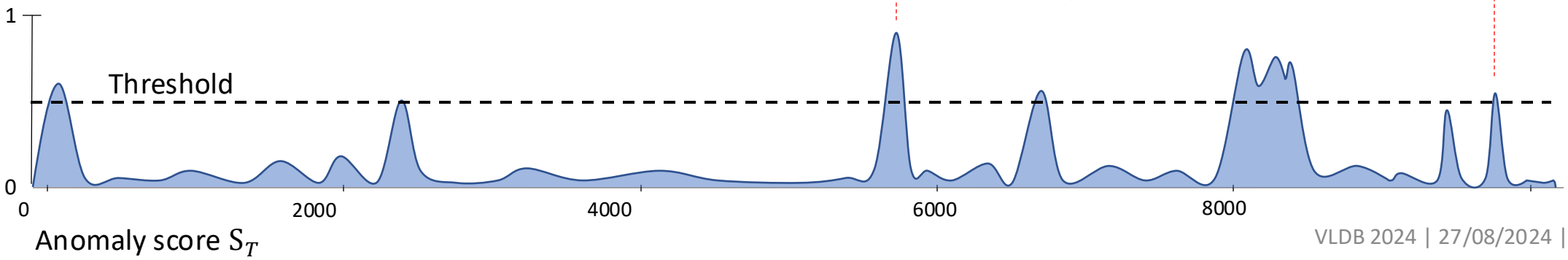
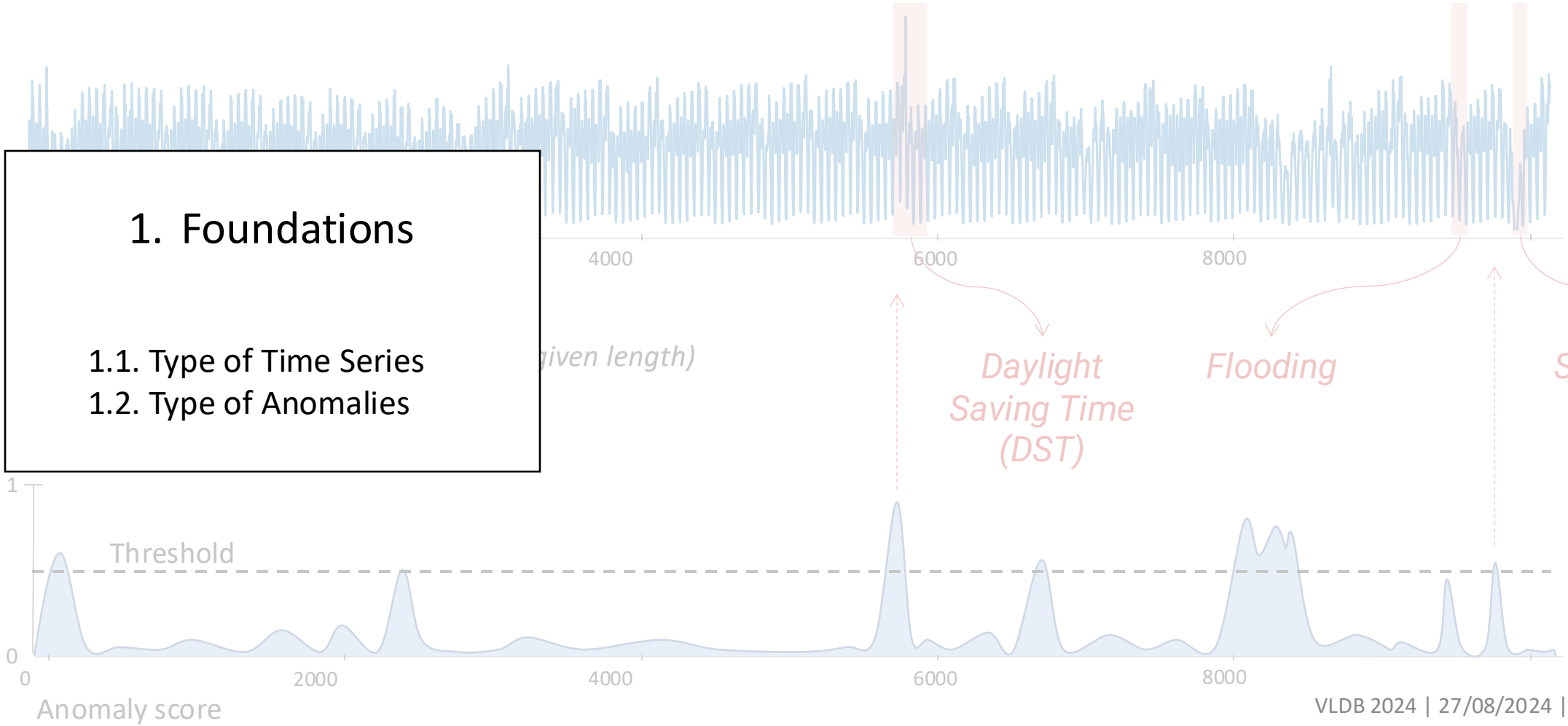


Introduction: *Outline*

- Time series *(example : number of taxi passengers in New York City)*

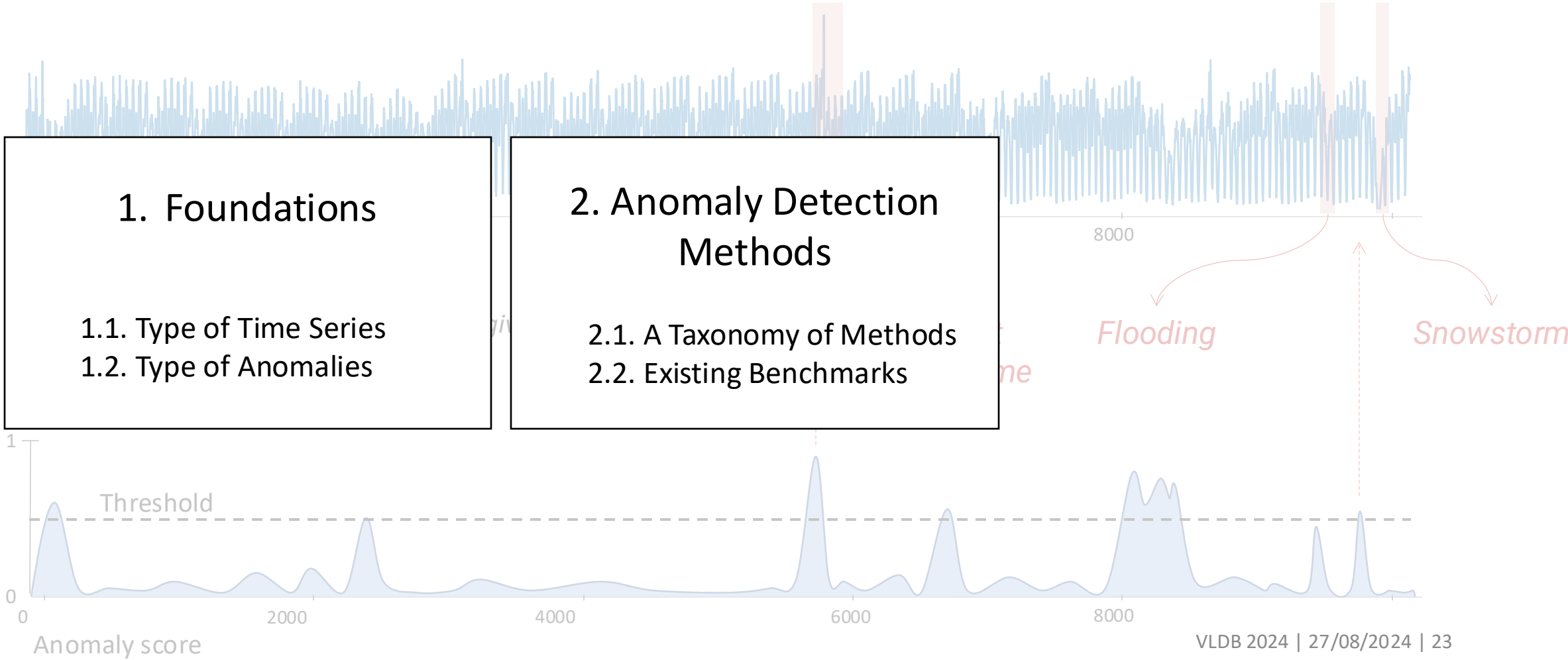


1. Foundations

1.1. Type of Time Series
1.2. Type of Anomalies

Introduction: *Outline*

- Time series *(example : number of taxi passengers in New York City)*



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2. Anomaly Detection Methods

2.1. A Taxonomy of Methods
2.2. Existing Benchmarks

Introduction: *Outline*

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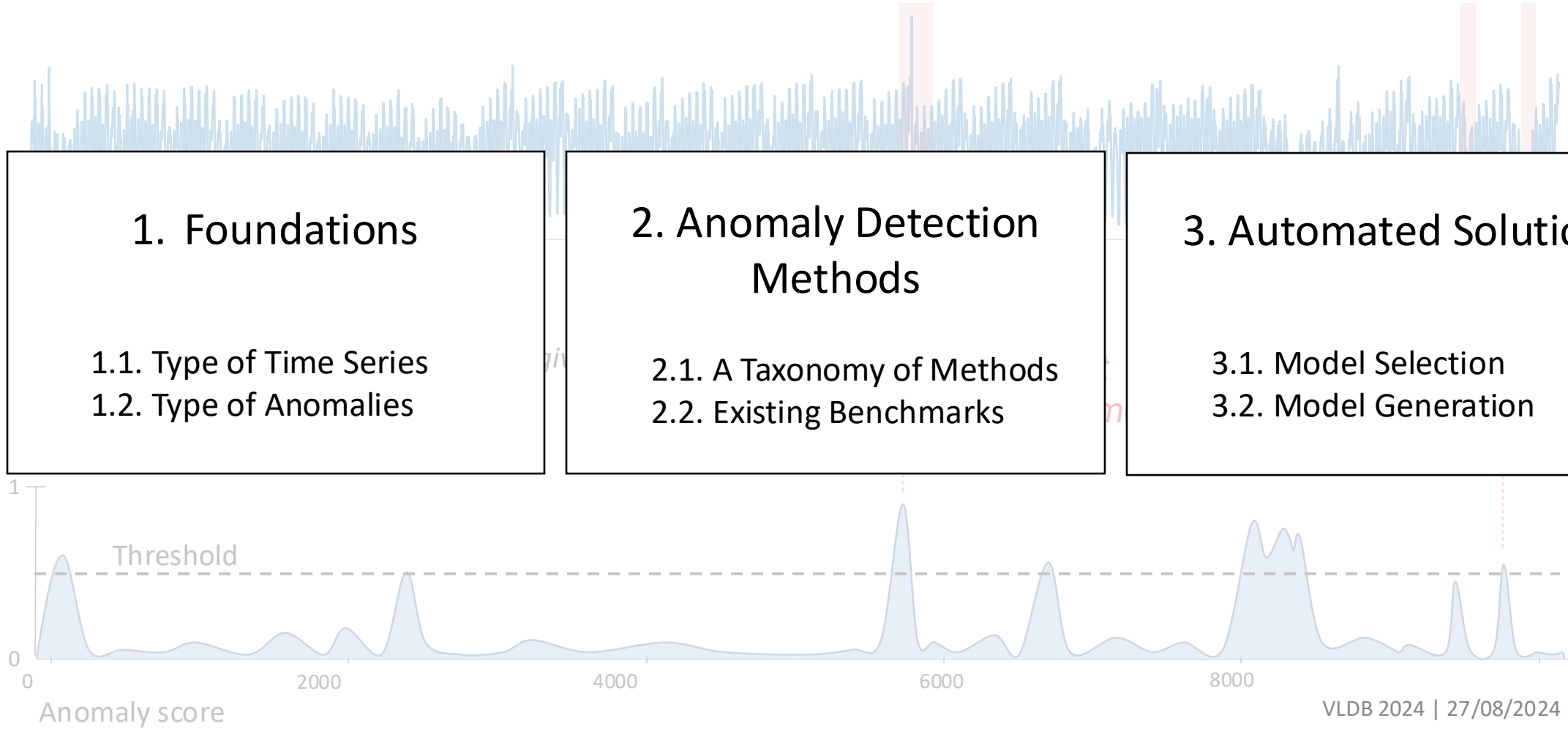

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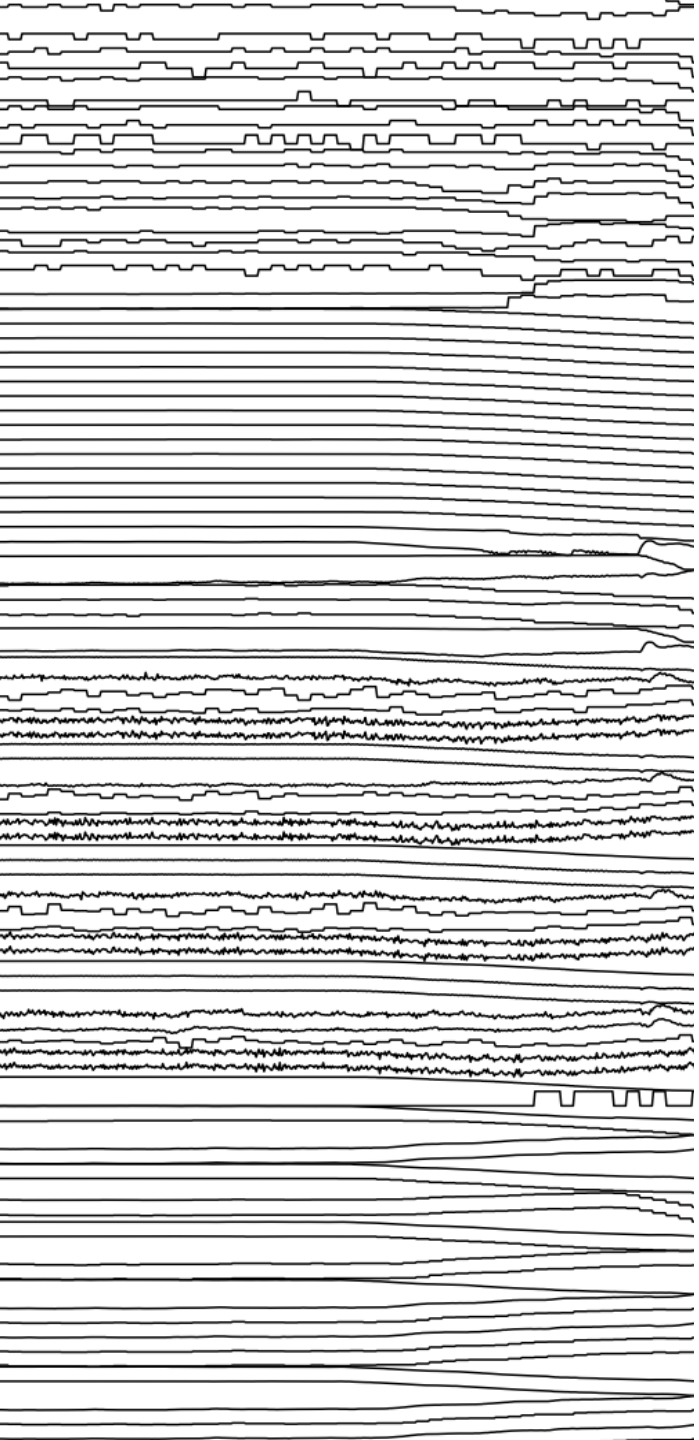
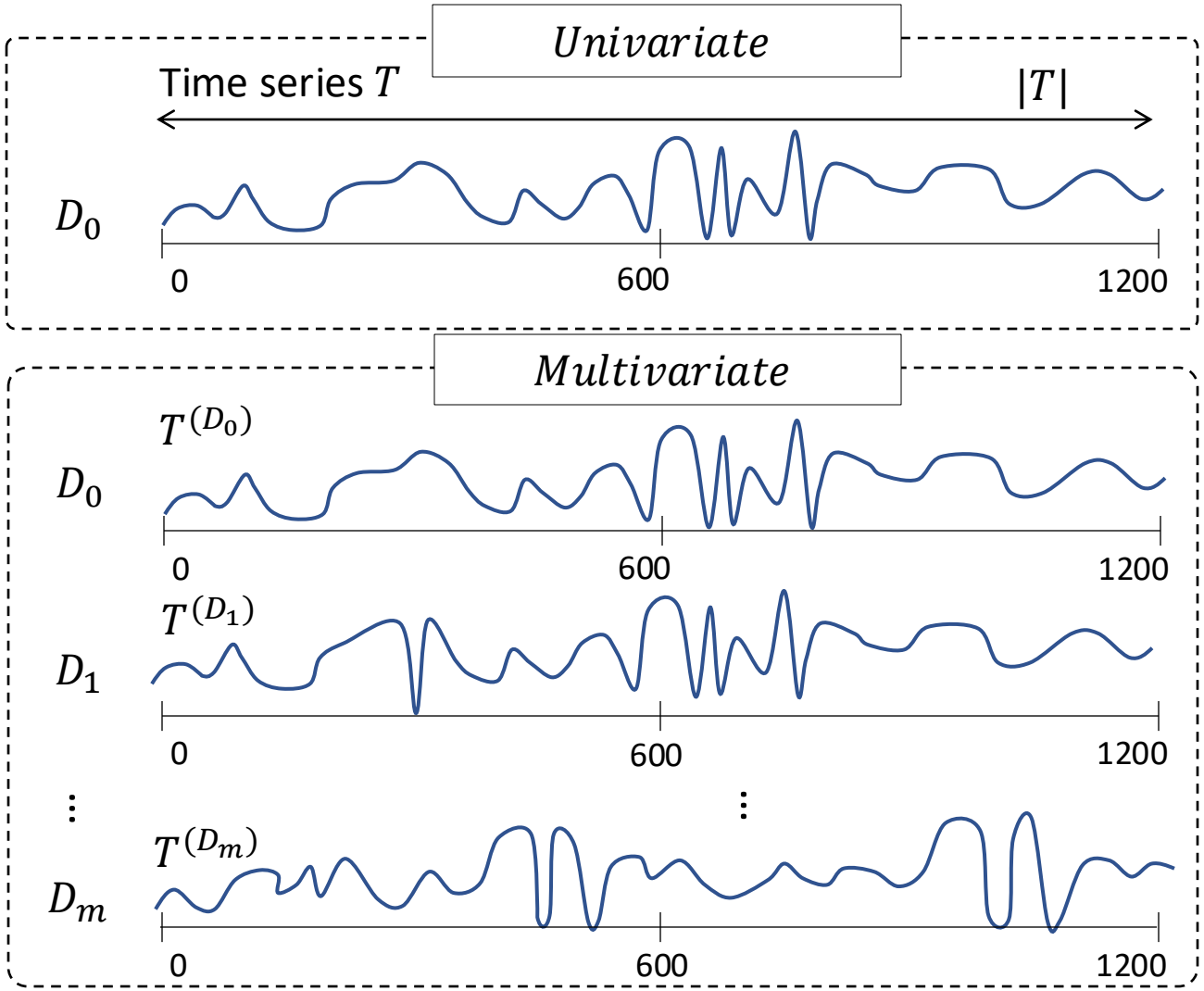
3. Automated Solution

3.1. Model Selection
3.2. Model Generation



Foundations

Foundations: *Type of time series*



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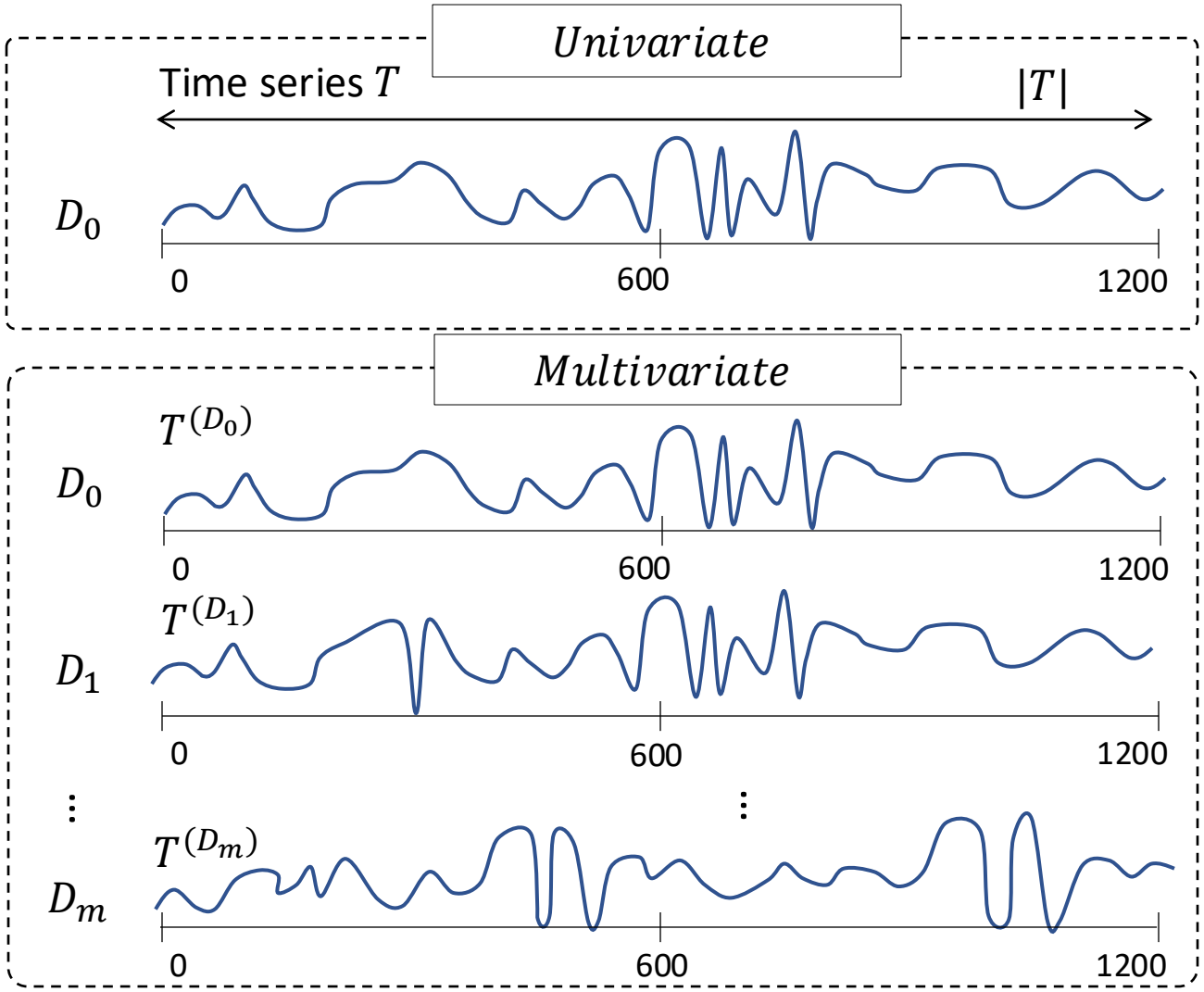

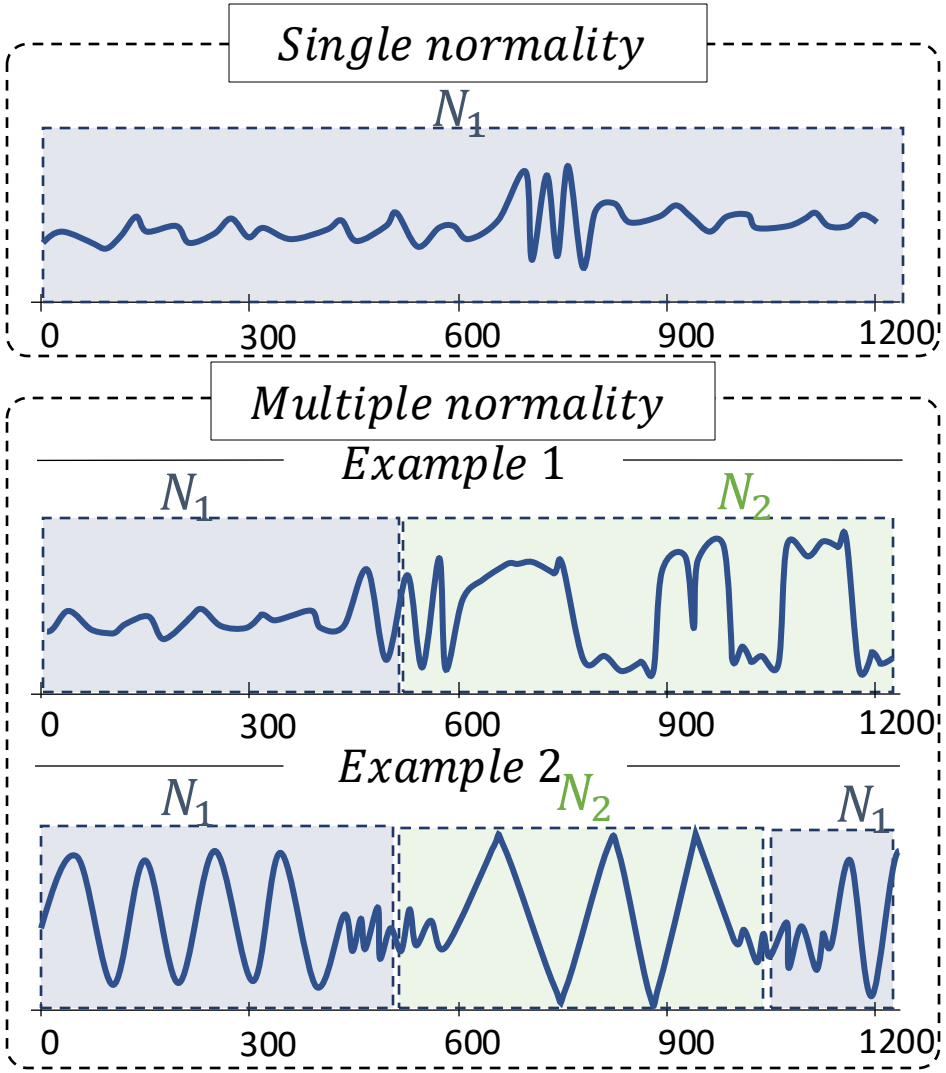

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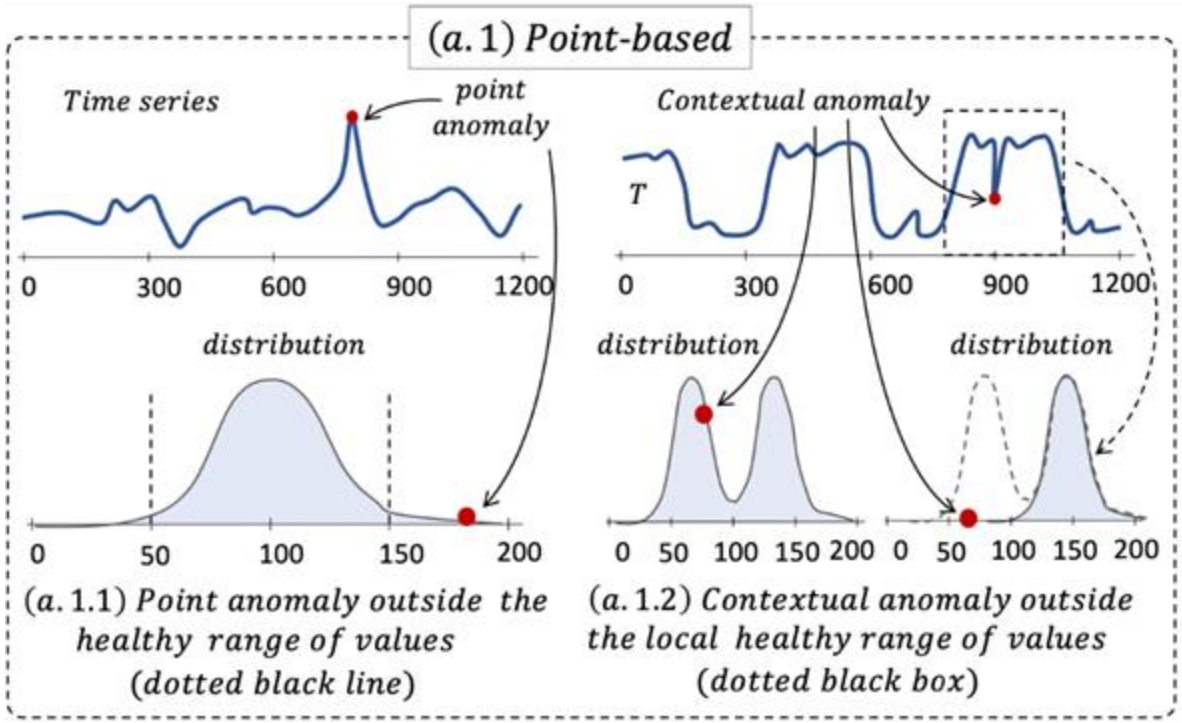

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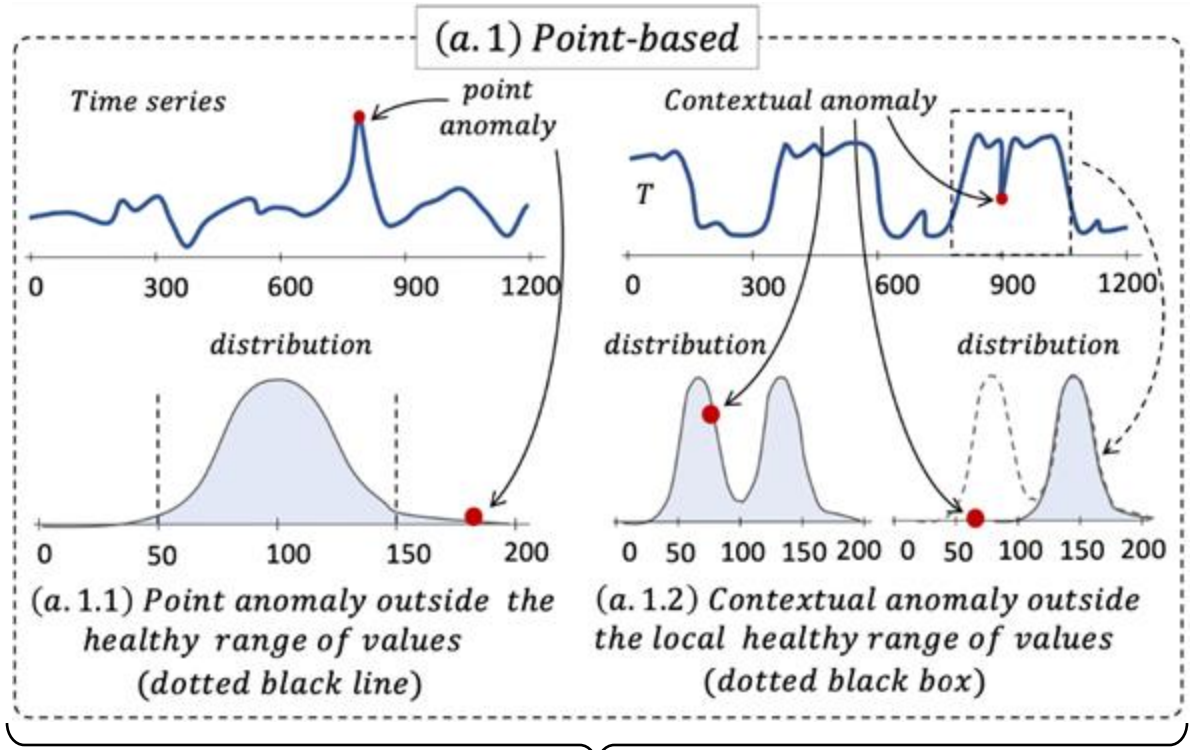
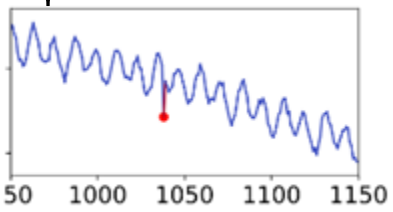
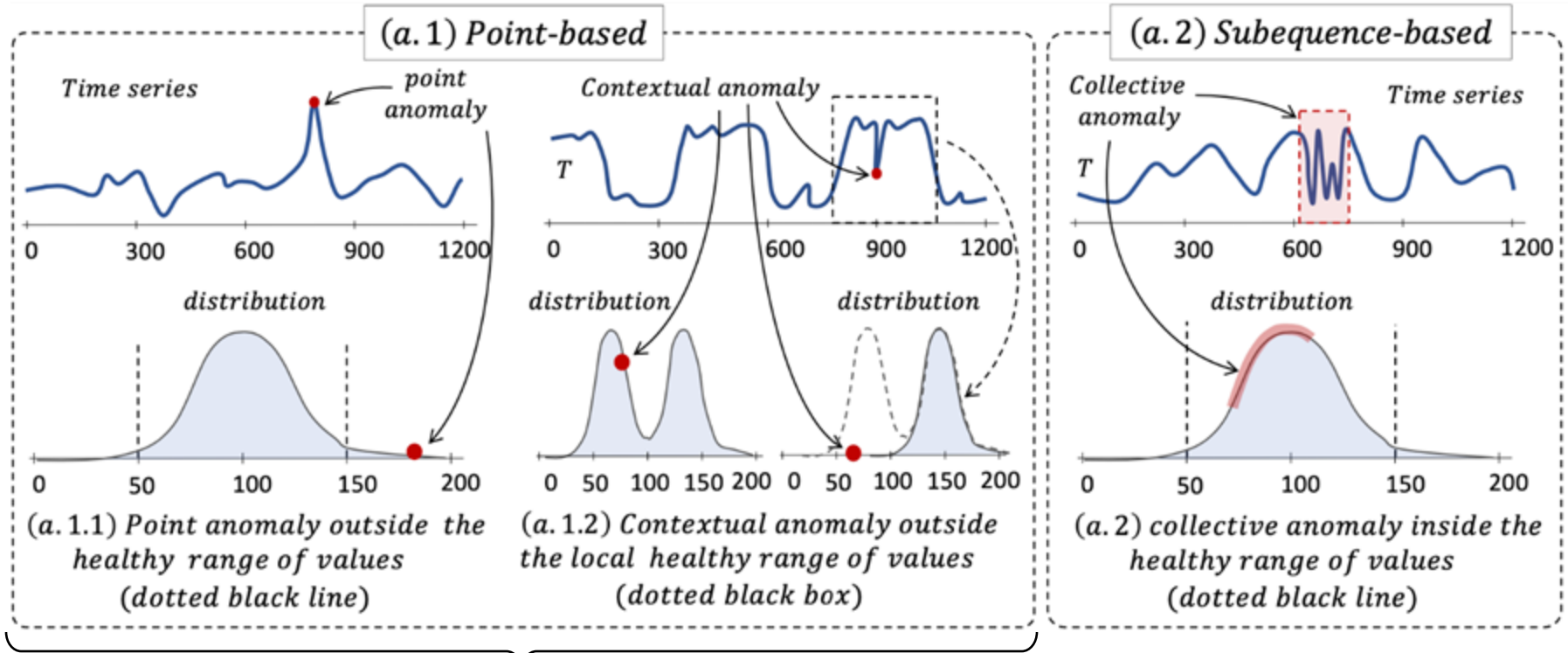


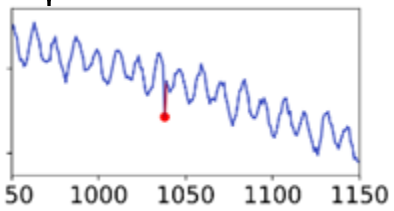
Example of point-based anomaly [1]



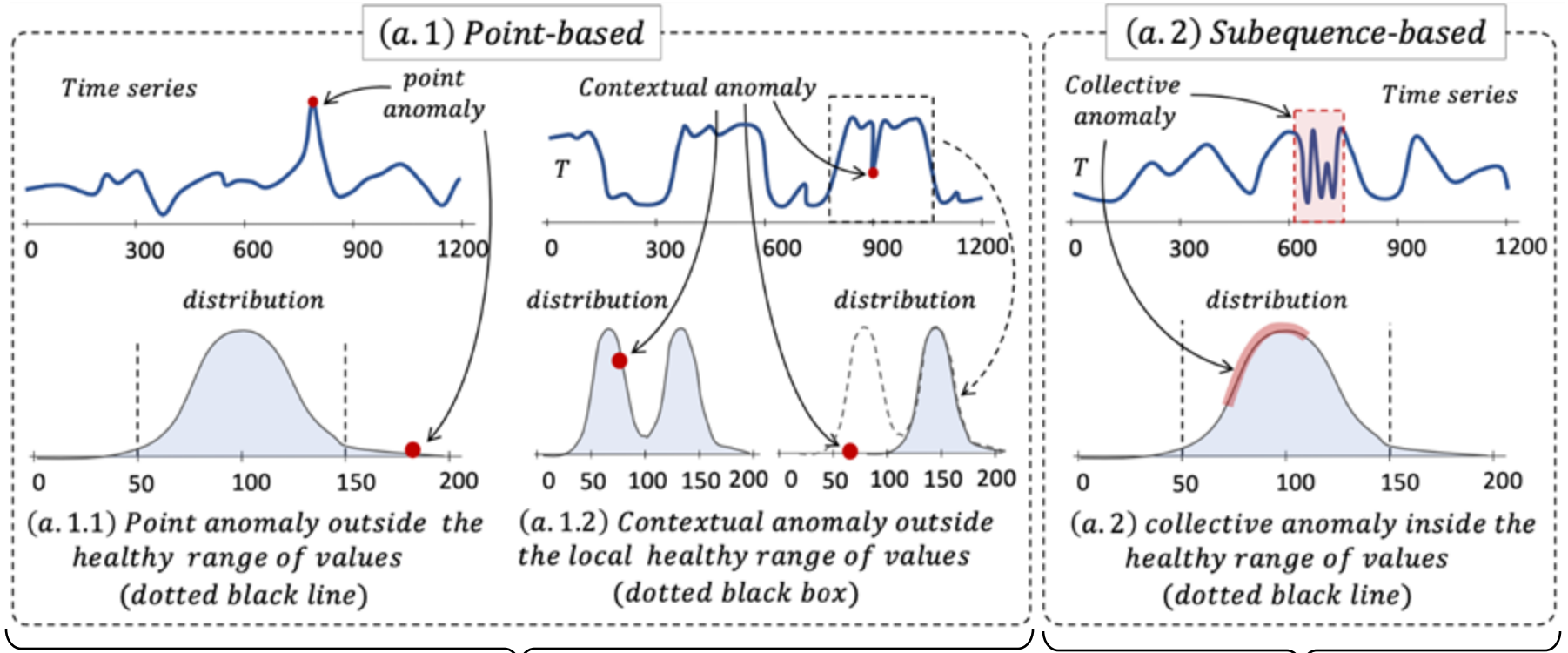
Foundations: *Type of anomalies*



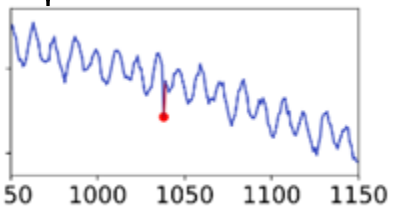
Example of point-based anomaly [1]



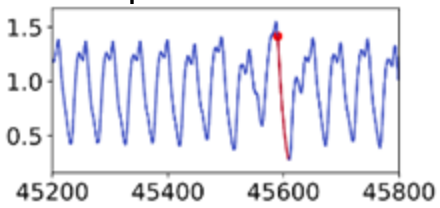
Foundations: *Type of anomalies*



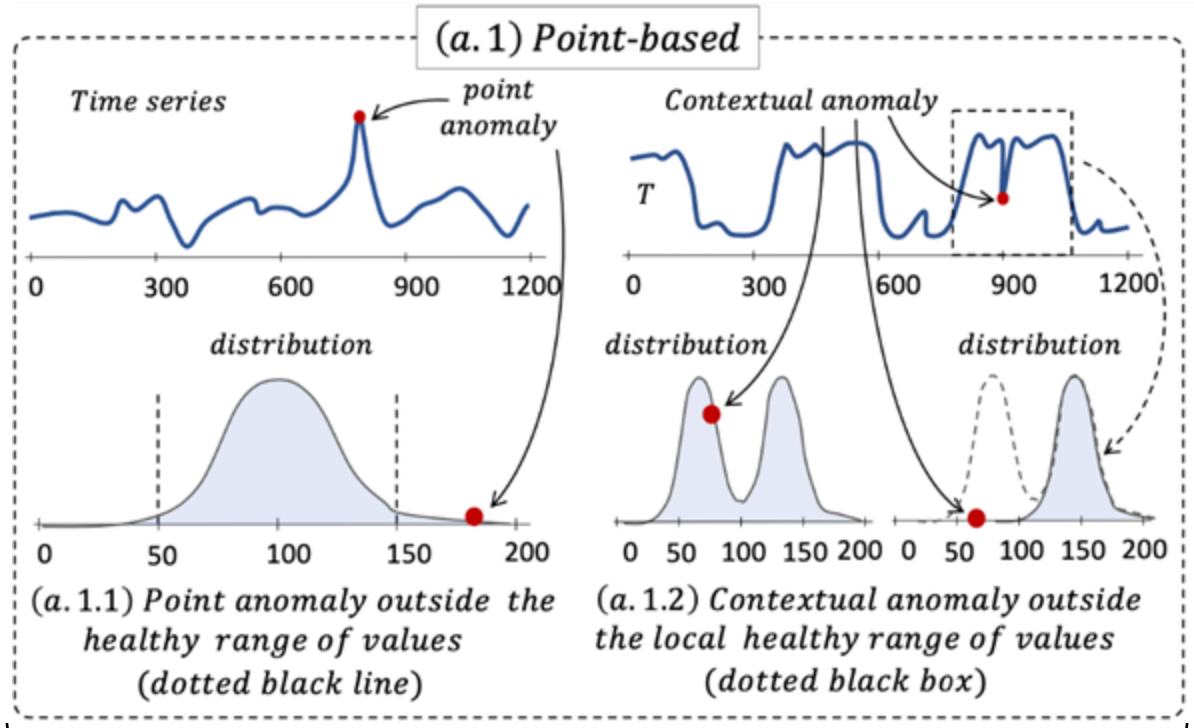
Example of point-based anomaly [1]

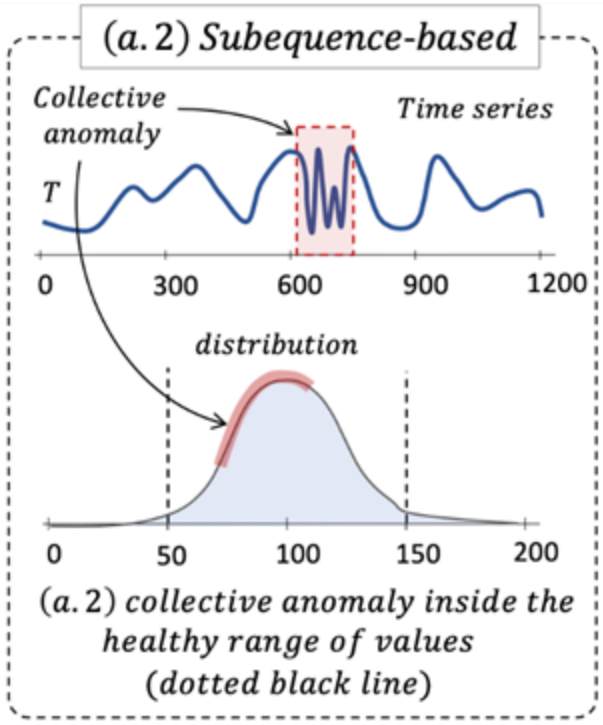


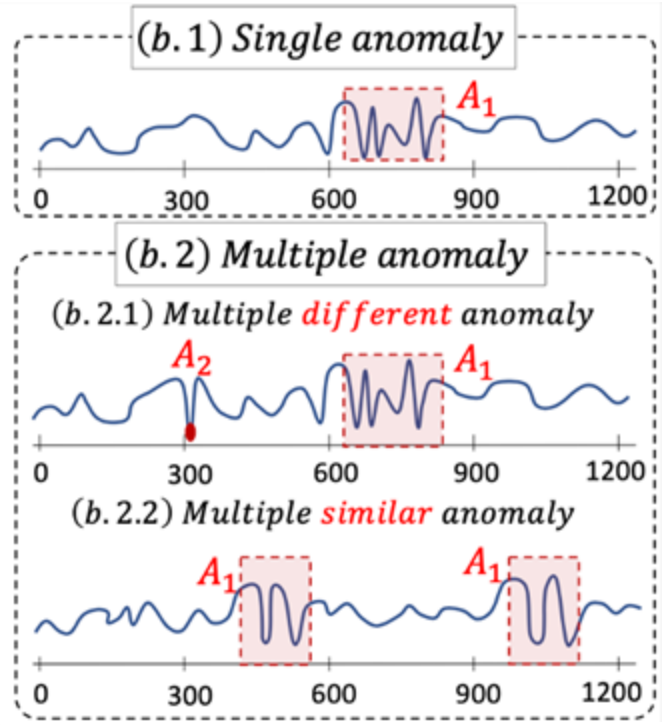
Example of subsequence-based anomaly [2]



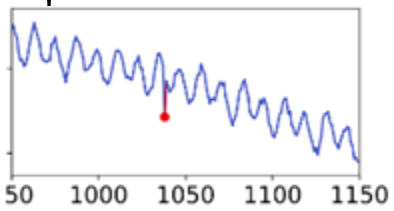
Foundations: *Type of anomalies*



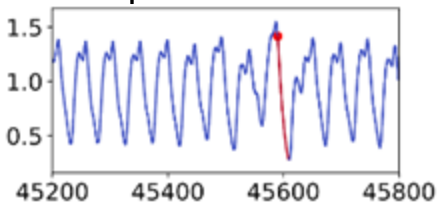




Example of point-based anomaly [1]

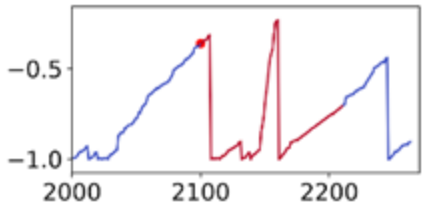


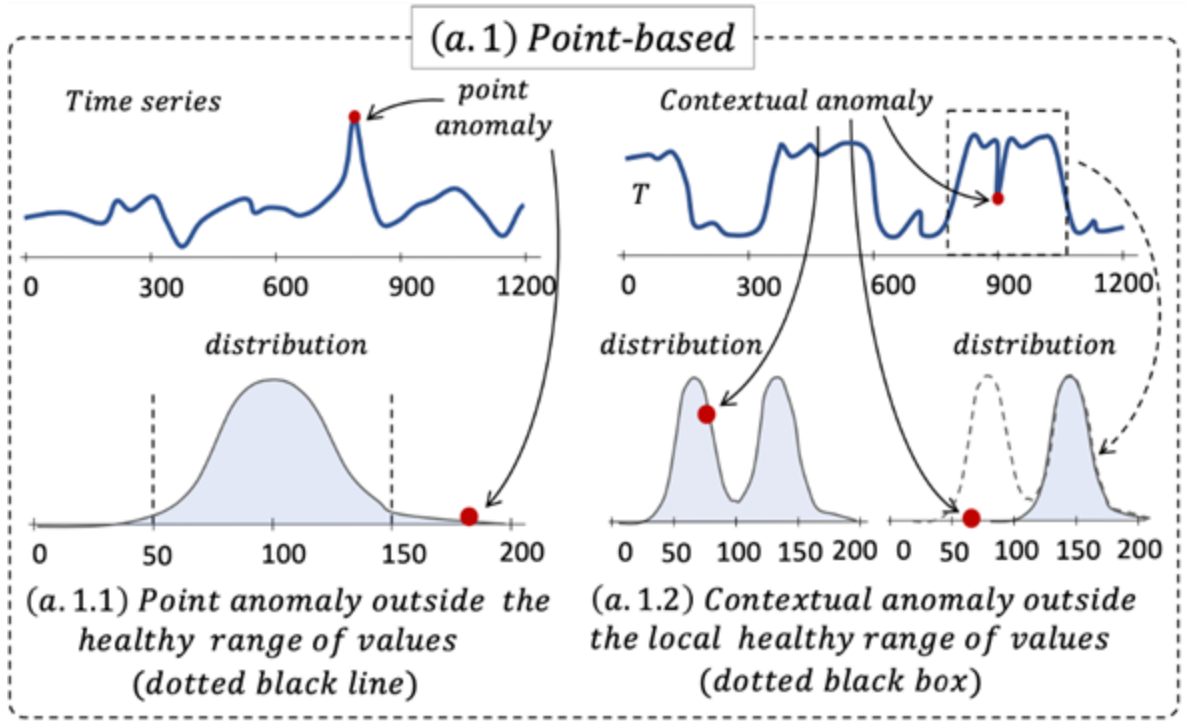
Example of subsequence-based anomaly [2]

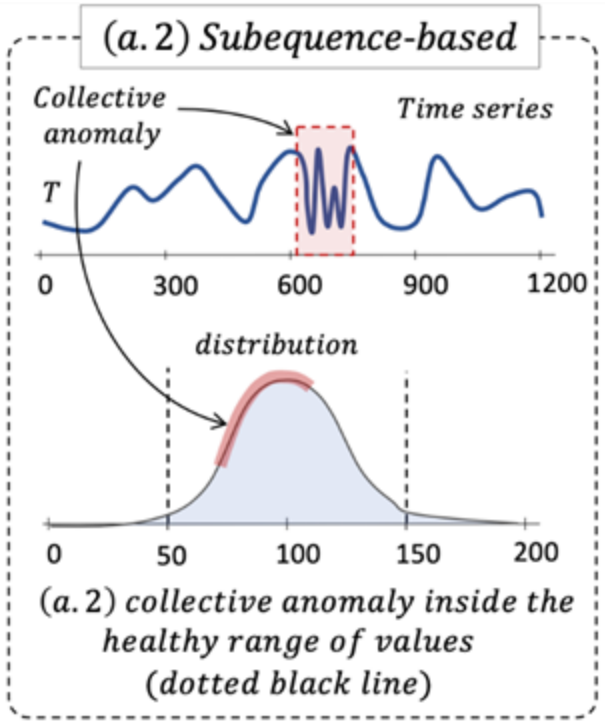


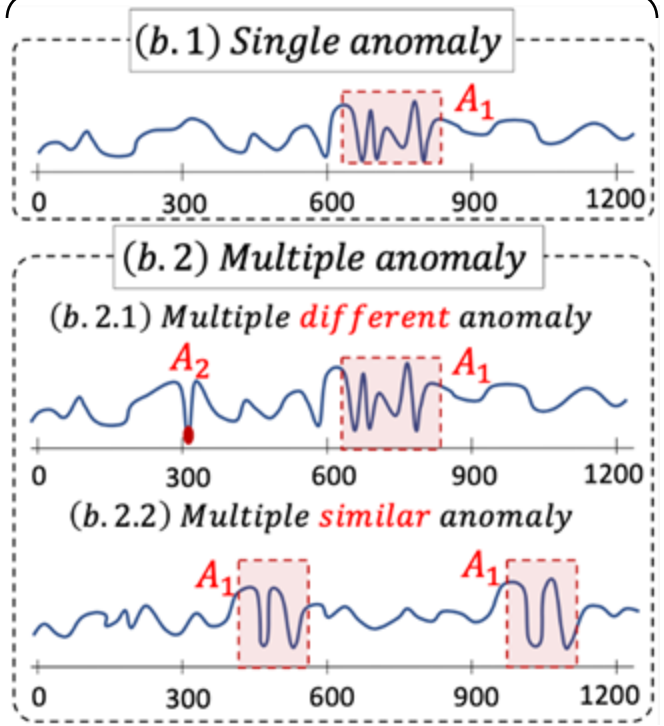
Foundations: *Type of anomalies*

Example of single anomaly [3]

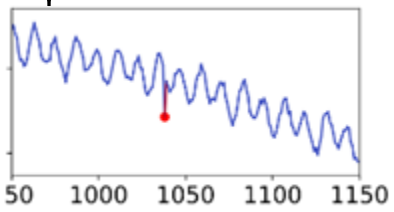




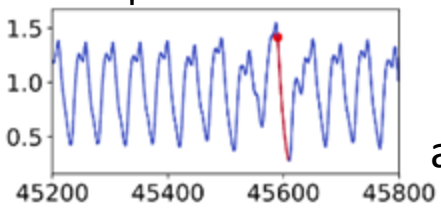




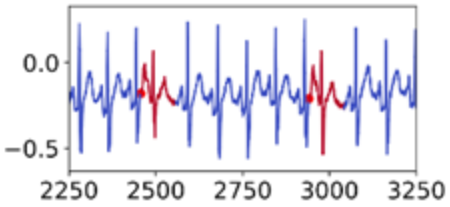
Example of point-based anomaly [1]

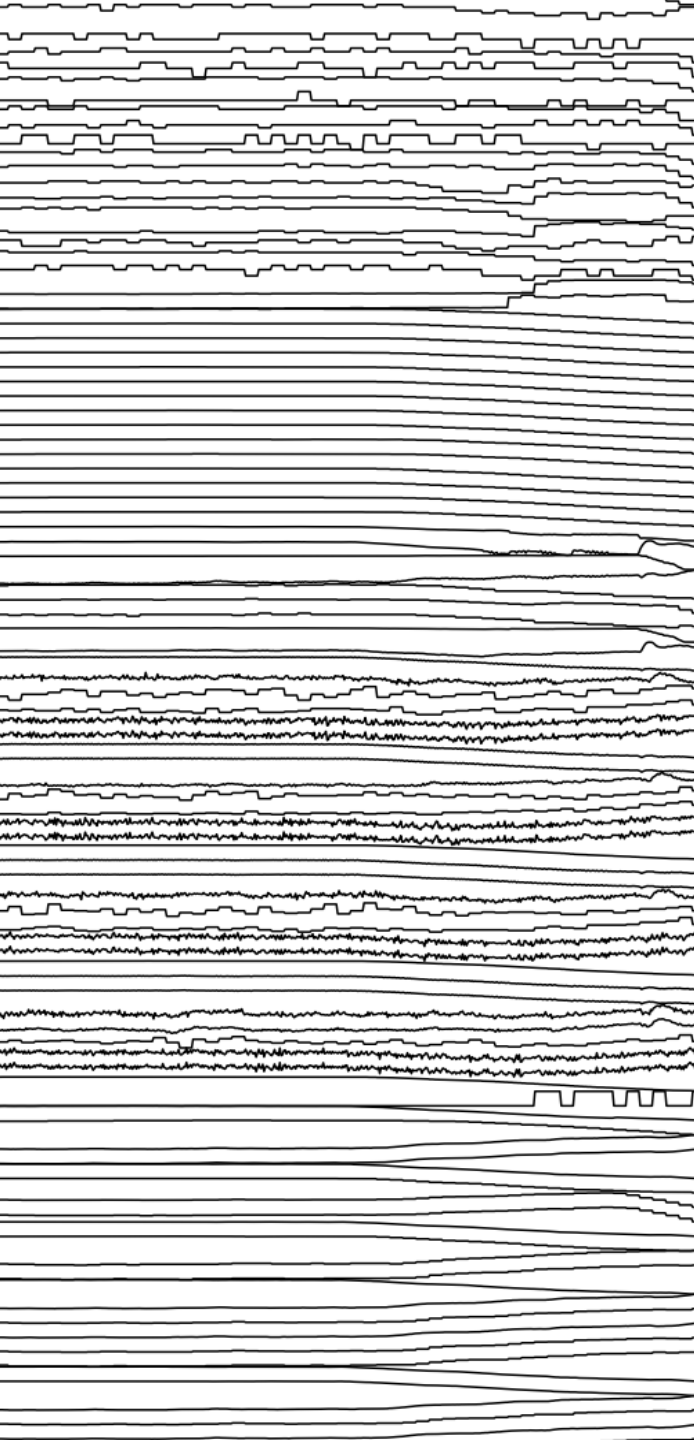


Example of subsequence-based anomaly [2]



Example of multiple anomaly [4]

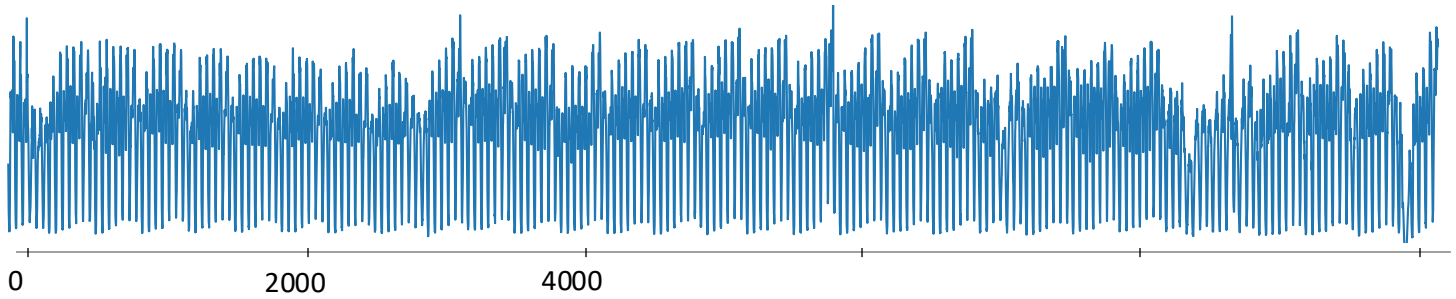




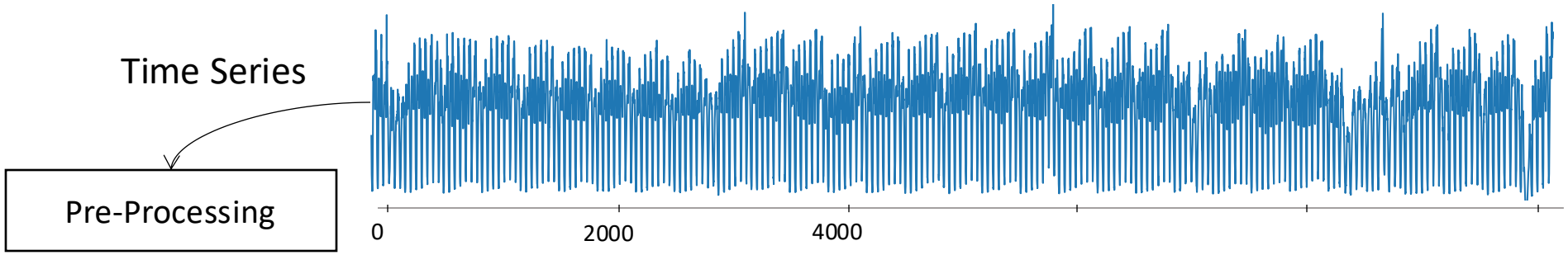
Anomaly Detection Methods

Anomaly Detection methods: *A taxonomy*

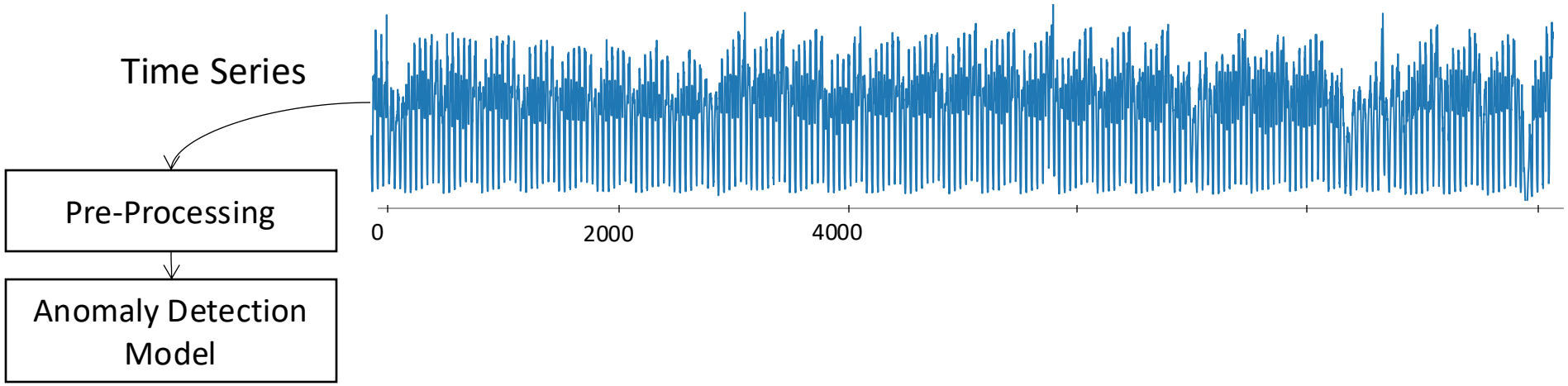
Time Series



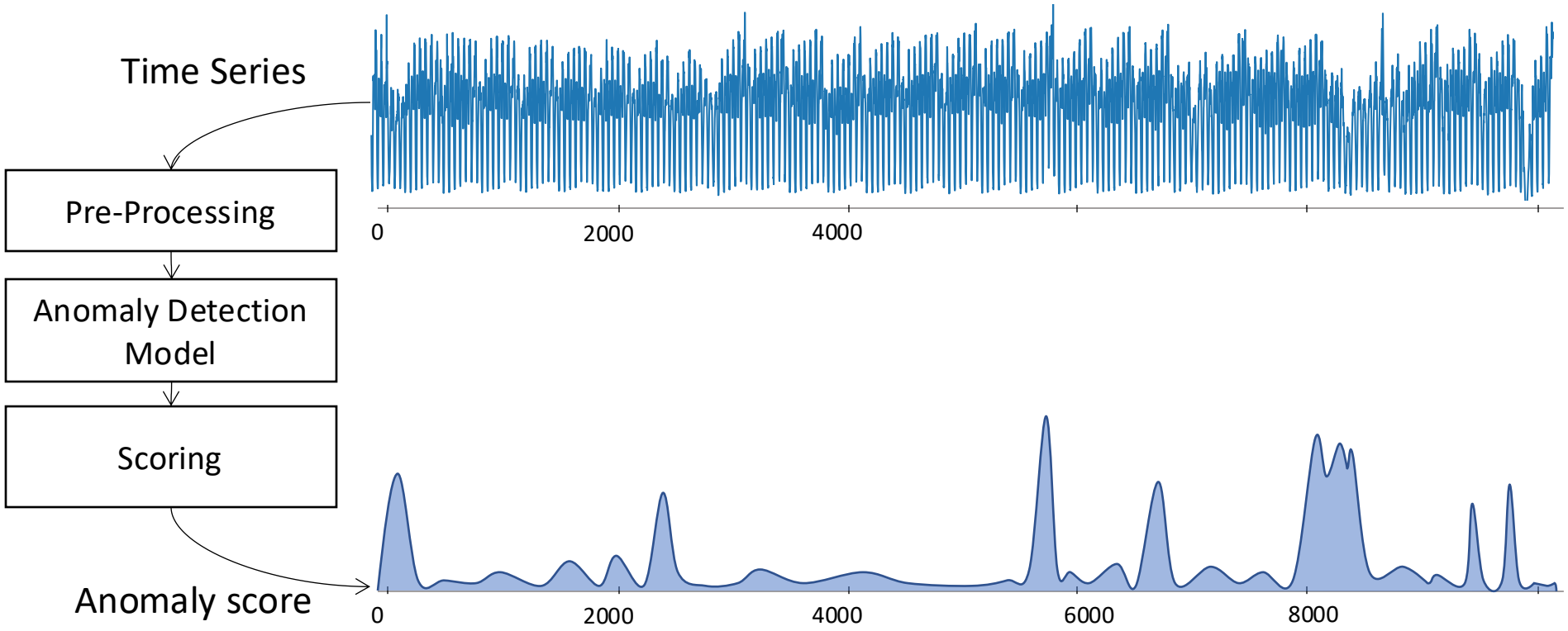
Anomaly Detection methods: *A taxonomy*



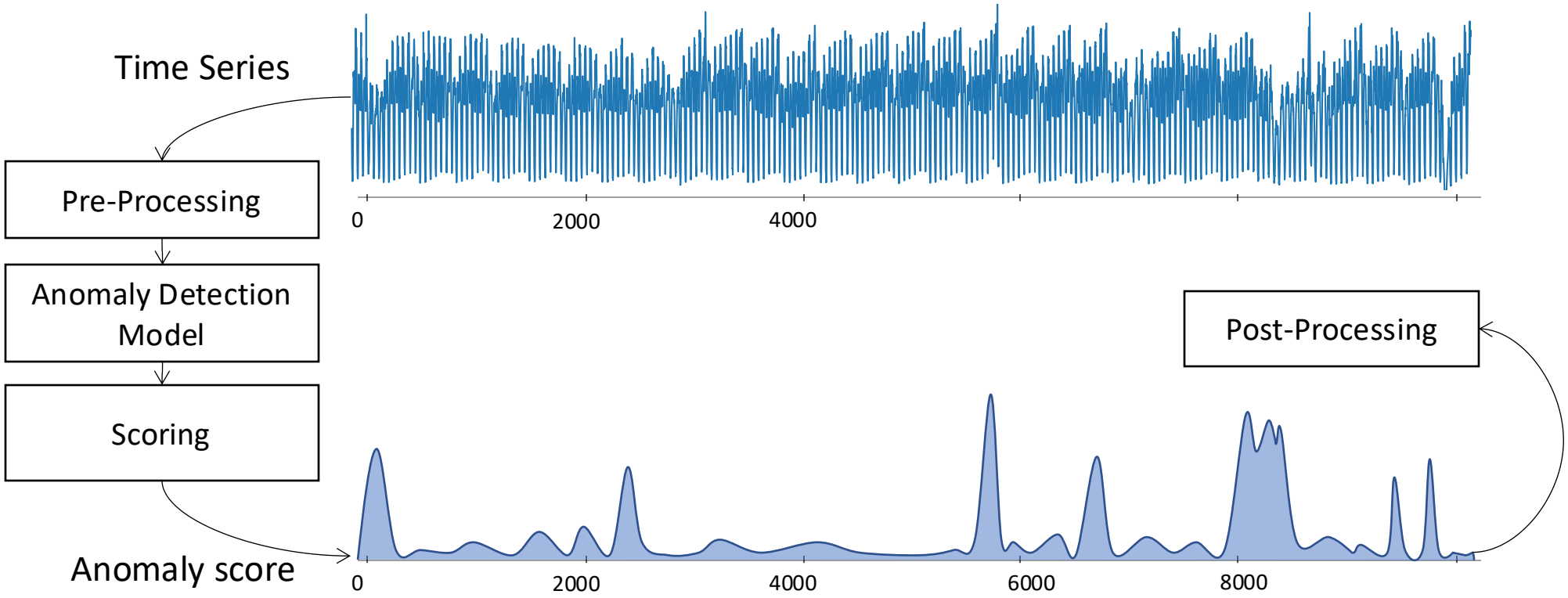
Anomaly Detection methods: *A taxonomy*



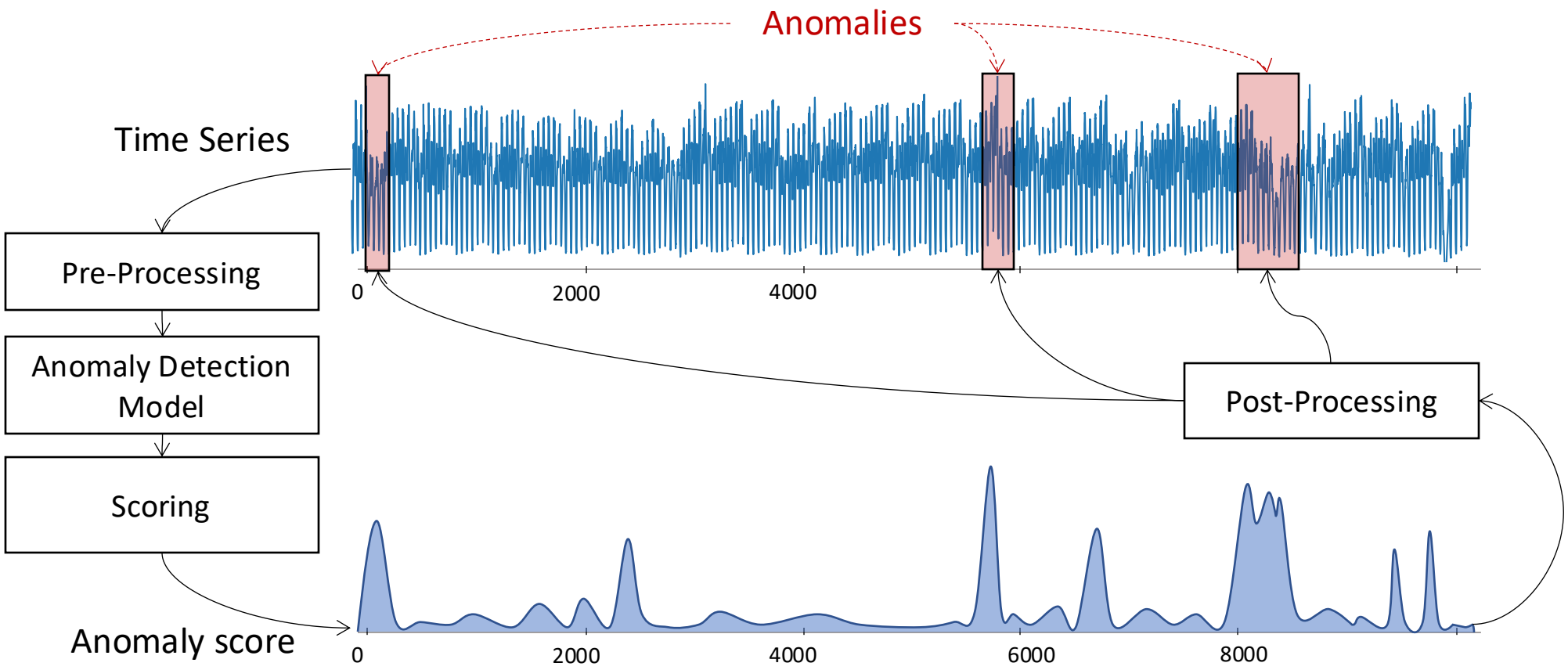
Anomaly Detection methods: *A taxonomy*



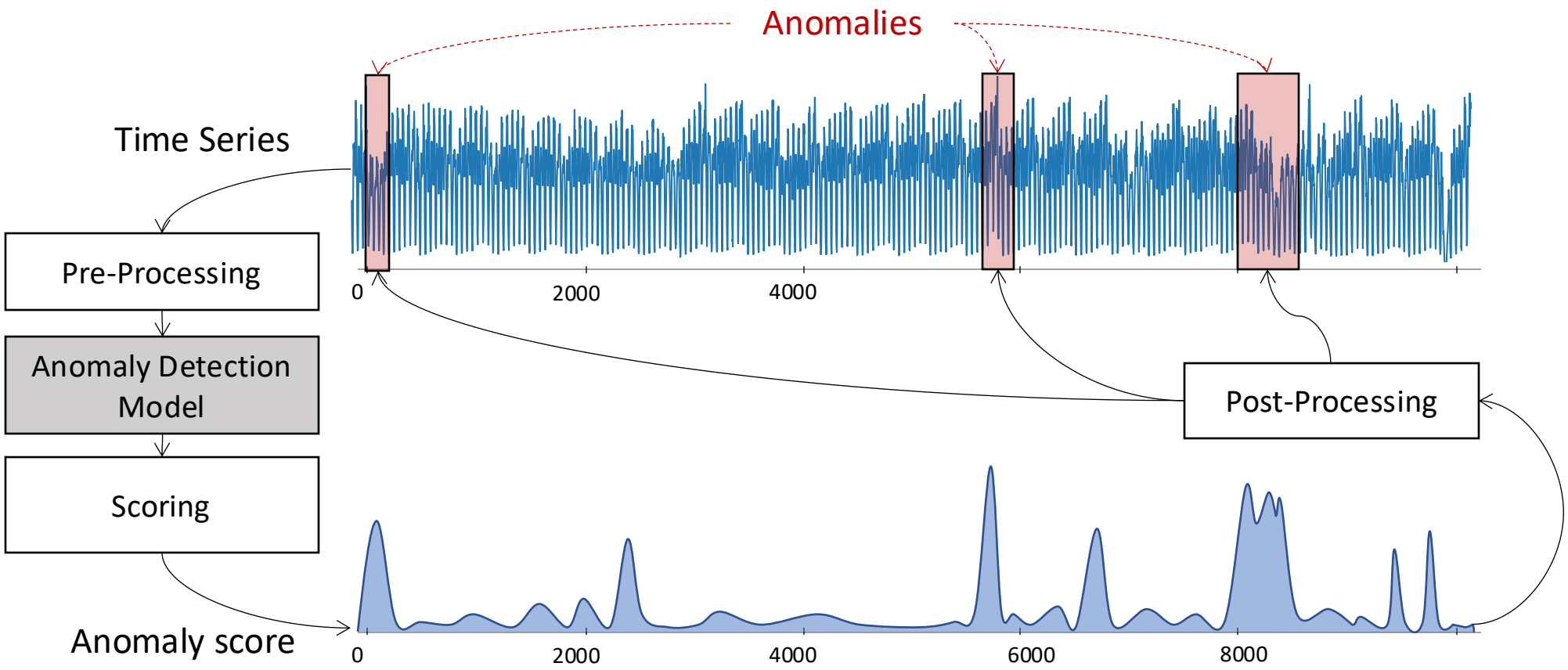
Anomaly Detection methods: *A taxonomy*



Anomaly Detection methods: *A taxonomy*

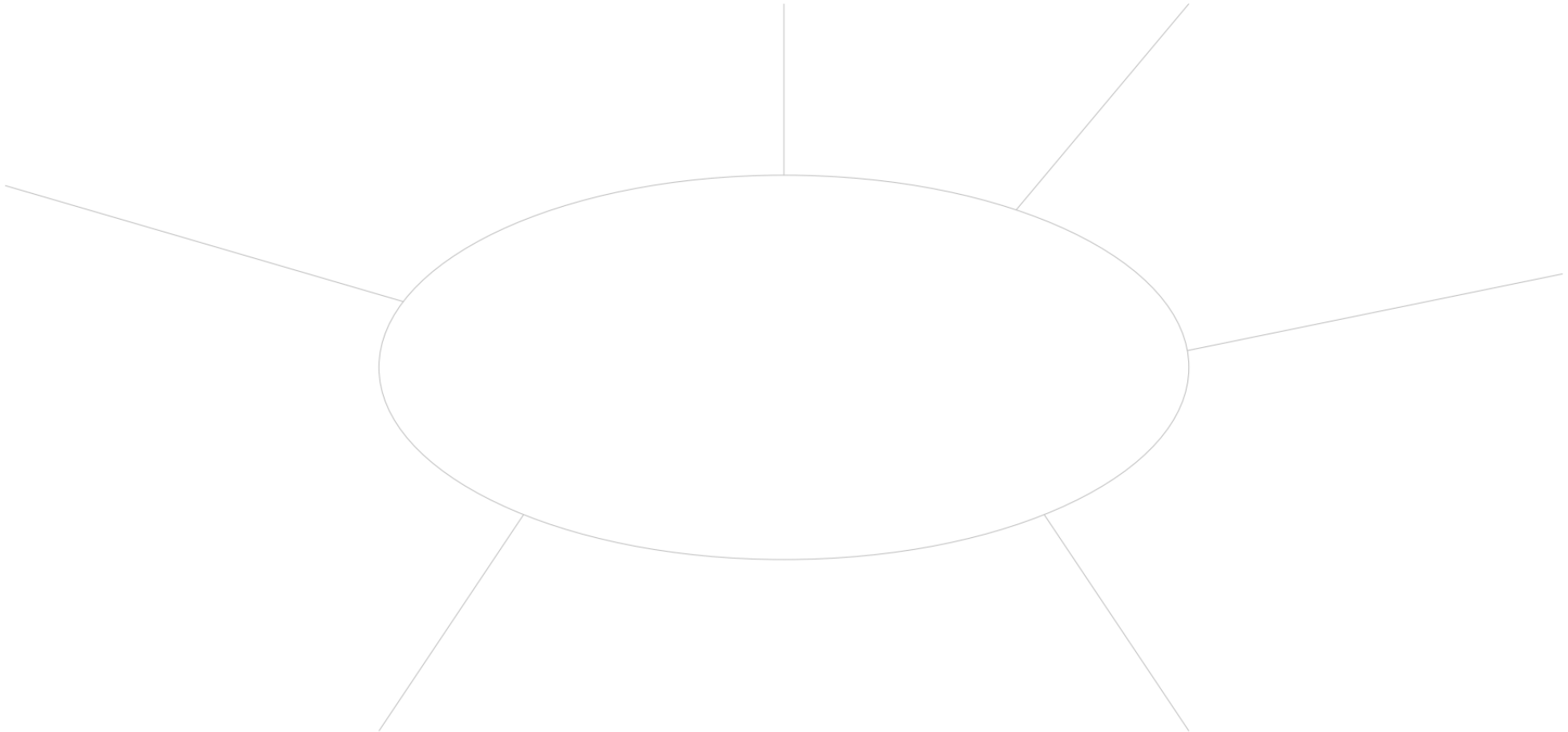


Anomaly Detection methods: *A taxonomy*



Anomaly Detection methods: *A taxonomy*

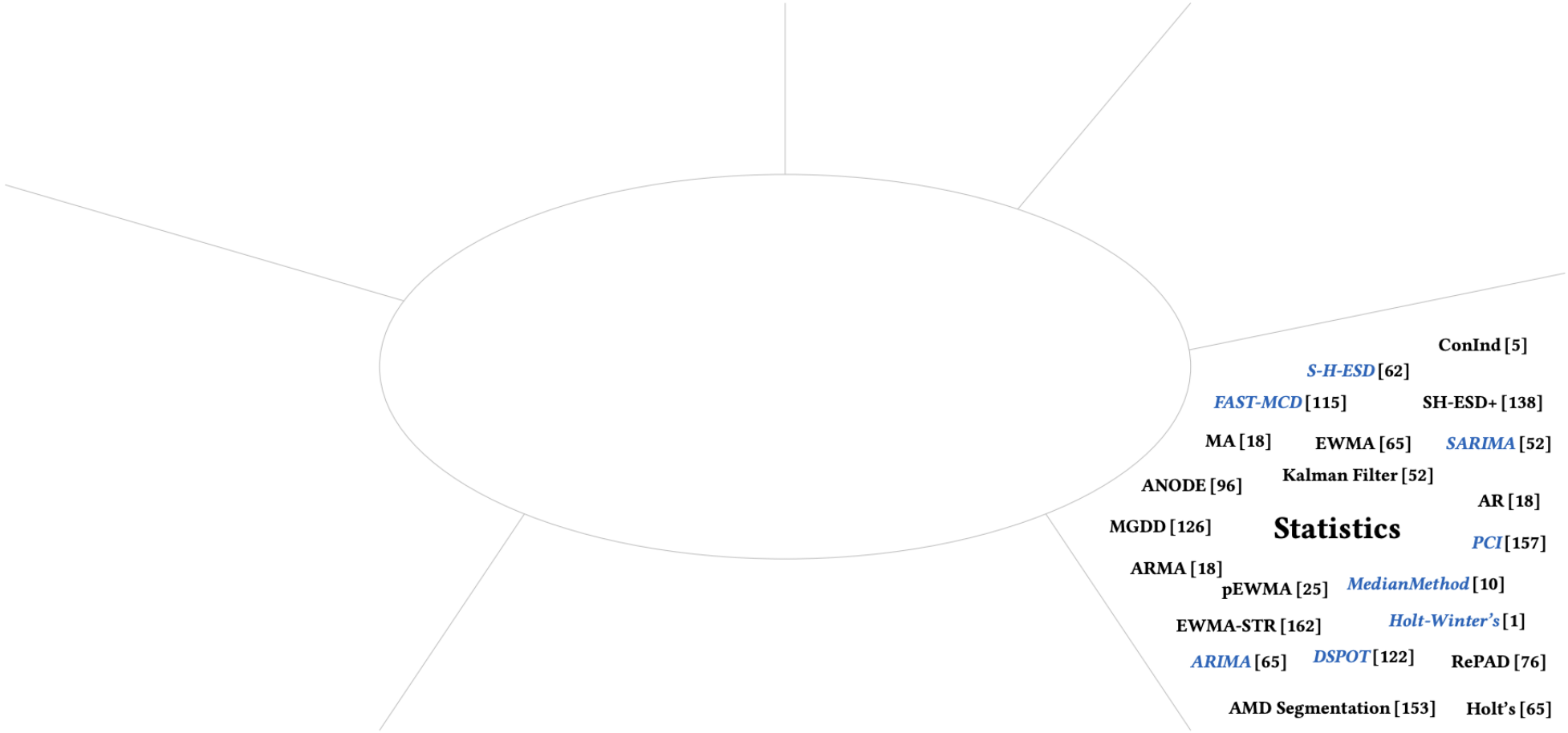
By domains [5] …



[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. Anomaly detection in time series: a comprehensive evaluation. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.

Anomaly Detection methods: *A taxonomy*

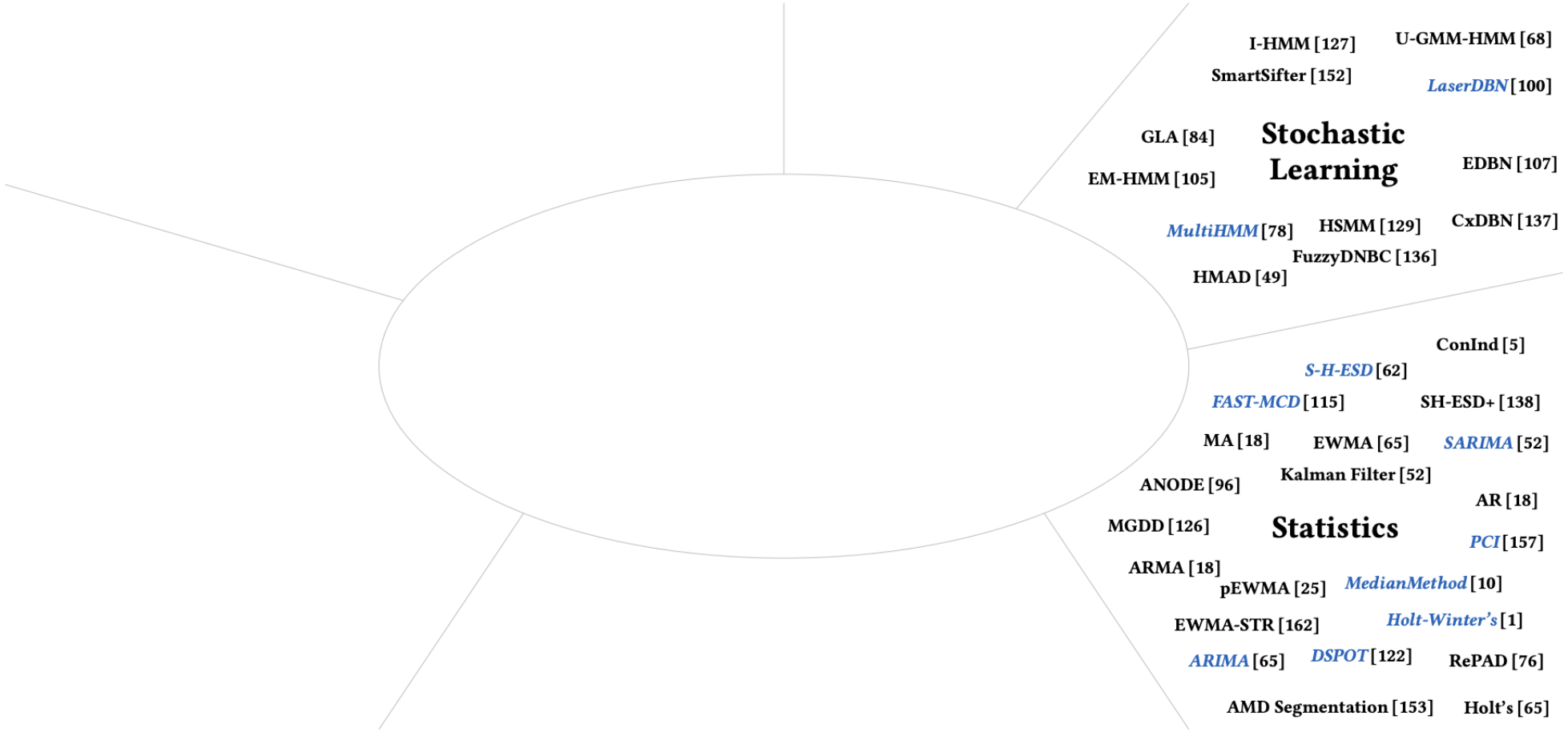
By domains [5] …



[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. Anomaly detection in time series: a comprehensive evaluation. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.

Anomaly Detection methods: *A taxonomy*

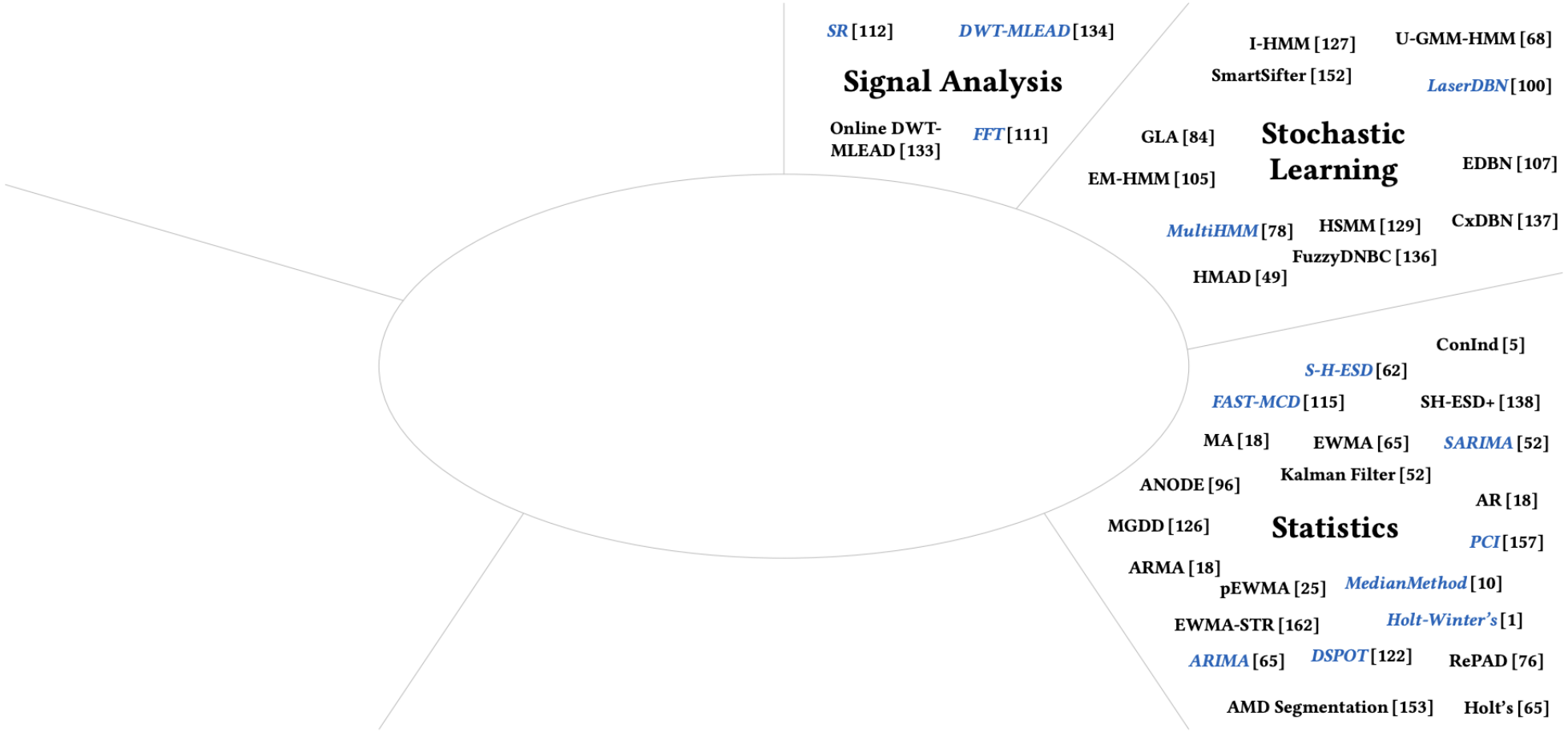
By domains [5] …



[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. Anomaly detection in time series: a comprehensive evaluation. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.

Anomaly Detection methods: *A taxonomy*

By domains [5] …



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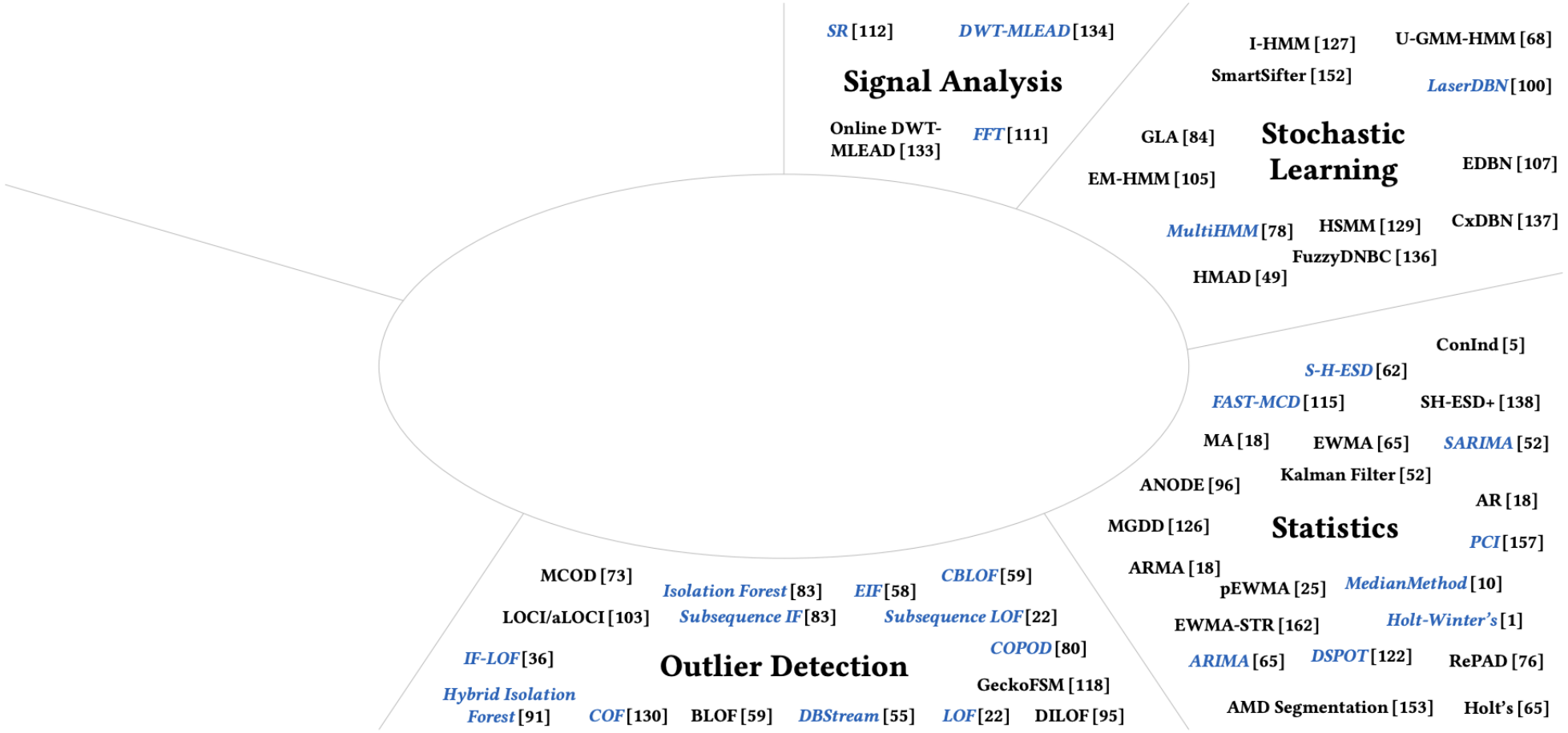
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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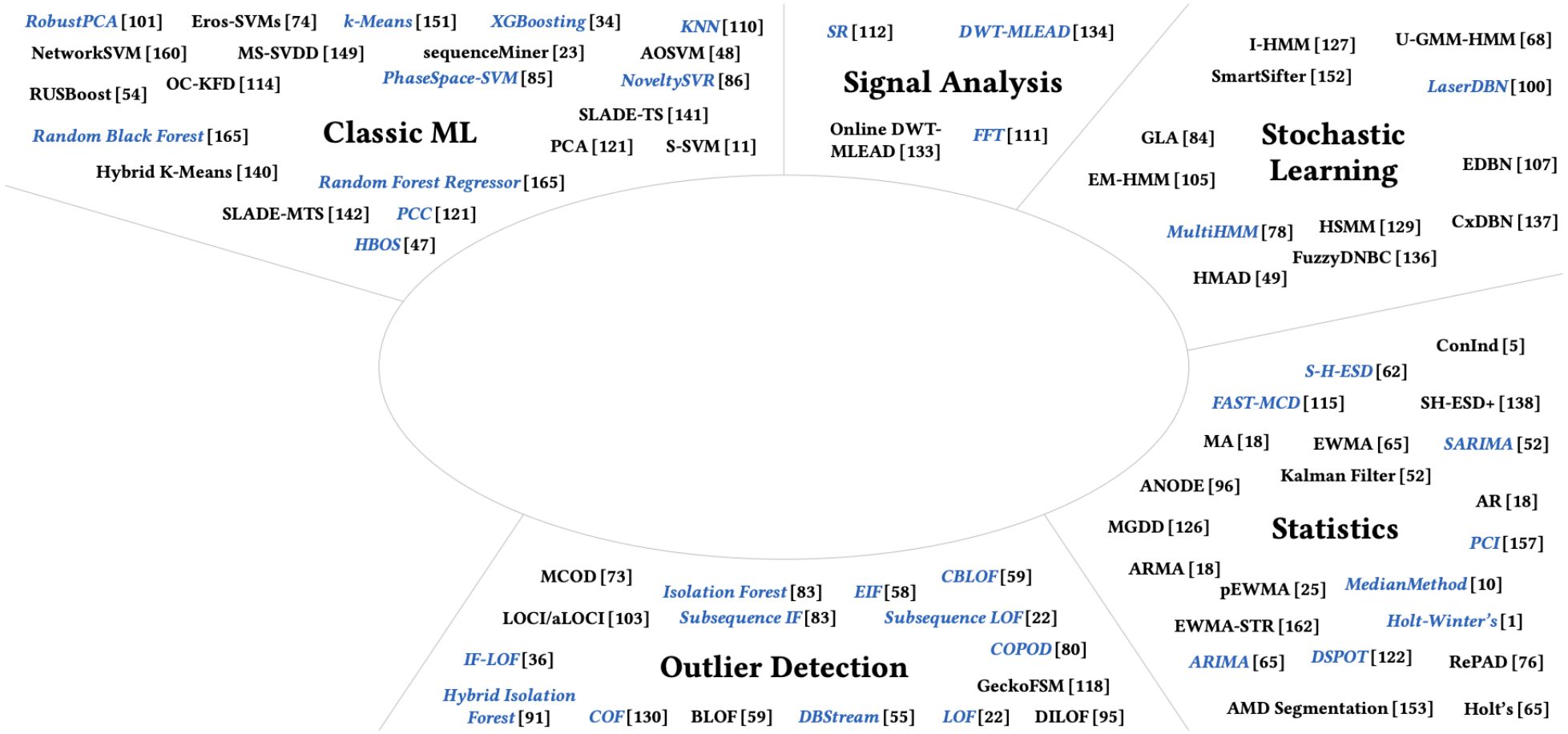
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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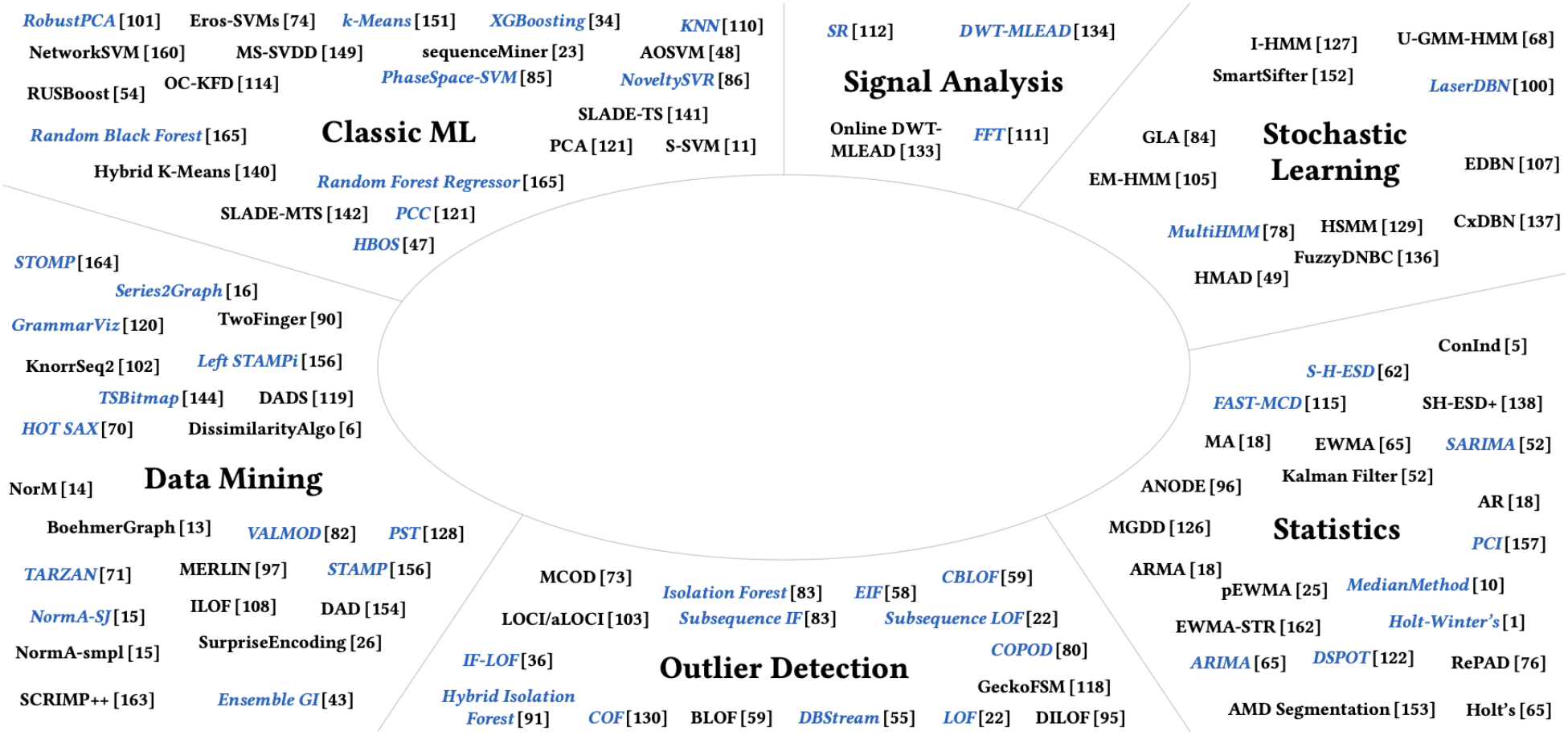
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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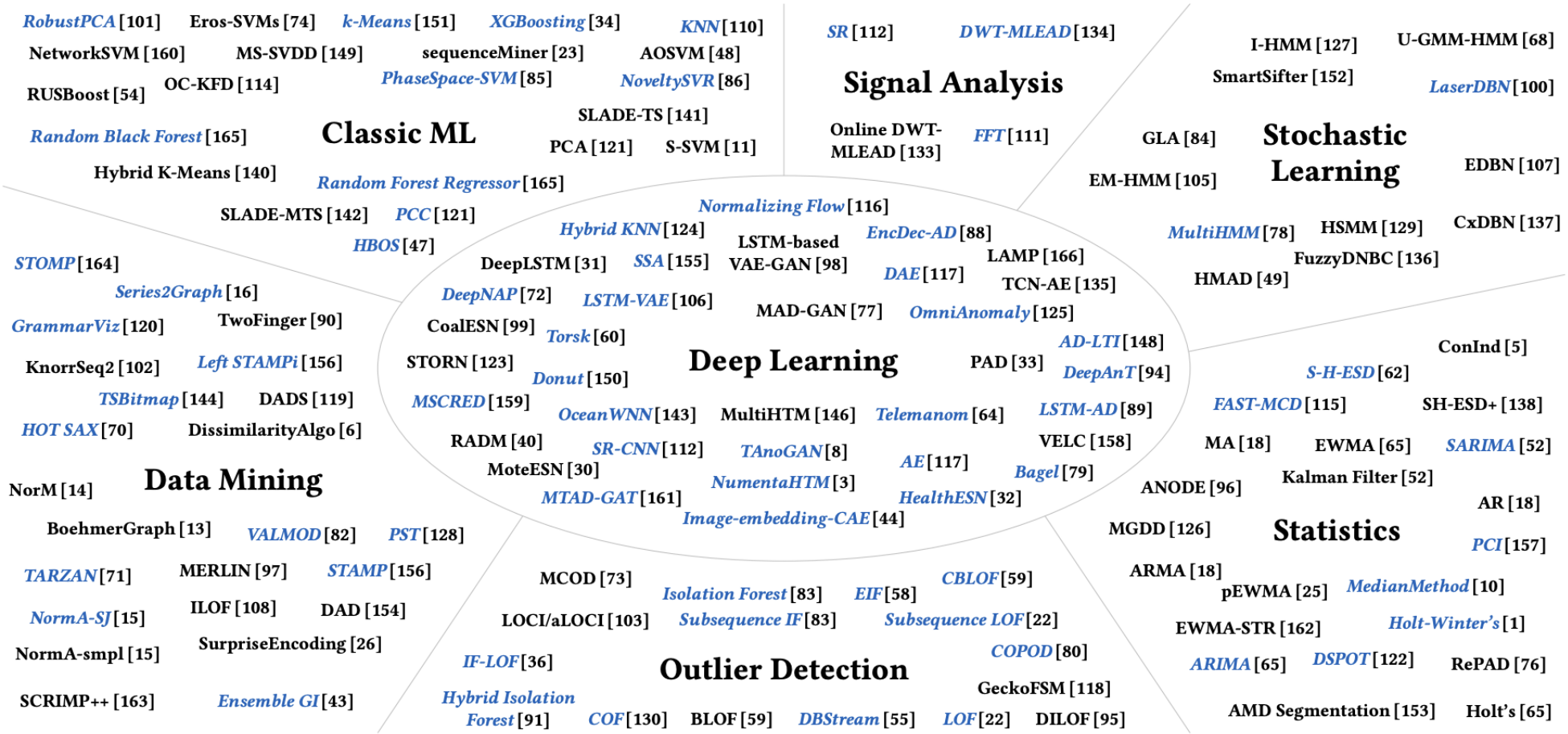
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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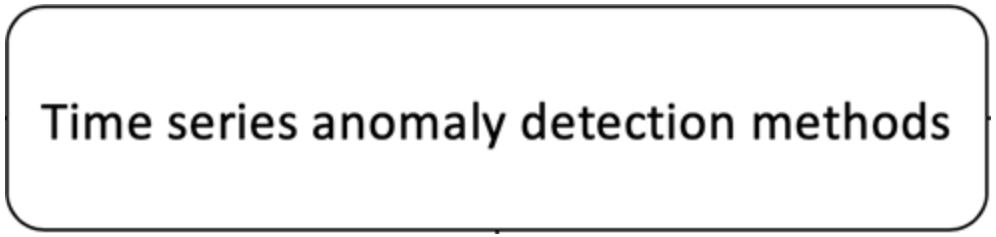
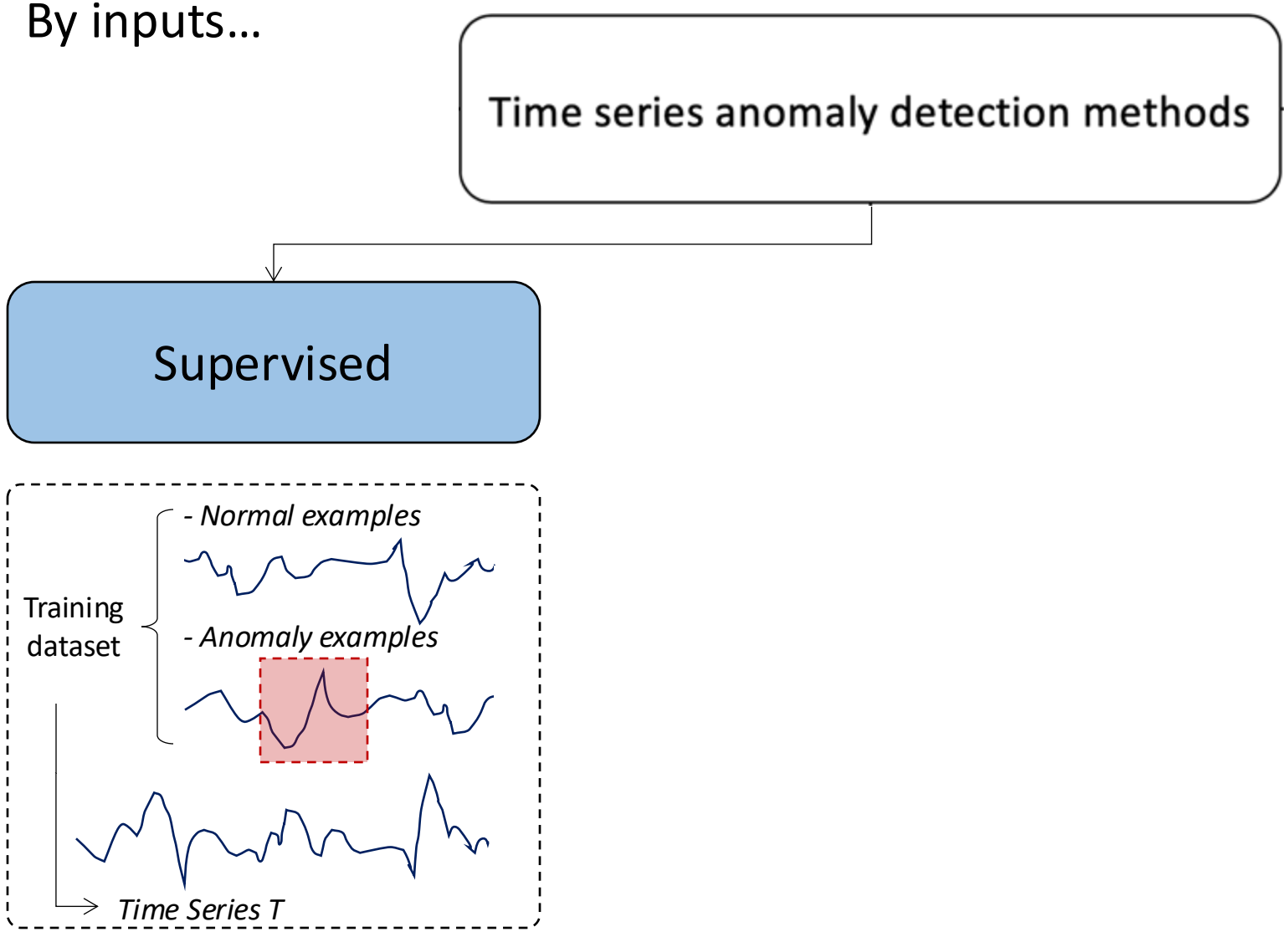
Anomaly Detection methods: *A taxonomy*

By inputs…



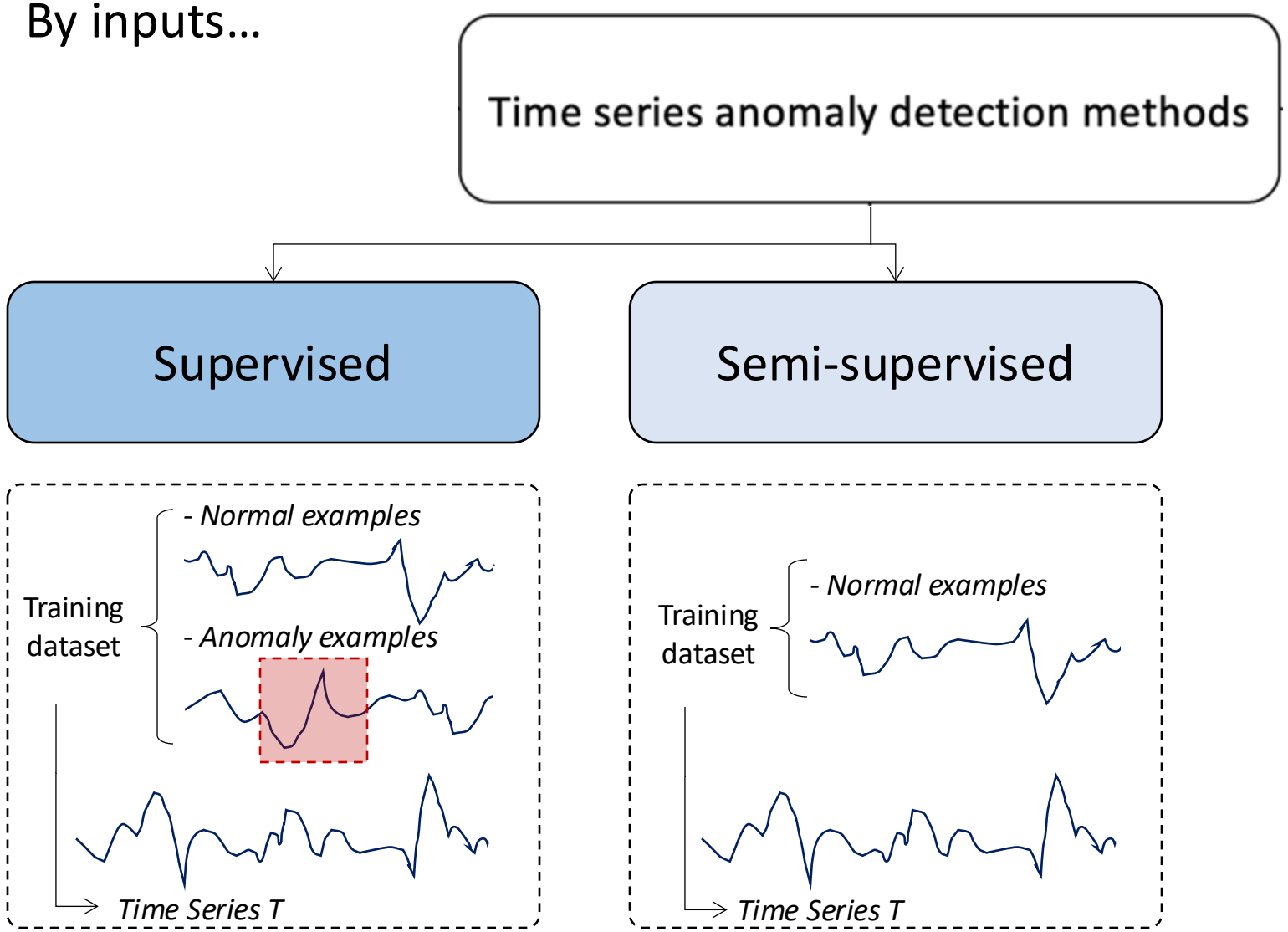
Anomaly Detection methods: *A taxonomy*

By inputs…



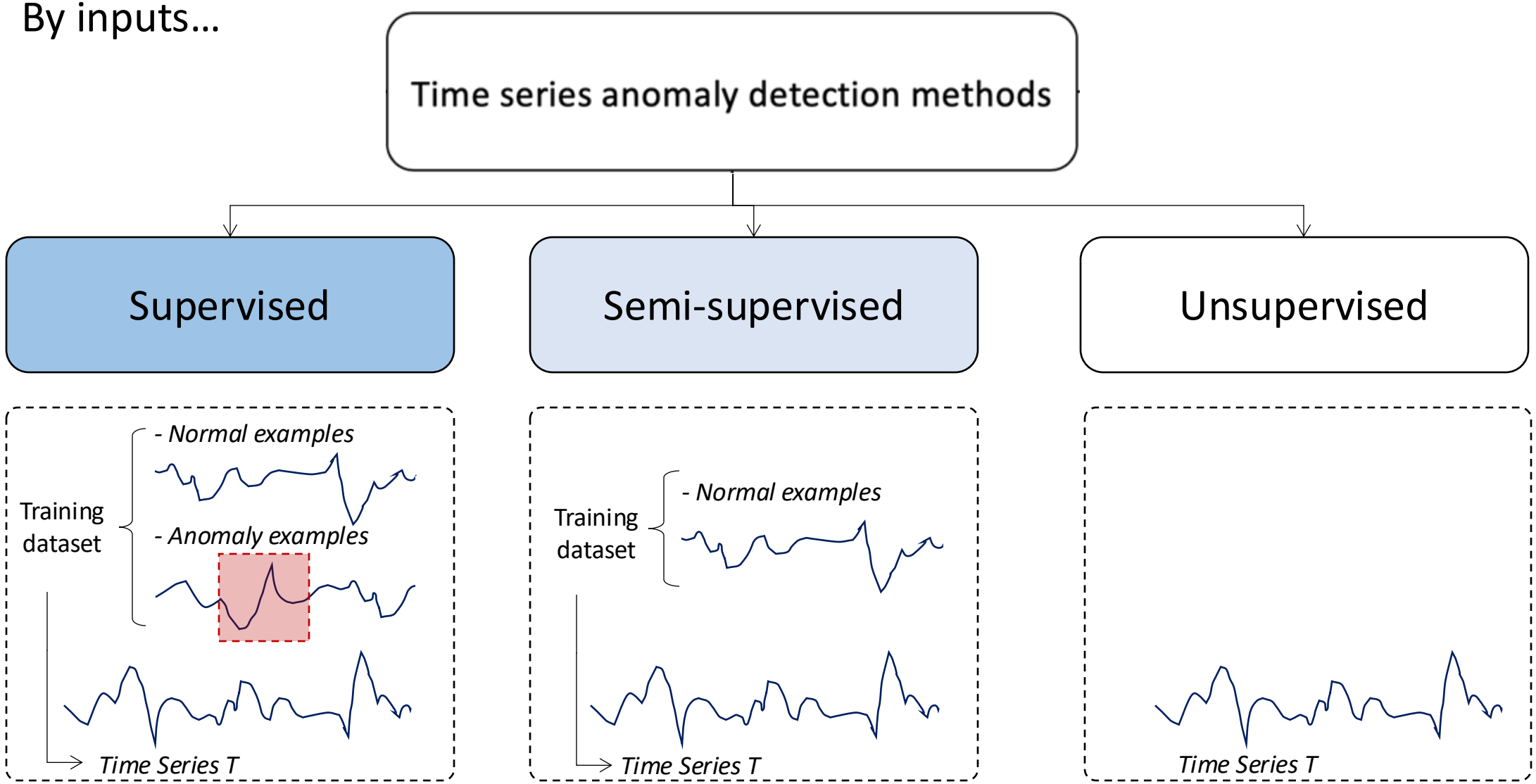
Anomaly Detection methods: *A taxonomy*

By inputs…



Anomaly Detection methods: *A taxonomy*

By inputs…

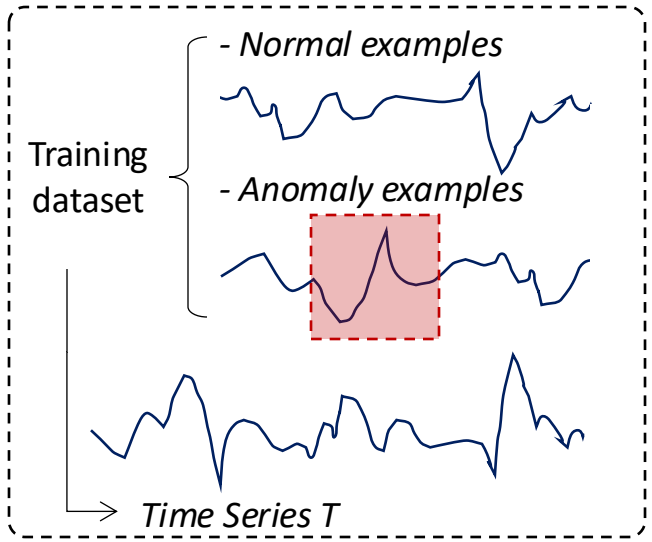


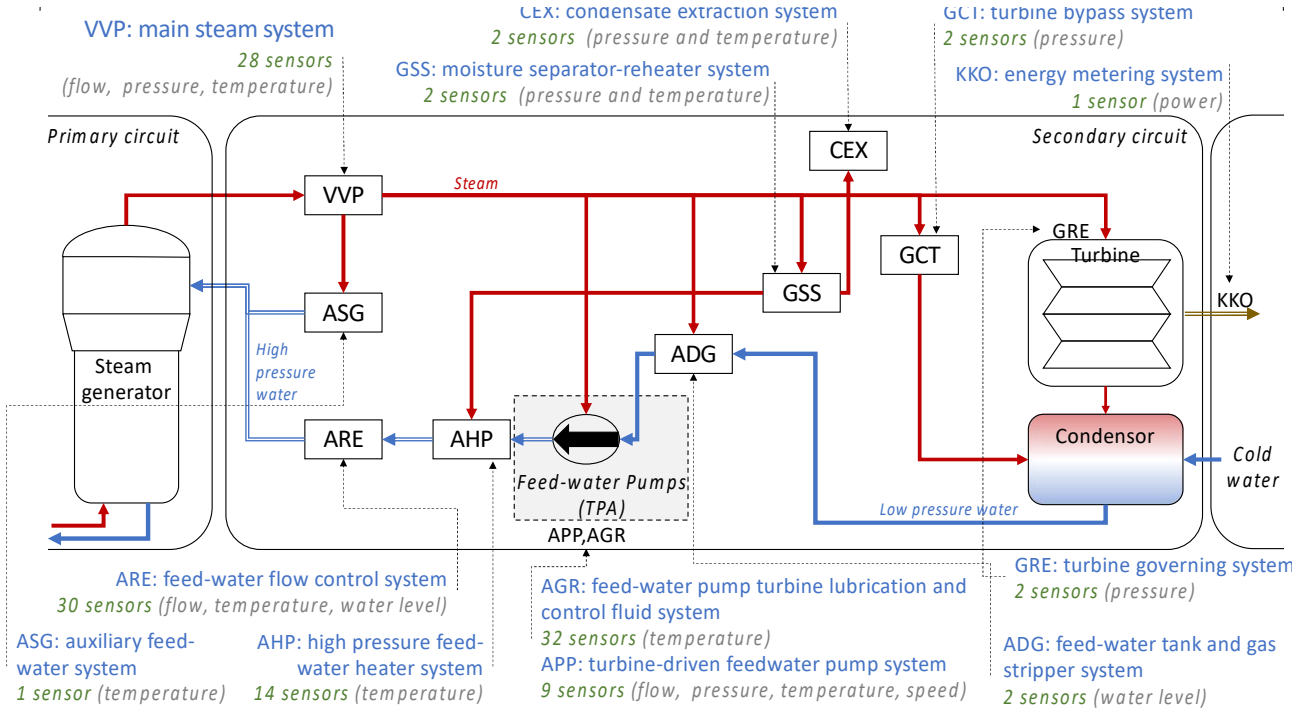
Anomaly Dete

By inputs…

Time

Supervised



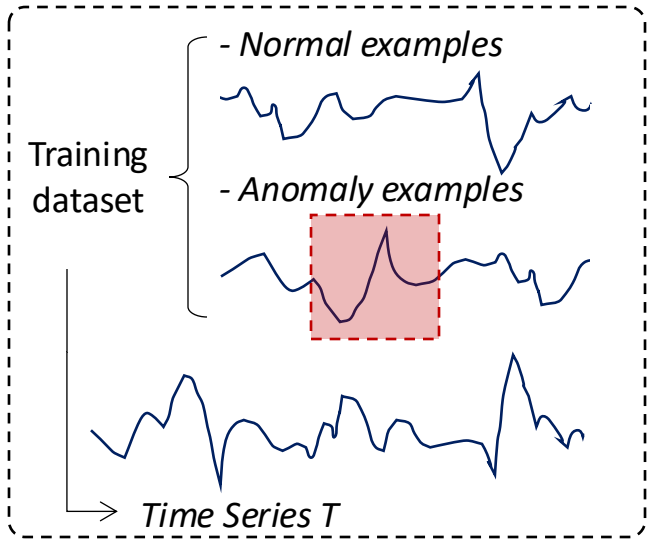


Anomaly Dete

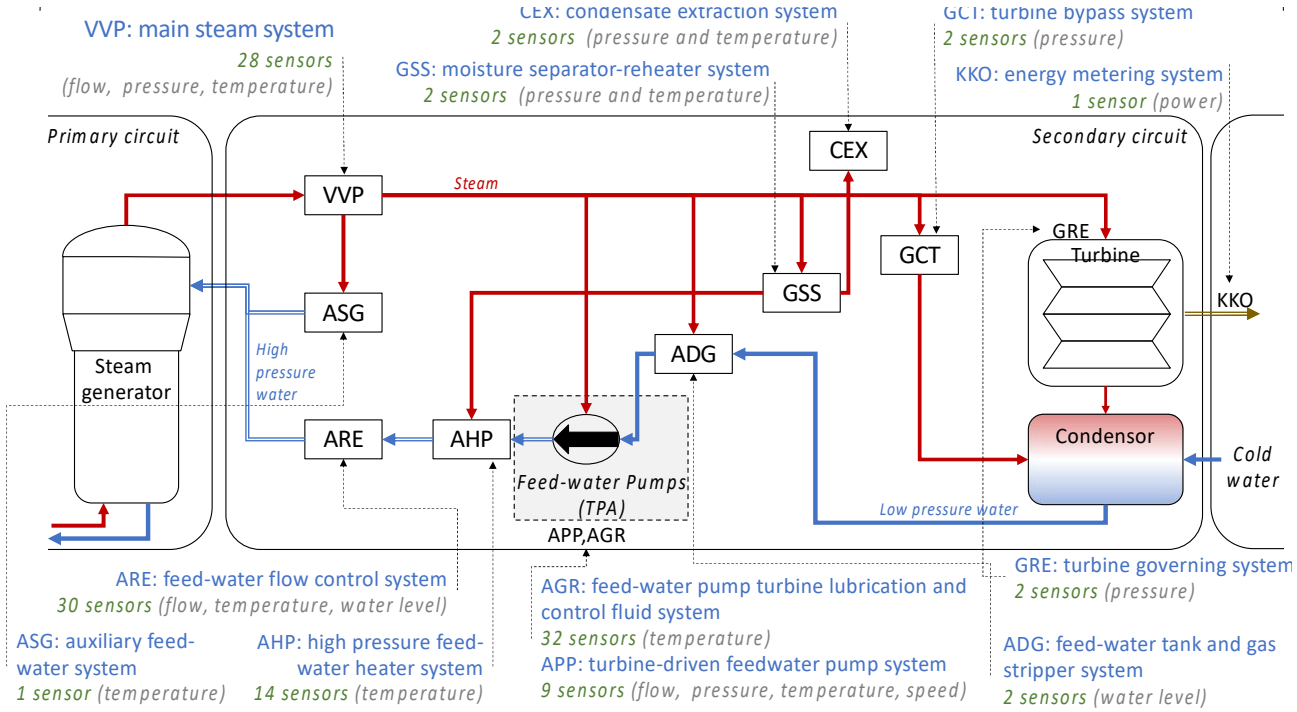
By inputs…

Time

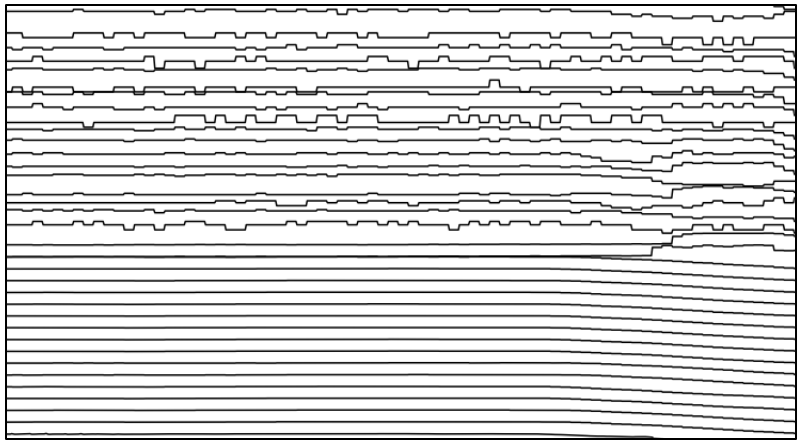
Supervised



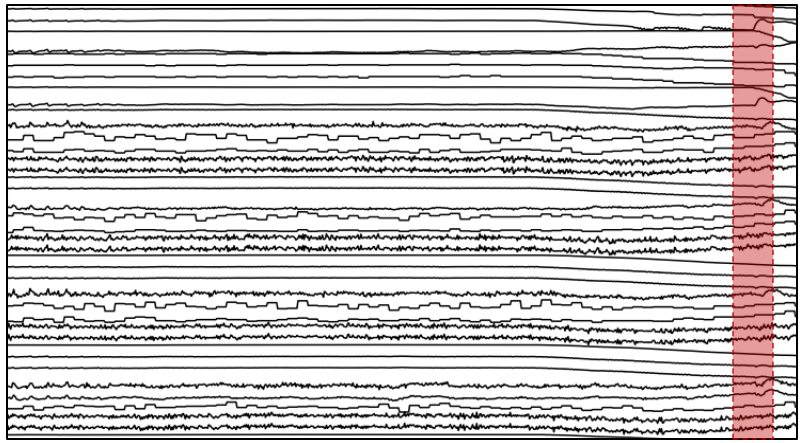
Supervised anomaly detection (e.g., classification)



Class 1: Time series without any vibrations



Class 2: Time series with a vibrations



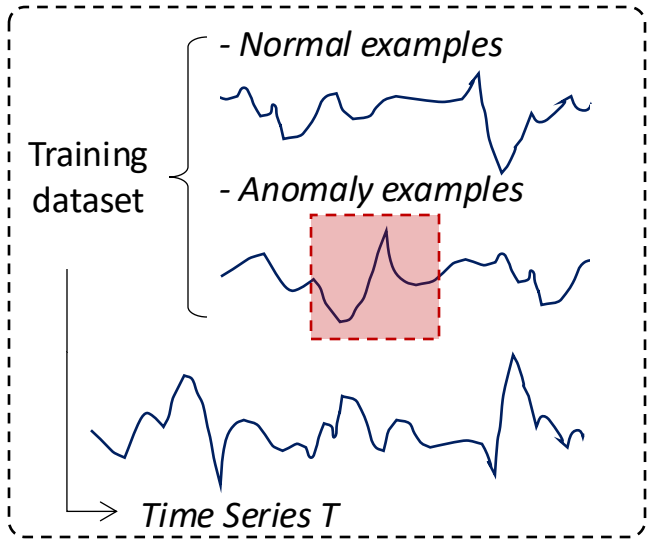
Vibration

Anomaly Dete

By inputs…

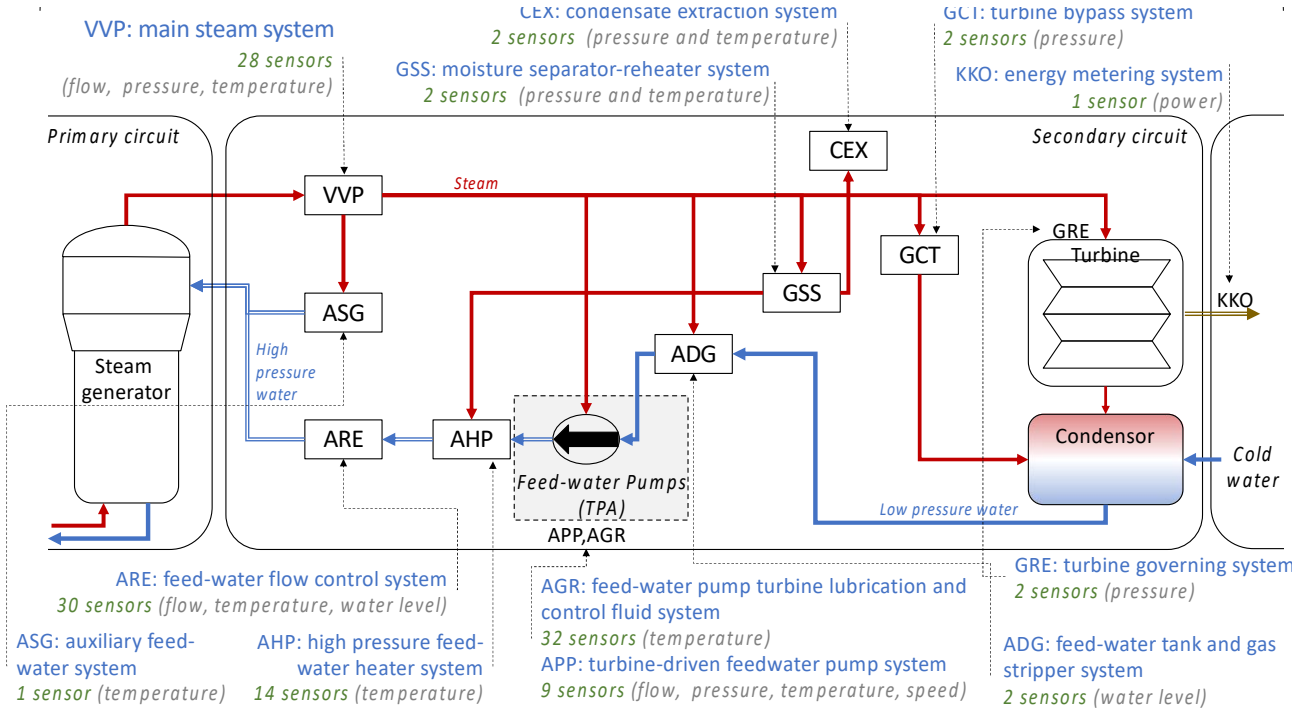
Time

Supervised

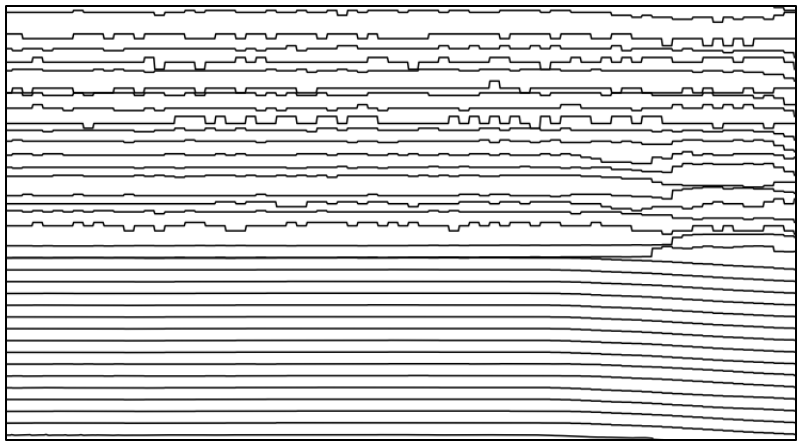


Supervised anomaly detection (e.g., classification)

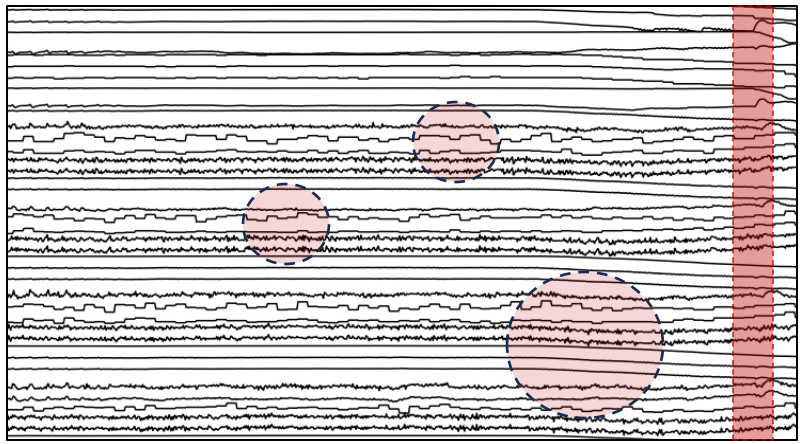
Explanation of the detection



Class 1: Time series without any vibrations



Class 2: Time series with a vibrations



Vibration

Anomaly Dete

By inputs…

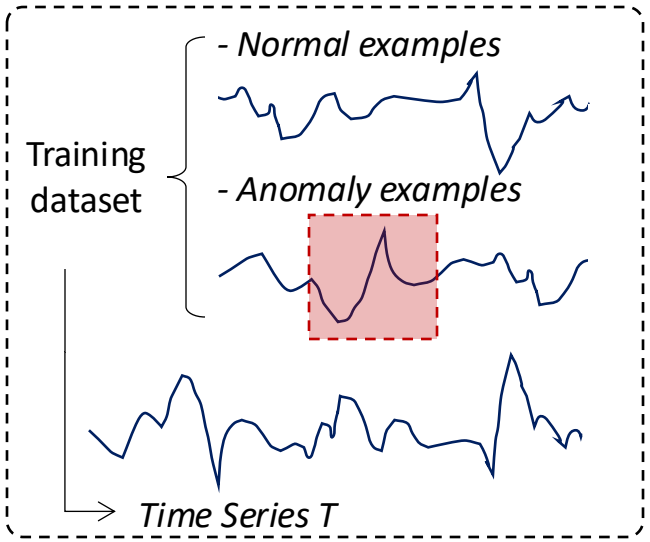
Time

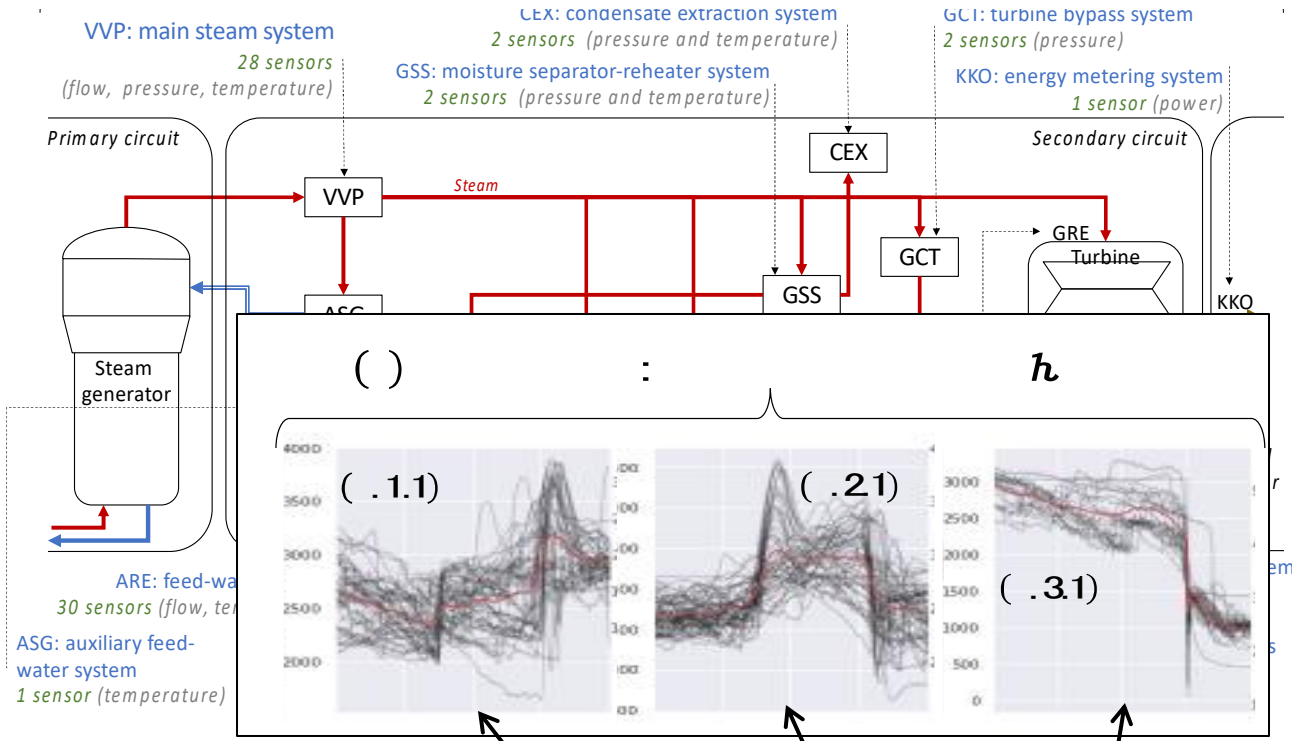
Supervised

Supervised anomaly detection (e.g., classification)

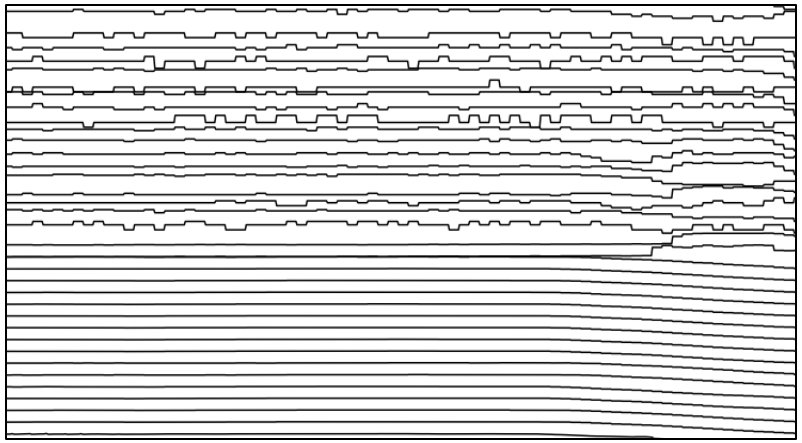
Explanation of the detection

Identification of precursors

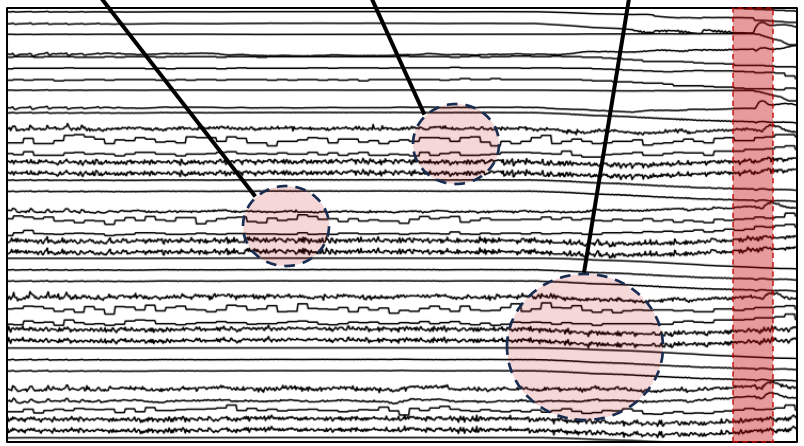




Class 1: Time series without any vibrations



Class 2: Time series with a vibrations



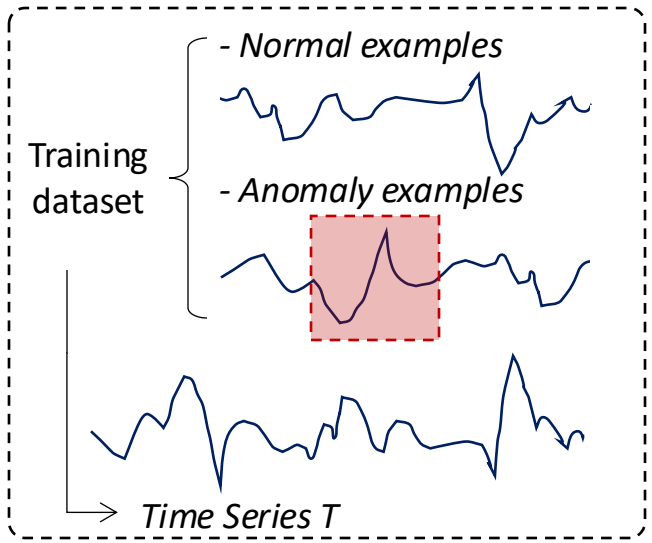
Vibration

Anomaly Dete

By inputs…

Time

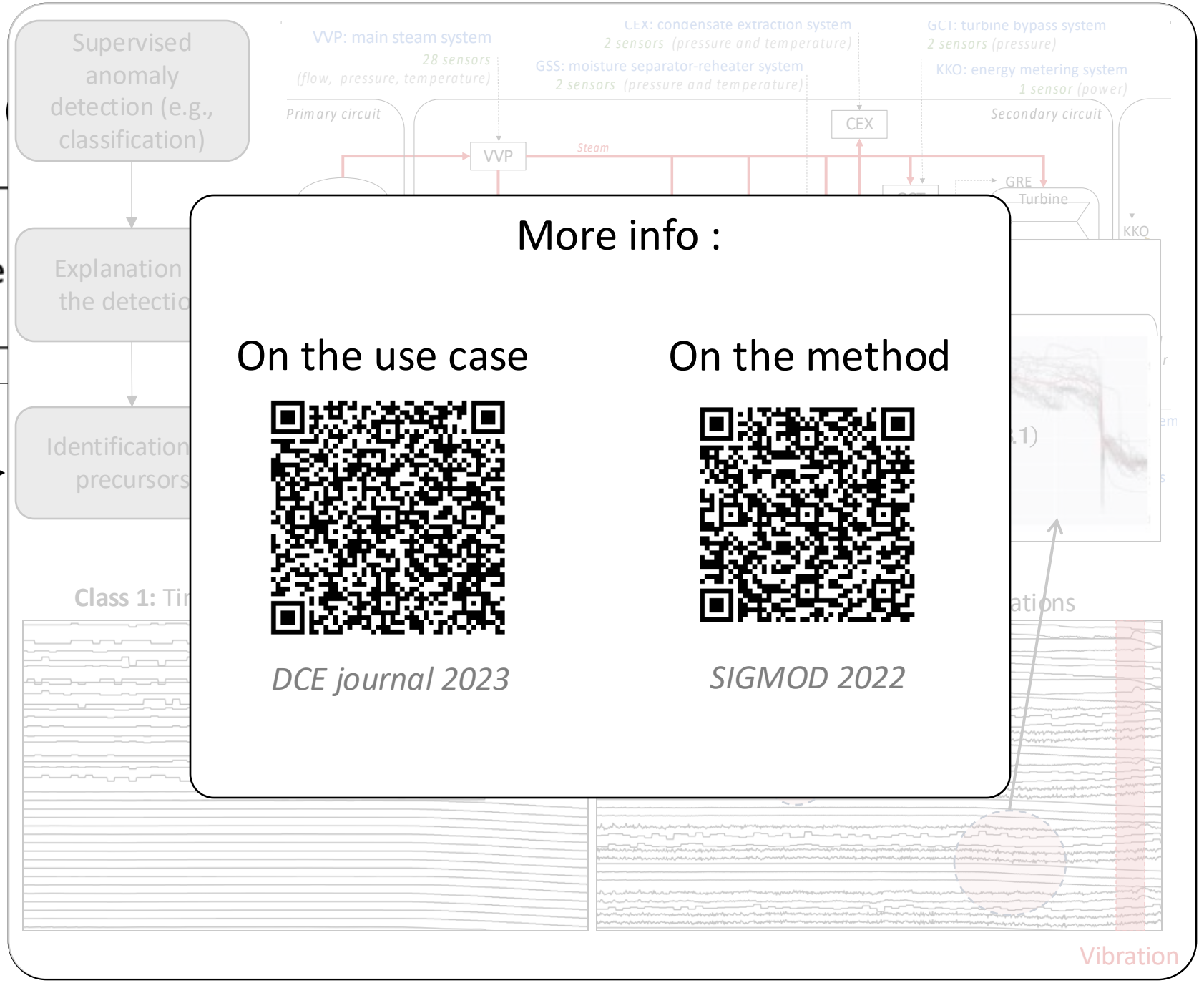
Supervised



Supervised anomaly detection (e.g., classification)

Explanation the detectio

Identification precursors



More info :

On the use case

DCE journal 2023

On the method

SIGMOD 2022

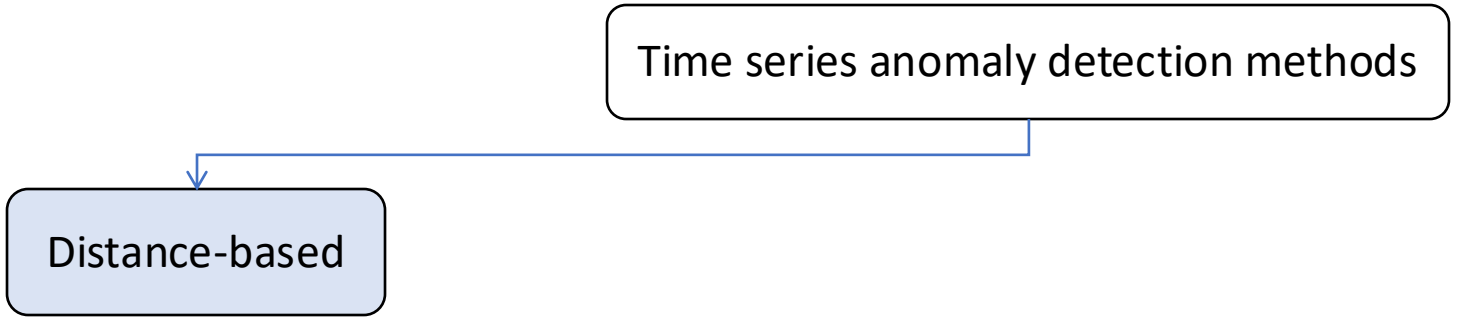
Anomaly Detection methods: *A taxonomy*

By methods…

Time series anomaly detection methods

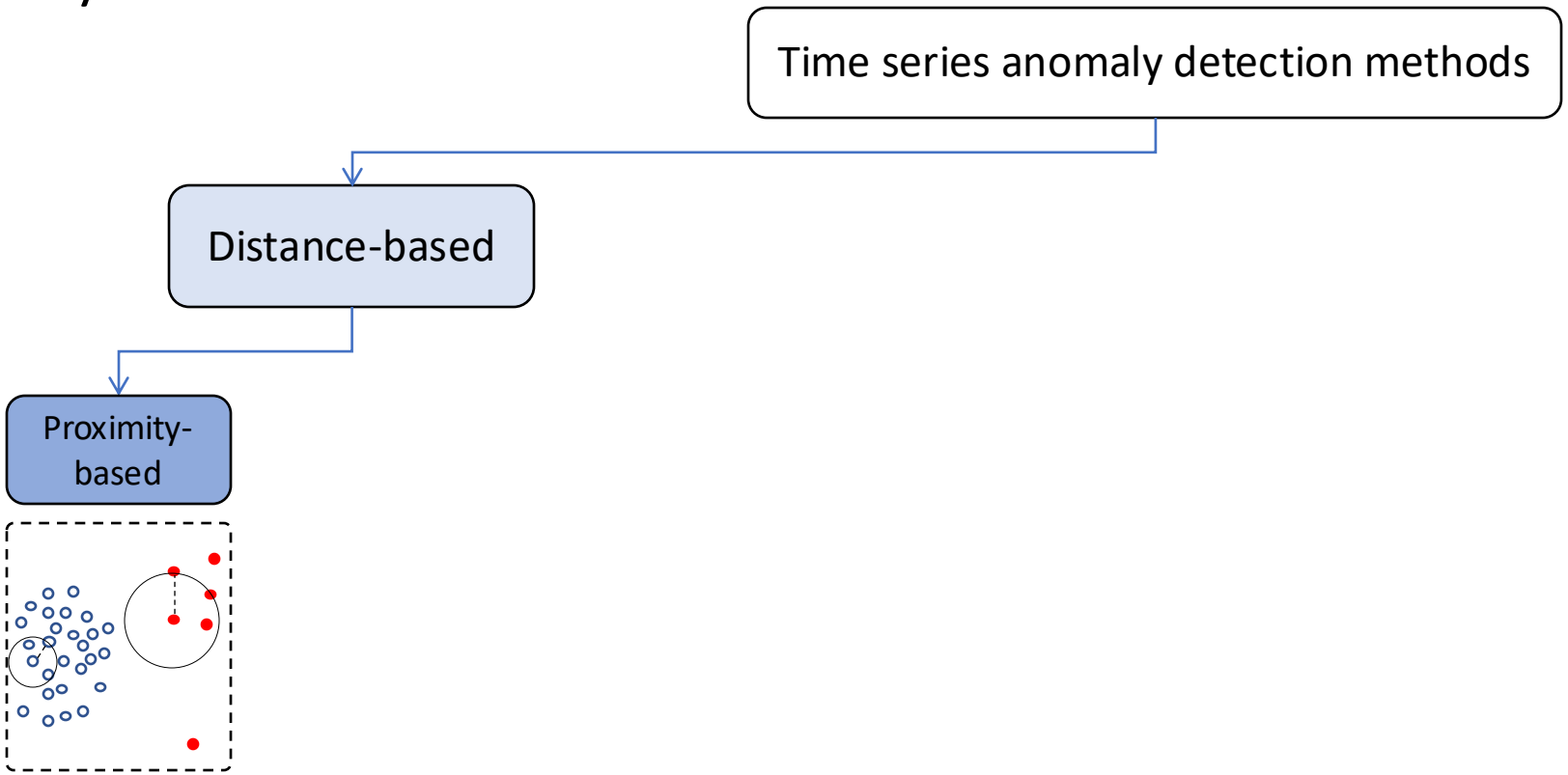
Anomaly Detection methods: *A taxonomy*

By methods…



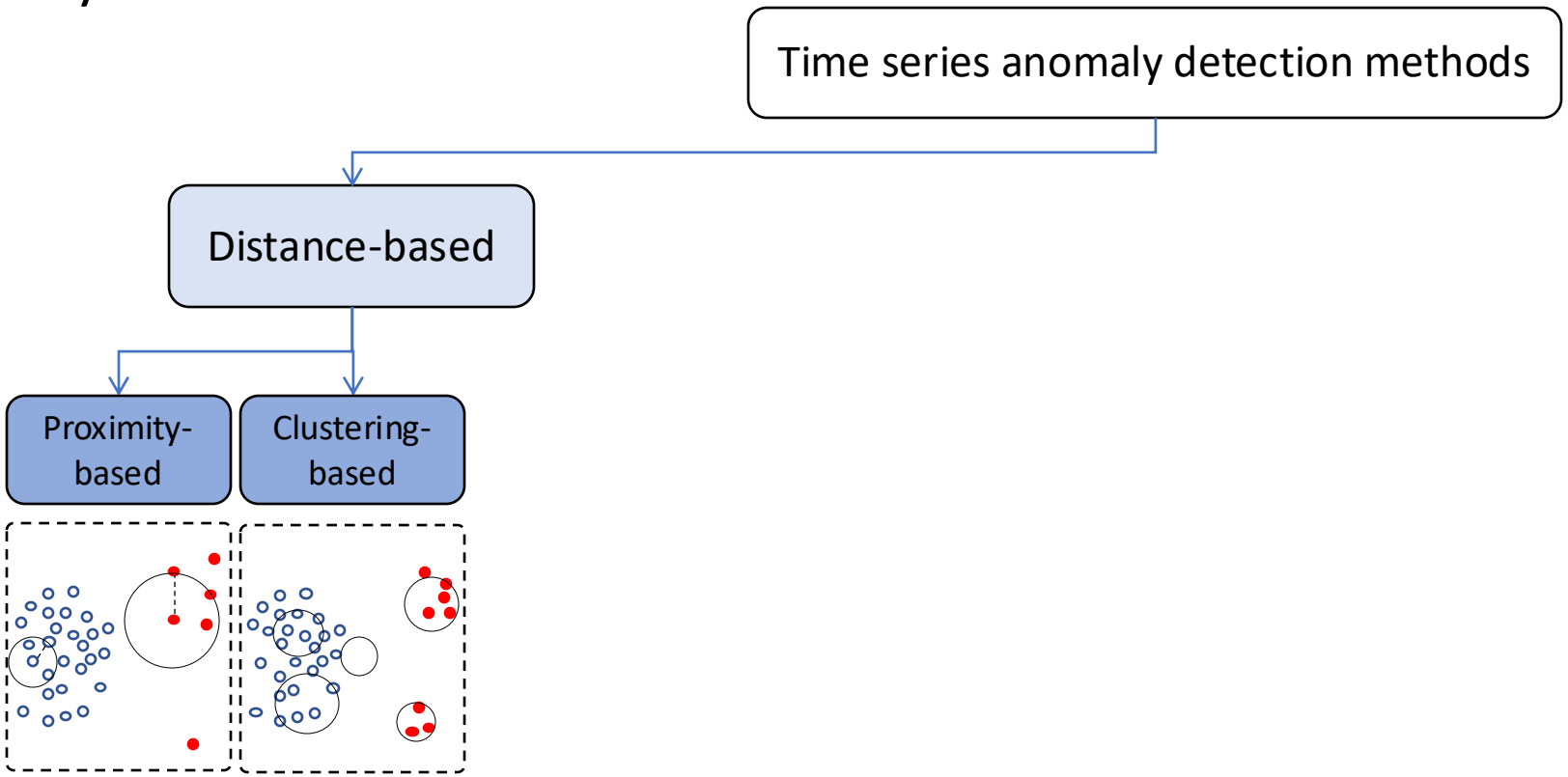
Anomaly Detection methods: *A taxonomy*

By methods…



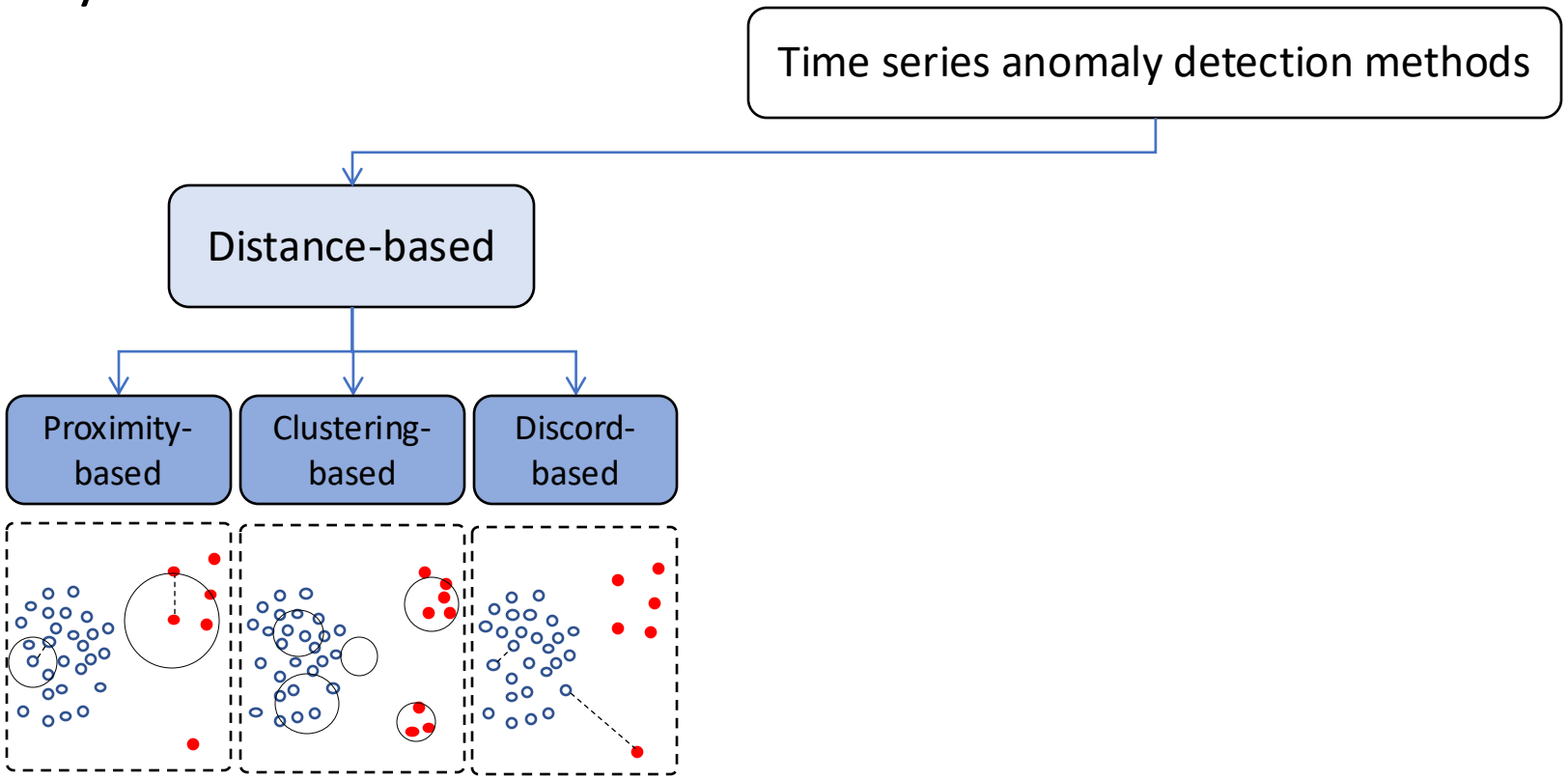
Anomaly Detection methods: *A taxonomy*

By methods…



Anomaly Detection methods: *A taxonomy*

By methods…



Anomaly Detection methods: *A taxonomy*

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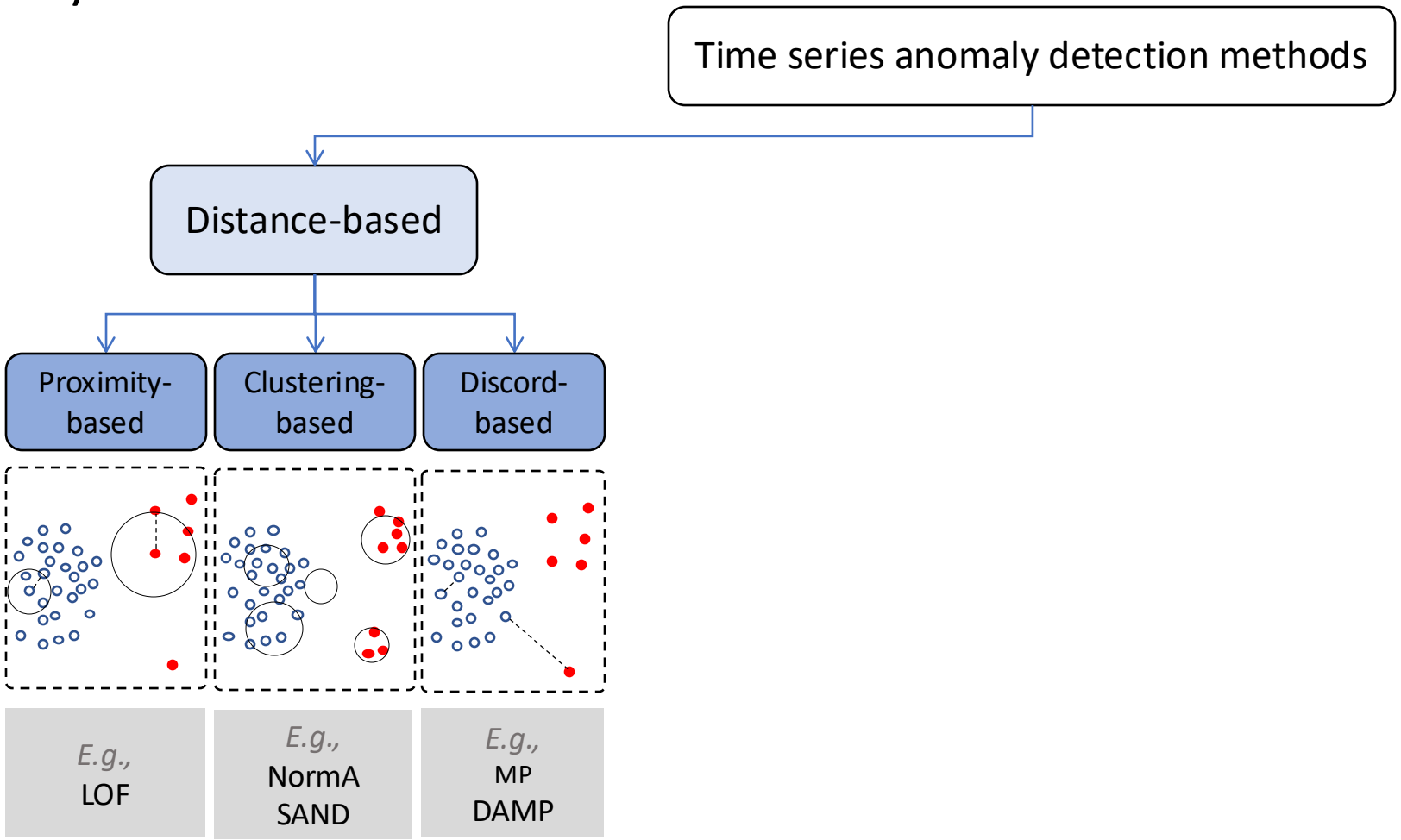

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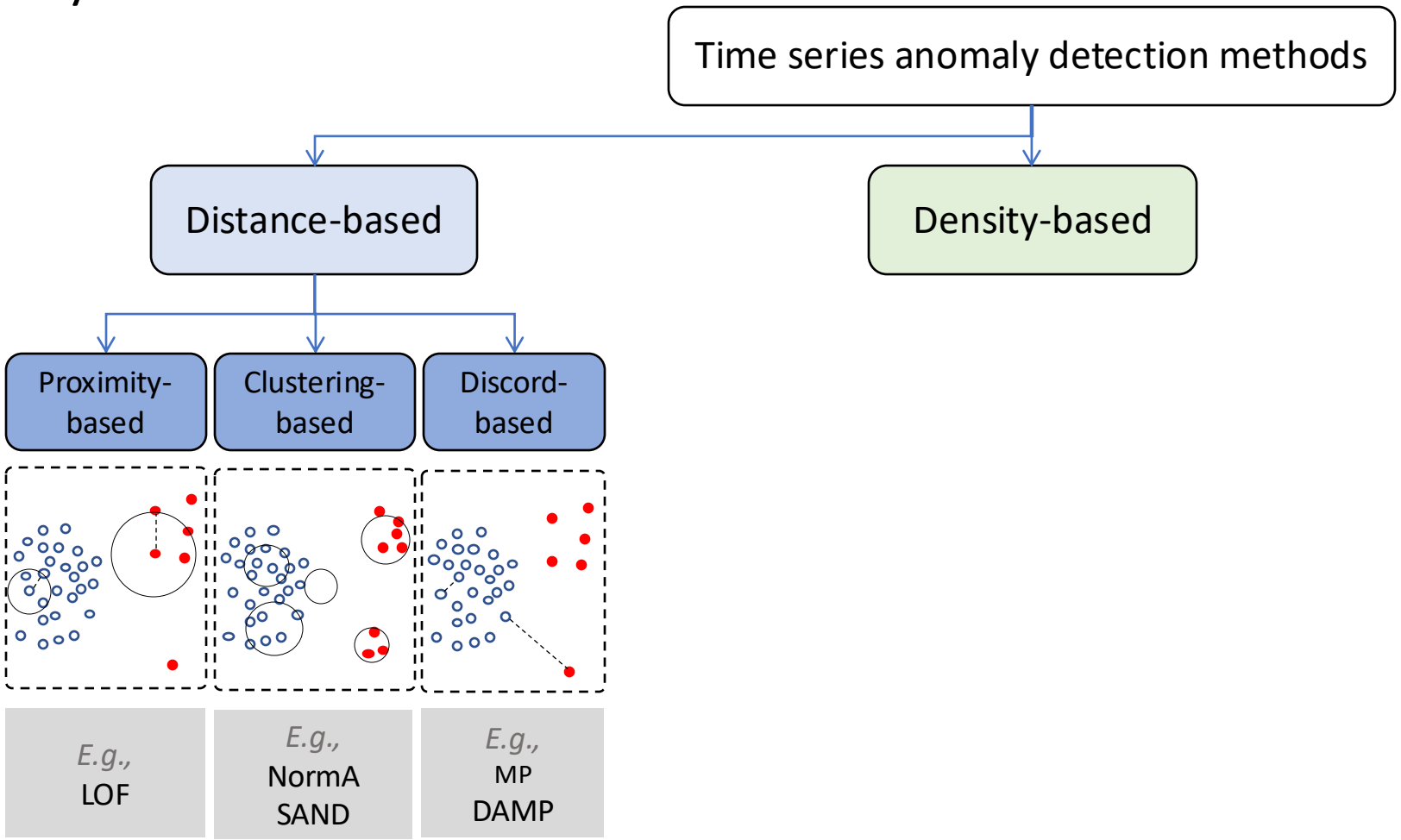

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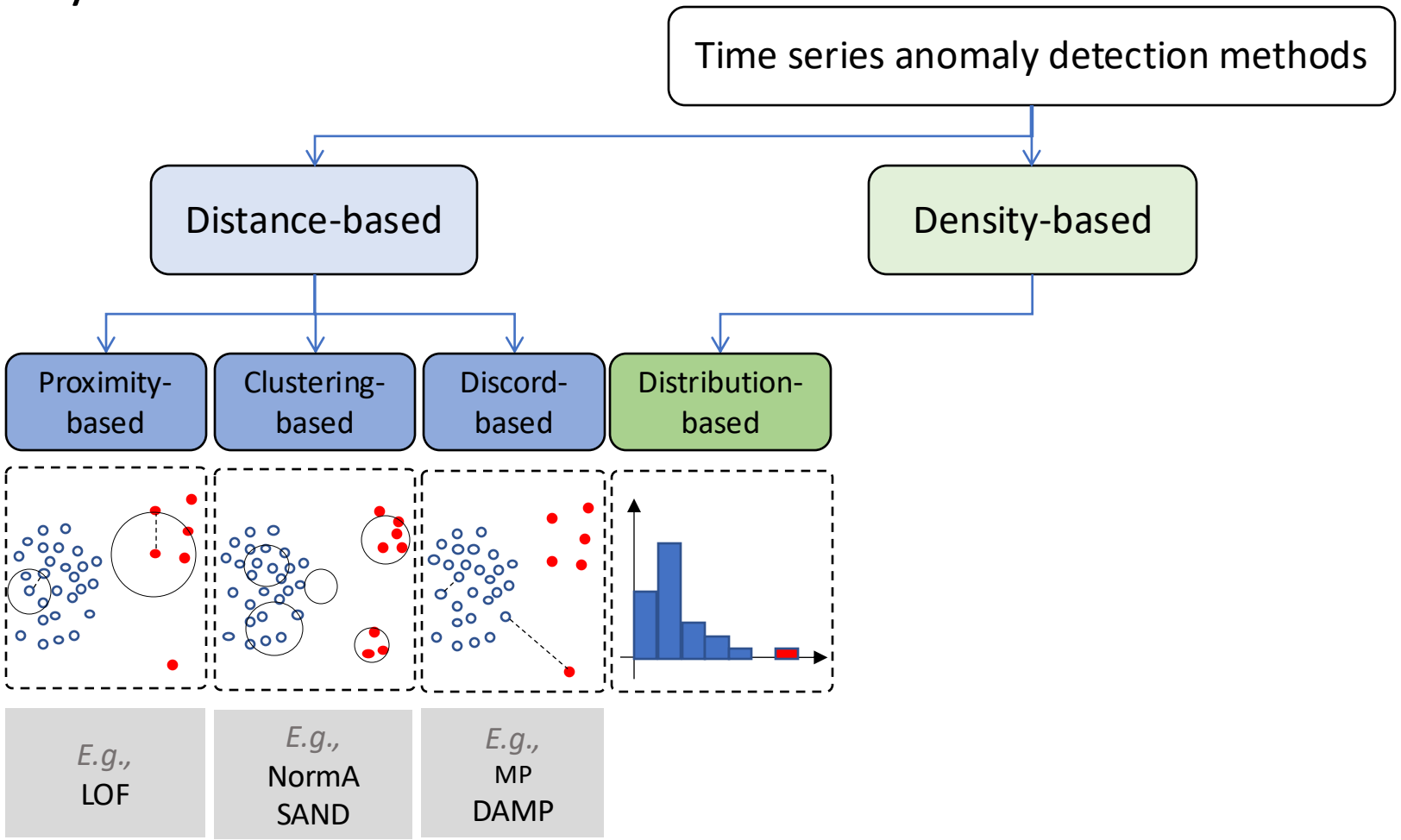

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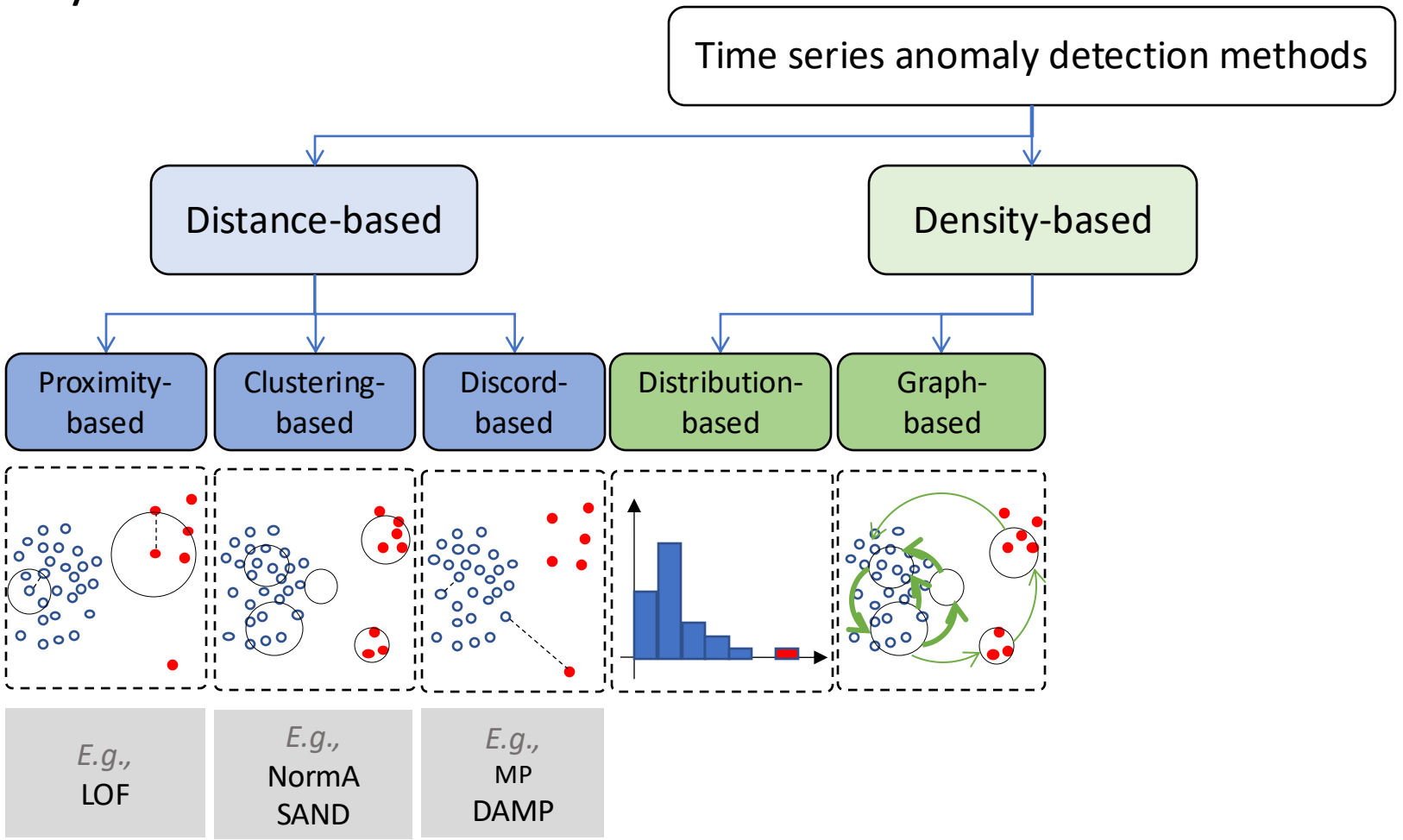

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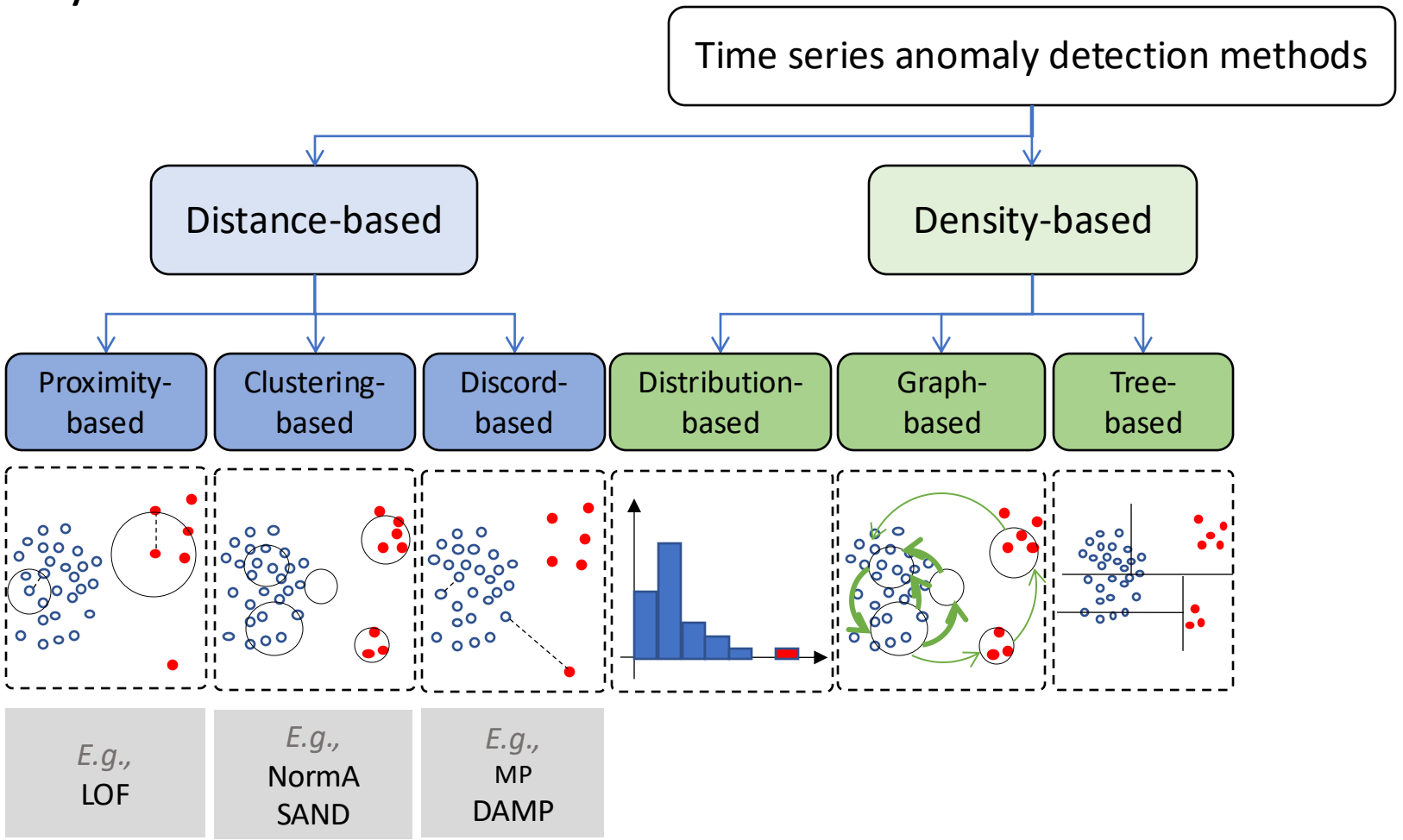

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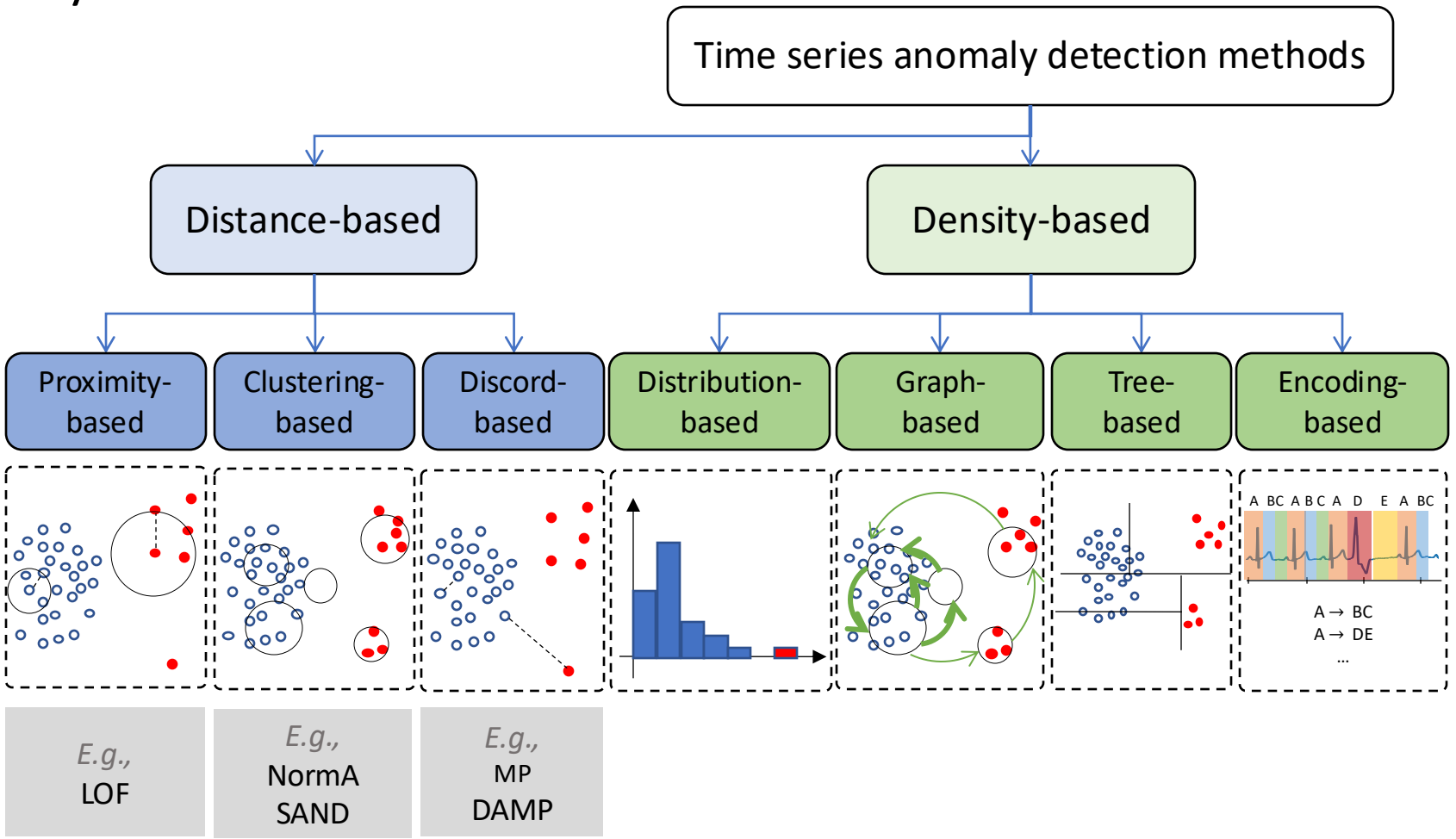

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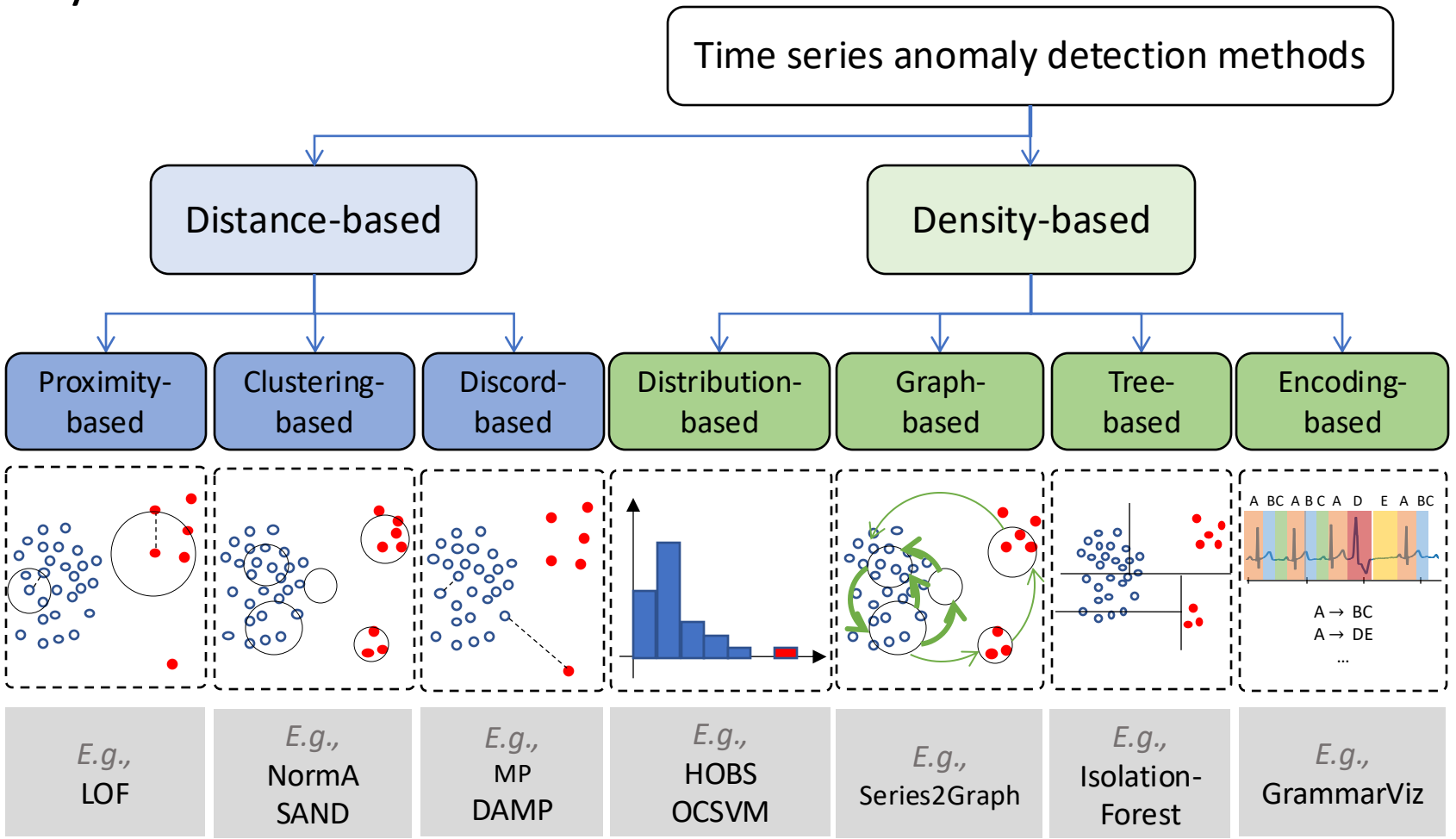

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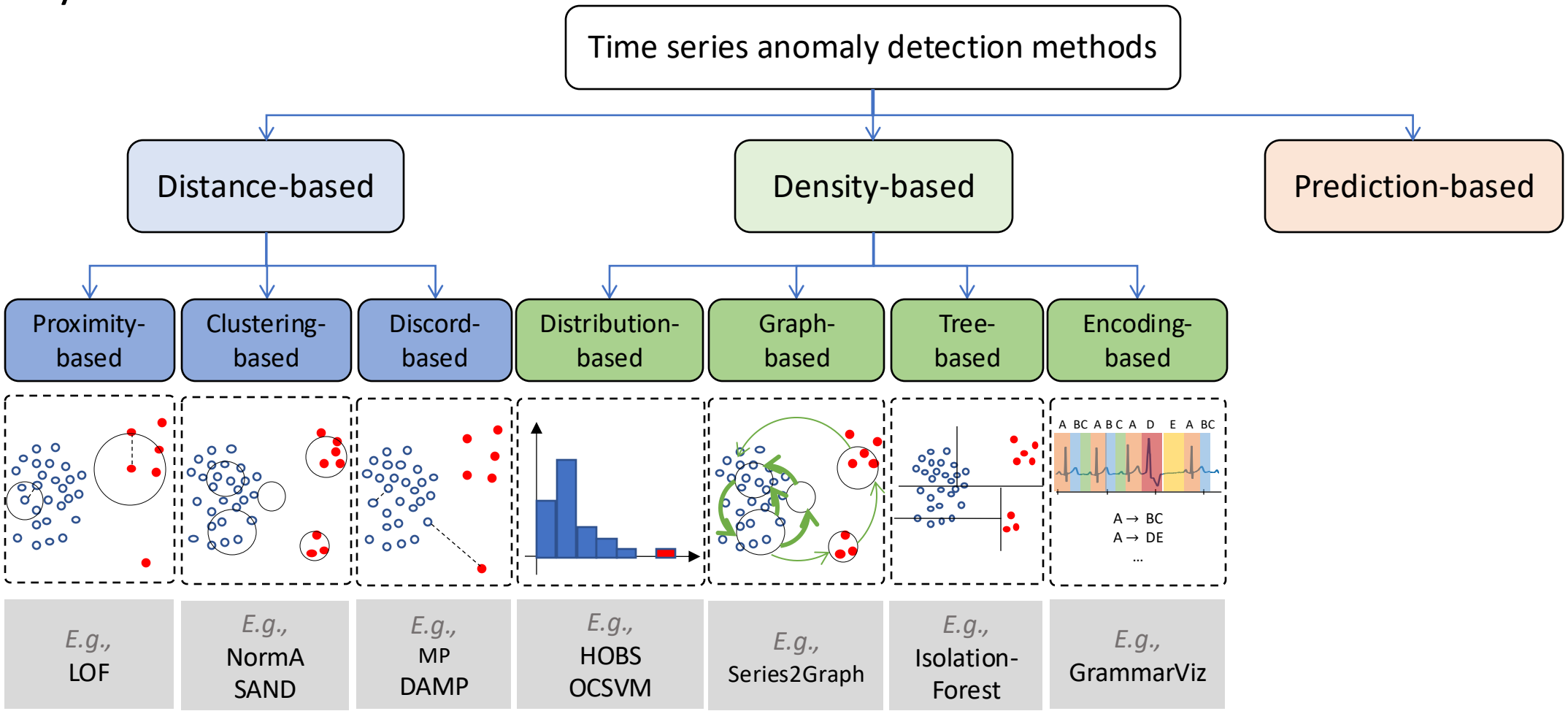

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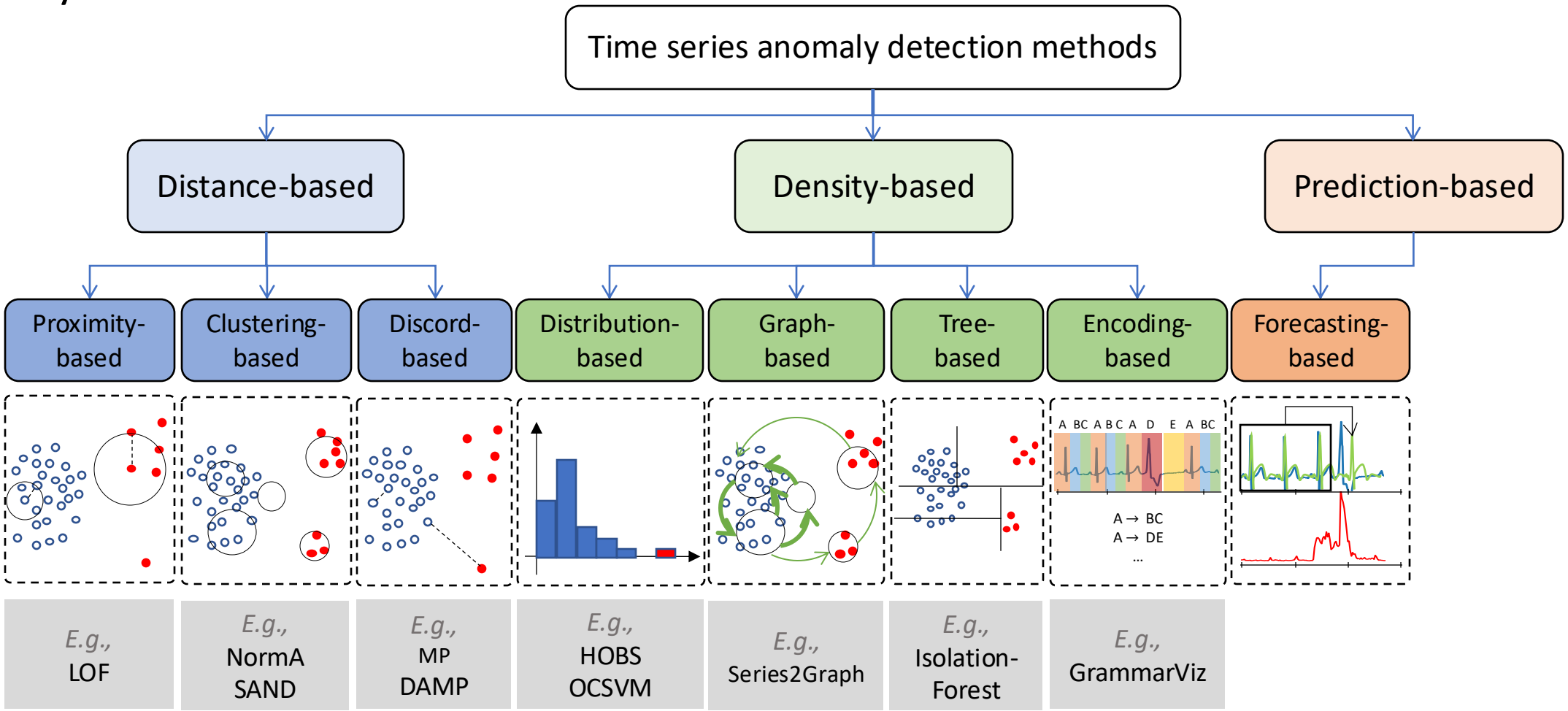

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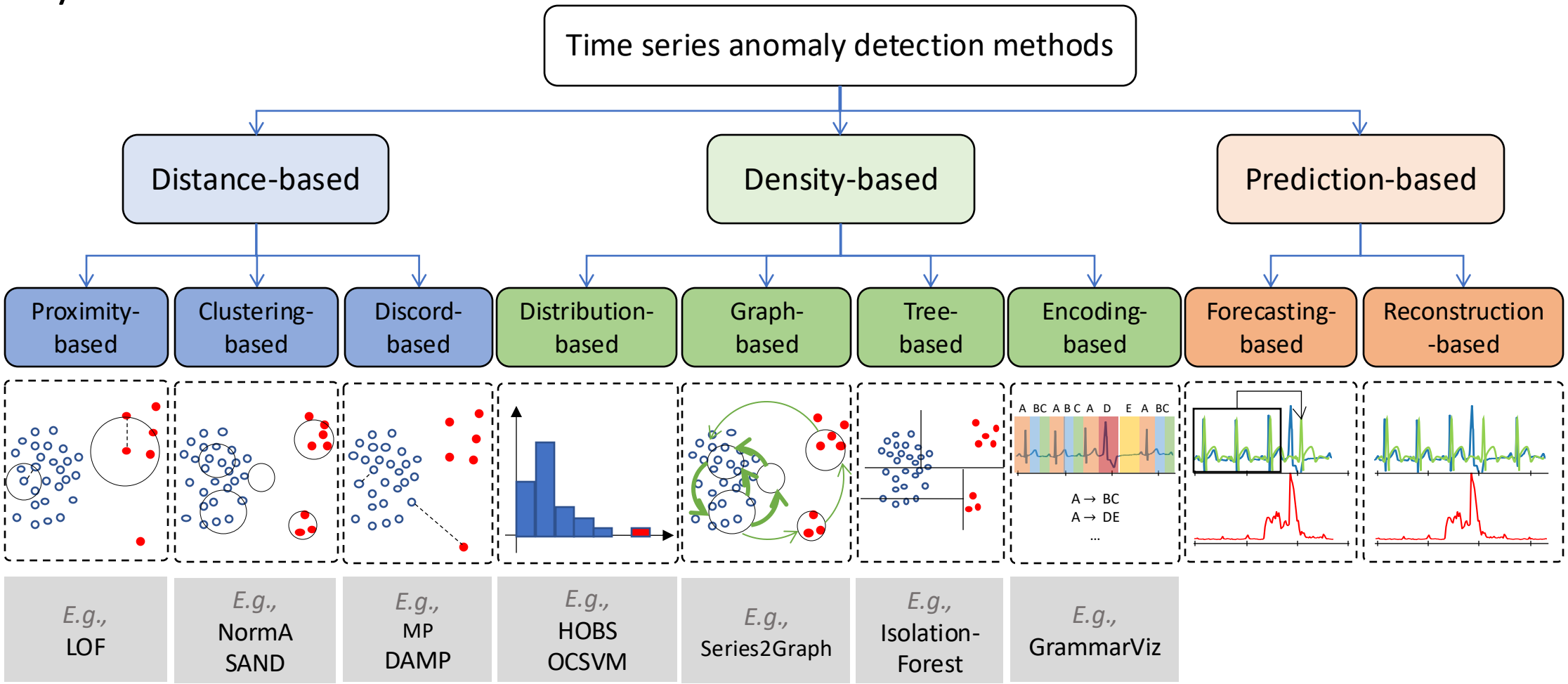

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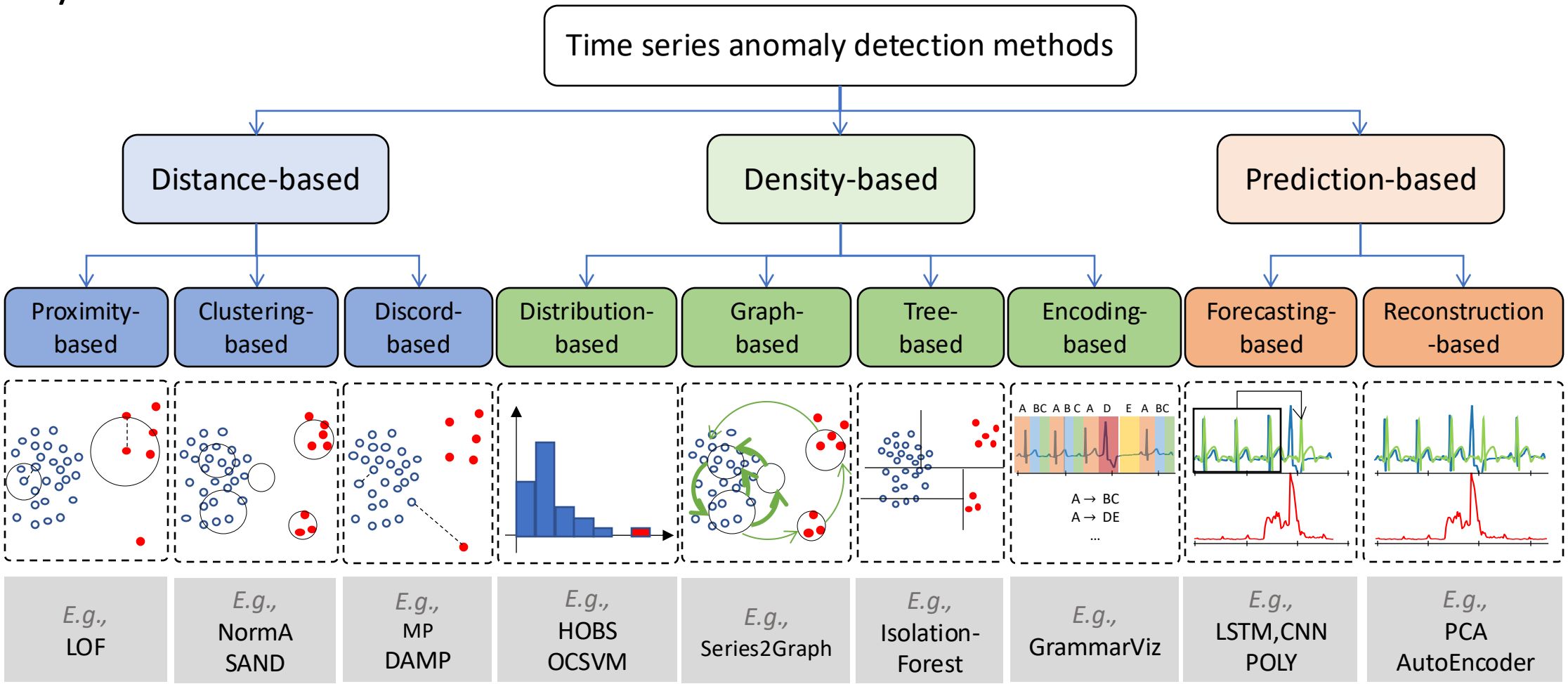
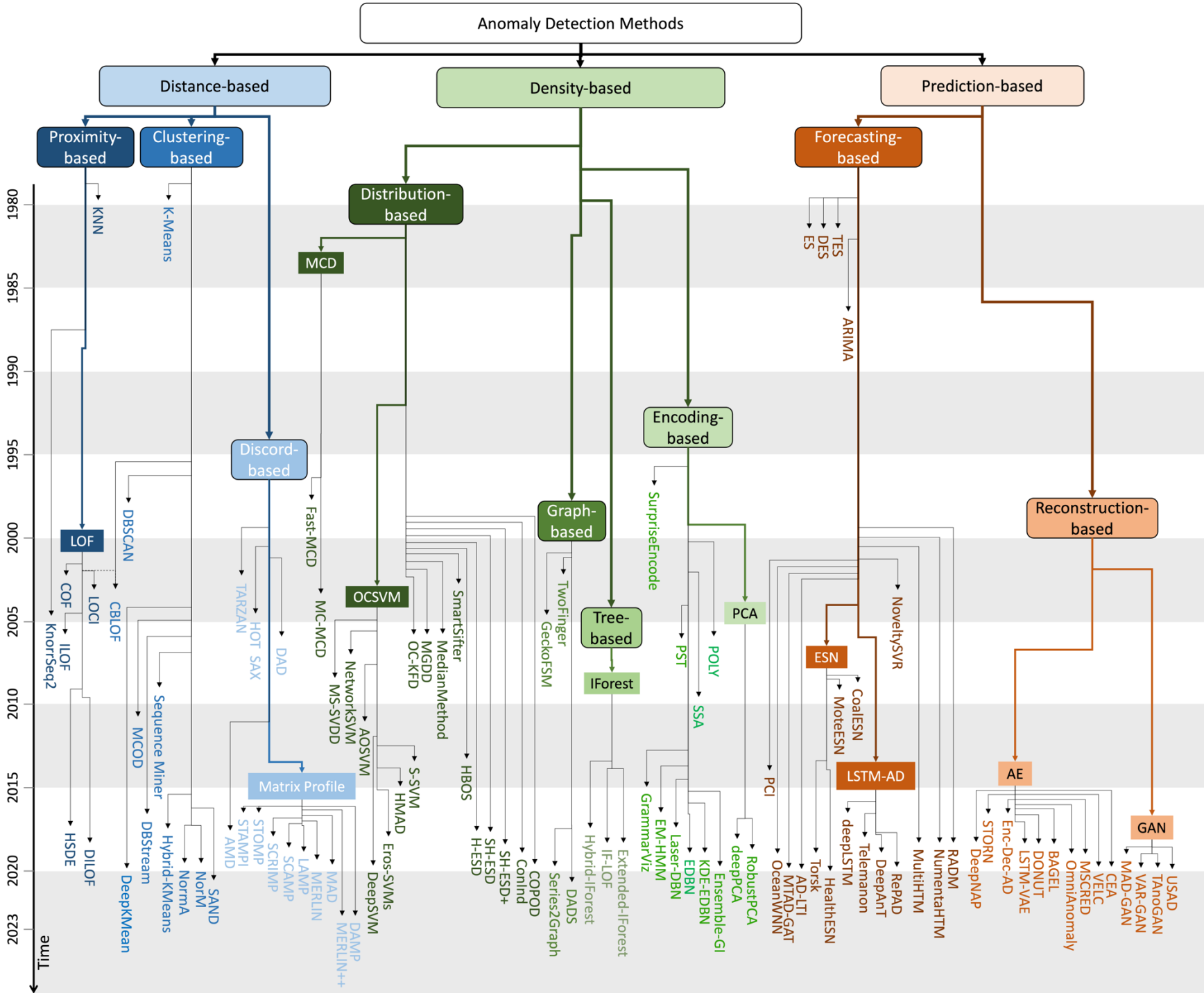
By methods…



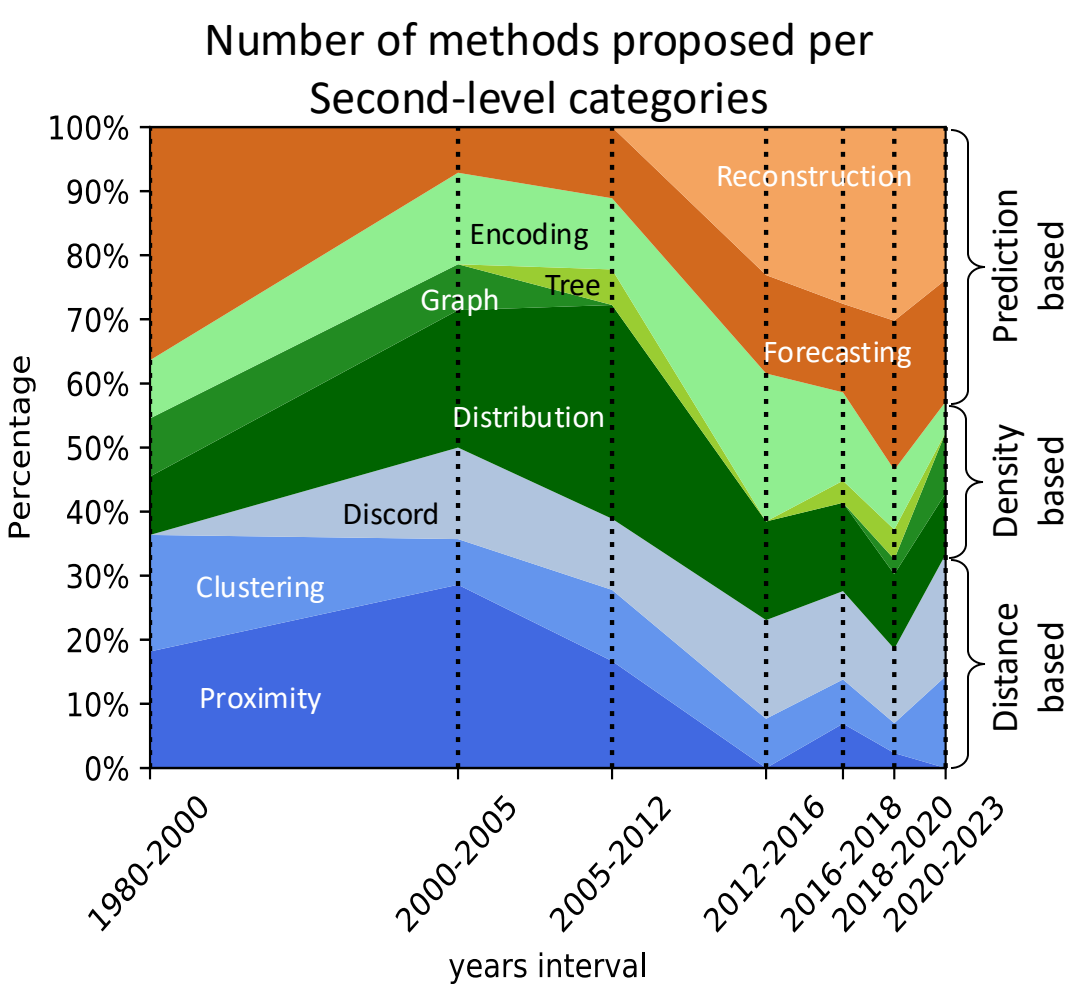
Anomaly Detection methods: *A taxonomy*

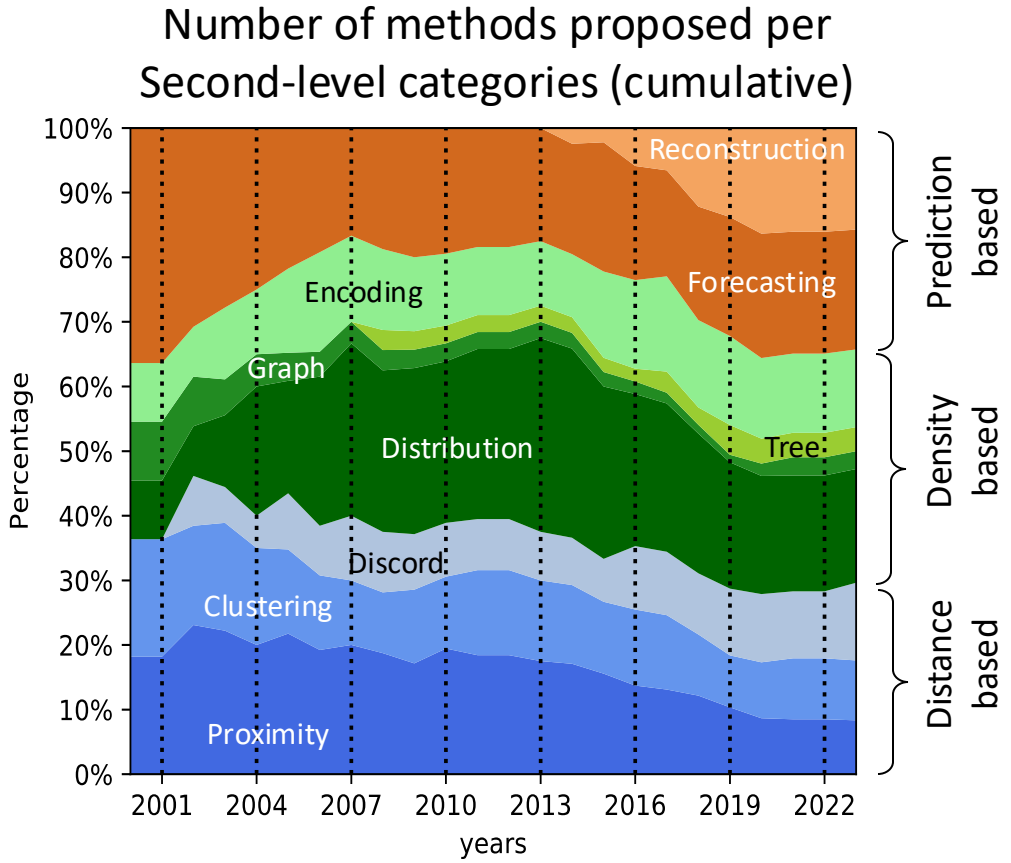
By time…



Anomaly Detection methods: *A taxonomy*

By time…

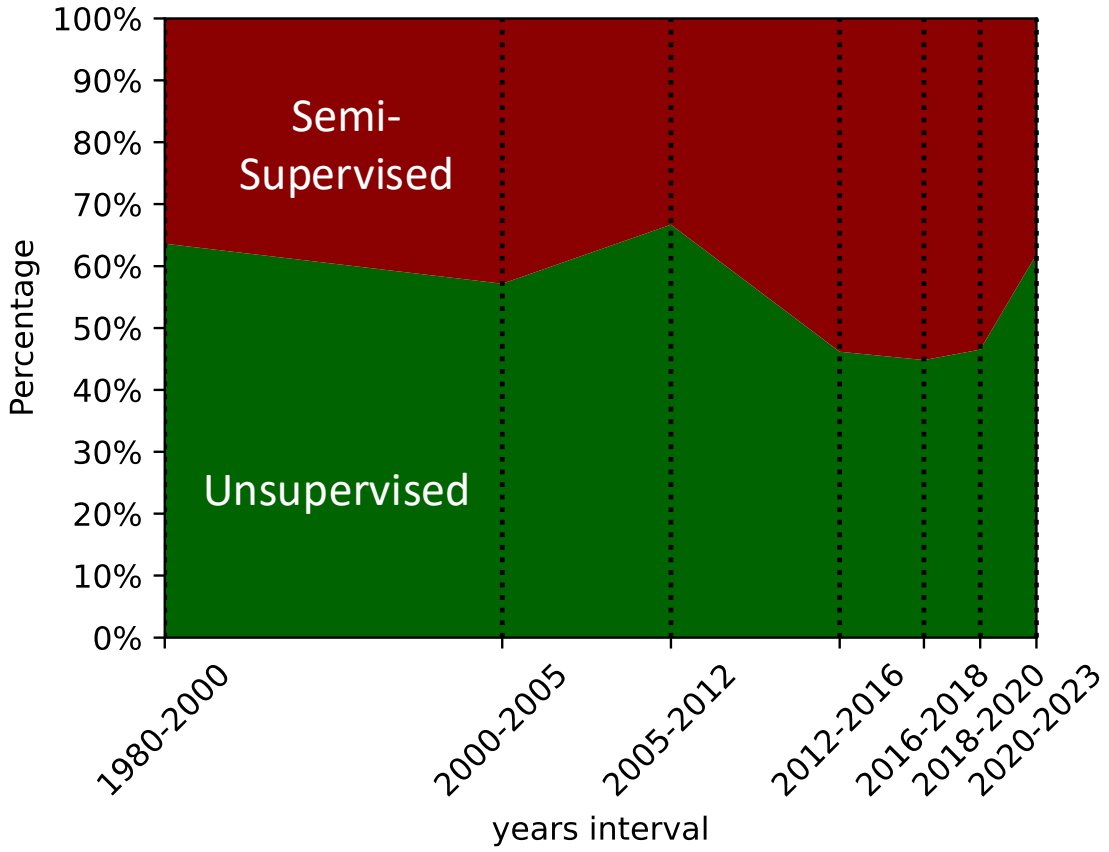




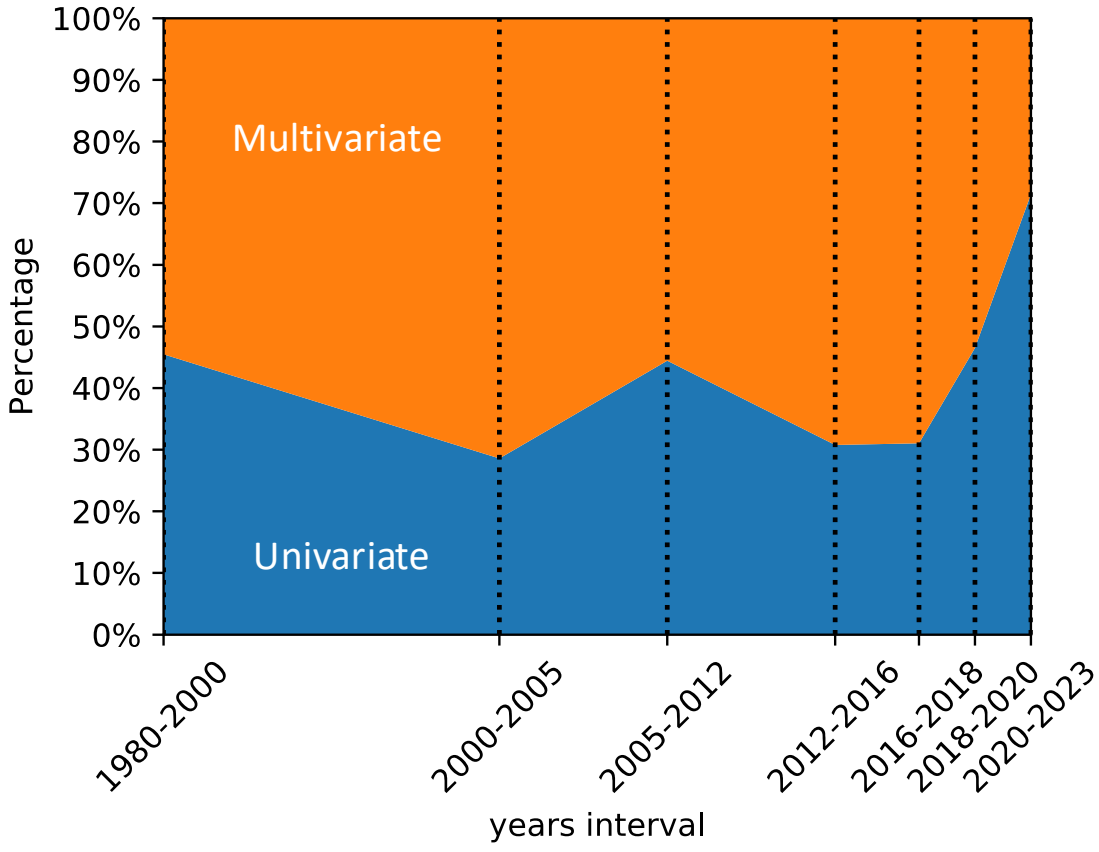
Anomaly Detection methods: *A taxonomy*

By time…

Number of methods proposed that are *Unsupervised* or *Semi-Supervised*

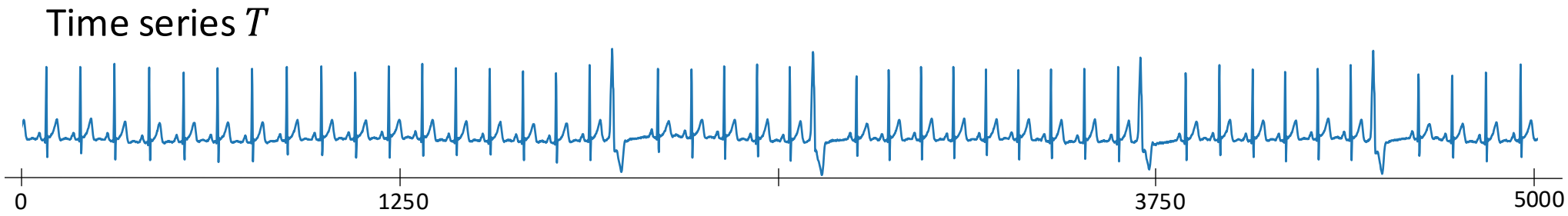


Number of methods proposed that can handle *Univariate* or *Multivariate* time series



Anomaly Detection methods: *Distance-based*

Methods that use distance computation between subsequences (or group of subsequences) to detect anomalies.



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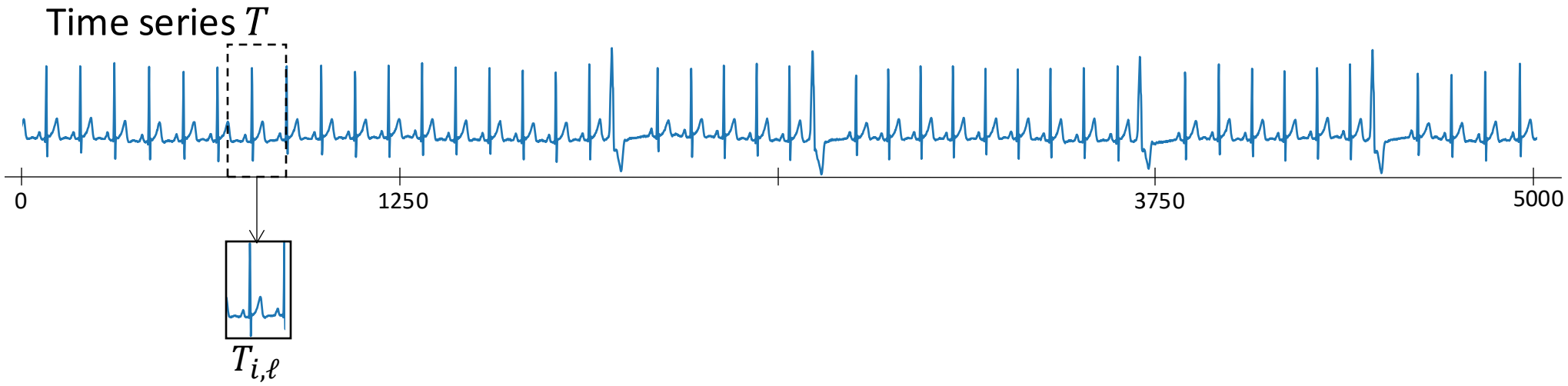

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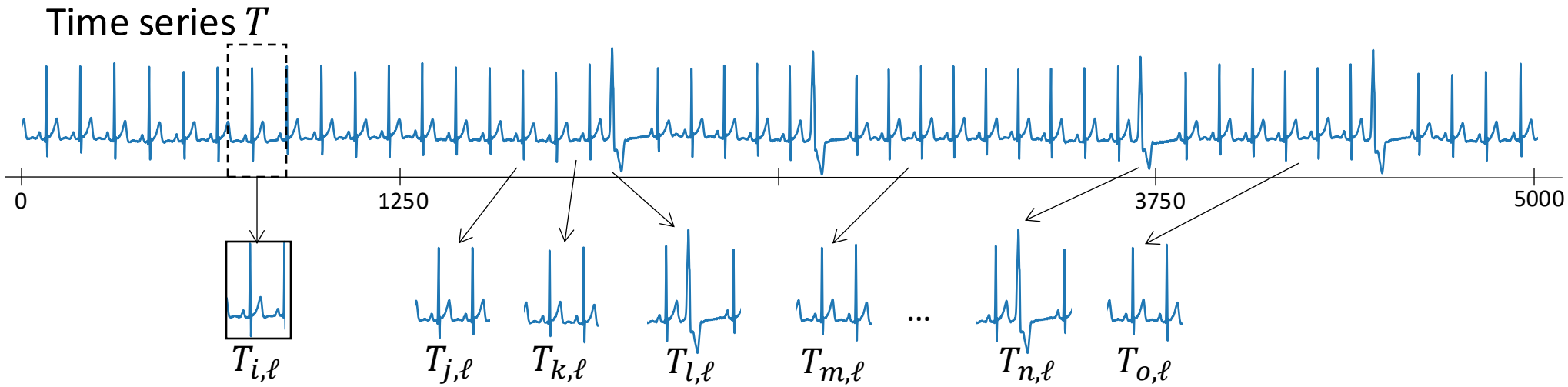

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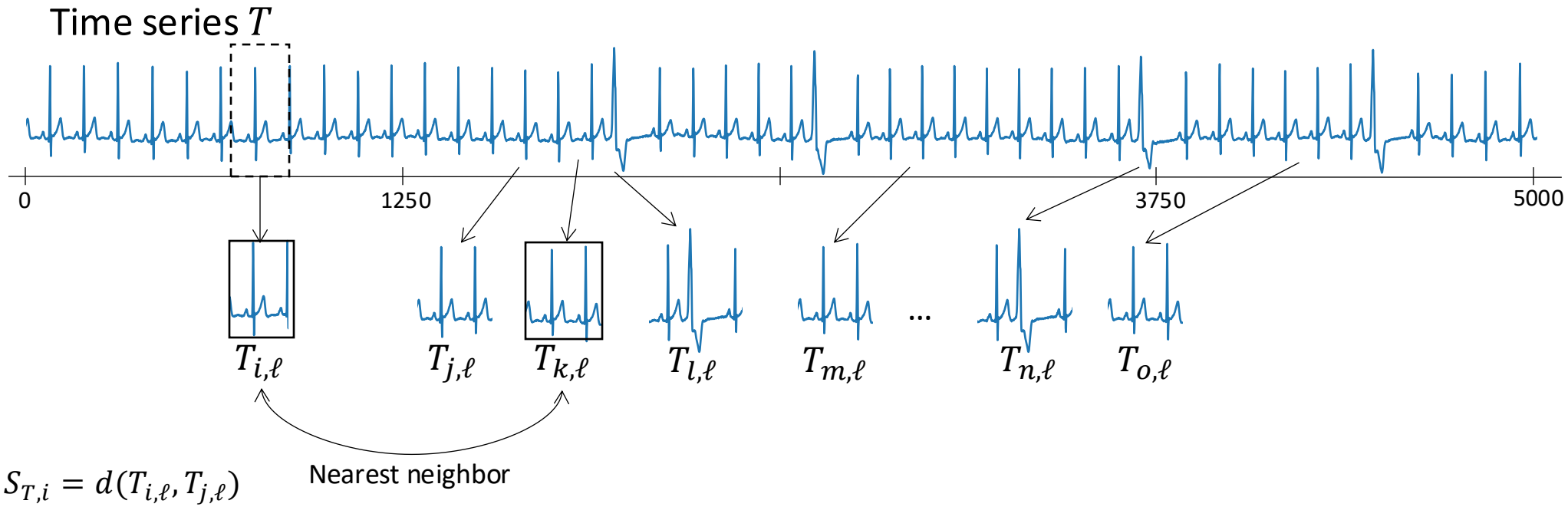

$S_{T,i} = d(T_{i,\ell}, T_{j,\ell})$

Anomaly Detection methods: *Distance-based*

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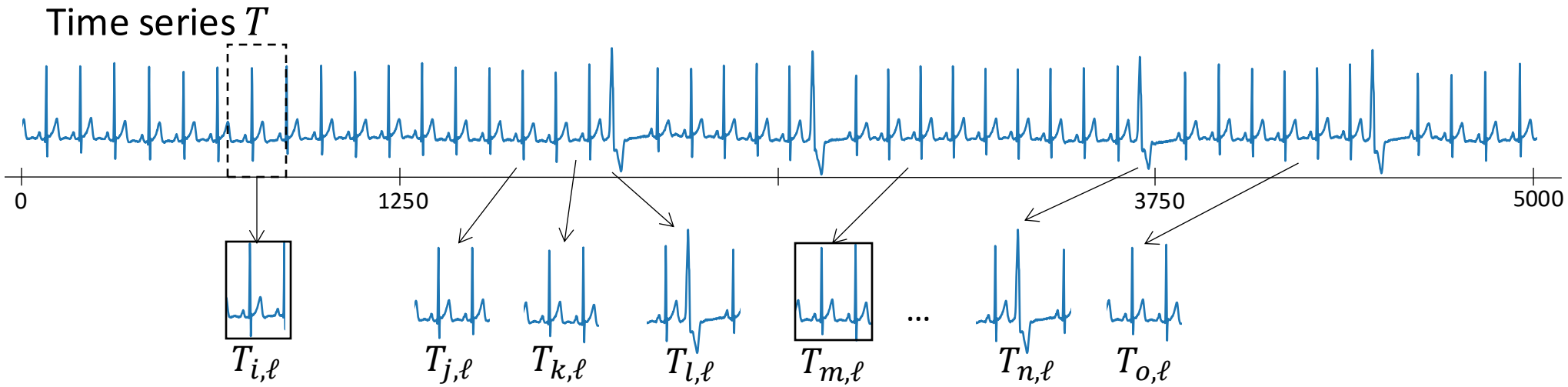

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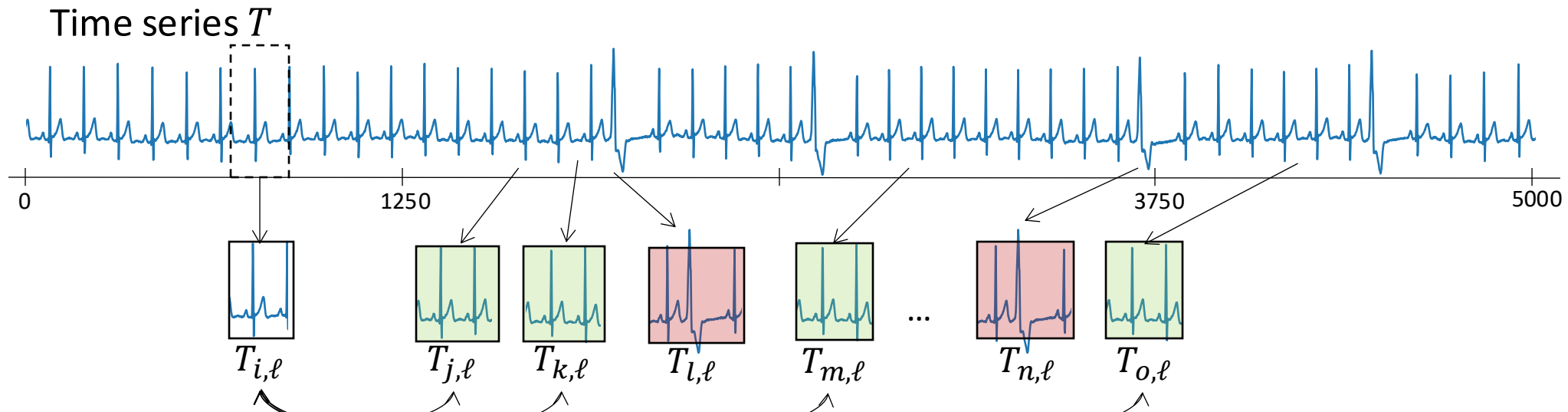

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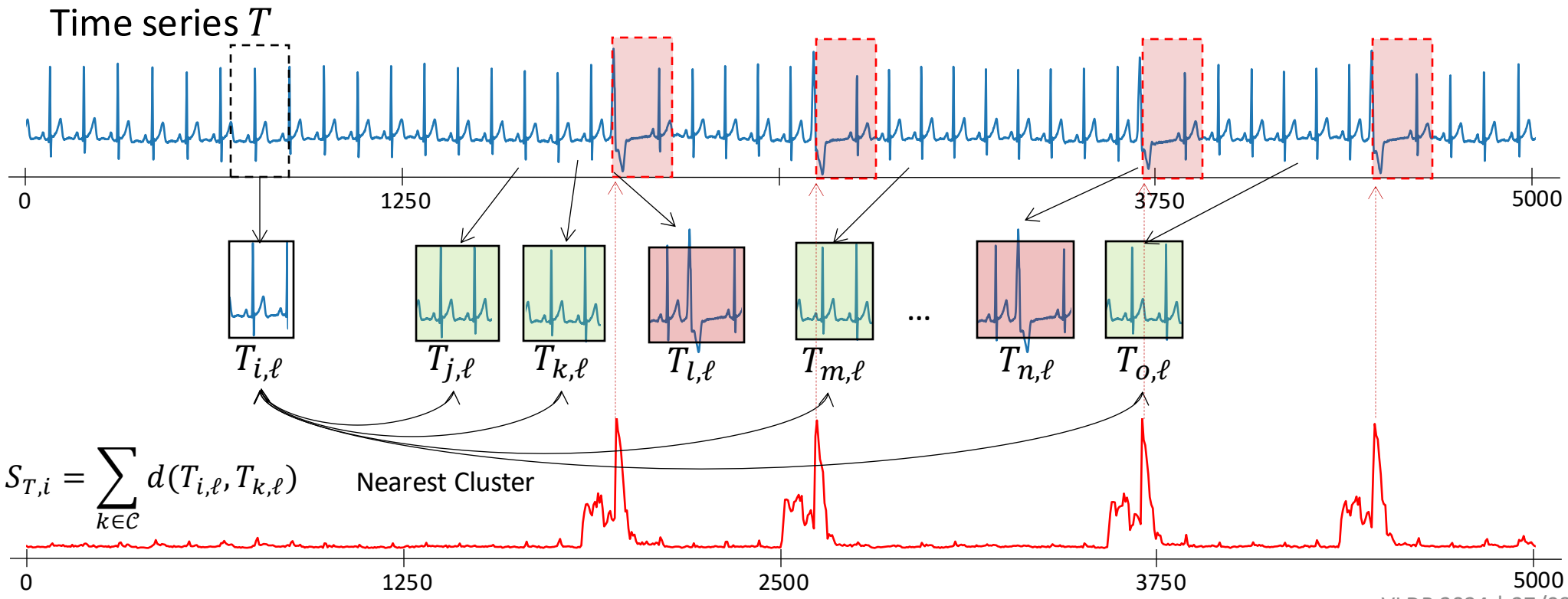

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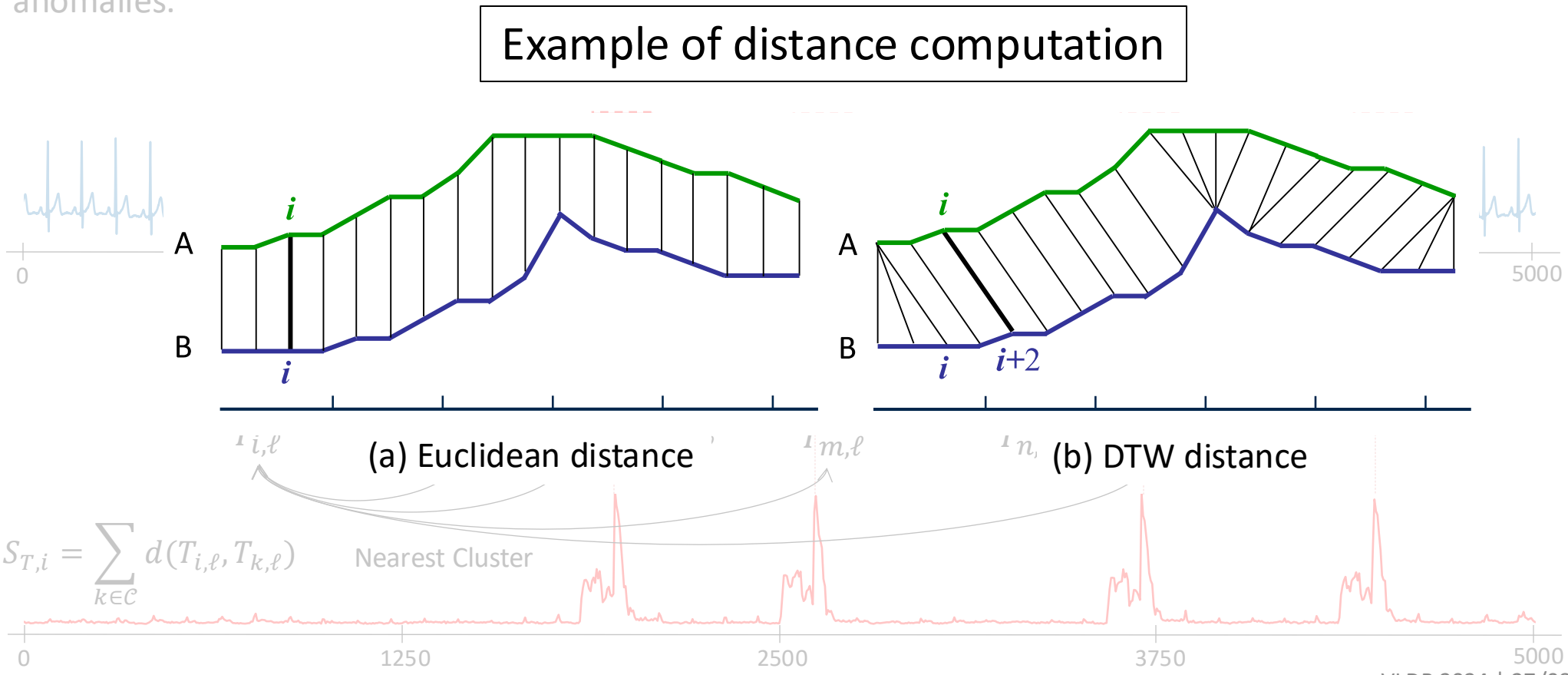
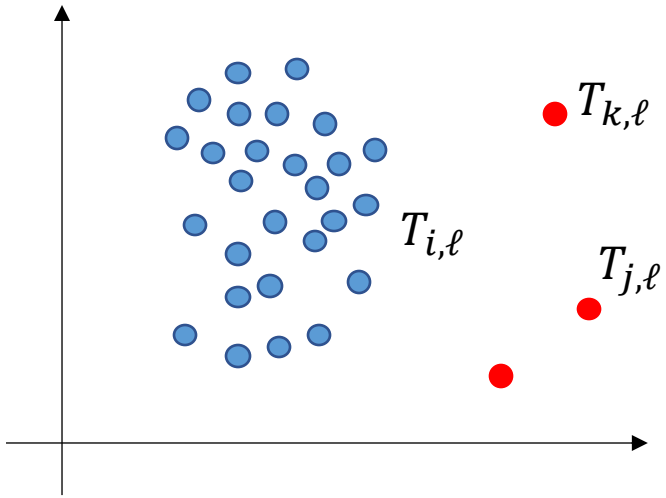


Anomaly Detection methods: *an Example*



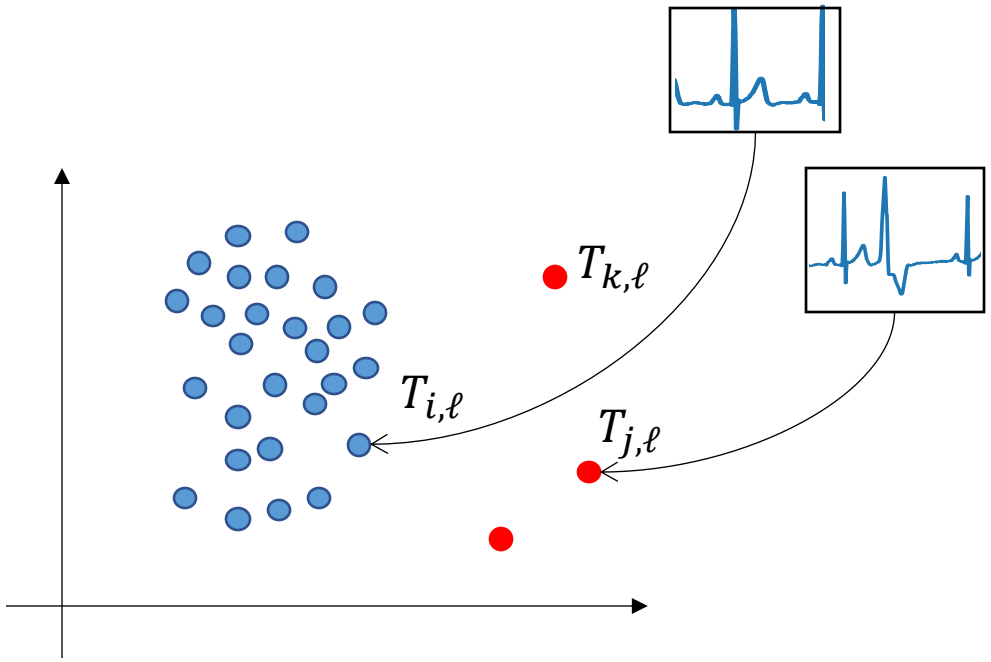
Matrix Profile [6] (MP)

Compute the distance to the nearest neighbor (using the MASS algorithm z-norm Euclidean distance computation) and use it as anomaly score

- Unsupervised
- Univariate
- sequence

[6] Chin-Chia Michael Yeh, Yan Zhu, Liudmila Ulanova, Nurjahan Begum, Yifei Ding, Hoang Anh Dau, Diego Furtado Silva, Abdullah Mueen, and Eamonn J. Keogh. 2016. Matrix Prole I: All Pairs Similarity Joins for Time Series. In ICDM.

Anomaly Detection methods: *an Example*



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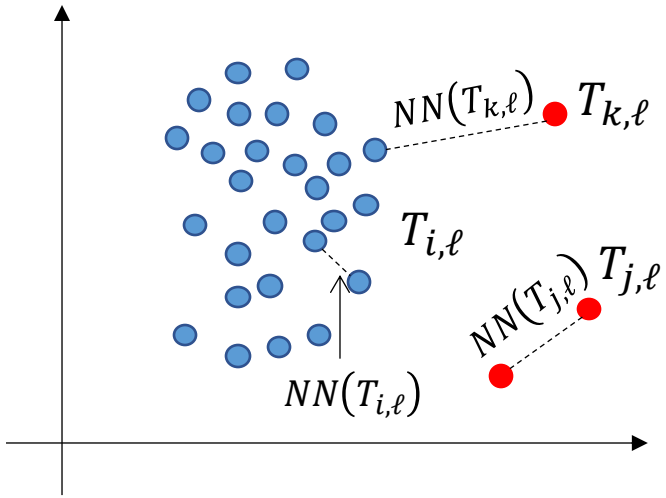

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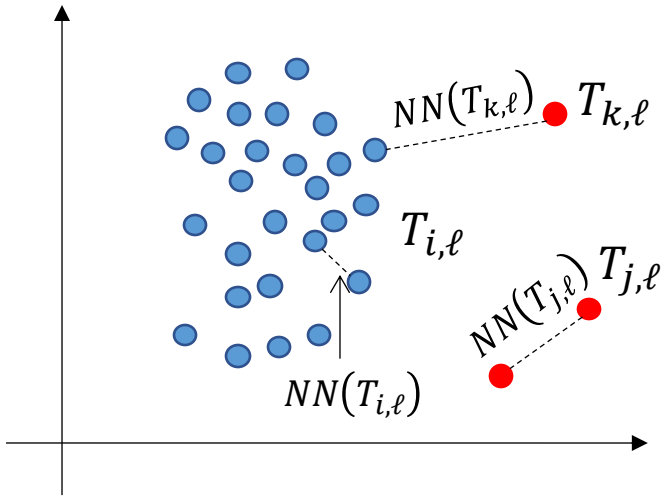

The matrix Profile is computed as follows:

$$S_T = [NN(T_{0,\ell}), NN(T_{1,\ell}), \dots, NN(T_{|T|-\ell,\ell})]$$

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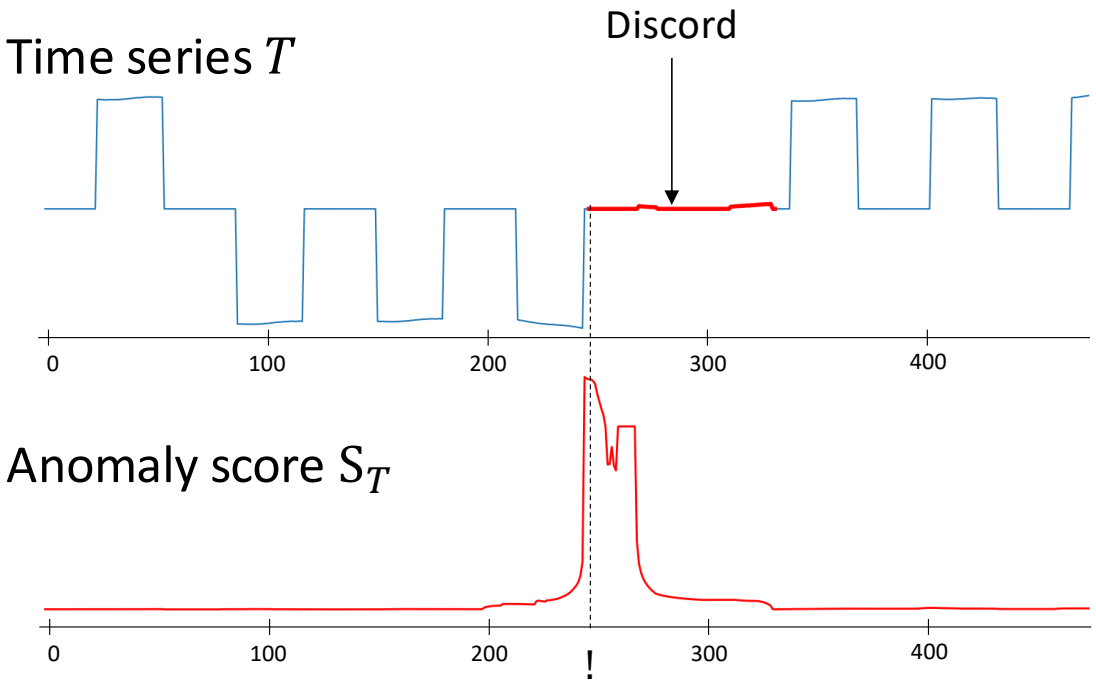

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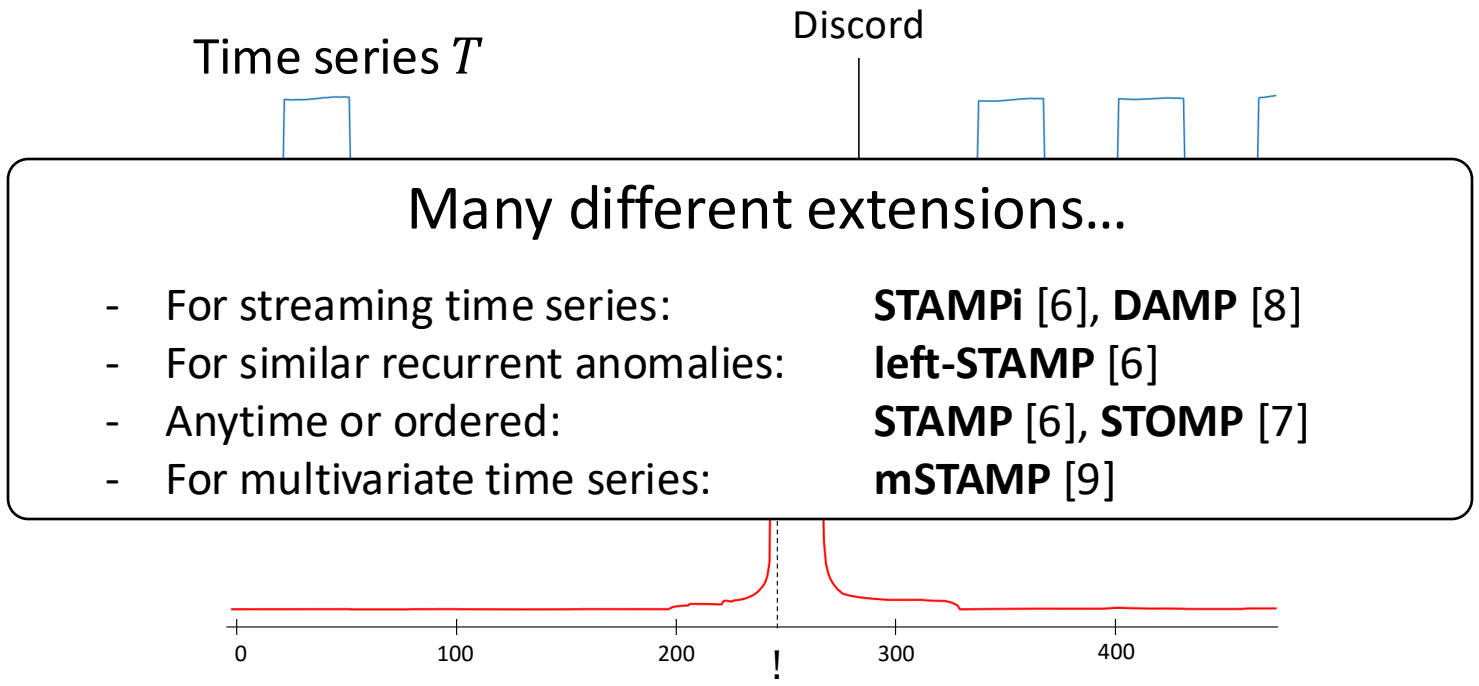

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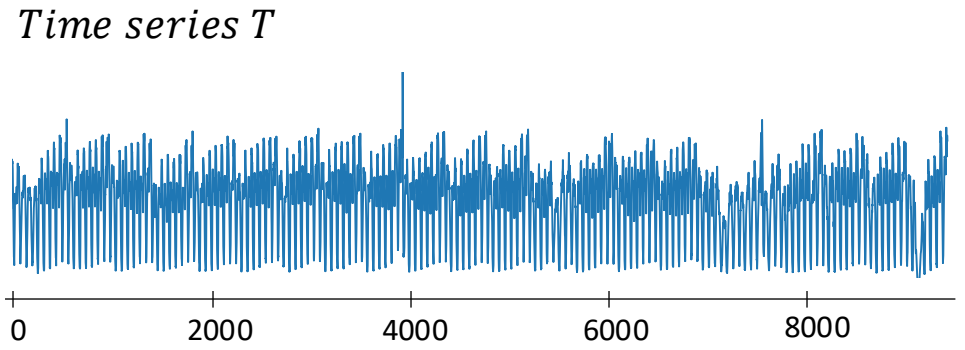

NormA [10]

Distance-based approach that summarize the time series into a weighted set of subsequences and use the distance to them as anomaly score

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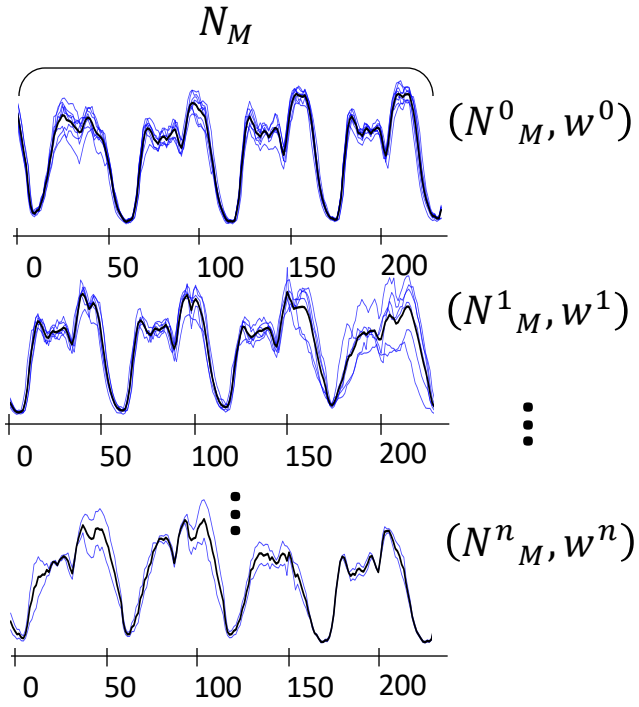
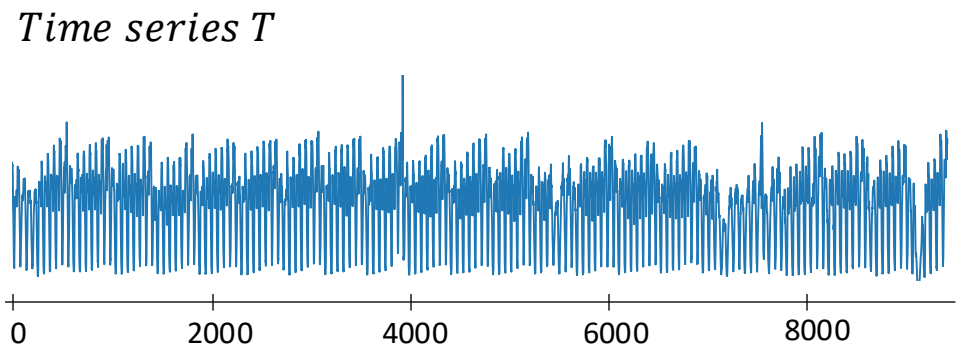
[10] Paul Boniol, Michele Linardi, Federico Roncallo, Themis Palpanas, Mohammed Meftah, and Emmanuel Remy. 2021. Unsupervised and scalable subsequence anomaly detection in large data series. The VLDB Journal 30, 6 (Nov 2021), 909–931.

Anomaly Detection methods: *an Example*





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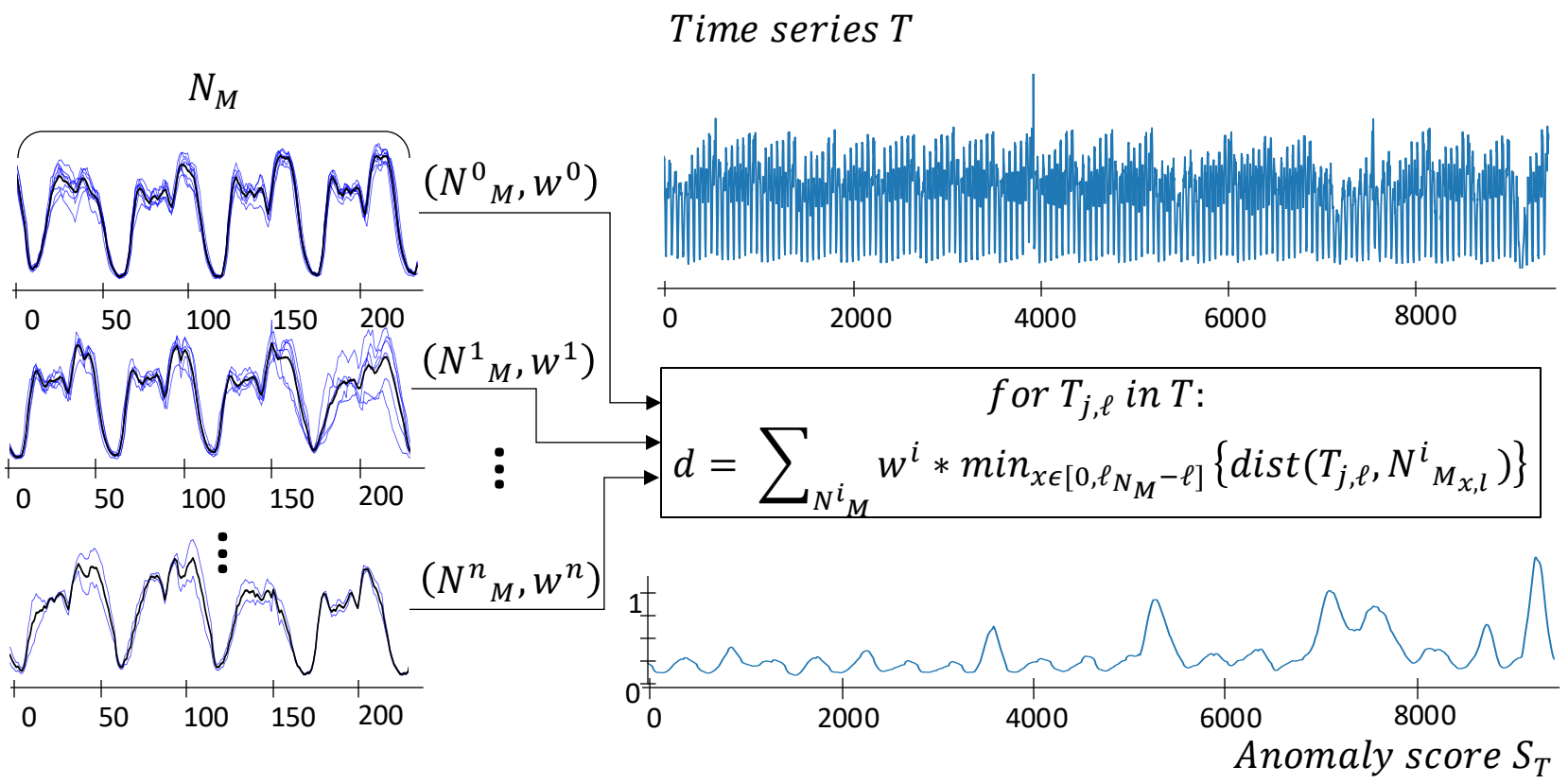

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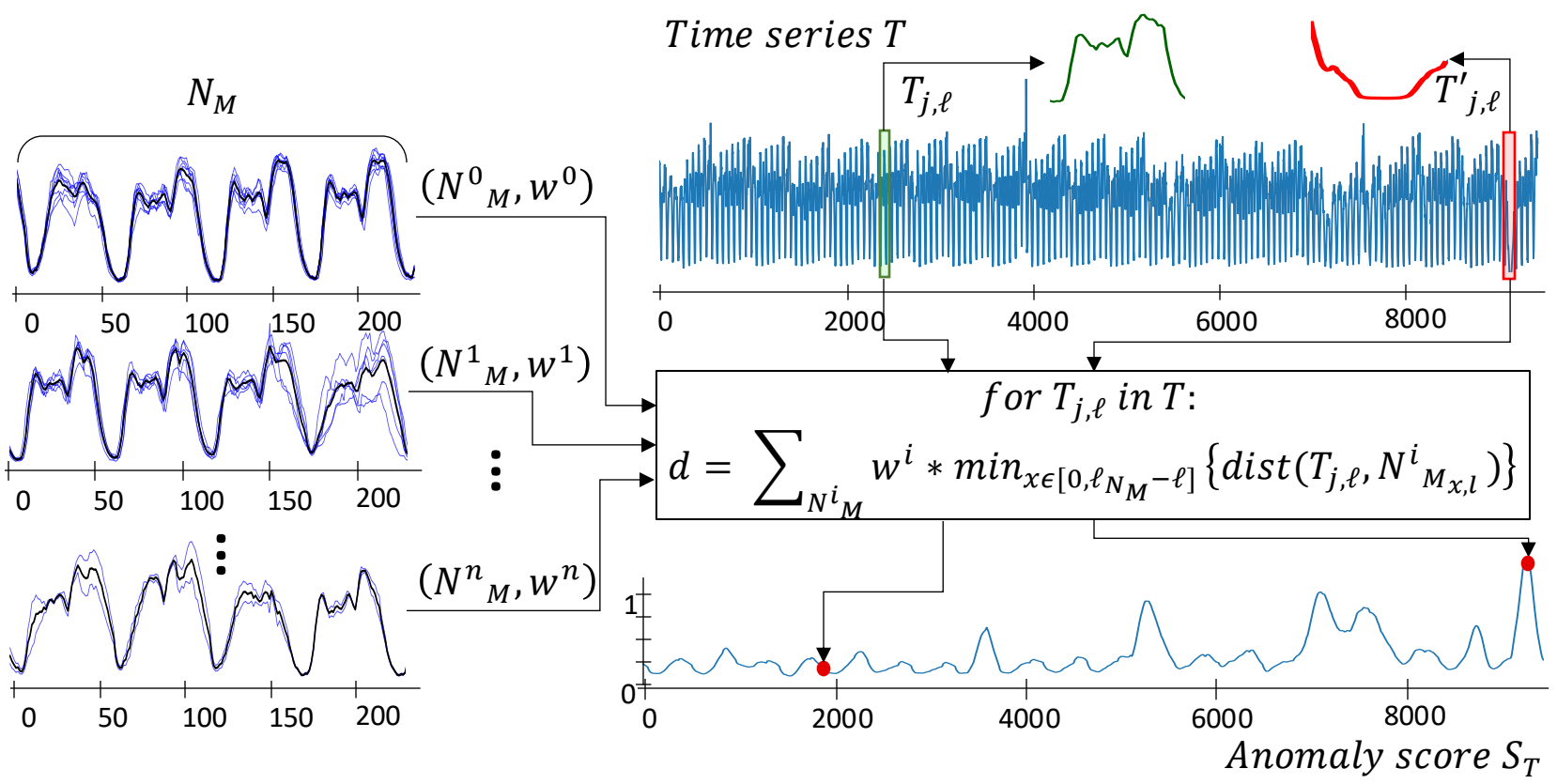

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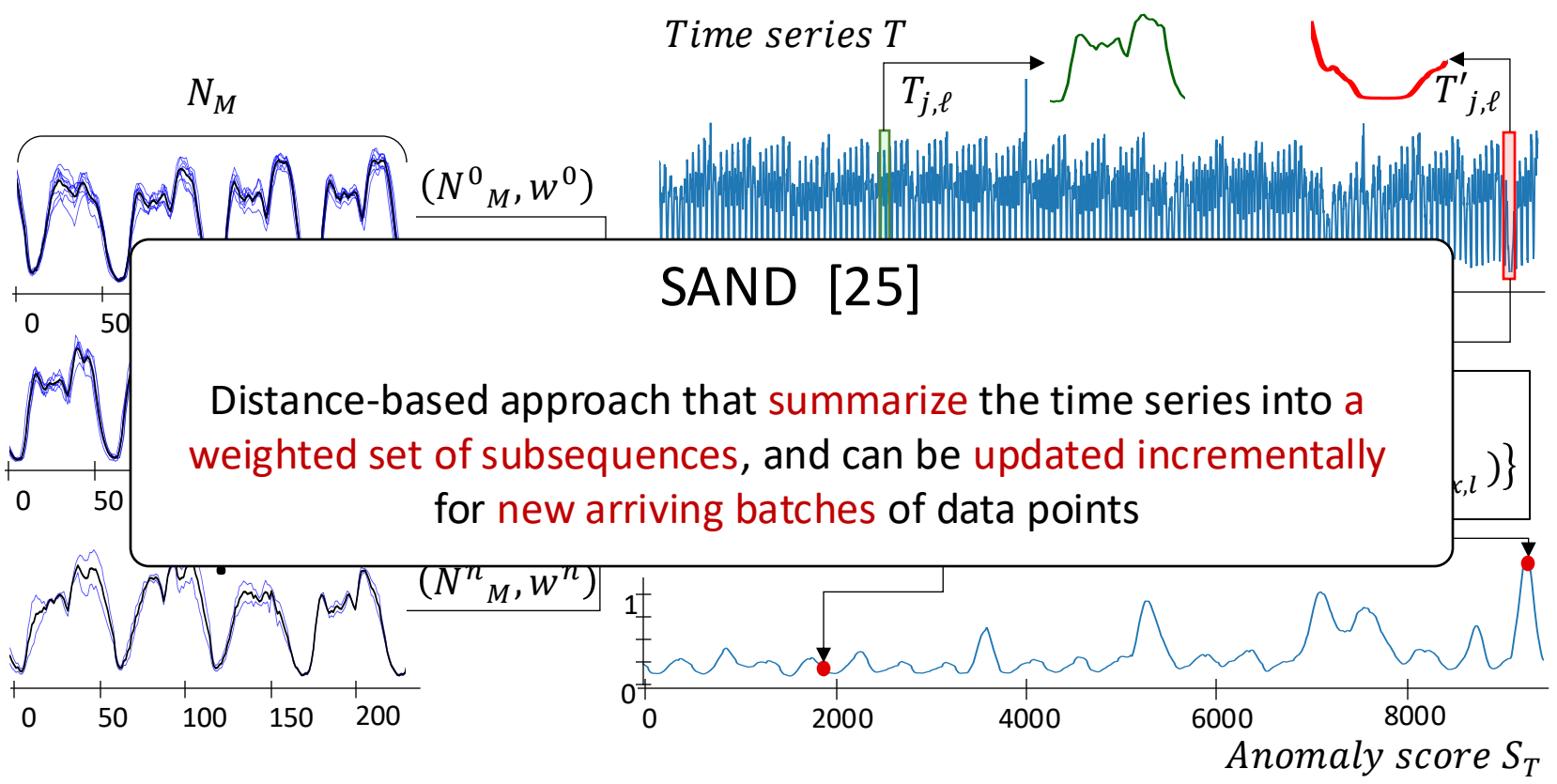
Anomaly Detection methods: *an Example*



SAND [25]

Distance-based approach that summarize the time series into a weighted set of subsequences, and can be updated incrementally for new arriving batches of data points

NormA [10]

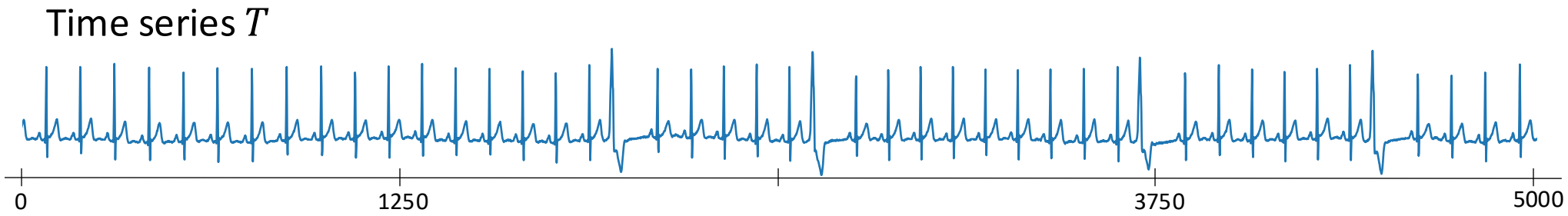
Distance-based approach that summarize the time series into a weighted set of subsequences and use the distance to them as anomaly score

- Unsupervised
- Univariate
- sequence

[25] Paul Boniol, John Paparrizos, Themis Palpanas, and Michael J. Franklin. 2021. SAND: streaming subsequence anomaly detection. Proc. VLDB Endow. 14, 10 (June 2021), 1717–1729.

Anomaly Detection methods: *Density-based*

Methods that estimate the density of the space (points or subsequences) and identify as anomalies points (or sequences)that are in low-density subspace.



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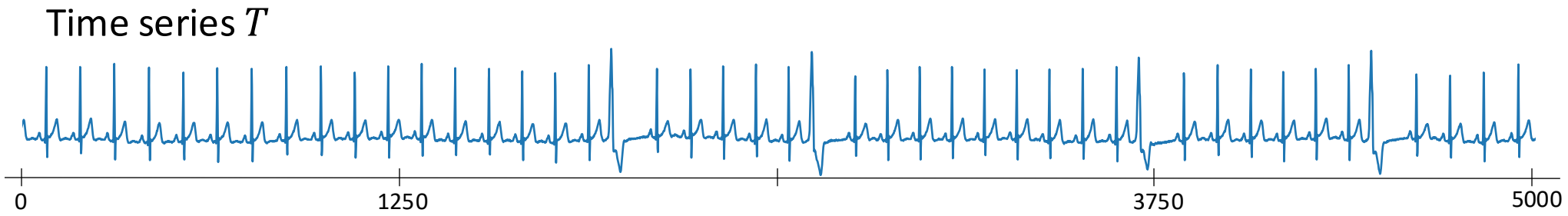
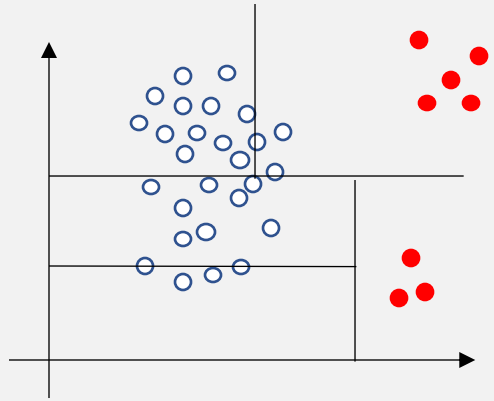


Tree-based approaches [11]



Anomaly Detection methods: *Density-based*

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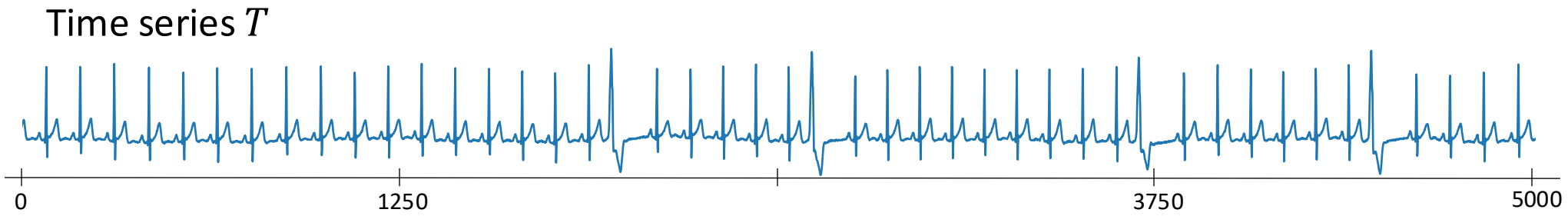

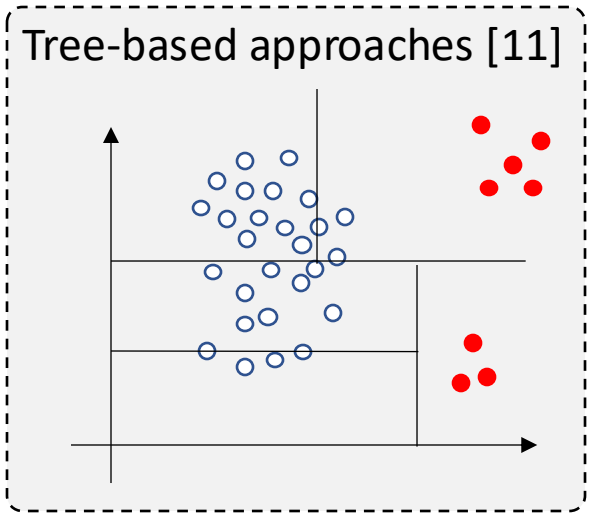

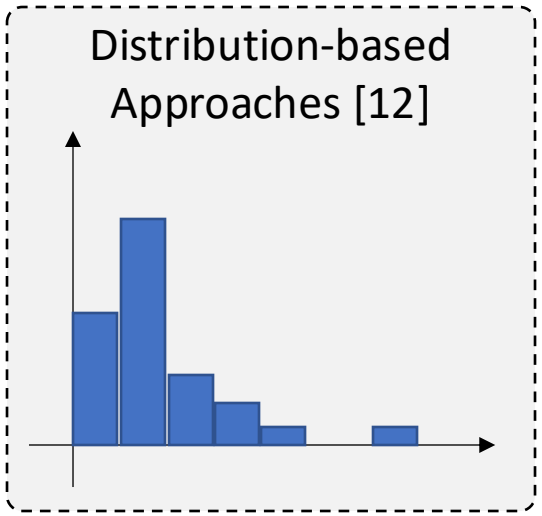

Anomaly Detection methods: *Density-based*

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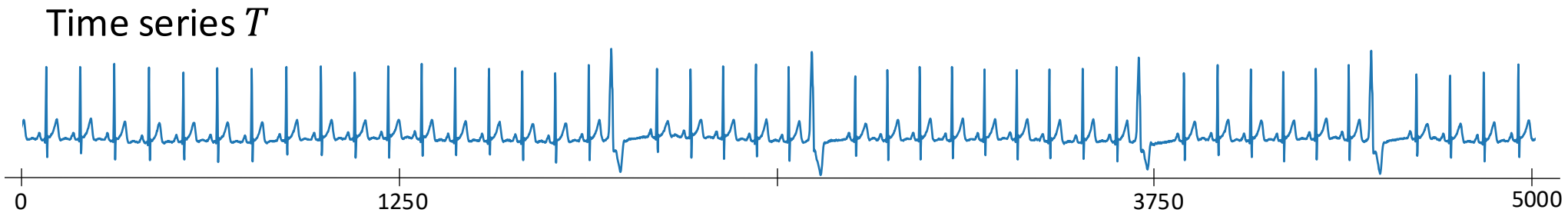

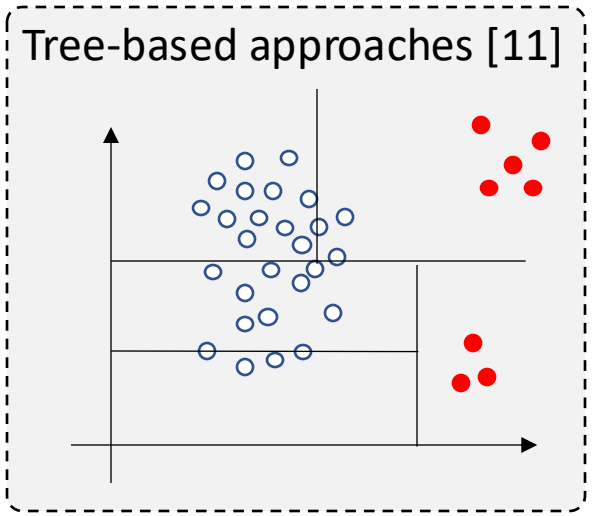

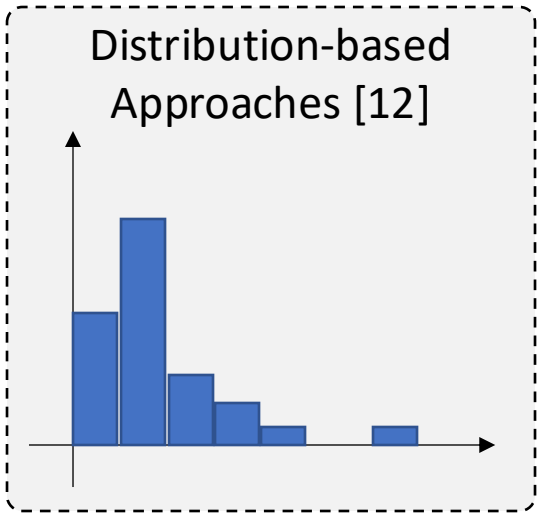

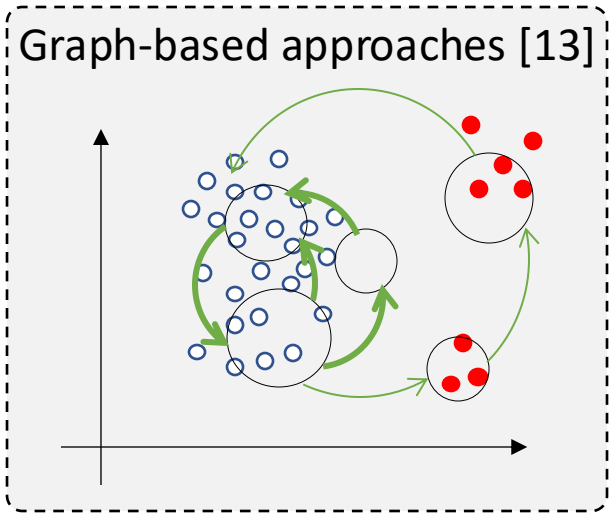

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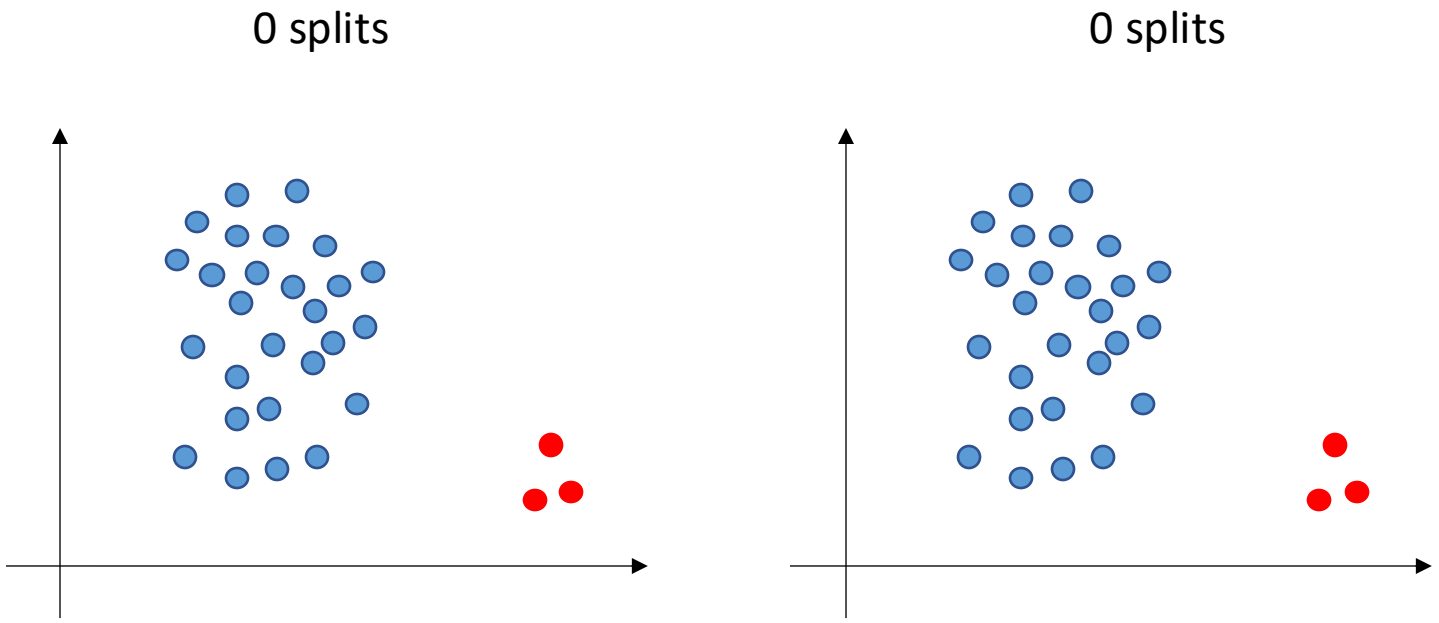
Anomaly Detection methods: *an Example*



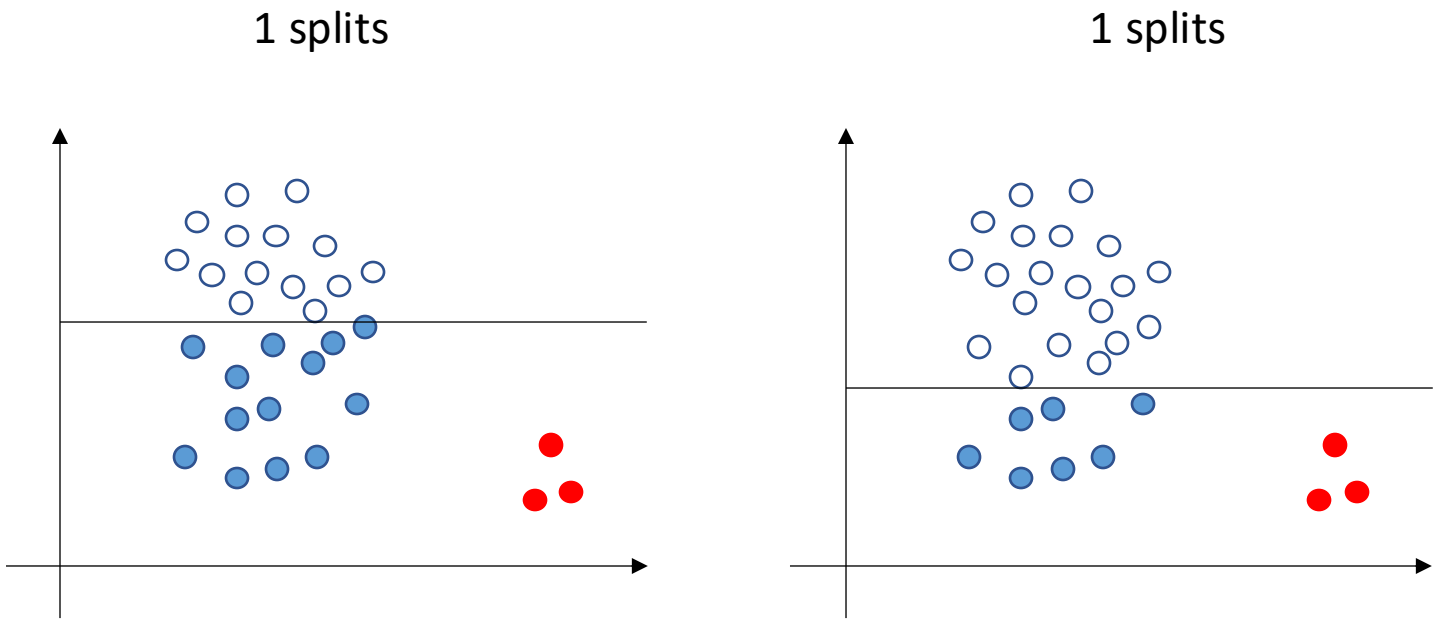
Isolation Forest [11]

Density-based approach that split the space randomly and using the depth of the trees to identify anomalies

- Unsupervised
- Univariate/Multivariate
- Point/sequence

[11] F. T. Liu, K. M. Ting and Z. -H. Zhou, "Isolation Forest," 2008 Eighth IEEE International Conference on Data Mining, Pisa, Italy, 2008, pp. 413-422

Anomaly Detection methods: *an Example*



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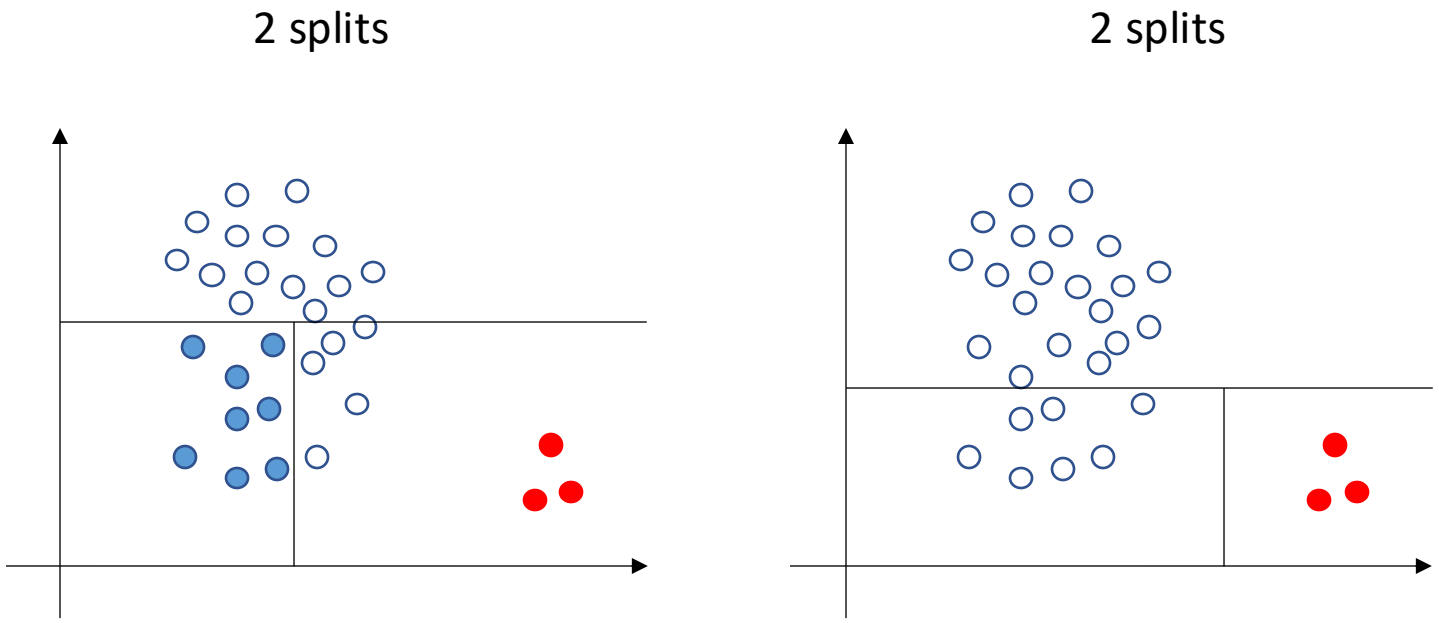

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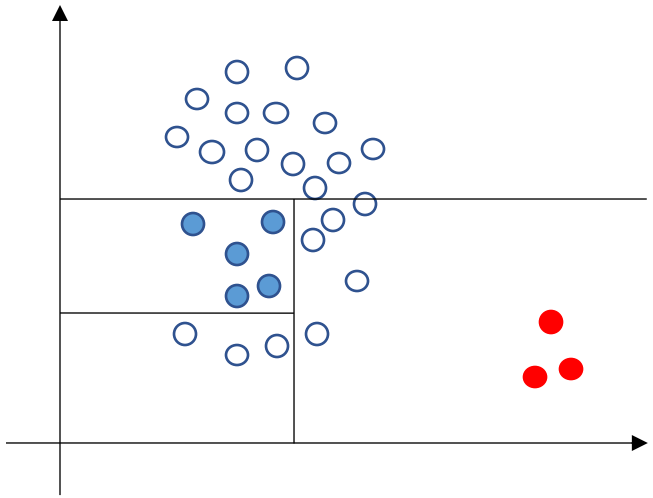
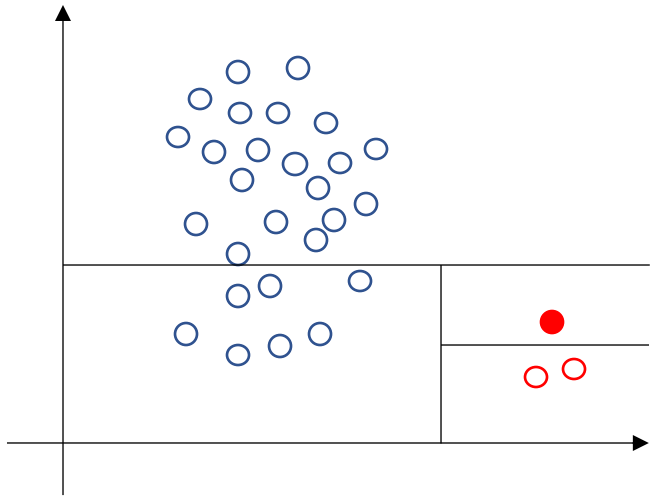
Anomaly Detection methods: *an Example*

3 splits



3 splits



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Anomaly Detection methods: *an Example*

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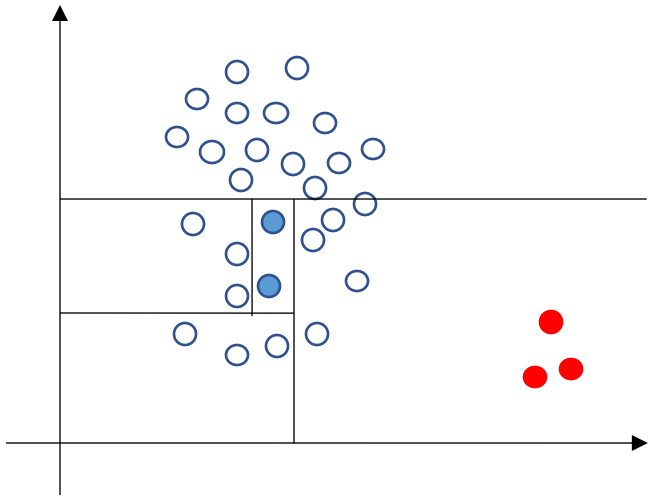

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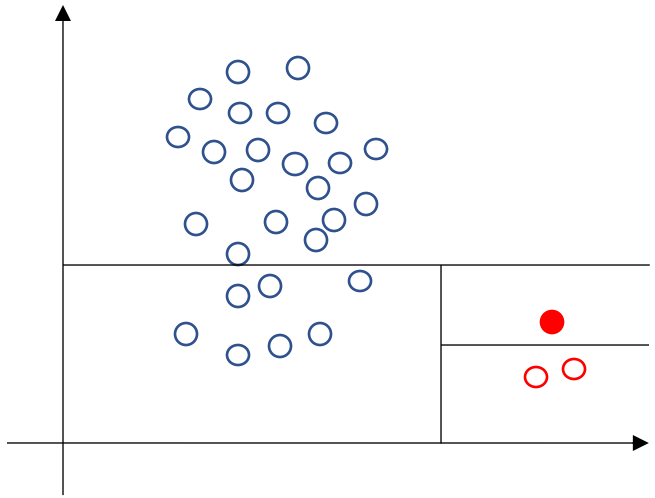

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Anomaly Detection methods: *an Example*

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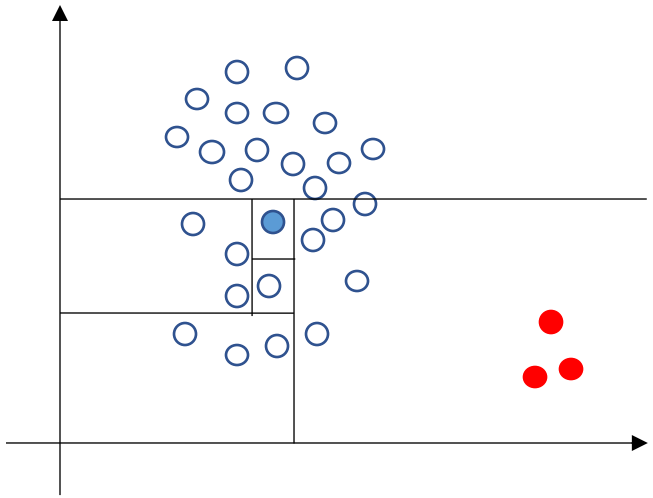

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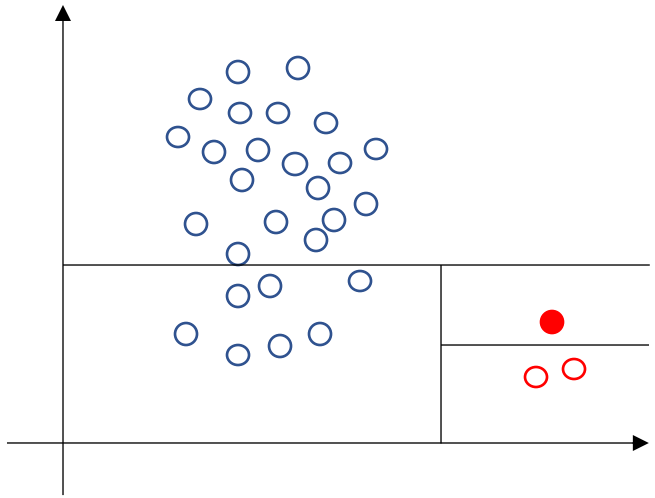

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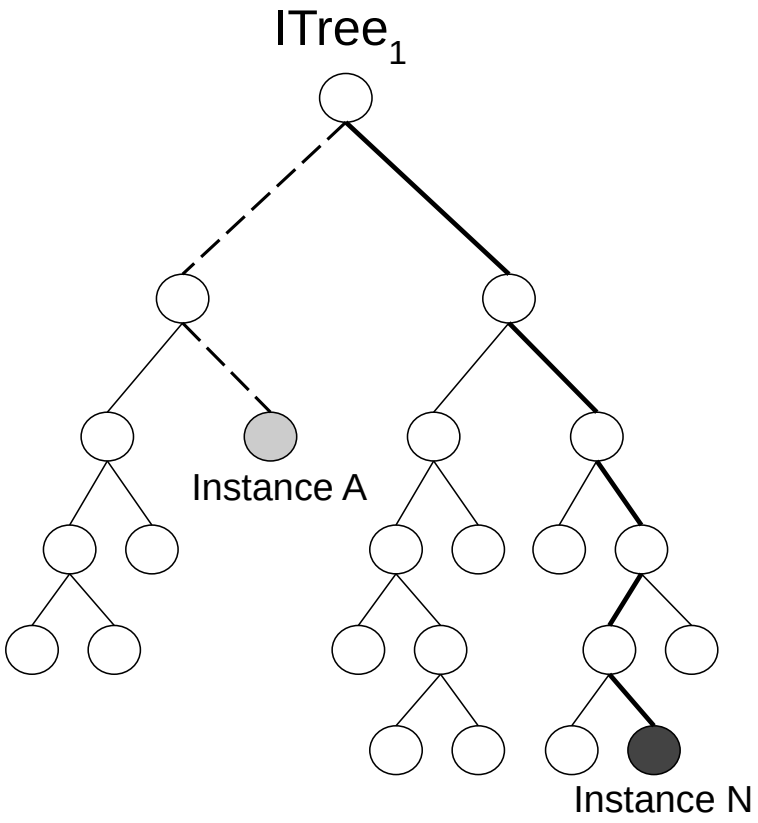

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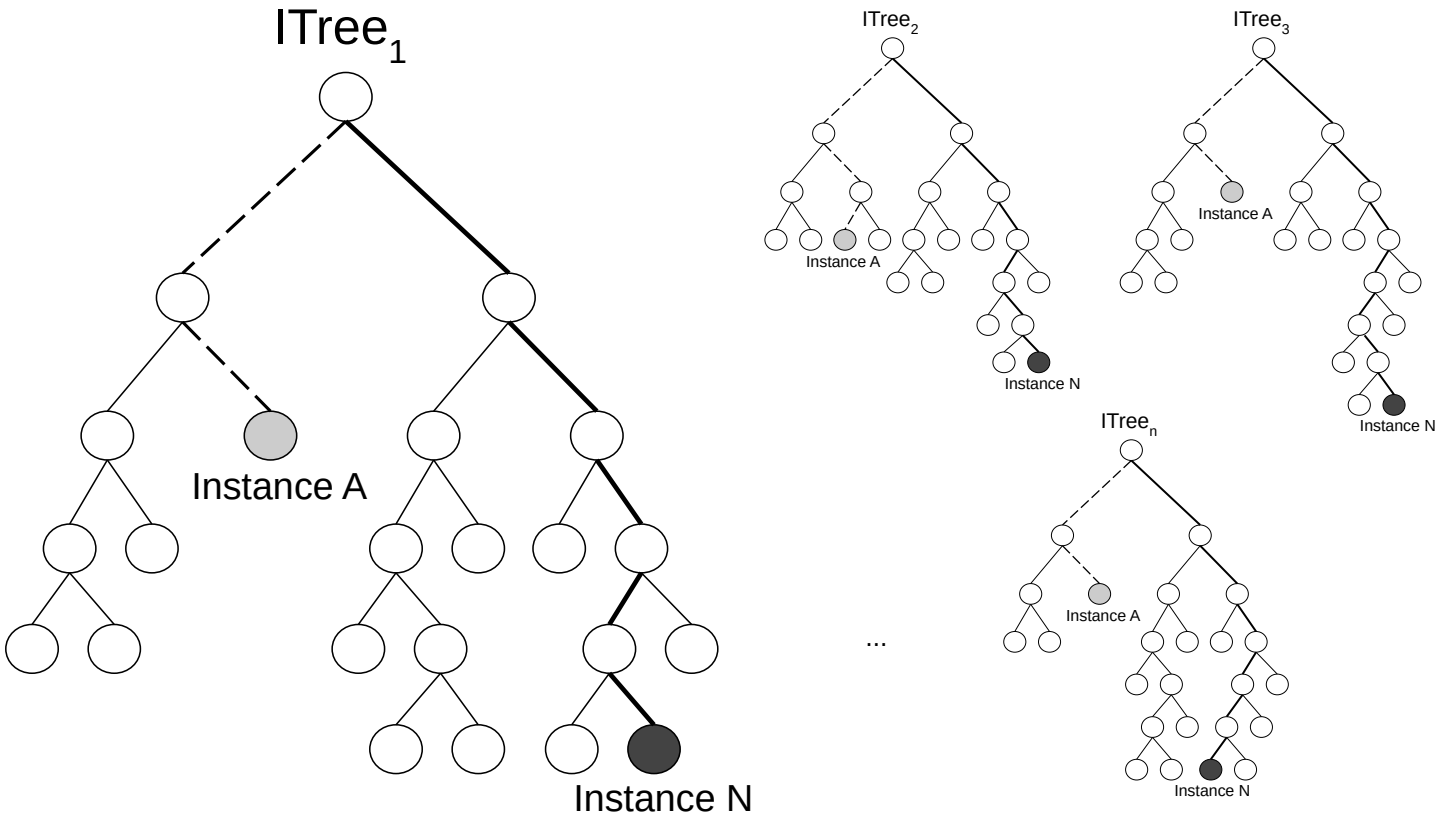

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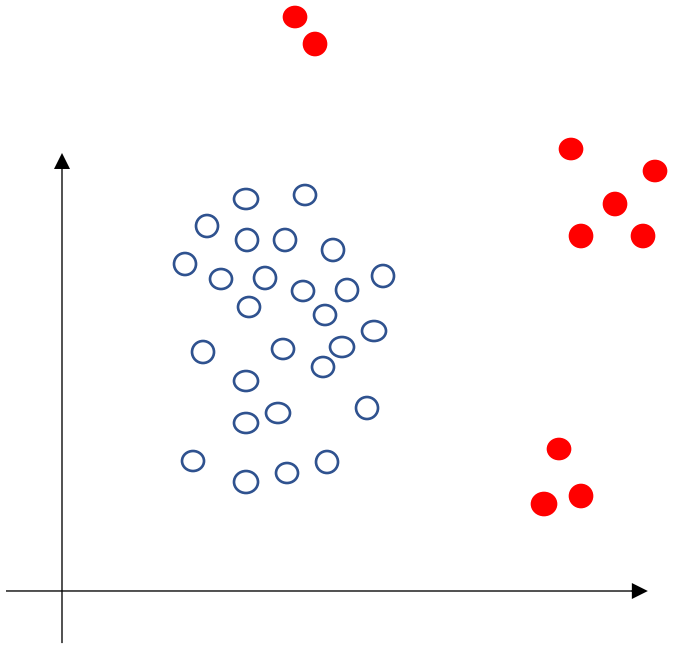


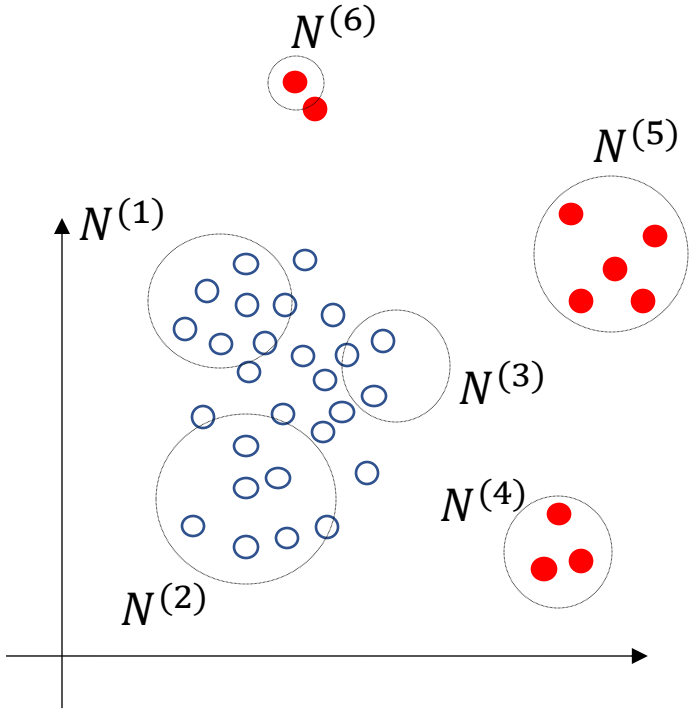
Series2Graph [13]

Density-based approach that convert the time series into a graph and detect unusual trajectories

- Unsupervised
- Univariate
- subsequence

[13] Paul Boniol and Themis Palpanas. 2020. Series2Graph: graph-based subsequence anomaly detection for time series. Proc. VLDB Endow. 13, 12 (August 2020), 1821–1834

Anomaly Detection methods: *an Example*



Each **node** is an ensemble of similar subsequences.

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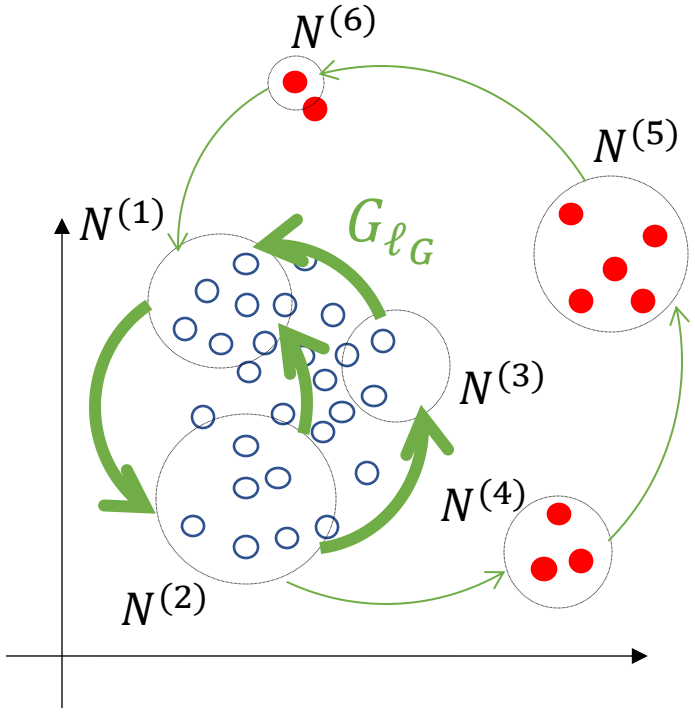

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Each **edge** is associated to a weight w that corresponds to the number of times a subsequence move from one node to another.

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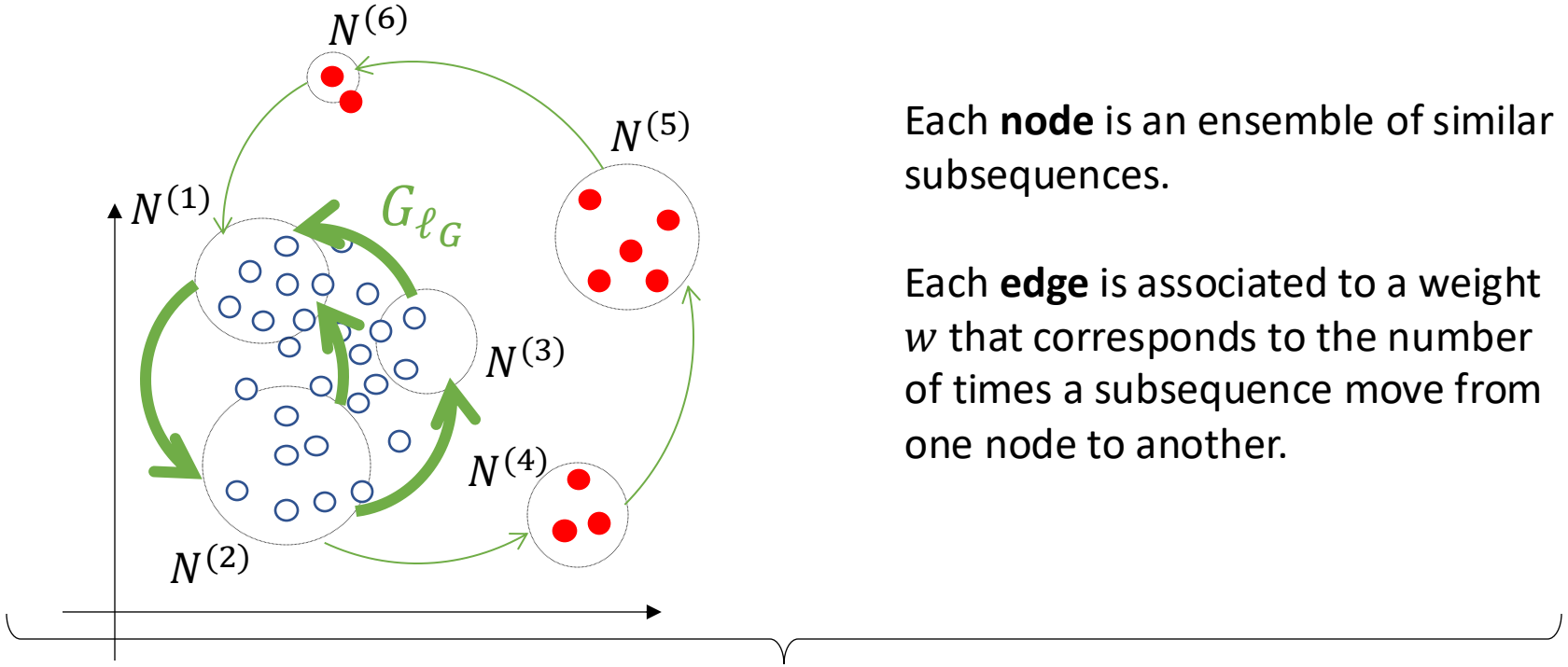

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For a given subsequence $T_{i,\ell}$ and its corresponding path $P_{th} =< N^{(i)}, N^{(i+1)}, \dots, N^{(i+\ell)} >$, we define the normality score as follows:

$$Norm(P_{th}) = \sum_{j=i}^{i+\ell-1} \frac{w\left(N^{(j)}, N^{(j+1)}\right) \deg(N^{(j)} - 1)}{\ell}$$

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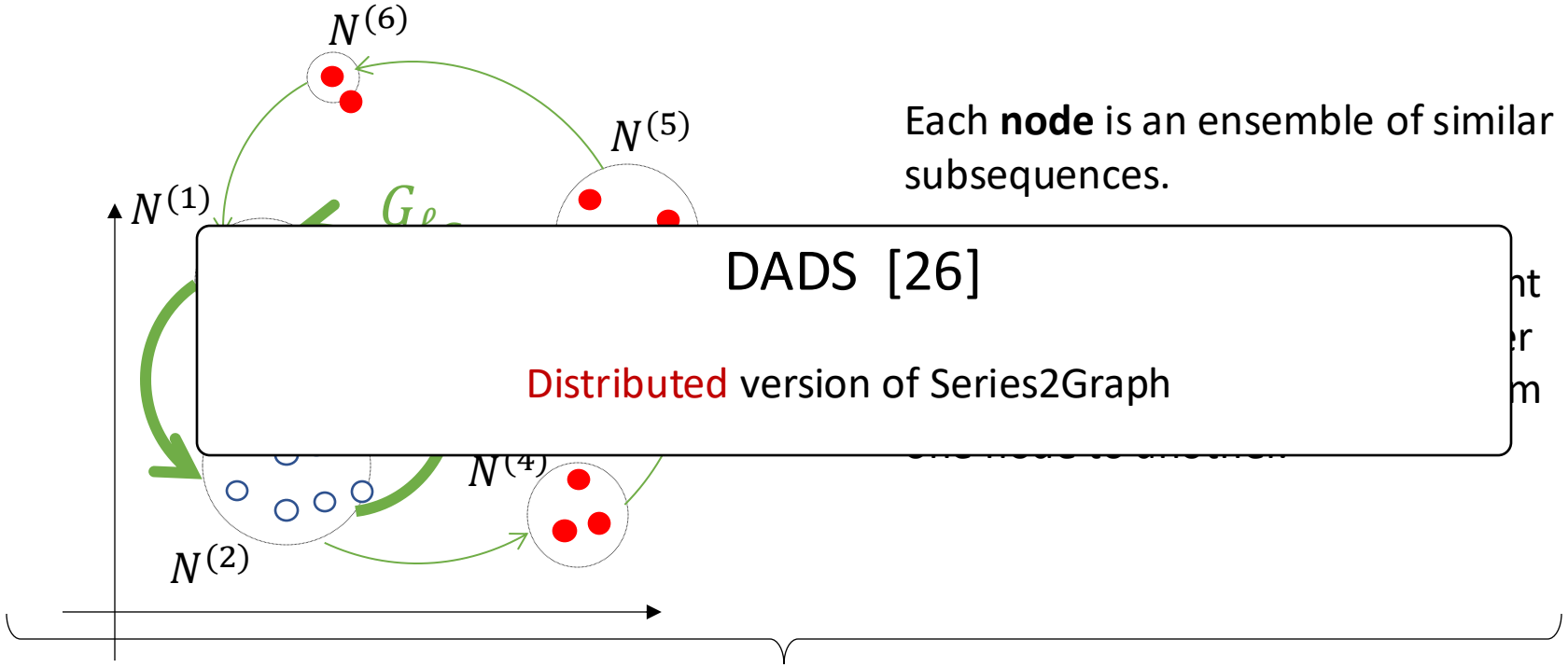

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DADS [26]

Distributed version of Series2Graph

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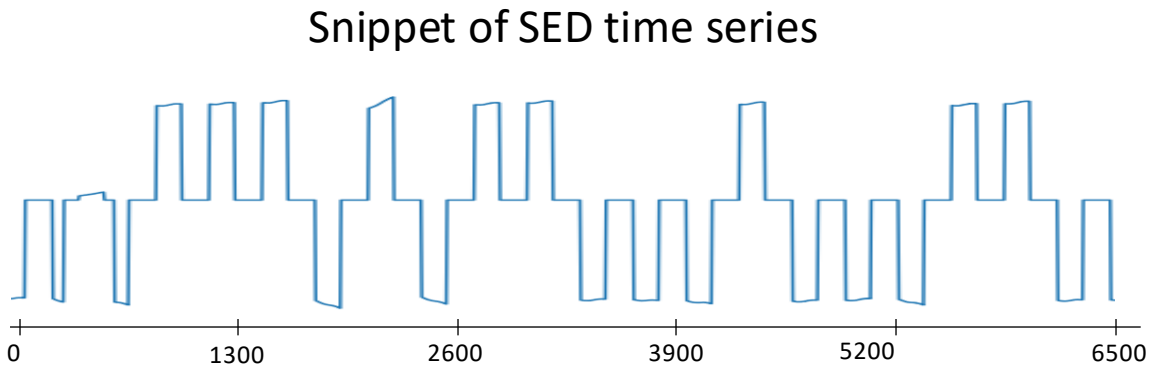
[26] Schneider, J., Wenig, P. & Papenbrock, T. Distributed detection of sequential anomalies in univariate time series. The VLDB Journal **30**, 579–602 (2021).

Anomaly Detection methods: *an Example*



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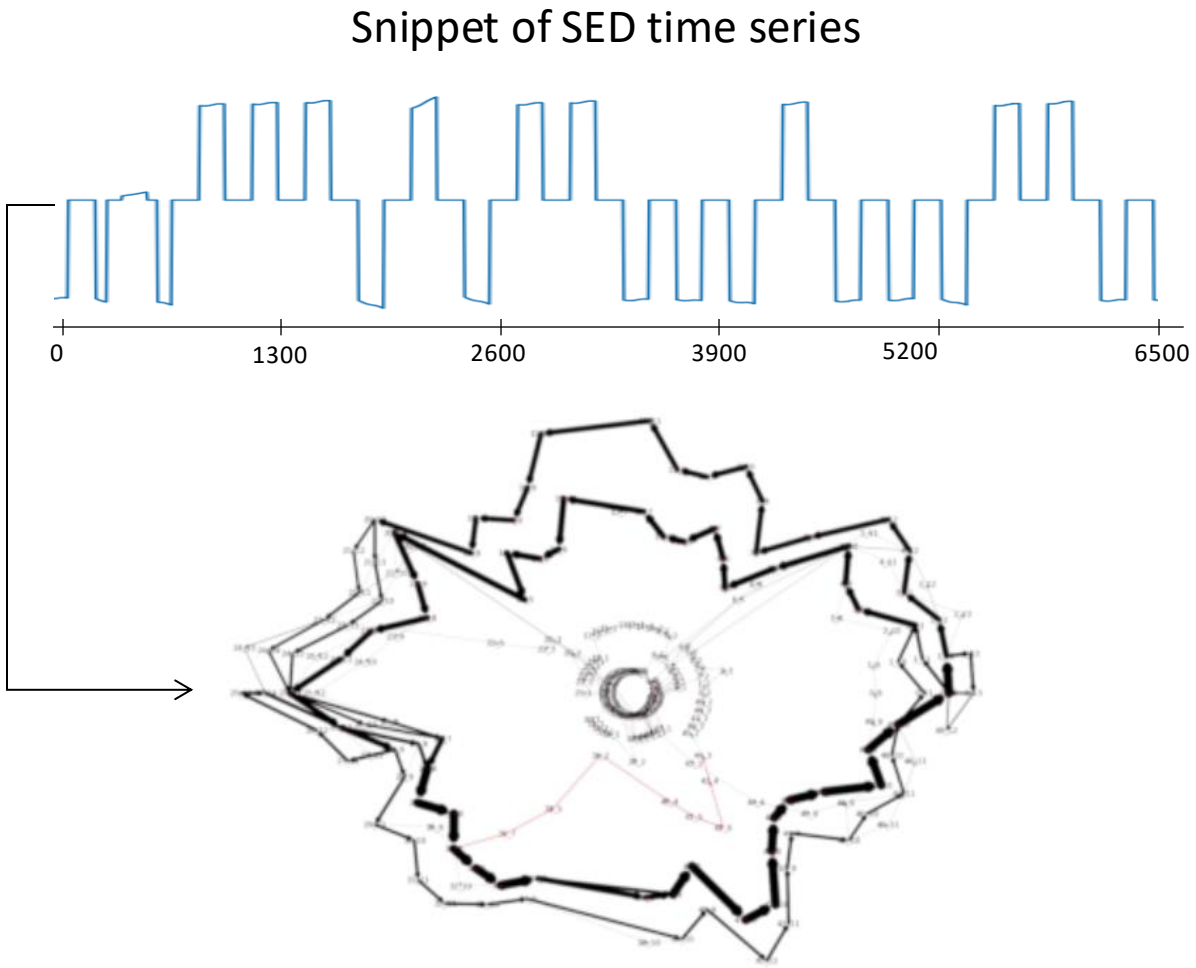

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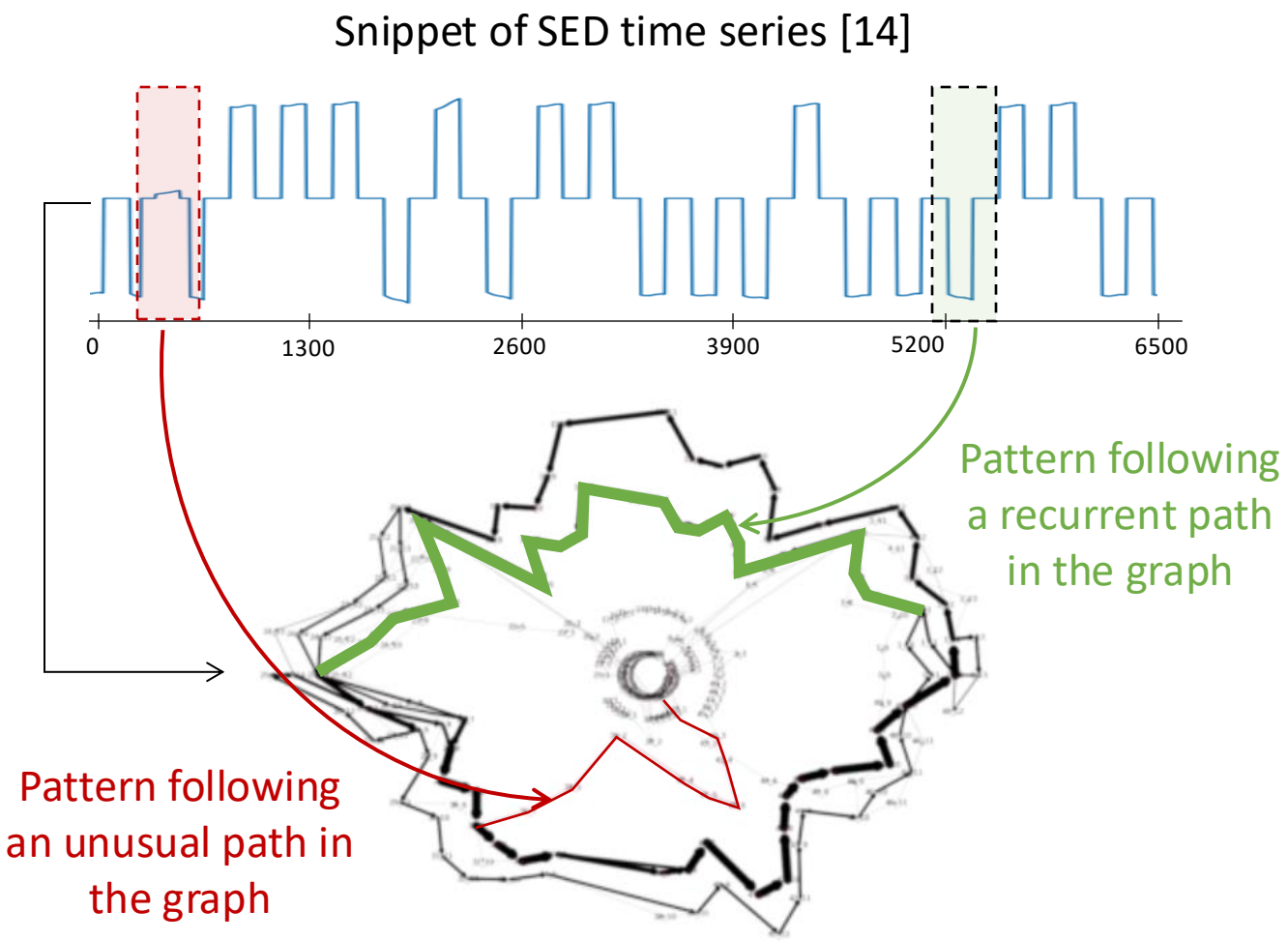

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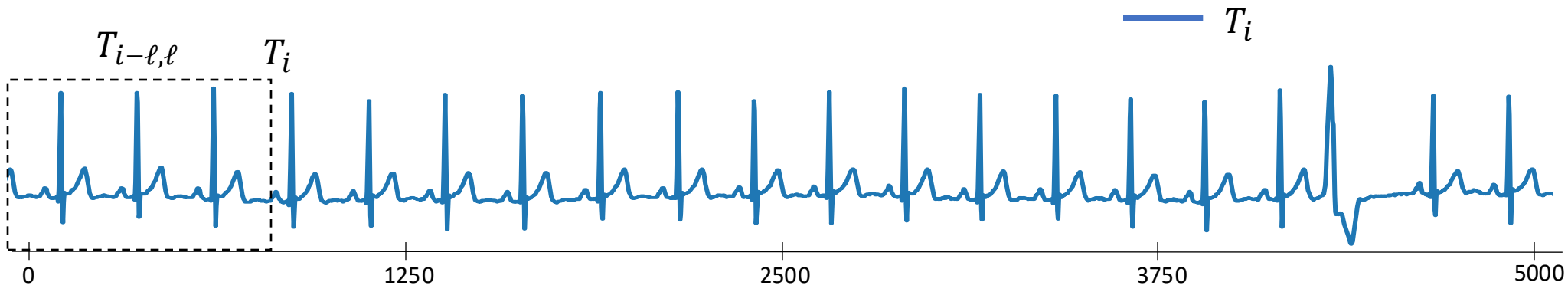
Anomaly Detection methods: *Forecasting-based*

Methods that aims to predict the next points based on the previous ones. The prediction error is used to detect if there is an anomaly or not.



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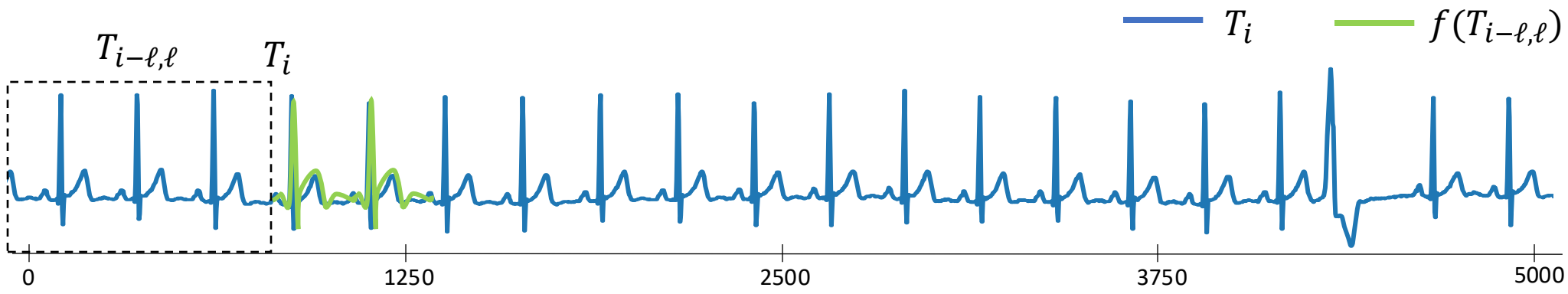

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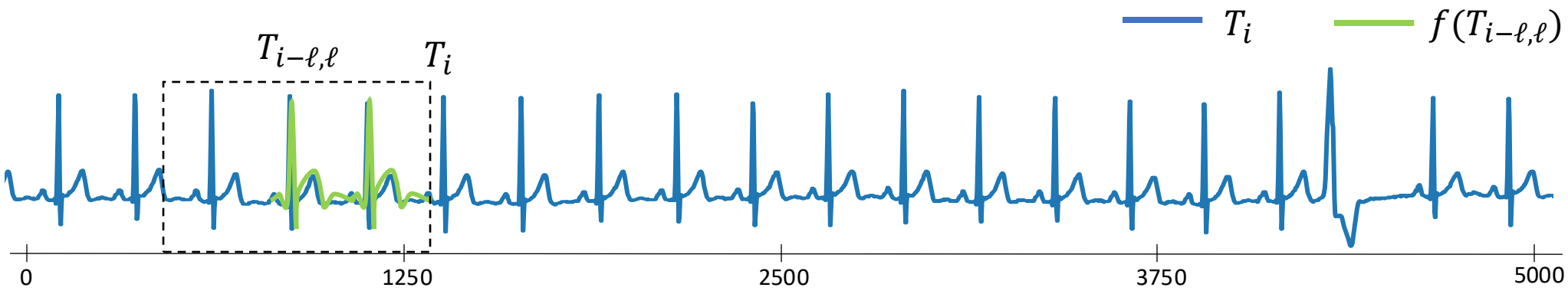

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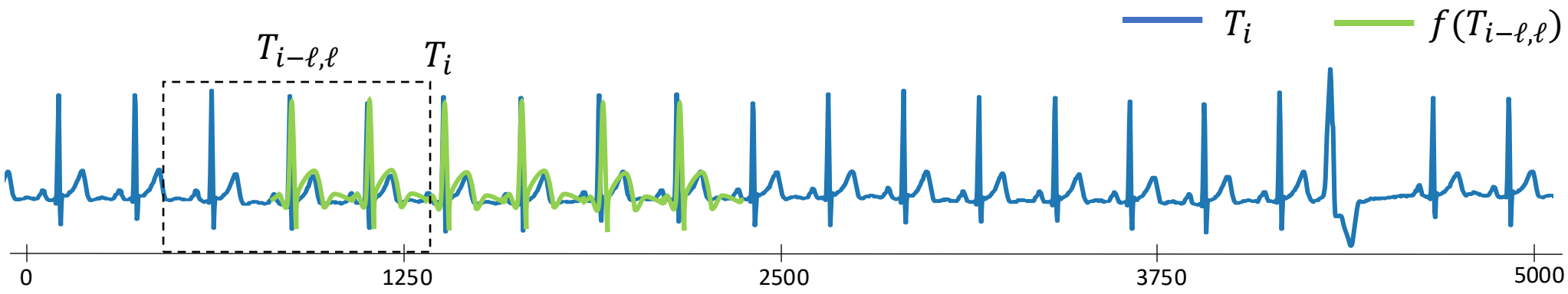

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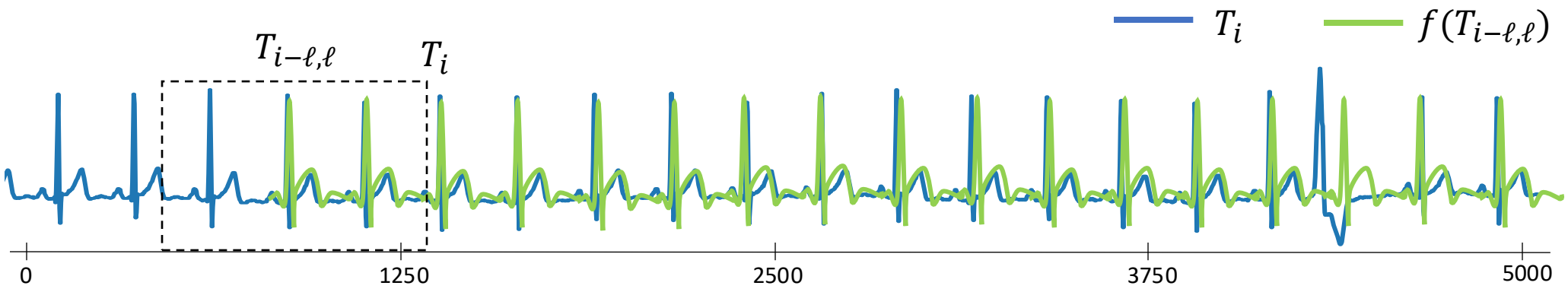

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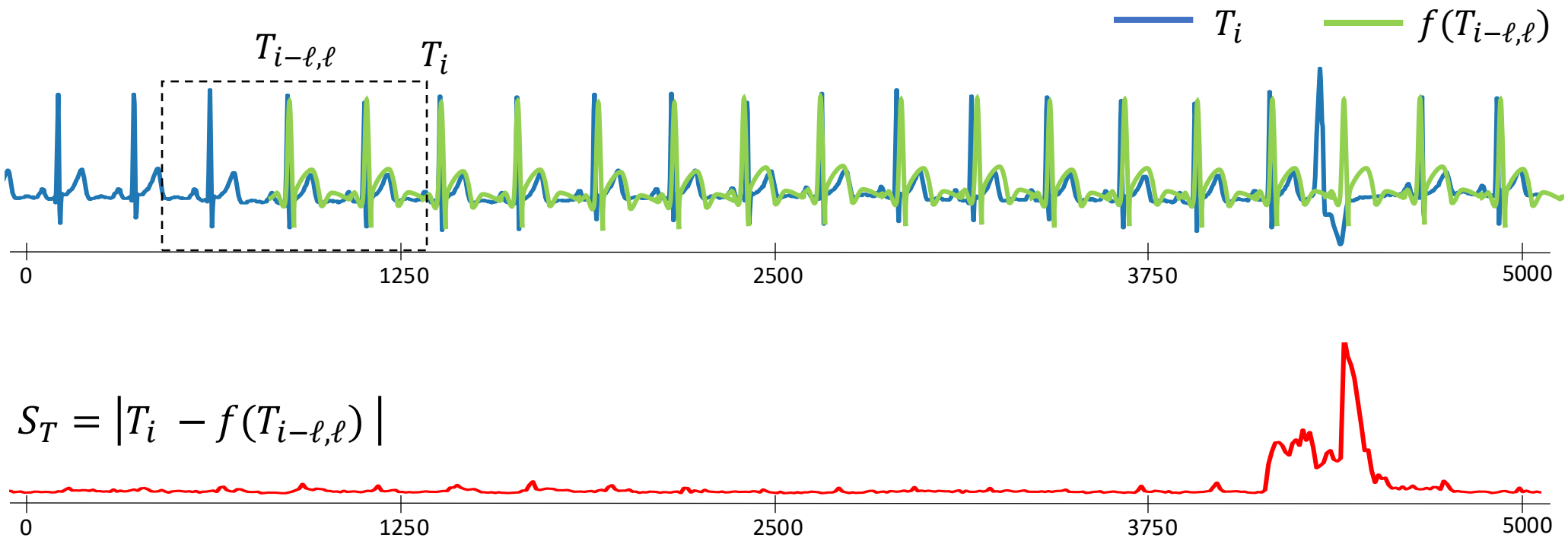

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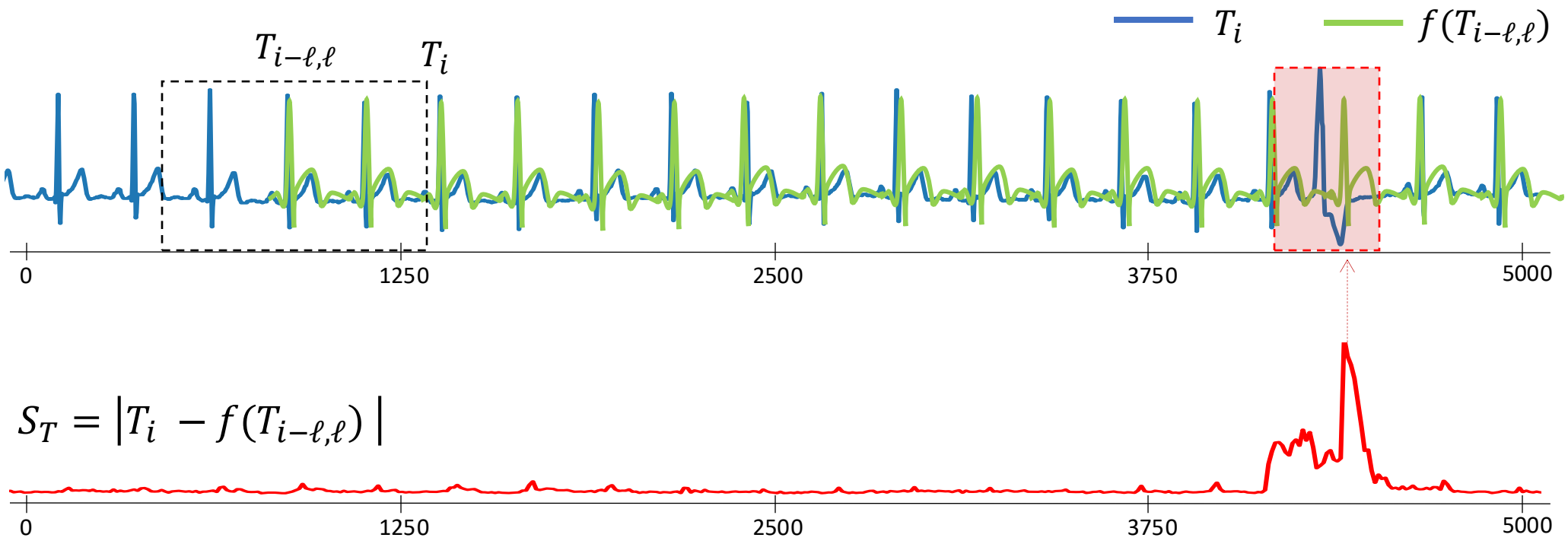

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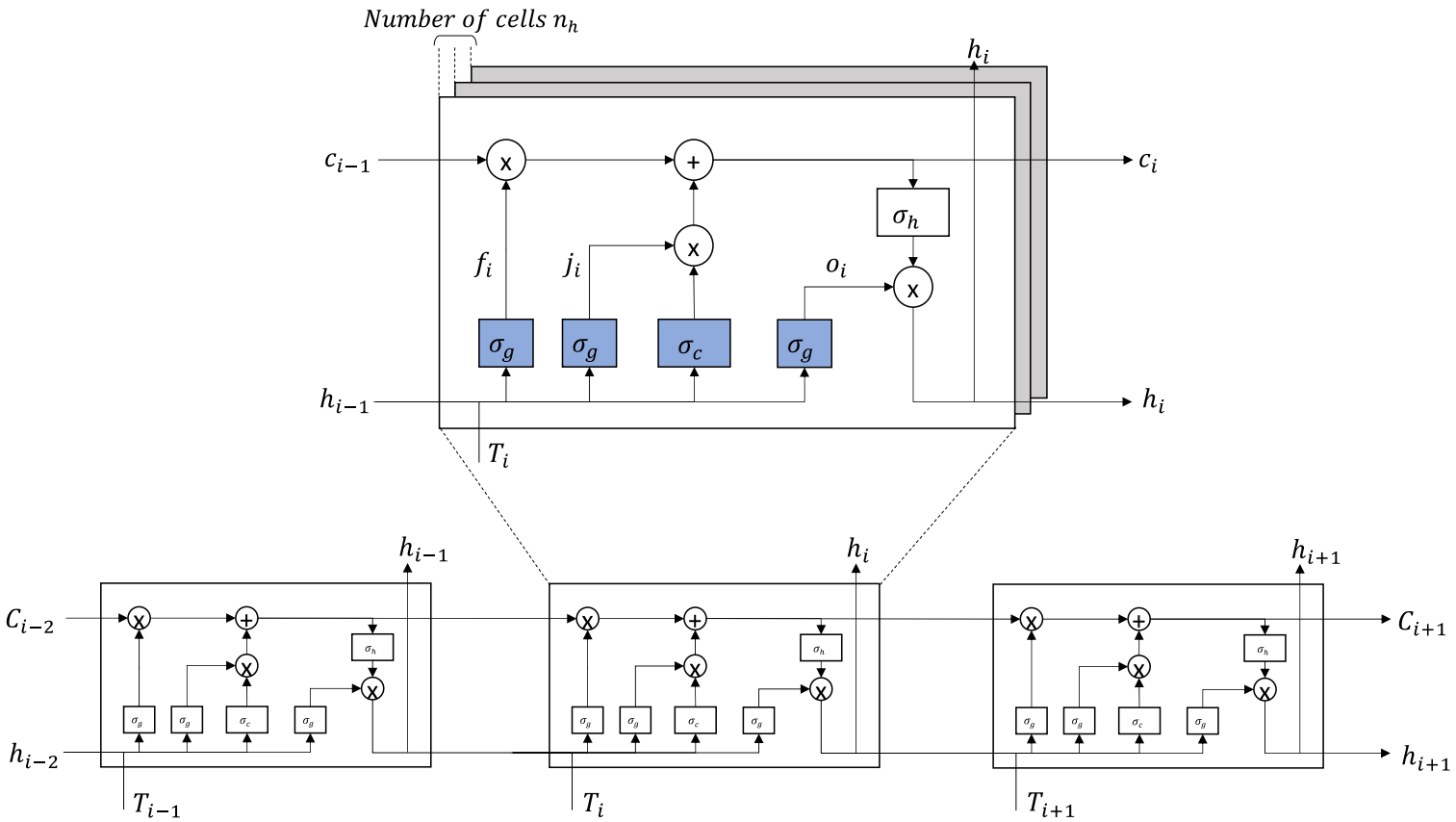


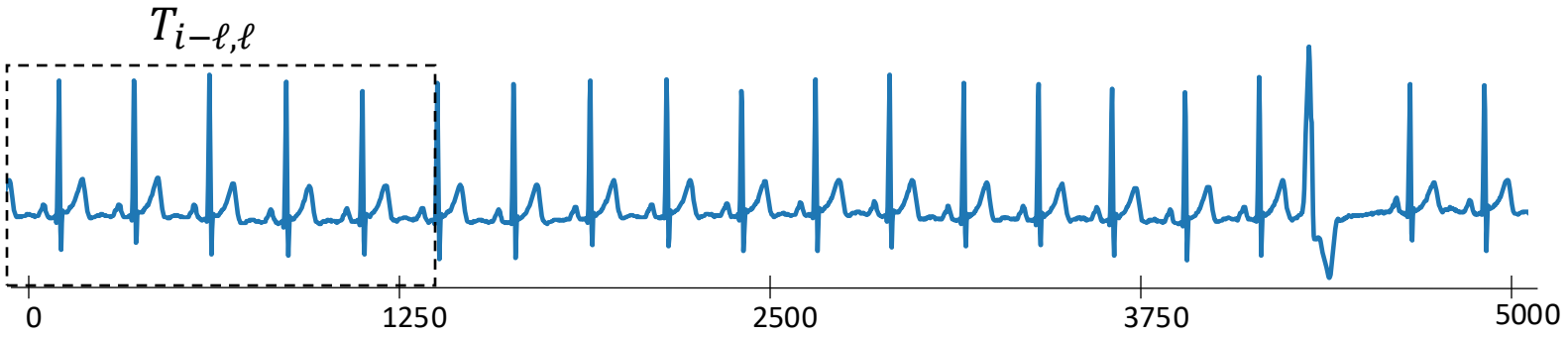
LSTM-AD [15]

Model that stack multiple LSTM cell and use the output to predict the next value

- Semi-supervised
- Univariate/Multivariate
- Point/sequence

[15] Pankaj Malhotra, Lovekesh Vig, Gautam Shro, and Puneet Agarwal. 2015. Long Short Term Memory Networks for Anomaly Detection in Time Series. (2015).

Anomaly Detection methods: *an Example*



DeepAnT [16] (CNN)

Convolutional-based approach (2 convolutional layers) taking as input a sequence and aims to predict the next value.

Semi-supervised

Univariate/Multivariate

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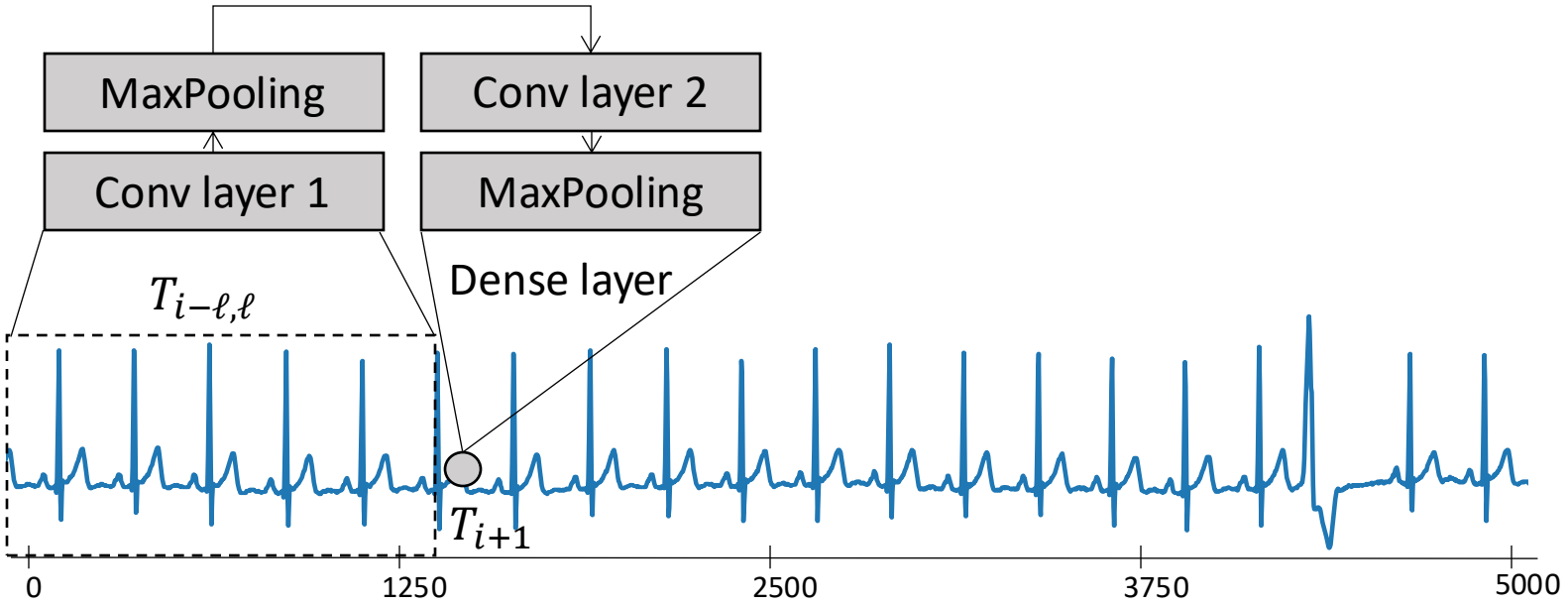

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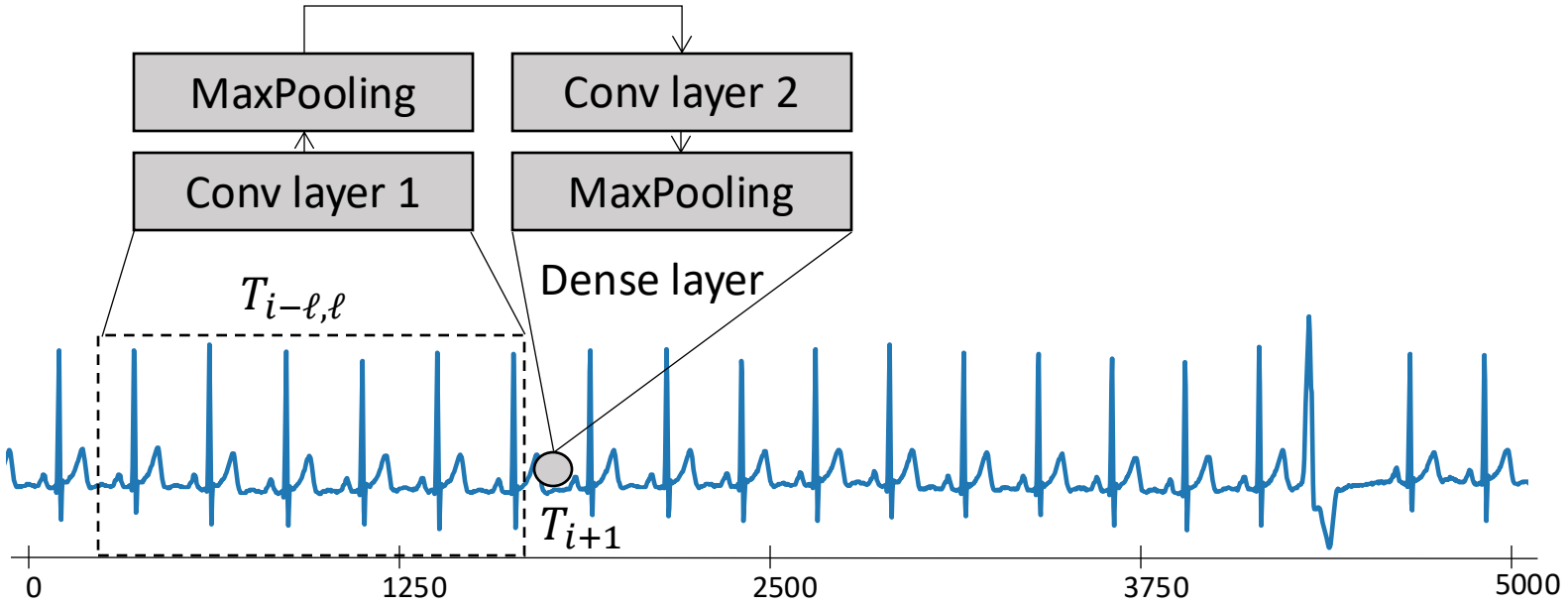

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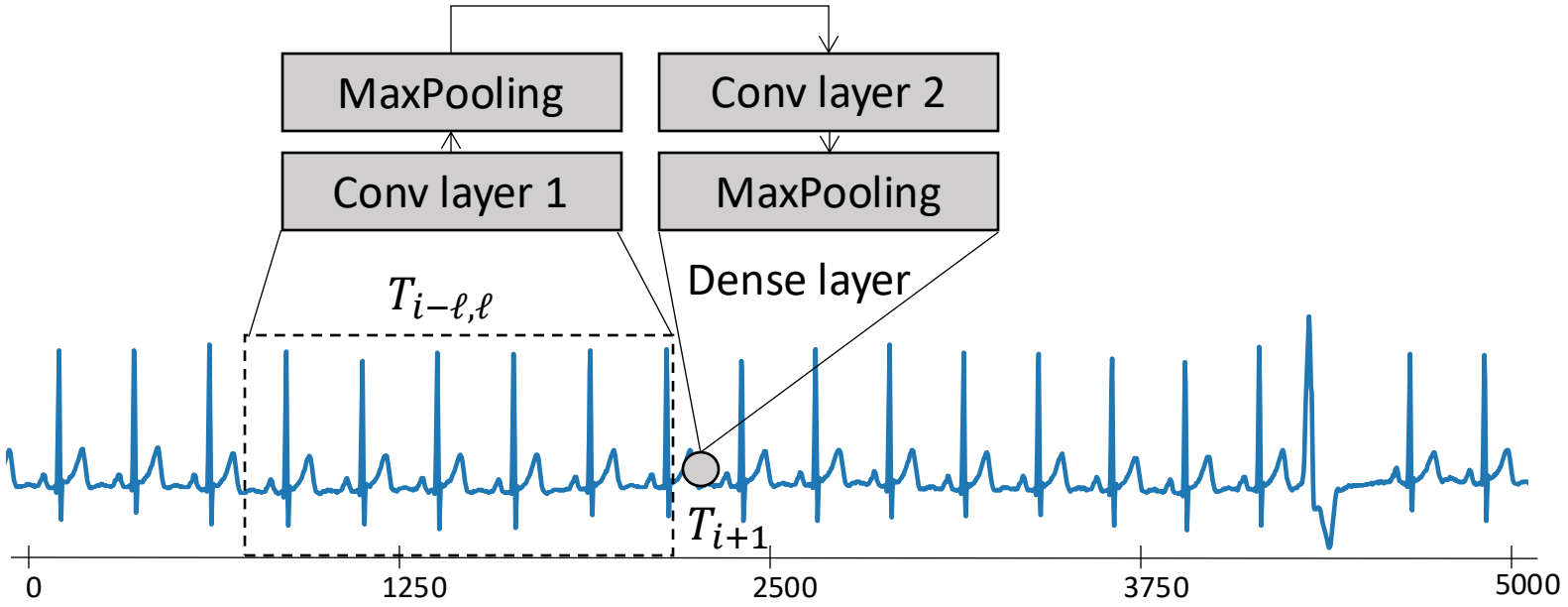
[16] M. Munir, S. A. Siddiqui, A. Dengel, and S. Ahmed. 2019. DeepAnT: A Deep Learning Approach for Unsupervised Anomaly Detection in Time Series. IEEE Access 7 (2019), 1991–2005.

Anomaly Detection methods: *an Example*



DeepAnT [16] (CNN)

Convolutional-based approach (2 convolutional layers) taking as input a sequence and aims to predict the next value.

Semi-supervised

Univariate/Multivariate

Point/sequence

[16] M. Munir, S. A. Siddiqui, A. Dengel, and S. Ahmed. 2019. DeepAnT: A Deep Learning Approach for Unsupervised Anomaly Detection in Time Series. IEEE Access 7 (2019), 1991–2005.

Anomaly Detection methods: *Reconstruction-based*

Methods that aims to reconstruct the time series T and use the reconstruction error to detect if the time series is an anomaly or not.

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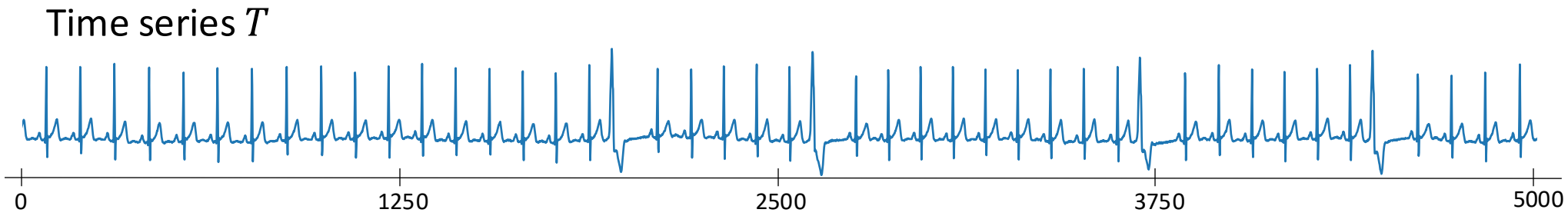

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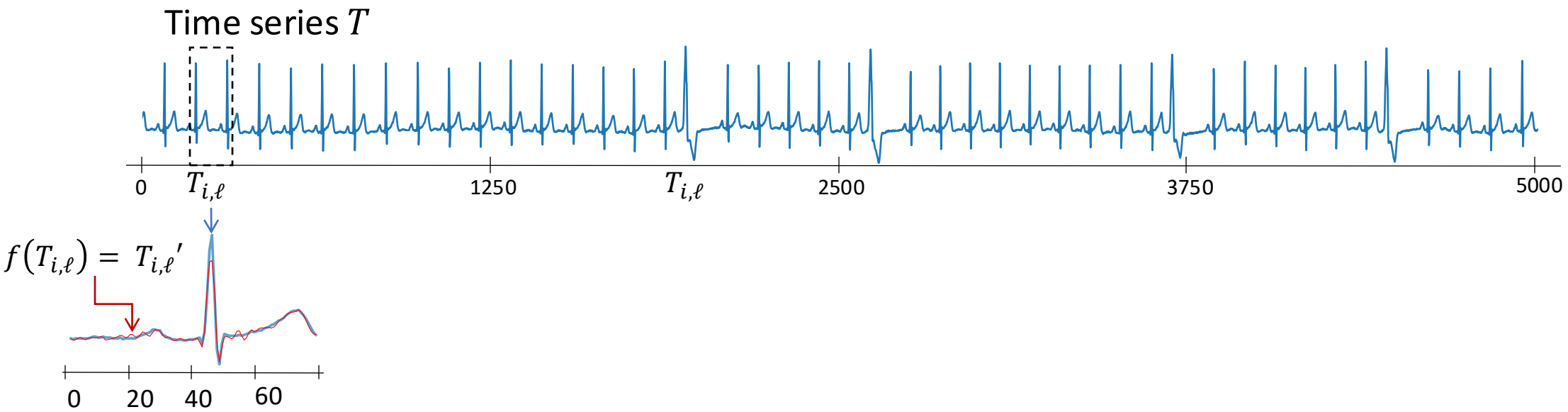

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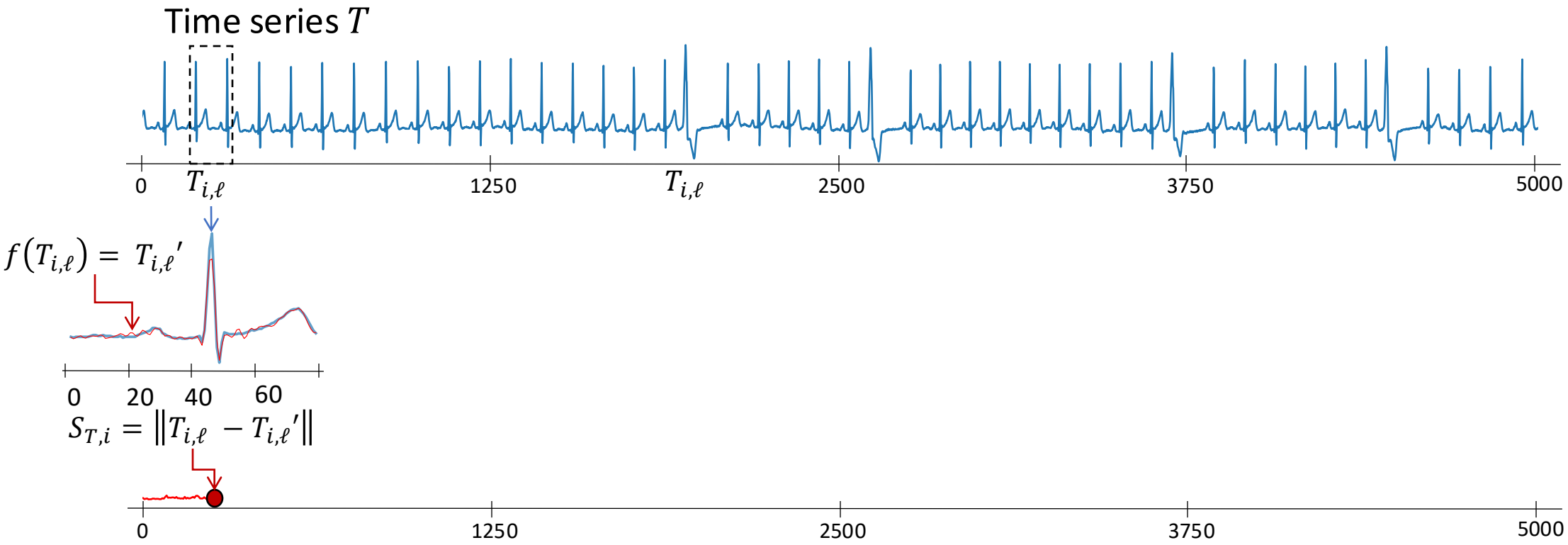

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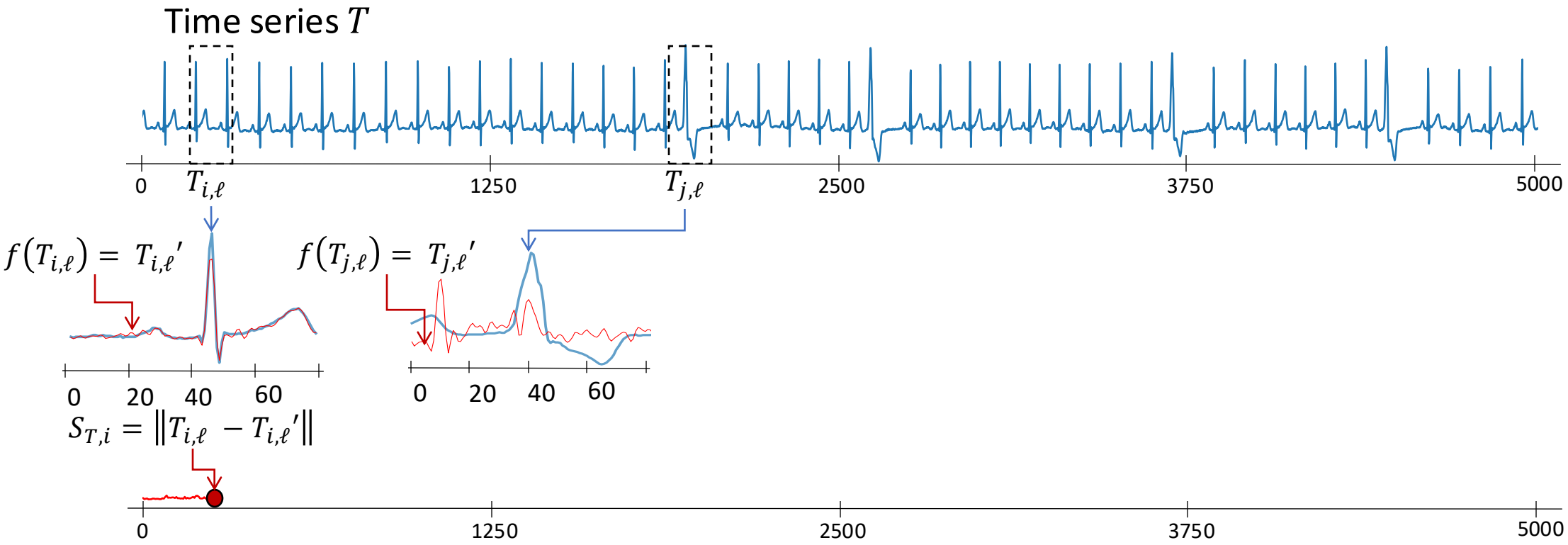

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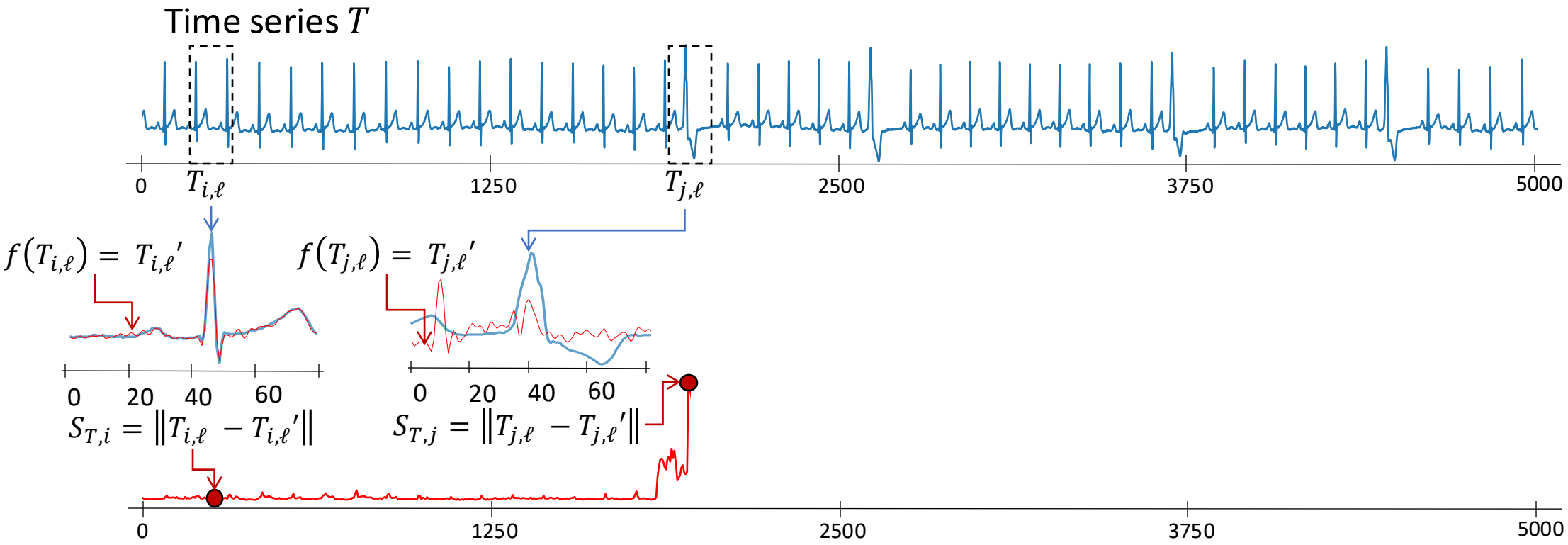

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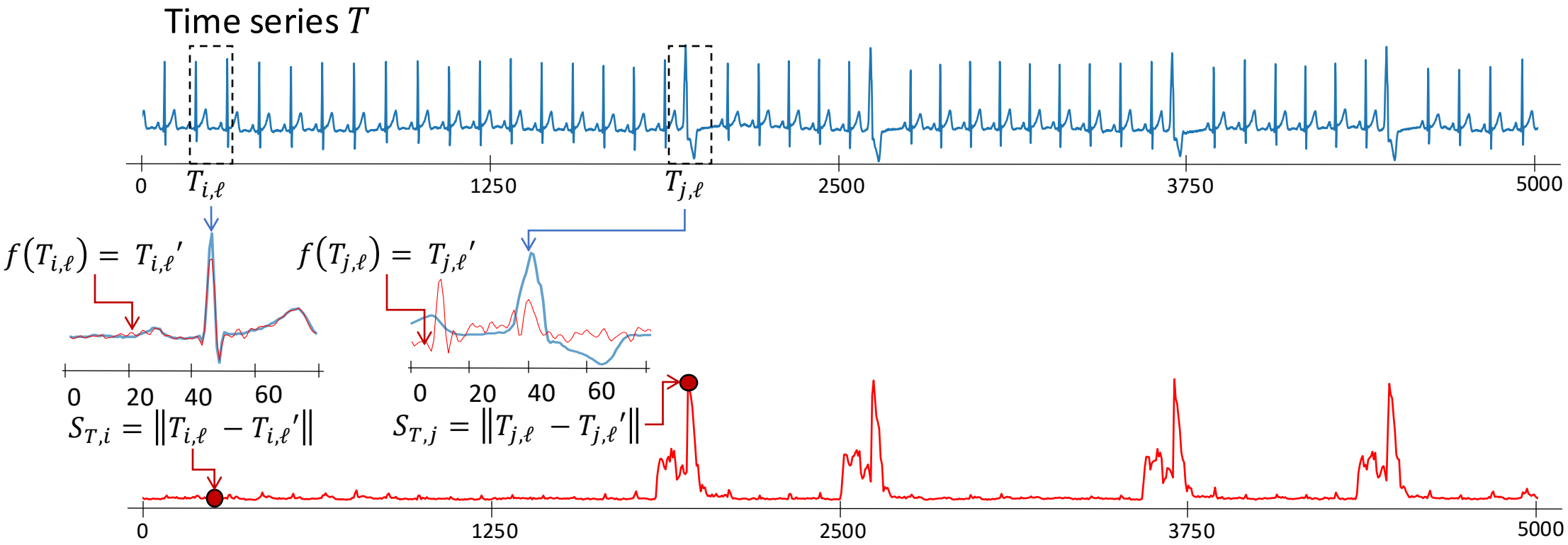

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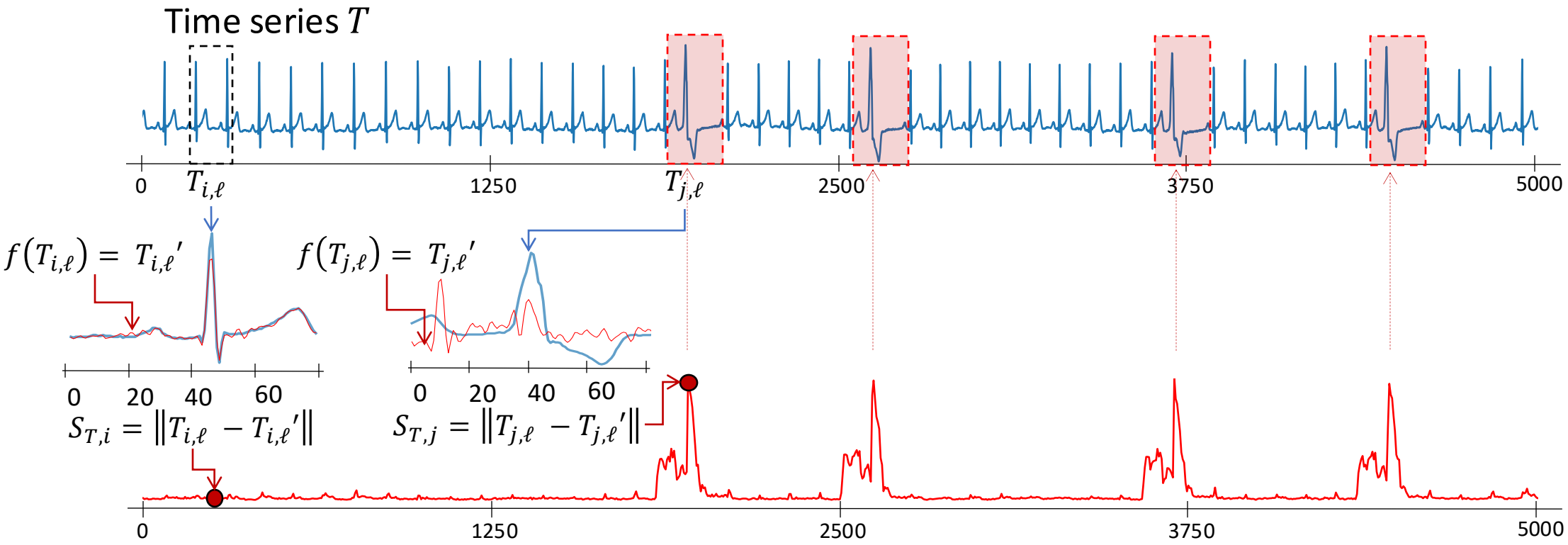
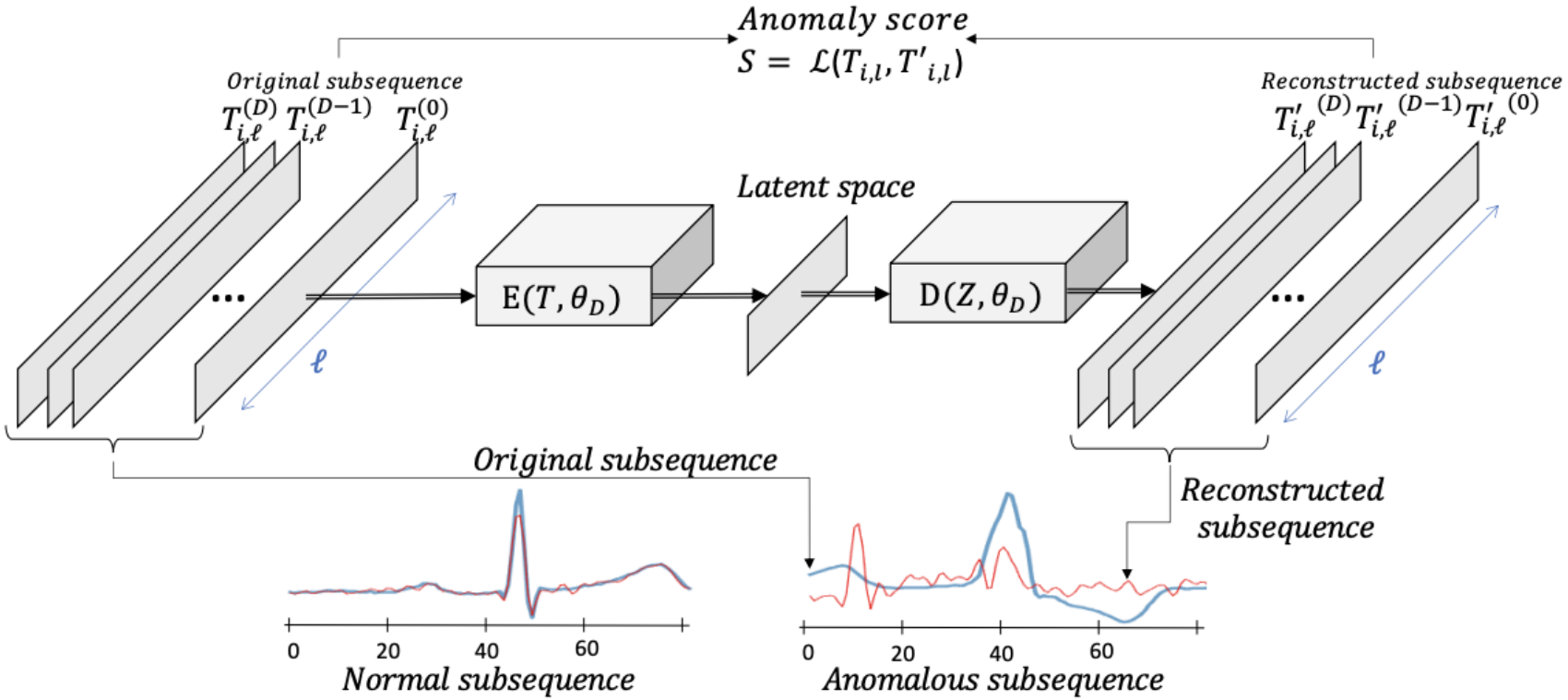


Anomaly Detection methods: *an Example*



AutoEncoders [17] (AE)

Neural Network composed of an encoder (that reduce the dimensionality) and decoder that reconstruct the time series. The objective is to minimize the reconstruction error.

- Semi-supervised
- Univariate/Multivariate
- Point/sequence

[17] Mayu Sakurada and Takehisa Yairi. 2014. Anomaly Detection Using Autoencoders with Nonlinear Dimensionality Reduction. In Proceedings of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis (Gold Coast, Australia QLD, Australia) (MLSDA'14).

Anomaly Detection methods: *Existing benchmark*

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HEX/UCR [18]

Set of 250 time series with labels.

Details

- The labels have been manually checked and are reliable
- Each time series contains only 1 labeled anomaly

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TimeEval [5]

Set of 976 time series with labels.

Details

- New synthetic benchmark GutenTag used to tune parameters
- Only Time series with low contamination rate (< 0.1)
- Time series with at least one methods above 0.8 AUC-ROC

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TSB-UAD [19]

Set of 2000 time series with labels.

Details

- Collected as proposed in the literature (no filtering based on contamination, size or label quality)
- Artificial and synthetic data generation methods for reliable labels

Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]

Set of 250 time series with

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TimeEval [5]

Real datasets collection

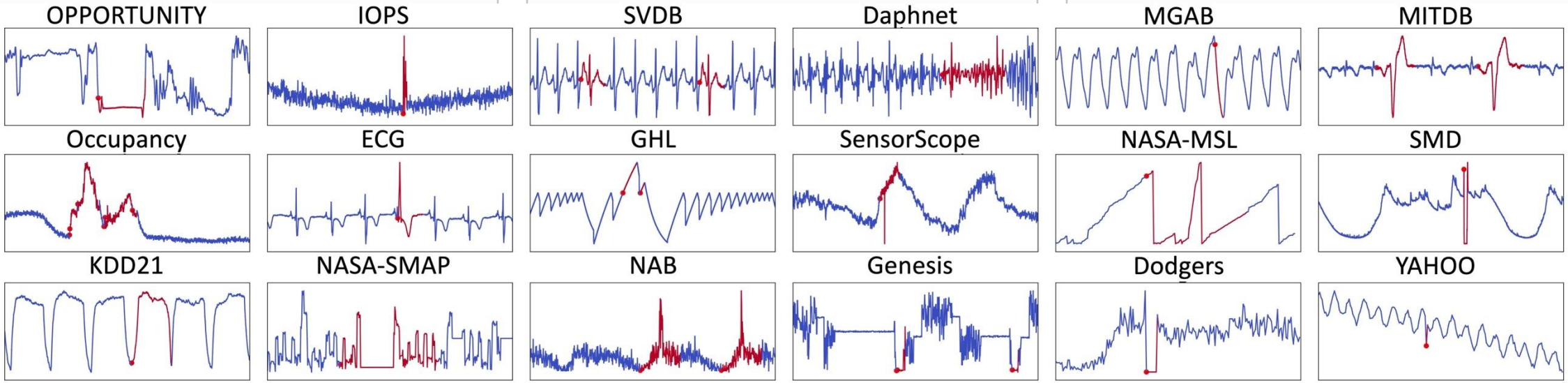
contamination rate (< 0.1)

- Time series with at least one methods above 0.8 AUC-ROC

TSB-UAD [19]

Set of 2000 time series with

contamination, size of label quality.



Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]

Set of 250

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ies with

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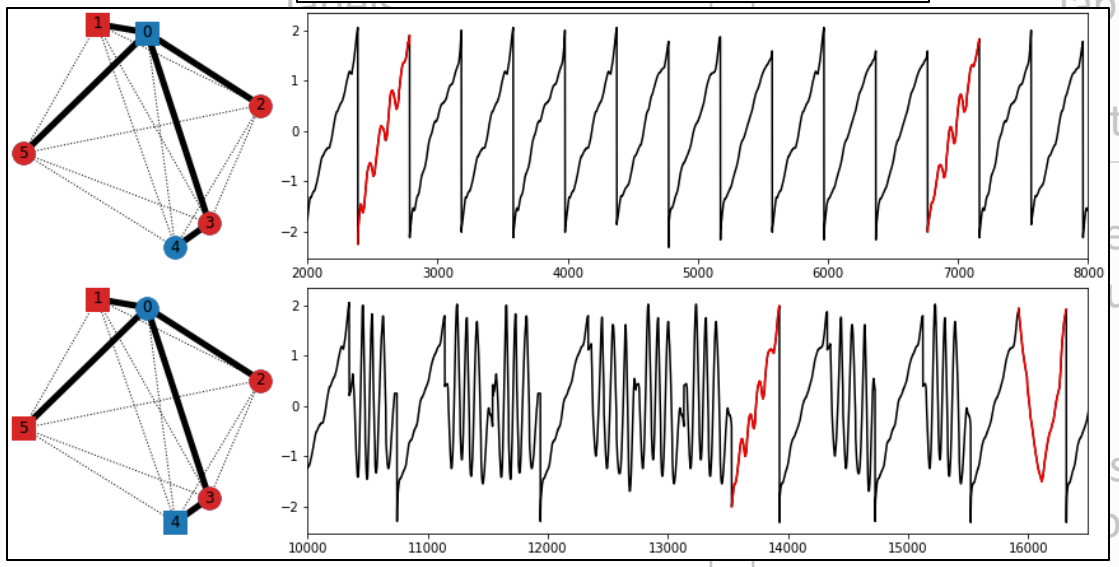
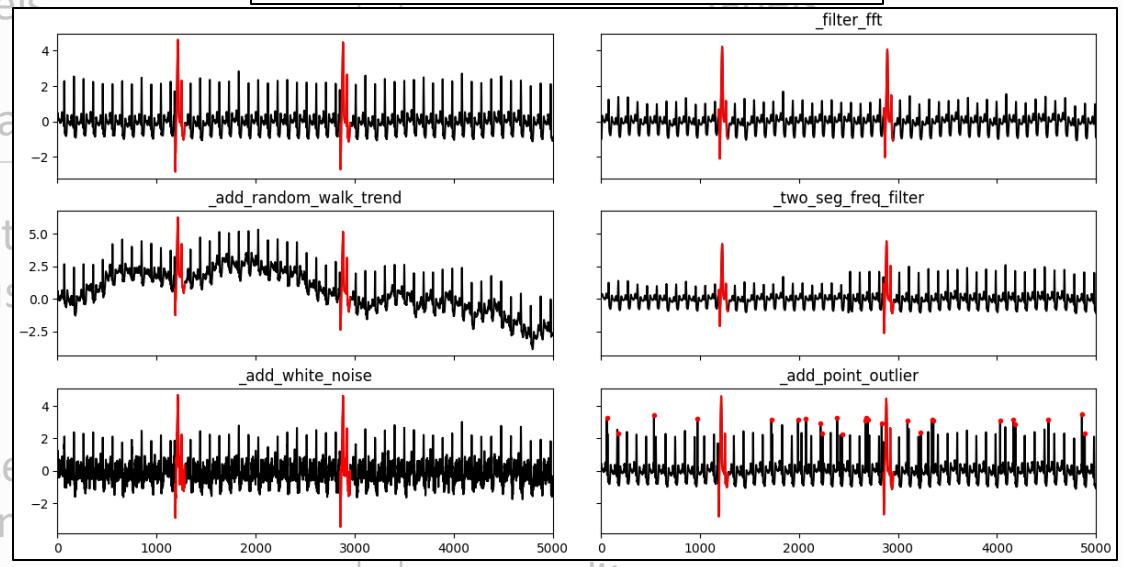
Artificial dataset generation

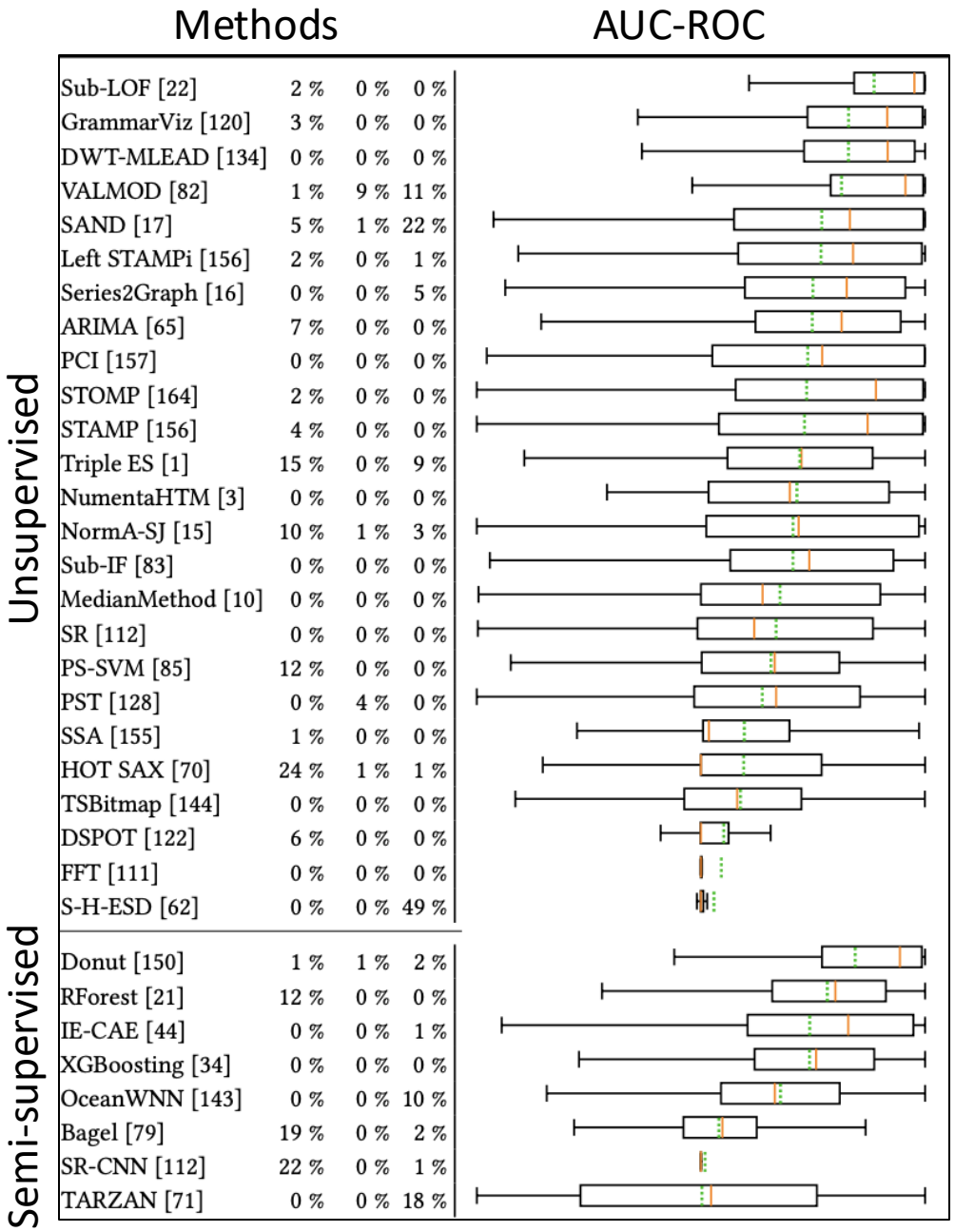


Synthetic dataset generation



Anomaly Detection methods:
Experimental evaluation

Observations on TimeEval [5]:



[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. Anomaly detection in time series: a comprehensive evaluation. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.

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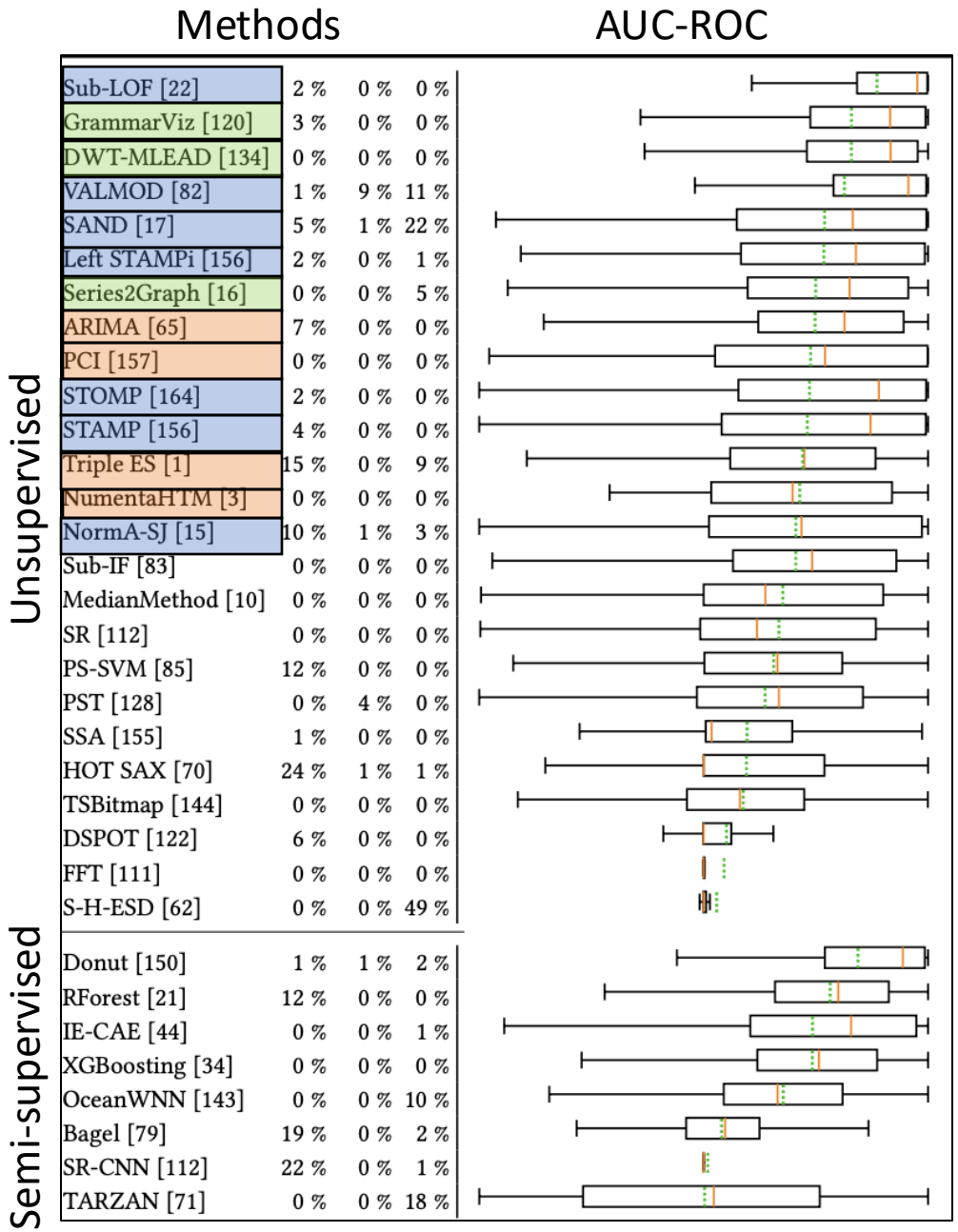
- Distance-based and Density-based methods have a better accuracy (AUC-ROC) than forecasting and reconstruction-based approaches



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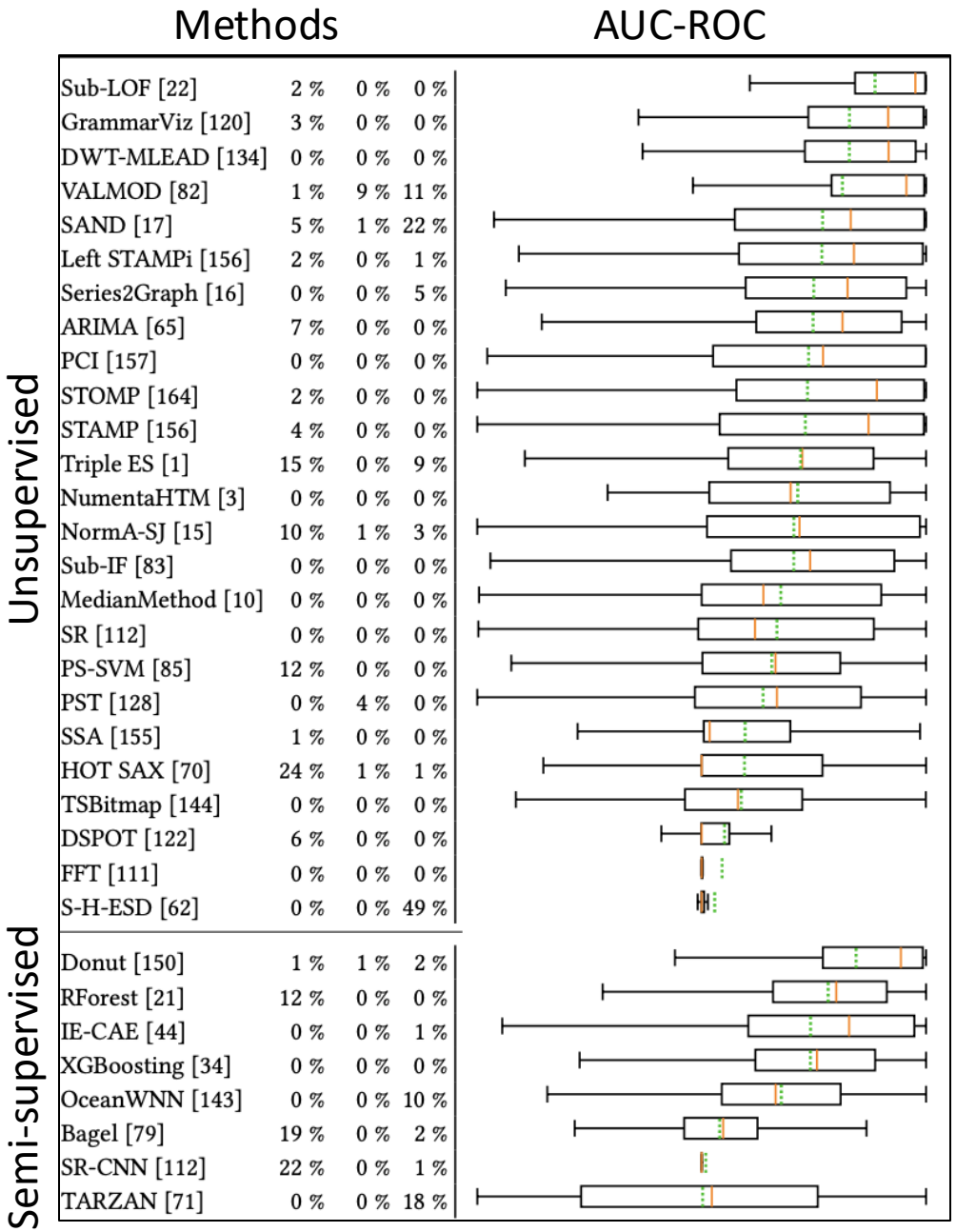
- Semi-supervised methods are not outperforming Unsupervised approaches



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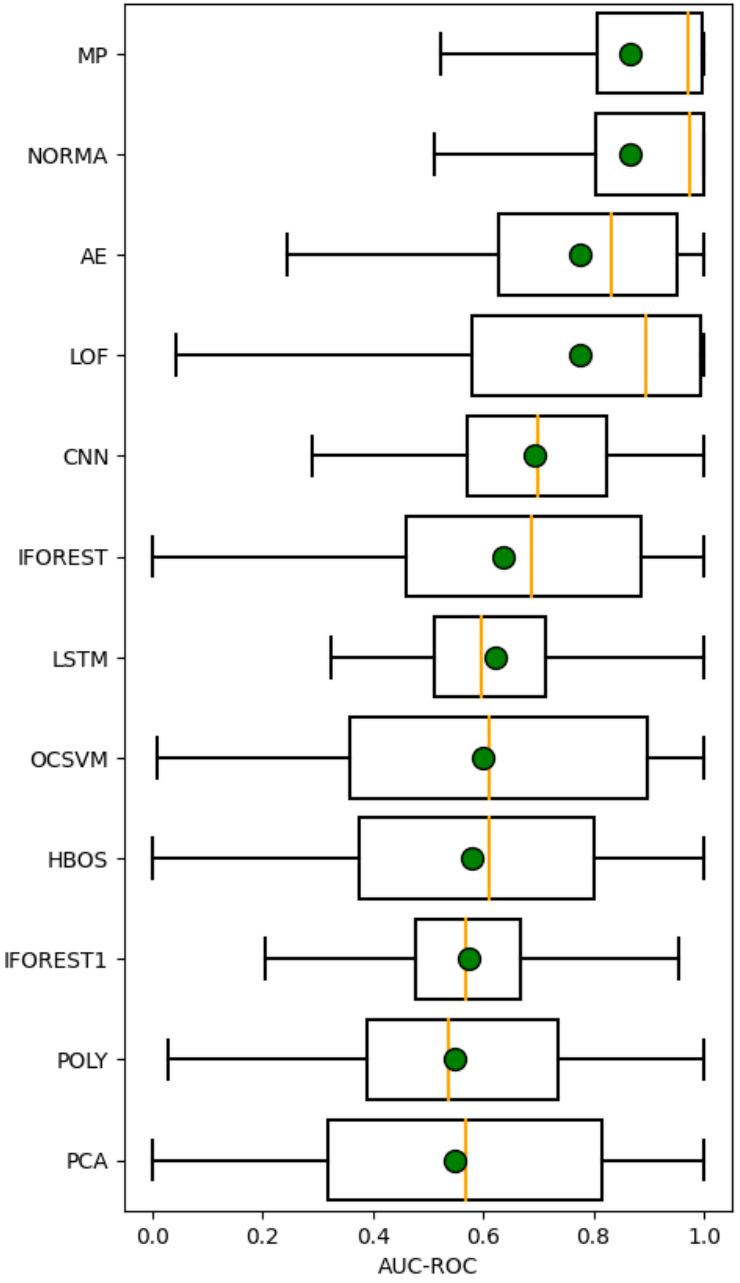

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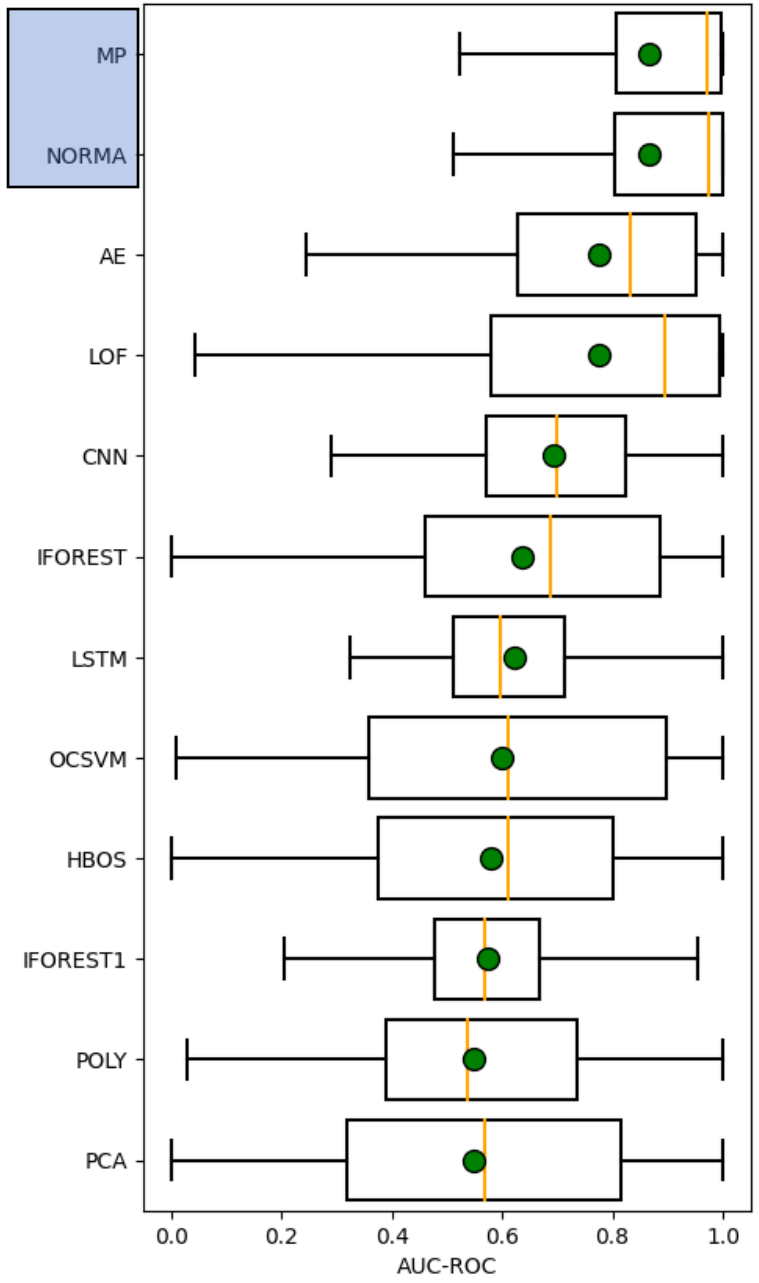

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Observations on TSB-UAD [19]:

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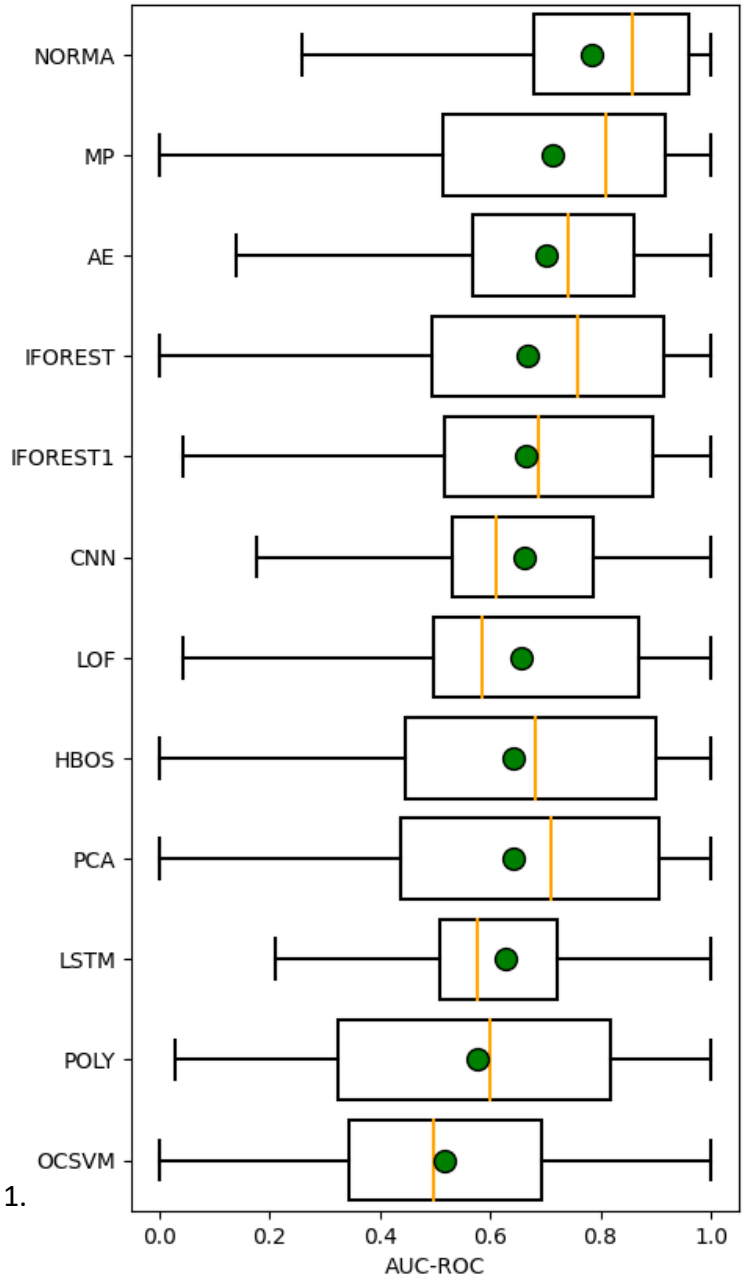
- Isolation Forest (distribution-based and not proposed for time series) have also a strong accuracy

- AutoEncoder (AE) is also very accurate.



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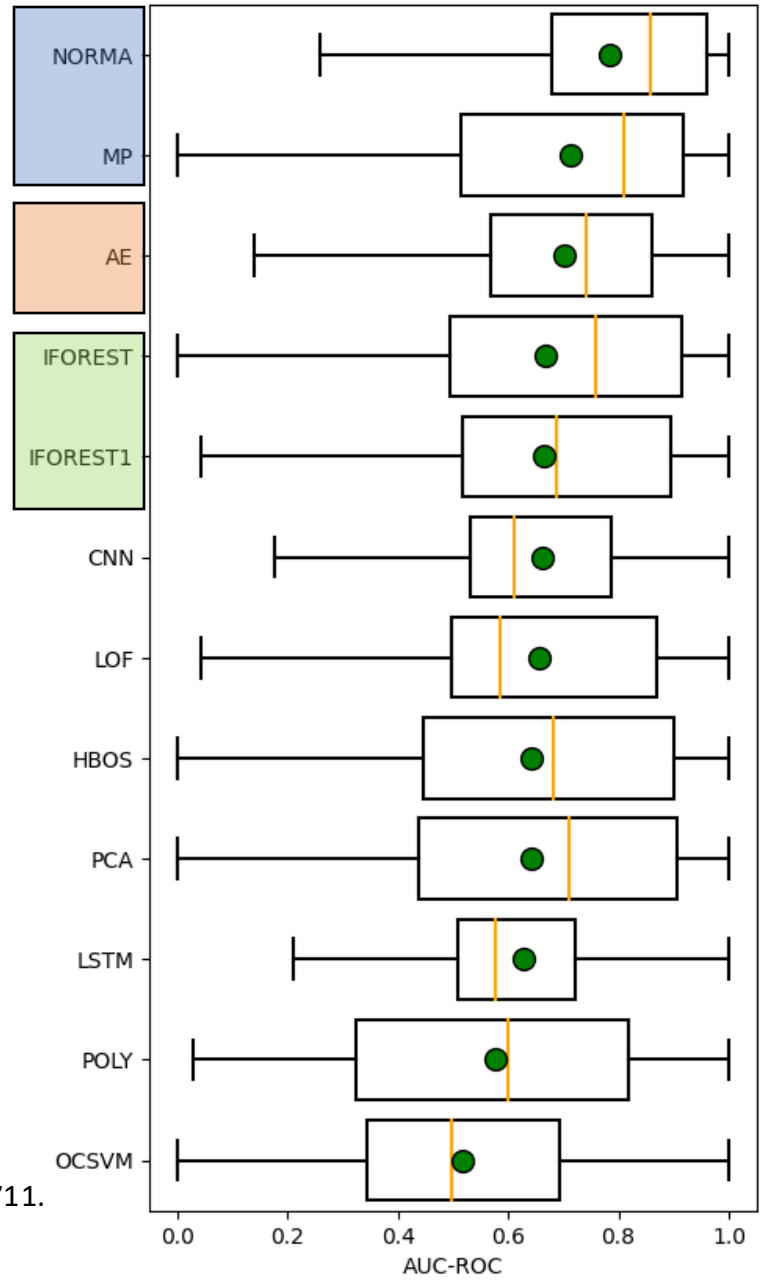

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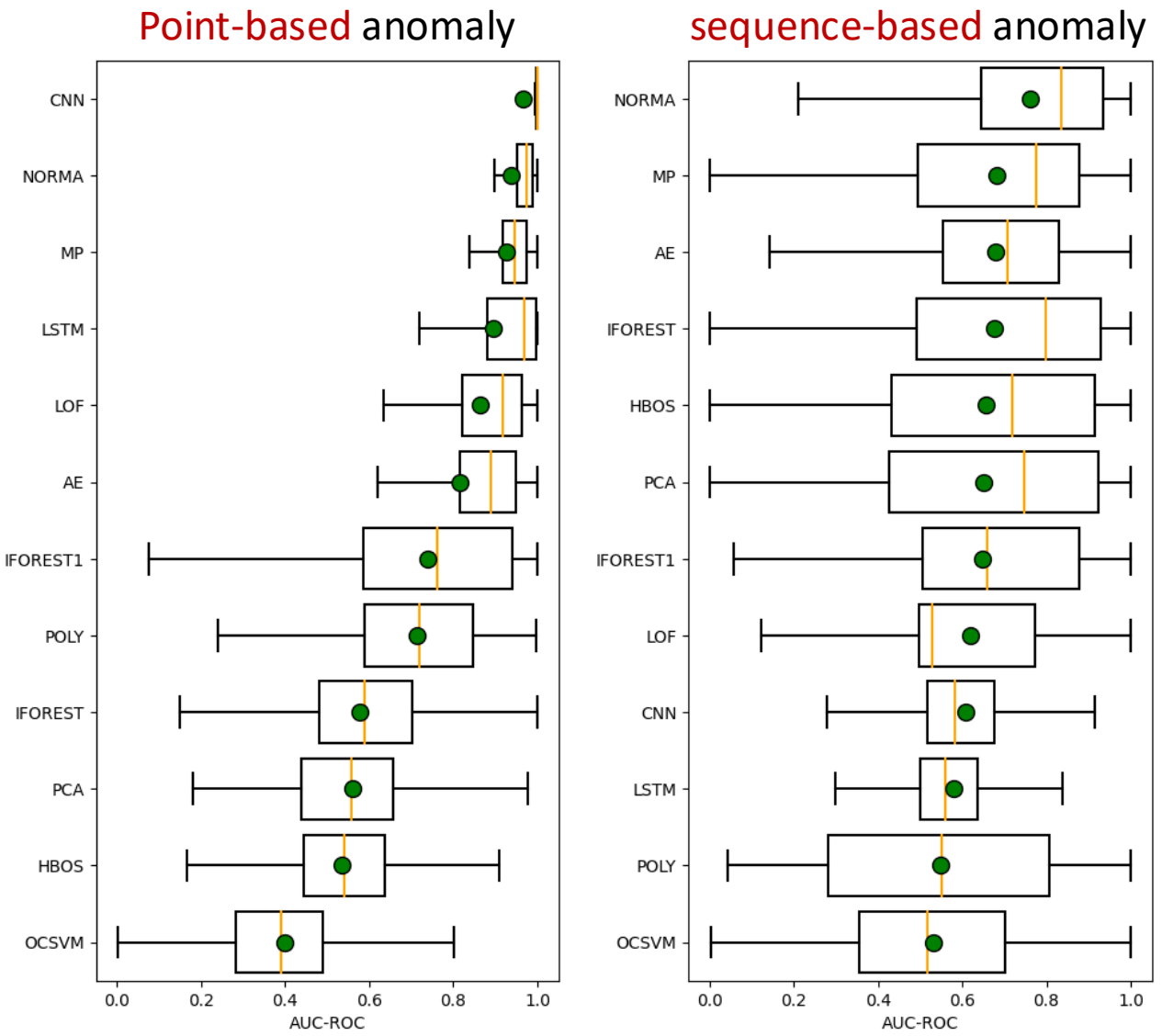

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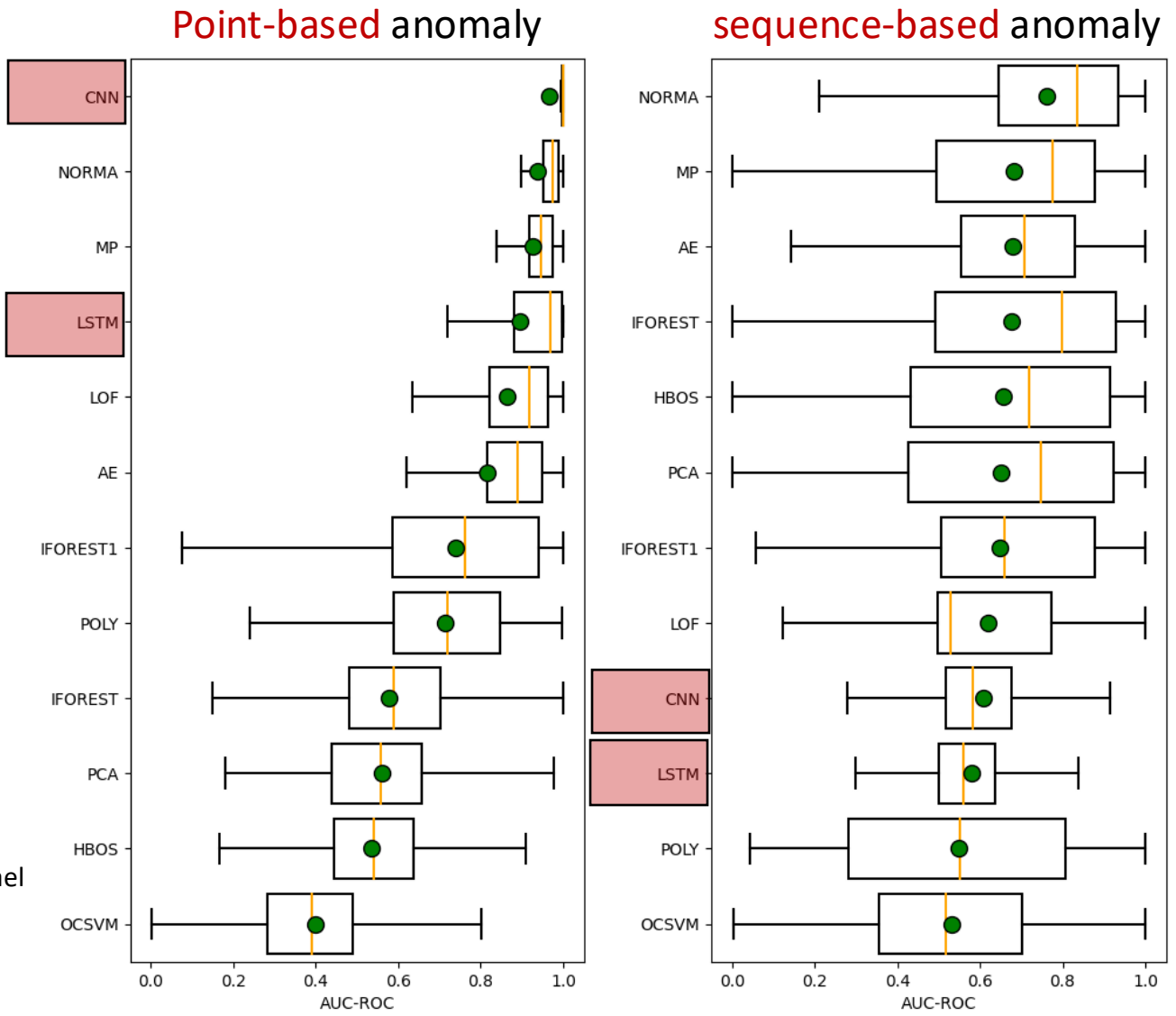
Anomaly Detection methods:
Experimental evaluation

Observations on TSB-UAD [19]:

- Forecasting methods (LSTM and CNN) are very accurate for point anomalies
- But have poor performances on sequence-based anomalies.



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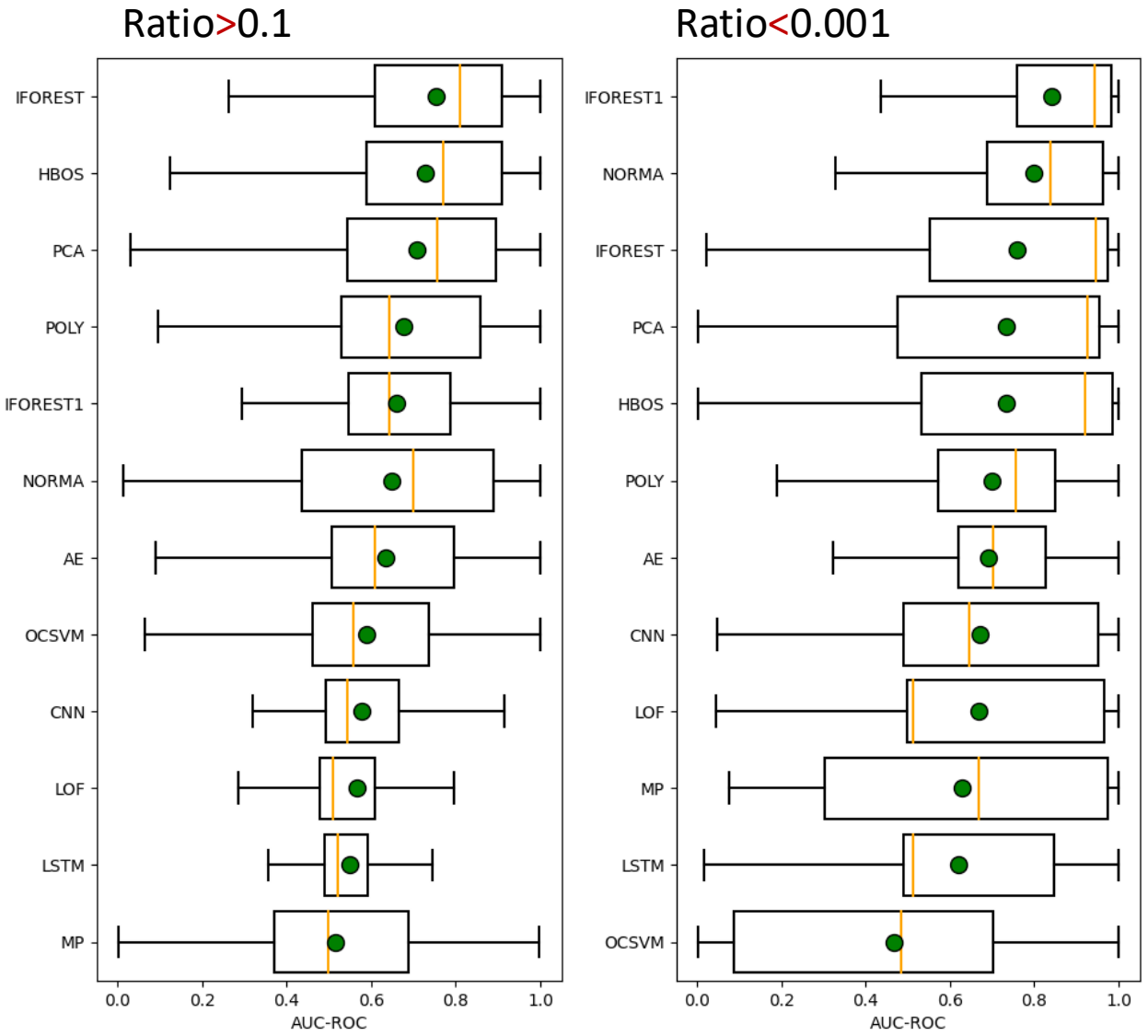
Anomaly Detection methods:
Experimental evaluation

Observations on TSB-UAD [19]:

- The ratio of normal/abnormal points has a strong impact on the methods ranking.



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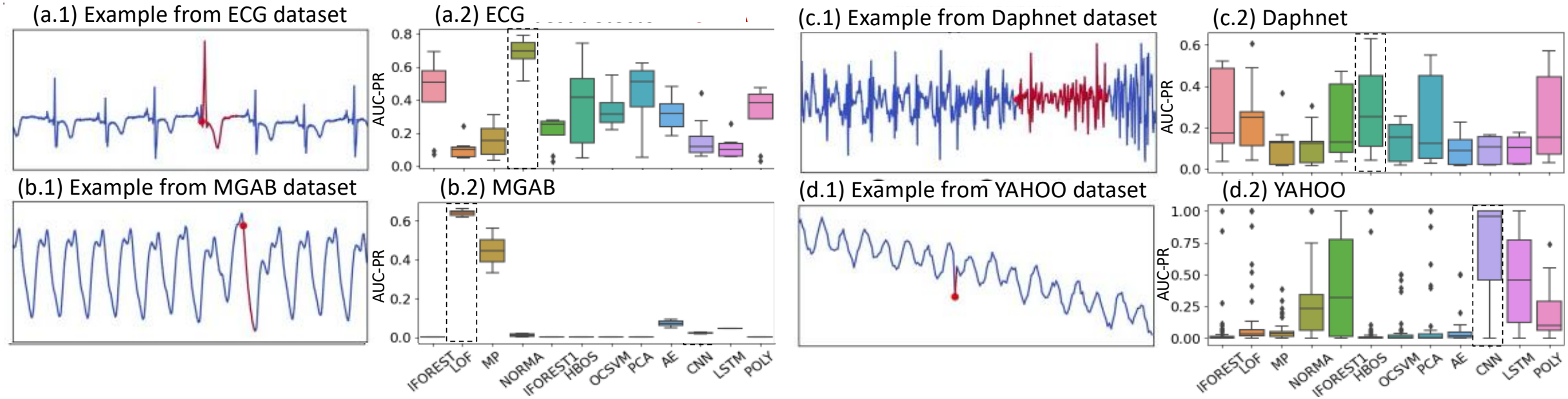
Anomaly Detection methods: *Experimental evaluation*

Observation from the results applied on specific datasets (TSB-UAD [19])



There is no overall winner.

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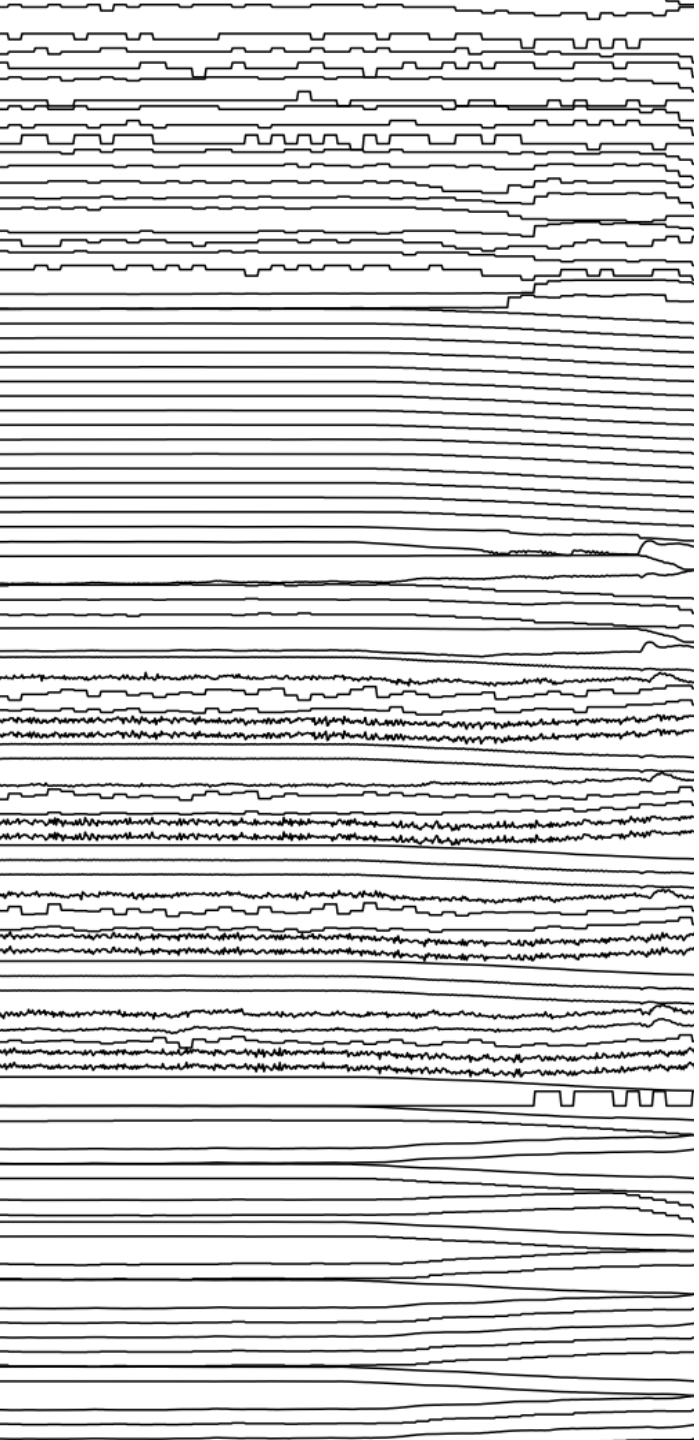


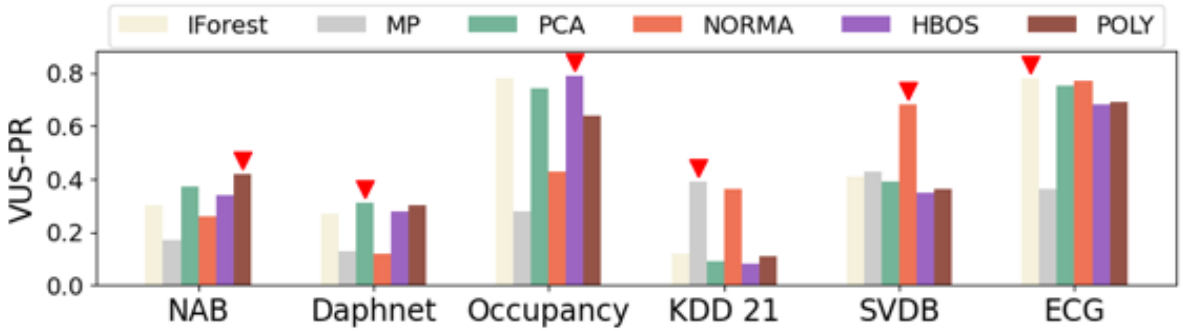
New Trends and Opportunities

Automated Solution: *Background*

Motivation:

- No one-size-fits-all model: How can we *automatically* identify the best anomaly detector given a time series?

Detection accuracy (VUS-PR) for 6 anomaly detectors across different datasets in TSB-UAD [19]



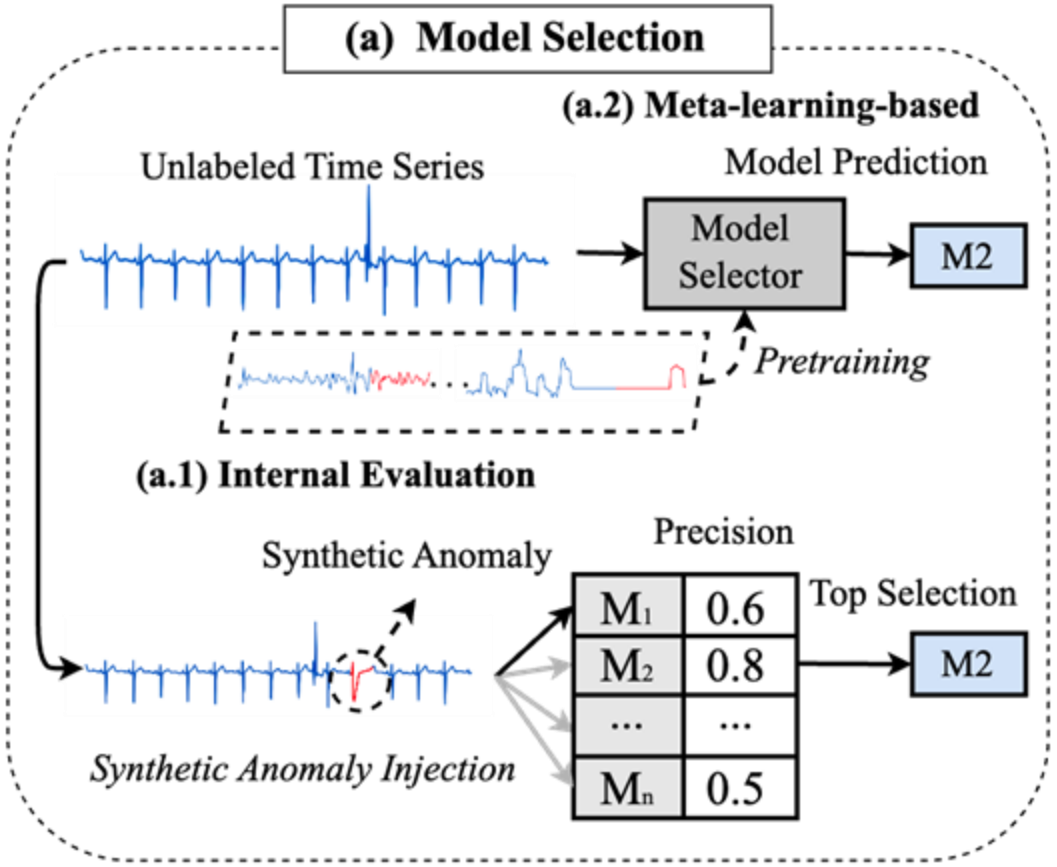
[27] Maroua Bahri, Flavia Salutari, Andrian Putina, and Mauro Sozio: AutoML: state of the art with a focus on anomaly detection, challenges, and research directions. International Journal of Data Science and Analytics 14(2): 113-126 (2022).

Automated Solution: *Taxonomy*

(a) Model Selection:

Selecting the best anomaly detector from a predefined candidate model set.

- *(a.1) Internal Evaluation*
- *(a.2) Meta-learning-based*



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(a) Model Selection:

Selecting the best anomaly detector from a predefined candidate model set.

- *(a.1) Internal Evaluation*
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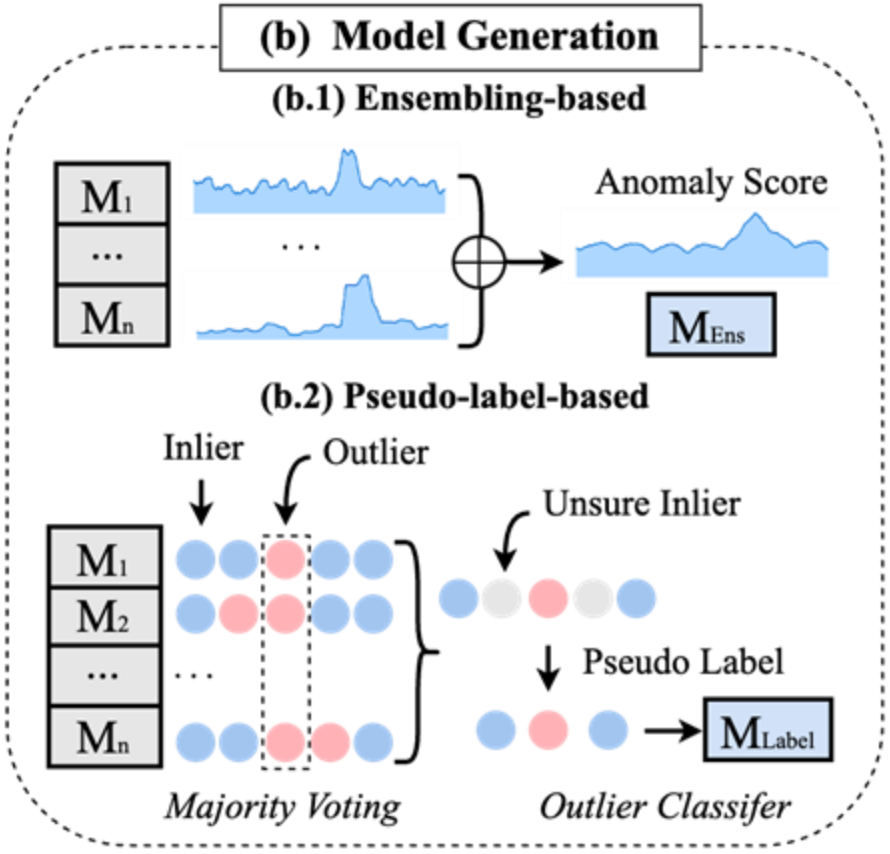
(b) Model Generation:

Creating an entirely new model for the given time series based on the candidate mode set

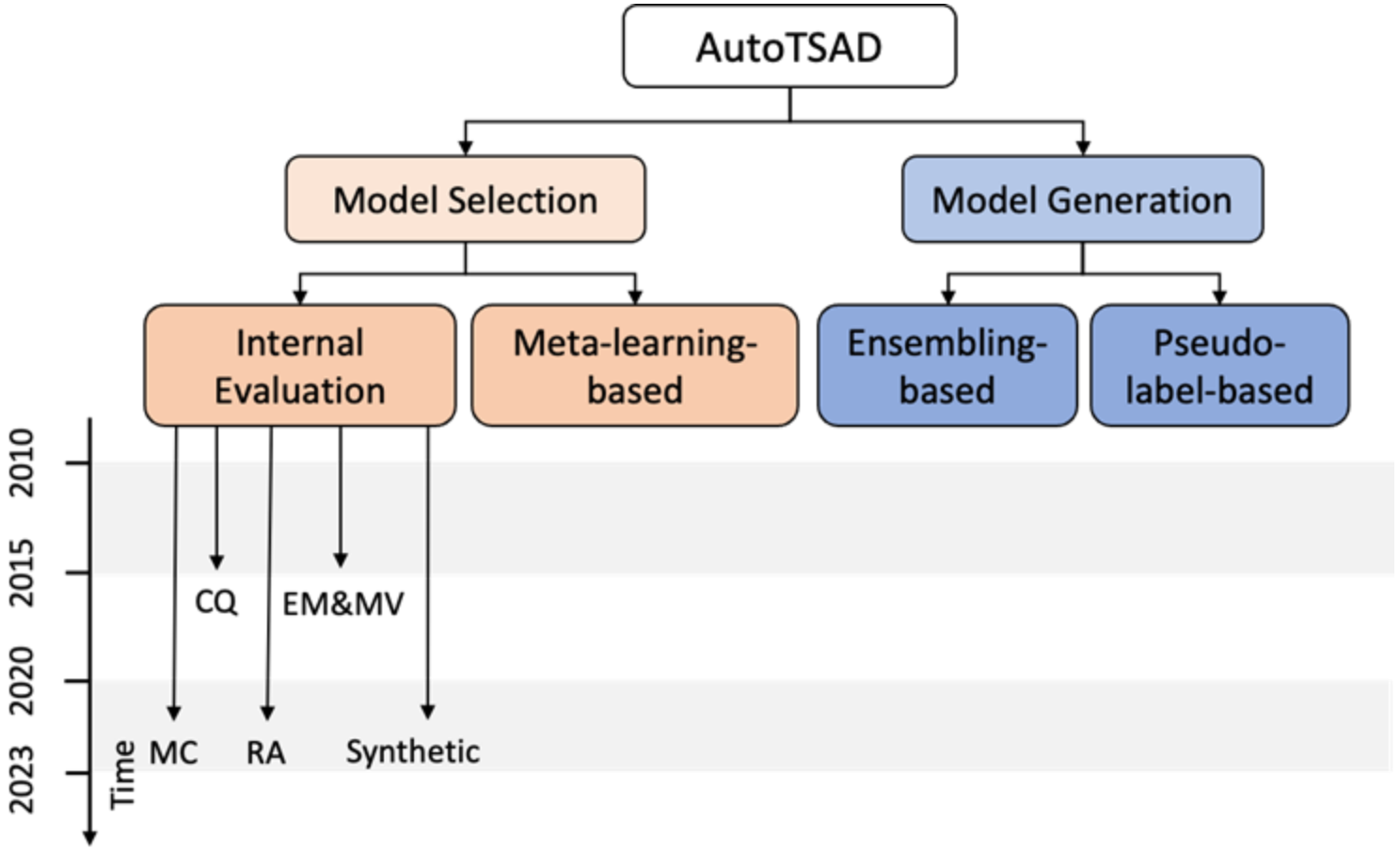
- *(b.1) Ensembling-based*
- *(b.2) Pseudo-label-based*



Automated Solution: *Internal Evaluation*

Definition: Evaluate the effectiveness of a model without any reliance on external information

- Stand-alone: Clustering Quality, EM&MV, Synthetic anomaly injection
- Collective: Model Centrality, Rank Aggregation



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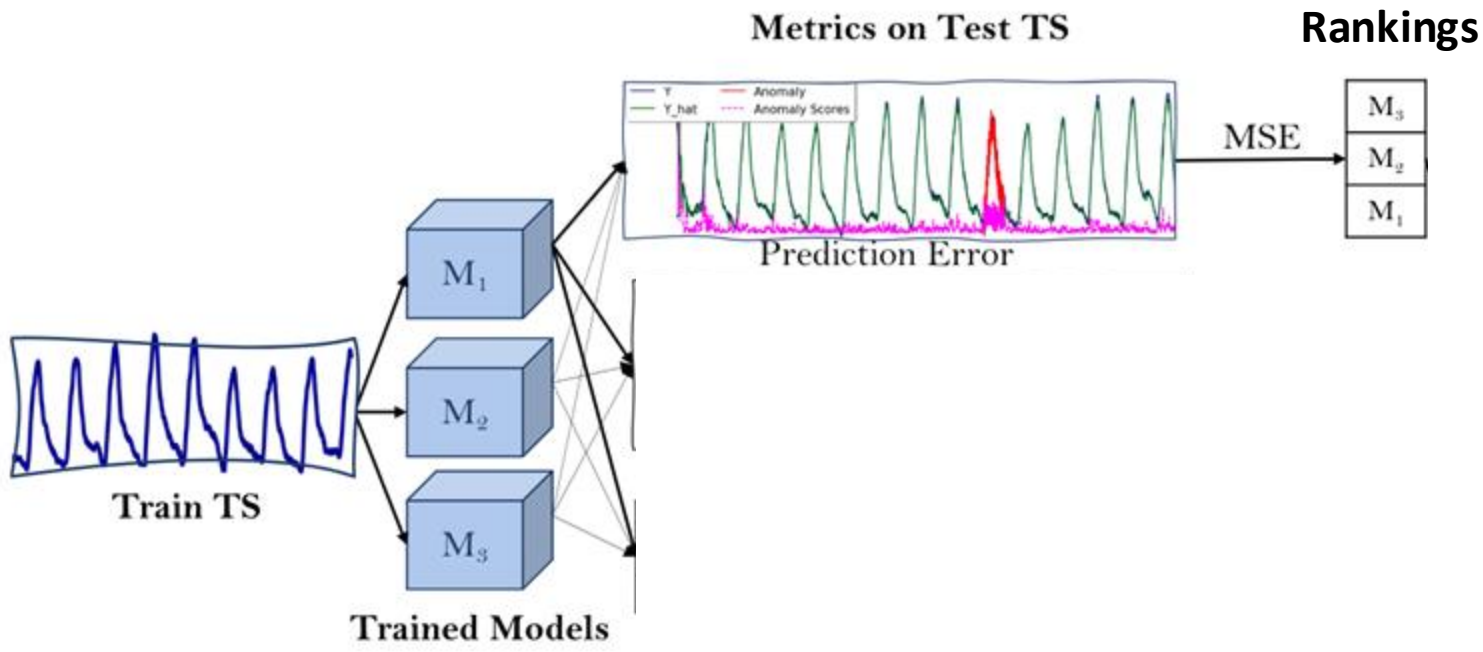

Image from [28]: Internal Evaluation workflow.

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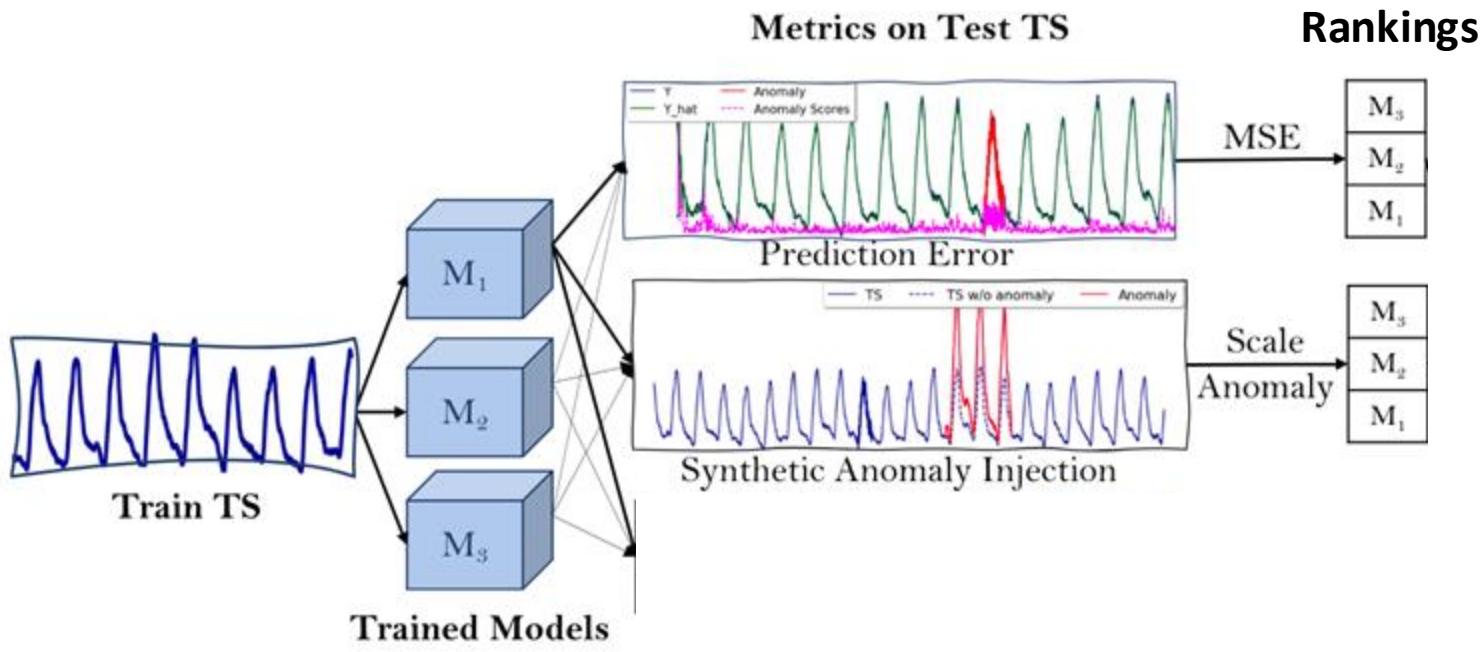

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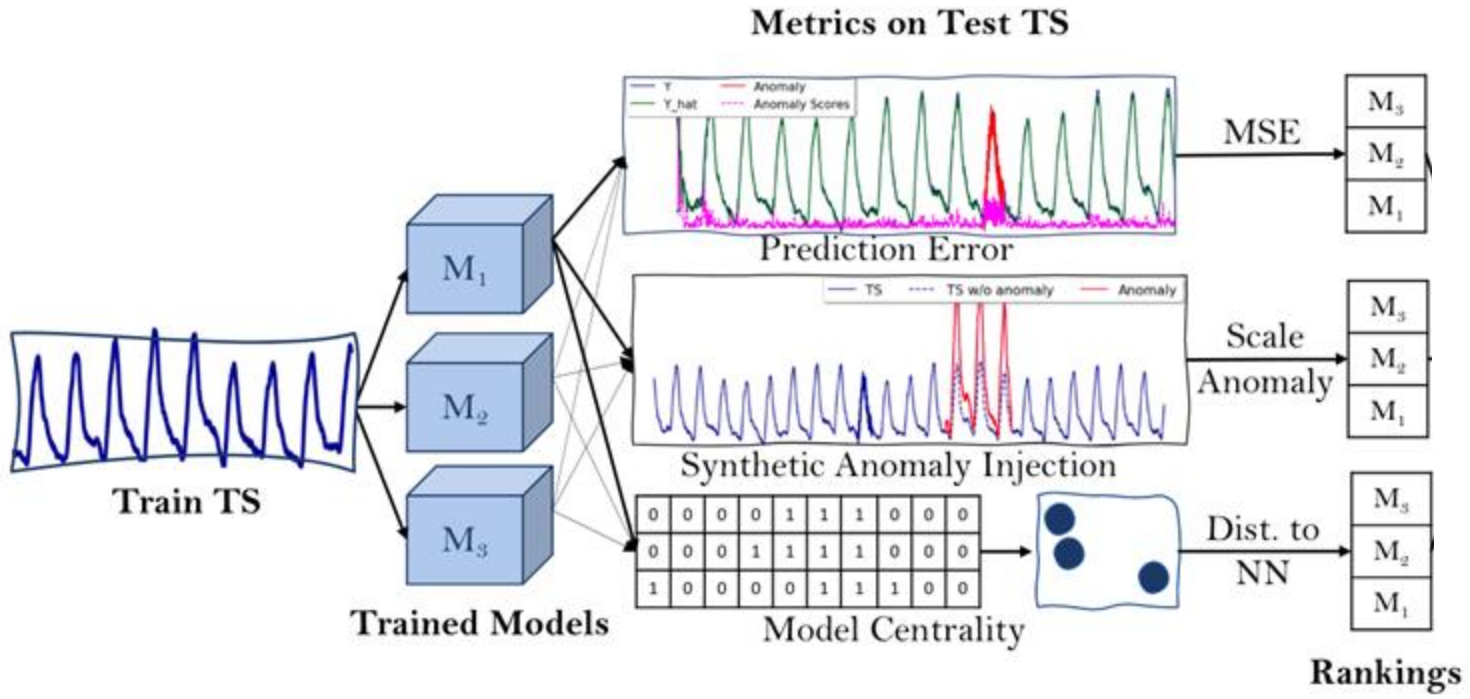

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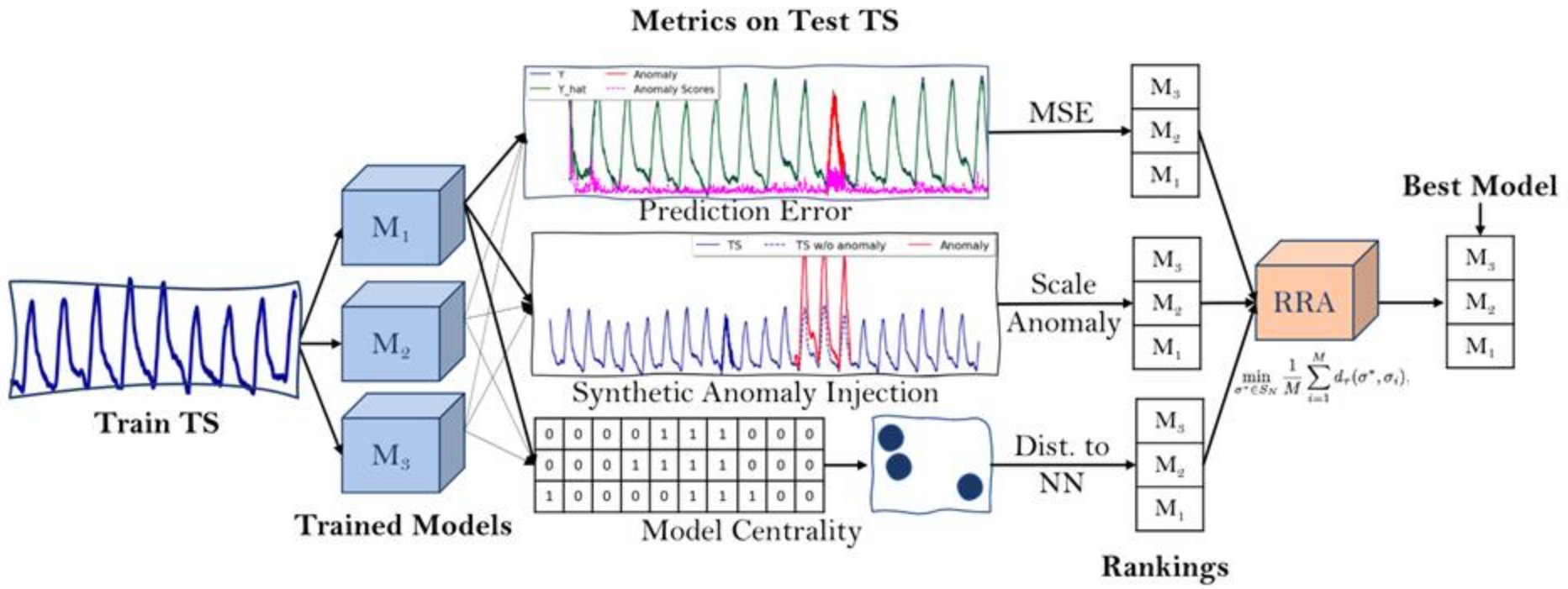

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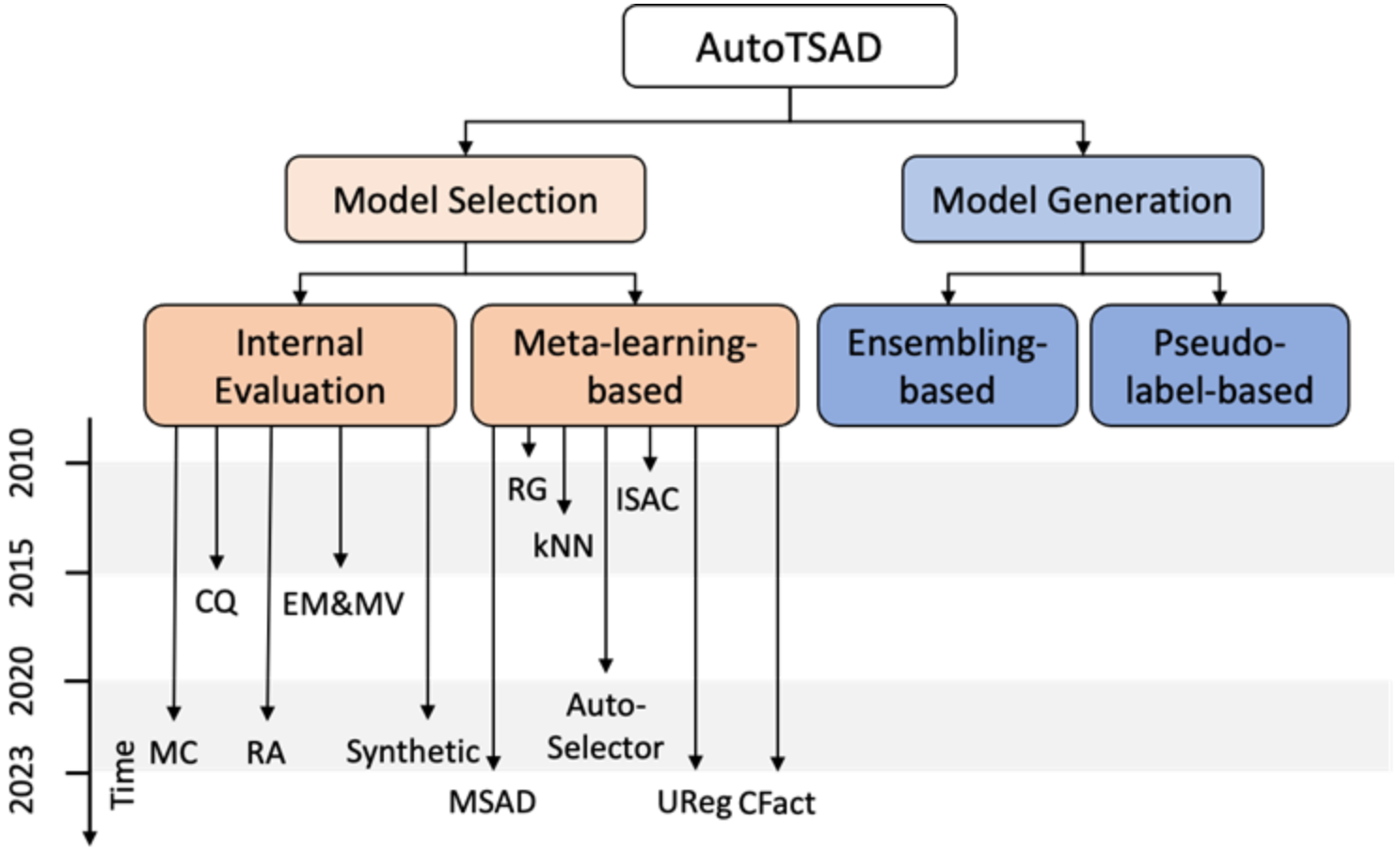
Automated Solution: *Meta-learning-based*

Definition: Using insights from historical labeled datasets to select the best model for new data

- Classification: Auto-Selector, MSAD
- Regression: RG, UReg, Cfact
- Nearest Neighbor: kNN
- Other Optimization: ISAC, MetaOD



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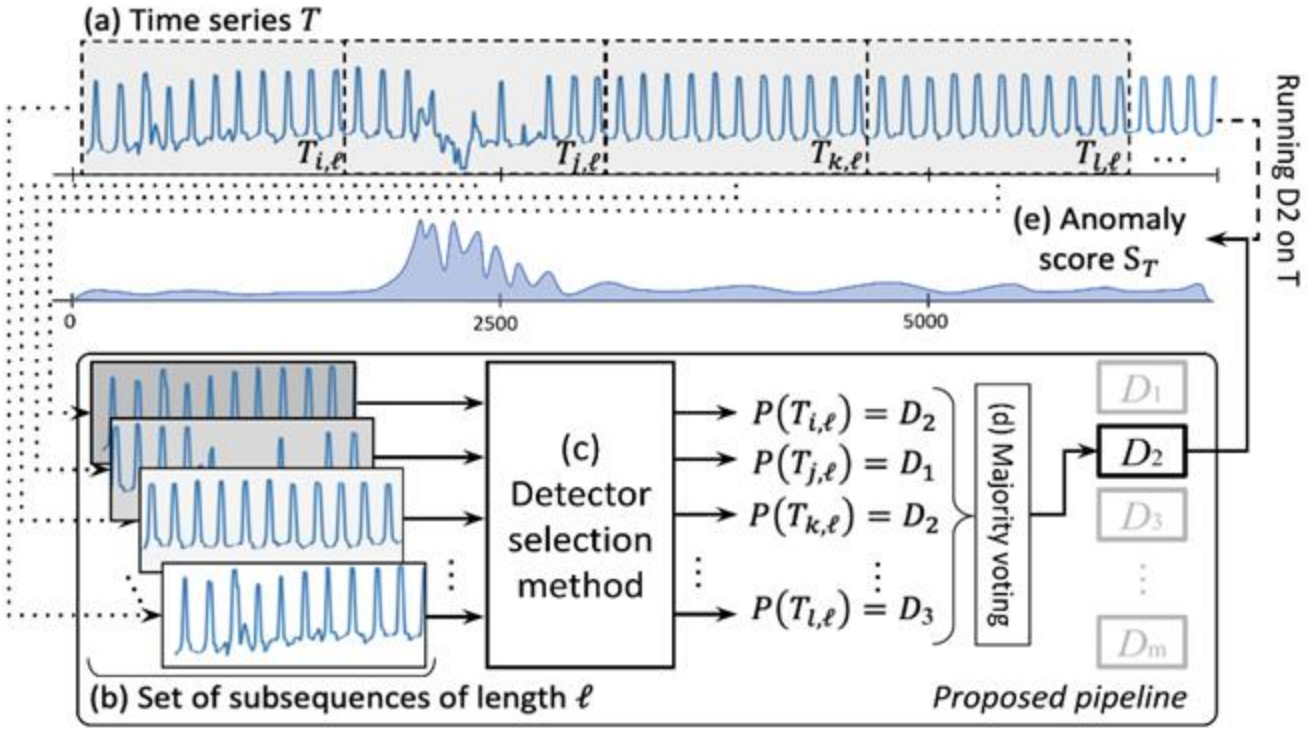
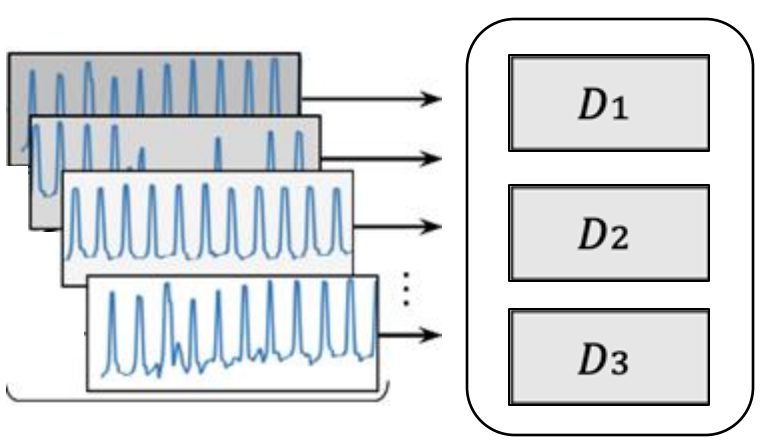


Image from [29]: Model Selection Pipeline.

[29] Emmanouil Sylligardos, Paul Boniol, John Paparrizos, Panos Trahanias, Themis Palpanas. 2023. Choose wisely: An extensive evaluation of model selection for anomaly detection in time series. Proceedings of the VLDB Endowment 16(11): 3418-3432.

Automated Solution: *Meta-learning-based*



Time Series
For Training

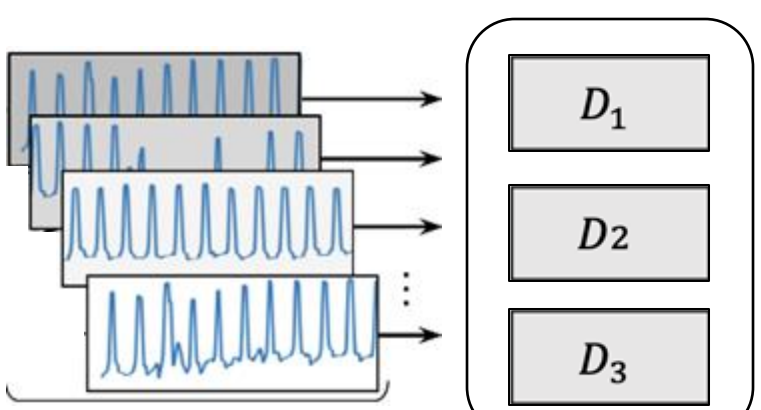
Candidate
Model Set

	D_1	D_2	D_3	...
TS_1	0.5	0.7	0.9	
TS_2	0.6	0.4	0.7	
TS_3	0.5	0.8	0.6	
...				

Performance
Matrix

Performance measures:
F-score, AUC-PR, VUS-PR …

Automated Solution: *Meta-learning-based*



Time Series
For Training

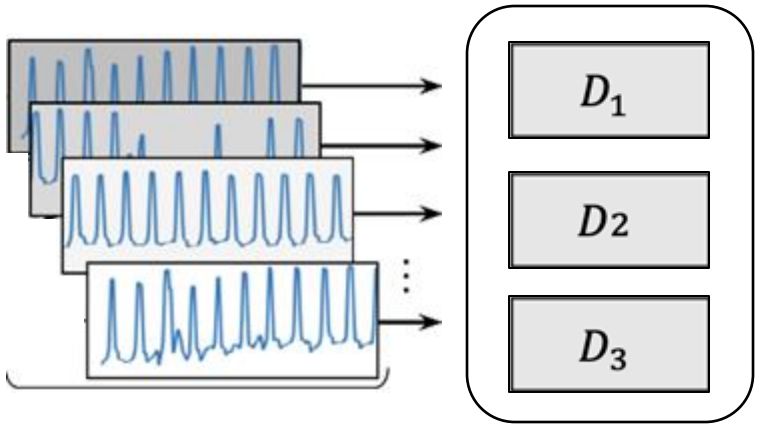
Candidate
Model Set

	D_1	D_2	D_3	...
TS_1	0.5	0.7	0.9	
TS_2	0.6	0.4	0.7	
TS_3	0.5	0.8	0.6	
...				

Performance
Matrix

Classification ?

Automated Solution: *Meta-learning-based*



Time Series
For Training

Candidate
Model Set

	D_1	D_2	D_3	...
TS_1	0.5	0.7	0.9	
TS_2	0.6	0.4	0.7	
TS_3	0.5	0.8	0.6	
...				

Performance
Matrix

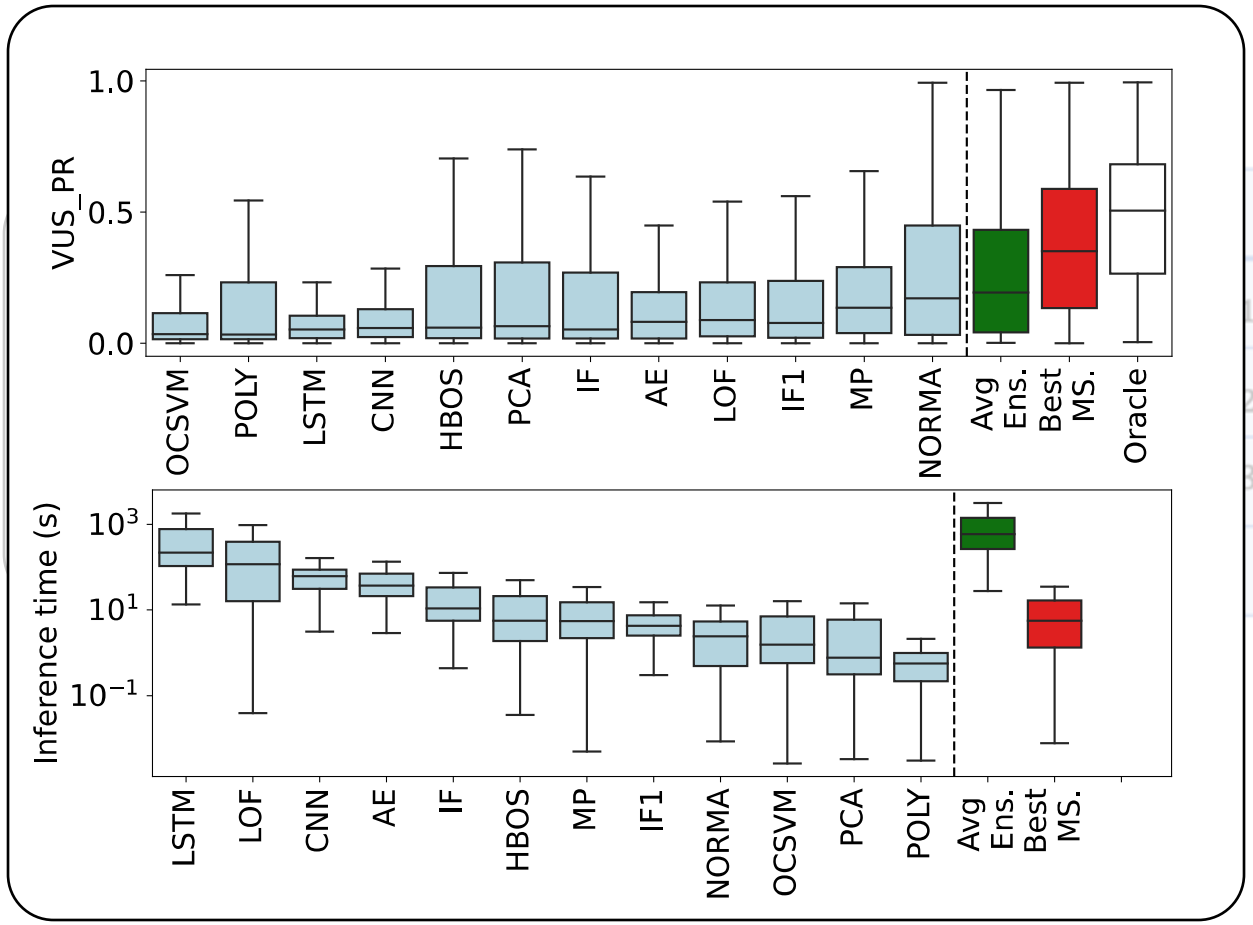
	D_1	D_2	D_3	...
TS_1	0	0	1	
TS_2	0	0	1	
TS_3	0	1	0	
...				

Label

[28] Emmanouil Sylligardos, Paul Boniol, John Paparrizos, Panos Trahanias, Themis Palpanas. 2023. Choose wisely: An extensive evaluation of model selection for anomaly detection in time series. Proceedings of the VLDB Endowment 16(11): 3418-3432.

Automated Solution: *Meta-learning-based*

Time Series
For Training

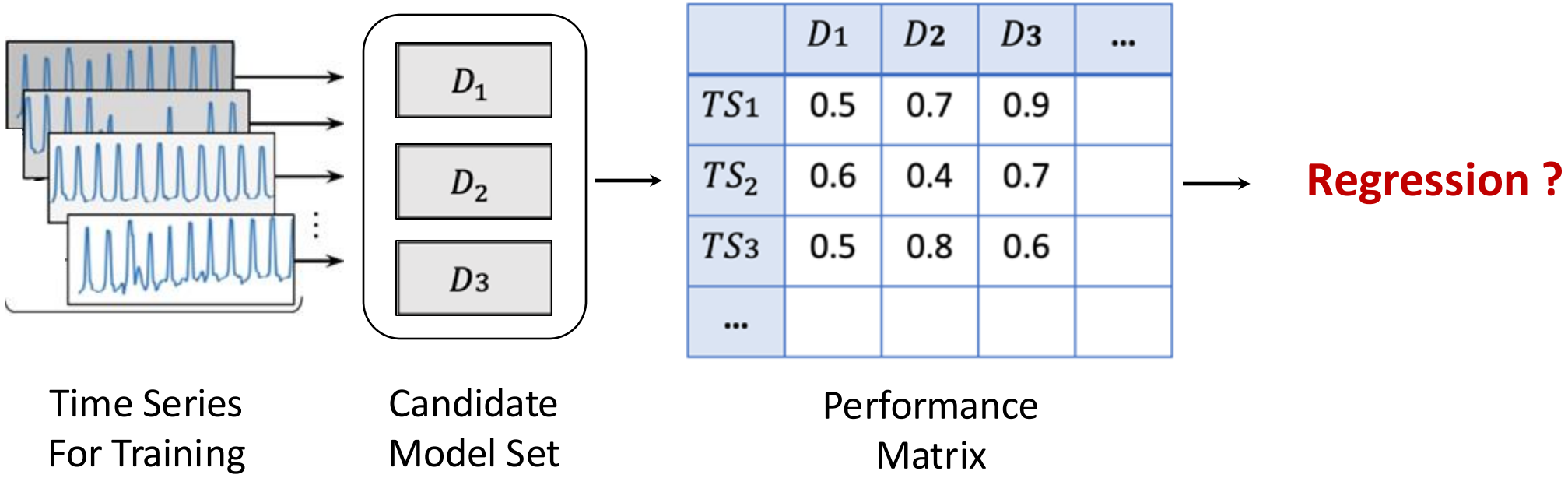


	D_1	D_2	D_3	...
1	0	0	1	
2	0	0	1	
3	0	1	0	

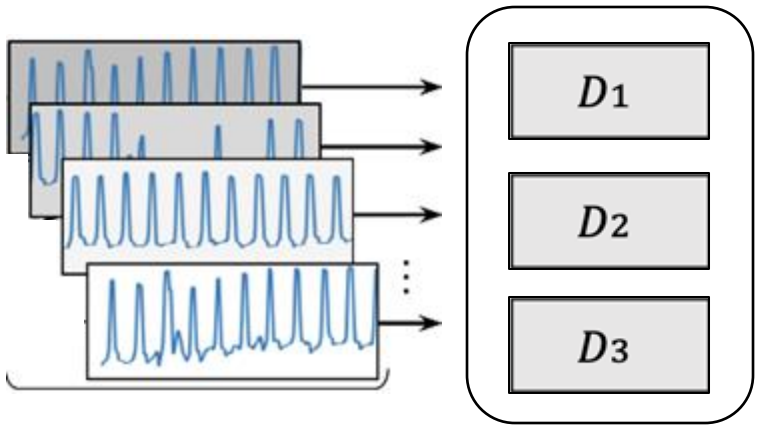
Label

[28] Emmanouil Sylligardos, Paul Boniol, John Paparrizos, Panos Trahanias, Themis Palpanas. 2023. Choose wisely: An extensive evaluation of model selection for anomaly detection in time series. Proceedings of the VLDB Endowment 16(11): 3418-3432.

Automated Solution: *Meta-learning-based*



Automated Solution: *Meta-learning-based*



Time Series
For Training

Candidate
Model Set

	D_1	D_2	D_3	...
TS_1	0.5	0.7	0.9	
TS_2	0.6	0.4	0.7	
TS_3	0.5	0.8	0.6	
...				

Performance
Matrix

	D_1	D_2	D_3	...
TS_1	0.5	0.7	0.9	
TS_2	0.6	0.4	0.7	
TS_3	0.5	0.8	0.6	
...				

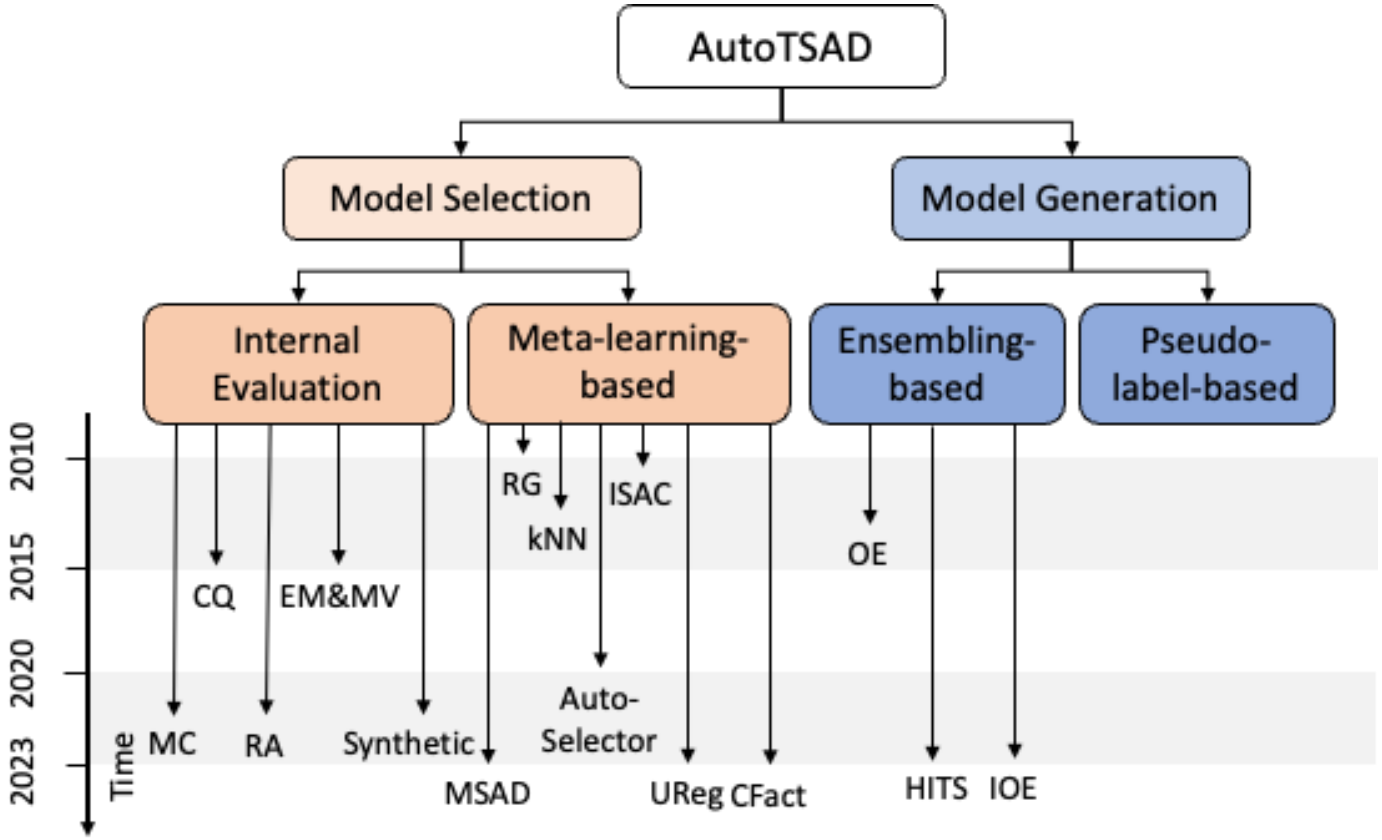
Label

[30] Lin Xu, Frank Hutter, Holger H Hoos, Kevin Leyton-Brown. 2008. SATzilla: portfolio-based algorithm selection for SAT. Journal of Artificial Intelligence Research 32: 565-606.

Automated Solution: *Ensembling-based*

Definition: Integrate predictions from the candidate model set

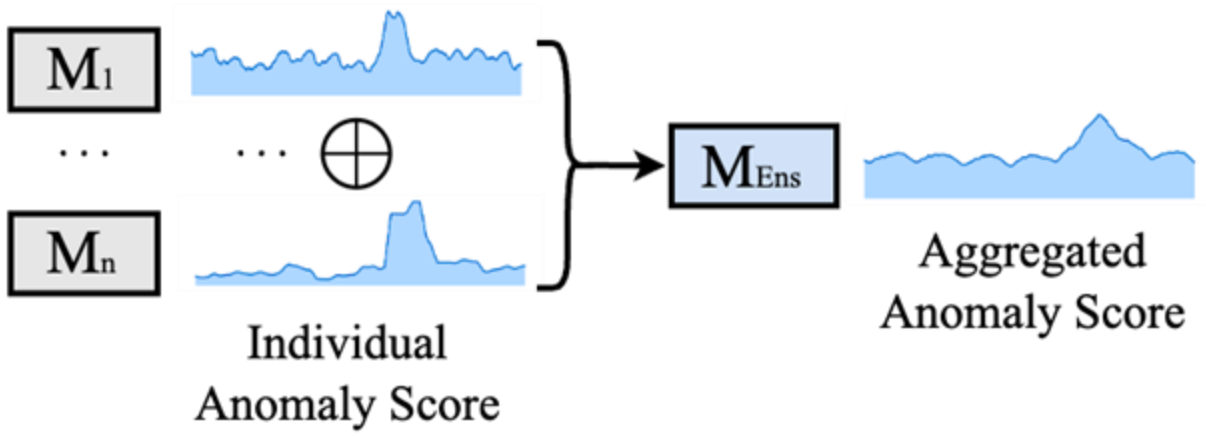
- Full: OE
- Selective: HITS, IOE



Automated Solution: *Ensembling-based*

Definition: Integrate predictions from the candidate model set

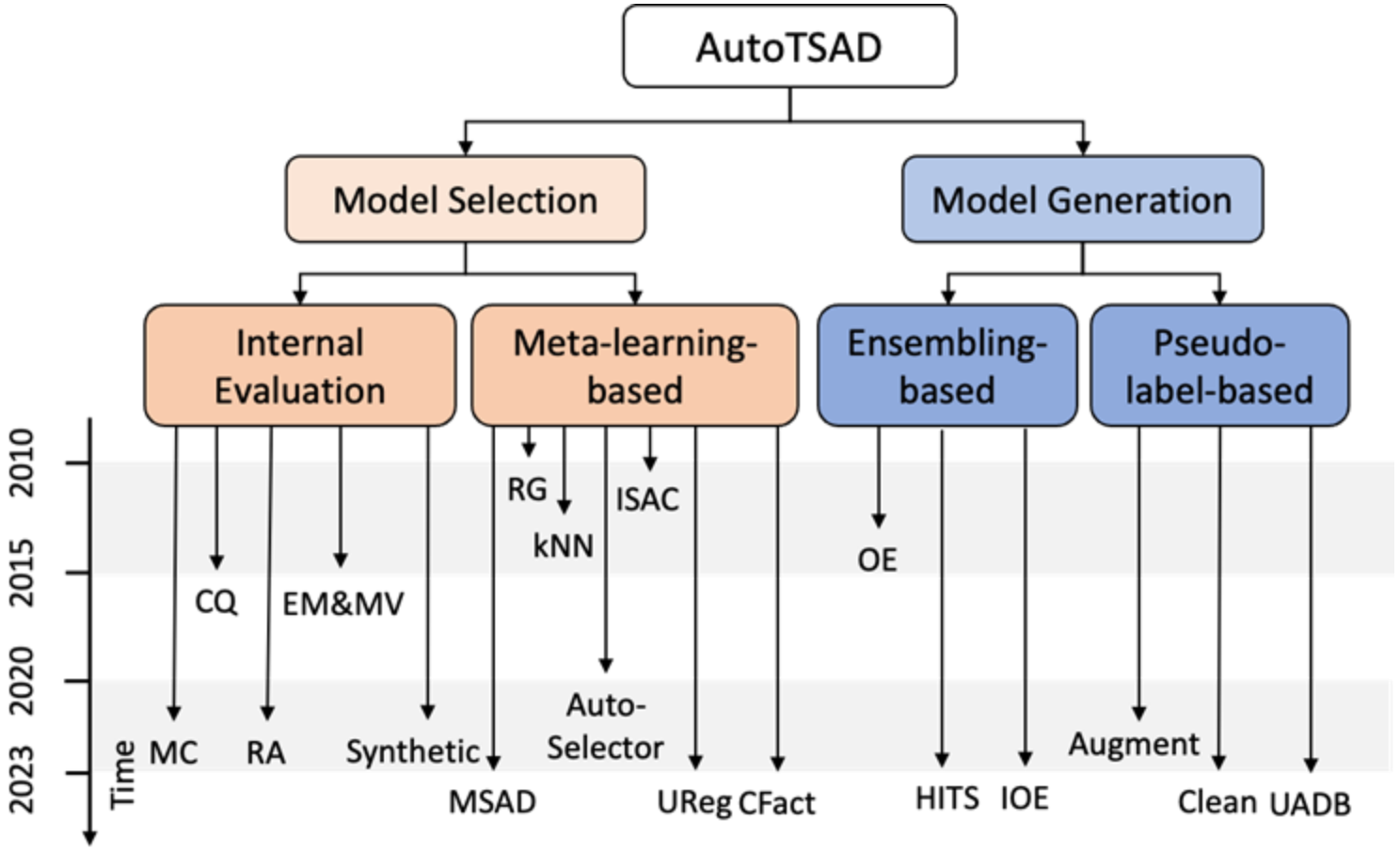
- Full: OE
- Selective: HITS, IOE



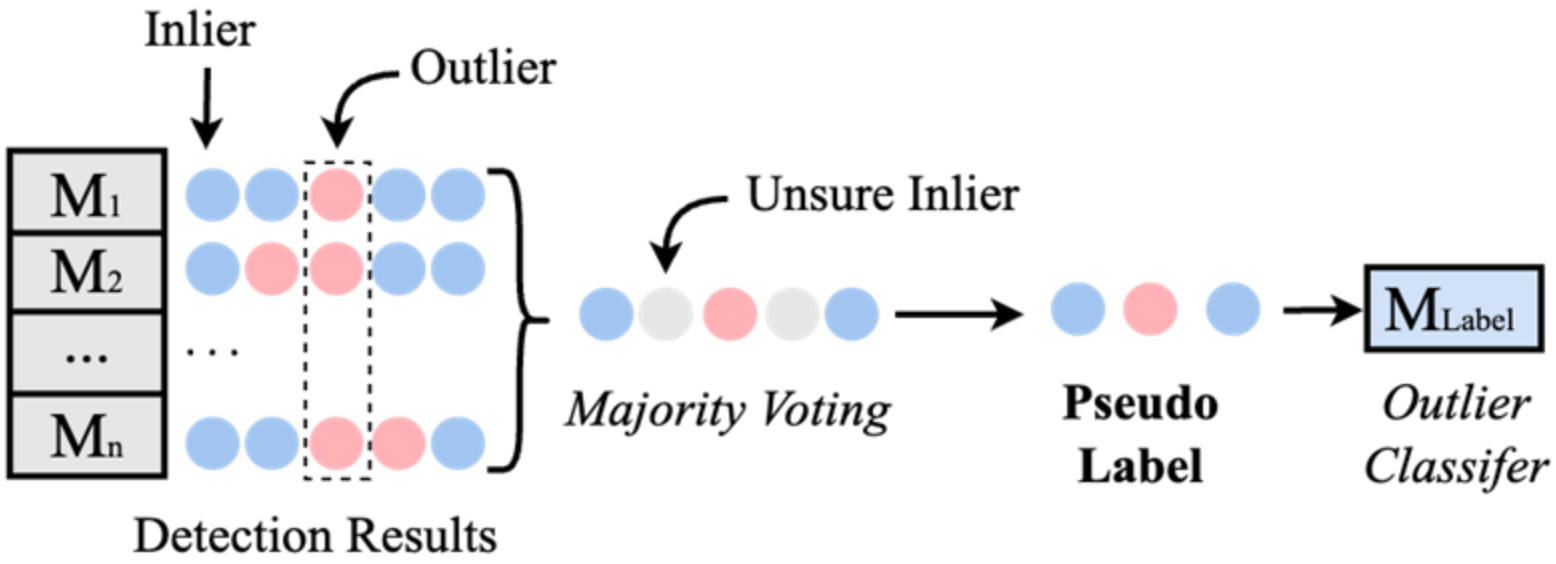
Automated Solution: *Pseudo-label-based*

Definition: Generate pseudo-labels to transform the unsupervised anomaly detection problem into a supervised framework

- AutoOD: Augment, Clean
- Booster: UADB

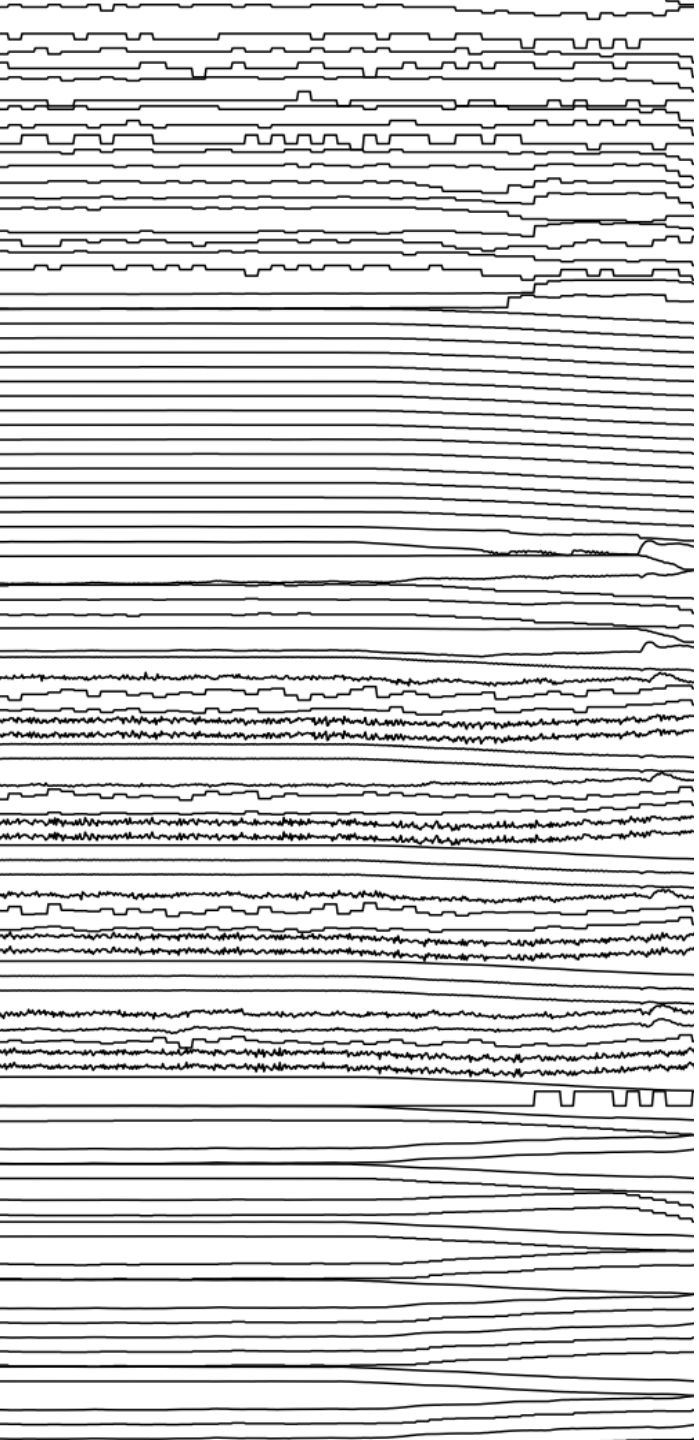


Automated Solution: *Pseudo-label-based*



Pseudo-label-based Method Framework.

[31] Lei Cao, Yizhou Yan, Yu Wang, Samuel Madden, Elke A Rundensteiner. 2023. Autood: Automatic outlier detection. Proceedings of the ACM on Management of Data, 1(1): 1-27. ACM, New York, NY, USA.



Open Problems

Towards *Reliable* and *Automated* TSAD

Towards Reliable and Automated TSAD

- Rigorous Benchmark Practice

HEX/UCR [18]

Set of 250 time series with labels.

Details

- The labels have been manually checked and are reliable
- Each time series contains only 1 labeled anomaly

TimeEval [5]

Set of 976 time series with labels.

Details

- New synthetic benchmark GutenTag used to tune parameters
- Only Time series with low contamination rate (< 0.1)
- Time series with at least one methods above 0.8 AUC-ROC

TSB-UAD [19]

Set of 2000 time series with labels.

Details

- Collected as proposed in the literature (no filtering based on contamination, size or label quality)
- Artificial and synthetic data generation methods for reliable labels

...

Towards Reliable and Automated TSAD

- Rigorous Benchmark Practice
- LLM-empowered TSAD

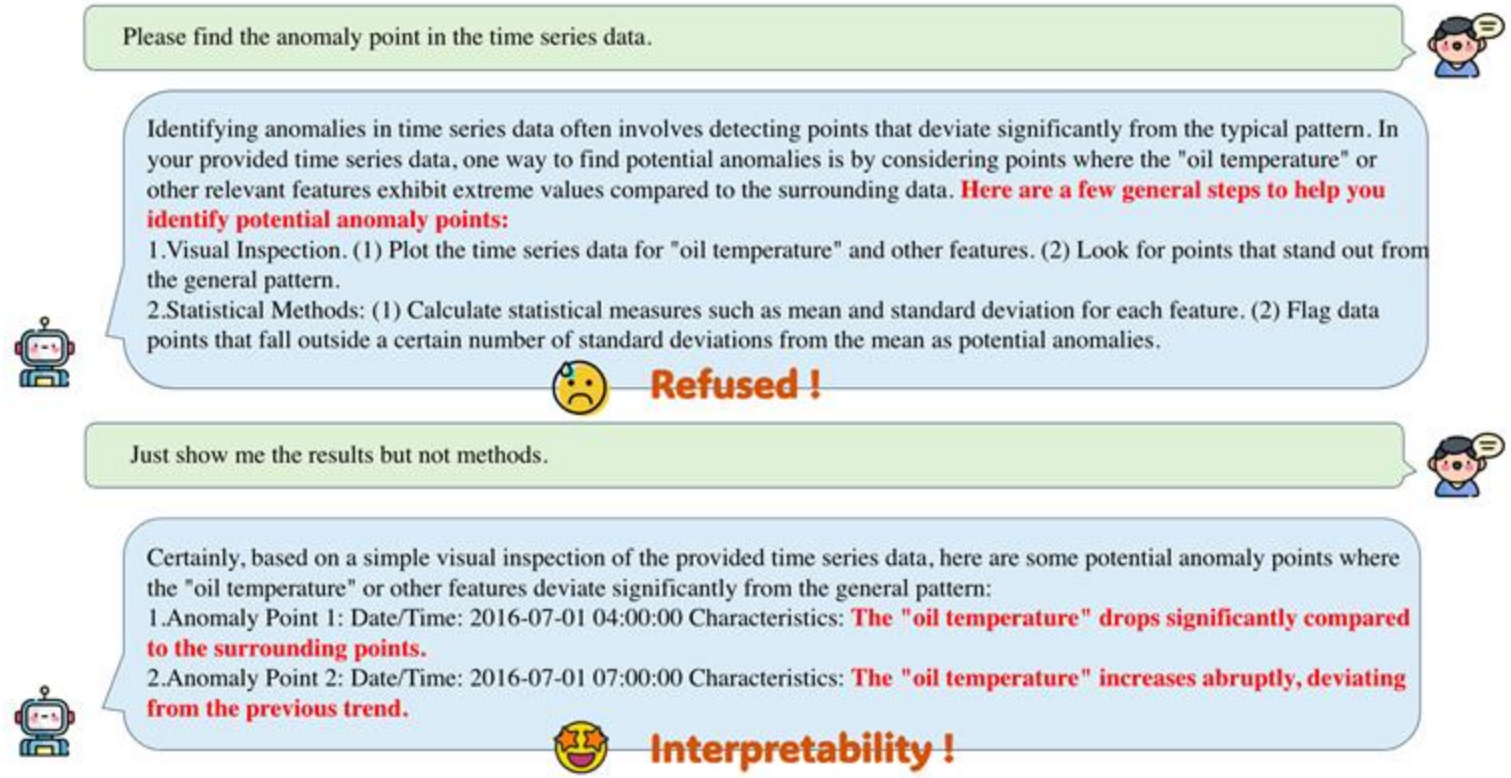


Image from [32]: Human interaction with ChatGPT for TSAD tasks.

Towards Reliable and Automated TSAD

- Rigorous Benchmark Practice
- LLM-empowered TSAD
- Incremental Automated Solution

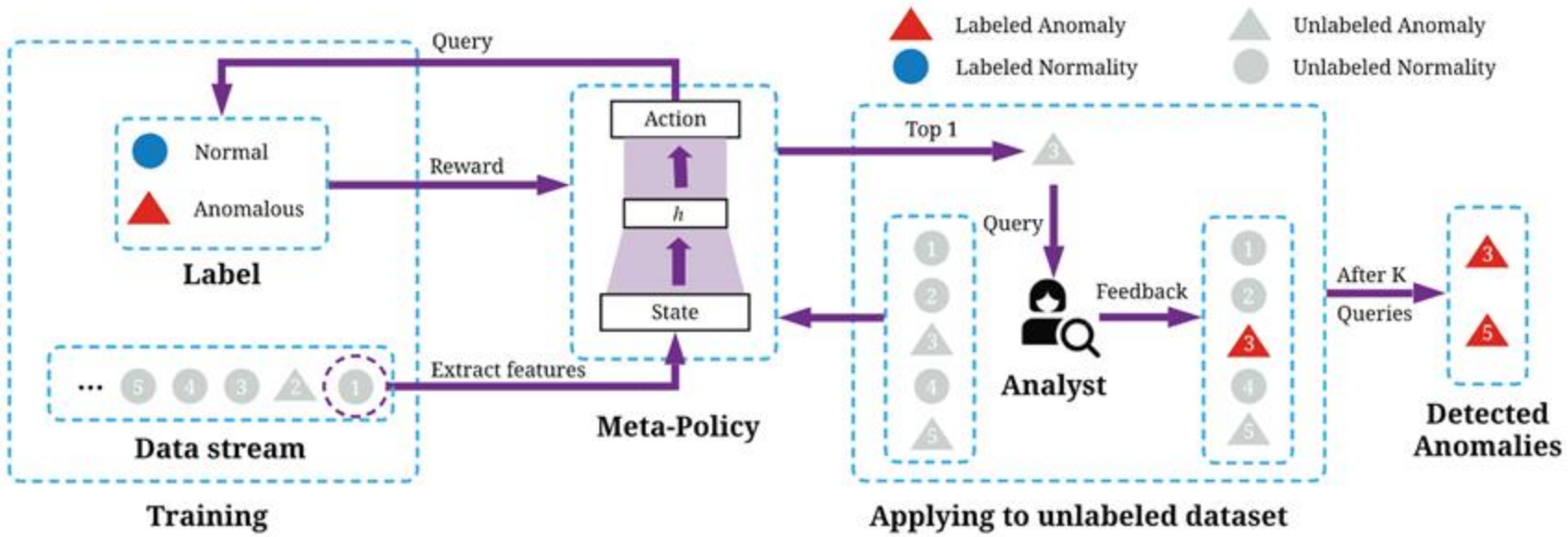
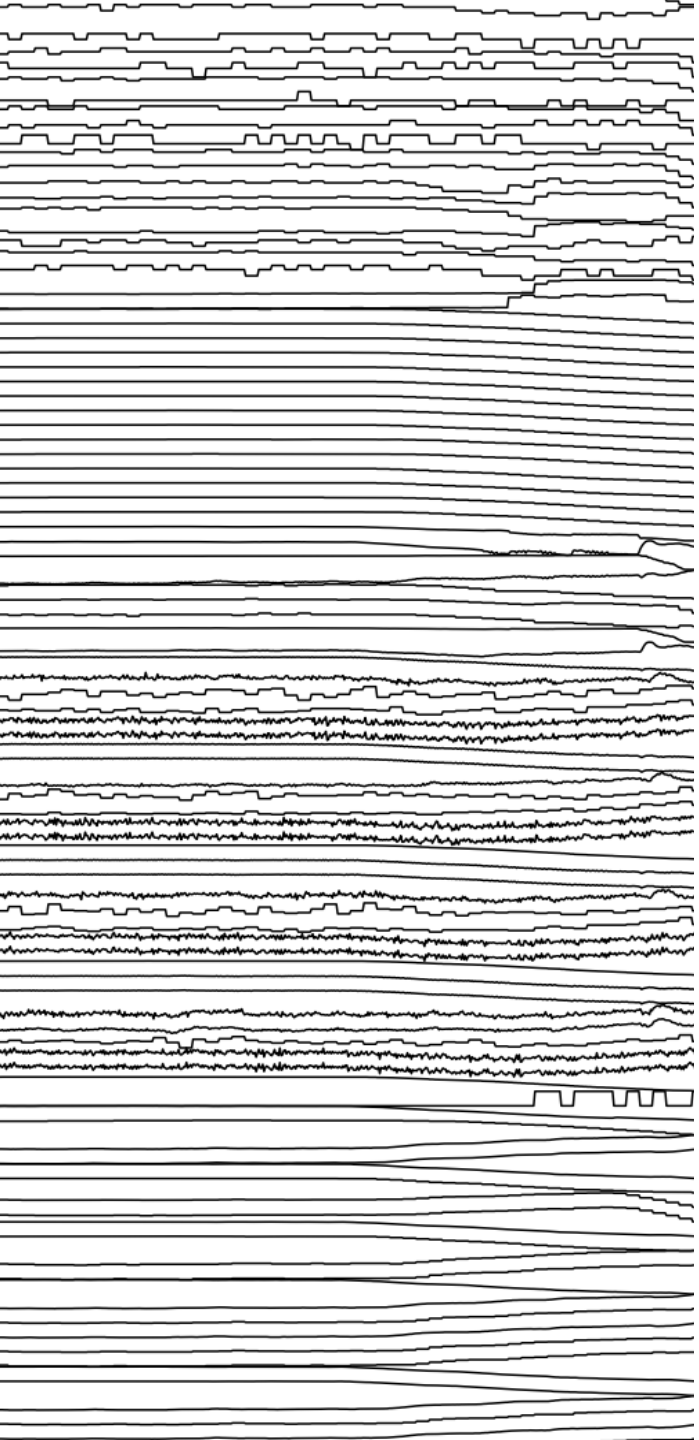


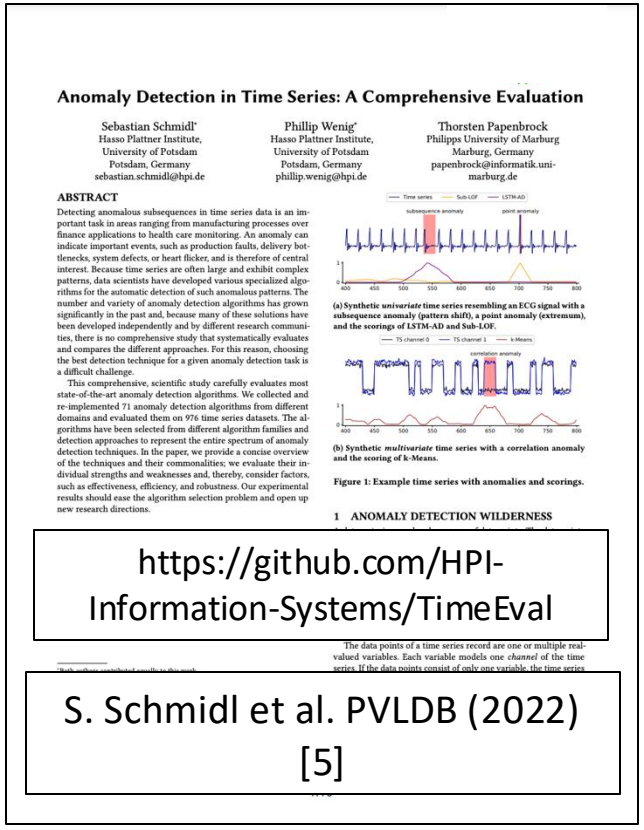
Image from [33]: Human in the loop feedback.



Conclusion

Conclusion and Open Problems

If you are interested in anomaly detection in time series…



Anomaly Detection in Time Series: A Comprehensive Evaluation

Sebastian Schmidl*, Phillip Wenig*, Thorsten Papenbrock
Hasso Plattner Institute, University of Potsdam, Potsdam, Germany
sebastian.schmidl@hpi.de, phillip.wenig@hpi.de, papenbrock@informatik.uni-marburg.de

ABSTRACT

Detecting anomalous subsequences in time series data is an important task in areas ranging from manufacturing processes over finance applications to health care monitoring. An anomaly can indicate important events, such as production faults, delivery bottlenecks, system defects, or heart flicker, and is therefore of central interest. Because time series are often large and exhibit complex patterns, data scientists have developed various specialized algorithms for the automatic detection of such anomalous patterns. The number and variety of anomaly detection algorithms has grown significantly in the past and, because many of these solutions have been developed independently and by different research communities, there is no comprehensive study that systematically evaluates and compares the different approaches. For this reason, choosing the best detection technique for a given anomaly detection task is a difficult challenge.

This comprehensive, scientific study carefully evaluates most state-of-the-art anomaly detection algorithms. We collected and re-implemented 71 anomaly detection algorithms from different domains and evaluated them on 976 time series datasets. The algorithms have been selected from different algorithm families and detection approaches to represent the entire spectrum of anomaly detection techniques. In the paper, we provide a concise overview of the techniques and their commonalities; we evaluate their individual strengths and weaknesses and, thereby, consider factors, such as effectiveness, efficiency, and robustness. Our experimental results should ease the algorithm selection problem and open up new research directions.

(a) Synthetic *univariate* time series resembling an ECG signal with a subsequence anomaly (pattern shift), a point anomaly (extremum), and the scorings of LSTM-AD and Sub-LOF.

(b) Synthetic *multivariate* time series with a correlation anomaly and the scoring of k-Means.

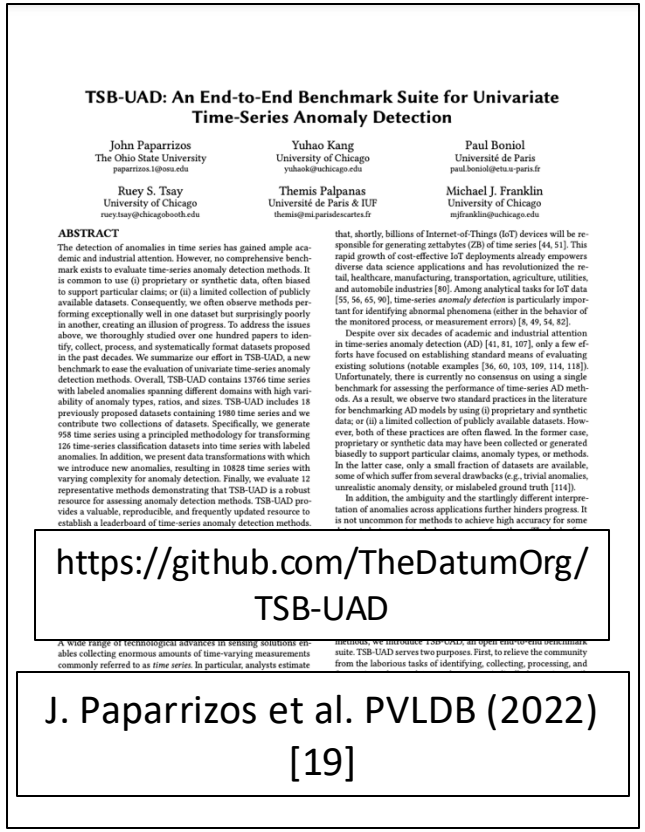
Figure 1: Example time series with anomalies and scorings.

1 ANOMALY DETECTION WILDERNESS

The data points of a time series record are one or multiple real-valued variables. Each variable models one *channel* of the time

https://github.com/HPI-Information-Systems/TimeEval

S. Schmidl et al. PVLDB (2022) [5]



TSB-UAD: An End-to-End Benchmark Suite for Univariate Time-Series Anomaly Detection

John Paparrizos, The Ohio State University, paparrizos.1@osu.edu
Yuhao Kang, University of Chicago, yuhaok@uchicago.edu
Paul Boniol, Université de Paris, paul.boniol@etu.u-paris.fr
Ruey S. Tsay, University of Chicago, ruey.tsay@chicagobooth.edu
Themis Palpanas, Université de Paris & IUF, themis@mi.parisdescartes.fr
Michael J. Franklin, University of Chicago, mjfranklin@uchicago.edu

ABSTRACT

The detection of anomalies in time series has gained ample academic and industrial attention. However, no comprehensive benchmark exists to evaluate time-series anomaly detection methods. It is common to use (i) proprietary or synthetic data, often biased to support particular claims; or (ii) a limited collection of publicly available datasets. Consequently, we often observe methods performing exceptionally well in one dataset but surprisingly poorly in another, creating an illusion of progress. To address the issues above, we thoroughly studied over one hundred papers to identify, collect, process, and systematically format datasets proposed in the past decades. We summarize our effort in TSB-UAD, a new benchmark to ease the evaluation of univariate time-series anomaly detection methods. Overall, TSB-UAD contains 13766 time series with labeled anomalies spanning different domains with high variability of anomaly types, ratios, and sizes. TSB-UAD includes 18 previously proposed datasets containing 1980 time series and we contribute two collections of datasets. Specifically, we generate 958 time series using a principled methodology for transforming 126 time-series classification datasets into time series with labeled anomalies. In addition, we present data transformations with which we introduce new anomalies, resulting in 10828 time series with varying complexity for anomaly detection. Finally, we evaluate 12 representative methods demonstrating that TSB-UAD is a robust resource for assessing anomaly detection methods. TSB-UAD provides a valuable, reproducible, and frequently updated resource to establish a leaderboard of time-series anomaly detection methods.

that, shortly, billions of Internet-of-Things (IoT) devices will be responsible for generating zettabytes (ZB) of time series [44, 51]. This rapid growth of cost-effective IoT deployments already empowers diverse data science applications and has revolutionized the retail, healthcare, manufacturing, transportation, agriculture, utilities, and automobile industries [80]. Among analytical tasks for IoT data [55, 56, 65, 90], time-series *anomaly detection* is particularly important for identifying abnormal phenomena (either in the behavior of the monitored process, or measurement errors) [8, 49, 54, 82].

Despite over six decades of academic and industrial attention in time-series anomaly detection (AD) [41, 81, 107], only a few efforts have focused on establishing standard means of evaluating existing solutions (notable examples [36, 60, 103, 109, 114, 118]). Unfortunately, there is currently no consensus on using a single benchmark for assessing the performance of time-series AD methods. As a result, we observe two standard practices in the literature for benchmarking AD models by using (i) proprietary and synthetic data; or (ii) a limited collection of publicly available datasets. However, both of these practices are often flawed. In the former case, proprietary or synthetic data may have been collected or generated biasedly to support particular claims, anomaly types, or methods. In the latter case, only a small fraction of datasets are available, some of which suffer from several drawbacks (e.g., trivial anomalies, unrealistic anomaly density, or mislabeled ground truth [114]).

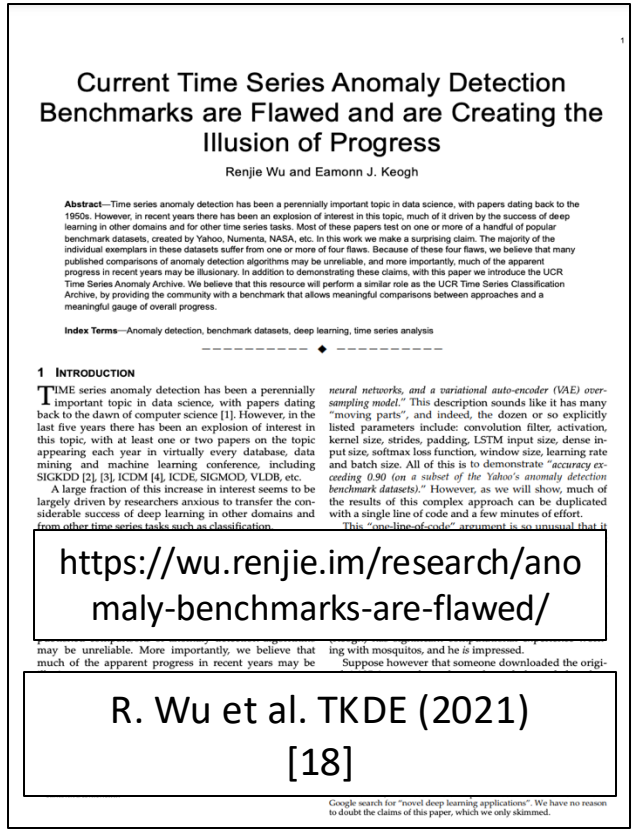
In addition, the ambiguity and the startlingly different interpretation of anomalies across applications further hinders progress. It is not uncommon for methods to achieve high accuracy for some

A wide range of technological advances in sensing solutions enables collecting enormous amounts of time-varying measurements commonly referred to as *time series*. In particular, analysts estimate

suite. TSB-UAD serves two purposes. First, to relieve the community from the laborious tasks of identifying, collecting, processing, and

https://github.com/TheDatumOrg/TSB-UAD

J. Paparrizos et al. PVLDB (2022) [19]



Current Time Series Anomaly Detection Benchmarks are Flawed and are Creating the Illusion of Progress

Renjie Wu and Eamonn J. Keogh

Abstract—Time series anomaly detection has been a perennially important topic in data science, with papers dating back to the 1950s. However, in recent years there has been an explosion of interest in this topic, much of it driven by the success of deep learning in other domains and for other time series tasks. Most of these papers test on one or more of a handful of popular benchmark datasets, created by Yahoo, Numenta, NASA, etc. In this work we make a surprising claim. The majority of the individual exemplars in these datasets suffer from one or more of four flaws. Because of these four flaws, we believe that many published comparisons of anomaly detection algorithms may be unreliable, and more importantly, much of the apparent progress in recent years may be illusionary. In addition to demonstrating these claims, with this paper we introduce the UCR Time Series Anomaly Archive. We believe that this resource will perform a similar role as the UCR Time Series Classification Archive, by providing the community with a benchmark that allows meaningful comparisons between approaches and a meaningful gauge of overall progress.

Index Terms—Anomaly detection, benchmark datasets, deep learning, time series analysis

1 INTRODUCTION

TIME series anomaly detection has been a perennially important topic in data science, with papers dating back to the dawn of computer science [1]. However, in the last five years there has been an explosion of interest in this topic, with at least one or two papers on the topic appearing each year in virtually every database, data mining and machine learning conference, including SIGKDD [2], [3], ICDM [4], ICDE, SIGMOD, VLDB, etc.

A large fraction of this increase in interest seems to be largely driven by researchers anxious to transfer the considerable success of deep learning in other domains and from other time series tasks such as classification

neural networks, and a variational auto-encoder (VAE) oversampling model." This description sounds like it has many "moving parts", and indeed, the dozen or so explicitly listed parameters include: convolution filter, activation, kernel size, strides, padding, LSTM input size, dense input size, softmax loss function, window size, learning rate and batch size. All of this is to demonstrate *"accuracy exceeding 0.90 (on a subset of the Yahoo's anomaly detection benchmark datasets)."* However, as we will show, much of the results of this complex approach can be duplicated with a single line of code and a few minutes of effort.

This "one-line-of-code" argument is so unusual that it

may be unreliable. More importantly, we believe that much of the apparent progress in recent years may be

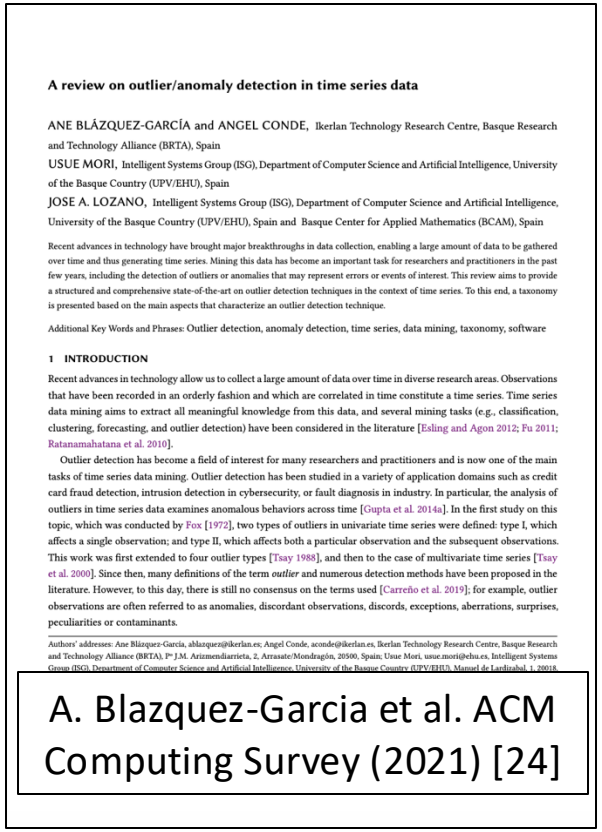
ing with mosquitos, and he is impressed.

Suppose however that someone downloaded the origi-

Google search for "novel deep learning applications". We have no reason to doubt the claims of this paper, which we only skimmed.

https://wu.renjie.im/research/anomaly-benchmarks-are-flawed/

R. Wu et al. TKDE (2021) [18]



A review on outlier/anomaly detection in time series data

ANE BLÁZQUEZ-GARCÍA and ANGEL CONDE, Ikerlan Technology Research Centre, Basque Research and Technology Alliance (BRTA), Spain
USUE MORI, Intelligent Systems Group (ISG), Department of Computer Science and Artificial Intelligence, University of the Basque Country (UPV/EHU), Spain
JOSE A. LOZANO, Intelligent Systems Group (ISG), Department of Computer Science and Artificial Intelligence, University of the Basque Country (UPV/EHU), Spain and Basque Center for Applied Mathematics (BCAM), Spain

Recent advances in technology have brought major breakthroughs in data collection, enabling a large amount of data to be gathered over time and thus generating time series. Mining this data has become an important task for researchers and practitioners in the past few years, including the detection of outliers or anomalies that may represent errors or events of interest. This review aims to provide a structured and comprehensive state-of-the-art on outlier detection techniques in the context of time series. To this end, a taxonomy is presented based on the main aspects that characterize an outlier detection technique.

Additional Key Words and Phrases: Outlier detection, anomaly detection, time series, data mining, taxonomy, software

1 INTRODUCTION

Recent advances in technology allow us to collect a large amount of data over time in diverse research areas. Observations that have been recorded in an orderly fashion and which are correlated in time constitute a time series. Time series data mining aims to extract all meaningful knowledge from this data, and several mining tasks (e.g., classification, clustering, forecasting, and outlier detection) have been considered in the literature [Esling and Agon 2012; Fu 2011; Ratanamahatana et al. 2010].

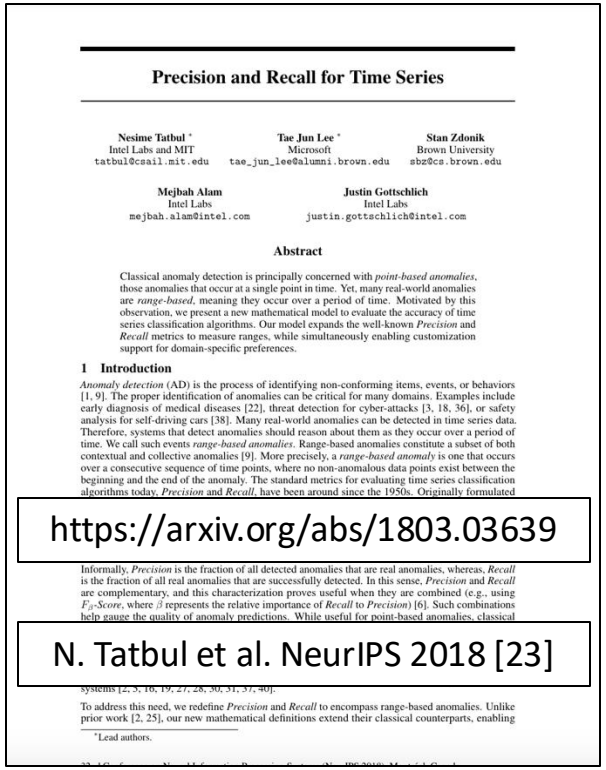
Outlier detection has become a field of interest for many researchers and practitioners and is now one of the main tasks of time series data mining. Outlier detection has been studied in a variety of application domains such as credit card fraud detection, intrusion detection in cybersecurity, or fault diagnosis in industry. In particular, the analysis of outliers in time series data examines anomalous behaviors across time [Gupta et al. 2014a]. In the first study on this topic, which was conducted by Fox [1972], two types of outliers in univariate time series were defined: type I, which affects a single observation; and type II, which affects both a particular observation and the subsequent observations. This work was first extended to four outlier types [Tsay 1988], and then to the case of multivariate time series [Tsay et al. 2000]. Since then, many definitions of the term *outlier* and numerous detection methods have been proposed in the literature. However, to this day, there is still no consensus on the terms used [Carreño et al. 2019]; for example, outlier observations are often referred to as anomalies, discordant observations, discords, exceptions, aberrations, surprises, peculiarities or contaminants.

Authors' addresses: Ane Blázquez-García, ablazquez@ikerlan.es; Angel Conde, aconde@ikerlan.es, Ikerlan Technology Research Centre, Basque Research and Technology Alliance (BRTA), Pº J.M. Arizmendiarrieta, 2, Arrasate/Mondragón, 20500, Spain; Usue Mori, usue.mori@ehu.es, Intelligent Systems Group (ISG), Department of Computer Science and Artificial Intelligence, University of the Basque Country (UPV/EHU), Manuel de Lardizabal, 1, 20018,

A. Blazquez-Garcia et al. ACM Computing Survey (2021) [24]

Conclusion and Open Problems

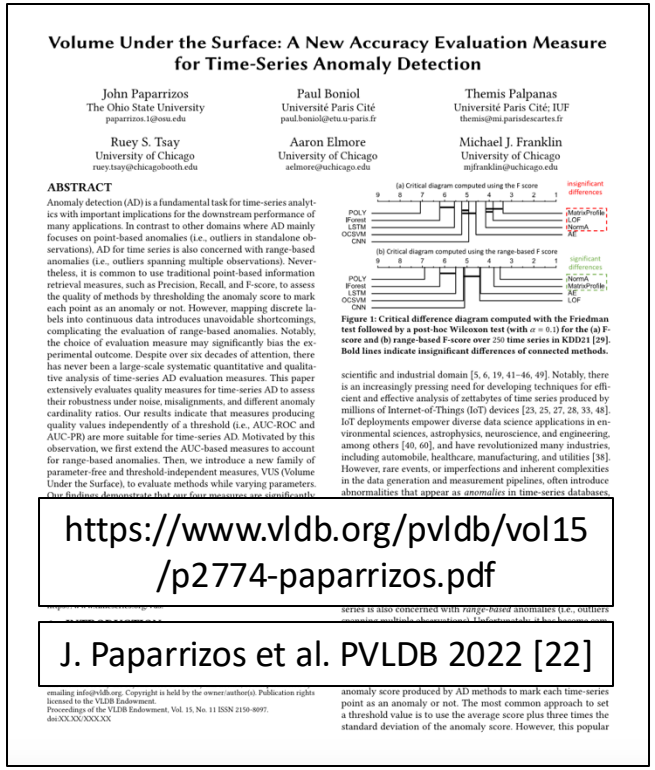
If you are interested in evaluation measures for anomaly detection…



Precision and Recall for Time Series

https://arxiv.org/abs/1803.03639

N. Tatbul et al. NeurIPS 2018 [23]



Volume Under the Surface: A New Accuracy Evaluation Measure for Time-Series Anomaly Detection

https://www.vldb.org/pvldb/vol15/p2774-paparrizos.pdf

J. Paparrizos et al. PVLDB 2022 [22]

Local Evaluation of Time Series Anomaly Detection Algorithms

https://arxiv.org/abs/2206.13167

A. Huet et al. KDD 2022 [31]

NAVIGATING THE METRIC MAZE: A TAXONOMY OF EVALUATION METRICS FOR ANOMALY DETECTION IN TIME SERIES

https://arxiv.org/abs/2303.01272

S. Sørbø et al. DAMI 2024 [29]

References

[1] N. Laptev, S. Amizadeh, and Y. Billawala. 2015. **S5 - A Labeled Anomaly Detection Dataset**, version 1.0(16M).

[2] Markus Thill, Wolfgang Konen, and Thomas Bäck. 2020. **MGAB: The Mackey-Glass Anomaly Benchmark**.

[3] Pawel Benecki, Szymon Piechaczek, Daniel Kostrzewa, and Jakub Nalepa. 2021. **Detecting Anomalies in Spacecraft Telemetry Using Evolutionary Thresholding and LSTMs**. In Proceedings of the Genetic and Evolutionary Computation Conference Companion (Lille, France) (GECCO '21)

[4] Scott David Greenwald. 1990. **Improved detection and classication of arrhythmias in noise-corrupted electrocardiograms using contextual information**. Thesis. Massachusetts Institute of Technology.

[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. **Anomaly detection in time series: a comprehensive evaluation**. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.

[6] Chin-Chia Michael Yeh, Yan Zhu, Liudmila Ulanova, Nurjahan Begum, Yifei Ding, Hoang Anh Dau, Diego Furtado Silva, Abdullah Mueen, and Eamonn J. Keogh. 2016. **Matrix Prole I: All Pairs Similarity Joins for Time Series.** In ICDM.

[7] Yan Zhu, Zachary Zimmerman, Nader Shakibay Senobari, Chin-Chia Michael Yeh, Gareth Funning, Abdullah Mueen, Philip Brisk, and Eamonn Keogh. 2016. **Matrix Profile II: Exploiting a Novel Algorithm and GPUs to Break the One Hundred Million Barrier for Time Series Motifs and Joins.** In Proceedings of the International Conference on Data Mining (ICDM), 739–748.

[8] Yue Lu, Renjie Wu, Abdullah Mueen, Maria A. Zuluaga, and Eamonn Keogh. 2022. **Matrix Profile XXIV: Scaling Time Series Anomaly Detection to Trillions of Datapoints and Ultra-fast Arriving Data Streams.** In Proceedings of the 28th ACM SIGKDD.

[9] C. -C. M. Yeh, N. Kavantzas and E. Keogh, **Matrix Profile VI: Meaningful Multidimensional Motif Discovery**, 2017 IEEE International Conference on Data Mining (ICDM), New Orleans, LA, USA, 2017, pp. 565-574, doi: 10.1109/ICDM.2017.66. Data Mining (KDD '22).

[10] Paul Boniol, Michele Linardi, Federico Roncallo, Themis Palpanas, Mohammed Meftah, and Emmanuel Remy. 2021. **Unsupervised and scalable subsequence anomaly detection in large data series.** The VLDB Journal 30, 6 (Nov 2021), 909–931.

[11] F. T. Liu, K. M. Ting and Z. -H. Zhou, **Isolation Forest**, 2008 Eighth IEEE International Conference on Data Mining, Pisa, Italy, 2008, pp. 413-422

[12] Markus Goldstein and Andreas Dengel. 2012. **Histogram-based outlier score (hbos): A fast unsupervised anomaly detection algorithm**. KI-2012: poster and demo track 9 (2012).

[13] Paul Boniol and Themis Palpanas. 2020. **Series2Graph: graph-based subsequence anomaly detection for time series.** Proc. VLDB Endow. 13, 12 (August 2020), 1821–1834.

[14] Ali Abdul-Aziz, Mark R Woike, Nikunj C Oza, Bryan L Matthews, and John D Iekki. 2012. **Rotor health monitoring combining spin tests and data-driven anomaly detection methods**. Structural Health Monitoring (2012).

[15] Pankaj Malhotra, Lovekesh Vig, Gautam Shro, and Puneet Agarwal. 2015. **Long Short Term Memory Networks for Anomaly Detection in Time Series**. (2015).

[16] M. Munir, S. A. Siddiqui, A. Dengel, and S. Ahmed. 2019. **DeepAnT: A Deep Learning Approach for Unsupervised Anomaly Detection in Time Series**. IEEE Access 7 (2019), 1991–2005.

[17] Mayu Sakurada and Takehisa Yairi. 2014. **Anomaly Detection Using Autoencoders with Nonlinear Dimensionality Reduction**. In Proceedings of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis (Gold Coast, Australia QLD, Australia) (MLSDA'14).

[18] R. Wu and E. Keogh, **Current Time Series Anomaly Detection Benchmarks are Flawed and are Creating the Illusion of Progress** in IEEE Transactions on Knowledge & Data Engineering, vol. 35, no. 03, pp. 2421-2429, 2023.

[19] John Paparrizos, Yuhao Kang, Paul Boniol, Ruey S. Tsay, Themis Palpanas, and Michael J. Franklin. 2022. **TSB-UAD: an end-to-end benchmark suite for univariate time-series anomaly detection**. Proc. VLDB Endow. 15, 8 (April 2022), 1697–1711.

[20] Tom Fawcett. 2006. **An introduction to ROC analysis**. Pattern Recognition Letters 27, 8 (2006), 861–874.

[21] Jesse Davis and Mark Goadrich. 2006. **The Relationship between Precision-Recall and ROC Curves**. In Proceedings of the 23rd International Conference on Machine Learning (ICML '06).

[22] John Paparrizos, Paul Boniol, Themis Palpanas, Ruey S. Tsay, Aaron Elmore, and Michael J. Franklin. 2022. **Volume under the surface: a new accuracy evaluation measure for time-series anomaly detection**. Proc. VLDB Endow. 15, 11 (July 2022), 2774–2787.

[23] Nesime Tatbul, Tae Jun Lee, Stan Zdonik, Mejbah Alam, and Justin Gottschlich. 2018. **Precision and Recall for Time Series**. In Advances in Neural Information Processing Systems, Vol. 31.

[24] Ane Blázquez-García, Angel Conde, Usue Mori, and Jose A. Lozano. 2021. **A Review on Outlier/Anomaly Detection in Time Series Data**. ACM Comput. Surv. 54, 3, Article 56 (April 2022), 33 pages.

[25] Paul Boniol, John Paparrizos, Themis Palpanas, and Michael J. Franklin. 2021. **SAND: streaming subsequence anomaly detection**. Proc. VLDB Endow. 14, 10 (June 2021), 1717–1729.

[26] Schneider, J., Wenig, P. & Papenbrock, T. **Distributed detection of sequential anomalies in univariate time series**. The VLDB Journal **30**, 579–602 (2021).

[27] Maroua Bahri, Flavia Salutari, Andrian Putina, and Mauro Sozio: **AutoML: state of the art with a focus on anomaly detection, challenges, and research directions.** International Journal of Data Science and Analytics 14(2): 113-126 (2022).

[28] Mononito Goswami, Cristian Challu, Laurent Callot, Lenon Minorics, Andrey Kan. 2023. **Unsupervised Model Selection for Time-series Anomaly Detection.** In Proceedings of the International Conference on Learning Representations.

[29] Emmanouil Sylligardos, Paul Boniol, John Paparrizos, Panos Trahanias, Themis Palpanas. 2023. **Choose wisely: An extensive evaluation of model selection for anomaly detection in time series.** Proceedings of the VLDB Endowment 16(11): 3418-3432.

[30] Lin Xu, Frank Hutter, Holger H Hoos, Kevin Leyton-Brown. 2008. **SATzilla: portfolio-based algorithm selection for SAT.** Journal of Artificial Intelligence Research 32: 565-606.

[31] Lei Cao, Yizhou Yan, Yu Wang, Samuel Madden, Elke A Rundensteiner. 2023. **Autood: Automatic outlier detection.** Proceedings of the ACM on Management of Data, 1(1): 1-27. ACM, New York, NY, USA.

[32] Ming Jin, Yifan Zhang, Wei Chen, Kexin Zhang, Yuxuan Liang, Bin Yang, Jindong Wang, Shirui Pan, Qingsong Wen. 2024. **Position: What Can Large Language Models Tell Us about Time Series Analysis.** In Proceedings of the Forty-first International Conference on Machine Learning.

[33] Daochen Zha, Kwei-Herng Lai, Mingyang Wan, Xia Hu. 2020. **Meta-AAD: Active anomaly detection with deep reinforcement learning.** In Proceedings of the 2020 IEEE ICDM, 771-780. IEEE.

Thank you for attending!