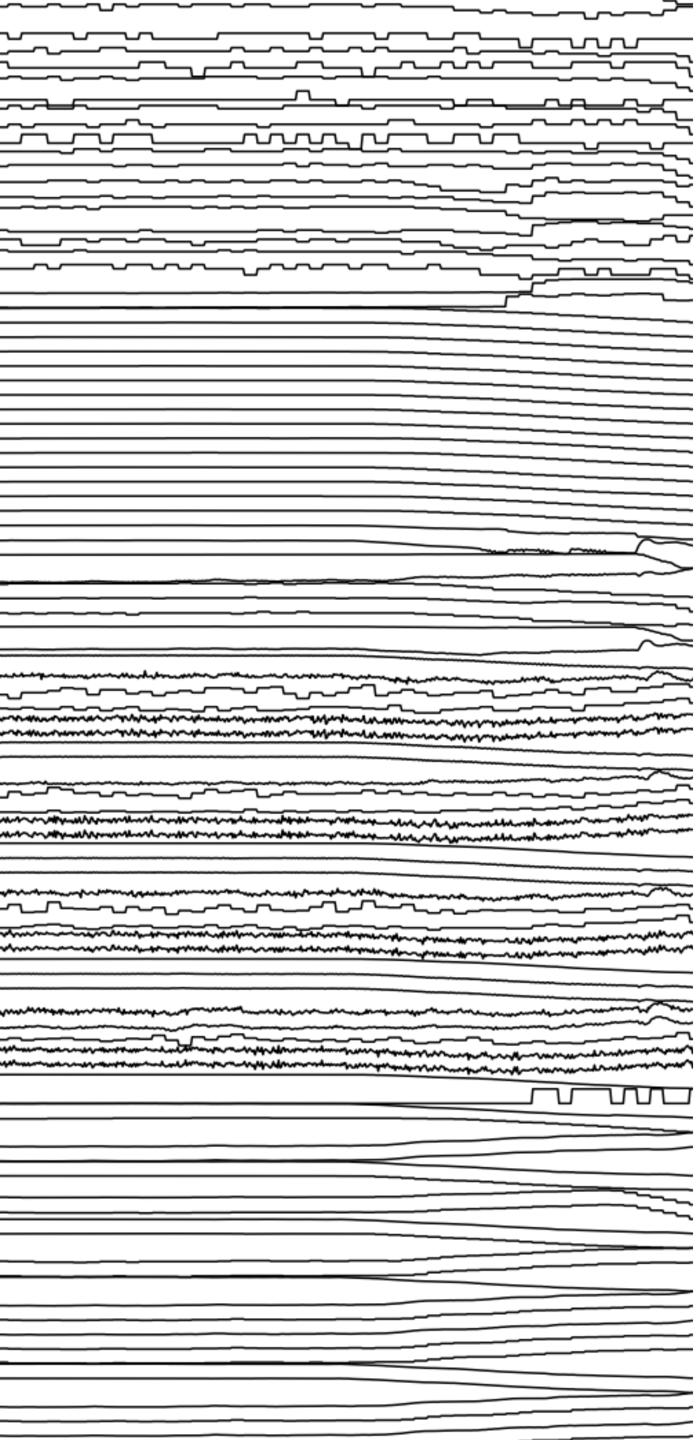

New Trends in Time Series Anomaly Detection

Paul Boniol
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Université Paris Cité | The Ohio State University

Introduction: *Time series are Everywhere*

Energy Production

Edf.fr: tinyurl.com/yc7x5xje

Astrophysics

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

Medicine

tinyurl.com/39dx2us4

Volcanology

tinyurl.com/ybcttmfz

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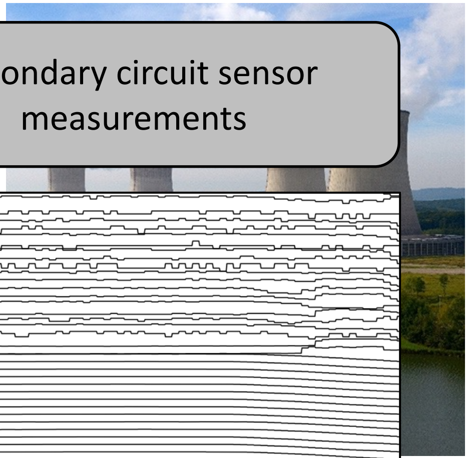
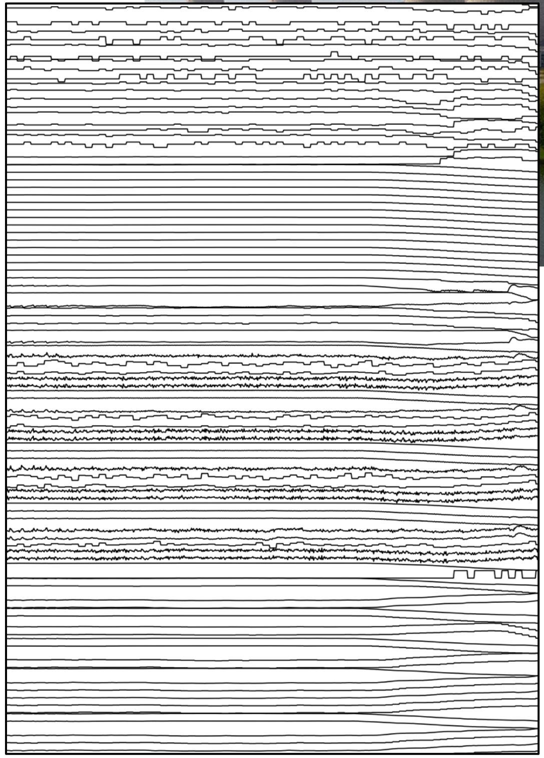


Secondary circuit sensor measurements



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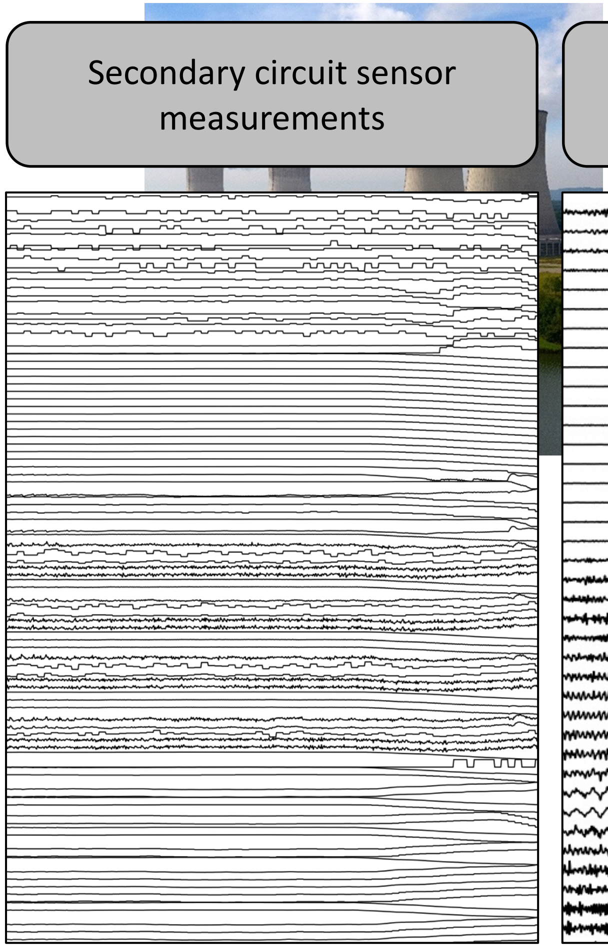

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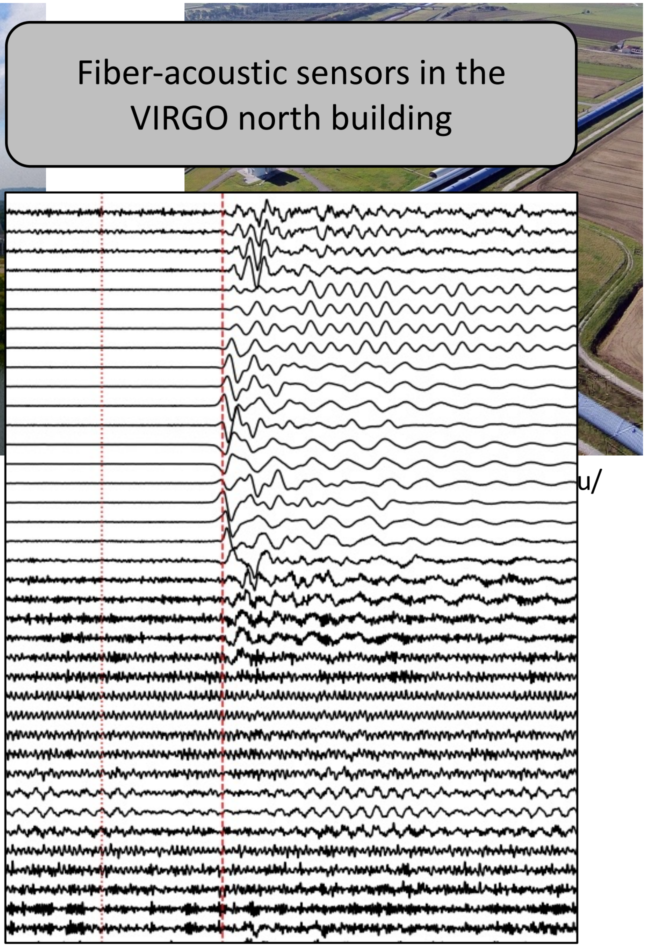

Fiber-acoustic sensors in the VIRGO north building

u/

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tinyurl.com/39dx2us4

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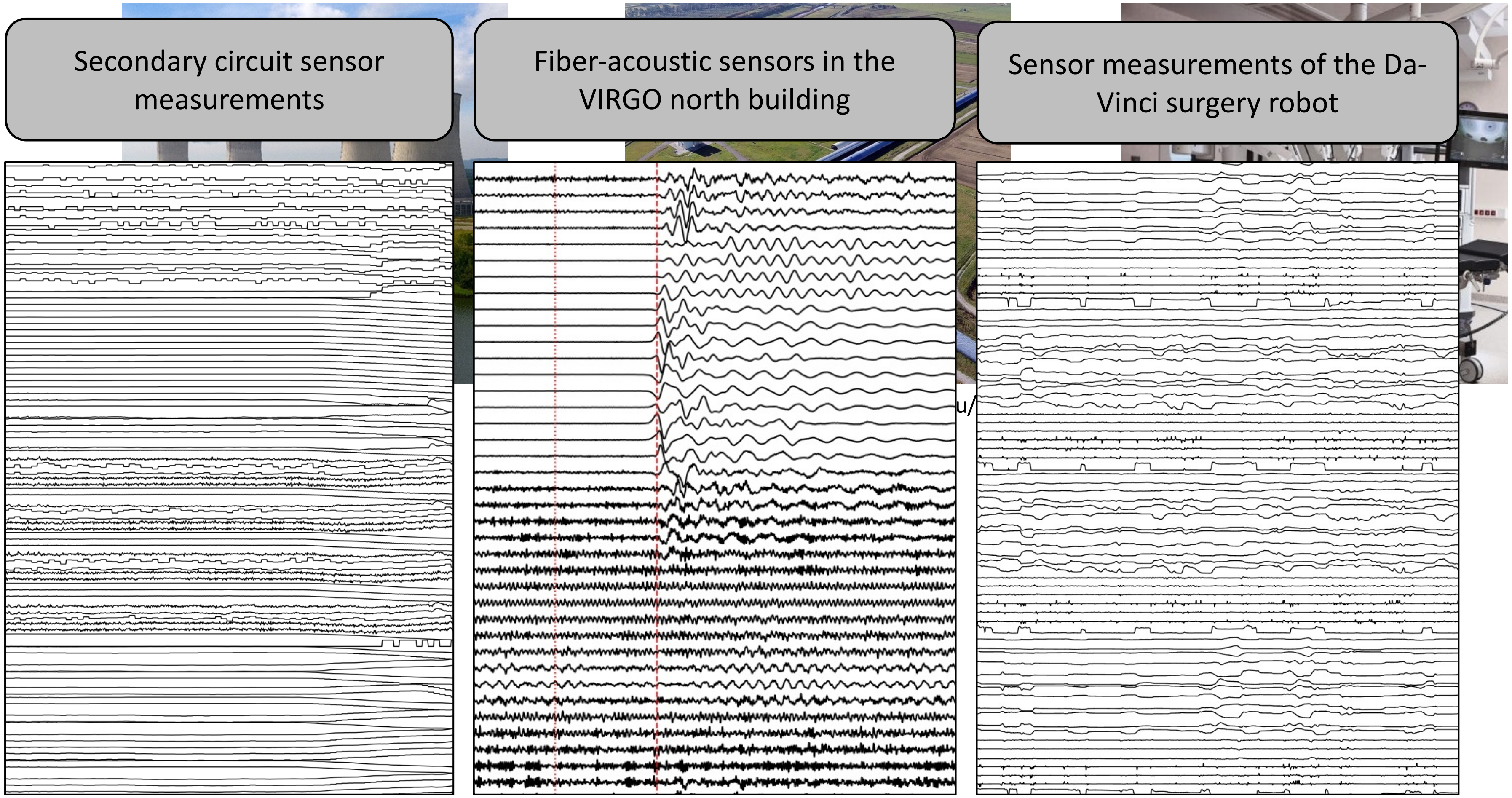

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Sensor measurements of the Da-Vinci surgery robot

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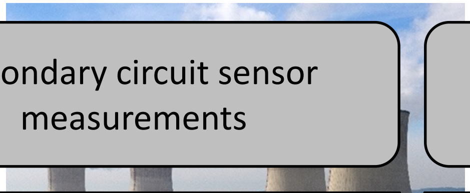

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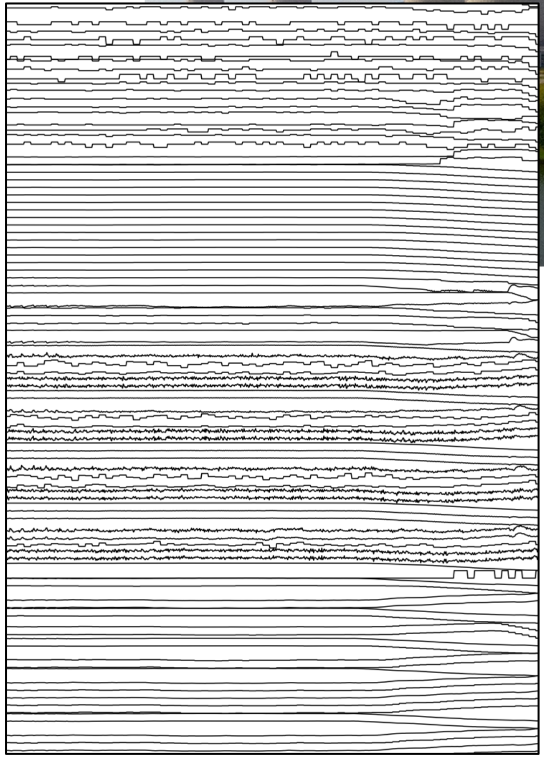

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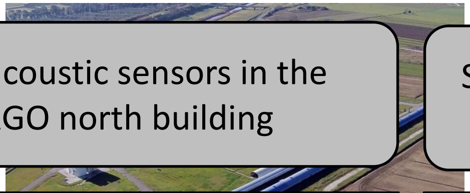

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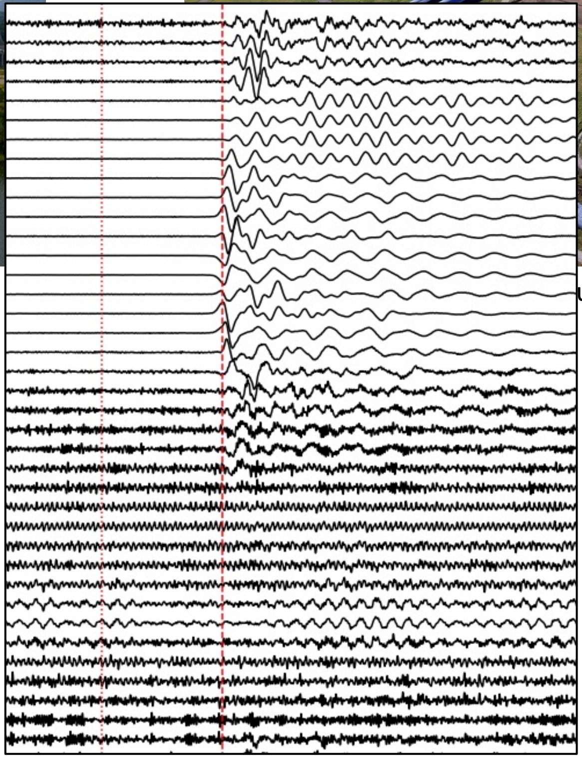

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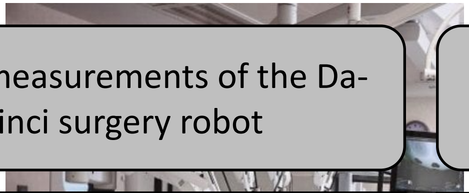
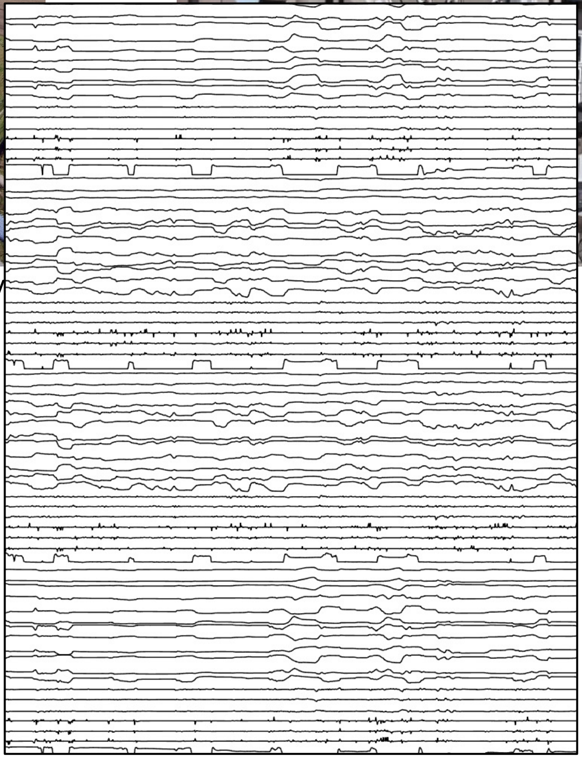
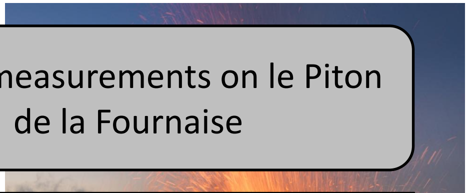


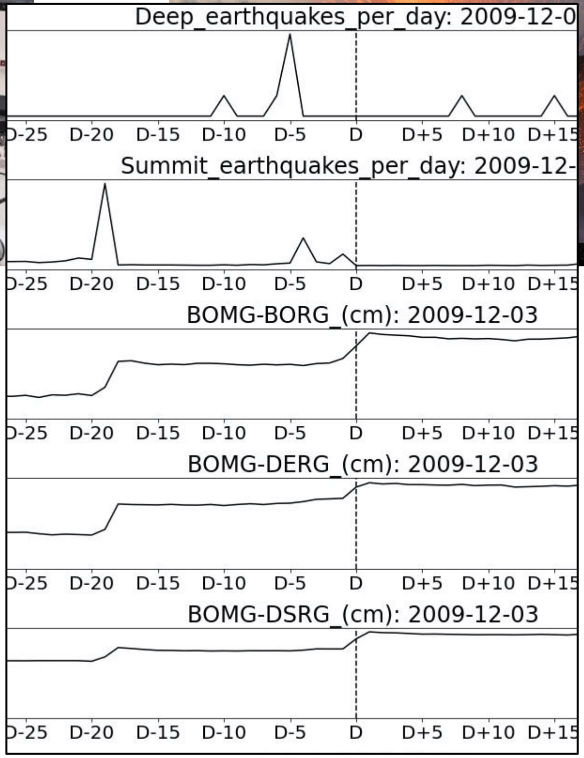
Sensor measurements of the Da-Vinci surgery robot



Volcanology



Sensor measurements on le Piton de la Fournaise



Introduction: *with Important Challenges*

Energy Production

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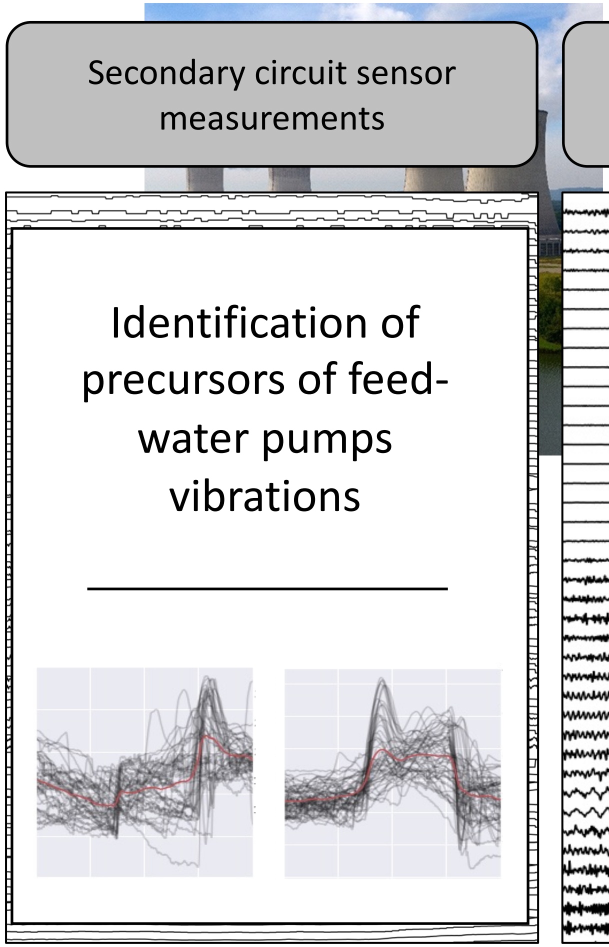
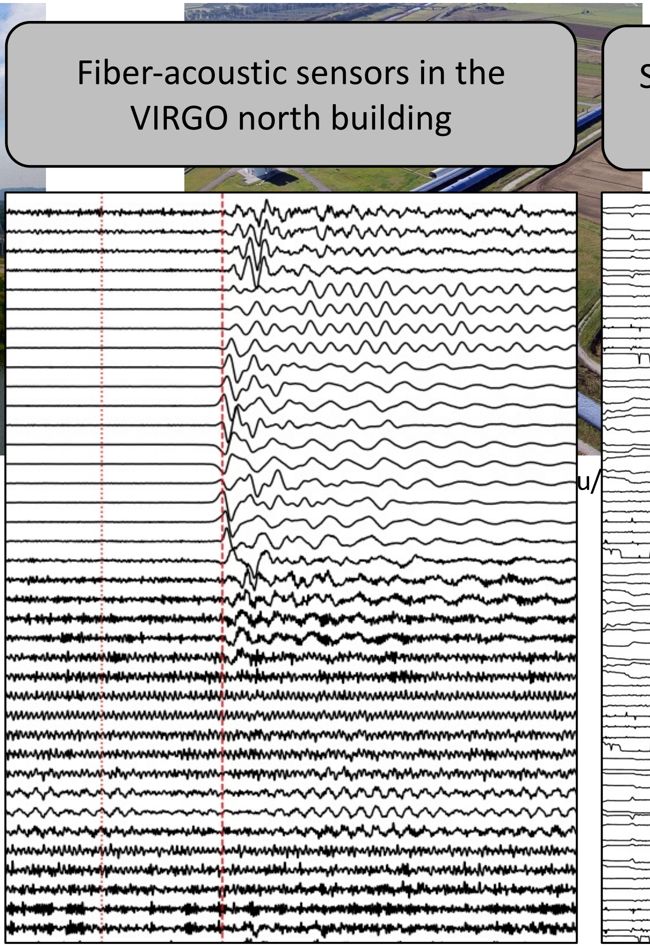


Identification of precursors of feed-water pumps vibrations

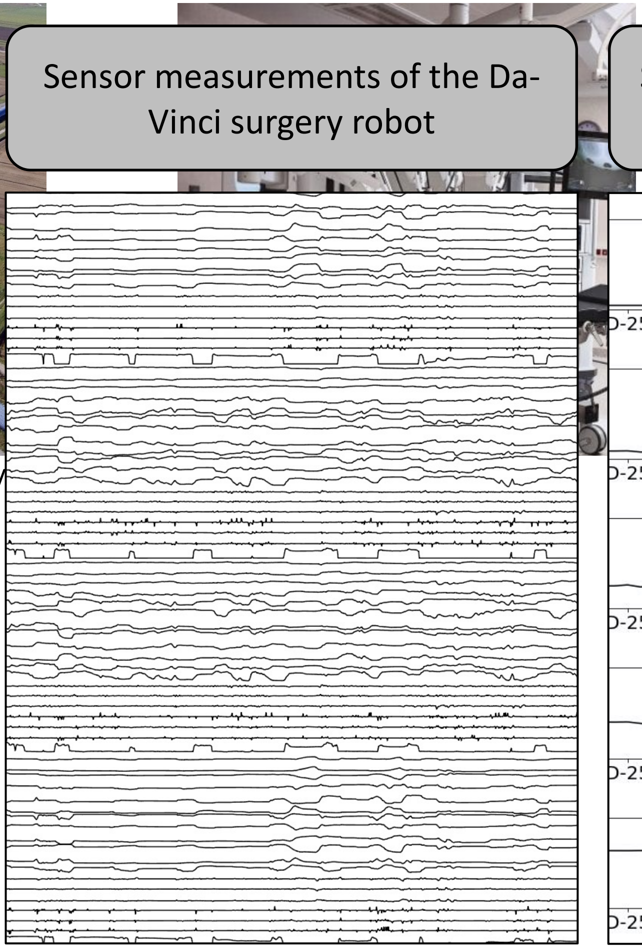
Astrophysics

Fiber-acoustic sensors in the VIRGO north building



Medicine

Sensor measurements of the Da-Vinci surgery robot



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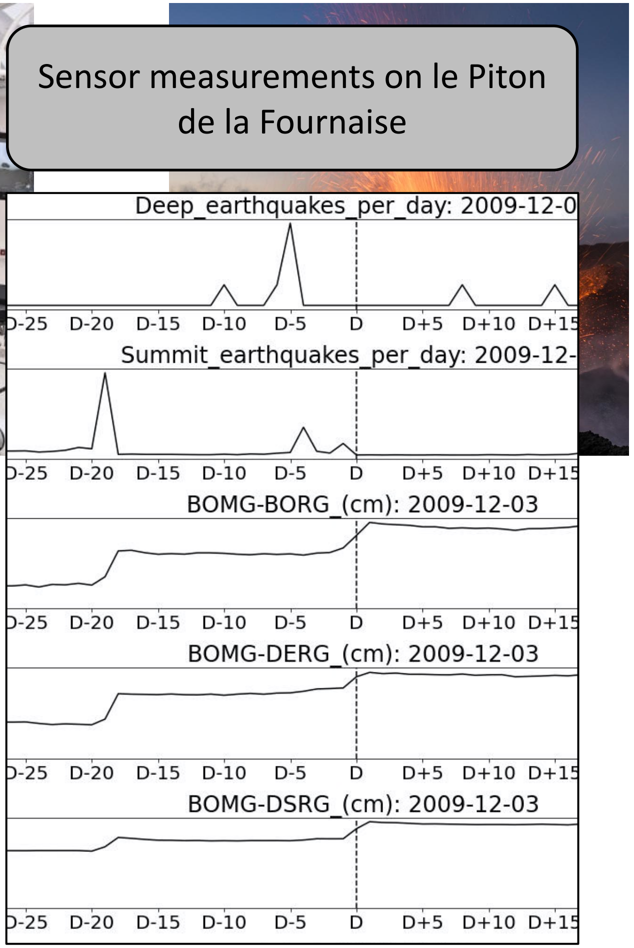

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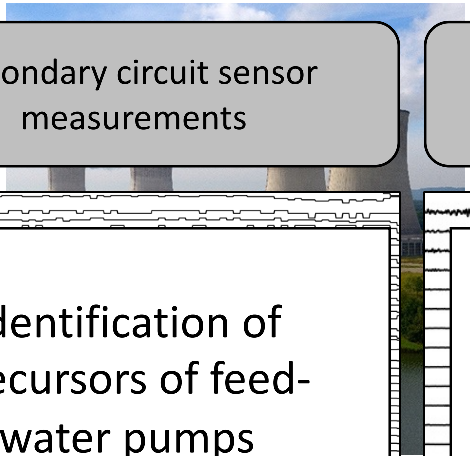

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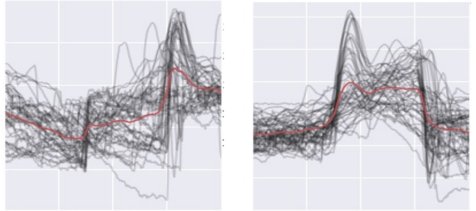

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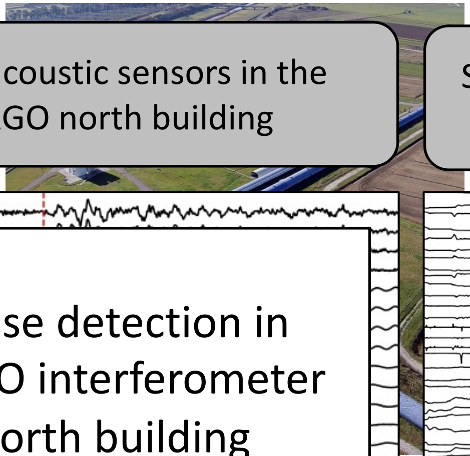
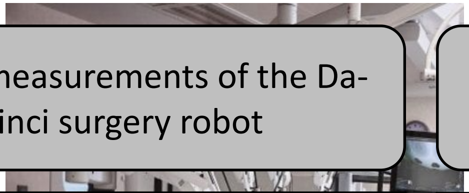


Fiber-acoustic sensors in the VIRGO north building

Noise detection in VIRGO interferometer north building

Medicine



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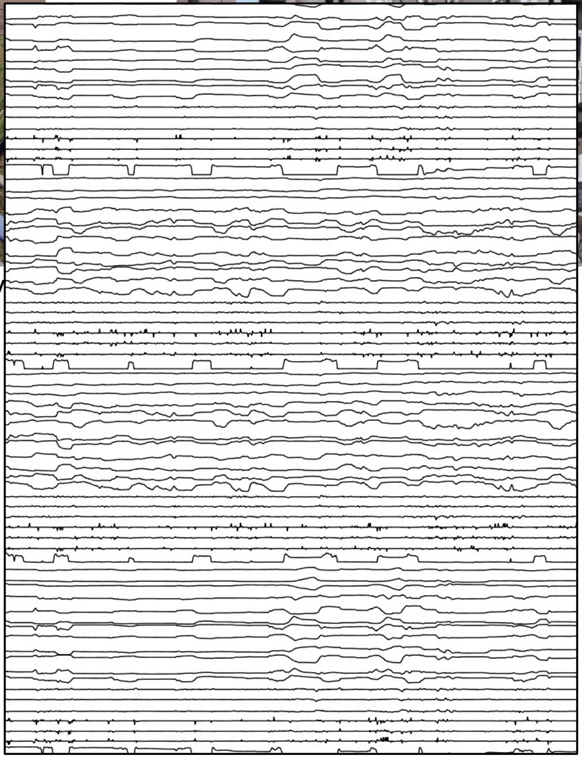
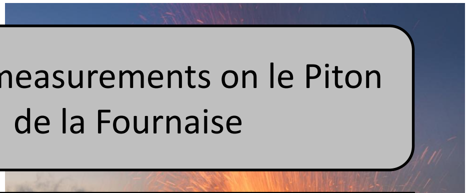
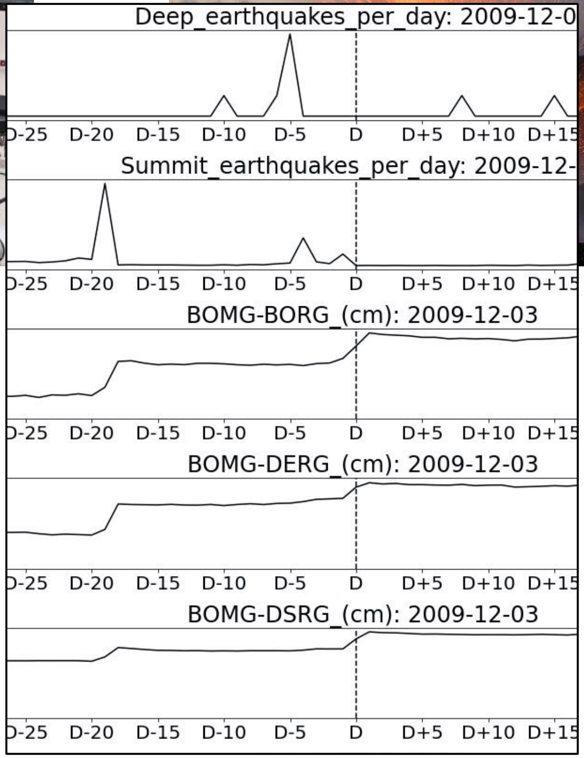


Volcanology



Sensor measurements on le Piton de la Fournaise



Introduction: *with Important Challenges*

Energy Production

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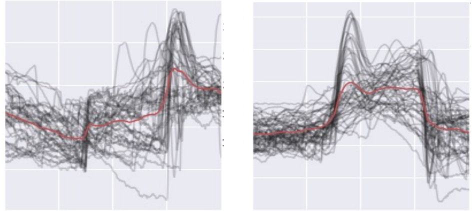

Astrophysics

Fiber-acoustic sensors in the VIRGO north building

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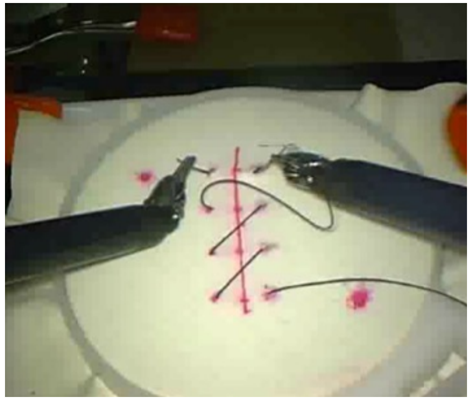
Unusual surgeons gestures detection



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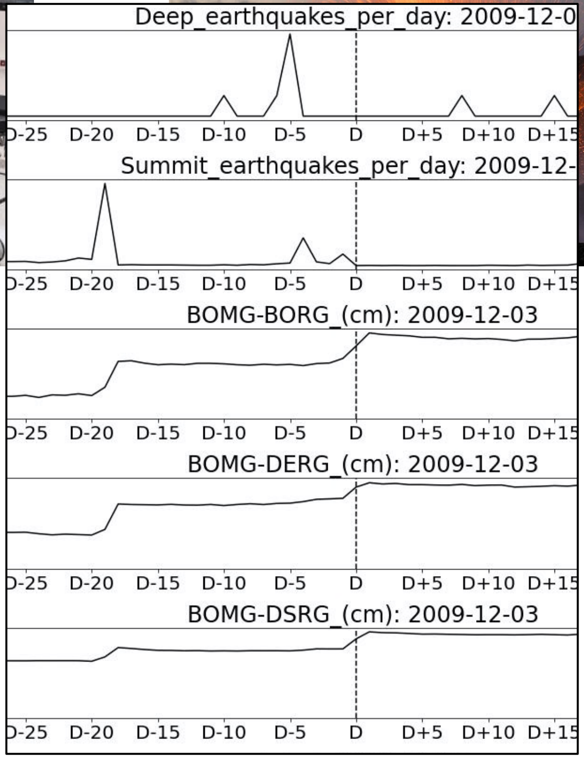

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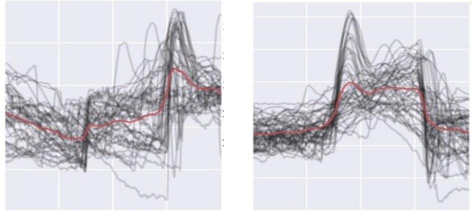

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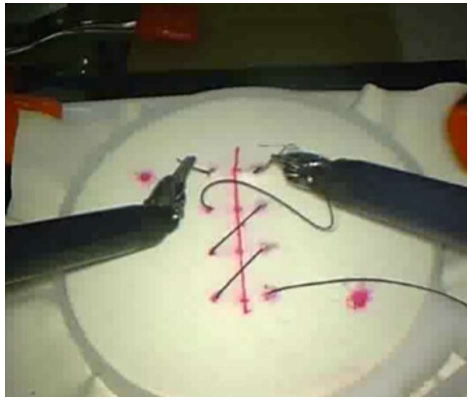
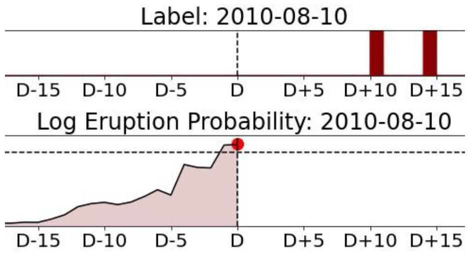


Volcanology

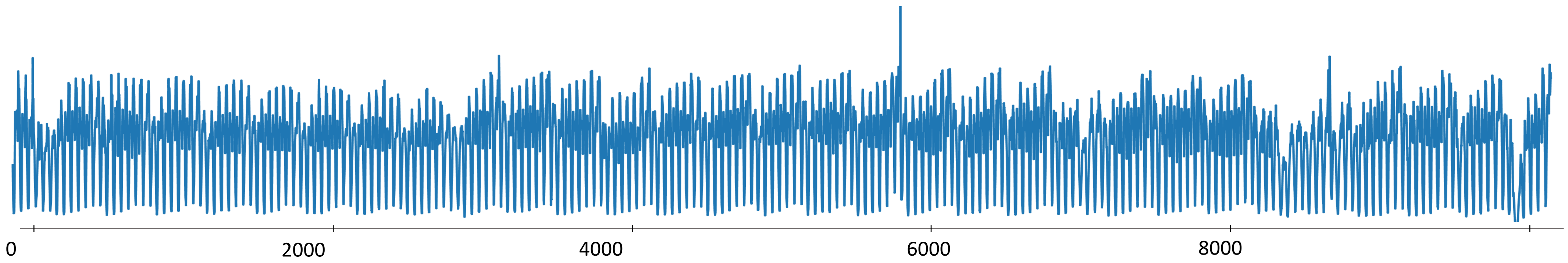
Sensor measurements on le Piton de la Fournaise

Detection of abnormal events on the volcano for predicting eruptions



Introduction: *Anomaly Detection in Time Series*

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



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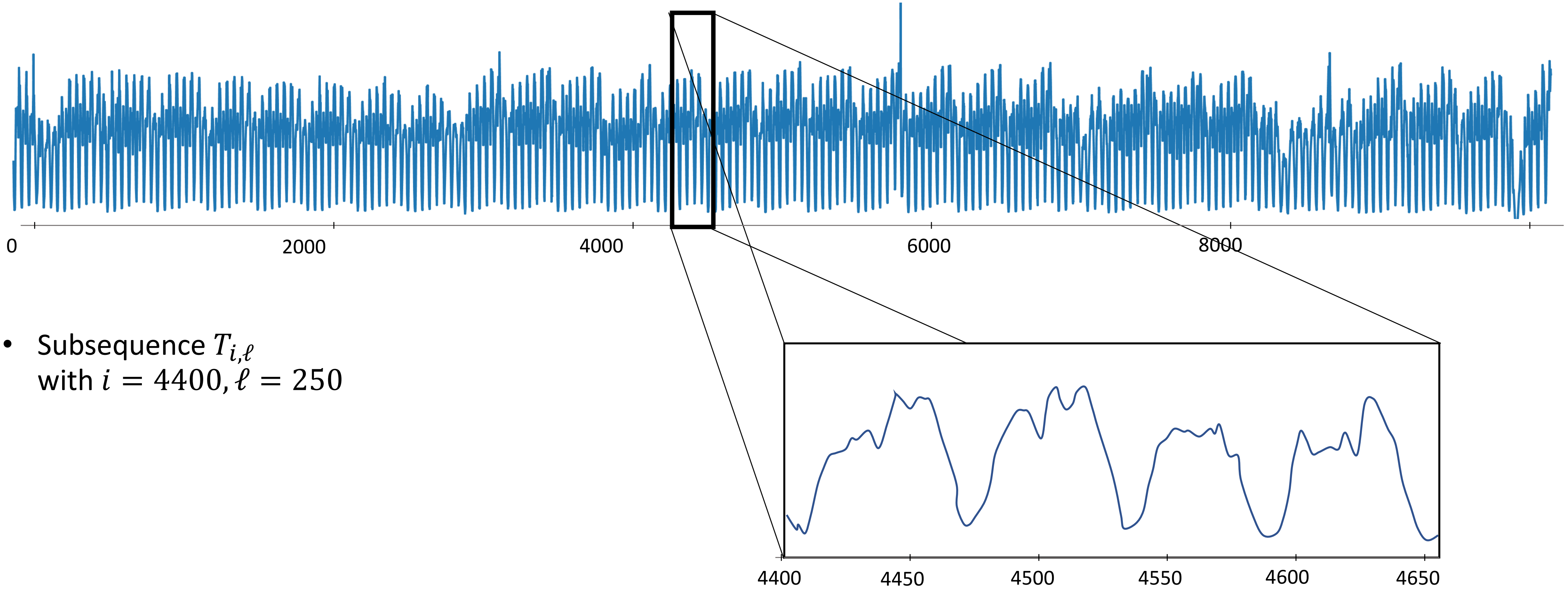

- Subsequence $T_{i,\ell}$
  with $i = 4400, \ell = 250$

Introduction: *Anomaly Detection in Time Series*

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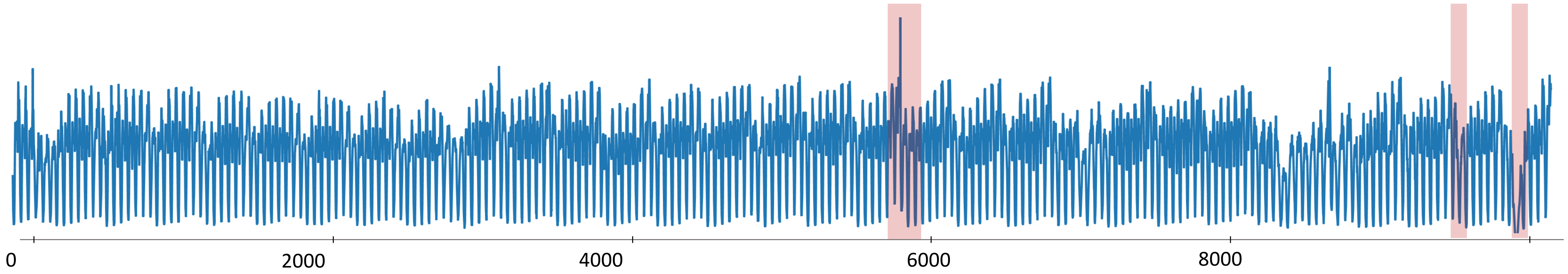

- *Anomaly: rare point or sequence (of a given length)*
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Introduction: *Anomaly Detection in Time Series*

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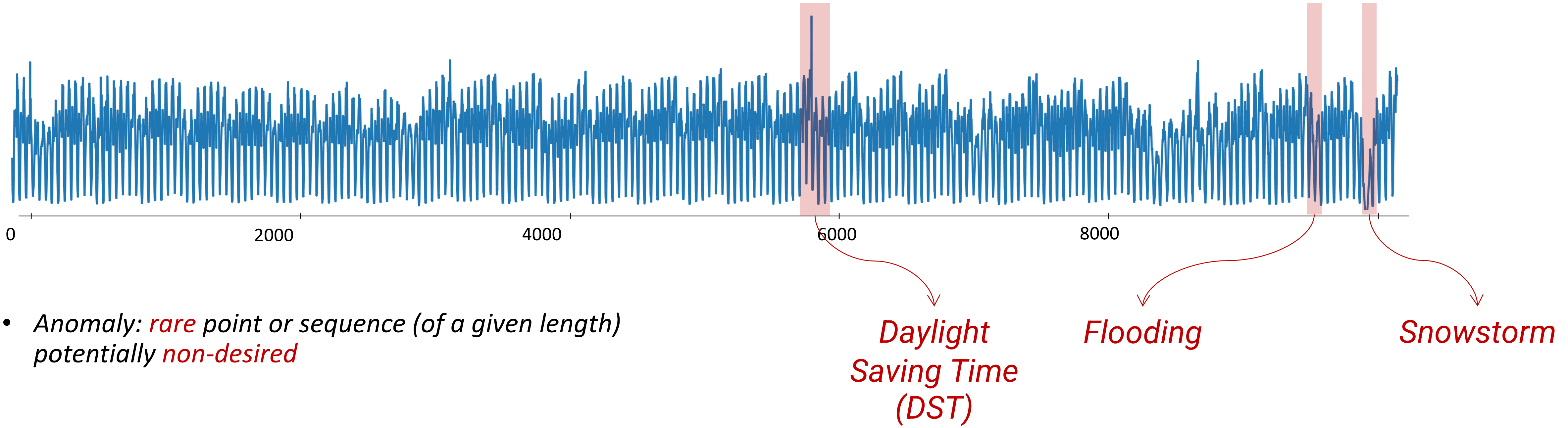

- *Anomaly: rare point or sequence (of a given length) potentially non-desired*

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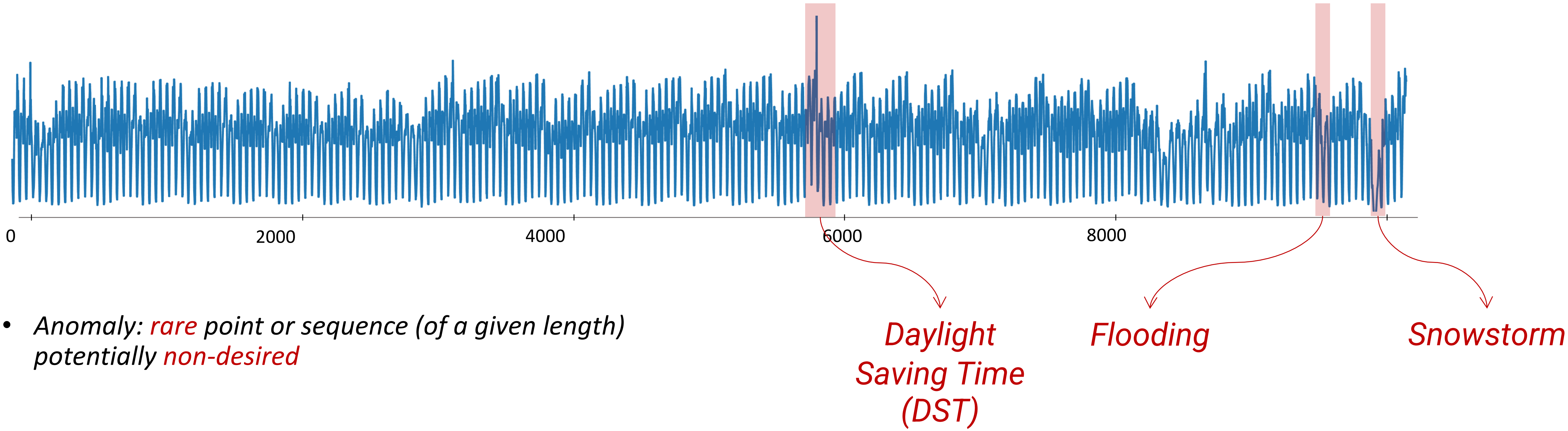

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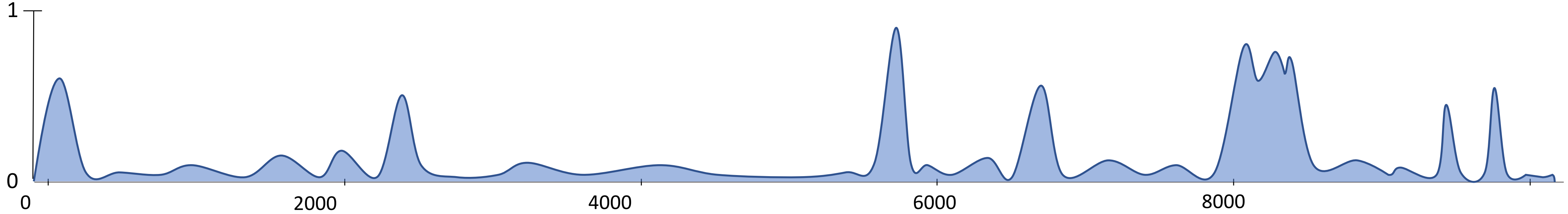

Anomaly score S_T

Introduction: *Anomaly Detection in Time Series*

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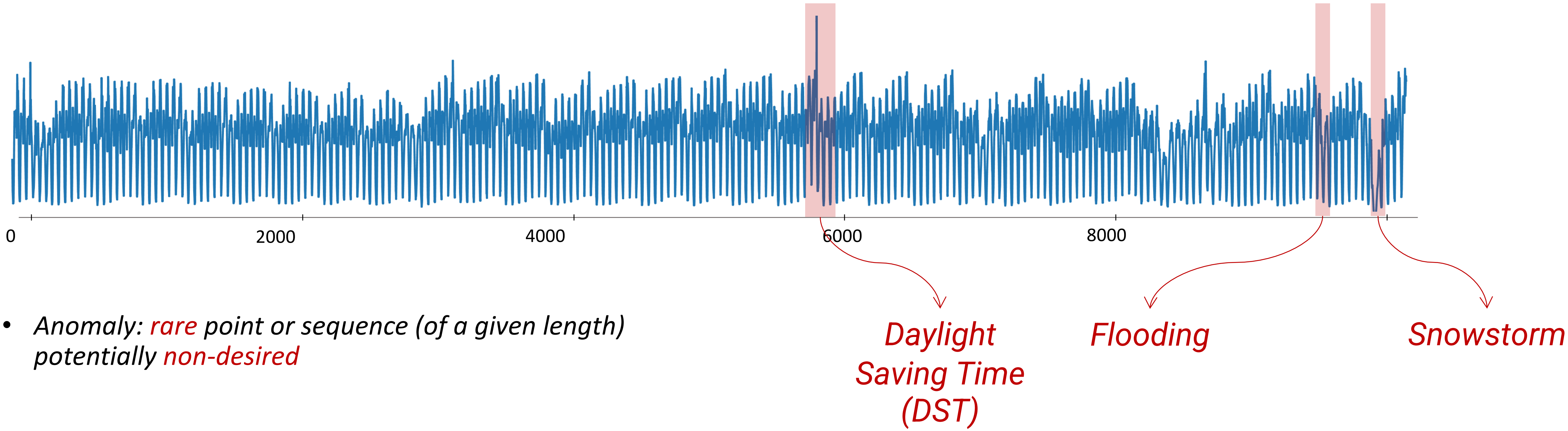

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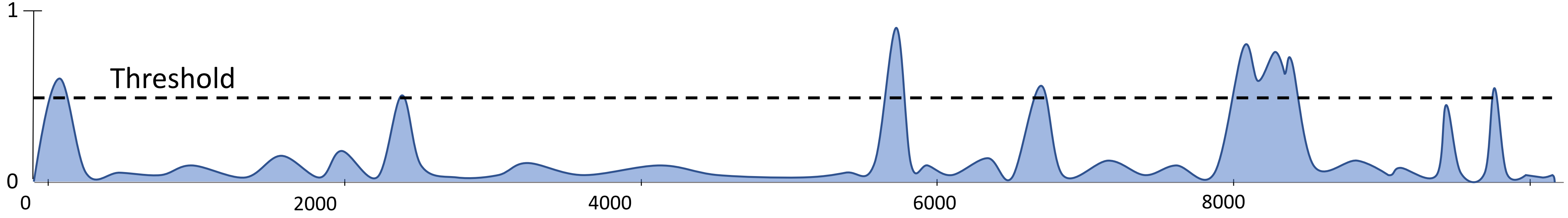

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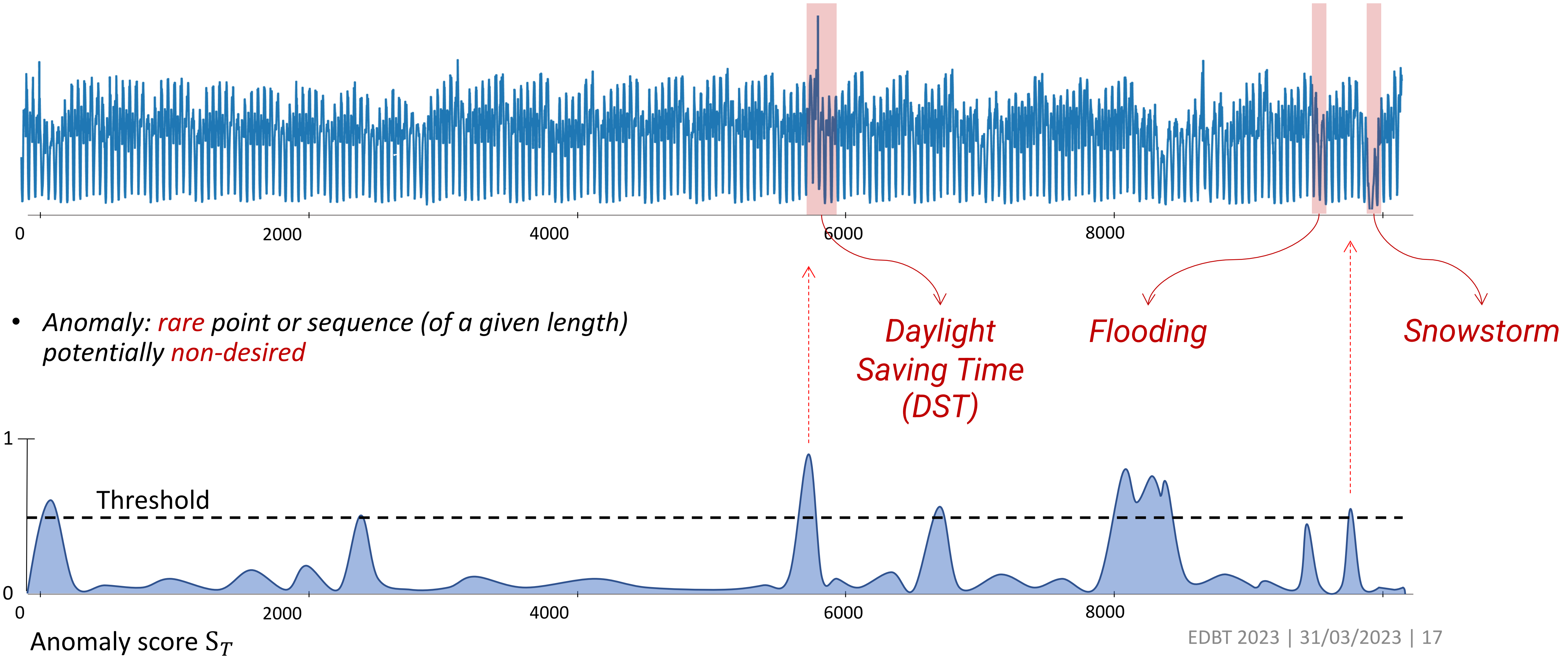
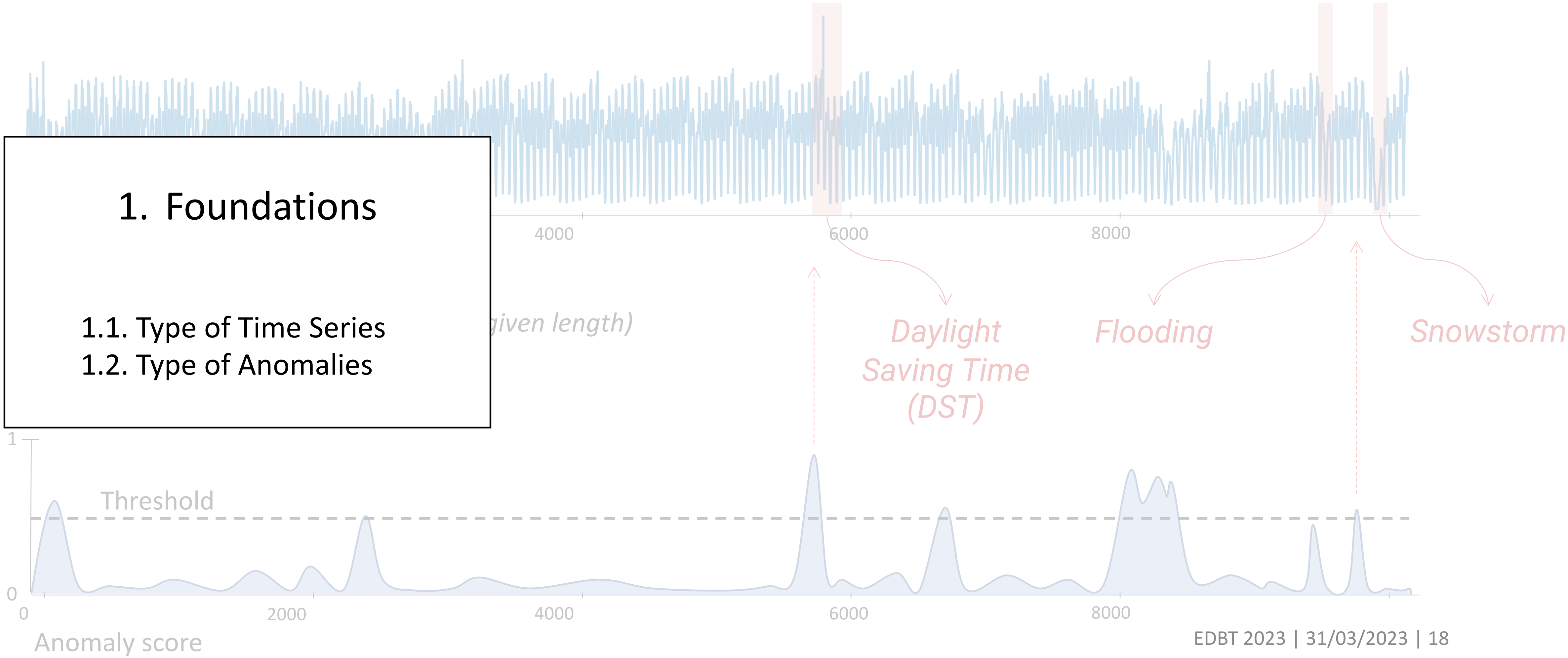


- *Anomaly: rare point or sequence (of a given length) potentially non-desired*

Introduction: *Outline*

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

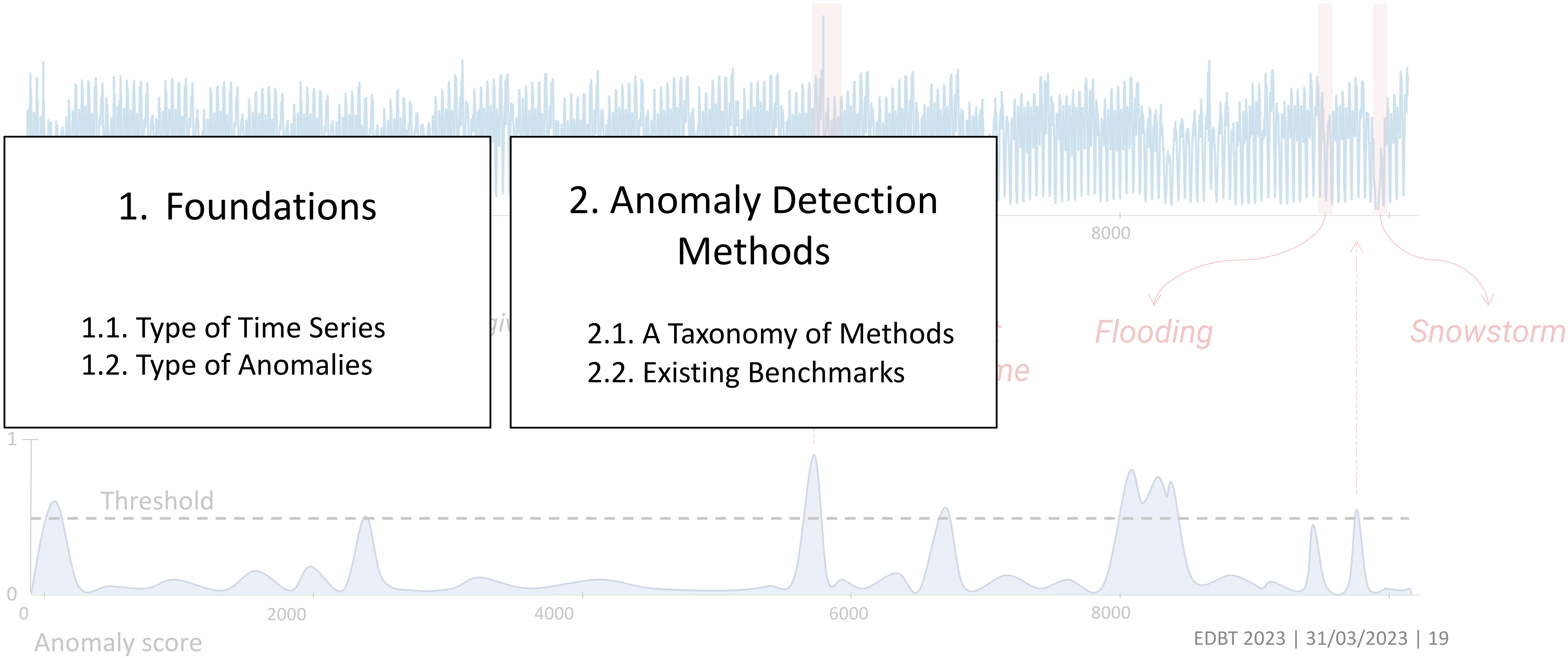


1. Foundations

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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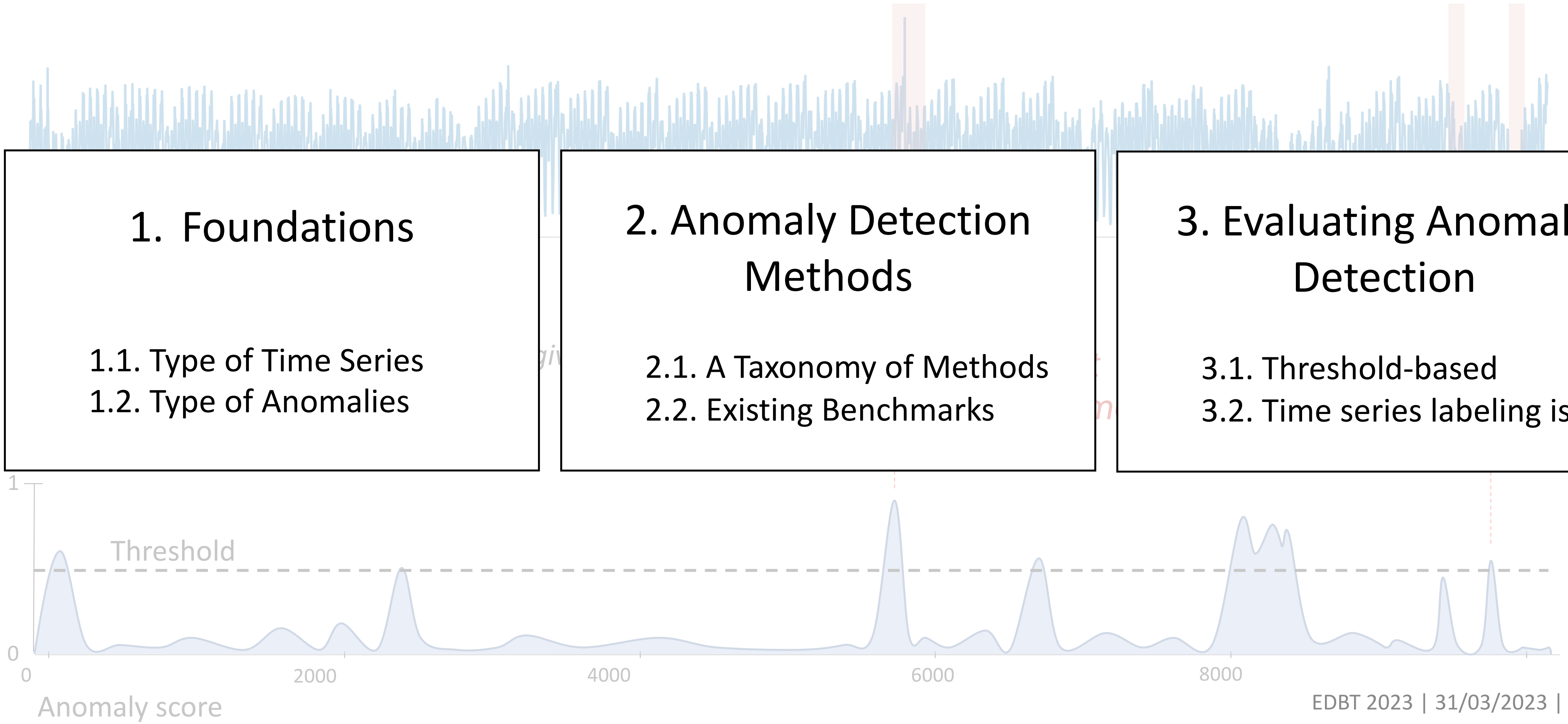

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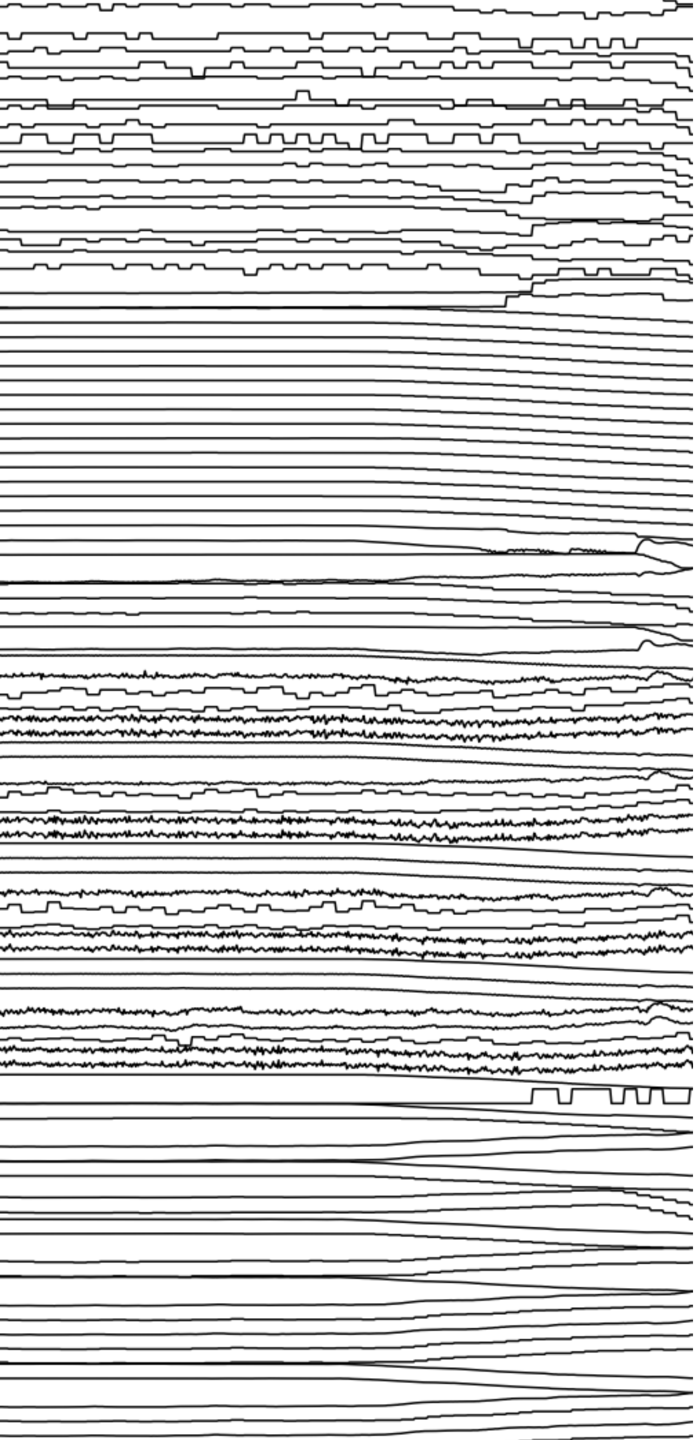
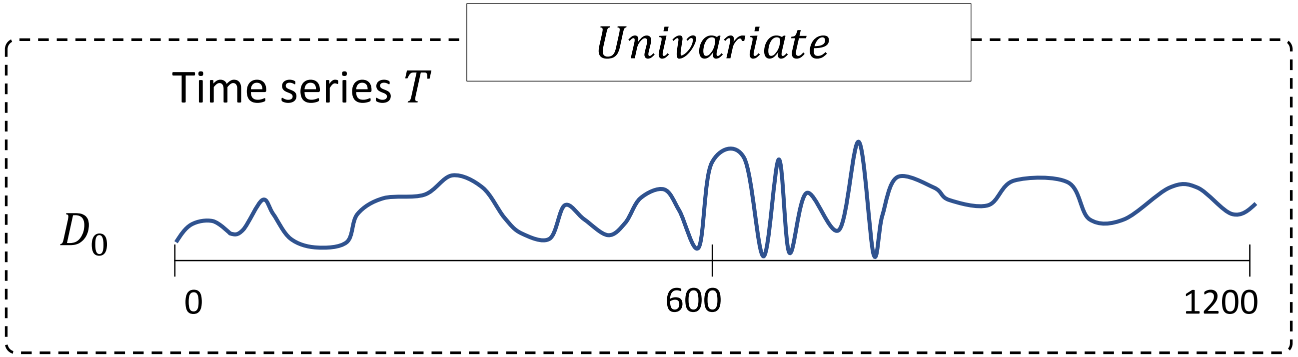
3. Evaluating Anomaly Detection

3.1. Threshold-based
3.2. Time series labeling issues



Foundations

Foundations: *Type of time series*



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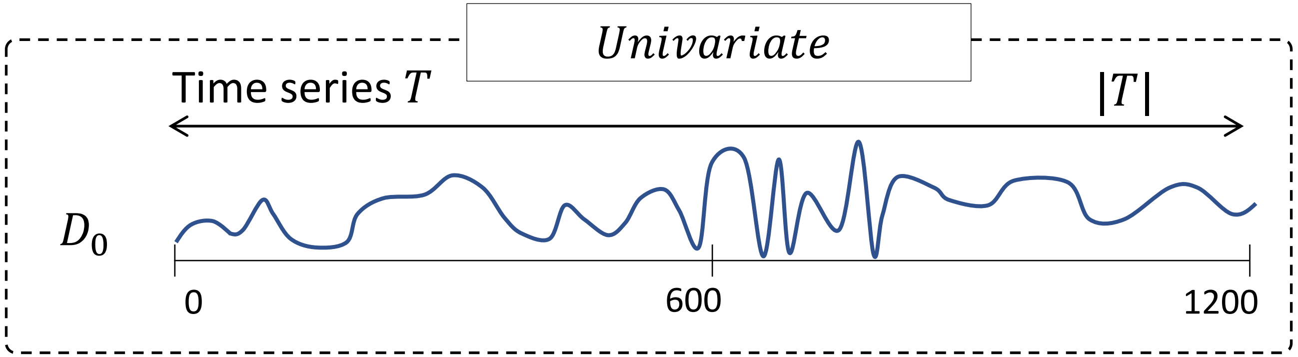

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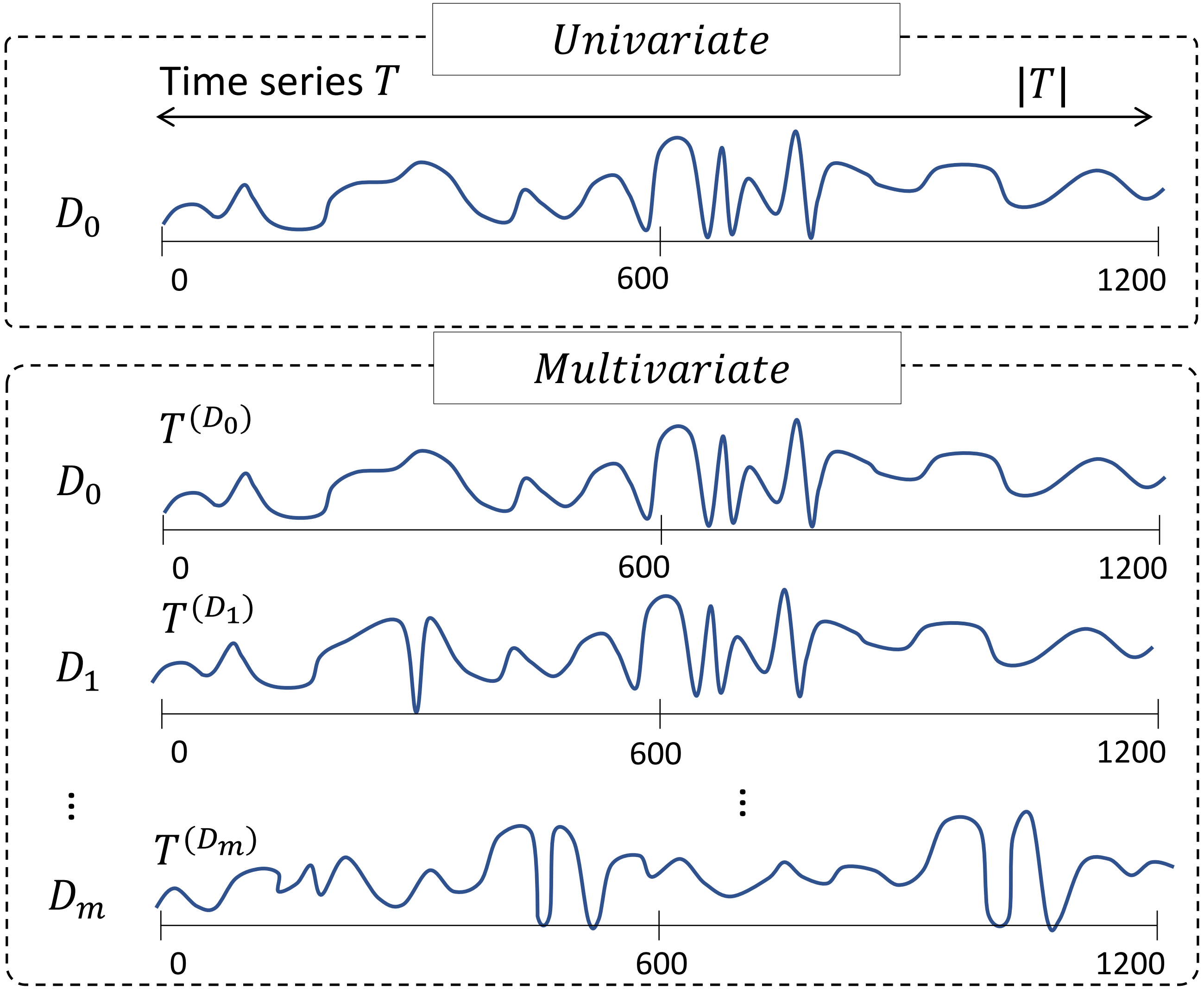

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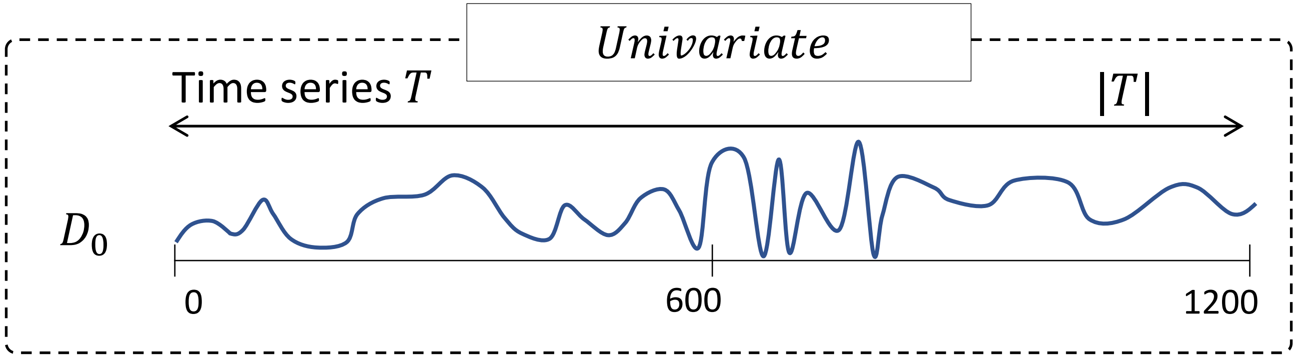

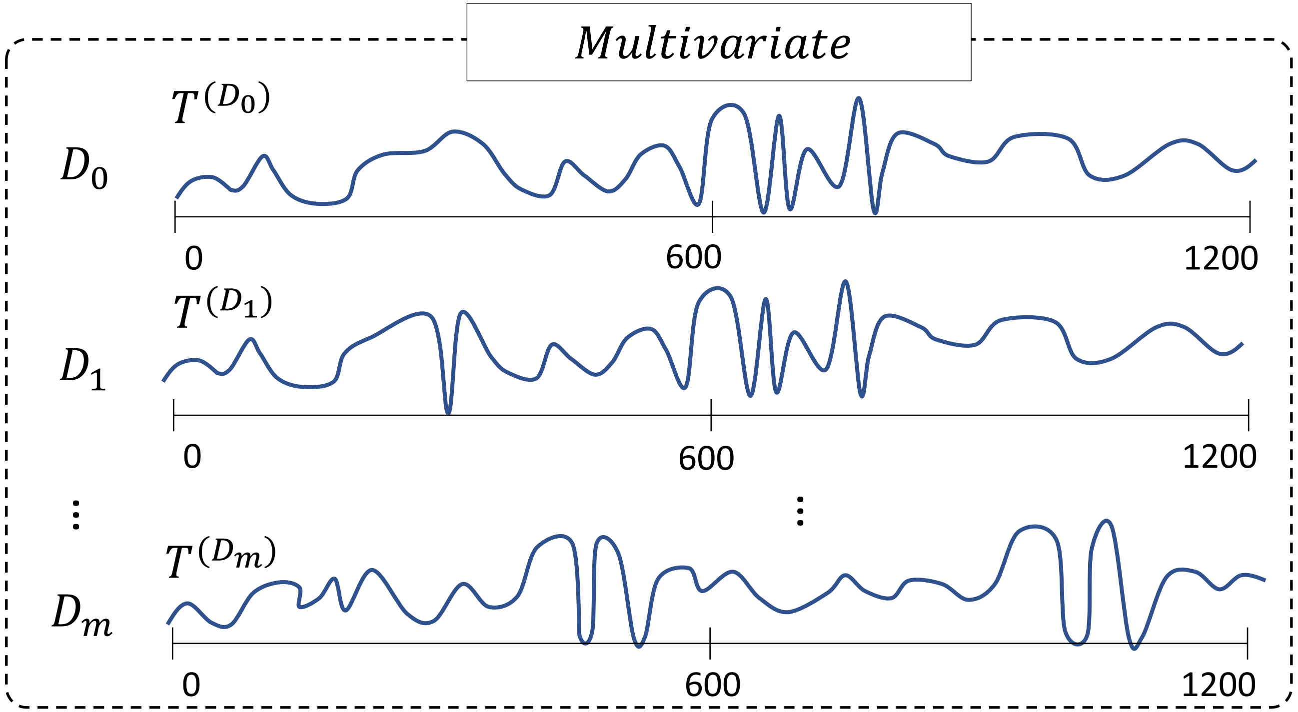

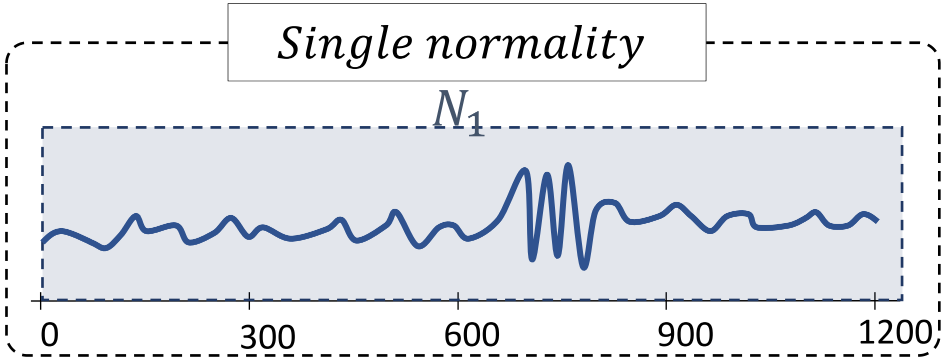

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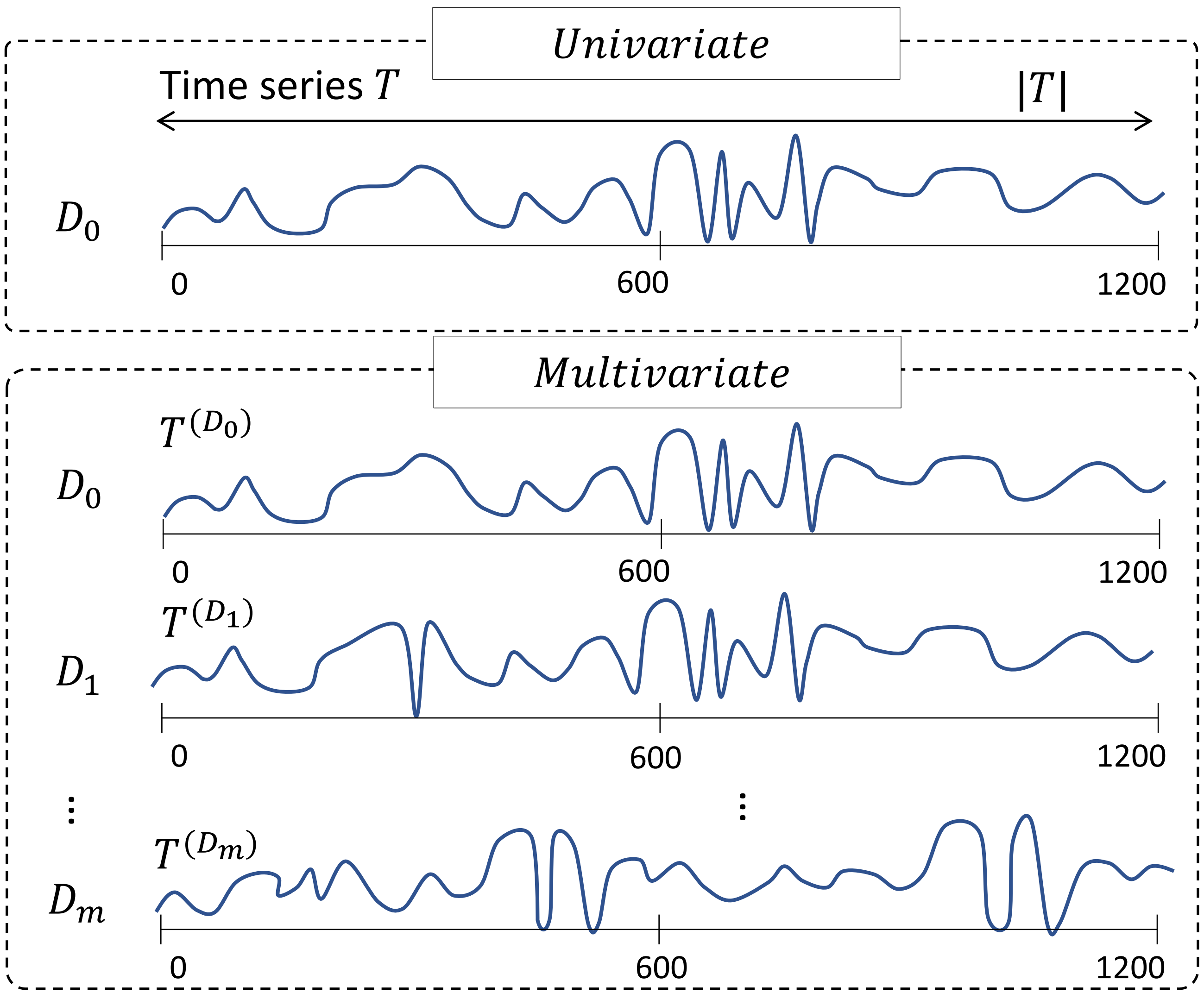
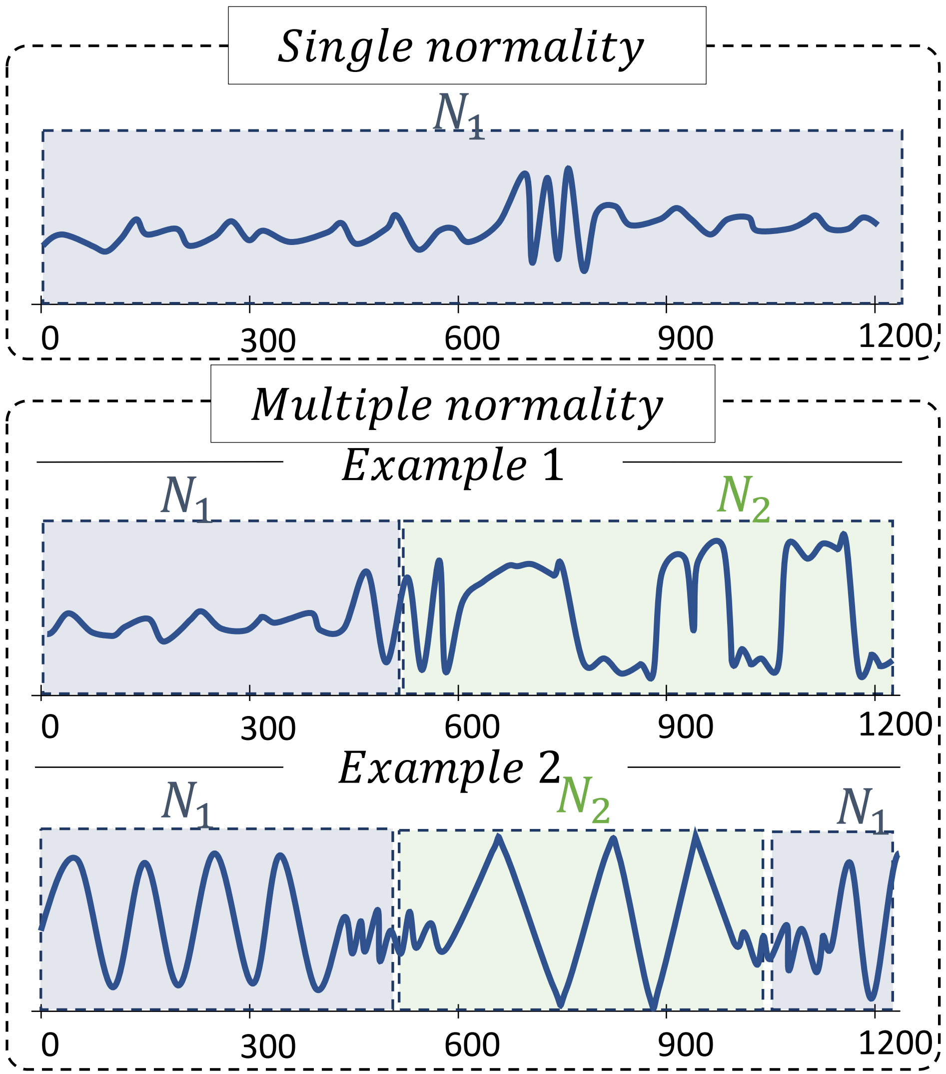
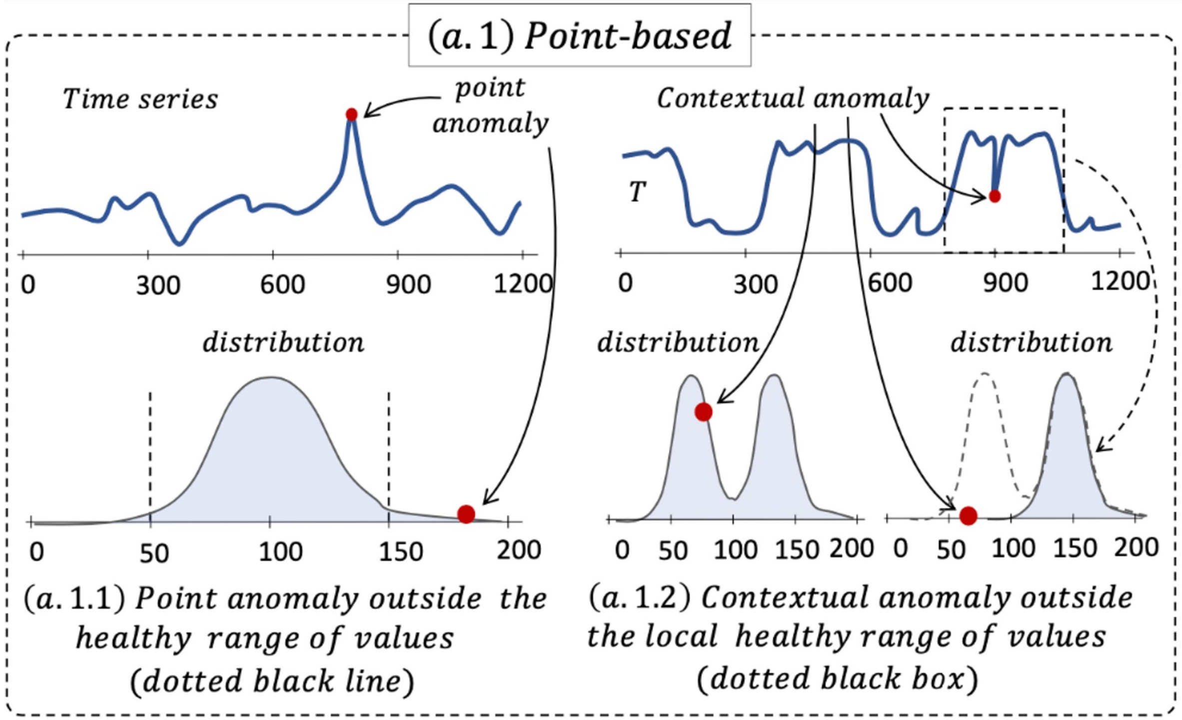




Foundations: *Type of anomalies*



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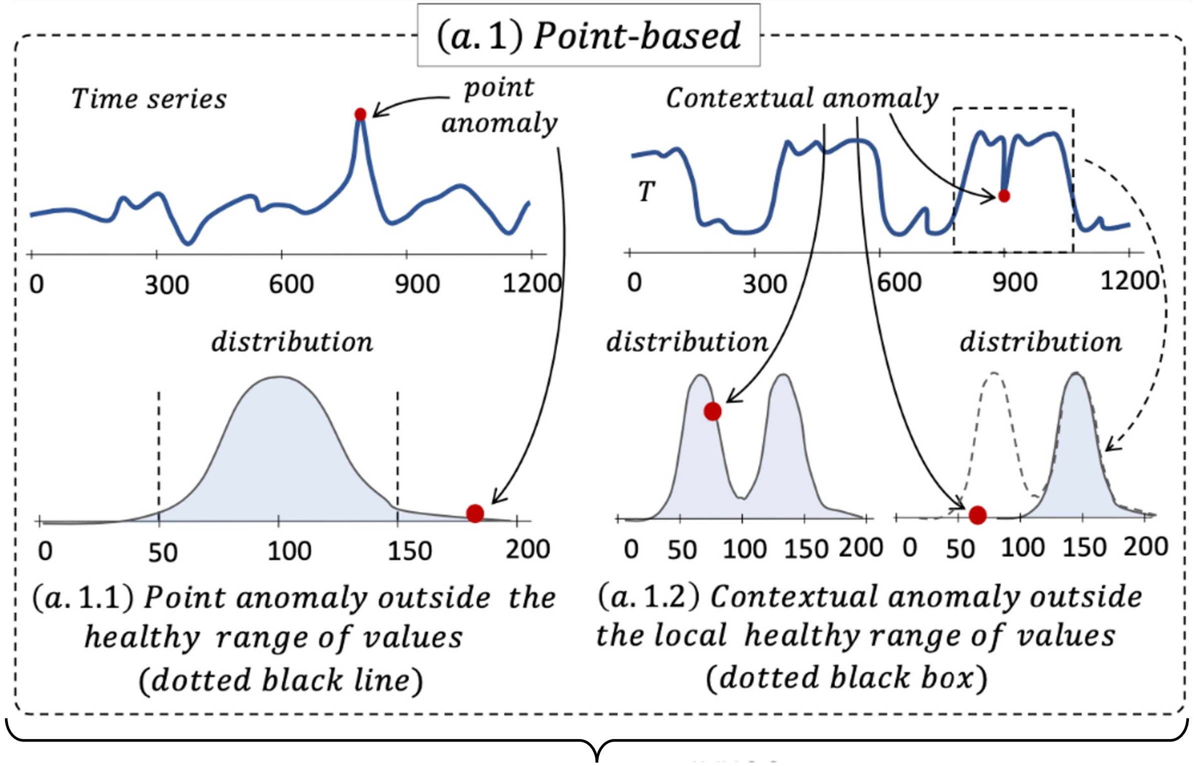
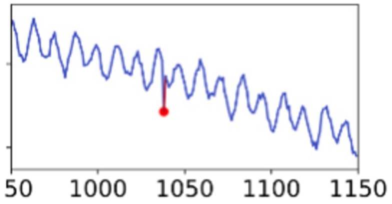


Example of point-based anomaly [1]



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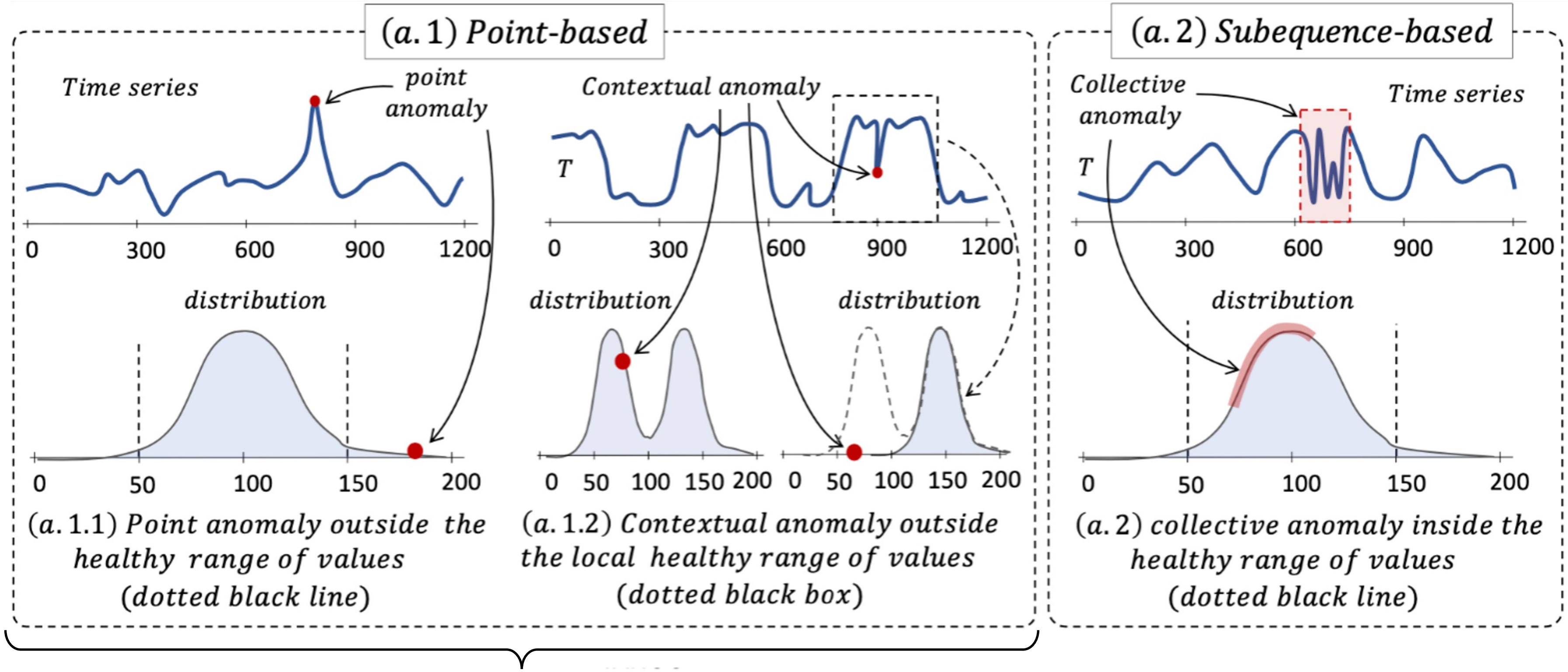

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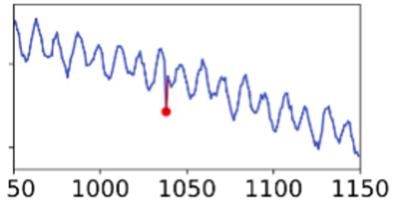

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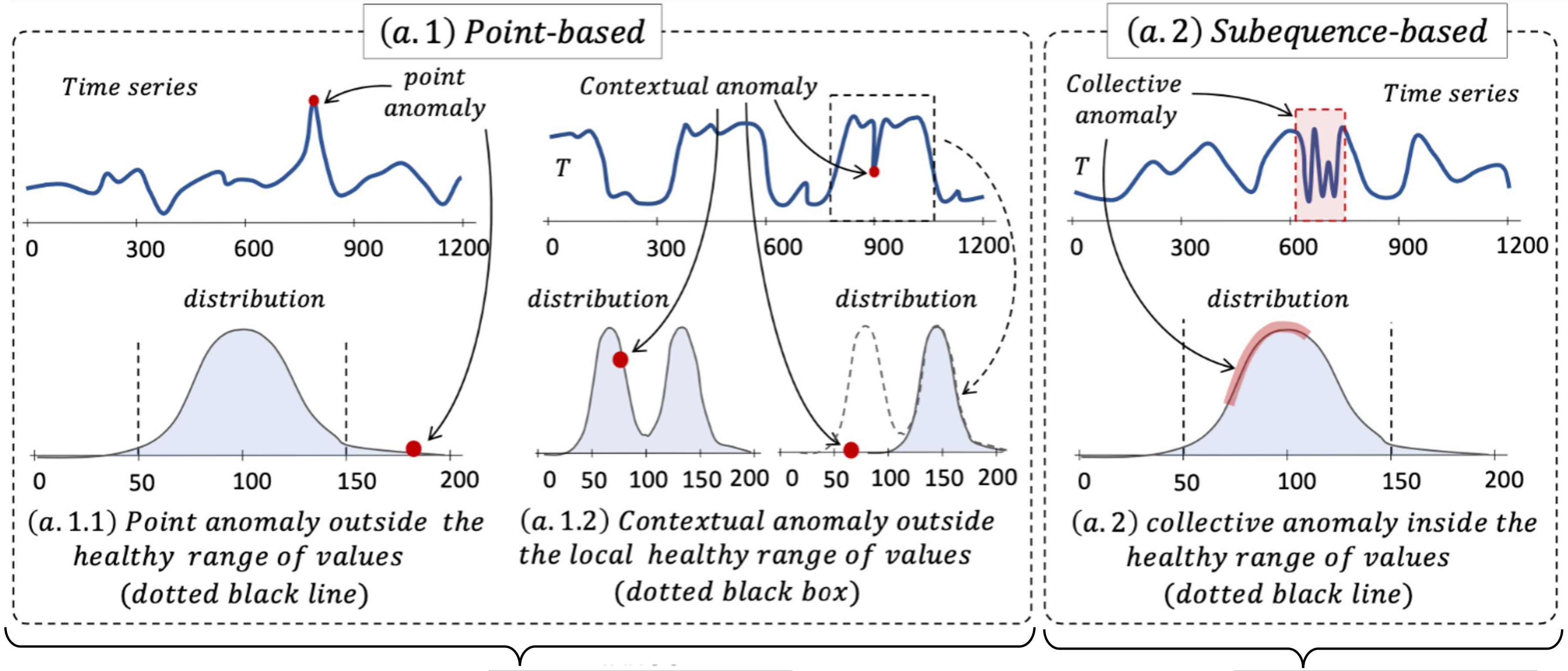

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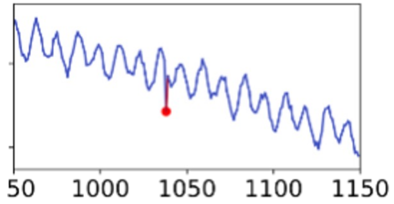
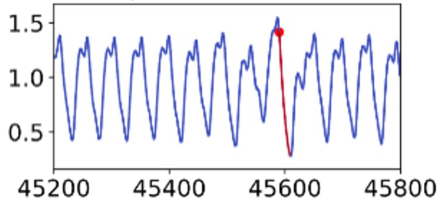


Example of subsequence-based anomaly [2]



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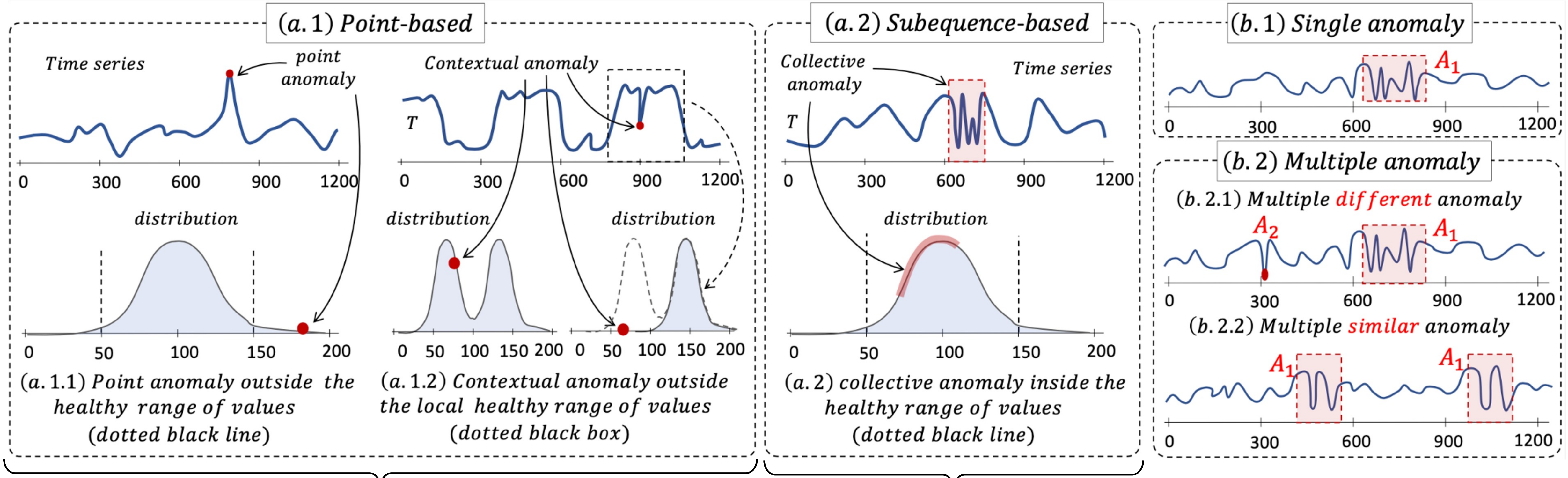

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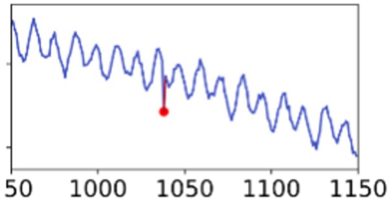
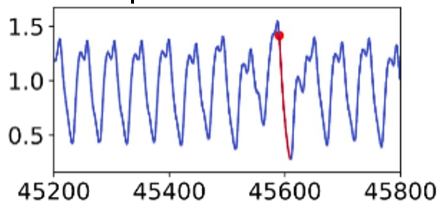
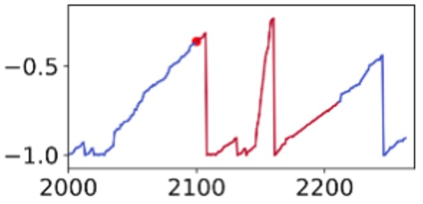


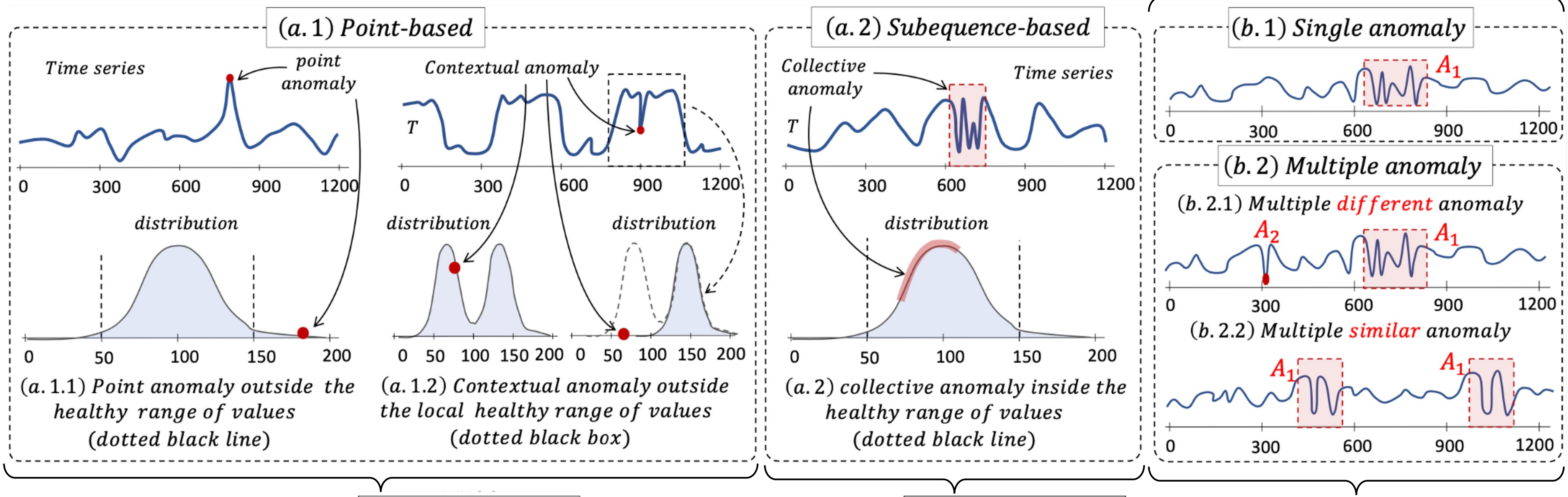
Example of subsequence-based anomaly [2]



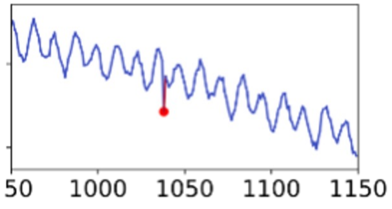
Foundations: *Type of anomalies*

Example of single anomaly [3]

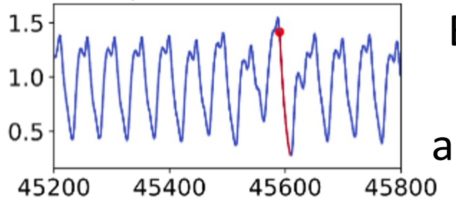




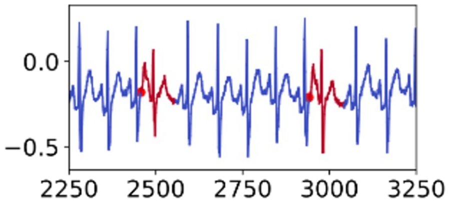
Example of point-based anomaly [1]

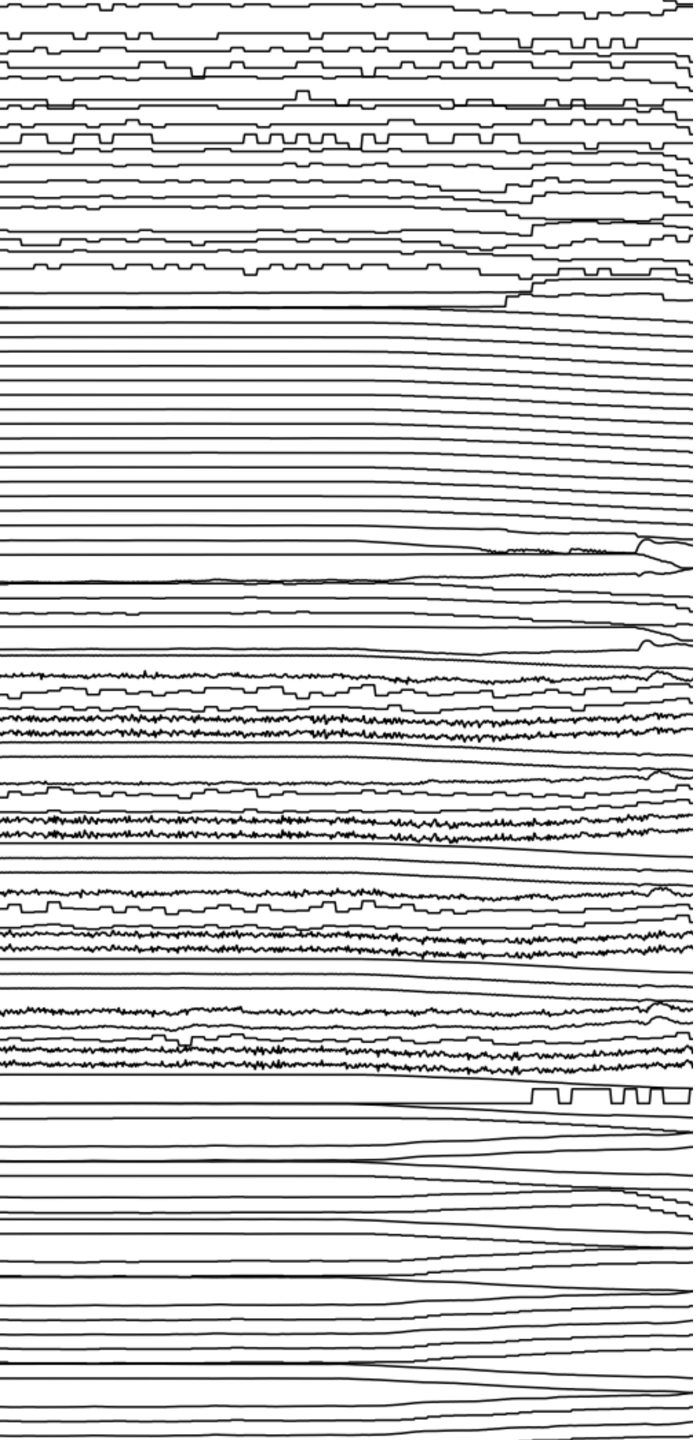


Example of subsequence-based anomaly [2]



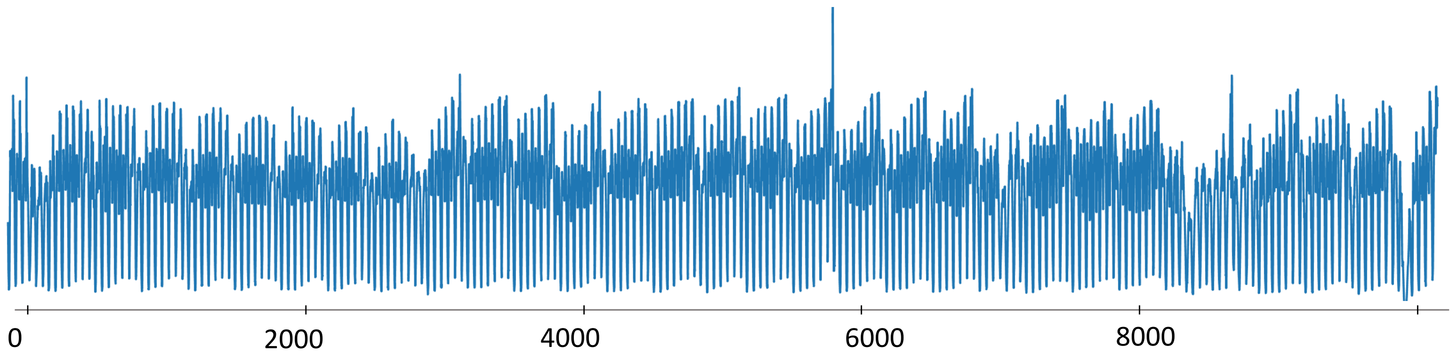
Example of multiple anomaly [4]





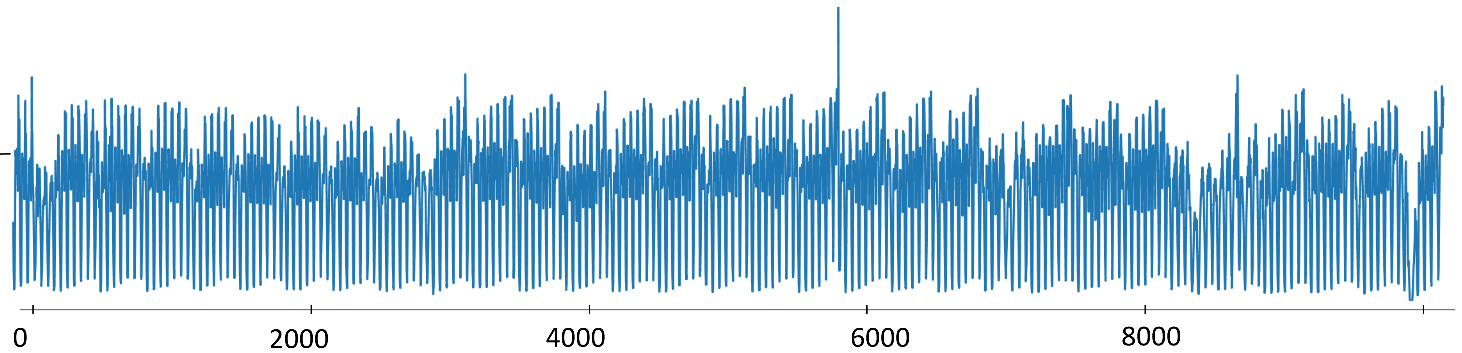
Anomaly Detection Methods

Anomaly Detection methods: *A taxonomy*



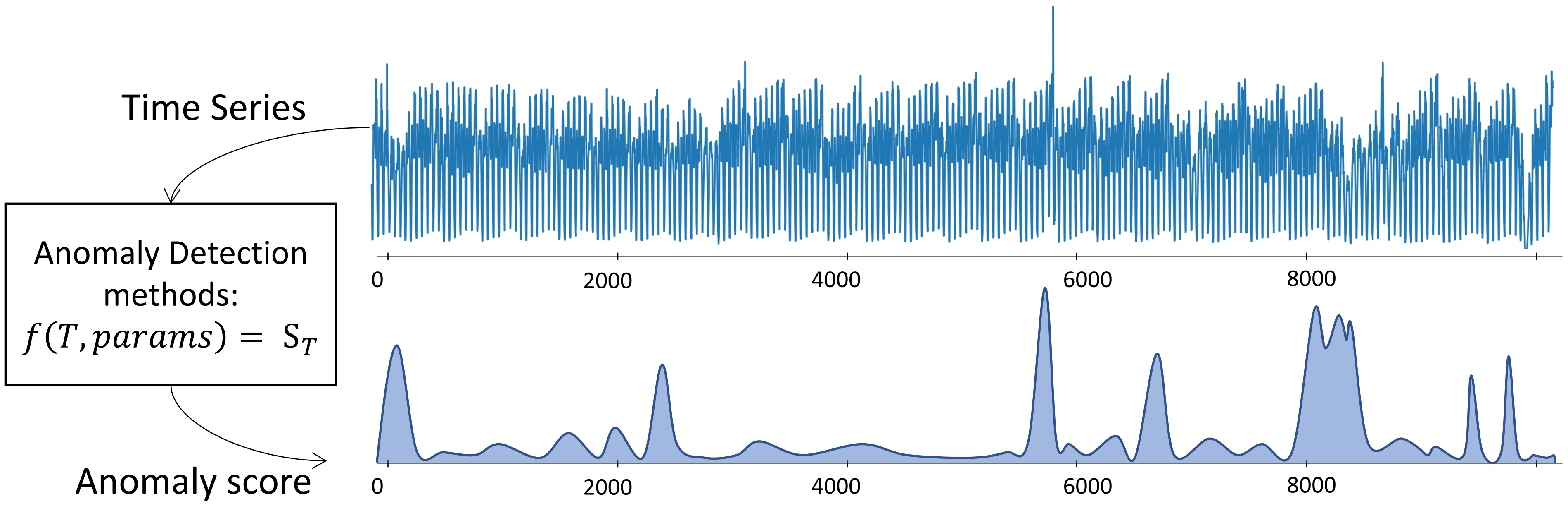
Anomaly Detection methods: *A taxonomy*

Time Series



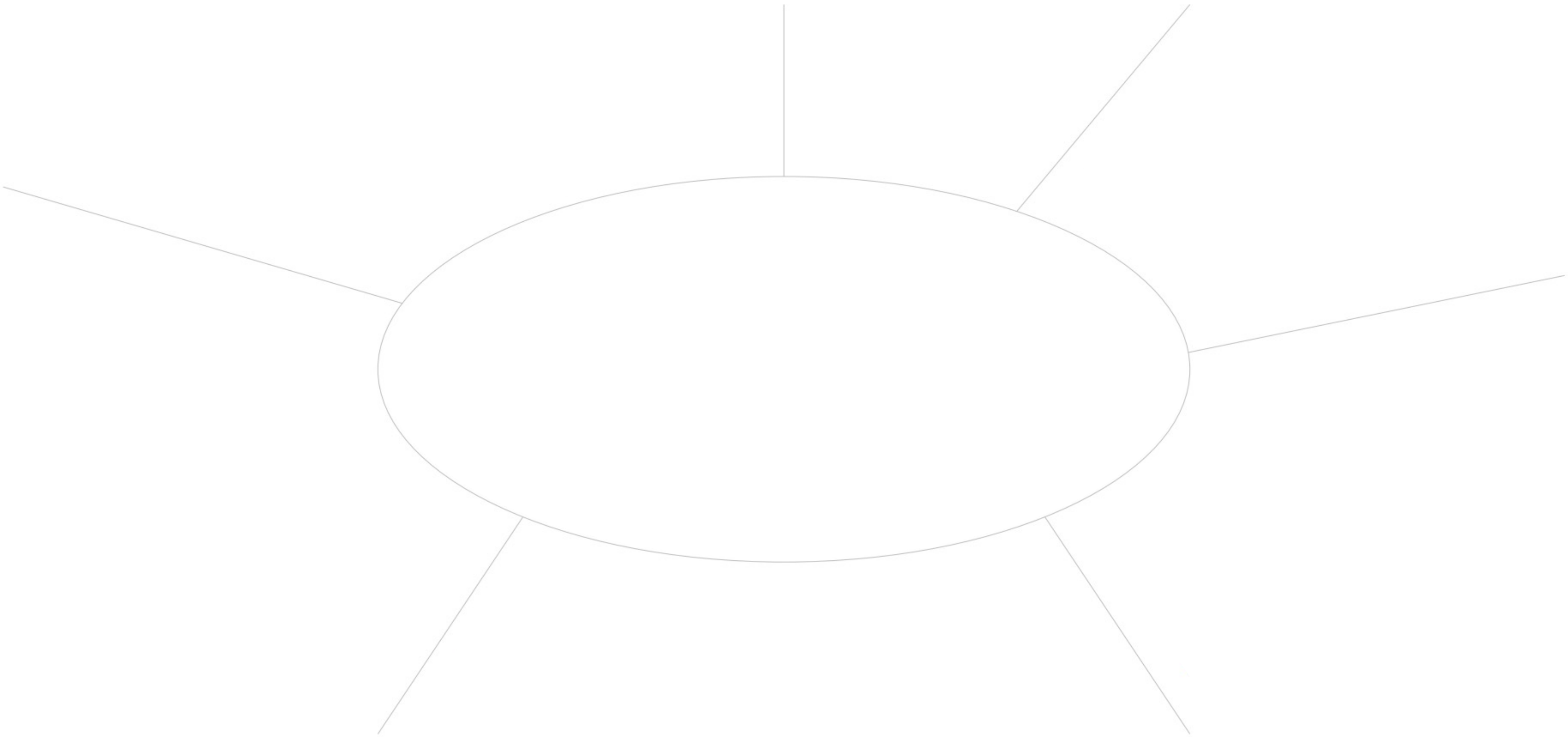
Anomaly Detection methods:
$f(T, params) = S_T$

Anomaly Detection methods: *A taxonomy*



Anomaly Detection methods: *A taxonomy*

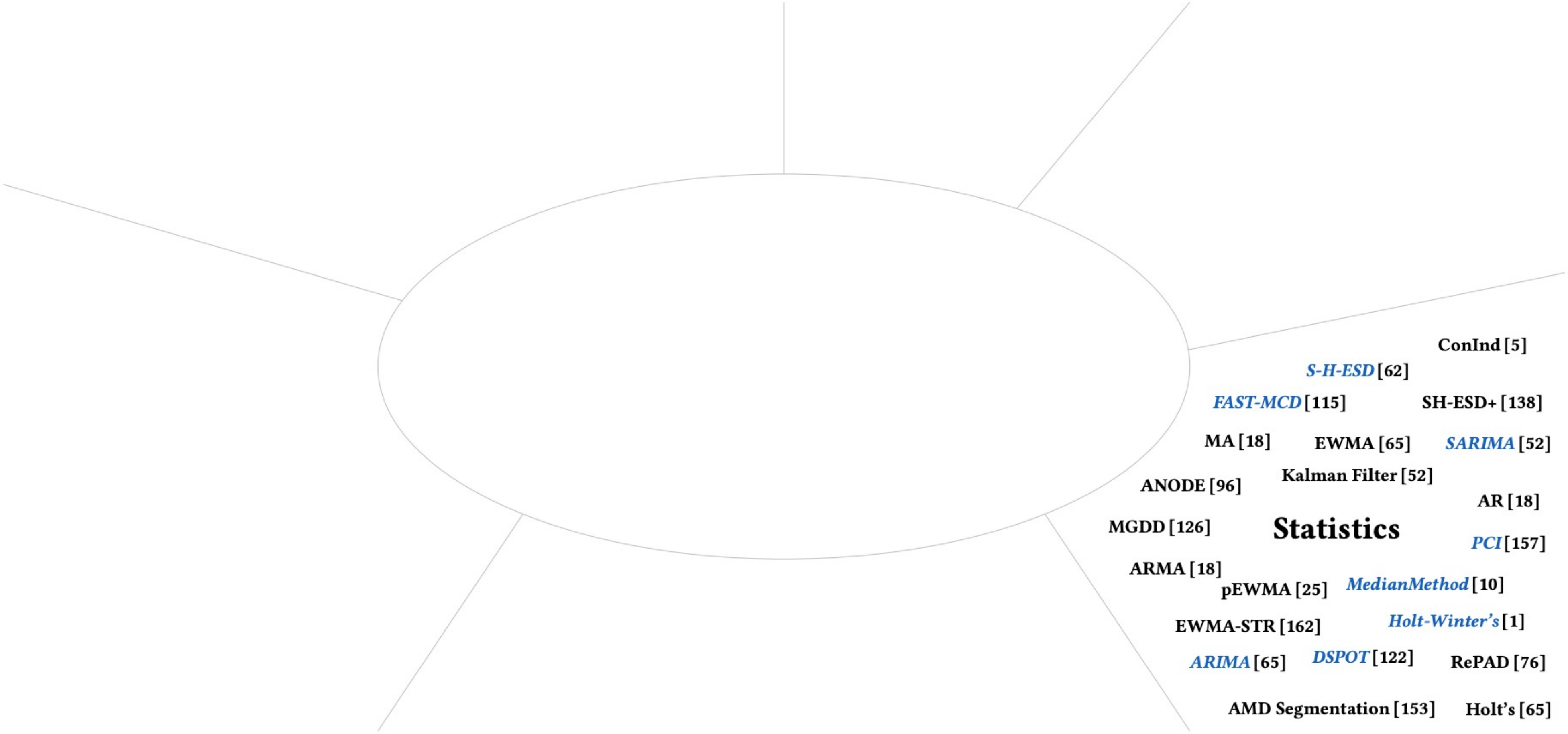
By domains [5] …



[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] …



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Anomaly Detection methods: *A taxonomy*

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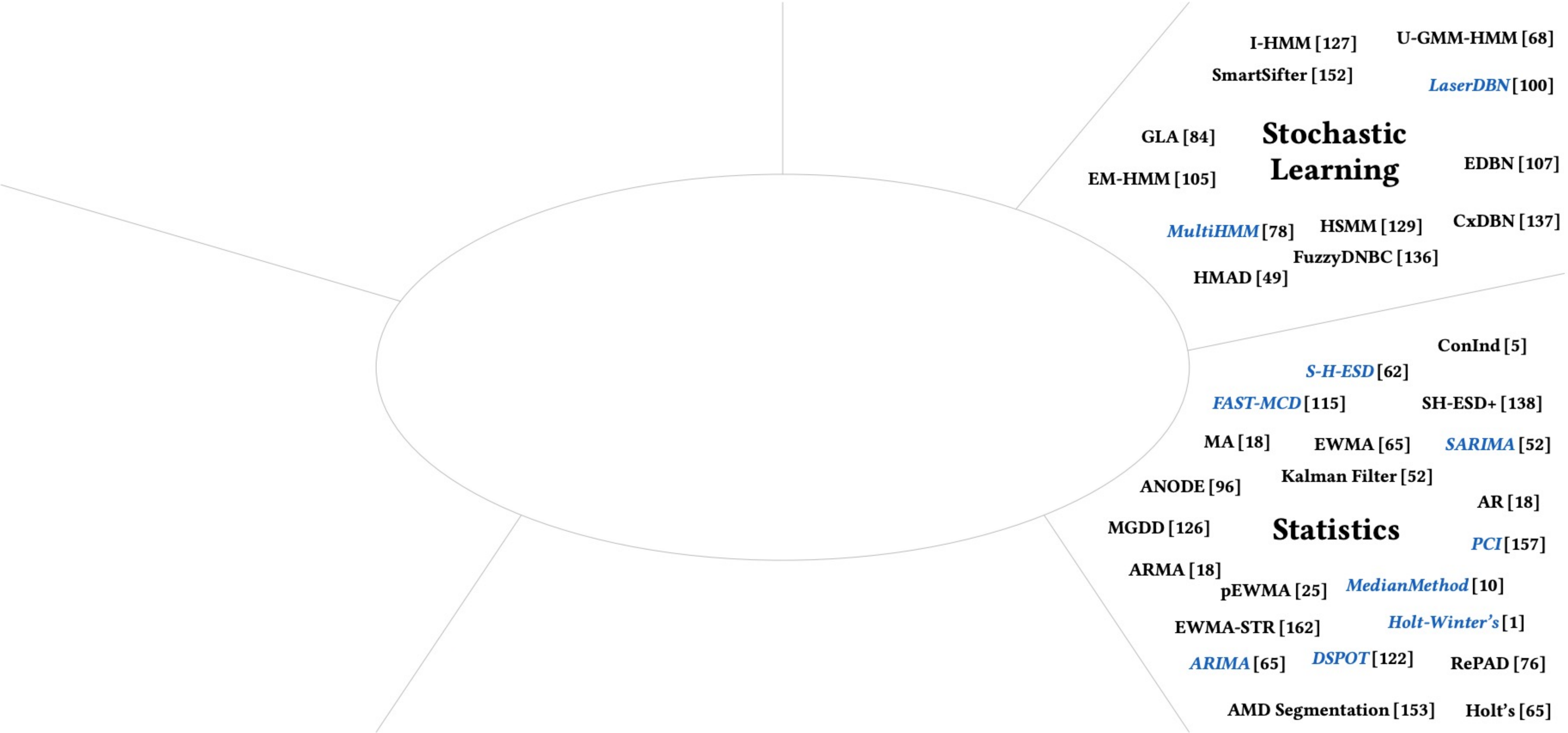

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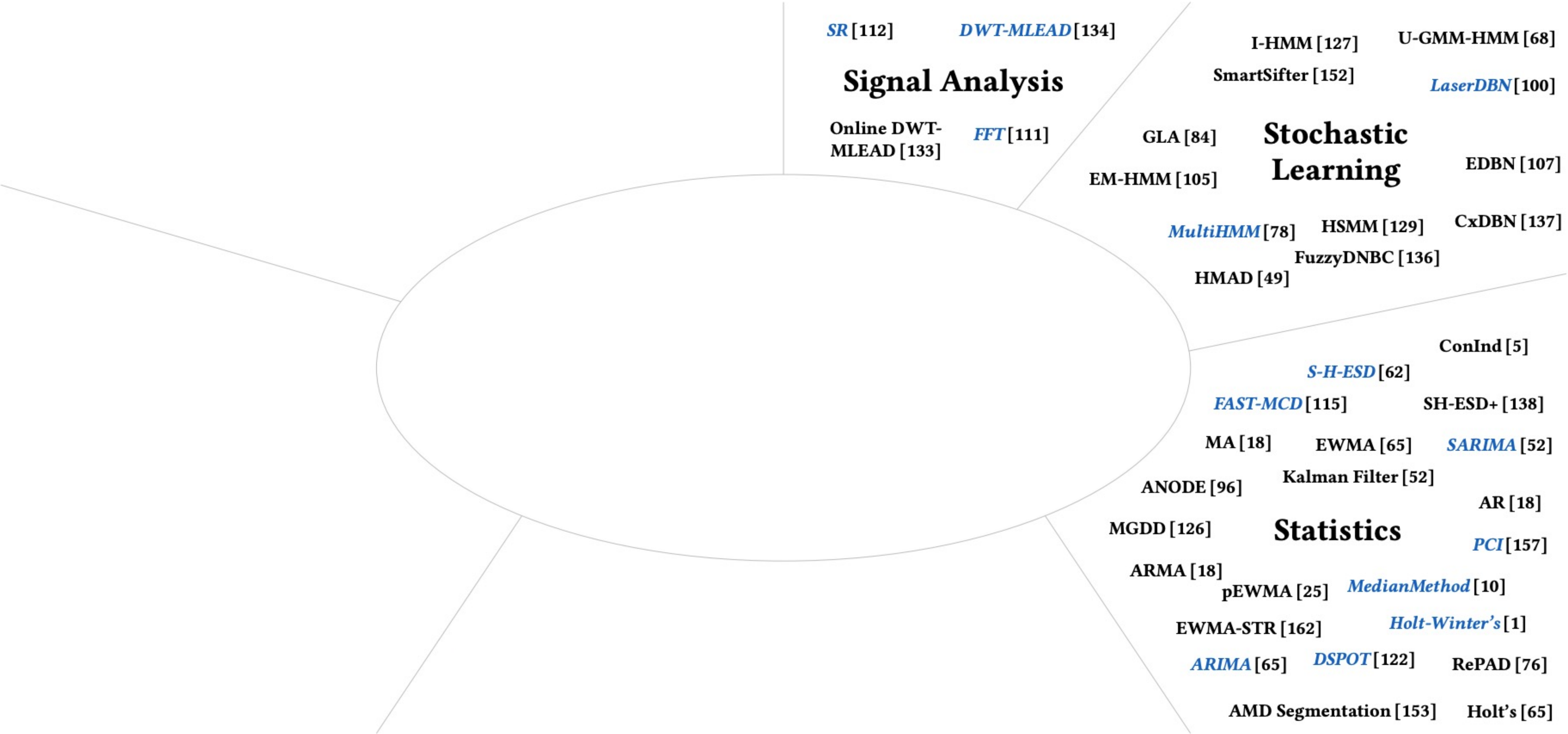
By domains [5] …



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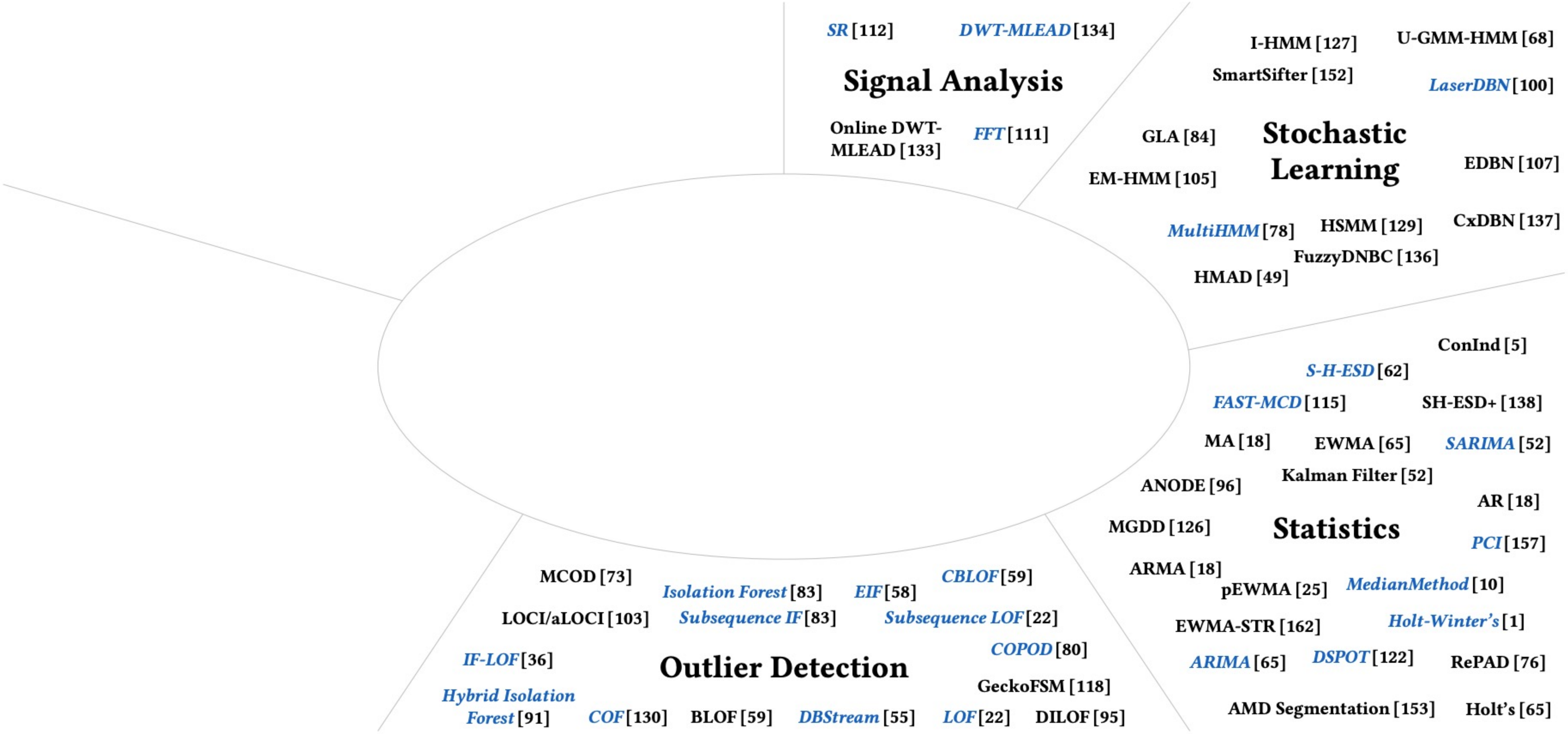
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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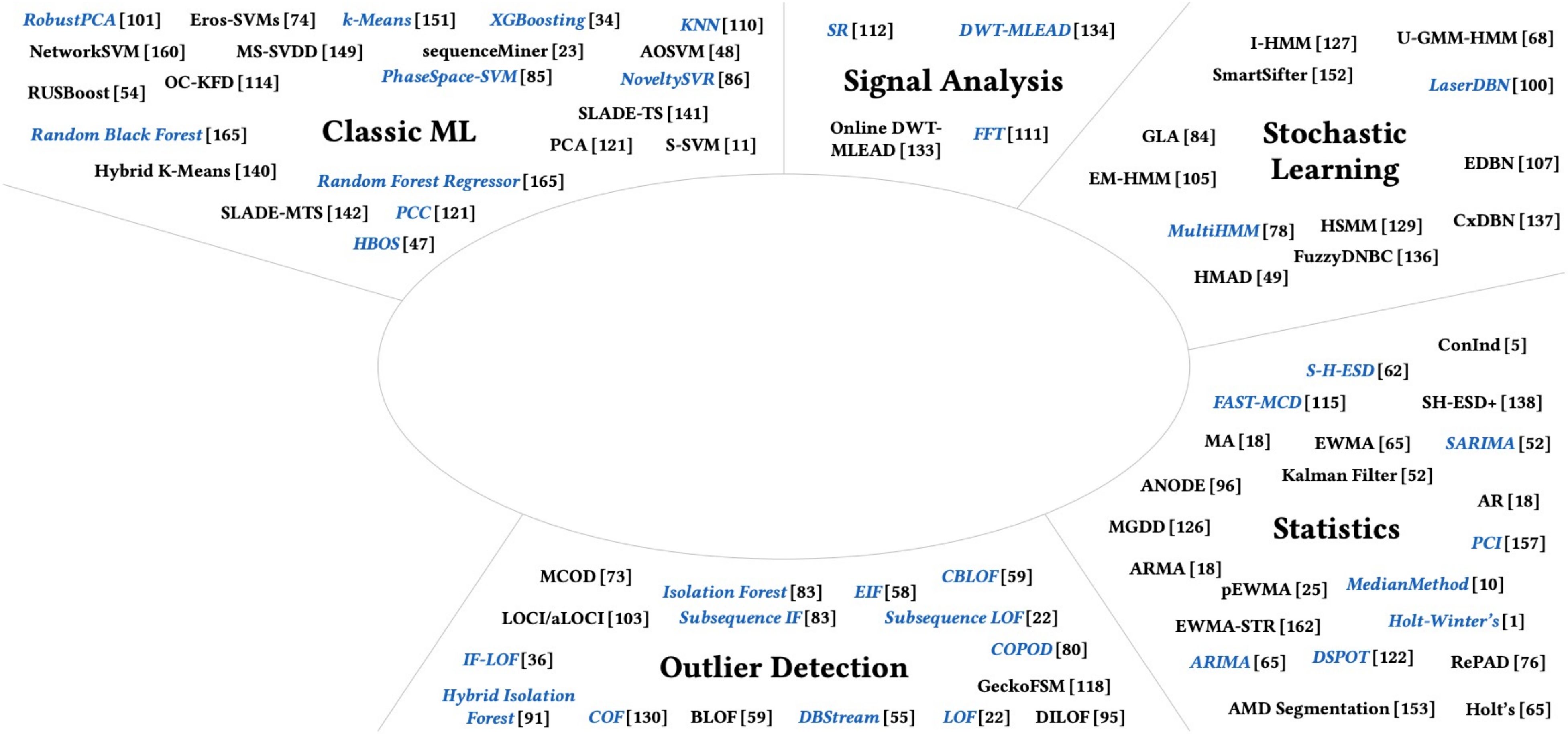
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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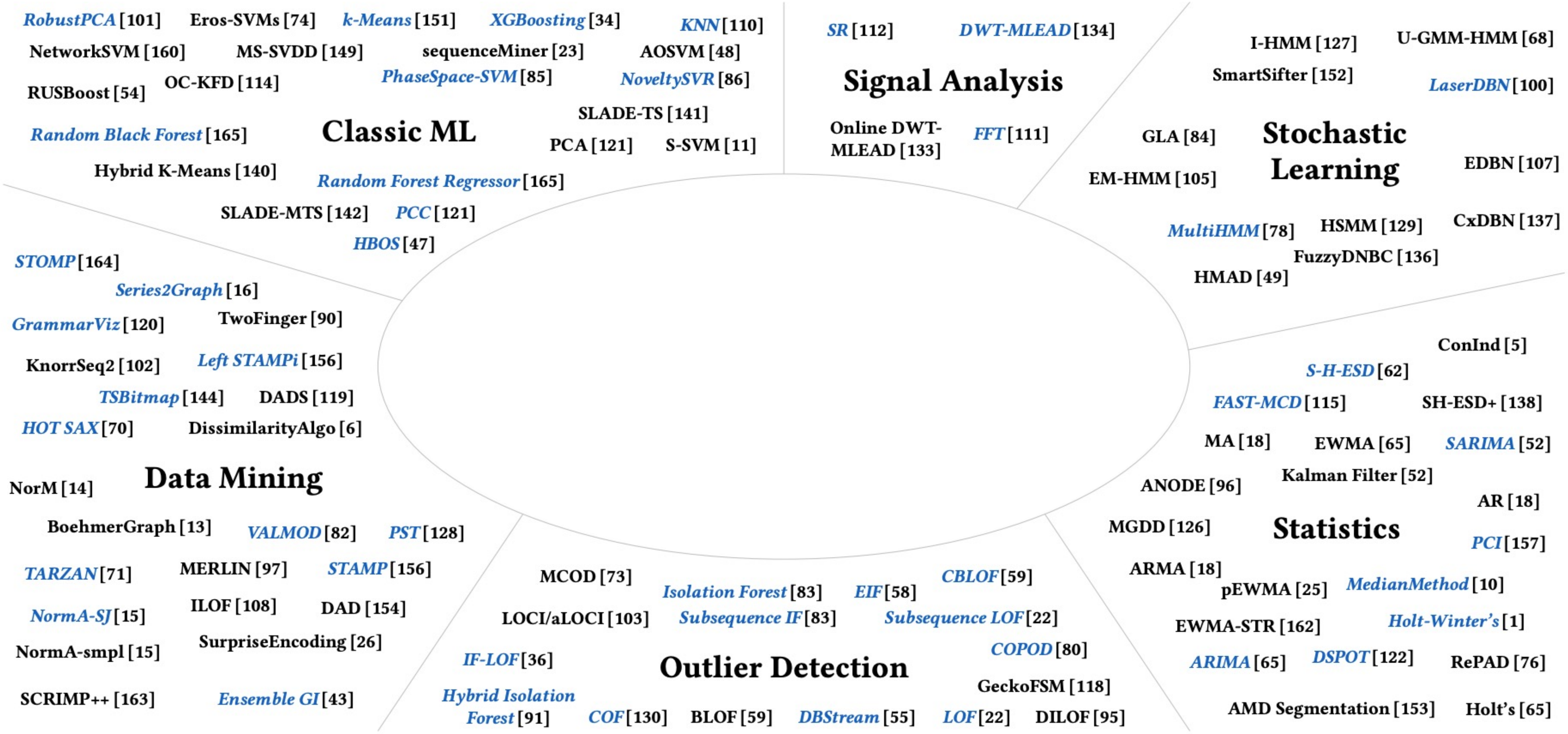
Anomaly Detection methods: *A taxonomy*

By domains [5] …



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Anomaly Detection methods: *A taxonomy*

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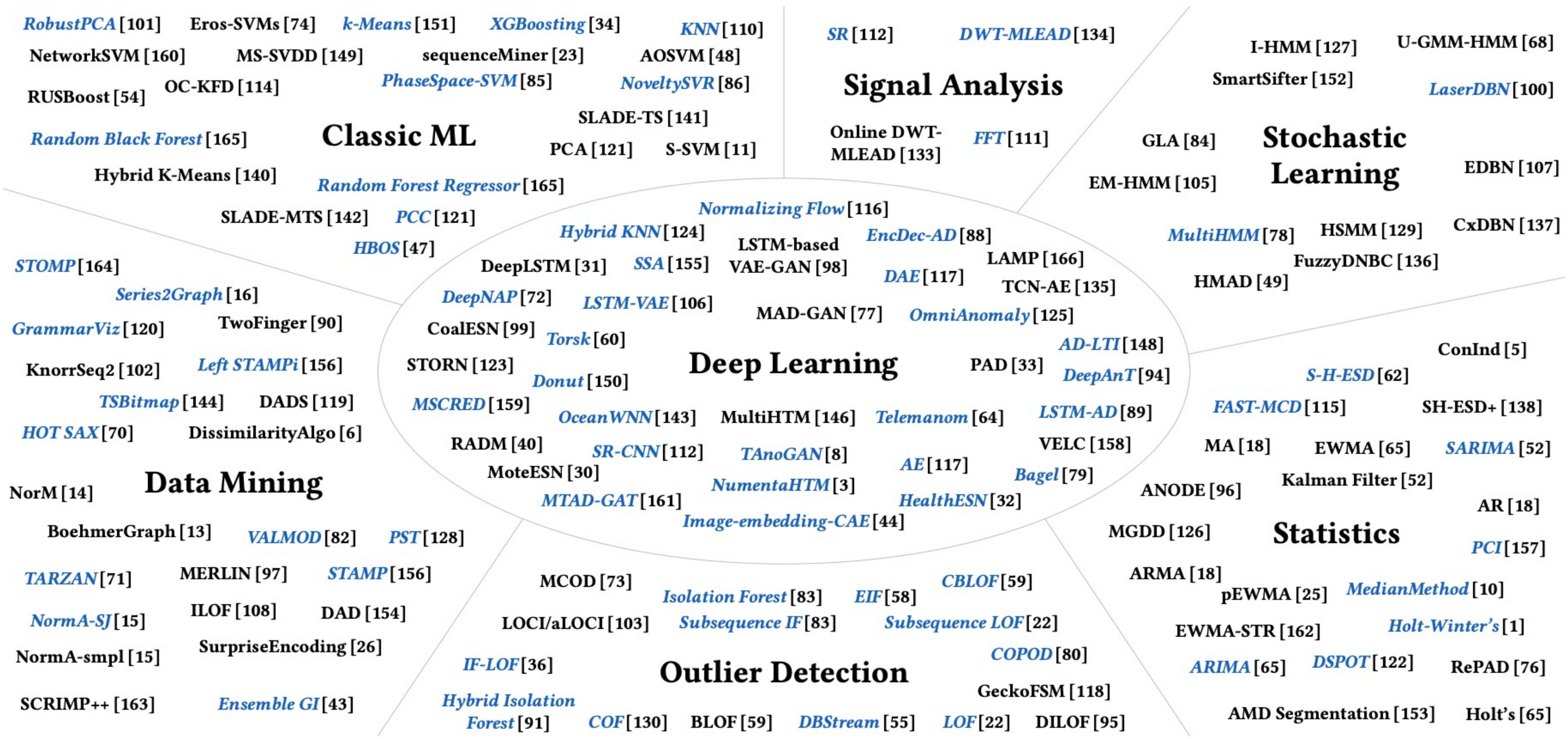

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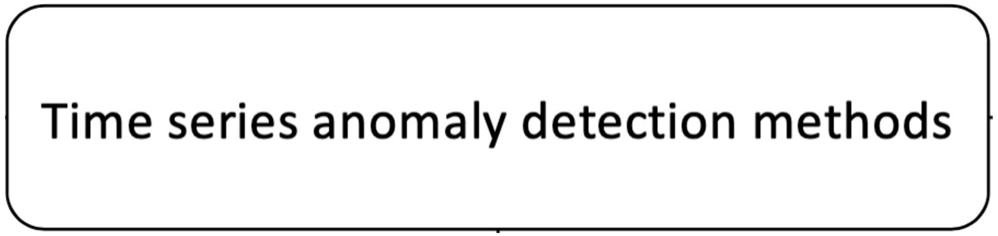
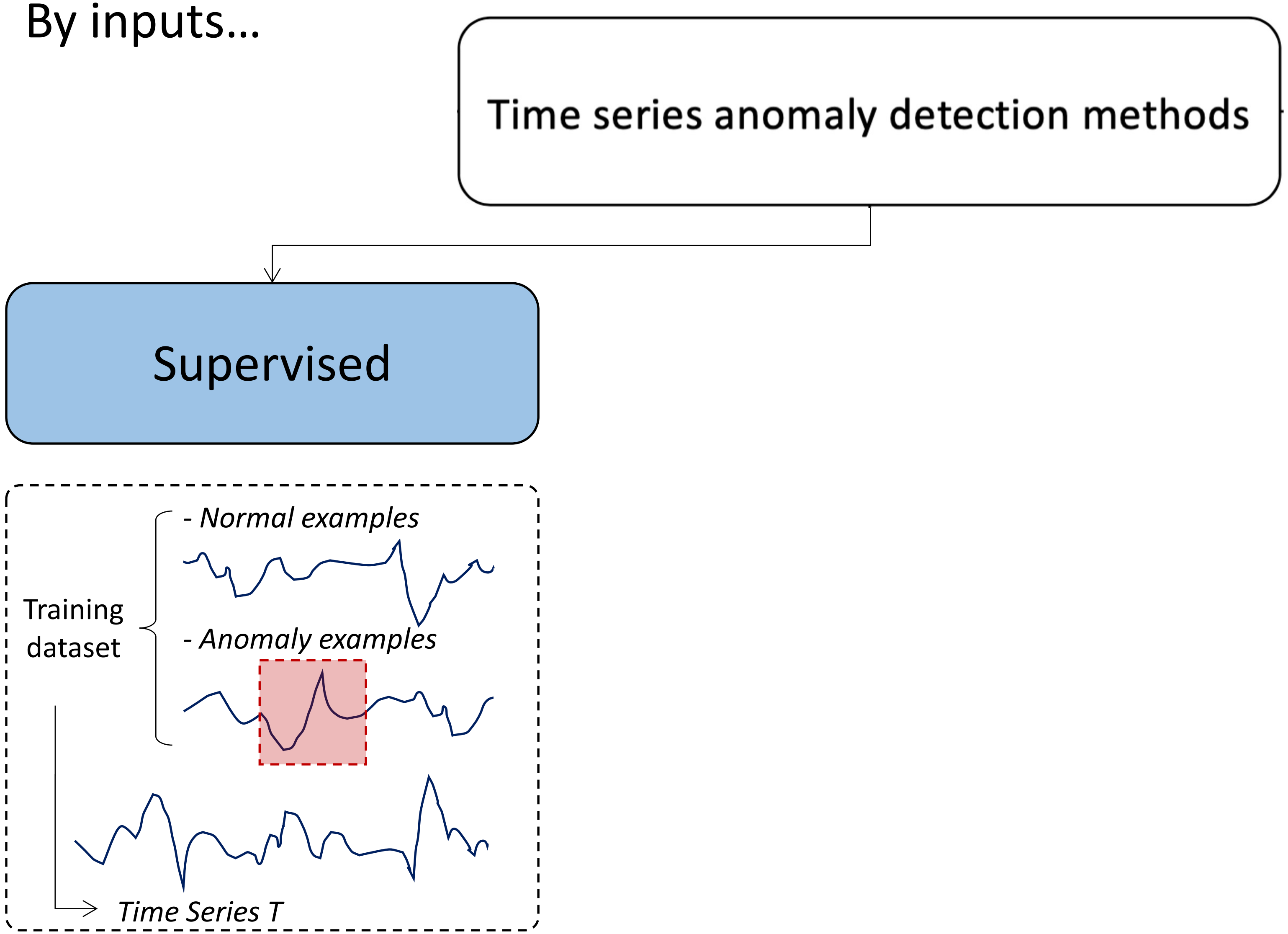
Anomaly Detection methods: *A taxonomy*

By inputs…



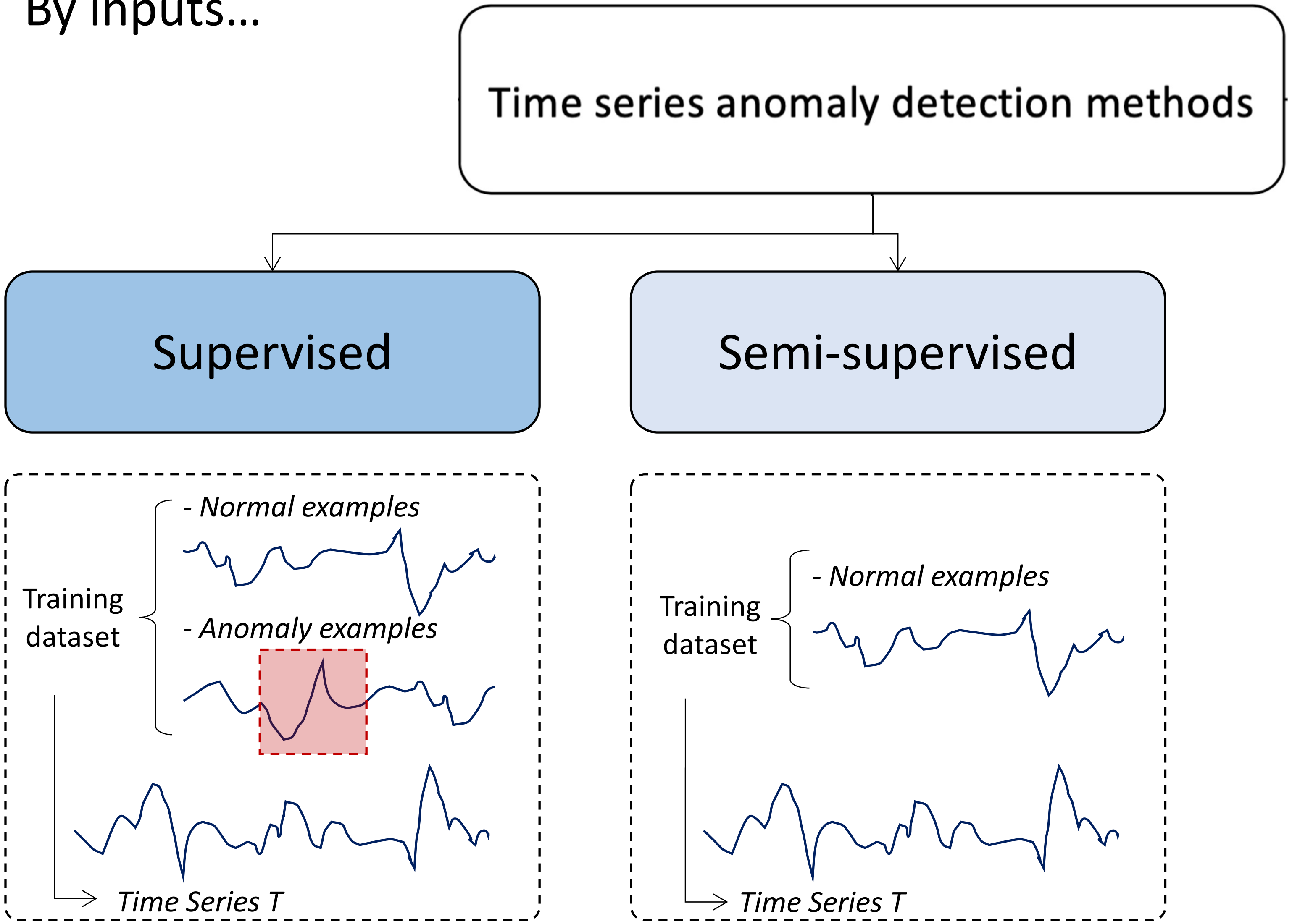
Anomaly Detection methods: *A taxonomy*

By inputs…



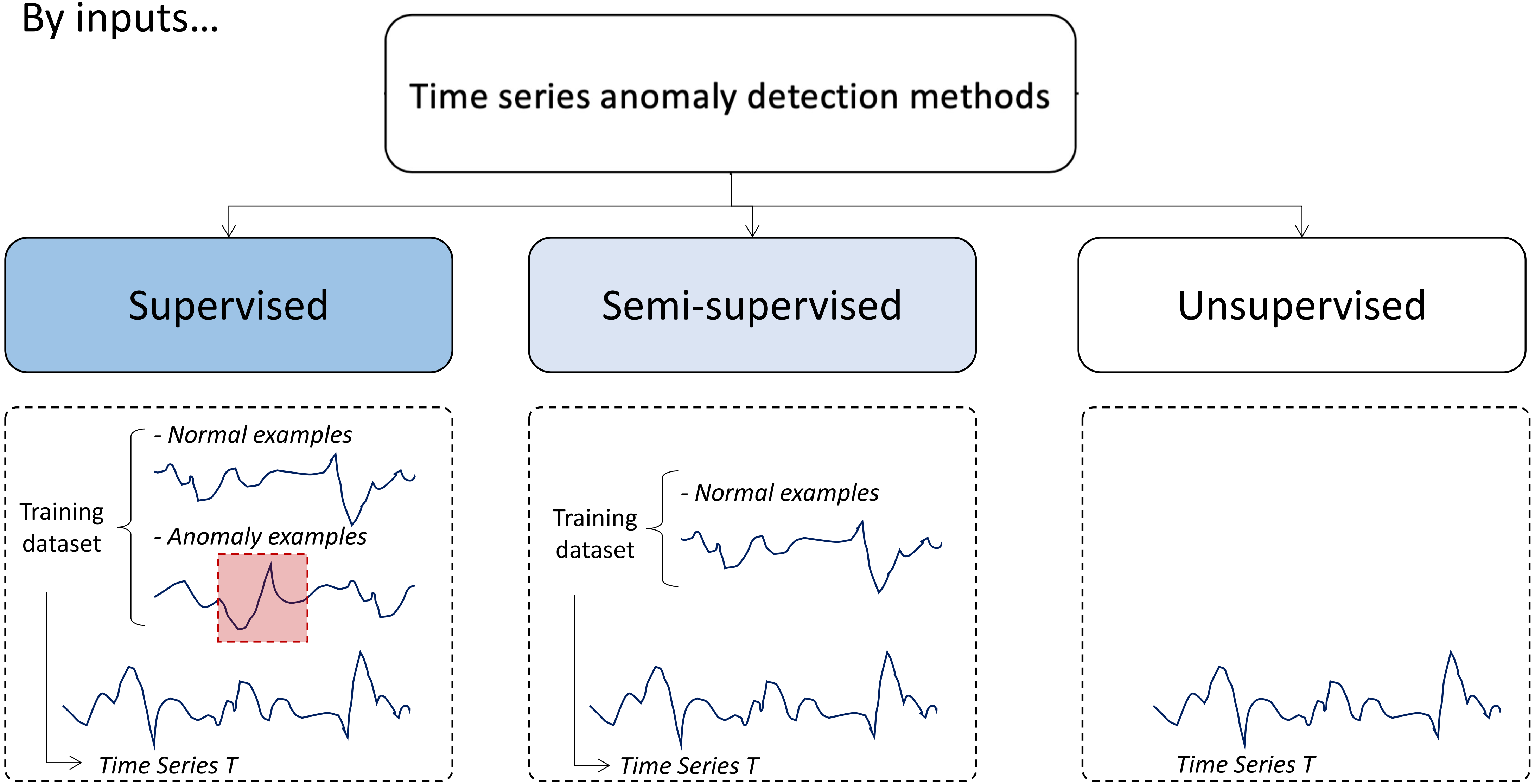
Anomaly Detection methods: *A taxonomy*

By inputs…



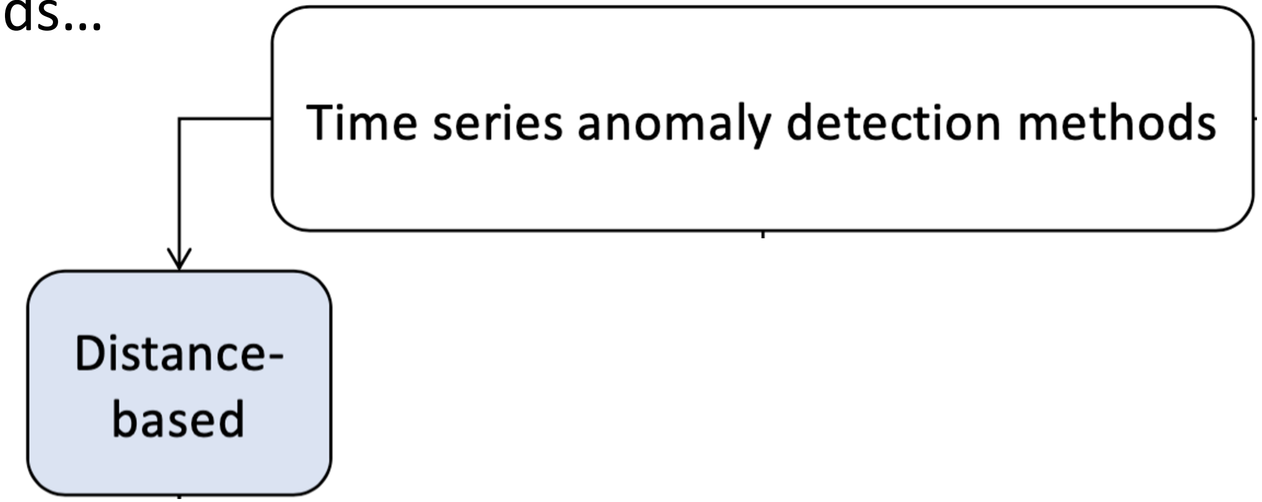
Anomaly Detection methods: *A taxonomy*

By inputs…



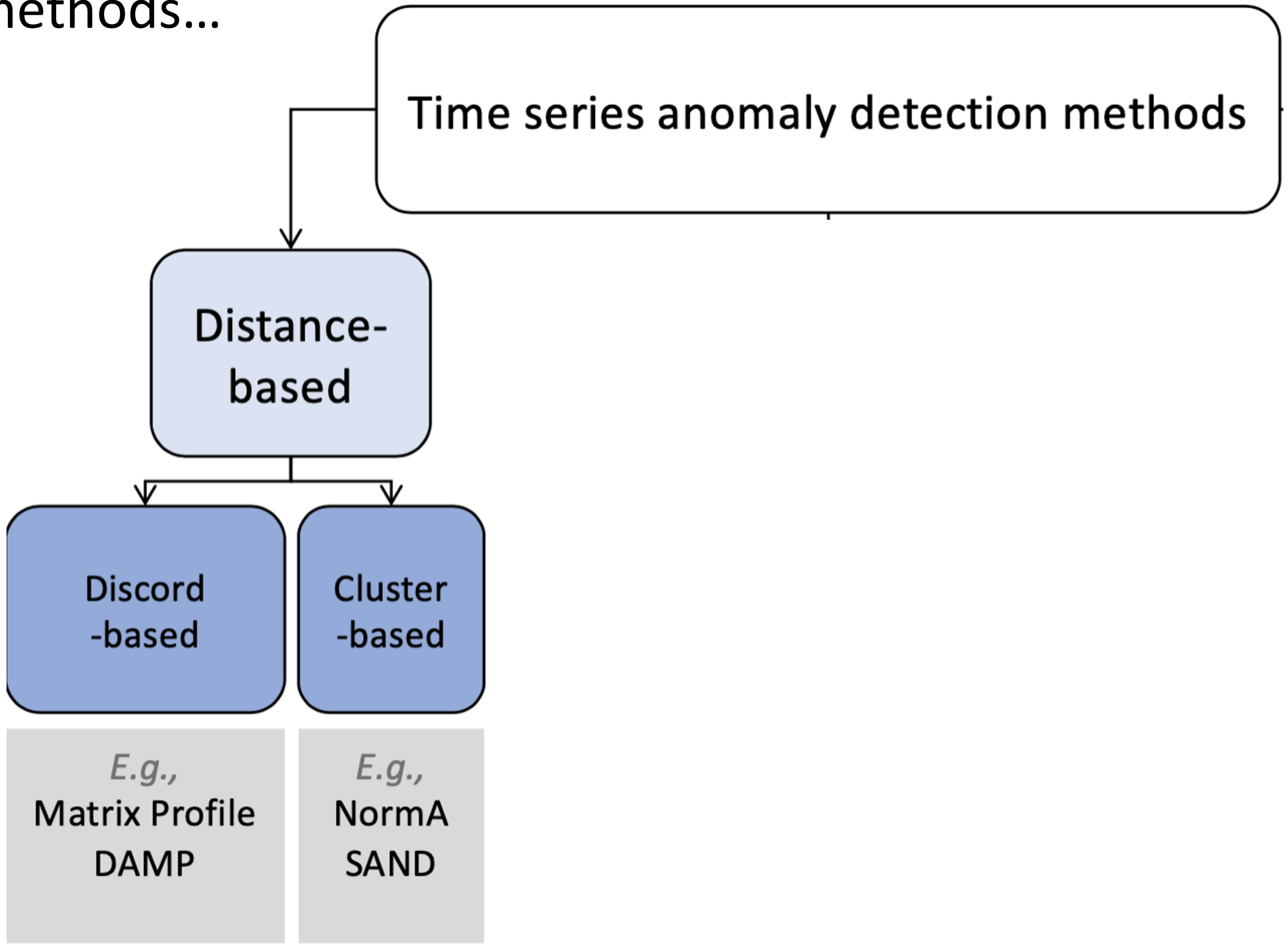
Anomaly Detection methods: *A taxonomy*

By methods…



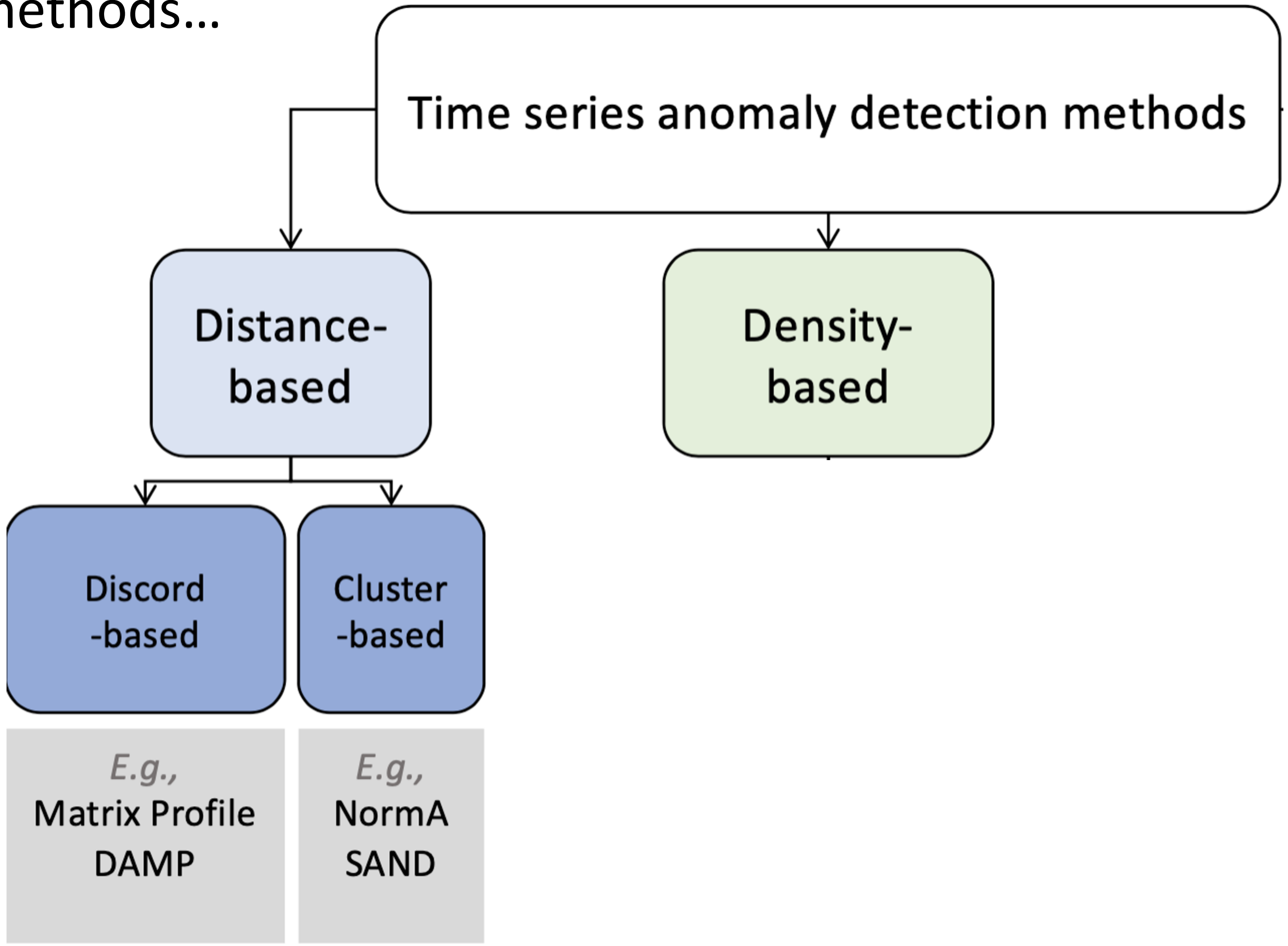
Anomaly Detection methods: *A taxonomy*

By methods…



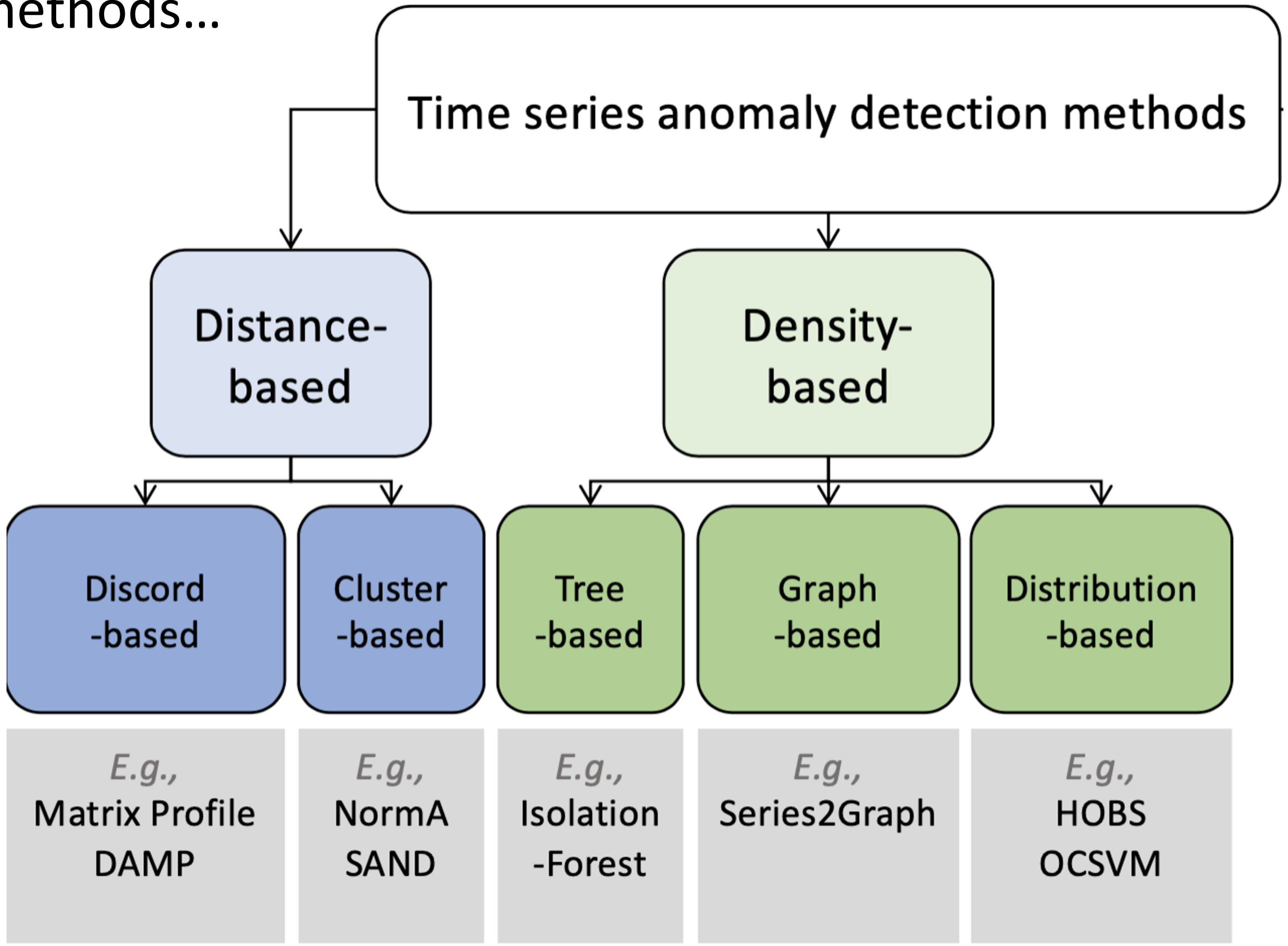
Anomaly Detection methods: *A taxonomy*

By methods…



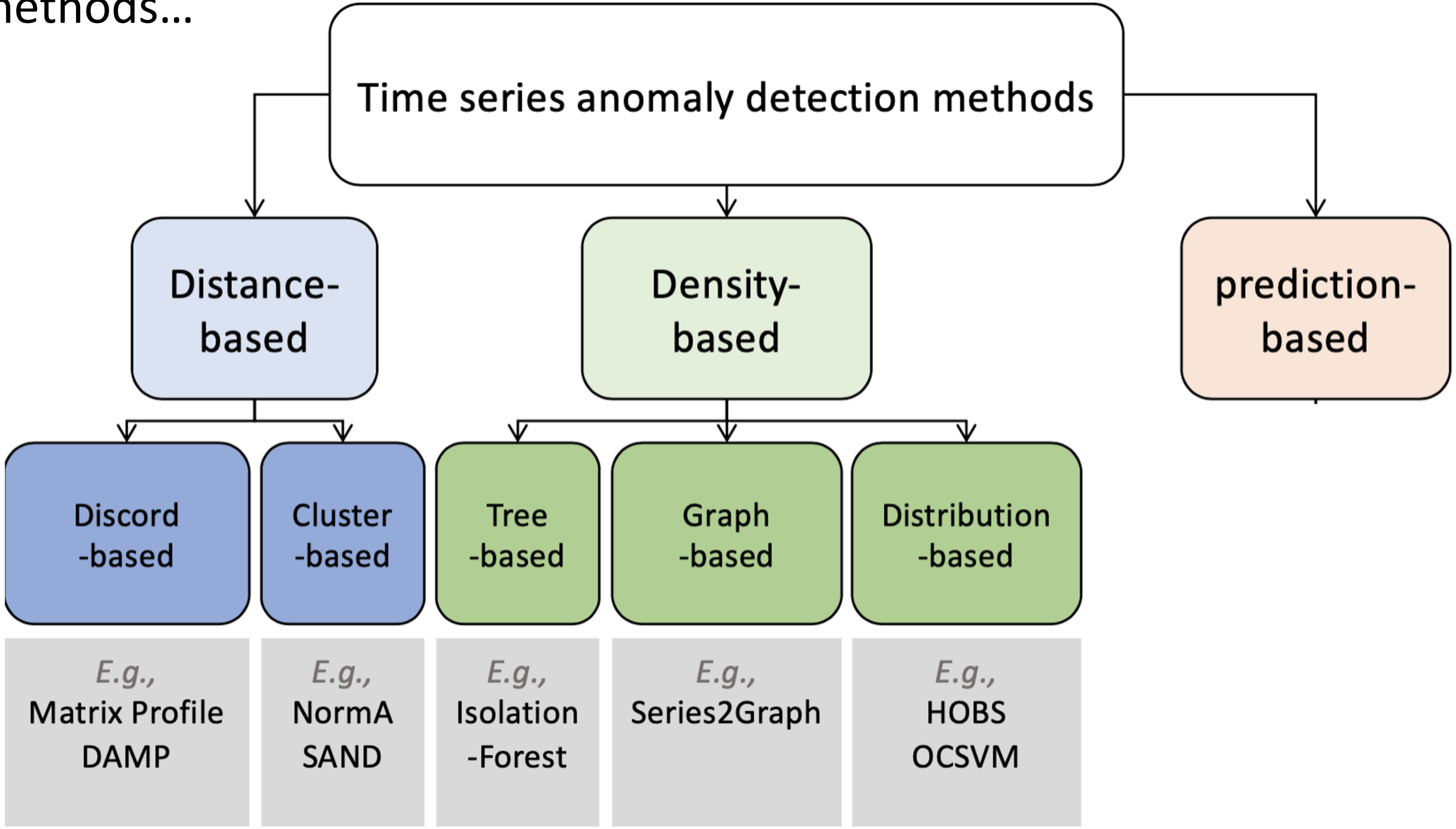
Anomaly Detection methods: *A taxonomy*

By methods…



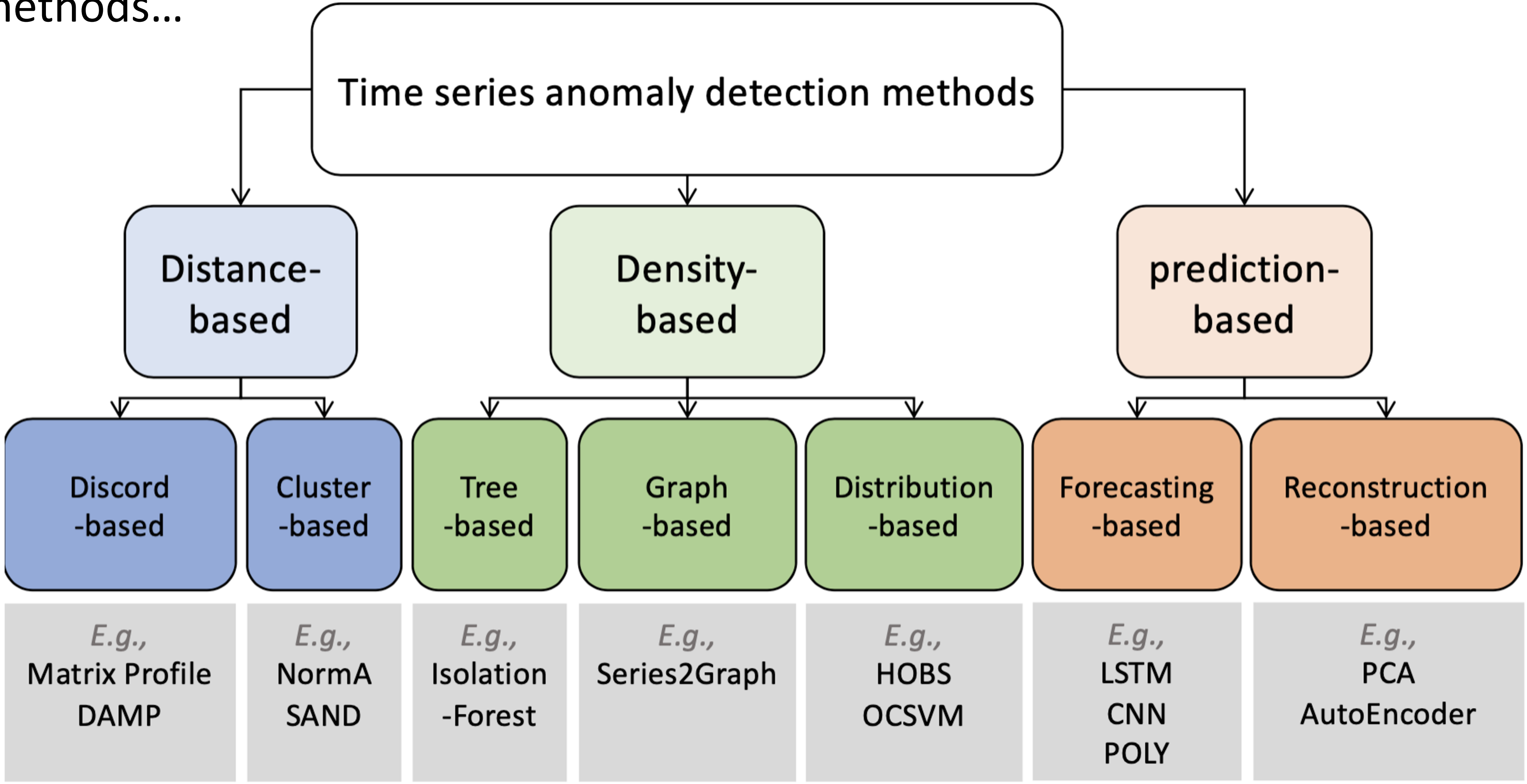
Anomaly Detection methods: *A taxonomy*

By methods…



Anomaly Detection methods: *A taxonomy*

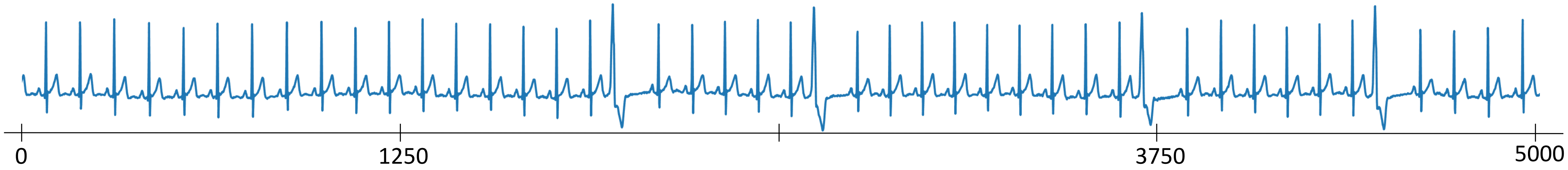
By methods…



Anomaly Detection methods: *Distance-based*

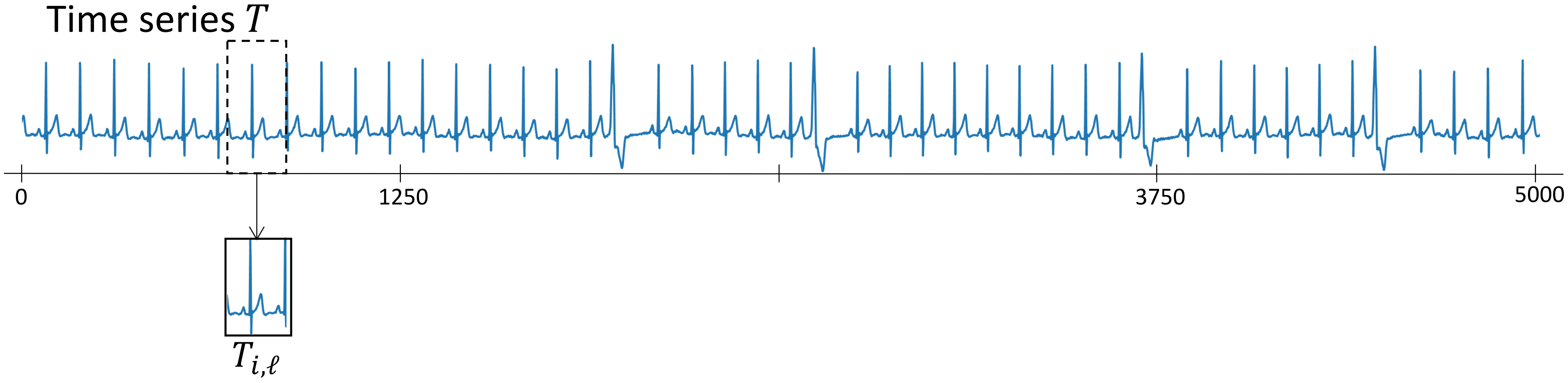
Methods that use distance computation between subsequences (or group of subsequences) to detect anomalies.

Time series T



Anomaly Detection methods: *Distance-based*

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



Anomaly Detection methods: *Distance-based*

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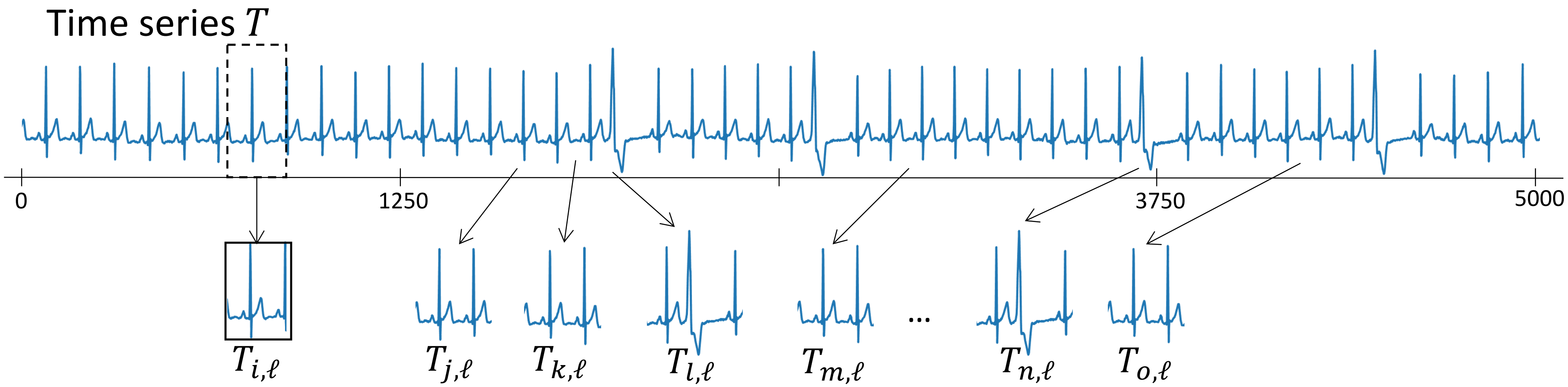
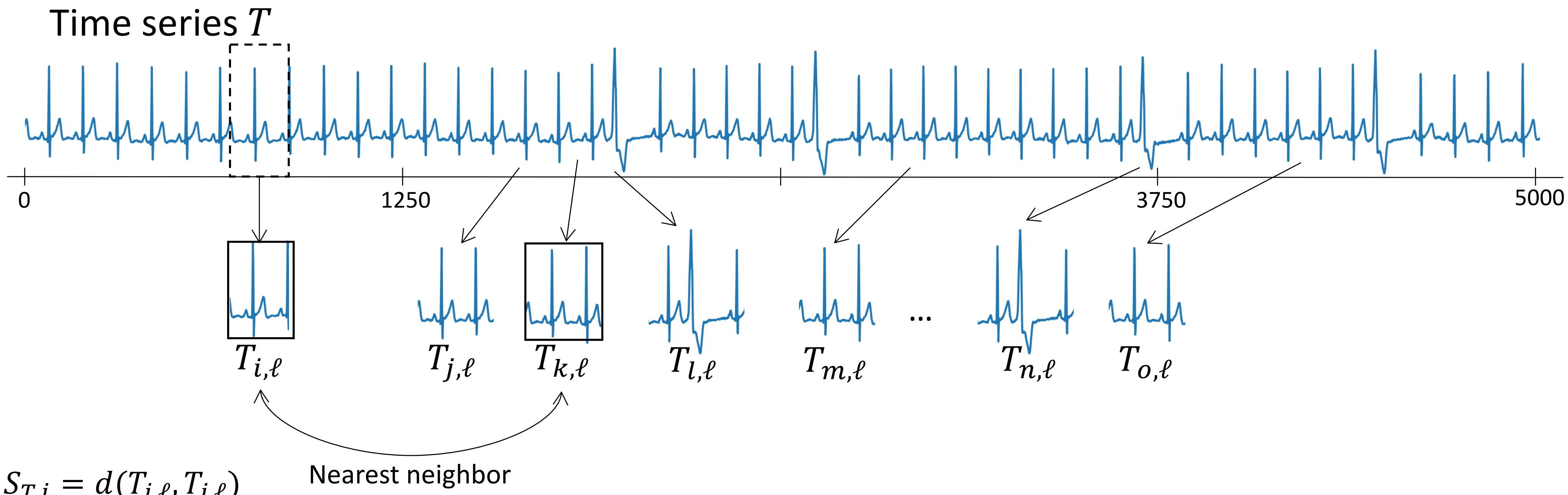


Anomaly Detection methods: *Distance-based*

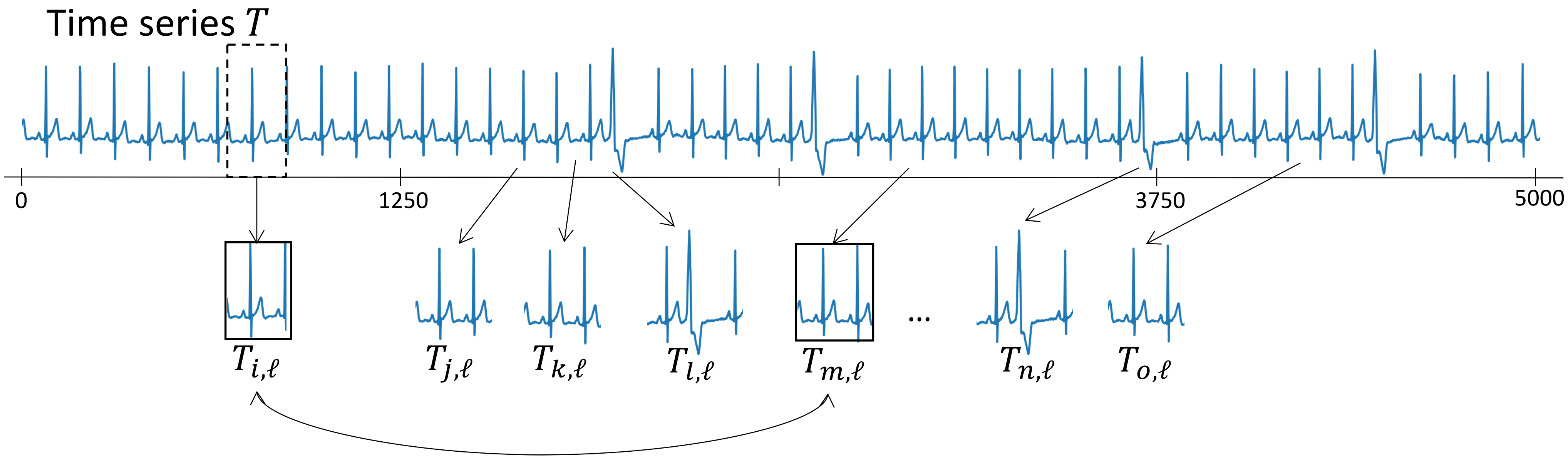
Methods that use distance computation between subsequences (or group of subsequences) to detect anomalies.



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

Anomaly Detection methods: *Distance-based*

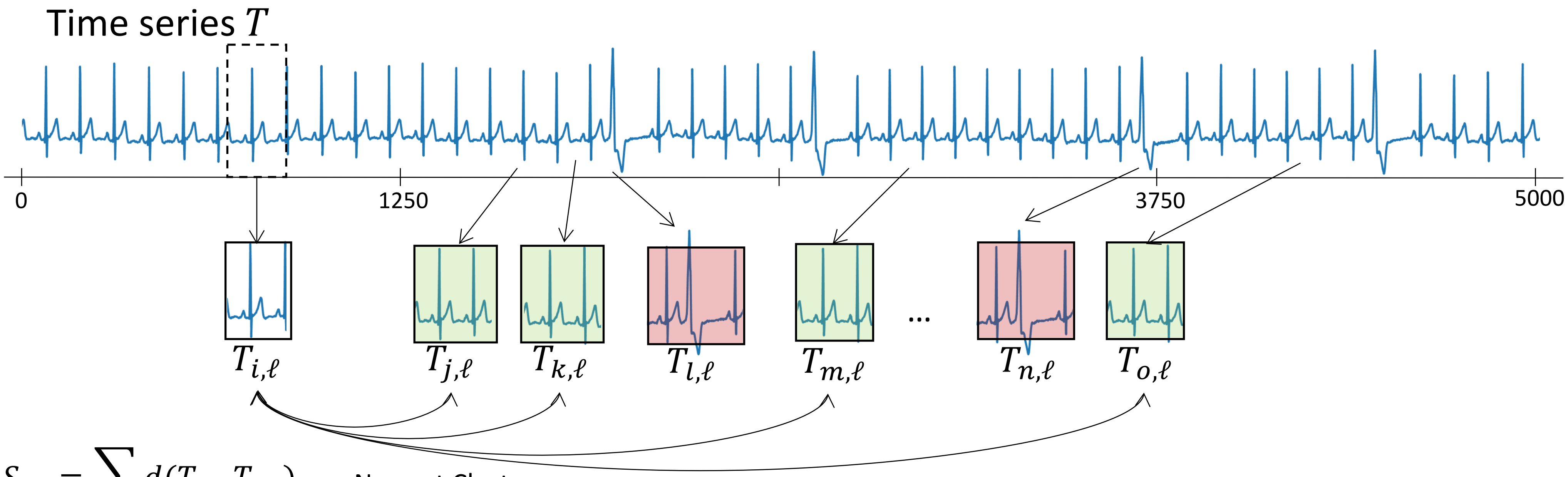
Methods that use distance computation between subsequences (or group of subsequences) to detect anomalies.



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

Anomaly Detection methods: *Distance-based*

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

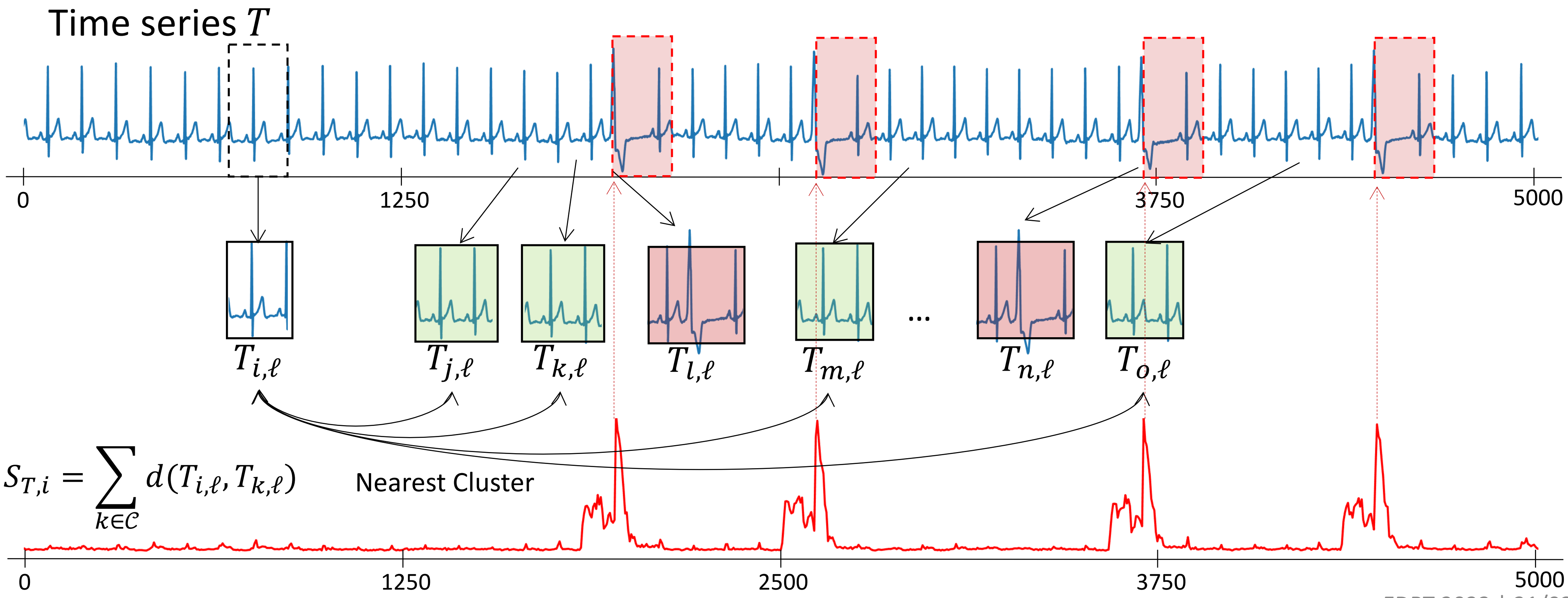


$$S_{T,i} = \sum_{k \in \mathcal{C}} d(T_{i,\ell}, T_{k,\ell})$$

Nearest Cluster

Anomaly Detection methods: *Distance-based*

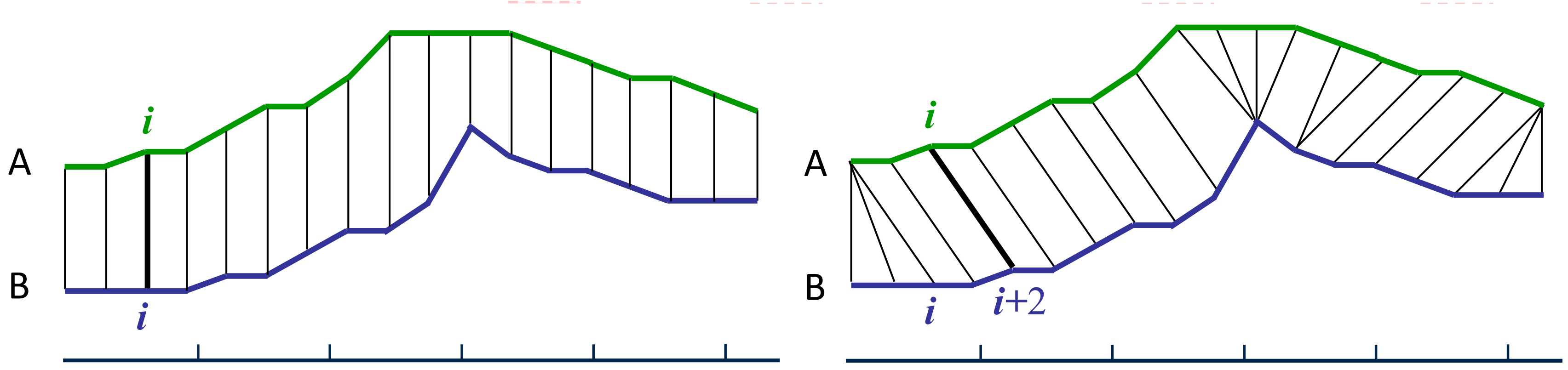
Methods that use distance computation between subsequences (or group of subsequences) to detect anomalies.



Anomaly Detection methods: *Distance-based*

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

Example of distance computation

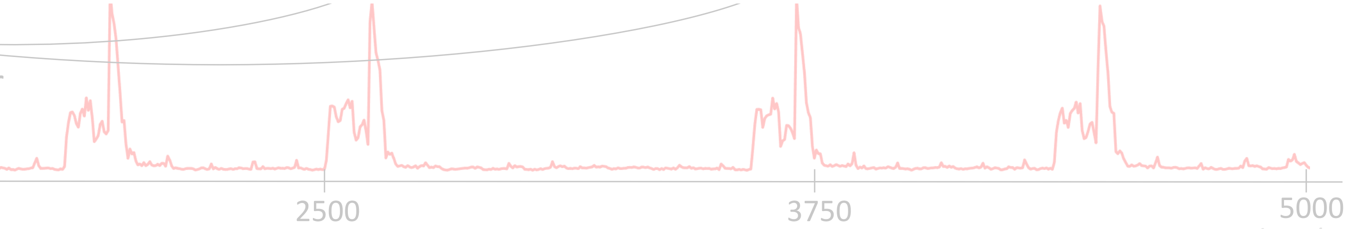


(a) Euclidian Distance

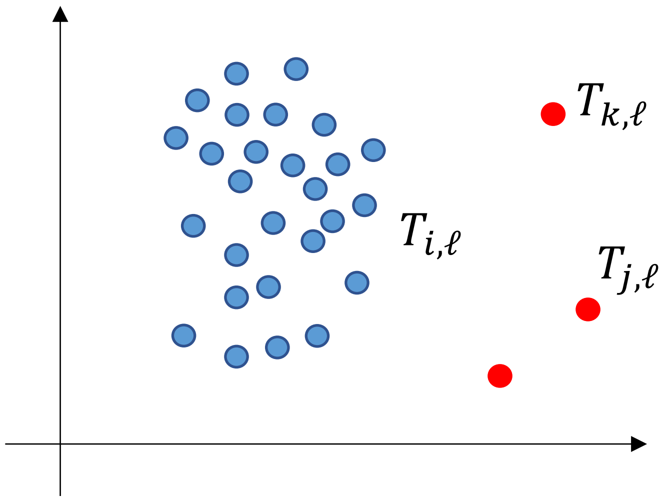
(b) DTW distance

$$S_{T,i} = \sum_{k \in \mathcal{C}} d(T_{i,\ell}, T_{k,\ell})$$

Nearest Cluster



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

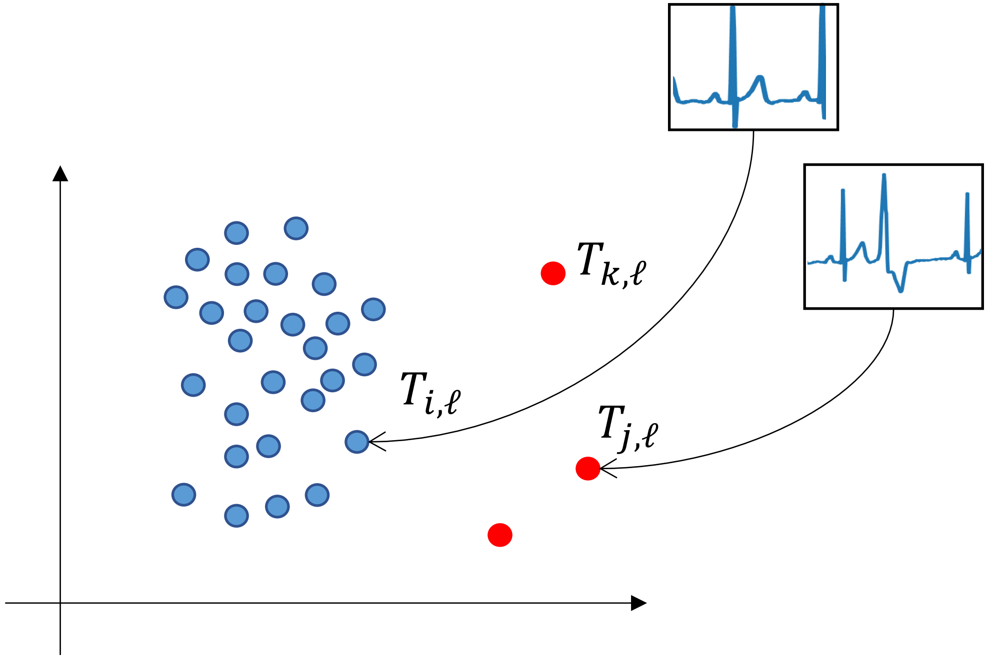
Unsupervised

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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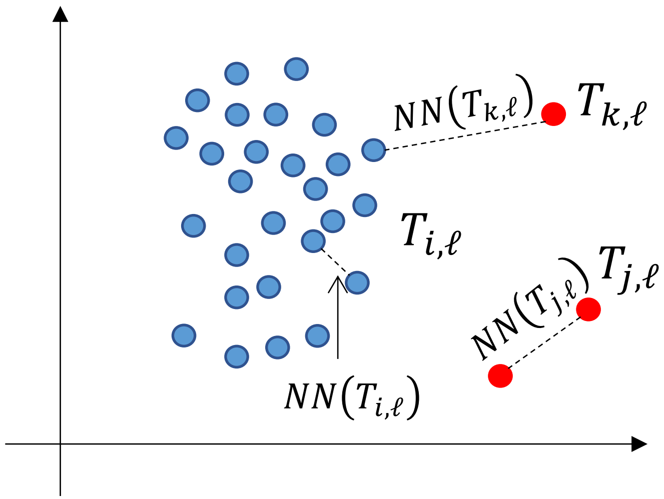

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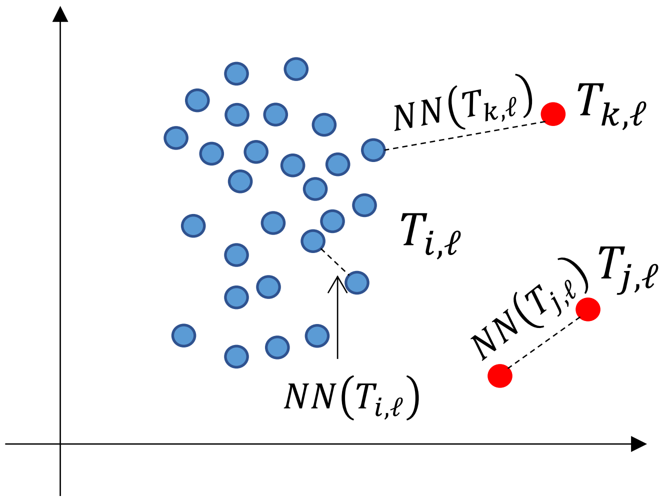
Anomaly Detection methods: *an Example*



The matrix Profile is computed as follows:

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

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

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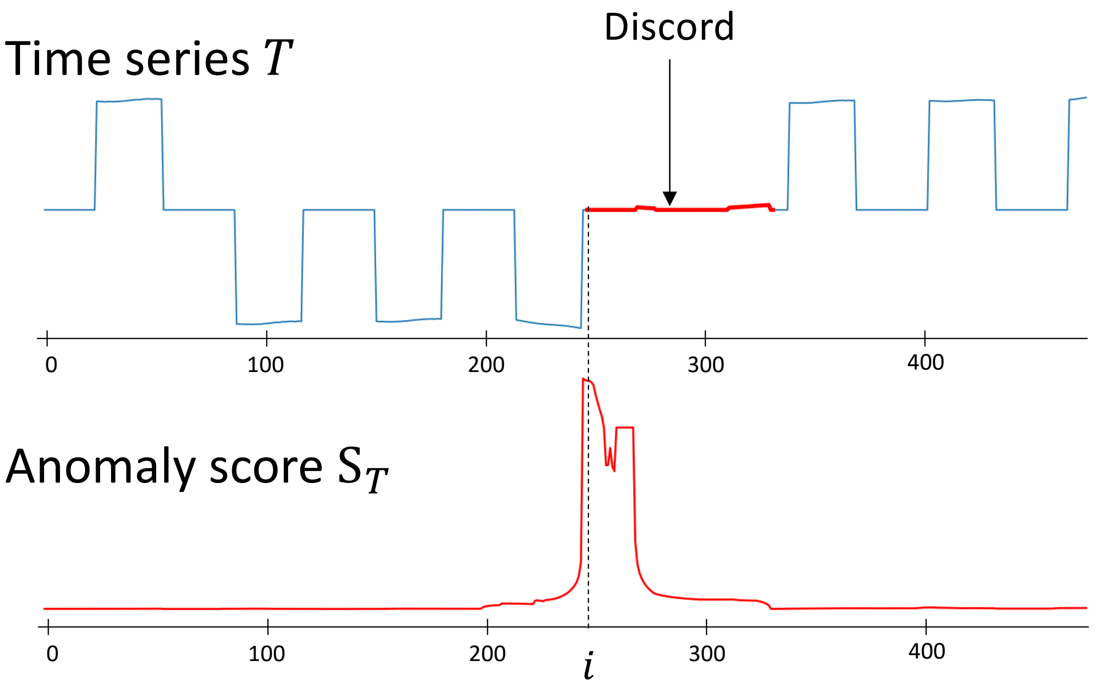
Anomaly Detection methods: *an Example*



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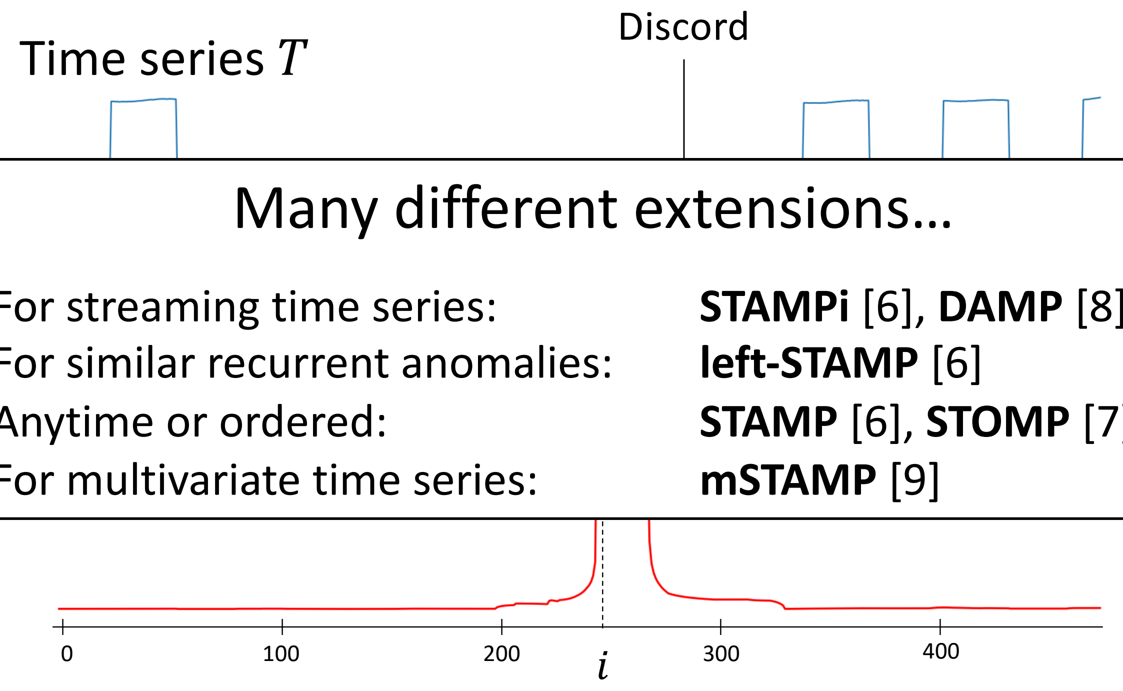
Anomaly Detection methods: *an Example*



Many different extensions…

- For streaming time series: **STAMPi** [6], **DAMP** [8]
- For similar recurrent anomalies: **left-STAMP** [6]
- Anytime or ordered: **STAMP** [6], **STOMP** [7]
- For multivariate time series: **mSTAMP** [9]

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

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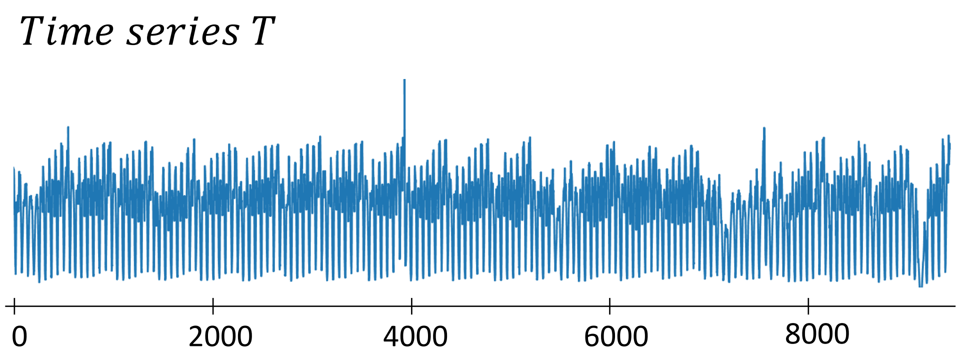
Anomaly Detection methods: *an Example*



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

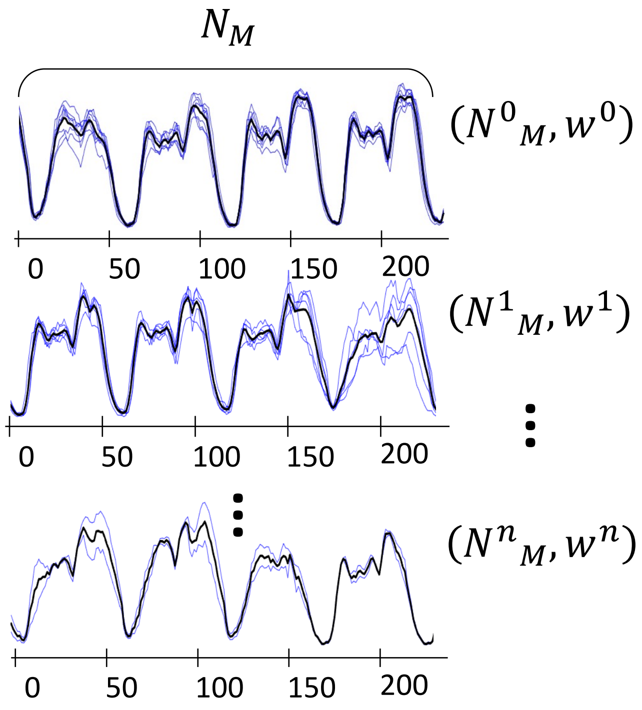
Unsupervised

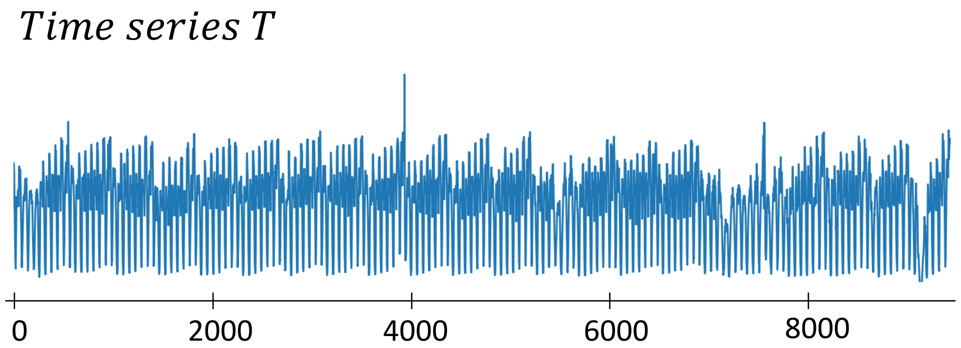
Univariate

sequence

[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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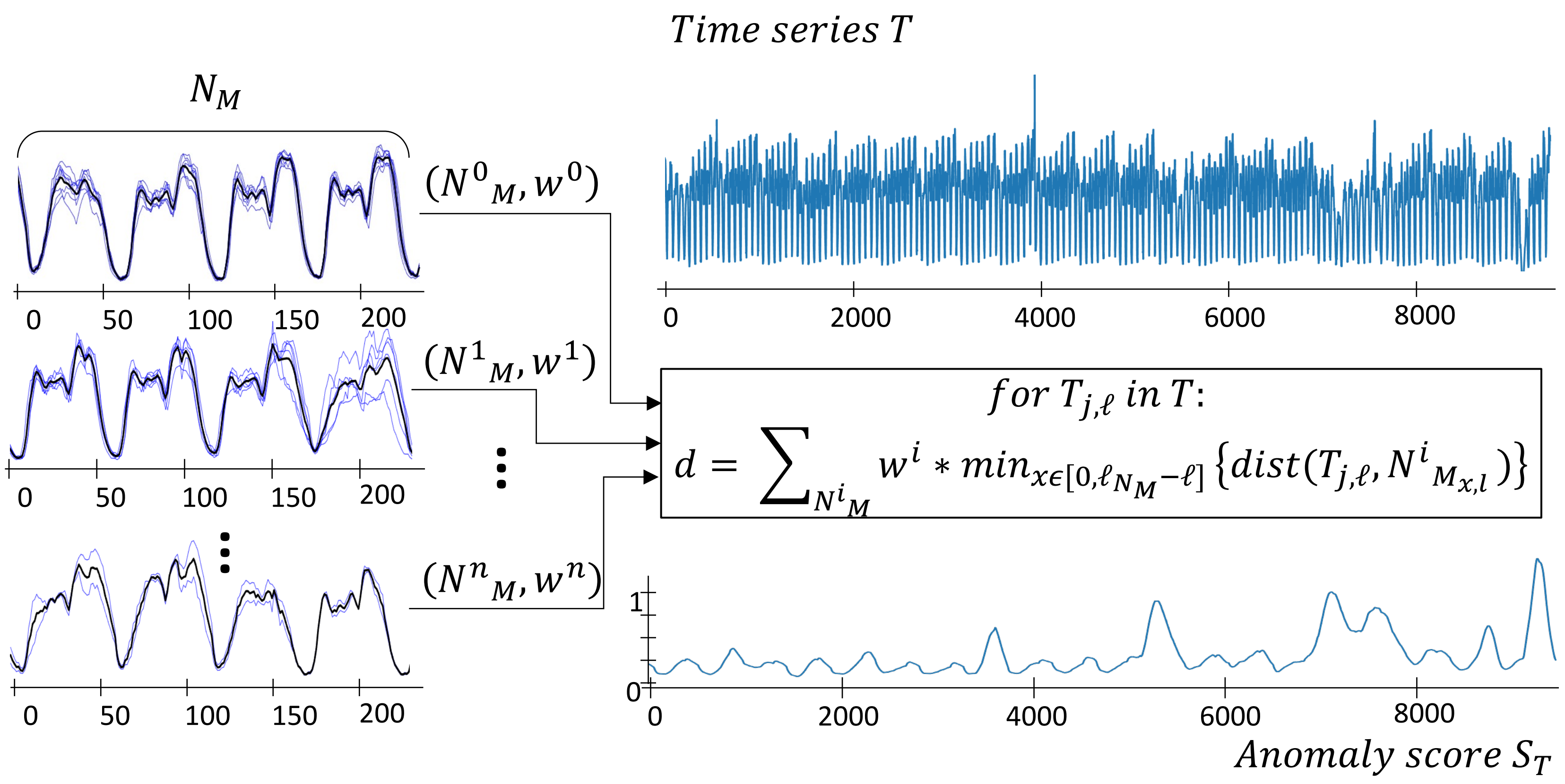
Anomaly Detection methods: *an Example*



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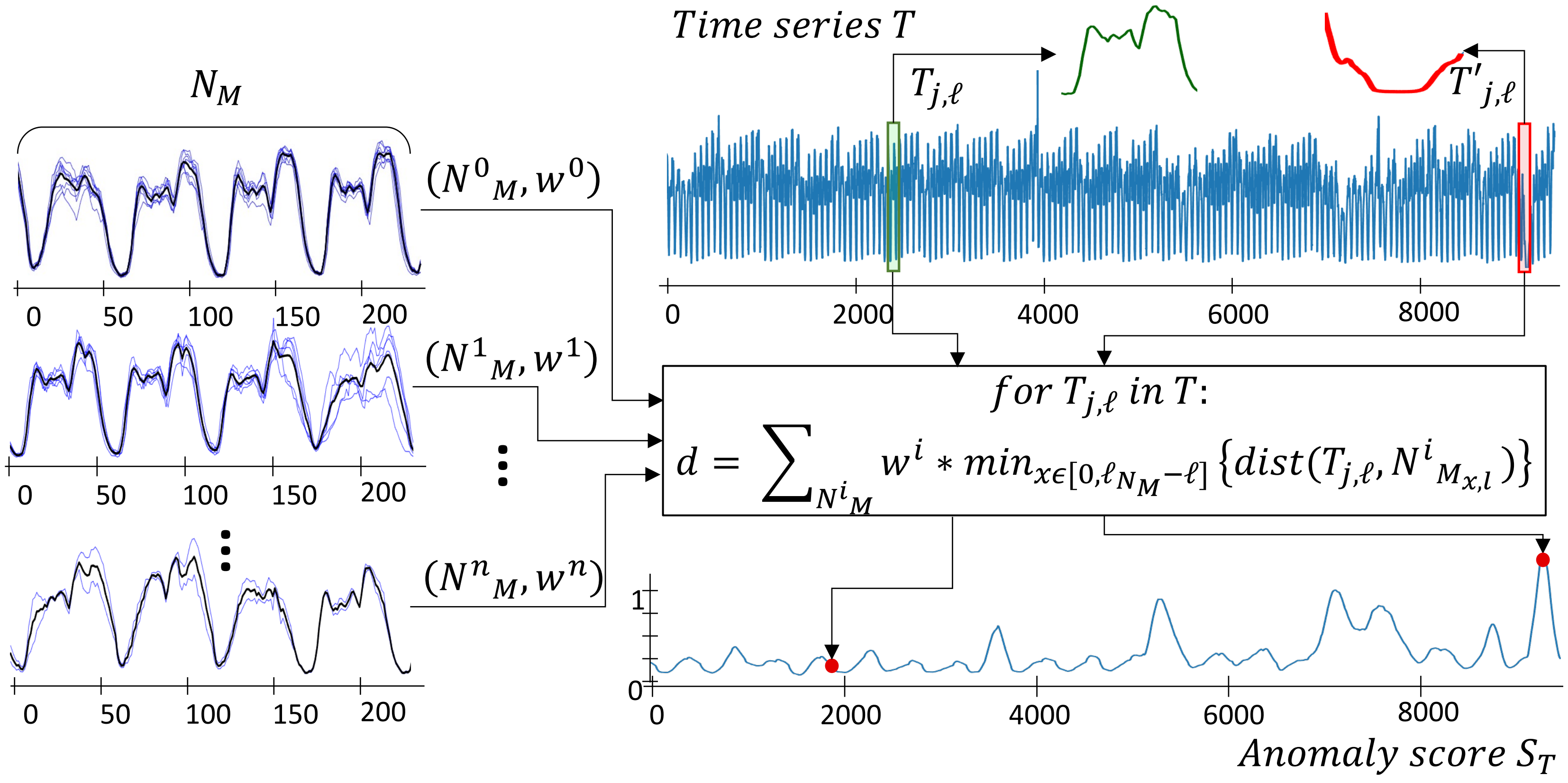
Anomaly Detection methods: *an Example*



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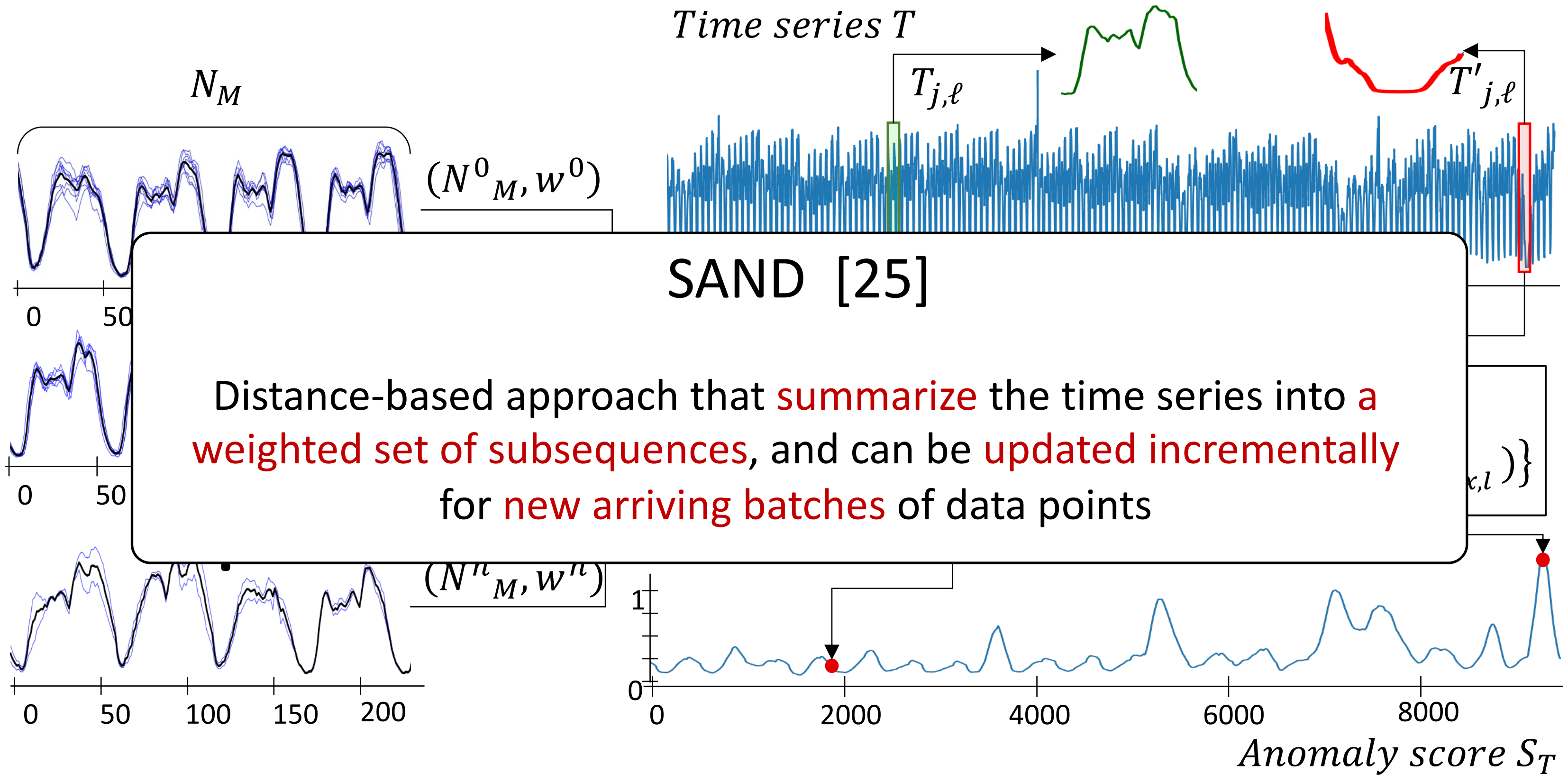
Anomaly Detection methods: *an Example*



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

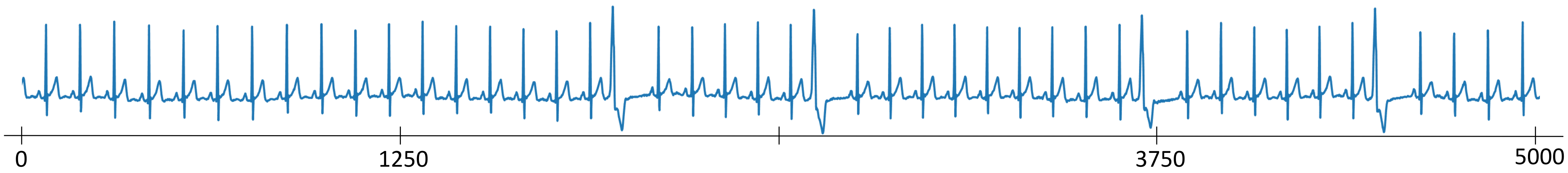
sequence

[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.

Time series T



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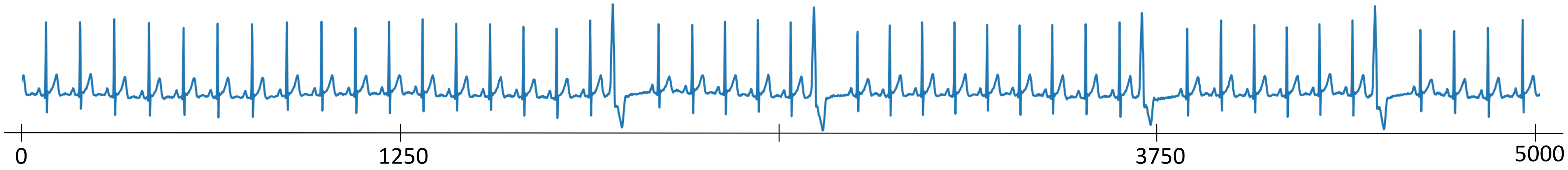
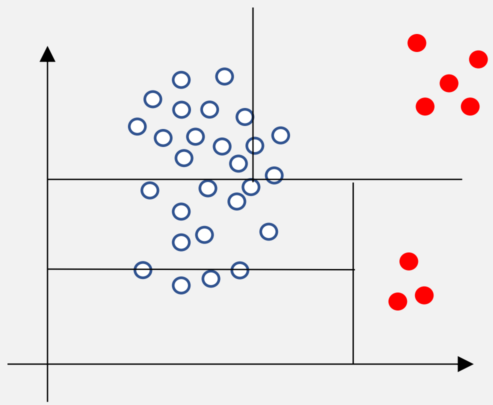


Tree-based approaches [11]



Anomaly Detection methods: *Density-based*

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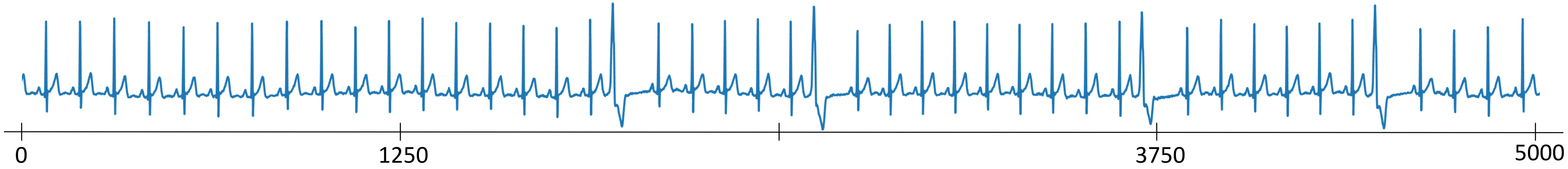
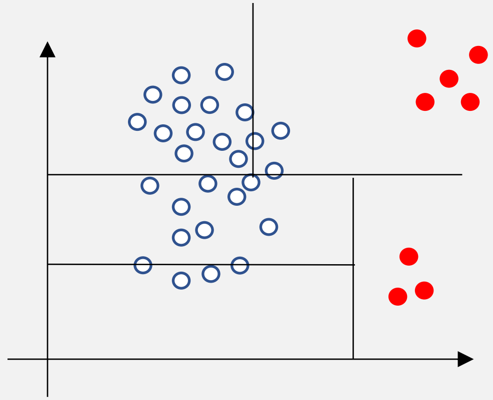
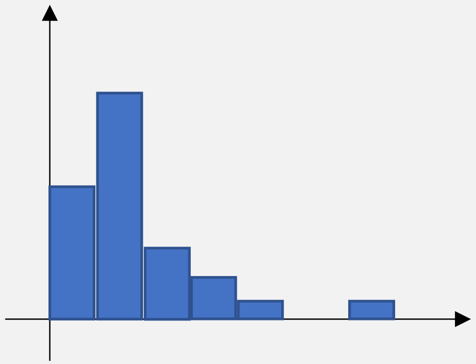
Time series T



Tree-based approaches [11]



Distribution-based Approaches [12]



Anomaly Detection methods: *Density-based*

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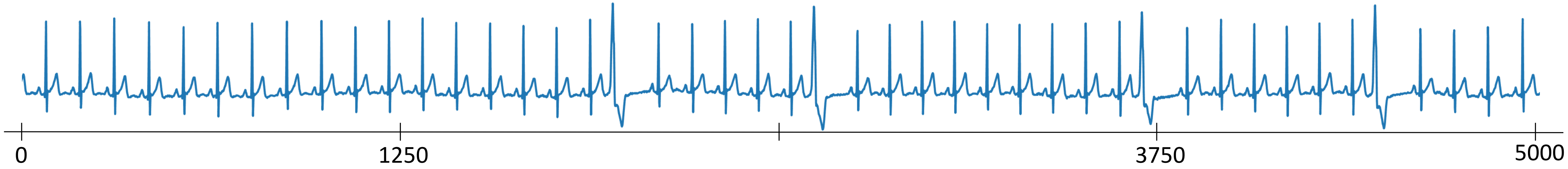

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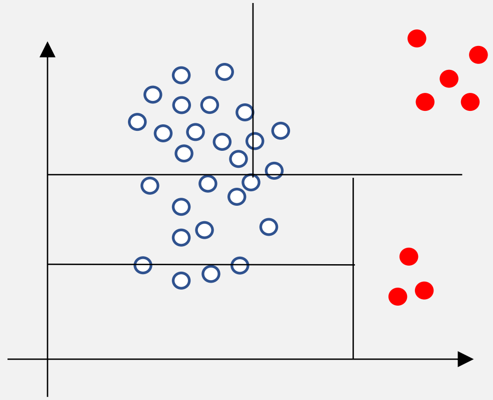

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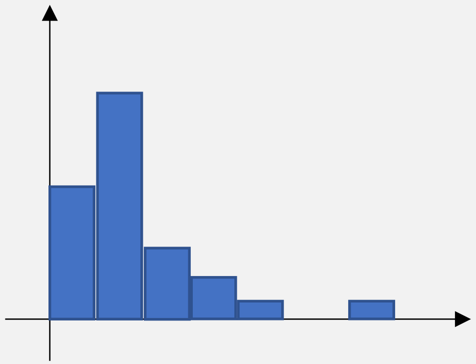
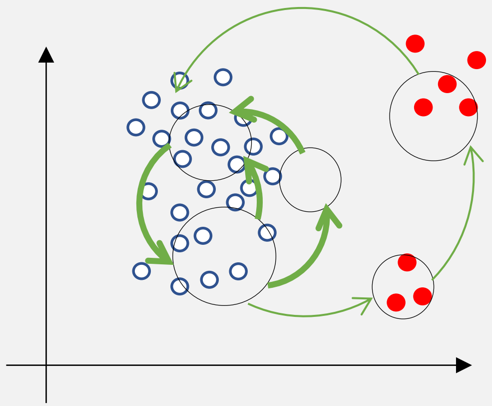


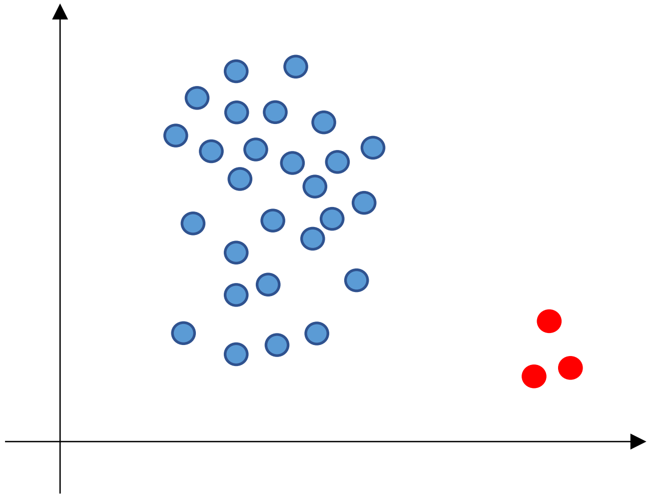
Graph-based approaches [13]



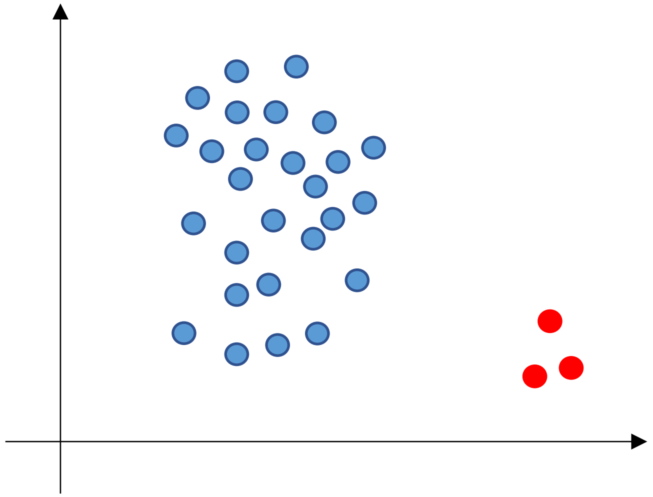
...

Anomaly Detection methods: *an Example*

0 splits



0 splits



Isolation Forest [11]

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

Unsupervised

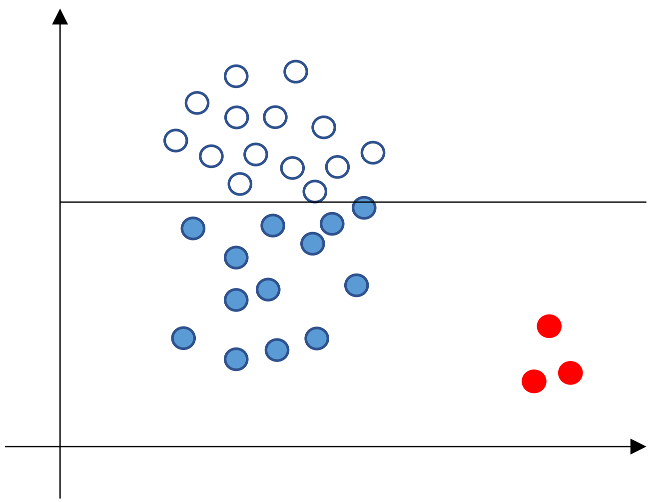
Univariate/Multivariate

Point/sequence

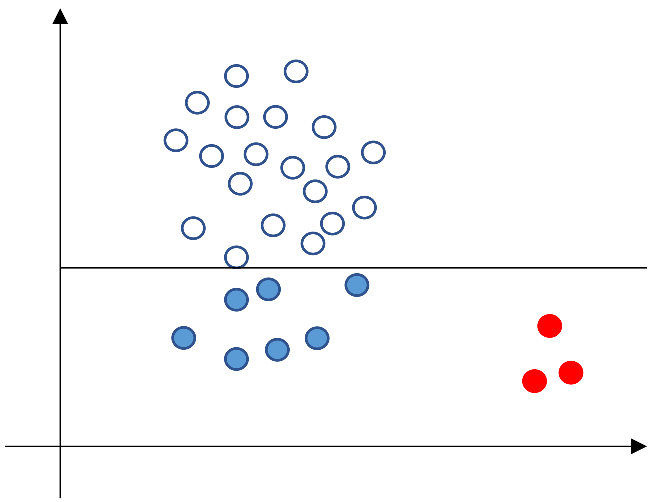
[11] F. T. Liu, K. M. Ting and Z. -H. Zhou, "Isolation Forest," 2008 Eighth IEEE International Conference on Data Mining, Pisa, Italy, 2008, pp. 413-422

Anomaly Detection methods: *an Example*

1 splits



1 splits



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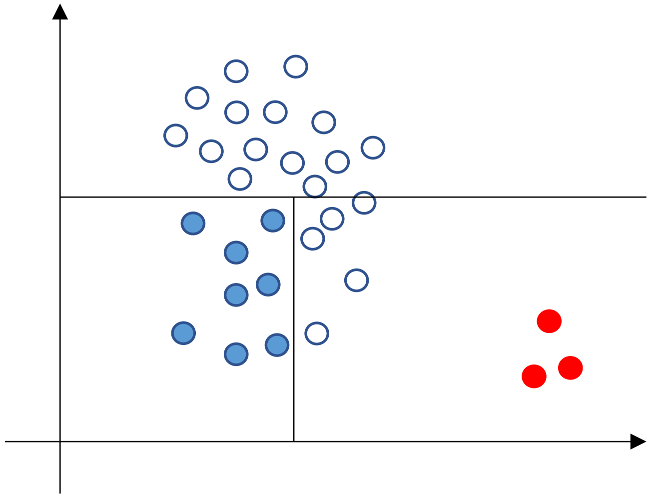
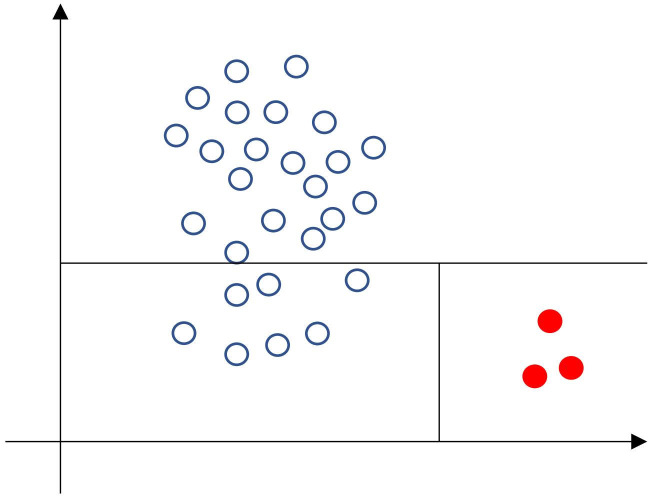
Anomaly Detection methods: *an Example*

2 splits



2 splits



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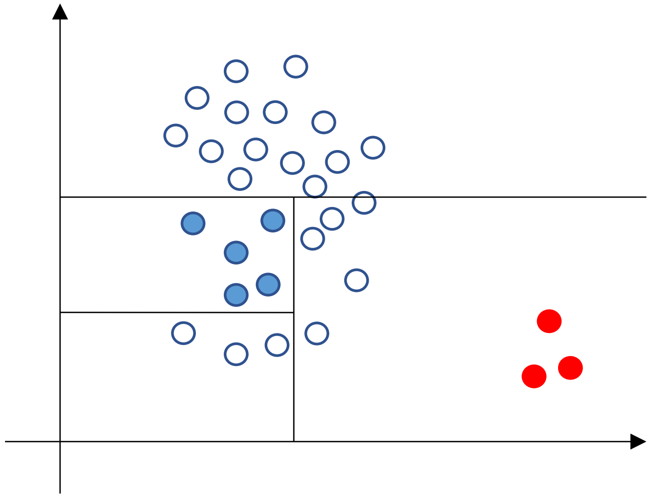
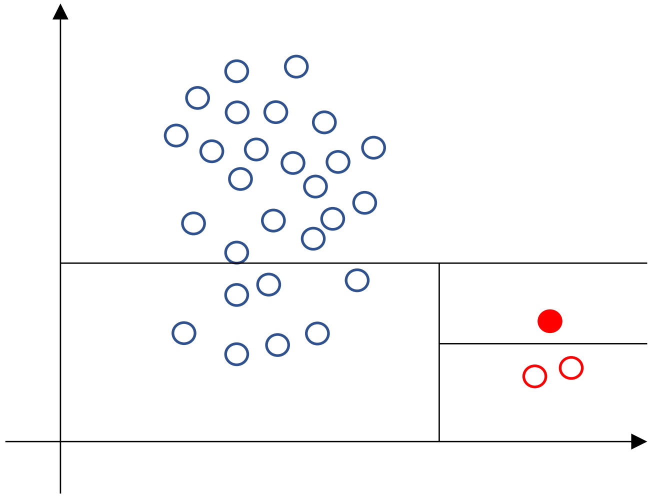
Anomaly Detection methods: *an Example*

3 splits



3 splits



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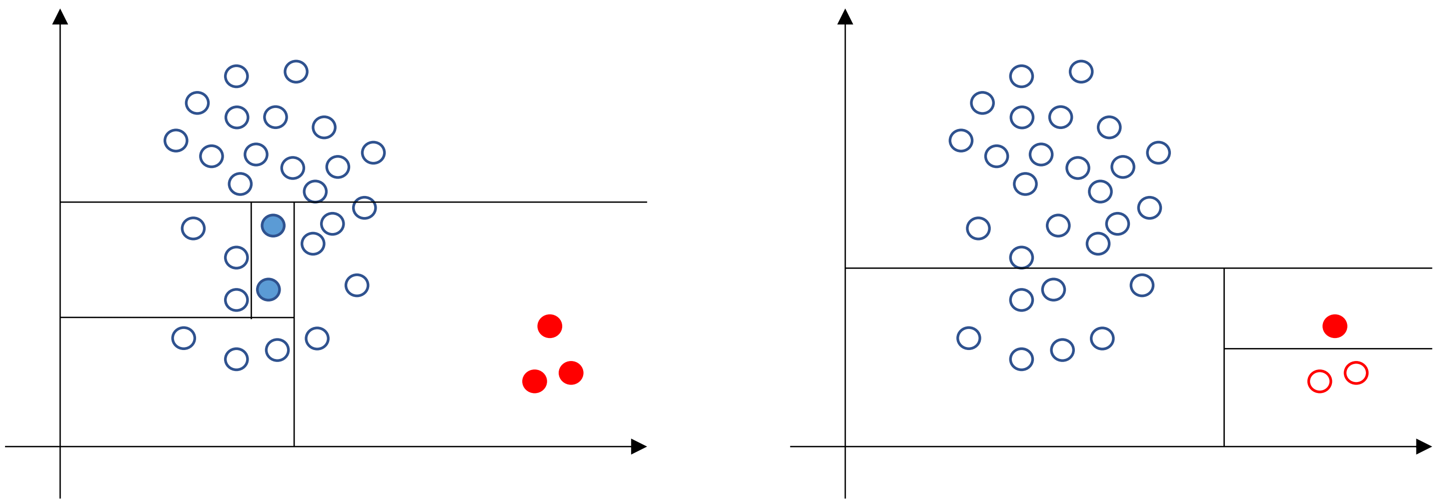
Anomaly Detection methods: *an Example*

4 splits 3 splits



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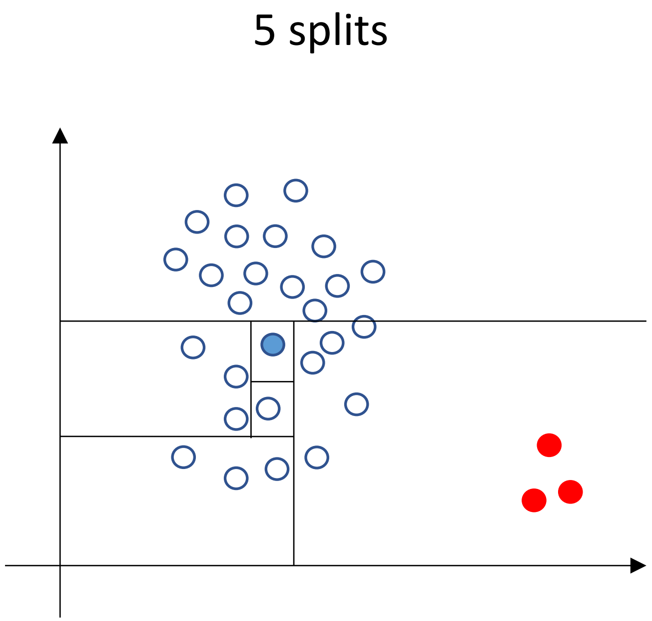

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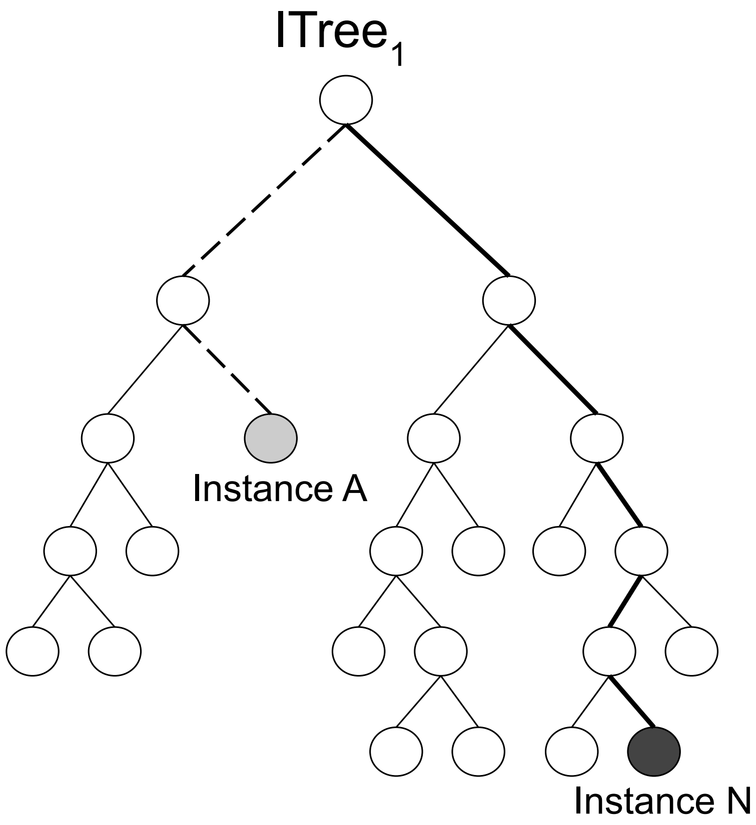

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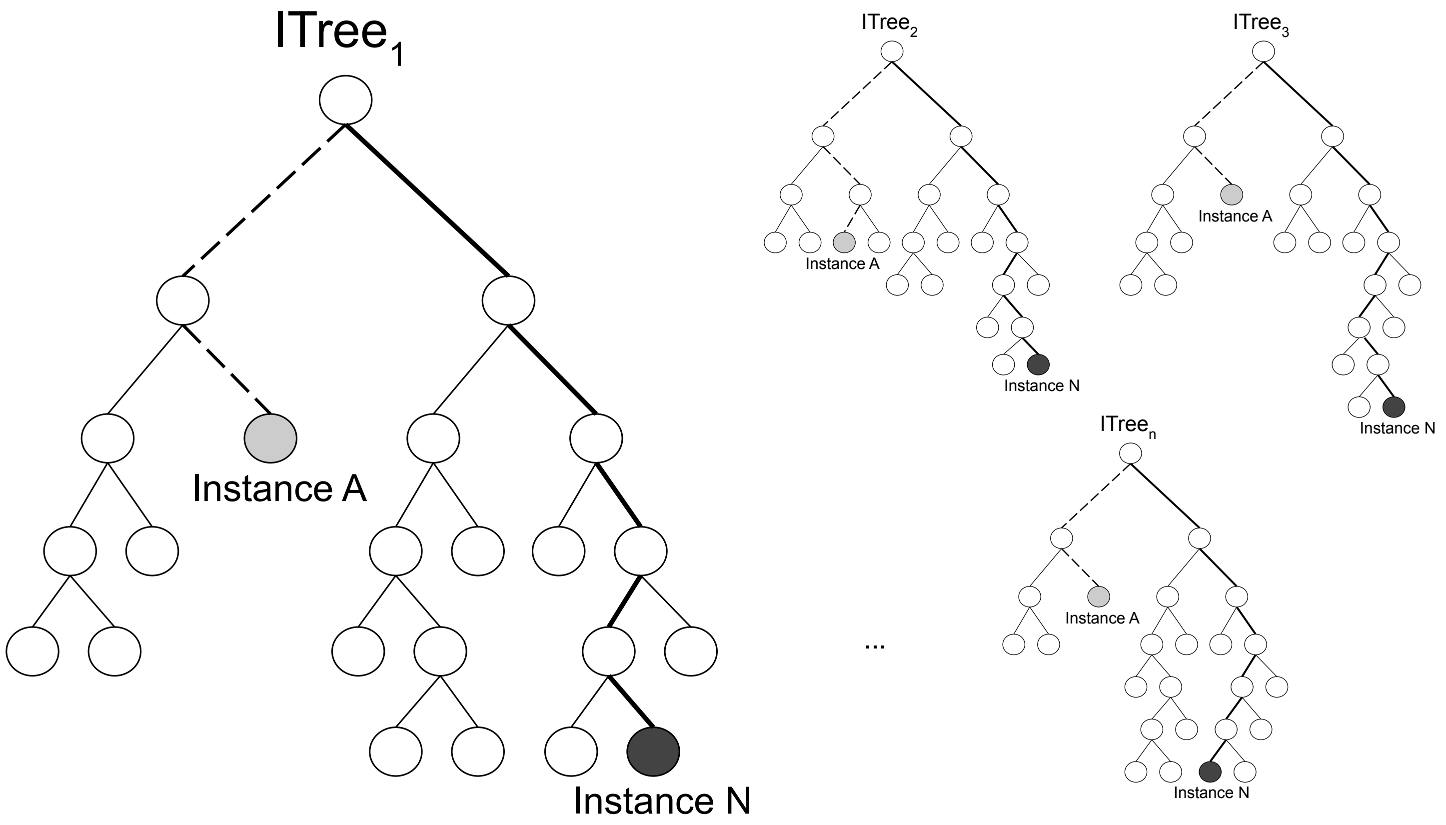

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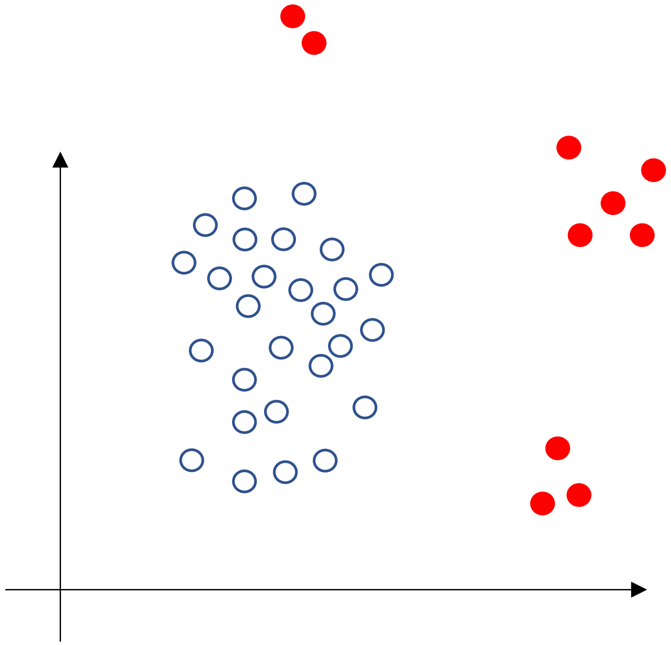


Series2Graph [13]

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

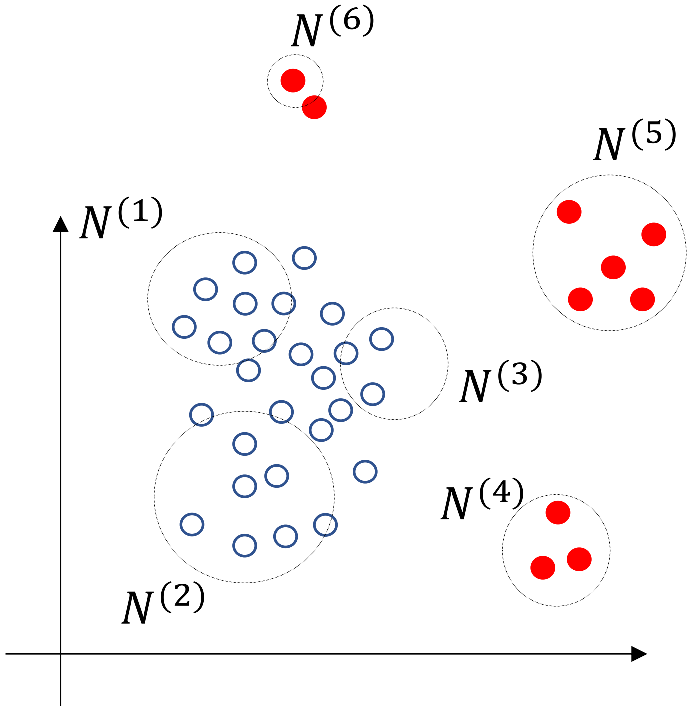
Unsupervised

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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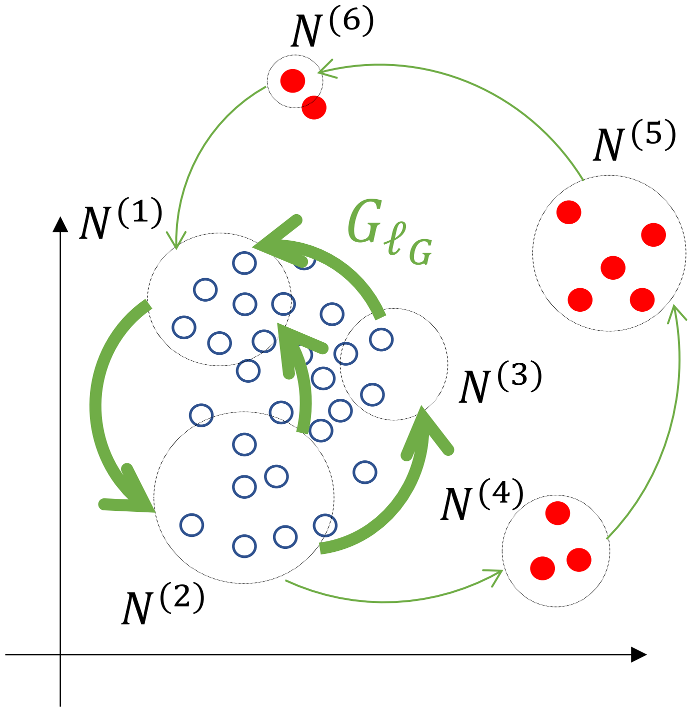

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Each **edge** is associated to a weight w that corresponds to the number of times a subsequence move from one node to another.

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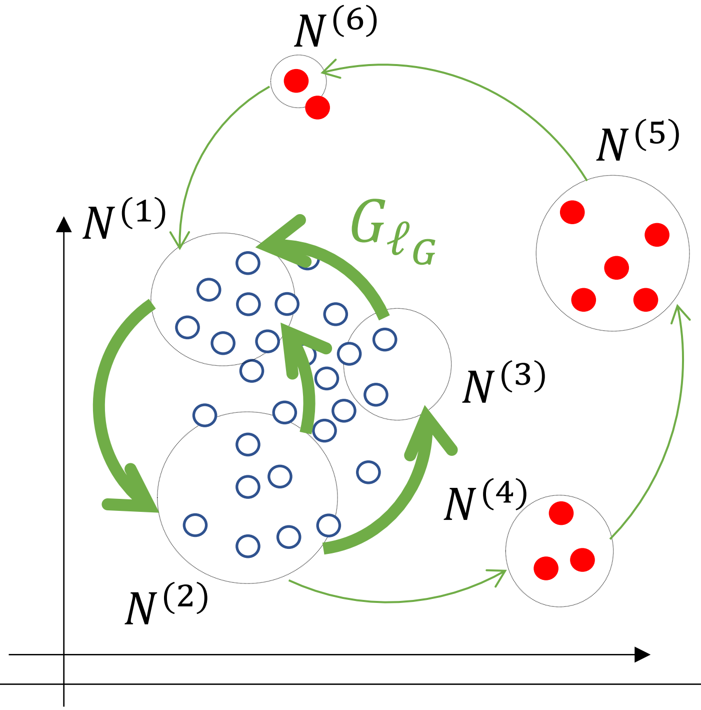

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Each **edge** is associated to a weight w that corresponds to the number of times a subsequence move from one node to another.

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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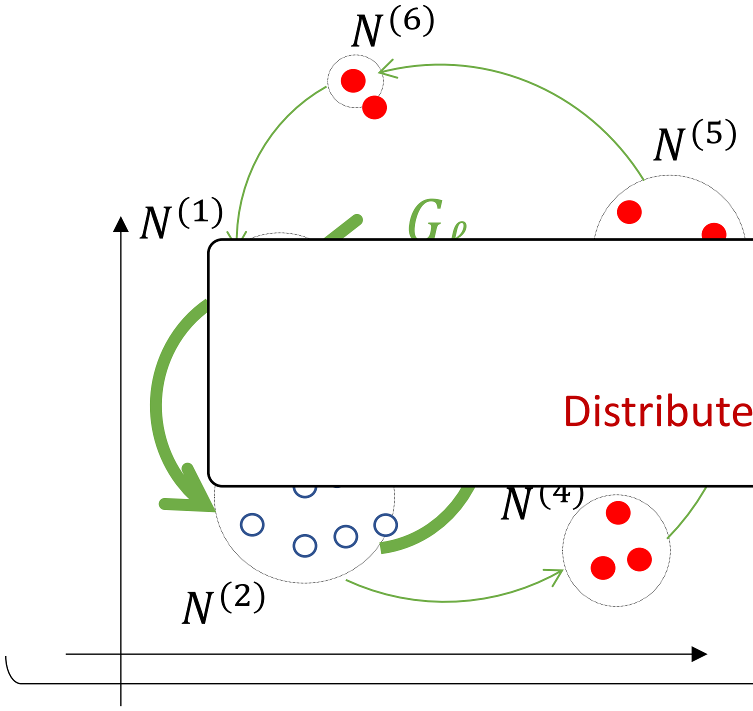

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DADS [26]

Distributed version of Series2Graph

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Series2Graph [13]

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Unsupervised

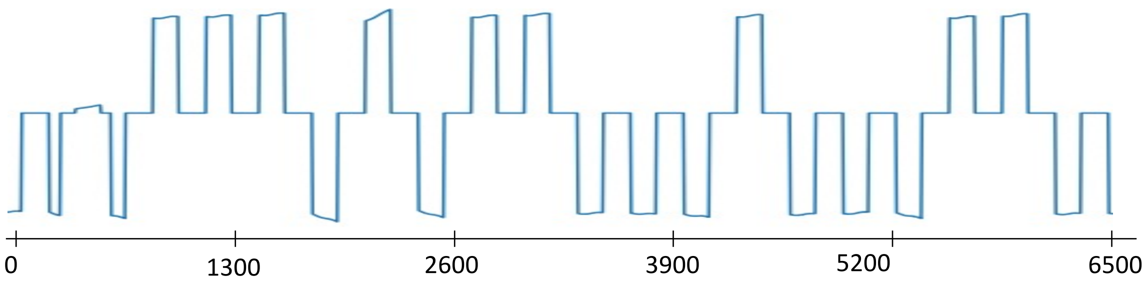
Univariate

subsequence

[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*

Snippet of SED time series



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Univariate

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Anomaly Detection methods: *an Example*

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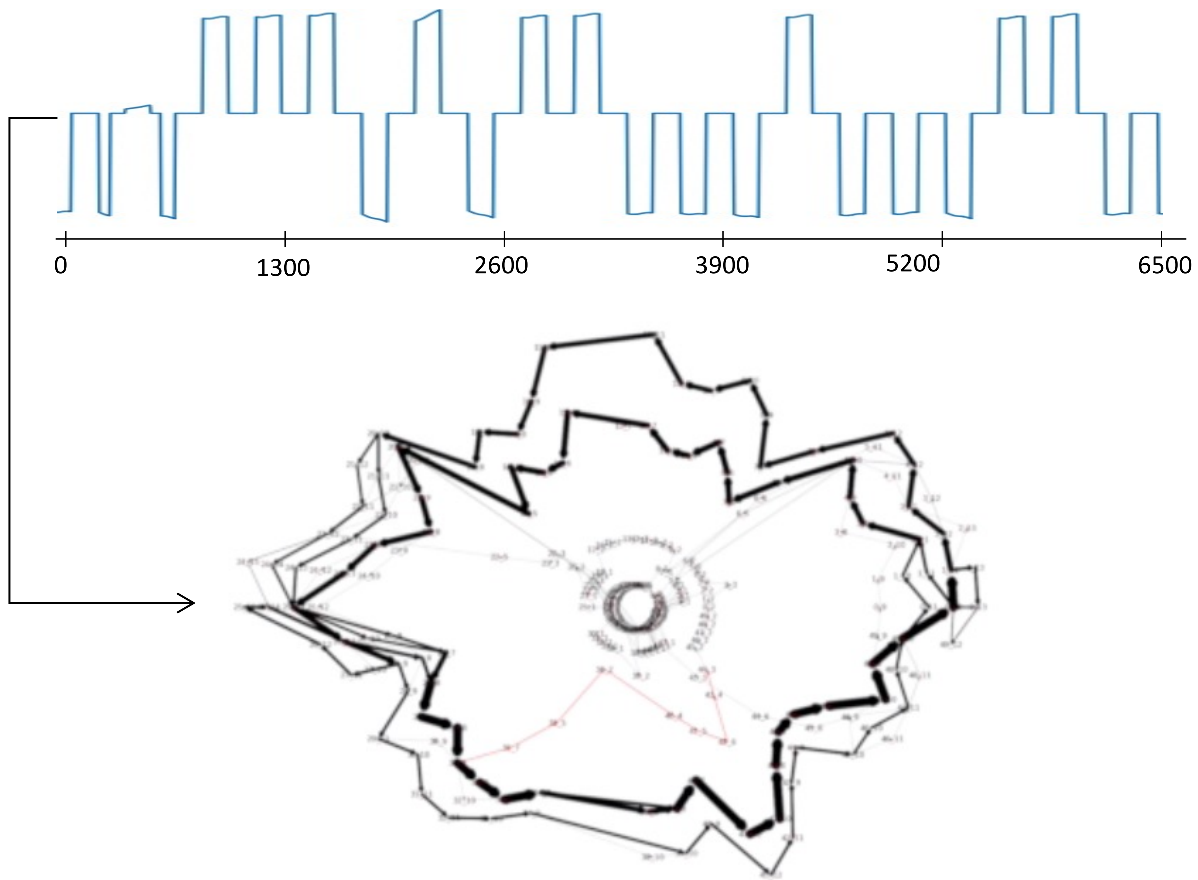

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Anomaly Detection methods: *an Example*

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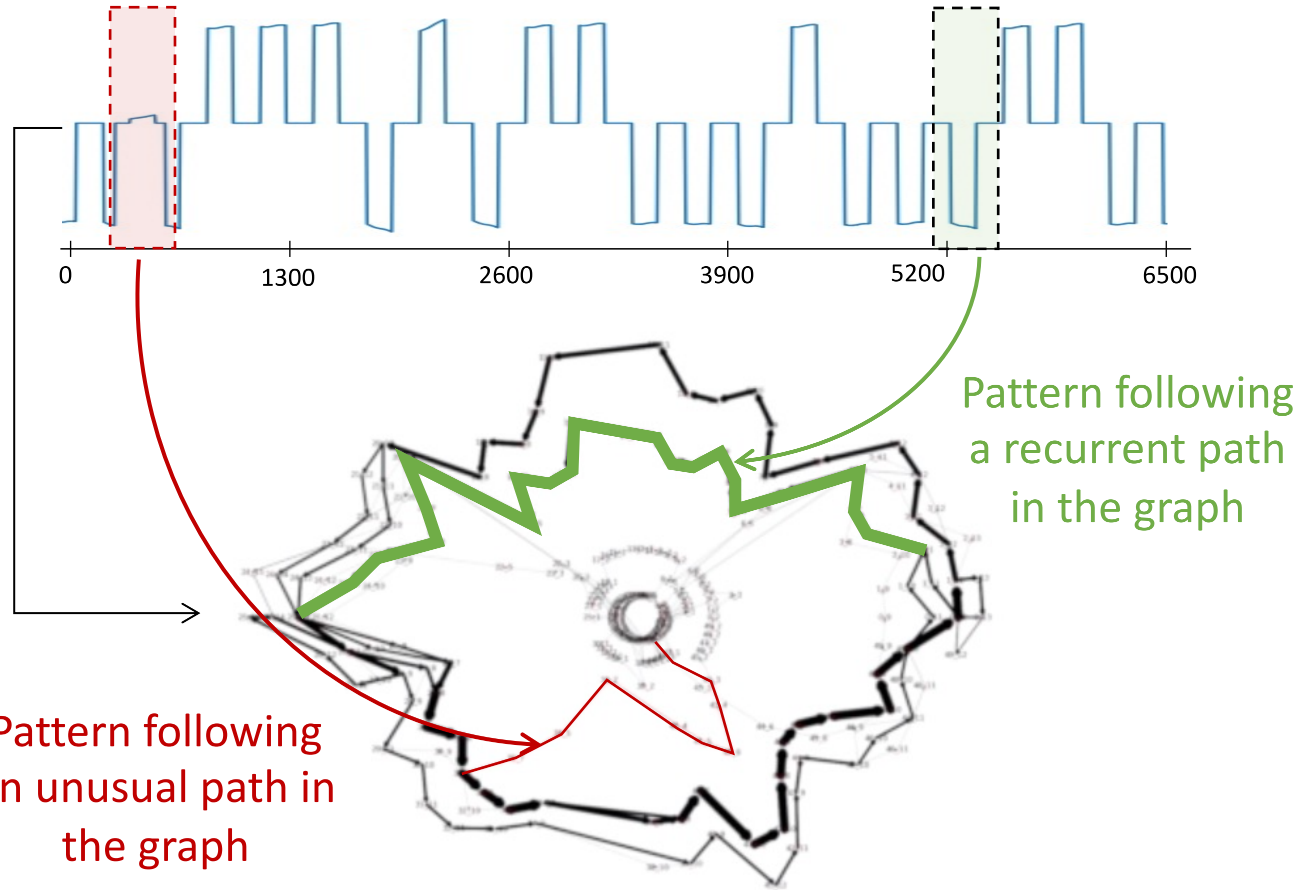

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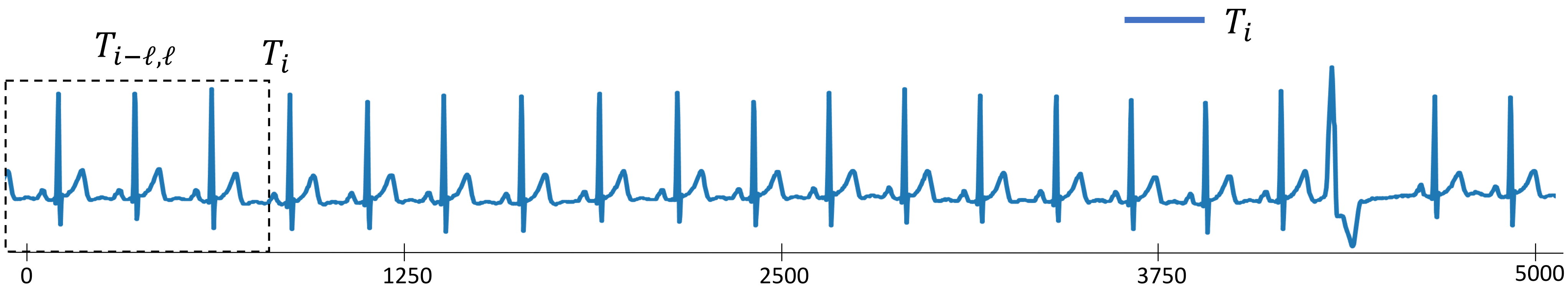
Anomaly Detection methods: *Forecasting-based*

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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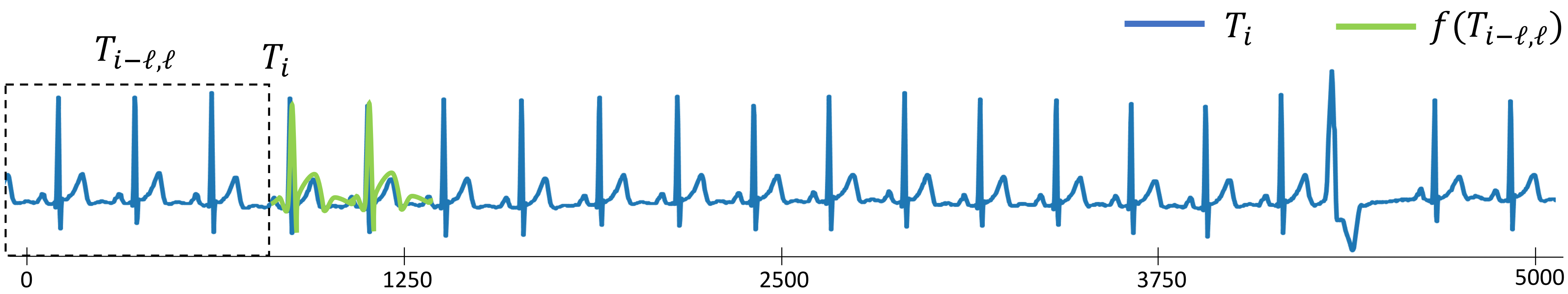

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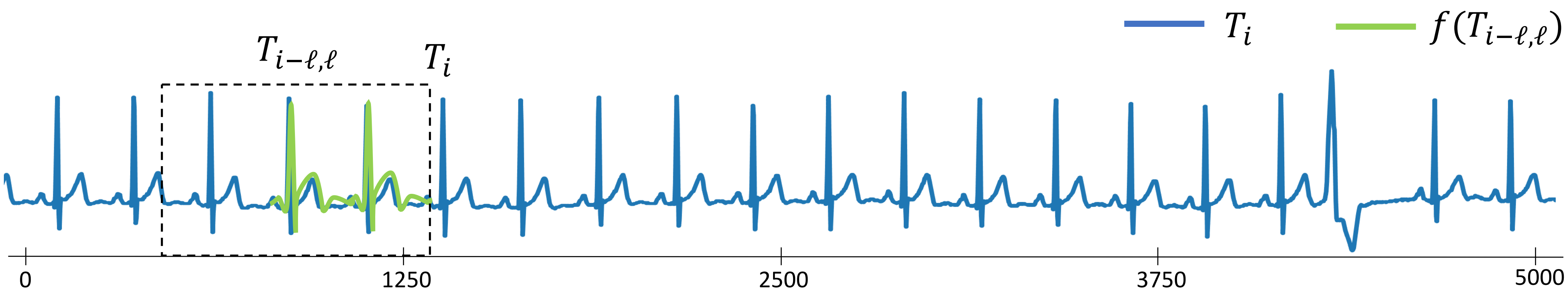

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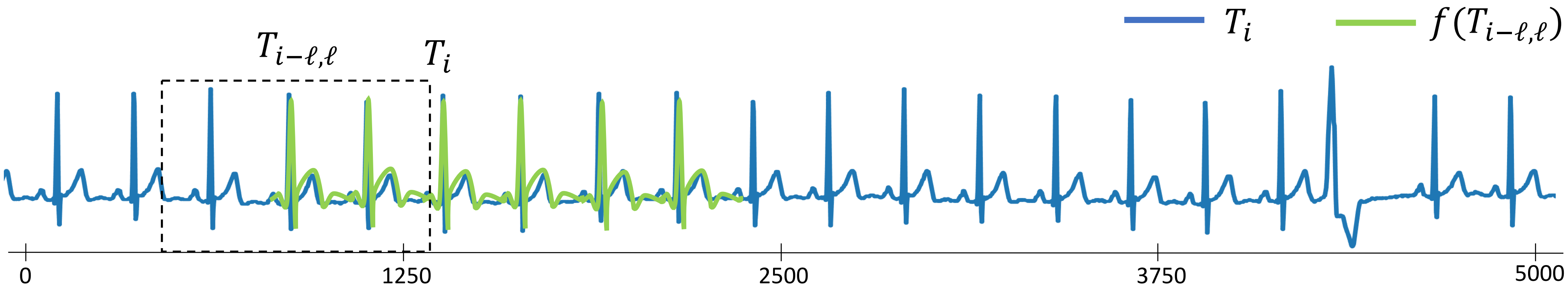

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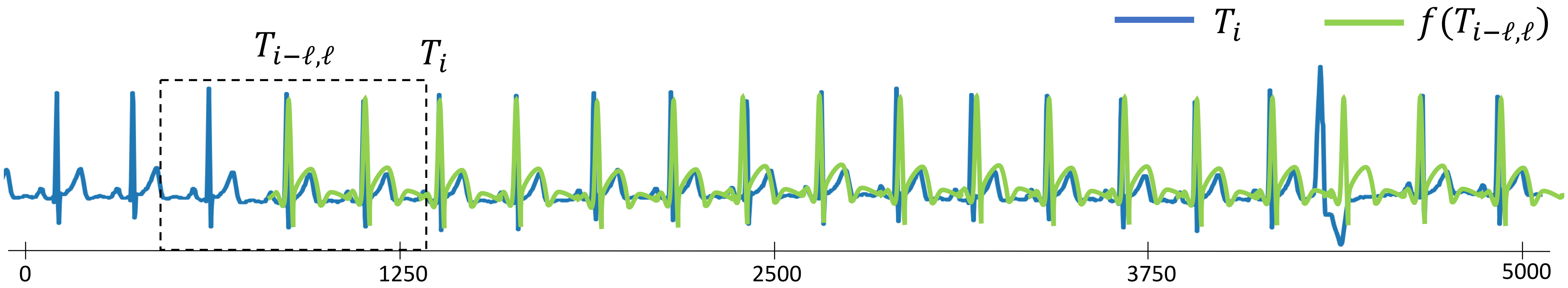

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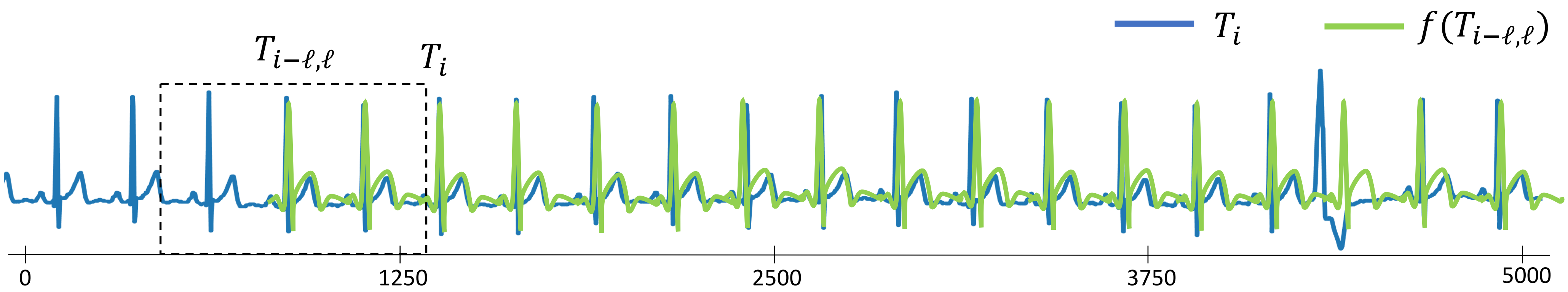
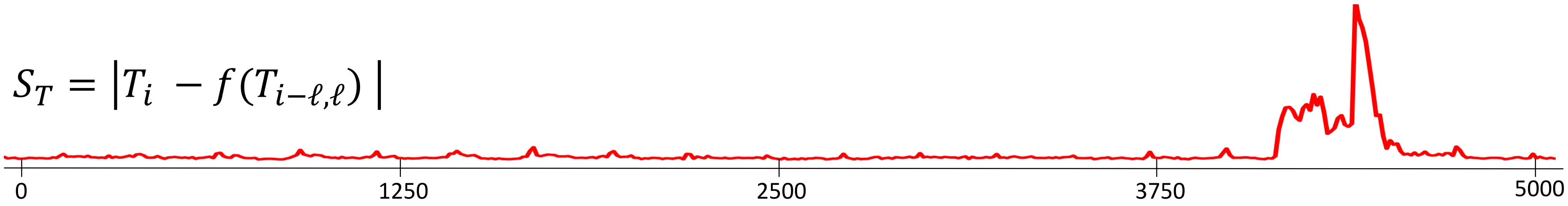


$$S_T = \left| T_i - f(T_{i-\ell,\ell}) \right|$$



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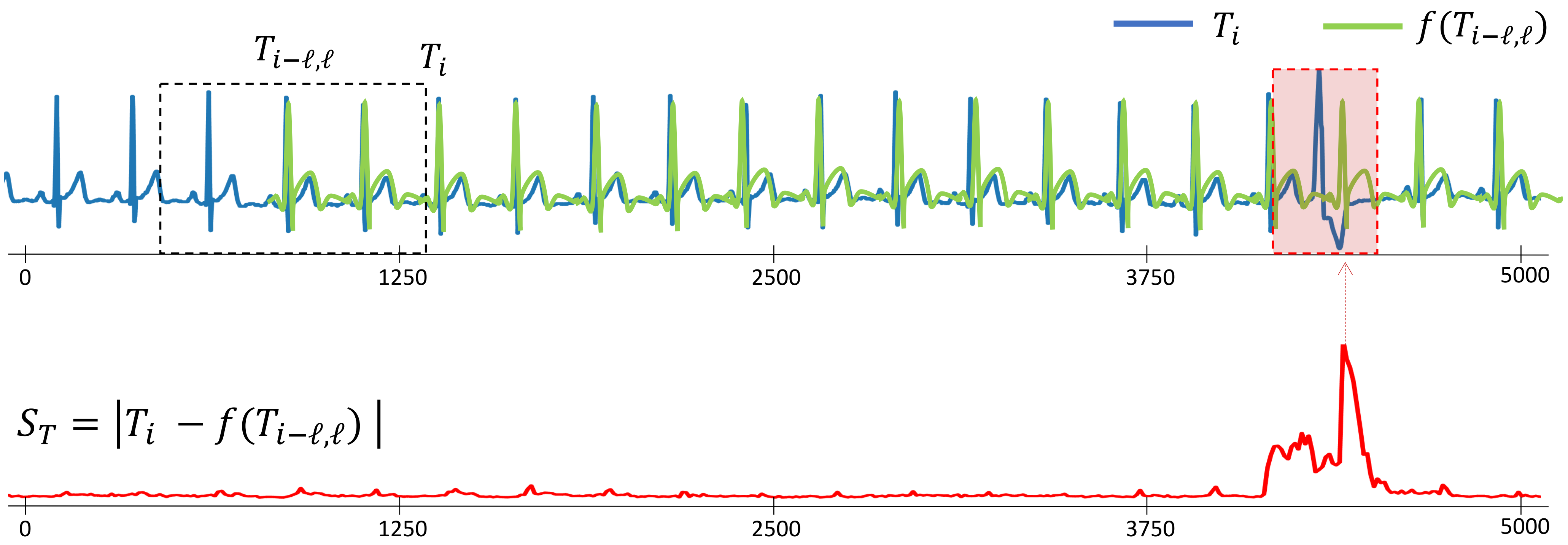
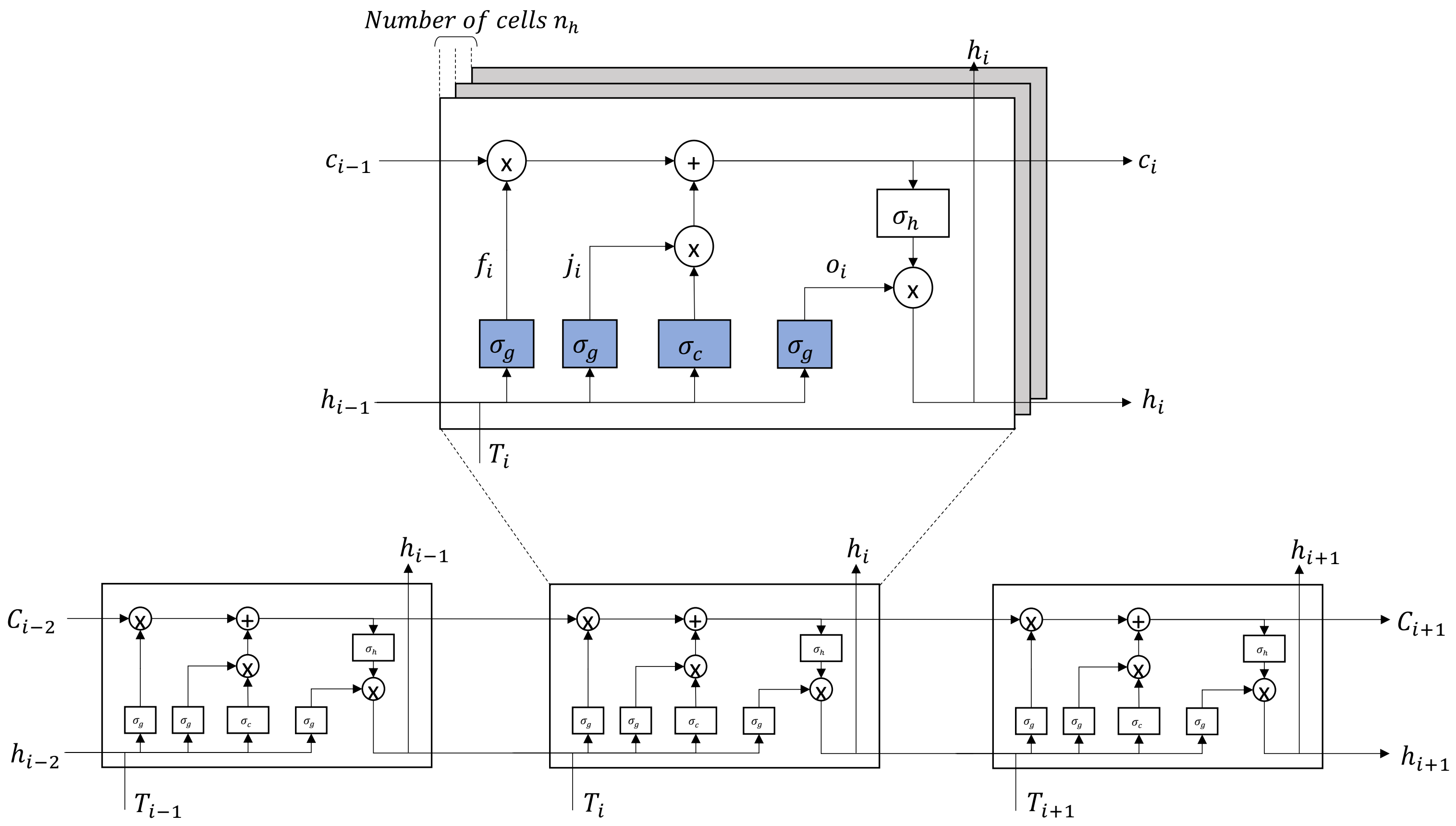


Anomaly Detection methods: *an Example*



LSTM-AD [15]

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

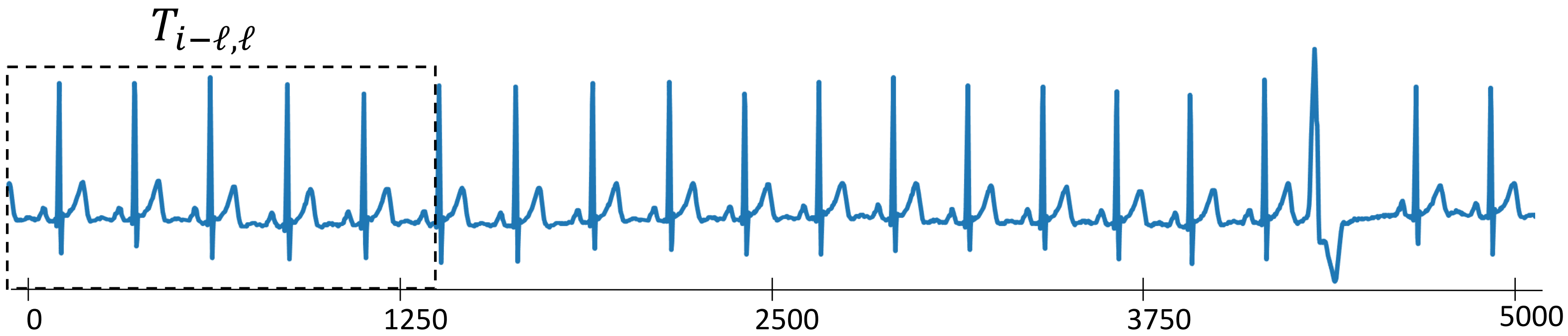
Semi-supervised

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.

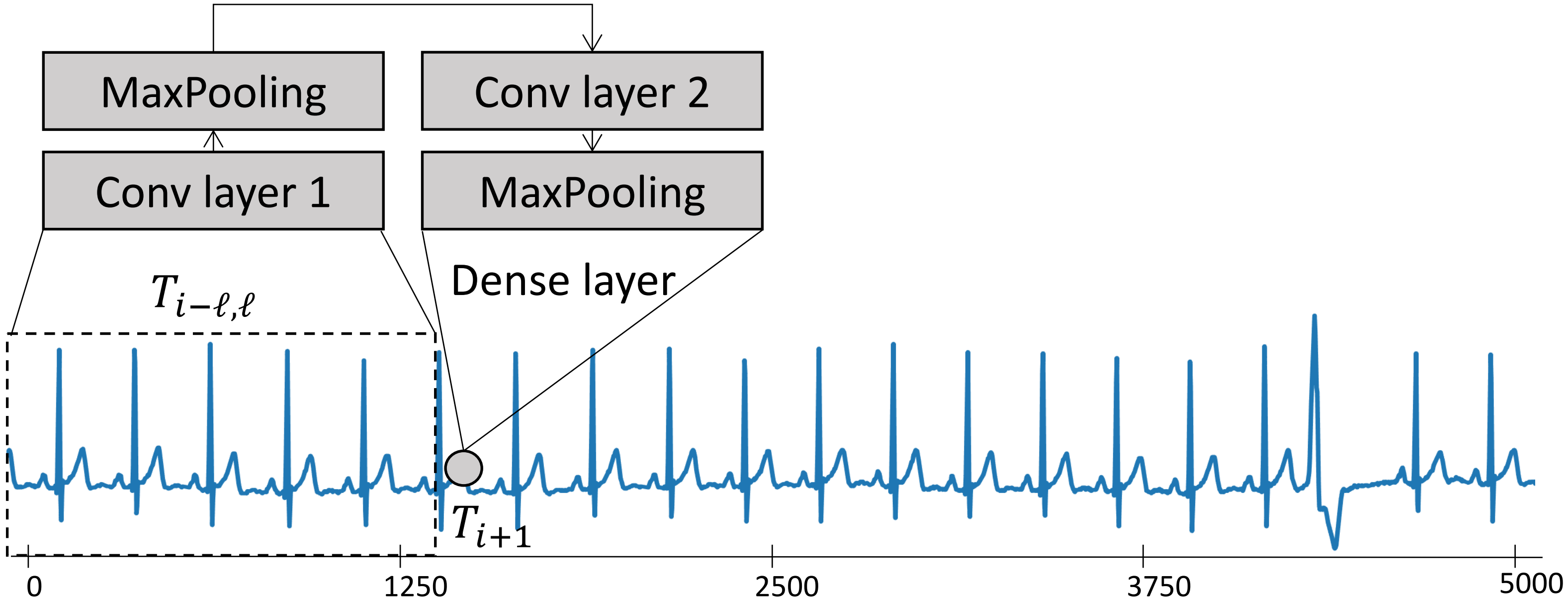
Semi-supervised

Univariate/Multivariate

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: *an Example*



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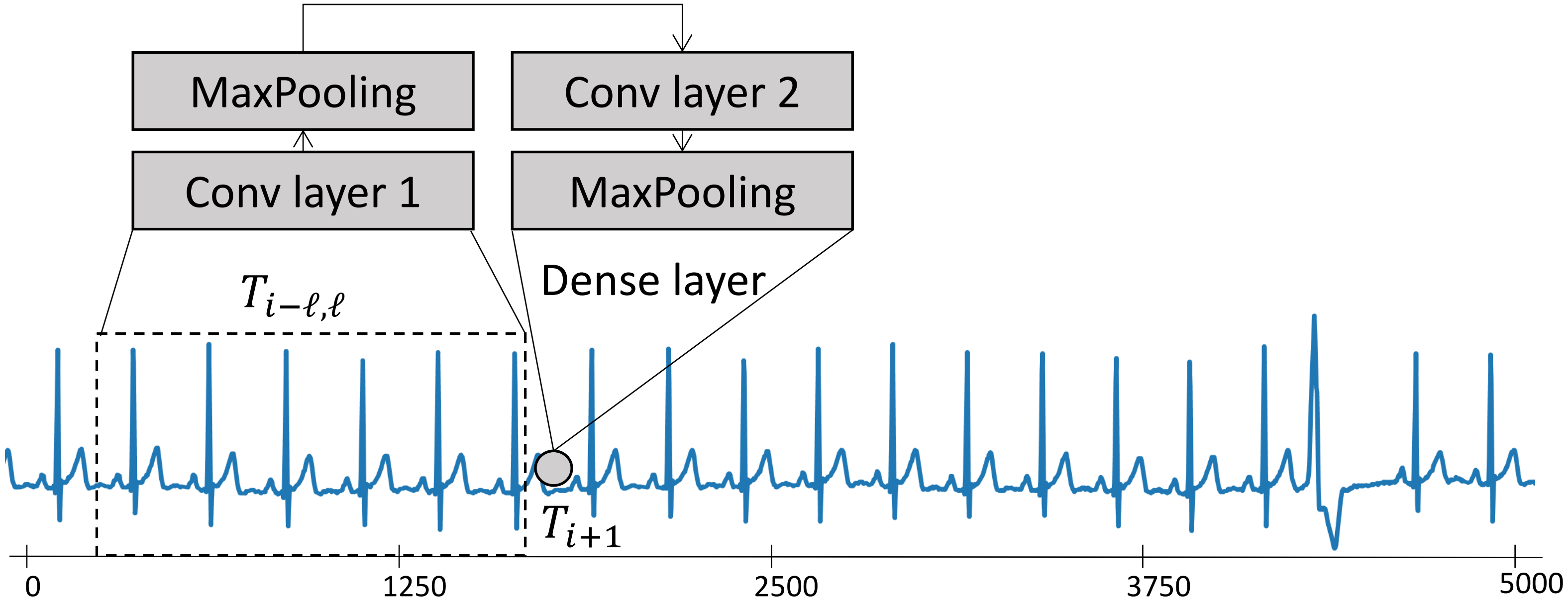

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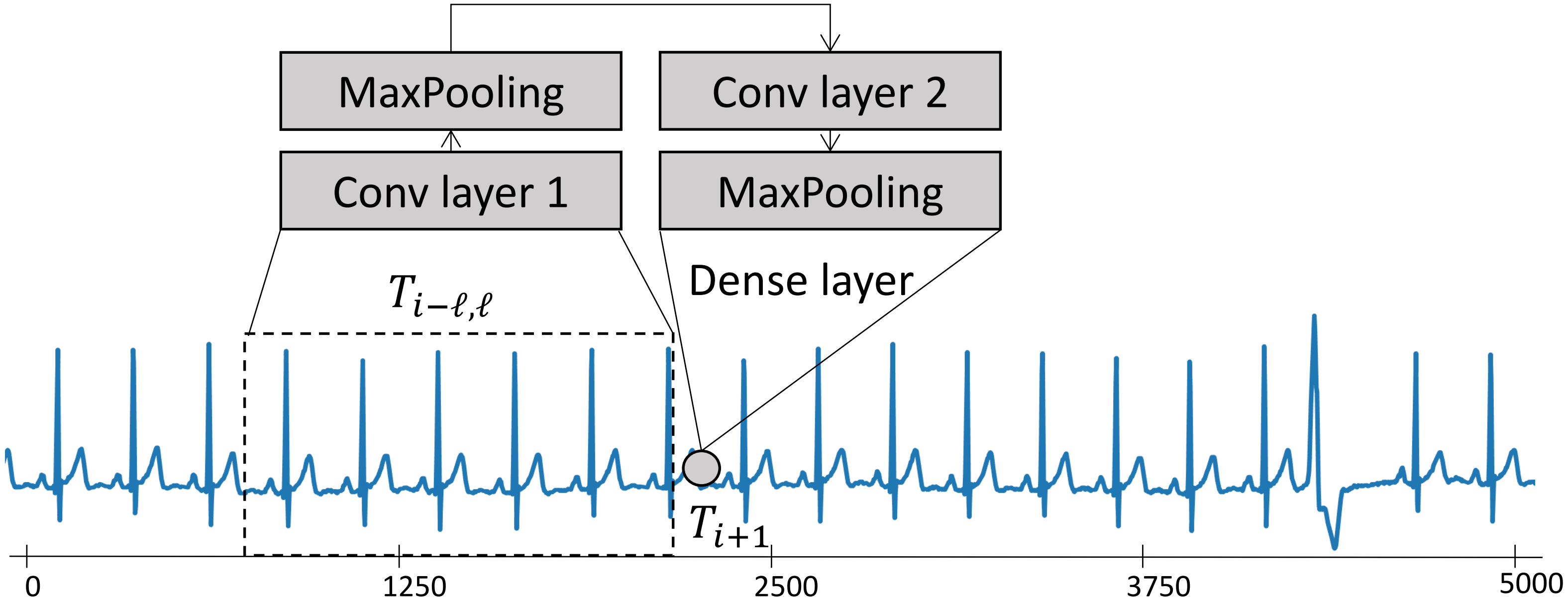

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Anomaly Detection methods: *Reconstruction-based*

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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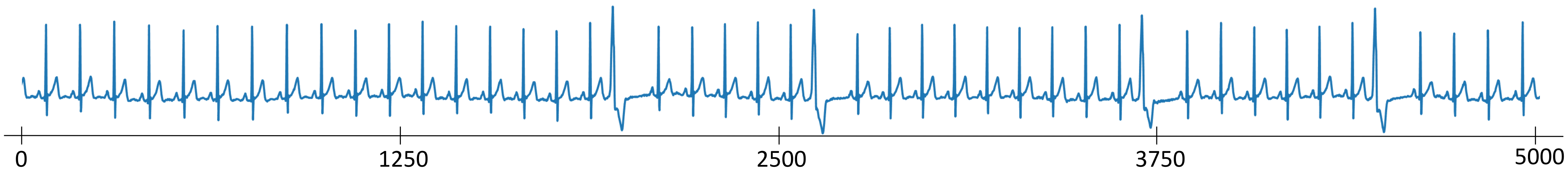
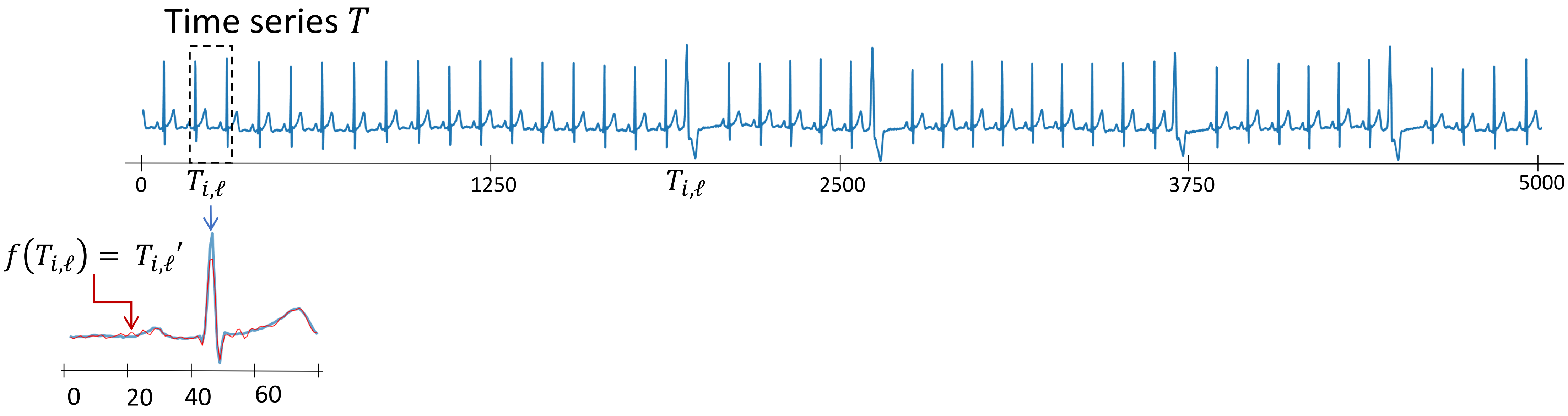
Time series T



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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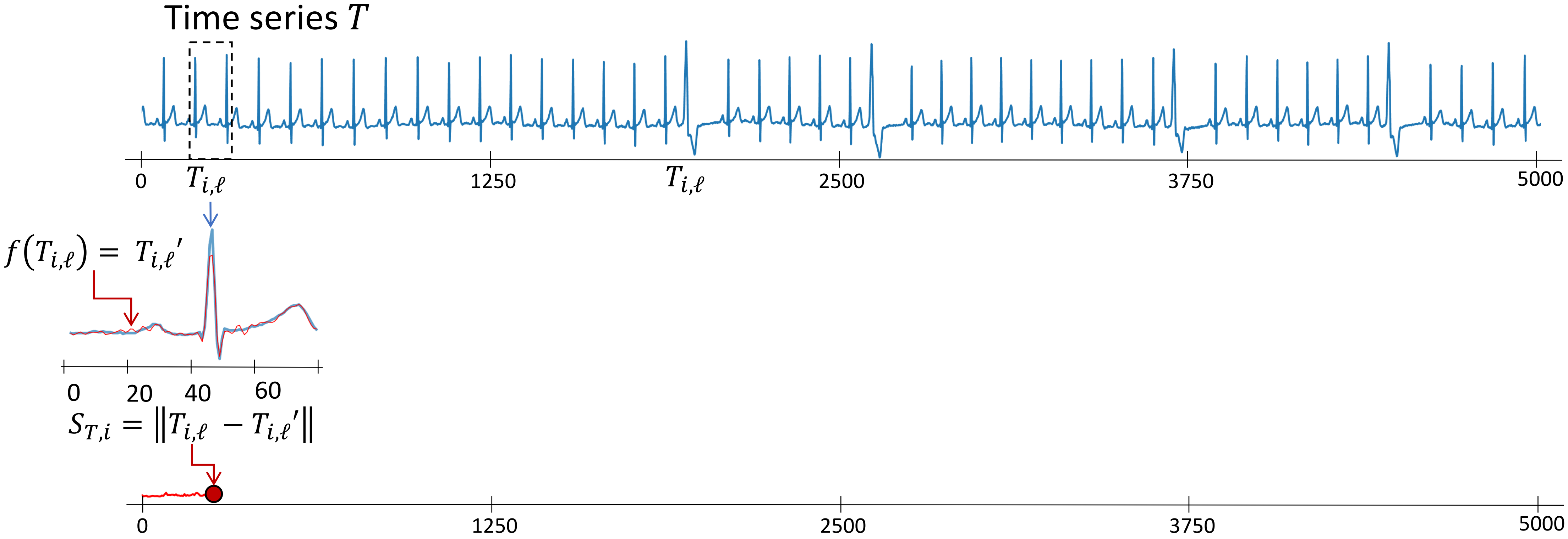

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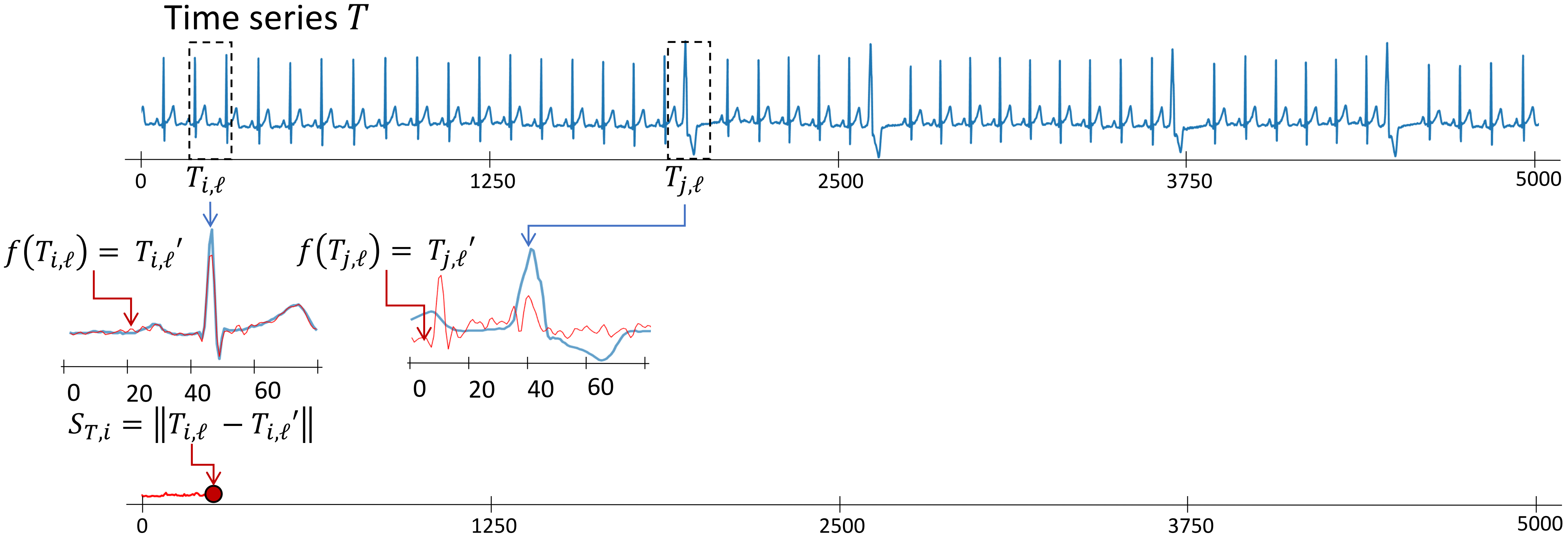

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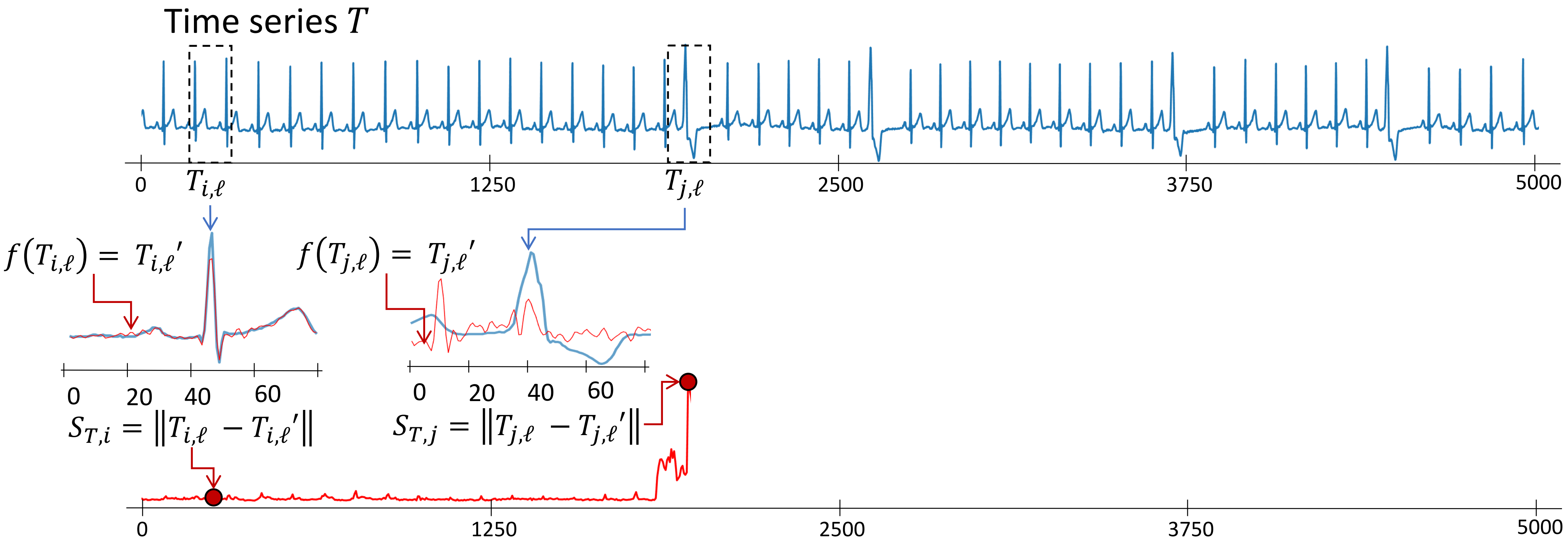

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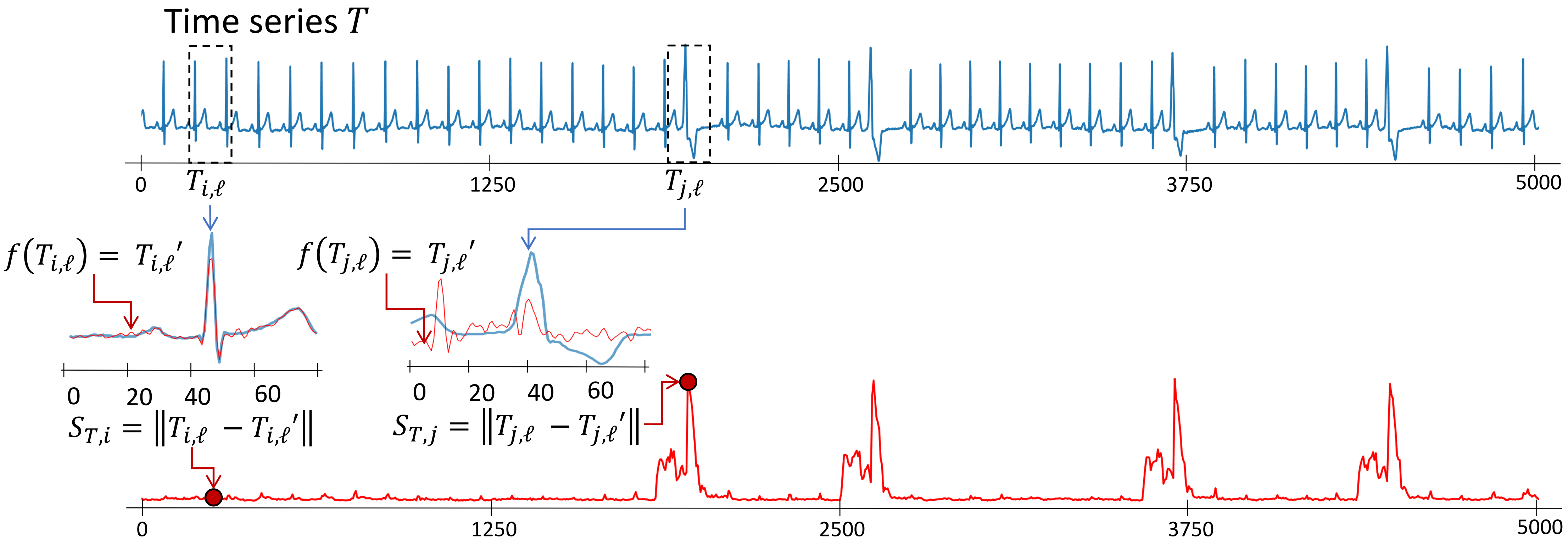

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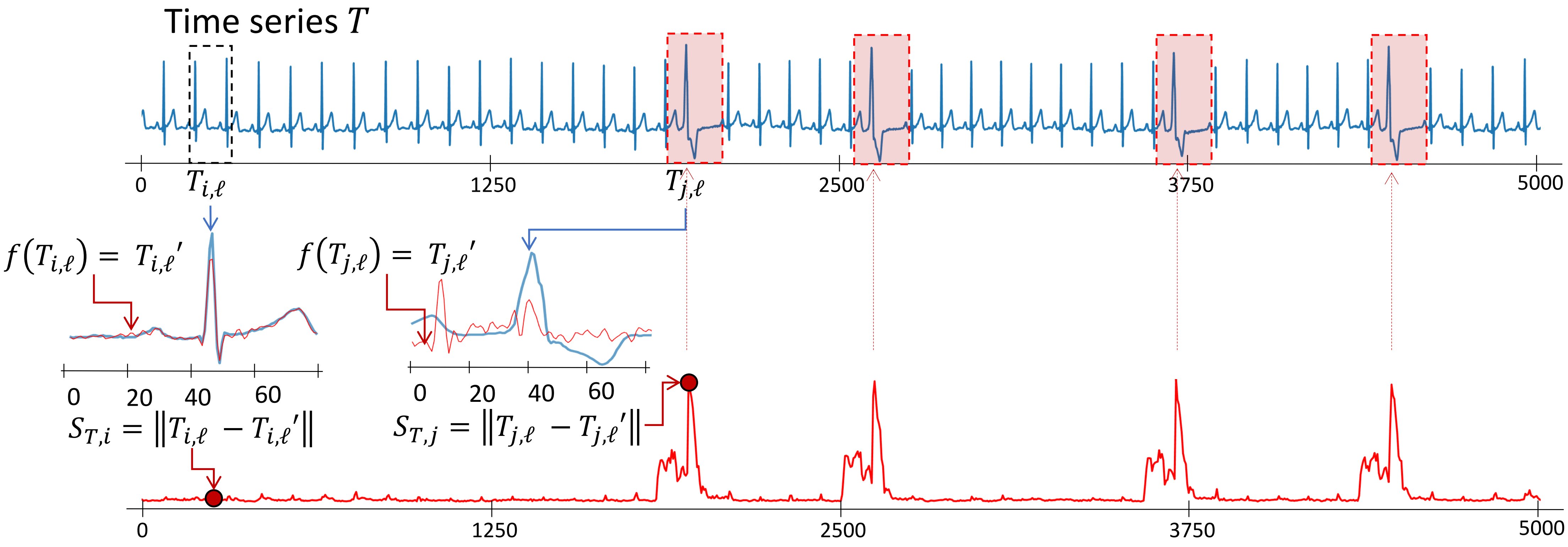
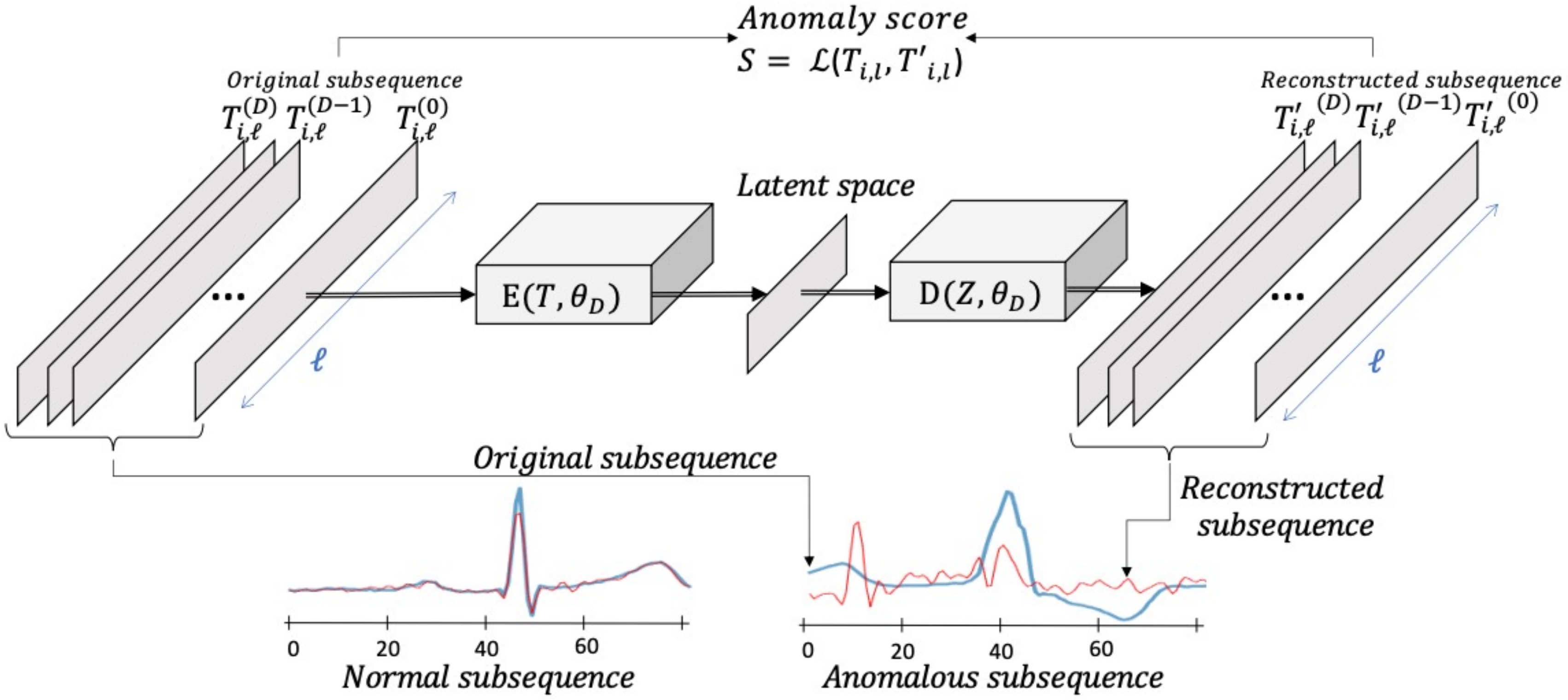


Anomaly Detection methods: *an Example*



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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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

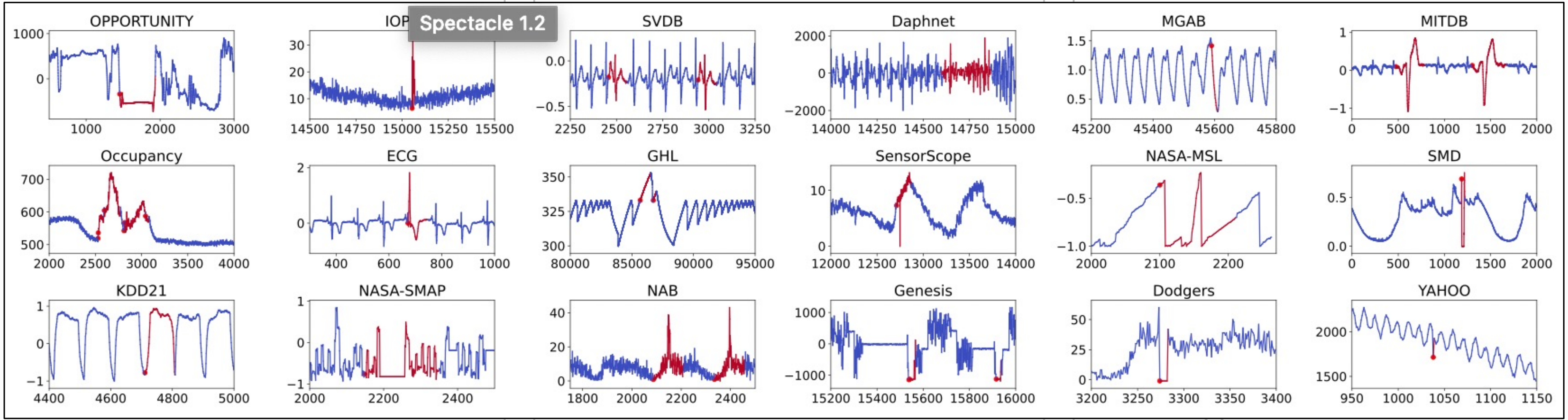
Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]

Set of 250 time series with

TimeEval [5]

Real datasets collection



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Set of 2000 time series with

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Anomaly Detection methods: *Existing benchmark*

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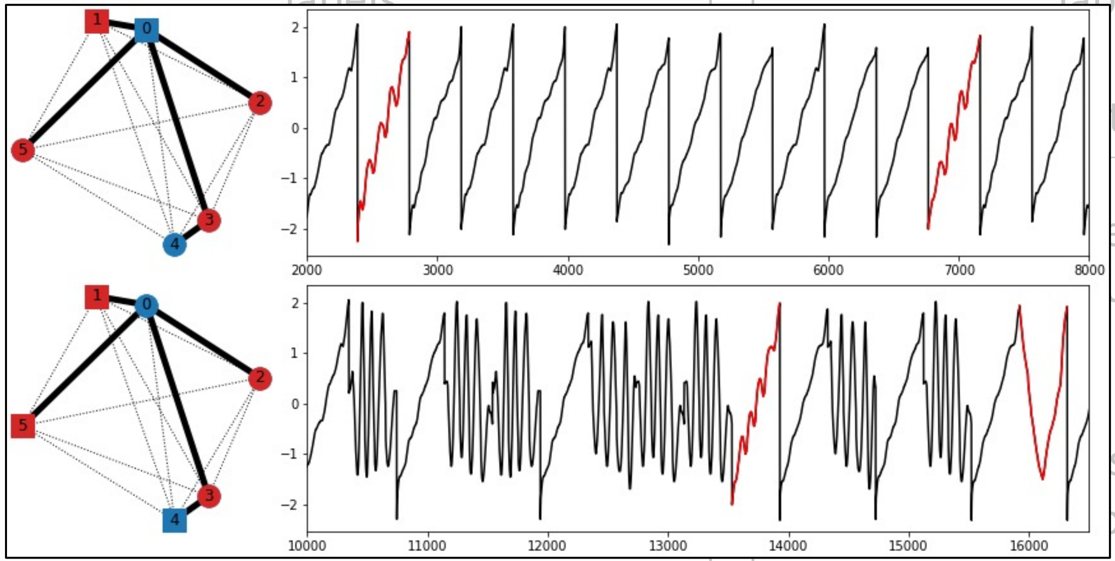
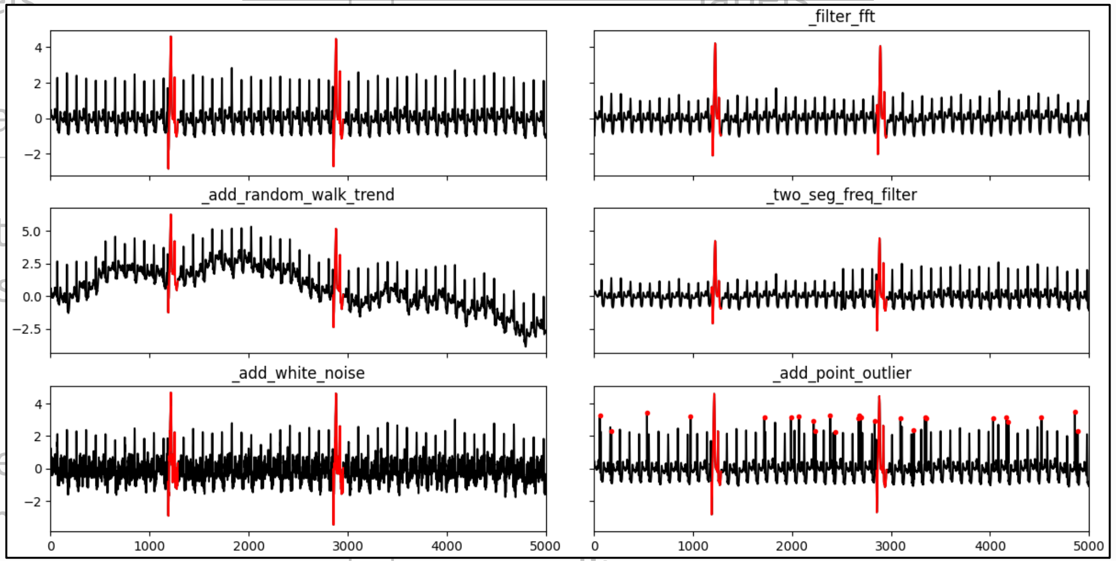
Artificial dataset generation

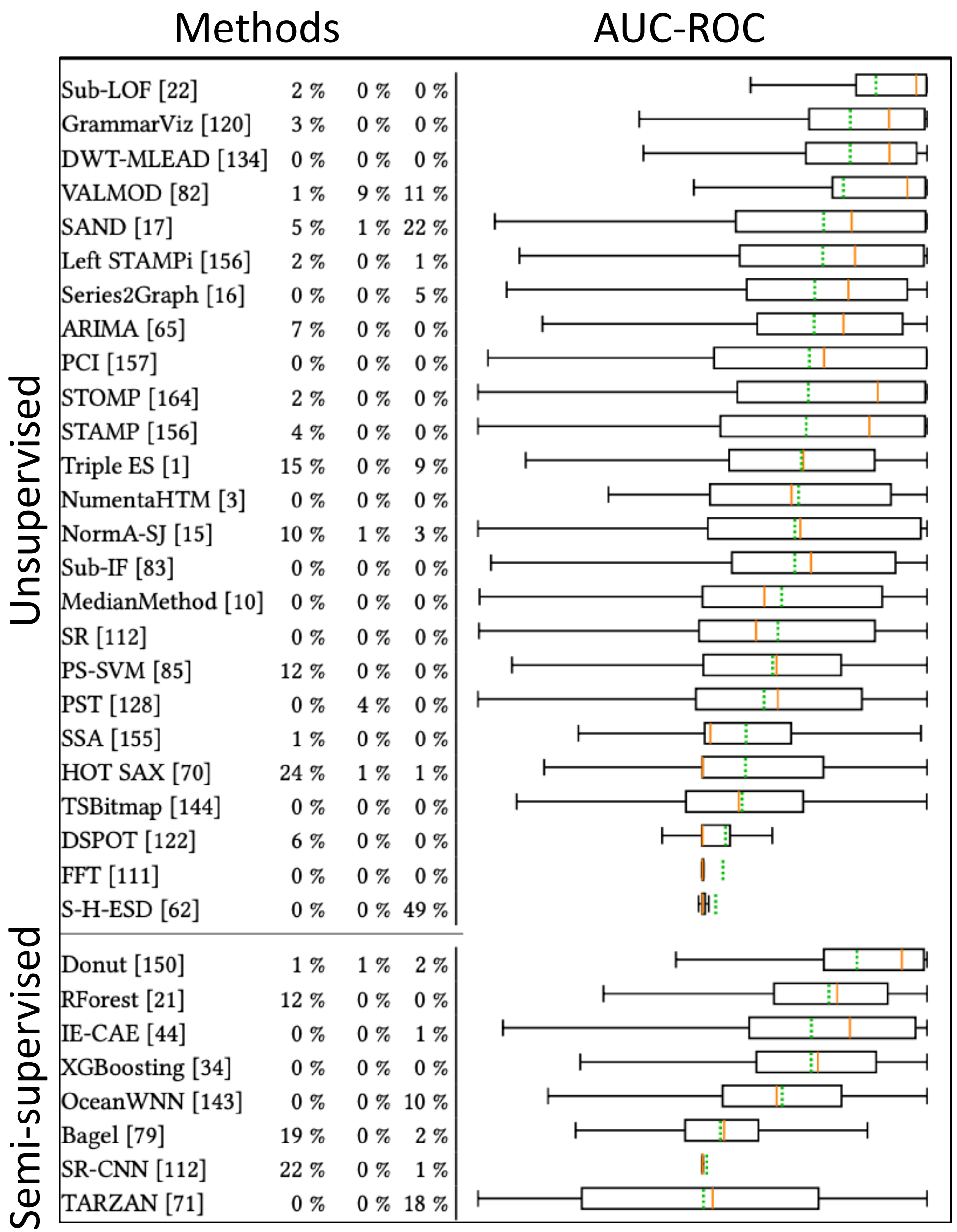


Synthetic dataset generation



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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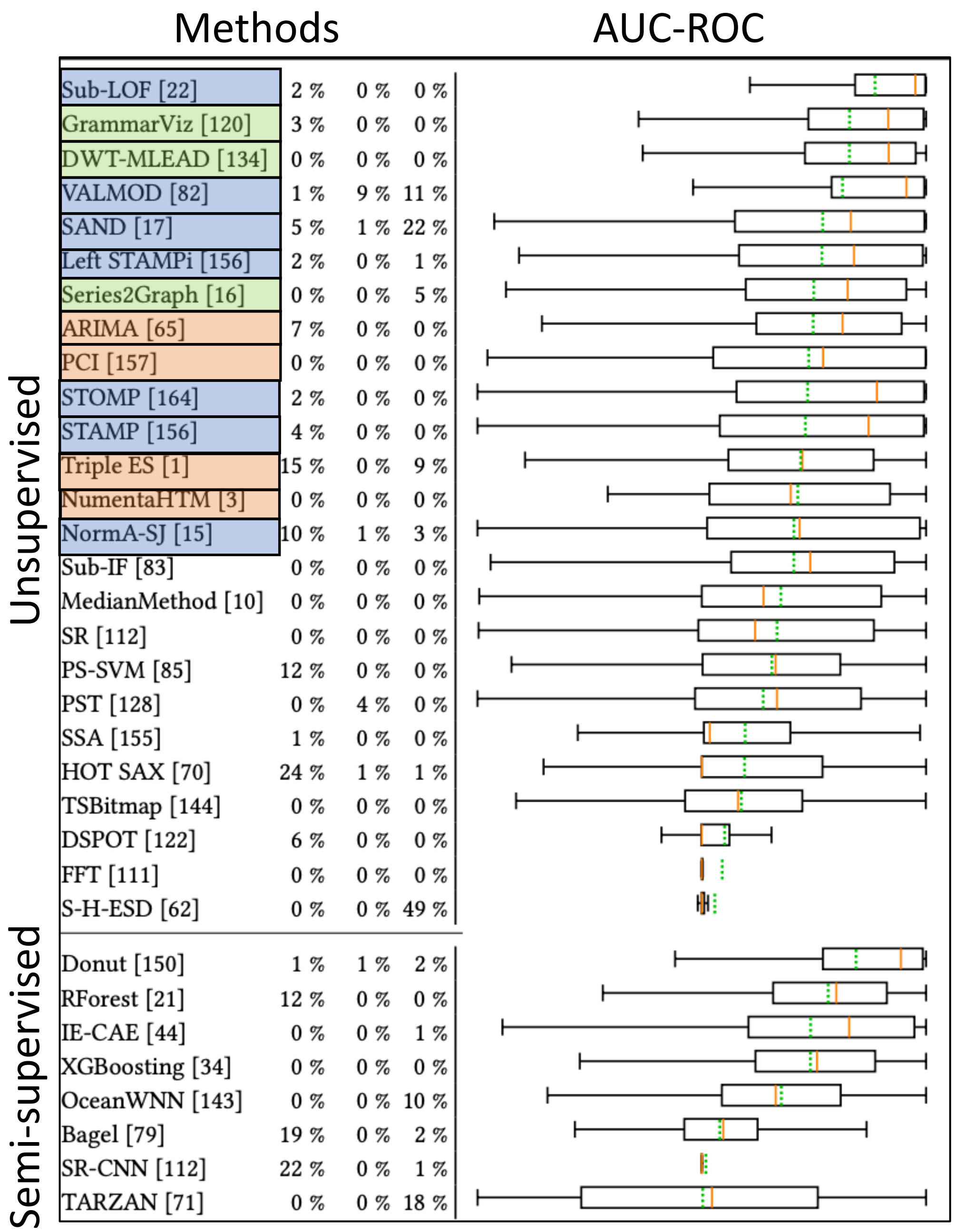
Observations on TimeEval [5]:

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



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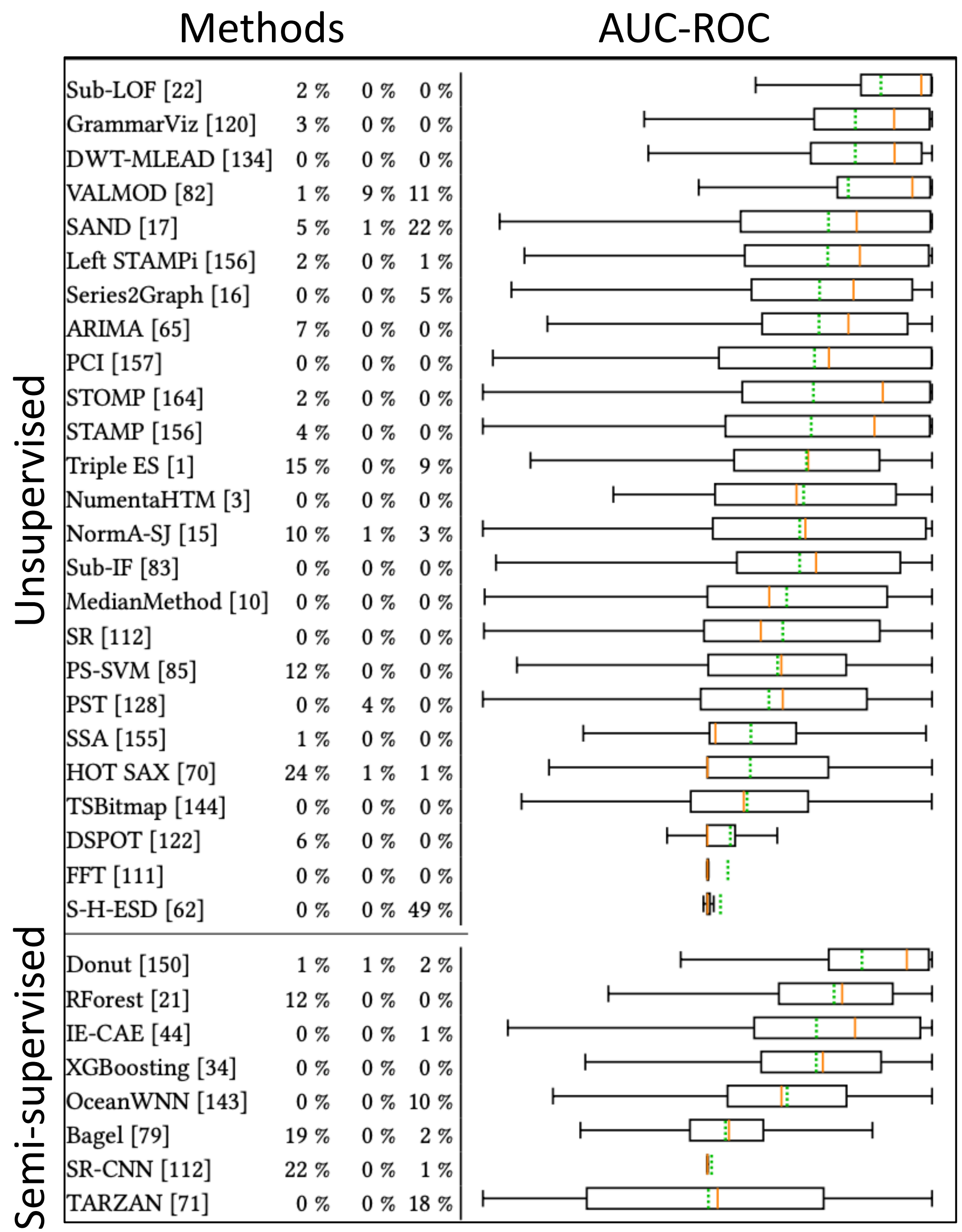

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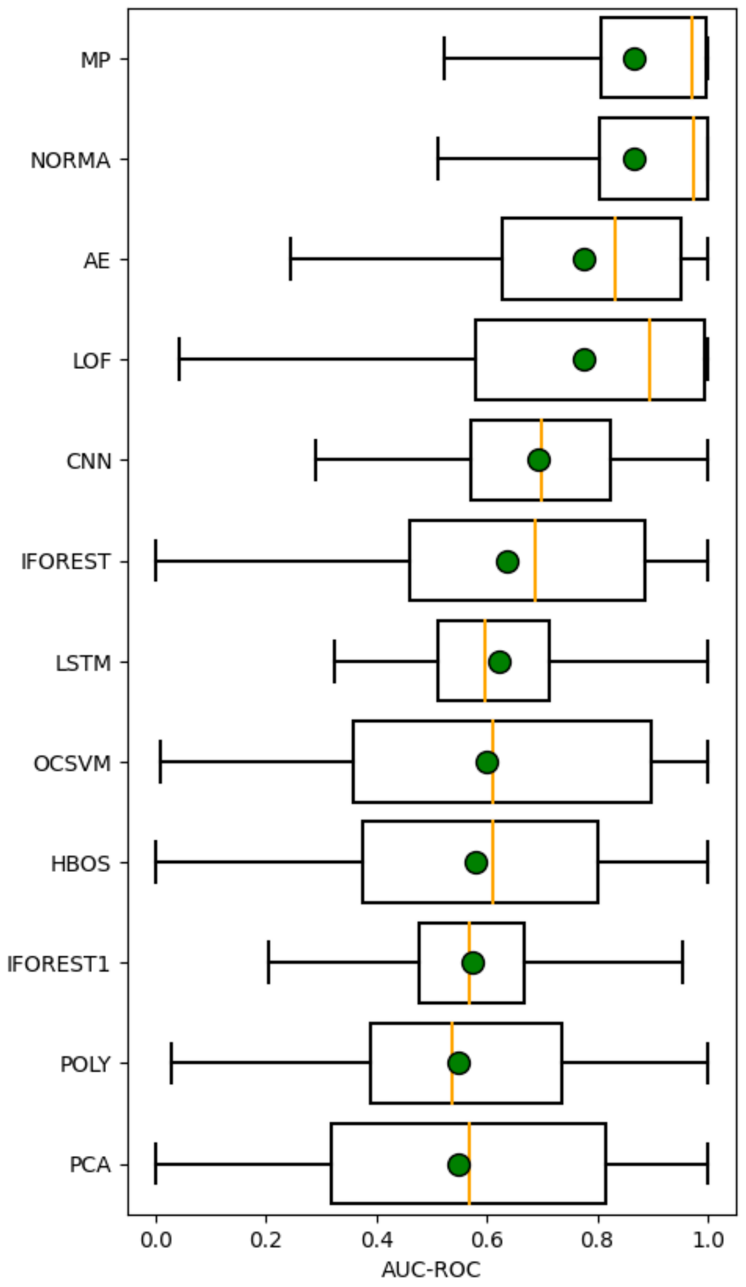

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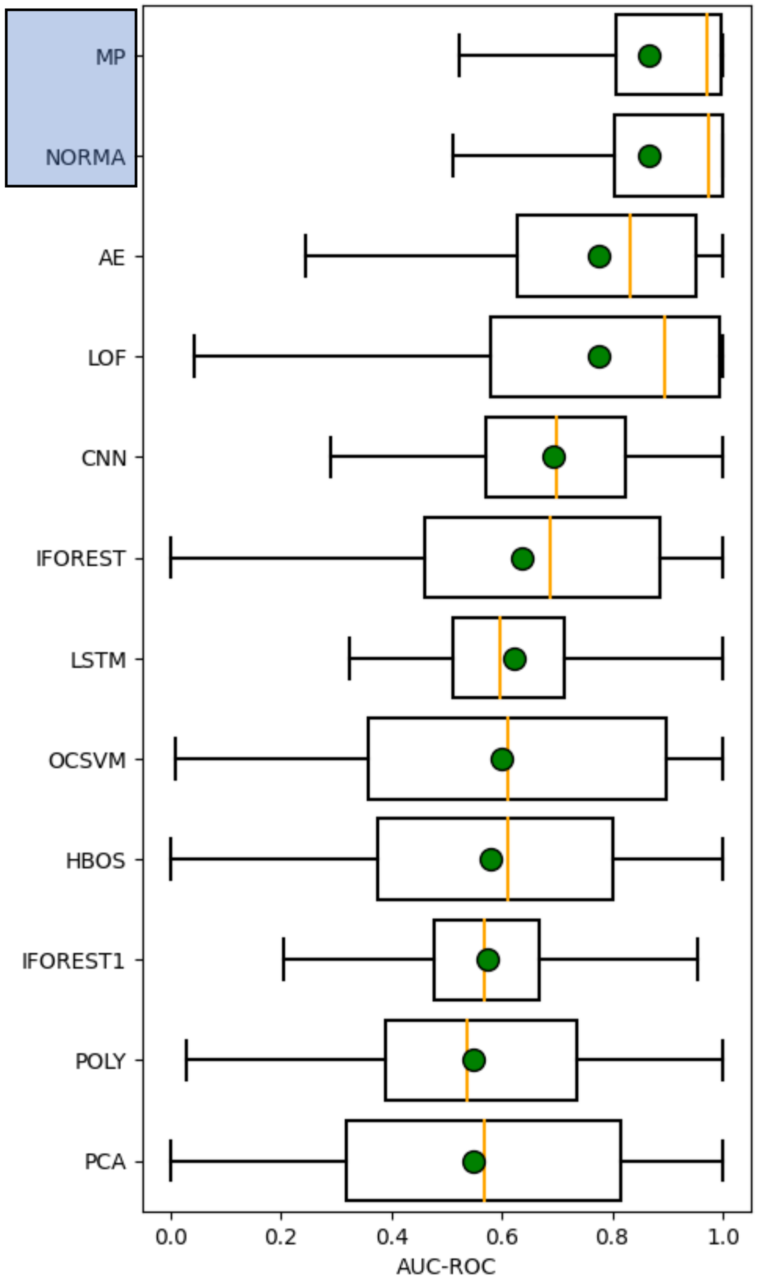

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Anomaly Detection methods:
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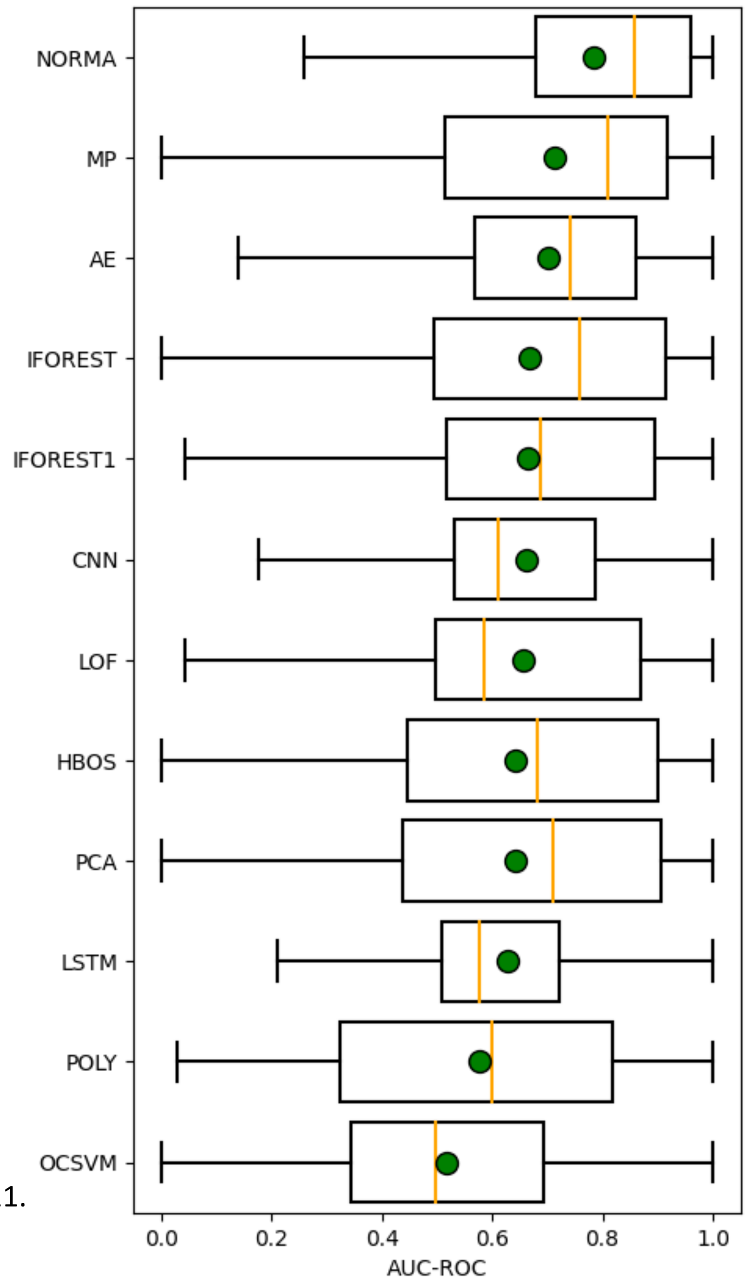
Observations on TSB-UAD [19]:

- Distance-based methods have a better accuracy (AUC-ROC) than forecasting-based methods.
- 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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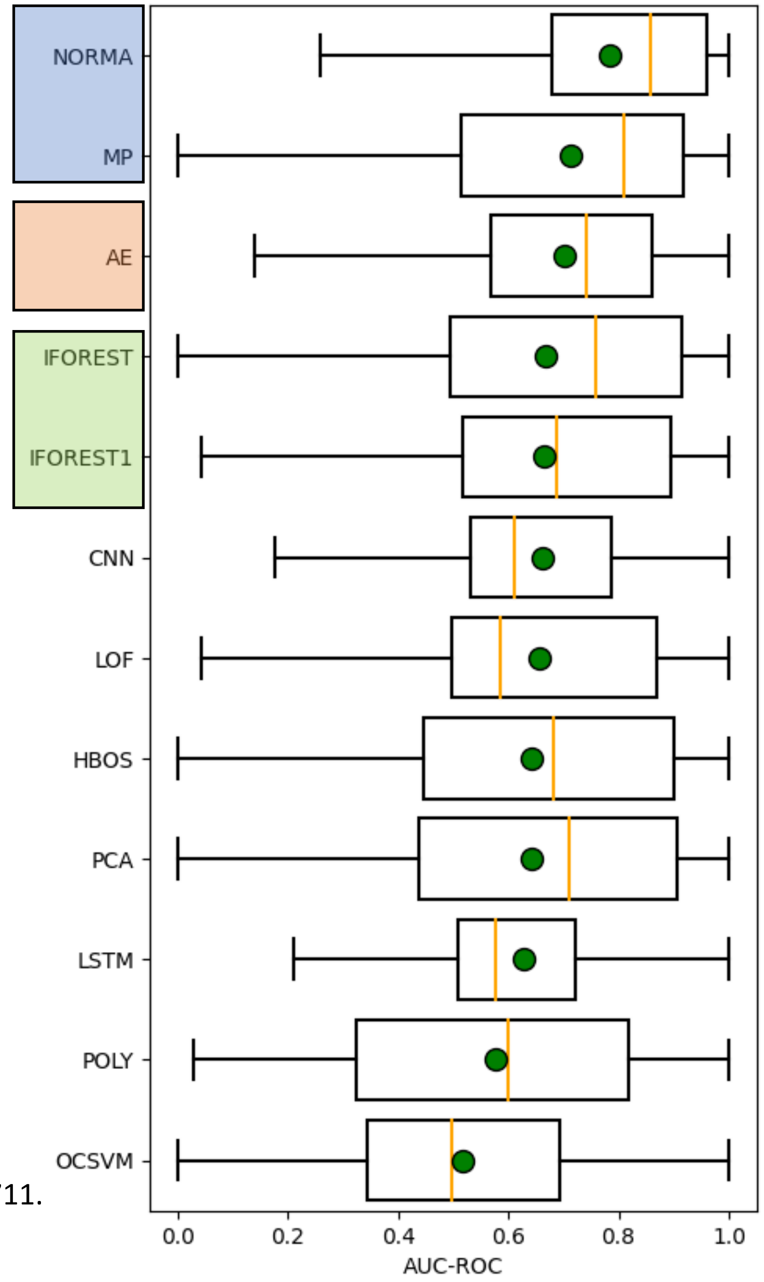

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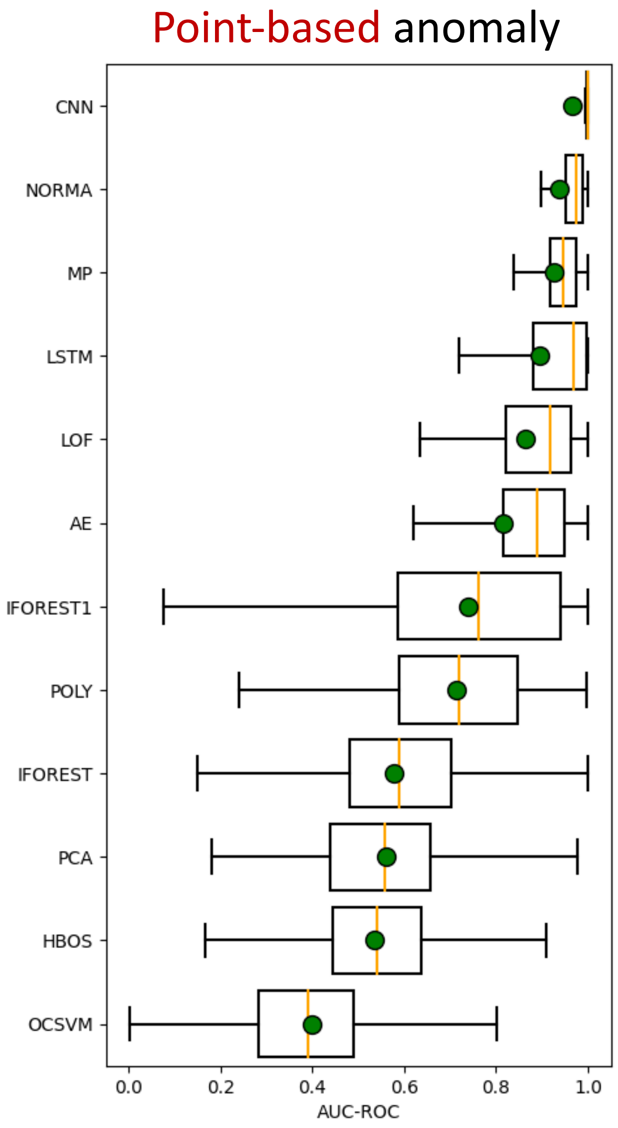

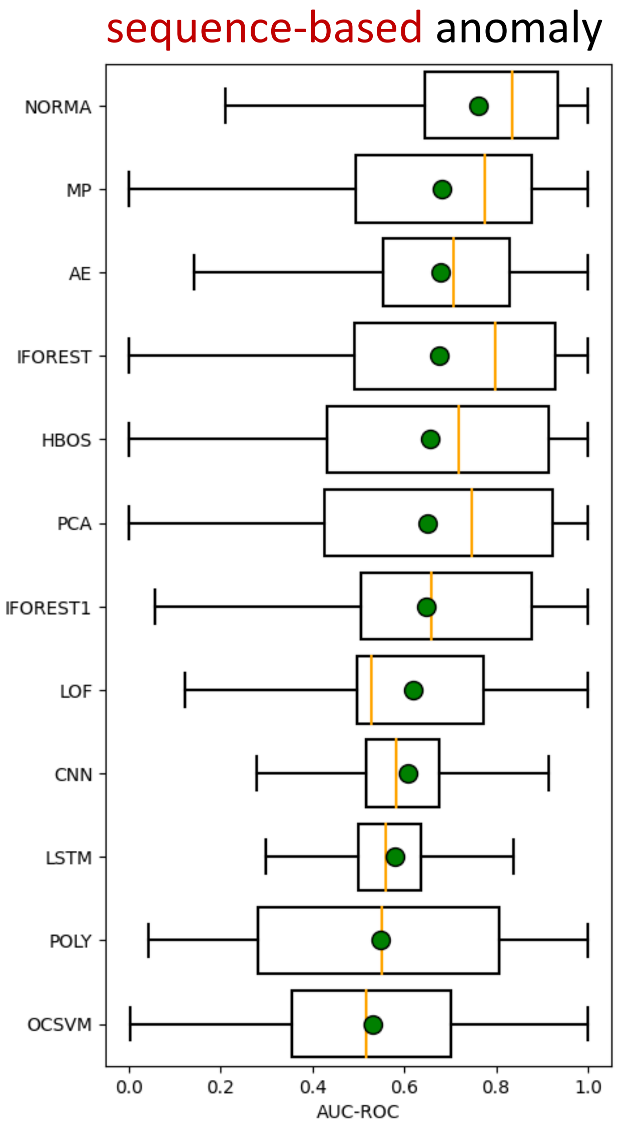

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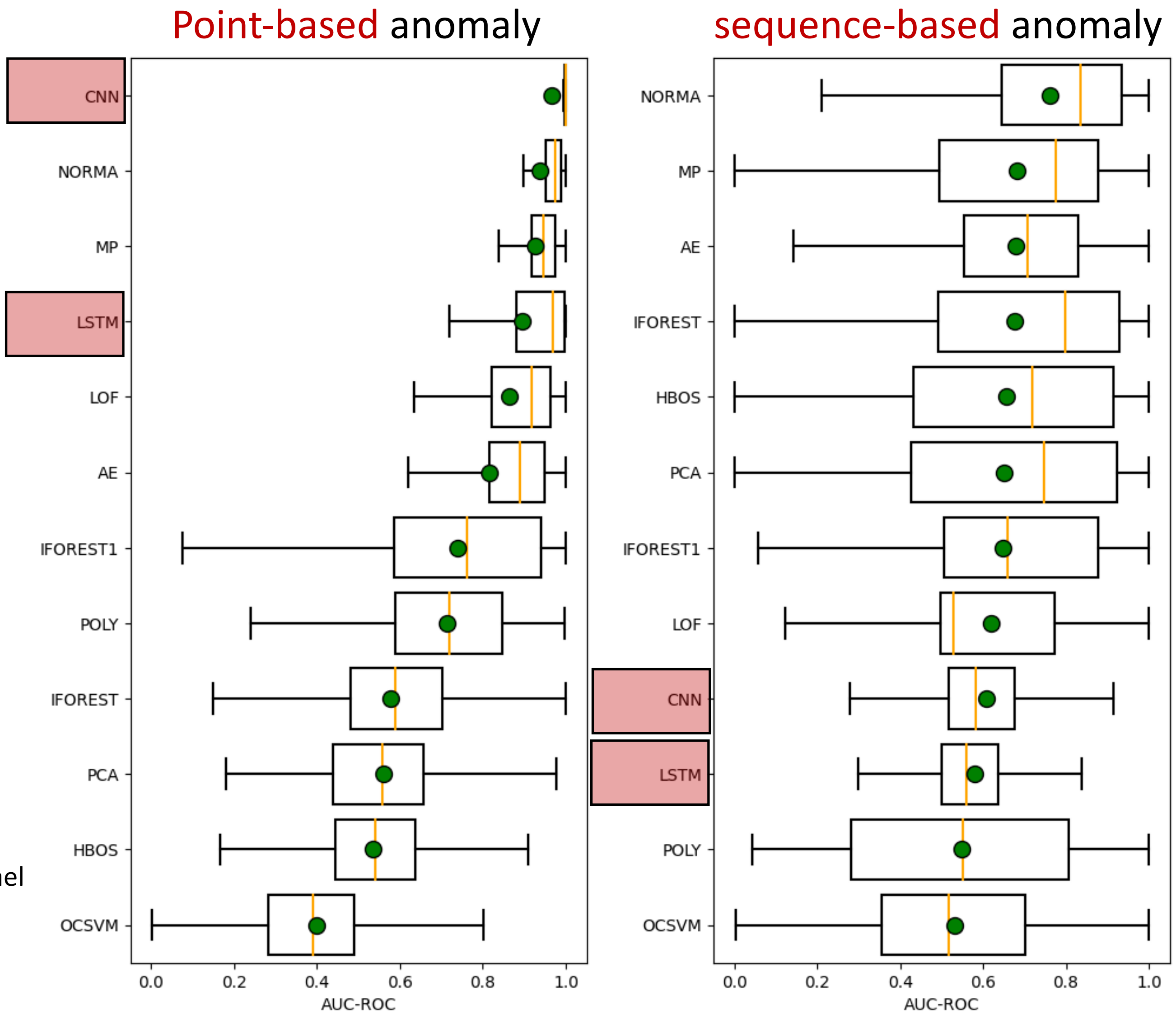

Observations on TSB-UAD [19]:

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

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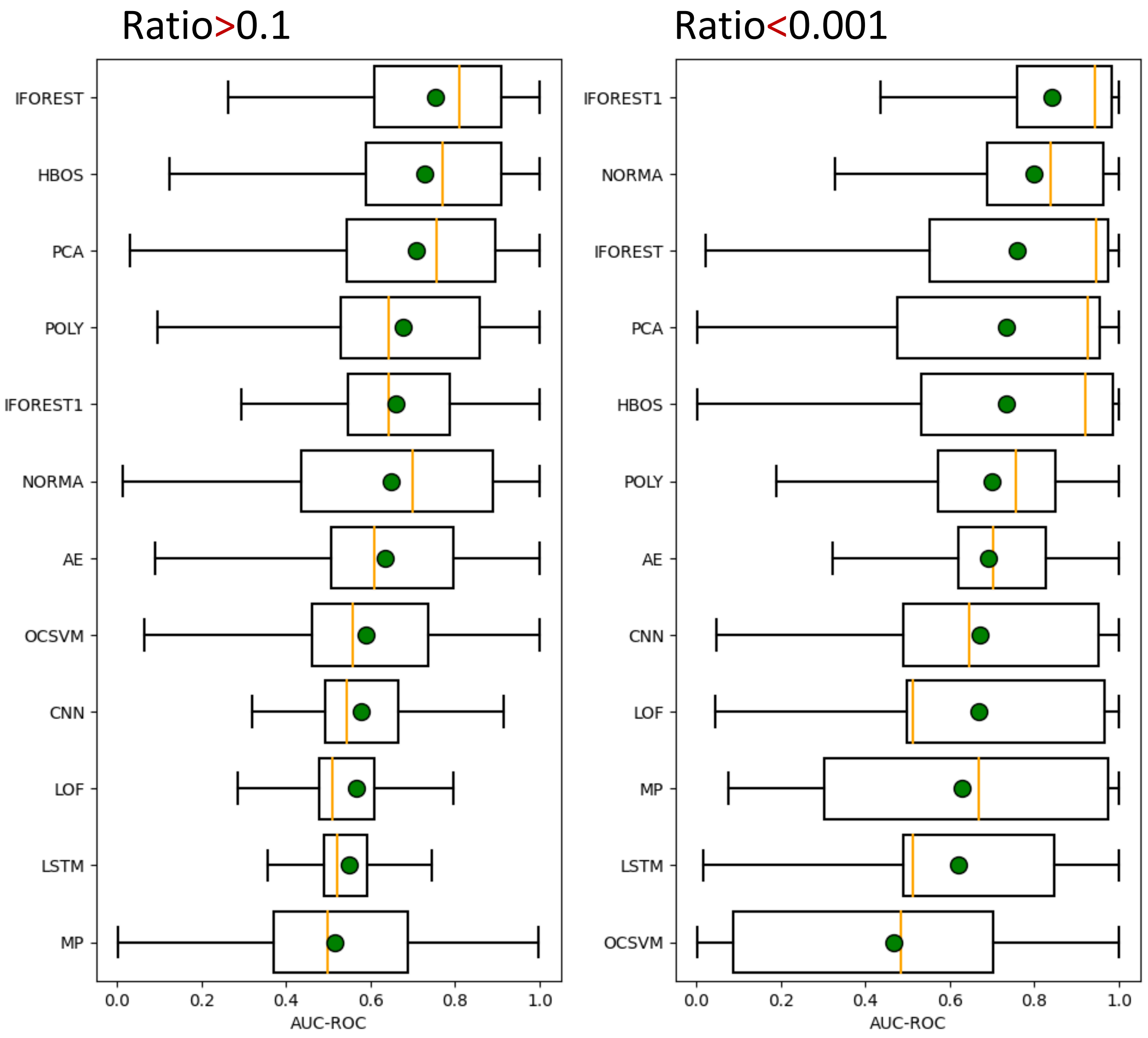
Anomaly Detection methods:
Experimental evaluation

Observations on TSB-UAD [19]:

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



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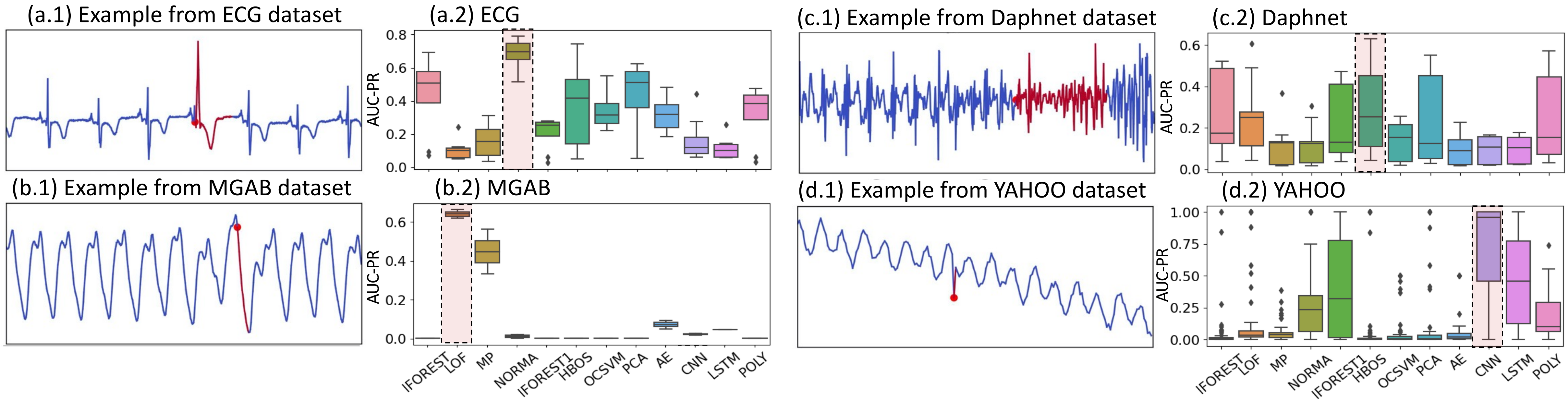
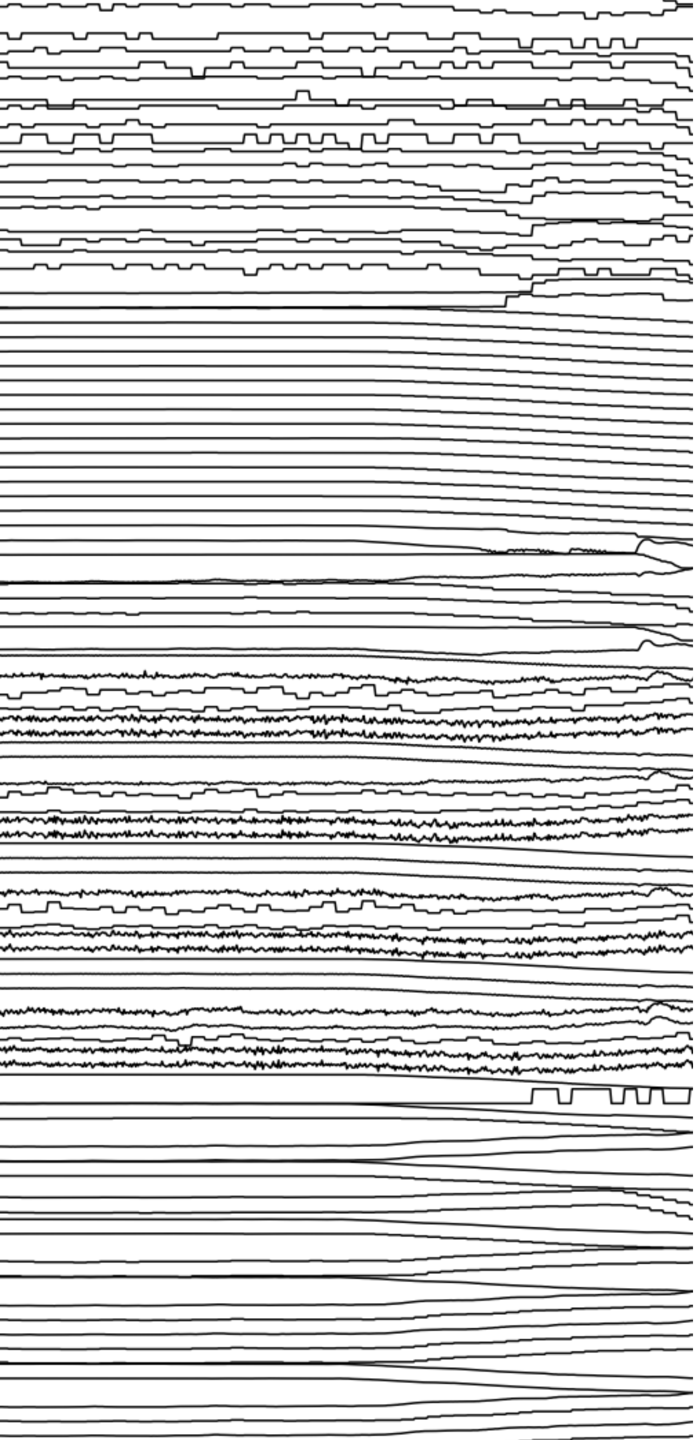
Anomaly Detection methods: *Experimental evaluation*

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



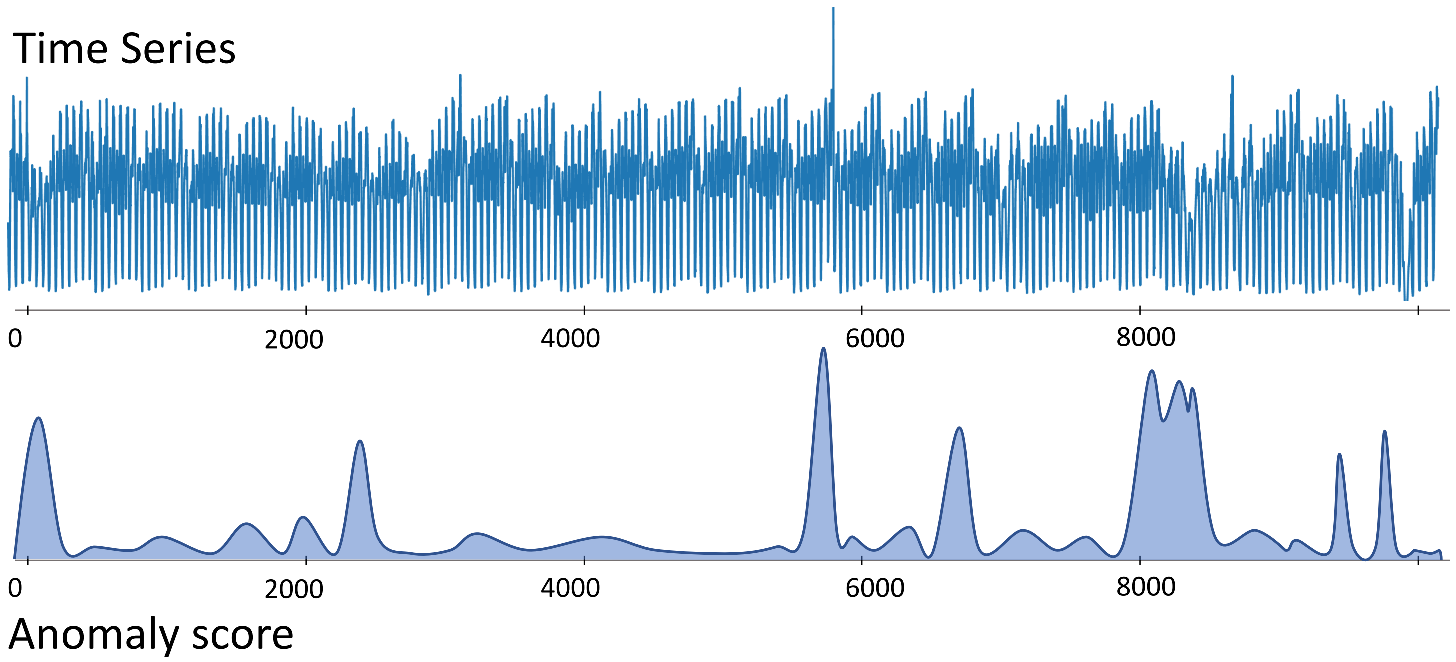
There is no overall winner.

[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.



Evaluation Measures

Evaluation measures: *A general overview*



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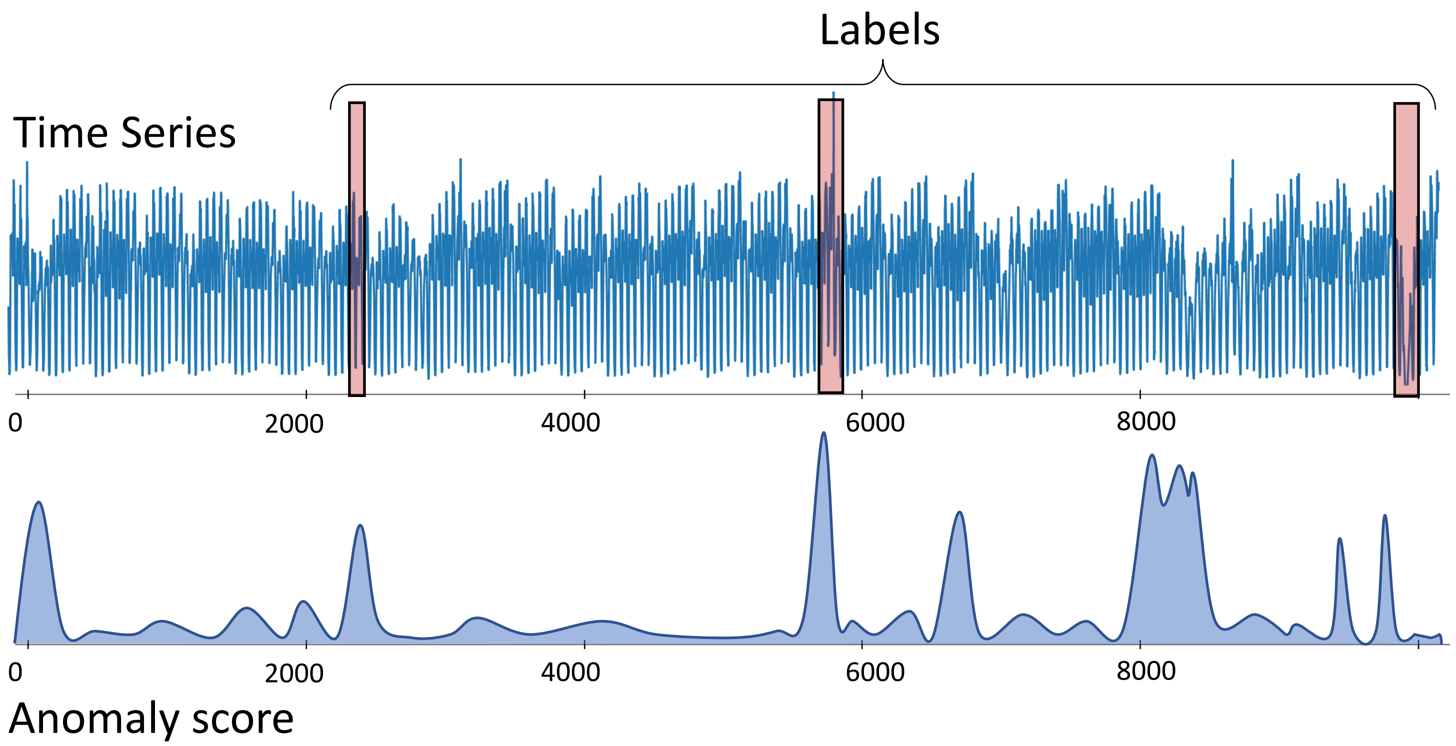
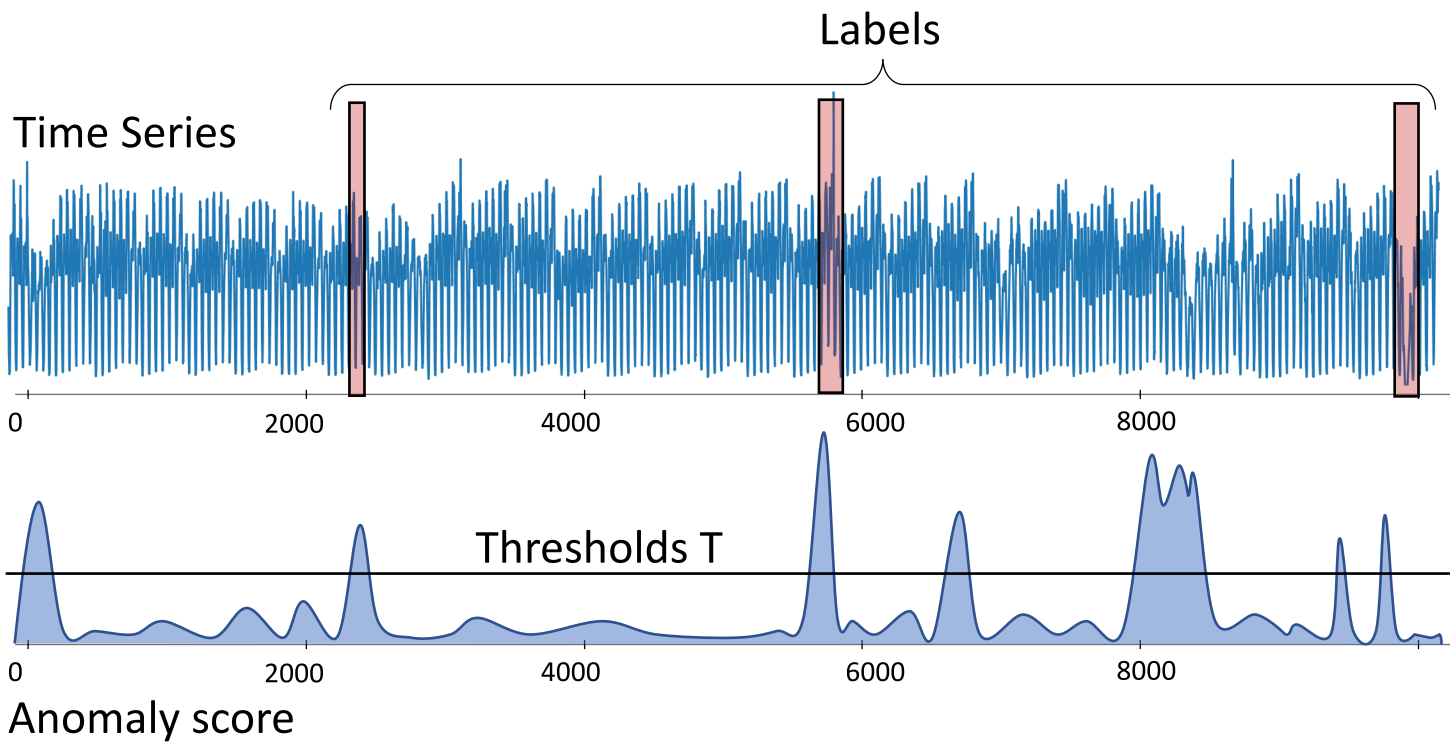


Evaluation measures: *Threshold-based*

Threshold-based Evaluation Measures:



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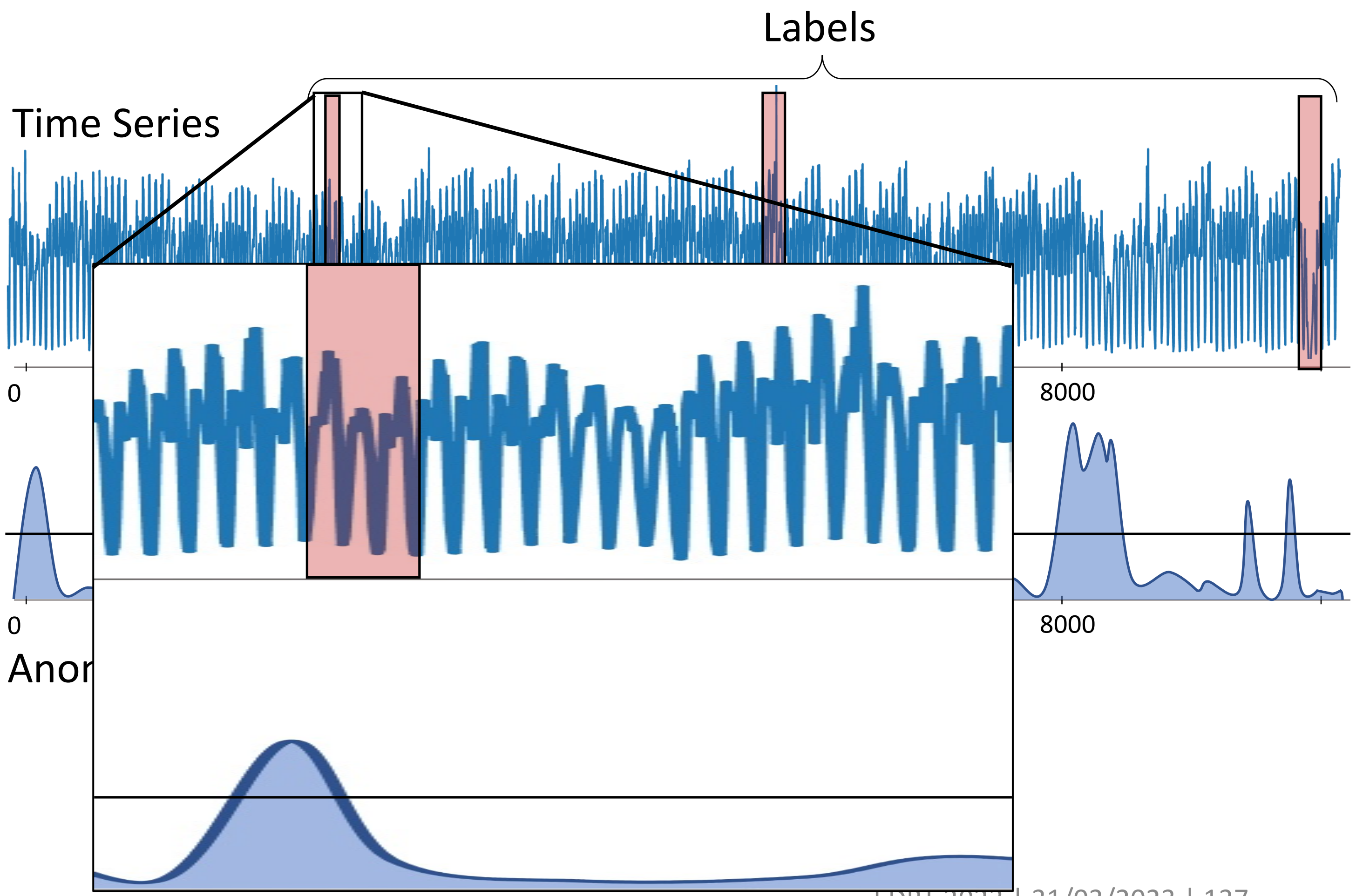

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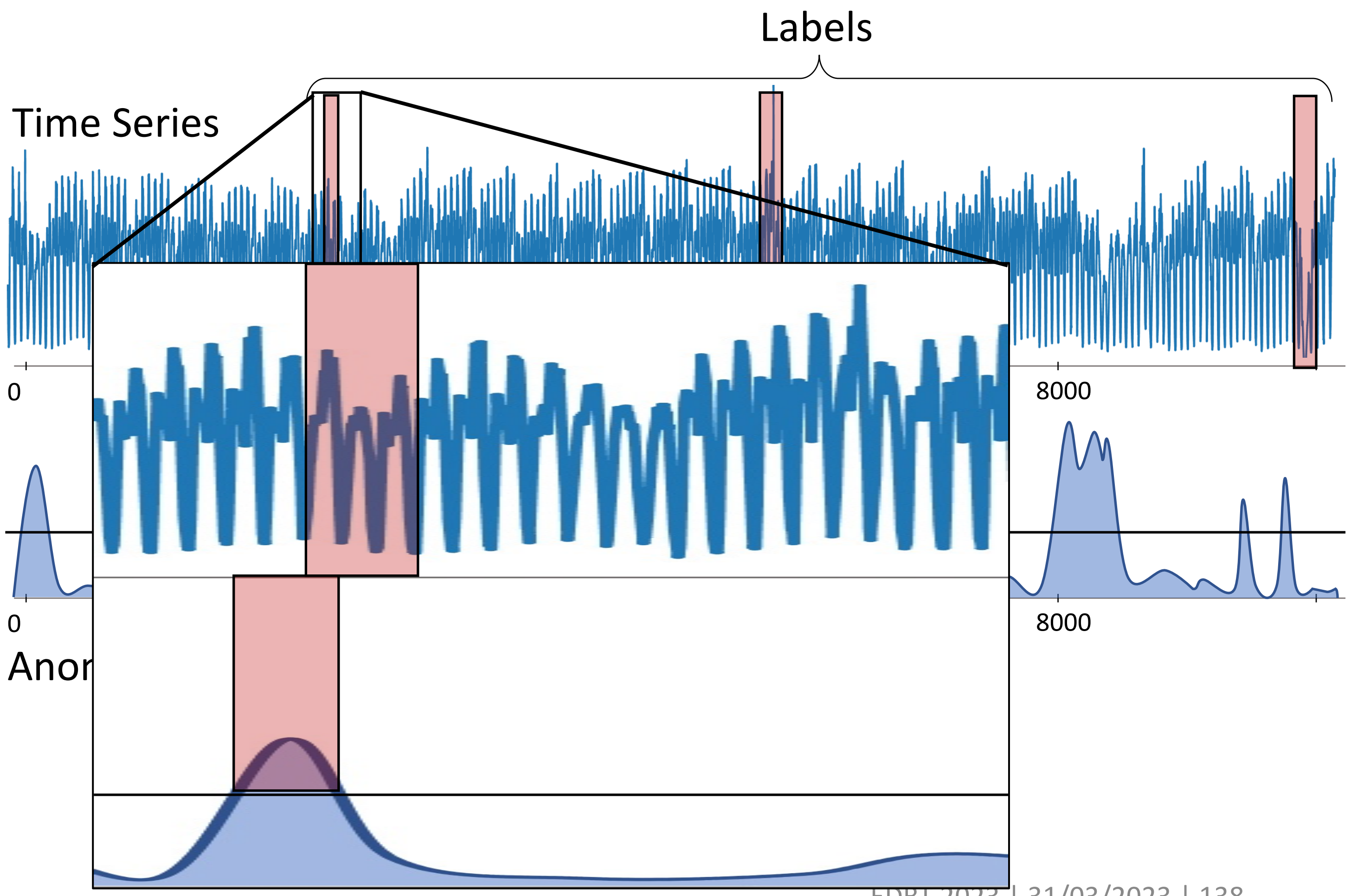

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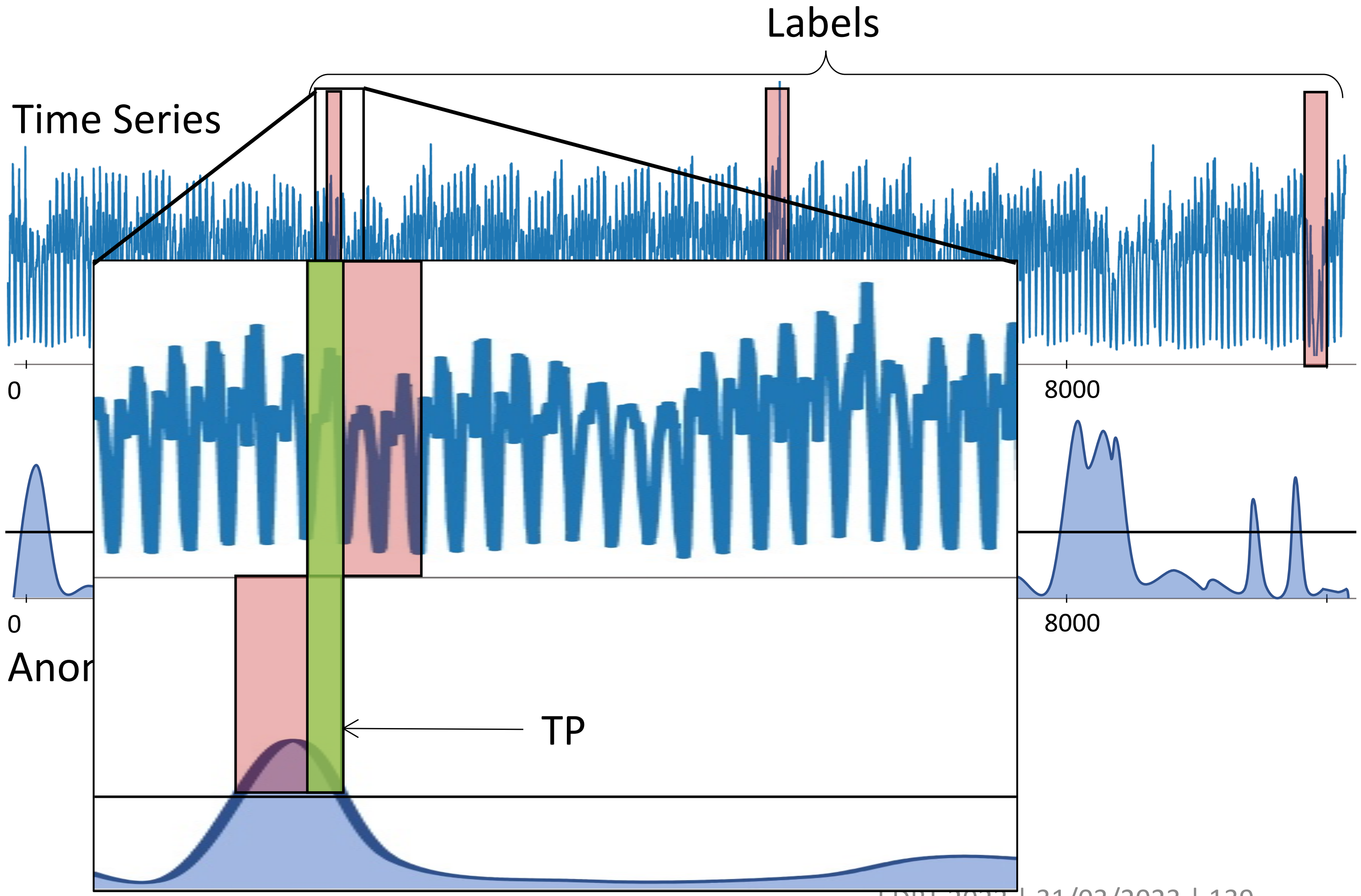

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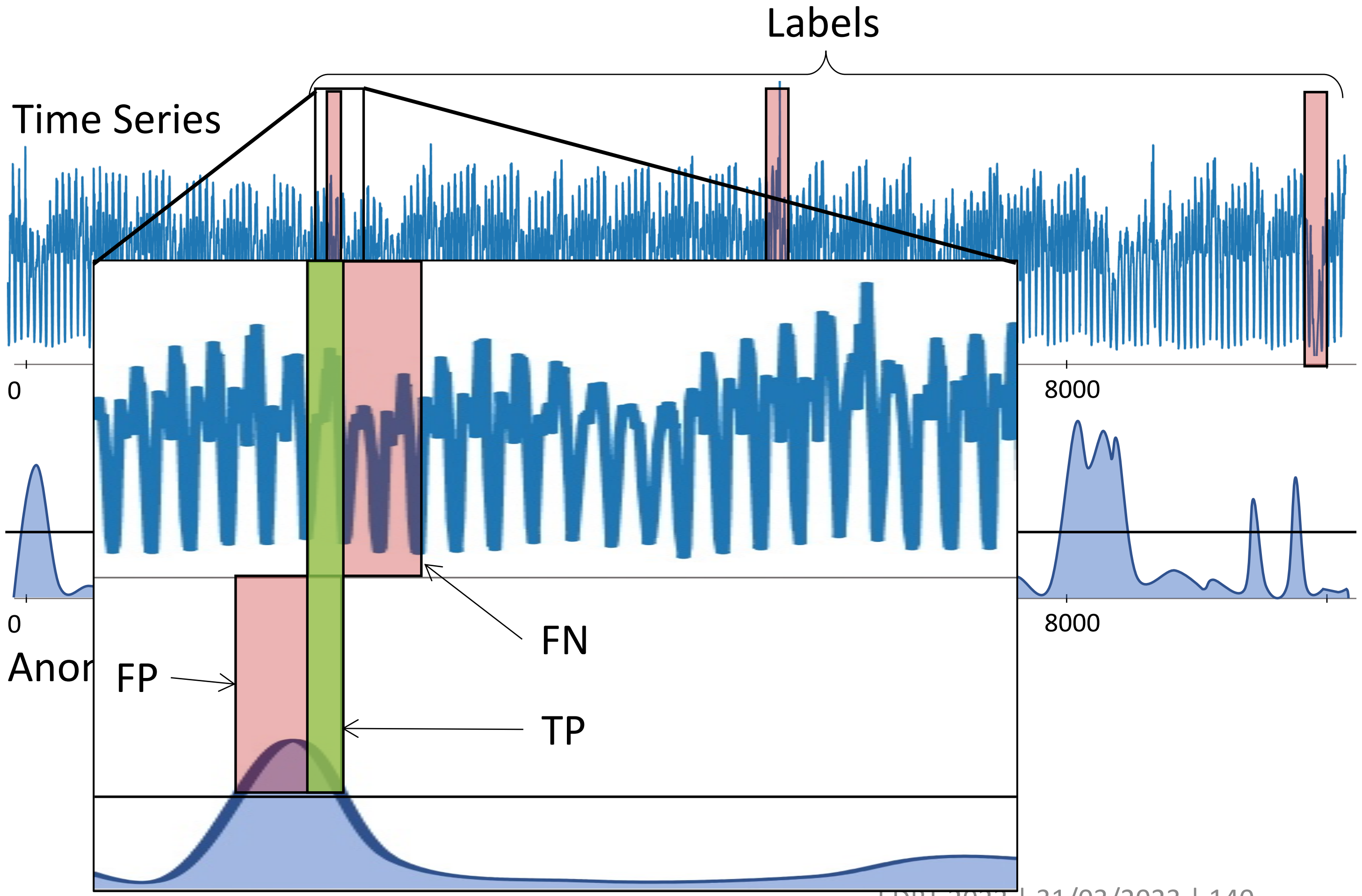

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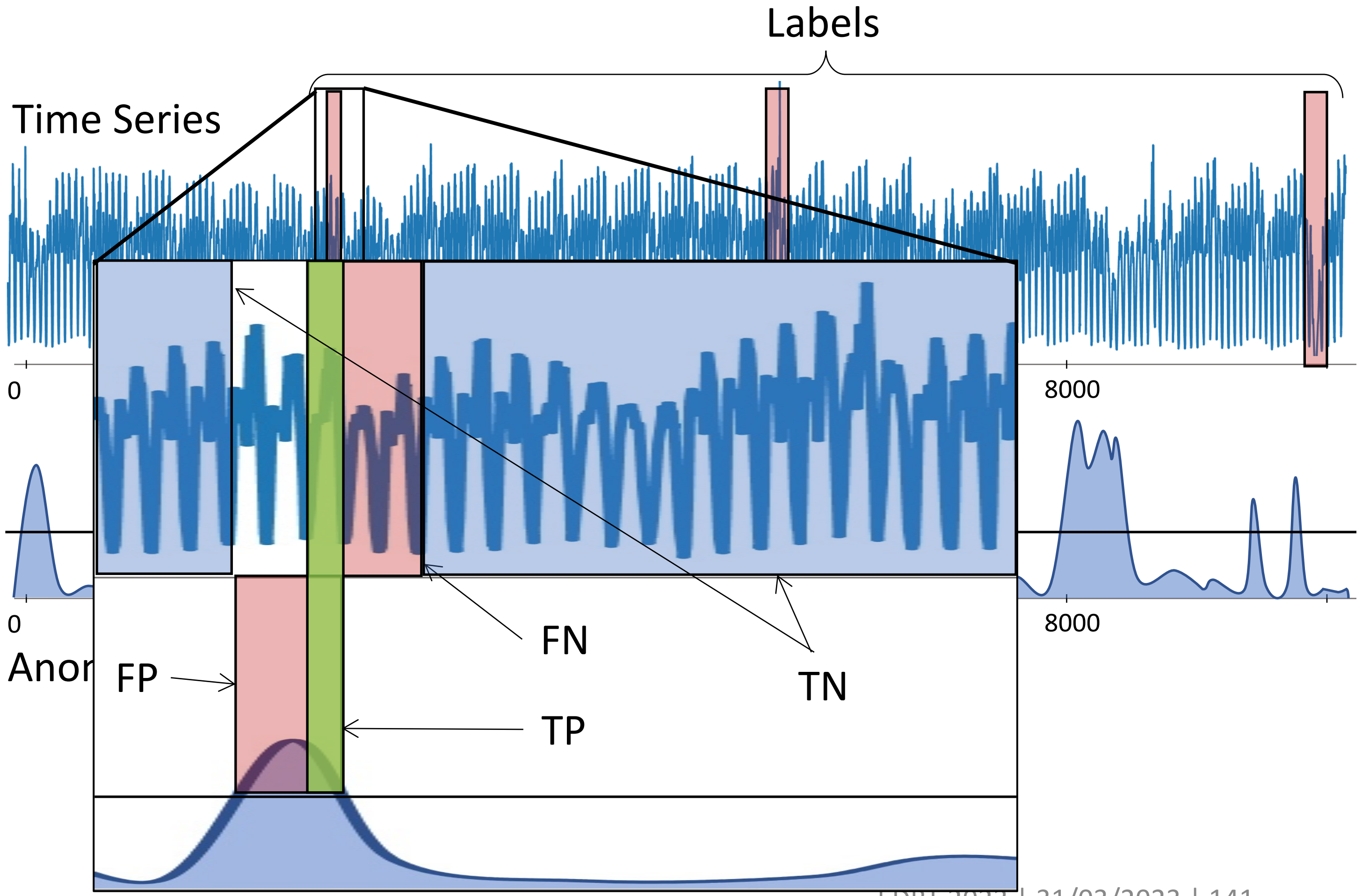
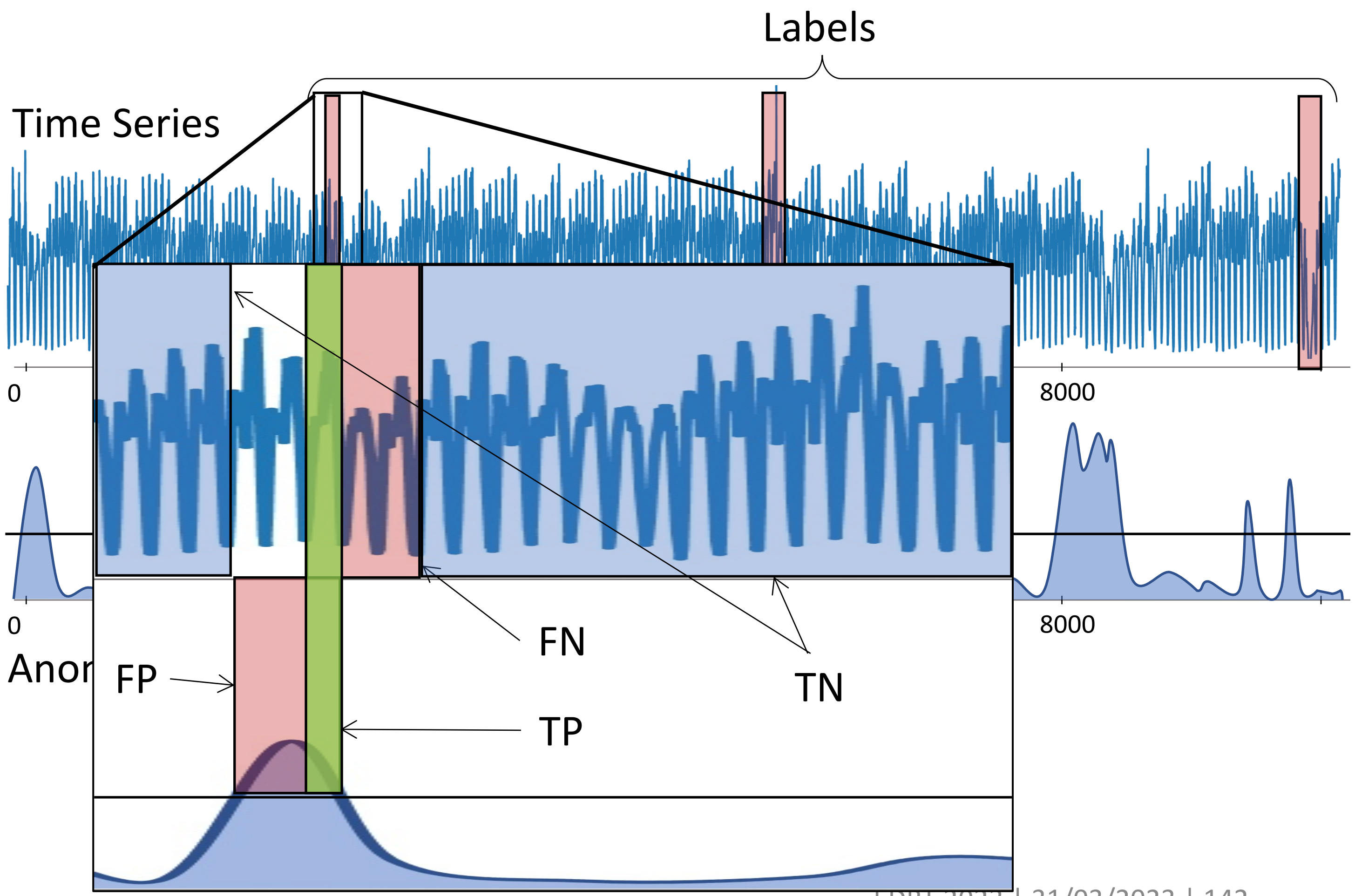


Evaluation measures: *Threshold-based*

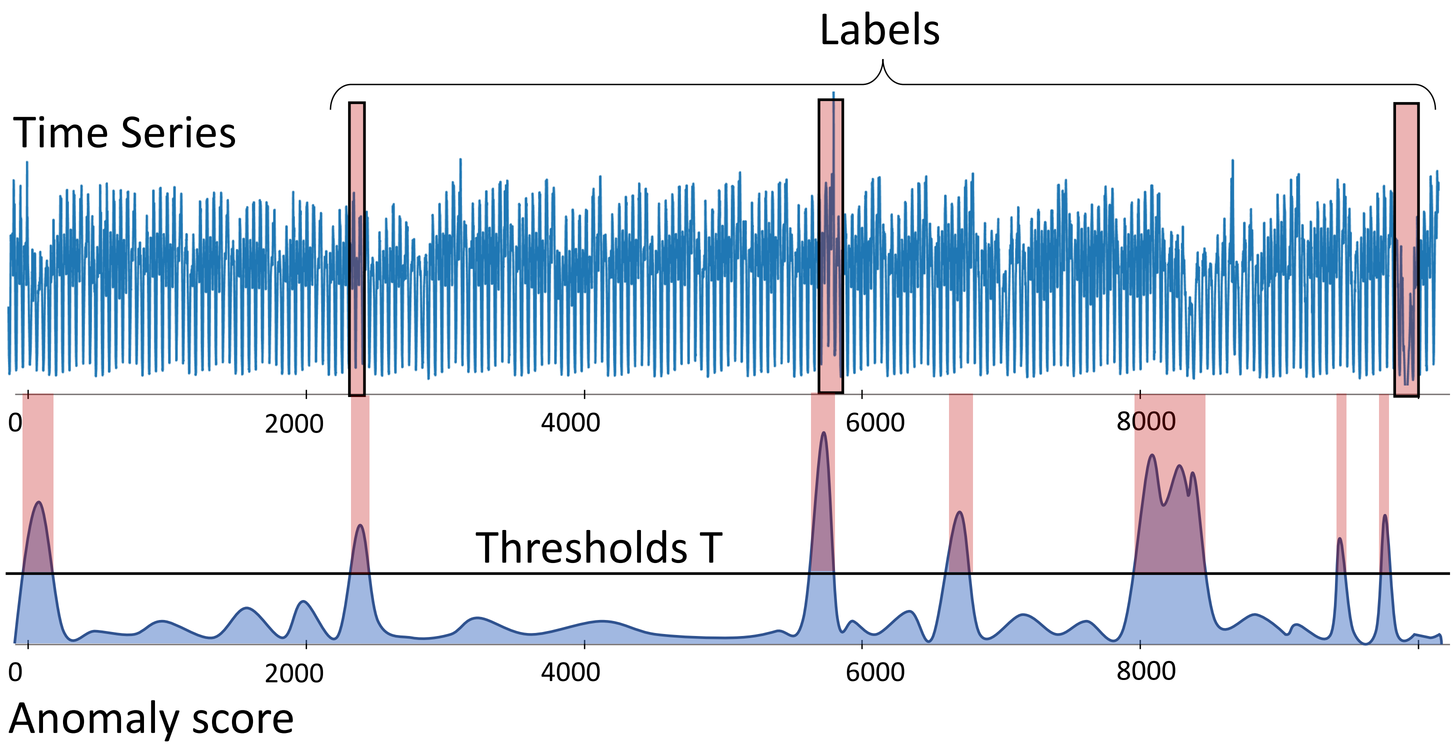
Threshold-based Evaluation Measures:

- Precision: $\frac{TP}{TP+FP}$
- Recall (true positive rate): $\frac{TP}{TP+FN}$
- False positive rate: $\frac{FP}{FP+TN}$
- F-score: $\frac{(1+\beta^2)*Precision}{\beta^2*Precision+Recall}$



Evaluation measures: *AUC-based*

How do we set the threshold?



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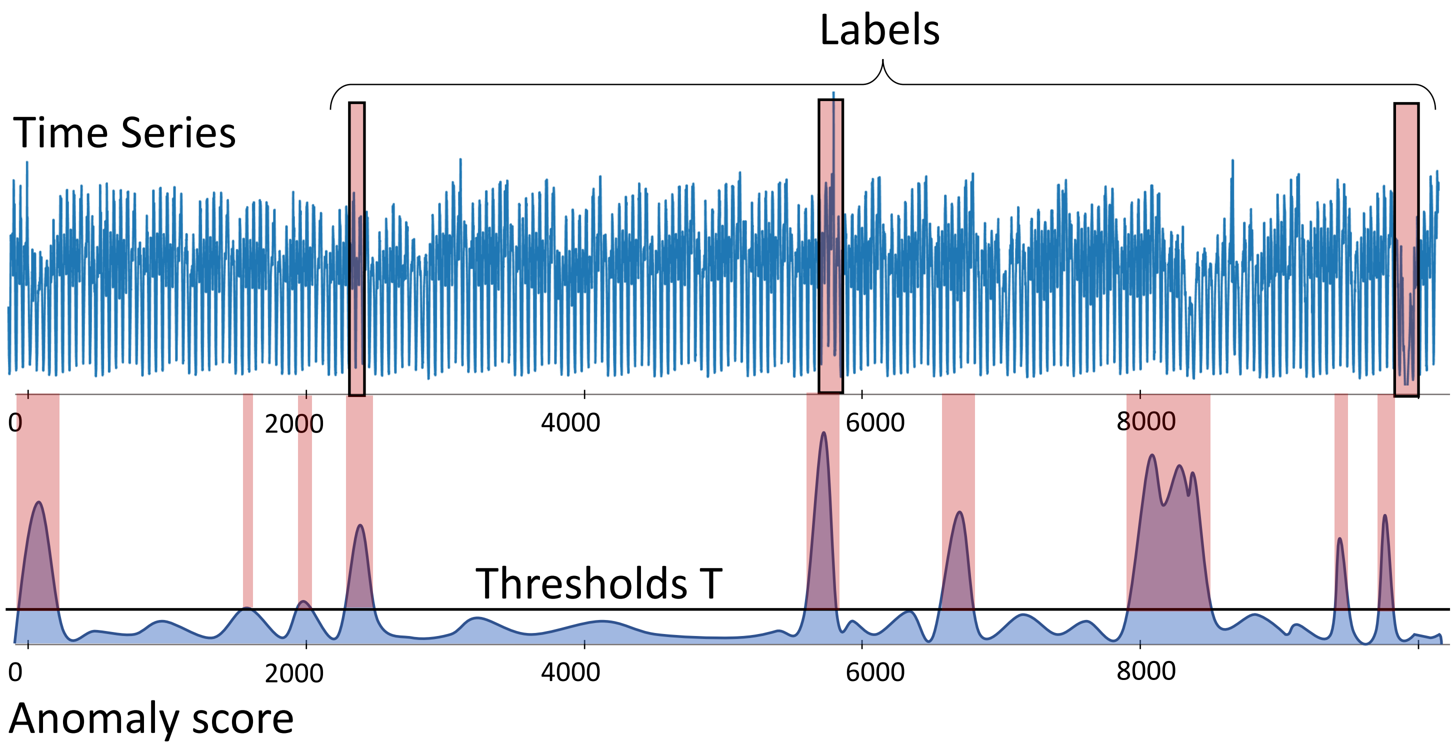

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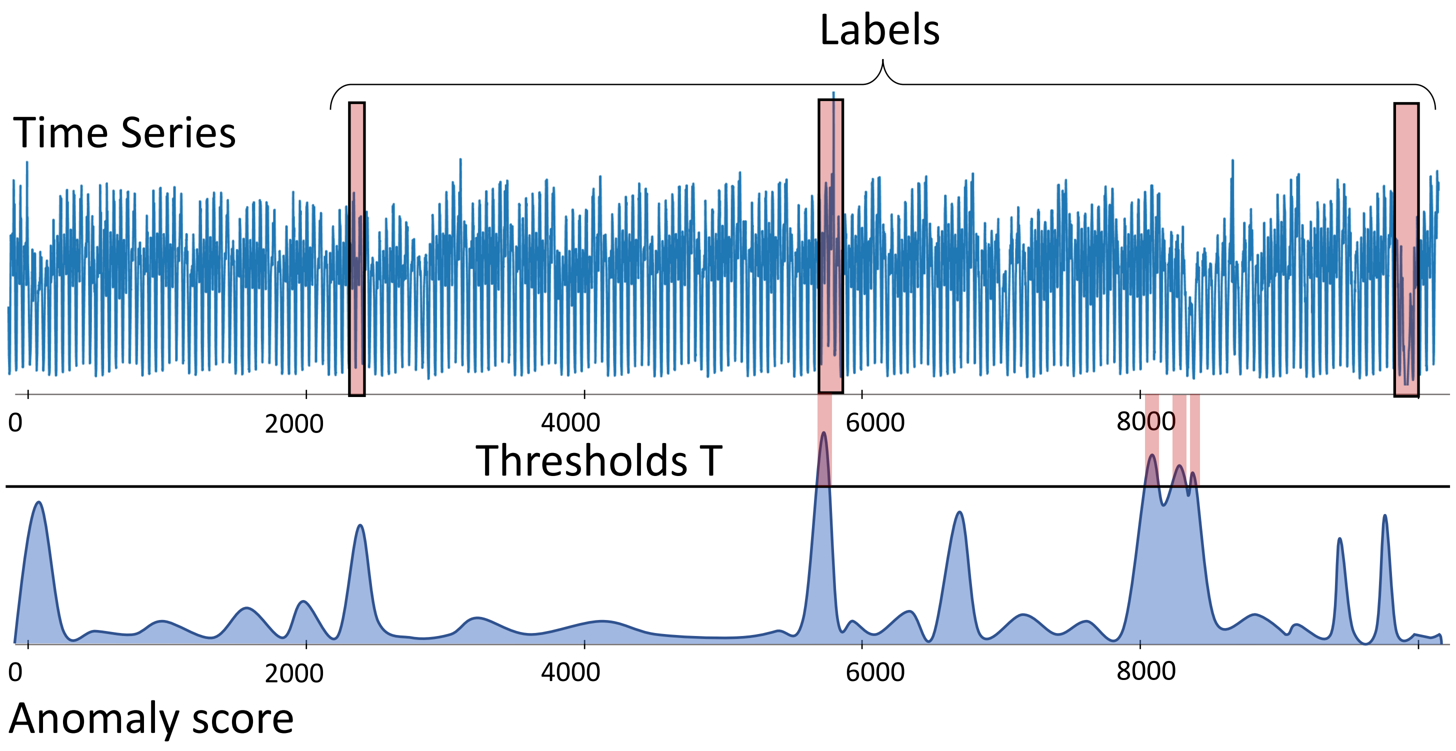

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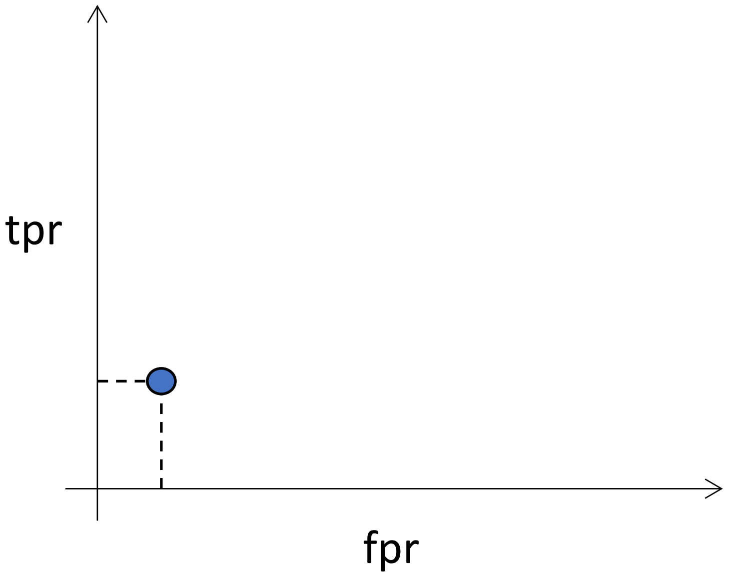
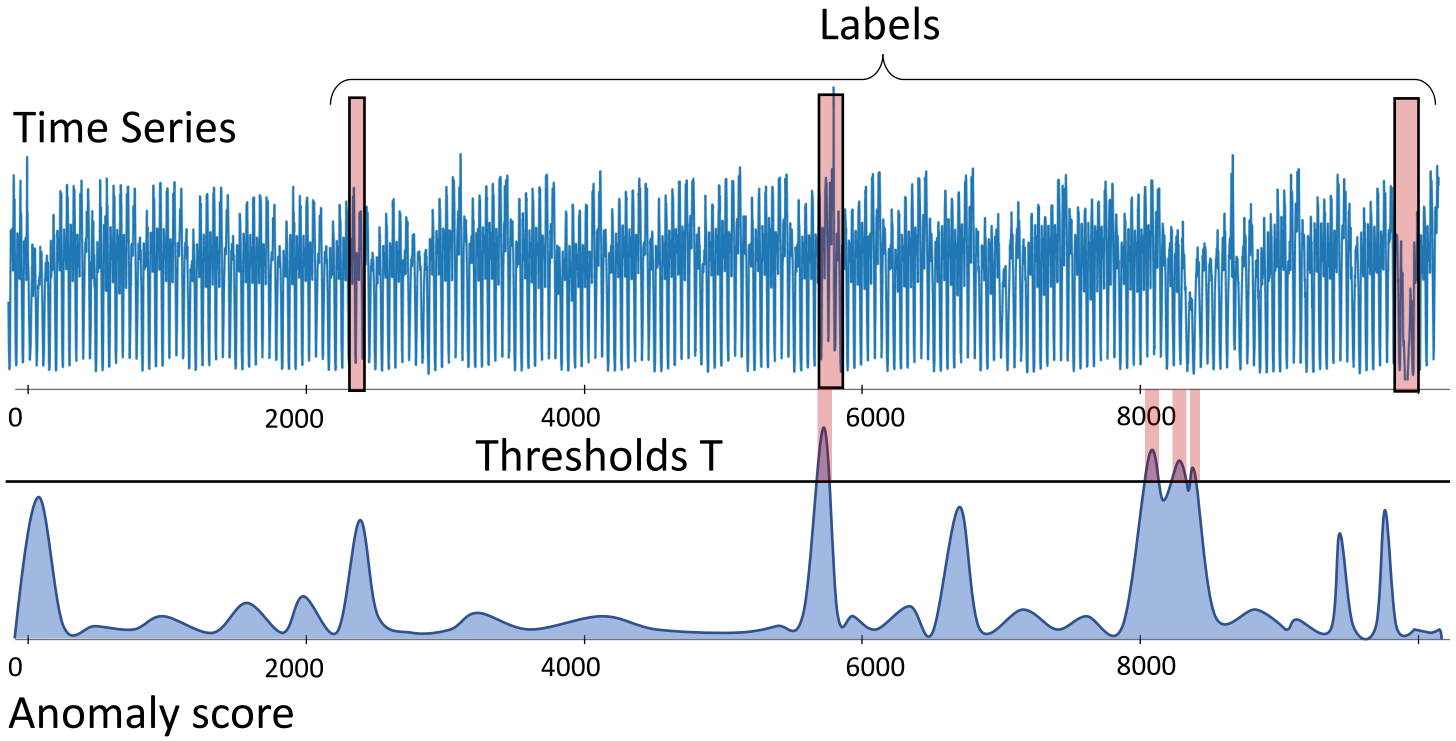
AUC-based Evaluation Measures:





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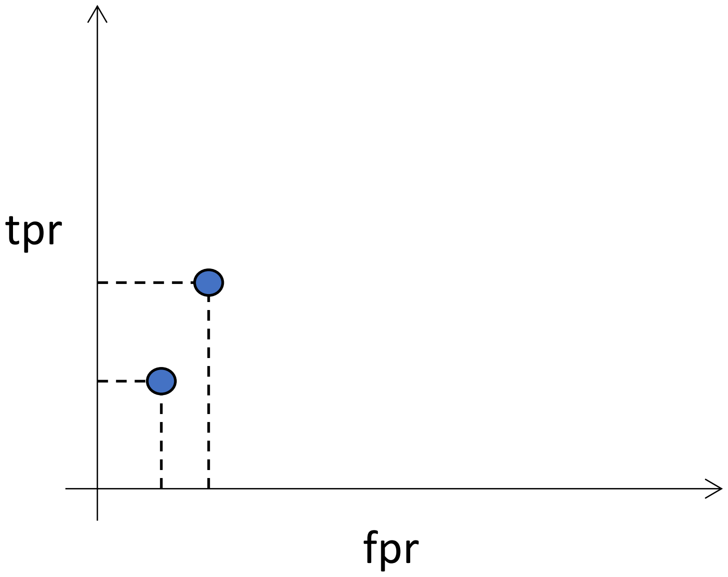

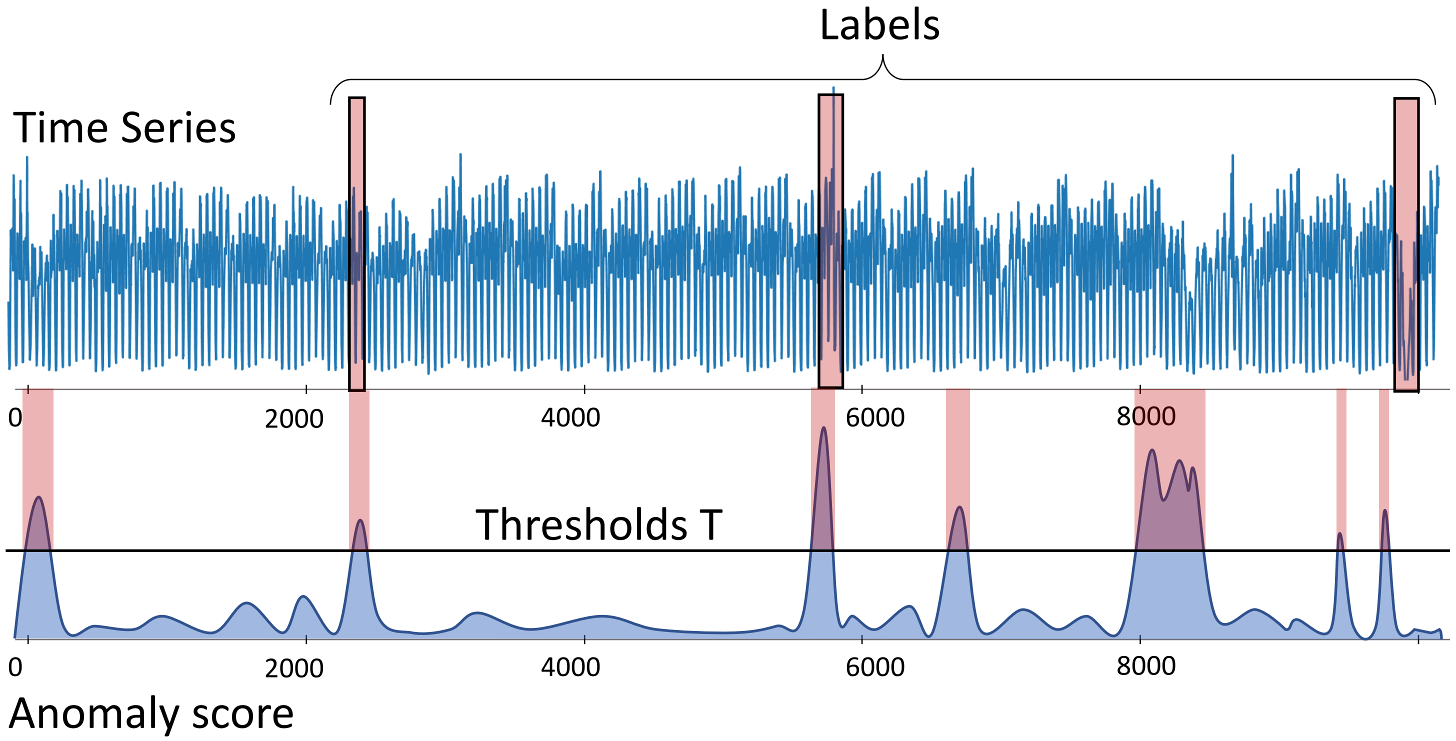

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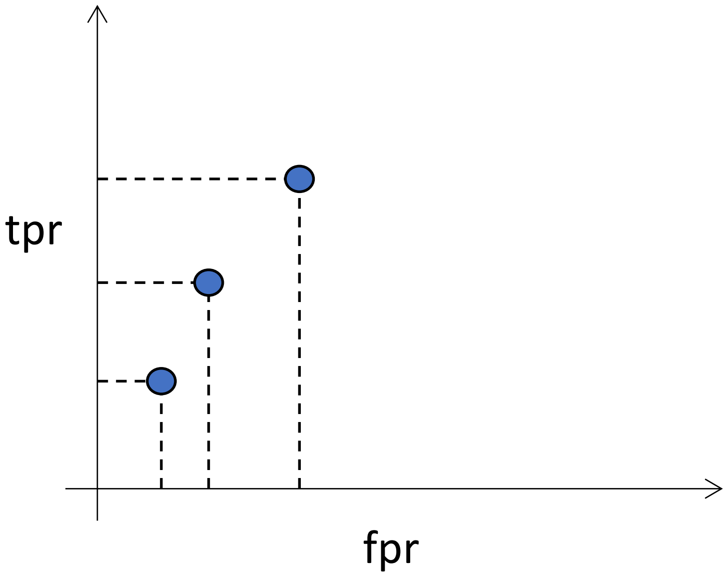

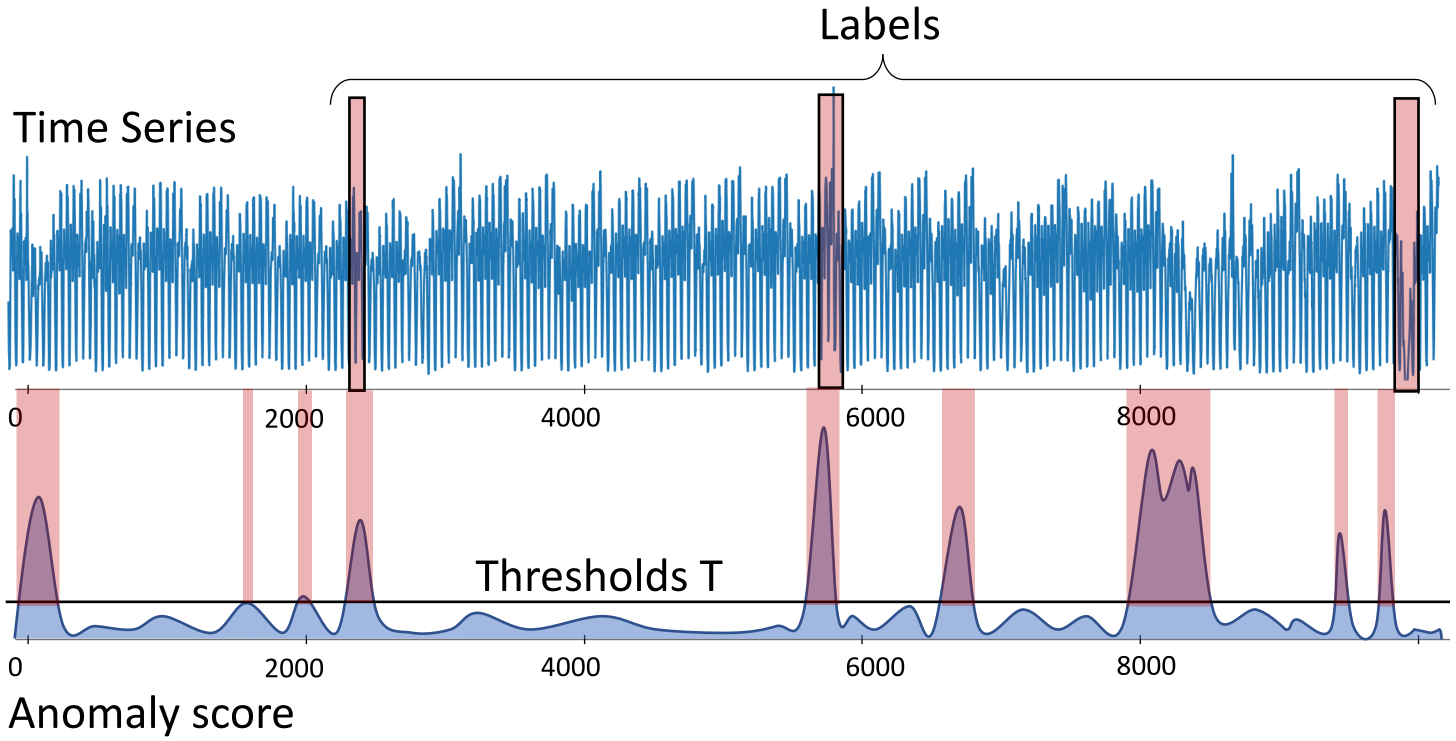

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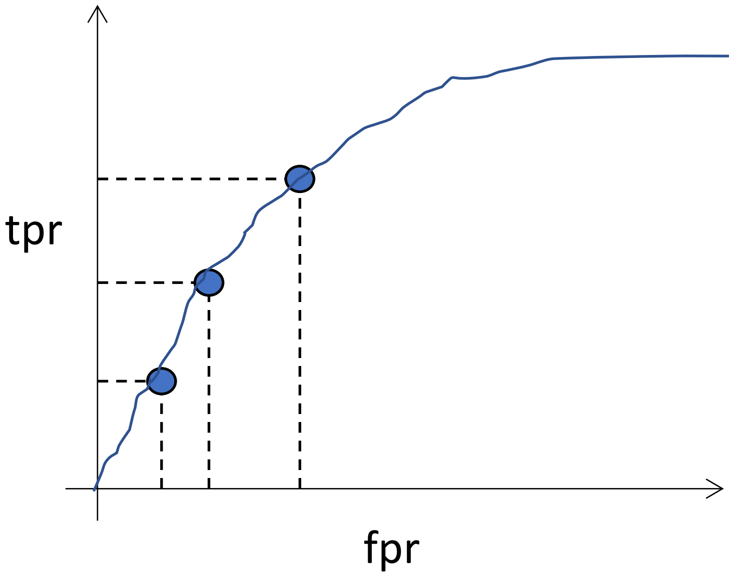

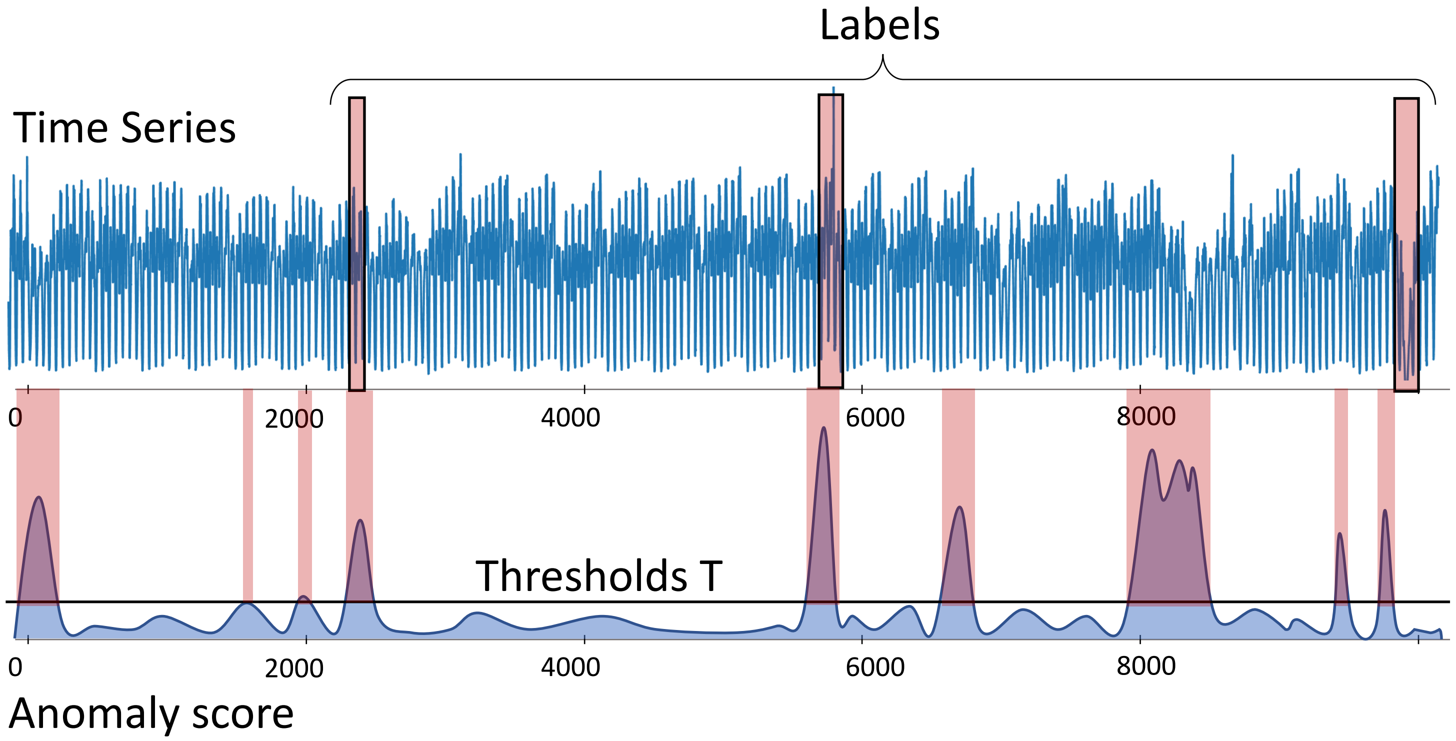

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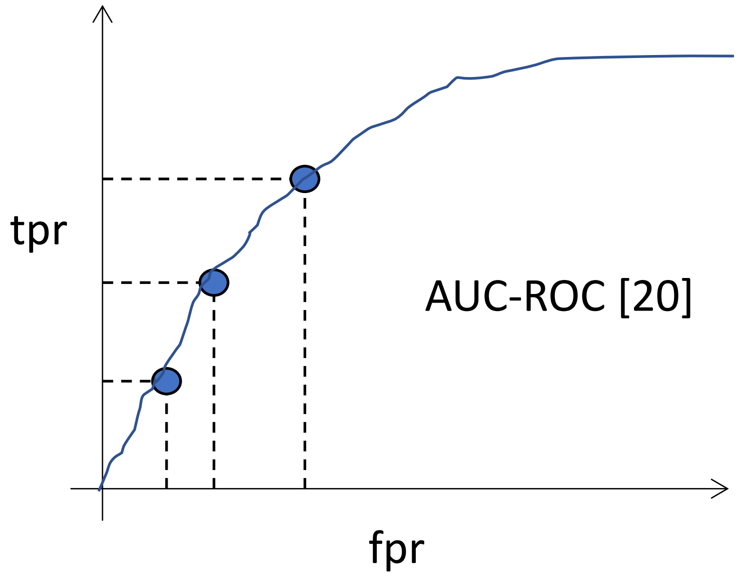

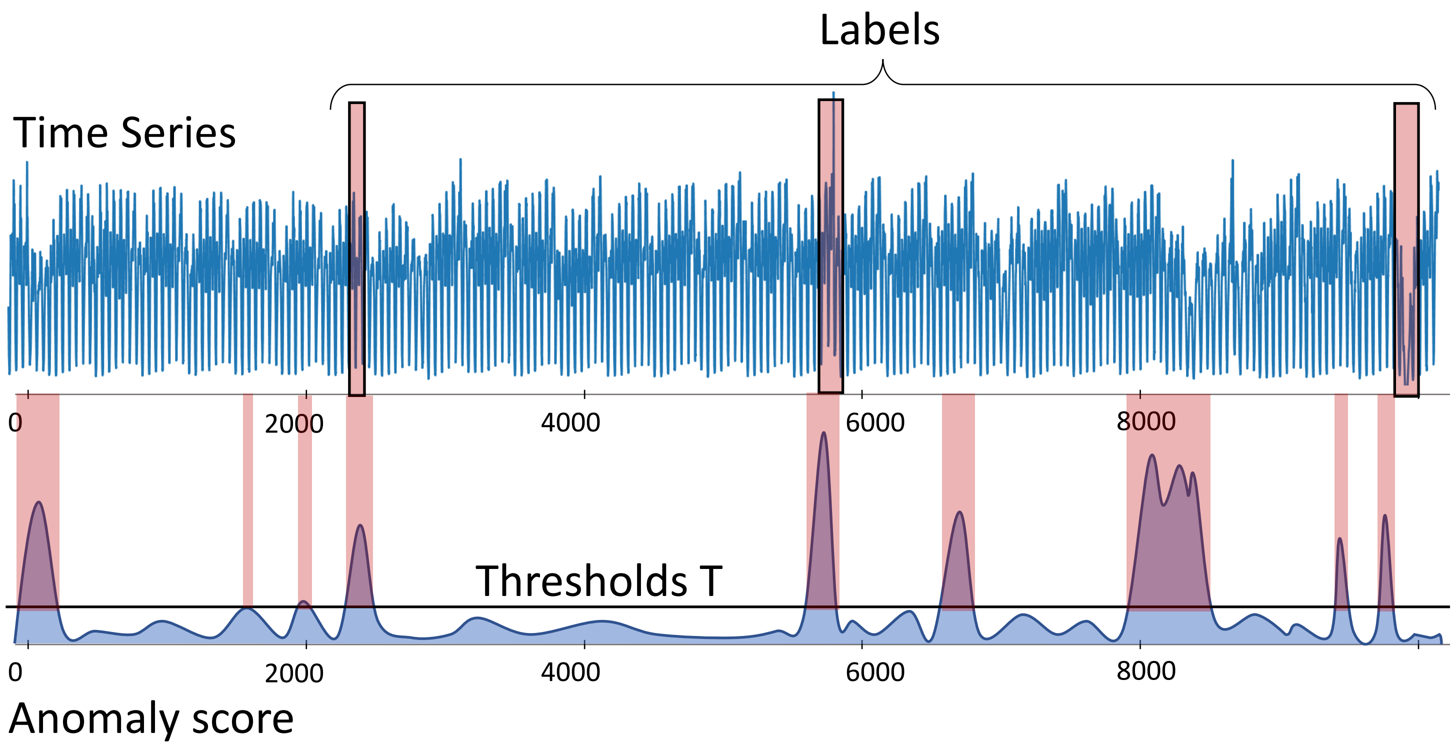

[20] Tom Fawcett. 2006. An introduction to ROC analysis. Pattern Recognition Letters 27, 8 (2006), 861–874.

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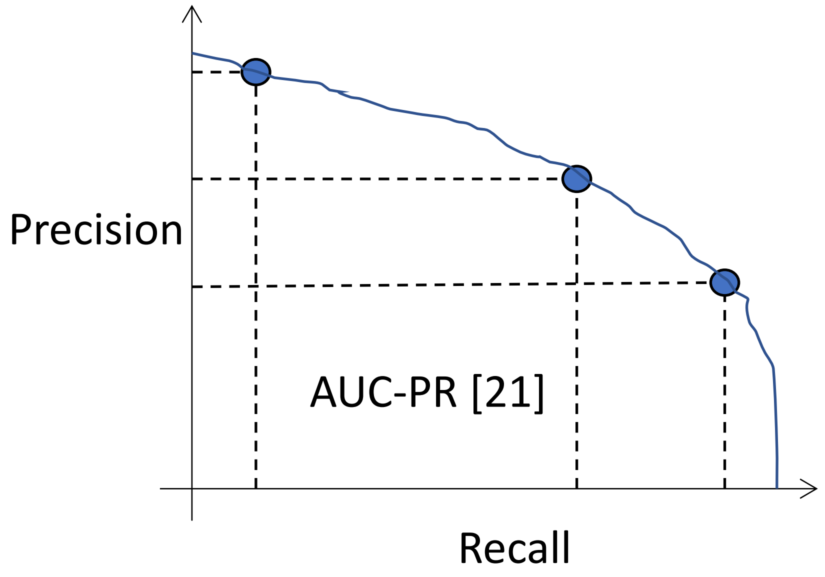
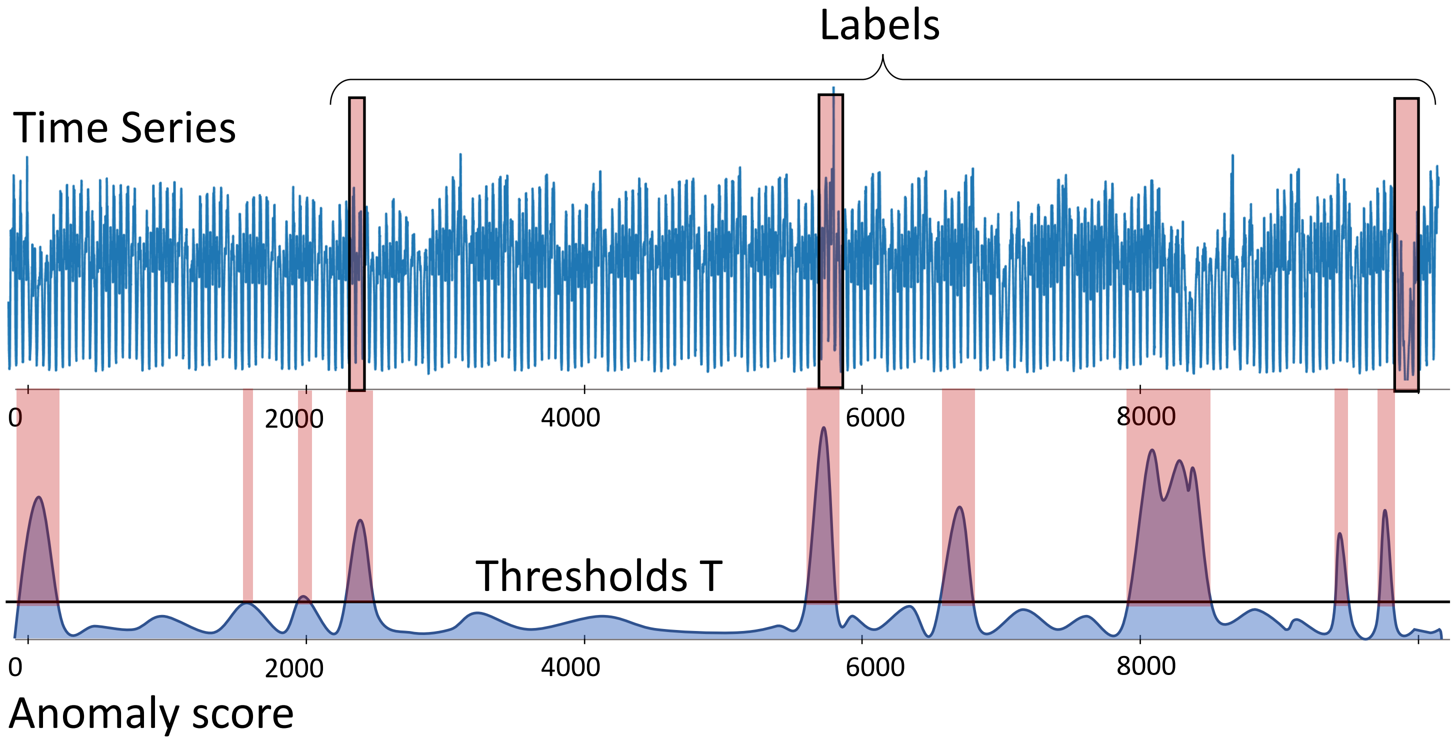
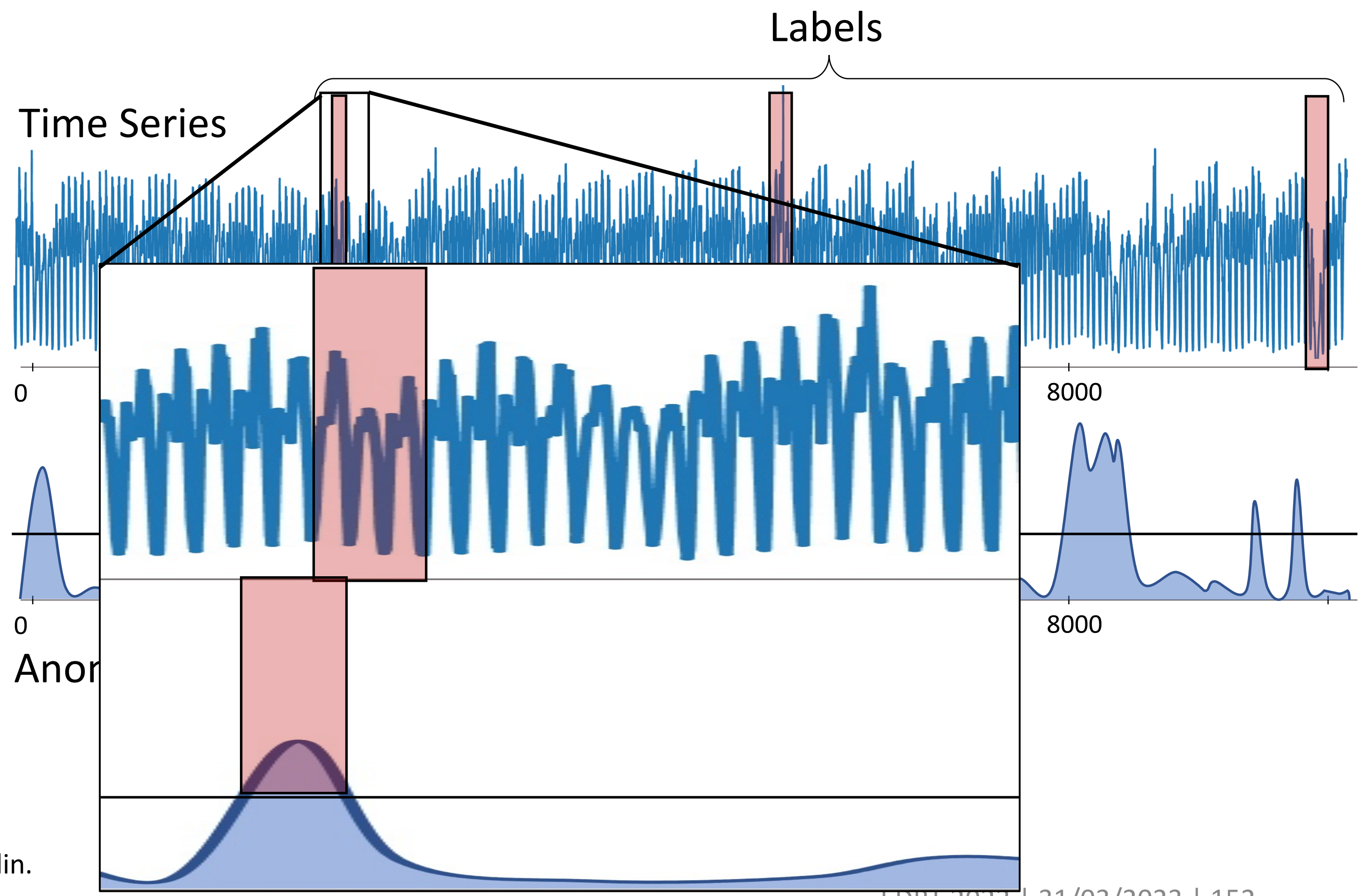




[21] Jesse Davis and Mark Goadrich. 2006. The Relationship between Precision-Recall and ROC Curves. In Proceedings of the 23rd International Conference on Machine Learning (ICML ’06).

Evaluation measures: *Labeling issue*

Labeling can be an issue for time series [22]:



[22] J. Paparrizos, P. Boniol, T. Palpanas, R. S. Tsay, A. Elmore, and M. J. Franklin. Volume under the surface: a new accuracy evaluation measure for time-series anomaly detection. Proc. VLDB Endow. 15, 11 (2022), 2774–2787.

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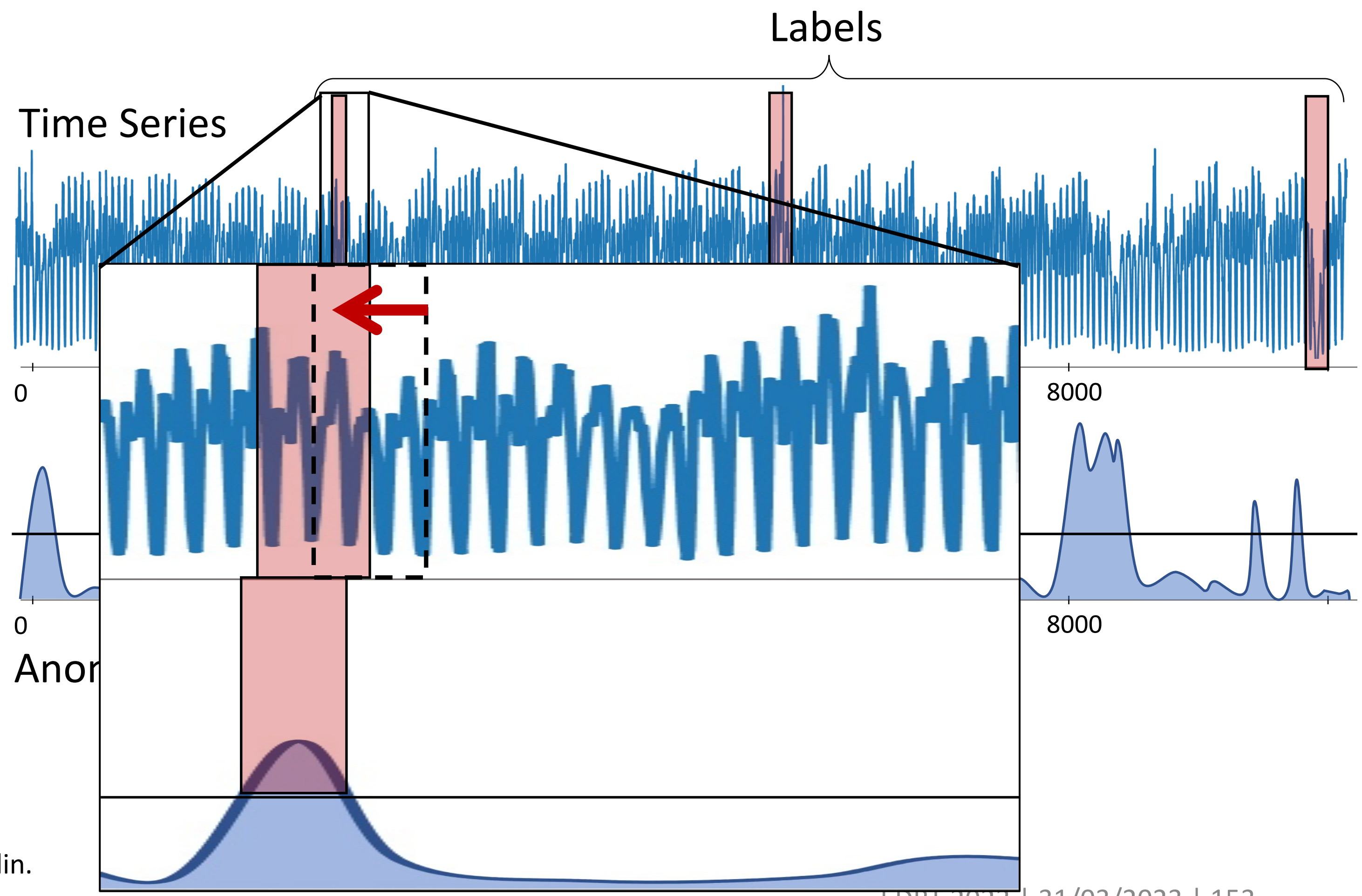

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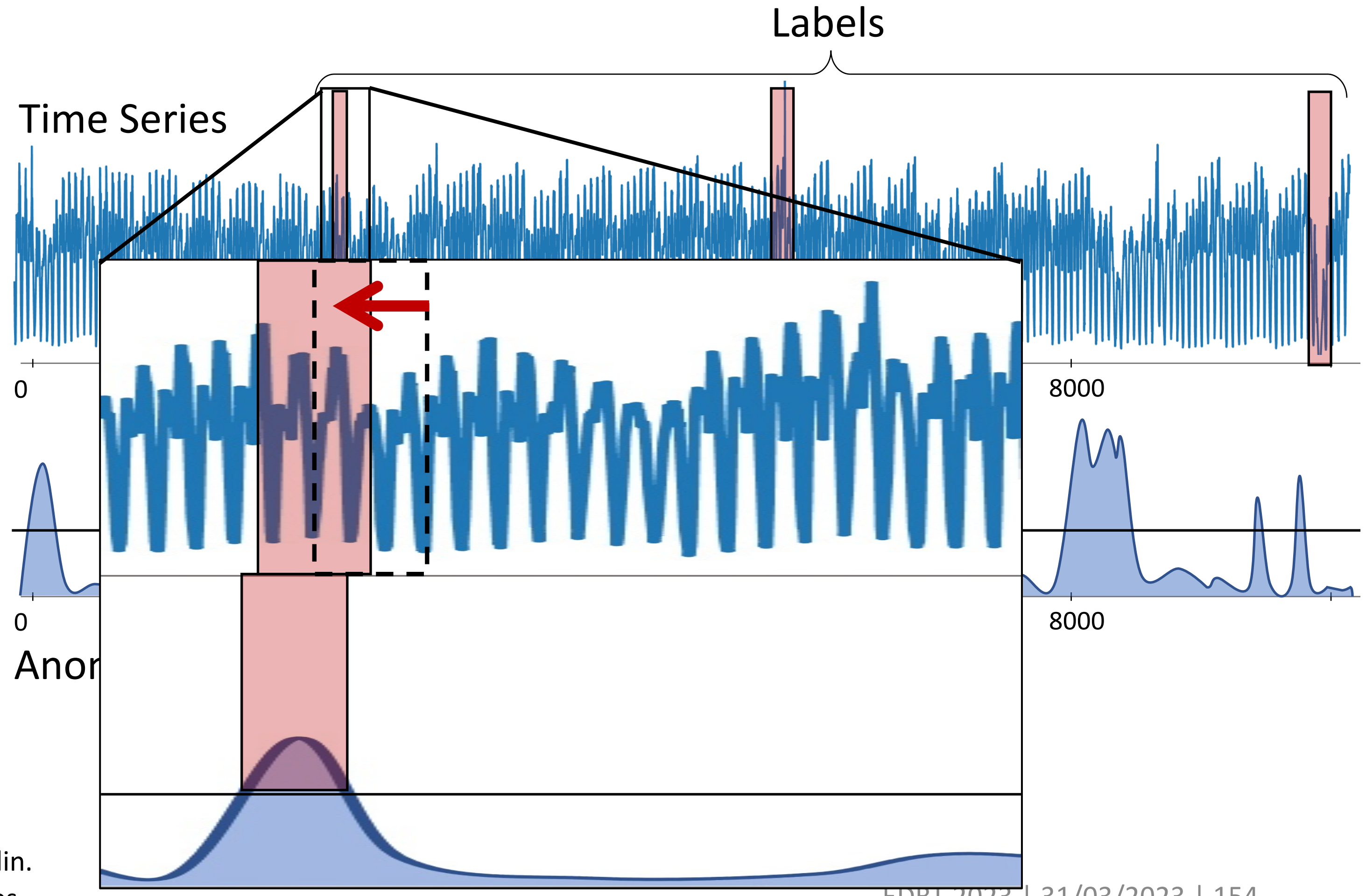
Labeling can be an issue for time series [22]:

- Misalignment can lead to significant changes of accuracy values.



[22] J. Paparrizos, P. Boniol, T. Palpanas, R. S. Tsay, A. Elmore, and M. J. Franklin. Volume under the surface: a new accuracy evaluation measure for time-series anomaly detection. Proc. VLDB Endow. 15, 11 (2022), 2774–2787.

Evaluation measures: *Labeling issue*

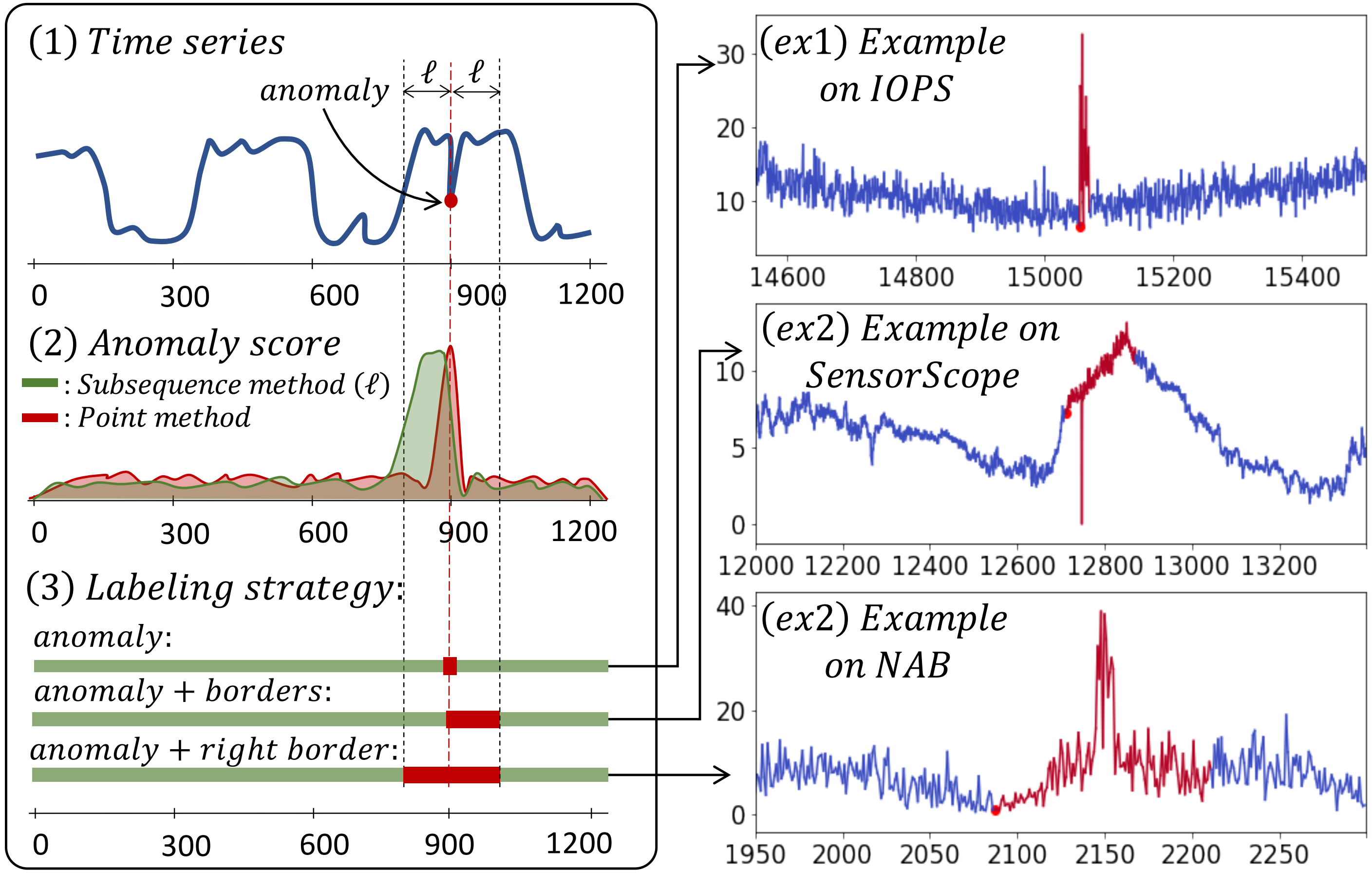
Labeling can be an issue for time series [22]:

- Misalignment can lead to significant changes of accuracy values.

- This is a real issue because of:

  - Different Labeling strategies between domains and applications

  - Methods that produce misaligned anomaly scores.



Evaluation measures: *Labeling issue*

Existing solutions:

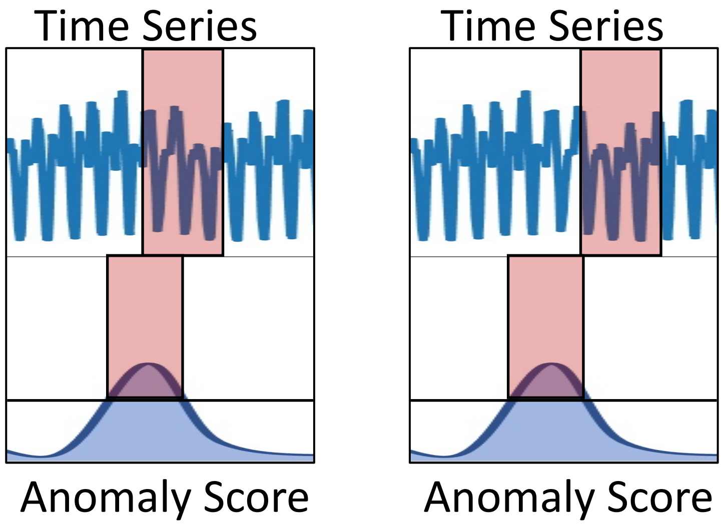
- Range Precision and Recall [23]:

- $Recall_T(R,P) = \frac{\sum_{i=1}^{N_r} Recall_T(R_i,P)}{N_r}$
- $Recall_T(R\_i,P) = \alpha * ExistenceR(R_i,P) + (1-\alpha) * OverlappingR(R\_i,P)$

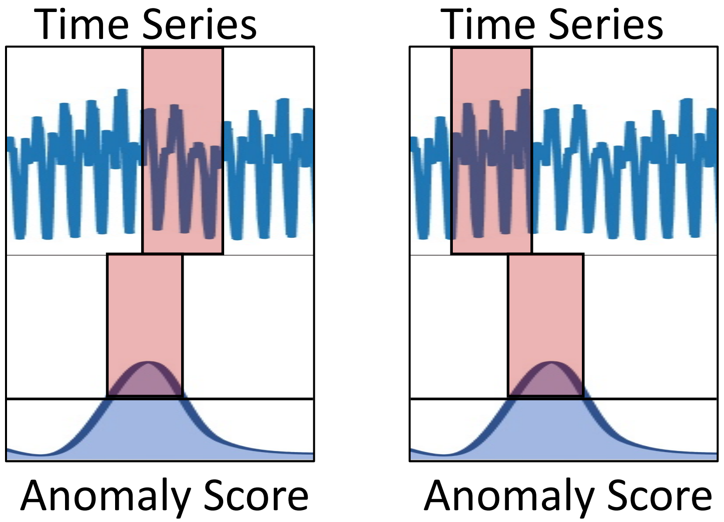
- $Precision_T(R,P) = \frac{\sum_{i=1}^{N_p} Precision_T(R,P_i)}{N_p}$
- $Precision_T(R,P_i) = CardinalityFactor(P_i,R) * \sum_{j=1}^{N_r} w\left(P_i, P_i \cap R_j, \delta\right)$

- Functions $w(\,), \delta(\,)$ are tunable functions to represent the overlap size and position respectively.

Reward Existence or Overlapping?



Reward the beginning or the end?

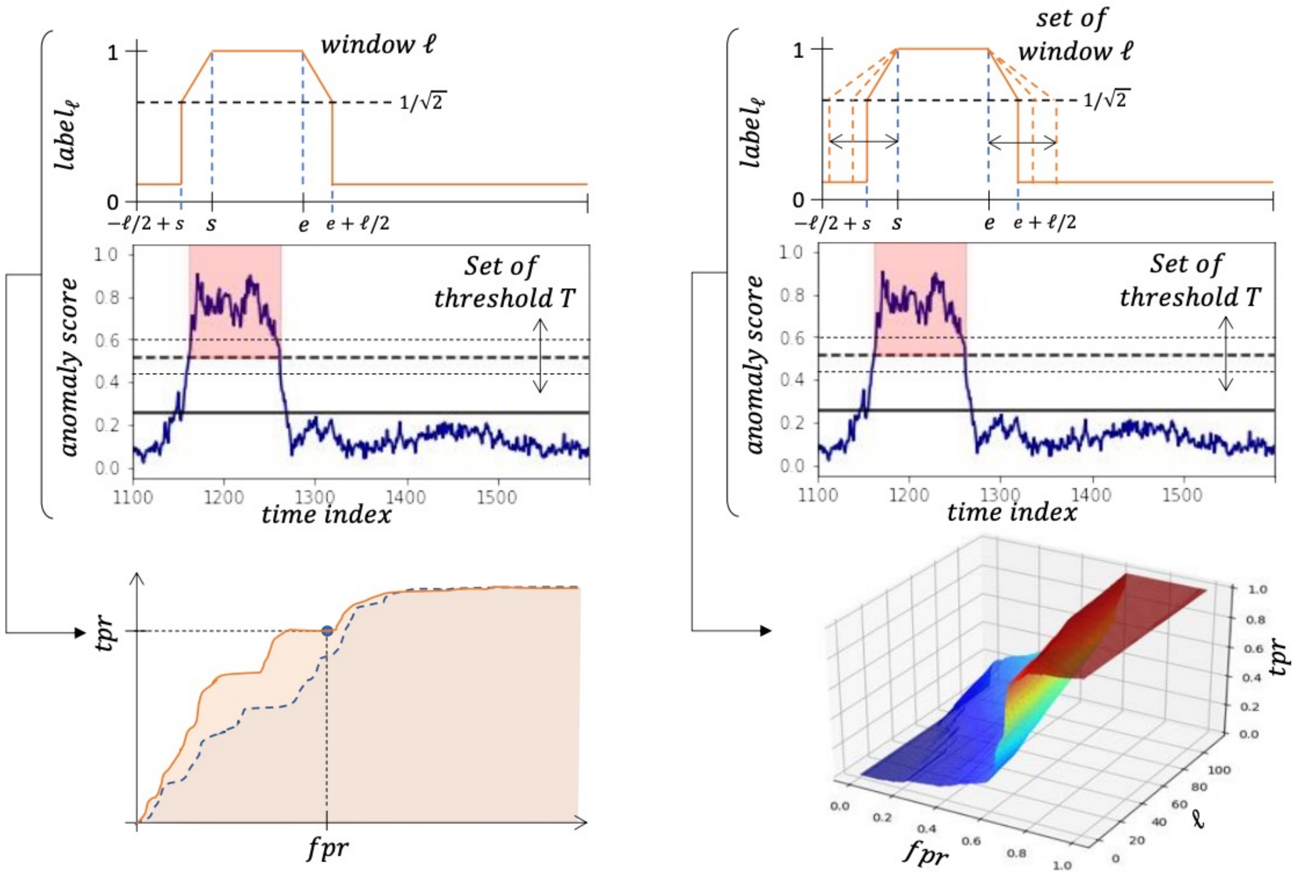


[23] Nesime Tatbul, Tae Jun Lee, Stan Zdonik, Mejbah Alam, and Justin Gottschlich. 2018. Precision and Recall for Time Series. In Advances in Neural Information Processing Systems, Vol. 31.

Evaluation measures: *Labeling issue*

Existing solutions:

- Volume Under the Surface [22] (VUS):
- Modify the labels with buffer regions at the beginning and at the end of an anomaly
- We vary the buffer size (as well as the threshold) and we obtain a surface
- We use the volume under the surface (VUS) as accuracy



(c) R-AUC-based Accuracy measure (ex: R-AUC-ROC, R-AUC-PR)

(d) VUS-based Accuracy measure (ex: VUS-ROC, VUS-PR)

[22] J. Paparrizos, P. Boniol, T. Palpanas, R. S. Tsay, A. Elmore, and M. J. Franklin. Volume under the surface: a new accuracy evaluation measure for time-series anomaly detection. Proc. VLDB Endow. 15, 11 (2022), 2774–2787.

Conclusion and Open Problems

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

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, Yuhao Kang, Paul Boniol, Ruey S. Tsay, Themis Palpanas, Michael J. Franklin

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

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

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

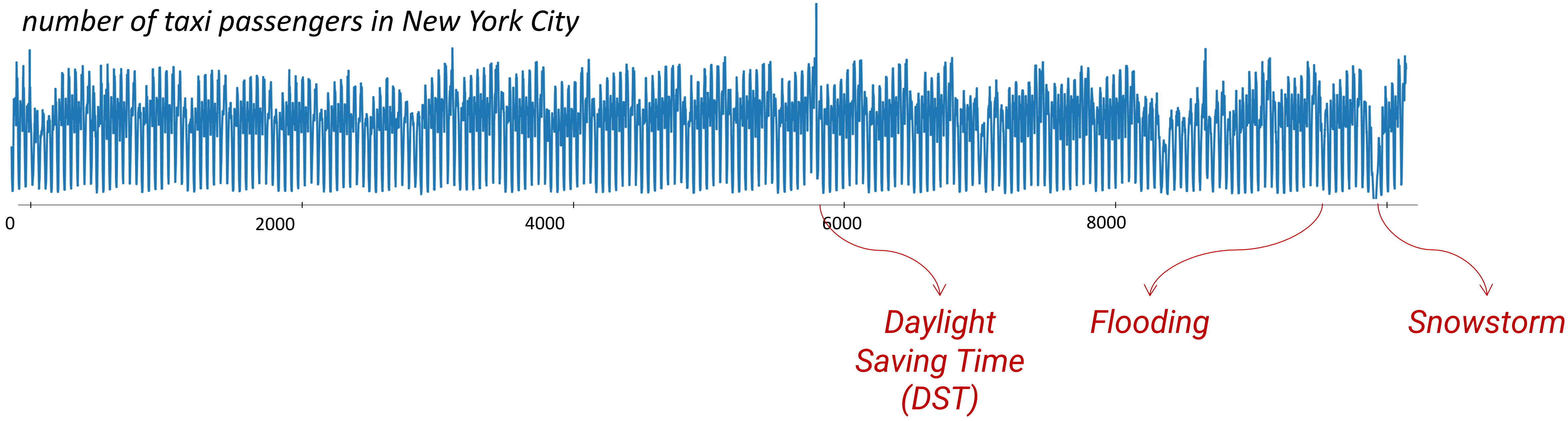
A review on outlier/anomaly detection in time series data

ANE BLÁZQUEZ-GARCÍA and ANGEL CONDE, USUE MORI, JOSE A. LOZANO

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

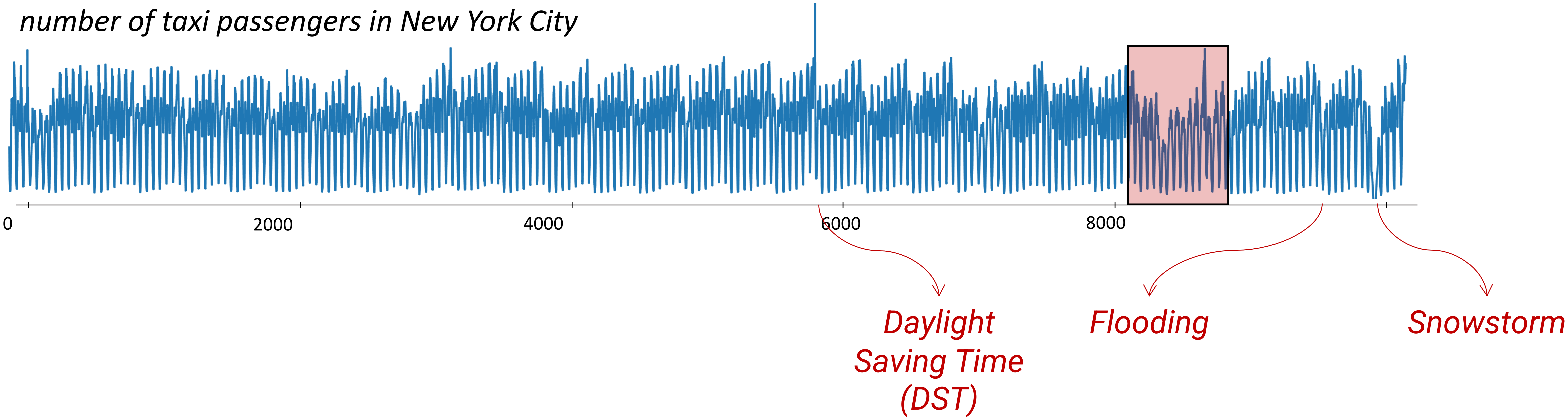
Conclusion and Open Problems

Context-aware Unsupervised Anomaly Detection



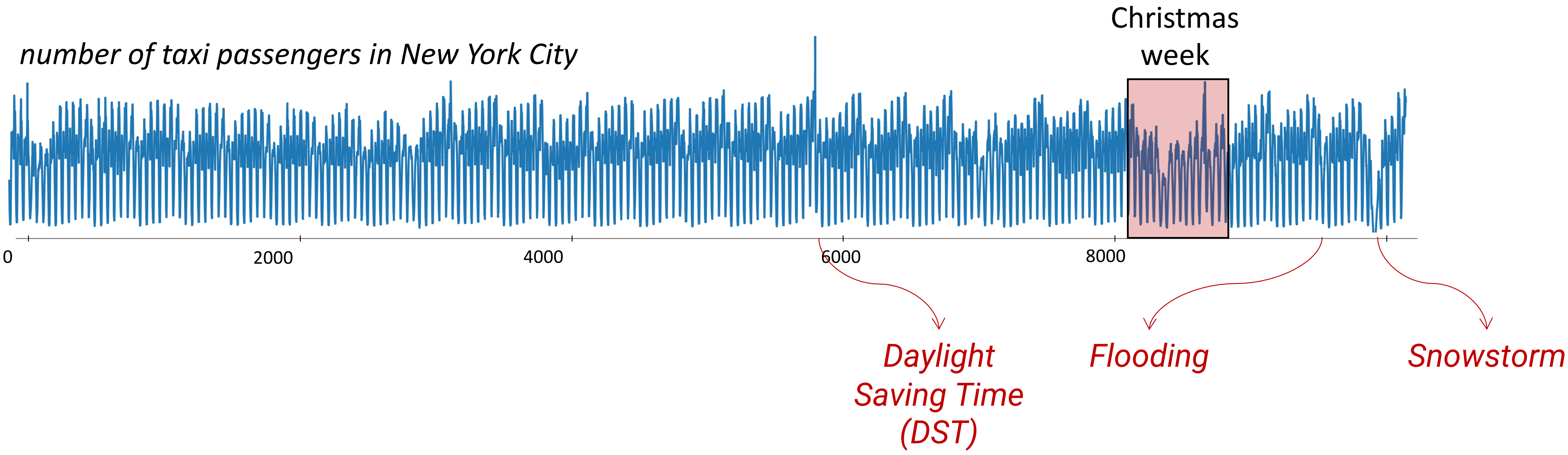
Conclusion and Open Problems

Context-aware Unsupervised Anomaly Detection



Conclusion and Open Problems

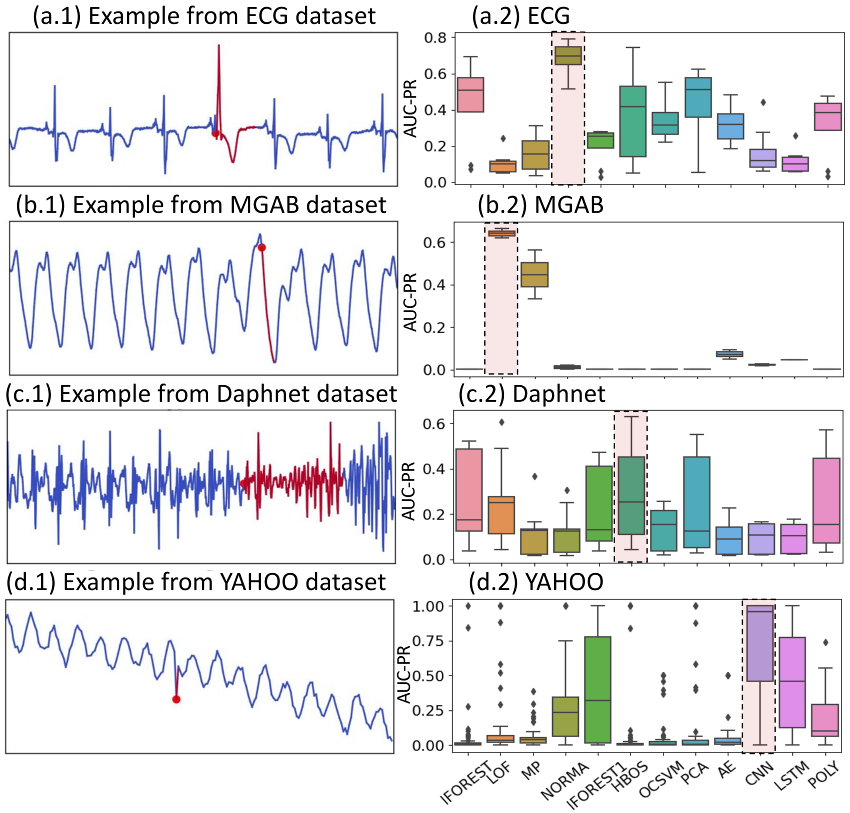
Context-aware Unsupervised Anomaly Detection



Conclusion and Open Problems

Model selection for anomaly detection

Methods ranking changes
significantly between datasets [19]



Conclusion and Open Problems

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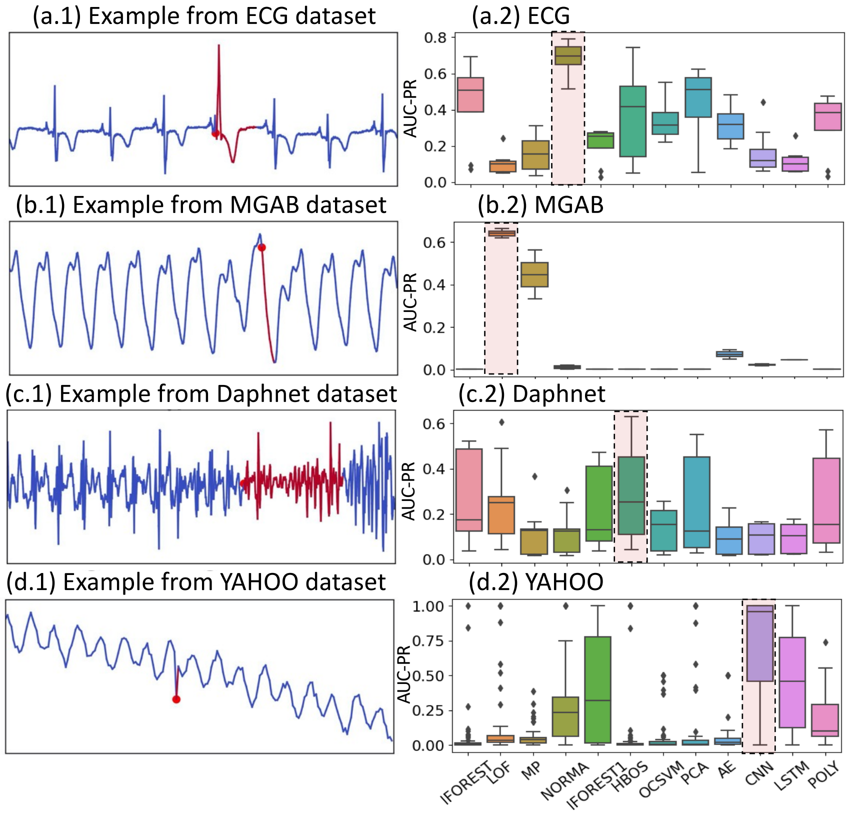
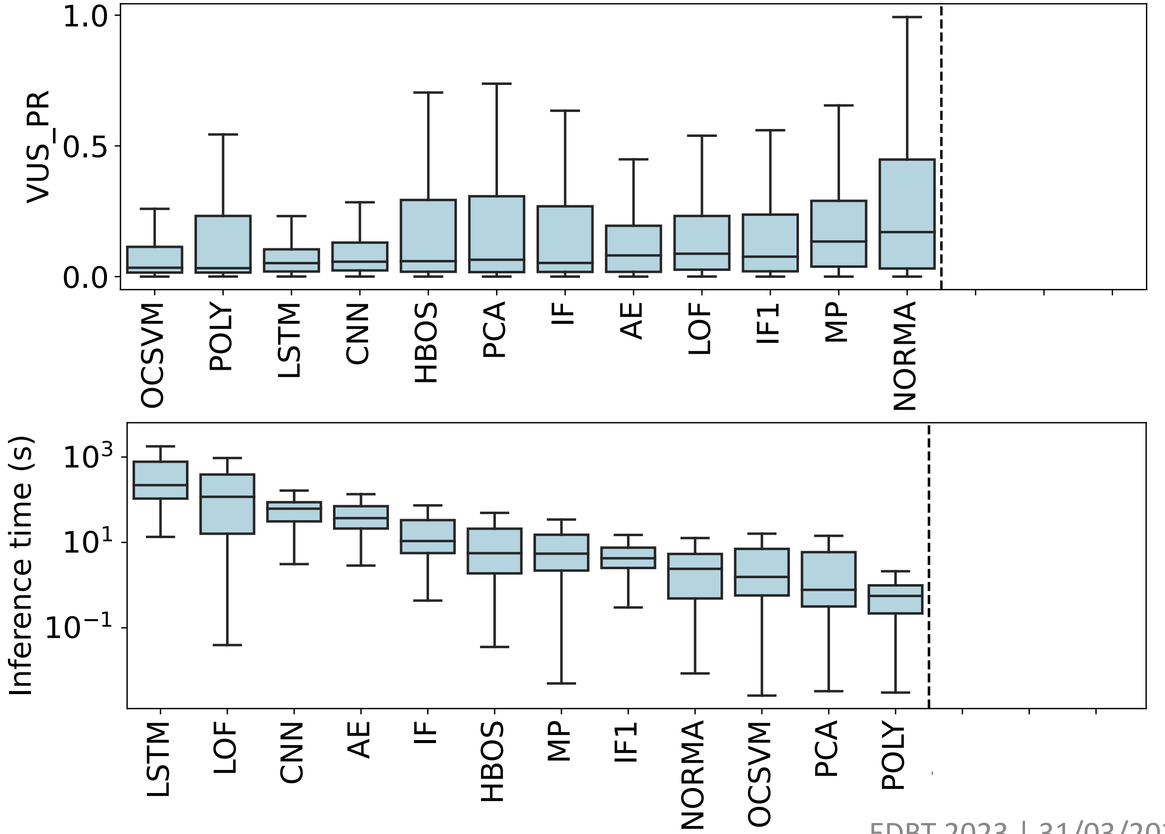


Results over TSB-UAD



Conclusion and Open Problems

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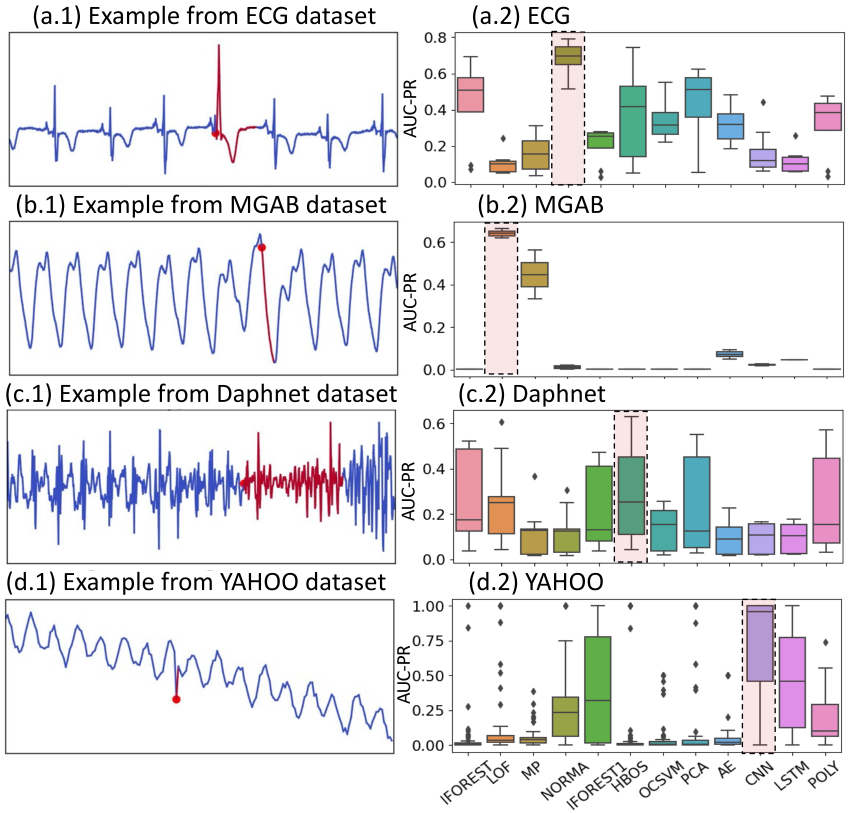
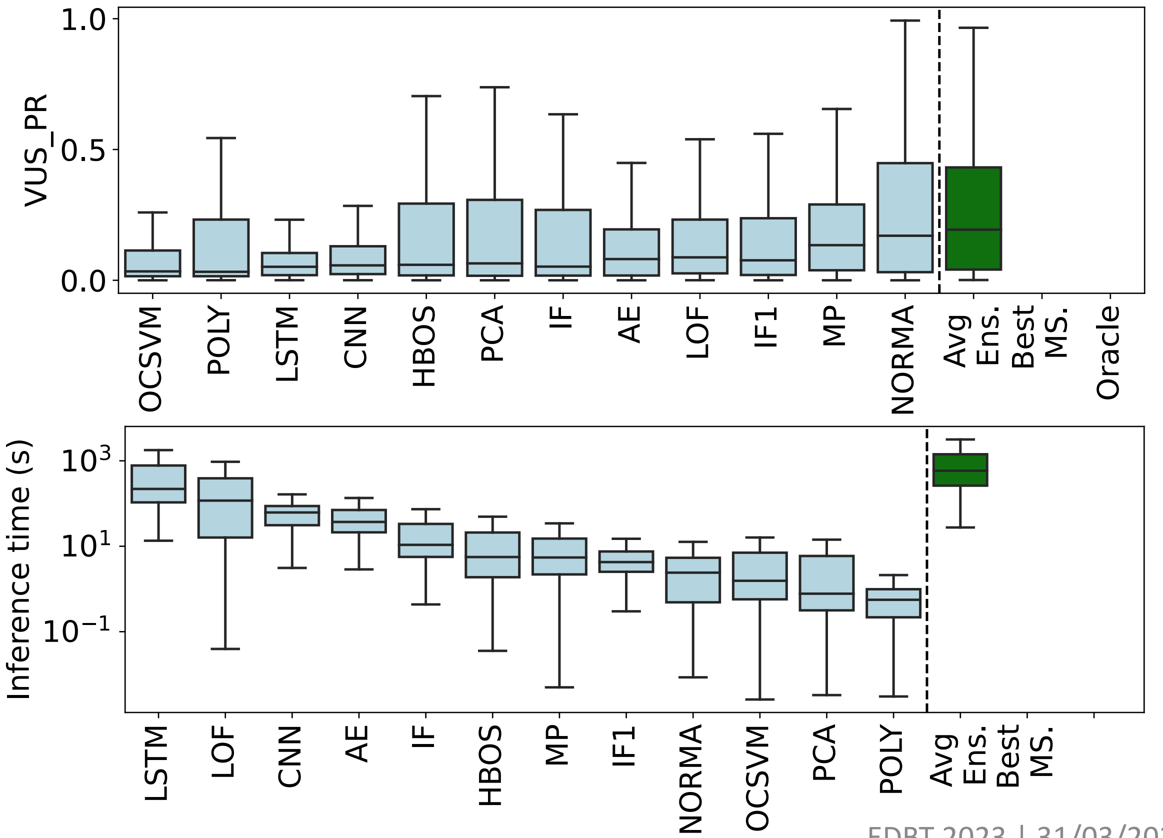


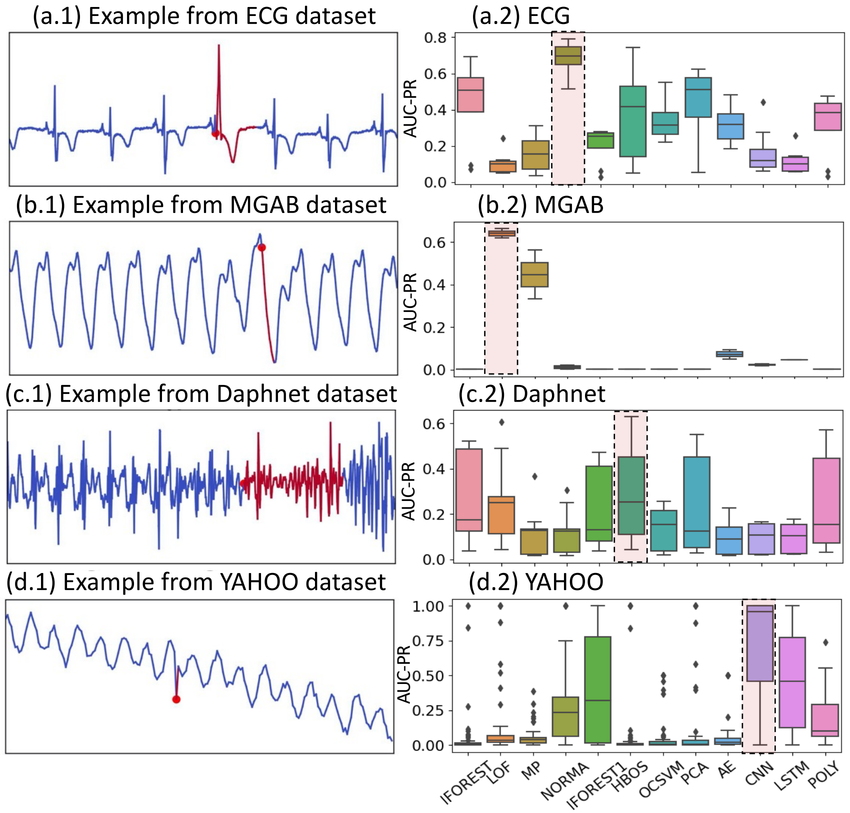
Can *Ensembling* methods solve the problem?



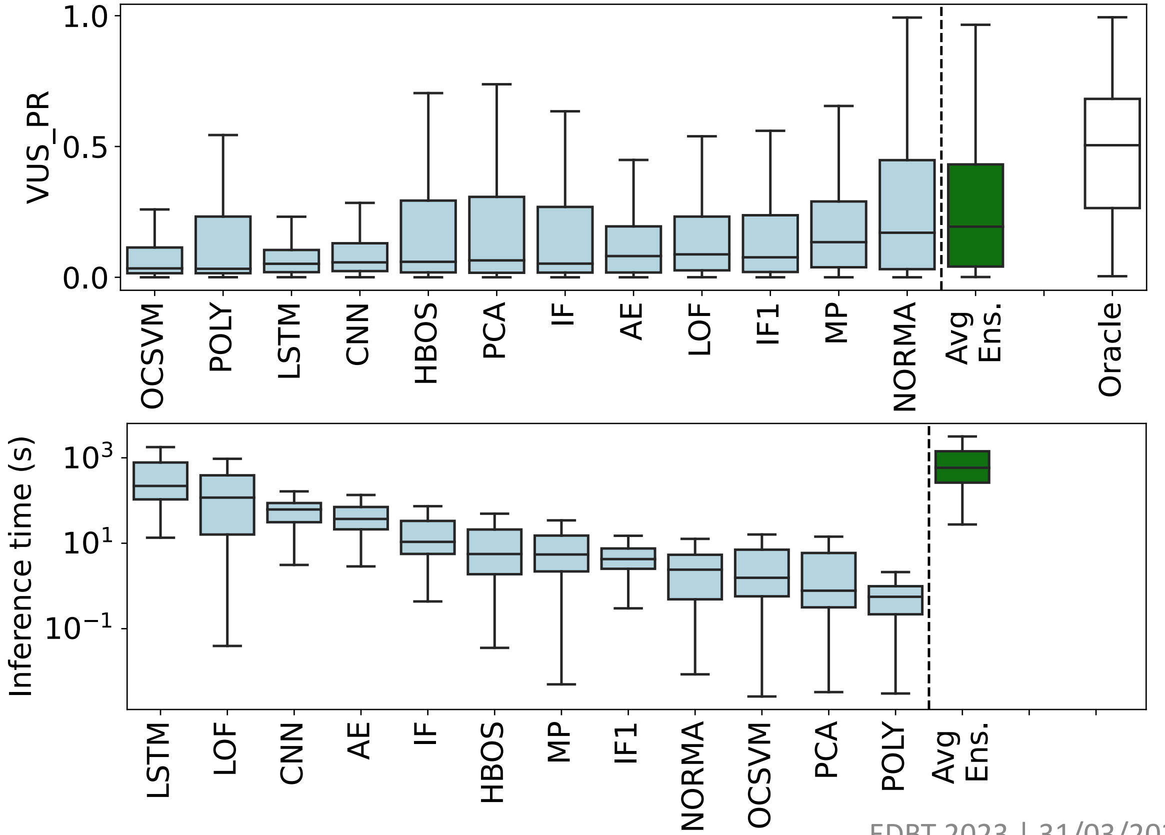
Conclusion and Open Problems

Model selection for anomaly detection

Methods ranking changes significantly between datasets [19]



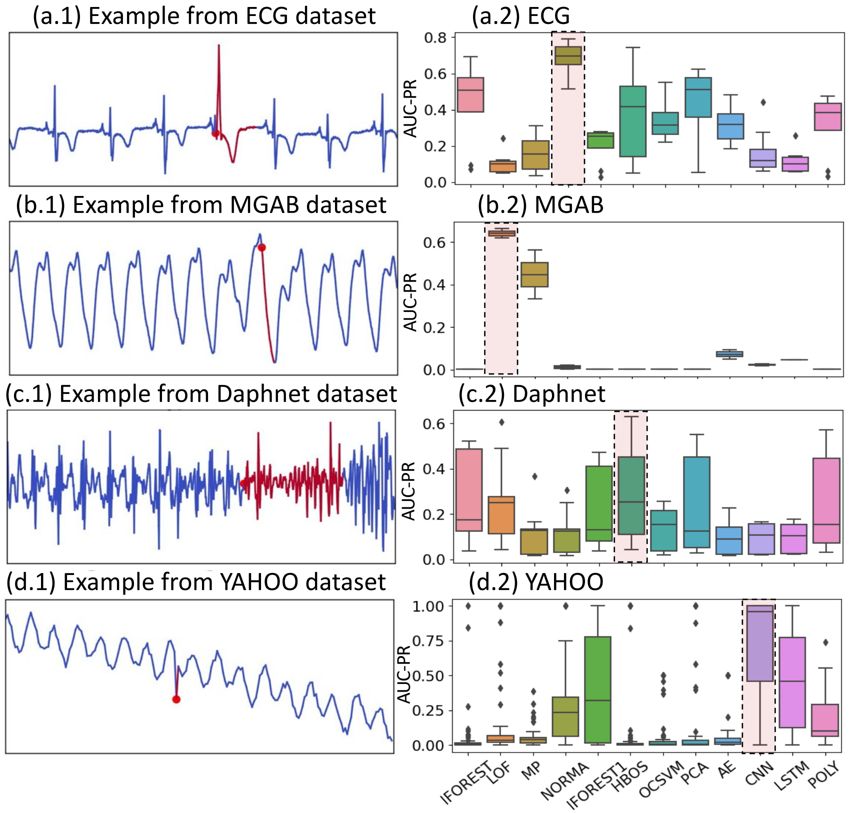
Can *automatic model selection solve the problem*?



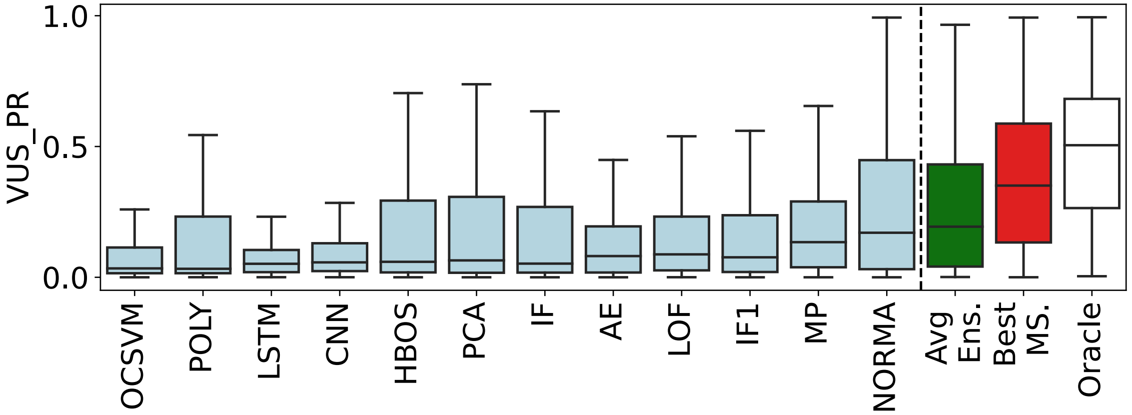
Conclusion and Open Problems

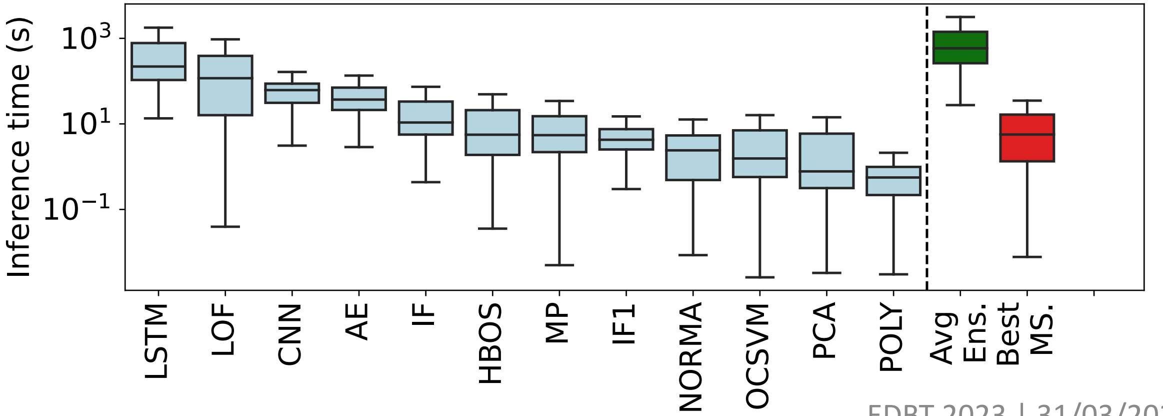
Model selection for anomaly detection

Methods ranking changes significantly between datasets [19]



Can *automatic model selection solve the problem*?





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Thank you for attending!

Any Questions?