

New Trends in Time Series Anomaly Detection

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Université
Paris Cité



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Introduction: *Time series are Everywhere*

Energy Production



[Edf.fr: tinyurl.com/yc7x5xje](https://www.edf.fr/tourisme/)

Astrophysics



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

Medicine



tinyurl.com/39dx2us4

Volcanology

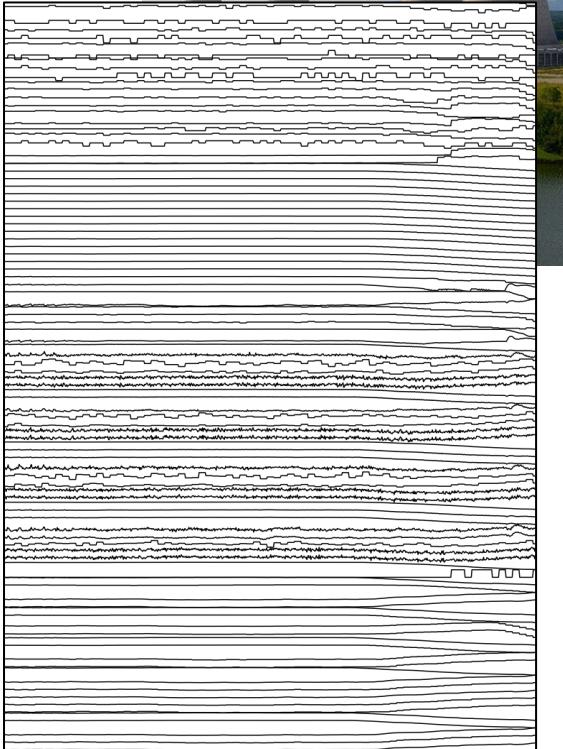


tinyurl.com/ybcttmfz

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Secondary circuit sensor measurements



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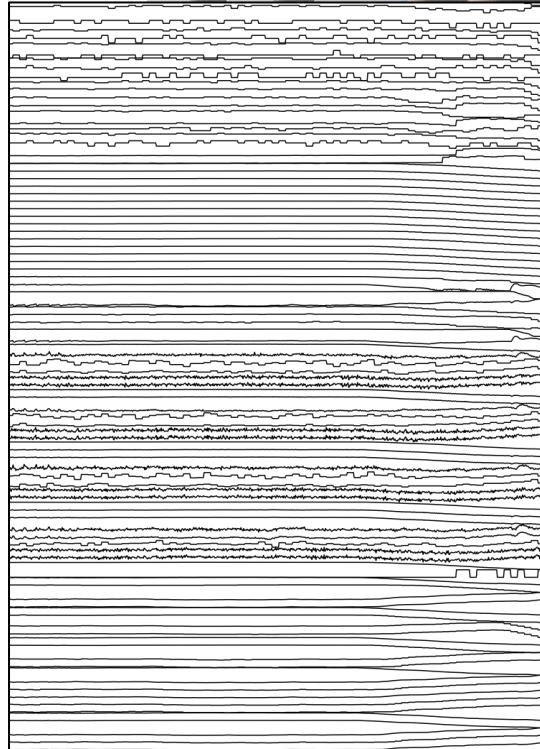


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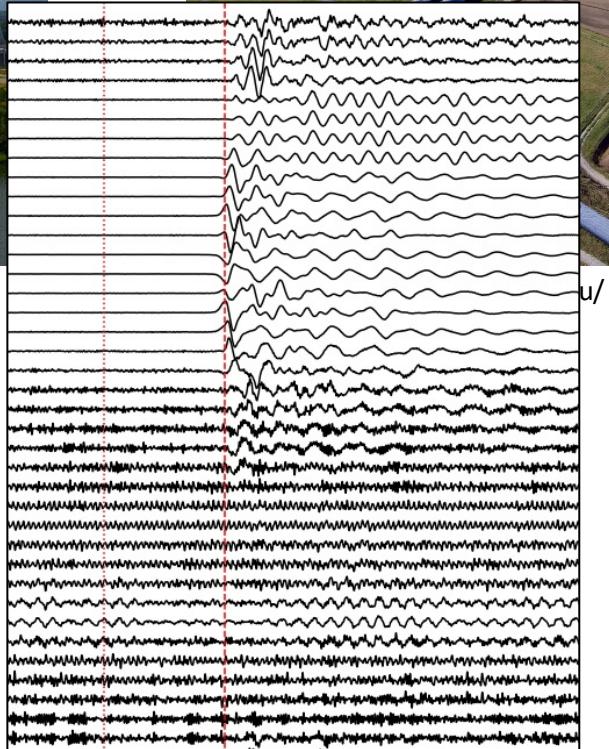
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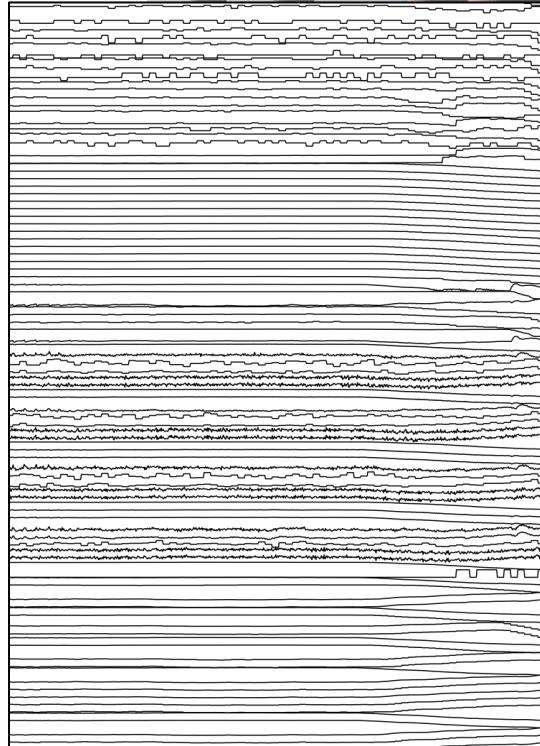
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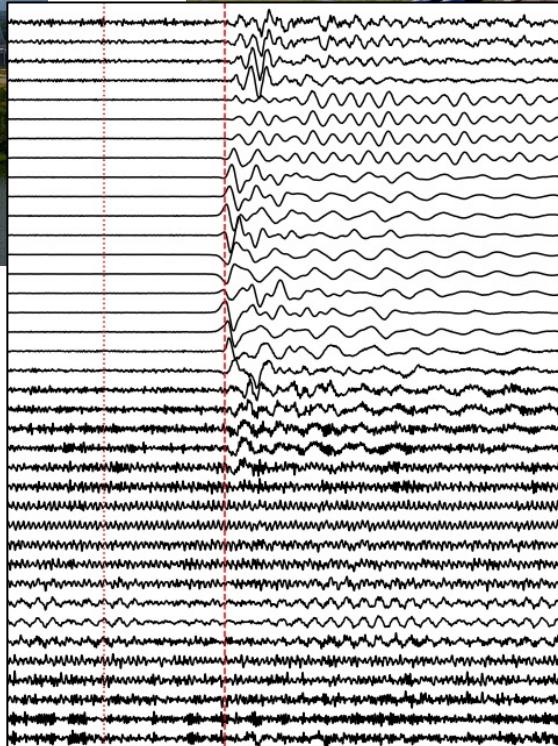
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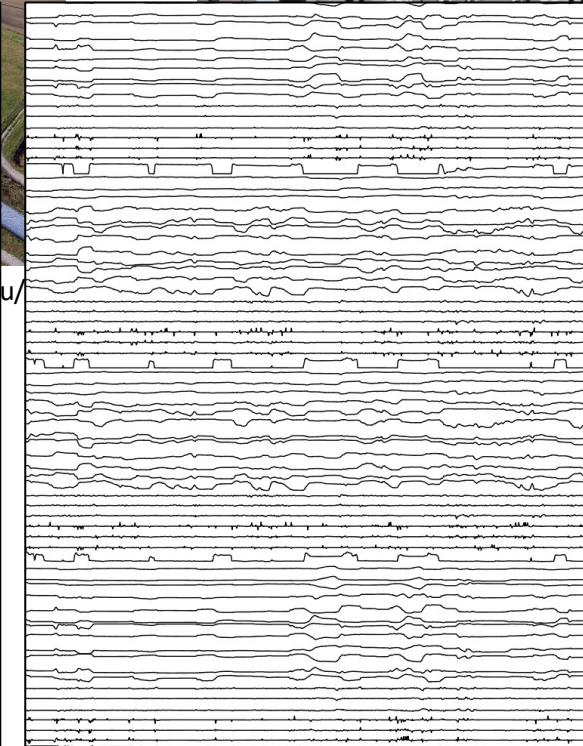
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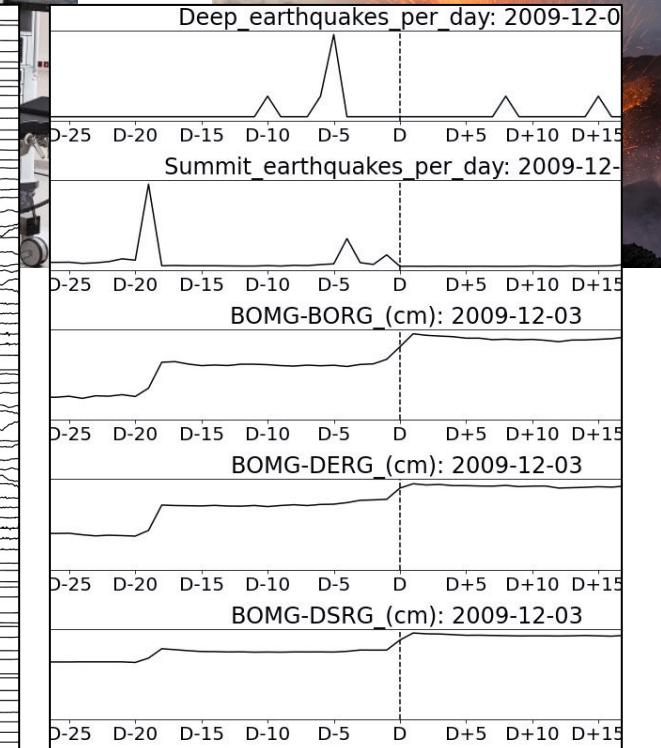
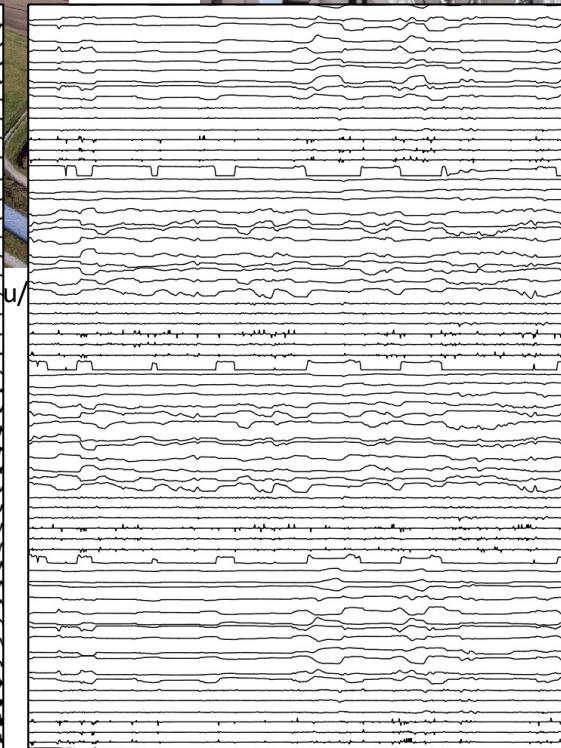
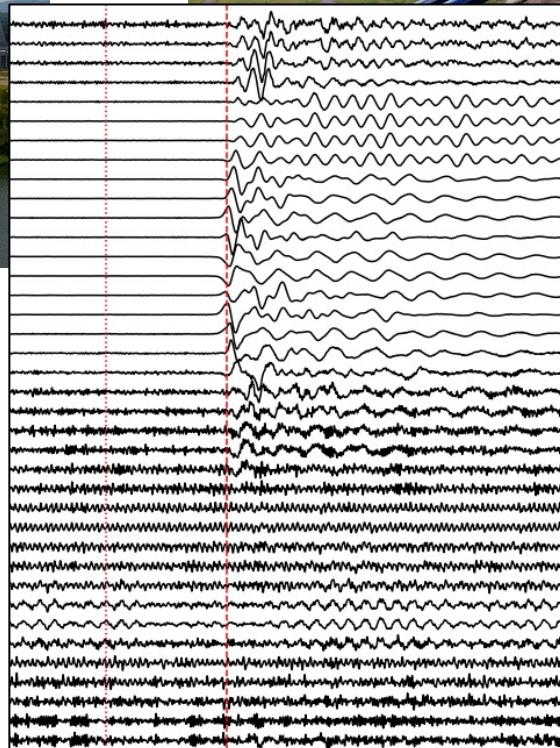
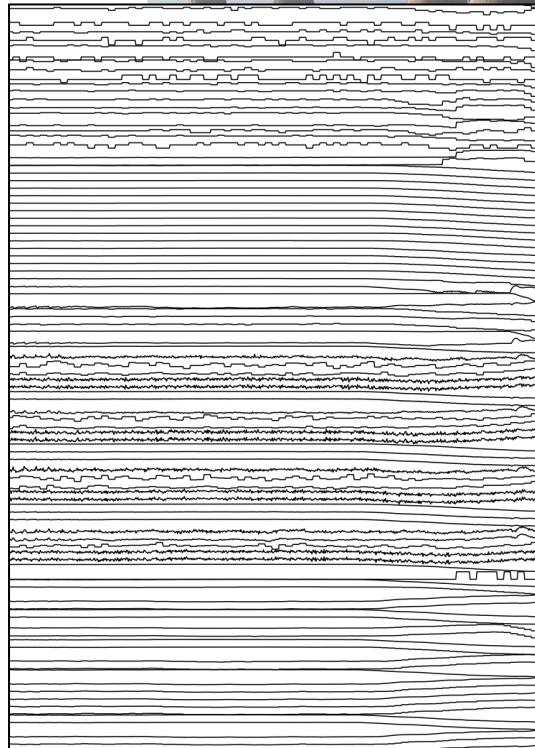
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Sensor measurements on le Piton de la Fournaise



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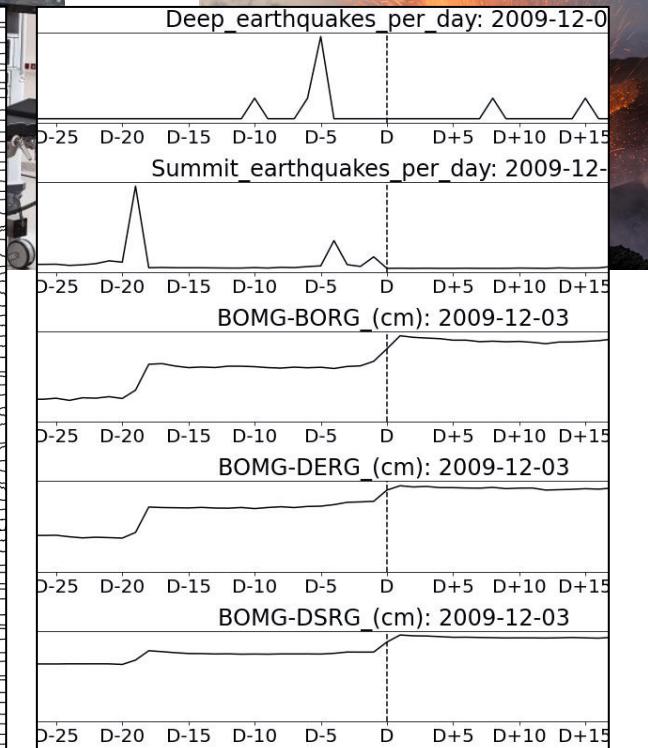
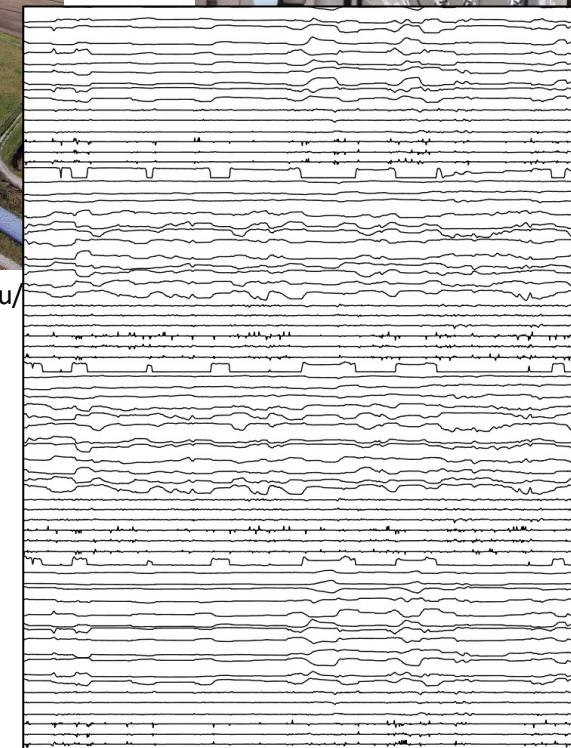
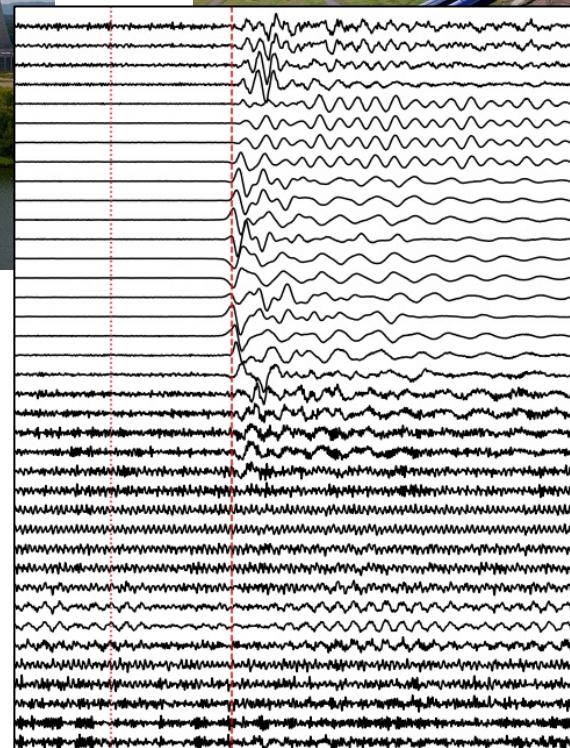
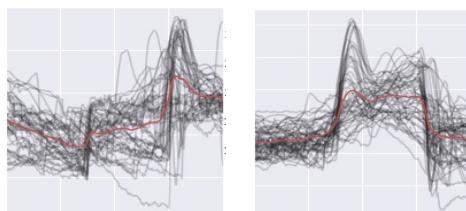
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Identification of precursors of feed-water pumps vibrations



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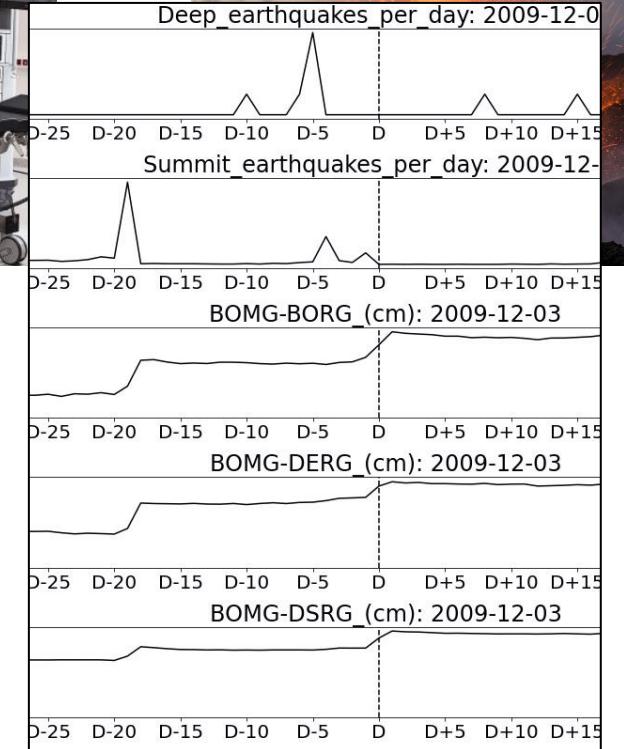
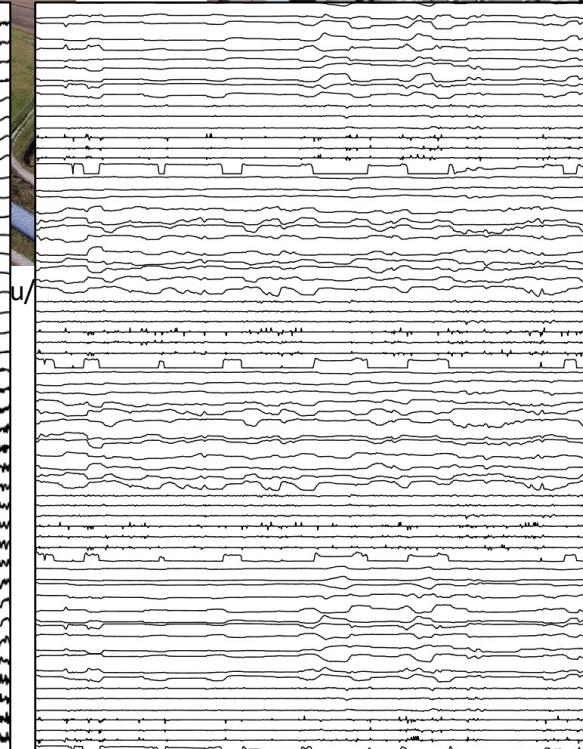
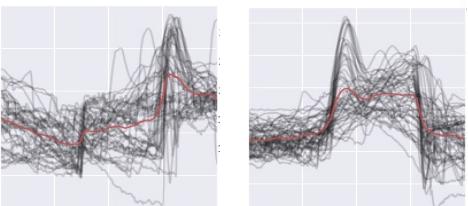
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Noise detection in VIRGO interferometer north building



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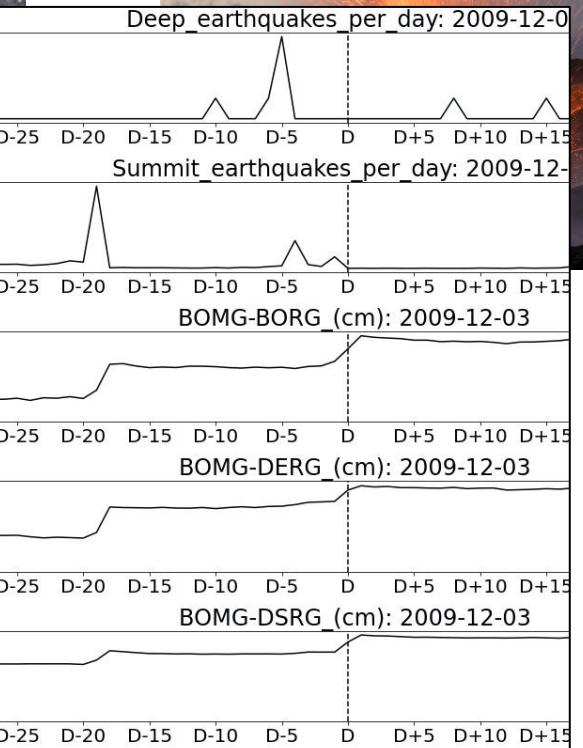
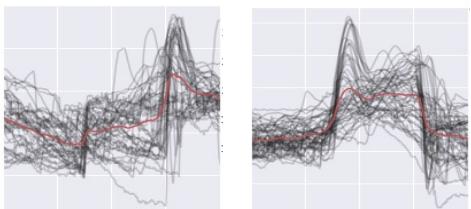
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Unusual surgeons gestures detection



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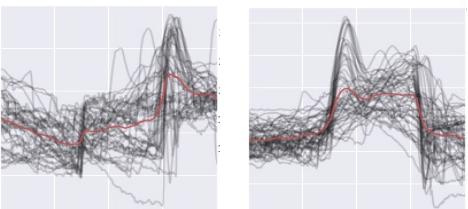
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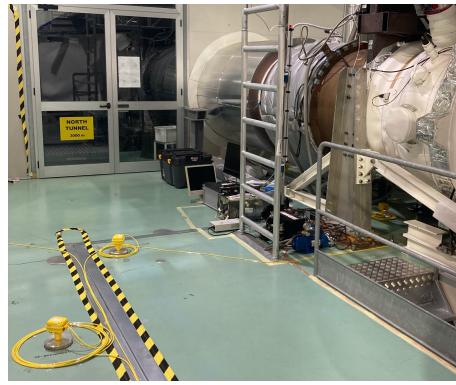
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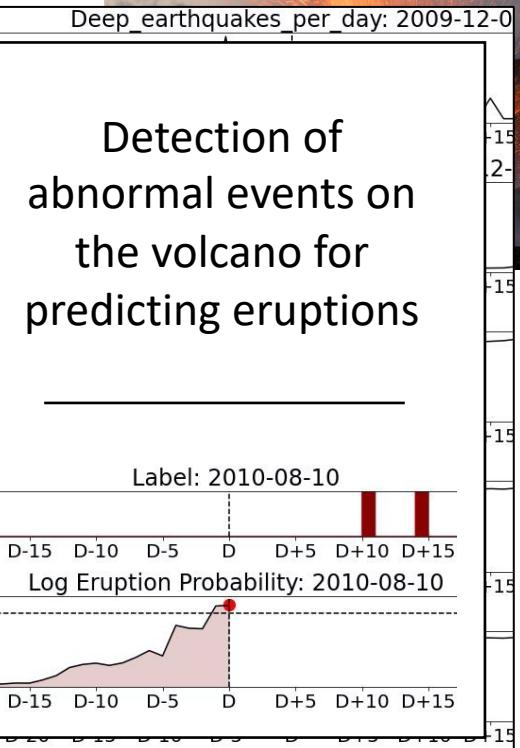
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Unusual surgeons gestures detection

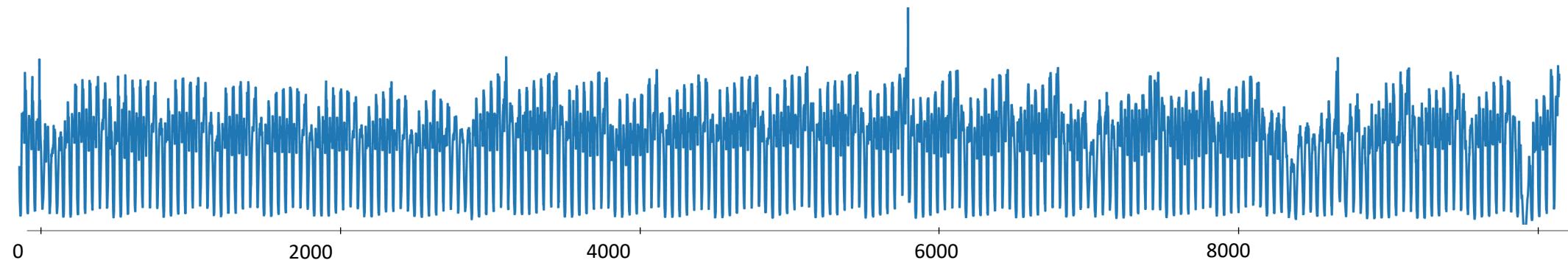


Detection of abnormal events on the volcano for predicting eruptions



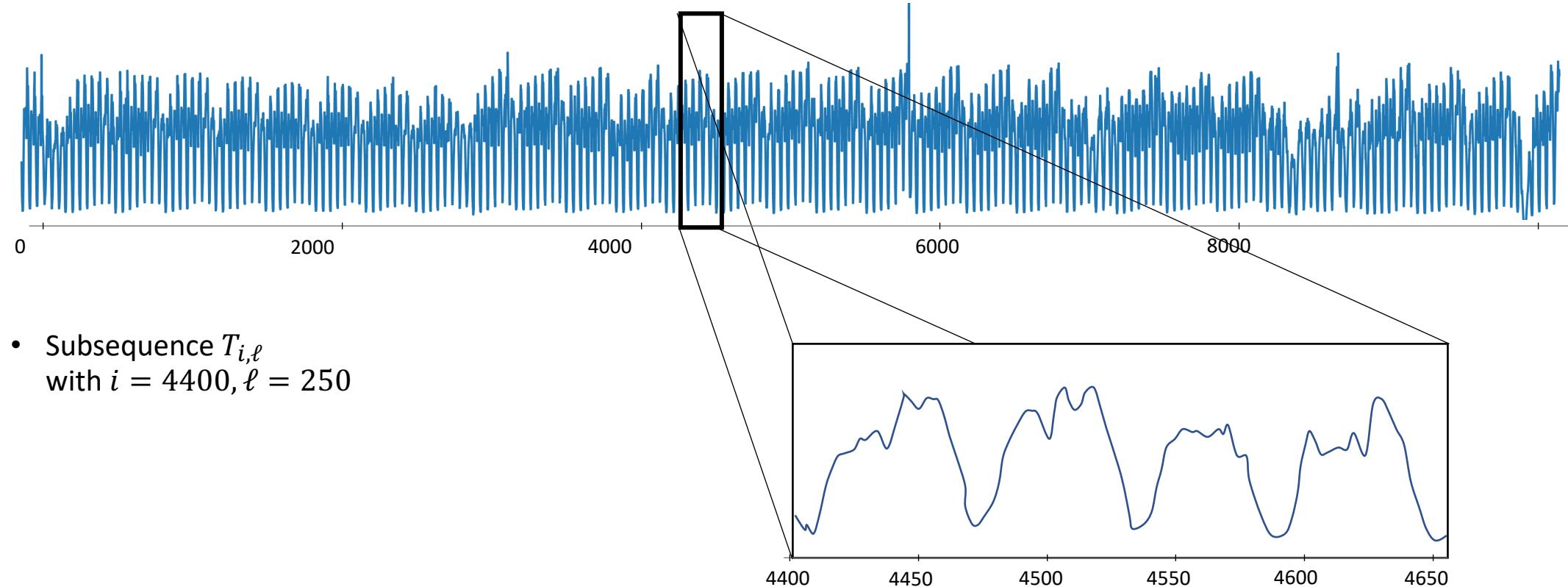
Introduction: *Anomaly Detection in Time Series*

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



Introduction: Anomaly Detection in Time Series

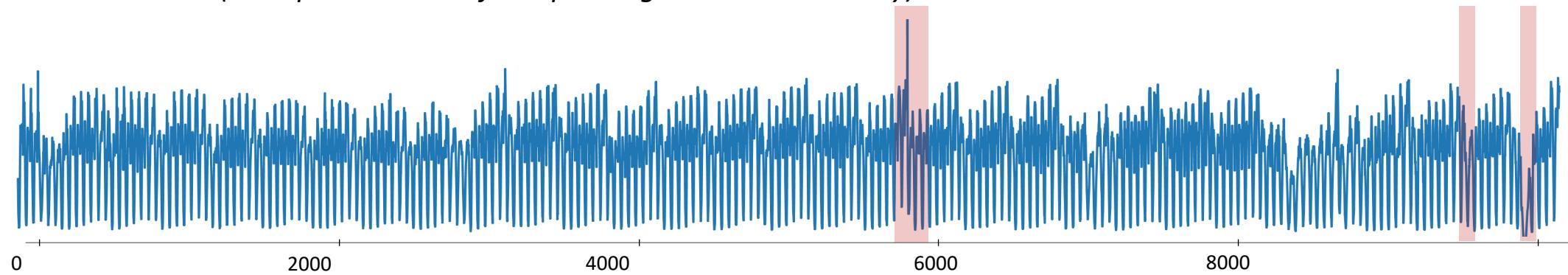
- Time series T (example : number of taxi passengers in New York City)



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

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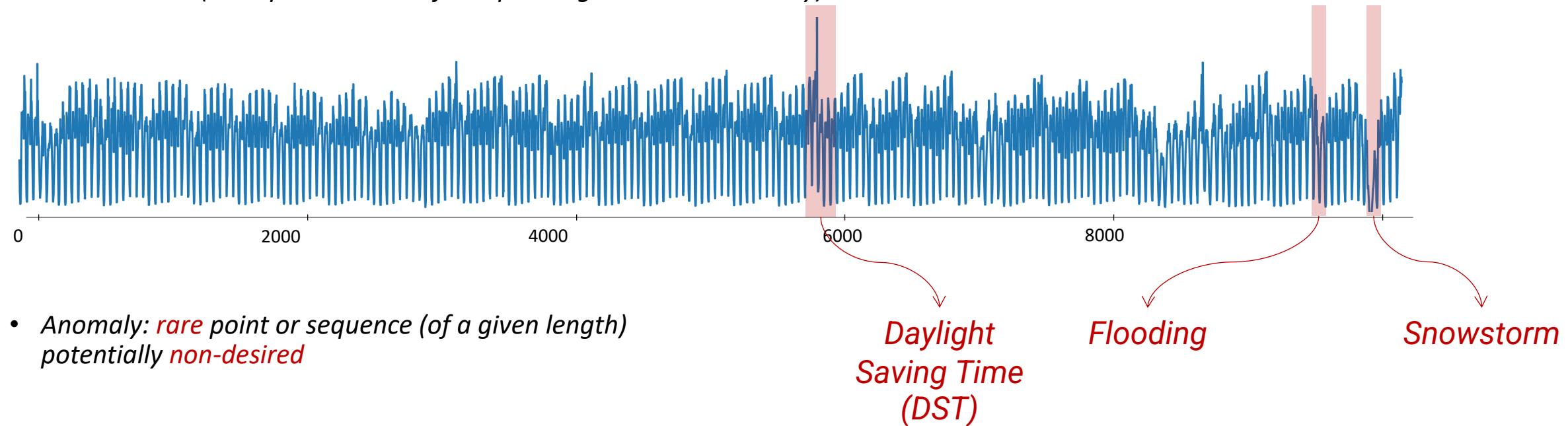
- Time series T (example : number of taxi passengers in New York City)



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

Introduction: Anomaly Detection in Time Series

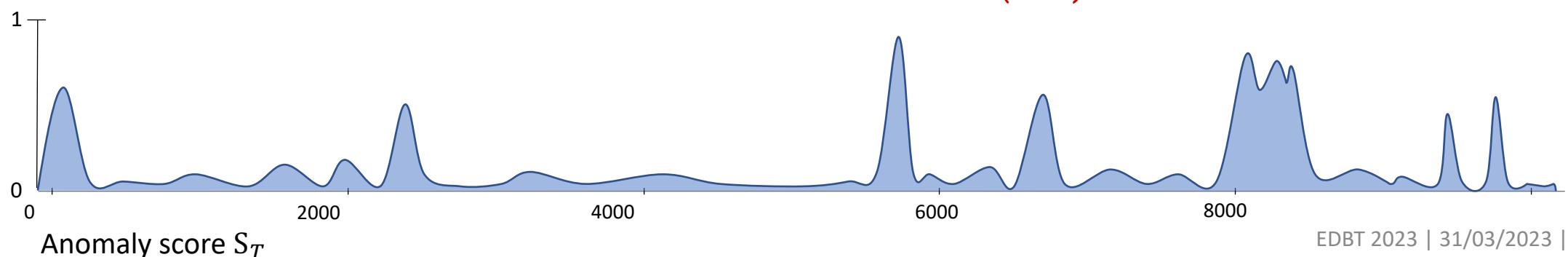
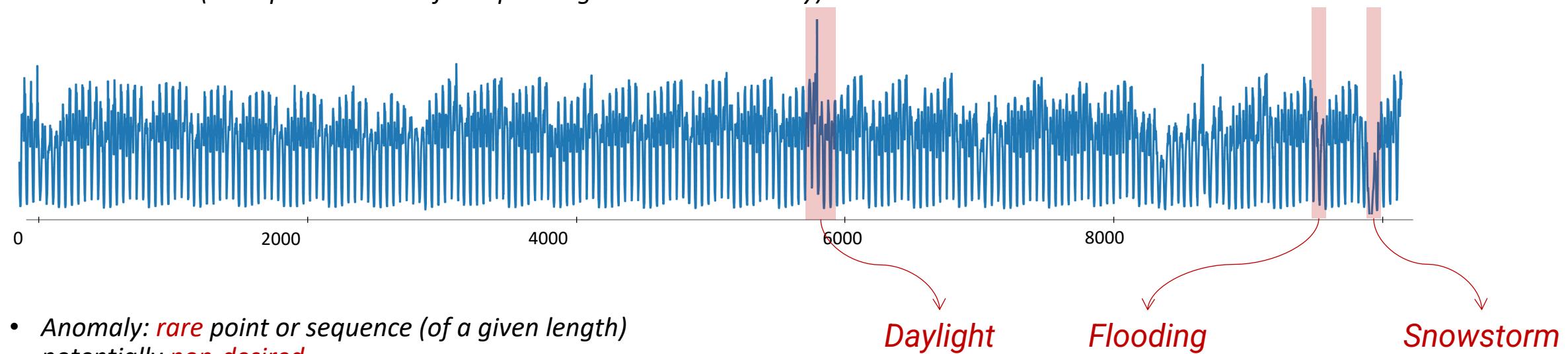
- Time series T (example : number of taxi passengers in New York City)



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

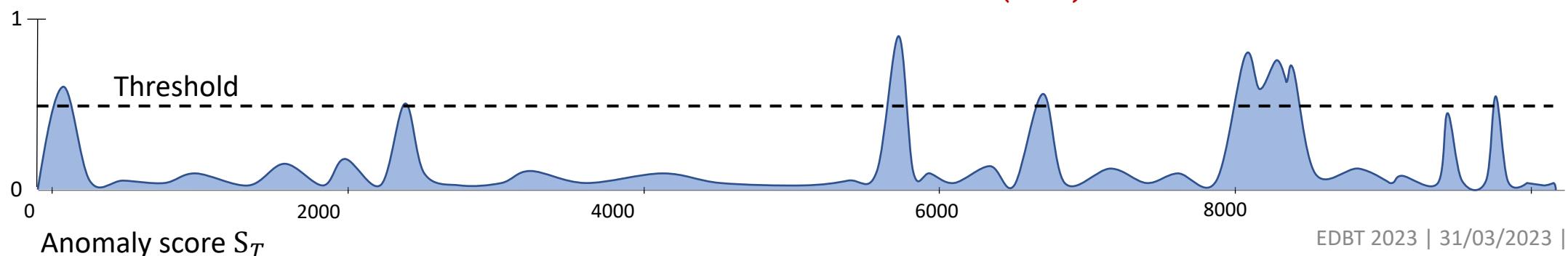
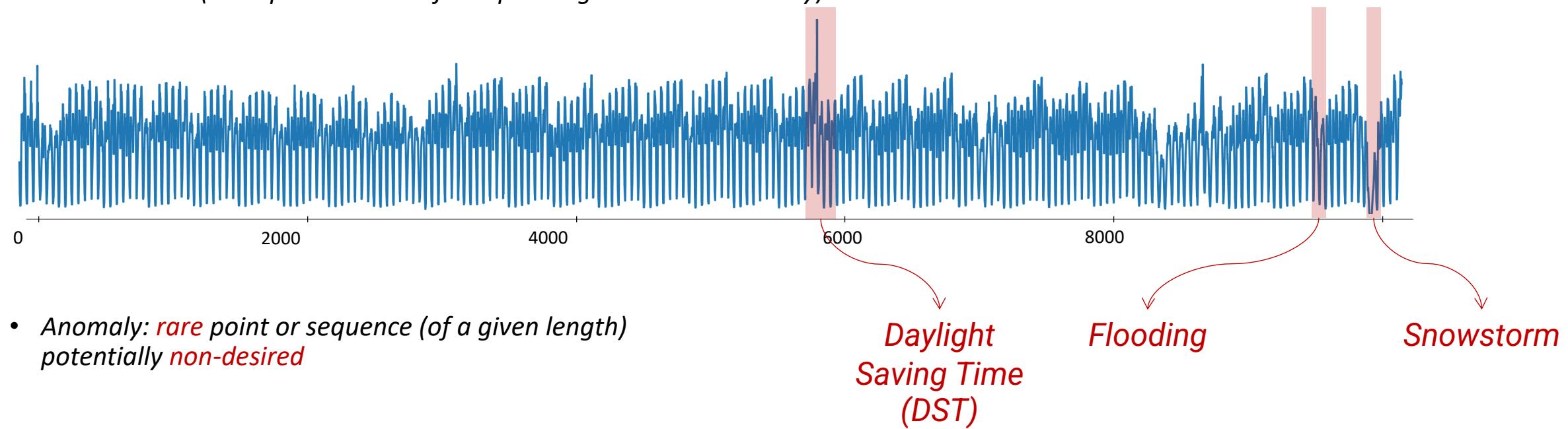
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- Time series T (example : number of taxi passengers in New York City)



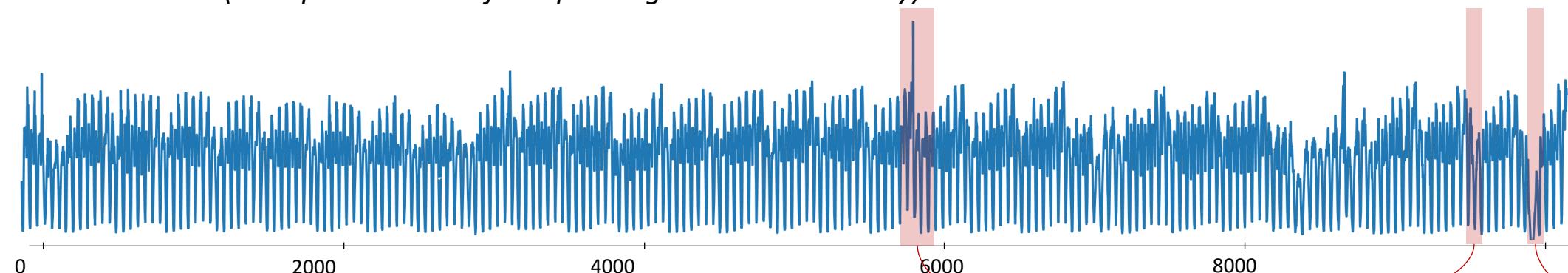
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- Time series T (example : number of taxi passengers in New York City)

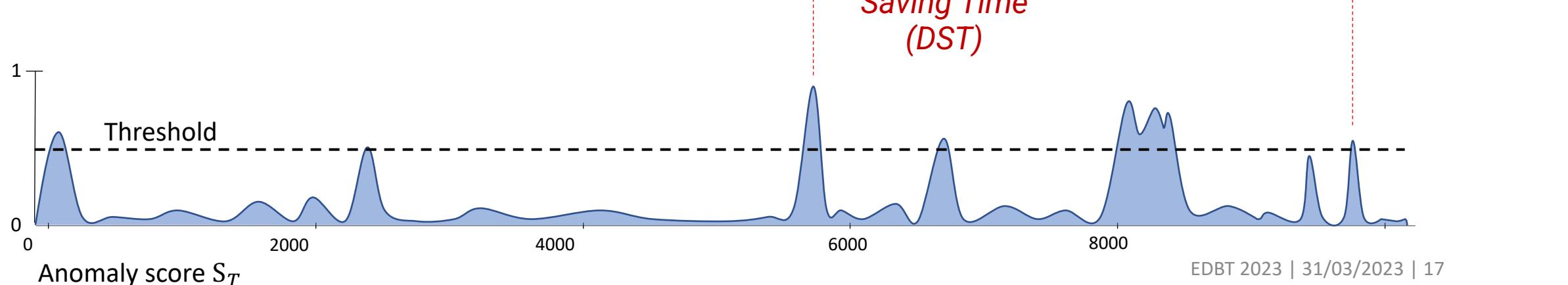


Introduction: Anomaly Detection in Time Series

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

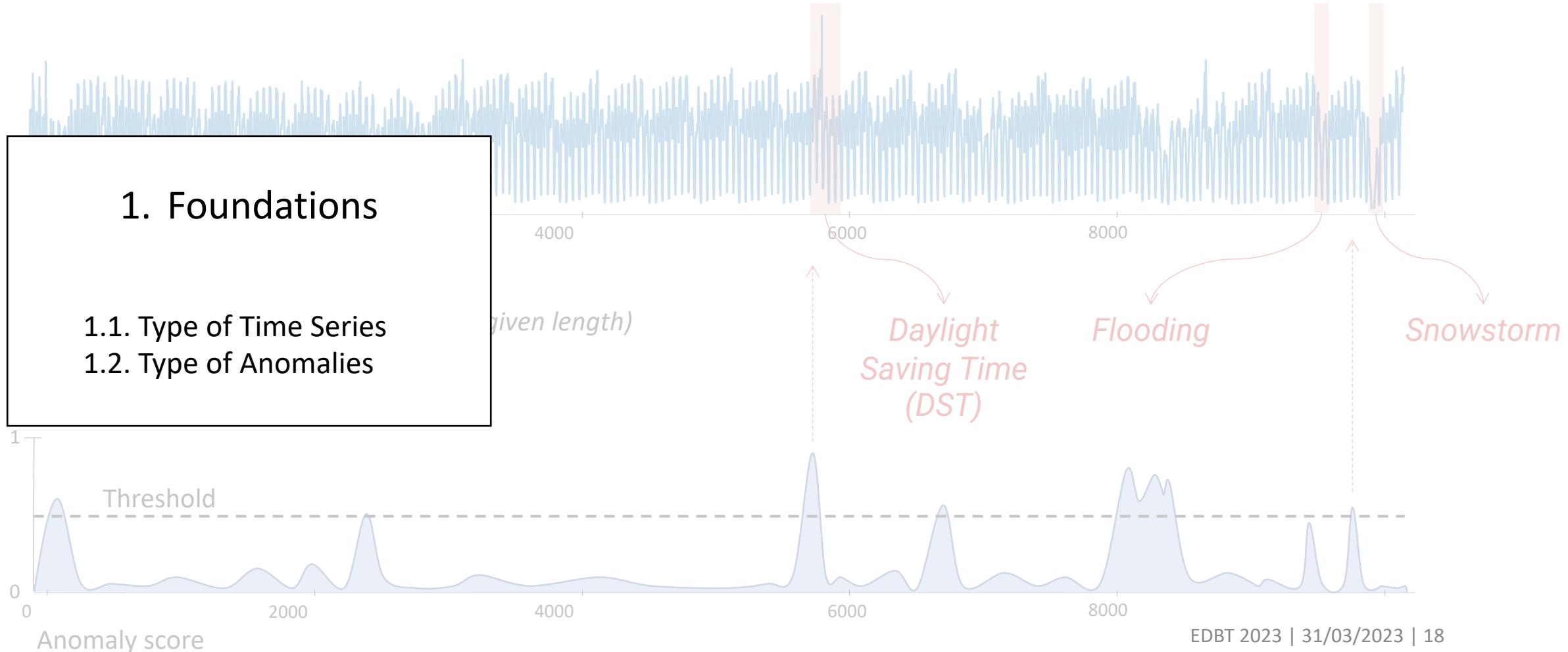


- Anomaly: *rare* point or sequence (of a given length) potentially *non-desired*



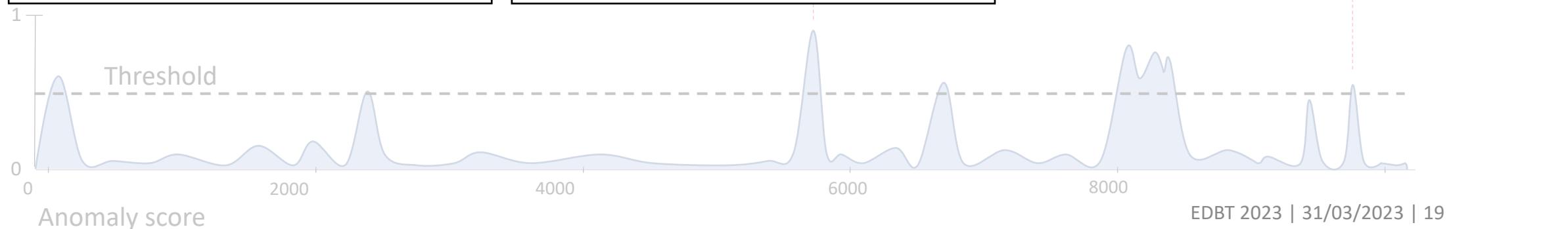
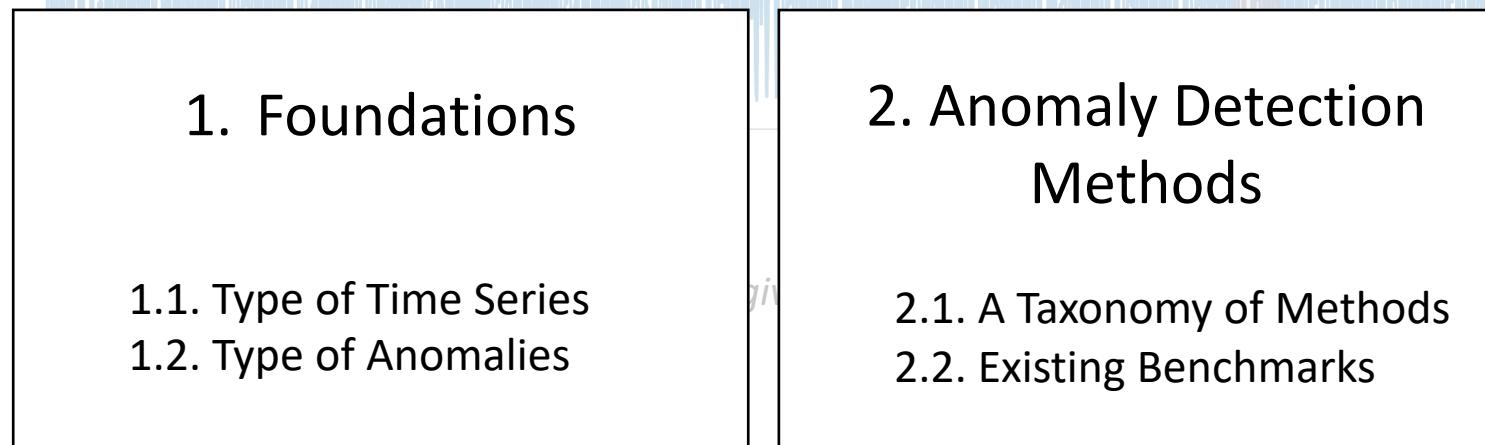
Introduction: Outline

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



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1. Foundations

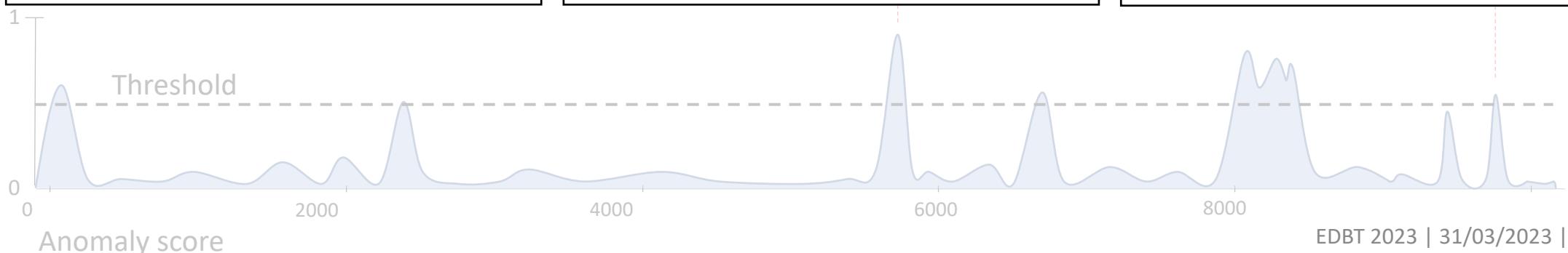
- 1.1. Type of Time Series
- 1.2. Type of Anomalies

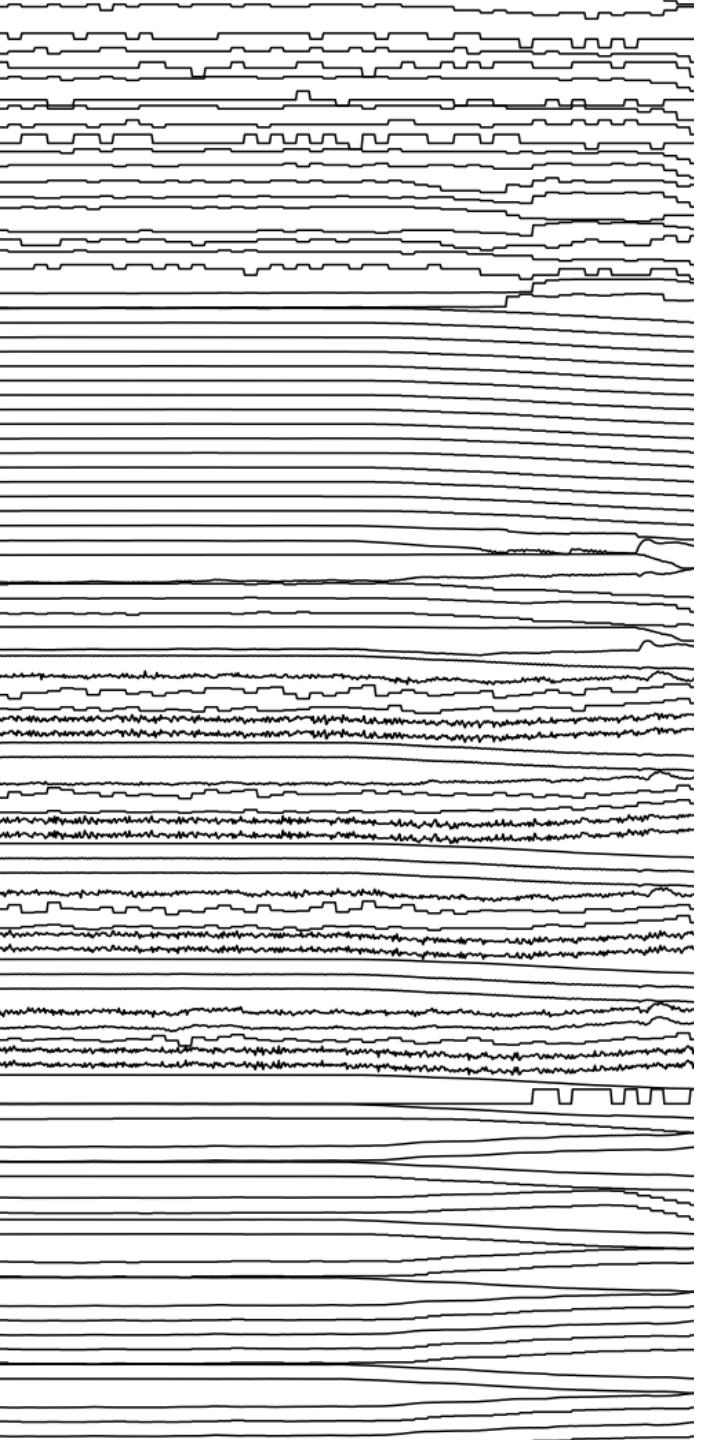
2. Anomaly Detection Methods

- 2.1. A Taxonomy of Methods
- 2.2. Existing Benchmarks

3. Evaluating Anomaly Detection

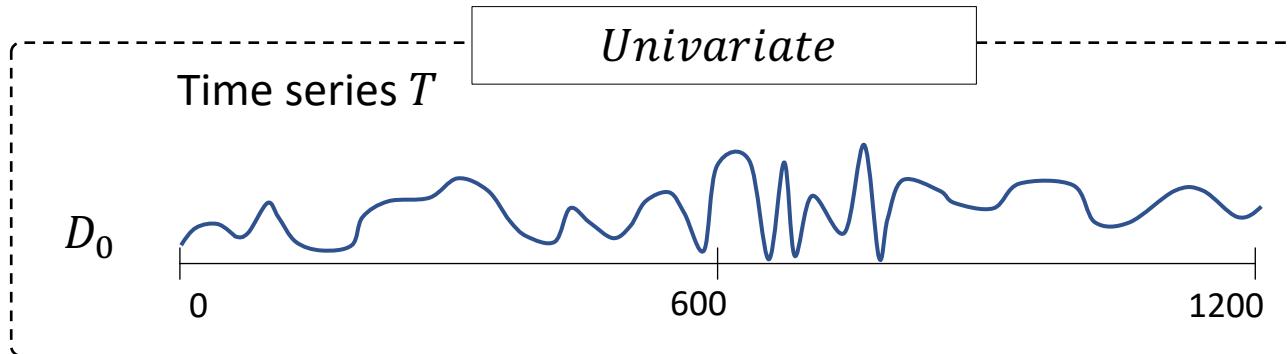
- 3.1. Threshold-based
- 3.2. Time series labeling issues



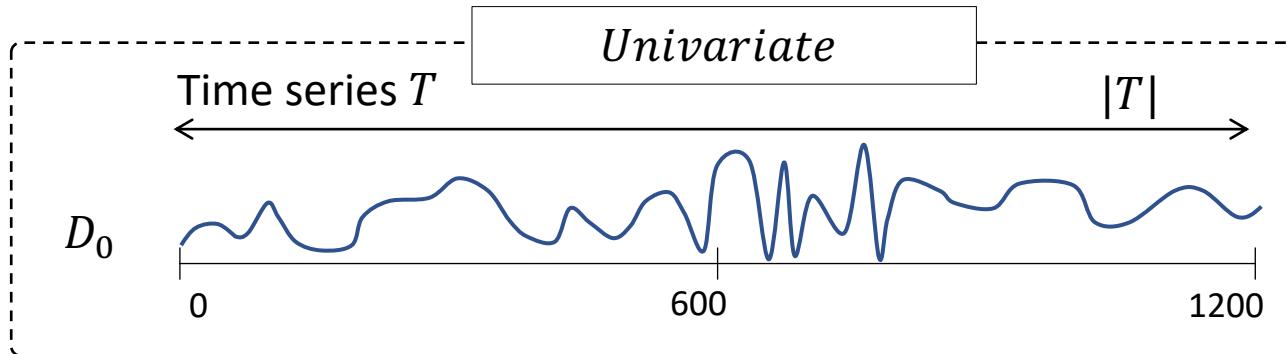


Foundations

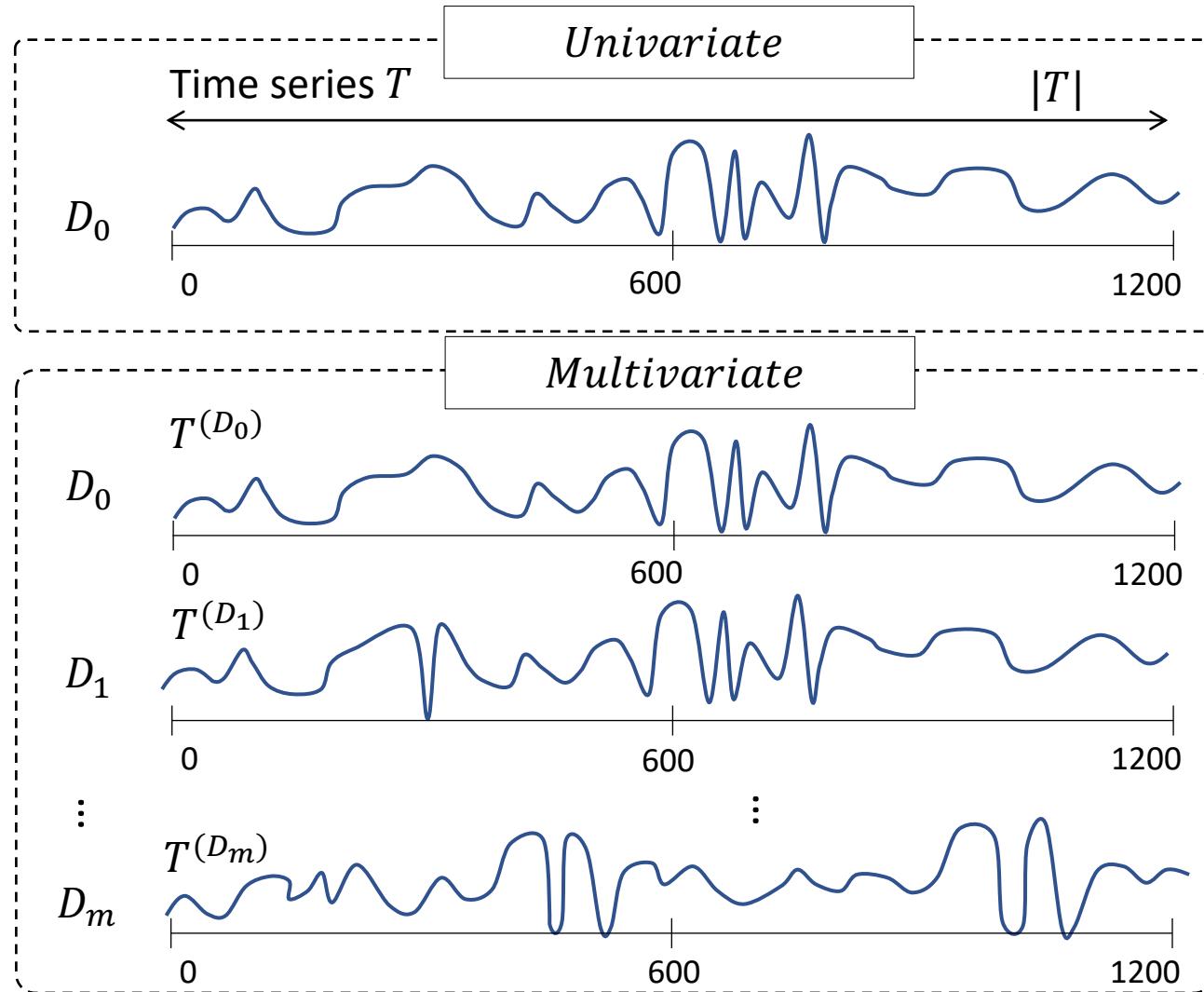
Foundations: *Type of time series*



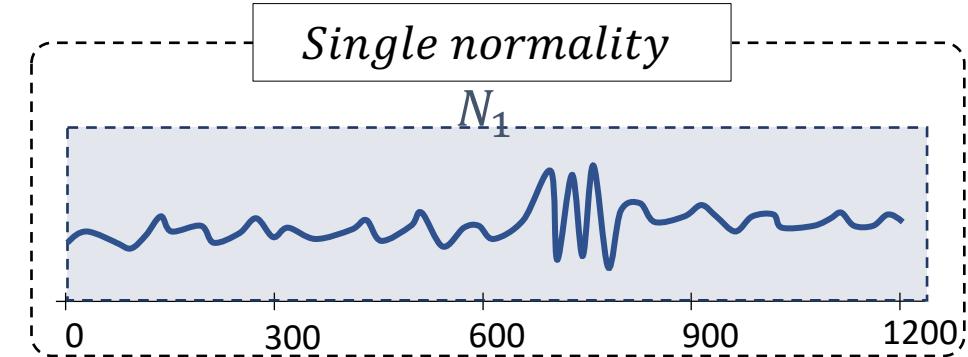
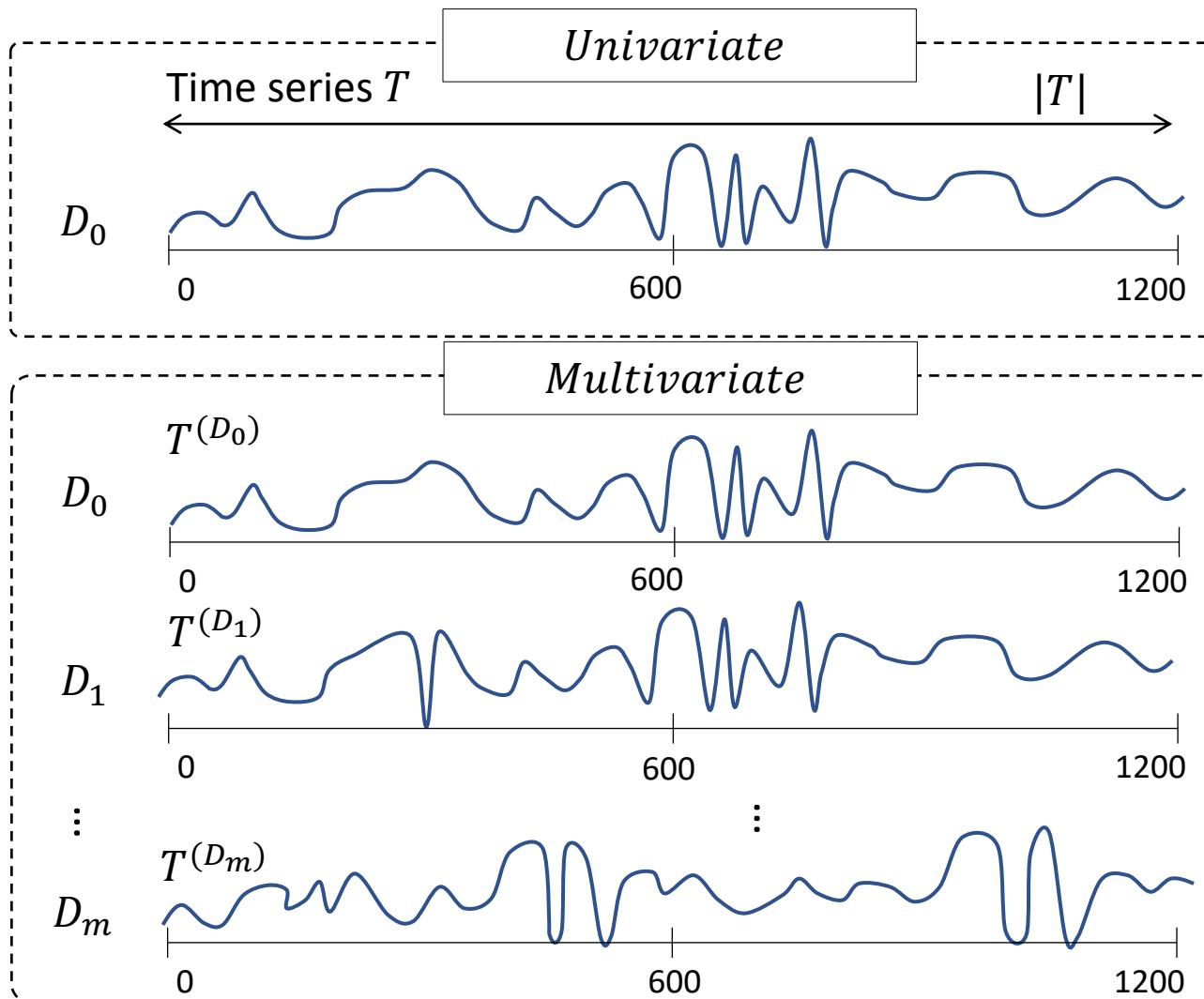
Foundations: *Type of time series*



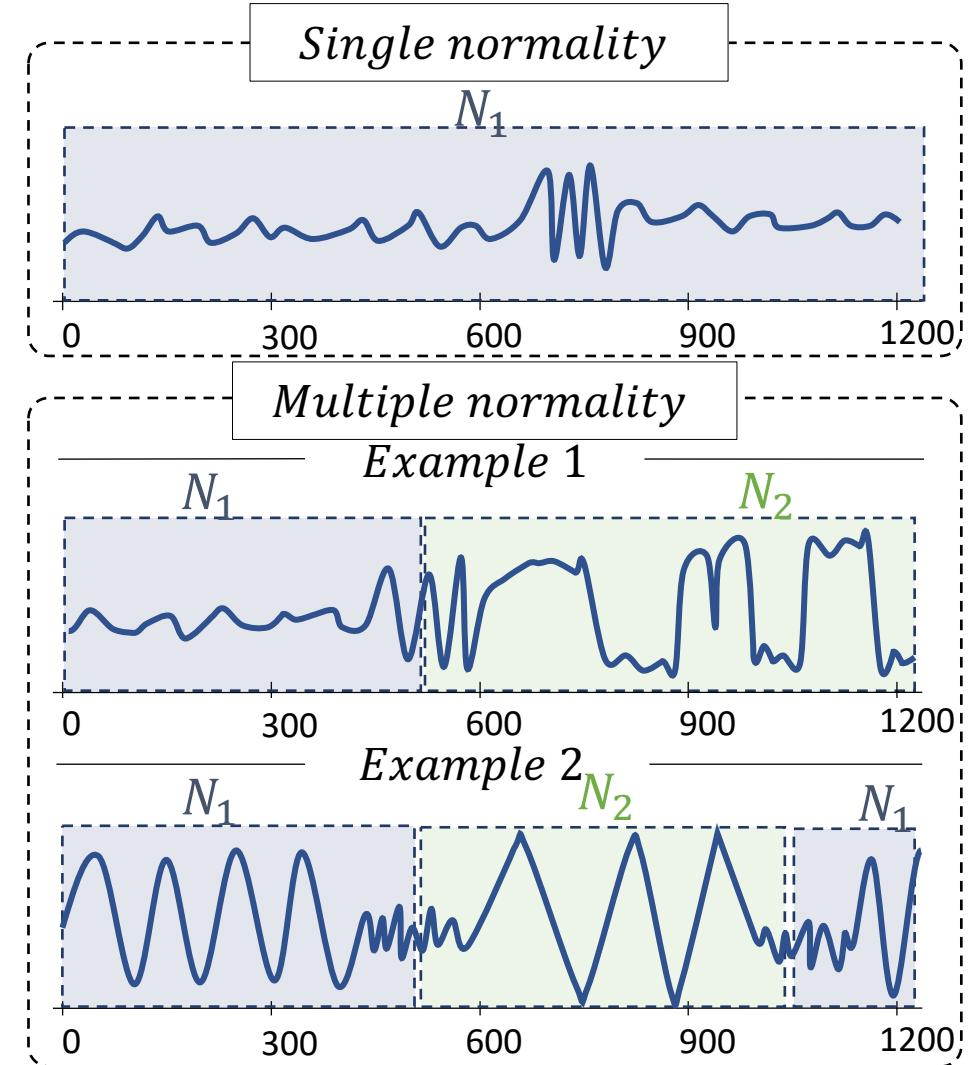
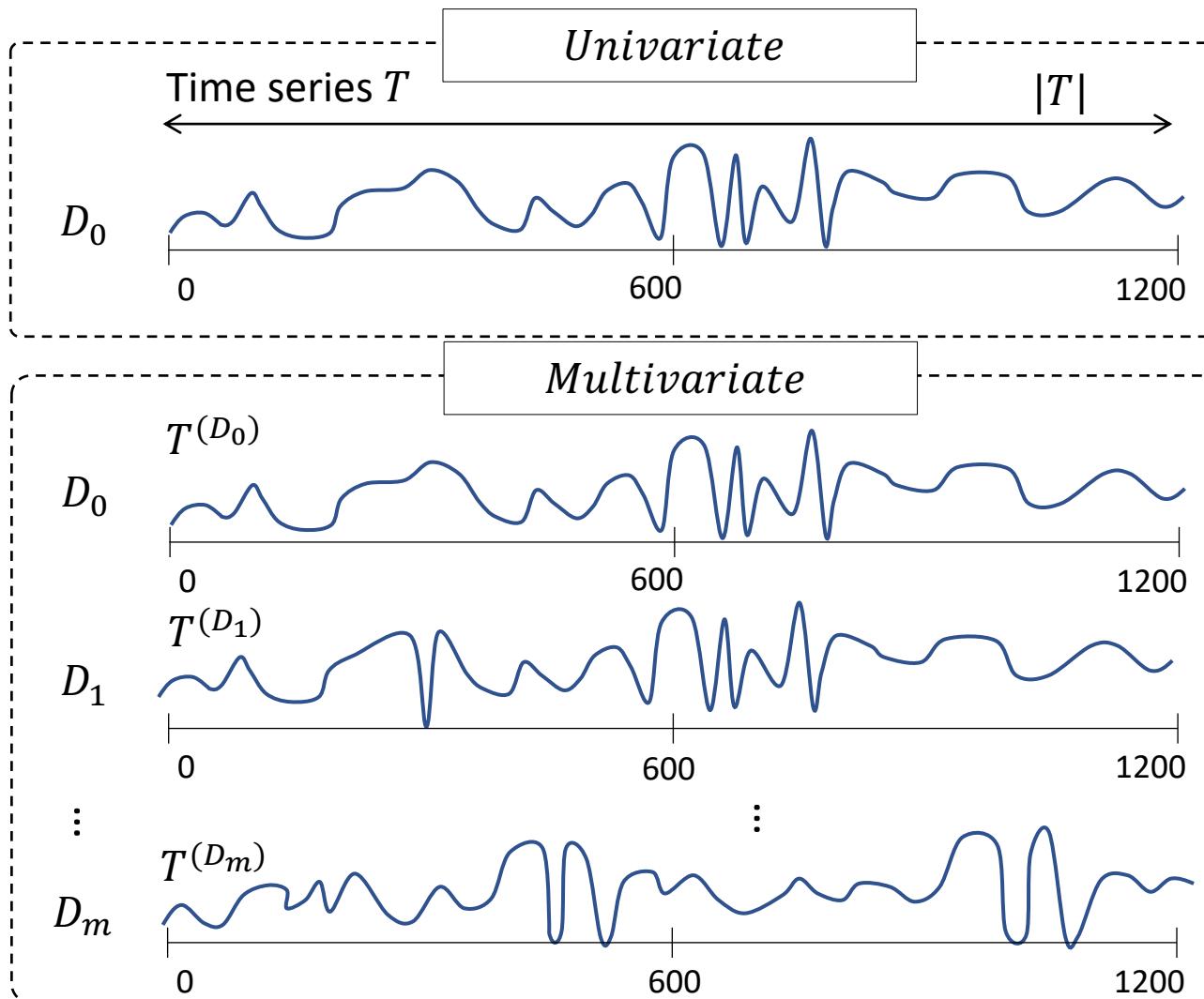
Foundations: Type of time series



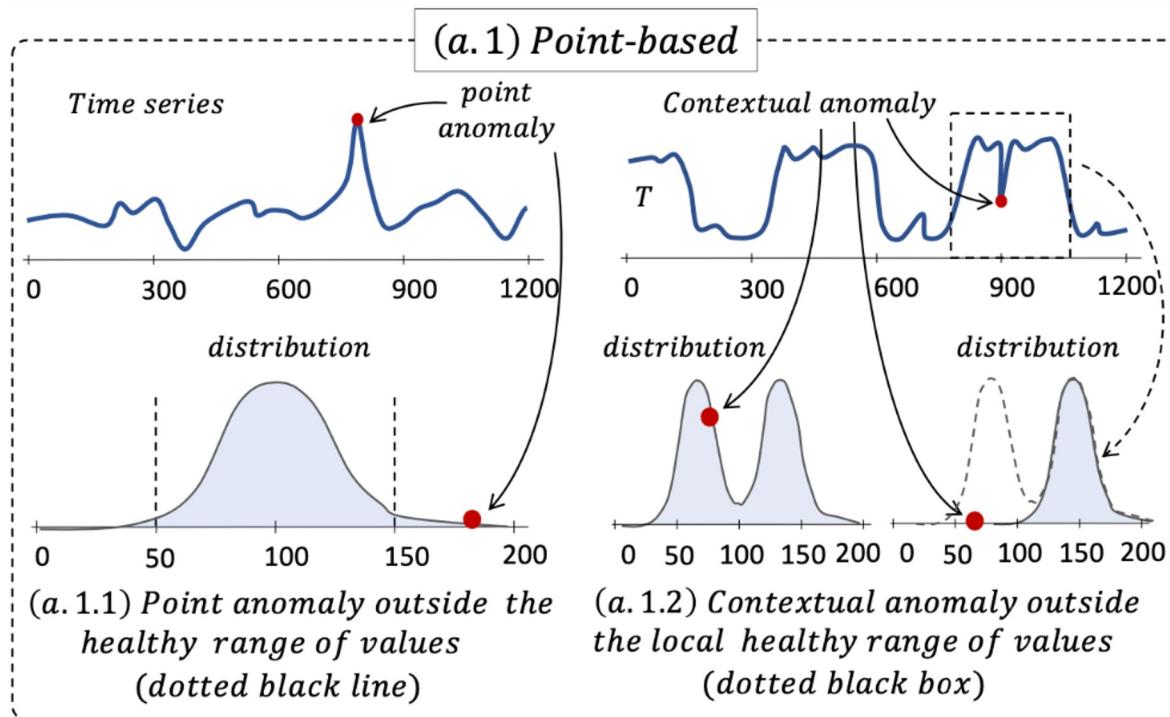
Foundations: Type of time series



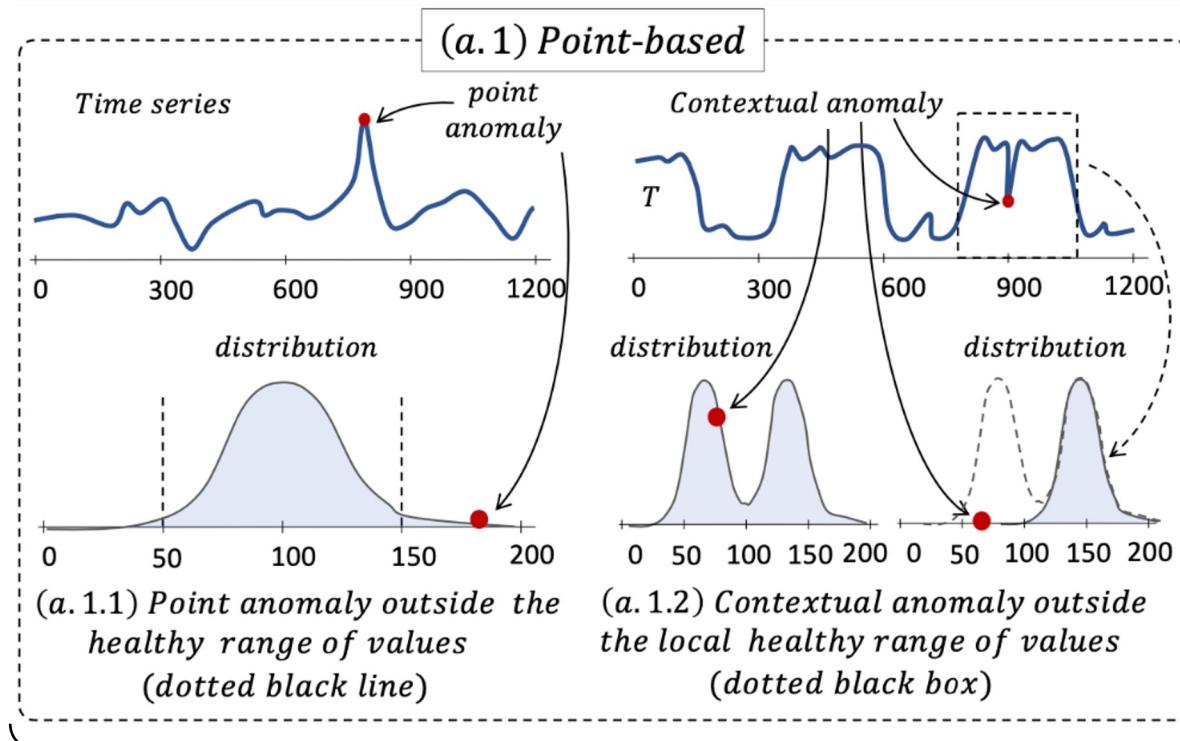
Foundations: Type of time series



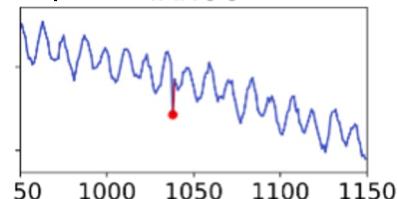
Foundations: Type of anomalies



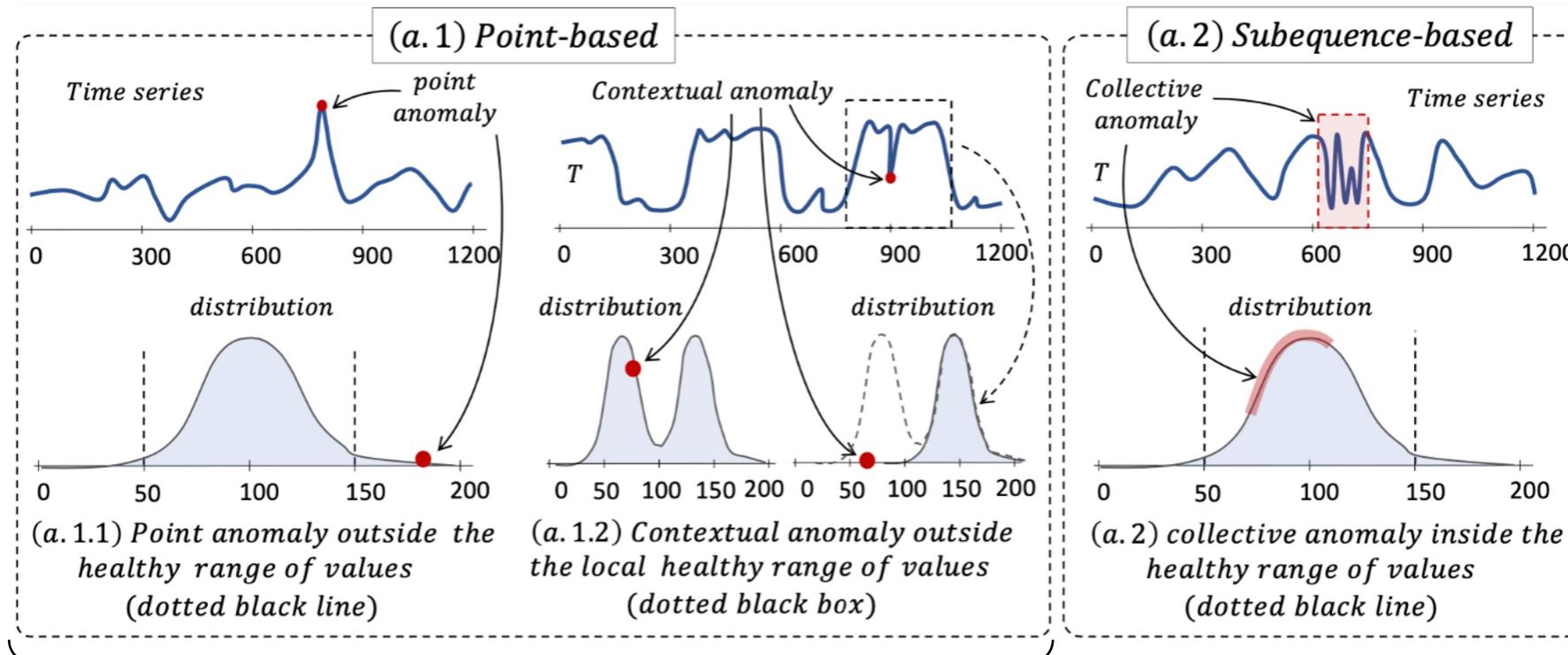
Foundations: Type of anomalies



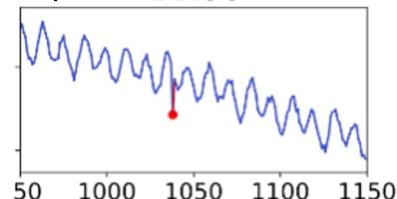
Example of
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anomaly [1]



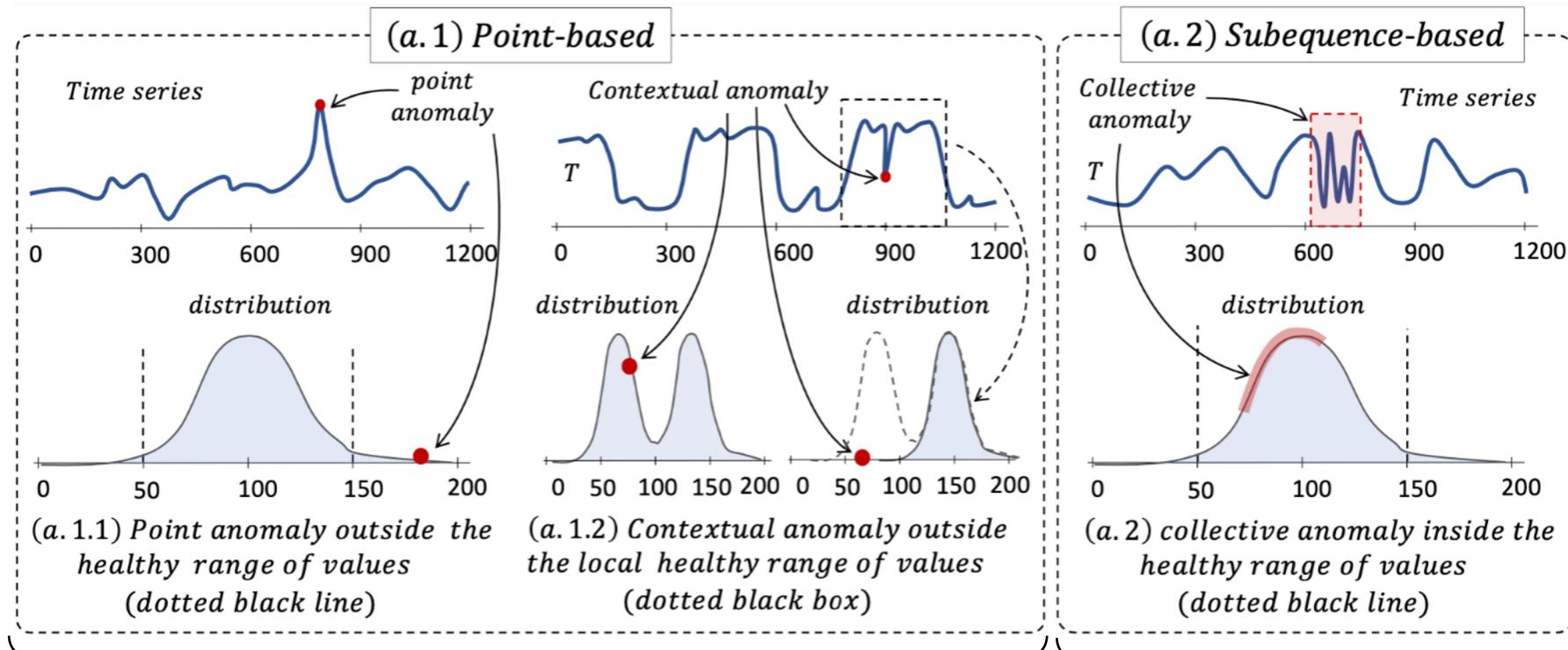
Foundations: Type of anomalies



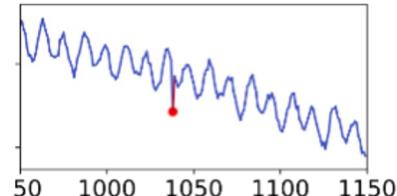
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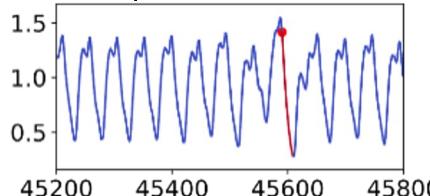
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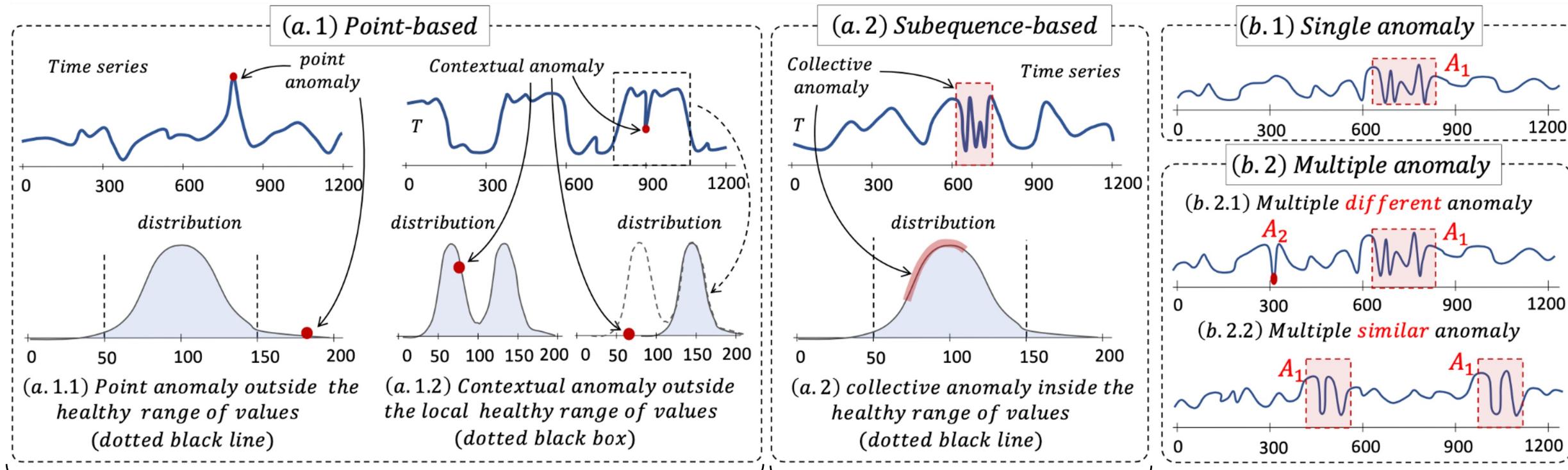
Example of point-based anomaly [1]



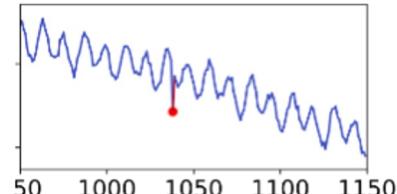
Example of subsequence-based anomaly [2]



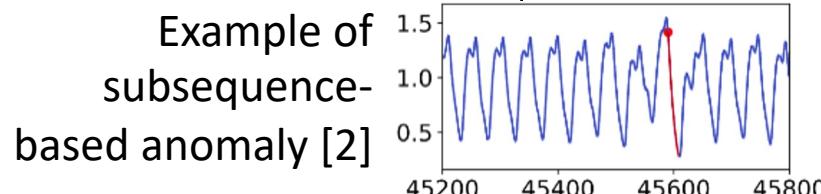
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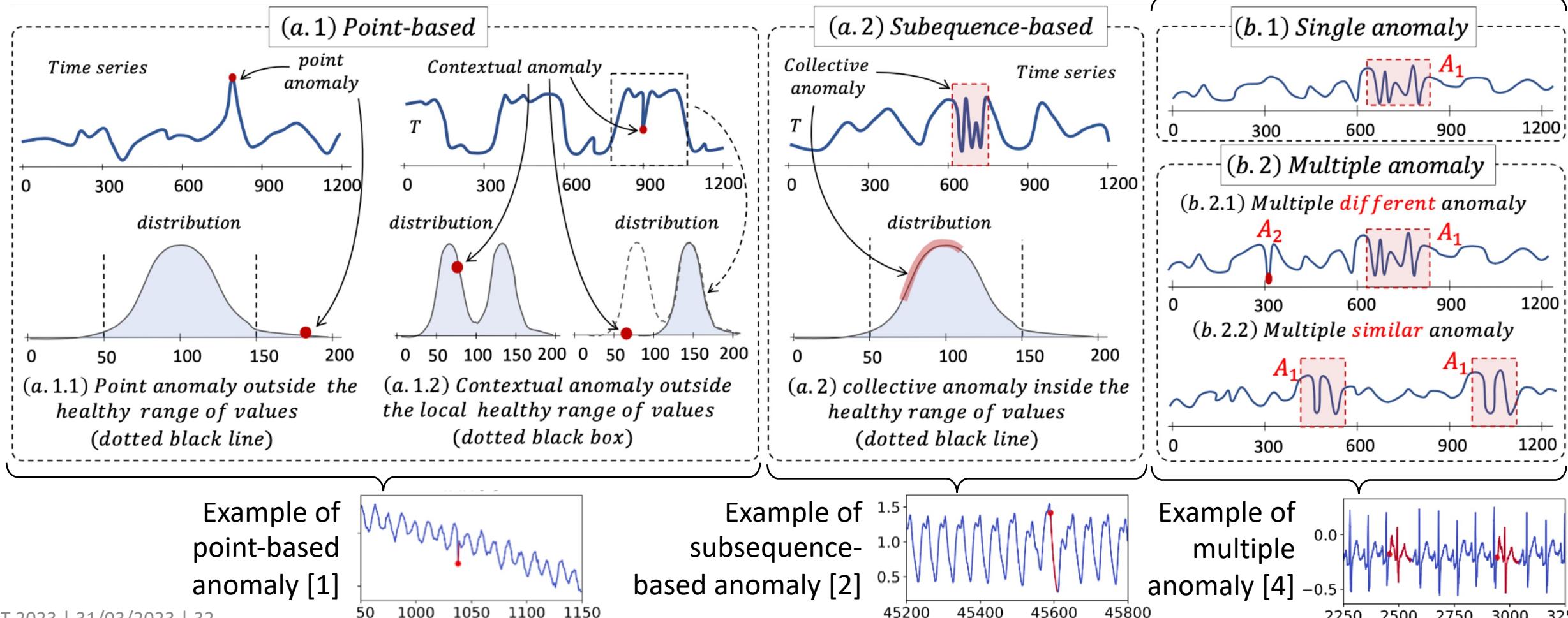
Example of
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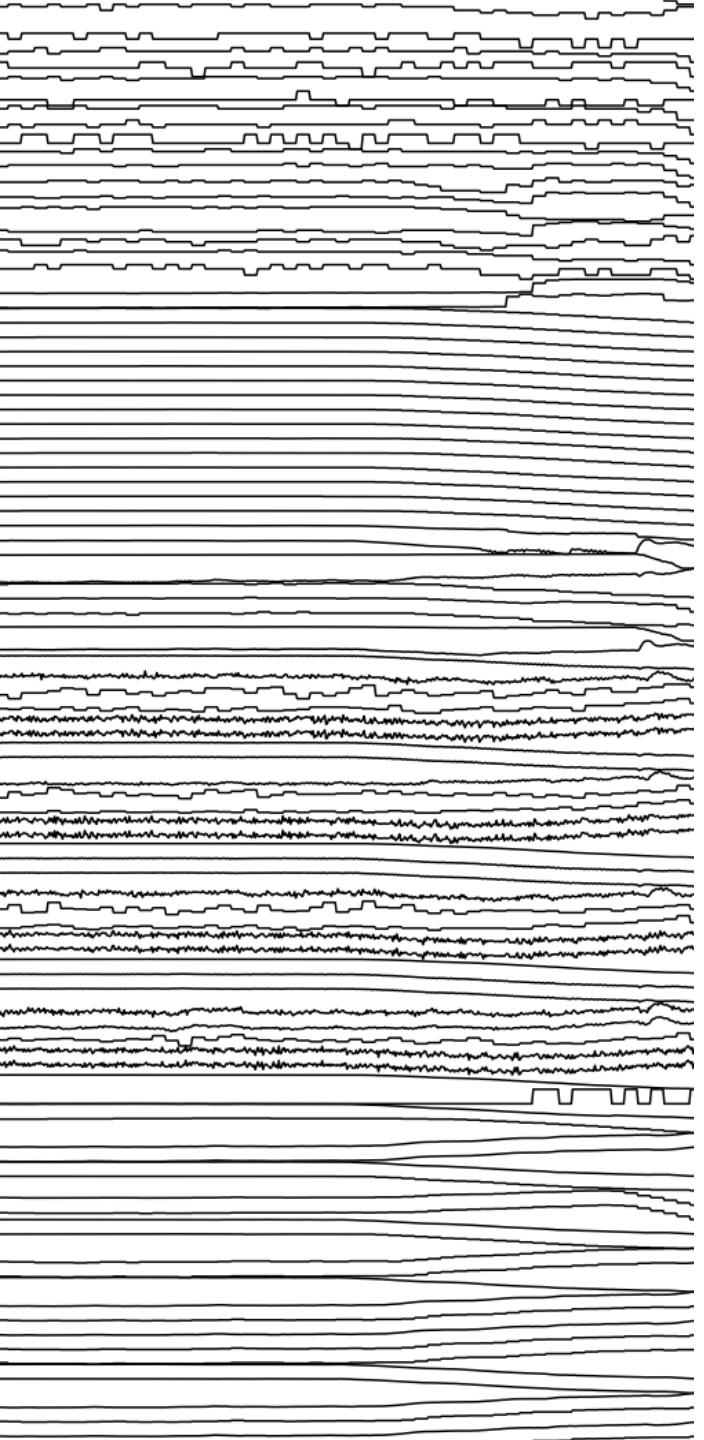


Example of
subsequence-
based anomaly [2]



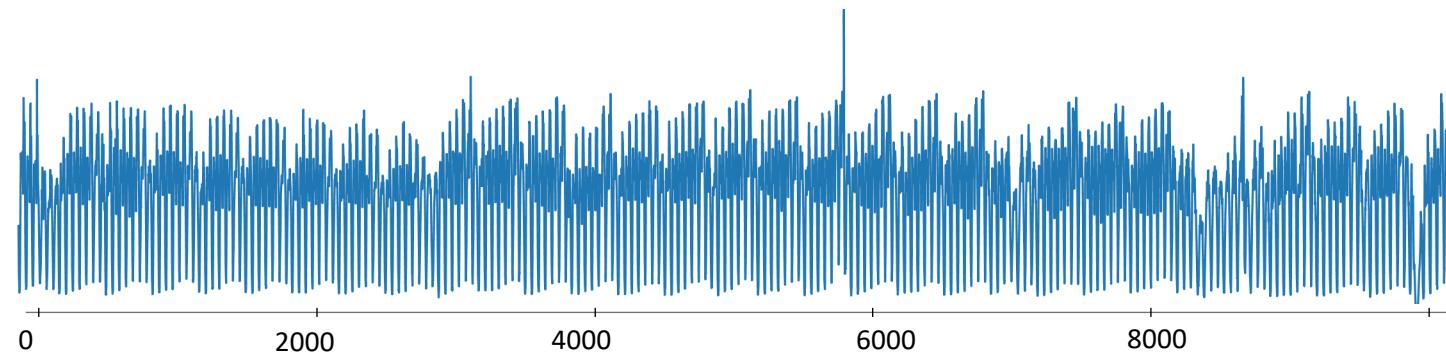
Foundations: Type of anomalies



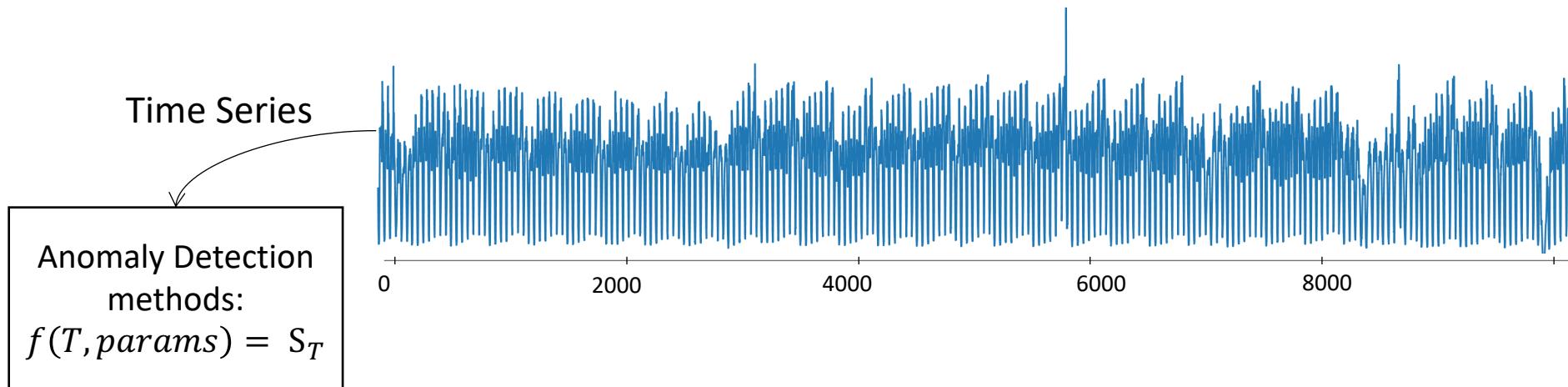


Anomaly Detection Methods

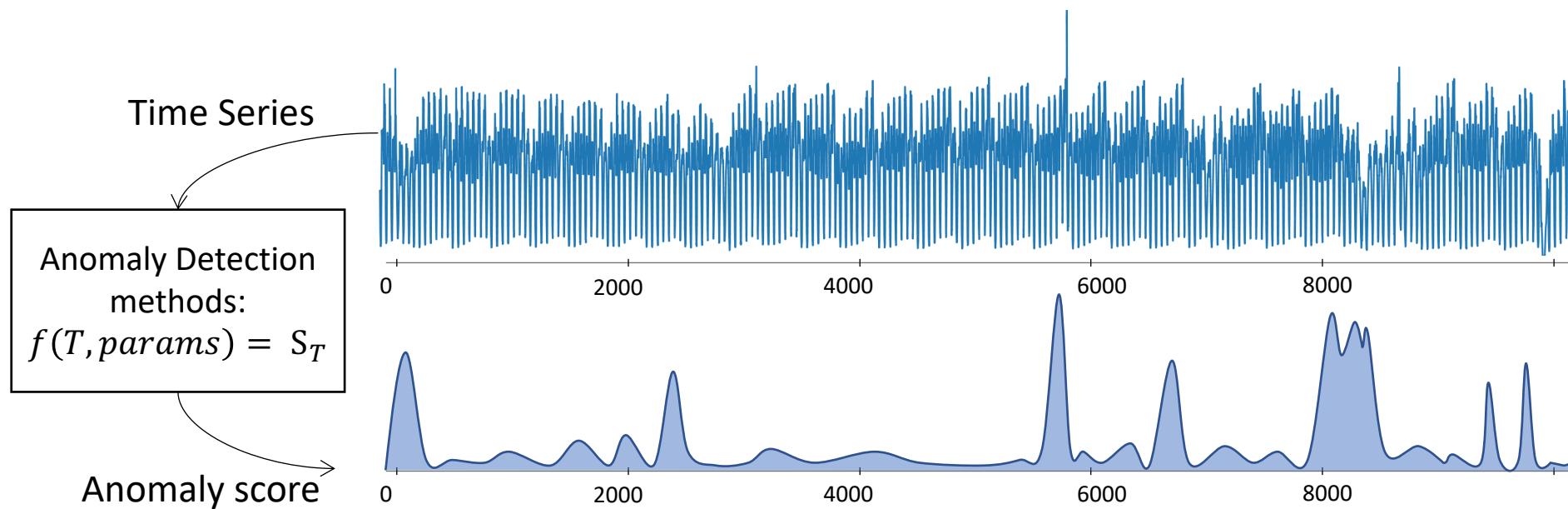
Anomaly Detection methods: *A taxonomy*



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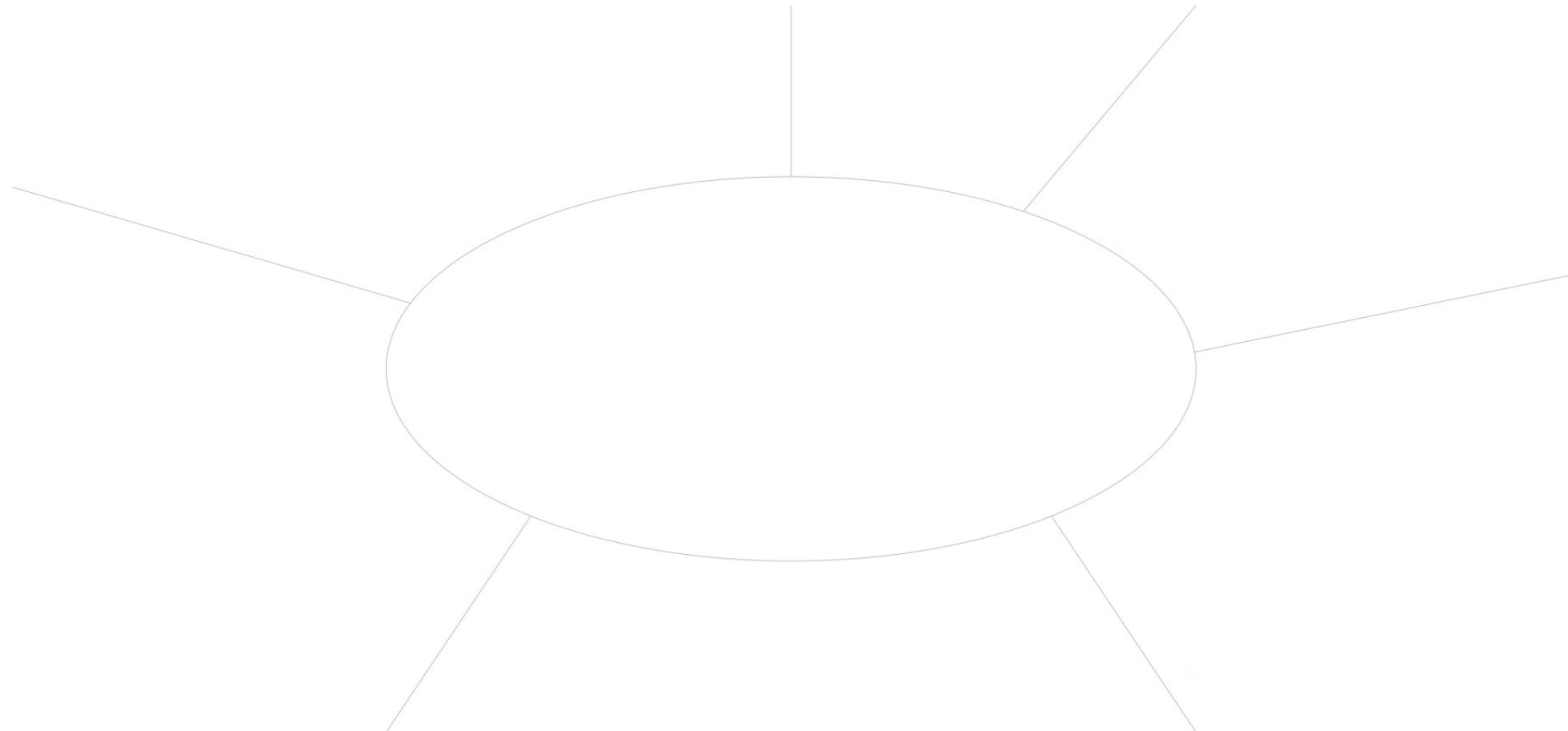


Anomaly Detection methods: A taxonomy



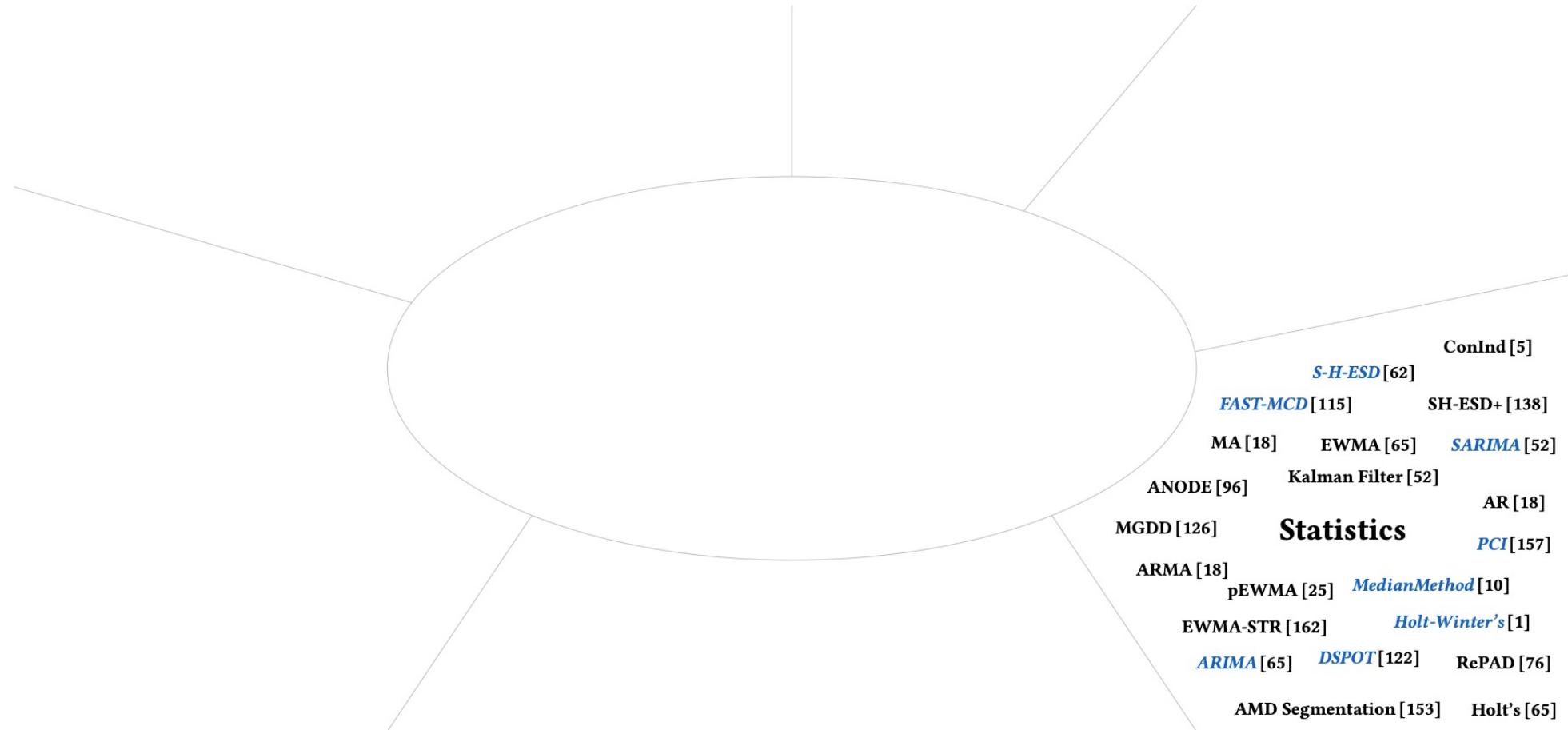
Anomaly Detection methods: *A taxonomy*

By domains [5] ...



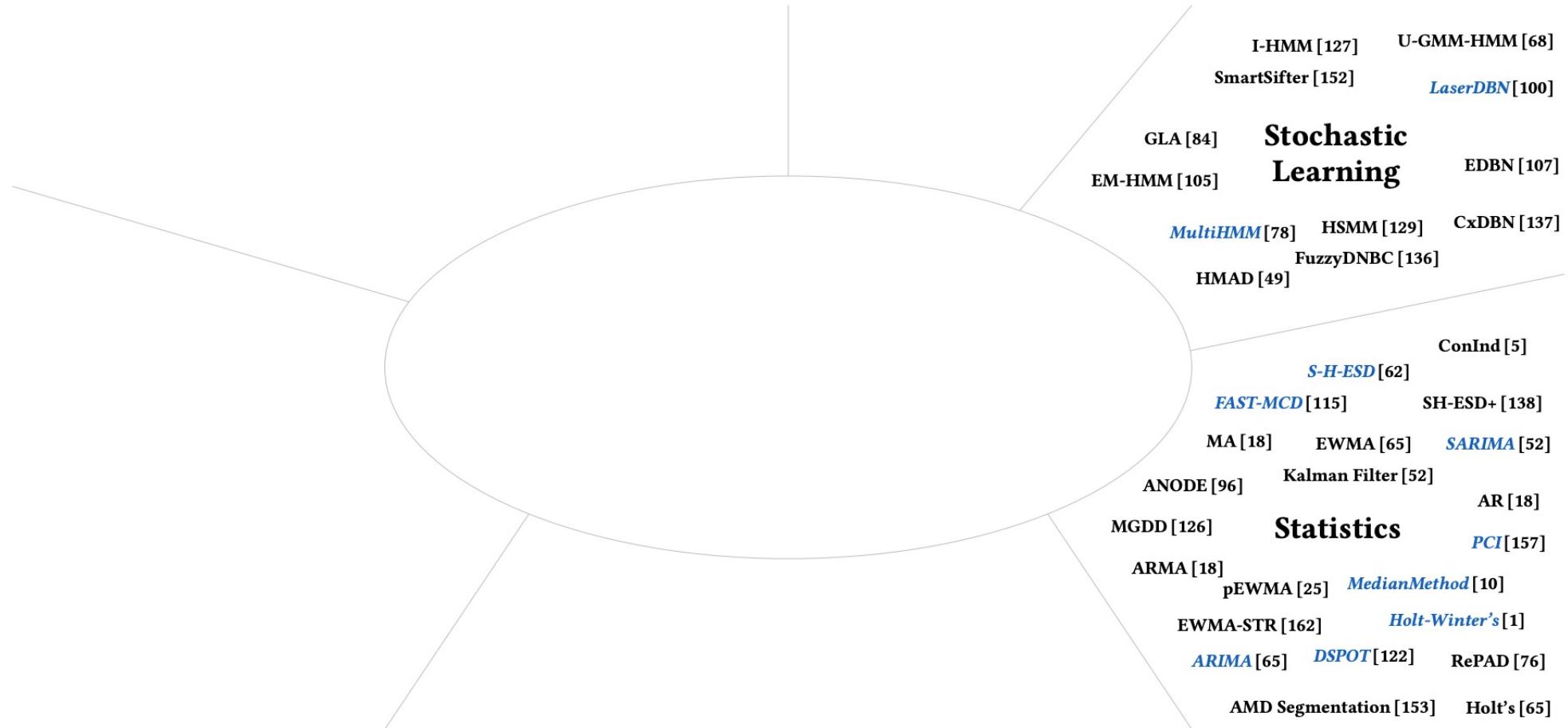
Anomaly Detection methods: *A taxonomy*

By domains [5] ...



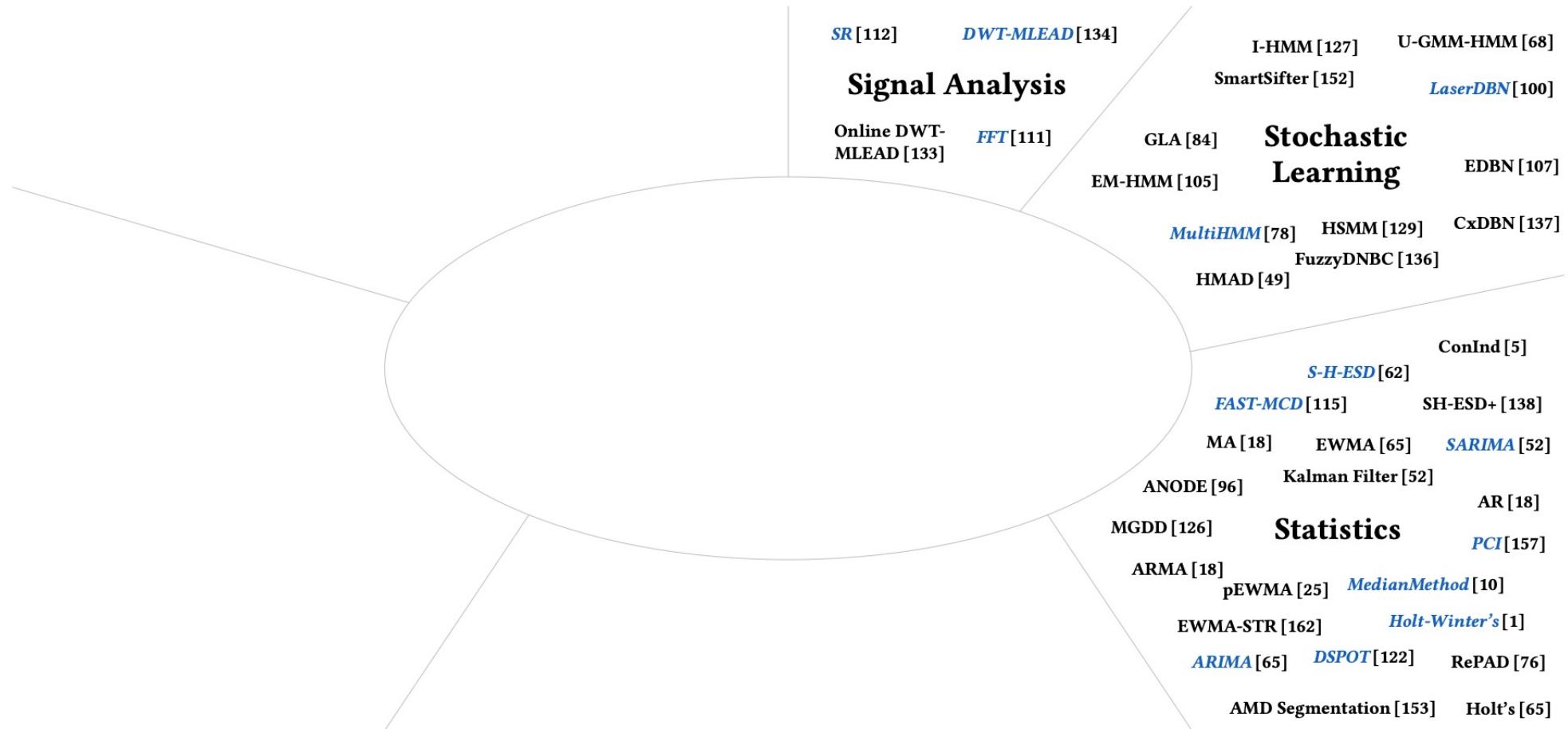
Anomaly Detection methods: A taxonomy

By domains [5] ...



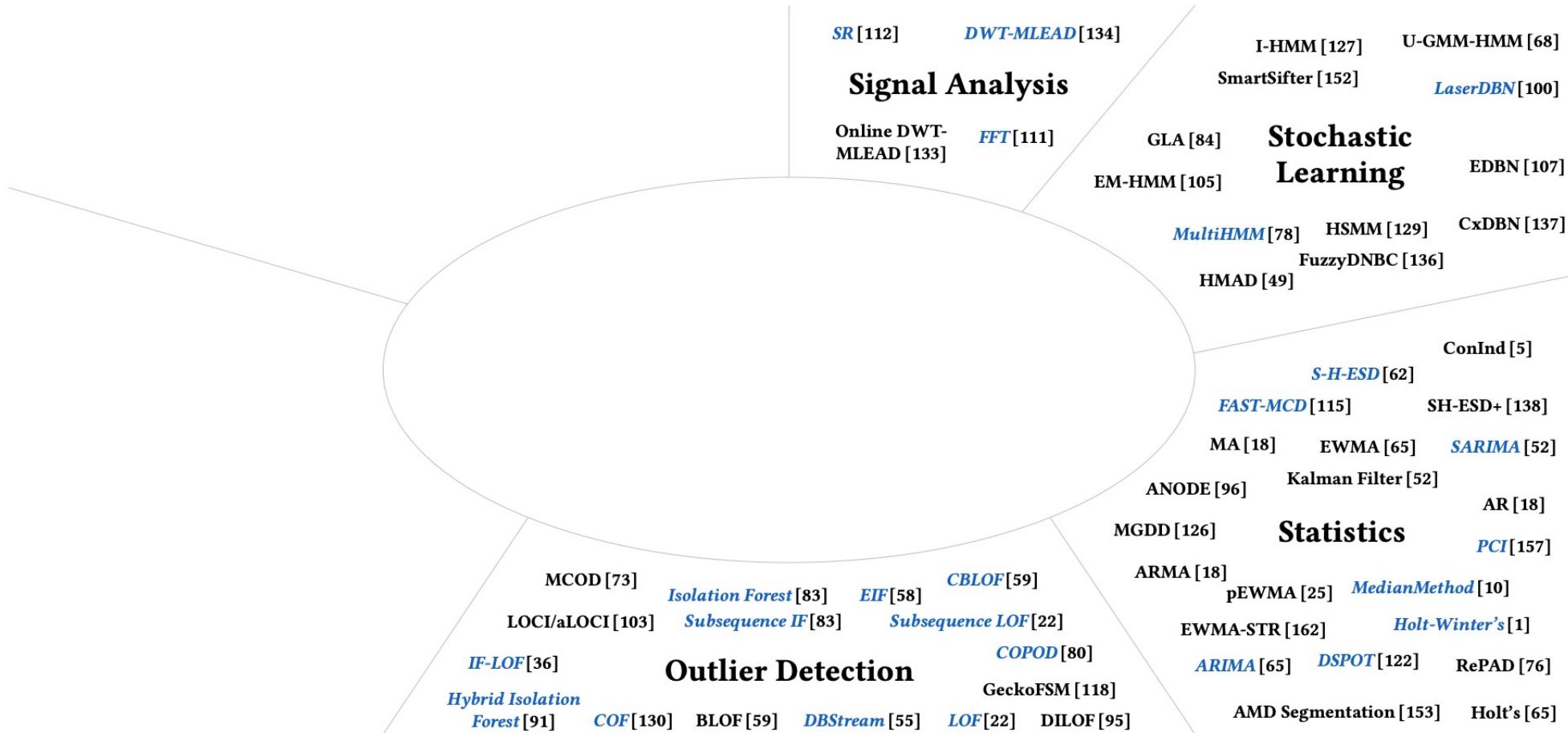
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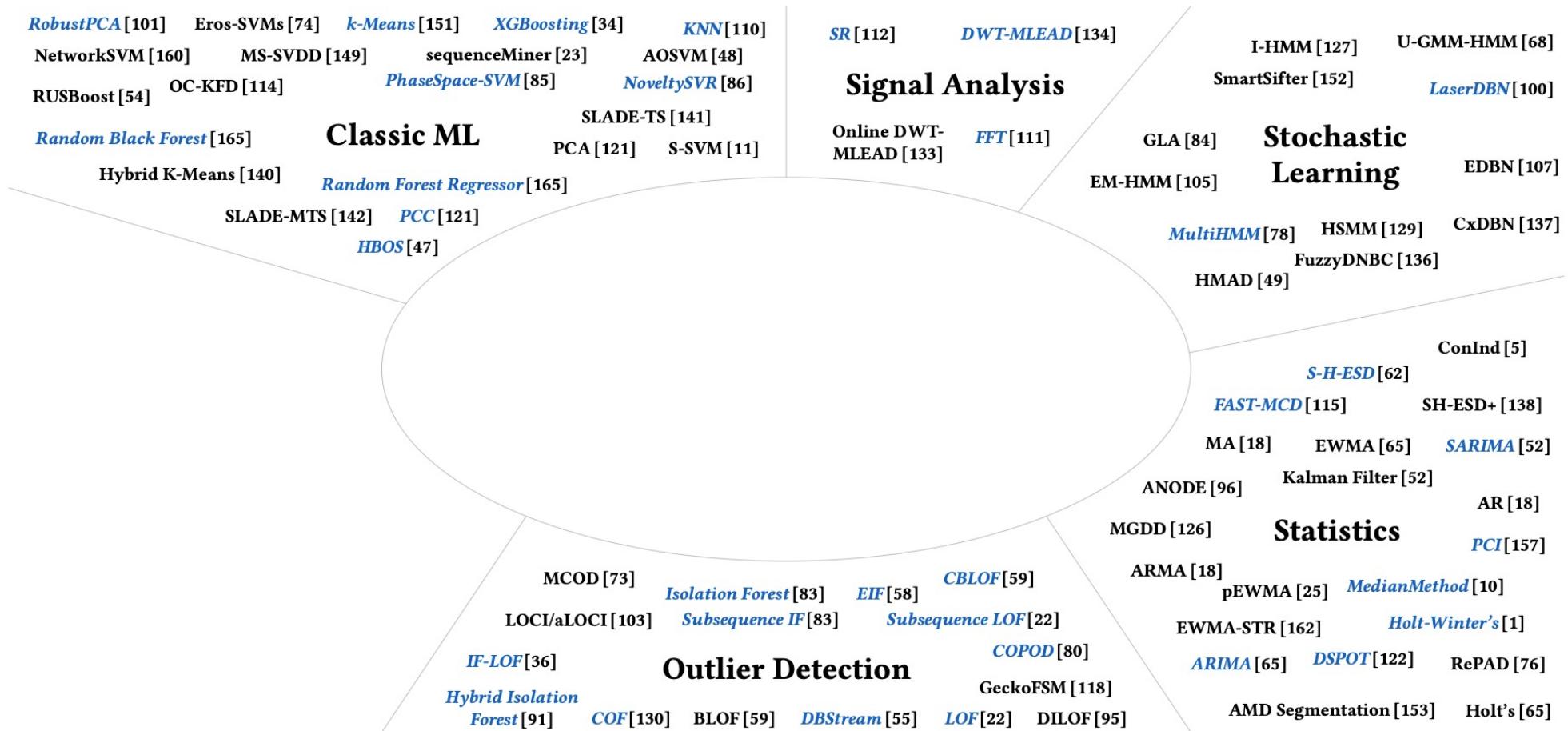
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By domains [5] ...



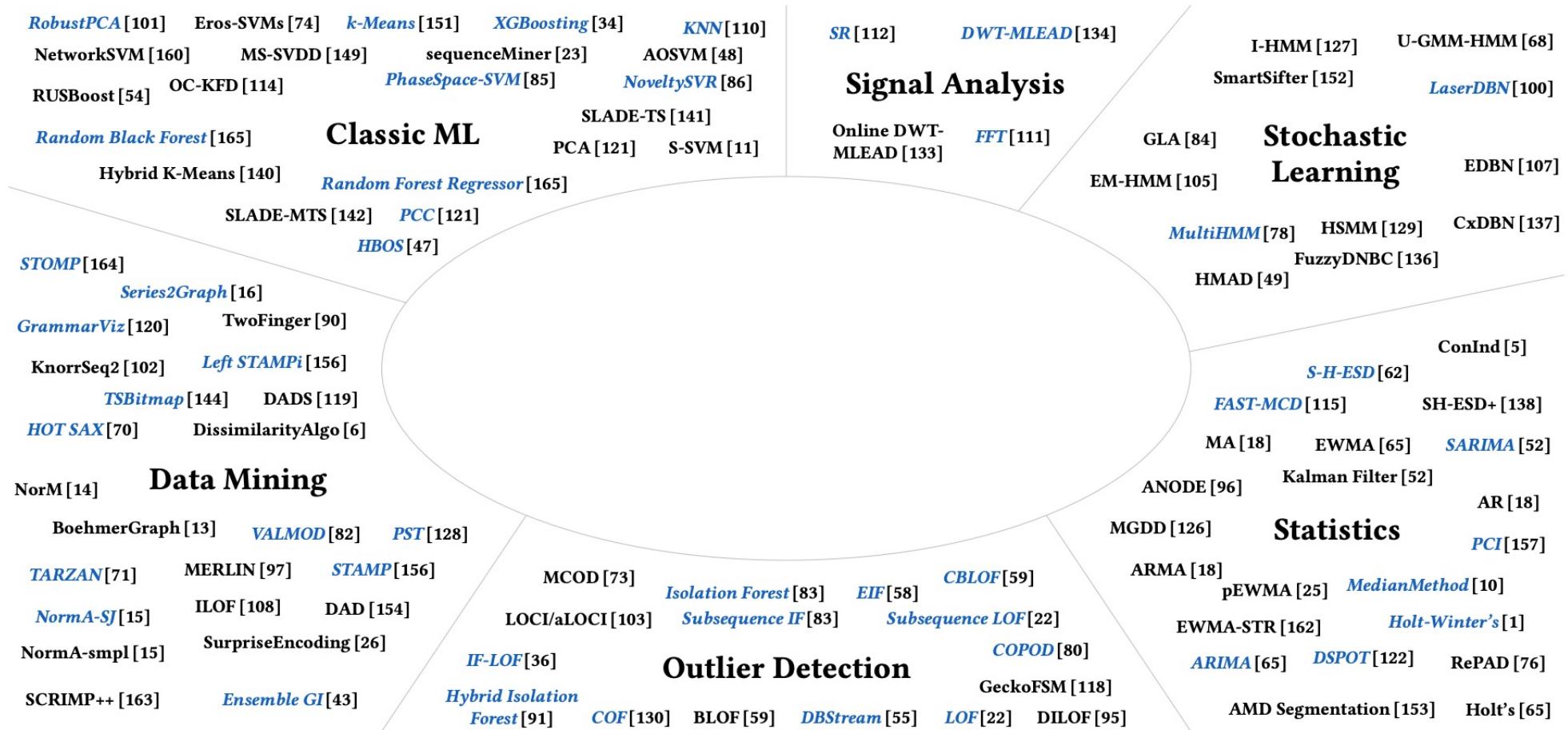
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By domains [5] ...



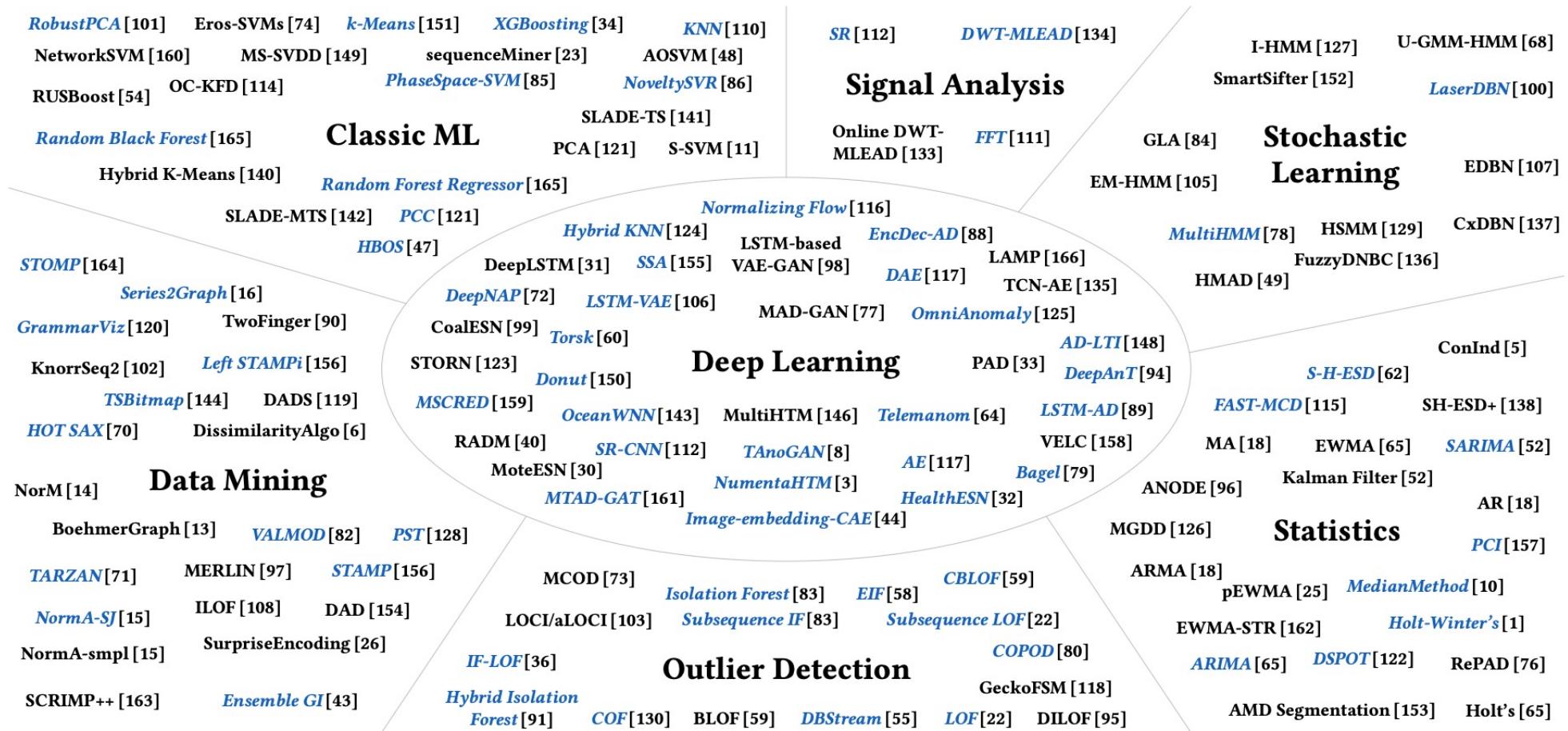
Anomaly Detection methods: A taxonomy

By domains [5] ...



Anomaly Detection methods: A taxonomy

By domains [5] ...



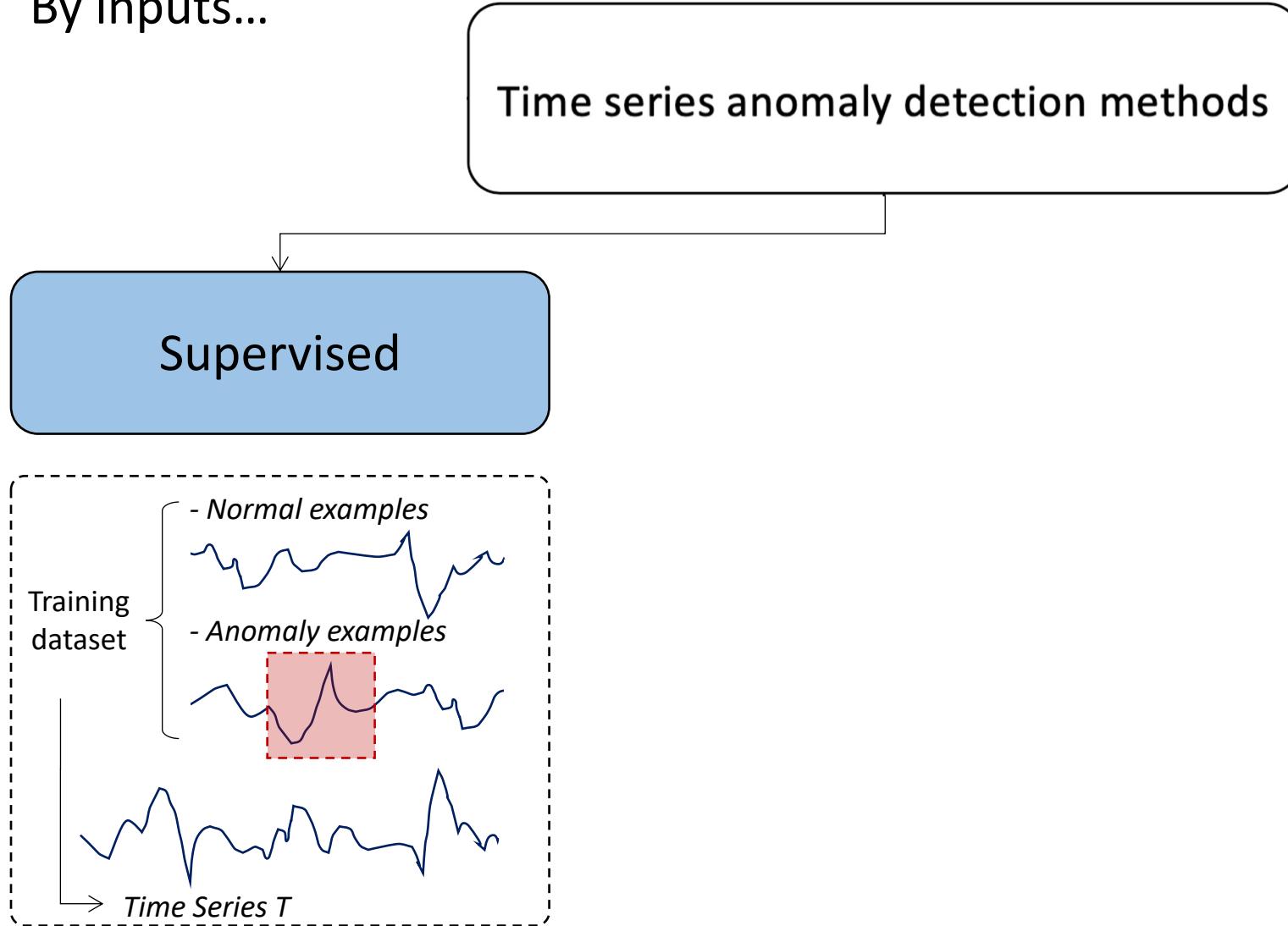
Anomaly Detection methods: *A taxonomy*

By inputs...

Time series anomaly detection methods

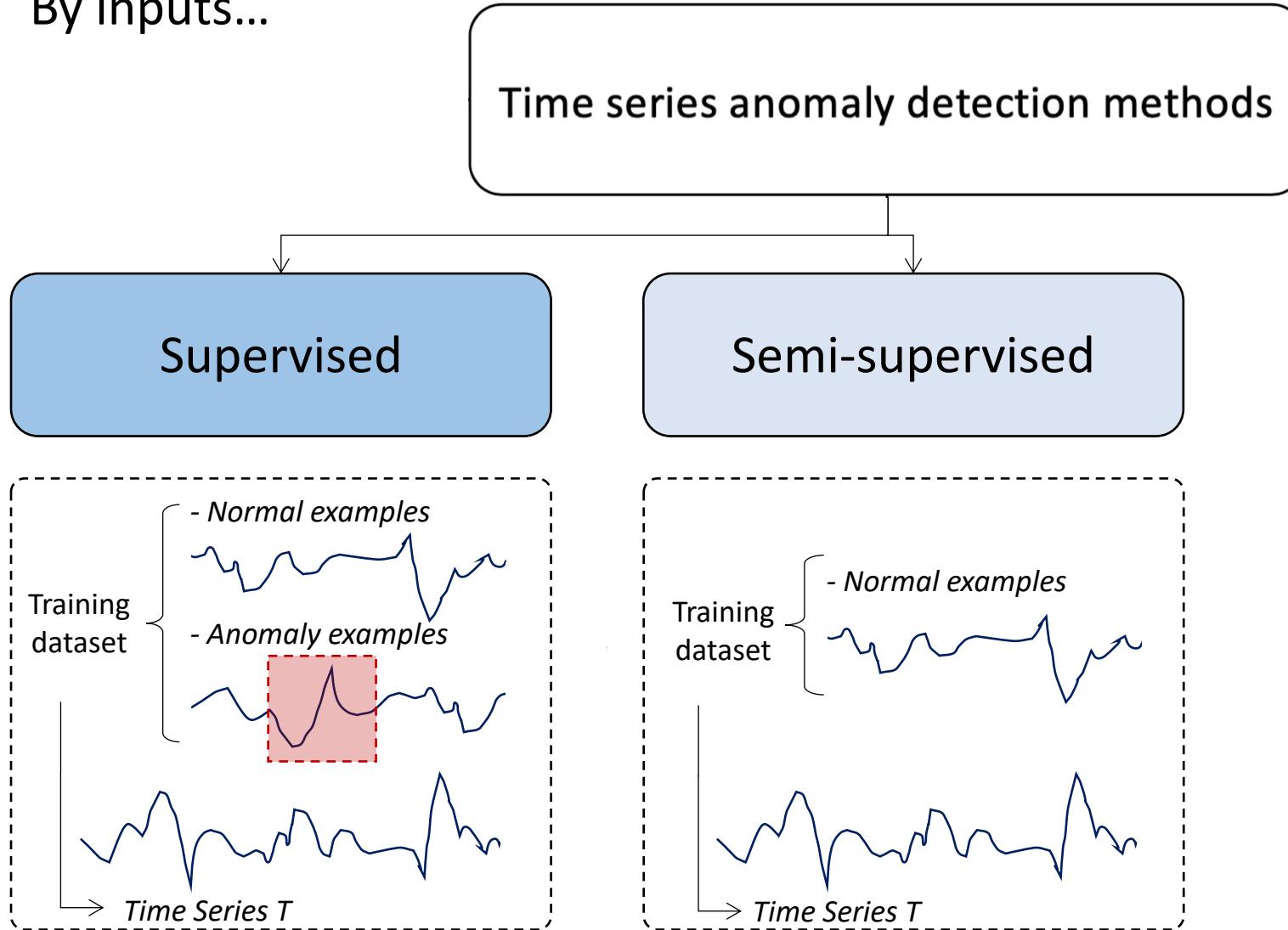
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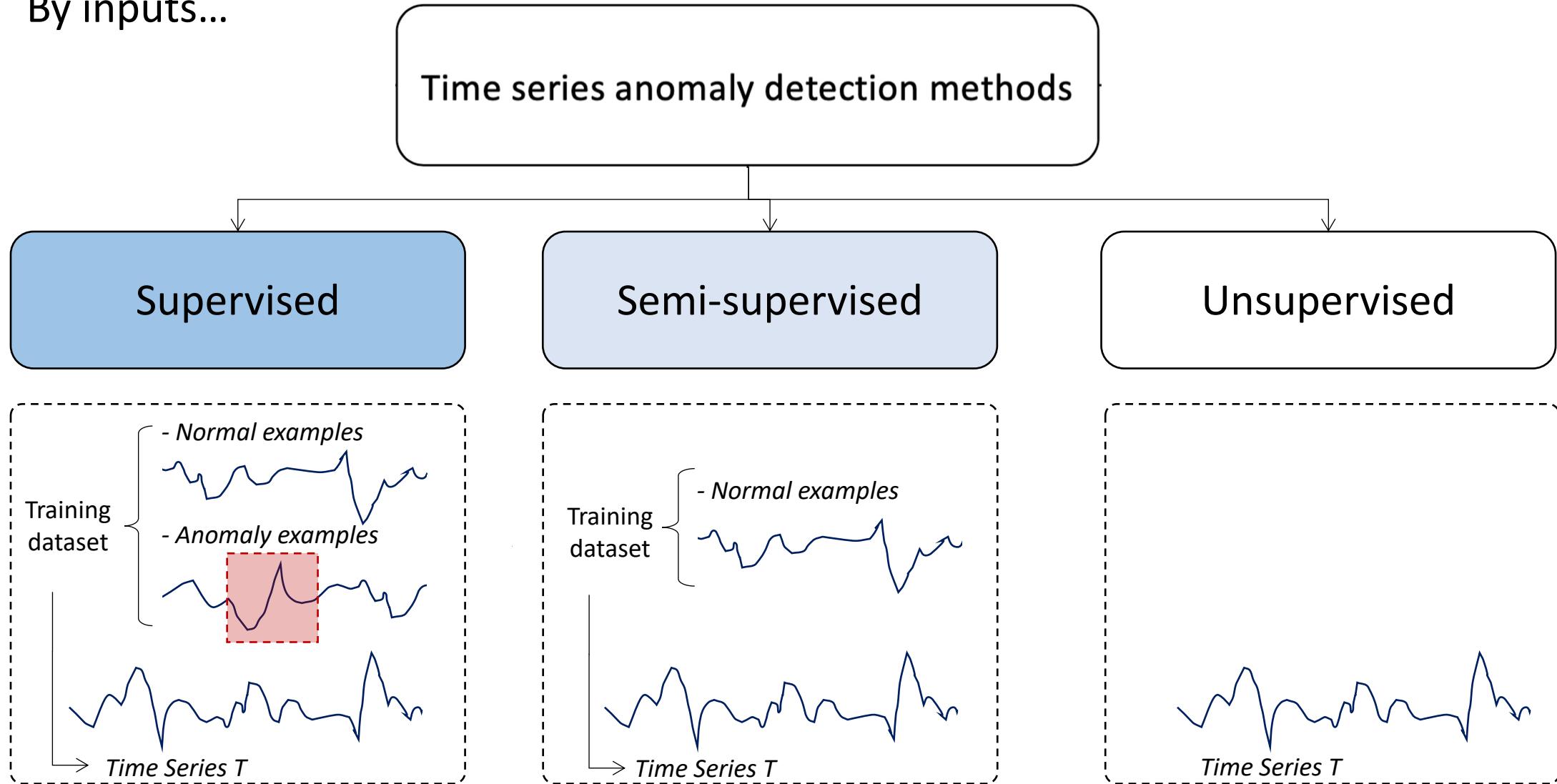
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By inputs...



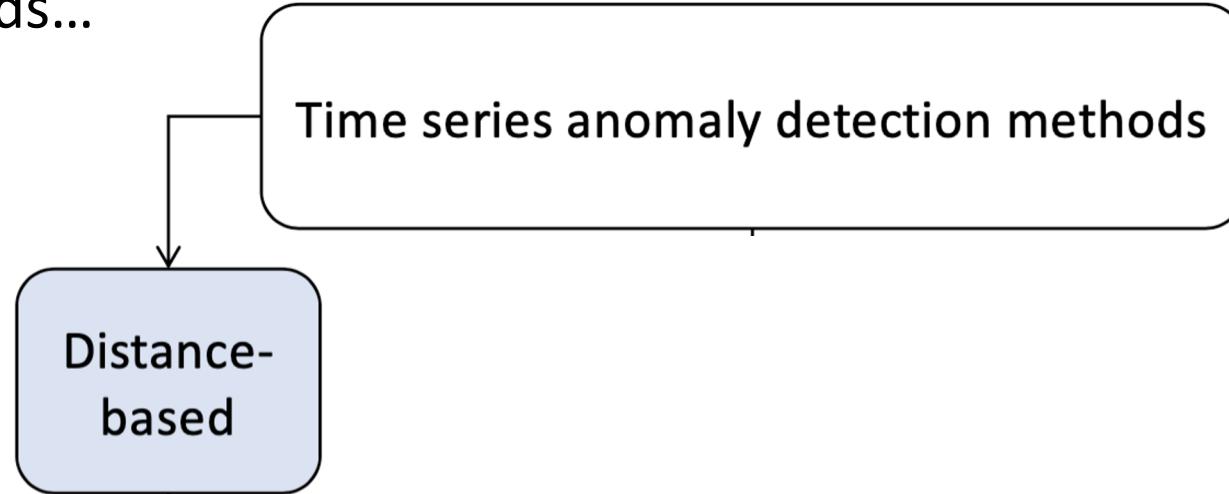
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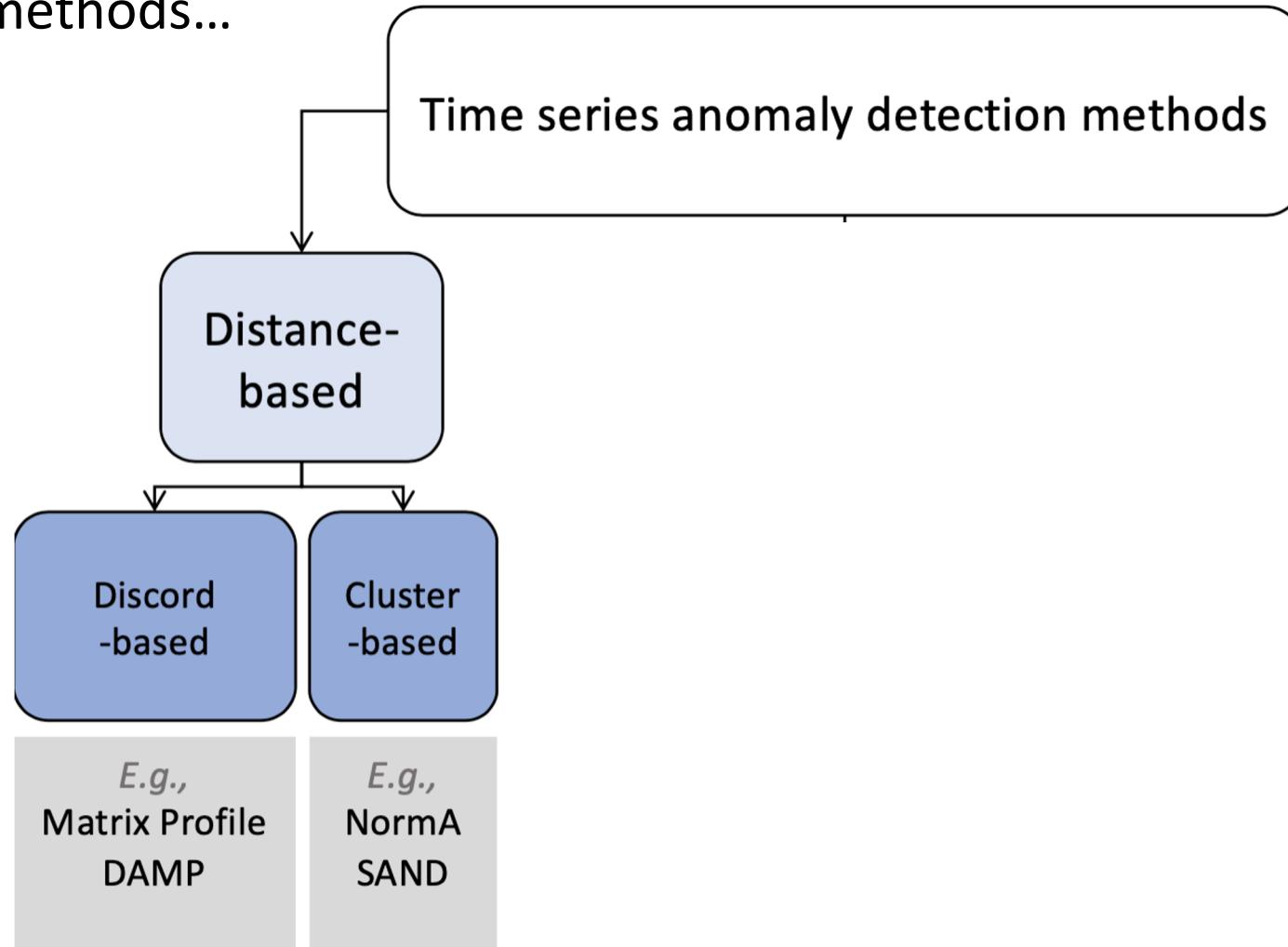
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By methods...



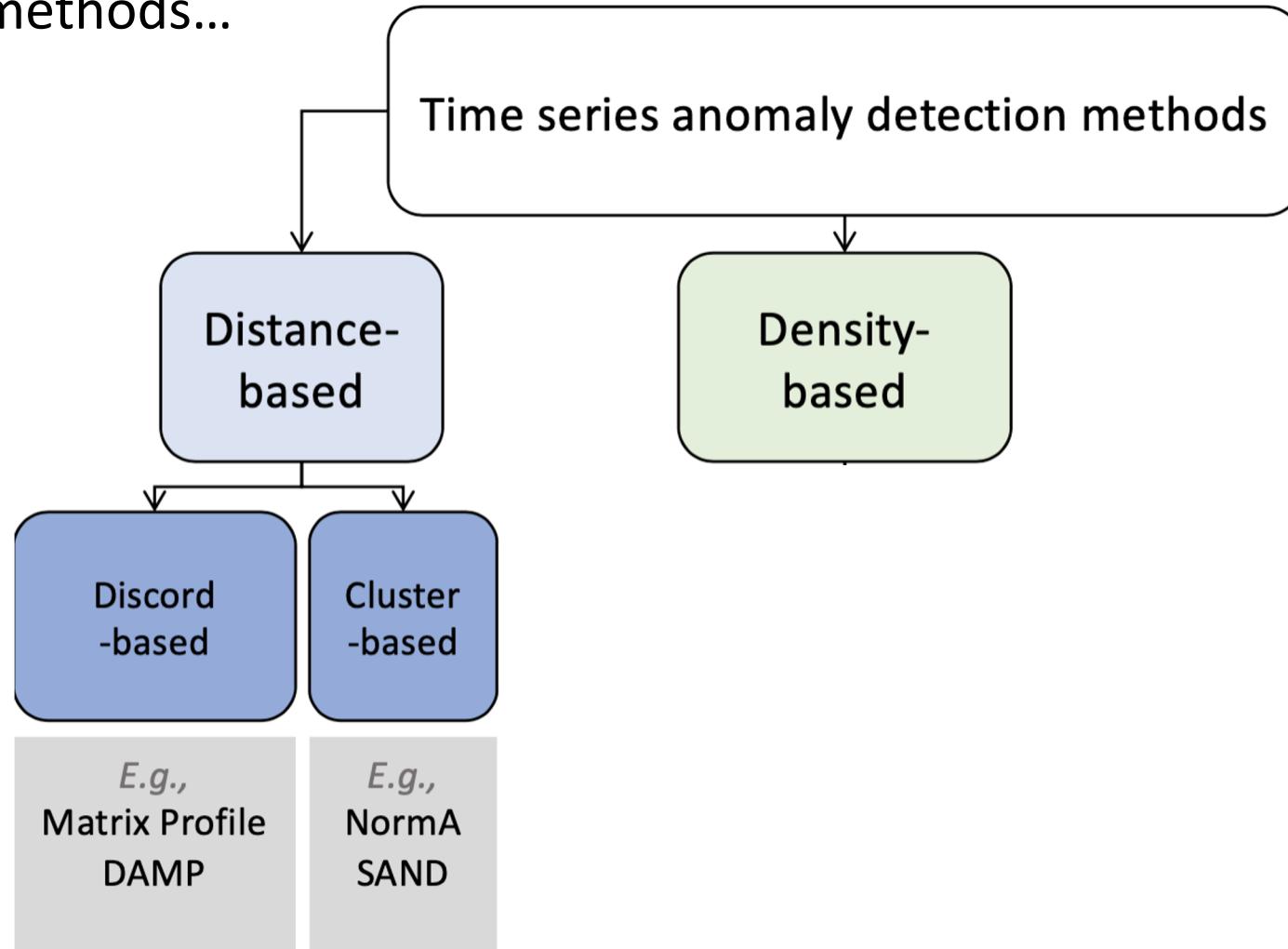
Anomaly Detection methods: *A taxonomy*

By methods...



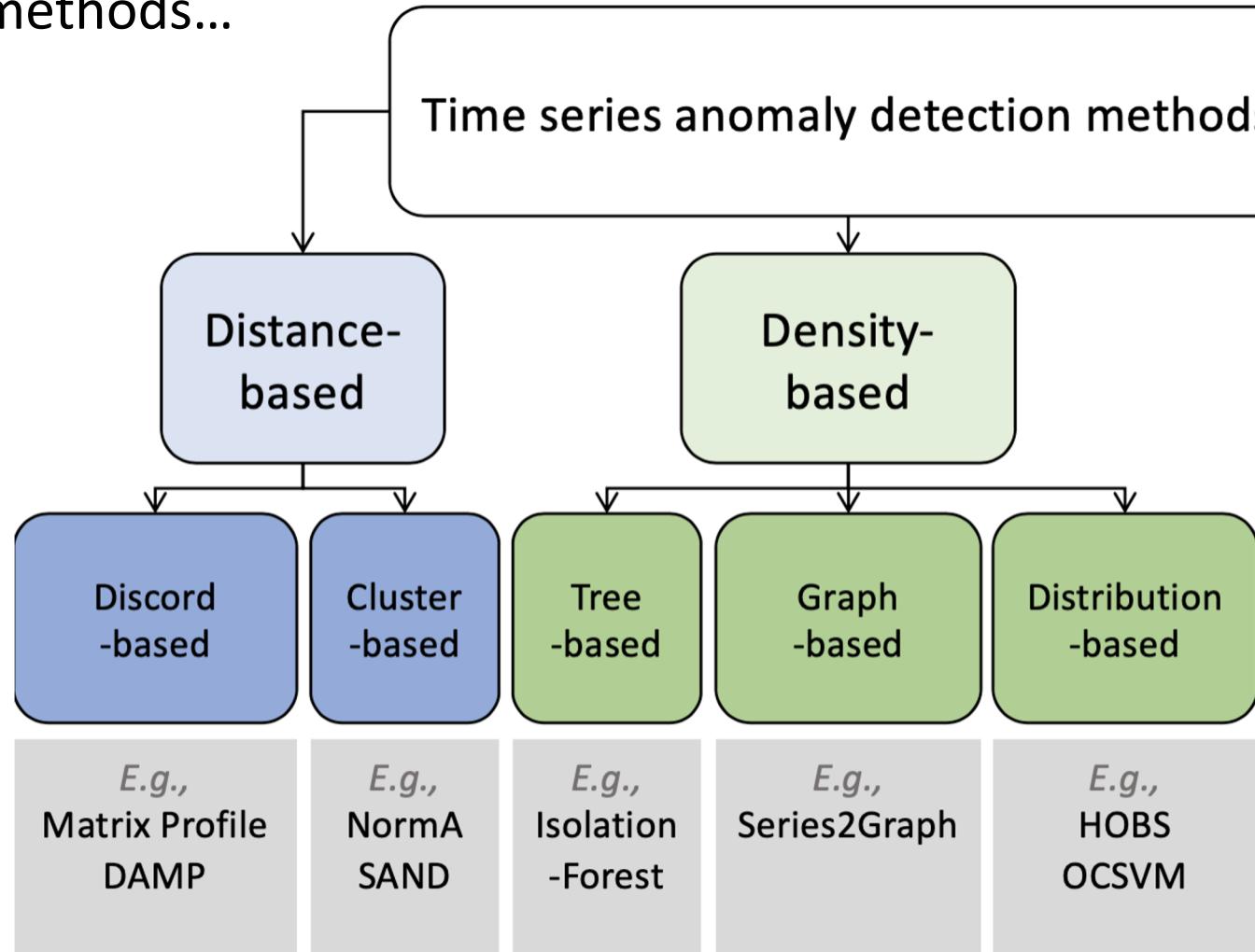
Anomaly Detection methods: *A taxonomy*

By methods...



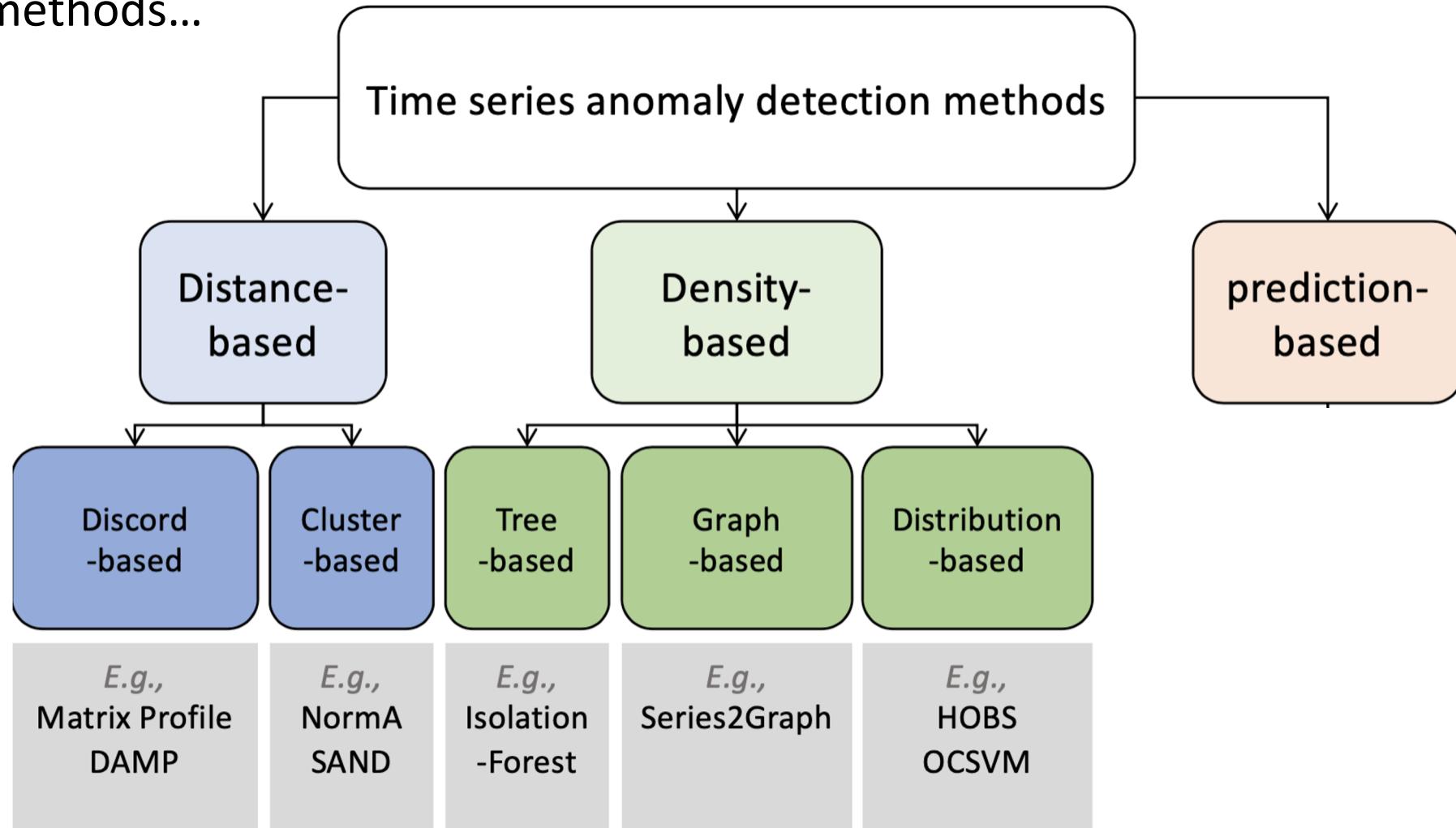
Anomaly Detection methods: *A taxonomy*

By methods...



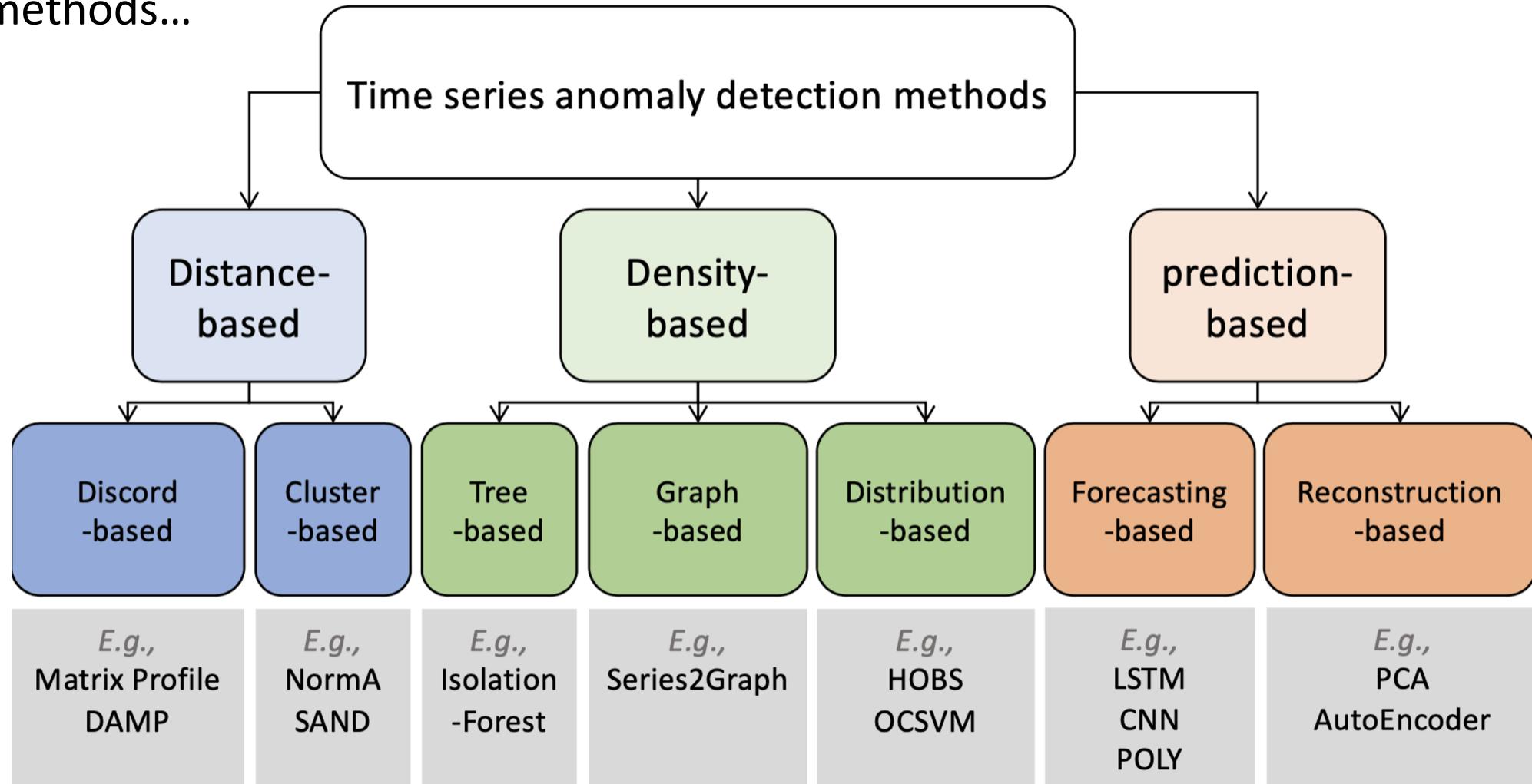
Anomaly Detection methods: A taxonomy

By methods...



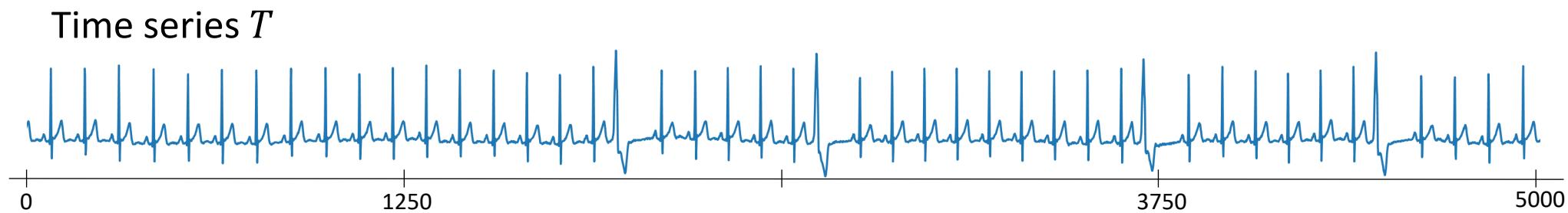
Anomaly Detection methods: A taxonomy

By methods...



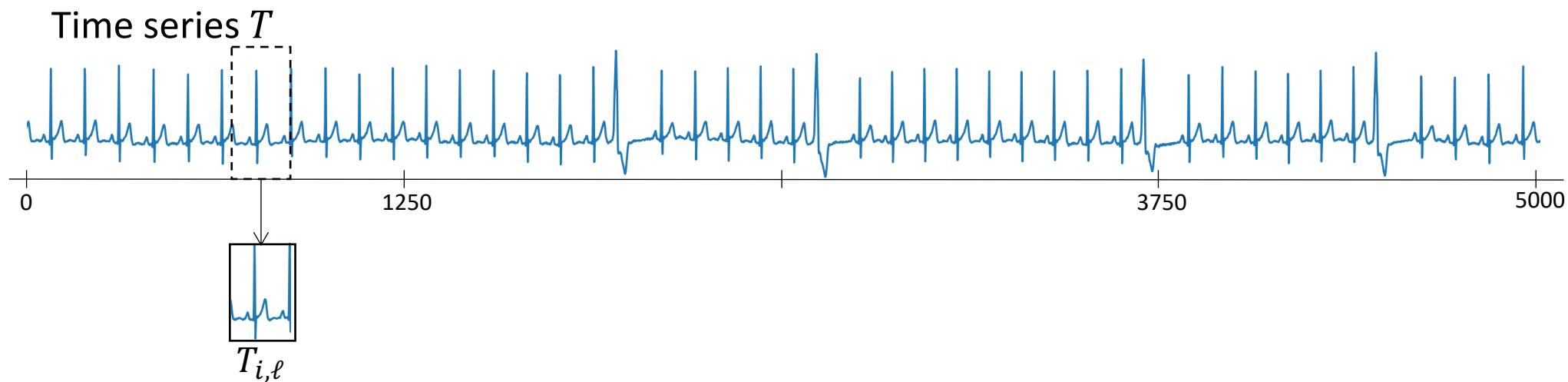
Anomaly Detection methods: *Distance-based*

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



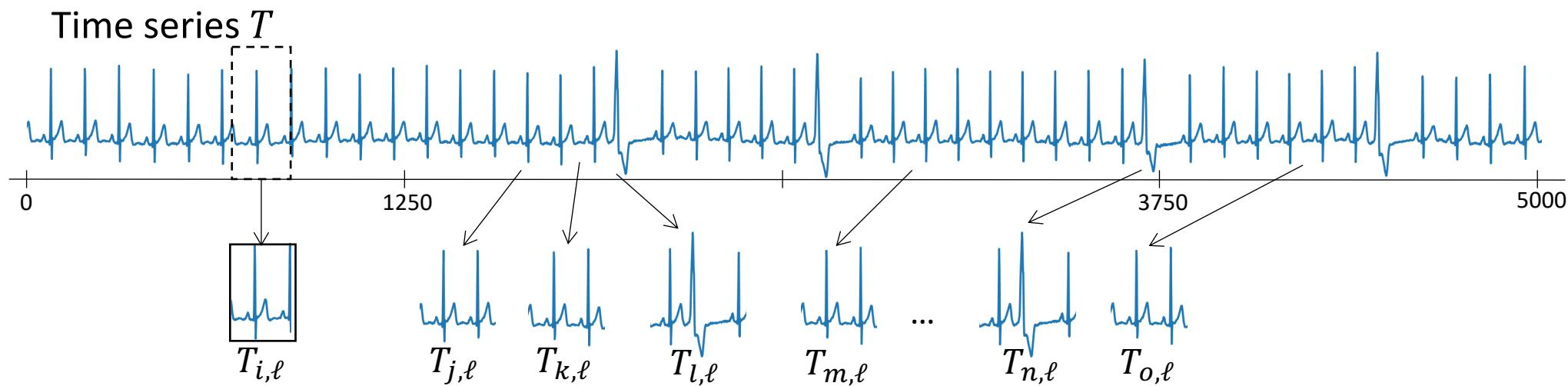
Anomaly Detection methods: *Distance-based*

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



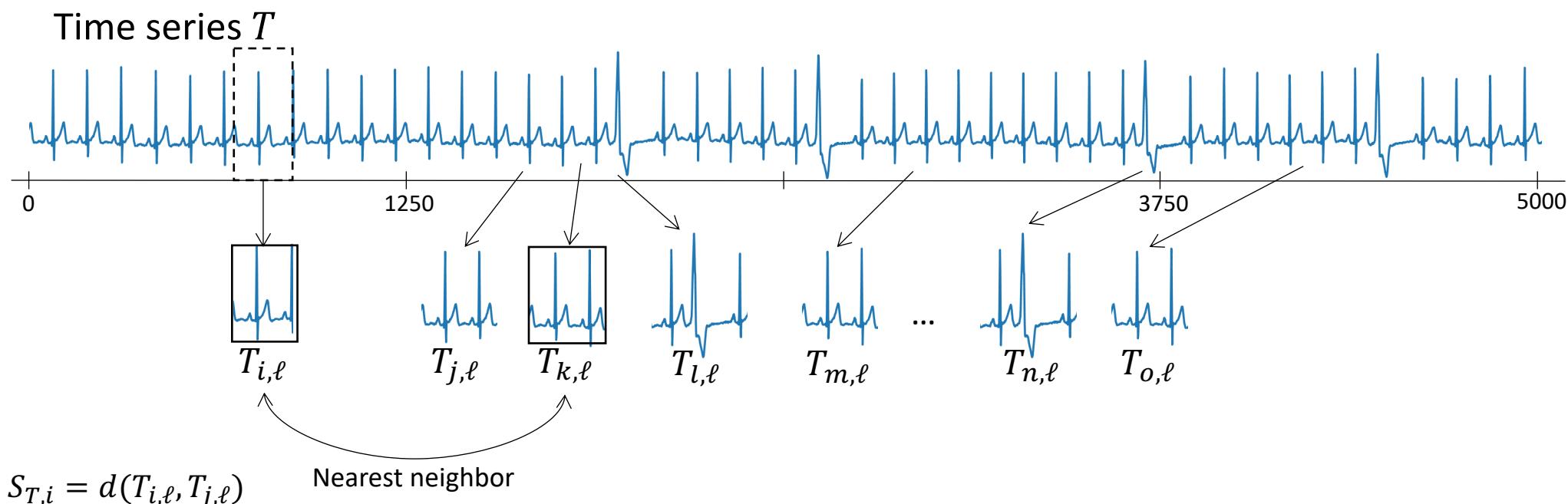
Anomaly Detection methods: *Distance-based*

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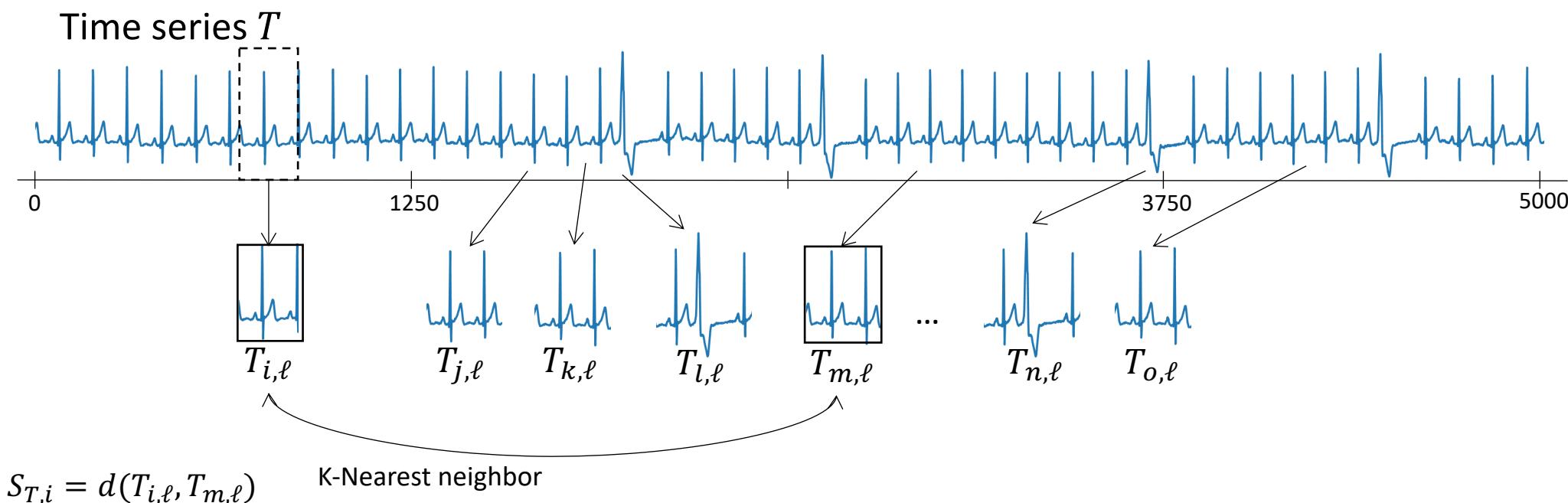
Anomaly Detection methods: *Distance-based*

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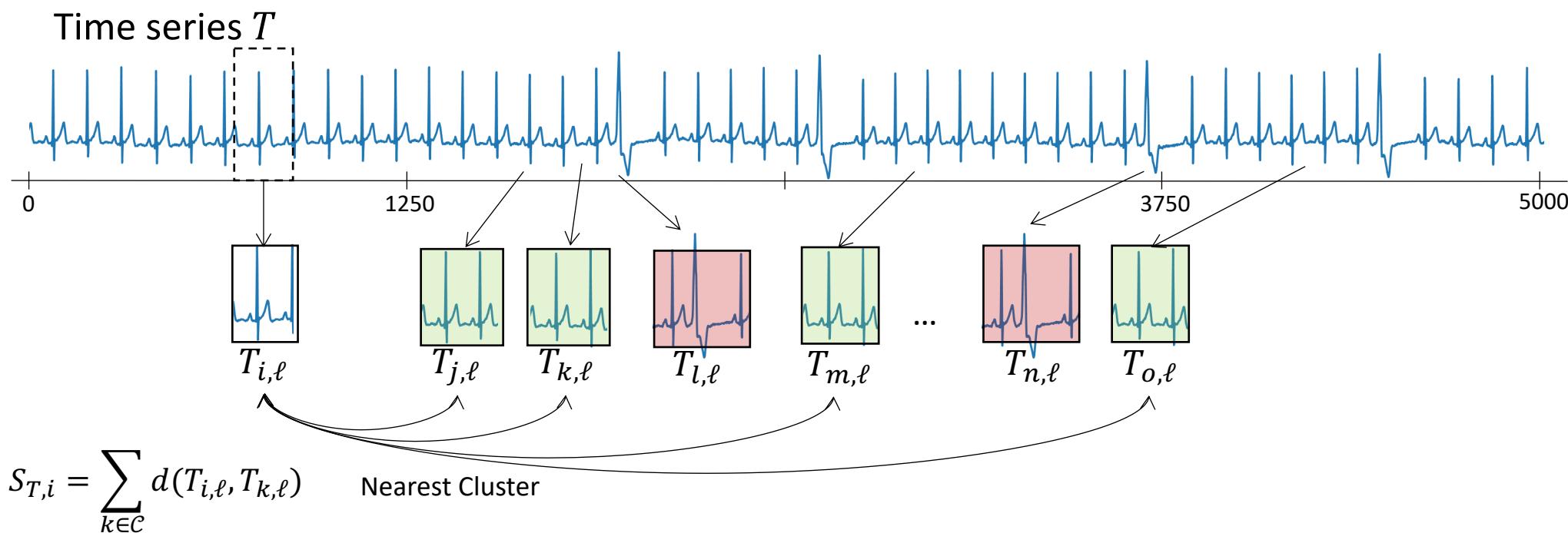
Anomaly Detection methods: *Distance-based*

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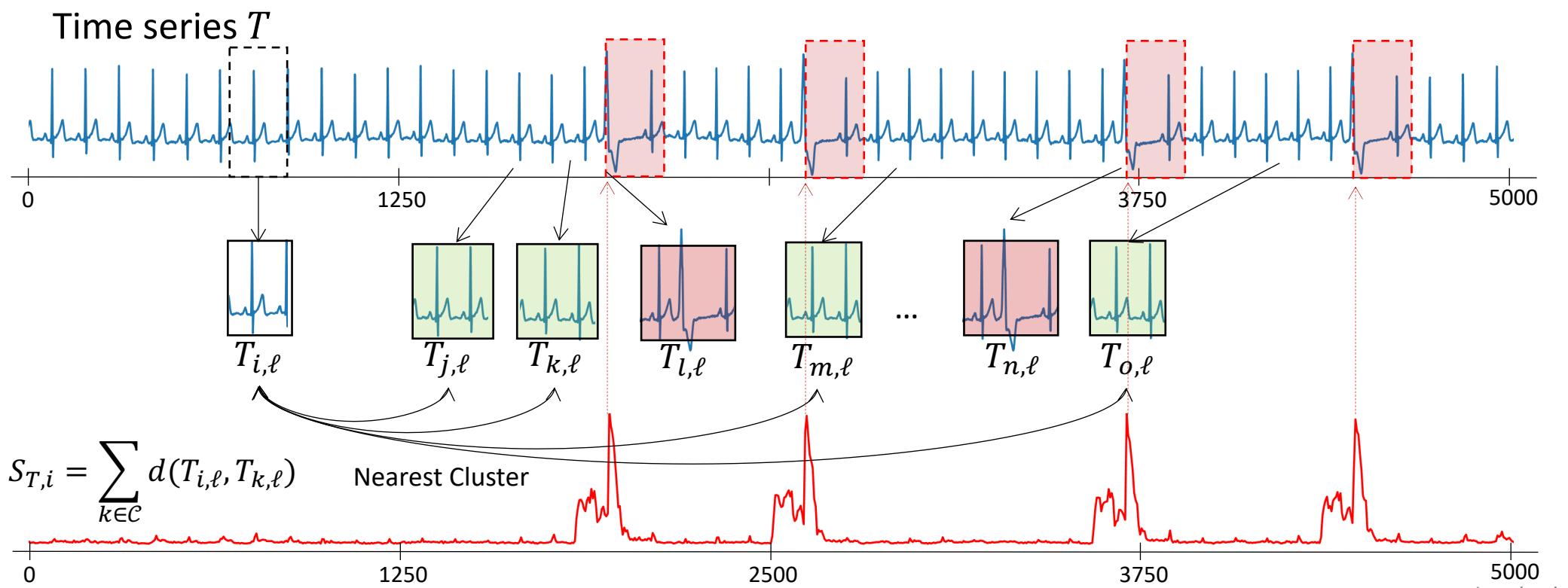
Anomaly Detection methods: *Distance-based*

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



Anomaly Detection methods: *Distance-based*

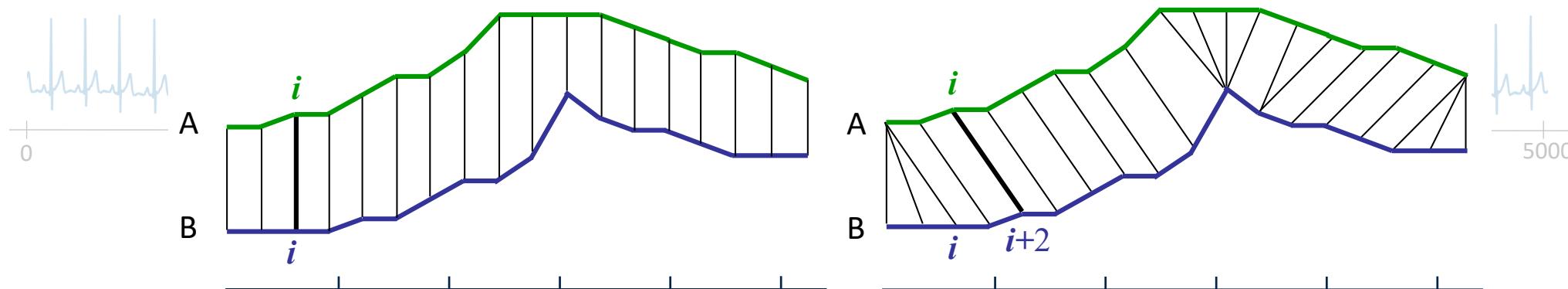
Methods that use **distance computation** between subsequences (or group of subsequences) to detect anomalies.



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

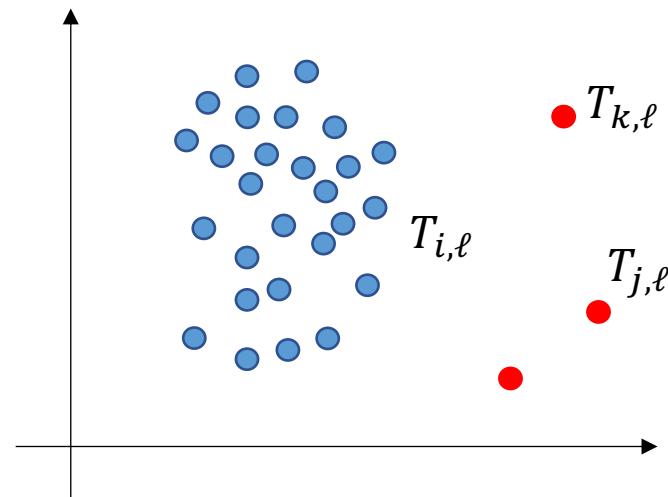
(b) DTW distance

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

Nearest Cluster



Anomaly Detection methods: *an Example*



Matrix Profile [6] (MP)

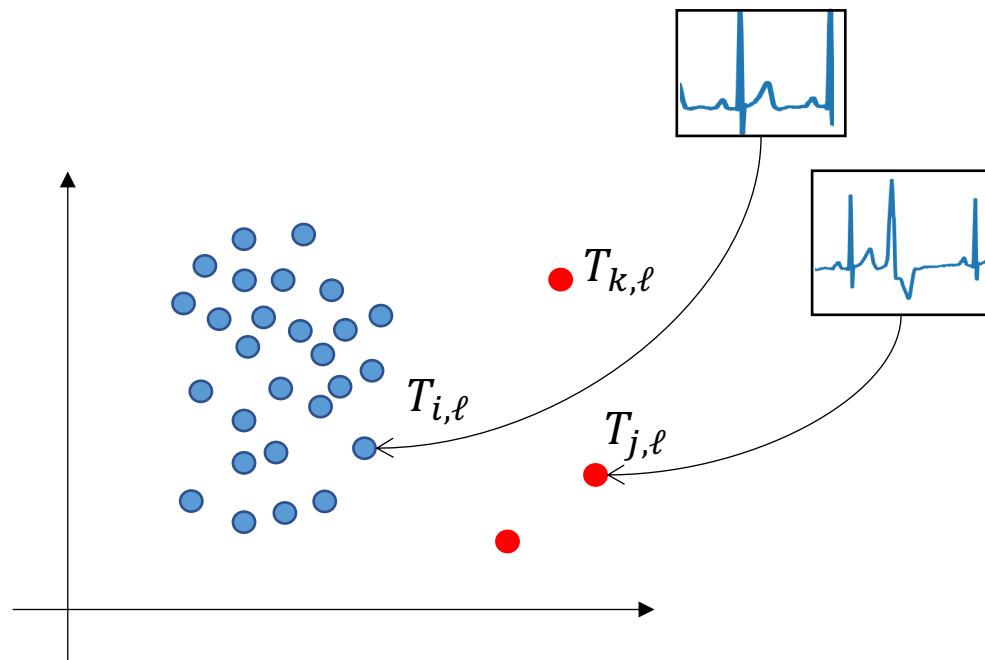
Compute the **distance to the nearest neighbor** (using the MASS algorithm z-norm Euclidean distance computation) and use it as anomaly score

Unsupervised

Univariate

sequence

Anomaly Detection methods: *an Example*



Matrix Profile [6] (MP)

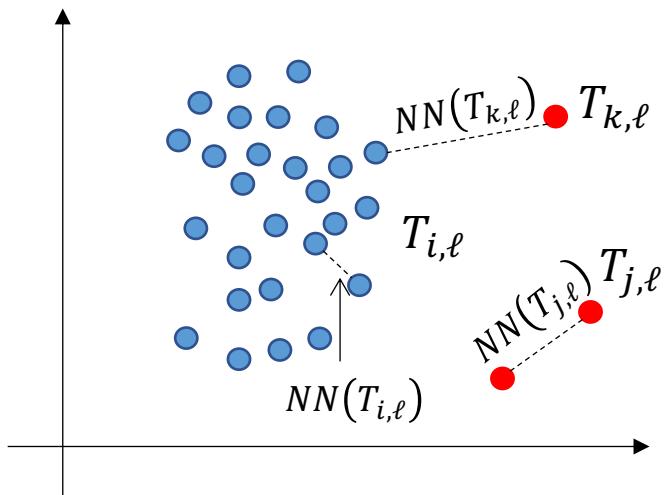
Compute the **distance to the nearest neighbor** (using the MASS algorithm z-norm Euclidean distance computation) and use it as anomaly score

Unsupervised

Univariate

sequence

Anomaly Detection methods: *an Example*



Matrix Profile [6] (MP)

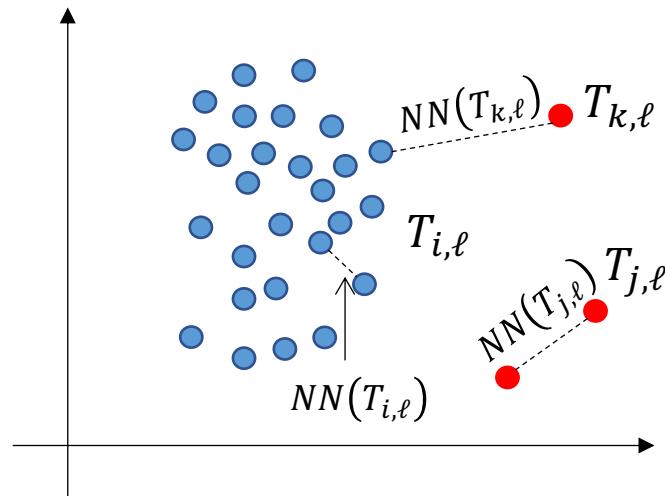
Compute the **distance to the nearest neighbor** (using the MASS algorithm z-norm Euclidean distance computation) and use it as anomaly score

Unsupervised

Univariate

sequence

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)

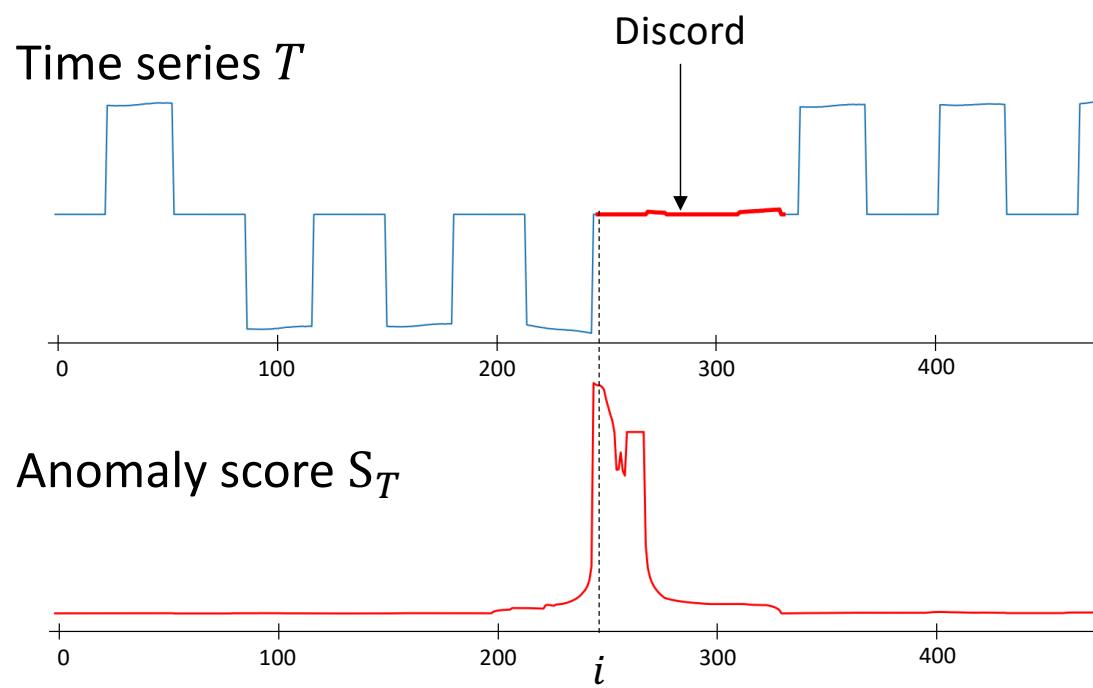
Compute the **distance to the nearest neighbor** (using the MASS algorithm z-norm Euclidean distance computation) and use it as anomaly score

Unsupervised

Univariate

sequence

Anomaly Detection methods: an Example

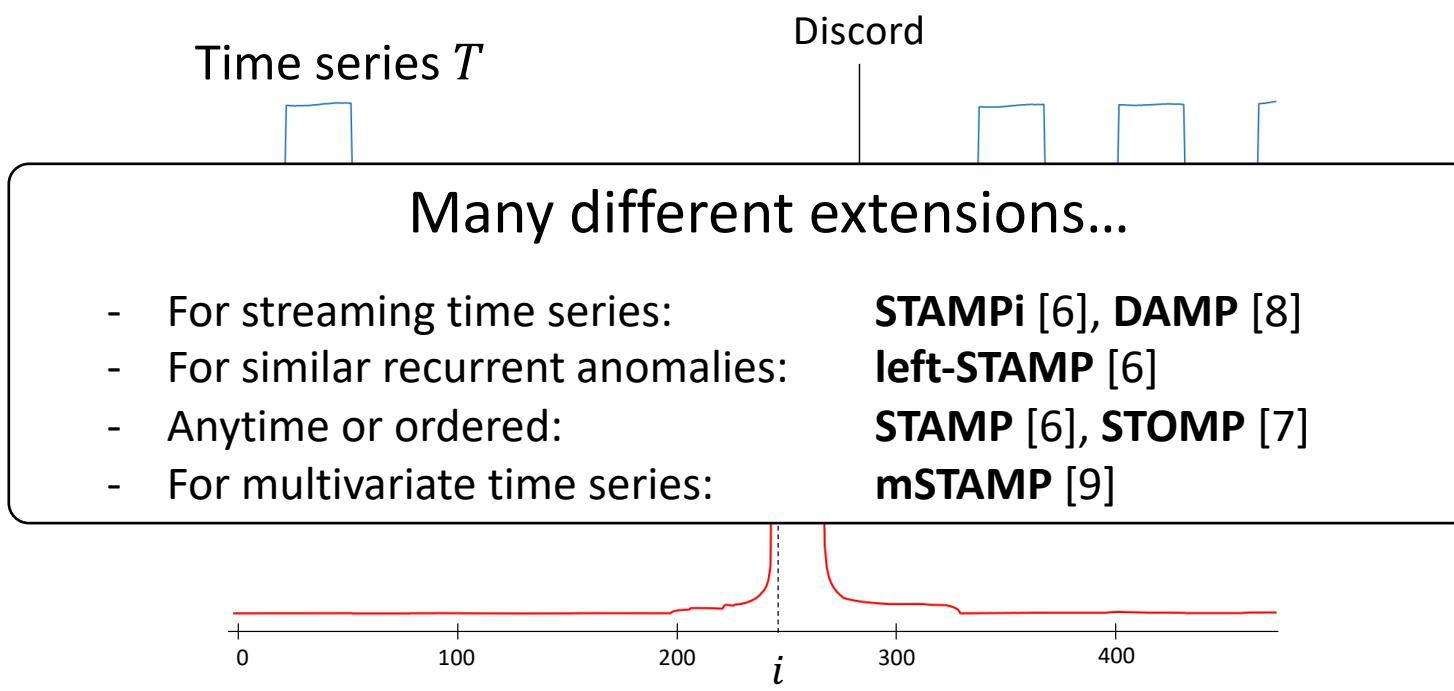


Matrix Profile [6] (MP)

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

Anomaly Detection methods: *an Example*



Matrix Profile [6] (MP)

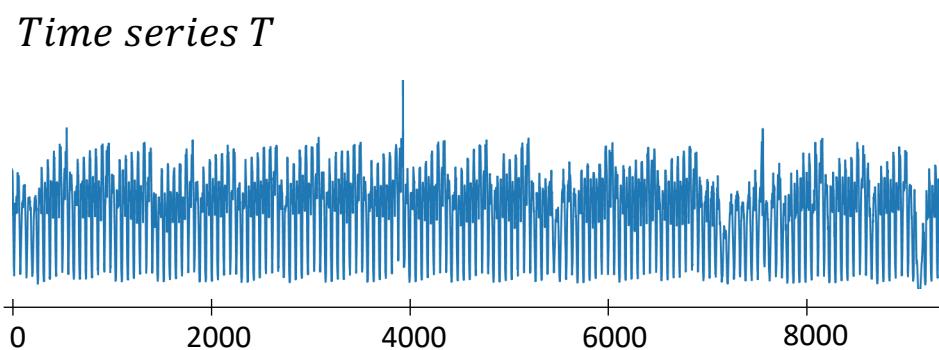
Compute the **distance to the nearest neighbor** (using the MASS algorithm z-norm Euclidean distance computation) and use it as anomaly score

Unsupervised

Univariate

sequence

Anomaly Detection methods: *an Example*



NormA [10]

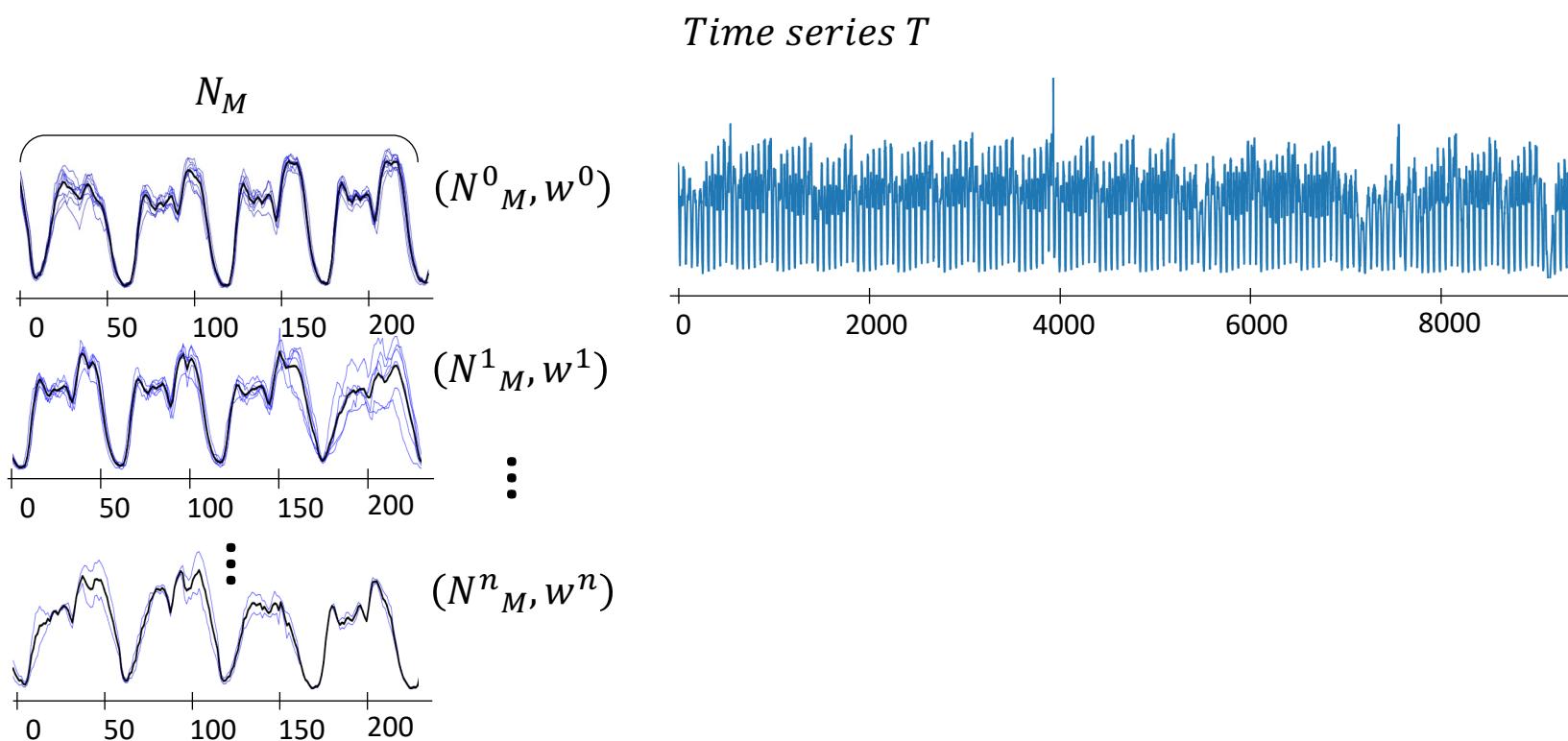
Distance-based approach that **summarize** the time series into a **weighted set of subsequences** and use the distance to them as anomaly score

Unsupervised

Univariate

sequence

Anomaly Detection methods: an Example



NormA [10]

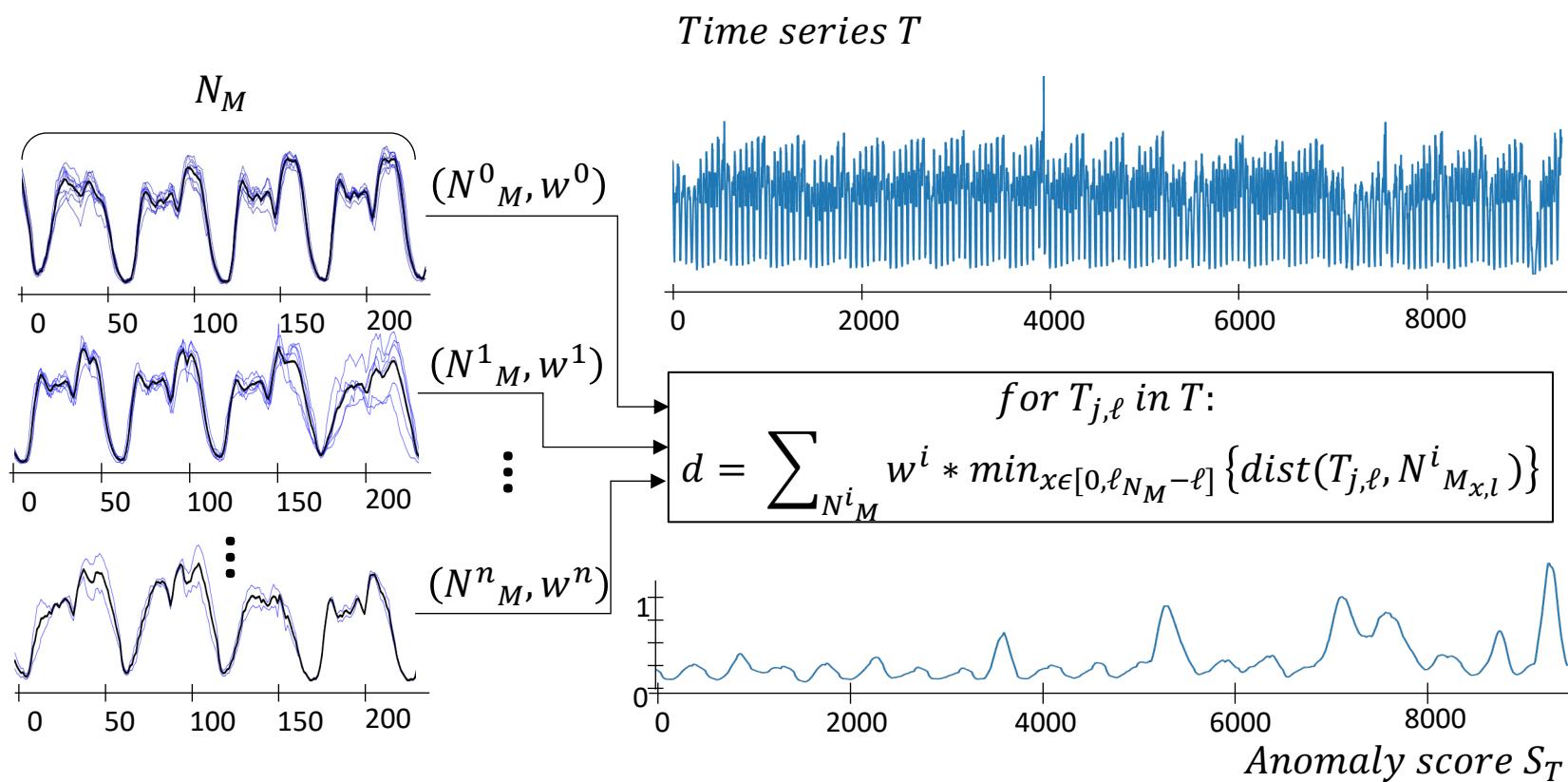
Distance-based approach that
summarize the time series into
a weighted set of subsequences
and use the distance to them as
anomaly score

Unsupervised

Univariate

sequence

Anomaly Detection methods: an Example



NormA [10]

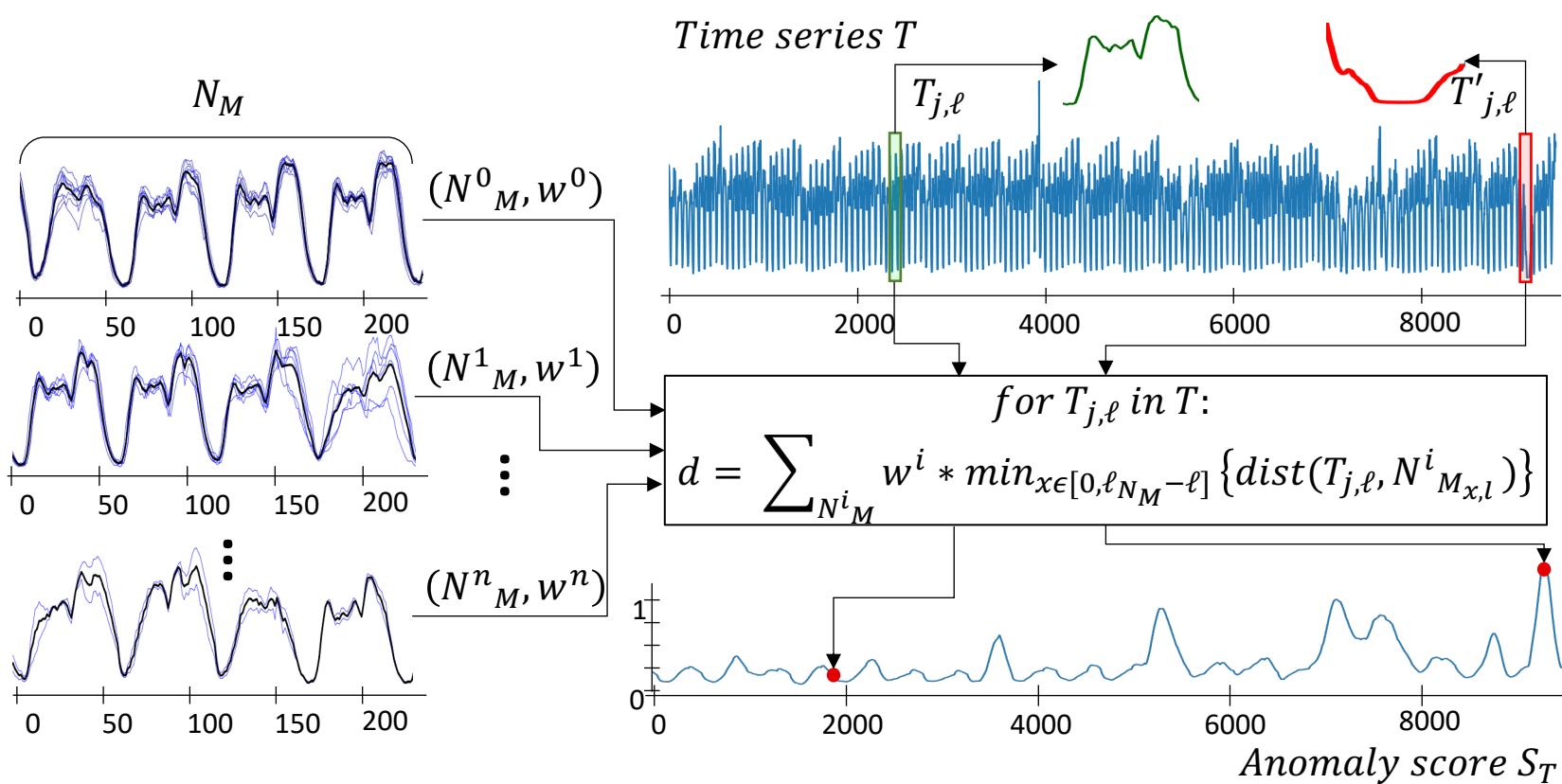
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Unsupervised

Univariate

sequence

Anomaly Detection methods: an Example



NormA [10]

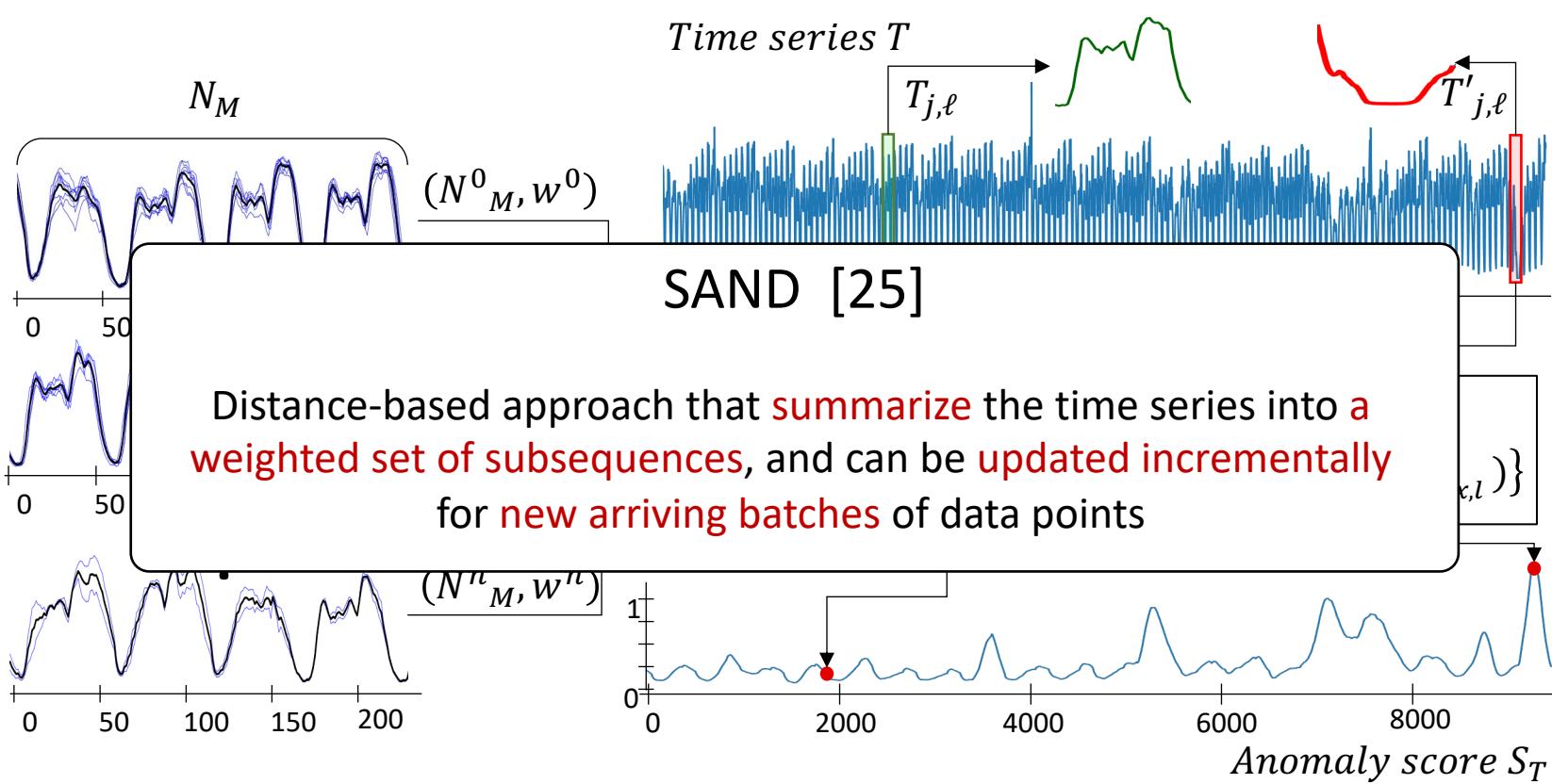
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Unsupervised

Univariate

sequence

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

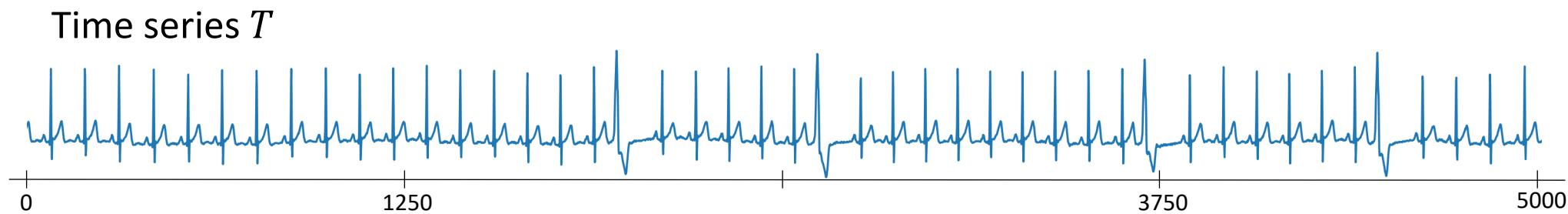
Unsupervised

Univariate

sequence

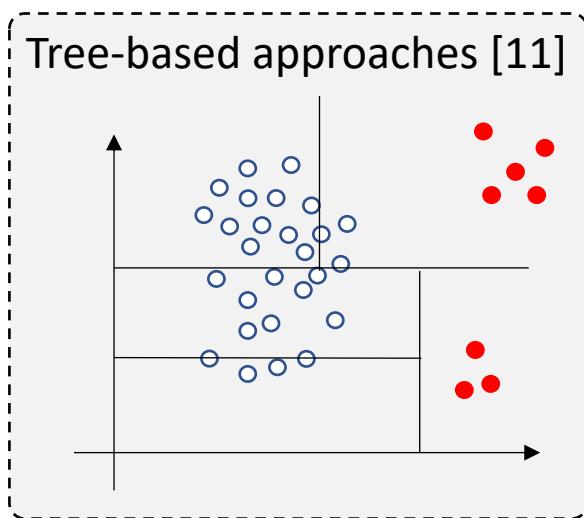
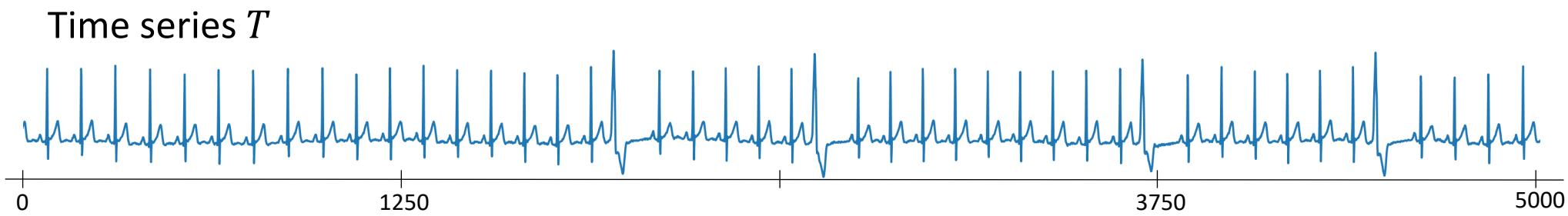
Anomaly Detection methods: *Density-based*

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



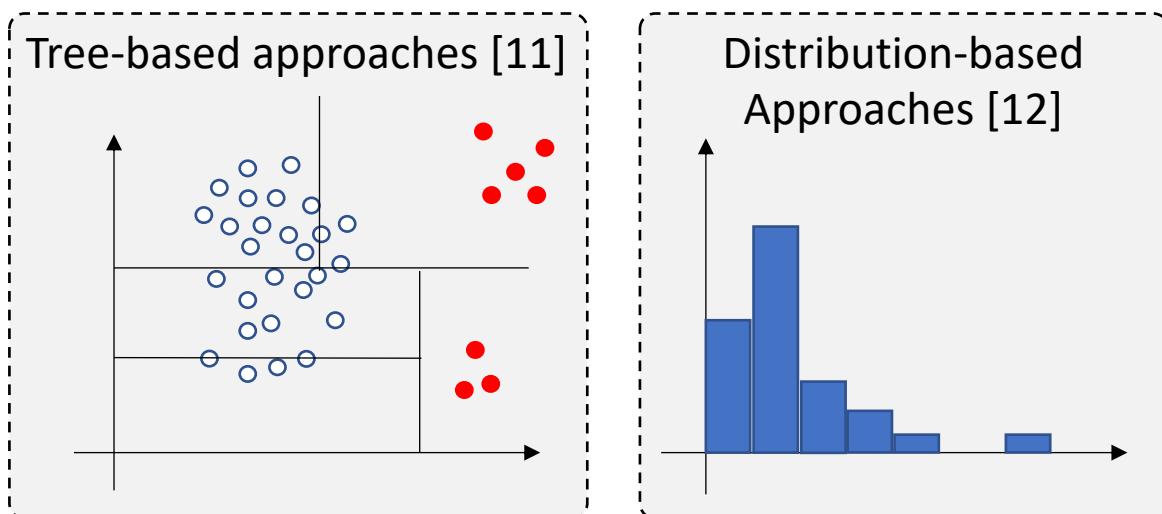
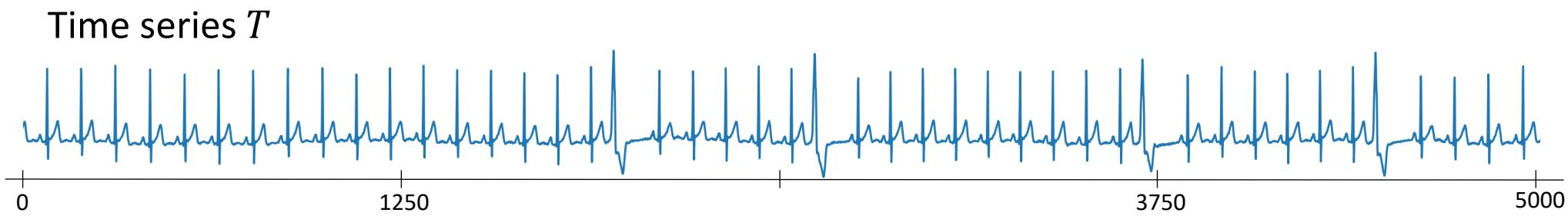
Anomaly Detection methods: *Density-based*

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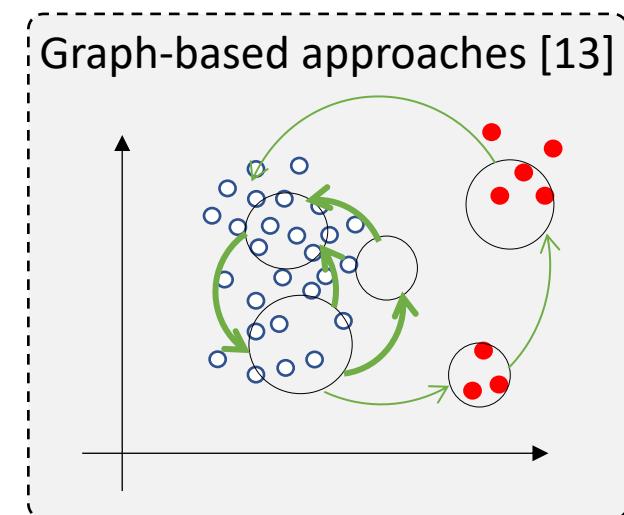
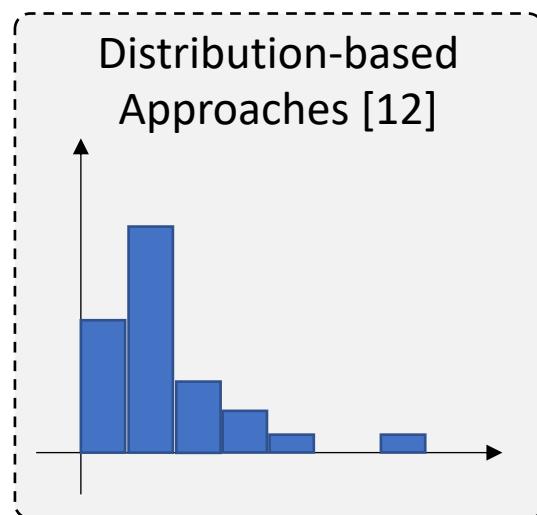
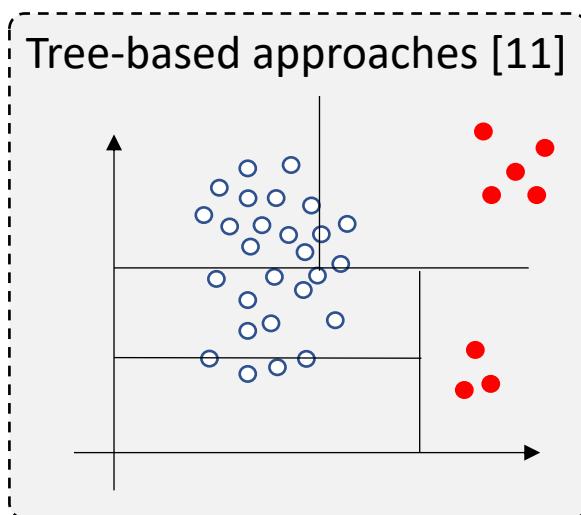
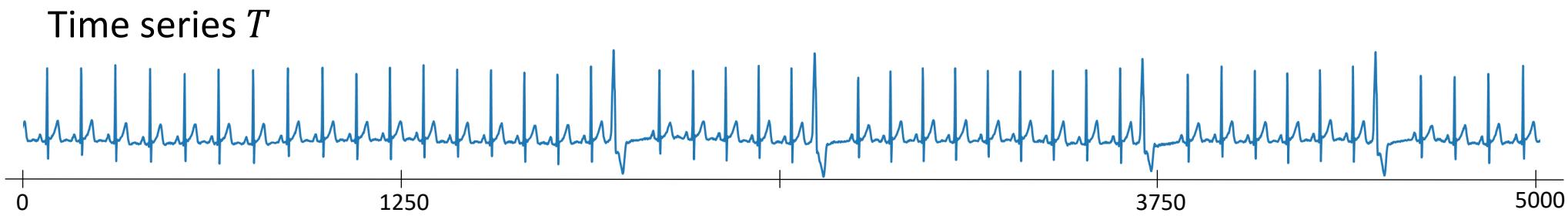
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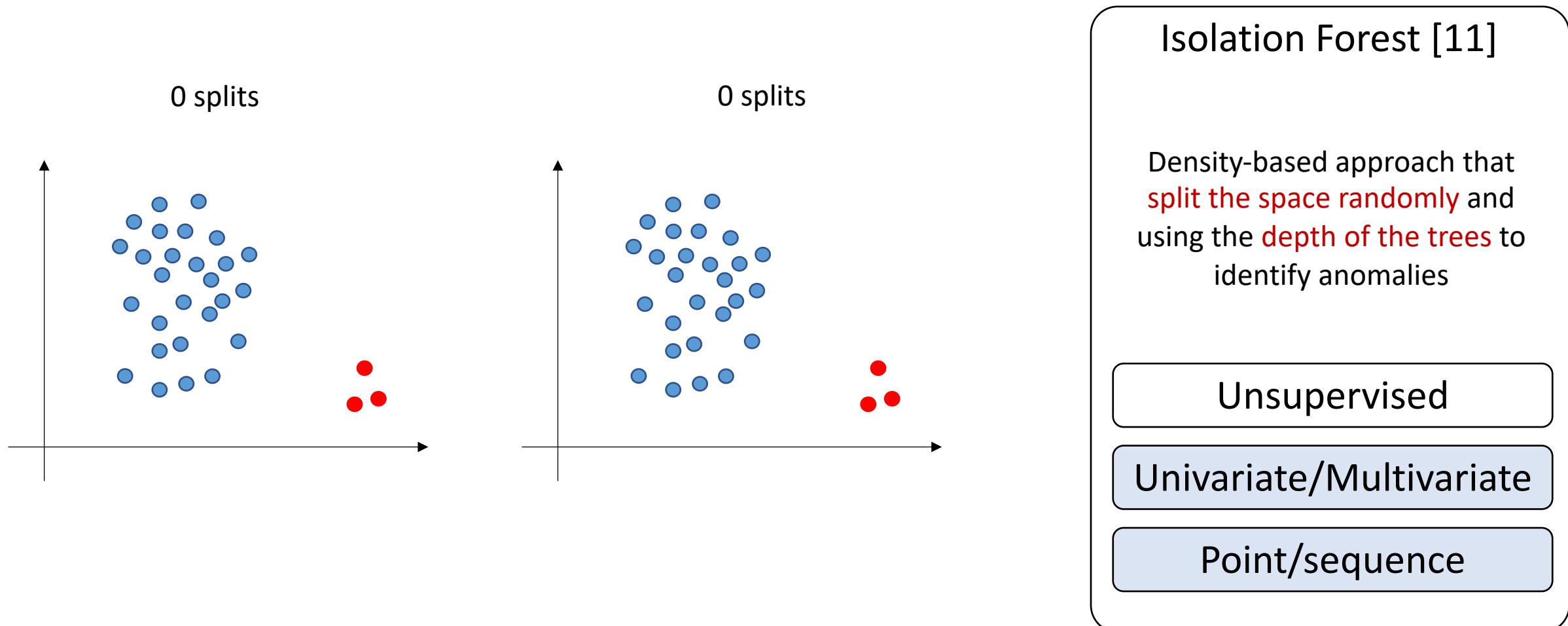
Anomaly Detection methods: *Density-based*

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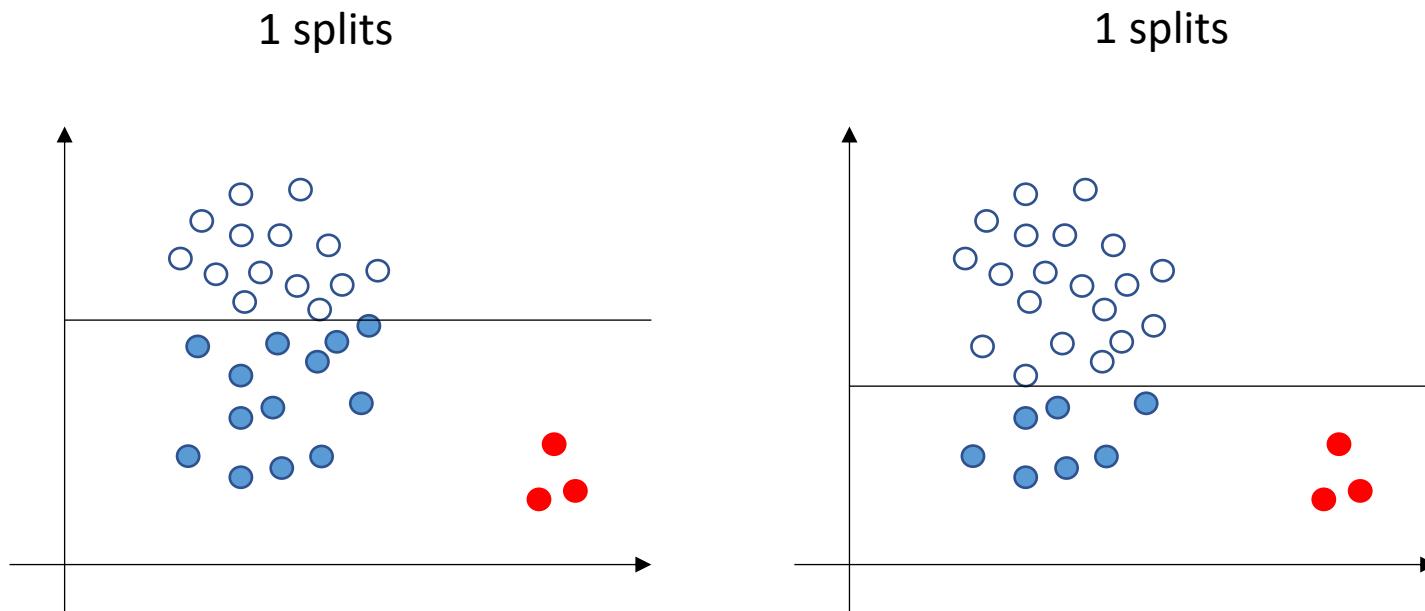


...

Anomaly Detection methods: *an Example*



Anomaly Detection methods: *an Example*



Isolation Forest [11]

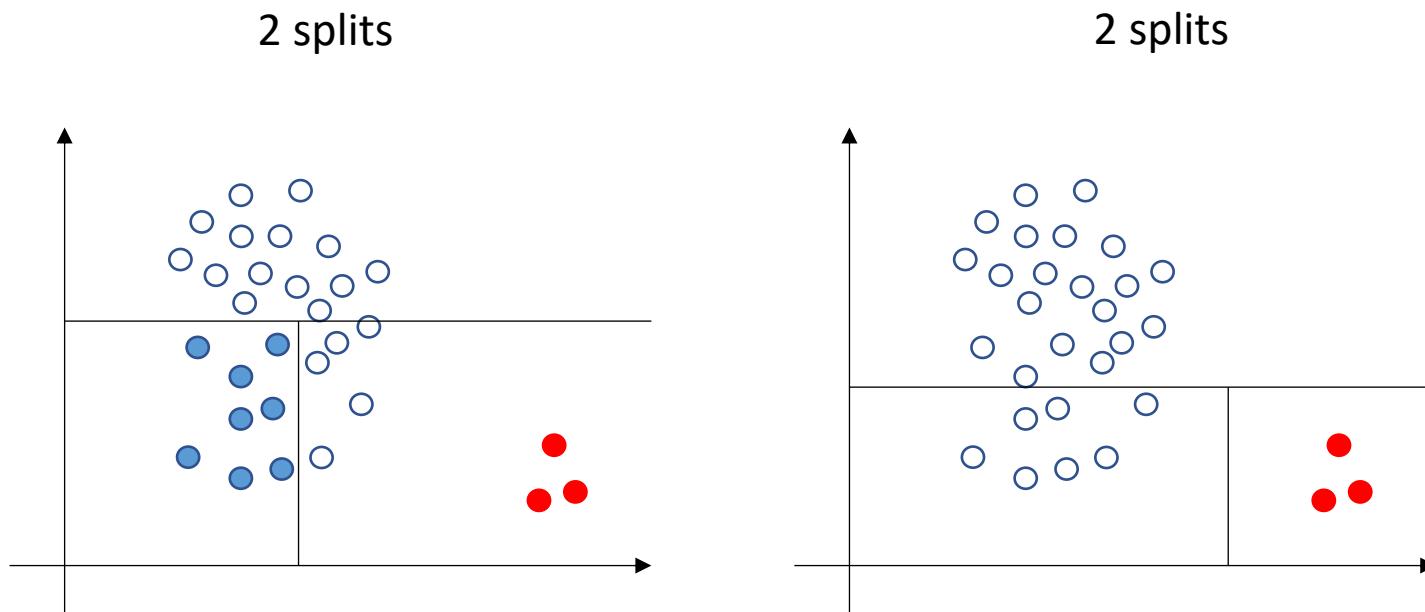
Density-based approach that **split the space randomly** and using the **depth of the trees** to identify anomalies

Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



Isolation Forest [11]

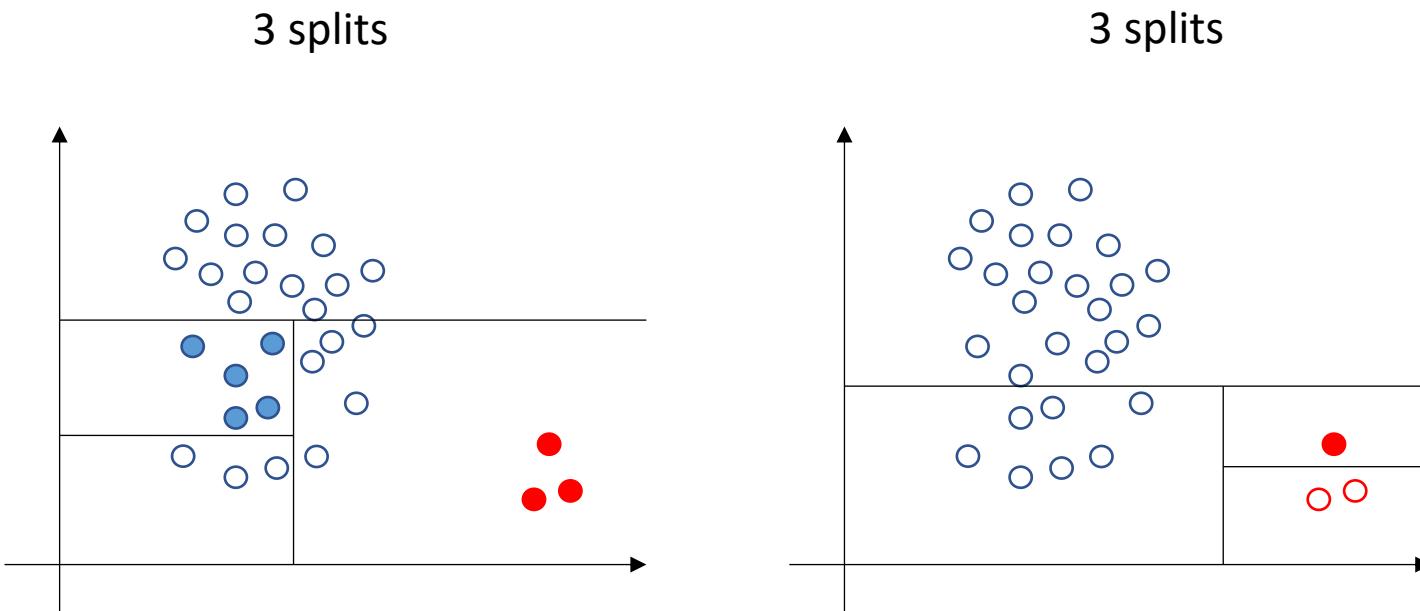
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Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



Isolation Forest [11]

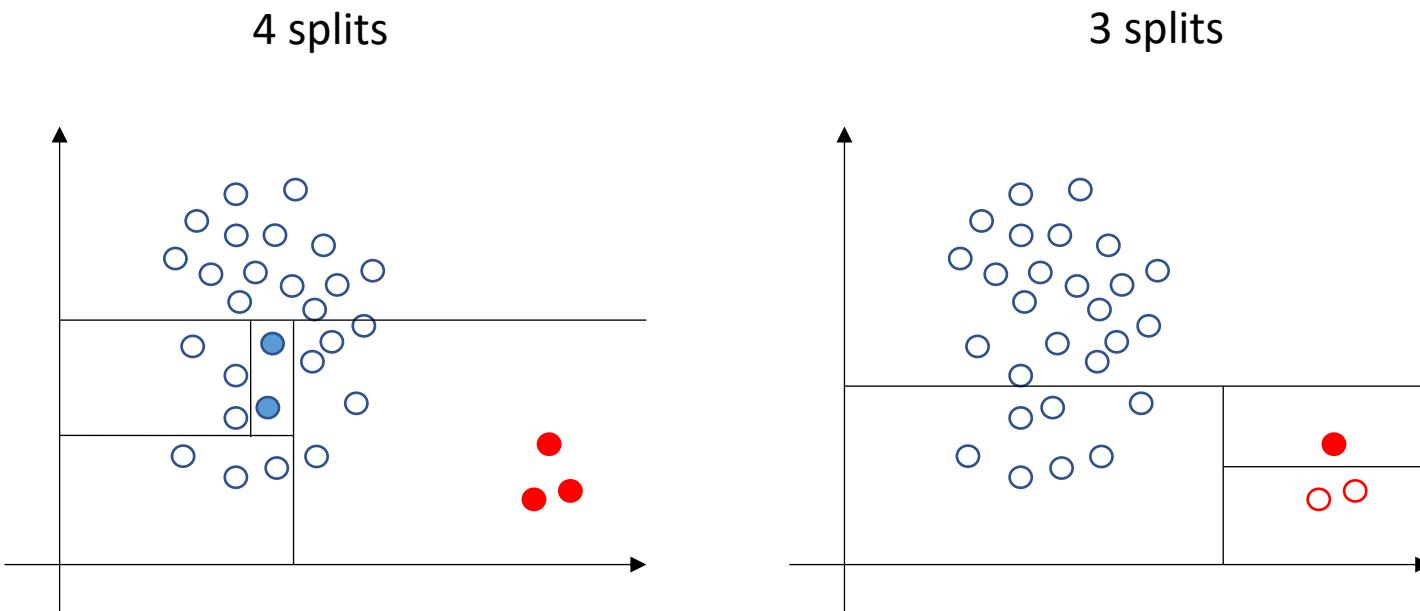
Density-based approach that **split the space randomly** and using the **depth of the trees** to identify anomalies

Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



Isolation Forest [11]

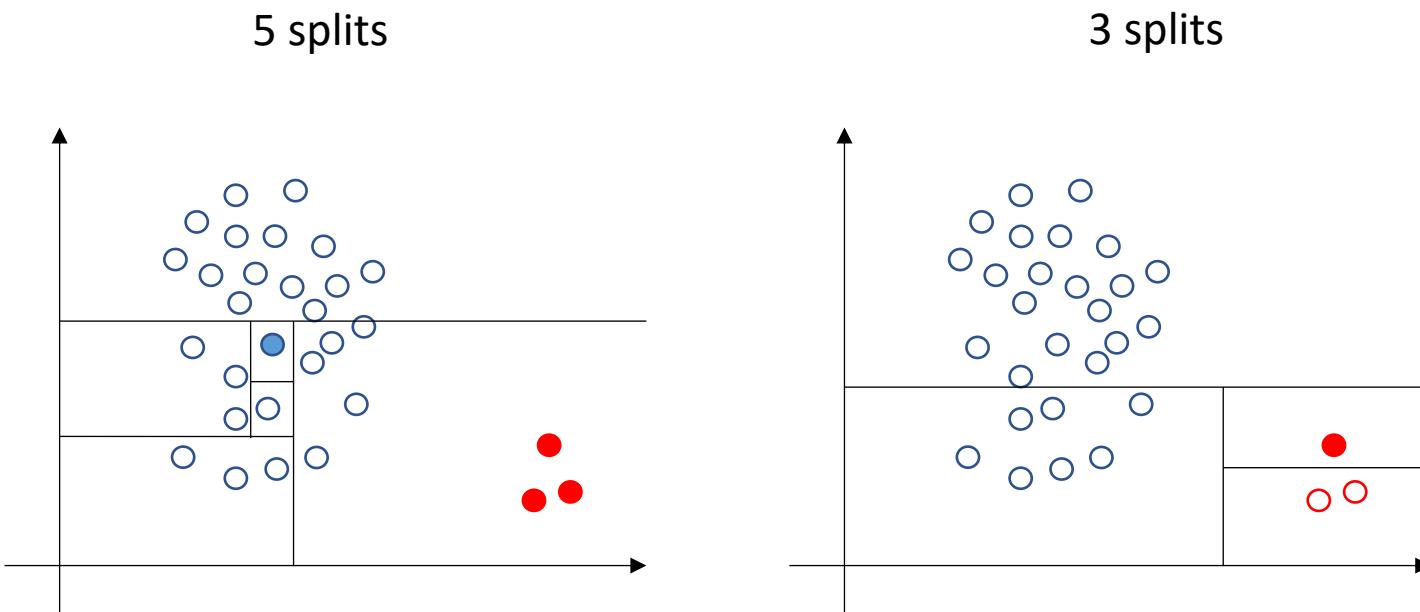
Density-based approach that **split the space randomly** and using the **depth of the trees** to identify anomalies

Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



Isolation Forest [11]

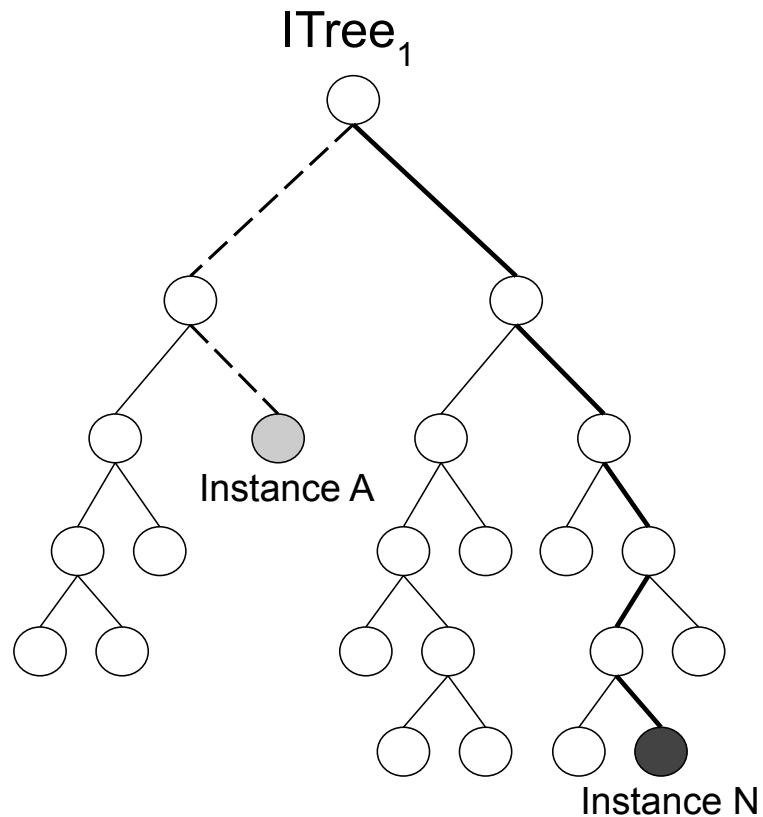
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Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



Isolation Forest [11]

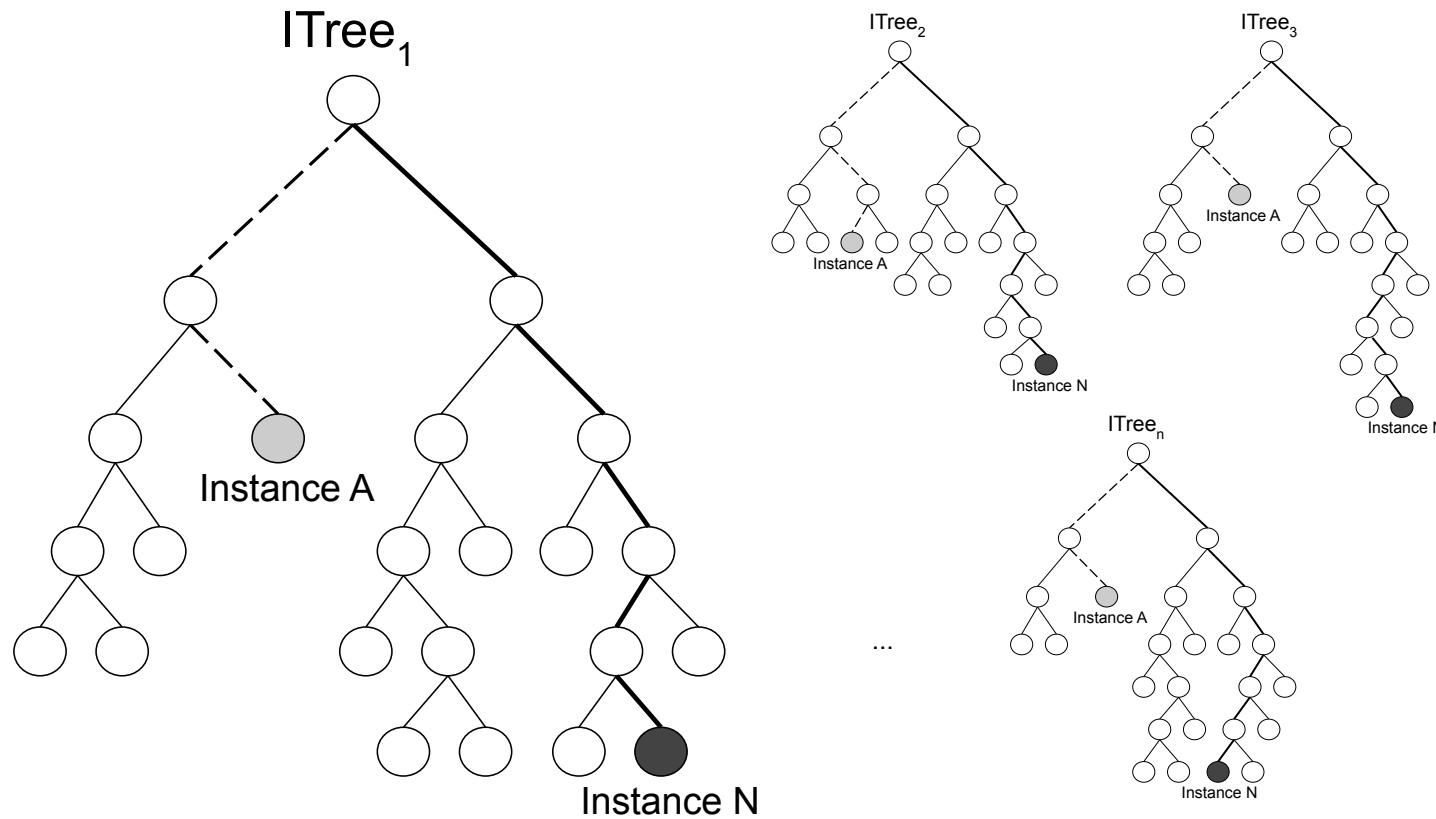
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Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: an Example



Isolation Forest [11]

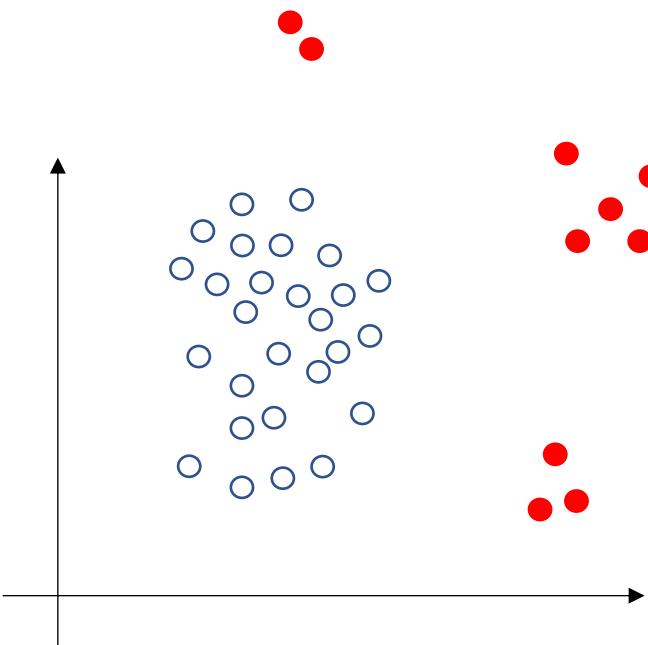
Density-based approach that **split the space randomly** and using the **depth of the trees** to identify anomalies

Unsupervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



Series2Graph [13]

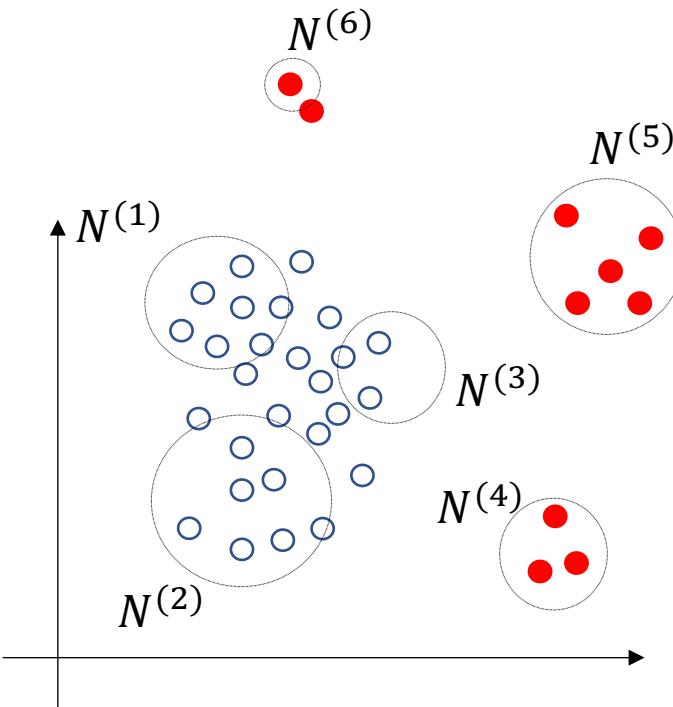
Density-based approach that
convert the time series into a
graph and detect **unusual**
trajectories

Unsupervised

Univariate

subsequence

Anomaly Detection methods: *an Example*



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

Series2Graph [13]

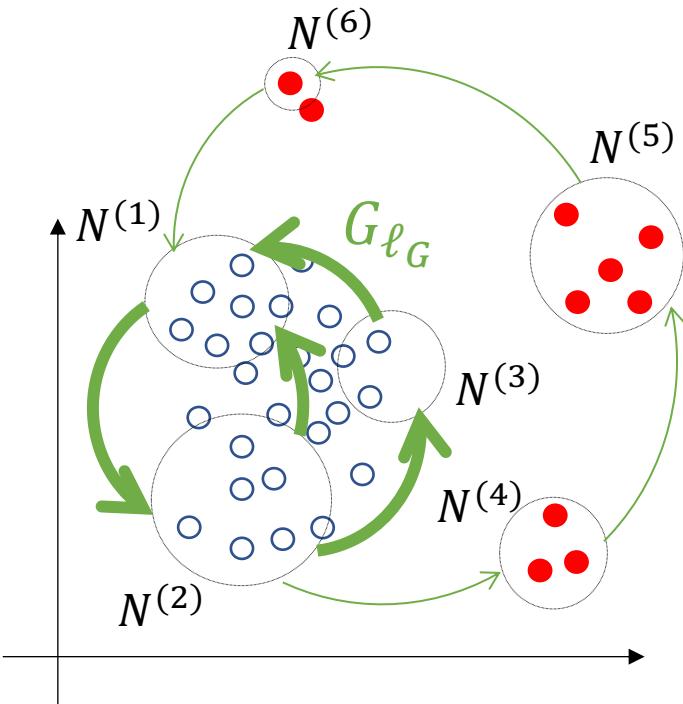
Density-based approach that
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Unsupervised

Univariate

subsequence

Anomaly Detection methods: an Example



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

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

Series2Graph [13]

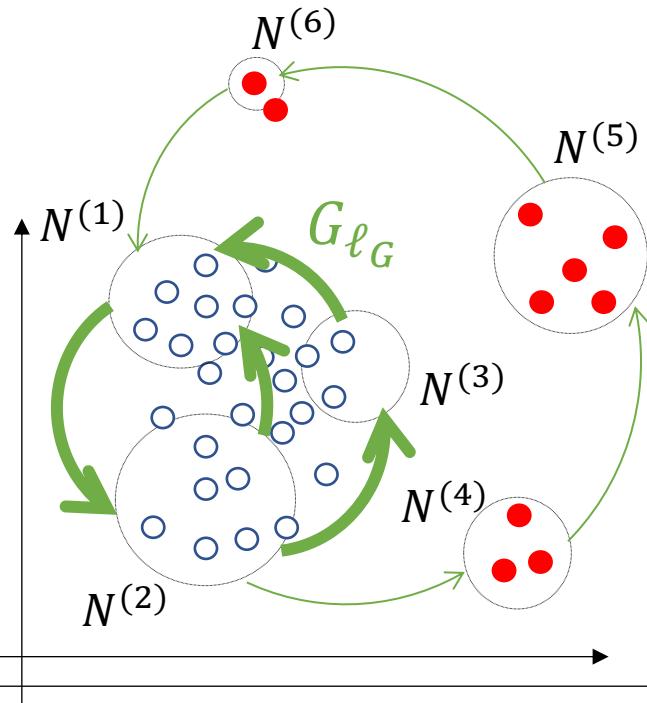
Density-based approach that **convert** the time series into a **graph** and detect **unusual trajectories**

Unsupervised

Univariate

subsequence

Anomaly Detection methods: an Example



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

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

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

Series2Graph [13]

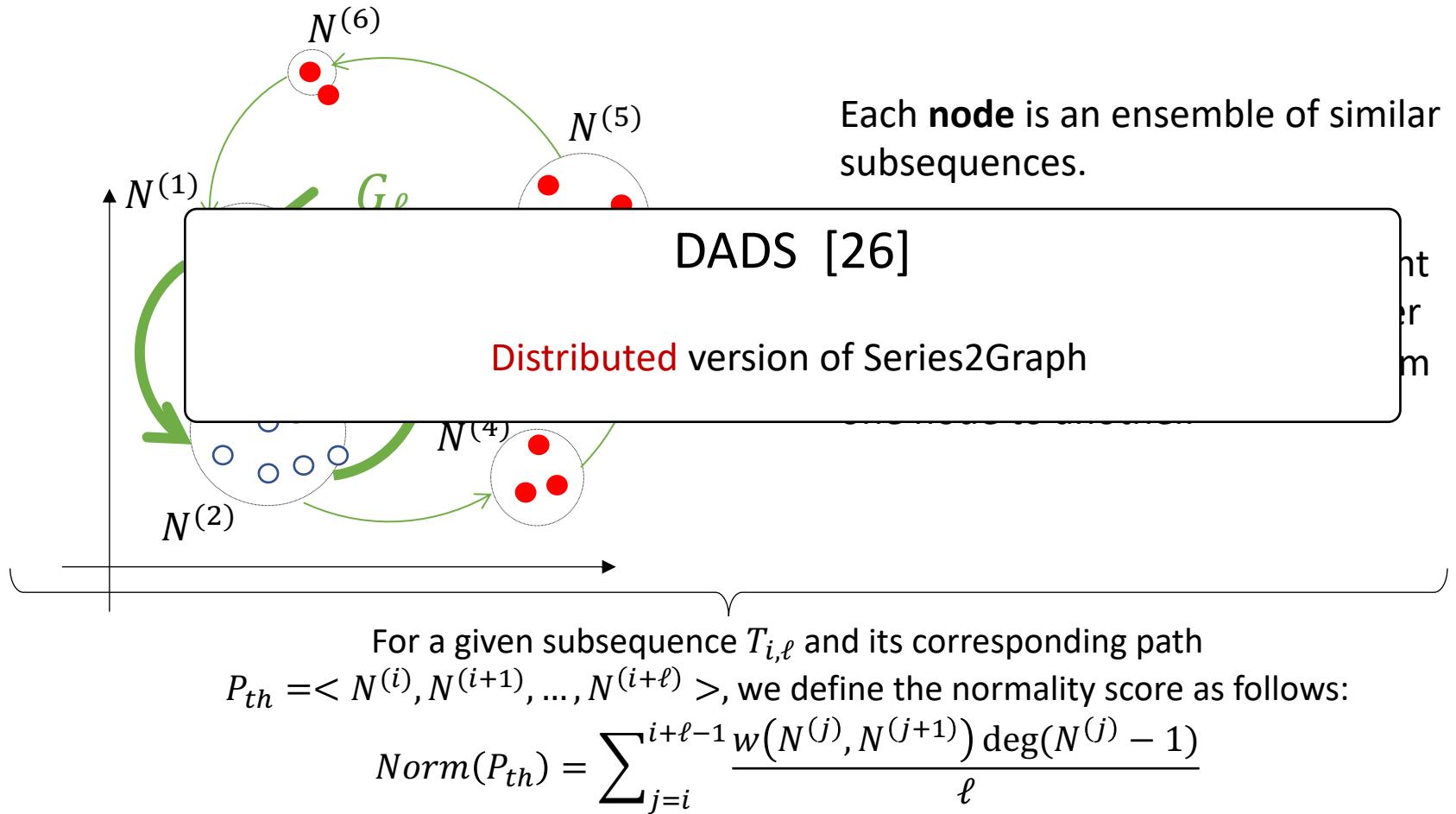
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Unsupervised

Univariate

subsequence

Anomaly Detection methods: an Example



Series2Graph [13]

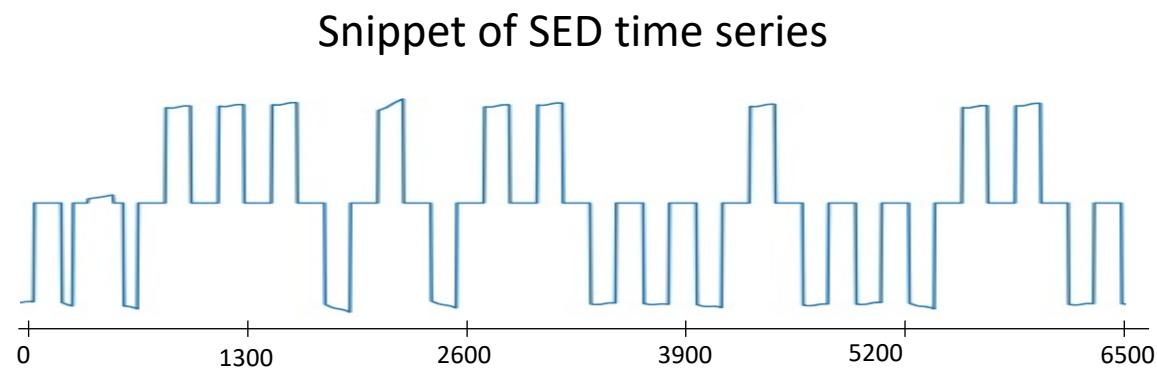
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Unsupervised

Univariate

subsequence

Anomaly Detection methods: *an Example*



Series2Graph [13]

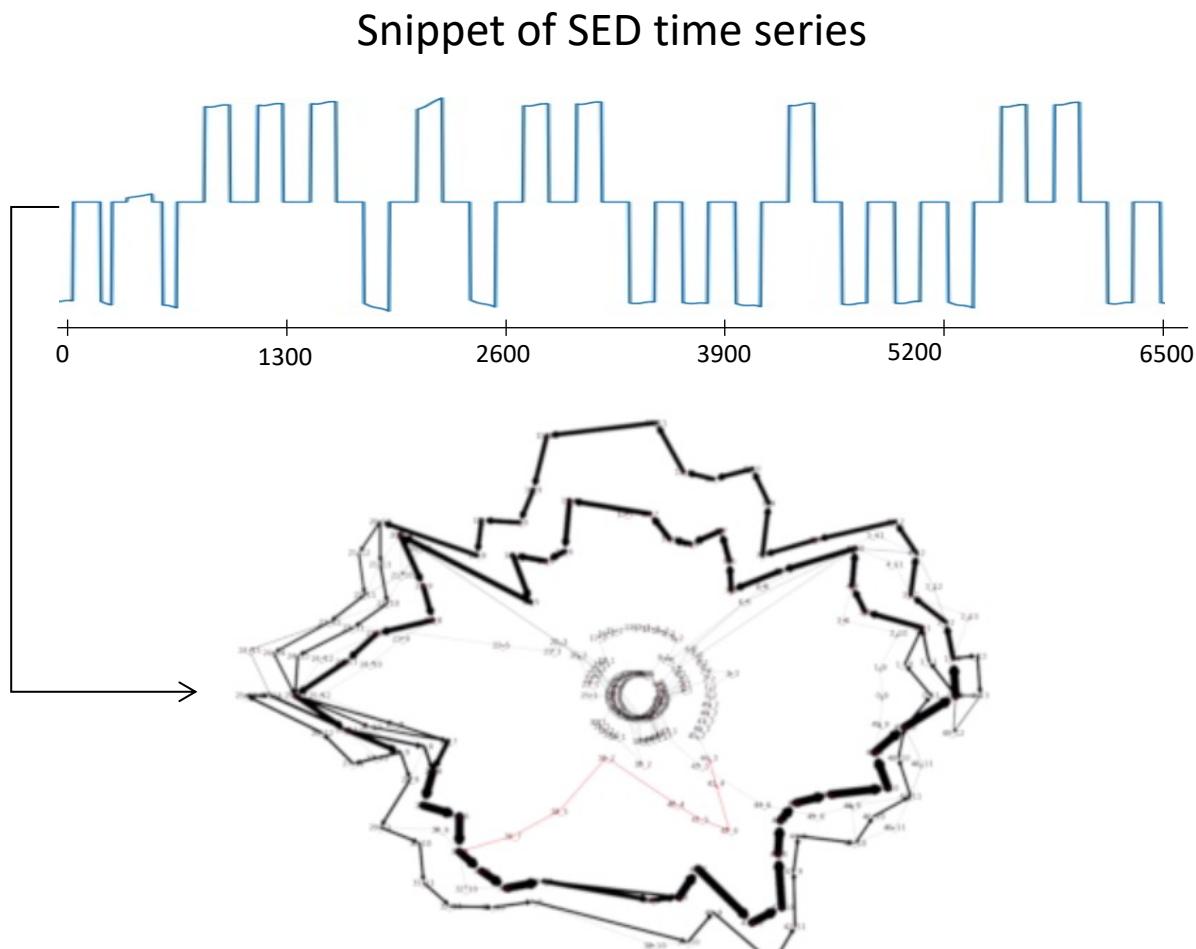
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Unsupervised

Univariate

subsequence

Anomaly Detection methods: an Example



Series2Graph [13]

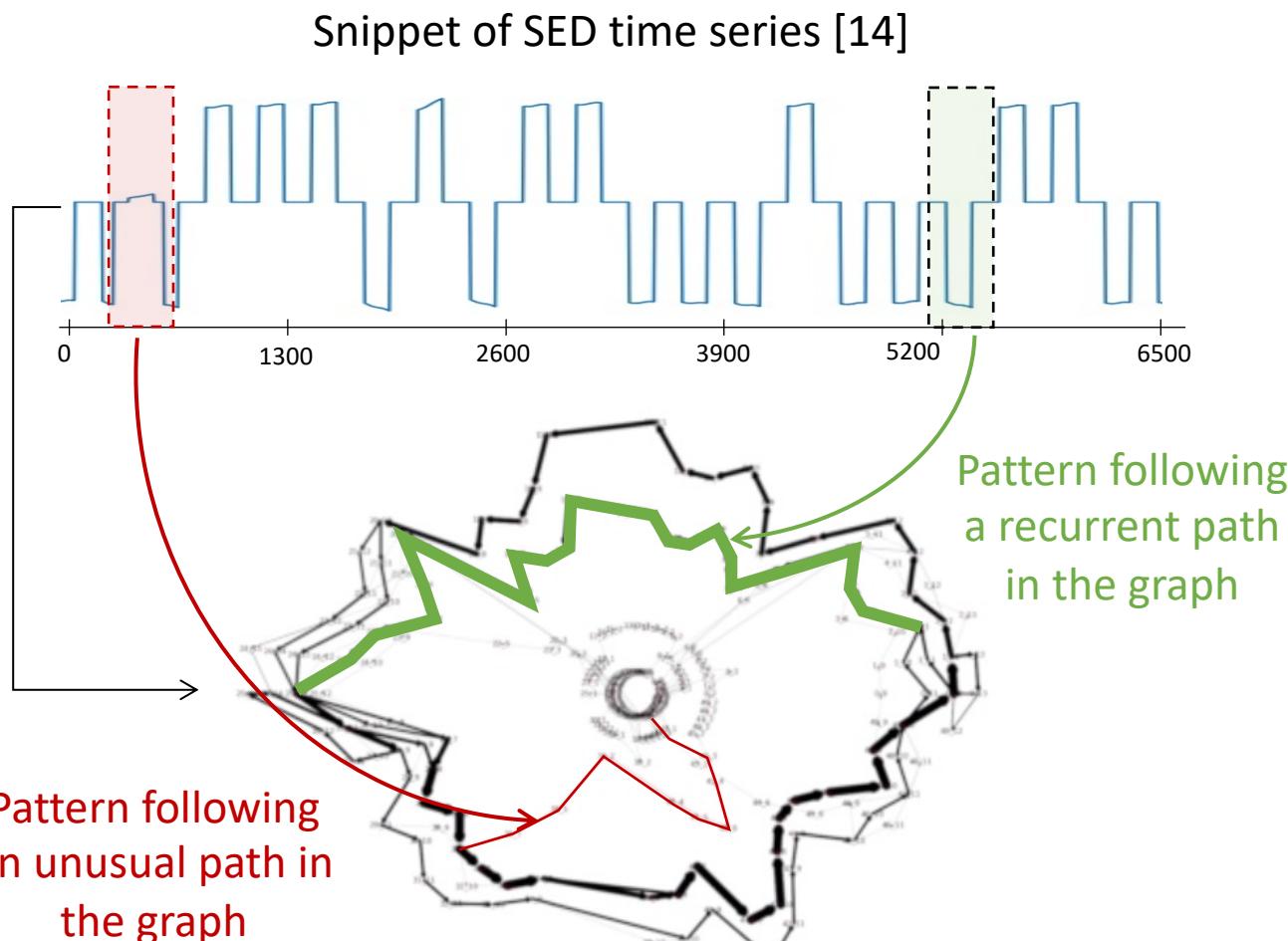
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Unsupervised

Univariate

subsequence

Anomaly Detection methods: an Example



Series2Graph [13]

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

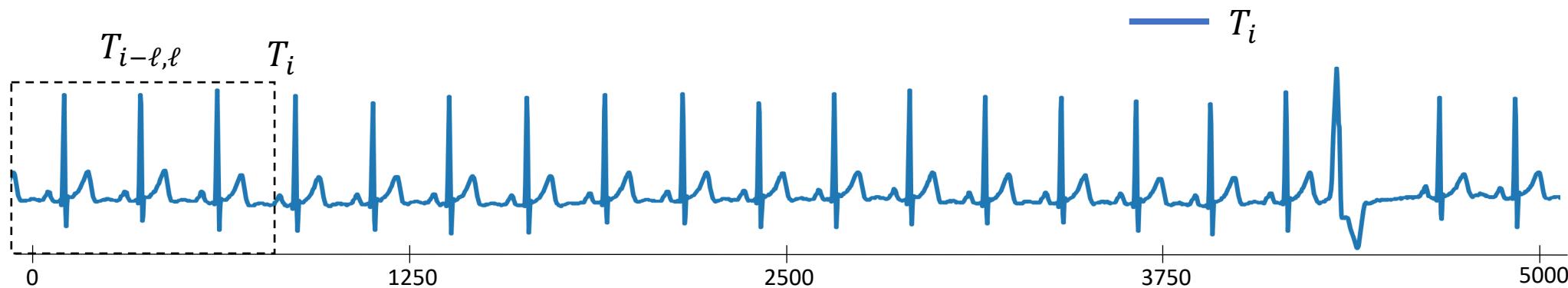
Unsupervised

Univariate

subsequence

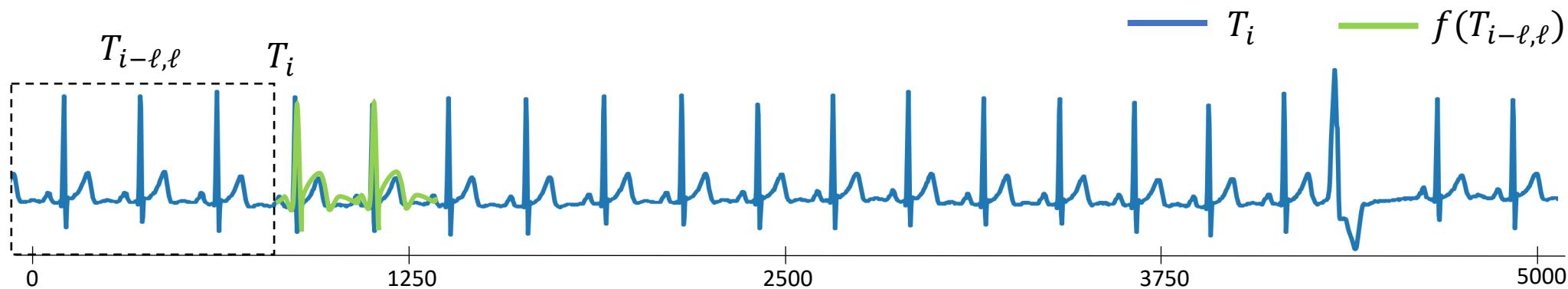
Anomaly Detection methods: *Forecasting-based*

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.



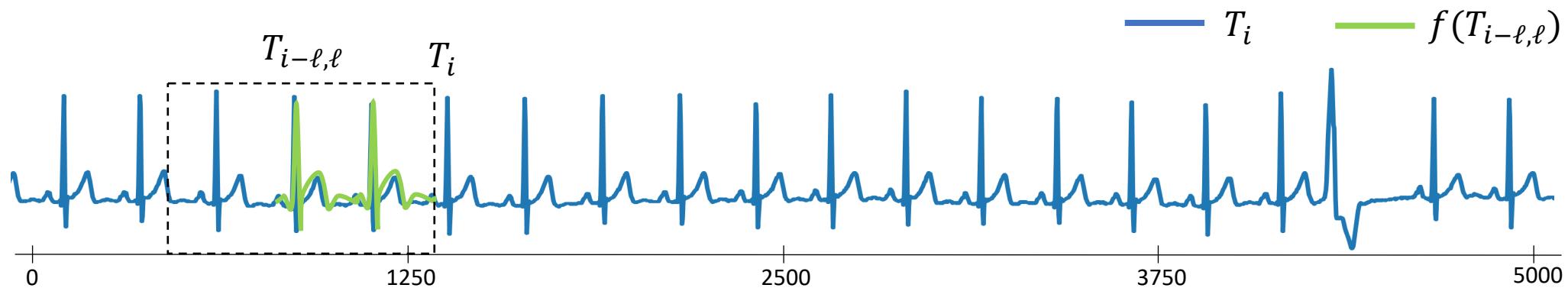
Anomaly Detection methods: *Forecasting-based*

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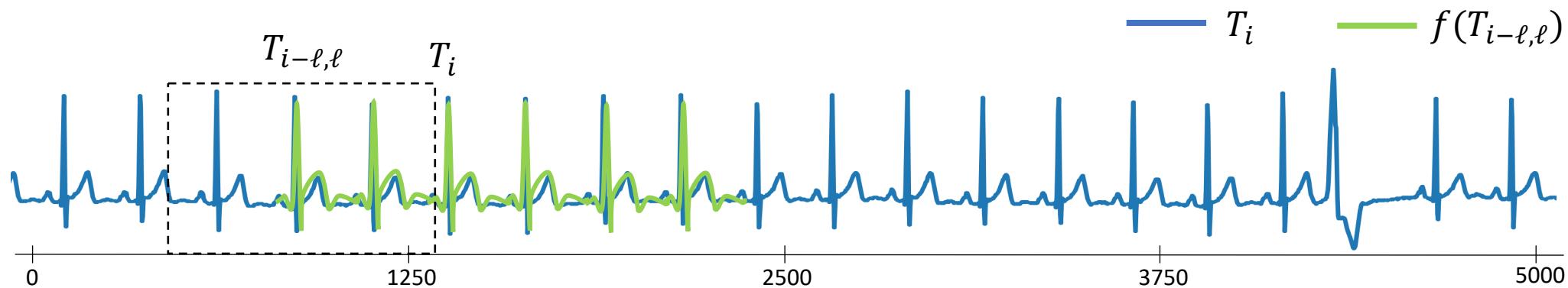
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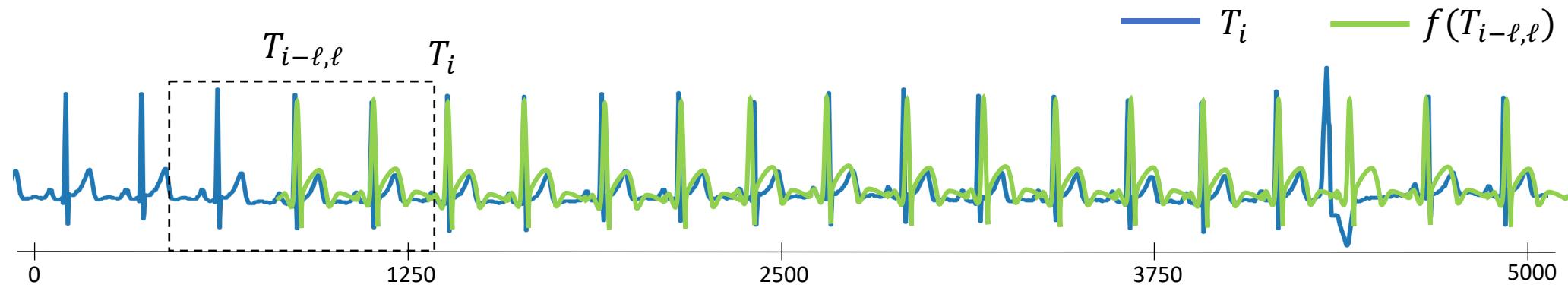
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Methods that aims to **predict the next points** based on the previous ones. The **prediction error** is used to detect if there is an anomaly or not.



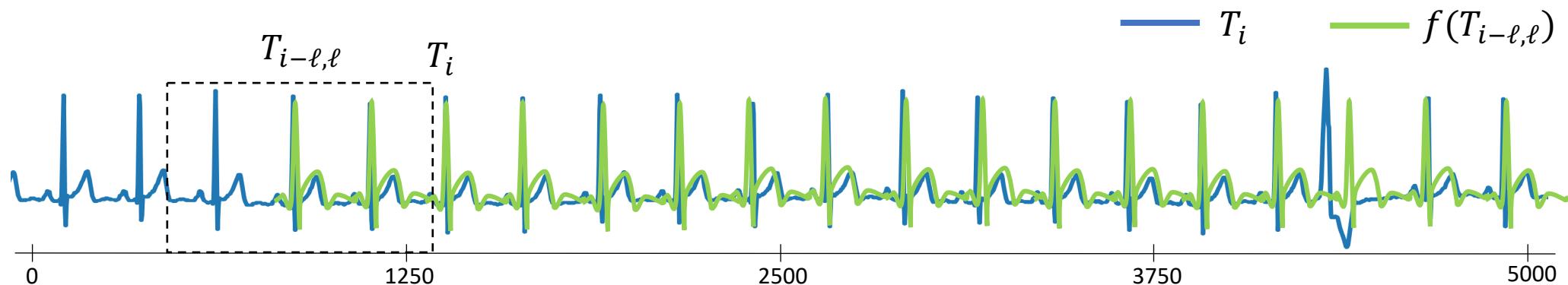
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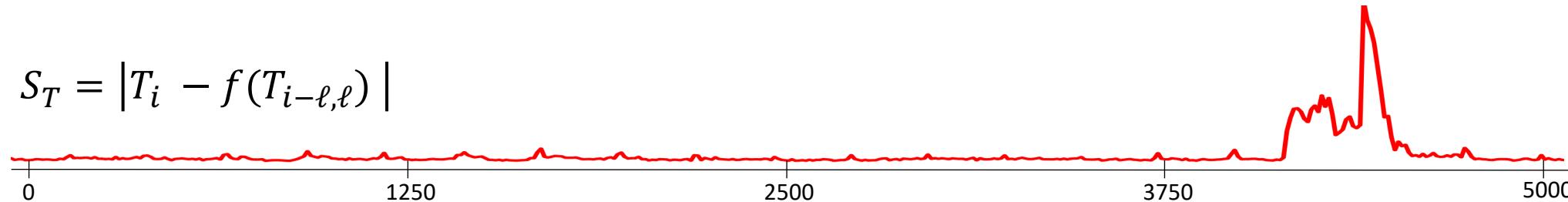


Anomaly Detection methods: *Forecasting-based*

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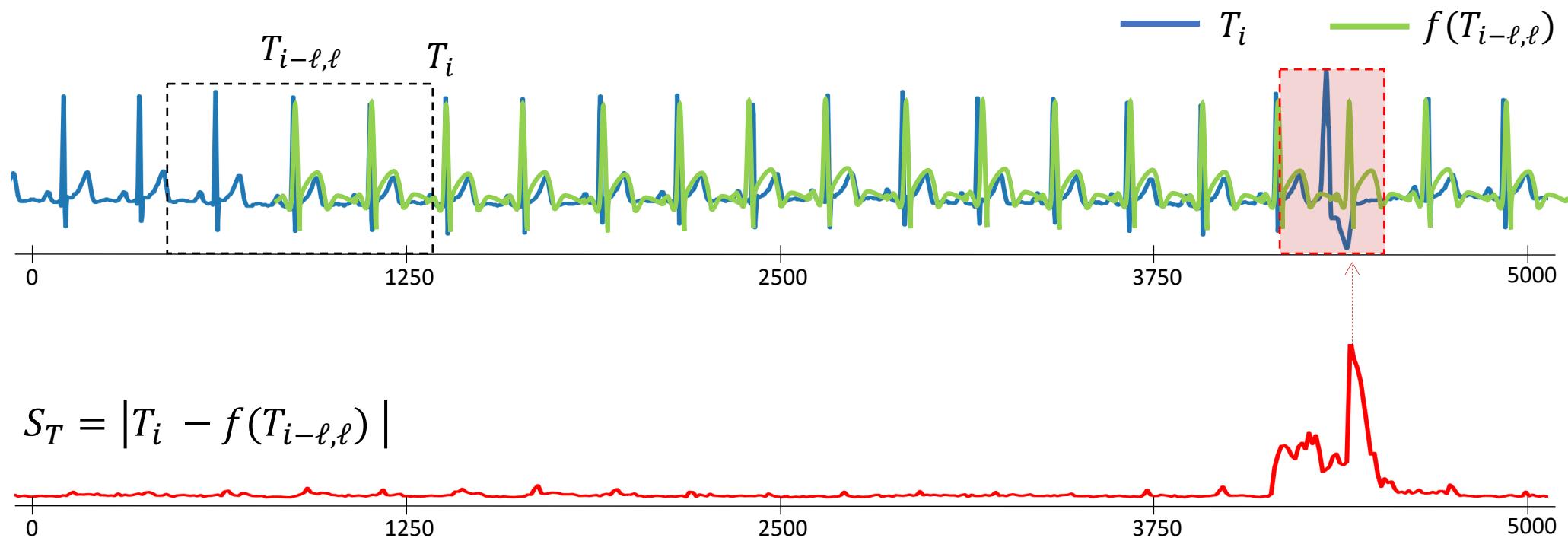


$$S_T = |T_i - f(T_{i-\ell,\ell})|$$

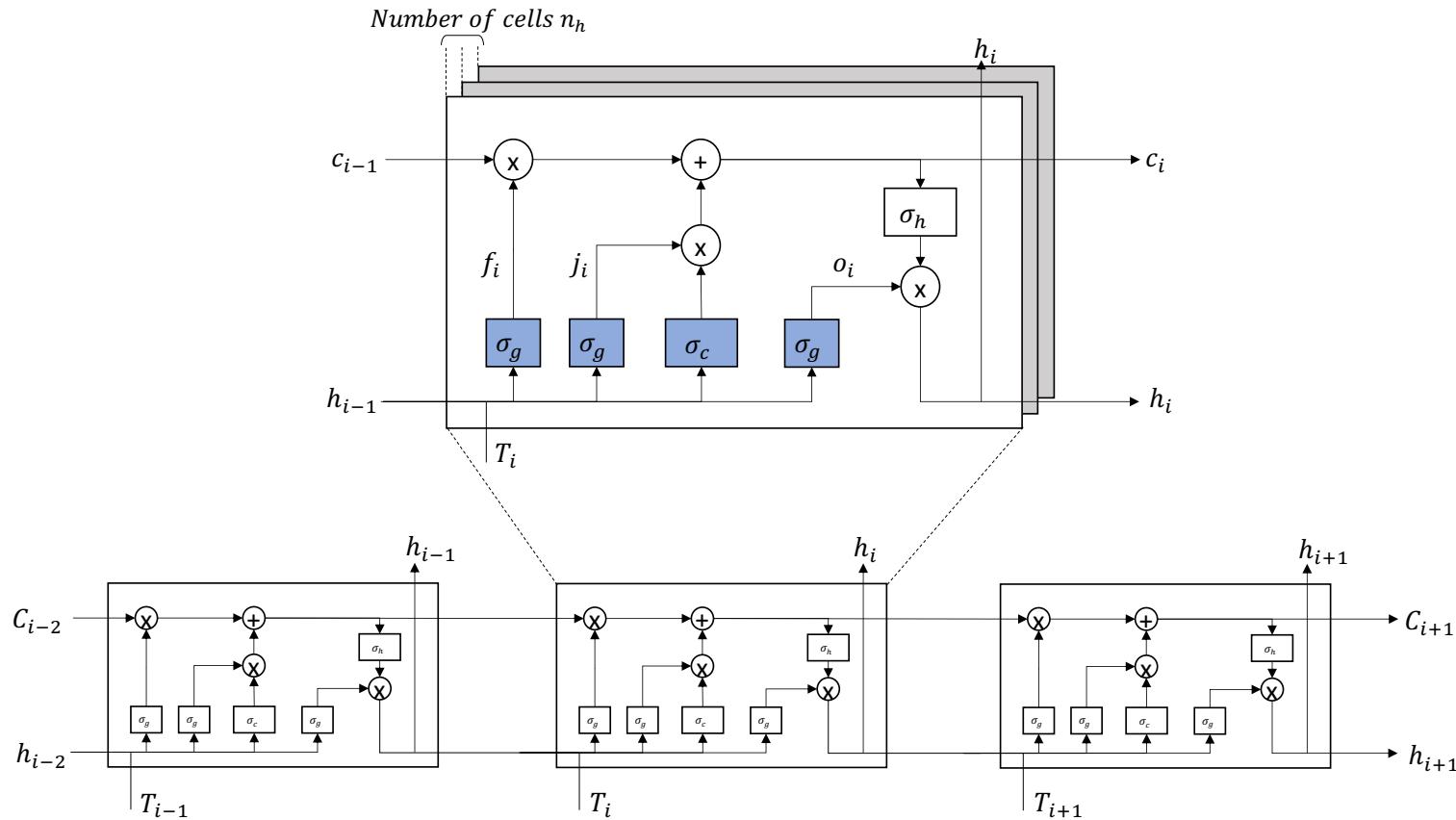


Anomaly Detection methods: *Forecasting-based*

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.



Anomaly Detection methods: an Example



LSTM-AD [15]

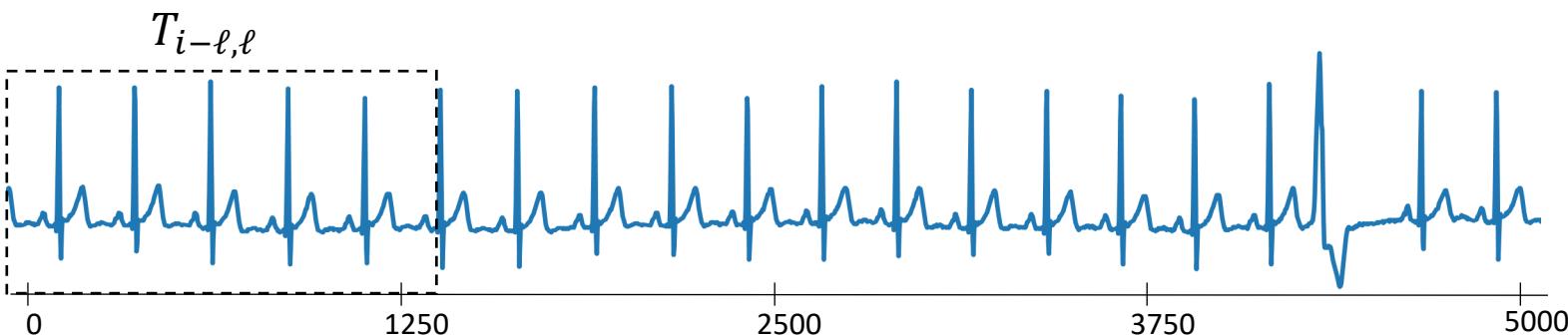
Model that stack multiple LSTM cell and use the output to predict the next value

Semi-supervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



DeepAnT [16] (CNN)

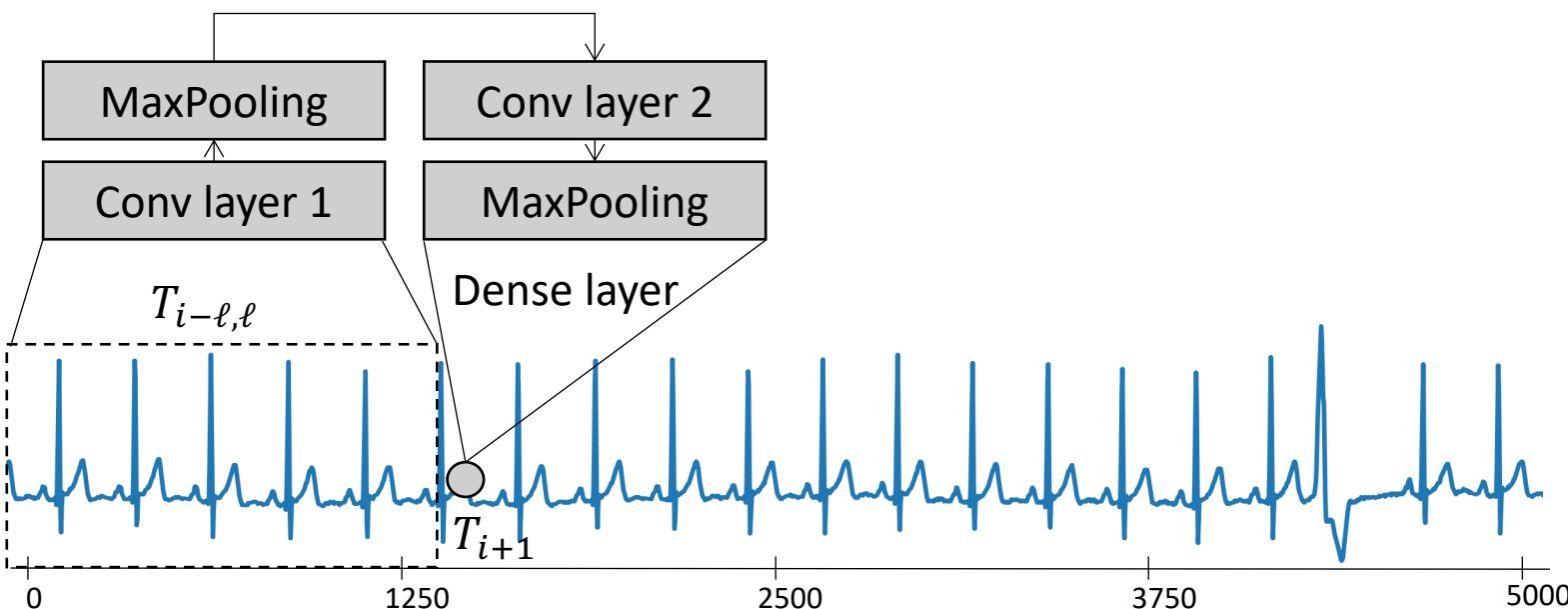
Convolutional-based approach
(2 convolutional layers) taking
as input a sequence and aims to
predict the next value.

Semi-supervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



DeepAnT [16] (CNN)

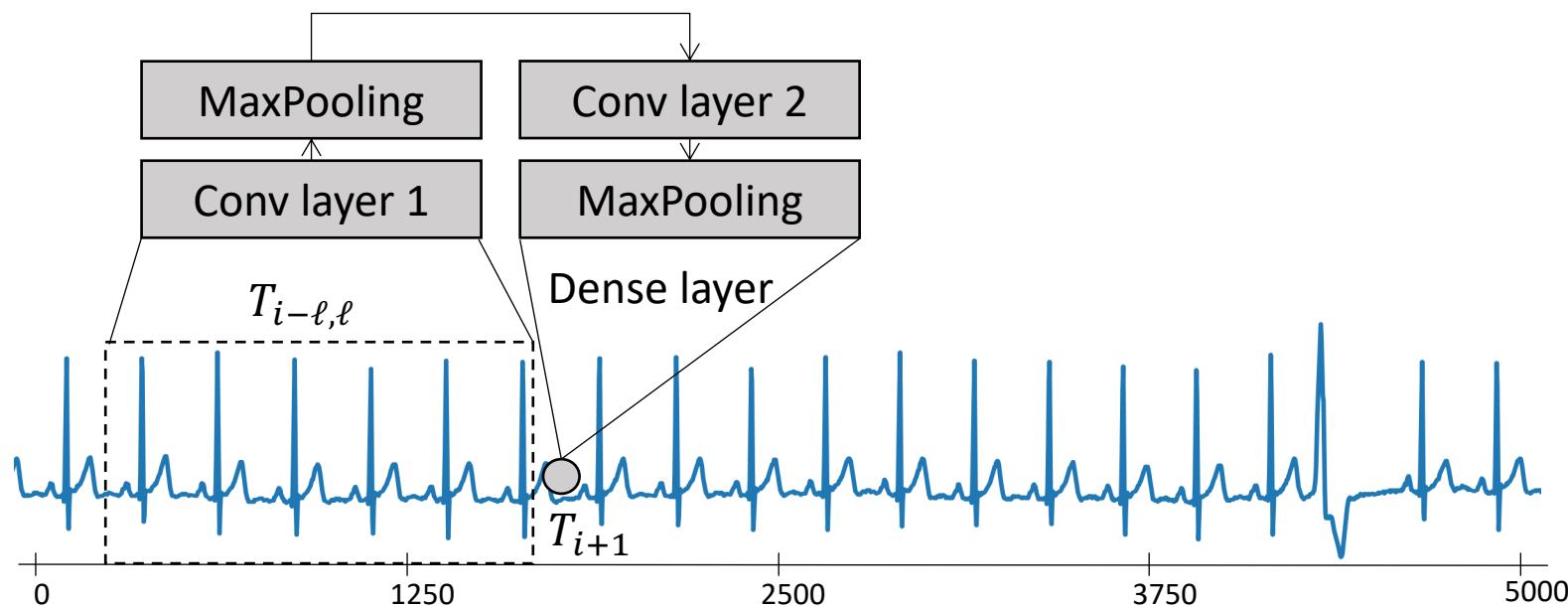
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Semi-supervised

Univariate/Multivariate

Point/sequence

Anomaly Detection methods: *an Example*



DeepAnT [16] (CNN)

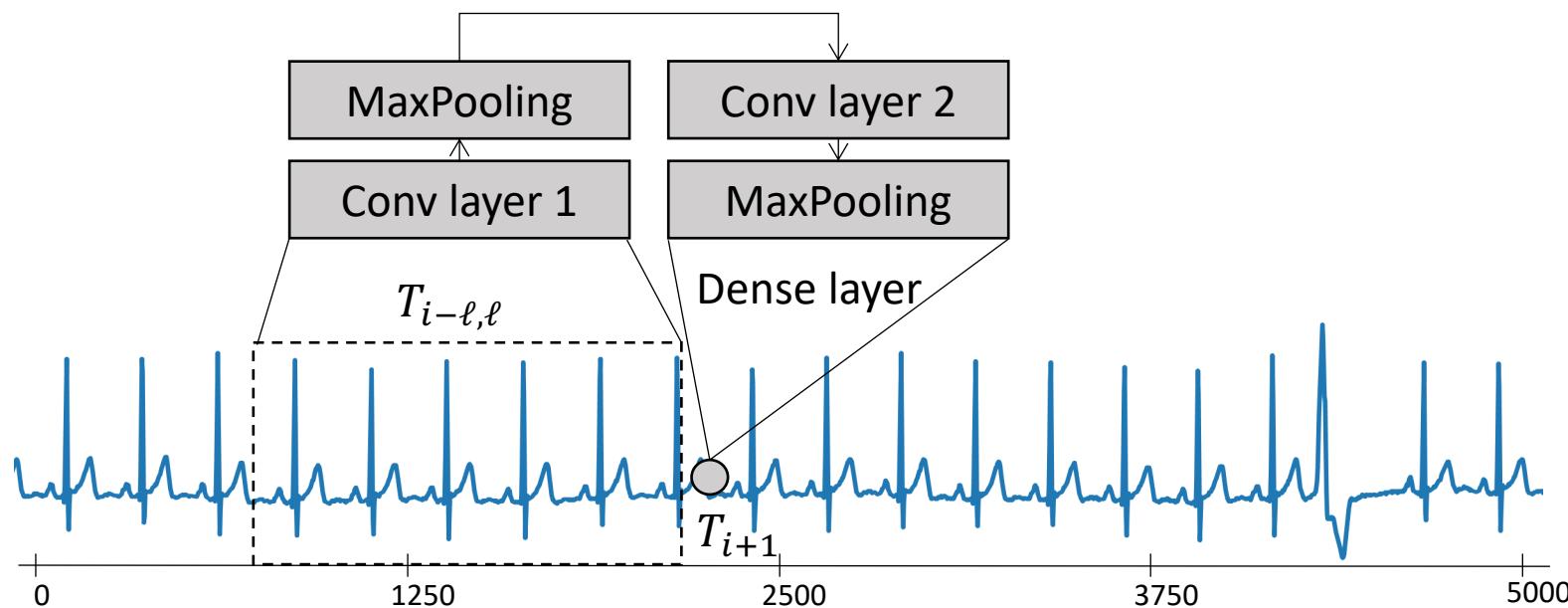
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Semi-supervised

Univariate/Multivariate

Point/sequence

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

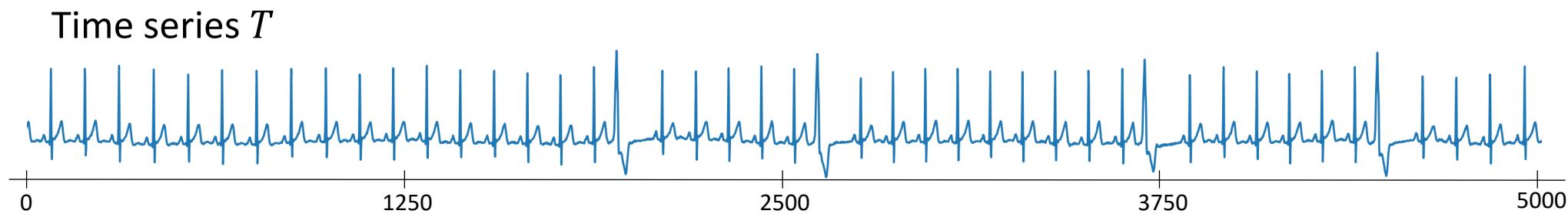
Point/sequence

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.

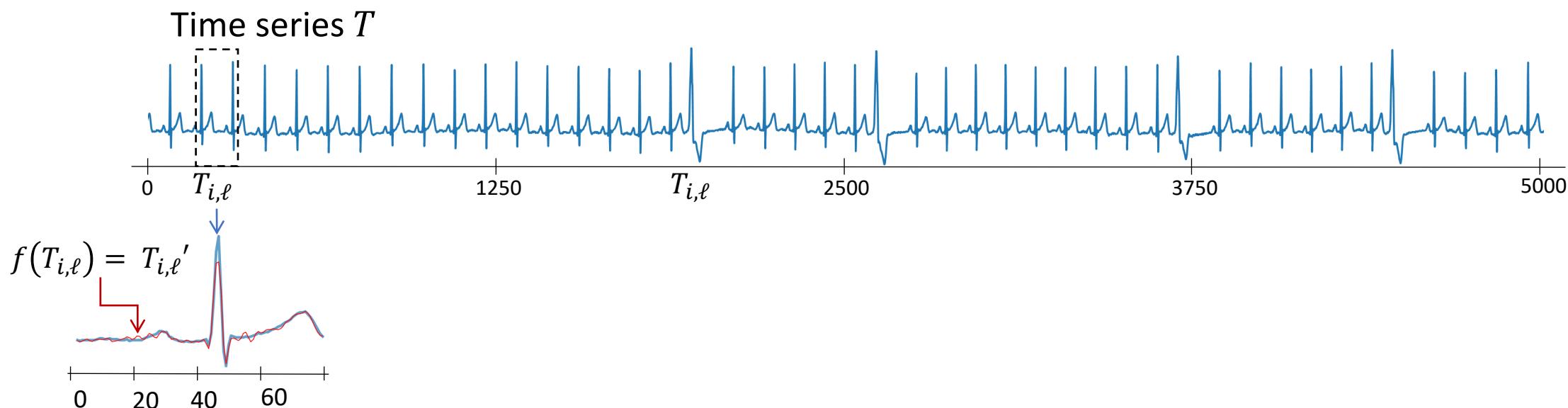
Anomaly Detection methods: *Reconstruction-based*

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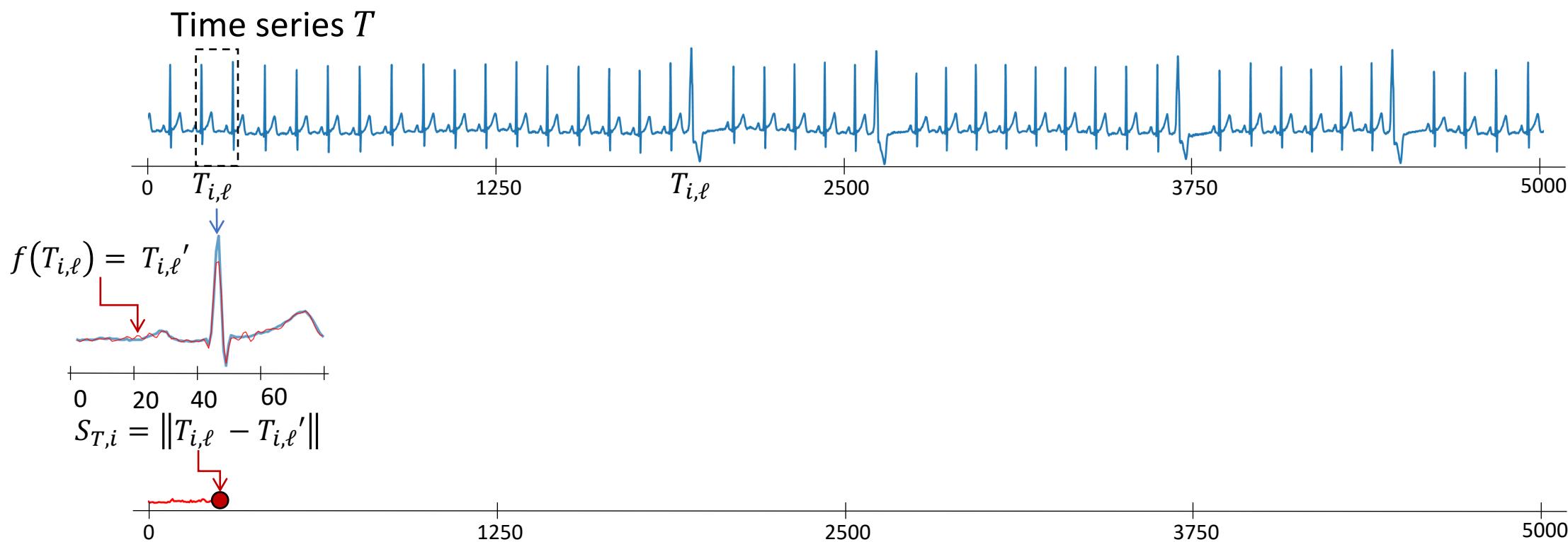
Anomaly Detection methods: *Reconstruction-based*

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.



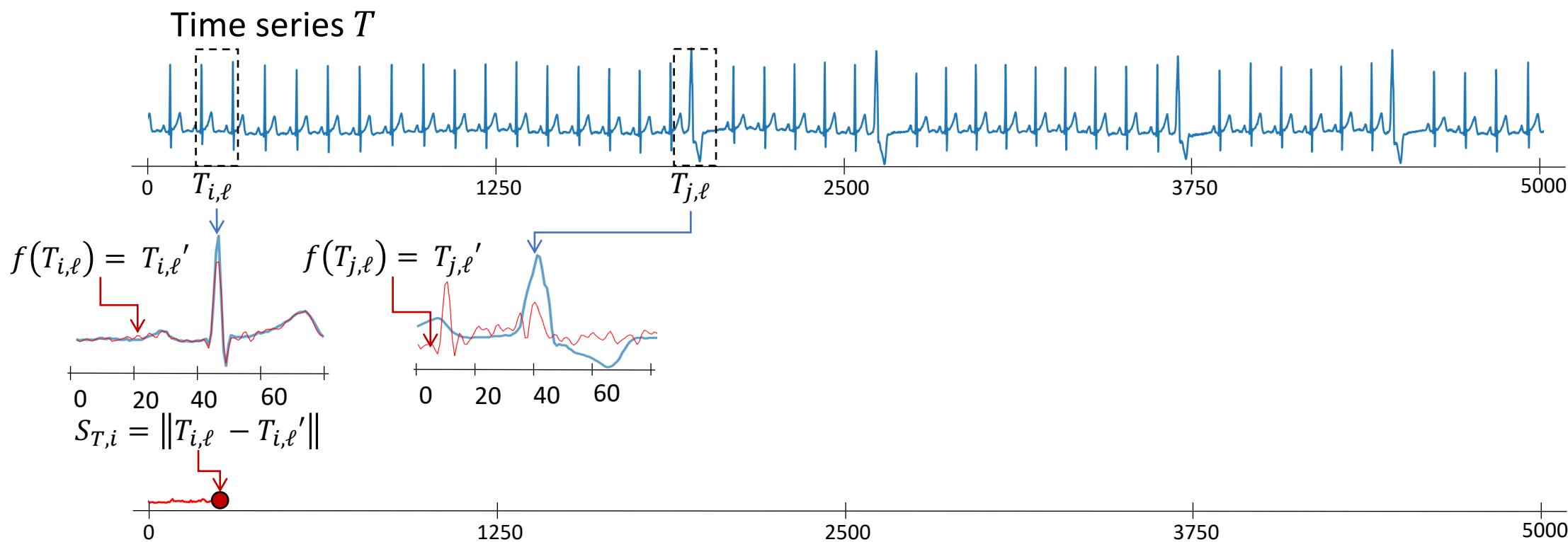
Anomaly Detection methods: Reconstruction-based

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.



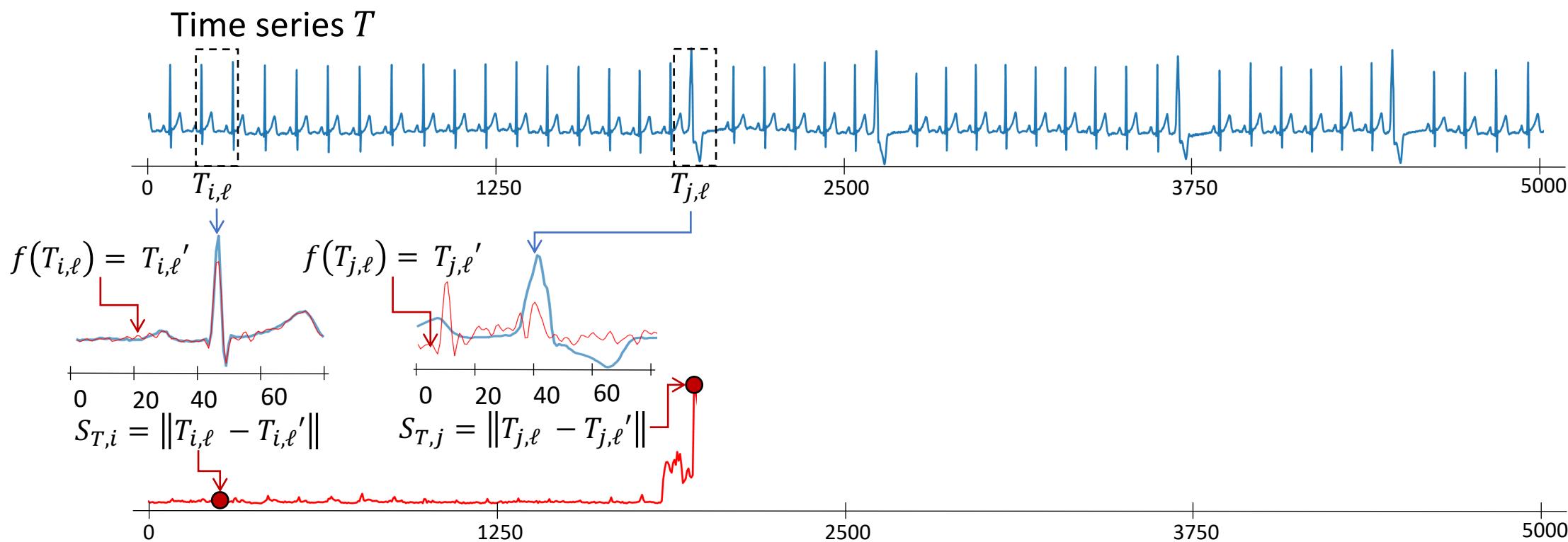
Anomaly Detection methods: Reconstruction-based

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.



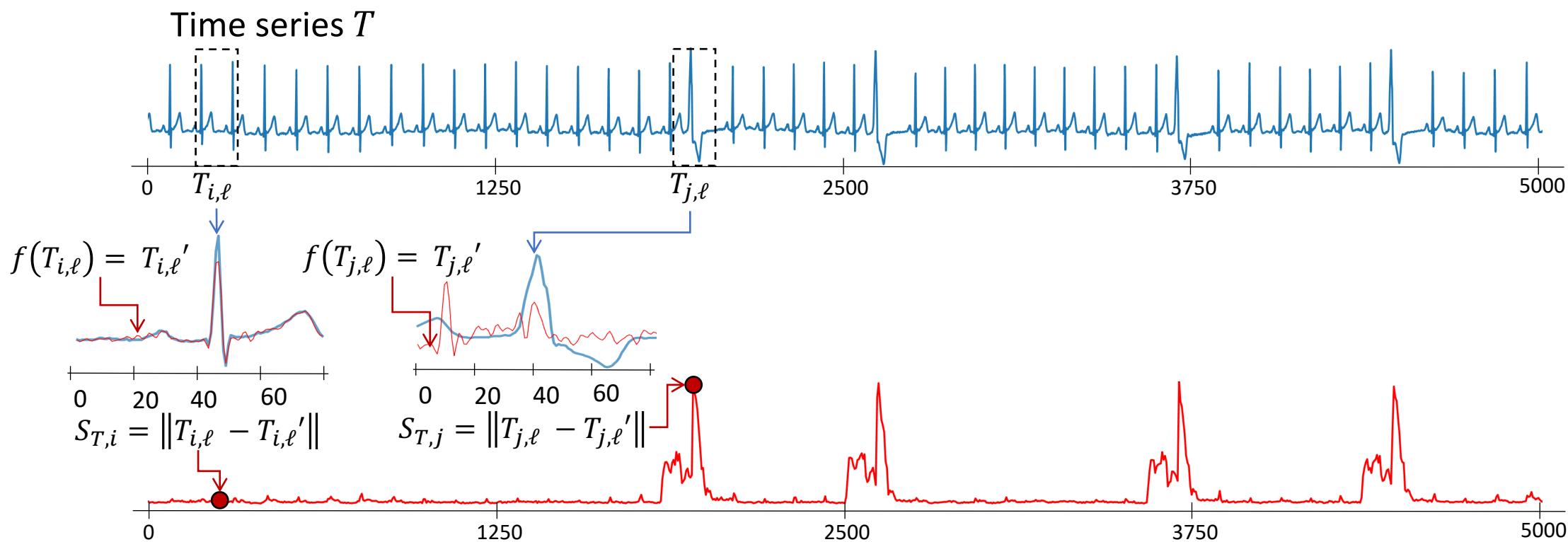
Anomaly Detection methods: Reconstruction-based

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.



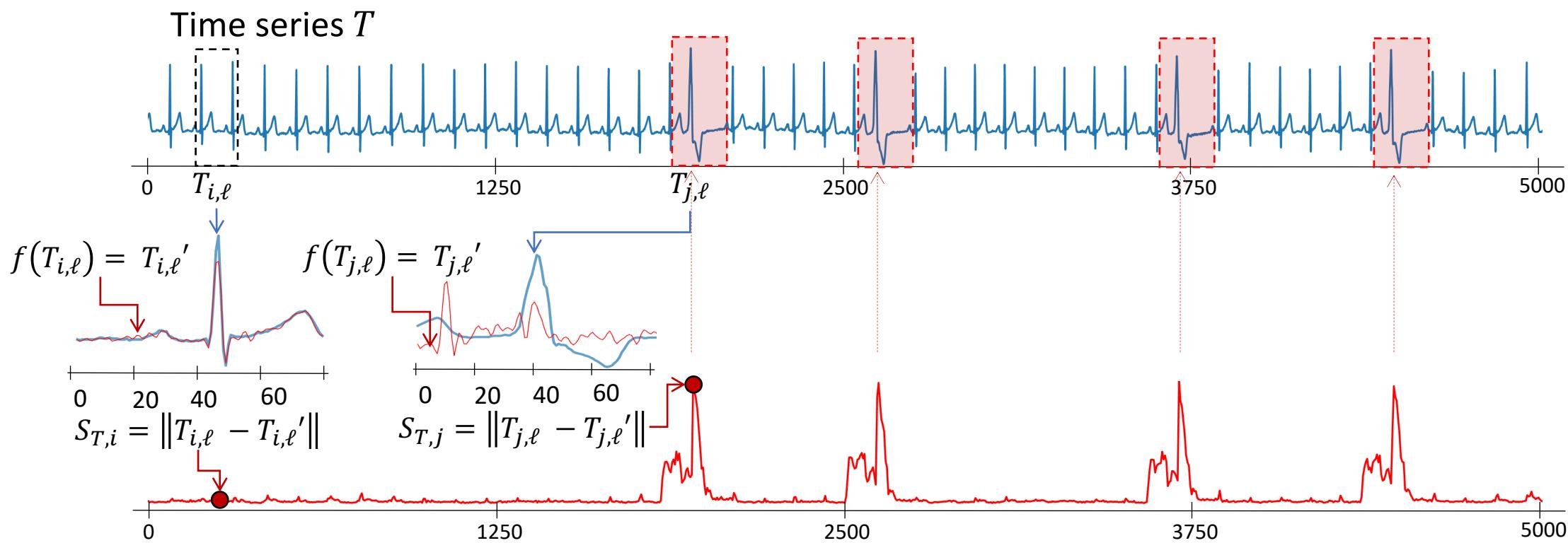
Anomaly Detection methods: Reconstruction-based

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.

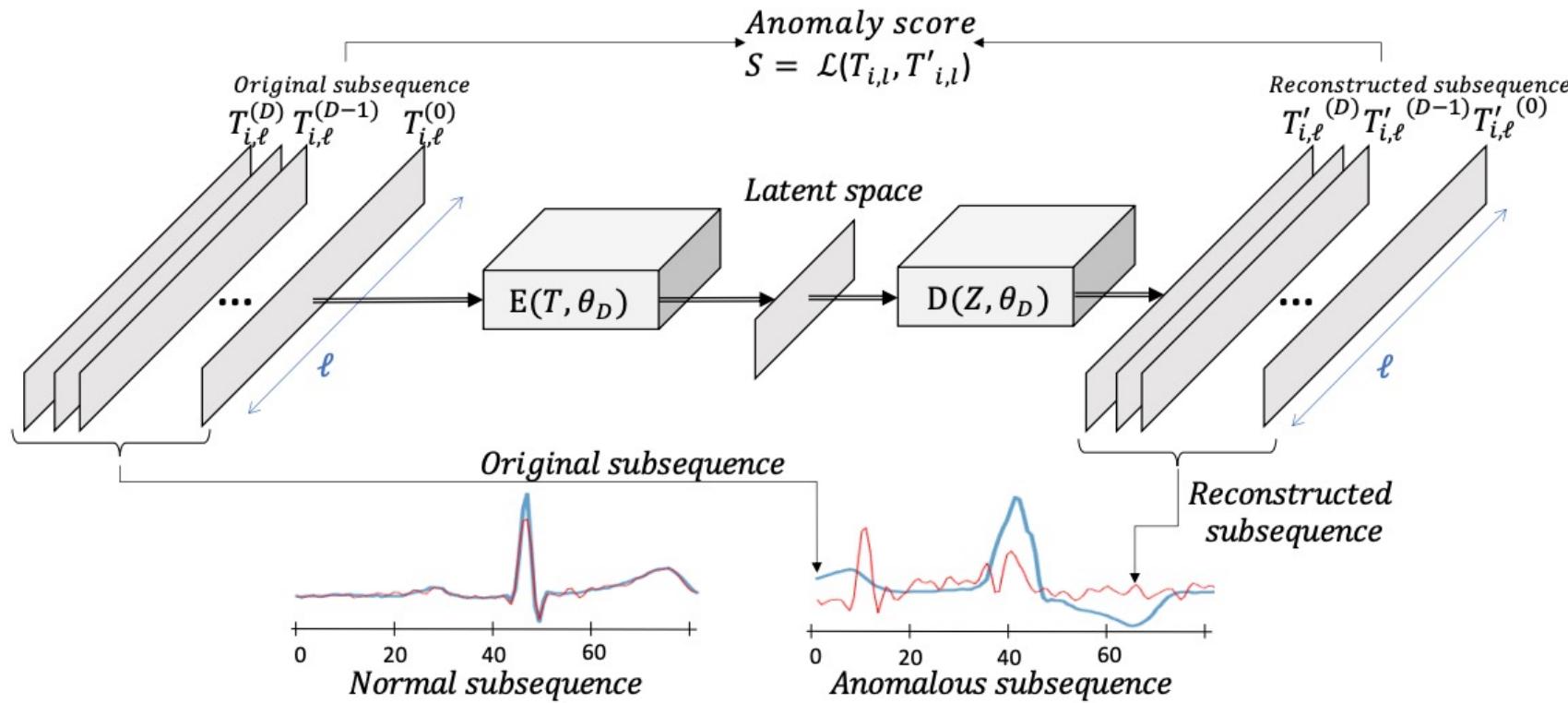


Anomaly Detection methods: Reconstruction-based

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.



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

Anomaly Detection methods: *Existing benchmark*

Anomaly Detection methods: *Existing benchmark*

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

Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]

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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 method above 0.8 AUC-ROC

Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]

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TSB-UAD [19]

Set of **2000 time series** with labels.

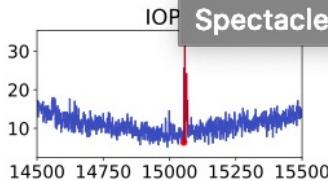
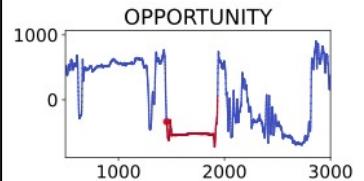
Details

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

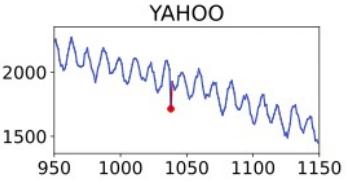
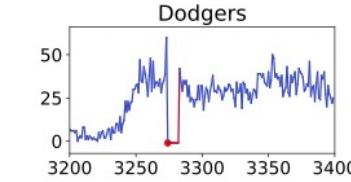
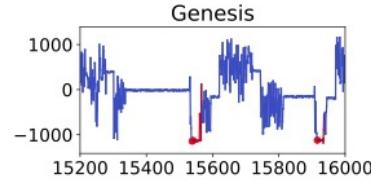
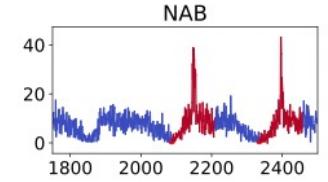
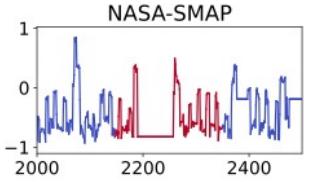
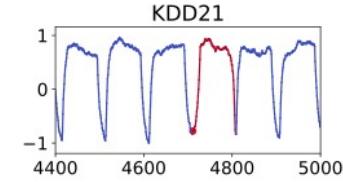
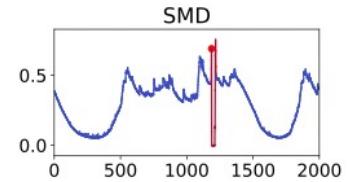
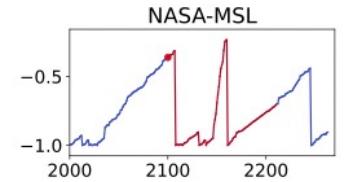
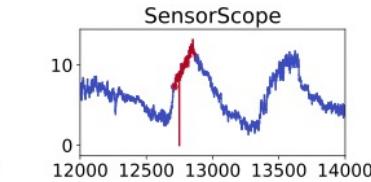
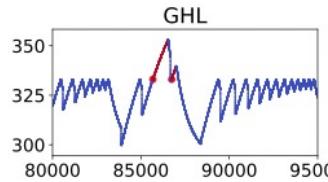
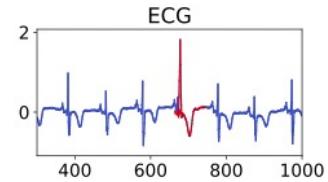
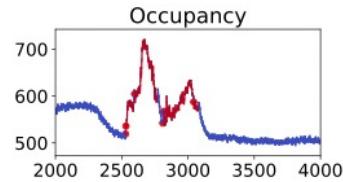
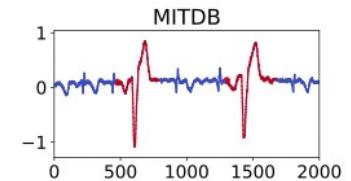
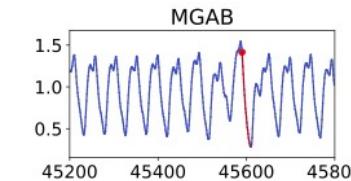
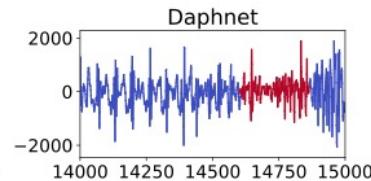
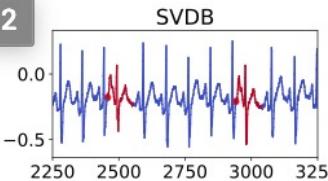
Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]

Set of 250 time series with



Spectacle 1.2



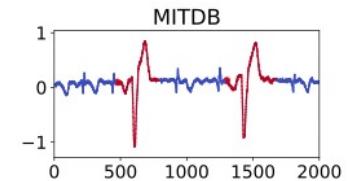
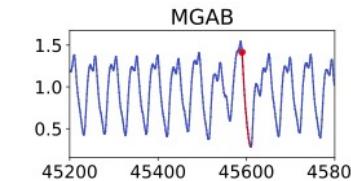
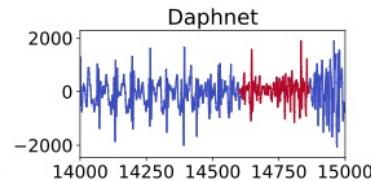
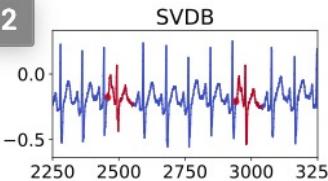
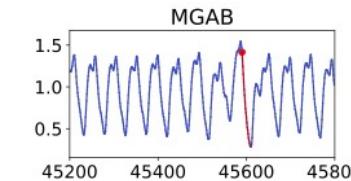
TimeEval [5]

Real datasets collection

Set of 370 time series with

TSB-UAD [19]

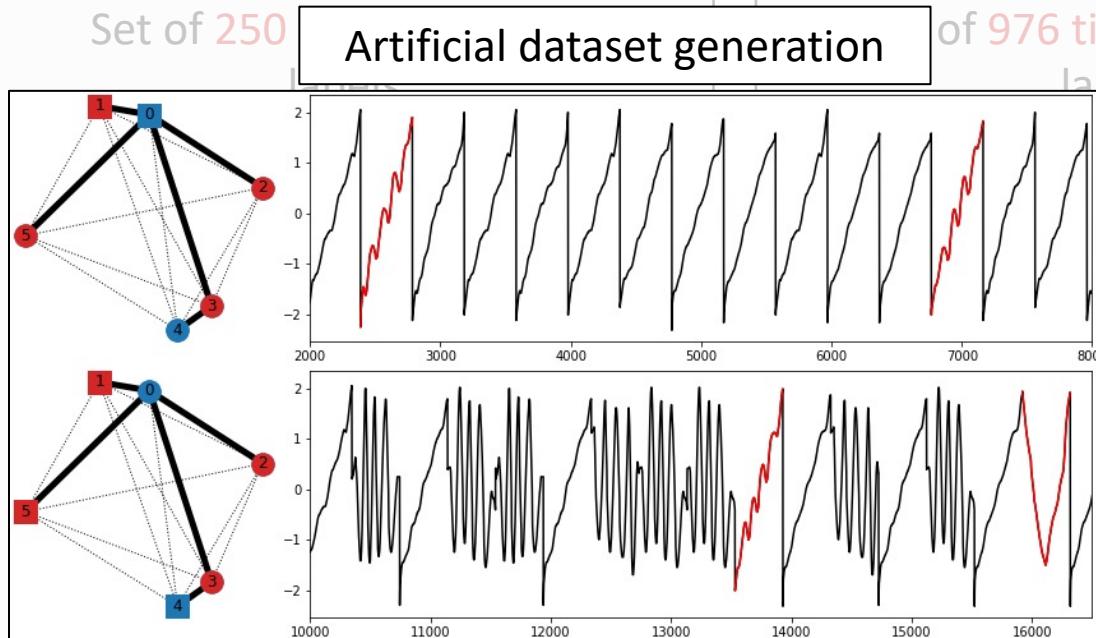
Set of 2000 time series with



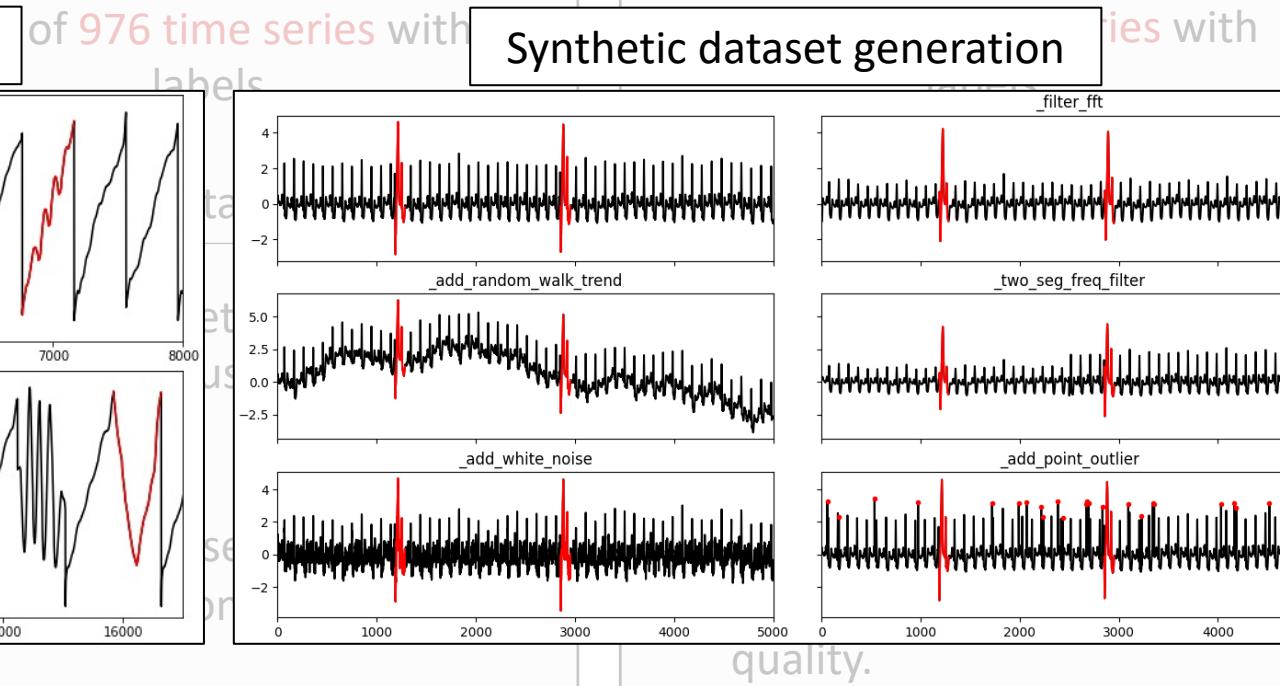
- Time series with at least one method above 0.8 AUC-ROC

Anomaly Detection methods: *Existing benchmark*

HEX/UCR [18]



TimeEval [5]



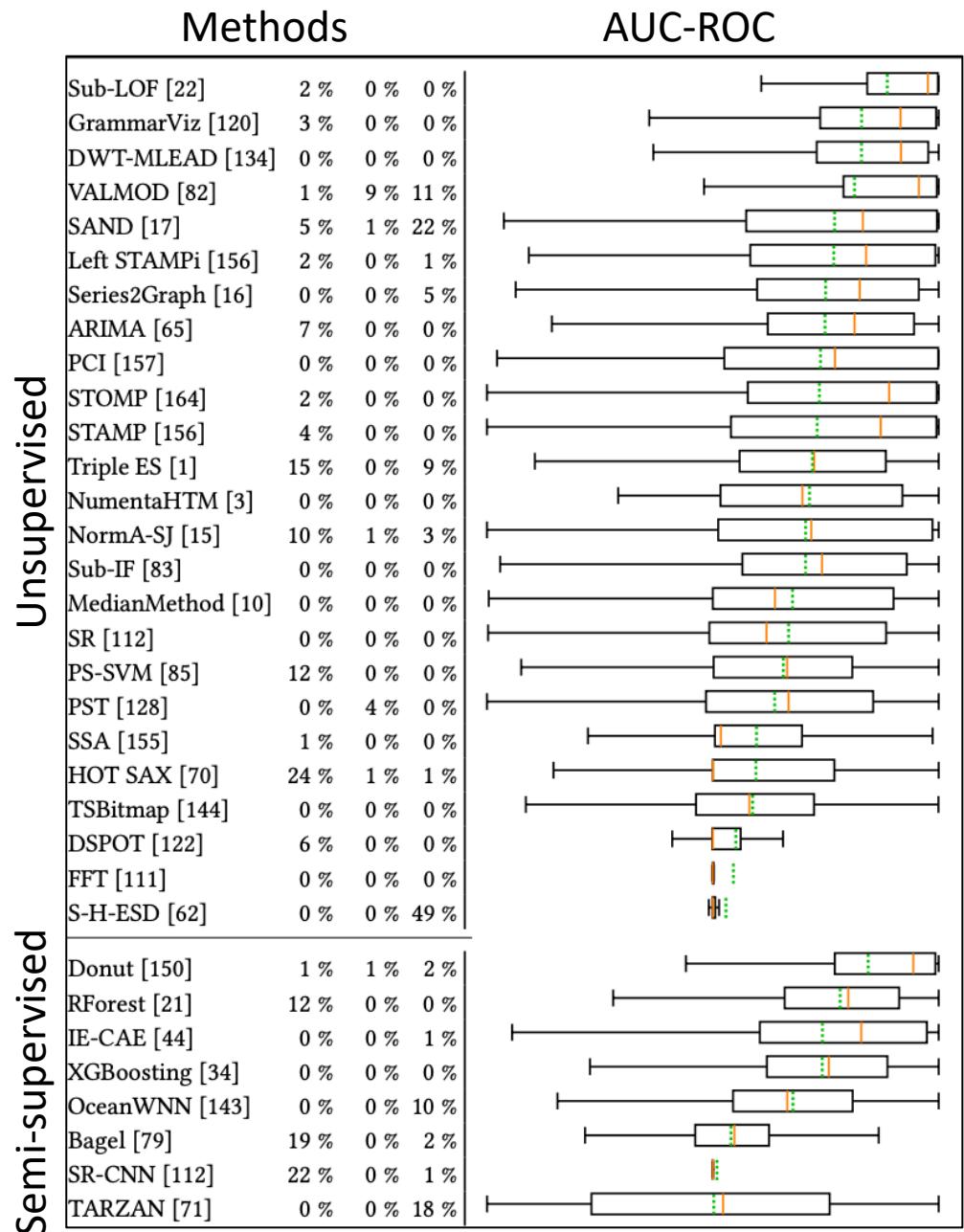
TSB-UAD [19]

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Anomaly Detection methods: *Experimental evaluation*

Observations on TimeEval [5]:

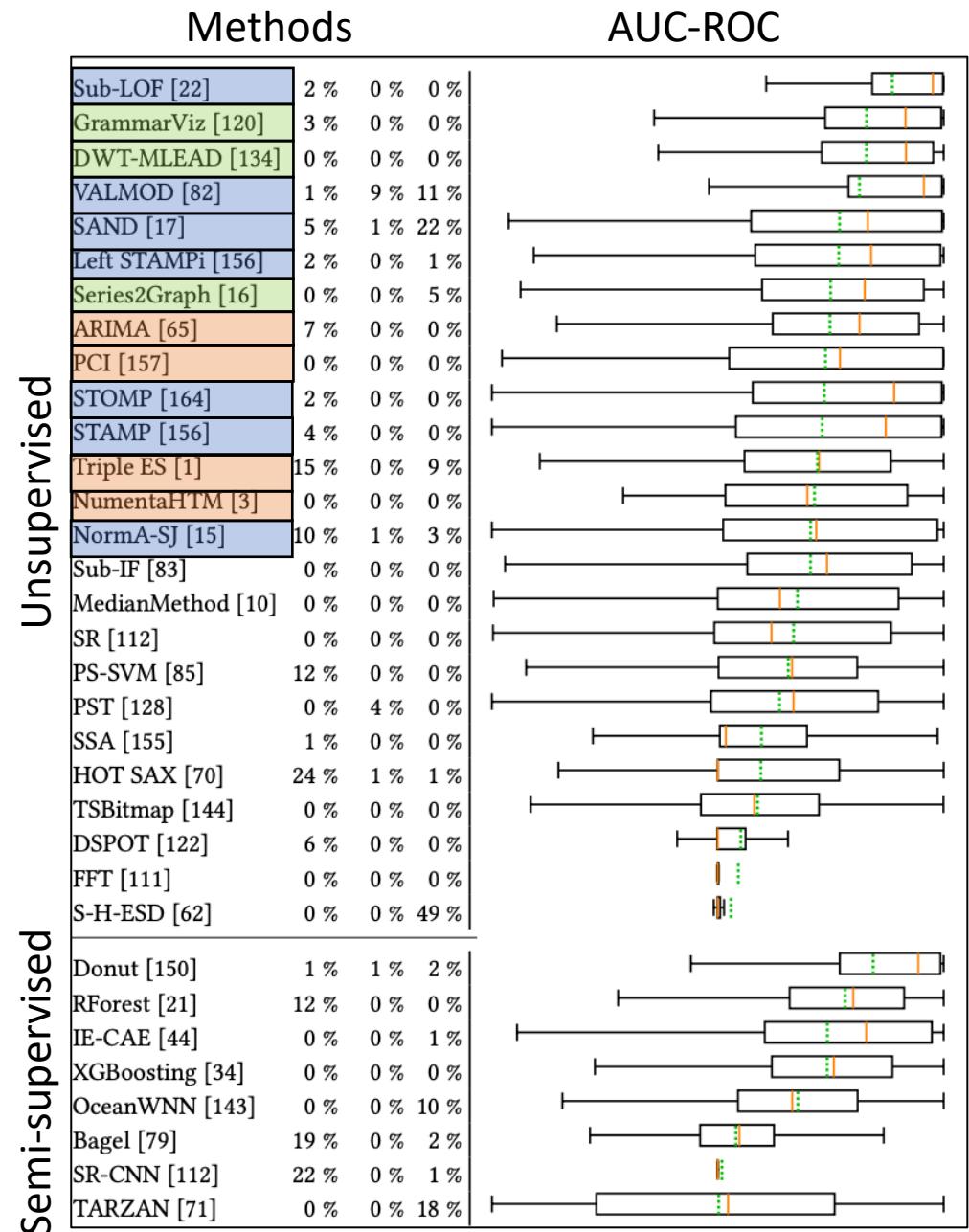
[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. Anomaly detection in time series: a comprehensive evaluation. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.



Anomaly Detection methods: *Experimental evaluation*

Observations on TimeEval [5]:

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



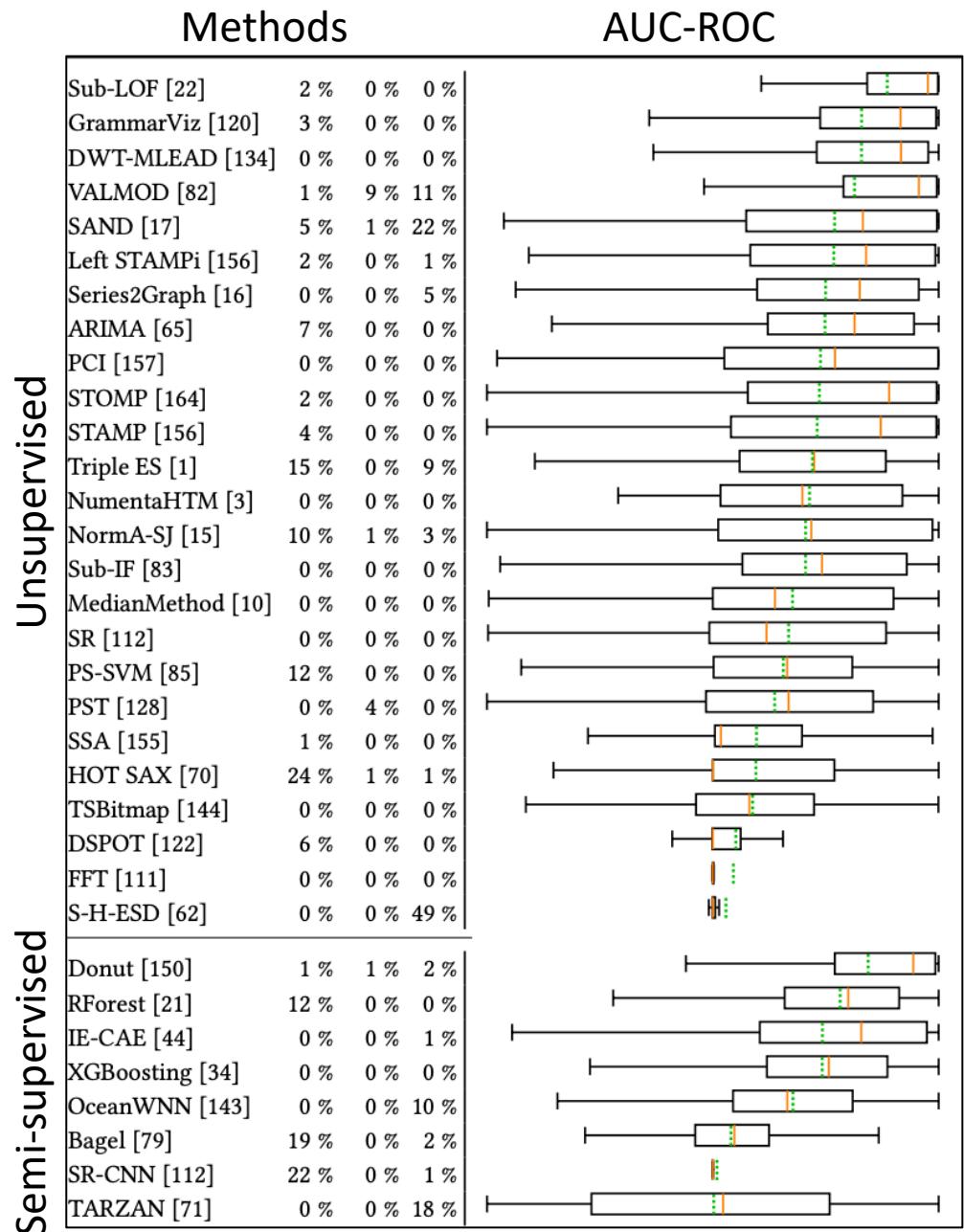
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Anomaly Detection methods: *Experimental evaluation*

Observations on TimeEval [5]:

- Distance-based and Density-based methods have a better accuracy (AUC-ROC) than forecasting and reconstruction-based approaches
- Semi-supervised methods are not outperforming Unsupervised approaches

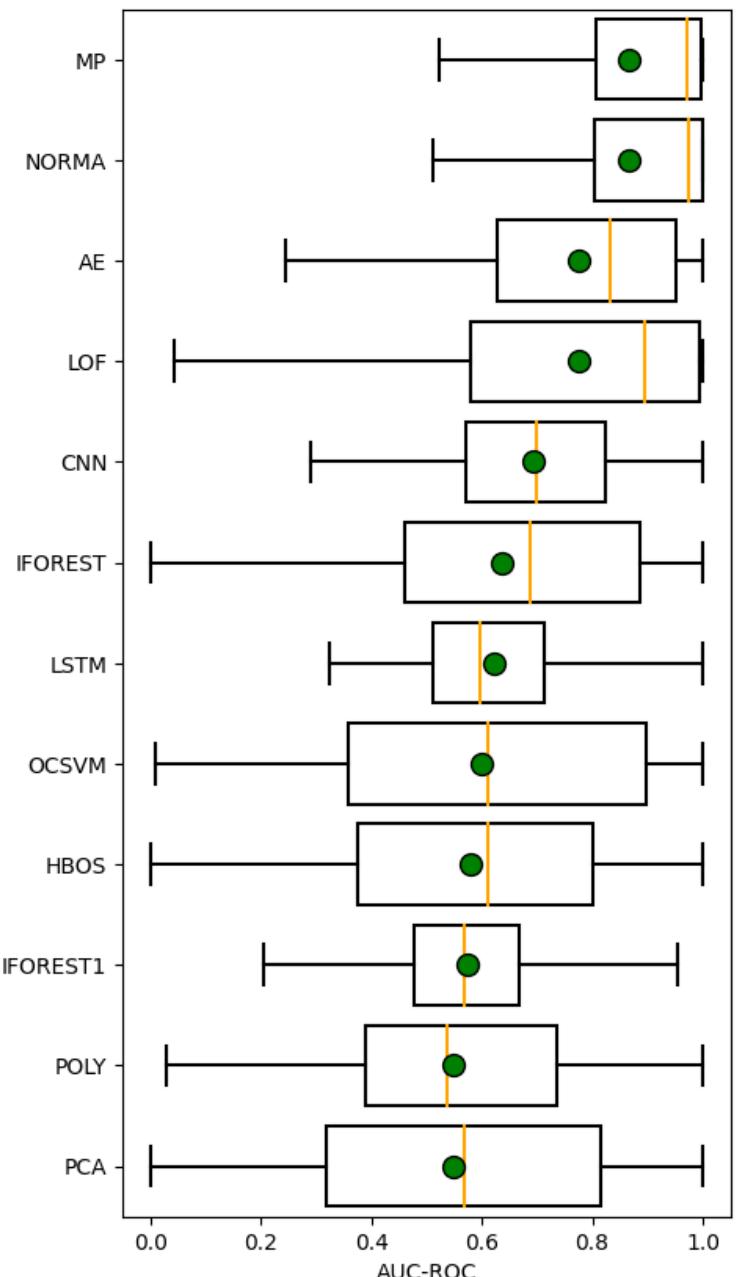
[5] Sebastian Schmidl, Phillip Wenig, and Thorsten Papenbrock. 2022. Anomaly detection in time series: a comprehensive evaluation. Proc. VLDB Endow. 15, 9 (May 2022), 1779–1797.



Anomaly Detection methods: *Experimental evaluation*

Observations on HEX/UCR [18]:

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

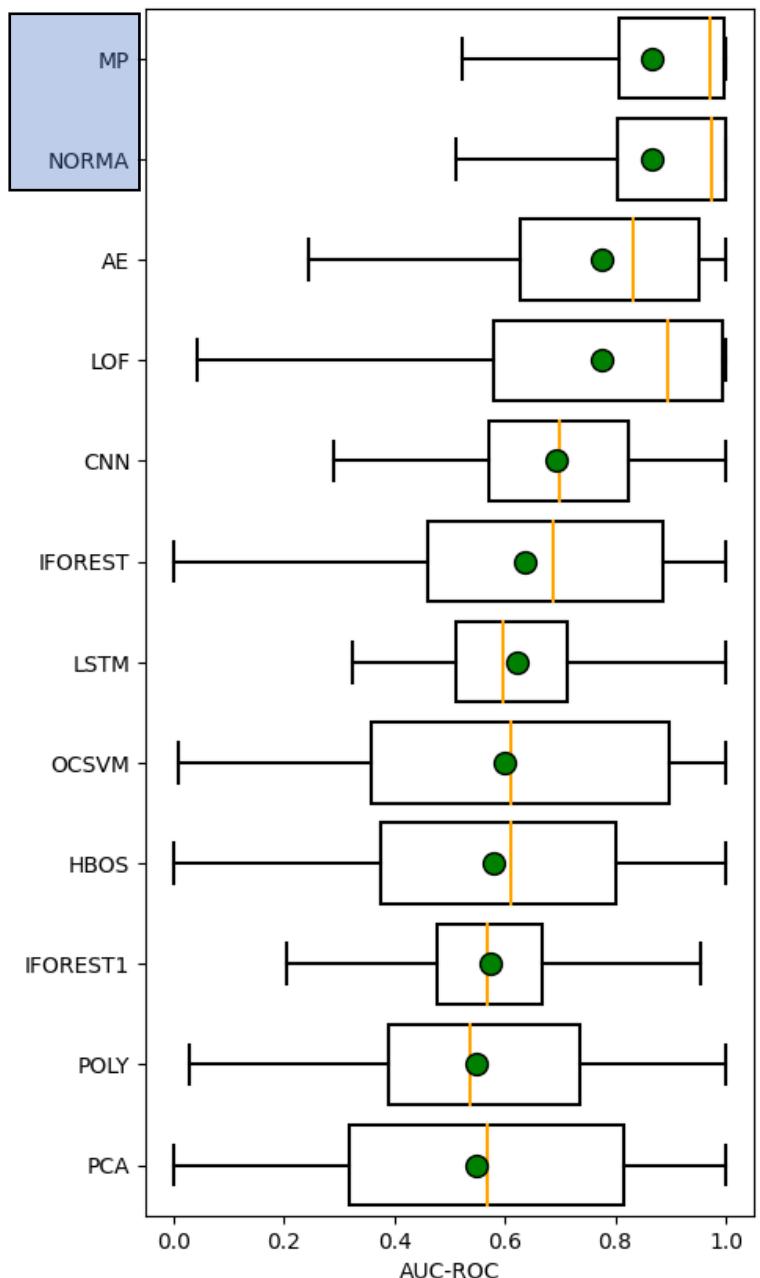


[18] R. Wu and E. Keogh, "Current Time Series Anomaly Detection Benchmarks are Flawed and are Creating the Illusion of Progress" in IEEE Transactions on Knowledge & Data Engineering, vol. 35, no. 03, pp. 2421-2429, 2023.

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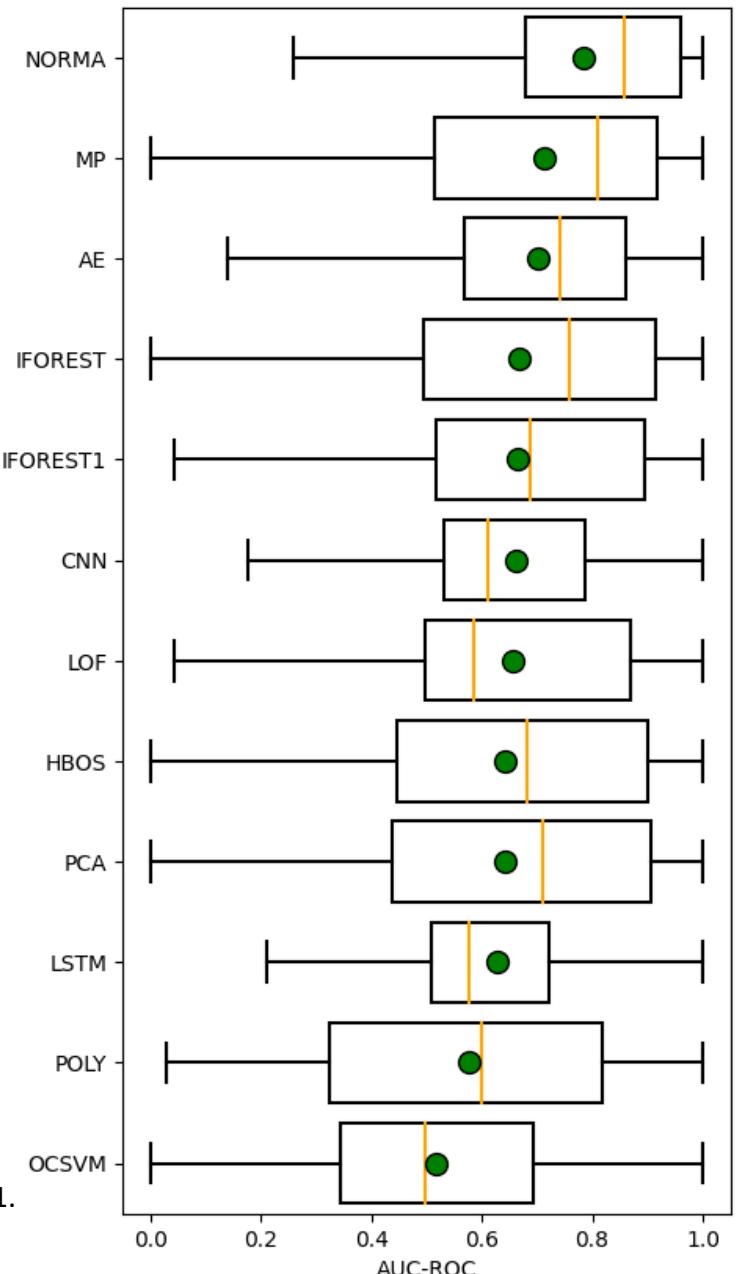


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Anomaly Detection methods: *Experimental evaluation*

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.

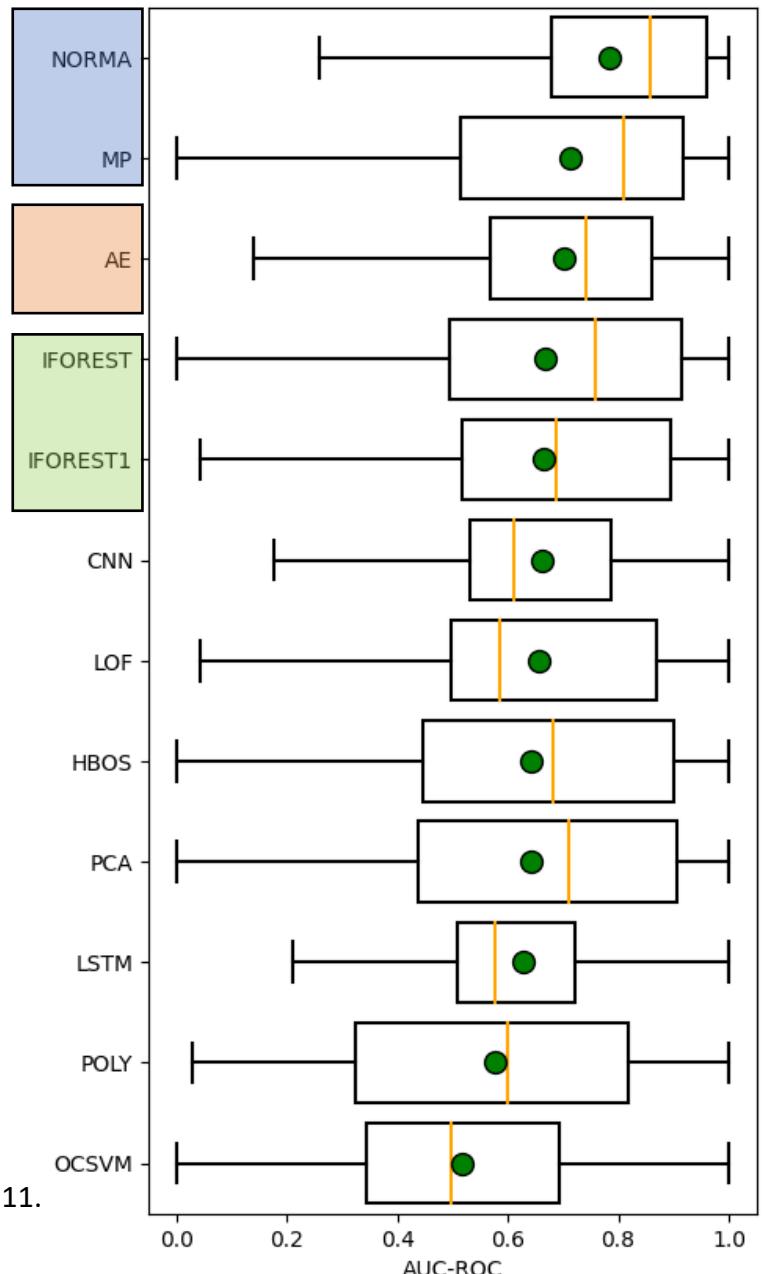


[19] John Paparrizos, Yuhao Kang, Paul Boniol, Ruey S. Tsay, Themis Palpanas, and Michael J. Franklin. 2022. TSB-UAD: an end-to-end benchmark suite for univariate time-series anomaly detection. Proc. VLDB Endow. 15, 8 (April 2022), 1697–1711.

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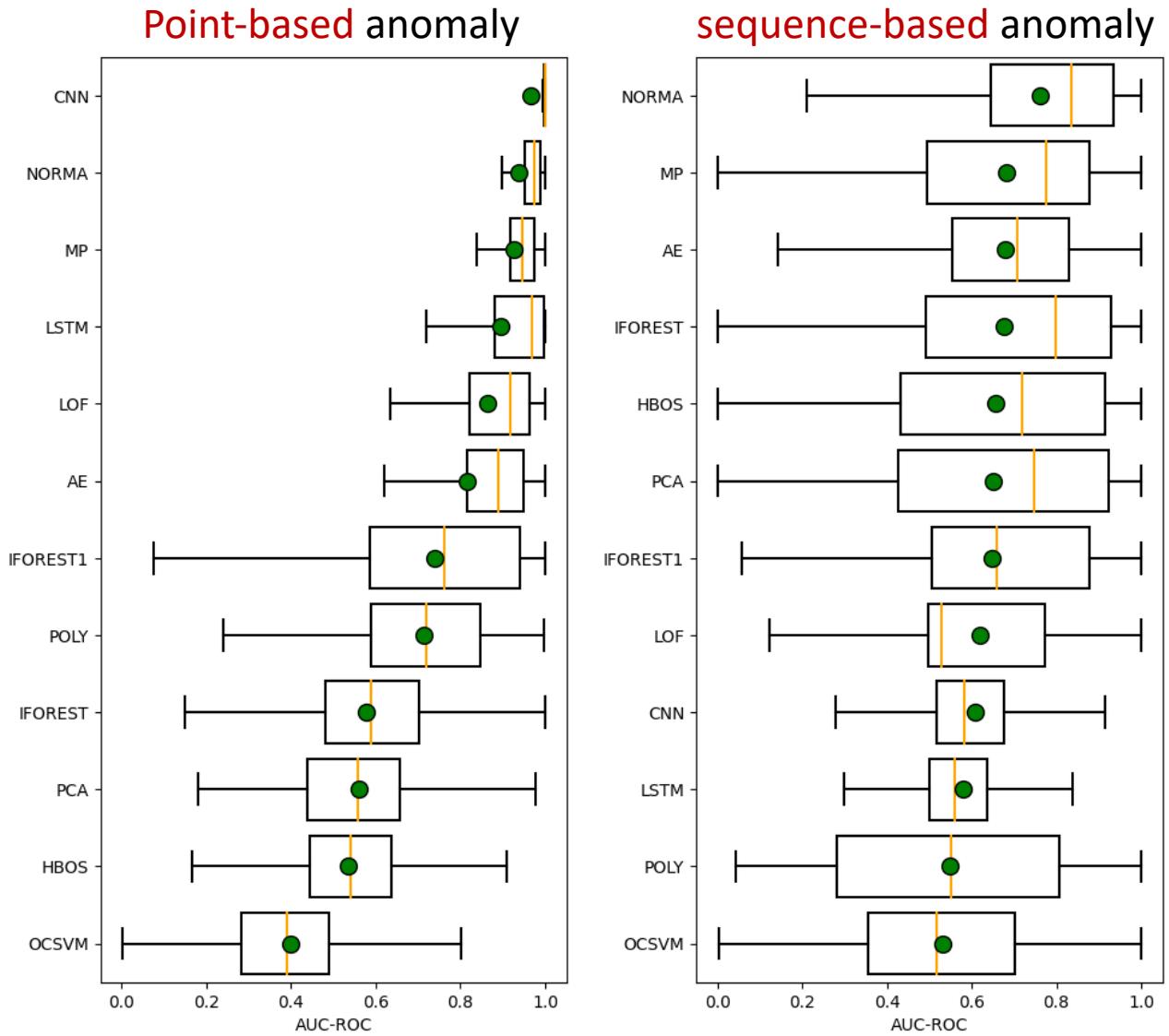


[19] John Paparrizos, Yuhao Kang, Paul Boniol, Ruey S. Tsay, Themis Palpanas, and Michael J. Franklin. 2022. TSB-UAD: an end-to-end benchmark suite for univariate time-series anomaly detection. Proc. VLDB Endow. 15, 8 (April 2022), 1697–1711.

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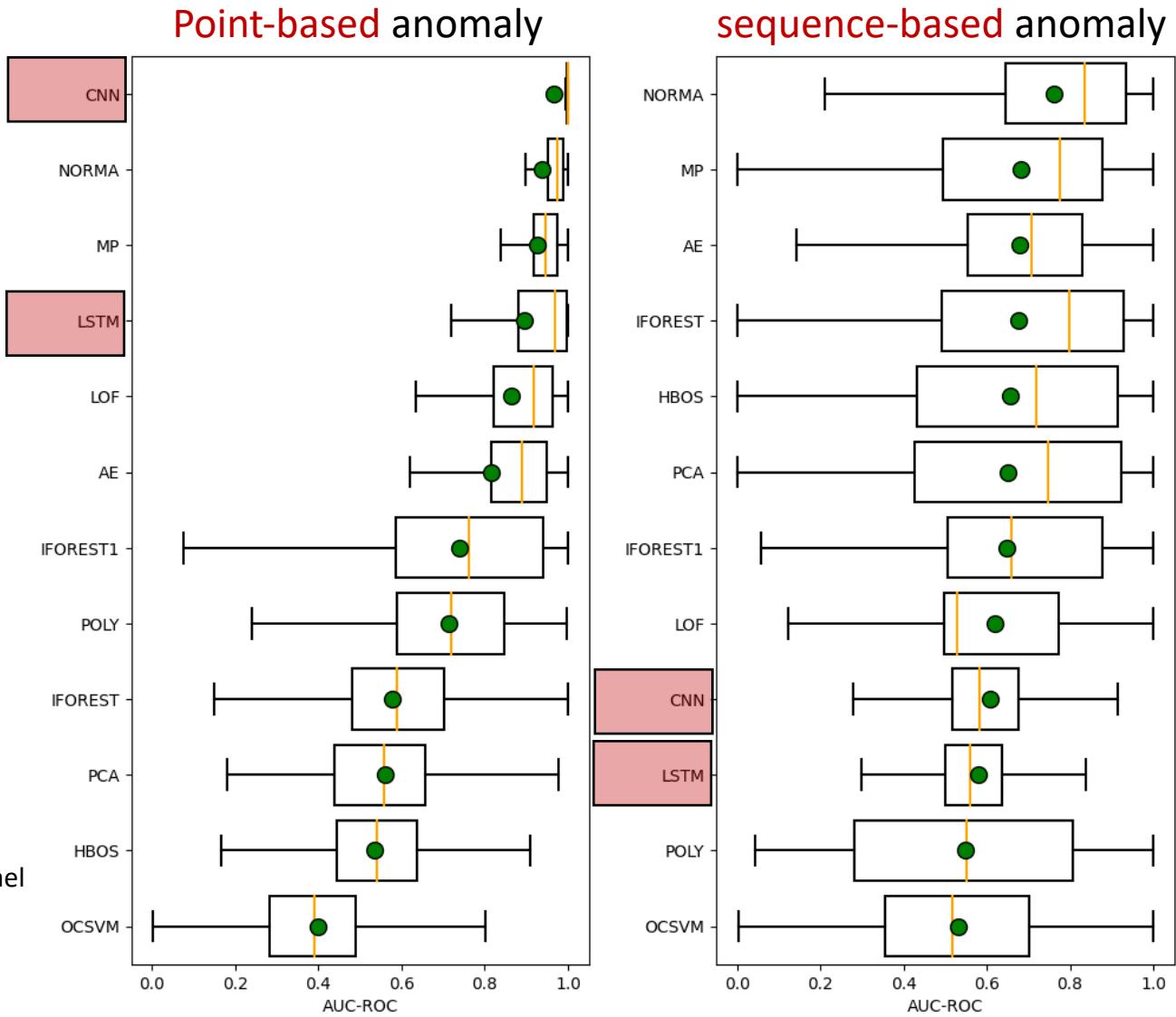


Anomaly Detection methods: *Experimental evaluation*

Observations on TSB-UAD [19]:

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

[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.

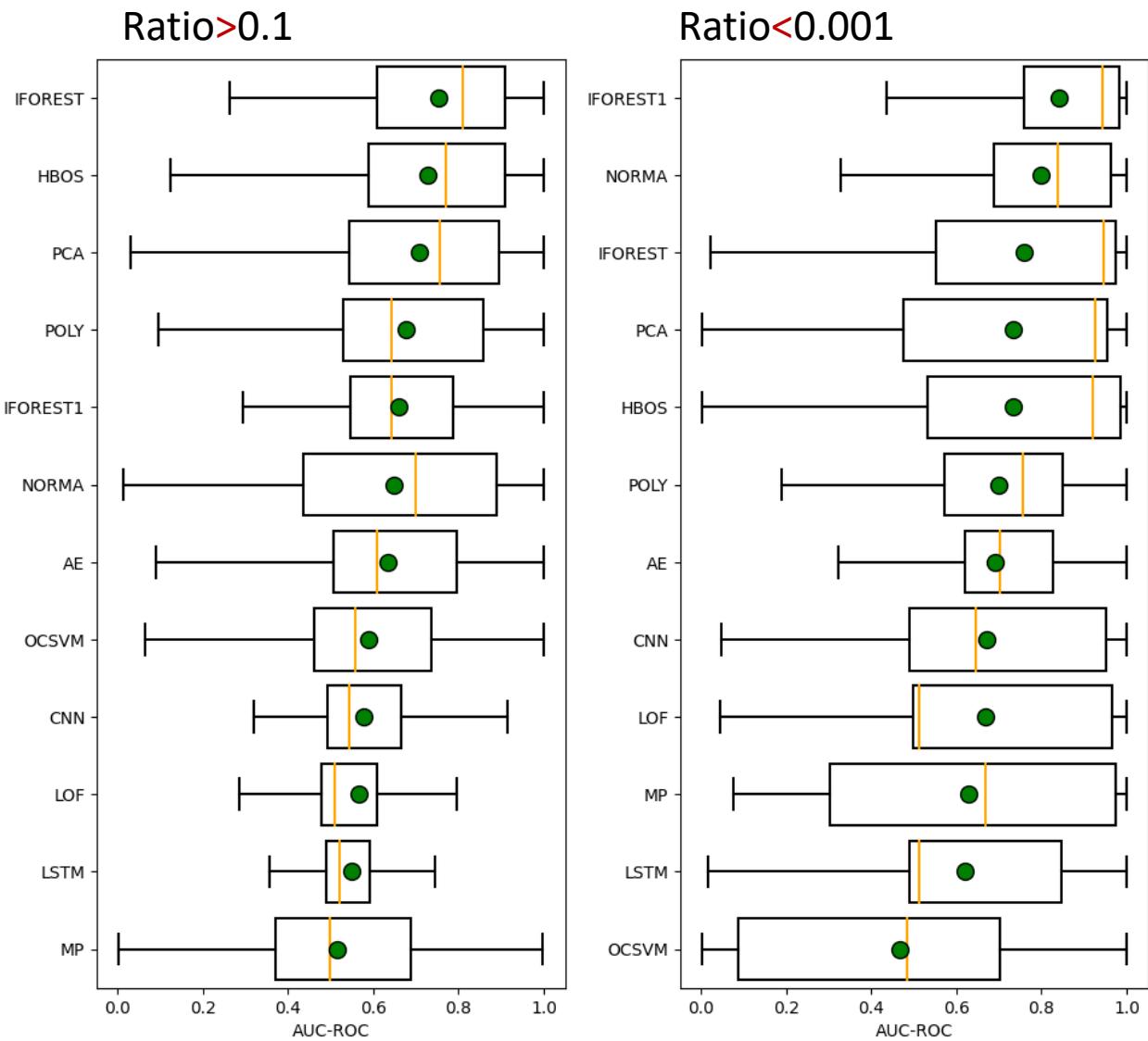


Anomaly Detection methods: *Experimental evaluation*

Observations on TSB-UAD [19]:

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

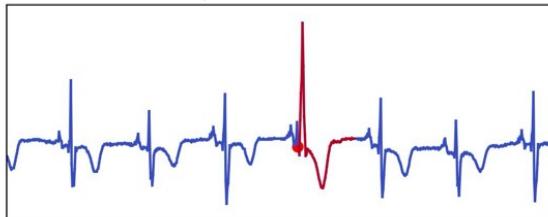
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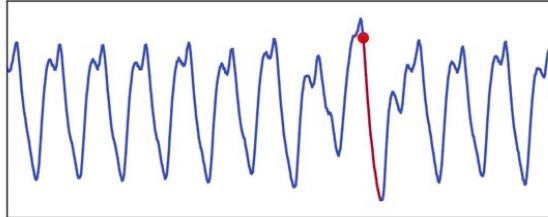
Anomaly Detection methods: *Experimental evaluation*

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

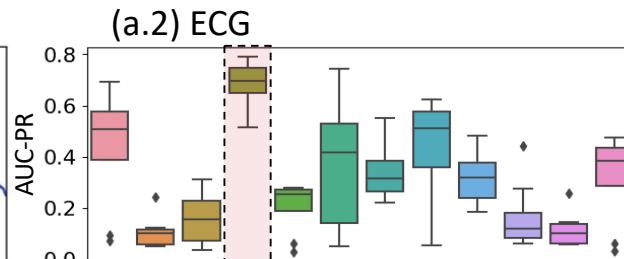
(a.1) Example from ECG dataset



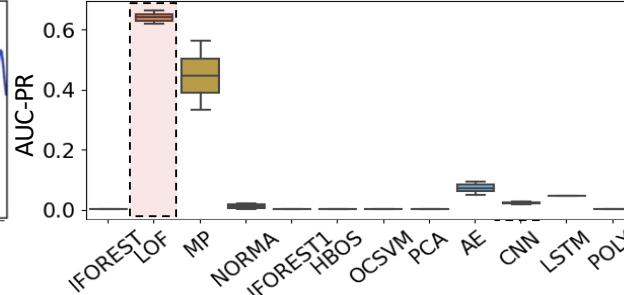
(b.1) Example from MGAB dataset



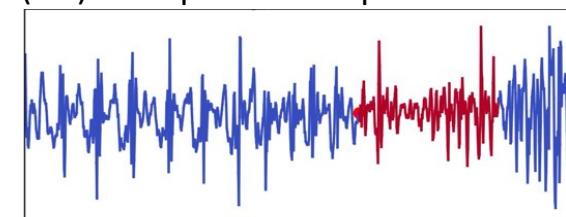
(a.2) ECG



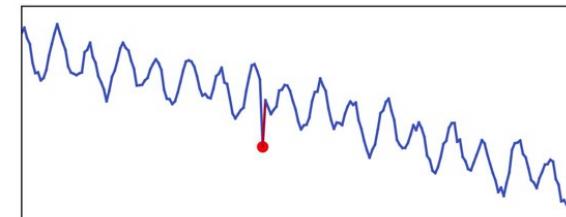
(b.2) MGAB



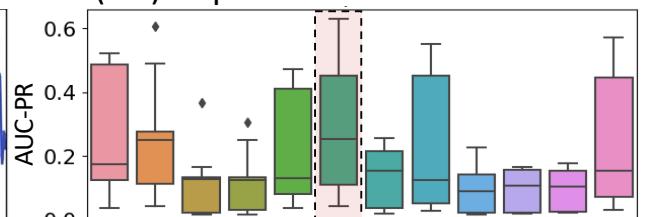
(c.1) Example from Daphnet dataset



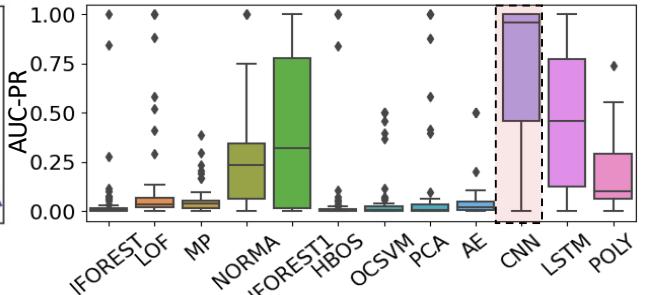
(d.1) Example from YAHOO dataset



(c.2) Daphnet

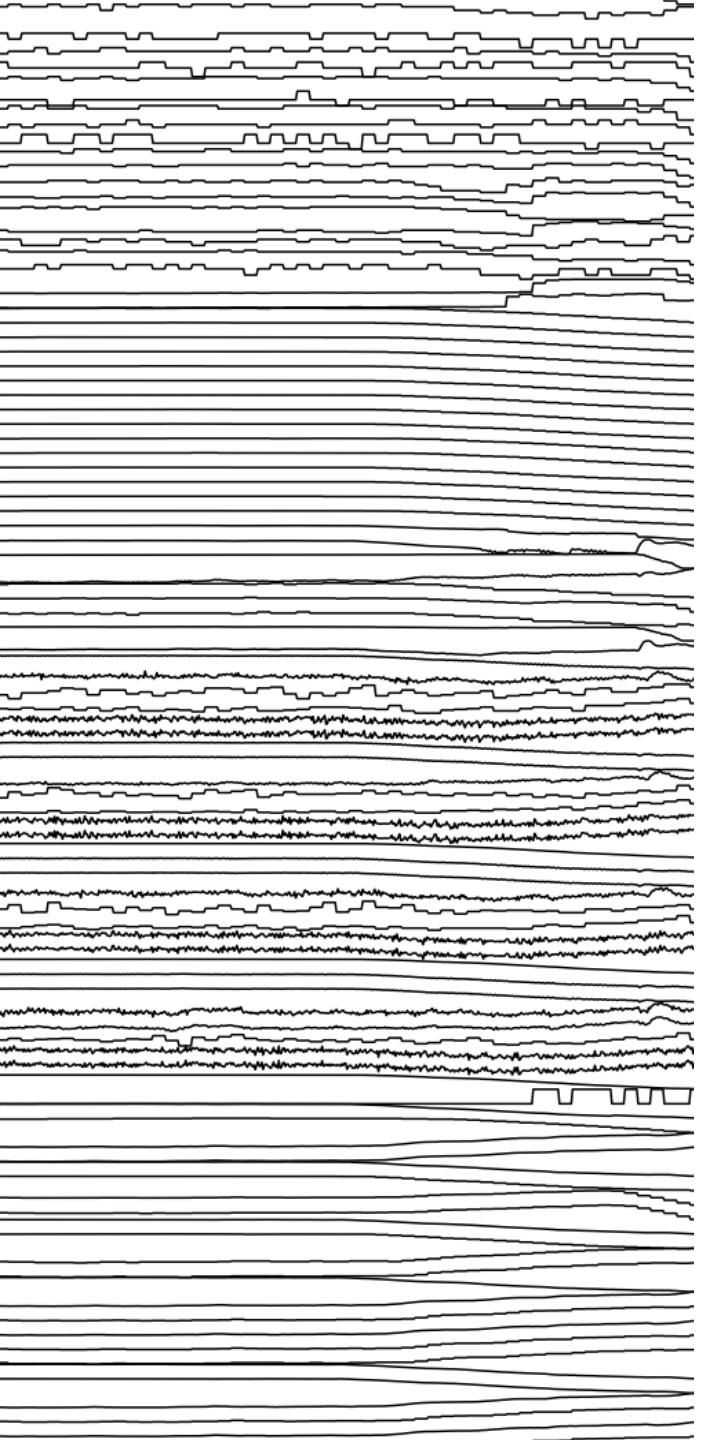


(d.2) YAHOO



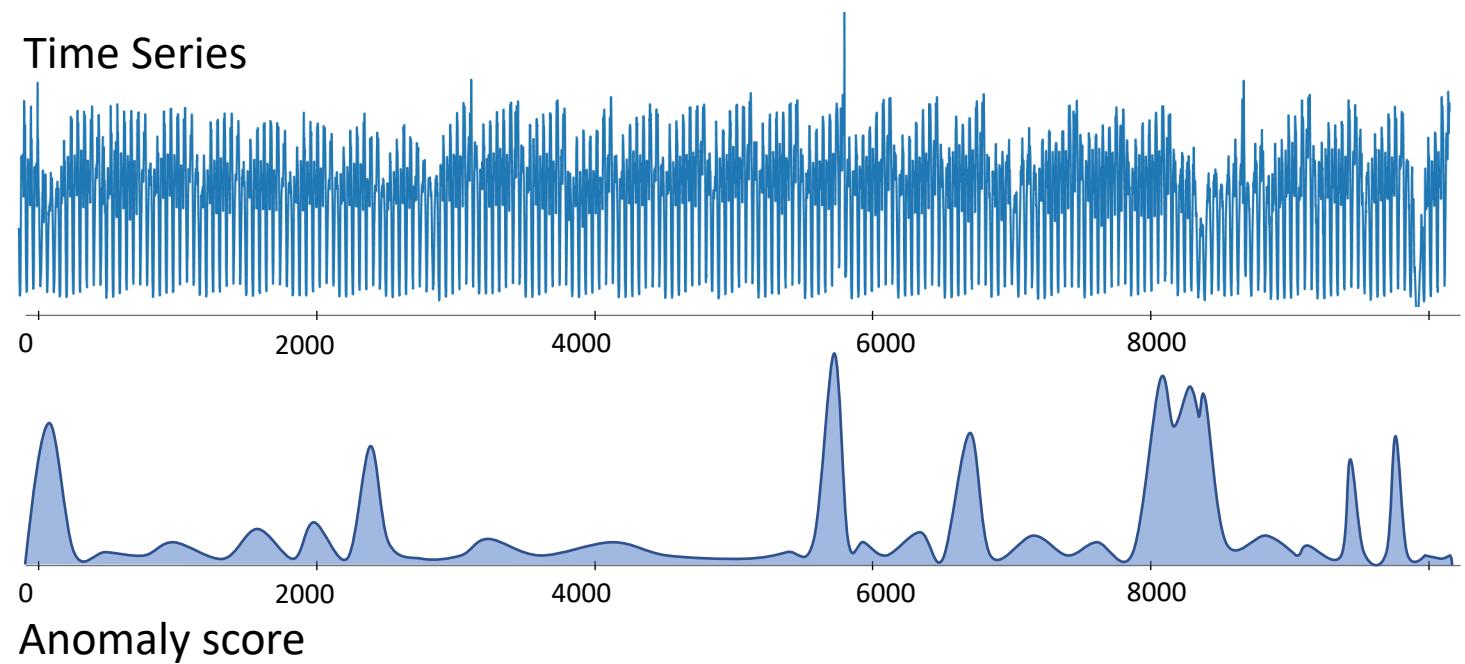
There is **no overall winner.**

[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.

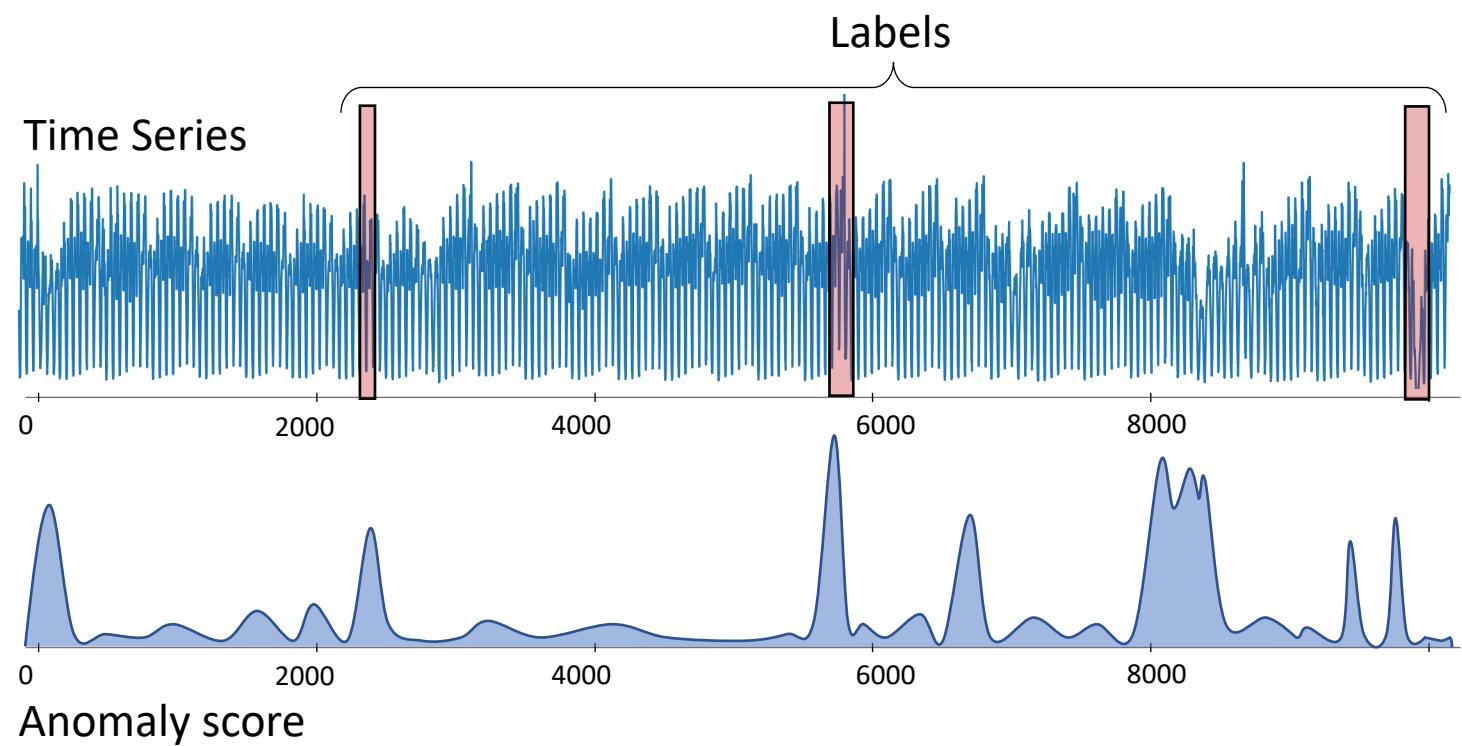


Evaluation Measures

Evaluation measures: A general overview

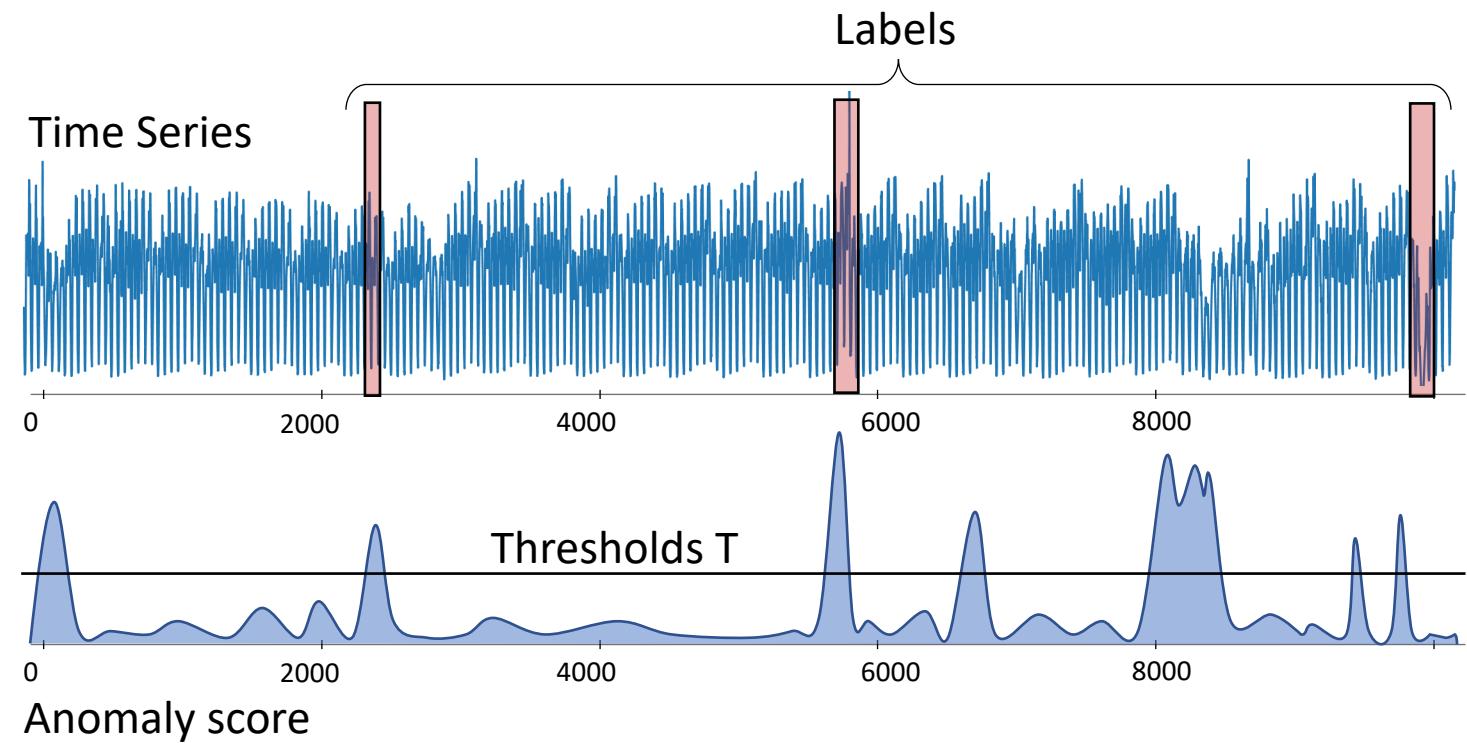


Evaluation measures: A general overview



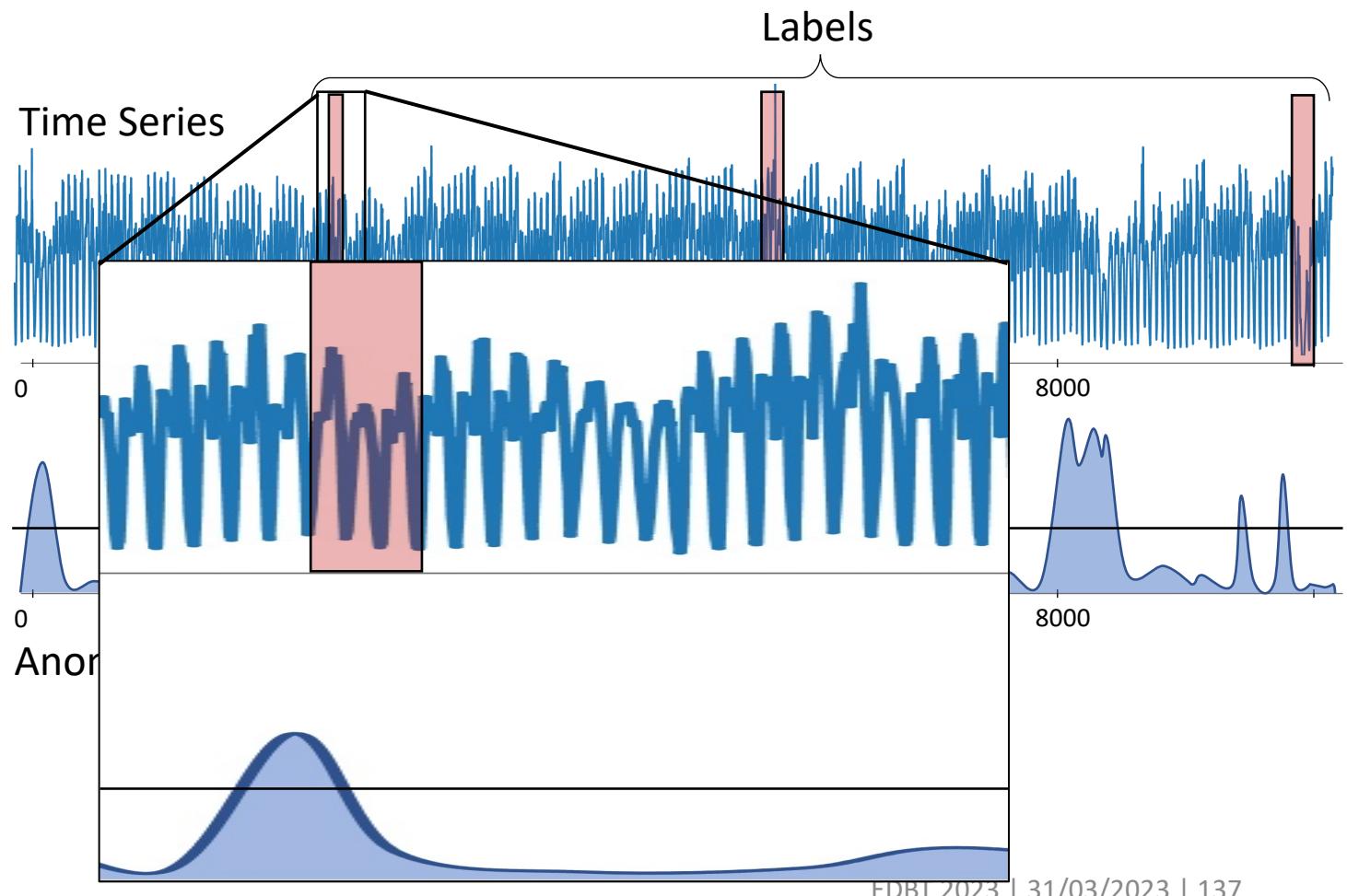
Evaluation measures: *Threshold-based*

Threshold-based Evaluation
Measures:



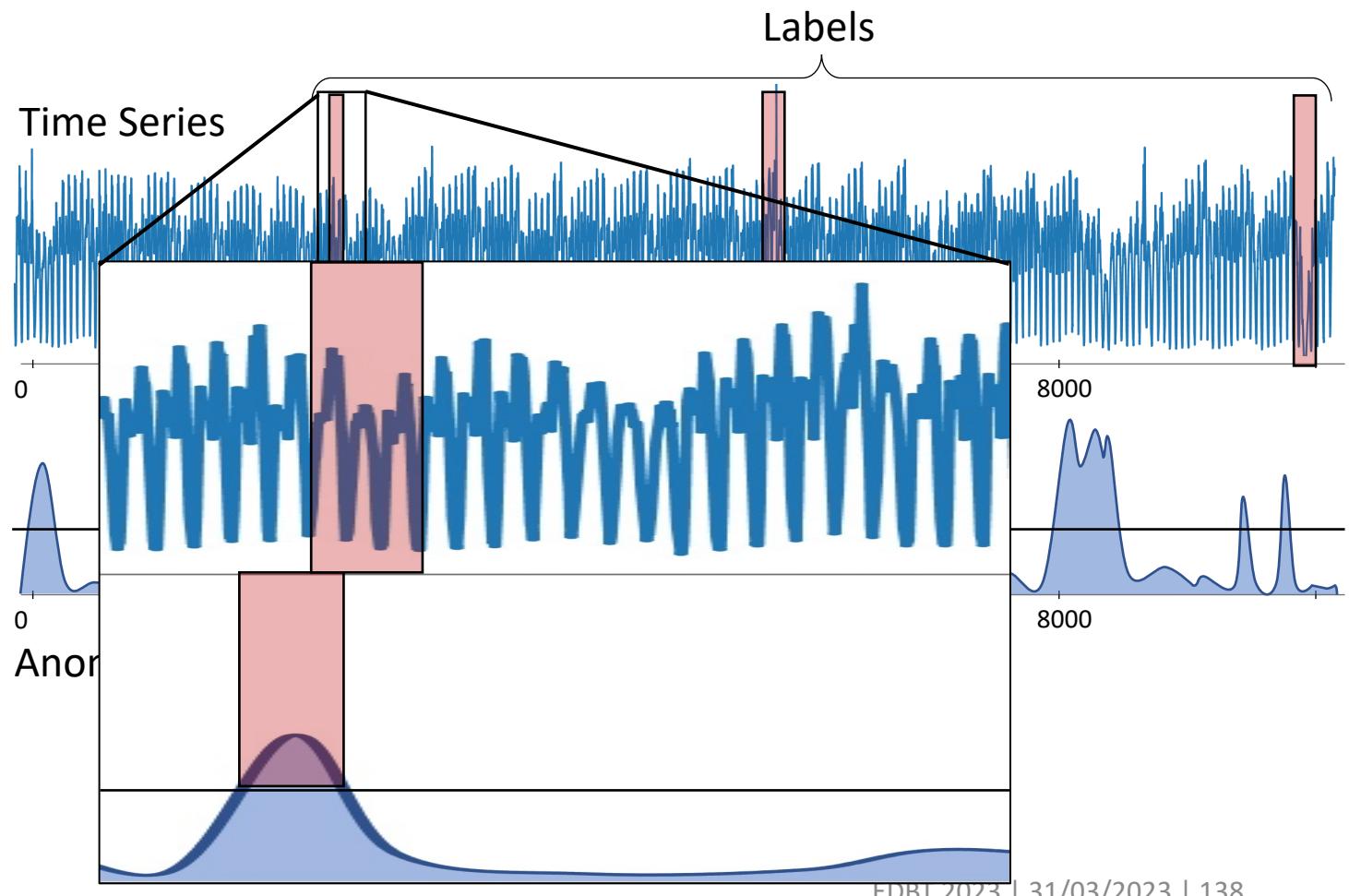
Evaluation measures: *Threshold-based*

Threshold-based Evaluation
Measures:



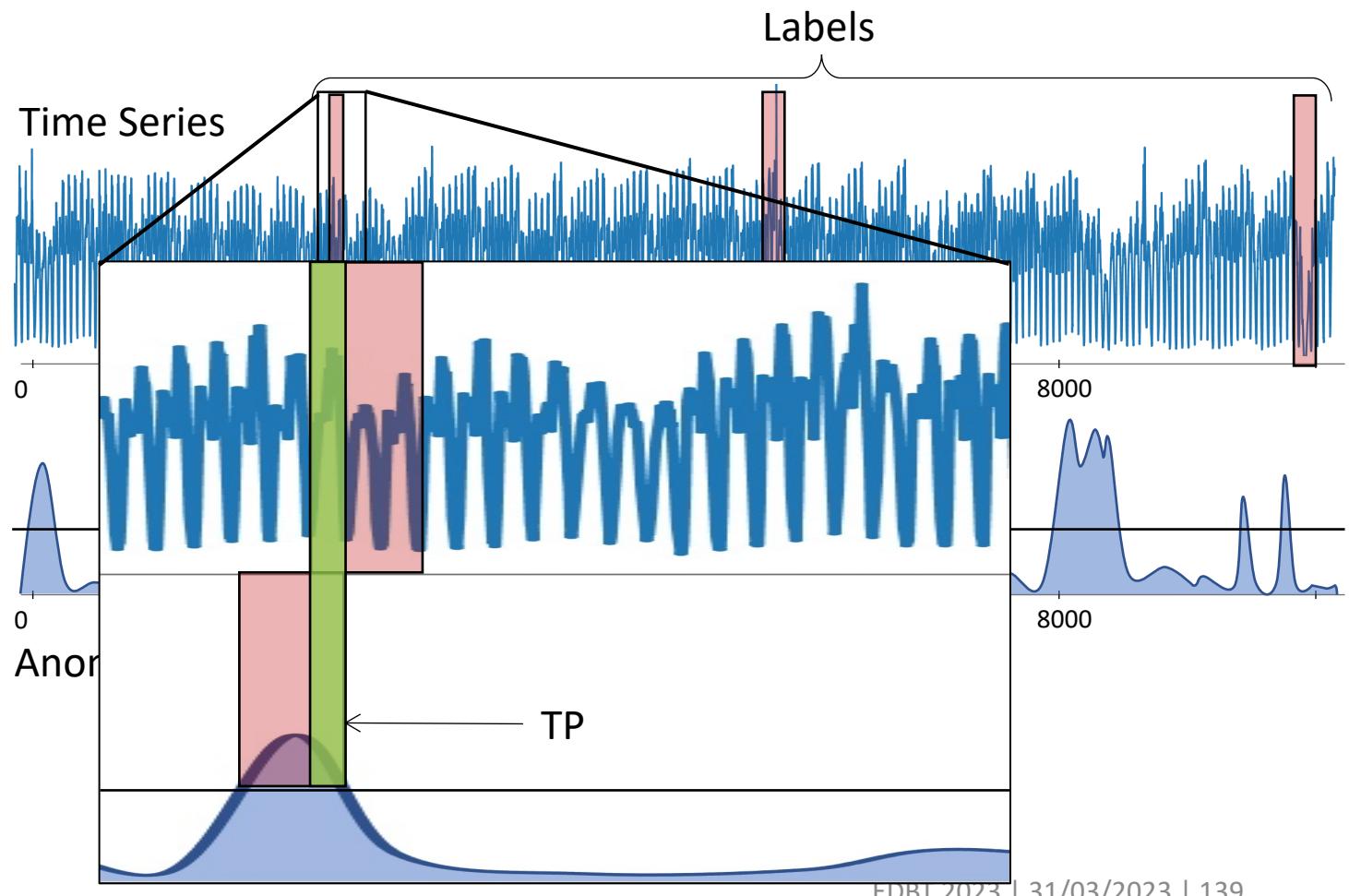
Evaluation measures: *Threshold-based*

Threshold-based Evaluation
Measures:



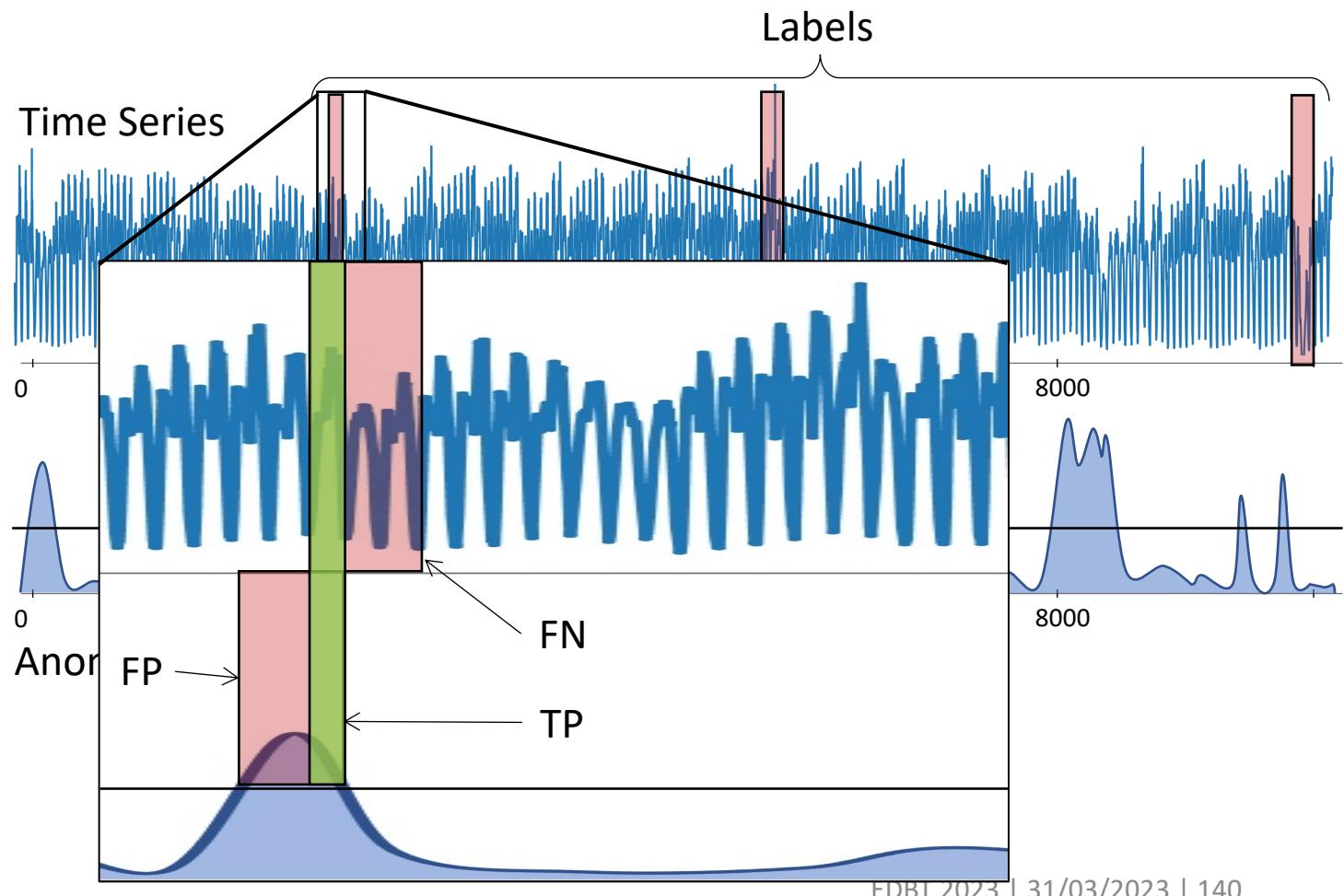
Evaluation measures: *Threshold-based*

Threshold-based Evaluation
Measures:



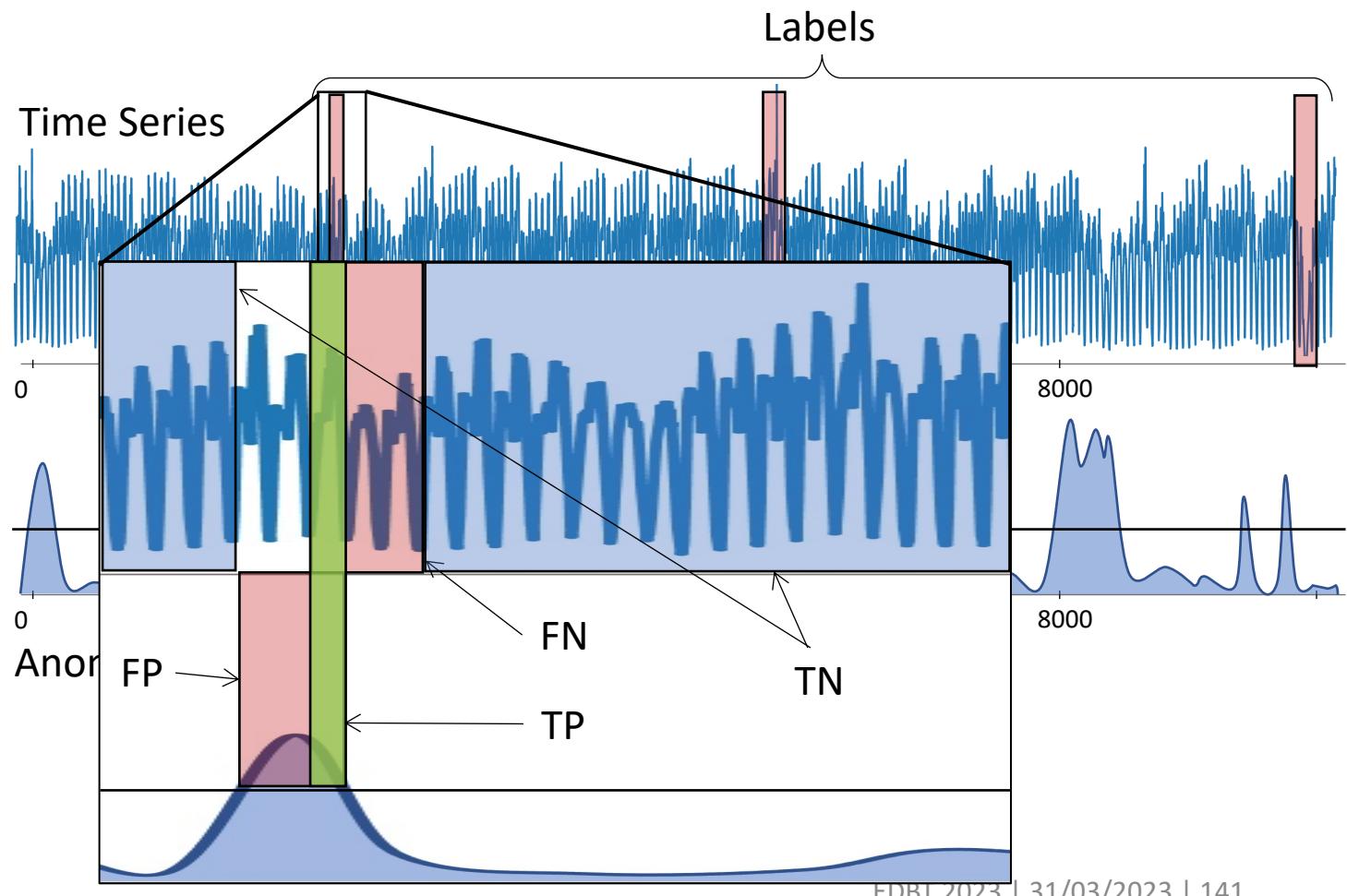
Evaluation measures: *Threshold-based*

Threshold-based Evaluation Measures:



Evaluation measures: *Threshold-based*

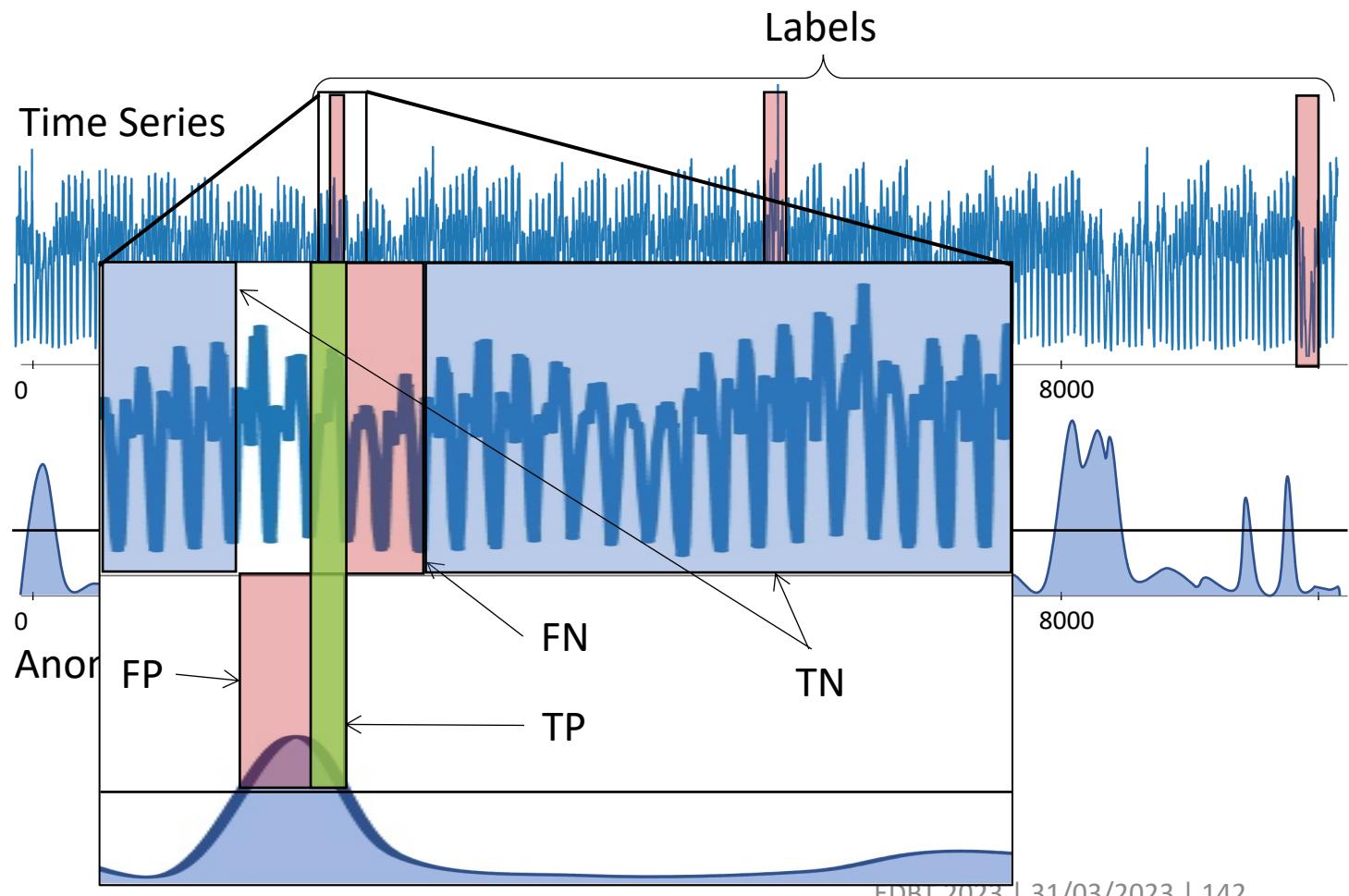
Threshold-based Evaluation
Measures:



Evaluation measures: *Threshold-based*

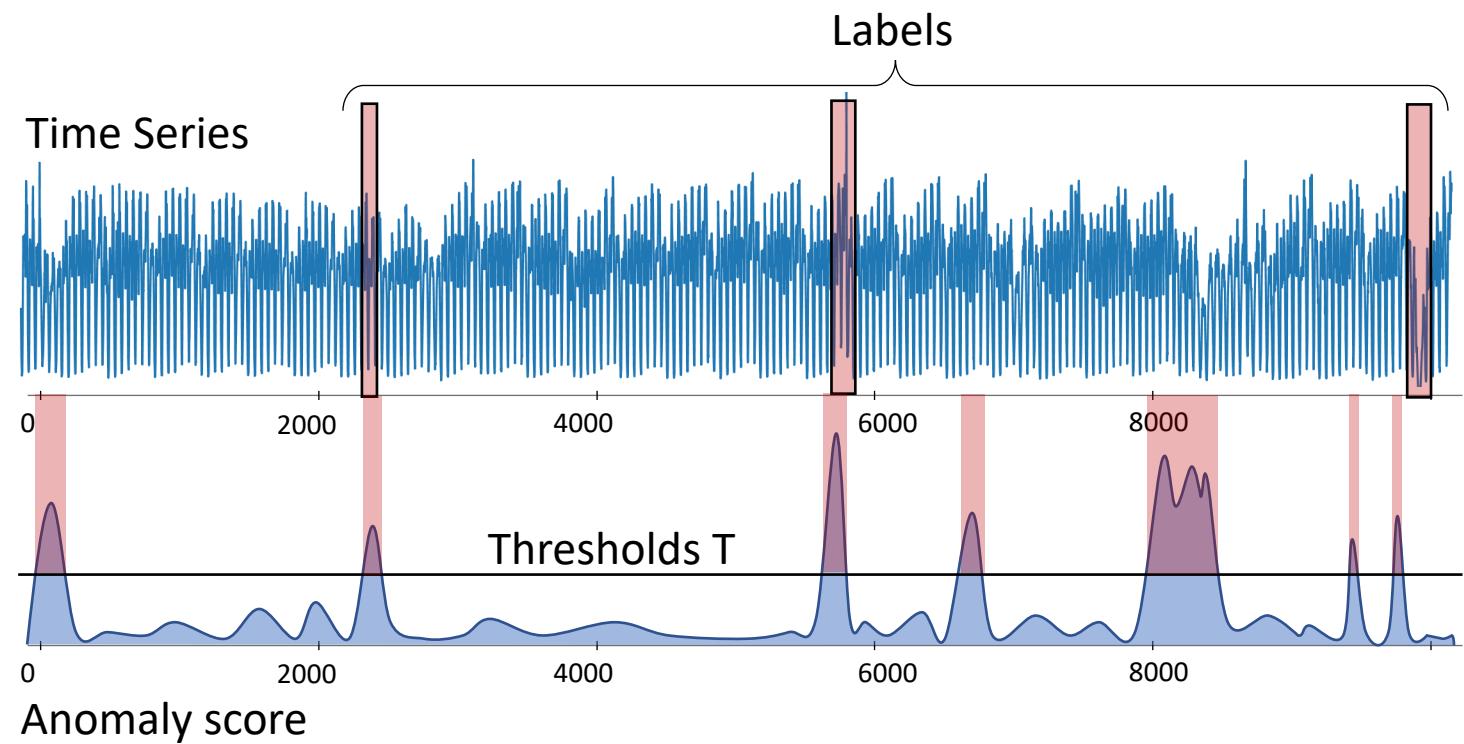
Threshold-based Evaluation Measures:

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



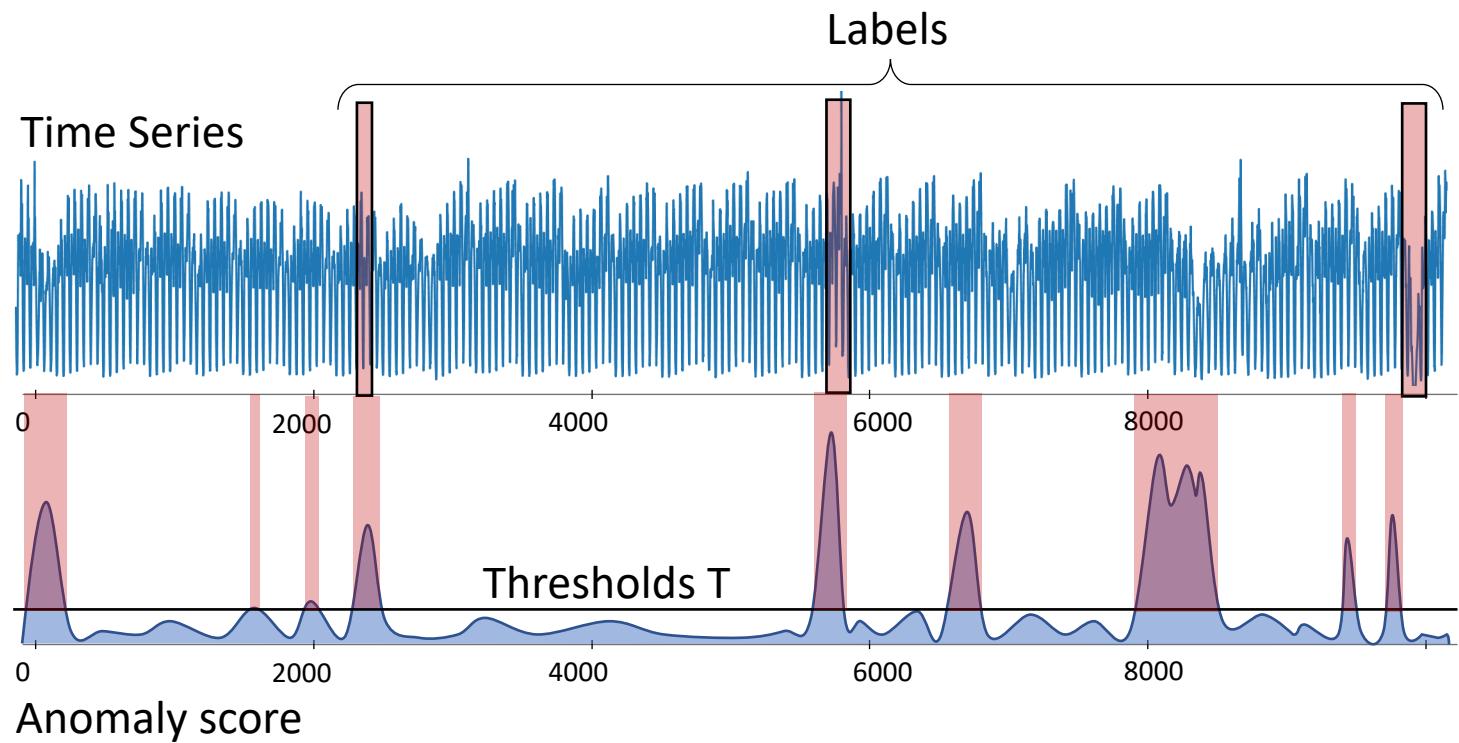
Evaluation measures: *AUC-based*

How do we set the threshold?



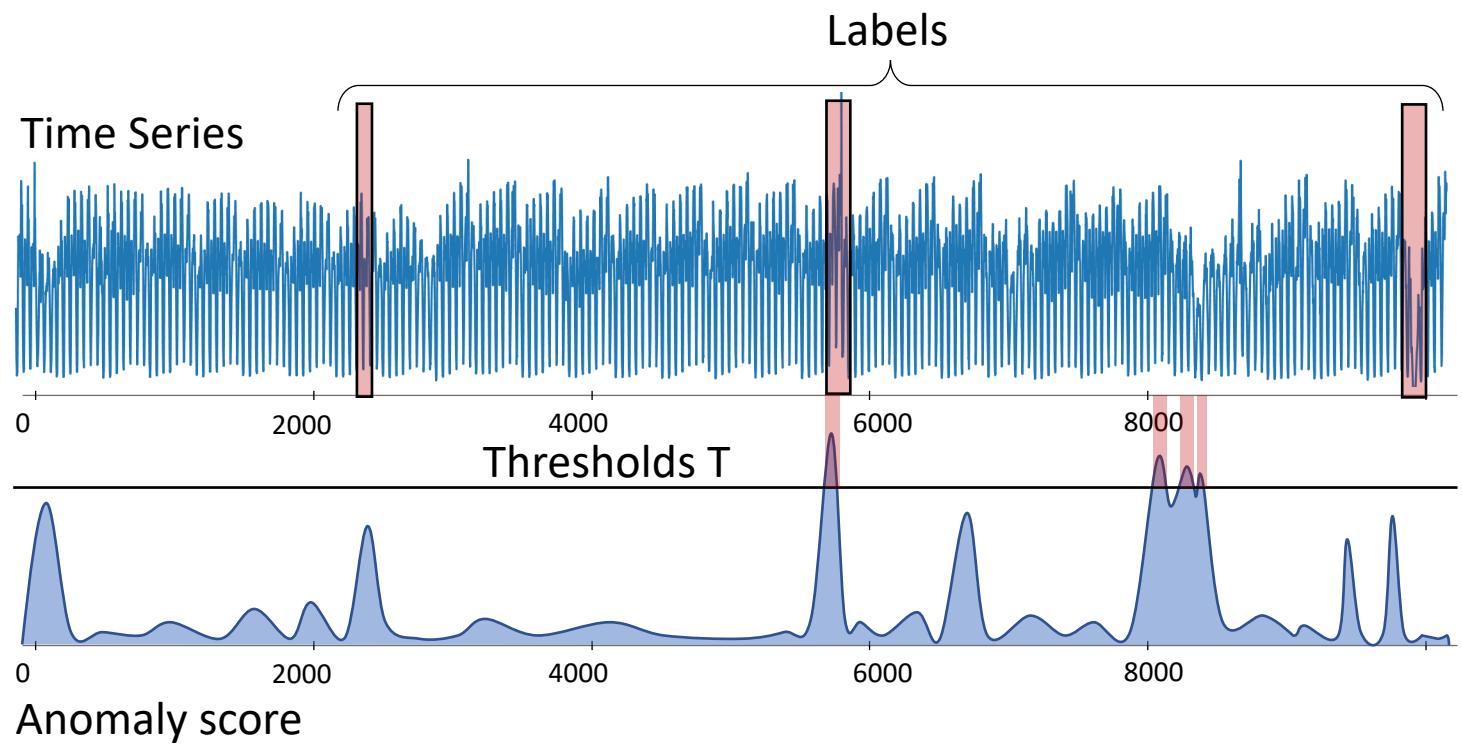
Evaluation measures: *AUC-based*

How do we set the threshold?

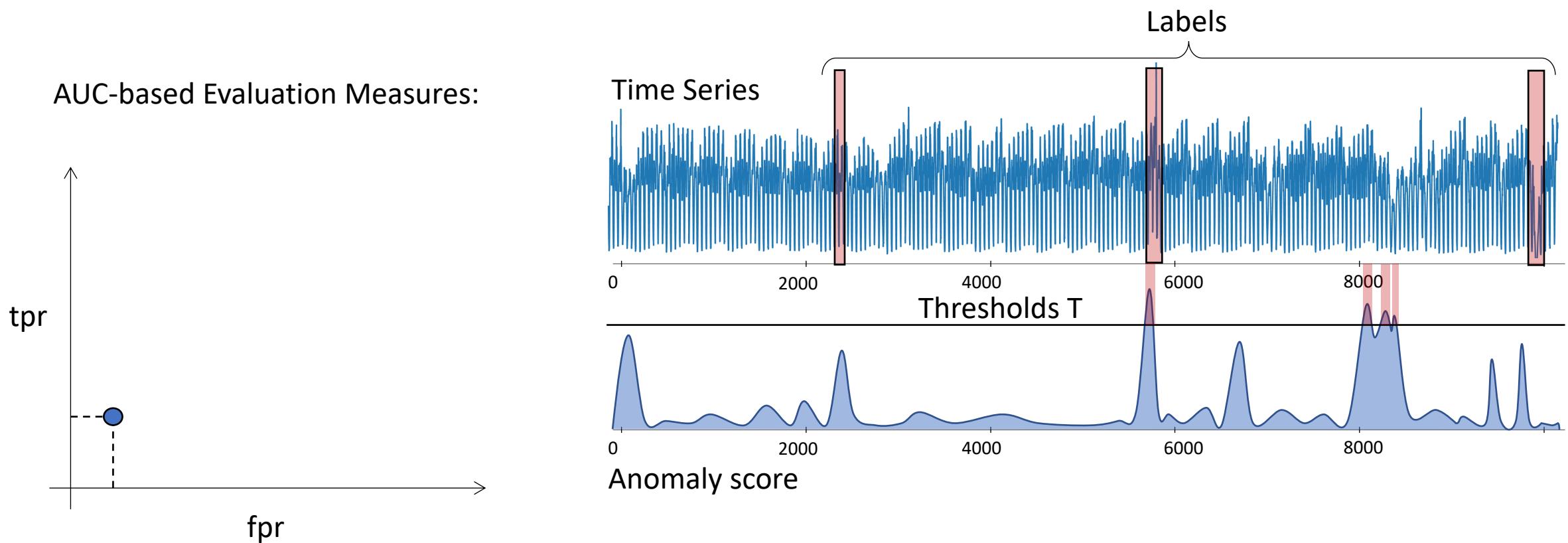


Evaluation measures: *AUC-based*

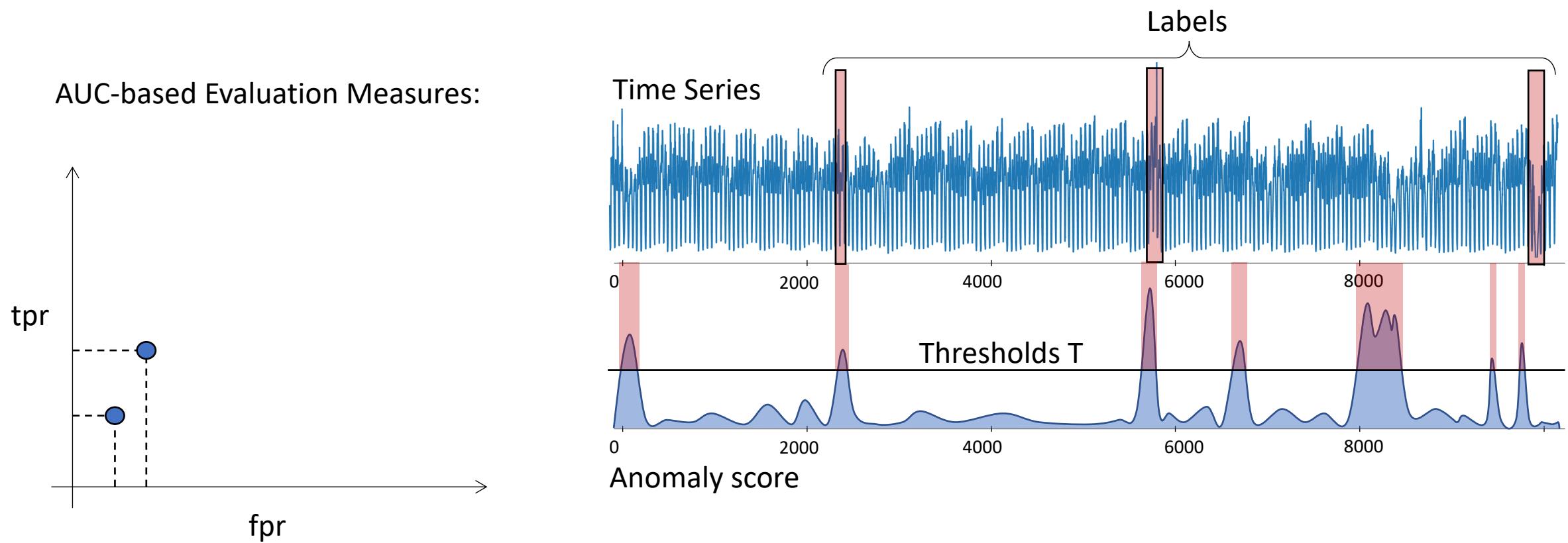
How do we set the threshold?



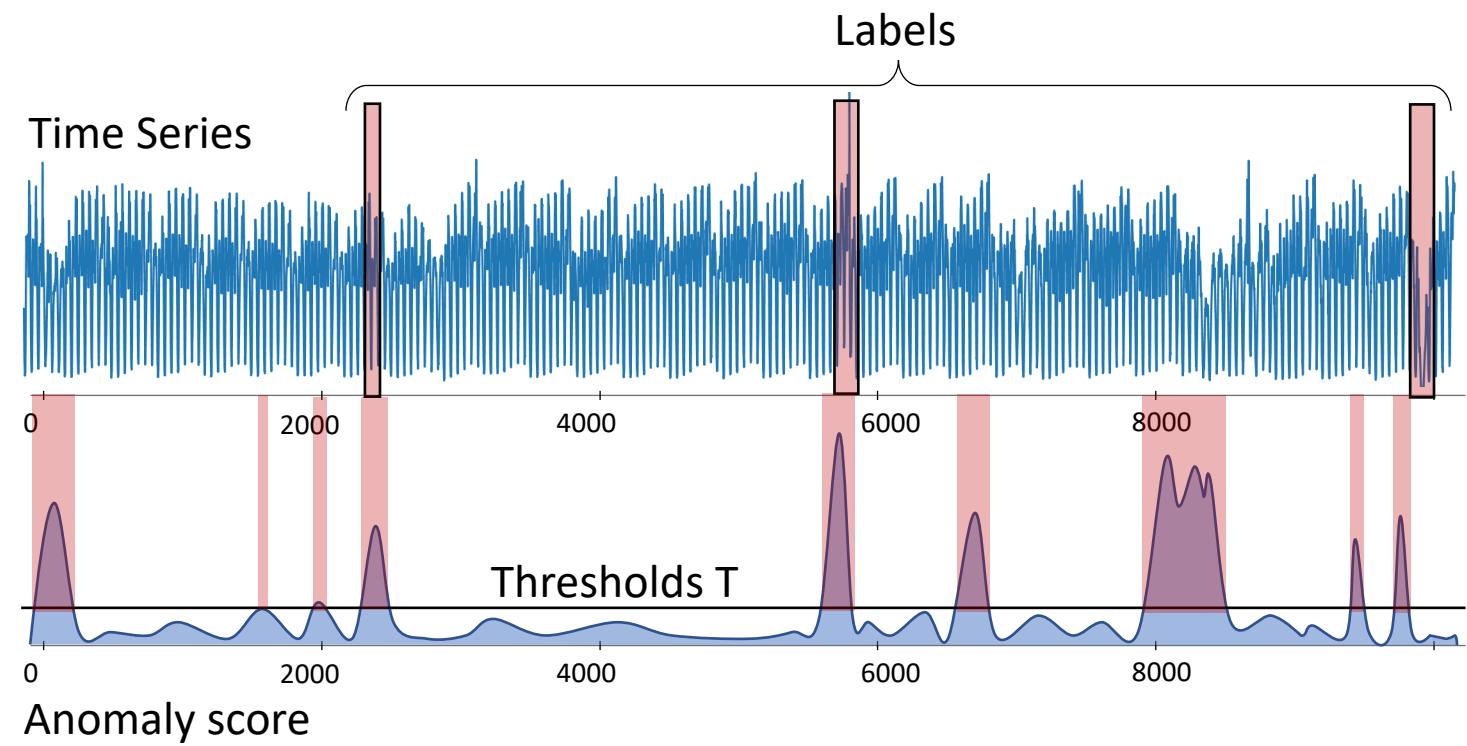
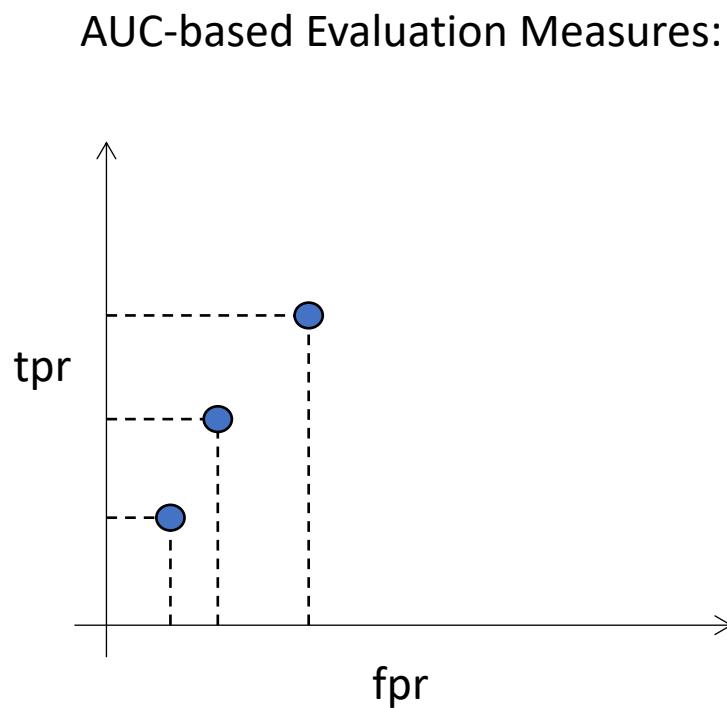
Evaluation measures: *AUC-based*



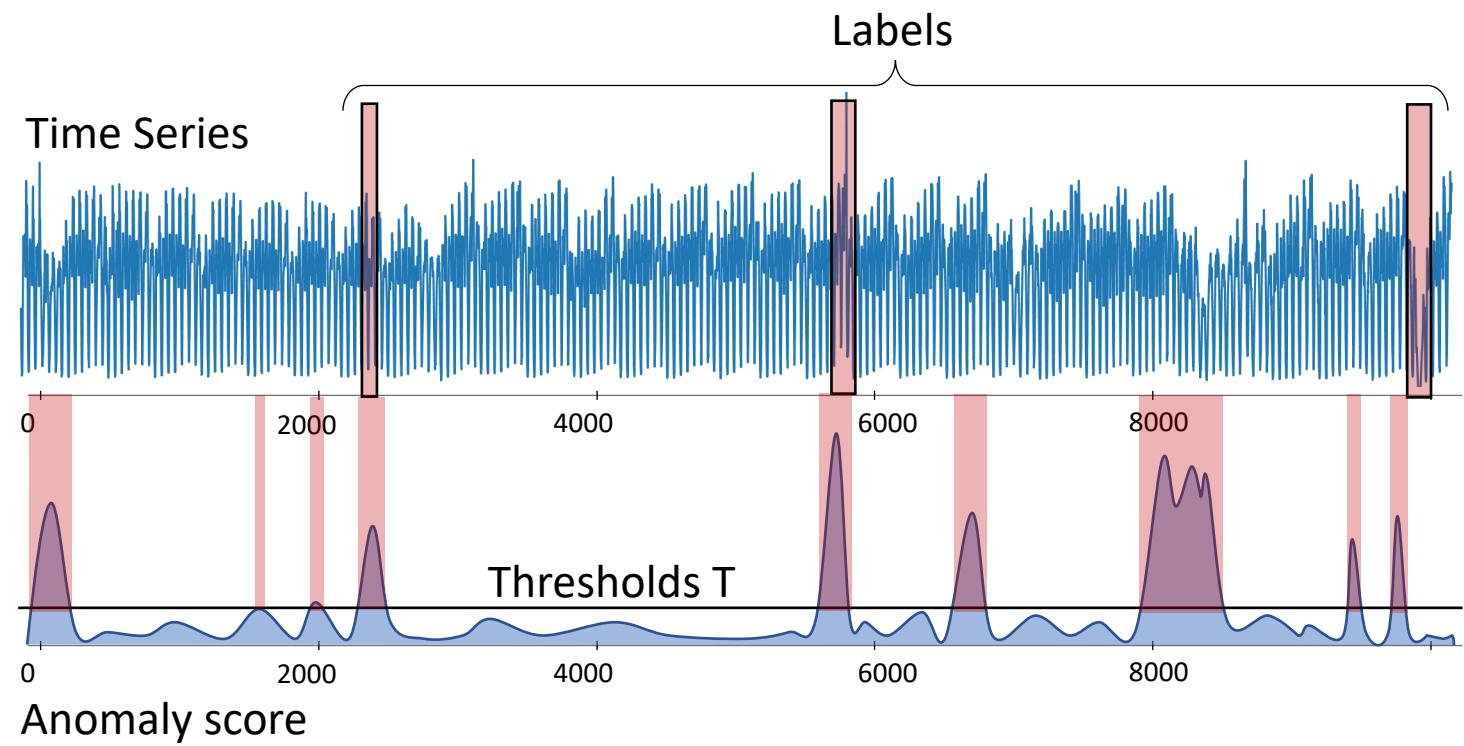
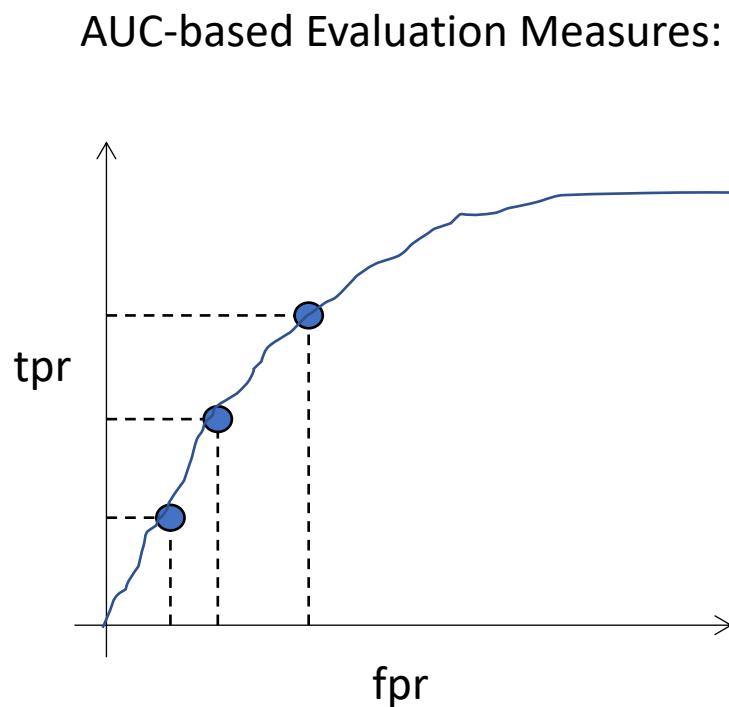
Evaluation measures: *AUC-based*



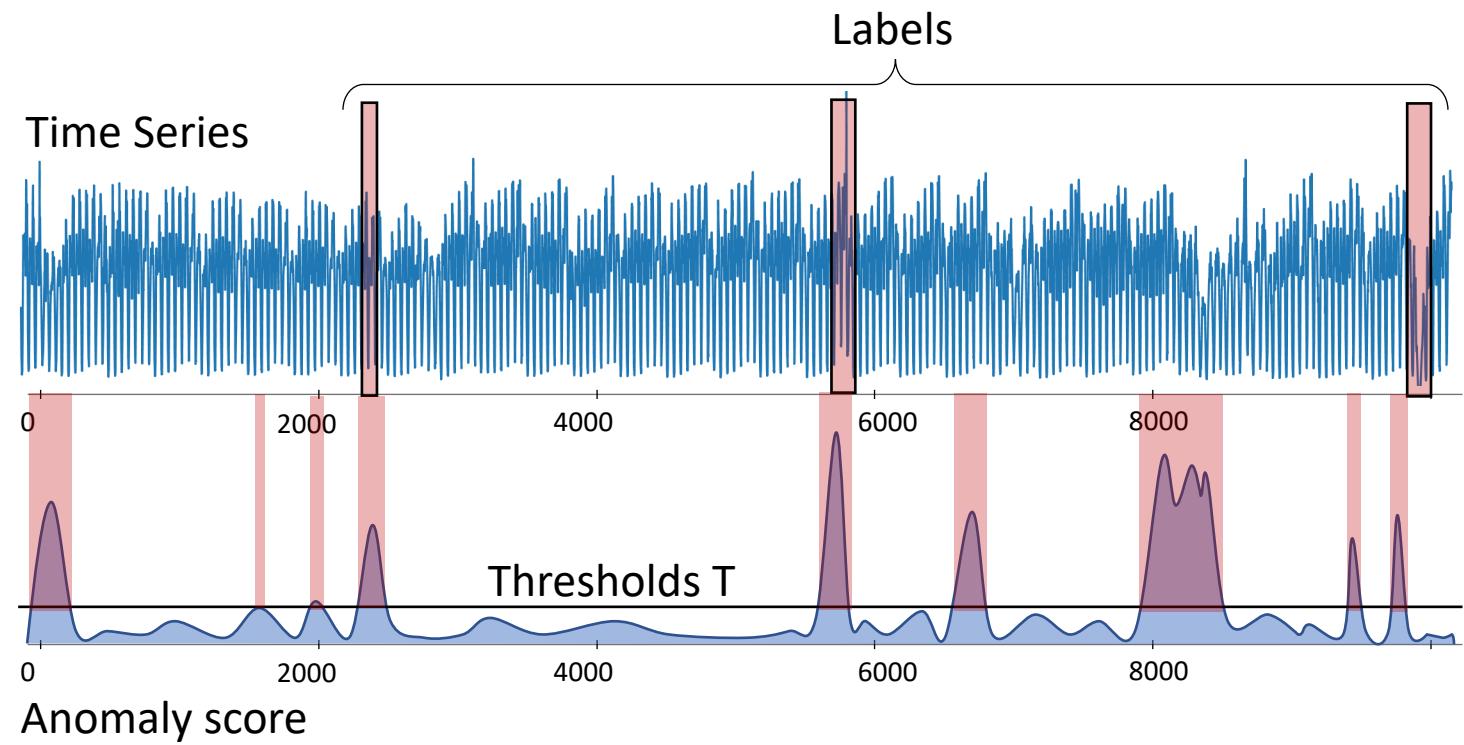
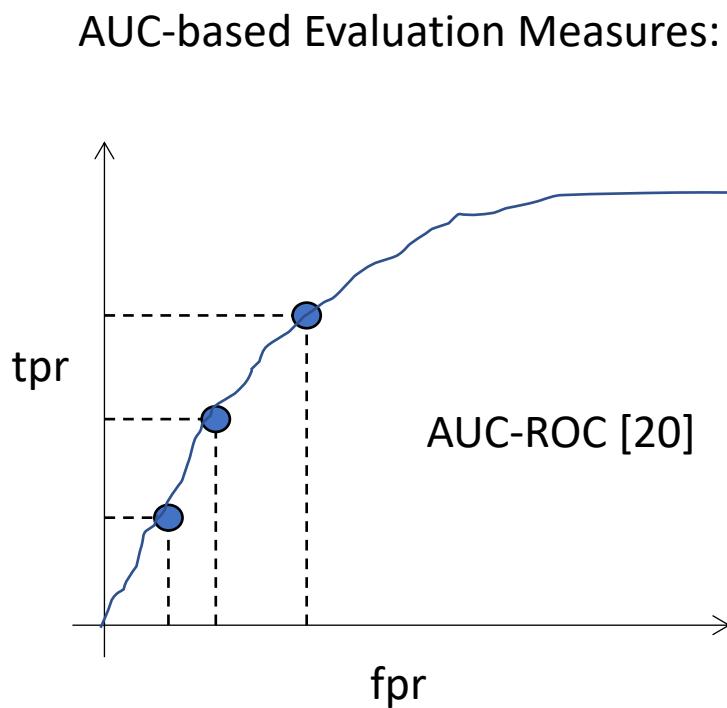
Evaluation measures: *AUC-based*



Evaluation measures: *AUC-based*

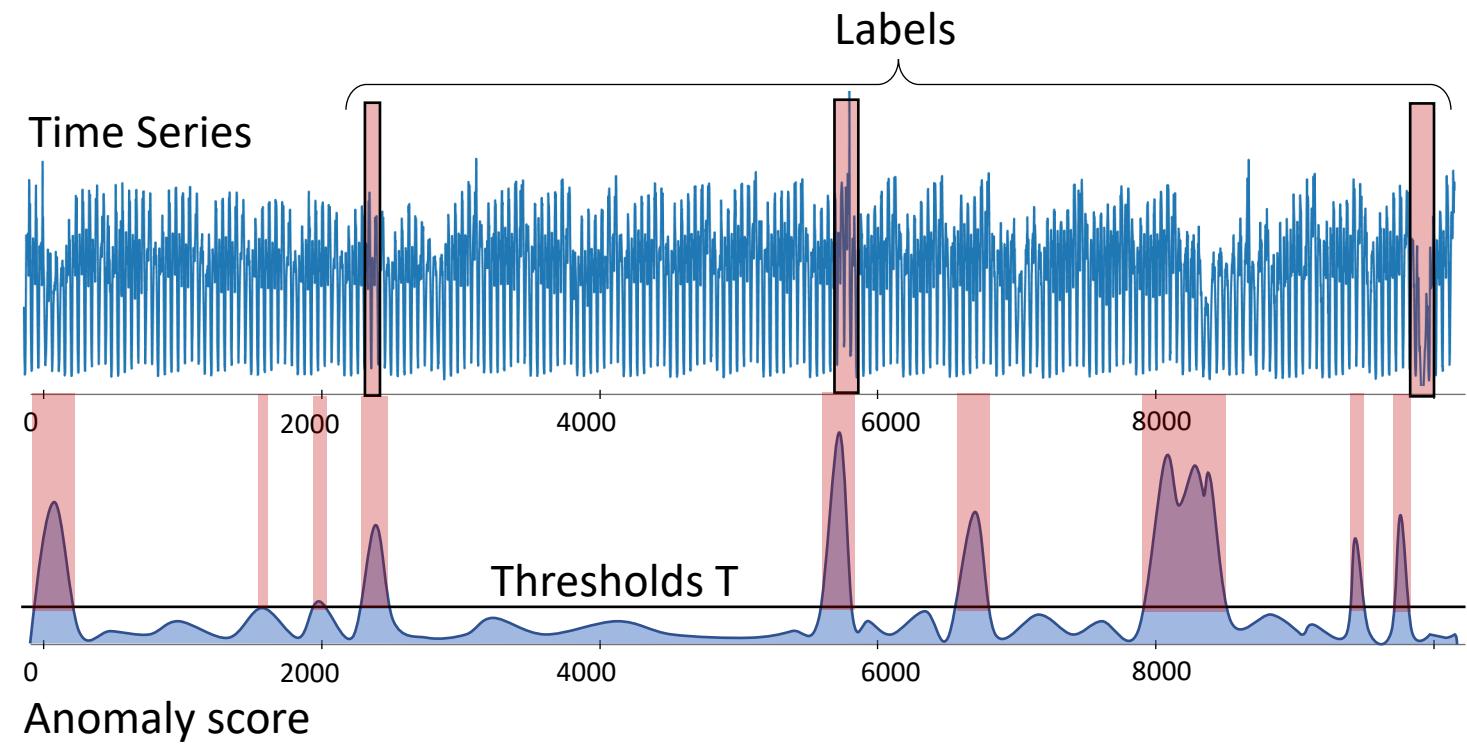
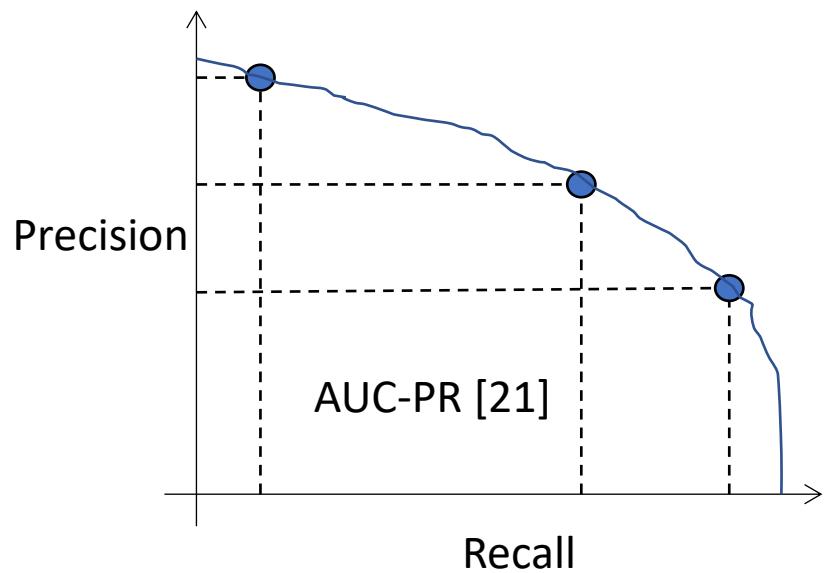


Evaluation measures: *AUC-based*



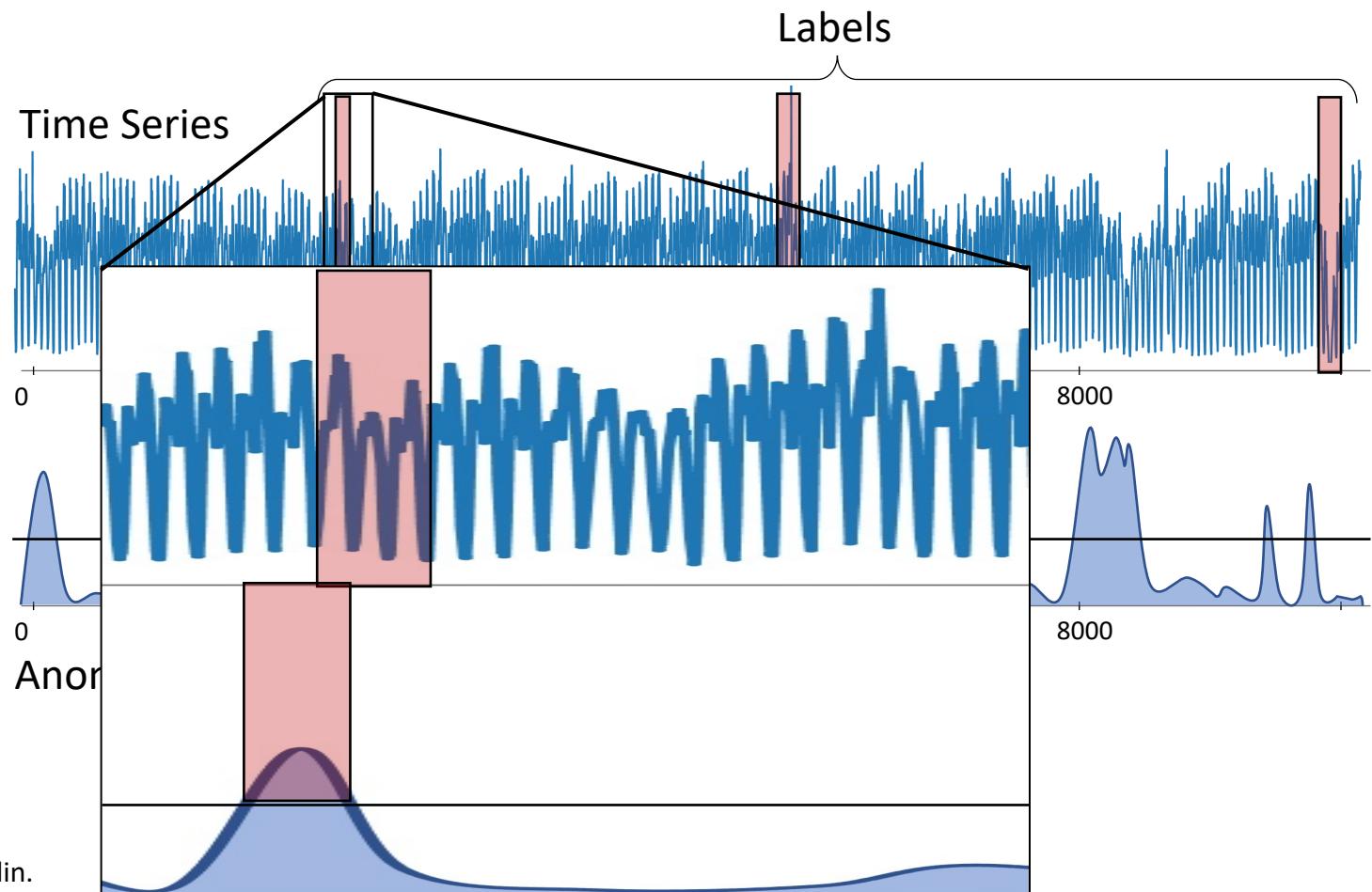
Evaluation measures: *AUC-based*

AUC-based Evaluation Measures:



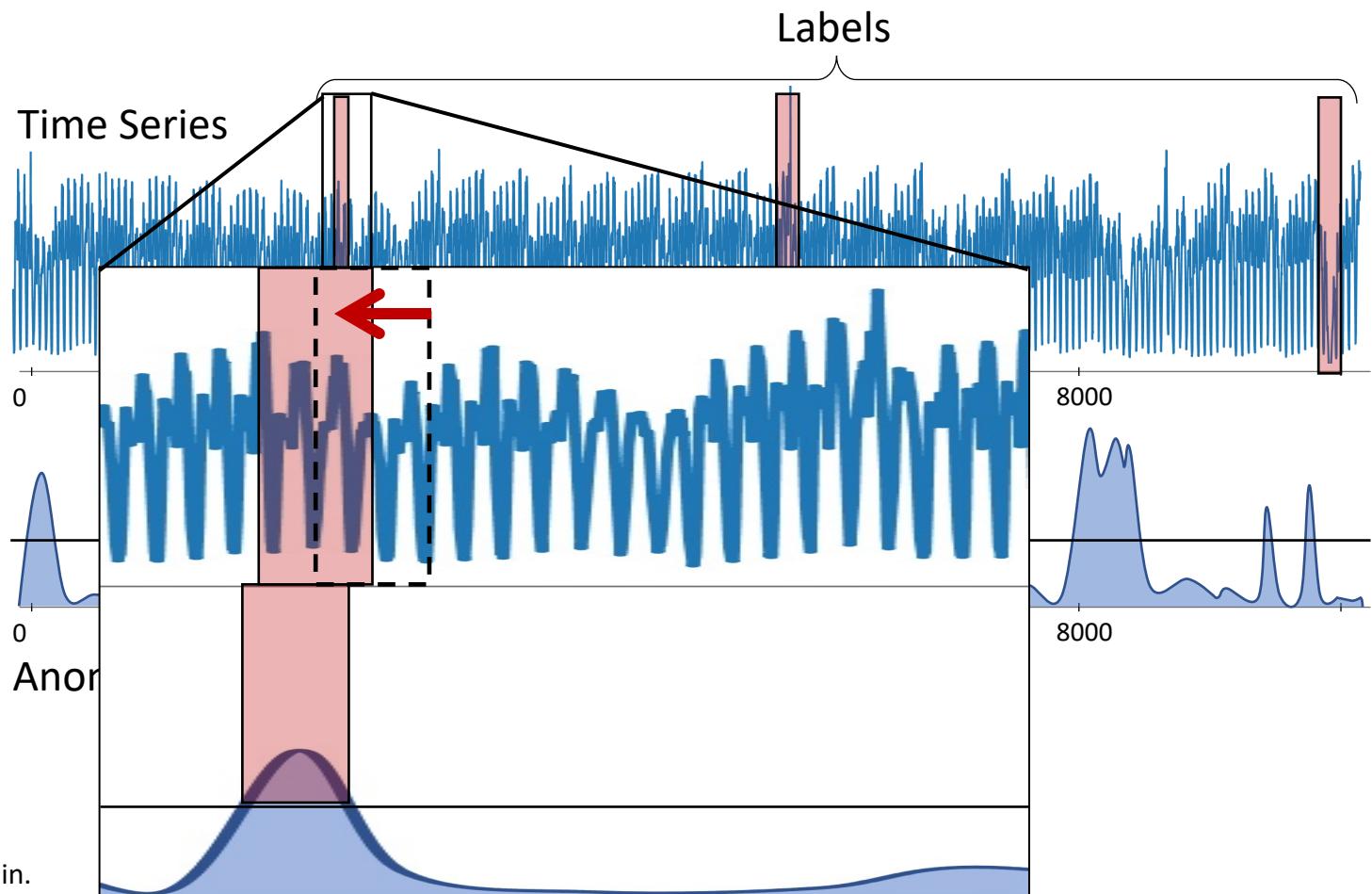
Evaluation measures: *Labeling issue*

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



Evaluation measures: *Labeling issue*

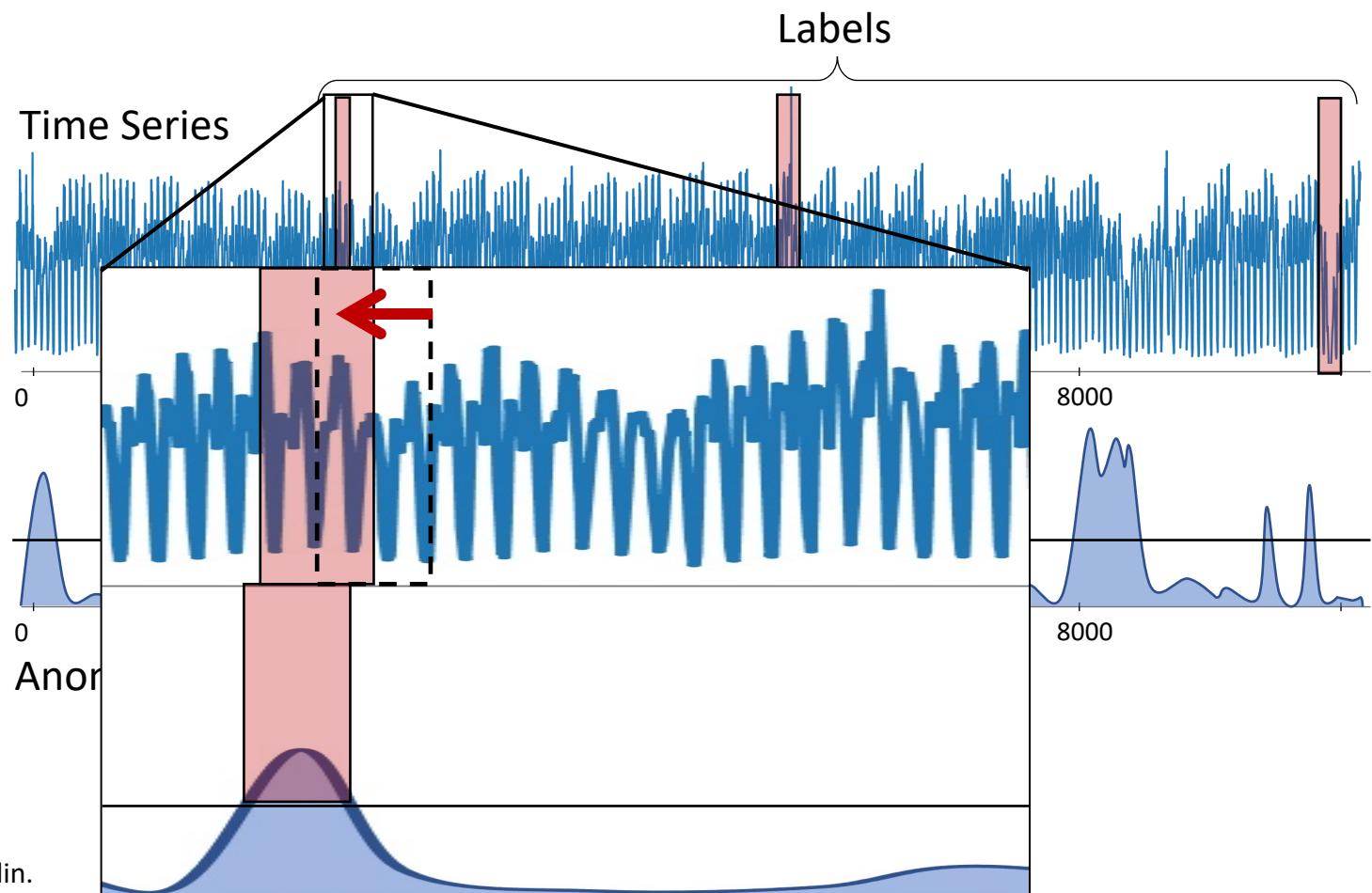
Labeling can be an issue for time series [22]:



Evaluation measures: *Labeling issue*

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

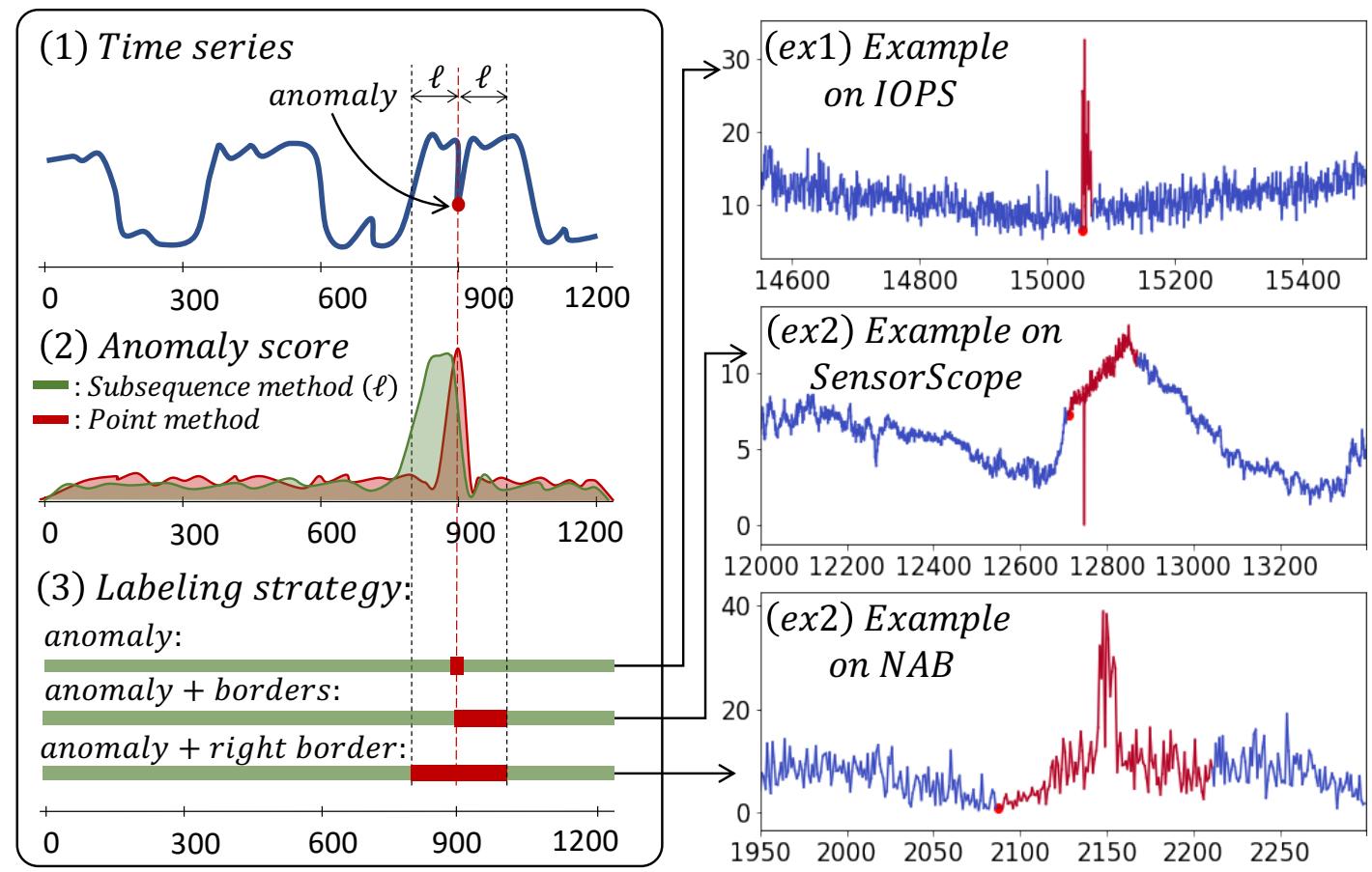
- Misalignment can lead to significant changes of accuracy values.



Evaluation measures: *Labeling issue*

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

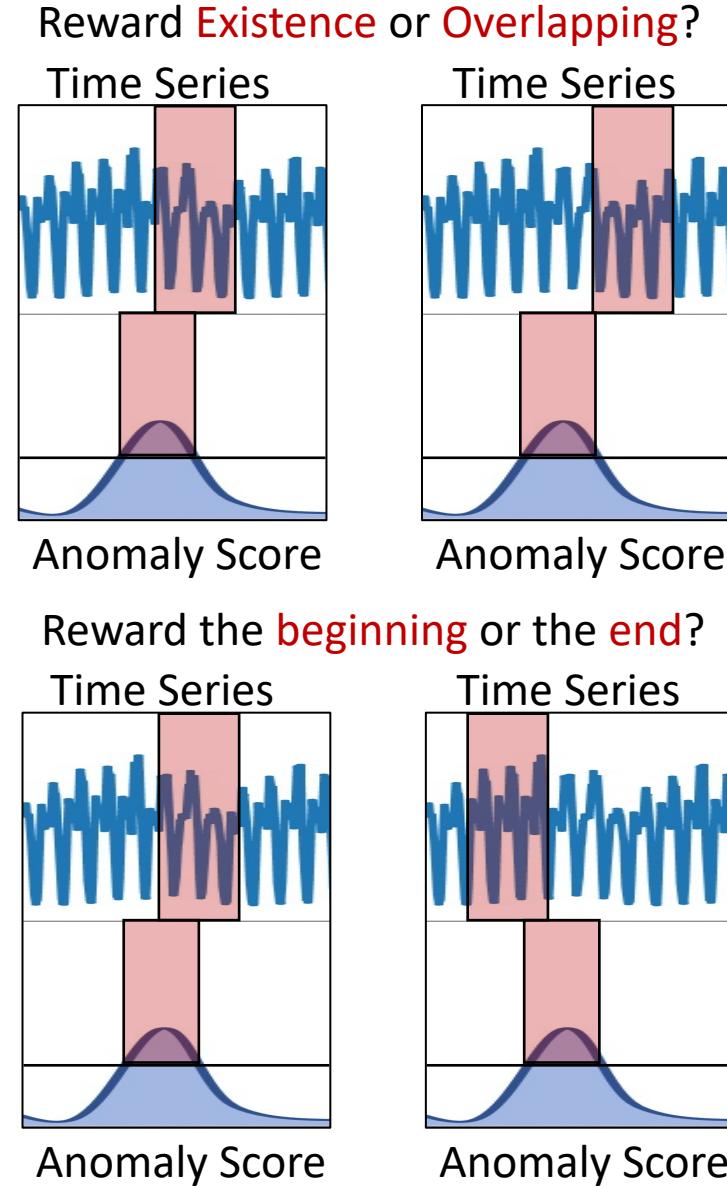
- Misalignment can lead to significant changes of accuracy values.
- This is a real issue because of:
 - **Different Labeling strategies** between domains and applications
 - Methods that produce **misaligned anomaly scores**.



Evaluation measures: *Labeling issue*

Existing solutions:

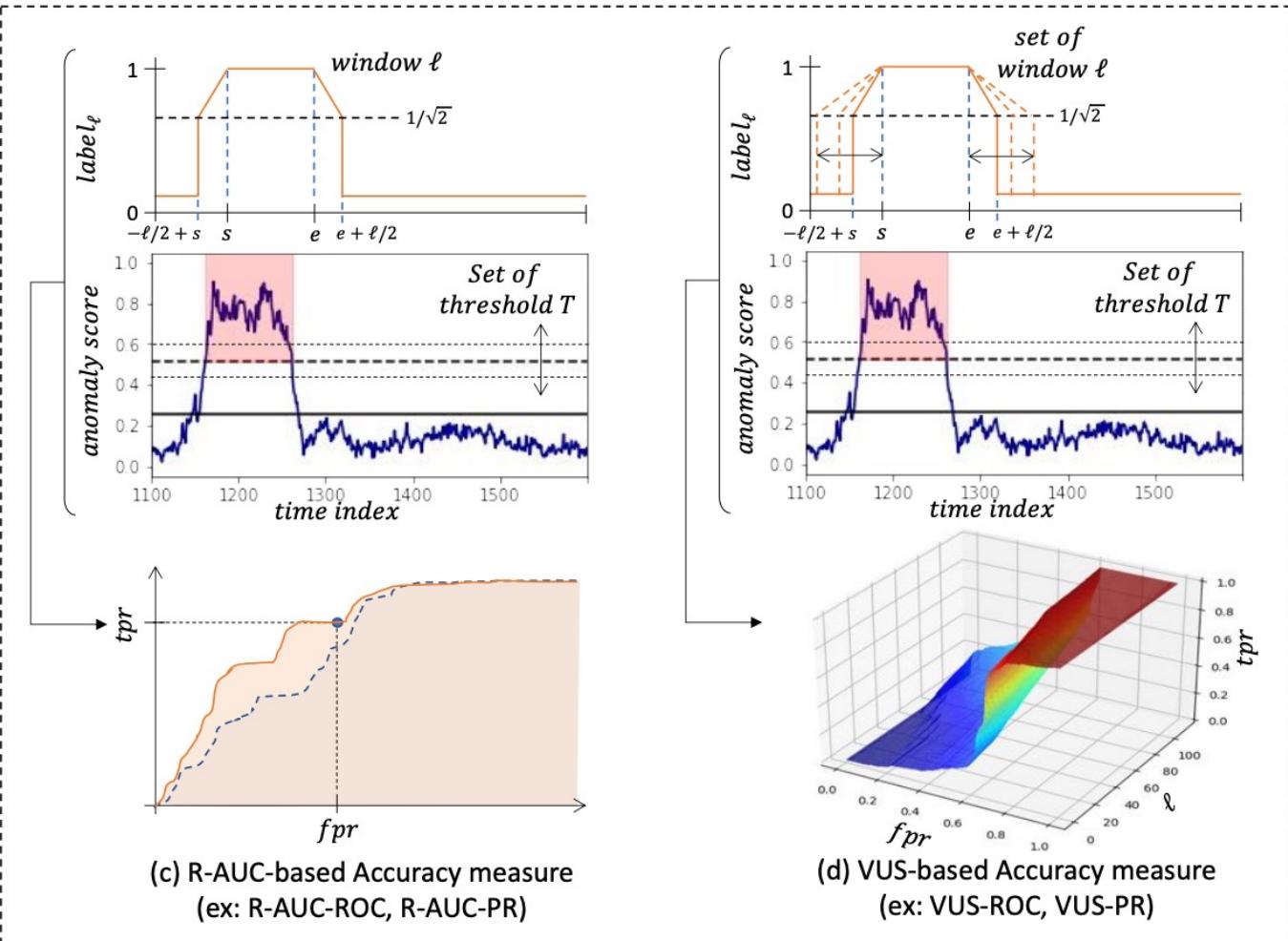
- Range Precision and Recall [23]:
- $Recall_T(R, P) = \frac{\sum_{i=1}^{N_r} Recall_T(R_i, P)}{N_r}$
- $Recall_T(R_i, P) = \alpha * ExistenceR(R_i, P) + (1 - \alpha) * OverlappingR(R_i, P)$
- $Precision_T(R, P) = \frac{\sum_{i=1}^{N_p} Precision_T(R, P_i)}{N_p}$
- $Precision_T(R, P_i) = CardinalityFactor(P_i, R) * \sum_{j=1}^{N_r} w(P_i, P_i \cap R_j, \delta)$
- Functions $w()$, $\delta()$ are tunable functions to represent the overlap size and position respectively.



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



Conclusion and Open Problems

Conclusion and Open Problems

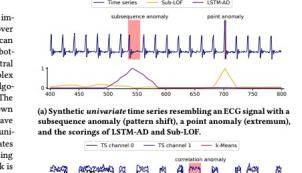
If you are interested in anomaly detection in time series...

Anomaly Detection in Time Series: A Comprehensive Evaluation

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1. ANOMALY DETECTION WILDERNESS

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

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

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

1.1.1.0

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

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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 either (i) use synthetic datasets that have been built 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 seemingly poorly in another, raising an important question: To address this issue, 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 suite for univariate time-series anomaly detection methods. Overall, TSB-UAD contains 1790 univariate 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 univariate time series and we combine two types of datasets. Specifically, we generate 958 time series using a primary methodology for generating 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 1082 time series with varying degrees of difficulty for anomaly detection. Finally, we provide 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.

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 benchmarks of evaluating existing solutions (notable examples [98, 60, 108, 109, 114, 115]). 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 standards in the literature for evaluating AD methods: (i) a primary methodology for generating datasets 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, leading to false claims, artificially types, or anomalies. In the latter case, while a small number 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, ambiguity and the still-different interpretation of anomalies across applications further hinders progress. It is not uncommon for methods to achieve high accuracy for some

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

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

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

comicsenses.net/2020

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 if it driven by the success of deep learning in other domains. At the same time, there has been a lack of a comprehensive taxonomy and a collection of popular benchmarks datasets, created by Yahoo, Numeria, 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 illusory. 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 at nearly every major data mining, machine learning, and data mining conference, including SIGKDD [2], 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.¹ 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, hidden size, window size, weight decay, batch size. All of this is to demonstrate “accuracy exceeding 9.90 (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

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

published comparisons of anomaly detection algorithms may be unreliable. More importantly, we believe that much of the apparent progress in recent years may be

overoptimistic, computational experience working with mosquitoes, and he is impressed.

Suppose however that someone downloaded the origi-

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

comicsenses.net/2020

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

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 [Eslami and Agon 2012; Fu 2011; Ramamahabhan et al. 2010].

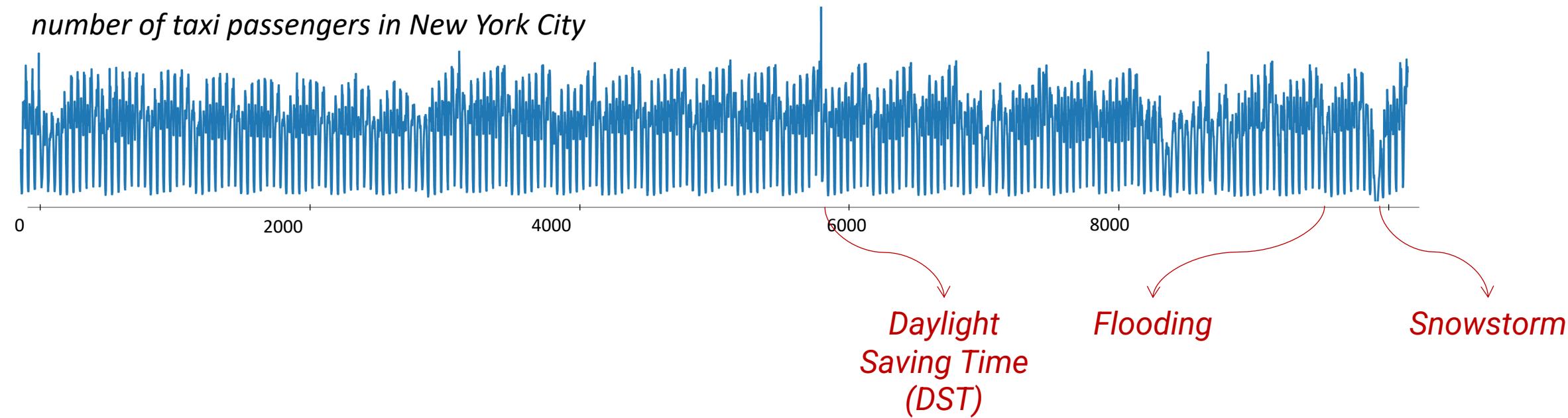
Outlier detection has become a field of interest for many researchers and practitioners and is now one of the main tasks of time series data mining. Outlier detection has been studied in a variety of application domains such as credit card fraud detection, intrusion detection in cybersecurity, or fault diagnosis in industry. In particular, the analysis of outliers in time series data examines anomalous behaviors across time [Gupta et al. 2014]. In the first study on this topic, which was conducted by Fox [1972], two types of outliers were identified: 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 [Carreto et al. 2019]; for example, outlier observations are often referred to as anomalies, discordant observations, discards, exceptions, aberrations, surprises, peculiarities or contaminants.

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A. Blázquez-García et al. ACM Computing Survey (2021) [24]

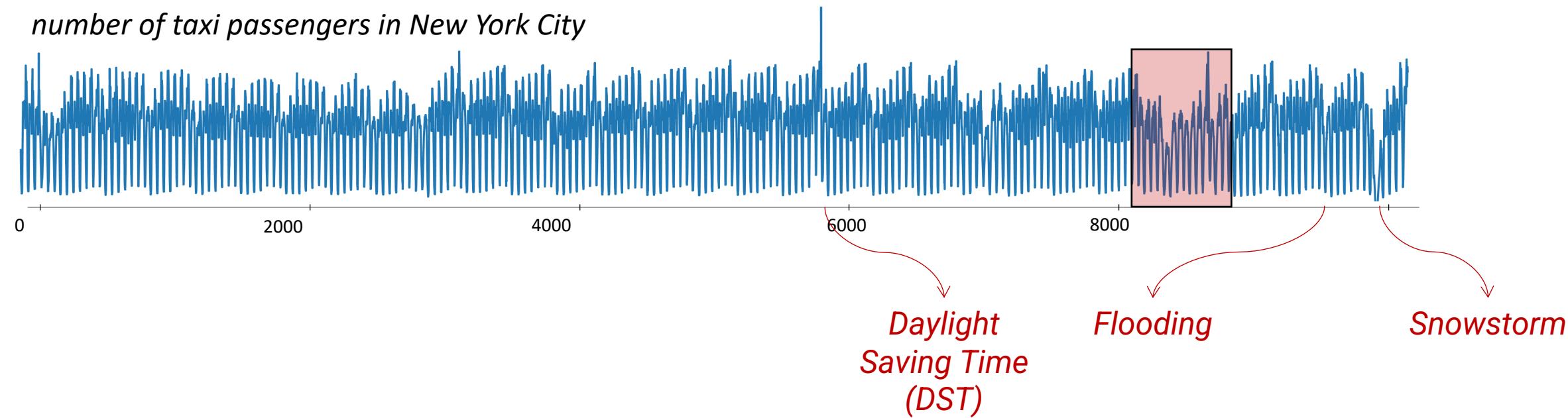
Conclusion and Open Problems

Context-aware Unsupervised Anomaly Detection



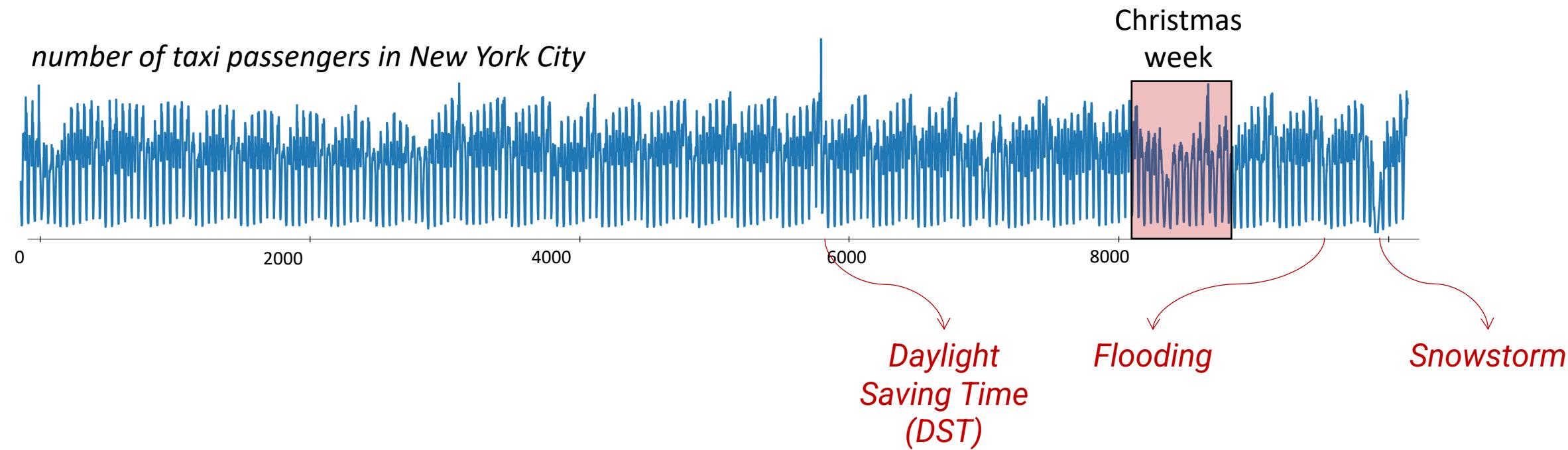
Conclusion and Open Problems

Context-aware Unsupervised Anomaly Detection



Conclusion and Open Problems

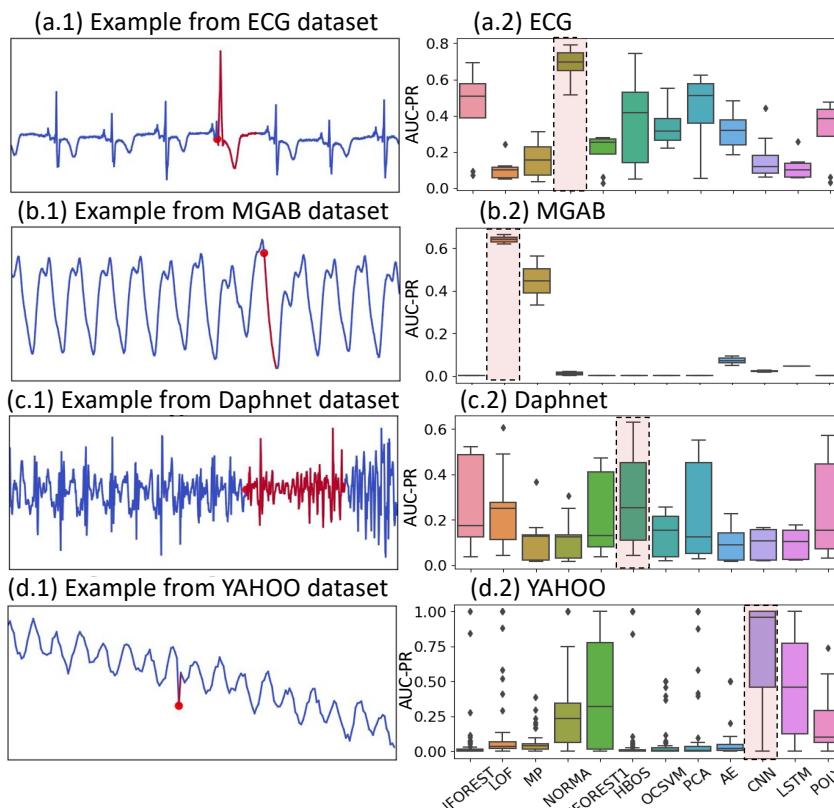
Context-aware Unsupervised Anomaly Detection



Conclusion and Open Problems

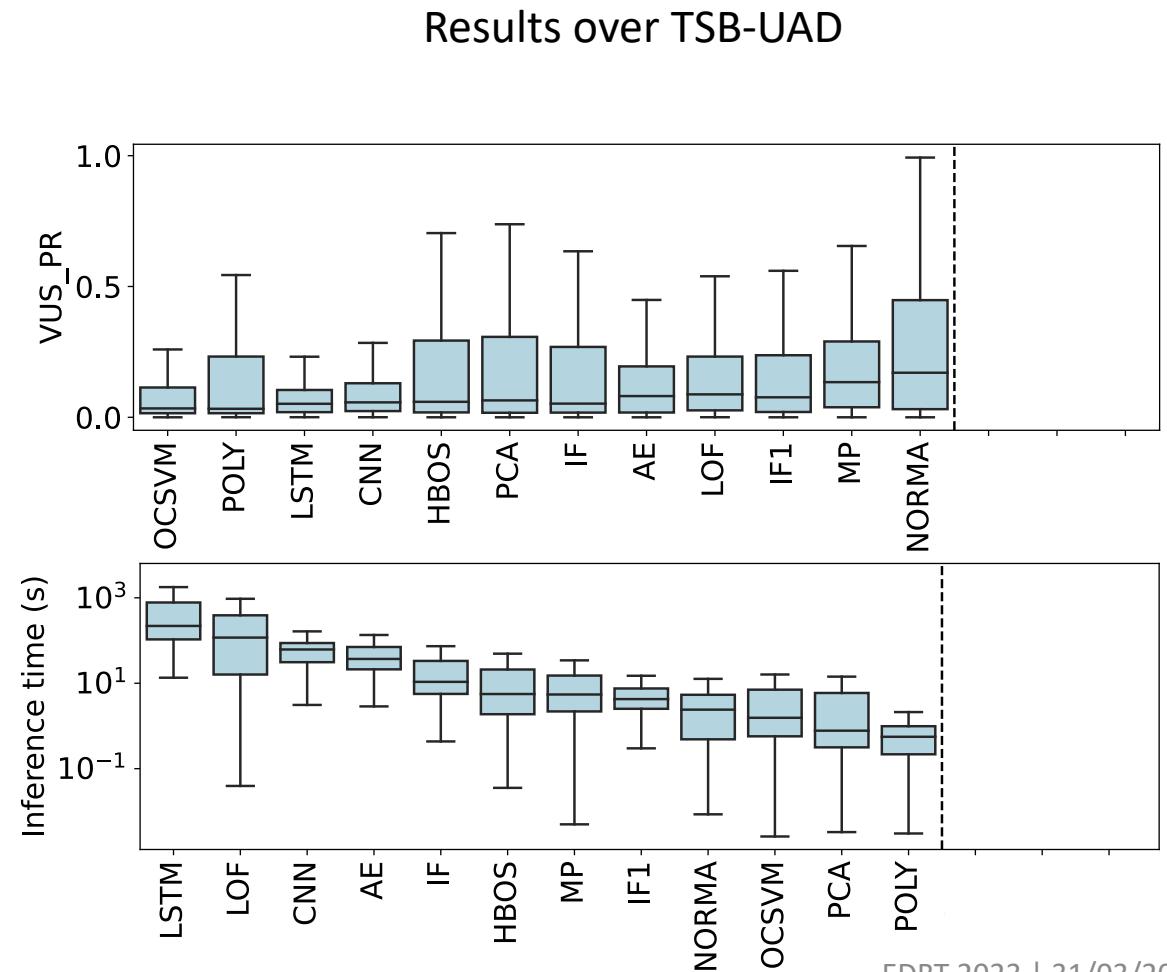
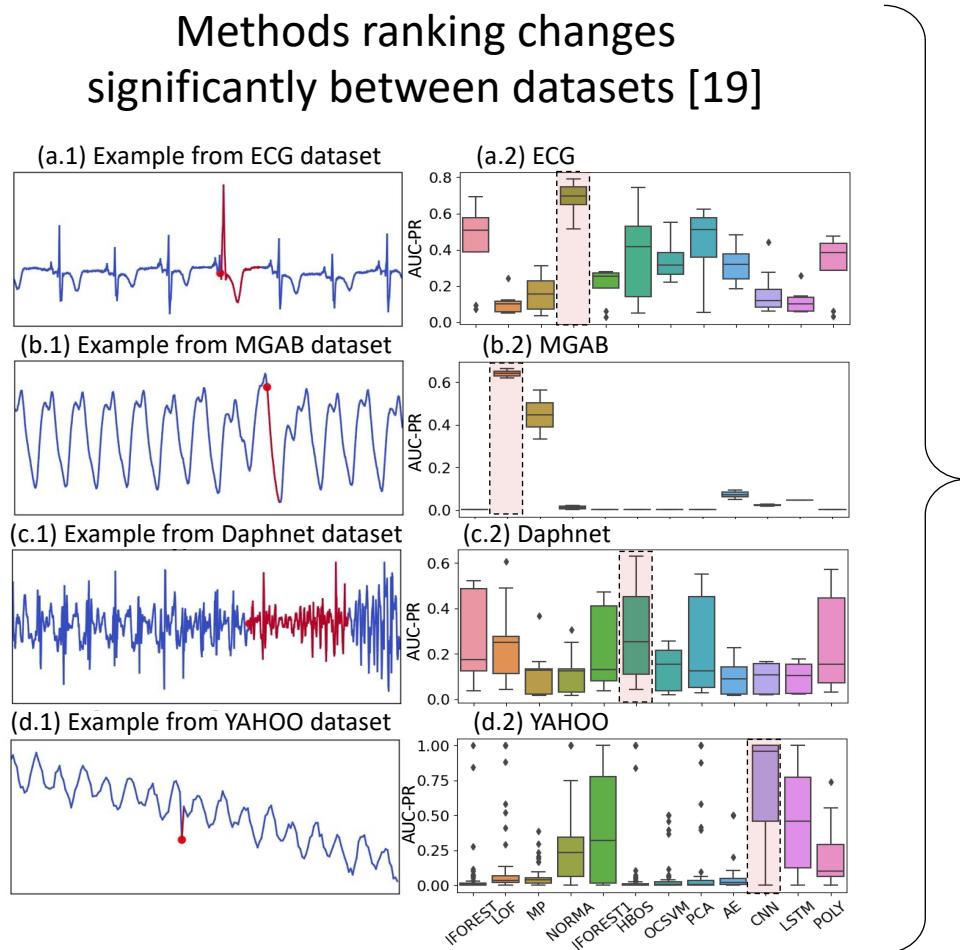
Model selection for anomaly detection

Methods ranking changes
significantly between datasets [19]



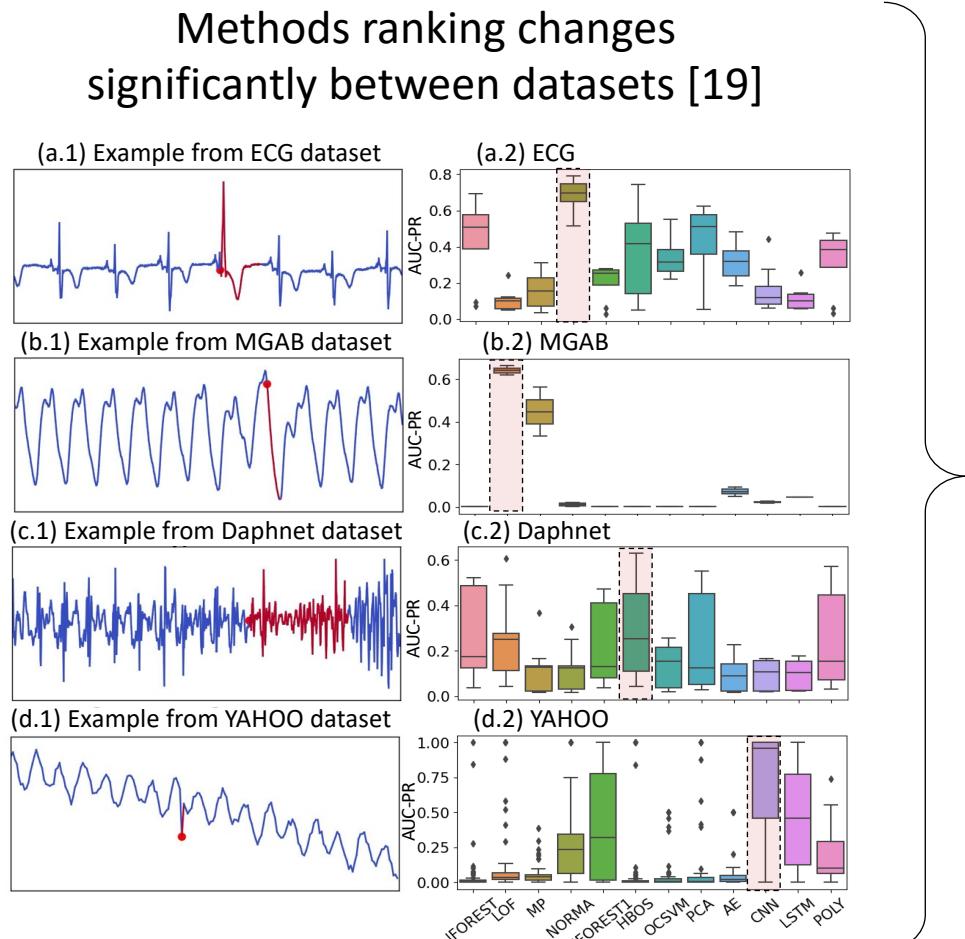
Conclusion and Open Problems

Model selection for anomaly detection

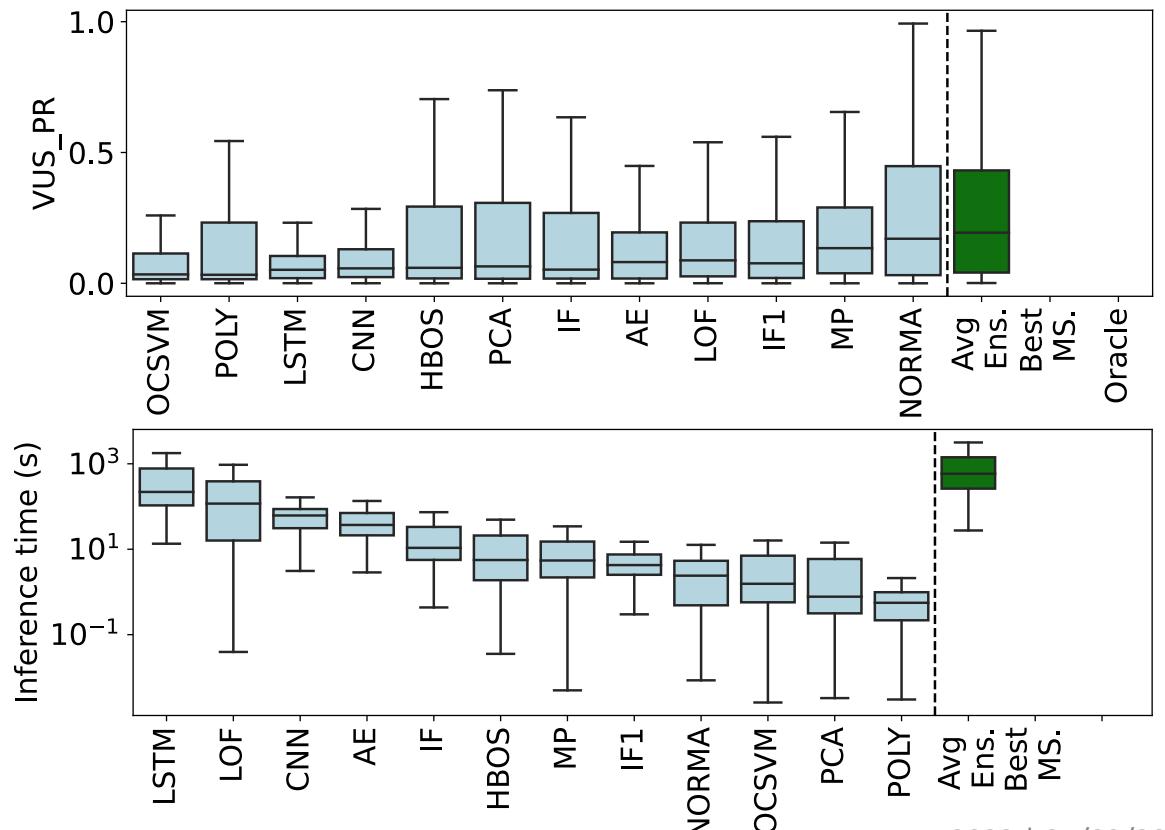


Conclusion and Open Problems

Model selection for anomaly detection

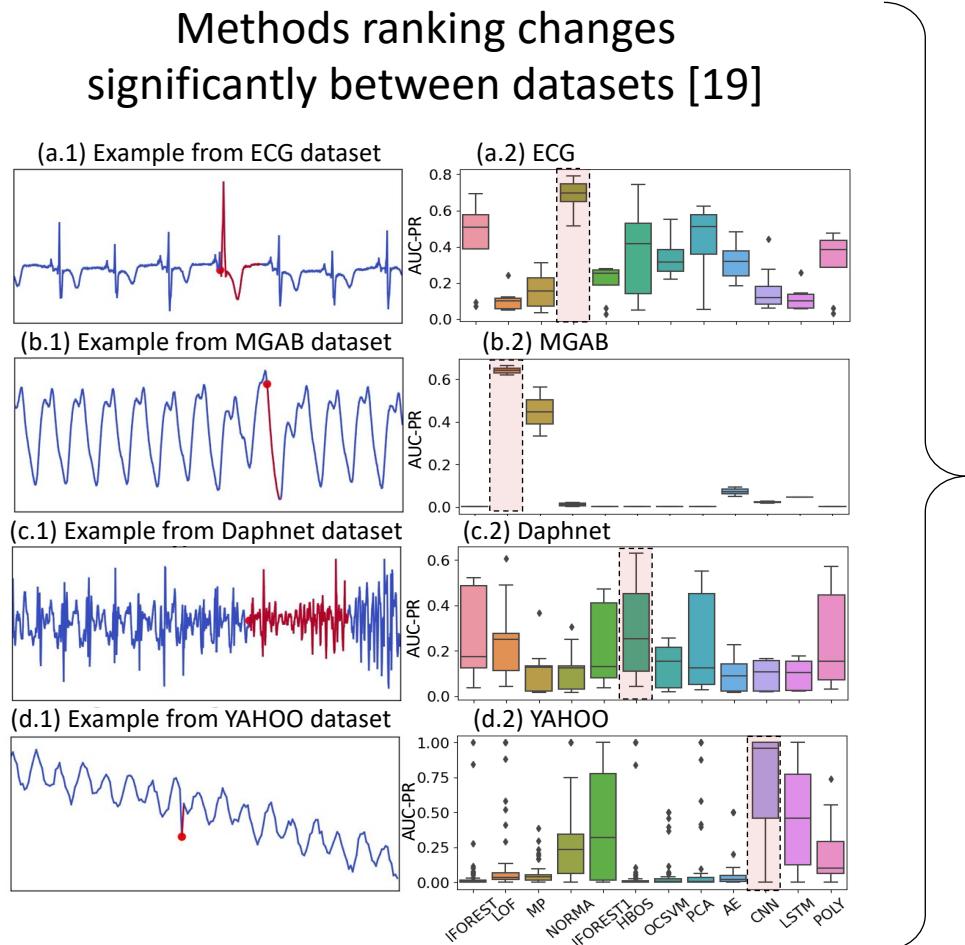


Can *Ensembling* methods solve the problem?

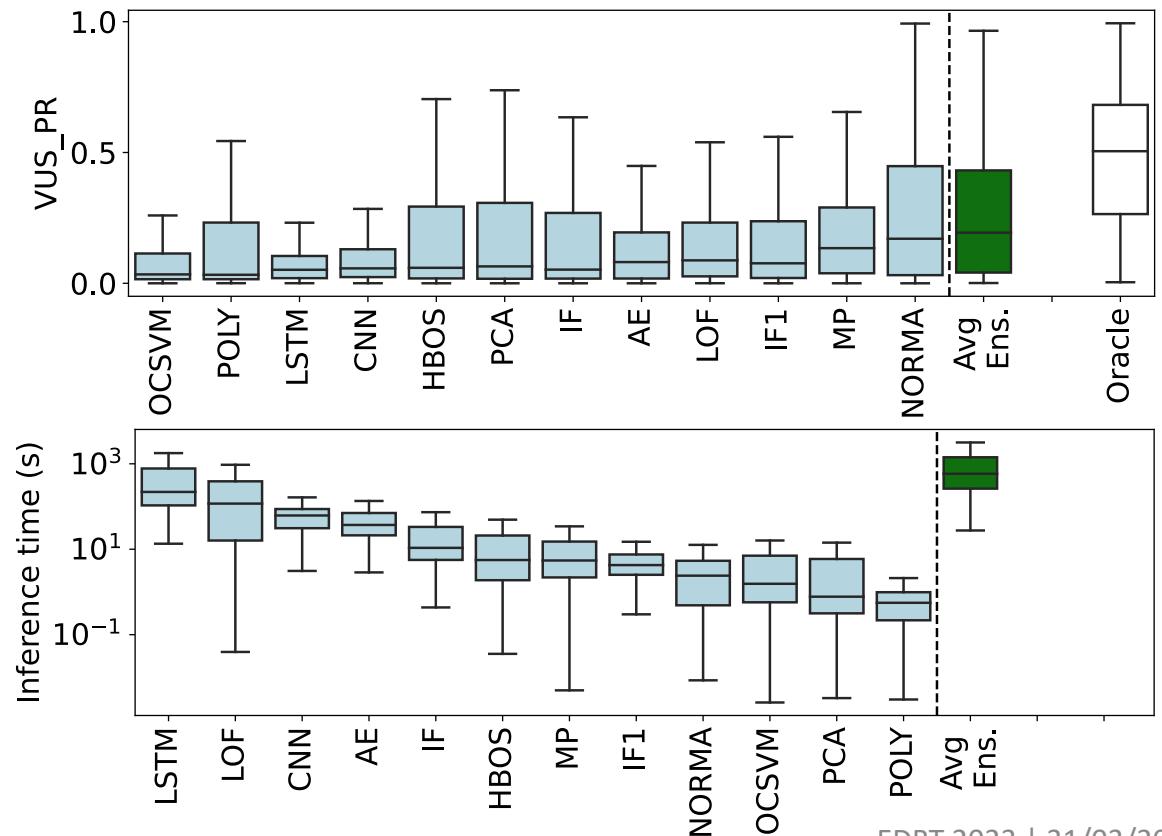


Conclusion and Open Problems

Model selection for anomaly detection

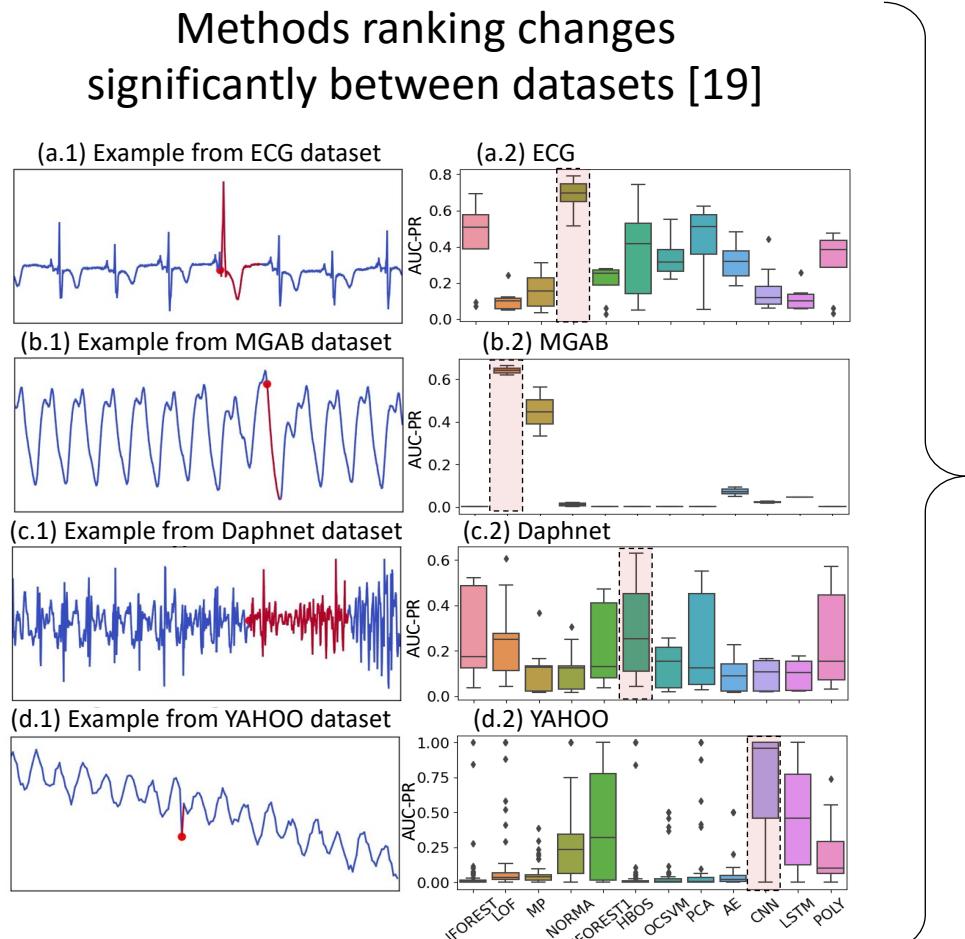


Can *automatic model selection* solve the problem?

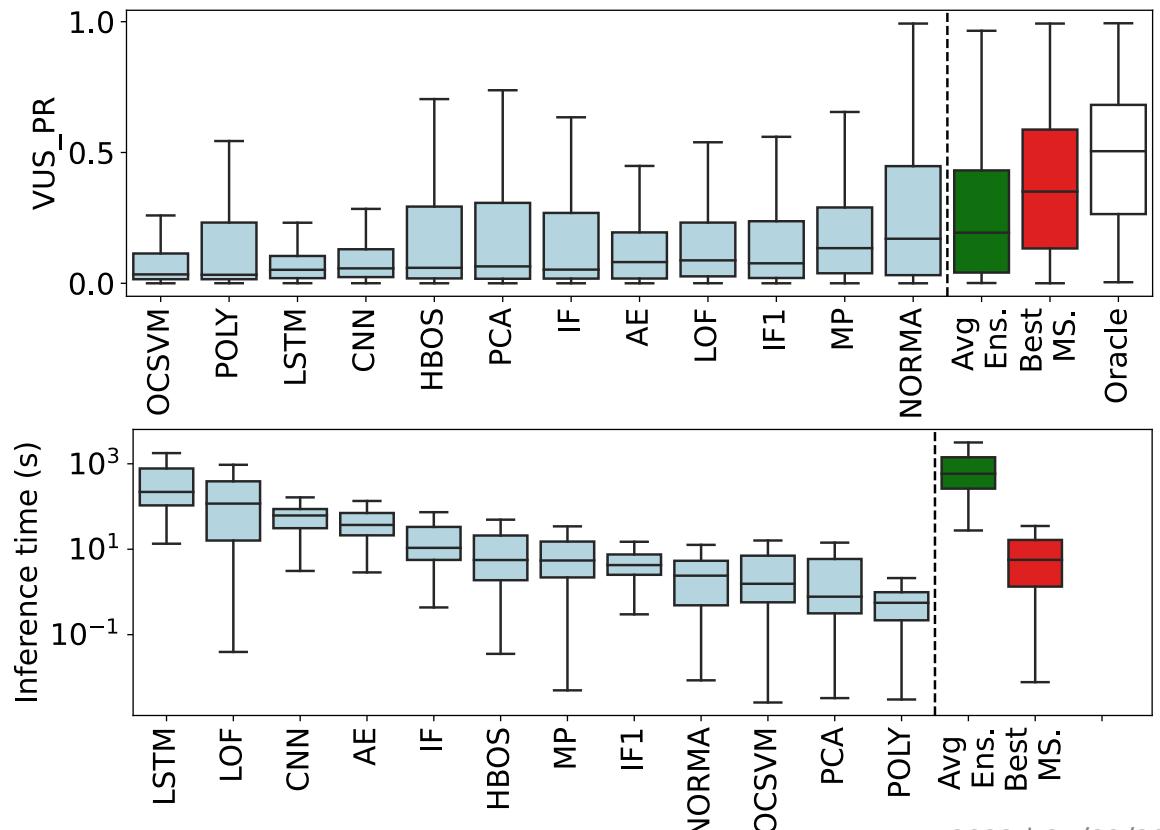


Conclusion and Open Problems

Model selection for anomaly detection



Can *automatic model selection* solve the problem?



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Thank you for attending!

Any Questions?