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Time-Series xAI Methods

Faizan Ahmed

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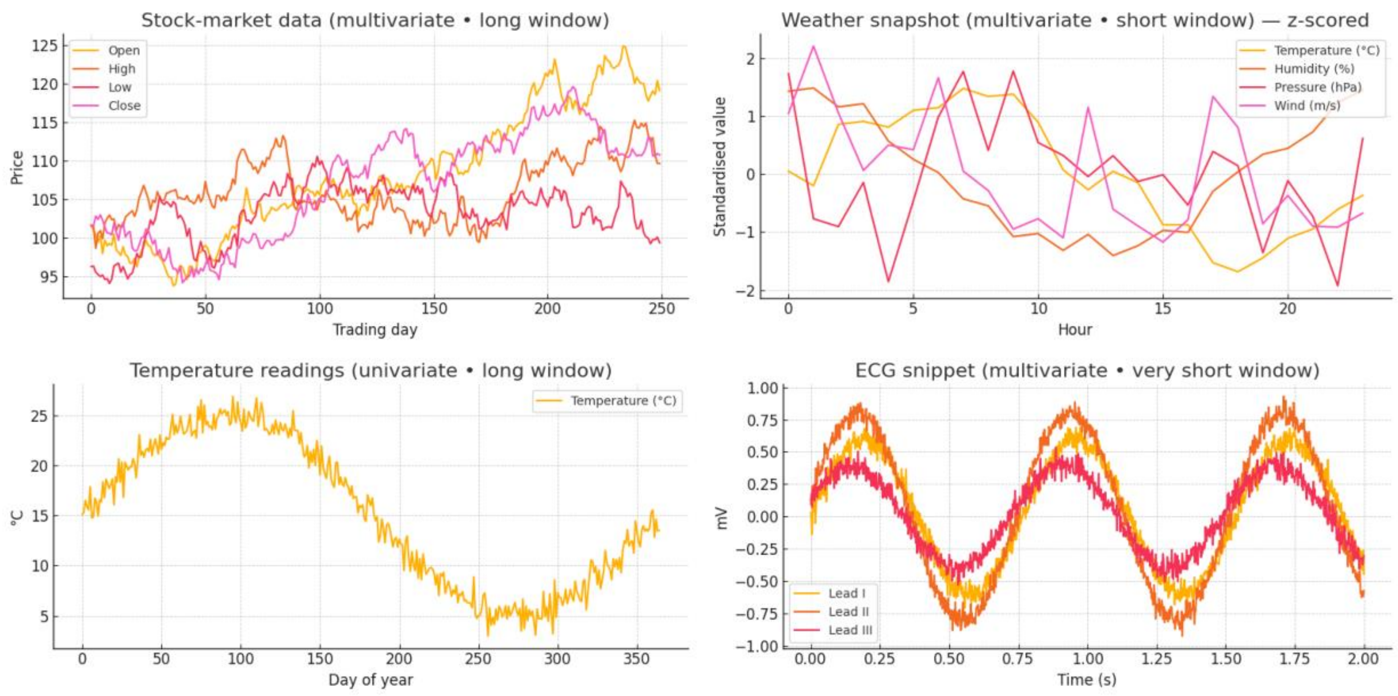
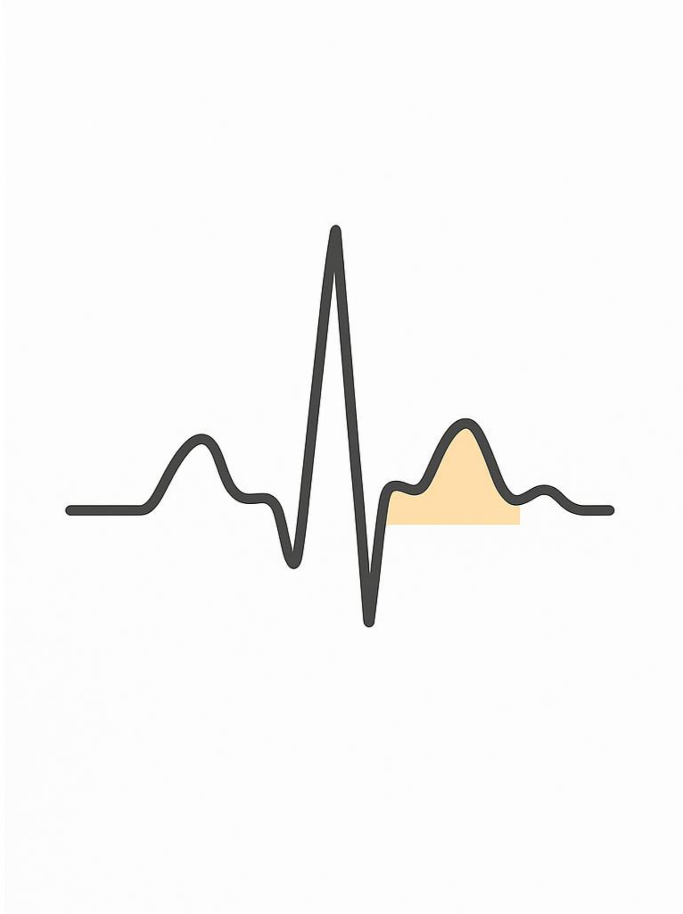
Time series



Number of observations collected over a successive period of time.

- Variable — *anything that changes over time*
- Time periods — *Can be daily, weekly, monthly, yearly*
- Variable Behaviour — *Quantifiable value*

Image vs TS



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Why Special methods for XAI?

Time series lack the spatial structure—no pixels, colours or shapes to **rely on.**

- Image saliency is visually intuitive; temporal signals rarely offer such anchors.
- Peaks and valleys alone seldom explain domain meaning; context over time is key.
- ECG example: subtle disturbances become clear only across several cardiac cycles.

Explanation methods for sequences must account for temporal dynamics.

Challenges

- Choosing an in-distribution baseline
- Interpretable temporal representation
- Capturing temporal interactions
- Managing computational cost

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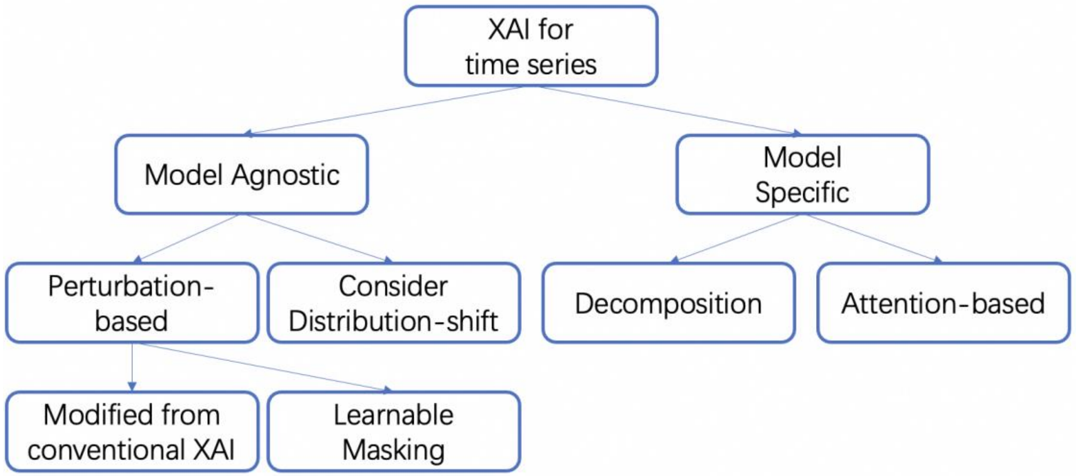

XAI for time series

TAXONOMY MODEL TYPE: GU, XINYUE & YANG, LINXIAO & SUN, LIANG. (2024). EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR TIME SERIES: A SYSTEMATIC SURVEY. 10.13140/RG.2.2.23062.56642.

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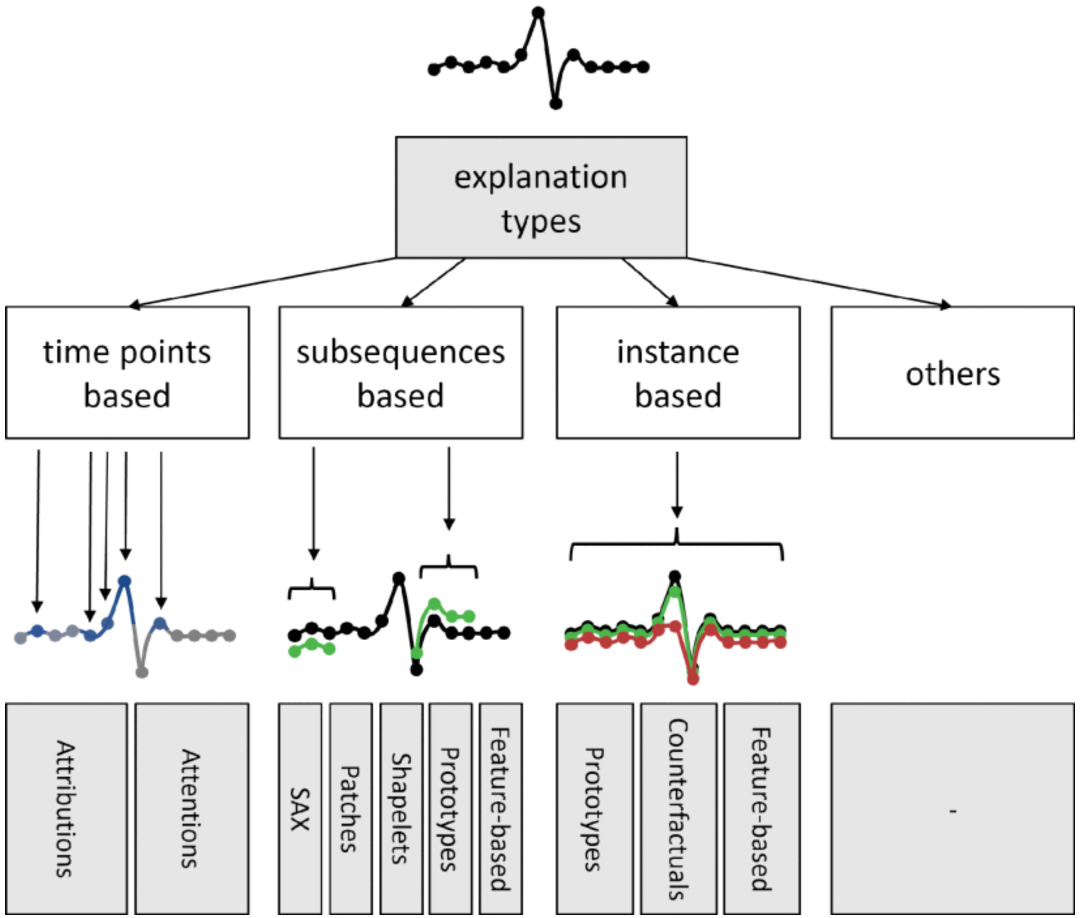
Family	Bucket	One-liner intuition
Model-agnostic	**Perturbation-based**	Mask or alter inputs and see how the prediction shifts (e.g., TimeSHAP, LIME-Segment, Dynamask).
	Distribution-aware	Replace inputs with *in-distribution* counterfactual samples; measure distributional shift (e.g., FIT).
Model-specific	**Decomposition-based**	Algebraically split the model into additive parts (e.g., Contextual Decomposition, ACD, REAT).
	Attention-score	Treat attention weights in RNNs/Transformers as importance indicators (e.g., RETAIN, TFT).

XAI for time series



- Taxonomy: Explanation Type
- See: https://ieeexplore.ieee.org/document/9895252

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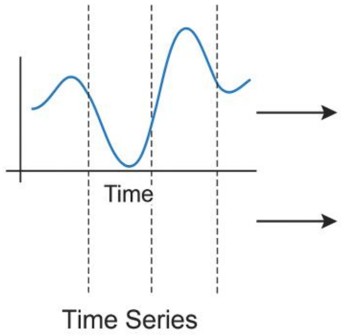
XAI for TS: Windowing and Tabeling



Feature Engineering

Mean	Std. Dev.	Max
10.2	1.5	12,8
9.8	2.1	13,6
10.6	1.8	12,2
⋮	⋮	5.9
10.6	1.8	6,3
⋮	⋮	⋮

- **Window the raw signal** – slice it into fixed-length segments so each row in the future table corresponds to a "view" of the sequence.
- **Compute hand-crafted features** for each window
  - *Time-domain*: mean, variance, max/min, zero-crossings, slope, etc.
  - *Frequency-domain*: dominant frequency, band-power, spectral entropy, etc.
- **Result: a tabular matrix** (rows = windows, columns = features)
  - Now you can apply any tabular XAI tool (SHAP, LIME, feature permutation, global surrogate trees, etc.).
- **Pros & Cons**
  - **Pros:** interpretable features, fast inference, mature XAI support.
  - **Cons:** may discard fine-grained temporal patterns; requires domain knowledge to choose features.

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Time Series Grad-CAM

Algorithm 3: Gradient-weighted Class Activation Mapping

Input: (Multi/single variate) time series t, trained CNN, target class c

Output: Heat-map L_{GradCAM}

; /* Forward pass */

$A^k \leftarrow$ feature-maps of the *last conv* layer;

$S_c \leftarrow$ predicted score for class c;

; /* Backward pass */

$\frac{\partial S_c}{\partial A^k} \leftarrow$ gradients w.r.t. each map;

; /* Channel importance */

$\alpha_k = \frac{1}{T} \sum_t \frac{\partial S_c}{\partial A_t^k}$

* average only along the time axis

; /* Linear combination & ReLU */

$L_{\text{GradCAM}} = \text{ReLU}(\sum_k \alpha_k A^k)$;

; /* Upsample */

Resize L_{GradCAM} to the resolution of T and overlay;

Generate Heatmap?

Mandatory:

1. Assaf, R., & Schumann, A. (2019, August). Explainable deep neural networks for multivariate time series predictions. In *IJCAI* (pp. 6488-6490).

2. *J. Van Der Westhuizen and J. Lasenby. Techniques for visualizing lstms applied to electrocardiograms. arXiv preprint arXiv:1705.08153, 2017.*

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Family	Typical design	Strengths	Pain-points called out by the authors
A. Point-wise heat-maps	Put colour directly on the data marks (circles, dots).	extremely compact; preserves raw signal shape	heavy over-plotting, colour perception issues, later points over-draw earlier ones, hard beyond toy sequences
B. Gradient line segments	Encode relevance as a colour ramp along the poly-line.	keeps temporal ordering; no extra screen space	if the ramp is poorly chosen the signal itself becomes illegible; still juxtaposes high & low values without structure
C. Line-over-background heat-maps	Original curve in front, rectangular heat-map behind.	separates data & attribution layers; easy to add multiple attribution rows	overwhelms non-experts; small line vs huge heat-map; adjacent extremes visually clash
D. Dense pixel heat-maps (no signal)	Drop the line, show only a colour grid of relevance.	exposes recurrent patterns; good when the signal itself is distracting	eliminates temporal reference—experts struggle to relate colours back to real values
E. Pipe / tube overlays	Draw a variable-width, colour-coded "pipe" around the line.	width + colour jointly guide attention; low-relevance still visible	needs careful scale setting; may hide small fluctuations of the original series
F. Separate attribution lanes	Stack a second line plot (or small multiples) for relevance.	clean split—data intact, attribution legible; easy brushing & linking	relation between series & attribution requires eye jumps; less screen-efficient
G. Additive bar / arrow charts	Use SHAP additivity to draw positive/negative bars above & below the series, sometimes with arrows to compare models.	communicates direction (↑ helpful, ↓ harmful); supports multi-model comparison	only works for additive attributions; unsuitable for uni-variate series
H. Counter-factual-first workflows	Show "what would flip the prediction" examples first; drill down with attributions + what-if sliders.	aligns with Shneiderman mantra (overview → zoom → details); empirically easier for lay users	still a research vision; needs interactive tooling

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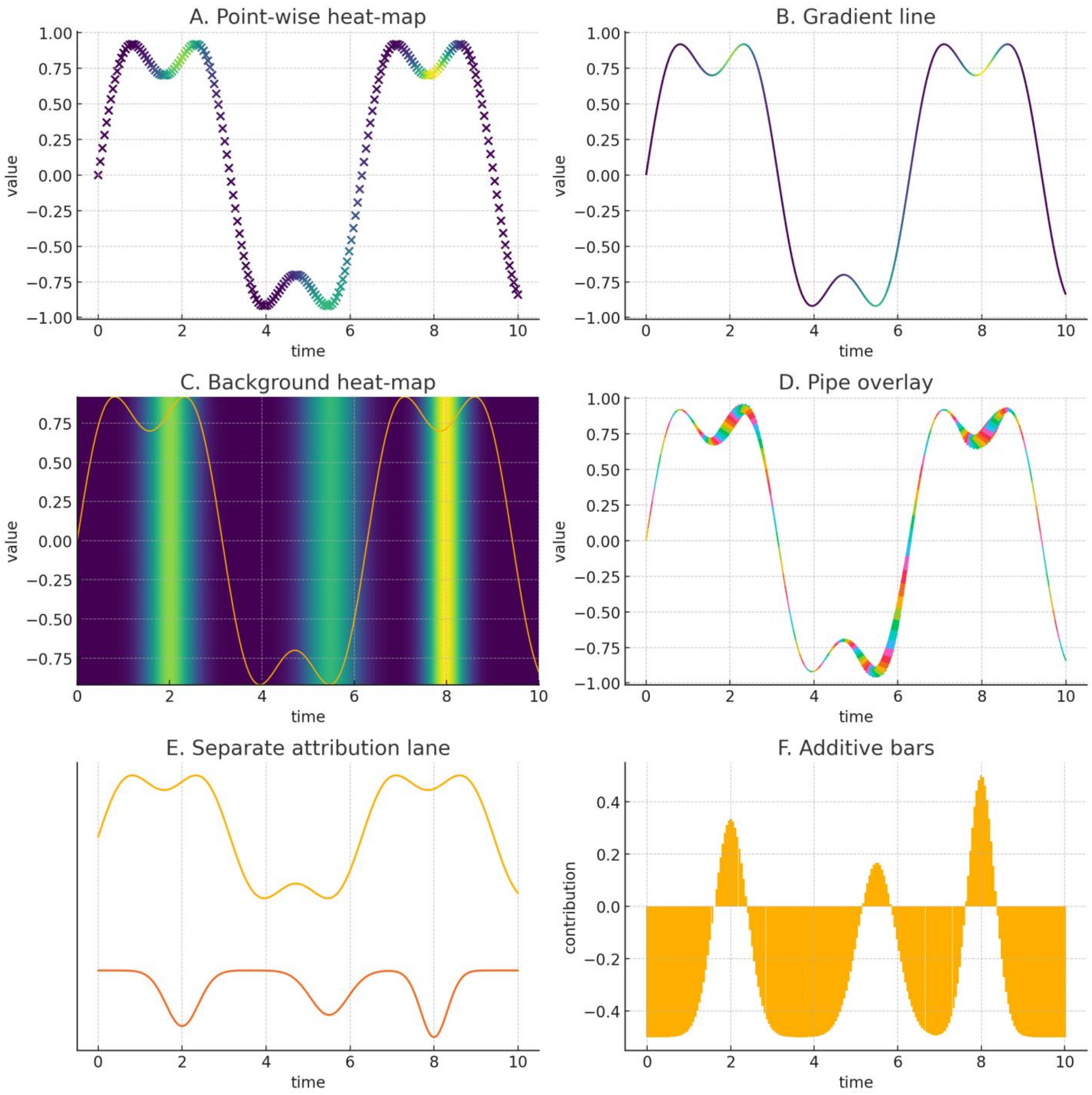
Visualizing TS explanation

Time Series Model Attribution Visualizations as Explanations

Visualizing TS explanation



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Explaining LSTM

TimeSHAP, WindowSHAp and C-SHAP

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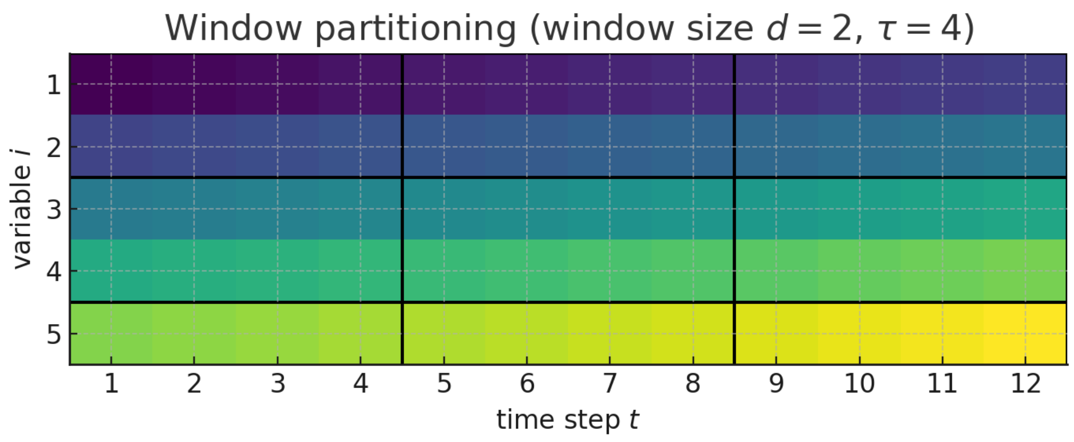
Shapley Values for Time Series

- Consider the multivariate time series $X \in \Re^{D\times L}$
- D is the number of variables
- L is the length of time series
- $\boldsymbol{\Delta} = \{(i,t) : 1 \leq i \leq D, 1 \leq t \leq T\}\}$ – set of all combination of time and variables.
- $\phi_{i,t} = \sum_{(S\subset\Delta\backslash\{(\mathrm{i,j})\}} \frac{|S|!(D\times L-|S|-1)!}{(D\times L)!} [v_{X^*}(S \cup \{(i,t)\}) - v_{X^*}(S)]$



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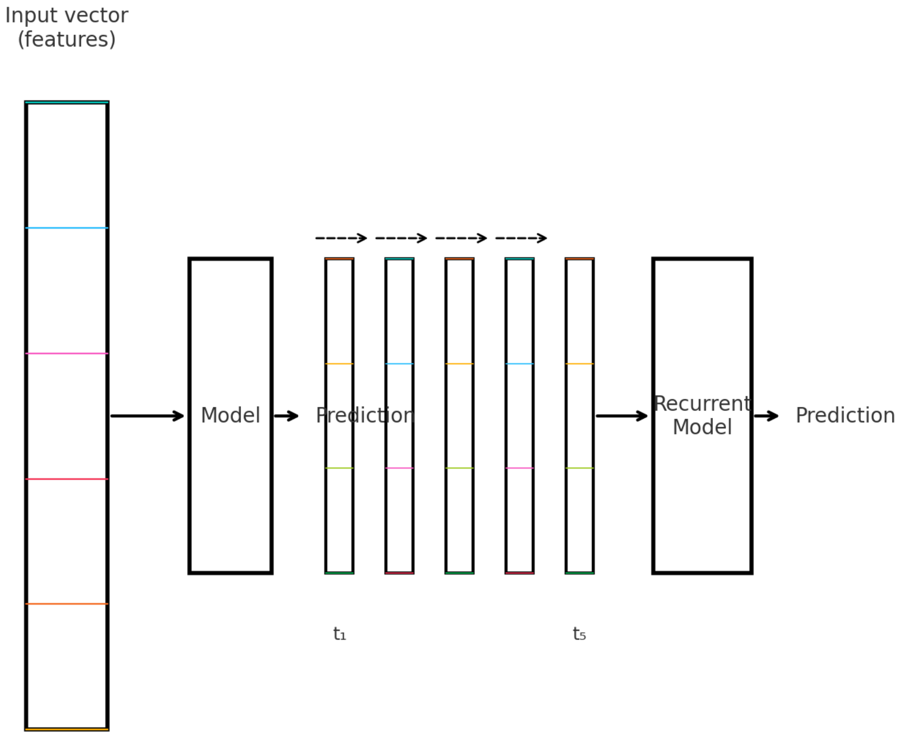
TimeSHAP



KernelSHAP on a static input vector
(one attribution vector)

TimeSHAP perturbs features × timesteps
(two-axis attributions)

- Tabular KernelSHAP treats the whole history as **one** feature vector → loses temporal context.
- RNNs, TCNs, Transformers output predictions **because of specific features at specific timesteps**.
- **Question:** "Which past events actually drove the prediction?"
- Requires attributions on **two axes** → *variables* × *timesteps*.

TimeSHAP

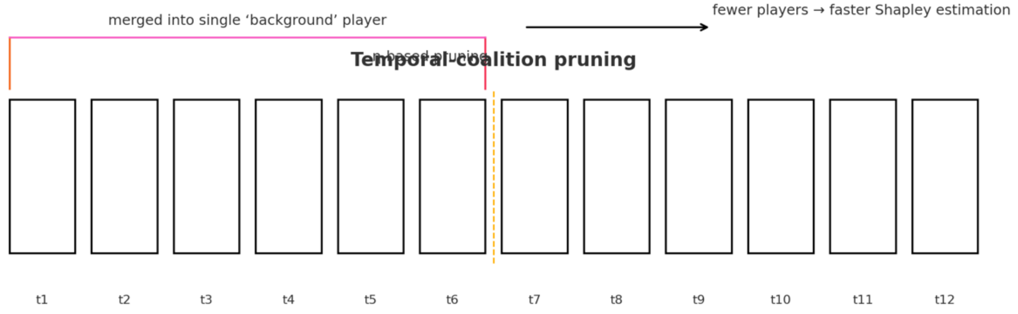
- Events are sorted by recency.

- Starting from the far past, merge events into one **background player** until

$$\sum_{j \in merged} \phi_{event_j} \leq \eta$$

where η is a user-set tolerance (e.g. 0.05).

- Reduces the exponential coalition space without violating Shapley axioms.



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TimeSHAP

Keep top-*k* rows (important features) and top-*k* columns (important timesteps).

Perturb only the **k^2 intersection cells** → quadratic, not exponential.

Produces fine-grained insights:

"This unusually large transfer amount at $t = k$ triggered the fraud alert."

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TimeSHAP

João Bento, Pedro Saleiro, André F. Cruz, Mário A.T. Figueiredo, and Pedro Bizarro. 2021. TimeSHAP: Explaining Recurrent Models through Sequence Perturbations. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining (KDD '21). Association for Computing Machinery, New York, NY, USA, 2565–2573. https://doi.org/10.1145/3447548.3467166

- **TimeSHAP** extends KernelSHAP to sequences, producing **feature-, event- and cell-level Shapley attributions** while remaining model-agnostic and post-hoc.
  - **Sequence-wide Shapley perturbations:** Extends KernelSHAP to *two* axes—features *and* timesteps—so you can ask "which past events and which variables actually drove the RNN's output?"
  - **Temporal-coalition pruning:** Groups the oldest, low-impact events into a single "background" coalition once their combined attribution falls below a tolerance η, slashing the exponential search space and runtime without losing Shapley guarantees.
  - **Cell-level zoom-in:** After isolating the few critical rows (features) and columns (events), it perturbs the individual cells at their intersections, yielding fine-grained attributions like "this unusually large transfer amount in event k triggered the fraud alert."

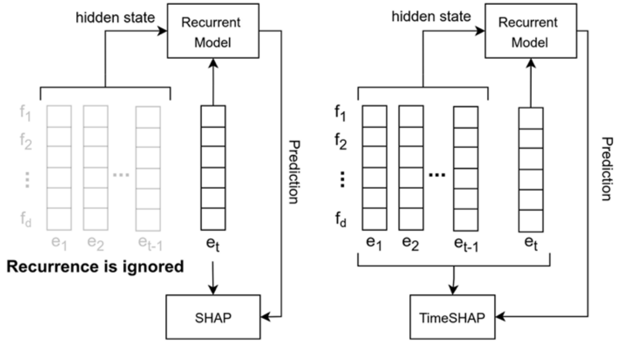

Figure 1: Current SHAP-based methods (left) only calculate attributions for a single input vector. TimeSHAP (right) applies perturbations throughout the input sequence.

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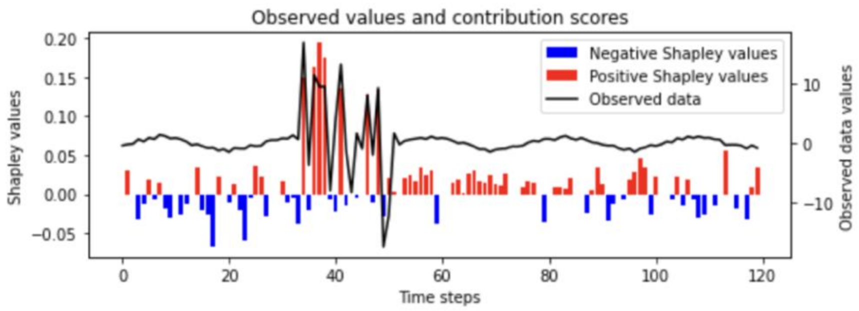
WindowSHAP

KernelSHAP



- Drawbacks (Kernel)SHAP for time series:
- Not originally intended to be used with time-series data.
- KernelSHAP approximates Shapley values and reduces computational time, but is still computationally expensive for high-dimensional data.
- Sequential data points are often highly dependent. For dependent features, their joint contribution is distributed among them, resulting in many small Shapley values.
    - Difficult to draw conclusions

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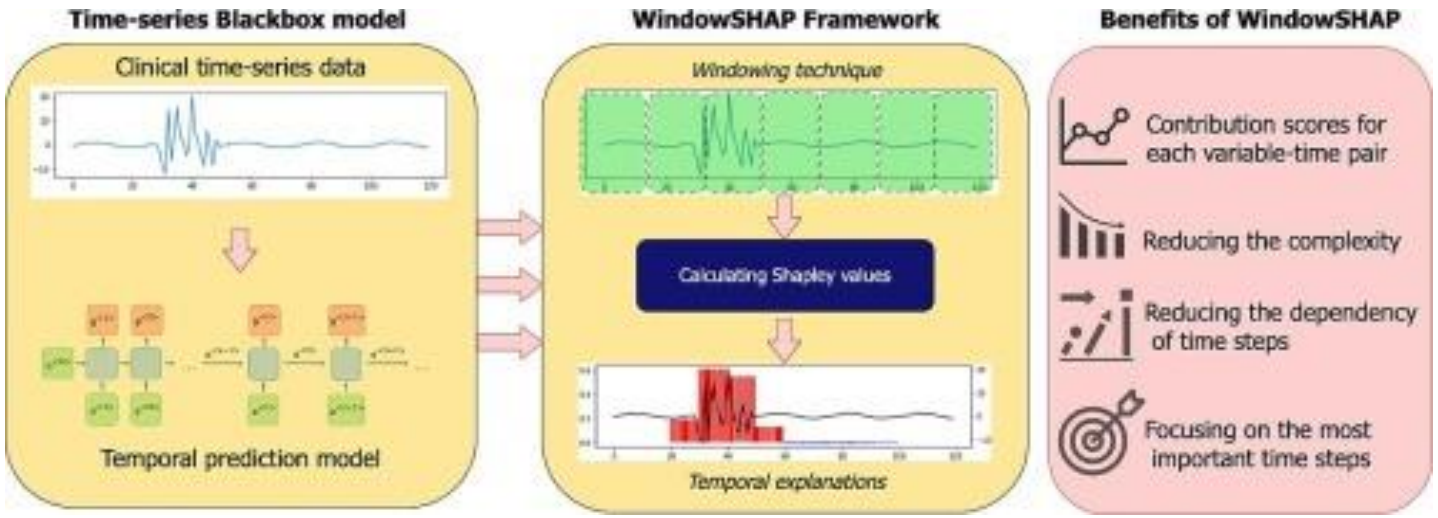
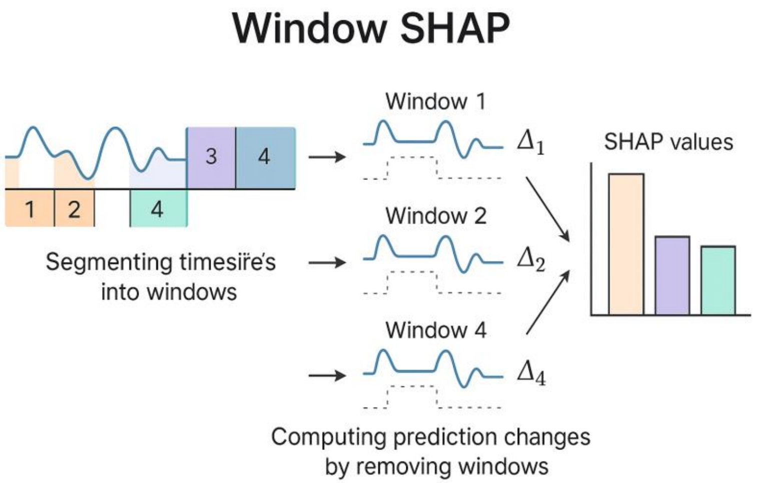
WindowSHAP

Nayebi, A., Tipirneni, S., Reddy, C. K., Foreman, B., & Subbian, V. (2023). WindowSHAP: An efficient framework for explaining time-series classifiers based on Shapley values. *Journal of biomedical informatics*, *144*, 104438.





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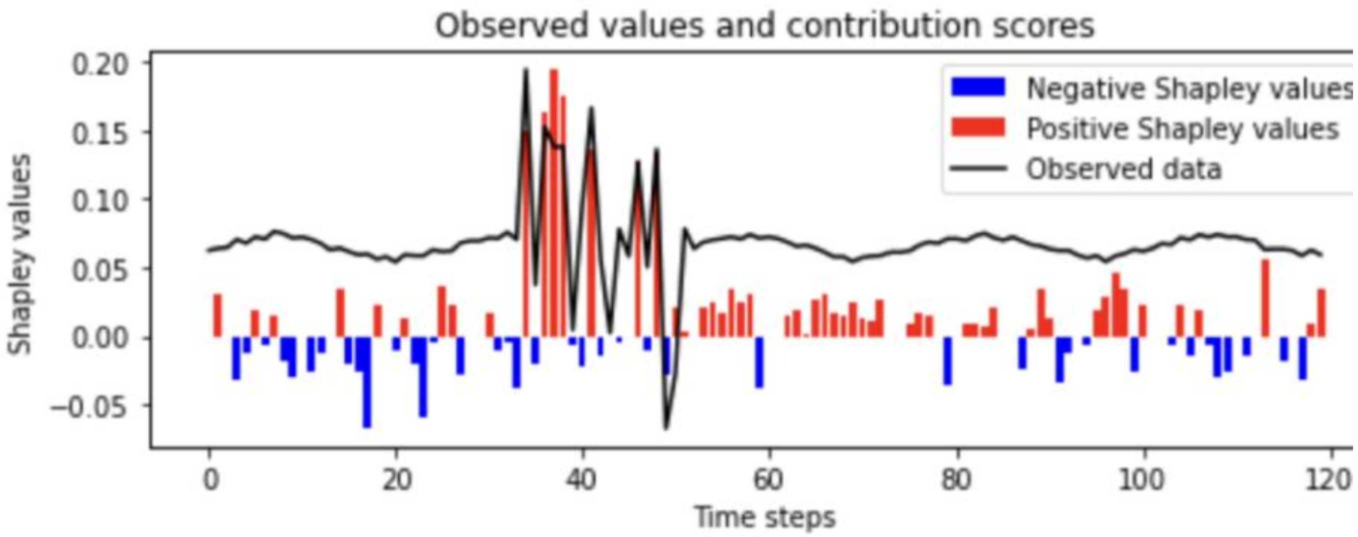
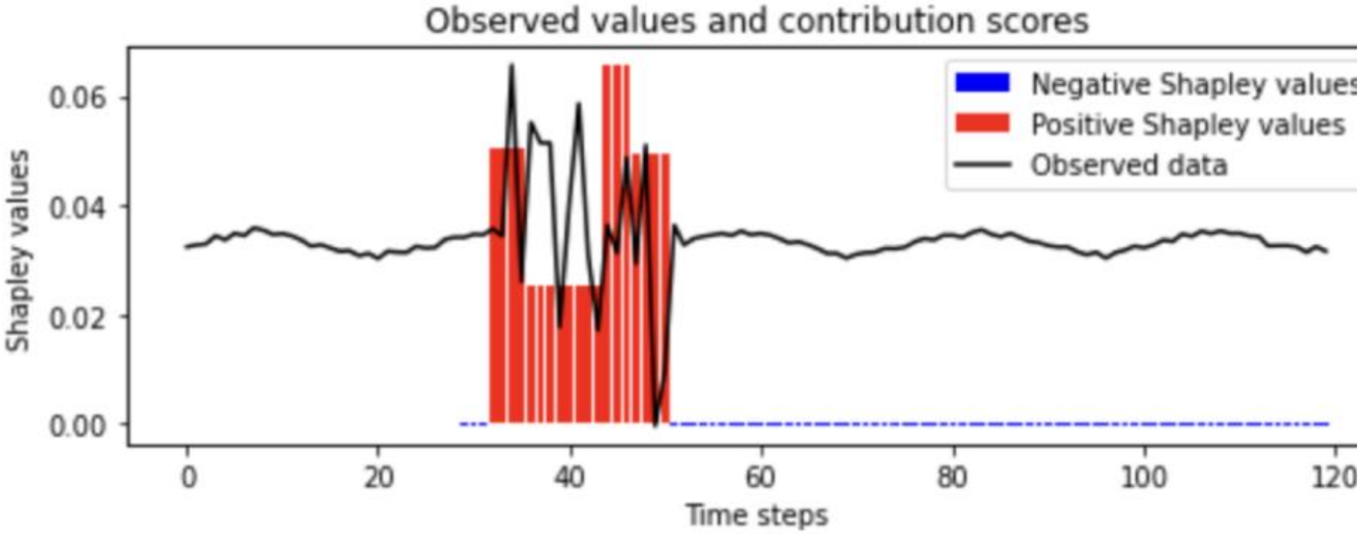
WindowSHAP





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WindowSHAP

KernelSHAP:

- To mask a feature (=data point) replace it by an uninformative value
  - For example: zero, sampling from training data, …

WindowSHAP

- To mask a feature (=partition of data points) replace them all by an uninformative value
  - For example: zero, sampling from training data (subsequences), …

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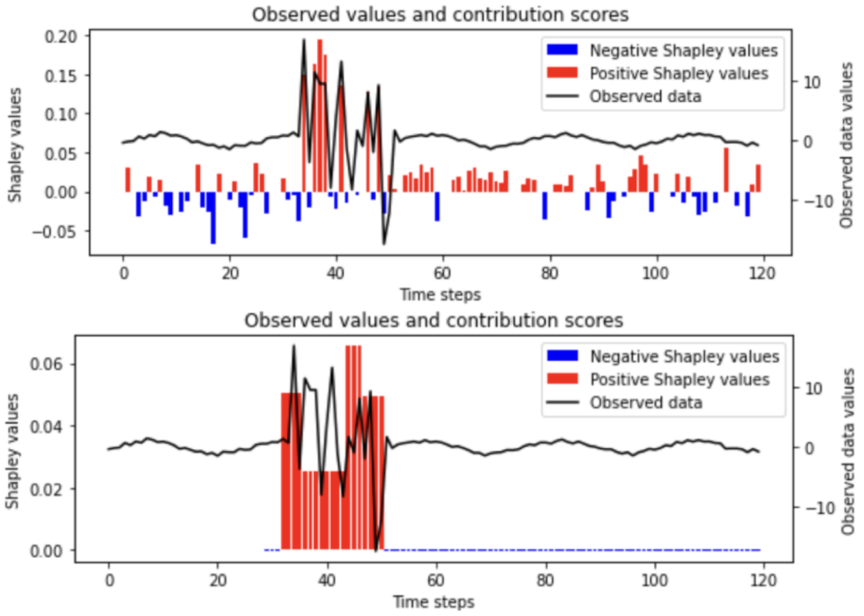
WindowSHAP

WindowSHAP solves these issues by partitioning data points and treating the partitions as features for SHAP:

- Partitioning means less features, so lower computational complexity
- Partitioning balances out small SHAP values and instead leads to more meaningful explanations

KernelSHAP

WindowSHAP



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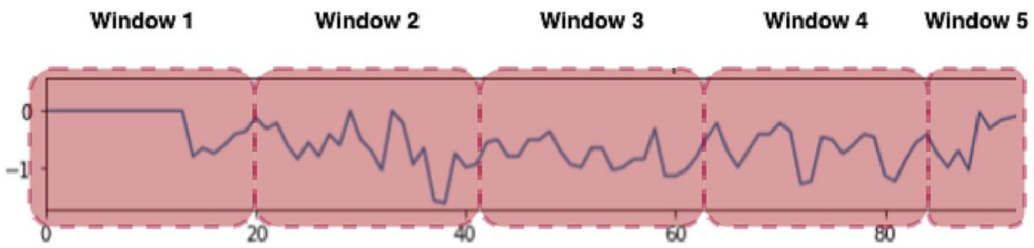
WindowSHAP – partitioning

- Stationary WindowSHAP
  - Segment time series into adjacent fixed length windows



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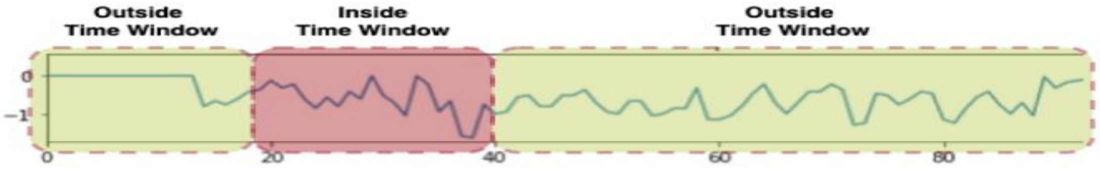
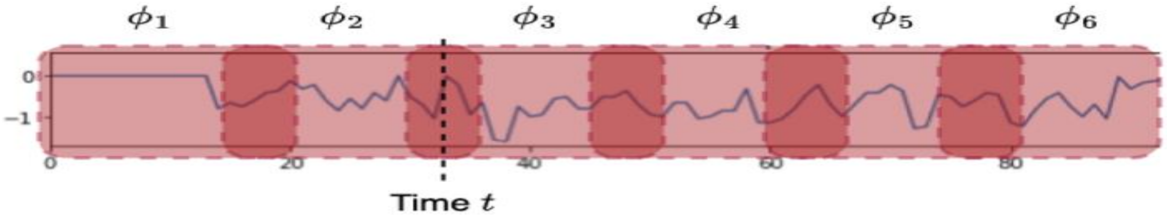
WindowSHAP – partitioning

Stationary WindowSHAP

Sliding WindowSHAP

- Segment time series into overlapping fixed length windows to mitigate boundary issues
- SHAP is repeatedly applied for each segment
- Average out SHAP values for overlapping windows





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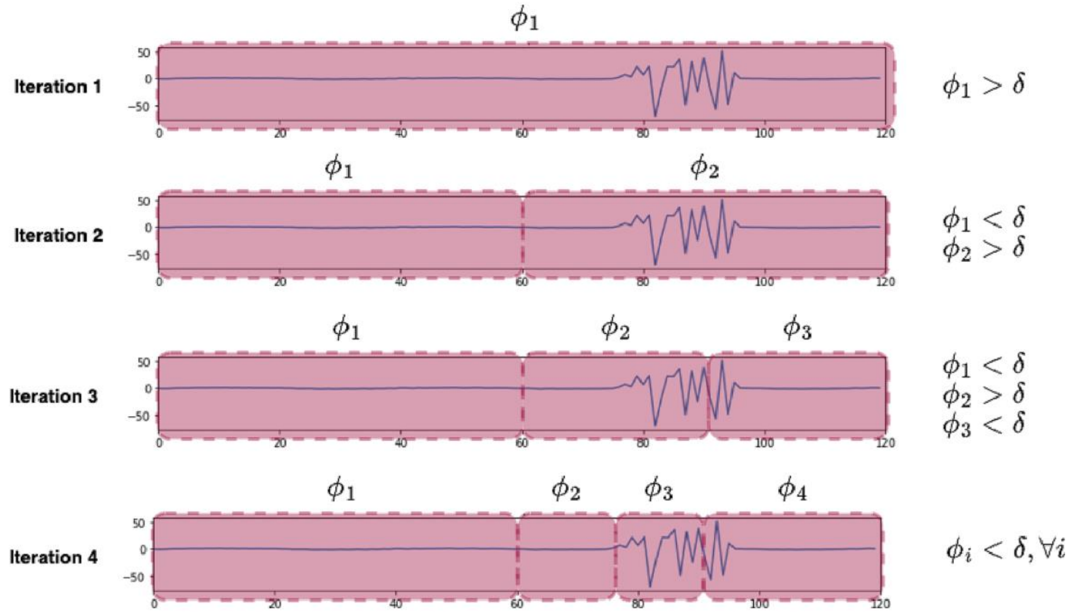
WindowSHAP – partitioning

- Stationary WindowSHAP
- Sliding WindowSHAP
- Dynamic WindowSHAP
  - Flexible length windows
  - Repeatedly apply WindowSHAP and split partitions with high SHAP values



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WindowSHAP

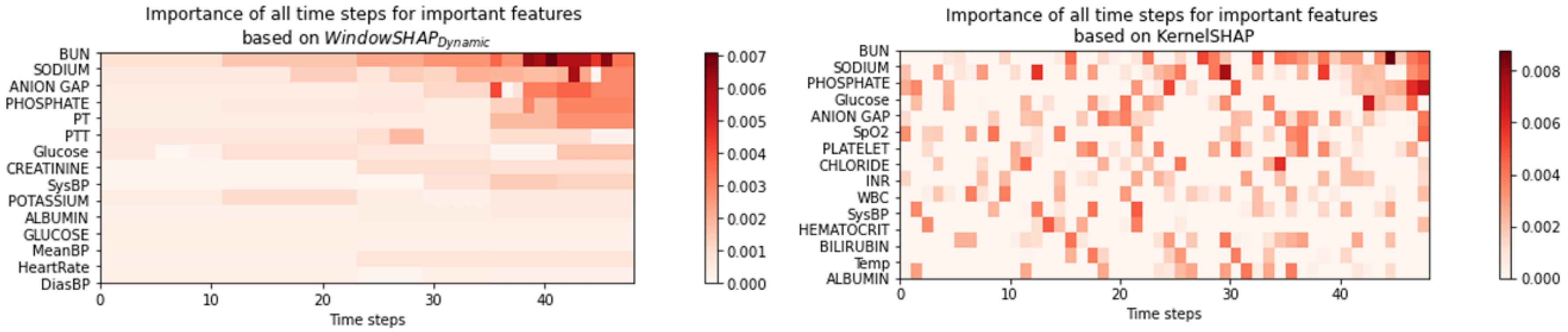
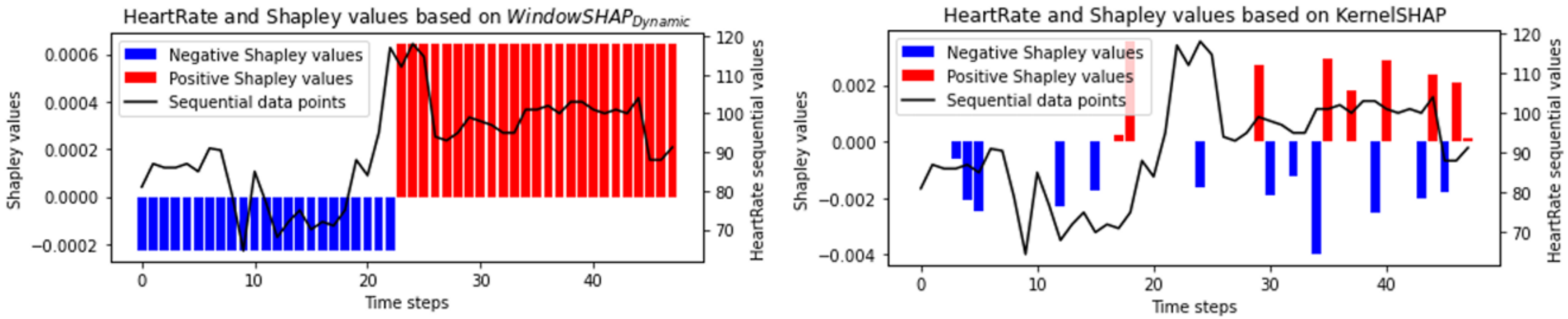
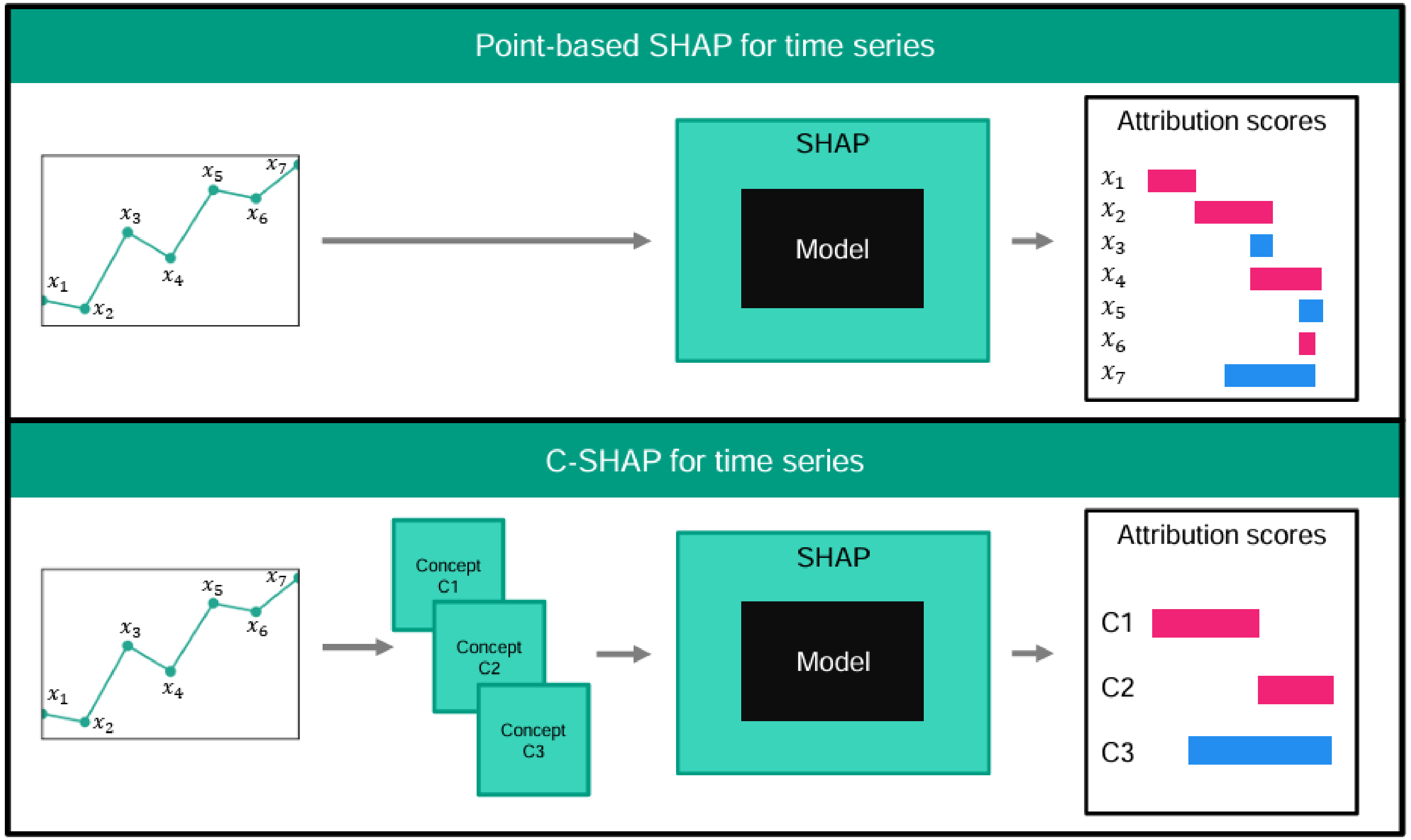


Figure 7. *Heatmaps depicting the importance of all time steps for the important features for a certain patient record from the MIMIC-III dataset. The top 15 variables depicted on the y axis are ranked according to their importance. The darker the color is, the higher the absolute value of the assigned Shapley value is.*



C-SHAP



(https://arxiv.org/abs/2504.11159)

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