Contextual anomaly detection in time series: A temporal context perspective

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Digitized Production enabling end-to-end design-operation

Goal

Create a generic wrapper approach for time series anomaly detection to **leverage the temporal context** of the system, thereby **enhancing the anomaly detection** capabilities.

Motivation

The automatic detection of anomalies is critical in many applications because anomalies have many severe consequences:

Industry	Machine breakdown
	Production halts
	Missing deadlines
	Reduced product quality
	Financial losses
	Safety-critical situations
Healthcare	Disease detection
	Medical data analysis
Financial	Money laundering
	Credit card fraud

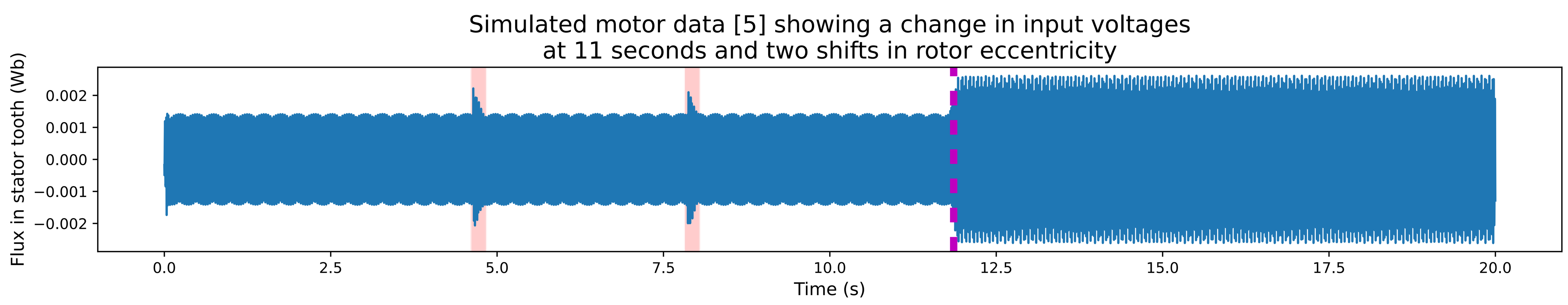
These applications contain numerous temporal contexts, i.e., time intervals or segments that share a similar meaning in the application domain:

Industry	Product specification
	Production cycle
	Machine settings
	Operator
	Working hours
Healthcare	Clinical trial phases
	Recovery cycles
Financial	Tax filing deadlines
	Billing periods

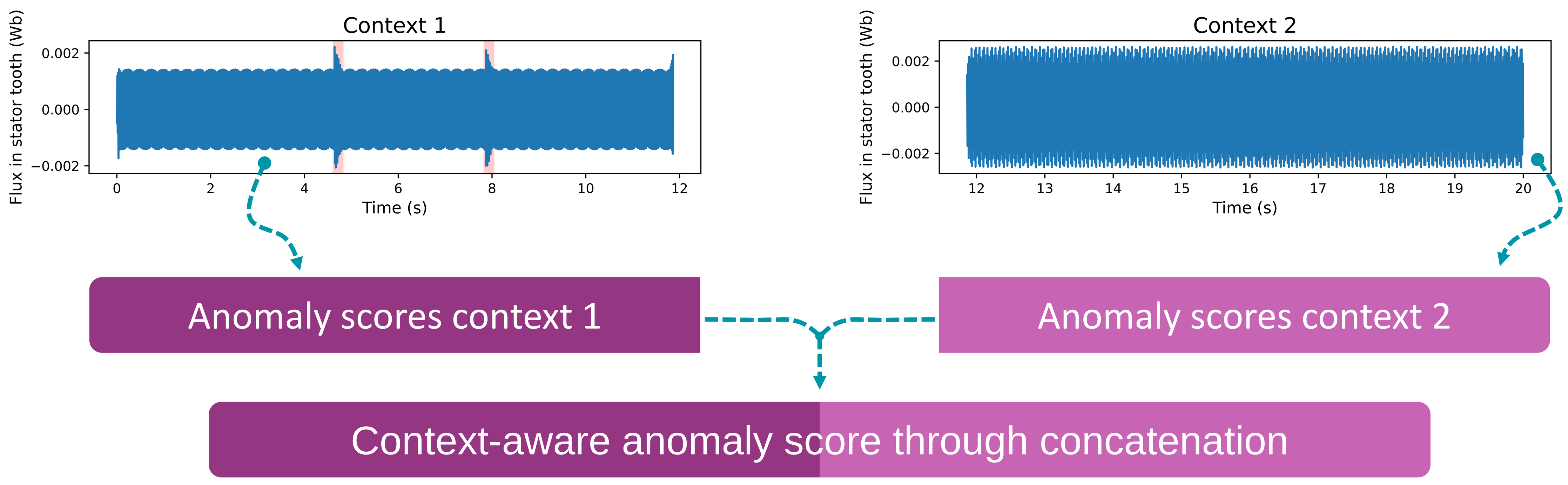
However, “normality” largely depends on the context [1]. A sequence may be anomalous in one context but like the normal subsequences of some other other context [2].

Approach

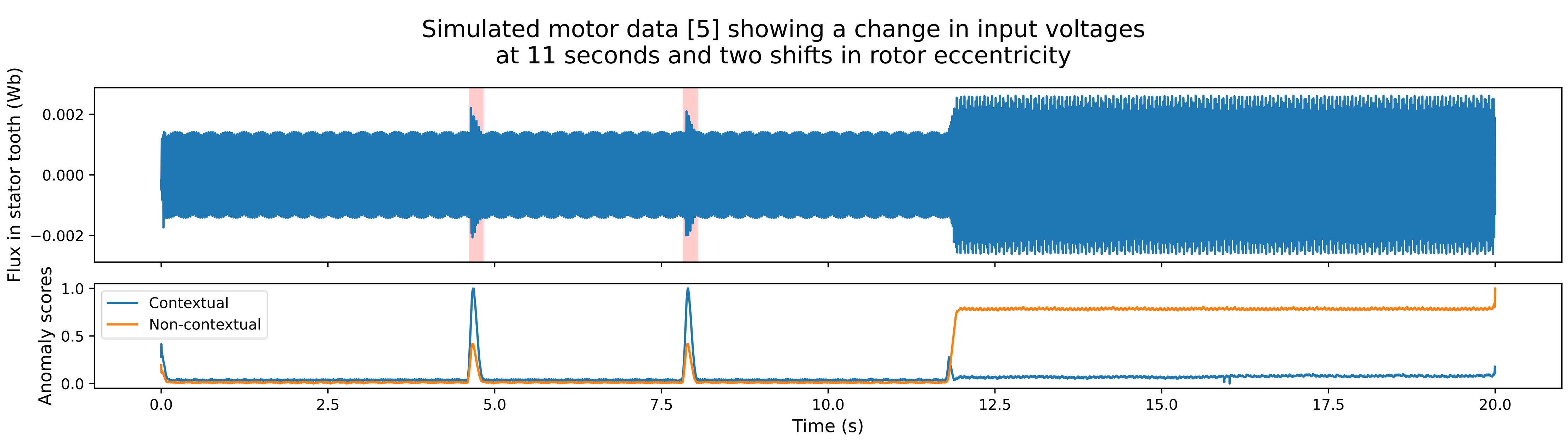
Extract the temporal context of a time series through state-of-the-art semantic segmentation algorithms [3, 4].

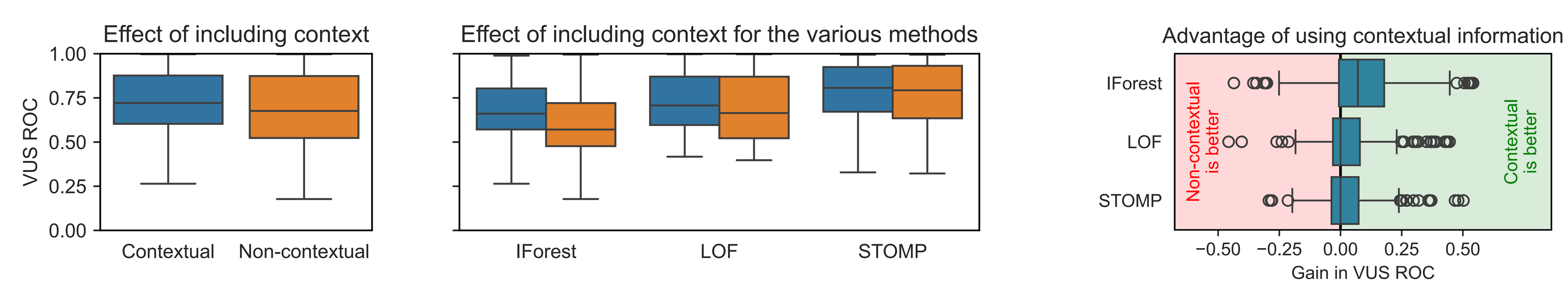


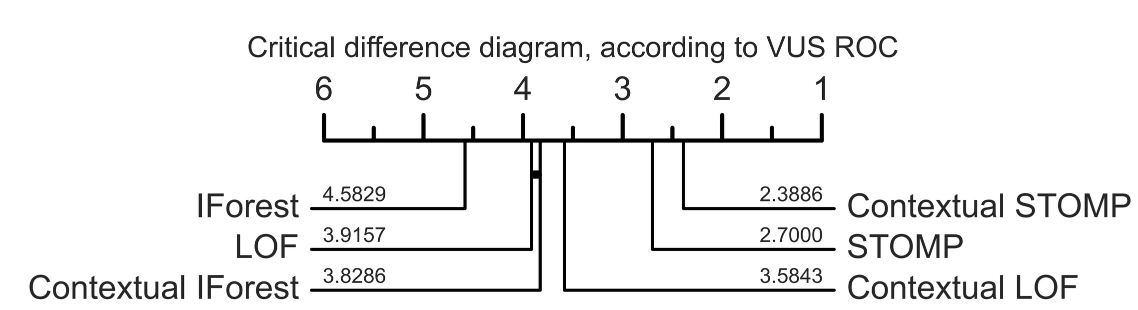
Detect anomalies within each temporal context



Results







The number of times the contextual version had a better VUS ROC than its non-contextual variant

	#wins	#losses	#ties
IForest	241	107	2
LOF	174	143	33
STOMP	161	143	46

Key take-aways

By **injecting the temporal context in existing anomaly detection methods** – in the form of semantic segmentation – we **significantly improve anomaly detection performance**.

Further reading

[1] M. Thill, W. Konen, and T. Back, “Time Series Anomaly Detection with Discrete Wavelet Transforms and Maximum Likelihood Estimation,” Proceedings of the International Conference on Time Series (ITISE), Sep. 2017.
[2] P. Boniol, M. Linardi, F. Roncallo, T. Palpanas, M. Meftah, and E. Remy, “Unsupervised and scalable subsequence anomaly detection in large data series,” The VLDB Journal, Nov. 2021, 10.1007/s00778-021-00655-8.
[3] L. Carpentier, L. Feremans, W. Meert, and M. Verbeke, “Pattern-based Time Series Semantic Segmentation with Gradual State Transitions,” SIAM international conference of data mining (SDM), Apr. 2024.
[4] A. Ermshaus, P. Schäfer, and U. Leser, “ClaSP: parameter-free time series segmentation,” Data Min Knowl Disc, Feb. 2023, doi: 10.1007/s10618-023-00923-x.
[5] P. Desenfans, Z. Gong, D. Vanoost, K. Gryllias, J. Boydens, and D. Pissoort, “The influence of the unbalanced magnetic pull on fault-induced rotor eccentricity in induction motors,” Journal of Vibration and Control, Mar. 2023, doi: 10.1177/10775463231162908.

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