Window	Start timestamp	Duration	# Events	Event	Frequency	Contribution
1	Day 1 10:07	65 min	1	Disk utilization	1	0.00
2	Day 3 10:02	395 min	9	Disk utilization Read transfer size	5 4	0.00 0.00
3	Day 4 2:07	195 min	2	Read transfer size	2	<0.01
4	Day 6 8:37	15 min	2	Read response time	2	<0.01
5	Day 10 15:07	25 min	1	Read response time	1	0.04
6	Day 11 18:22	65 min	2	Read transfer size	2	0.05
7	Day 13 2:47	135 min	5	Read response time Disk utilization	2 3	0.04 0.02

Table 4: Weights associated with 22 anomalous events clustered in 7 windows for a storage device predicted not to fail.

Window	Start timestamp	Duration	# Events	Event	Frequency	Contribution
1	Day 2 15:17	35 min	5	Peak backend write response time Read response time	2 3	0.05 0.00
2	Day 5 12:02	105 min	2	Peak backend write response time	2	0.06

Table 5: Highlighted weights associated with 5 peak backend write response time anomalous events clustered in 2 windows for a storage device predicted not to fail.

mizes for fidelity to the black-box model and interpretability of the explanation. (**?**) focuses on pixel-wise decomposition of nonlinear classifiers, which allows to visualize contributions of single pixels to predictions for kernel-based classifiers. (**?**) extracts explanations from latent factor recommendation systems by training association rules on the output of a matrix factorization black-box model. All approaches have been applied on text and images, but are not built to take into consideration temporal progressions in time or event series. *Ante-hoc approaches* are interpretable by design (**?**). Typical examples include decision trees, decision sets (**?**; **?**), fuzzy inference models (**?**) or additive models (**?**). However, none of these fit temporal data well.

The vast majority of explainable models for time series target their classification. (**?**) propose grammar-based decision trees to classify heterogeneous time series. (**?**; **?**) extract interpretable features from series, expressed as local shapelets, while (**?**) learn such shapelets via stochastic gradient learning and use them for early classification. In (**?**), the authors propose reversible and irreversible explainable tweaking, where given a time series and an opaque classifier, the objective is to find the minimum number of changes to the time series such that the classifier changes its decision. Closest to our problem is the method proposed in (**?**). There, the objective is to predict a future neural event based on a sequence of previously occurred events. Current approaches are mostly concerned with time-independent sequences, in which the actual time span between events is irrelevant and the difference between events is the difference between their order positions in the sequence. The authors extract and use the information provided by the time span between events in an RNN-based model to achieve some accuracy gain over baseline models. We also opt for an RNN architecture, but we additionally incorporate attention mechanisms (**?**) into the network to quantify how much an anomalous event contributed to a predicted critical incident.

Conclusions

Predictive modeling based on temporal data is key in many domains, from healthcare to IT and industries, particularly when it is concerned with critical incidents, such as failures. Providing explanations for these predictions is crucial, as it enables experts to gain trust in AI-powered models and take into consideration their outputs in the decision process. State of the art explainable models mostly focus on images and text and are not easily applicable to time or event series. We propose a deep learning approach that takes into consideration the irregularity and frequency of anomalous events extracted from time series and uses attention mechanisms to aggregate context information of these events in order to quantify how much information from each event flows into the network. A preliminary evaluation on 266081 events collected from real world storage environments shows that our approach is comparable in accuracy with traditional LSTMs, while at the same time being able to quantify the contribution of each past event recorded to a failure prediction.

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