

CausalAnomalies: Robust Anomaly Detection on Satellite Telemetry

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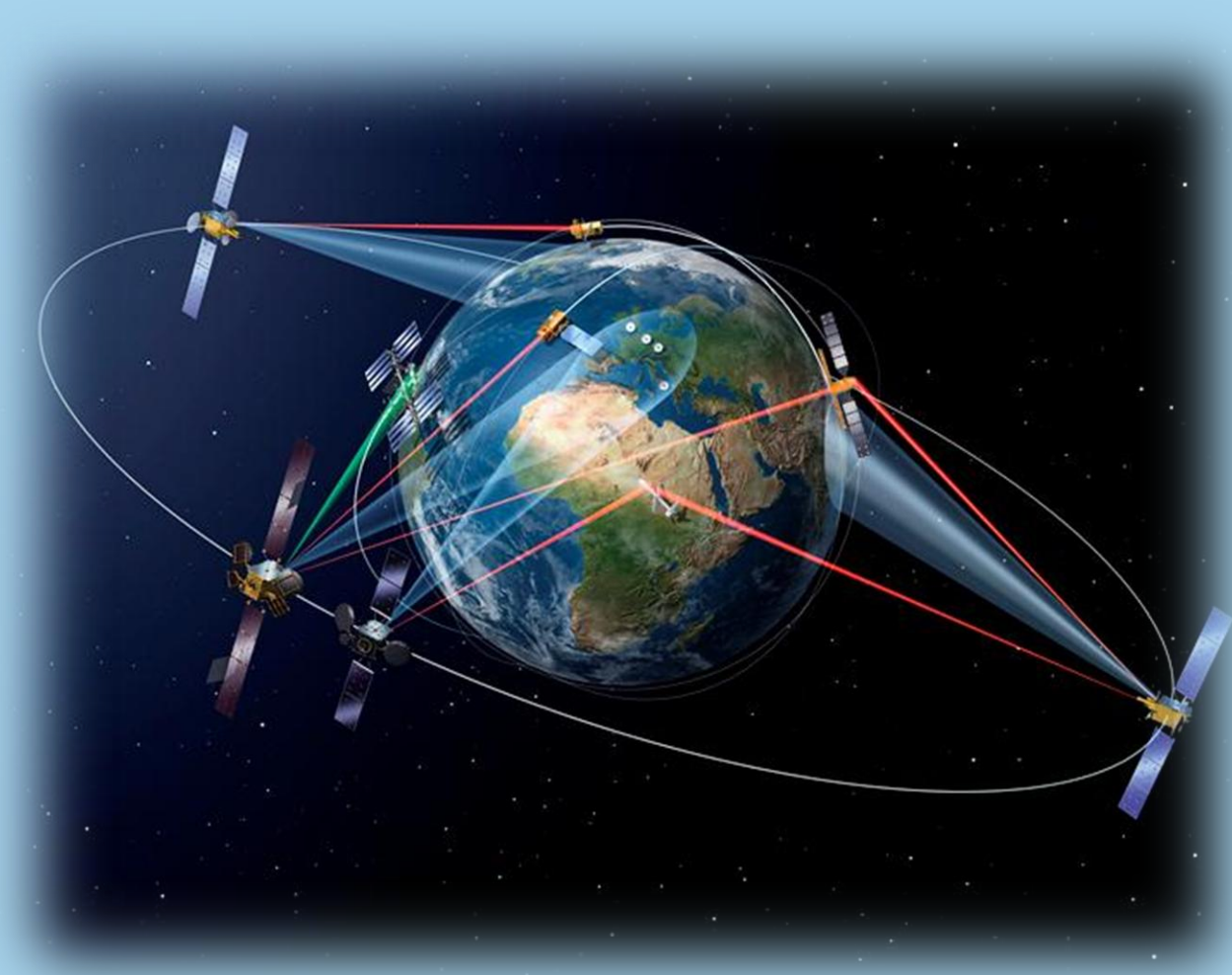
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Motivation

Challenges

- Satellite telemetry is dirty (gaps, noise, etc.)
- No labels, no nominal data
- Novelty vs. anomalies
- Few novelties in data
- No black box systems, engineers need explanations
- Data are confidential, must stay on premise



Objective

- Integration into the GSOC novelty detection (ATHMoS) pipeline to enhance multi-parameter anomaly detection
- Incorporate temporal/spatial relationships, aiming to provide more explainable results for satellite operators

Use Cases

1. Satellite Telemetry During Ground Station Contacts^{1,3}

- Satellite communication systems require understanding of telemetry data during ground station contacts
- Effective monitoring and analysis are crucial for maintaining integrity and diagnosing issues
 - The project focuses on analyzing satellite telemetry with a focus on ground station contact events
 - Anomalous interactions are identified, and causes explained using causal inference techniques

2. Satellite Telemetry During Image Acquisition^{2,3}

- Satellites are composed of several components including camera, reaction wheels, temperature sensors, etc.
- Each component plays a crucial role in the satellite's performance, e.g., during image acquisition
- Issues with one component can impact the entire system
 - Anomalous components are identified
 - Causes explained using causal inference techniques and their roots identified by Root Cause Analysis

Methods

Use Case 1

Anomaly Detection

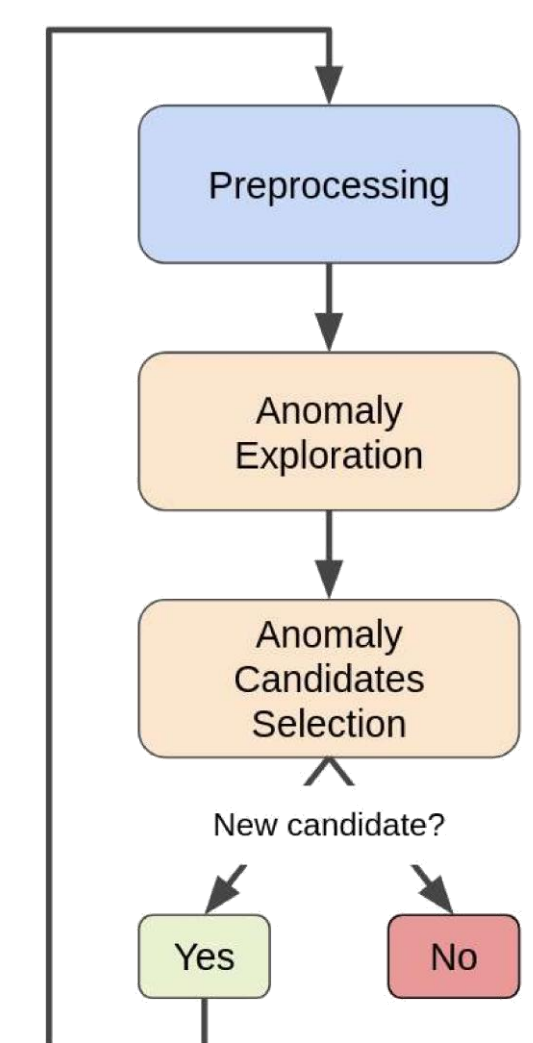
Use Case 2

Ensemble approach:

- Traditional machine learning methods:
 - Maximally Divergent Intervals (MDI)
- Deep learning methods:
 - Graph-Augmented Normalizing Flow (GANF)
 - Multi-Scale Temporal Variational Autoencoder (MST-VAE)

Three phase iterative ensemble approach:

- 100 models per method with different hyperparameters
- Traditional ML methods:
 - Isolation Forest, One-Class SVM, Cluster-Based Local Outlier Factor
- DL methods:
 - Graph-Augmented Normalizing Flow
- Anomaly Candidates identified by at least 50% of the models



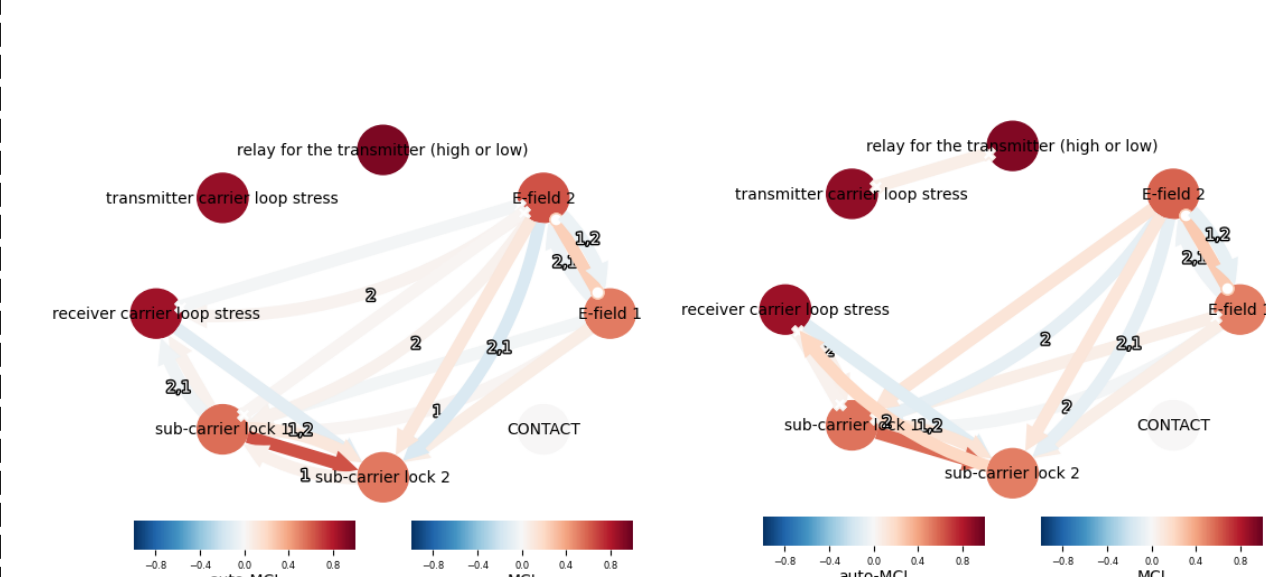
Use Case 1

Causal Inference⁴

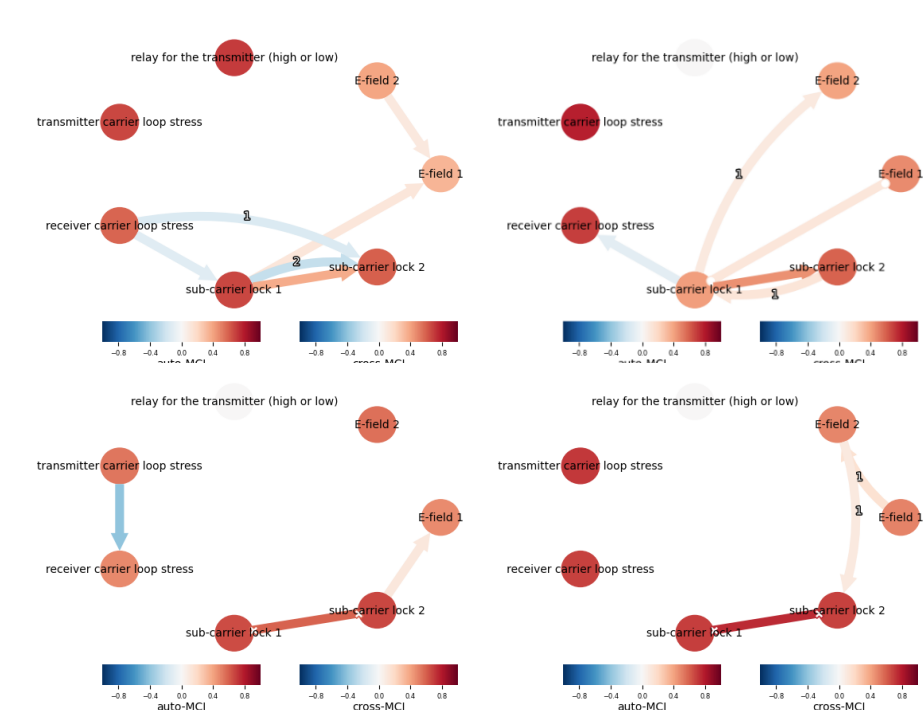
Use Case 2

J-PCMCI+

PCMCI+

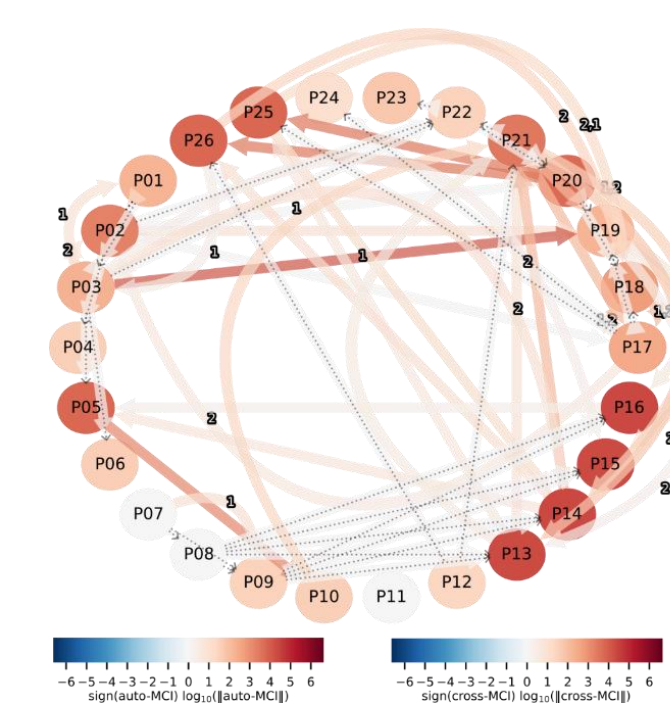


Left: Causal graph learned by J-PCMCI+ on 20 randomly selected normal contacts, using ParCorrMult for independence testing. Right: Result for 20 others randomly selected normal contacts with unchanged settings.



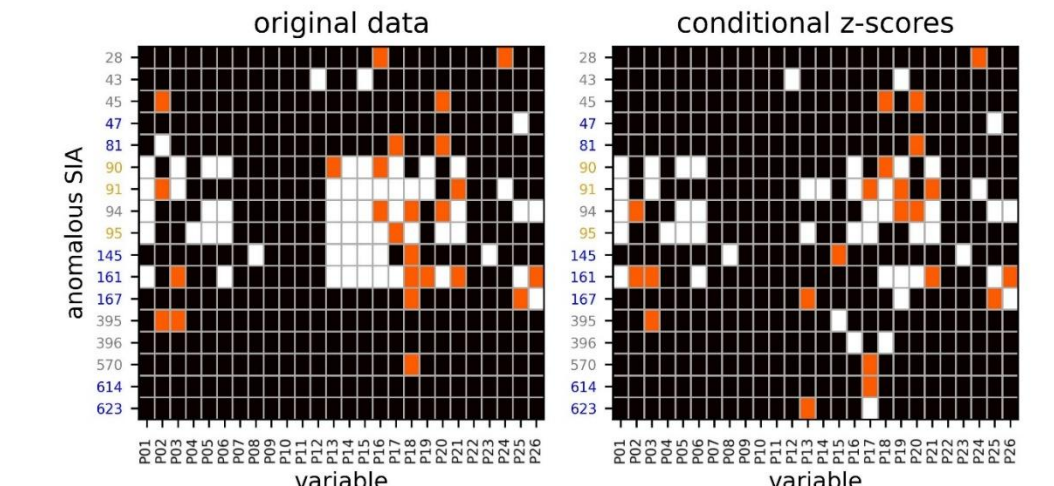
Upper left: Causal graph obtained by applying PCMCI+. Other parts: Results for three different randomly selected single normal contacts with otherwise unchanged settings.

PCMCI+



Common causal graph G_{com} of the telemetry data acquired with the multivariate PCMCI+ algorithm from 20 sets of 50 SIAs by pruning.

Root Cause Analysis



Root cause candidates per anomalous SIA based on a generalised ordinal pattern analysis of the original data (left) and conditional z-scores (right).
• Diagram: (Orange) root cause candidates / (White) considered significant (not explained by chance) / (Black) behaviour of original data or conditional z-scores
• Axes: (Blue) anomalies were found with the original data / (Gray) anomalies with the conditional z-scores / (Gold) anomalies with both data sets

Graphs: Vertices represent the telemetry data variables. Straight edges represent contemporaneous causal relationships between variables and point from causal parent to child variables. Curved edges depict relationships at a non-zero delay indicated by the black-rimmed numbers (in units of the sampling rate). Edge color shows the value of the test statistic of the employed conditional independence test (right color scale), node color for auto-independence, i.e., between variables and their own past (left color scale). Grey dotted cores of edges indicate causal relationships that were identified by expert knowledge.

Results: 1. Use Case

- No true anomaly was predicted by more than one method, suggesting an ensemble approach (see Use Case 2)
- J-PCMCI+: For satellite telemetry, conditional independence tests are suggested, but could not combined with J-PCMCI+

Results: 2. Use Case

- 16 anomaly candidates were detected
- For 16 anomalies, two causal variables were detected
- 27 causal relationships
- Causal graph (20 sets with 50 SIA telemetry sets each)

¹C. Schefels, B. Ben Salem, A. Gerhardus, K. Helmsauer, B. Lambert, J. Niebling, O. Popescu, M. Rabel, F. Rewicki, and L. Schlag: Explaining Satellite Anomalies-Causal Inference for Space Operations. In 18th International Conference on Space Operations (SpaceOps 2025), May 2025. (<https://elib.dlr.de/218254/>)

²C. Schefels, A. Balan, B. Ben Salem, A. Gerhardus, K. Helmsauer, B. Lambert, J. Niebling, F. Rewicki, T. Rings, and L. Schlag: Towards Explainable Anomaly Detection for Satellite Telemetry. In 74th Deutsche Luft- und Raumfahrtkongress (DLRK 2025), October 2025. (<https://elib.dlr.de/217923/>)

³C. Schefels, A. Balan, B. Ben Salem, A. Gerhardus, K. Helmsauer, B. Lambert, J. Niebling, F. Rewicki, T. Rings, and L. Schlag: Towards Explainable Anomaly Detection for Satellite Telemetry. In Review: CEAS Aeronautical Journal, Springer.

⁴Tigramite is a causal inference for time series python package: <https://github.com/jakobrunge/tigramite> (access: 2025-11-18).