SMARTHEP
REAL-TIME ANALYSIS FOR SCIENCE AND INDUSTRY

Synthetic Data Generation with Lorenzetti

for Time Series Anomaly Detection in High-Energy Physics Calorimeters

Laura Boggia, Bogdan Malaescu and the Lorenzetti Team (Edmar De Souza, Juan Marin, Eduardo De Simas, Lucas Nunes and many more)

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ATLAS EXPERIMENT IBM LPNHE PARIS MARIE CURIE ACTIONS

Artificial (synthetic) anomalies

With Lorenzetti shower simulation framework

- **Motivation:** Anomaly detection in multivariate time series is crucial for various fields
  - Healthcare, financial services, cybersecurity, manufacturing lines, **data quality monitoring at physics detectors**, etc.
  - Often serious lack of reliable labels —> **artificial anomalies**

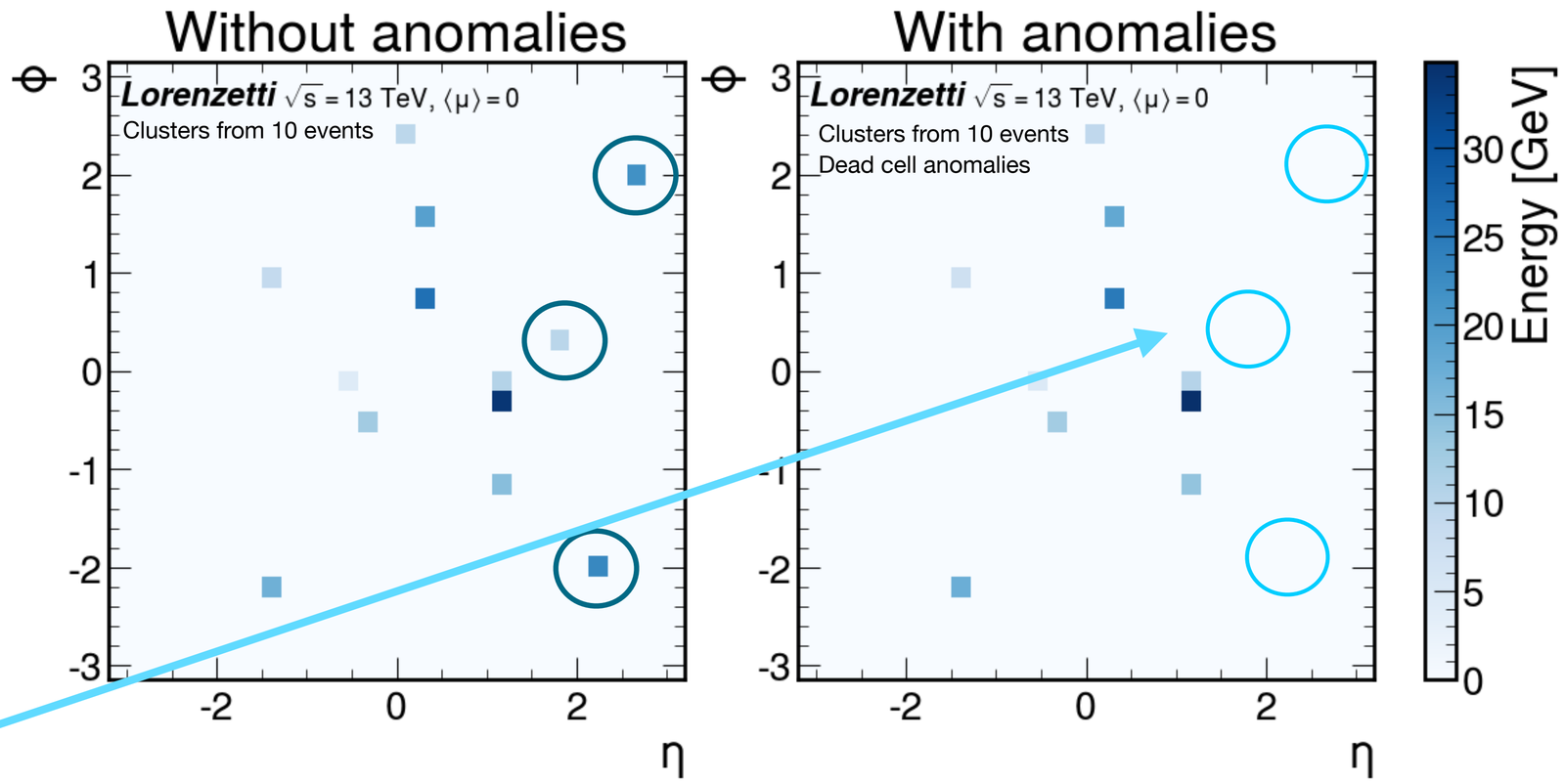
- **Project:** Lorenzetti calorimeter simulation with artificial anomalies
  1. Insert various anomaly rates and types
  2. Identify the anomalies with deep learning anomaly detection for time series

Lorenzetti code: github.com/lorenzetti-hep/

Lorenzetti

Calorimeter simulation

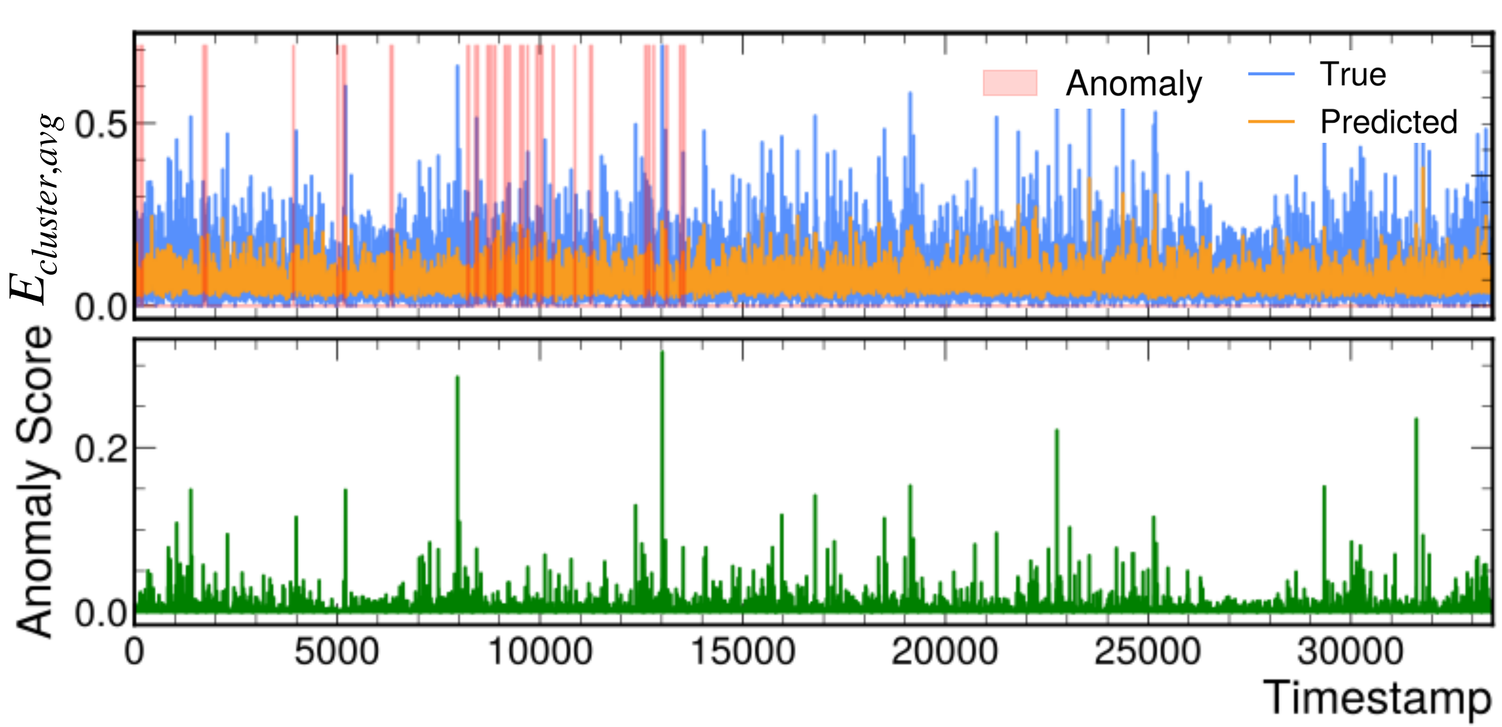
- Open source framework
- Simulation of general-purpose calorimeter, based on ATLAS
- Introduce various synthetic anomalies:
  - Increase noise for cells containing physics signal
  - Dead detector cells

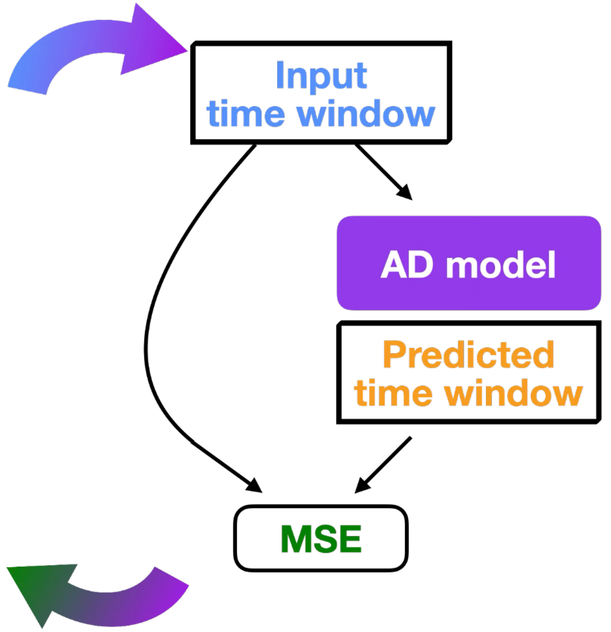


Lorenzetti paper: M.V. Araújo et al. "Lorenzetti Showers - A general-purpose framework for supporting signal reconstruction and triggering with calorimeters."

Time series anomaly detection

With reconstruction-based model





- **Anomaly score** defined as reconstruction error (computed with MSE)
- Compare 3 deep learning approaches and one unsupervised baseline

Thank you for your attention…

& see you at the Wednesday poster session!

Feel free to reach out:
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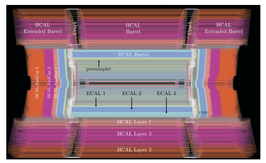
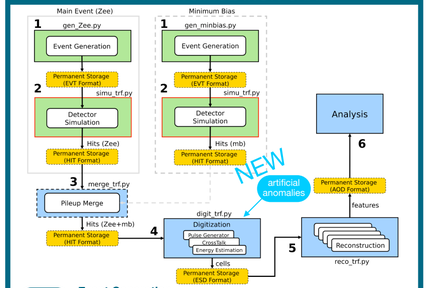
LORENZETTI SHOWER SIMULATION FRAMEWORK

The **Lorenzetti Showers** (LZT) simulation is an integrated software framework that provides complete calorimeter information [1].



- Simulates general-purpose calorimeter, though calorimeter cell granularity is based on ATLAS technical design
- Provides complete calorimeter information (no tracking), including pileup and crosstalk effects
- Open-source code can be found on github.com/lorenzetti-hep/ or scan:

LORENZETTI SIMULATION CHAIN



1 EVT — Event Generation
- Physics event generation with Pythia8 particle generator [2]
- For our studies: $pp \rightarrow$ jets

2 HIT — Detector Simulation
- Detector simulation with Geant4 [3]
- Simulates interaction of particles with detector
- Produces energy deposits (hits) in calorimeter from particles

3 MB — Pileup Merge (optional)
- Repeat 1 and 2 once for signal particles and once for background (soft QCD) events
- Merge the energy deposits in the calorimeters

4 ESD — Digitization
- Simulates electronic pulses reacting to energy deposits in calorimeter cells

NEW: insert artificial anomalies corresponding to detector defects

5 AOD — Reconstruction
- Build energy clusters from cell signals
- Construct various other high-level variables based on cell signals such as shower shape variables

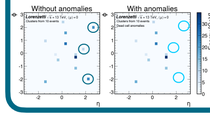
REFERENCES

[1] M.V. Araújo et al. "Lorenzetti Showers - A general-purpose framework for supporting signal reconstruction and triggering with calorimeters."
[2] T. Sjöstrand. "The Pythia Event Generator: Past, Present and Future."
[3] S. Agostinelli et al. "Geant4—a Simulation Toolkit."
[4] A. Siffer et al. "Anomaly Detection in Streams with Extreme Value Theory."
[5] Y. Liu et al. "iTransformer: Inverted Transformers Are Effective for Time Series Forecasting."
[6] S. Tuli et al. "TranAD: deep transformer networks for anomaly detection in multivariate time series data."
[7] J. Audibert et al. "USAD: UnSupervised Anomaly Detection on Multivariate Time Series."

DATA QUALITY / SYNTHETIC ANOMALIES

Anomaly detection in **multivariate time series** is crucial to ensure the **quality of data** coming from a physics experiment.

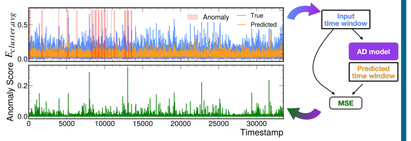
- Introduce **artificial anomalies** into detector ⟼ complete control over anomalies & labels



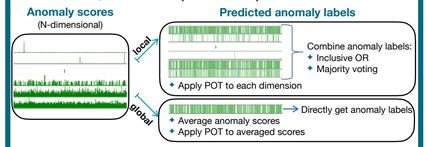
- Focus on QCD jet events
- Artificially increase noise for some cells
- Simulate **dead cells** (i.e. no detector signal)
  - Some clusters disappeared due to dead cells (see figure)

TIME SERIES ANOMALY DETECTION

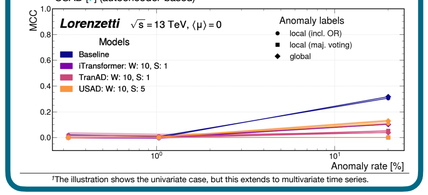
- Time series anomaly detection aims to identify anomalous time stamps in **sequential data**.
- Focusing on **reconstruction-based anomaly detection** as visualised here:†
  - **Anomaly score** defined as reconstruction error (computed with MSE)



- Dimensions correspond to cluster energy (2), position (2) and shower shapes (5) aggregated (mean and std) over each event ⟼ $2 \cdot 9 = 18$ dimensions
- Compare unsupervised deep learning models for anomaly detection on multivariate time series using **Peak-over-threshold (POT)** method [4]
- For all models, combine anomaly scores in 3 ways:



- Anomalies correspond to increased noise convoluted with physics signal
- Same train data, variable anomaly rate in test data
- For comparison: unsupervised baseline
  - Use absolute value of time series as input for POT
- Deep time series anomaly detection models:
  - iTransformer [5] and TranAD [6] (transformer-based)
  - USAD [7] (autoencoder-based)



†The illustration shows the univariate case, but this extends to multivariate time series.

OUTLOOK

- Insert noise signals that can create clusters independently of the physics signal
- More complex noise structures like larger coherent noise signals, detector blackouts etc.
- Feature selection:
  - What cluster-level variables are the most relevant to identify anomalies?
  - Can shower shape variables pick up on injected noise?

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