

Anomaly detection for the ATLAS trigger system

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Project Overview

ATLAS Level-0 Global Trigger:

- Real-time selection mechanism that filters interesting collision events from detector data at the HL-LHC.

Event Selection:

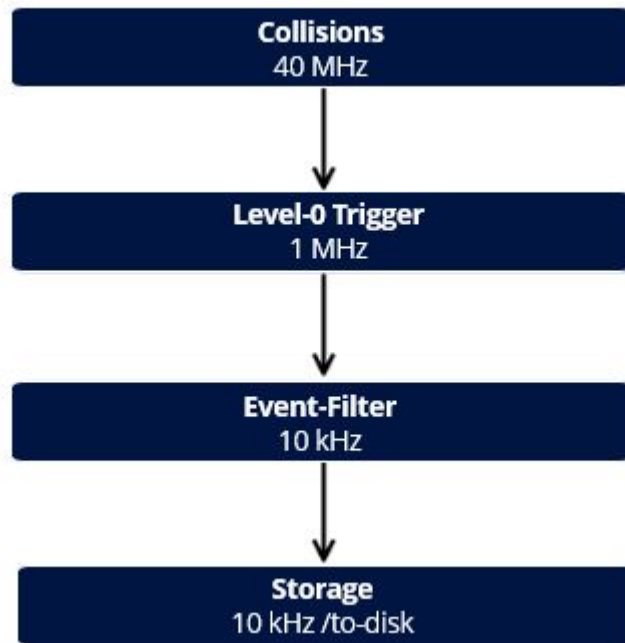
- Traditional trigger algorithms rely on predefined signatures and thresholds, potentially missing **rare** or **unusual** events.

Anomaly Detection:

- Instead of enforcing fixed conditions for event selection, an unsupervised ML model learns to identify events that are unusual or rare, enabling detection of events missed by the current triggers.

“Develop an unsupervised anomaly detection pipeline for finding interesting events missed by current trigger selections.”

ATLAS Trigger Data Reduction Flow



Data

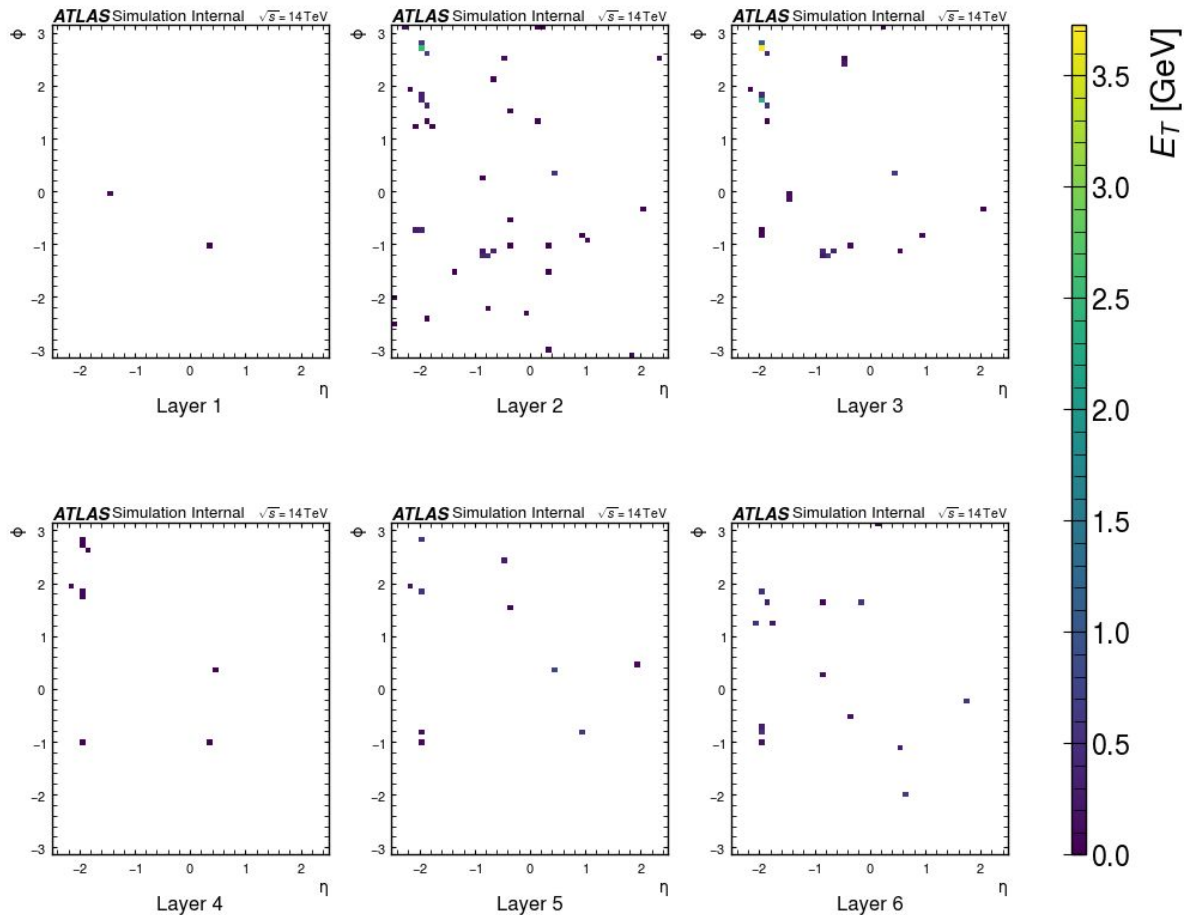
HL-LHC simulated data

Pile-up suppressed using a CNN. Pile-up $\langle\mu\rangle \approx 200$, meaning approximately 200 overlapping collisions per bunch crossing.

Calorimeter images ($50 \times 64 \times 6$):

- 50 bins in pseudorapidity (η) covering the barrel region from -2.5 to 2.5
- 64 bins in azimuthal angle (ϕ)
- 6 layers representing different layers of the calorimeter

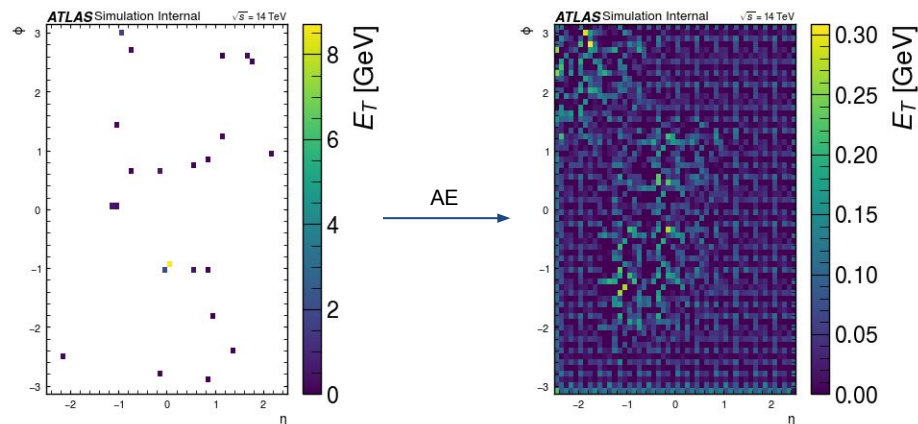
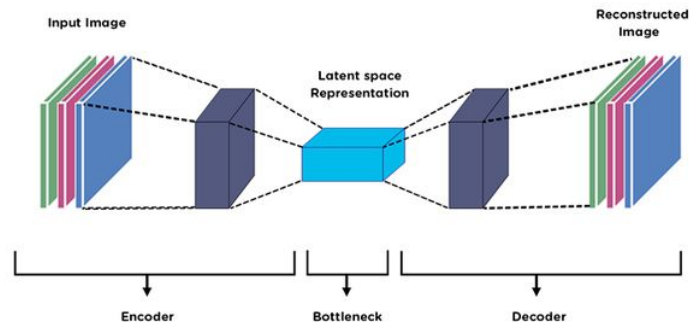
The images map **energy deposits** in the calorimeter layers.



Autoencoder

1. Encoder compresses calorimeter images into a low-dimensional latent space.
2. Decoder reconstructs events from the latent representation.
3. Events that are rare in the training data are poorly reconstructed.

Calorimeter data is very sparse due to **pile-up suppression**, which challenges convolutional AEs in maintaining accurate energy deposit patterns.

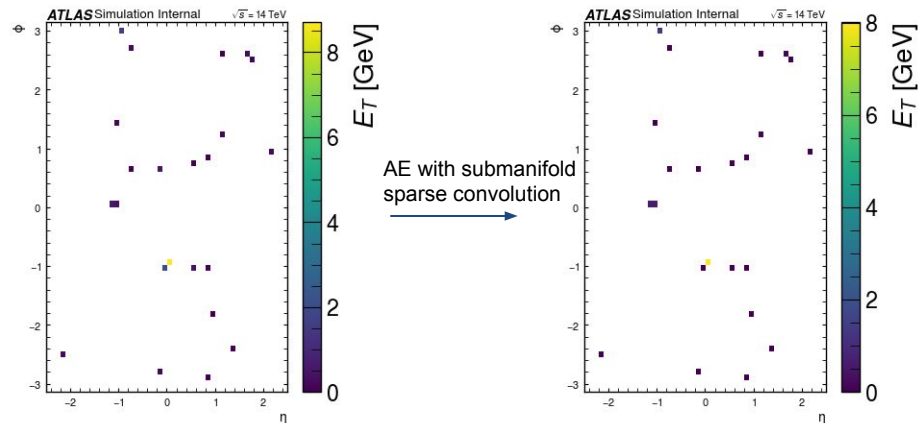


Submanifold Sparse Convolution

Submanifold convolutions operate only on active (non-zero) calorimeter cells, preserving the data sparsity and spatial structure.

Sparse convolutions operate only on active inputs but can write to any site in the receptive field → introduce new active sites and enable downsampling.

Combining these architectures allows for efficient reconstruction without losing sparsity pattern!!!

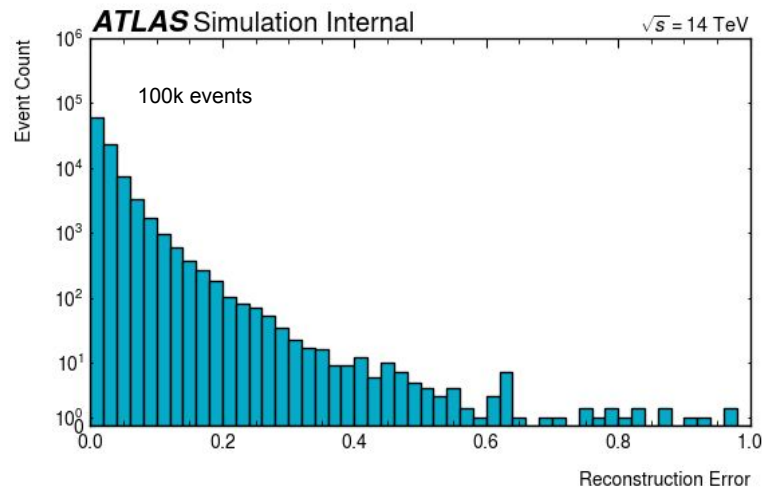


Anomaly Detection

Reconstruction error is calculated as the difference between input and reconstructed event, serving as a metric to detect anomalies.

Majority of the events have low reconstruction error, confirming reliable identification of typical events.

Remaining high-error events are flagged as potential anomalies.



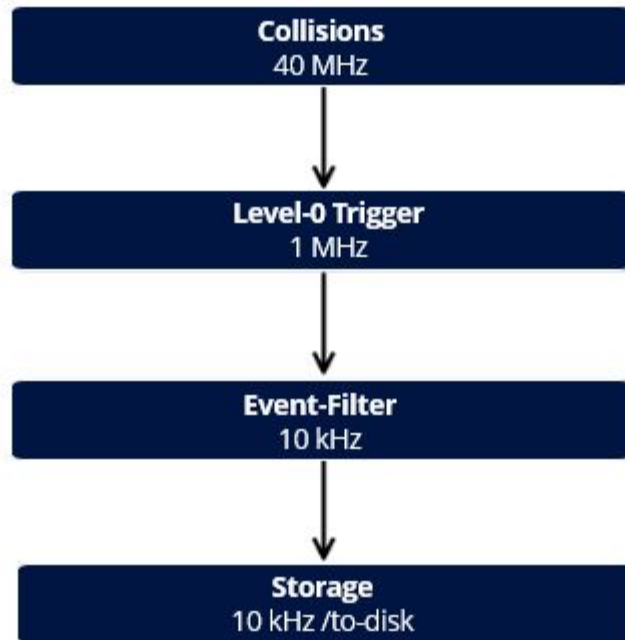
Conclusion

The ATLAS trigger system, relying on fixed signatures and thresholds, can potentially miss rare or unusual collision events.

Anomaly detection with an autoencoder addresses this by learning to recognise events that deviate from typical patterns.

Events with high reconstruction error are flagged as potential anomalies for further analysis.

ATLAS Trigger Data Reduction Flow



Thank you!

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