LABORATÓRIO DE INSTRUMENTAÇÃO
E FÍSICA EXPERIMENTAL DE PARTÍCULAS
partículas e tecnologia

Expanding the ATLAS Physics reach with anomaly detection at trigger level

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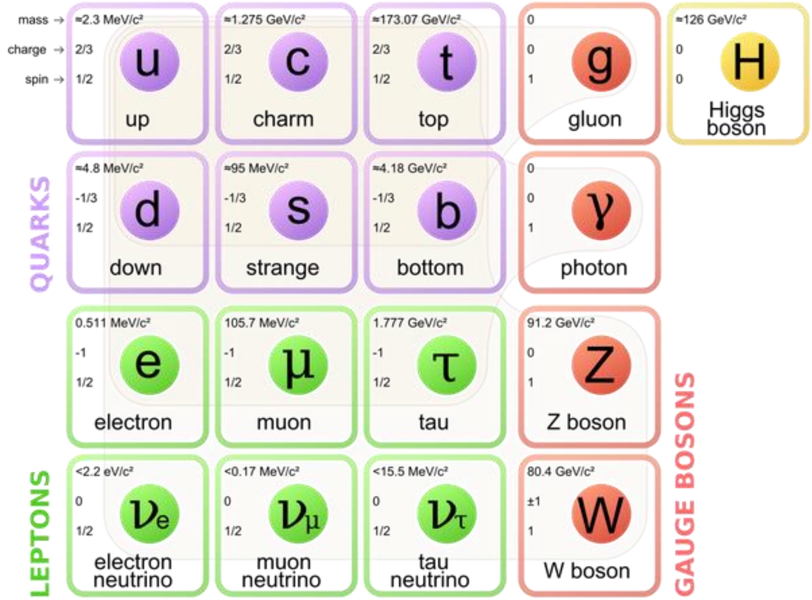
Introduction



Standard Model: Remarkably successful, yet incomplete theory

↓

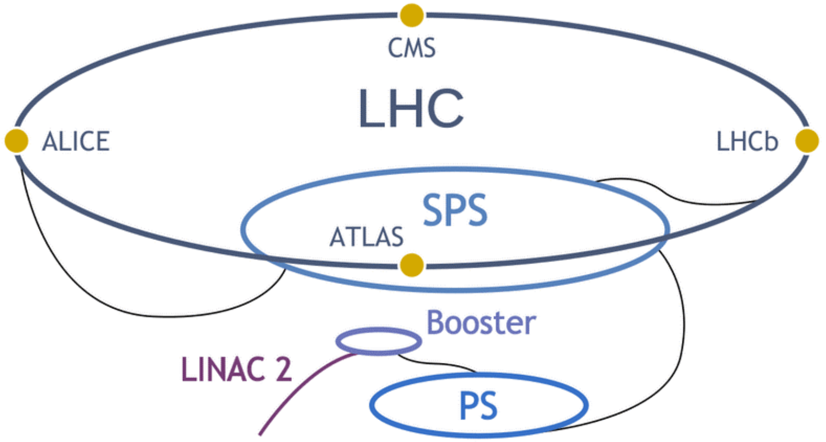
Anomaly Detection: Model independent approach to the detection of beyond the Standard Model (BSM) physics.

→ Selecting events that differ from the background

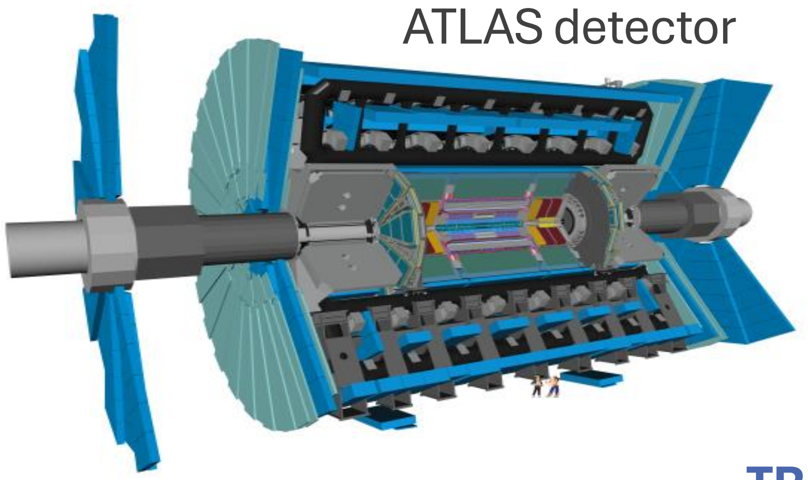
→ Machine learning methods can be employed

Large Hadron Collider (LHC)

→ Two general purpose detectors: **ATLAS** and CMS

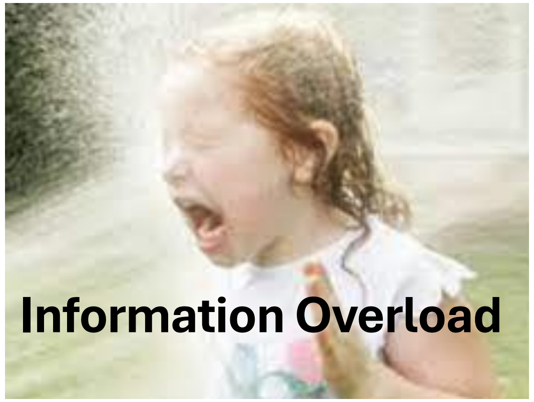


ATLAS Trigger System



Collision rate: 40MHz

(one bunch crossing every 25 ns)



TRIGGER SYSTEM

Level 1 (L1) Trigger
- Hardware based
- Uses reduced-granularity information from the calorimeters and the muon system

High Level Trigger (HLT)
- Reconstruction algorithms with higher levels of detail
- Trigger menu: list of chains applying specific selections

Can we use anomaly detection at trigger level to select "anomalous" and potentially signal-like events?

Datasets

Two datasets: background (658537 events) and SM signal of a di-Higgs production HH→bbbb (99720 events)

– For each event, the first and second leading p_T jets were used:

→ Three variables considered: jets p_T and $|\eta_1-\eta_2|$

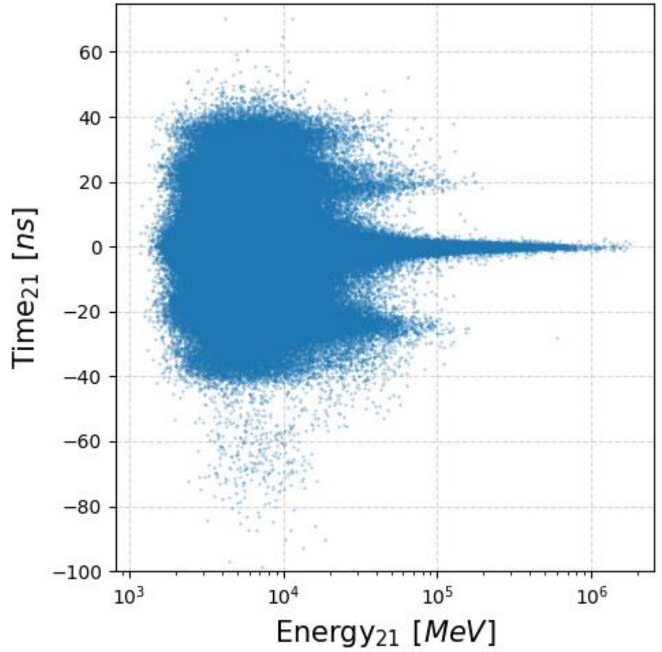
The background corresponds to real data!

– Each jet comprises several **constituents:** clusters of cells in the calorimeter where the incoming particles deposit their energy.

→ Two leading p_T constituents were considered;

→ The variables used were: p_T, nCells, time, dη, dϕ and dr.

The time and energy correlation of each cluster show the out-of-time pile-up contributions from the previous and next bunch crossings.



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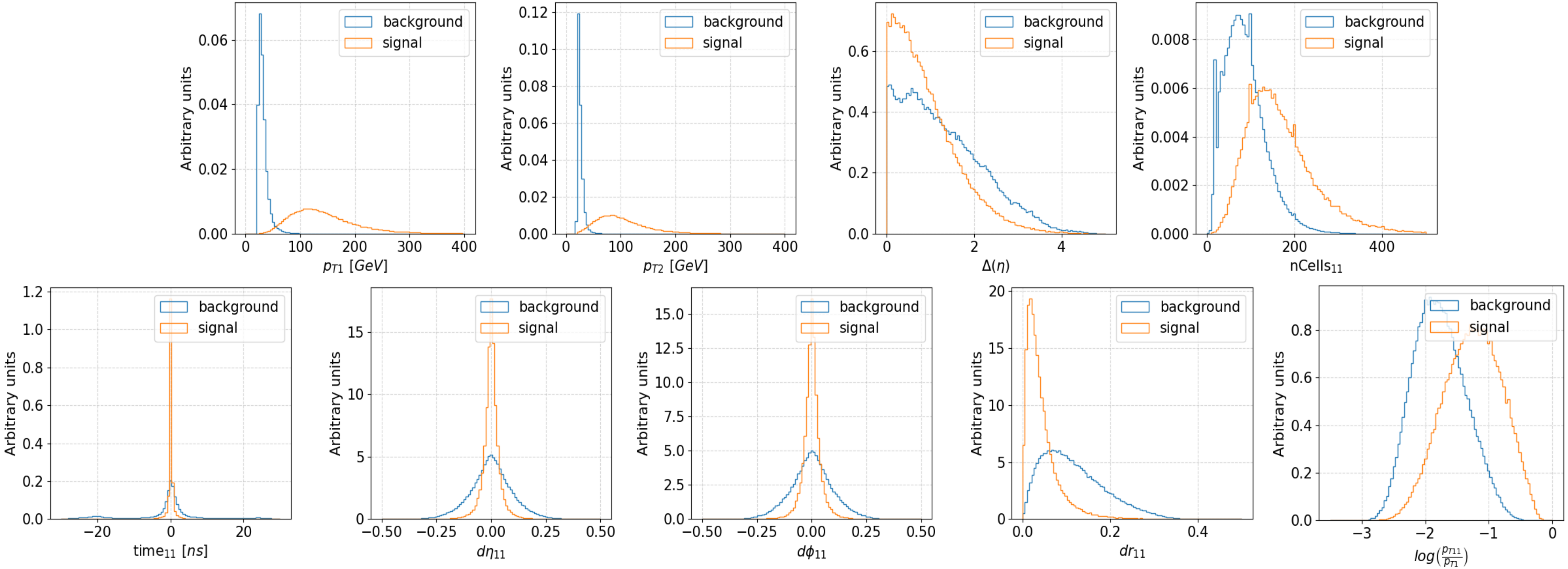


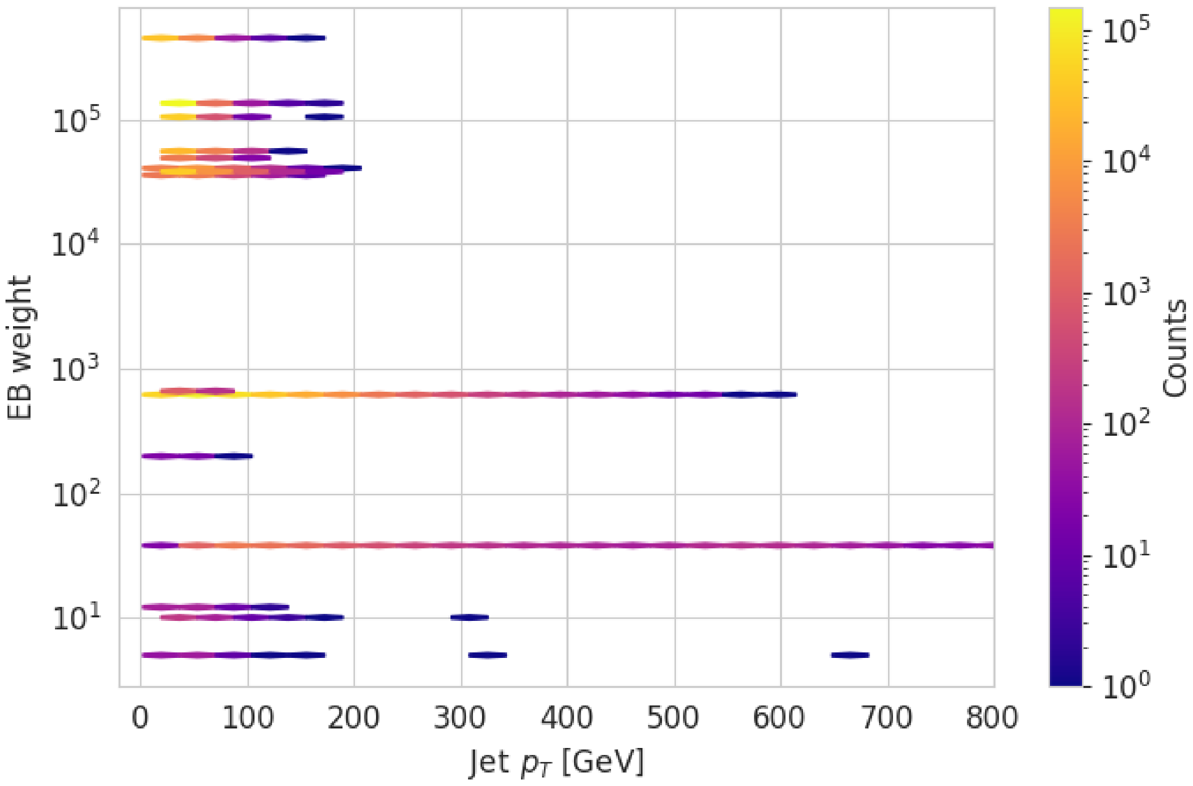
Plot of the jet variables and the input variables of the leading constituents of the leading jets

Enhanced Bias Mechanism

EB datasets: a mix of events selected by the L1 trigger system constructed such that the higher energy and object multiplicity bias is removable with event weights.

→ EB dataset from 2022 was considered.

EB weights
- Discrete values that recover the zero bias;
- Higher for low p_T jets;
- Can be added to the training of our model.



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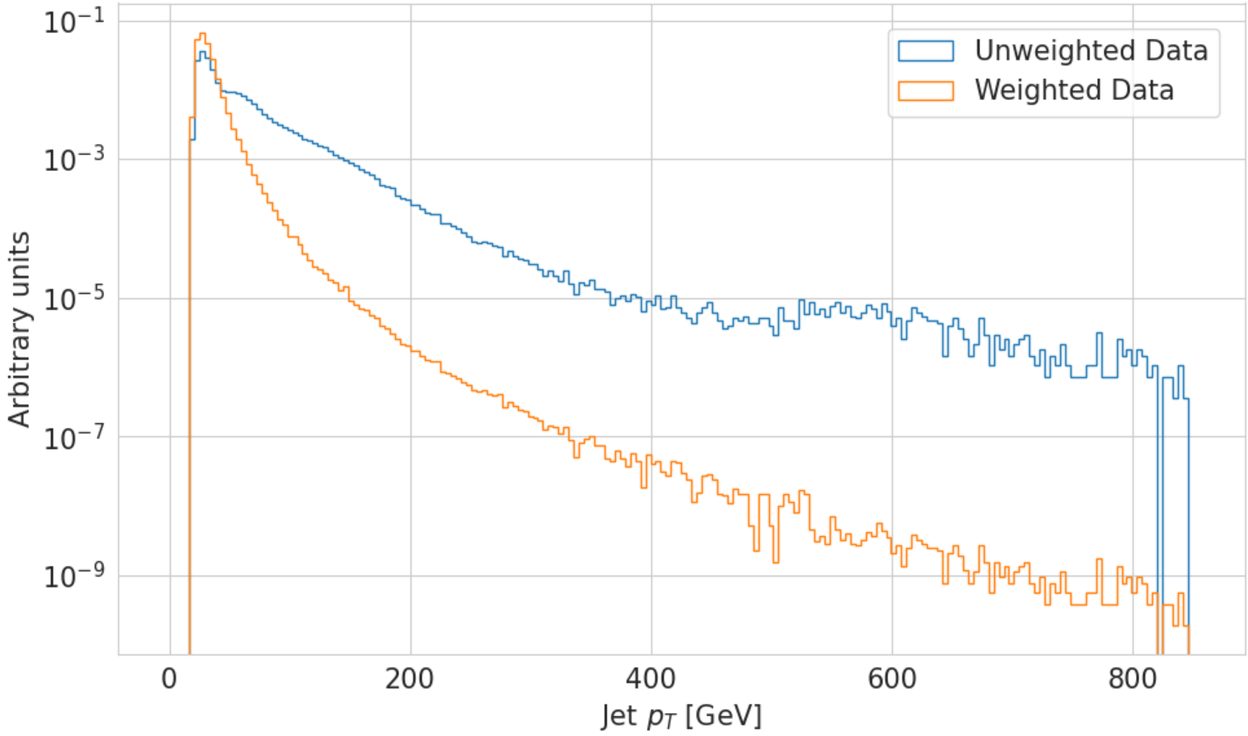
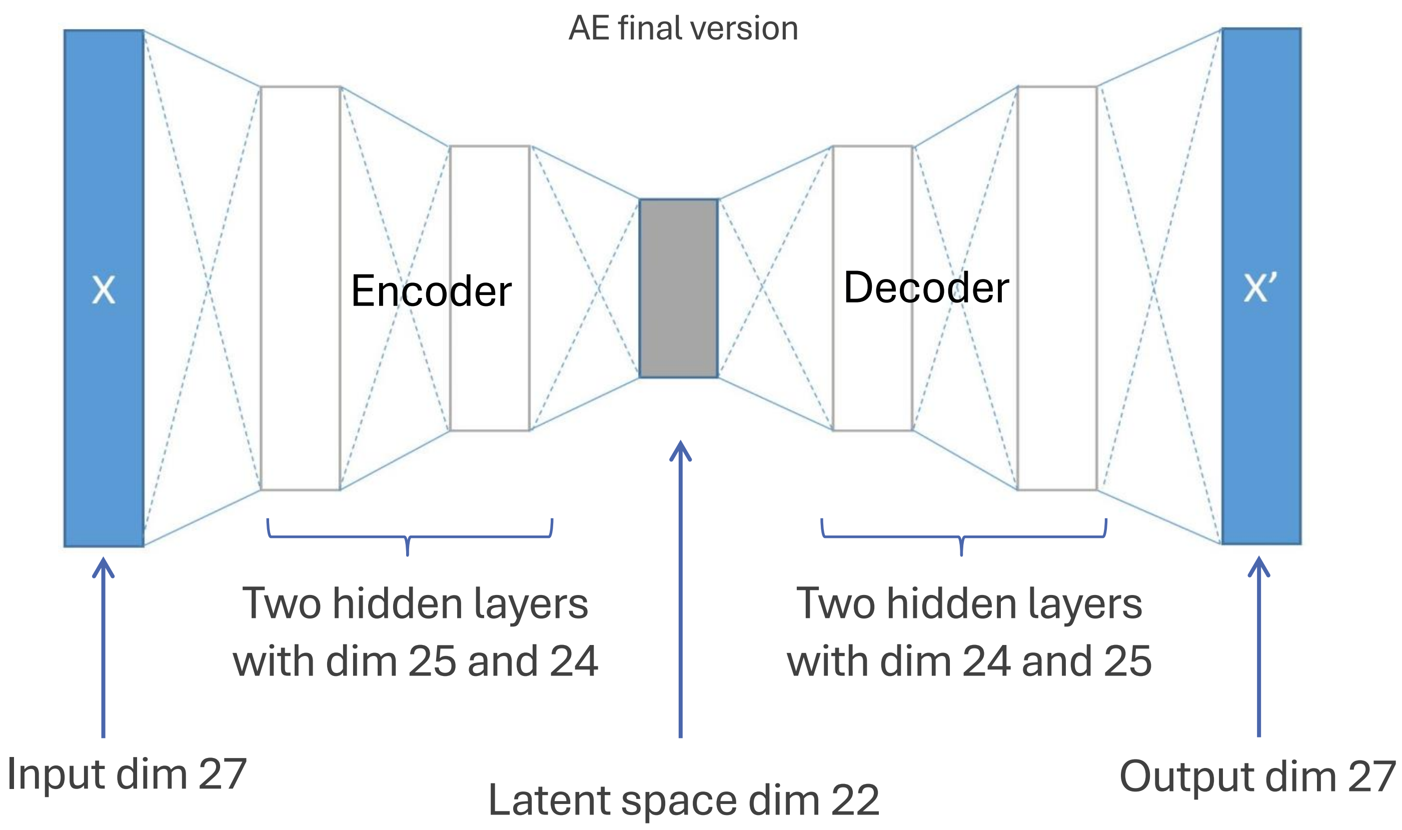


Autoencoder (AE)



Autoencoder (AE)

→ **Standardization** of input data

→ EB **weights** added during training

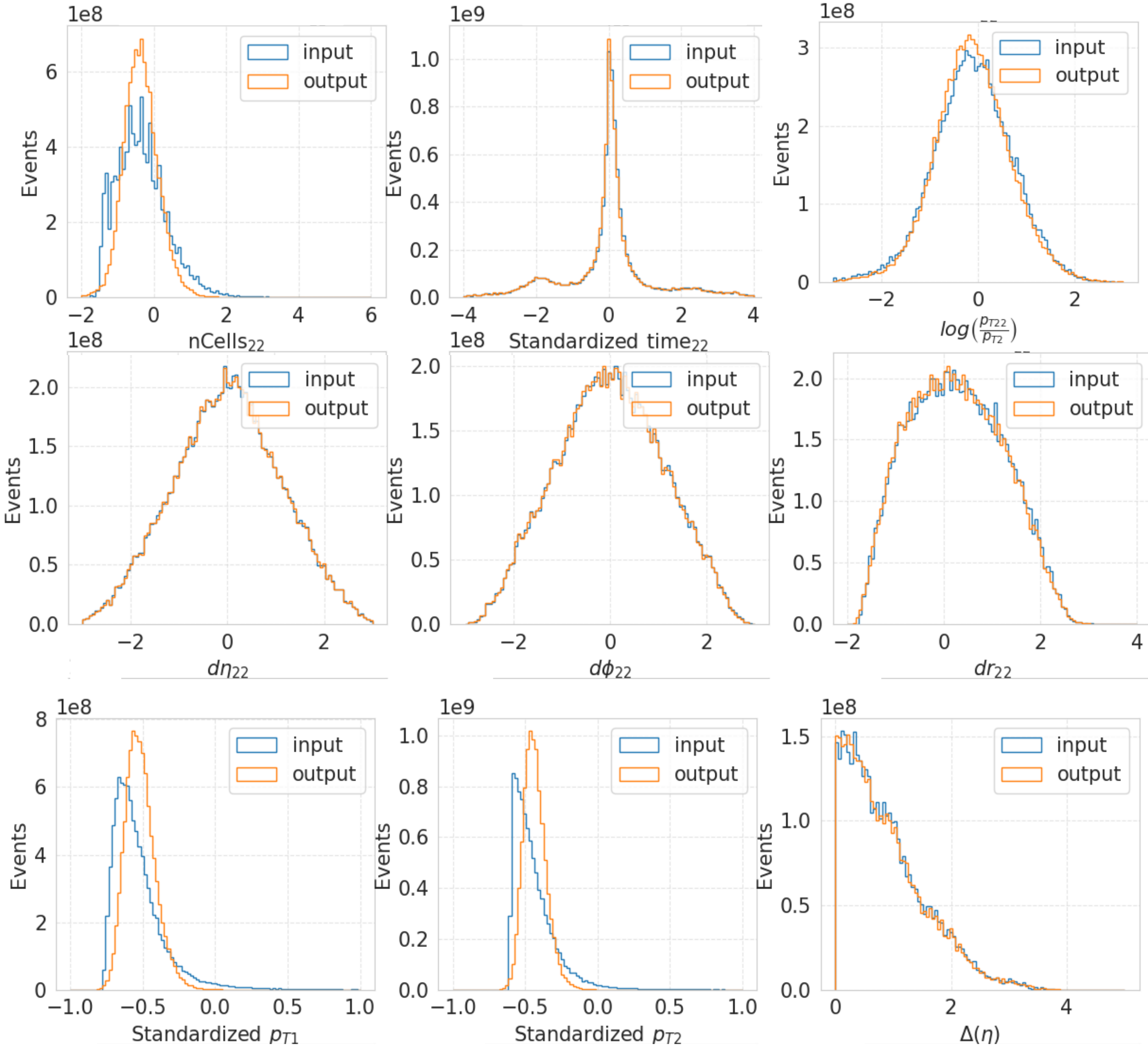
→ Choice of **input features**:

$p_{T22} \rightarrow \log\left(\frac{p_{T22}}{p_{T2}}\right)$ Improved the AE performance

$p_{T1}, p_{T2} \rightarrow \log\left(\frac{p_{T1}}{p_{T2}}\right)$ Did not improve the AE performance

→ **AE architecture** (hidden layers, latent space dimension, training hyperparameters).

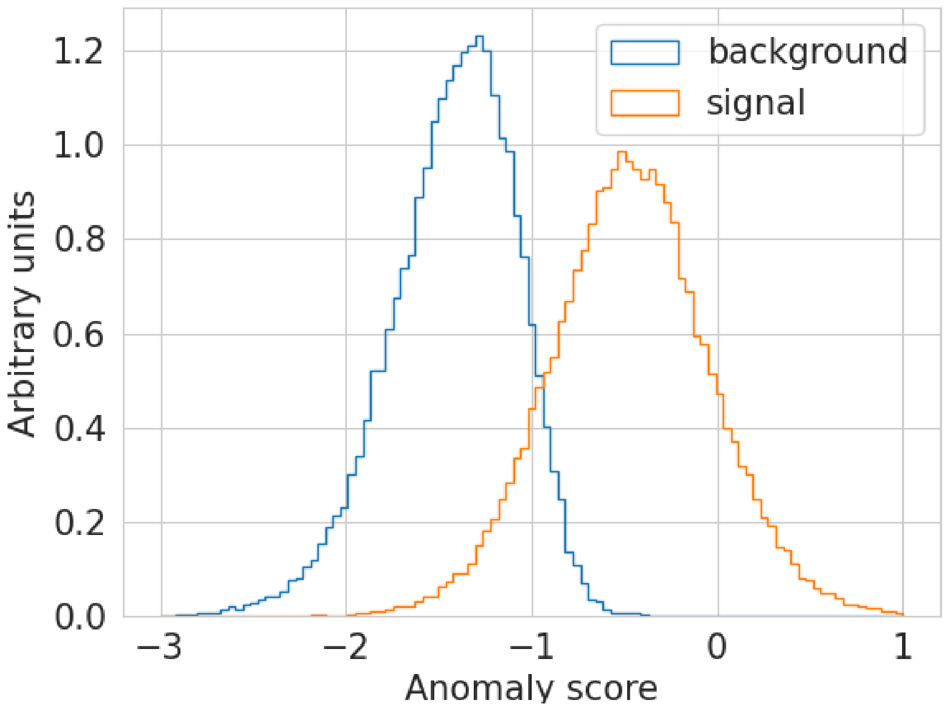
Several different architectures were tested, but the reconstruction of some variables can still be optimized.



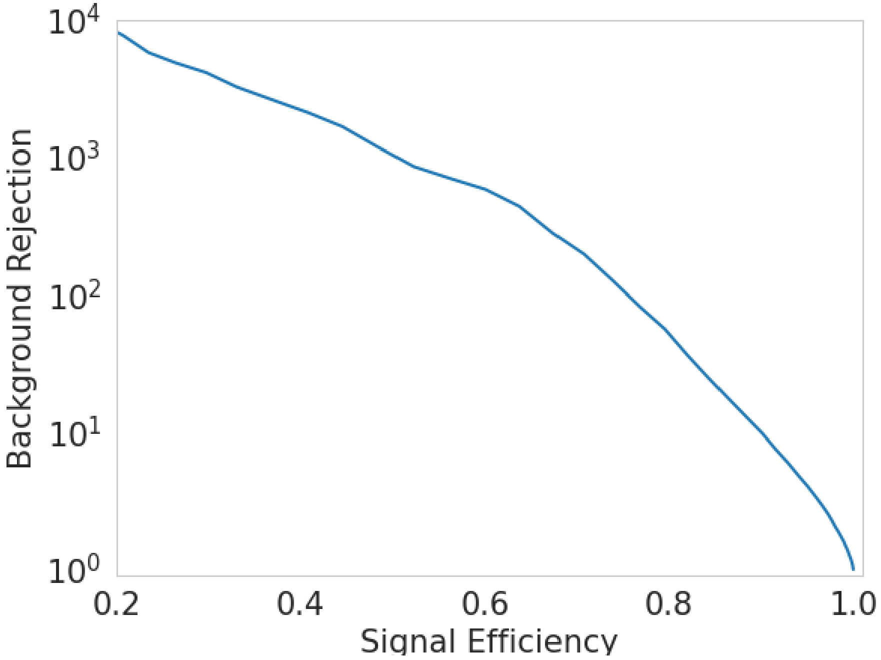
Reconstruction error and ROC curve

Unsupervised learning: the anomaly score is obtained using the mean squared error of each event, mse

$$log_{10}(mse)$$



ROC curve: plot of the background rejection against the signal efficiency at various thresholds settings.



Background Rate Distribution

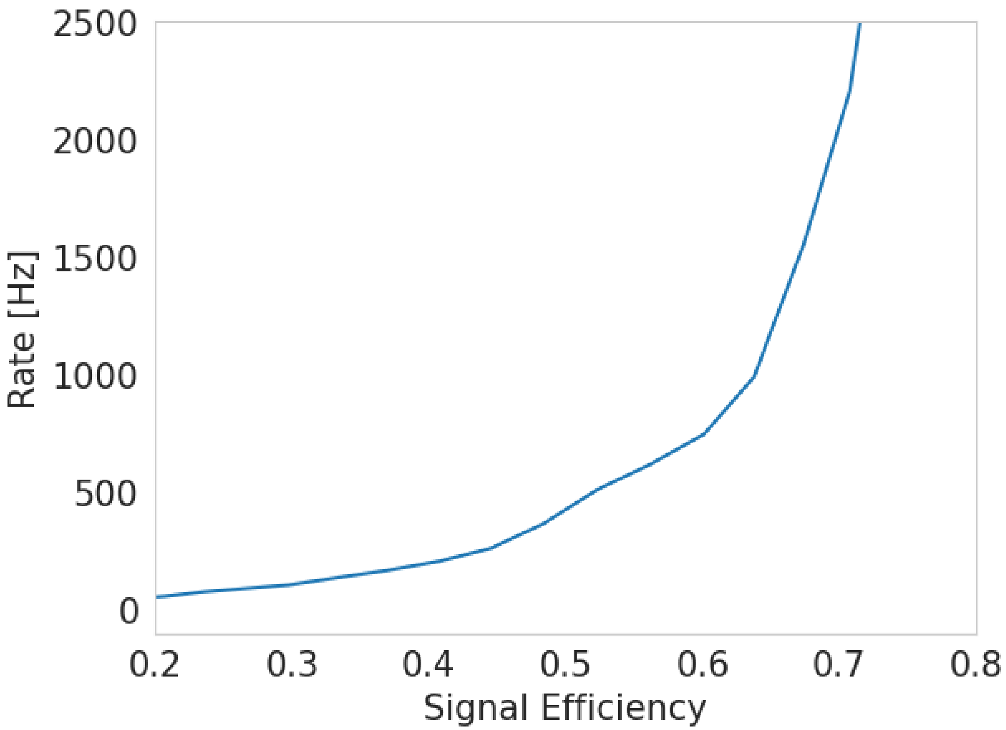
Sum over the events with anomaly score higher than threshold

EB weight of event e

$$R = \frac{\sum_{e=1}^{N} w_{EB}}{\Delta t}$$

Rate [Hz]: effective number of events passed by the chain per second

Time period over which the dataset was collected



The background rate distribution, along with dynamical restrictions of the operations and trigger menu, sets the threshold for the anomaly score.

Conclusion

→ Developed AE model using low-level input variables that are readily available at HLT;

→ This work follows form previous work using track-based variables with considerable CPU cost but better performance.

Future directions

1) EB datasets reflect the L1 configuration and LHC beam parameters at the time they are taken. In this work, an EB dataset from 2022 was considered.

→ The performance of the model could also be evaluated by considering other EB datasets.

2) Explore other architectures (deep sets, SVDD models) where the data from all the constituents could be used.

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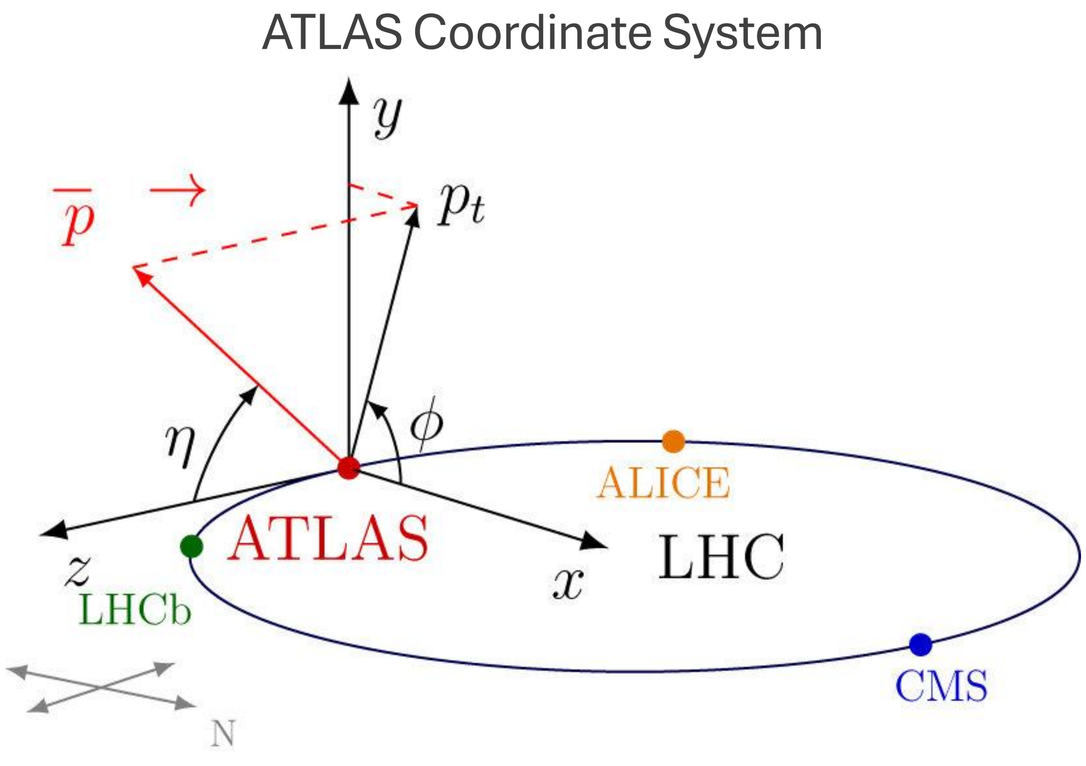
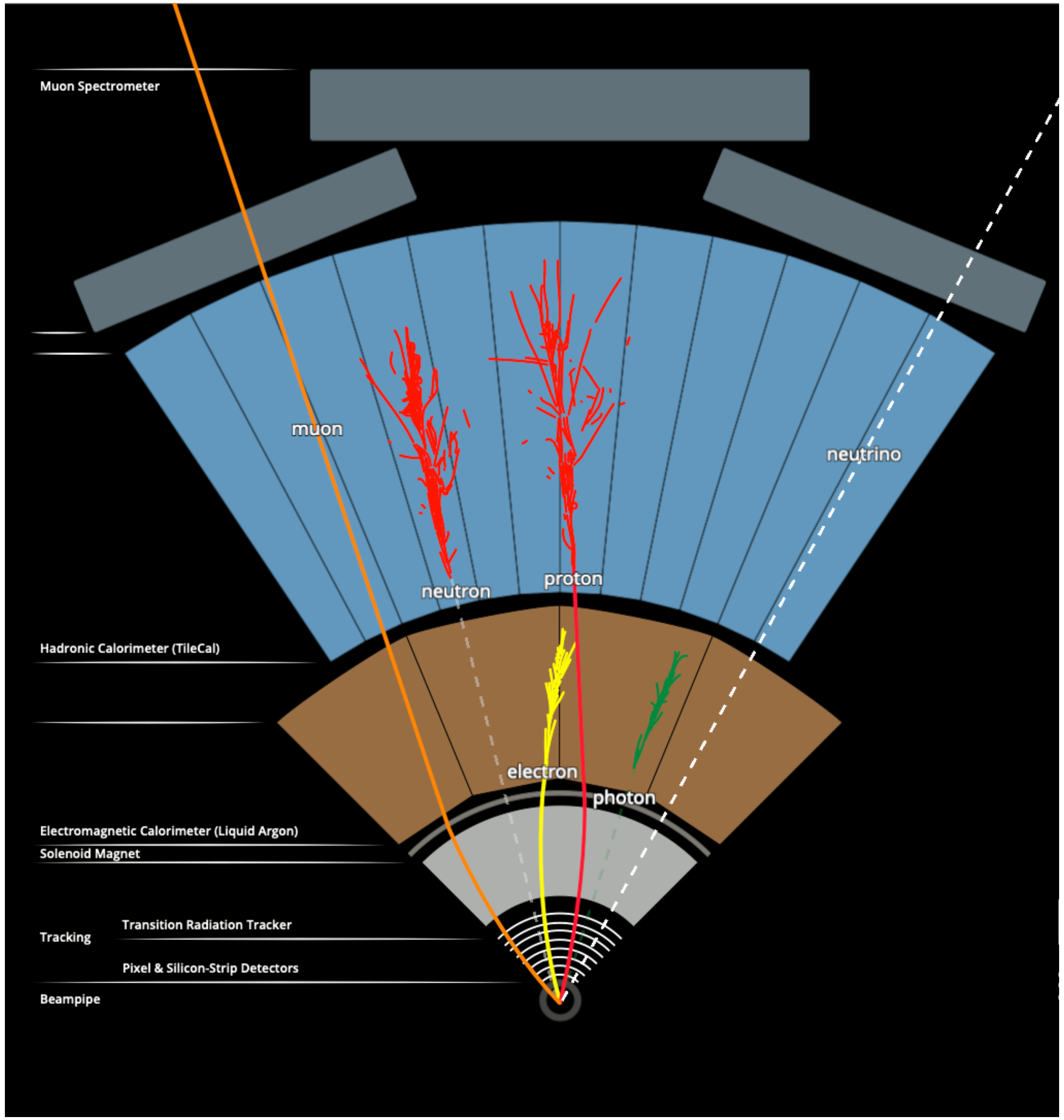
Backup Slides

ATLAS detector



$$\eta = -\ln \tan\left(\frac{\theta}{2}\right)$$

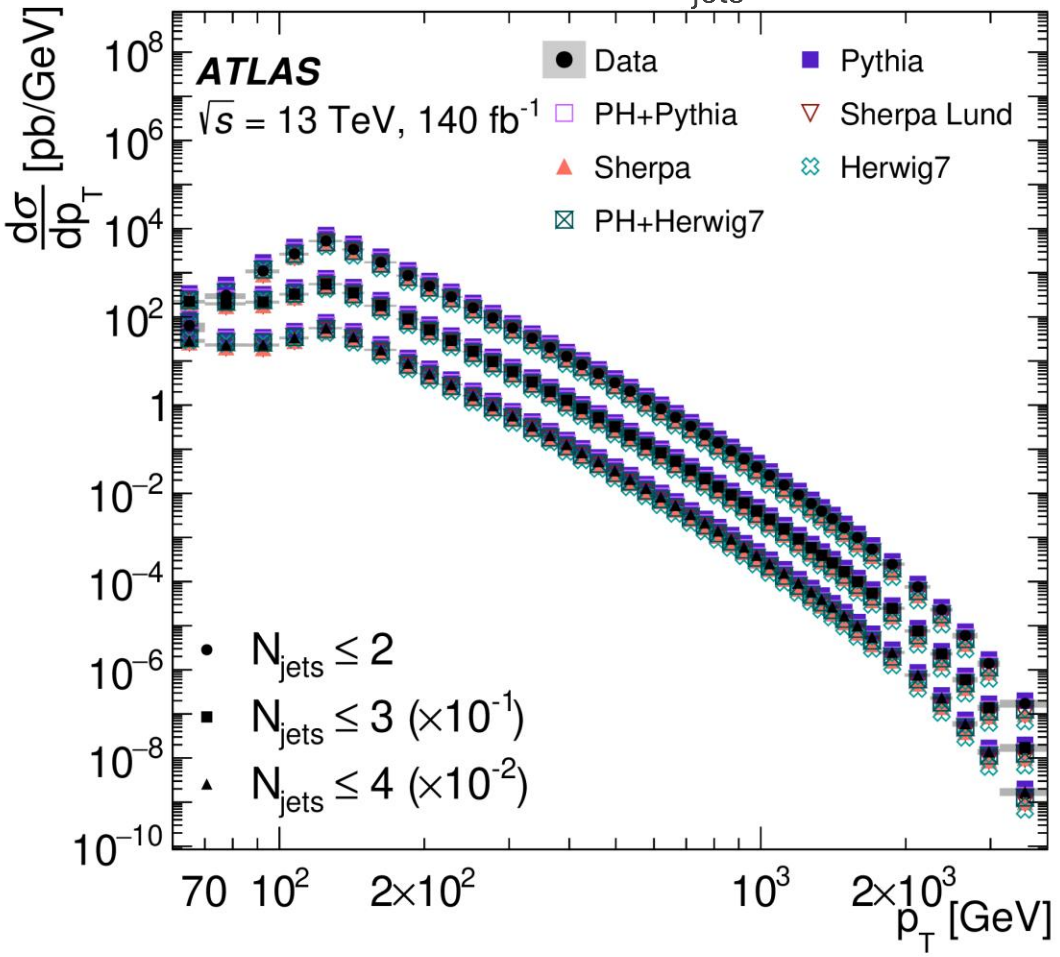


EB weights

EB weight calculation

$$\frac{1}{w_{EB}} = 1 - \prod_{j=1}^{EB\,chains} \left(1 - \frac{r_{je}}{p_j}\right)$$

Differential cross-section as a function of p_T^{Nincl} in inclusive bins of N_{jets}



Choice of input variables