Review of AI and Machine Learning Methods for Anomaly Detection in CMS

XIX Mexican Workshop on Particles and Fields 2025

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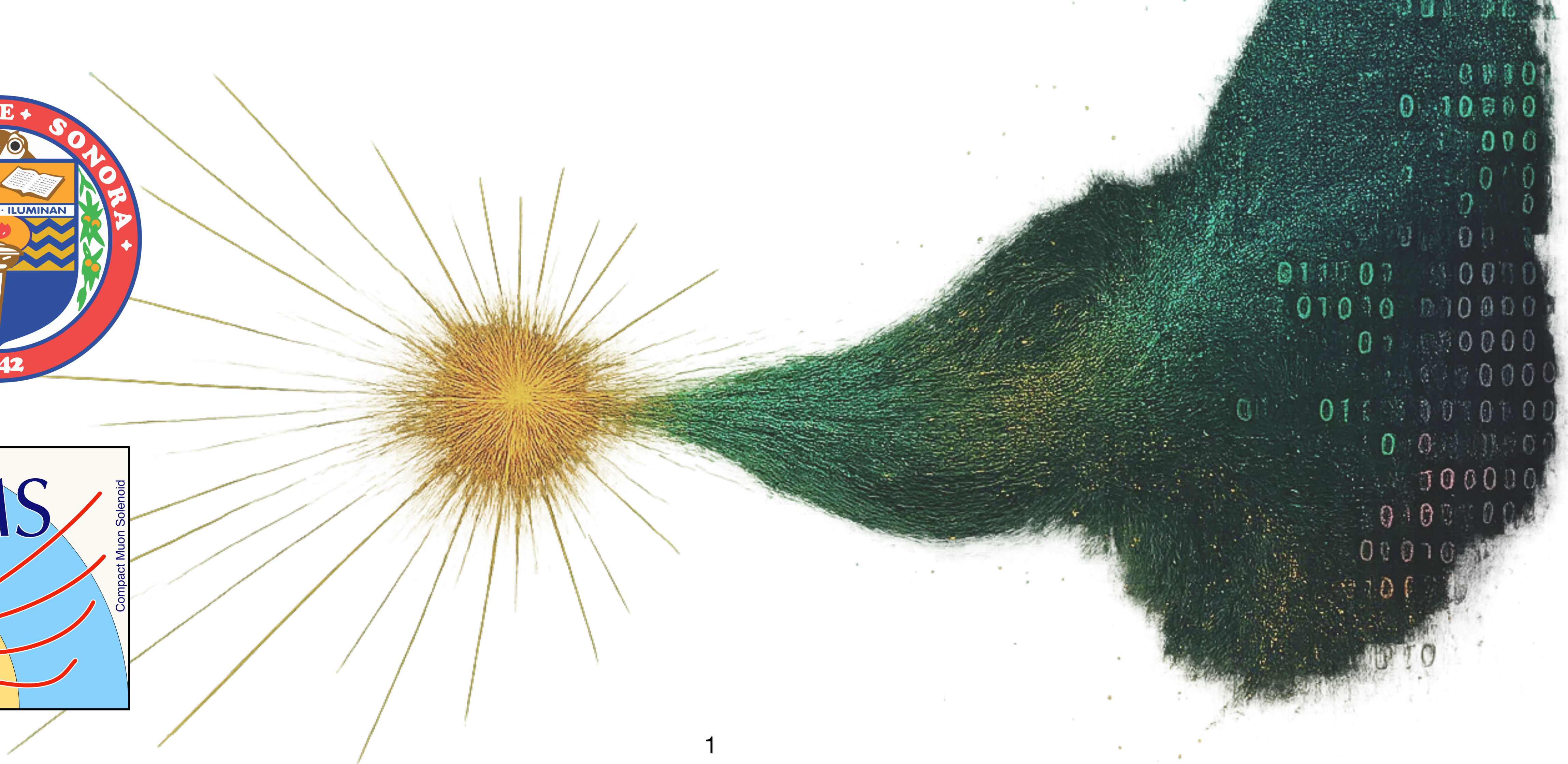
On behalf of the CMS collaboration

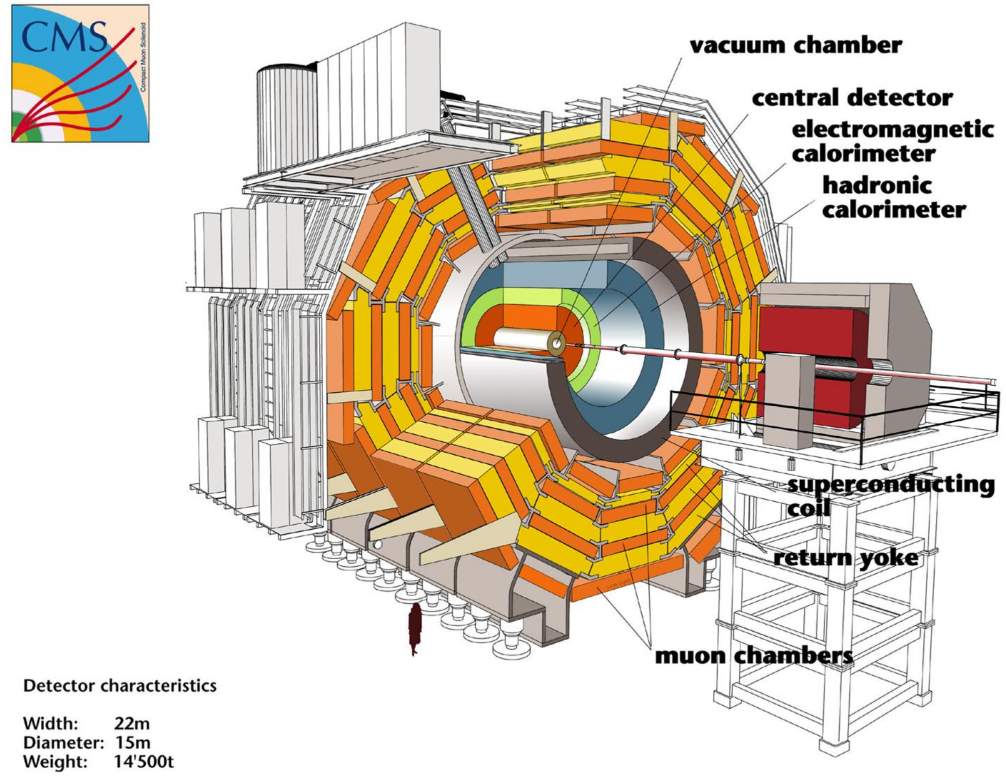


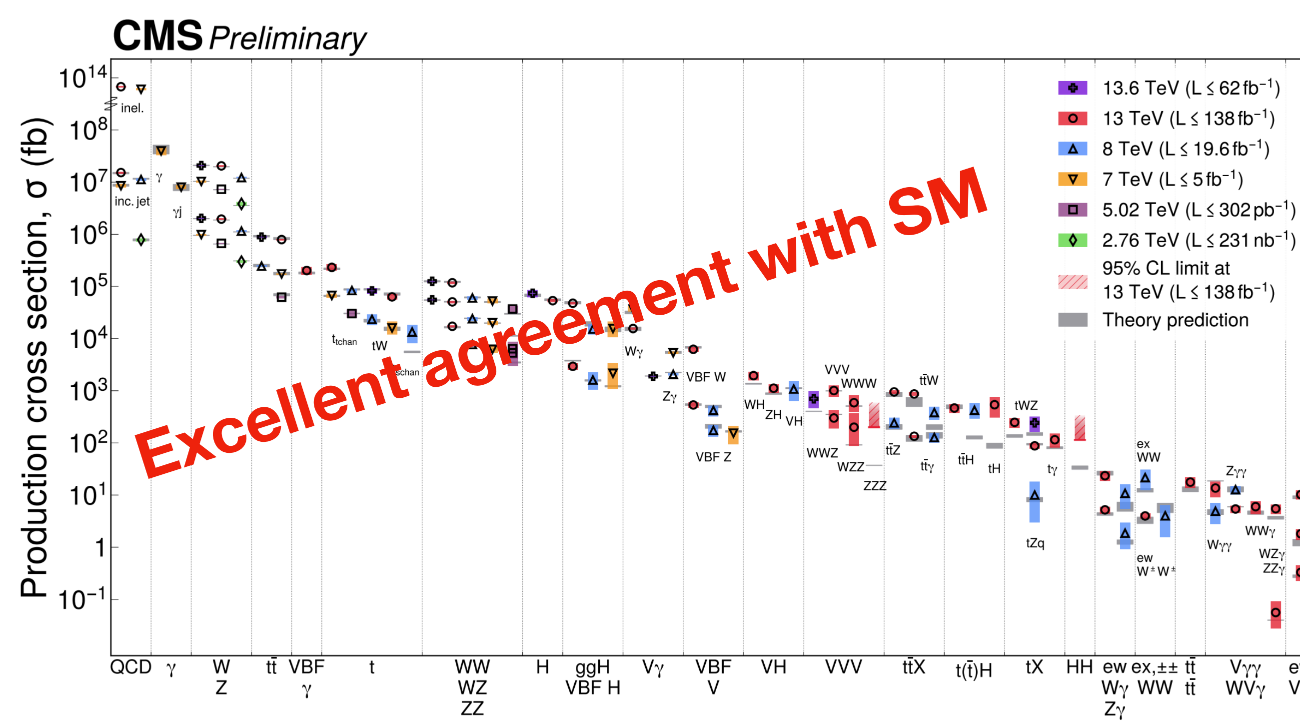
Motivation

- **CMS** is one of the two multipurpose detectors at the Large Hadron Collider (LHC) designed to measure SM interactions and search for possible new physics phenomena

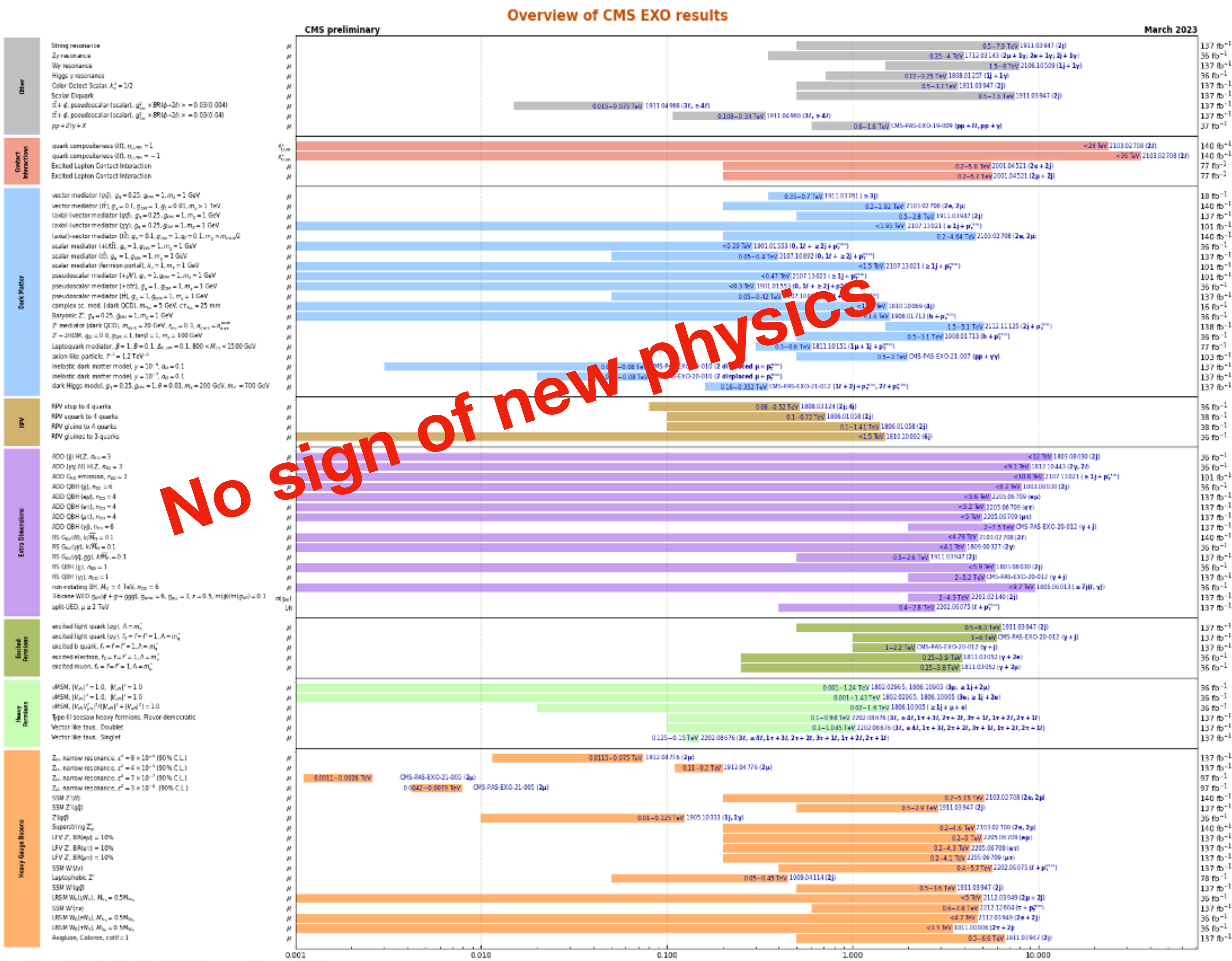
- The complexity and high dimensionality of CMS data, combined with the reduced cross section for interesting processes, limit the potential for new discoveries.

- Traditional analysis, relying on predefined hypotheses optimized for specific models, risks overlooking unforeseen phenomena.





Overview of CMS Exotic searches



- Despite the unprecedented precision and dataset size achieved during LHC Runs 1–3, no significant deviation from the Standard Model has been observed so far.
- The CMS program continues to refine its sensitivity and expand its coverage using advanced reconstruction and machine learning techniques.
- **Anomaly Detection (AD)** methods constitute an approach designed to identify events that could arise from statistical fluctuations, detector-related artifacts, or manifestations of new physics.

Outline

- **Anomaly Detection (AD) in searches for new physics**
    - Dijet Resonances (CMS)

- **Real time Anomaly detection (AD)**
    - L1 triggering for rare events (LLP, SUSY, Dark matter candidates, etc.)

- **Anomaly Detection** for Data Quality Monitoring (DQM) in CMS

Anomaly detection for Dijet resonance searches in CMS

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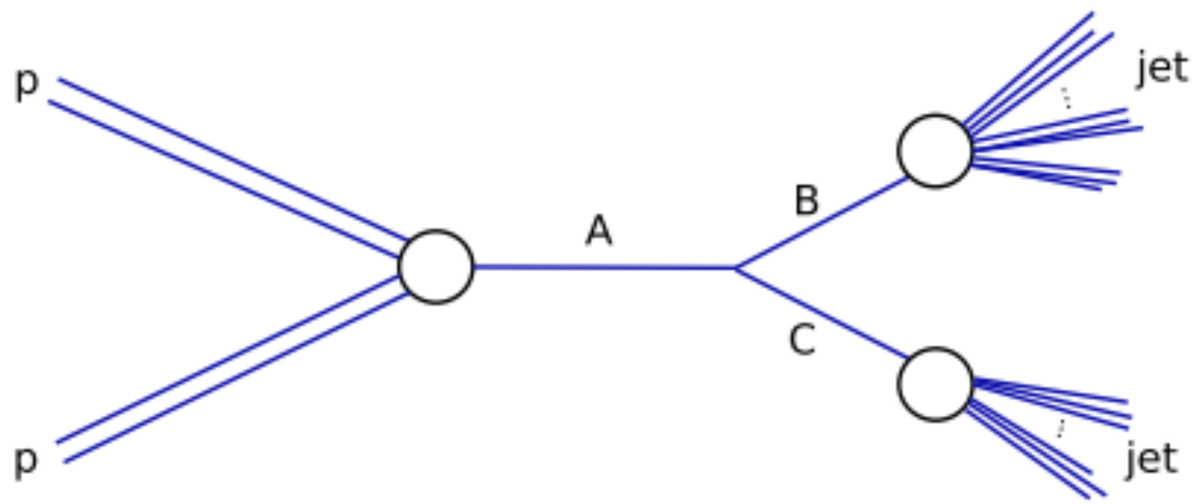

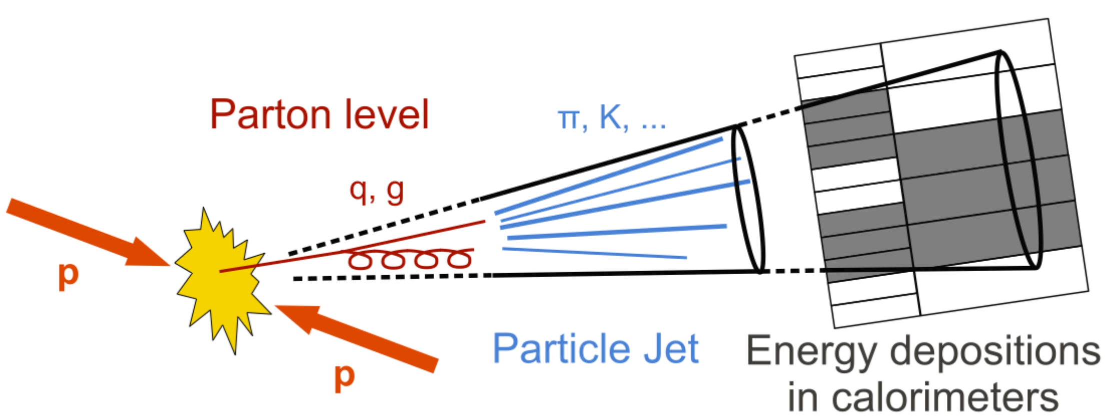

- Search for a narrow width heavy resonance A within the TeV-scale mass decaying into two other B and C resonances
- B and C being produced with high Lorentz boost, such that their decay products are contained in large-radius jets
- Traditional searches are severely challenged by the overwhelming background from QCD processes
- AD methods developed aiming to explode **jet sub-structure** properties to discriminate between signals and background

5 anomaly detection techniques

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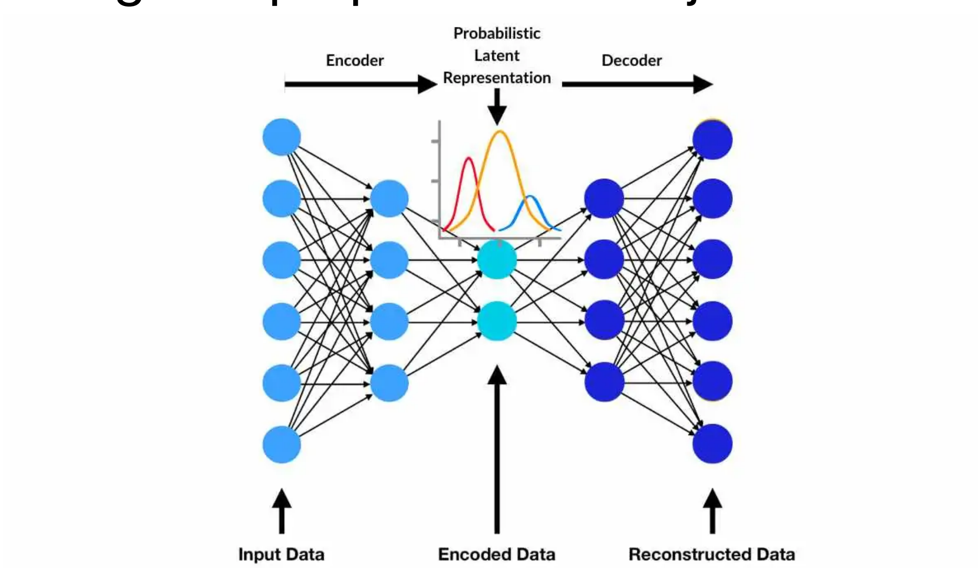
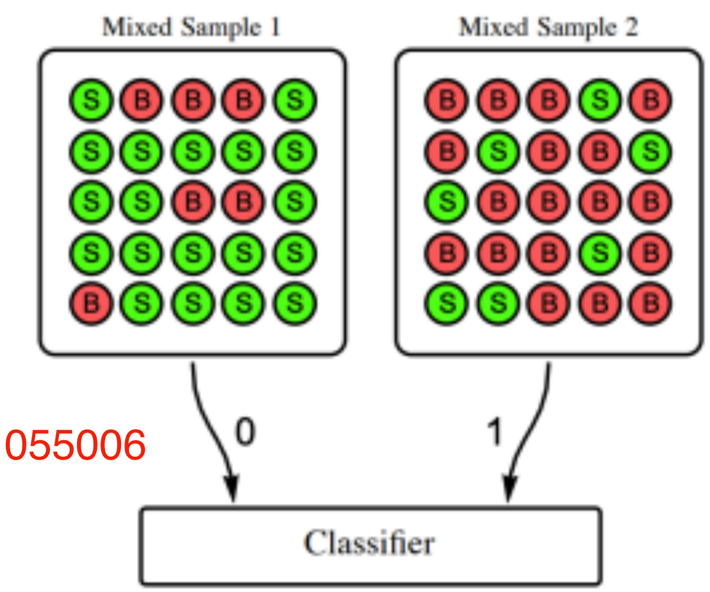
- **1 VAE (Variational AutoEncoder)**, unsupervised learning algorithm aims to identify anomalous jets, in case of dijet search employee as input the 100 highest pT particles of a jet



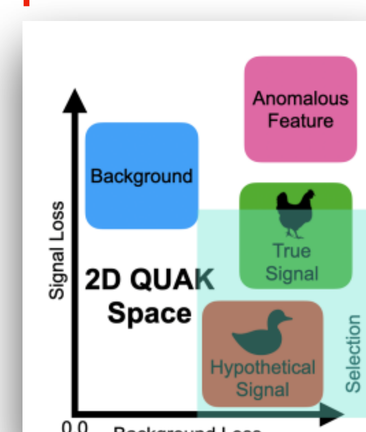
- **3 Weakly supervised methods:** signal vs background classifier is trained exclusively on data (no use of MC simulation), CWoLa, TNT, CATHODE

Phys. Rev. D **106**, 055006



https://arxiv.org/pdf/2011.03550

- **1 Semi-supervised method** middle ground between fully agnostic-methods and a standard dedicated search. Quasi-anomalous search (QUAK) uses a density estimator to encode a ‘prior’ for the likely signature of a new physics signal based on MC



Performance on signal models

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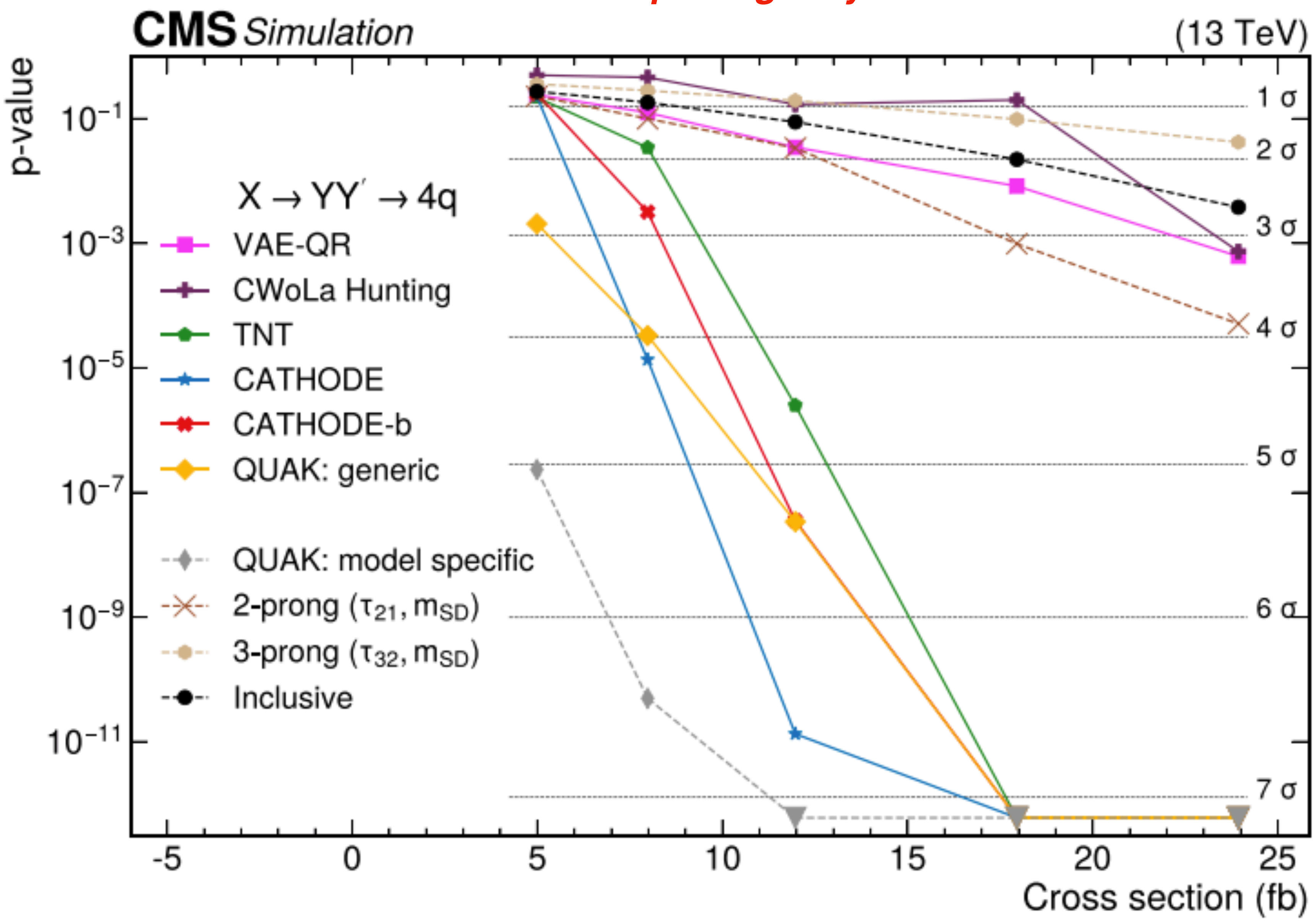
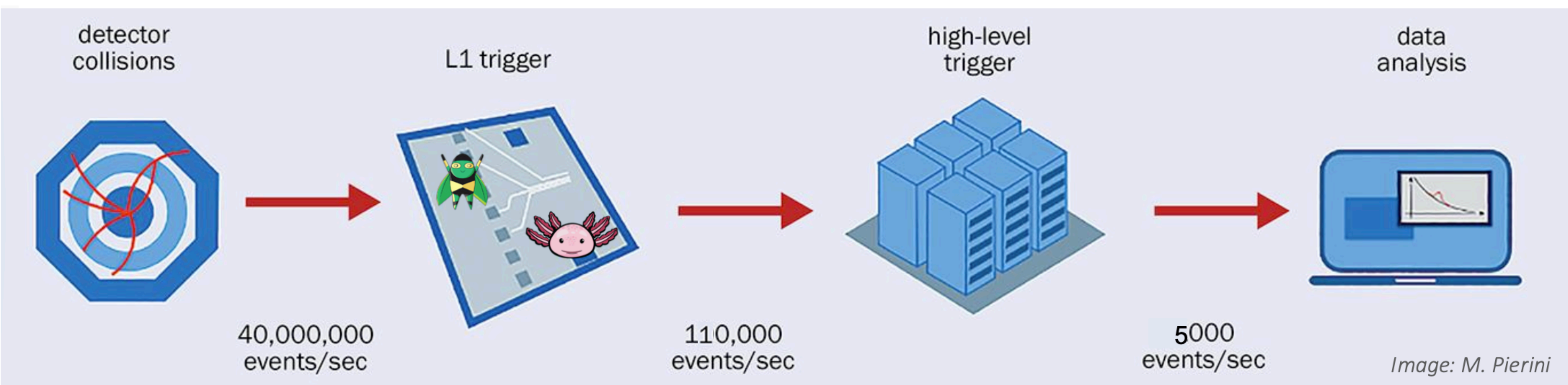


- Performance verified in a simulated pseudo dataset constructed from different bkg processes (**QCD dominated**) with an equivalent luminosity of 26.8 fb^{-1}
- Pseudo-data is injected with signals to test the sensitivity of the anomaly detection methods
- Inclusive search sensitive to both signal models, but **unable** to reach evidence for discovery

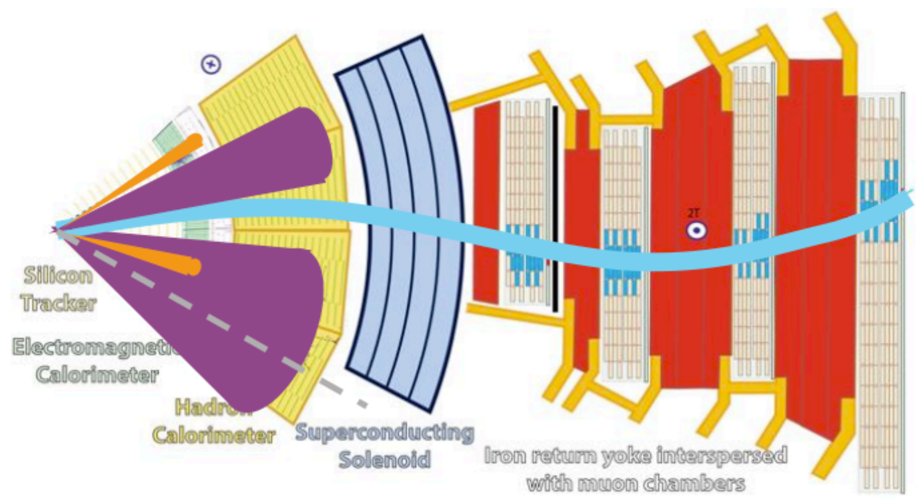
Real time Anomaly Detection

- CMS L1 trigger system filter **99.75**% of collisions events
- What if new physics is missing?
- AXOL1TL and CICAD AD algorithms are employed to trigger interesting events that would otherwise be absent in conventional streams.



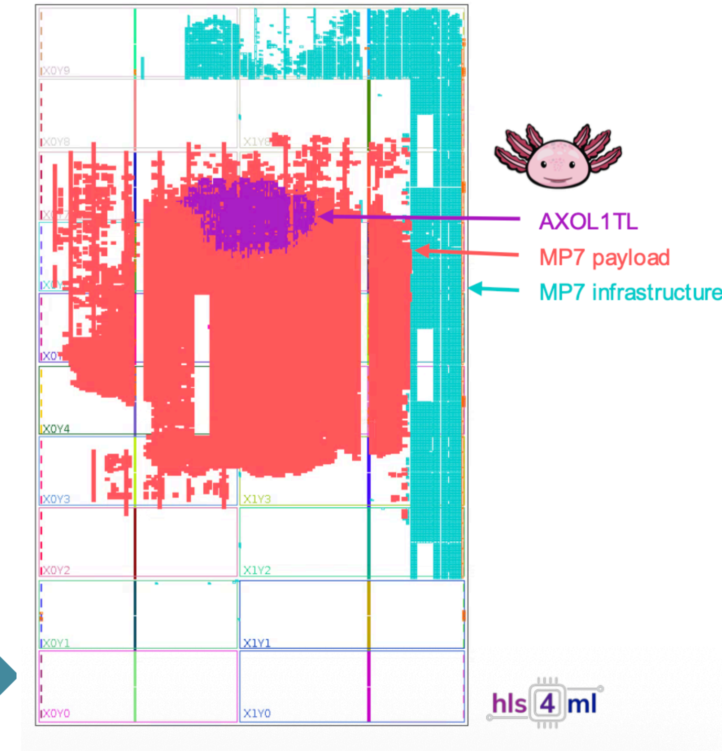
AXOL1TL

AXOL1TL



Deployed neural network on FPGA

- Implemented on Xilinx Vertex 7 FPGA
- 50ns latency and resources requirements met



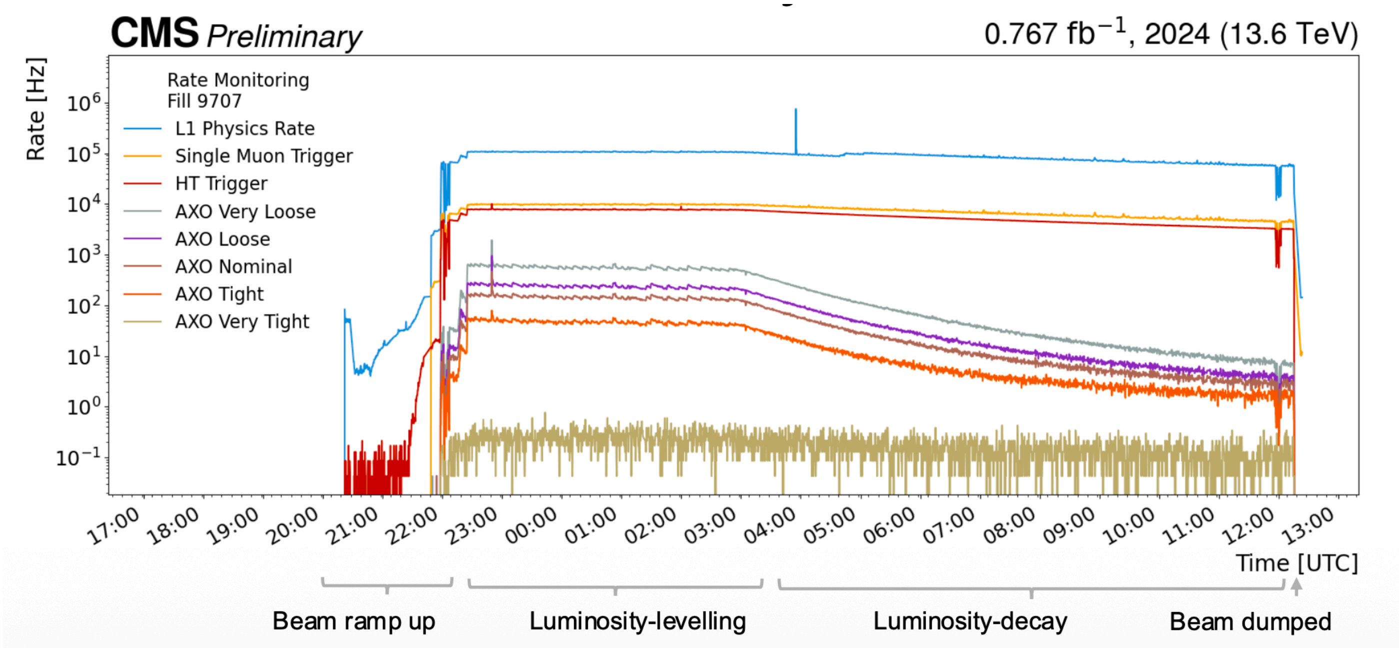
56 inputs from L1 trigger objects

- Missing Energy
- Up to 10 Jets
- Up to 4 muons
- Up to 4 electrons/photons

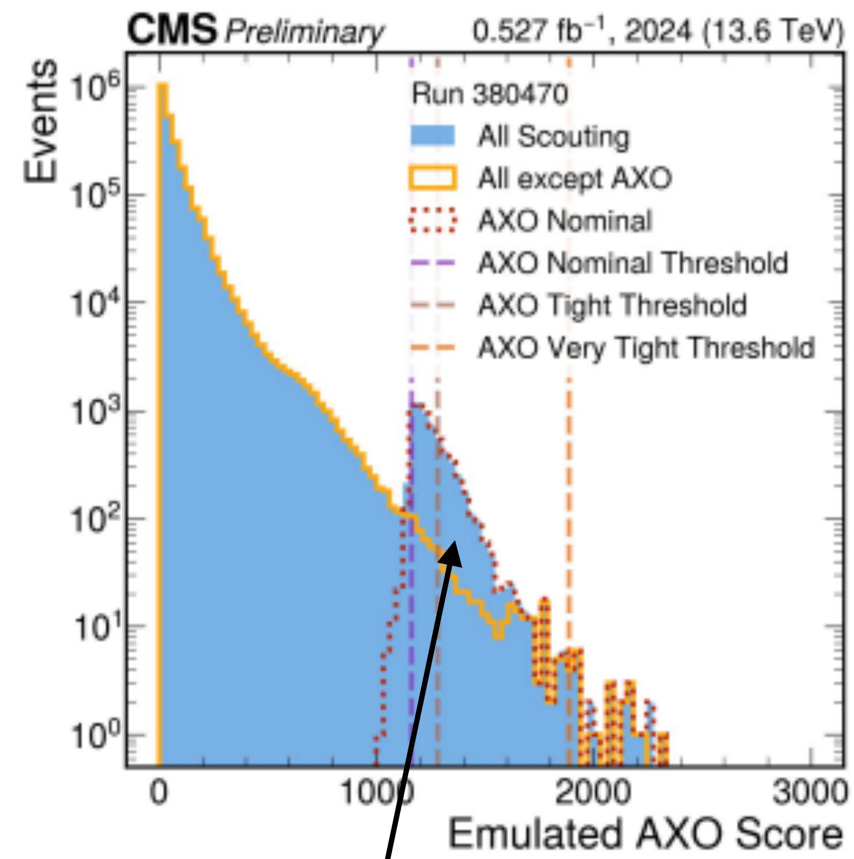
- The AXOL1TL Anomaly Detection uses a Variational autoencoder (VAE), which is a dense feed-forward neural network. The encoder network computes a latent space vector of Gaussian probability distributions. The decoder network reconstruct the original input from the latent space

$$\text{Loss} = \underbrace{(1-\beta)\left\|x-\hat{x}\right\|^2}_{\text{Reconstruction term}} + \underbrace{\beta\frac{1}{2}(\mu^2+\sigma^2-1\ -\log\sigma^2)}_{\text{Full regularization term}}$$

AXOL1TL Rate stability

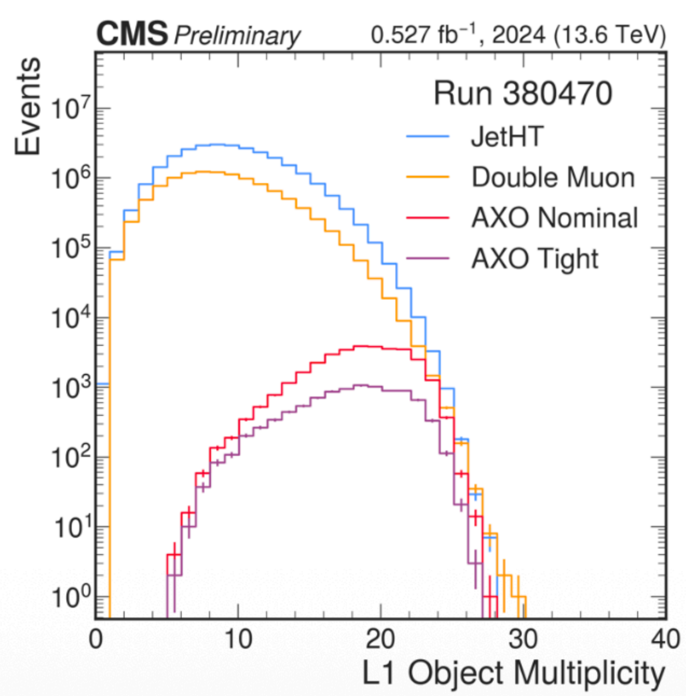


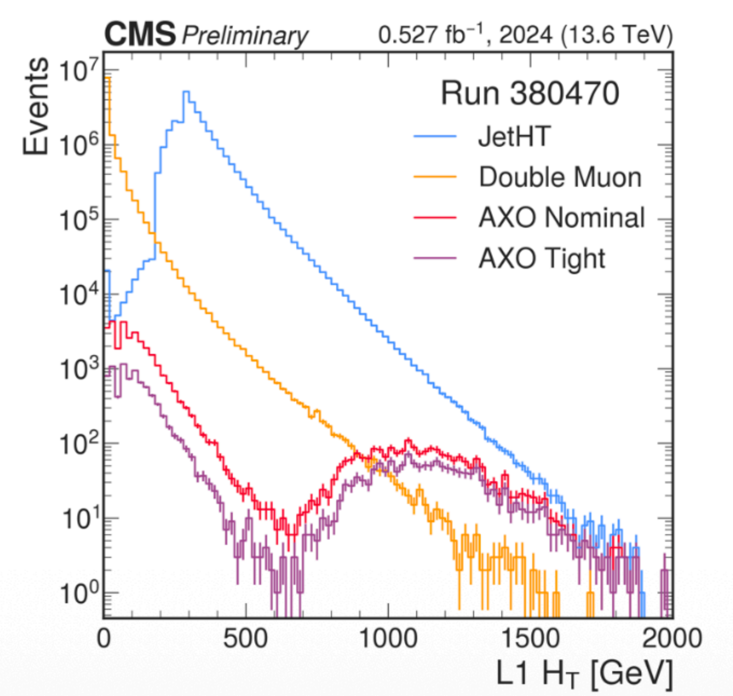
https://cds.cern.ch/record/2904695?ln=en



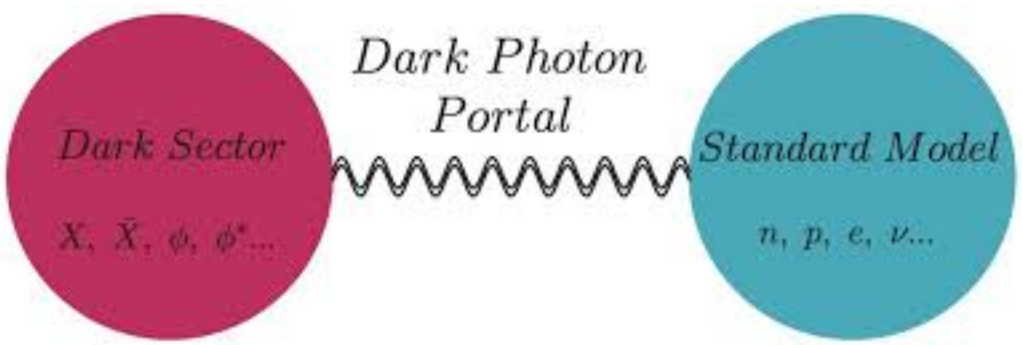
New data that otherwise wouldn't been collected

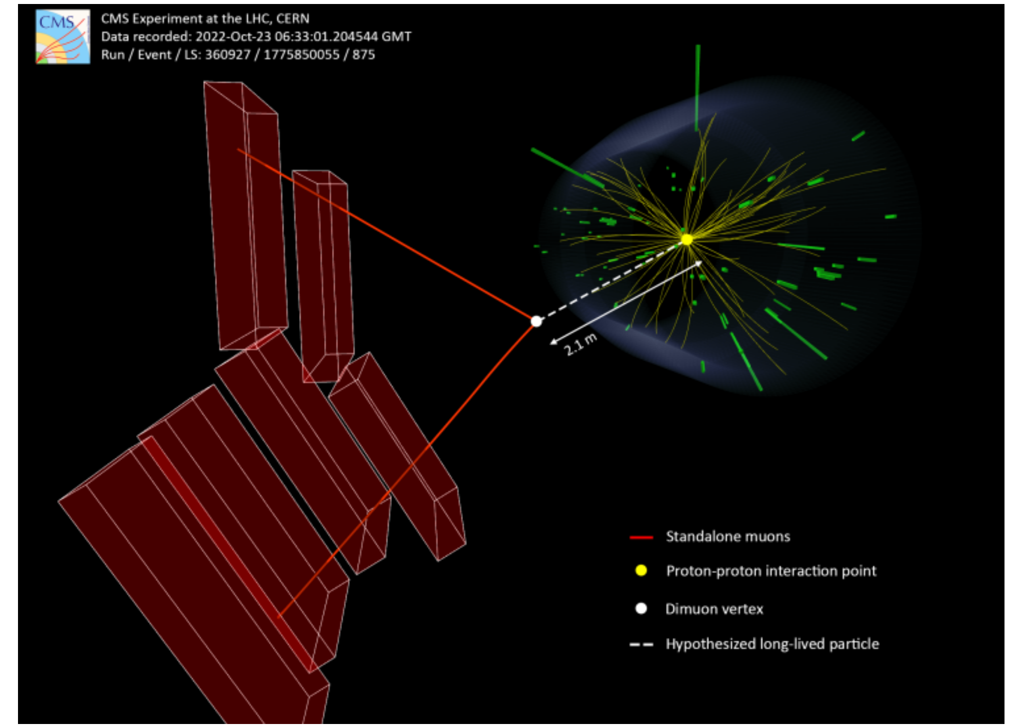
High object multiplicity and total transverse momentum.





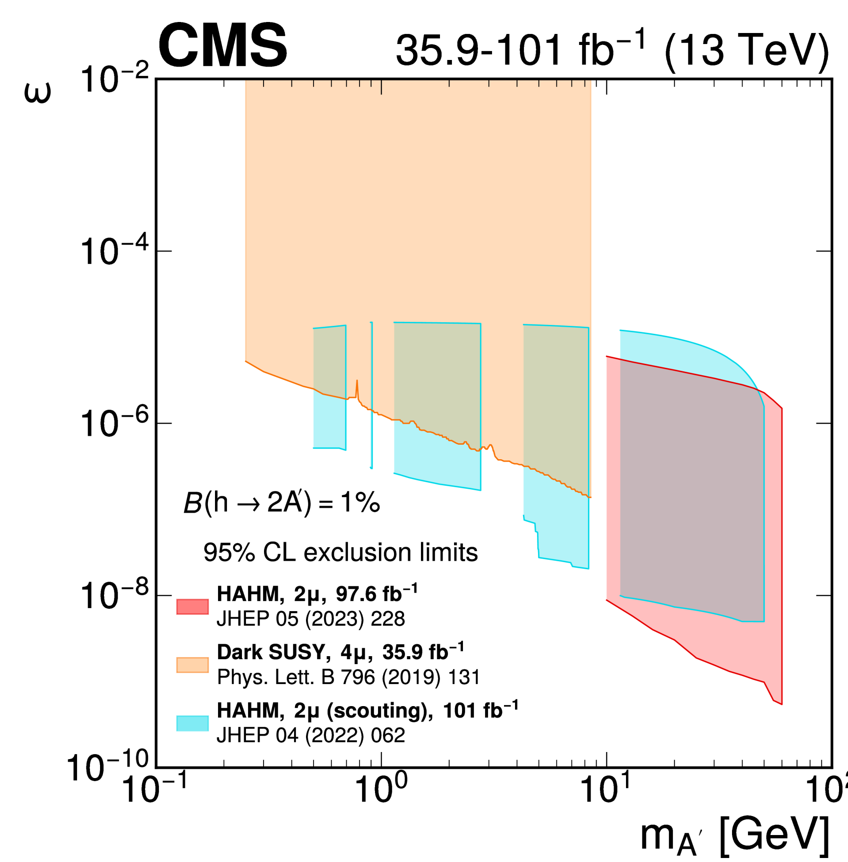
Sensitivity to rare signals





- LLPs are anomalies in the training dataset
- Current implementations in AXO1LT don't use LLPs specific inputs
- Current searches are limited by muon reconstruction and triggering
- Future ideas to **increase AD sensitivity to LLPs** are
  - Incorporate muon detector shower bits
  - Incorporate muon impact parameter bits
  - Incorporate HCAL depth and timing

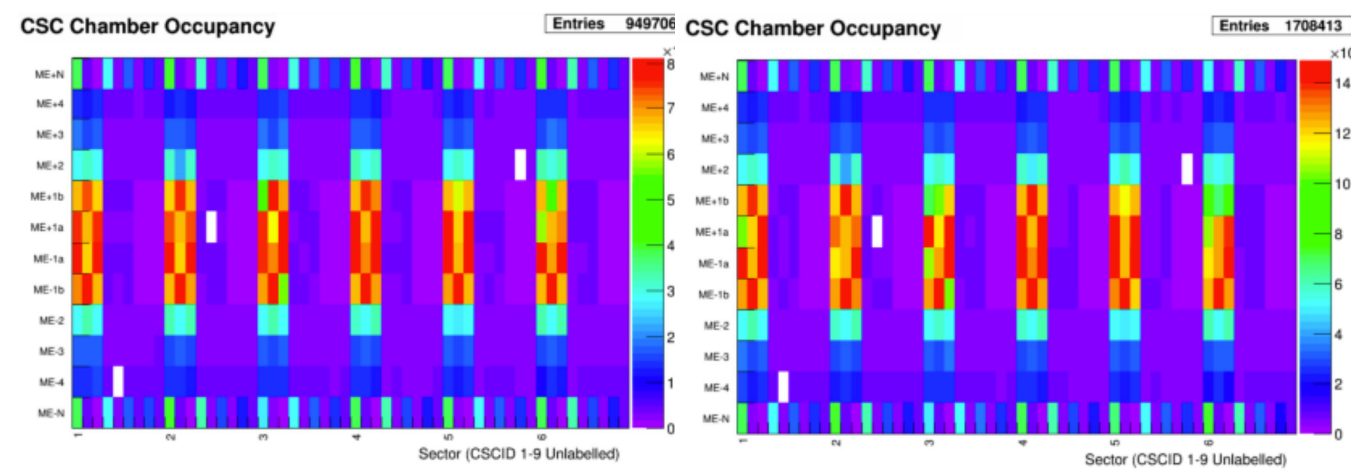
https://doi.org/10.1016/j.physrep.2024.09.013



AD for data quality monitoring

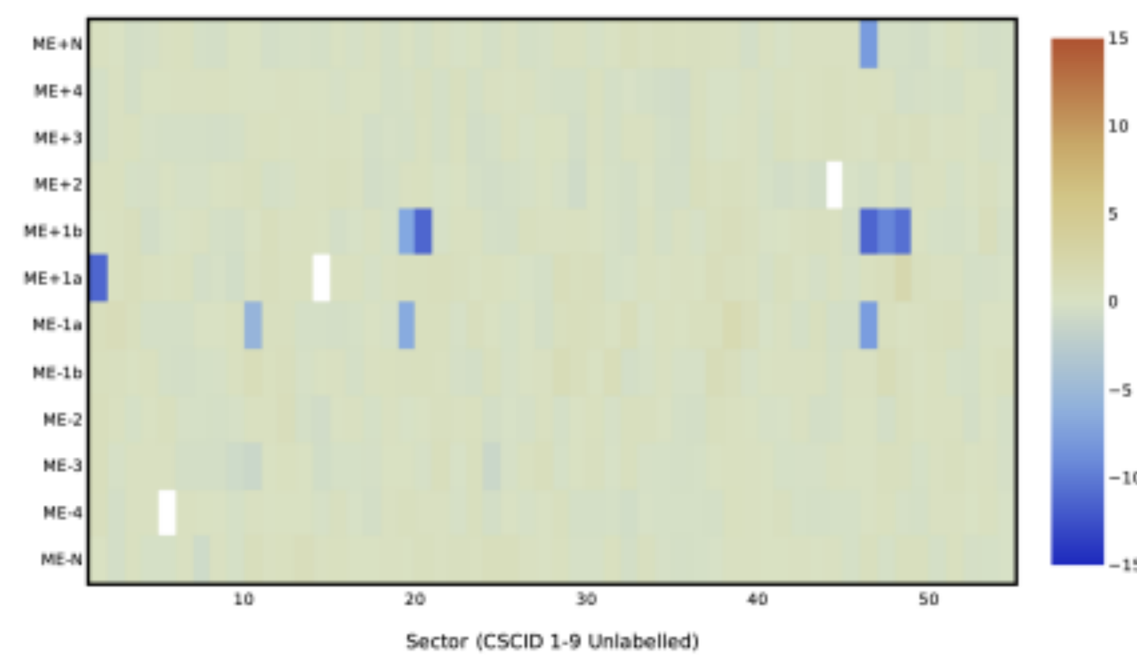
https://doi.org/10.48550/arXiv.2501.13789

- Data Quality Monitoring (DQM) is one of the most important tasks in any particle physics experiment



- Traditional DQM is performed using online and offline web-based GUIs, which contain hundreds of histograms for each CMS sub detector system.

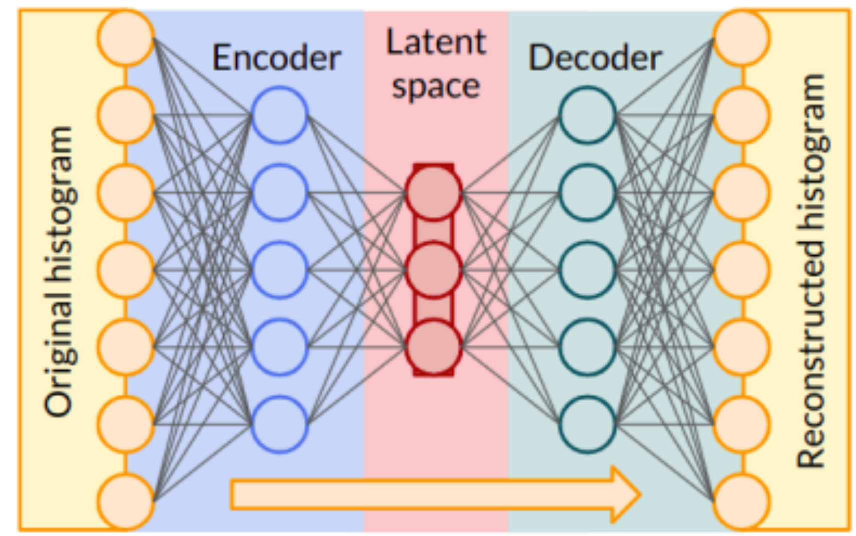
- DQM shifters examine selected histograms for a particular run and compare them with reference ones, looking for possible anomalies indicating detector misbehavior or degradation.

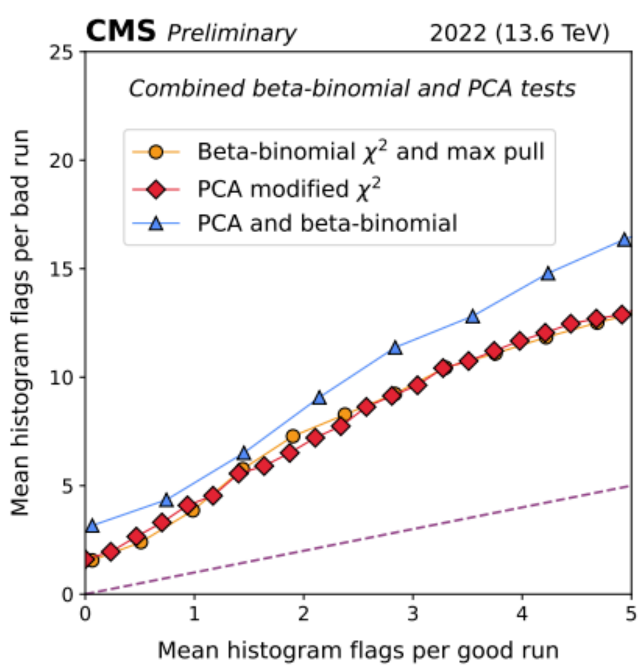


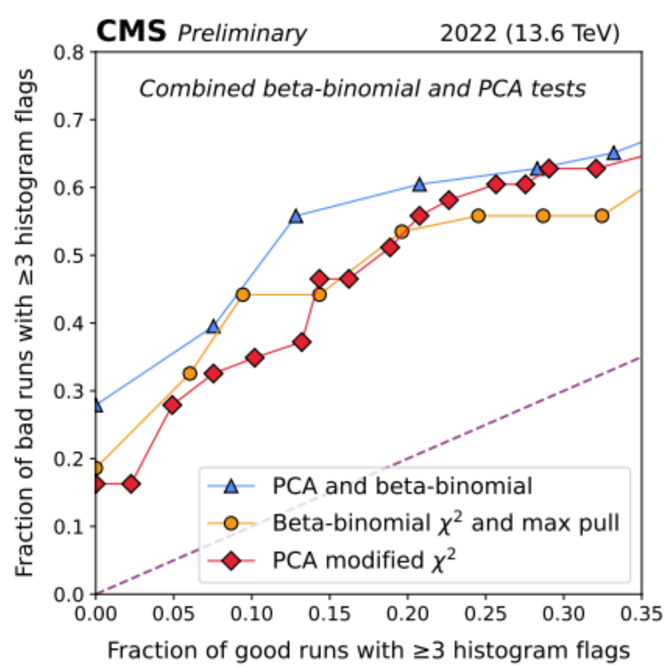
- AutoDQM utilizes χ^2 or single-bin pulled value to look for anomalies in a given set of histograms and compared to data from reference runs

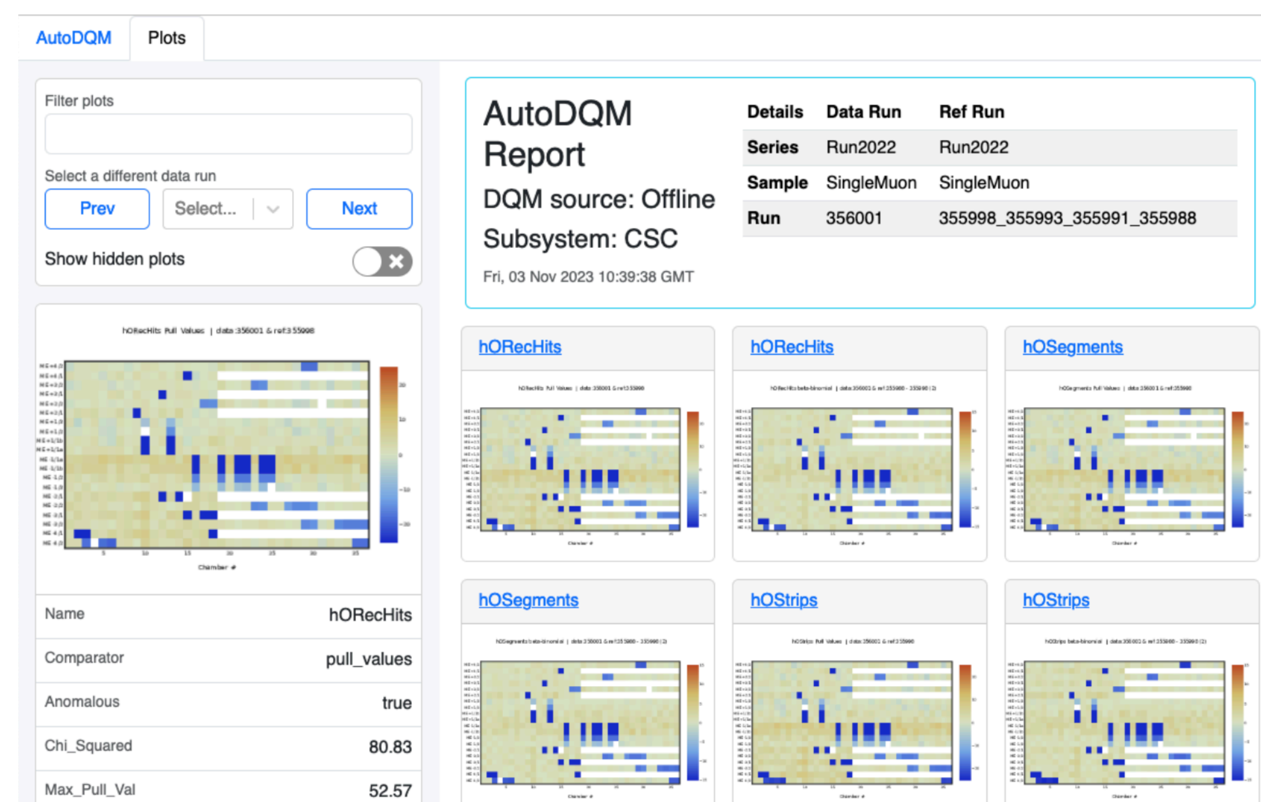
Machine learning for DQM

- No need for a reference dataset
- Two different unsupervised ML algorithms based on Principal Component Analysis (PCAs) and AutoEncoders (AEs)
- Better performance for PCA





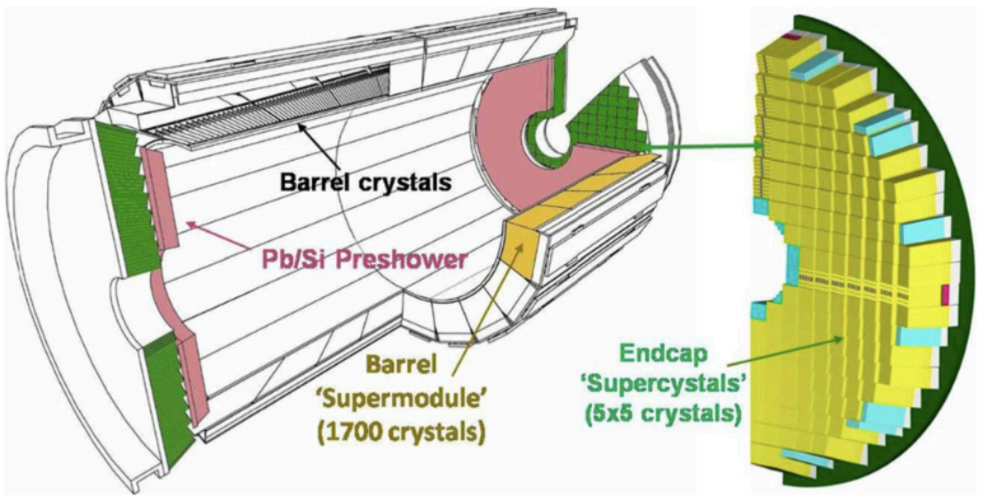




Anomaly detection for DQM in Ecal CMS system

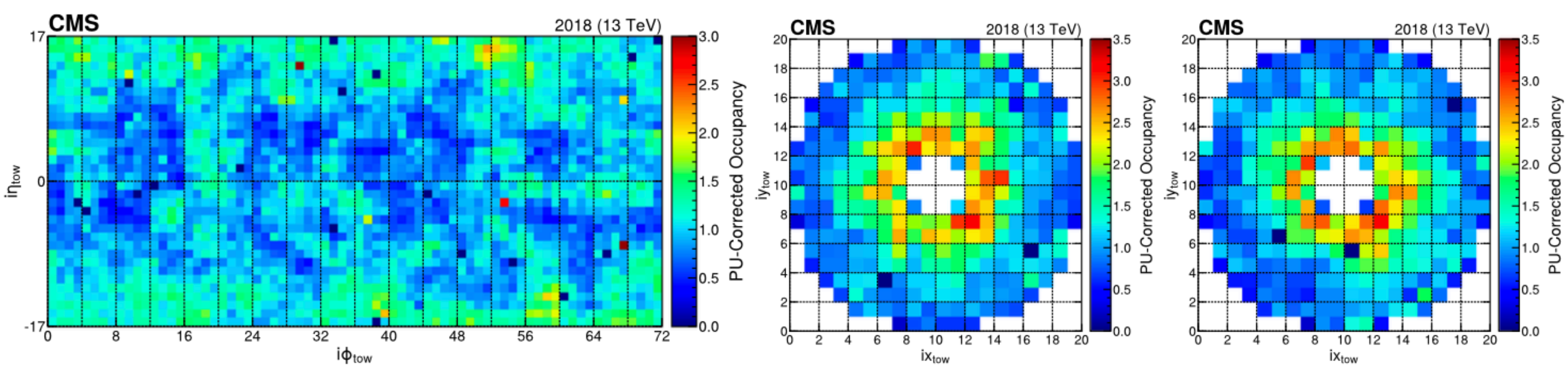
Schematic view of the ECAL

Comput Softw Big Sci (2024) 8:11
https://doi.org/10.1007/s41781-024-00118-z

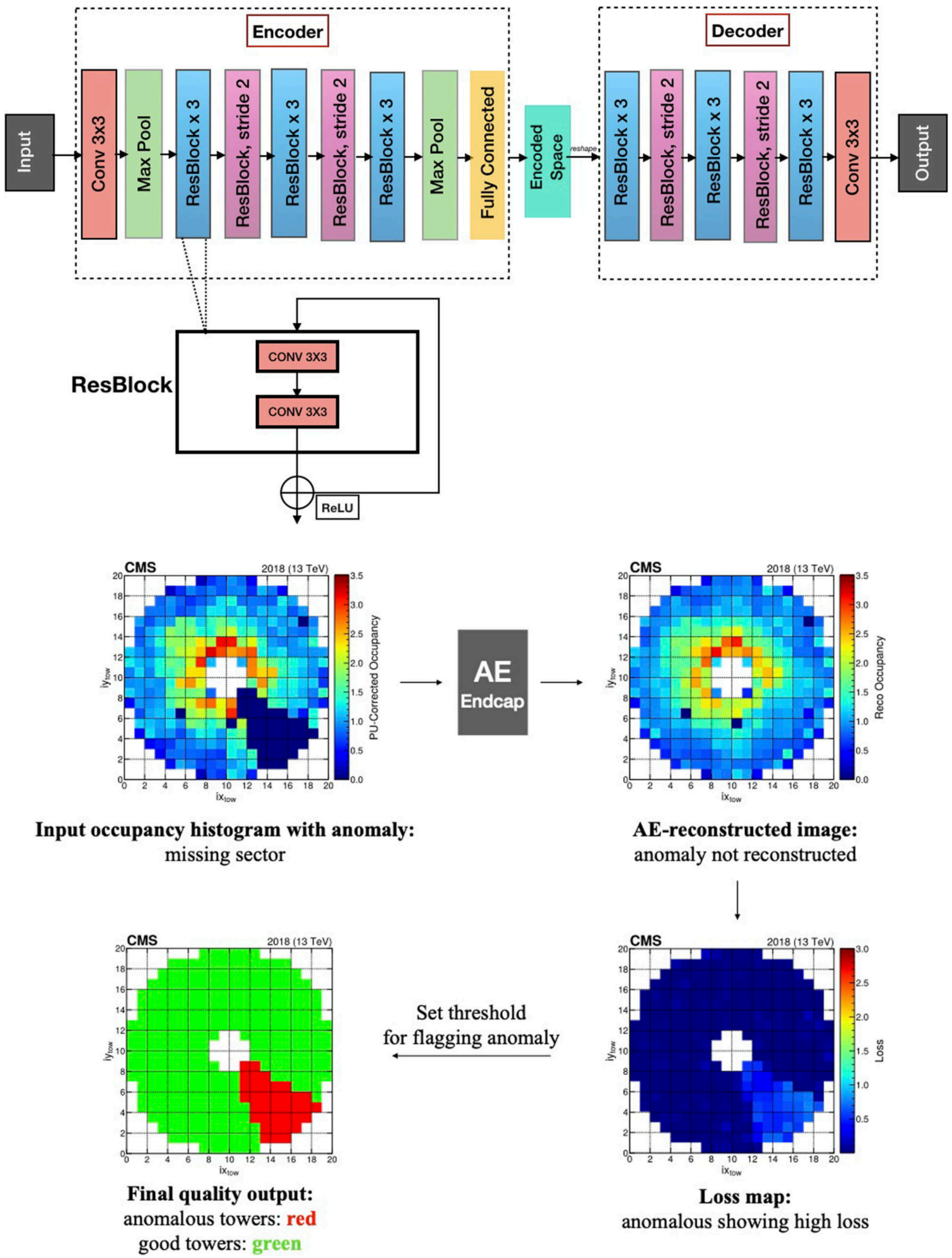


- Ecal consists of 75848 lead tungstate ($PbWO_4$) crystals
- Light signal from ECAL crystals is detected, amplified and digitalized every 25ns

Typical occupancy maps for single LS for a training dataset in Endcap barrel (a) and two endcap regions (b) and (c)



(a) (b) (c)



- AutoEncoder architecture
- Trained with typical occupancy maps
- The model learns to identify “healthy” data and in case of missbehaviour it produces a loss map
- Towers above the threshold are tagged as anomalous and shown in red
- The final quality plot can be easily interpreted by a DQM shifter

Conclusions

- **Anomaly Detection (AD)** algorithms are a promising tool to enhance the sensitivity of searches for new physics.

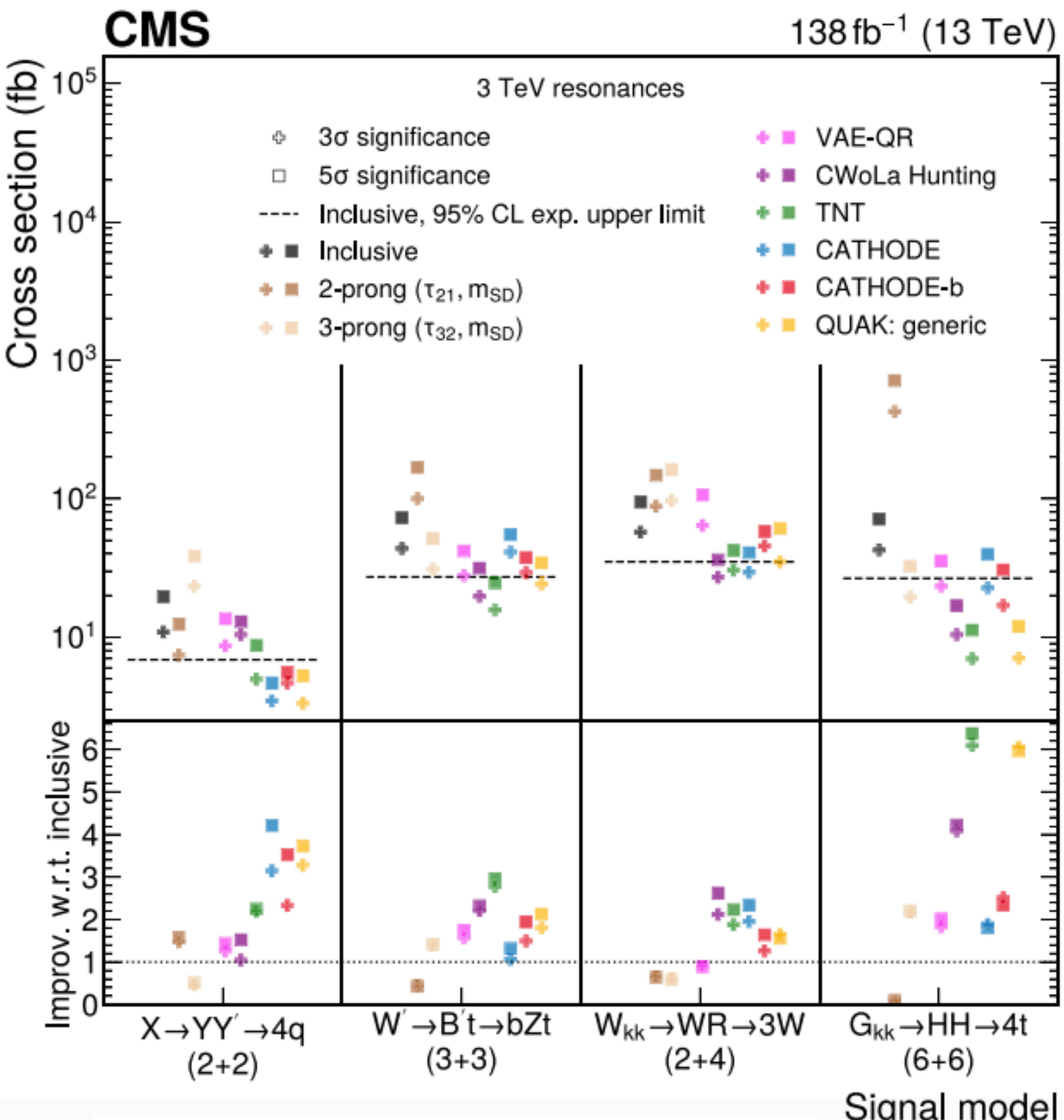
- Recent implementations in CMS have demonstrated increased sensitivity in **dijet searches**, also L1 implementations enable the triggering of new types of events that may contain unexpected or interesting phenomena, with possibility to increase the implementations on new signatures (e.g. Multilepton final states)

- **Data Quality Monitoring (DQM)** is also automating its workflows through the integration of AD algorithms, which are already deployed in the CMS Data Acquisition (DAQ) system.

- The continued development and integration of these tools will be crucial during the High-Luminosity LHC (HL-LHC) era.

Backup

Discovery sensitivity



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- Comparison of AD methods to inclusive search
- For all signal models at least one anomaly detection method is able to achieve an expected 5sigma significance
- Lower panel show the ratio of the cross section sensitivity from the inclusive search to the corresponding of each AD method