

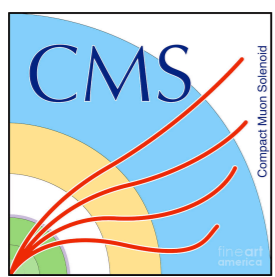


# NextTGen

Next Generation Triggers

## NGT Work Package 3.7: CMS L1T anomaly detection & data compression

**Jennifer Ngadiuba (Fermilab)**  
*on behalf of the NGT WP 3.7 team*

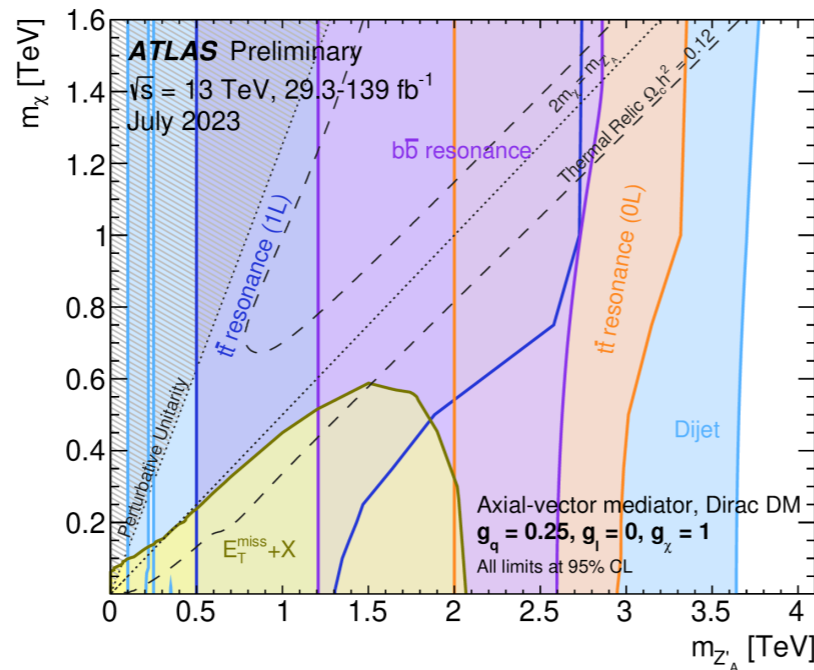
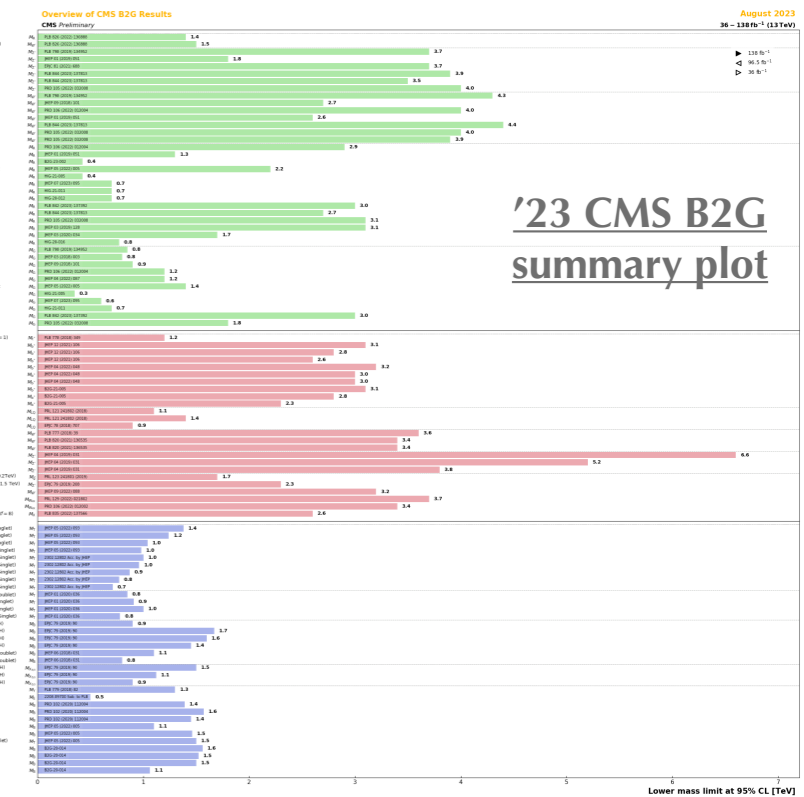
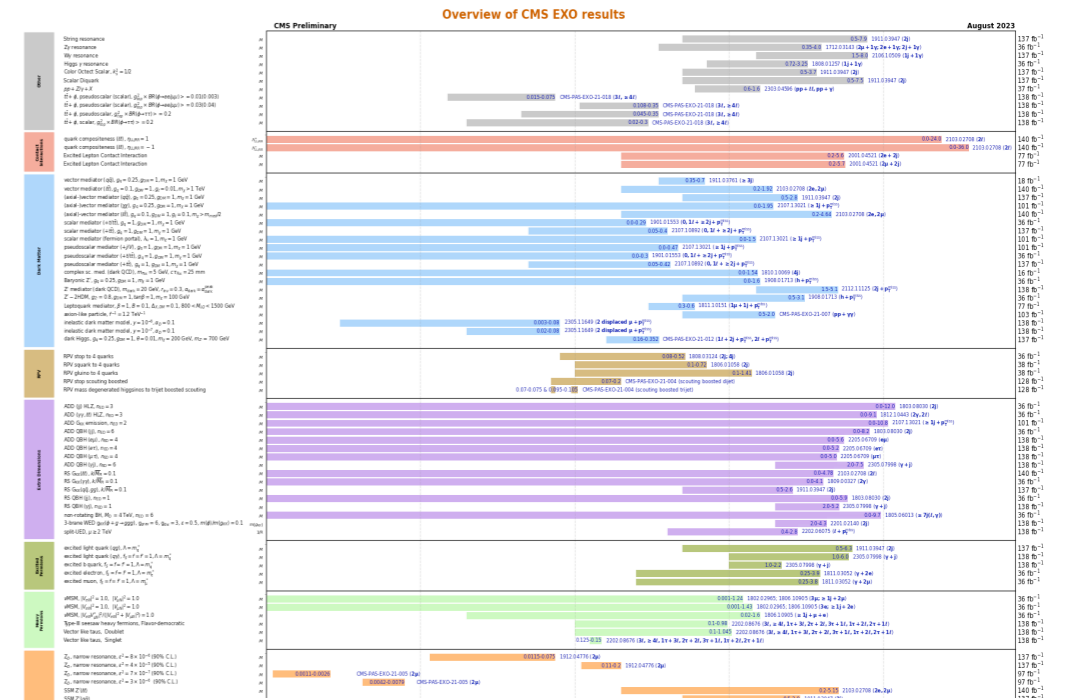


# Anomaly detection @ LHC

'23 CMS EXO summary plot

- Goal: generalize new physics searches to a large variety of BSM models at once

- and even to the ones we have not thought about it yet!

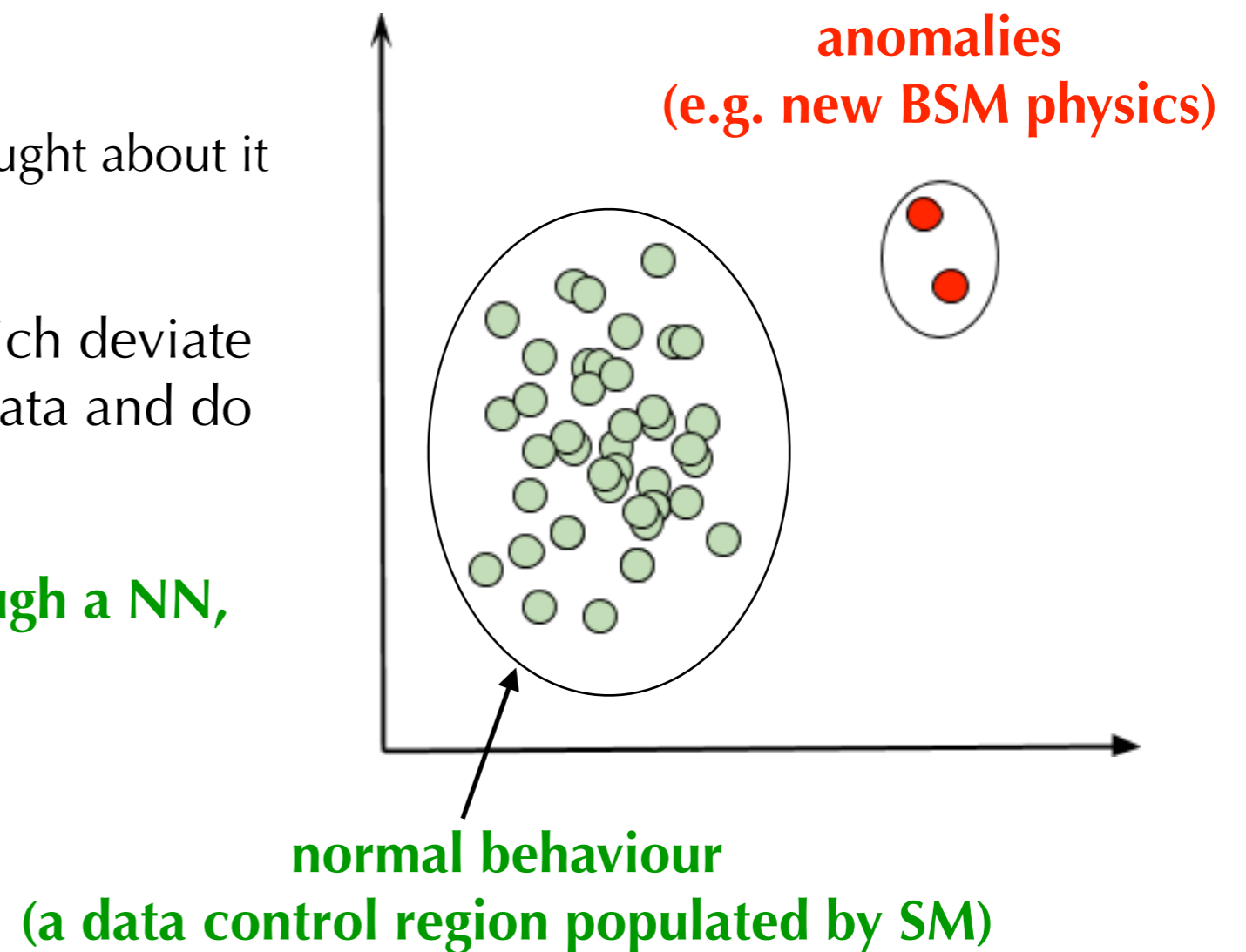


'23 ATLAS Dark Matter summary

'23 CMS B2G summary plot

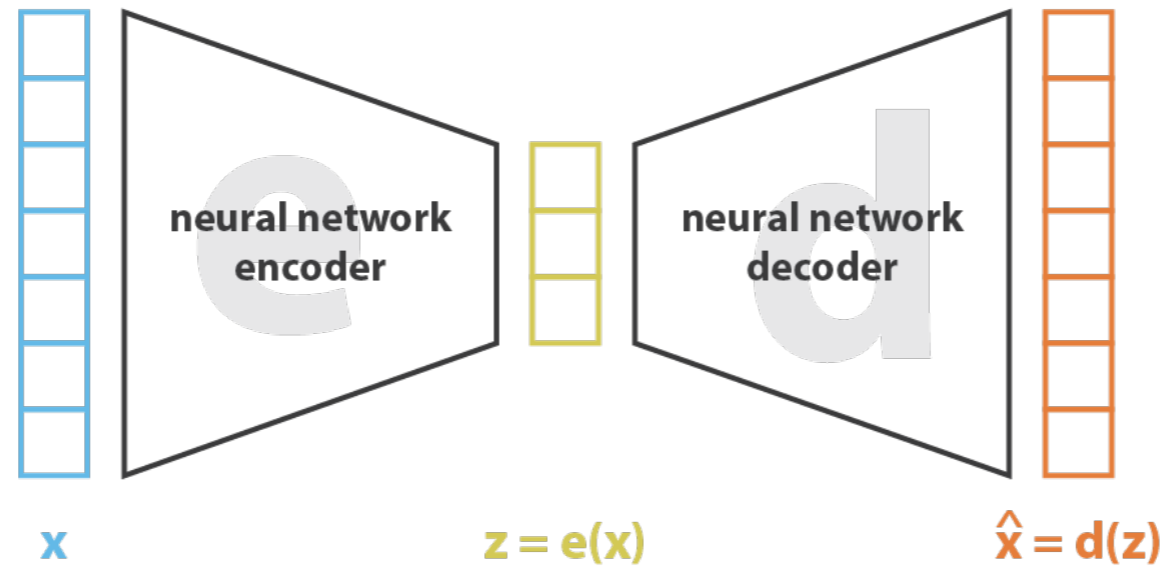
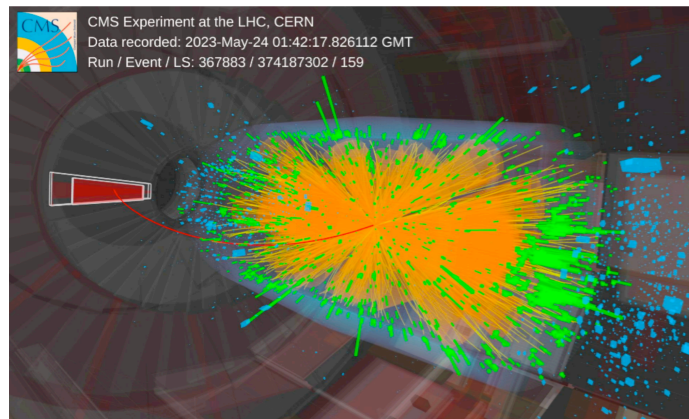
# Anomaly detection @ LHC

- **Goal: generalize new physics searches to a large variety of BSM models at once**
  - and even to the ones we have not thought about it yet !
- Identifying **rare events** in data sets which deviate significantly from the majority of the data and do not conform to “normal” behaviour
- **Normal behaviour can be learnt through a NN, for example with AUTOENCODERS**

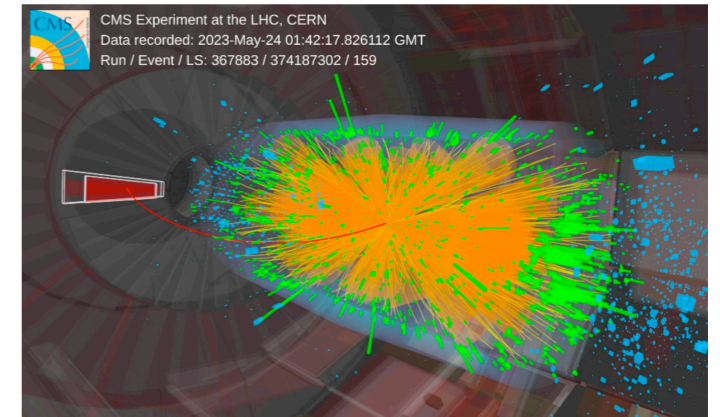


# Autoencoders in a nutshell

Input data



Reconstructed data

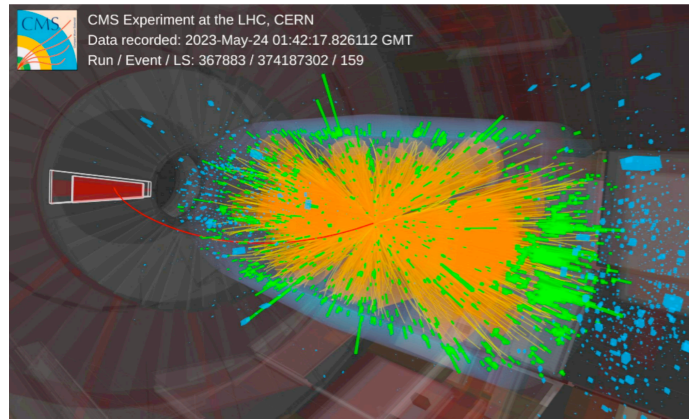


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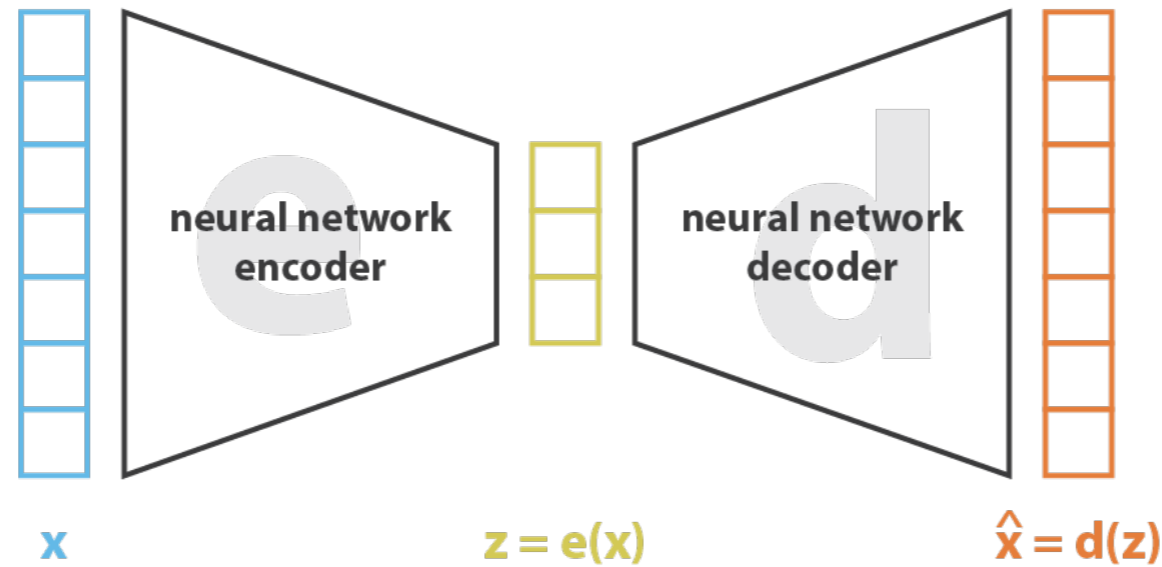
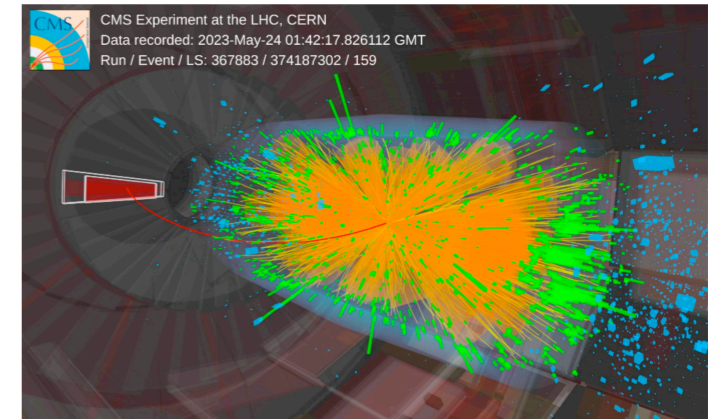
$$\mathcal{L}_{reco} = ||x - \hat{x}||^2 = MSE(input, output)$$

# Autoencoders in a nutshell

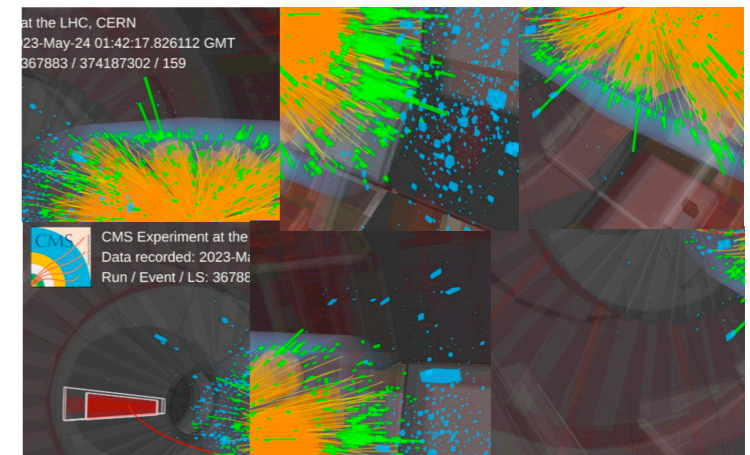
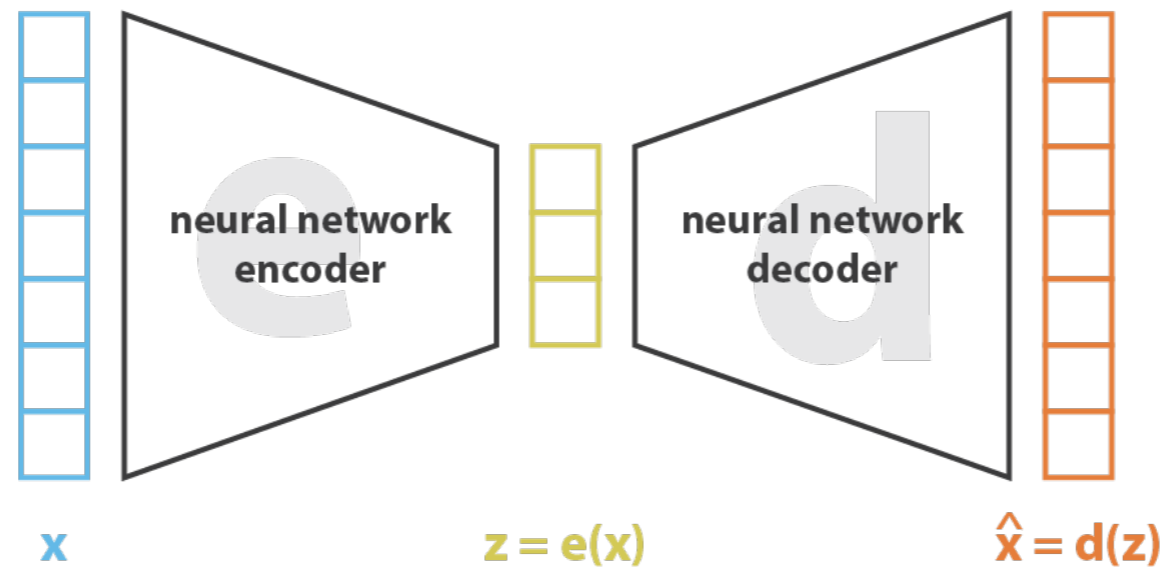
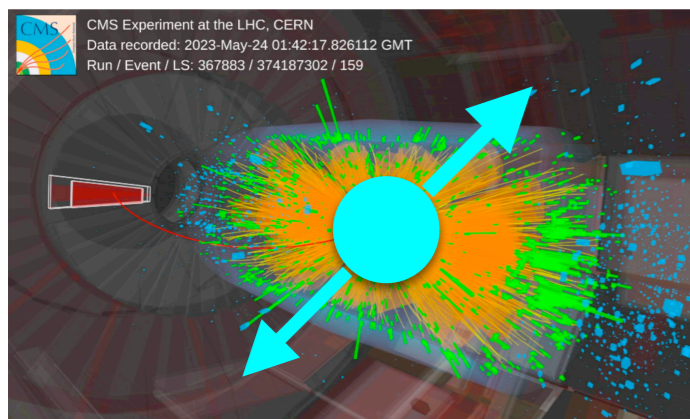
Input data



Reconstructed data



$$\mathcal{L}_{reco} = ||x - \hat{x}||^2 = MSE(input, output)$$



# Anomaly detection @ LHC: results

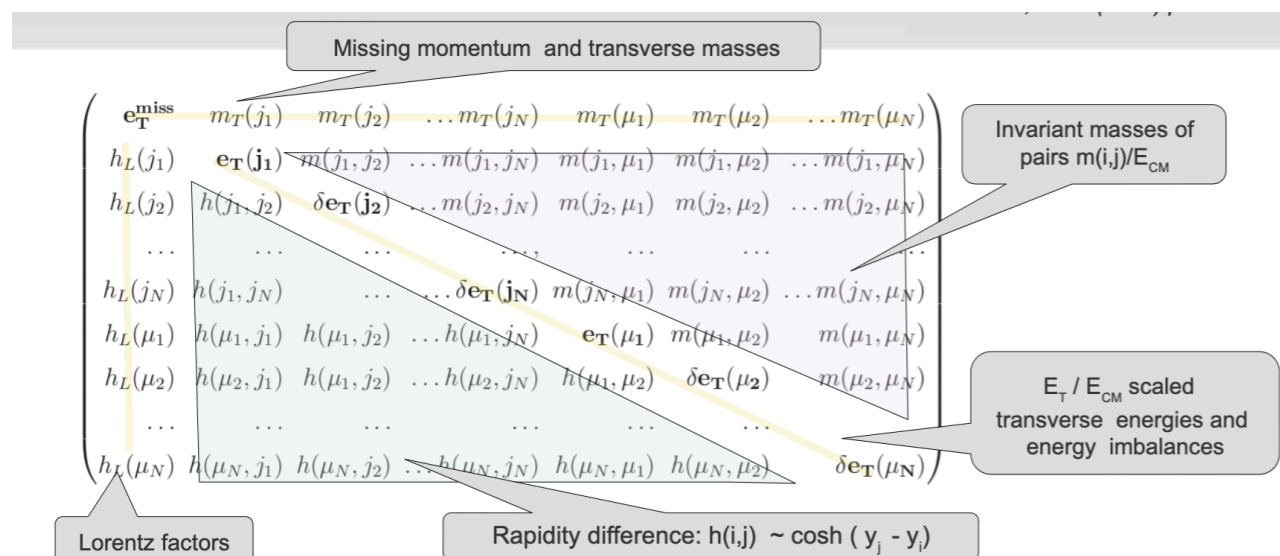
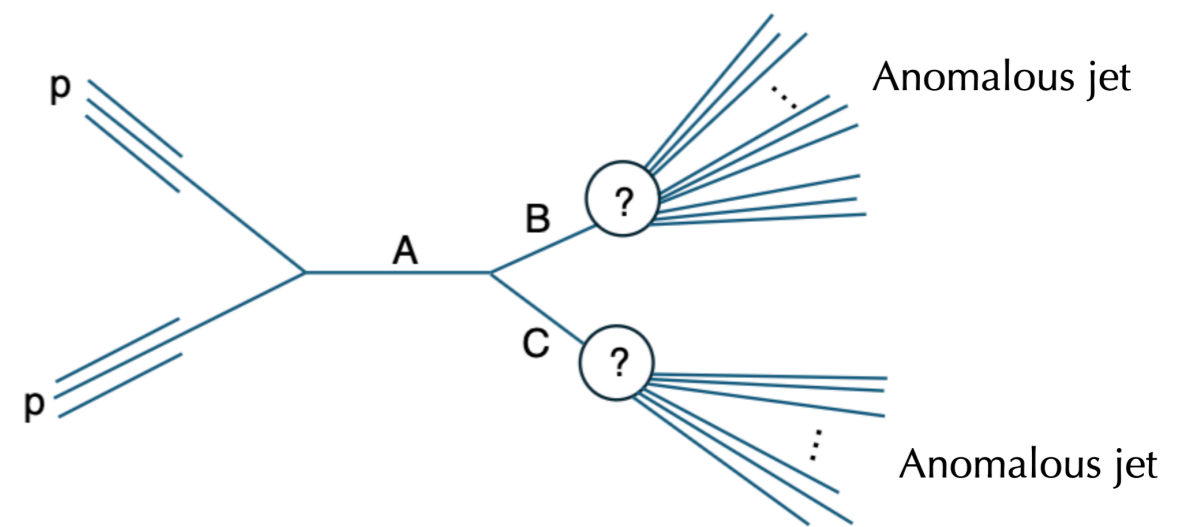
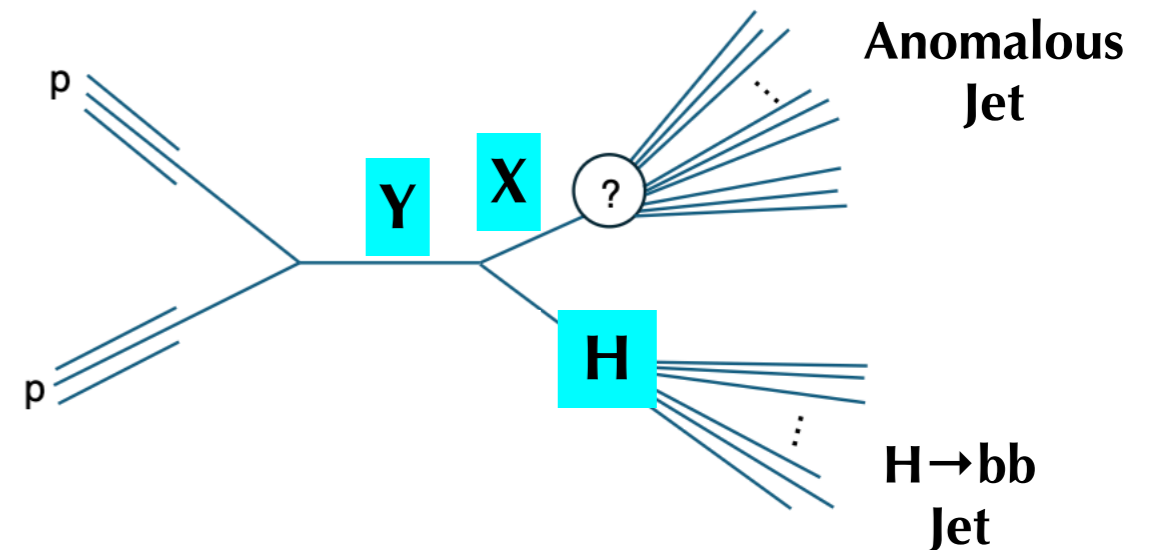
- Two ATLAS searches using autoencoders:

- two boosted jets [\[PRD 108 \(2023\) 052009\]](#)
- dijet, lepton + jet(s), and photon + jet(s) [\[PRL 132 \(2024\) 081801\]](#)

- One CMS search in boosted dijet final state

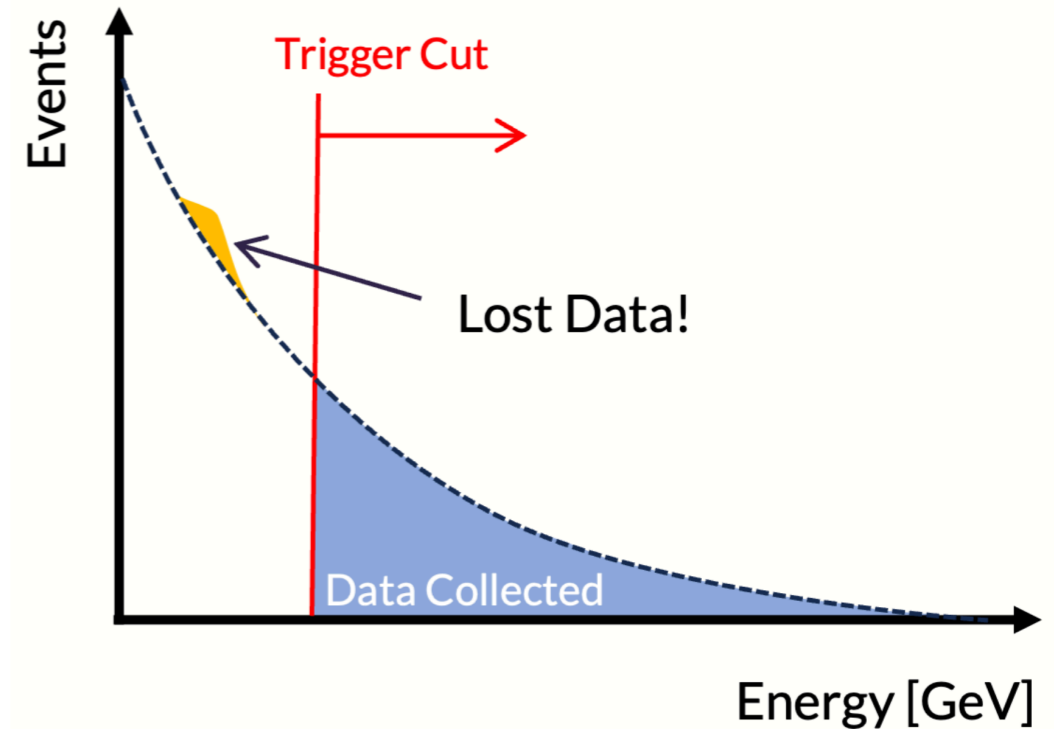
[\[CMS-PAS-EXO-22-026\]](#):

- several AD methods designed and applied, not only autoencoders

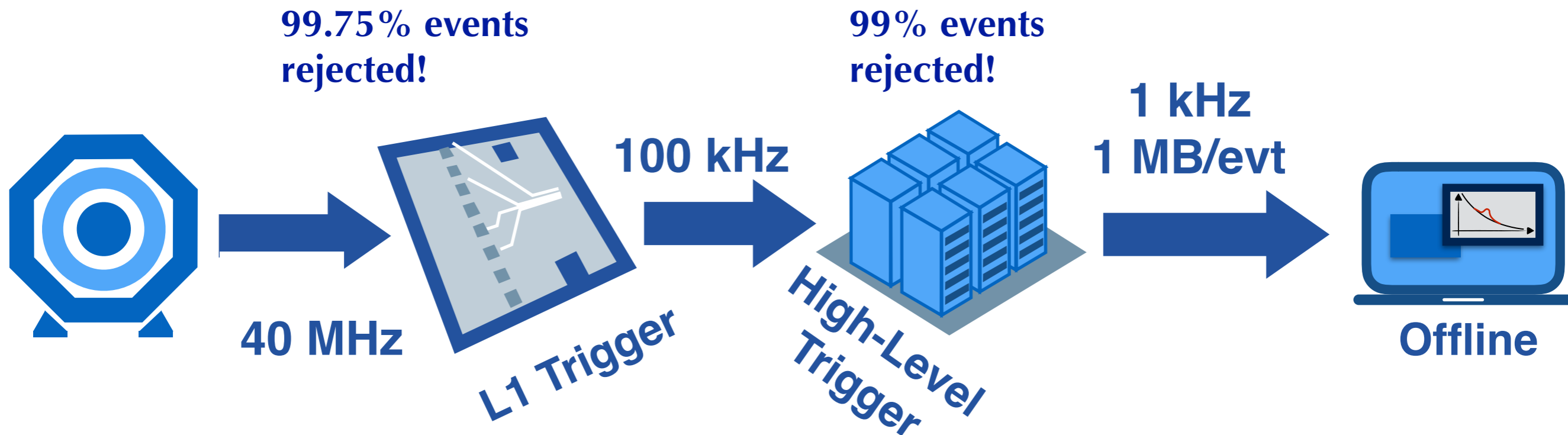


# Data reduction @ LHC

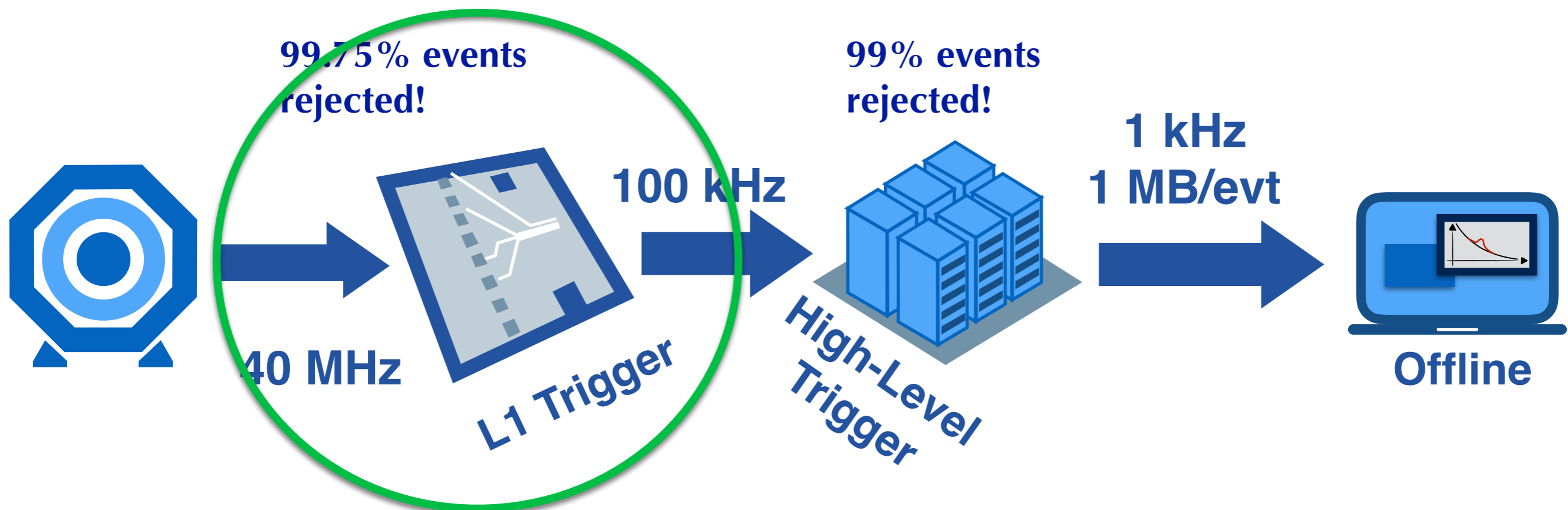
- The CMS L1T rejects 99.75% of the events
- Currently, we use simple heuristics to define trigger algorithms
  - Energy, charge, direction, momentum, etc.
- In this approach, we need to know what we're looking for to target it



- What if we are missing new physics because we did not design the right trigger?



# THE ANOMALY MIGHT BE DISCARDED BY THE TRIGGER

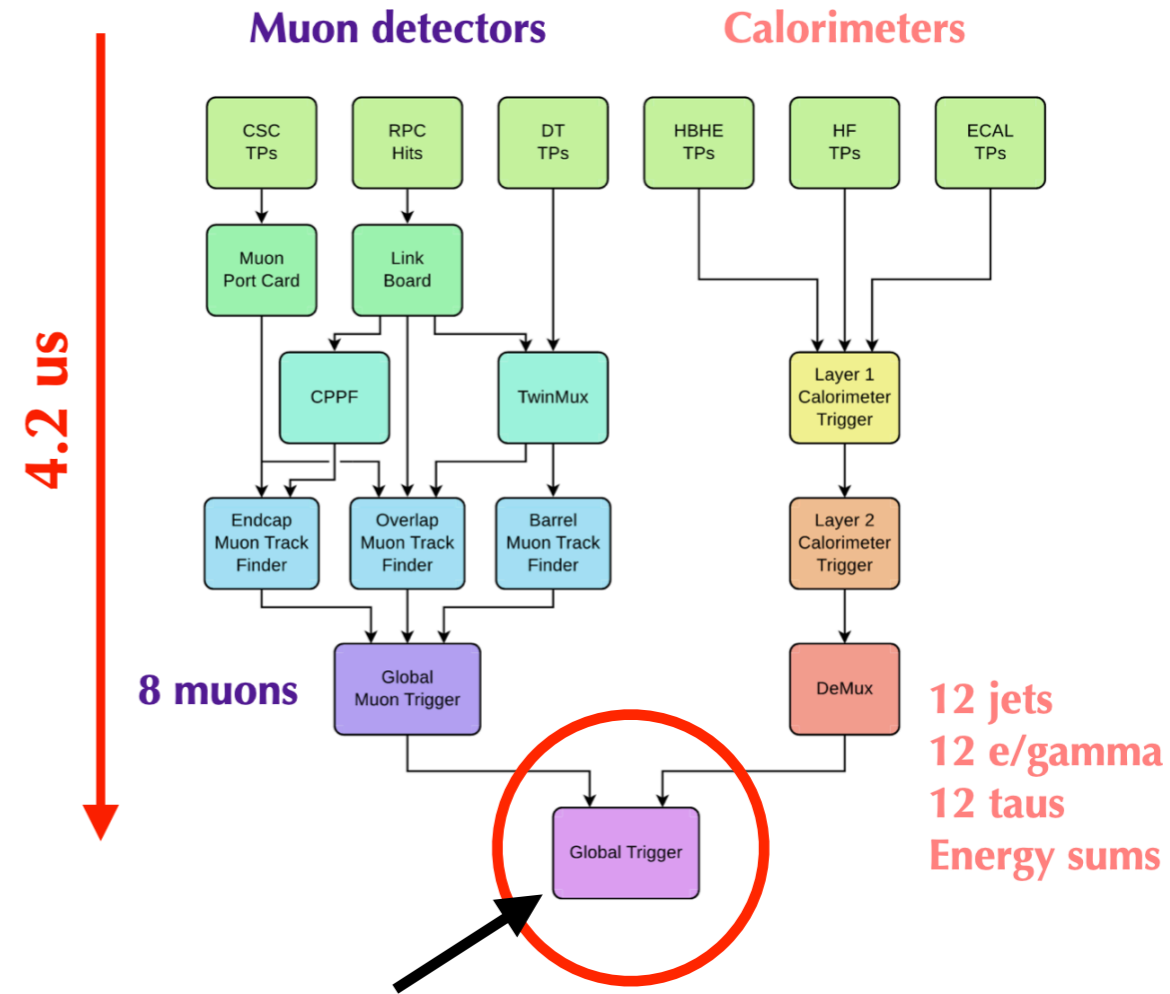


Correct the problem as early as possible in the data reduction workflow!

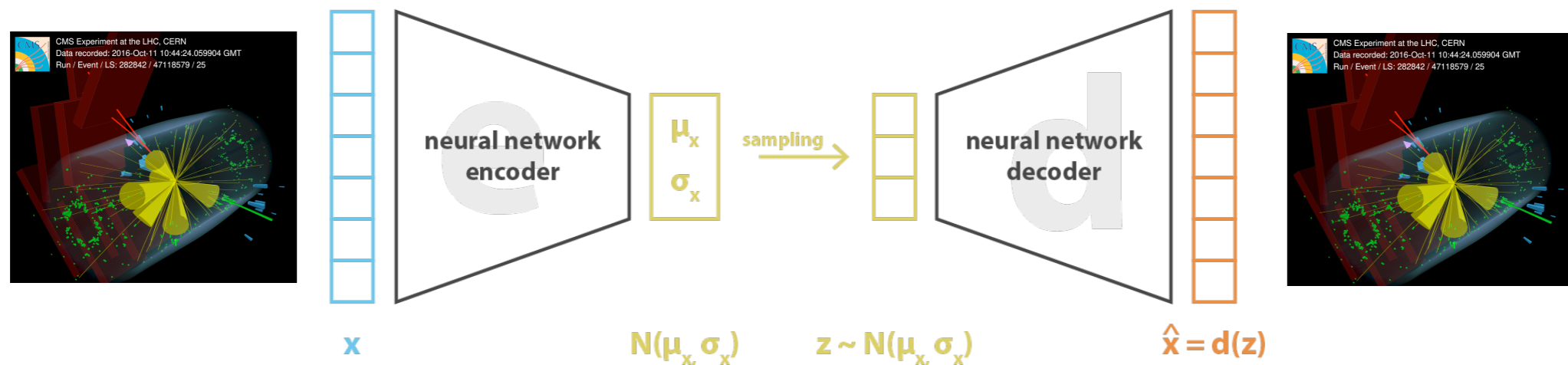


# Ultra-fast anomaly detection @ CMS

- Train a variational autoencoder on **unbiased data collected by CMS in 2023 at 13.6 TeV** (~10.5 million)
  - ~ same inputs as Global Trigger (GT): **4-vector of muons, jets, MET, e/γ**
  - **learn to reconstruct the average collision event**, i.e. mostly soft hadronic collisions with large number of low energy jets
  - usually rejected by cut-based algo

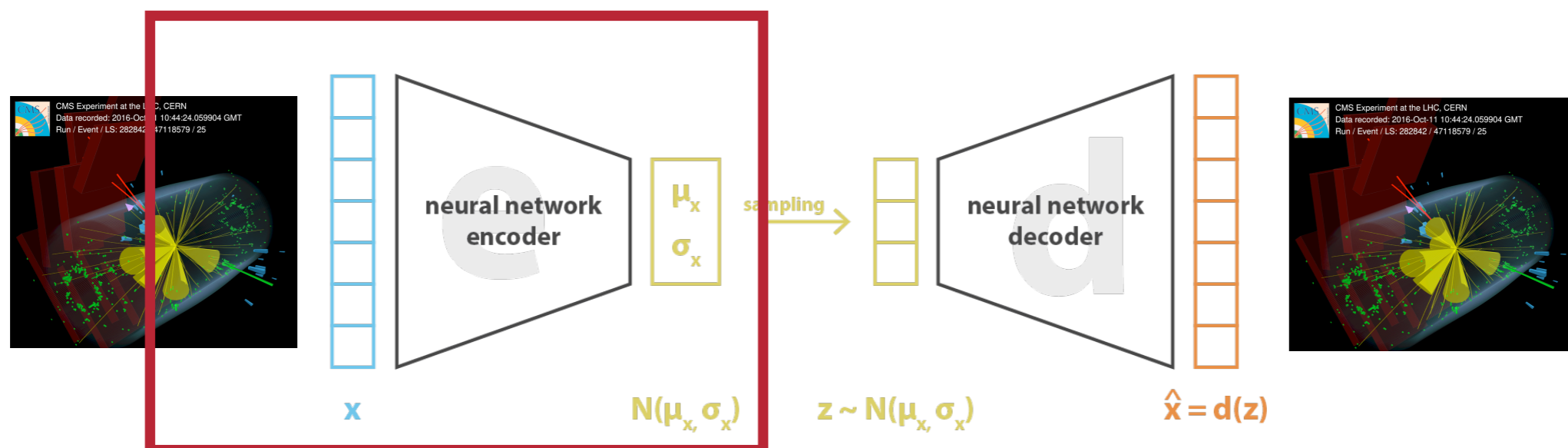
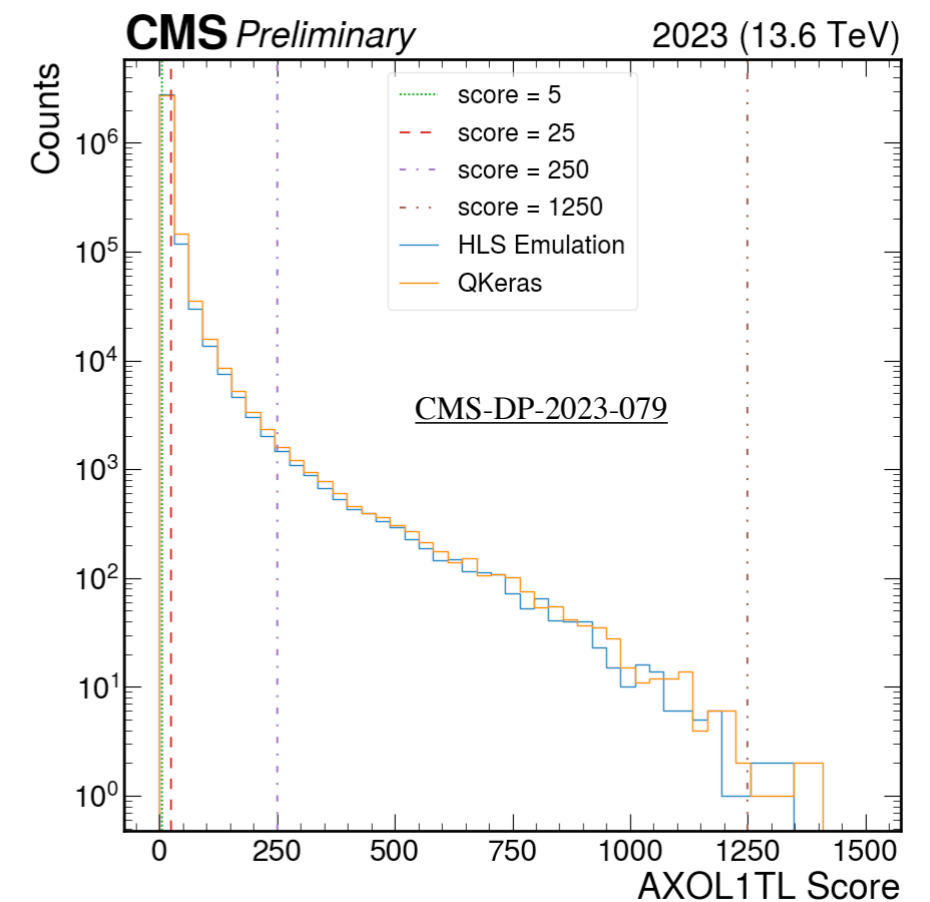


**Strict latency constraint of 50 ns to run in the GT!**



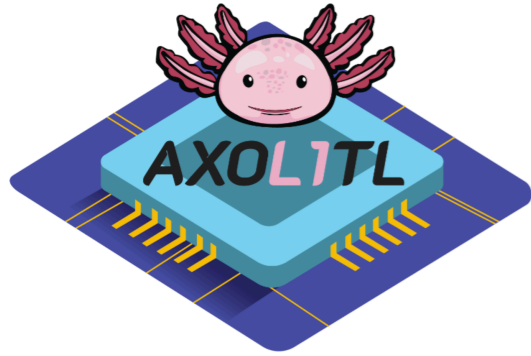
# Ultra-fast anomaly detection @ CMS

- **Small, fully connected network architecture** (encoder: 32,16,8 nodes per layer)
- **TRICK:** define anomaly metric in the latent space ( $\mu^2$ )
  - allows us to deploy only the encoder part
  - half model size and latency!
- **Quantization aware training with QKeras** to reduce FPGA resources utilization
- **hls4ml** to translate NN into firmware, then final integration with rest of trigger algorithms
- **Define different thresholds** on anomaly score based on allocated output rate

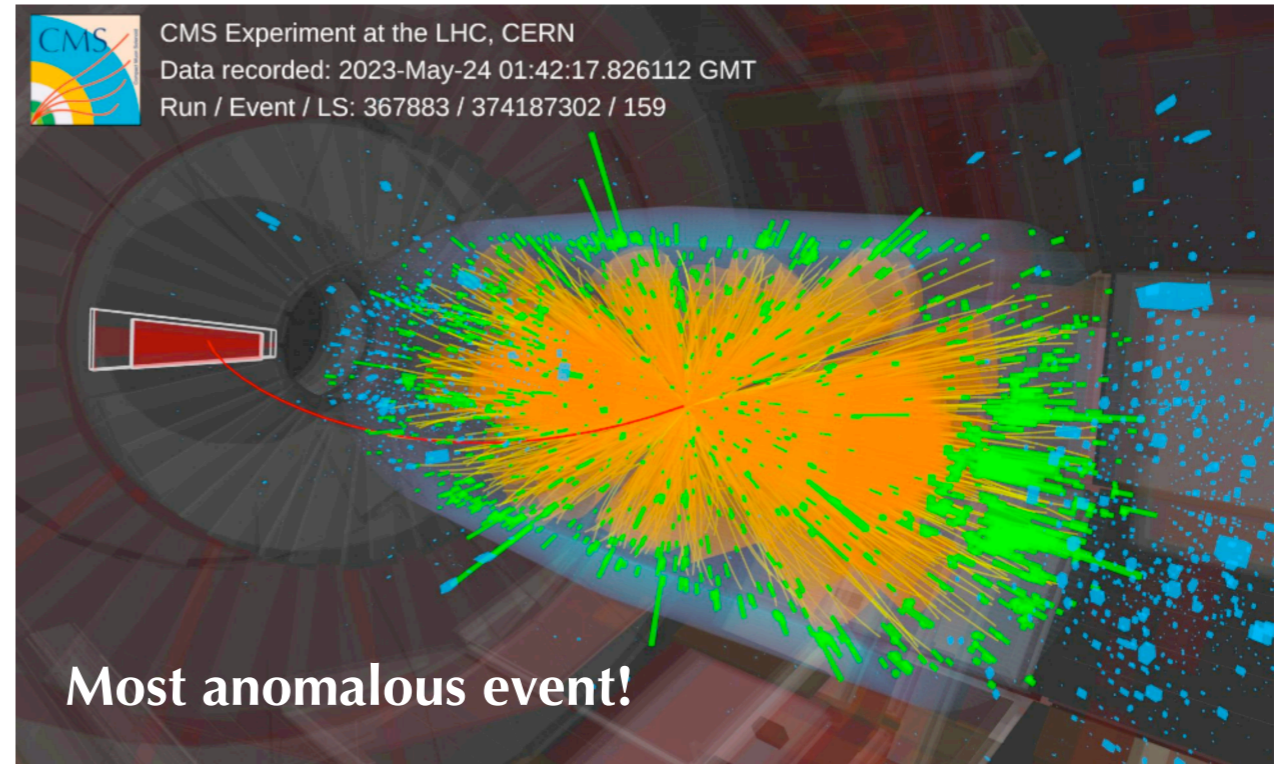


# Ultra-fast anomaly detection @ CMS

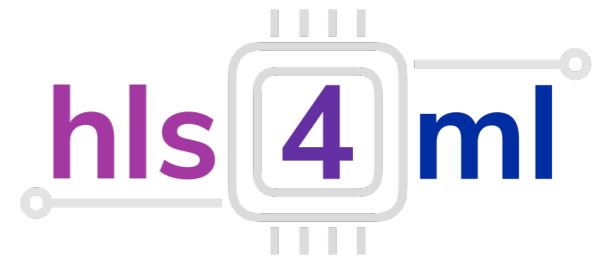
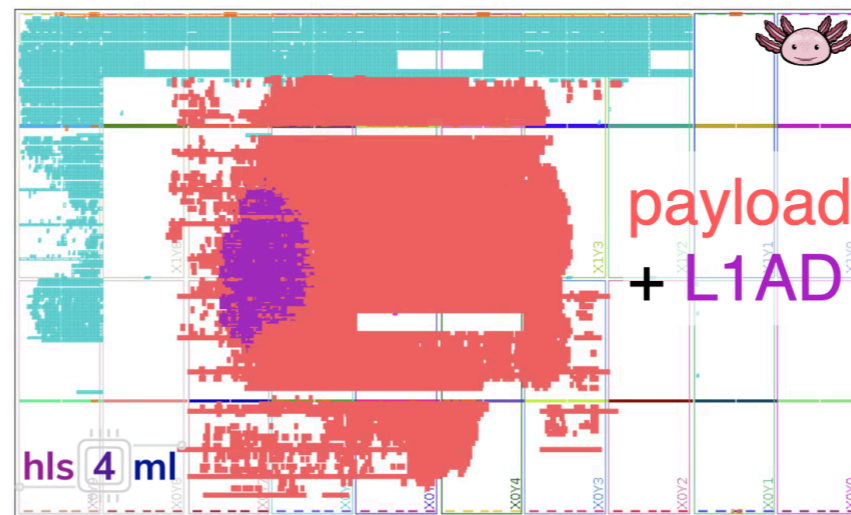
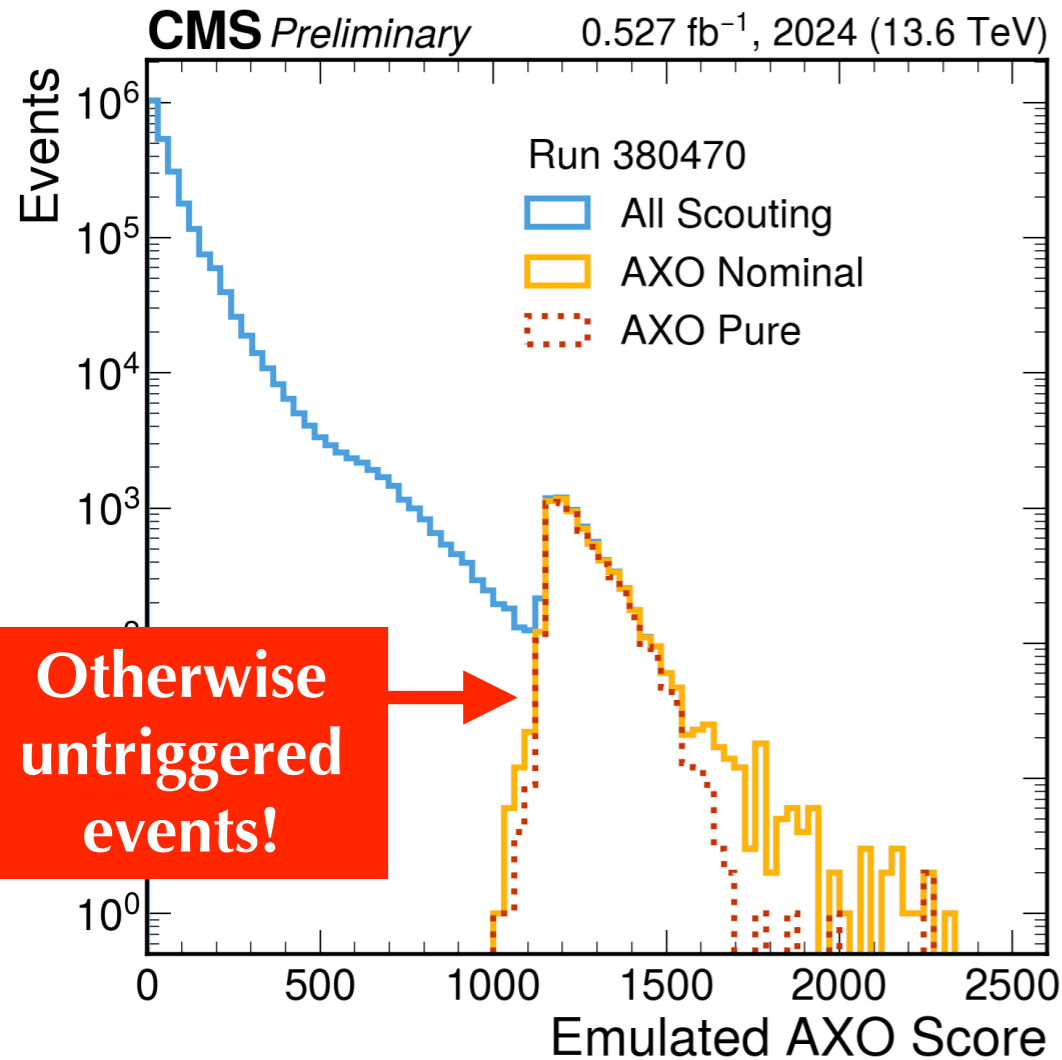
Anomaly eXtraction Online Level-1 Trigger aLgorithm



**Online since  
Spring this year!  
(~ 100/fb)**



[CMS-DP-2023-079](#)  
[CMS-DP-2024-059](#)



	Latency	LUTs	FFs	DSPs	BRAMs
<b>AXOLITL</b>	2 ticks 50 ns	2.1%	~0	0	0

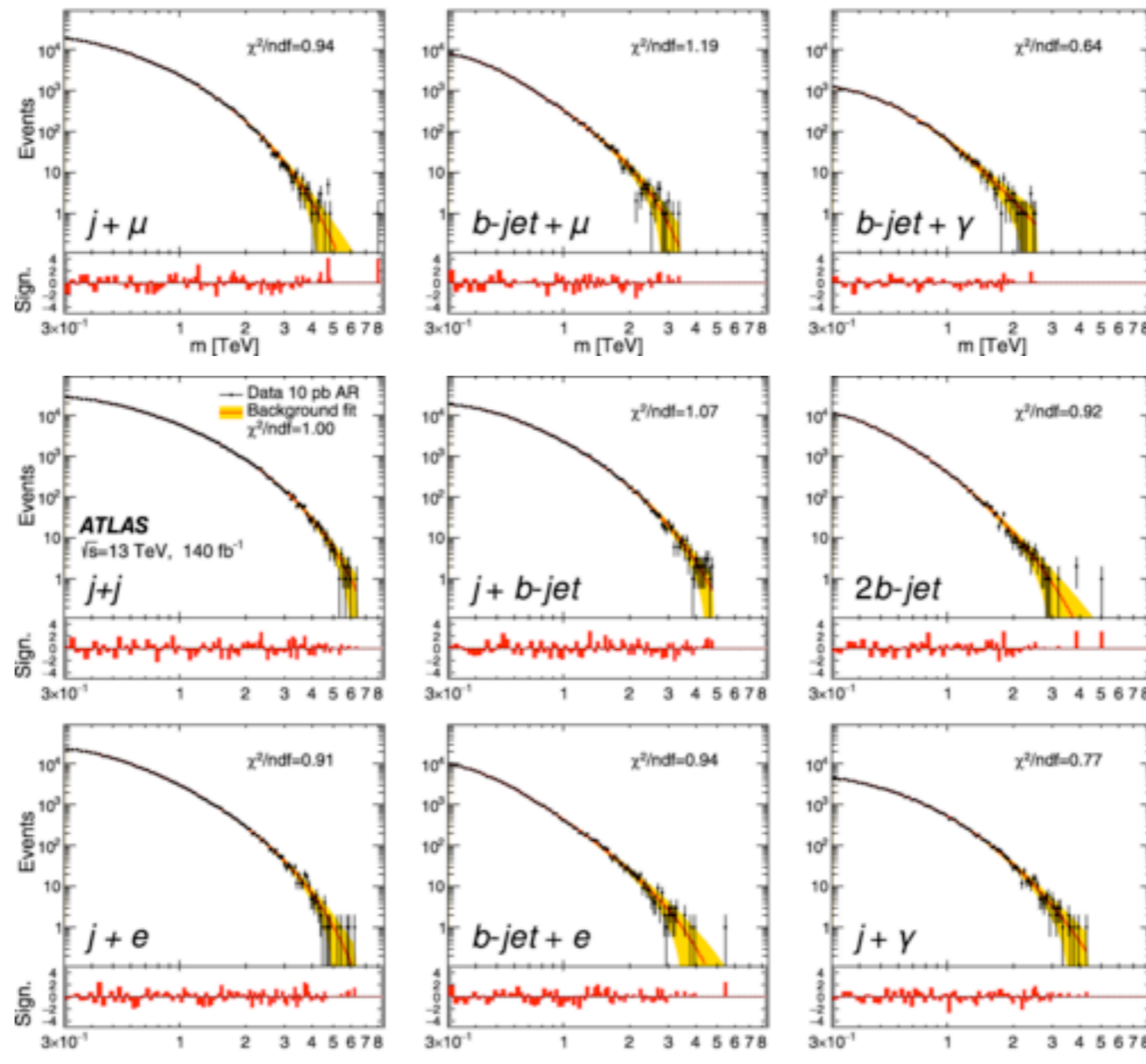
# Boosting AXOL1TL with NGT

- AXOL1TL was designed and integrated over last ~ 3 years by CMS collaborators
- **Within NGT we aim at pushing this novel technology to its frontier!**
- The team is currently **advancing multiple aspects of the project** in synergy and collaboration with the original AXOL1TL team:
  - **Physics Analysis:** Investigating the collected anomalous event data for potential new physics signals [Sabrina Giorgetti, Phd student w/ Padova University + Jannicke Pearkes, Colorado Boulder Project Associate from Jan '25]
  - **Model Development:** Designing a more robust model based on representation learning techniques [Diptarko Choudhury, Technical student]
  - **Operational Automation:** Enhancing the efficiency and reliability of the trigger system's operations [Diptarko Choudhury, Technical student + Maciej Glowacki, CERN Fellow + Eric Moreno, Phd Student w/ MIT]
  - **Phase 2 Preparation:** Developing an upgraded model tailored to the Phase 2 trigger system, incorporating new inputs and architectures [Maciej Glowacki, CERN Fellow]



# Physics analysis

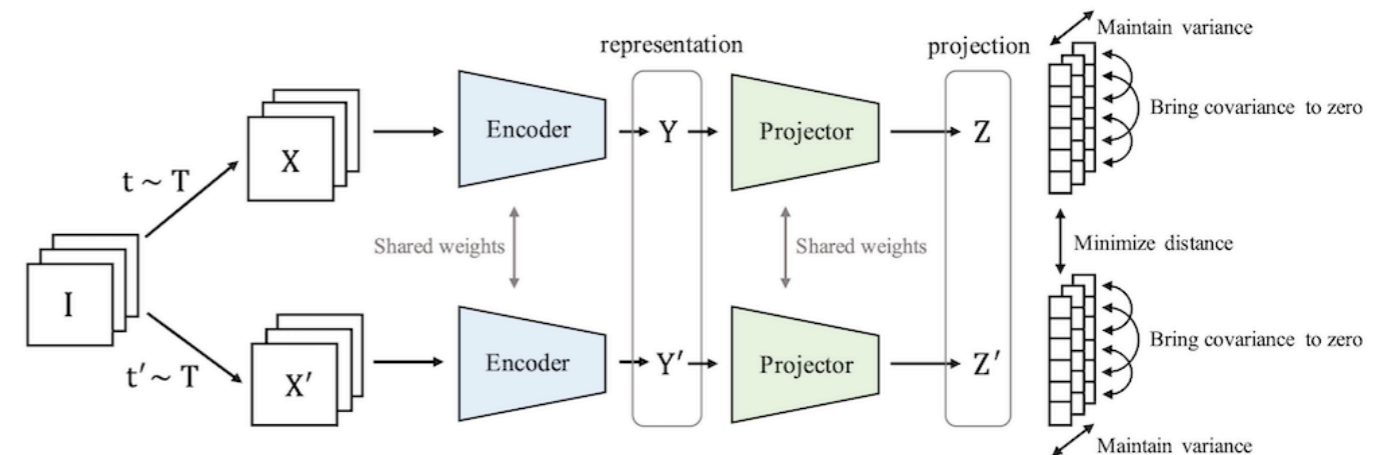
- Characterization of trigger performance in 2024 data on SM candles ( $J/\Psi/Z$  peak, etc...)
- Designing first physics analysis with bump-hunt in many di-object invariant masses as in [\[PRL 132 \(2024\) 081801\]](#)



# Model development

- Studying architectural improvement beyond VAE baseline → **Contrastive Learning** approach to improve embeddings (latent space) expressiveness
- **Contrastive learning** is a self-supervised learning (SSL) technique that aims to learn representations by comparing similar and dissimilar samples (called “augmentations”)

- We are considering **VicReg**:  
*Variance-Invariance-Covariance  
Regularization for SSL*



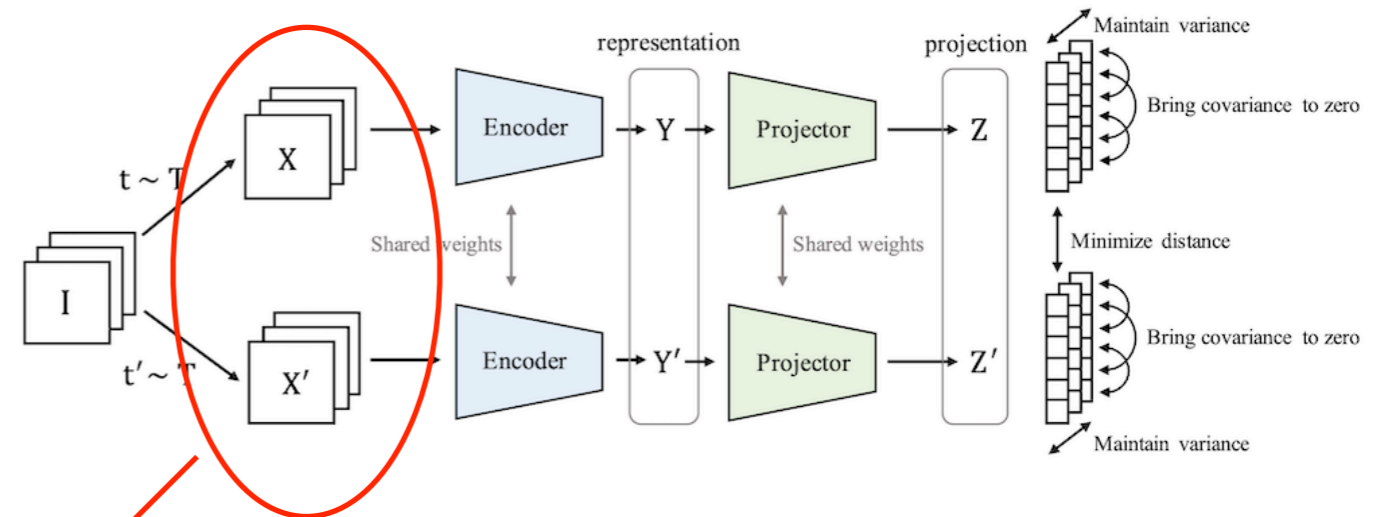
- **Invariance**: the two augmented views should produce similar embeddings
- **High Variance**: each dimension of embeddings should contain meaningful information and not collapse to a constant value
- **Low Covariance**: embedding dimensions should not have redundant information and should be independent

$$L_{\text{VicReg}} = \alpha \left( \frac{1}{N} \sum_{i=1}^N \|z_1^{(i)} - z_2^{(i)}\|^2 \right) + \beta \left( \frac{1}{d} \sum_{j=1}^d \max(0, \gamma - \sigma(z_j))^2 \right) + \gamma \left( \frac{1}{d} \sum_{i \neq j} \text{Cov}(z_i, z_j)^2 \right)$$

**invariance**
**variance**
**covariance**

# Model development

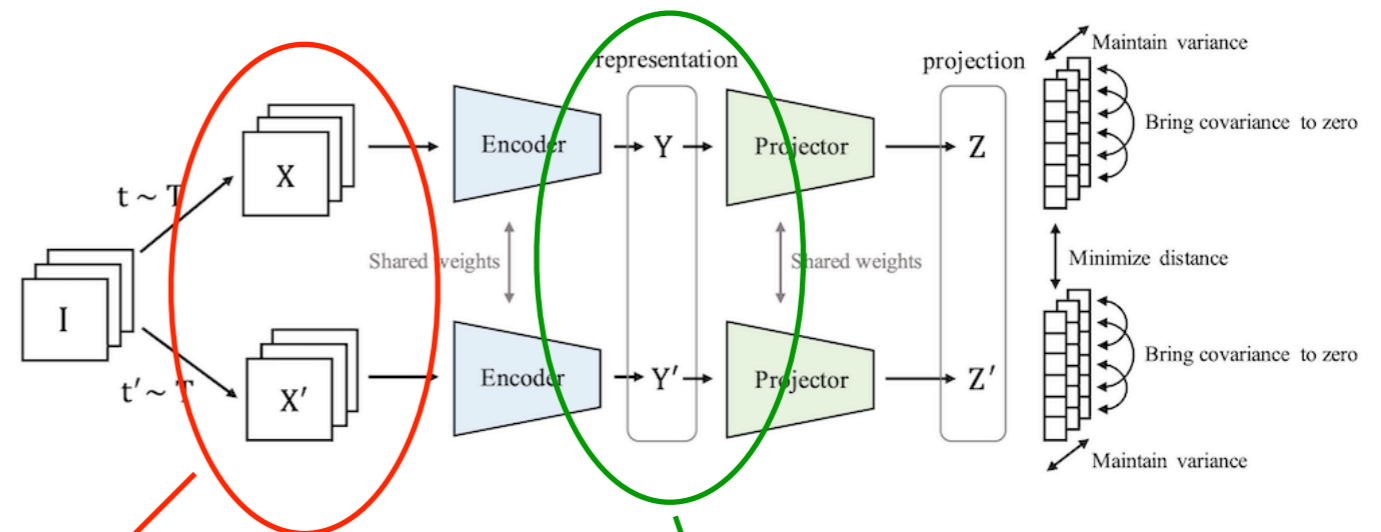
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Augmentations considered:  
 gaussian smearing in within reconstruction  
 resolutions and objects masking

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gaussian smearing in within reconstruction  
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Different strategies being explored for AD  
downstream task:

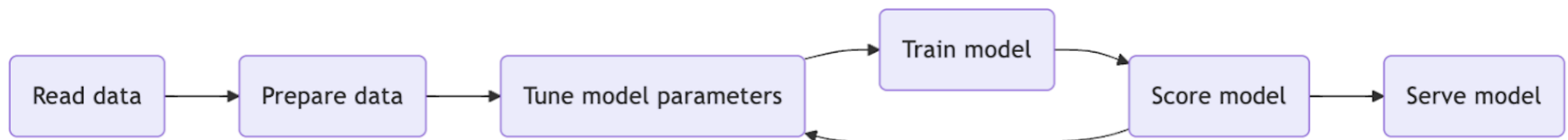
VAE or multi-dimensional distances  
— TBD based on latency constraints  
and physics performance



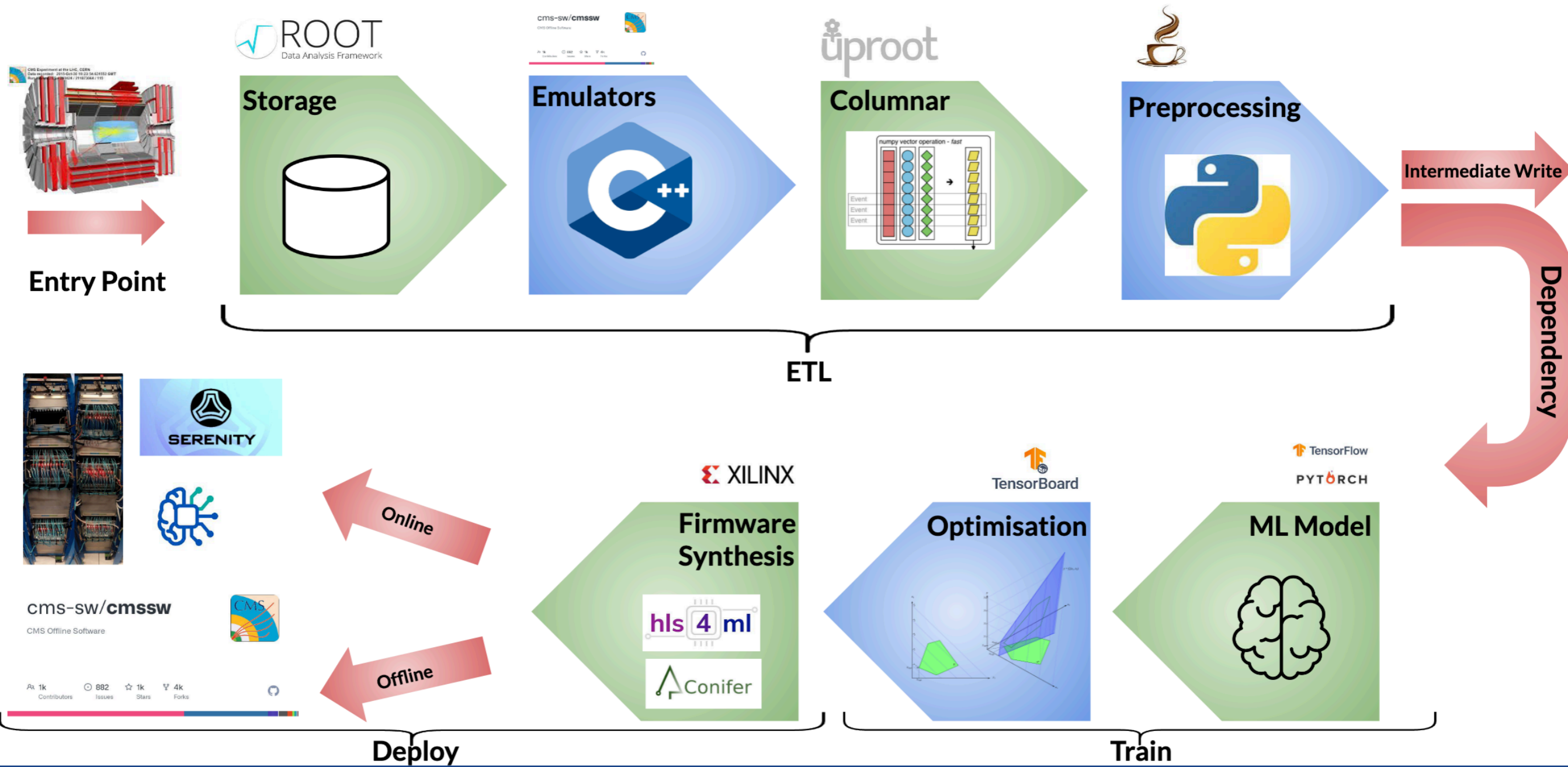
# Operational Automation: MLOps

- **A typical Machine Learning Lifecycle:**

- Data integration from multiple sources
- Data processing
- Data loading and batching
- Hyperparameter tuning, establish a Pareto front based on *some* metrics
- Model deployment — Version *everything*: data, model, code



# CMS L1T Workflow



# How often?

**Necessary to automate and speed up the workflow!**

Possible time scale of  
trigger ML retraining  
and redeployment



Current time scale of  
trigger ML retraining  
and redeployment

**Seconds**

**Days**

**Months**

Beam  
fluctuations

Beam conditions  
and detector  
variation

Large scale  
detector changes

Built in trigger  
robustness

Subsystem  
calibration

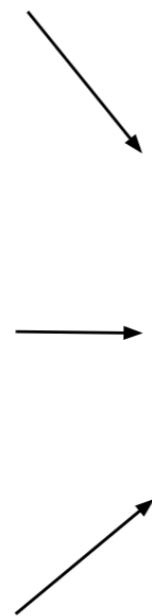
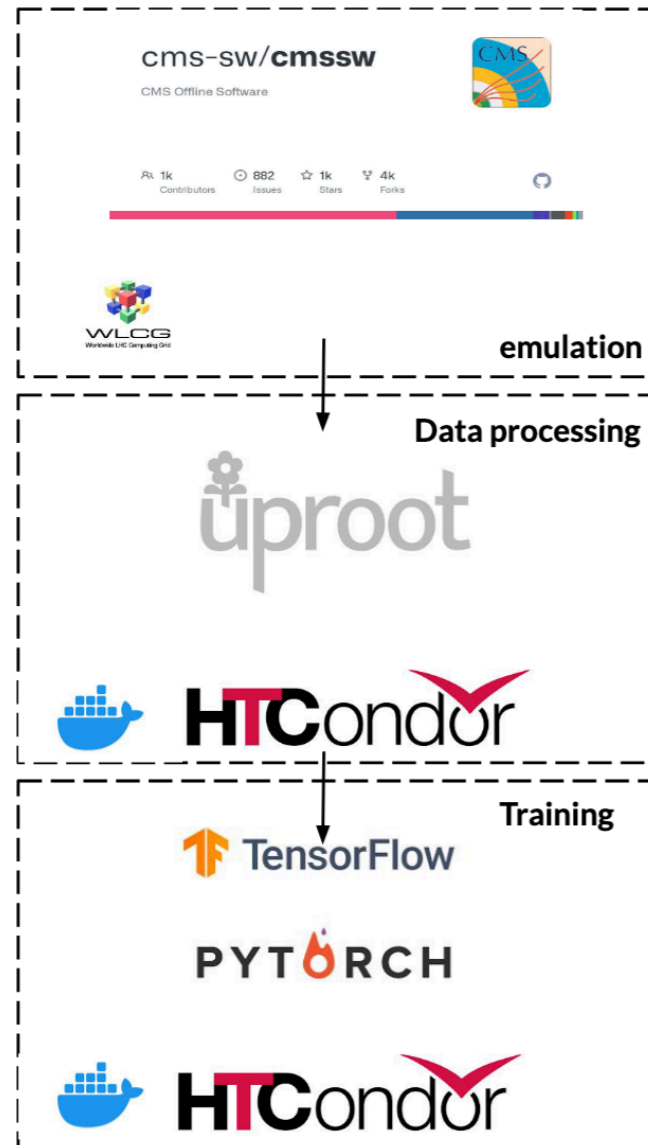
New physics  
goals

Reconfigure and  
rebuild trigger

# MLOPs initial implementation

Made for   AXOLITL

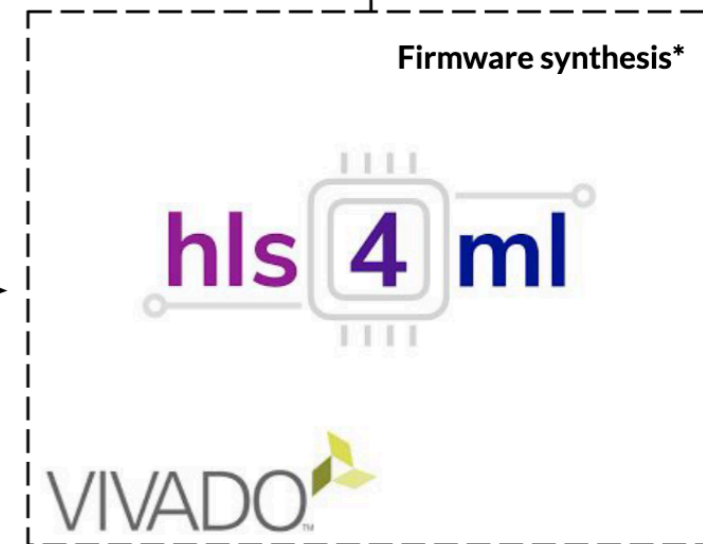
Entry Point  
→



**mlflow mlflow**  
TRACKING MODEL REGISTRY

MLflow server deployed on Kubernetes  
Mounts /eos for backend storage

Firmware block



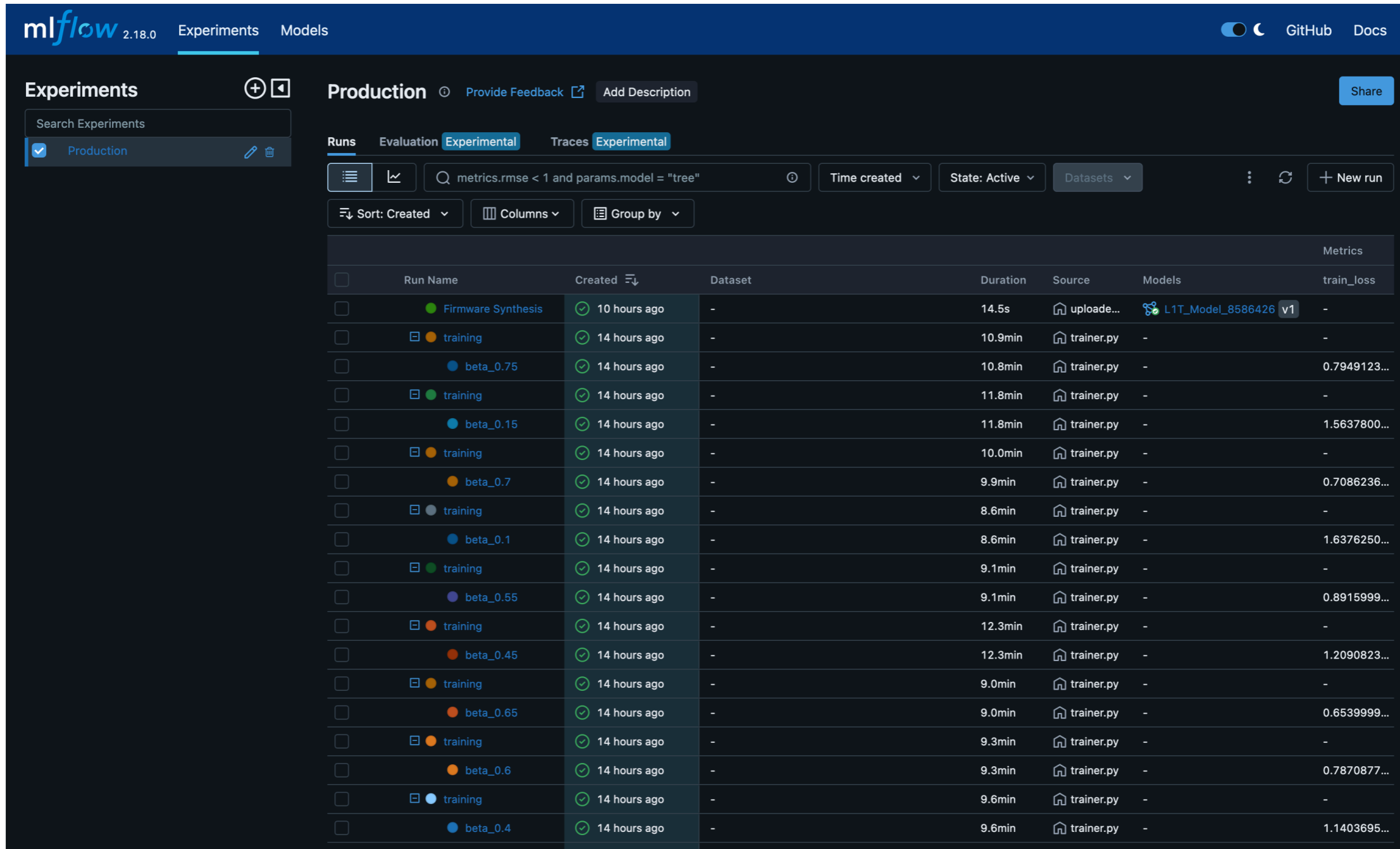
\*specialised hardware for firmware synthesis

- **Developed end-to-end workflow reducing redeployment procedure from around one week to around one hour:**
  - Producing data files for training of models
  - Training and evaluate models on produced data files
  - Producing firmware for trained models

- Code on CERN's GitLab instance with execution orchestrated using GitLab CI/CD

# Example pipeline w/ MLFlow

- An MLFlow server was set up, used for logging ML training experiments and registering trained models

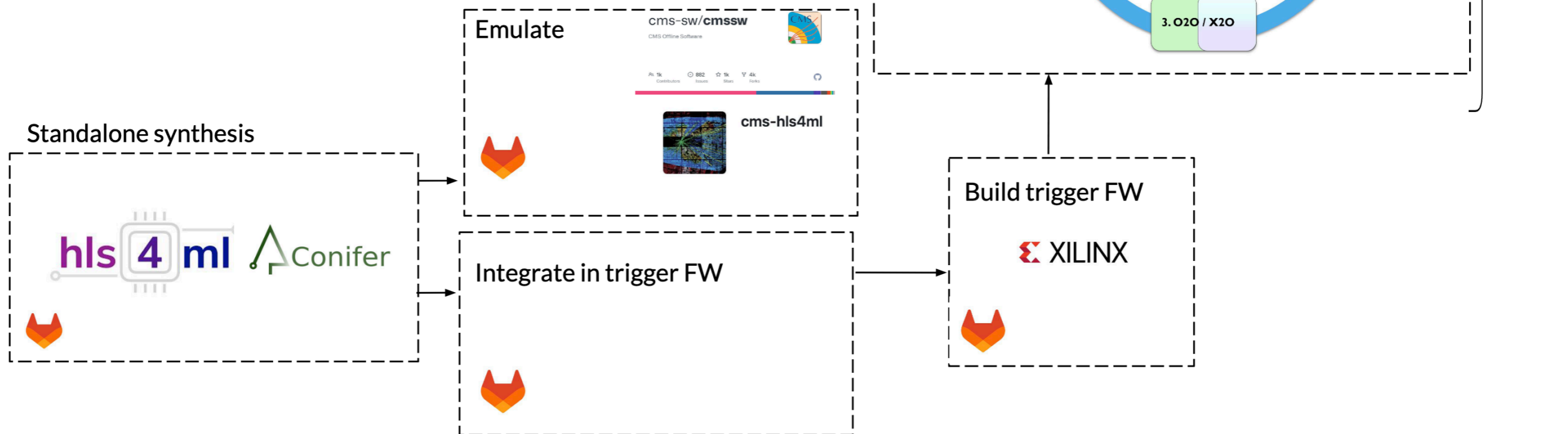


The screenshot displays the MLFlow web interface for an experiment named "Production". The interface includes a search bar, a list of runs, and a table of run details. The runs are sorted by "Created" time, showing a sequence of training runs with varying "beta" parameters. The table columns include Run Name, Created time, Dataset, Duration, Source, Models, and Metrics (train\_loss).

Run Name	Created	Dataset	Duration	Source	Models	Metrics
Firmware Synthesis	10 hours ago	-	14.5s	uploade...	L1T_Model_8586426 v1	-
training	14 hours ago	-	10.9min	trainer.py	-	-
beta_0.75	14 hours ago	-	10.8min	trainer.py	-	0.7949123...
training	14 hours ago	-	11.8min	trainer.py	-	-
beta_0.15	14 hours ago	-	11.8min	trainer.py	-	1.5637800...
training	14 hours ago	-	10.0min	trainer.py	-	-
beta_0.7	14 hours ago	-	9.9min	trainer.py	-	0.7086236...
training	14 hours ago	-	8.6min	trainer.py	-	-
beta_0.1	14 hours ago	-	8.6min	trainer.py	-	1.6376250...
training	14 hours ago	-	9.1min	trainer.py	-	-
beta_0.55	14 hours ago	-	9.1min	trainer.py	-	0.8915999...
training	14 hours ago	-	12.3min	trainer.py	-	-
beta_0.45	14 hours ago	-	12.3min	trainer.py	-	1.2090823...
training	14 hours ago	-	9.0min	trainer.py	-	-
beta_0.65	14 hours ago	-	9.0min	trainer.py	-	0.6539999...
training	14 hours ago	-	9.3min	trainer.py	-	-
beta_0.6	14 hours ago	-	9.3min	trainer.py	-	0.7870877...
training	14 hours ago	-	9.6min	trainer.py	-	-
beta_0.4	14 hours ago	-	9.6min	trainer.py	-	1.1403695...

# MLOPs initial implementation

- FW deployment into online (FPGA) and offline (CMSSW emulator) settings under development
- Interfacing with the GT protocol
- Currently to deploy a new model at P5 requires a CMSSW release
  - Tied to HLT CMSSW release (quarterly schedule)



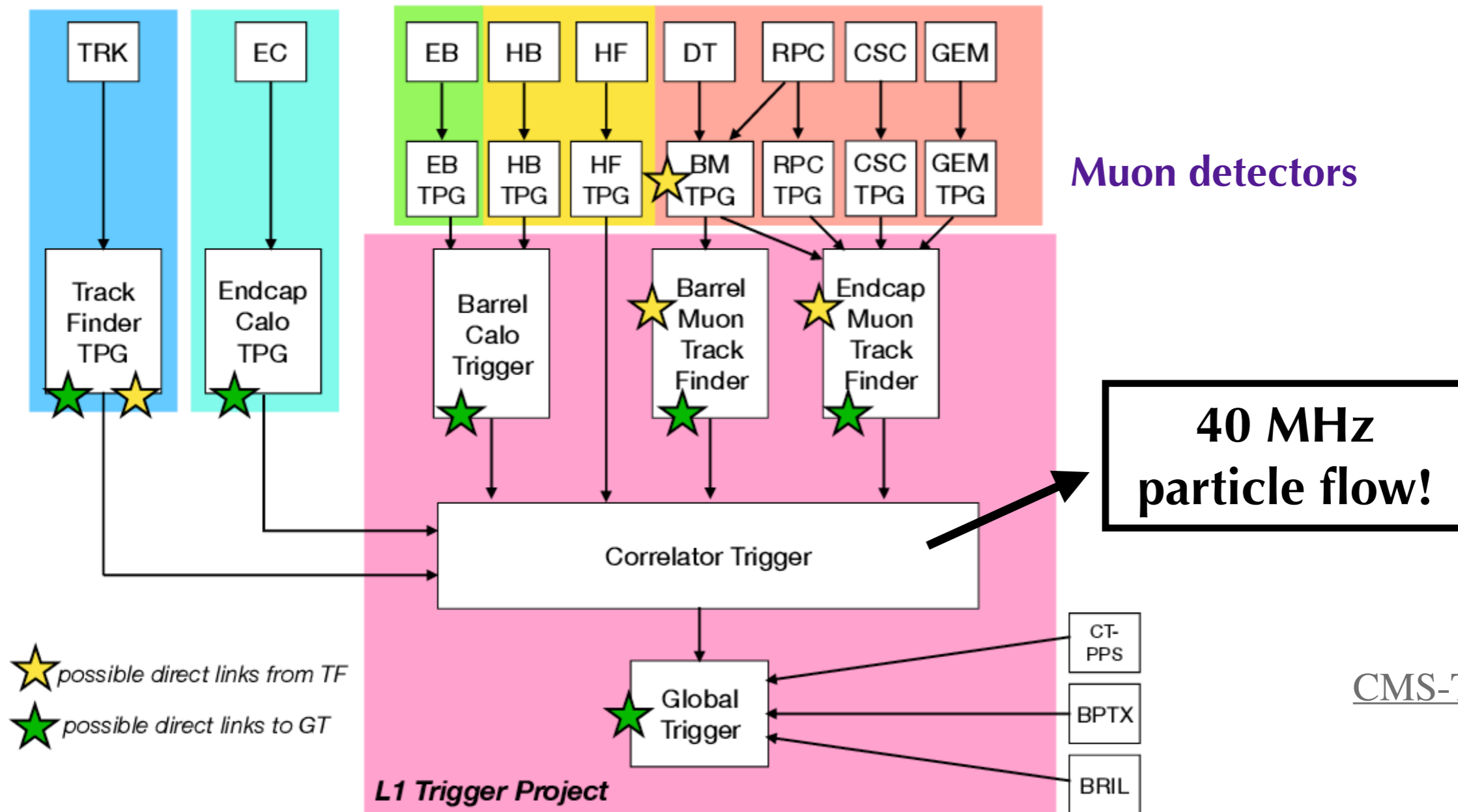
# Anomaly detection @ Phase 2

At HL-LHC, up to 200 pile-up interactions: CMS is upgrading the L1T and HLT to enable the same physics program we are doing now (at @60 PU)

40 MHz tracking!

Calorimeters

- \* input data from 2 Tb/s to 63 Tb/s
- \* latency of 12.5 $\mu$ s to take decision

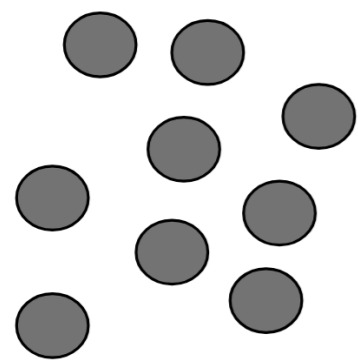


CMS-TDR-021

# Kick starting: Anomaly detection @ Phase 2

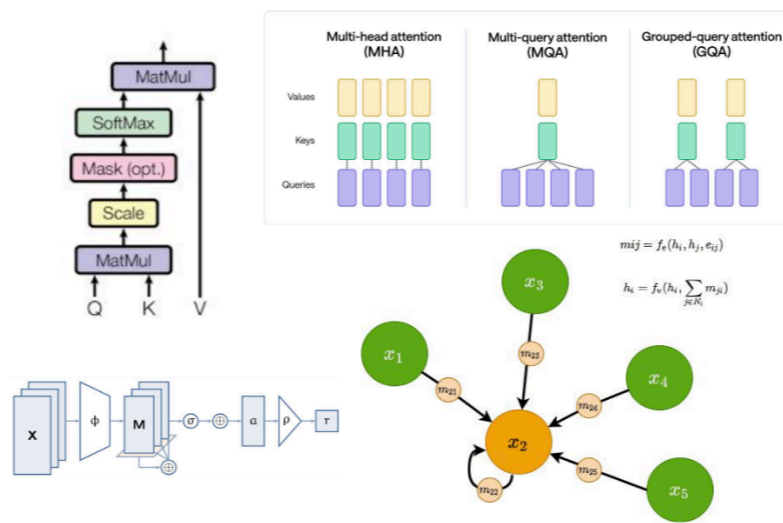
- **First phase of R&D:** take improved reconstructed objects in the Global Trigger and reproduce baseline AXOL1TL with VAE to understand gain from better reconstruction
- **Second phase of R&D:** design novel point-cloud based AD algo that takes as input all reconstructed particles from L1 CT
  - inspiration from jet tagging work guaranteeing permutation invariance & equivariance through equivariant layers (DeepSets, GNN, Self-Attention)
  - multiple representation learning strategies to be explored: fully unsupervised, SSL, as well weakly supervised with noisy labels [\[e.g. Abhijith G. et al 2401.08777\]](#)

## Representation Learning

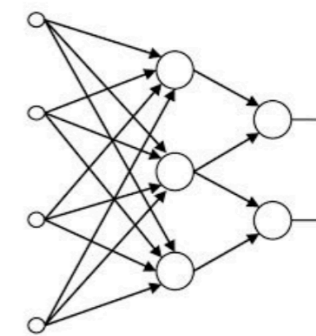


$$\begin{pmatrix} p_T^1 & \dots & p_T^N \\ \eta^1 & \dots & \eta^N \\ \phi^1 & \dots & \phi^N \end{pmatrix}$$

Point-Cloud representation  
(Particles / Reco objects)



Feature space

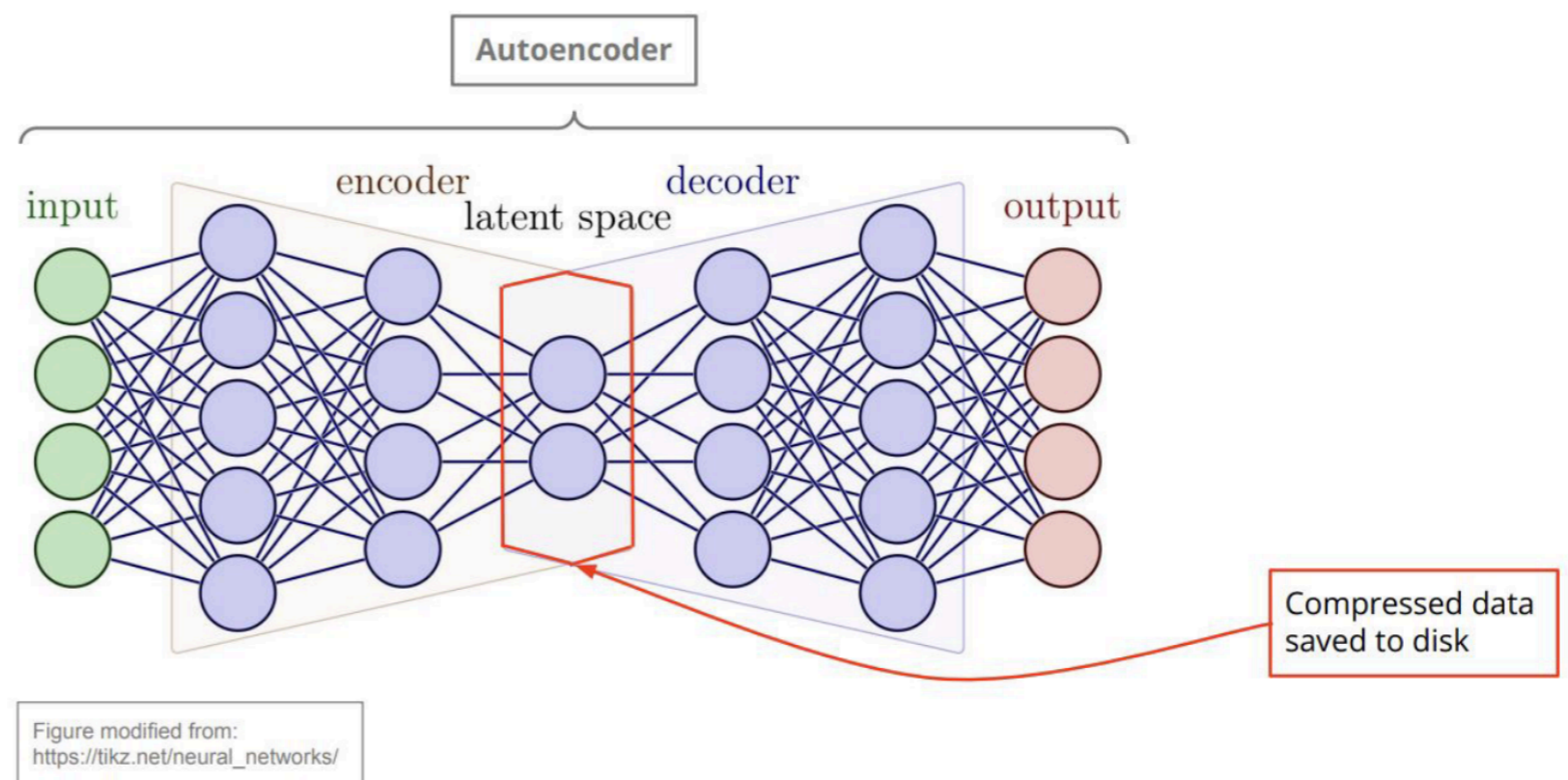


Downstream task (latent embedding for AD)



# Kick starting: Phase 2 L1T Scouting

- CMS L1T data (trigger passthrough) reaching ~ Millions of PB
- Too much data to store
  - demand for efficient compression for downstream storage
- Use Machine Learning to obtain an expressive embedding for downstreams physics
- Scope for larger, sophisticated architectures due to relaxed constraints of the buffer
- Baseline idea to be explored makes use of autoencoders but imagine SOA representation learning approaches to be more expressive and still be implementable on hardware



# Summary

- A first baseline CMS anomaly detection trigger was designed and integrated in the system by CMS collaborators in the past ~ 3 years
  - already collected ~ 100/fb this year
- NGT to push the frontier of this innovative technology to enhance the physics reach of CMS by allowing us to hire personnel fully dedicated to it
- The team is advancing on multiple fronts of the project and we expect major advancements in the next couple of years
  - 2025 & 2026 data taking and analysis
  - MLOps to aid current and future ML-based trigger algos
  - Phase 2 R&D
- Stay tuned!

See also public talks:

Noah's talk at FastML [\[Conference Talk\]](#)  
Melissa's talk at CHEP [\[Conference Talk\]](#)  
Jennifer's talk at ML4Jets [\[Conference Talk\]](#)