A3D3 Workshop HEP Hackathon Project

Real-Time Anomaly Detection with HEP Open Data

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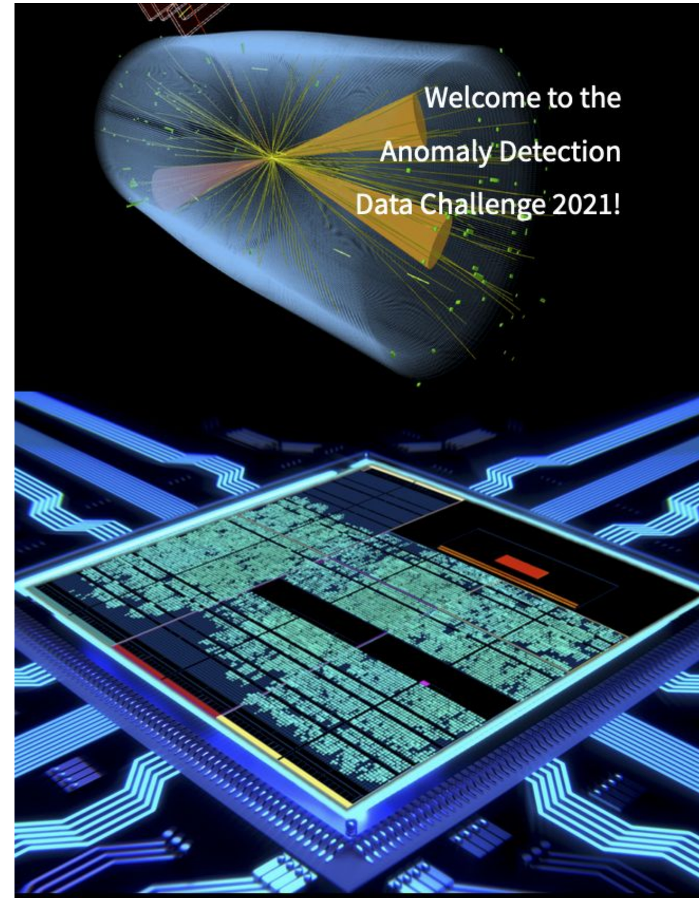
Introduction

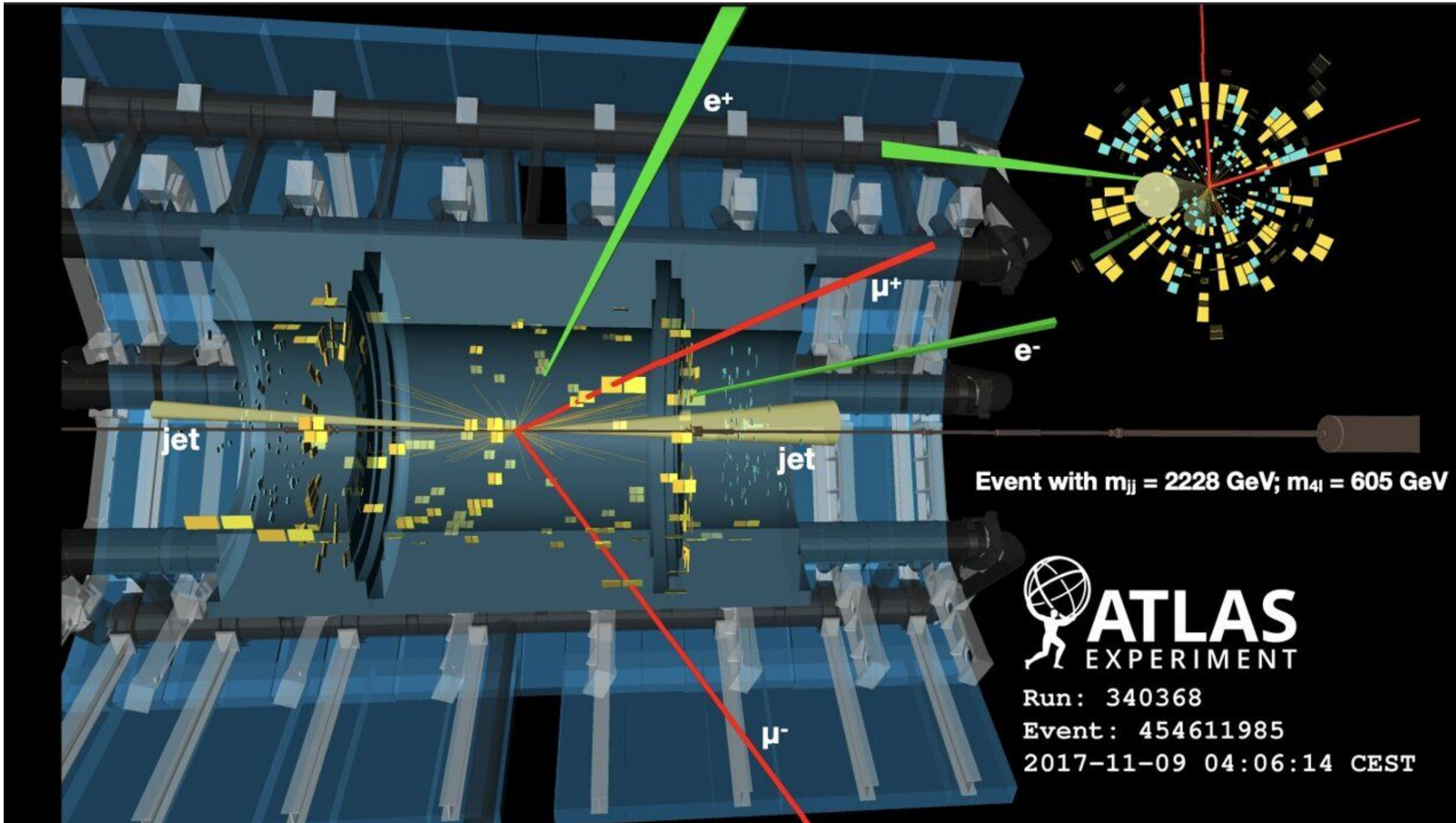
- We are going to work on the Anomaly Detection Data Challenge 2021

  Unsupervised new physics detection at 40 MHz

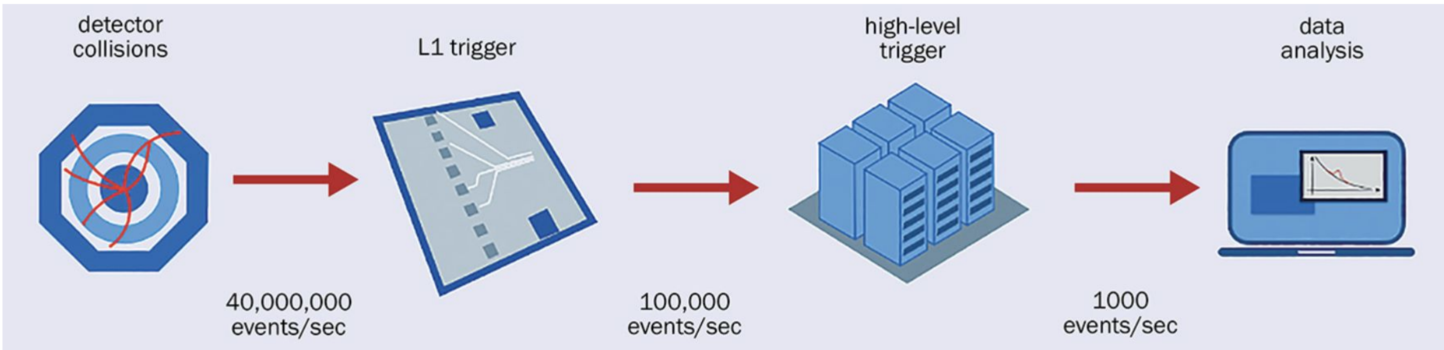
- Resources:
  - Challenge website
  - Challenge introduction from ML4Jets 2021
  - Challenge example code



Particle physics collisions



HEP Data Processing



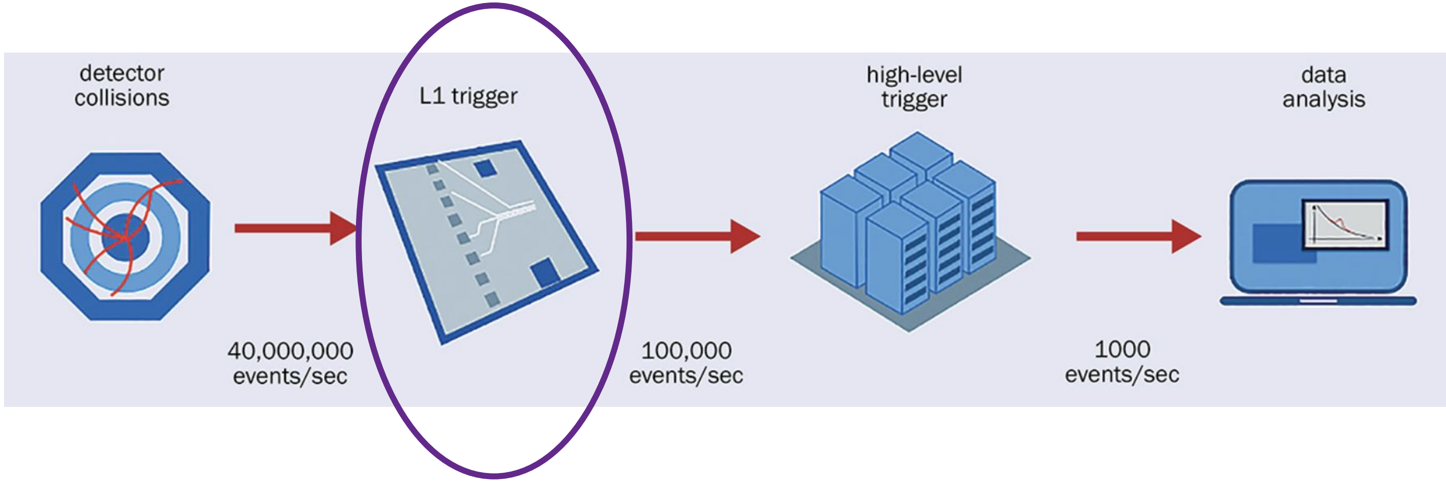
L1 Trigger (hardware: FPGAs) – *O(μs) hard latency*

- Typically coarse selections are applied

High Level Trigger (software: CPUs) – *O(100 ms) soft latency*

- More complex algorithms (full detector information available), some BDTs and DNNs used

Focus of the challenge: L1 Trigger



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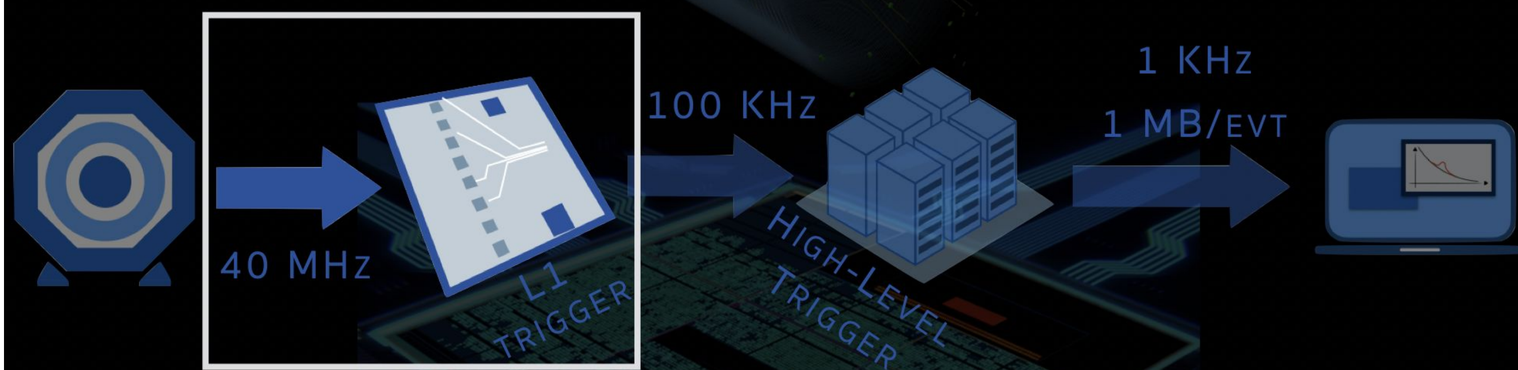
Unsupervised new physics detection at 40 MHz

Idea is to **look for** something **very rare and unusual** directly in the **Level-1 Trigger** without any signal hypothesis in mind

The challenge is to find a-priori **unknown** and **rare New Physics** hidden in a data sample dominated by ordinary Standard Model processes



The deliverable is a developed **algorithm** that can be deployed and run **in L1** with strict **latency** requirement of **< 1 microsecond**

The task is therefore to design an architecture that maximises the **sensitivity for New Physics** but at the **lowest** possible **resource** and **latency** budget

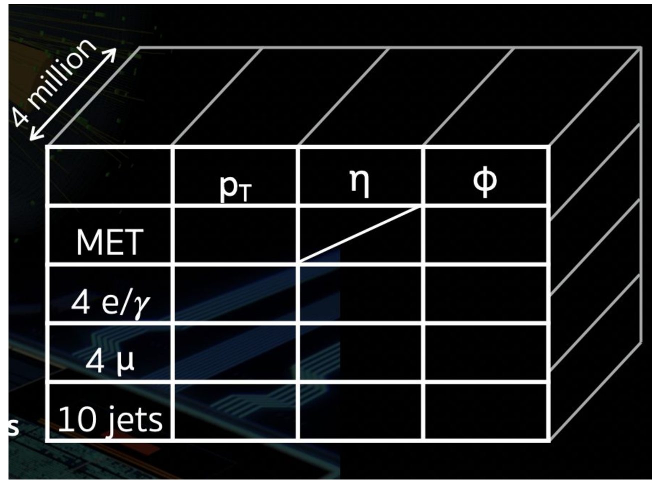
Taken from

[Challenge introduction from ML4Jets 2021]

Hackathon Dataset

- Get the dataset from here: https://mpp-hep.github.io/ADC2021/
- There are 5 dataset files
  - Background dataset
  - 4 different signal datasets

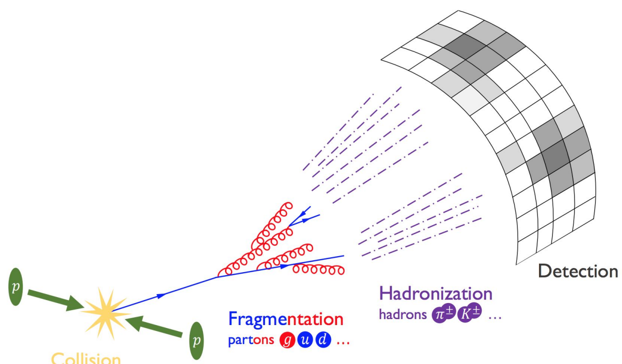
- **Dataset dimensionality:** 57 = 19x3 “particles”
  - 10 jets
  - 4 electrons
  - 4 muons
  - MET



Relevant Particle Responses

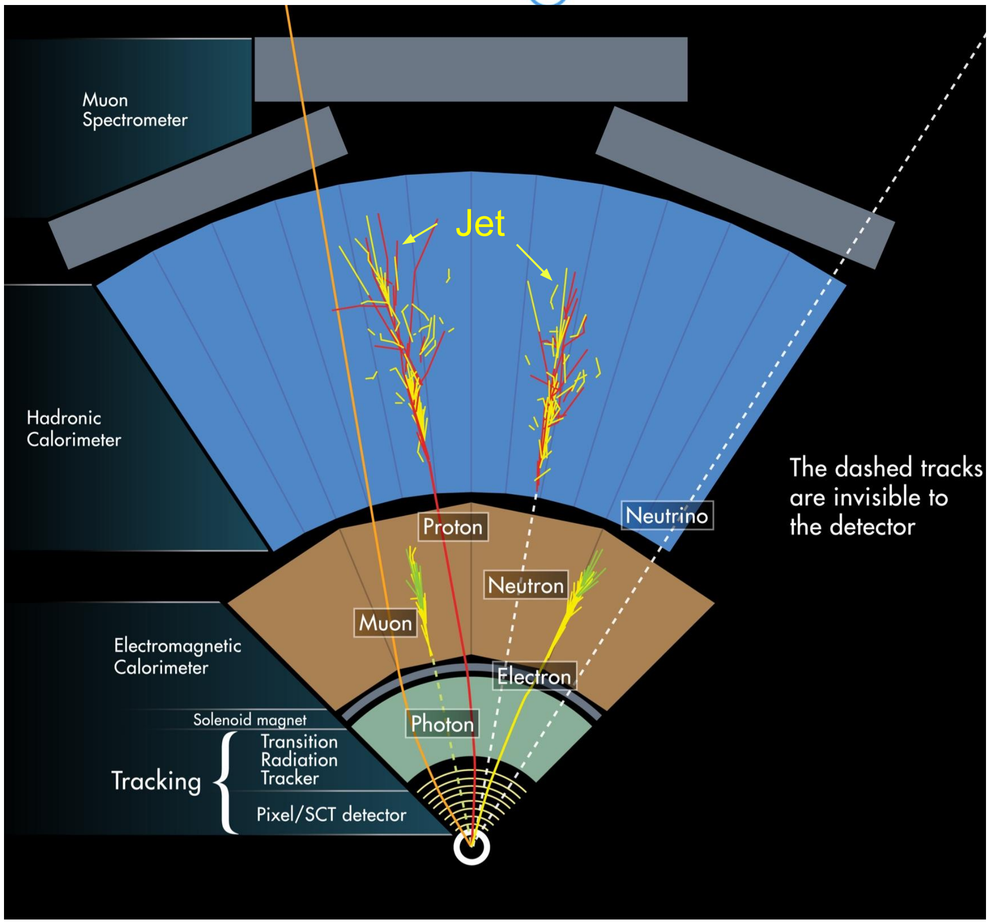
A quark always forms a spay of particle before getting detected

→ **Jet**



MET = Missing Transverse Energy

corresponds to all the missing particles, invisible to the detector



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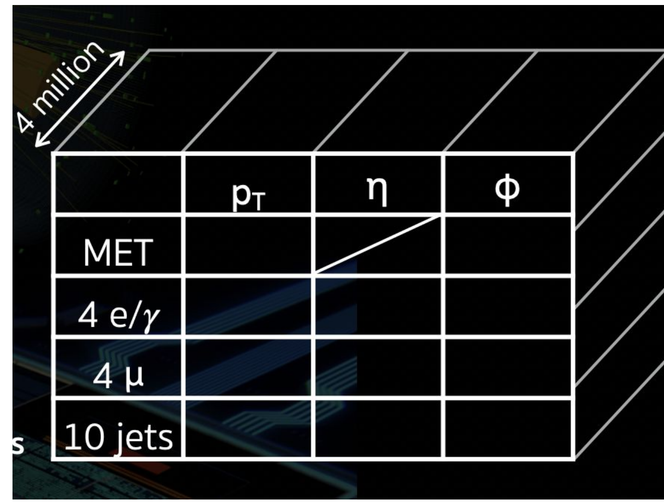

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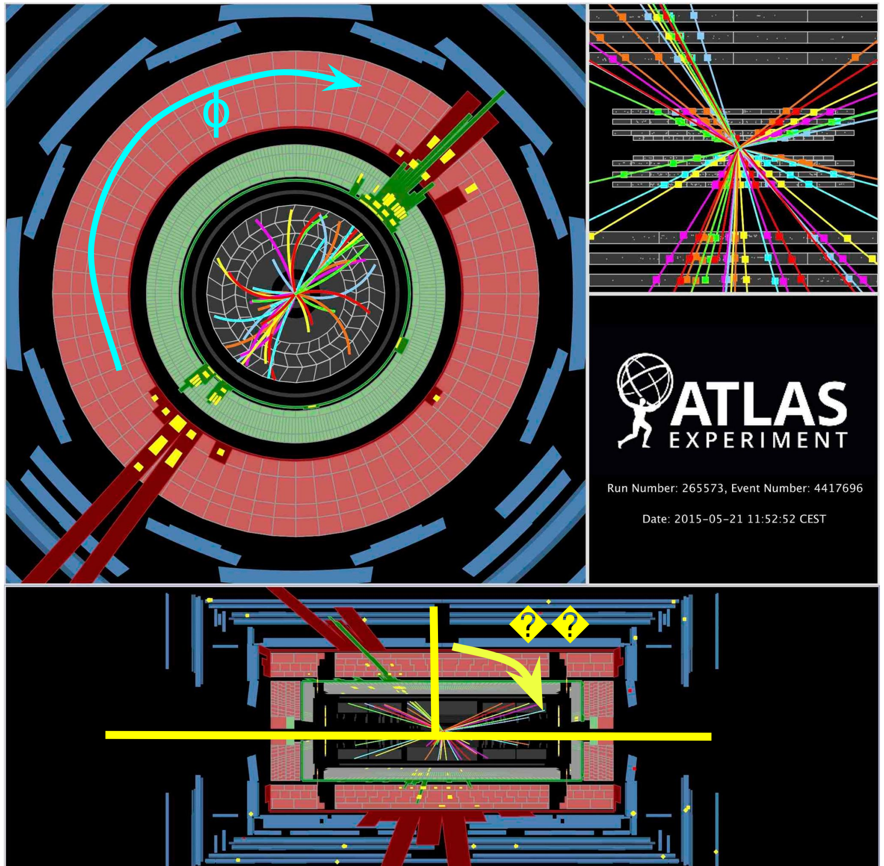
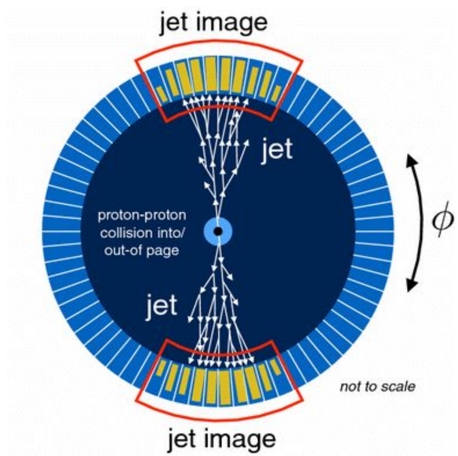
Eta and Phi


φ
ATLAS
EXPERIMENT
Run Number: 265573, Event Number: 4417696
Date: 2015-05-21 11:52:52 CEST

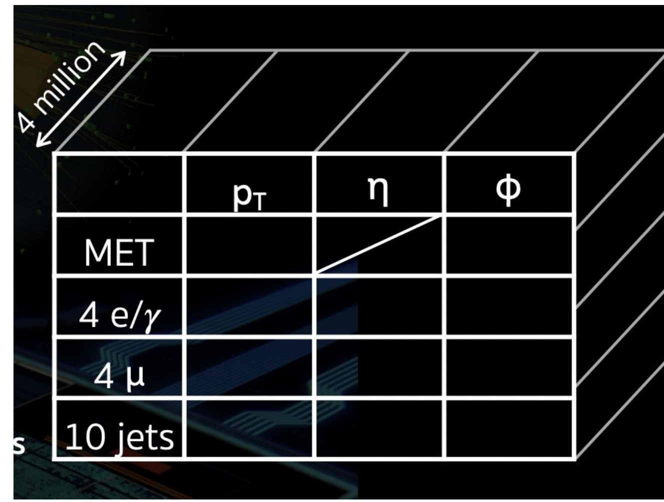

jet image
jet
proton-proton
collision into/
out-of page
jet
ϕ
not to scale
jet image

Hackathon Training Dataset

Train with 4 million background-like events

The file contains:

- Inclusive W production, with W → lν (59.2%)
- Inclusive Z production, with Z → ll (6.7%)
- tt production (0.3%)
- QCD multijet production (33.8%)



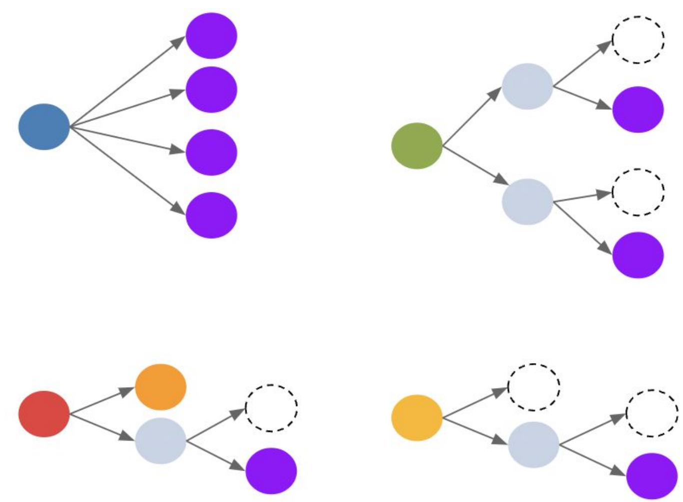
Paper describing the dataset: https://arxiv.org/abs/2107.02157

Model Development and Evaluation

Evaluate performance on several different New Physics simulated samples

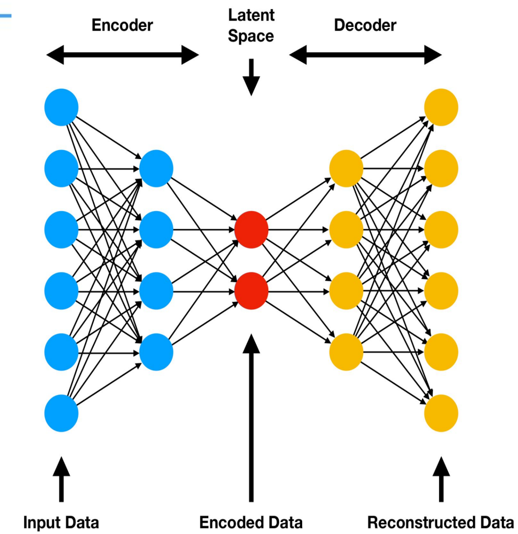
New physics benchmarks

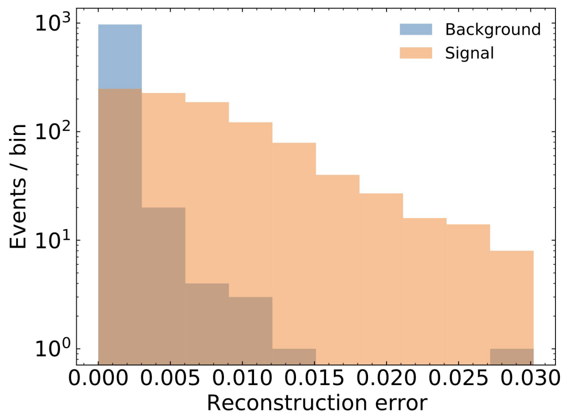
- Neutral scalar boson (**A**), 50 GeV → 4 l
- Leptoquark (LQ), 80 GeV → b τ
- Scalar boson (h^0), 60 GeV → τ τ
- Charged scalar boson(h^+), 60 GeV → τ ν



Autoencoder: One of the popular choice

- Train the model with **background-enriched data**
- Encode the inputs to a low dimensional representation and try to decode it back to the input set
- **Anomalous events** are often **poorly reconstructed** given low, if any, examples present during training





Some Published Solutions:

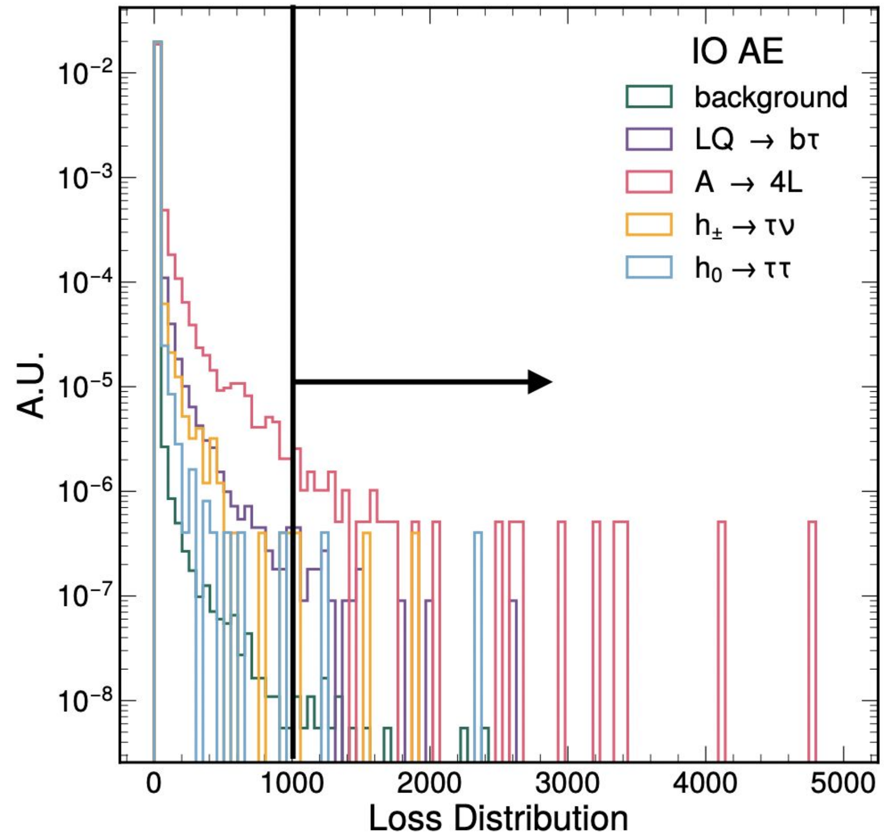
The first paper by the ADC2021 challenge organizers:

https://arxiv.org/abs/2108.03986

⇒ Studies Autoencoders and Variational Autoencoders (VAE)

Another solution-based on contrastive learning (using Autoencoders):

https://arxiv.org/abs/2301.04660



Challenges and Expectations

Real-life application: Low-Latency inference (~ 1 μs)

⇒ Make sure your model is not too huge and can obey this latency constraints

- An estimate of the algorithm efficiency can be obtained by calculating the floating- point operations per second (FLOPs)
- Example code to compute FLOPs: computeFLOPs.ipynb

Some results are already published based on Autoencoders and VAEs

⇒ Do not use vanilla Autoencoders and Variational Autoencoders

Useful Resources

We will use a3d3-hackathon/hep-ad-2023 repository to develop our code

Other Resources:

- Challenge website
- Challenge introduction from ML4Jets 2021
- Challenge example code
- Toolkit for implementing ML inference on FPGAs: hls4ml