



# Exploring Data Challenges and Leveraging Codabench

A Practical Journey With Unsupervised New Physics Detection at 40 MHz



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## UNSUPERVISED NEW PHYSICS DETECTION AT 40 MHZ CHALLENGE

**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



1 KHz

1 MB/EVT



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



## Unsupervised New Physics detection at 40 MHz Step-by-Step

- Gather in a team/by yourself
- Get a cool name for your team, for example team " DeepAnomaly "
- Get yourself familiar with the details on the <u>challenge webpage</u>
- Investigate available datasets and example codes



- Design your AD model
- Evaluate performance and submit results
- Best models will be published in a White Paper (and perhaps deployed in L1 trigger of CMS!!)



## UNSUPERVISED NEW PHYSICS DETECTION AT 40 MHZ DATA SAMPLES

**The data** is represented as an array of MET, up to 4 e/ $\gamma$ , 4  $\mu$  and 10 jets each described by  $p_T$ ,  $\eta$  and  $\phi$  to **mimic L1 data format** 

Train using provided 4 million background-like events simulated with <u>Delphes</u>

Events are pre-filtered to have at least one lepton

- ▶ Inclusive W production, with W → I $\nu$  (59.2%)
- ▶ Inclusive Z production, with  $Z \rightarrow II$  (6.7%)
- ▶ tt production (0.3%)
- QCD multijet production (33.8%)

Evaluate performance on several different New Physics simulated samples

- Neutral scalar boson A, 50 GeV → 4 I
- ▶ Leptoquark, 80 GeV → b τ 💾
- Scalar boson, 60 GeV → τ τ
- ▶ Charged scalar boson, 60 GeV  $\rightarrow \tau \nu$
- Black Box 100 Place



WE CHOOSE A LOW-MASS, RARE SIGNALS THAT WOULD PASS PRE-FELTIRING



#### OVERVIEW AND TIMELINE OF THE CHALLENGE



2020 — we had a dataset that represents data in the L1 trigger of CMS and we started working on an algorithm for the L1 trigger

February 2021 — developed an unsupervised Anomaly Detection (AD) algorithm The idea was to release the datasets and set up a public challenge based on it

- July 2021 released <u>the datasets paper</u> on arXiv
- July 2021 published the datasets in Zenodo
- July 2021 set up a challenge using GitHub io <u>https://mpp-hep.github.io/ADC2021/</u>
- July 2021 announced the challenge at the ML4Jets2021

August 2021 — released the AD algorithm paper on arXiv

February 2022 — published the AD algorithm paper in nature Machine Intelligence March 2022 — published the datasets paper in nature Scientific Data

2022/2023 — the data has been used to publish other research, but not to participate in the challenge

## CHALLENGE SETUP



We provided

O A website with all the details <u>https://mpp-hep.github.io/ADC2021/</u>

**O** Datasets

- 1. <u>Signal h+ -> tau nu</u>
- 2. <u>Signal h^0 -> tau tau</u>
- 3. <u>Signal LQ -> b tau</u>
- 4. <u>Signal A -> 4 leptons</u>
- 5. <u>Training dataset</u>
- 6. <u>BlackBox dataset</u>



#### Unsupervised New Physics detection at 40 MHz

In this challenge, you will develop algorithms for detecting New Physics by reformulating the problem as an out-of-distribution detection task. Armed with four-vectors of the highest-momentum jets, electrons, and muons produced in a LHC collision event, together with the missing transverse energy (missing  $E_T$ ), the goal is to find a-priori unknown and rare New Physics hidden in a data sample dominated by ordinary Standard Model processes, using anomaly detection approaches.

The algorithms are intended to be deployed in the first stage of the real-time event filter processing system of LHC experiments (Level 1 or L1 trigger), where the available bandwidth, latency and resources are strictly limited. Such limitations constrain the design of the algorithm. To emulate the constraints in terms of bandwith only the leading 10 jets, 4 muons, 4 electrons and the missing  $E_{T}$  will be provided to be used as input to the algorithm. Furthermore, only a maximum of X, Y, and Z bits are available for the representation of the  $\eta$ ,  $\phi$ , and the transverse momentum  $p_{T}$  of each physics object, respectively.

- **O** A paper with details about the data
- **O** Example algorithms
- O Example analysis pipeline
- **O** A script to estimate FLOPS
- O A repo to upload the contributions to <u>https://github.com/mpp-hep/ADC2021-results</u>
- O "Further reading" mostly about hls4ml and AD

# UNSUPERVISED NEW PHYSICS DETECTION AT 40 MHZ EXAMPLE TEAM "DEEPANOMALY"

Decide on the algorithm that you want to explore

The Example Team " **DeepAnomaly** " has chosen **Autoencoders** 

- Encode input in smaller dimensional space
- Train on typical LHC background
- Anomalous data will have higher loss
- Calculating the loss requires to store the input until the output is computed











# UNSUPERVISED NEW PHYSICS DETECTION AT 40 MHZ EXAMPLE TEAM "DEEPANOMALY"

### DESIGNS ALGORITHM

The " **DeepAnomaly** " team has also considers **Variational Autoencoders** 

- The latent space is sampled from Encoder output
- Can be used to generate new samples
- Inference can be done only on the latent space
- No need to store input and deployment of Encoder is enough

(e.g. saves resources and latency in comparison to AE)









## Unsupervised New Physics detection at 40 MHz Example Team "DeepAnomaly"



### Evaluates Performance on Signal samples

**Goal is** to **maximise** TPR at FPR 10<sup>-5</sup> (roughly corresponding to the available output data rate budget for a trigger algorithm) for each of the provided anomaly

The Team " **DeepAnomaly** " checks AE vs VAE

- The **Inference** can be done only **on the latent space**, either with  $D_{KL}$  or  $R_z$ Shoutout to DarkMachines for the  $R_z$  idea
- No need to store input and deployment of Encoder is enough



# Unsupervised New Physics detection at 40 MHz Example Team "DeepAnomaly"

# CERN

### SUBMITS RESULTS

- For the Blackbox dataset get the event number of the 1000 most anomalous events based on the algorithm metrics
- An estimate of the algorithm efficiency can be obtained by calculating the floatingpoint operations per second (FLOPS) <u>Second</u>



The submission should be in a form of a HDF5 file, <u>DeepAnomaly.h5</u>, containing a numpy array with the identification numbers of each selected event, plus a dictionary with the algorithm deployment performance

**Upload contribution!** 

# Unsupervised New Physics detection at 40 MHz Example Team "DeepAnomaly"

# CERN

## SUBMITS RESULTS

- For the Blackbox dataset get the event number of the 1000 most anomalous events based on the algorithm metrics
- An estimate of the algorithm eff

point operations per second



WE ONLY ACCEPTED THE FINAL SUBMISSIONS, WHILE MANY WERE ASKING US FOR AN INTERMEDIATE RESULT TO ITERATIVELY IMPROVE THE ALGORITHM

The submission should be in a fornumpy array with the identification number with the algorithm deployment performance Section 2012

Upload contribution!

actionary

# UNSUPERVISED NEW PHYSICS DETECTION AT 40 MHZ

\*if needed







#### UNSUPERVISED NEW PHYSICS DETECTION AT 40 MHz

#### Advanced Challenge

Keras

TensorFlow

PyTorch

NO ONE EVER GOT TO

THIS POINT ..

WHY?

MOST LIKELY BECAUSE IT IS

A VERY TIME CONSUMING TASK.

PERHAPS, IF WE PROVIDED AN INTERMEDIATE

**LEADERBOARD** WITH RESULTS, PARTICIPANTS

Those that challenge

saul with hise

Model

WOULD BE MORE INTERESTED TO INVEST

THEIR TIME

ASIC flow

from

Outcomes

THERE WAS ONLY ONE OFFICIAL SUBMISSIONS IN THE GITHUB REPO BUT SEVERAL PAPERS PUBLISHED USING THE DATASET WE PROVIDED

#### ANOMALIES, REPRESENTATIONS, AND SELF-SUPERVISION

BARRY M. DILLON, LUIGI FAVARO, FRIEDRICH FEIDEN, TANMOY MODAK, TILMAN PLEHN

#### ONLINE-COMPATIBLE UNSUPERVISED NON-RESONANT ANOMALY DETECTION

VINICIUS MIKUNI, BENJAMIN NACHMAN, DAVID SHIH

NANOSECOND ANOMALY DETECTION WITH DECISION TREES FOR HIGH ENERGY PHYSICS AND REAL-TIME APPLICATION TO EXOTIC HIGGS DECAYS STEPHEN ROCHE, QUINCY BAYER, BENJAMIN CARLSON, WILLIAM OULIGIAN, PAVEL SERHIAYENKA, JOERG STELZER, TAE MIN HONG

#### CODABENCH.ORG

#### A platform to create your own challenges, see the talk by Wahid

#### Codabench

#### Announcement

Welcome to Codabench!

Join the Google group to connect with the community!

**Featured Benchmarks** 

#### **Popular Benchmarks**



Find benchmarks that pique your interest! A benchmark allows you to test new algorithms against reference datasets OR (inverted benchmark) submit challenging data to reference algorithms.

Organize a benchmark on Interested in joining the development tutorial.

Codabench. Start with our team? Join us on Github or contact us directly.

#### EXPERIENCE WITH CODABENCH.ORG



## CLASSIFY STANDARD MODEL EVENTS IN HEP DATASET



ORGANIZED BY: Katyag CURRENT PHASE ENDS: Never CURRENT SERVER TIME: 19 November 2023 At 15:53 CET Docker image: codalab/codalab-legacy:gpu

I've made a test challenge to learn how to use Codabench

Things that are very useful:

- ✓ Datasets+code examples in one place
- $\checkmark$  Clear deadline that is easily updated if need to
- $\checkmark$  Easy to reach out and to advertise the challenge to the communit
- $\checkmark$  Infinite submissions and automatic check of it
- ✓ Leaderboard
- Past challenges can be used as educational materials

Perhaps if our challenge was hosted on Codabench, we would get more submissions (and we could automate FLOPS estimation)

#### FUTURE ANOMALY DATA CHALLENGES

#### "Can we make an anomaly detection algorithm capable of

anomaly detection in many domains? "



From the slides of Phil Harris



At A3D3 we are looking to lead a challenge across NSF HDR initiative institutes on anomaly detection and would like to host this on <u>Codabench.org</u>

Possible Suggested datasets

- **Imageomics**: Images of animals for classification and new species
- **Iguide**: Rainfall data to predict anomalous local weather
- **iHARP**: Ice data from anomalous melts?
- **ID4**: new materials identification?
- **A3D3**: Astrophysical anomalies (LIGO/...)



The plan is to write **two white papers** 

- 1. A white paper on making ML Workflows fair not just the dataset, but we want the whole workflow reproducible
- 2. A second whitepaper **comparing and contrasting anomaly detection** on the different datasets