Search for New Physics using un-supervised ML techniques

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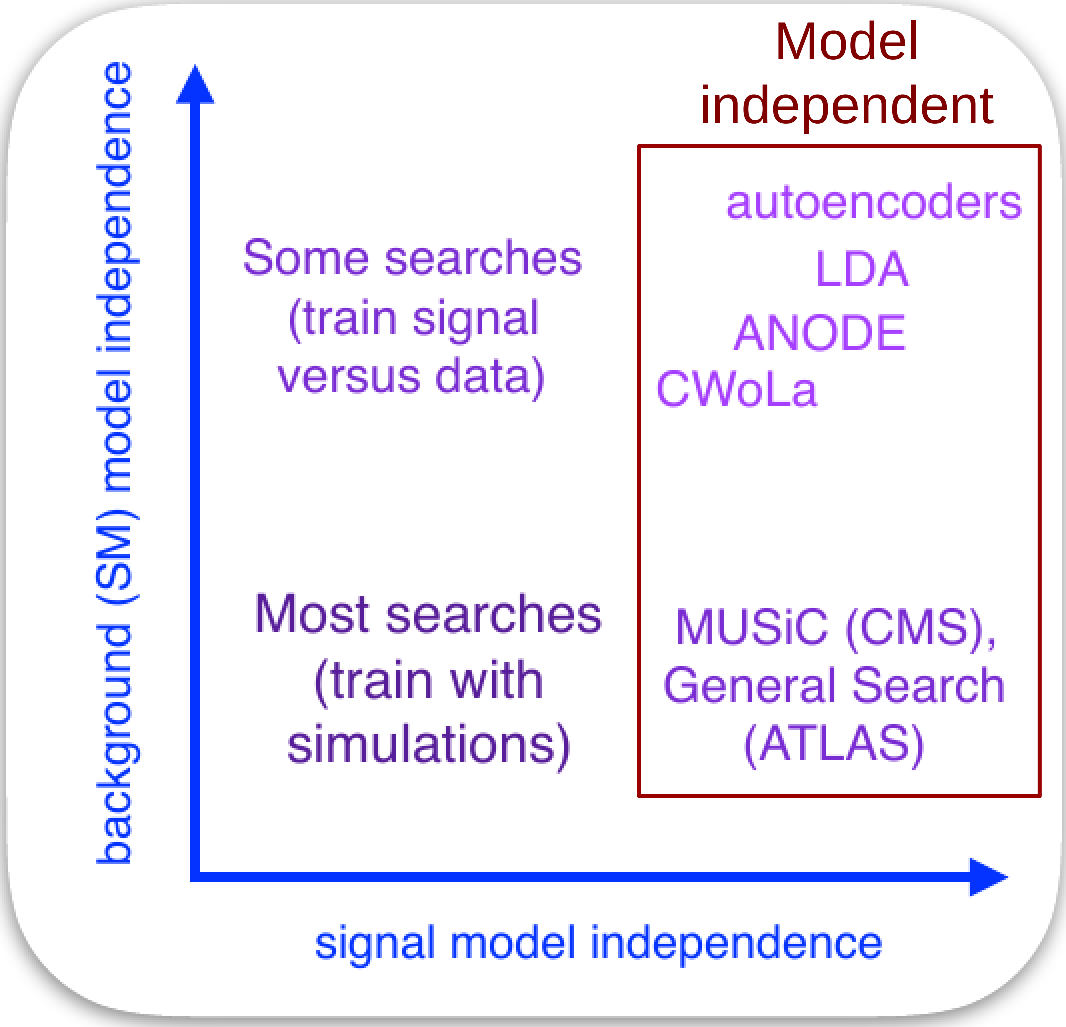
Direct Searches for New Physics

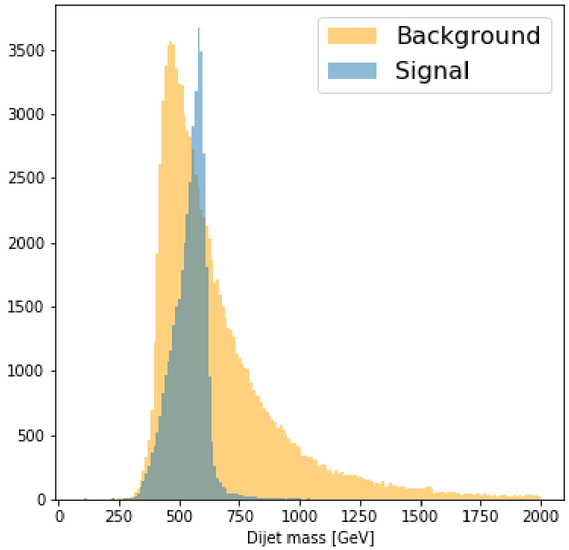


→ [6-15]

→ [1-5]

B. Nachman, D. Shih, arxiv:2001.04990

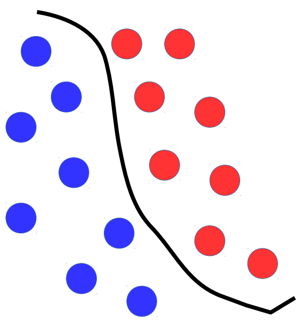
Bump hunt use-case



Search for resonance in a spectrum using ML

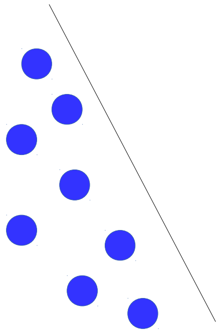
Supervised (labels)

DNN, BDT, SVM



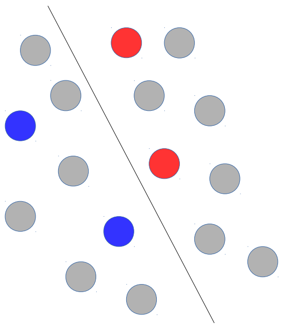
Unsupervised
(no labels)

SVM-1class, **AE**, VAE, WAE, **GAN-AE**,...



Semi-supervised
(some labels)

triplet NN,...



Outline

Direct search for New Physics at the LHC using **Autoencoders**

Two use-cases with **dijet** simulated samples

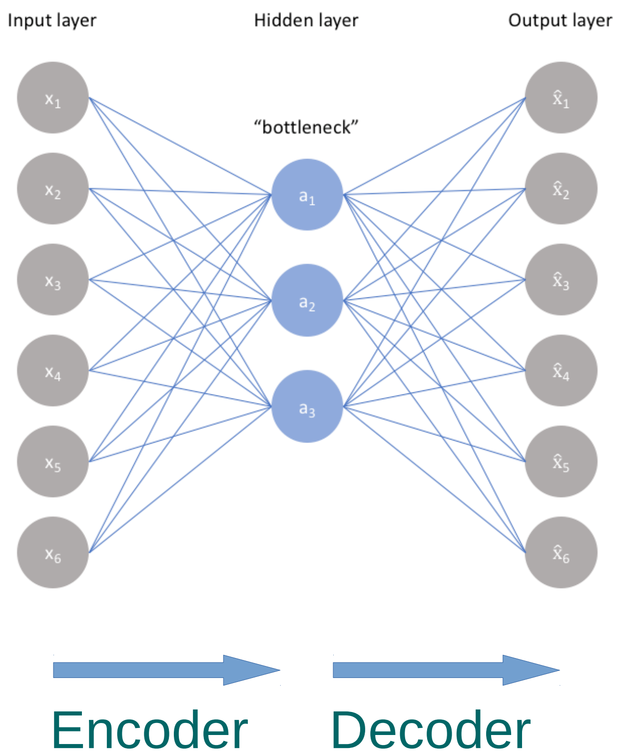
- **LHC Olympics challenge** → AE (jet substructure variables)
- Simulated **dijet data** → GAN-AE (Event variables)

Conclusion and outlook

Why Autoencoders ?

An **Autoencoder** is a network trained to copy it input to its output

$$x \rightarrow h = f(x) \rightarrow \hat{x} = g(h)$$



Reproducing the **identity** is not useful

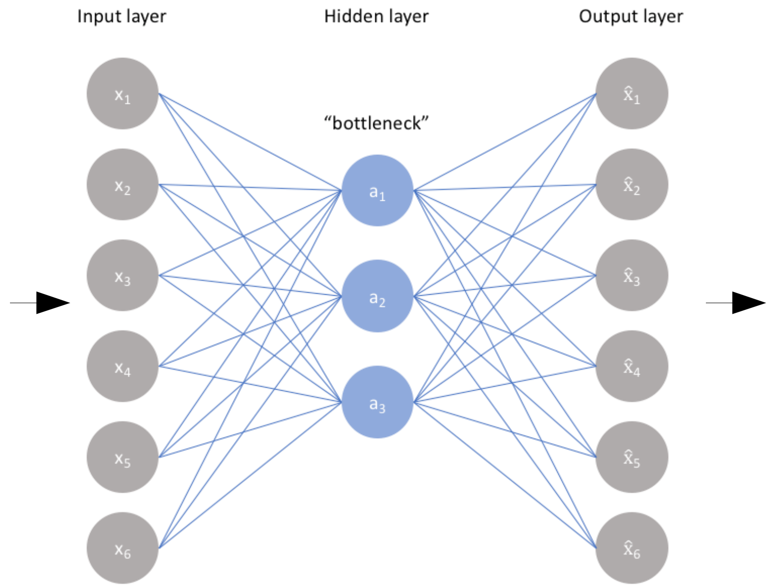
→ Restricted to **copy imperfectly**: forces the AE to **prioritize** information to **learn useful features**

Undercomplete or regularized AE

Usage: dimensionality reduction, representation learning, manifold learning, generative network, **anomaly detection**, ...

Train AE on **background** samples: **reconstructed error** $\ell = ||x - \hat{x}||^2$

Input x



Output $\hat{x}$

The idea being that the network will **learn** to main background features and **fail** to reconstruct **anomalous** sample → **larger reconstruction error**

LHC Olympic challenge

Anomaly detection challenge for **ML4Jets2020** conference (15-17/01/20)

- **Simulated Background** (dijet data) + Signal
  - **Benchmark** samples to develop method
  - Three LHCO 2020 **Black Boxes "data"** with unknown signal
- **Datasets**
  - Event selection: >=1 anti-kT R = 1.0 jet, |η| < 2.5 and pT > 1.2 TeV.
  - Data consists of [pt,eta,phi] for of up to 700 hadrons
- **What was asked**
  - **p-value** of dataset (for null hypothesis)
  - As complete as possible **description** of NP process
  - **Number** of signal events in the data (with uncertainties
- Challenge ran until Jan 12th, **10 team** submitted their results

High level features

I. Dinu

Pre-processing was necessary to extract jet features from raw data

Jet Features ($\times$ two jets)

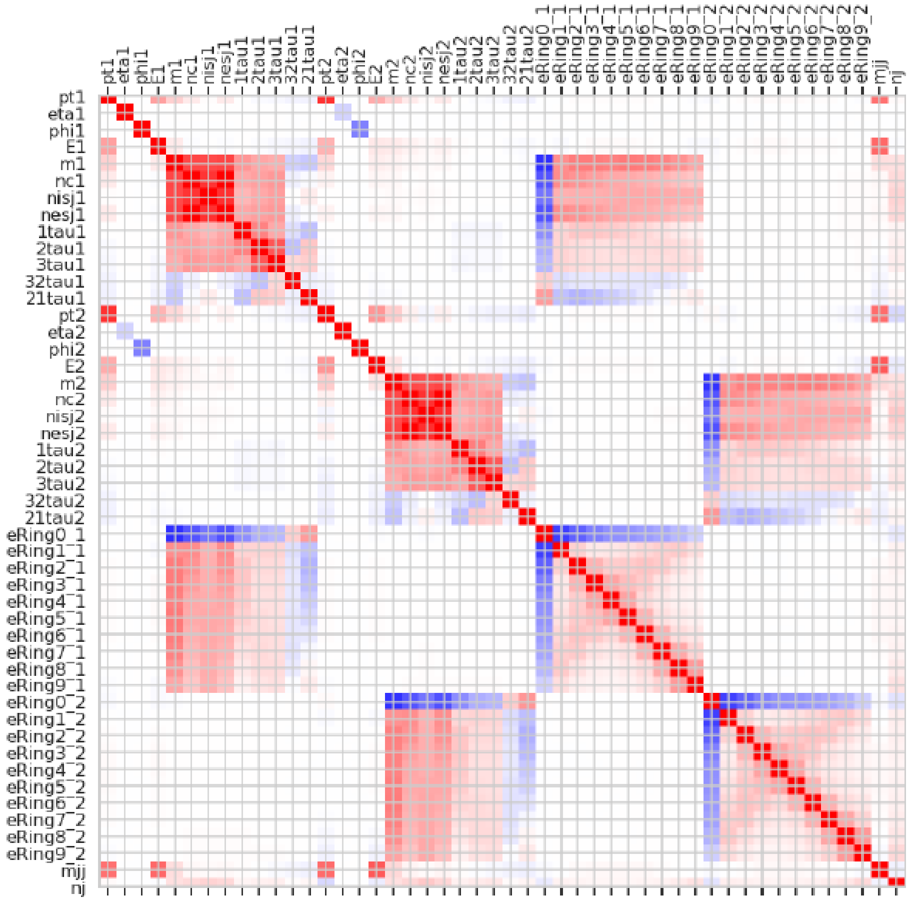
- $(p_T,\ \eta,\ \phi,\ m)$, E
- $nsj_{inclusive}$, $nsj_{exclusive}$ (based on d_{cut}), $n_{constit}$
- $\tau_1,\ \tau_2,\ \tau_3,\ \tau_3/\tau_2,\ \tau_2/\tau_1$(subjettinesses)
- Energy rings $E_i = (\sum E_{constit})/E_{jet}$, where $\Delta R(jet, constit) \in [R_{jet}(i/n); R_{jet}((i+1)/n)]$, n=10

Event Features

- m_{jj}, $n_{jets}(p_T \geq 20 GeV)$

High level features

Correlation



Importance

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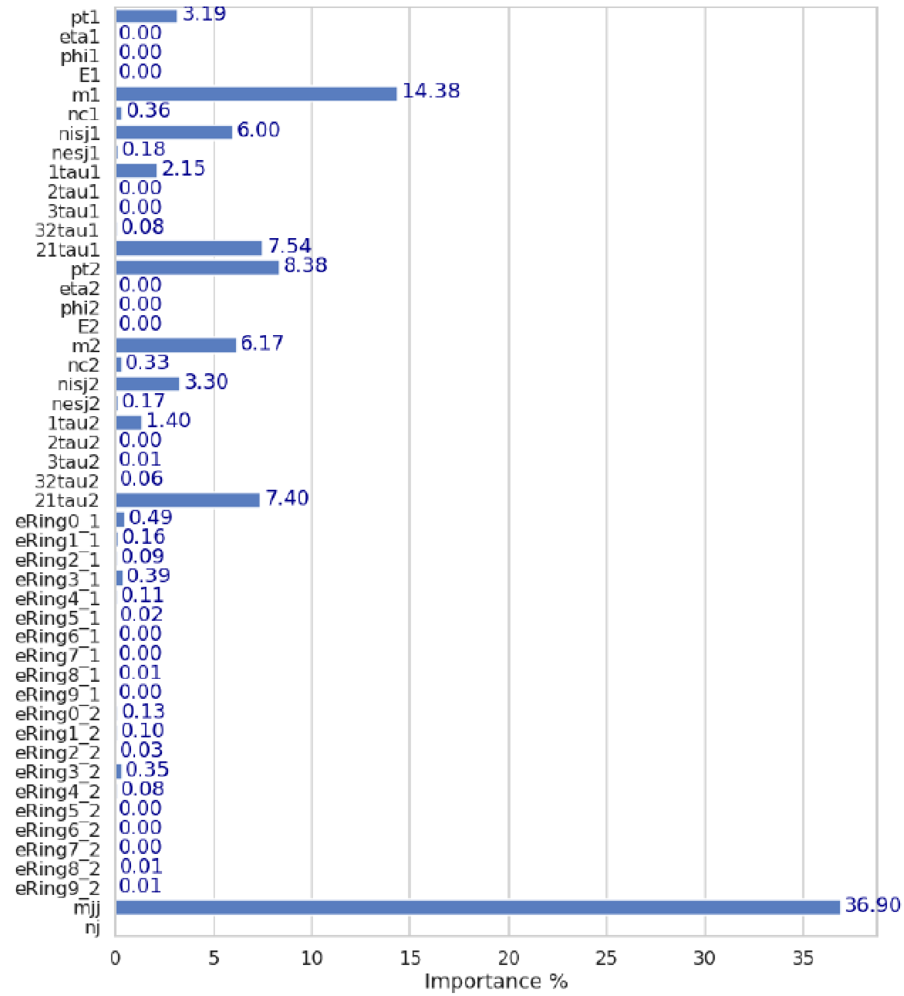
(ranked with Gradient BDT)



HLF-AE: High Level Feature AE

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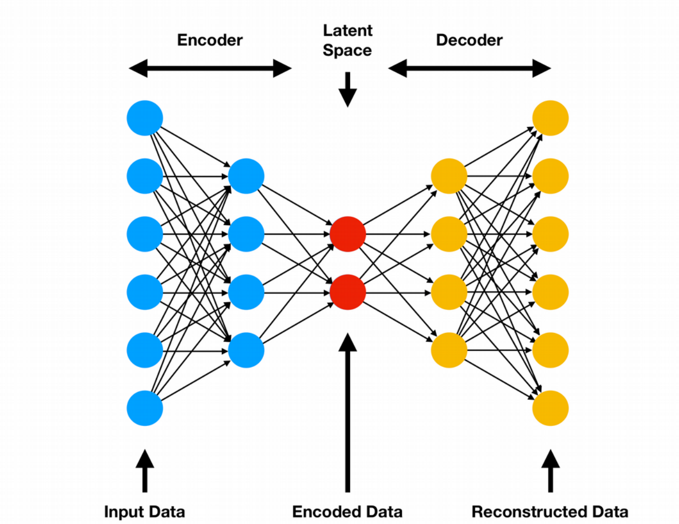
Hyperparameter space scan

- Learning rate: $0.01, 0.005, 0.001, 0.0005, 0.0001$
- Features used: 44
- 1^{st} hidden layer nodes: $30, 25$
- 2^{nd} hidden layer nodes: $20, 15$
- Encoding dimension: $10, 7, 5$
- Activations: ReLU, Leaky ReLU, ELU
- Batch size: $32, 64, 128, 256, 512, 1024$



Grid Task on Manchester GPU Test Site

- 1180 configurations spread among 10 jobs
- custom Docker container for this architecture
  - → gitlab link to code

Hyper Parameter Optimization

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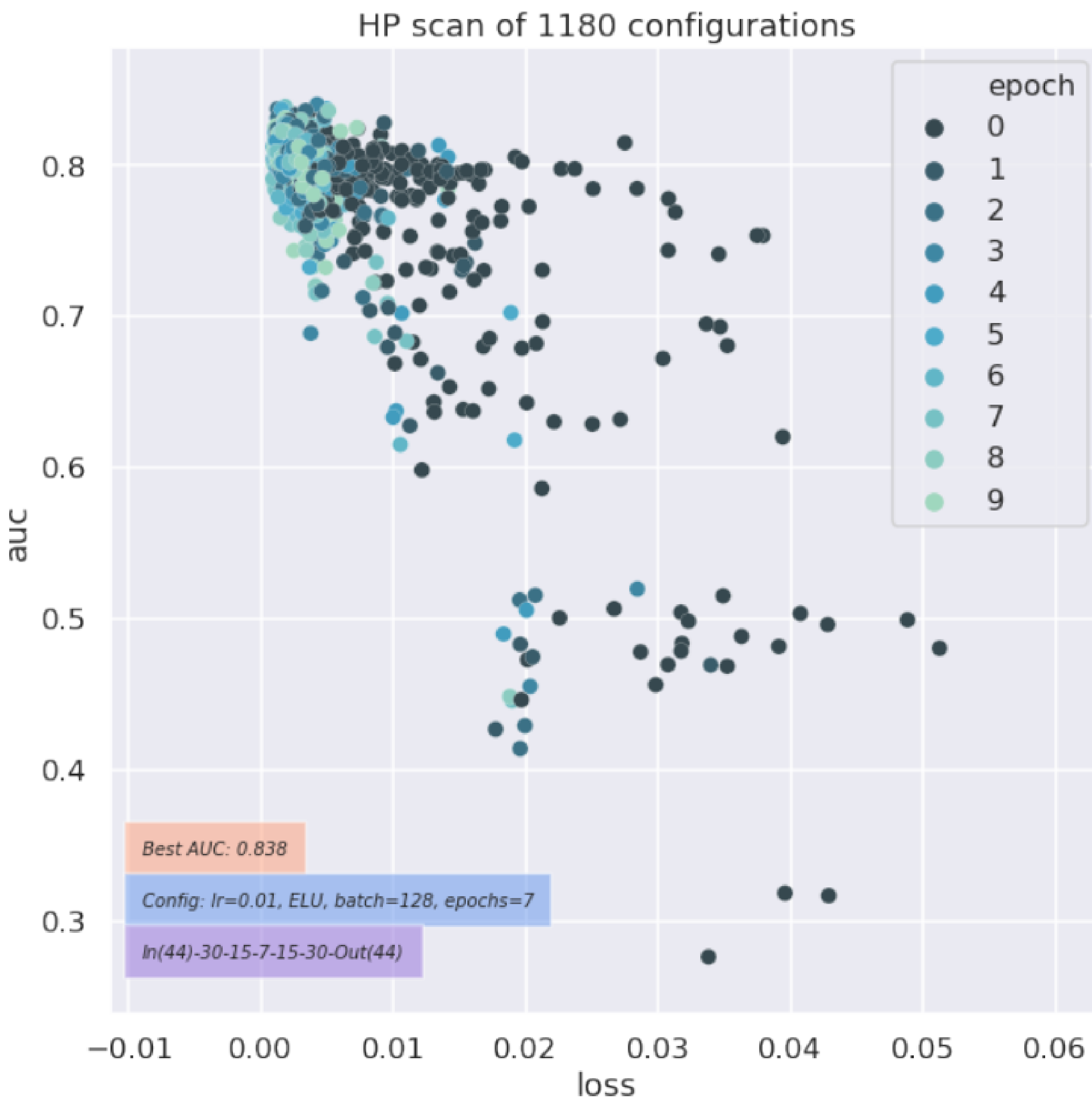
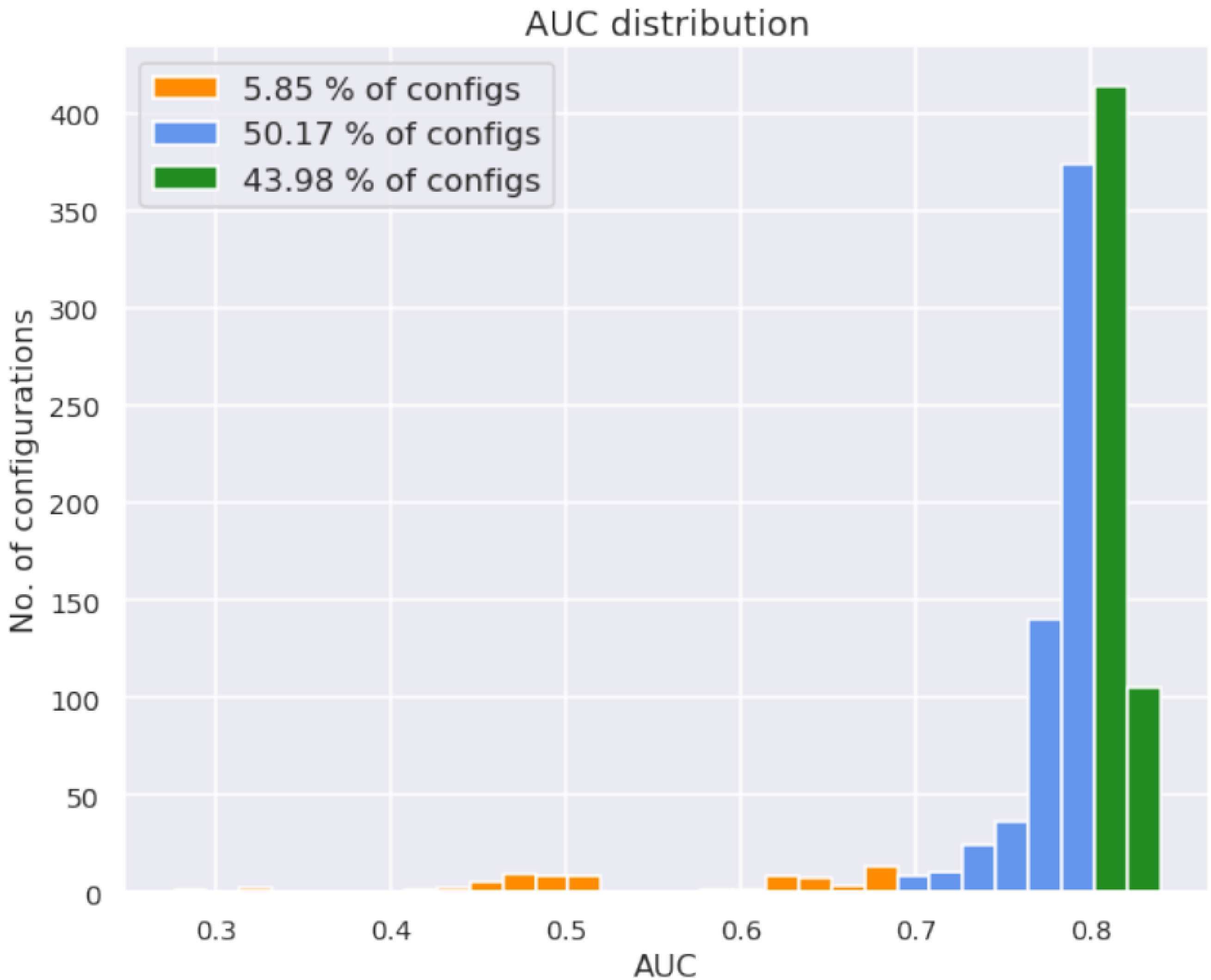


Hyper Parameter Optimization

I. Dinu



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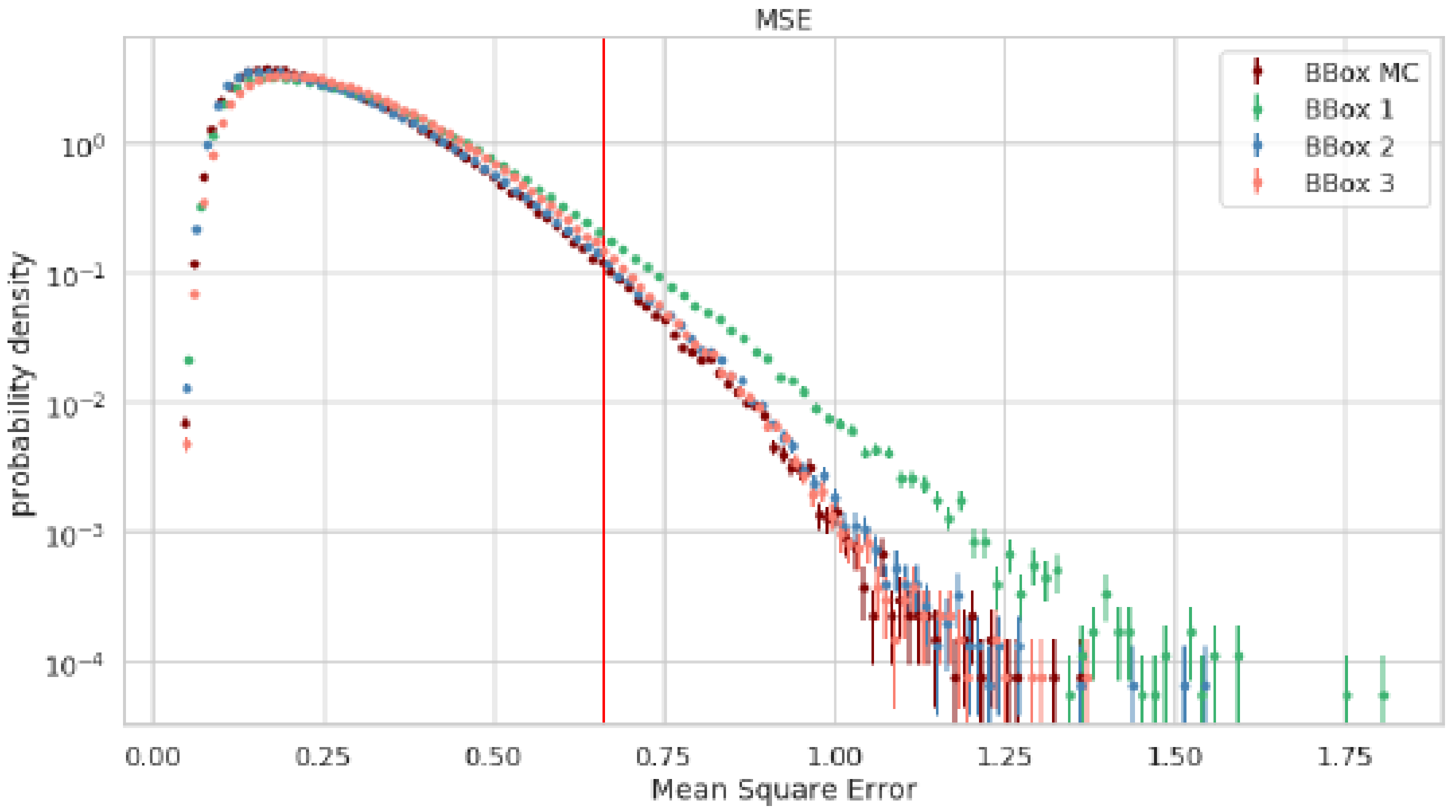
Mean square error returned by AE

→ **training** dataset (background) and **black box** samples 1-3:



A **threshold** value is applied and feature distributions are compared.

Results on Bbox-1 dataset

Invariant mass distribution after **threshold** on MSE error:

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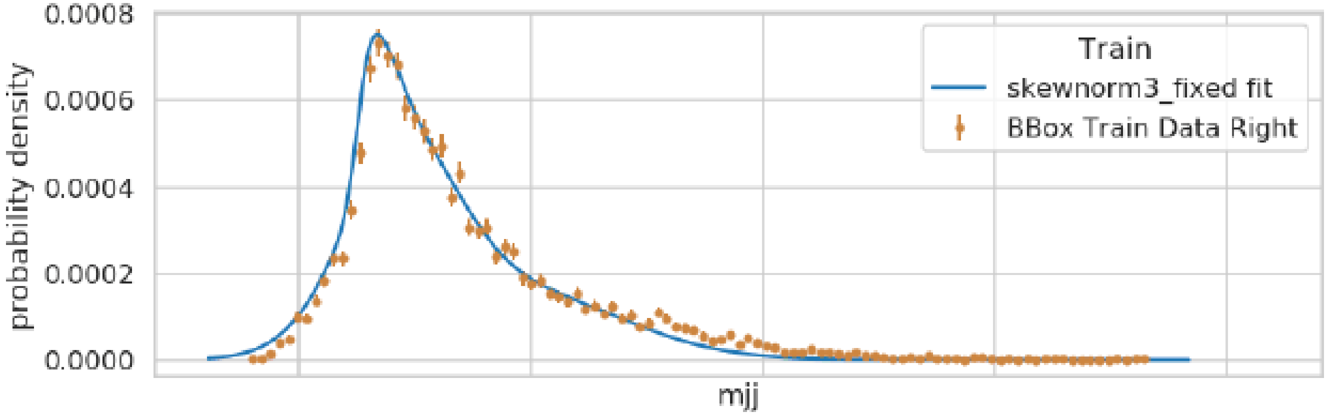
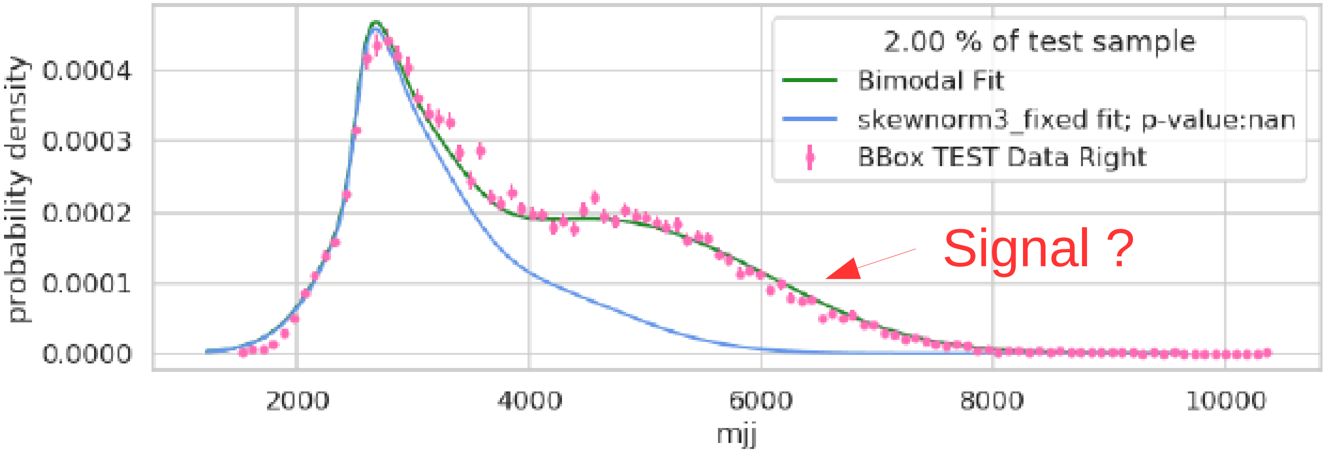
Train BG dataset



Black box 1 data

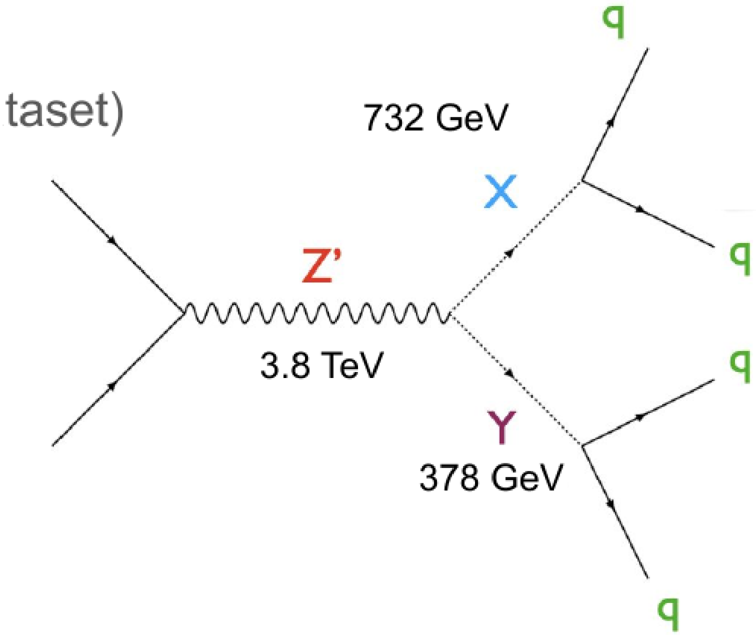


Possible signal around 5.2 TeV ?

LHC Olympics outcome: these slides

Black box 1 signal

Z'->XY; X,Y->qq



mZ' = 3823 GeV, mX = 732 GeV, mY = 378 GeV

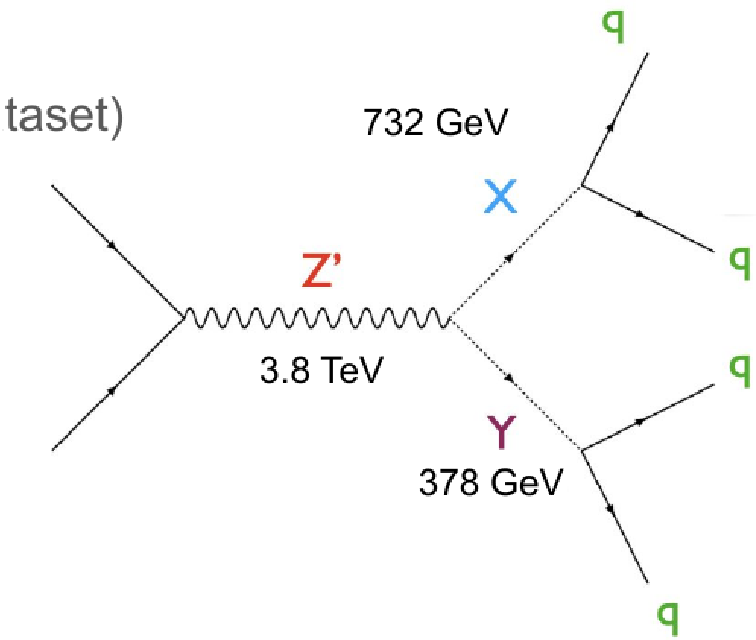
Signal: 834 events

Team results: fitted mass

LHC Olympics outcome: these slides

Black box 1 signal

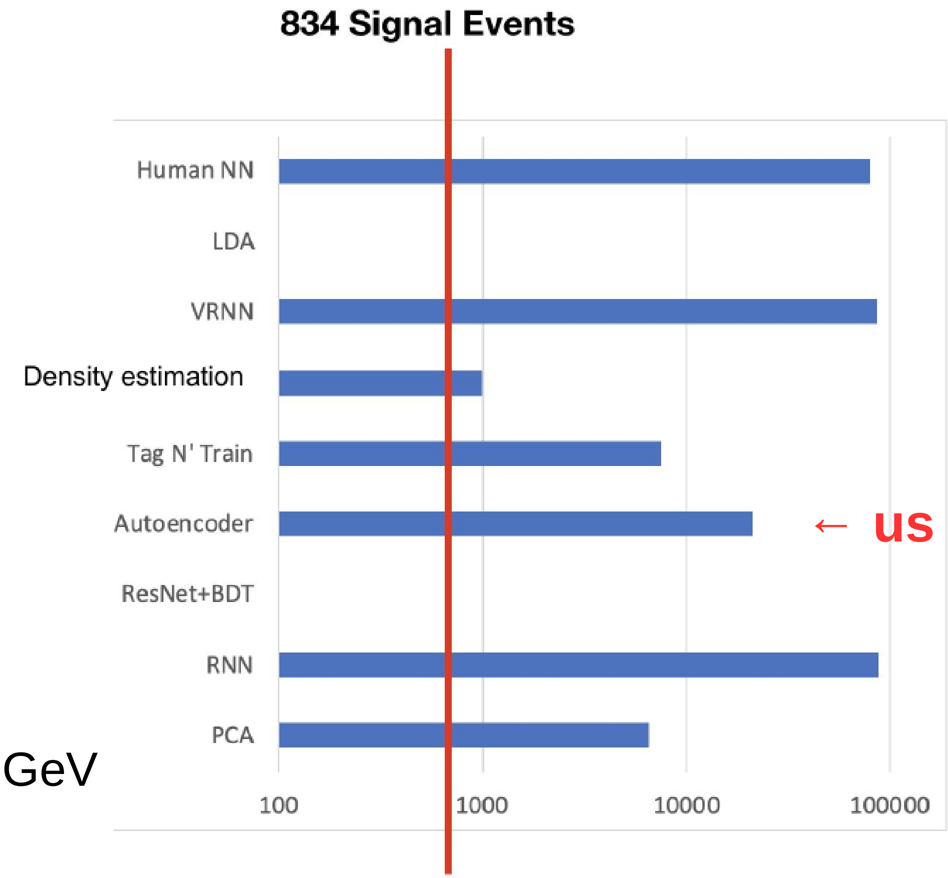
Z'->XY; X,Y->qq



mZ' = 3823 GeV, mX = 732 GeV, mY = 378 GeV

Signal: 834 events

Team results: number of events



→ **Our approach finds something but clearly biased ...**

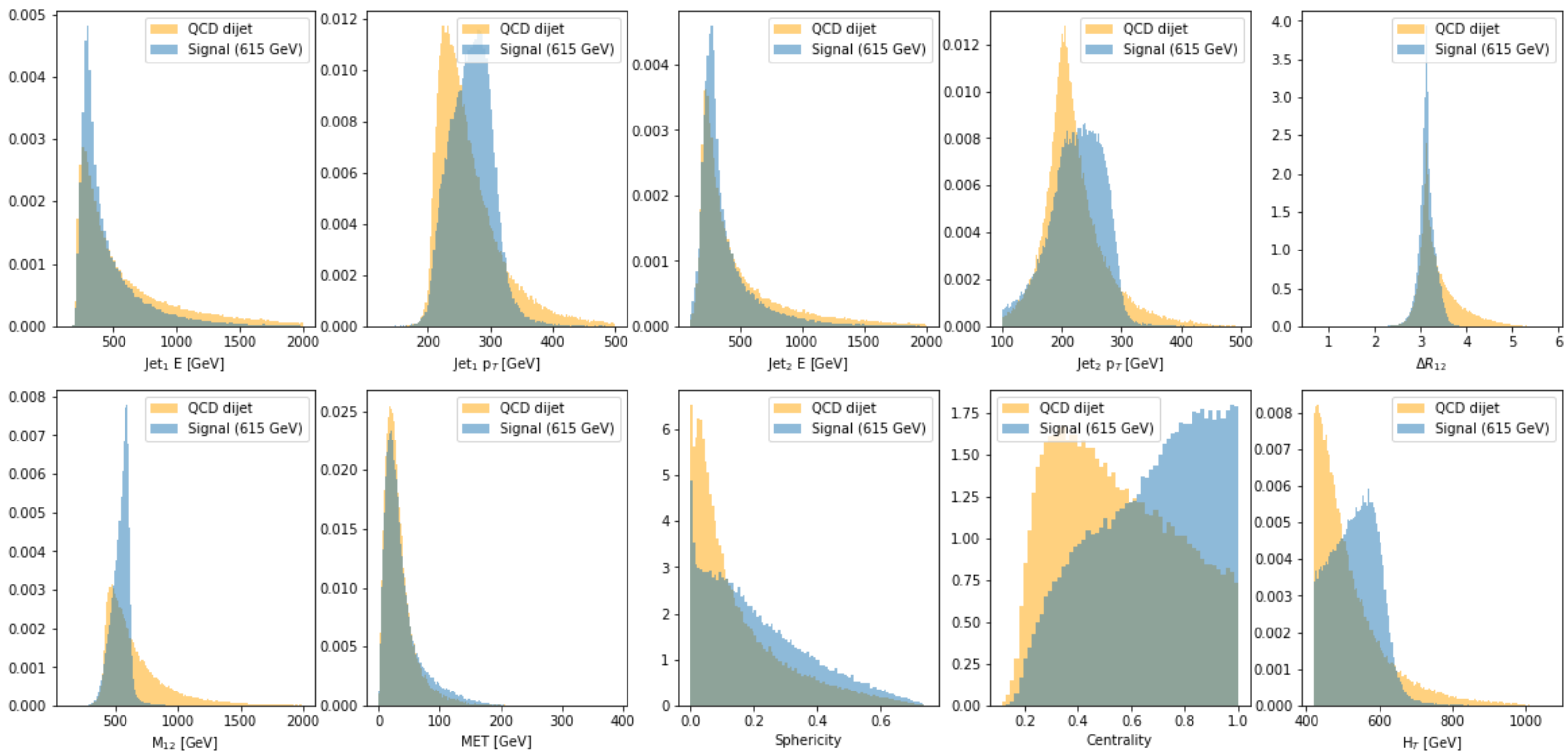
Simulated samples: dijet events

Dijet events (Madgraph+Pythia+Delphes):

- Background: 500k QCD dijets (H_T > 400 GeV)

- Signal: 500k RPV-MSSM stop (615 GeV, 1 TeV)

10 input variables (selected using supervised BDT ranking)



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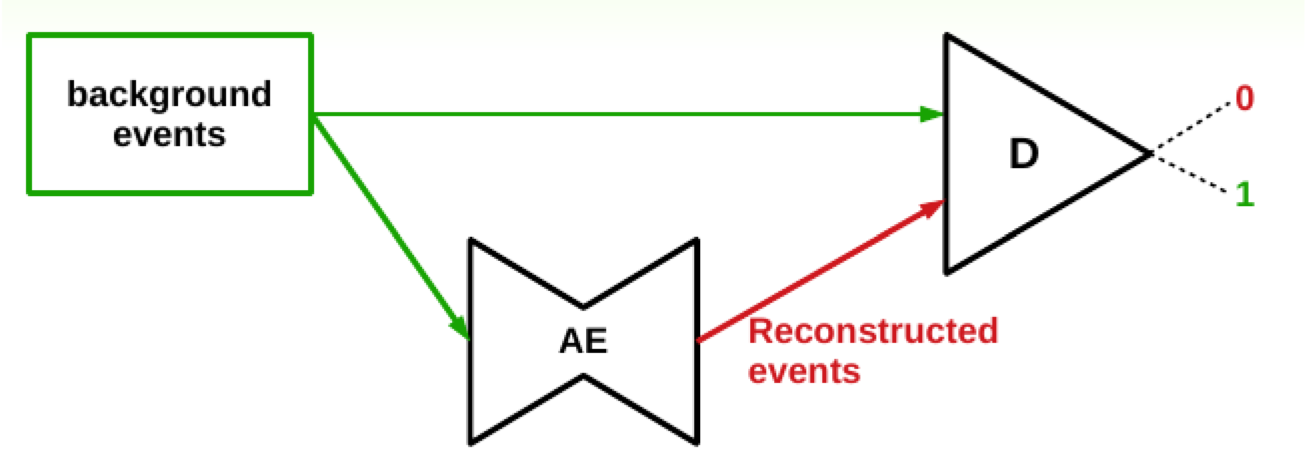
Network architecture



→ Discriminant objective : learn AE’s weaknesses

→ AE objective : correct these weaknesses

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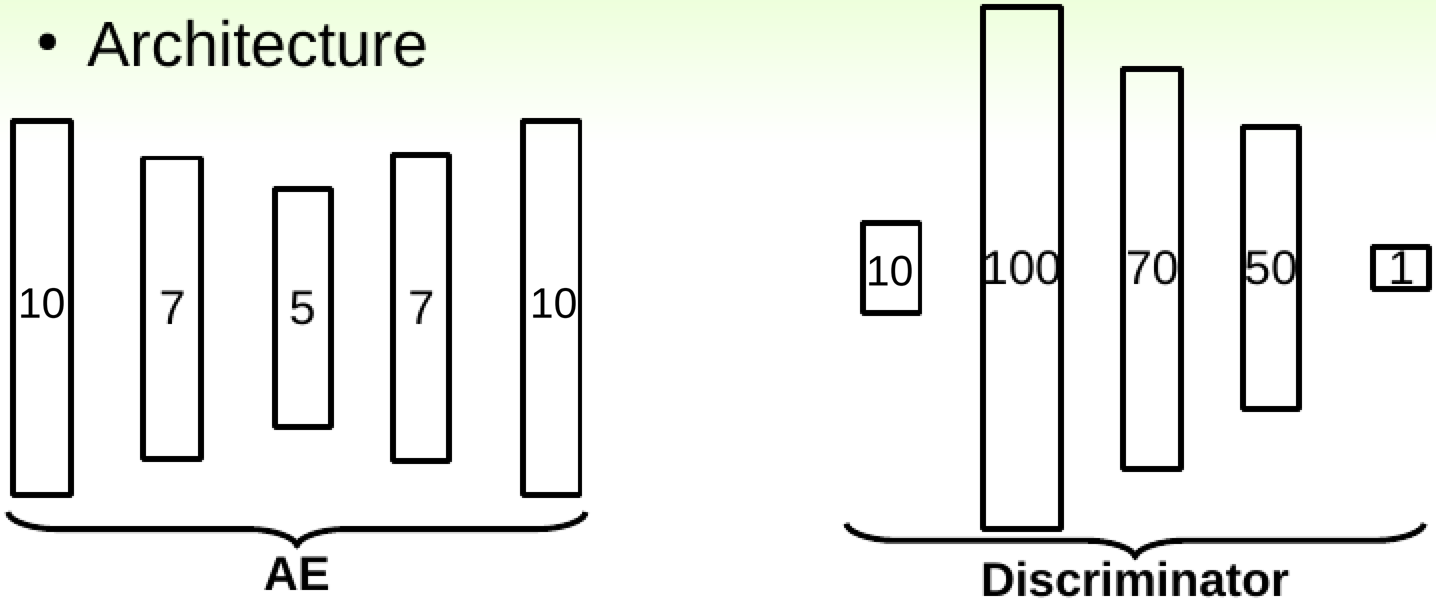
- Architecture



Activation : ReLU / sigmoid (out)
Optimizer : Adam (lr=0.0002, $\beta_1 = 0.5$)
Initialization : Glorot normal

Activation : LeakyReLU / sigmoid (out)
Optimizer : Adam (lr=0.0002, $\beta_1 = 0.5$)
Initialization : Glorot normal

$$\sigma_{Glorot} = \sqrt{\frac{2}{N+P}} \qquad \mu_{Glorot} = 0$$

Dropout rate: up to 20% or 40% depending on the layer

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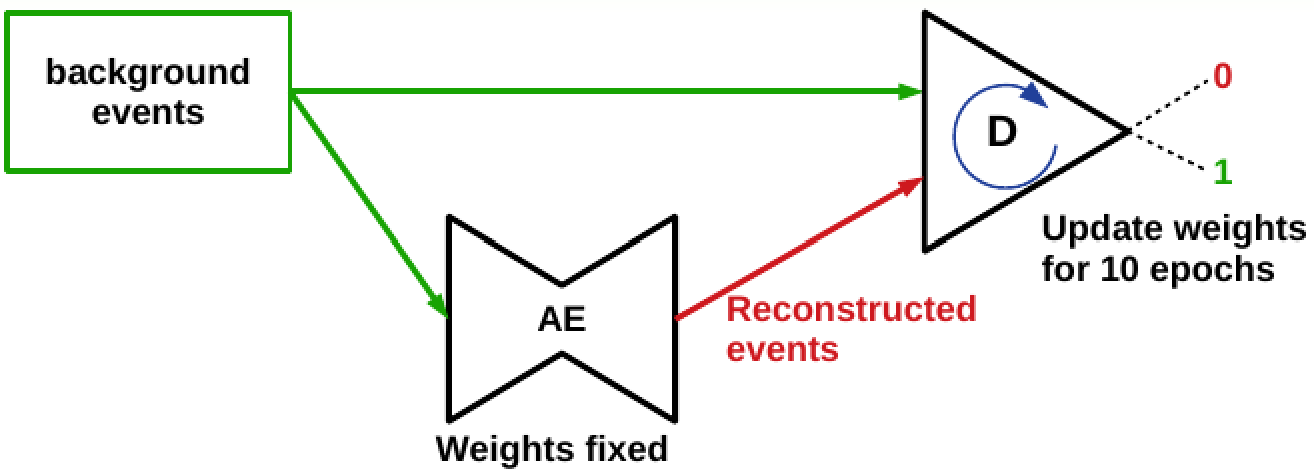
Training of discriminant



Loss function: binary cross-entropy

$$\ell = -\sum_j y_j \log(p_j) + (1 - y_j) \log(1 - p_j)$$

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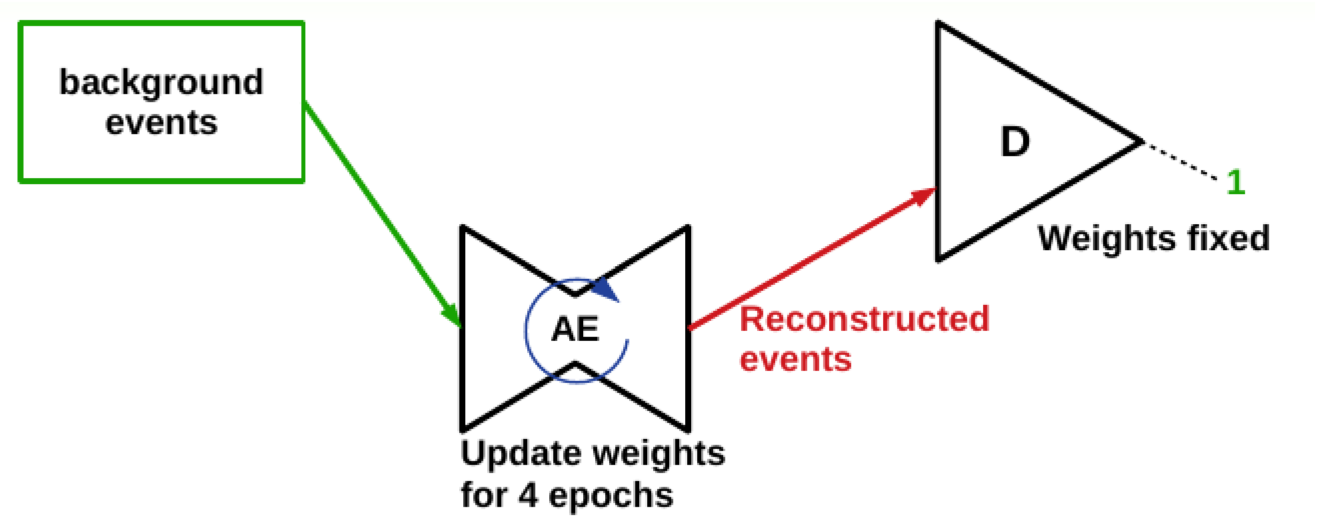
Training of AE



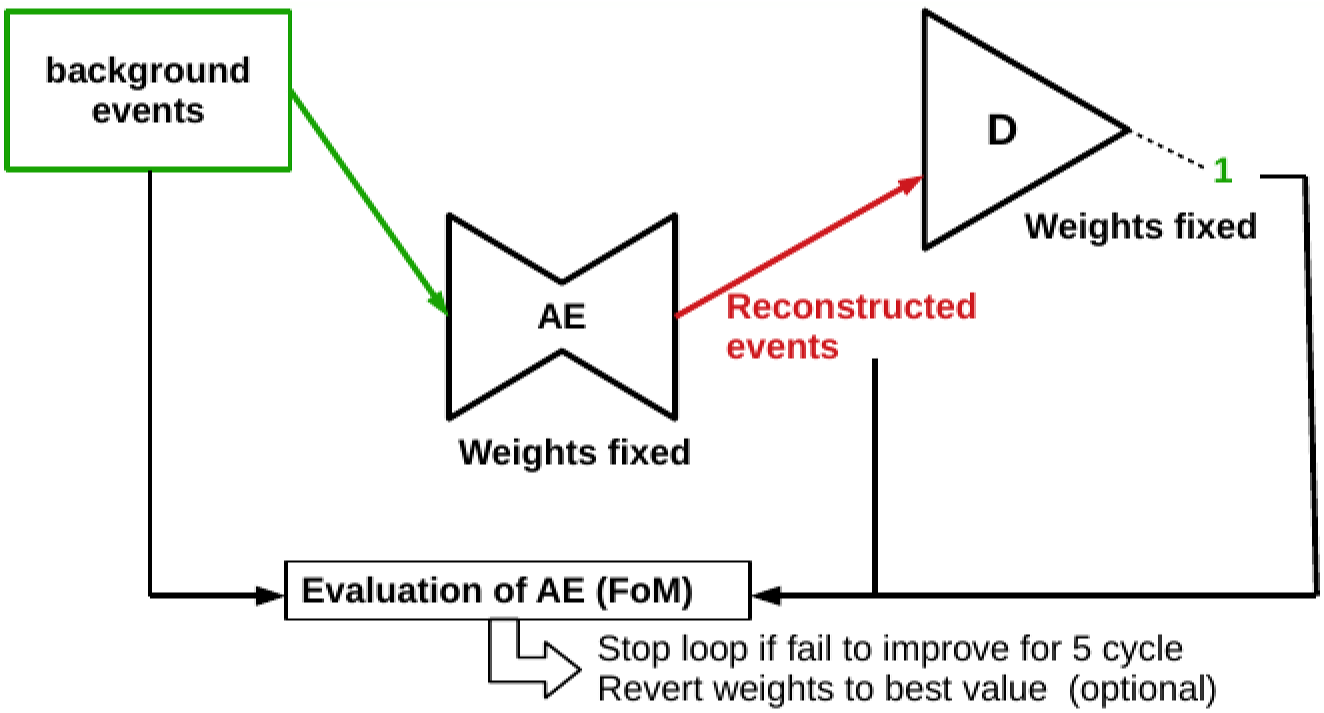
Loss function: binary cross-entropy + ε x mean distance [ε=2%]

$$\ell = -\sum_{j=1}^{N} y_j \log(p_j) + (1-y_j)\log(1-p_j) + \frac{\epsilon}{N}||\mathbf{x_j^{in}} - \mathbf{x_j^{out}}||$$

Training

Training cycle: 10 epochs on D, 4 epochs on AE (asymmetric training)

Stopping criterion: evaluation of AE performance (validation sample)



FOM = Mean distance + (1- mean D output)

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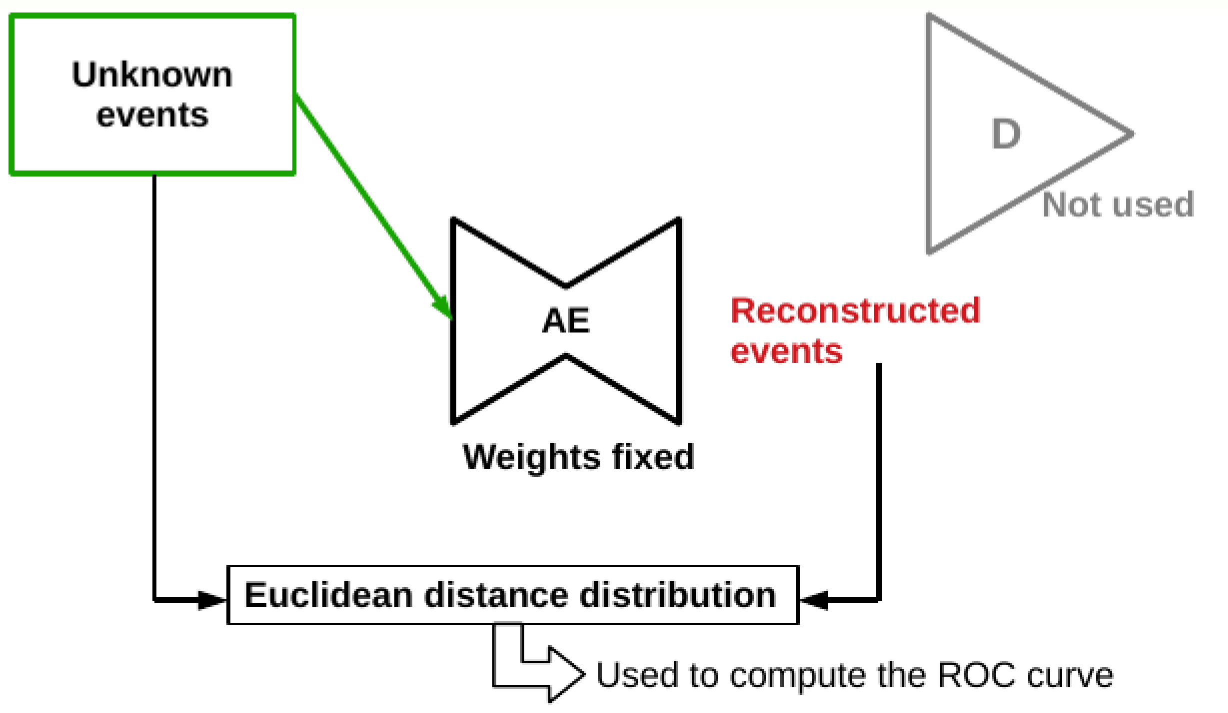
Application: only the AE is used on test events



Trained AE is applied on both background and signal test samples

Preliminary results

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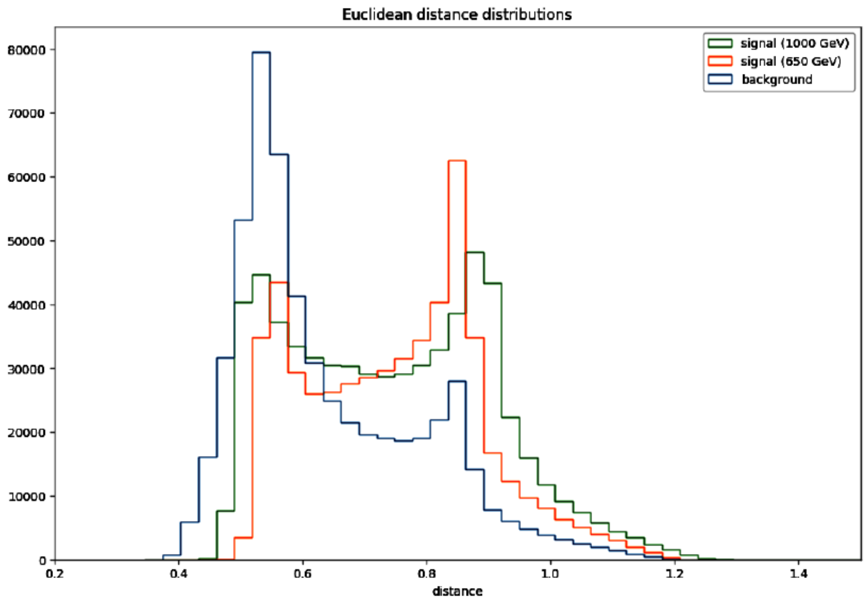
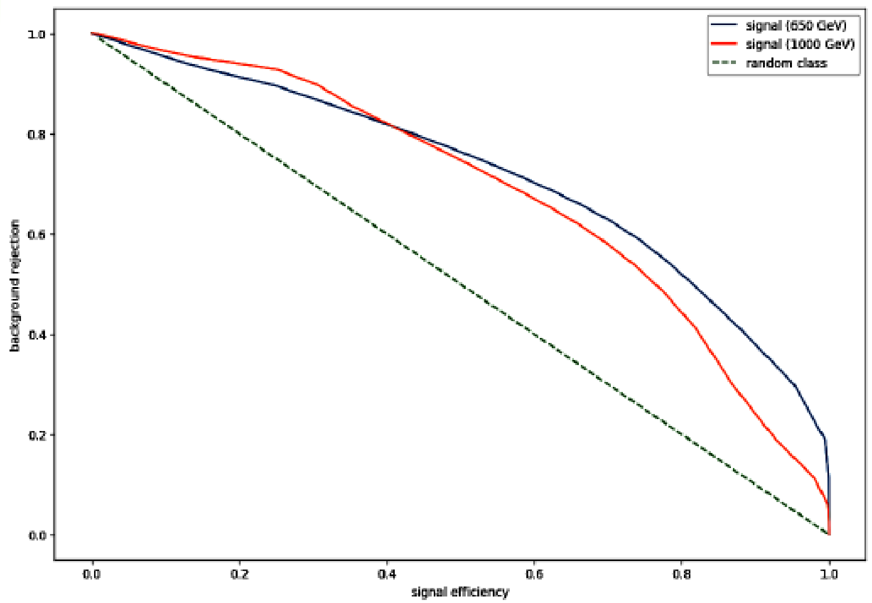
Mean Euclidean distance



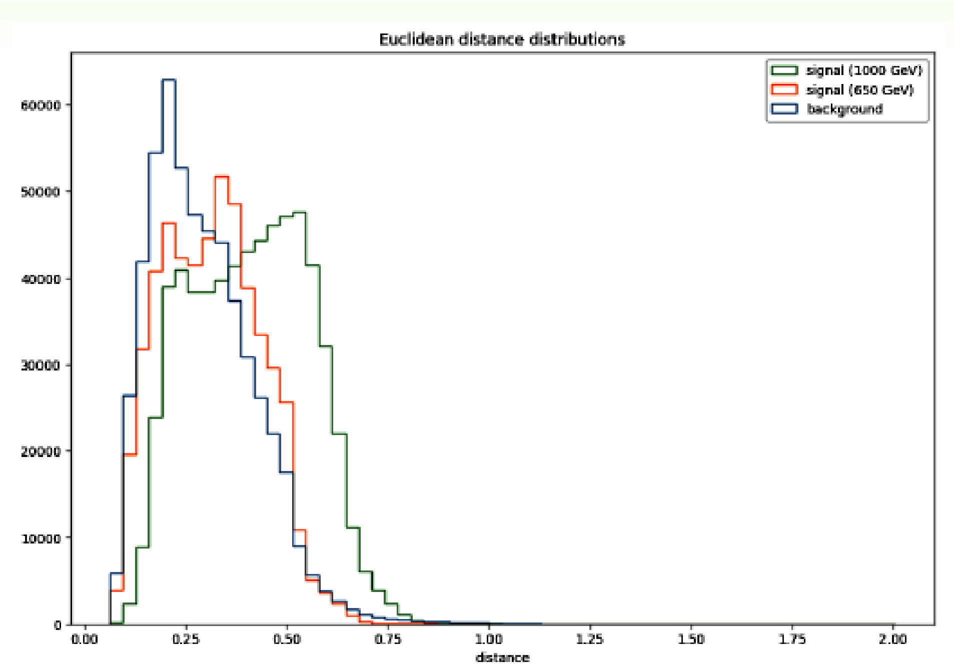
ROC Curve

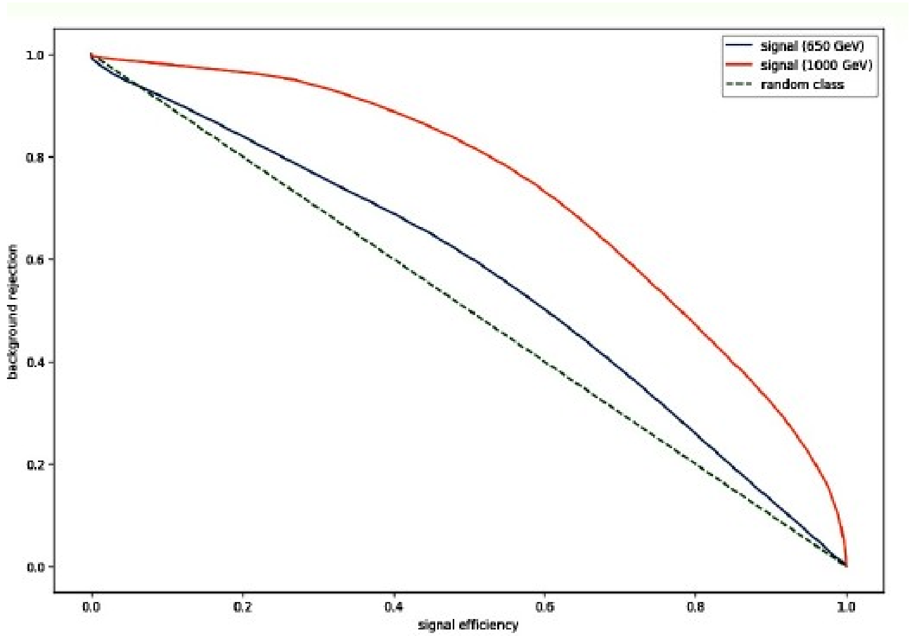


Double peaks in distance calculation: to be understood

AUC ~ 0.7 for both signal masses

Comparison with standalone AE





GAN-AE performs better for low mass signal (most difficult)

Issues with unstability

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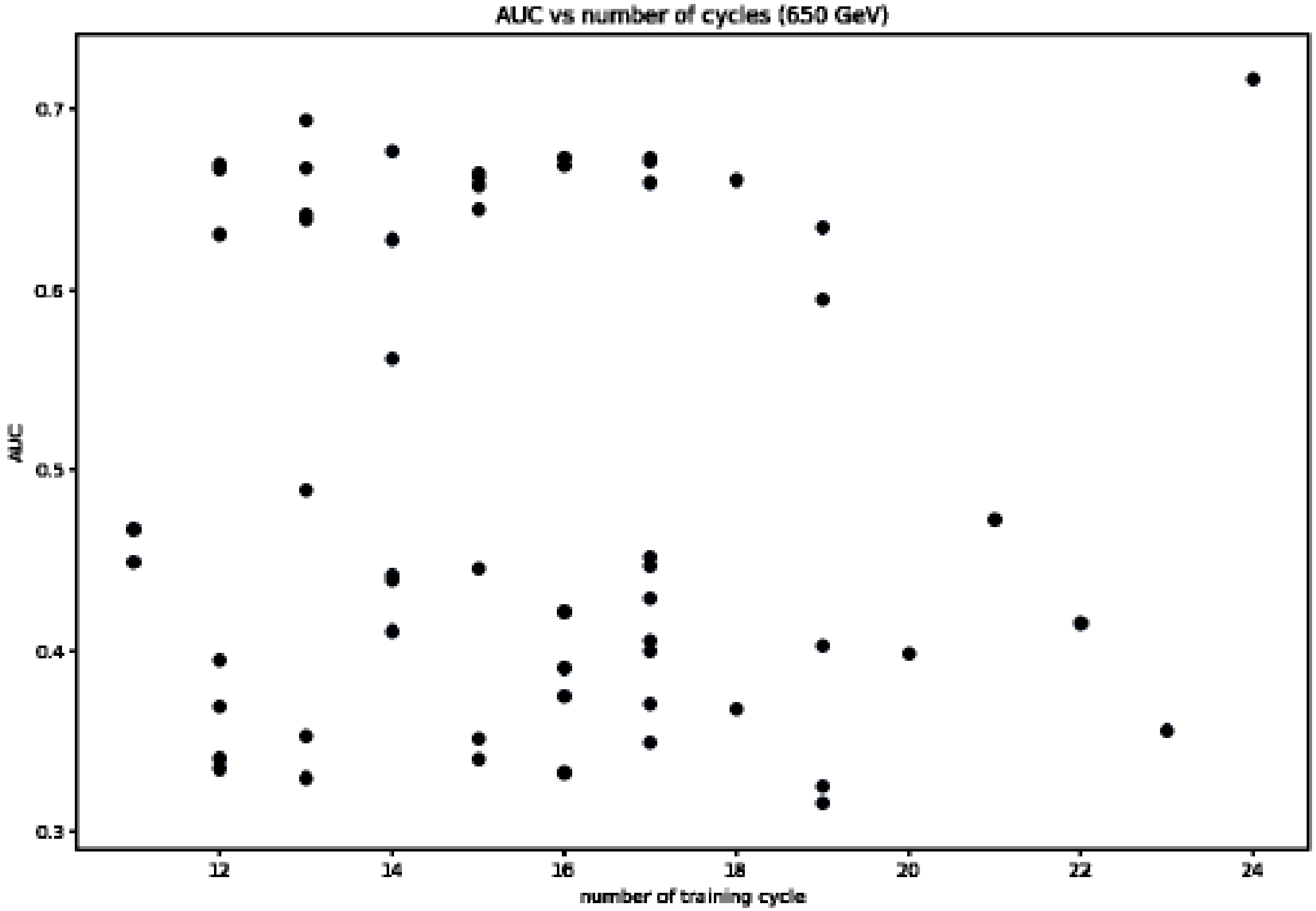
Results (AUC) show high variance: here for 60 GAN-AE (signal m=615 GeV)



Conclusion and Outlook

AE seem a good idea for unsupervised searches

However simple use case are not conclusive

- Appearance of spurious signal ? (LHC Olympics dataset)
- Instabilities (dijet sample)

More work needed on NN architectures (GAN-AE could be promizing)

Try to generalize to more complex signatures

Model independent methods

General searches in CMS & ATLAS

[1] CMS Collaboration, MUSiC, a Model Unspecific Search for New Physics, in pp Collisions at √s = 8 TeV, CMS-PAS-EXO-14-016 (2017).

[2] CMS Collaboration, Model Unspecific Search for New Physics in pp Collisions at √s = 7 TeV, CMS-PAS-EXO-10-021 (2011).

[3] ATLAS Collaboration, M. Aaboud et al., A strategy for a general search for new phenomena using data-derived signal regions and its application within the ATLAS experiment, Eur. Phys. J. C79 (2019) 120, [arXiv:1807.07447].

[4] ATLAS Collaboration, A general search for new phenomena with the ATLAS detector in pp collisions at √s = 8 TeV, ATLAS-CONF-2014-006 (2014).

[5] ATLAS Collaboration, A general search for new phenomena with the ATLAS detector in pp collisions at √s = 7 TeV, ATLAS-CONF-2012-107 (2012).

Latent Dirichlet Allocation (LDA)

[6] B. M. Dillon, D. A. Faroughy, and J. F. Kamenik, Uncovering latent jet substructure, Phys. Rev. D100 (2019), no. 5 056002, [arXiv:1904.04200].

[7] D. M. Blei, A. Y. Ng, and M. I. Jordan, Latent dirichlet allocation, J. Mach. Learn. Res. 3 (Mar., 2003) 993-1022.

Model independent methods

Autoencoders approaches

[8] M. Farina, Y. Nakai, and D. Shih, Searching for New Physics with Deep Autoencoders, arXiv:1808.08992.

[9] T. Heimel, G. Kasieczka, T. Plehn, and J. M. Thompson, QCD or What?, SciPost Phys. 6 (2019), no. 3 030, arXiv:1808.08979.

[10] T. S. Roy and A. H. Vijay, A robust anomaly finder based on autoencoder, arXiv:1903.02032.

[11] O. Cerri, T. Q. Nguyen, M. Pierini, M. Spiropulu, and J.-R. Vlimant, Variational Autoencoders for New Physics Mining at the Large Hadron Collider, JHEP 05 (2019) 036, arXiv:1811.10276.

[12] A. Blance, M. Spannowsky, and P. Waite, Adversarially-trained autoencoders for robust unsupervised new physics searches, JHEP 10 (2019) 047, arXiv:1905.10384.

[13] J. Hajer, Y.-Y. Li, T. Liu, and H. Wang, Novelty Detection Meets Collider Physics, arXiv:1807.10261

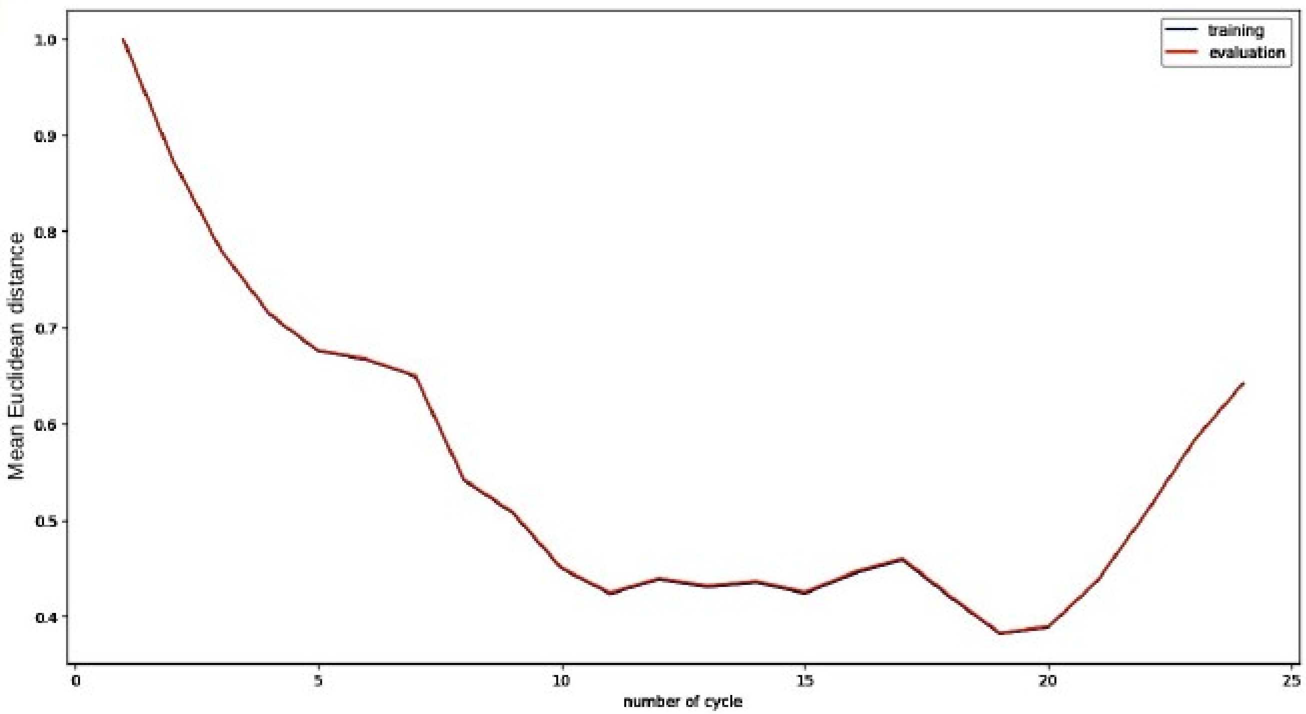
Bump hunt approaches

[14] J. H. Collins, K. Howe, and B. Nachman, Extending the search for new resonances with machine learning, Phys. Rev. D99 (2019), no. 1 014038, arXiv:1902.02634.

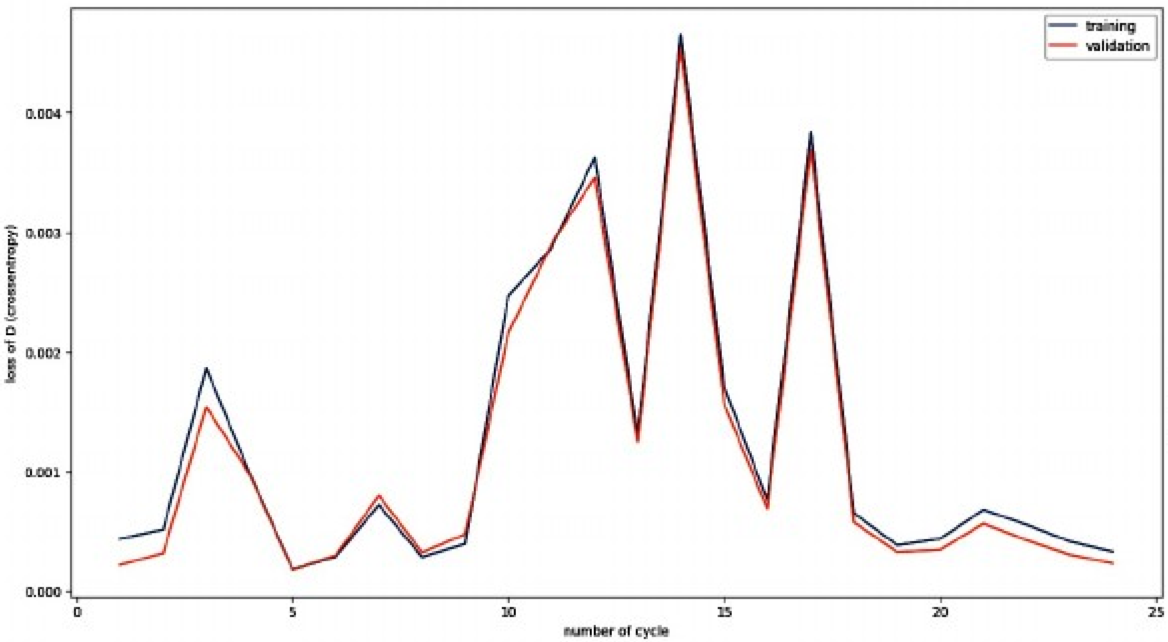
[15] B. Nachman, D. Shih, Anomaly Detection with Density Estimation, arxiv:2001.04990

backup

- Reconstruction error evolution



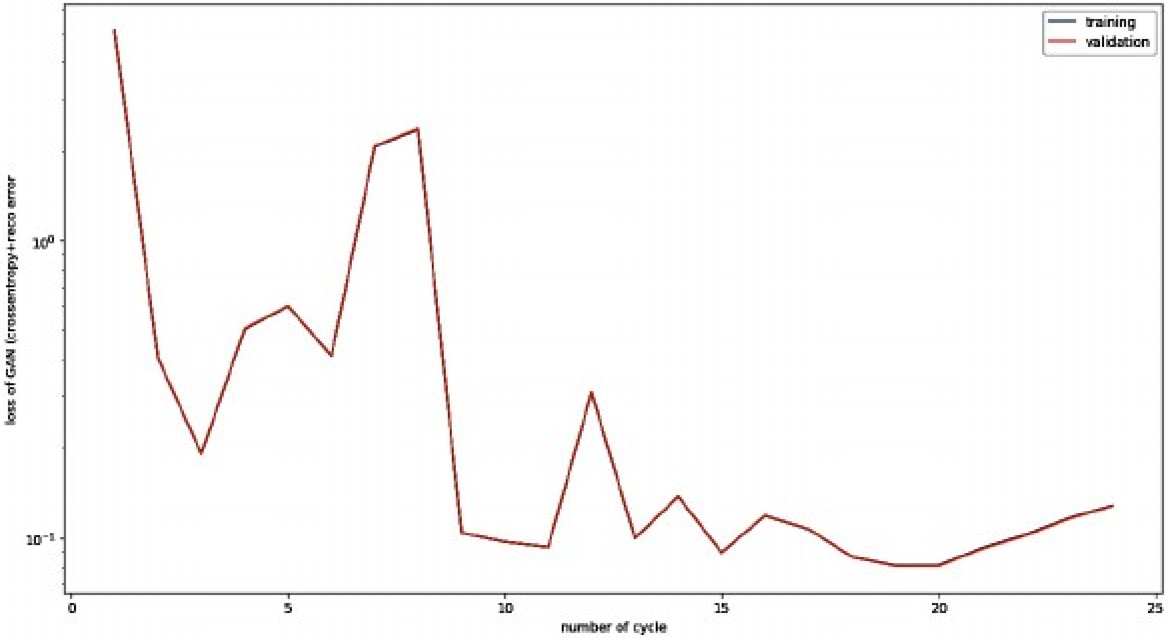
- Loss curve of the discriminant



Loss evaluated at each cycle after D training phase

Spiky behavior :
AE as changed between each evaluations
=> Performence of D varies at each cycle

- Loss curve of the AE+D model



Loss evaluated at each cycle after AE training phase

More stable behavior : Comes from the 2nd term