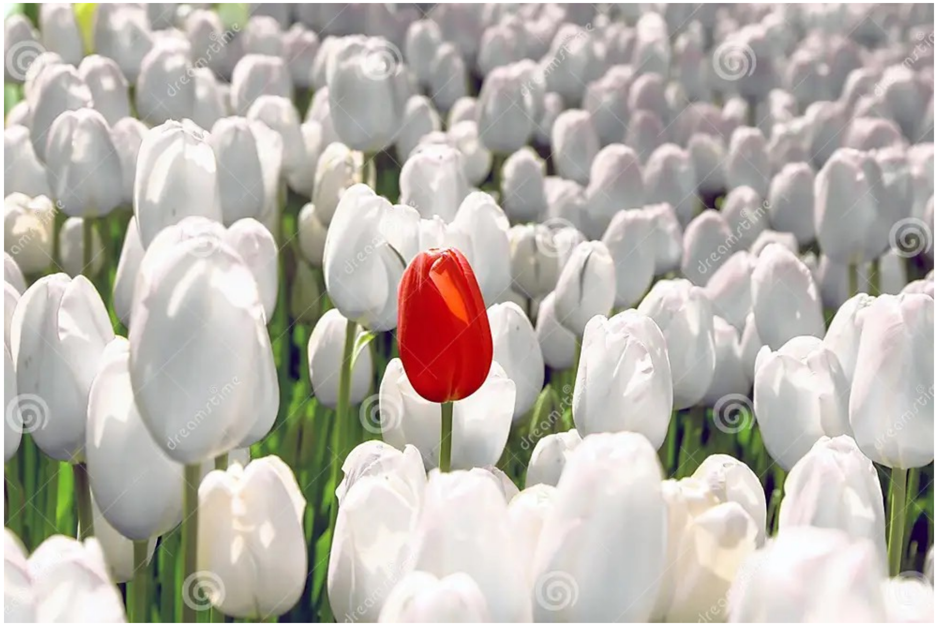
Search for new physics in two-body mass distributions using unsupervised ML for anomaly detection



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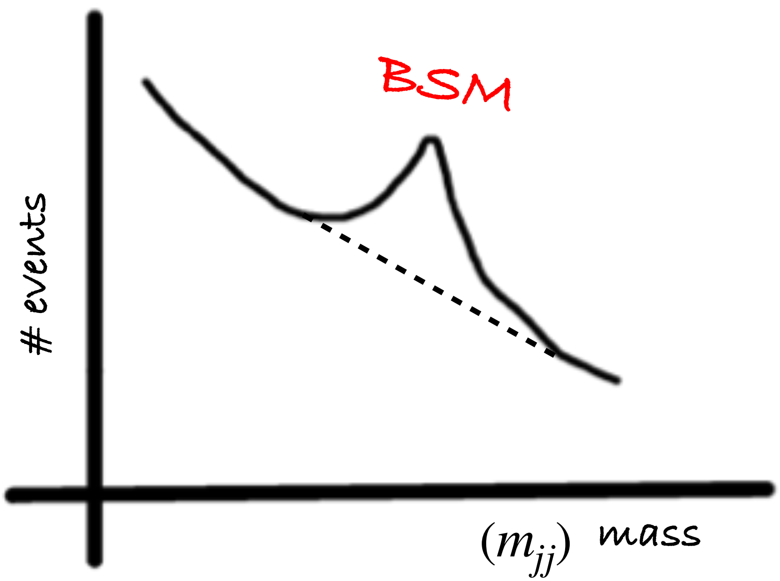
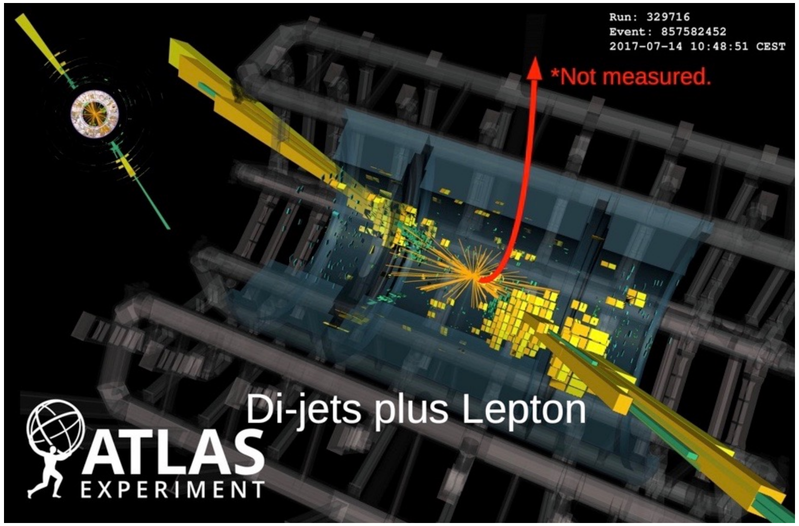
Motivation



- Two body (& dijet) searches are very common in collider experiments.
- New phenomena produced in parton collision can decay to partons predicated by BSM & can manifest as narrow resonances above the observable spectra.
- Investigate a wide range of BSM theories
- Many studies have been performed on Dijet final states. (by UA1, UA2 Collaborations at the CERN SppS; CDF, D0 at the Tevatron & by both CMS and ATLAS experiments)

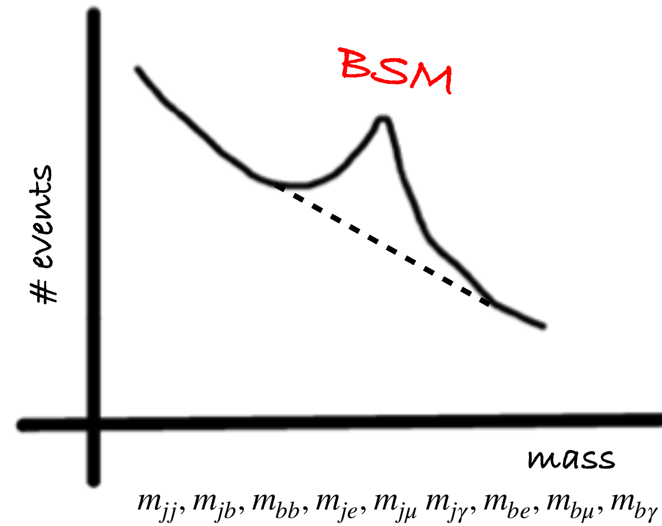
- Inclusive searches are typically restricted to $m_{jj} > 1.0$ TeV due to $p_{\mathrm{T}}^{\mathrm{jet}}$ trigger thresholds.
- Overcome trigger limitations by exploiting spectator objects, e.g. photons, leptons.
- We searched for dijet resonances using leptons as spectator objects/for triggering purpose.
- Requiring an additional lepton reduces the QCD multi-jet background rate.



JHEP07(2023)202

Motivation

- Model-independent searches in dijets are very common in ATLAS/CMS Experiments
- Example: Inclusive searches use “signal region” (y*<0.6). Ref : JHEP03(2020)145
- This y* cut cannot be effective when dijets are associated with other objects (leptons, photons..)
- Machine learning (ML) anomaly-detection methods open a new ways to study the collision events.
- Replace such cuts with a selection based on machine learning (ML) that defines “Anomaly region”, i.e. collision events that are most distinct from the Standard Model (pp events)



Our anomaly detection approach

~~Apply kinematics selection~~ → Background shape modeling → Look for excess “BumpHunter” Perform likelihood fits → No excess? Set limits on cross section

Apply “AD” selection Find “Anomaly region” → Background shape modeling

Advantages:

No need Monte Carlo simulations

Agnostic to BSM & unexpected signatures

Improves S/B sensitivity for new physics

What’s new ?

See Elham’s talk for other ML approaches in ATLAS. Ours is **Event based** anomaly detection using Unsupervised ML !

Analysis strategy

Reference : arxiv:2307.01612

Trigger (one lepton) and pre-selection (p_T^{lepton}*(trigger)*> 60 GeV , p_T^{jet} > 30 GeV)

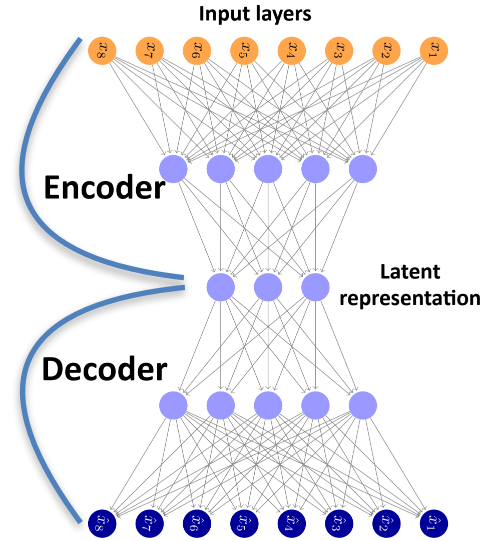
Reconstruct Rapidity Mass Matrix for each event

Rapidity-mass matrix

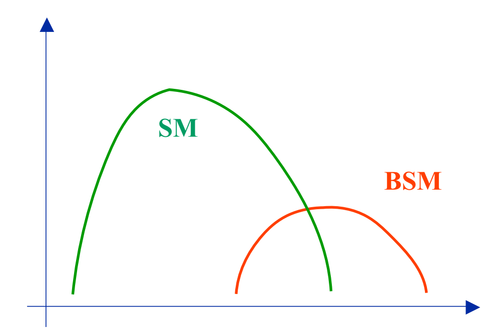
$$\begin{pmatrix} e_T^{miss} & m_T(j_1) & m_T(j_2) & \ldots m_T(j_N) & m_T(\mu_1) & \ldots m_T(\mu_N) \\ h_L(j_1) & e_T(j_1) & m(j_1,j_2) & \ldots m(j_1,j_N) & m(j_1,\mu_1) & ..m(j_1,\mu_N) \\ h_L(j_2) & h(j_1,j_2) & \delta e_T(j_2) & \ldots m(j_2,j_N) & m(j_2,\mu_1) & ..m(j_2,\mu_N) \\ \ldots & \ldots & \ldots & \ldots, & \ldots & \ldots \\ h_L(j_N) & h(j_1,j_N) & \ldots & \ldots \delta e_T(j_N) & m(j_N,\mu_1) & ..m(j_N,\mu_N) \\ h_L(\mu_1) & h(\mu_1,j_1) & h(\mu_1,j_2) & \ldots h(\mu_1,j_N) & e_T(\mu_1) & m(\mu_1,\mu_N) \\ h_L(\mu_2) & h(\mu_2,j_1) & h(\mu_1,j_2) & \ldots h(\mu_2,j_N) & h(\mu_1,\mu_2) & m(\mu_2,\mu_N) \\ \ldots & \ldots & \ldots & \ldots & \ldots & \\ h_L(\mu_N) & h(\mu_N,j_1) & h(\mu_N,j_2) & \ldots h(\mu_N,j_N) & h(\mu_N,\mu_1) & \delta e_T(\mu_N) \end{pmatrix}$$

Train unsupervised ML model - autoencoder using 1% ATLAS Run 2 data

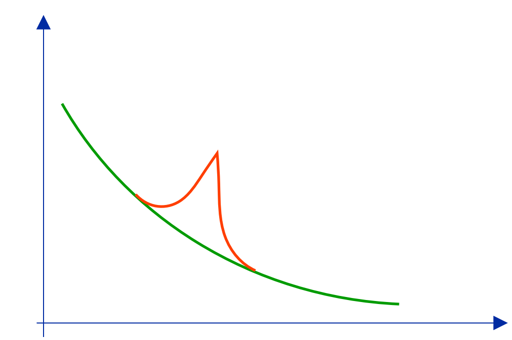
Autoencoder



Define signal region using reconstruction loss from autoencoder



Fit invariant mass spectrum, do statistical analysis, look for bumps in 9 different channels jet+X (b-jet+X) [X=e, μ, γ]



Rapidity mass matrix (RMM) for event representation

Missing momentum & Transverse masses

$$
\begin{pmatrix}
\mathbf{e}_{\mathbf{T}}^{\mathbf{miss}} & m_T(j_1) & m_T(j_2) & \ldots m_T(j_N) & m_T(\mu_1) & m_T(\mu_2) & \ldots m_T(\mu_N) \\
h_L(j_1) & \mathbf{e}_{\mathbf{T}}(\mathbf{j}_1) & m(j_1,j_2) & \ldots m(j_1,j_N) & m(j_1,\mu_1) & m(j_1,\mu_2) & \ldots m(j_1,\mu_N) \\
h_L(j_2) & h(j_1,j_2) & \delta\mathbf{e}_{\mathbf{T}}(\mathbf{j}_2) & \ldots m(j_2,j_N) & m(j_2,\mu_1) & m(j_2,\mu_2) & \ldots m(j_2,\mu_N) \\
\ldots & \ldots & \ldots & \ldots, & \ldots & \ldots & \ldots \\
h_L(j_N) & h(j_1,j_N) & \ldots & \ldots \delta\mathbf{e}_{\mathbf{T}}(\mathbf{j}_N) & m(j_N,\mu_1) & m(j_N,\mu_2) & \ldots m(j_N,\mu_N) \\
h_L(\mu_1) & h(\mu_1,j_1) & h(\mu_1,j_2) & \ldots h(\mu_1,j_N) & \mathbf{e}_{\mathbf{T}}(\mu_1) & m(\mu_1,\mu_2) & m(\mu_1,\mu_N) \\
h_L(\mu_2) & h(\mu_2,j_1) & h(\mu_1,j_2) & \ldots h(\mu_2,j_N) & h(\mu_1,\mu_2) & \delta\mathbf{e}_{\mathbf{T}}(\mu_2) & m(\mu_2,\mu_N) \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \\
h_L(\mu_N) & h(\mu_N,j_1) & h(\mu_N,j_2) & \ldots h(\mu_N,j_N) & h(\mu_N,\mu_1) & h(\mu_N,\mu_2) & \delta\mathbf{e}_{\mathbf{T}}(\mu_N)
\end{pmatrix}
$$

Invariant masses m_{ij}/E_{CM}

E_T/E_{CM} scaled transverse energies & energy imbalances

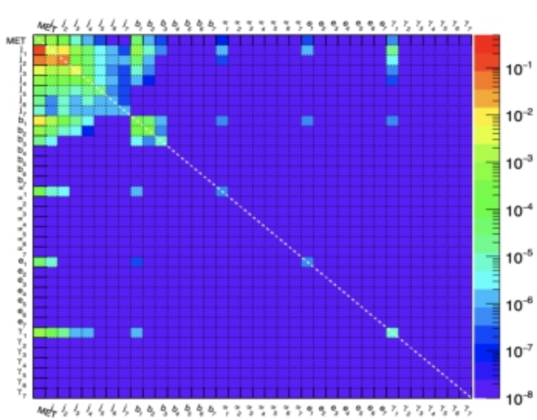
Lorentz factors

Rapidity difference h(i,j)~cosh(y_j - y_i)

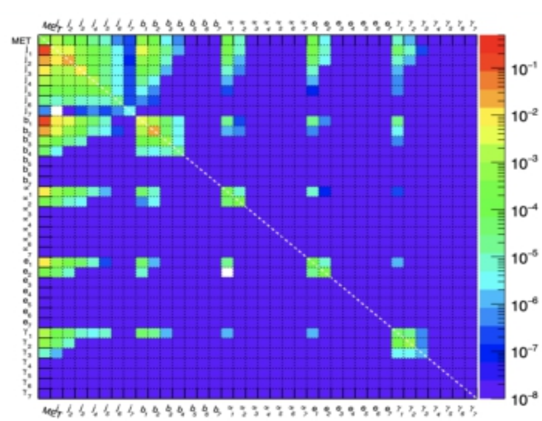
Reference : https://arxiv.org/abs/1805.11650

Examples :

Multi-jet QCD process



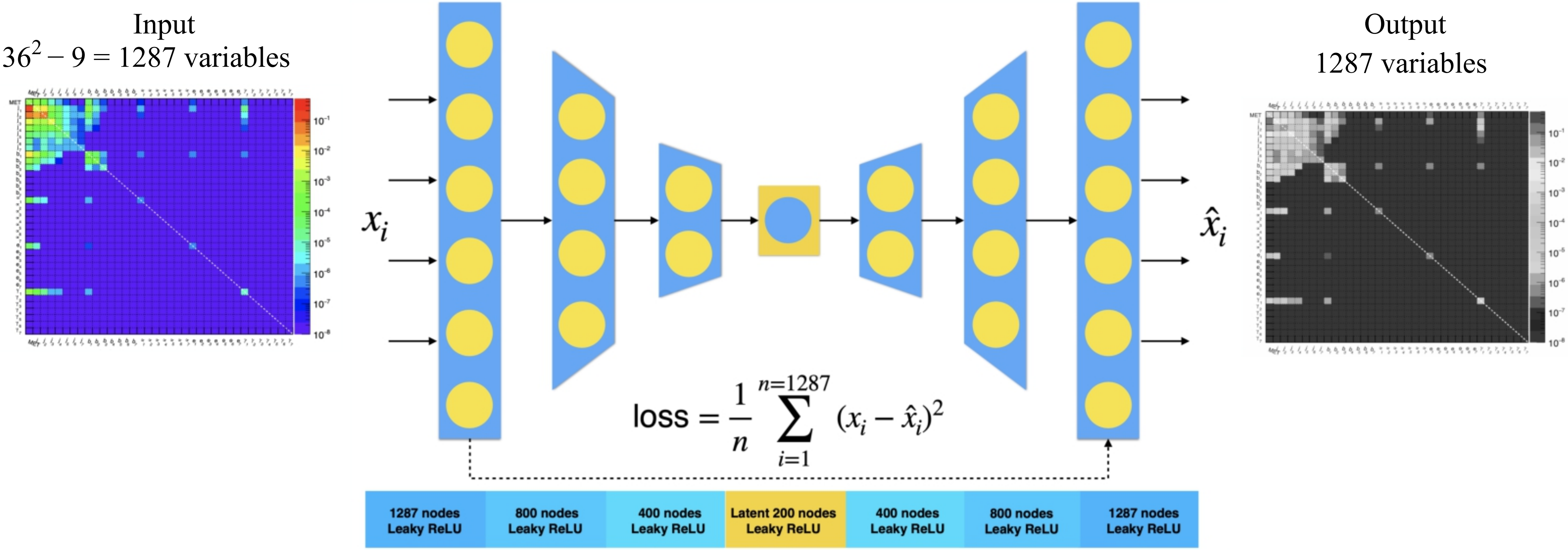
Higgs process



- Expected to have different characteristics for different processes
- RMM matrix is flattened to a 1-dimensional input vector before being fed into the AE
- Using event topologies on the standard reconstructed objects— object type & multiplicity, 4-momenta, two-body system information, all will contribute to the anomaly score.

Training with autoencoder
(using Unsupervised ML)

- Using randomly selected 1% collision data
  - · Sufficient statistics to train and well represent the full collision dataset
  - · Split to 7:3 for training and validation, monitor validation loss for early stopping
  - · 50 variations of random seed
- Tried other architectures such as Variational (convolutional) autoencoder and various sizes of the autoencoder. The selected one gives better performance
- TensorFlow is used to implement AE



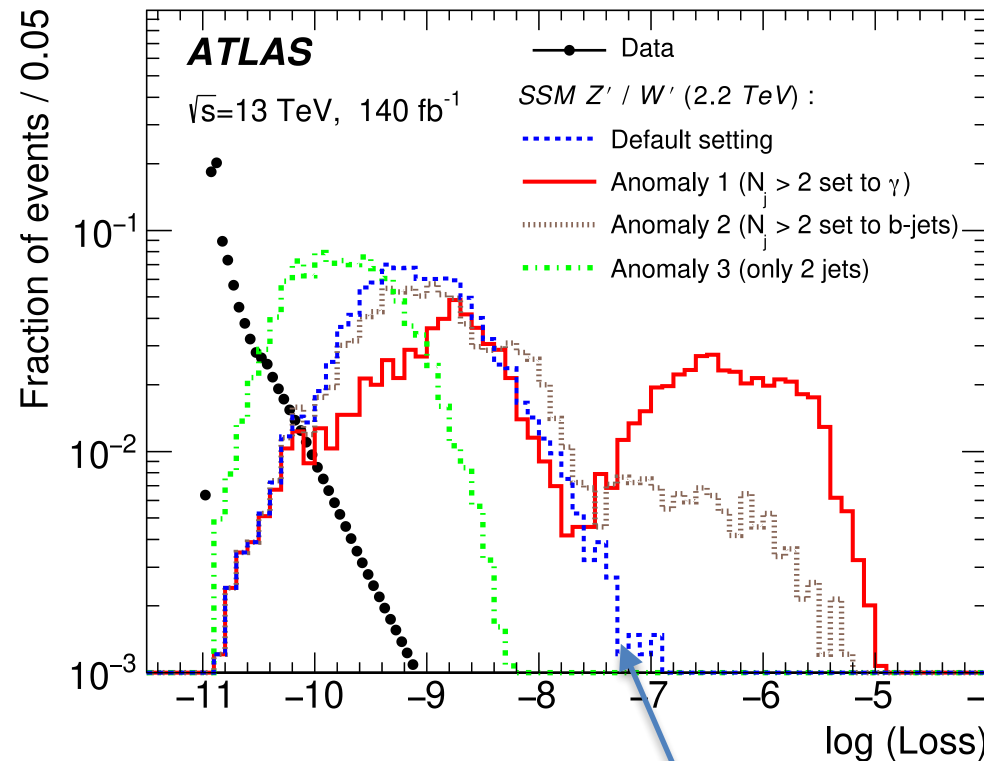
$$\text{loss} = \frac{1}{n}\sum_{i=1}^{n=1287}(x_i - \hat{x}_i)^2$$

Anomaly signal test

Can model detect anomalous events ?

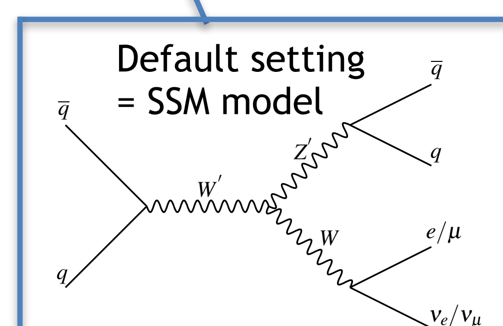
Make up anomaly events by shuffling objects and re-calculating RMM

- Anomaly 1: jets beyond 2 are set to photon
- Anomaly 2: jets beyond 2 are set to b-jets
- Anomaly 3: keep only 2 jets and 1 lepton
  - Less anomaly even than the original events



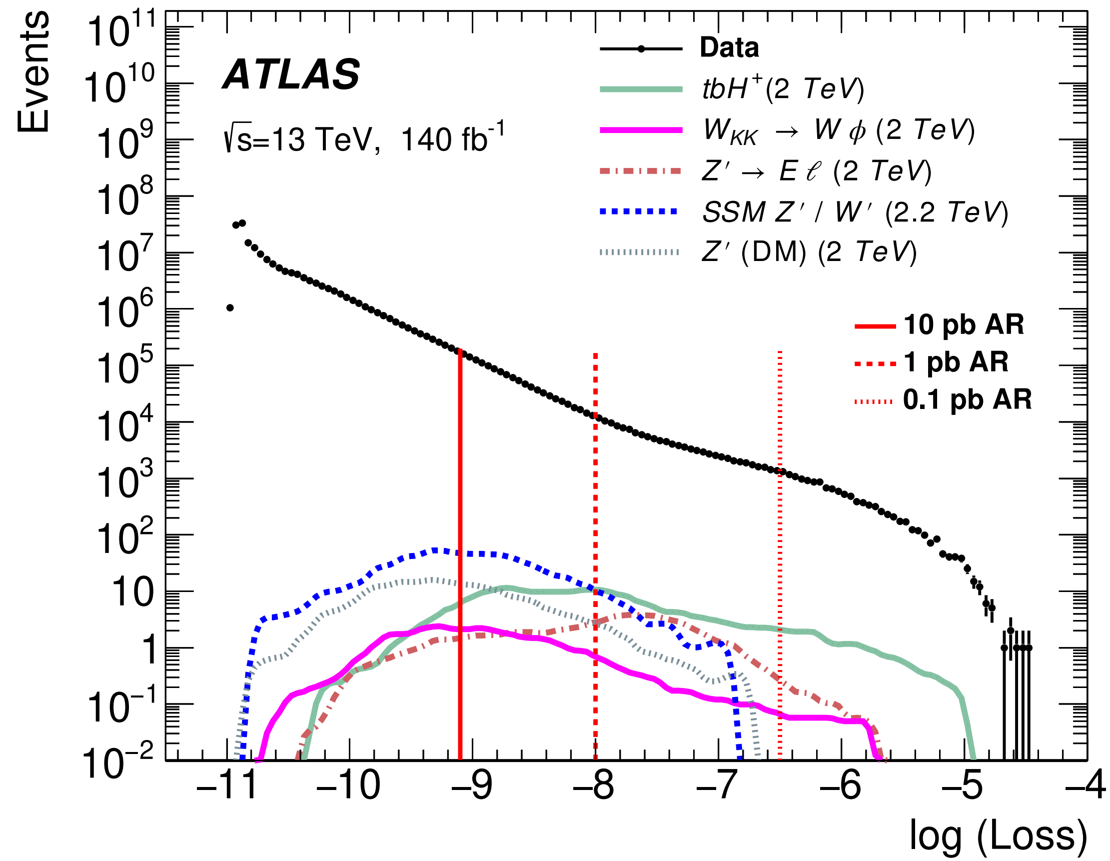
They all show up with large loss, in addition:

- More anomalous is seen when b-jet or photon multiplicity increases - expected
- Less anomalous is seen when multiplicity is low, anomaly may come from large p_{T}, $E_{\mathrm{T}}^{\mathrm{miss}}$, etc -expected



Anomaly region definitions

- Anomaly region should enhance BSM signal and suppress SM bkg
  - Need enough bkg for modelling
- We studied theoretical cross sections of various BSM models for two-body resonances for AR cuts.
- Select events corresponding to 10pb, 1pb, 0.1pb (× 140 fb -1) as 3 anomaly regions to cover different sensitivities.
- With Run 2 data, these correspond to1.4M, 140K, 14K events.
- 10pb AR is the main region to study in this analysis *(Corresponds to maximum value of cross sections for various BSM models considered)*



Loss distributions for BSM models

Background hypothesis testing

The mass spectra of background (SM) are expected to be smoothing falling.

Background hypothesis tested using:
1. Loose-electron control region (LE-CR)
2. LE-CR+MC control region
3. 10% of data (scaled, smoothed)

- For all the invariant masses, fits with different analytic functions were performed & the following p5 function was selected to describe background hypothesis.

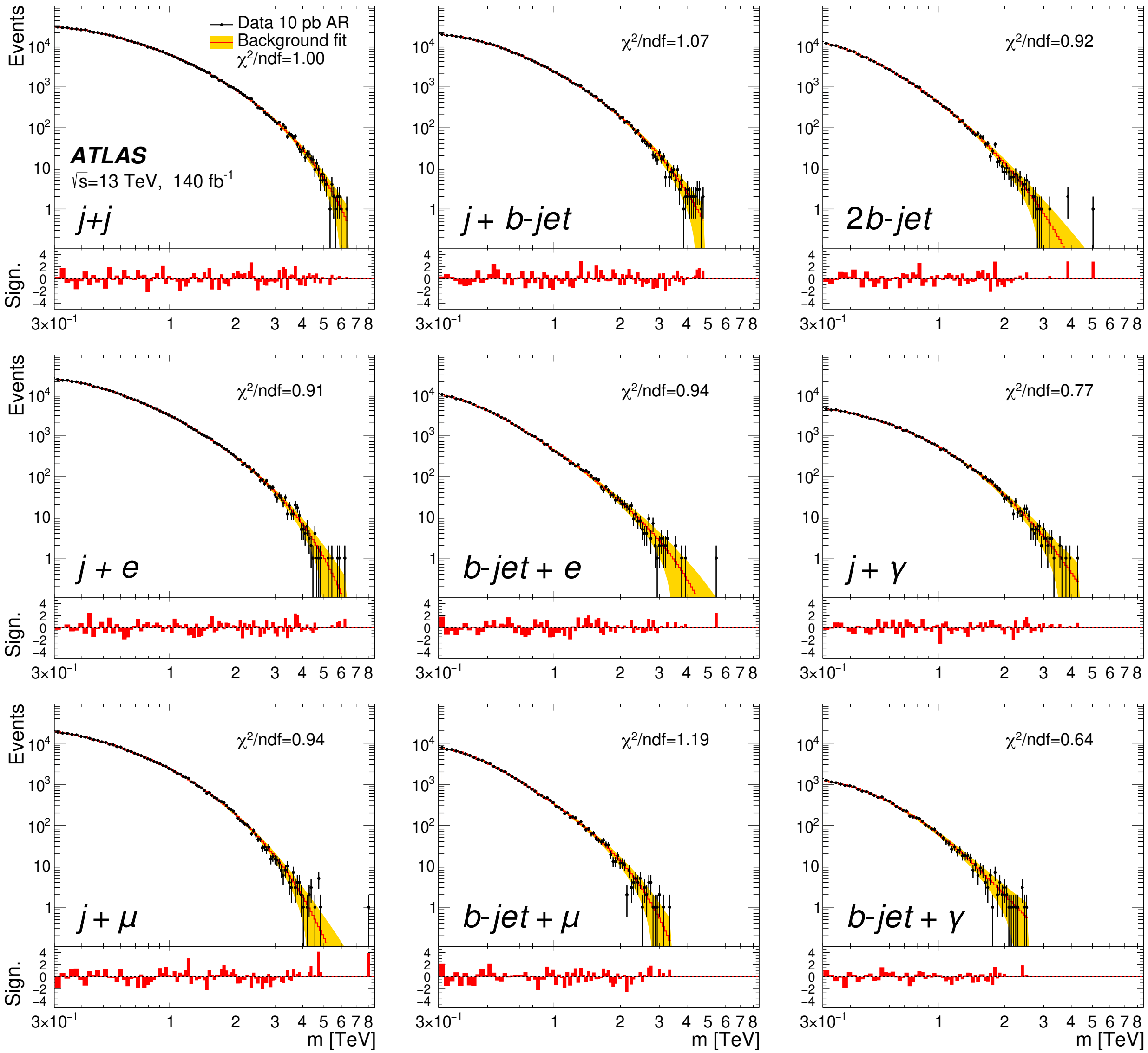
p5 function : $f(x) = p_1(1-x)^{p_2}x^{p_3+p_4 lnx+p_5 ln^2 x}$ Where x ≡ m_{jj} /√s ∈ [0,1]

Also used an alternative function form to estimate systematics

$$f(x)_{alt} = p_1(1-x)^{p_2}x^{p_3+p_4 lnx+p_5/\sqrt{x}}$$

The background shapes are well described by the p5 after selecting events with AE (with high loss values) for all the 9 invariant masses.

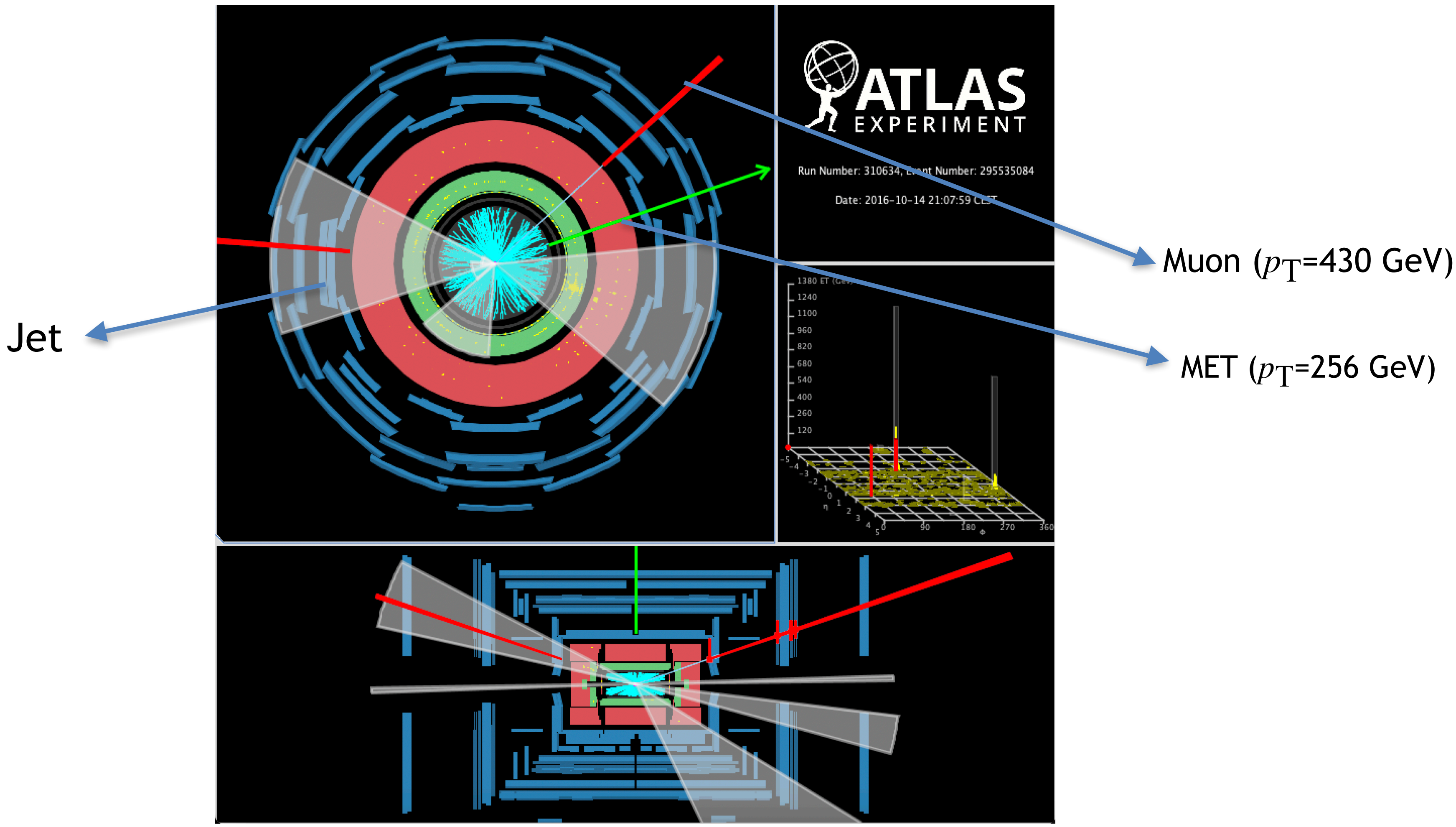
BumpHunter results for 10 pb AR



- BumpHunter results agree with p5 fit
- Tests of normality on pulls passed for all masses passed
- Background shape uncertainty using alternative function shown in yellow
- Largest deviation reported by BumpHunter is at $m_{j\mu} = \sim 4.8$ TeV
- The distributions are binned with increasing bin widths from 16 GeV to 150 GeV to reflect the jet energy resolution of detector

Event display in the j+μ channel

(An event passing 10 pb Anomaly Region with $m_{j\mu}$ = 4.72 TeV)



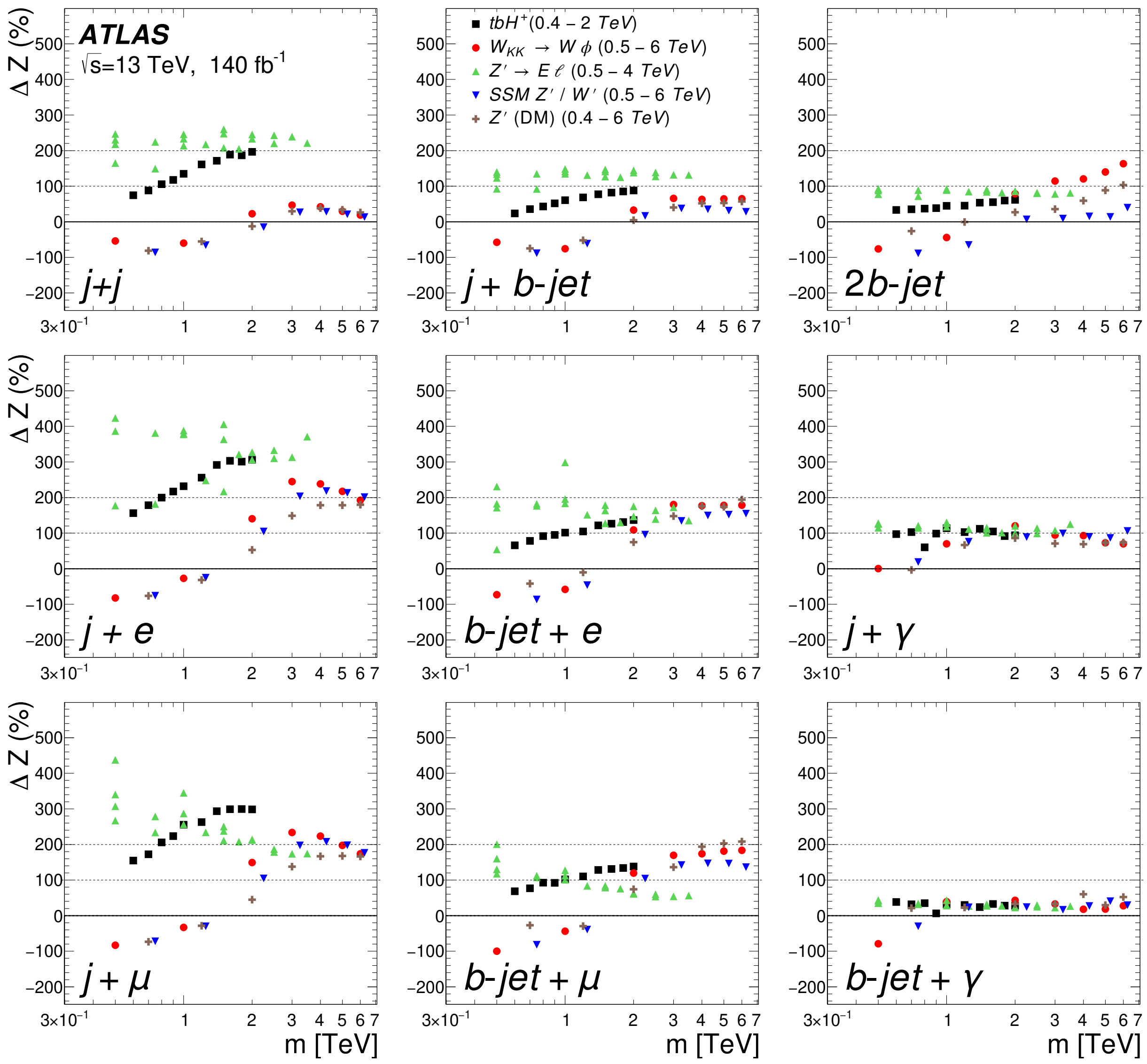
Discovery sensitivity of BSM models
(for 10 pb AR)

Sensitivity improvement quantified by ΔZ

$$Z = \sqrt{2\left((s+b)\ln\left(1+\frac{s}{b}\right)-s\right)}$$

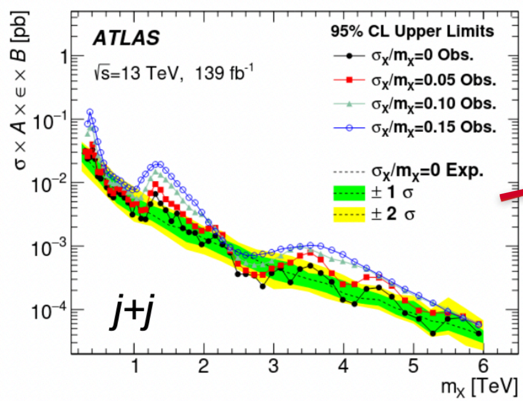
$$\Delta Z = ((Z_{AE}/Z)-1)\times 100\%$$

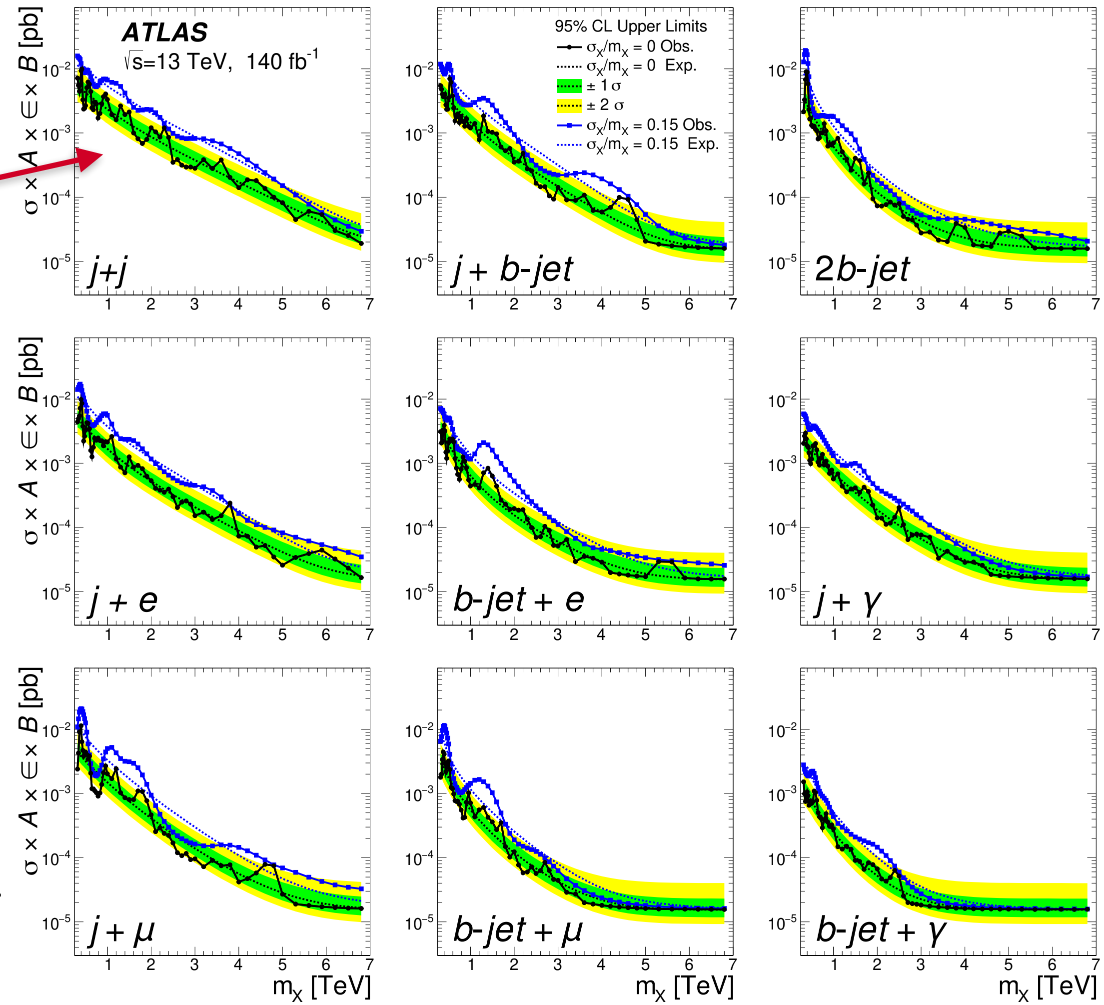
- Improvement tend to enhance with high mass as expected
- Higher pT, higher mass => more anomalous
- $\Delta Z > 0 \Rightarrow$ improvement
- Improvement directly translates into competitive limits



Upper limits of Gaussian signals

Published: JHEP 06 (2020) 151





- Signal width of $\sigma/m = 0\%$ and $\sigma/m = 15\%$ shown
- Mass points are spaced 5% apart from their preceding point starting from 0.3 TeV.
- Narrow signals have better limits as expected
- $\pm 1\sigma$, $\pm 2\sigma$ Error bands are from $\sigma/m = 0$ signals.
- Waves are similar, subject to local fluctuations
- Local significance 2.9 σ at $m_{j\mu} = 4.8$TeV, 2.8 σ at $m_{j\mu} = 1.2$TeV

- At masses < 1 TeV the limits are factor 2-3 better than for similar selection without autoencoder (JHEP 06 (2020) 151).

Summary & conclusions

- Searched for anomalies in 9 invariant masses in 3 Anomaly Regions in a mass range of 0.3 TeV - 8 TeV using full Run 2 data. Ref : arXiv:2307.01612 (Submitted to PRL).
- No statistically significant excess found in any channel.
- Largest deviation was found in j+μ channel near 4.8 TeV in 10 pb AR, with 2.9σ local excess.
- Limits have been set on generic gaussian signals of various widths and on different BSM physics scenarios.
- Model-independent limits have stronger potential to exclude generic heavy states with complex decays.
- Discovery sensitivity shows a large improvement after the anomaly region selection
- A successful application of unsupervised machine learning for anomaly detection using event level information has been demonstrated.

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EXPERIMENT

Backup slides

Determination of Anomaly regions

We studied theoretical cross sections of various BSM models for two-body resonances (near 400 GeV mass scale). Some of the models we studied were :

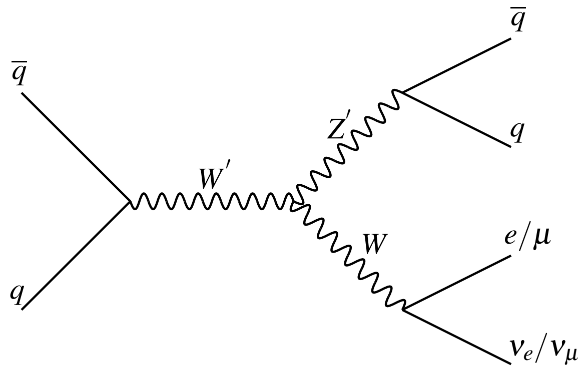
Sequential Standard Model
Charged Higgs (hMSSM, tan(β) = 1)
Charged Higgs (hMSSM, tan(β) = 0.5)
Simplified dark matter model
Composite lepton model (E=250 GeV)
Composite lepton model (E=500 GeV)
Technilocolr model
Radion model
Scalar Leptoquarks at B = 0.5
1st gen. scalar Leptoquarks
3rd gen. Leptoquarks
1st and 2nd gen. scalar Leptoquarks
SUSY with 1 lepton + jets
SUSY directRPVLQ (CC)
Heavy Higgs with lepton+jets

Anomaly region cuts of 10 pb, 1 pb & 0.1 pb could cover cross sections of most of the these models.

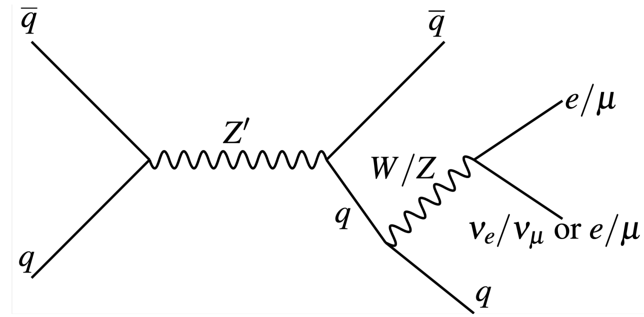
Three Anomaly Regions based on cuts on reconstruction loss from autoencoder :

1. 1st "BSM-region" (10 pb): Maximum value of the cross section for all BSM models
2. "2nd " region (1 pb)
3. 3rd "Data-region" (0.1 pb): Upper bound on published experimental limits for di-jet masses.

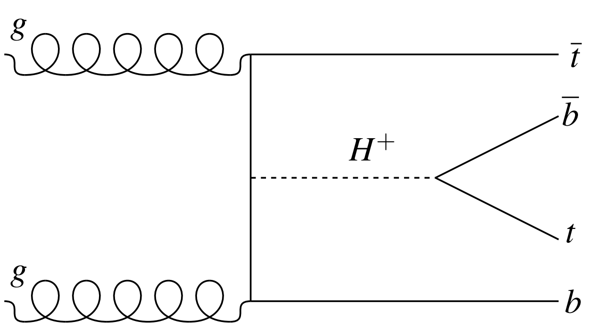
BSM models used



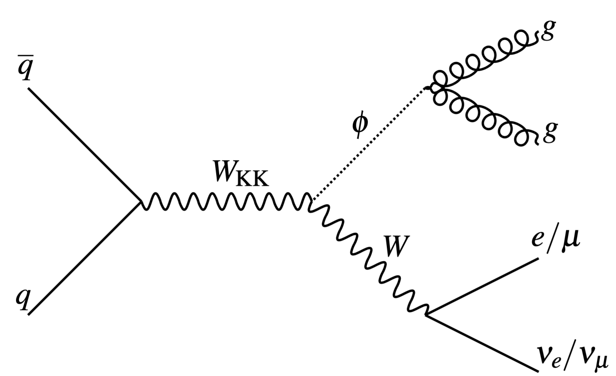
Sequential Standard Model



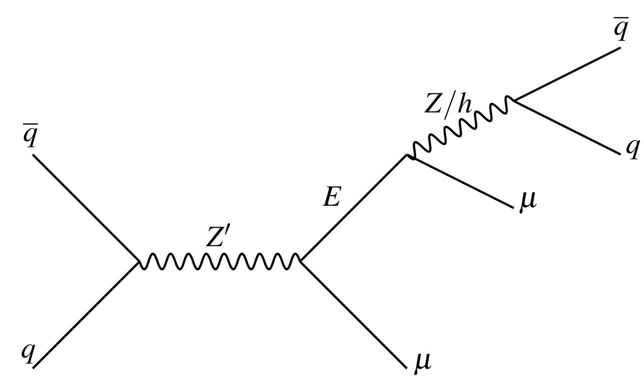
Simplified Dark Matter model



Charged Higgs model



Radion model



Composite lepton model

Usual LHC searches vs our anomaly-detection

Previous model-independent searches in dijet invariant masses (2009-Now)	Proposed strategy for searches in invariant masses using anomaly detection
1) Define “signal region” in terms of rapidity space y*=0.5*|y1-y2| or some other variable	1) Define “Anomaly region”, i.e. a region with large reconstruction loss of autoencoder trained on a fraction of data
2) Define background hypothesis for masses in signal region in the form of a monotonically decreasing function (or smoothing etc) for leading in pT jets	2) Define background hypothesis for masses in Anomaly region in the form of a monotonically decreasing function
3) Unblind: Run a likelihood fit on dijet invariant mass in the signal region and calculate local and global p-value for a largest deviation (“BumpHunter”)	3) Unblind: Run likelihood fits on invariant masses in the Anomaly region to calculate local and global p-value for largest deviation for all masses (modified “BumpHunter”)
4) Nothing found according to global p value? Run limits using Gaussian signal shapes or specific BSM models	4) Nothing found according to global p-value? Limits depending on availability of untested BSM models

Advantages:

No need Monte Carlo simulations

Agnostic to BSM & unexpected signatures

BumpHunter results for 10 pb WP

without Anomaly region cut