Search for new physics using unsupervised machine learning for anomaly detection with ATLAS

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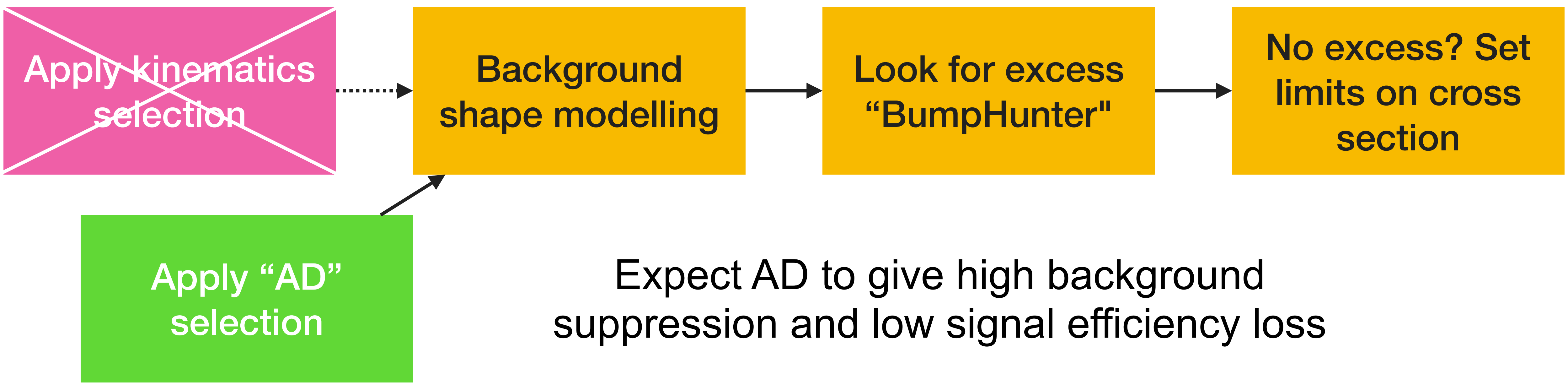
Introduction

- Model independent search provides broader and more efficient searches for new physics
  - Try not to be model specific, namely loose event selection criteria
  - Usually lead to high background
- Anomaly detection (AD) can help identify rare events that differ significantly from majorities



- Today: Using anomaly detection to look for new phenomena in two body invariant masses

ATLAS-CONF-2023-022

Analysis strategy

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

Reconstruct Rapidity Mass Matrix for each event

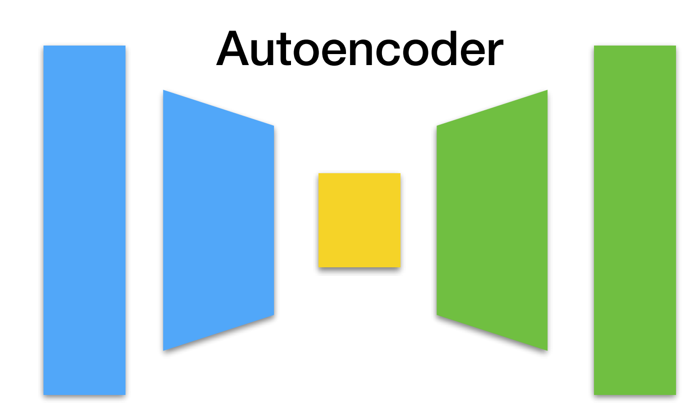
Train autoencoder using 1% ATLAS Run2 data

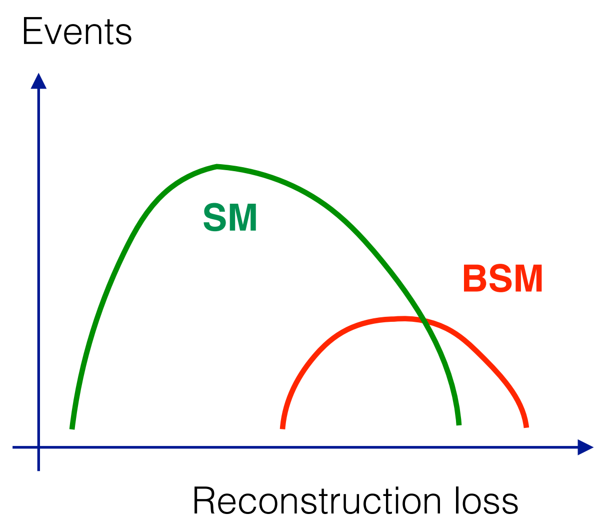
Define signal region using reconstruction loss from autoencoder

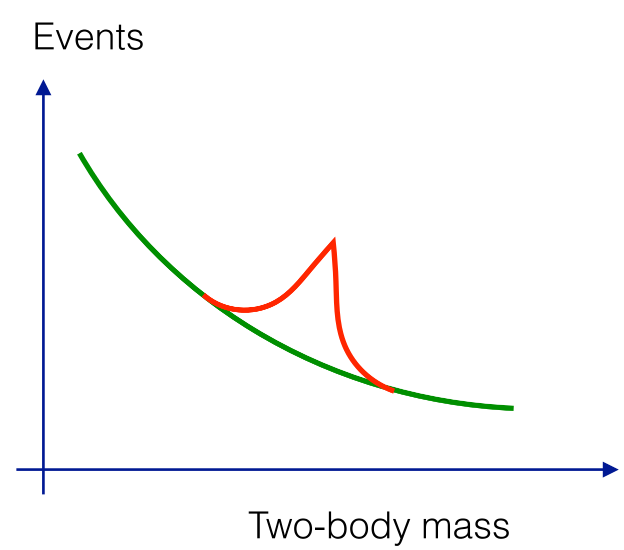
Fit invariant mass spectrum, statistical analysis, look for bumps

Rapidity-mass matrix

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







Advantage of using Anomaly Detection

- Not relying on specific signal hypothesis — model independent search.
- Unsupervised anomaly detection trained on data — no MC modelling dependence
- Using event topologies on the standard reconstructed objects (jet, b-jet, e, μ, γ, met) — object type & multiplicity, 4-momenta, two-body system information, all will contribute to the anomaly score.

Event representation: Rapidity Mass Matrix

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Missing momentum and transverse masses

Invariant masses of pairs m(i,j)/E_{CM}

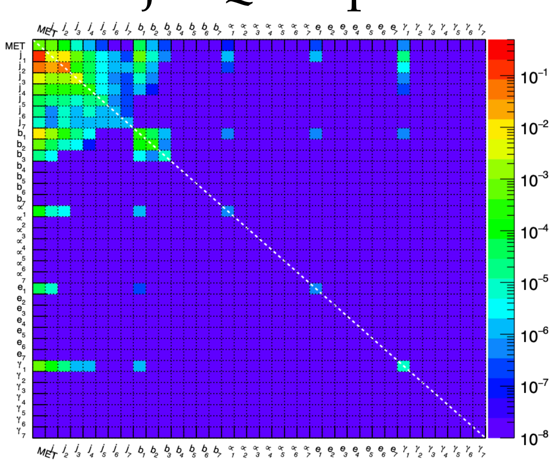
$$\begin{pmatrix}
\mathbf{e}_\mathbf{T}^{\mathbf{miss}} & m_T(j_1) & m_T(j_2) & \ldots m_T(j_N) & m_T(\mu_1) & m_T(\mu_2) & \ldots m_T(\mu_N) \\
h_L(j_1) & \mathbf{e}_\mathbf{T}(\mathbf{j_1}) & m(j_1,j_2) & \ldots m(j_1,j_N) & m(j_1,\mu_1) & m(j_1,\mu_2) & \ldots m(j_1,\mu_N) \\
h_L(j_2) & h(j_1,j_2) & \delta\mathbf{e}_\mathbf{T}(\mathbf{j_2}) & \ldots m(j_2,j_N) & m(j_2,\mu_1) & m(j_2,\mu_2) & \ldots m(j_2,\mu_N) \\
\ldots & \ldots & \ldots & \ldots, & \ldots & \ldots & \ldots \\
h_L(j_N) & h(j_1,j_N) & \ldots & \ldots \delta\mathbf{e}_\mathbf{T}(\mathbf{j_N}) & m(j_N,\mu_1) & m(j_N,\mu_2) & \ldots m(j_N,\mu_N) \\
h_L(\mu_1) & h(\mu_1,j_1) & h(\mu_1,j_2) & \ldots h(\mu_1,j_N) & \mathbf{e}_\mathbf{T}(\mu_\mathbf{1}) & m(\mu_1,\mu_2) & m(\mu_1,\mu_N) \\
h_L(\mu_2) & h(\mu_2,j_1) & h(\mu_1,j_2) & \ldots h(\mu_2,j_N) & h(\mu_1,\mu_2) & \delta\mathbf{e}_\mathbf{T}(\mu_\mathbf{2}) & m(\mu_2,\mu_N) \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \\
h_L(\mu_N) & h(\mu_N,j_1) & h(\mu_N,j_2) & \ldots h(\mu_N,j_N) & h(\mu_N,\mu_1) & h(\mu_N,\mu_2) & \delta\mathbf{e}_\mathbf{T}(\mu_\mathbf{N})
\end{pmatrix}$$

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

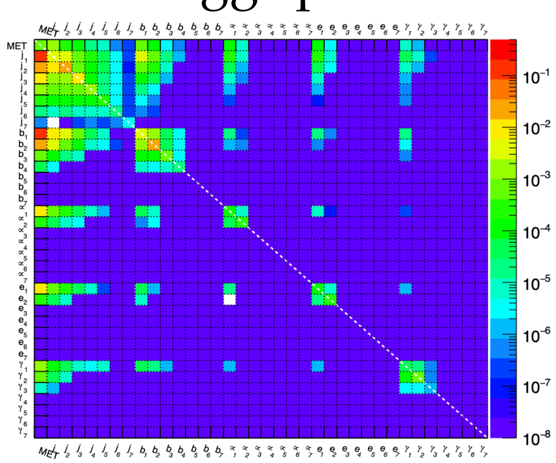
Lorentz factors

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

Multi-jet QCD process



Higgs process



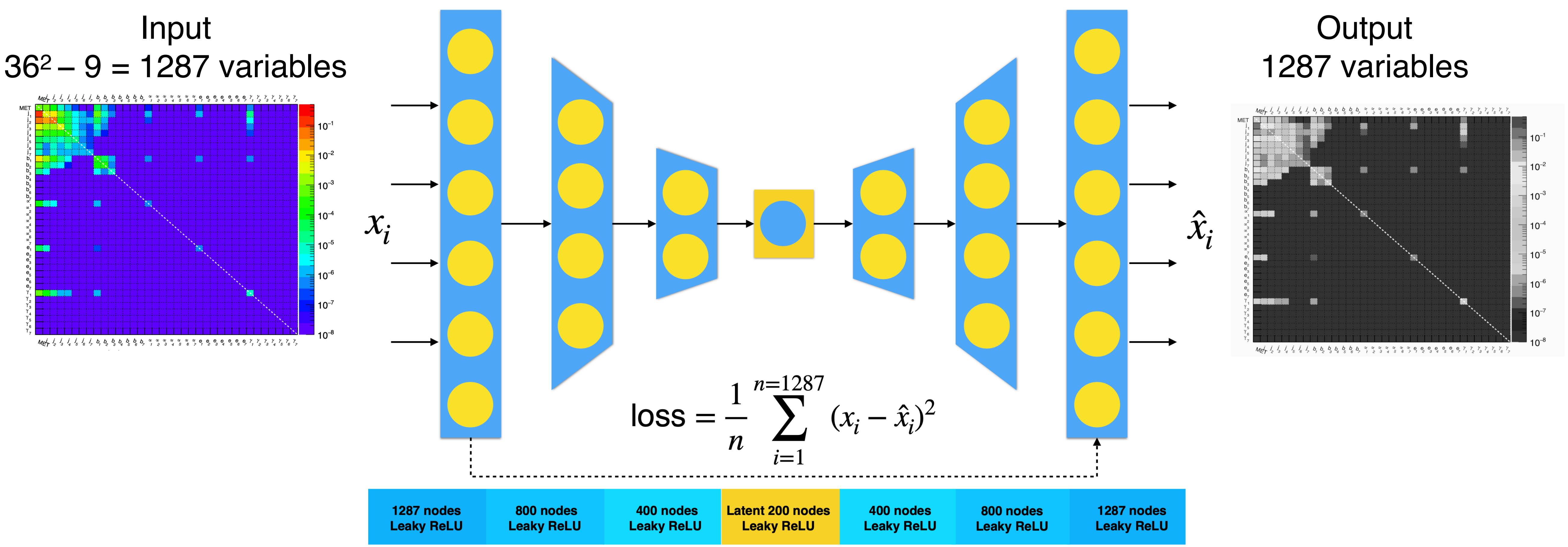
- Expected to have different characteristics for different processes

Source: 1810.06669

Analog to a QR code

Train autoencoder

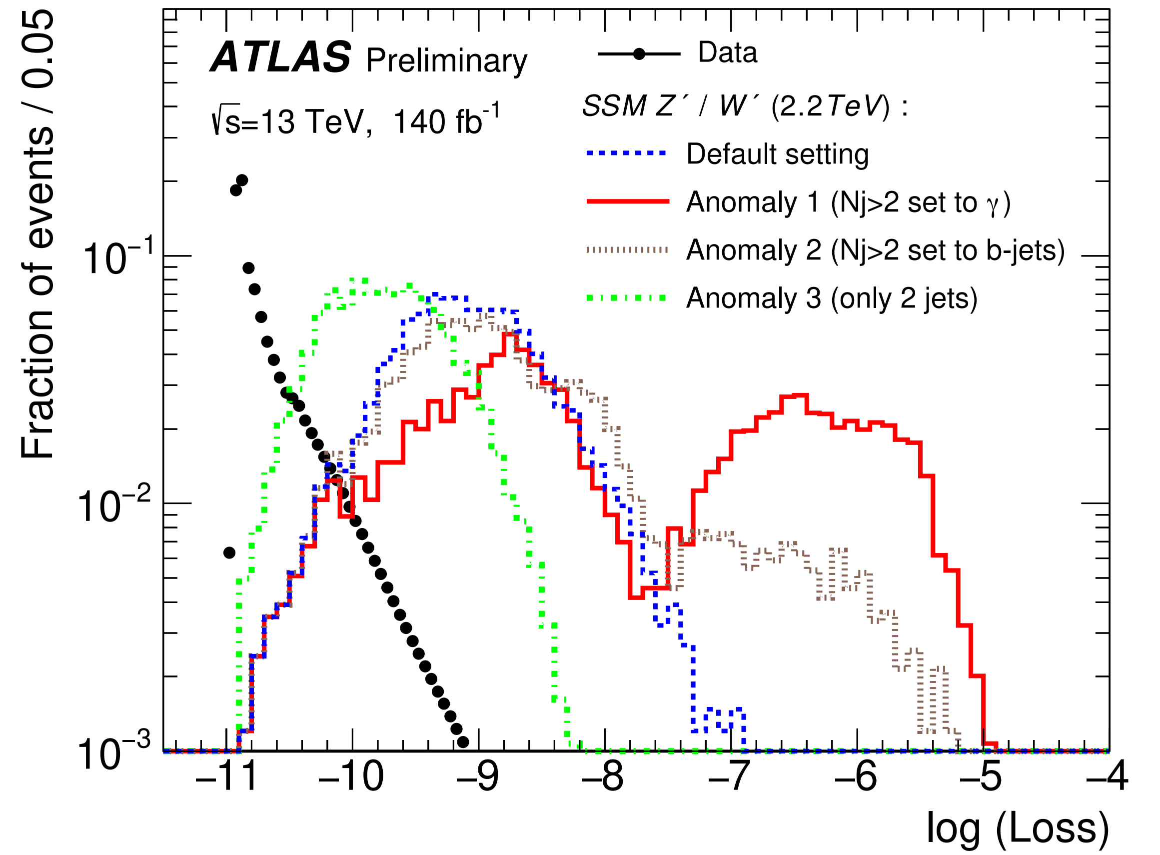
- Using randomly selected 1% collision data
  - Sufficient statistics to train and well represent the full collision dataset
  - Split to 7:3 for training and validation, monitor validation loss for early stopping
- Tried other architectures such as Variational (convolutional) autoencoder and various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



Anomaly signal test

- **Can model detect anomalous?**

- 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



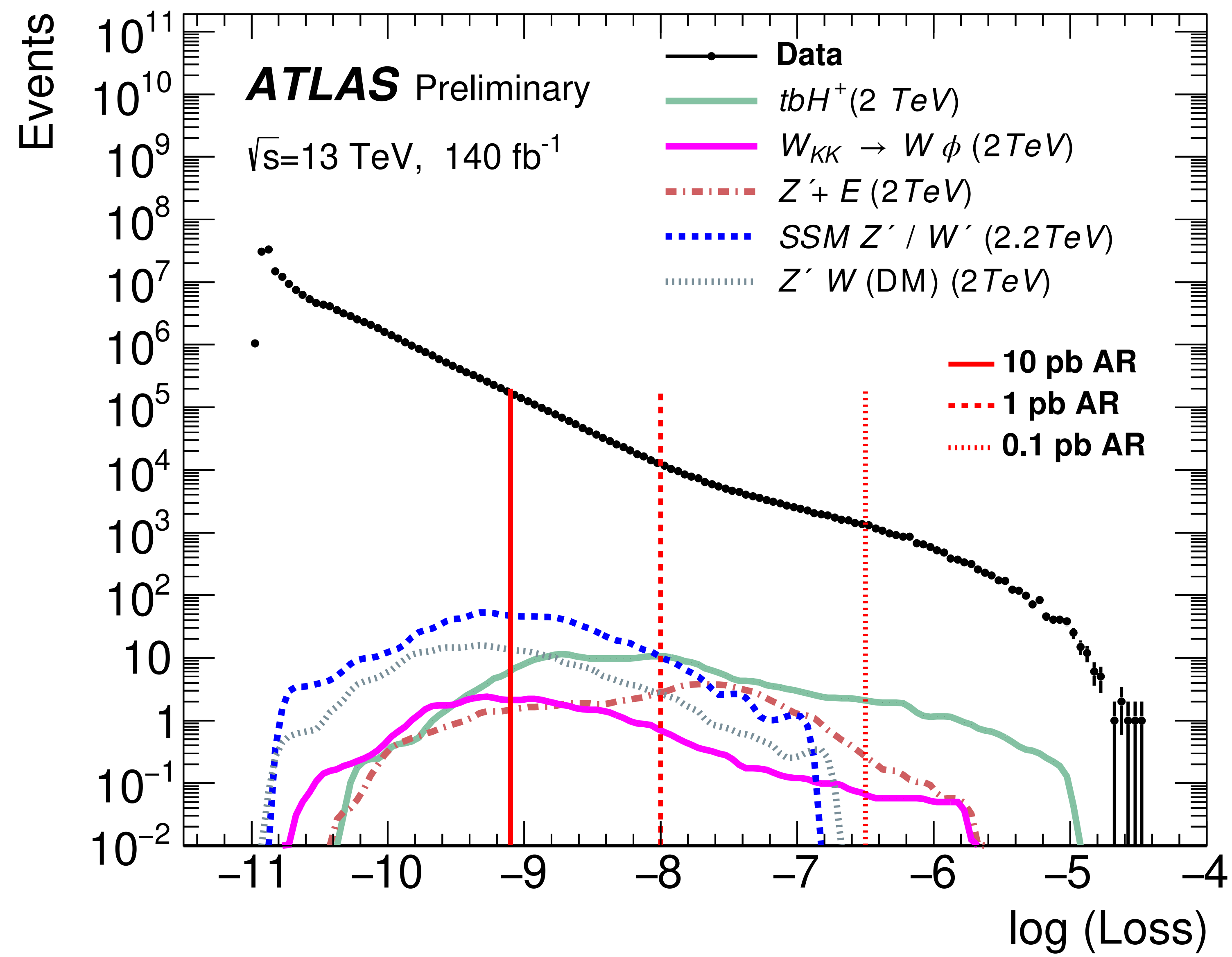
- They all show up with large loss, in addition:
  - More anomalous is seen when b-jet or photon multiplicity increases - expected
  - Less anomalous is seen when multiplicity is low, anomalous may come from large pT, Etmiss, etc - expected

Anomaly region definitions

- Anomaly region should enhance BSM signal and suppress SM bkg
  - Need enough bkg for modelling

- Select events corresponding to 10pb, 1pb, 0.1pb (×140 fb^{-1}) as 3 anomaly regions to cover different sensitivities

- 10pb AR is the main one to study in this analysis



Background modelling

- The mass spectra of background (SM) are expected to be smoothing falling.
- Using SM MC and loose-lepton control regions to establish background function form (five parameters, hence “p5”)

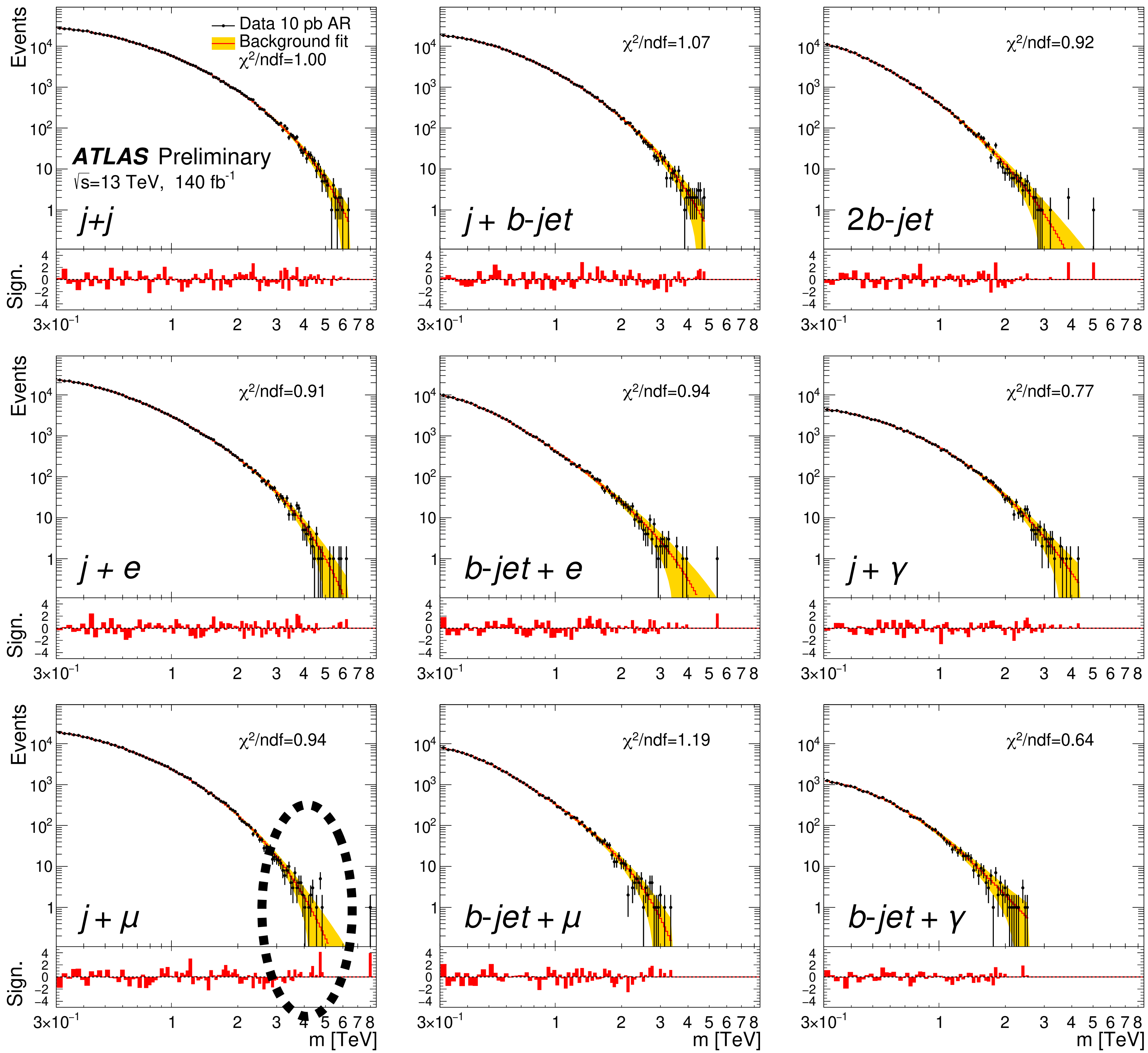
$$f(x) = p_1(1-x)^{p_2} x^{p_3 + p_4 \ln x + p_5 \ln^2 x}$$

- Also used an alternative function form to estimate systematics
  - Replace the highest order term with a different from that will affect the tail most

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

Results

BumpHunter results for 10 pb WP



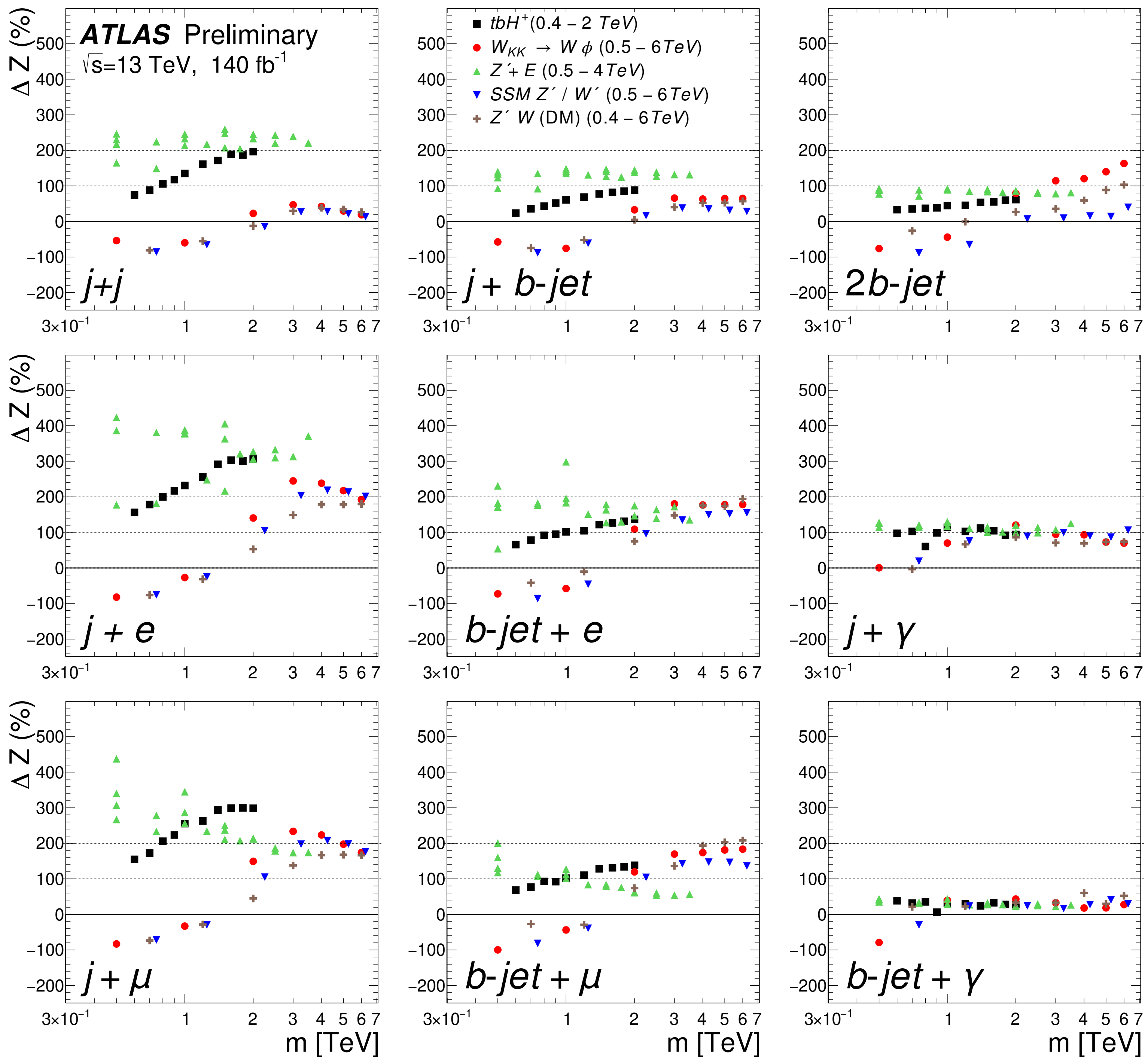
- Agree with p5 fit
  - Tests of normality on pulls passed for all masses passed
  - Background shape uncertainty shown in yellow
- Largest deviation reported by BumpHunter is $m_{j\mu}$ at ~4.8 TeV

Demonstration of sensitivity to BSM signals

- Sensitivity improvement quantified by ΔZ

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

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



$\Delta Z > 0 \Rightarrow$ improvement

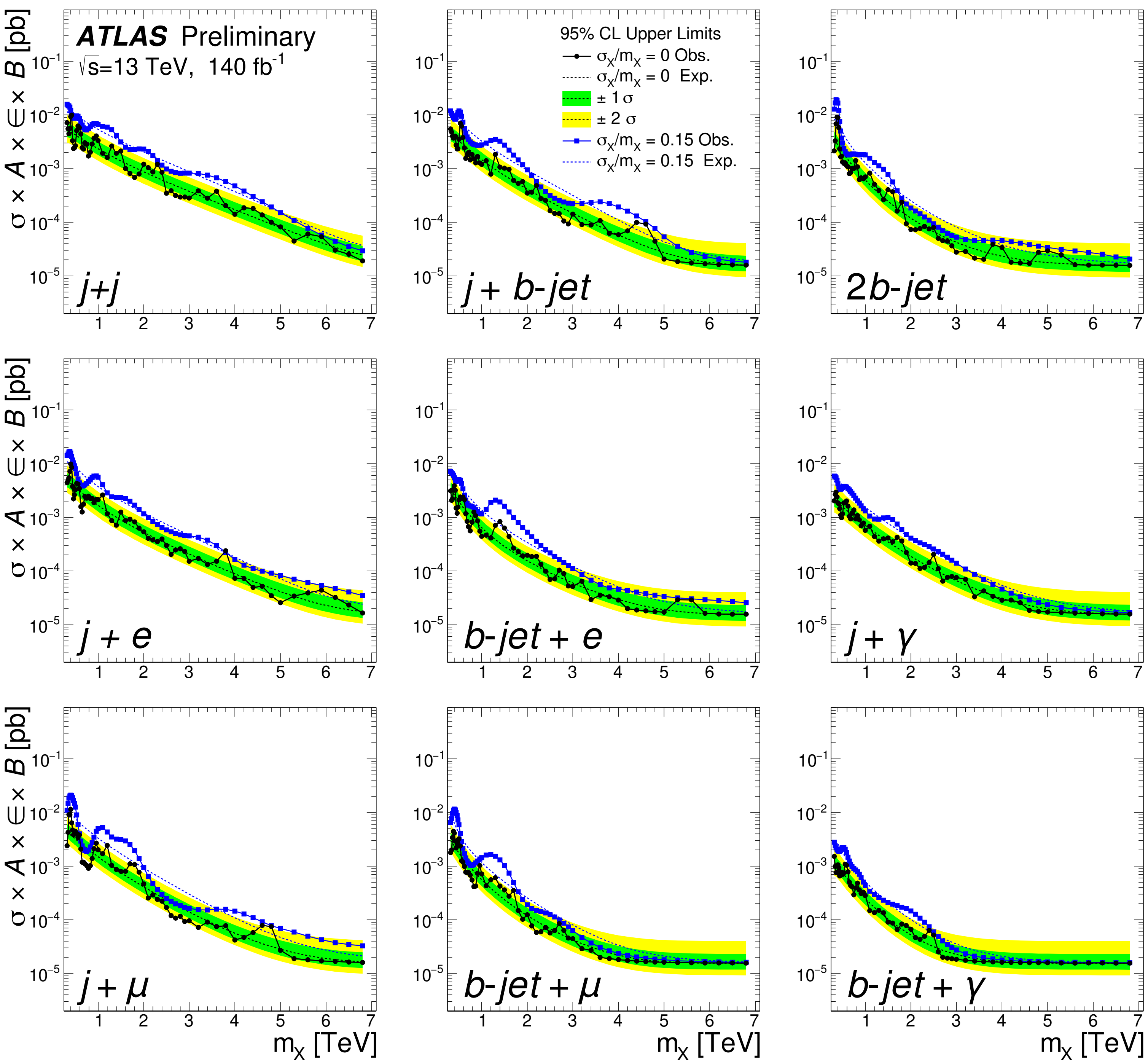
Limit setting using generic Gaussian signals

- Uncertainties include:
  - Luminosity
  - Experimental uncertainties in signal derived from SSM W′/Z′ MC simulation and applied to Gaussian signal
    - JES, JER, Lepton energy scale, etc
  - Alternative bkg functional shape in bkg modelling

$$f(x) = p_1(1-x)^{p_2} x^{p_3+p_4 \ln x + p_5 \ln^2 x} \quad \text{vs} \quad f(x)^{alt} = p_1(1-x)^{p_2} x^{p_3+p_4 \ln x + p_5/\sqrt{x}},$$

  - Spurious signal uncertainty

Upper limits of Gaussian signals

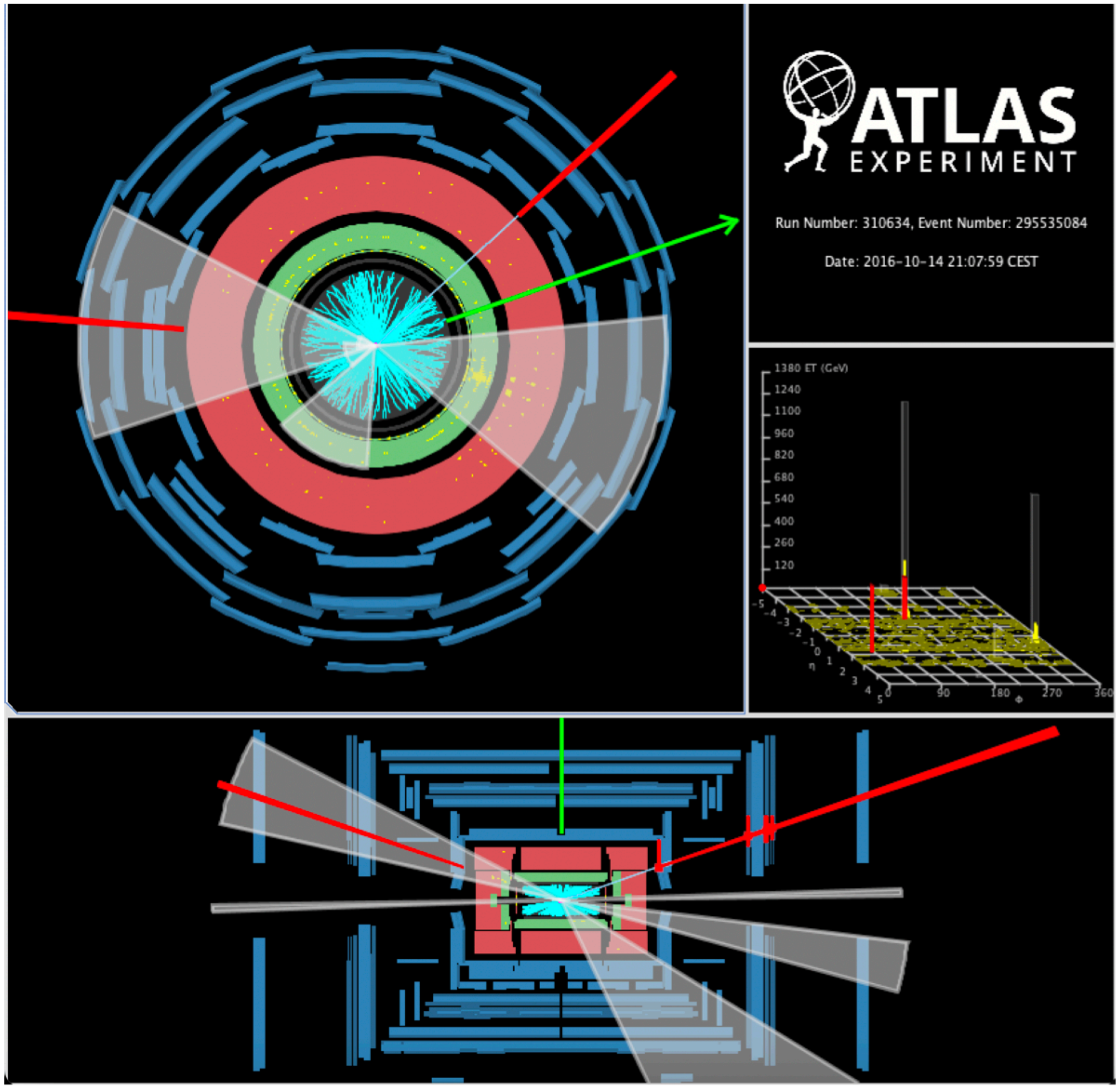


- Signal width of σ=0 and σ/m=15% are shown
  - Narrow signals have better limits as expected
- Error band is from σ=0
- Waves are similar, σ=0 is subject to local fluctuations
- Local 2.9 σ @ $m_{j\mu}$ = 4.8TeV, 2.8 σ @ $m_{j\mu}$ = 1.2TeV

Conclusions

- An successful application of unsupervised machine learning for anomaly detection using event level information
- Searched for new phenomena in 9 invariant masses for jet+X (b-jet+X) from 3 outlier regions
- Largest deviation for j+μ near 4.8 TeV is consistent with a statistical fluctuation
- Analysis method shows improvement of sensitivity up to ~300%
- Model-independent limits (gaussian signal) is presented

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



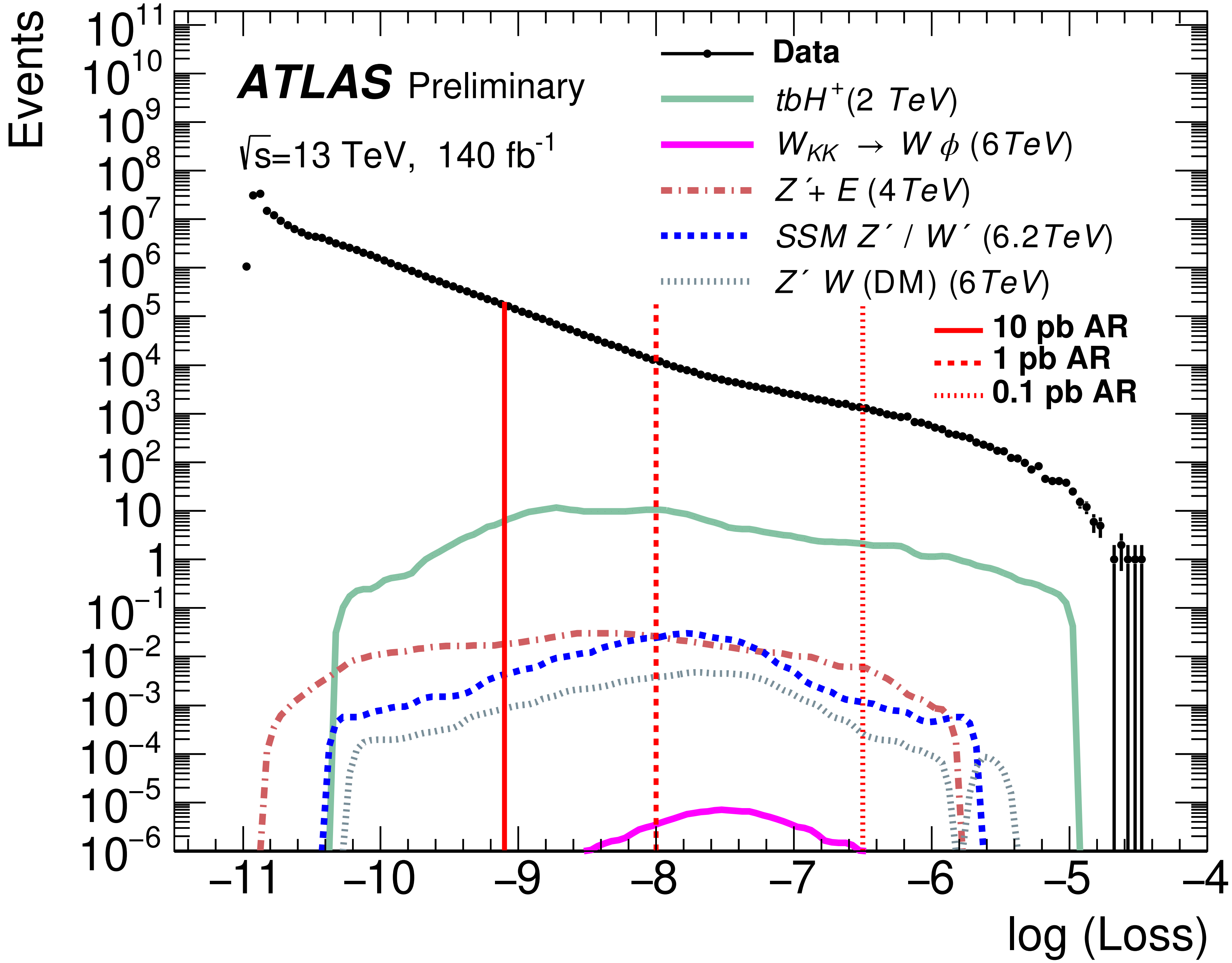
Left grey cones: $p_T^j = 1376$ GeV, $\eta = -1.79$, $\phi = 3.059$

Red: $p_T^\mu = 430$ GeV

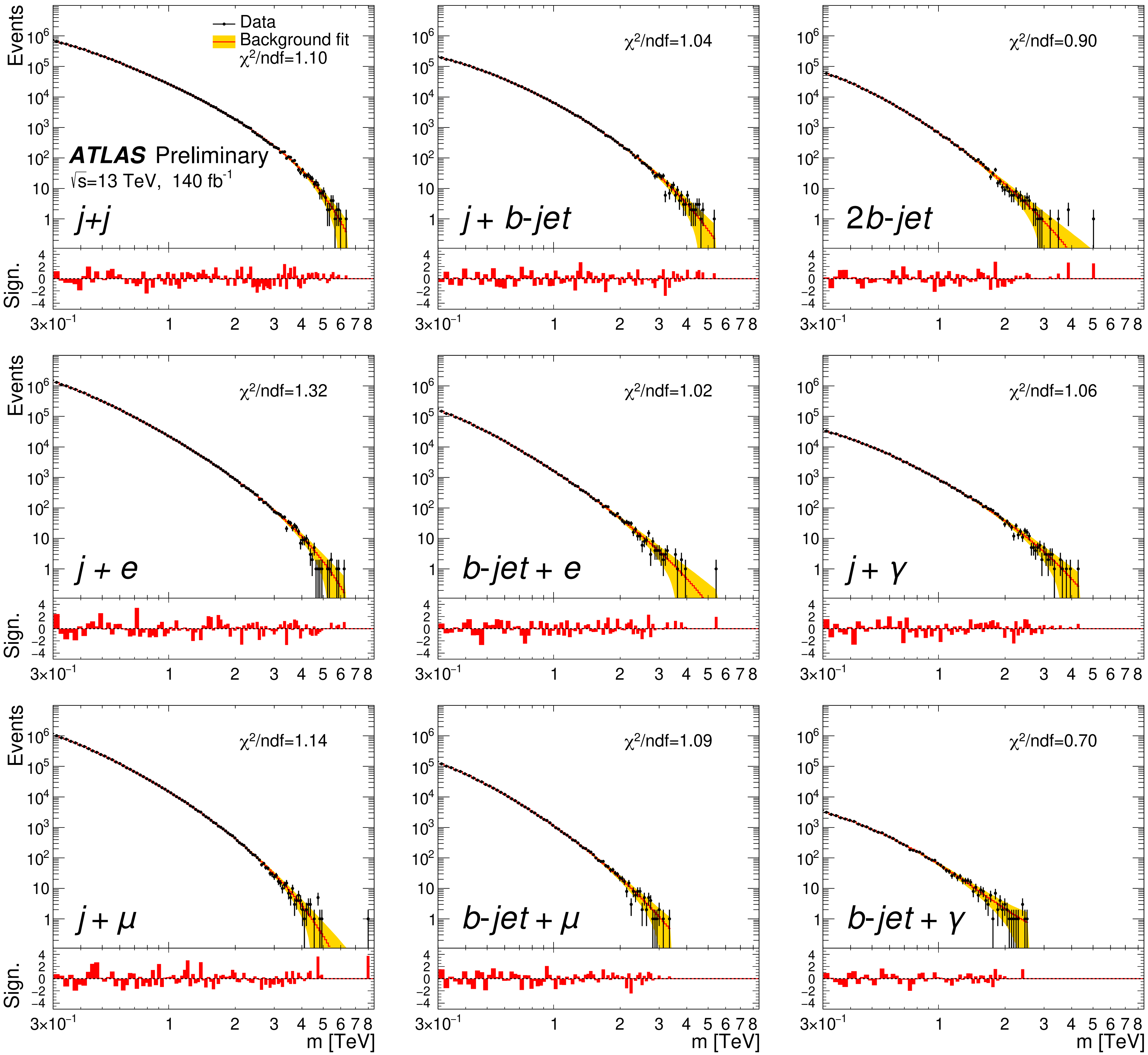
Green: $E_T^{miss} = 256$ GeV

Thank you!

Backup



Loss distributions for BSM models with high mass



Fit results without applying Anomaly Region cut