UNIVERSITY OF OREGON

BERKELEY LAB

Non-resonant Anomaly Detection with background extrapolation

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Based on arXiv:2311.12924

The need for signal-agnostic searches in hadronic final states

ATLAS hadronic resonance search summary.

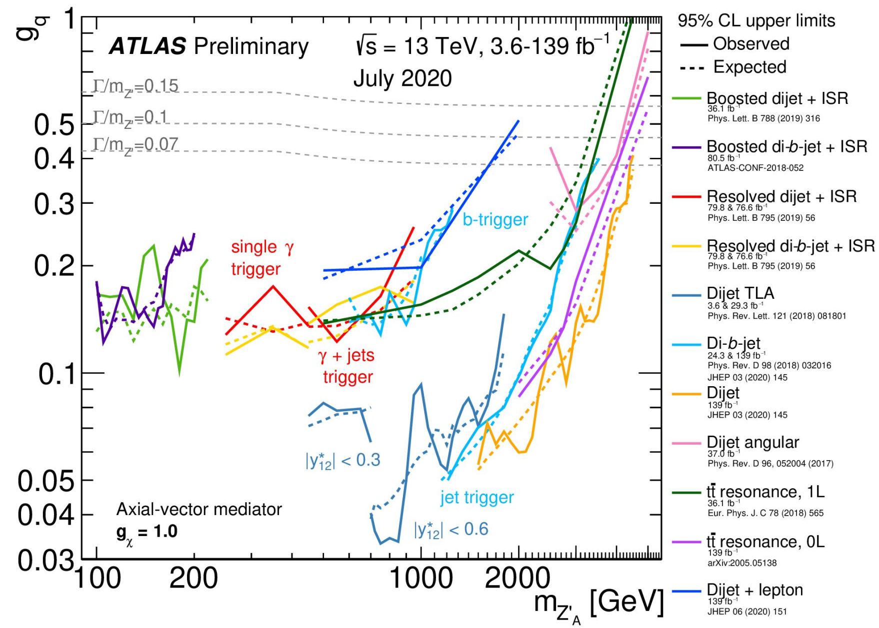
- Only an interpretation in a specific Z' model.
- There are many more models, each with a large parameter space.

It is impossible to scan all models and phase space.

Model-independent searches are complementary,

➔ **but also necessary!**

ML-based Anomaly Detection (AD) provides us with more sophisticated tools for model-independent searches.



[ATLAS exotics results]

Requirements for complete anomaly detection

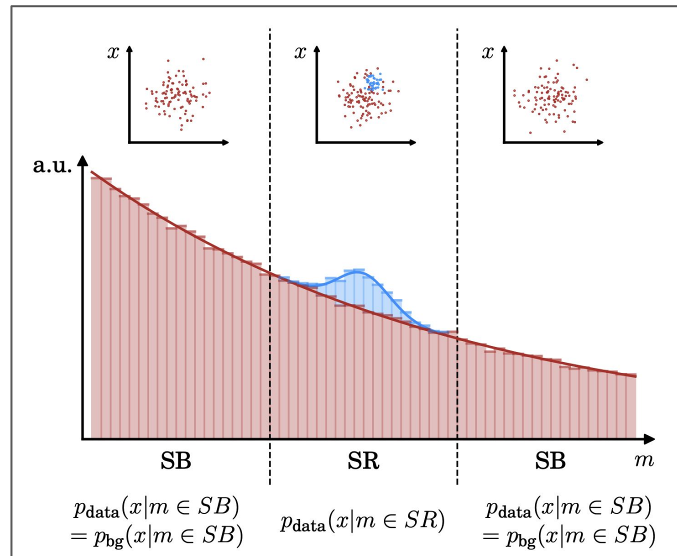
AD in particle physics looks for "outliers" or "overdensities" in the SM background without model assumptions.

Successful background estimation + Sensitive to signal

Overdensity AD example:

Classifying Anomalies THrough Outer Density Estimation (CATHODE) [2109.00546]

Weakly-supervised.



Current landscape of overdensity anomaly detection

Many proposals and all data results have targeted resonant signals by interpolating background from a sideband.

Background interpolation from sideband + **Resonant signal**

Existing methods for background interpolation:

- MC-to-data reweighting (SALAD [2001.05001])
- Density estimation using generative models (CATHODE [2109.00546])
- MC-to-data feature morphing (FETA [2212.11285])
- Other variations…

Available technologies

➔ **A binary classifier for reweighting**

Neural networks ($f(x)$) can learn to approximate the likelihood ratio.

$$w(x) \equiv \frac{f(x)}{1-f(x)} = \frac{p(x|\text{data})}{p(x|\text{simulation})} \begin{array}{l} \longrightarrow \text{Class 1} \\ \longrightarrow \text{Class 0} \end{array}$$

Available technologies

➔ **A binary classifier for reweighting**

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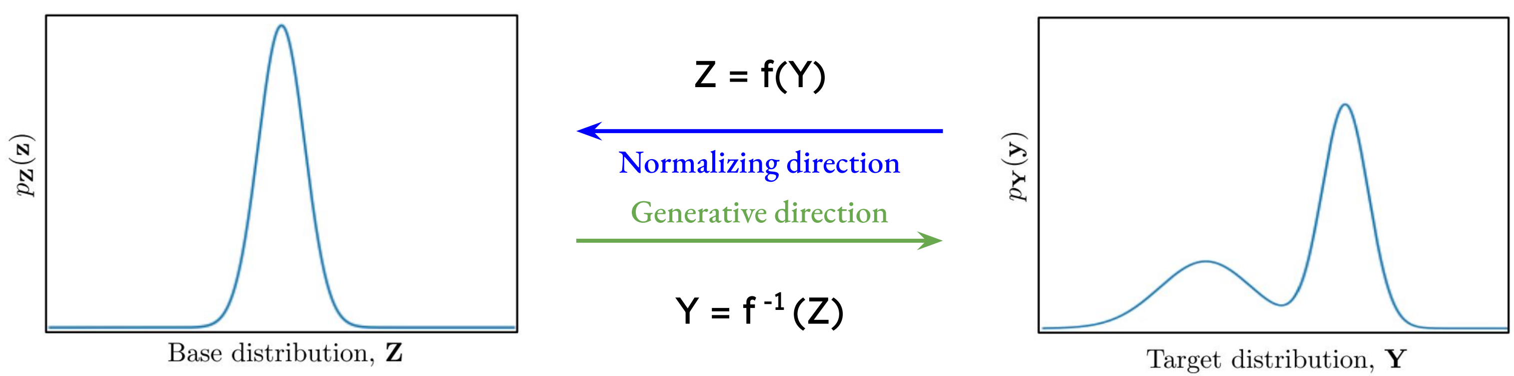
$$w(x) \equiv \frac{f(x)}{1-f(x)} = \frac{p(x|\text{data})}{p(x|\text{simulation})}$$

→ Class 1

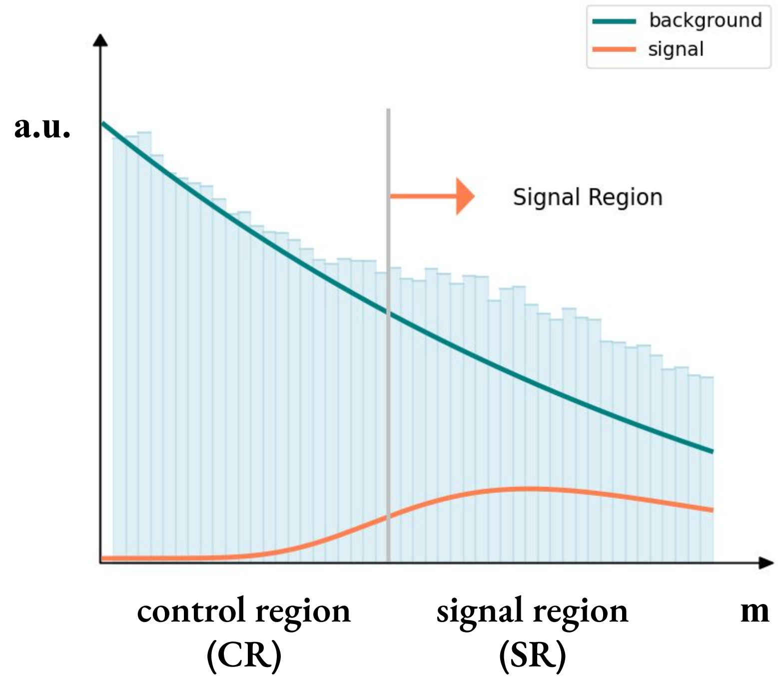
→ Class 0

➔ **Normalizing flow for generating and morphing**



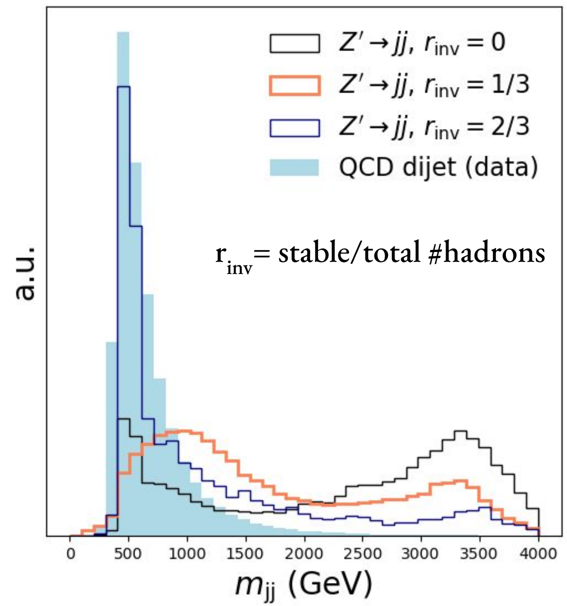
This proposal

Background extrapolation from one side ➕ non-resonant signal



Non–resonant signals

Case 1: large missing energy in the final states of a resonant production. Example here: semi-visible jets from Z'.



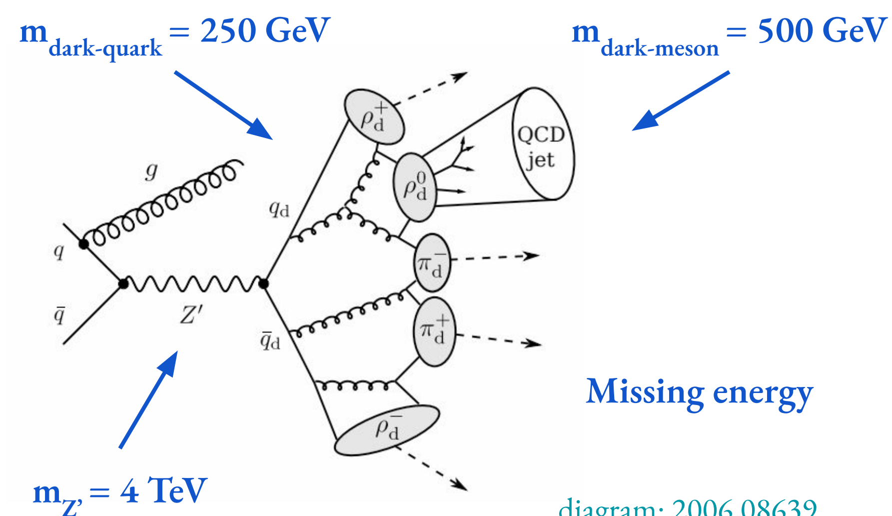


diagram: 2006.08639

Case 2: off-shell effects from heavy particles. Example: modifications to SMEFT coefficients, but not explored here.

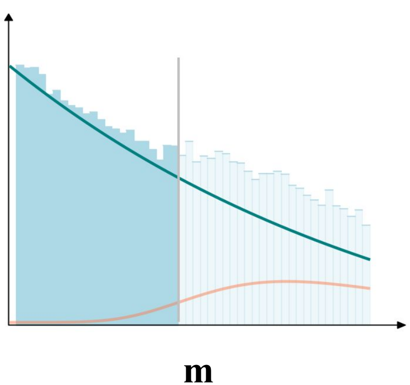
The idea

➔ **Why don't we just extrapolate with existing methods?**

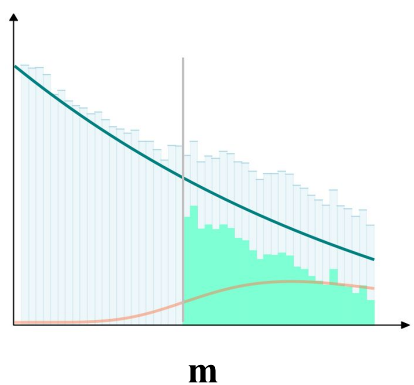
In principle we could directly use MC-to-data reweighting.

However, density estimation with generative models are **less robust without a sideband.**

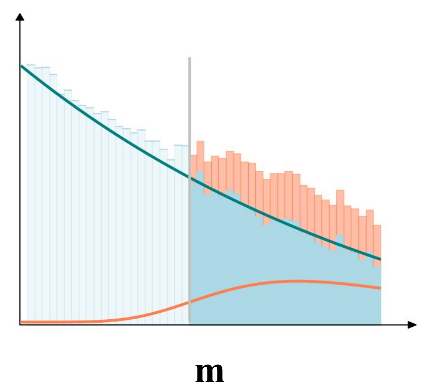
❶ Learn P(x|m) in CR.



❷ Predict P(x) in SR.



❸ Classification in SR



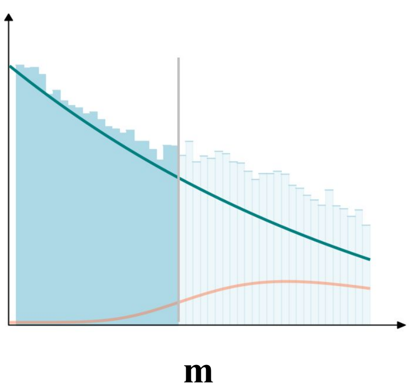
The idea

➔ Combine generative models and ML reweighting!

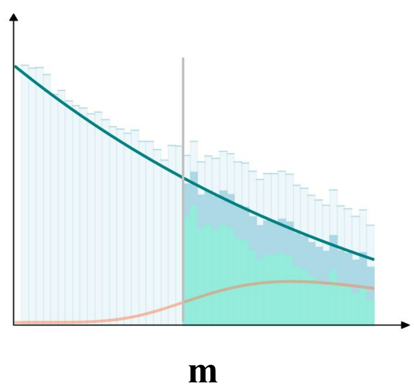
Reweight conditional variables from MC to data in SR.

$$
\begin{aligned}
P_{\text{data}}(x, m) &= P_{\text{data}}(x|m)P_{\text{data}}(m) \\
&= P_{\text{data}}(x|m)P_{\text{MC}}(m)\boxed{\frac{P_{\text{data}}(m)}{P_{\text{MC}}(m)}} \\
&= P_{\text{data}}(x|m)P_{\text{MC}}(m)\boxed{w(m)}
\end{aligned}
$$

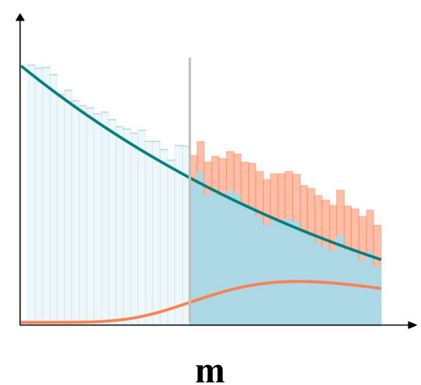
❶ Learn P(x|m) in CR.



❷ Predict P(x) in SR with reweighting.



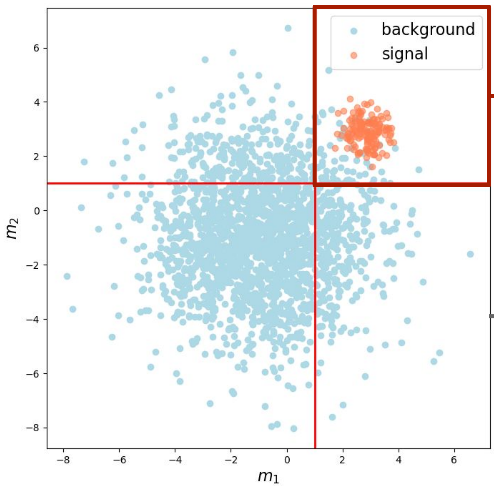
❸ Classification in SR



First, let's take a look at a toy example

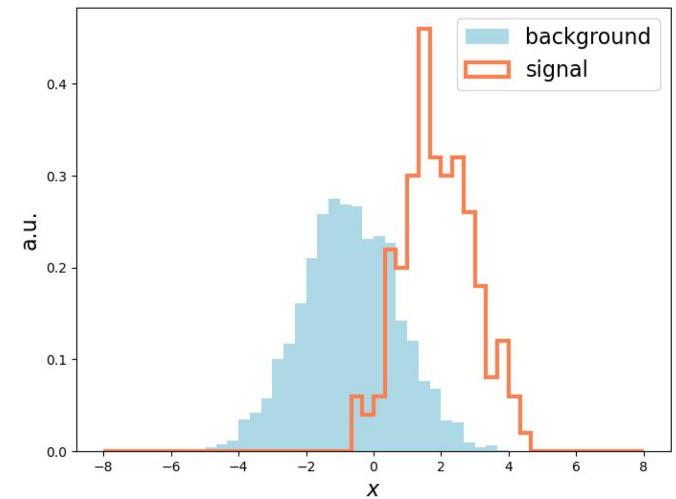
Context variables m1 and m2, used to define SR & CR.

A feature variable x.



Signal Region (SR)

Control Region (CR)



Extrapolate the background using Reweight, Generate, and Morph methods.

Anomaly detection methods

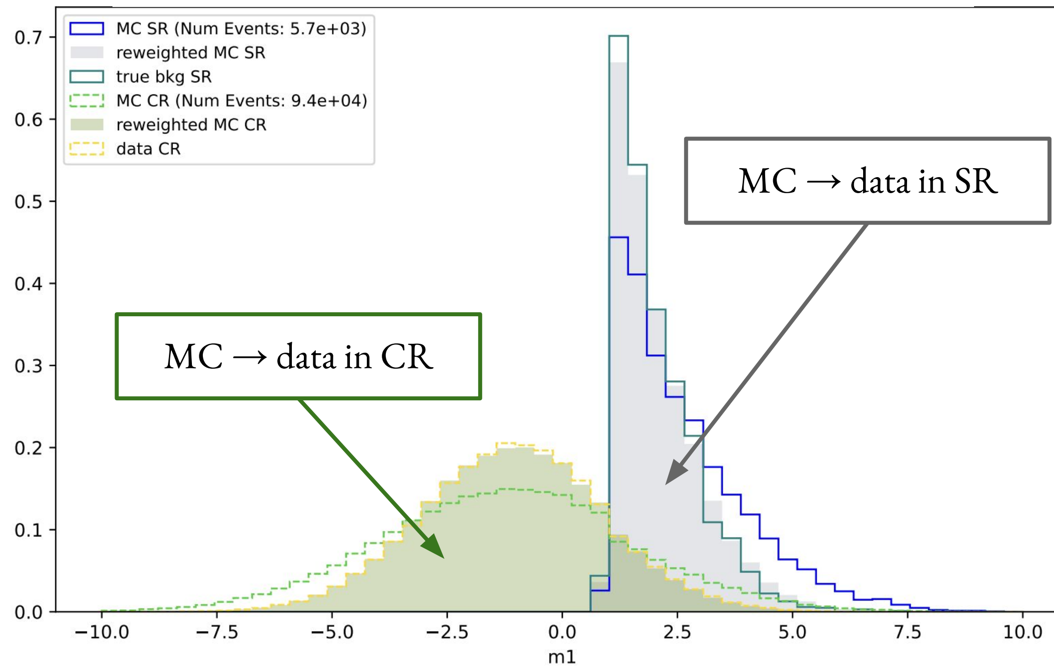
- **Reweight**

Assumption:

$$w(m) = \frac{P_{data}(m \in CR)}{P_{MC}(m \in CR)}$$

$$= \frac{P_{data}(m \in SR)}{P_{MC}(m \in SR)}$$

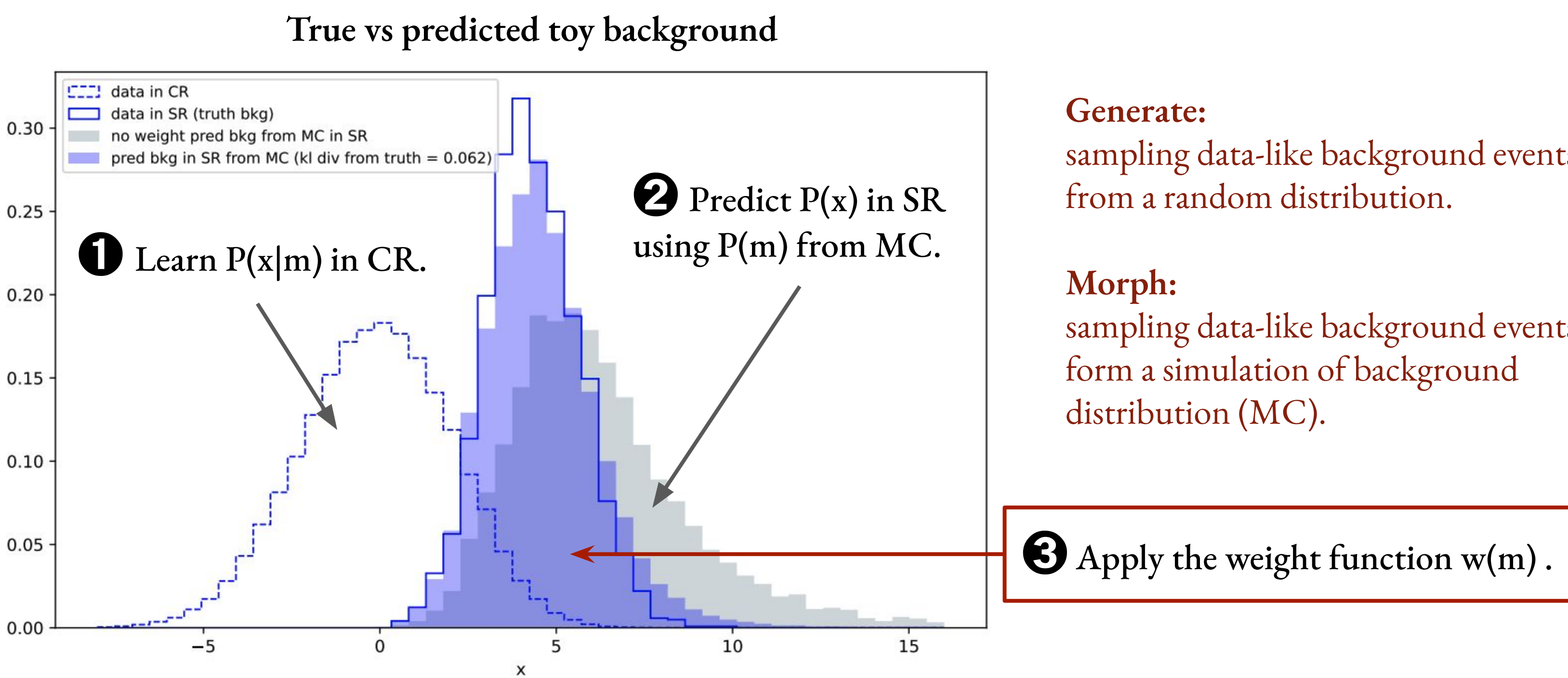
Reweighted MC vs data for the toy background



* This plot is used for illustration purpose only, not the final result.

Anomaly detection methods

- **Generate/Morph**



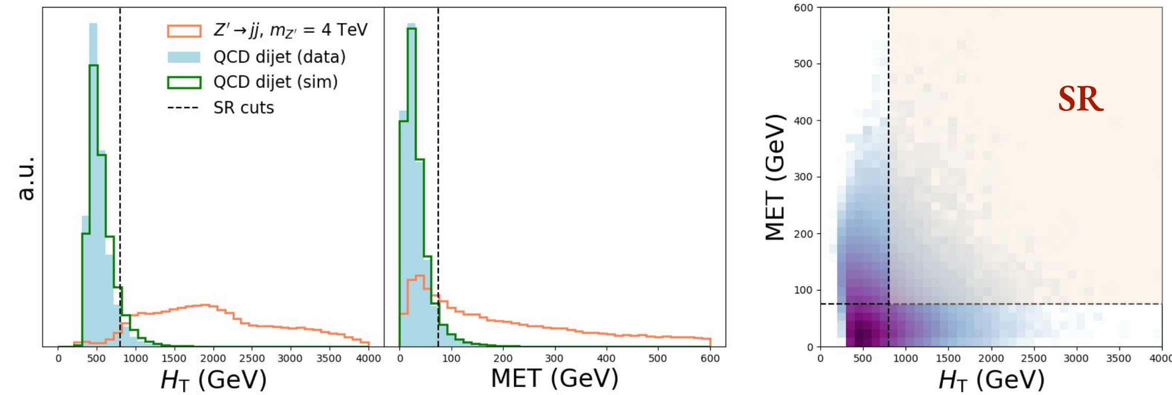
Generate:
sampling data-like background events from a random distribution.

Morph:
sampling data-like background events form a simulation of background distribution (MC).

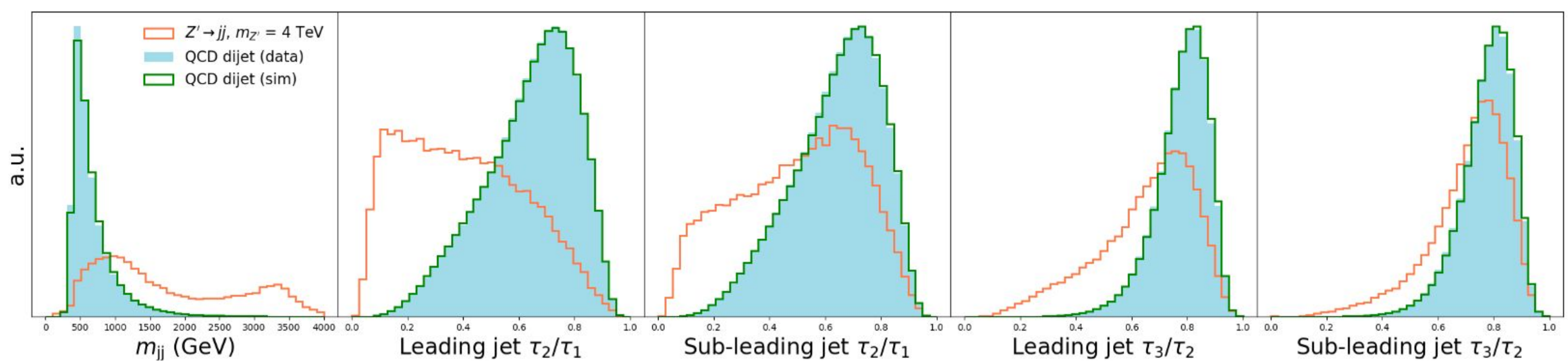
* This plot is used for illustration purpose only, not the final result.

Physics example

Context variables: HT &MET



Feature variables: m_{jj} & N-subjettiness

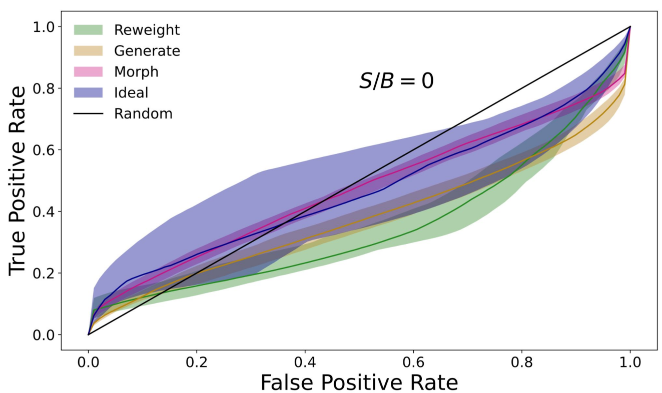


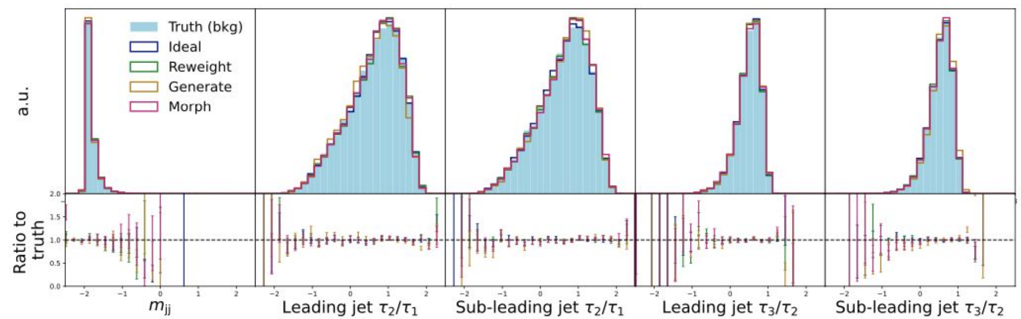
Background estimation results (no signal)

We see closures in CR, and agreements in SR for the 5 feature variables.

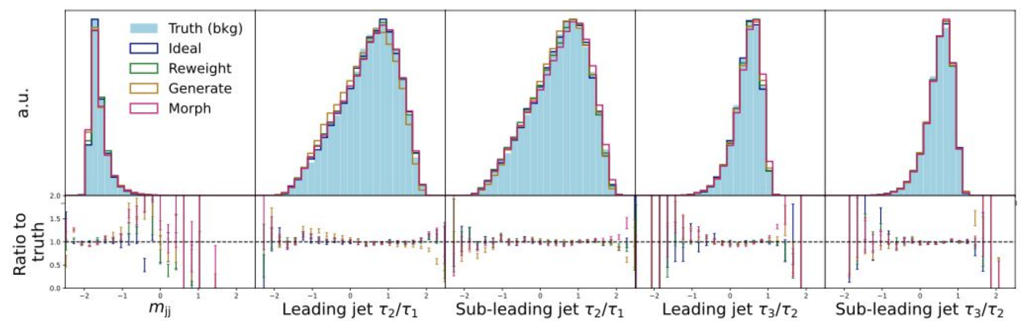
- ➔ Prediction matched truth.
- ➔ Minimum mis-modeling and false-positives.

Receiver Operating Characteristic (ROC)





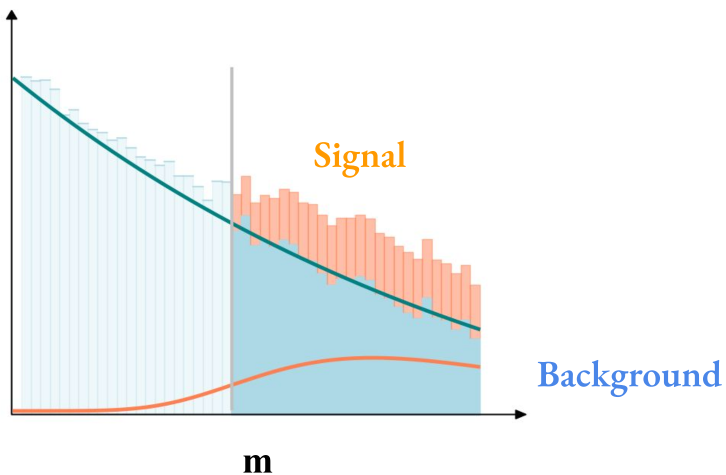
(a) Control region distributions.

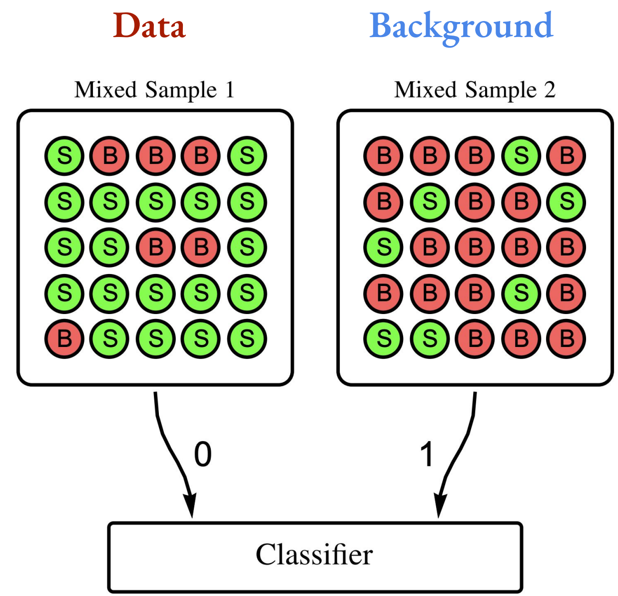


(b) Signal region distributions.

AD performance with injected signal events

❸ Classification in SR

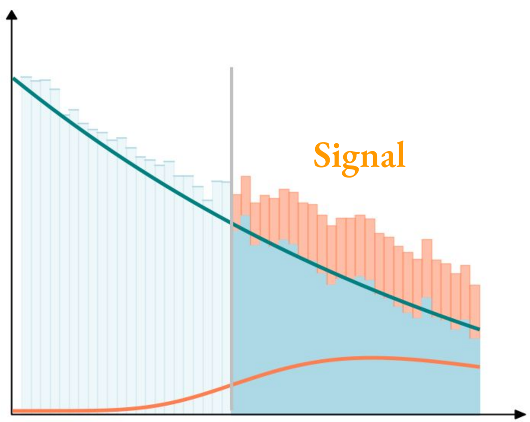




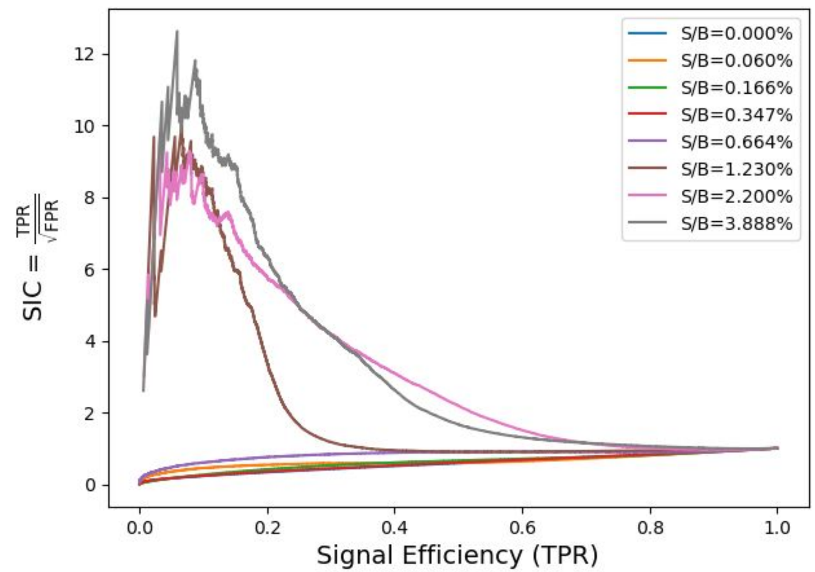
Classification without labels (CWoLa) [1708.02949]

AD performance with injected signal events

❸ Classification in SR



Significance Improvement Characteristic (SIC)



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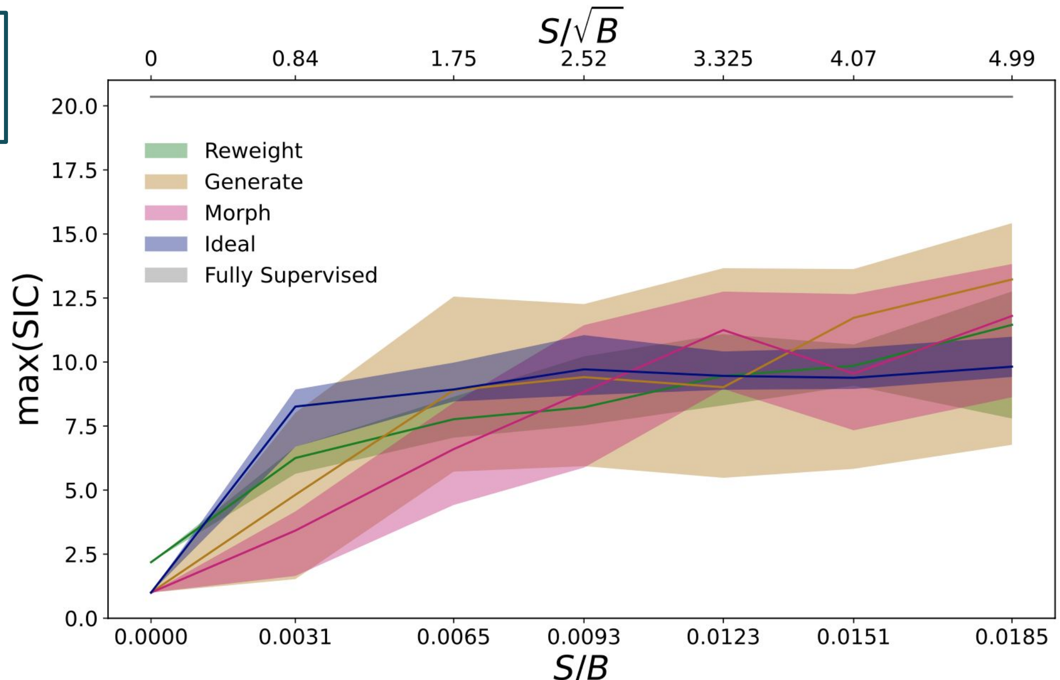
AD performance over increasing signal injections

Signal significance

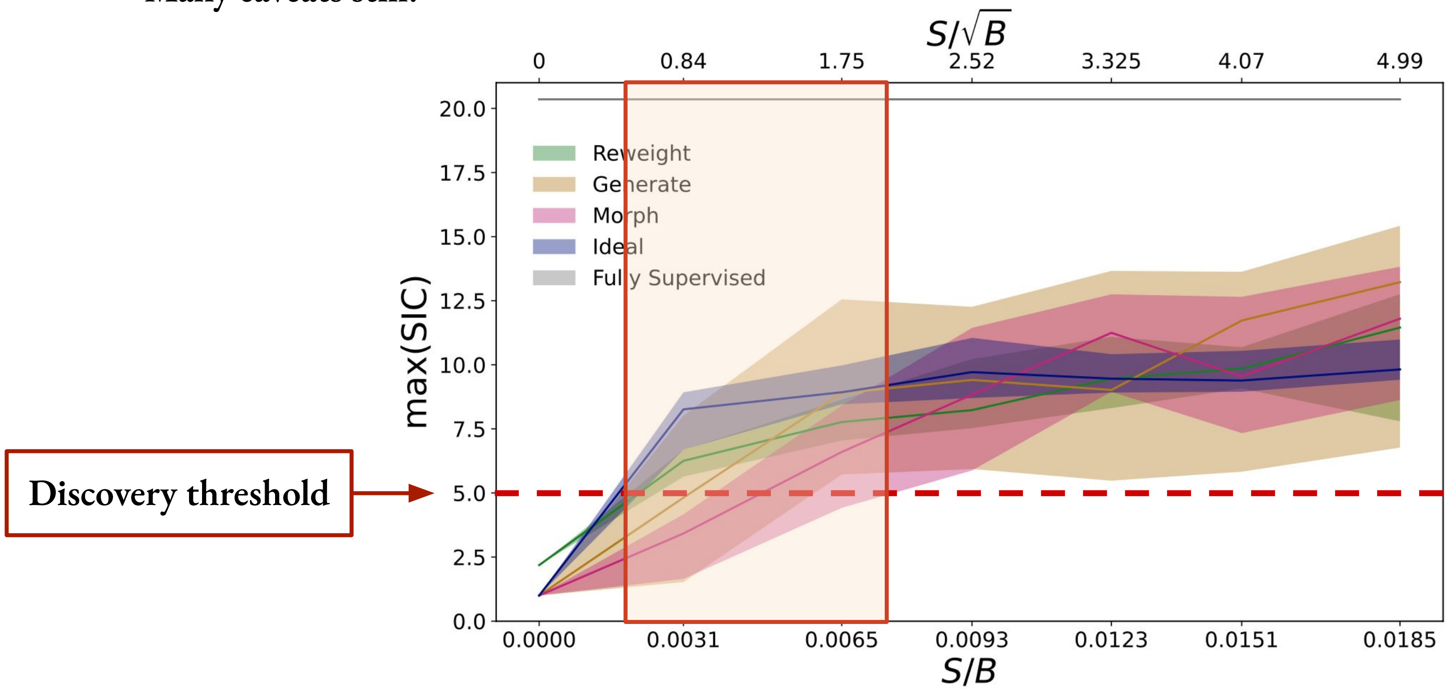
Maximum significance improvement



signal-to-background ratio

AD performance over increasing signal injections

- ➔ A 1-2 sigma signal significance is enhanced to reach the discover threshold of 5 sigma.
- ➔ Many caveats still!



How robust is this performance?

One needs to test these AD methods against many different signal models.

- Tested on lower Z' mass (2 and 3 TeV).
- Found that the performance is worse for lower mass Z' signals.

Did we make the problem easier by choosing a background simulation that looks similar to the "real" background?

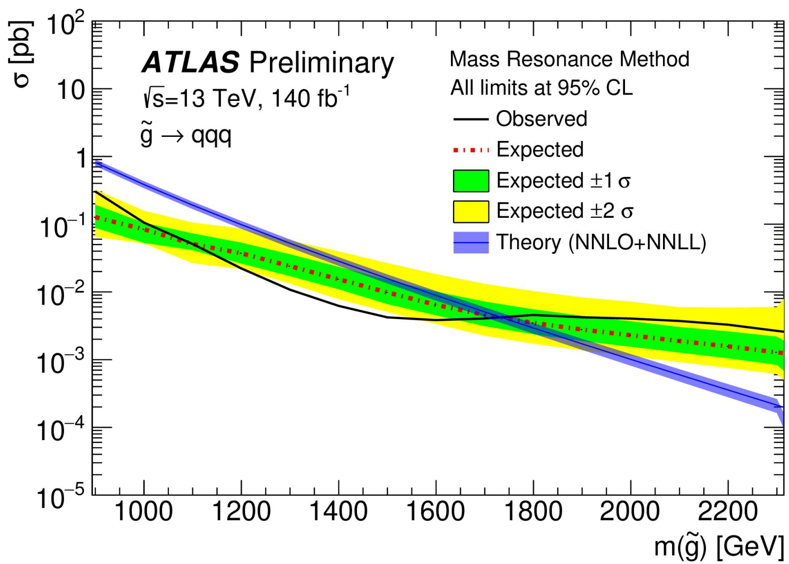
- Repeated the analysis with a hand-tuned simulation daset.
- Found that the performance are compatible with the current simulation.

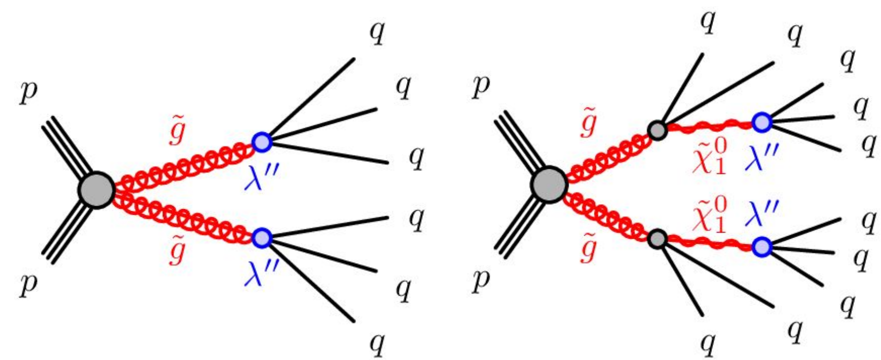
* This discussion will be included in the V2 paper. Stay tuned!

A few words on extensions to RPV SUSY

A full Run2 ATLAS search for R-parity-violating Supersymmetry (RPV SUSY) in hadronic final states is public!

➔ **My first analysis as a graduate student :)**

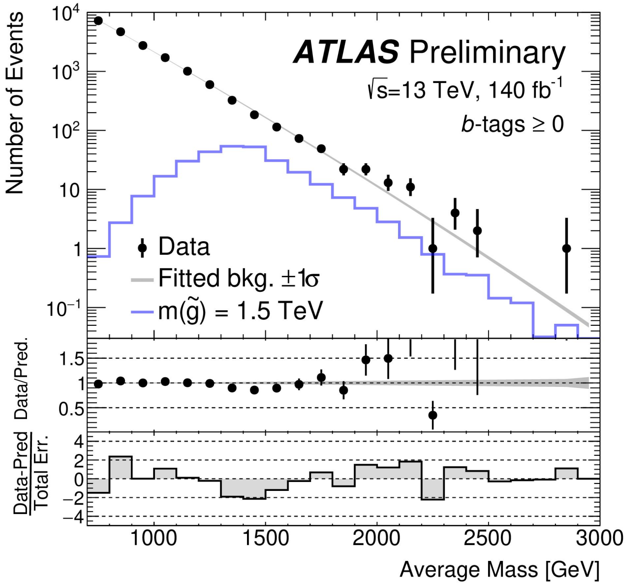


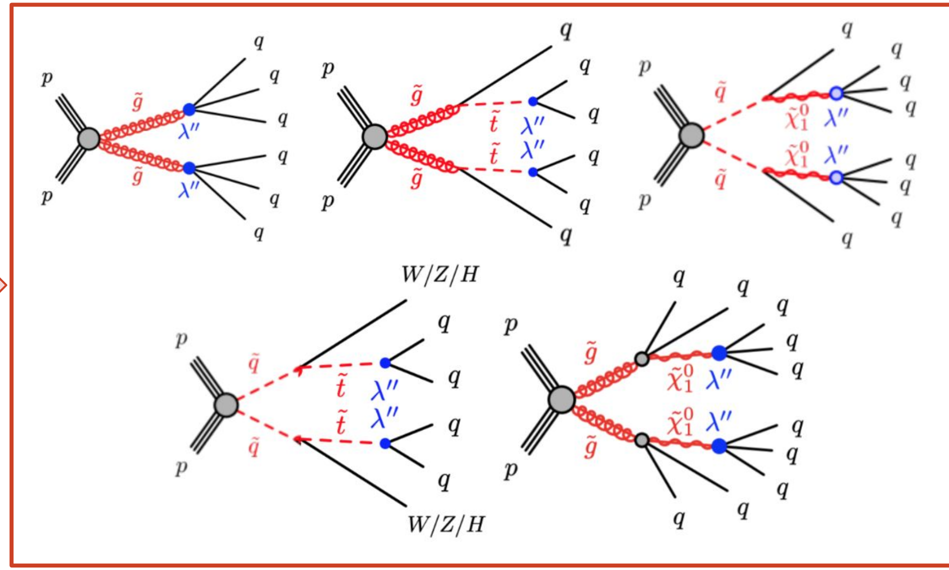


A few words on extensions to RPV SUSY

The analysis reconstructs the gluino mass with a jet-matching NN, additional to a cut & count approach.

The signal is however not so resonant! What about a non-resonant AD for a multi-jet search? ;)





Conclusions

- **This is the first proposal of non-resonant anomaly detection using extrapolation methods!**
- **There are many interesting problems associated with extrapolation that are worth exploring in the future.**
- **We encourage future work to make it possible to look for non-resonant BSM signals!**

Thank you!

Get in touch: kbai@uoregon.edu

Acknowledgement

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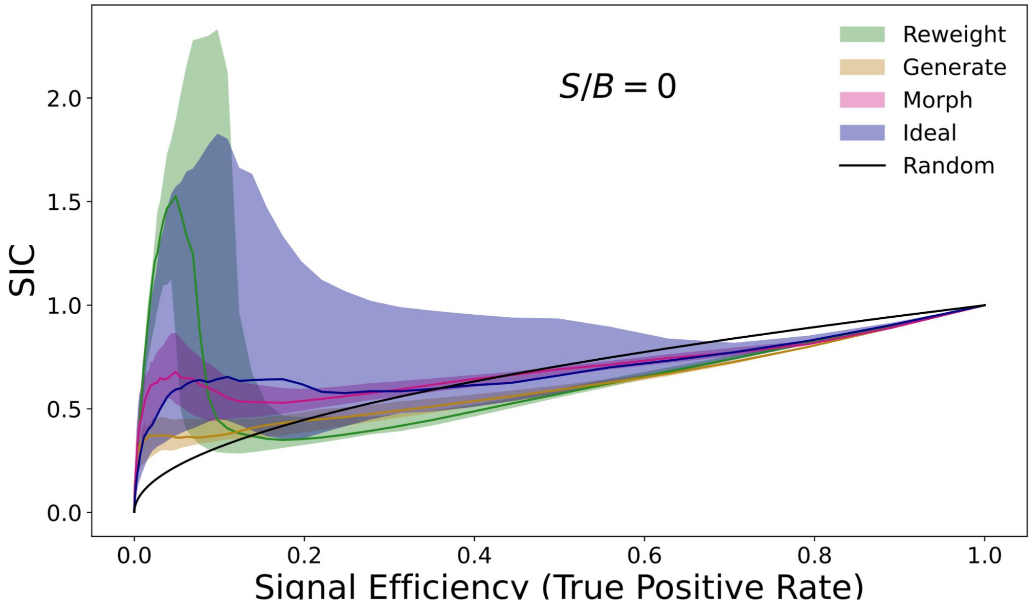
Back up

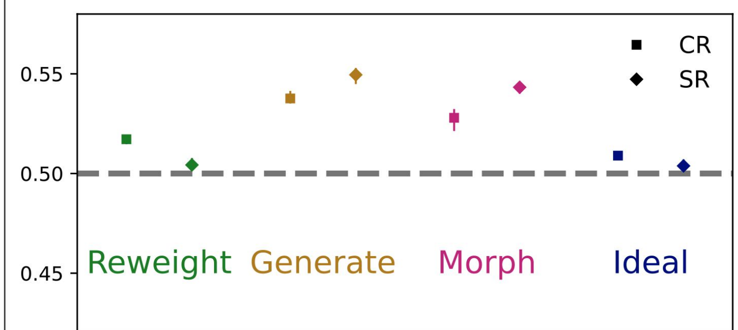
Zero-signal injection

SIC and ROC AUCs at zero-signal injection, showing a non-biased background estimation.

➔ Low false-positives.



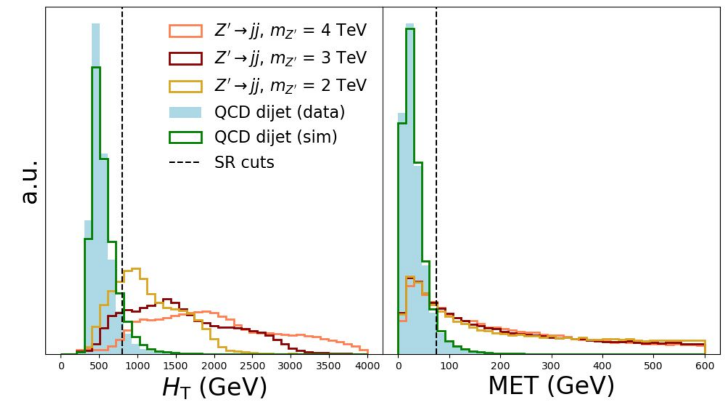
ROC AUCs (area-under-curves) compared with true random

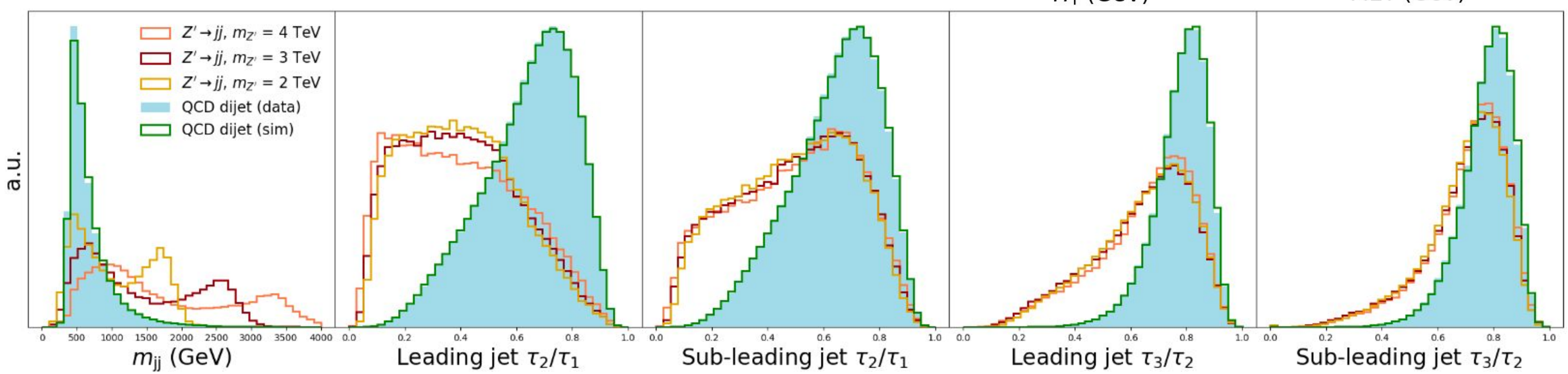


Other signal parameters

Lower Z' masses:

- $mZ' = 2$ TeV, $m_{\pi D} = m_{\rho D} = \Lambda_D = 200$ GeV, and $m_{qD} = 100$ GeV
- $mZ' = 3$ TeV, $m_{\pi D} = m_{\rho D} = \Lambda_D = 300$ GeV, and $m_{qD} = 150$ GeV





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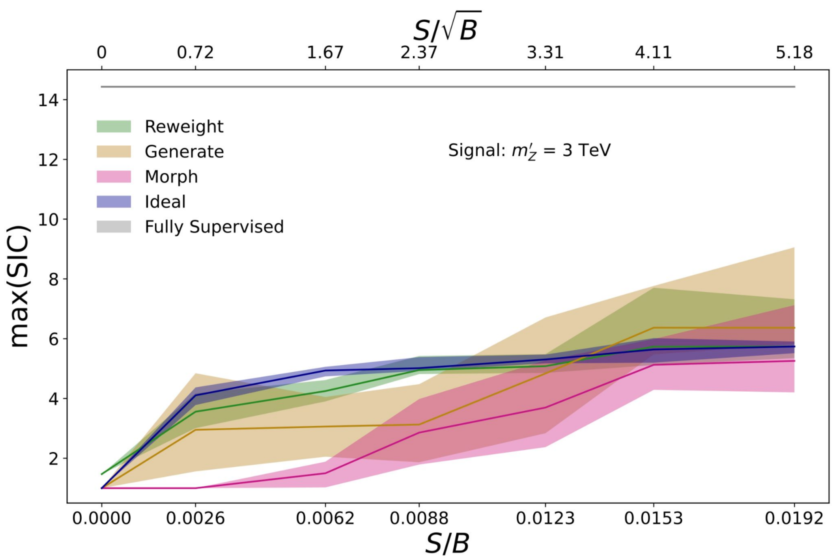
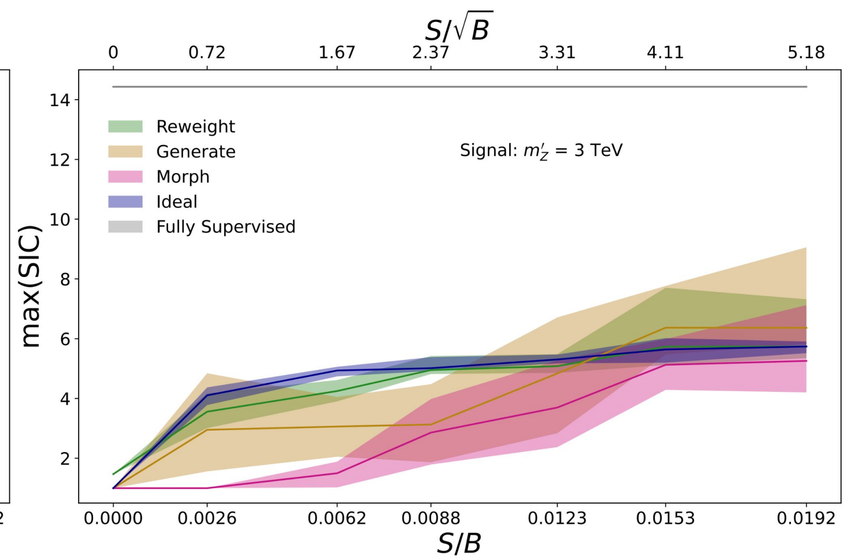
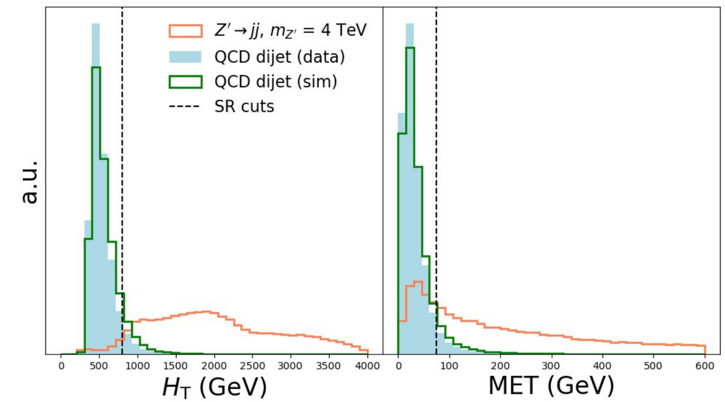


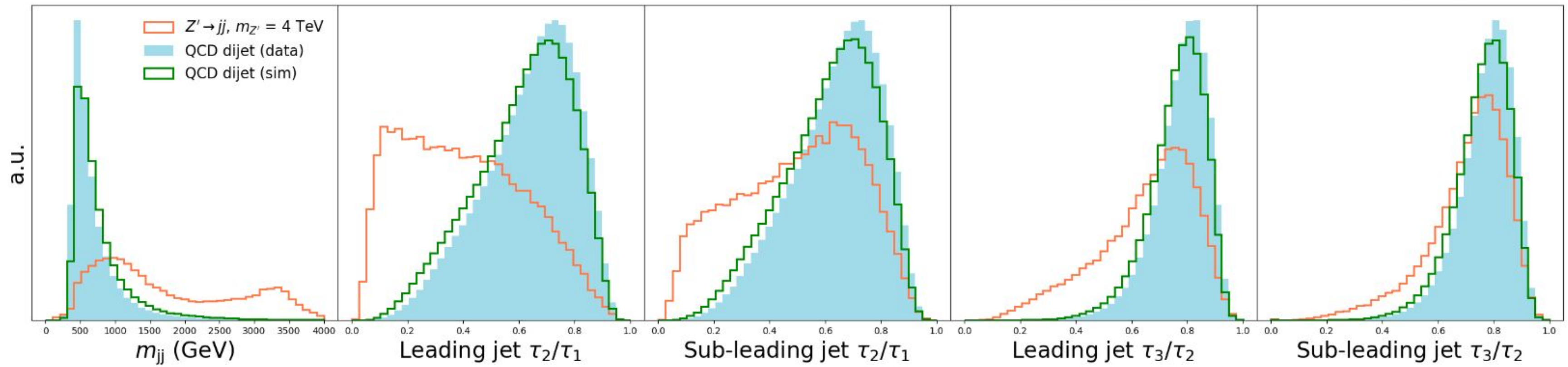


A hand-tuned background simulation

Change the simulation shape to look more different from the data.

$$H_T: \quad x \to x$$
$$\text{MET}: \quad x \to x(1+\frac{x}{500})$$
$$m_{jj}: \quad x \to x(1+\frac{x}{6000})$$
$$\tau_i: \quad x \to x^{1.1}.$$





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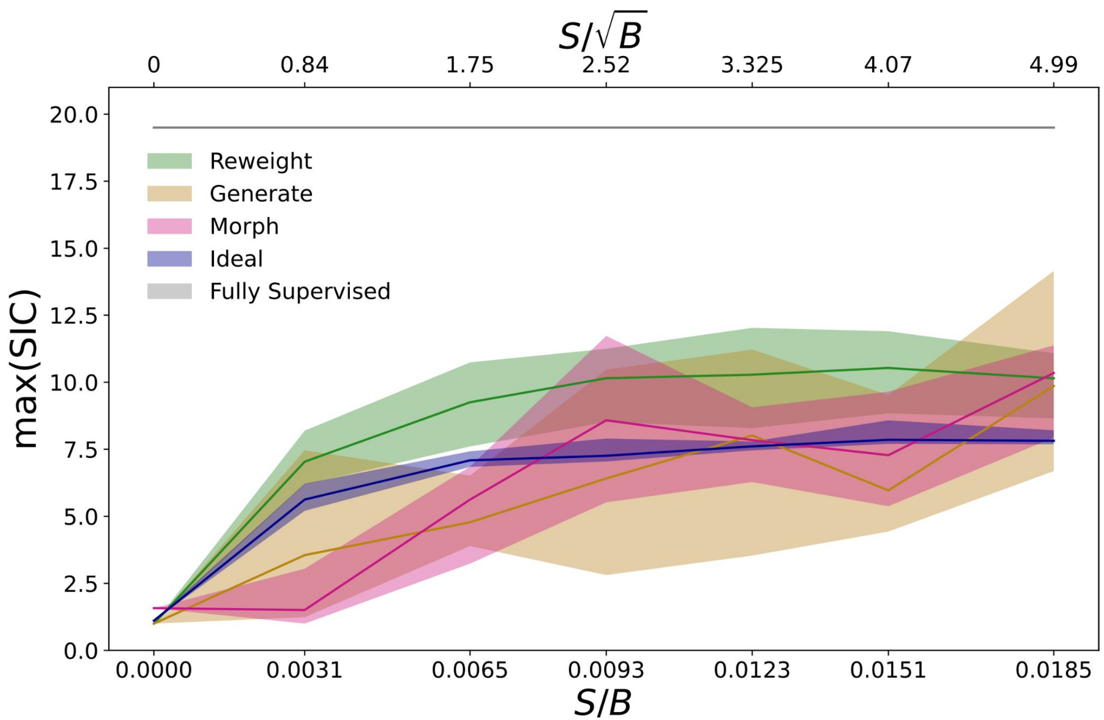

SIC evaluated at a rejection of 10^3