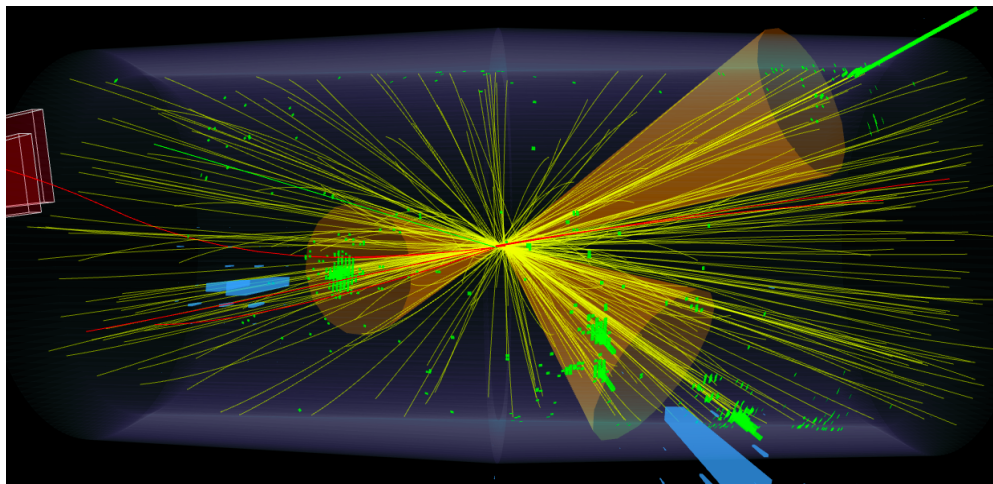


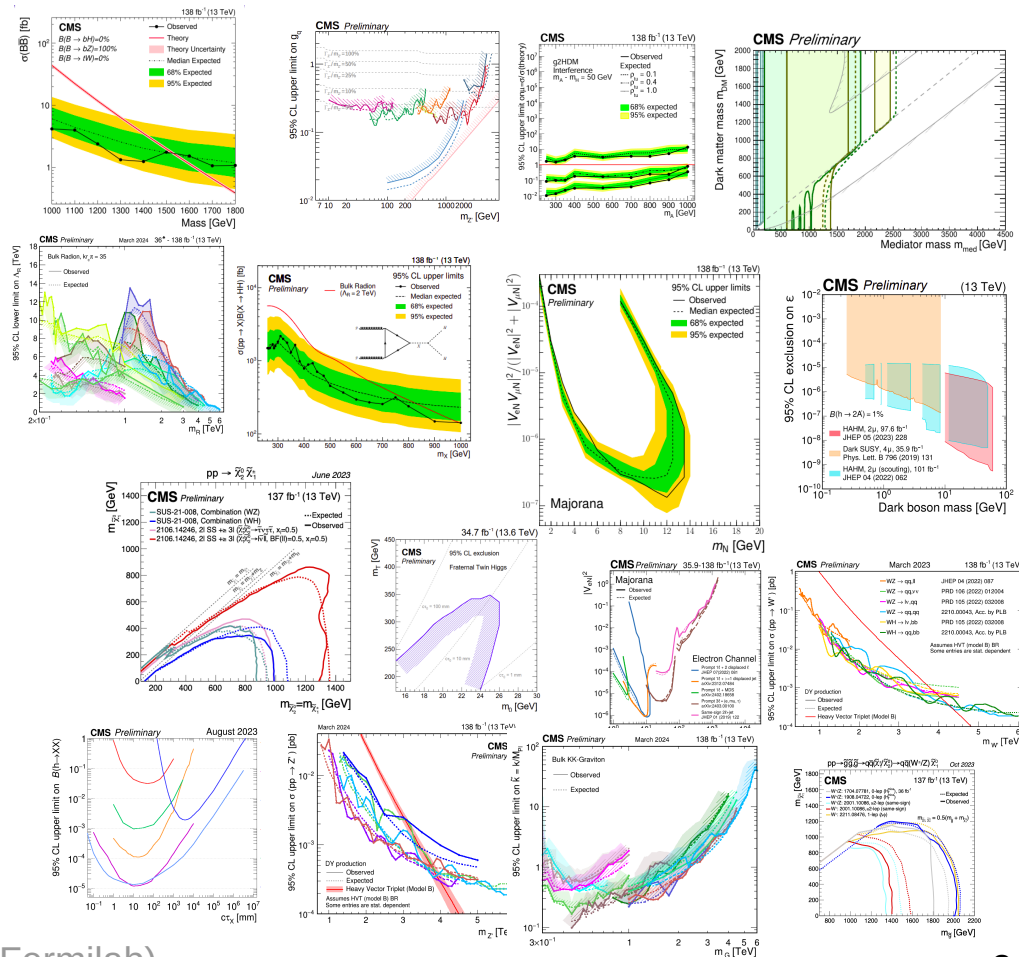
Results from CMS

Dijet Anomaly Detection Search



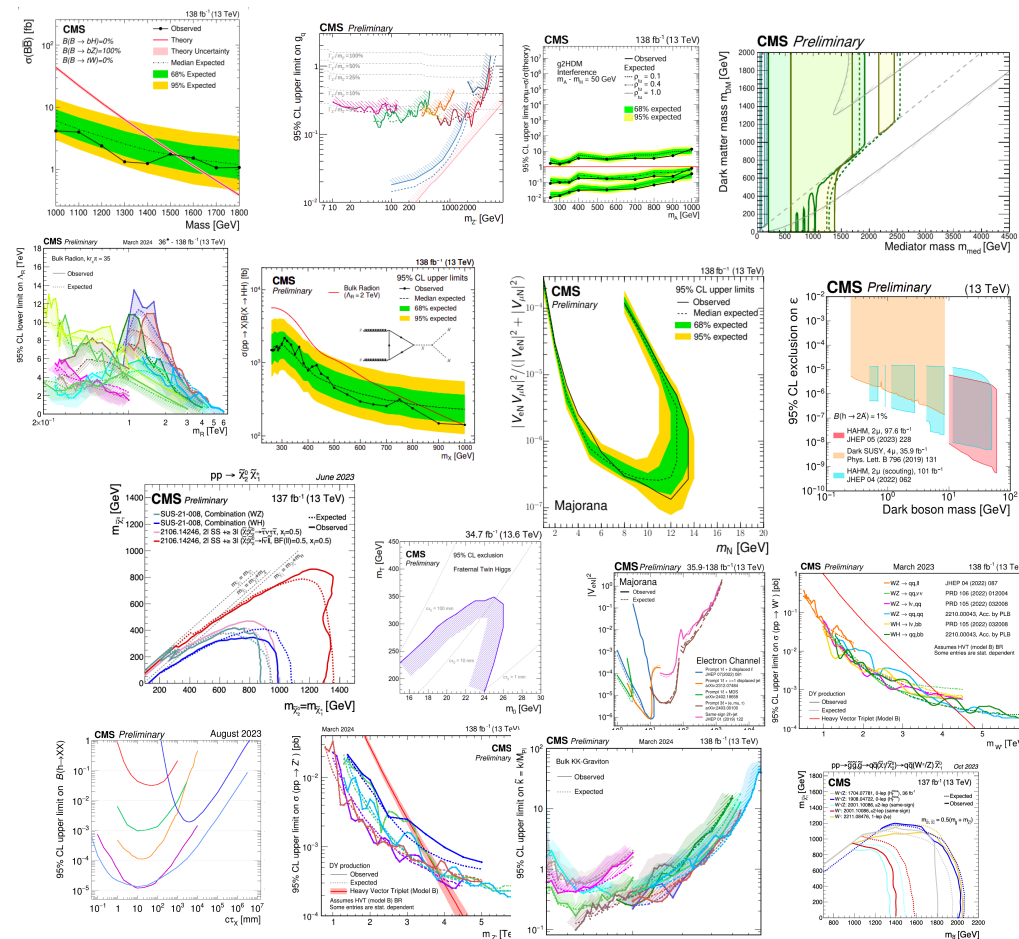
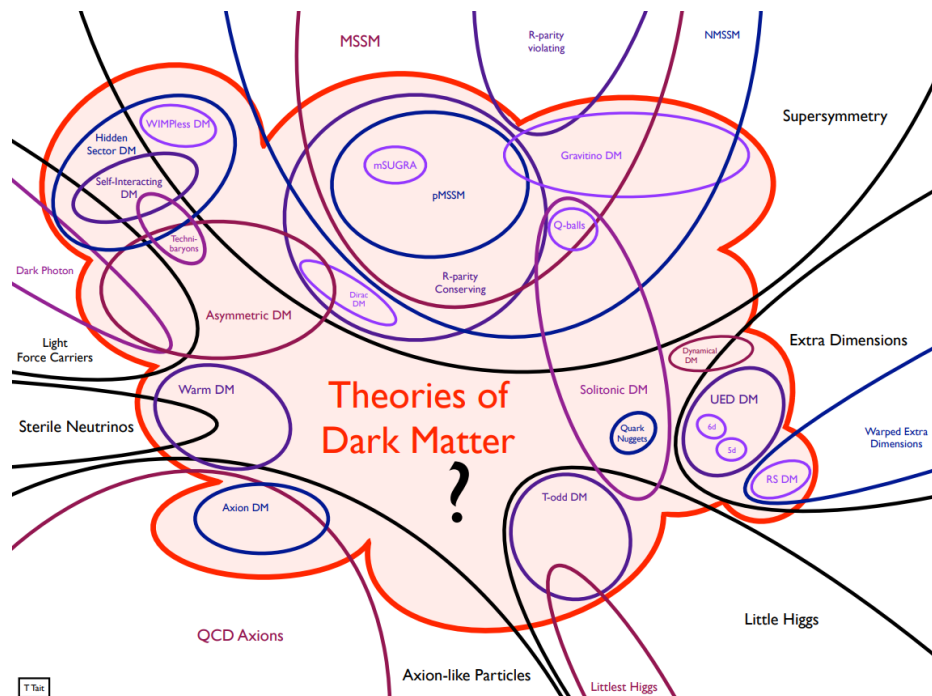
Motivation

Many LHC searches but no new physics so far



Motivation

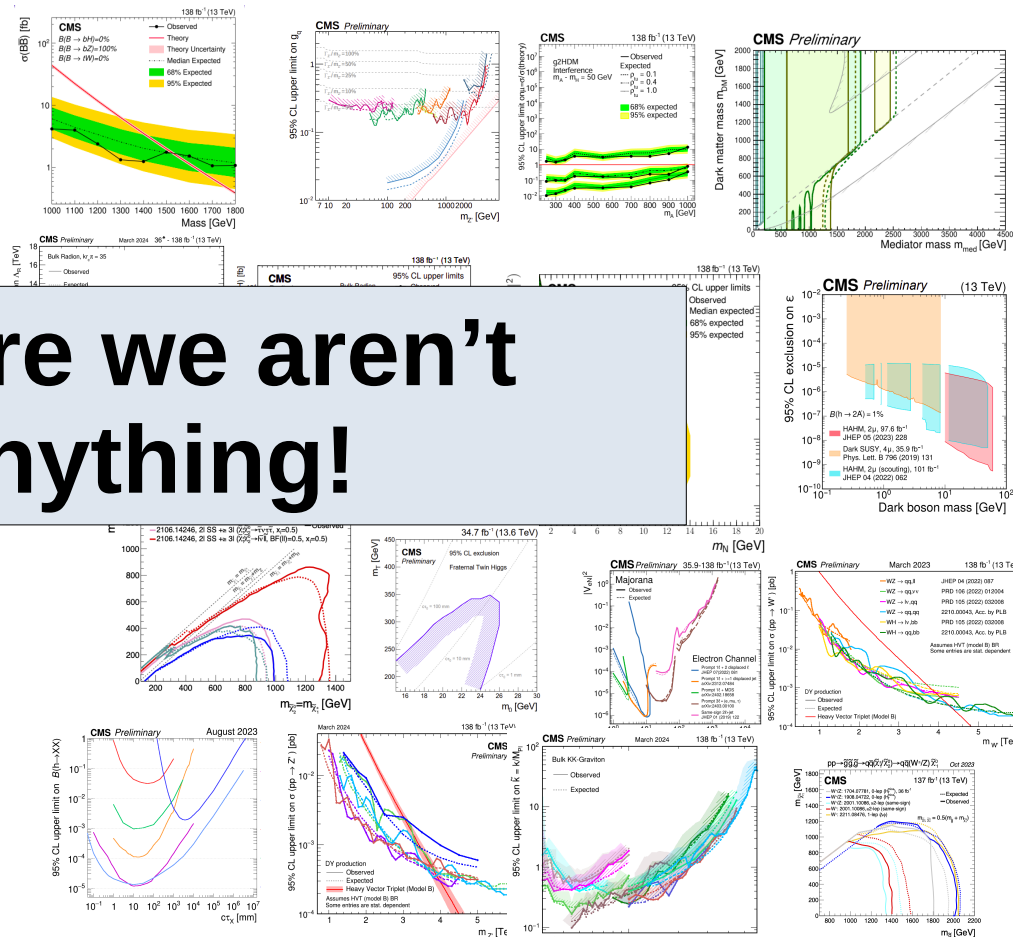
But...



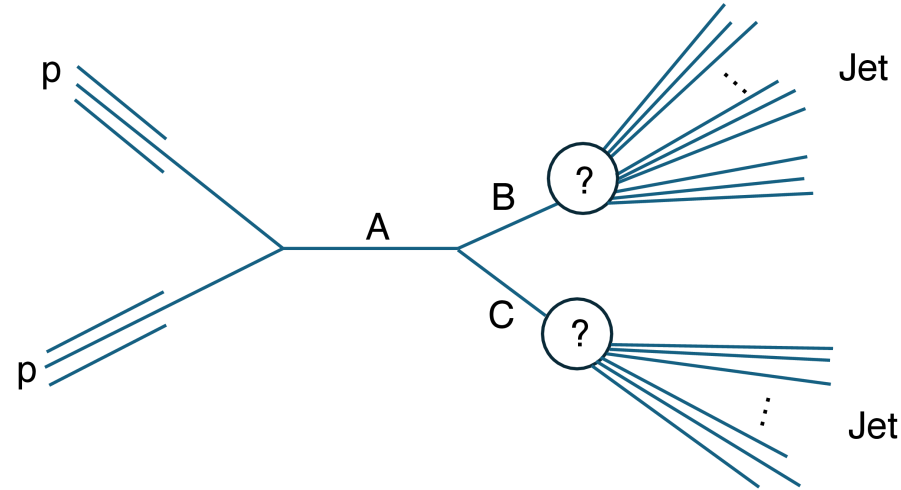
Motivation

But...

Lets make sure we aren't missing anything!



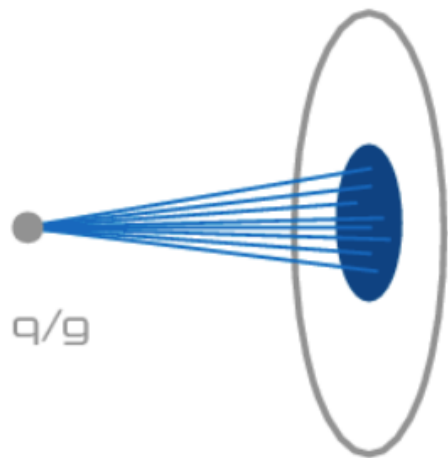
Dijet Resonance Anomaly Search



Results from
ROPP 88 067802
[arXiv:2412.03747](https://arxiv.org/abs/2412.03747)

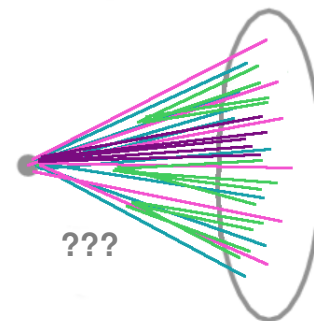
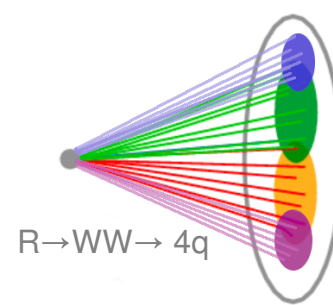
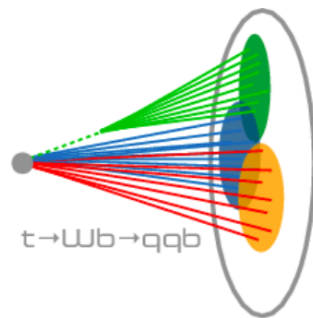
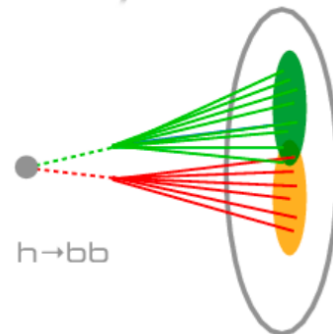
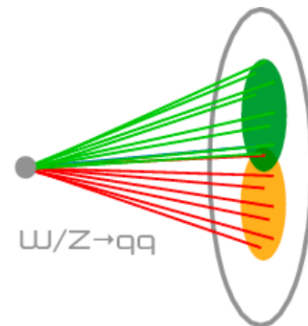
- **A** $\rightarrow$ **BC** topology
 - Heavy resonance (A) $\rightarrow$ daughters B and C
 - B & C are boosted $\rightarrow$ contained in a large radius jet
- Look for B & C jets with ‘anomalous’ substructure

Jet Substructure



Typical jet

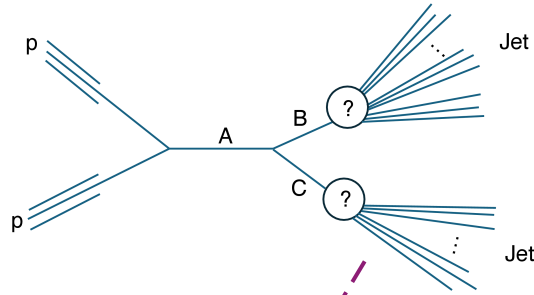
- One central axis (prong)
- From primary vertex
- ...



Anomalous jets

- Multiple prongs
- Displaced vertices
- ???

Signal Models



Picked a set of unexplored models to
evaluate performance

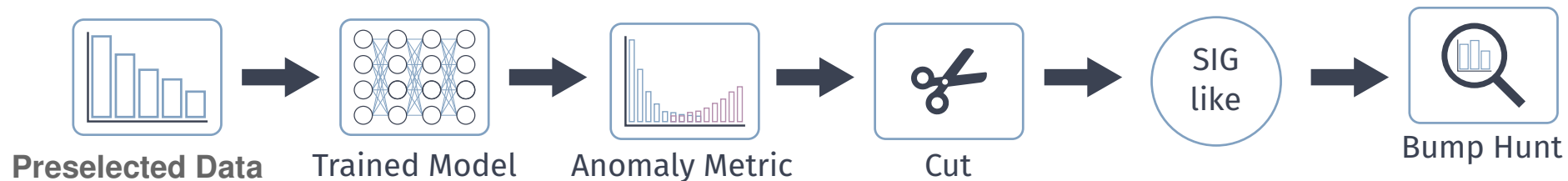
**B Jet
substructure**

**C Jet
substructure**

	1 prong	2 prong	3 prong	4 prong	5 prong	6 prong
1 prong		$Q^* \rightarrow qW$ $m_{Q^*} = [2,3,5] \text{ TeV}$ $m_W = [25,80,170,400] \text{ GeV}$				
2 prong		$X \rightarrow YY'$ $m_X = [2,3,5] \text{ TeV}$ $m_Y = [25,80,170,400] \text{ GeV}$ $m_{Y'} = [25,80,170,400] \text{ GeV}$		$W_{KK} \rightarrow RW \rightarrow WWW$ $m_{WWW} = [2,3,5] \text{ TeV}$ $m_R = [170,400] \text{ GeV}$		
3 prong			$W' \rightarrow tB'$ $m_{W'} = [2,3,5] \text{ TeV}$ $m_{B'} = [25,80,170,400] \text{ GeV}$			
4 prong				$X \rightarrow YH \rightarrow WWW$ $m_X = [2,3,5] \text{ TeV}$ $m_Y = [170,400] \text{ GeV}$ $m_H = [170,400] \text{ GeV}$		
5 prong					$Z' \rightarrow T'T' \rightarrow tZtZ$ $m_{Z'} = [2,3,5] \text{ TeV}$ $m_T = [400] \text{ GeV}$	
6 prong						$Y \rightarrow HH \rightarrow tttt$ $m_Y = [2,3,5] \text{ TeV}$ $m_H = [400] \text{ GeV}$

Expect
sensitivity to
many additional
kinds of signals!

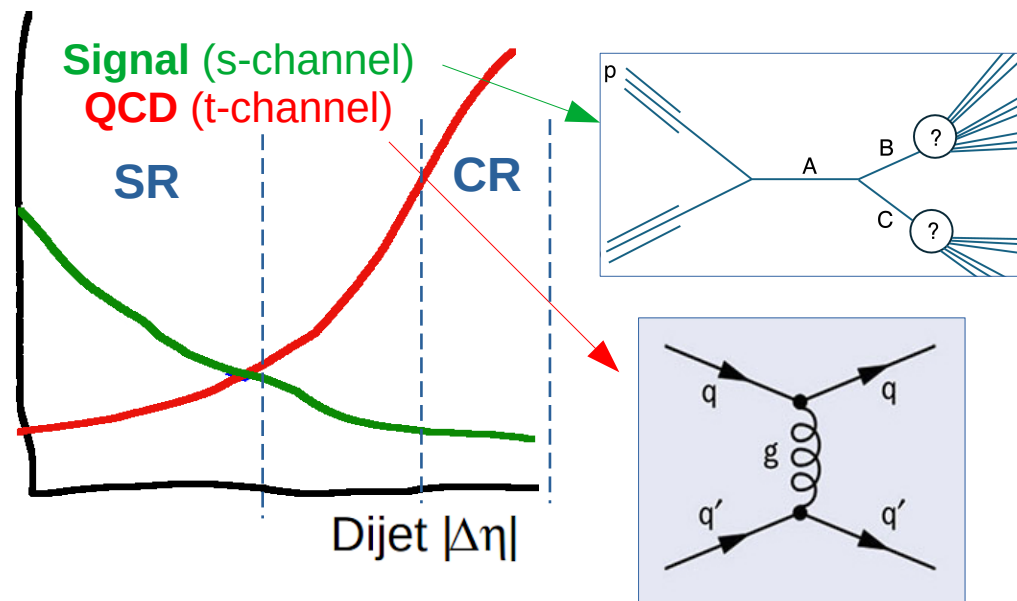
Analysis Overview



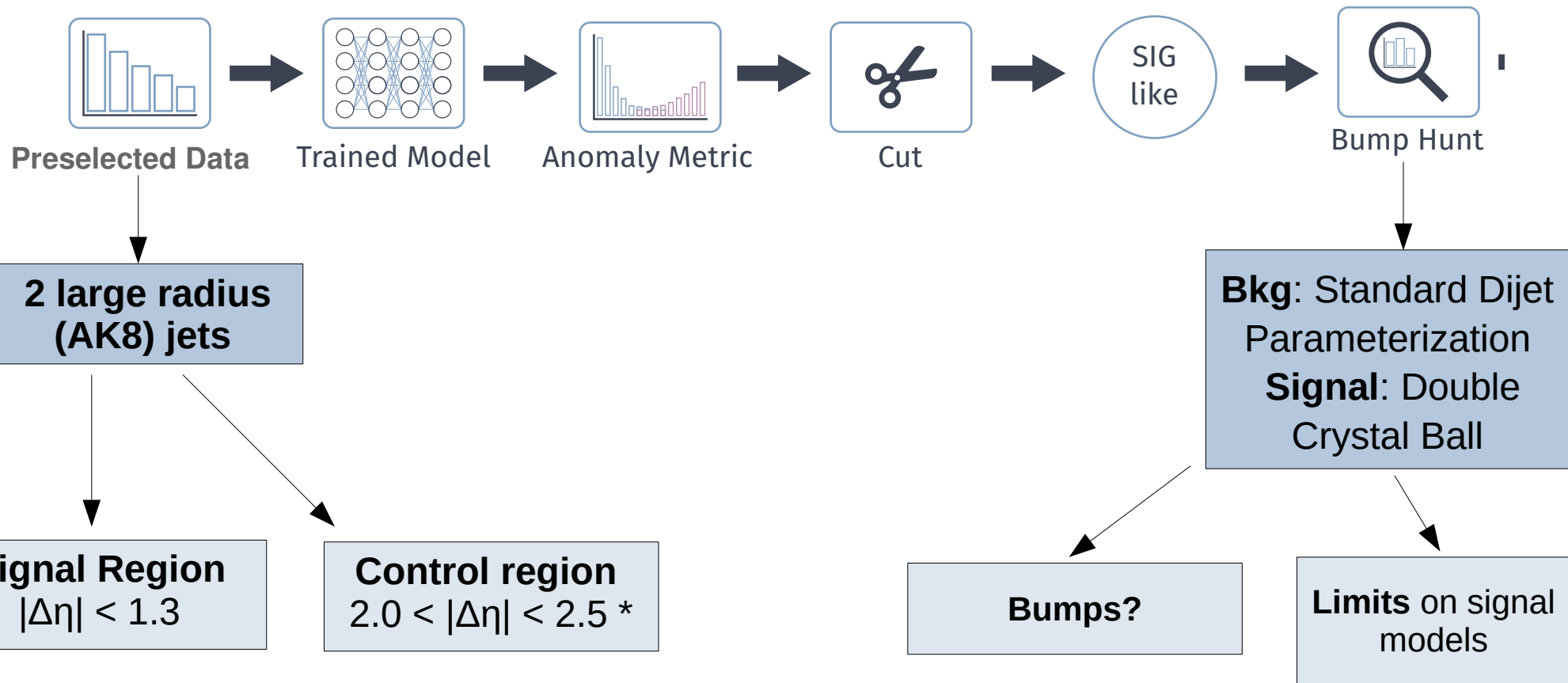
**2 large radius
(AK8) jets**

Signal Region
 $|\Delta\eta| < 1.3$

Control region
 $2.0 < |\Delta\eta| < 2.5^*$

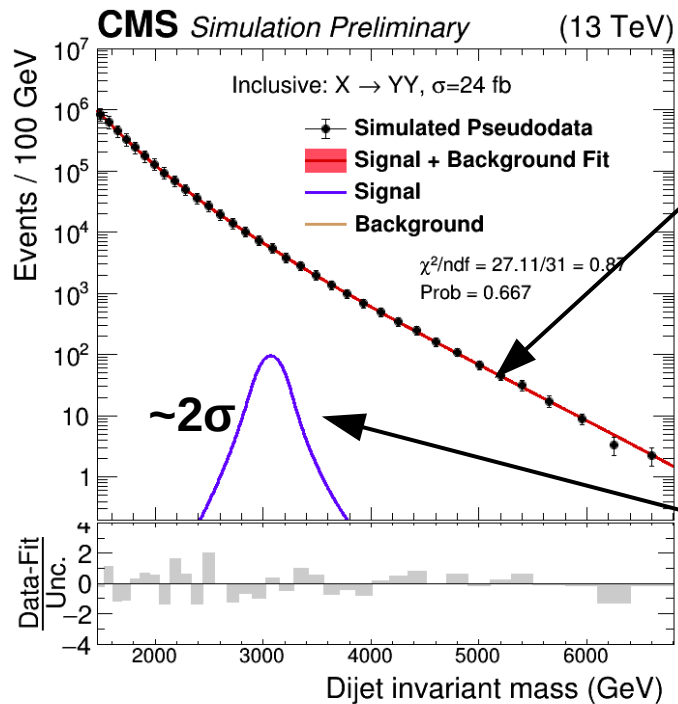


Analysis Overview



The Bump Hunt

CMS-NOTE
-2023-013



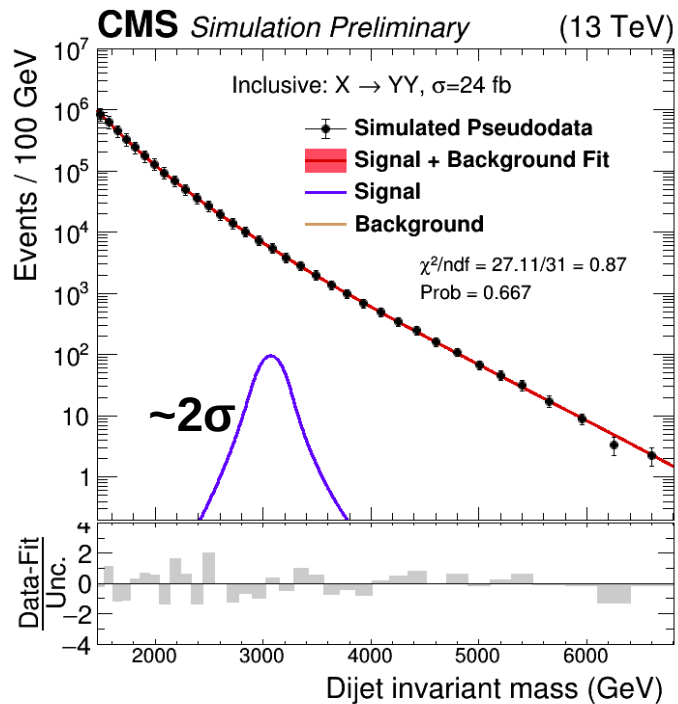
Background fit with
standard analytic functions

Double Crystal Ball
signal shape

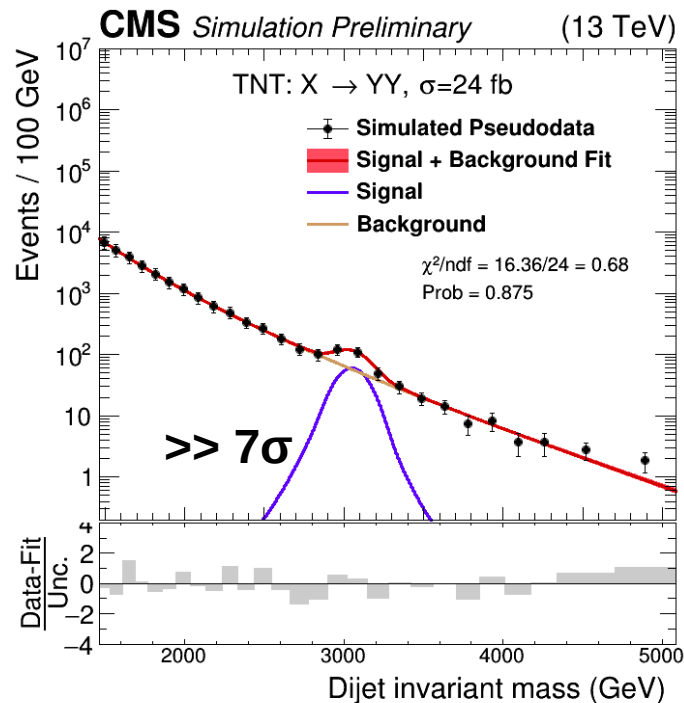
Without any substructure cuts →
Signal swamped by QCD background...

The Bump Hunt

CMS-NOTE
-2023-013

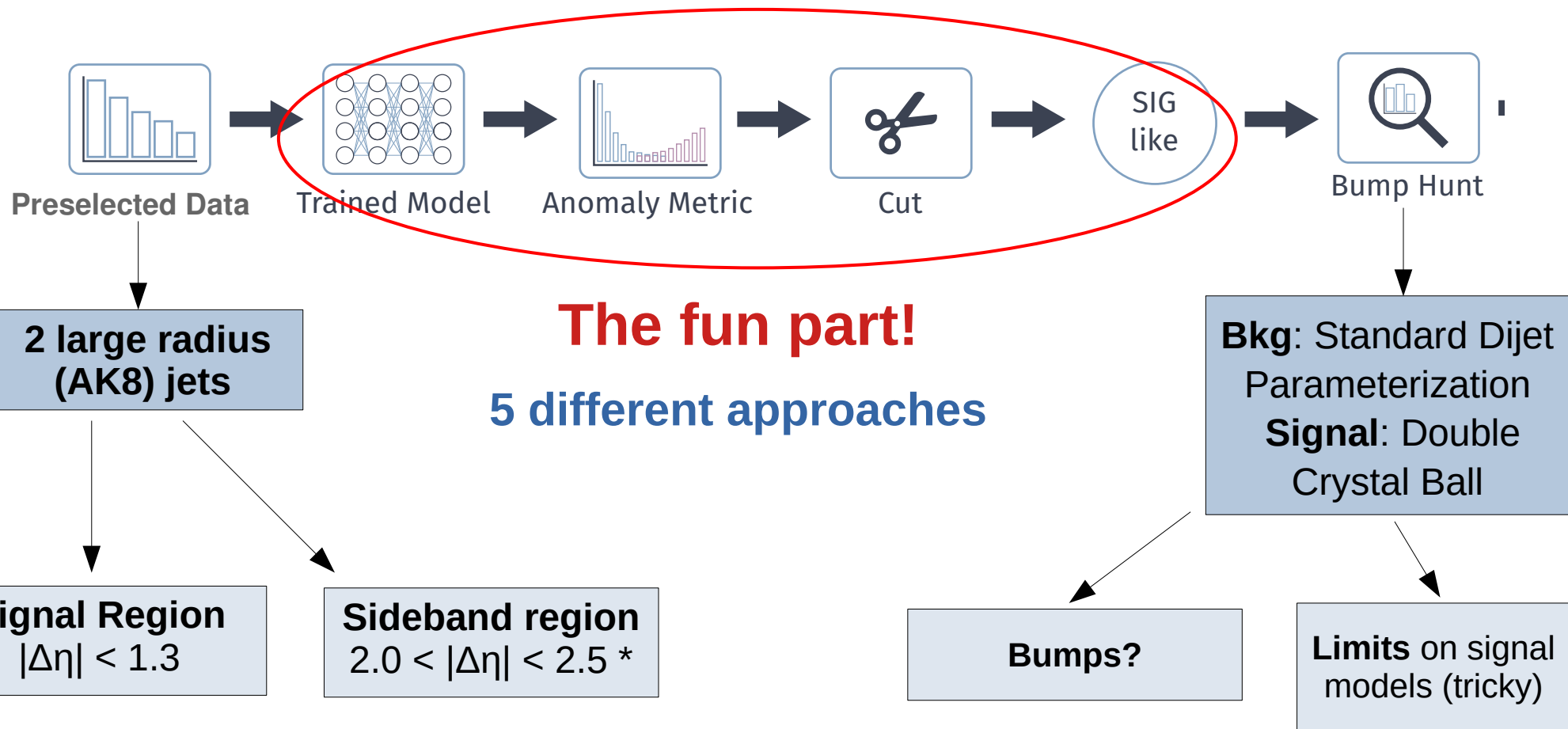


Cut on anomaly
score



**Anomaly detection
finds hidden resonance!**

Analysis Overview

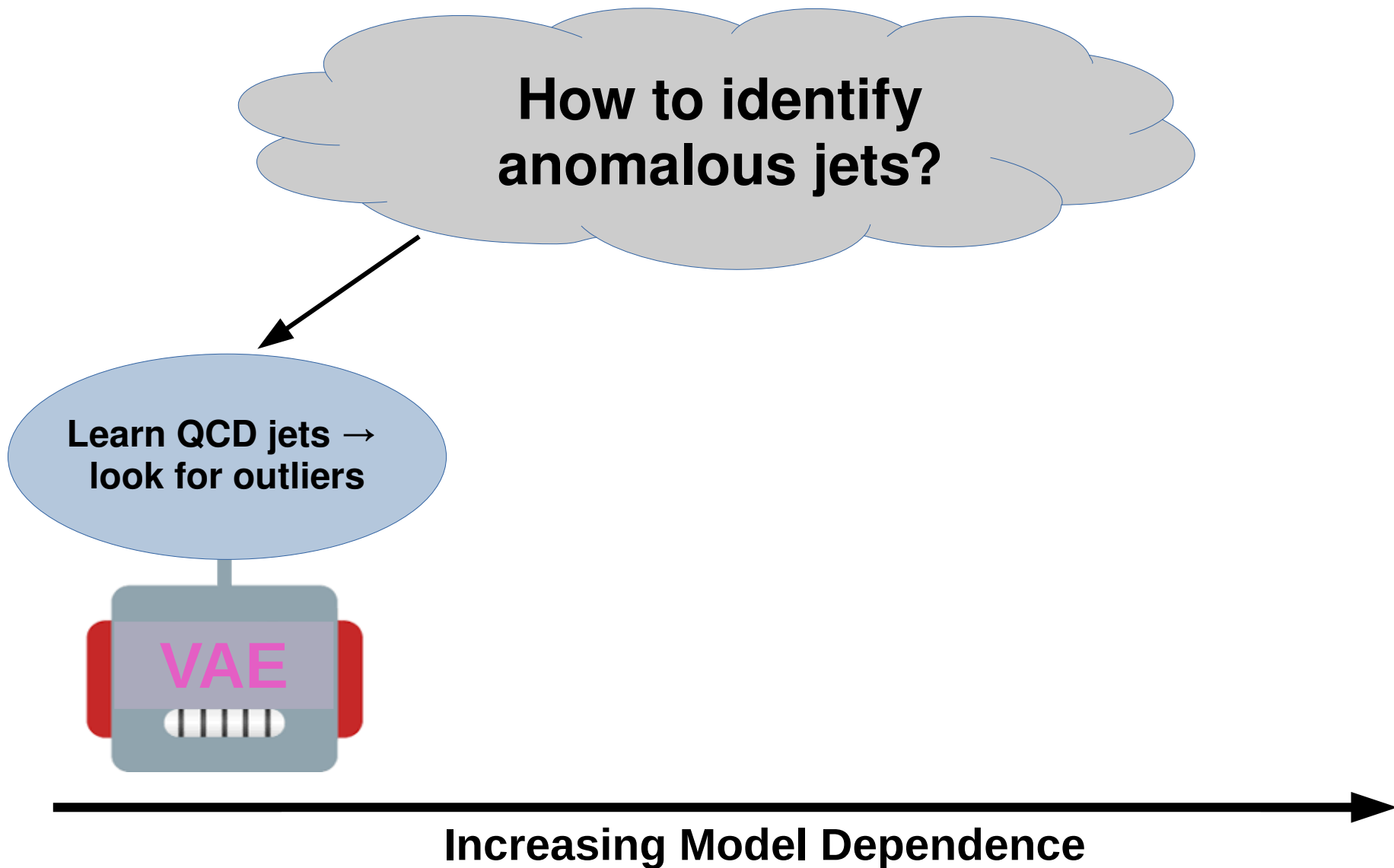


**How to identify
anomalous jets?**

**Learn QCD jets →
look for outliers**

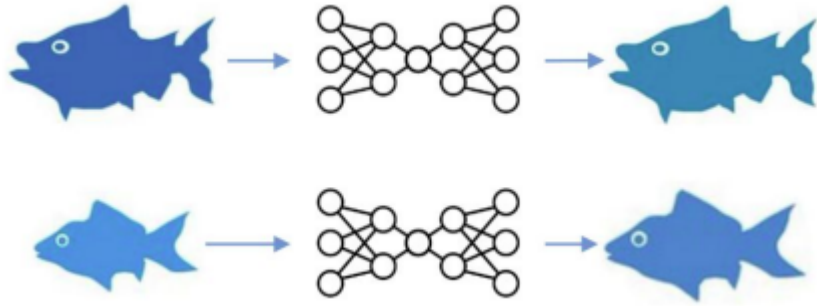
VAE

Increasing Model Dependence



Looking for Outliers

Train 'Autoencoder'

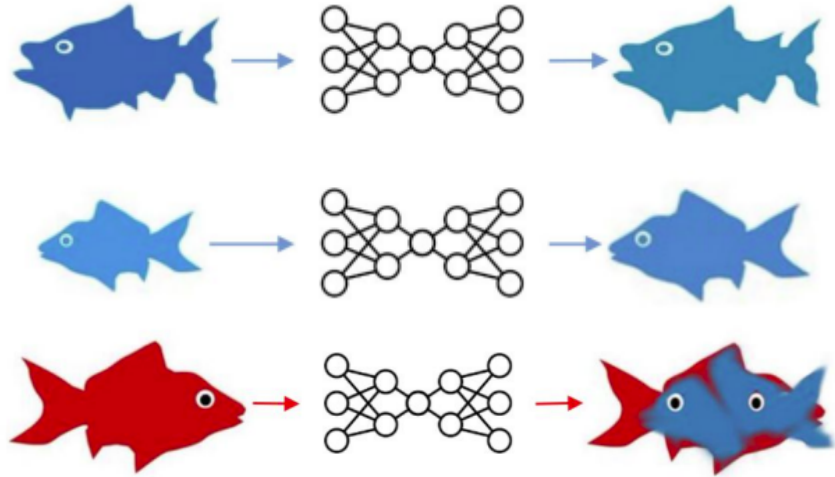


Training Sample from data sideband



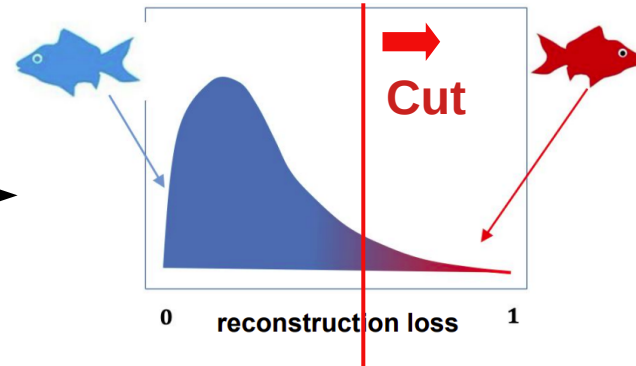
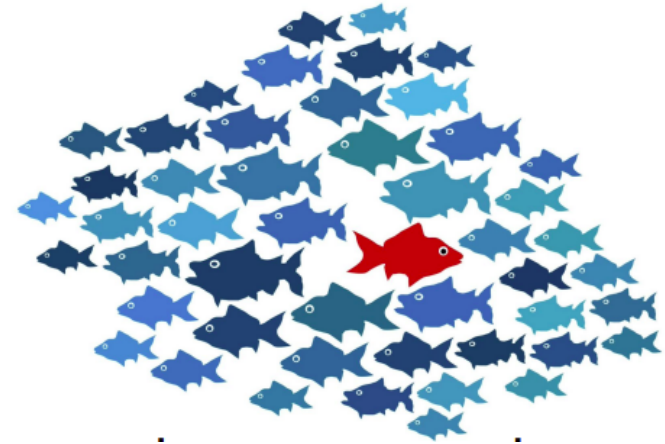
Looking for Outliers

Apply Autoencoder

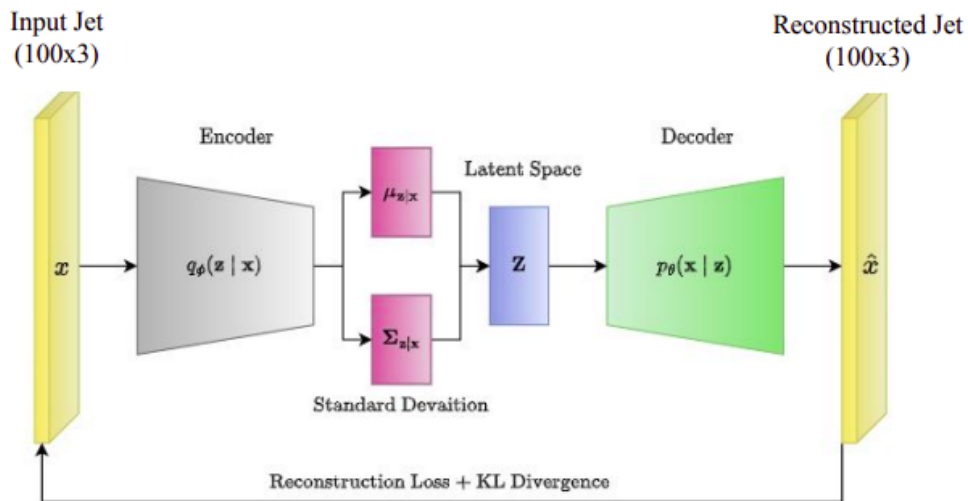


Take difference

Data from signal region



Variational Autoencoder (VAE)



Latent space forced to be Gaussian
thru additional term in loss

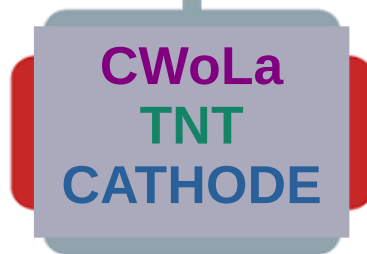
- Jet represented by up to 100 highest p_T constituents (p_x, p_y, p_z)
- 100×3 matrix compressed to latent space of size 12
- Trained on jets from $|\Delta\eta|$ sideband
 - Sampled to match SR kin.

How to identify anomalous jets?

Learn QCD jets →
look for outliers



Look for overdensities
of signal in data
→ Learn to tag sig vs bkg

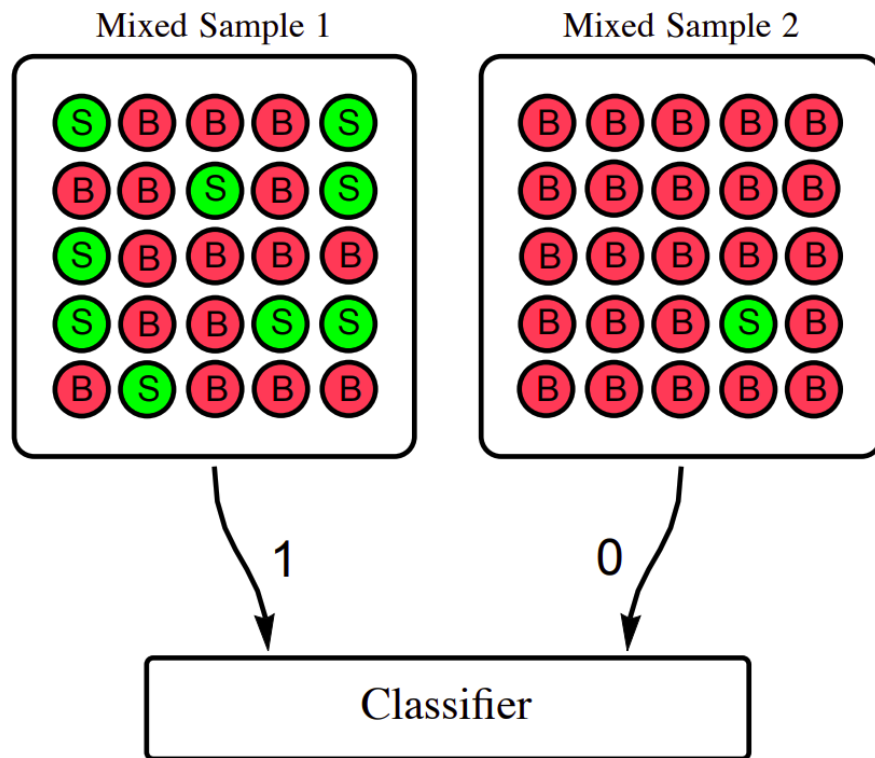


Increasing Model Dependence

Weak Supervision

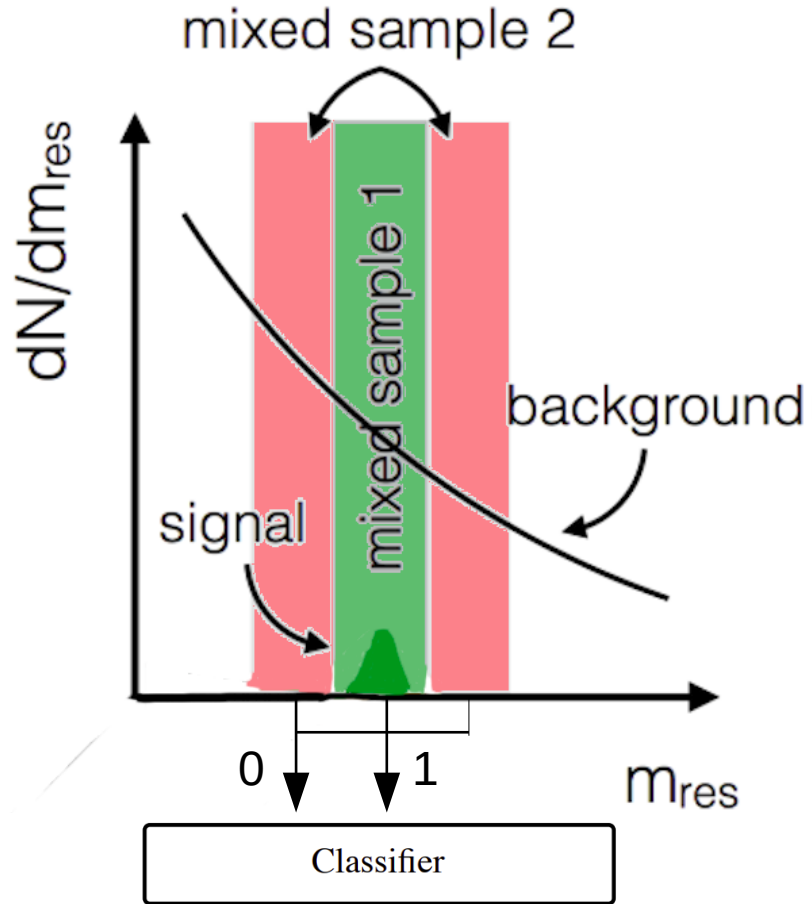
Aka 'Classification Without Labels' (CWoLa)

Train on two mixed samples



- Train a classifier between **signal-rich** and **background-rich** mixed samples
 - Learns to tag **signal** vs. **bkg**
- Performance changes with amount of **signal** in training data
 - No signal → learn random noise
 - Lots of signal → approach 'supervised' (optimal) classifier

CWoLa Hunting

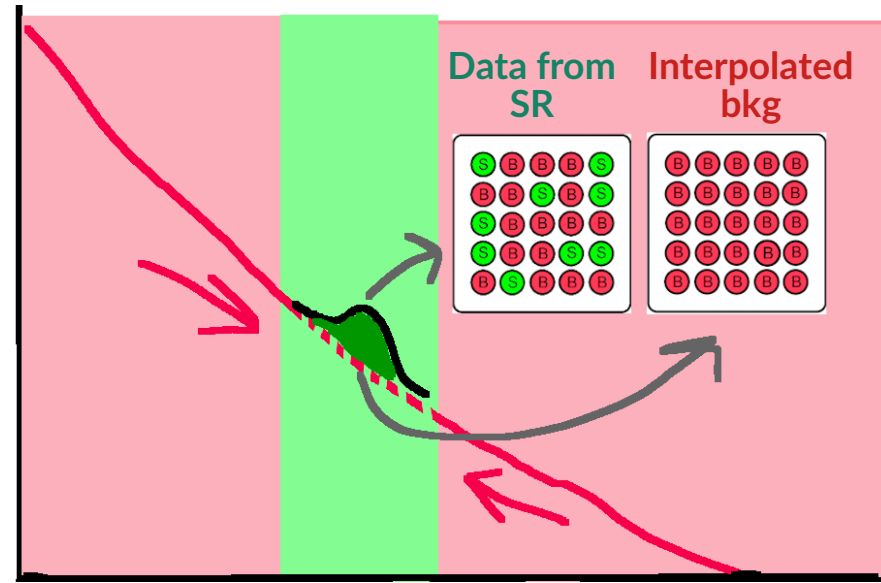


- Assume **signal** is a **narrow** resonance
- **Guess** a mass window where it lives
 - Train **signal window** vs. **narrow sidebands** using weak supervision
- **Repeat procedure**, scanning over different mass windows
 - (2x6 windows used)
- Need to be careful about correlations with M_{jj}

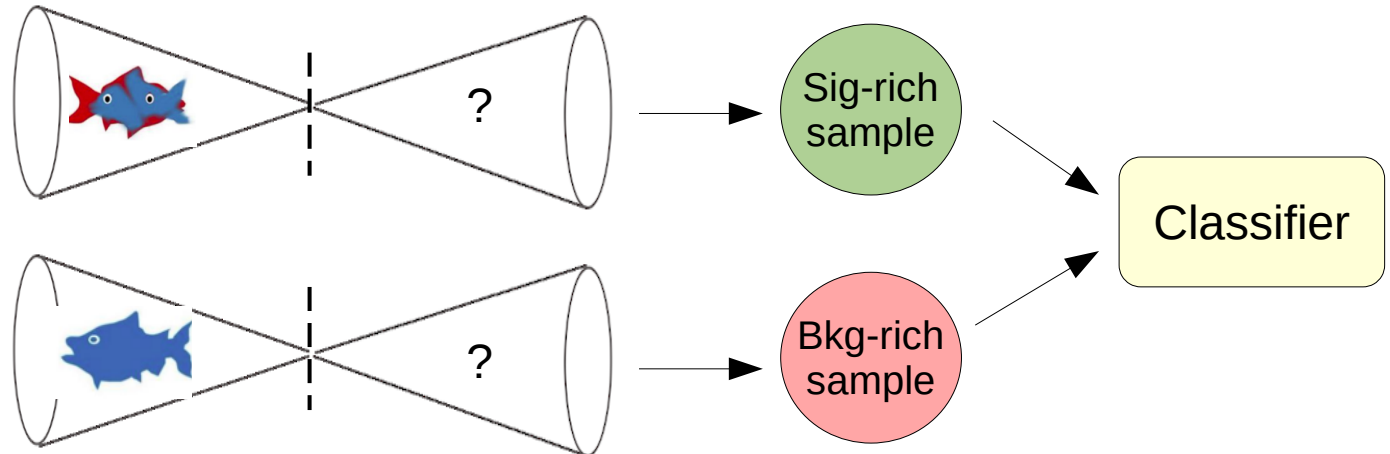
CATHODE

Interpolates bkg events into SR to construct sample

[Hallin et al [2109.00546](#)]



Tag N' Train
purifies samples by
first tagging with AE



[OA & Suarez [2002.12376](#)]

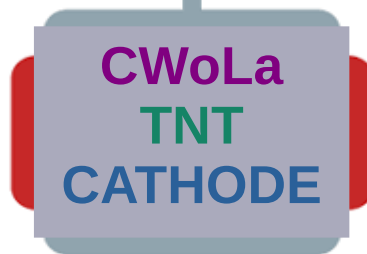
Oz Amram (Fermilab)

How to identify anomalous jets?

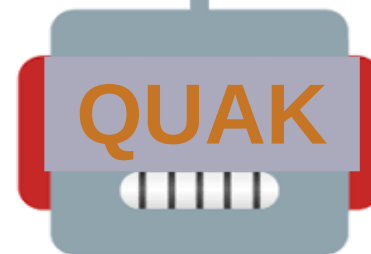
Learn QCD jets →
look for outliers



Look for overdensities
of signal in data
→ Learn to tag sig vs bkg



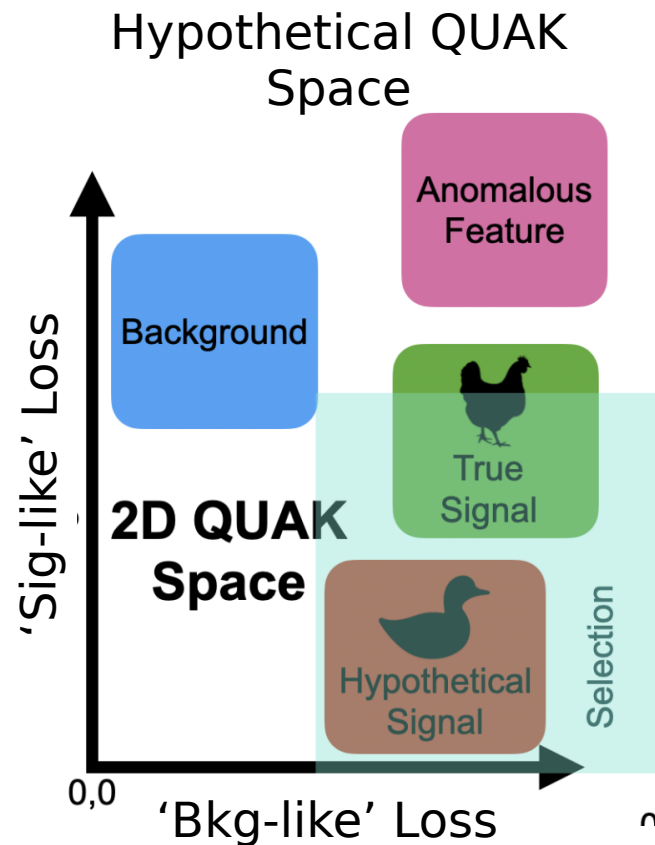
Encode a 'prior' of
potential signals →
look for similar



Increasing Model Dependence

Quasi Anomalous Knowledge (QUAK)

- **Hybrid approach** between fully model-indep. and standard search
- **Encode a prior** on what a potential signal may look like
 - Use an AE trained on a variety of different signal MC's
- Construct 'QUAK space':
 - Loss of signal AE vs bkg AE
- Select events with low sig loss and high bkg loss



Input Features

Low-level features

VAE

Jet Constituents

p_x, p_y, p_z

Hand-picked high-level features

**CWoLa
Hunting**

Jet mass

τ_{21}

τ_{32}

τ_{43}

N_{const}

Leptonic
energy frac.

Sub-jets b-tag
score

TNT

Same as
CWoLa Hunting

CATHODE

Jet masses

τ_{41} 's

CATHODE-b

+ Subjet b-tag
scores

QUAK

$\rho = \text{jet mass} / p_T$

τ_{21} 's

τ_{32} 's

τ_{43} 's

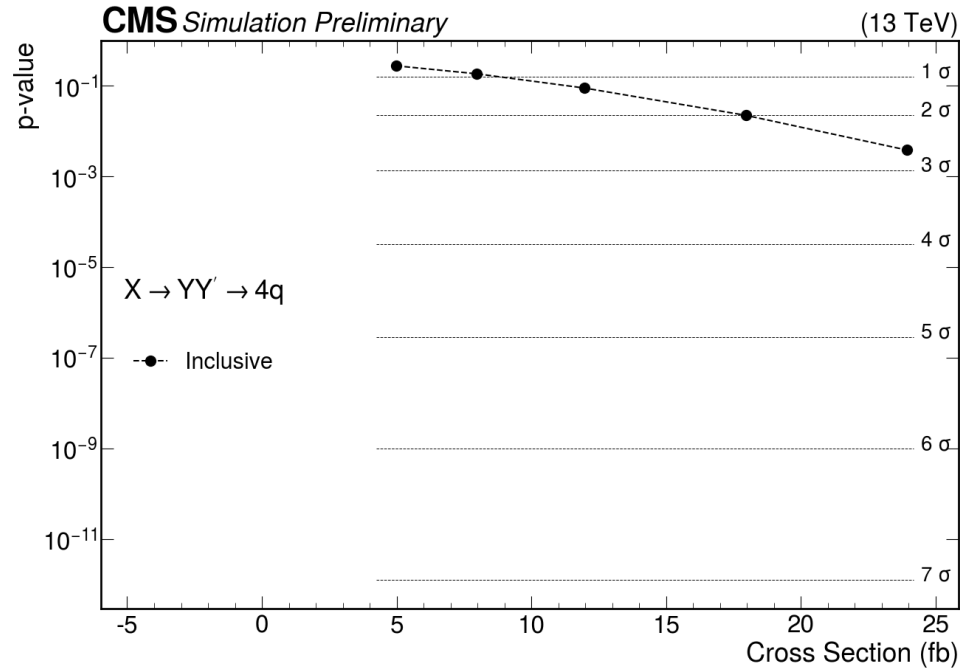
N_{const} 's

$\sqrt{\tau_{21}/\tau_1}$

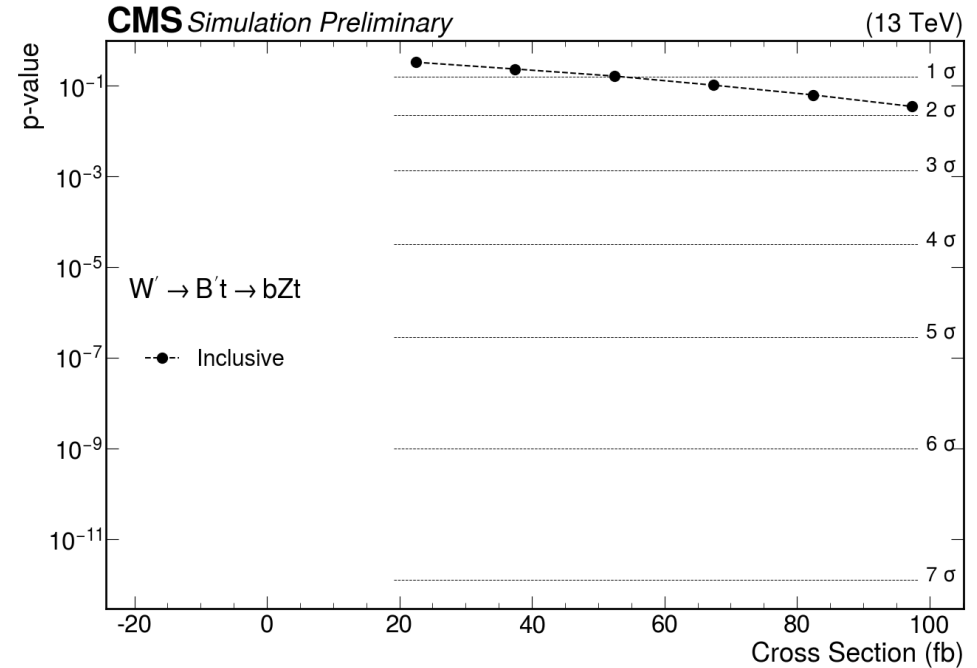
Sub-jets b-tag
scores

Sensitivity

2 Pronged Signal



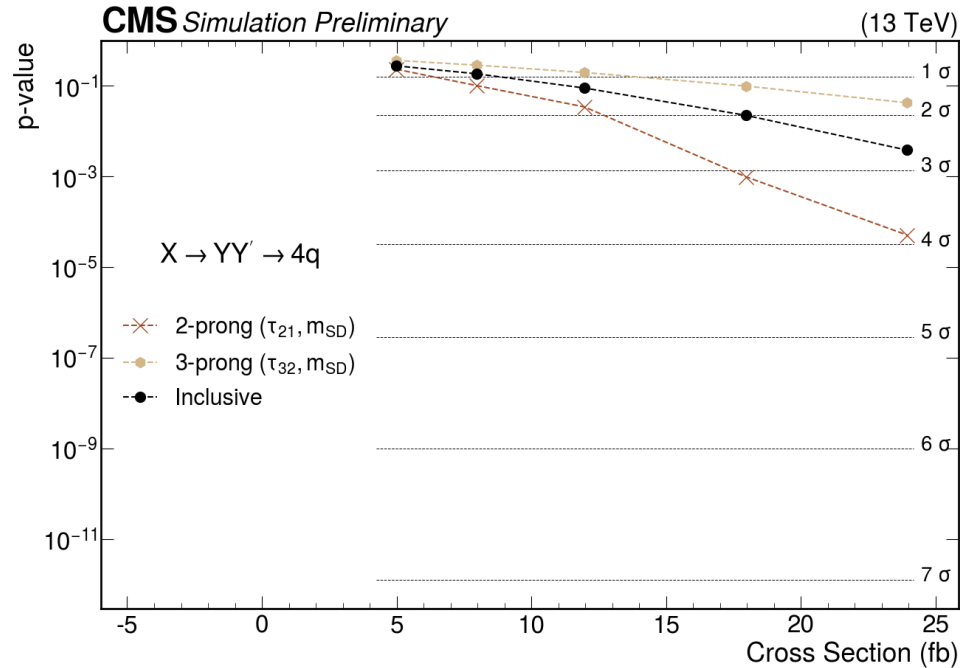
3 Pronged Signal



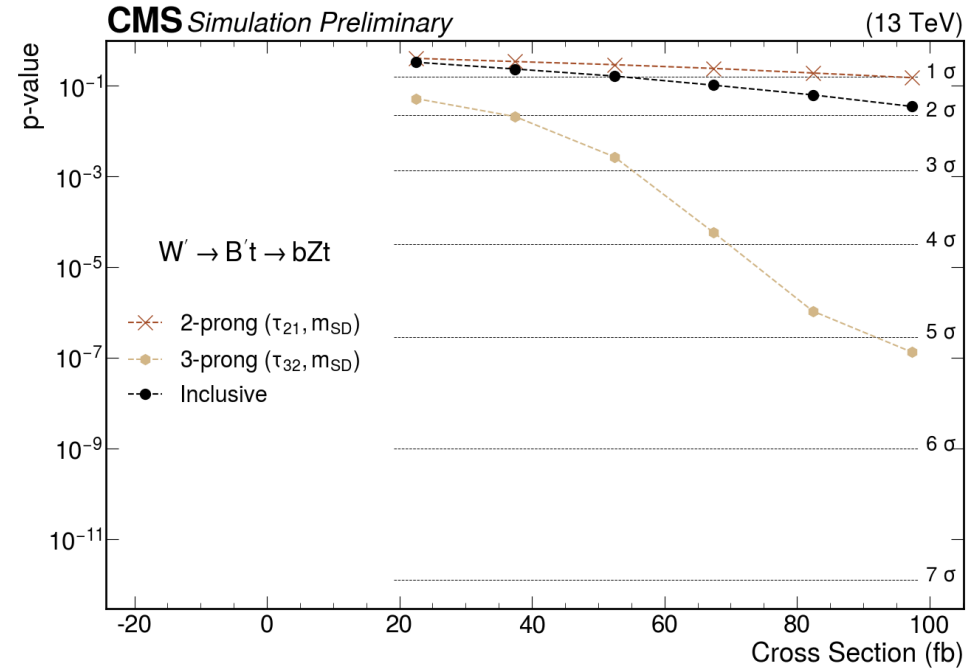
Inclusive analysis (no substructure cuts) sees only “hints”

Sensitivity

2 Pronged Signal



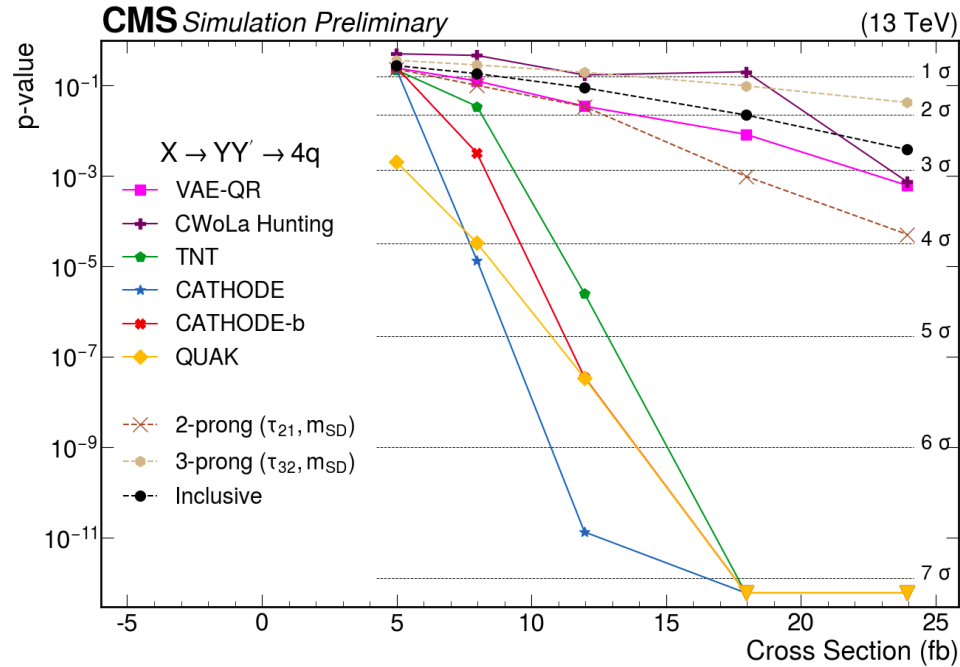
3 Pronged Signal



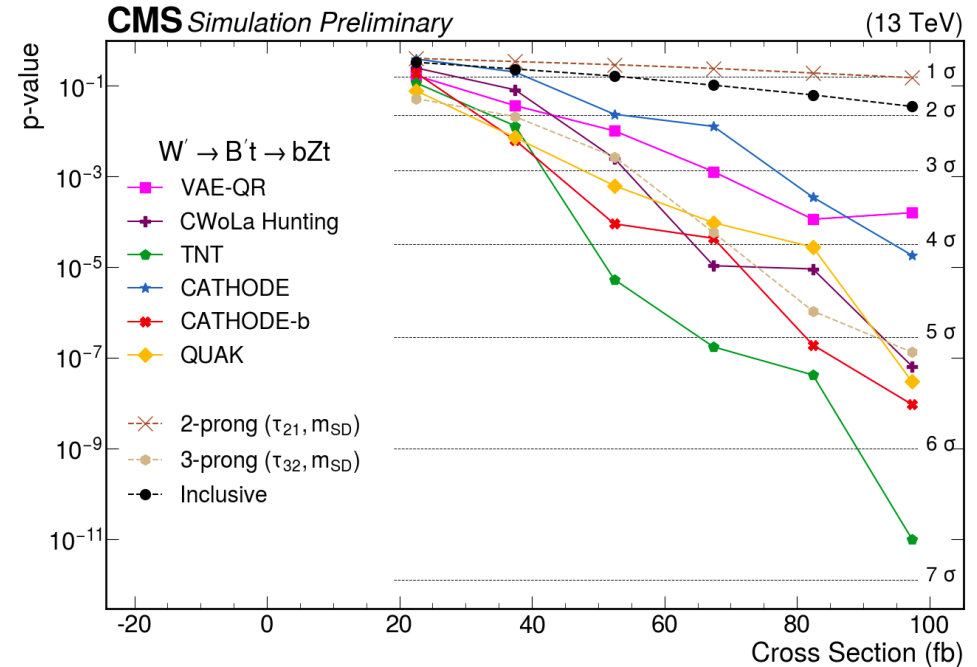
Traditional substructure cuts enhance sensitivity for a specific model, but not others

Sensitivity

2 Pronged Signal



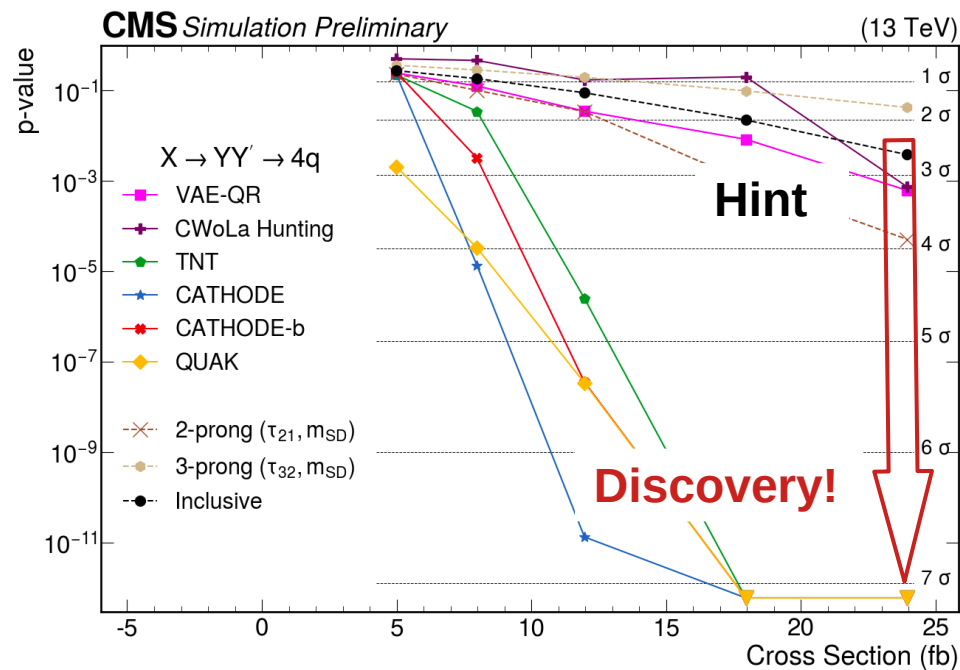
3 Pronged Signal



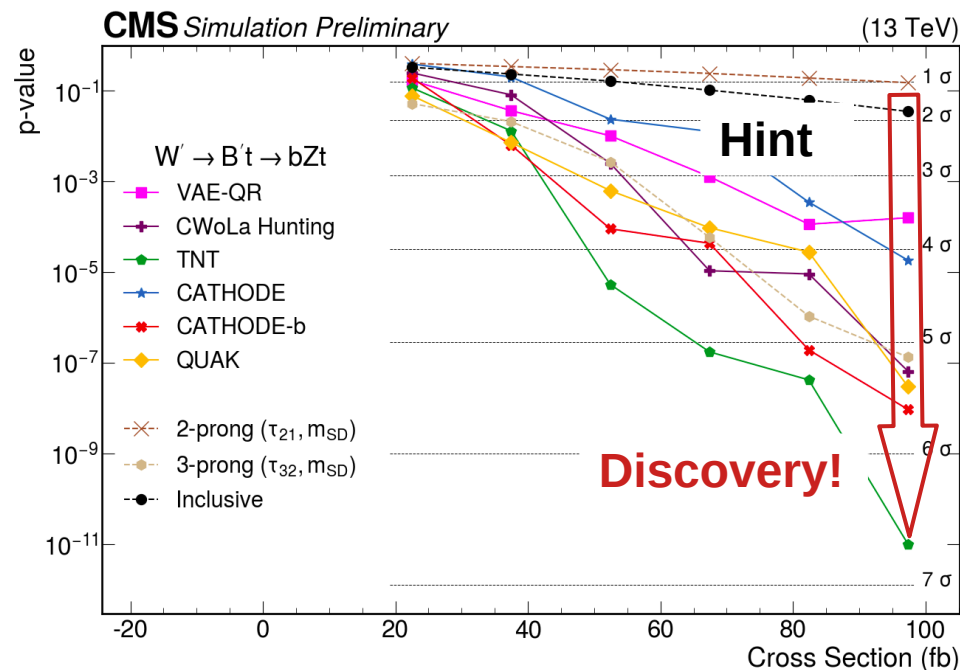
Anomaly detection enhances sensitivity for many models at once!

Sensitivity

2 Pronged Signal



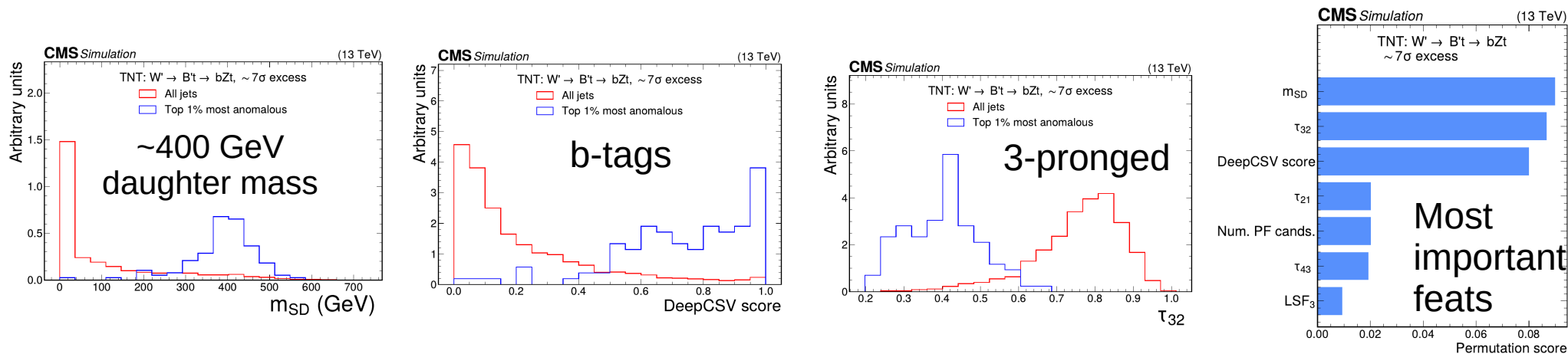
3 Pronged Signal



Anomaly detection enhances sensitivity for many models at once!

What if you see an excess?

Investigate features of most anomalous events!



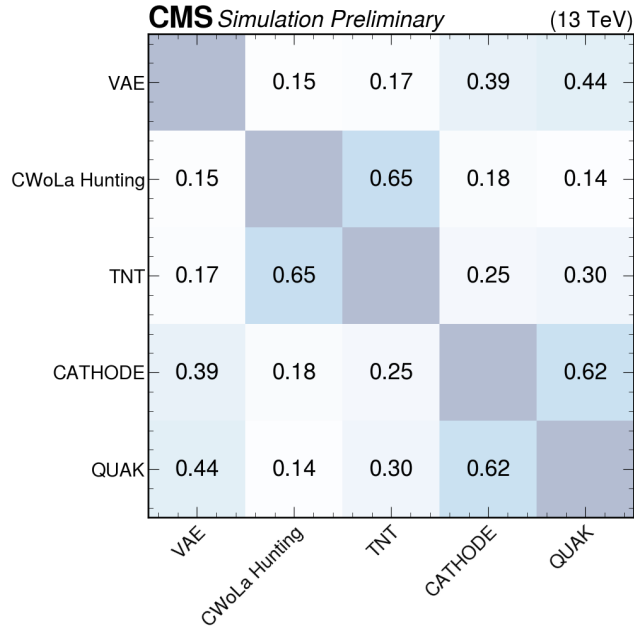
✓ Matches characteristics of injected signal

New plots from
journal version

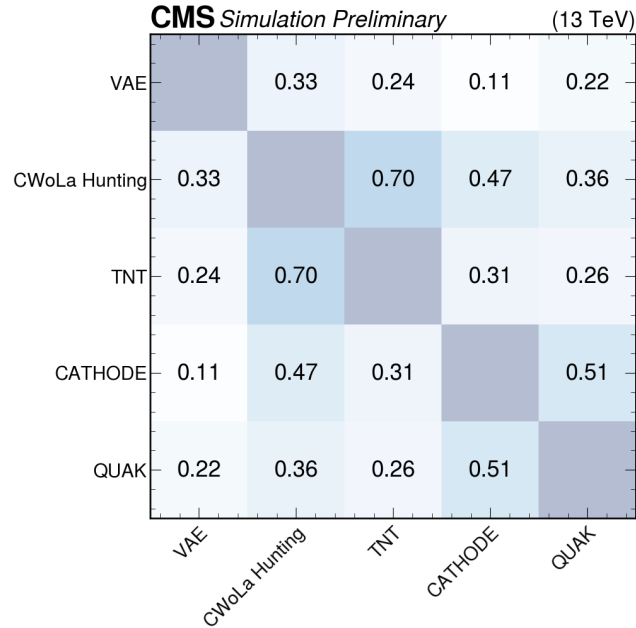
Complementary

CMS-NOTE
-2023-013

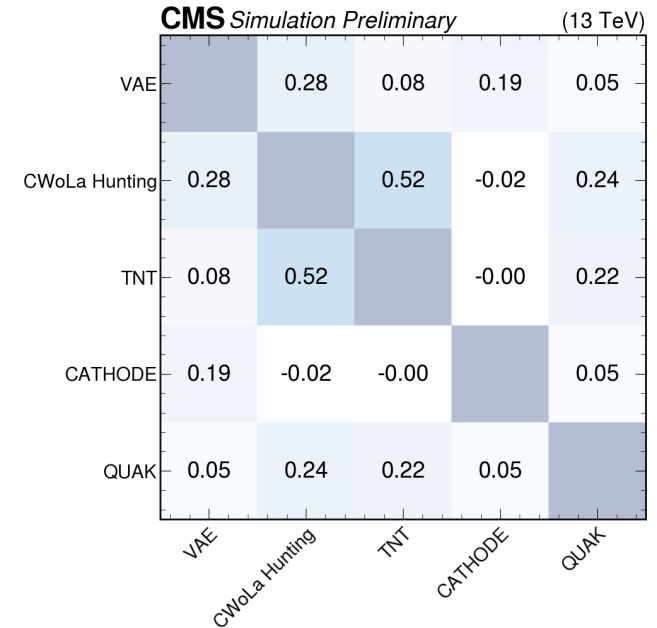
$X \rightarrow YY \rightarrow qq\, qq$



$W' \rightarrow B't \rightarrow bqq\, bqq$



QCD Bkg.



- Compute correlation coefficients between different anomaly scores
- Complementary approaches lead to relatively low correlations!

Steps to Unblinding

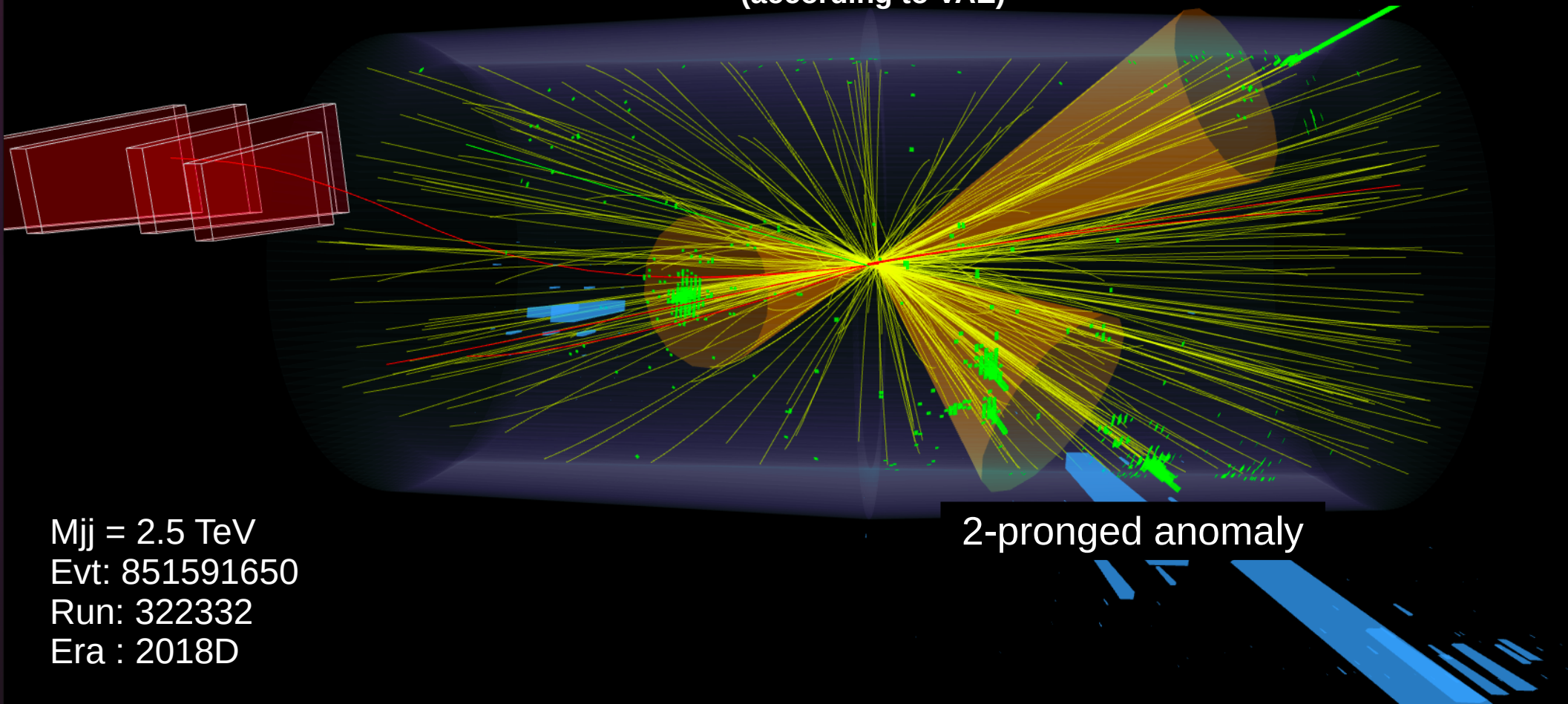
- ✓ No method creates artificial excesses in MC
- ✓ Can successfully find anomalies in MC
- ✓ Can characterize anomalies if found
- ✓ Apply to data $|\Delta\eta|$ sideband → no excesses

Time to apply to unblind!



One of our most anomalous events! (according to VAE)

High energy
constituents
anomaly

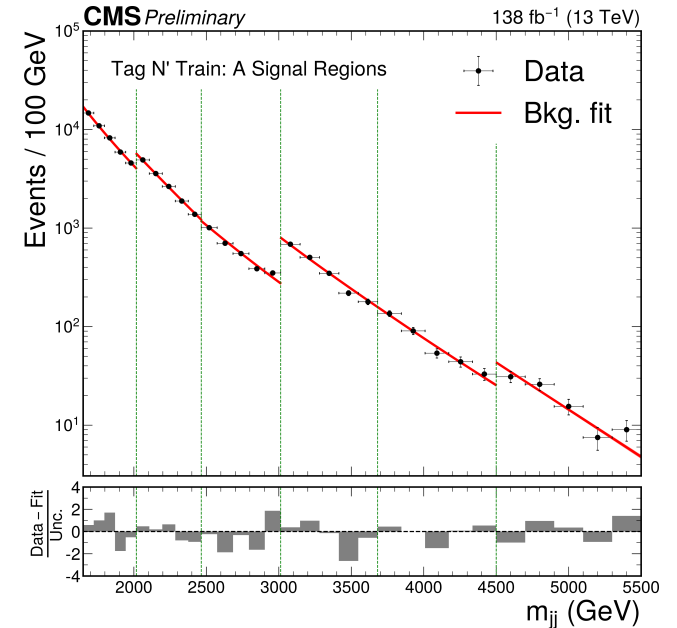
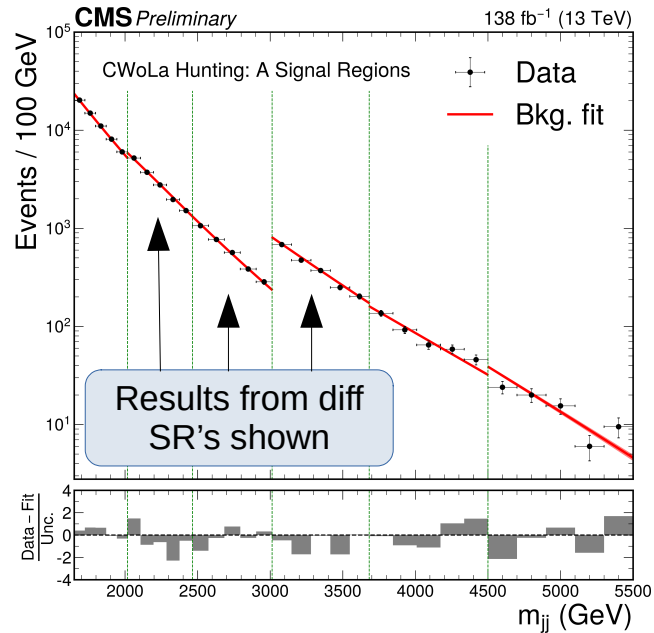
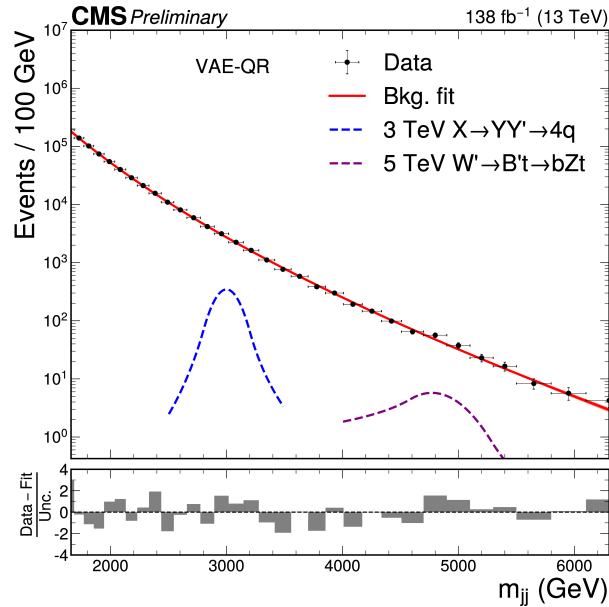


$M_{jj} = 2.5 \text{ TeV}$
Evt: 851591650
Run: 322332
Era : 2018D

2-pronged anomaly

Search Results

No significant excesses from any method



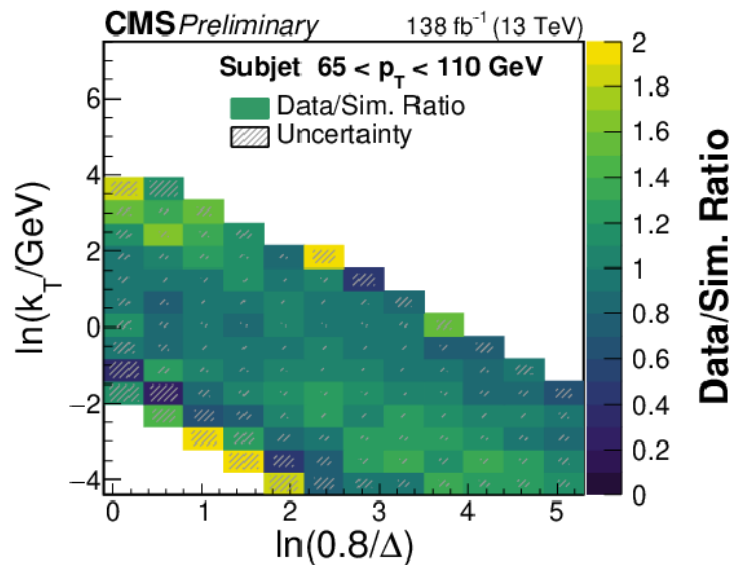
QUAK & CATHODE
results similar

What about uncertainties?

- Anomaly cut just like any other multivariate cut → no ‘special’ uncertainties
- Largest uncertainty is from MC **modeling of jet substructure**
 - Developed **new** data-driven correction + uncertainty for modeling high prong jets!

Data/MC Lund Jet Plane
Correction

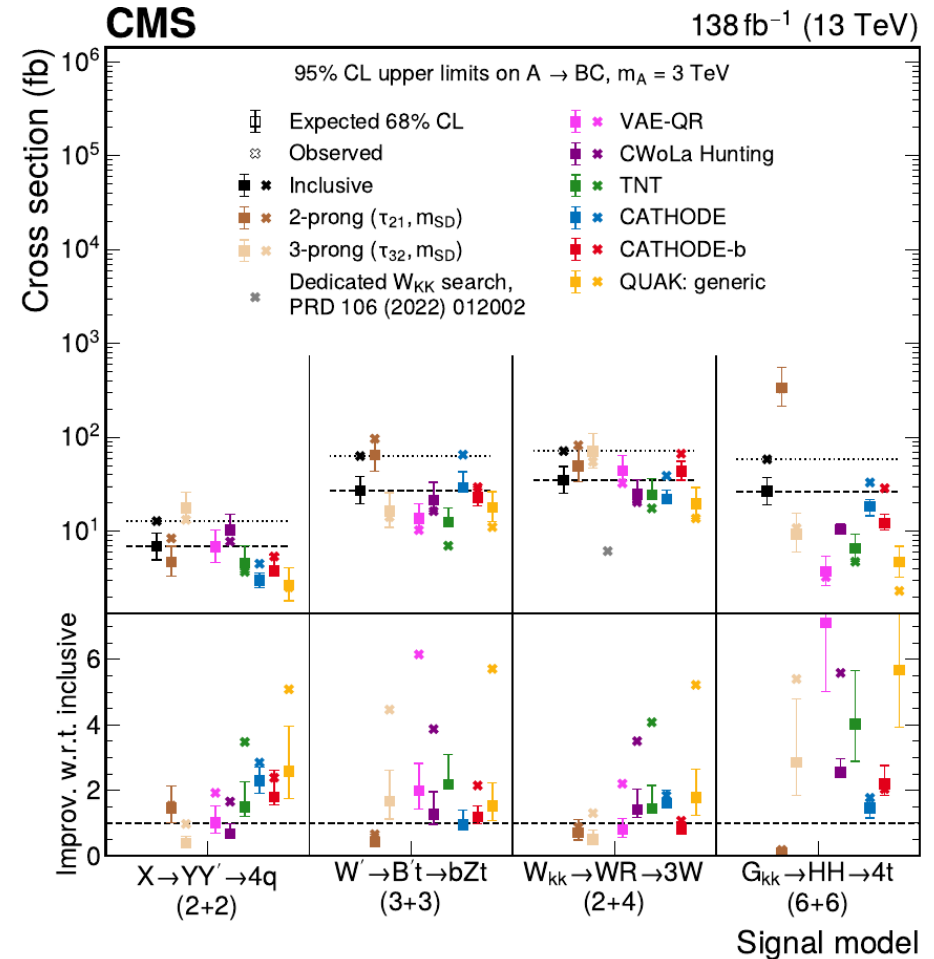
CMS-JME-23-001



Details in Backup

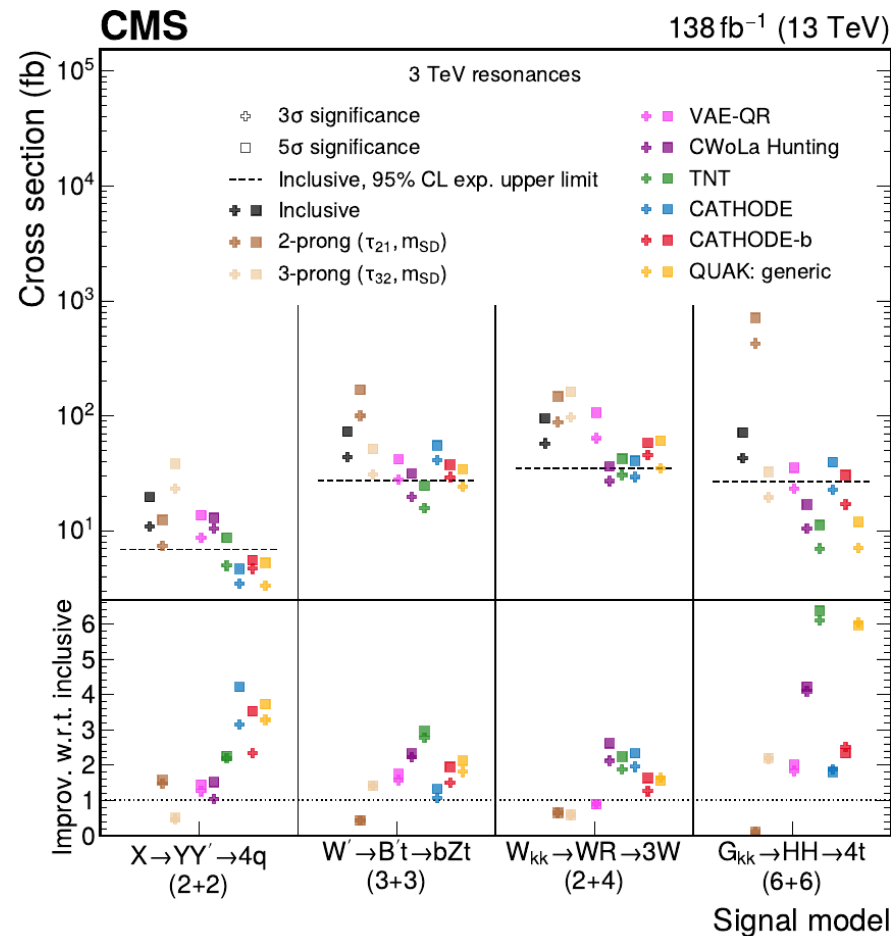
Limits

- Compute limits on benchmark from all **anomaly methods** on variety of signal models
 - Compare against **inclusive** & traditional **model-specific** approaches
 - First-ever limits on several models!
- Anomaly detection improves limits by **~2-6x!**
 - Does not reach sensitivity of **dedicated search**



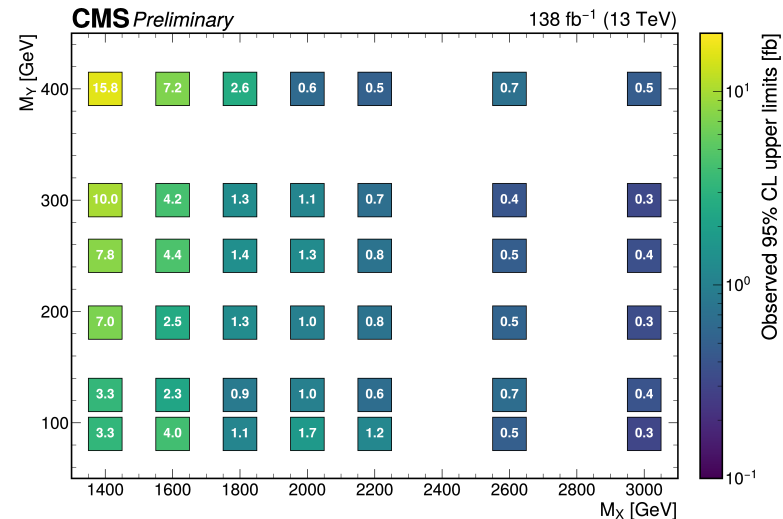
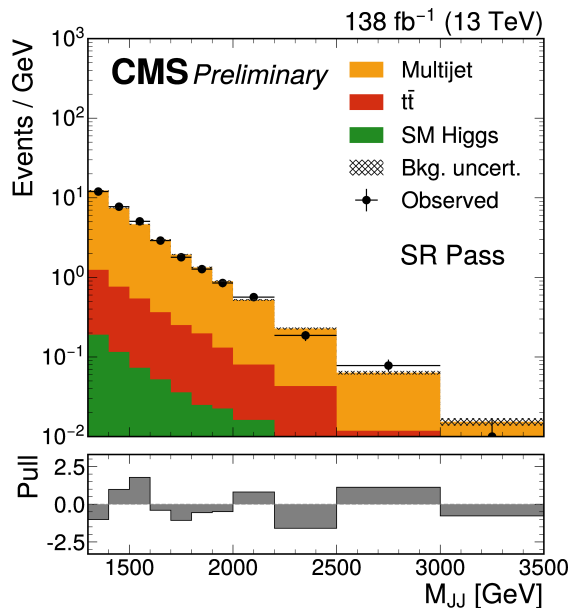
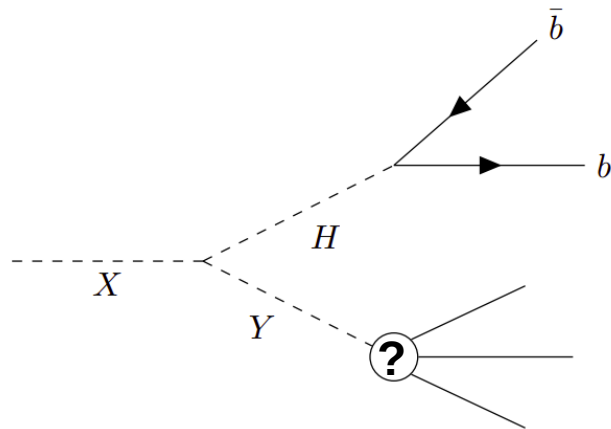
Discovery Sensitivity

- ‘**Discovery focused**’ performance metric
- “What cross section do I need to get an expected $3\sigma/5\sigma$ excess?”
- **Anomaly methods** improve sensitivity by **$\sim 3\text{-}6\times$** compared to inclusive



New: $X \rightarrow HY$ Search

CMS-PAS-
B2G-24-01
5



- Re-using an AE from the dijet search
- Limits on $Y \rightarrow WW$ and $Y \rightarrow bqq$

Conclusions

- **First** usage of **anomaly detection** in CMS
 - Dijet resonance search with anomalous substructure
- Demonstrated sensitivity to **broad range of signals**
- Hopefully more searches to follow!

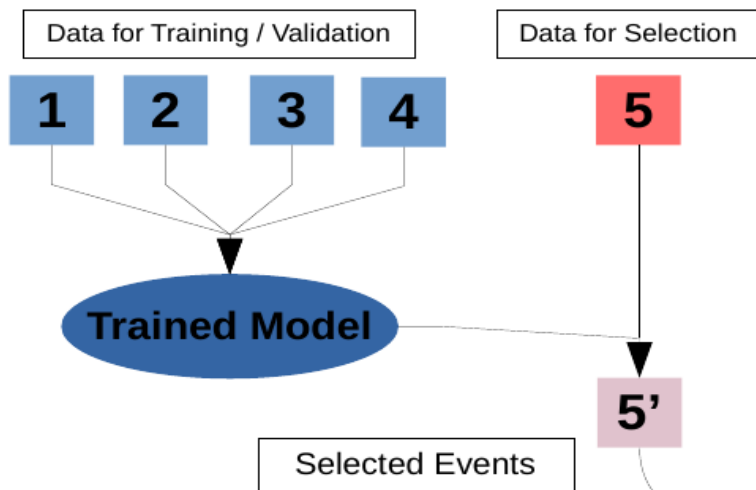
Conclusions

- **First** usage of **anomaly detection** in CMS
 - Dijet resonance search with anomalous substructure
- Demonstrated sensitivity to **broad range of signals**
- Hopefully more searches to follow!
- **Points I am interested to discuss!**
 - What should be reported for an anomaly detection search the case of null results? (ie do we **need** limits?)
 - Is reinterpretation of weakly supervised searches impossible?
 - How can we increase adoption of AD in our collaborations?

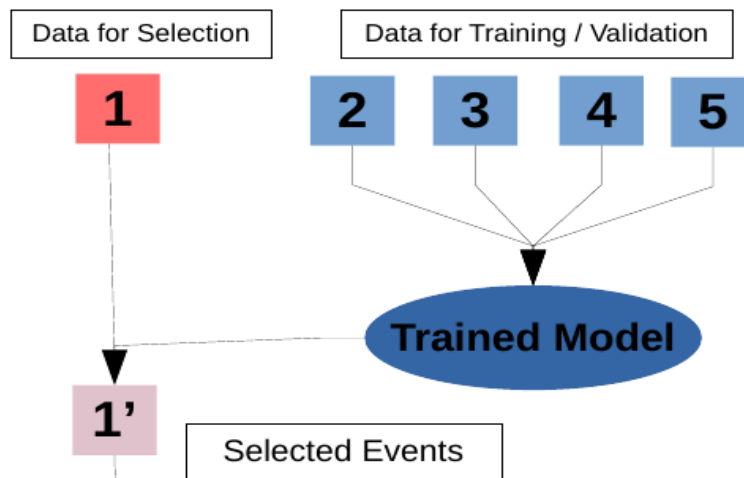
Backup

Cross Validation

K-Fold 1



K-Fold 2

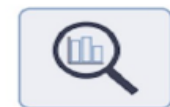


Repeat x5 total

...

Selected samples merged for bump hunt

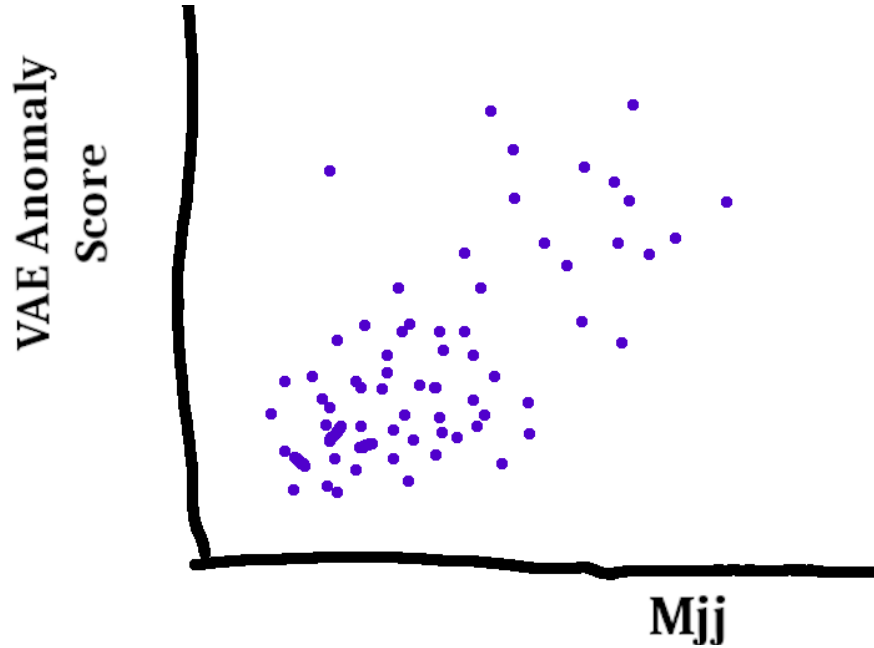
All Selected Events



Bump Hunt

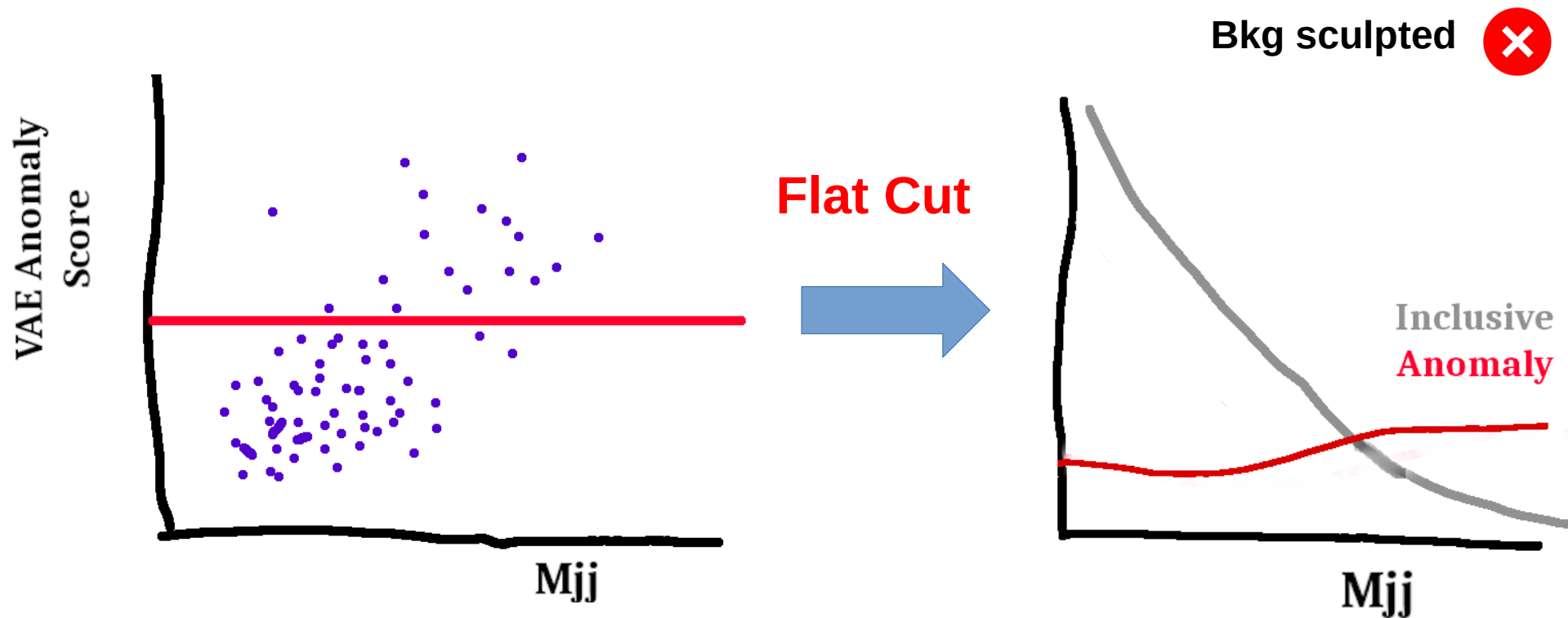
*Weakly supervised methods use additional layer of cross val for stability (see backup)

Decorrelate with Mjj



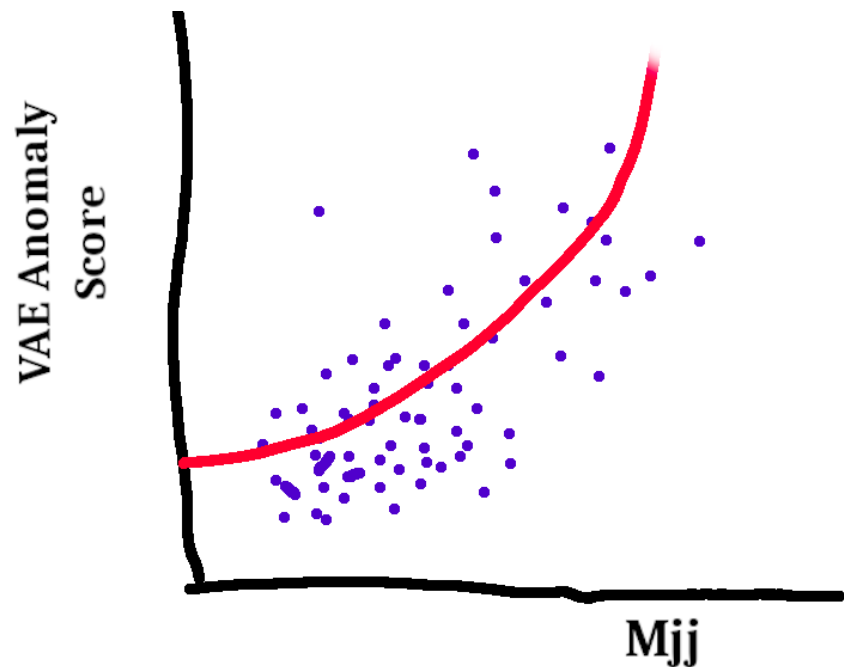
High Mjj events are rarer →
higher anomaly score

Decorrelate with M_{jj}



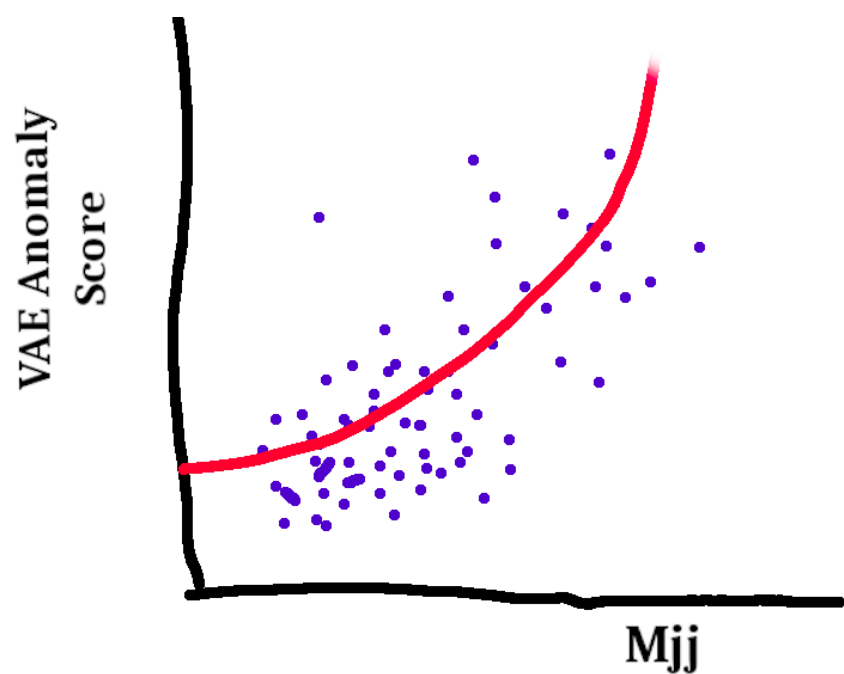
Decorrelate with M_{jj}

'Quantile Regression' (QR)

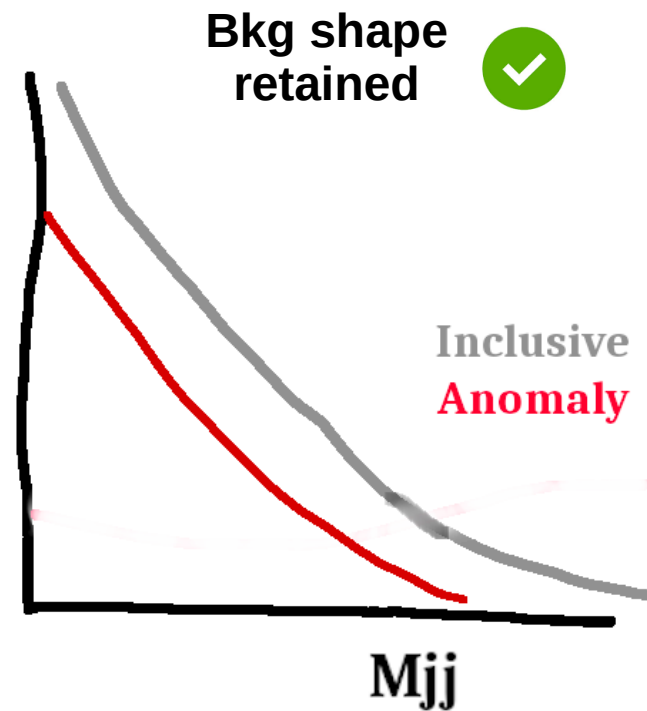


Adjust cut to have a
constant efficiency vs M_{jj}

Decorrelate with M_{jj}



Cut with
Flat Eff.



Efficiency & Uncertainties

To set a limit on a **specific signal model**
proceed as usual

- Signal MC + anomaly detector → efficiency
- One **complication** for weakly supervised methods :
signal eff depends on signal xsec!
 - Dedicated methods to calibrate this (requires training lots & lots of NN's), see backup