Generative Models for Resonant Anomaly Detection

Elham E Khoda[1], Ali Garabaglu[1], Hui-Chi Lin[2], Ben Nachman[3], David Shih[4], Shih-Chieh Hsu[1]

[1] University of Washington [2] University of Michigan [3] LBNL [4] Rutgers University

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Accelerated AI Algorithms for Data-Driven Discovery

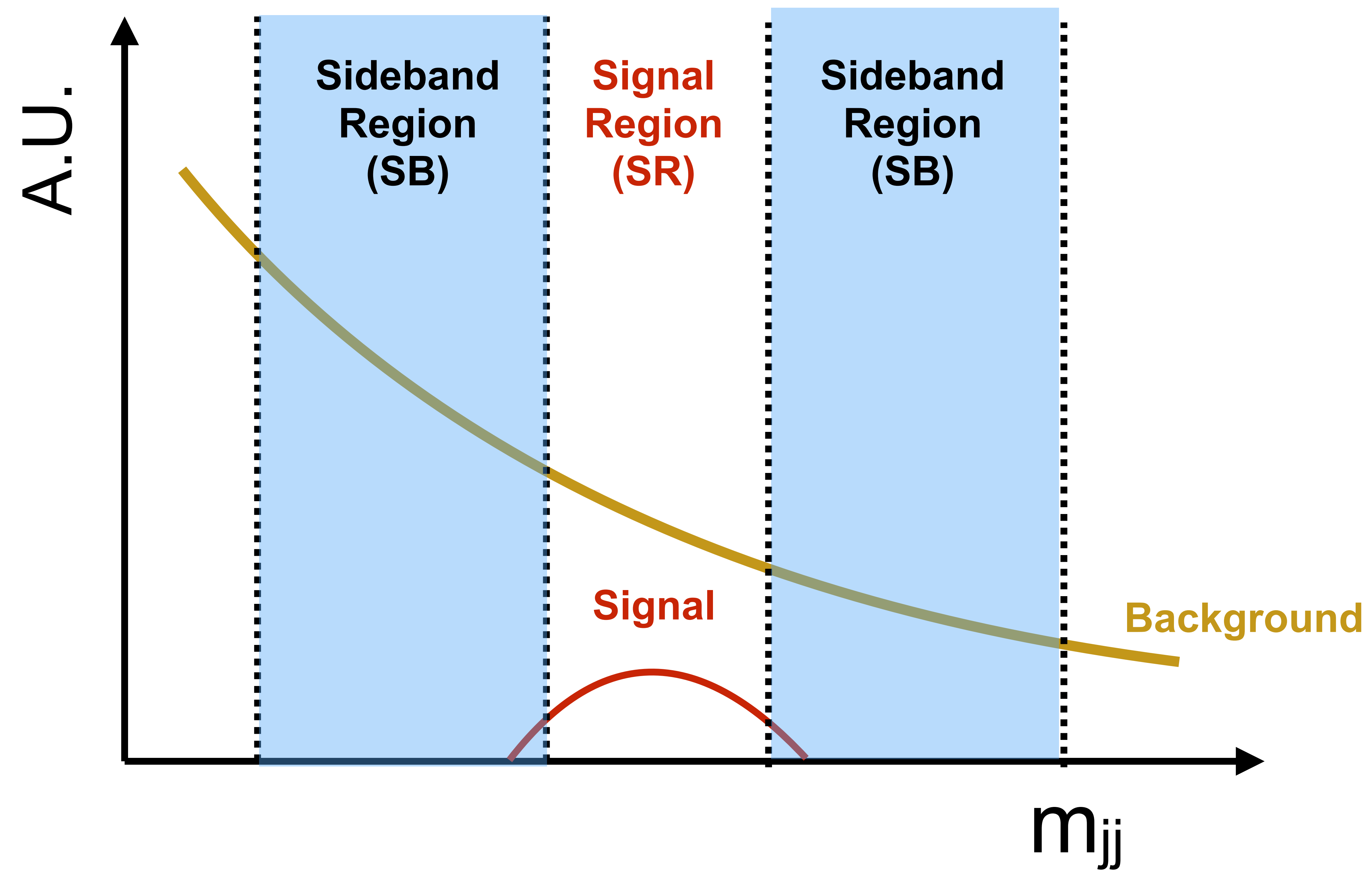
UNIVERSITY of WASHINGTON

Search for Resonant Signal

Assumption:

Signal is localized at least in one of the feature spaces

- Should appear as a bump



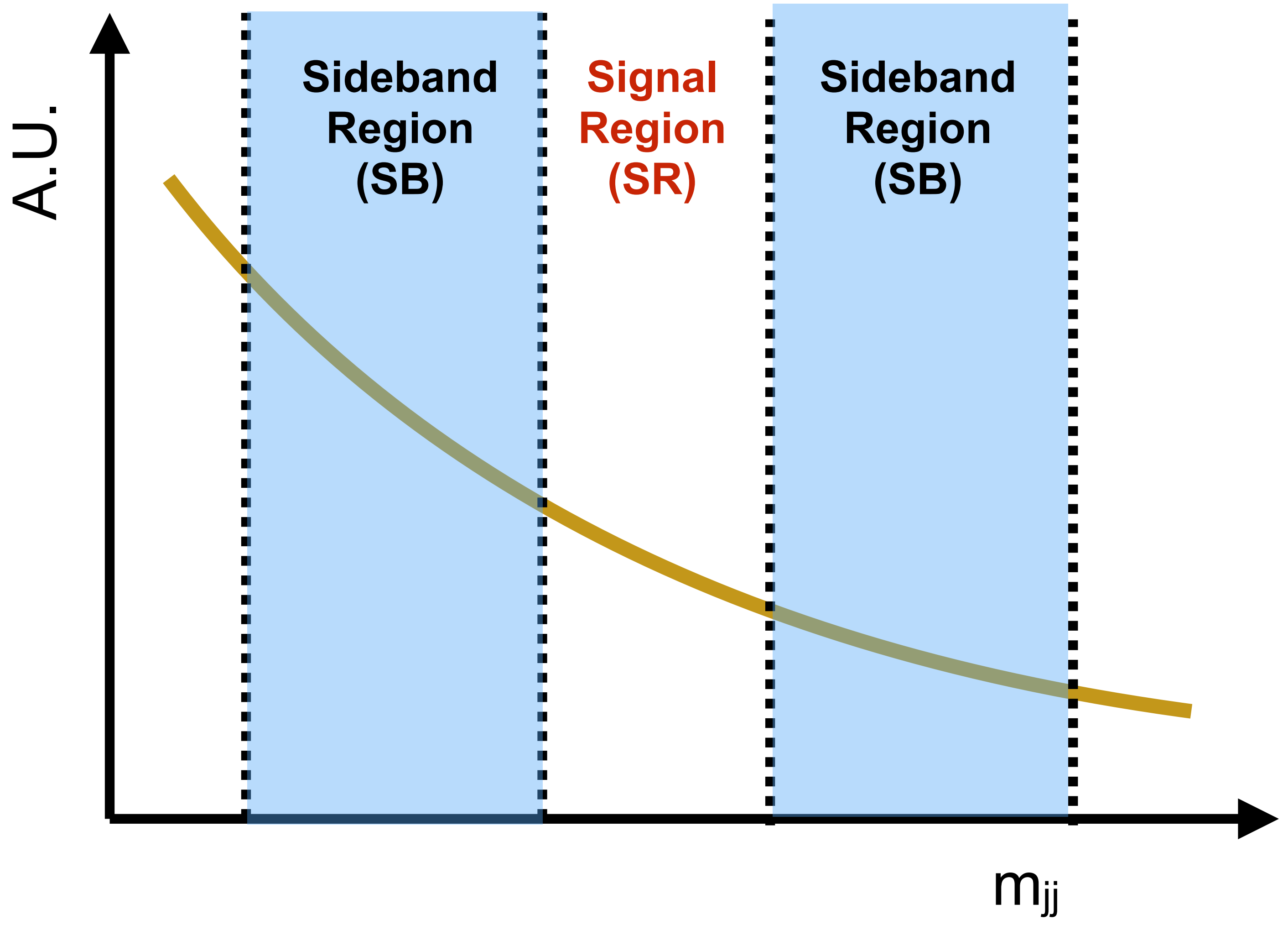
General search strategy (without ML):

- Choose a discriminant observable (often the mass)
- Define sideband regions → low signal contamination
- Fit background in the sidebands
- Interpolate the fit to the signal region

Relies only on one observable!

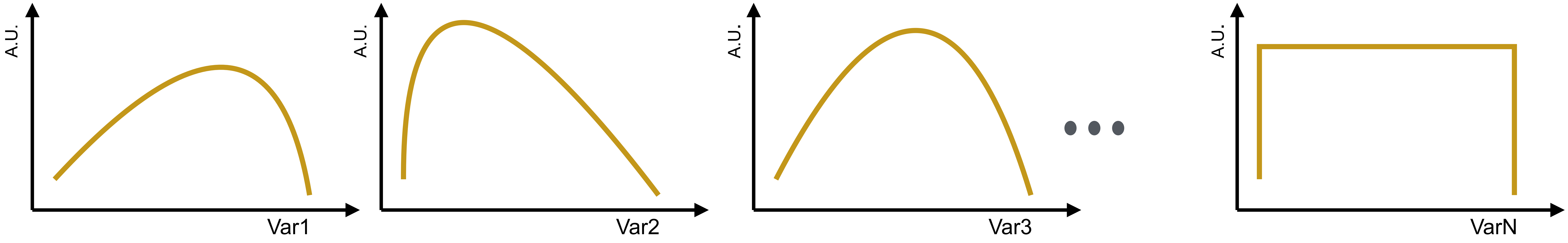
- Increase sensitivity by taking a multi-variate approach

Model background features in the SB



Side band is defined based on the observable where signal is expected to be resonant

Model the multiple observables in the sideband regions

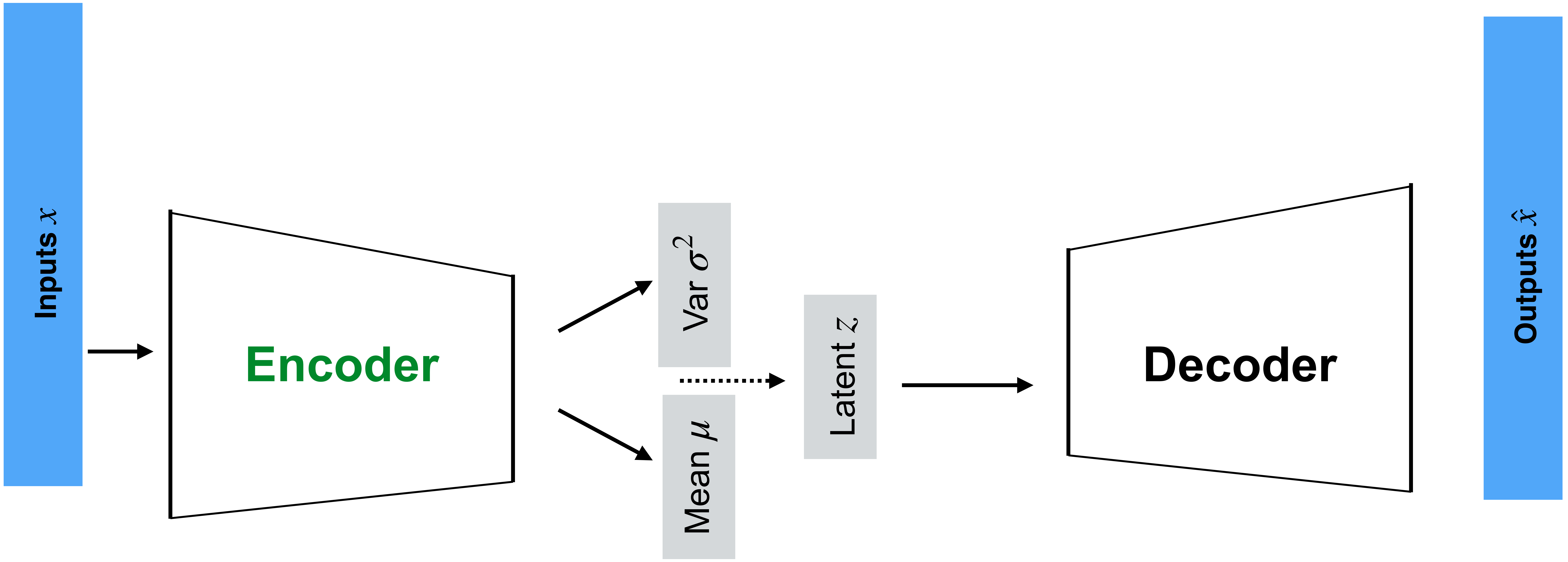


Feature modeling with VAE

VAE / GAN to estimate the distributions in the Sideband

- But then how do we know the distributions in the SR?

*In this talk I will focus on VAE

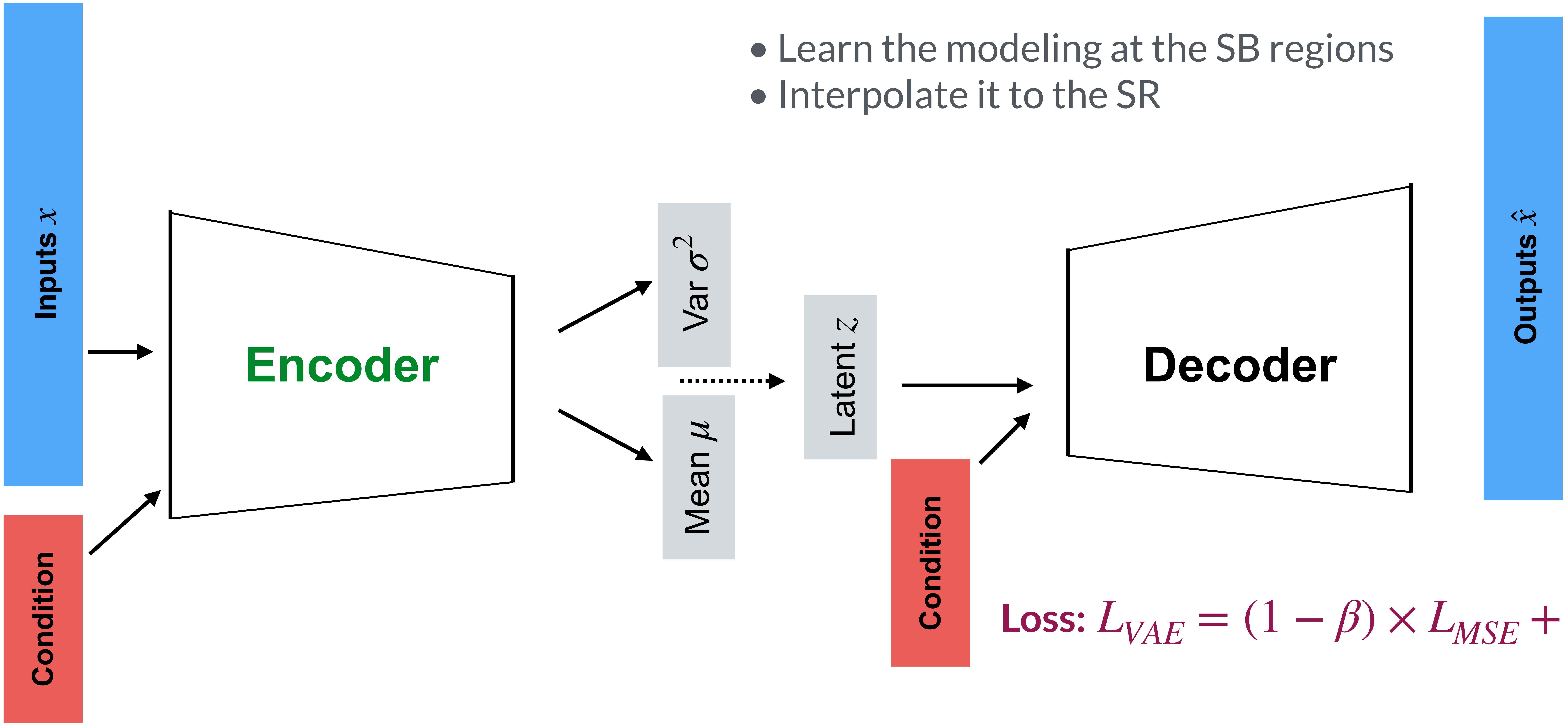


Feature modeling with cVAE

Conditional VAE (cVAE) to estimate the distributions in the Sideband

- Conditioned on the observable where signal is localized

- Learn the modeling at the SB regions
- Interpolate it to the SR



Loss: $L_{VAE} = (1-\beta) \times L_{MSE} + \beta \times KL$

Why another method?

There are similar existing methods like

- ANODE
  - Learns conditional density of data and background and classifies them
- CATHODE
  - Estimates the conditional density at the SB and extrapolate it to SR → generates events
  - Classify data from generated bkg in the SR

Both are flow-based density estimators

While Generative algorithms like cGAN and cVAE cannot estimate the explicit density

- Learns the approximate density quite well
- More flexible than Normalizing Flows
- Easy to scale to many variable

Complementarity:

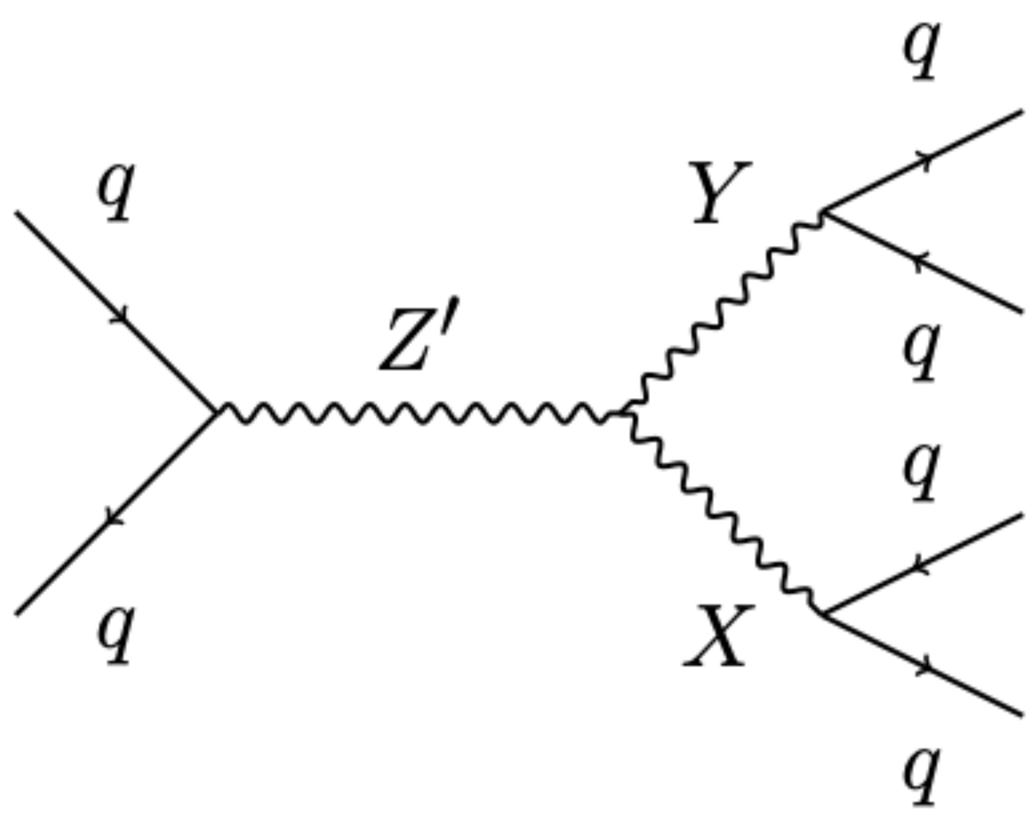
- Learn different features of the anomaly
- Fail differently in the absence of signal
  - Pick different anomalies (false signal detection) in bkg-only dataset
- Serve as a good complementary-check
- Help mitigate the overall bias uncertainty

Overview of the Problem

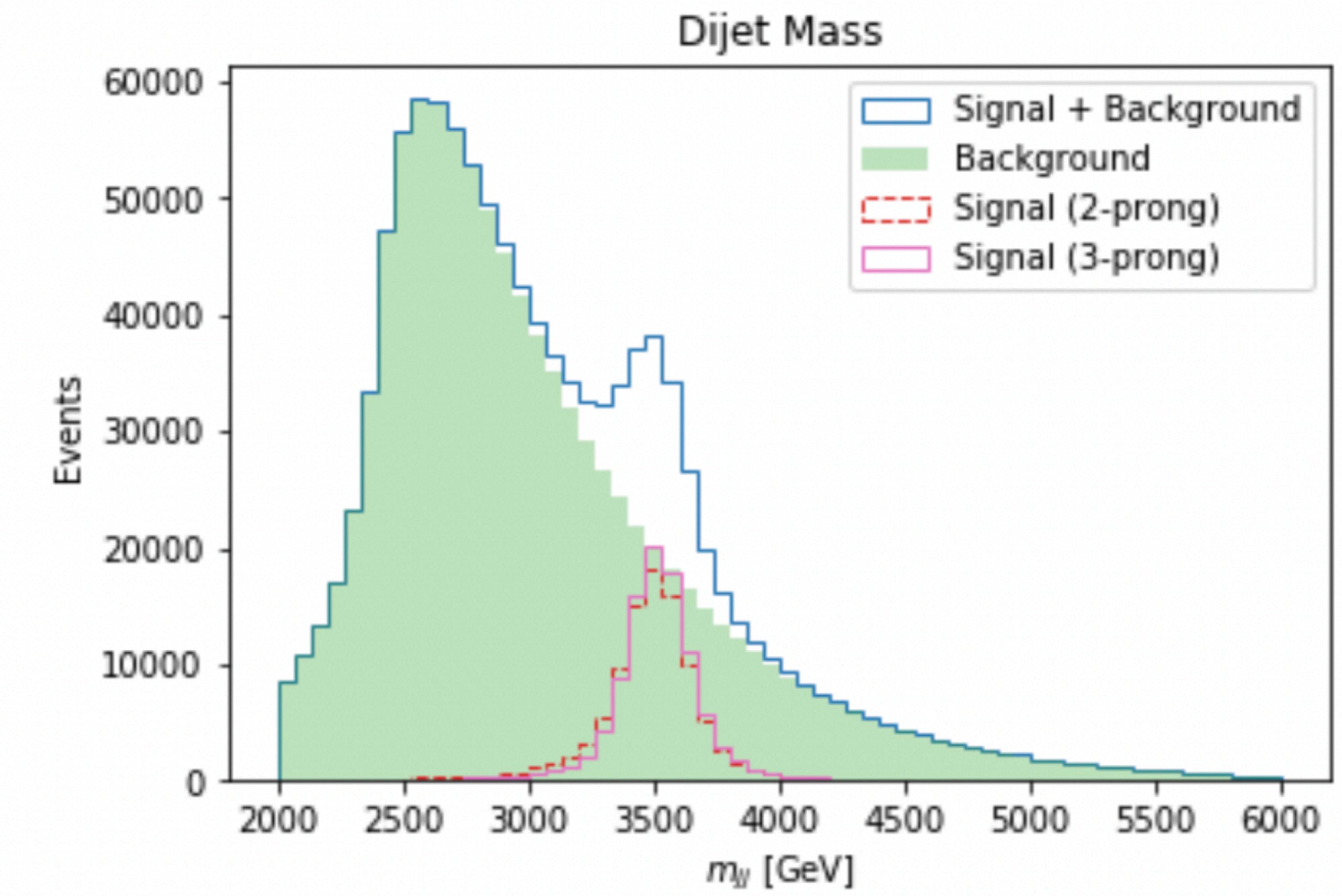
- We are working with the LHC Olympics 2020 anomaly detection challenge dataset

- **Target signature**: Final states with multiple jets

- **Background:** QCD multijet process
    - No particular structure inside the jets



- **Signal:** Heavy new particle decaying into quarks → forming large-R jets
    - with 2-prong or 3-prong structure inside (depending on the origin)

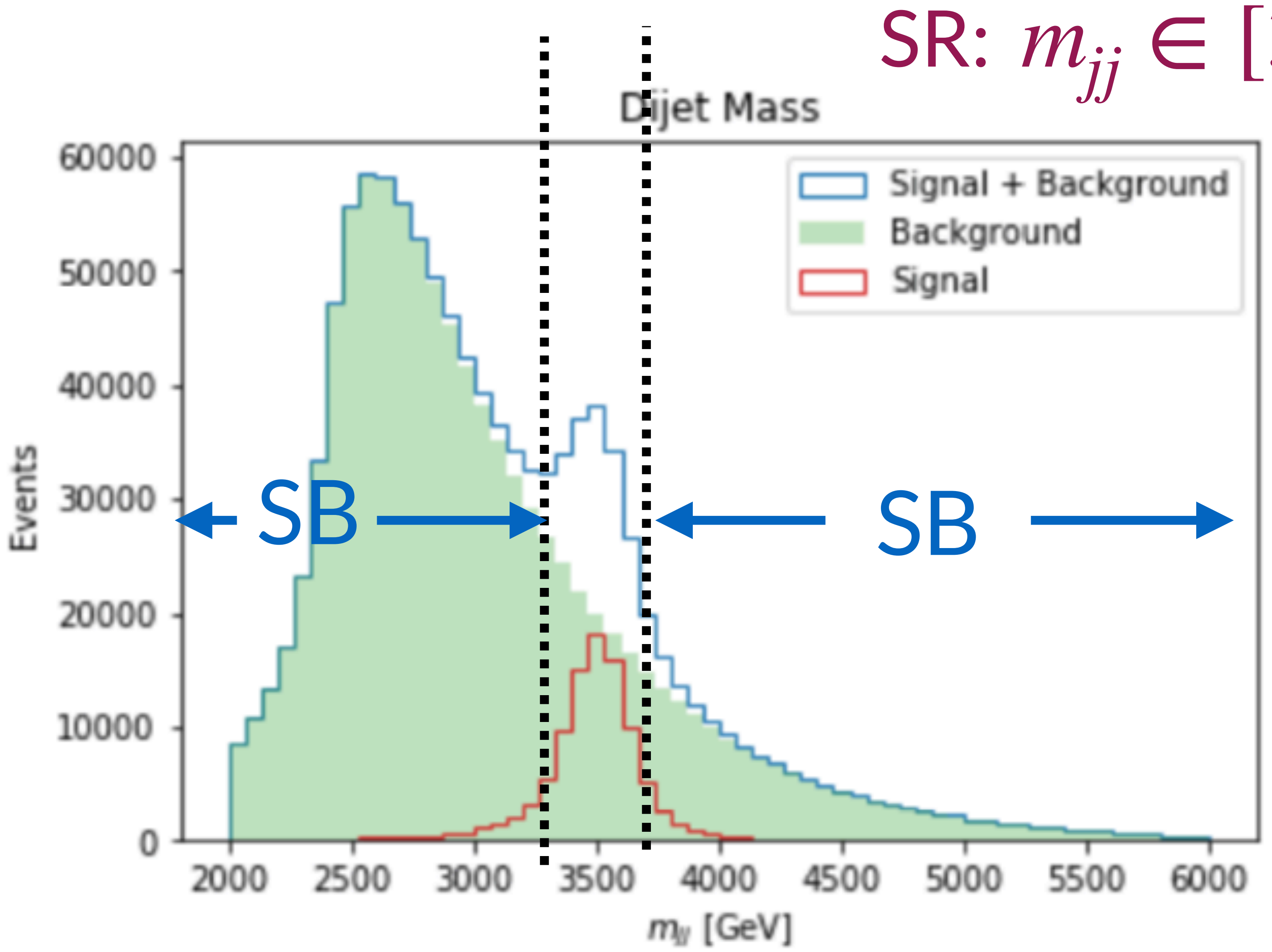


LHCO 2020 Dataset

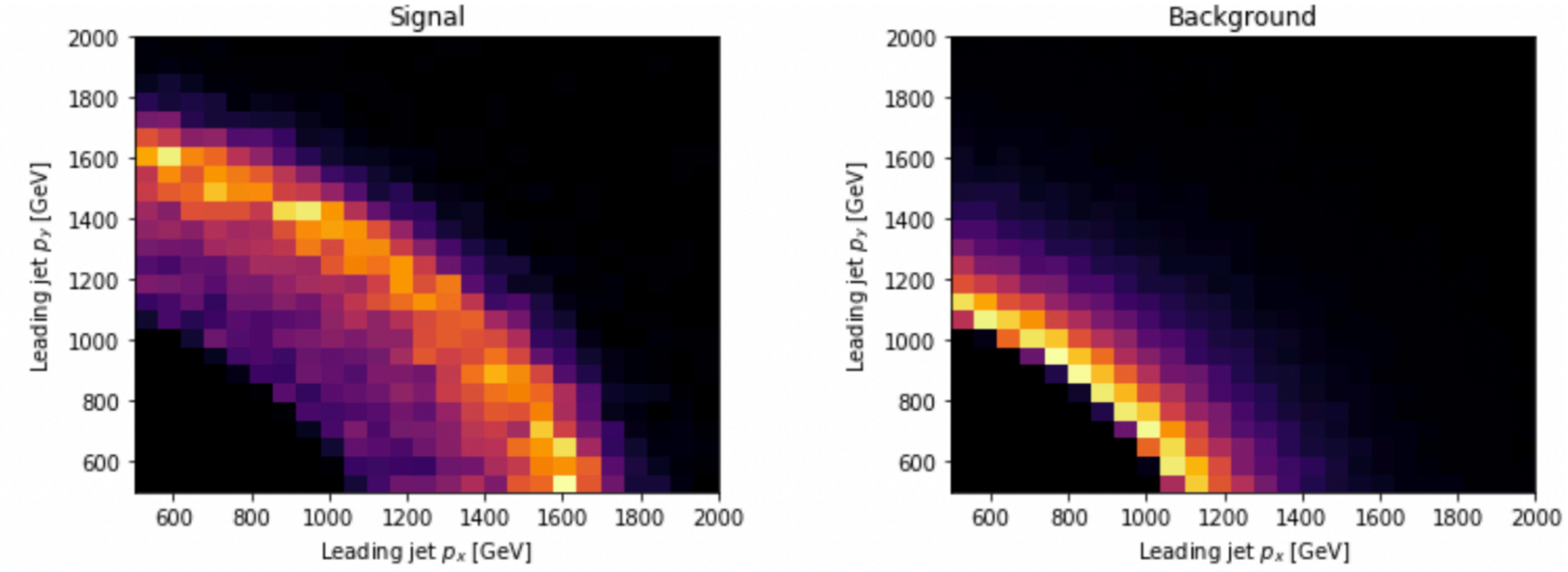
Dataset Summary:

- **Background:** 1M QCD dijet events
- **Signal:** 100k W' (3.5 TeV) → X (500 GeV) + Y (100 GeV) , with X→ qq/qqq and Y → qq/qqq
- Both **2-prong** and **3-prong** signals are used

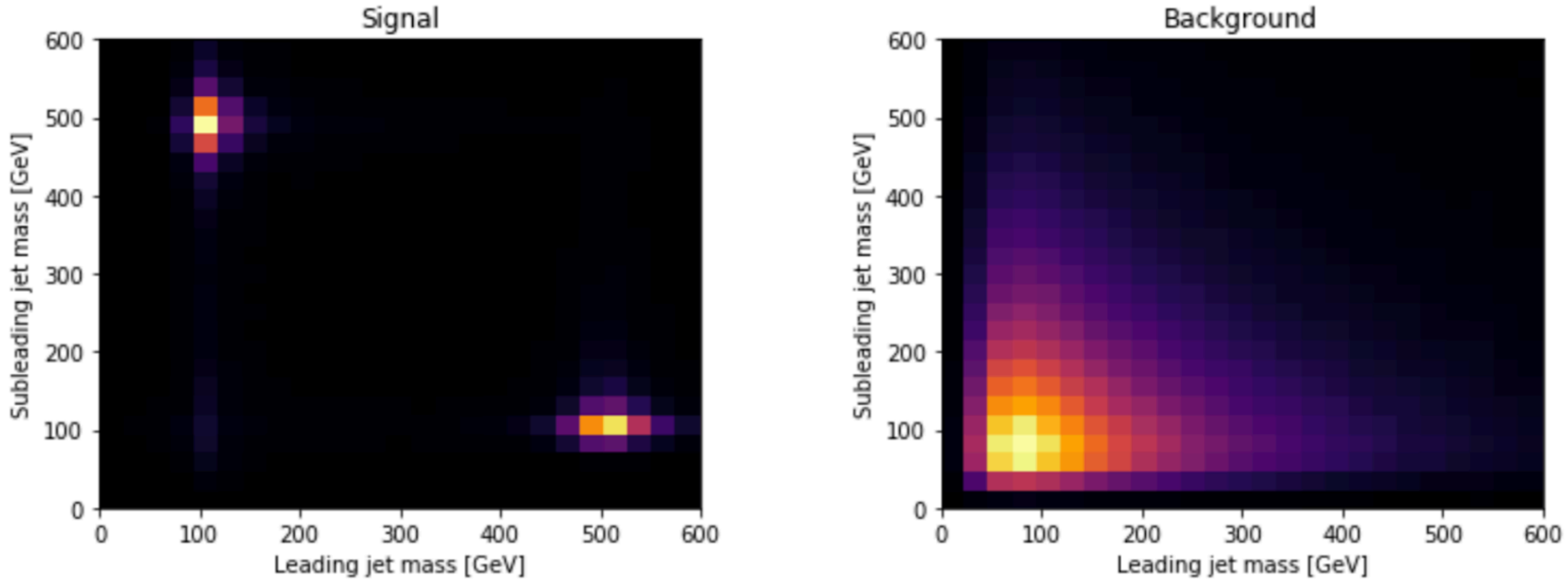
SR: $m_{jj} \in [3.3,\ 3.7]$ TeV



Jet Momentum

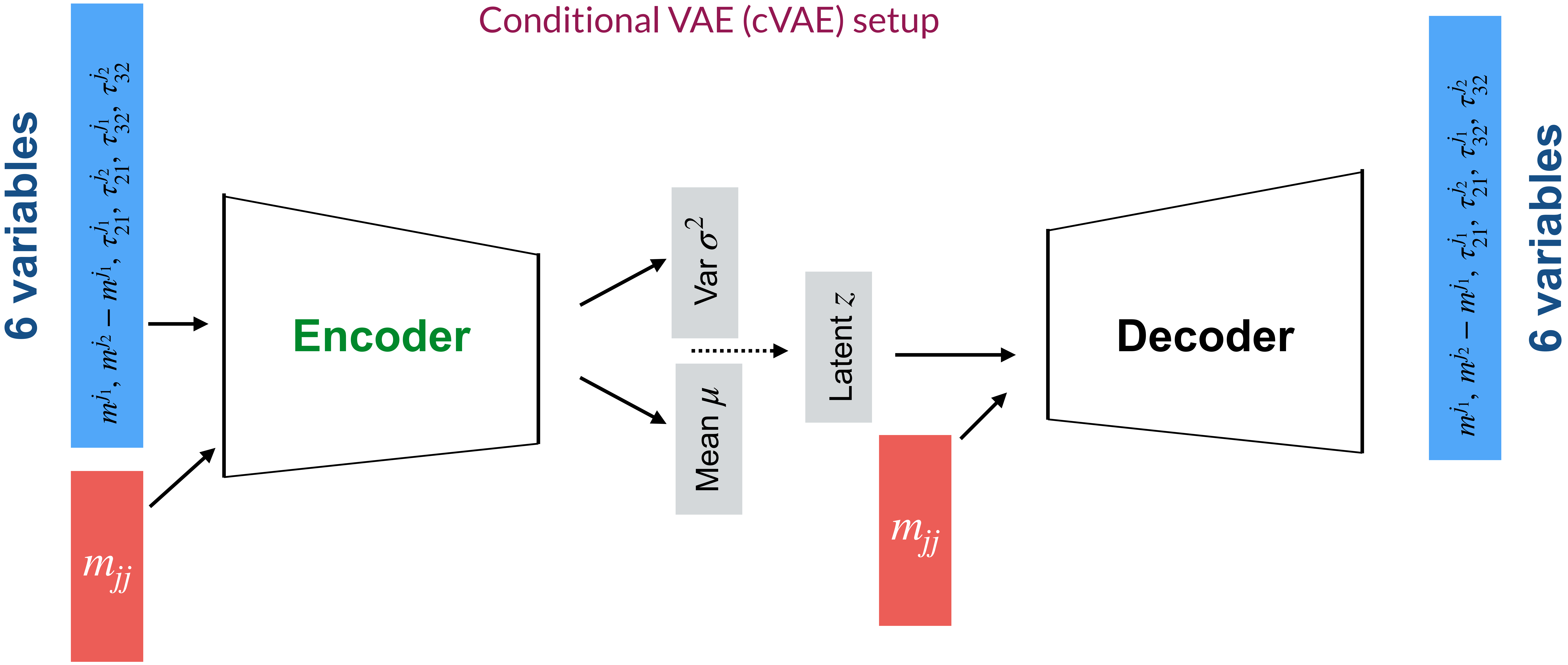


Jet Mass

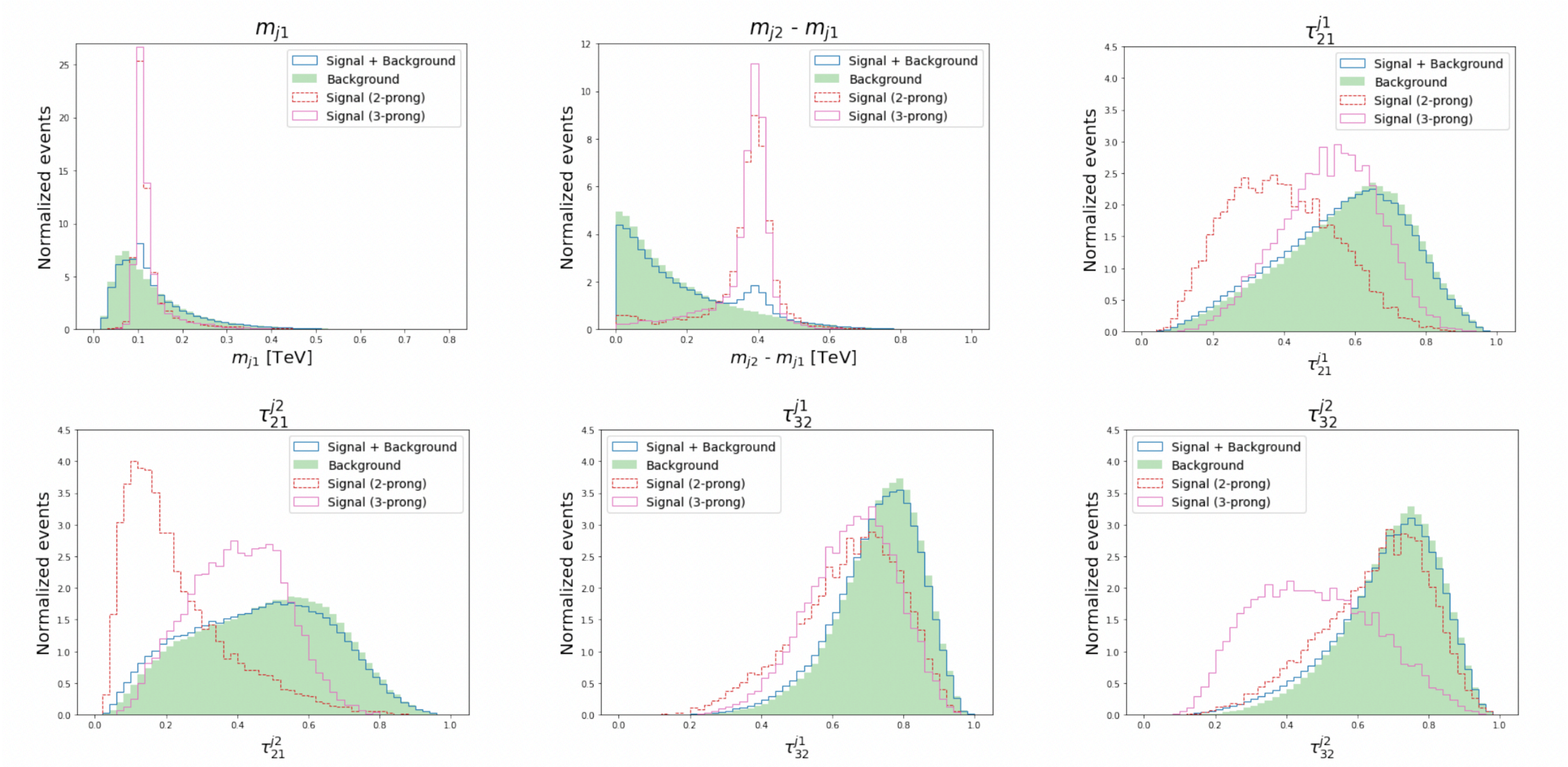


cVAE with 6 features

Conditional VAE (cVAE) setup



Features in the SR



Workflow

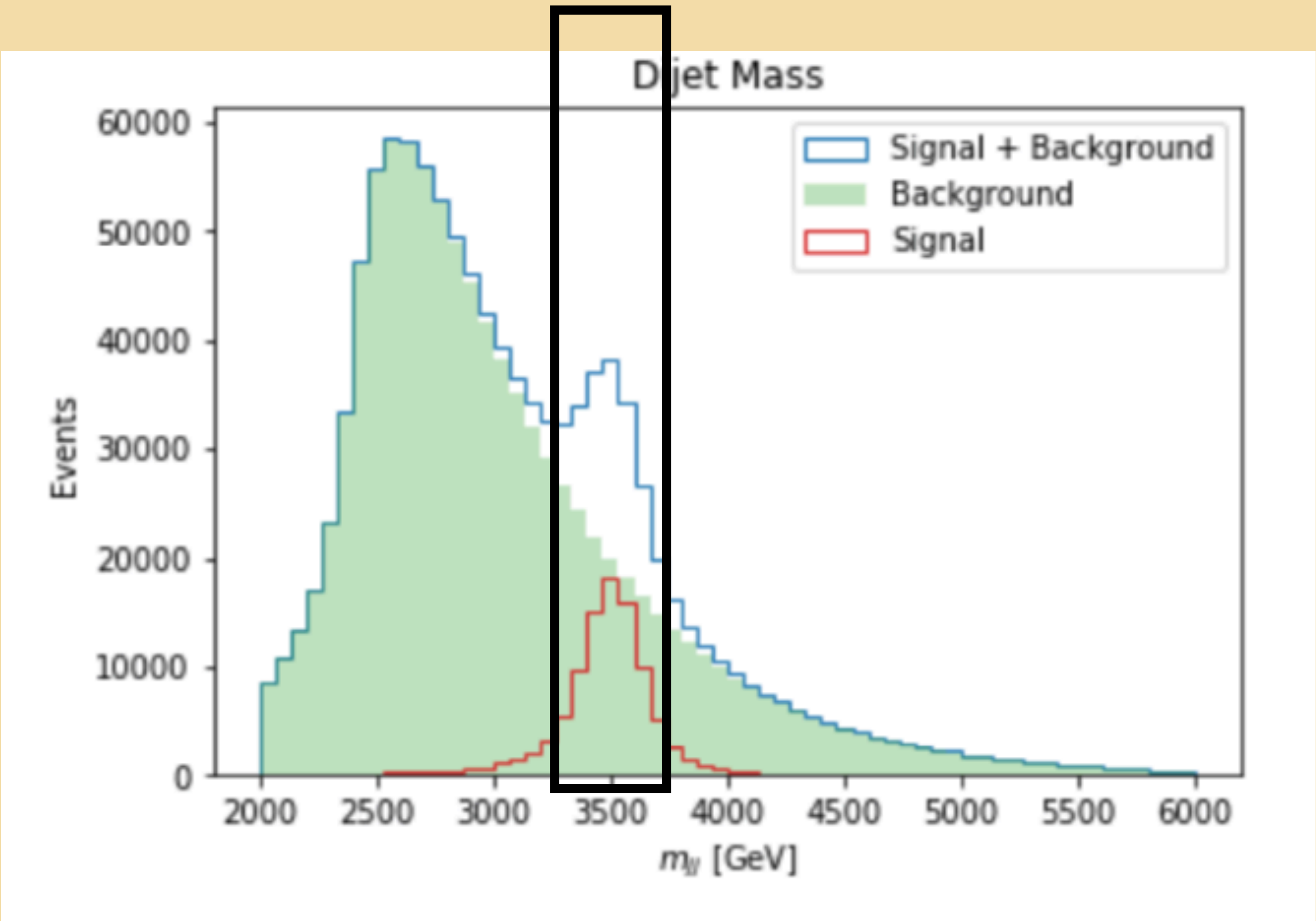
$m^{j_1},\ m^{j_2}-m^{j_1},\ \tau_{21}^{j_1},\ \tau_{21}^{j_2},\ \tau_{32}^{j_1},\ \tau_{32}^{j_2}$

m_{jj}

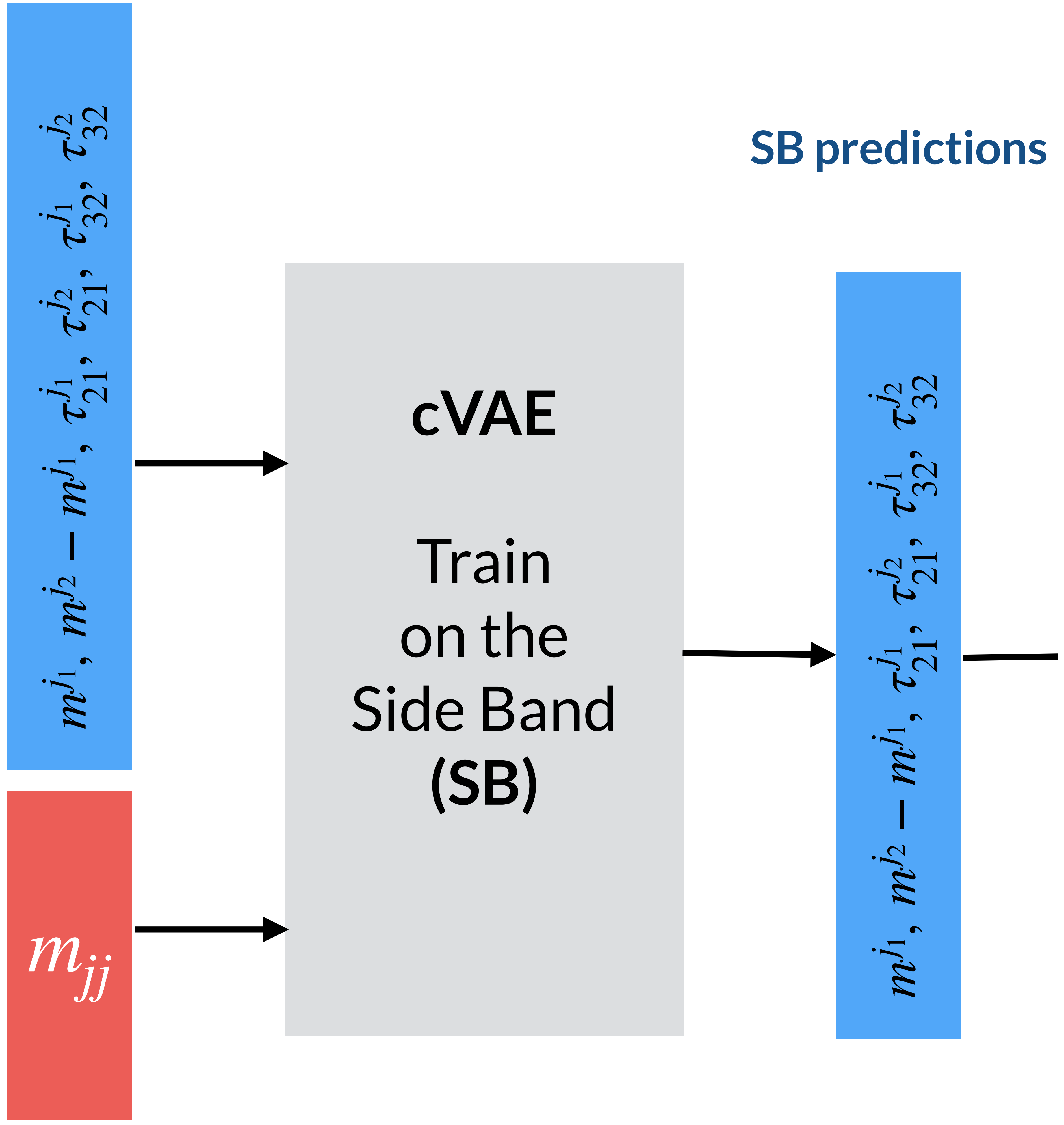
Define SR and SB regions

SR: $m_{jj} \in [3.3,\ 3.7]$ TeV

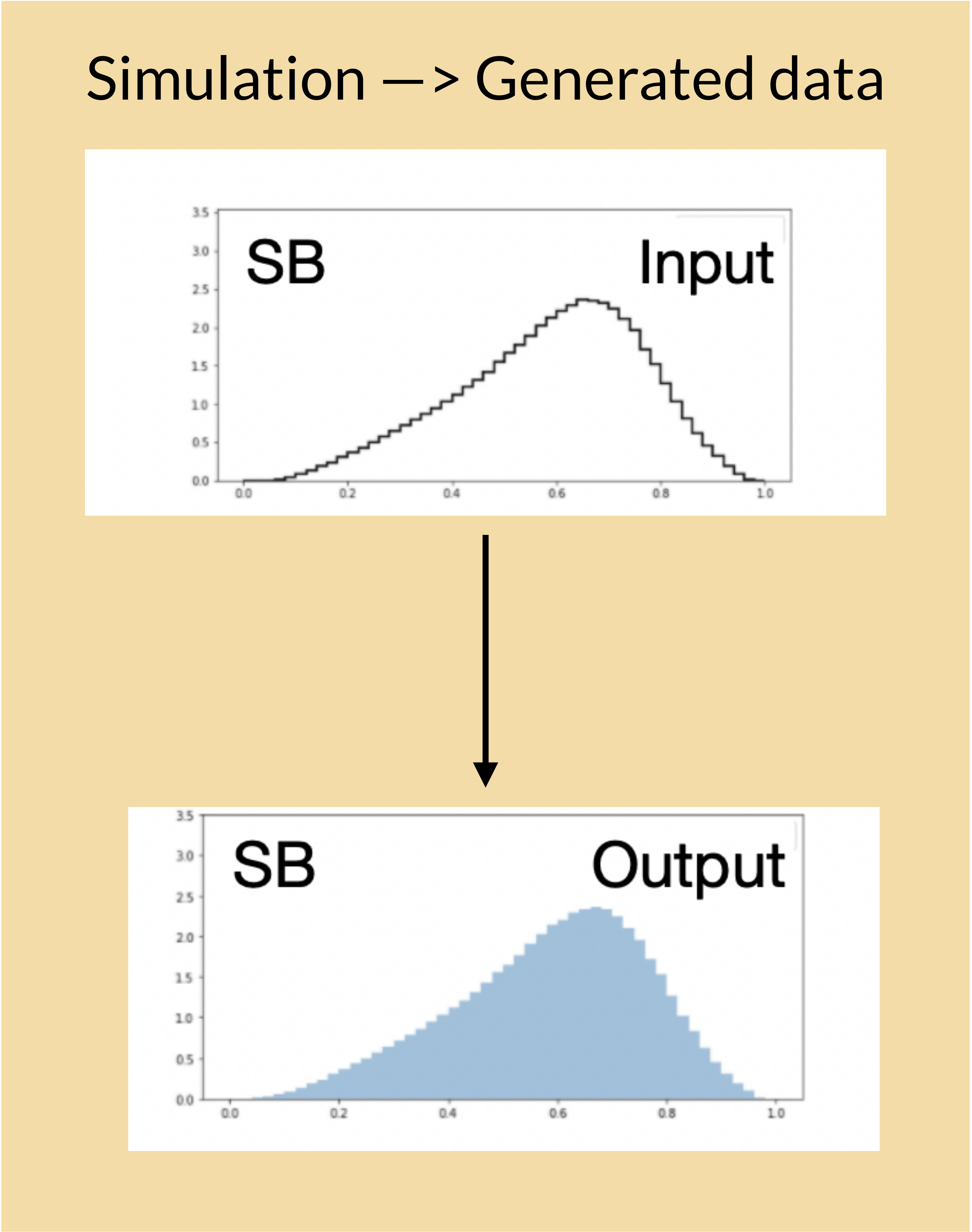
SB: $m_{jj} \notin [3.3,\ 3.7]$ TeV



Workflow



$m^{j_1}, m^{j_2} - m^{j_1}, \tau_{21}^{j_1}, \tau_{21}^{j_2}, \tau_{32}^{j_1}, \tau_{32}^{j_2}$
m_{jj}
cVAE
Train on the Side Band (SB)
SB predictions
$m^{j_1}, m^{j_2} - m^{j_1}, \tau_{21}^{j_1}, \tau_{21}^{j_2}, \tau_{32}^{j_1}, \tau_{32}^{j_2}$



Simulation —> Generated data
SB
Input
SB
Output

Workflow

$m^{j_1},\ m^{j_2} - m^{j_1},\ \tau_{21}^{j_1},\ \tau_{21}^{j_2},\ \tau_{32}^{j_1},\ \tau_{32}^{j_2}$

m_{jj}

cVAE

Train on the Side Band **(SB)**

SB predictions

$m^{j_1},\ m^{j_2} - m^{j_1},\ \tau_{21}^{j_1},\ \tau_{21}^{j_2},\ \tau_{32}^{j_1},\ \tau_{32}^{j_2}$

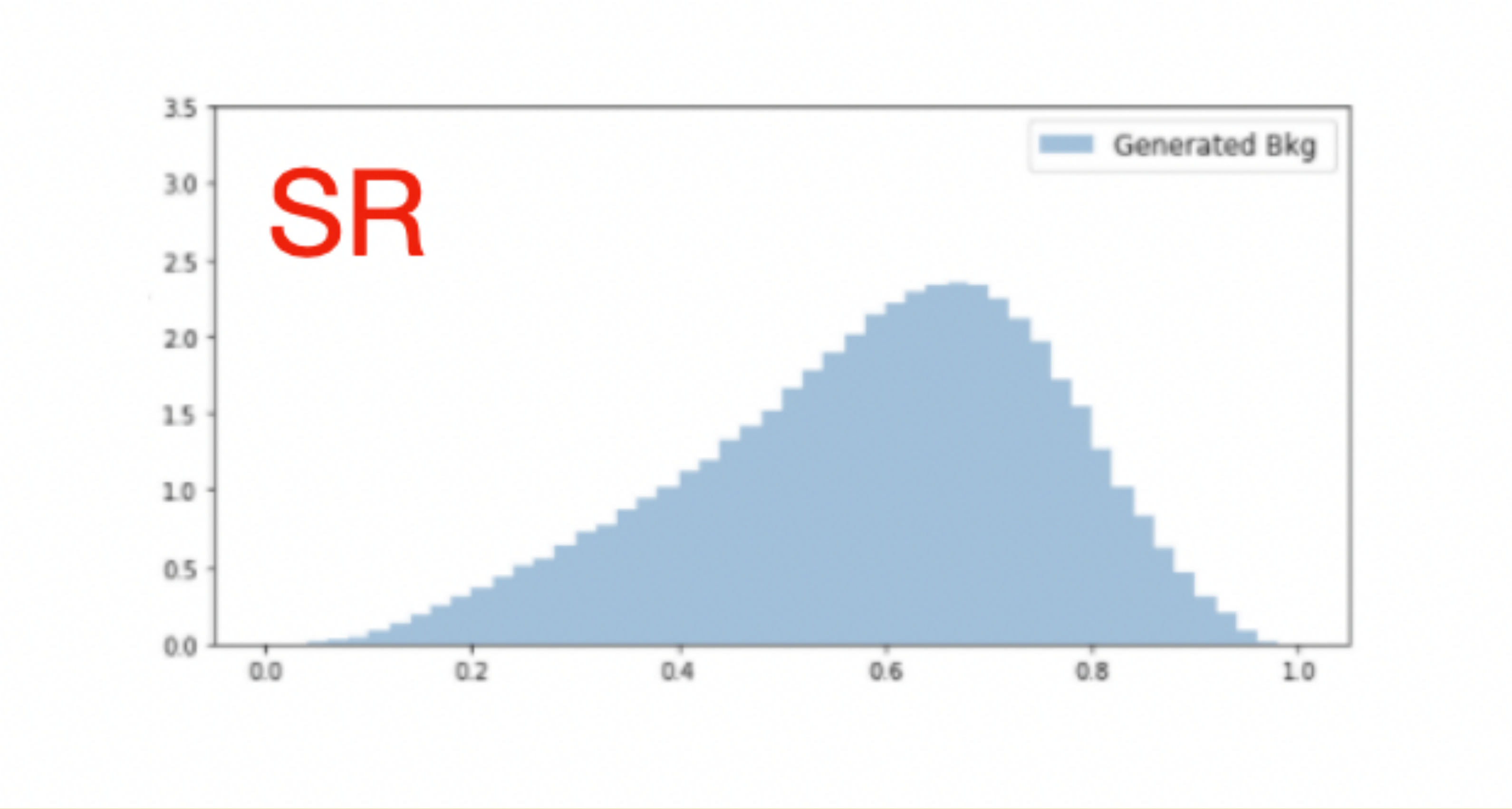
Interpolate to the SR

SR predictions

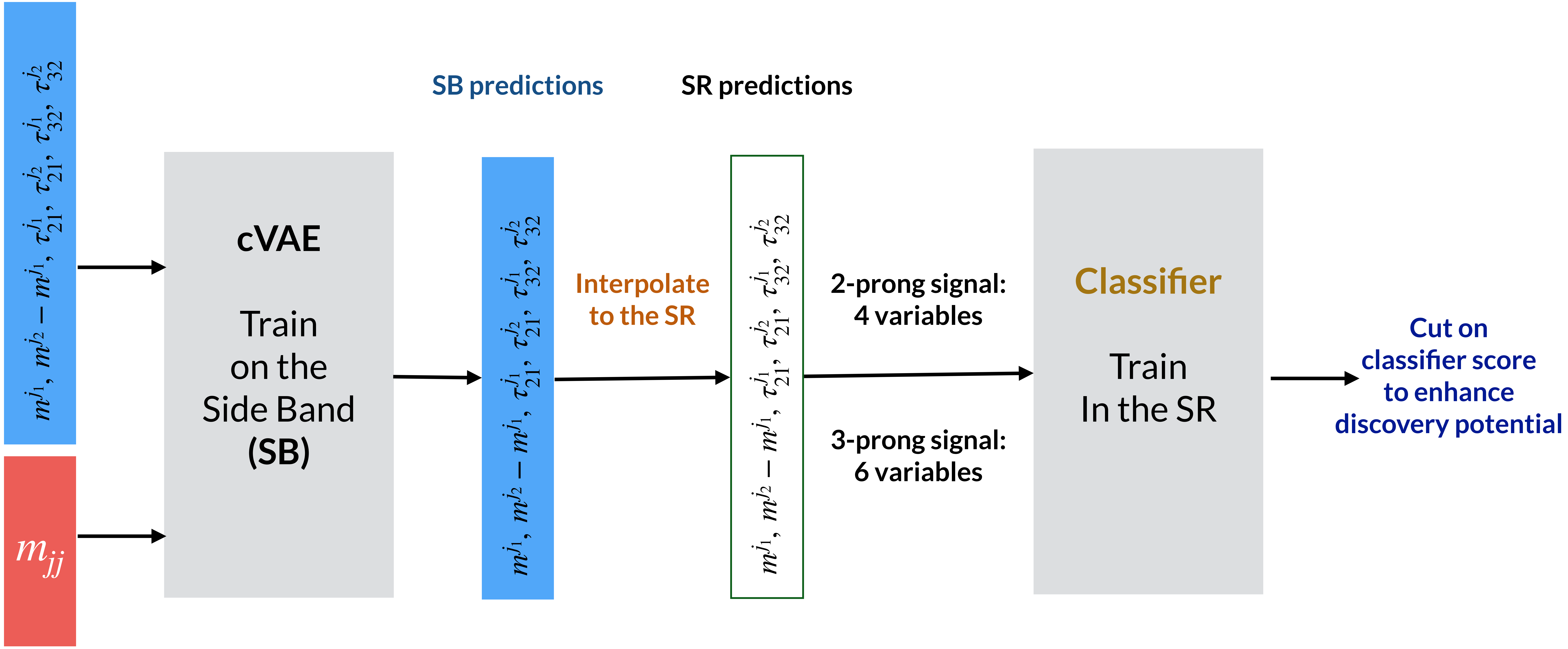
$m^{j_1},\ m^{j_2} - m^{j_1},\ \tau_{21}^{j_1},\ \tau_{21}^{j_2},\ \tau_{32}^{j_1},\ \tau_{32}^{j_2}$

Condition: $m_{jj} \in SR$

Run the decoder



Workflow


$m^{j_1}, m^{j_2} - m^{j_1}, \tau_{21}^{j_1}, \tau_{21}^{j_2}, \tau_{32}^{j_1}, \tau_{32}^{j_2}$
m_{jj}
cVAE
Train on the Side Band (SB)
SB predictions
$m^{j_1}, m^{j_2} - m^{j_1}, \tau_{21}^{j_1}, \tau_{21}^{j_2}, \tau_{32}^{j_1}, \tau_{32}^{j_2}$
Interpolate to the SR
SR predictions
$m^{j_1}, m^{j_2} - m^{j_1}, \tau_{21}^{j_1}, \tau_{21}^{j_2}, \tau_{32}^{j_1}, \tau_{32}^{j_2}$
2-prong signal: 4 variables
3-prong signal: 6 variables
Classifier
Train In the SR
Cut on classifier score to enhance discovery potential

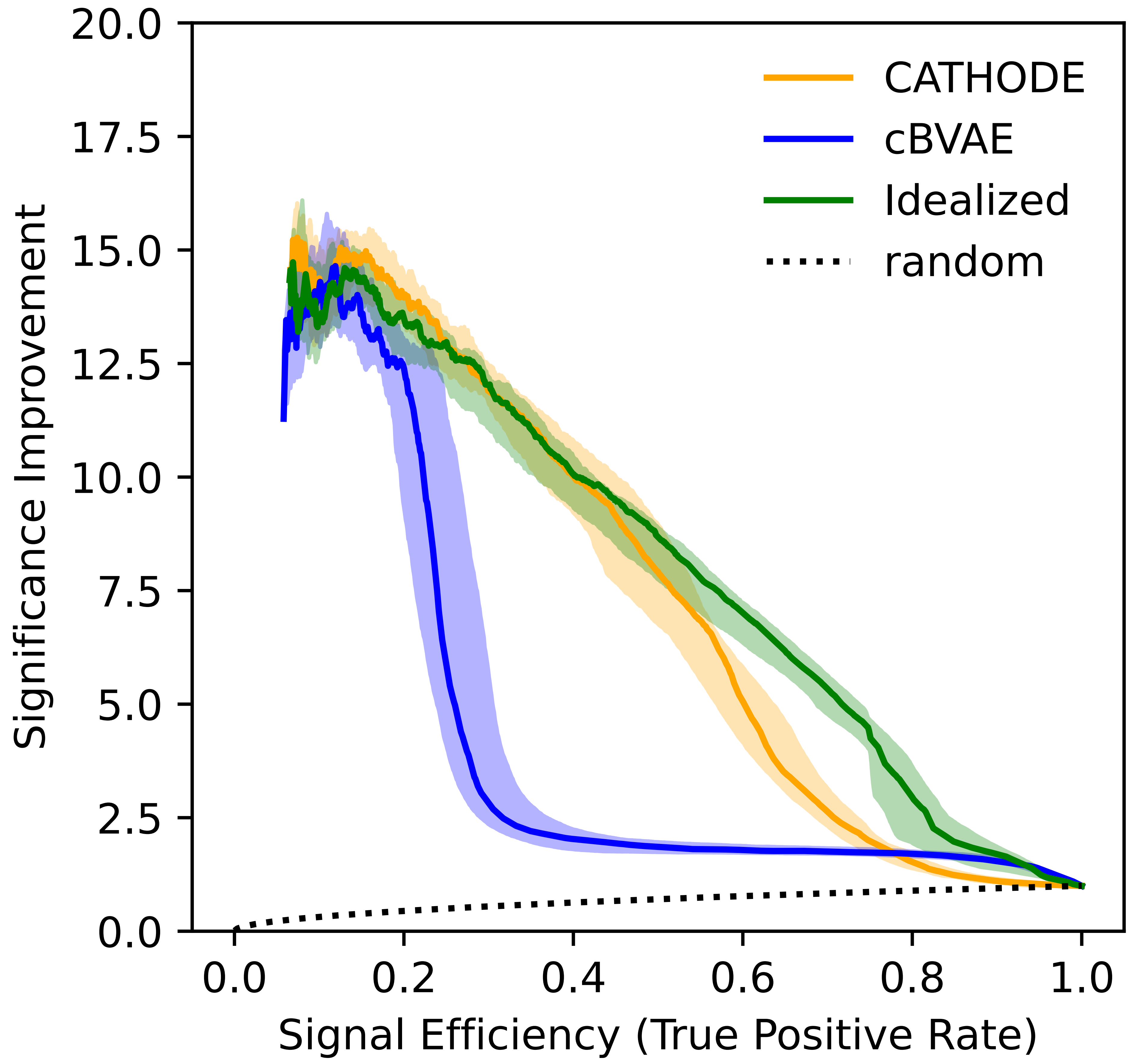
Significance Improvement: 2-prong signal

Classifier trained with 4 variables

- The VAE is trained with 6 variables
- Classifier is also trained with 4 variables

Max SIC matches CATHODE and Idealized

Currently it does not perform that well for high Signal Efficiency



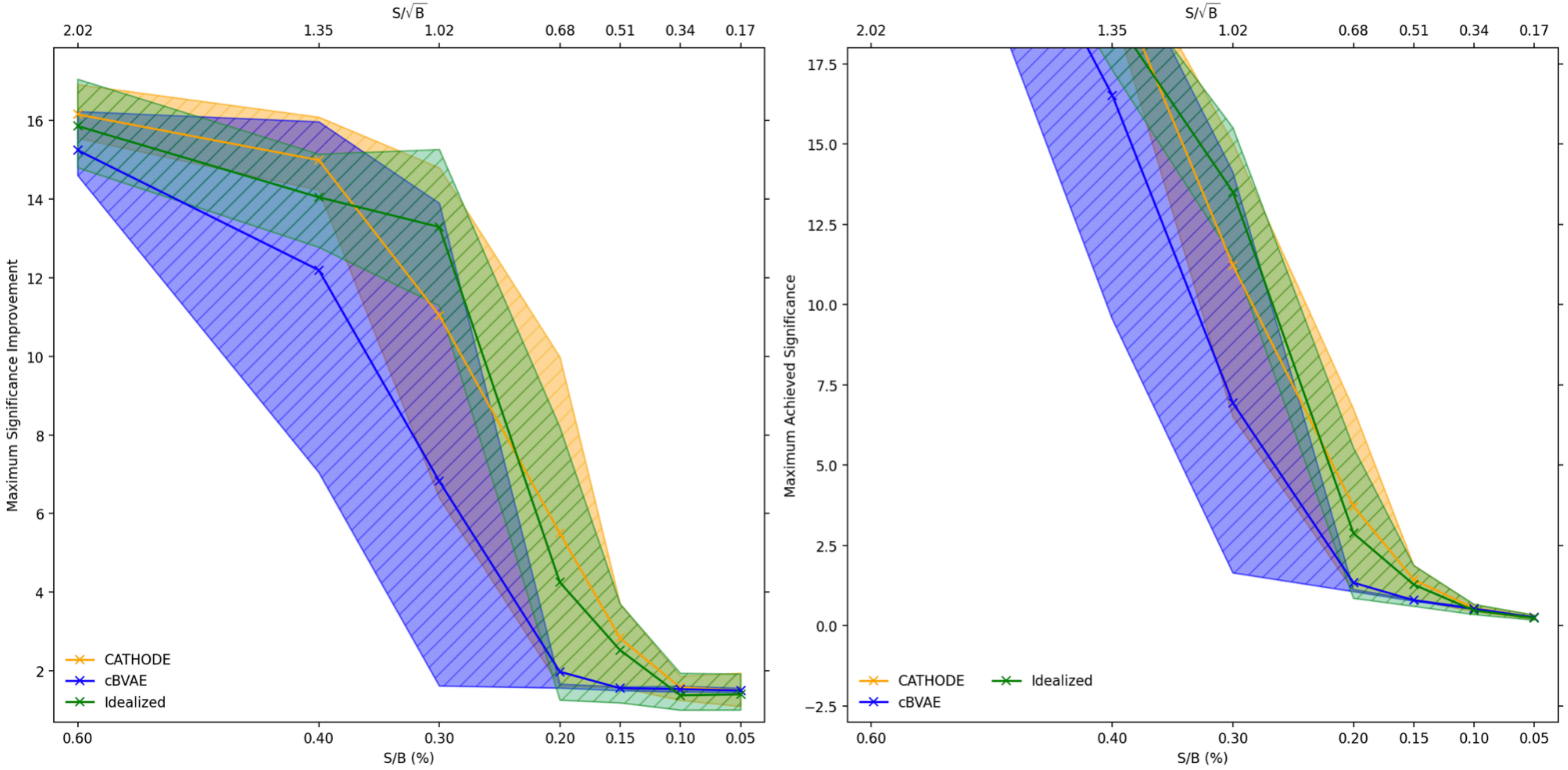
Significance Improvement (SIC) = TPR/ sqrt(FPR)

S/B scans: 2-prong signal

Classifier trained with 4 variables

- Similar signal sensitivity for S/B > 0.3%

$$\text{Maximum Achieved Significance} = \frac{S}{\sqrt{B}} \times \text{SIC}$$

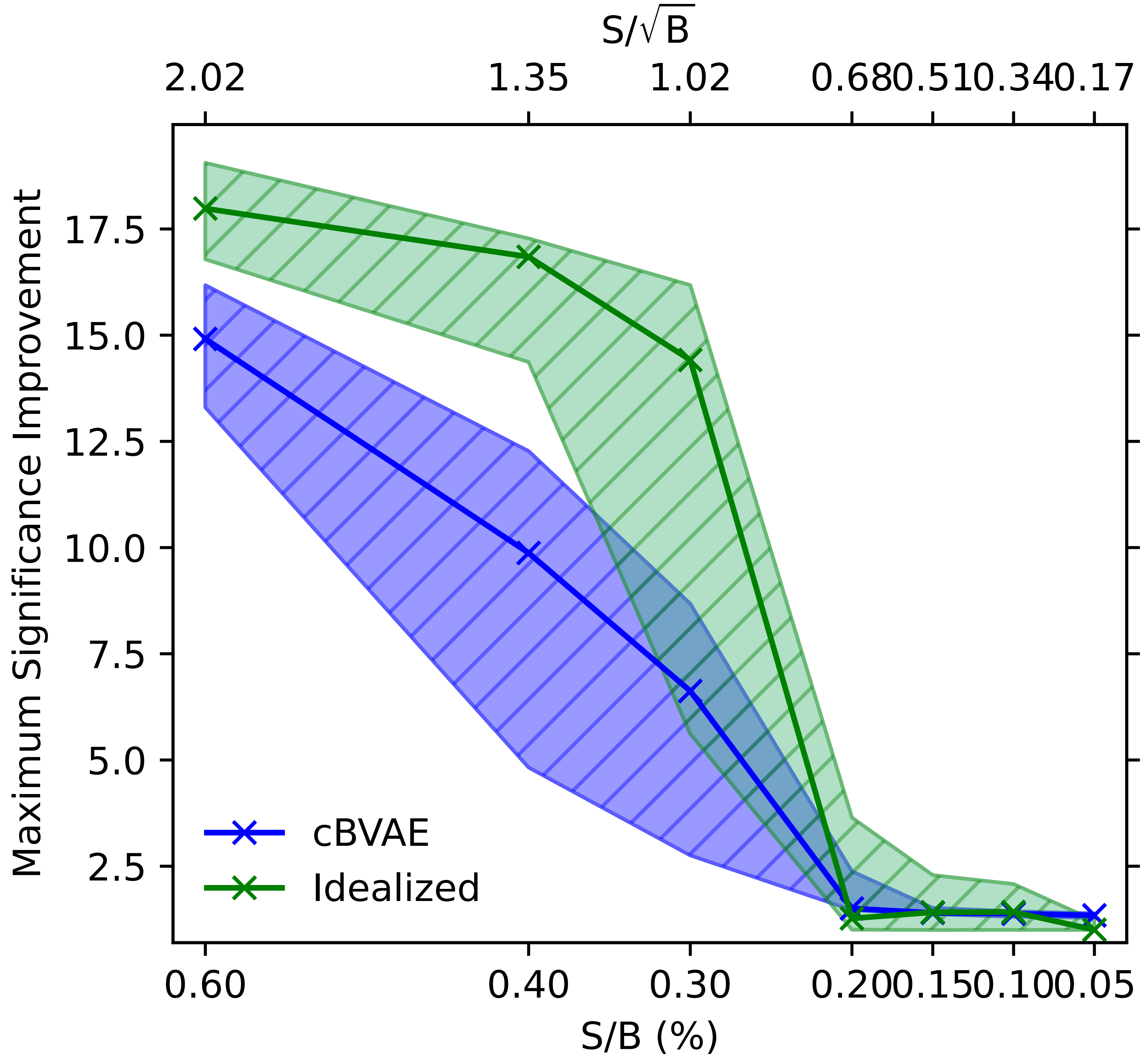


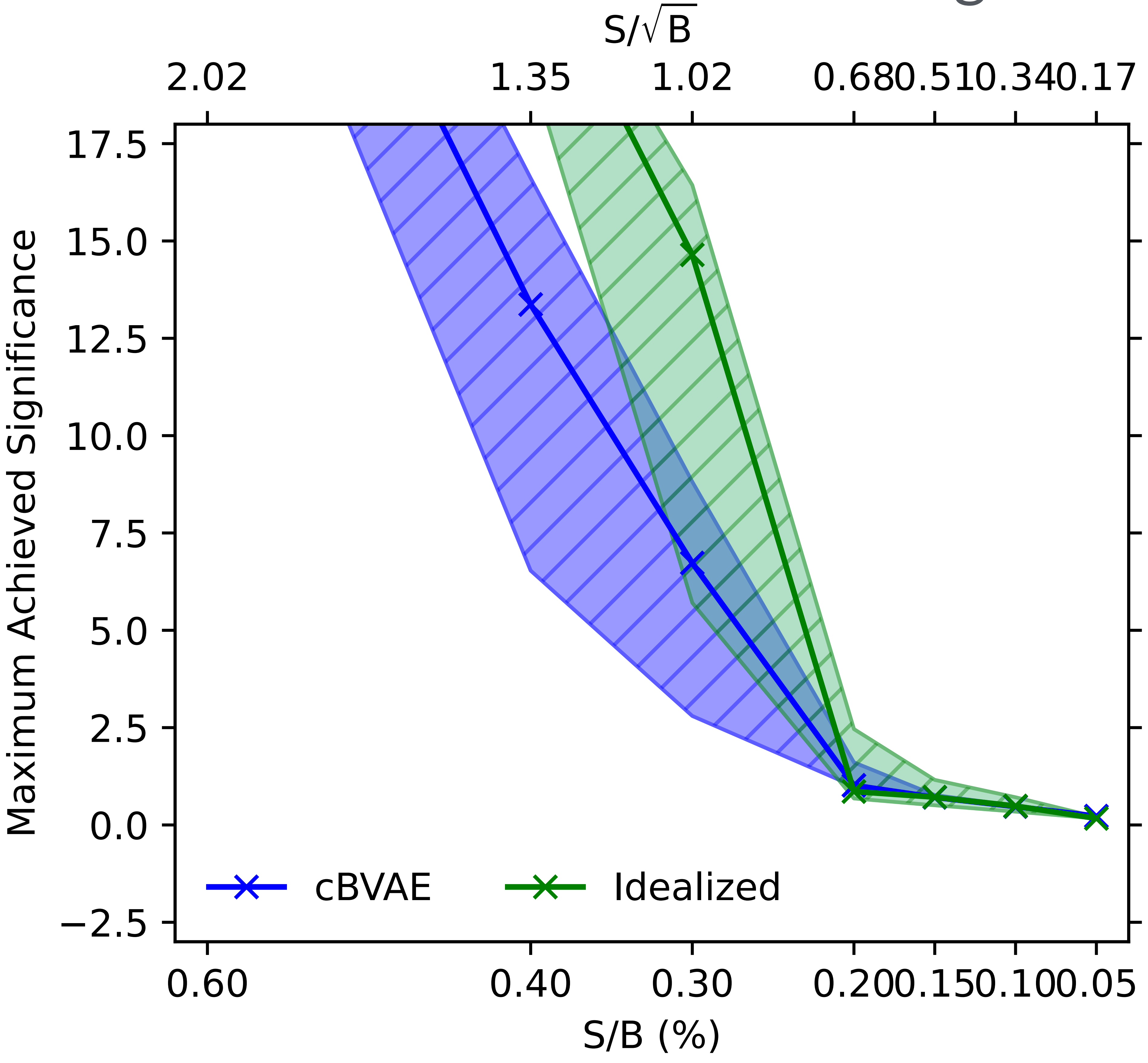
S/B scans: 2-prong signal

Classifier trained with 6 variables

- Similar signal sensitivity with 6 variables

$$\text{Maximum Achieved Significance} = \frac{S}{\sqrt{B}} \times \text{SIC}$$

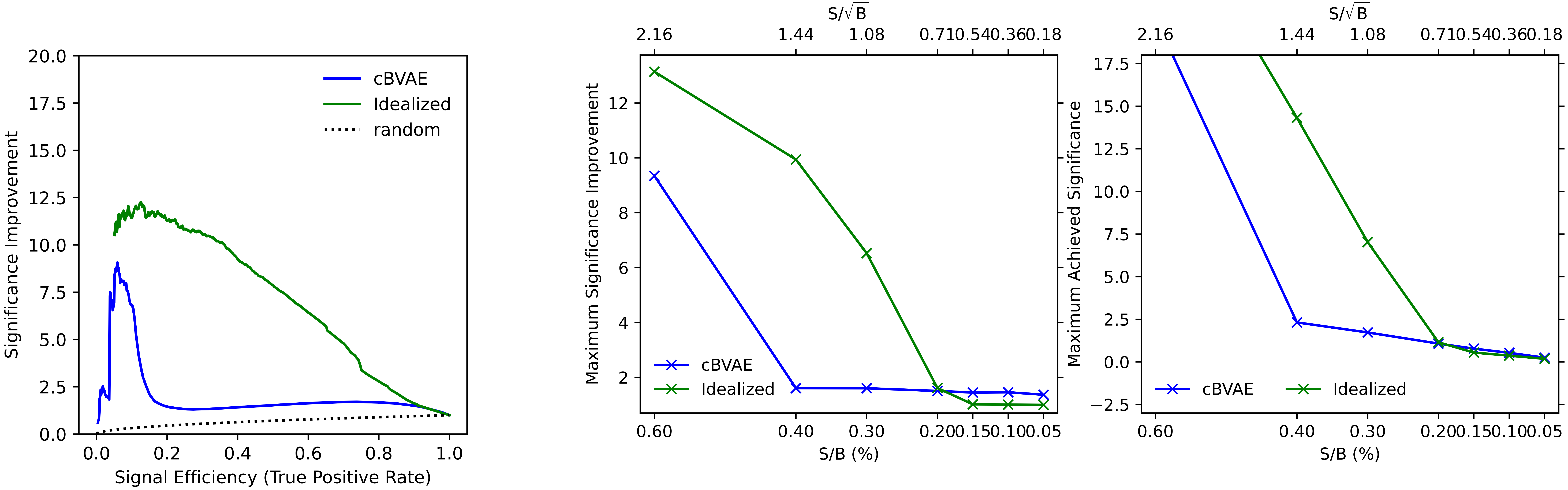




3-prong signal

Classifier trained with 6 variables

- Sensitive to the 3-prong signal as well!
- The sensitivity goes down as we start decreasing the injected signals
- **Currently studying it to find an optimal setup**



Summary and Outlook

Conditional VAE based approach looks promising

- Complementary to the density estimation methods (ANODE, CATHODE, e.t.c.)
- More flexible than Flows
- Max SIC is comparable to CATHODE

Easy to scale

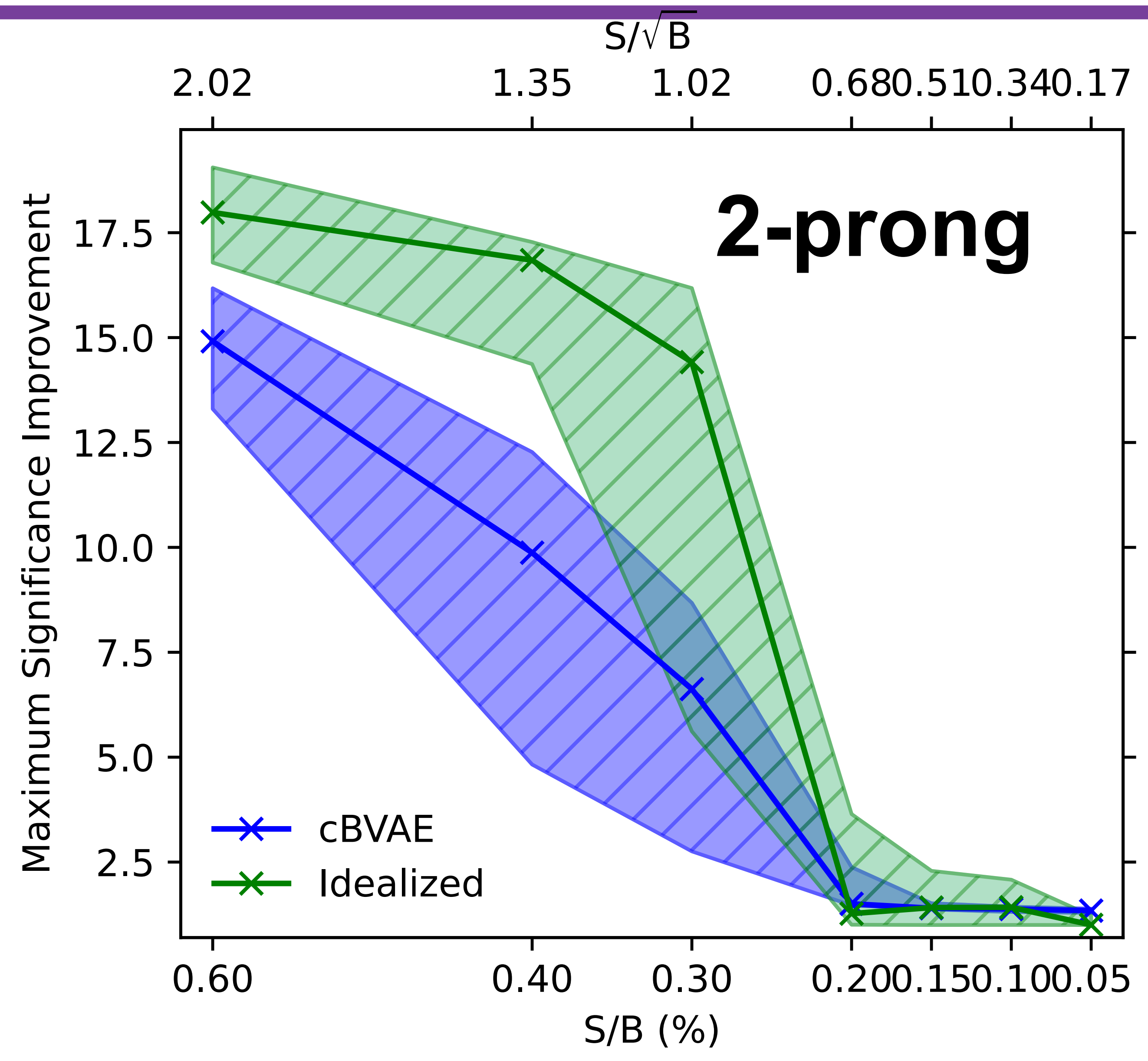
- Results with 6 variables, higher dimensional feature space is also studied

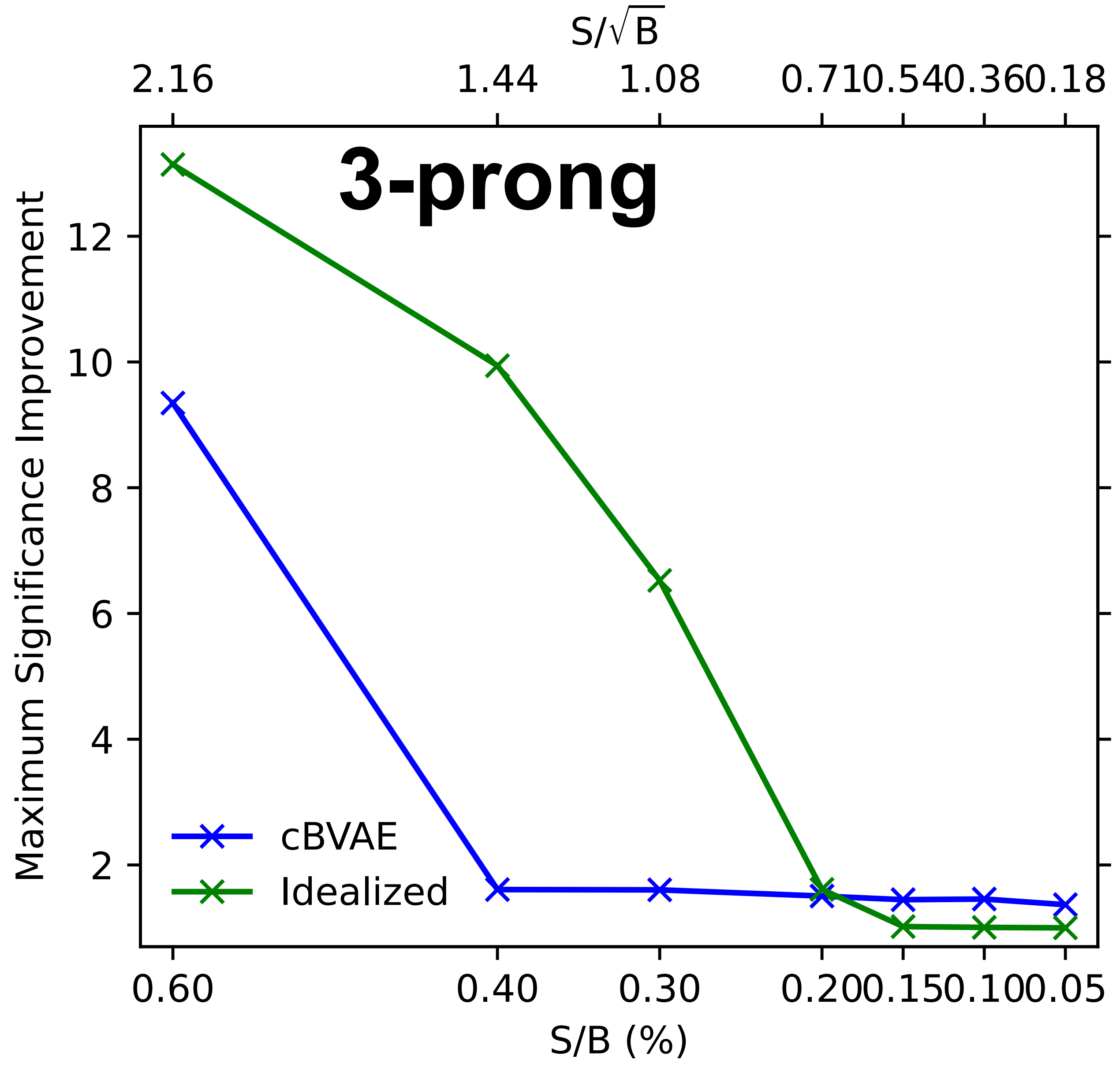
Sensitivity to different signatures

- Studying both 2-prong and 3-prong di-jet signals

Thanks!

Let me know if you have any suggestions





BackUp

Significance Improvement: 2-prong signal

Classifier trained with 6 variables

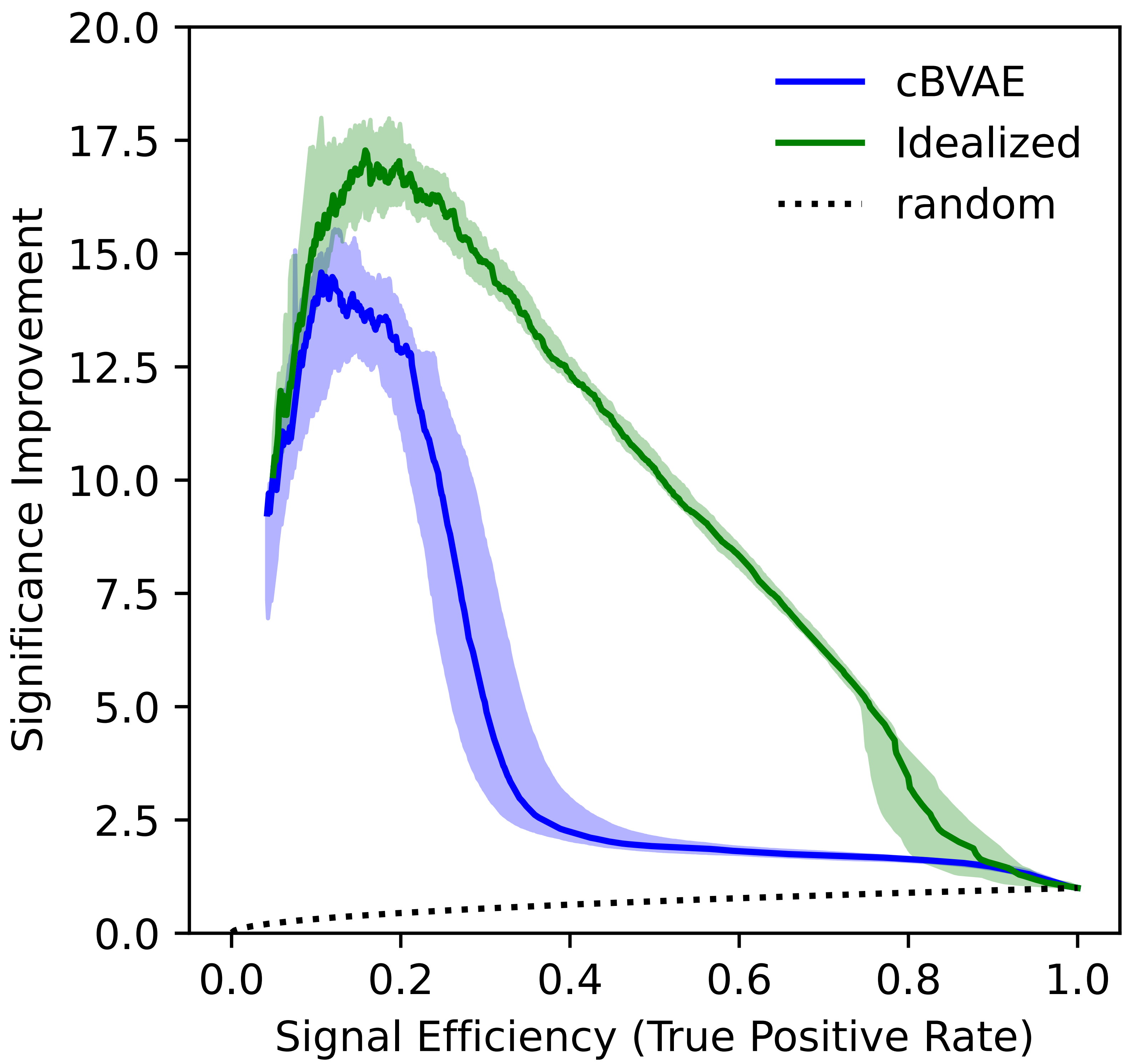
- The VAE is trained with 6 variables
- Classifier is trained with 6 variables

Still Sensitive to the signal!

- Max SIC is more than 10

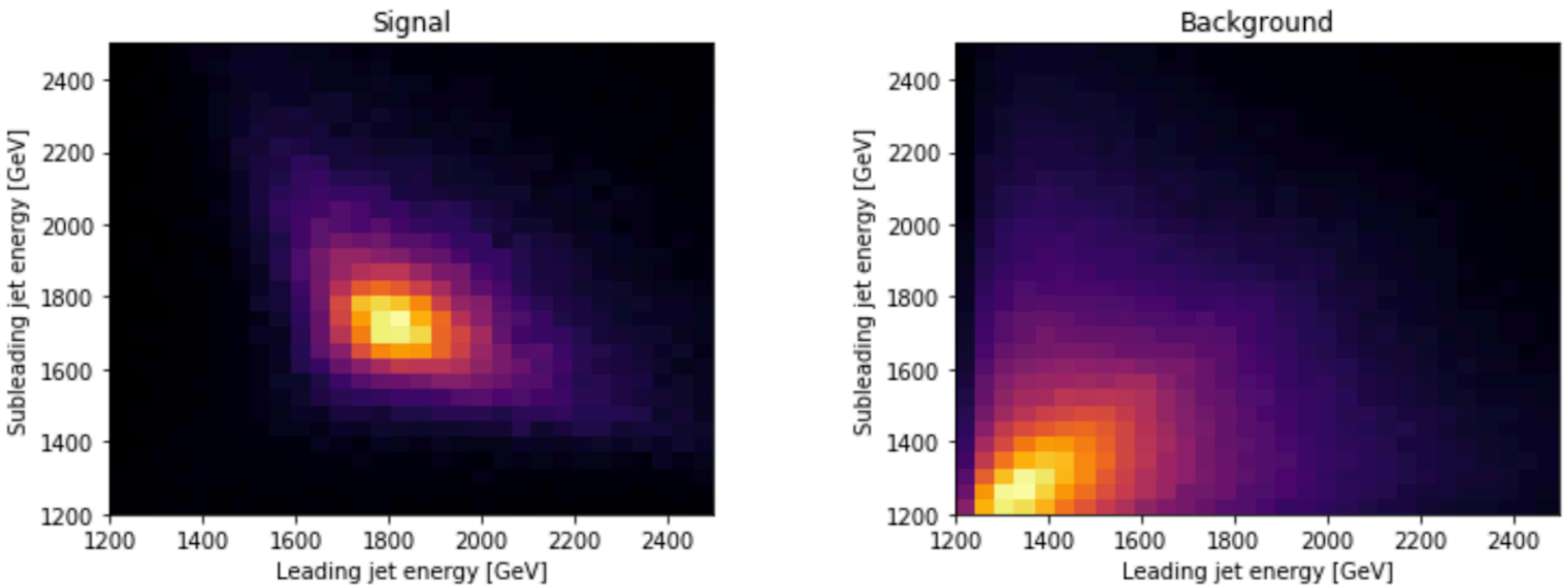
Currently it does not perform that well for high Signal Efficiency

Significance Improvement (SIC) = TPR/ sqrt(FPR)

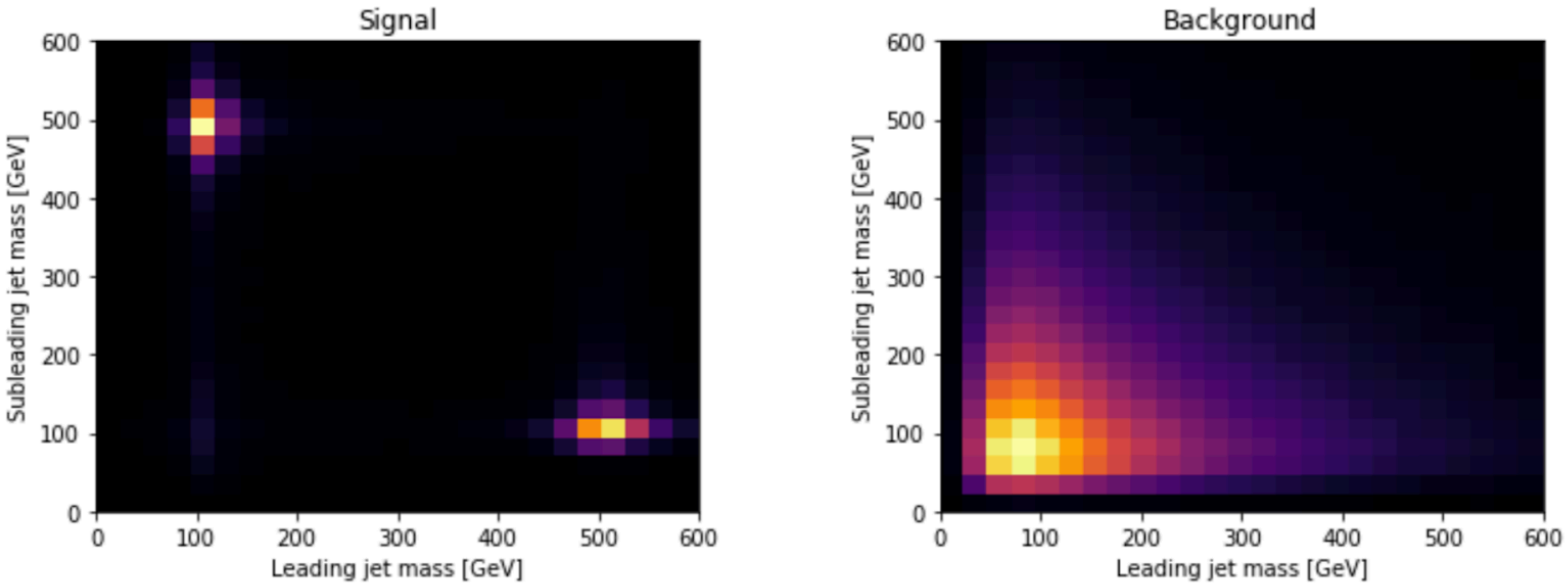


Dataset Features

Jet Energy

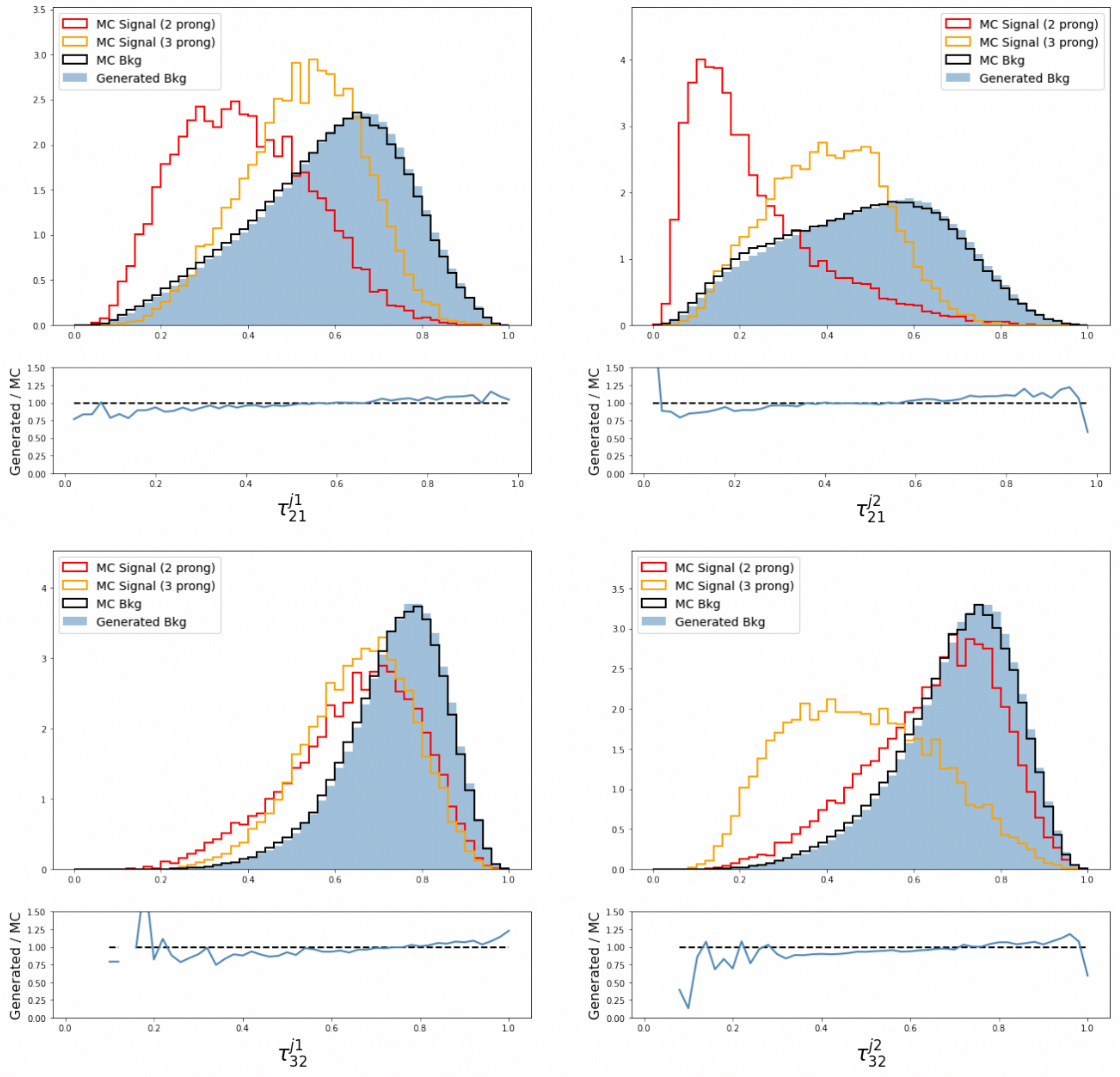


Jet Mass



Generated events in the SR

Generated events in the signal region



Currently working with the [R&D dataset]

It contains:

- **Background:** 1M QCD dijet events

- **Signal:** 100k W' (3.5 TeV) → X (500 GeV) + Y (100 GeV) , with X→ qq and Y → qq

Events are produced with **Pythia8** and **Delphes 3.4.1**, with no pileup or MPI included

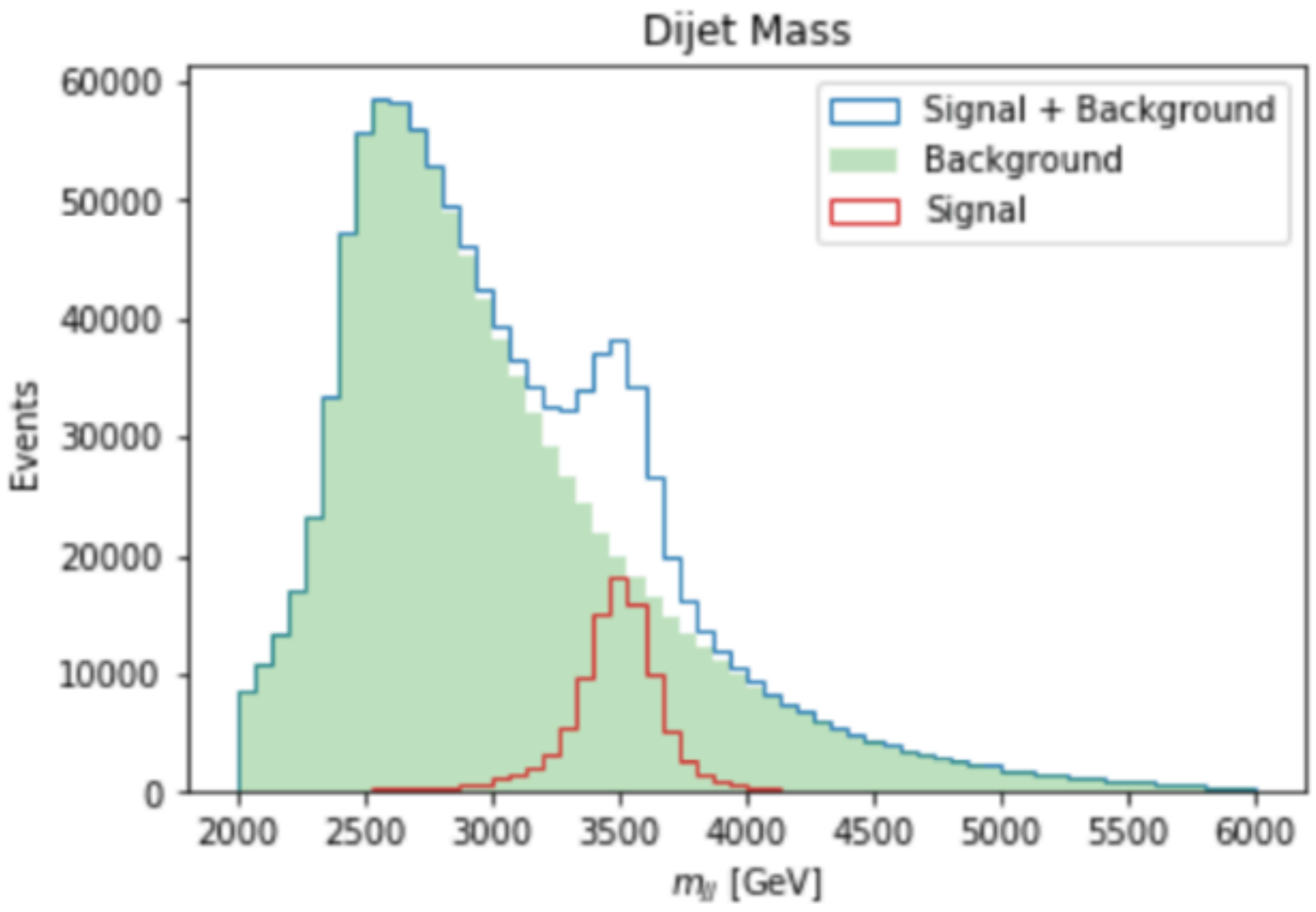
Event Selection:

- Single fat-jet (R=1) trigger with p_T > 1.2 TeV
- $|\eta| < 2.5$

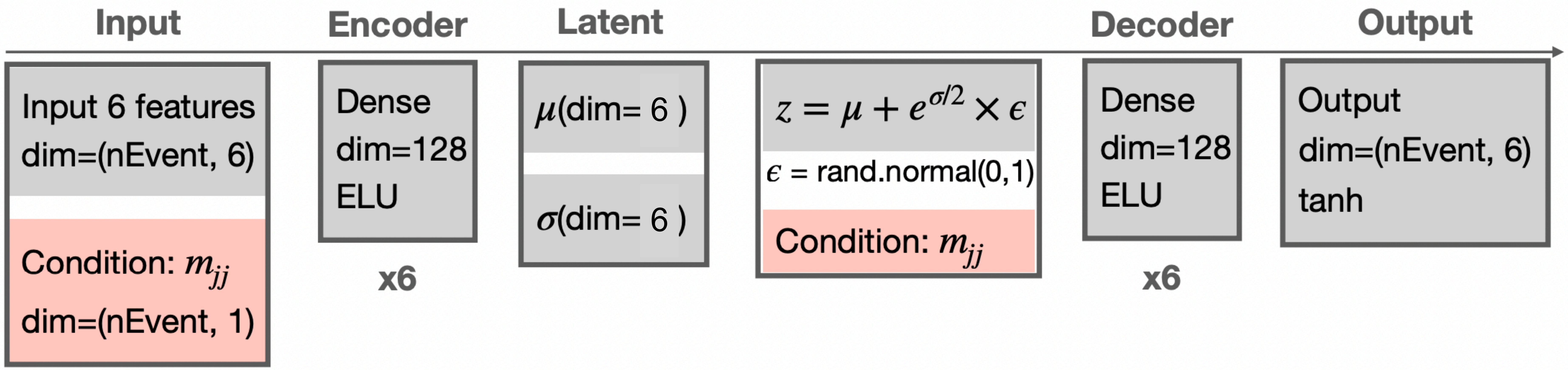
Dataset contains the kinematic variables of the leading and subleading jet (anti k_T R=1.0)

Currently working with 2-prong signals only

Signal and Sideband Regions



VAE Structure



$$L_{BVAE} = (1-\beta)*L_{MSE} + \beta*L_{KL} \quad , \beta = 10^{-6}$$