

SEARCHING FOR NEW PHYSICS IN A MODEL AGNOSTIC WAY

Rafał Masełek

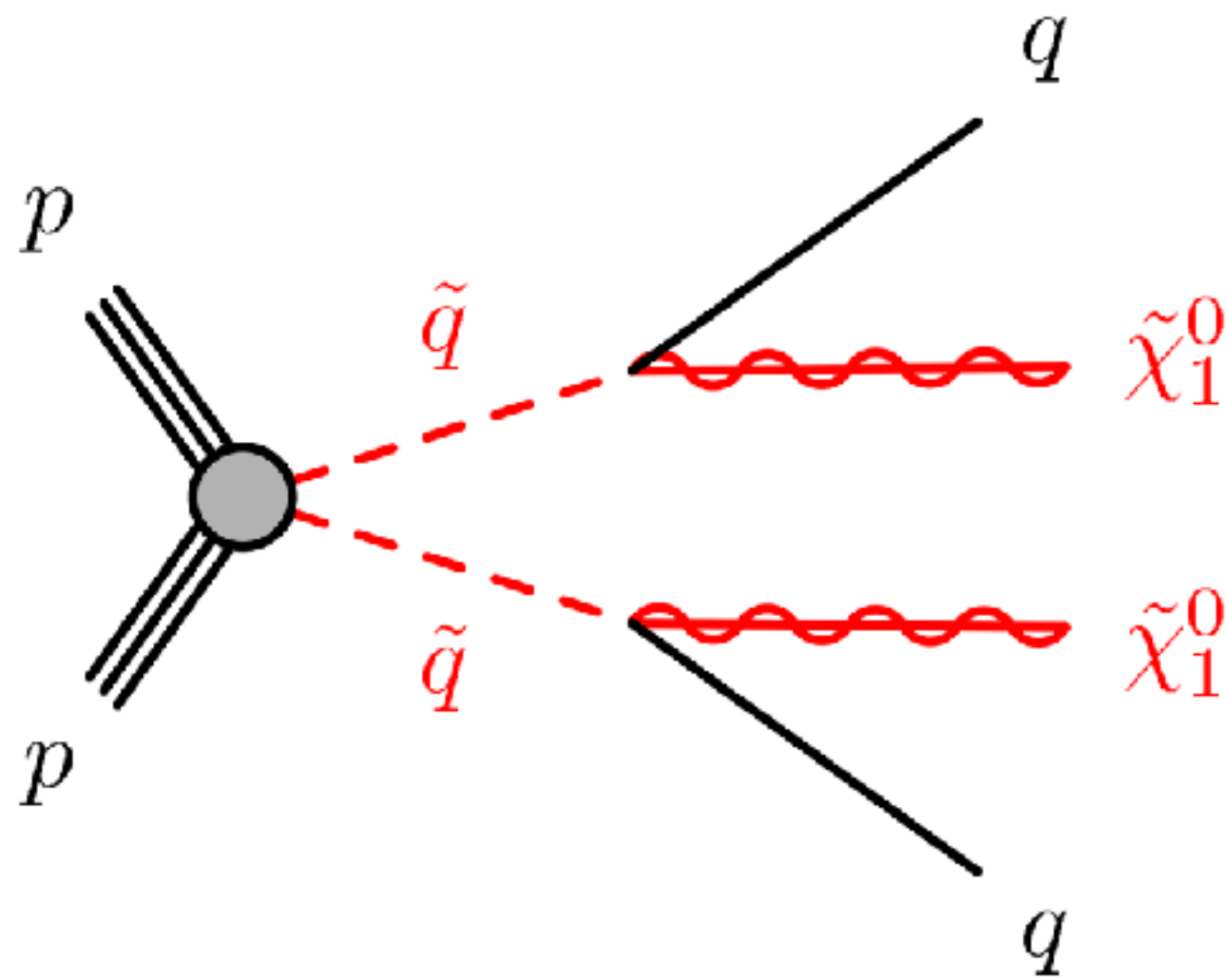
in collaboration with

Sabine Kraml, Kazuki Sakurai & David Shih

Brda 2026 15-10-2026

Classical approach to BSM searches

BSM scenario



event selection

Signal Region	$\geq 2\text{-jet}$
$E_{\text{T}}^{\text{miss}}$	> 130
Leading jet p_{T}	> 130
Second jet p_{T}	> 40
$\Delta\phi(\text{jet}, \vec{P}_{\text{T}}^{\text{miss}})_{\text{min}}$	> 0.4
$E_{\text{T}}^{\text{miss}}/m_{\text{eff}}$	> 0.3
m_{eff}	> 1000

background estimation

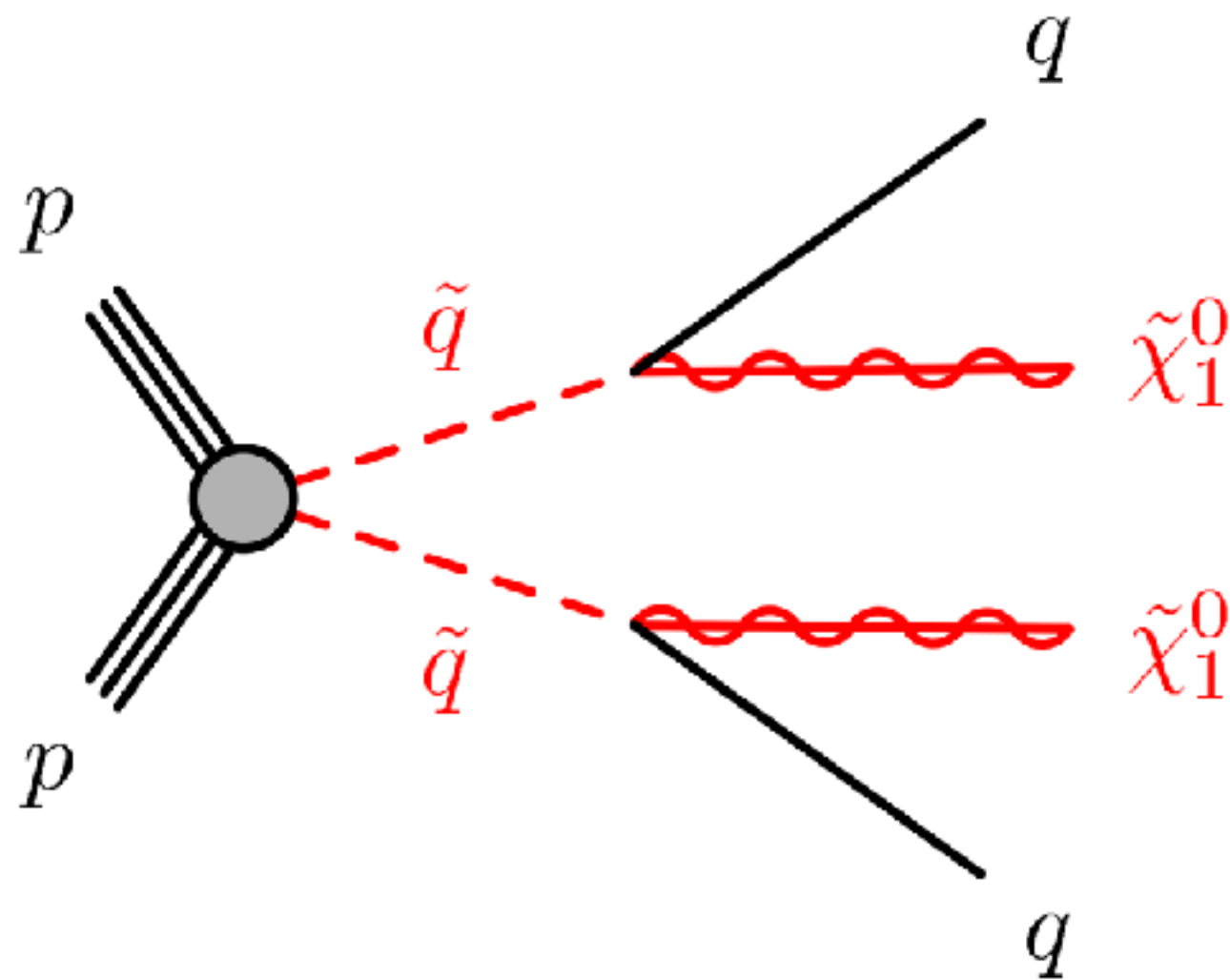
BG/signal estimation (MC sim)

Z/ γ +jets	$32.3 \pm 2.6 \pm 6.9$
W+jets	$26.4 \pm 4.0 \pm 6.7$
$t\bar{t}$ + single top	$3.4 \pm 1.6 \pm 1.6$
QCD multi-jet	$0.22 \pm 0.06 \pm 0.24$
SM total	$62.4 \pm 4.4 \pm 9.3$
$(m_{\tilde{q}}, m_{\tilde{\chi}_1^0}) = (1, 0.1) \text{ TeV}$	29.2 ± 5.1
Data	58

statistical
consistency

Classical approach to BSM searches

BSM scenario



limited by our biases

event selection

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$E_{\text{T}}^{\text{miss}}$	> 130
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specific to BSM scenario

background estimation

BG/signal estimation (MC sim)

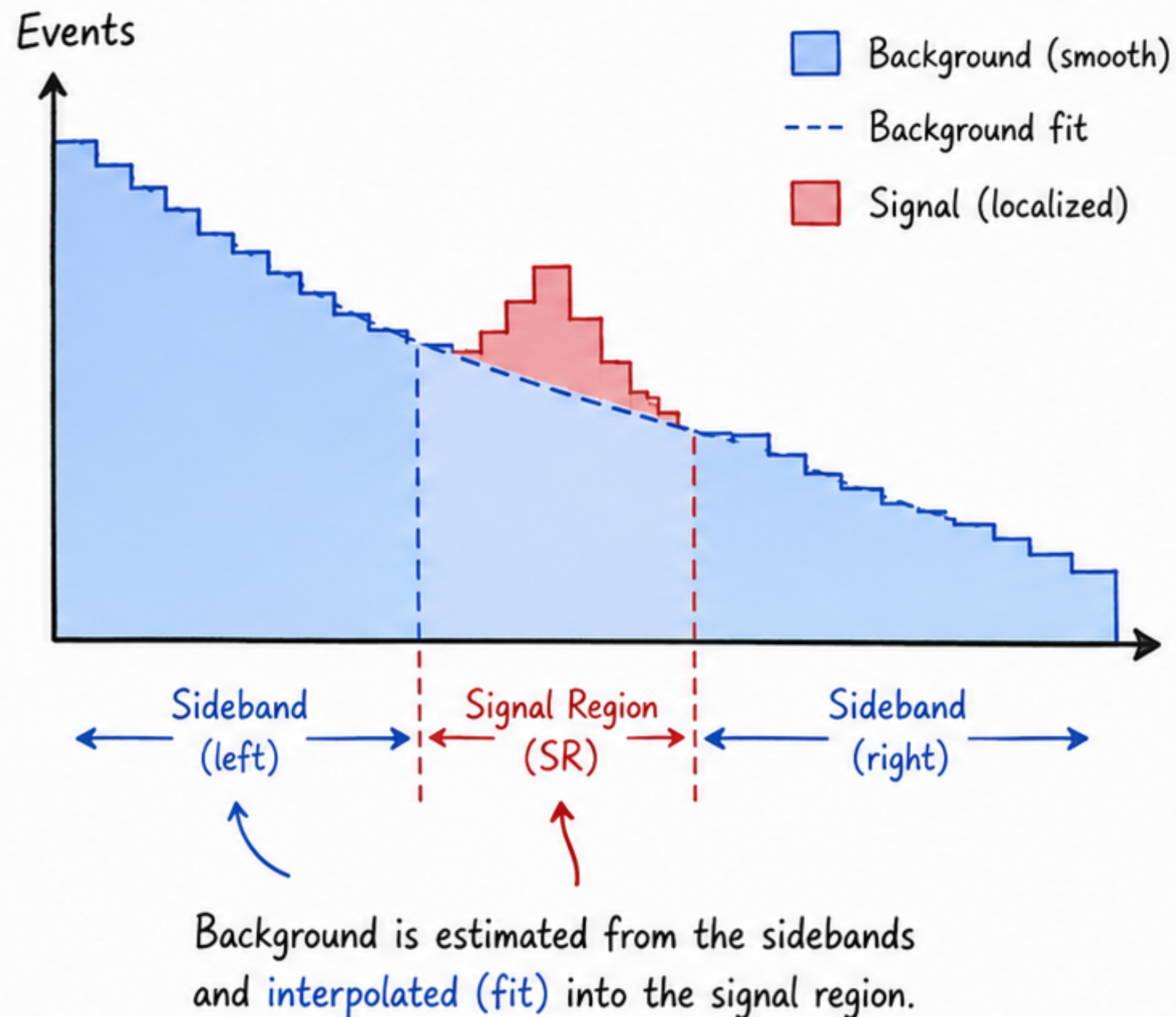
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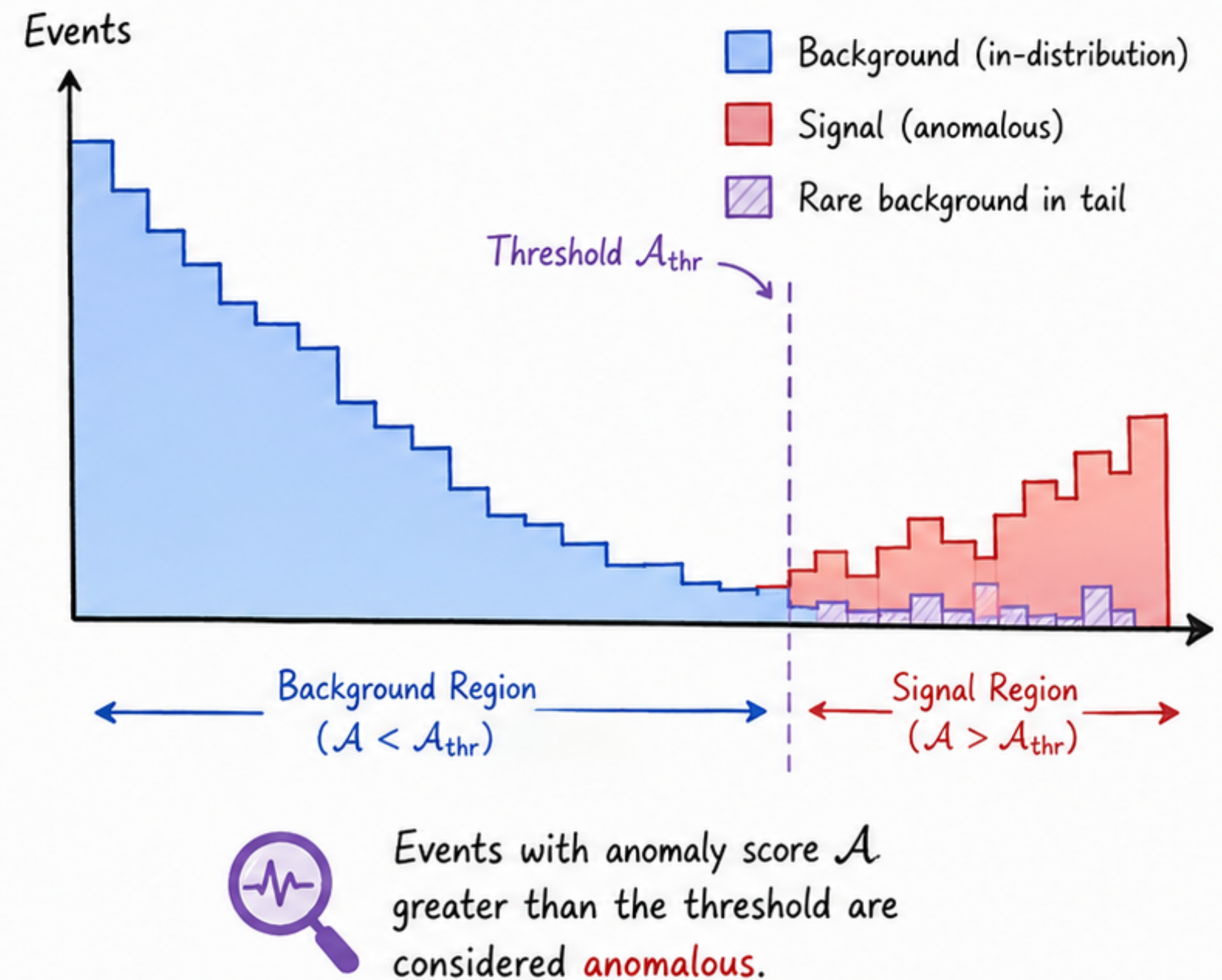
simulation dependent

Anomaly searches in HEP

Overdensity (Bump Hunting)

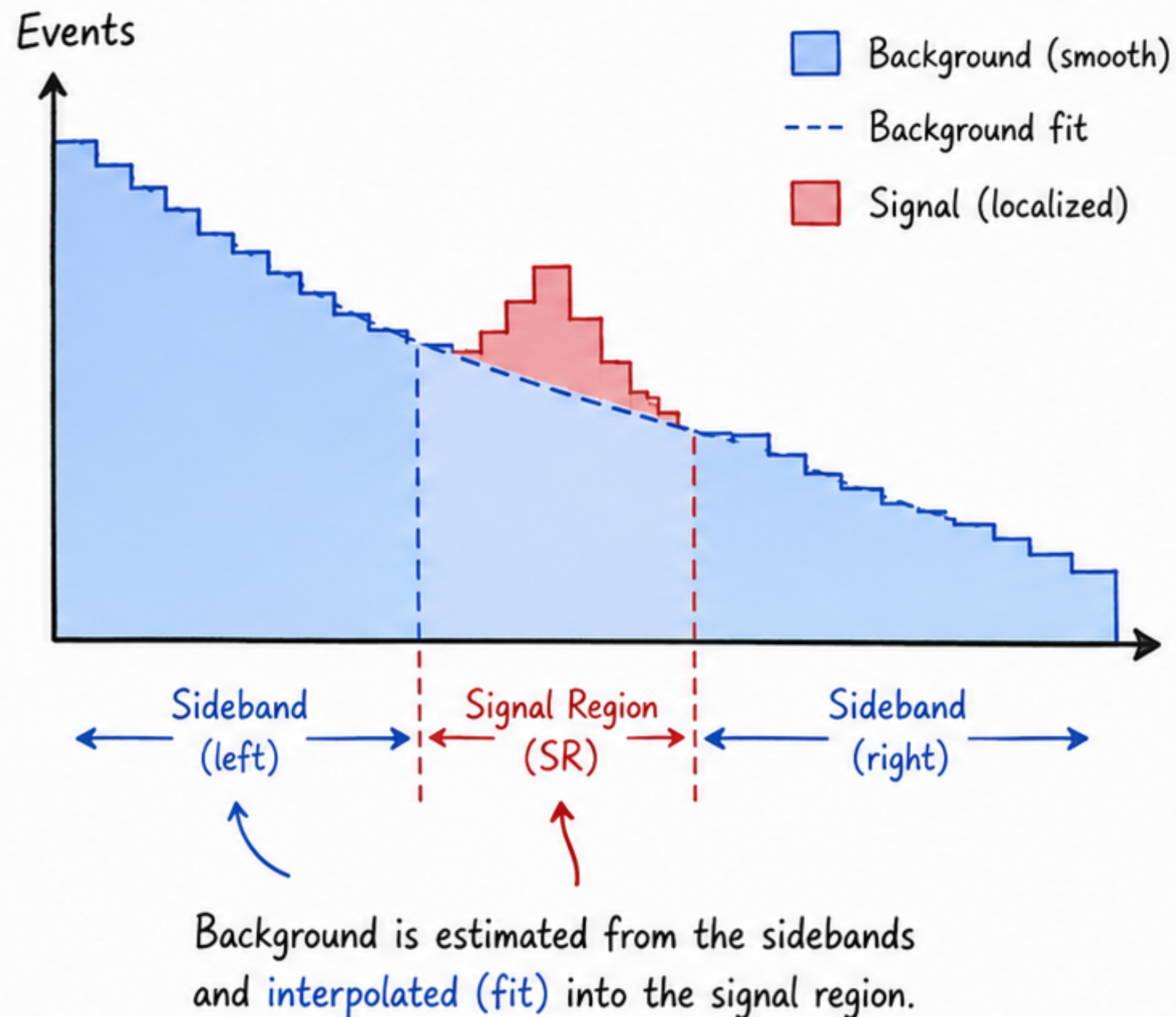


Out-of-Distribution (OOD) Anomaly Search



Anomaly searches in HEP

Overdensity (Bump Hunting)



Special resonant variable, e.g., m_{JJ}

Signal localised

Background smooth

Define:

Signal region

Two adjacent sideband regions

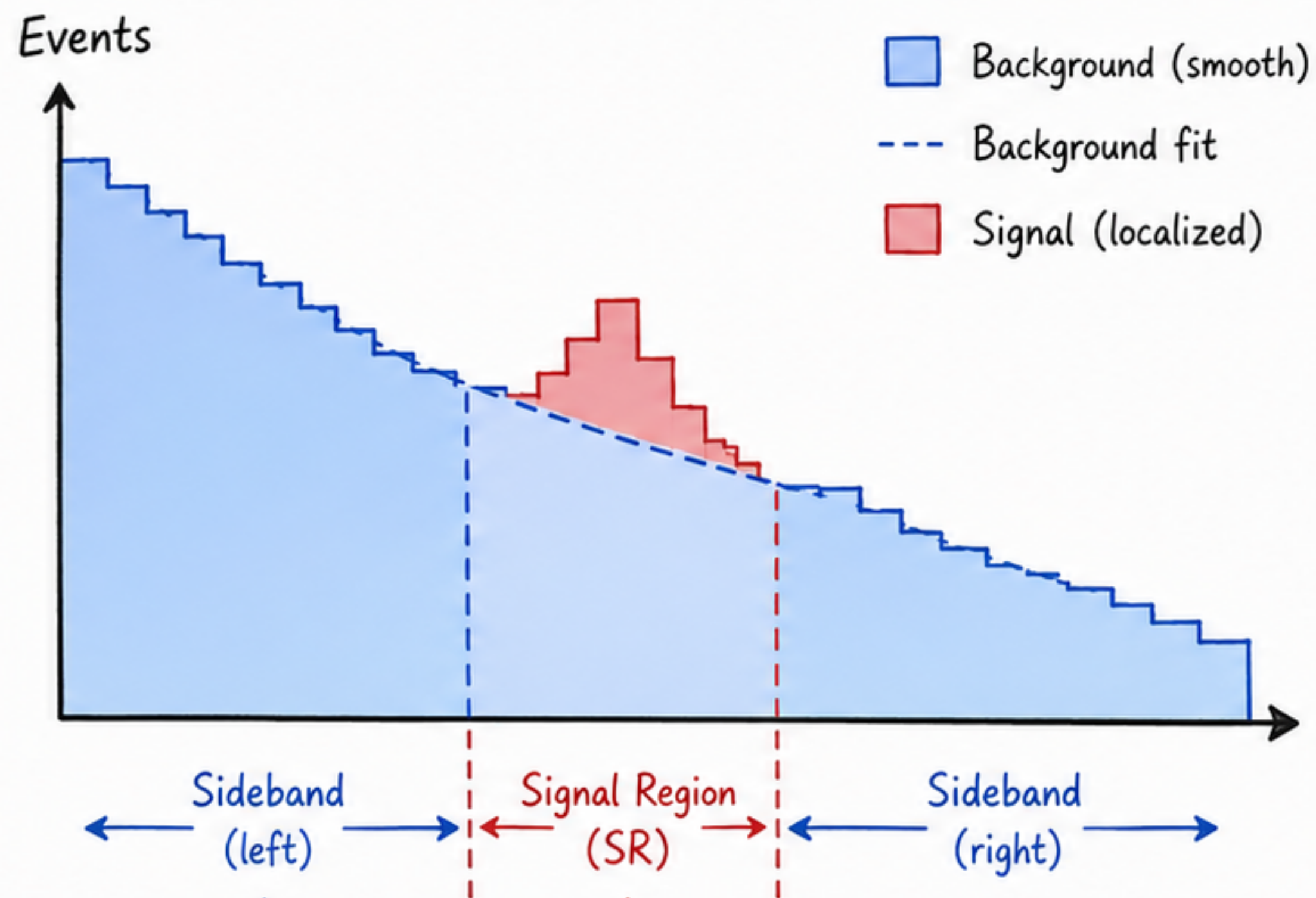
Look for an excess in the SR

Classically: **Bump Hunting**

ML: weakly-supervised methods using auxiliary variables

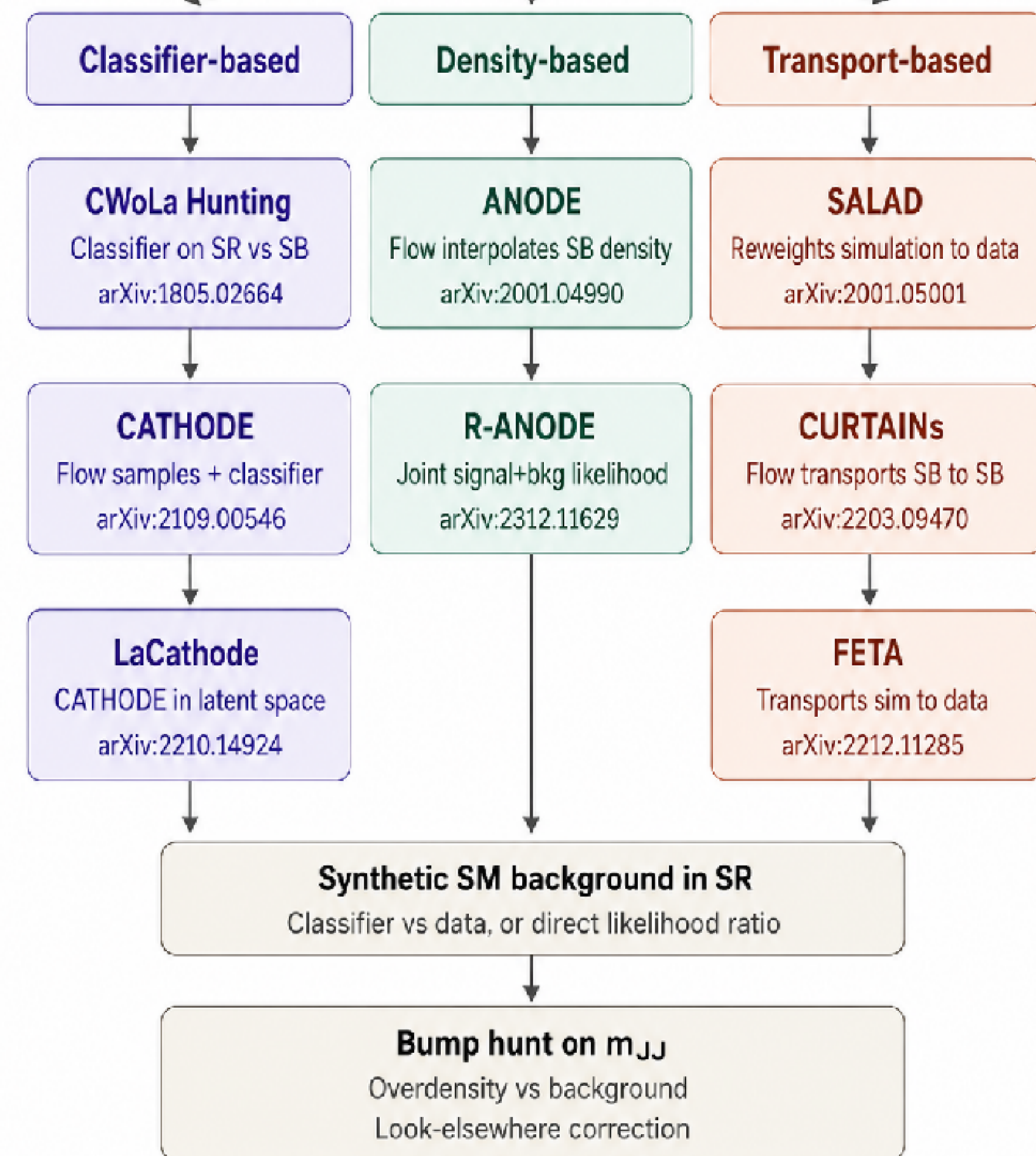
Anomaly searches in HEP

Overdensity (Bump Hunting)



Background is estimated from the sidebands and interpolated (fit) into the signal region.

Background estimation strategy

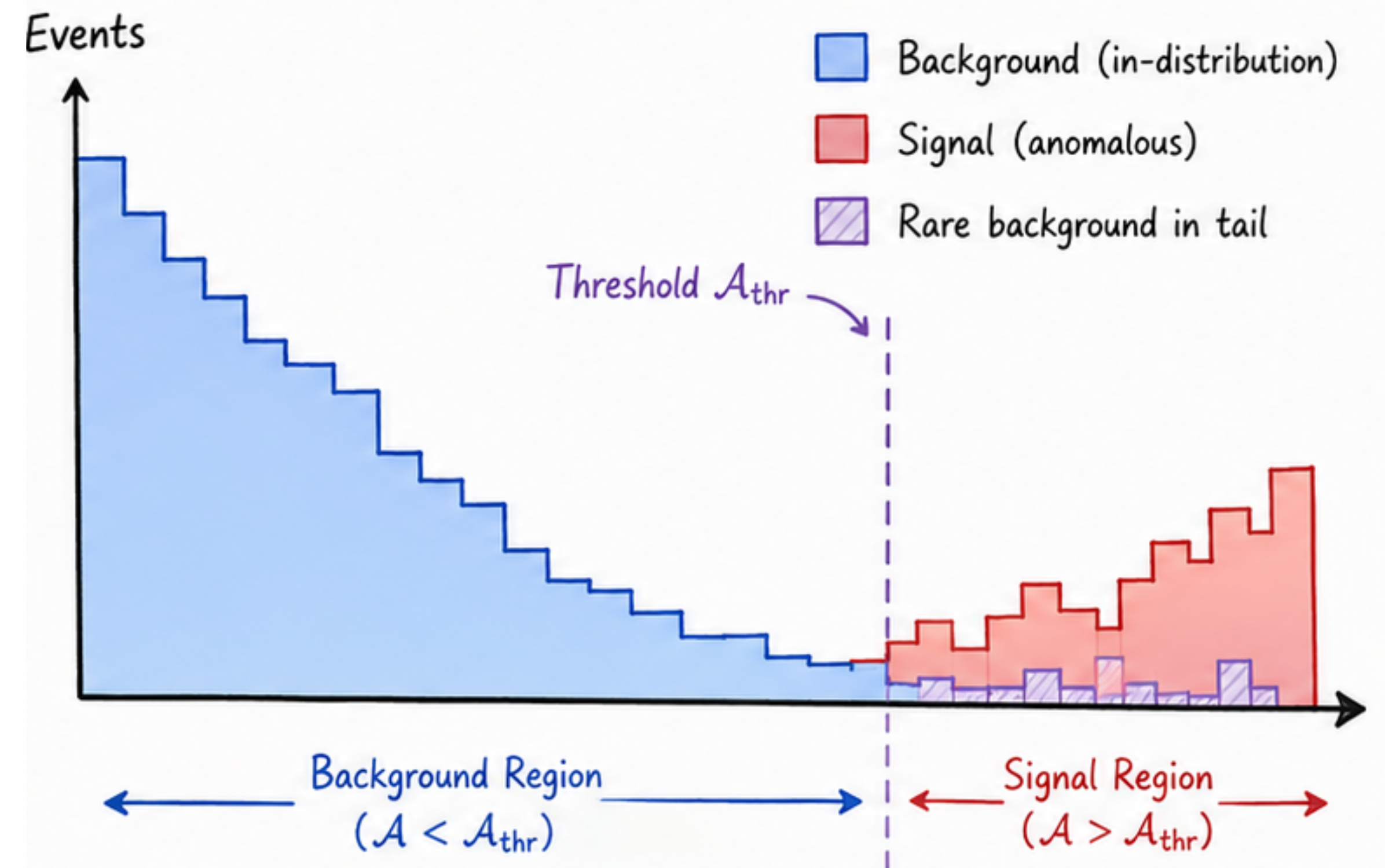


Benchmarked together on LHC Olympics 2020 - arXiv:2101.08320
and compared directly in arXiv:2307.11157

Anomaly searches in HEP

- Construct anomaly score A
- Background events have small A
- Signal events have large A
- Select a threshold: A_{thr}
- Define the signal region as $A > A_{\text{thr}}$

Out-of-Distribution (OOD) Anomaly Search



Events with anomaly score A greater than the threshold are considered **anomalous**.

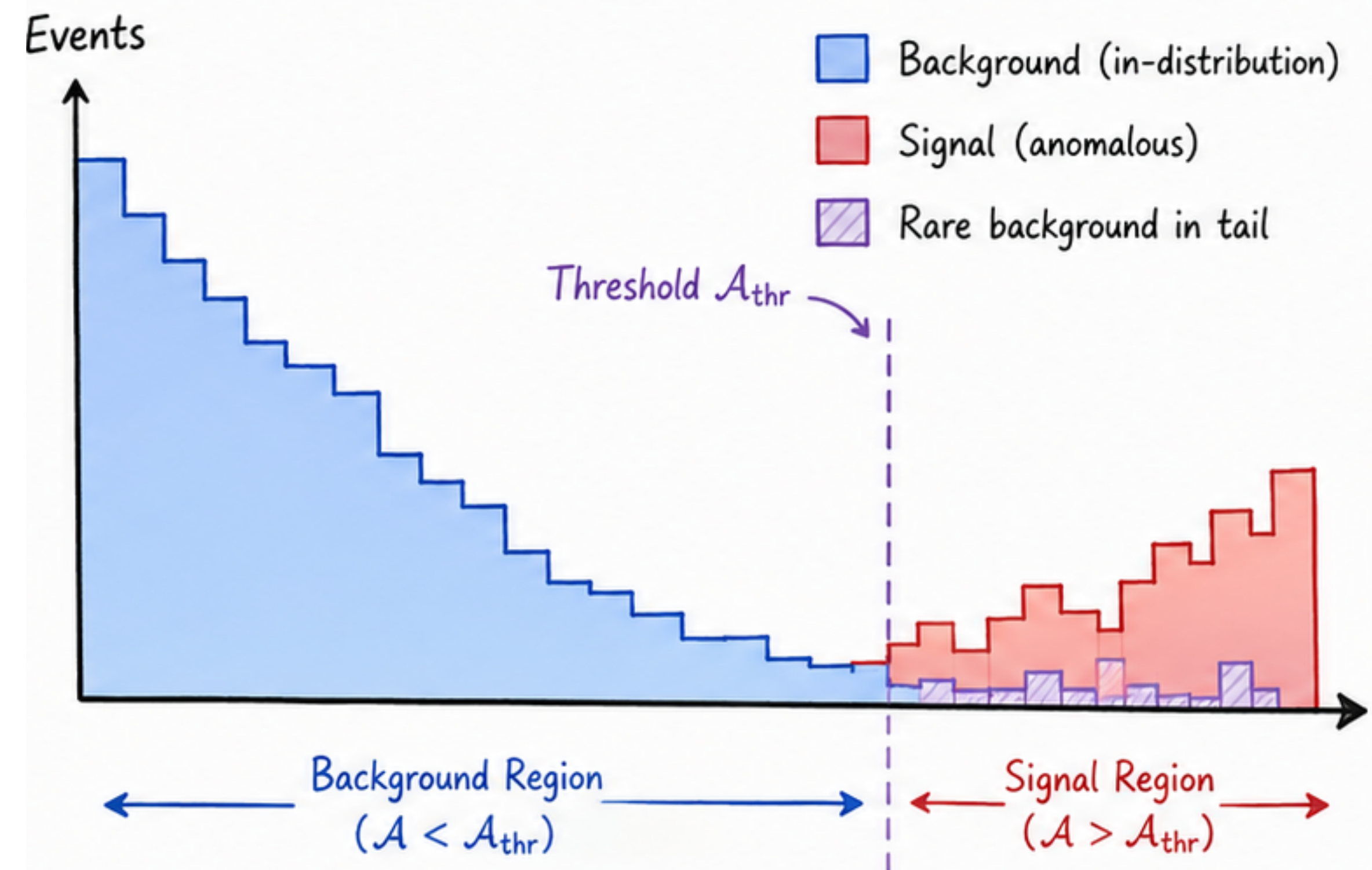
Anomaly searches in HEP

How?

- Construct anomaly score A
- Background events have small A
- Signal events have large A
- Select a threshold: A_{thr}
- Define the signal region as $A > A_{\text{thr}}$

What about background in the signal region?

Out-of-Distribution (OOD) Anomaly Search



Events with anomaly score A greater than the threshold are considered **anomalous**.

A wide-angle photograph of Moszna Castle in Poland, a large stone building with multiple towers and red-tiled roofs. The castle is reflected in a long, narrow pond in the foreground. The sky is clear blue, and there are green trees on either side of the castle.

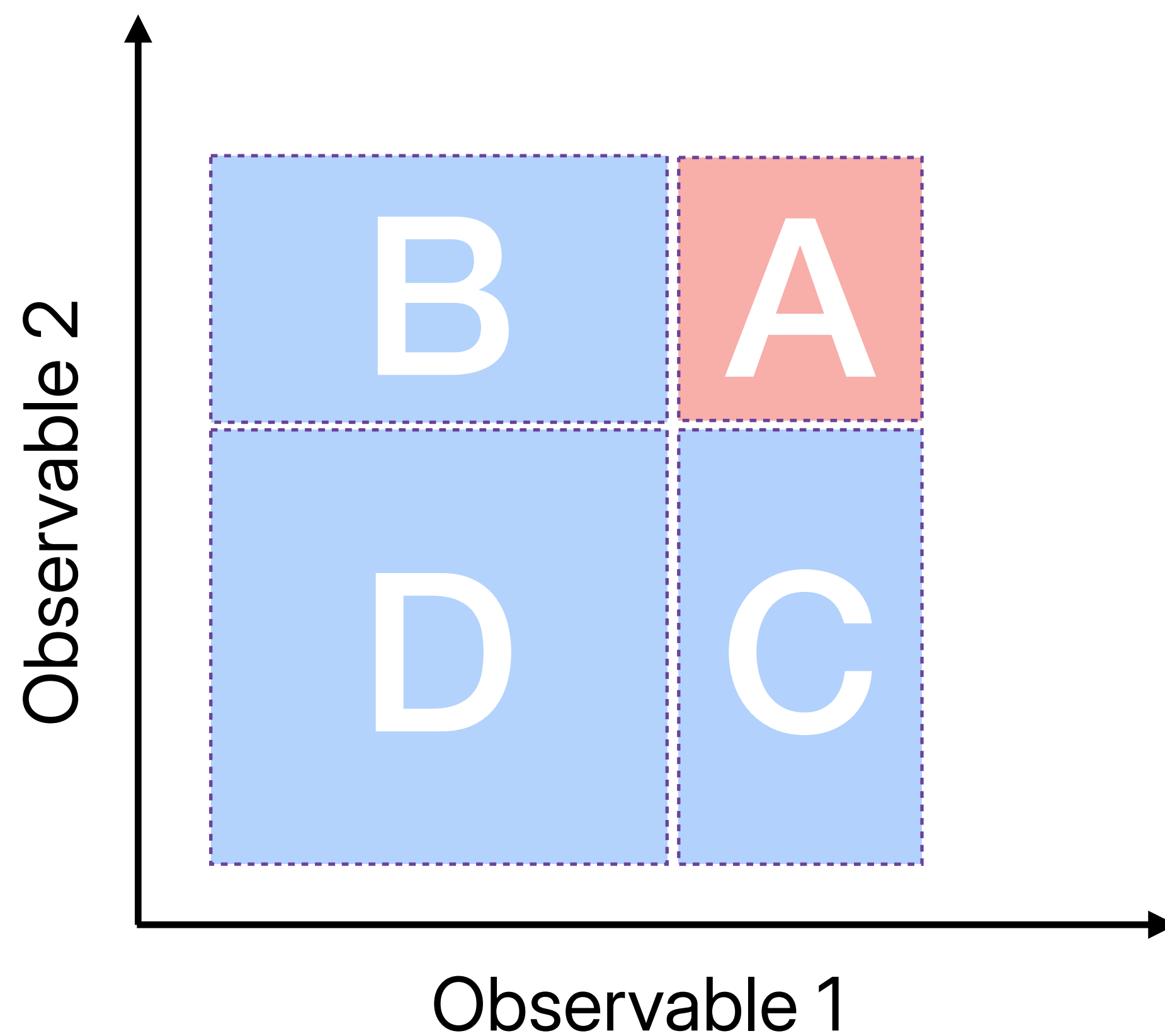
METHODOLOGY

Moszna Castle, Poland



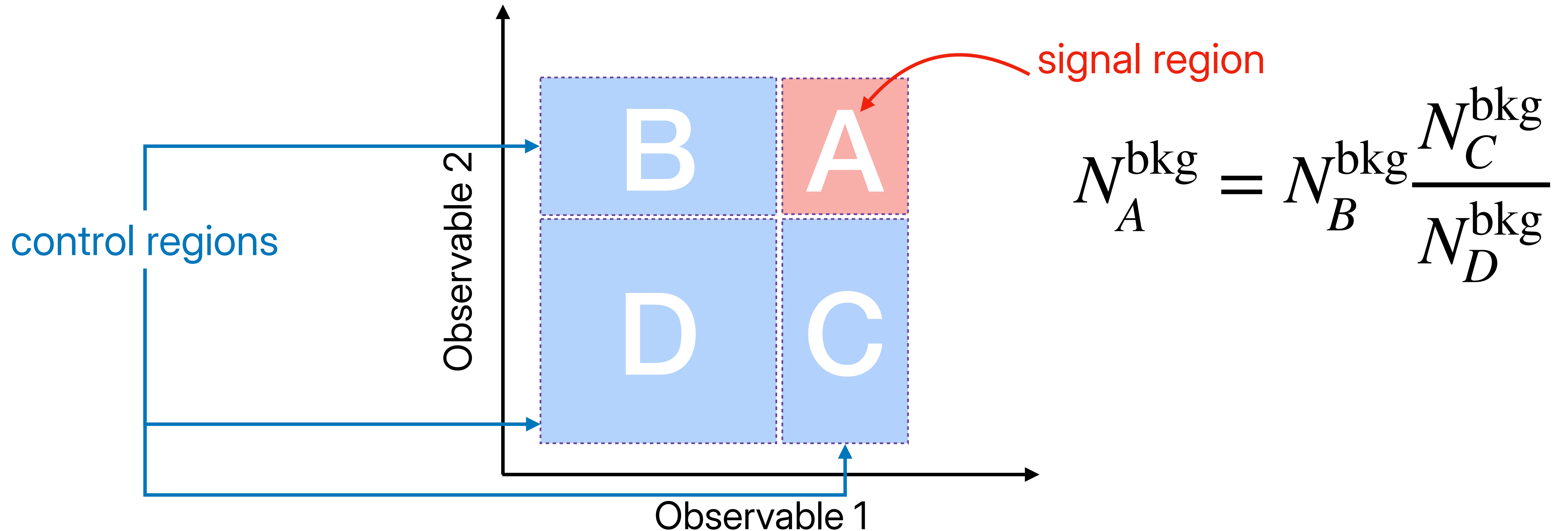
ABCD matrix method

Established method for data-driven background estimation



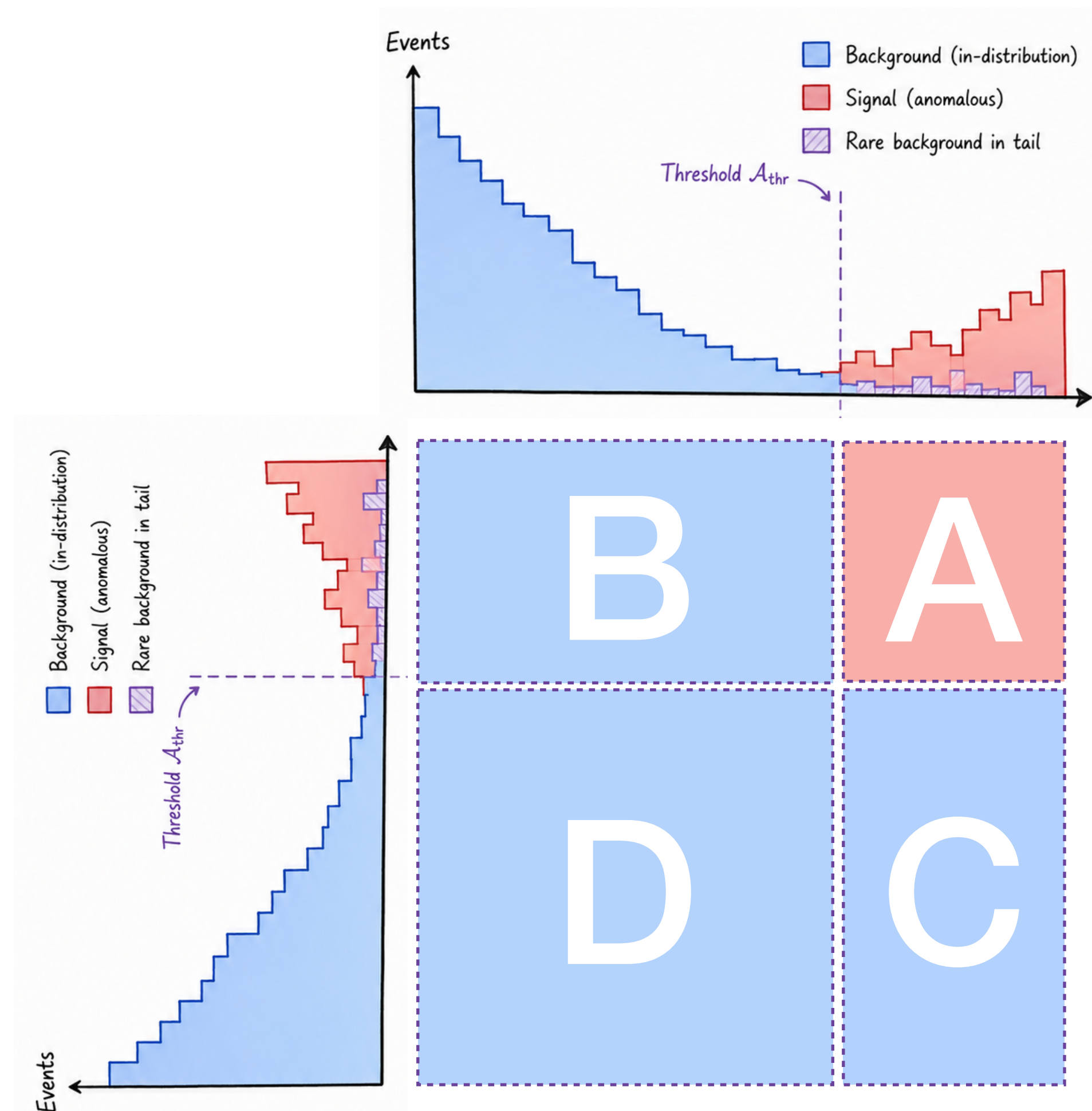
ABCD matrix method

Established method for data-driven background estimation



ABCD matrix method

Established method for data-driven background estimation



$$N_A^{bkg} = N_B^{bkg} \frac{N_C^{bkg}}{N_D^{bkg}}$$

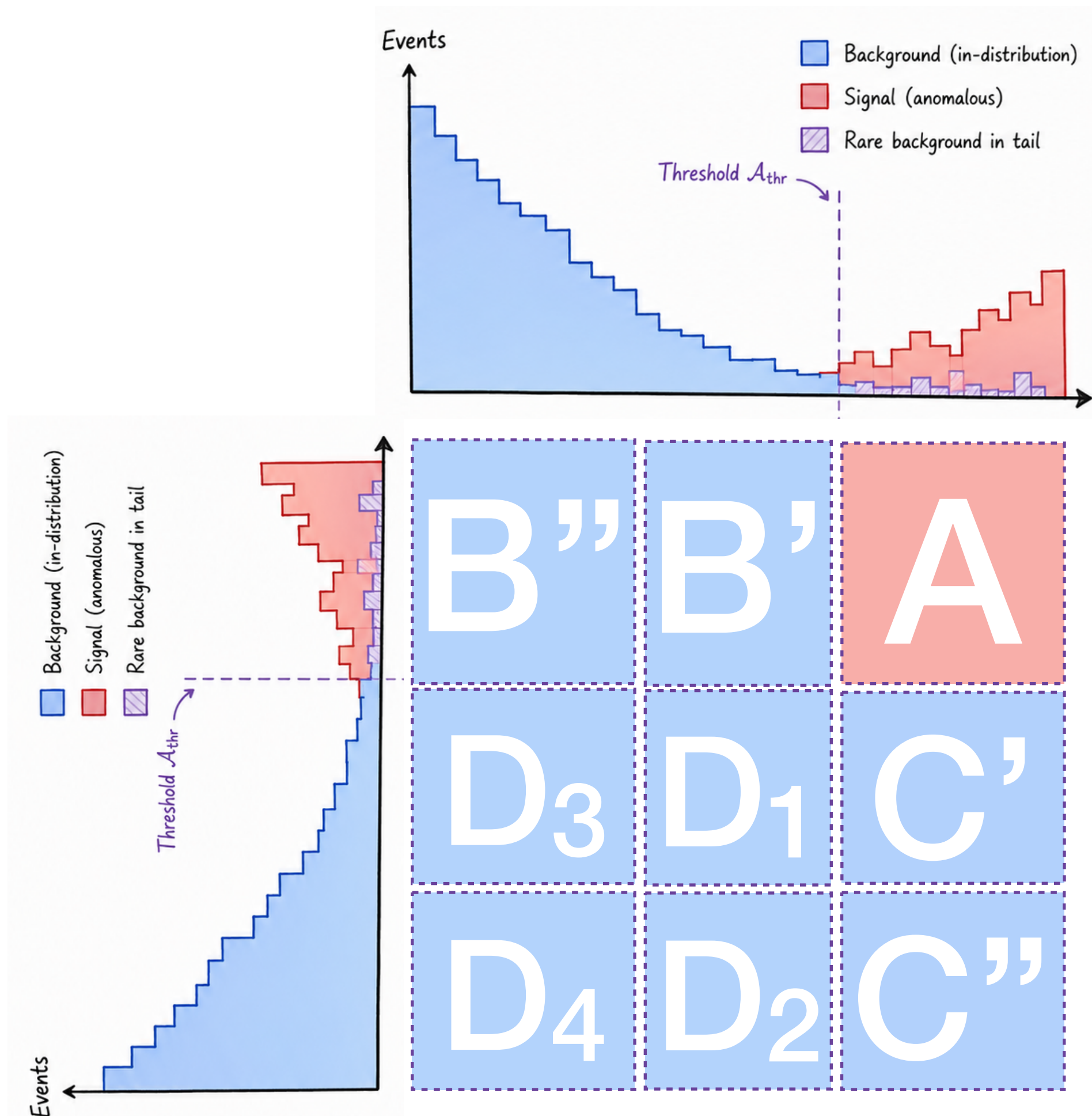
Both anomaly scores have to be independent!

Relevant past works:

- Kasieczka, Nachman, Schwartz, Shih [2007.14400]
- Mikuni, Nachman, Shih [2111.06417]

Extended ABCD matrix method

Established method for data-driven background estimation



$$N_A^{bkg} = \frac{\left(N_{B'}^{bkg} N_{C'}^{bkg} N_{D_2}^{bkg} N_{D_3}^{bkg} \right)^2}{N_{B''}^{bkg} N_{C''}^{bkg} N_{D_4}^{bkg} \left(N_{D_1}^{bkg} \right)^4}$$

Both anomaly scores have to be independent!

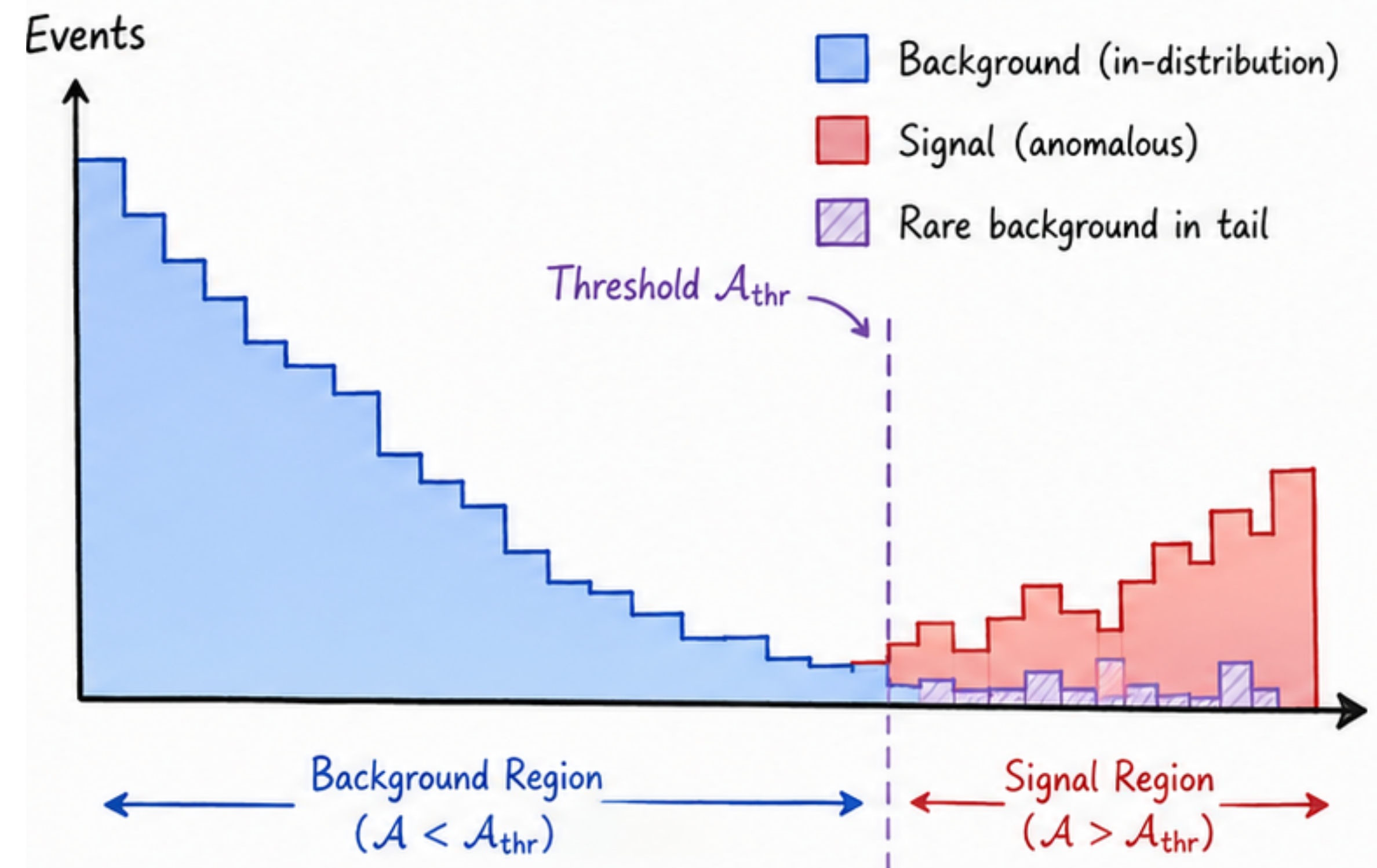
Anomaly searches in HEP

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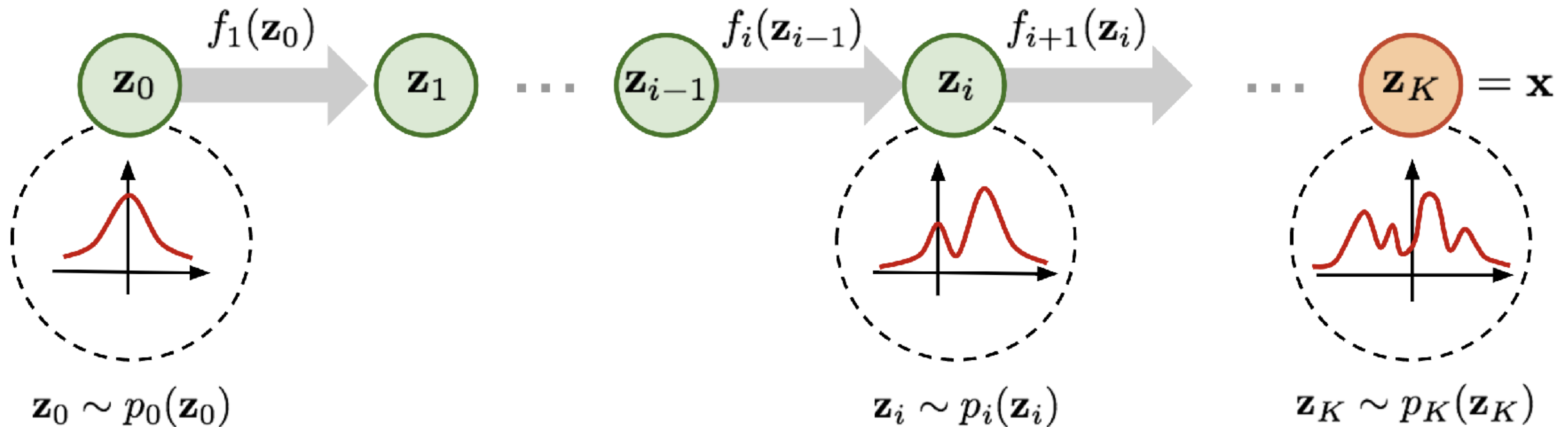
What about background in the signal region?

Out-of-Distribution (OOD) Anomaly Search



Events with anomaly score A greater than the threshold are considered **anomalous**.

Normalizing Flows

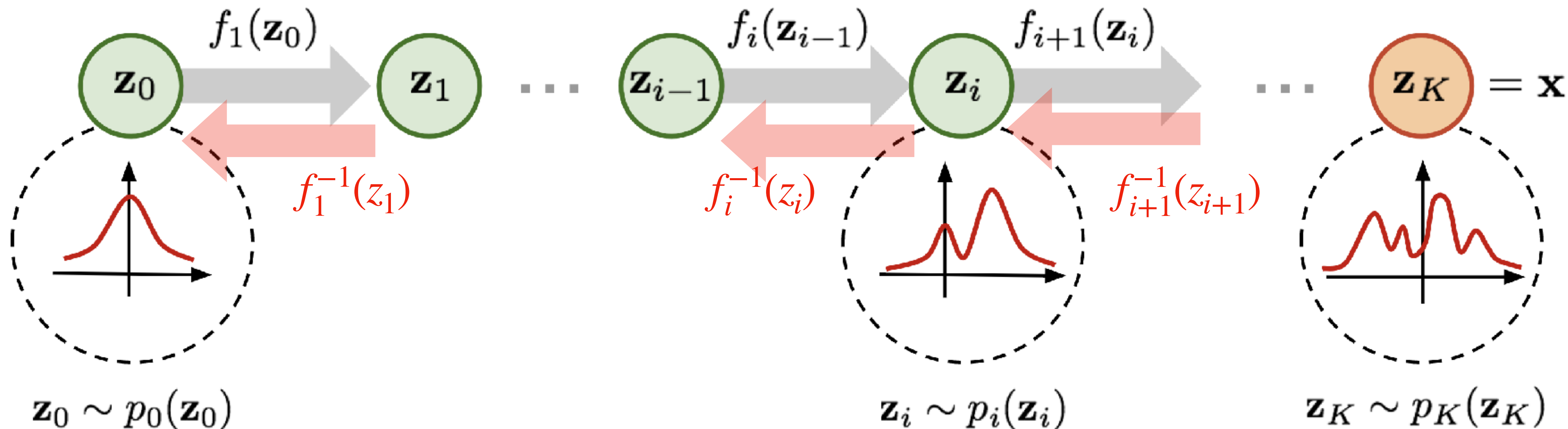


Normalizing Flows allow to efficiently sample from complicated data distributions.

We build a sequence of invertible parametrisable functions that transform a multivariate Gaussian distribution to data distribution.

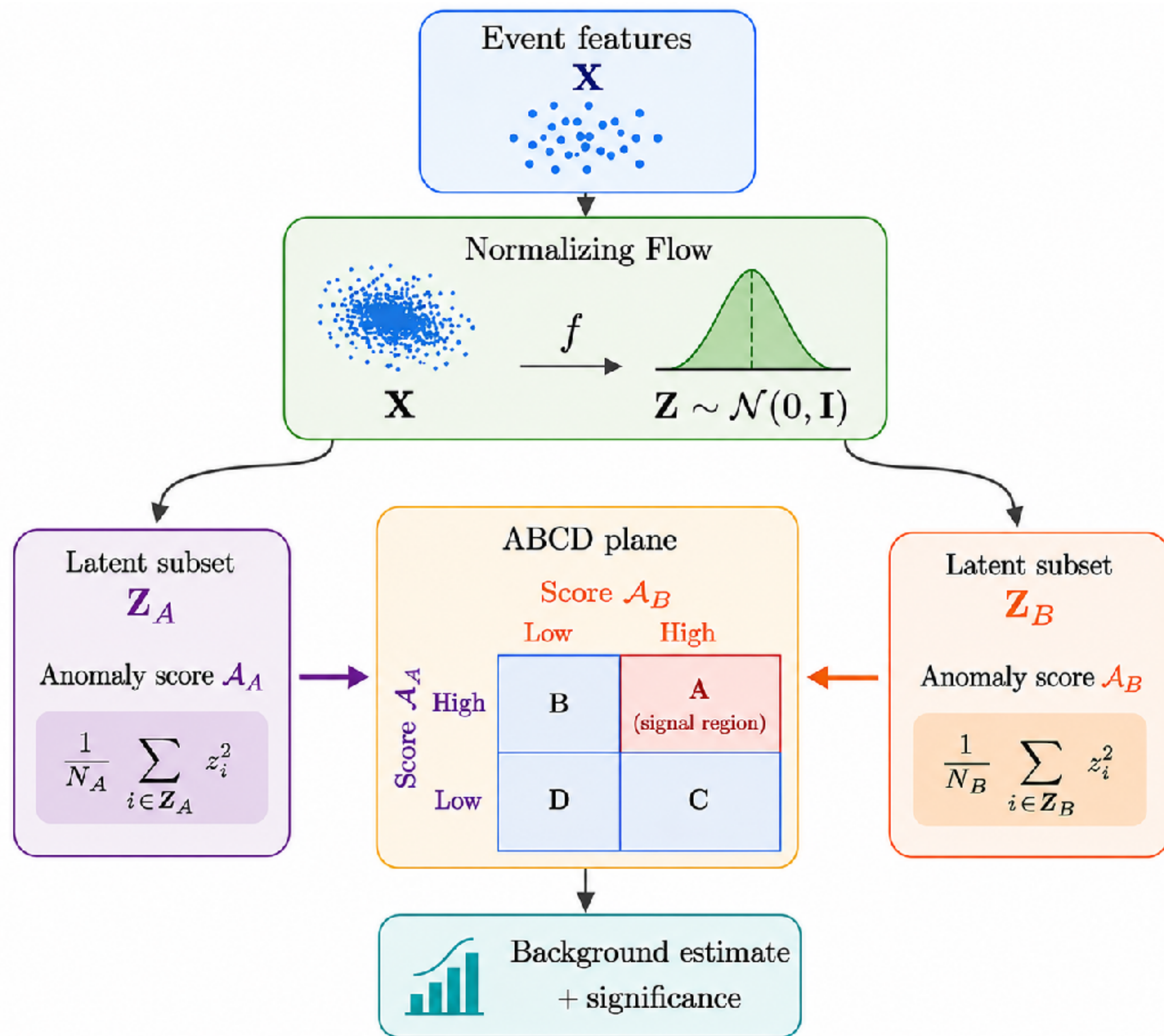


Normalizing Flows



Once we have trained the flow, we can reverse its direction to transform initial correlated variables into new approximately uncorrelated ones.

Overview of the method



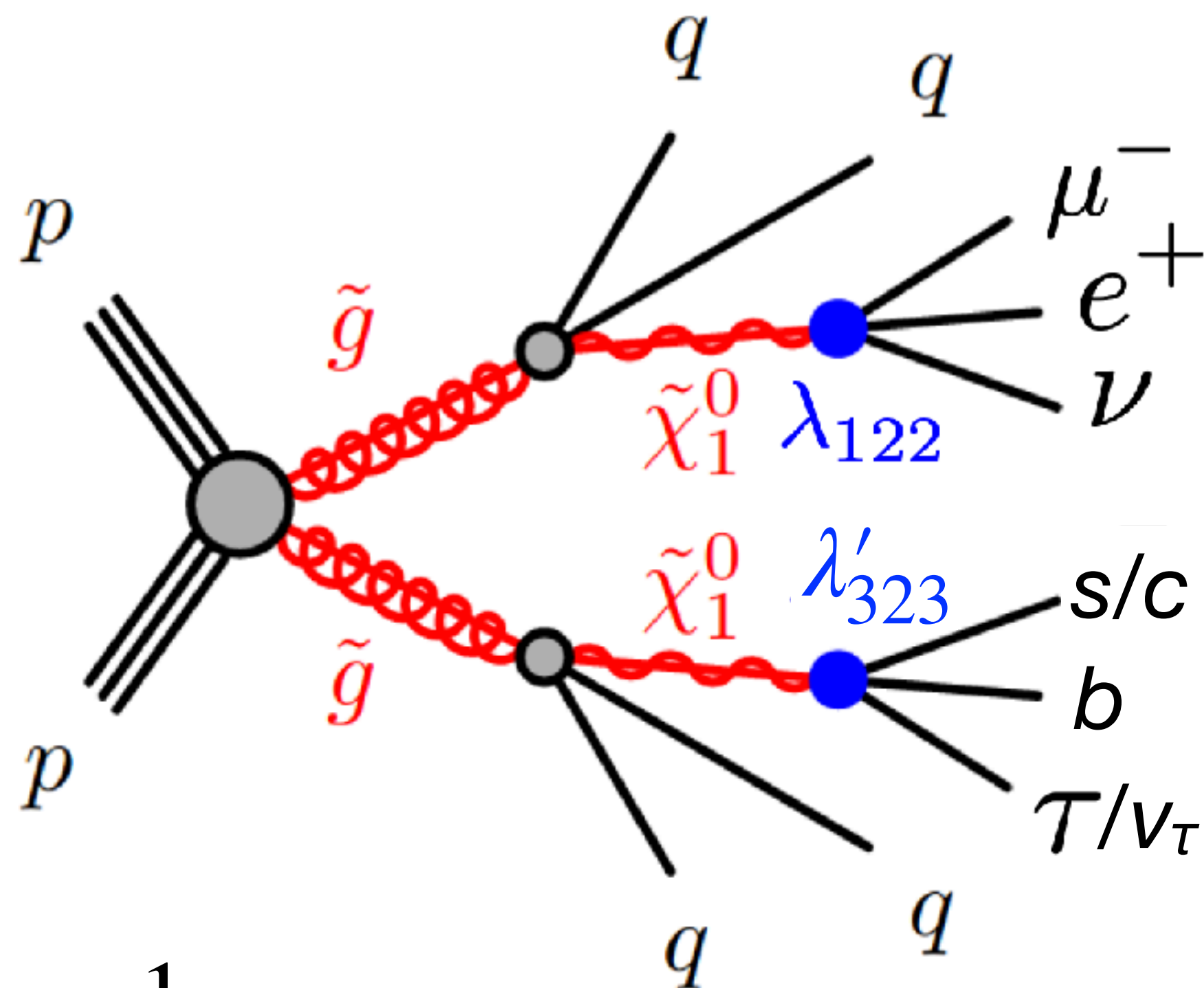
A photograph of Książ Castle in Poland at sunset. The castle is a large, multi-story building with a prominent central tower and several smaller spires. The sky is filled with orange and blue clouds, and the castle's lights are on, illuminating its facade. The castle is surrounded by lush green trees and a forested hillside.

BENCHMARK

Książ Castle, Poland

Benchmark model

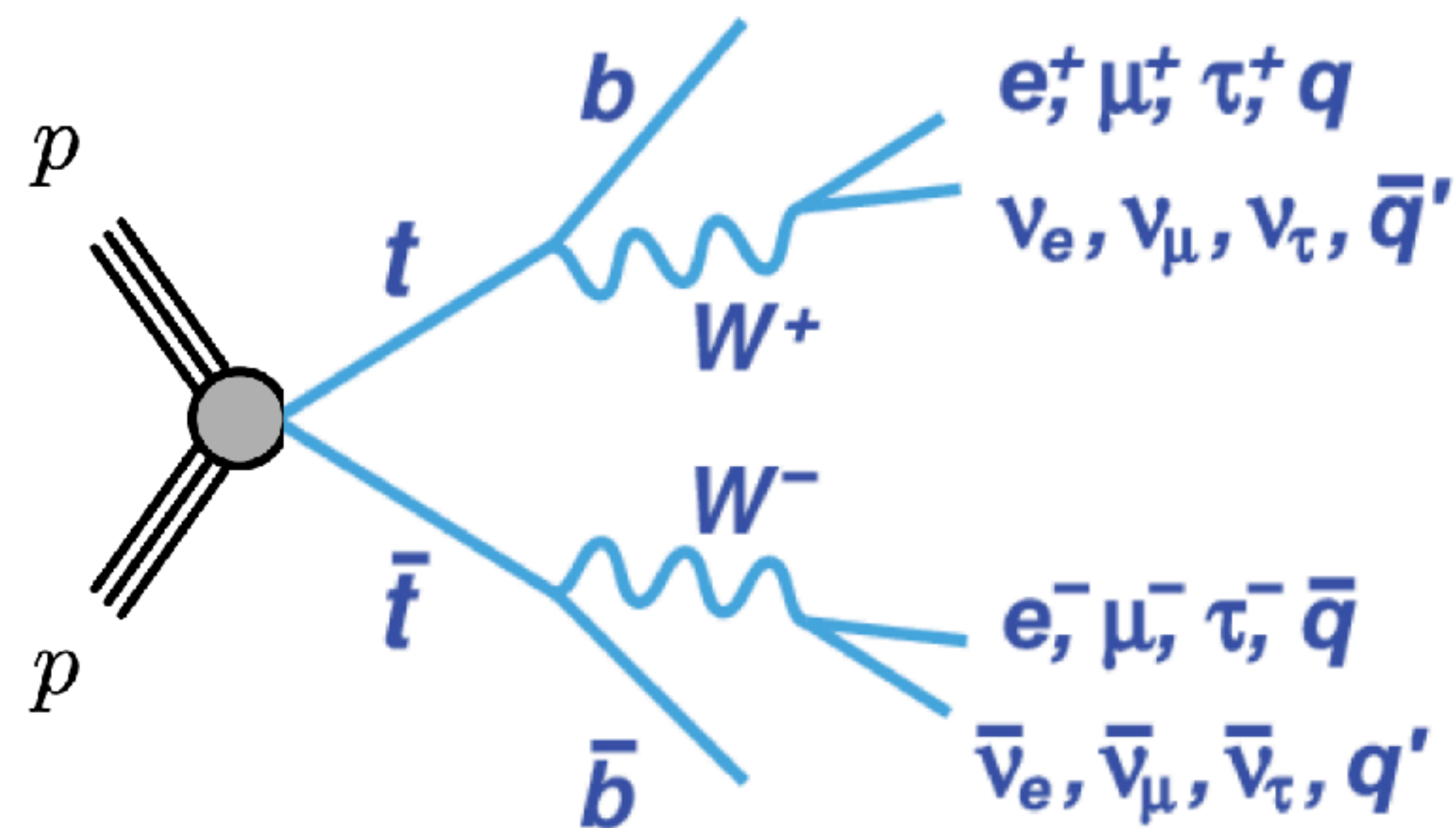
signal — RPV SUSY



$$\mathcal{L} \ni \frac{1}{2} \lambda^{ijk} L_i L_j \bar{e}_k + \lambda'^{ijk} L_i Q_j \bar{d}_k$$

$$\lambda_{122} \simeq \lambda_{323} \neq 0 \quad \begin{aligned} m_{\tilde{g}} &= 1.8 \text{ TeV} \\ m_{\tilde{\chi}_1^0} &= 1.7 \text{ TeV} \end{aligned}$$

background — $t\bar{t}$ bar



Preselection & 16 original variables

Table 1: Data preselection cuts

#	Description
1	$N_{\text{jets}} \geq 3$
2	$N_{\text{b-jets}} \geq 1$
3	$N_{\text{leptons}} = 2$
4	opposite sign leptons
5	$p_T^{\text{j1}} > 60 \text{ GeV}$
6	$p_T^{\text{j2}} > 30 \text{ GeV}$
7	$p_T^{\text{j3}} > 30 \text{ GeV}$
8	$\cancel{E}_T > 60 \text{ GeV}$
9	$p_T^{\text{l1}} > 120 \text{ GeV}$
10	$p_T^{\text{l2}} > 120 \text{ GeV}$

$L=3/\text{ab}$ $S = 432$ $S/B = 0.5\%$
 $B = 80100$ $S/\sqrt{B} = 1.5$

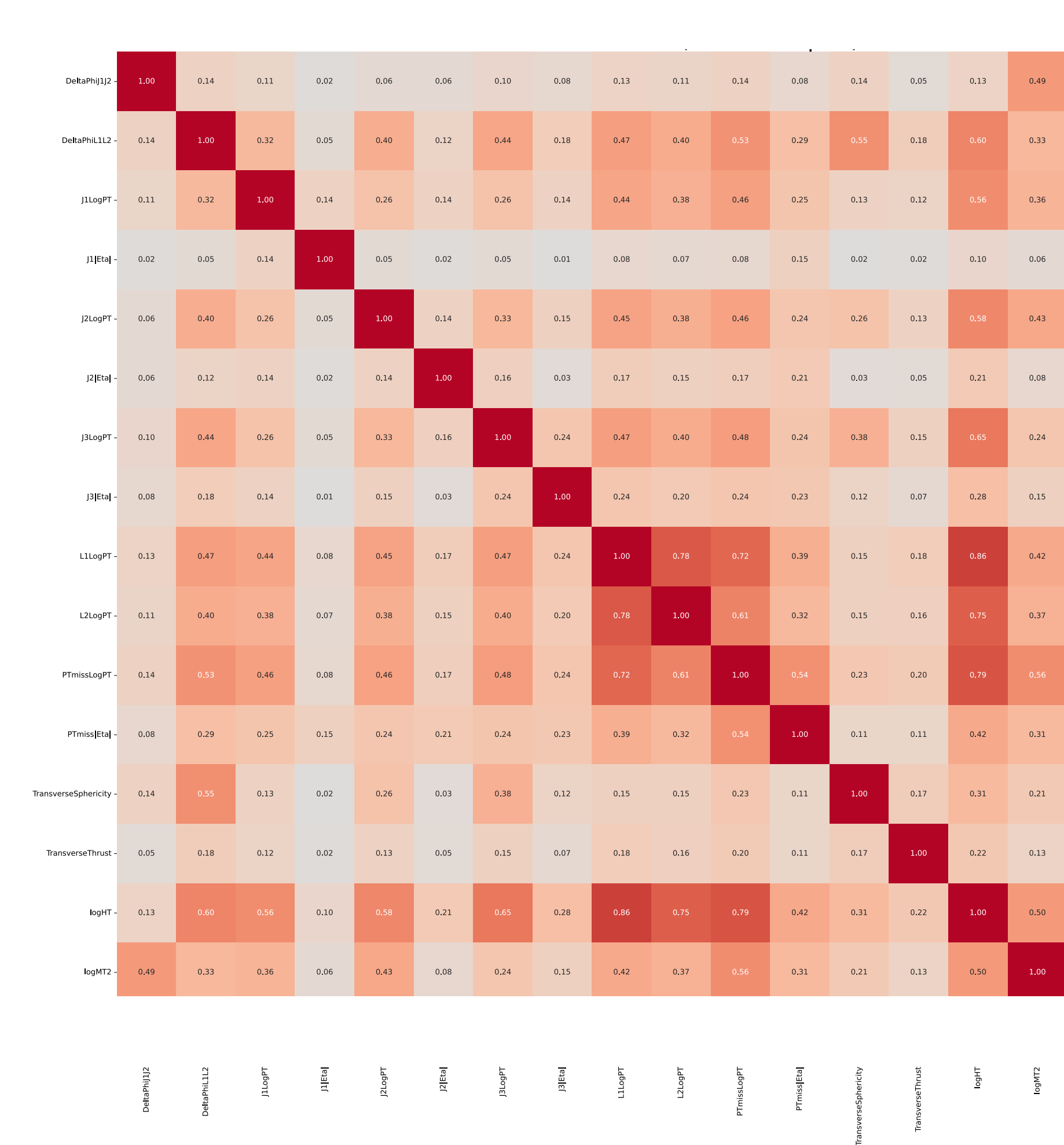
#	Name
1	$\log p_T^{\text{j1}}$
2	$\log p_T^{\text{j2}}$
3	$\log p_T^{\text{j3}}$
4	$\log p_T^{\text{l1}}$
5	$\log p_T^{\text{l2}}$
6	$\log p_T^{\text{miss}}$
7	$\log H_T$
8	$\log M_{\text{T2}}$
9	$ \eta^{\text{j1}} $
10	$ \eta^{\text{j2}} $
11	$ \eta^{\text{j3}} $
12	$ \eta^{\text{miss}} $
13	$\Delta\phi(j_1, j_2)$
14	$\Delta\phi(l_1, l_2)$
15	$T_\perp$
16	S_T



PRELIMINARY RESULTS (semi-supervised)

Lublin Castle, Poland

Decorrelation in practice

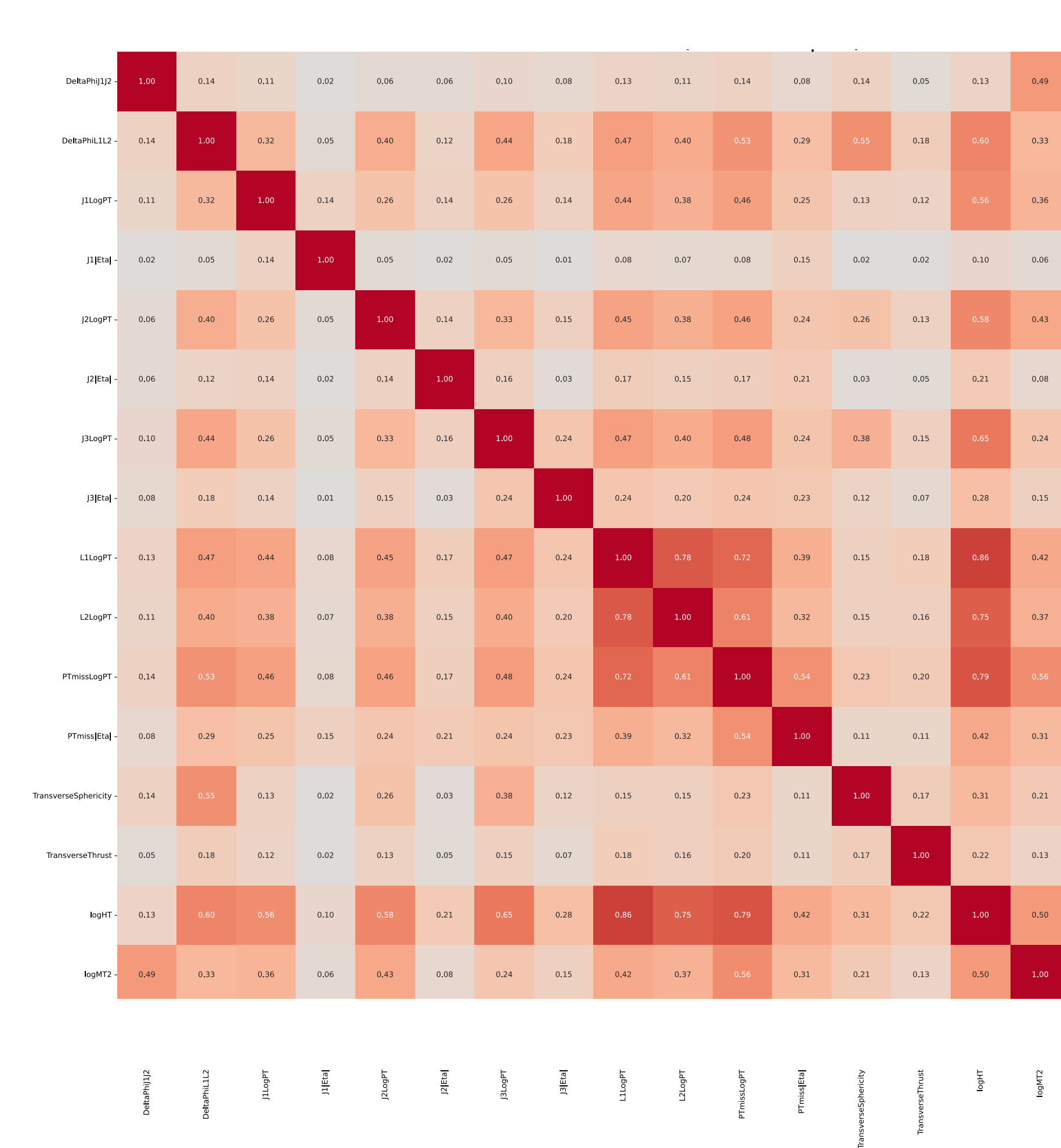


16 highly correlated variables

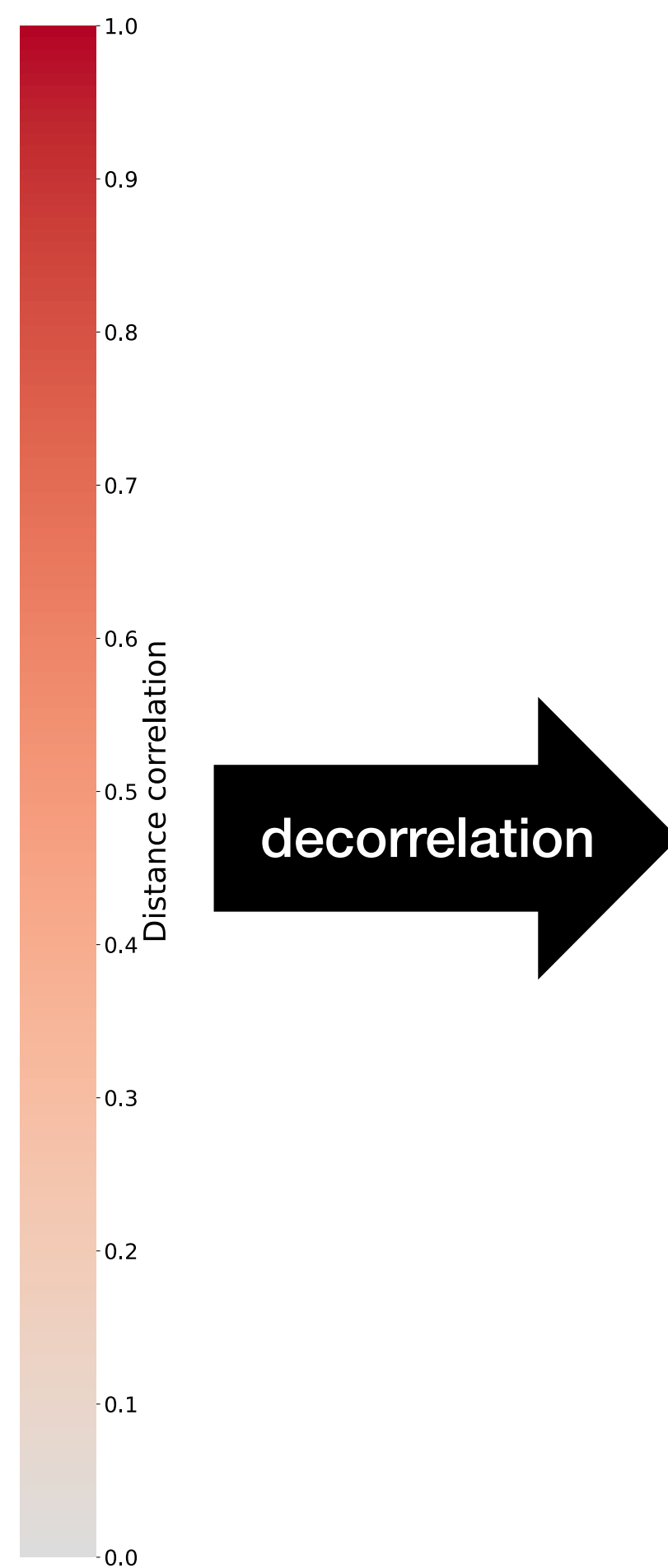
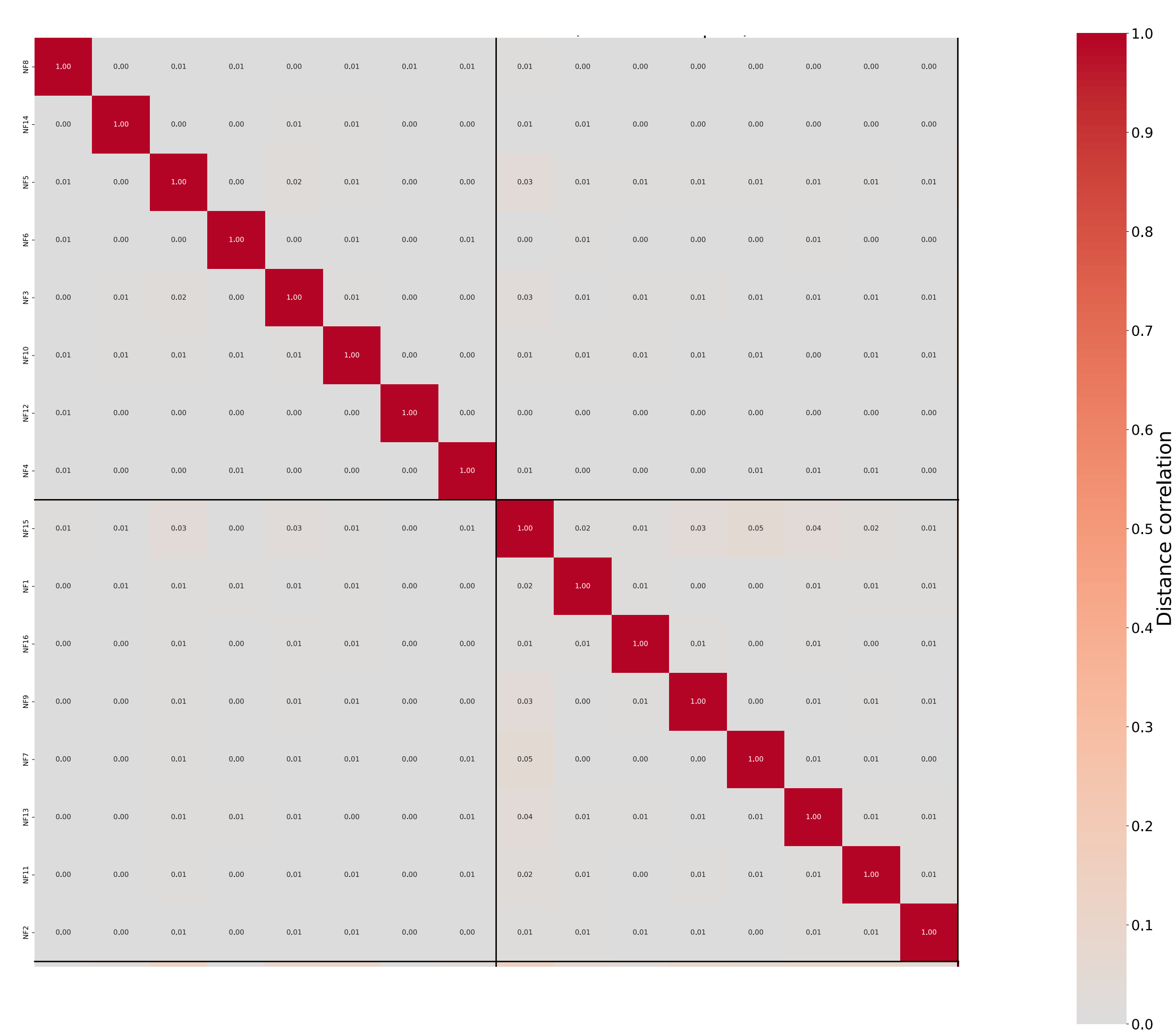
Fully correlated

Uncorrelated

Decorrelation in practice

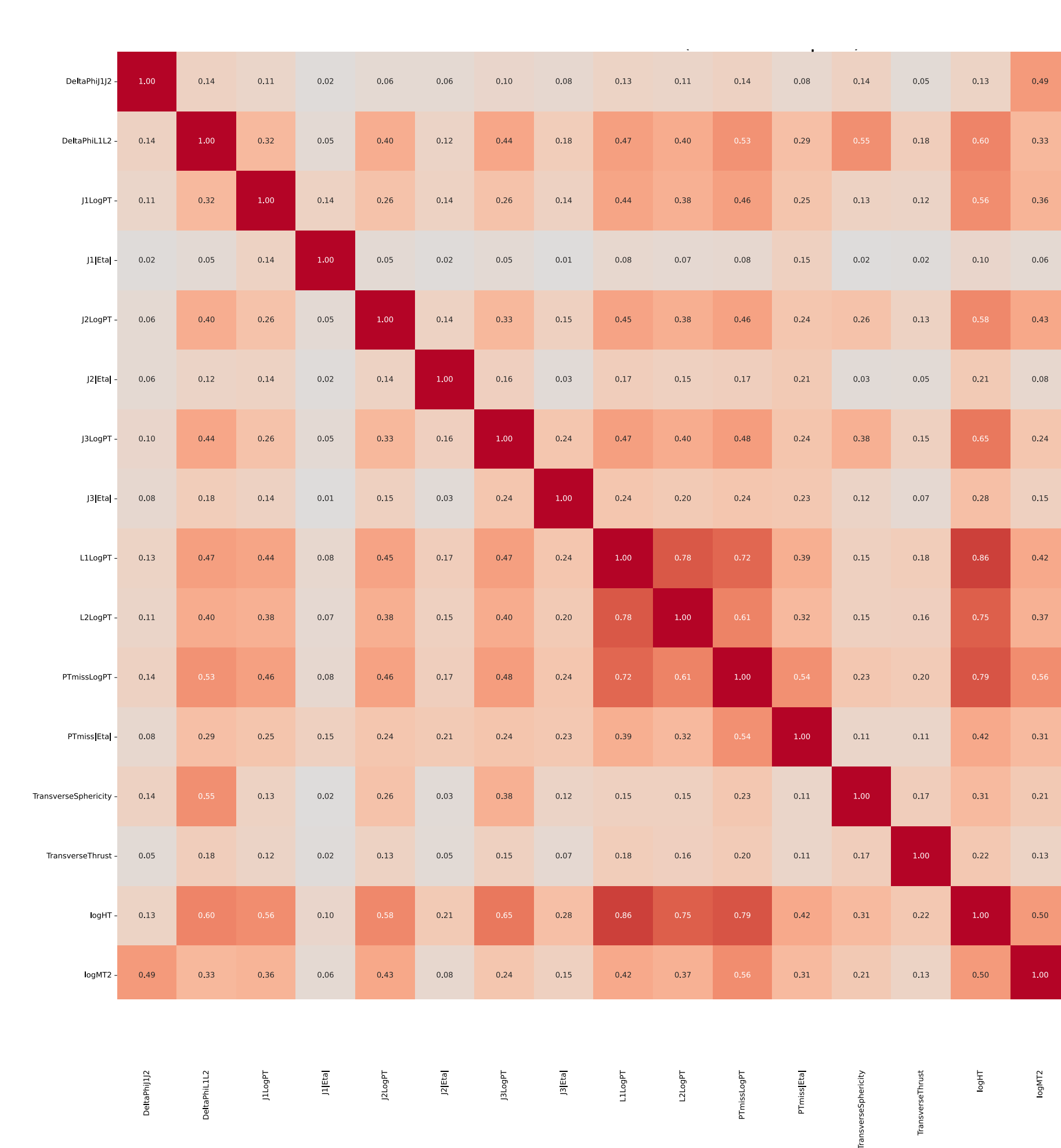


16 highly correlated variables

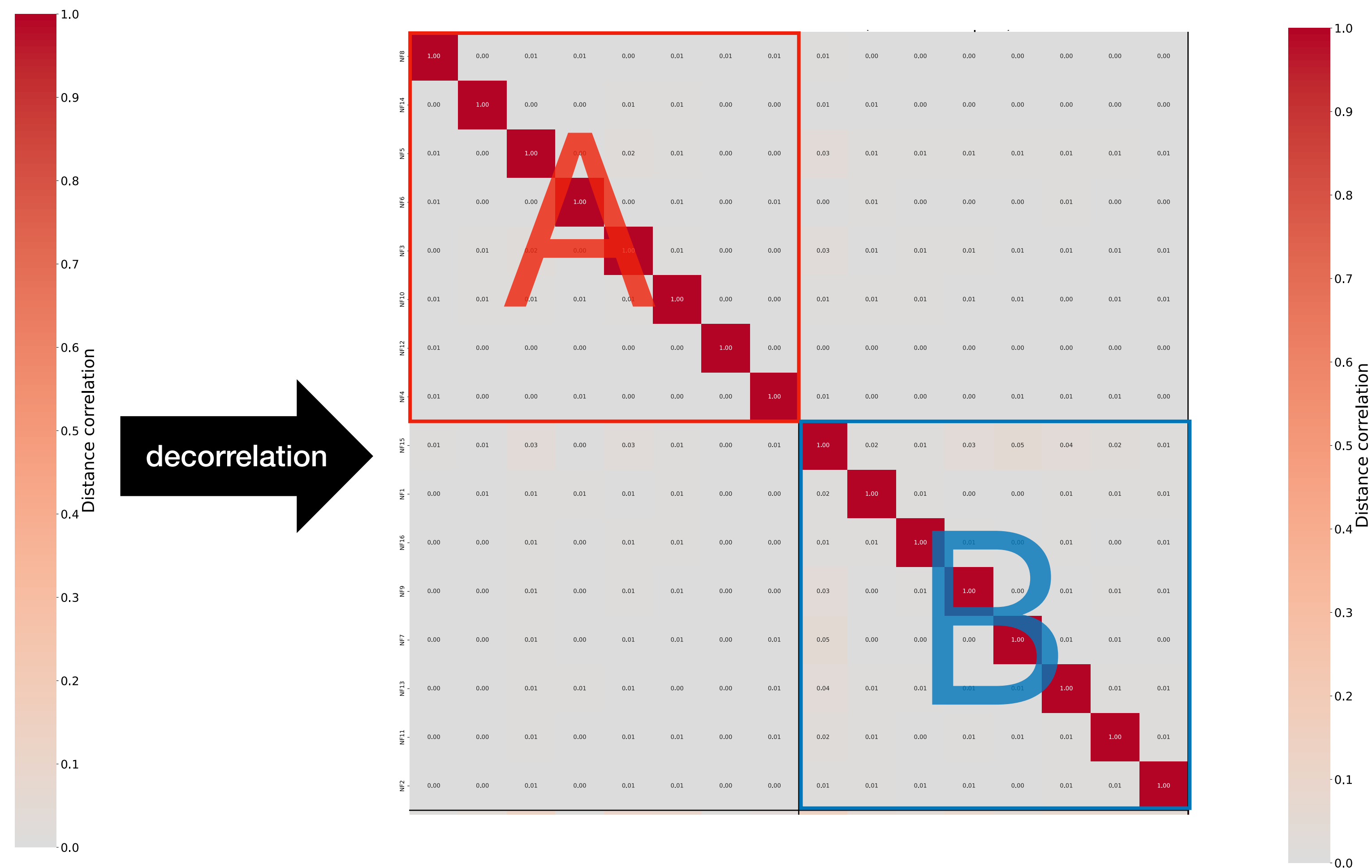


16 highly largely uncorrelated variables split into two subsets

Decorrelation in practice



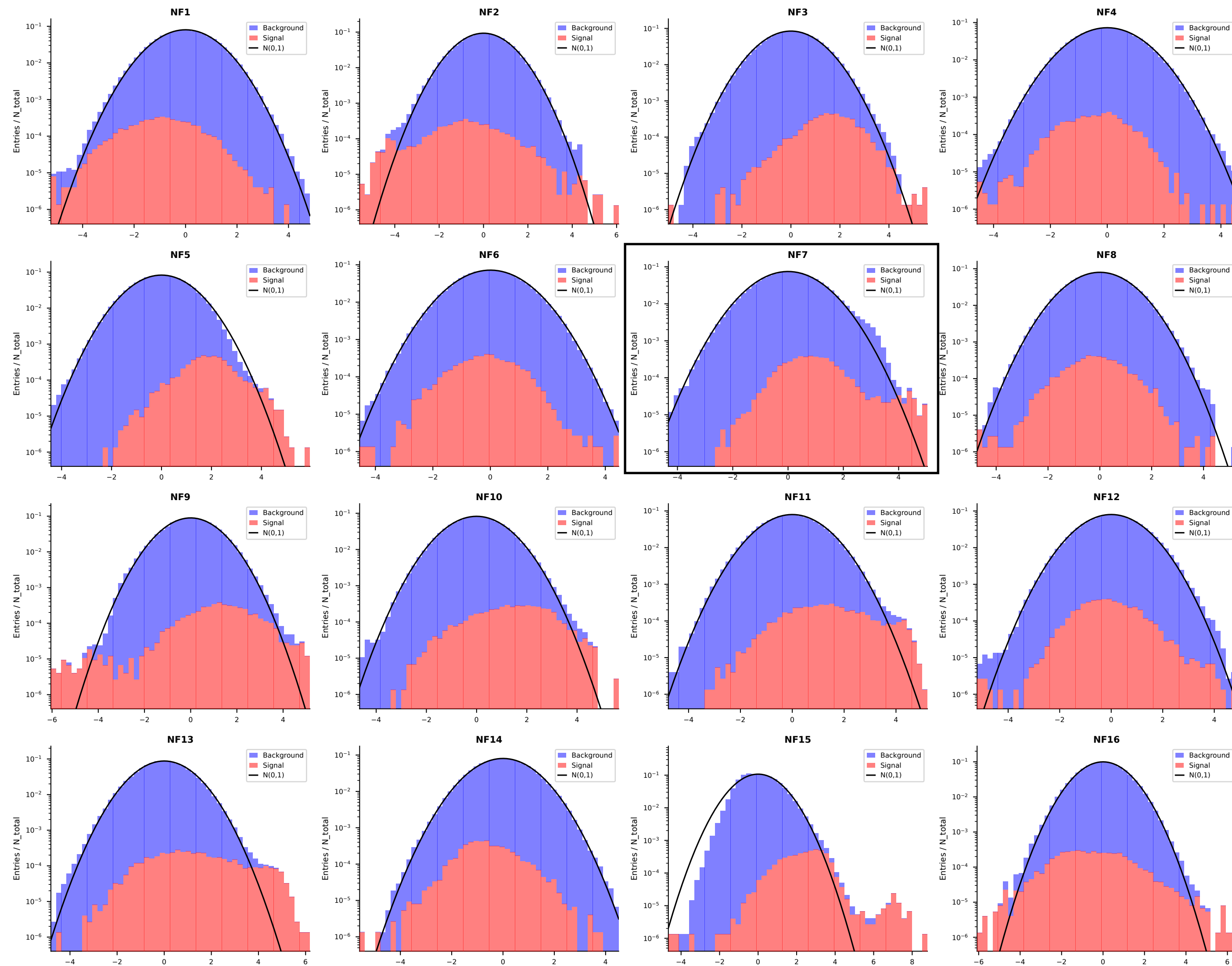
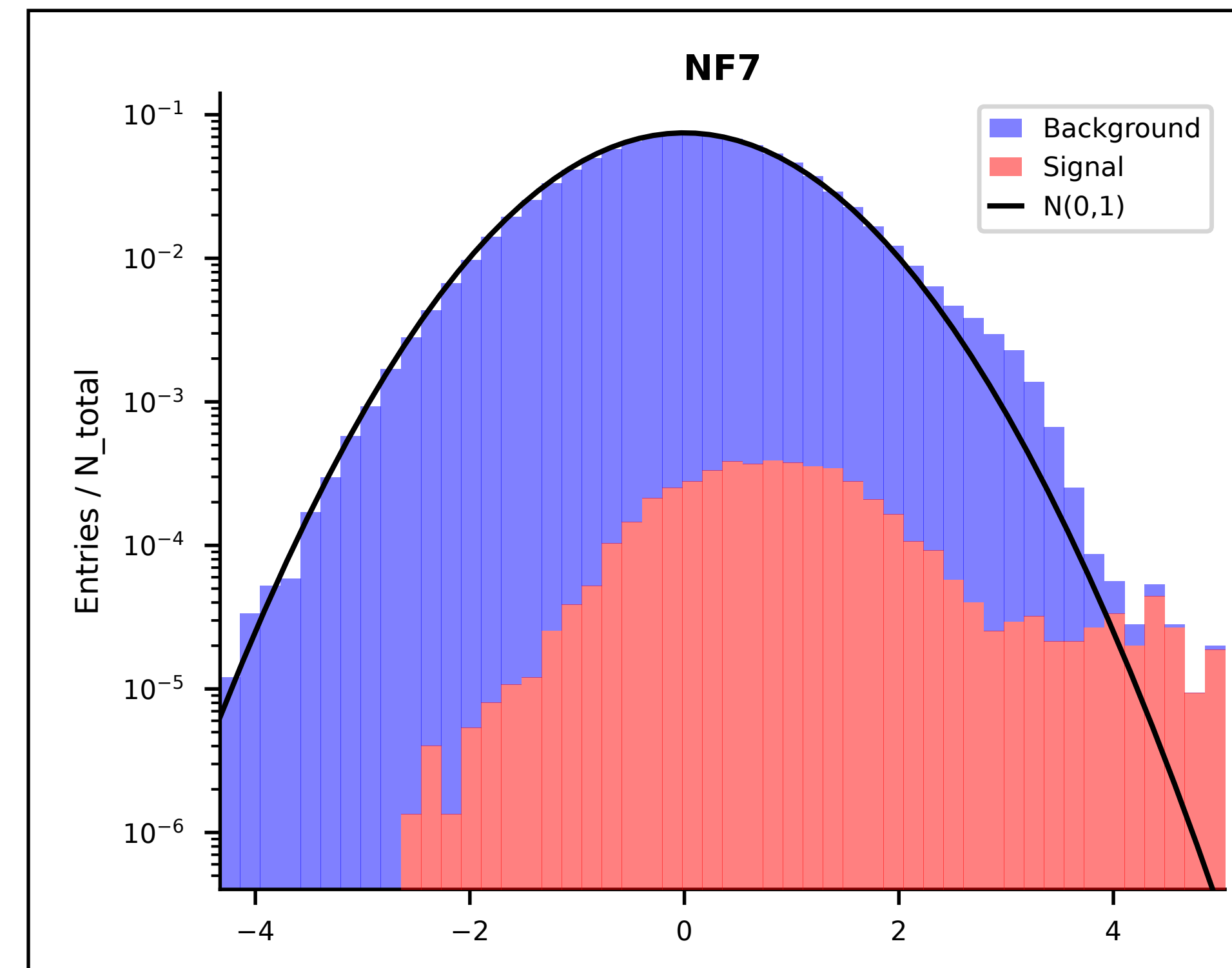
16 highly correlated variables



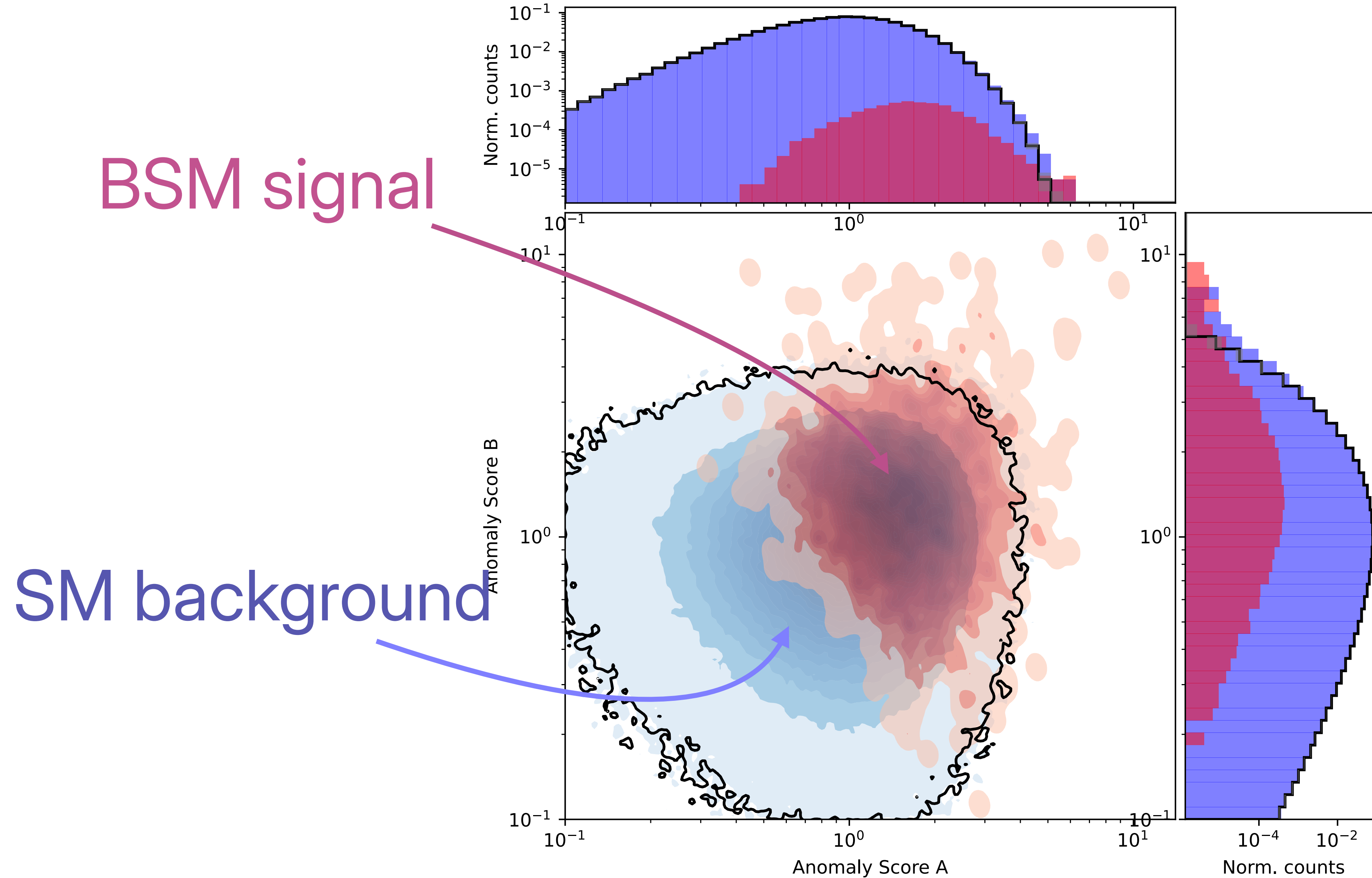
16 highly largely uncorrelated variables split into two subsets

Latent representation — semisupervised

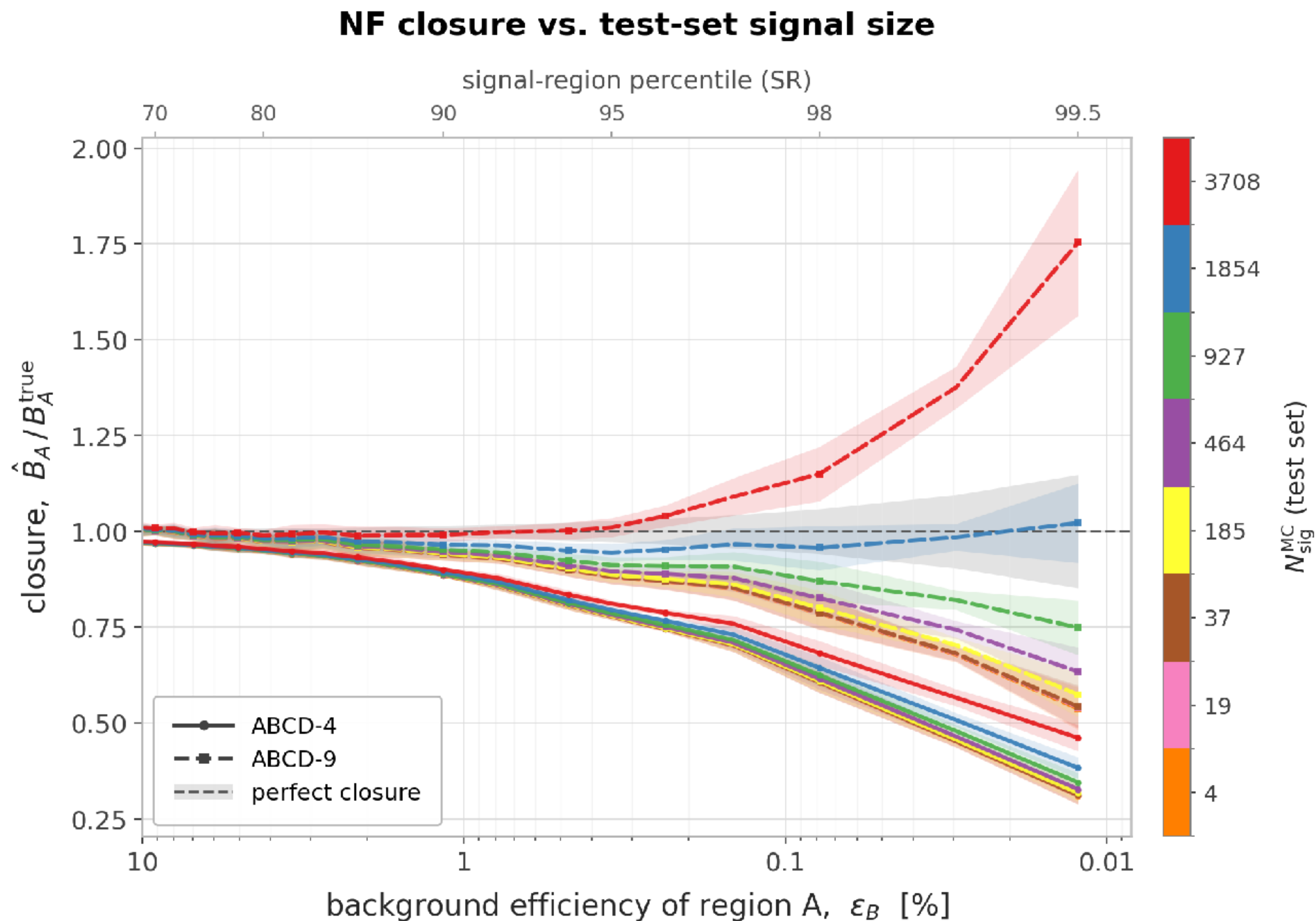
Latent-space signal vs. background — figure 1/1 (stacked)



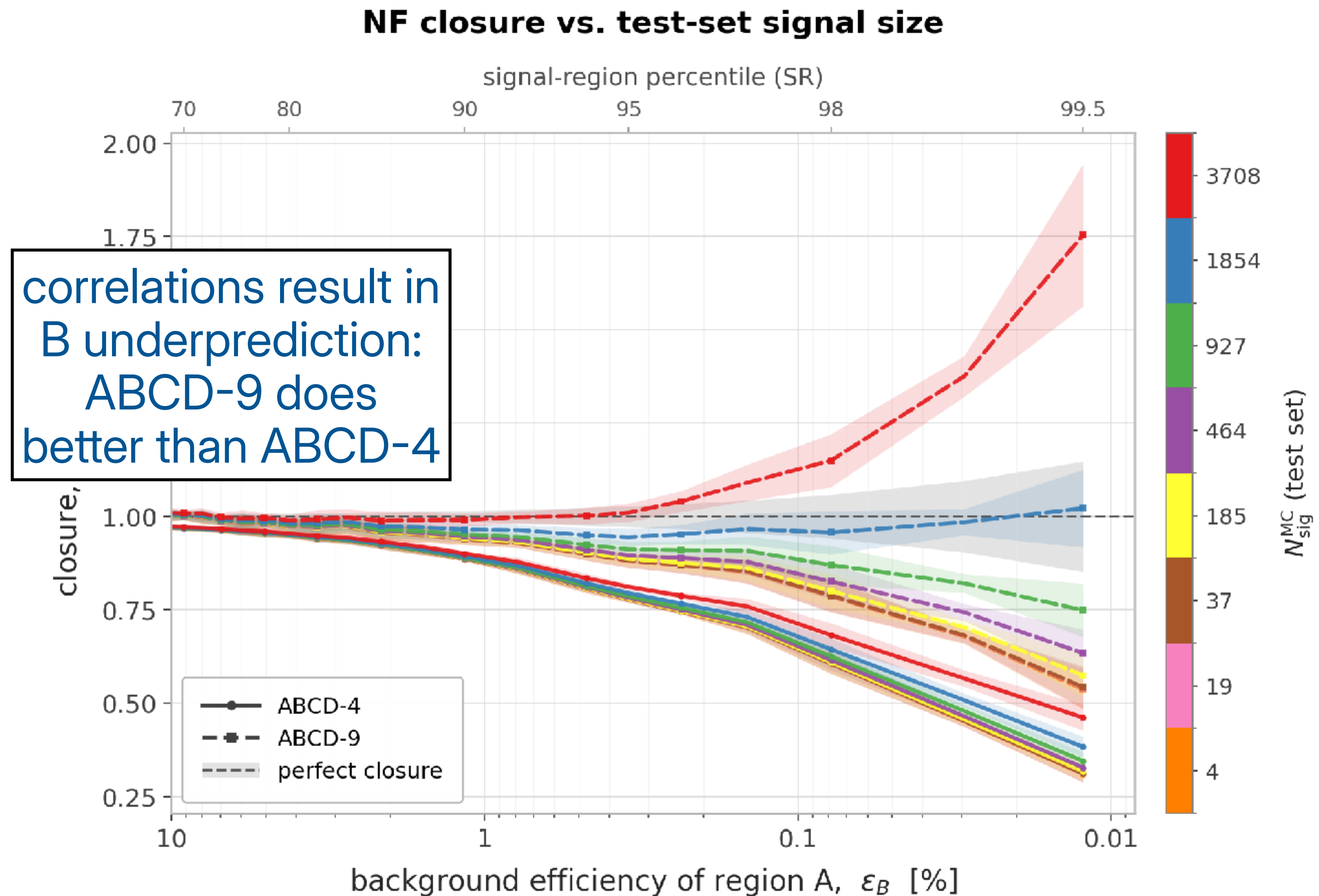
Anomaly score distribution



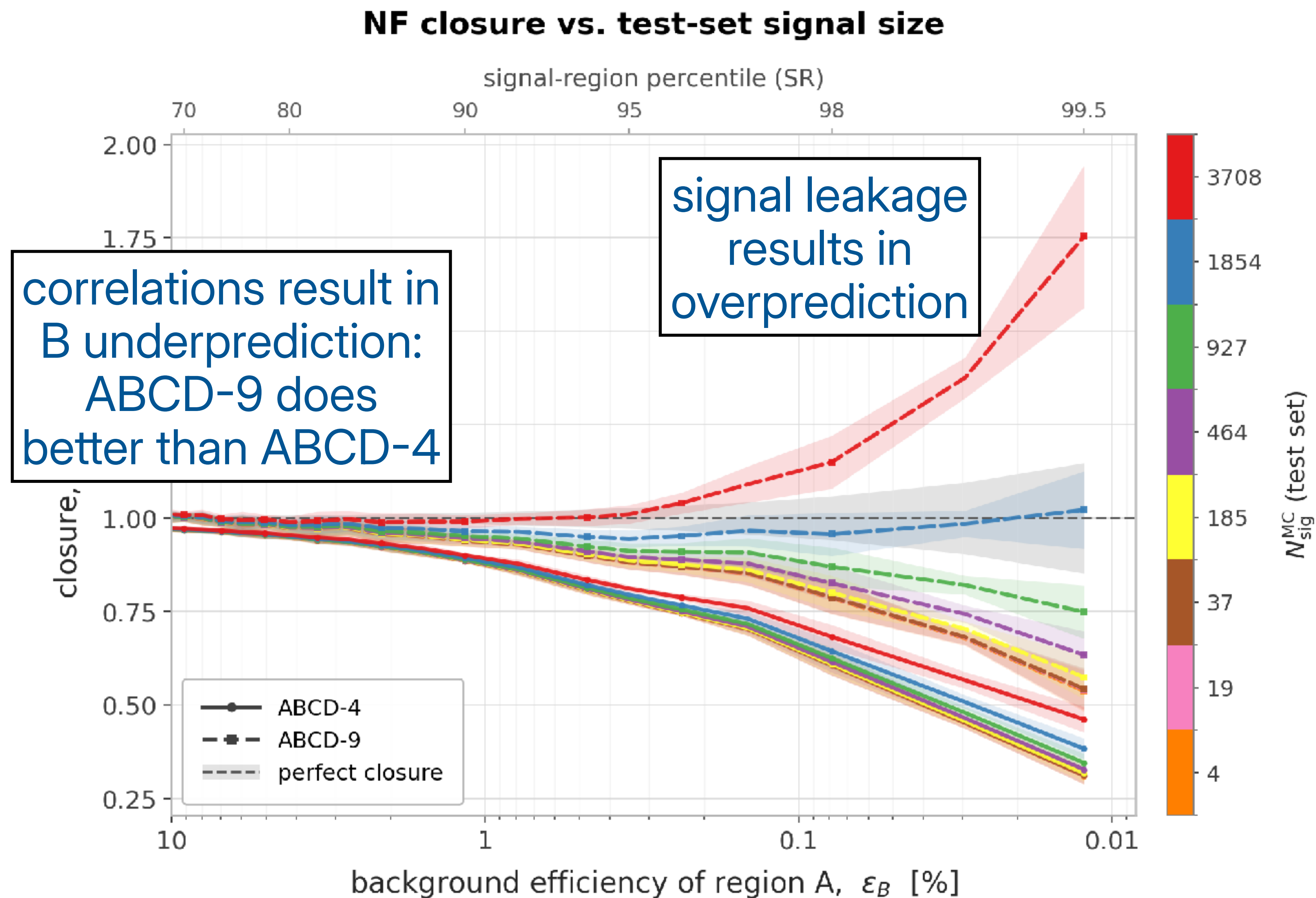
Selecting the threshold



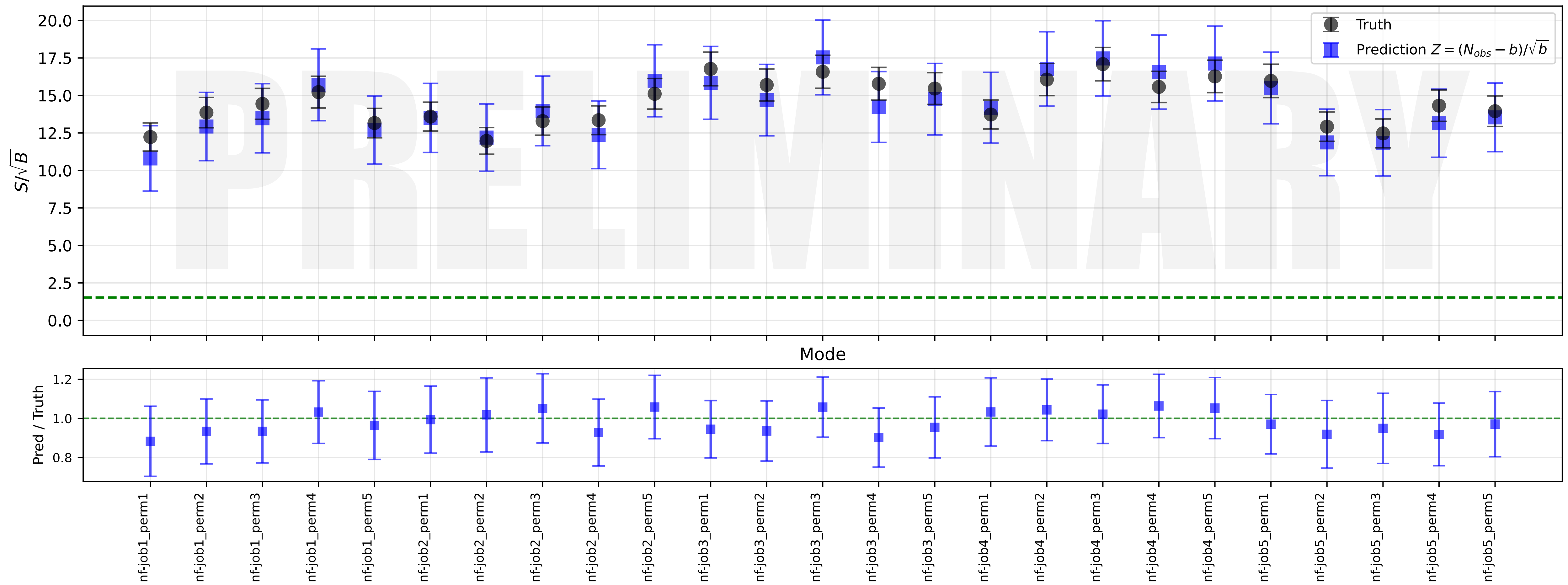
Selecting the threshold



Selecting the threshold



Results (absolute S/ $\sqrt{B}$) - Percentile Config: 95_48_0 - Method: xABCD_9

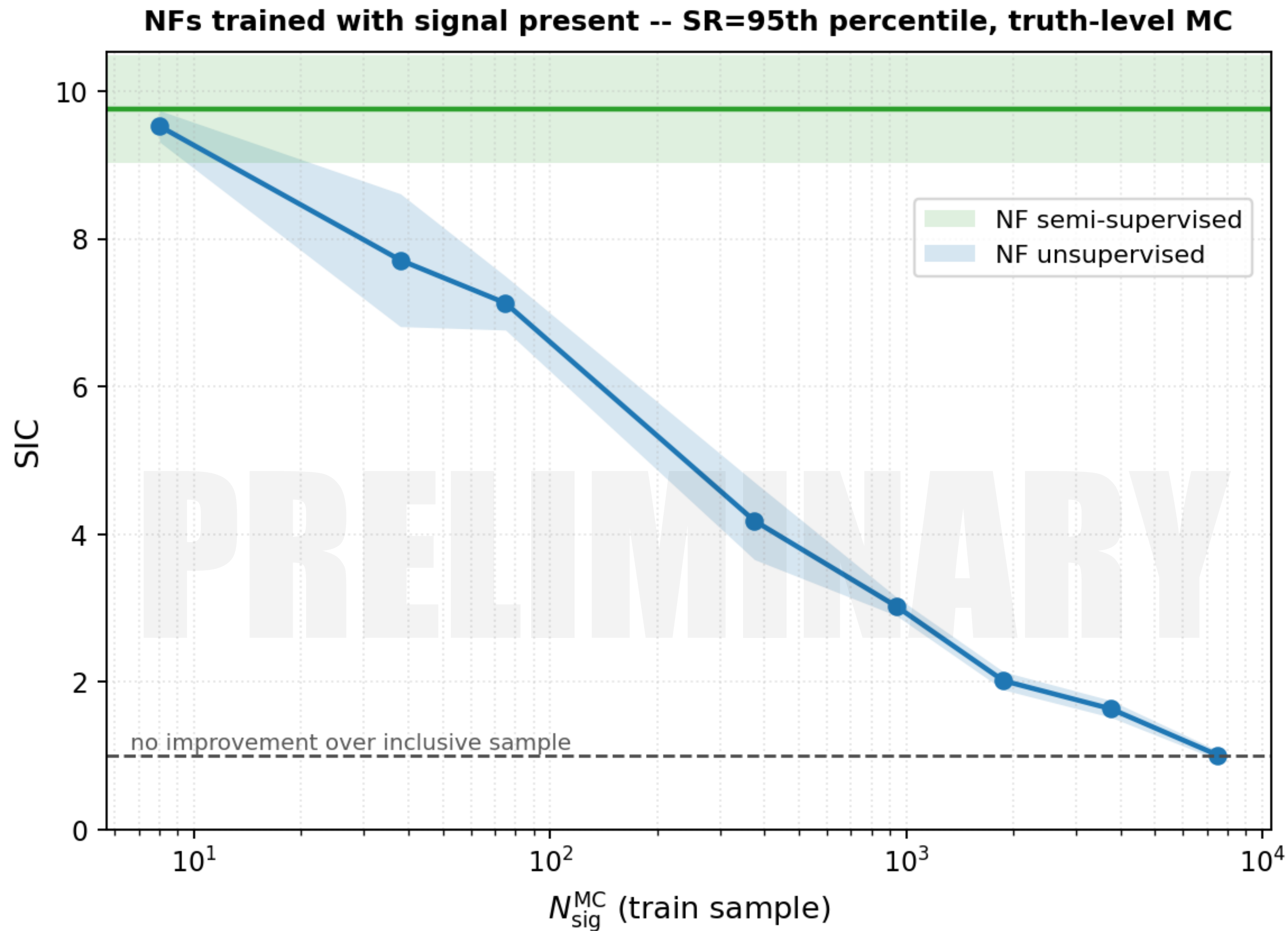


A wide-angle photograph of Marlbork Castle in Poland, featuring red brick walls, multiple towers with conical roofs, and a large central building with a red-tiled roof. The castle is situated on a grassy bank next to a body of water, with lush green trees in the foreground and a cloudy sky in the background. The castle's reflection is visible in the calm water.

TOWARDS UNSUPERVISED

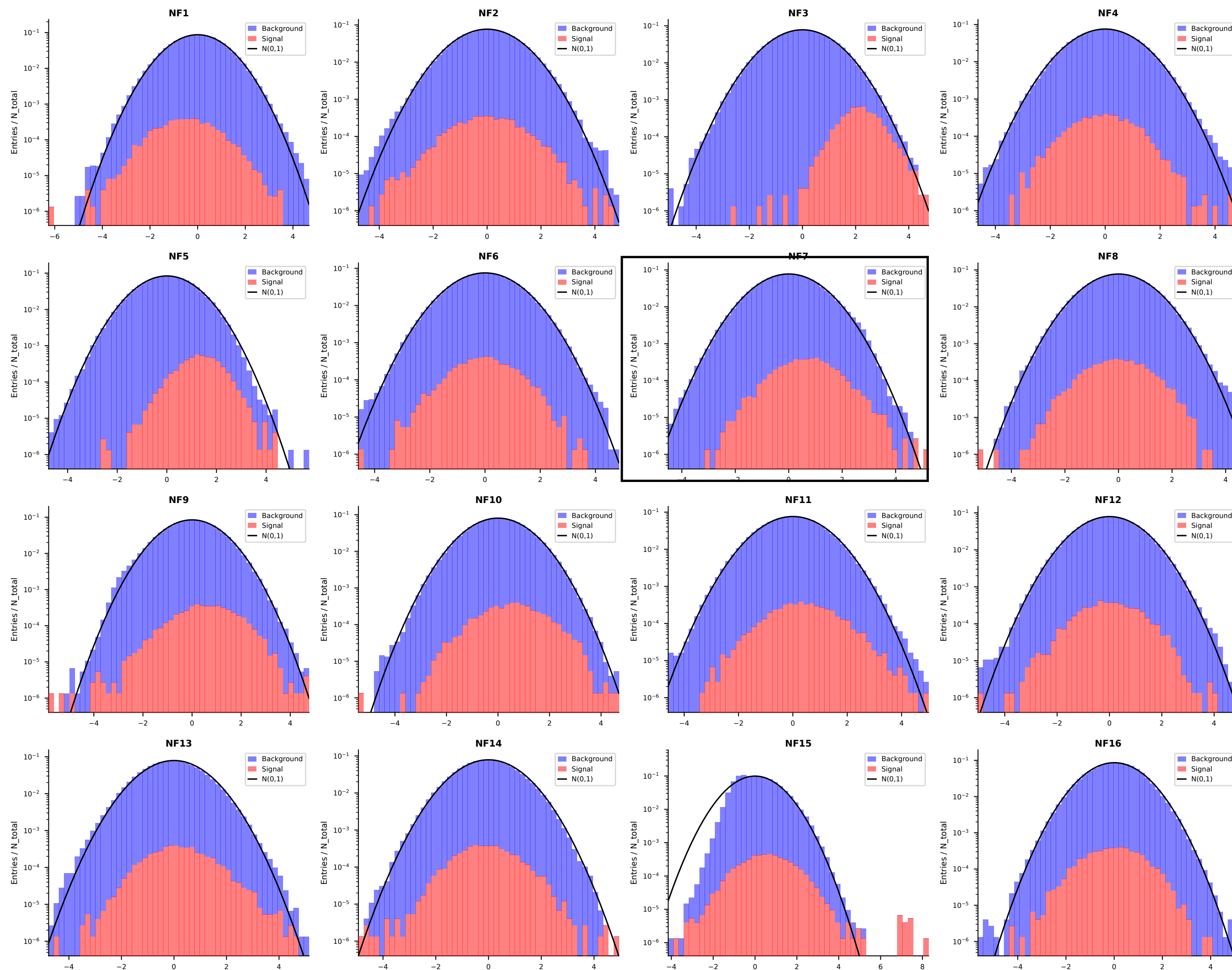
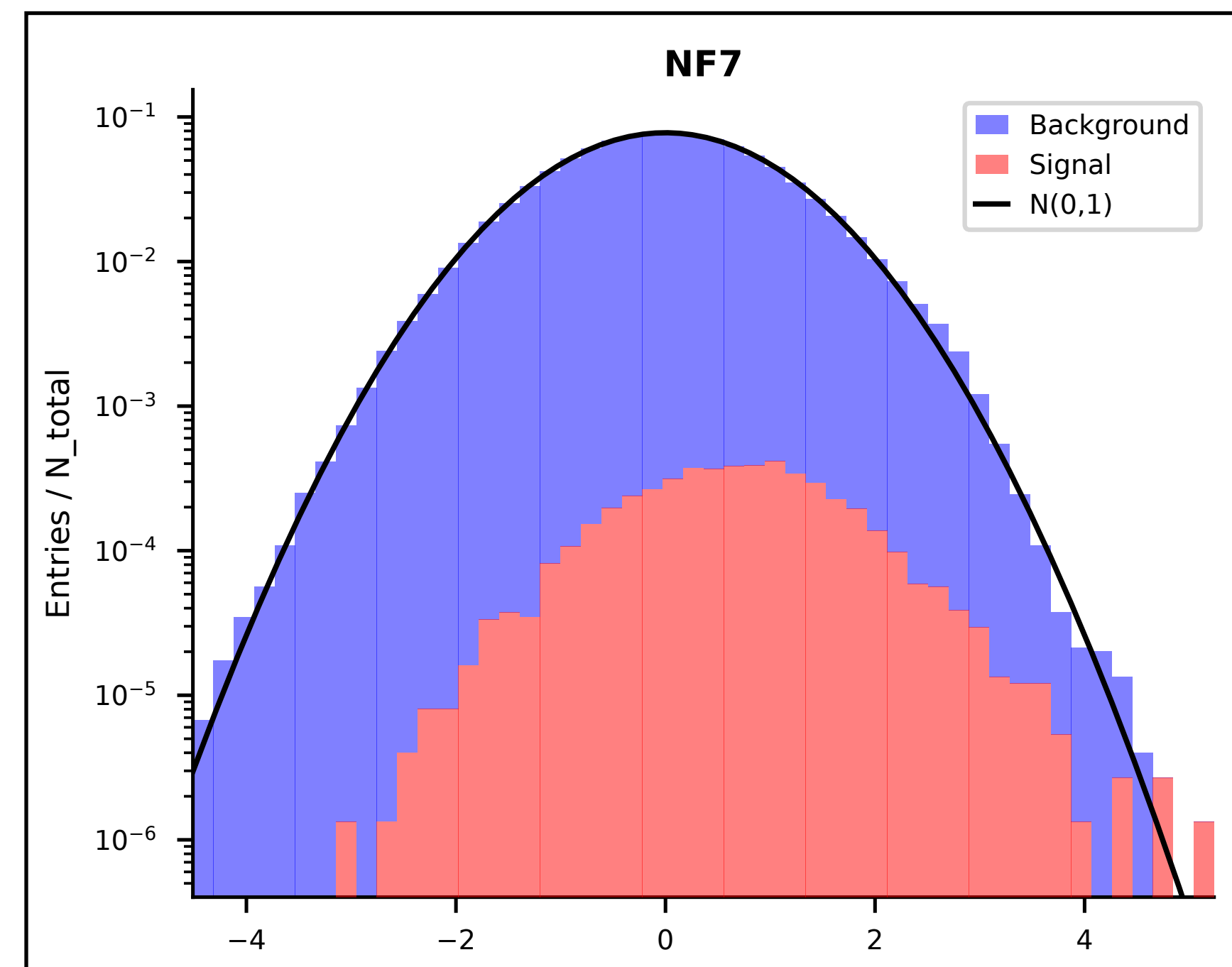
Marlbork Castle, Poland

Significance improvement for unsupervised training



Latent representation — unsupervised

Latent-space signal vs. background — figure 1/1 (stacked)



Summary & Outlook

✿ Out-of-distribution anomaly detection methods are challenging:

✿ How to construct a good anomaly score?

✿ How to estimate the background in the SR?

✿ We propose combining NFs with the ABCD matrix method:

✿ NF creates a new data representation with uncorrelated features

✿ Anomaly scores are approximately uncorrelated

✿ The method **works** for semi-supervised training (NF trained on background-only data)

✿ For fully unsupervised training, the sensitivity drops when signal increases → opposite behaviour to weakly-supervised methods

✿ Next steps include:

✿ Developing a method for fully unsupervised training

✿ Validating method on other benchmarks



Thank you for attention!

rafal.maselek@ijs.si

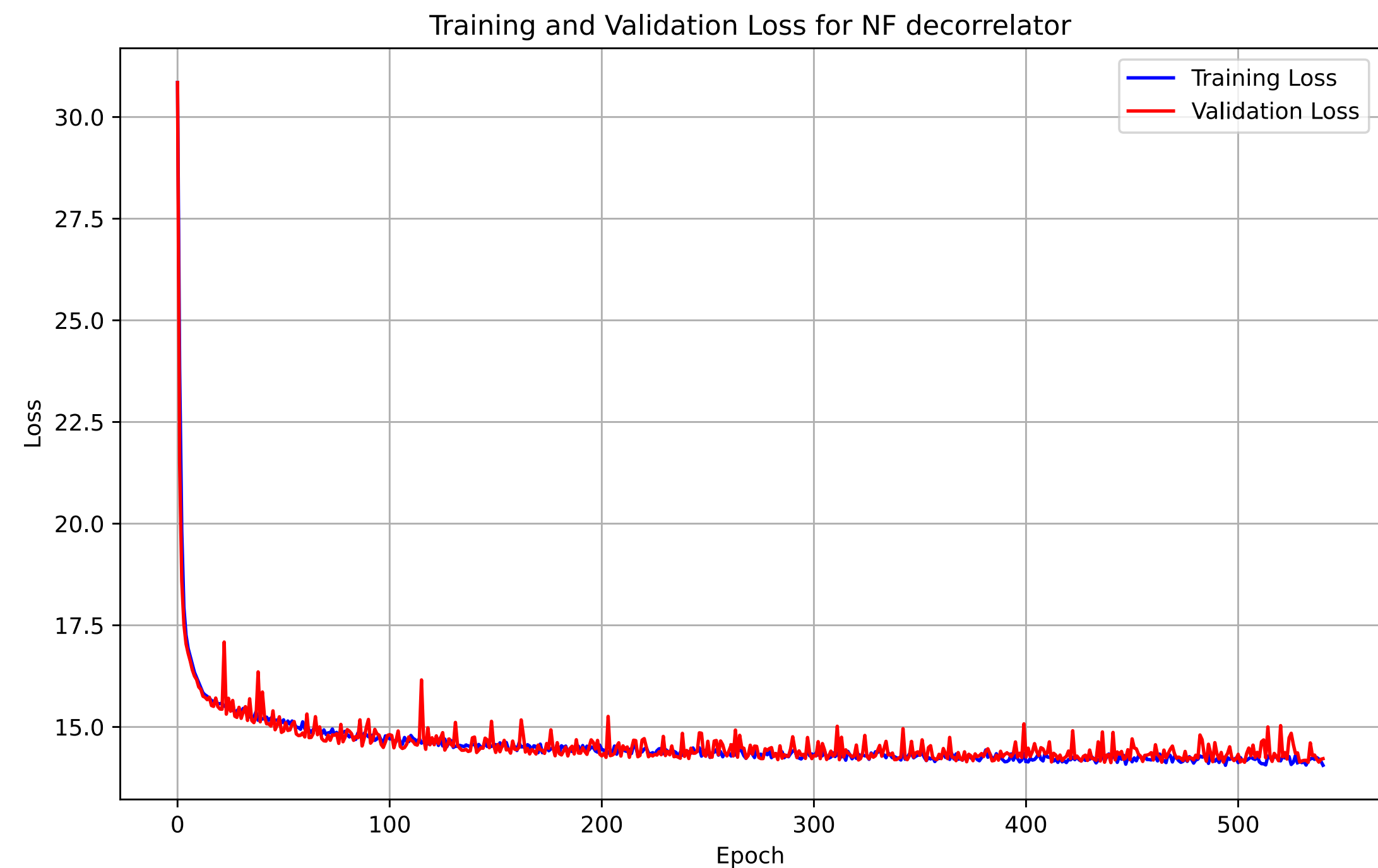
BACKUP

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Training strategy

- ✿ The dataset consists of $\sim 3\text{M}$ events.
- ✿ We randomly split the data 50-25-25 (train-val-test)
- ✿ We train a normalising flow on background-only data
- ✿ We randomly split the latent variables into two subsets and construct anomaly scores A and B
- ✿ We evaluate on background + BSM signal
- ✿ We repeat for 5×5 times



Anomaly score

anomaly scores

$$\mathcal{A}_A = \frac{1}{N_A} \sum_{z_i \in A} z_i^2 \leftarrow \text{latent variables}$$

$$\mathcal{A}_B = \frac{1}{N_B} \sum_{z_i \in B} z_i^2$$

$$\mathcal{A} = \frac{1}{N} \sum_{i=1}^N z_i^2 = -\frac{2}{N} \log N(0, I) - \log(2\pi)$$

$$\forall_{i,j} \left(z_i \sim N(0,1) \right) \wedge \left(z_i \perp z_j \right) \implies \mathcal{A}_{A/B} \sim \chi^2(N_A/N_B) \wedge \left(\mathcal{A}_A \perp \mathcal{A}_B \right)$$

