

ANOMALY DETECTION WITH NORMALIZING FLOWS FOR MODEL- AGNOSTIC NEW PHYSICS SEARCHES

Rafał Masełek

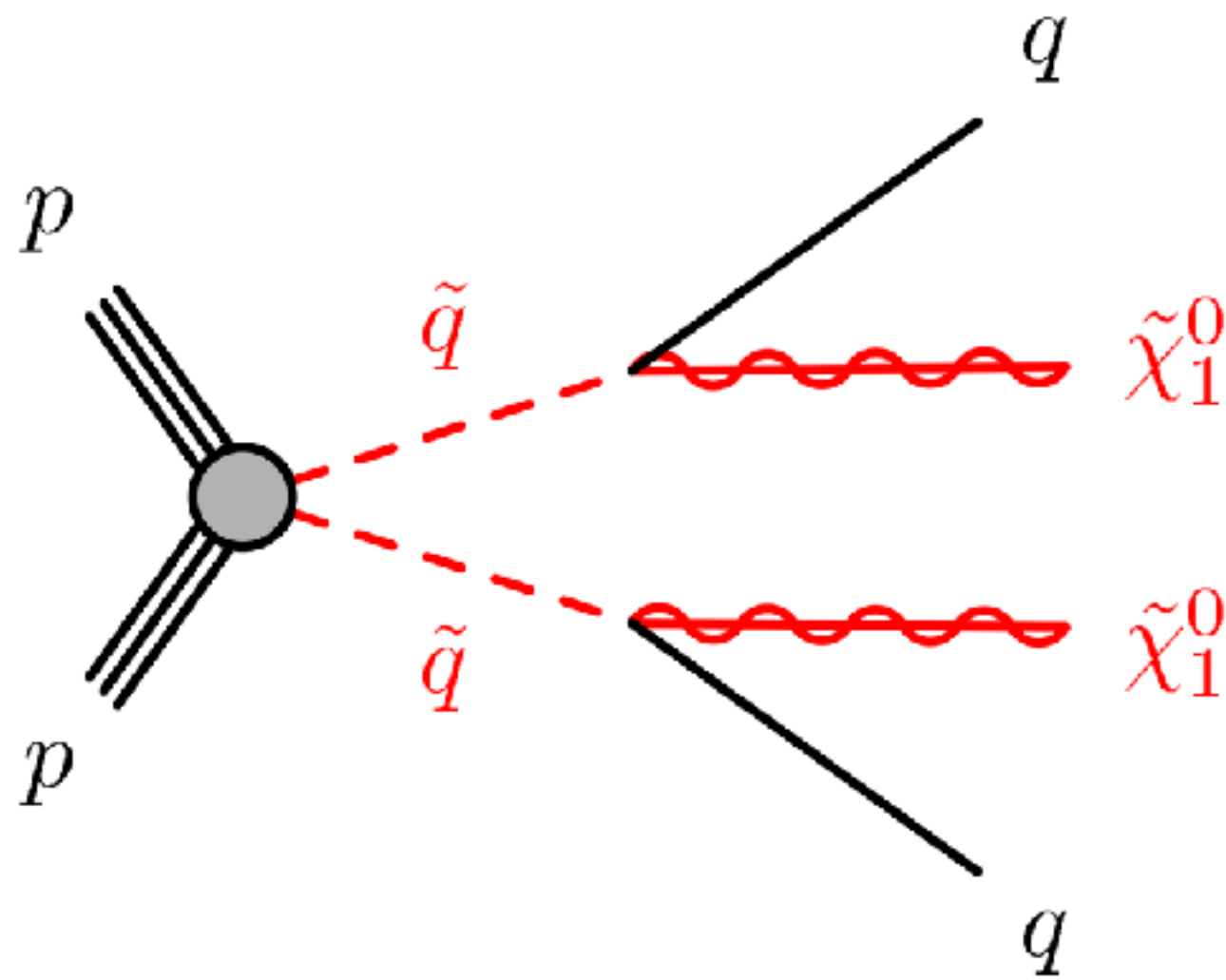
in collaboration with

Sabine Kraml, Kazuki Sakurai & David Shih

ML4Jets 2026 17-09-2026

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

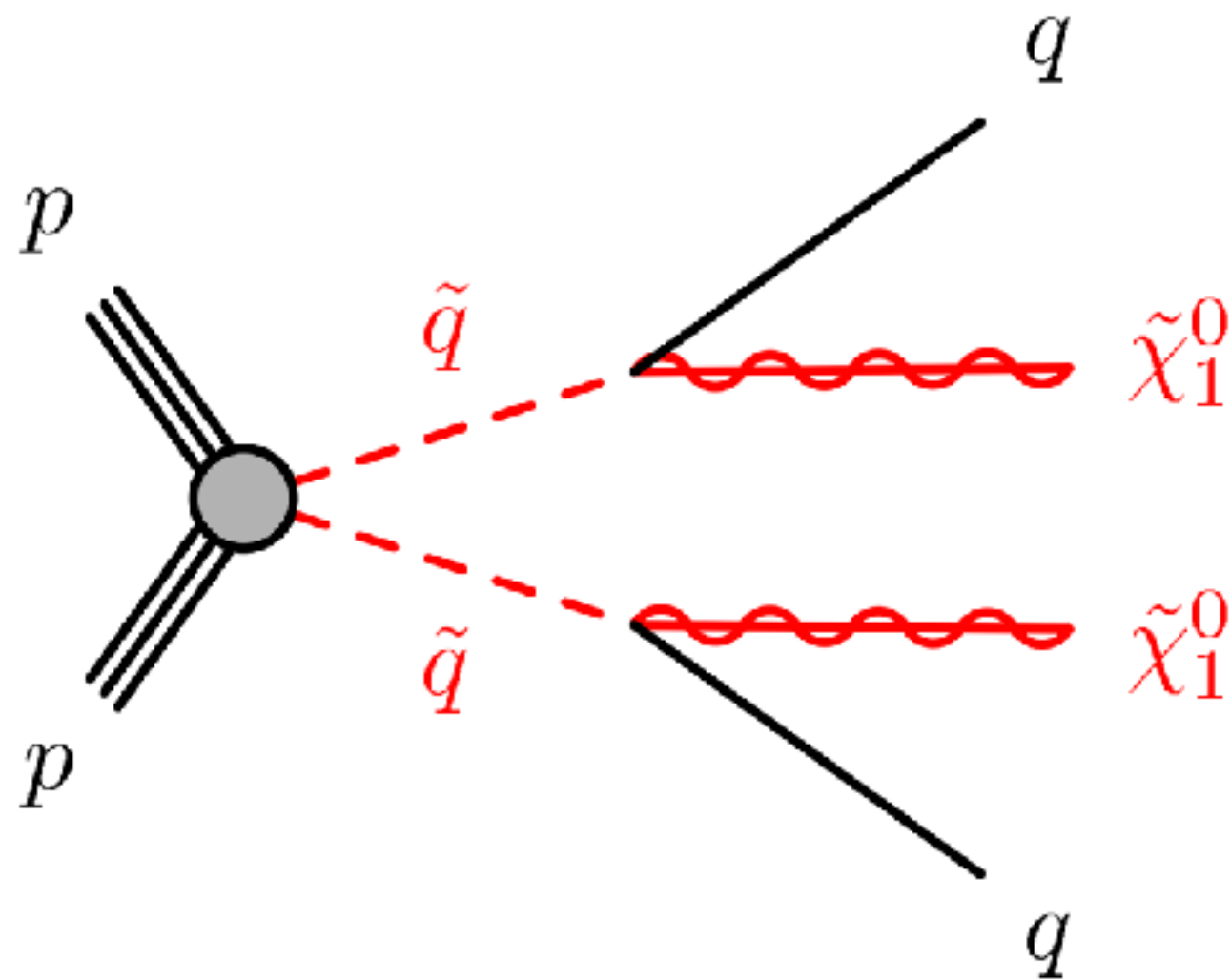
BG/signal estimation (MC sim)

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

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

specific to BSM scenario

background estimation

BG/signal estimation (MC sim)

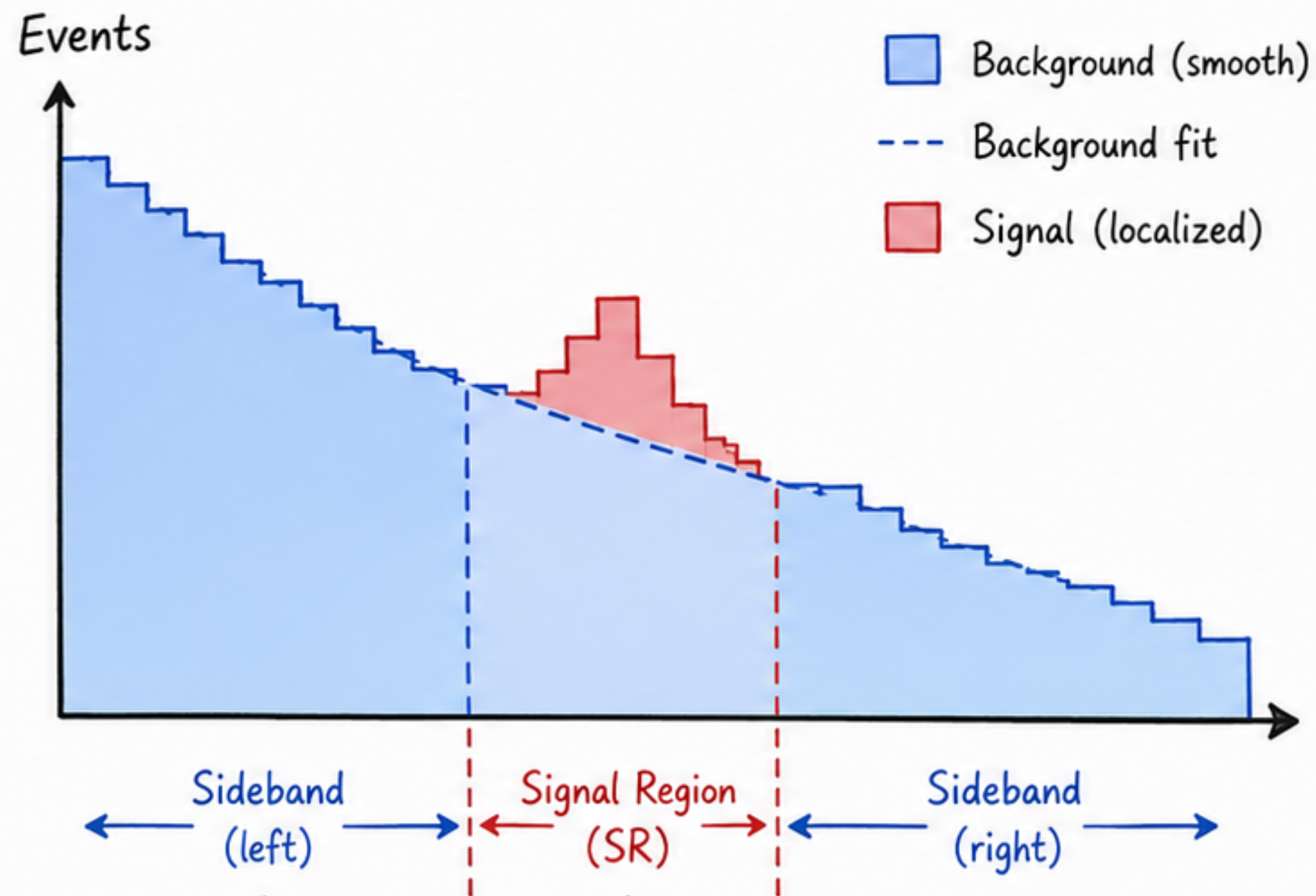
Z/ γ +jets	$32.3 \pm 2.6 \pm 6.9$
W+jets	$26.4 \pm 4.0 \pm 6.7$
$t\bar{t}$ + single top	$3.4 \pm 1.6 \pm 1.6$
QCD multi-jet	$0.22 \pm 0.06 \pm 0.24$
SM total	$62.4 \pm 4.4 \pm 9.3$
$(m_{\tilde{q}}, m_{\tilde{\chi}_1^0}) = (1, 0.1) \text{ TeV}$	29.2 ± 5.1
Data	58

statistical
consistency

simulation dependent

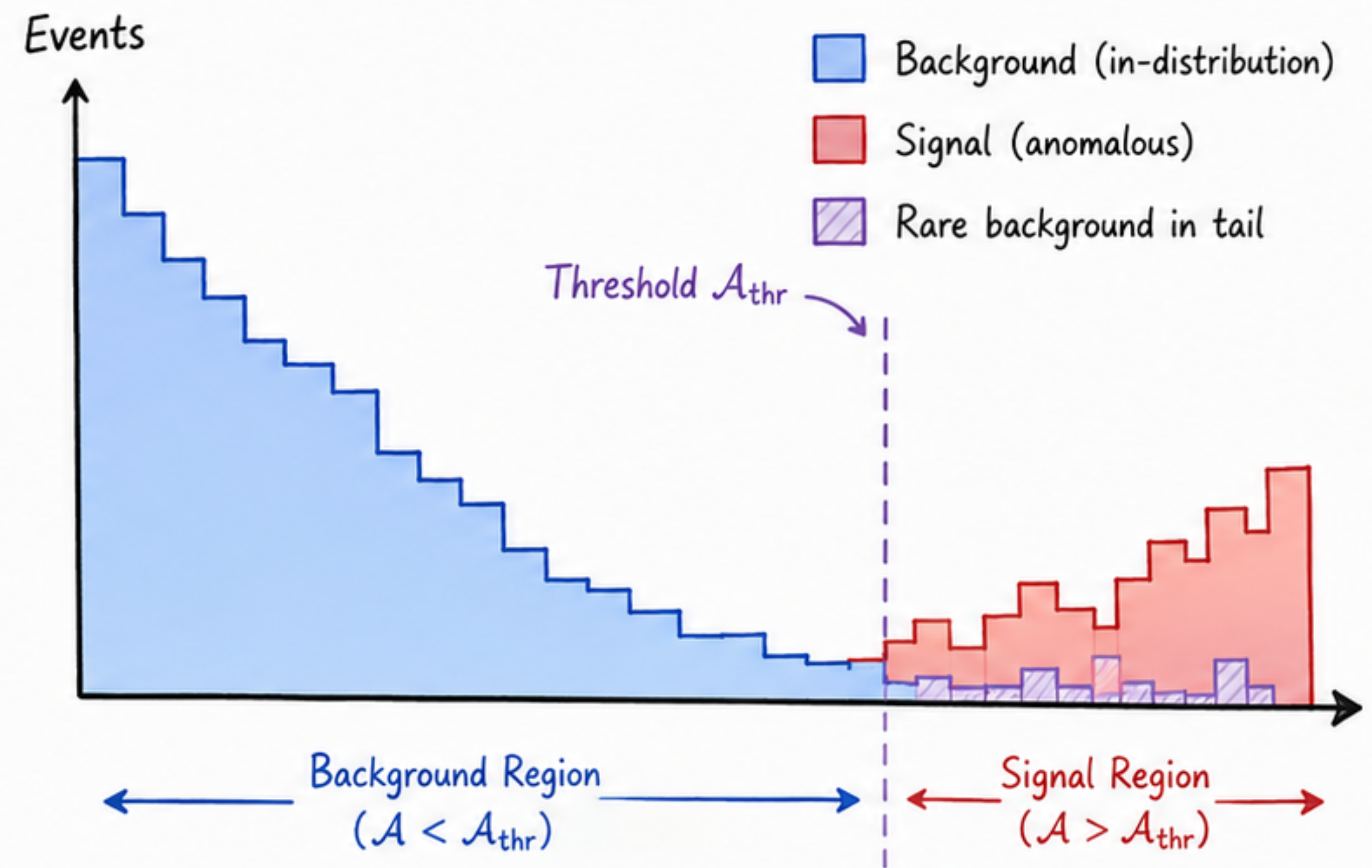
Anomaly searches in HEP

Overdensity (Bump Hunting)



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

Out-of-Distribution (OOD) Anomaly Search

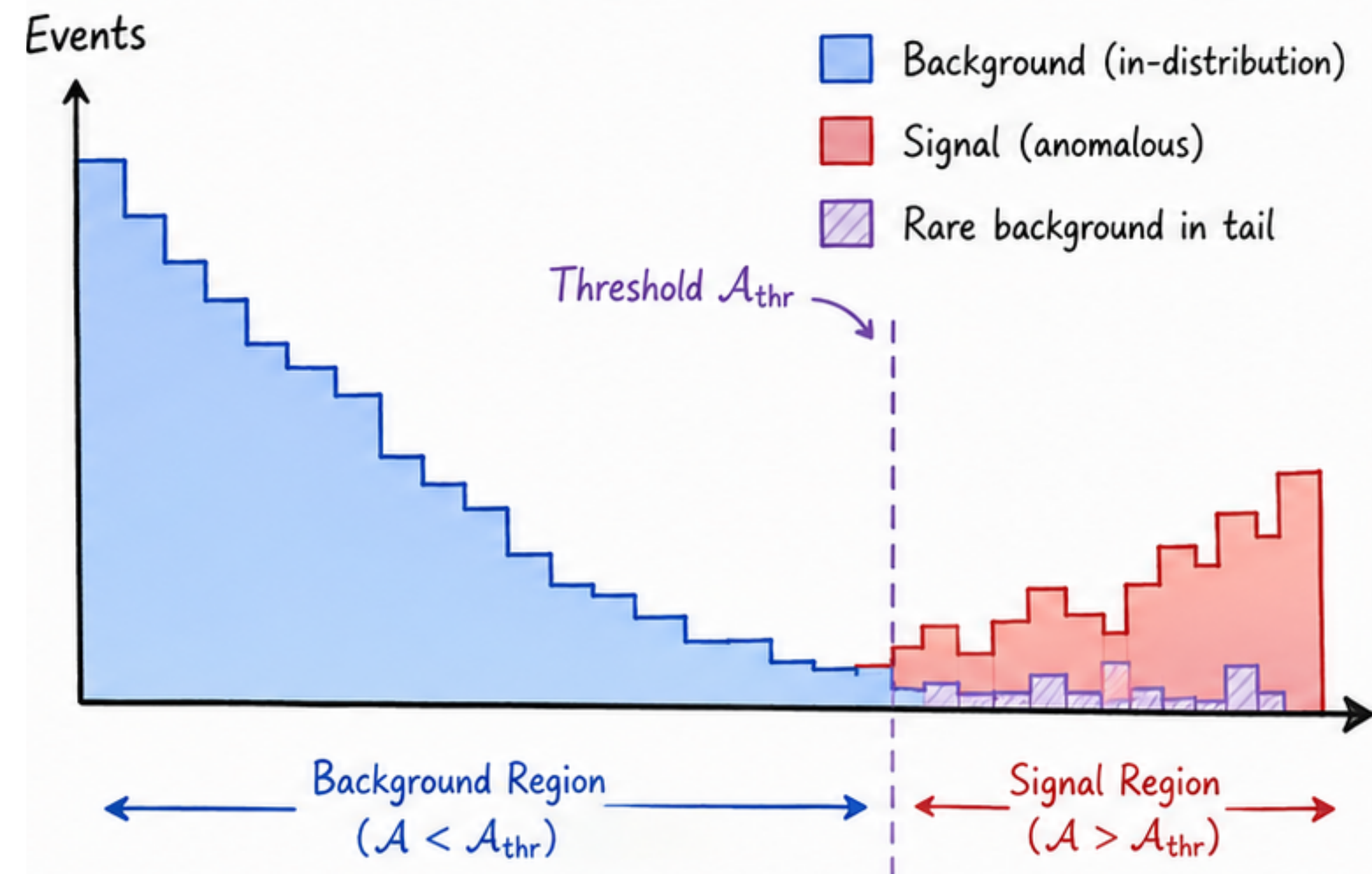


Events with anomaly score $\mathcal{A}$ greater than the threshold are considered **anomalous**.

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**.

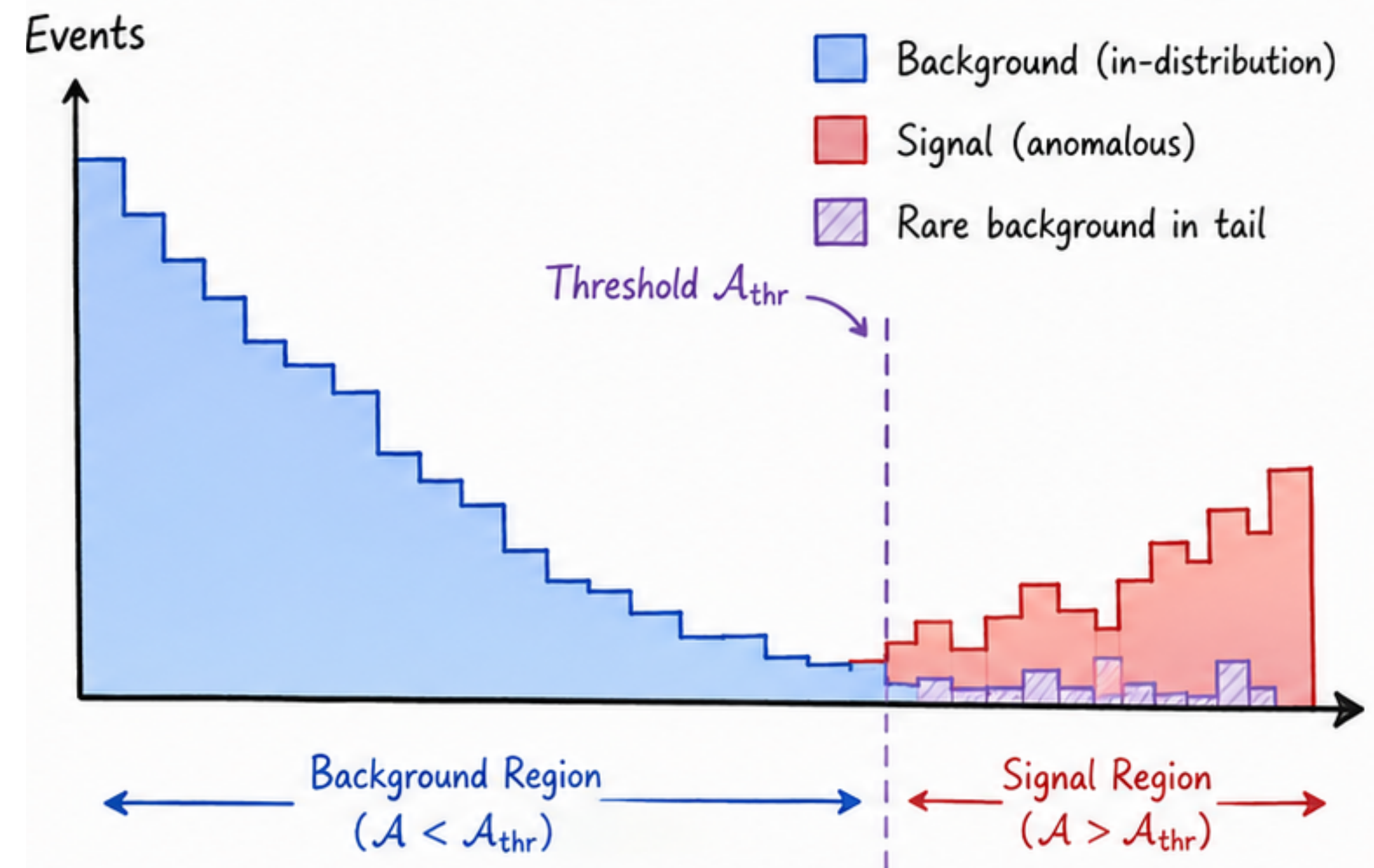
Anomaly searches in HEP

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 pool of water in the foreground. The sky is clear blue, and there are green trees on either side of the castle.

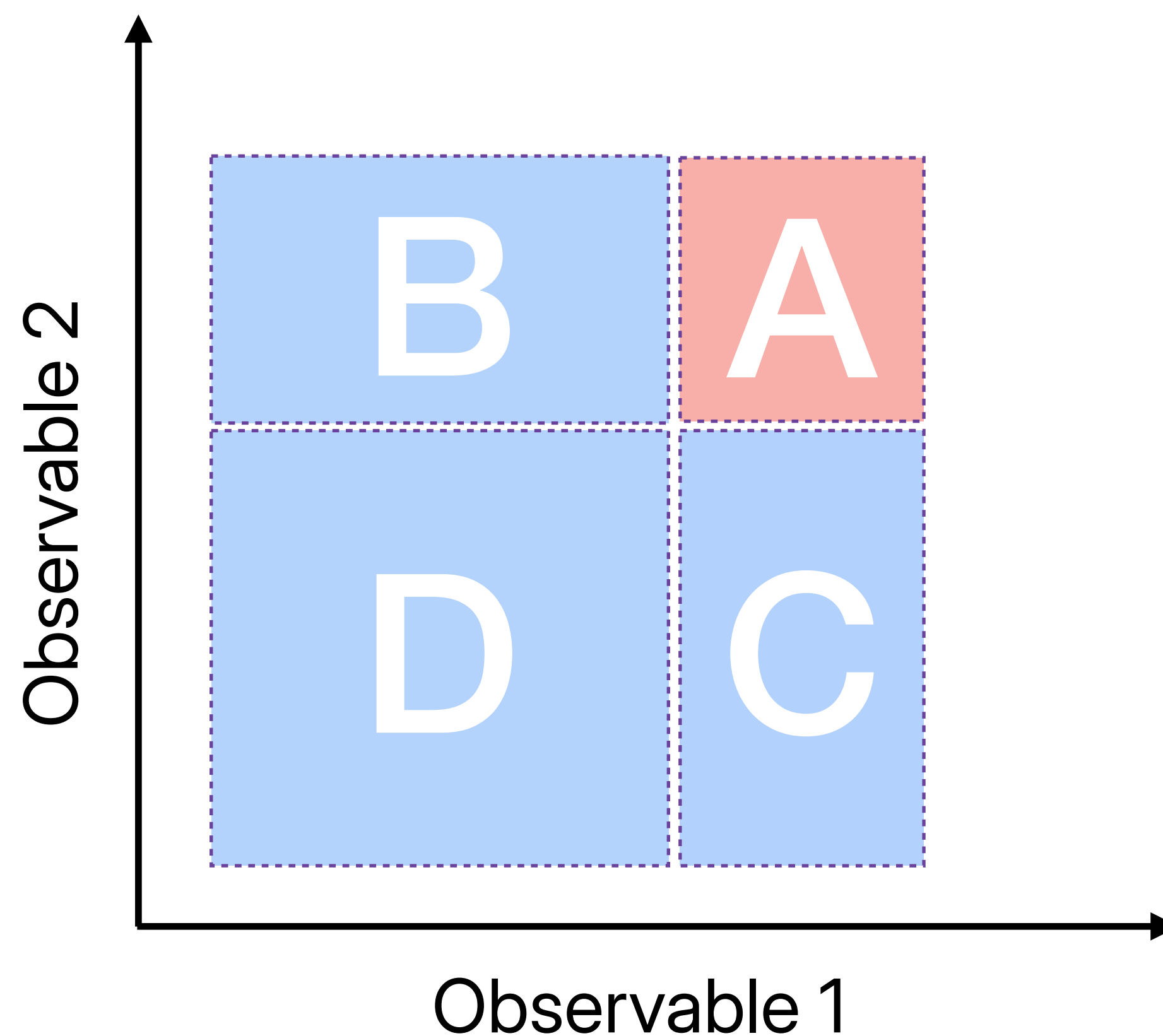
METHODOLOGY

Moszna Castle, Poland



ABCD matrix method

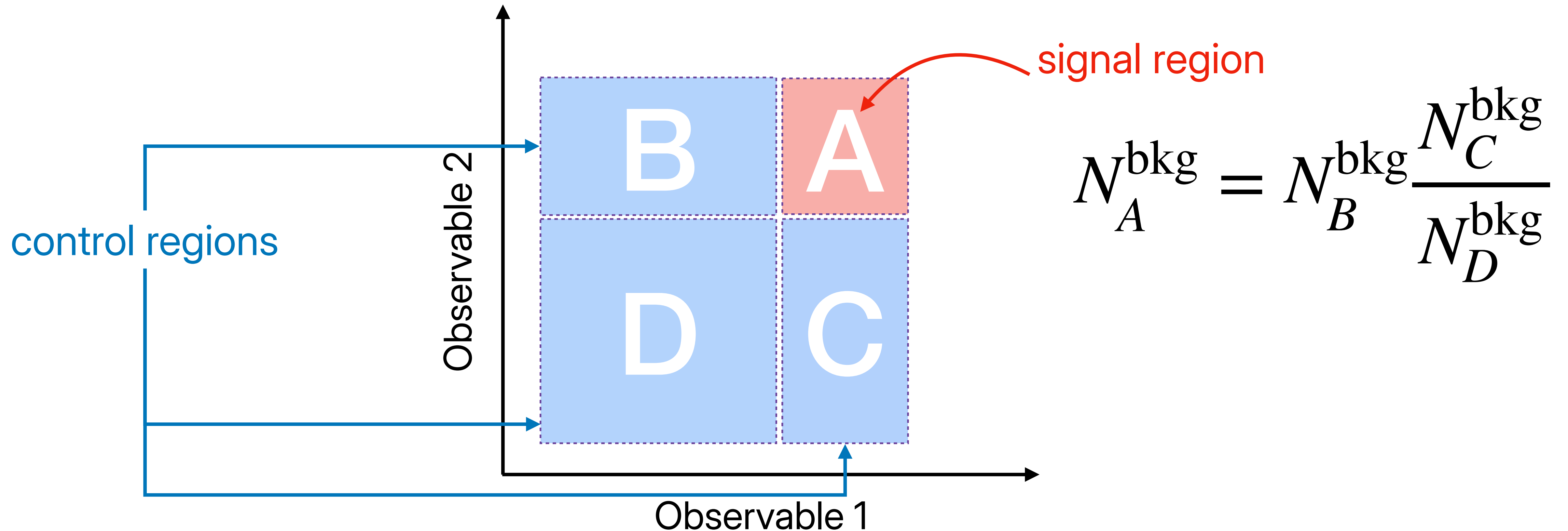
Established method for data-driven background estimation





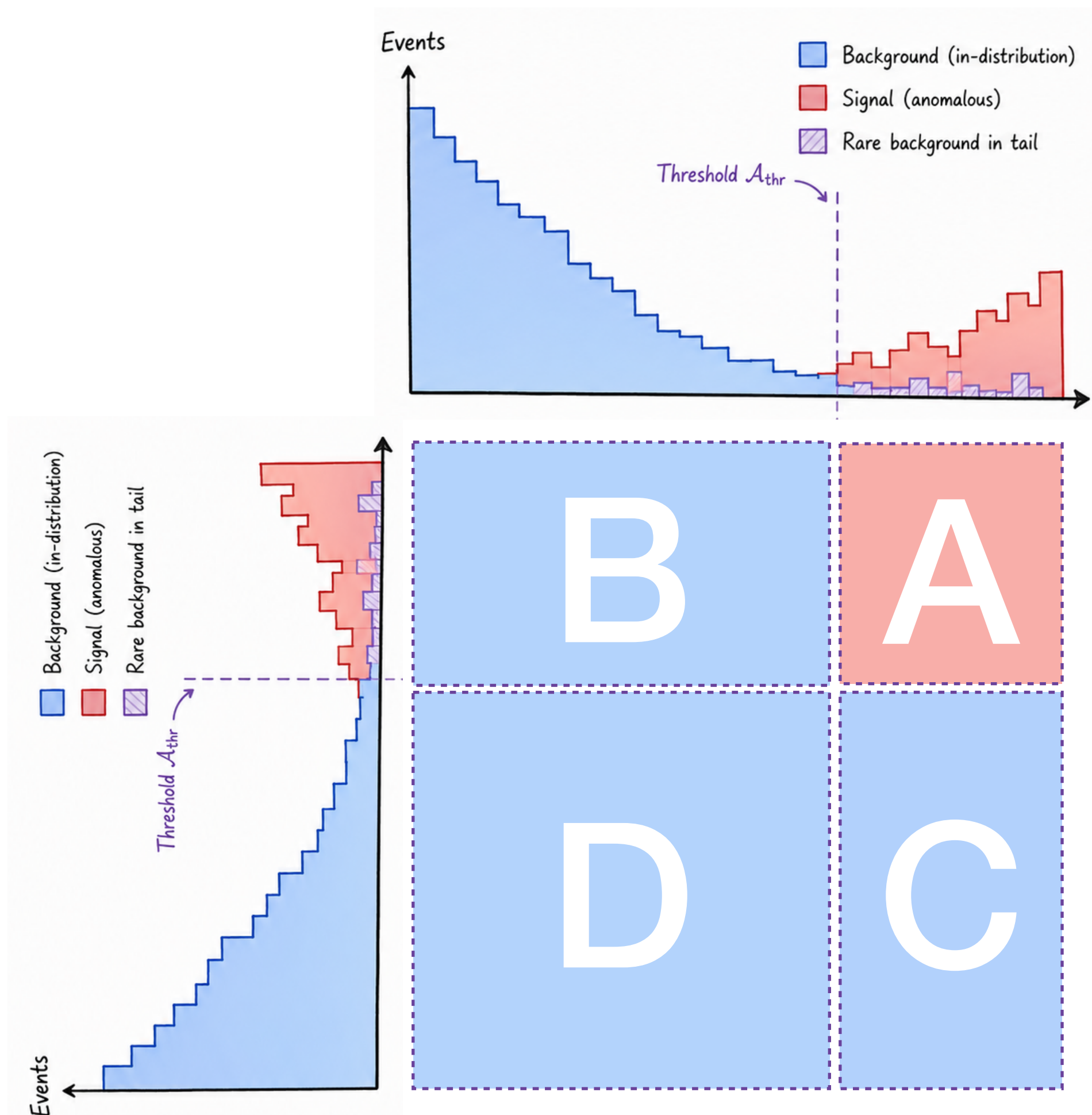
ABCD matrix method

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]

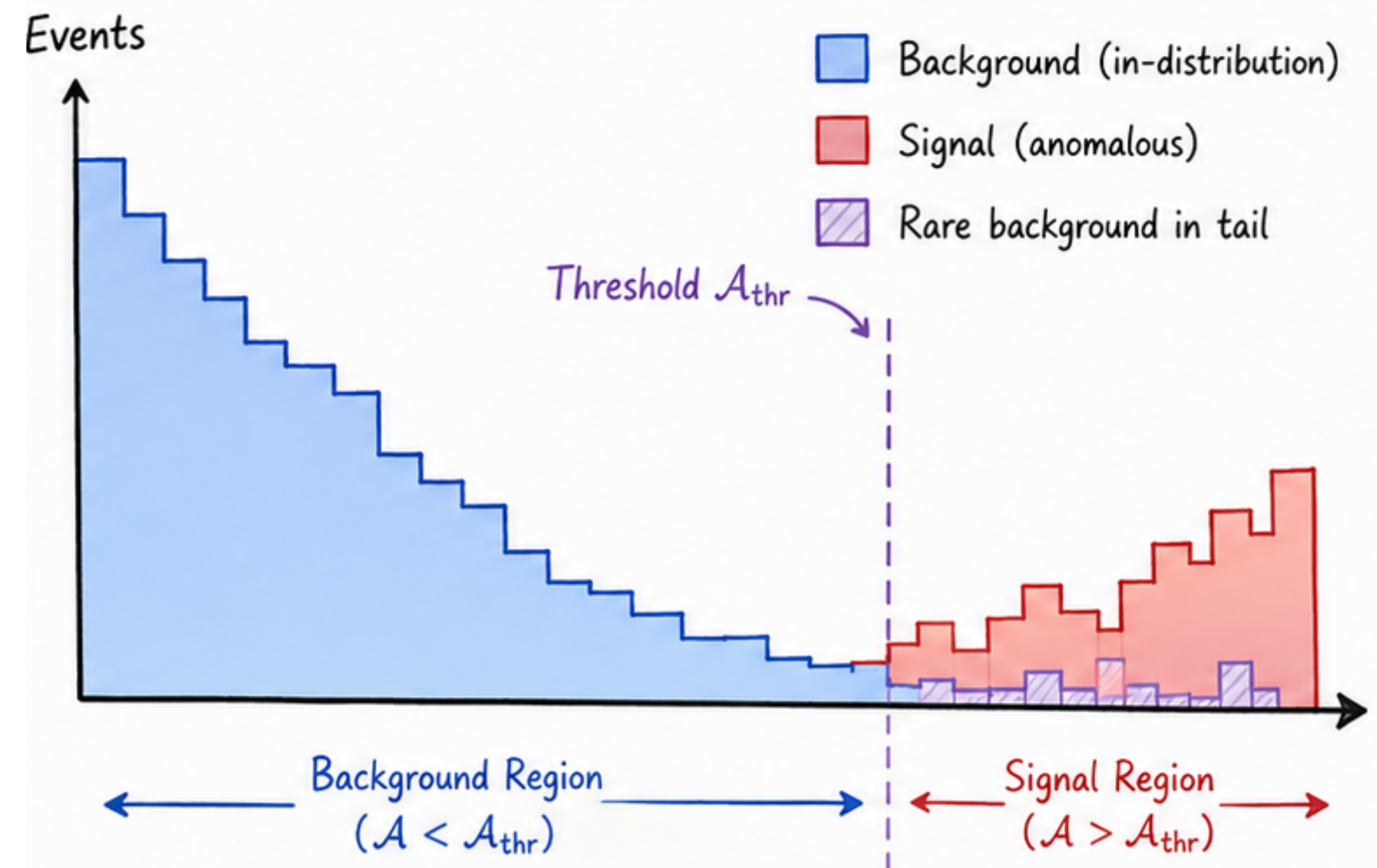
Anomaly searches in HEP

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 $A > A_{\text{thr}}$

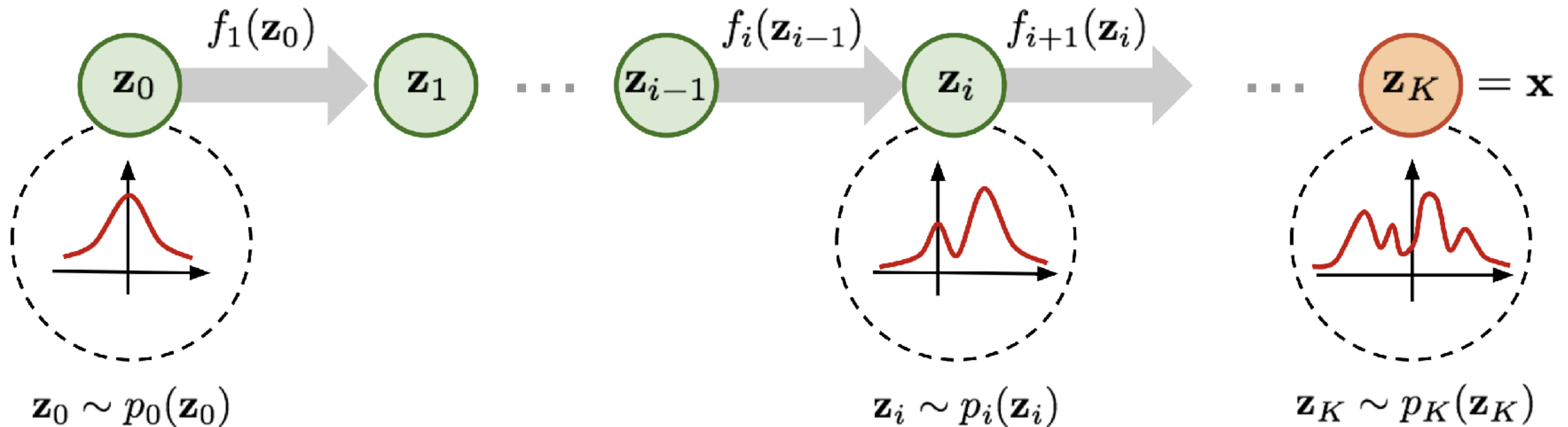
What about background in the signal region?

Out-of-Distribution (OOD) Anomaly Search



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

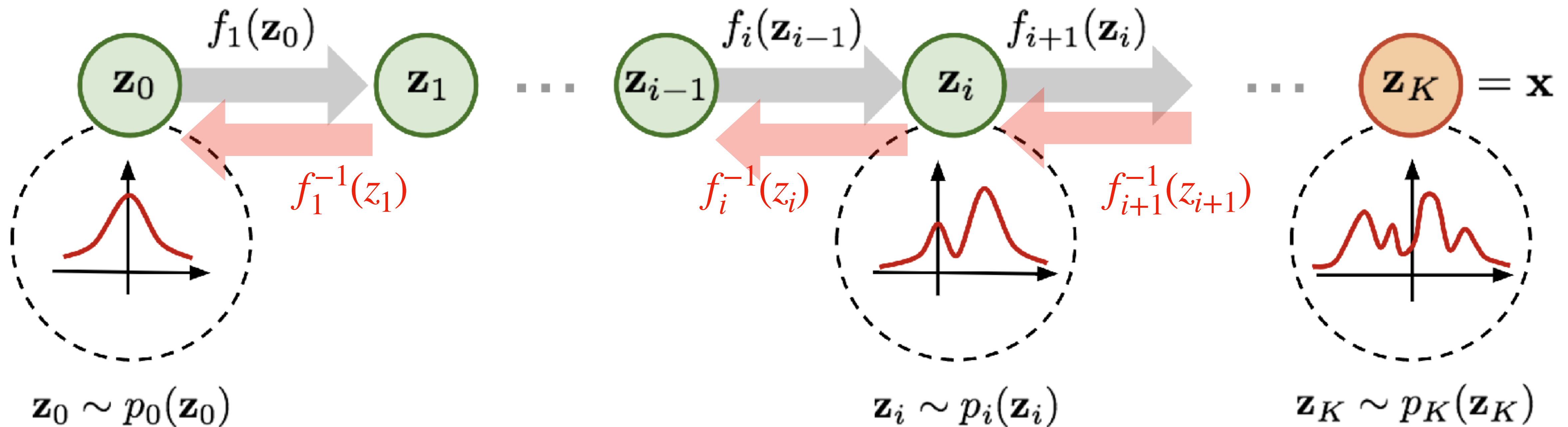
Normalizing Flows



Normalizing Flows allow to efficiently sample from complicated data distributions.

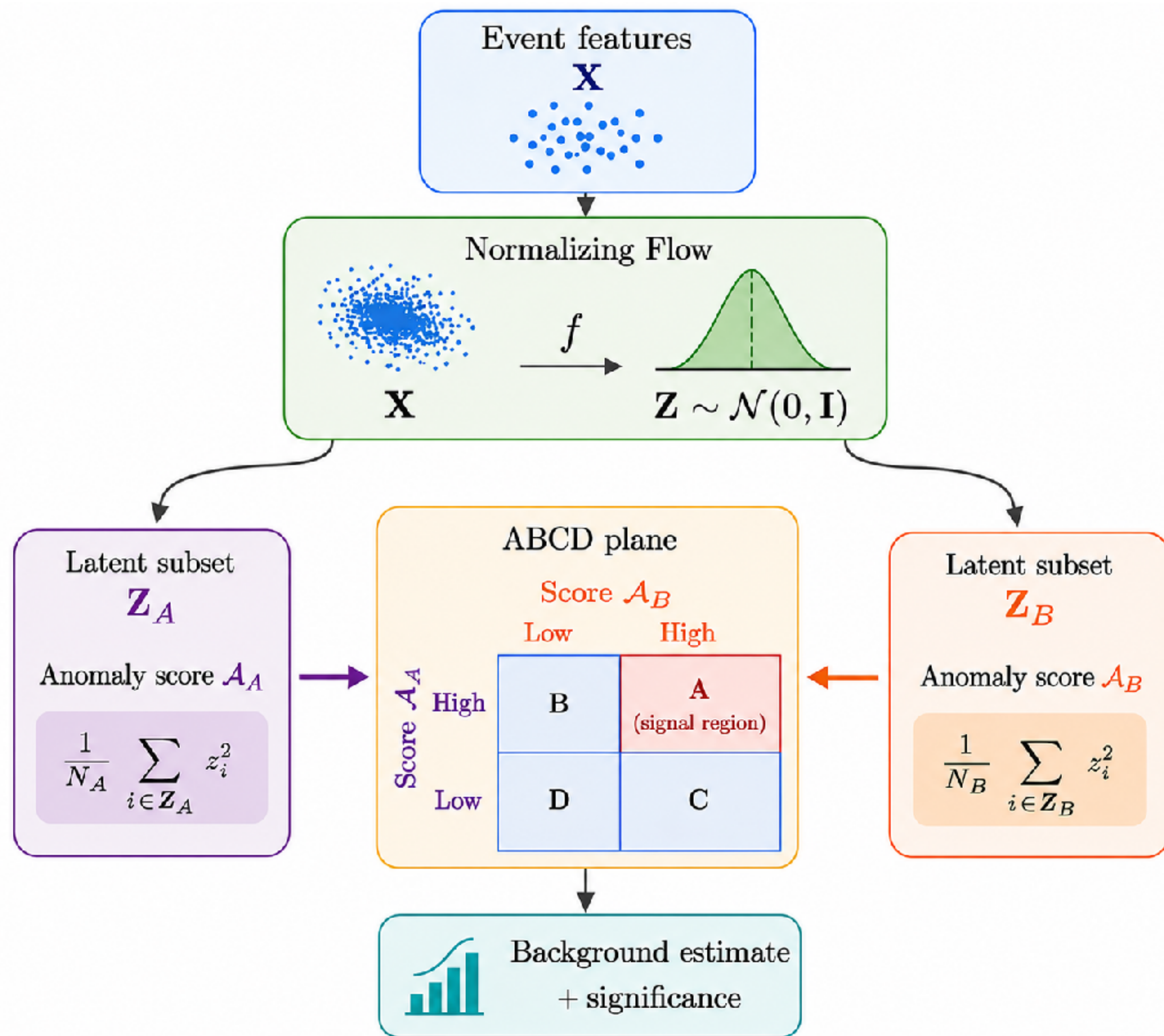
We build a sequence of invertible parametrisable functions that transform a multivariate Gaussian distribution to data distribution.

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



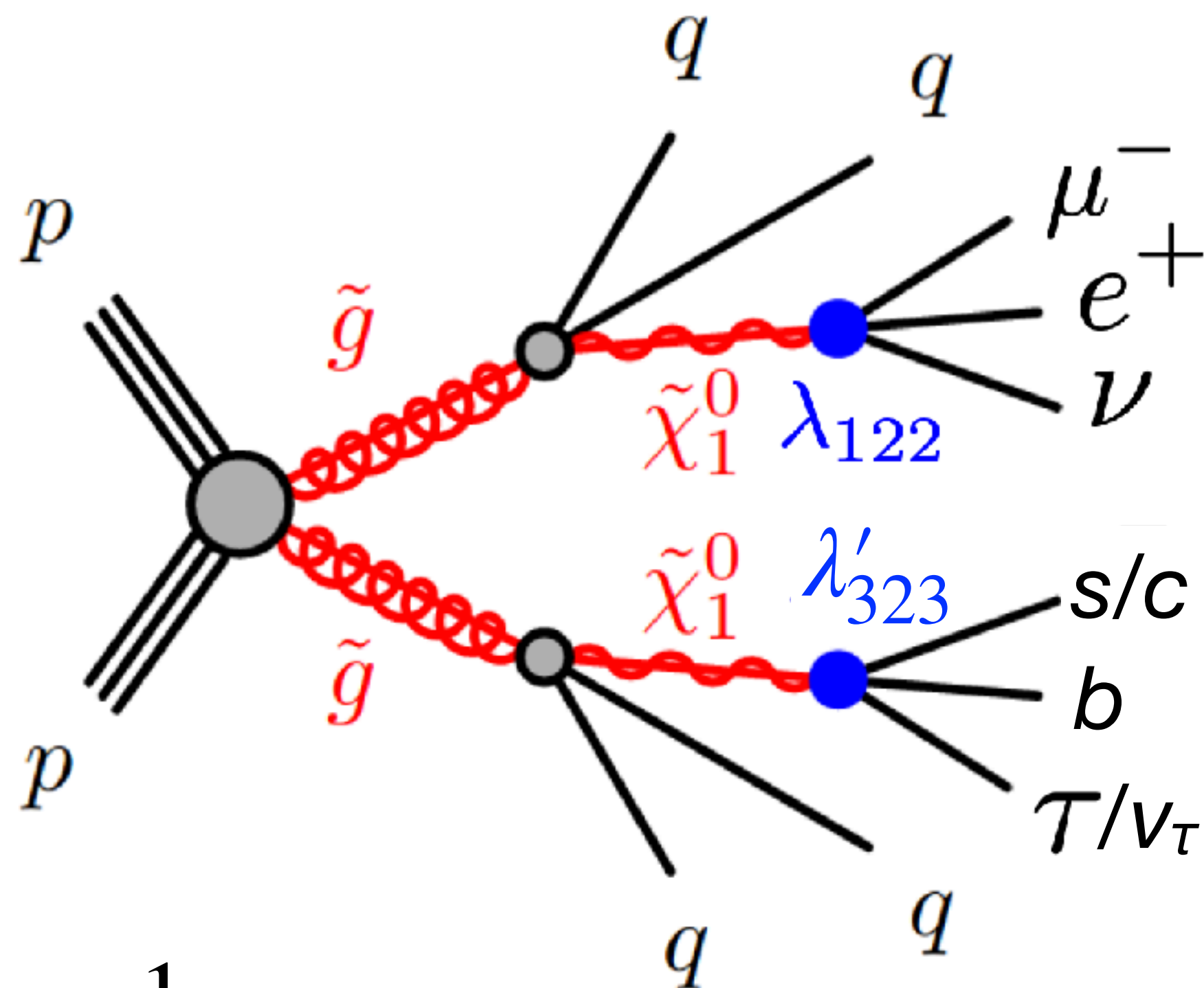
A photograph of Książ Castle in Poland at sunset. The castle is illuminated with warm lights, and its reflection is visible in a pool of water in the foreground. The sky is a mix of orange, yellow, and blue, with some clouds. The castle has a prominent tower with a dark roof and a smaller tower to the left. The foreground is filled with green trees.

BENCHMARK

Książ Castle, Poland

Benchmark model

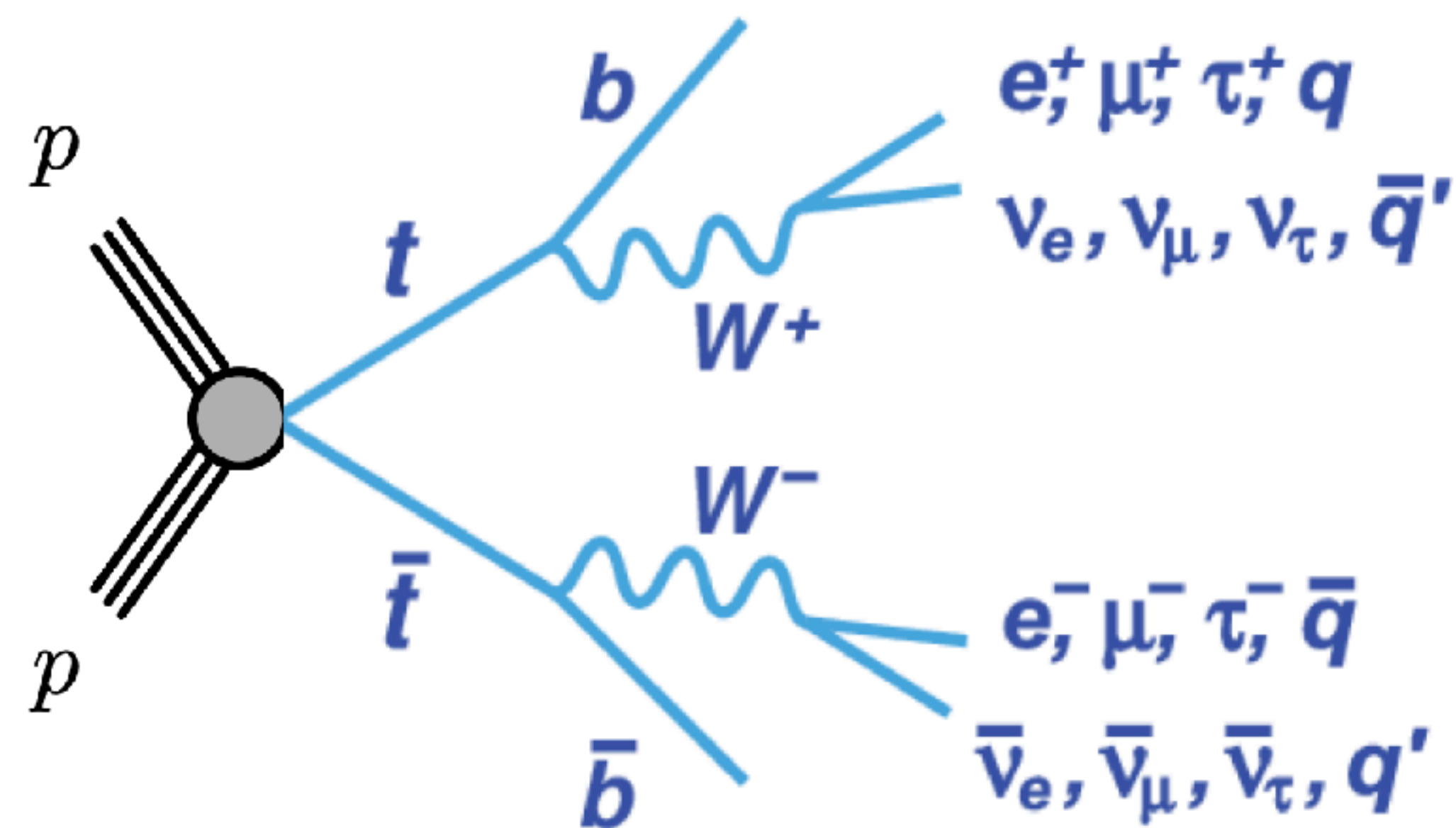
signal — RPV SUSY



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

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

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	$p_T^{j1} > 60 \text{ GeV}$
6	$p_T^{j2} > 30 \text{ GeV}$
7	$p_T^{j3} > 30 \text{ GeV}$
8	$\cancel{E}_T > 60 \text{ GeV}$
9	$p_T^{l1} > 120 \text{ GeV}$
10	$p_T^{l2} > 120 \text{ GeV}$

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

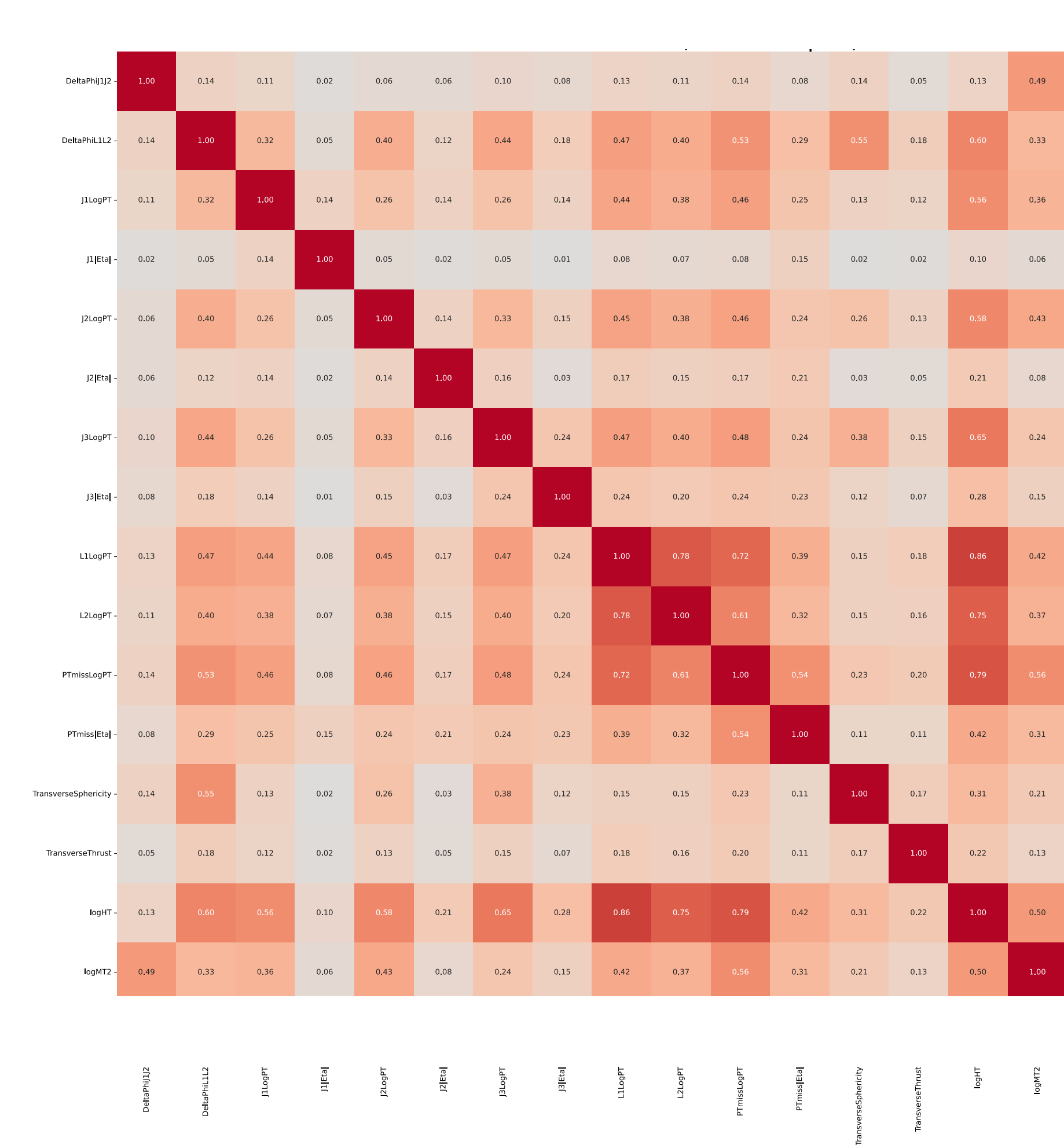
#	Name
1	$\log p_T^{j1}$
2	$\log p_T^{j2}$
3	$\log p_T^{j3}$
4	$\log p_T^{l1}$
5	$\log p_T^{l2}$
6	$\log p_T^{\text{miss}}$
7	$\log H_T$
8	$\log M_{T2}$
9	$ \eta^{j1} $
10	$ \eta^{j2} $
11	$ \eta^{j3} $
12	$ \eta^{\text{miss}} $
13	$\Delta\phi(j_1, j_2)$
14	$\Delta\phi(l_1, l_2)$
15	$T_\perp$
16	S_T



PRELIMINARY RESULTS (semi-supervised)

Lublin Castle, Poland

Decorrelation in practice

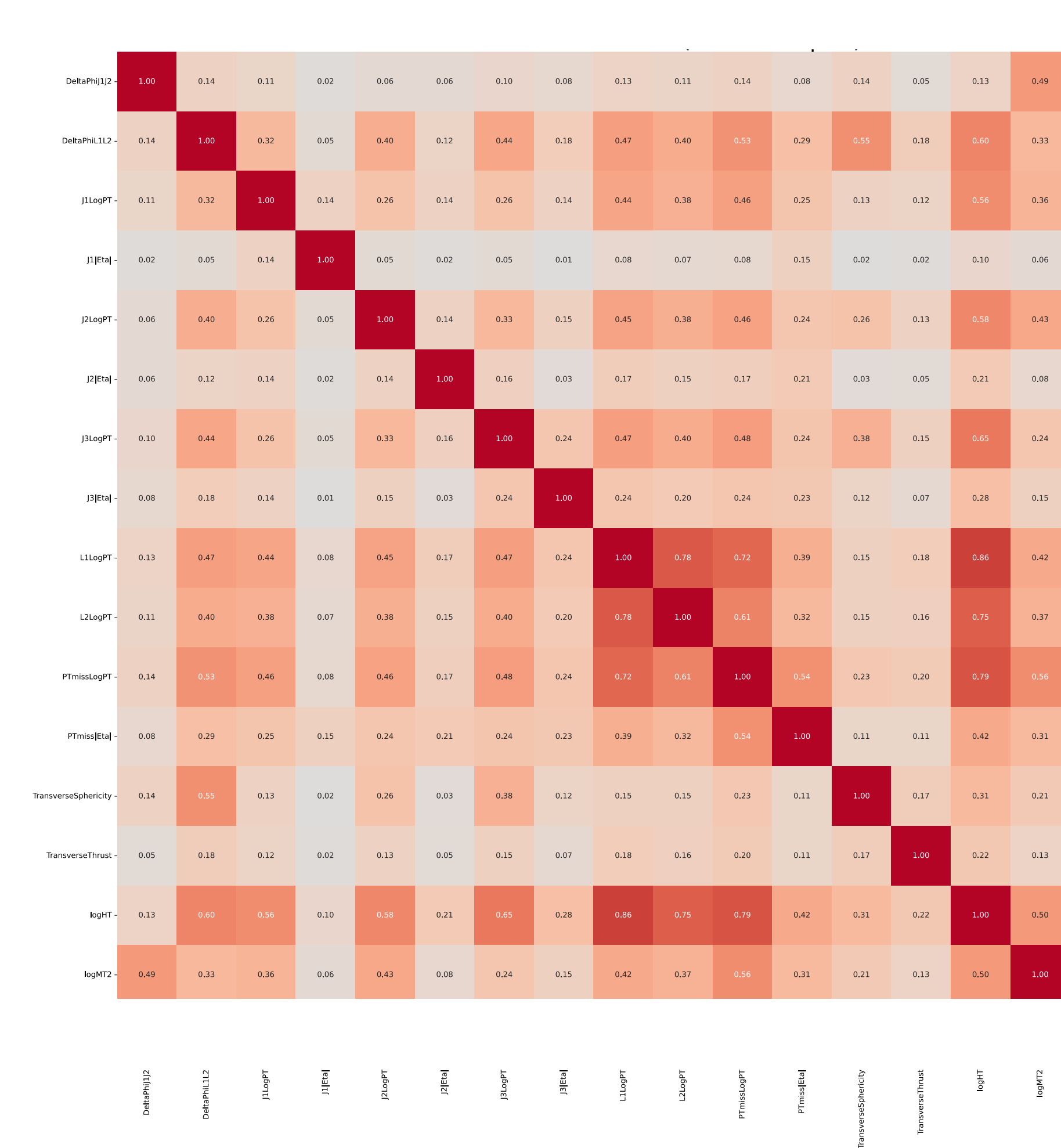


16 highly correlated variables

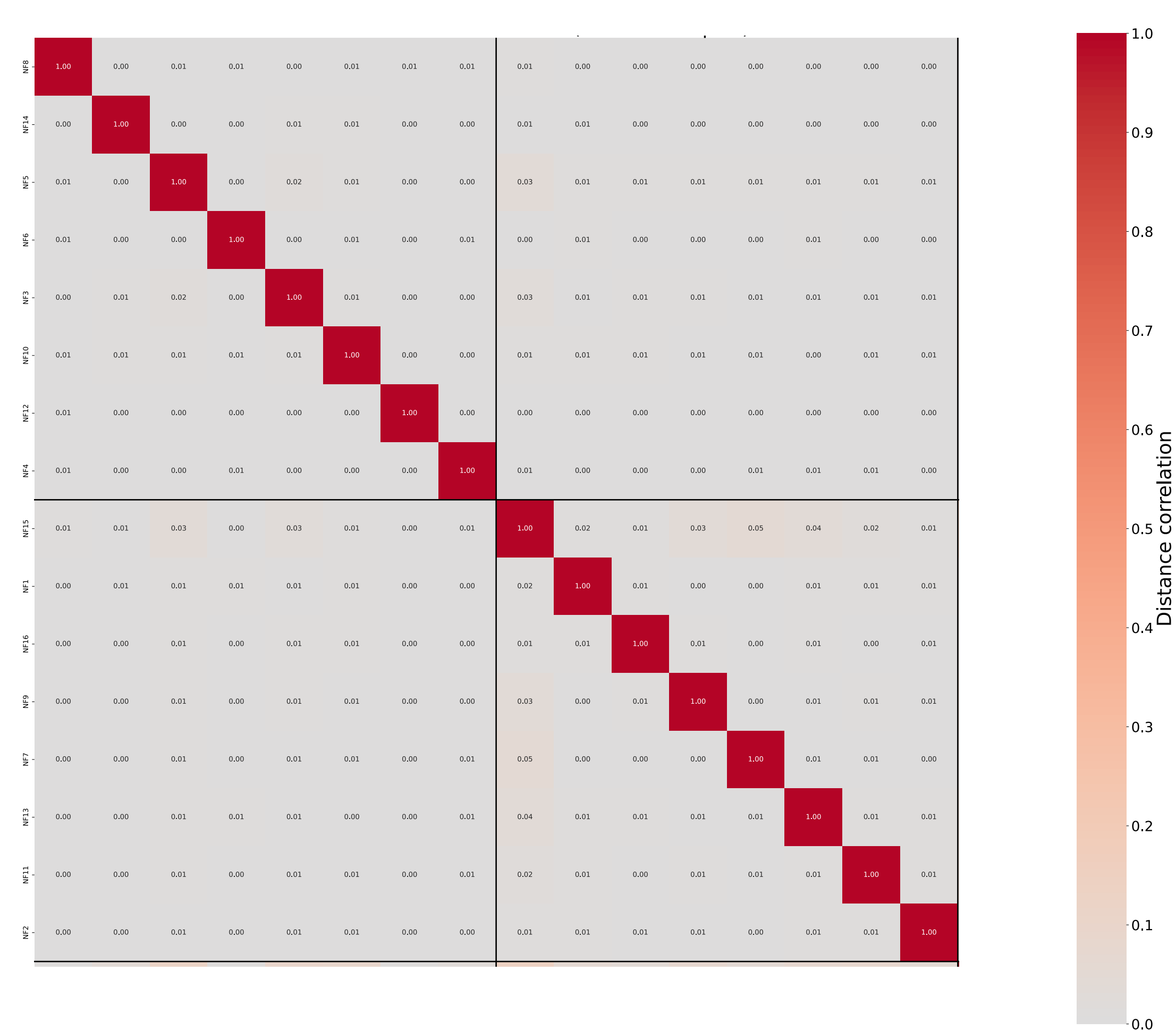
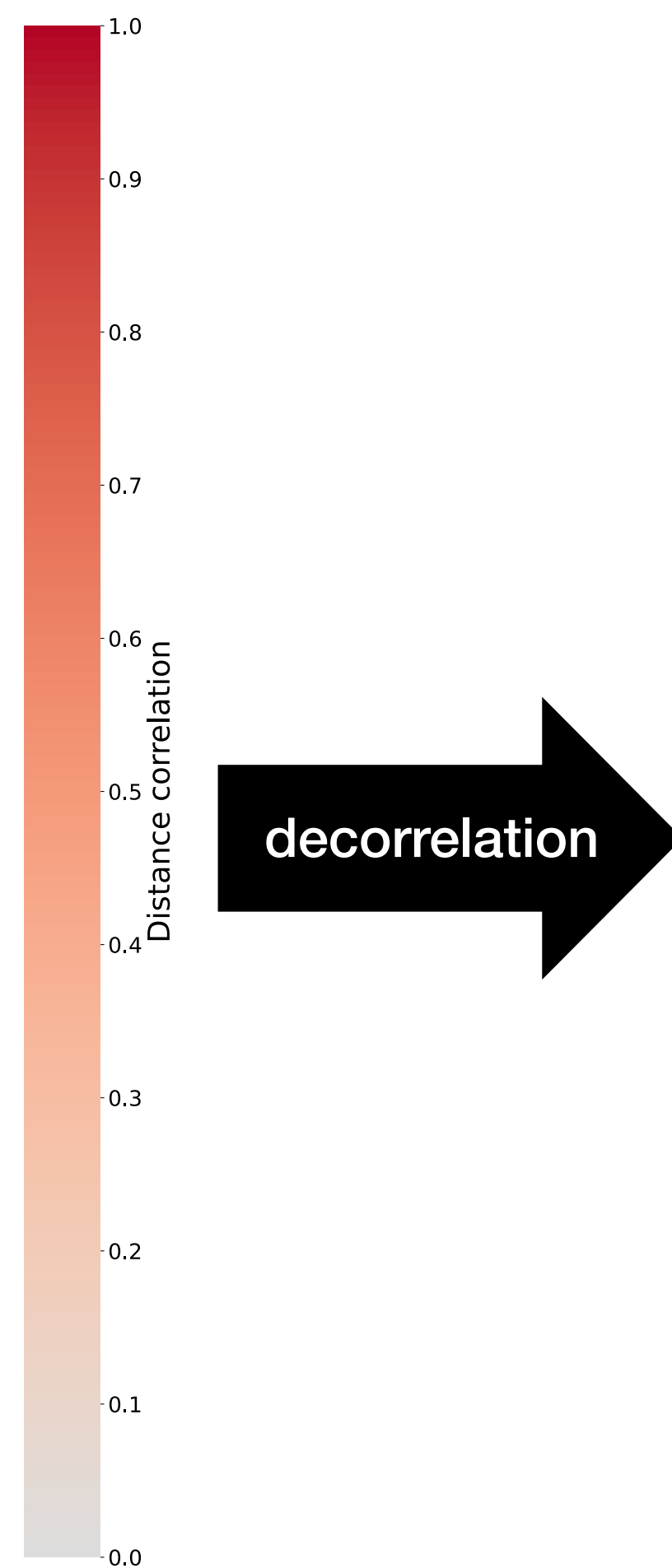
Fully correlated

Uncorrelated

Decorrelation in practice

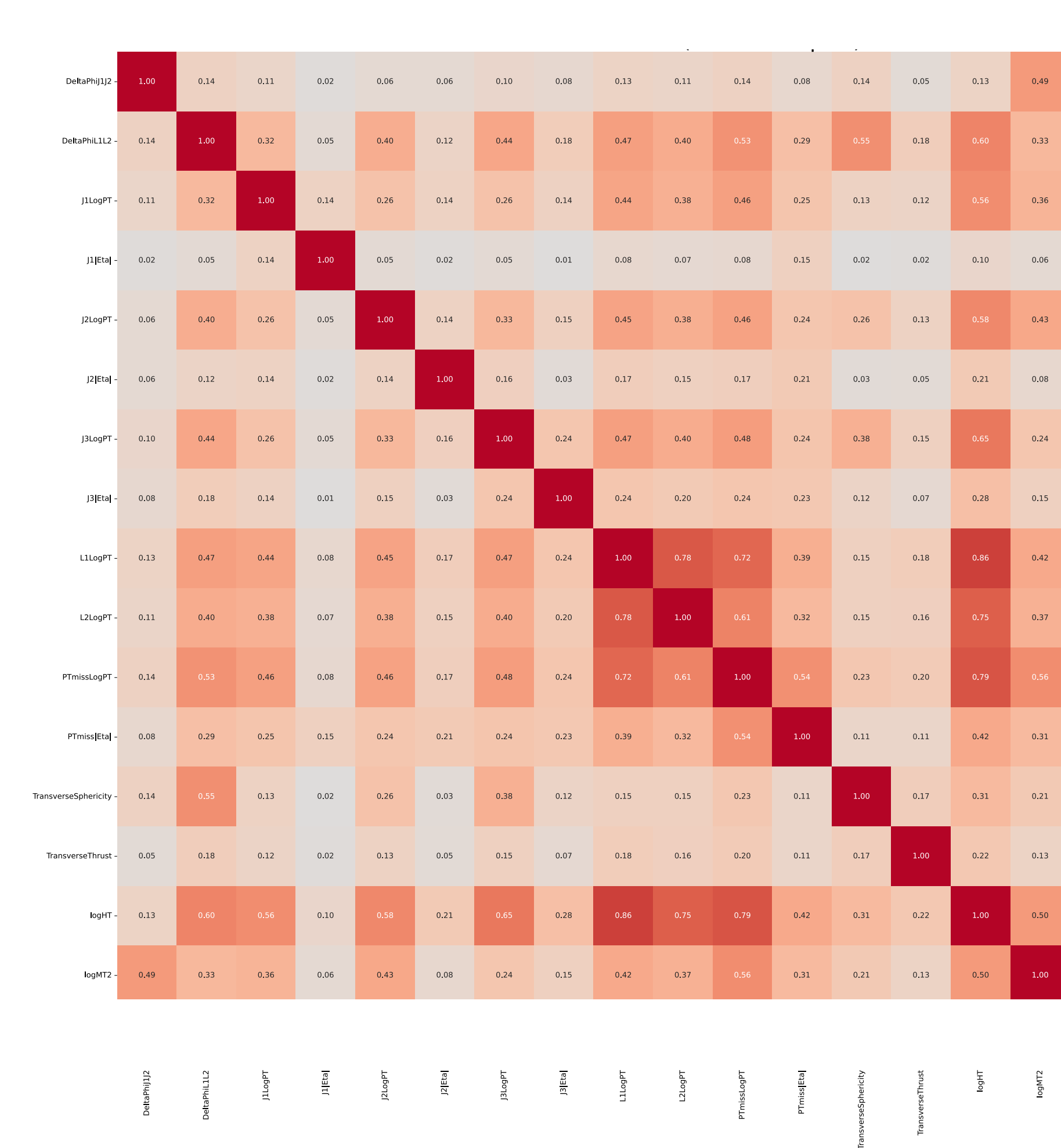


16 highly correlated variables

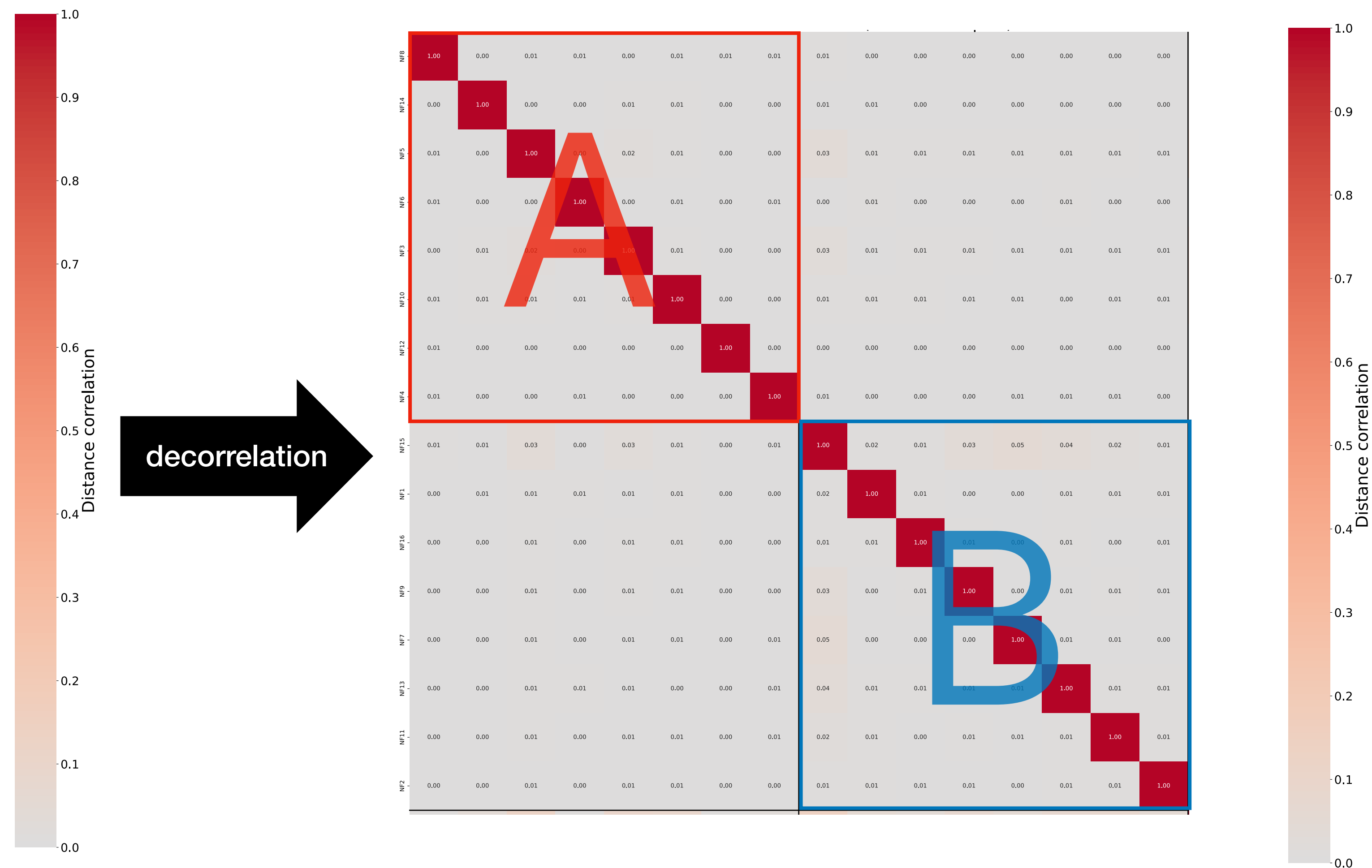


16 highly largely uncorrelated variables split into two subsets

Decorrelation in practice



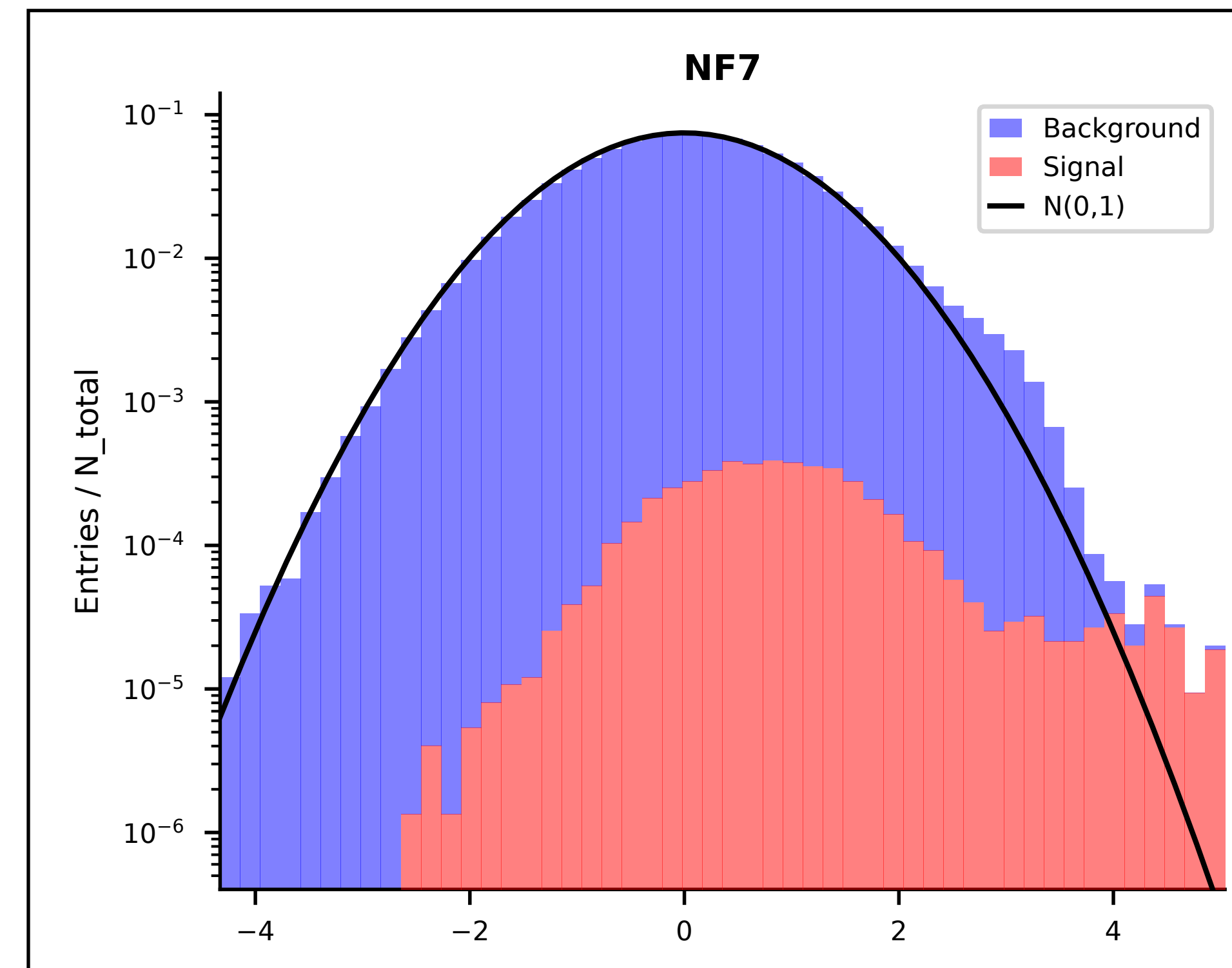
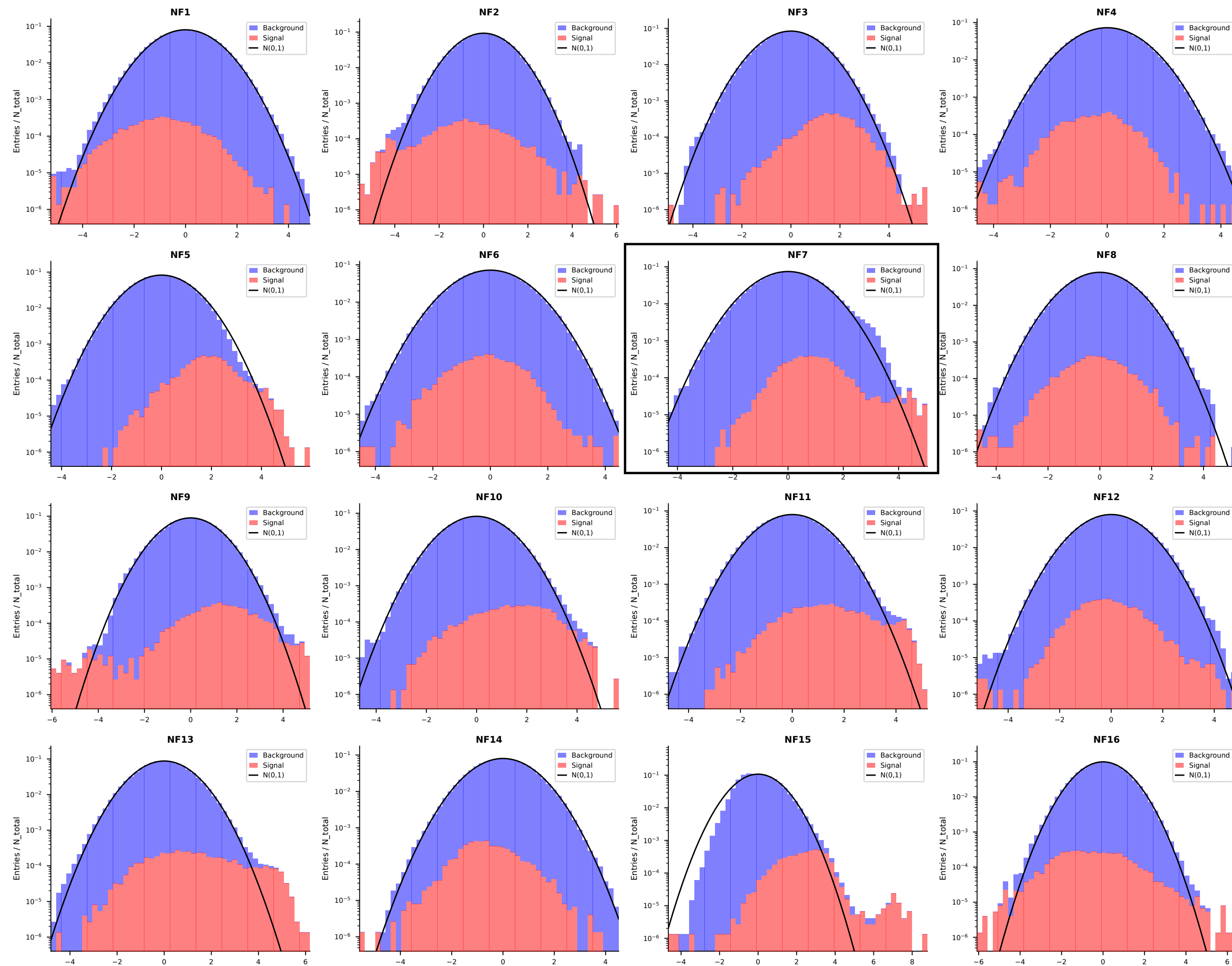
16 highly correlated variables



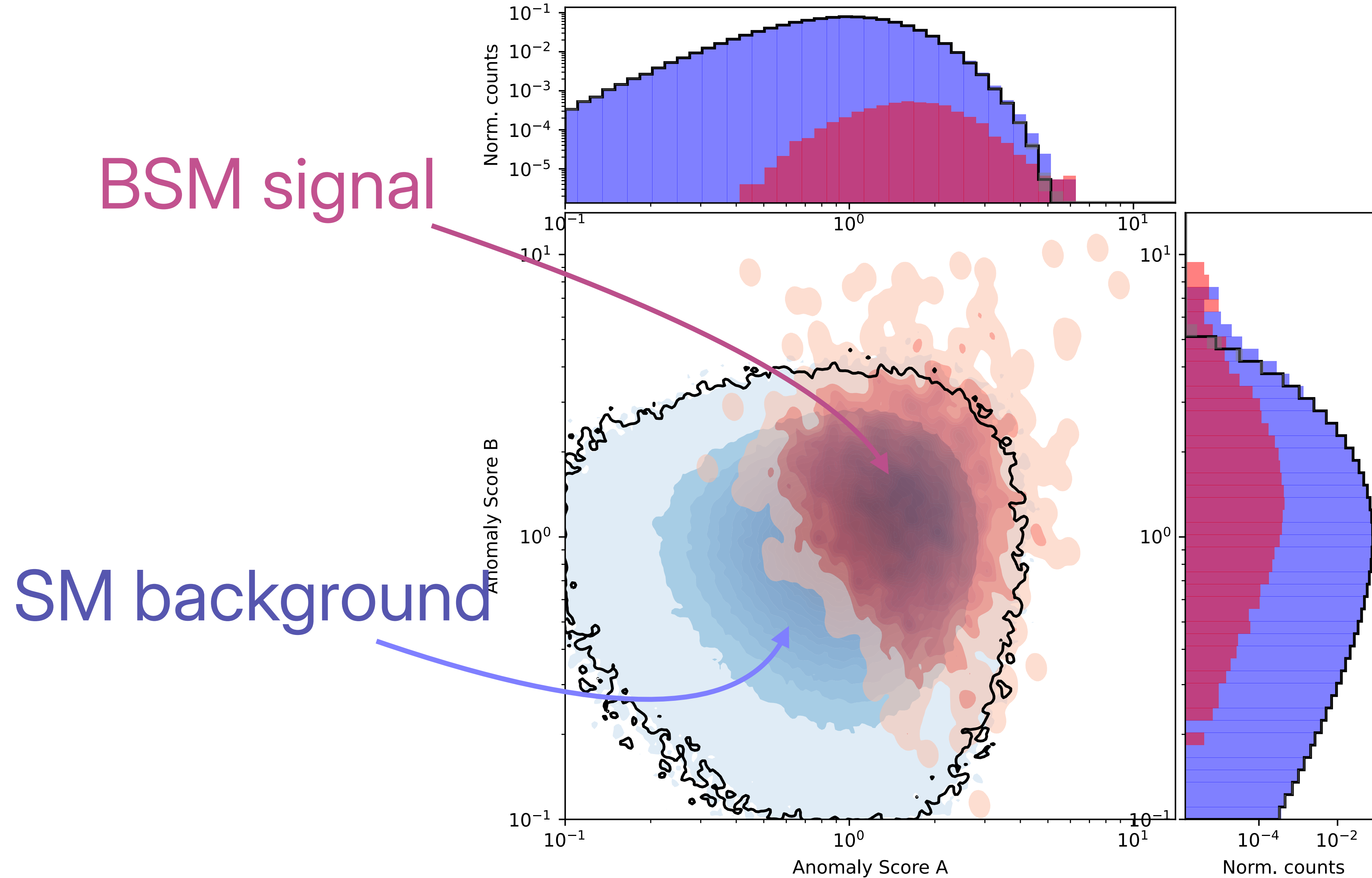
16 highly largely uncorrelated variables split into two subsets

Latent representation — semisupervised

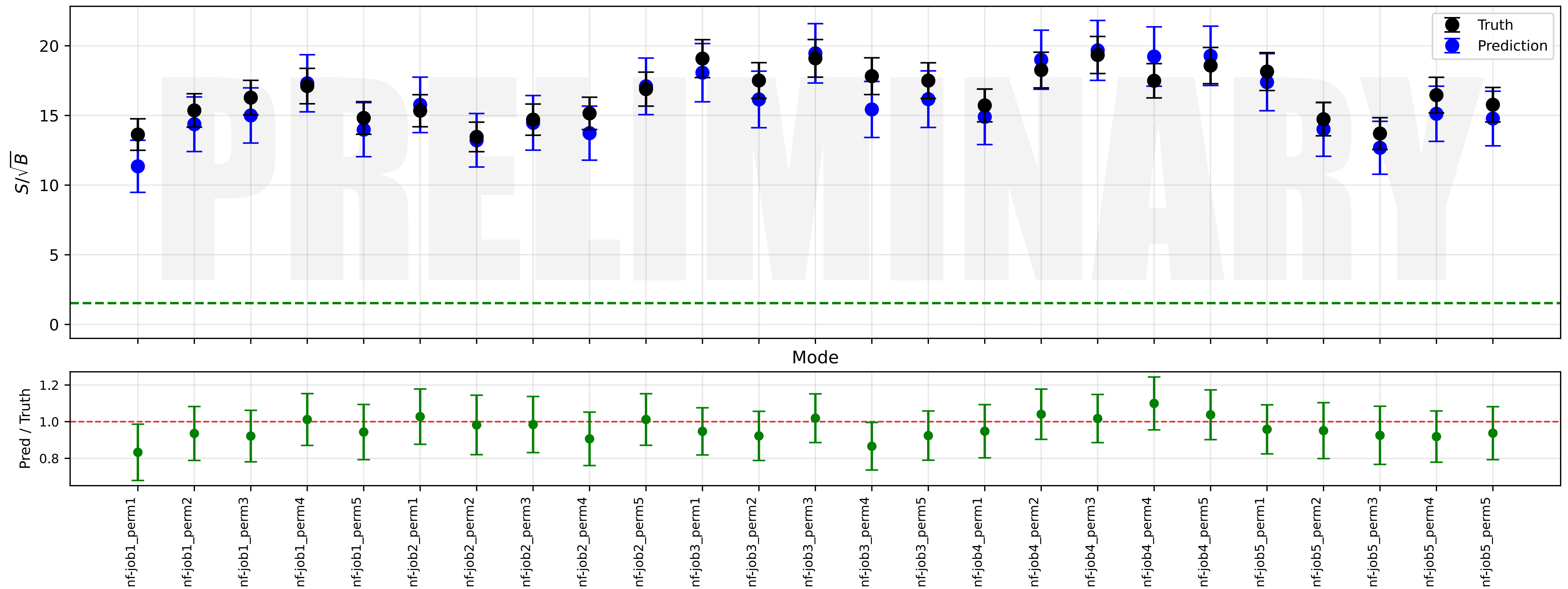
Latent-space signal vs. background — figure 1/1 (stacked)



Anomaly score distribution



Results Results (absolute S/ $\sqrt{B}$) - Percentile Config: 96_48_0 - Method: xABCD_9

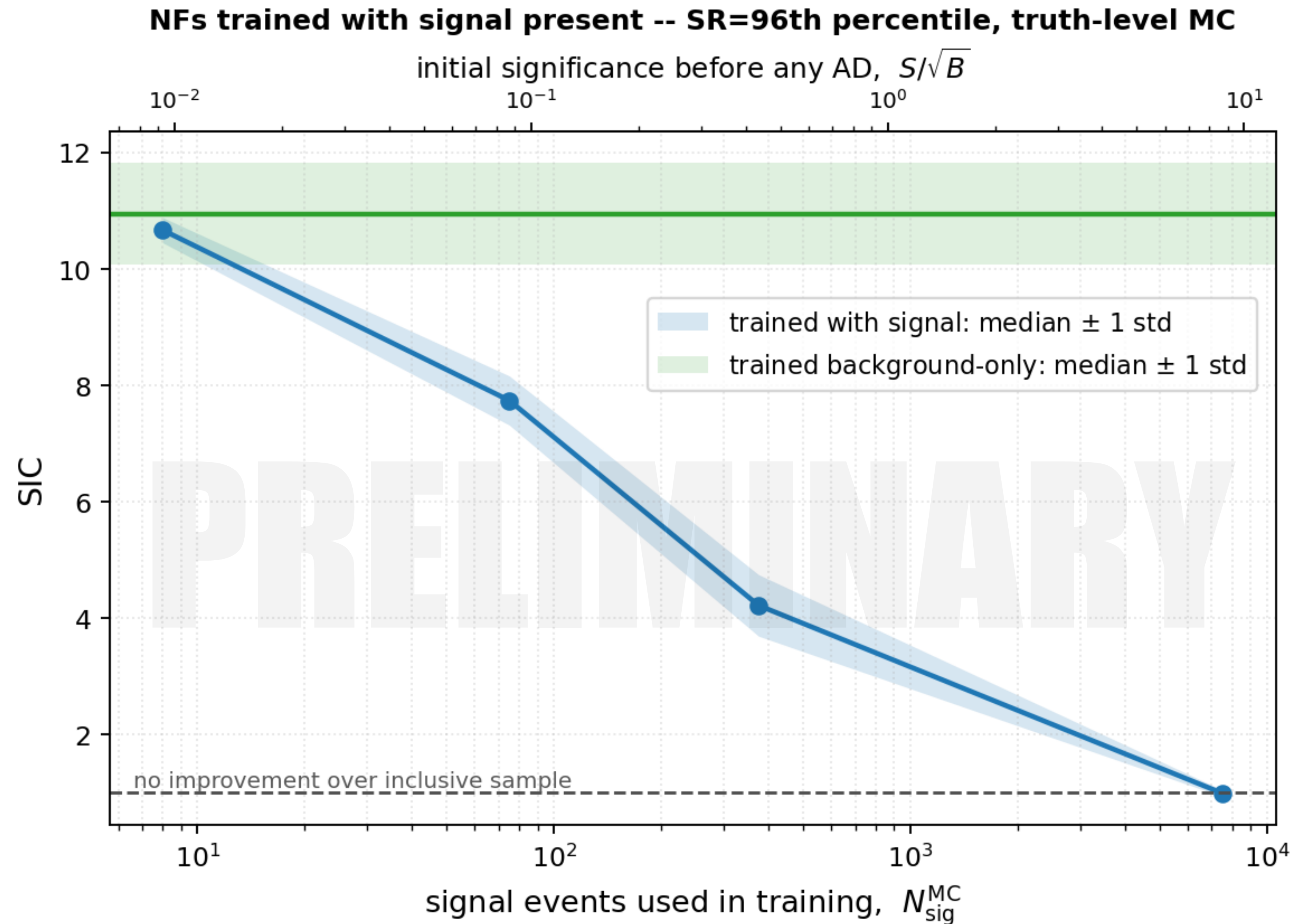


A wide-angle photograph of Marlbork Castle in Poland, featuring its iconic red brick walls and multiple towers with conical roofs. The castle is situated on a grassy bank next to a body of water, with its reflection visible in the calm surface. The sky is filled with soft, grey clouds. A semi-transparent white banner with rounded ends is positioned in the lower third of the image, containing the text 'TOWARDS UNSUPERVISED' in a dark blue, sans-serif font.

TOWARDS UNSUPERVISED

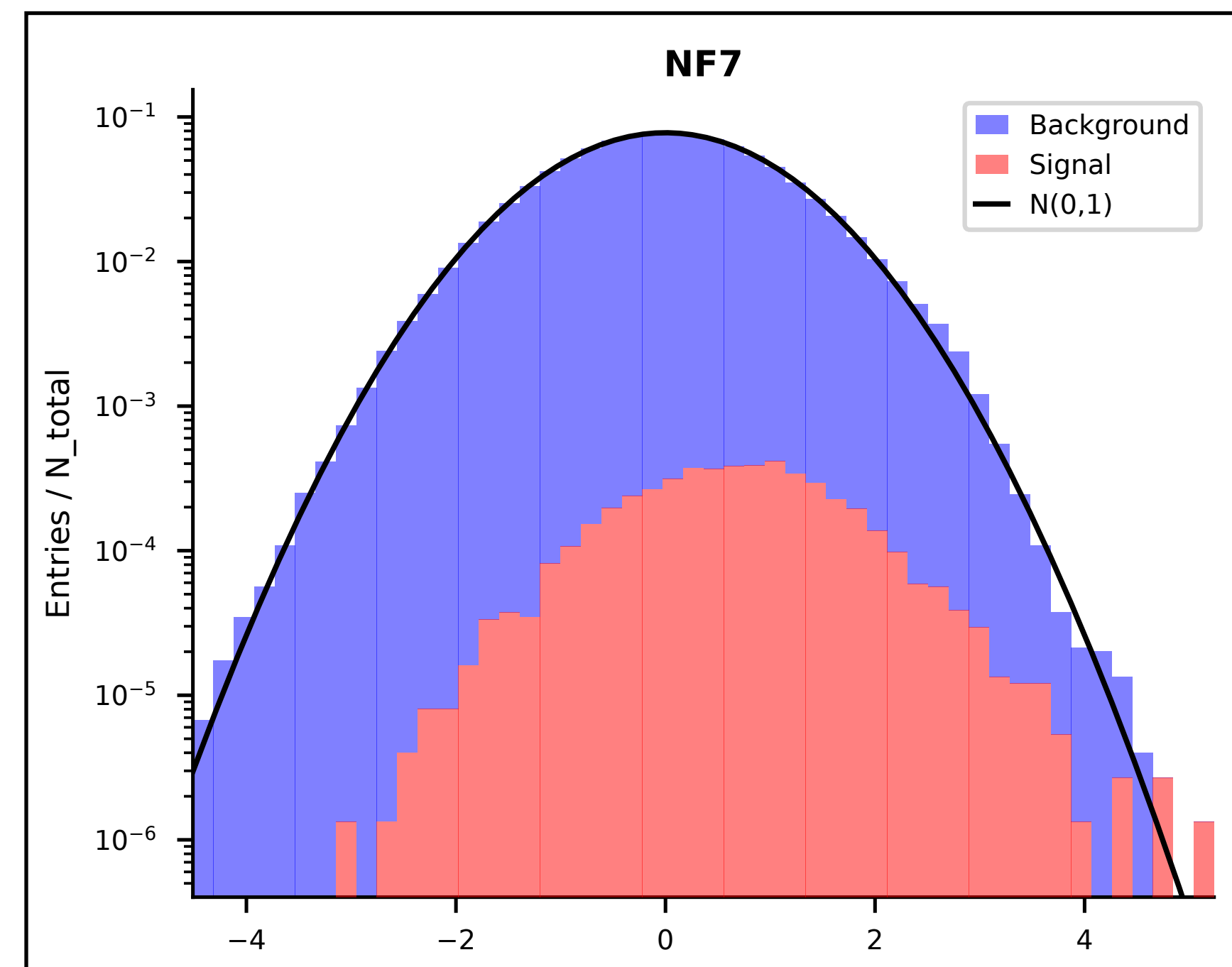
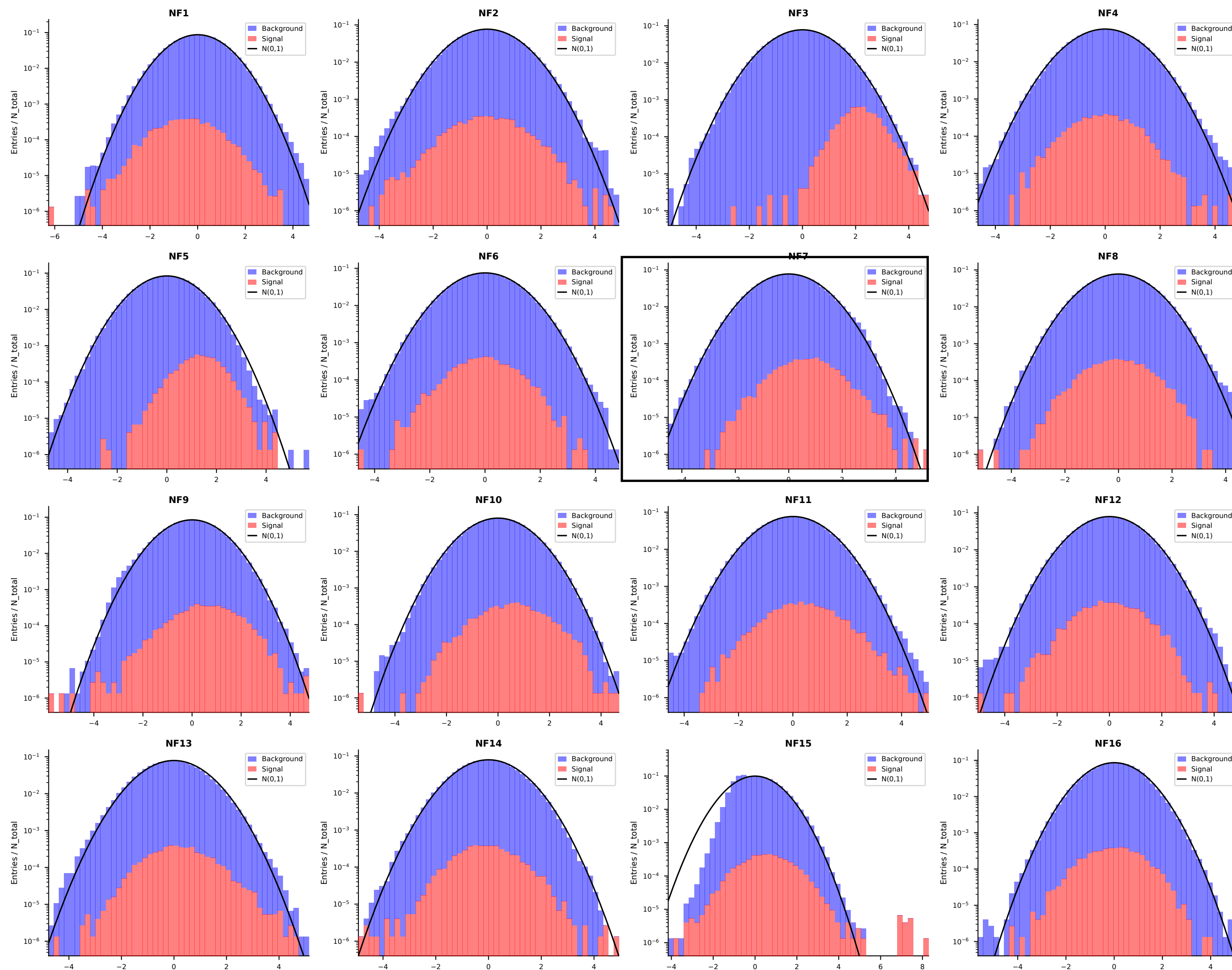
Marlbork Castle, Poland

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:

 - ✱ Understanding the effect of signal leakage to CRs

 - ✱ Validating method on other benchmarks

 - ✱ Developing method for fully unsupervised training

A wide-angle photograph of a desert landscape. In the foreground, there are sand dunes with distinct, wavy ripples in the sand. A large, dense bush of tall, dry grass stands on the right side of the dunes. Several dead, bleached tree trunks are scattered across the landscape, some standing upright and others lying flat. In the background, more sand dunes stretch towards a clear, bright blue sky. The lighting suggests it's either early morning or late afternoon, with long shadows cast across the sand.

Thank you for attention!

rafal.maselek@ijs.si

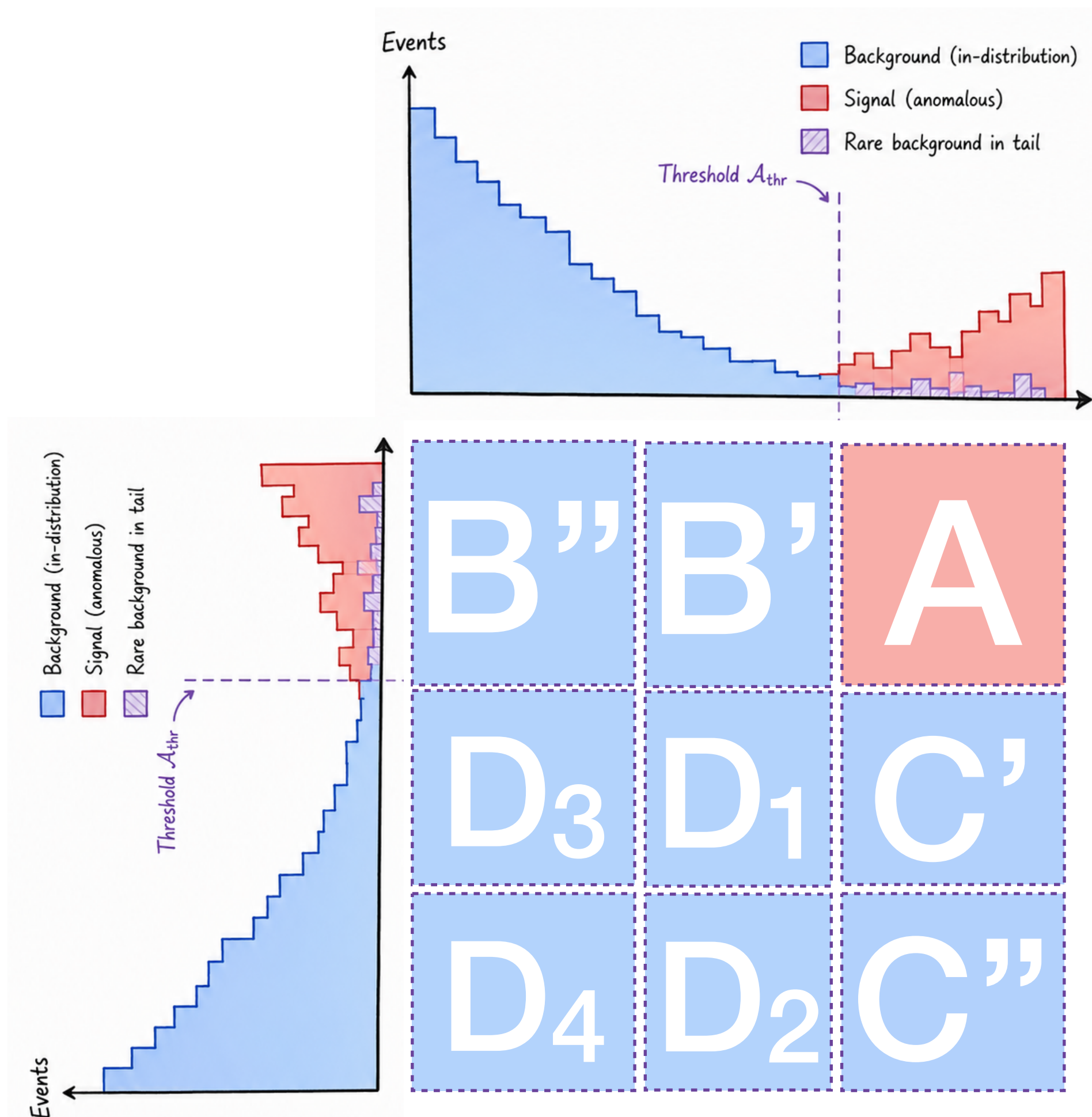
BACKUP

Rafał Masełek

ML4Jets 2026 17-09-2026

Extended ABCD matrix method

Established method for data-driven background estimation

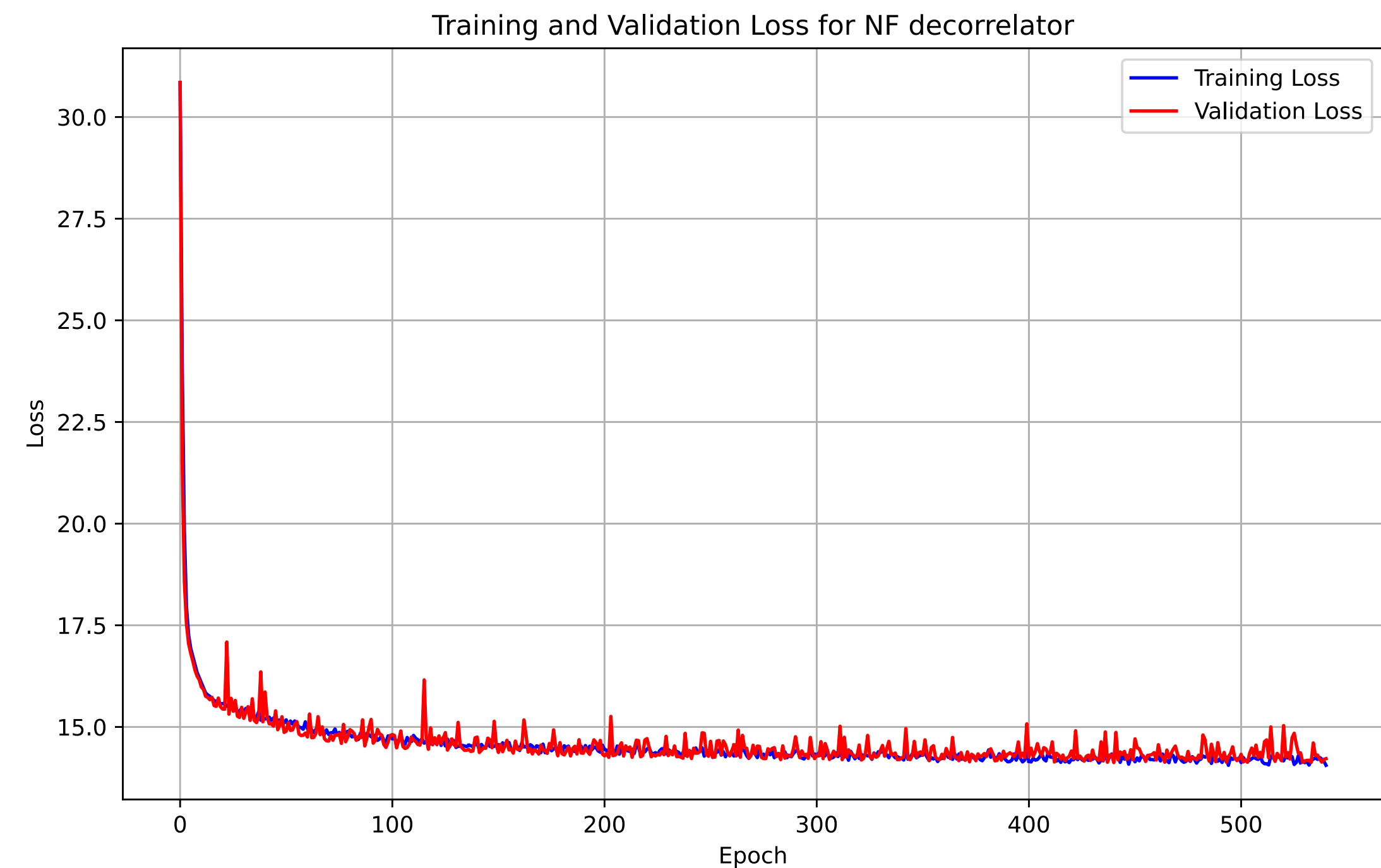


$$N_A^{bkg} = \frac{\left(N_{B'}^{bkg} N_{C'}^{bkg} N_{D_2}^{bkg} N_{D_3}^{bkg} \right)^2}{N_{B''}^{bkg} N_{C''}^{bkg} N_{D_4}^{bkg} \left(N_{D_1}^{bkg} \right)^4}$$

Both anomaly scores have to be independent!

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

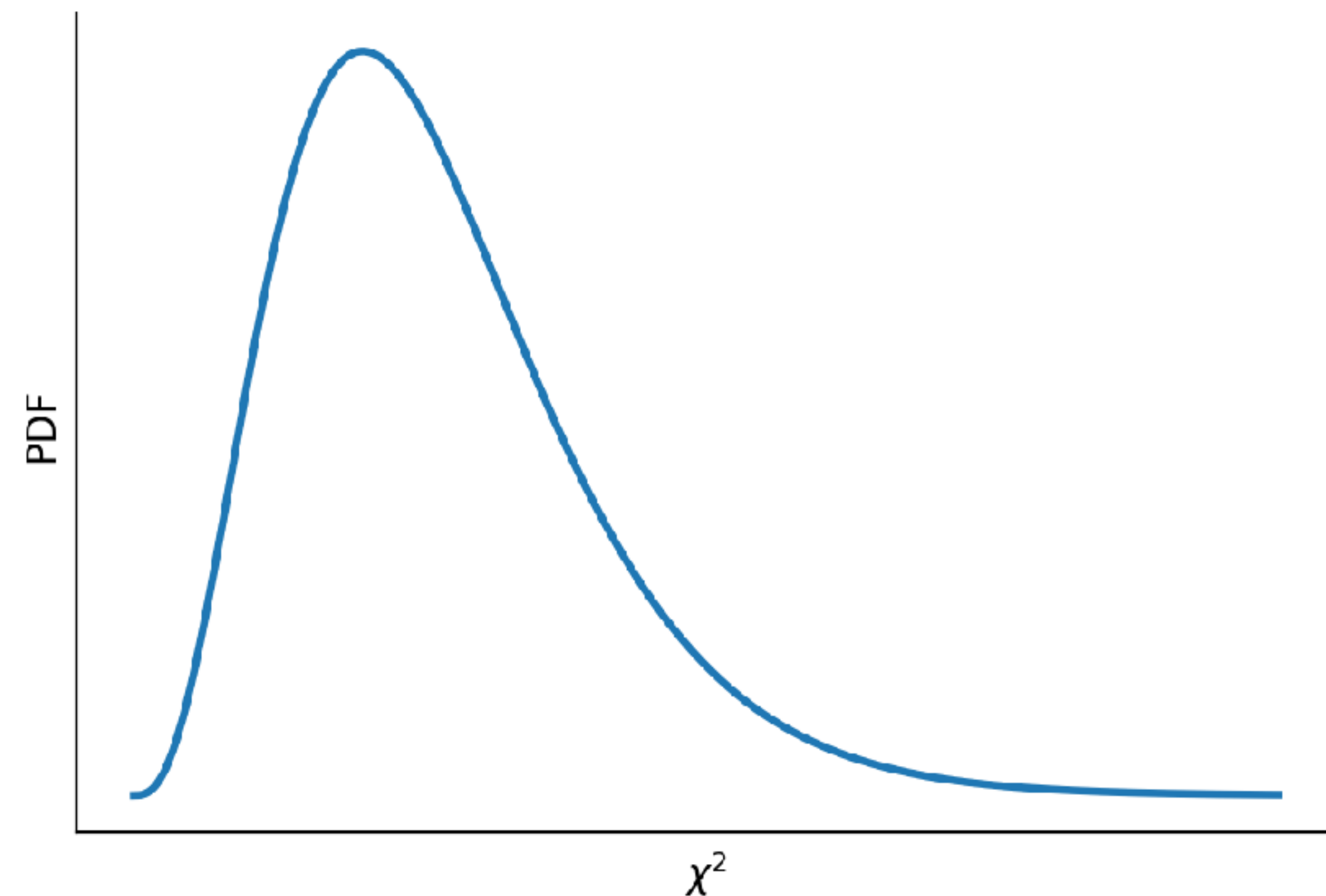
anomaly scores

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

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

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

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



ABCD-9, one sample, multiple definitions of control regions

BKG estimation vs percentiles — model: nf-job2_perm1 — method: xABCD_9

