

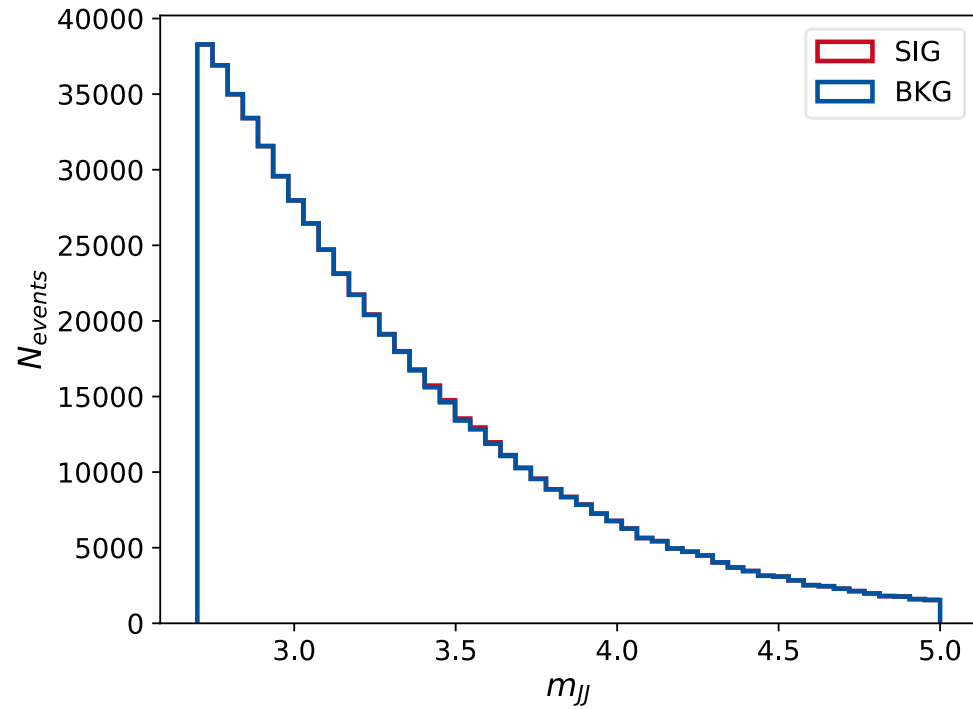
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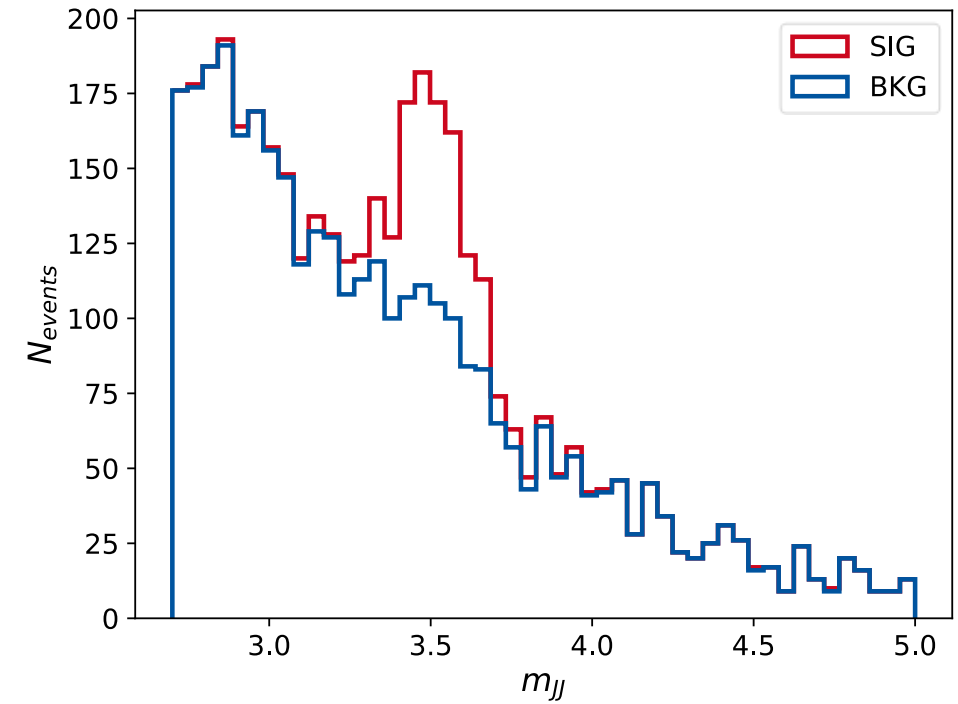
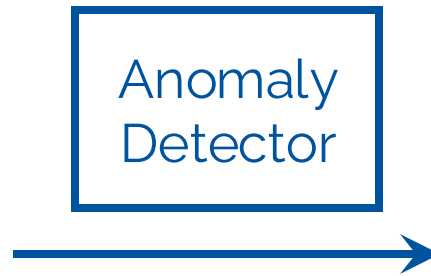
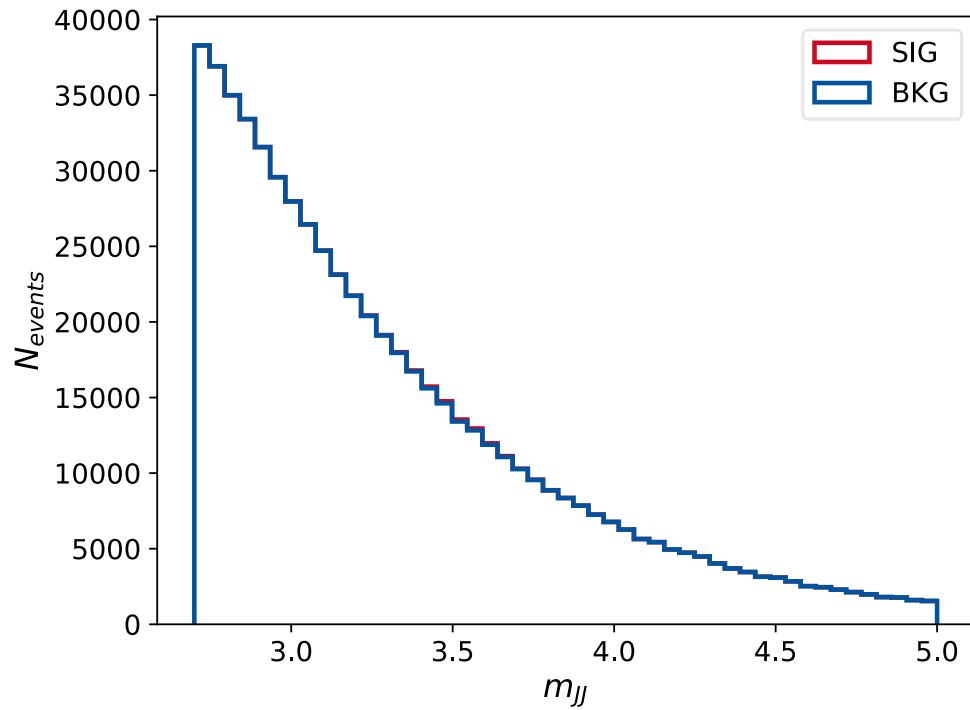
Resonant Searches as Cut and Count Experiments

Marie Hein

with Ranit Das, Thorben Finke, Gregor Kasieczka, Michael Krämer, Alexander Mück and David Shih

ML4Jets 2024





“Classification without labels: Learning from mixed samples in high energy physics” [1709.02949], E. Metodiev, B. Nachman, J. Thaler

- Optimal classifier

$$R_{\text{optimal}}(x) = \frac{p_S(x)}{p_B(x)}$$

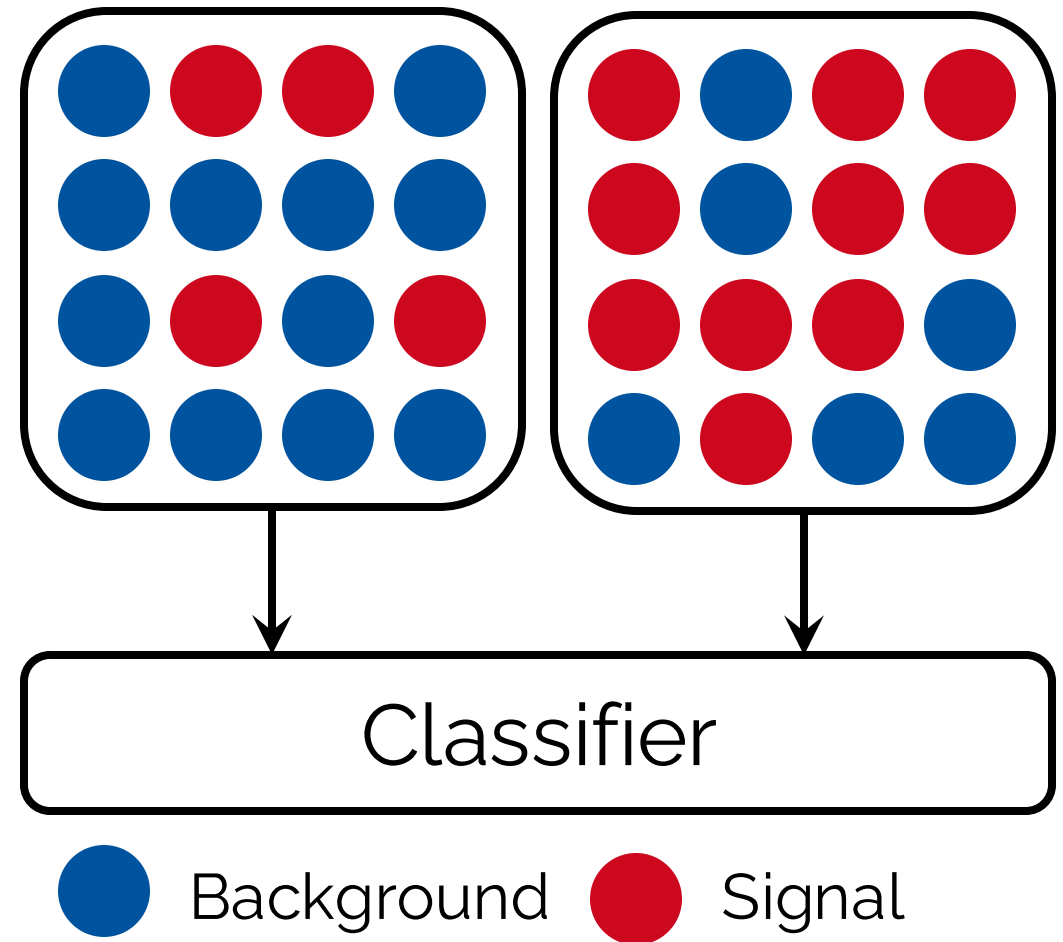
- For mixed datasets with signal fractions f_i

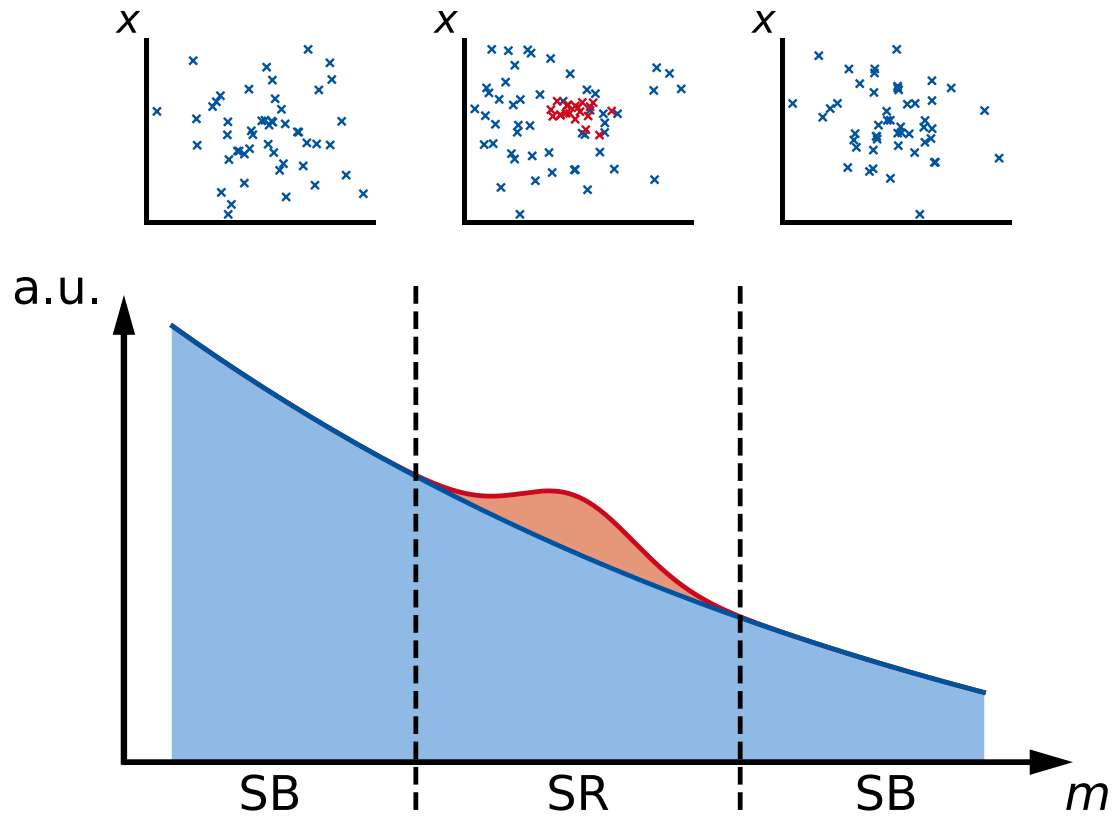
$$R_{\text{mixed}}(x) = \frac{f_1 R_{\text{optimal}}(x) + (1 - f_1)}{f_2 R_{\text{optimal}}(x) + (1 - f_2)}$$

→ Monotonically increasing function of

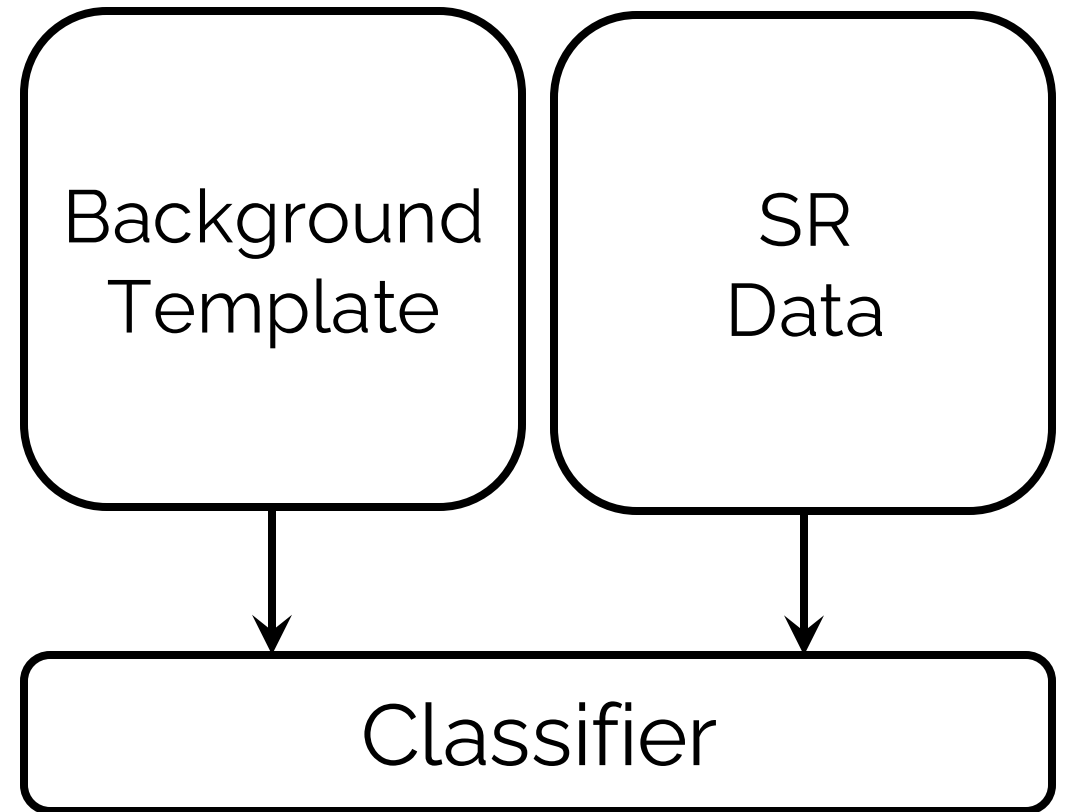
$R_{\text{optimal}}(x)$ as long as $f_1 > f_2$

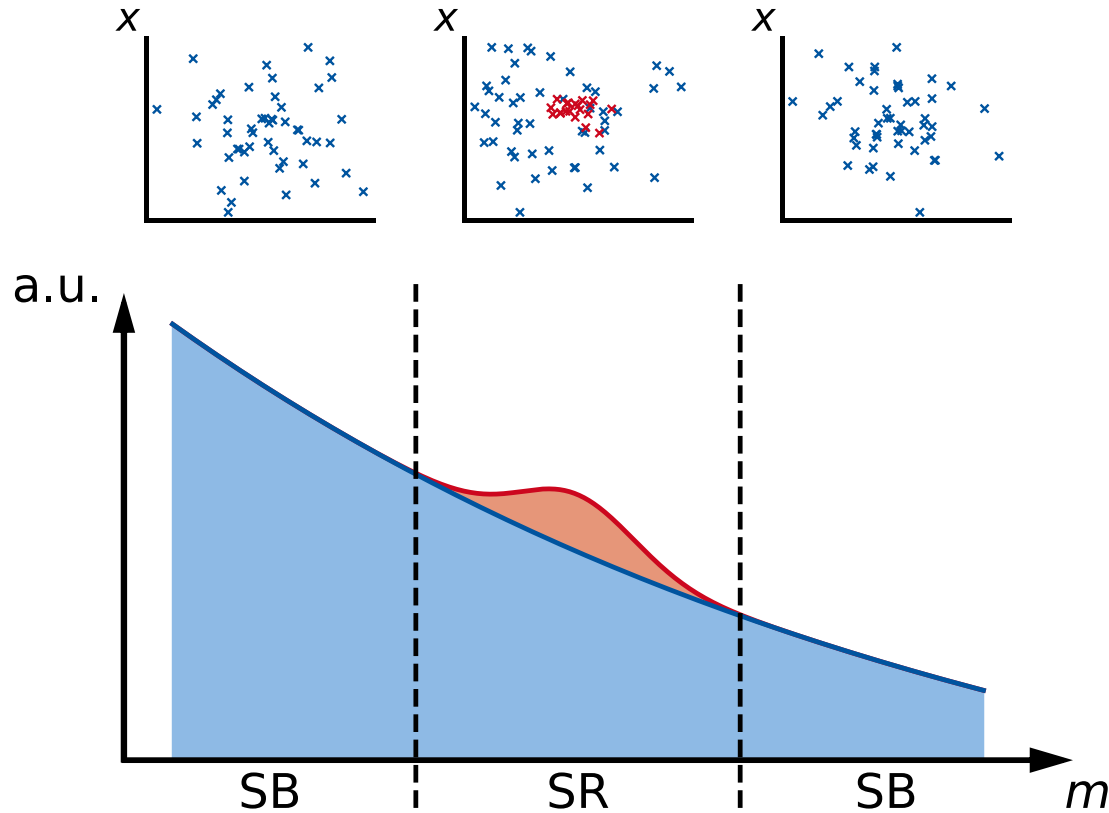
→ Same decision boundaries





Recreated from [\[2109.00546\]](#)



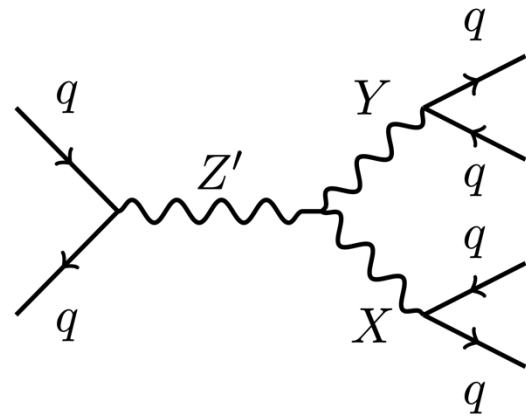


Recreated from [2109.00546]

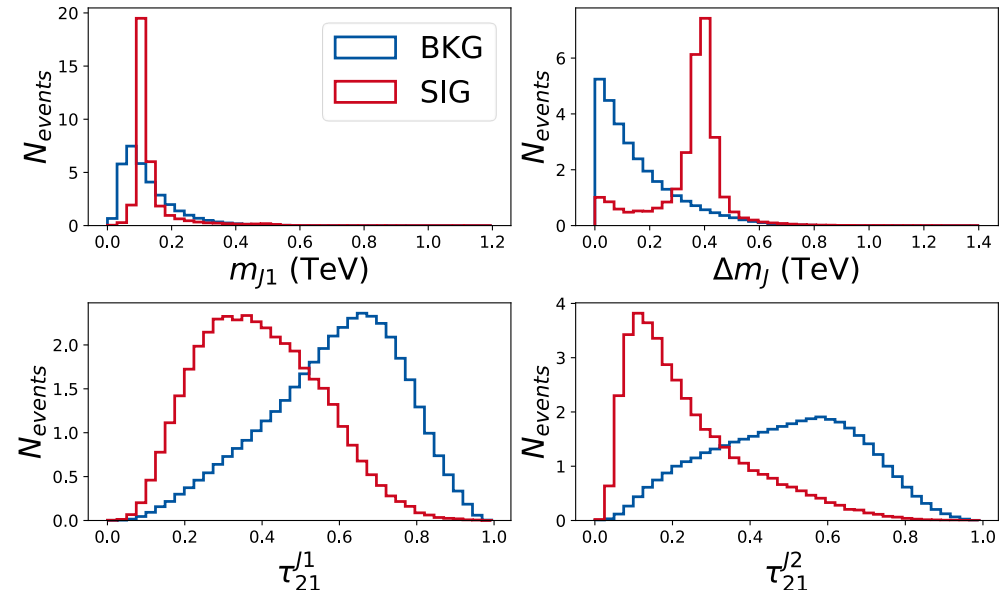
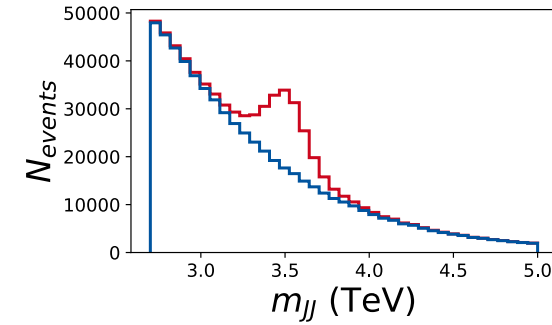
1. Idealized Anomaly Detector: SR background
2. CWoLa Hunting: SB data
3. CATHODE:
 - a. Train DE on SB data to learn $p_{\text{bkg}}(x|m)$
 - b. Sample into SR

“The LHC Olympics 2020: A Community Challenge for Anomaly Detection in High Energy Physics” [[2101.08320](#)], G. Kasieczka, B. Nachman, D. Shih et. al.

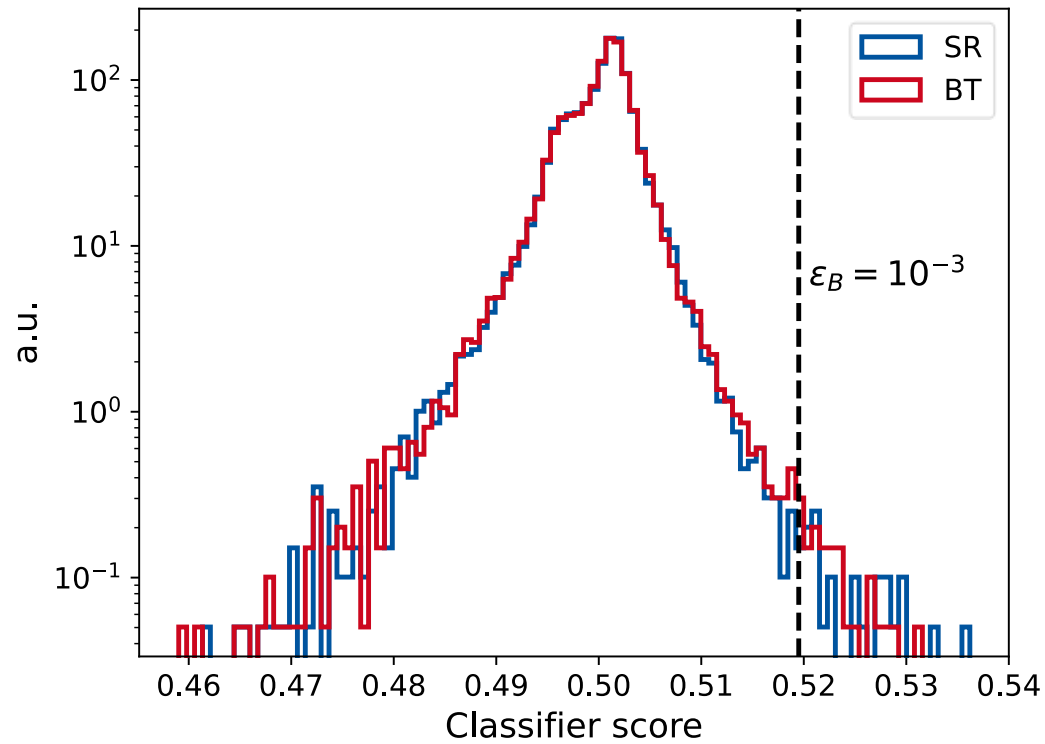
- Benchmark dataset for anomaly detection
- QCD dijet background (1M events)
- Signal (0 or 1000 events)



- Use 9 windows with centers at $m_{JJ,n} = 3.5 \text{ TeV} + (5 - n) \cdot 0.1 \text{ TeV}$

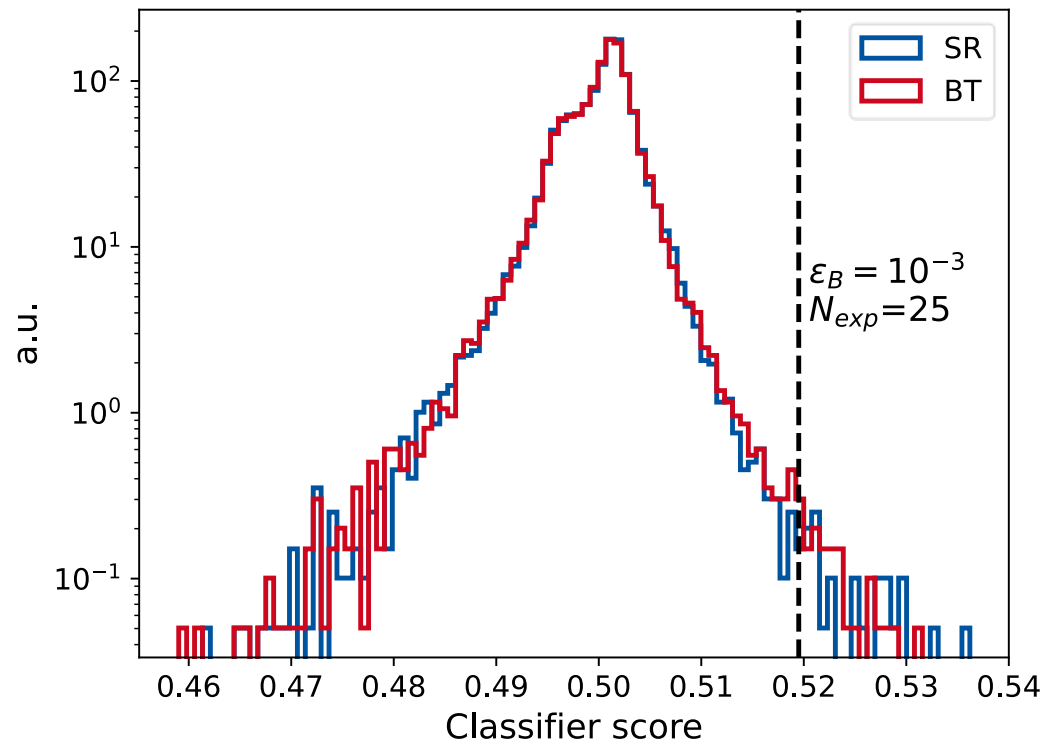


Without signal

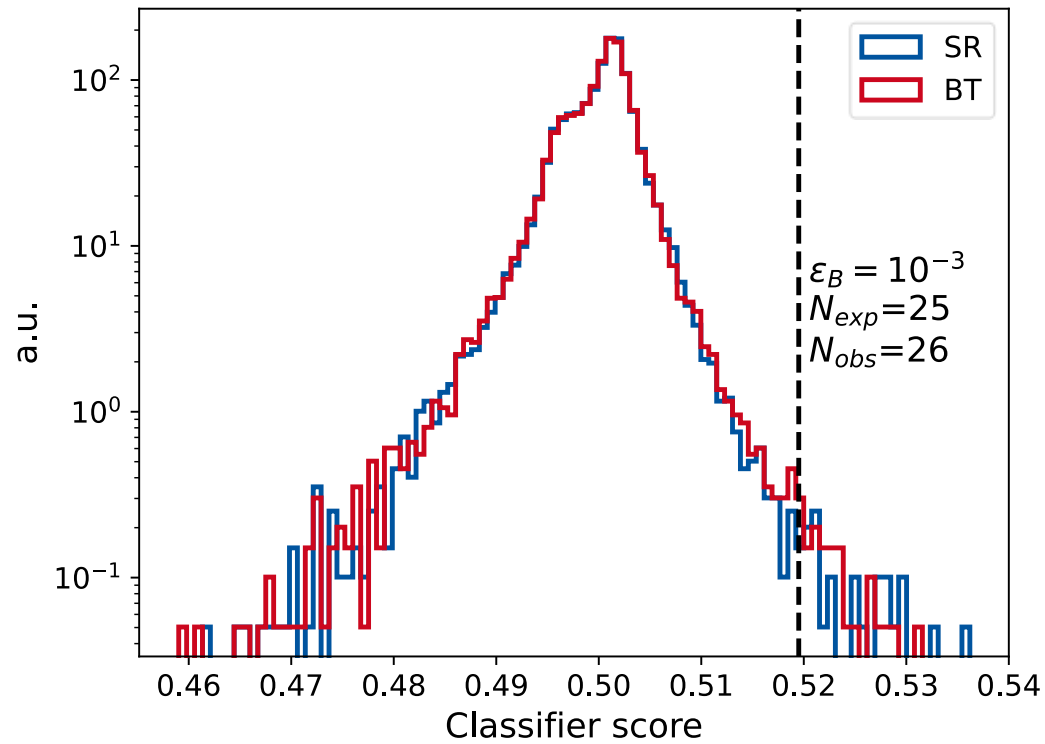


Without signal

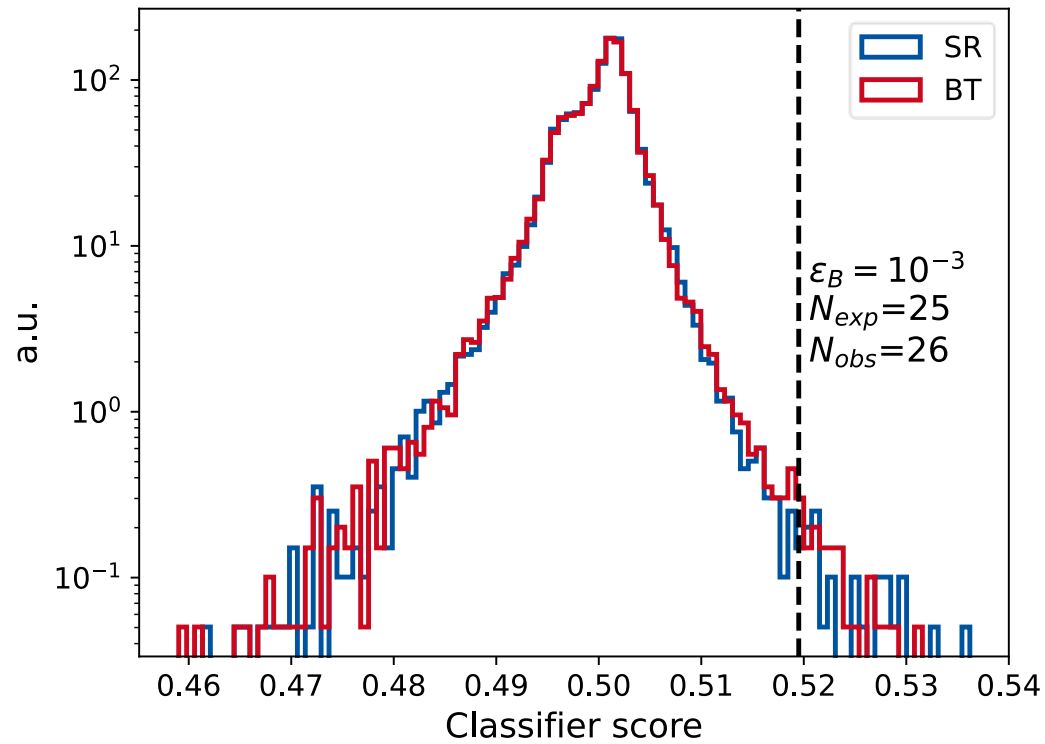
$$N_{exp} = \epsilon_B N_{SR}$$



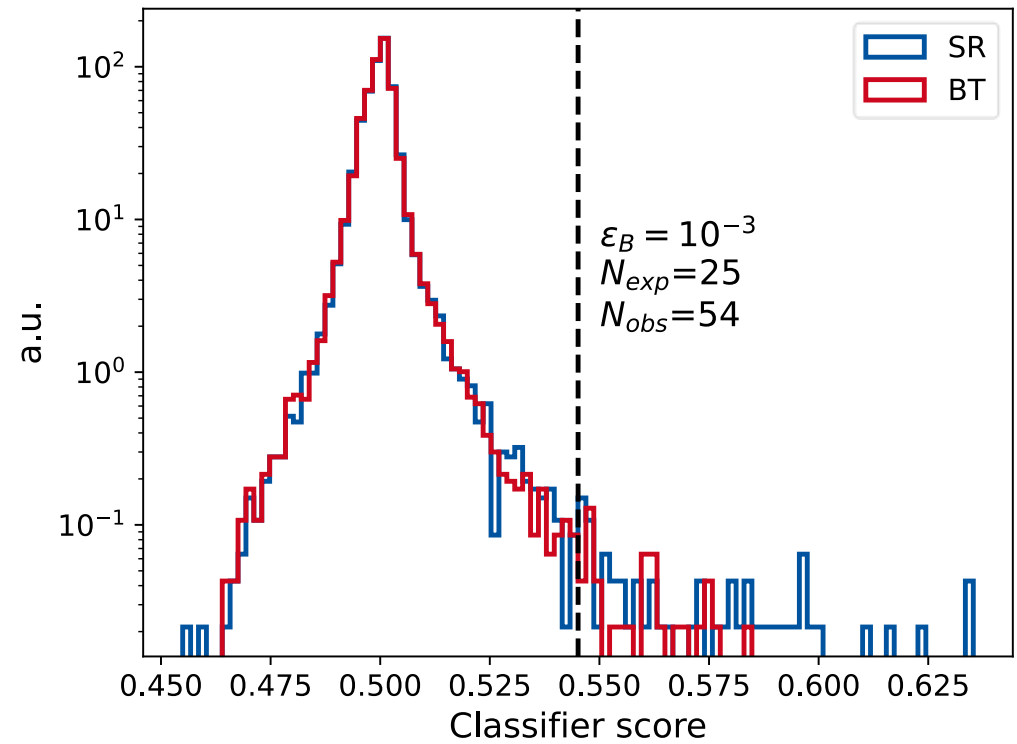
Without signal



Without signal



With signal



$$\mathcal{S} = \frac{N_{\text{obs}} - N_{\text{exp}}}{\sqrt{N_{\text{exp}}^2 (N_{\text{exp}}^{-1} + \sigma_{\text{exp}}^2)}}$$

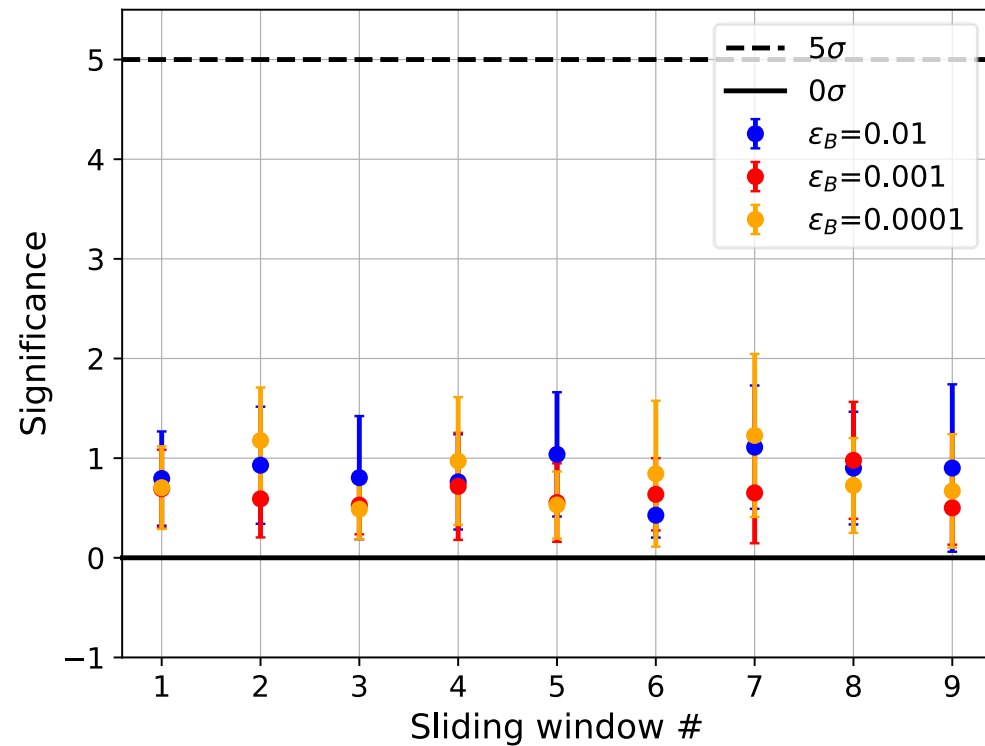
- ϵ_B Working point (determined on samples)
- $N_{\text{obs}}(\epsilon_B)$ Observed number of events
- $N_{\text{exp}}(\epsilon_B)$ Expected number of events (background-only assumption)
- $\sigma_{\text{exp}}(\epsilon_B)$ Relative error on expectation (from determination of working point)

“Asymptotic formulae for likelihood-based tests of new physics” [[1007.1727](#)], G. Cowan, K. Cranmer, E. Gross, and O. Vitells

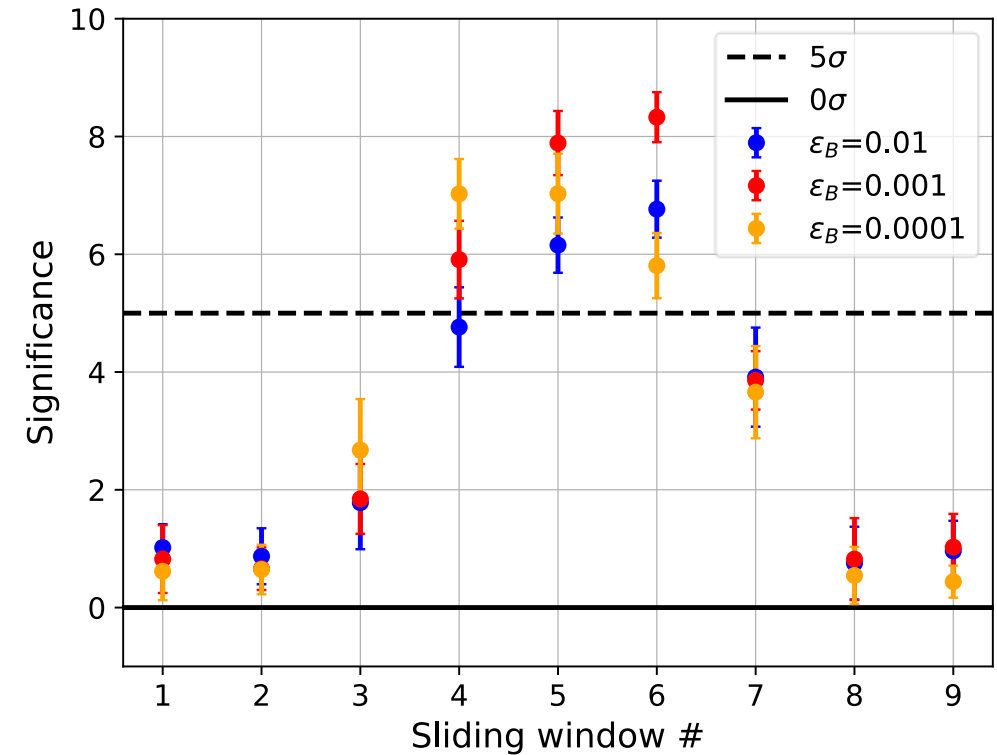
$$\mathcal{S} = \left[2 \left(N_{\text{obs}} \ln \frac{N_{\text{obs}}(N_{\text{exp}}^{-1} + \sigma_{\text{exp}}^2)}{1 + N_{\text{obs}}\sigma_{\text{exp}}^2} - \frac{1}{\sigma_{\text{exp}}^2} \ln \frac{1 + N_{\text{obs}}\sigma_{\text{exp}}^2}{1 + N_{\text{exp}}\sigma_{\text{exp}}^2} \right) \right]^{1/2}$$

- ϵ_B Working point (determined on samples)
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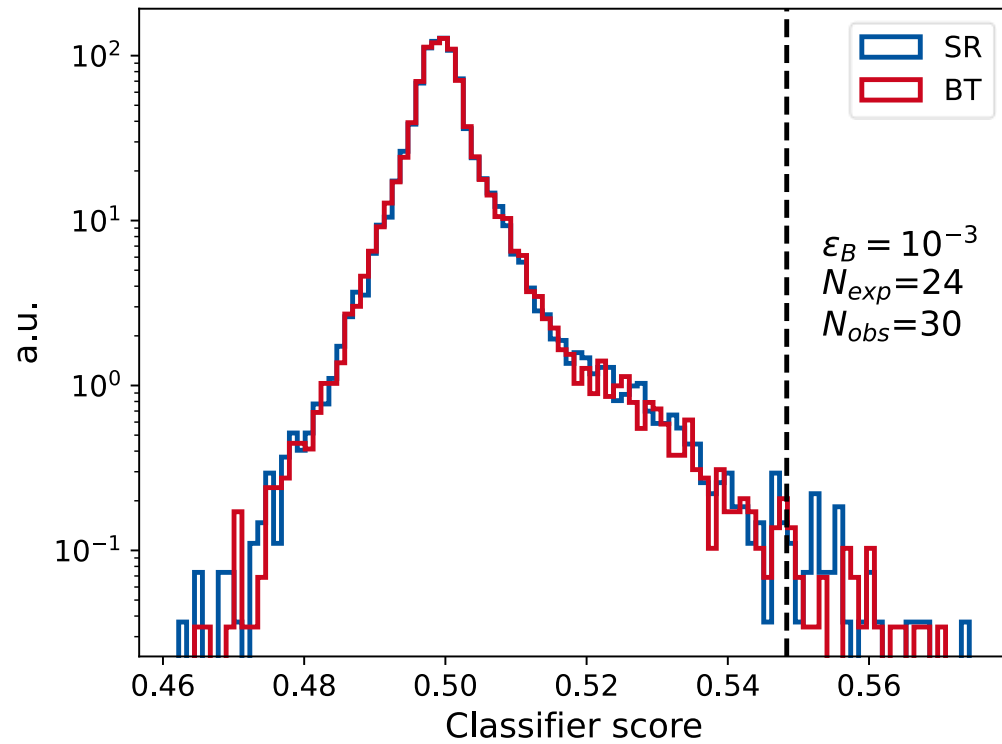
Without signal



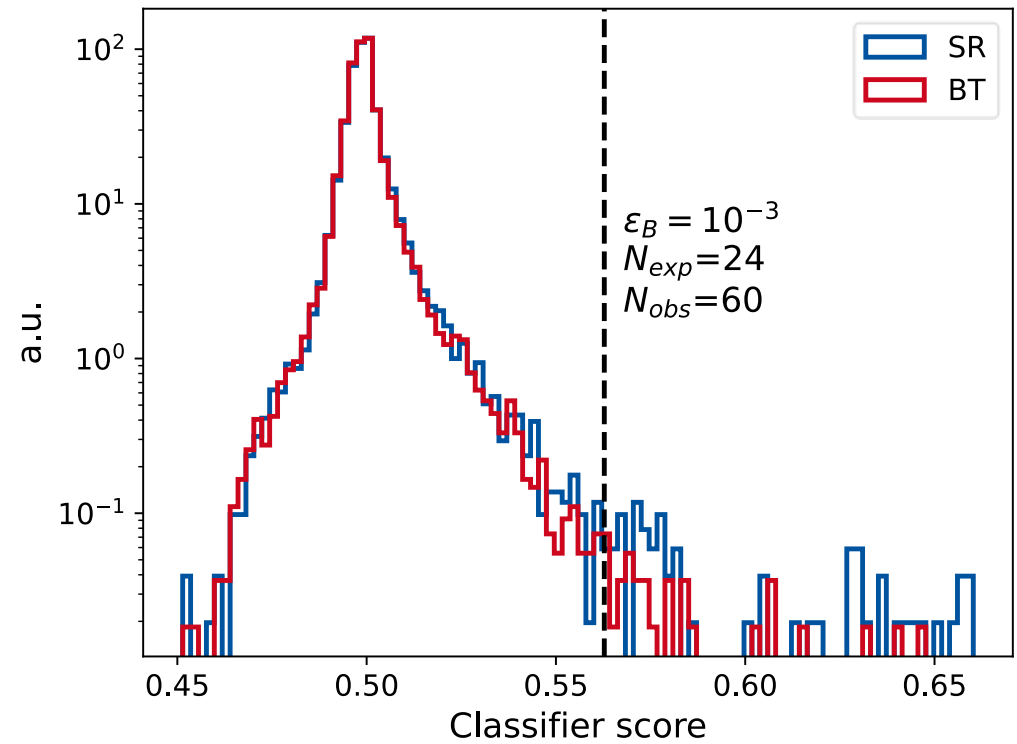
With signal



Without signal

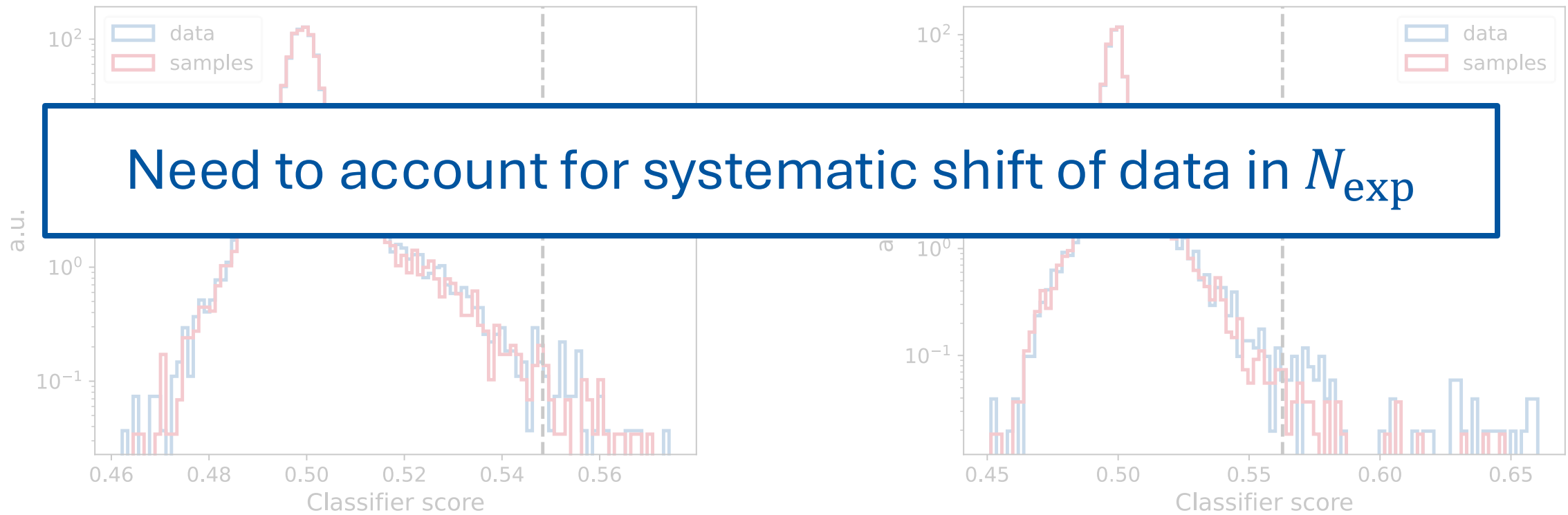


With signal



Without signal

With signal



Define a relative systematic shift per window n

$$\delta_{\text{sys}, n} = \frac{N_{\text{obs}, n} - \epsilon_B N_{\text{SR}, n}}{\epsilon_B N_{\text{SR}, n}}$$

and its average over all windows δ_{sys} .

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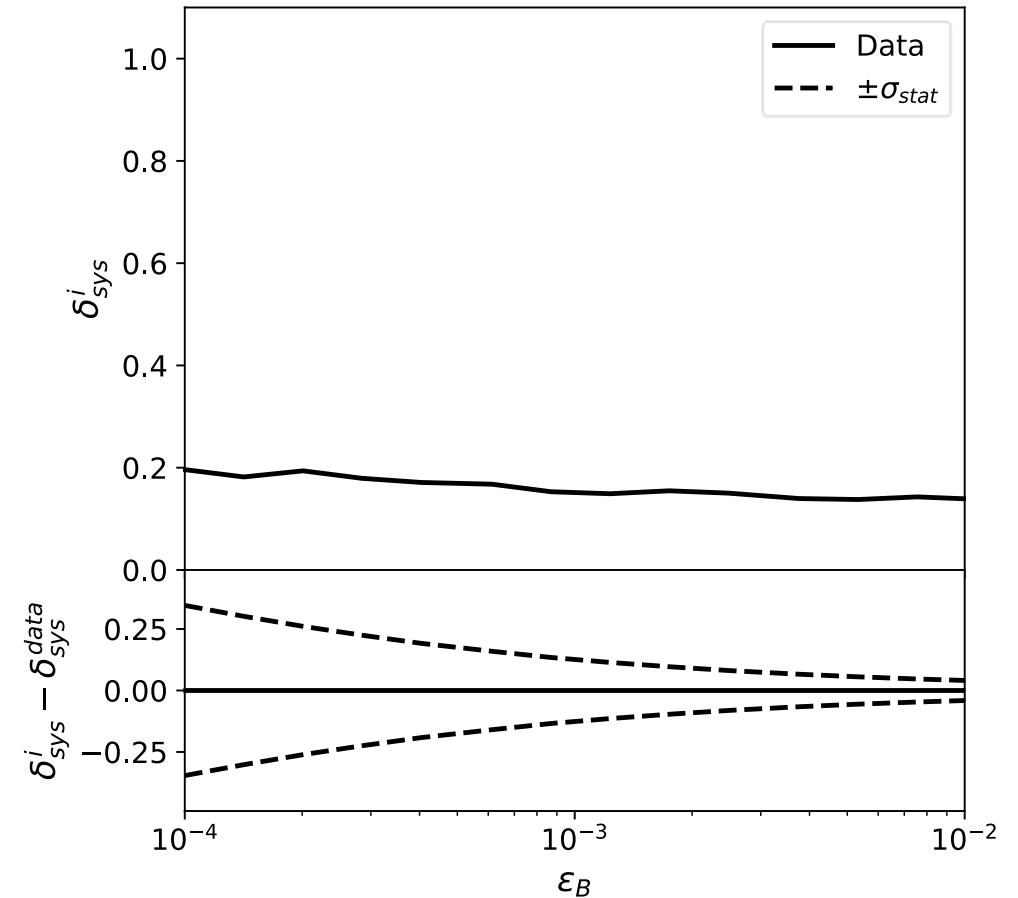
	IAD	CWoLa & CATHODE
N_{exp}	$\epsilon_B N_{\text{SR}}$	$\epsilon_B N_{\text{SR}}(1 + \delta_{\text{sys}})$
σ_{exp}	σ_{ϵ_B}	$\sqrt{\sigma_{\epsilon_B}^2 + \sigma_{\delta_{\text{sys}}}^2}$

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Systematic shift

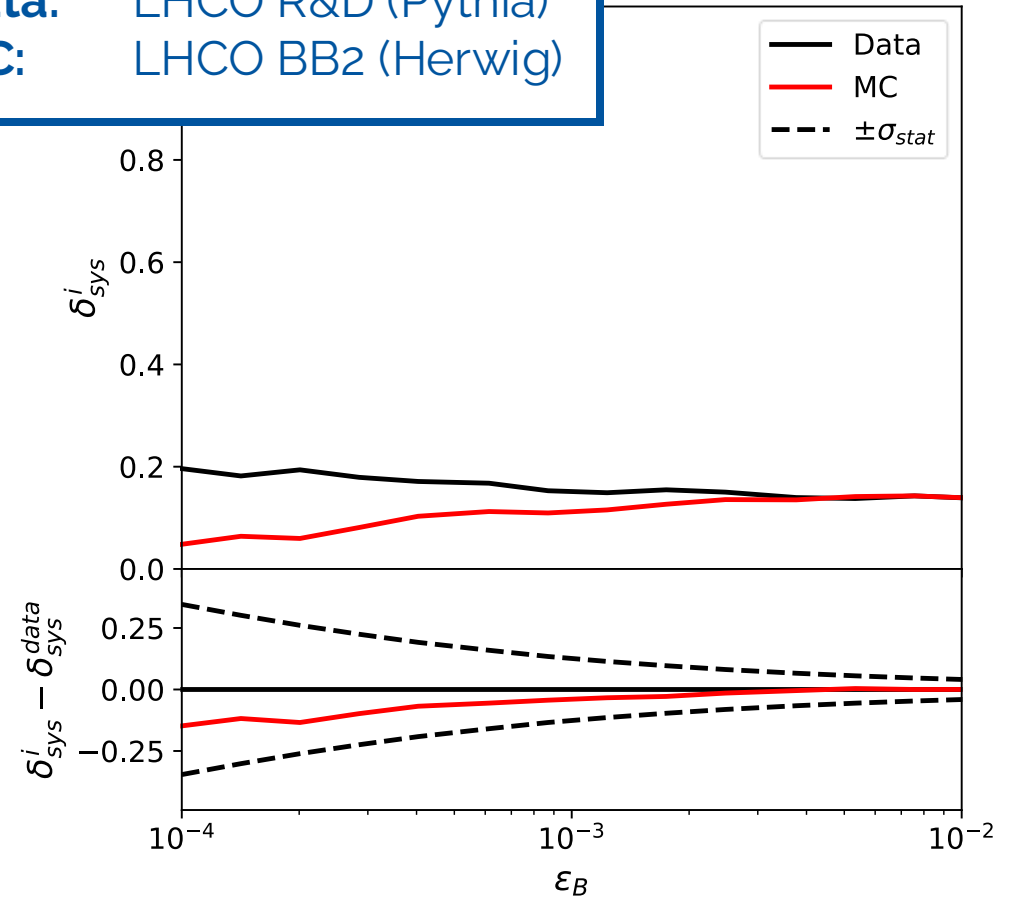
Define a relative systematic shift per window n

$$\delta_{\text{sys}, n} = \frac{N_{\text{obs}, n} - \epsilon_B N_{\text{SR}, n}}{\epsilon_B N_{\text{SR}, n}}$$

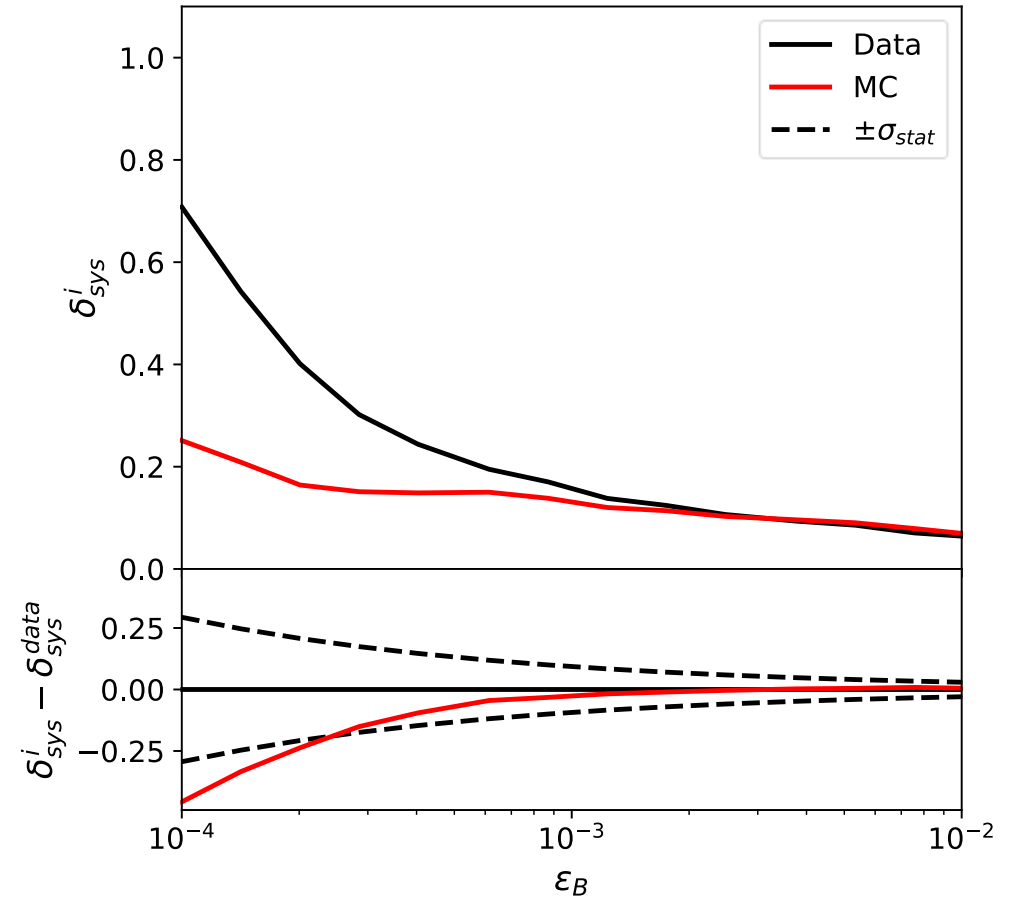
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N_{exp}	$\epsilon_B N_{\text{SR}}$	$\epsilon_B N_{\text{SR}}(1 + \delta_{\text{sys}})$
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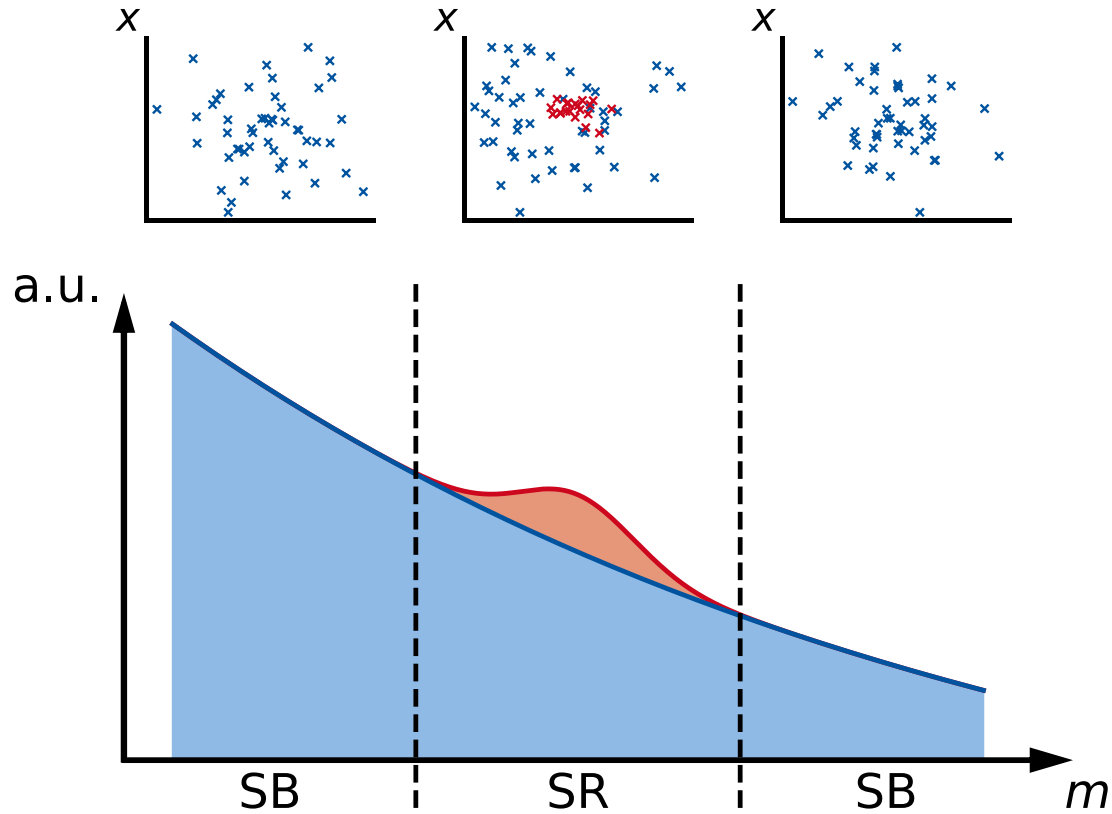
Data: LHC0 R&D (Pythia)
MC: LHC0 BB2 (Herwig)



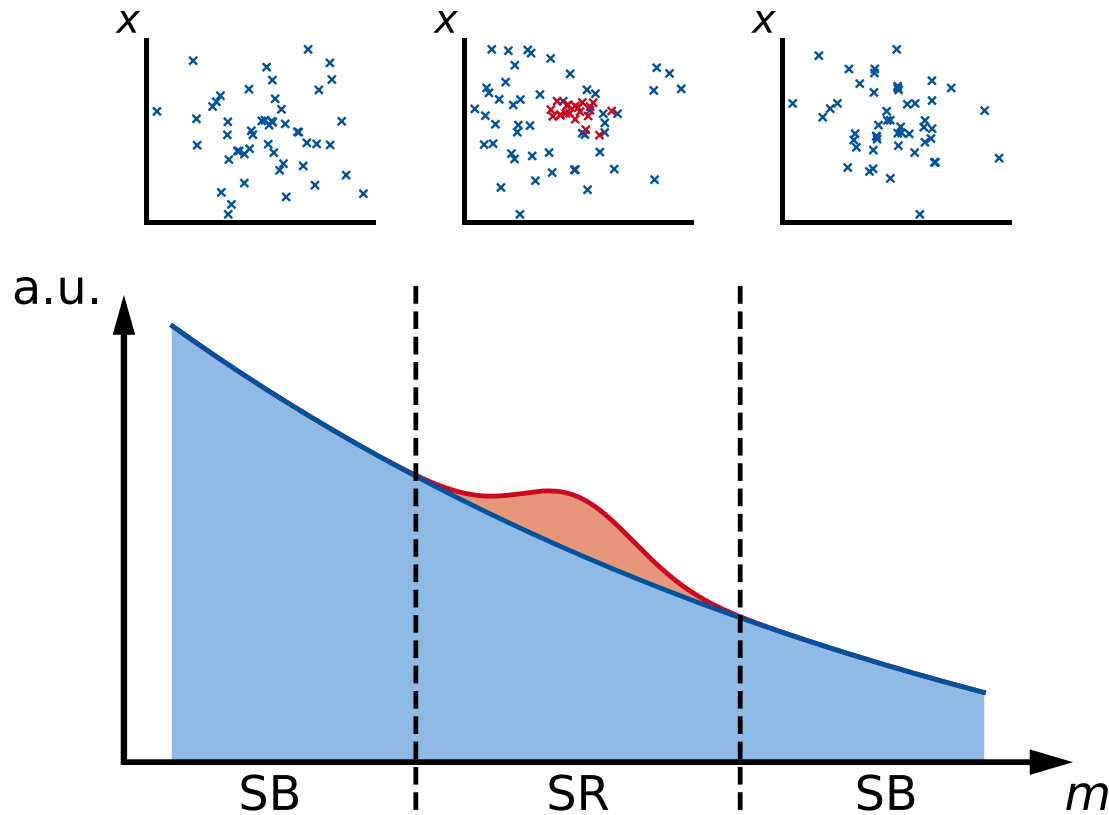
- For CATHODE, large deviation of MC value from data value visible



Data-driven determination of δ_{sys}



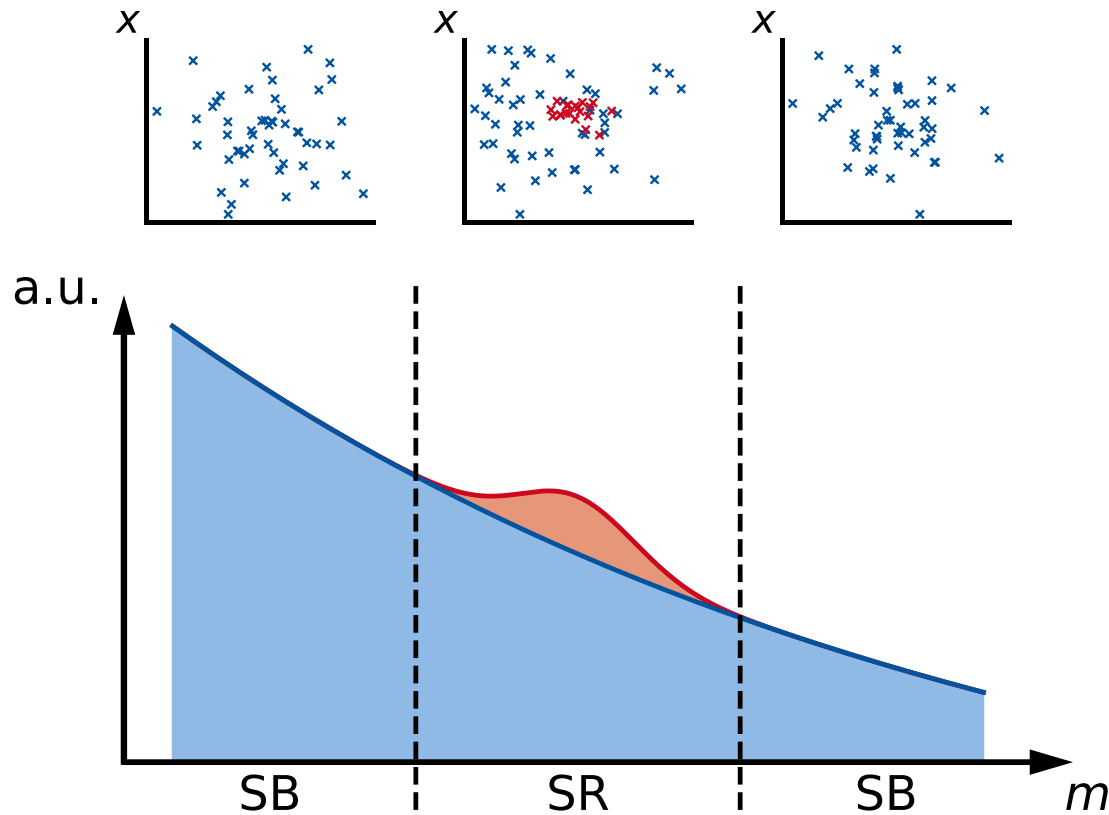
Recreated from [\[2109.00546\]](#)



Normal CATHODE procedure:

- Train DE on SB
- Sample DE in SR
- Train SR samples vs SR data classifier

Recreated from [\[2109.00546\]](#)



Recreated from [2109.00546]

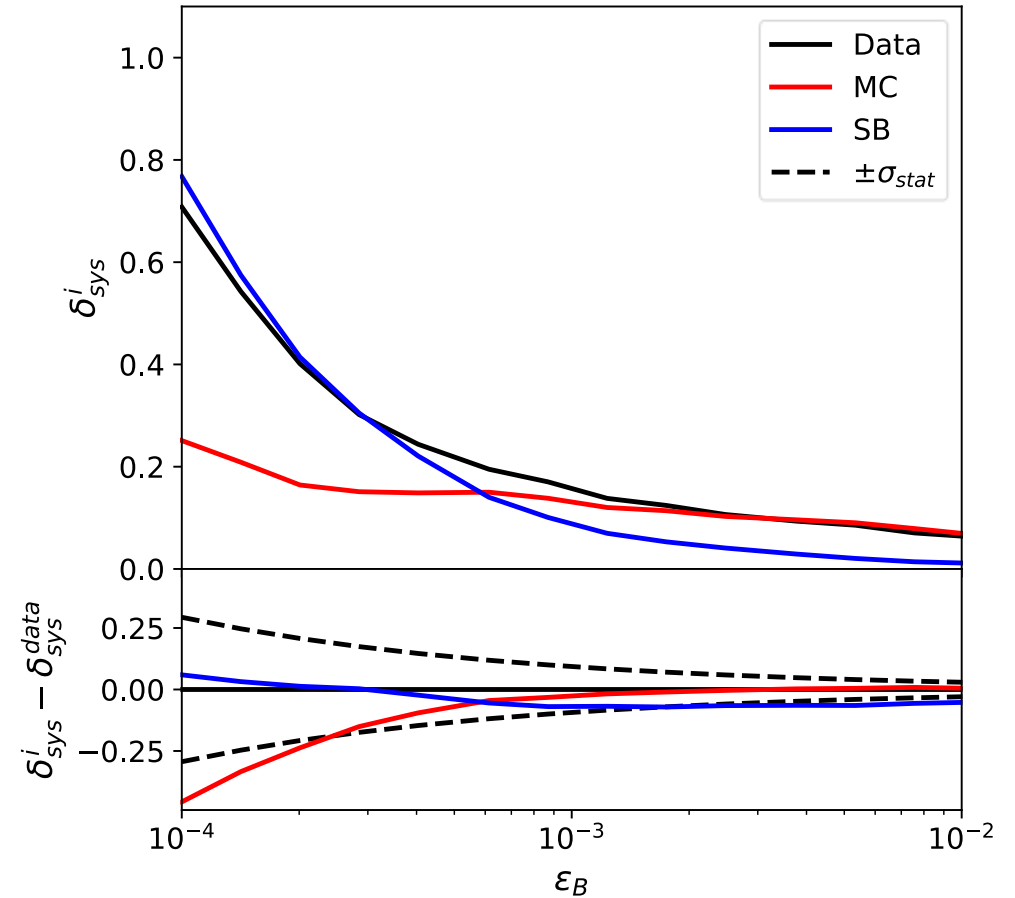
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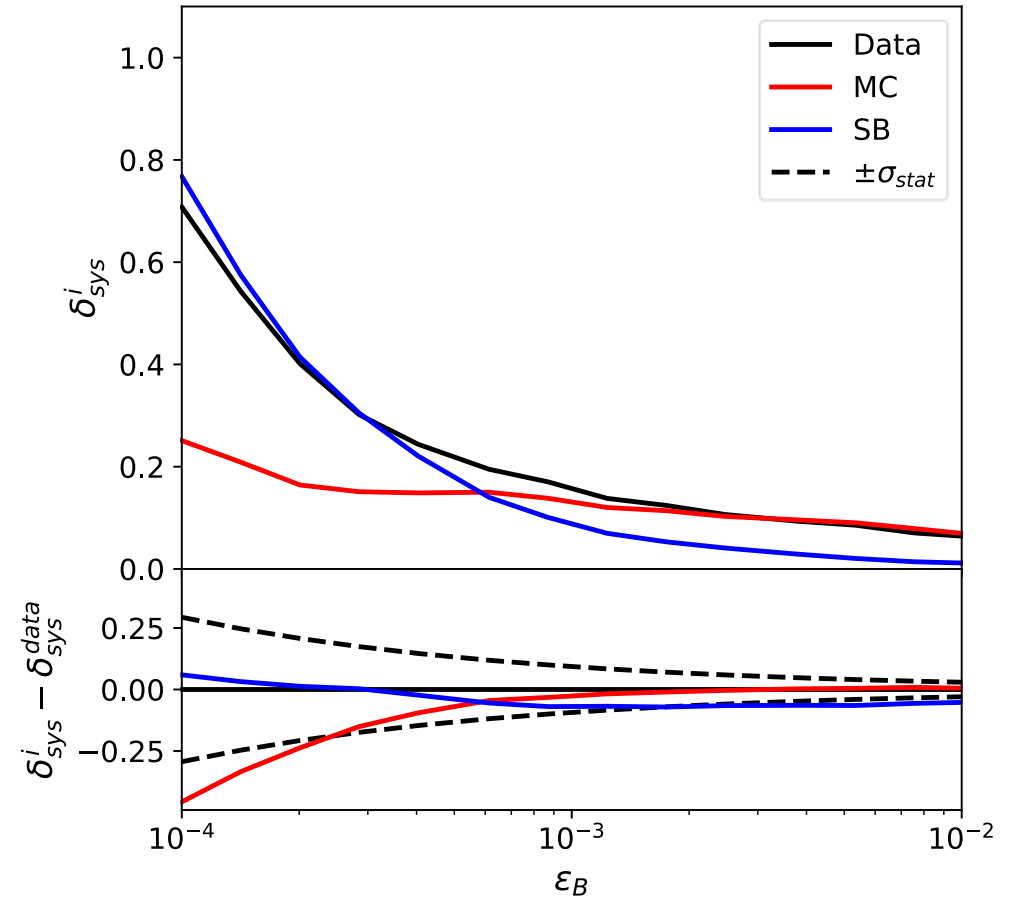
Determine δ_{sys} by

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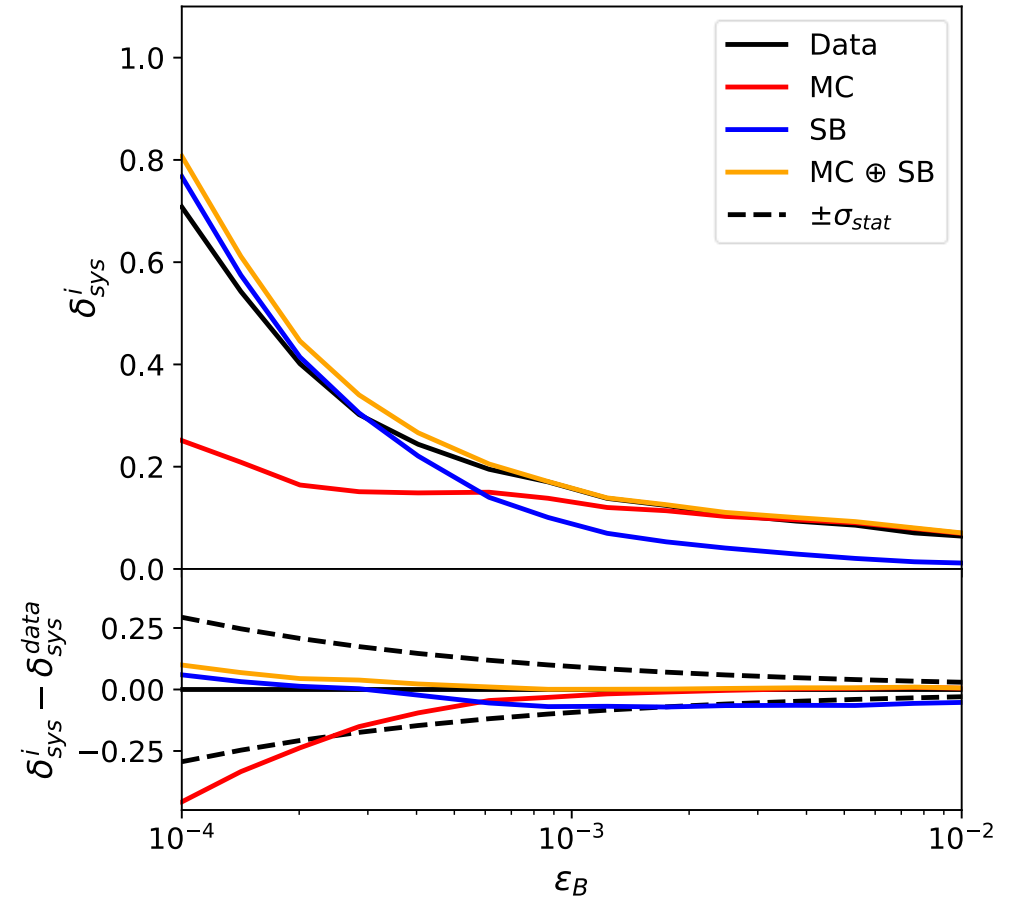
- For CATHODE, large deviation of MC value from data value visible
- δ_{sys} from SB fits other part of the spectrum



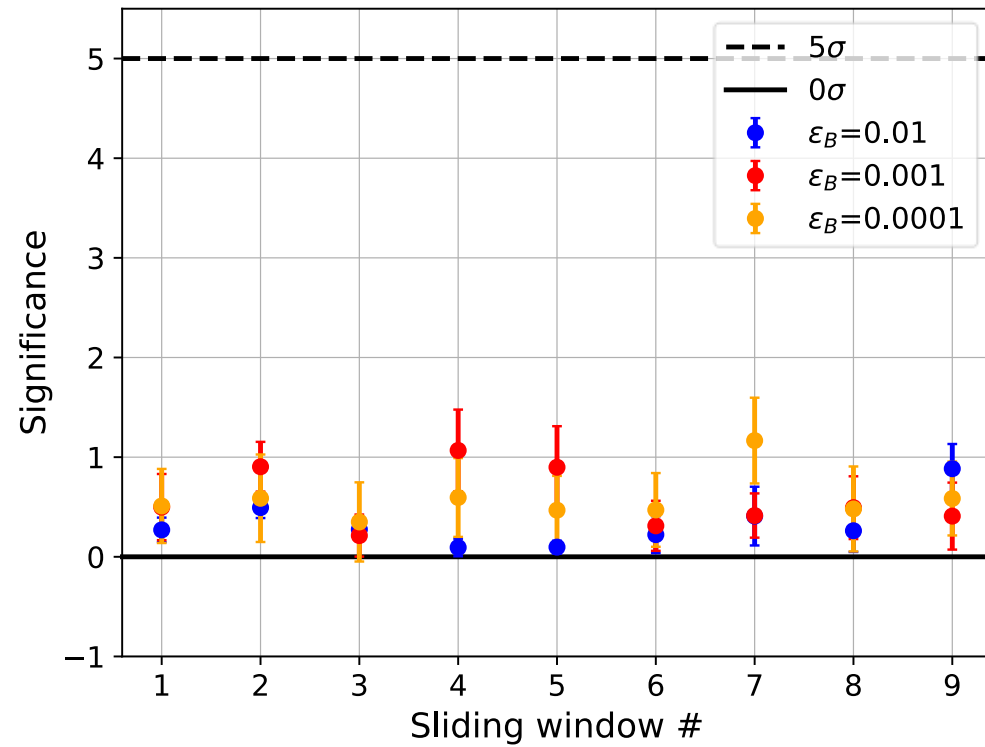
- For CATHODE, large deviation of MC value from data value visible
 - Estimates interpolation error
- δ_{sys} from SB fits other part of the spectrum
 - Estimates difficulty of DE on tails



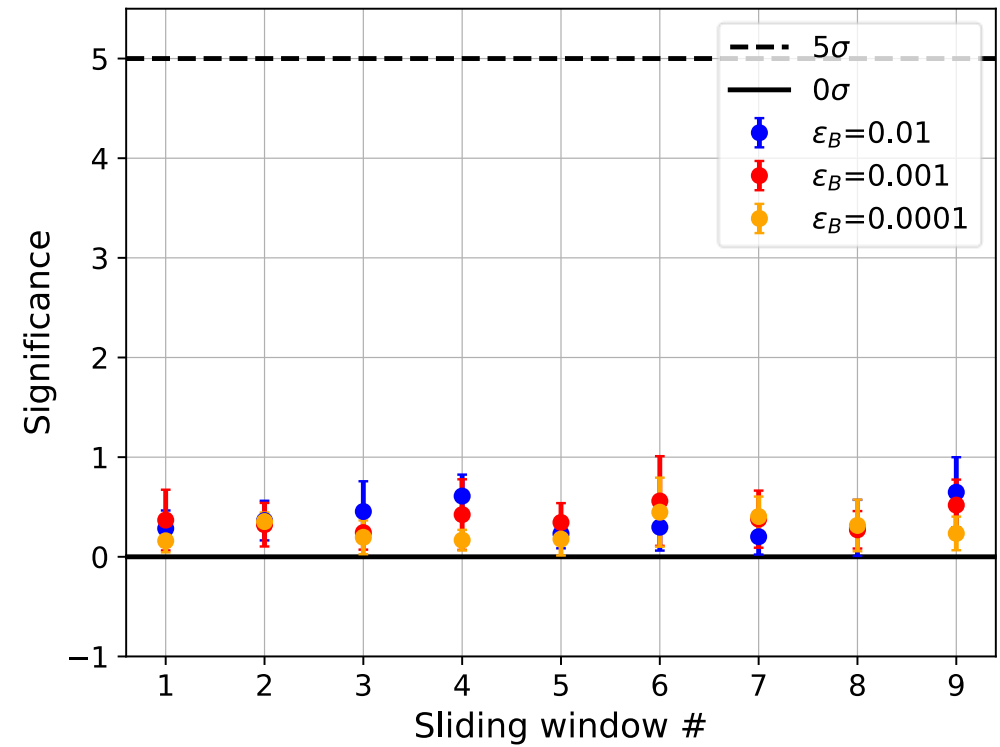
- For CATHODE, large deviation of MC value from data value visible
 - Estimates interpolation error
- δ_{sys} from SB fits other part of the spectrum
 - Estimates difficulty of DE on tails
- Quadratic addition of both error sources
 - Fits whole spectrum



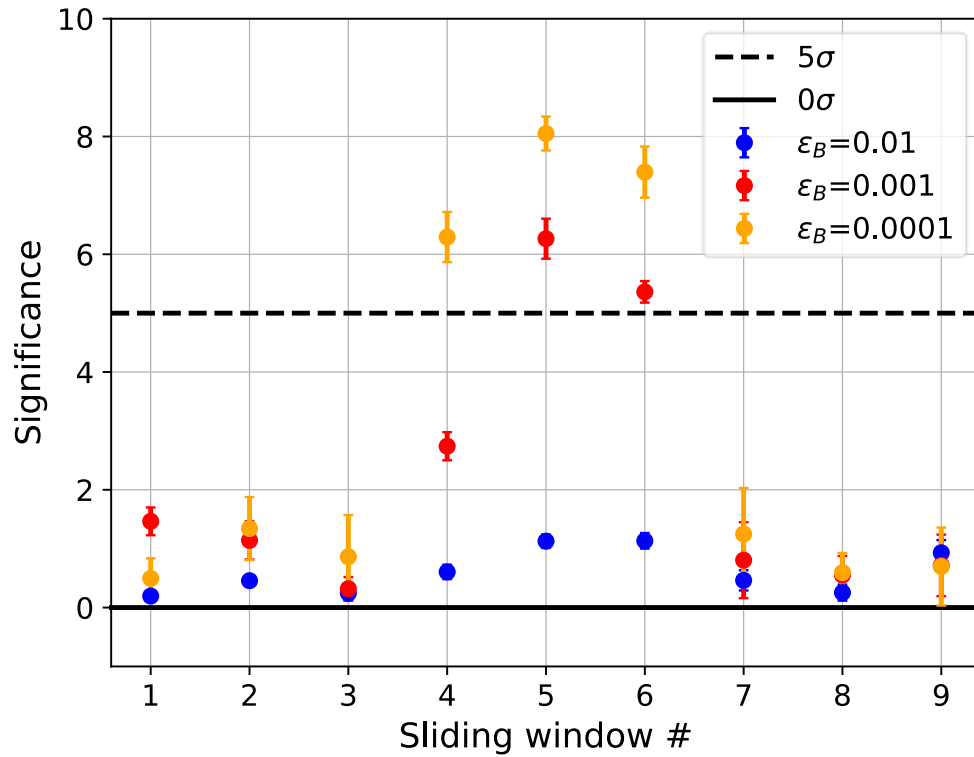
CWoLa Hunting



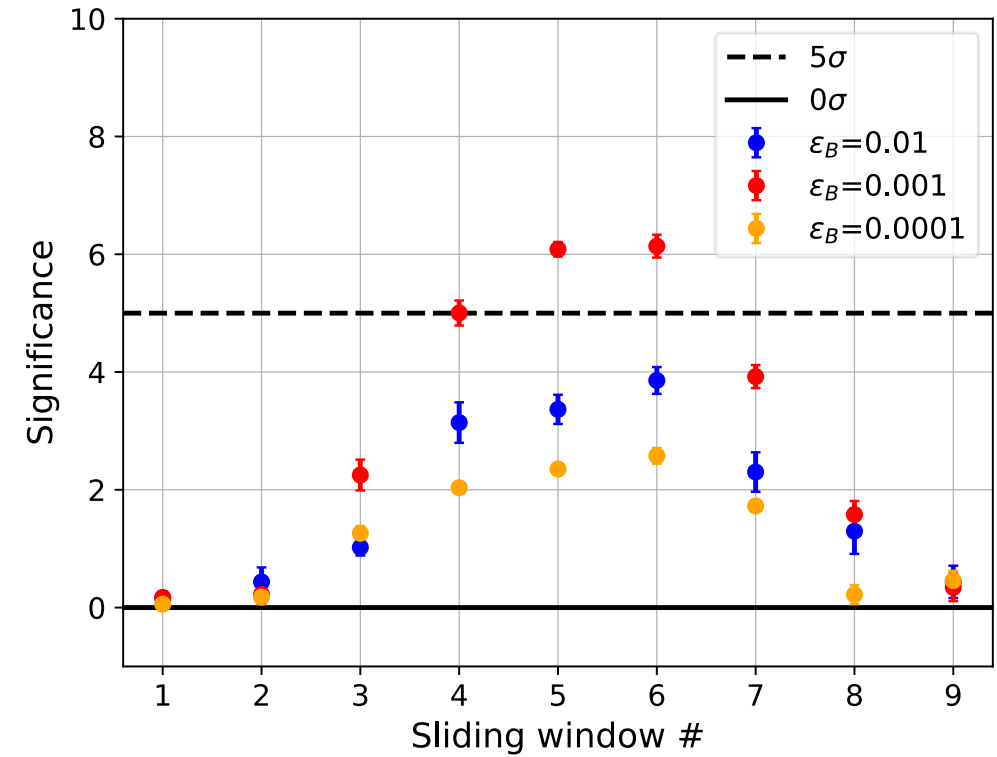
CATHODE



CWoLa Hunting

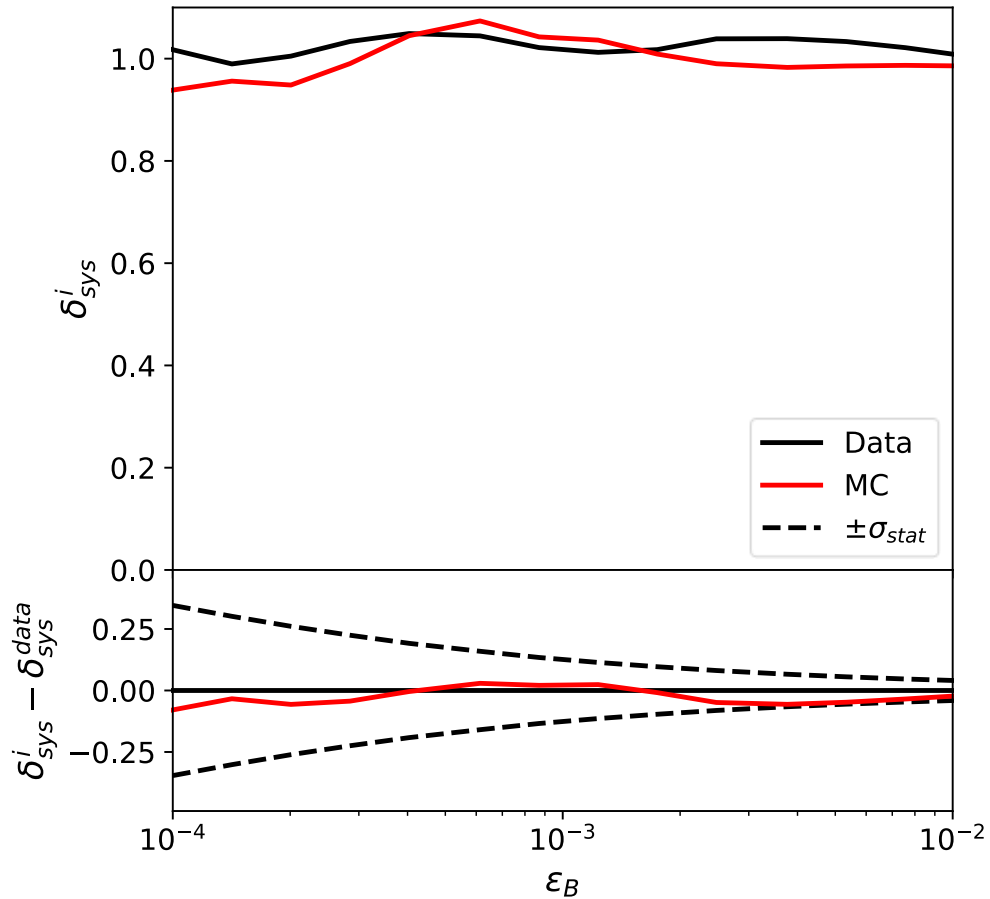


CATHODE



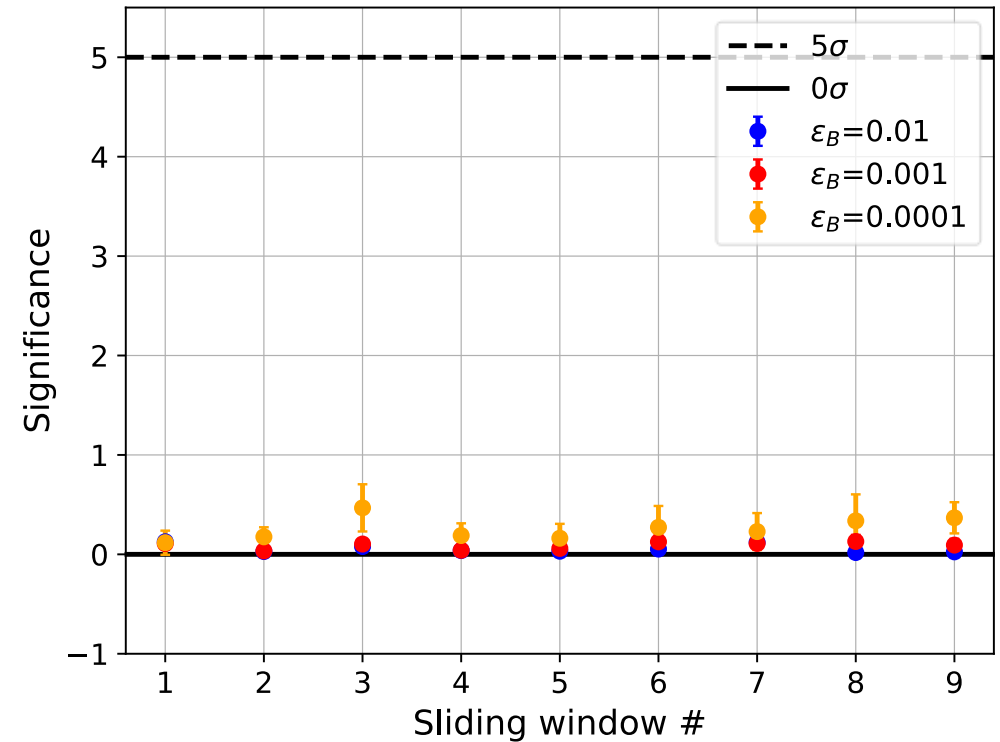
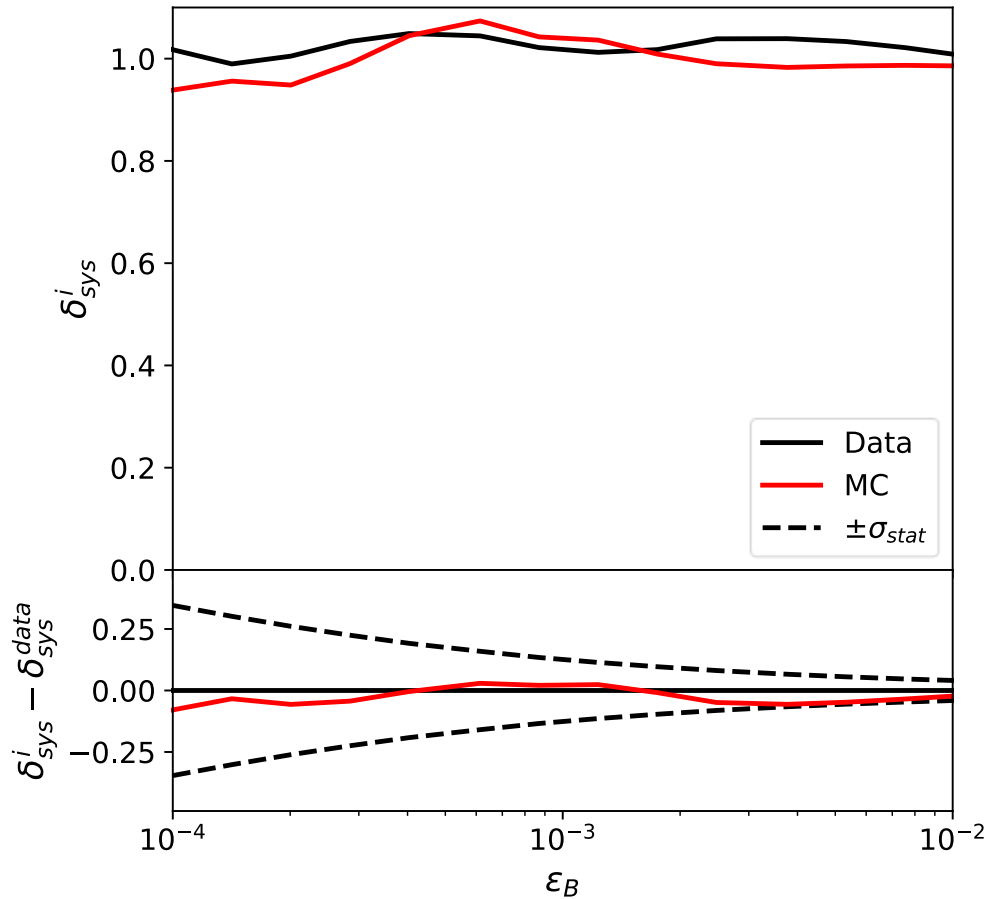
Add a feature correlated with m_{JJ} :

$$\Delta R = \sqrt{(\phi_{J1} - \phi_{J2})^2 + (\eta_{J1} - \eta_{J2})^2}$$



Add a feature correlated with m_{JJ} :

$$\Delta R = \sqrt{(\phi_{J1} - \phi_{J2})^2 + (\eta_{J1} - \eta_{J2})^2}$$



- Alternative approach to bump hunts with direct background estimation instead of fits
 - Robust
 - No false discoveries observed
 - Even when method assumptions are violated
 - Simple
 - Statistical procedure
 - Systematic bias evaluation
 - Powerful
 - Significant deviations observed

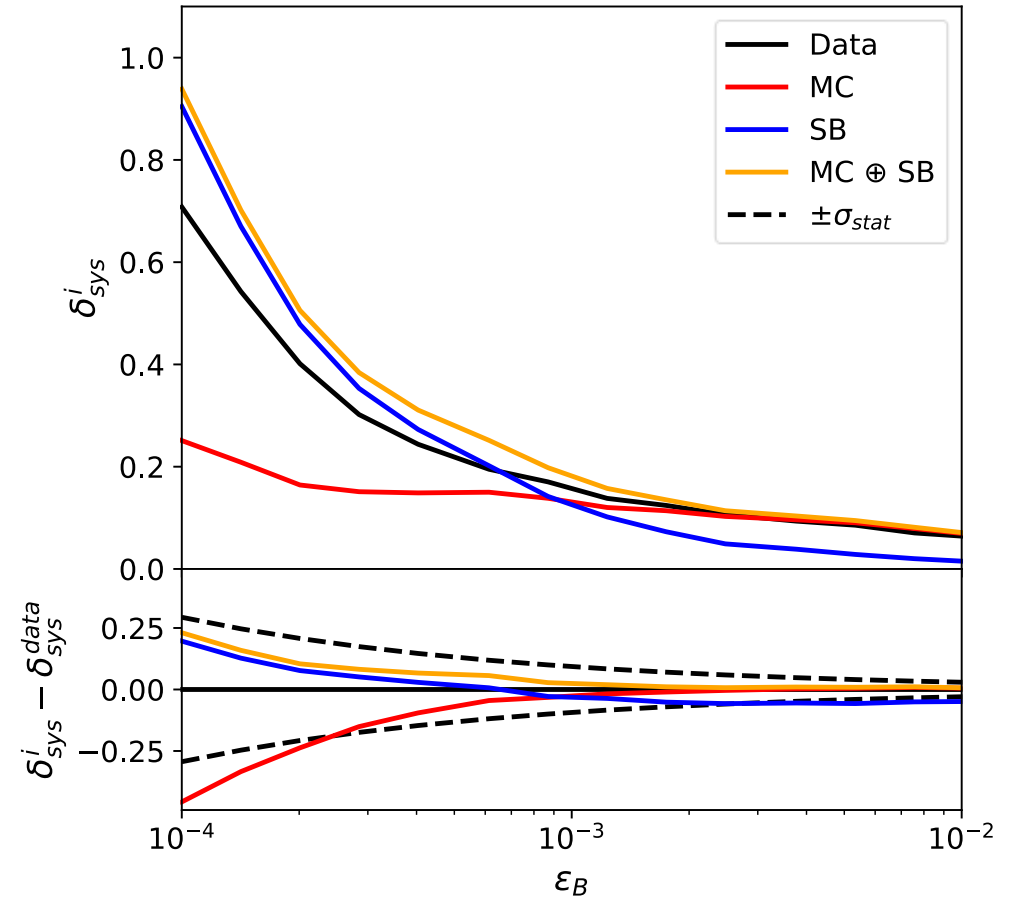
Accurate and robust methods
for direct background estimation
in resonant anomaly detection

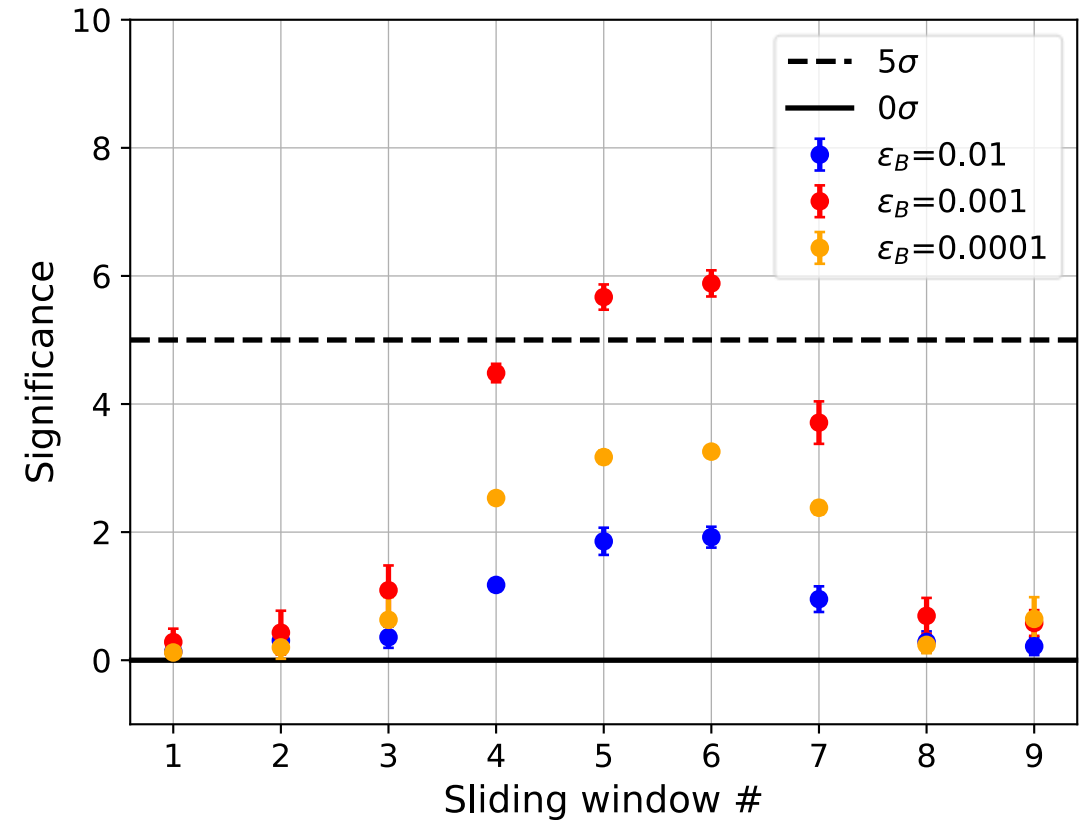
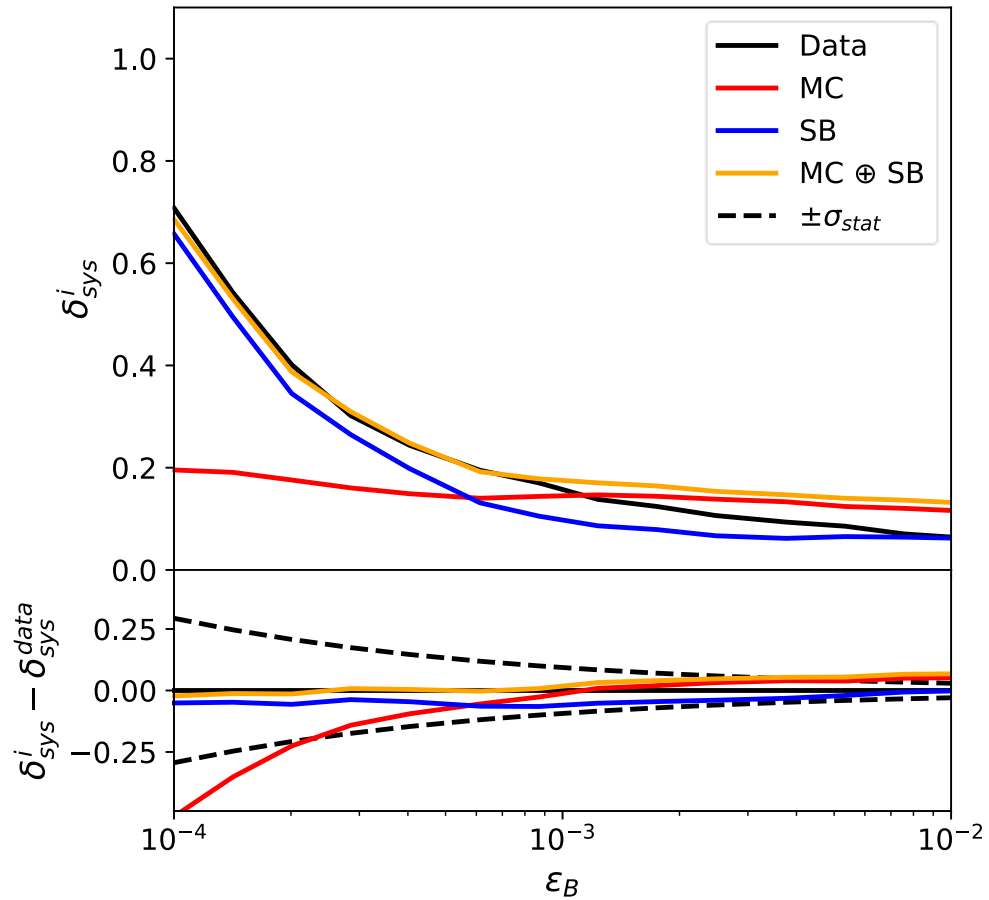
R. Das, T. Finke, **MH**, G. Kasieczka, M.
Krämer, A. Mück, D. Shih



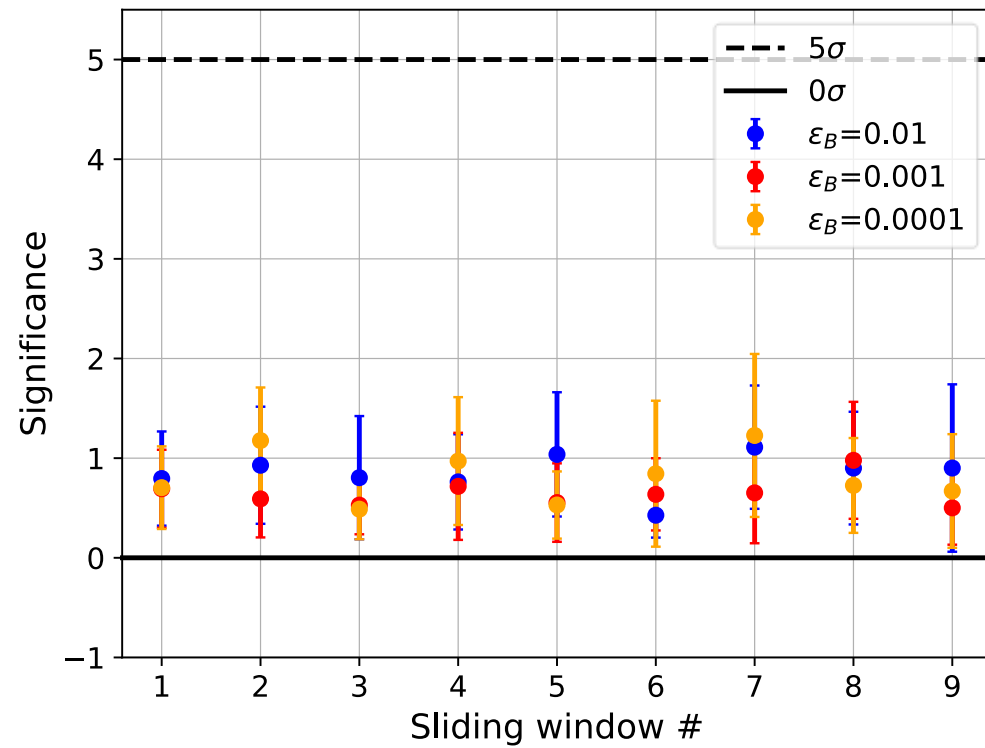
Backup

- Determination of δ_{sys} on SB is affected by the presence of signal
 - Obtain larger δ_{sys} with signal than without
 - Dampening of significances
- To mitigate this we use the whole sideband with the statistics present in the SR
 - Dilution of signal

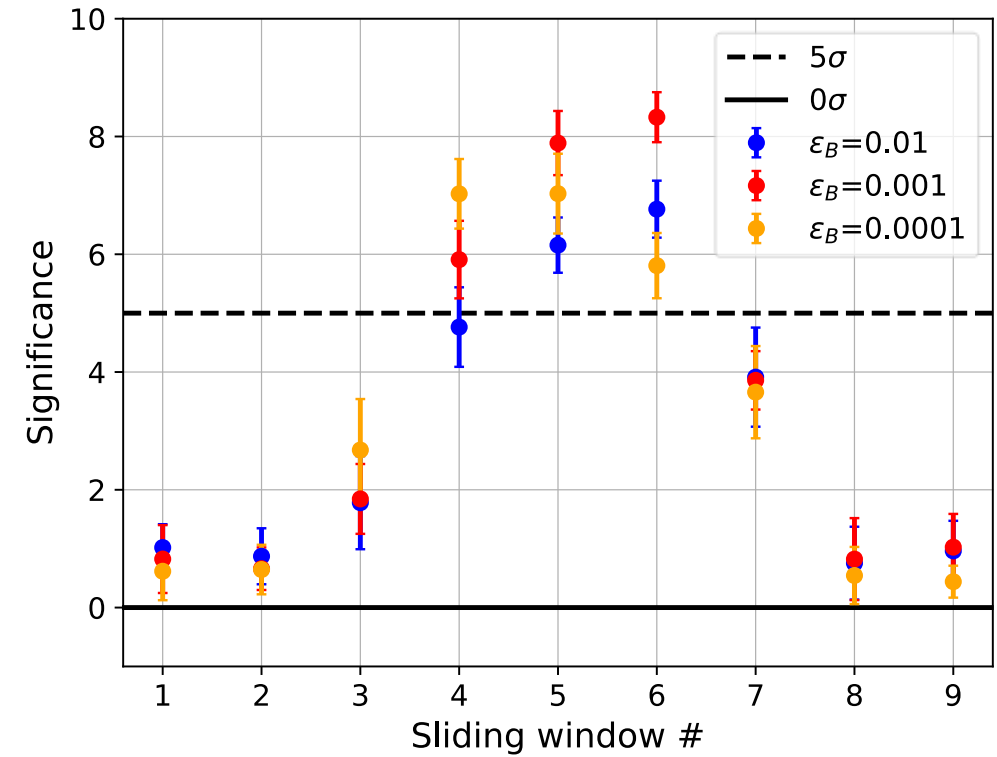




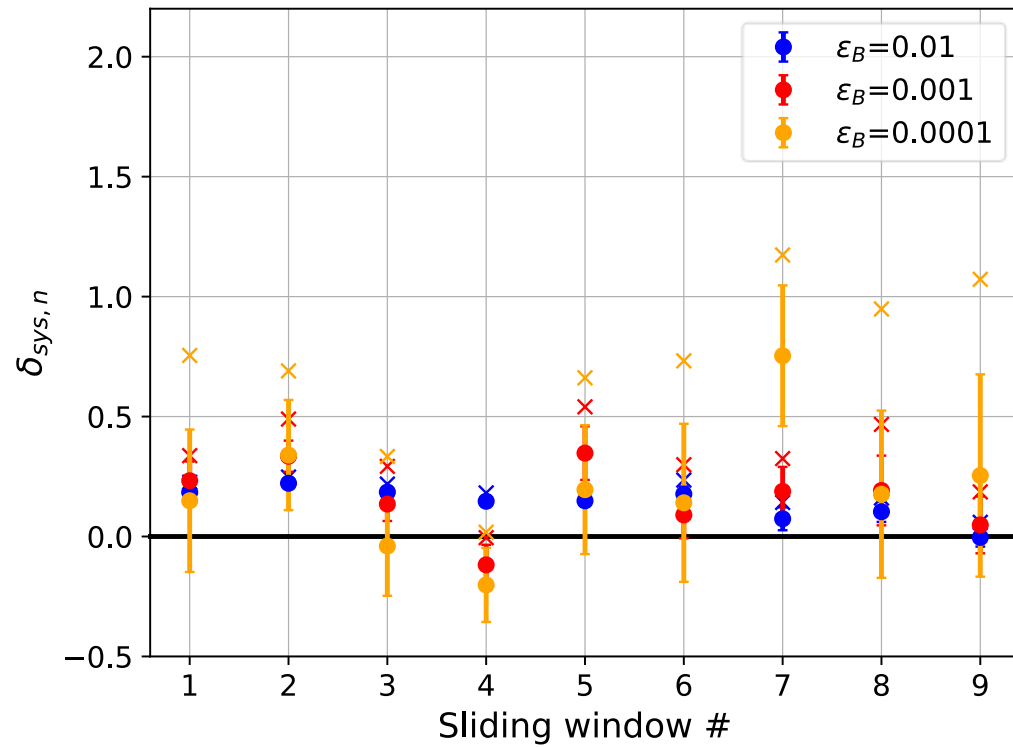
Without Signal



With Signal



CWoLa



CATHODE

