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Anomaly Detection: From Methods to Applications

Marie Hein

ML4Jets 2026, Vienna

New Physics Searches

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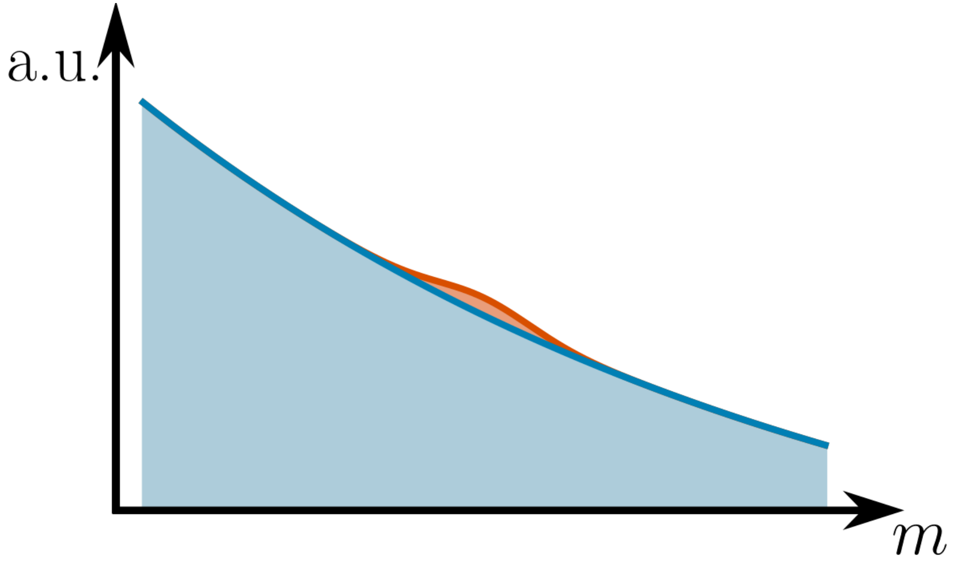
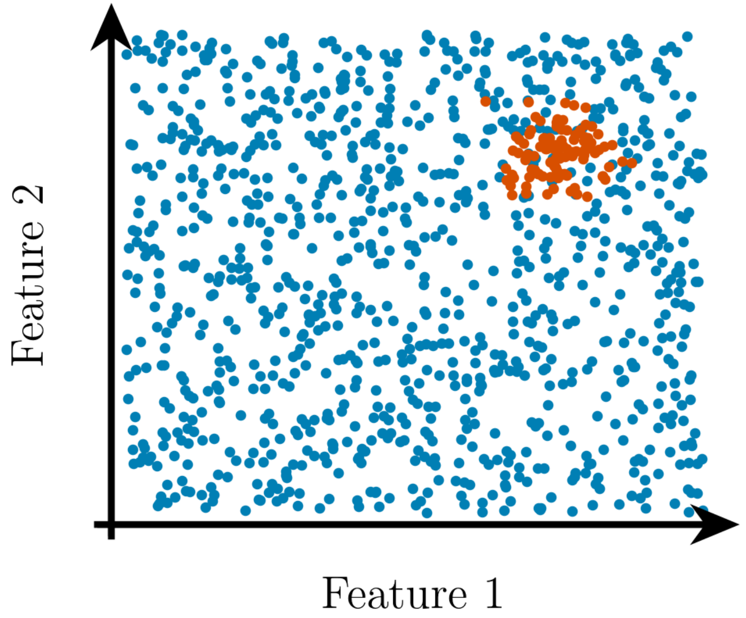




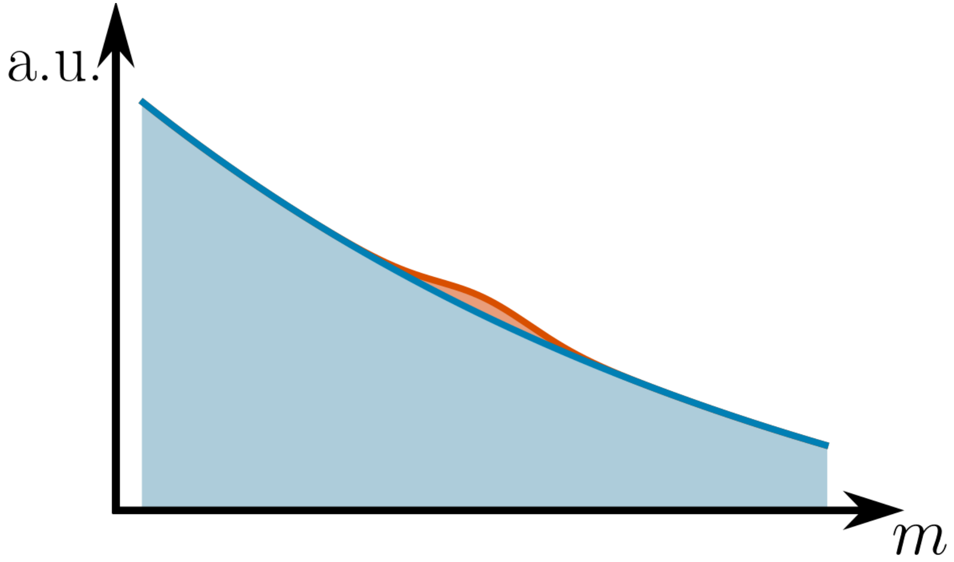
New Physics Searches

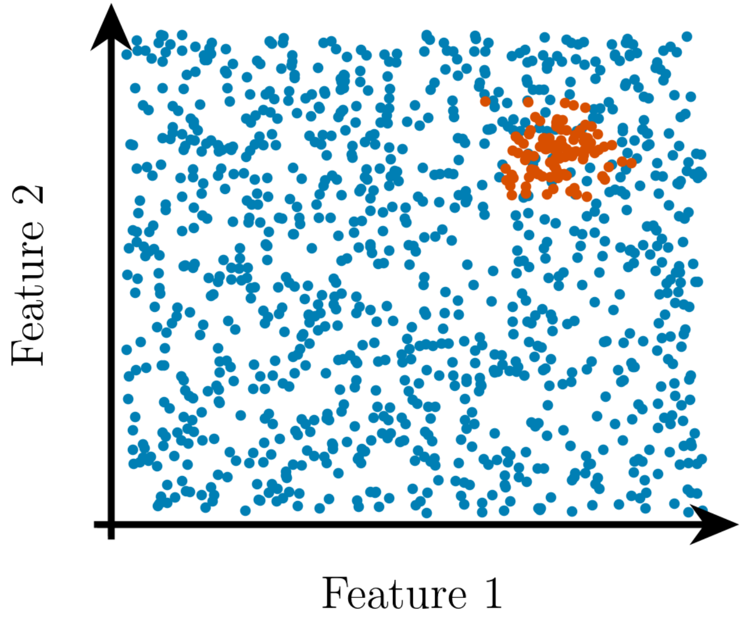
Coverage

Broad ⟷ Narrow

Sensitivity

Low ⟷ High





New Physics Searches

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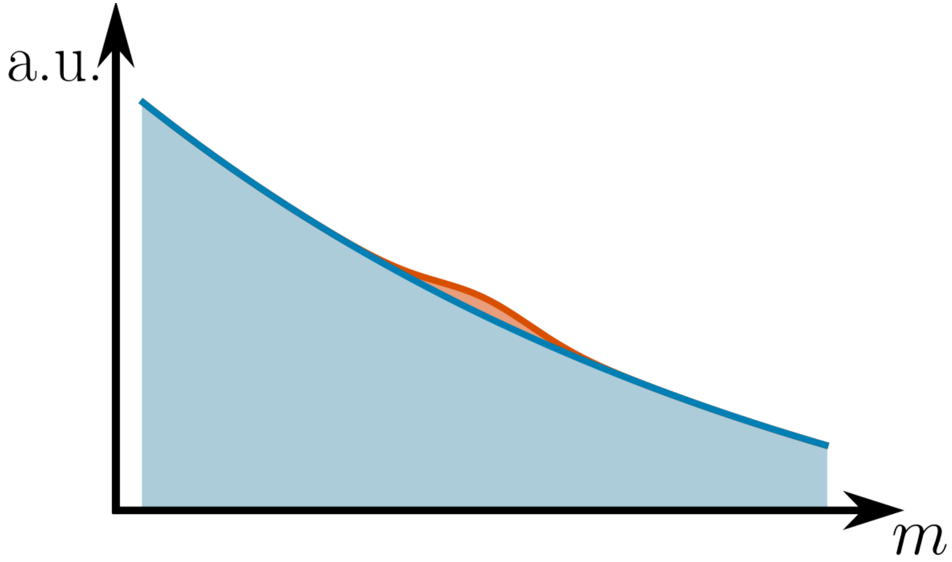
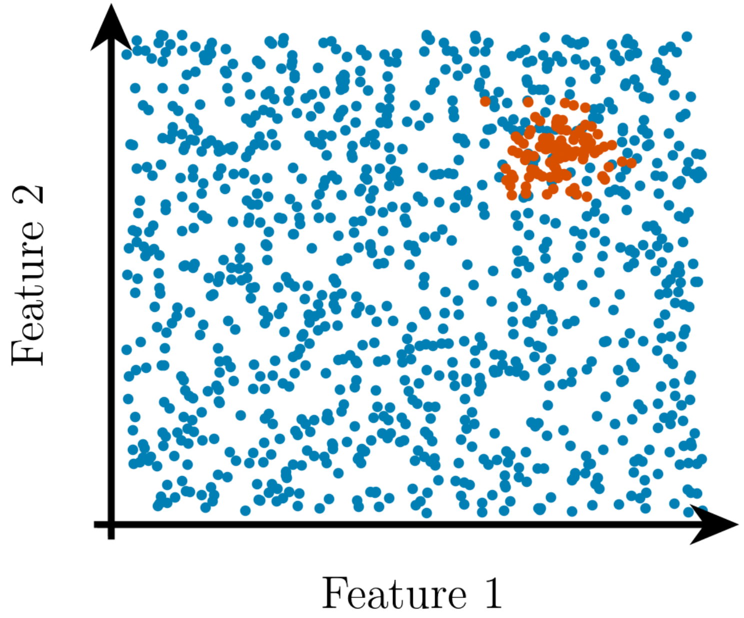
Coverage

Broad ← → Narrow

Sensitivity

Low ← → High





Inclusive

New Physics Searches

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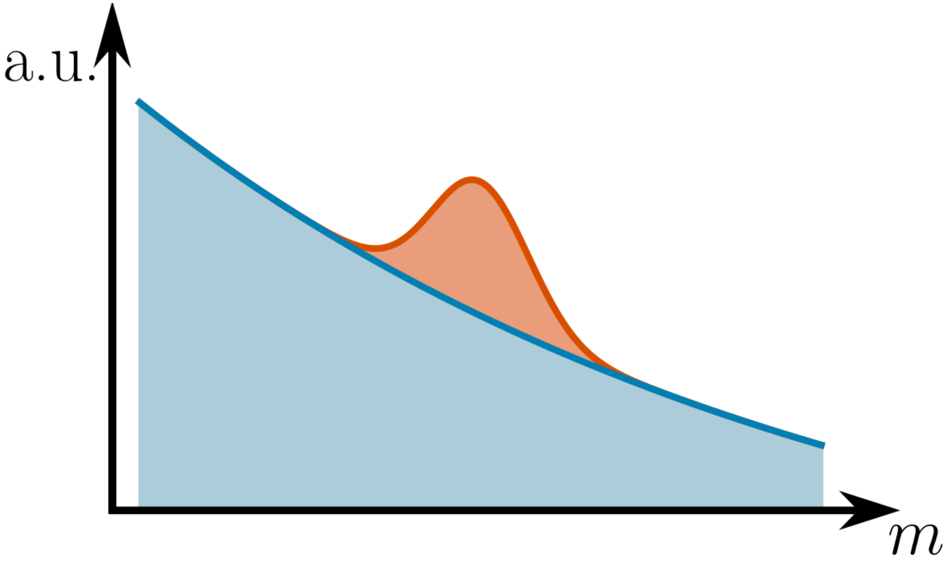

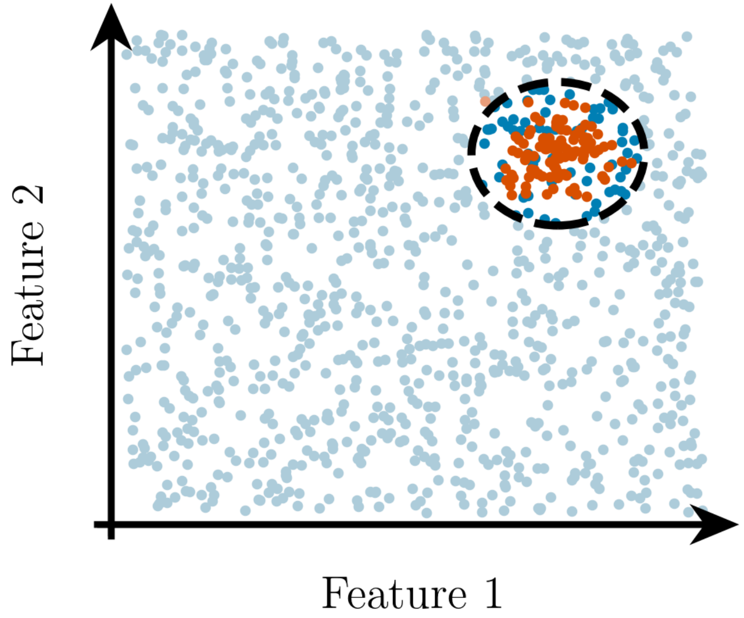

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Model-specific

New Physics Searches

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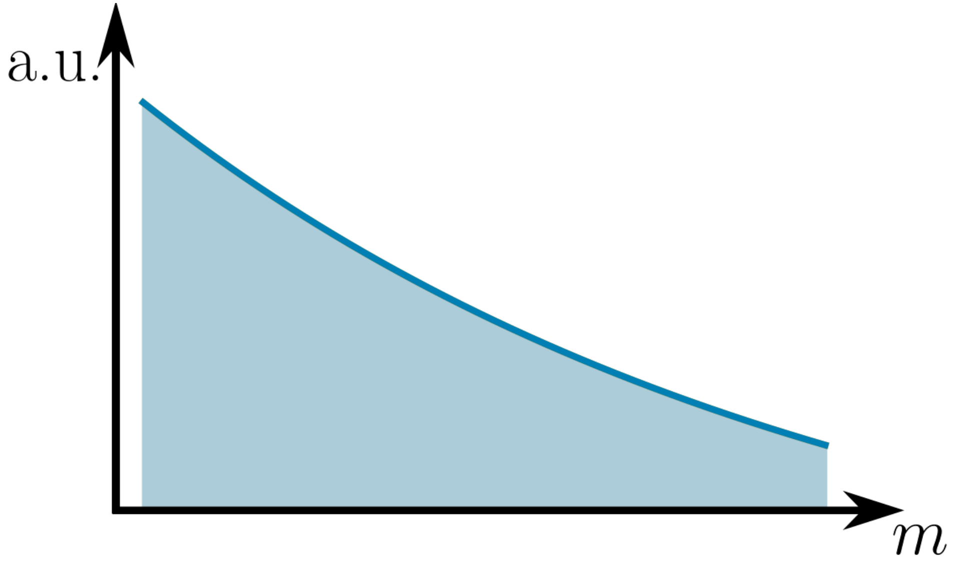

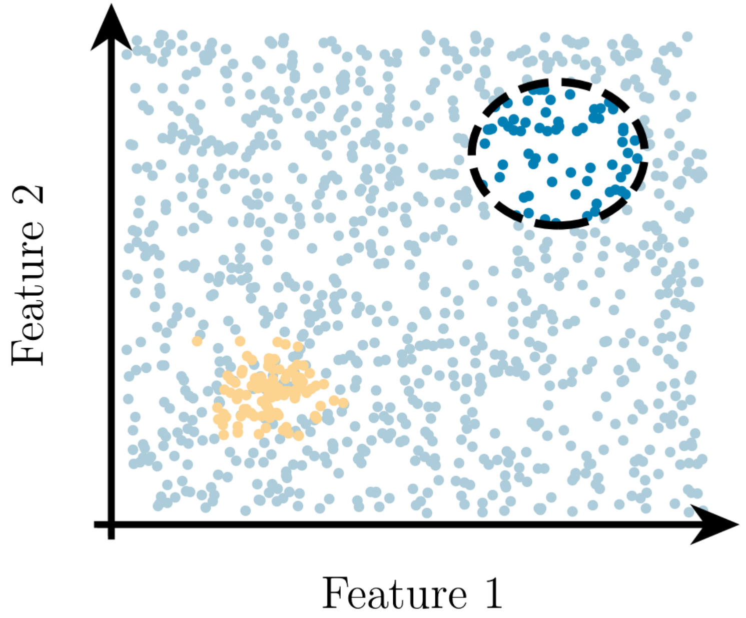

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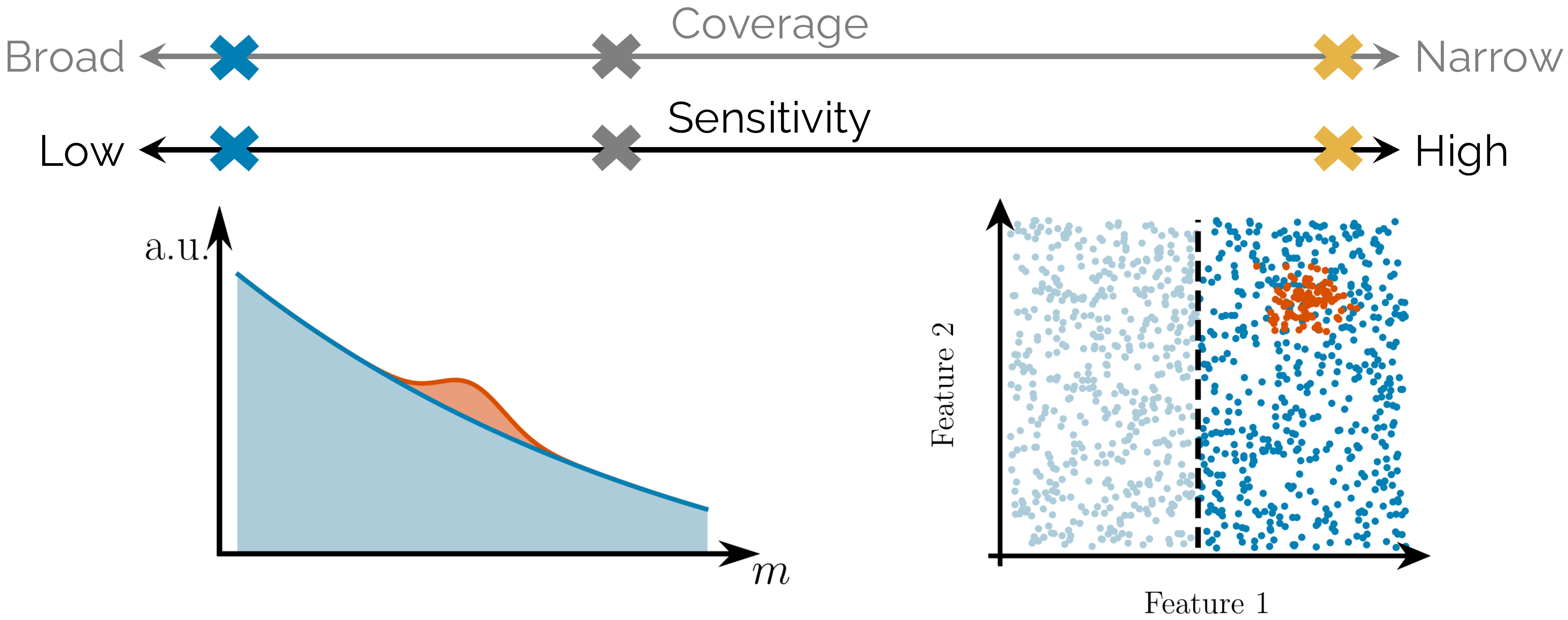

Inclusive

Single cut

Model-specific

Anomaly Detection

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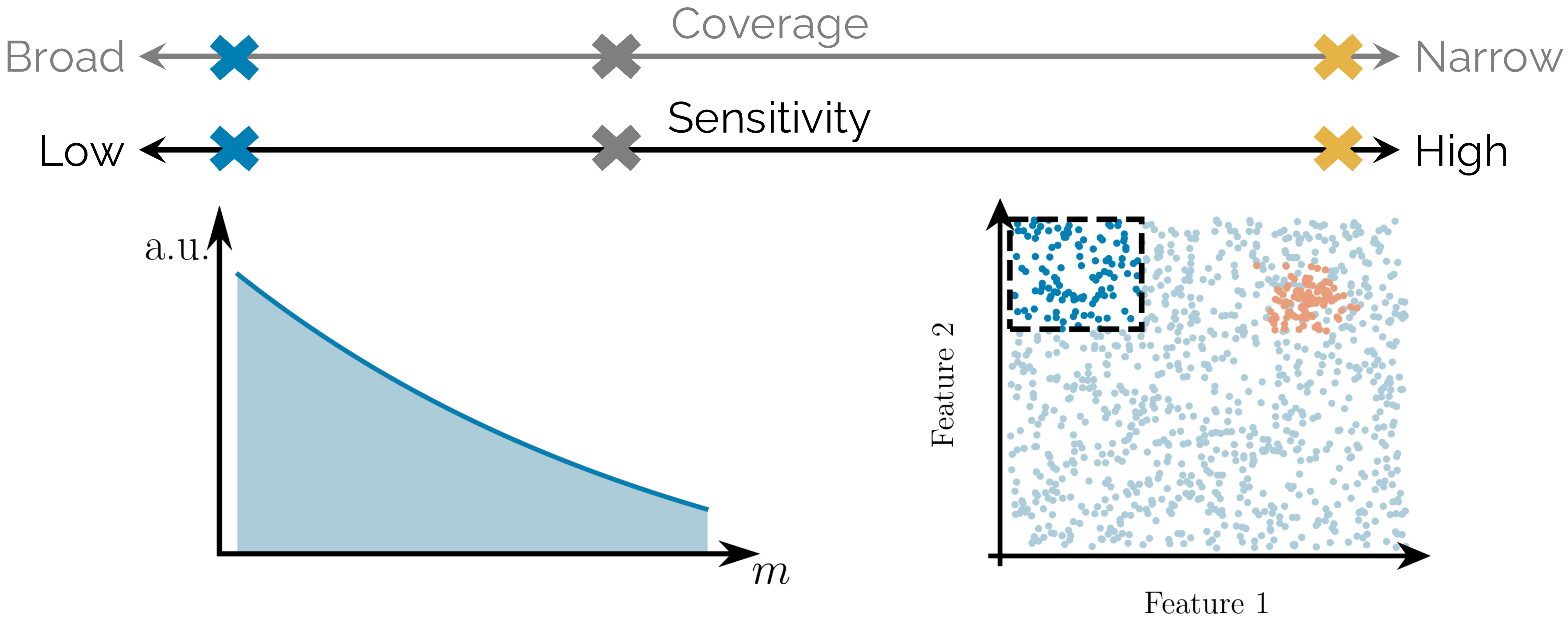

Inclusive | Single cut | Model-specific | Anomaly detection

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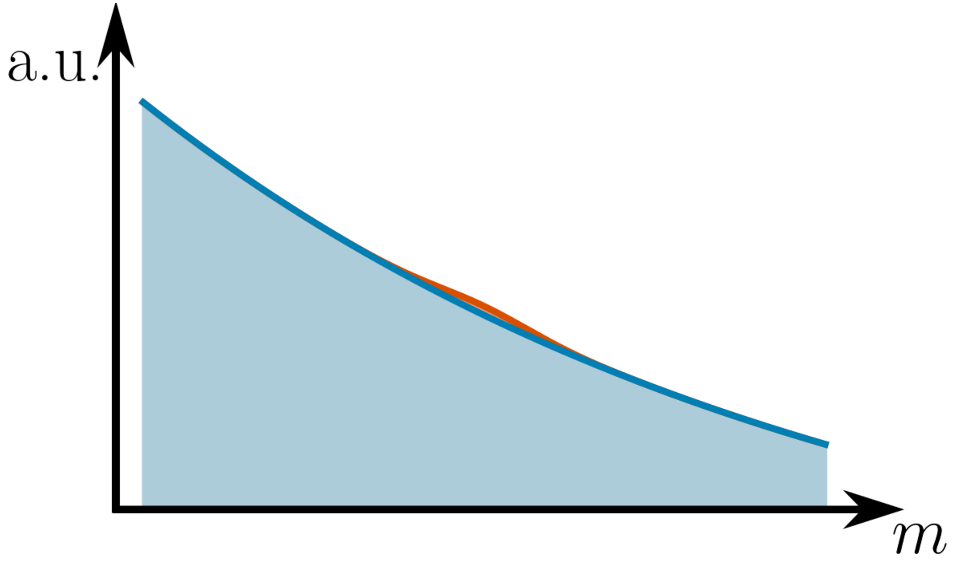

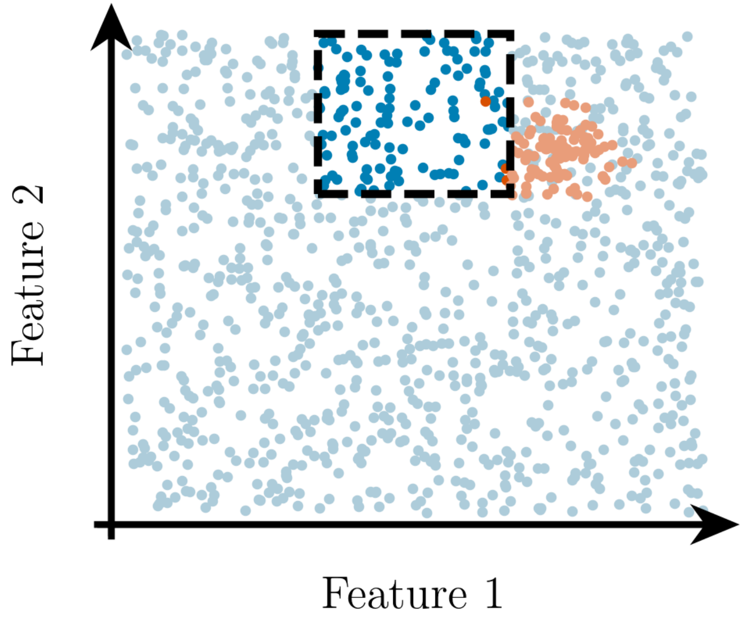

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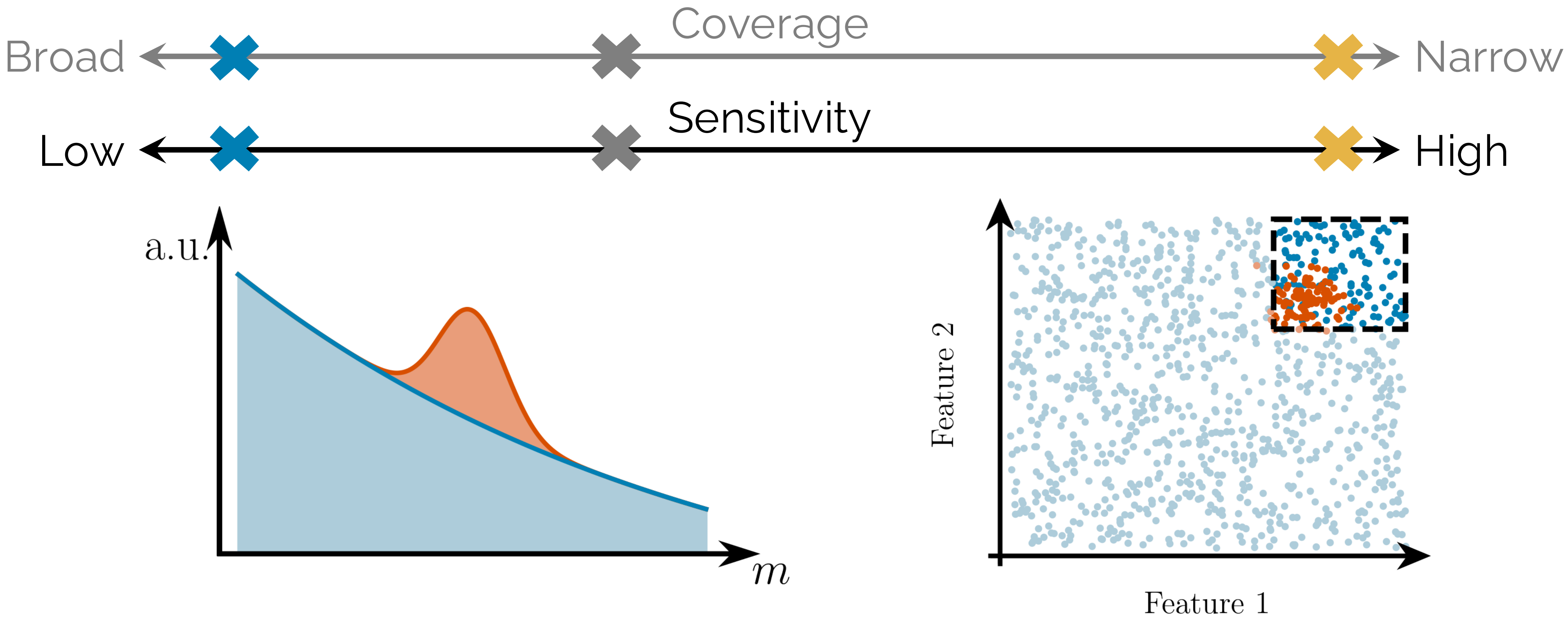

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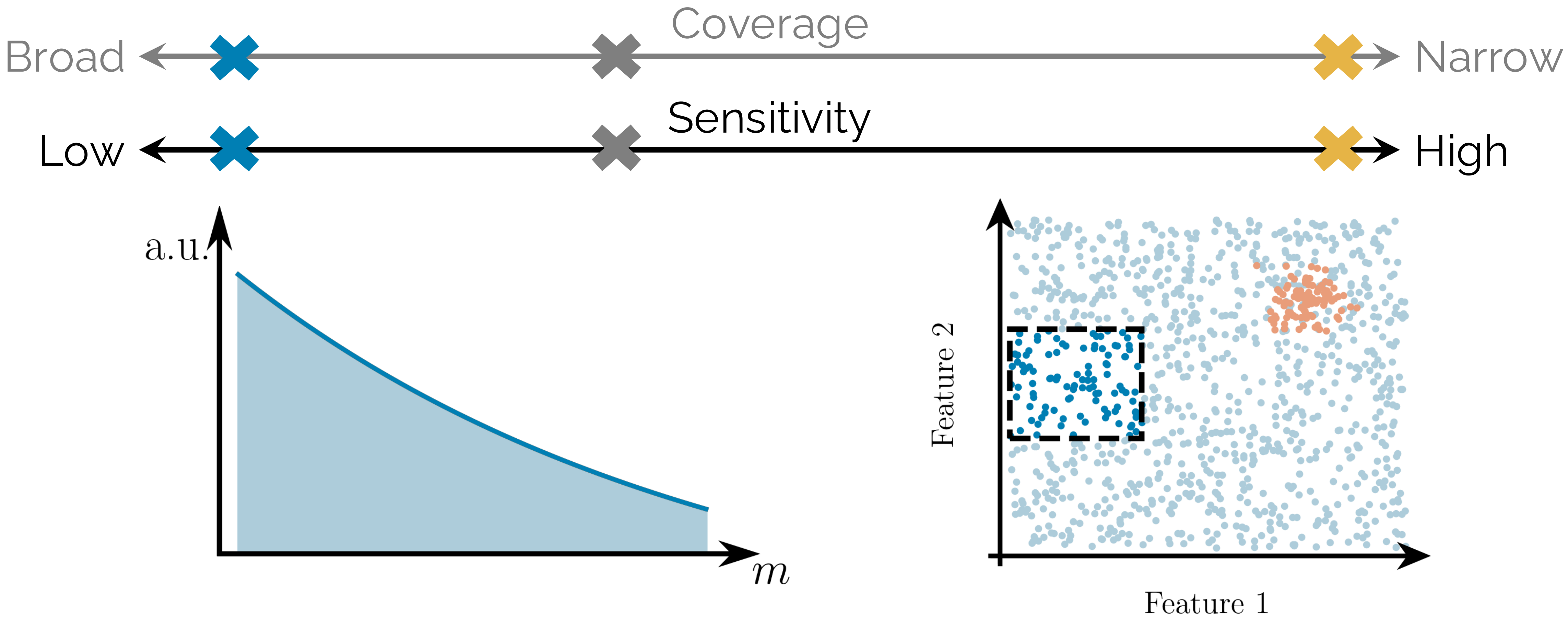

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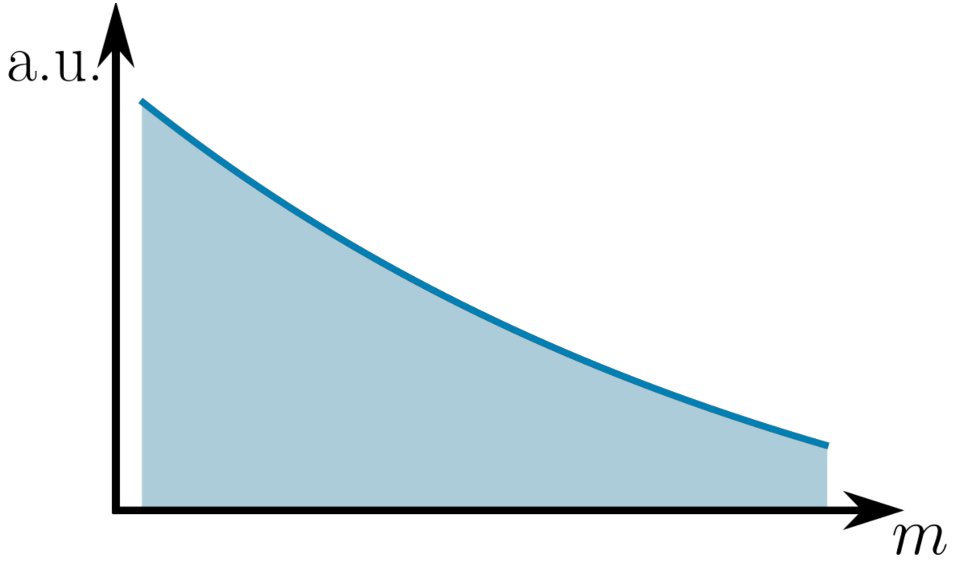

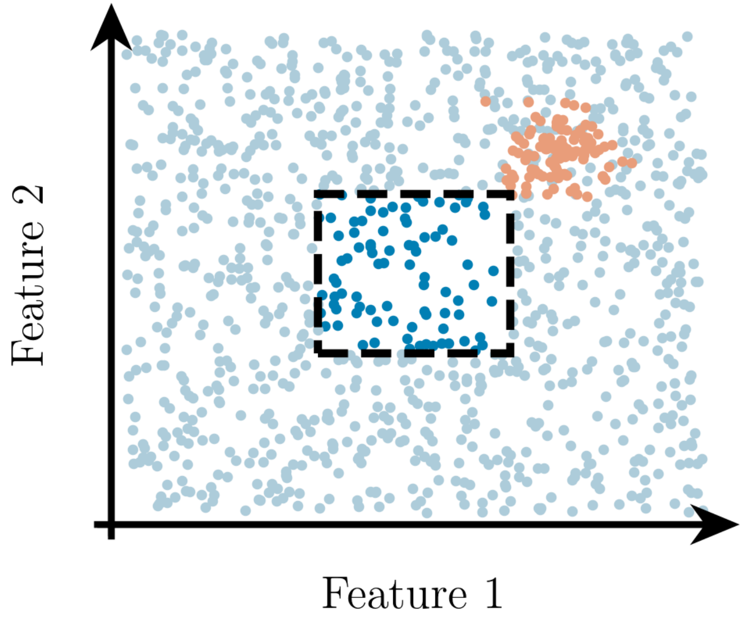

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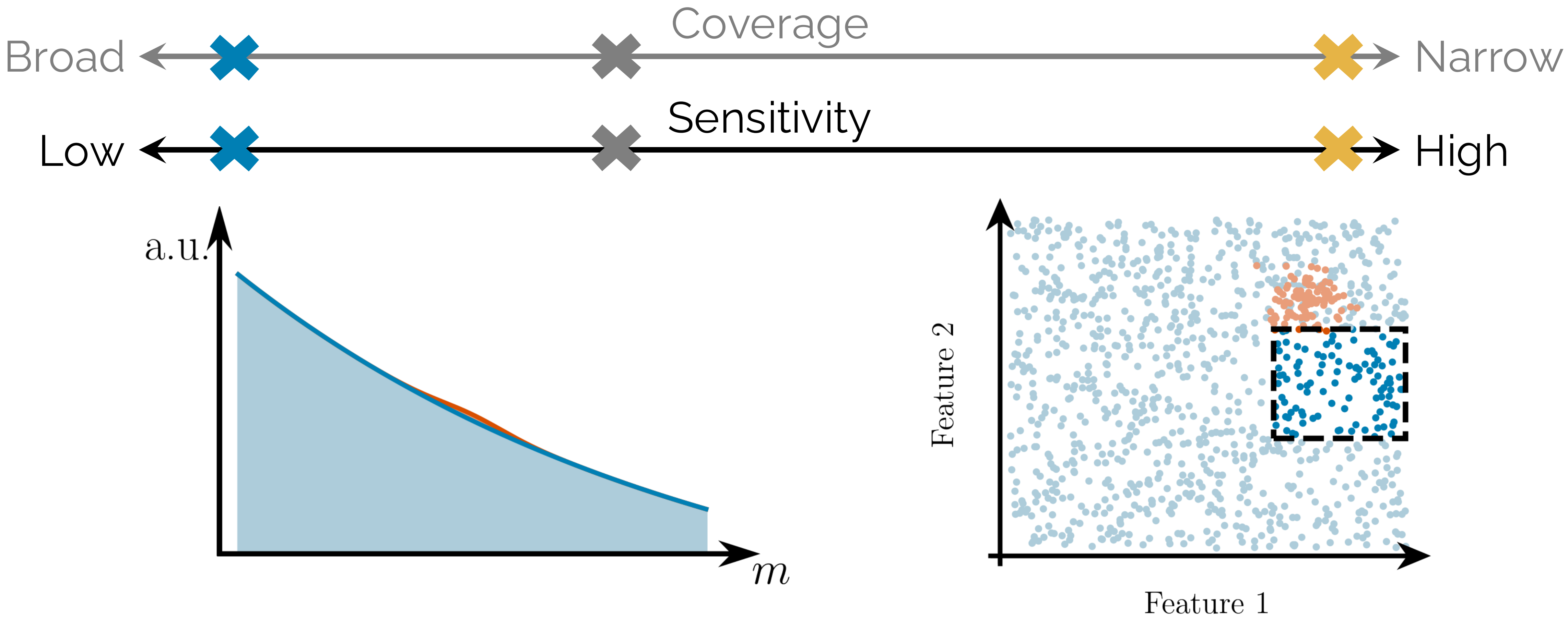

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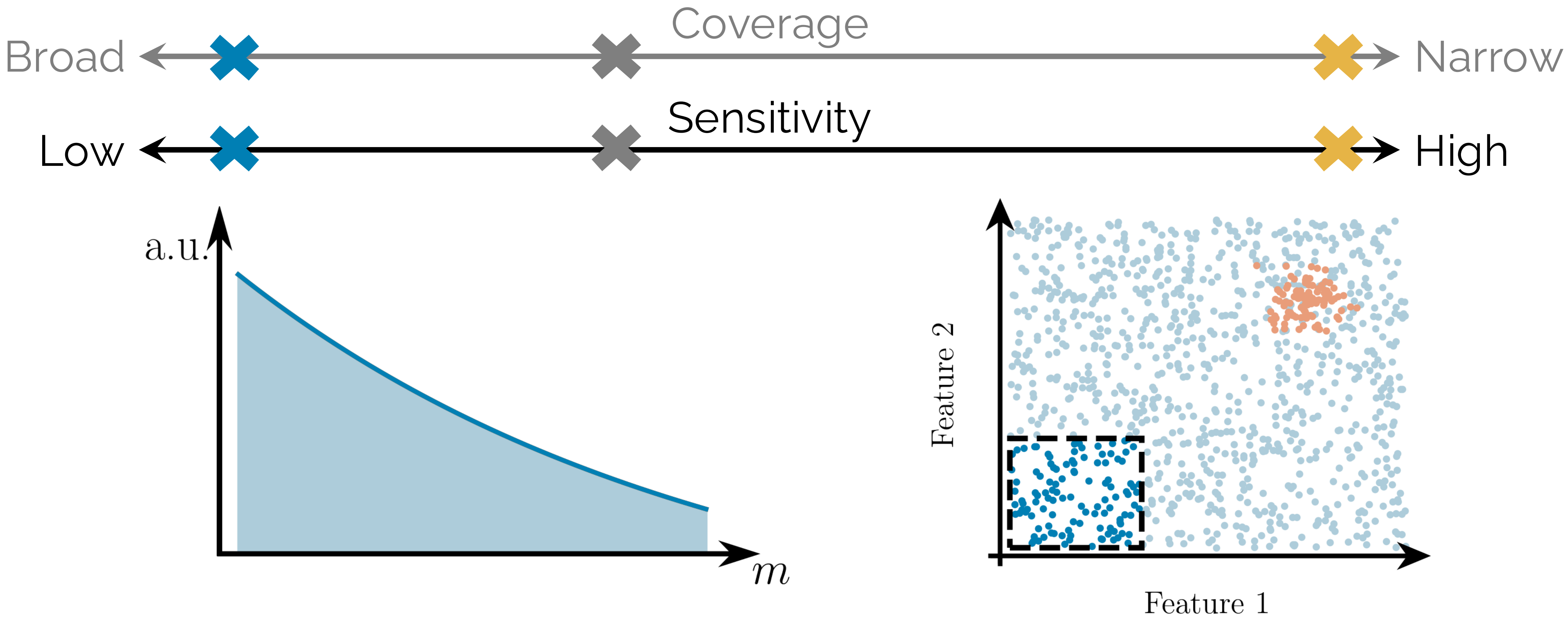

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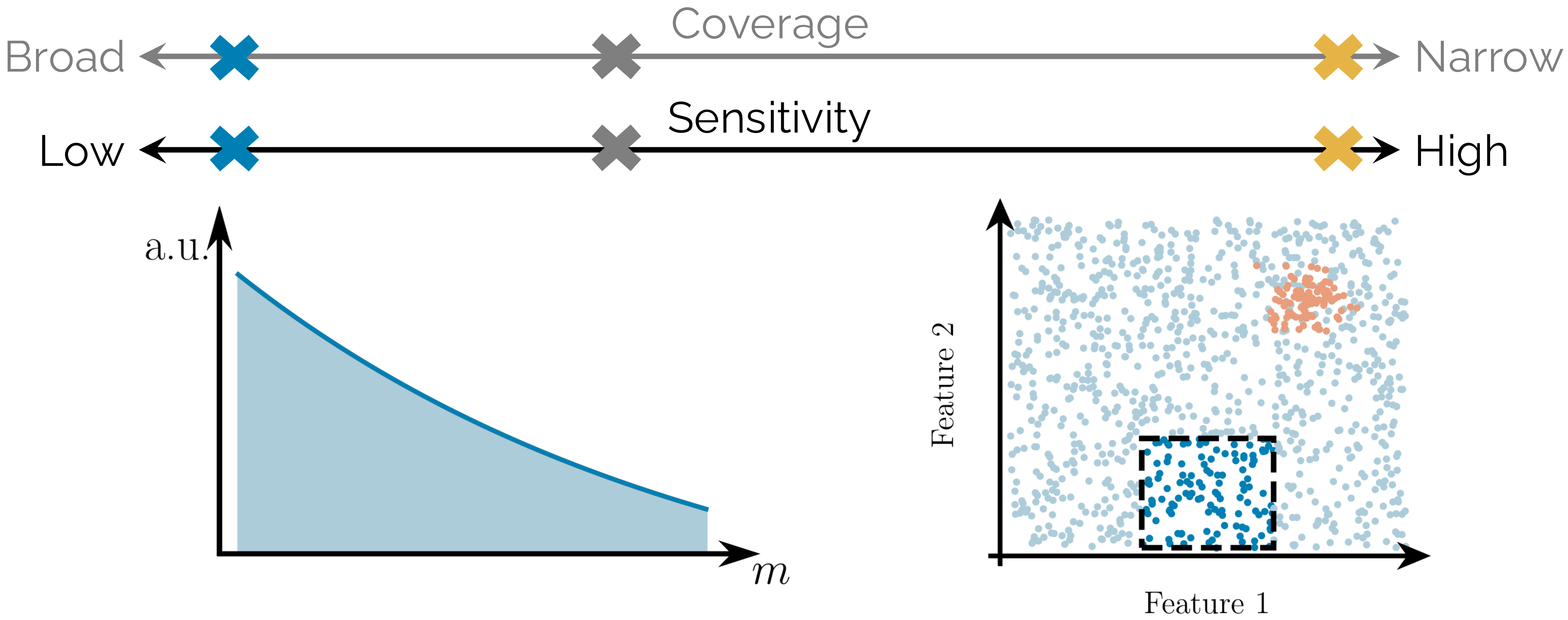

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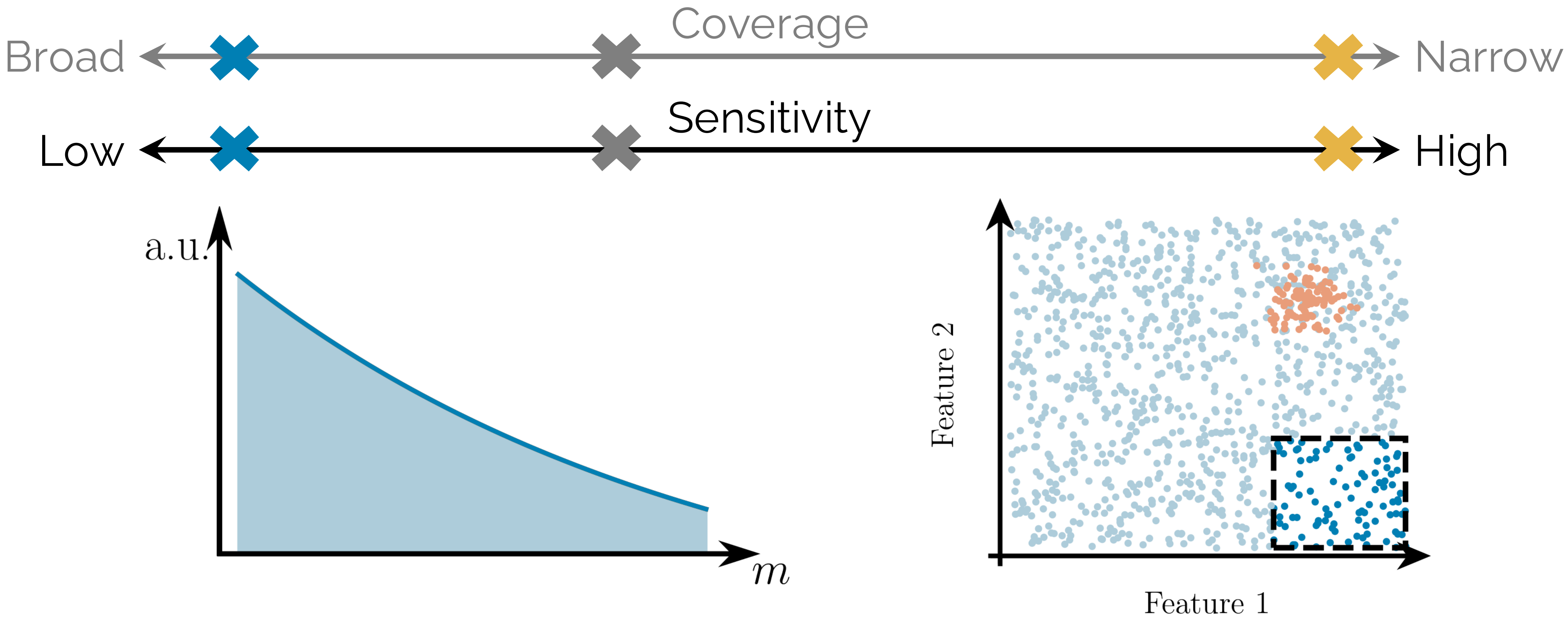

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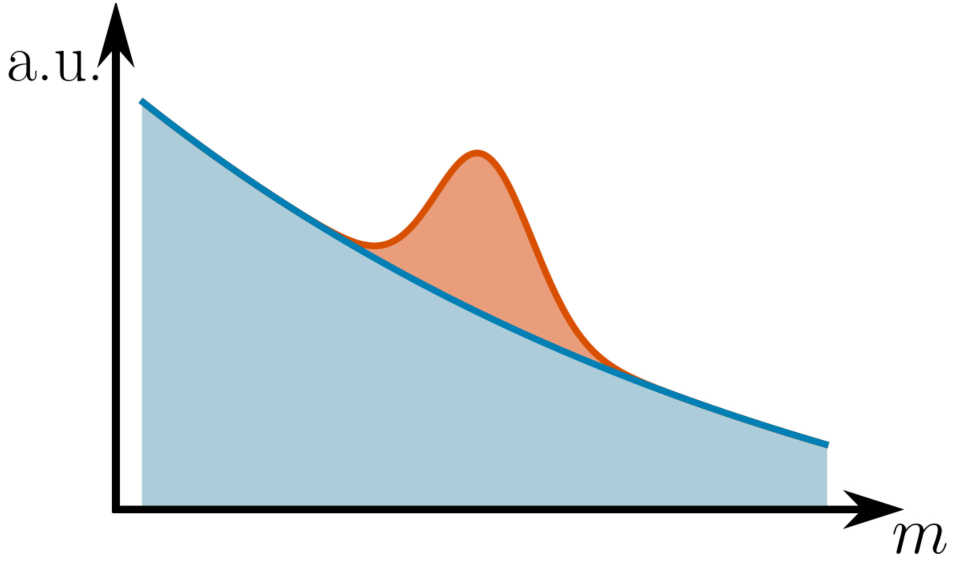

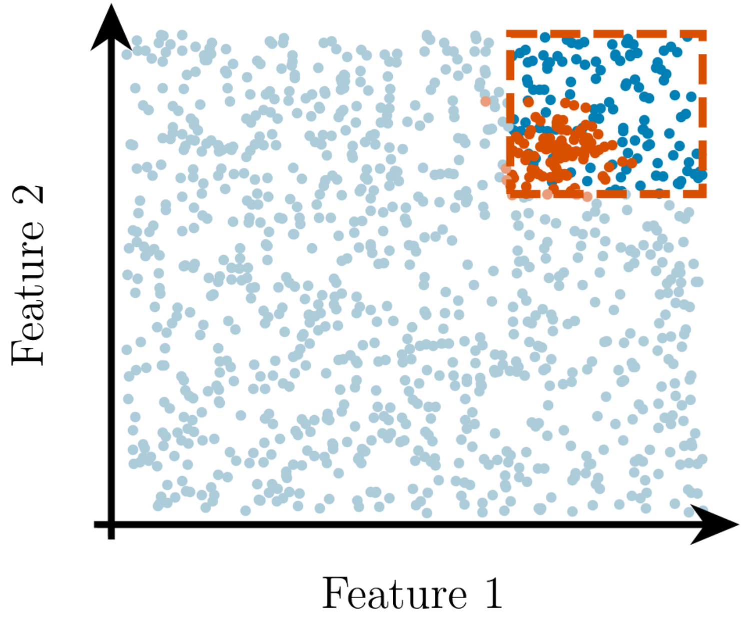

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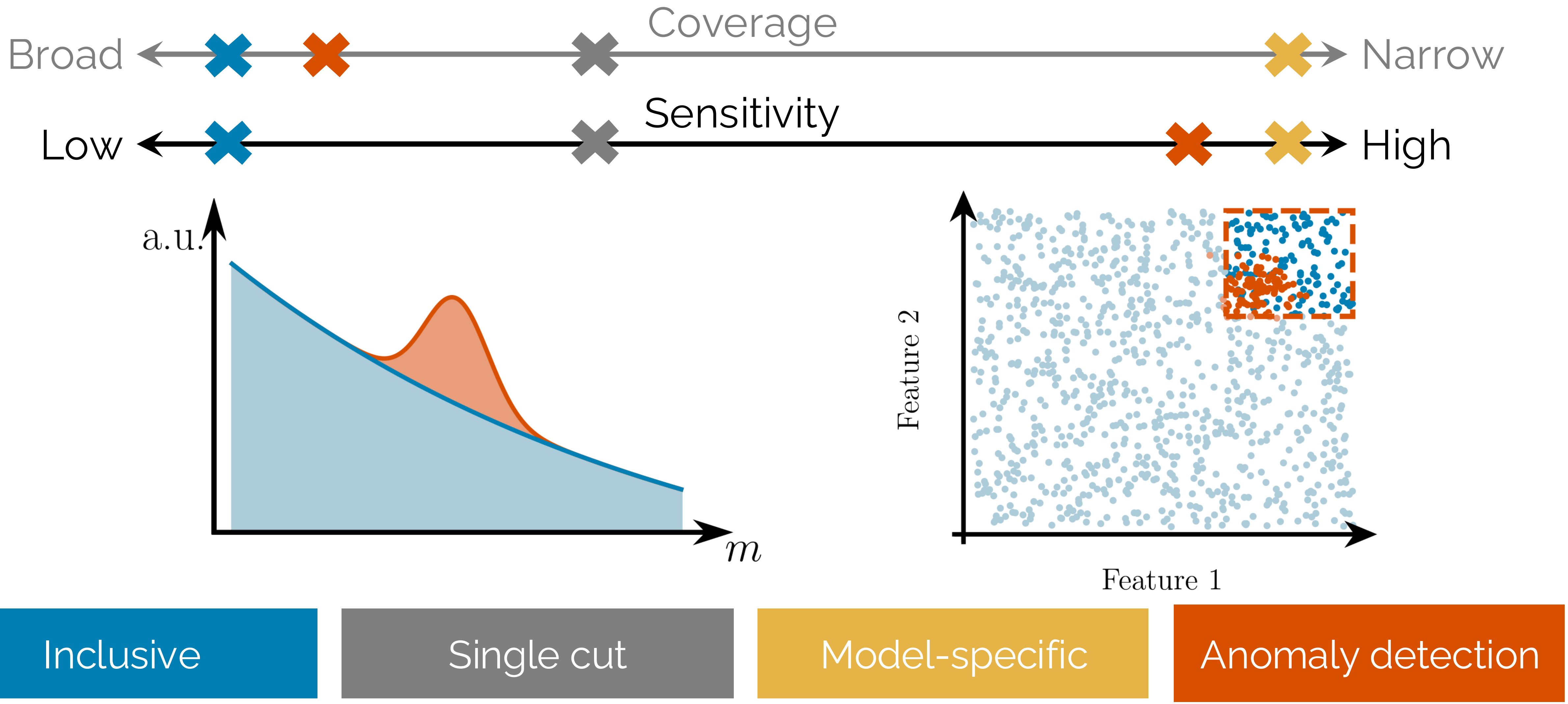

The Spectrum of Anomaly Detection

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Supervised

Unsupervised

The Spectrum of Anomaly Detection

Supervised ⟷ Unsupervised

Outlier anomaly detection, e.g. autoencoders etc.

The Spectrum of Anomaly Detection

Supervised ⟷ Unsupervised

Weakly supervised AD, using some physics information to construct AD

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The Spectrum of Anomaly Detection

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Supervised ⟷ Unsupervised

Semi-supervised AD, e.g. using signal templates

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The Spectrum of Anomaly Detection

Supervised ⟷ Unsupervised

At some point, the analysis stops being AD

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Many different AD methods have been constructed in the last decade
→ Current development moving away from method development to application and detailed studies

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Weakly Supervised Classification

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

- Optimal classifier

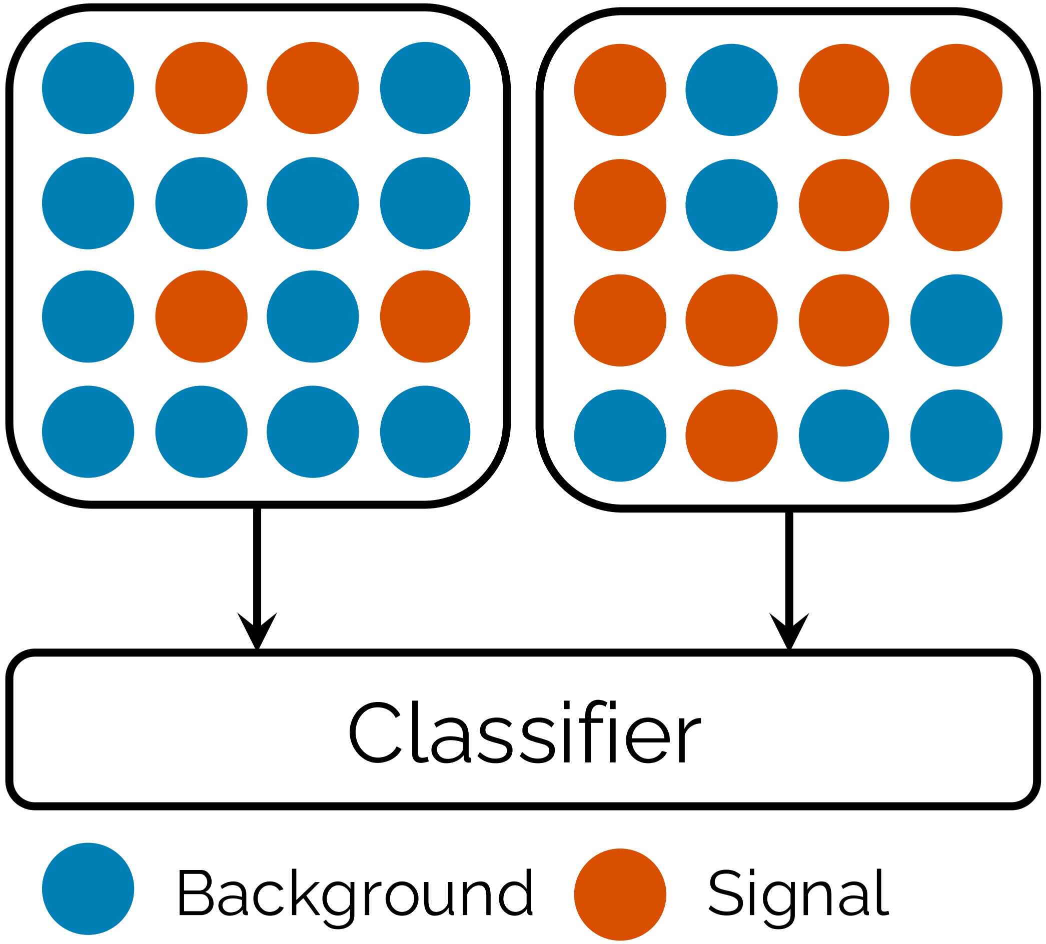
$$R_{\text{optimal}}(x) = \frac{p_S(x)}{p_B(x)}$$

- 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



Application to Resonance Searches

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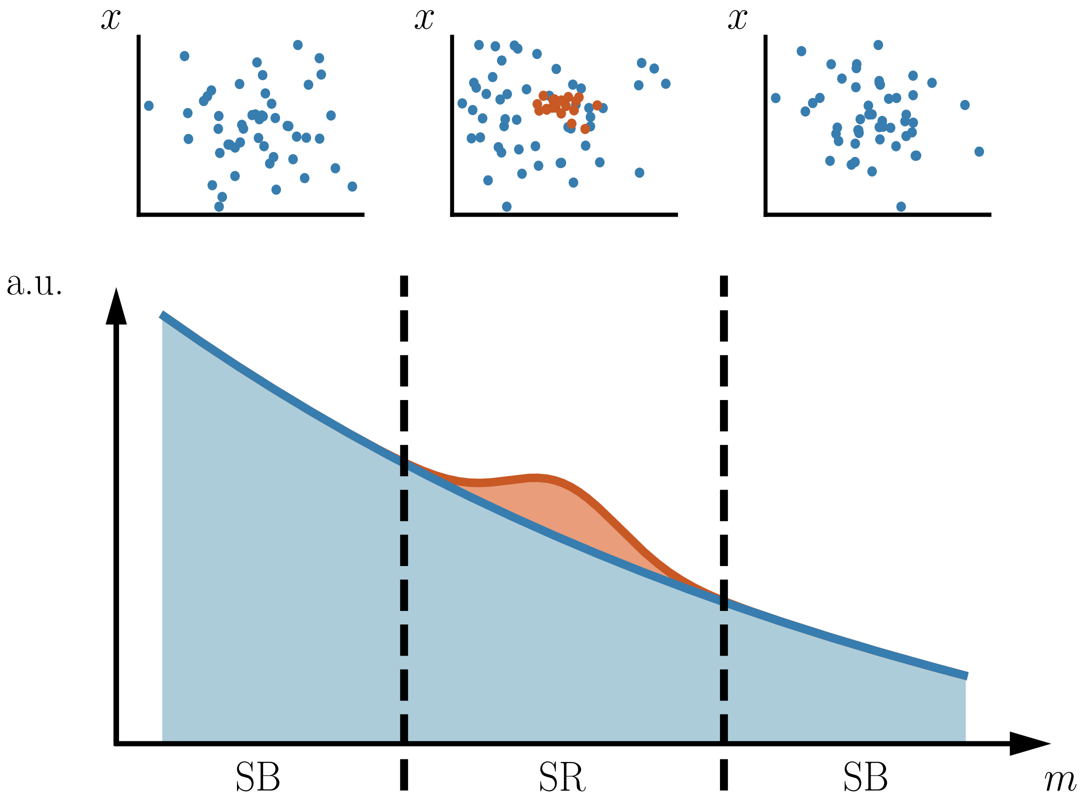
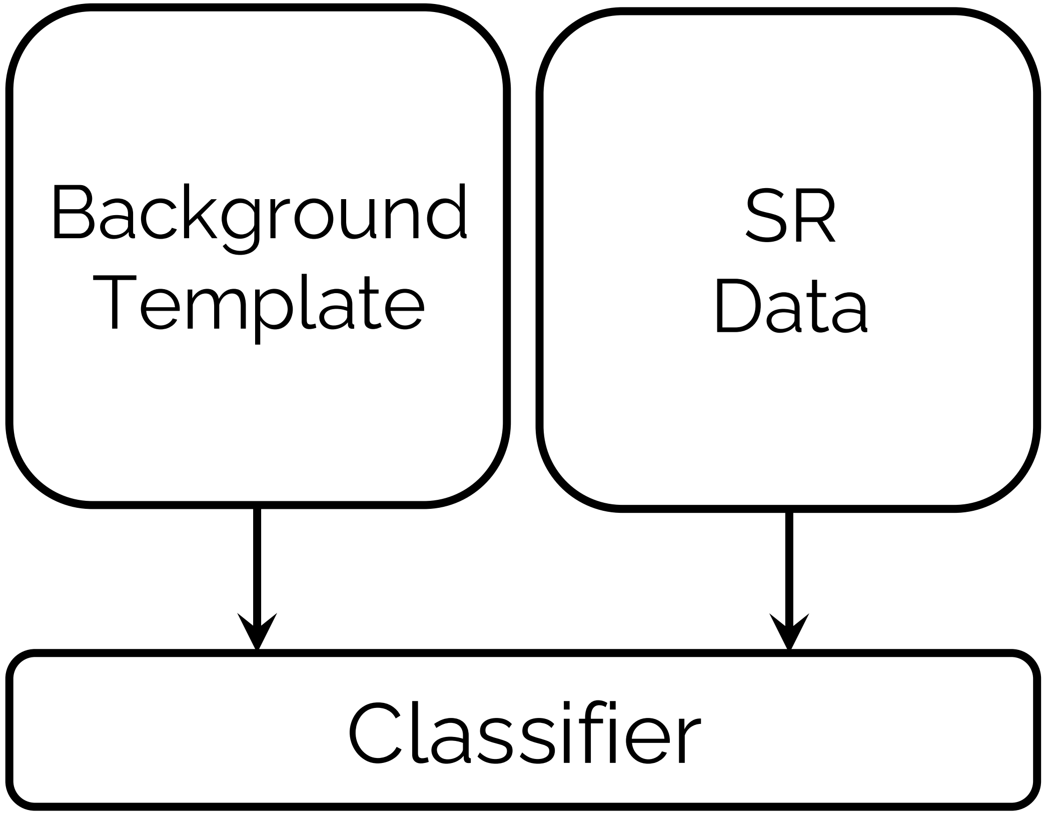


Recreated from [2109.00546]



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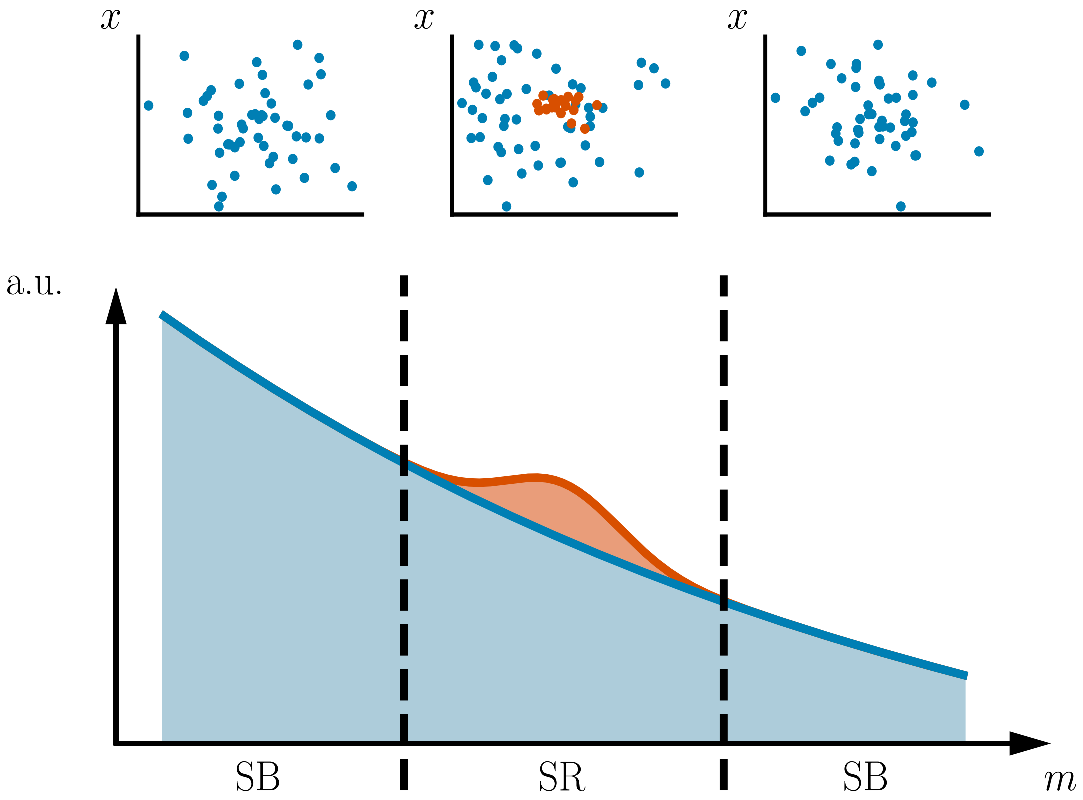

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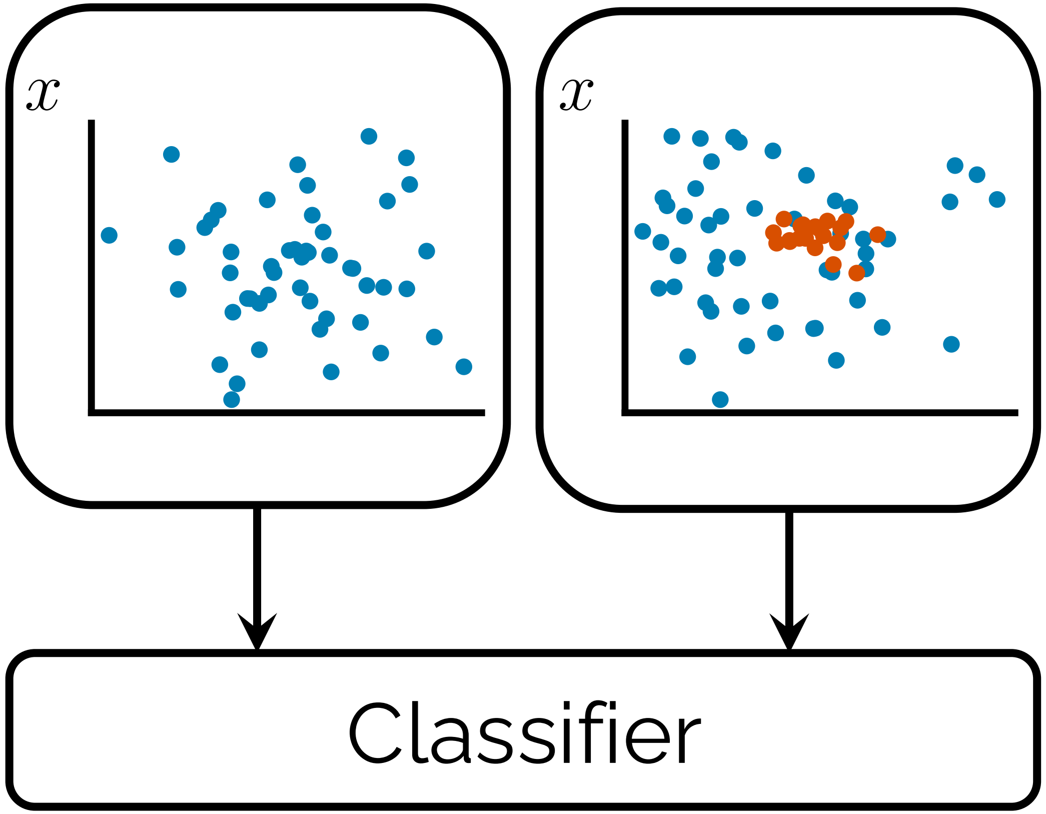
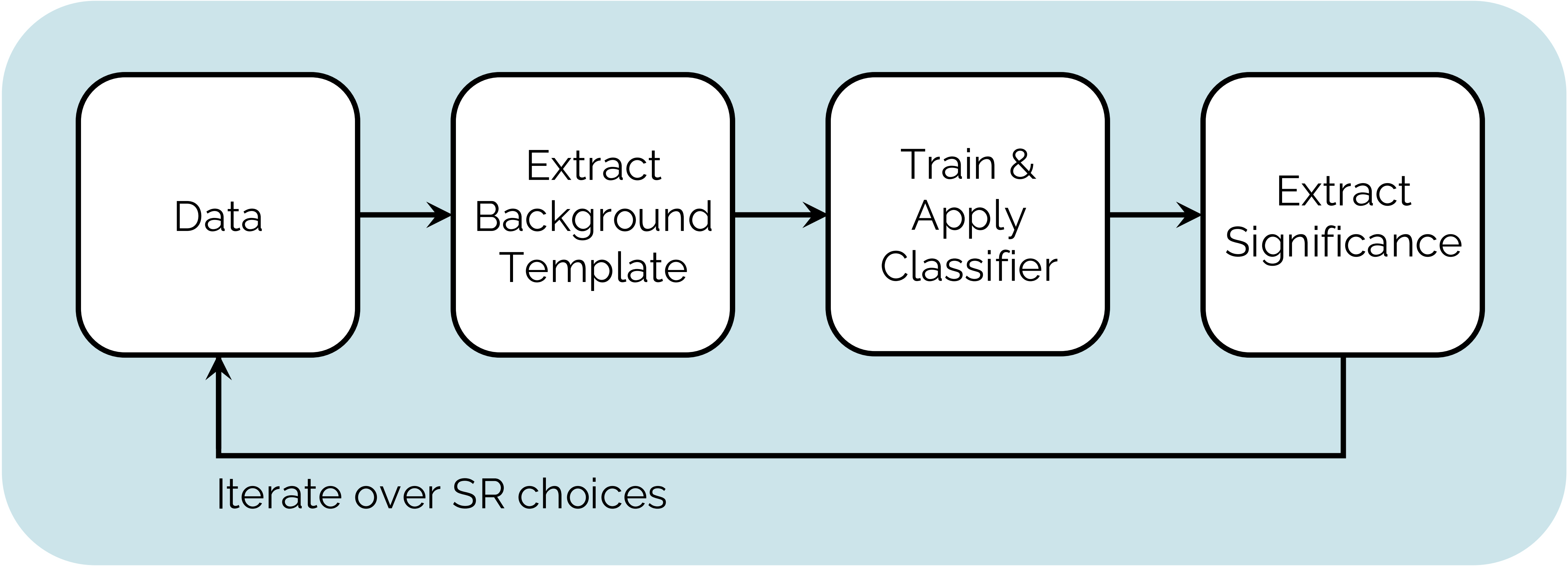


Weakly Supervised Analysis Chain

Full Analysis Chain



Recent Progress

Warning: This slide is not exhaustive!

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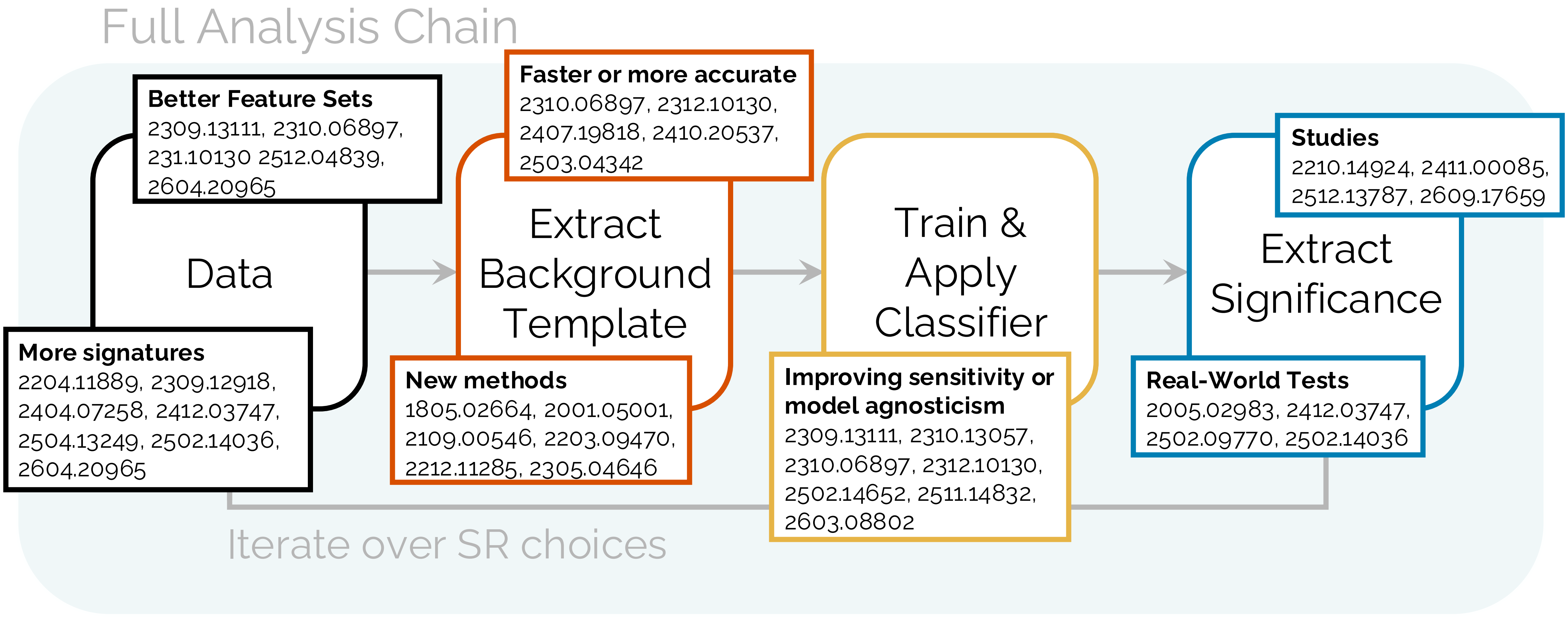
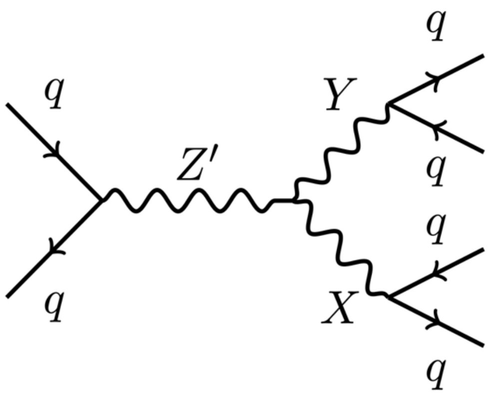


Data: Where We Started

Benchmark Datasets such as LHCO Olympics R&D data set [2101.08320]

→Compare method performance between different papers



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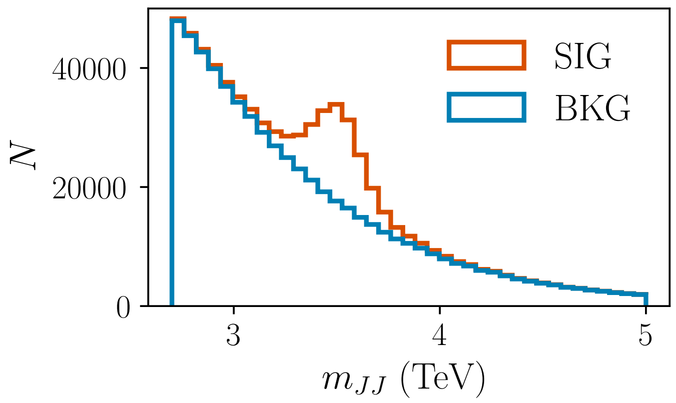
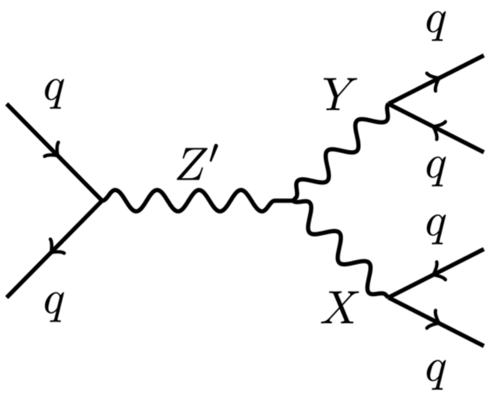
Signature
Resonance (dijet)





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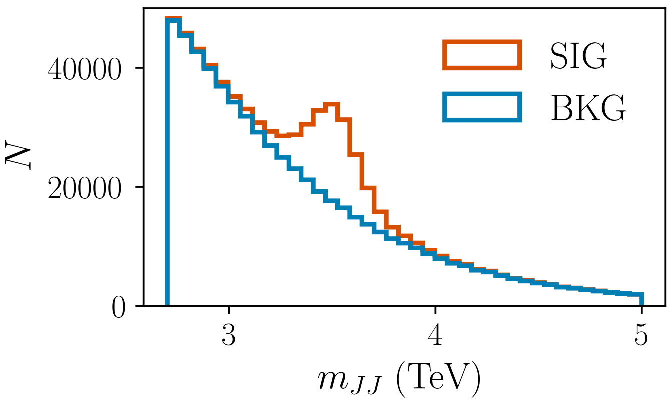
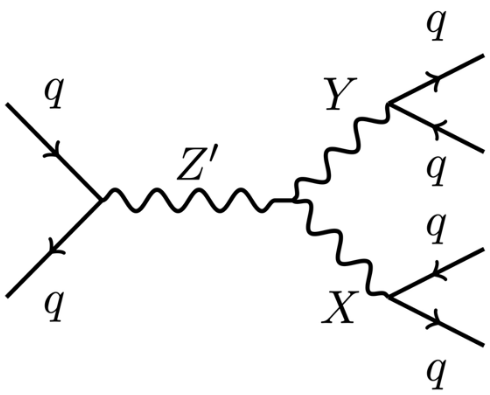
Signal

2-prong jets





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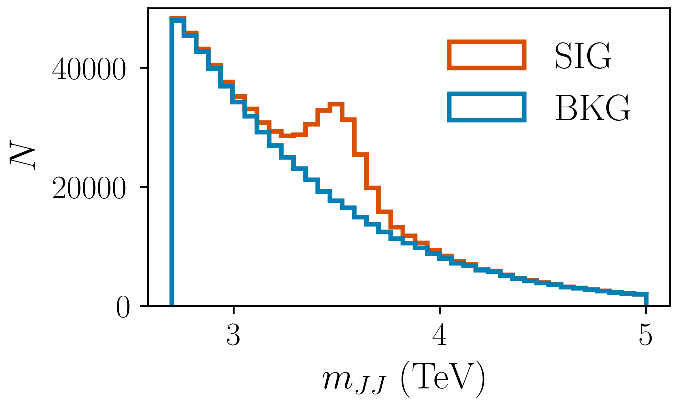

Signal
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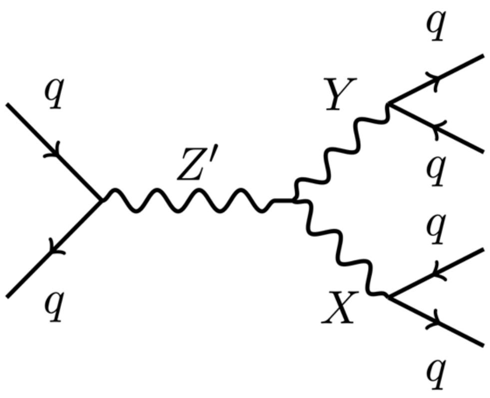
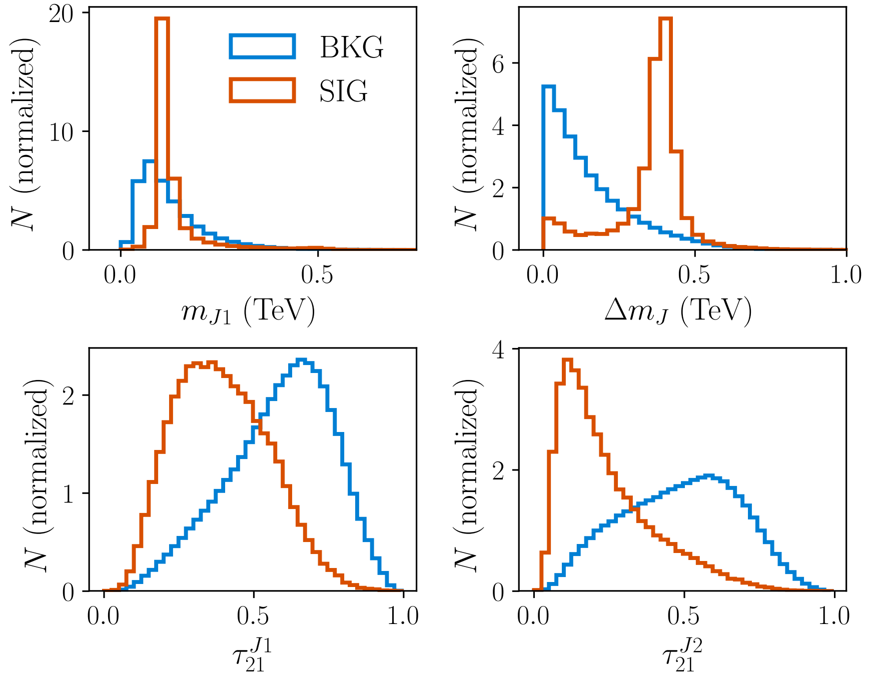
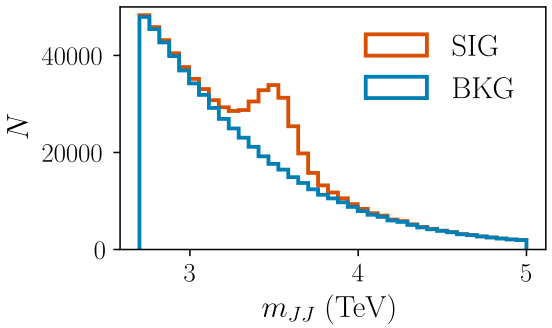


Feature Space
Few high-level observables



Data: Broadening the Signature Range

Starting point:
Dijet Resonance



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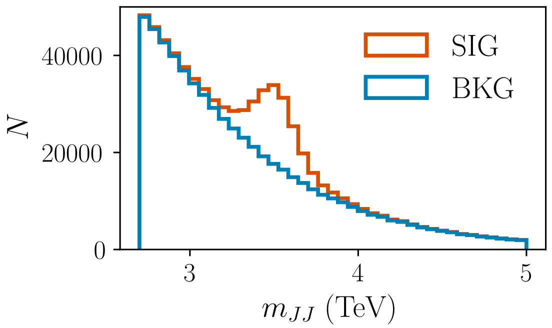

Mixture of dijet and trijet decays in resonant signal

LHCO Black Box 3, resonant G_{KK} with two decay modes:

- $G_{KK} \rightarrow Rq$, where $R \rightarrow qq$
- $G_{KK} \rightarrow qq$

→ Need to define a resonant mass carefully

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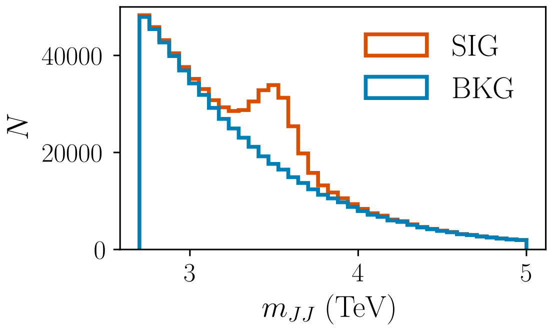

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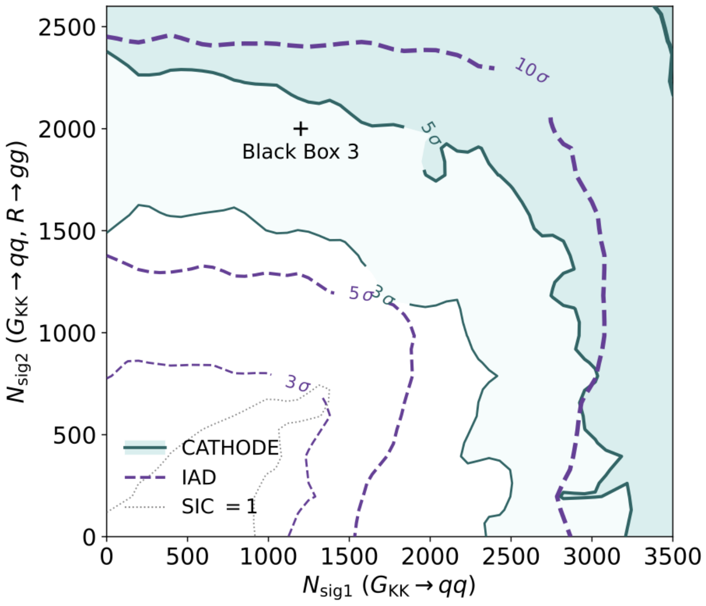
[2609.00132]



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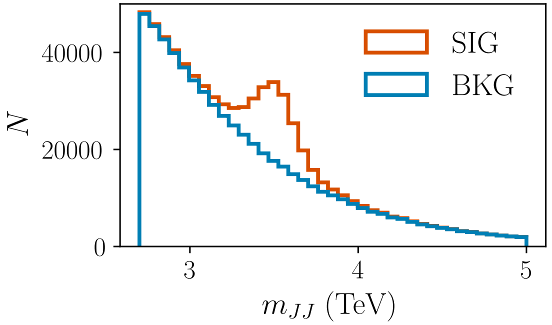

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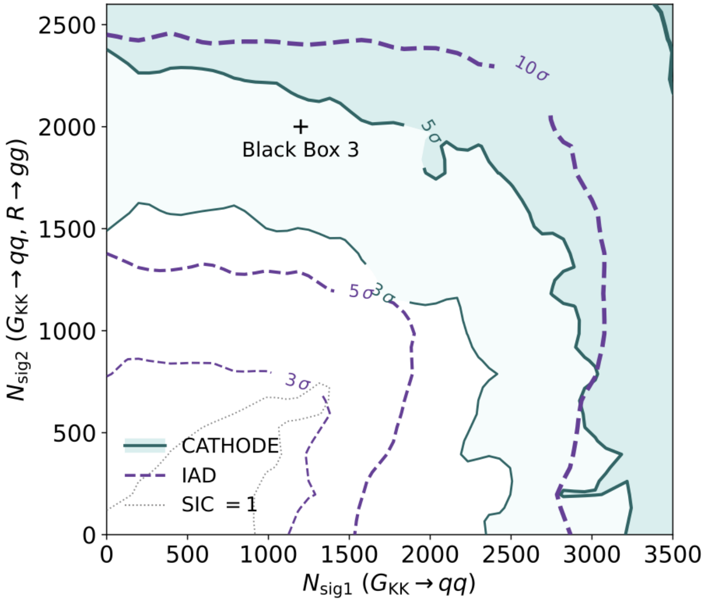
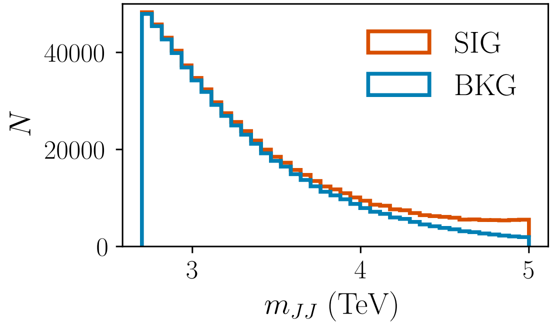


Tail-based anomalies

[2309.12918, 2404.07258]



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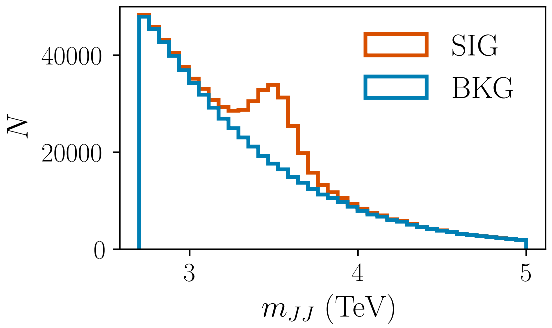

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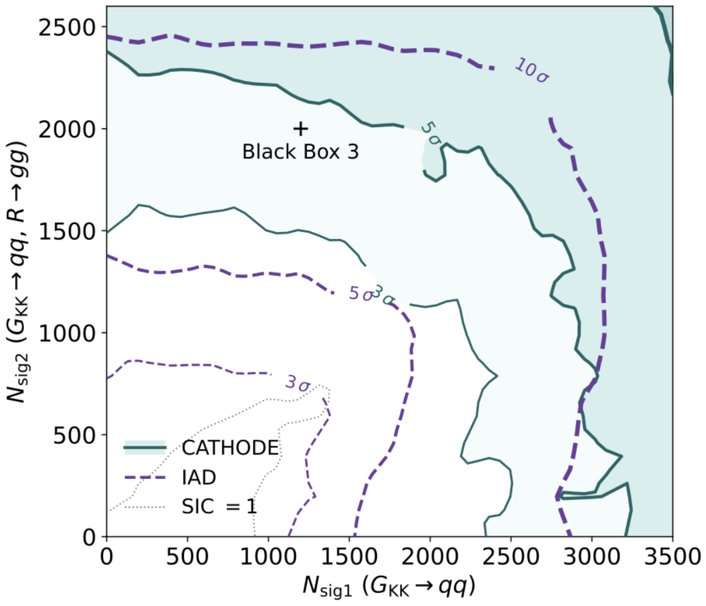

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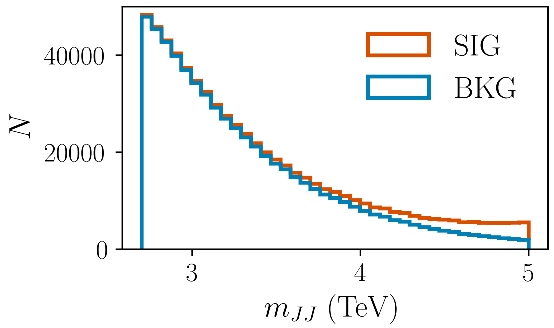
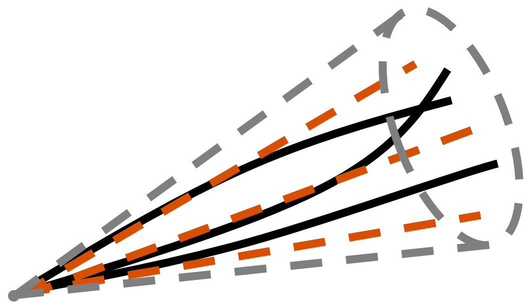


Dark sector jets

[2202.00686, 2204.11889]



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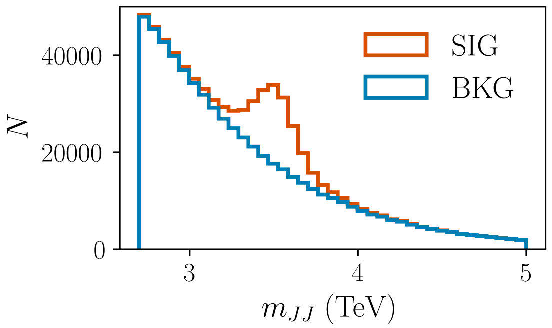

Related talks

→ *Dennis' talk for Higgs+X models*

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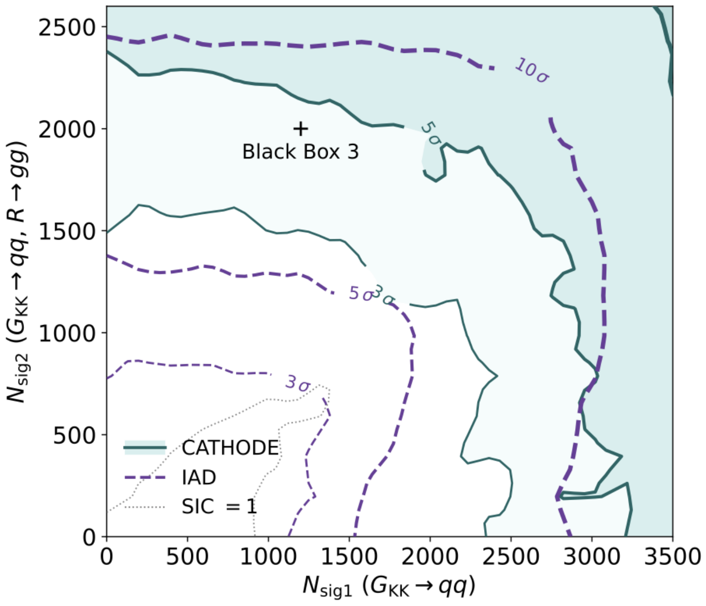

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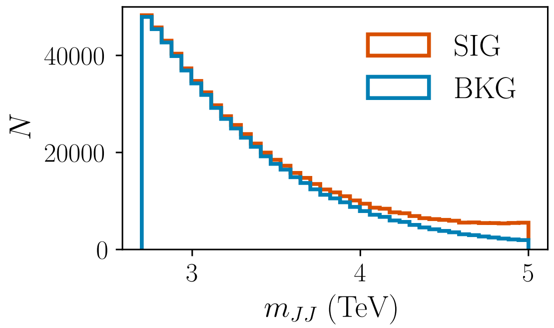

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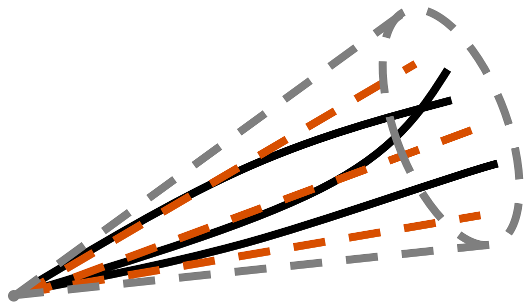
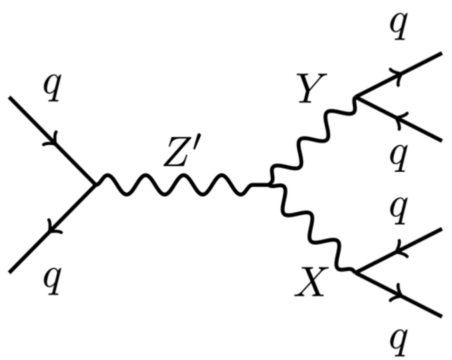


Data: Studying Sensitivity to More Signals

Starting point:
2-prong jets

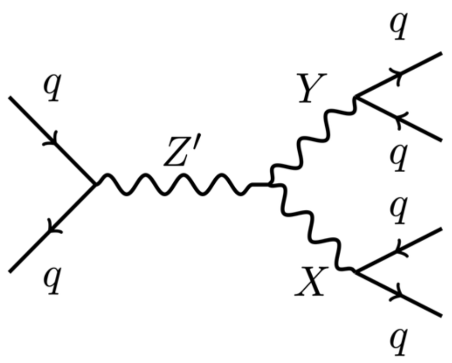


Data: Studying Sensitivity to More Signals

Testing Signal Sensitivity

- To estimate model agnostic sensitivity, need to consider more signals

Starting point:
2-prong jets



Data: Studying Sensitivity to More Signals

Testing Signal Sensitivity

- To estimate model agnostic sensitivity, need to consider more signals
- Even small changes to the signal can lead to large reduction in sensitivity
  → LHCO signal with $X/Y \rightarrow qqq$

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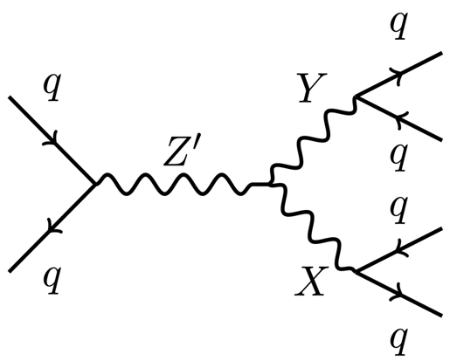

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ETH zürich

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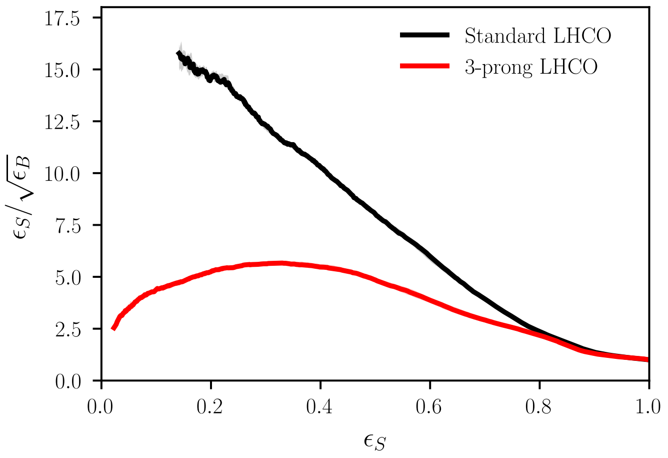

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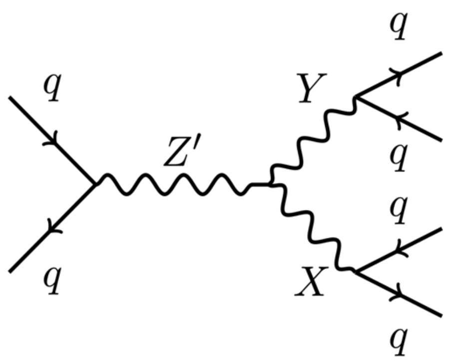

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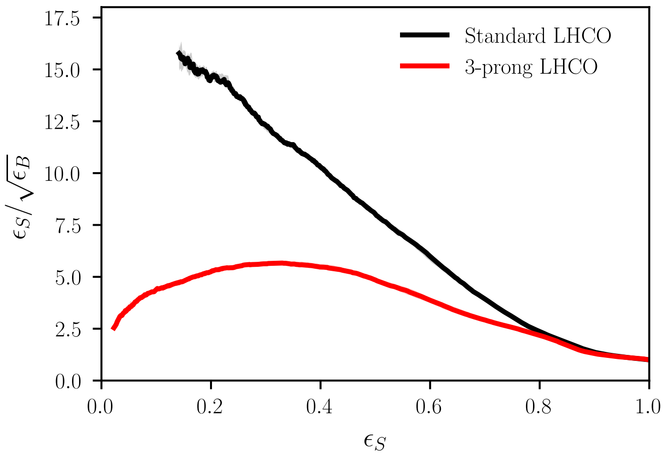

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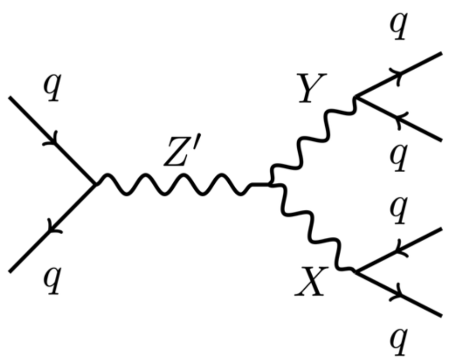

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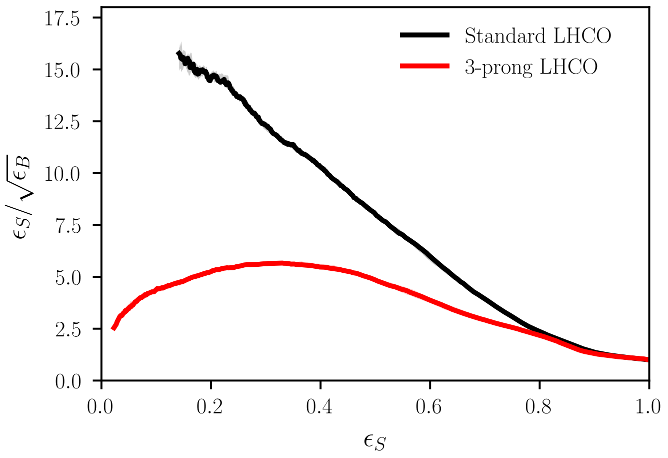

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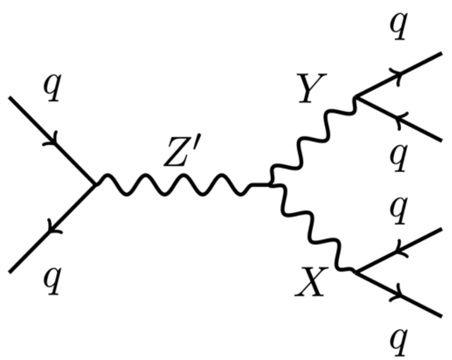

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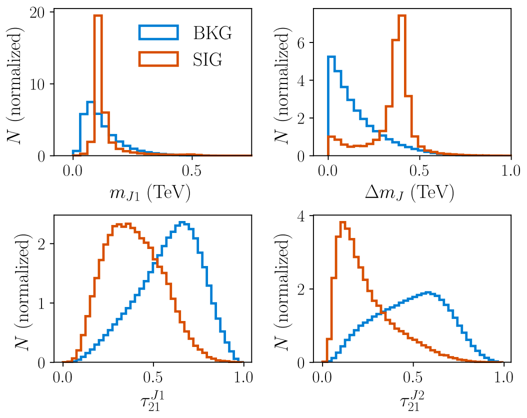

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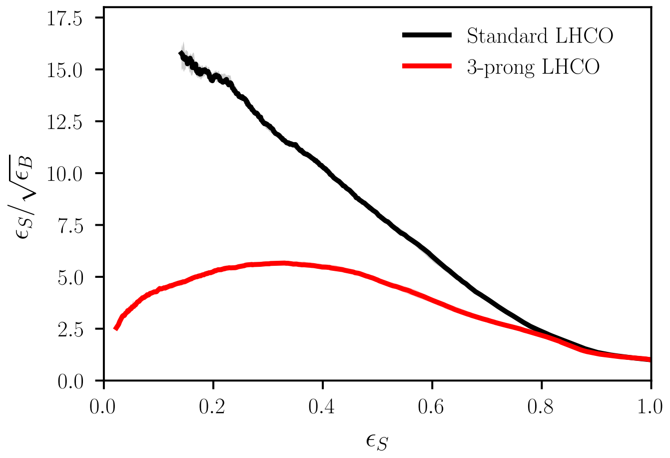

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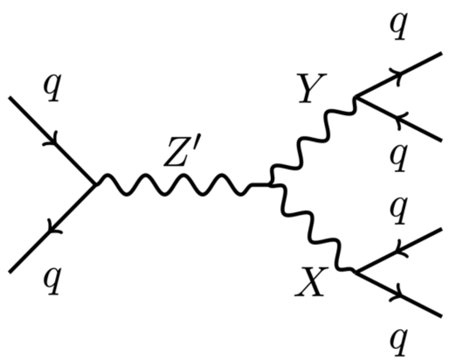

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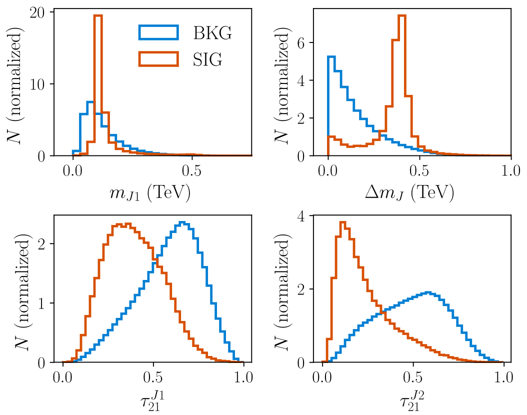

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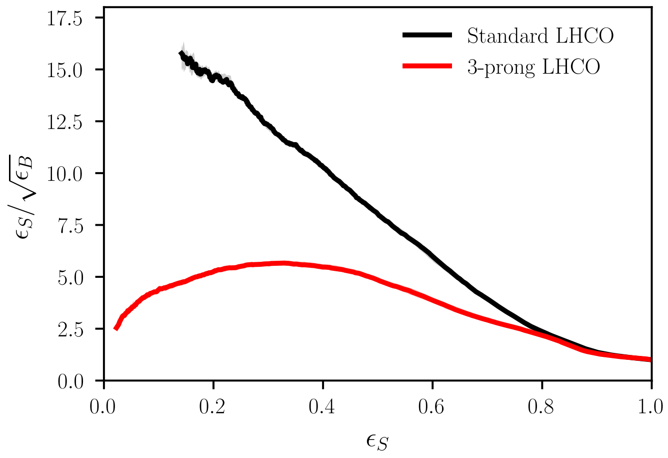

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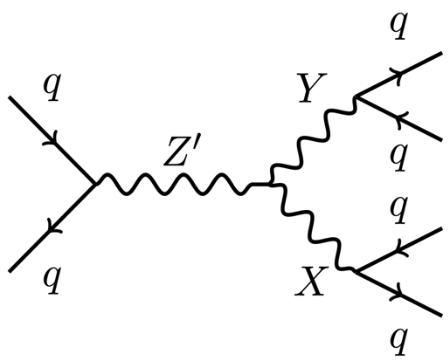

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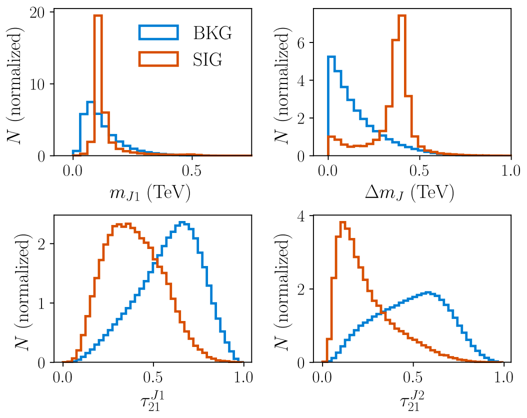

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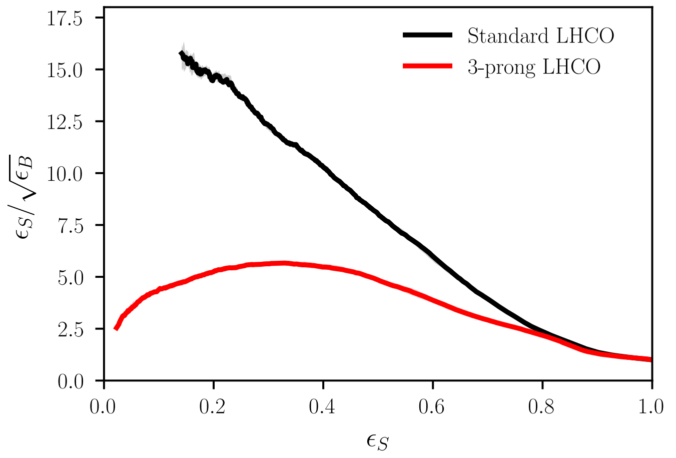

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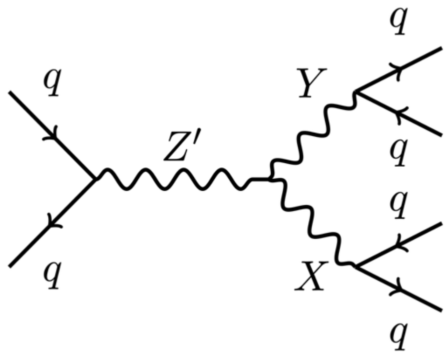

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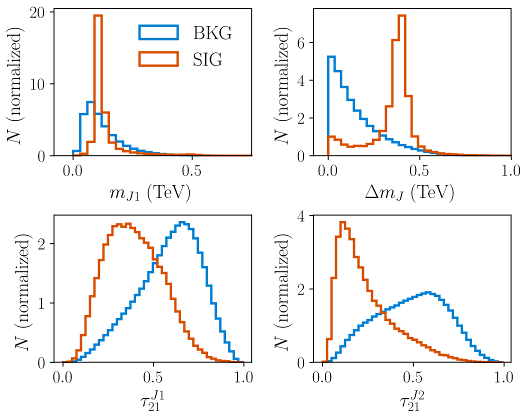

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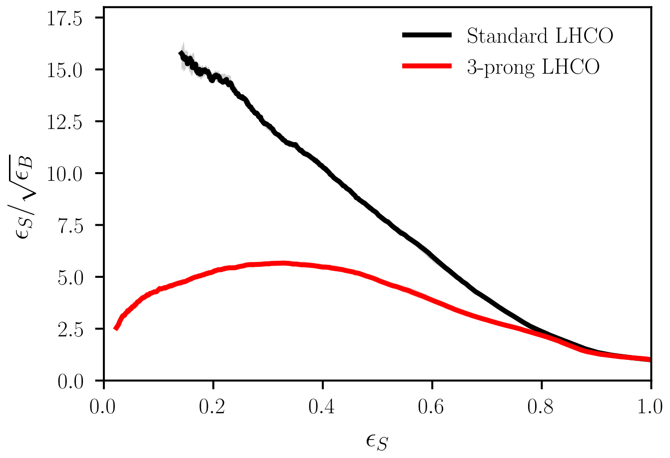

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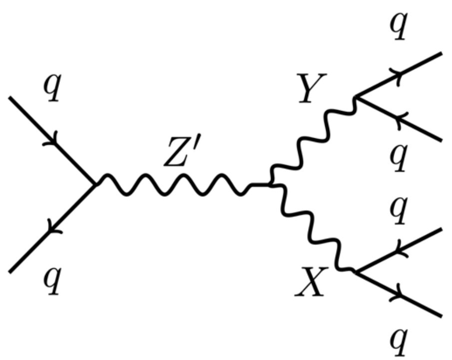

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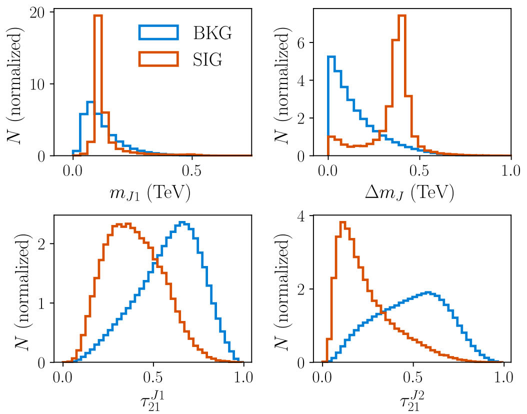

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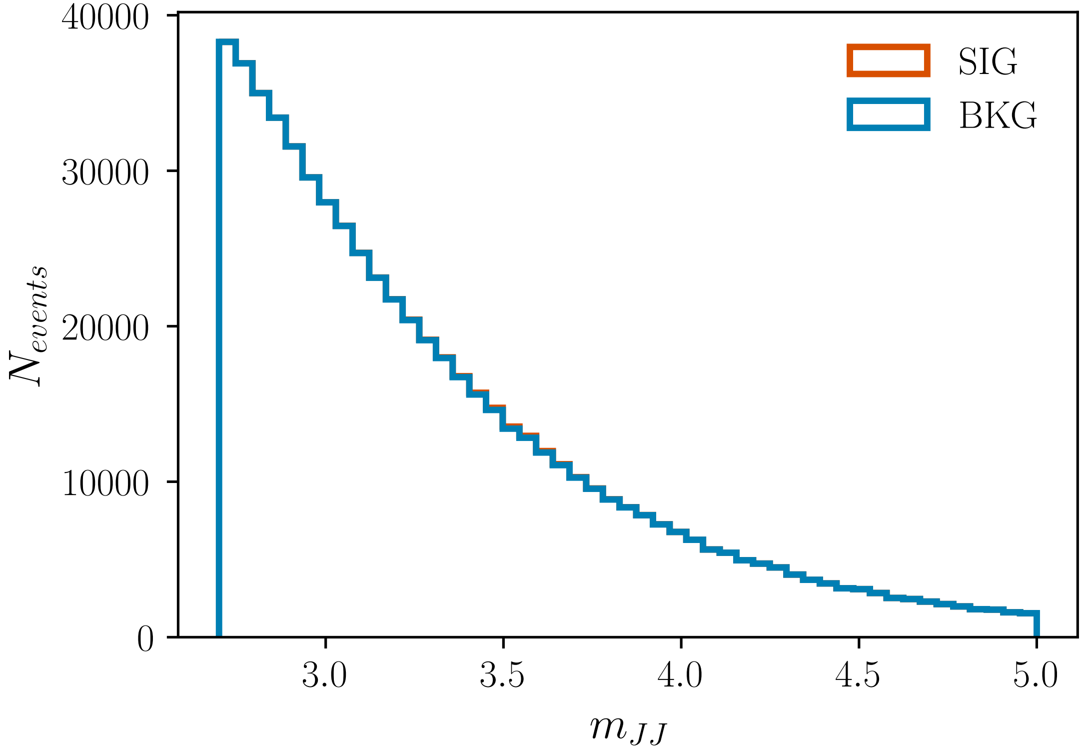
More high-level features

- Features designed to be useful
  → Can typically find low signal injections and find many signals with large feature sets
  → *Lukas' talk*

Background Sculpting: Problem



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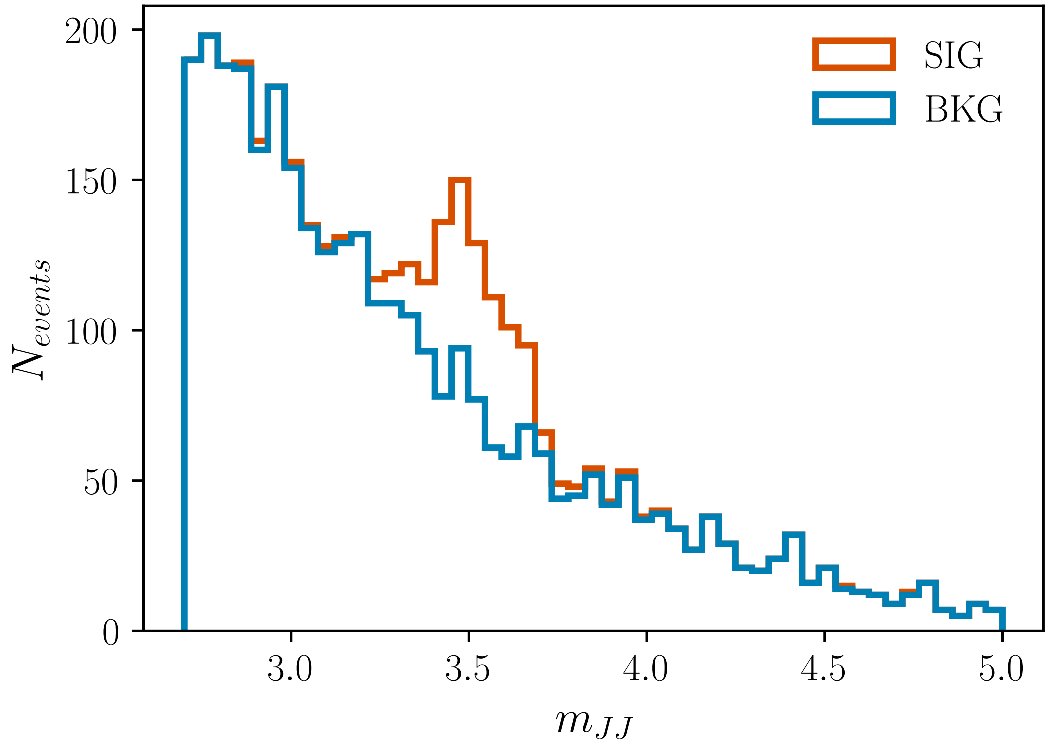

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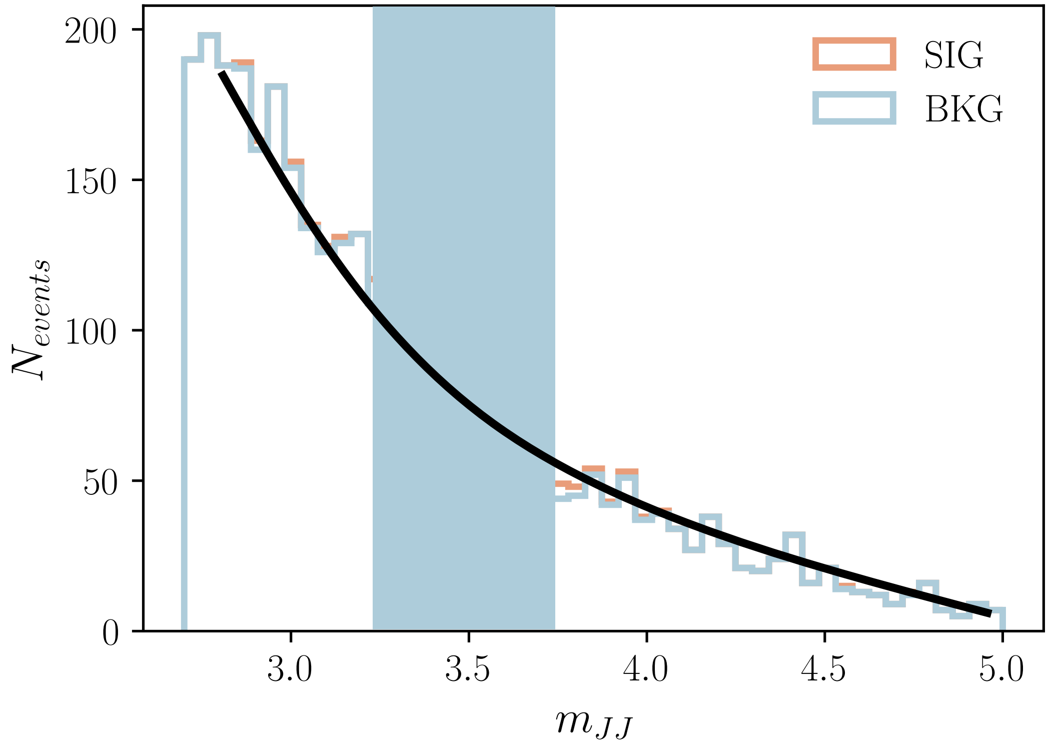

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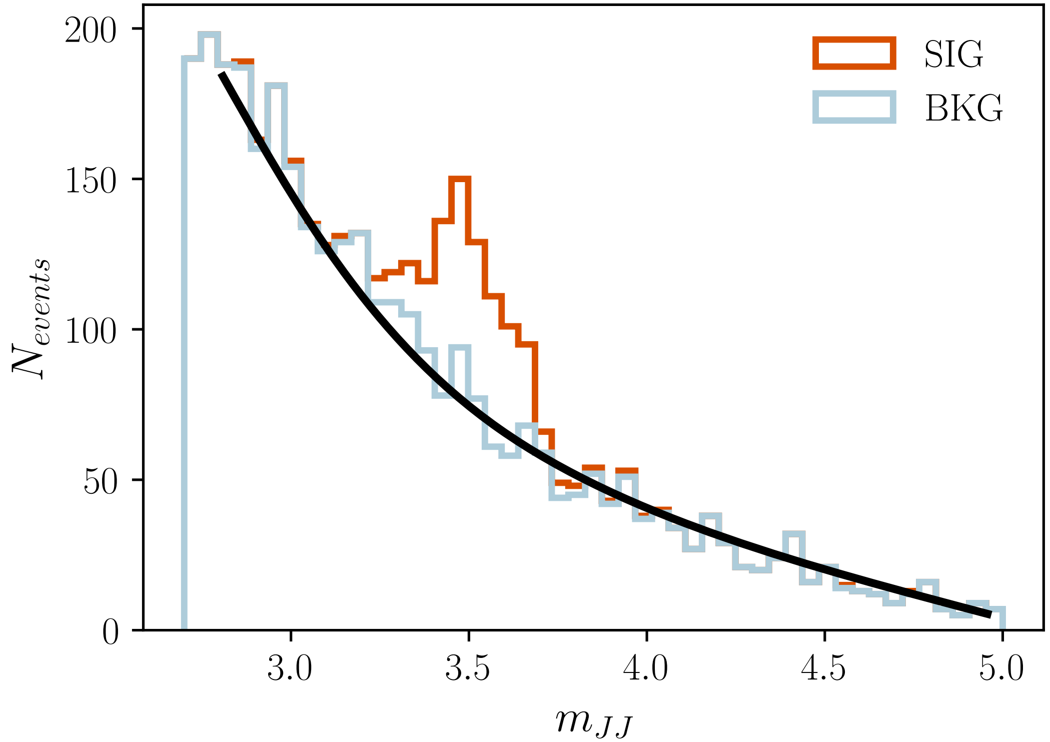
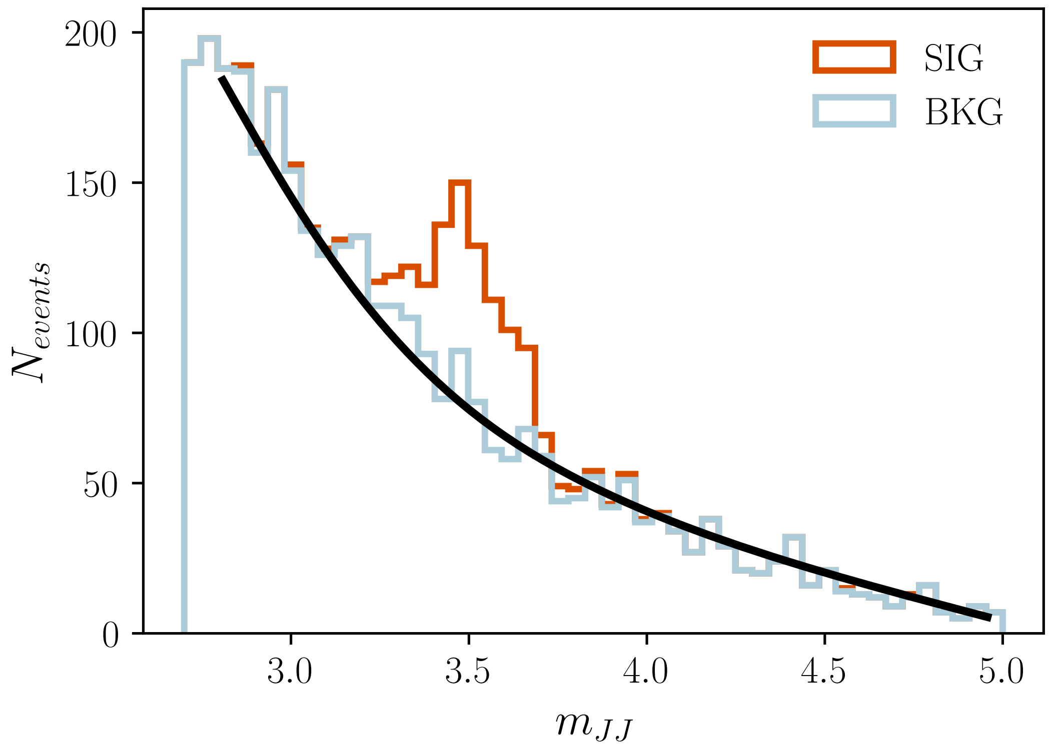


Background Sculpting: Problem

Features uncorrelated with m_{JJ}



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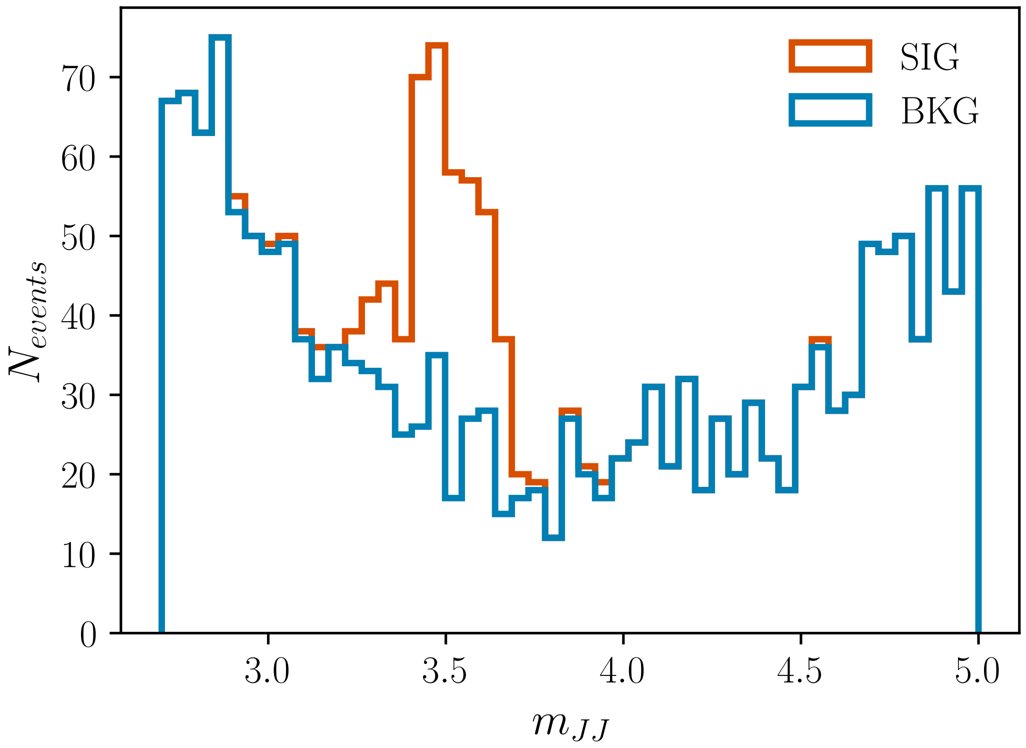

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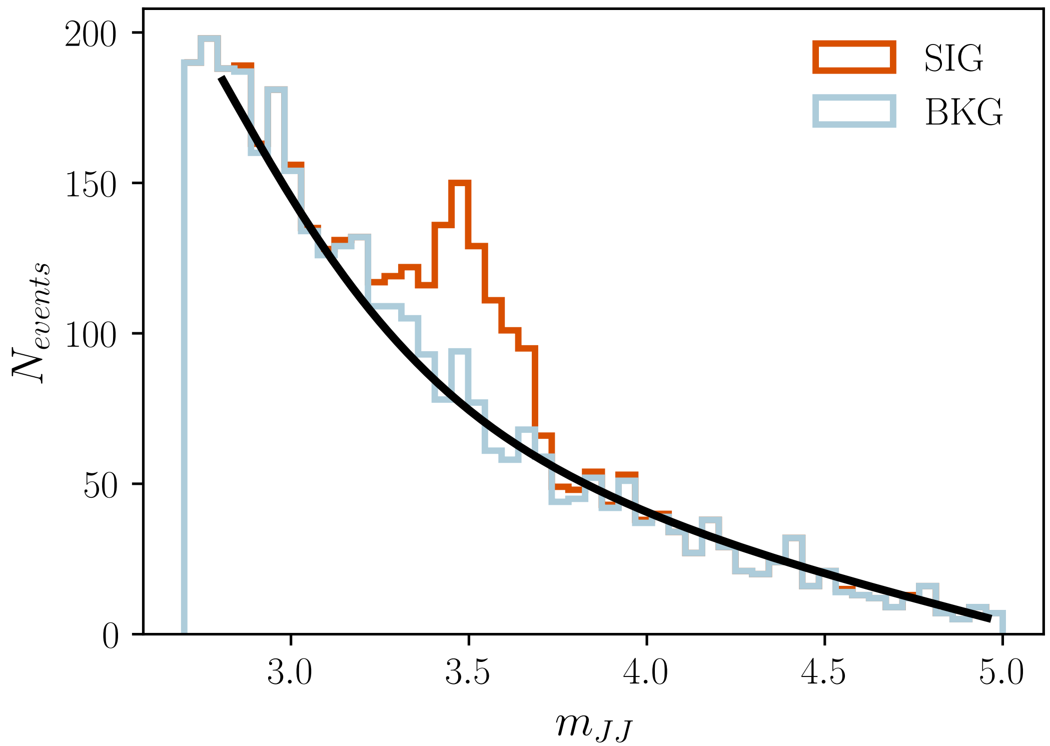

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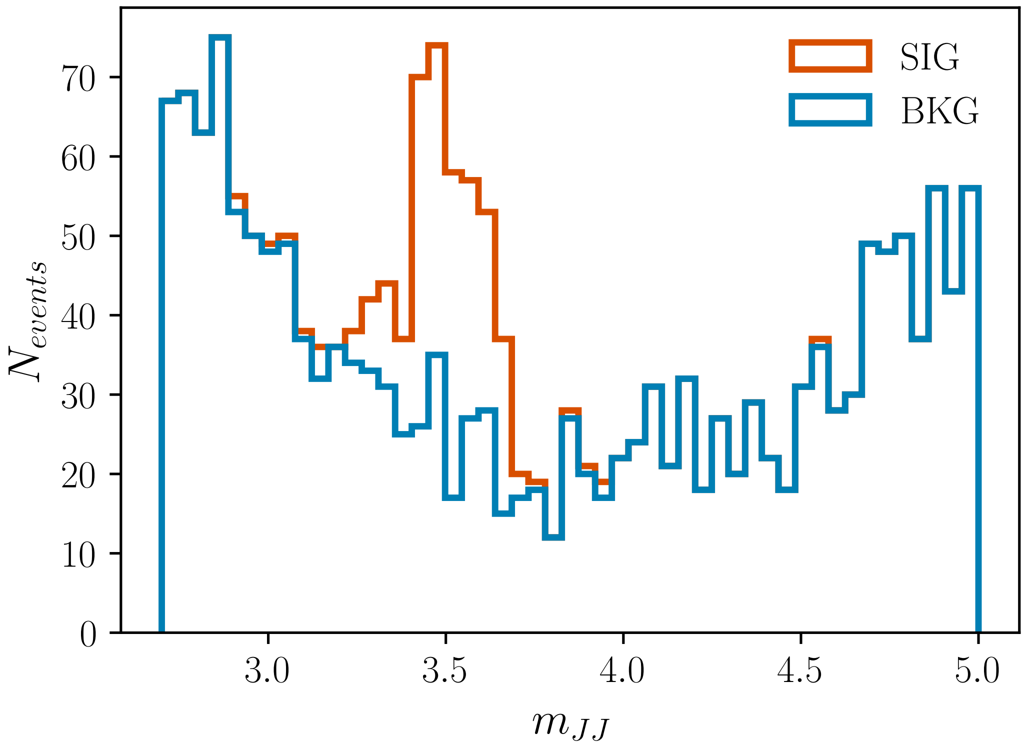

In some cases, fit becomes impossible. In others, sensitivity suffers as fit function becomes more flexible.

Background Sculpting: Solutions

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Decorrelate training input

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ETH zürich

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- Choose feature set explicitly to reduce correlations [2502.09770]

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  → LaCATHODE [2210.14924] allows this for DE-based background templates

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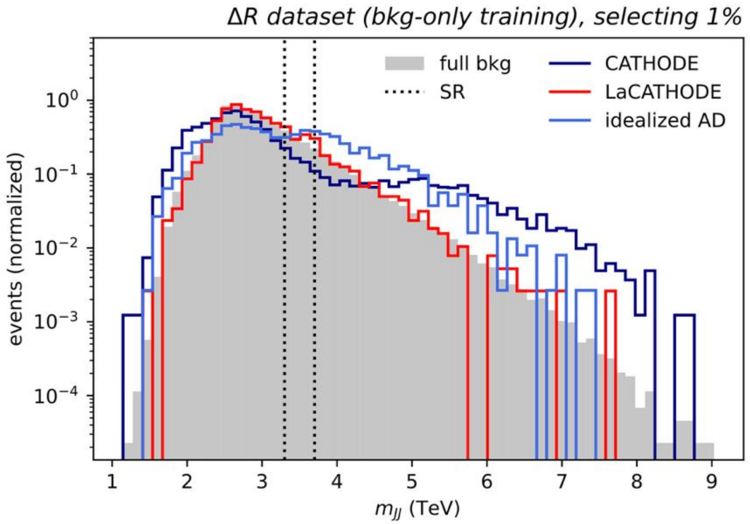

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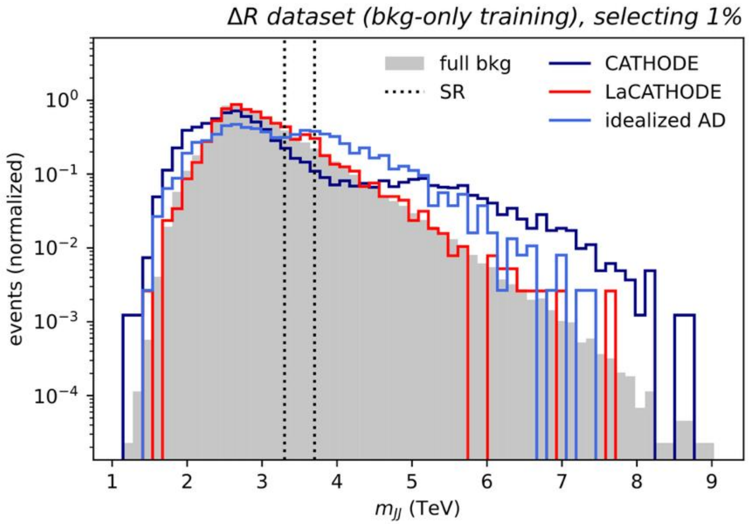

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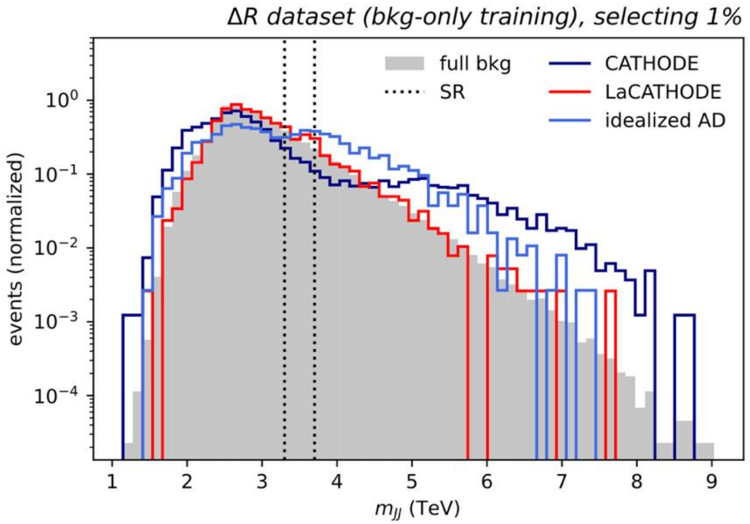

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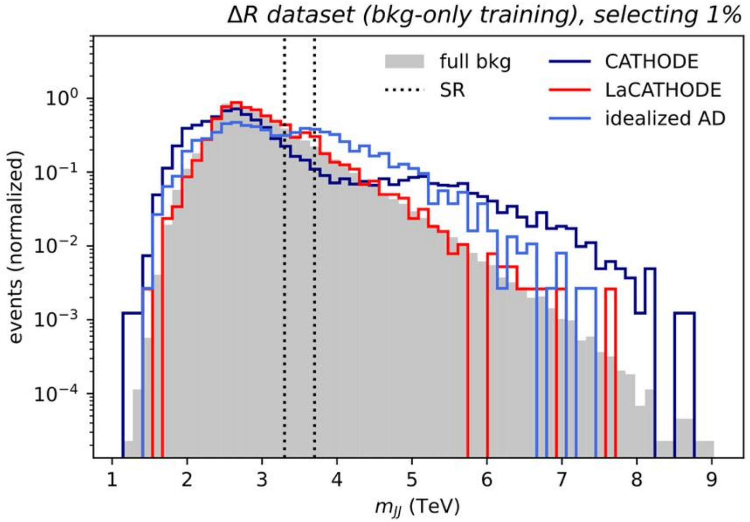

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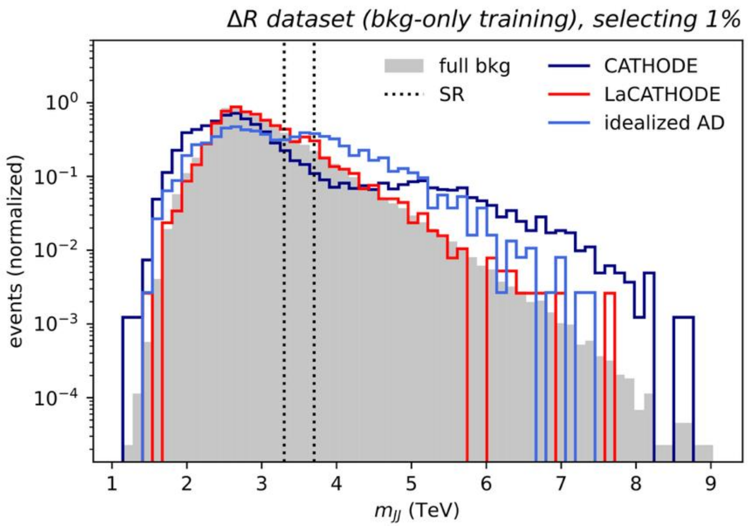

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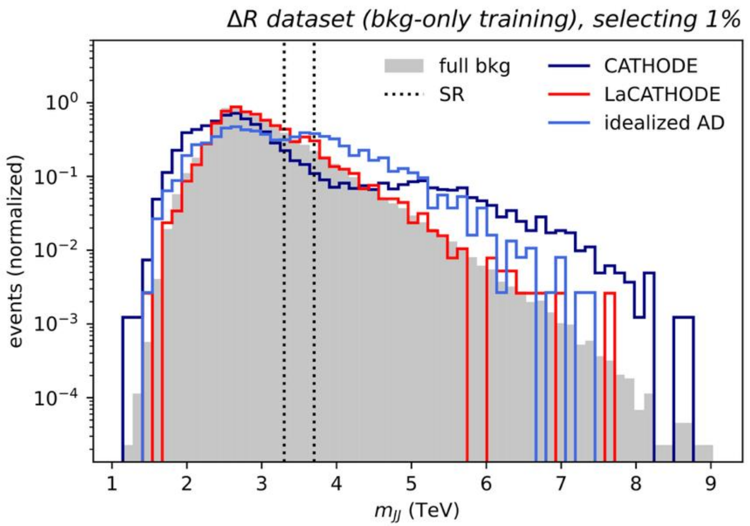

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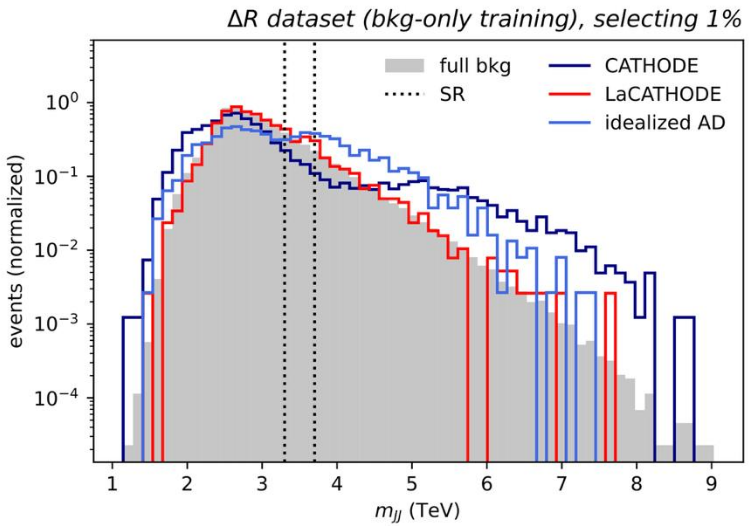

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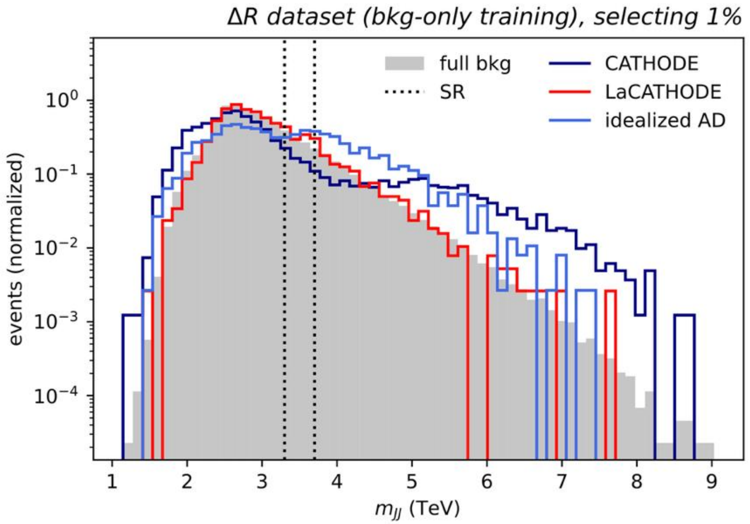

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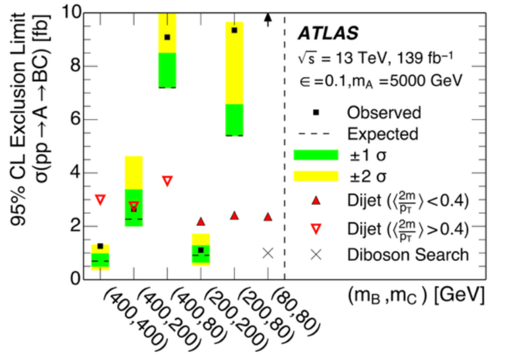
Conducting Analyses

ETH zürich

ATLAS '20 [2005.02983]



1st generation search:

- Simple background template
- Just 2 features
- Simple signal topology

Conducting Analyses

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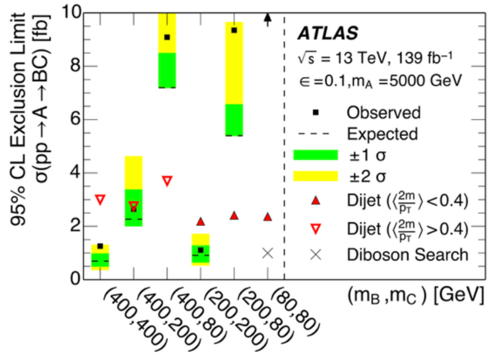

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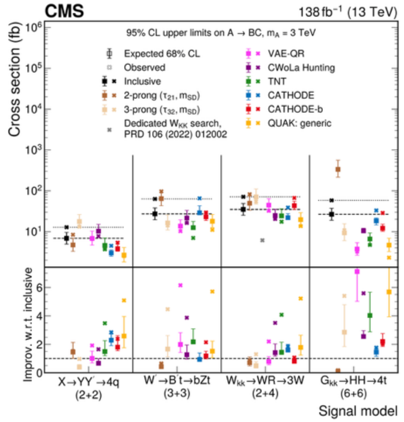
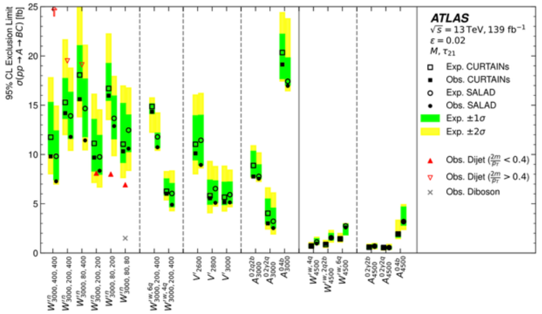


ATLAS '25 [2502.09770]



2^{nd} generation searches improve on:

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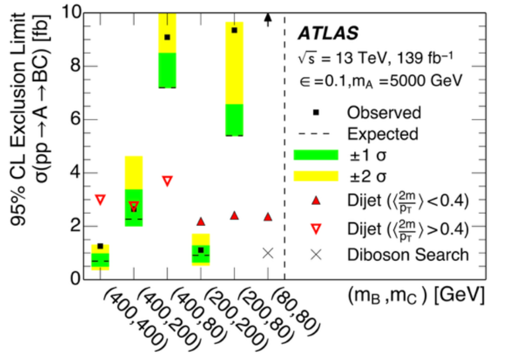

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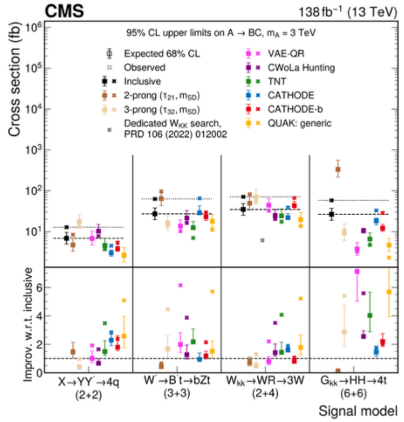

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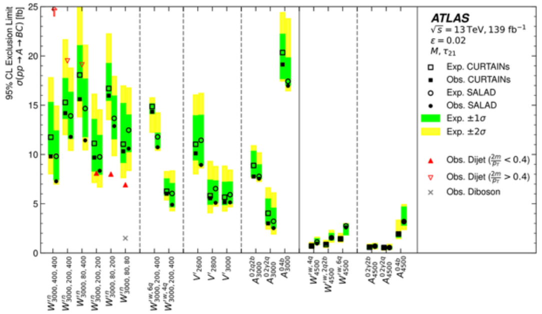

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Newer developments and learnings can be taken into account for 3rd generation searches

→ *Tore's talk on new CMS developments*

Anomaly Detection Task Force

- Task Force within the BSM WG
- First Meeting in May 2026

Marco Letizia
Theory

Tobias Golling
ATLAS

Roberto Seidita
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David Shih
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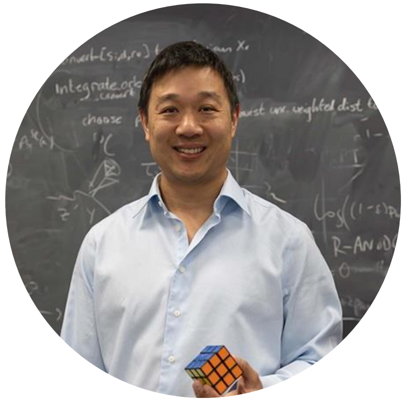

Oz Amram
CMS

Marie Hein
Theory/CMS

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ETH zürich

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- Goals:
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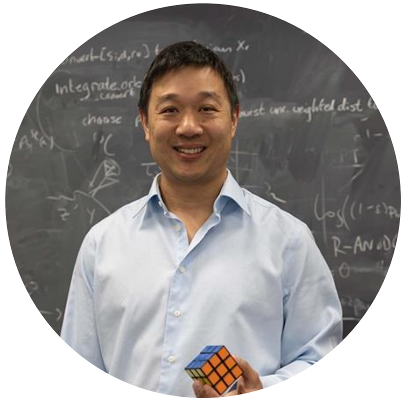

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- Waypoint:
  - Working on AD white paper summarizing state of the art and open questions

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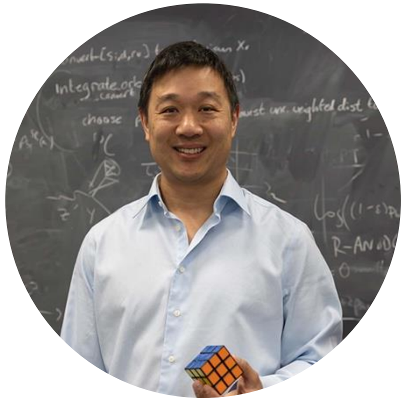

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Kick-Off Meeting and Community Survey

ETH zürich

July 14th 2026

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- Before meeting conducted community survey
  - 55 responses
  - Asked about background of respondents as well as potential, limitations and needs of AD analyses
- During the meeting
  - Presented the survey and ATLAS AD guidelines
  - Had an active discussion about the needs of the community

Survey

Indico

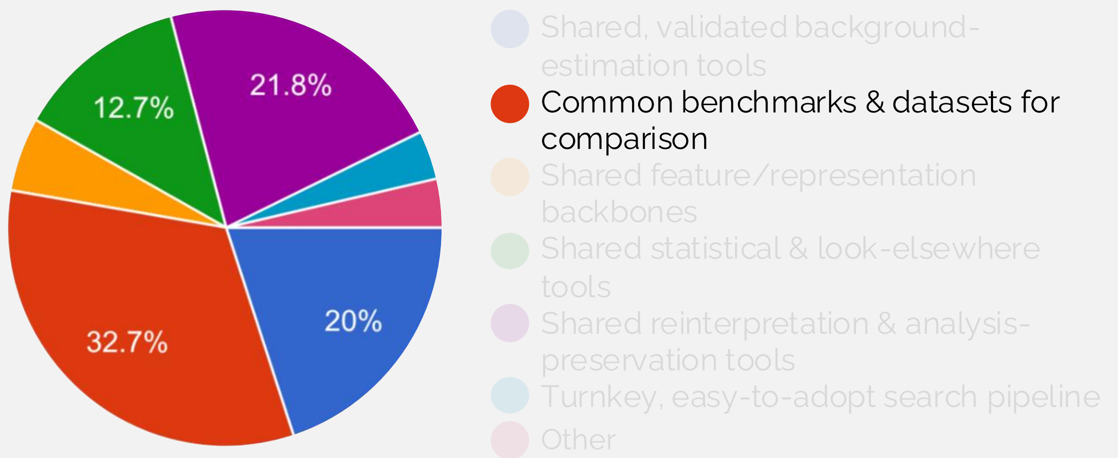
Kick-Off Meeting and Community Survey

ETH zürich

July 14th 2026

- Wanted to get an overview of community opinions on potential of AD and what is needed
- Before meeting conducted community survey
    - 55 responses
    - Asked about background of respondents as well as potential, limitations and needs of AD analyses
- During the meeting
    - Presented the survey and ATLAS AD guidelines
    - Had an active discussion about the needs of the community

Which of these would add the most value if made reusable and standardized across the community?



Survey

Indico

Signal Benchmarks and Common Pool

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September 10th 2026

First topical meeting of the AD task force

16:00 → 16:10 **Introduction** 10m

Sprecher: David Shih, Dr. Marco Letizia (INFN e Universita Genova (IT)), Marie Hein (RWTH Aachen University), Oz Amram (Fermi National Accelerator Lab. (US)), Roberto Seidita (ETH Zurich (CH)), Tobias Golling (Universite de Geneve (CH))

16:10 → 16:30 **ATLAS Efforts** 20m

Sprecher: Theresa Reisch (Universite de Geneve (CH))

ATL-COM-PHYS-2...

16:30 → 16:45 **Dark Shower Models** 15m

Sprecher: Kevin Pedro (Fermi National Accelerator Lab. (US))

dark_showers.mp4 | Dark Showers Tas...

16:45 → 17:05 **Theory Perspective** 20m

Sprecher: Guilherme Guedes (CERN)

AD_meeting.pdf | theory_perspectiv... | theory_perspectiv...

17:05 → 17:35 **Lightning Talks** 30m

Sprecher: Andre Lessa (IFGW - UNICAMP), Andre Lessa (Universidade de Sao Paulo), Dennis Noll (Stanford University), Julia Lynne Gonski (SLAC National Accelerator Laboratory (US)), Frau Swagata Biswas (National Institute of Technology Durgapur), Tania Robens (Rudjer Boskovic Institute (HR))

0910_jgonski_lhc... | 260910_noll-higg... | ADTaskForceMee... | AD-Taskforce_Sw... | andre_lessa.mp4

dennis_noll.mp4 | julia_gonski.mp4 | model_spec_robe... | swagata_biswas.... | tania_robens.mp4

Future Plans & How to Contribute

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Continuing to solicit input, e.g. with a

- Meeting with AD sceptics
  - Identify limitations of AD through listening to their concerns
  - Convince them that AD is useful
- Meeting on reinterpretation of AD analyses
- Pheno-experiment feedback session
  - Why are some things adopted and others not?
  - Talk about communication pathways
  - How to get from proof-of-concept to analyses

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We want the task force to be a useful resource for the community, so we want your contribution!

Mattermost invite to LHC-BSM-WG
→ Join, then join "LHC Anomaly Detection Task Force"

E-Group invite