Discovering Unanticipated New Physics with Machine Learning

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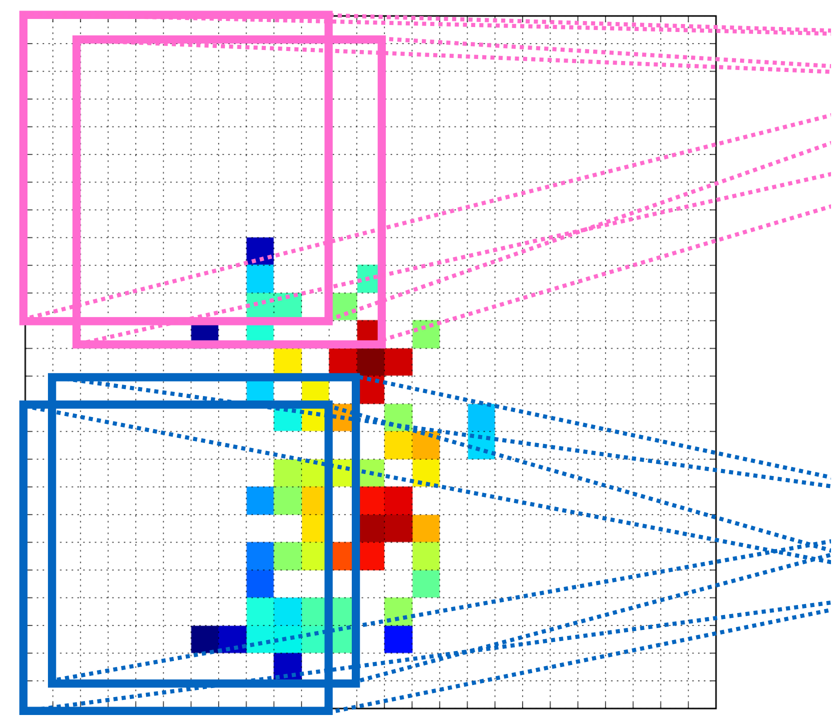

BERKELEY LAB

BIDS
BERKELEY INSTITUTE FOR DATA SCIENCE

HKUST IAS
HEP workshop
Jan. 15, 2021

Outline

Part I: **Brief motivation** (see also David's talk)

Part II: **New methods**

CWoLa, SA-CWoLa, and SALAD

Part III: **First results from data**

Part IV: **Outcome of the LHC Olympics**

(Brief) Motivation

Theoretical and **experimental** questions motivate a deep exploration **of the fundamental structure of nature**

Dark matter

Strong CP

Hierarchy problem

Dark energy

Flavor puzzles

Baryogengesis

We have performed thousands of hypothesis tests & have no significant evidence for physics beyond the Standard Model

Three possibilities

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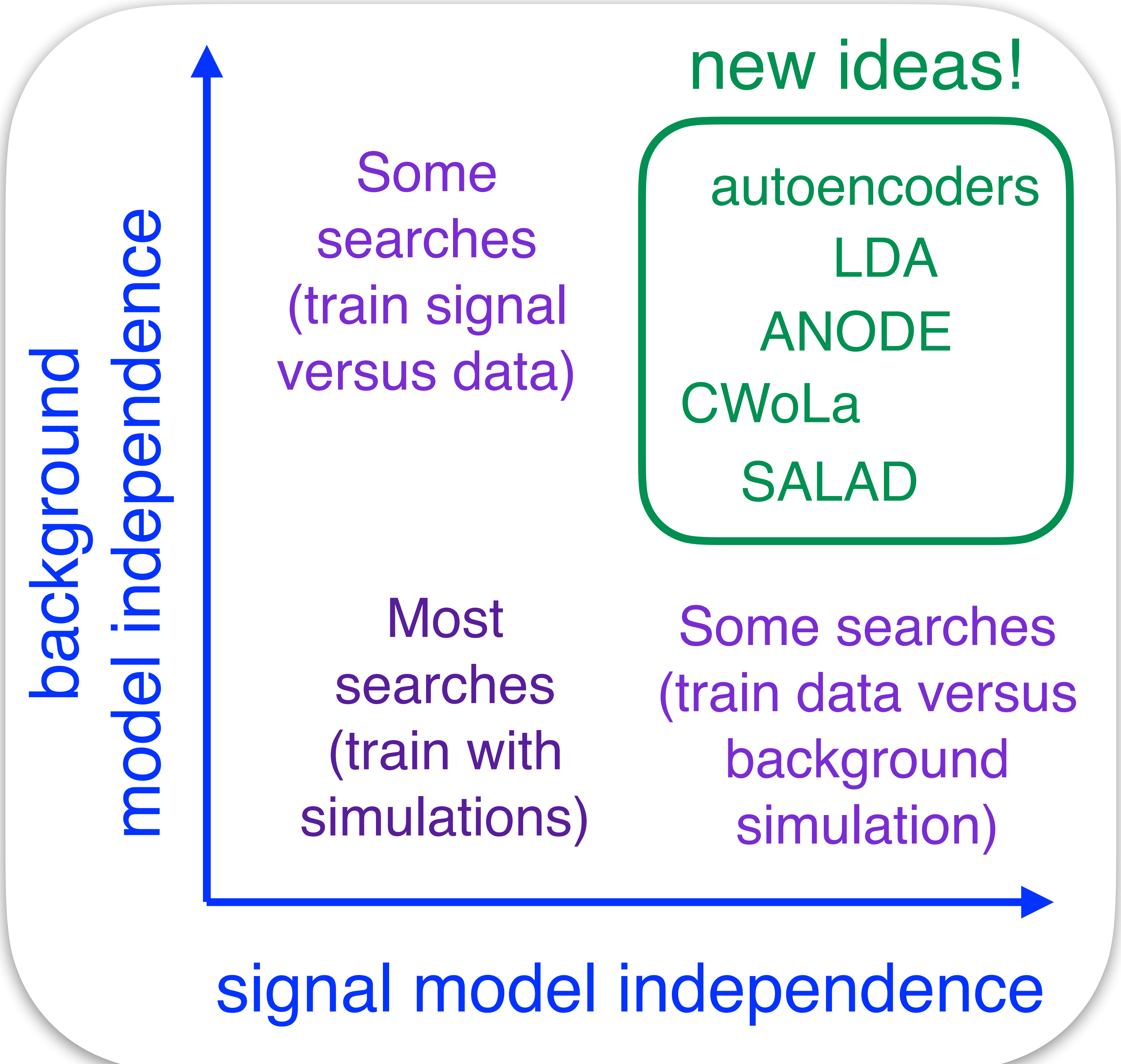
Three possibilities

This is what keeps me up at night!

(3) We are not looking in the right place

New Methods



There are many new ideas that make use of modern machine learning

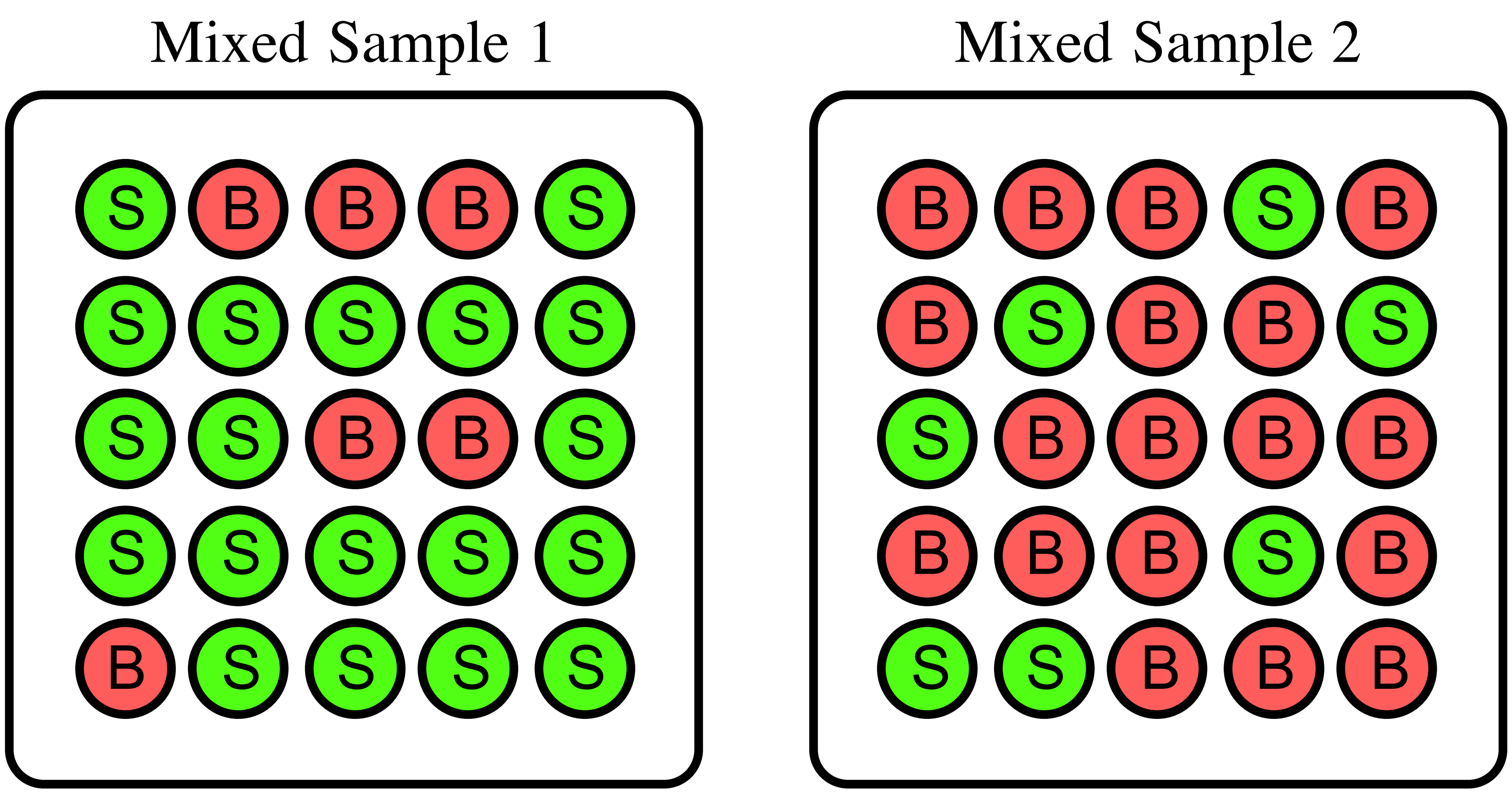
The goal is to learn **directly from data**, injecting as little bias as possible

N.B. this is just for signal sensitivity - there is also model dependence for determining the background

BN and D. Shih, 2001.04990

New Methods I: CWoLa

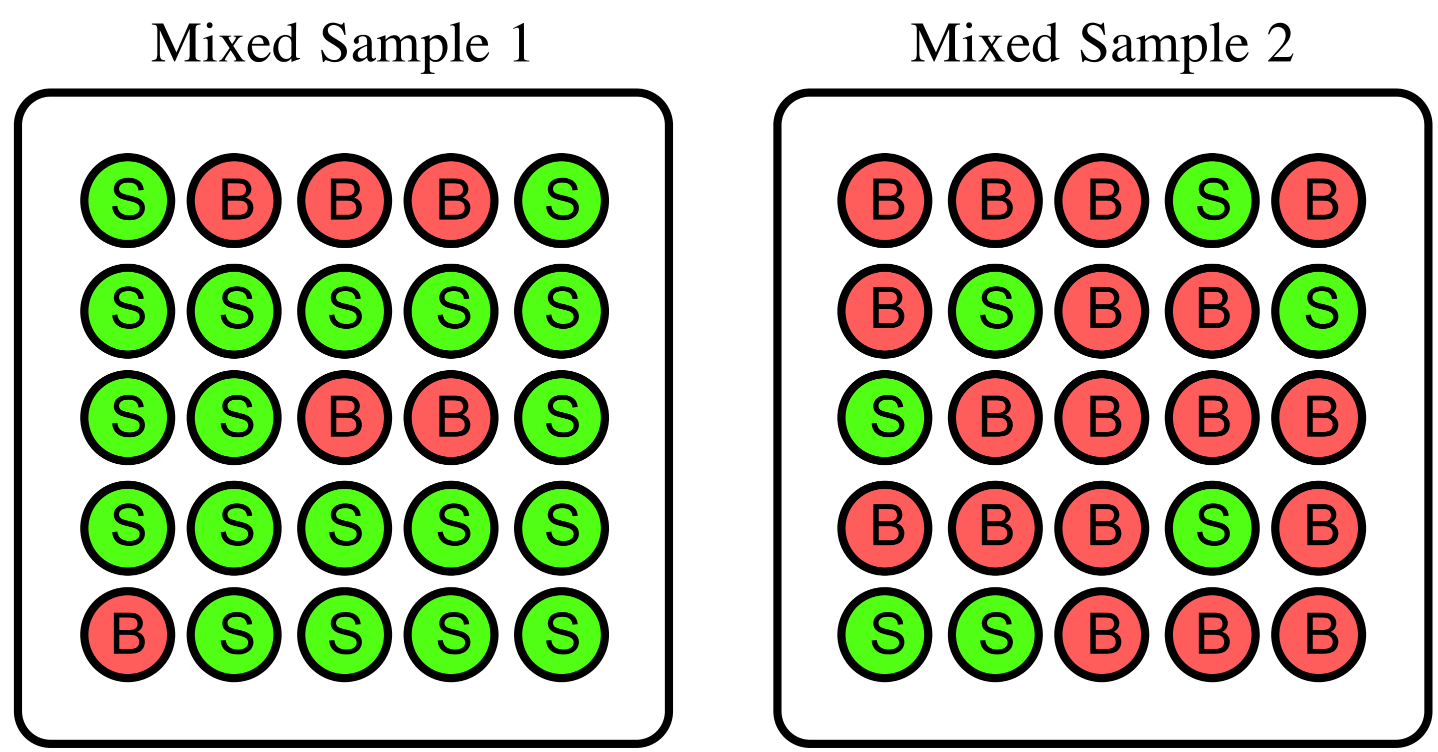
Data are unlabeled and in the best case, come to us as mixtures of two classes (“signal” and “background”).



(we don’t get to observe the color of the circles)

Weak supervision:
Classification Without Labels

Can we learn without any label information?



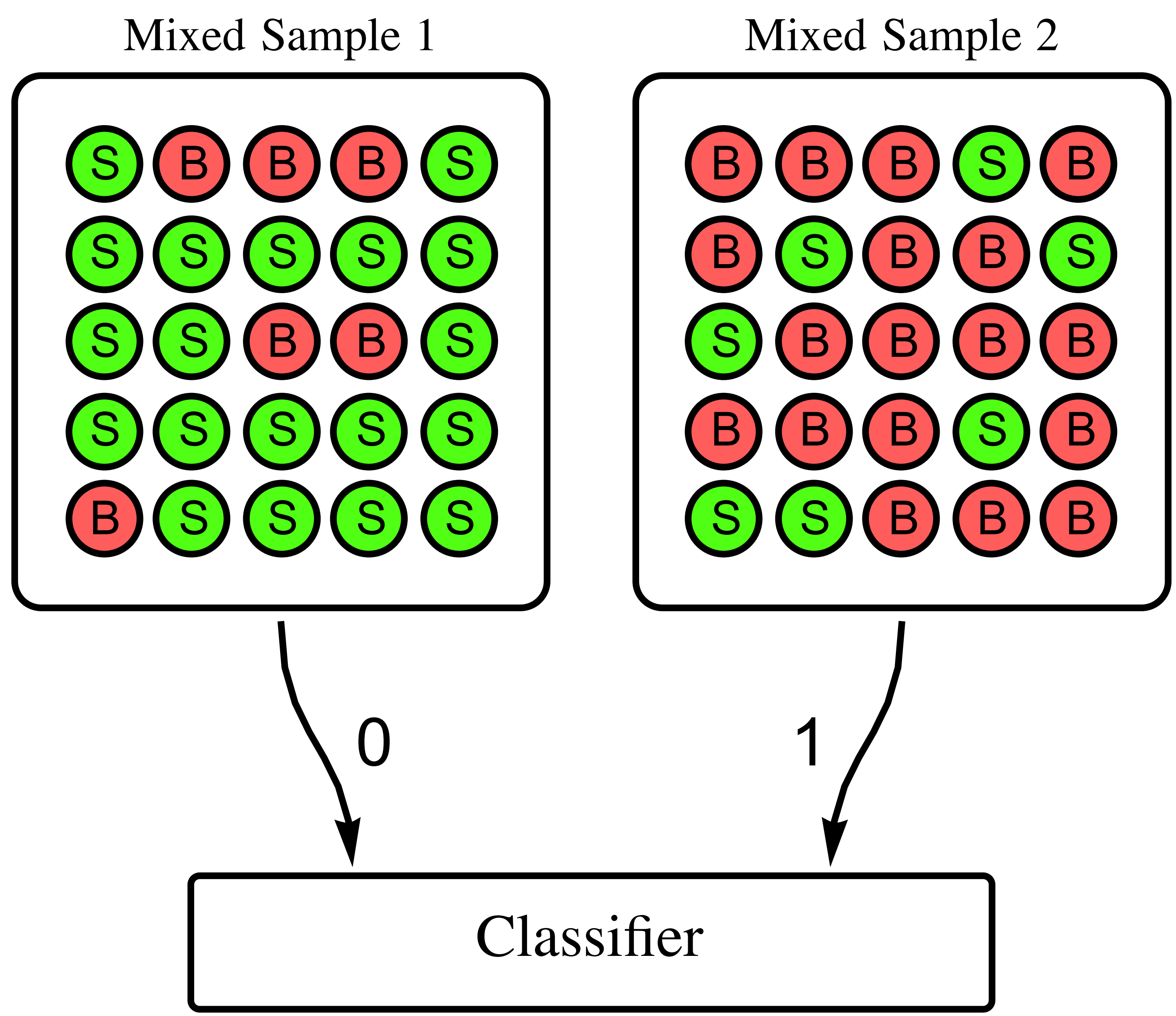
E. Metodiev, BPN, J. Thaler, JHEP 10 (2017) 51

Weak supervision: *Classification Without Labels*

Can we learn without any label information?

Yes !

Training on impure samples is (asymptotically) equivalent to training on pure samples



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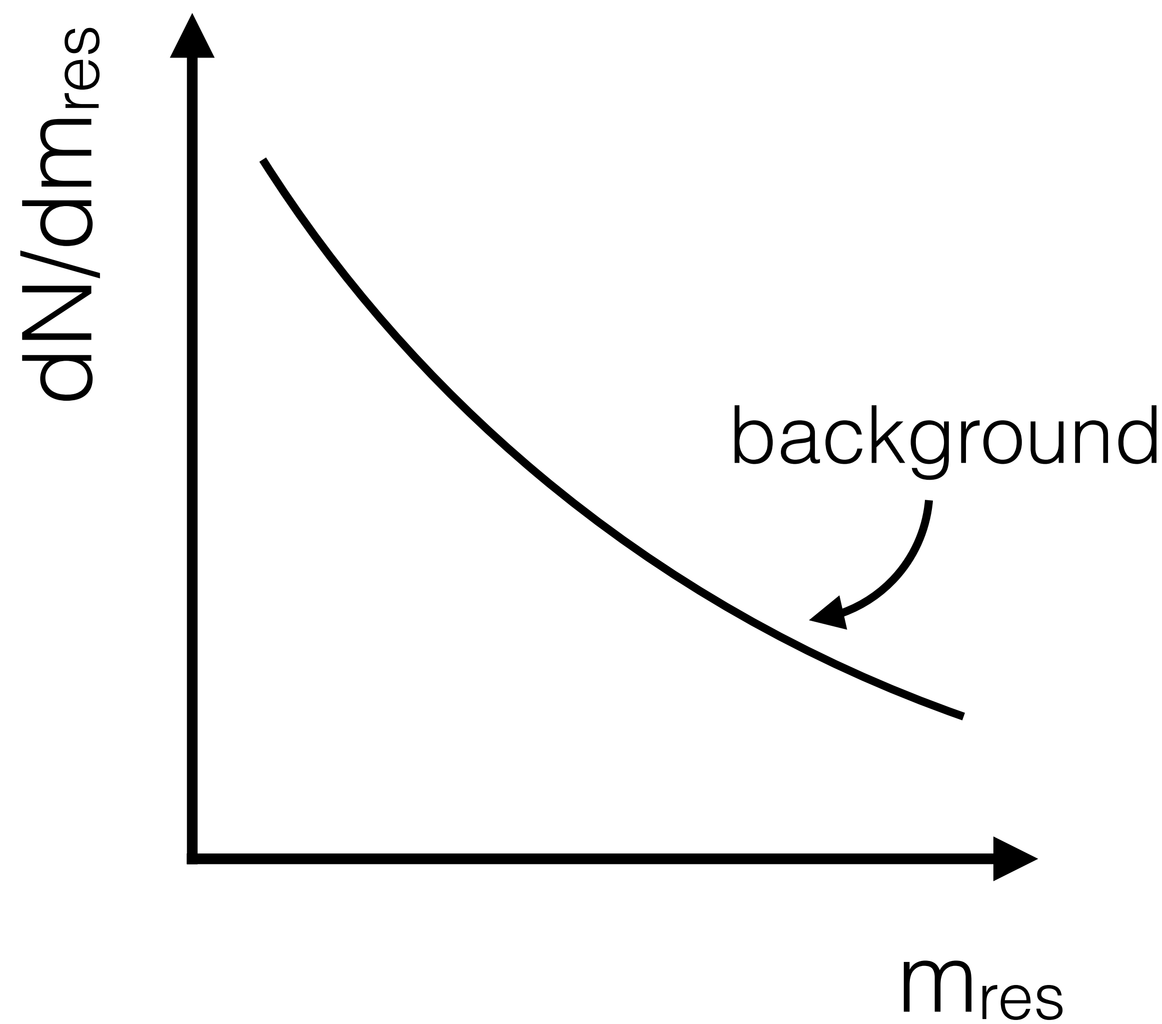
CWoLa for anomaly detection

J. Collins, K. Howe, **BPN**,
Phys. Rev. Lett. 121 (2018)
241803, 1805.02664



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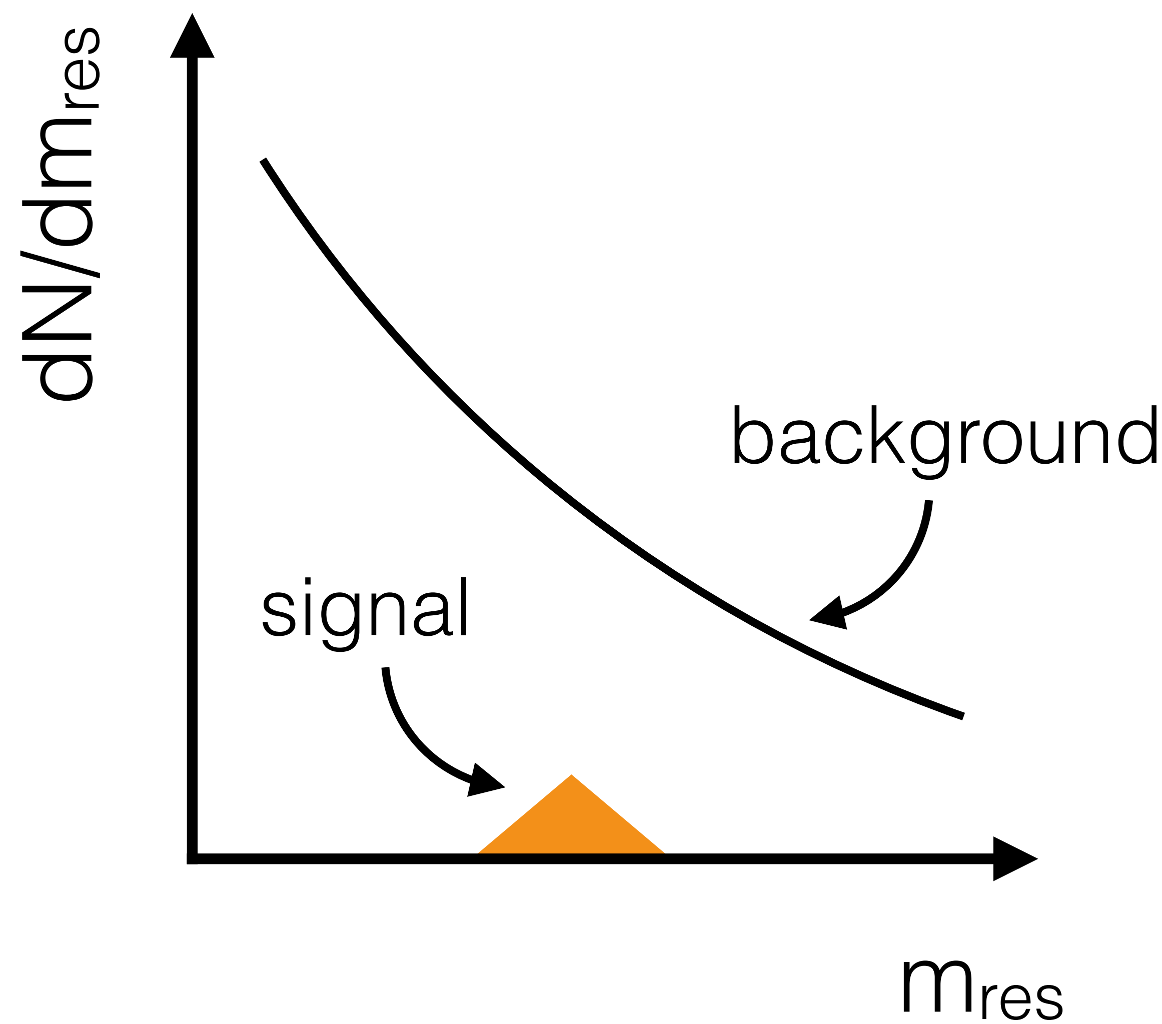

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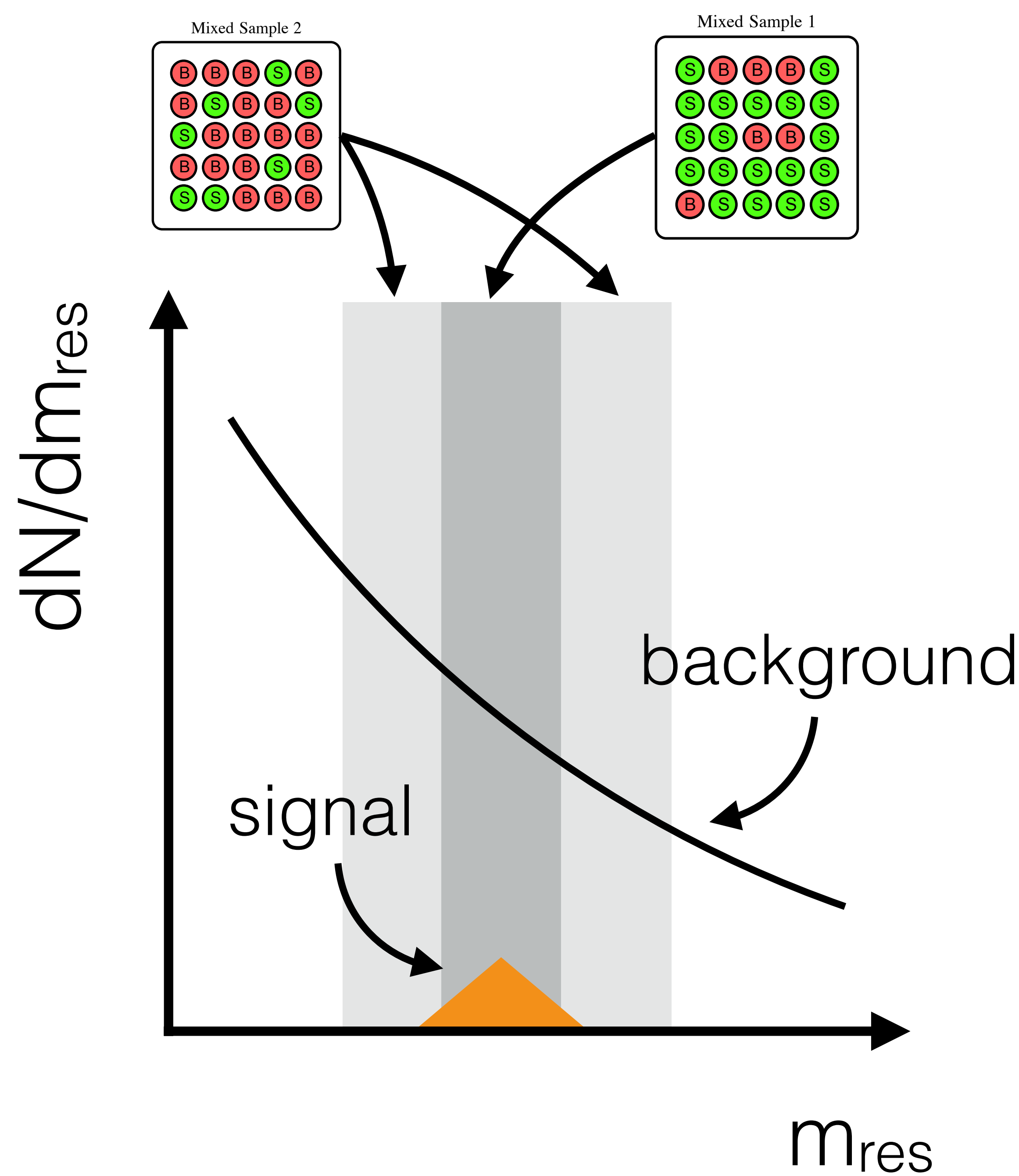

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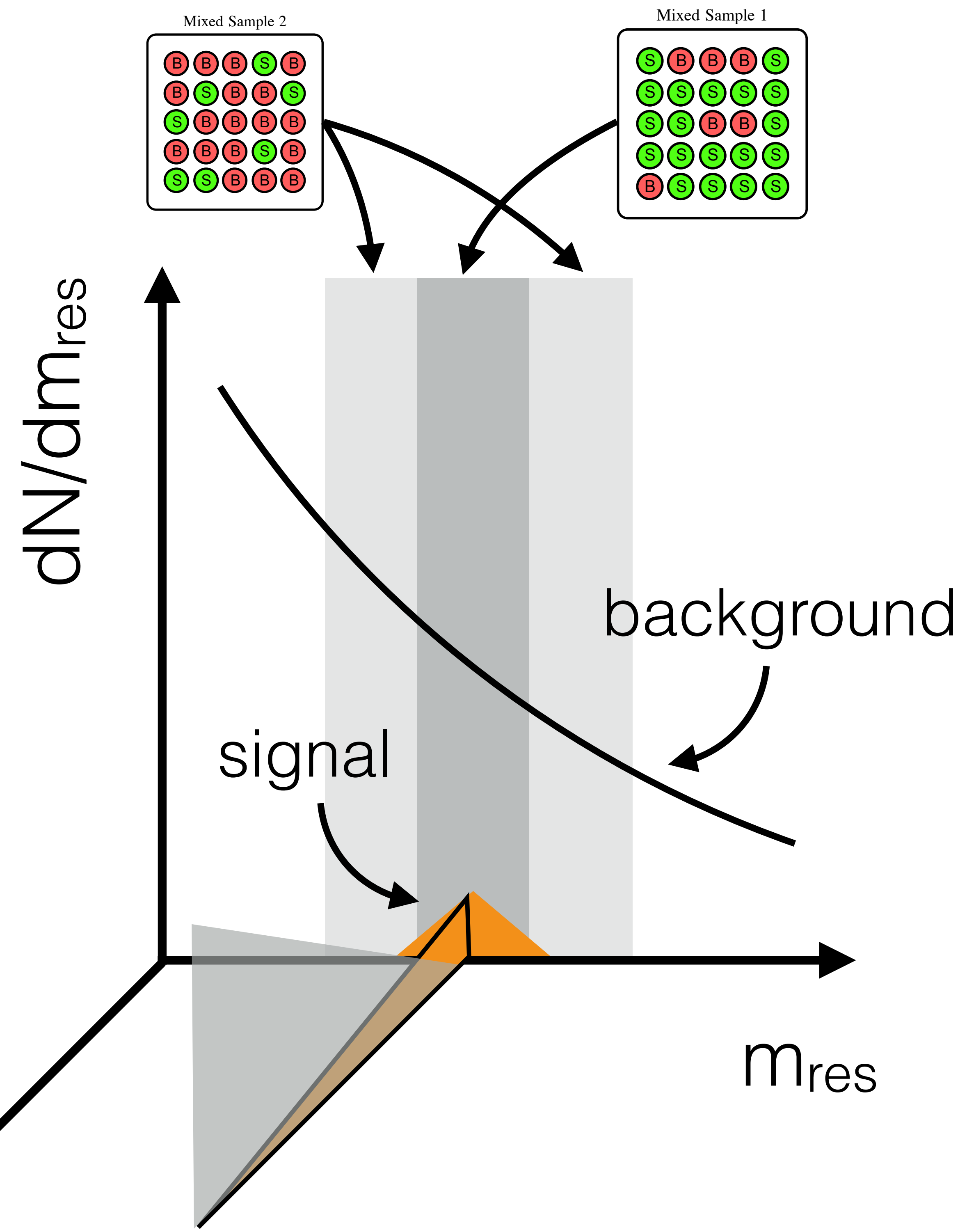
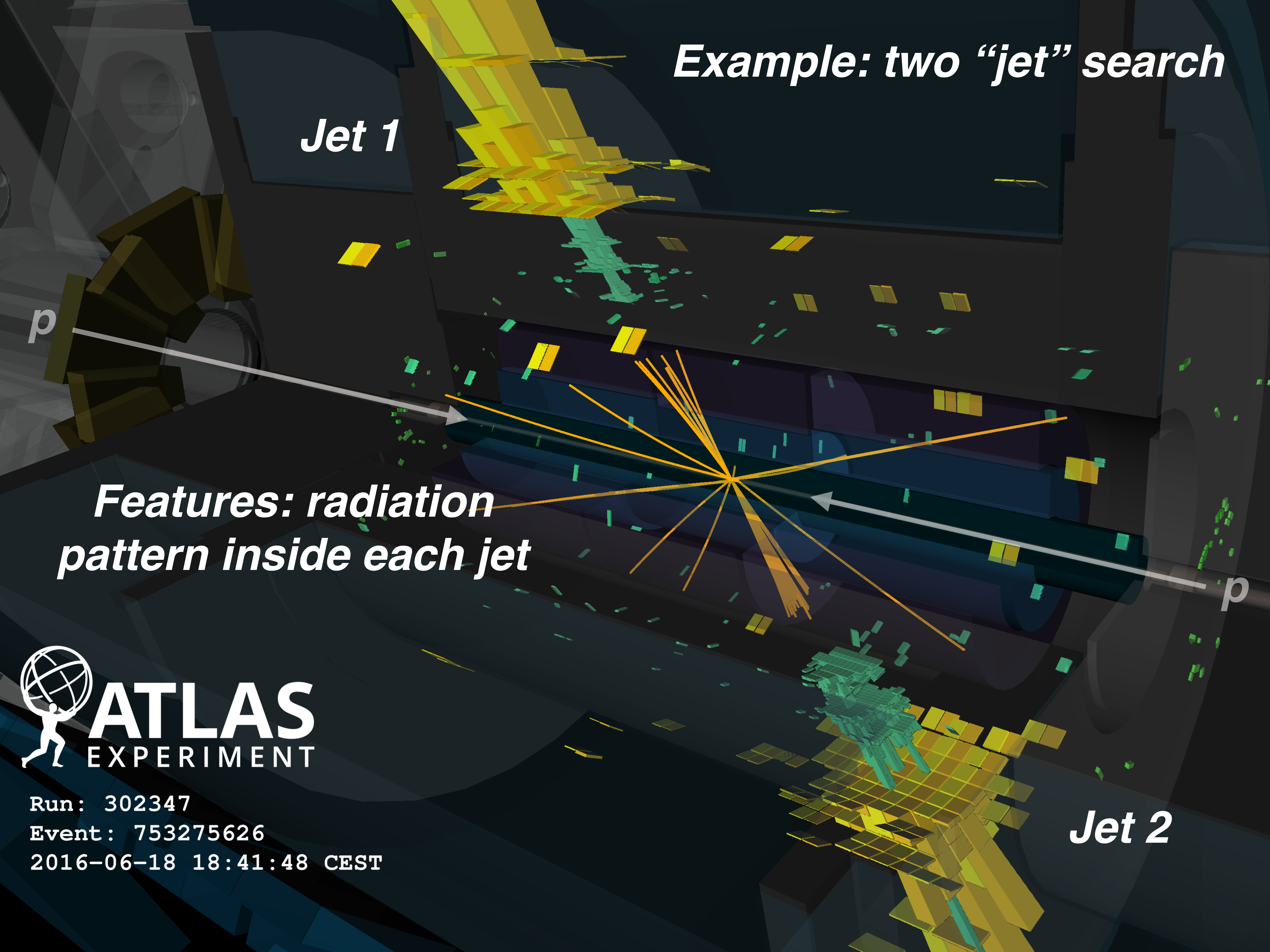
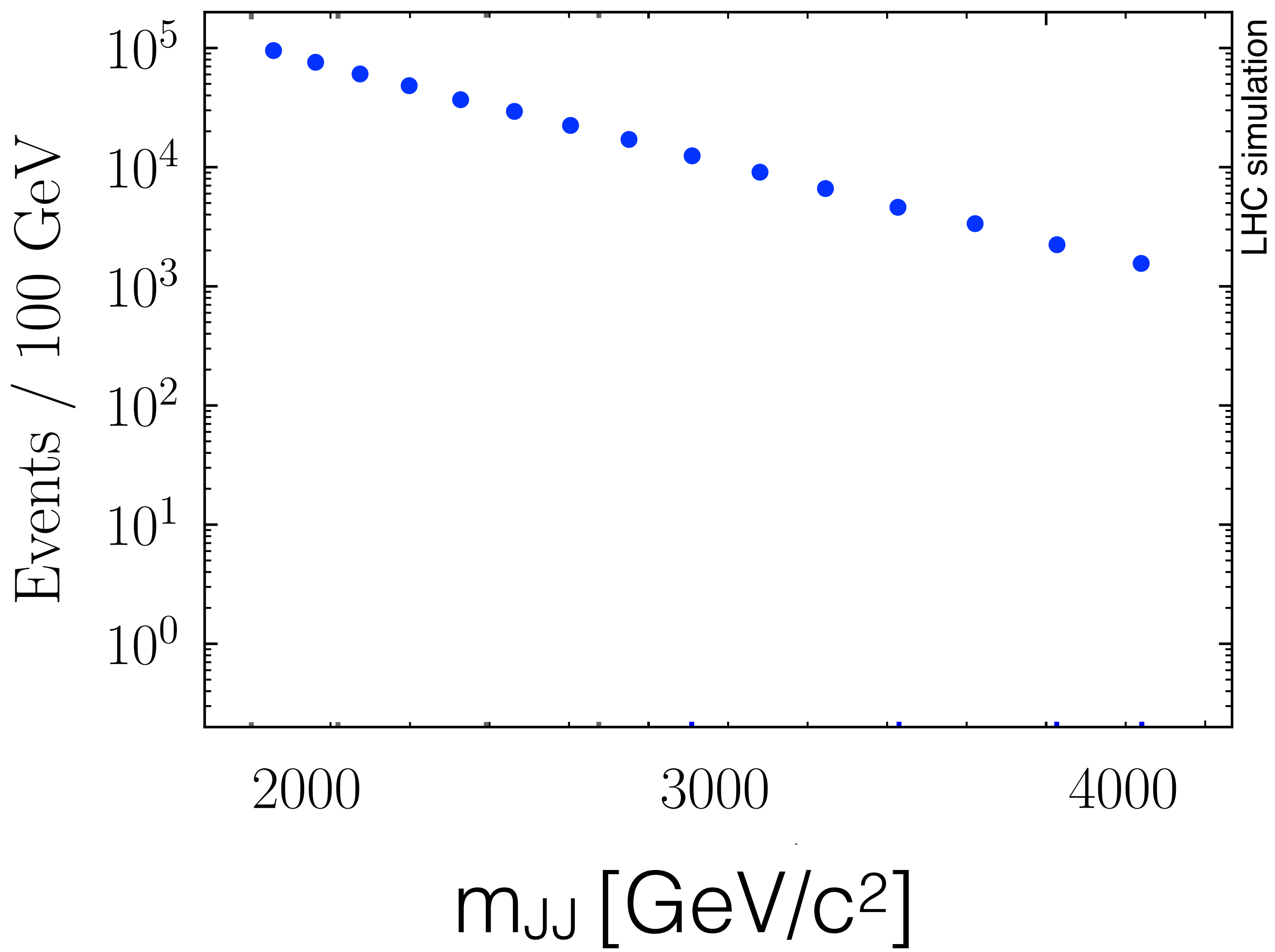


training
feature space

+ be careful to not pay a big trials factor
(ask if interested)


Example: two "jet" search
Jet 1
p
Features: radiation pattern inside each jet
p
ATLAS
EXPERIMENT
Run: 302347
Event: 753275626
2016-06-18 18:41:48 CEST
Jet 2

Example: two-“jet” search



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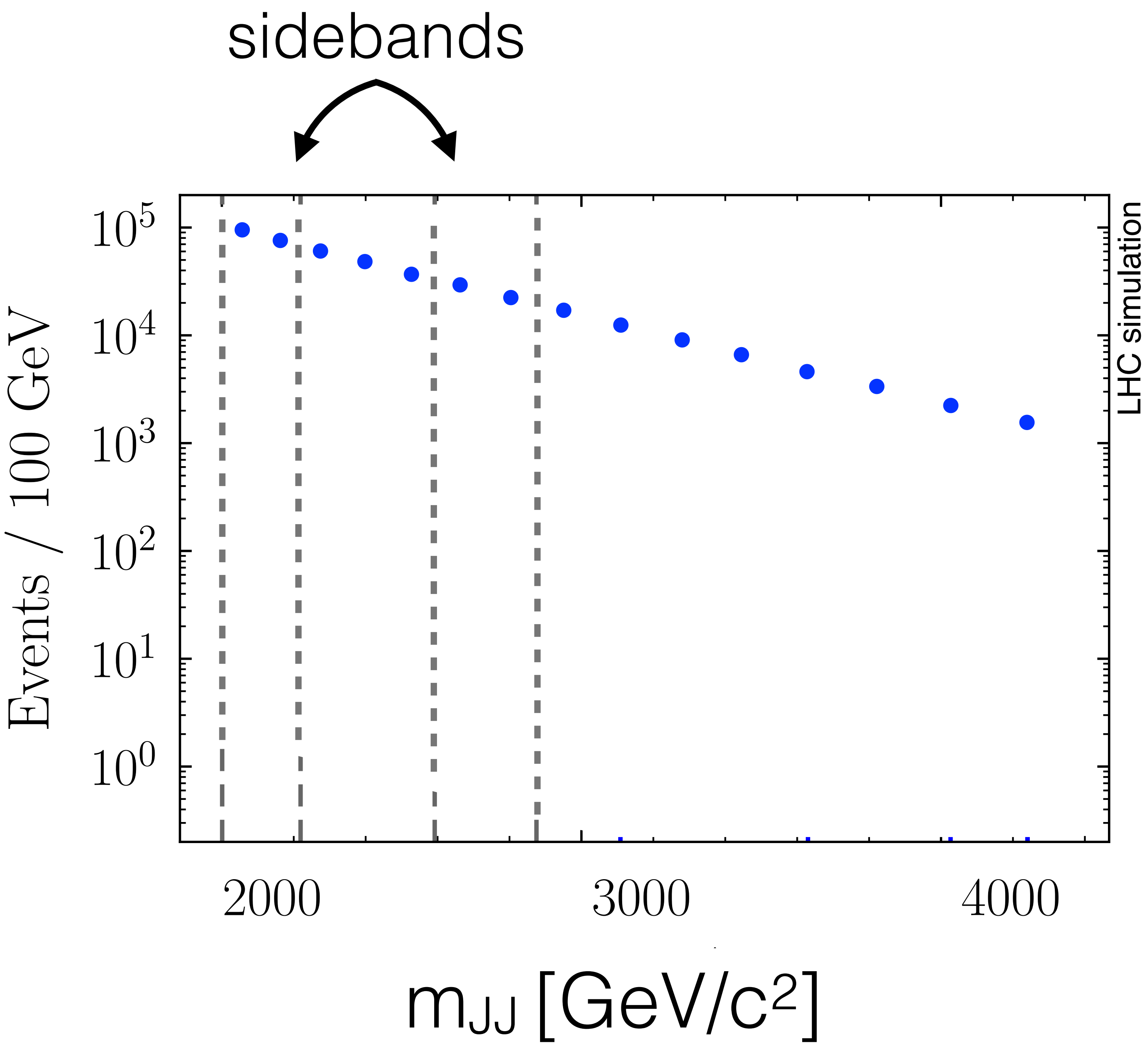

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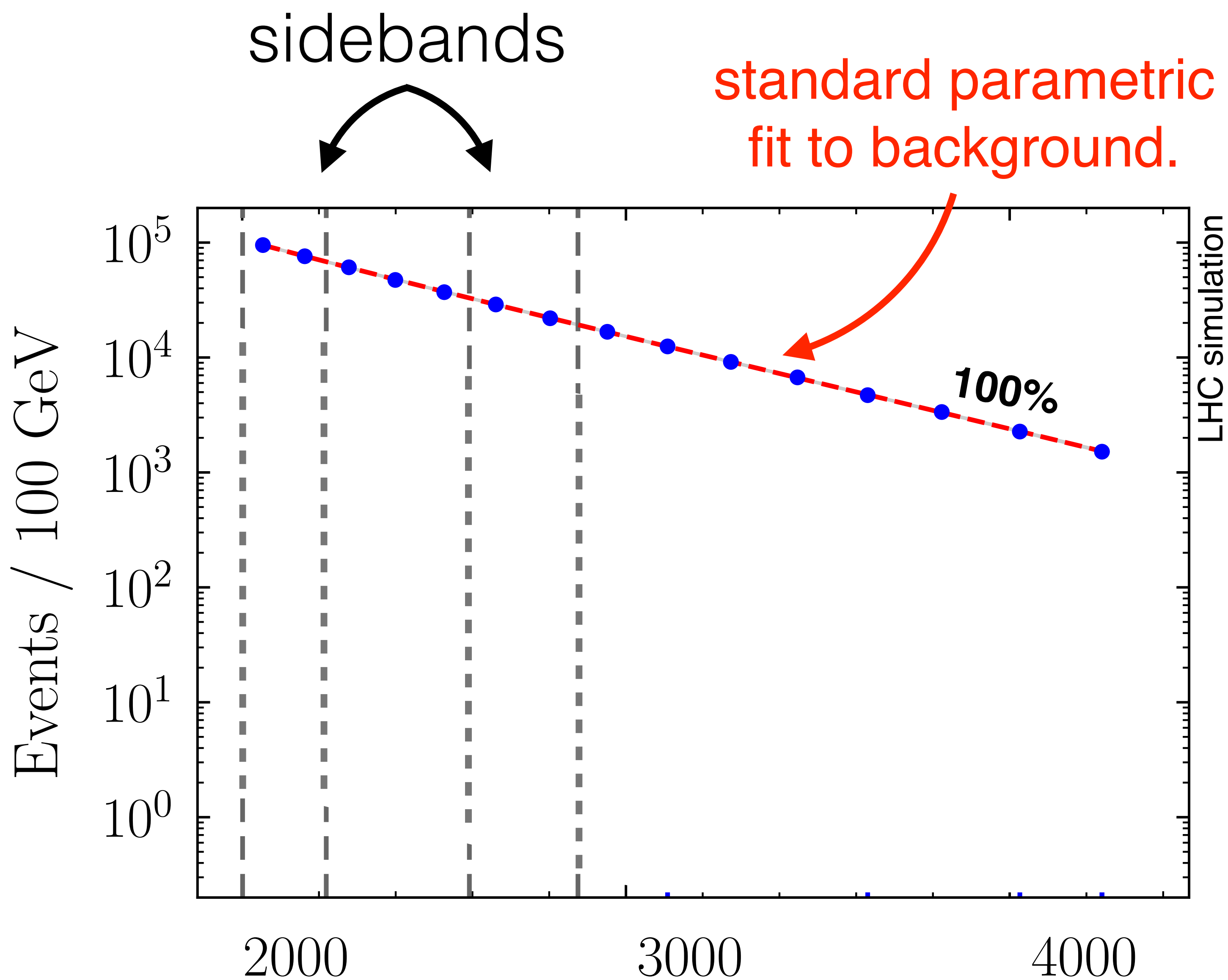

m_{JJ} [GeV/c^2]

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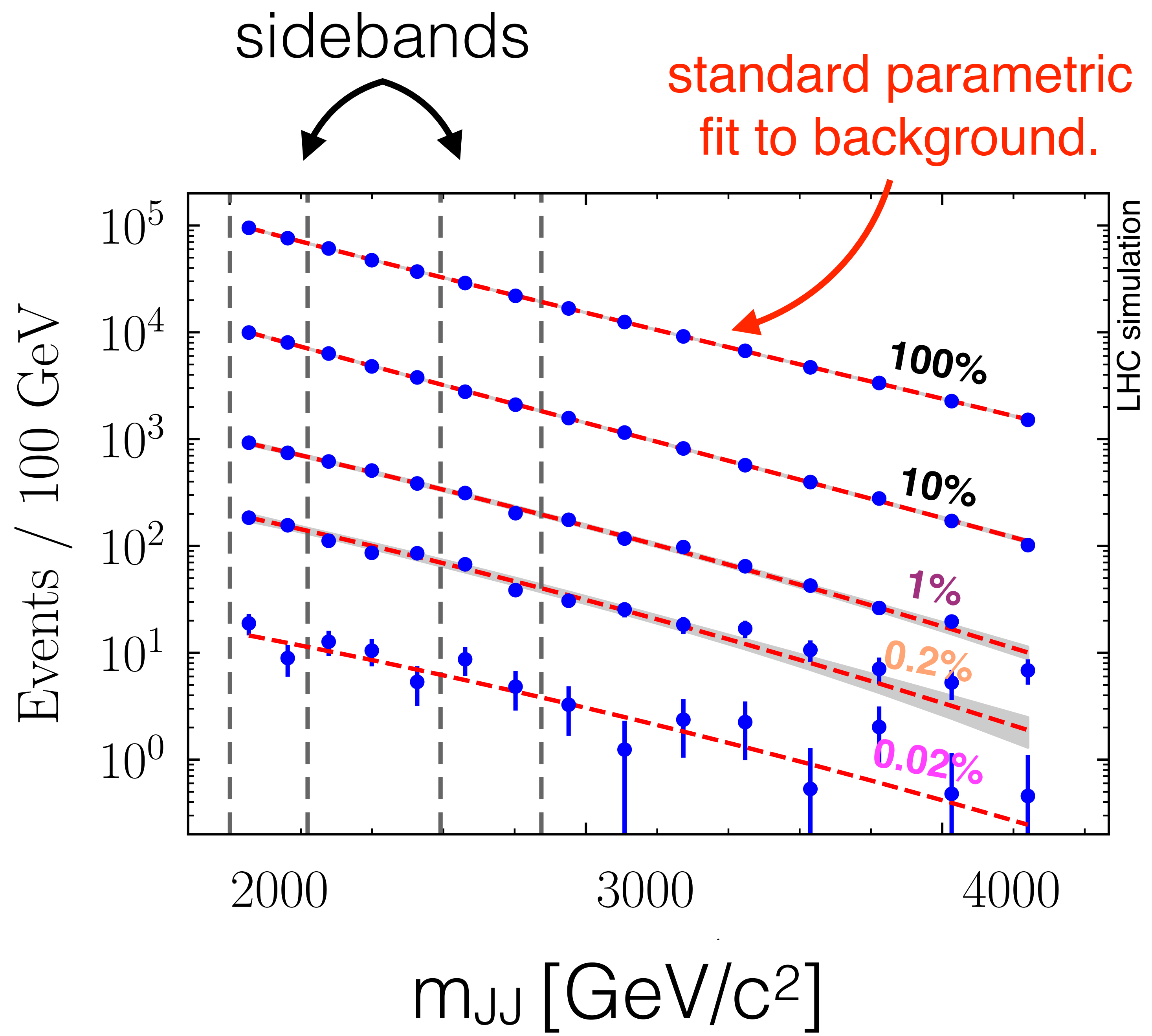

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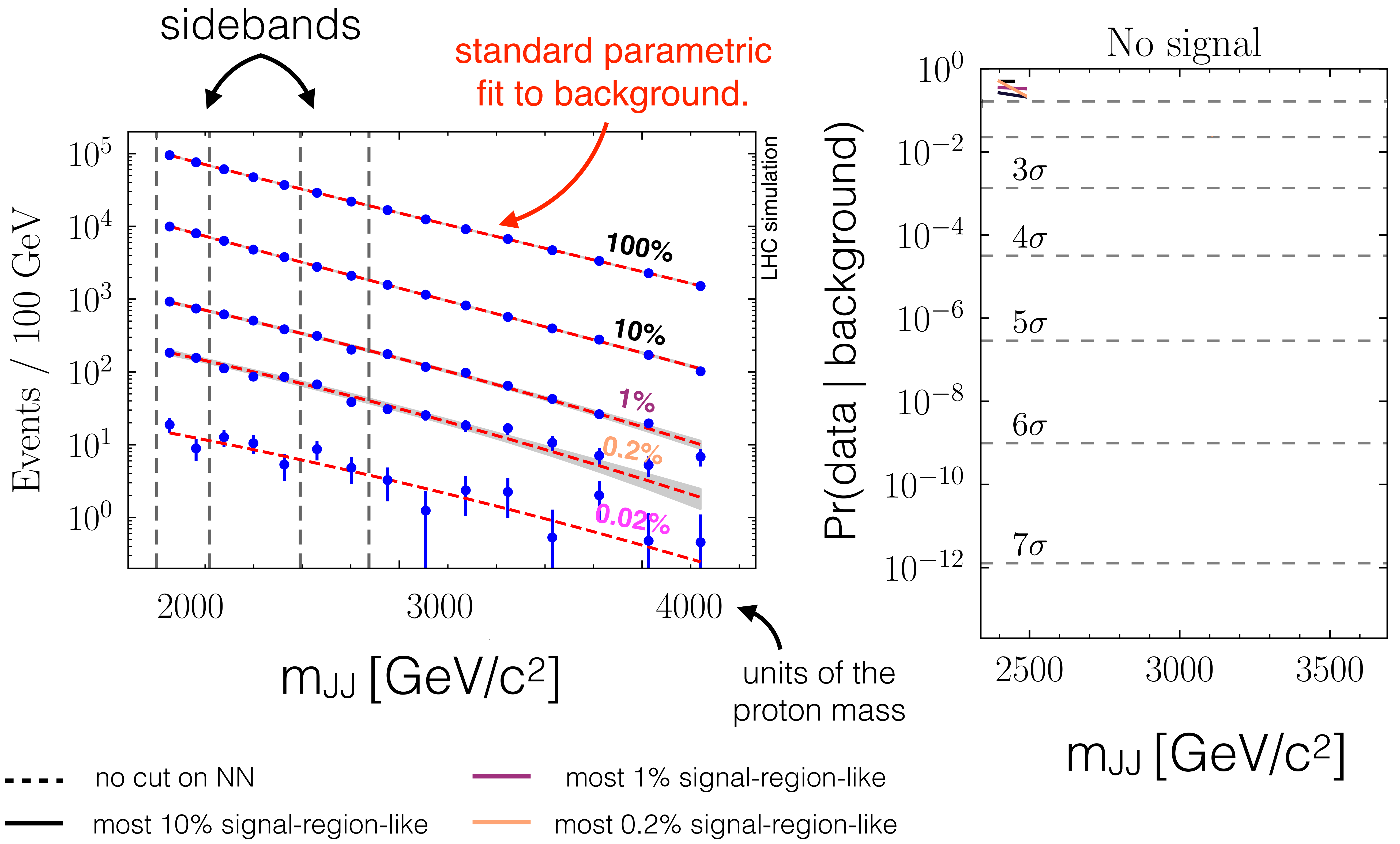

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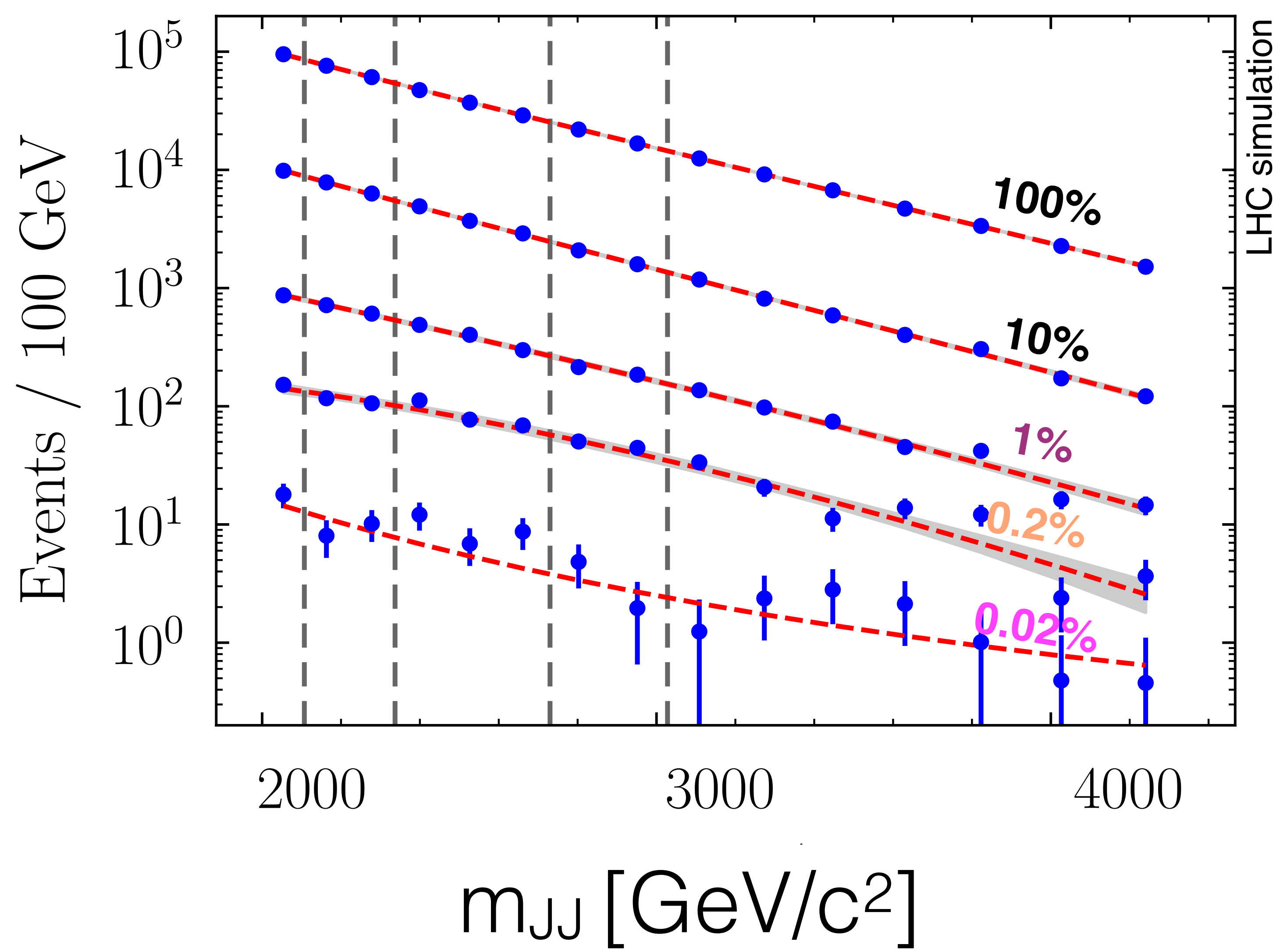

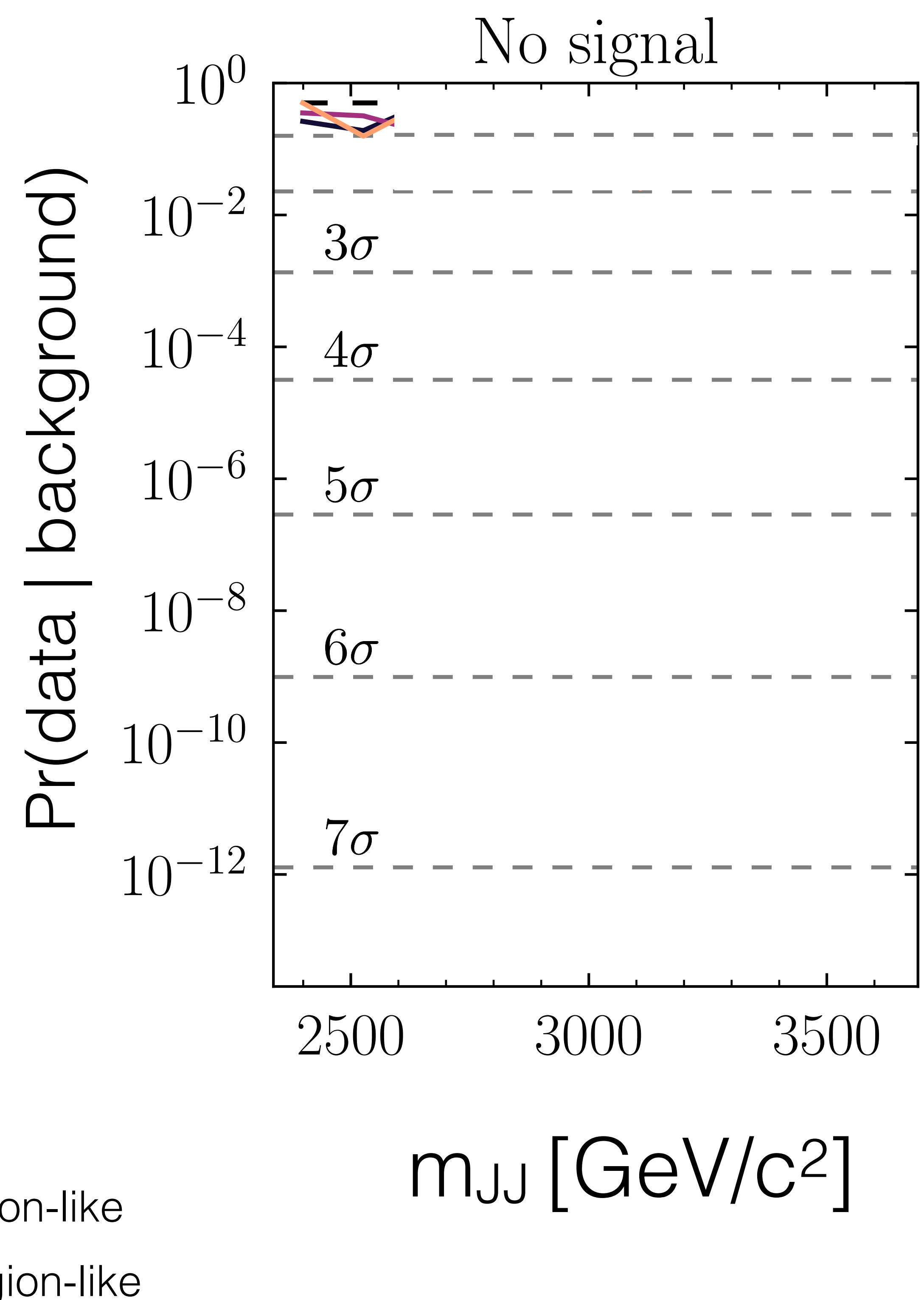

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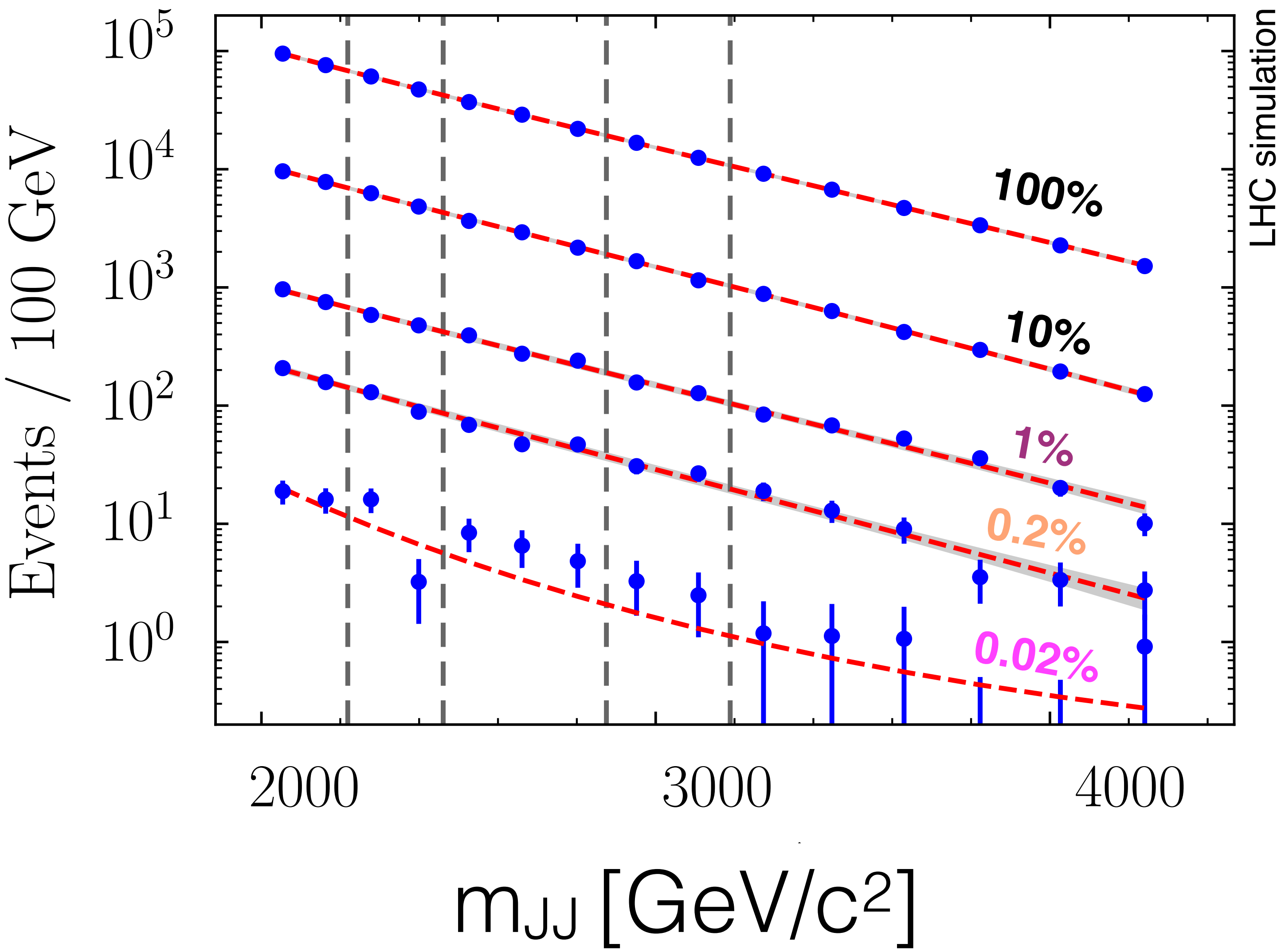

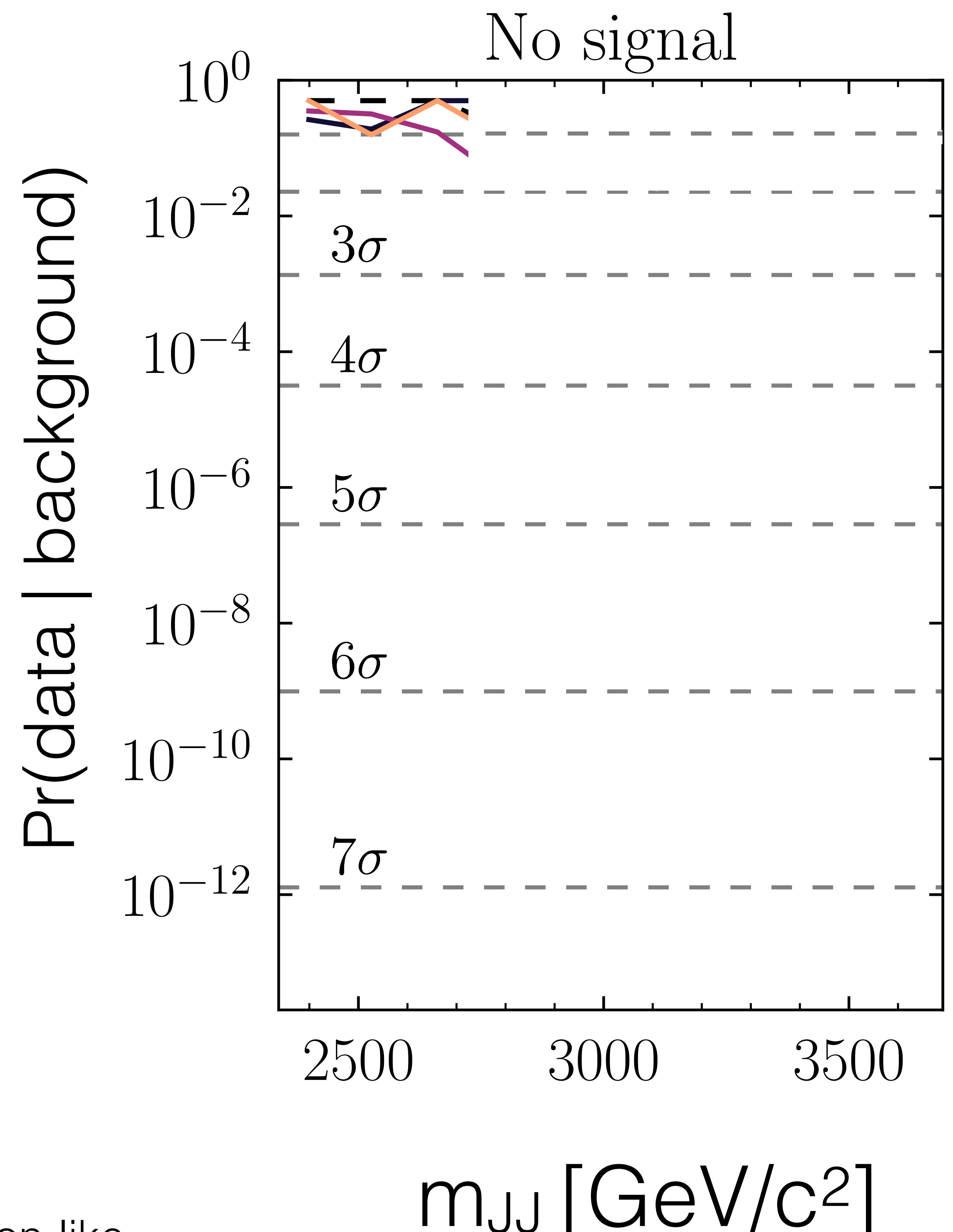

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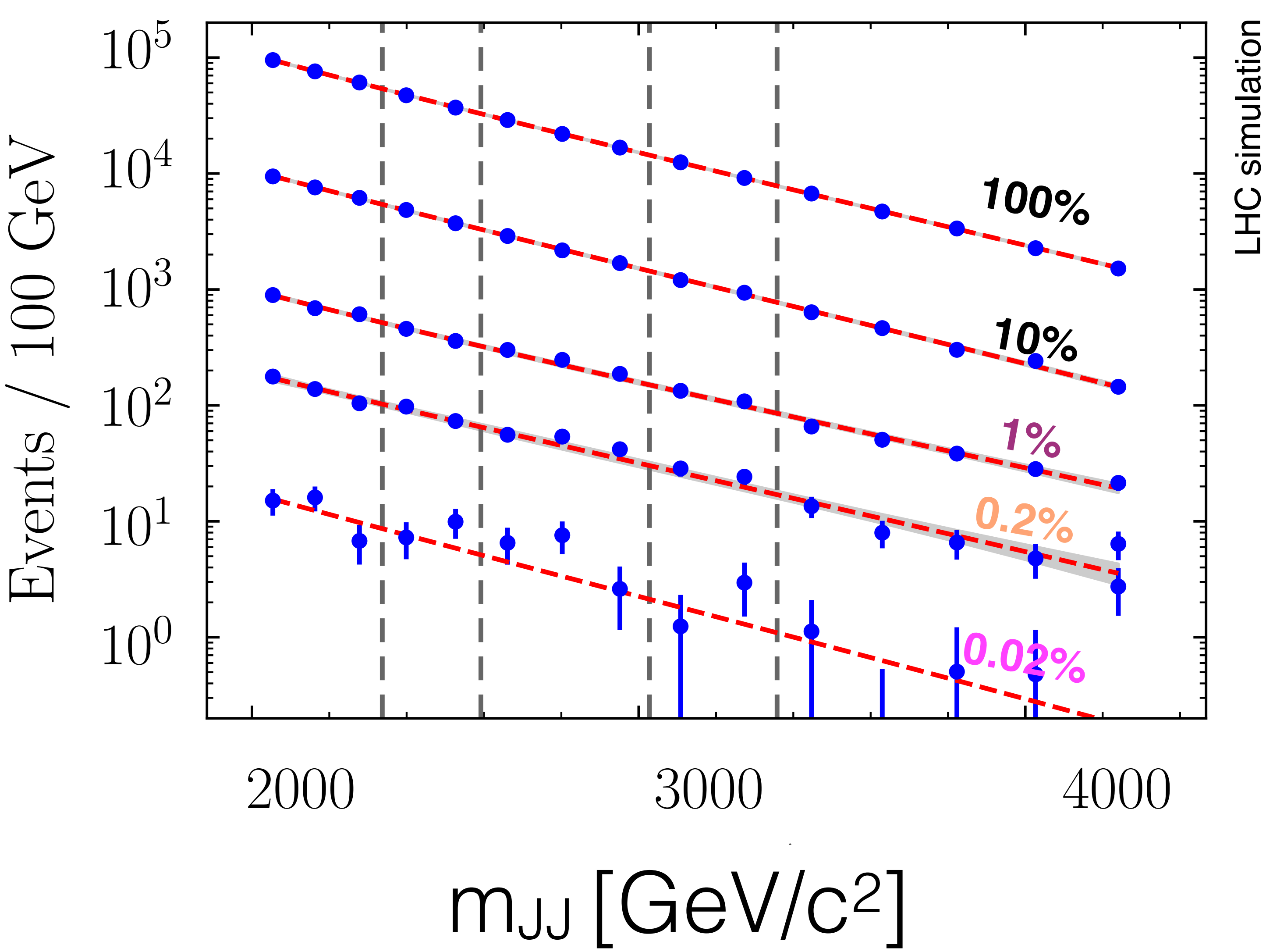

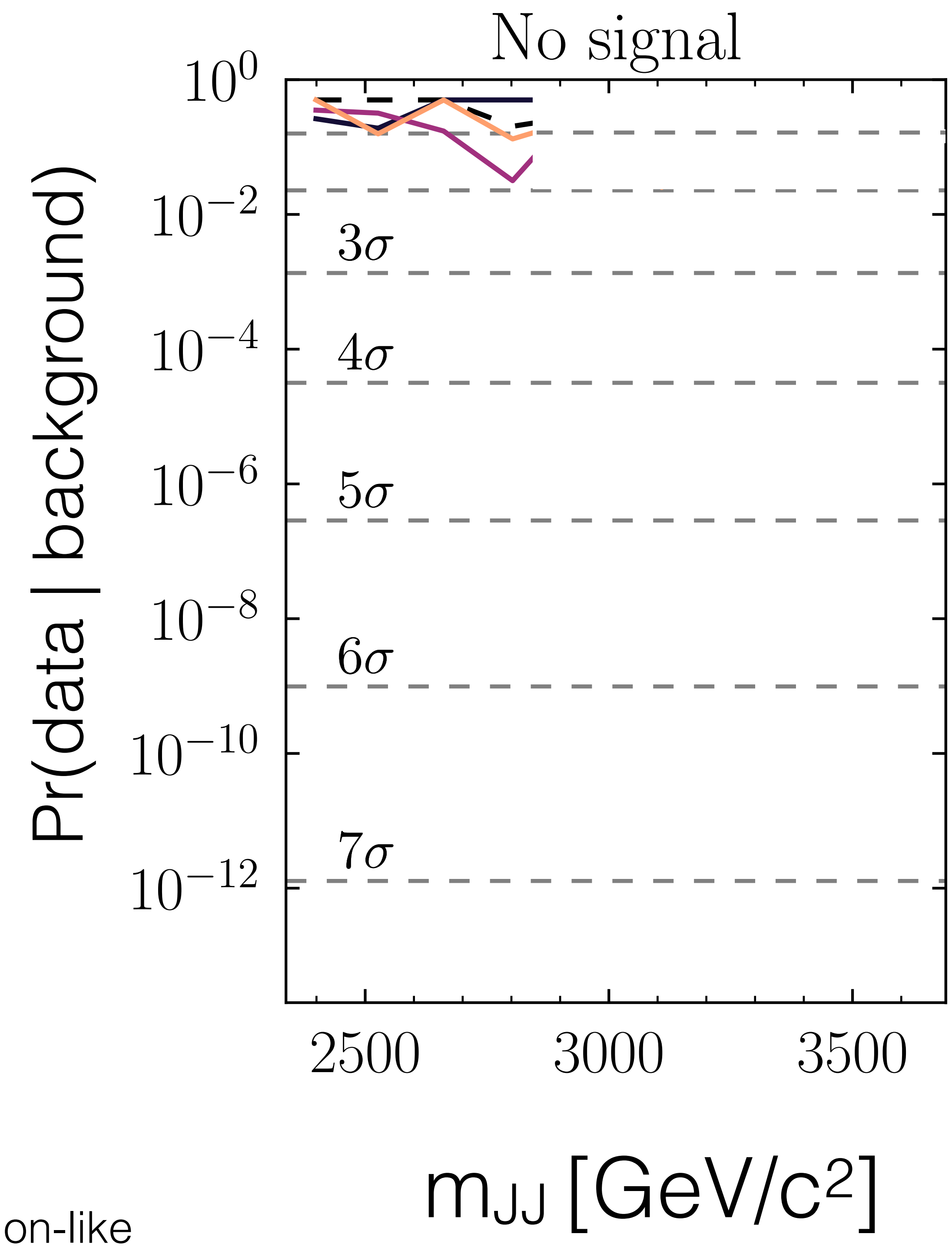

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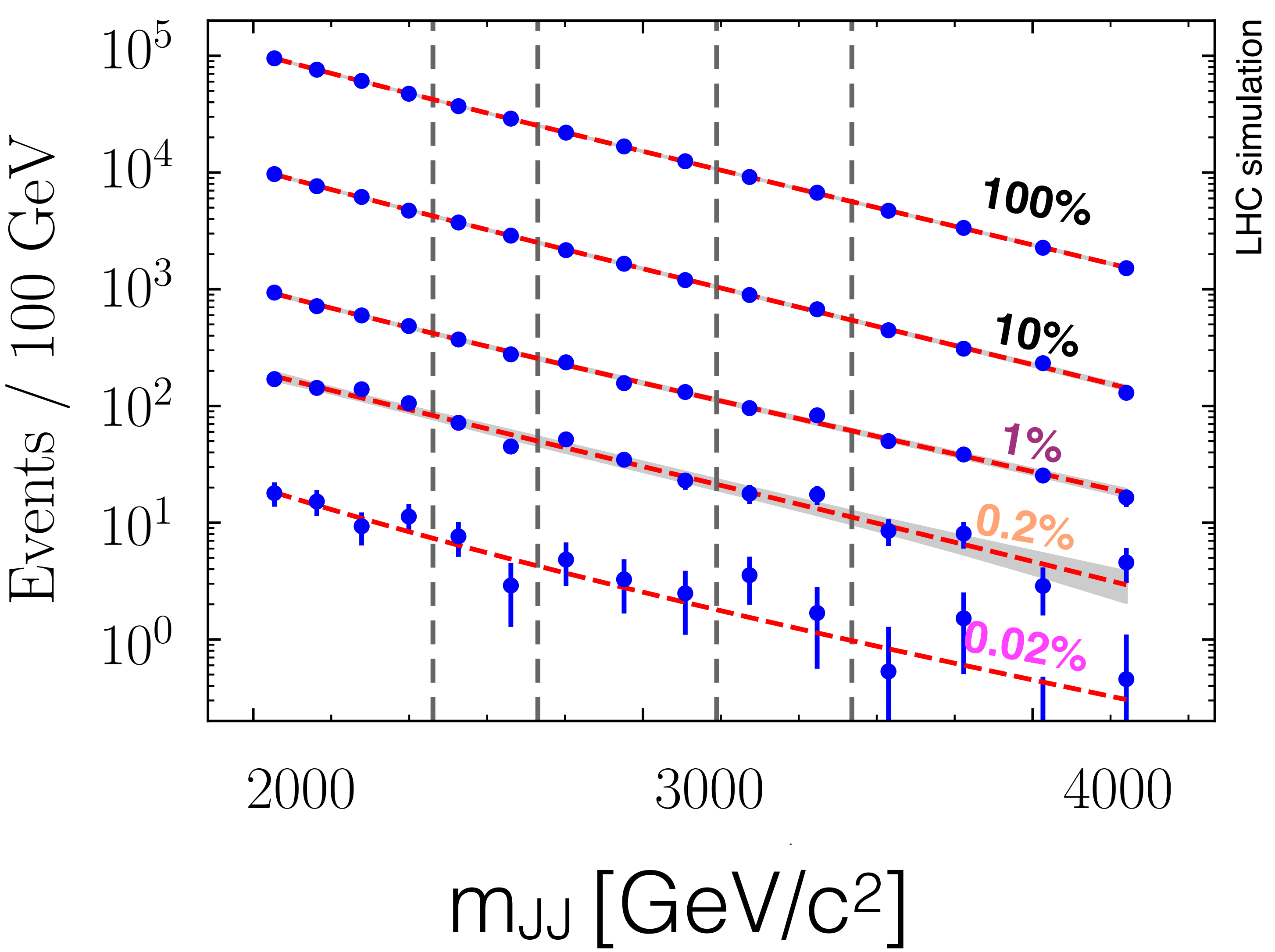

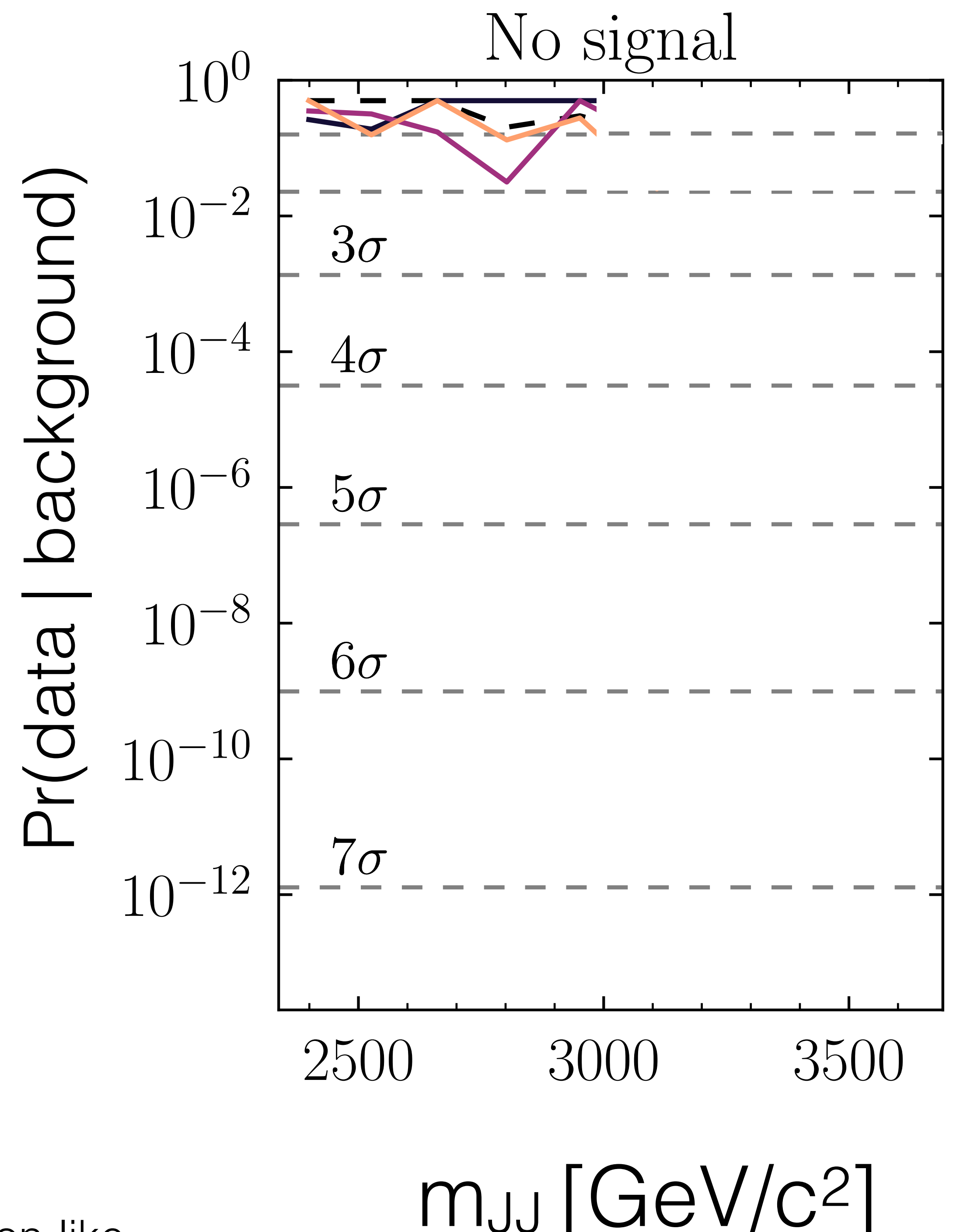

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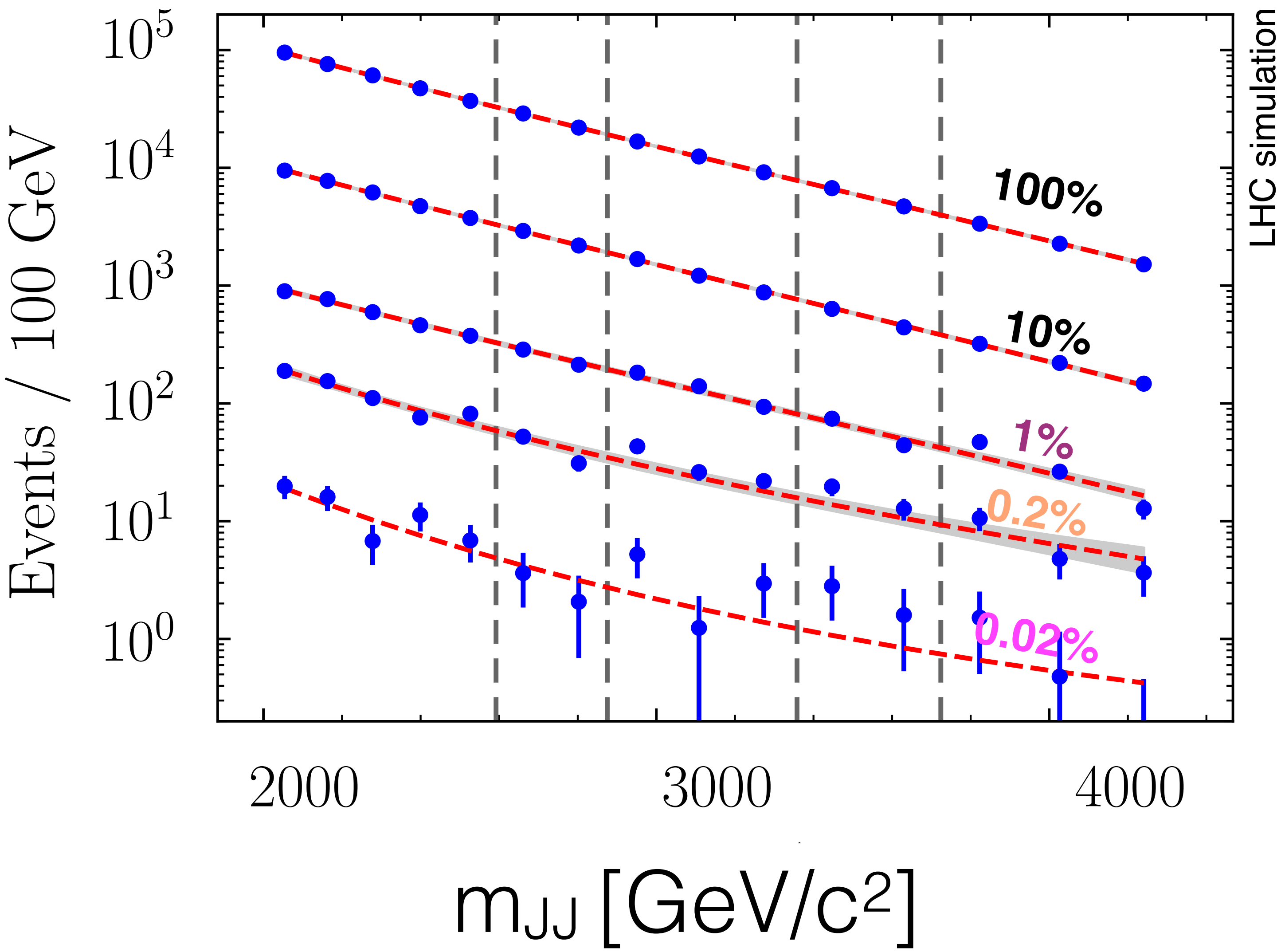

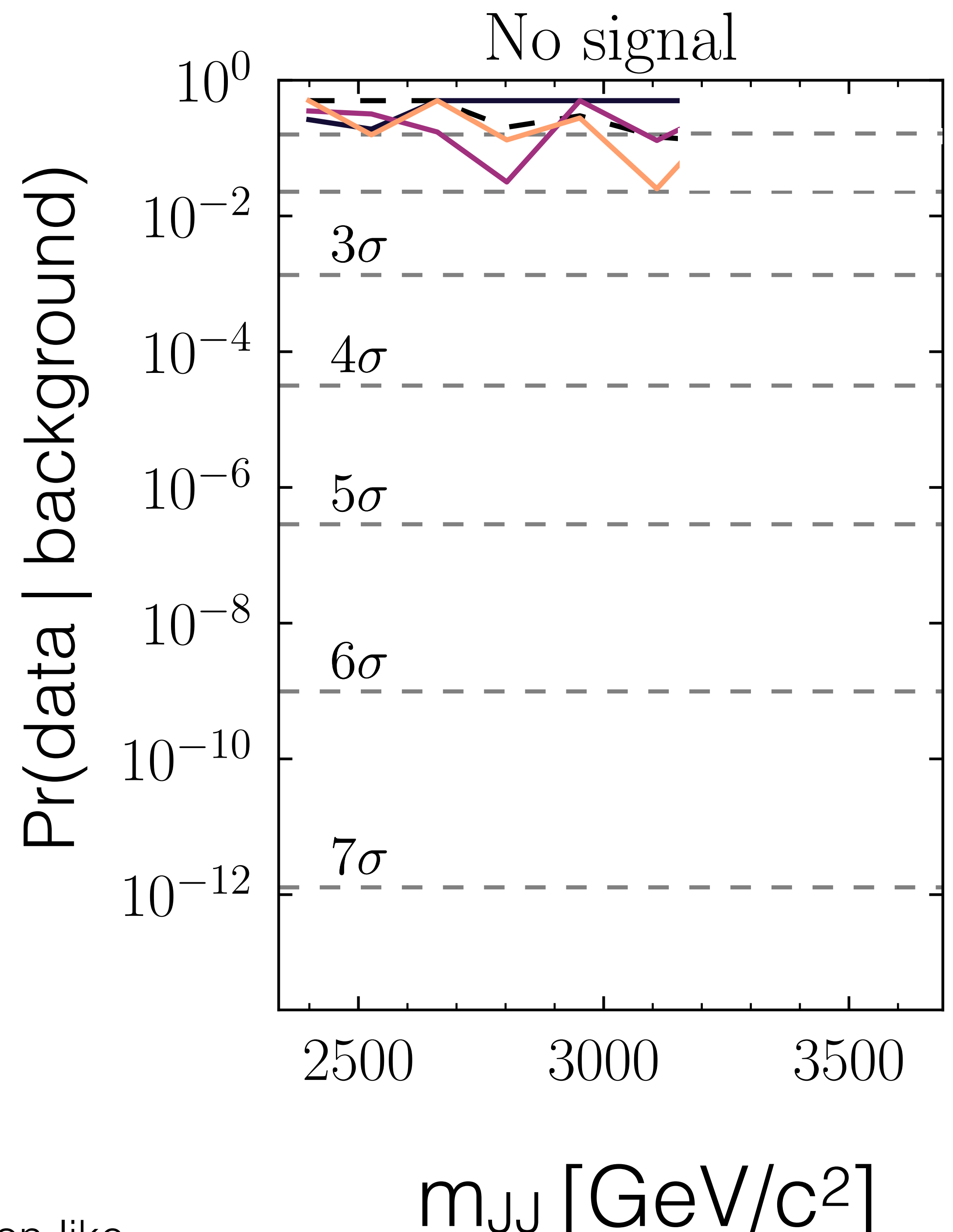

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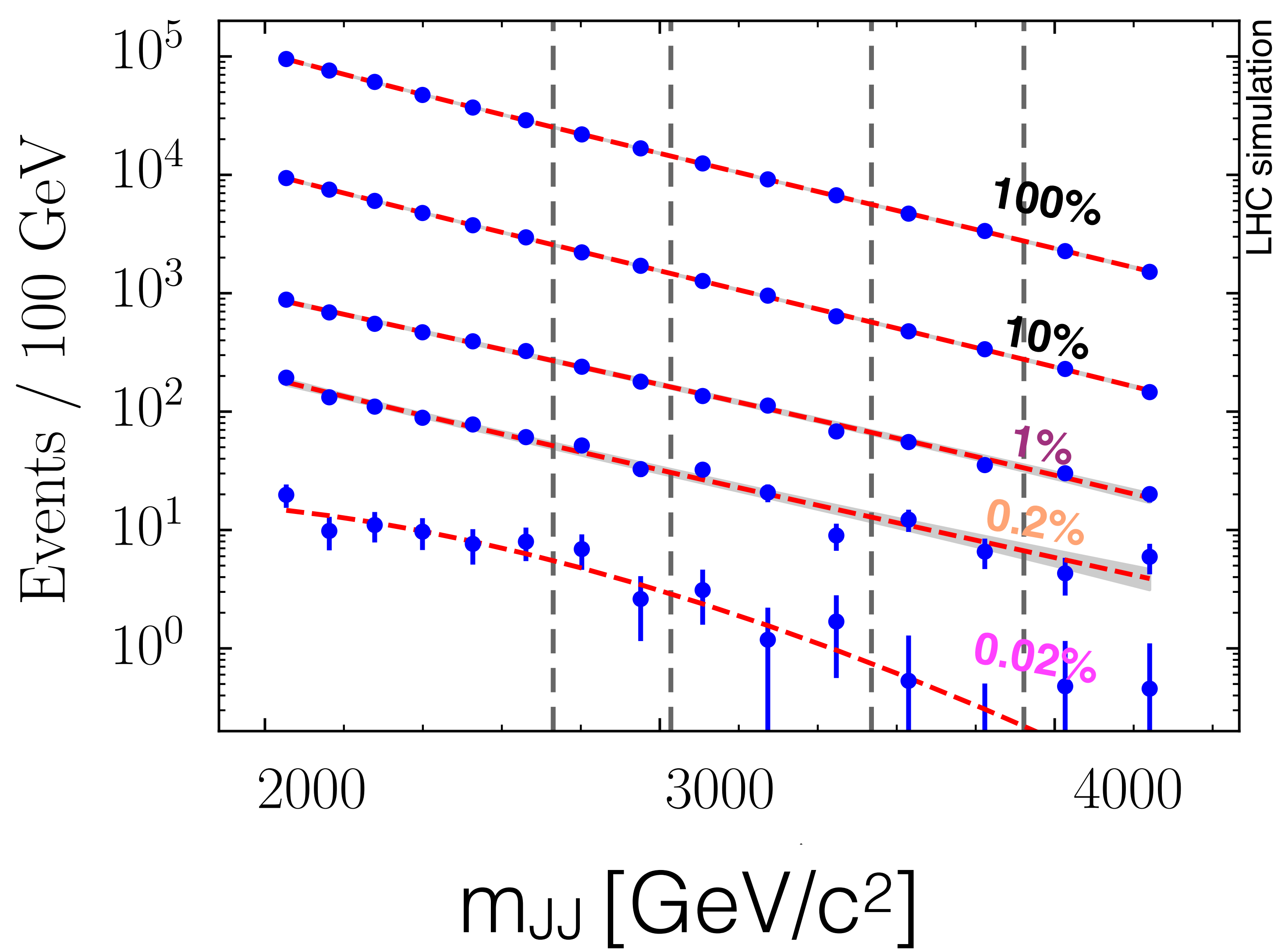

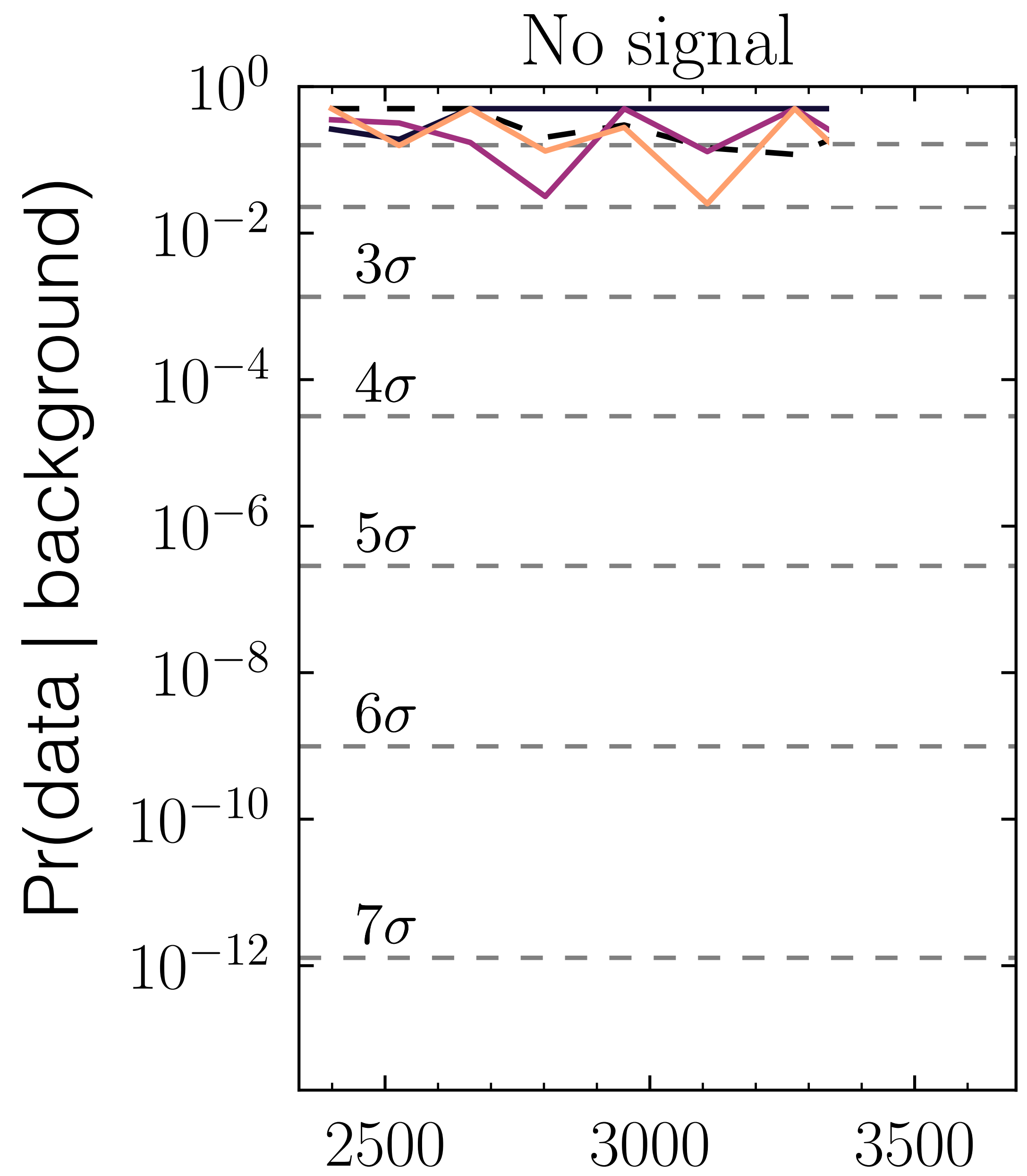

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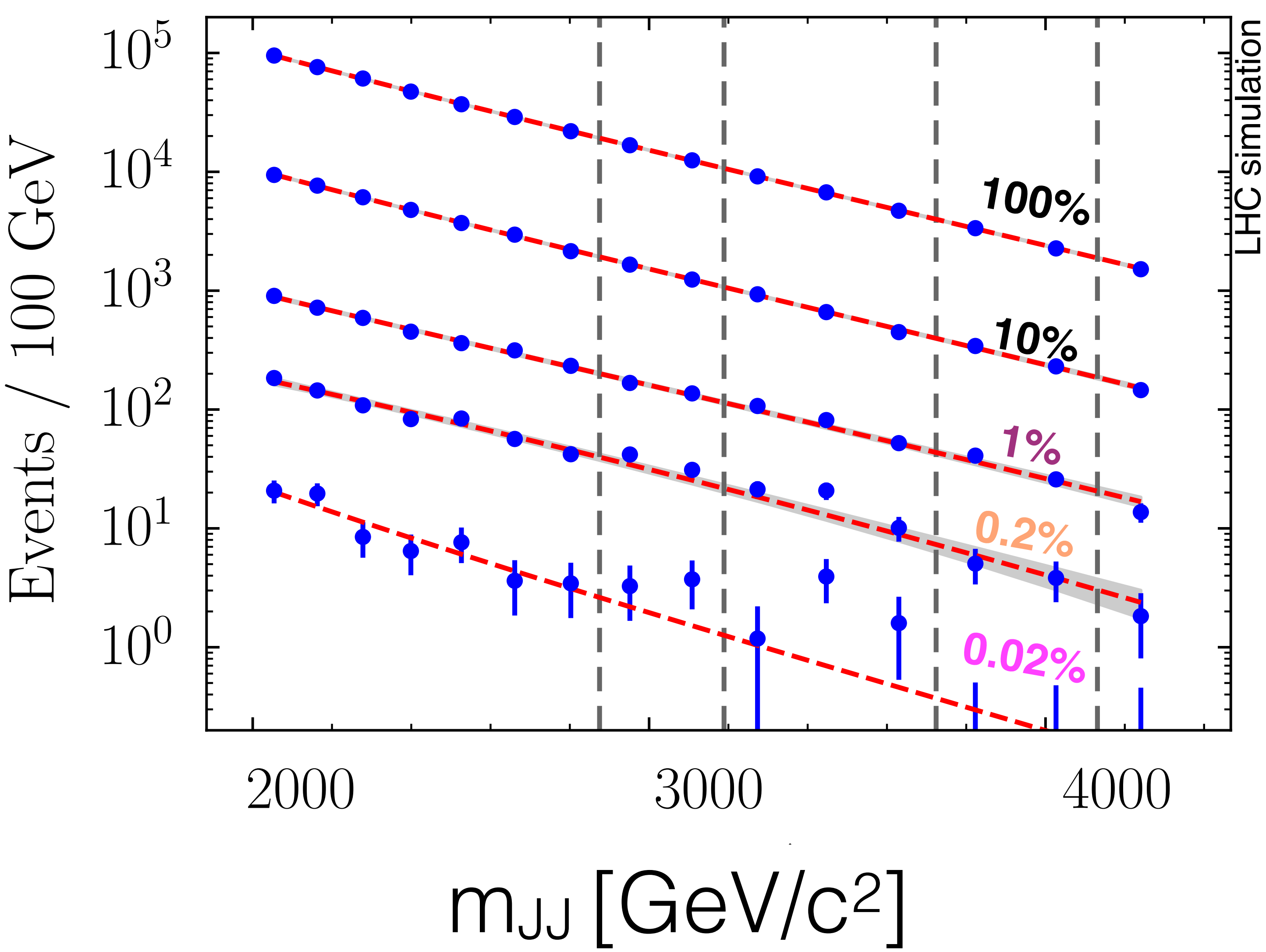

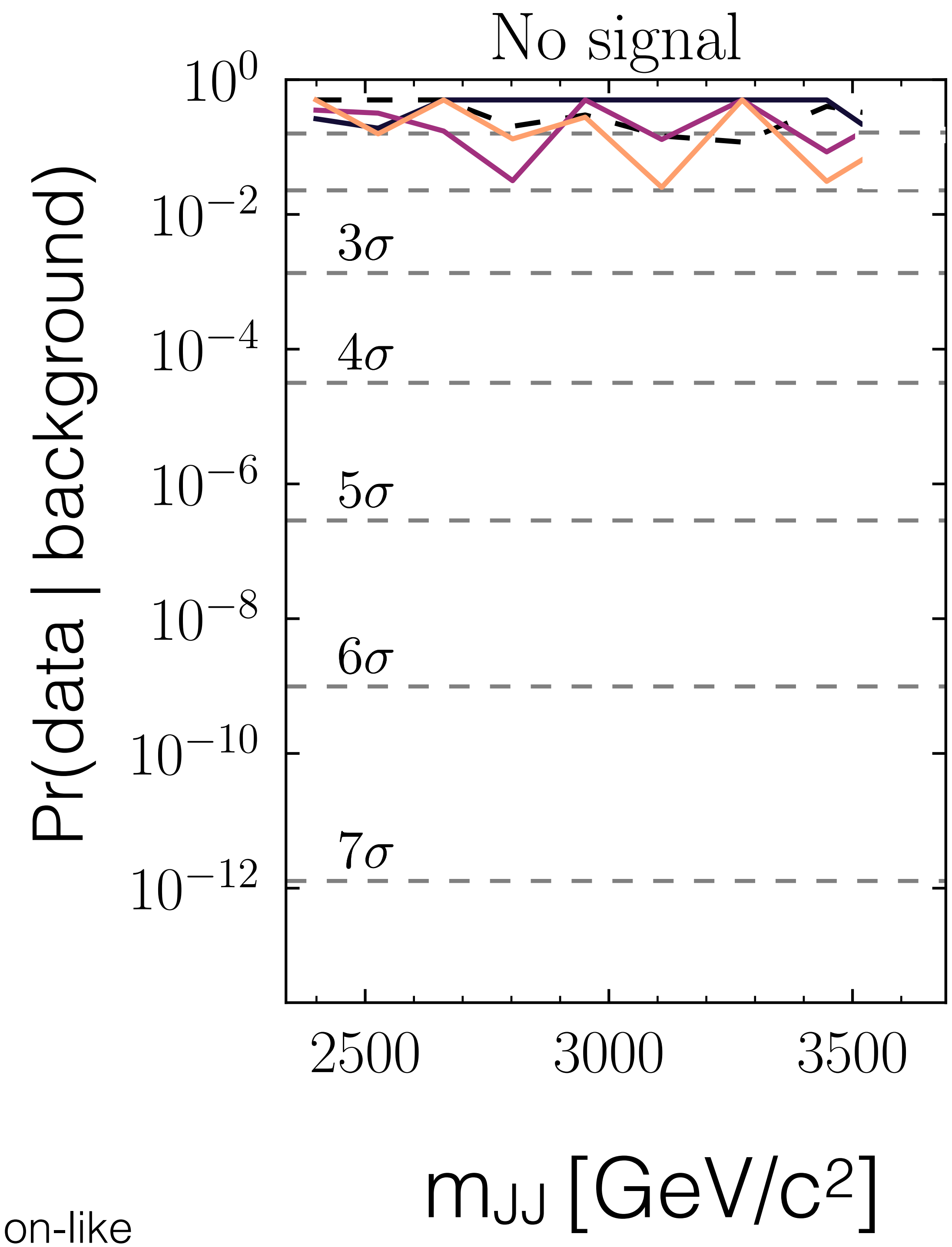

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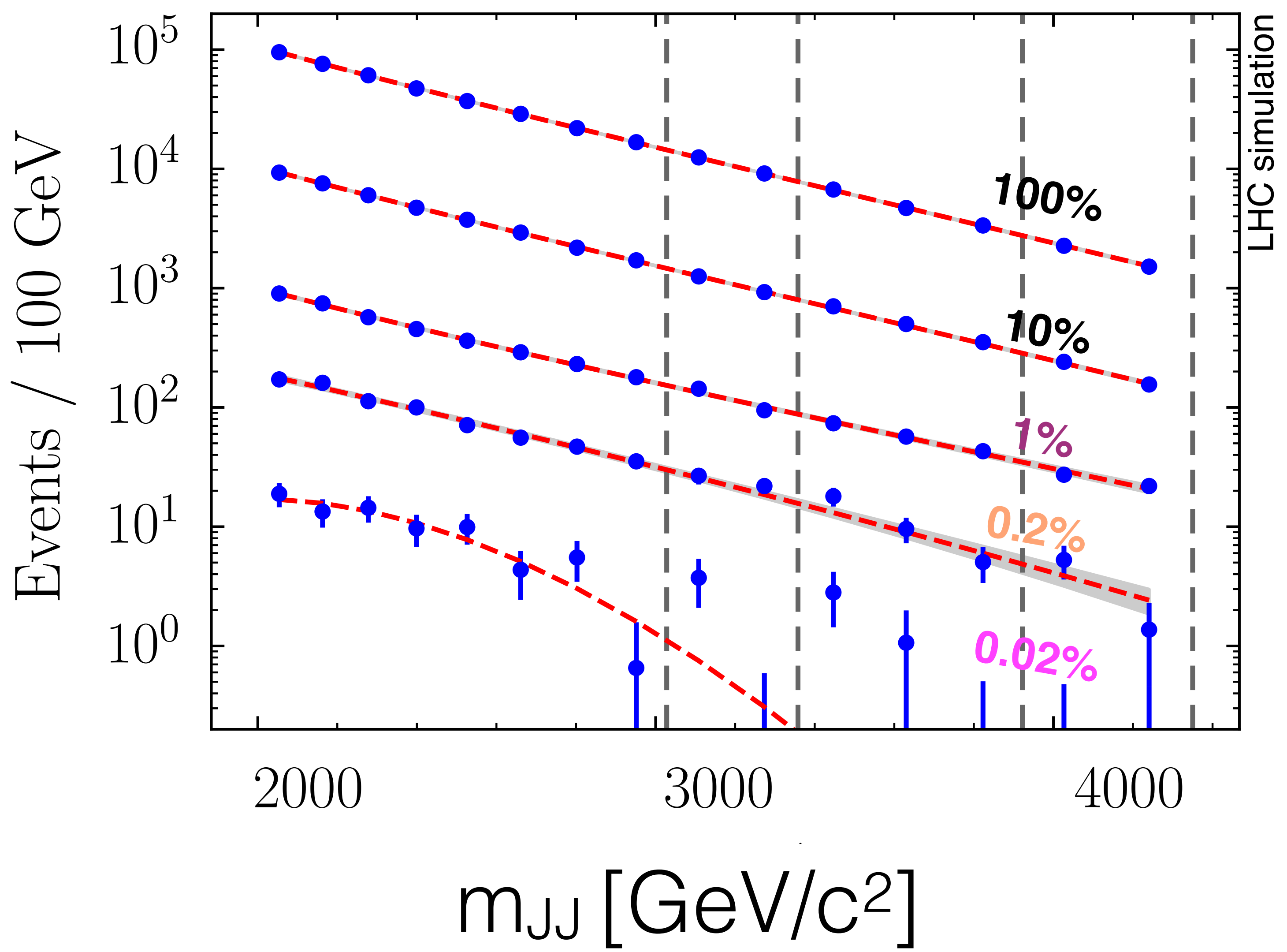

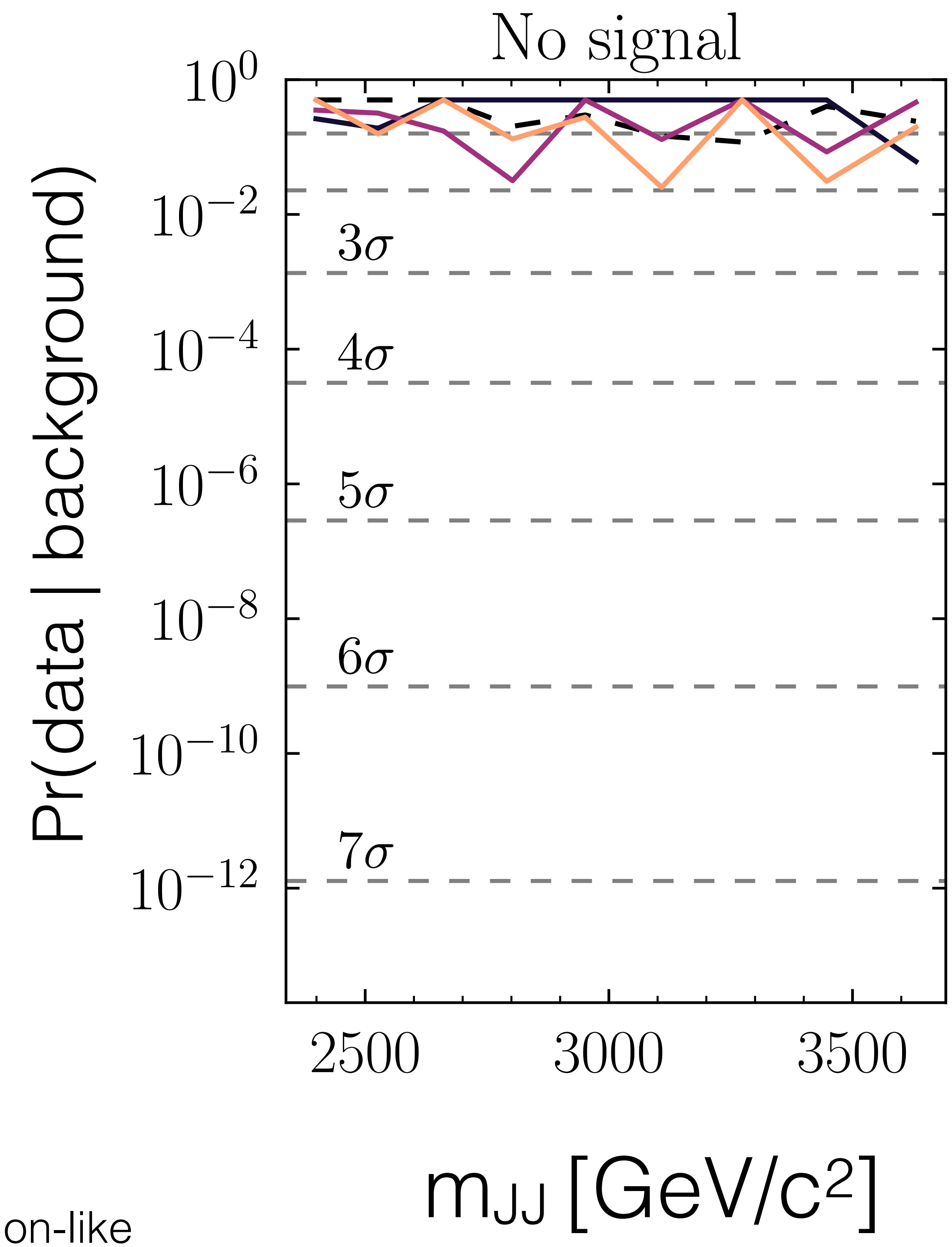

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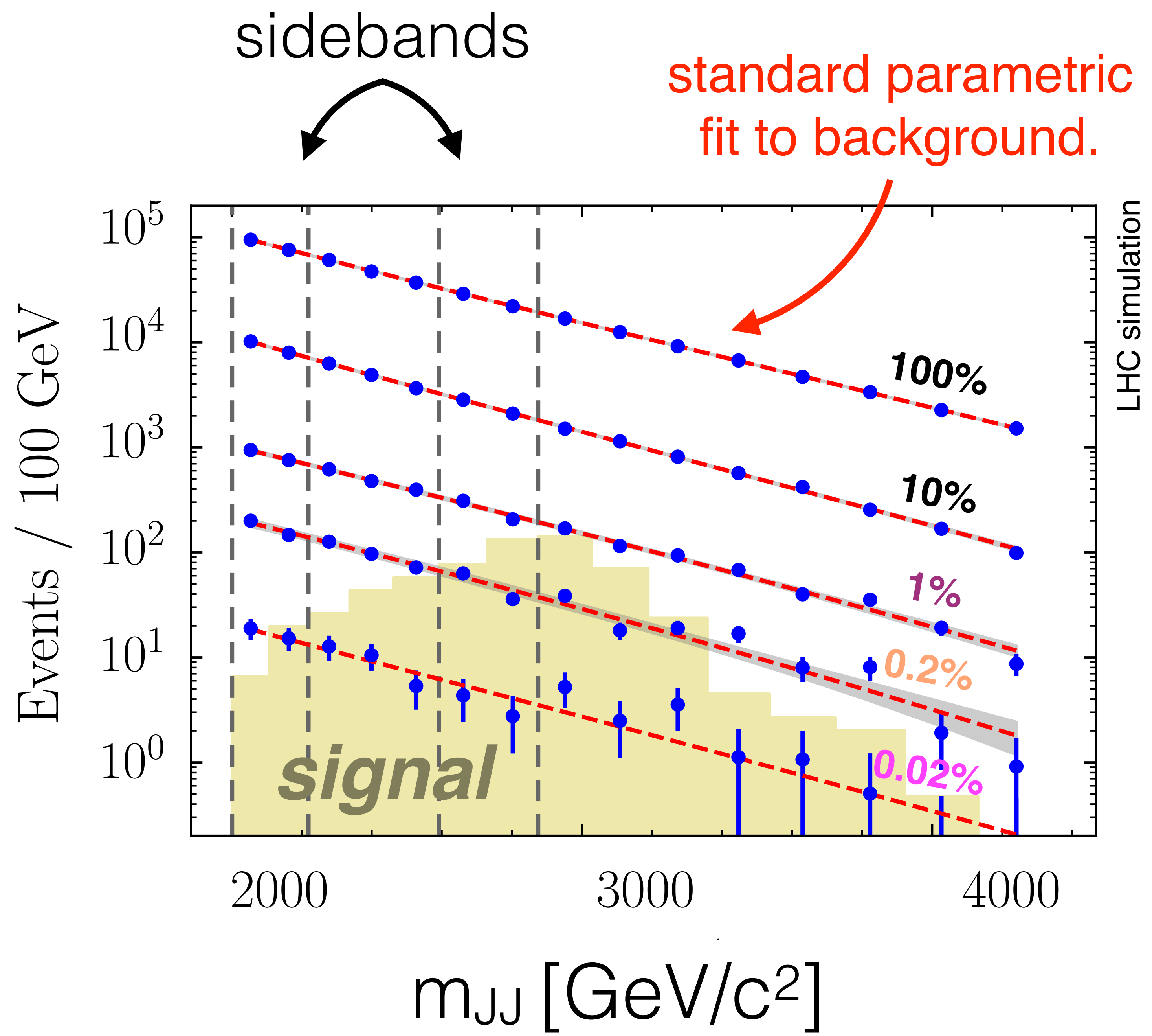

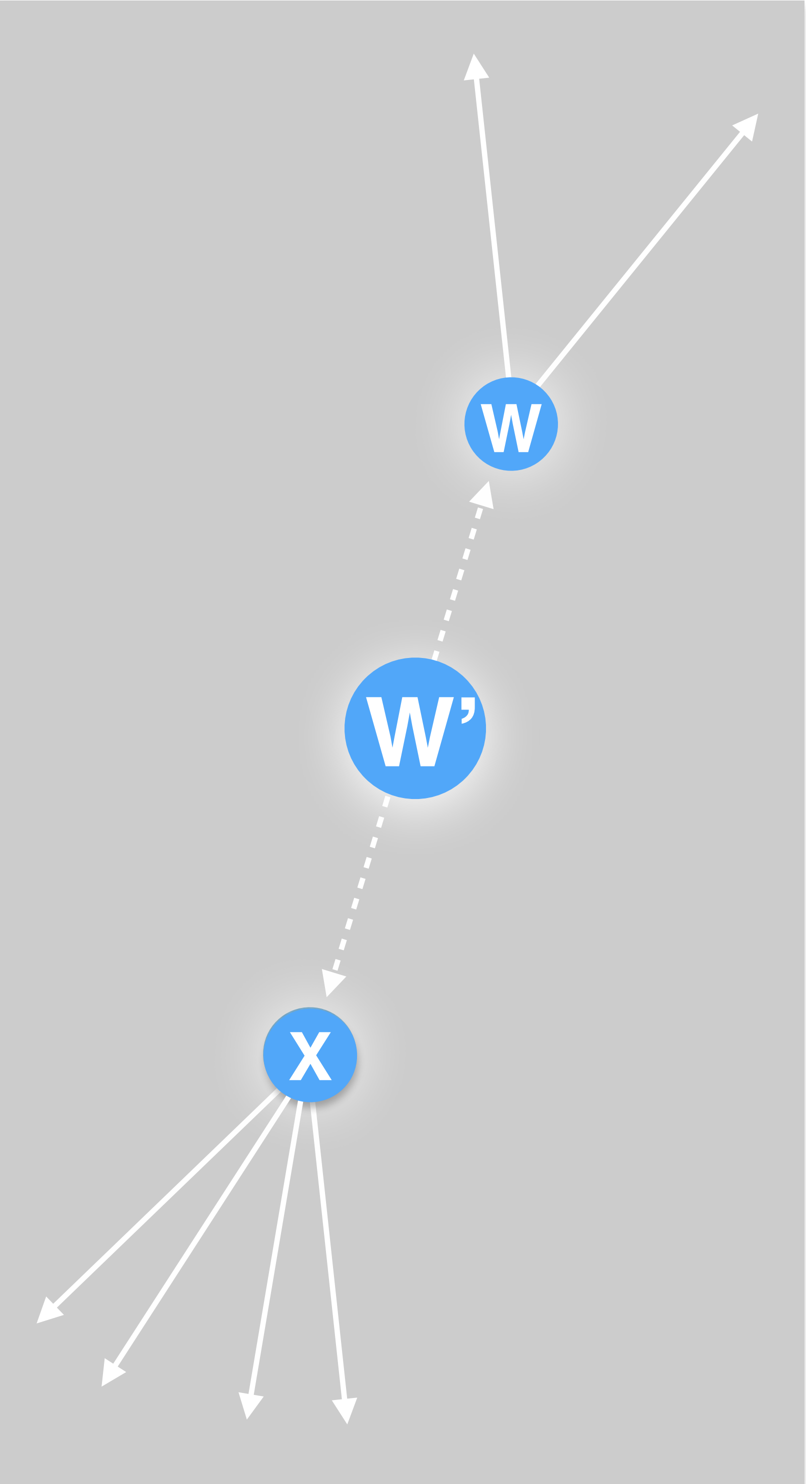

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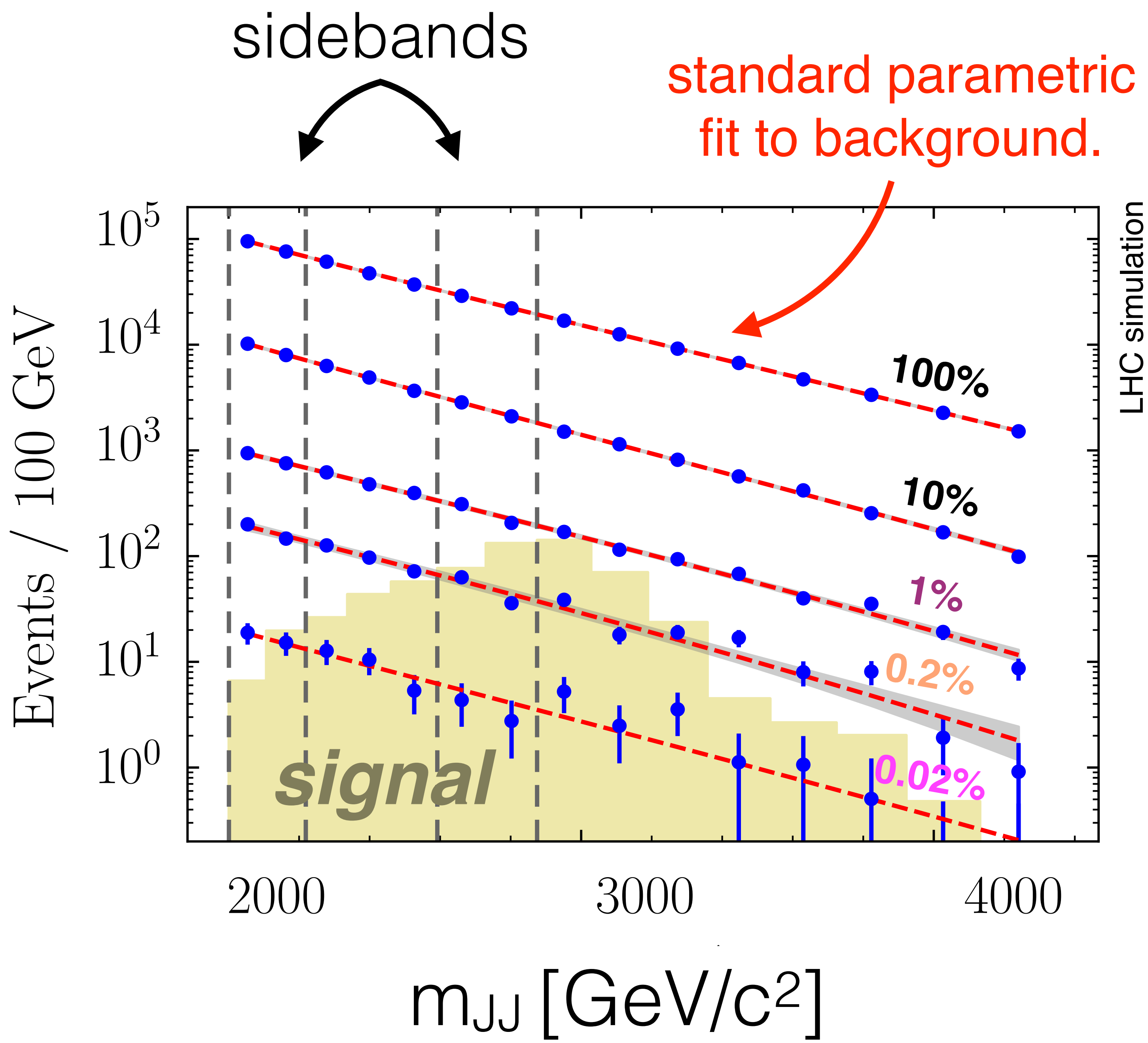

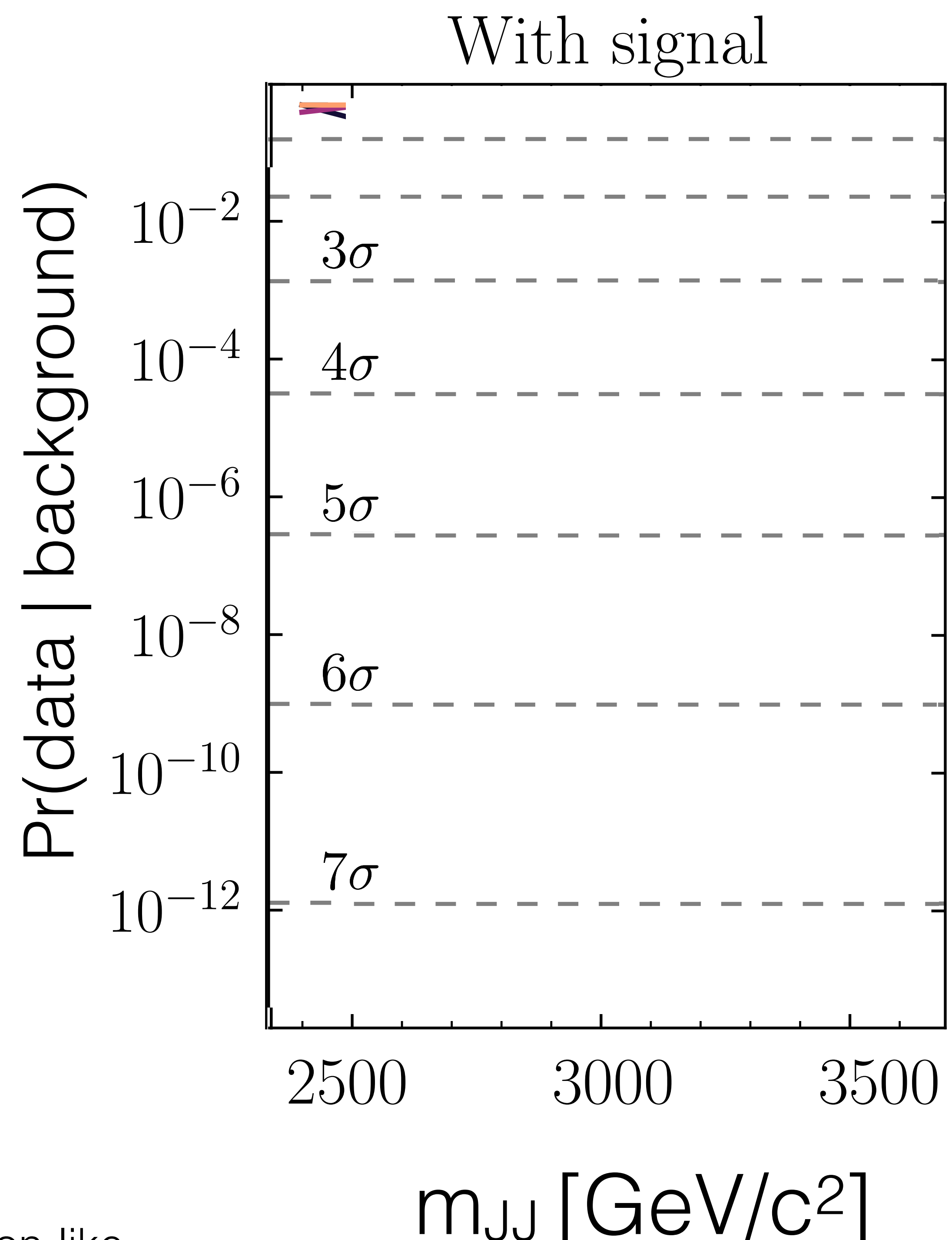

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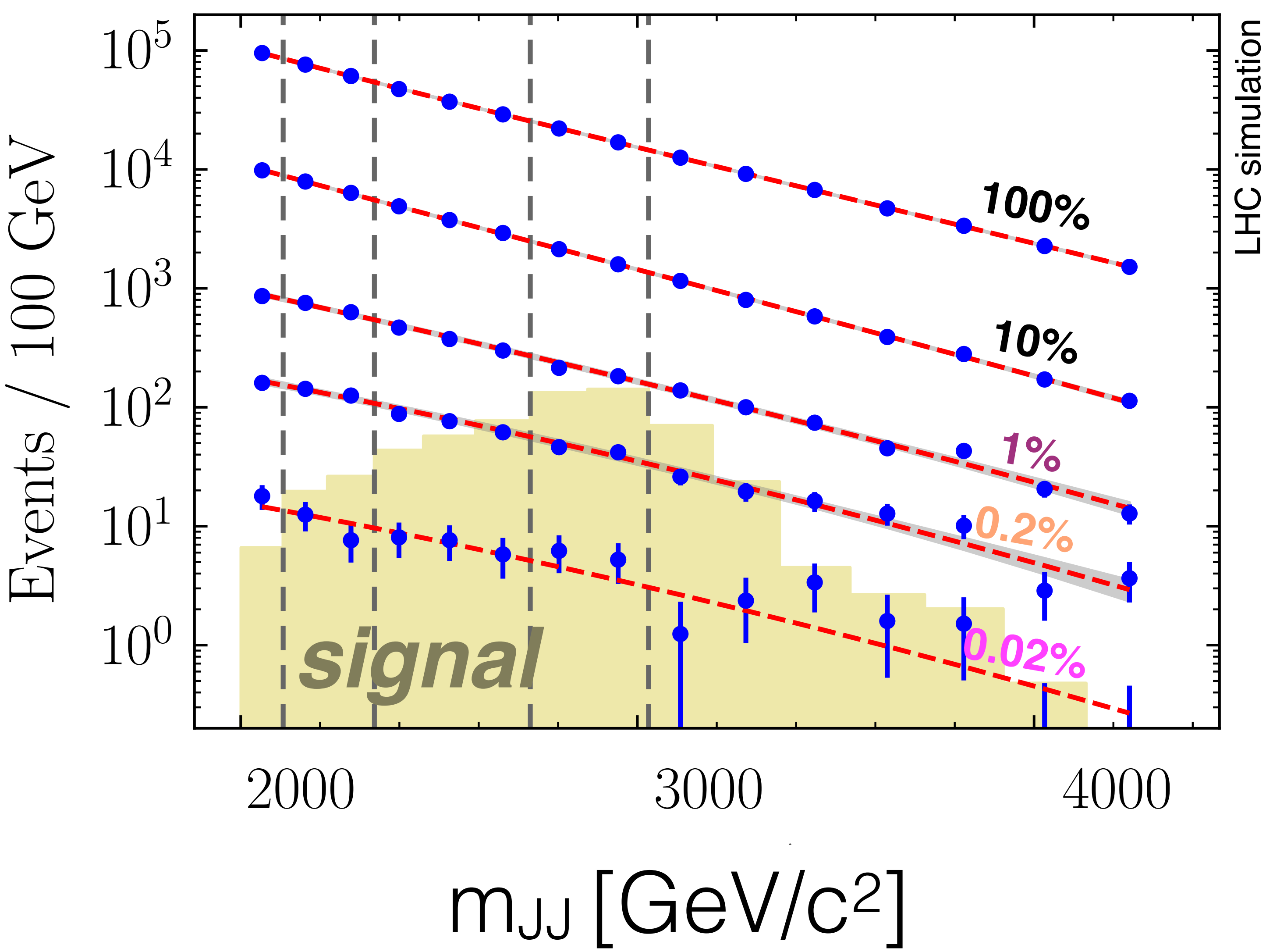

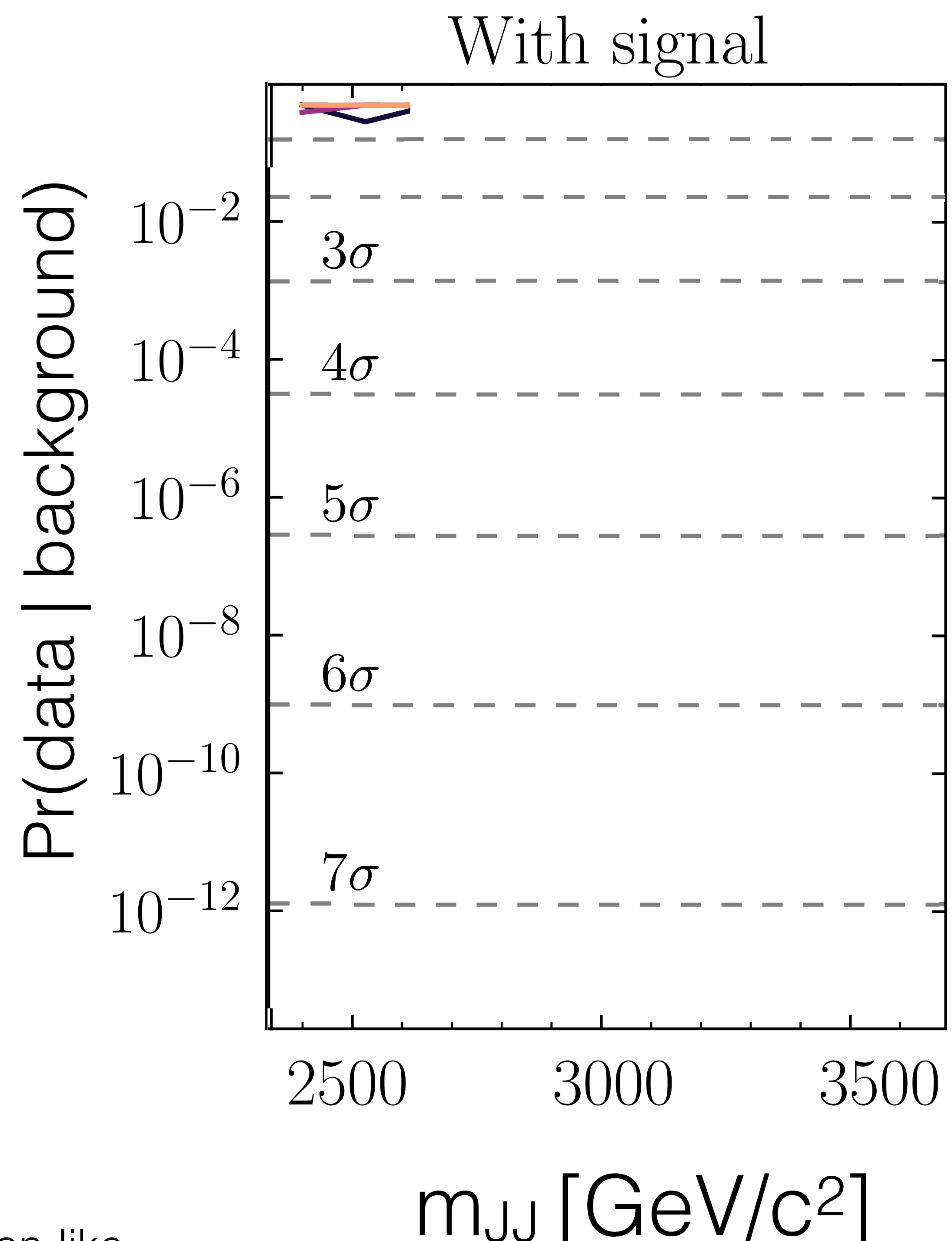

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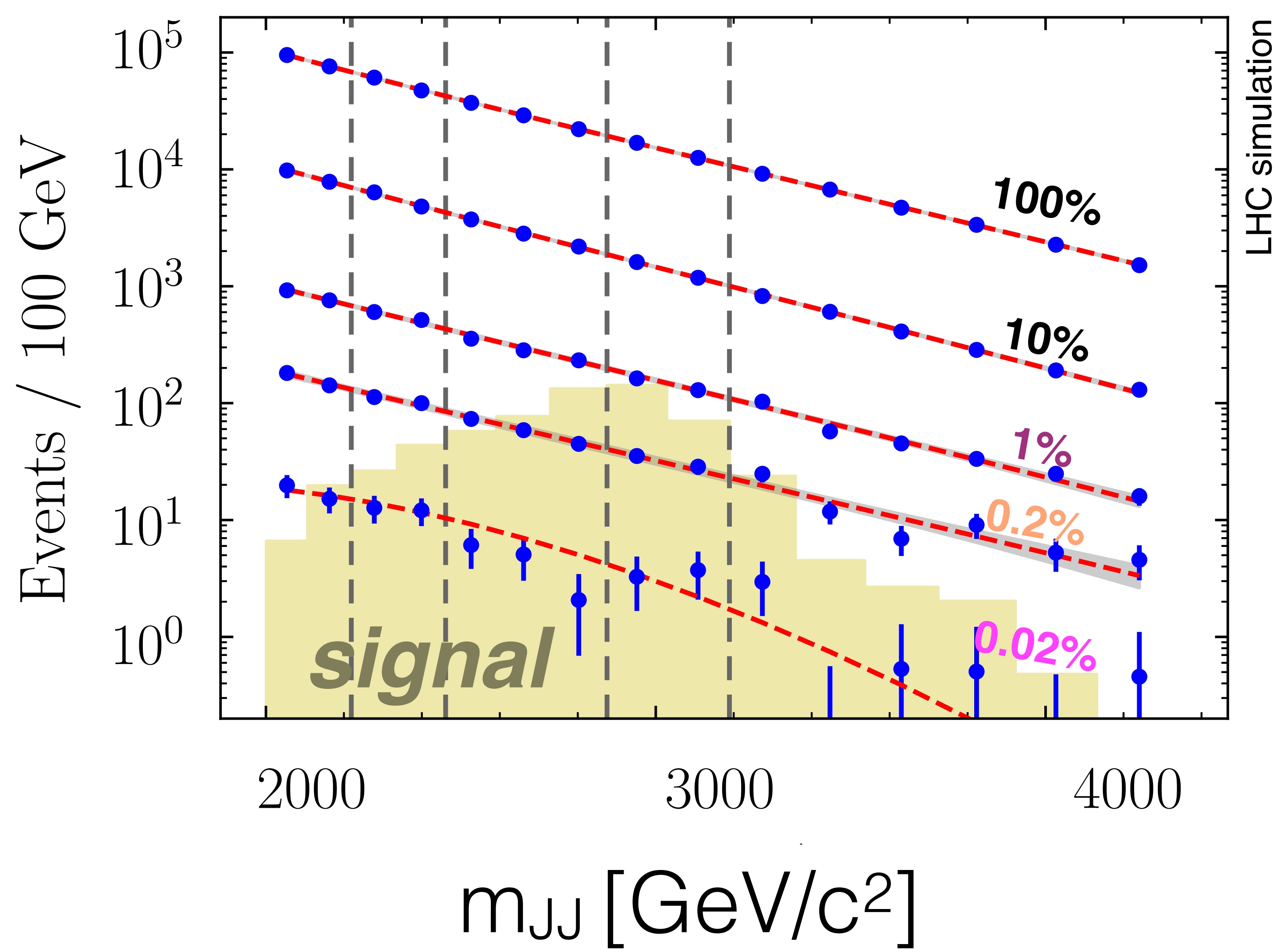

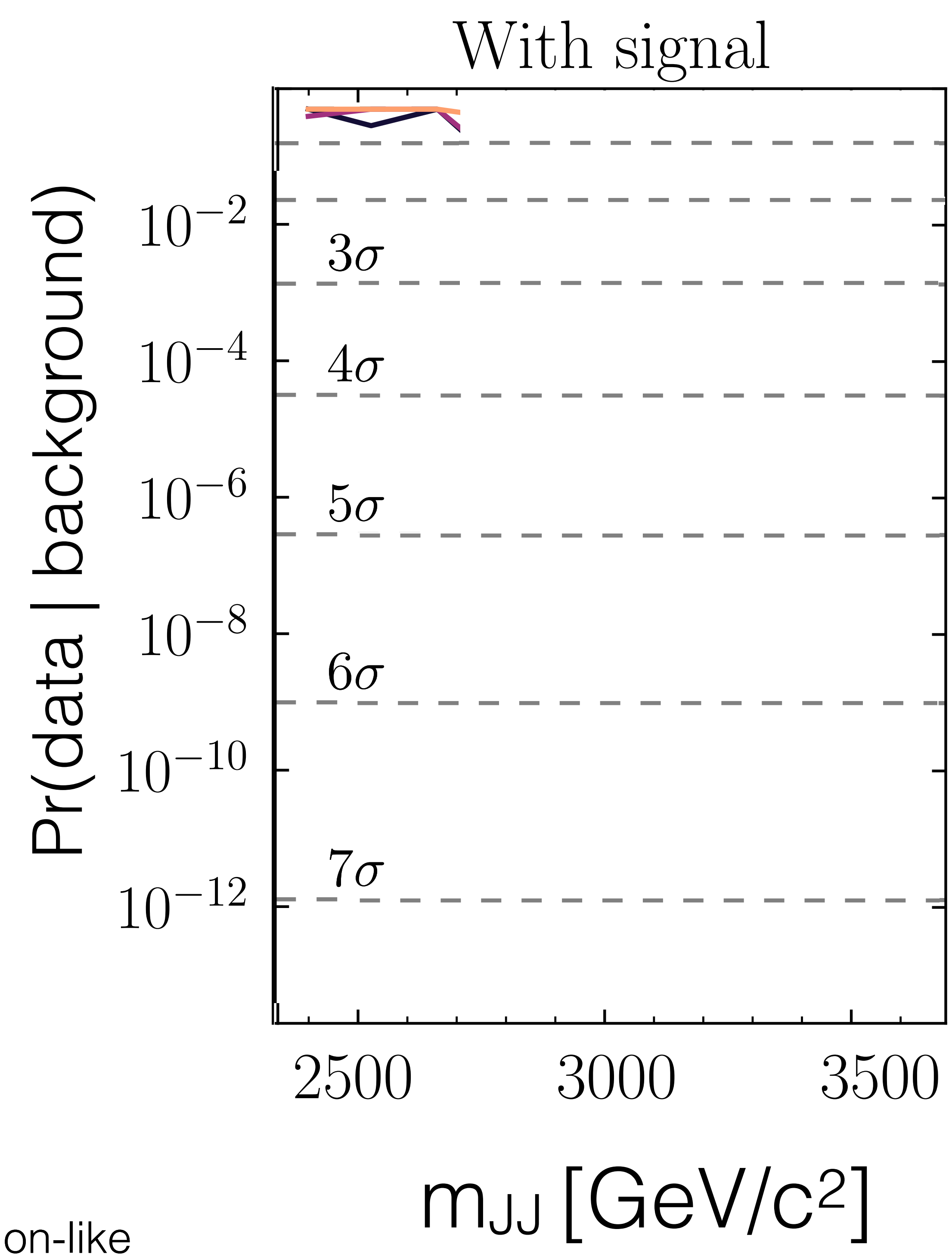

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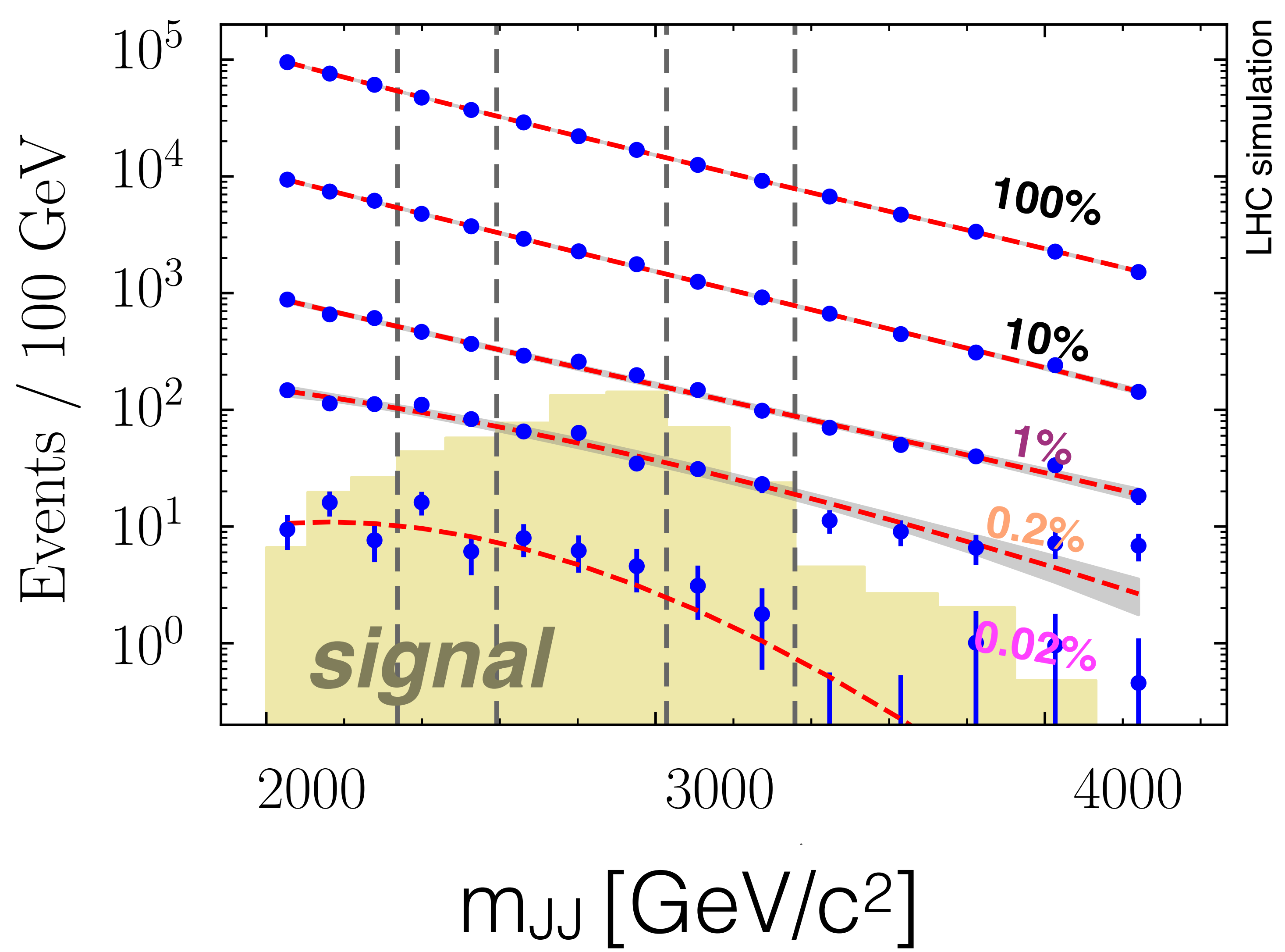

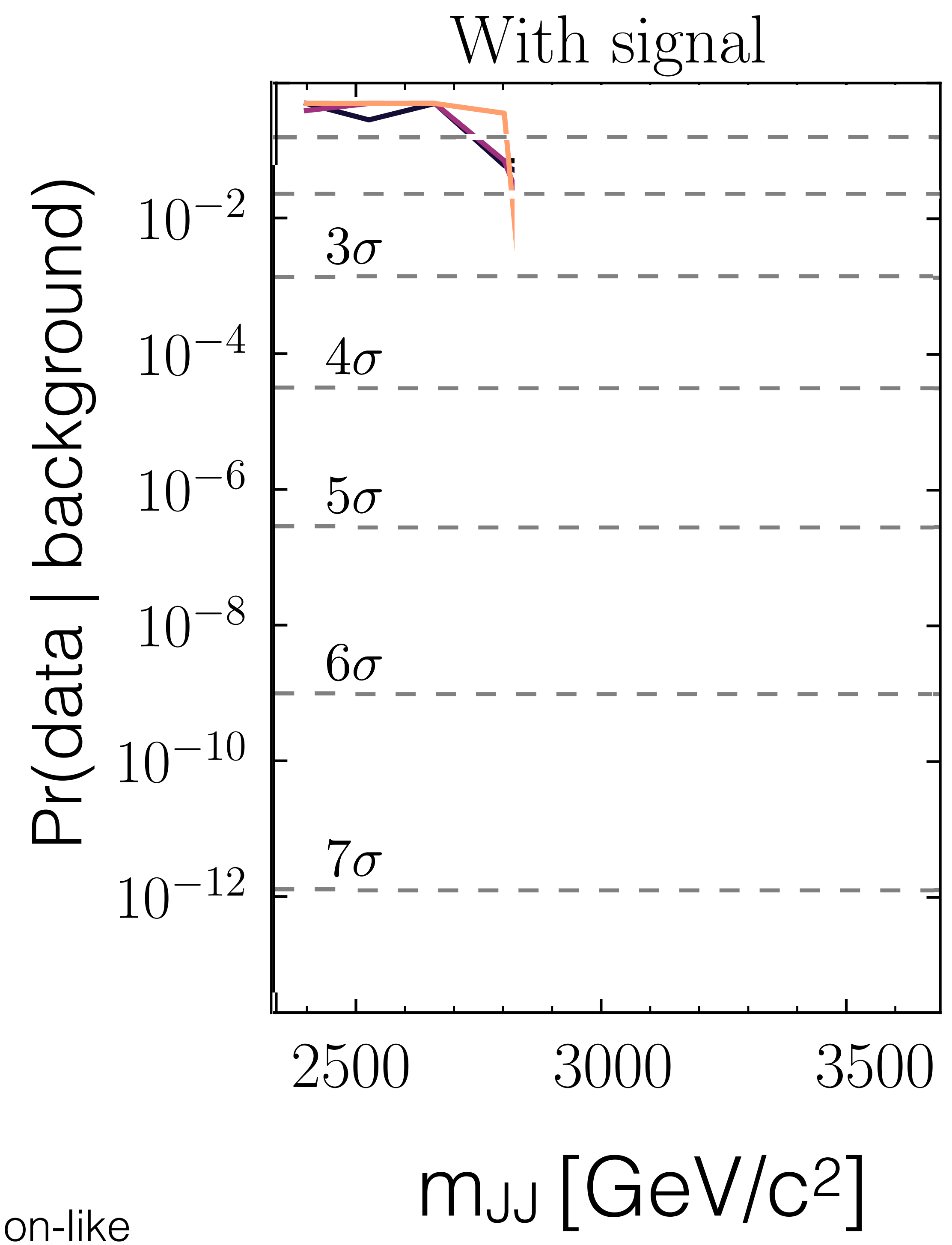

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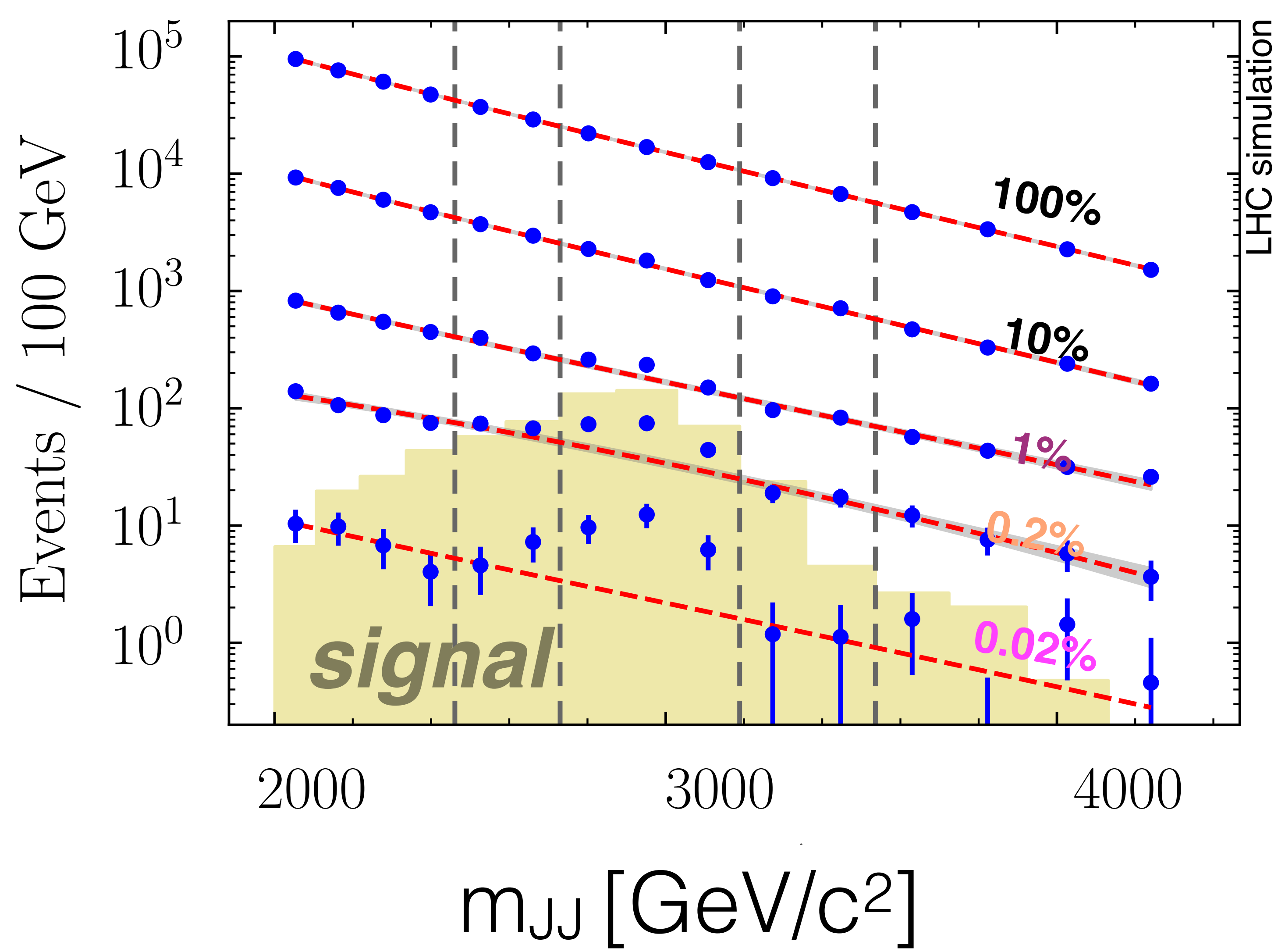

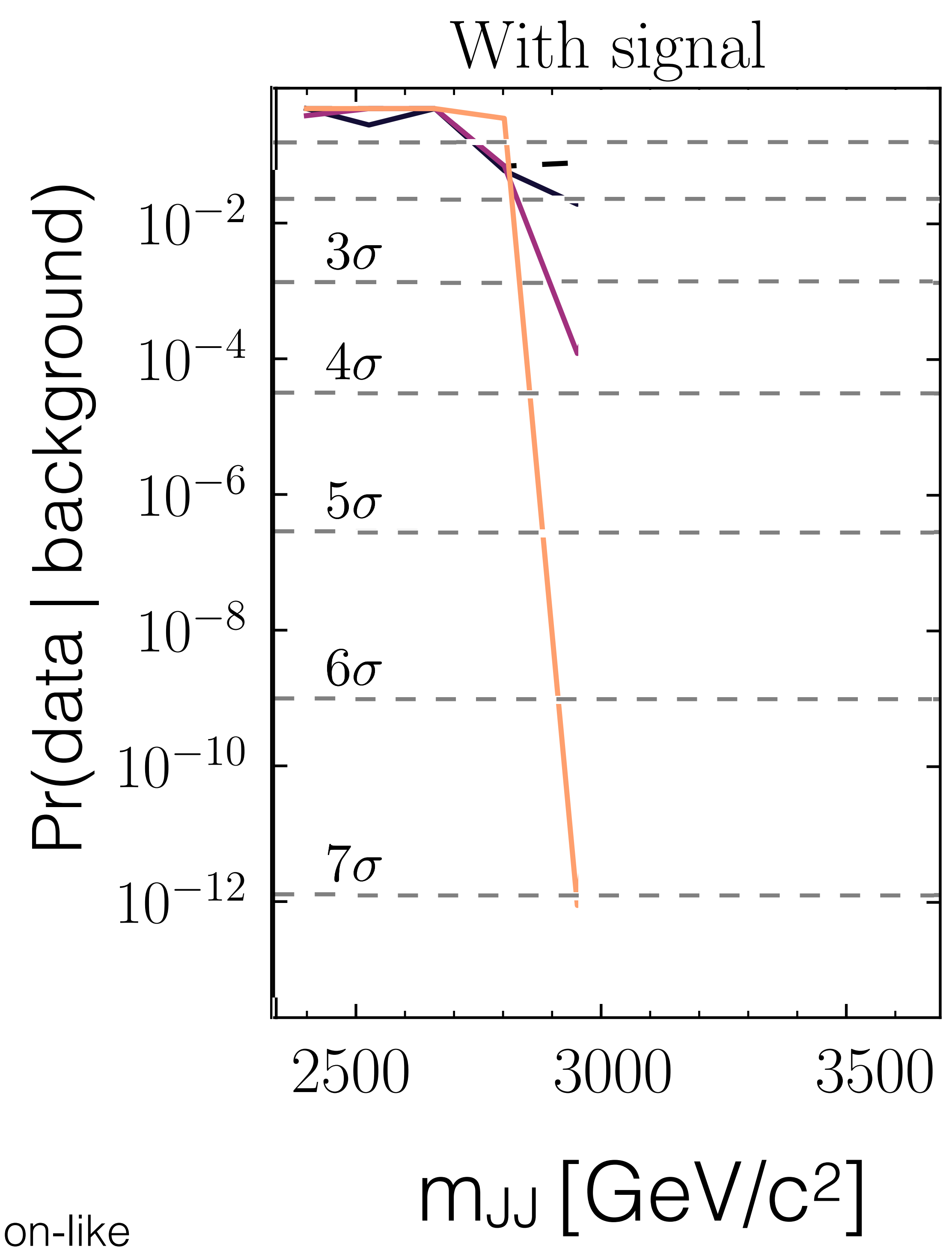

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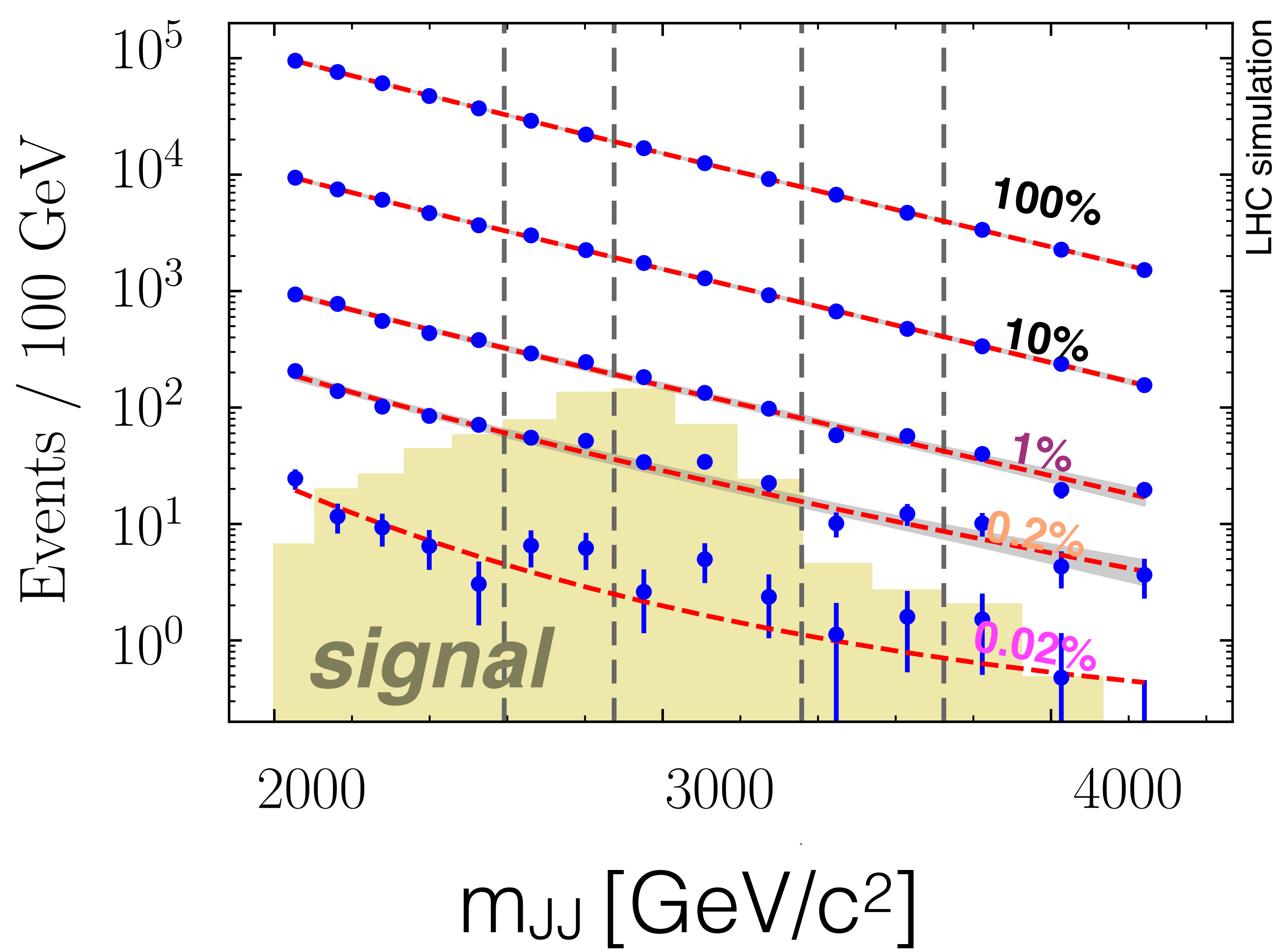

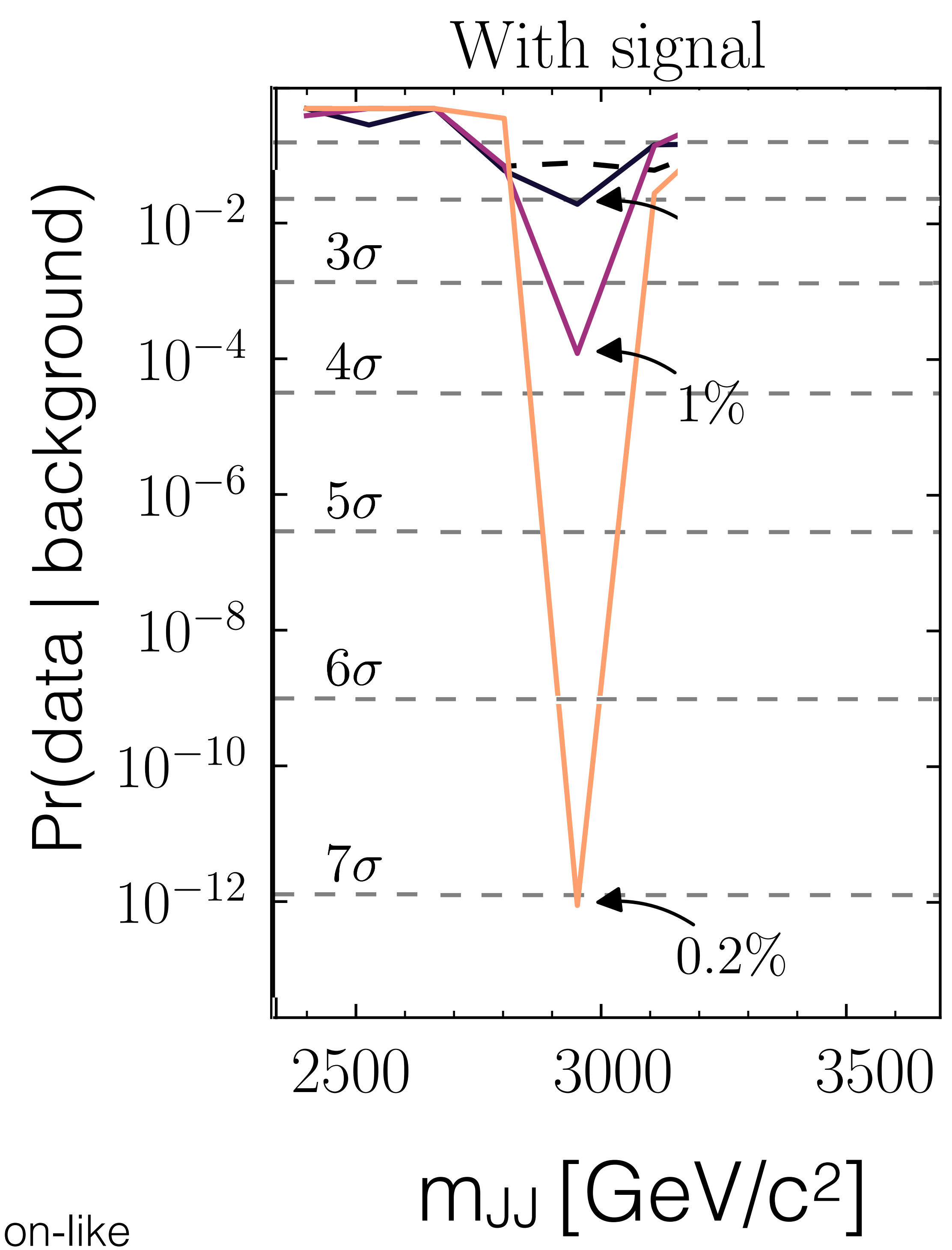

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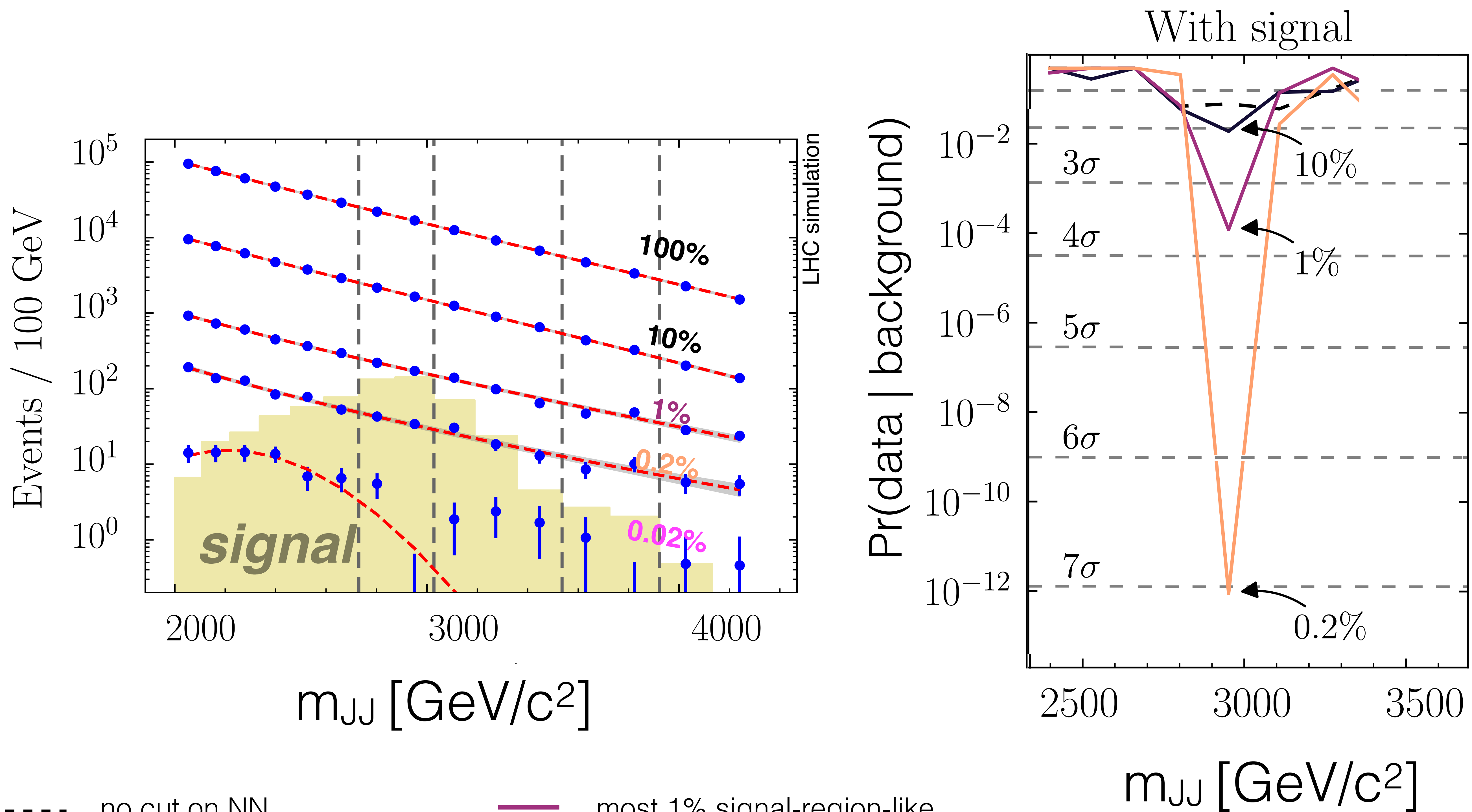

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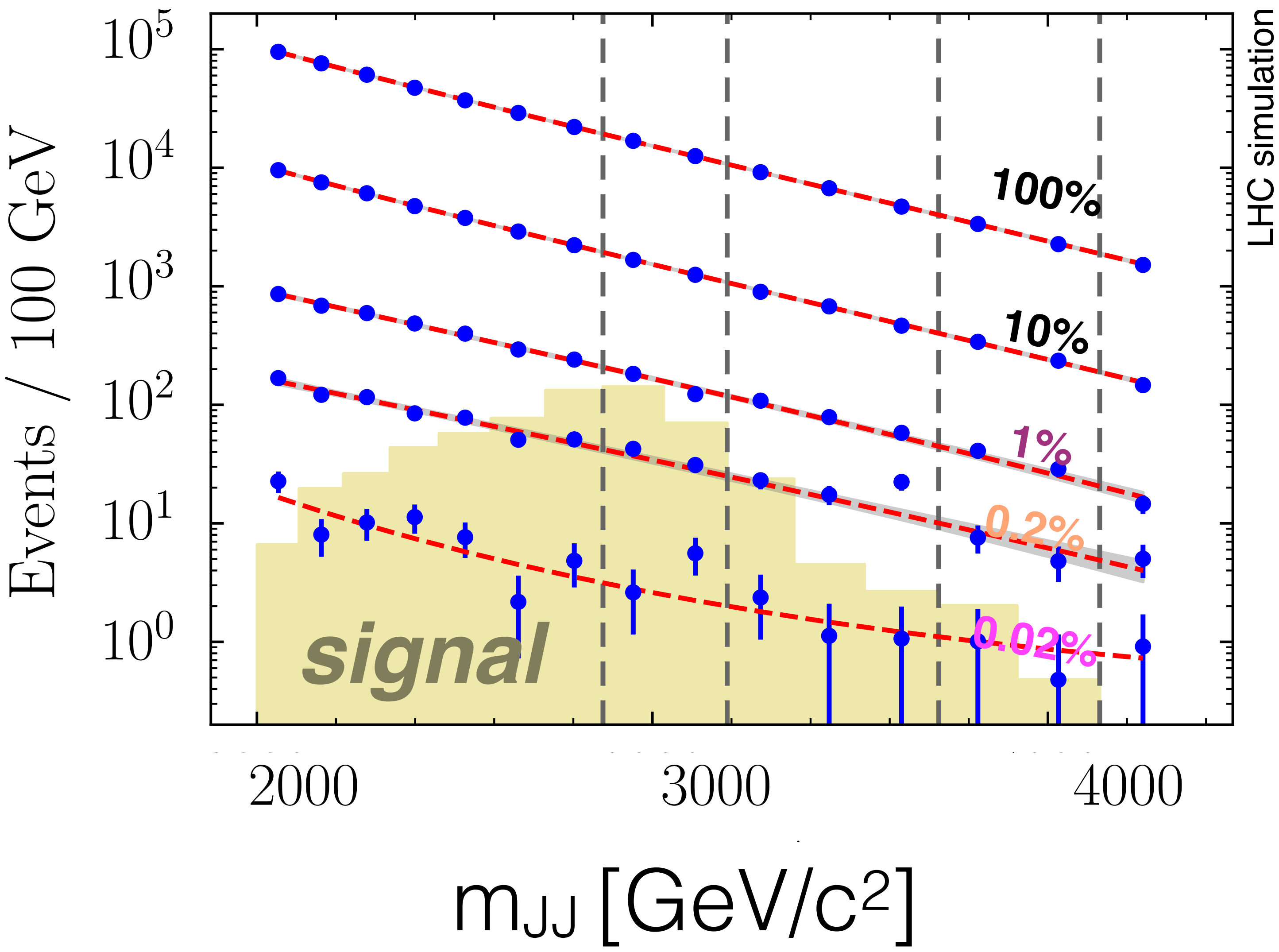

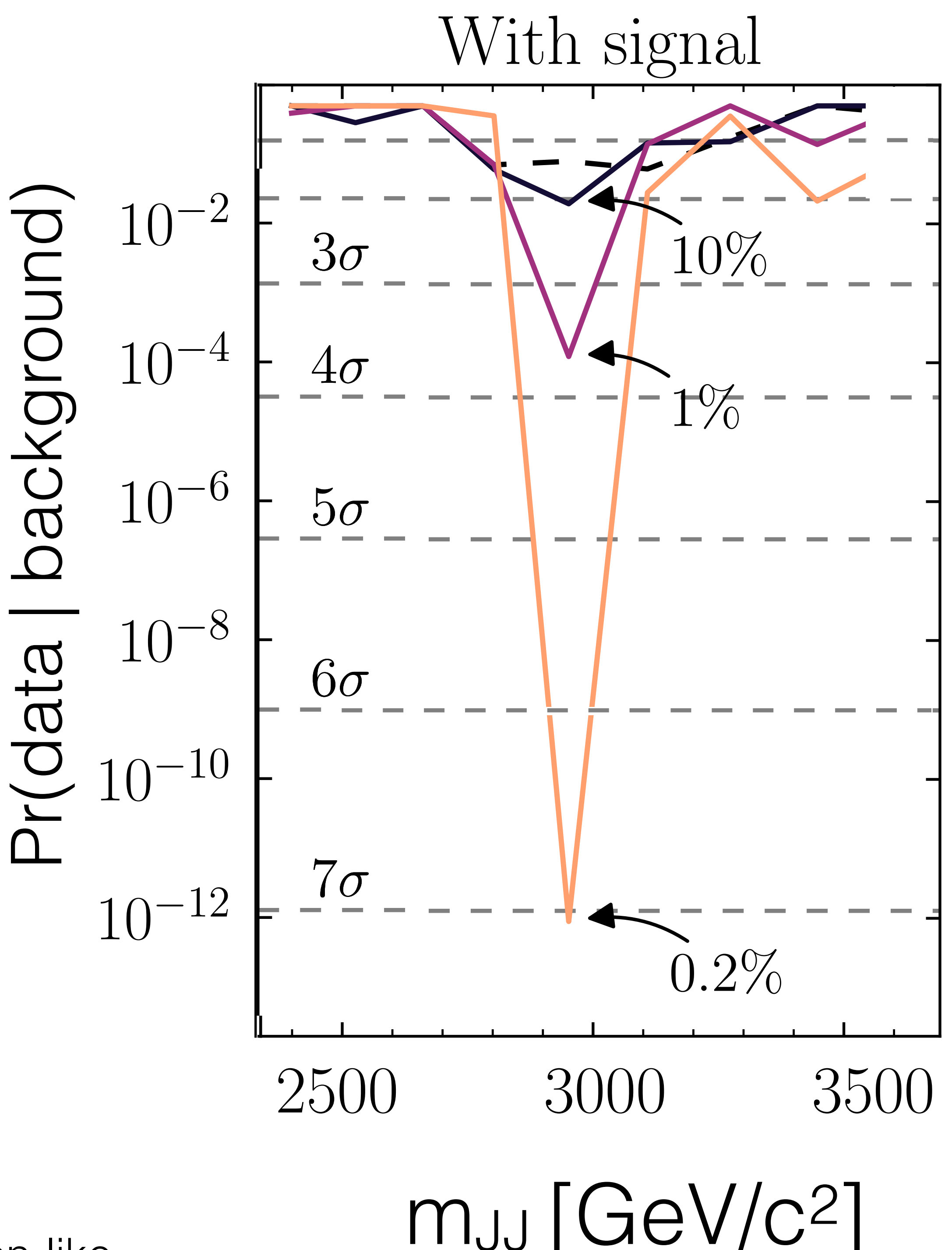

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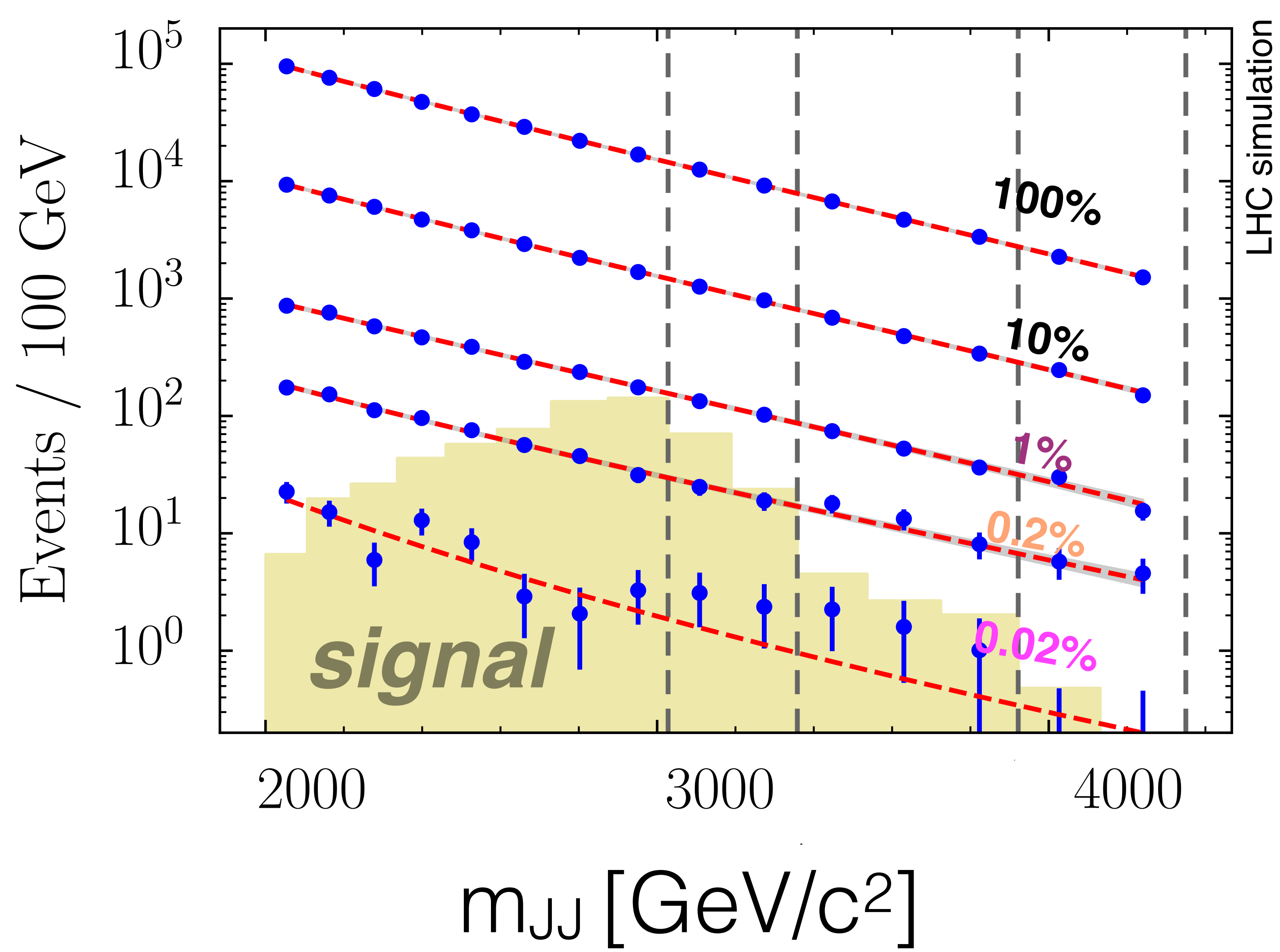

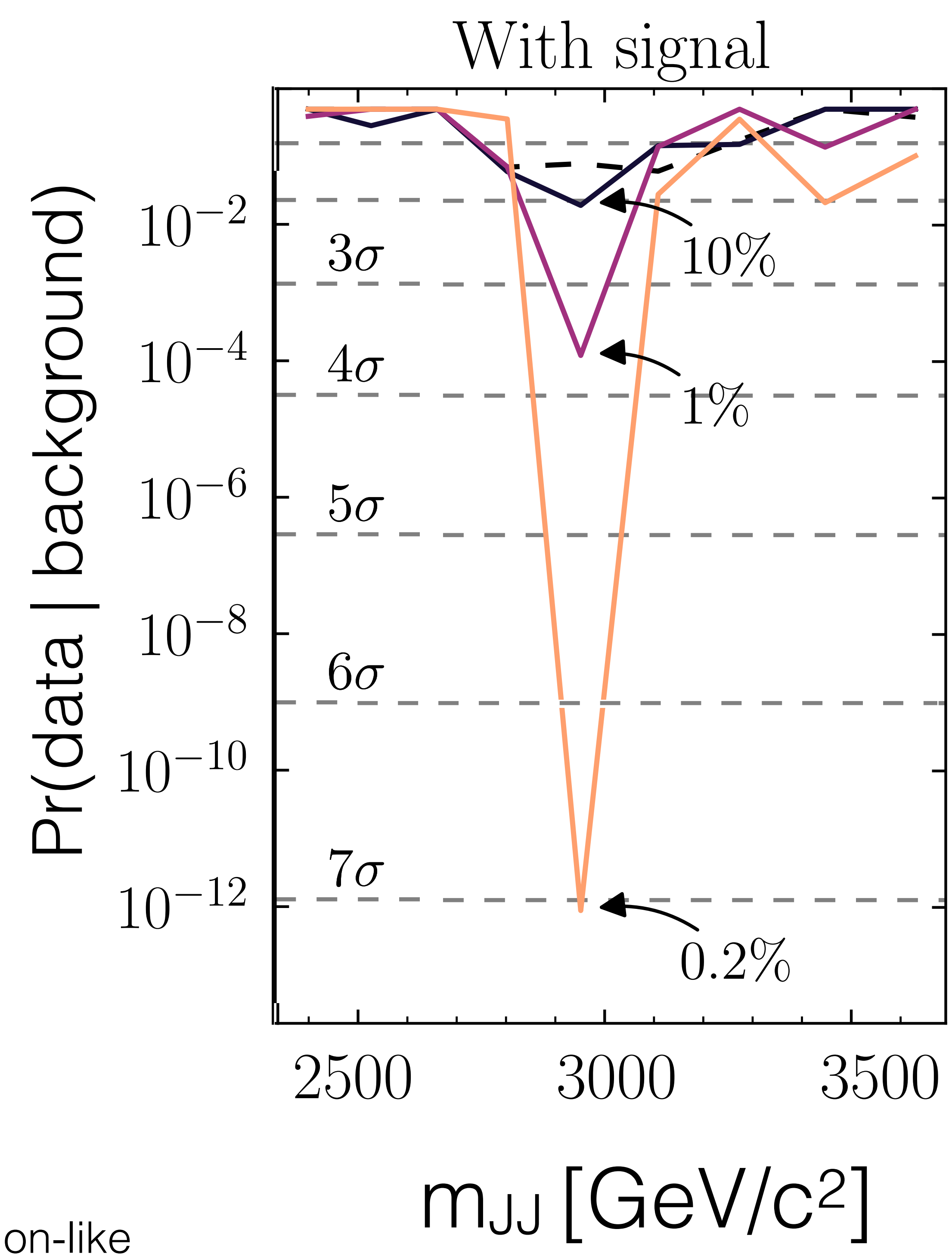

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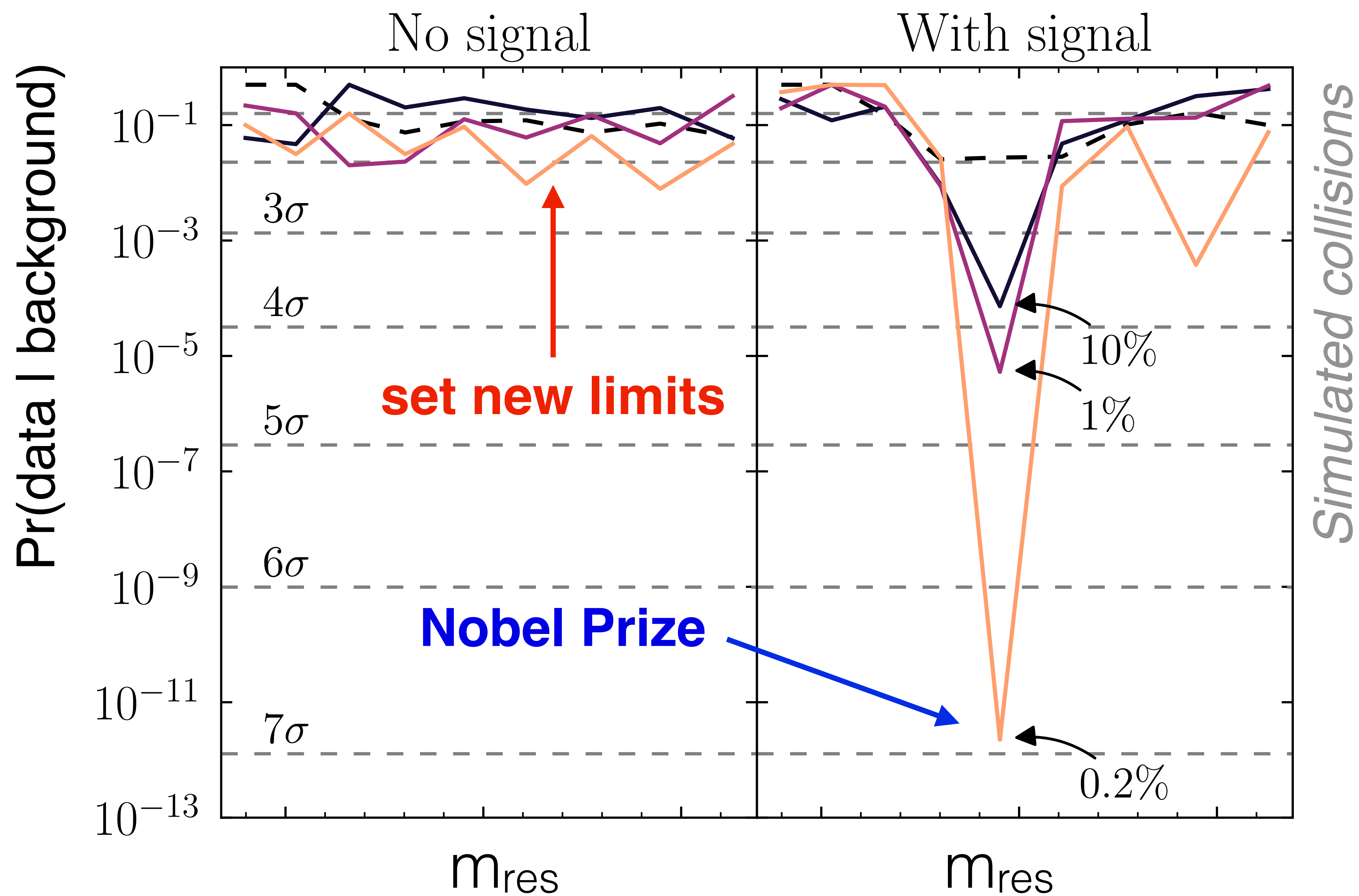
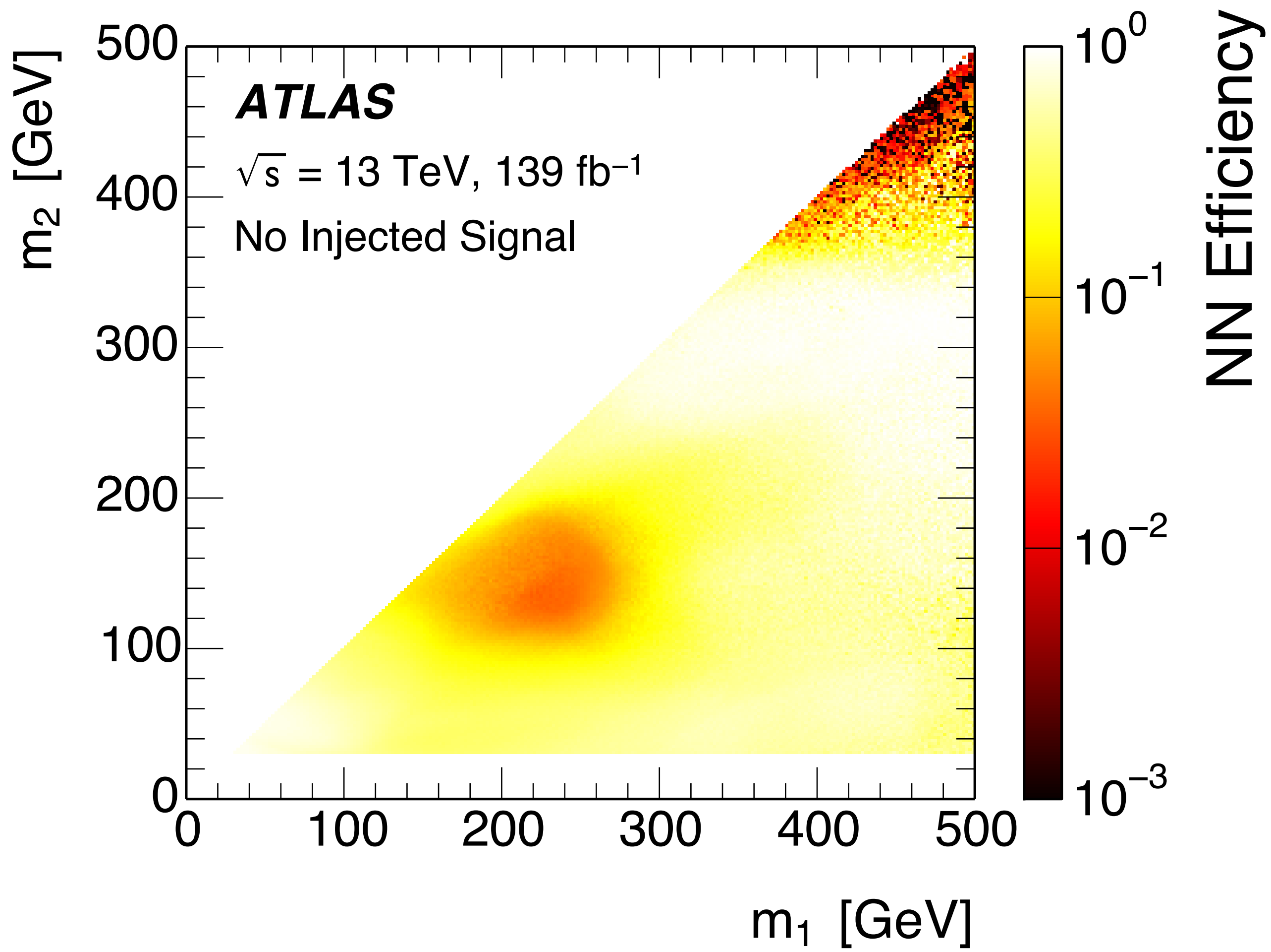
Anomaly detection: Overview

J. Collins, K. Howe, BPN, Phys. Rev. Lett. 121 (2018) 241803, 1805.02664



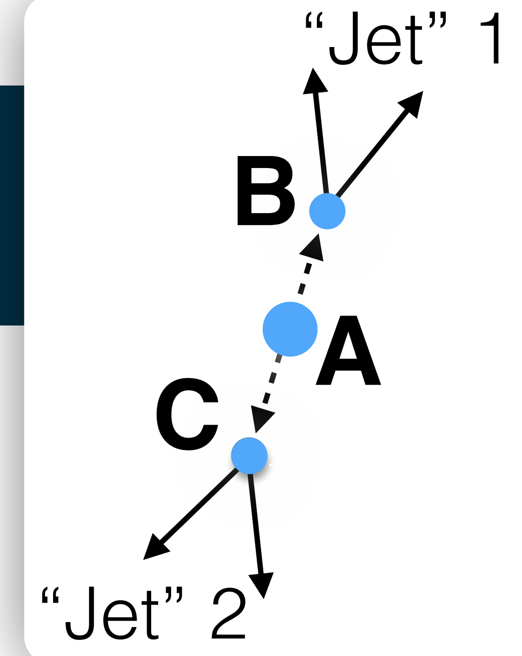
Collision data results

ATLAS Collaboration
PRL 125 (2020) 13801, 2005.02983



First round, keep it simple: feature space is 2D (jet masses)

Collision data results



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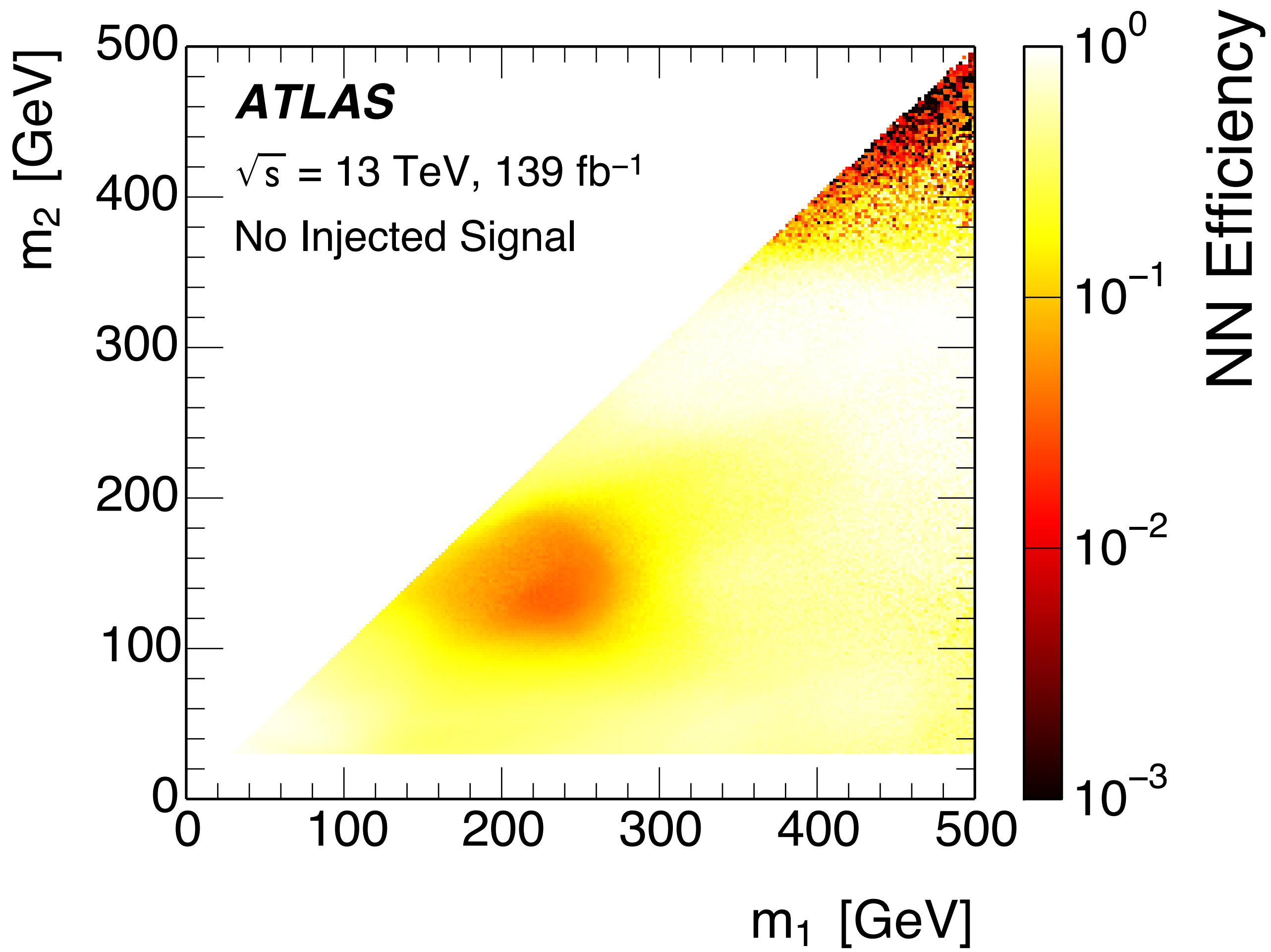

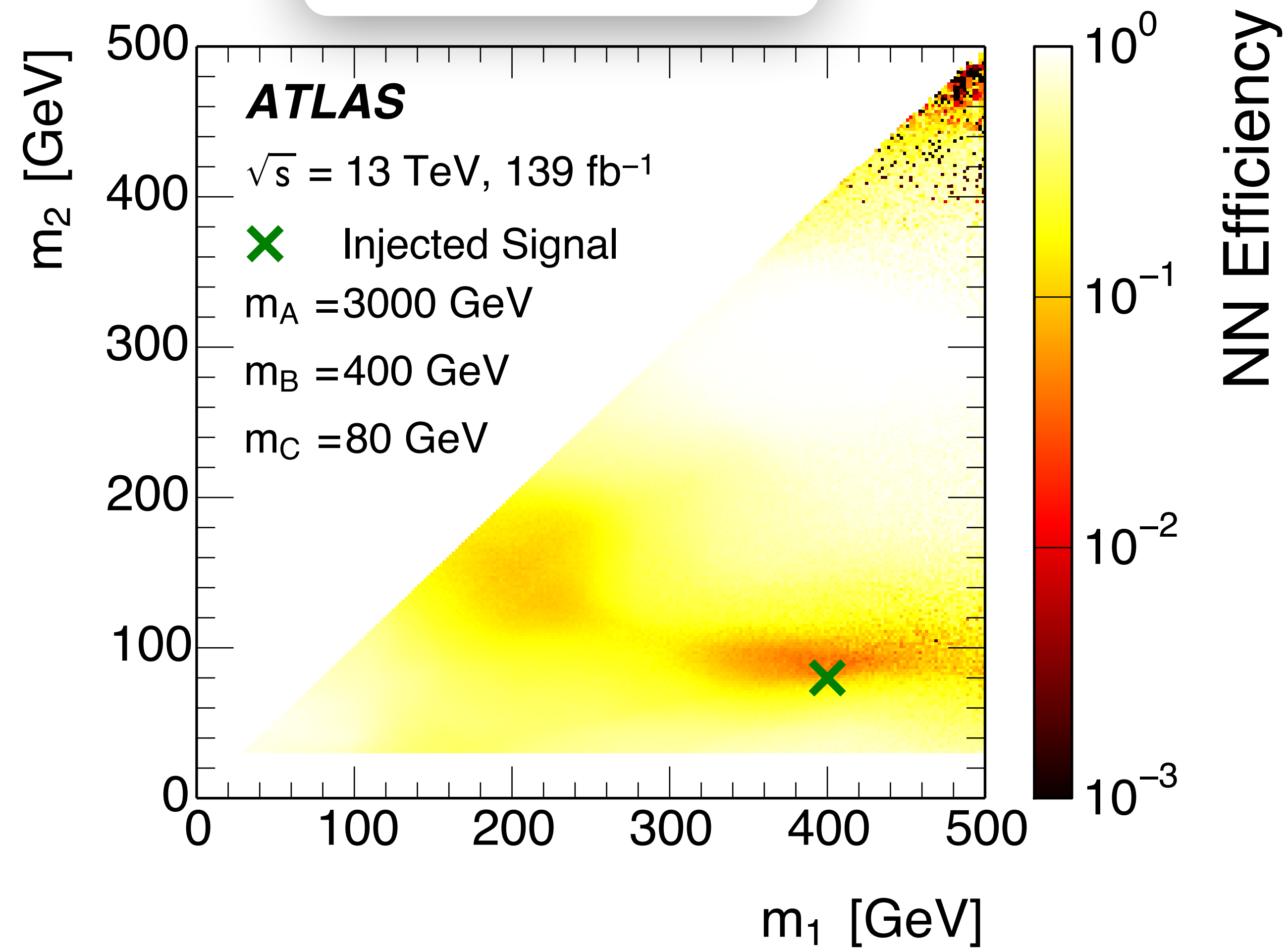

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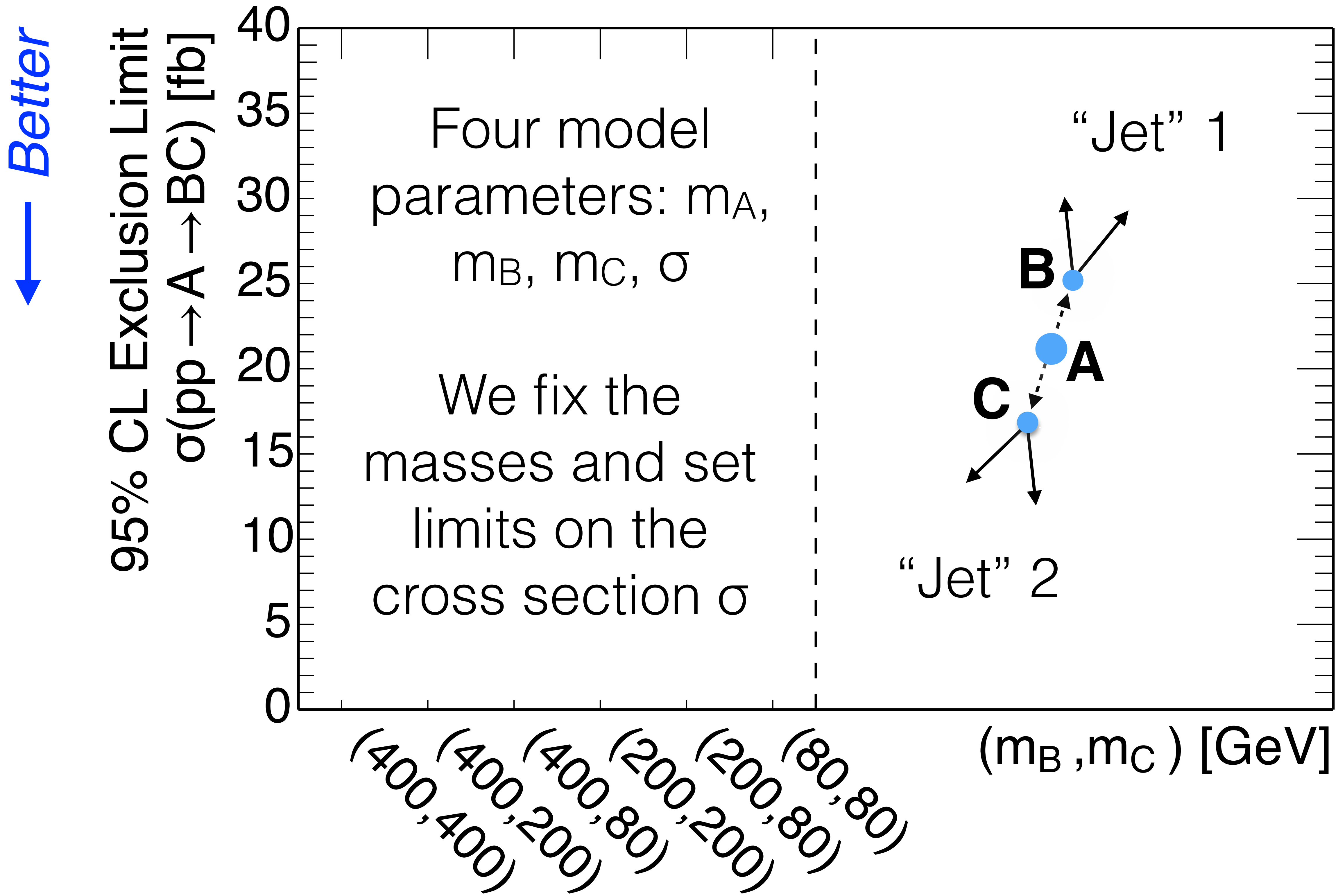

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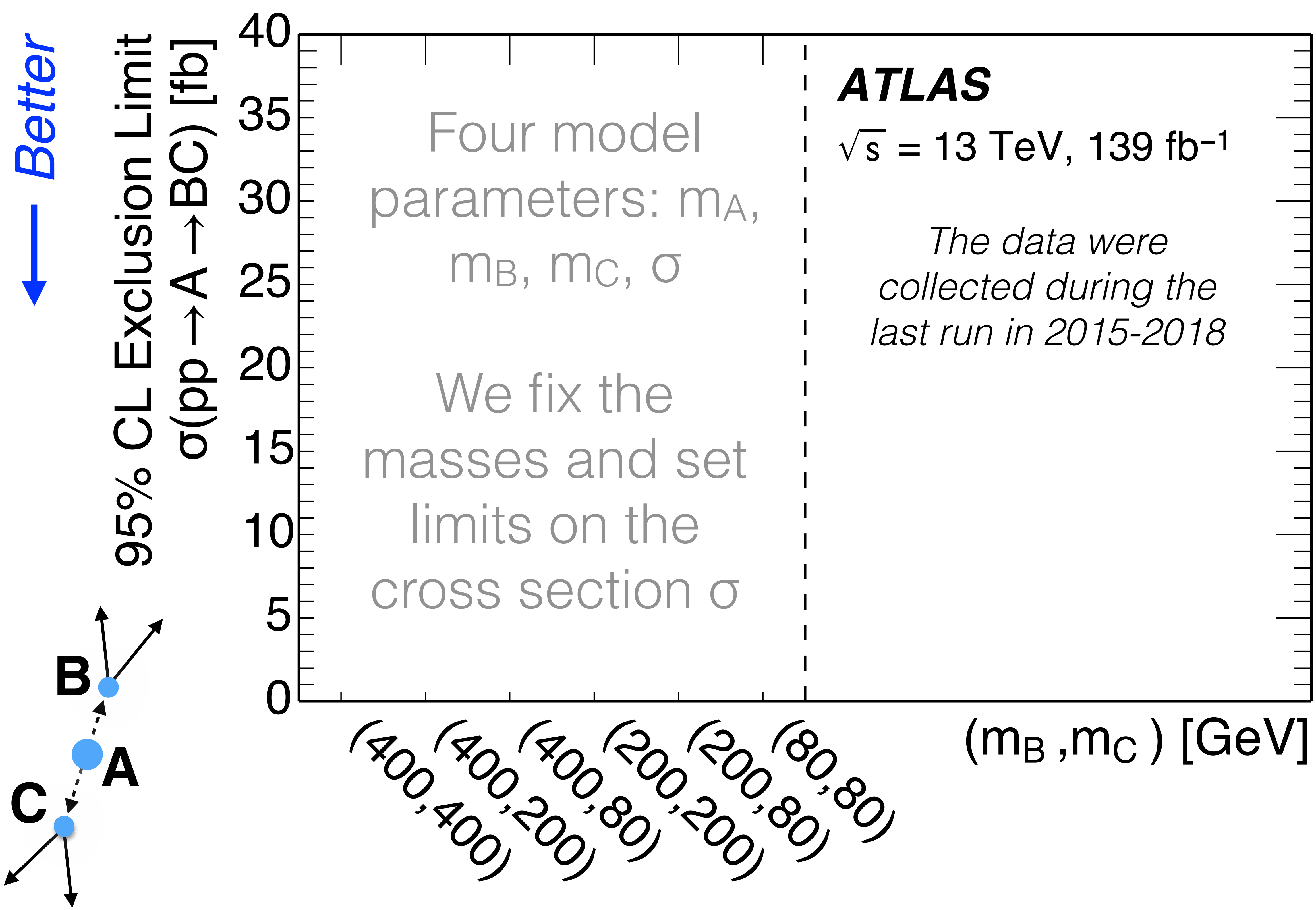
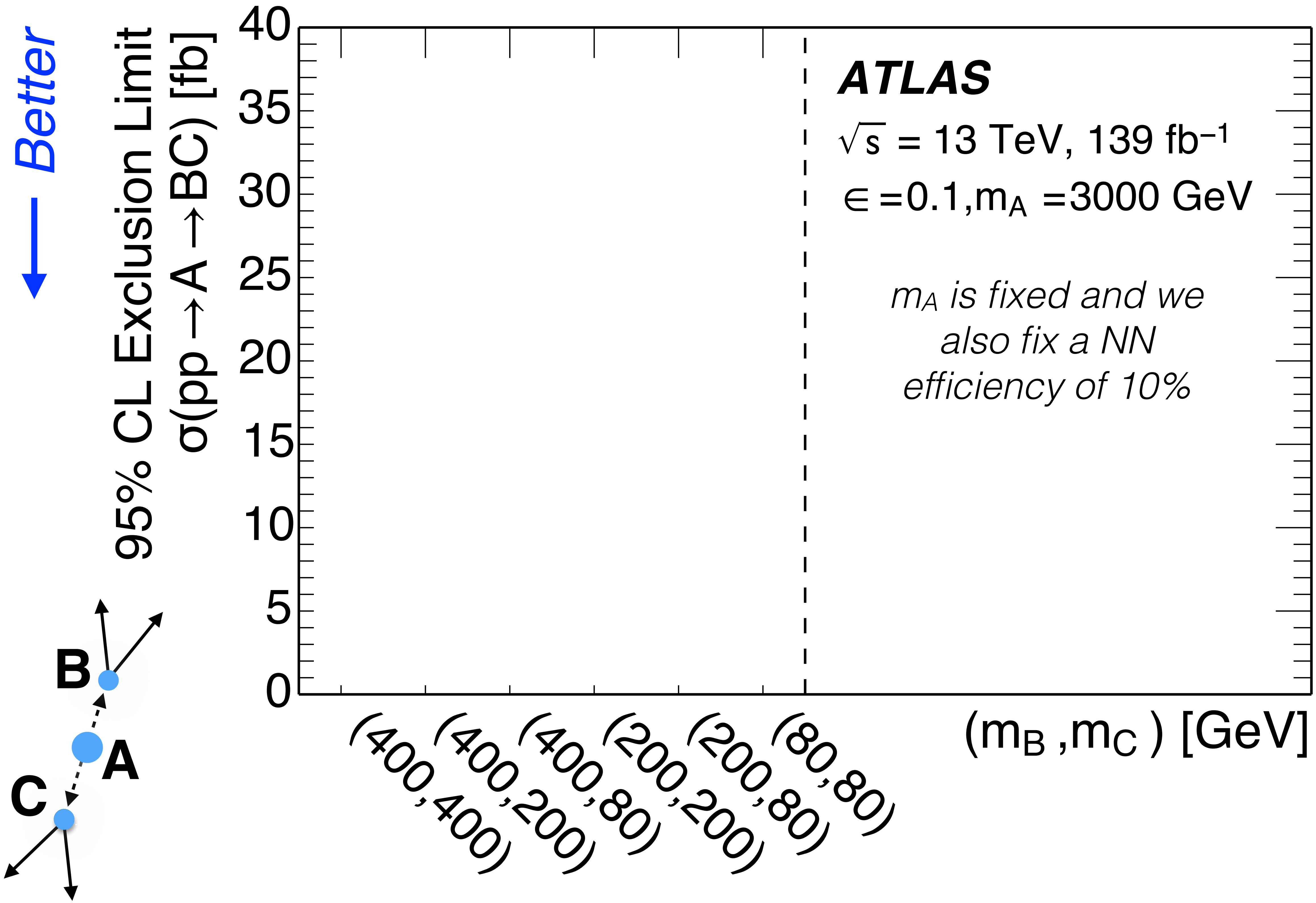


Collision data results



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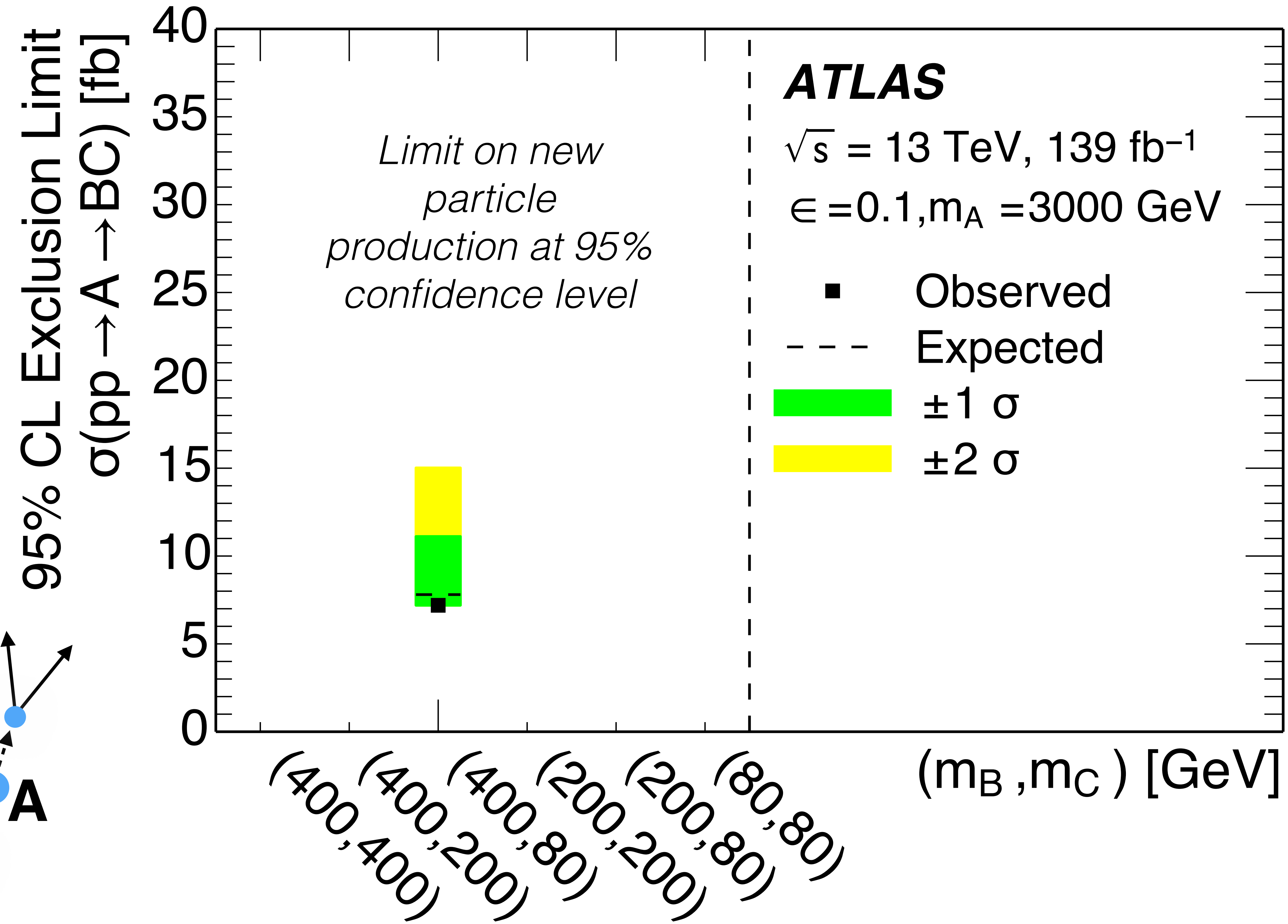
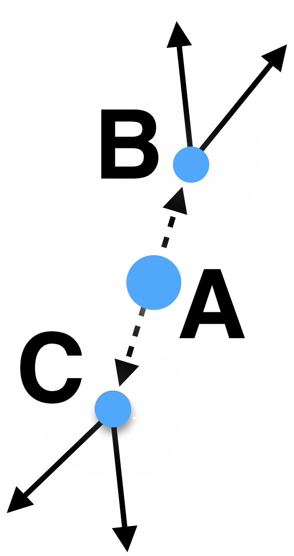
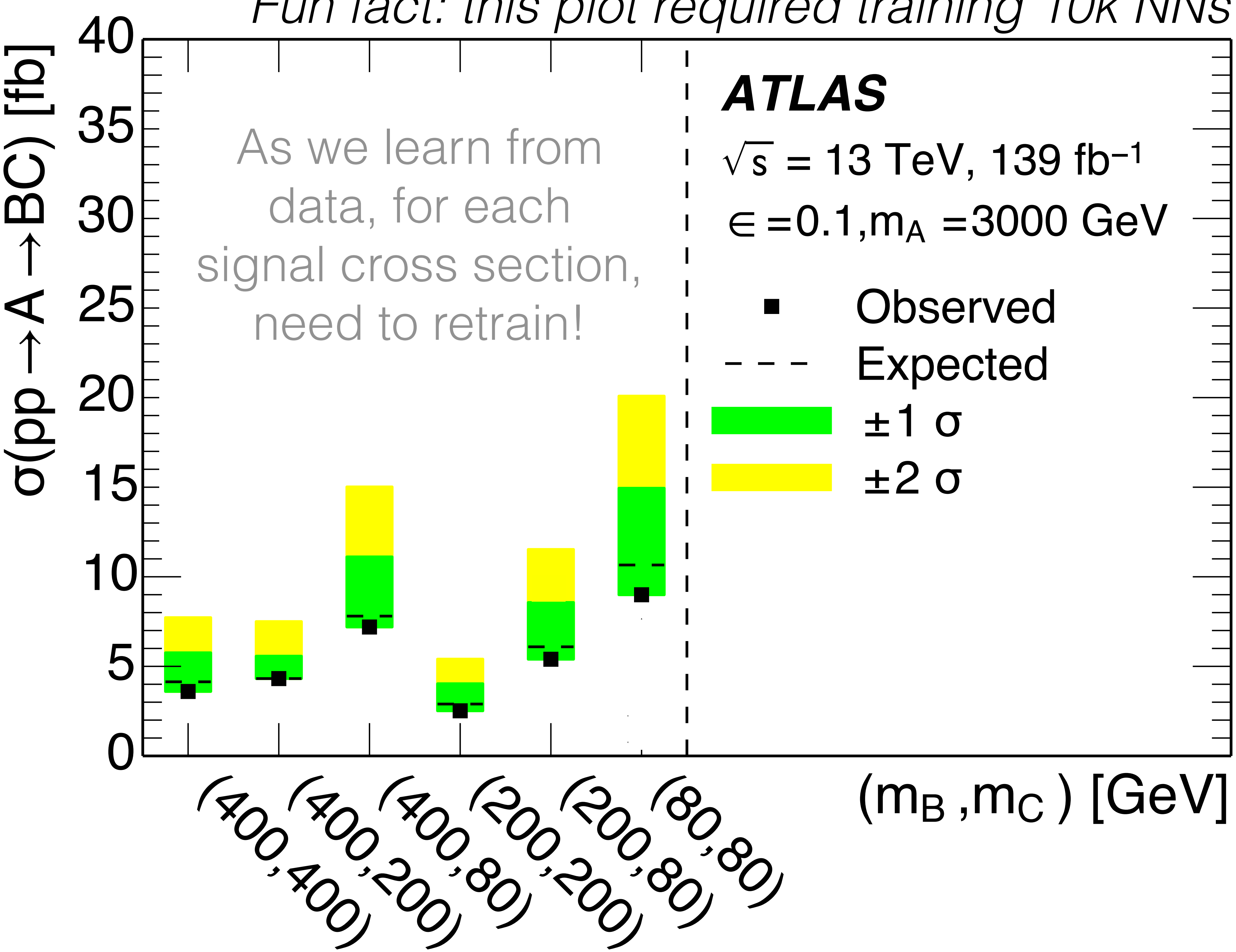
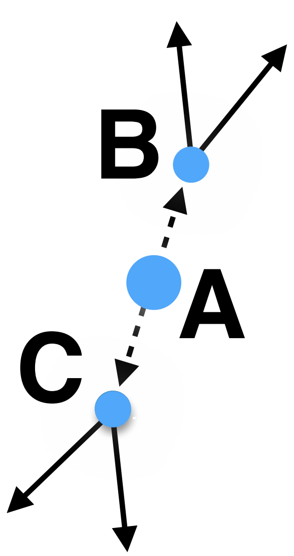




Collision data results

Fun fact: this plot required training 10k NNs





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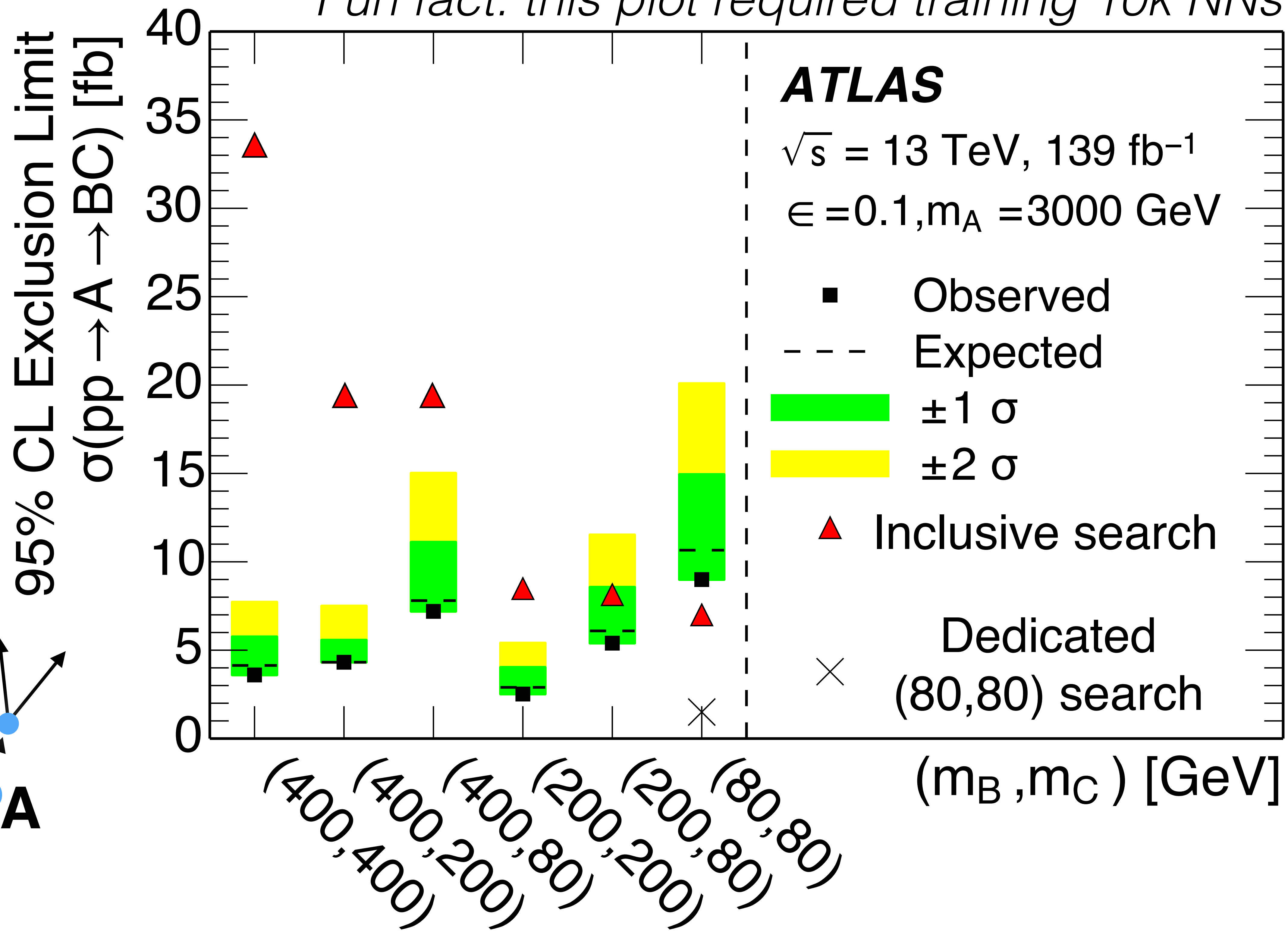

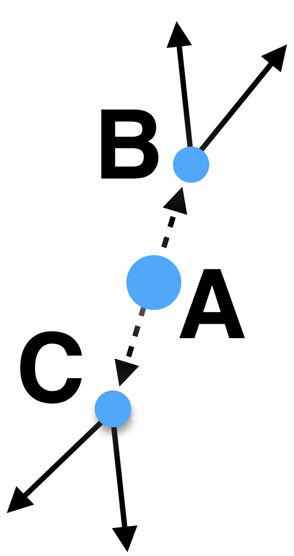

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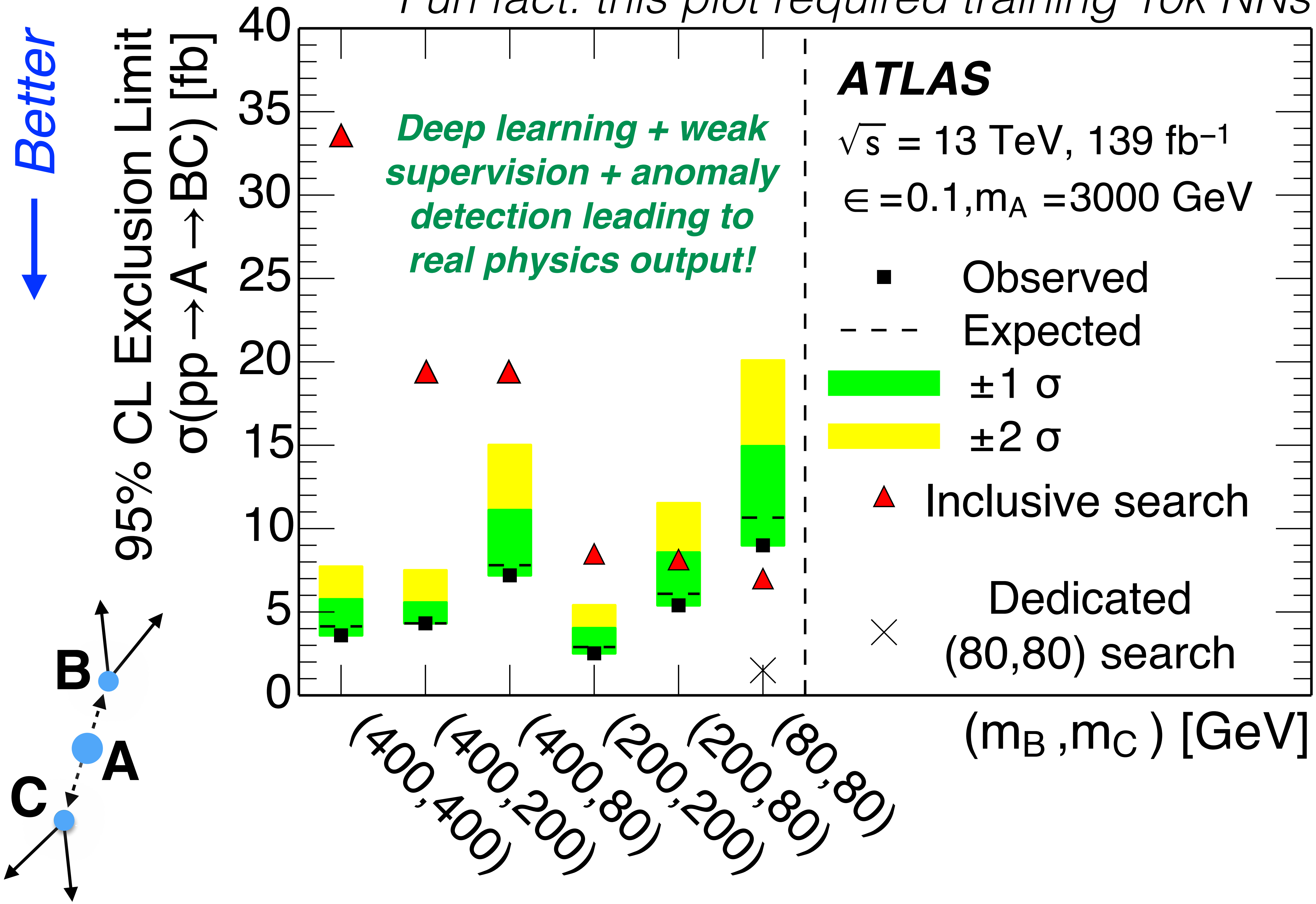

Extending CWoLa

CWoLa is 100% simulation independent.
Can we use simulation to improve it but still be as independent from simulation as possible?

General idea of CWoLa: **train a classifier** to distinguish data in the signal region from data in a **reference sample**.

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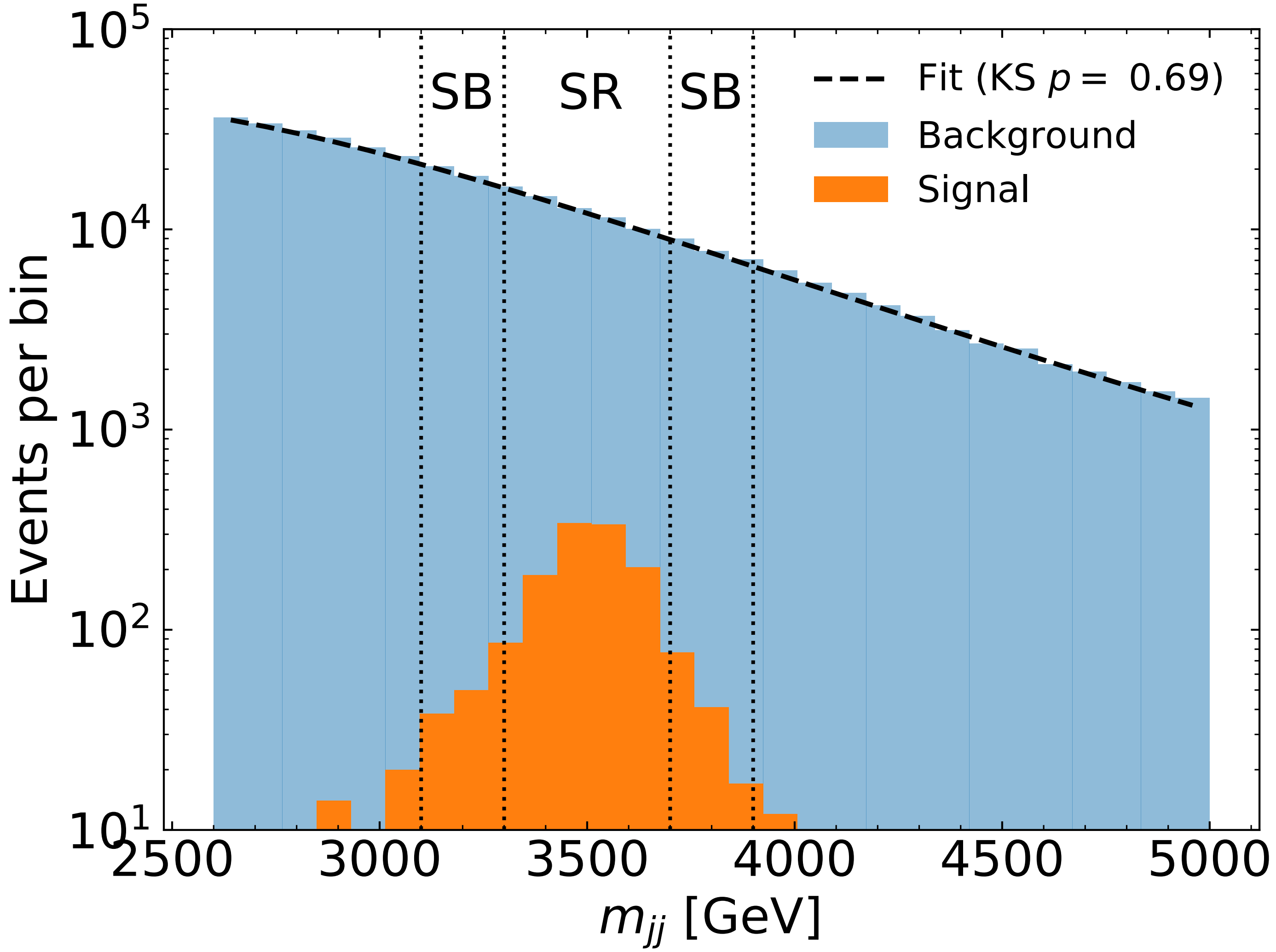
SA-CWoLa

SALAD

New Method I: SA-CWoLa



Need the CWoLa classifier to ignore information correlated with m_{jj}

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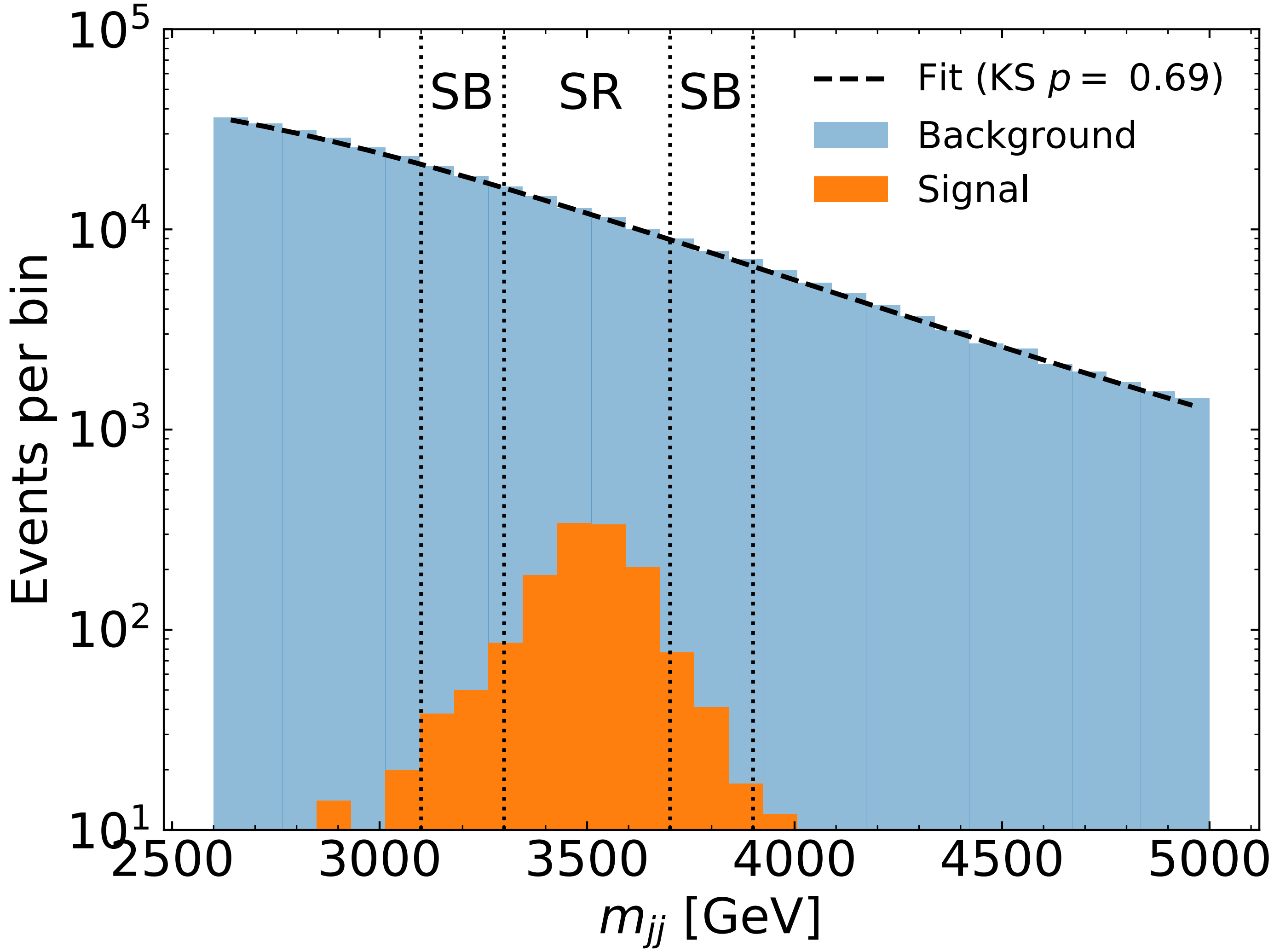

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Can use simulation to enforce this*!

Loss = **(SR vs. SB in data)** - λ **(SR vs. SB in MC)**

*Can't combine CWoLa with standard decorrelation approaches because they may wash out the signal

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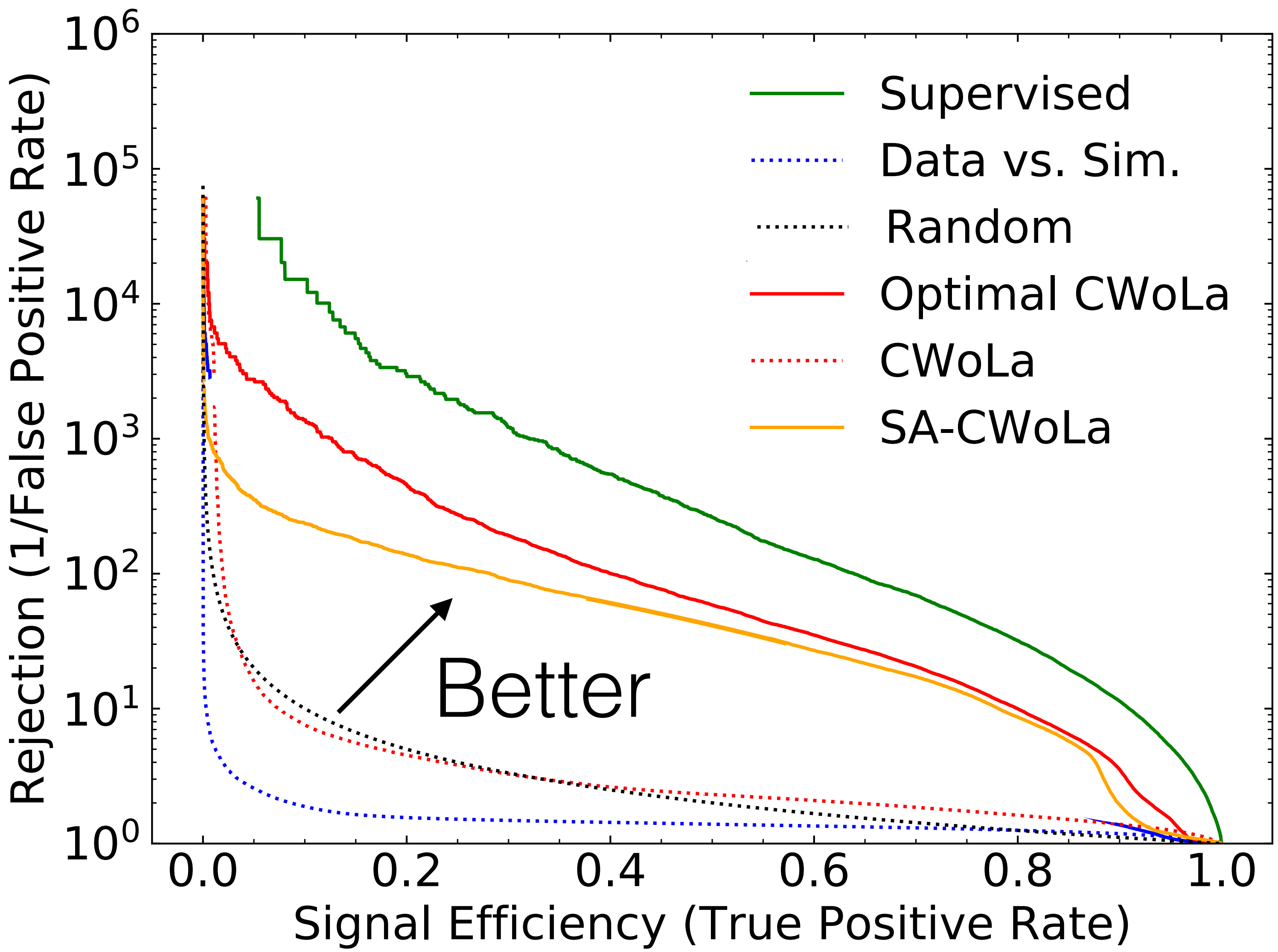

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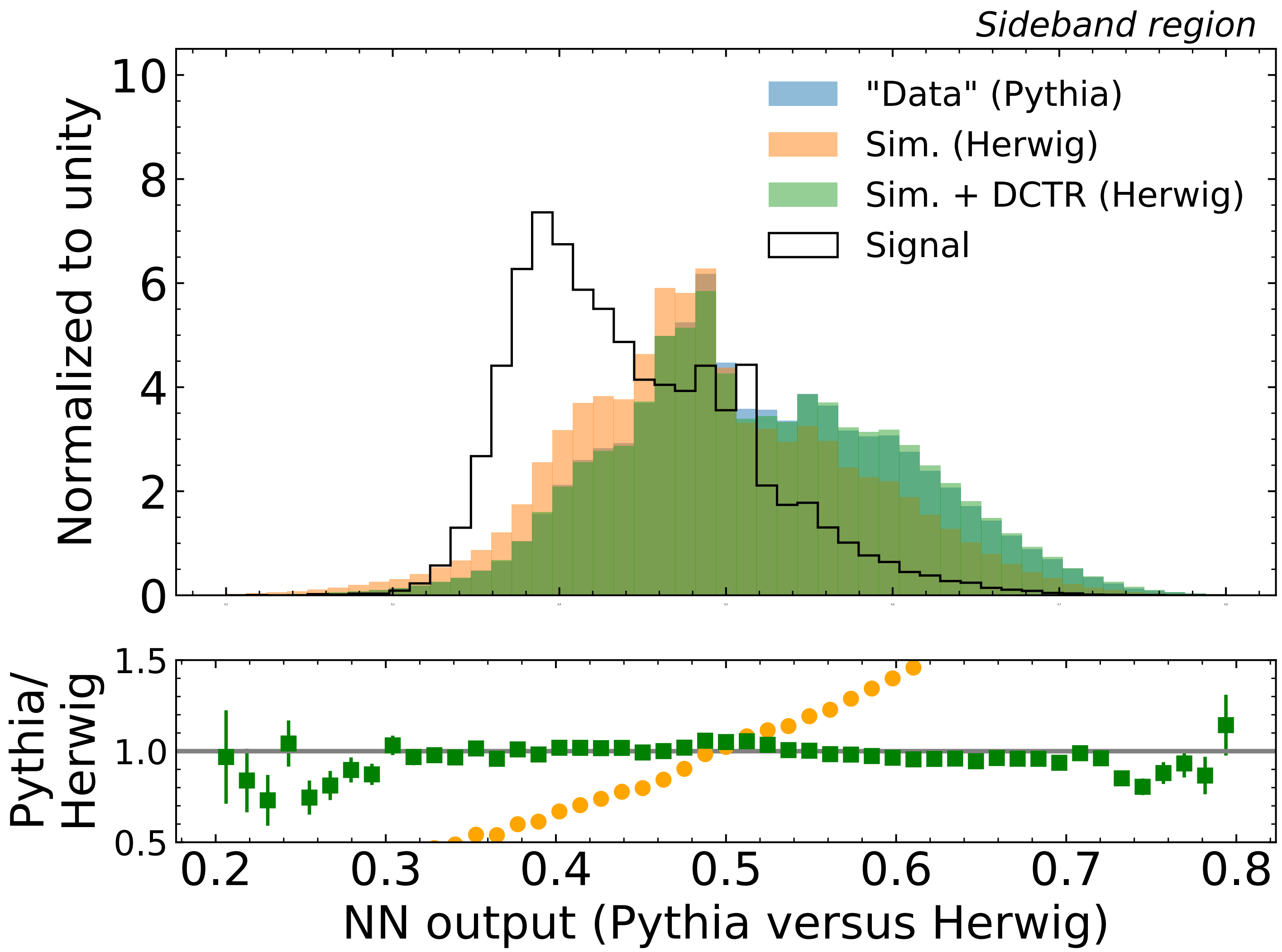

We want the reference sample to be as close to the SR background as possible.

We can take simulation as the reference, but train a parameterized **reweighting model** in the sidebands

The reweighting function (also a NN) is a function of m_{jj}

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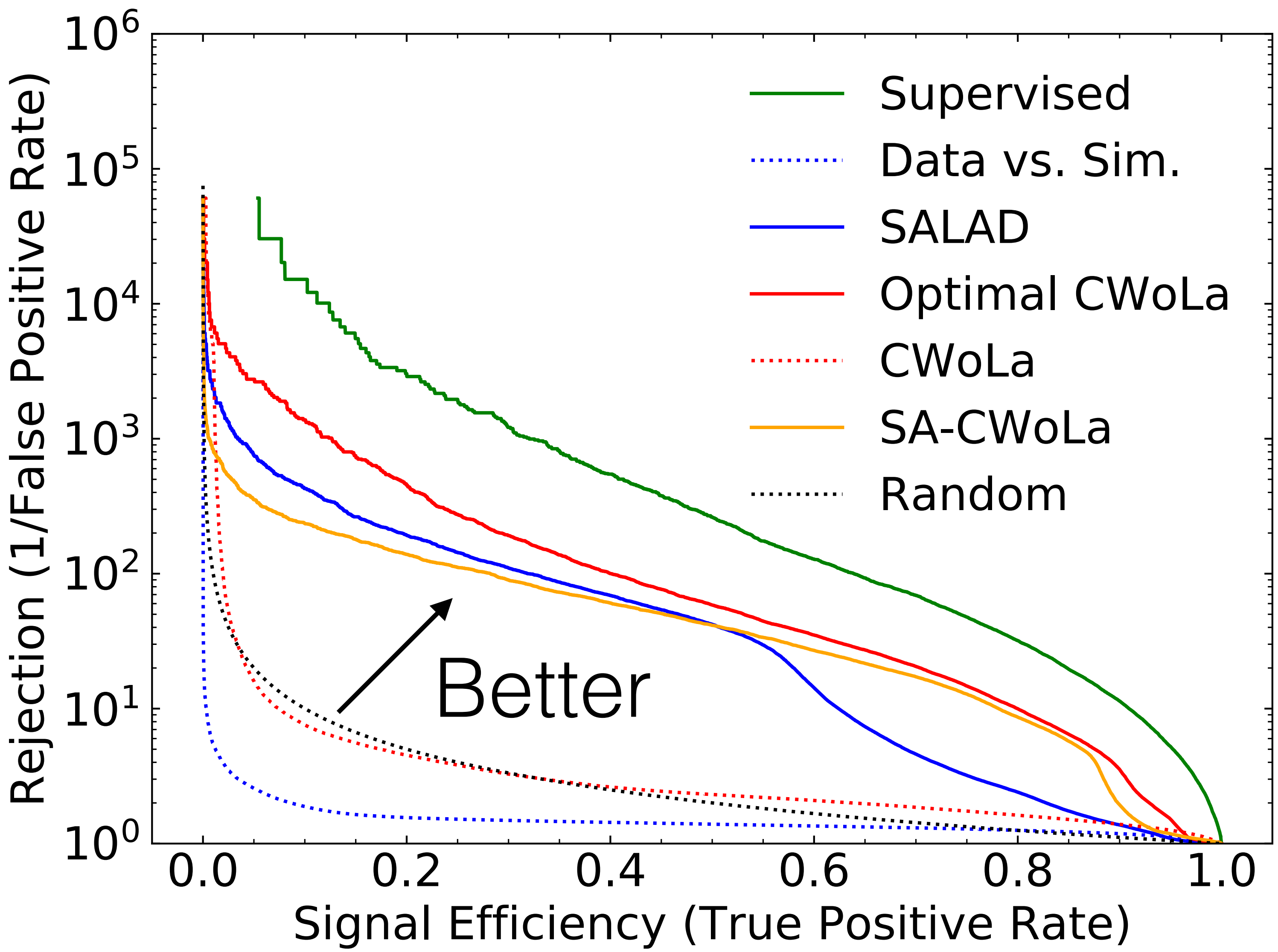

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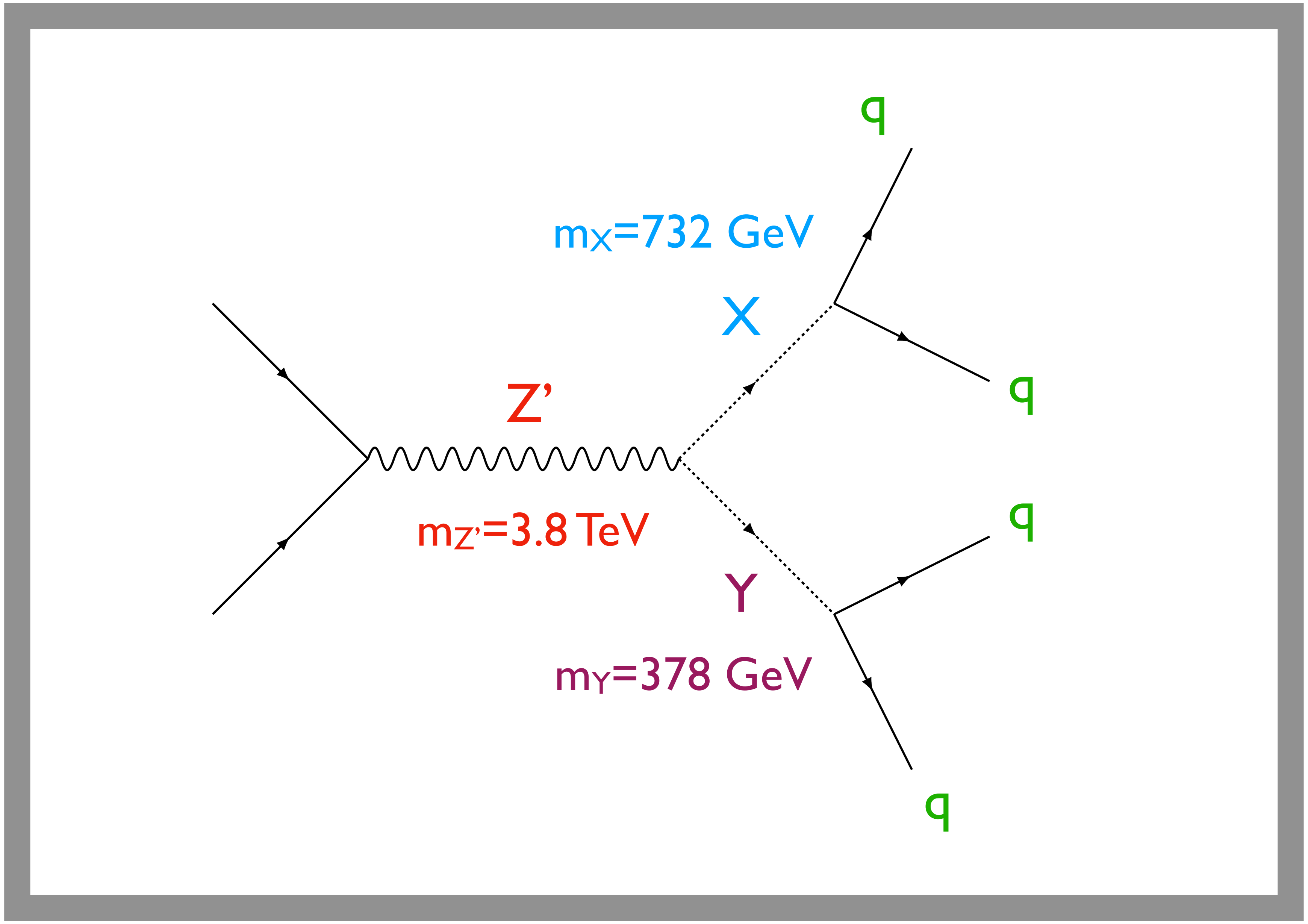
Selected Method Summary

Method	Reference Bin	Reference Sample	Approach
CWoLa	Sideband Region	Data	Standard classifier
SA-CWoLa	Sideband Region	Data	Decorrelated classifier
ANODE	Signal Region	Data	Density estimation
SALAD	Signal Region	Simulation	Reweighted classifier

Outcome of the LHC Olympics

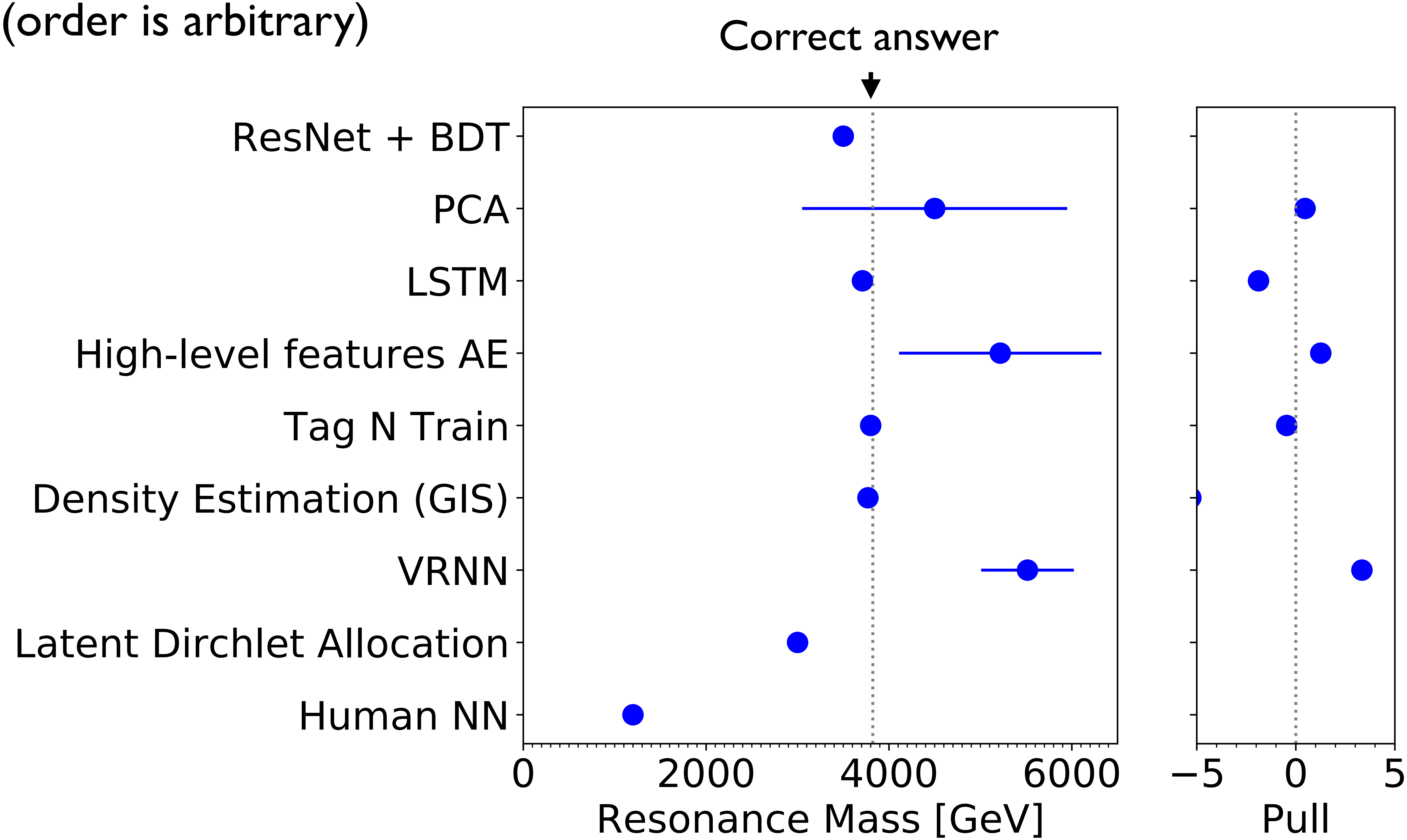
Outcome of the LHC Olympics



Black box 1 of 3

Sample outcomes

(order is arbitrary)



(answer - true)/uncert

N.B. not everyone reported an uncertainty

LHC Olympics, big picture

The LHC Olympics 2020

A Community Challenge for Anomaly Detection in High Energy Physics

Gregor Kasieczka (ed),[1] Benjamin Nachman (ed),[2,3] David Shih (ed),[4] Oz Amram,[5] Anders Andreassen,[6] Kees Benkendorfer,[2,7] Blaz Bortolato,[8] Gustaaf Brooijmans,[9] Florencia Canelli,[10] Jack H. Collins,[11] Biwei Dai,[12] Felipe F. De Freitas,[13] Barry M. Dillon,[8,14] Ioan-Mihail Dinu,[5] Zhongtian Dong,[15] Julien Donini,[16] Javier Duarte,[17] D. A. Faroughy[10] Julia Gonski,[9] Philip Harris,[18] Alan Kahn,[9] Jernej F. Kamenik,[8,19] Charanjit K. Khosa,[20,30] Patrick Komiske,[21] Luc Le Pottier,[2,22] Pablo Martín-Ramiro,[2,23] Andrej Matevc,[8,19] Eric Metodiev,[21] Vinicius Mikuni,[10] Inês Ochoa,[24] Sang Eon Park,[18] Maurizio Pierini,[25] Dylan Rankin,[18] Veronica Sanz,[20,26] Nilai Sarda,[27] Uroš Seljak,[2,3,12] Aleks Smolkovic,[8] George Stein,[2,12] Cristina Mantilla Suarez,[5] Manuel Szewc,[28] Jesse Thaler,[21] Steven Tsan,[17] Silviu-Marian Udrescu,[18] Louis Vaslin,[16] Jean-Roch Vlimant,[29] Daniel Williams,[9] Mikaeel Yunus[18]

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[12] *Berkeley Center for Cosmological Physics, University of California, Berkeley*
[13] *Departamento de Física da Universidade de Aveiro and CIDMA Campus de Santiago, 3810-183 Aveiro, Portugal*
[14] *Institute for Theoretical Physics, University of Heidelberg, Heidelberg, Germany*
[15] *Department of Physics & Astronomy, University of Kansas, 1251 Wescoe Hall Dr., Lawrence,*

Several teams did well on the first black box, but black boxes 2 (no signal) and 3 (multijet + multiple decays) were much harder.

This was an incredibly rewarding exercise and we hope it will be an important benchmark for the future!

Stay tuned for our community report with may more details ! (ETA: next week)

Conclusions and Outlook

Deep-learning based anomaly detection has a great potential for discovery!

Check out the LHC Olympics website and stay tuned for our community report (ETA: next week) → https://lhco2020.github.io/homepage/

We still need new ideas and clever ways of implementing (including computing challenges!) and extending current proposals.

Backup