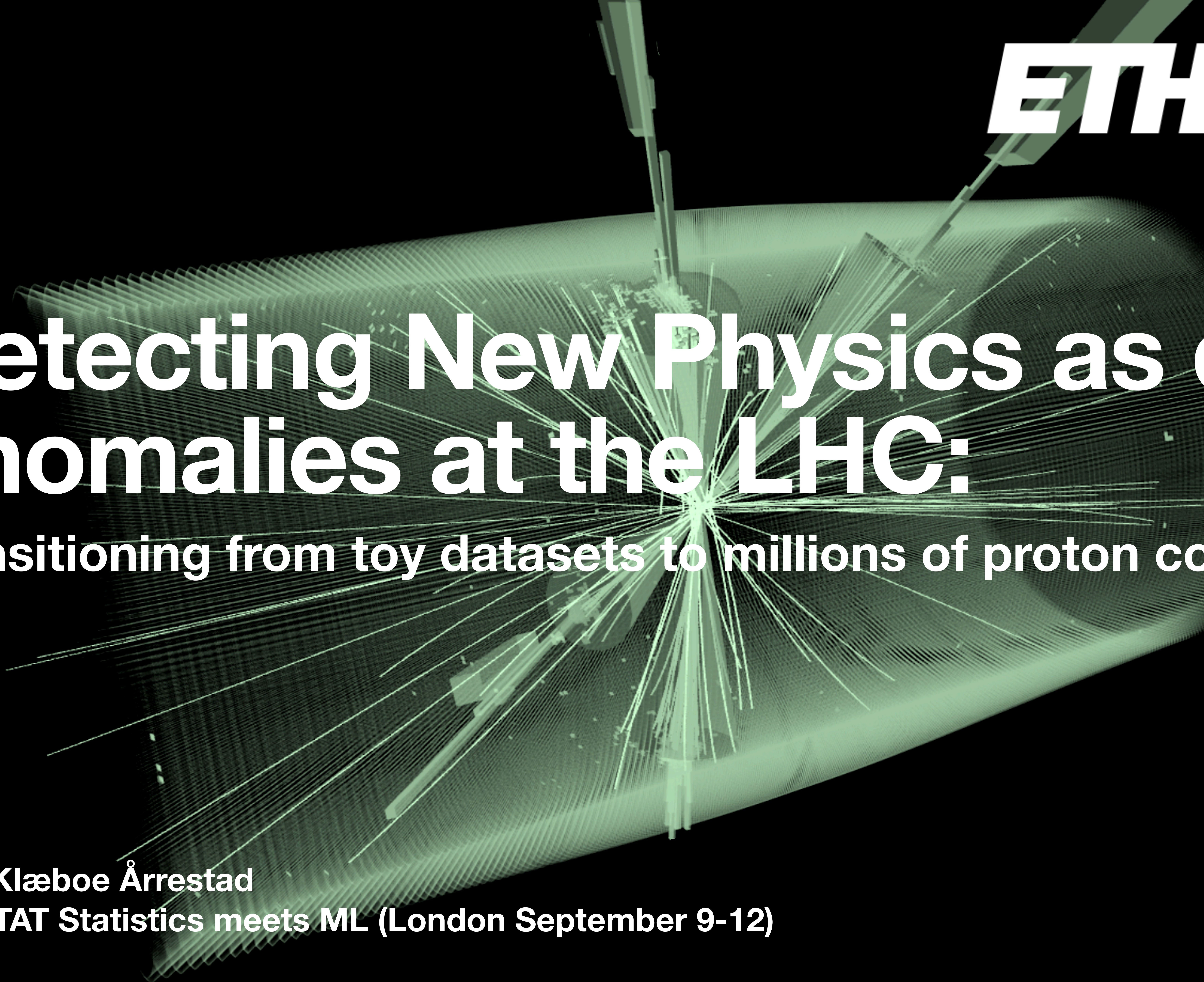

Detecting New Physics as data anomalies at the LHC:

Transitioning from toy datasets to millions of proton collisions

Thea Klæboe Årrestad

PHYSTAT Statistics meets ML (London September 9-12)

Semi-supervised permutation invariant particle-level anomaly detection
Gabriel Matos (Columbia U.), Elena Busch (Columbia U.), Ki Ryeong Park (Columbia U.), Juli
e-Print: 2408.17409 [hep-ph]
pdf cite claim

RODEM Jet Datasets
Knut Zoch (Geneva U. and Harvard U.), John Andrew Raine (Geneva U.), Debajyoti Sengupta
e-Print: 2408.11616 [hep-ph]
pdf cite claim

Interplay of Traditional Methods and Machine Learning Algorithms for Tag
Camellia Bose (Bangalore, Indian Inst. Sci.), Amit Chakraborty (Unlisted, IN), Shreecheta C
e-Print: 2408.01138 [hep-ph]
pdf DOI cite claim

Accelerating template generation in resonant anomaly detection searche
Matthew Leigh (Geneva U.), Debajyoti Sengupta (Geneva U.), Benjamin Nachman (LBL, Be
e-Print: 2407.19818 [hep-ph]
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Anomaly Detection Based on Machine Learning for the CMS Electromagn
CMS Collaboration • Abhirami Harilal (Carnegie Mellon U.) et al. (Jul 25, 2024)
Contribution to: CALOR2024 • e-Print: 2407.20278 [physics.ins-det]
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Unsupervised Beyond-Standard-Model Event Discovery at the LHC with
Callum Duffy (University Coll. London), Mohammad Hassanshah (University Coll. London),
Coll. London) (Jul 10, 2024)
e-Print: 2407.07961 [quant-ph]
pdf cite claim

Universal Anomaly Detection at the LHC: Transforming Optimal Classifiers
Sascha Caron, José Enrique García Navarro, María Moreno Llácer, Polina Moskvitina, Mats R
e-Print: 2406.18469 [hep-ph]
pdf cite claim

Review of searches for new physics at CMS
Anne-Mazarine Lyon (Zurich, ETH) (Jun 4, 2024)
Contribution to: Moriond QCD 2024 • e-Print: 2406.02010 [hep-ex]
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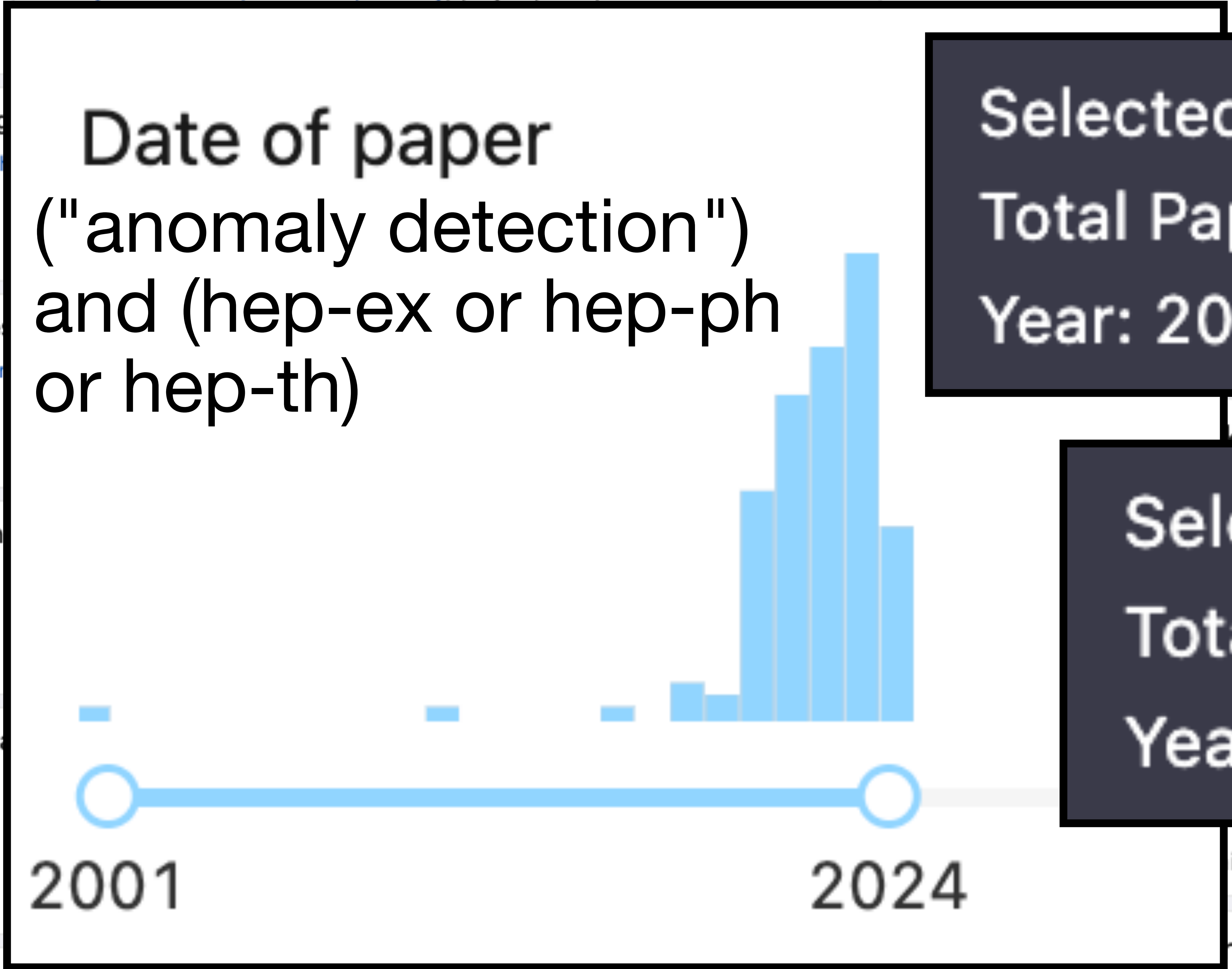
Accelerating Resonance Searches via Signature-Oriented Pre-training
Congqiao Li (Peking U., SKLNPT), Antonios Agapitos (Peking U., SKLNPT), Jovin Drews (Ham
SKLNPT) et al. (May 21, 2024)
e-Print: 2405.12972 [hep-ph]
pdf cite claim

Incorporating Physical Priors into Weakly-Supervised Anomaly Detection
Chi Lung Cheng (Wisconsin U., Madison and LBNL, Berkeley and Sao Paulo, IFT), Gurpreet Si
Berkeley and Sao Paulo, IFT and UC, Berkeley) (May 14, 2024)



Exploring Optimal Transport for Event-Level Anomaly Detection at the Larg
Nathaniel Craig (Unlisted and Santa Barbara, KITP), Jessica N. Howard (Santa Barbara, KITP)
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pdf cite claim

Robust Anomaly Detection for Particle Physics Using Multi-Background Re
Abhijith Gandrakota (Fermilab), Lily Zhang (New York U., Courant Inst. and Rochester U.), Aa
Cranmer (Wisconsin U., Madison), Jennifer Ngadiuba (Fermilab) et al. (Jan 16, 2024)
e-Print: 2401.08777 [hep-ex]
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Machine learning for anomaly detection in particle physics
Vasilis Belis (Zurich, ETH), Patrick Odagiu (Zurich, ETH), Thea Klaeboe Aarrestad (Zurich, ETH) (Dec 20, 2023
Published in: *Rev.Phys.* 12 (2024) 100091 • e-Print: 2312.14190 [physics.data-an]
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Residual ANODE
Ranit Das (Rutgers U., Piscataway), Gregor Kasieczka (Hamburg U.), David Shih (Rutgers U., Piscataway) (Dec

ulators
n (LBNL, Berkeley and Sao Paulo, IFT and
way and Northeastern U.) (Dec 18, 2023
8 [hep-ph]

for Anomaly Detection in the CMS Global Trigger Test Crate dur
12.10009 [hep-ex]

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tic gauge couplings at muon colliders using the autoencoder
Yu-Ting Zhang (Liaoning Normal U.), Xin-Tong Wang (Liaoning Normal U.), Ji-Chong Yang (Liaoning Normal U.
Published in: *Phys.Rev.D* 109 (2024) 9, 095028 • e-Print: 2311.16627 [hep-ph]
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Fast Particle-based Anomaly Detection Algorithm with Variational Autoencoder
Ryan Liu (LBL, Berkeley), Abhijith Gandrakota (Fermilab), Jennifer Ngadiuba (Fermilab), Maria Spiropulu (Calte
Contribution to: NeurIPS 2023 • e-Print: 2311.17162 [hep-ex]
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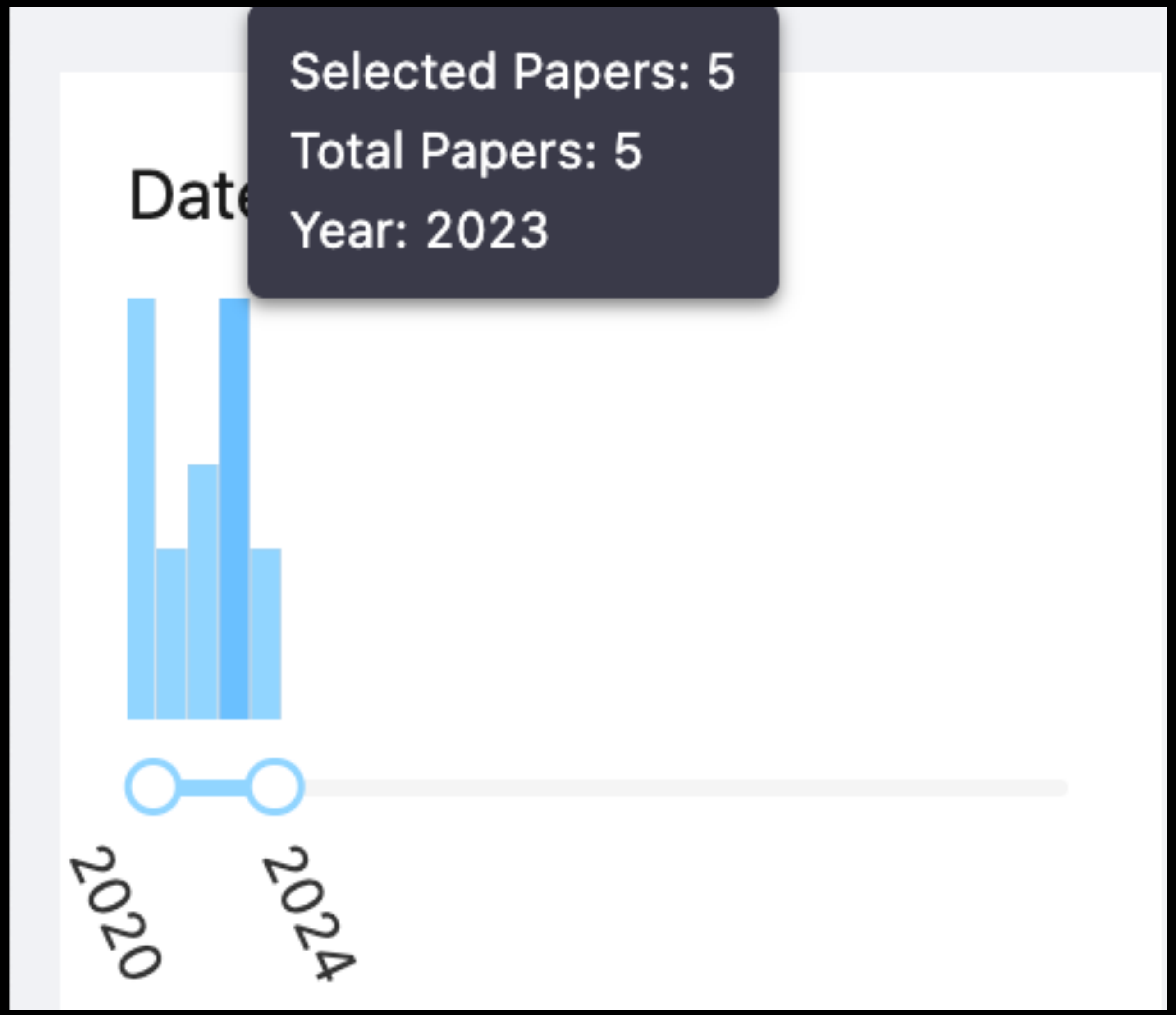

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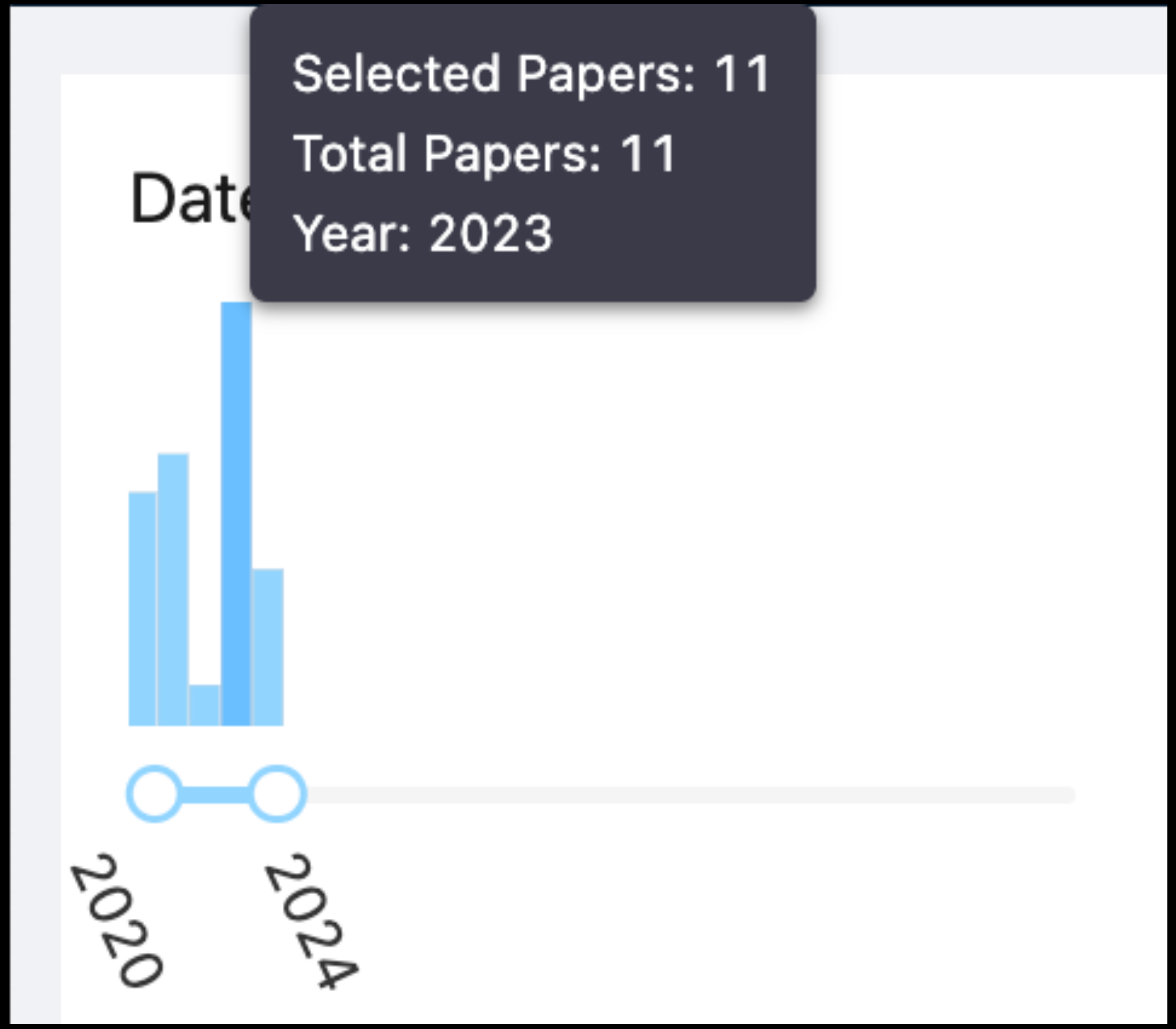

Selected Papers: 39
Total Papers: 39
Year: 2023

Tag N' Train: a technique to train improved classifiers on unlabeled data

Oz Amram (Johns Hopkins U.), Cristina Mantilla Suarez (Johns Hopkins U.) (Feb 27, 2020)

Published in: *JHEP* 01 (2021) 153 • e-Print: 2002.12376 [hep-ph]

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Eric M. Metodiev (MIT, Cambridge, CTP), Benjamin Nachman (LBL, Berkeley), Jesse Thaler

Published in: *JHEP* 10 (2017) 174 • e-Print: 1708.02949 [hep-ph]

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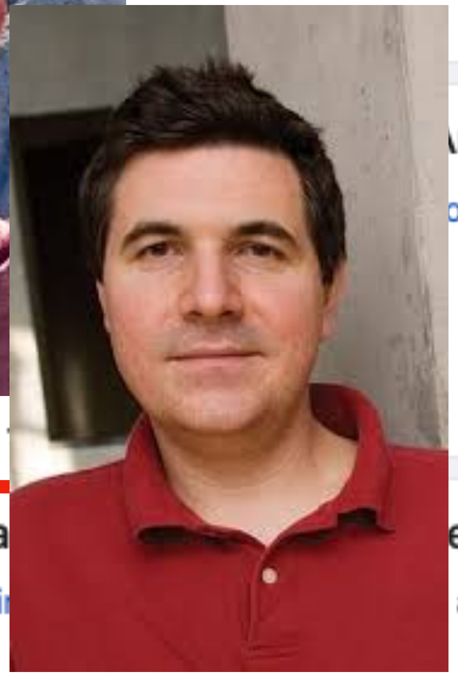

Signature-Oriented Pre-training

pitos (Peking U., SKLNPT), Jovin Drews (Ham

Anomaly Detection

Paulo, IFT), Gurpreet Si

Camellia Bose (Bangalore, Indian Inst. Sci.), Amit Chakraborty (Unlisted, IN), Shreecheta Ch

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Vinicius Mikuni (LBL, Berkeley), Benjami

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et Physics Tasks

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Quasi Anomalous Knowledge: Searching for new physics with embedded knowledge

#117

Sang Eon Park (MIT, LNS and IAIFI, Cambridge), Dylan Rankin (MIT, LNS and IAIFI, Cambridge), Silviu-Marian Udrescu (MIT, LNS and IAIFI, Cambridge), Mikaeel Yunus (MIT), Philip Harris (MIT, LNS and IAIFI, Cambridge) (Nov 6, 2020)

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CMS Collaboration • Abhirami Harilal (Carnegie Mellon U.) et al. (Jul 25,

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Machine learning for anomaly detection in particle physics

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Residual ANODE

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Claudius Krause (Heidelber ... Nachman (LBNL, Berkeley and Sao Paulo, IFT and

David Shih (Rutgers U., Pisc ... Piscat ... (Dec 18, 2023

Published in: *Phys.Rev.D* 1 ... 12.116

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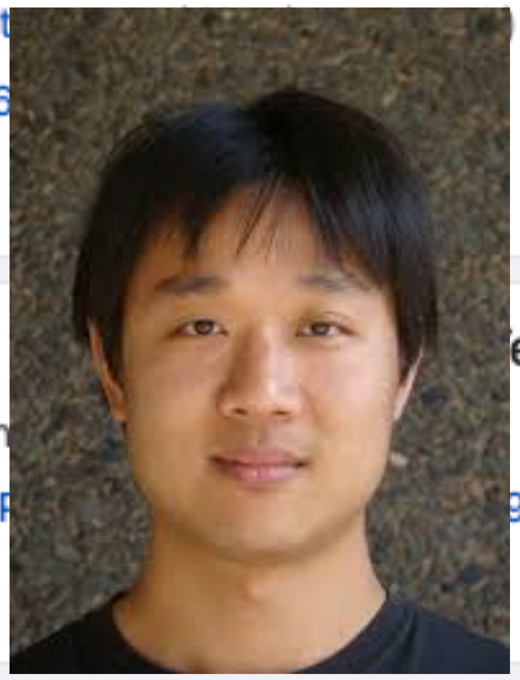

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Classifying anomalies through outer density estimation

Anna Hallin (Rutgers U., Piscataway), Joshua Isaacson (Fermilab), Gregor Kasieczka (Hamburg U.), Claudius Piscataway), Benjamin Nachman (LBNL, Berkeley) et al. (Sep 1, 2021)

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olina Mosk

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Coimbra U.), Márcio Ferreira (Coimbra U.), Constança Providência (Coimbr

024)

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al Transport for Event-Level Anomaly Detection at the Larg

listed and Santa Barbara, KITP), Jessica N. Howard (Santa Barbara, KITP)

Improving Variational Autoenco... ...tion at the LHC With Normalizing Flows

Pratik Jawahar (CERN), Thea Aarrestad (CERN), Nadezda Chernyavskaya (CERN), Maurizio Pierini (CERN), Kinga A. Wozniak (CERN) et al. (Oct 16, 2021)

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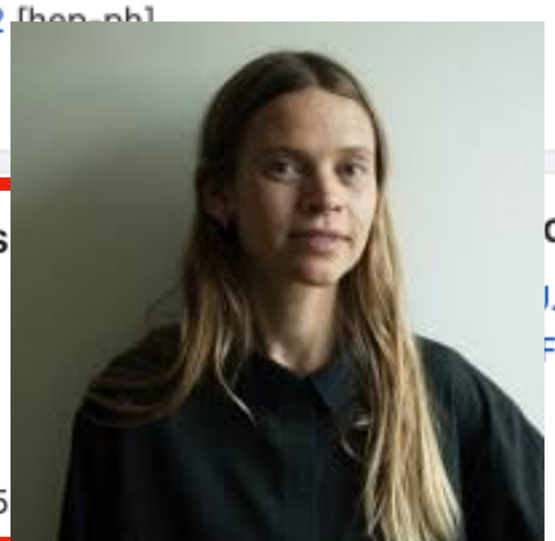

cs Using Multi-Background Re

., Courant Inst. and Rochester U.), Aa

Fermilab) et al. (Jan 16, 2024)

Searching f ... e coup ... rs u

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Fast Particl ... tection ... tion

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Contribution t ... 2311.1

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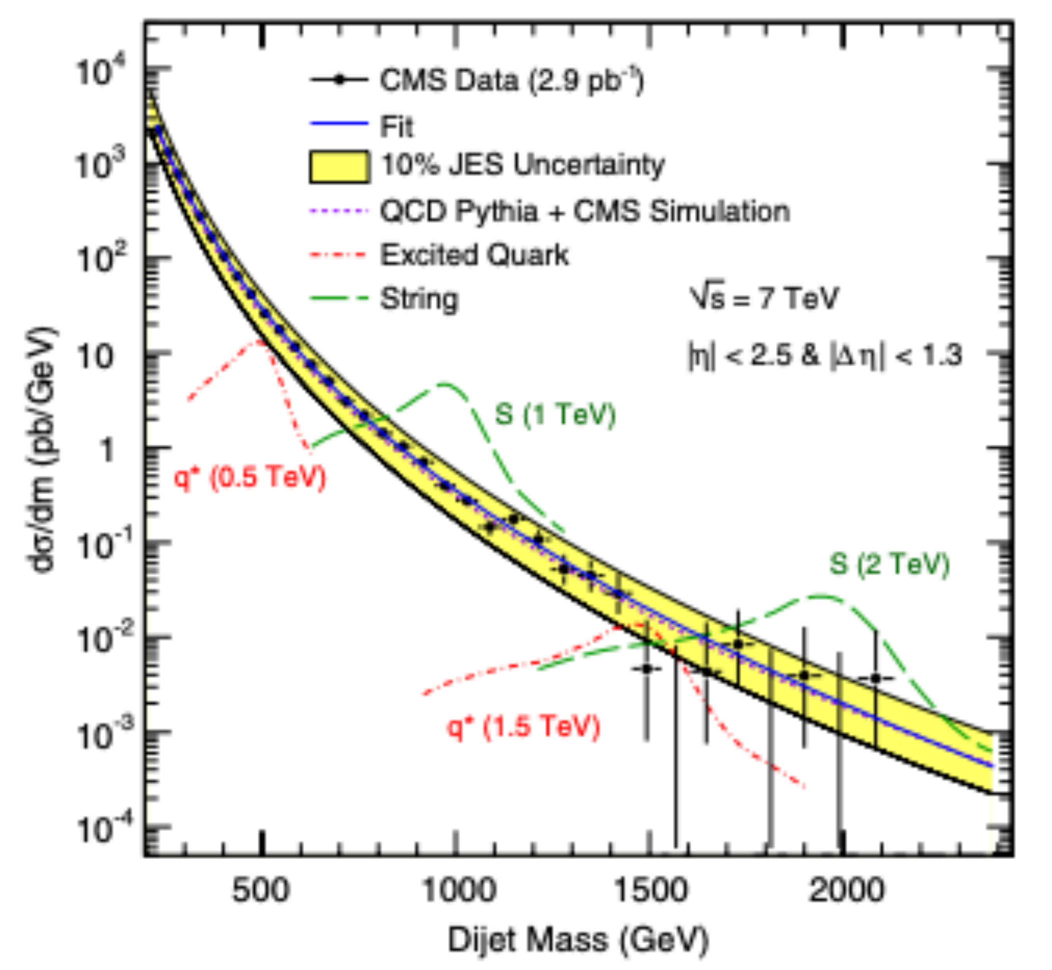
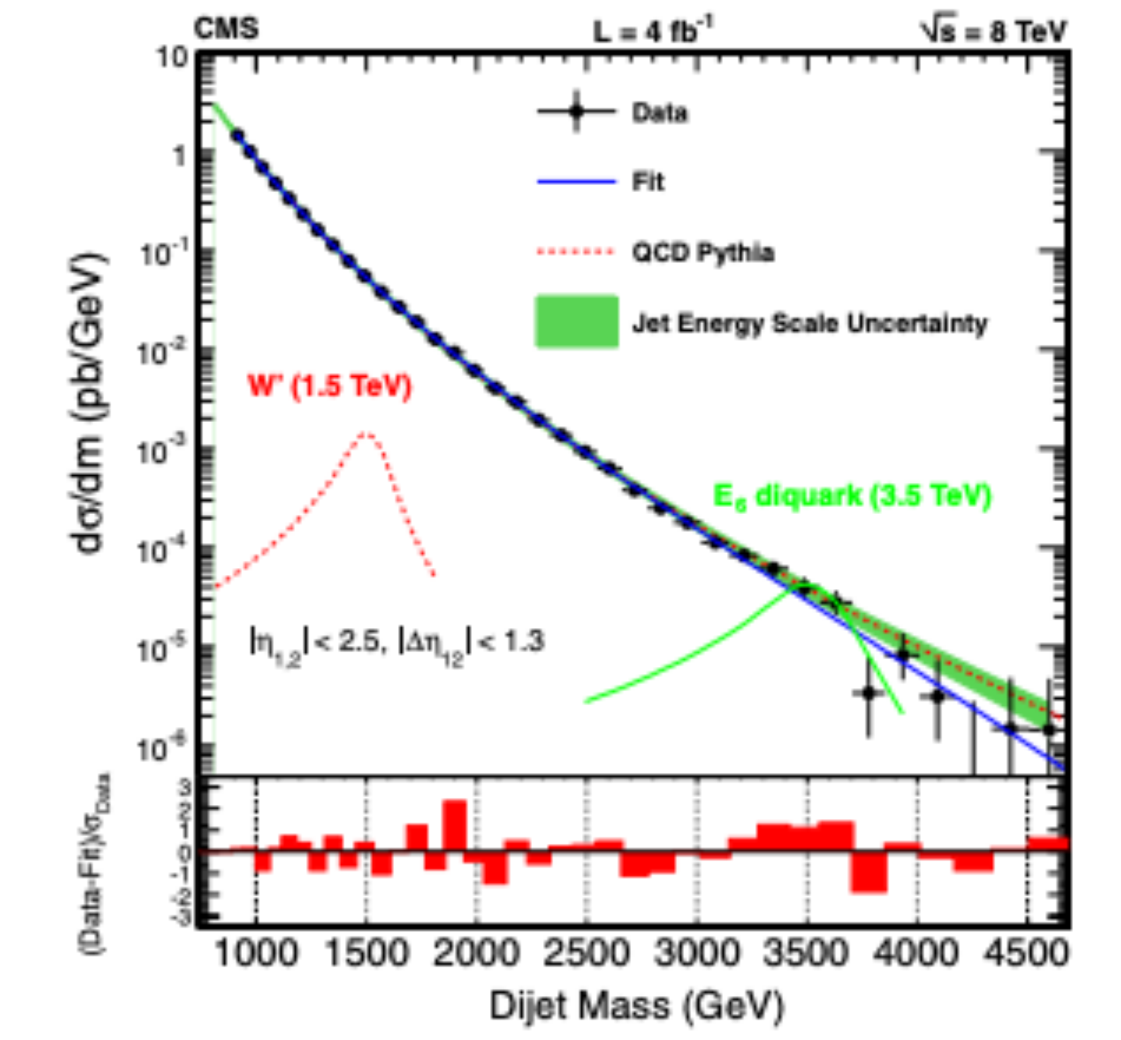
PRL **106**, 029902 (2011) PHYSICAL REVIEW LETTERS week ending 14 JANUARY 2011

Publisher's Note: Search for Dijet Resonances in 7 TeV pp Collisions at CMS [Phys. Rev. Lett. 105, 211801 (2010)]

V. Khachatryan *et al.**
(CMS Collaboration)
(Received 5 January 2011; published 13 January 2011)

DOI: 10.1103/PhysRevLett.106.029902 PACS numbers: 13.85.Rm, 13.87.Ce, 14.80.−j, 99.10.Fg





PHYSICAL REVIEW D **87**, 114015 (2013)

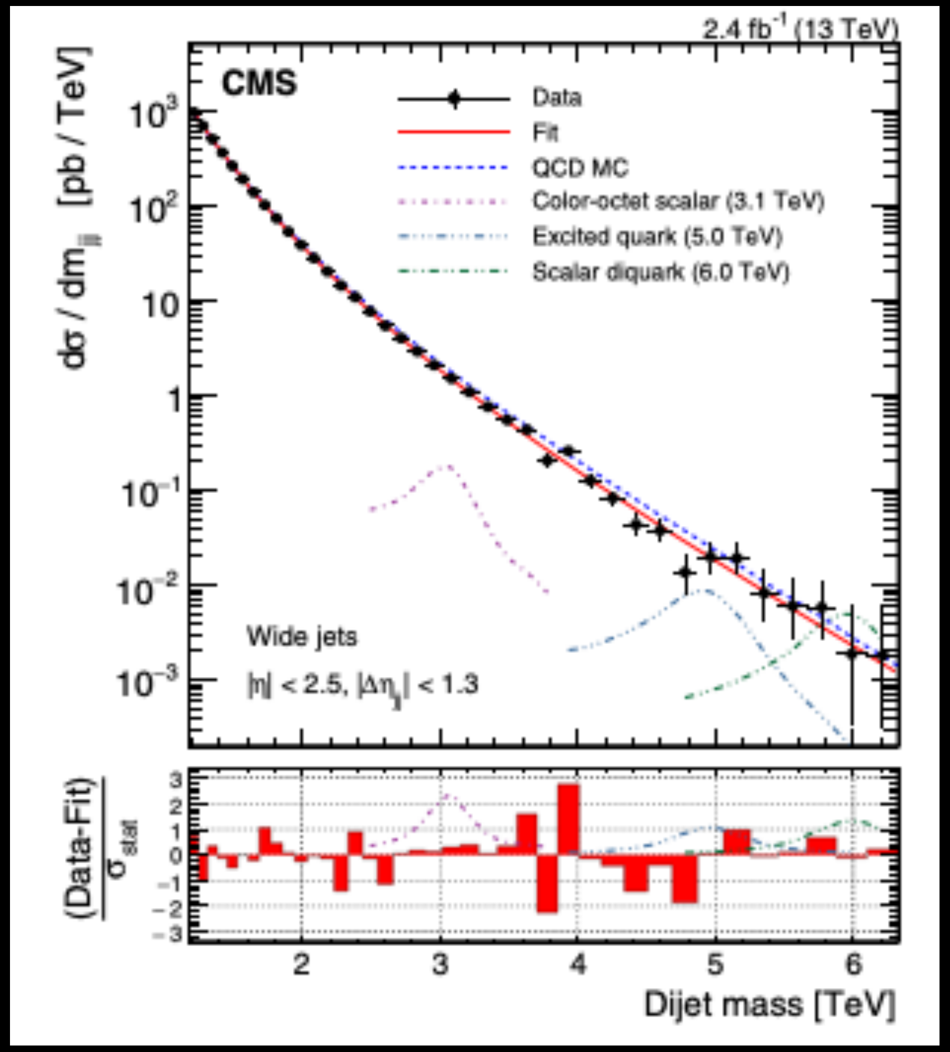
Search for narrow resonances using the dijet mass spectrum in pp collisions at $\sqrt{s} = 8$ TeV

S. Chatrchyan *et al.**
(CMS Collaboration)
(Received 19 February 2013; published 17 June 2013)

PRL **116**, 071801 (2016) PHYSICAL REVIEW LETTERS week ending 19 FEBRUARY 2016

Search for Narrow Resonances Decaying to Dijets in Proton-Proton Collisions at $\sqrt{s} = 13$ TeV

V. Khachatryan *et al.**
(CMS Collaboration)
(Received 3 December 2015; published 18 February 2016)



PRL 106, 029902 (2011) PHYSICAL REVIEW LETTERS week ending 14 JANUARY 2011

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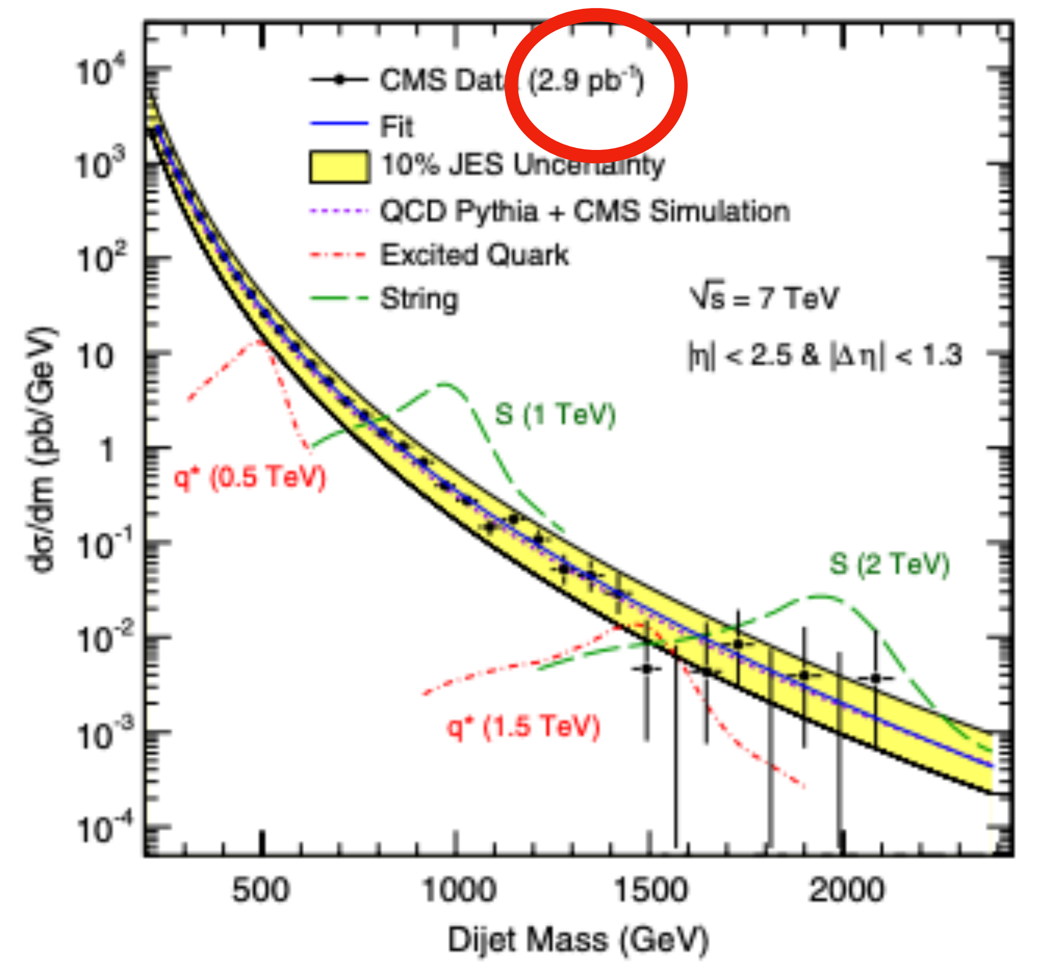

PRL 116, 071801 (2016) PHYSICAL REVIEW LETTERS week ending 19 FEBRUARY 2016

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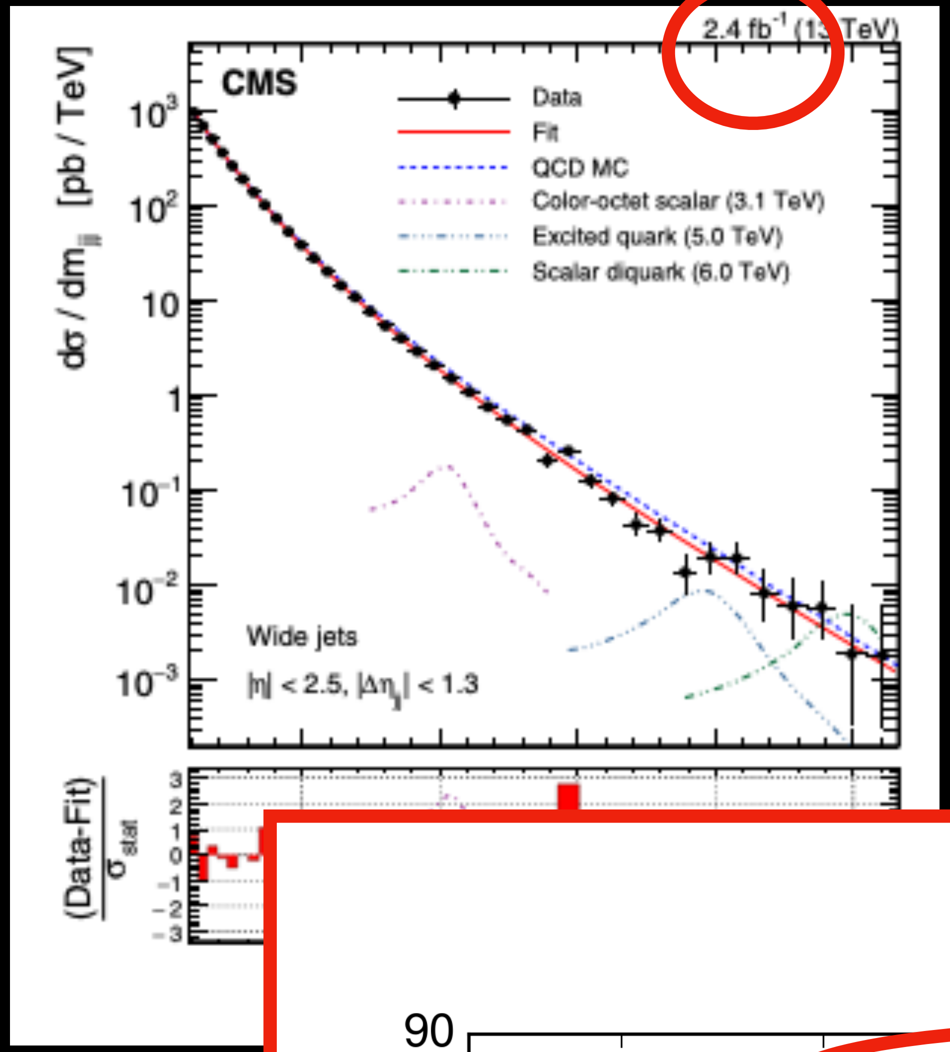

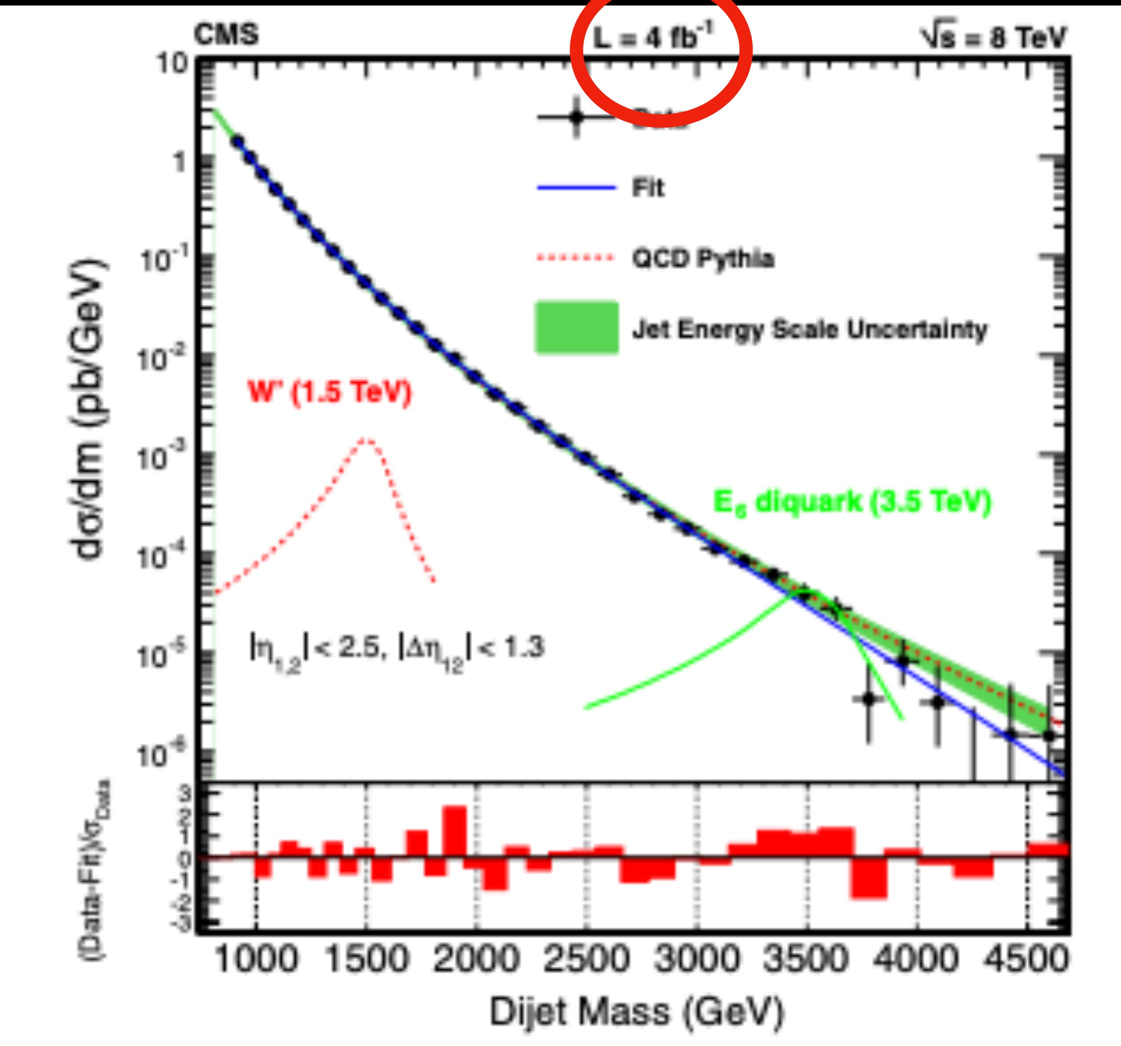

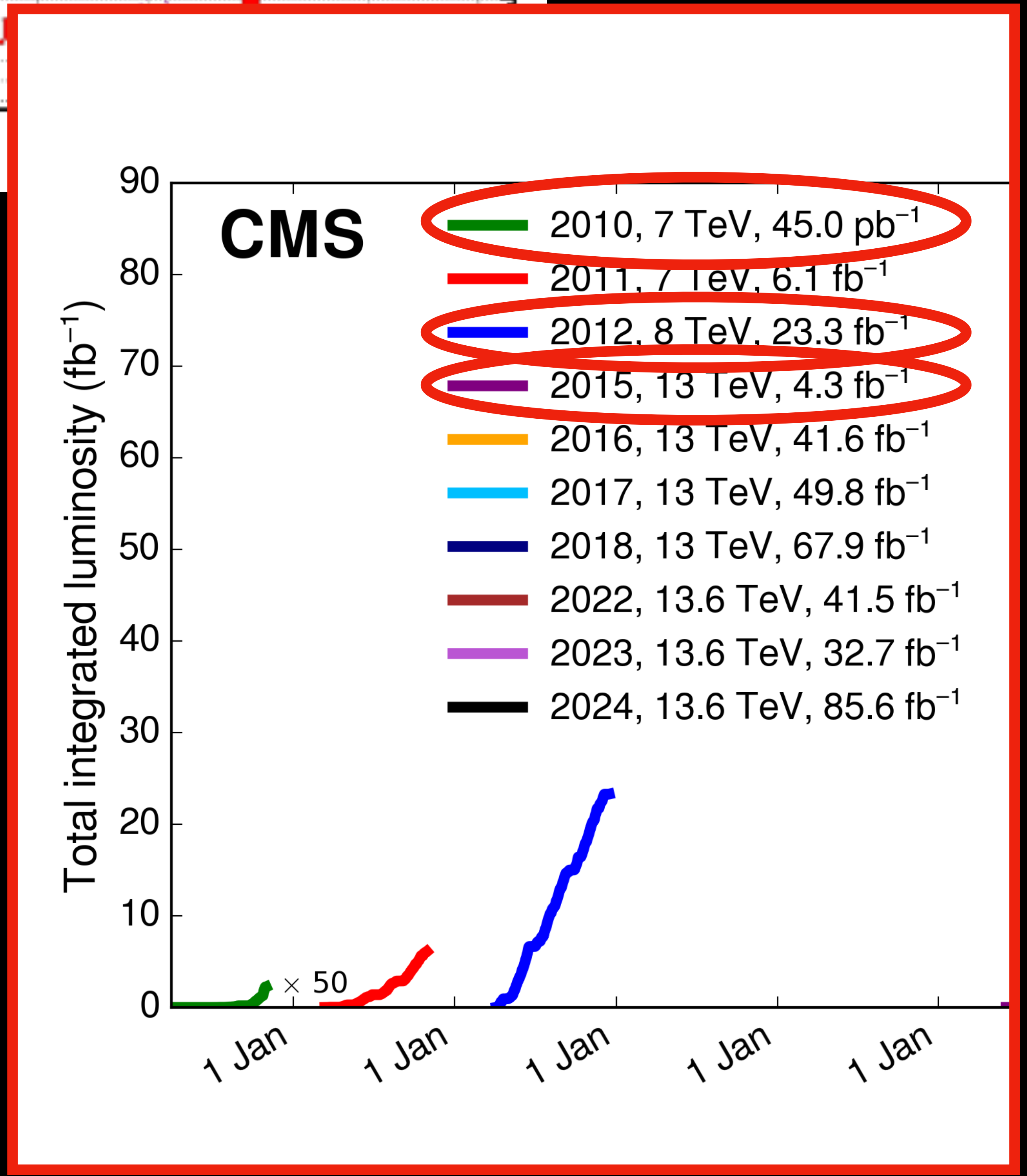

PHYSICAL REVIEW D 87, 114015 (2013)

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S. Chatrchyan *et al.**
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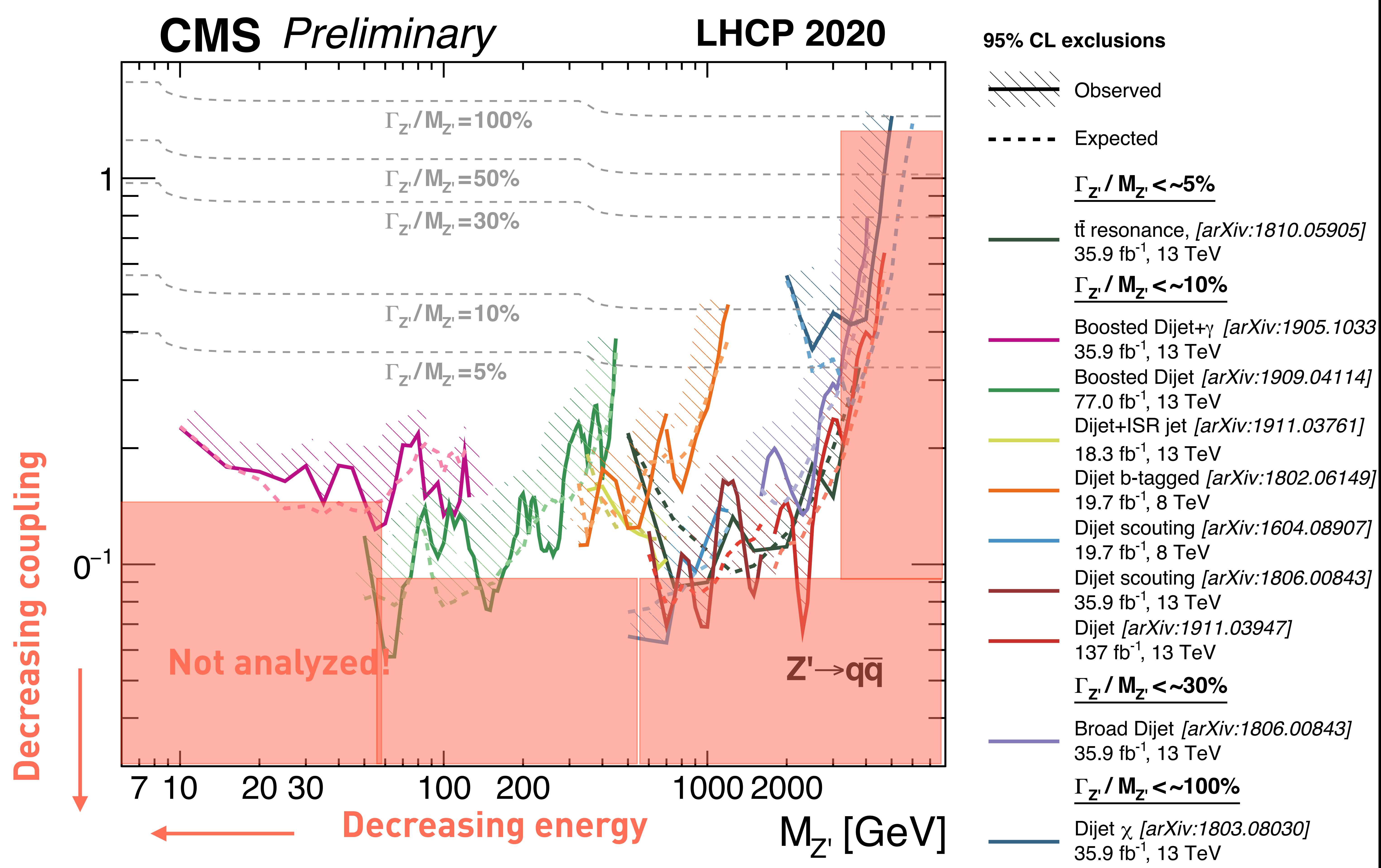
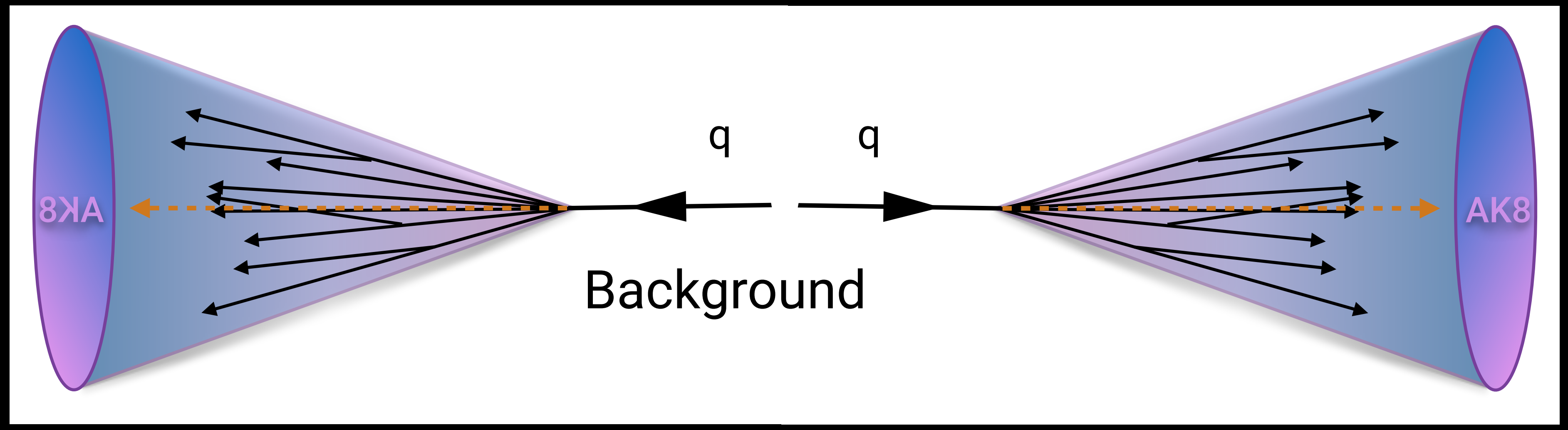

CMS Preliminary
LHCP 2020
95% CL exclusions
Observed
Expected
$\Gamma_{Z'}/M_{Z'}$ < ~5%
tt̄ resonance, [arXiv:1810.05905] 35.9 fb^{-1}, 13 TeV
$\Gamma_{Z'}/M_{Z'}$ < ~10%
Boosted Dijet+γ [arXiv:1905.1033 35.9 fb^{-1}, 13 TeV
Boosted Dijet [arXiv:1909.04114] 77.0 fb^{-1}, 13 TeV
Dijet+ISR jet [arXiv:1911.03761] 18.3 fb^{-1}, 13 TeV
Dijet b-tagged [arXiv:1802.06149] 19.7 fb^{-1}, 8 TeV
Dijet scouting [arXiv:1604.08907] 19.7 fb^{-1}, 8 TeV
Dijet scouting [arXiv:1806.00843] 35.9 fb^{-1}, 13 TeV
Dijet [arXiv:1911.03947] 137 fb^{-1}, 13 TeV
$\Gamma_{Z'}/M_{Z'}$ < ~30%
Broad Dijet [arXiv:1806.00843] 35.9 fb^{-1}, 13 TeV
$\Gamma_{Z'}/M_{Z'}$ < ~100%
Dijet χ [arXiv:1803.08030] 35.9 fb^{-1}, 13 TeV
$\Gamma_{Z'}/M_{Z'}$=100%
$\Gamma_{Z'}/M_{Z'}$=50%
$\Gamma_{Z'}/M_{Z'}$=30%
$\Gamma_{Z'}/M_{Z'}$=10%
$\Gamma_{Z'}/M_{Z'}$=5%
Not analyzed!
Z'→qq̄
Decreasing coupling
Decreasing energy
$M_{Z'}$ [GeV]
1
10^{-1}
7 10 20 30 100 200 1000 2000

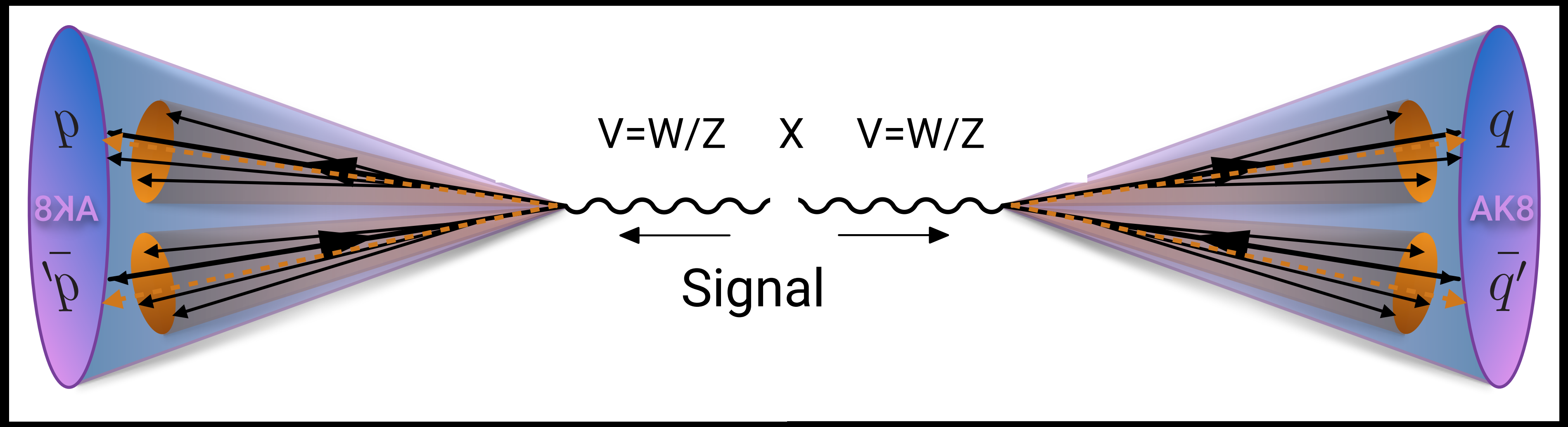

CMS
CMS Experiment at the LHC, CERN
Data recorded: 2017-Oct-28 09:41:12.692992 GMT
Run / Event / LS: 305814 / 971086788 / 610


CMS Experiment at the LHC, CERN
Data recorded: 2017-Oct-28 09:41:12.692992 GMT
Run / Event / LS: 305814 / 971086788 / 610
1.8 TeV
M_{jj} = 8 TeV
1.8 TeV


CMS
CMS Experiment at the LHC, CERN
Data recorded: 2017-Oct-28 09:41:12.692992 GMT
Run / Event / LS: 305814 / 971086788 / 610
Mb = 1.8 TeV
B
A
Ma = 8 TeV
C
Mc = 1.8 TeV

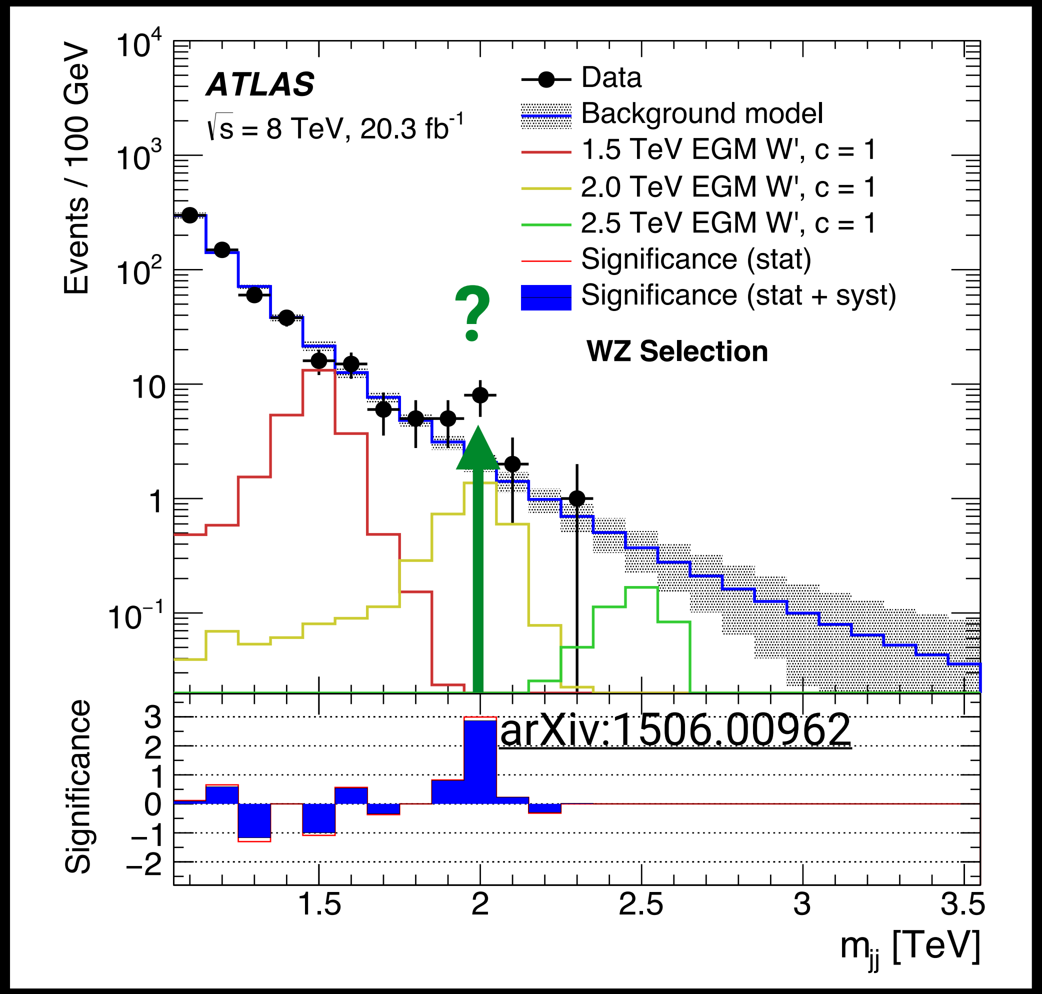

CMS
CMS Experiment at the LHC, CERN
Data recorded: 2017-Oct-28 09:41:12.692992 GMT
Run / Event / LS: 305814 / 971086788 / 610
M_{jj} = 1.8 TeV
M_{jjjj} = 8 TeV
M_{jj} = 1.8 TeV

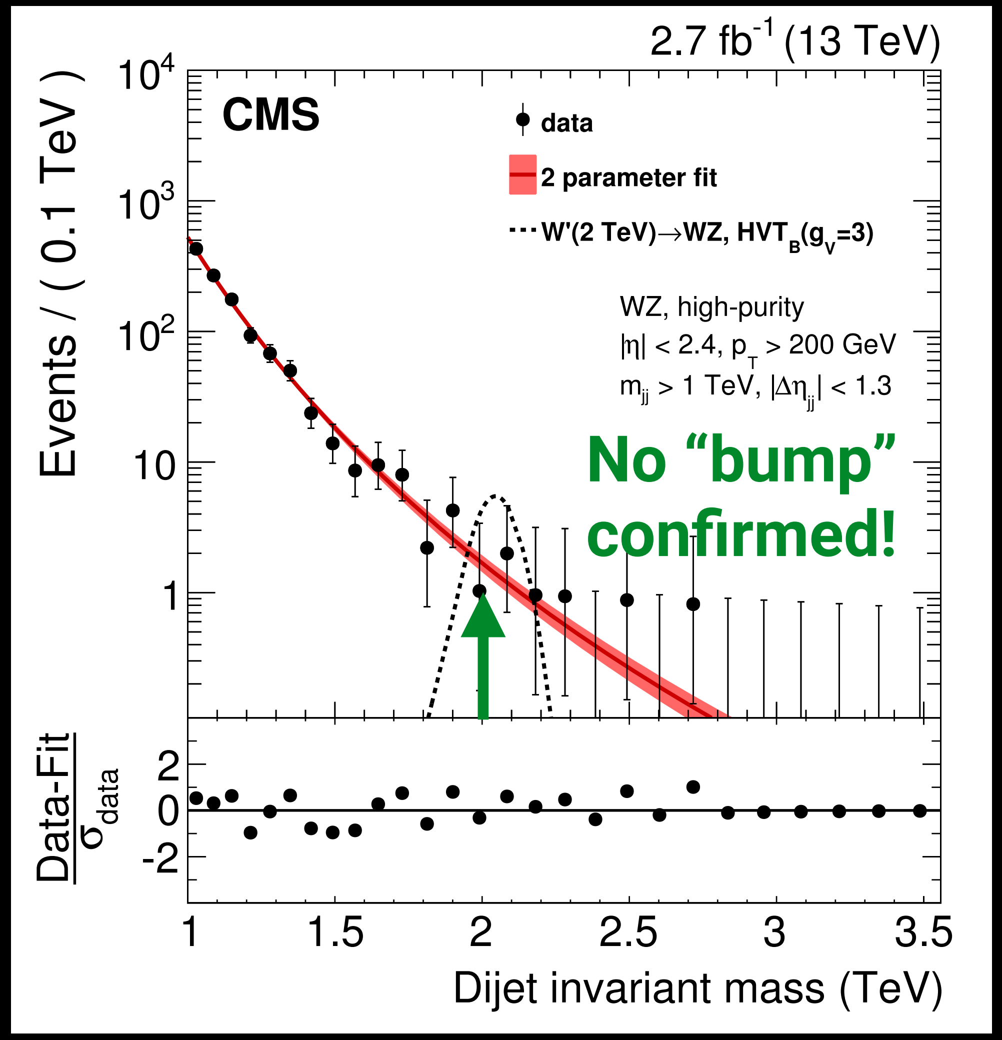


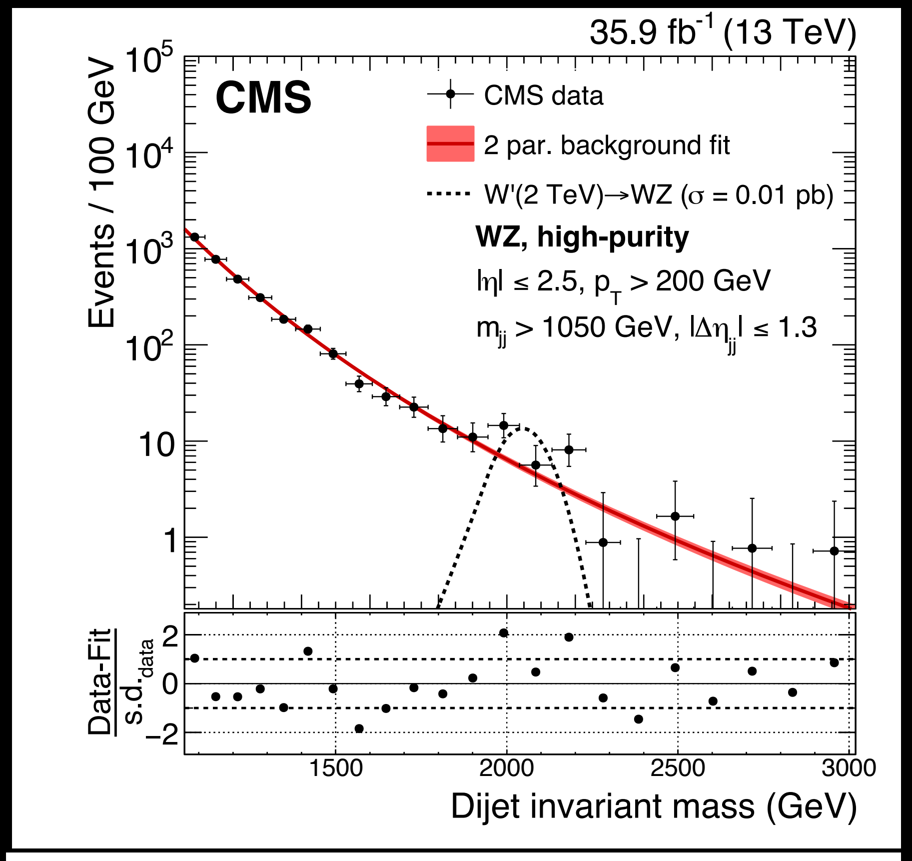


1 prong

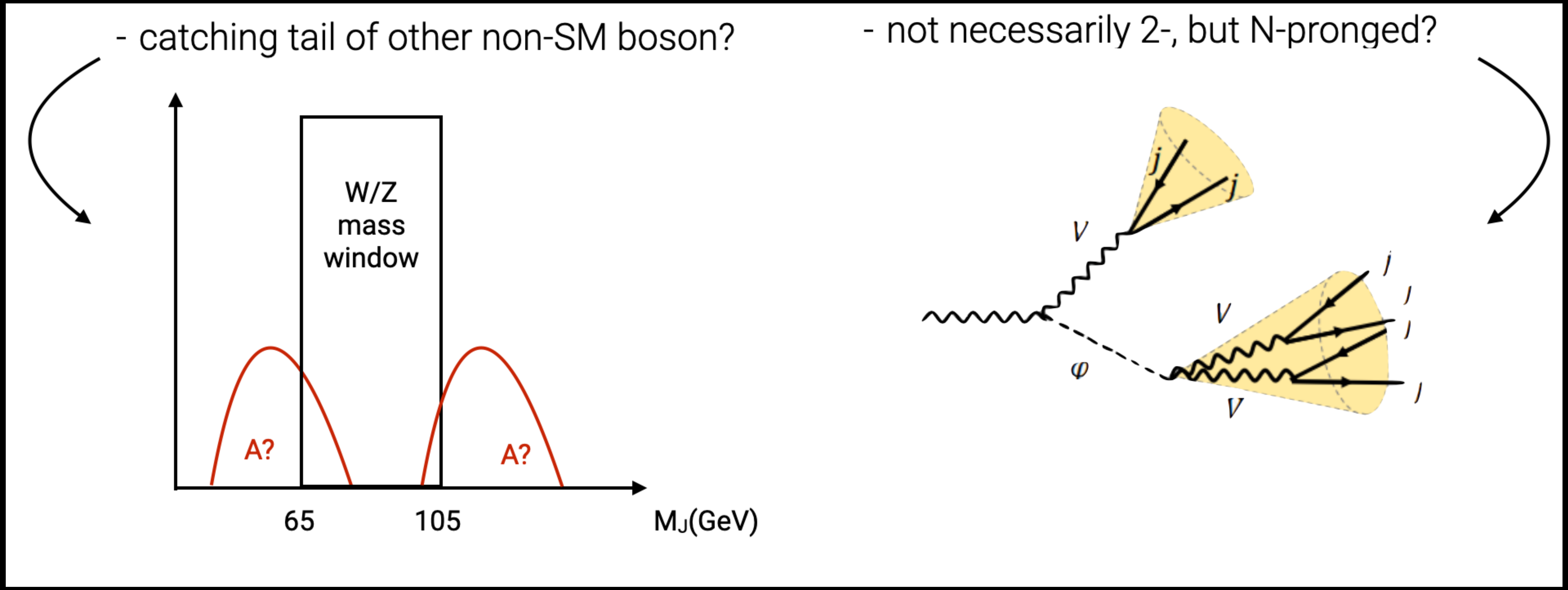
2 prong

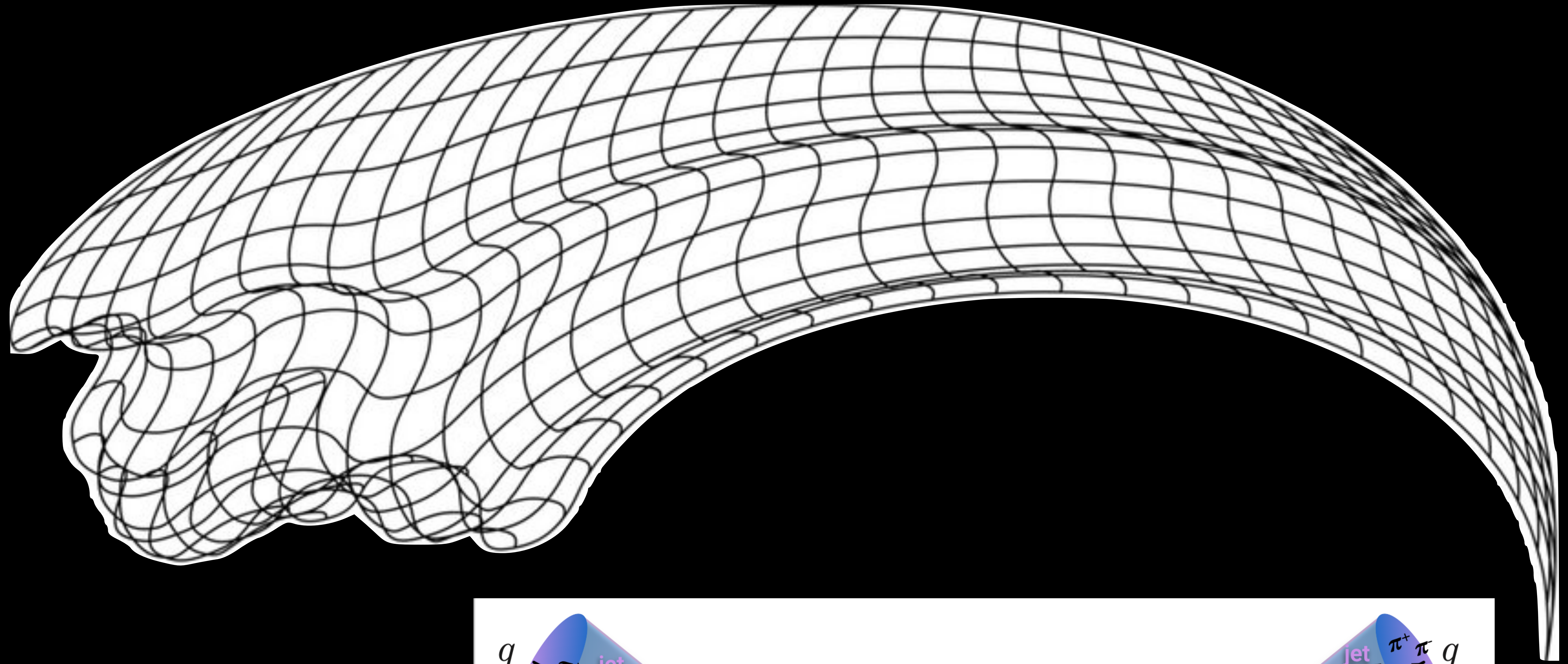


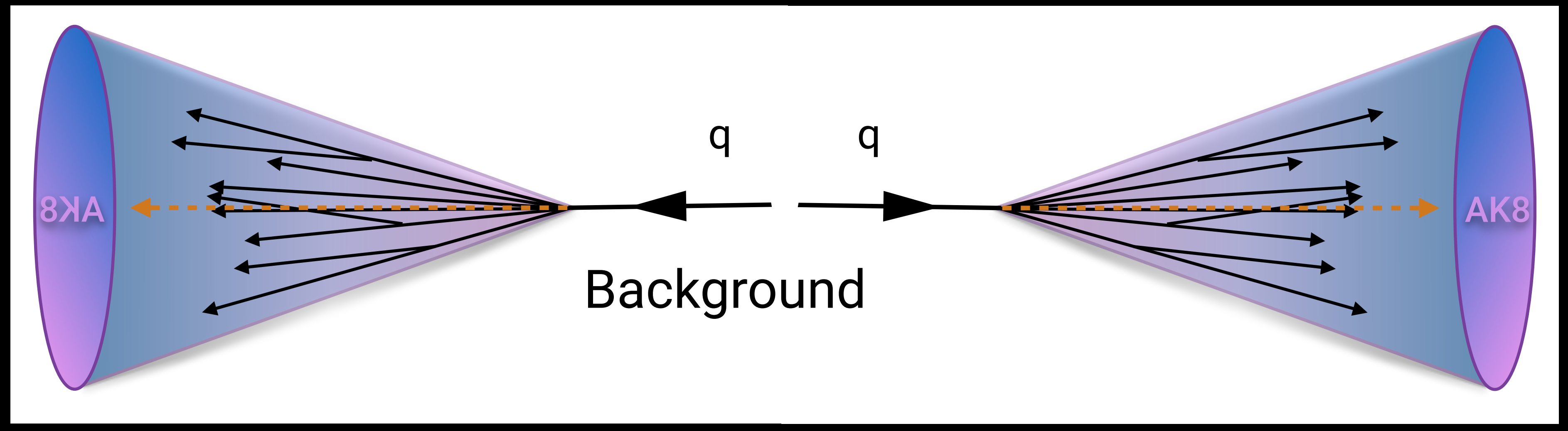




Signal might still be present in our data, but might look different

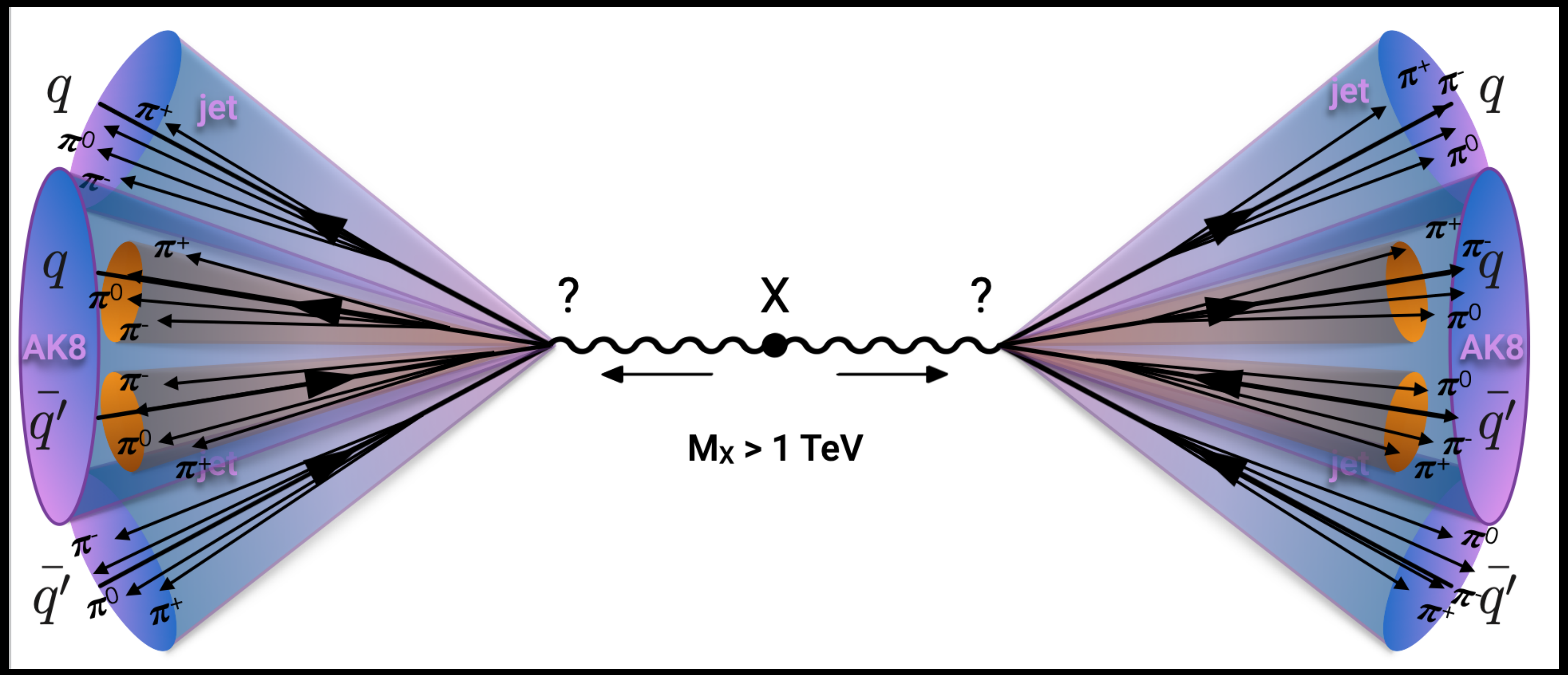




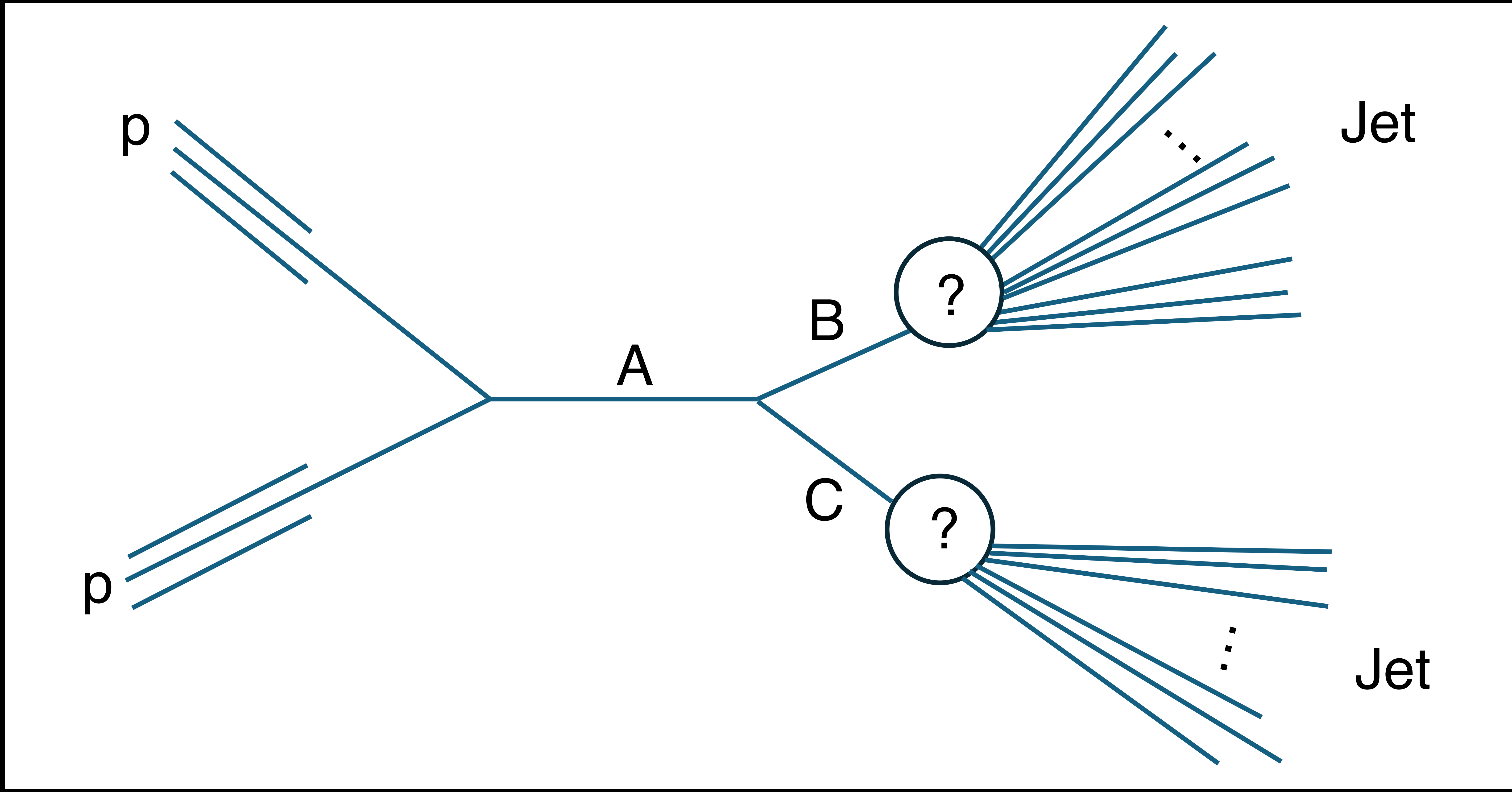


QCD dijet

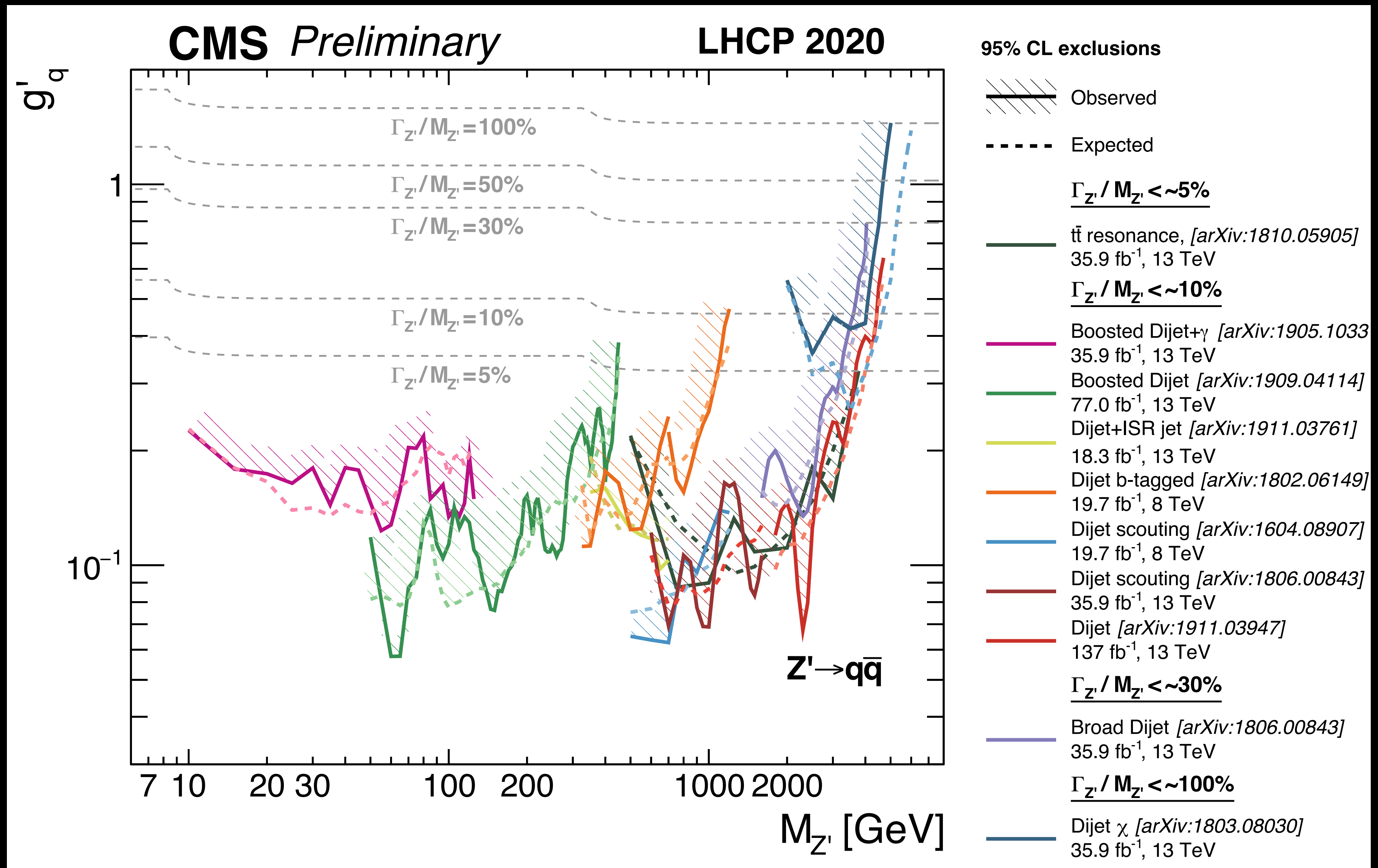
vs

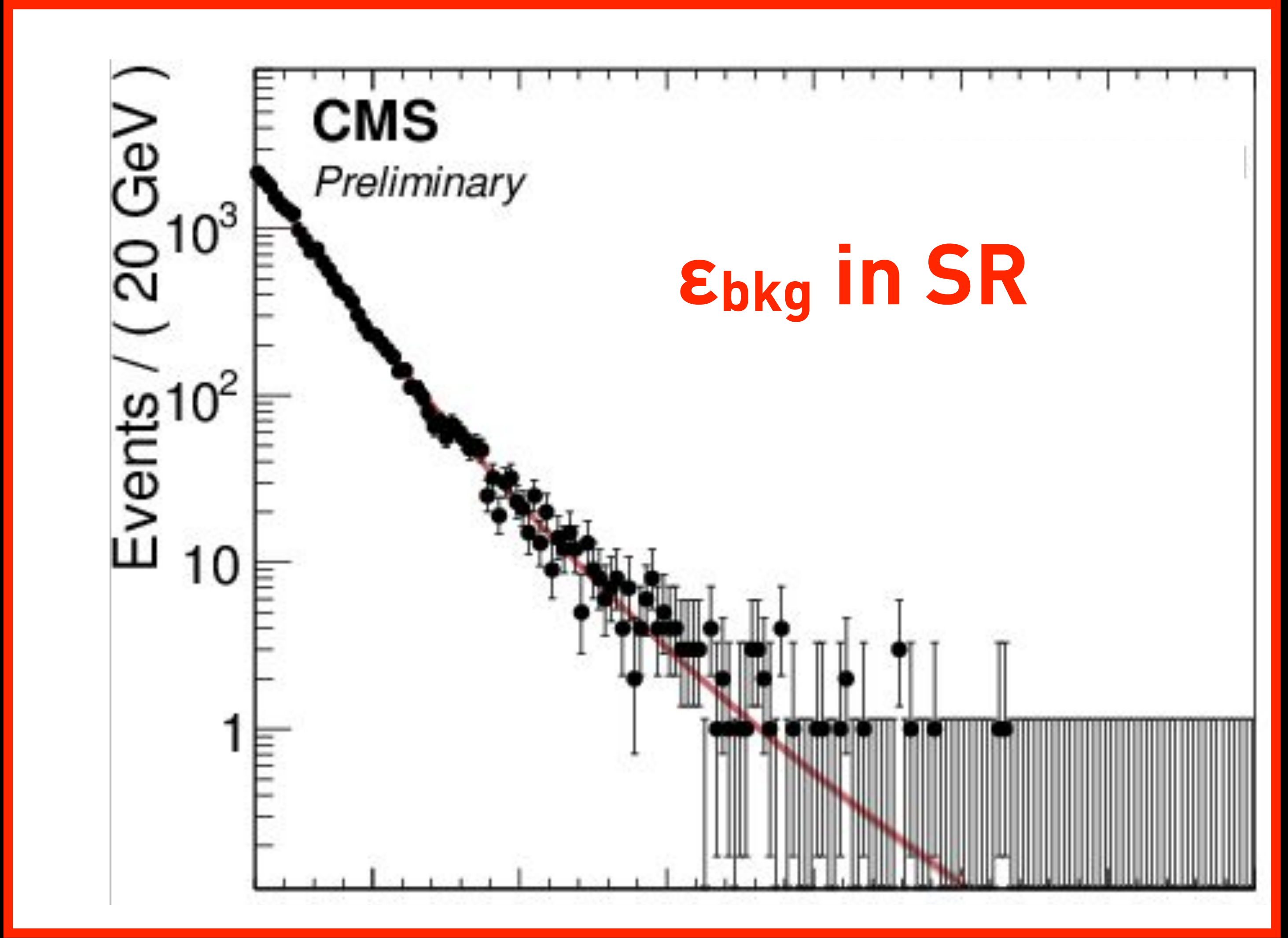


N-prong dijet, any mass


p
p
A
B
C
?
?
Jet
Jet

Anomaly detection for New Physics searches

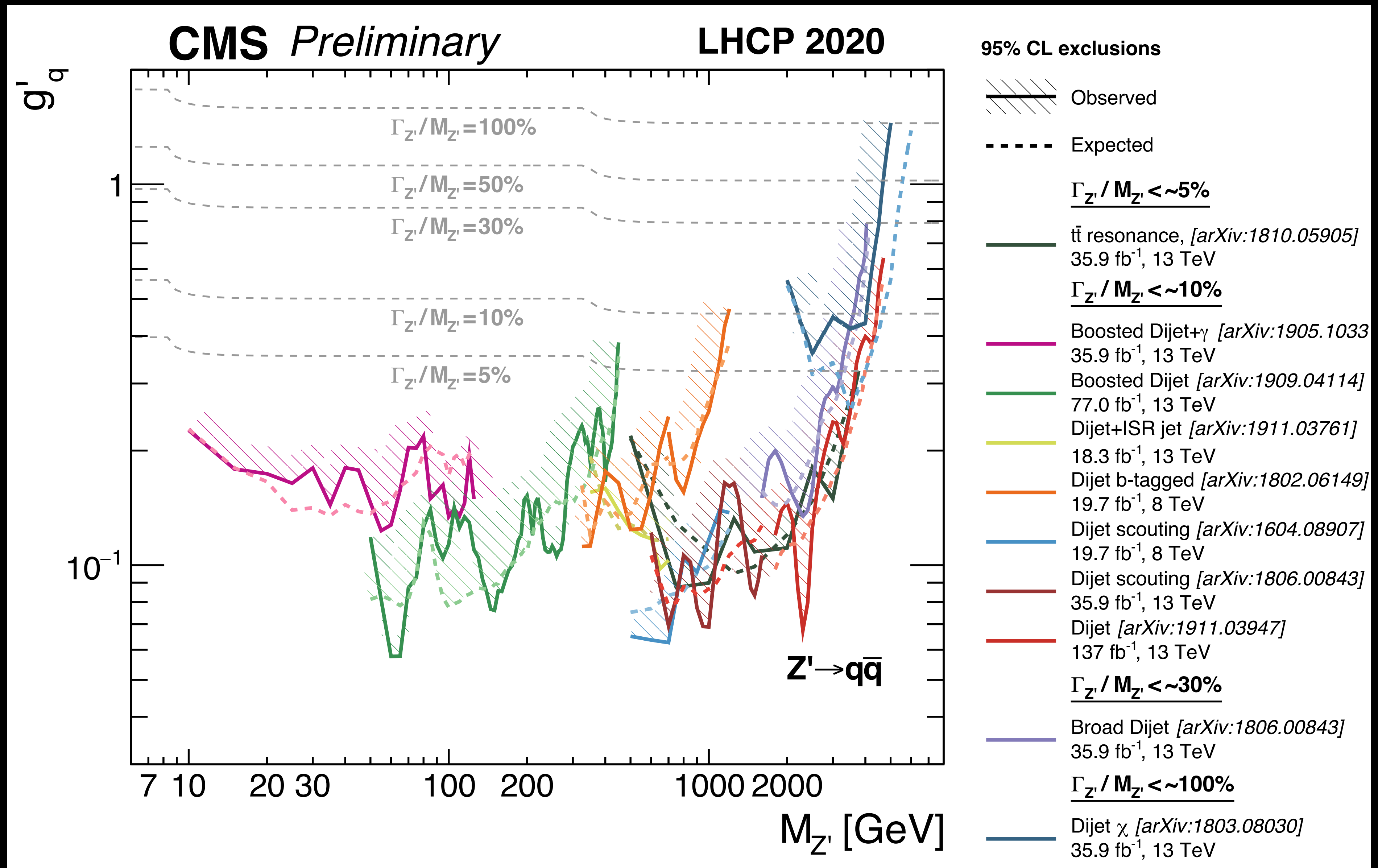


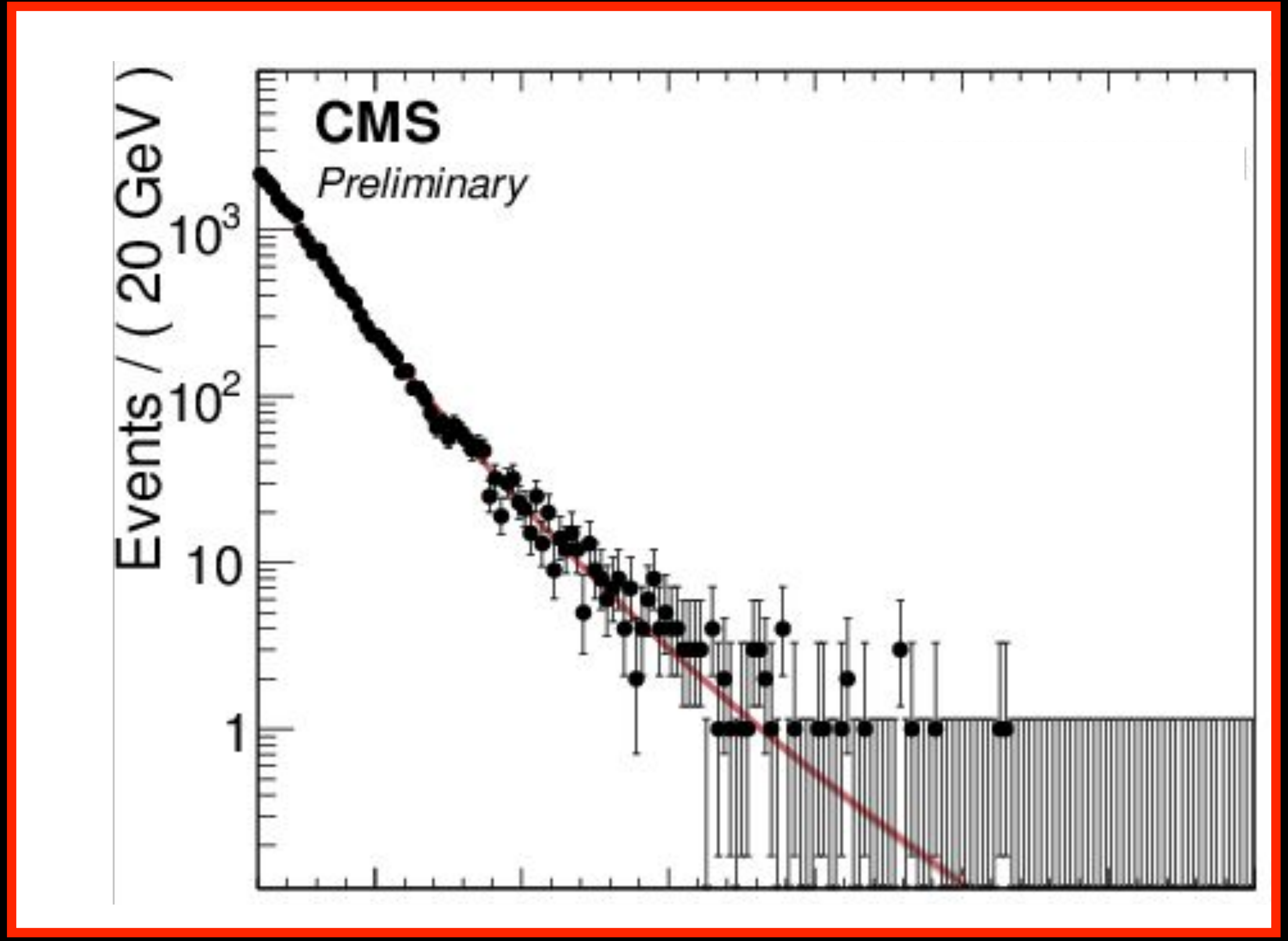


ε_{bkg} in SR

Can we reduce this

Anomaly detection for New Physics searches



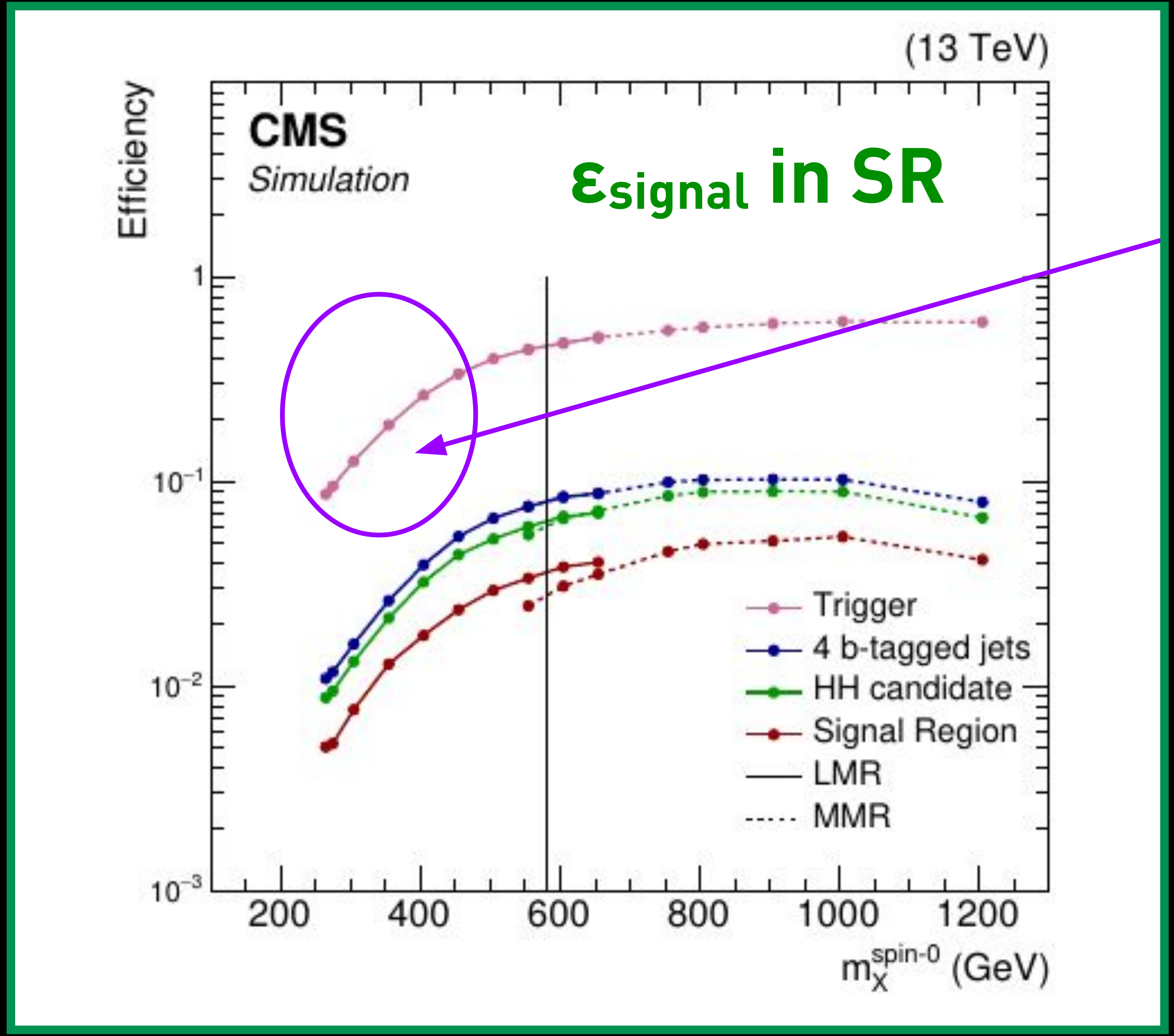


Can we reduce

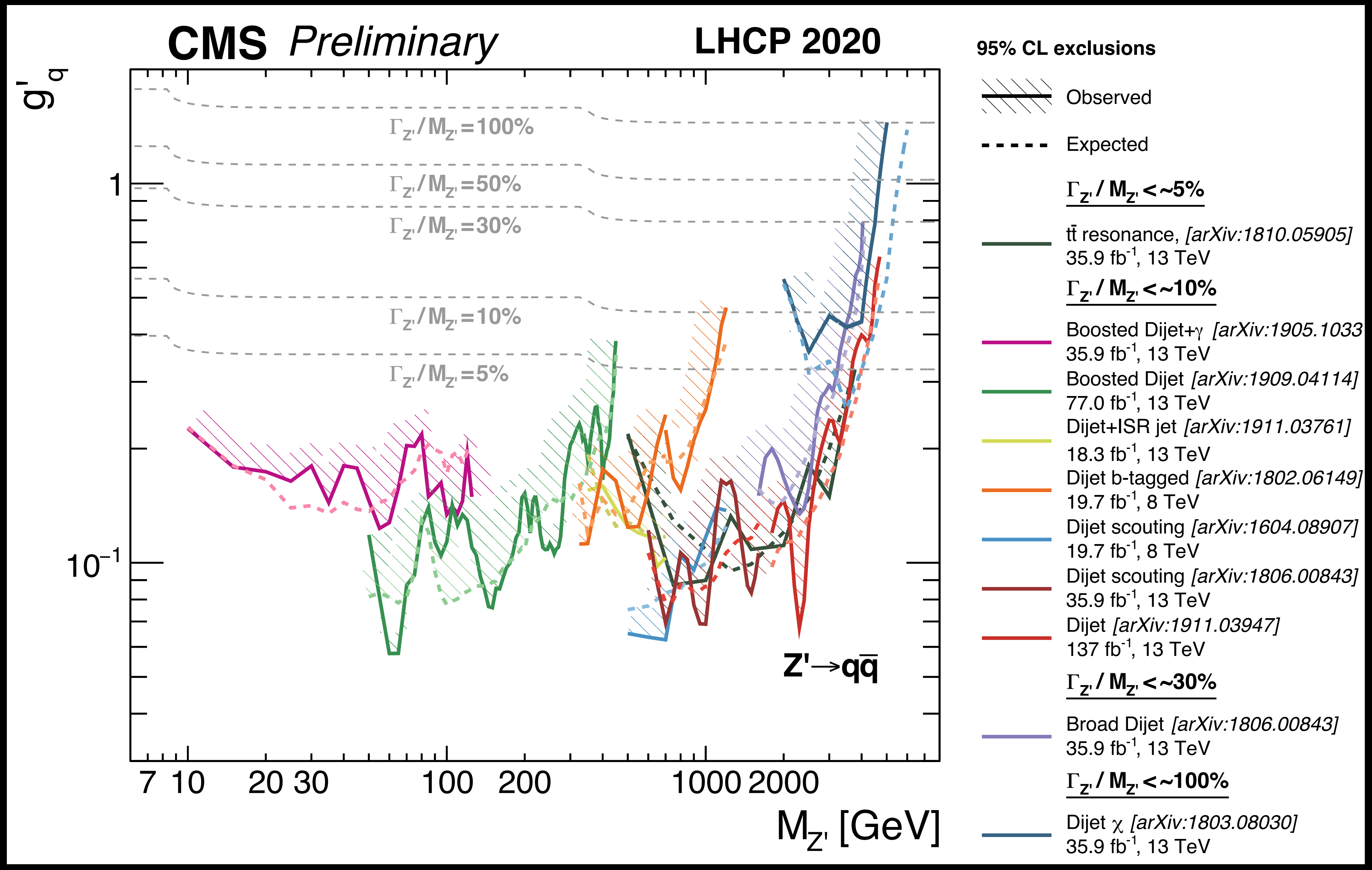
this

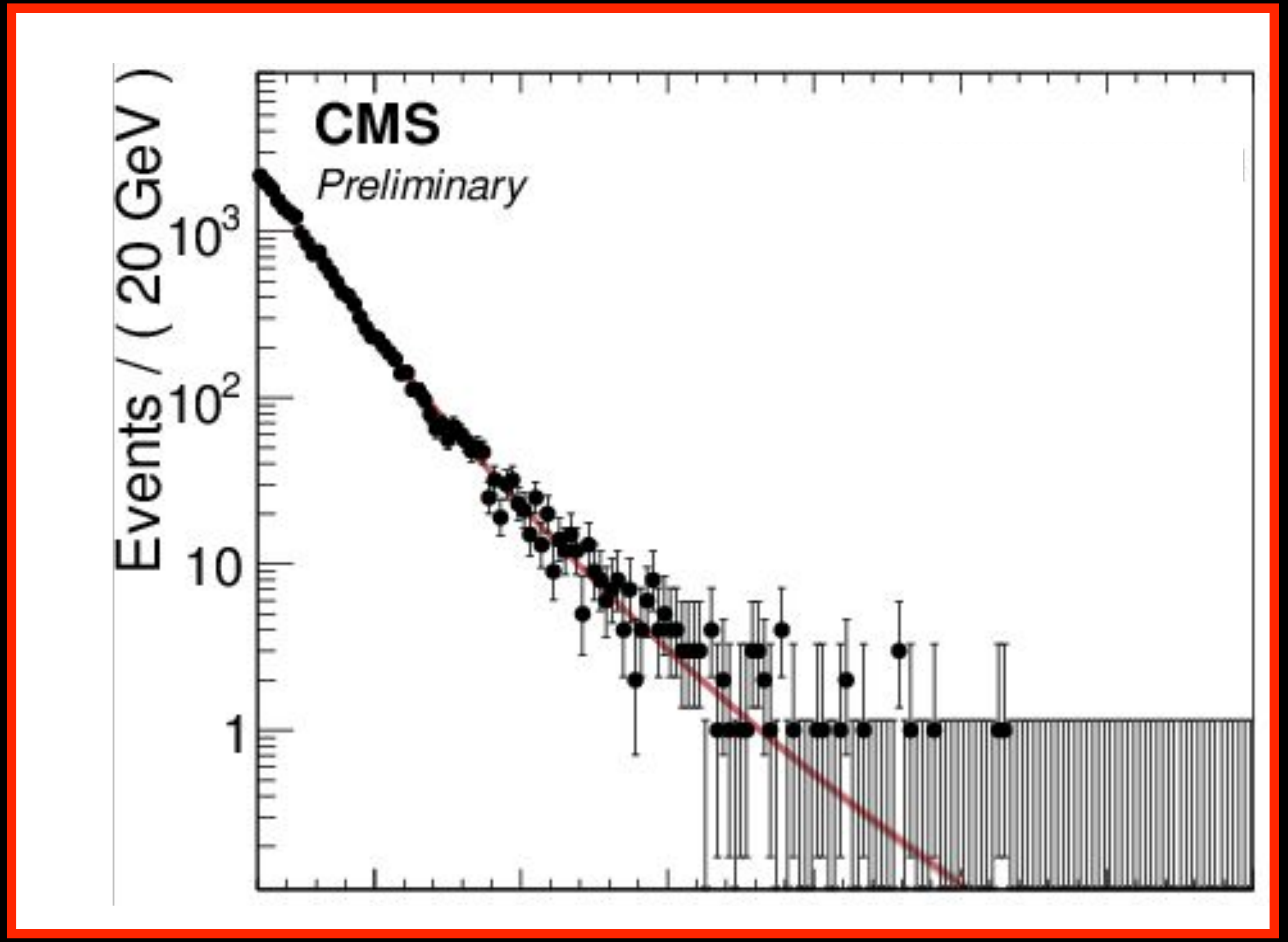
and maximise

this

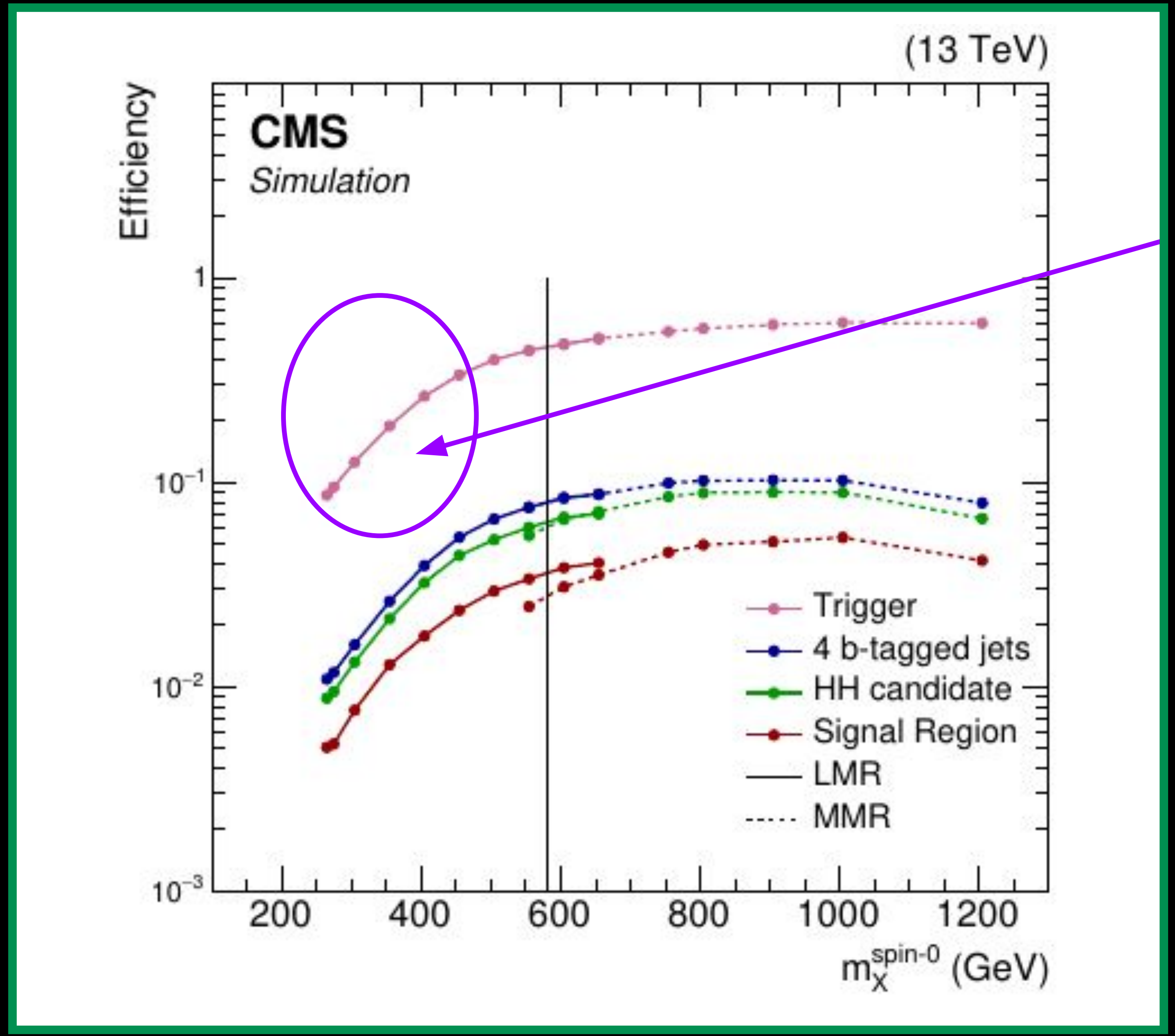


Anomaly detection for New Physics searches

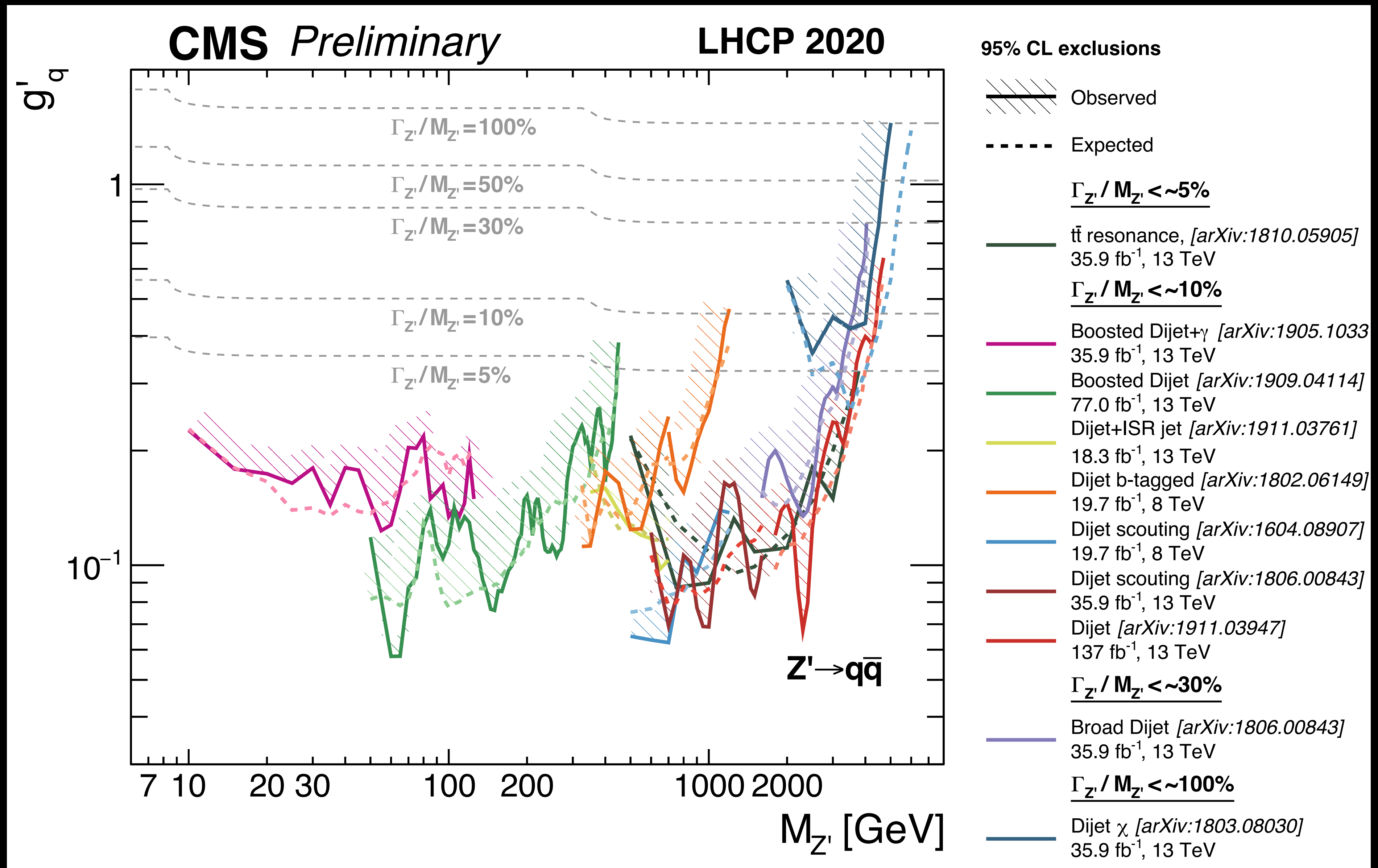


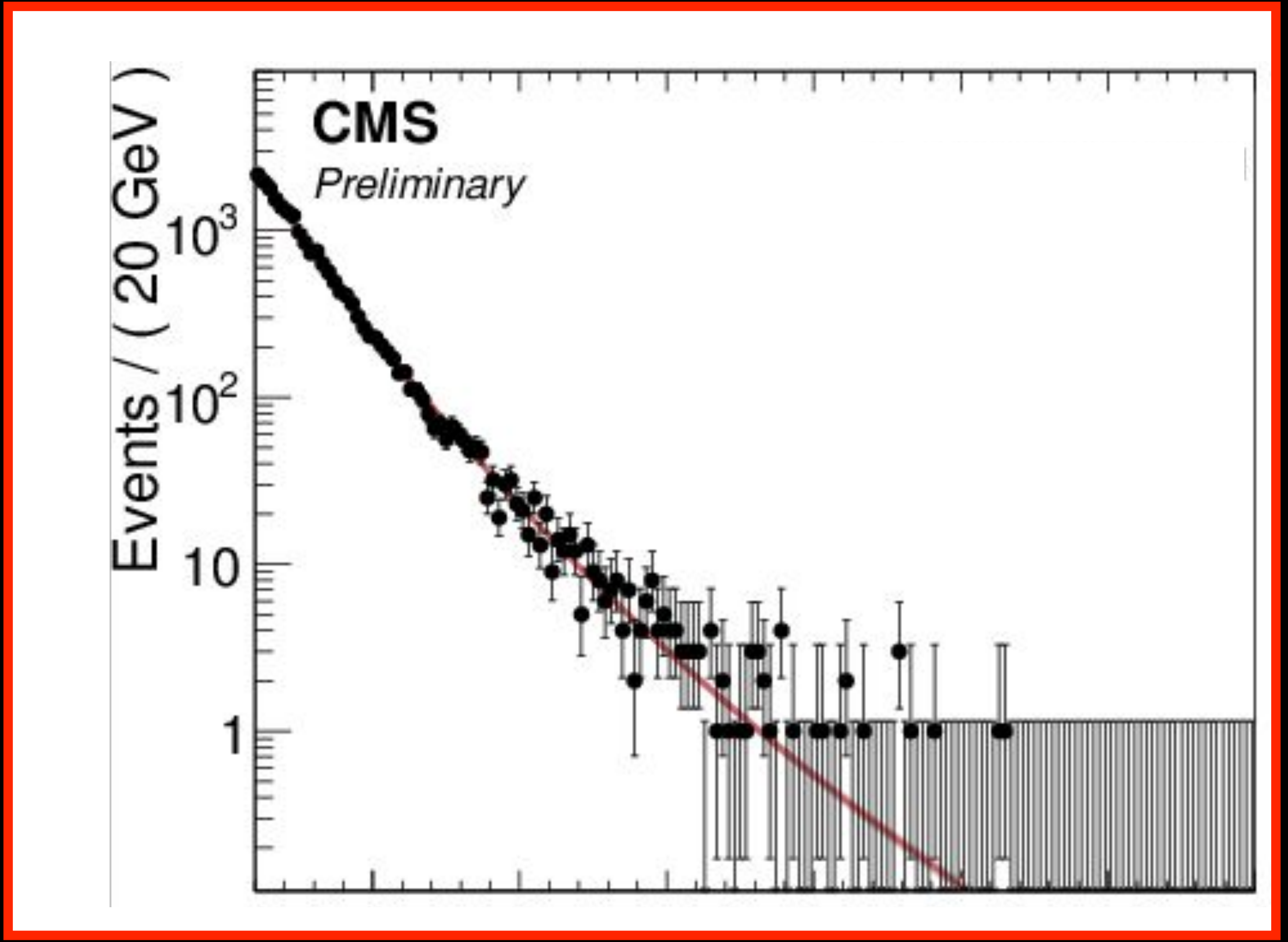


Can we reduce **this** and maximise **this** to probe hundreds of signal hypotheses all at once?



Anomaly detection for New Physics searches





Can we reduce

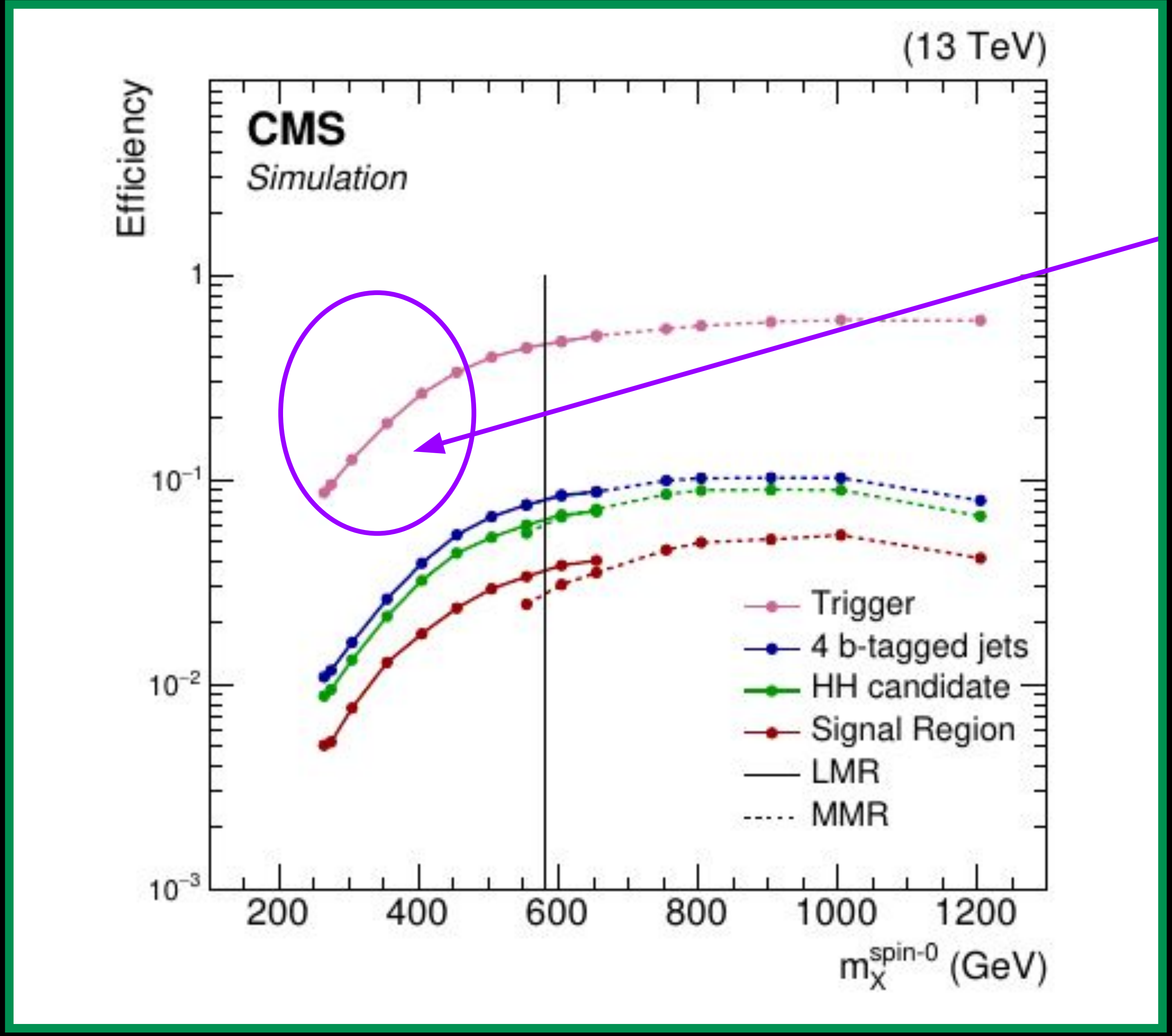
this

and maximise

this

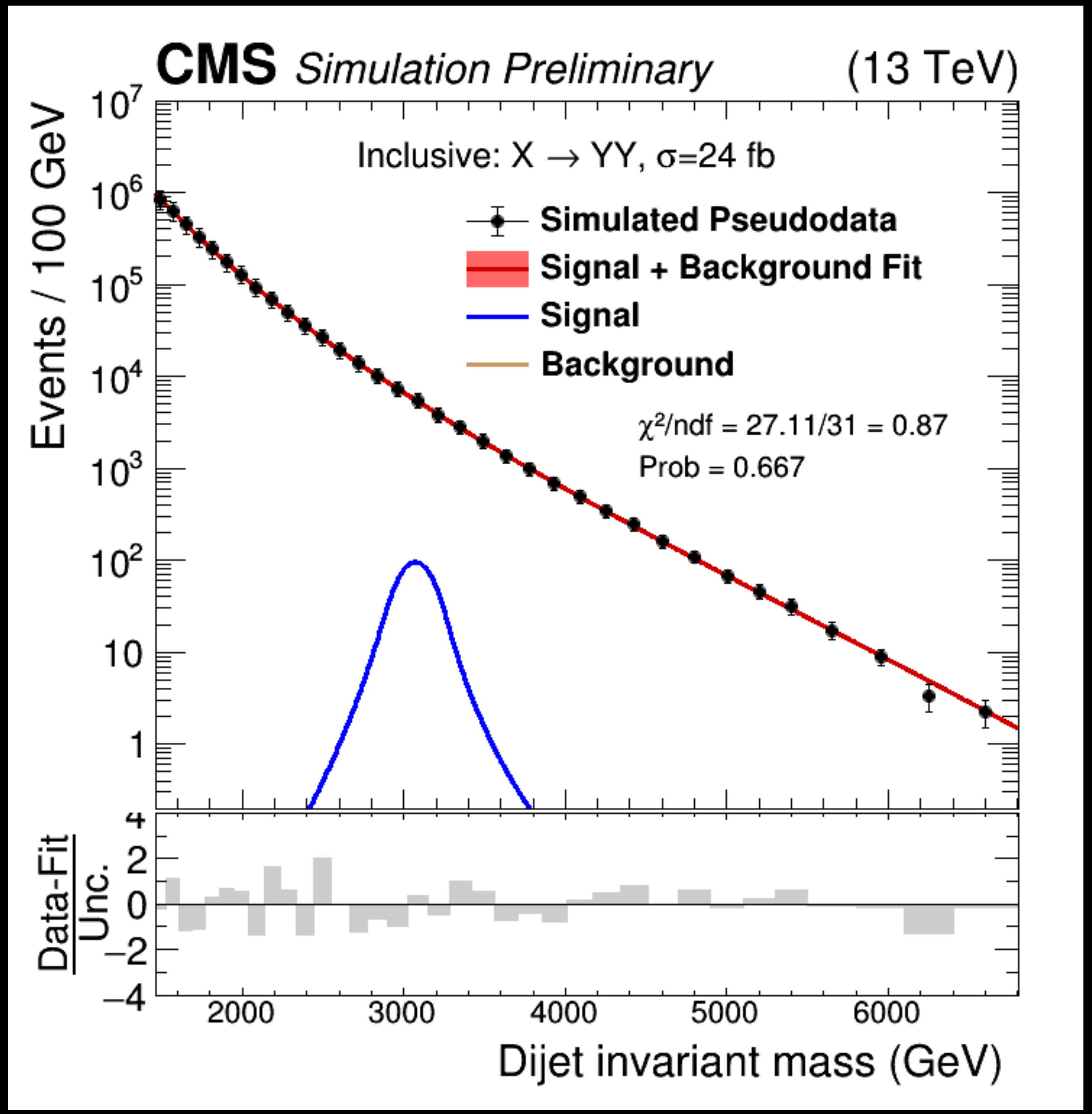
to probe hundreds of signal hypotheses all at once?

*(Maybe also some we didn't think of yet?)

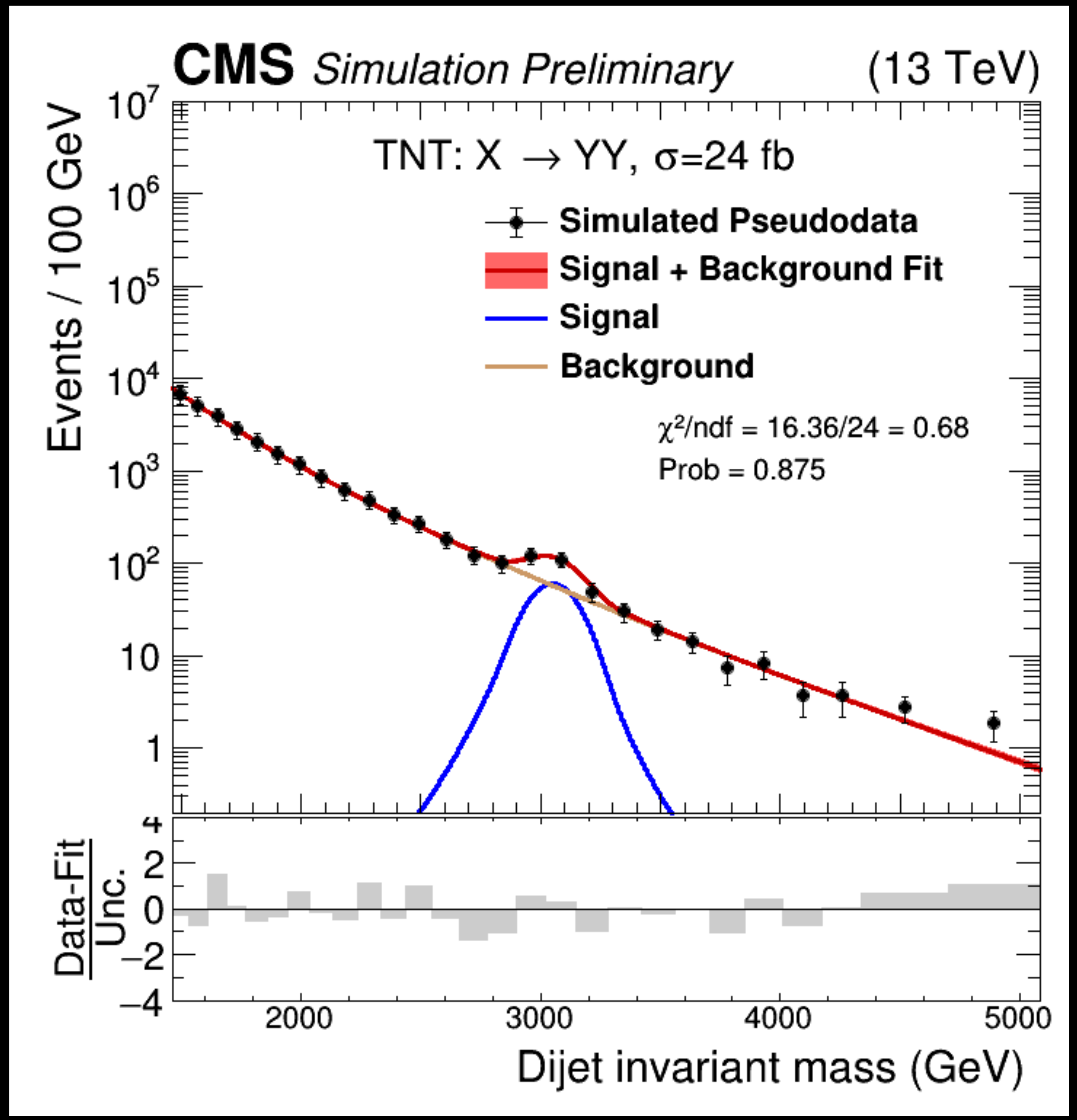


Anomaly detection in analysis

Before cut on anomaly score



After cut on anomaly score



CASE

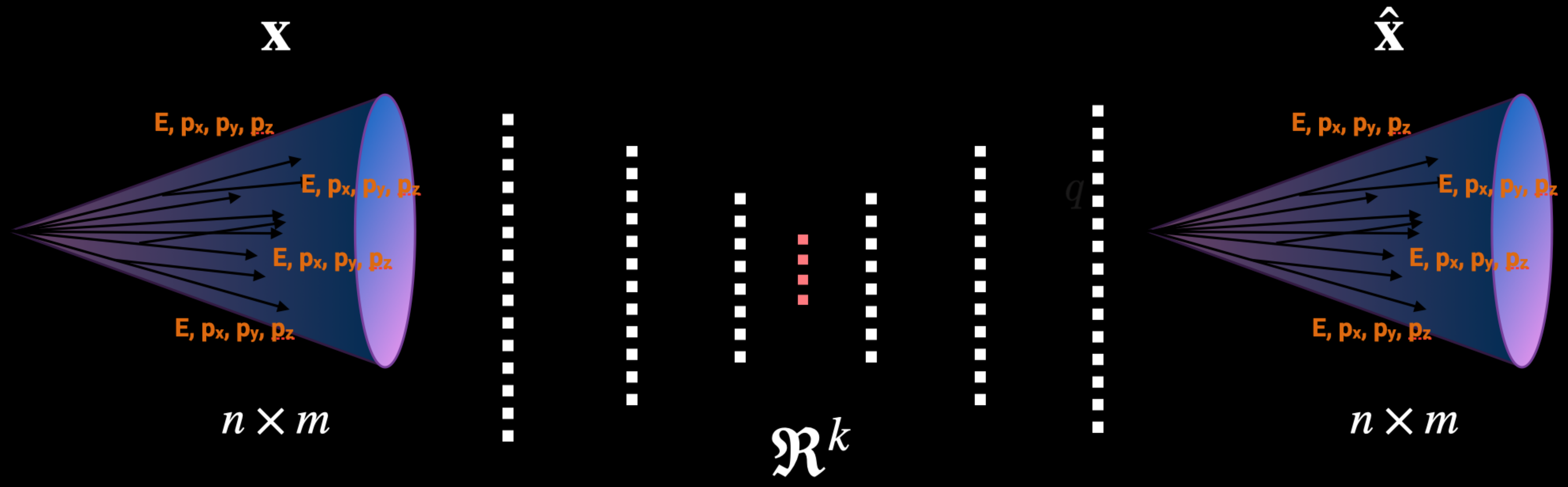
5 ways of identifying anomalous dijet events

Variational autoencoder

Unsupervised

Signal-hypothesis dependence

5 ways of identifying anomalous dijet events

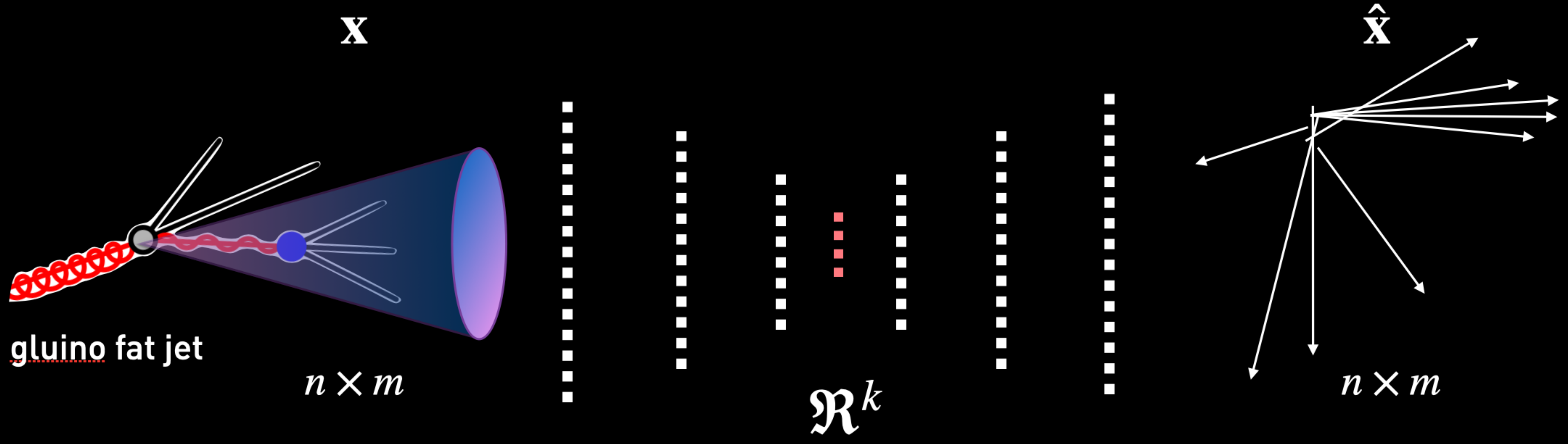


Variational autoencoder

Unsupervised

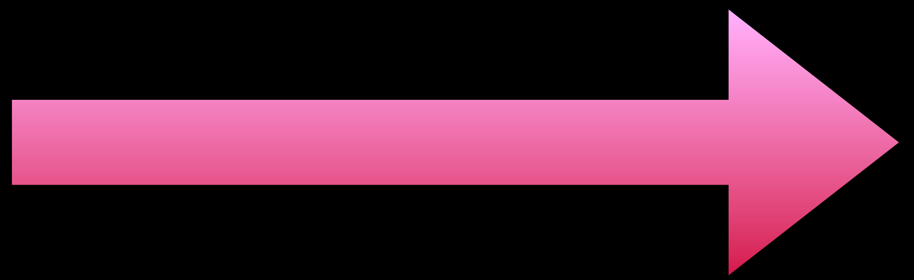
Signal-hypothesis dependence

5 ways of identifying anomalous dijet events



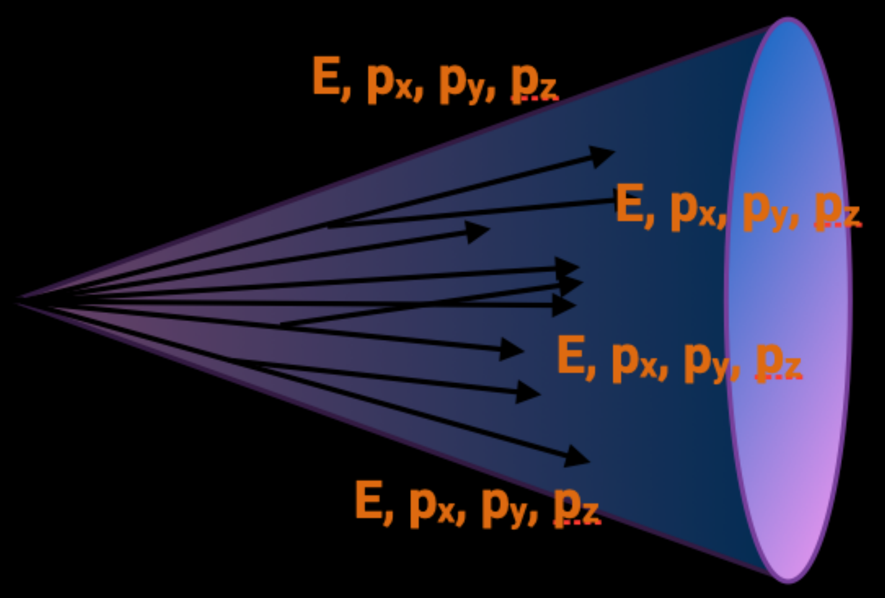
Variational autoencoder

Unsupervised



Signal-hypothesis dependence

5 ways of identifying anomalous dijet events



$n \times m$

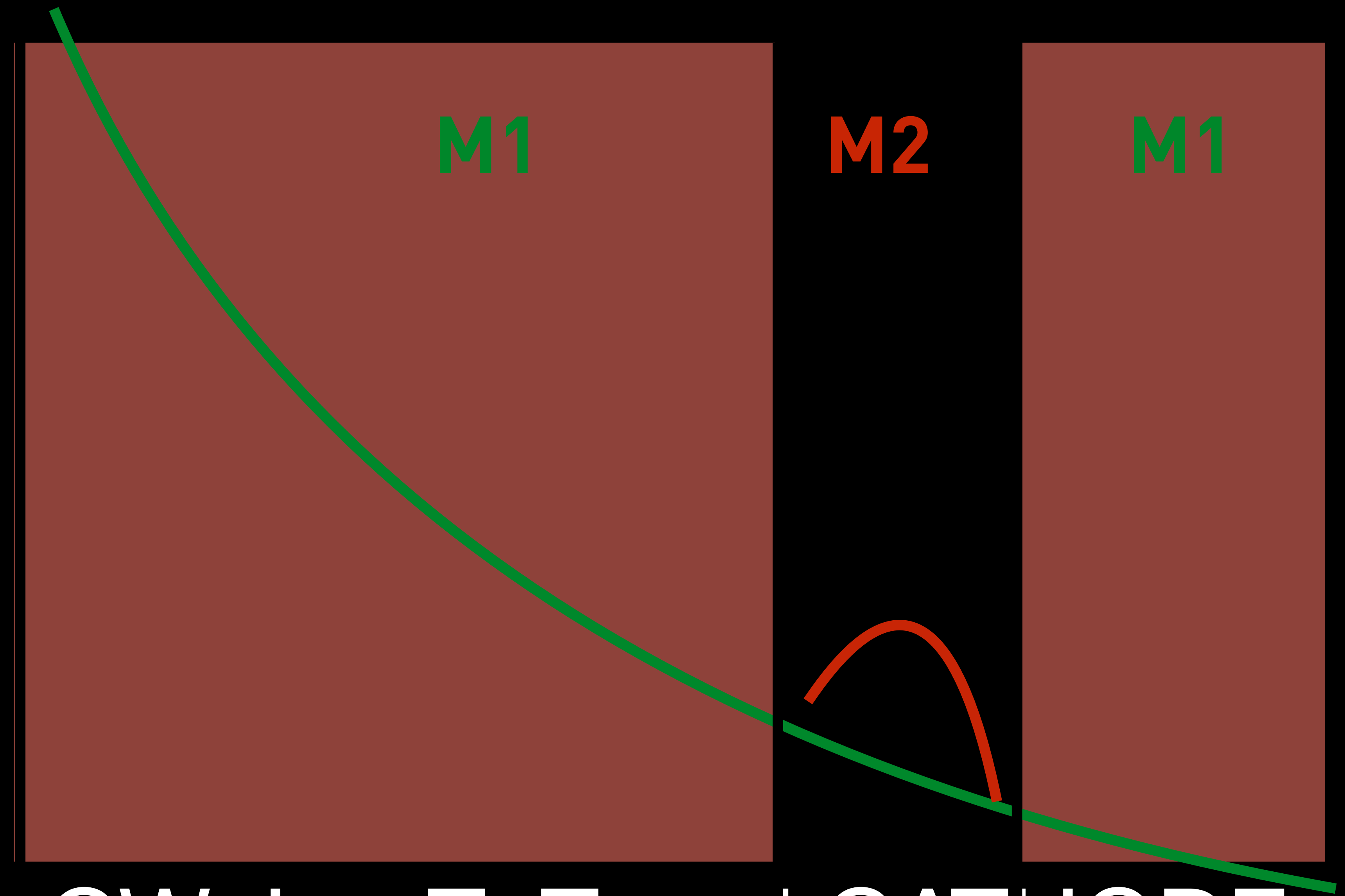
Variational autoencoder

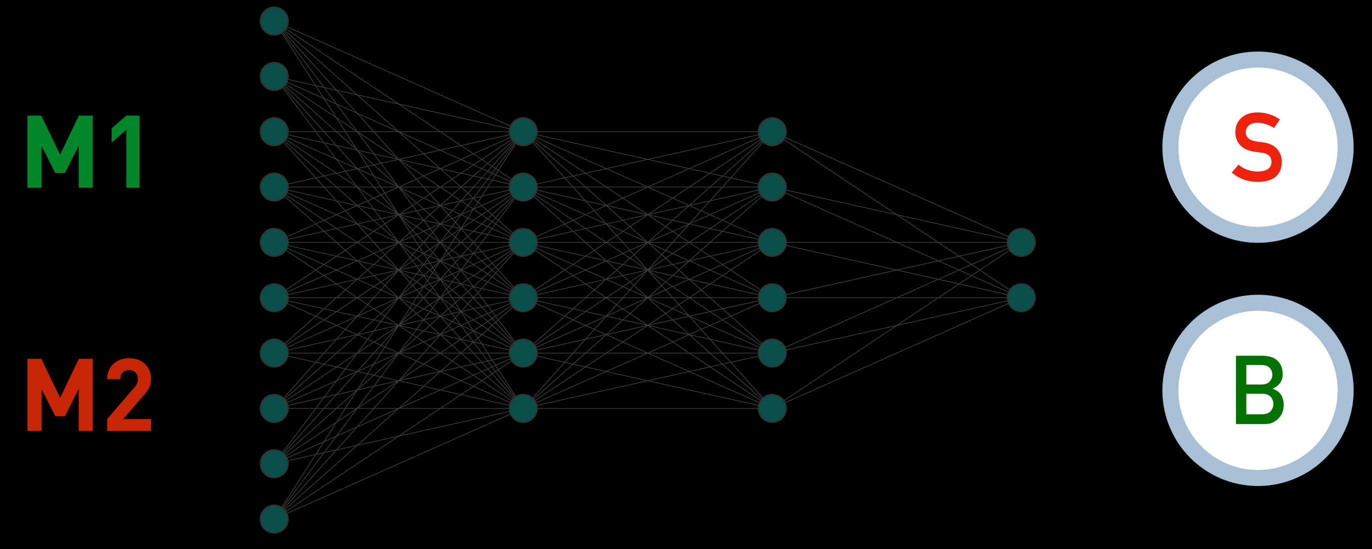
Unsupervised

Weakly supervised

Signal-hypothesis dependence

5 ways of identifying anomalous dijet events





Variational autoencoder

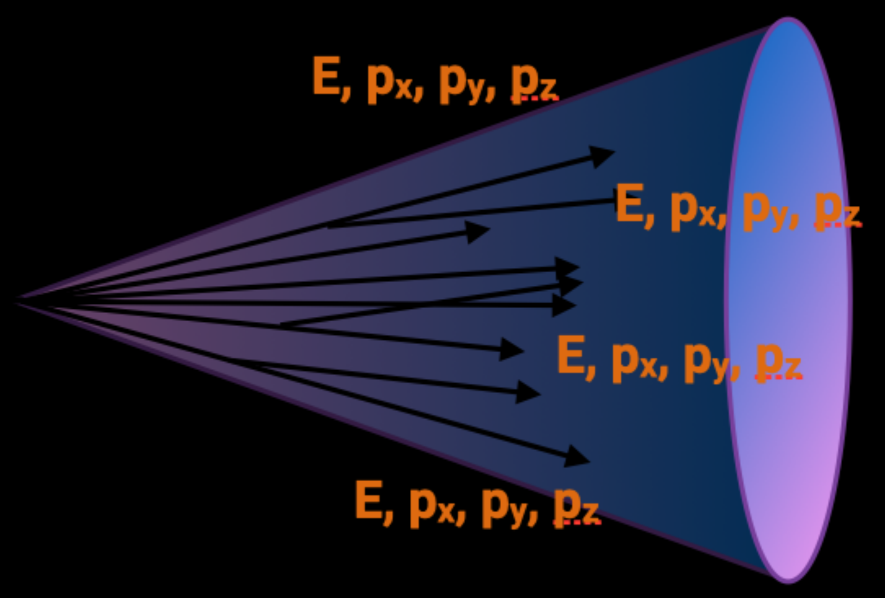
CWoLa, TnT and CATHODE

Unsupervised

Weakly supervised

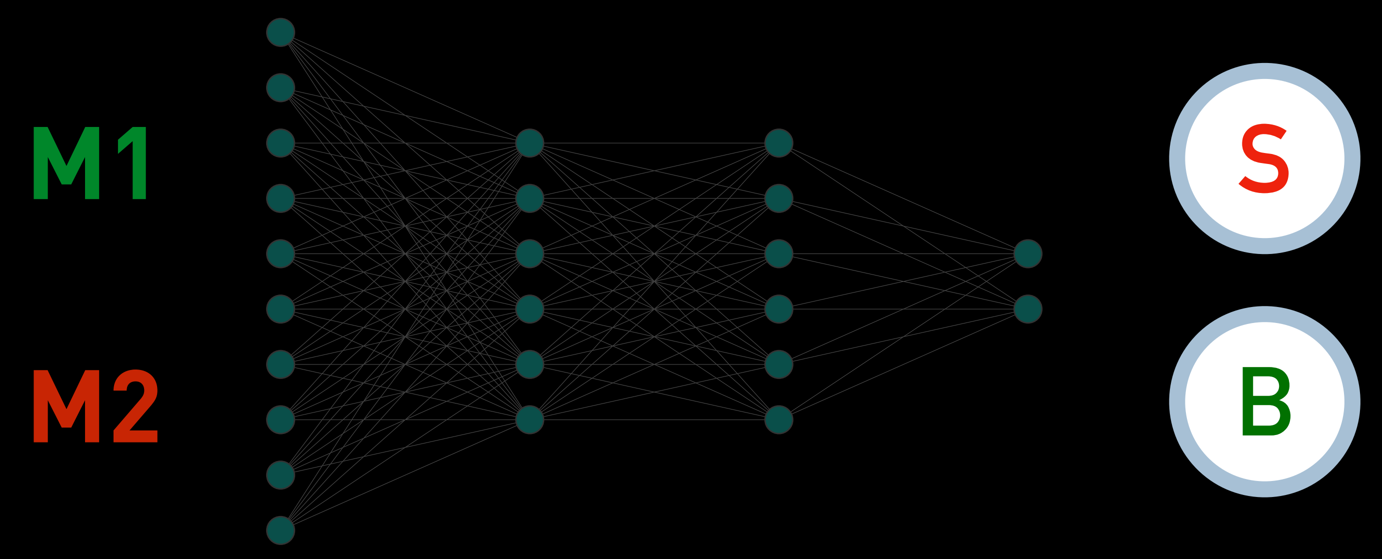
Signal-hypothesis dependence

5 ways of identifying anomalous dijet events



$n \times m$

Variational autoencoder



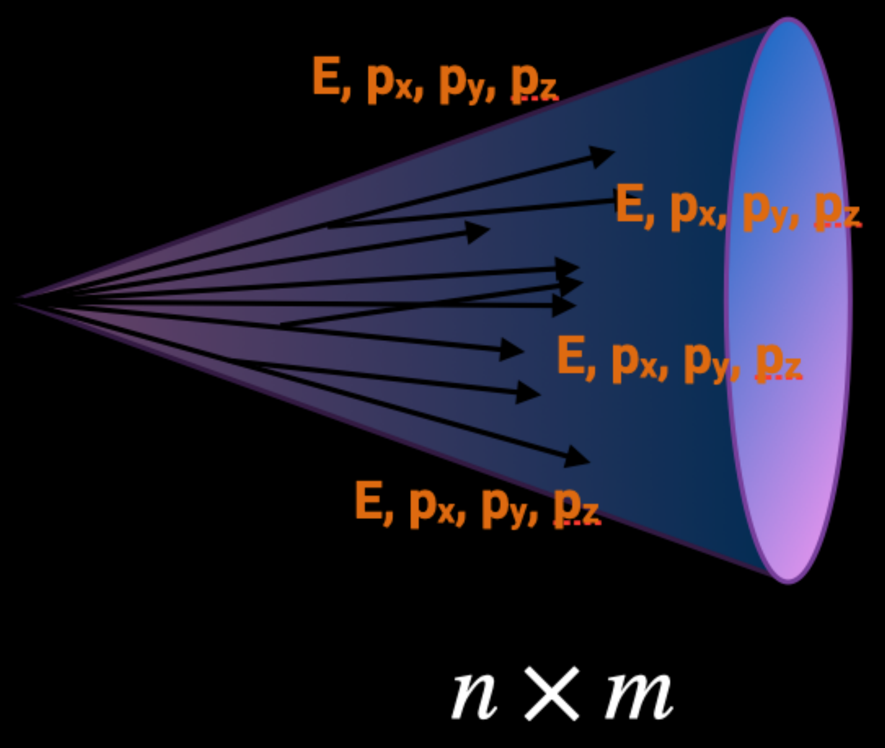
CWoLa, TnT and CATHODE

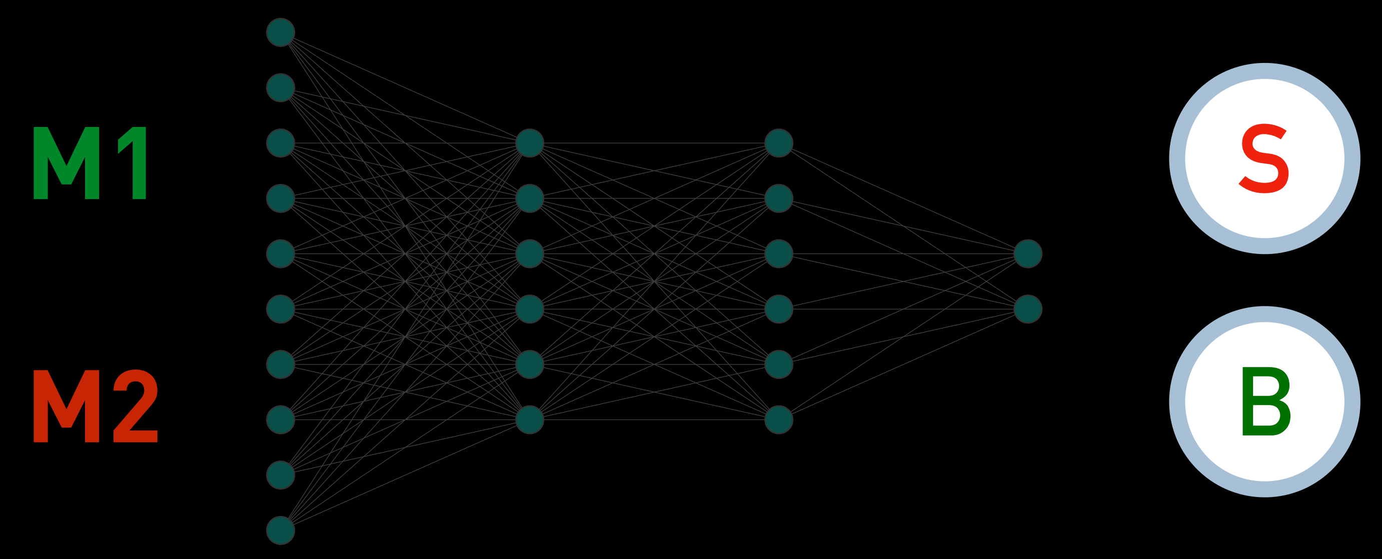
Unsupervised

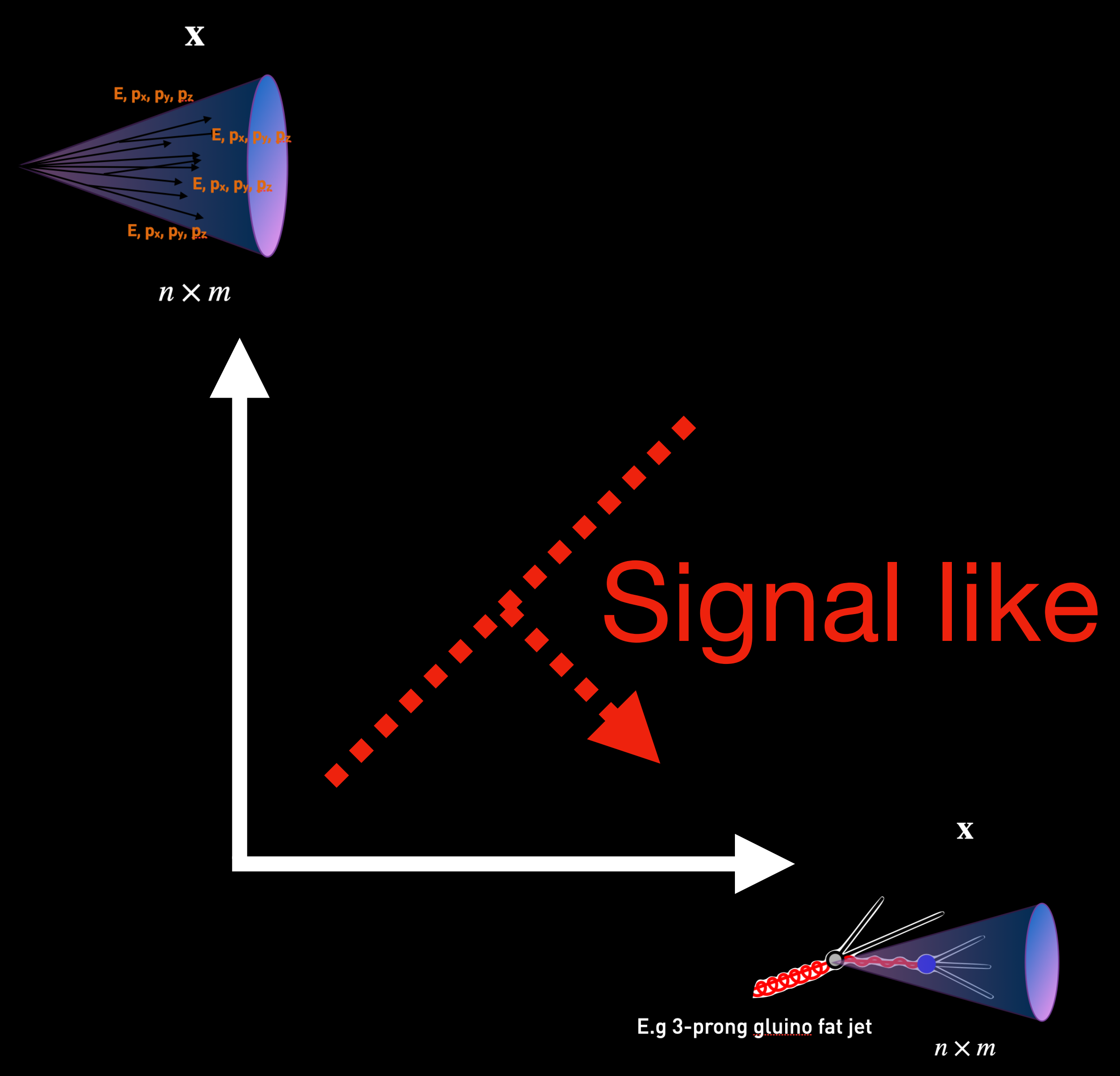
Weakly supervised

Signal-hypothesis dependence

5 ways of identifying anomalous dijet events







Variational autoencoder

CWoLa, TnT and CATHODE

QUAK

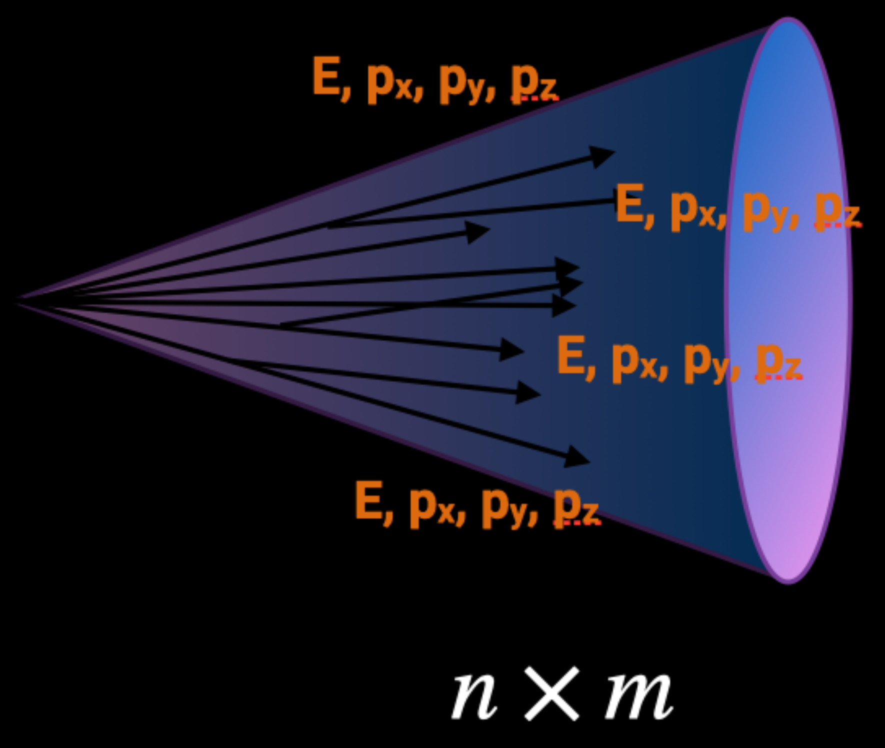
Unsupervised

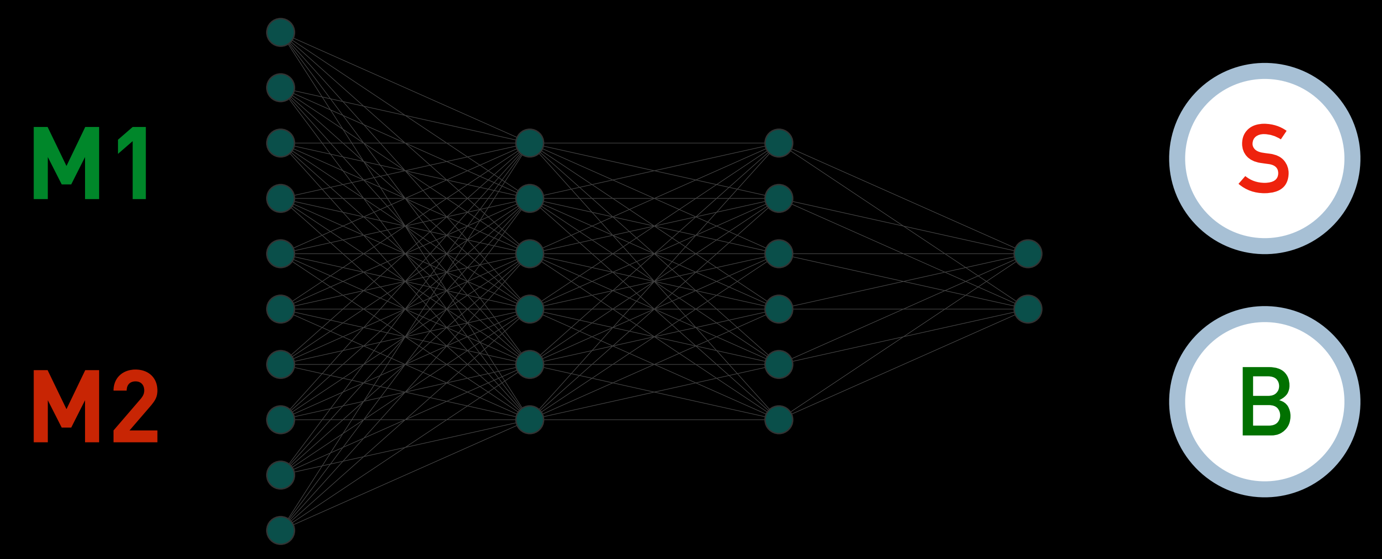
Weakly supervised

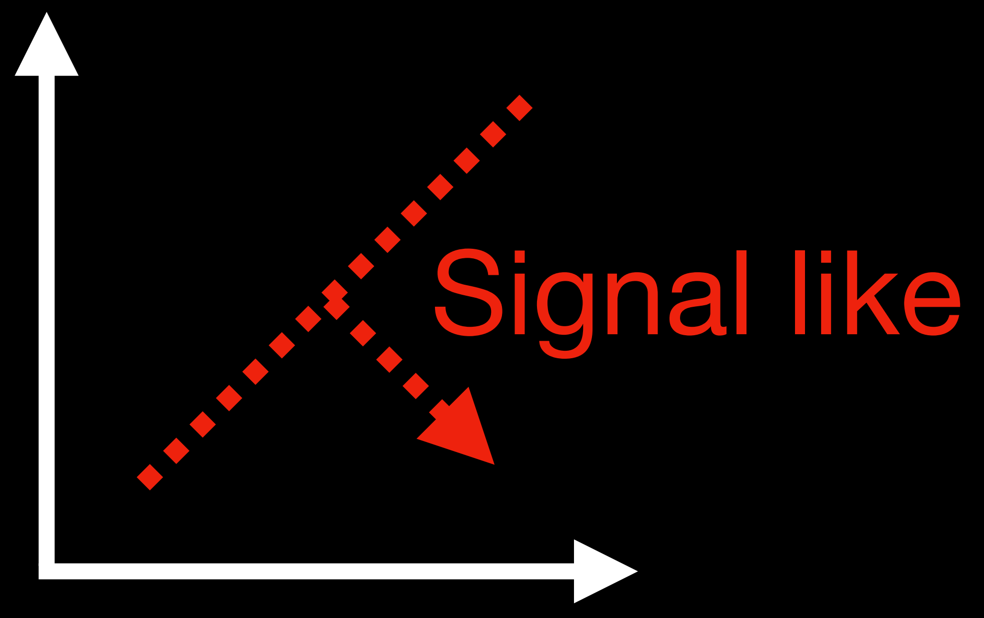
Hybrid

Signal-hypothesis dependence

5 ways of identifying anomalous dijet events







Variational autoencoder

CWoLa, TnT and CATHODE

(Likelihood-ratio based)

QUAK

(Log-likelihood based)

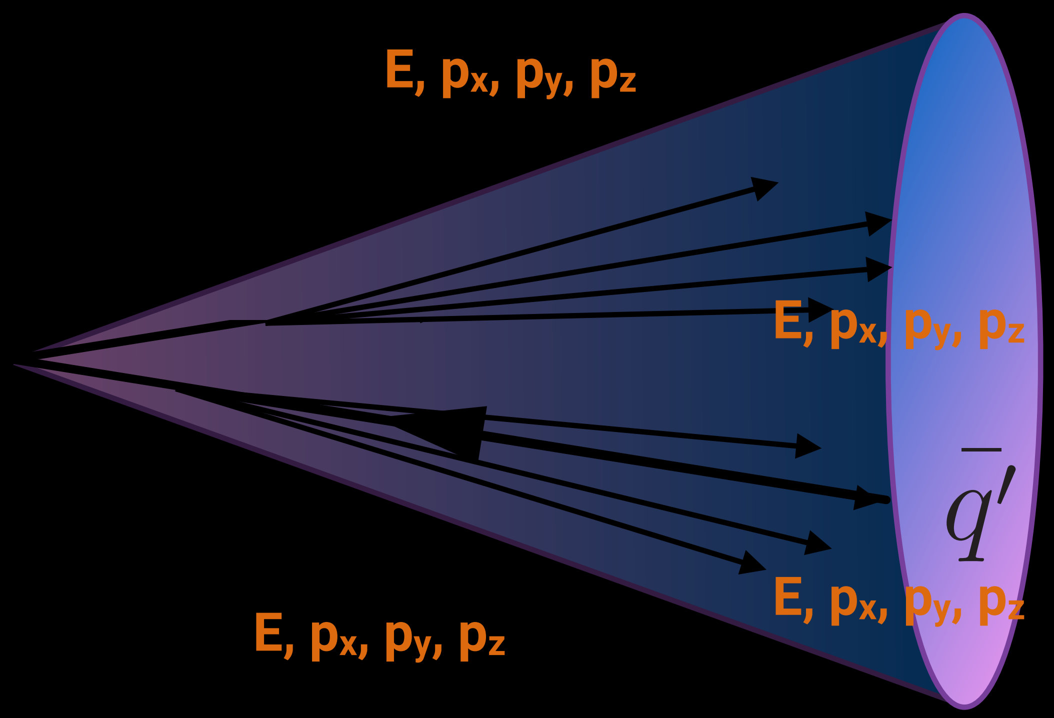
Unsupervised

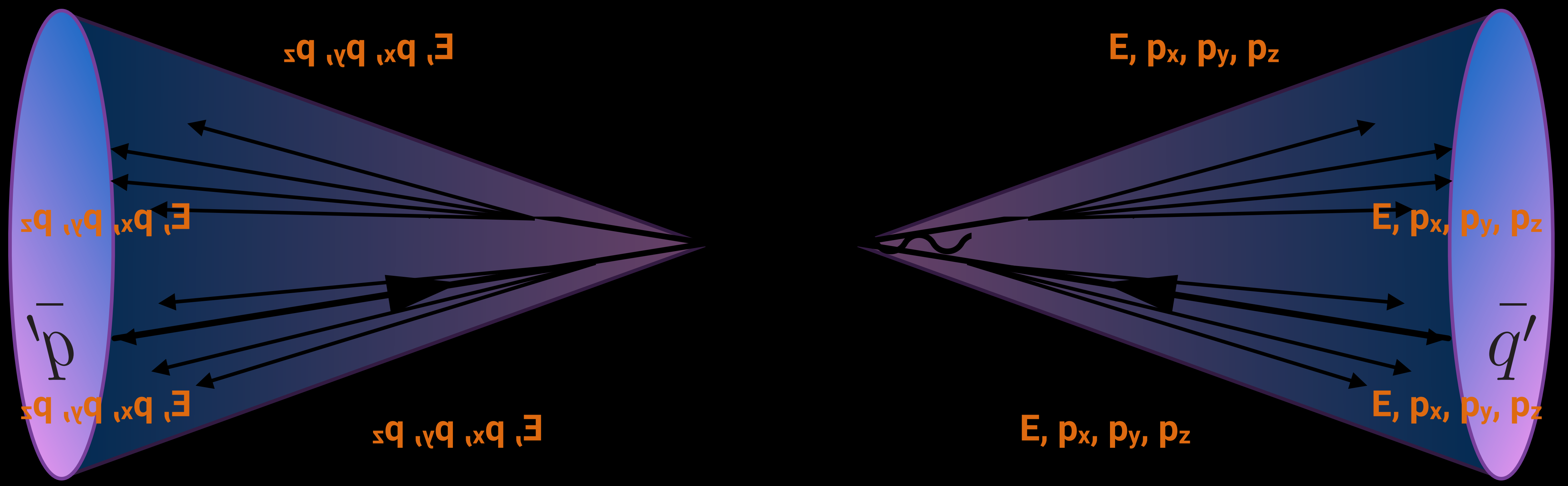
Weakly supervised

Hybrid

Signal-hypothesis dependence

Why so many methods?





Identify single anomalous jet

Variational autoencoder

Low-level constituent information

CWoLa, TnT

High-level substructure information

Identify anomalous dijet system

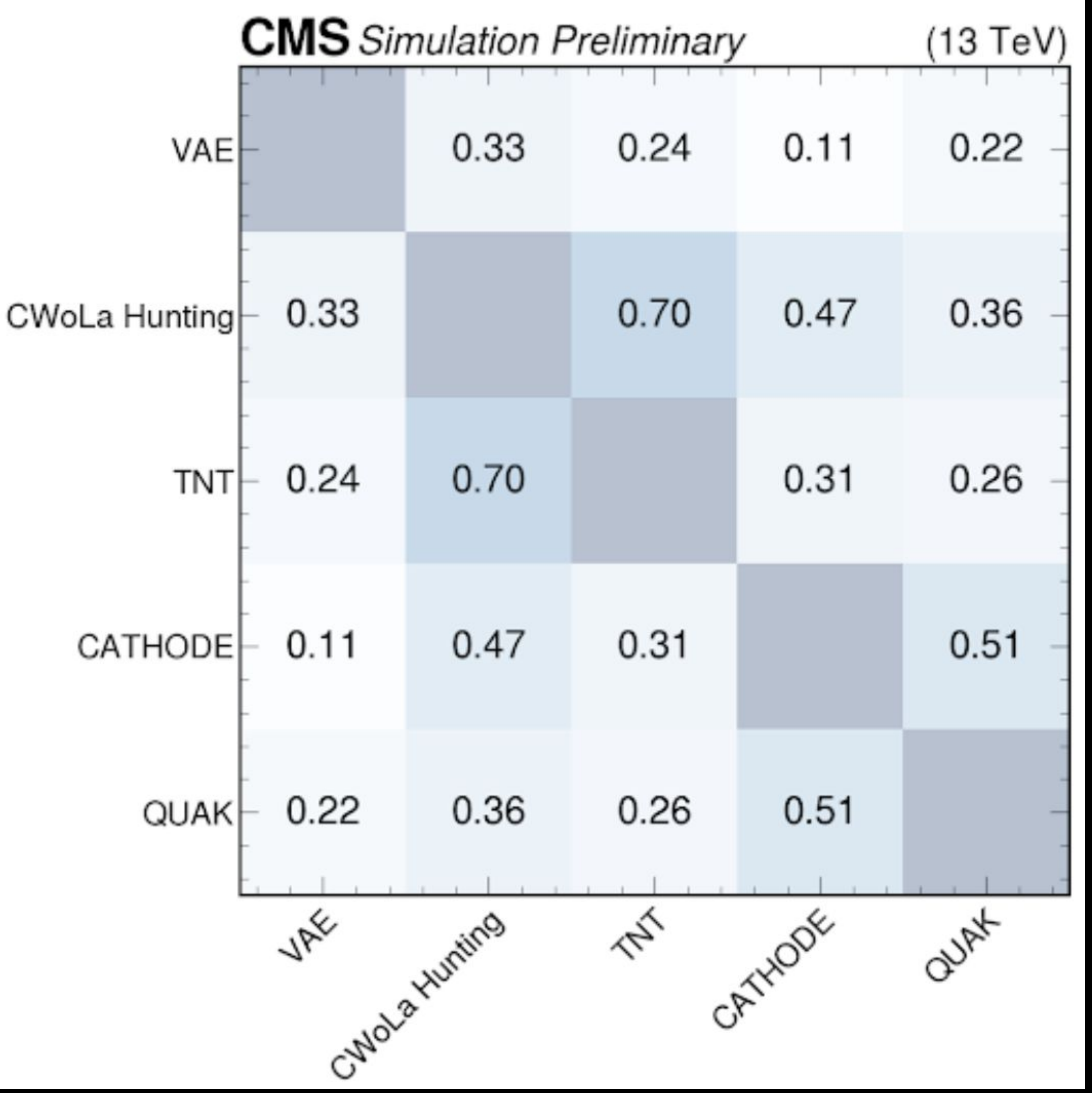
CATHODE

QUAK

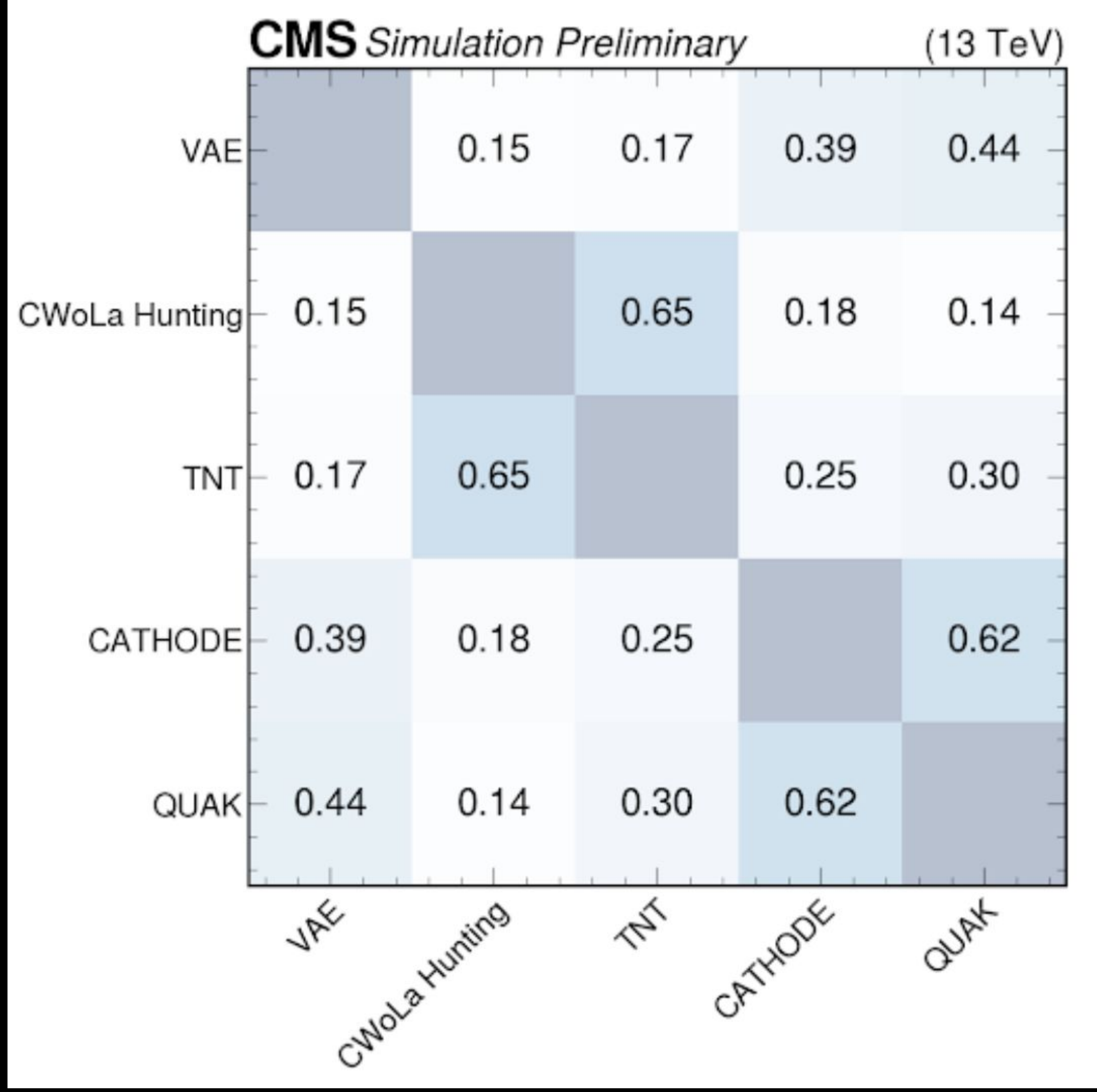
High-level substructure + dijet information

Why so many methods?

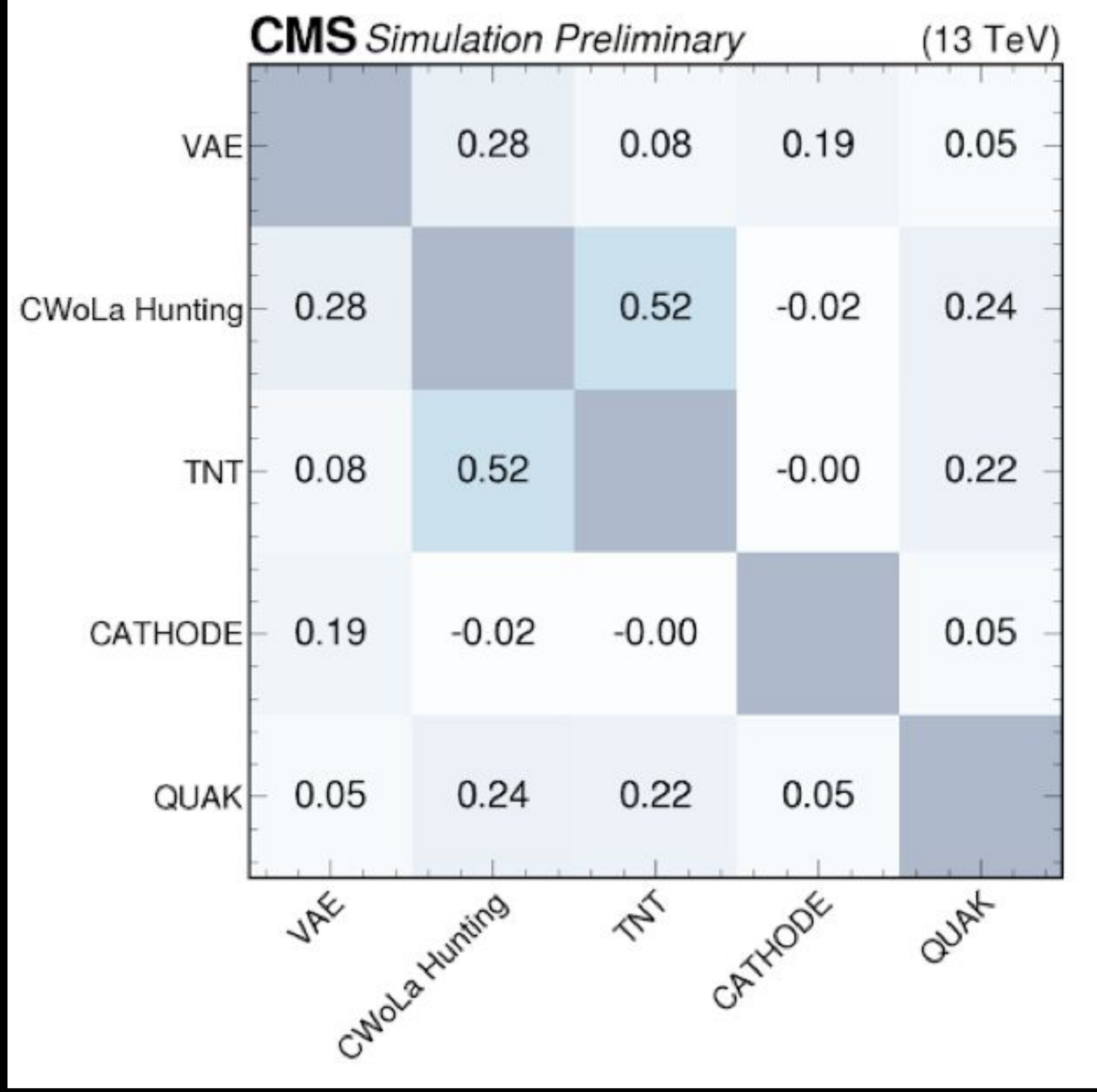
W’ → B’t → qqq qqq



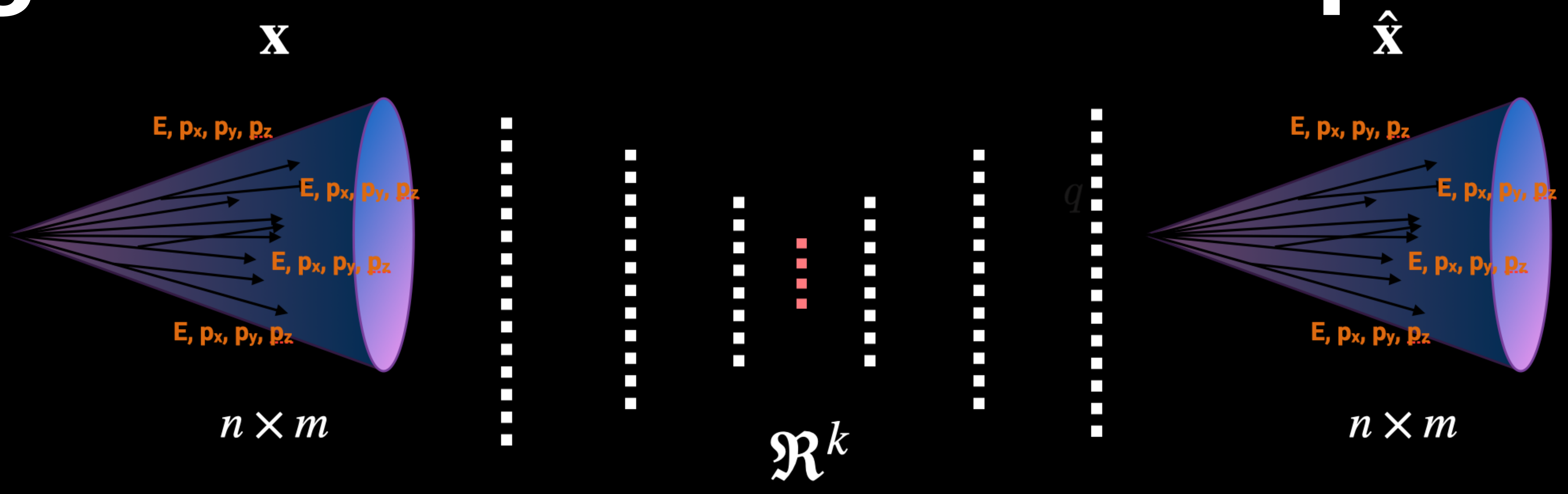
X → YY’ → qq qq



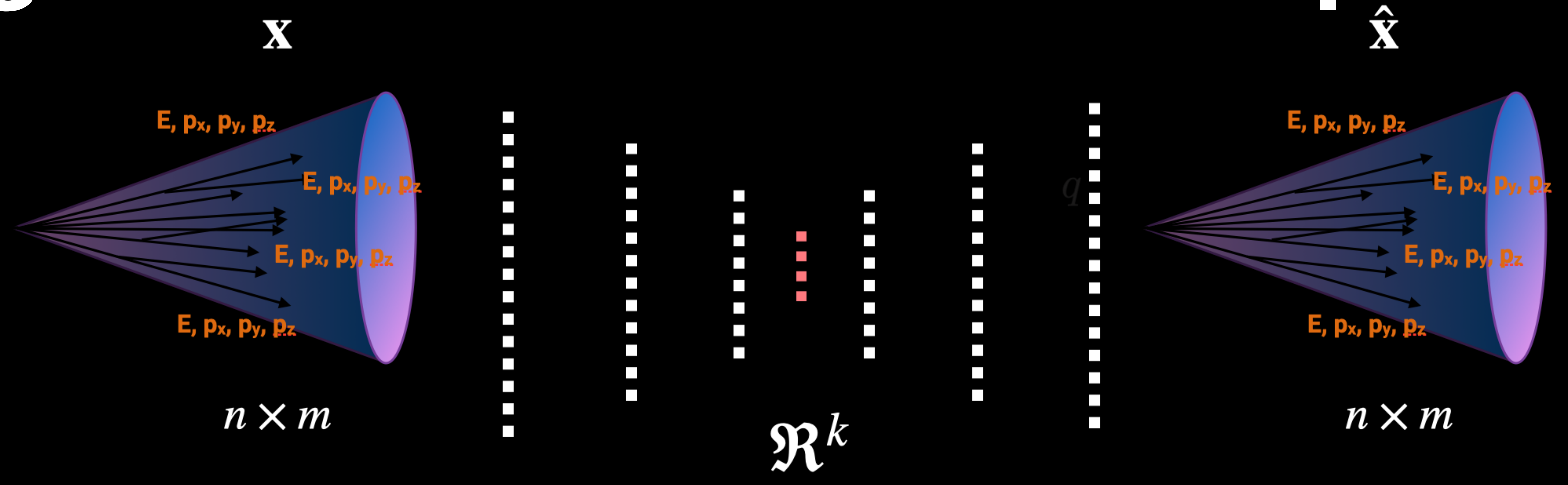
QCD background



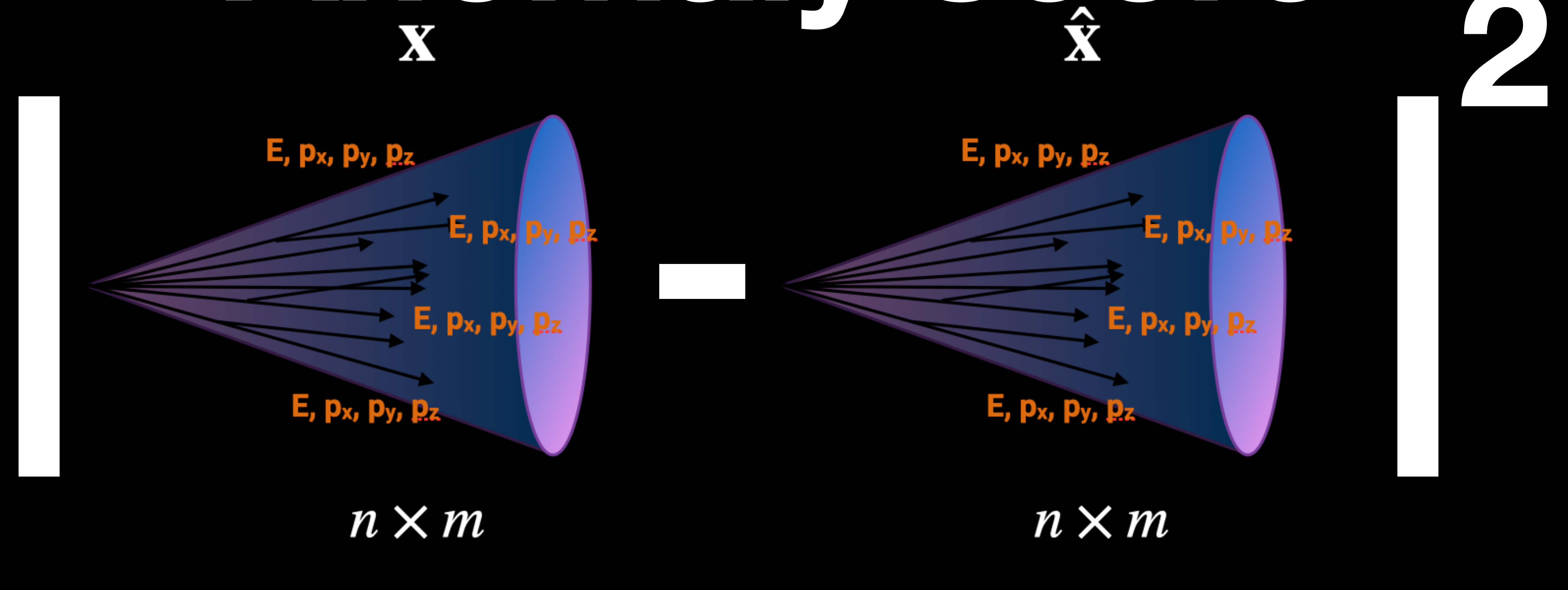
Getting a VAE for AD to work in practise

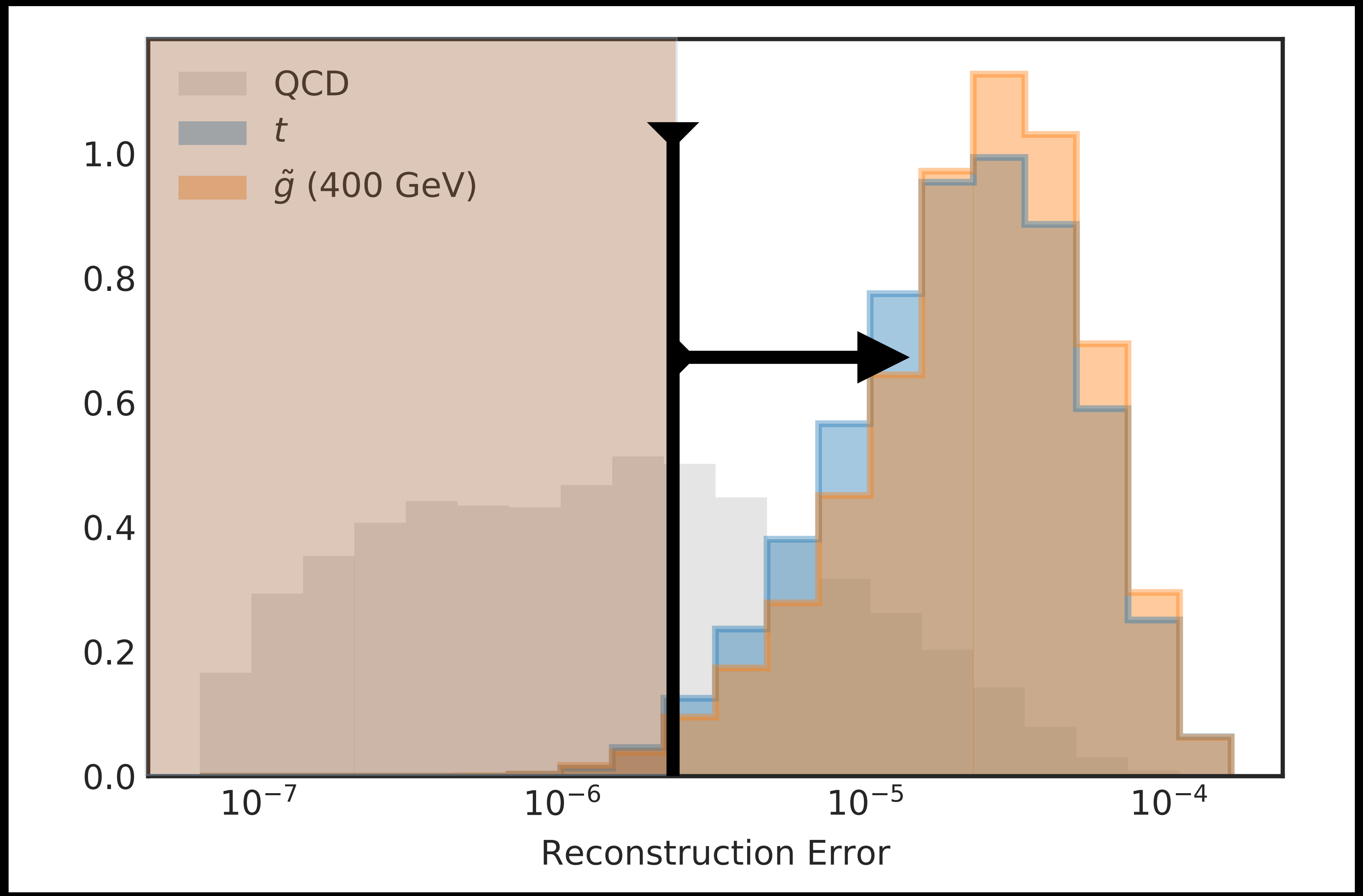


Getting a VAE for AD to work in practise

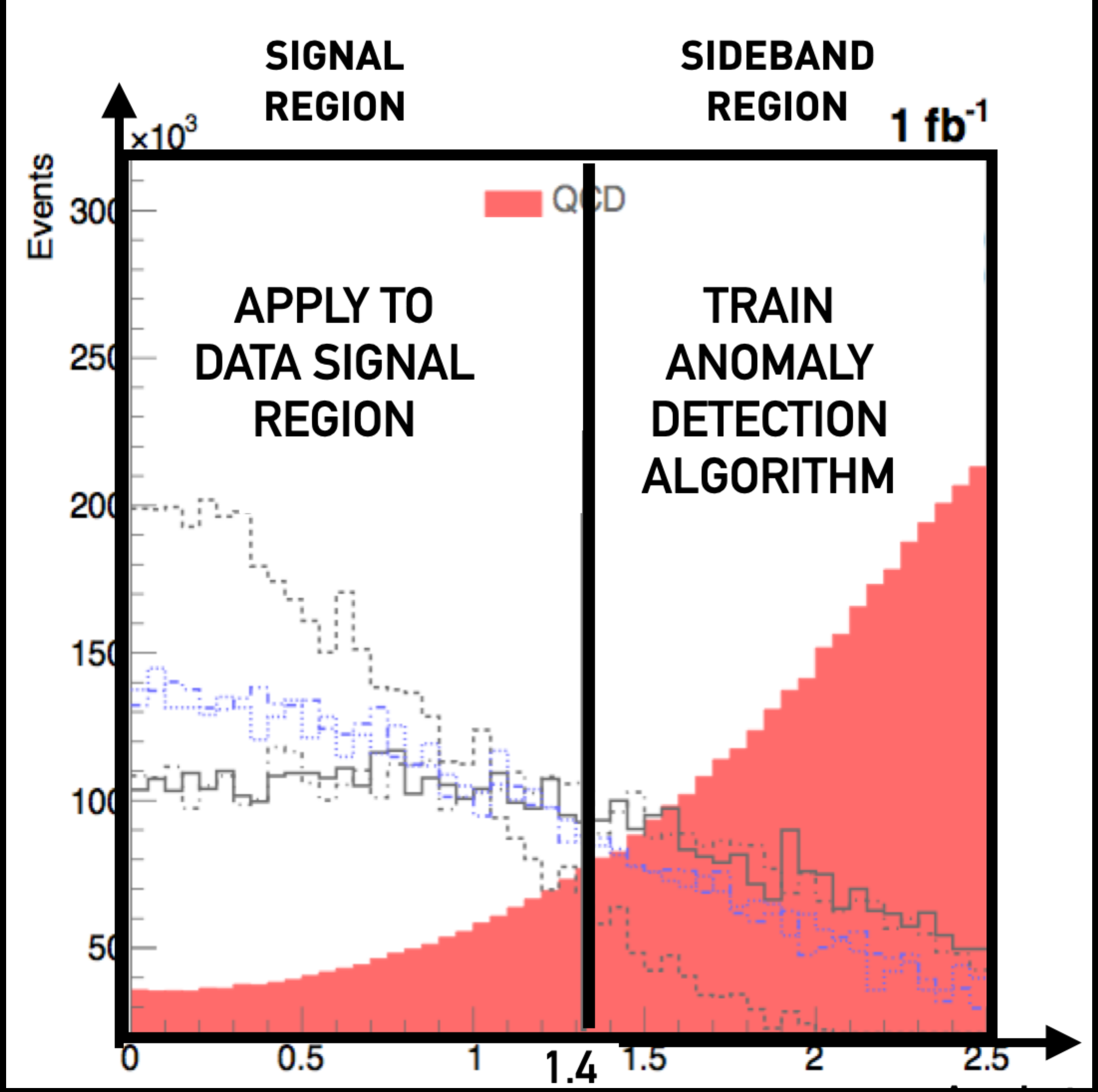


Anomaly score



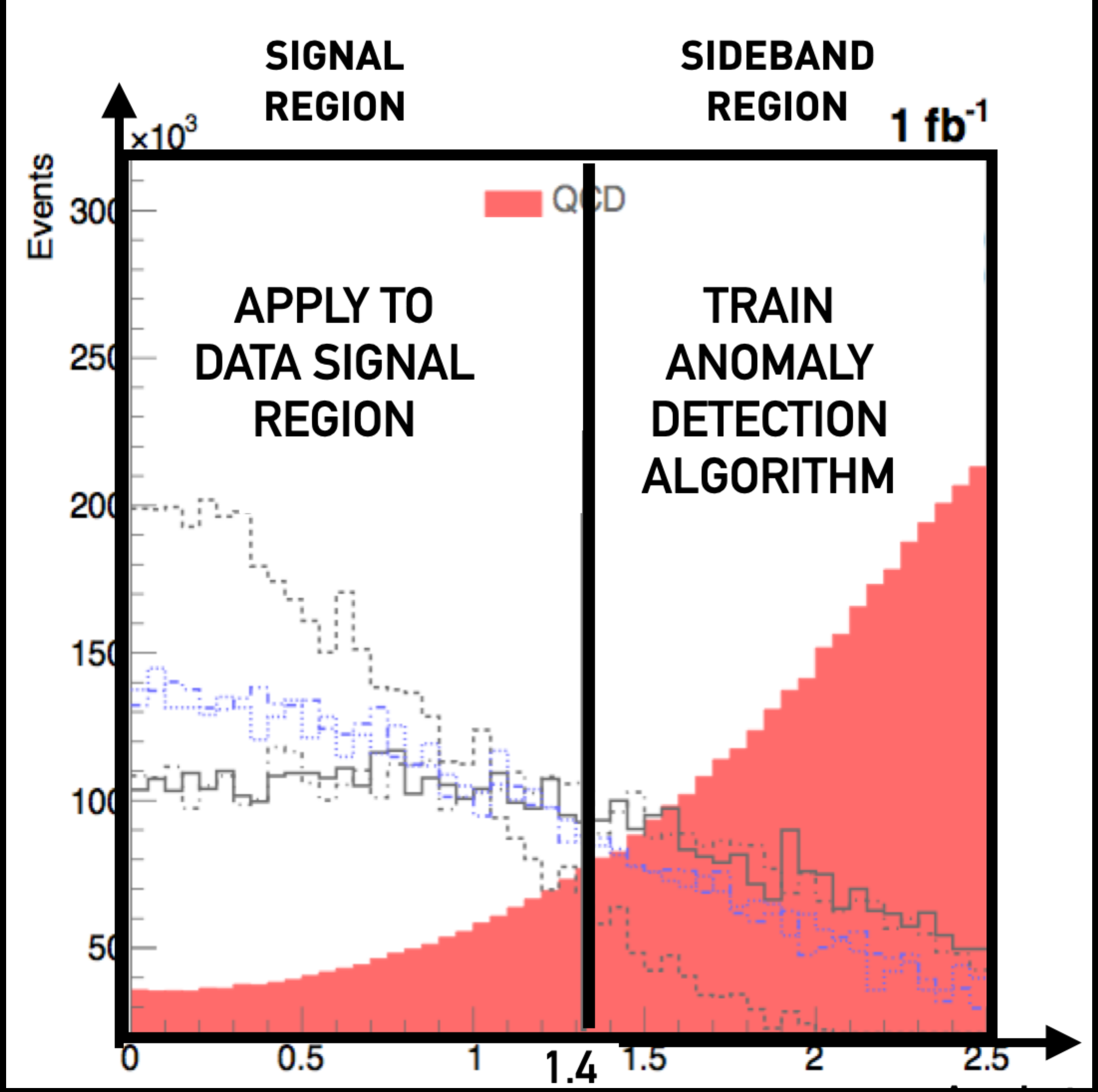


Where do you train?

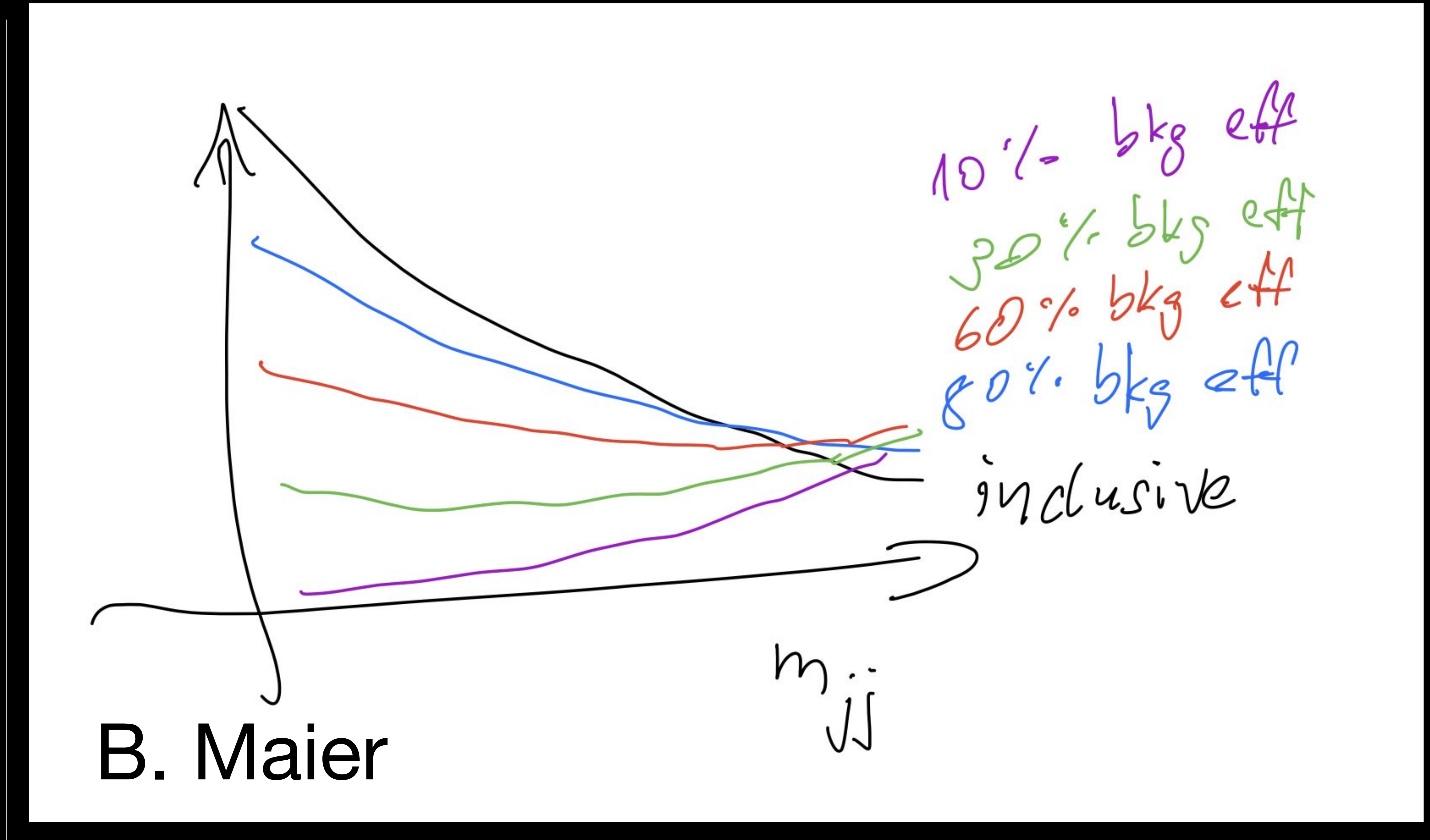


$\Delta\eta_{jj}$ between jets
(Signal s-channel,
QCD ~t-channel)

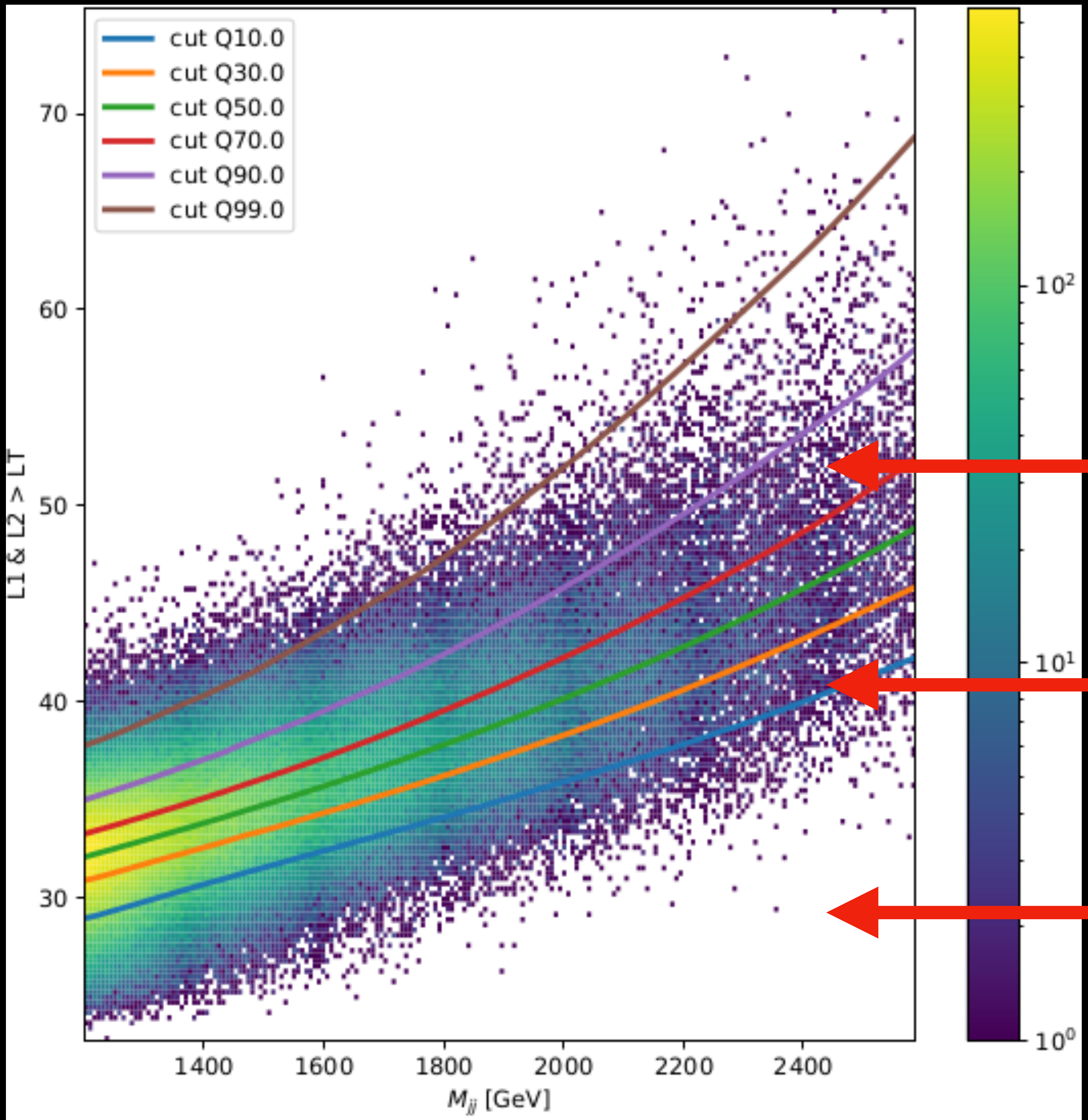
Invariant mass sculpting



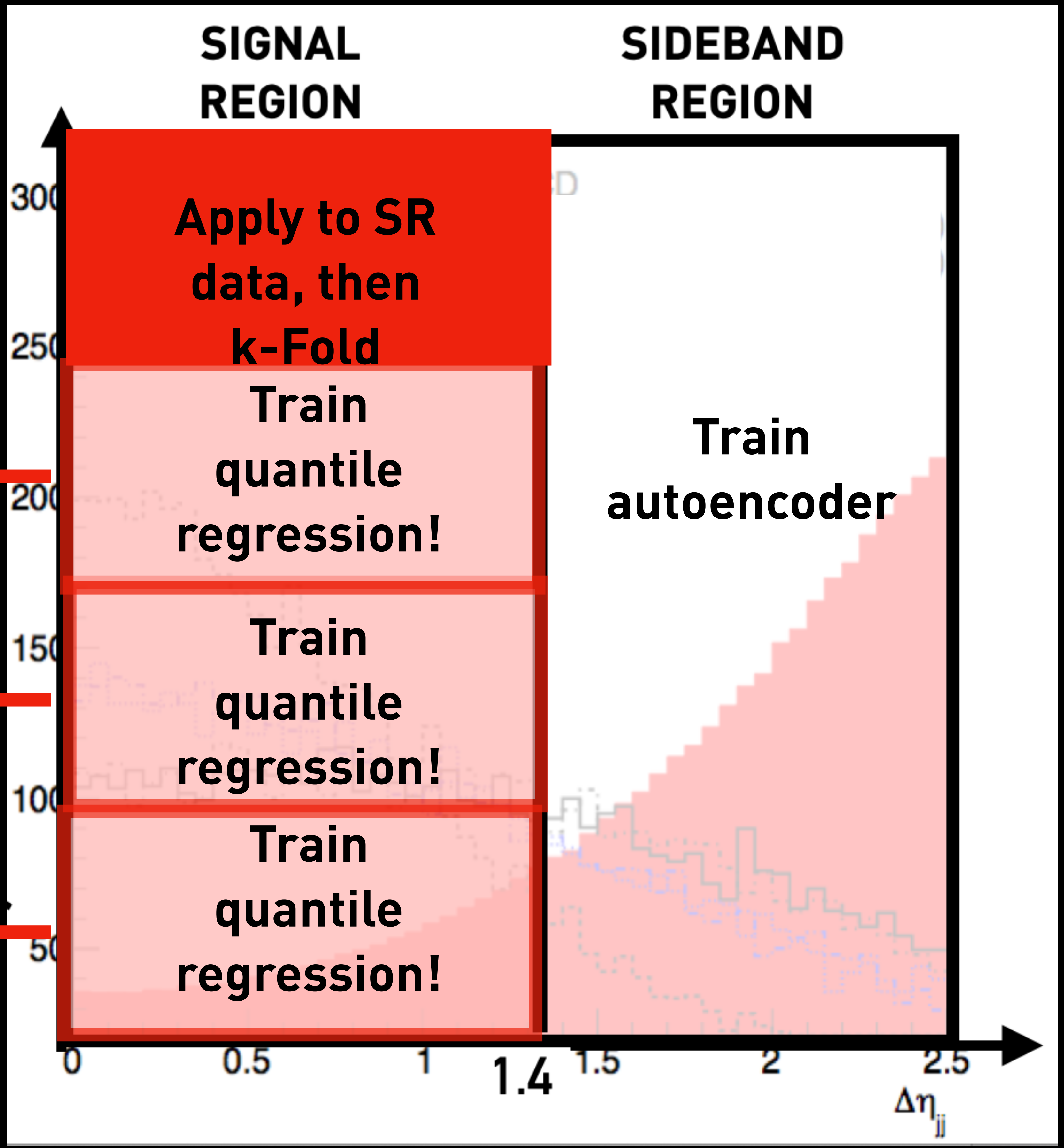
$\Delta\eta_{jj}$ between jets
(Signal s-channel,
QCD ~t-channel)



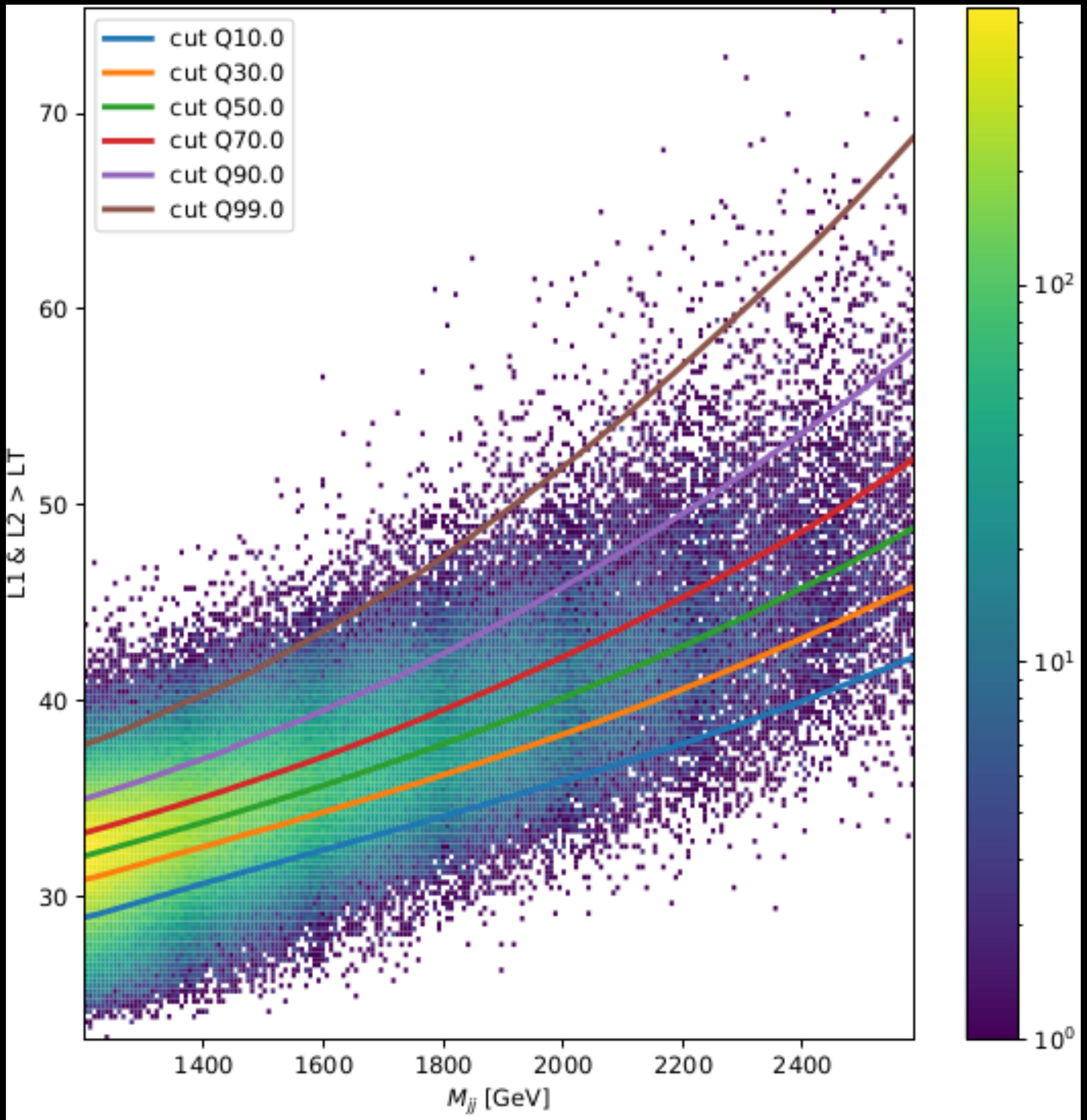
Quantile regression

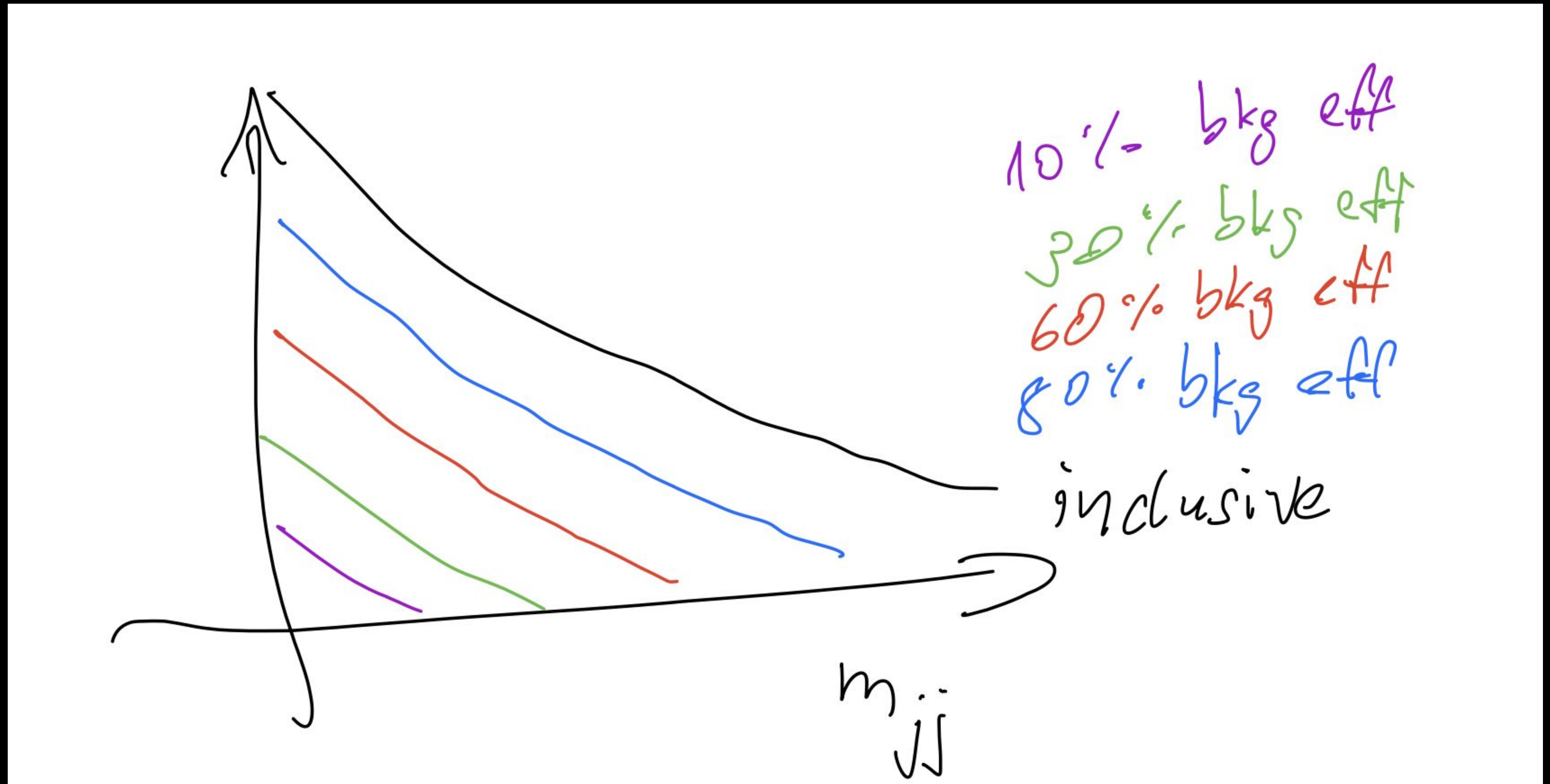


Cut corresponding to fixed X% mistag rate!



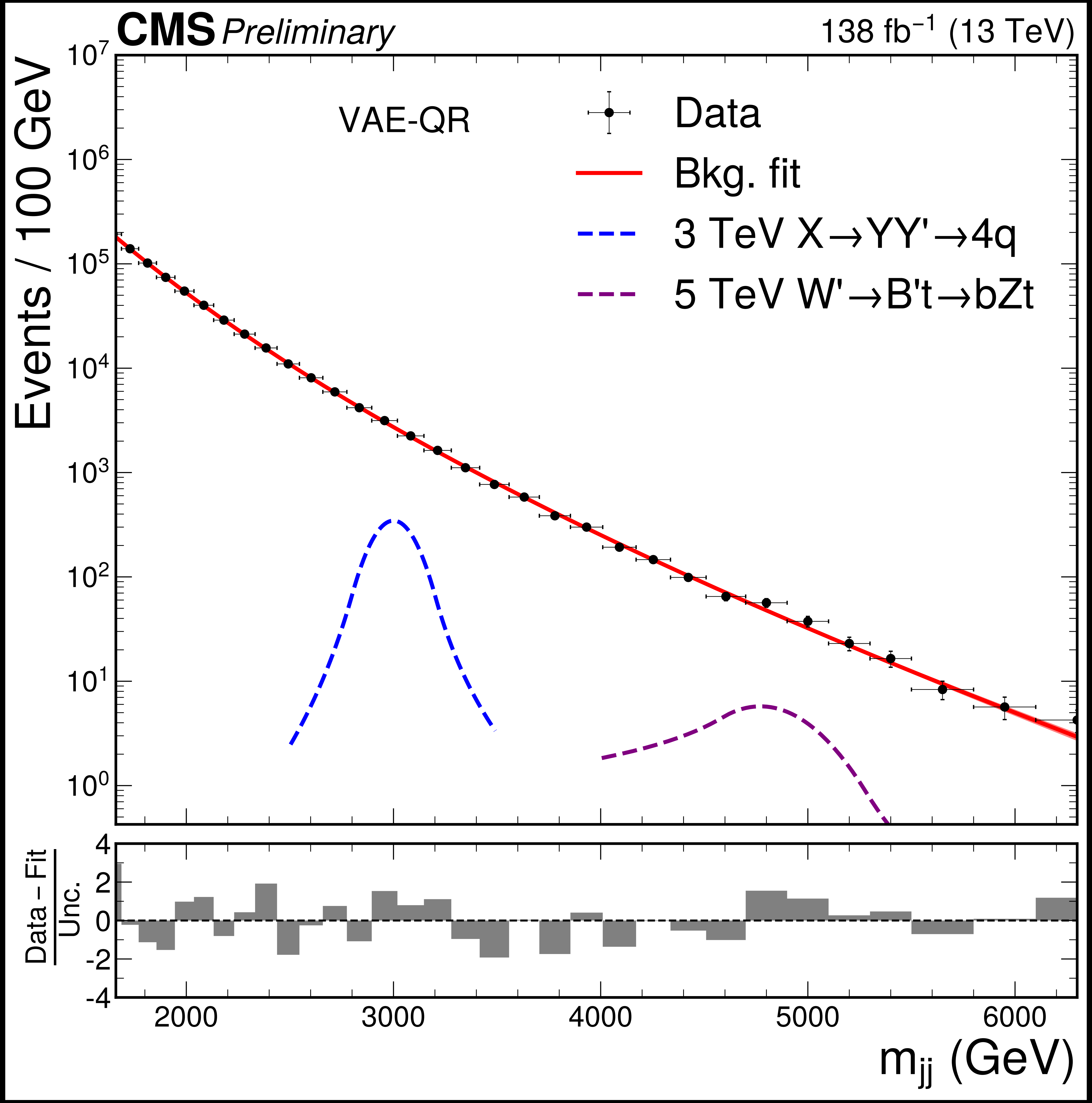
Quantile regression



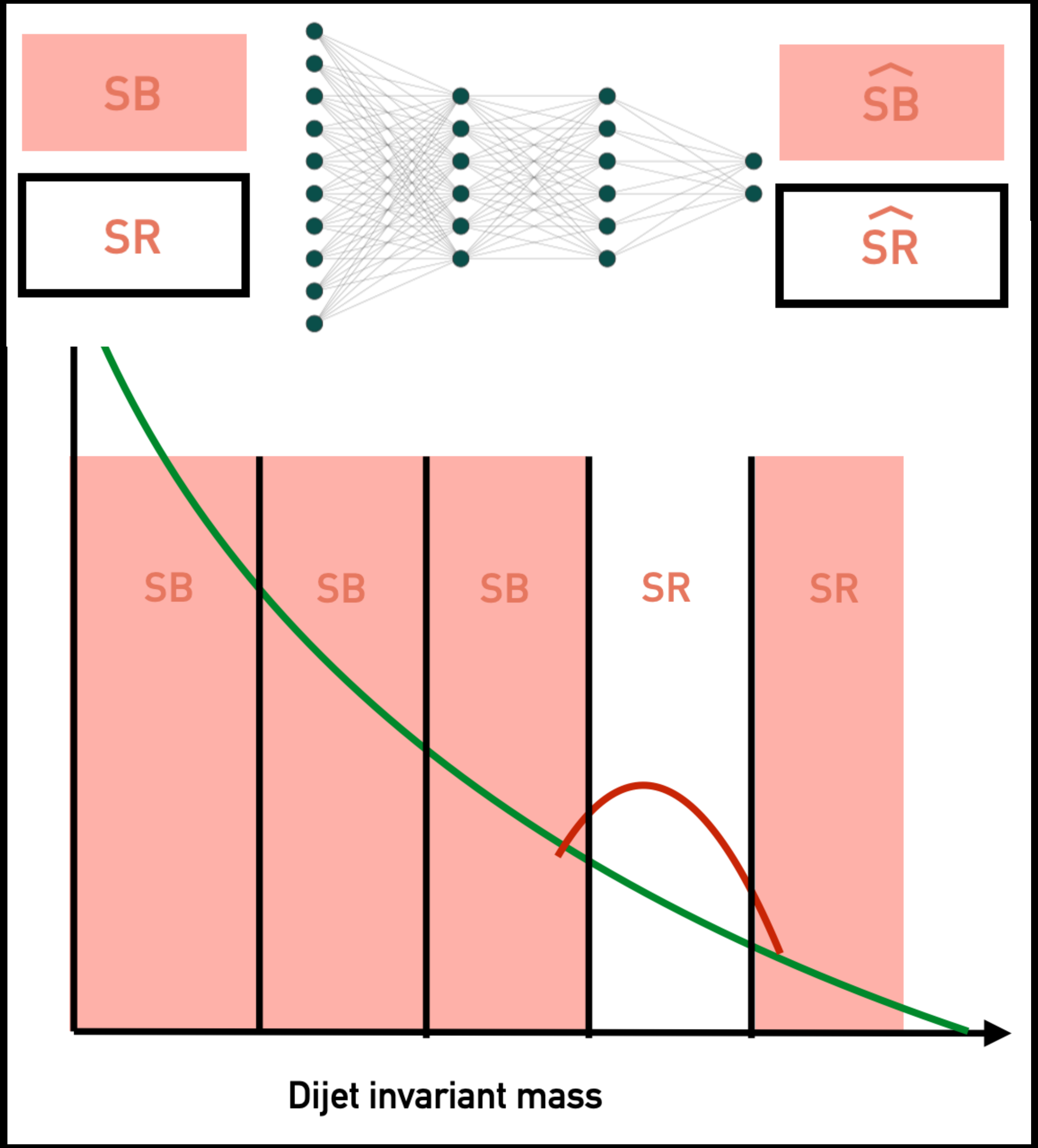


B. Maier

VAE + Quantile regression



Getting weak supervision to work in practise



CWoLa, TnT and CATHODE

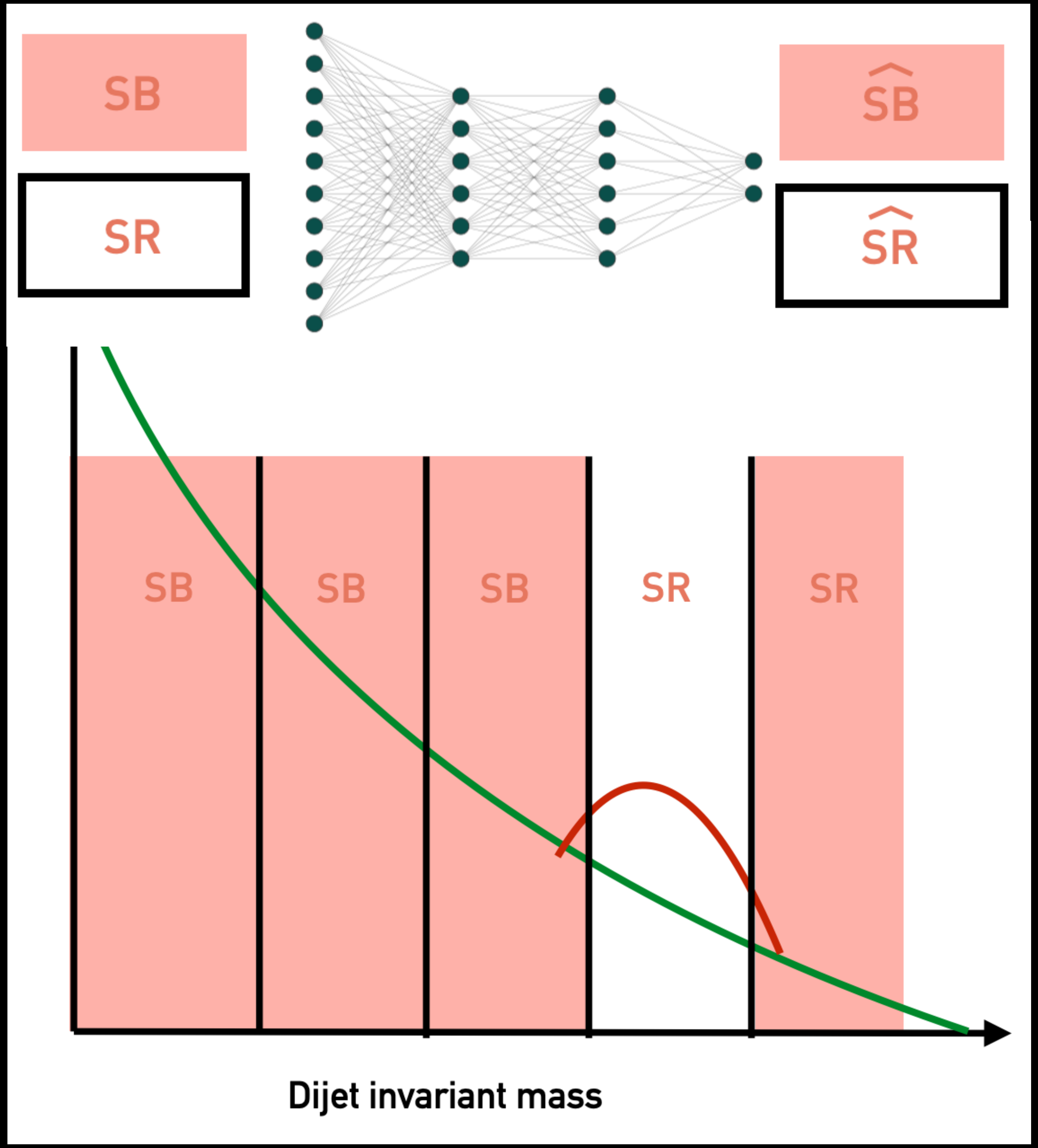
Getting weak supervision to work in practise

Mixed sample definition:

CWoLa: From M_{jj}

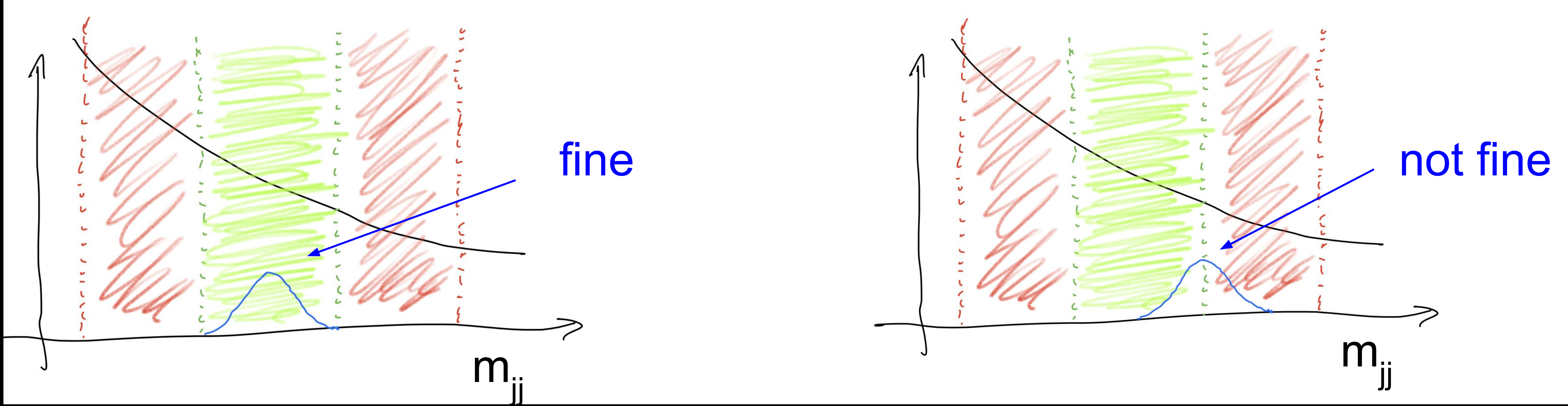
Tag N Train:
Autoencoder to further increase purity

CATHODE: Learn density from SB, interpolate into SR and sample



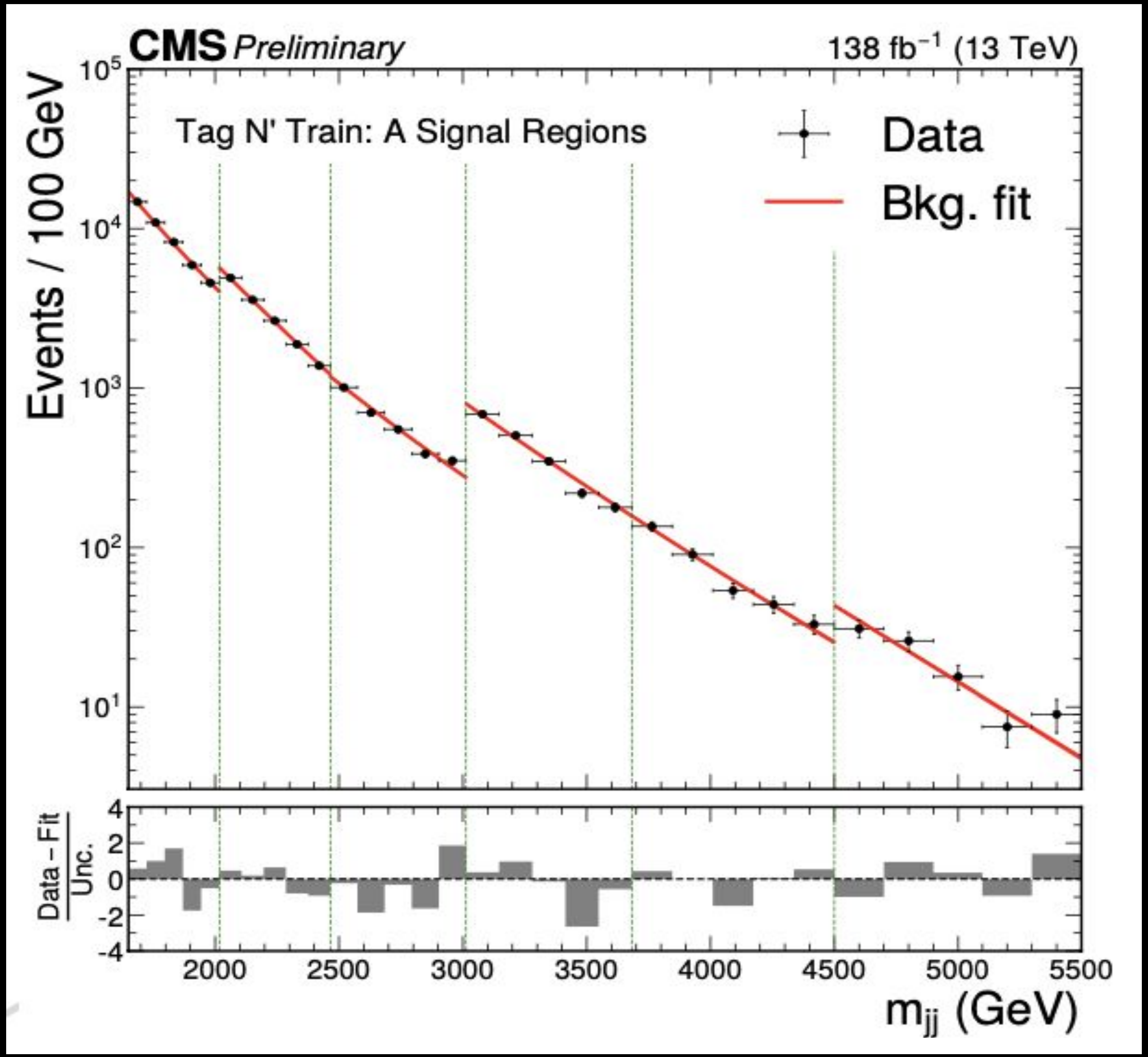
CWoLa, TnT and CATHODE

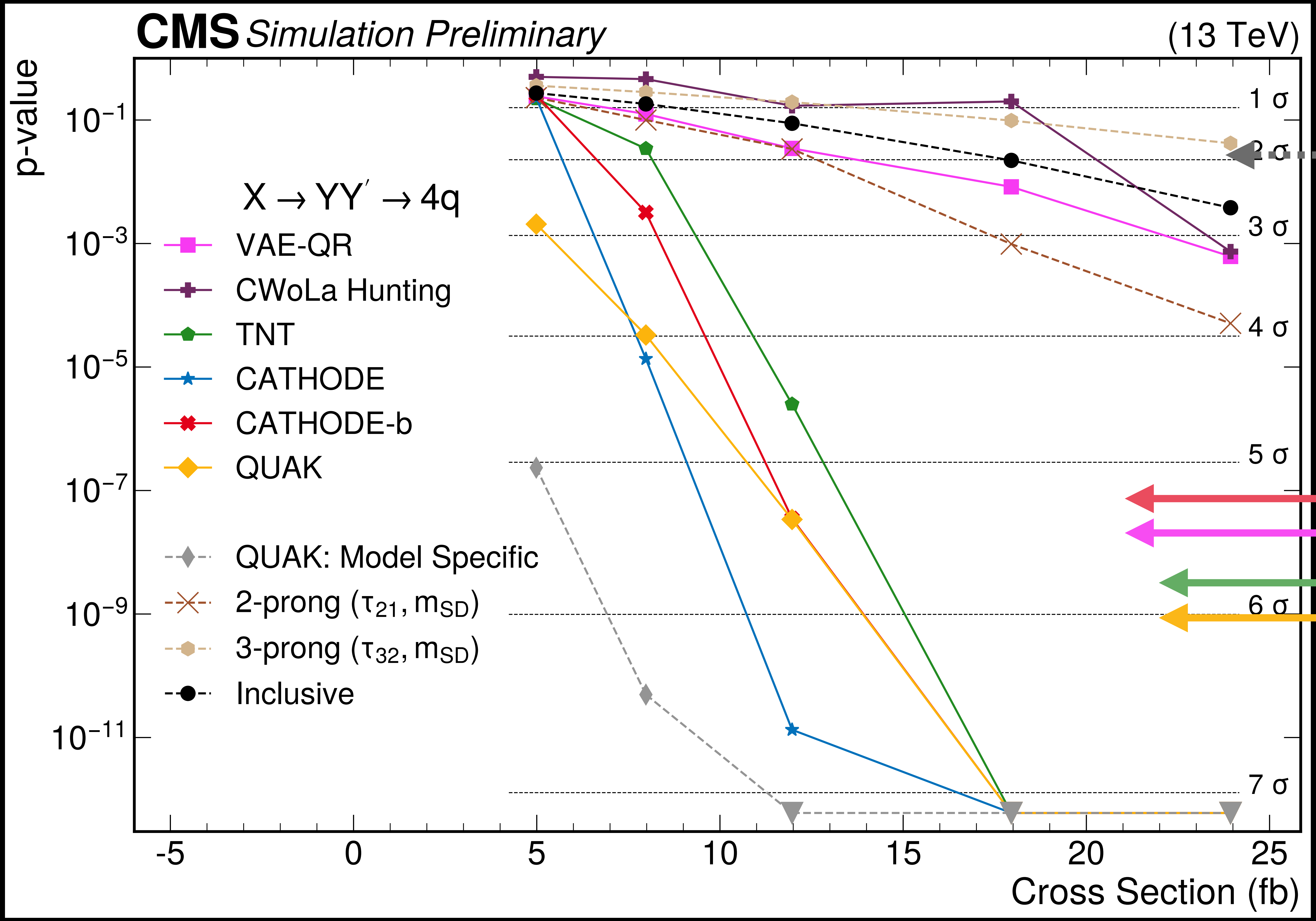
Getting weak supervision to work in practise

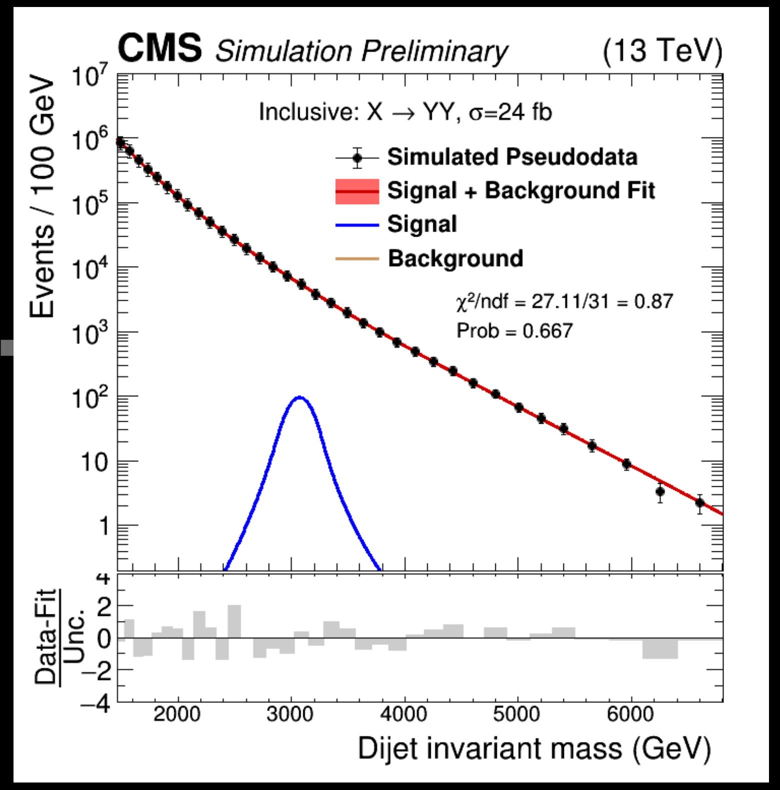


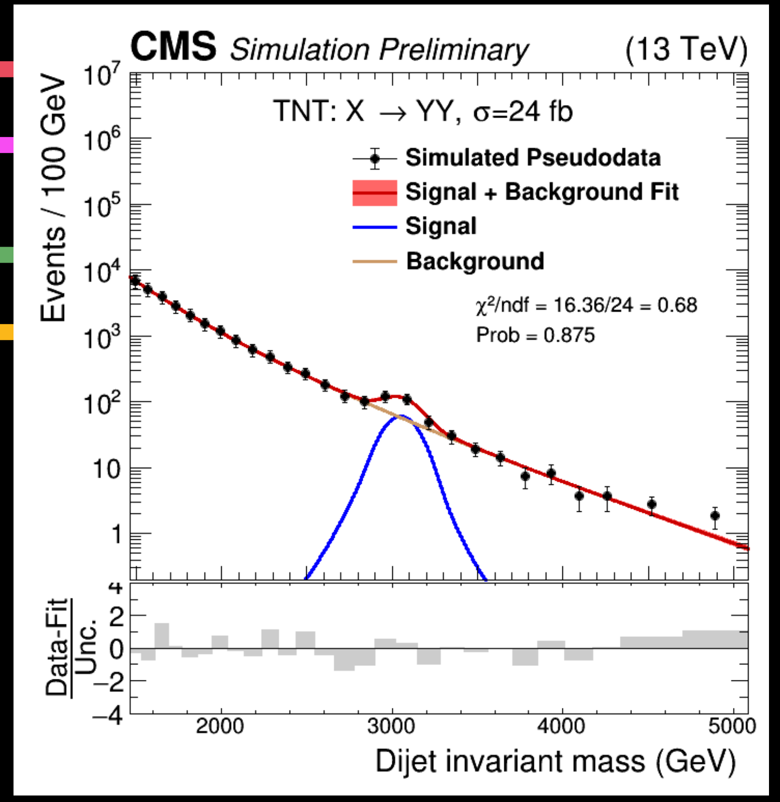
12 windows with different trainings and selection. Hardest part is to decorellate features from m_{jj}!

Weak supervision: CWoLa, TnT, CATHODE




CMS Simulation Preliminary
(13 TeV)
p-value
X → YY′ → 4q
VAE-QR
CWoLa Hunting
TNT
CATHODE
CATHODE-b
QUAK
QUAK: Model Specific
2-prong (τ21, mSD)
3-prong (τ32, mSD)
Inclusive
1 σ
2 σ
3 σ
4 σ
5 σ
6 σ
7 σ
Cross Section (fb)


CMS Simulation Preliminary
(13 TeV)
Inclusive: X → YY, σ=24 fb
Simulated Pseudodata
Signal + Background Fit
Signal
Background
χ²/ndf = 27.11/31 = 0.87
Prob = 0.667
Events / 100 GeV
Data-Fit / Unc.
Dijet invariant mass (GeV)


CMS Simulation Preliminary
(13 TeV)
TNT: X → YY, σ=24 fb
Simulated Pseudodata
Signal + Background Fit
Signal
Background
χ²/ndf = 16.36/24 = 0.68
Prob = 0.875
Events / 100 GeV
Data-Fit / Unc.
Dijet invariant mass (GeV)

Weak supervision limit-setting

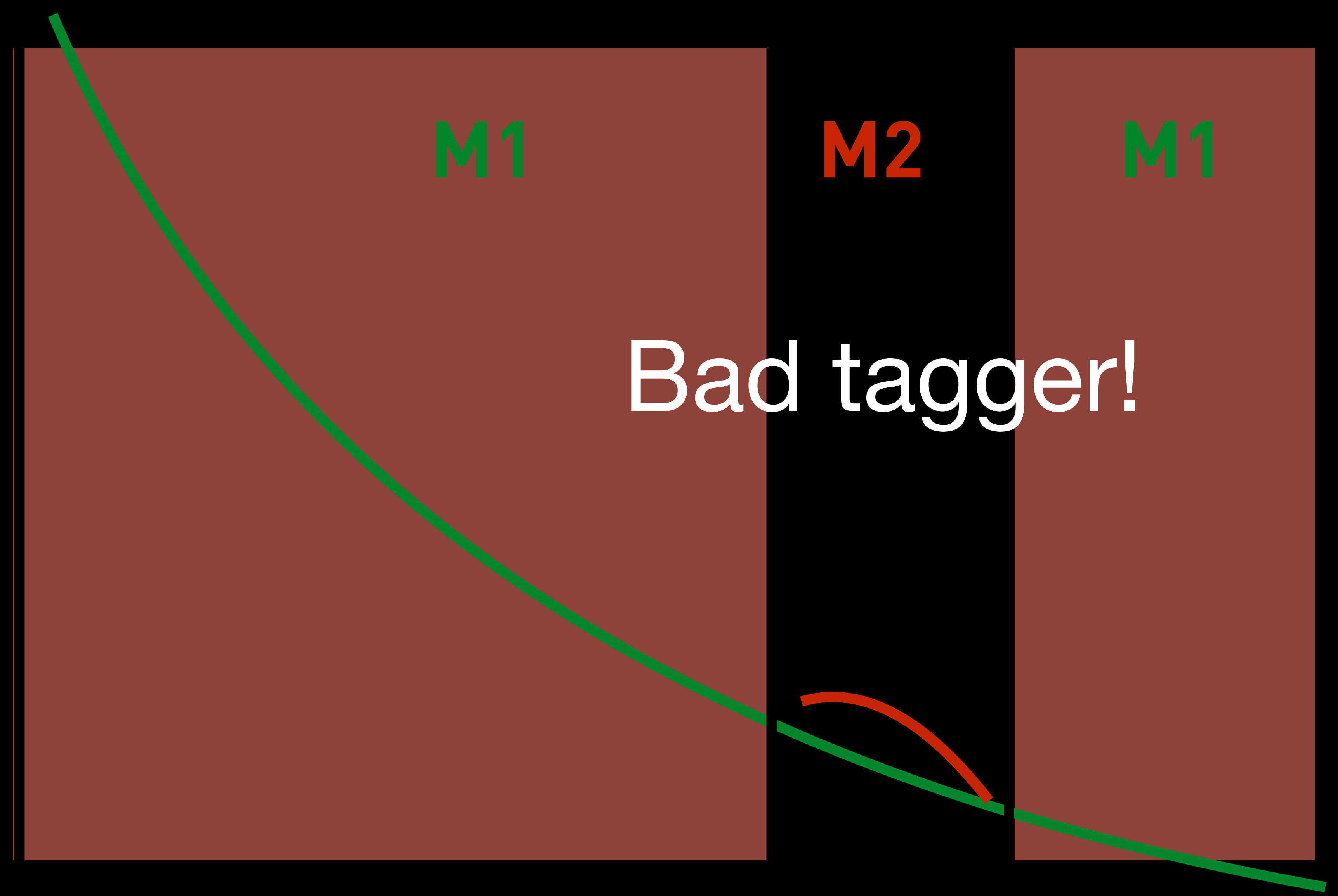
$$\mathrm{N}_{\mathrm{sig}}(\sigma) = \sigma \times \mathscr{L} \times \mathrm{A} \times \epsilon$$

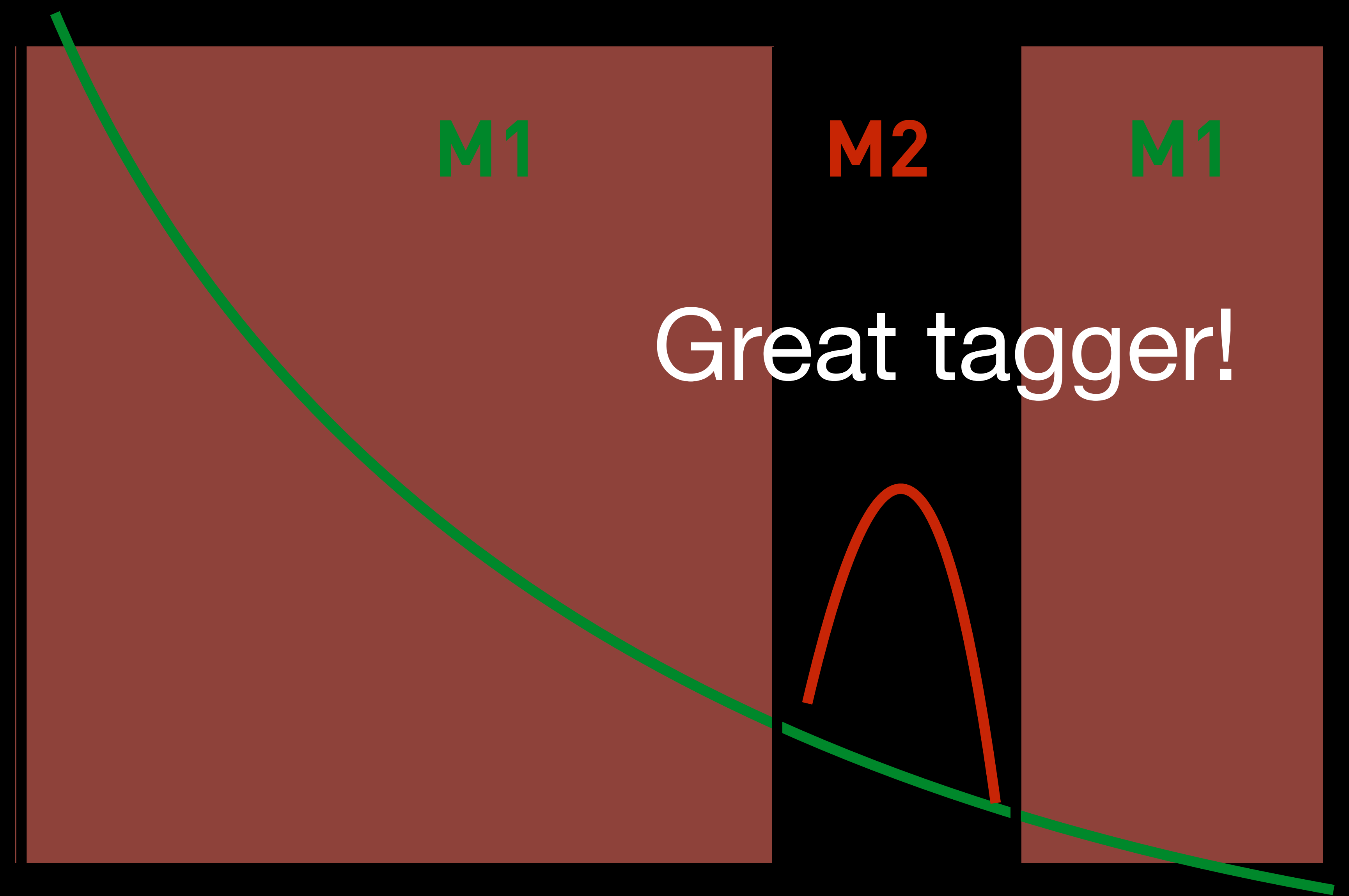
Weak supervision limit-setting

$$N_{sig}(\sigma) = \sigma \times \mathscr{L} \times A \times \epsilon$$

$$\Downarrow$$

$$N_{sig}(\sigma) = \sigma \times \mathscr{L} \times A \times \epsilon(\sigma)$$

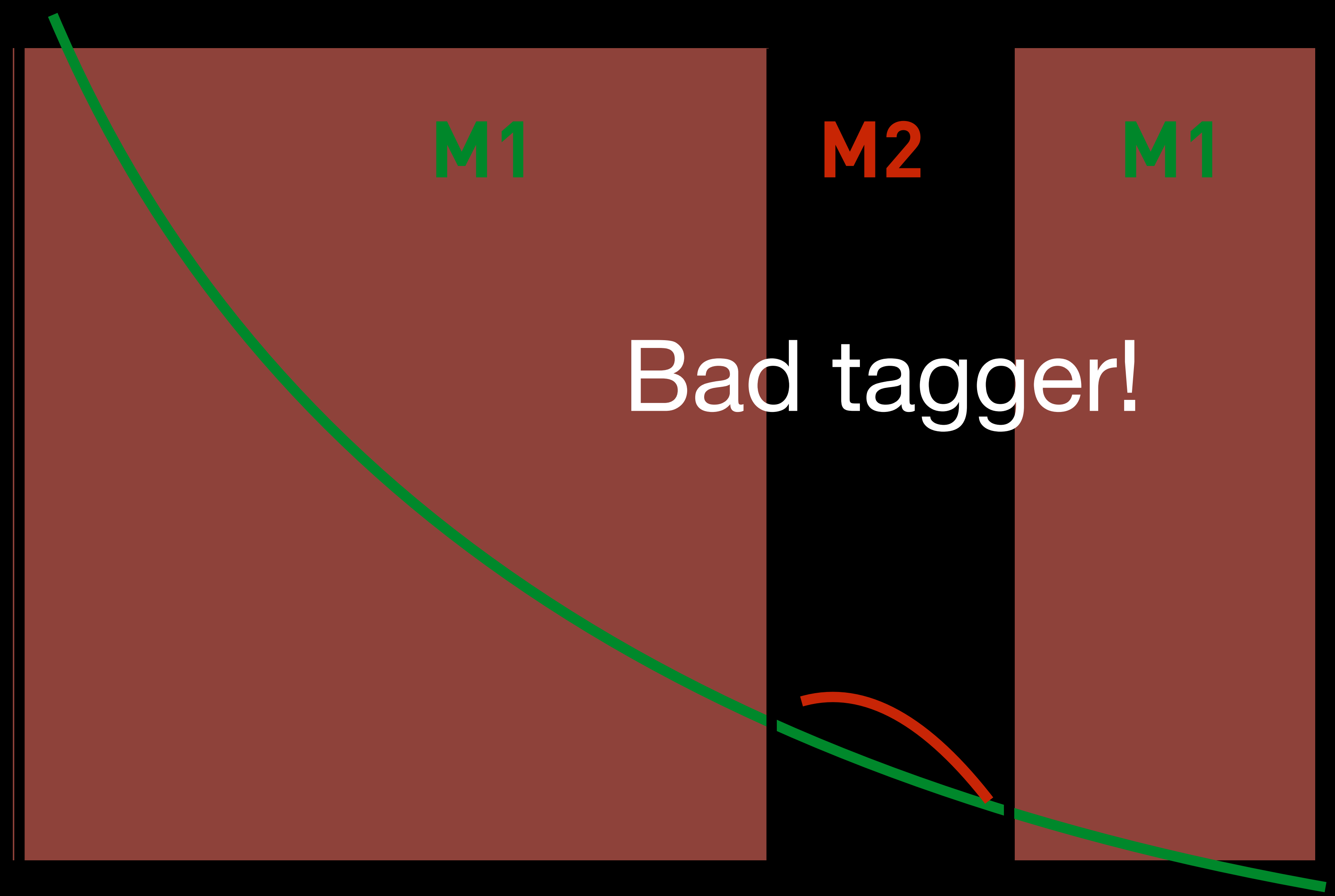


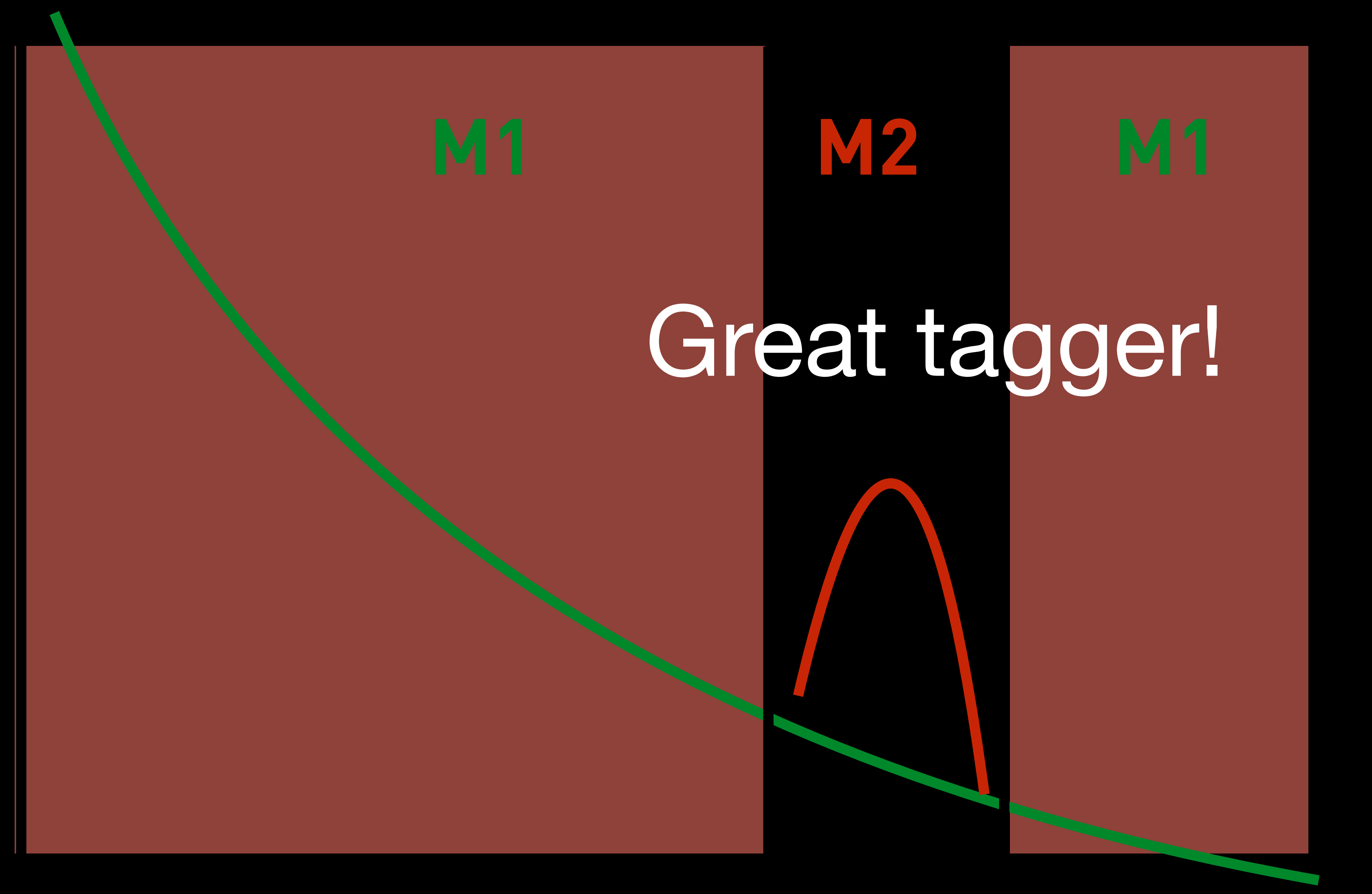


Weak supervision limit-setting

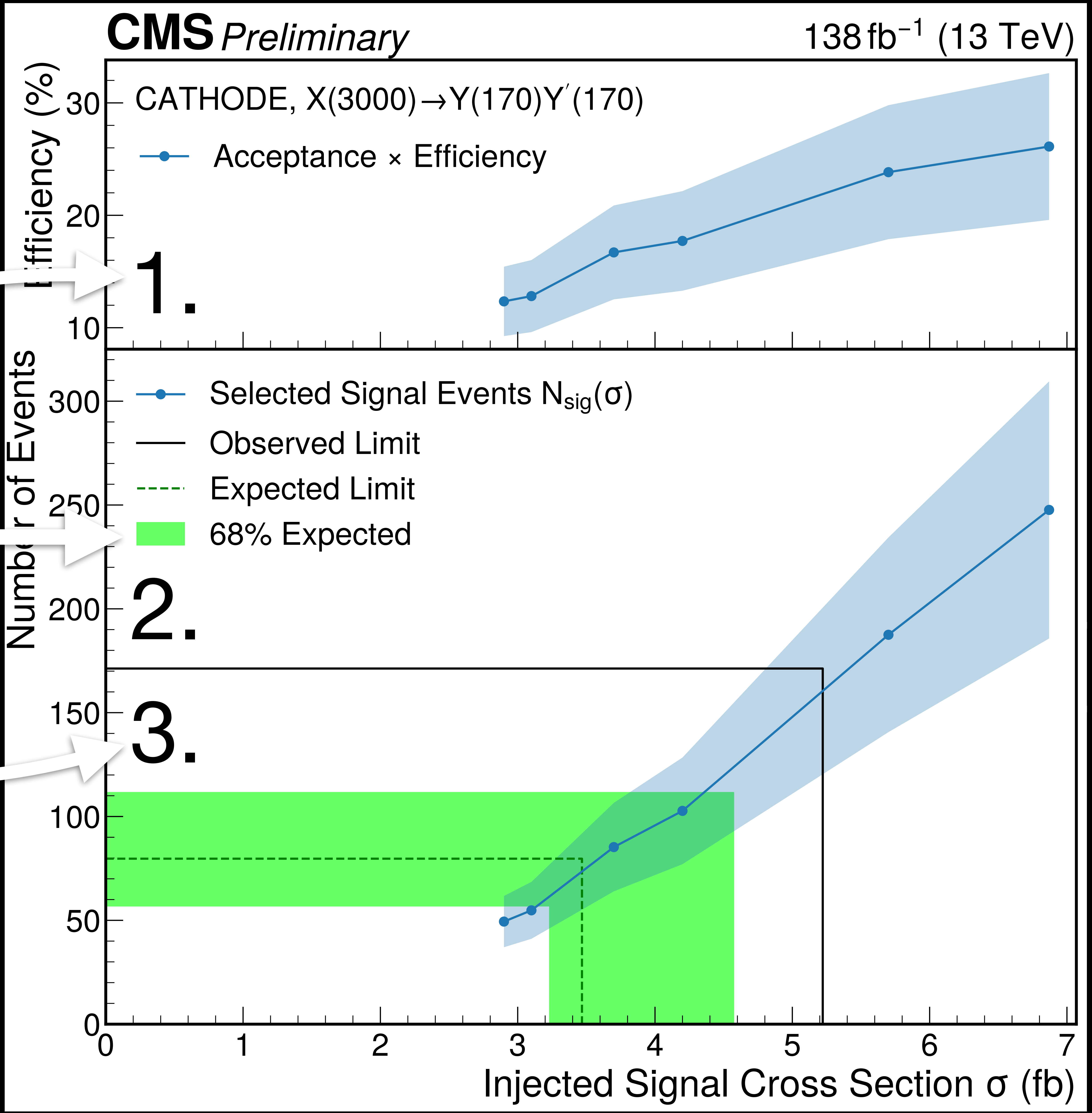
$$N_{\mathrm{sig}}(\sigma) = \sigma \times \mathscr{L} \times A \times \epsilon$$

To set limits: Inject signal, retrain each algorithm and estimate efficiency!

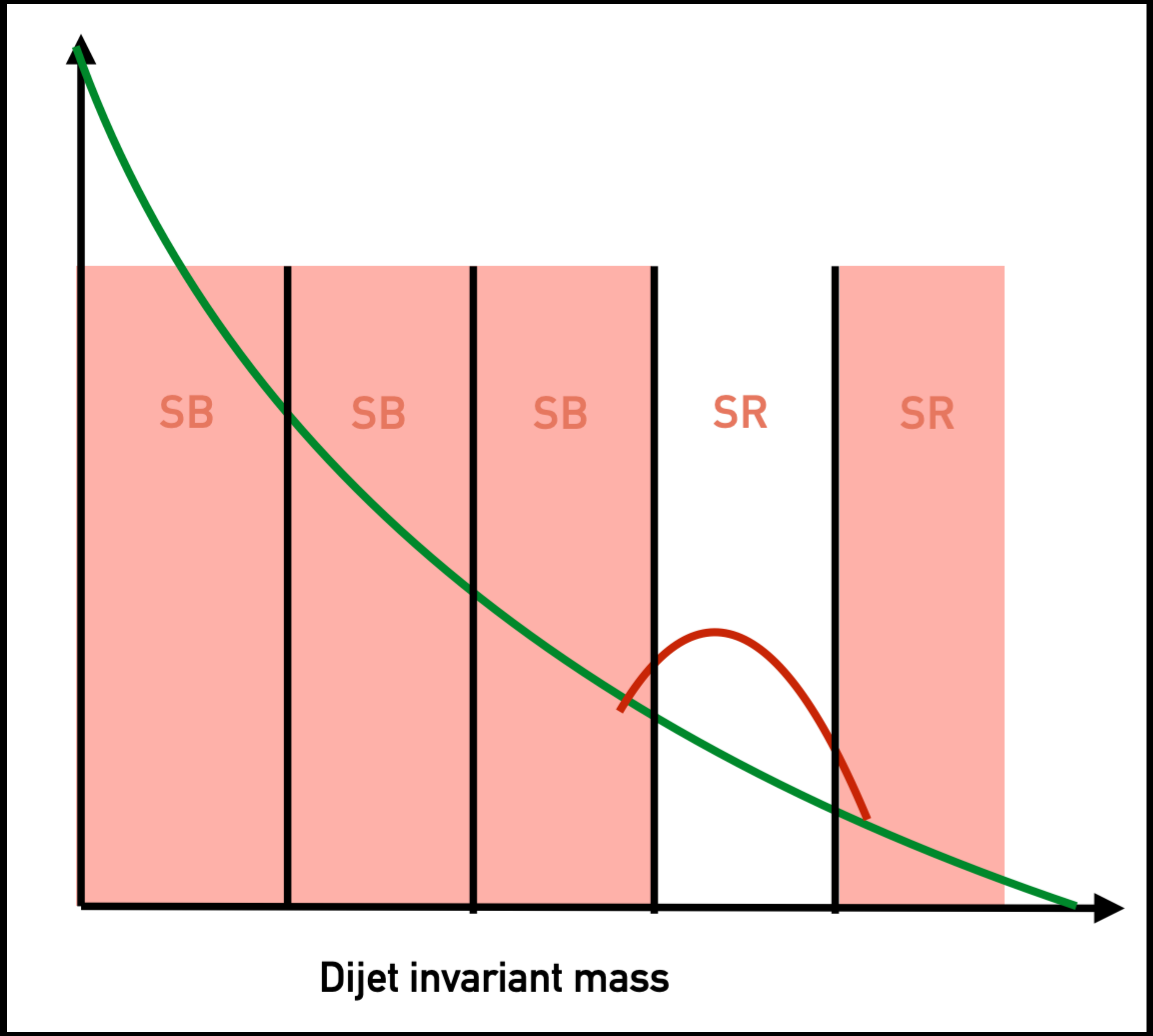




1. Inject signal, measure $\epsilon(\sigma)$
2. Gives number of selected signal events
3. Find intersection with obs/exp limit



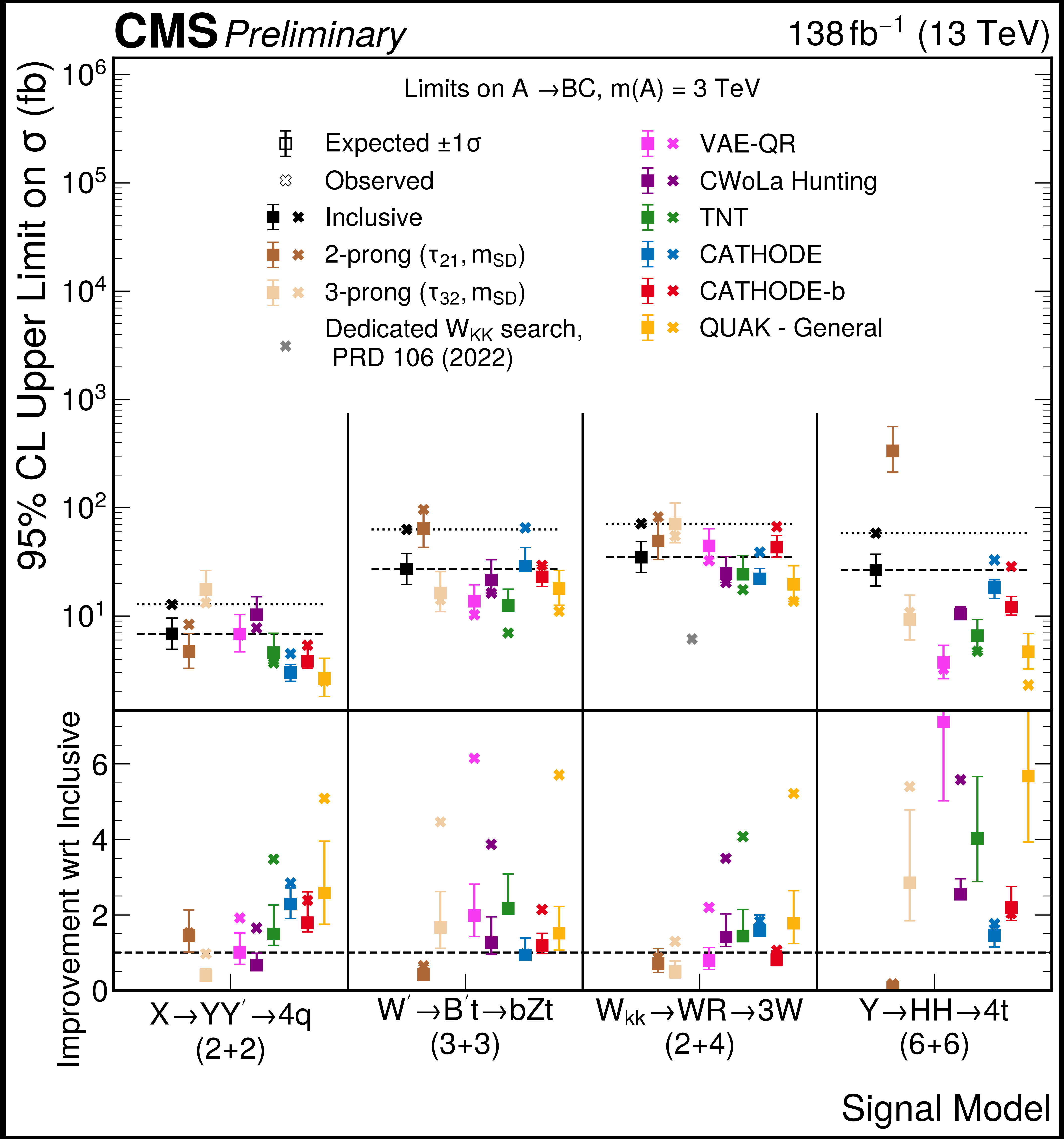
And how about look-elsewhere effect?



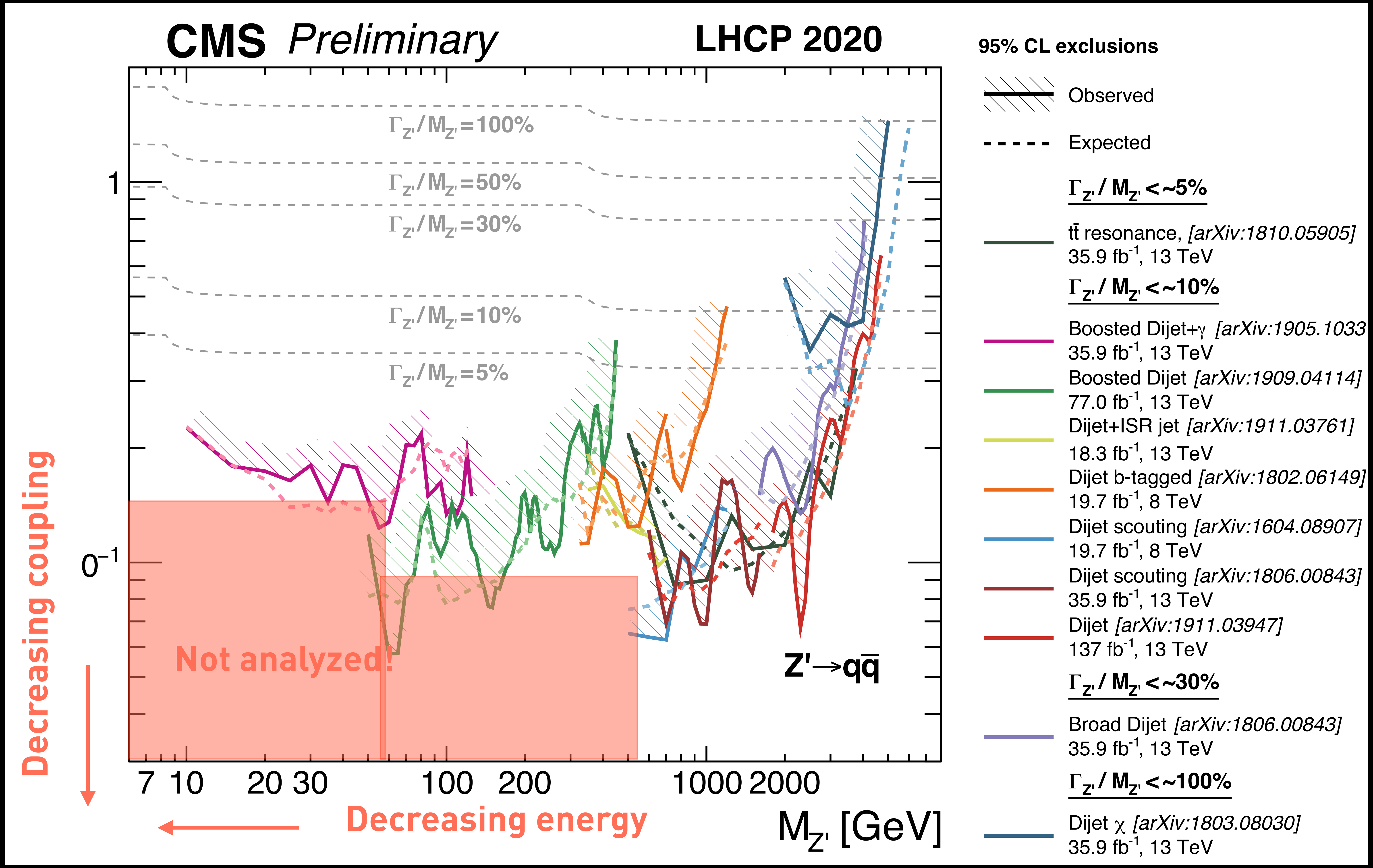
Each signal region fully independent search (trial factor = 12)

Toys to compute effective trial factor based on mass points (usual way)

$\text{p-value}_{global} = \text{p-value}_{local} \times \text{Trial Factor}_{SR} \times 12$



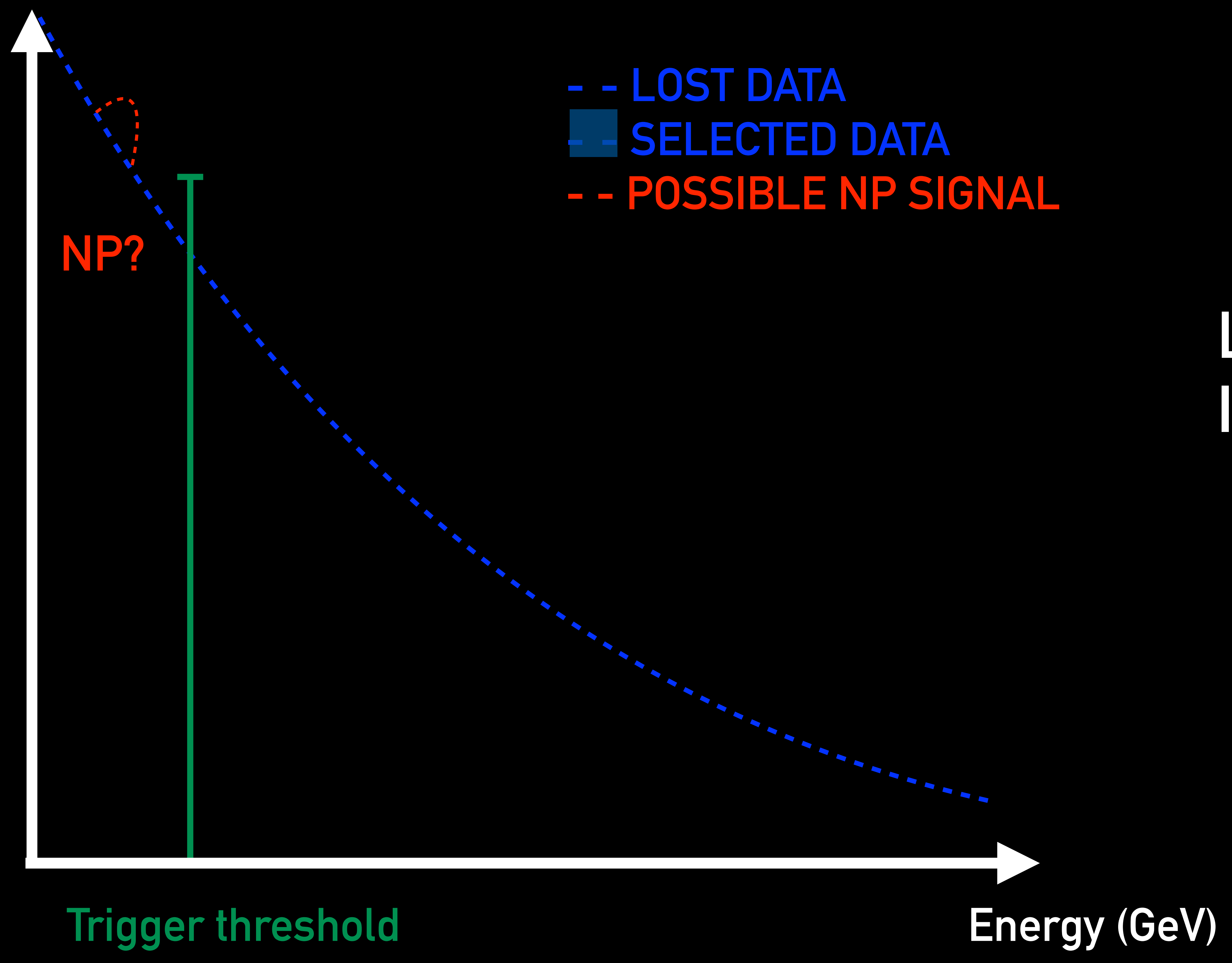
Setting limits on ~50 New Physics hypothesis in one go, many which have never been searched for!



CMS Preliminary
LHCP 2020
95% CL exclusions
Observed
Expected
Γ_Z'/M_Z' < ~5%
tt̄ resonance, [arXiv:1810.05905]
35.9 fb-1, 13 TeV
Γ_Z'/M_Z' < ~10%
Boosted Dijet+γ [arXiv:1905.1033
35.9 fb-1, 13 TeV
Boosted Dijet [arXiv:1909.04114]
77.0 fb-1, 13 TeV
Dijet+ISR jet [arXiv:1911.03761]
18.3 fb-1, 13 TeV
Dijet b-tagged [arXiv:1802.06149]
19.7 fb-1, 8 TeV
Dijet scouting [arXiv:1604.08907]
19.7 fb-1, 8 TeV
Dijet scouting [arXiv:1806.00843]
35.9 fb-1, 13 TeV
Dijet [arXiv:1911.03947]
137 fb-1, 13 TeV
Γ_Z'/M_Z' < ~30%
Broad Dijet [arXiv:1806.00843]
35.9 fb-1, 13 TeV
Γ_Z'/M_Z' < ~100%
Dijet χ [arXiv:1803.08030]
35.9 fb-1, 13 TeV
Γ_Z'/M_Z'=100%
Γ_Z'/M_Z'=50%
Γ_Z'/M_Z'=30%
Γ_Z'/M_Z'=10%
Γ_Z'/M_Z'=5%
Not analyzed!
Z'→qq̄
Decreasing coupling
Decreasing energy
M_Z' [GeV]

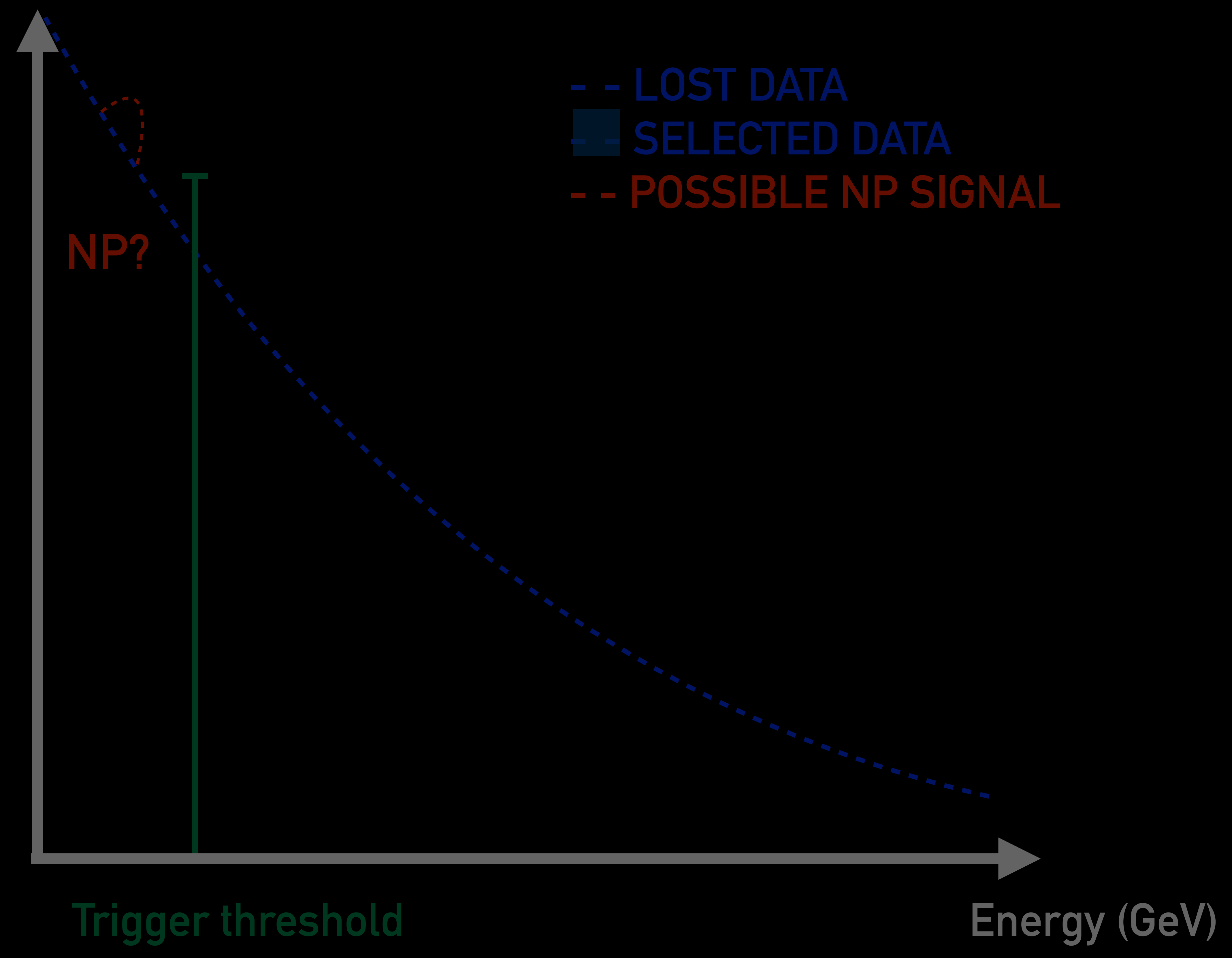

Geneva
Geneva Lake
LHCb
CMS
LHC
5% internet traffic to L1
(63 Tb/s)
L1 trigger:
Decide which event to keep within ~4 μs latency
Discard >99% of collisions!

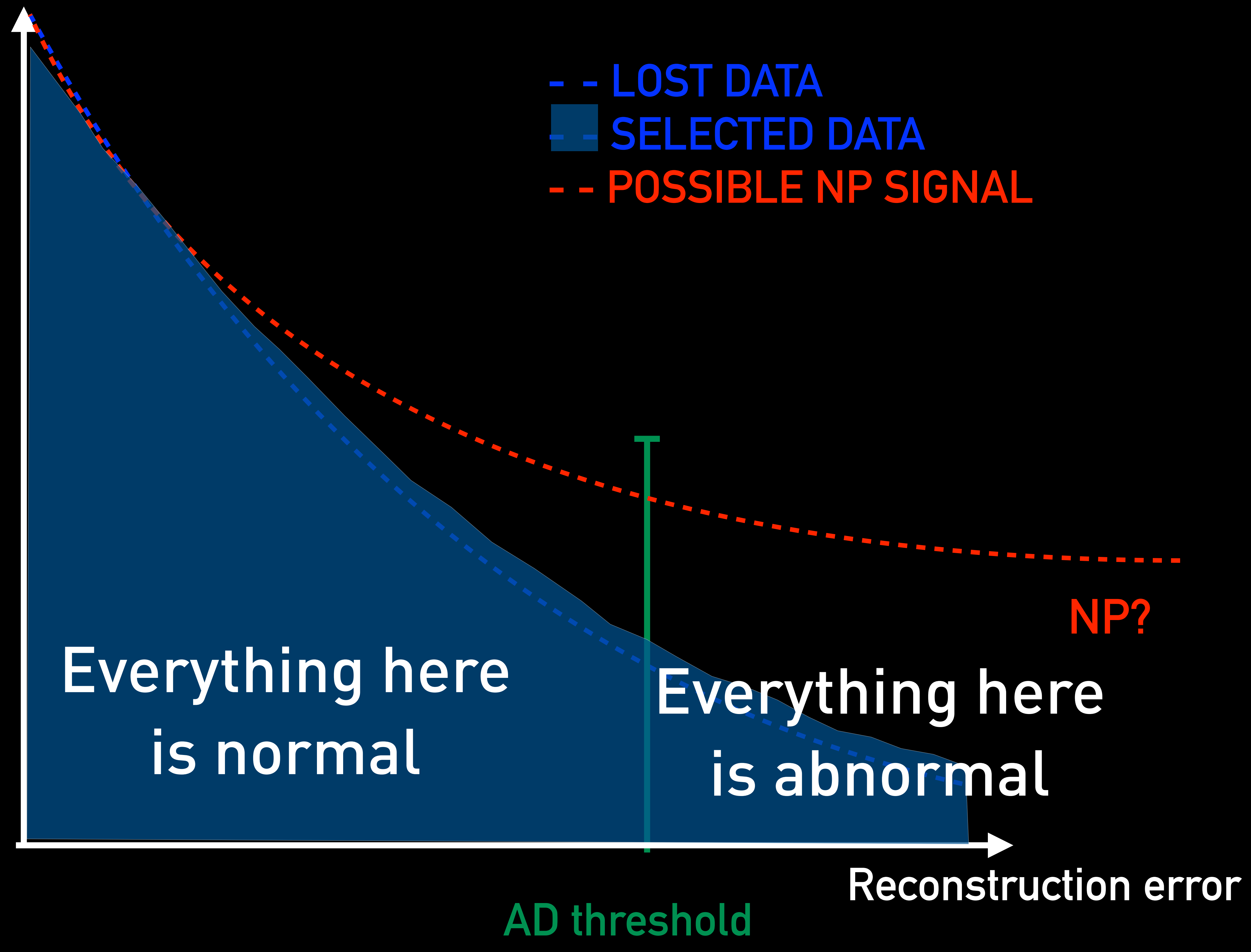
Anomaly Detection triggers



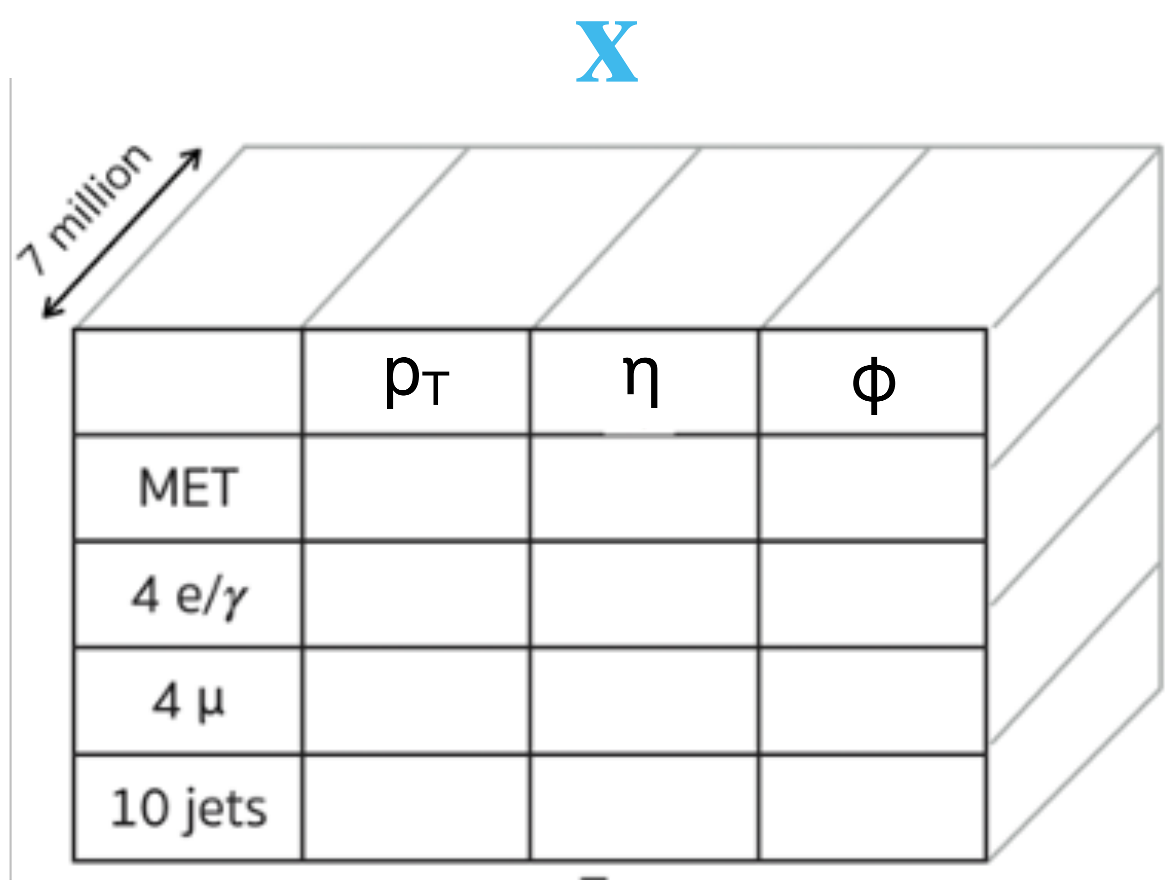
Level-1 rejects >99% of events!
Is there a smarter way to select?

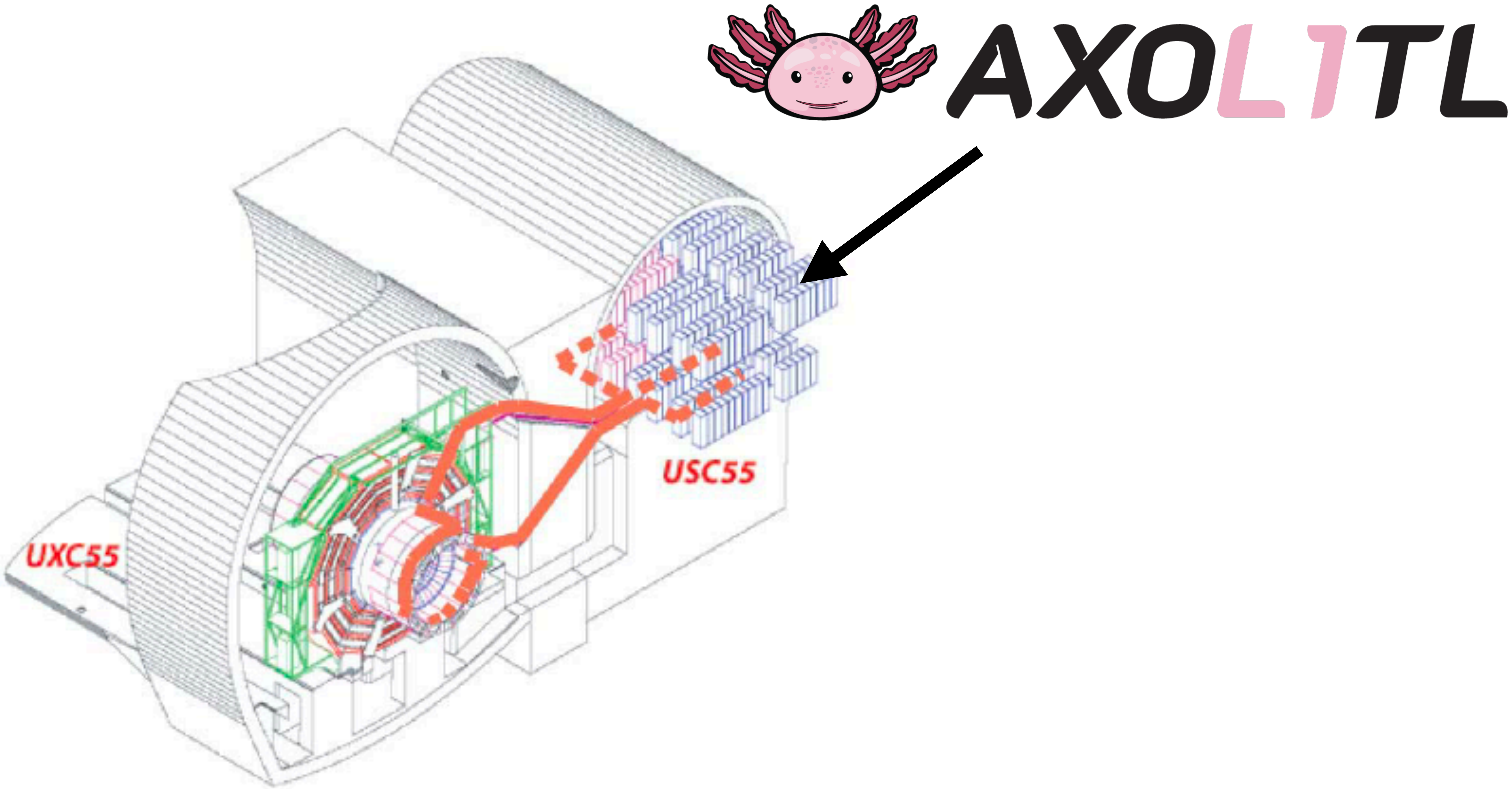
Anomaly Detection triggers



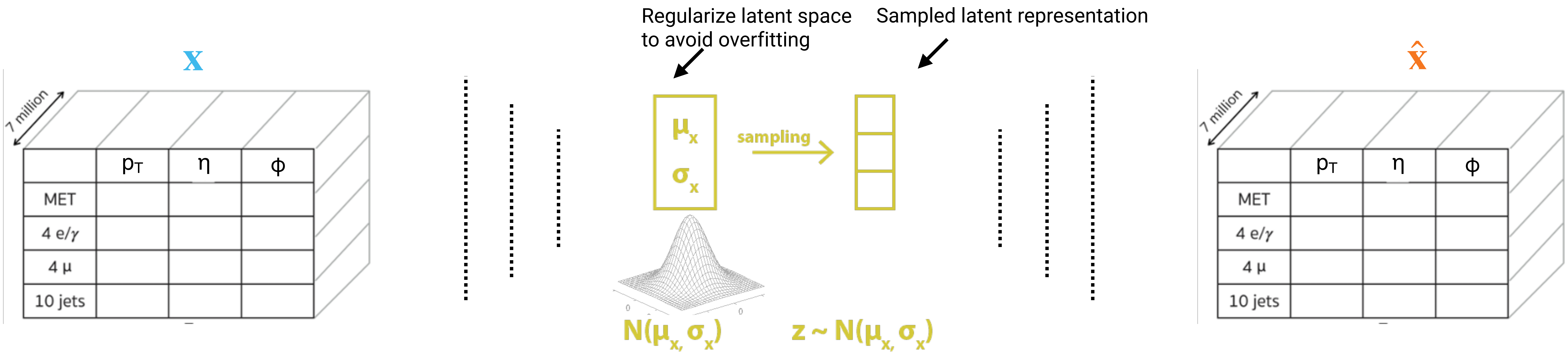


Anomaly Detection in the CMS Level 1 μGT taking 300 events/second now!





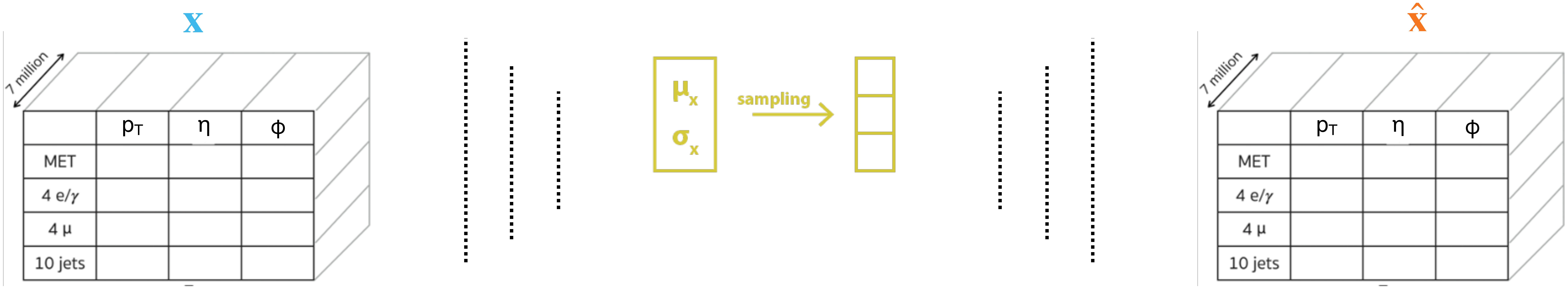
AXOL1TL



$$\text{loss} = \| x - \hat{x} \|^2 + \mathrm{KL}[\, N(\mu_x, \sigma_x), N(0, I) \,]$$

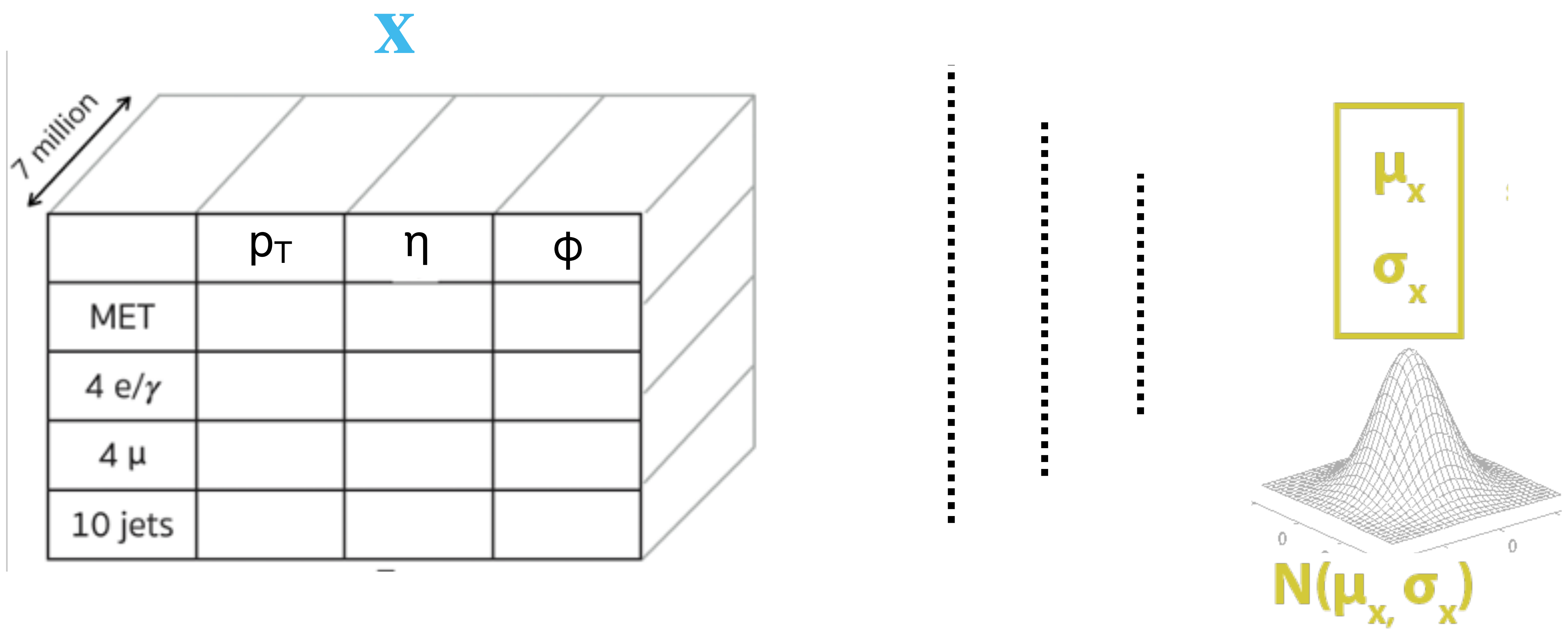
AXOL1TL

125 ns != 50 ns



AXOL1TL

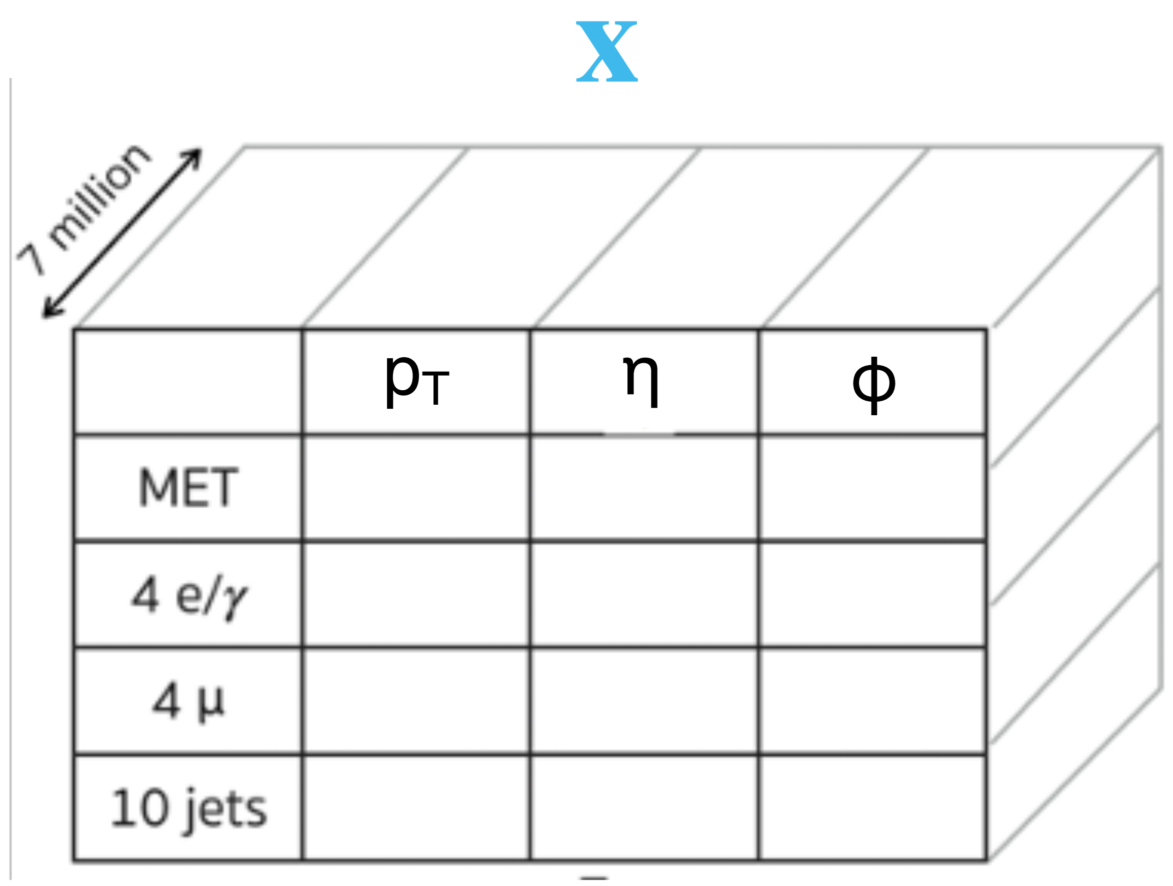
50 ns ✓

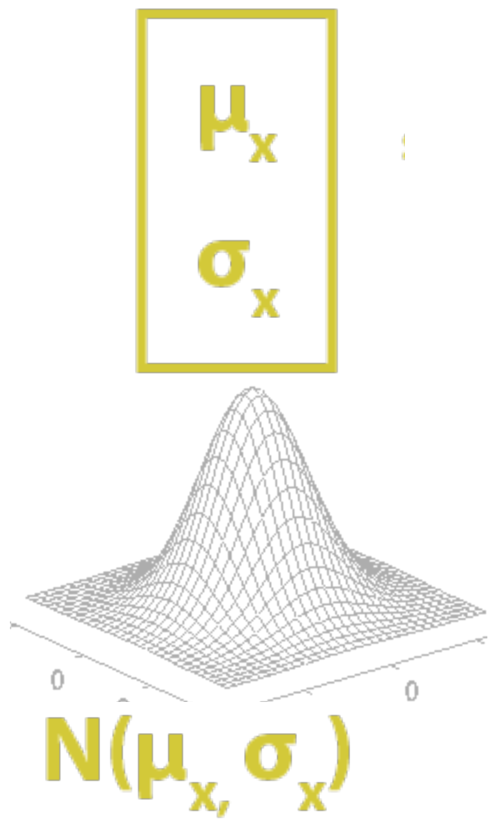


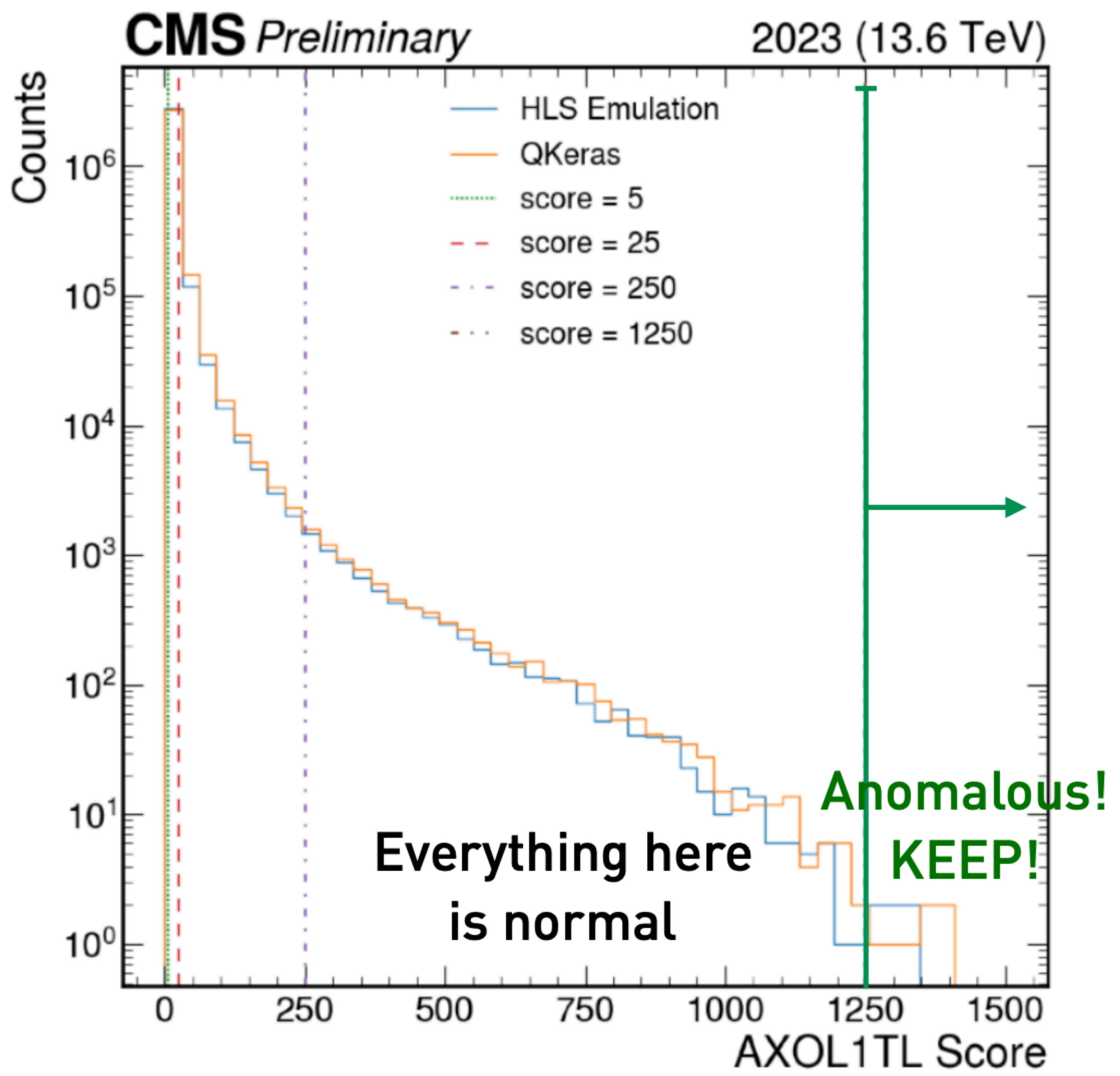
$$\text{loss} = \|x - \hat{x}\|^2 + \text{KL}[\,N(\mu_x, \sigma_x), N(0, I)\,]$$

AXOL1TL

$$\mathrm{KL}[\, N(\mu_x, \sigma_x), N(0, I) \,]$$

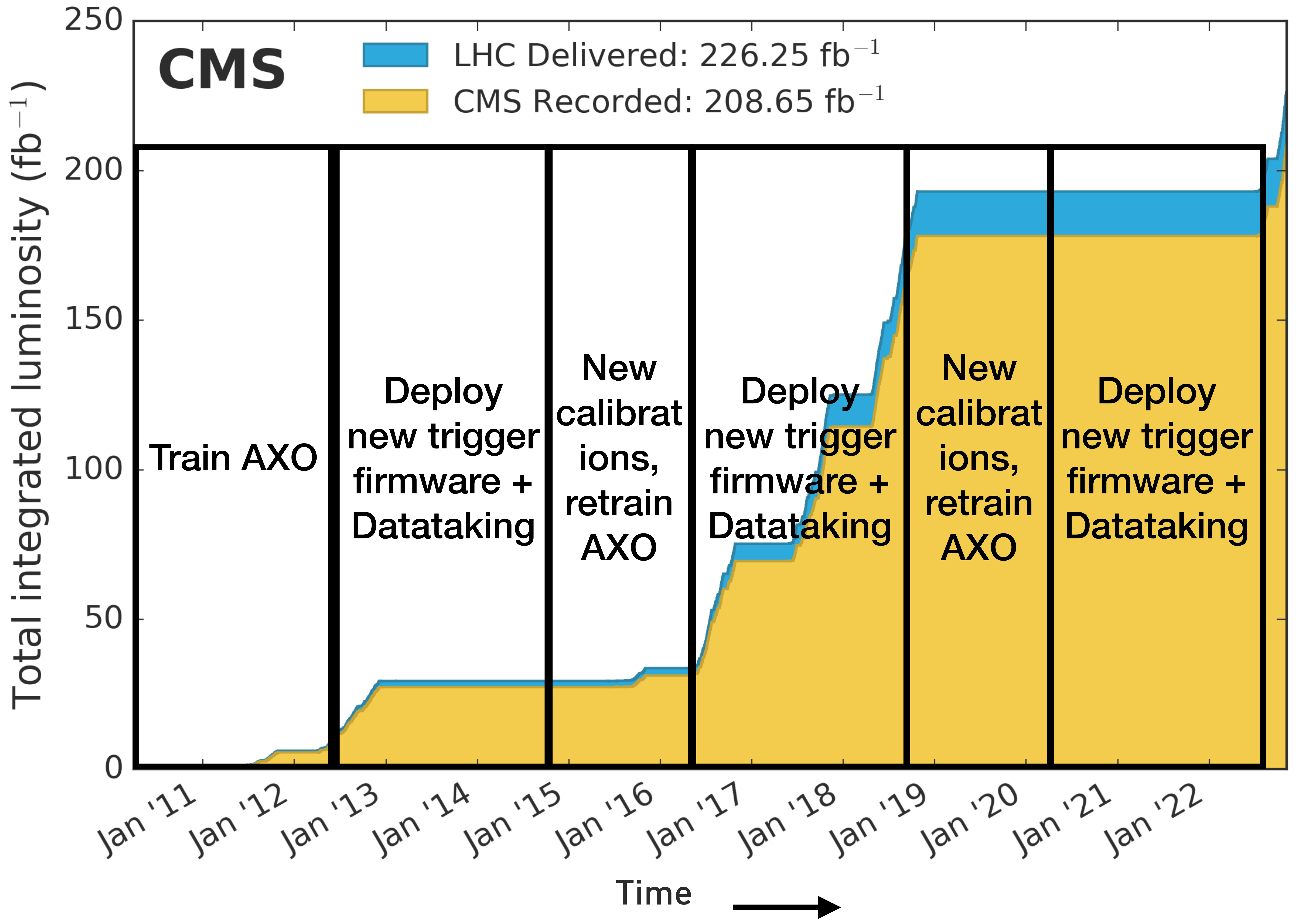






$$\text{loss} = \| x - \hat{x} \|^2 + \mathrm{KL}[\, N(\mu_x, \sigma_x), N(0, I) \,]$$

AXOL1TL


CMS
LHC Delivered: 226.25 fb^{-1}
CMS Recorded: 208.65 fb^{-1}
Total integrated luminosity (fb^{-1})
250
200
150
100
50
0
Train AXO
Deploy new trigger firmware + Datataking
New calibrations, retrain AXO
Deploy new trigger firmware + Datataking
New calibrations, retrain AXO
Deploy new trigger firmware + Datataking
Jan '11
Jan '12
Jan '13
Jan '14
Jan '15
Jan '16
Jan '17
Jan '18
Jan '19
Jan '20
Jan '21
Jan '22
Time

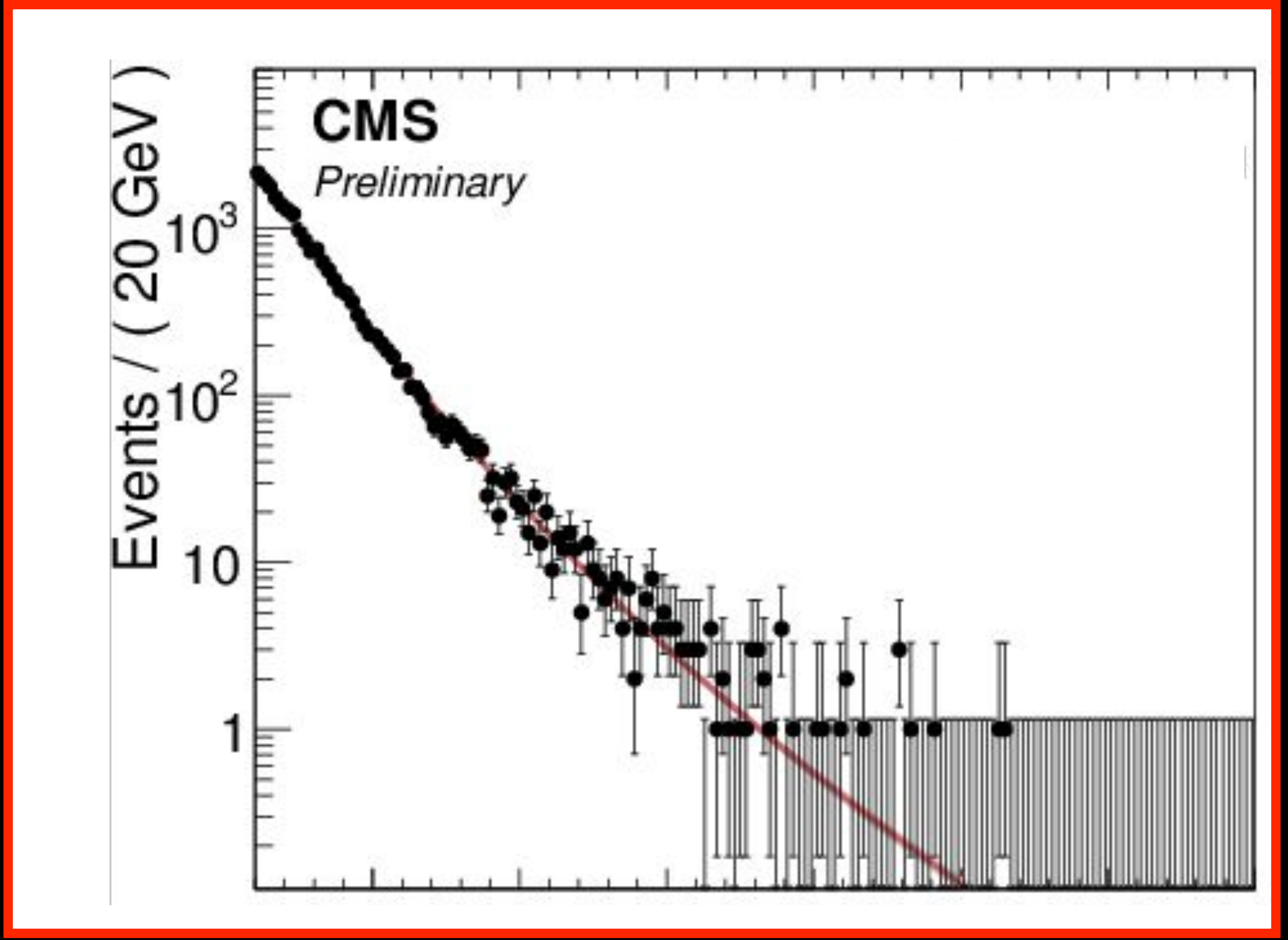
E.g Higgs → A(15 GeV) A(15 GeV) → 4b

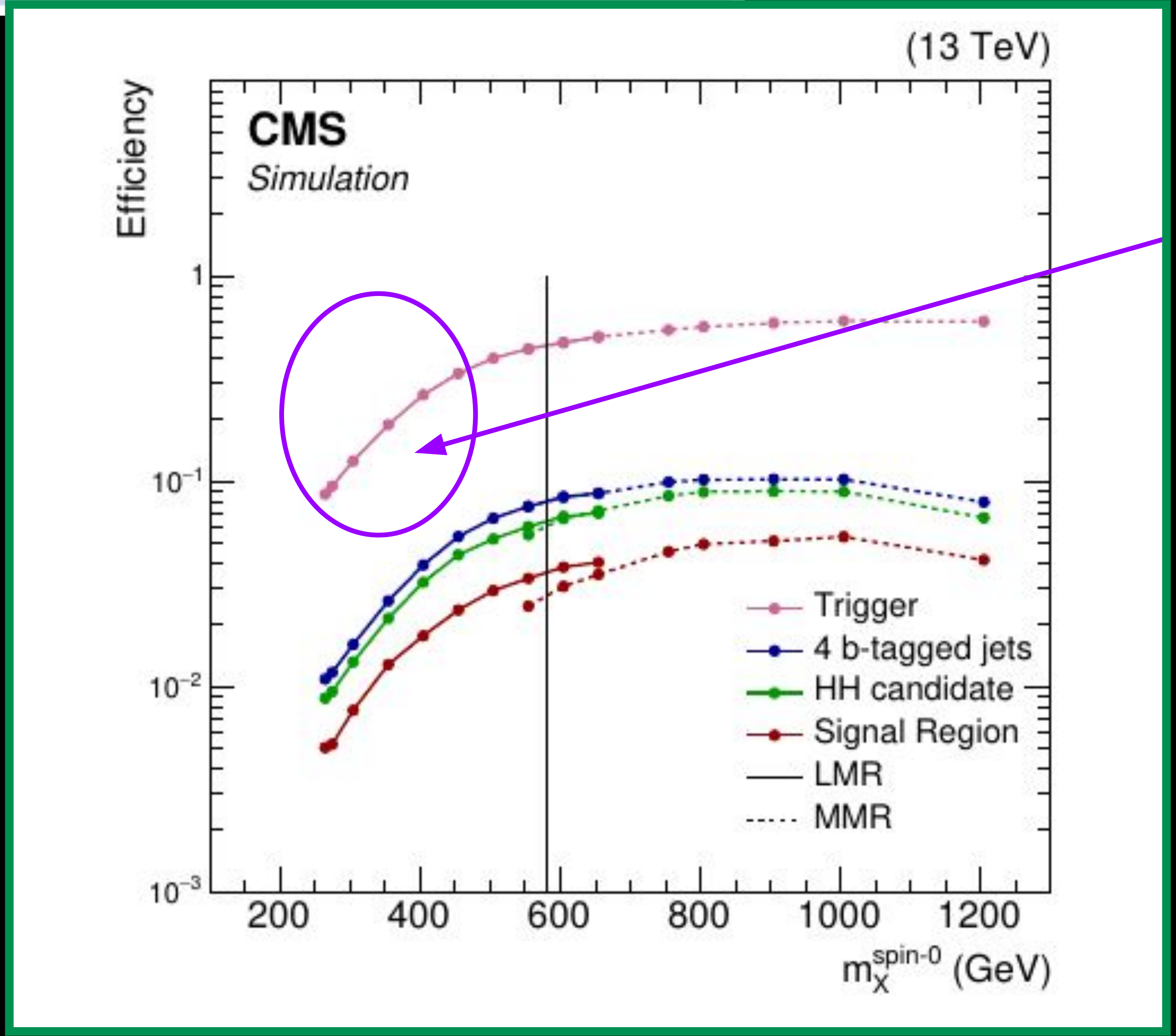
AXOL1TL Rate	1 kHz	5 kHz	10 kHz
Signal Efficiency Gain	46%	100%	133%

E.g Higgs → A(15 GeV) A(15 GeV) → 4b

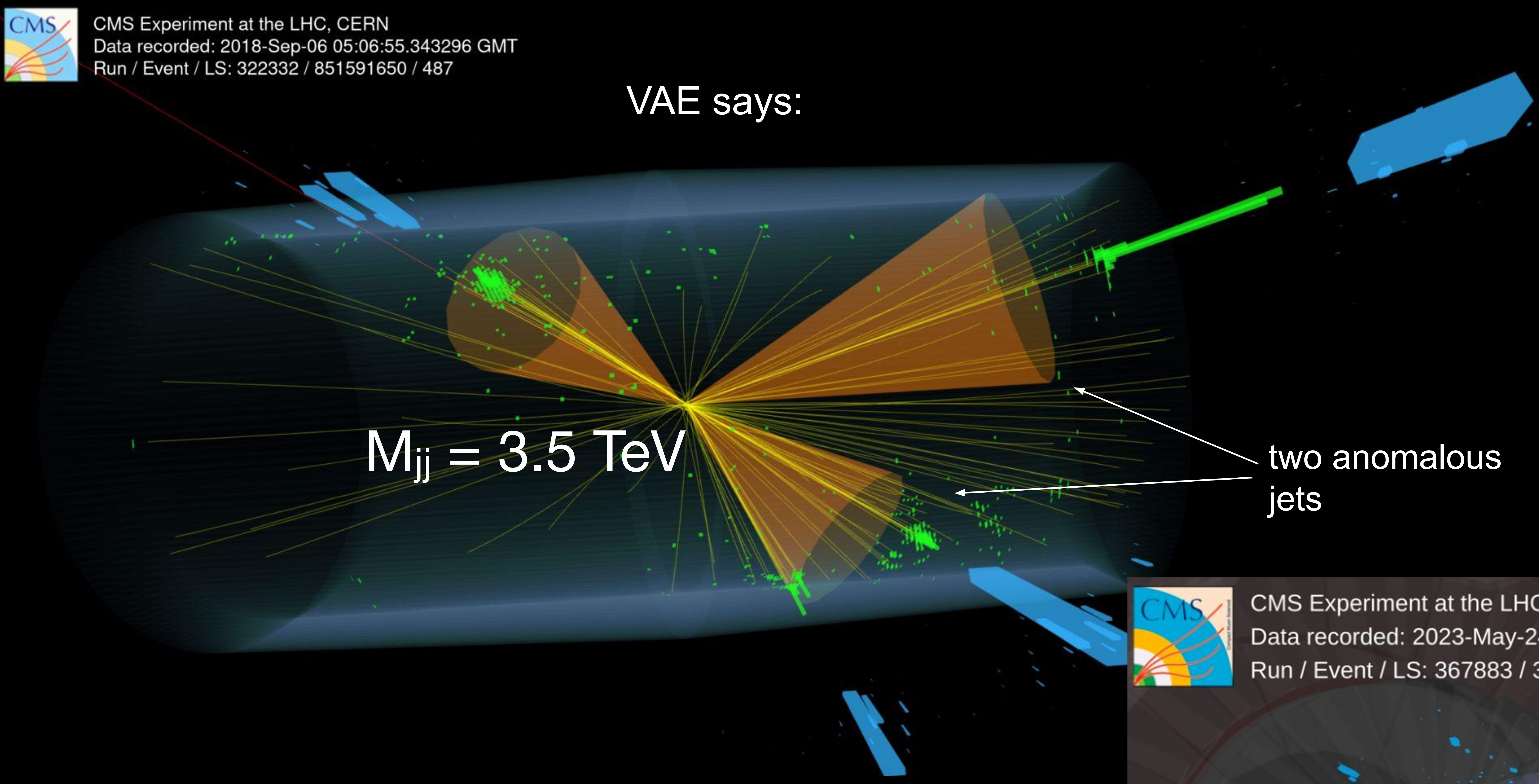
We can do both of these efficiently, model-agnostic and datadriven!

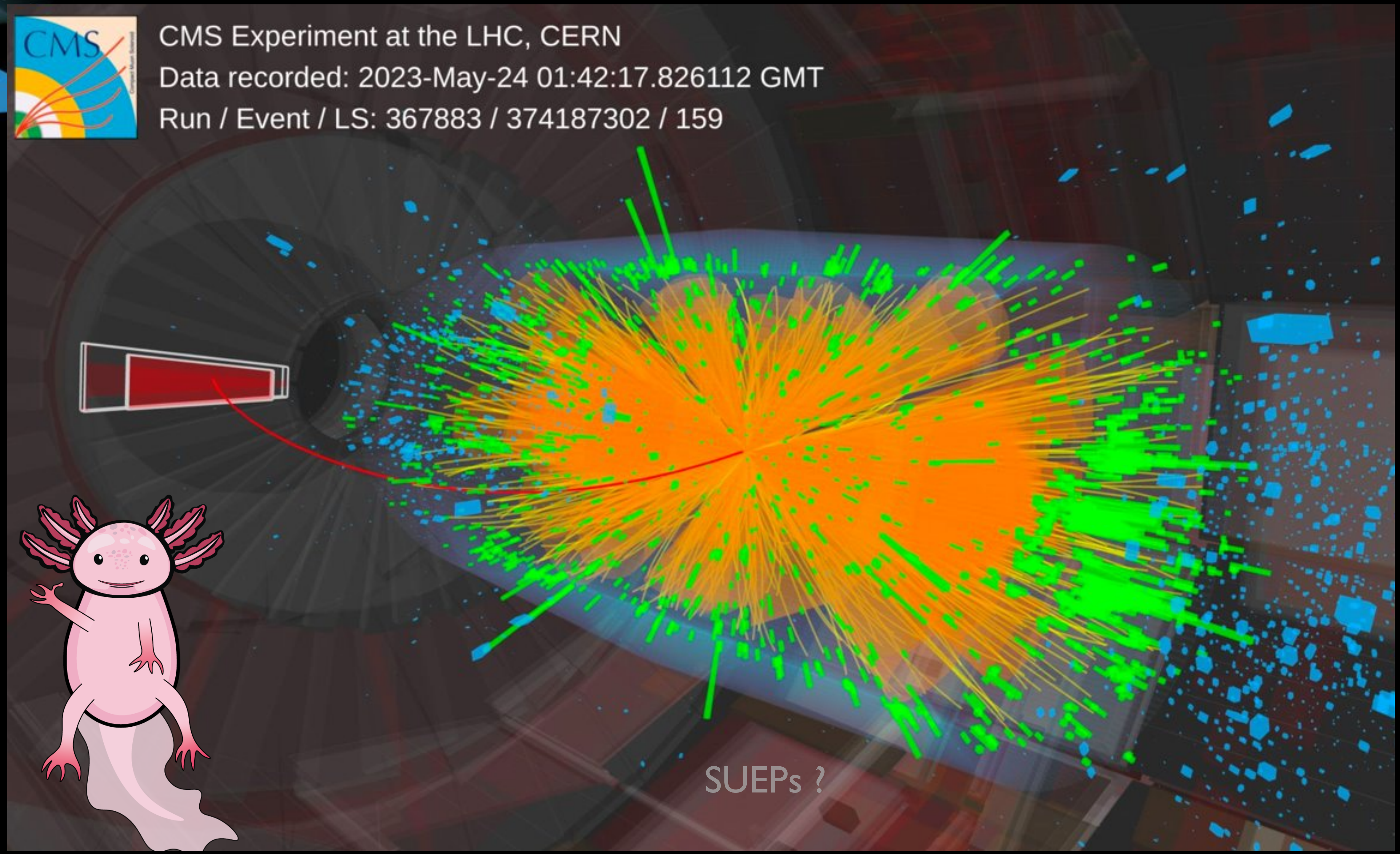
Signal Efficiency Gain	46%	100%	133%

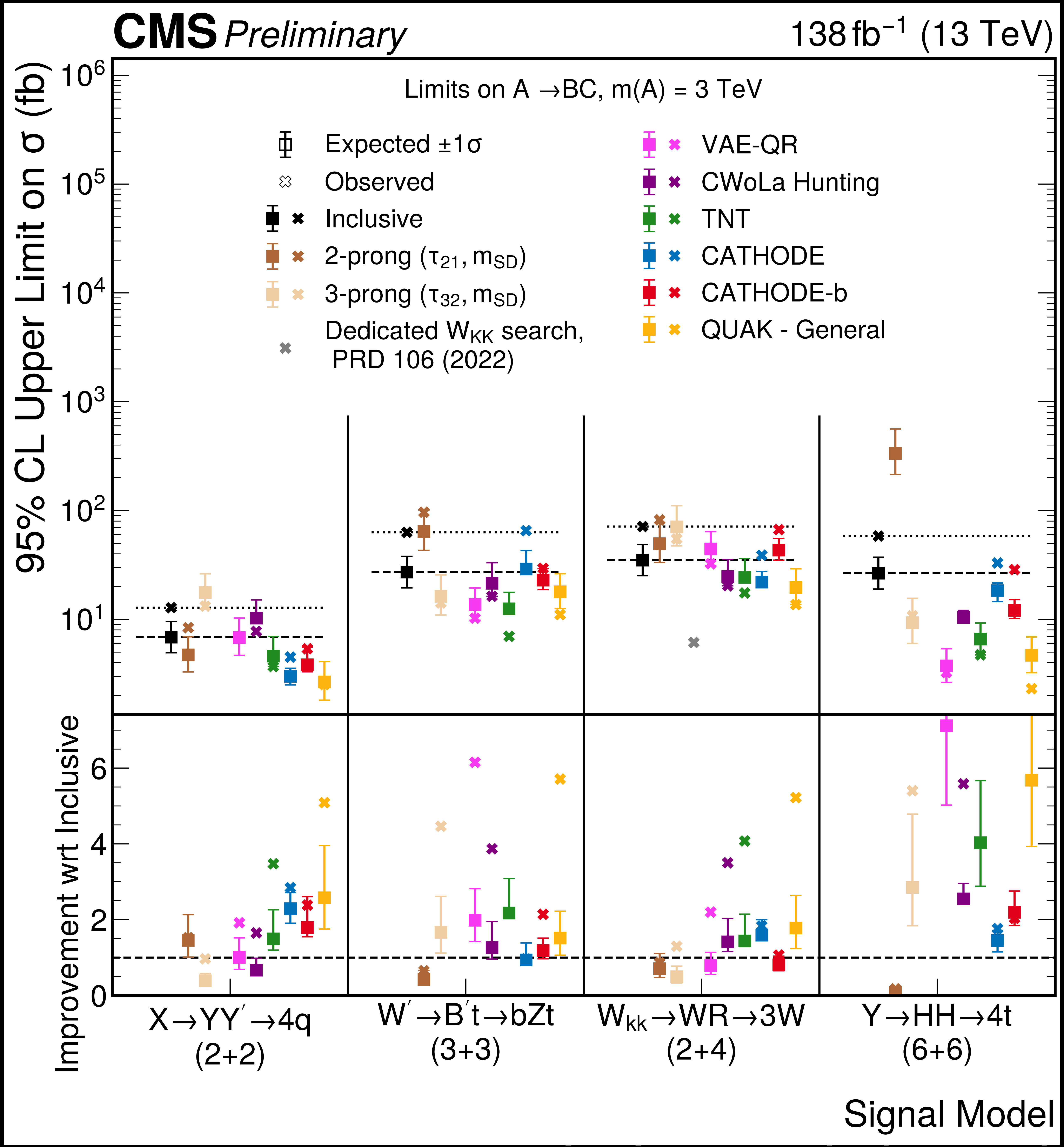




VAE says:


CMS Experiment at the LHC, CERN
Data recorded: 2018-Sep-06 05:06:55.343296 GMT
Run / Event / LS: 322332 / 851591650 / 487
M_{jj} = 3.5 TeV
two anomalous jets


CMS Experiment at the LHC, CERN
Data recorded: 2023-May-24 01:42:17.826112 GMT
Run / Event / LS: 367883 / 374187302 / 159
SUEPs ?


CMS Preliminary
138 fb^{-1} (13 TeV)
Limits on A →BC, m(A) = 3 TeV
Expected ±1σ
Observed
Inclusive
2-prong (τ_{21}, m_{SD})
3-prong (τ_{32}, m_{SD})
Dedicated W_{KK} search, PRD 106 (2022)
VAE-QR
CWoLa Hunting
TNT
CATHODE
CATHODE-b
QUAK - General
95% CL Upper Limit on σ (fb)
Improvement wrt Inclusive
X→YY′→4q (2+2)
W′→B′t→bZt (3+3)
W_{kk}→WR→3W (2+4)
Y→HH→4t (6+6)
Signal Model

Backup

Input features (from B. Maier)

VAE

Constituents

p_x, p_y, p_z

CWoLa

m_{SD}

τ_{21}

τ_{32}

τ_{43}

n_{const}

leptonic energy fraction

sub-jets B tag score

TNT

same as CWoLa

CATHODE

m_{SD}^{j1}

$m_{SD}^{j1} - m_{SD}^{j2}$

τ_{41}^{j1}

τ_{41}^{j2}

\+

B tag scores of j1, j2

CATHODE-b

QUAK

$\varrho = m_{SD}/p_T$

τ_{21}

τ_{32}

τ_{43}

n_{const}

$\sqrt{\tau_{21}} / \tau_1$

jet B tag score