Model independent searches at the LHC with anomaly detection

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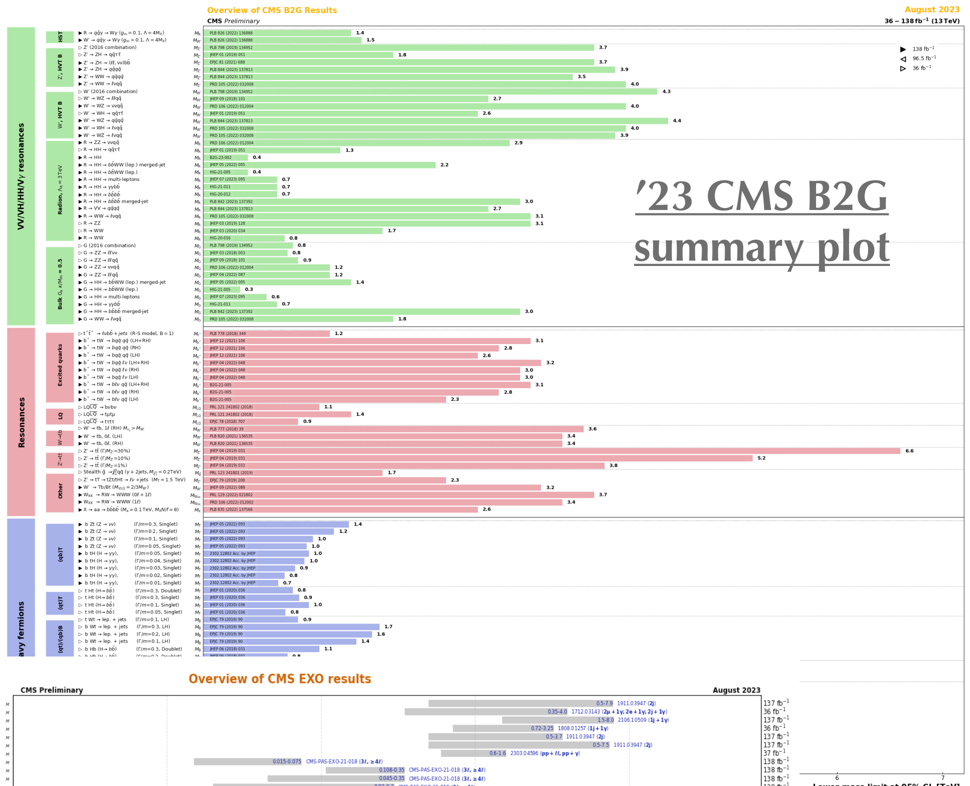
on behalf of the CMS and ATLAS Collaborations

58th Rencontres de Moriond
Electroweak Interactions & Unified Theories
24-31 March, 2024
La Thuile, Italy

Searches for new physics @ LHC

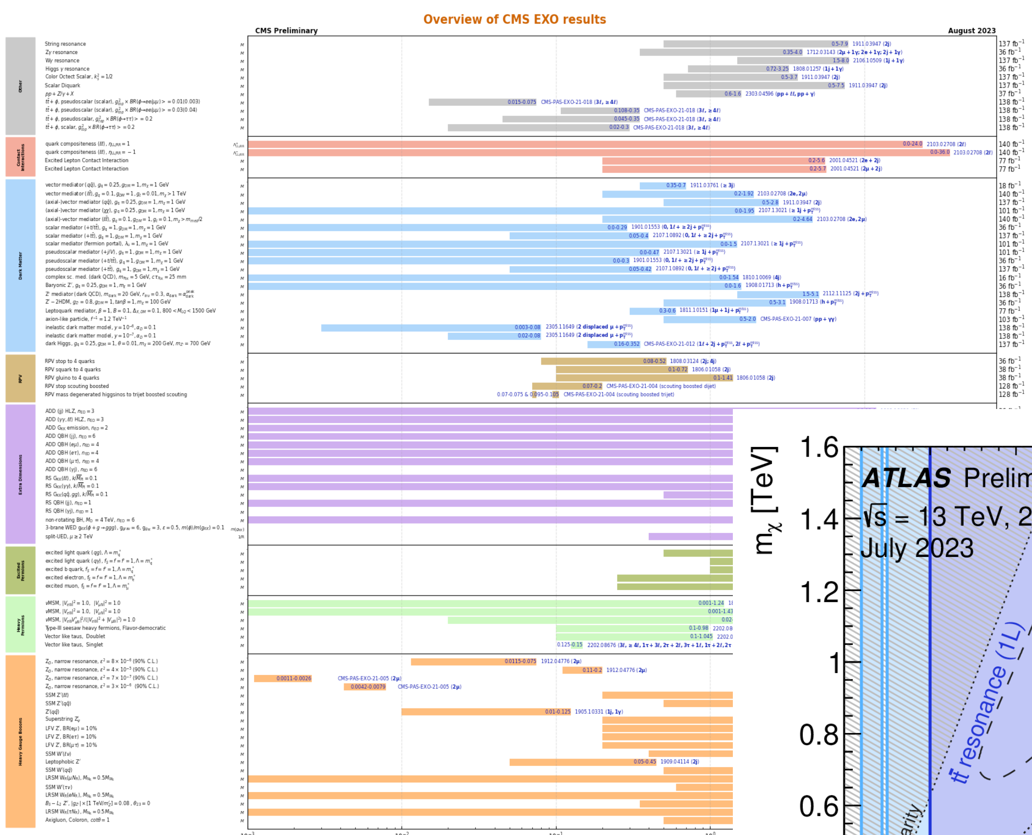


'23 CMS B2G summary plot

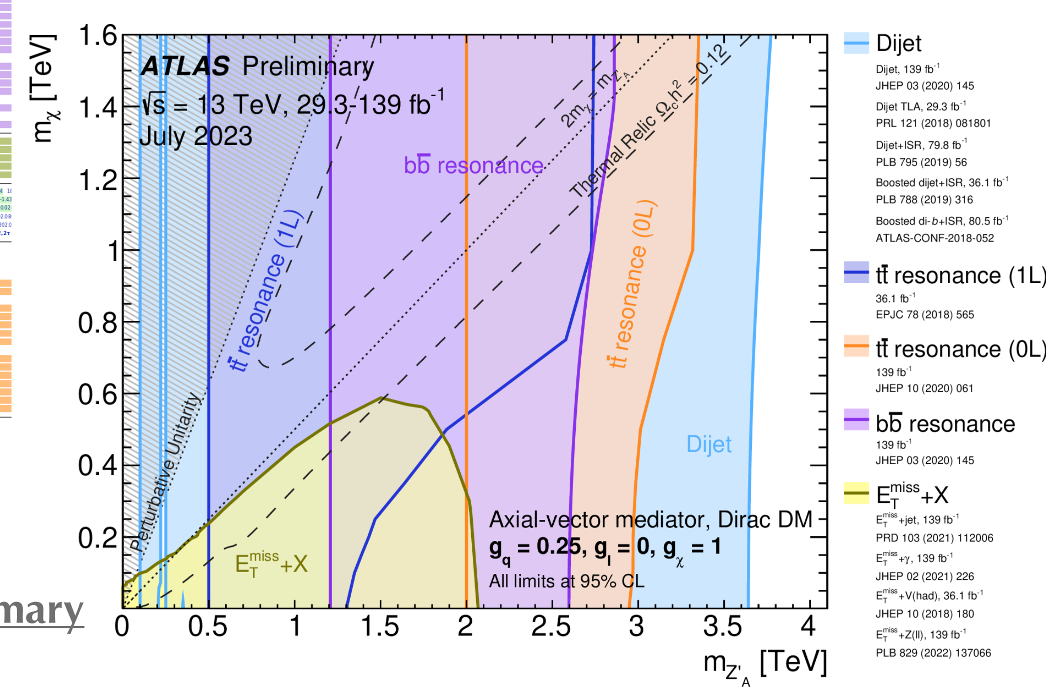
For each of these new physics scenario we design an analysis that aims at isolating the specific signal phase space

With O(1000) of these analyses we have not found any significant evidence for new physics

It might be that we are not looking in the right place because we might have not imagined (yet) how new physics look like



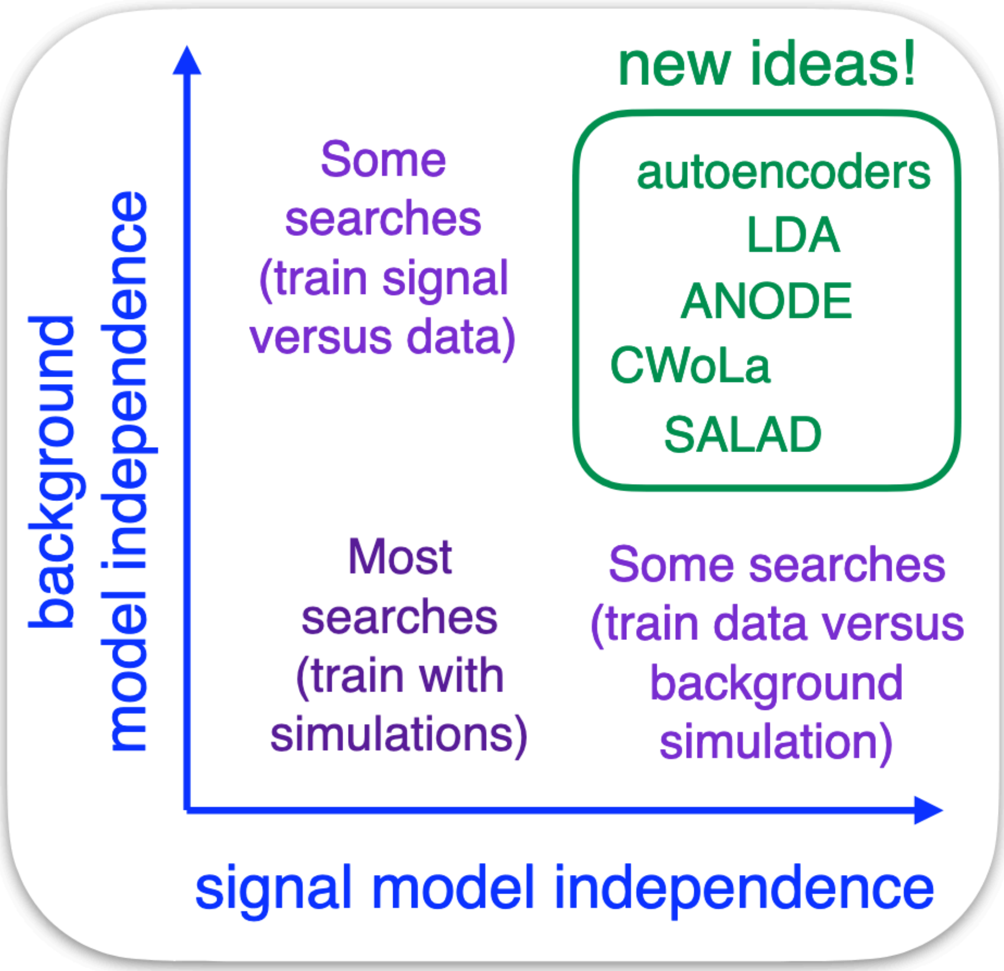
'23 CMS EXO summary plot



'23 ATLAS Dark Matter summary

HOW TO GENERALIZE?

Learn from data: anomaly detection



Credits: D. Shih, B. Nachman

HOW TO GENERALIZE?

Many new ideas that make use of deep learning to **learn directly from data how the standard model looks like**

$\Downarrow$

eliminate signal priors and search for anything anomalous wrt standard model

This approach is what we call:

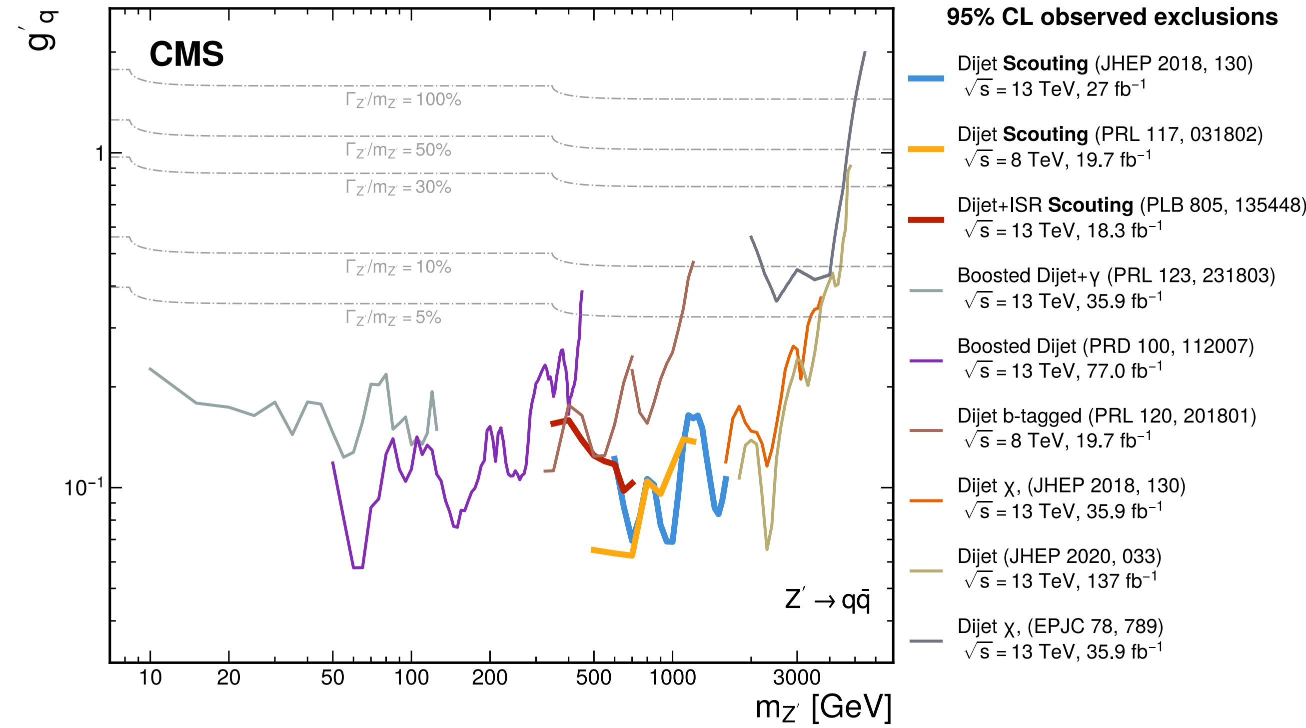
ANOMALY DETECTION

The physics case: dijet resonances

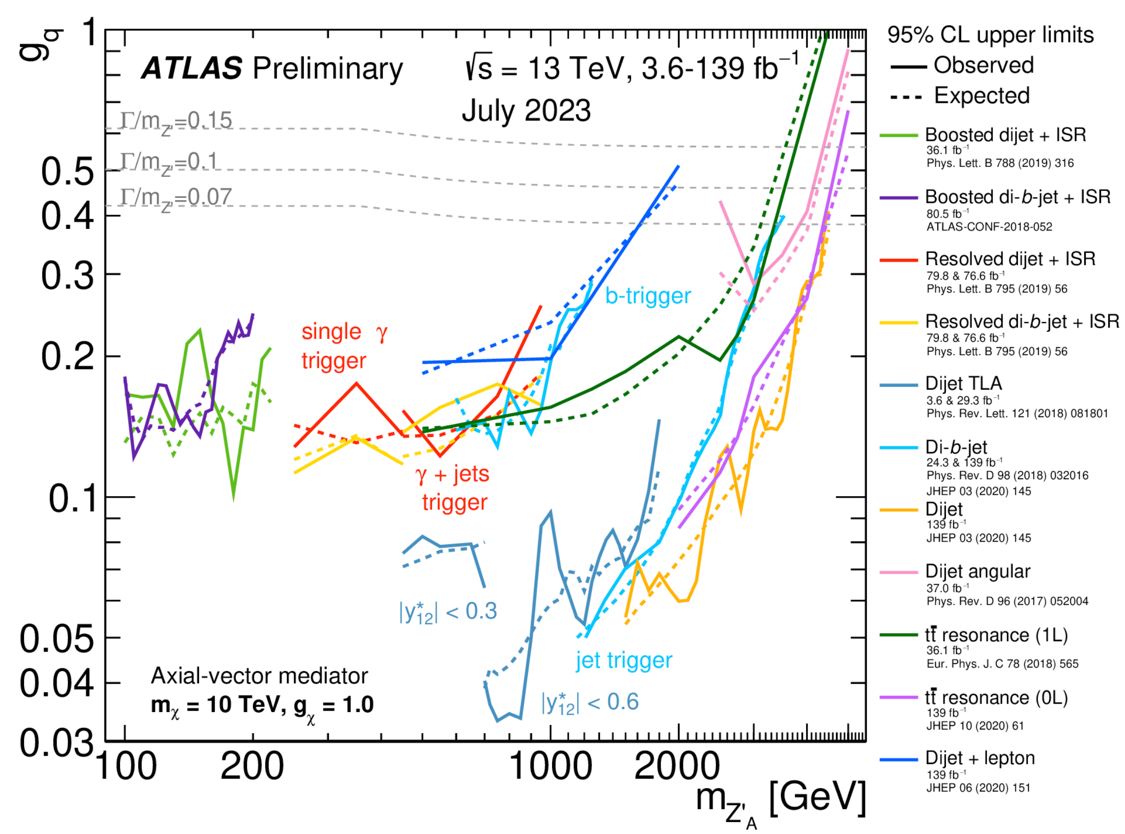
- **Extensively studied at colliders**
  - classic dijet w/ no jet tagging
  - $t\bar{t}$ w/ dedicated top tagging
  - diboson w/ dedicated SM boson jet tagging
  - multi b jets signatures
  - and even triboson
  - …

- **Natural place to explore novel analysis strategies**

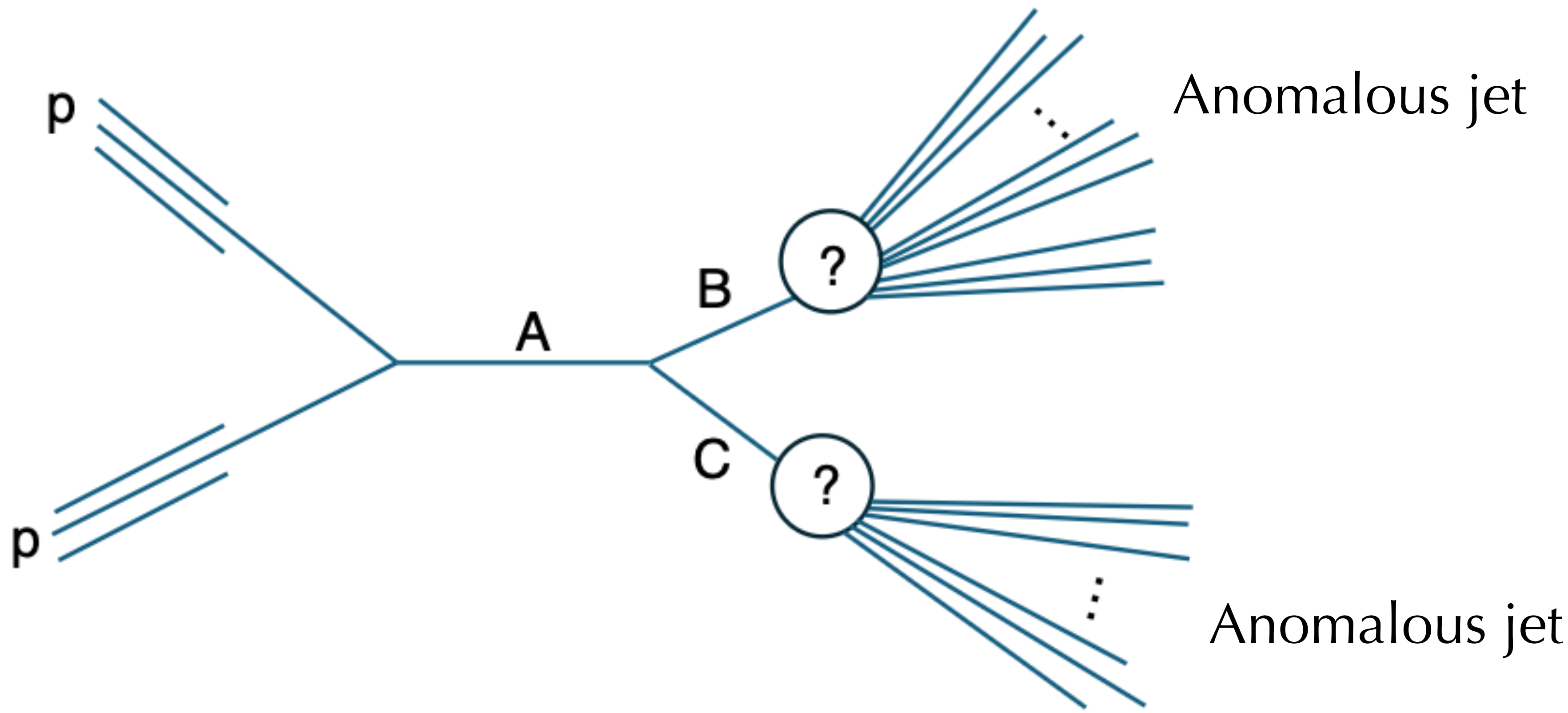
[CMS-EXO-23-007]



[ATL-PHYS-PUB-23-018]



The physics case: dijet resonances

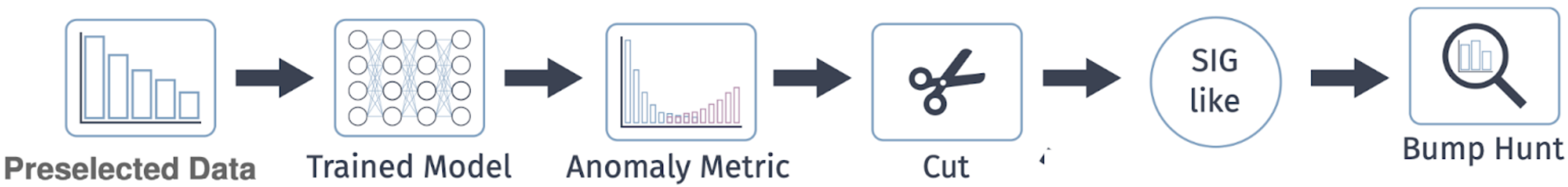


Focus on large-radius boosted jets

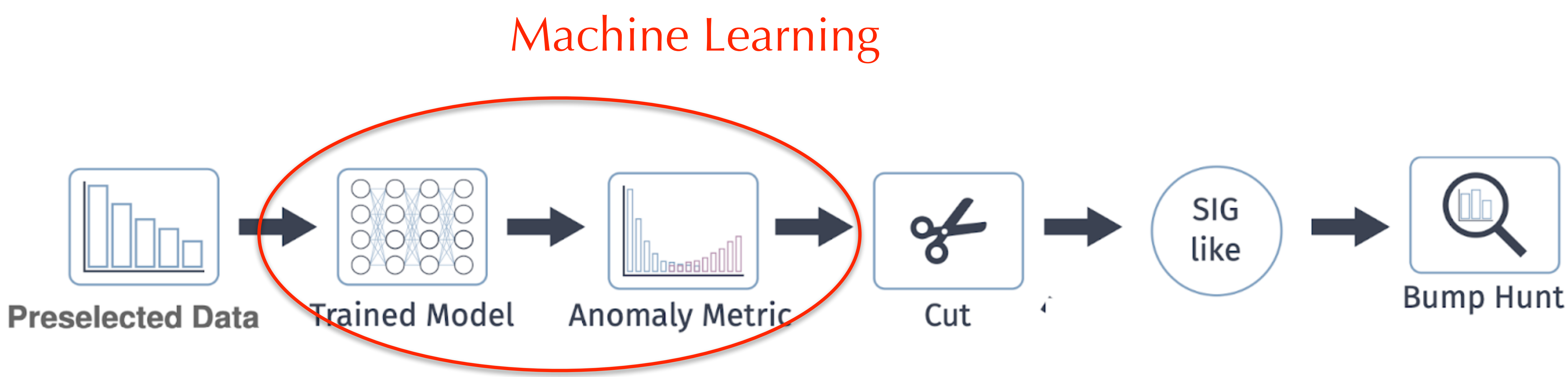
Tag each jet as anomalous with no assumption on how it looks like

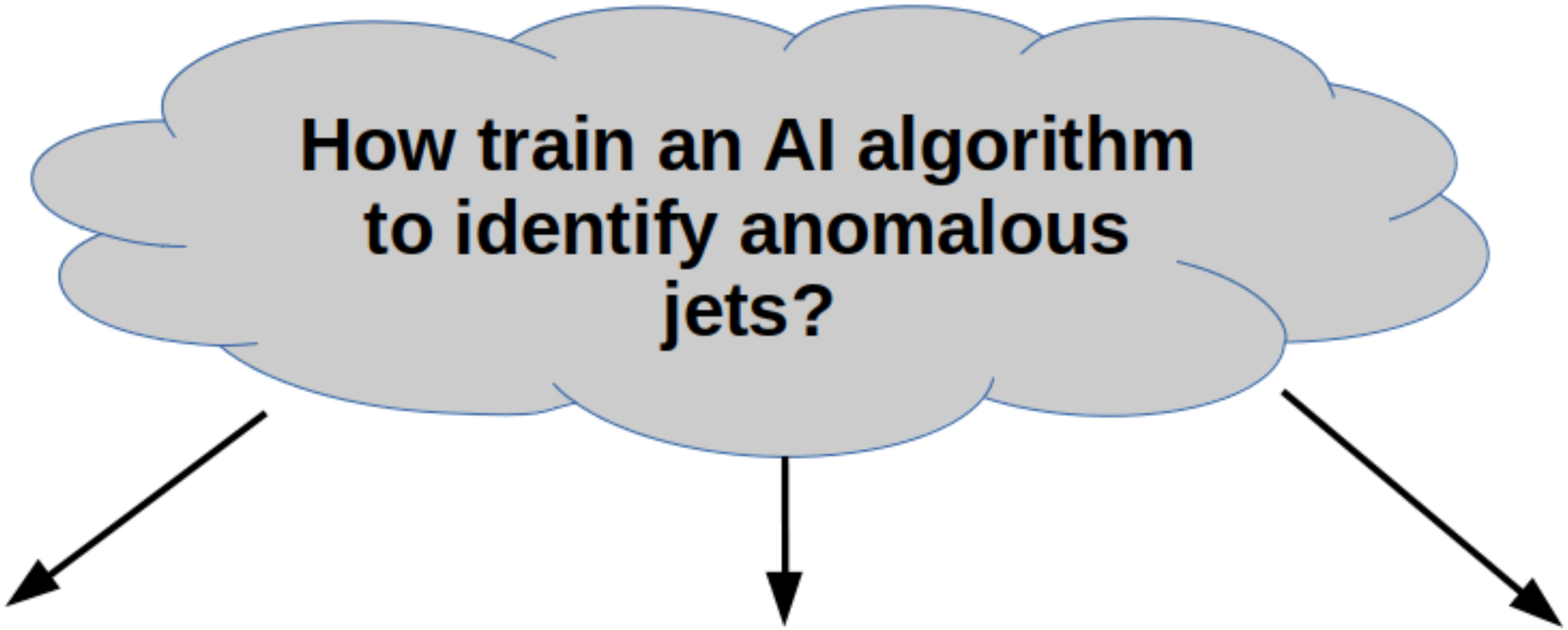
Do not rely on imperfect SM background simulation
→ train directly on data

Designing an anomaly detection search



Designing an anomaly detection search

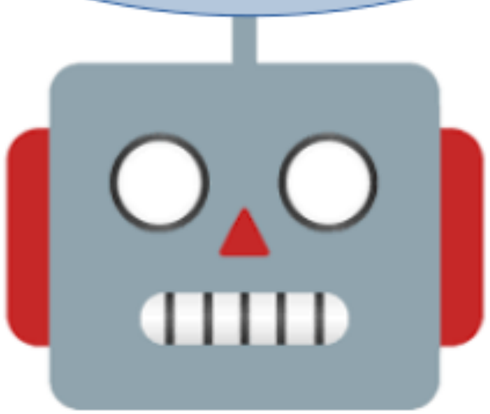




Increasing model dependence

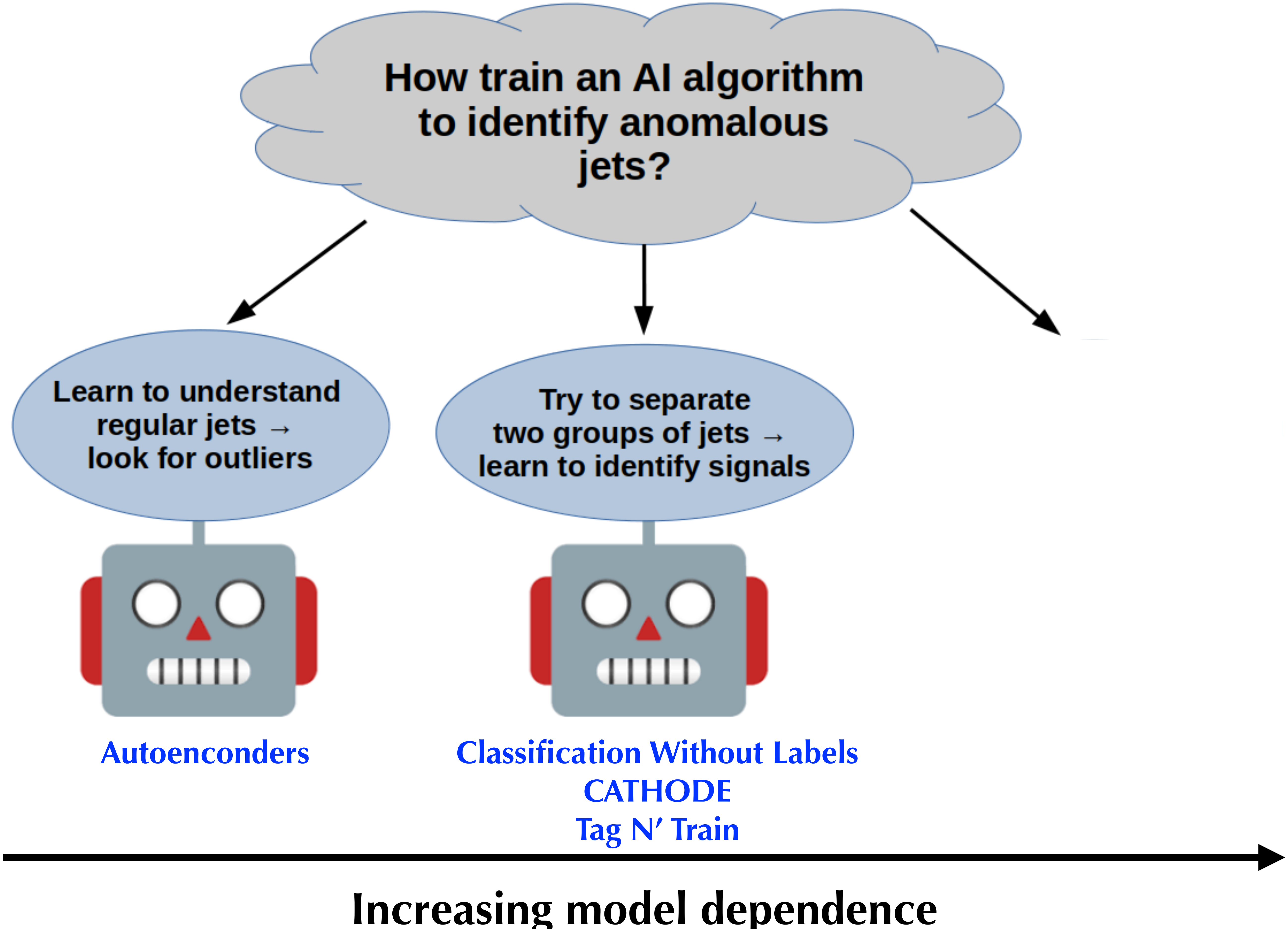
How train an AI algorithm to identify anomalous jets?

Learn to understand regular jets → look for outliers



Autoenconders

Increasing model dependence


How train an AI algorithm
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Learn to understand
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Try to separate
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Autoenconders
Classification Without Labels
CATHODE
Tag N' Train
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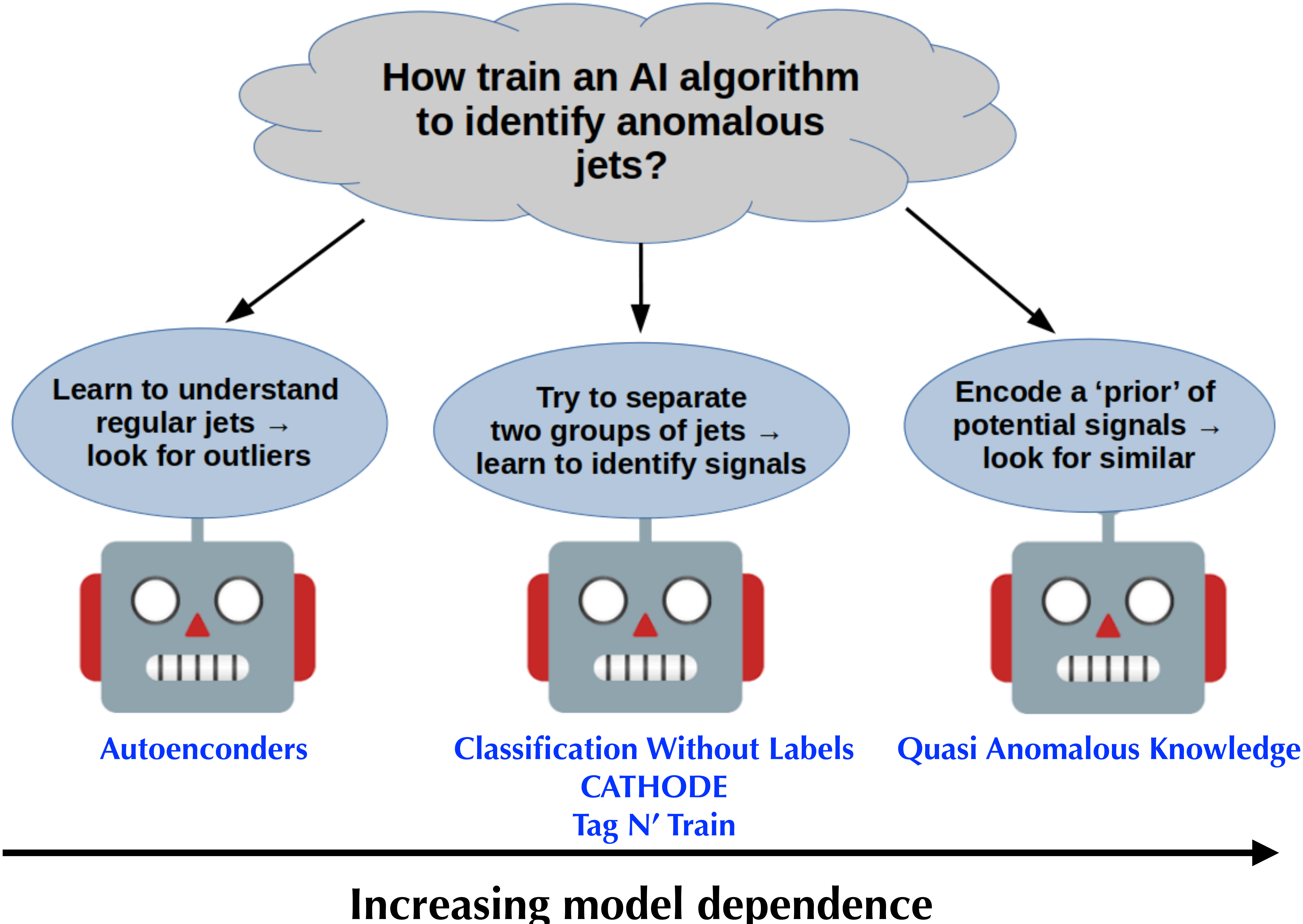

How train an AI algorithm to identify anomalous jets?
Learn to understand regular jets → look for outliers
Try to separate two groups of jets → learn to identify signals
Encode a ‘prior’ of potential signals → look for similar
Autoenconders
Classification Without Labels
CATHODE
Tag N’ Train
Quasi Anomalous Knowledge
Increasing model dependence

How train an AI algorithm to identify anomalous jets?

Learn to understand regular jets → look for outliers

Autoenconders

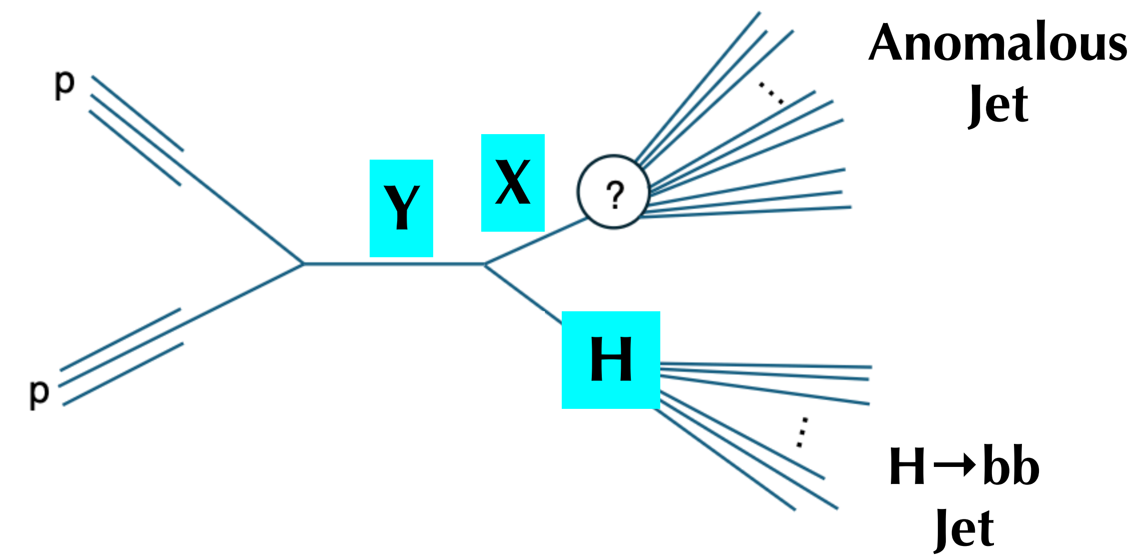
Two ATLAS searches using autoencoders in final states with:

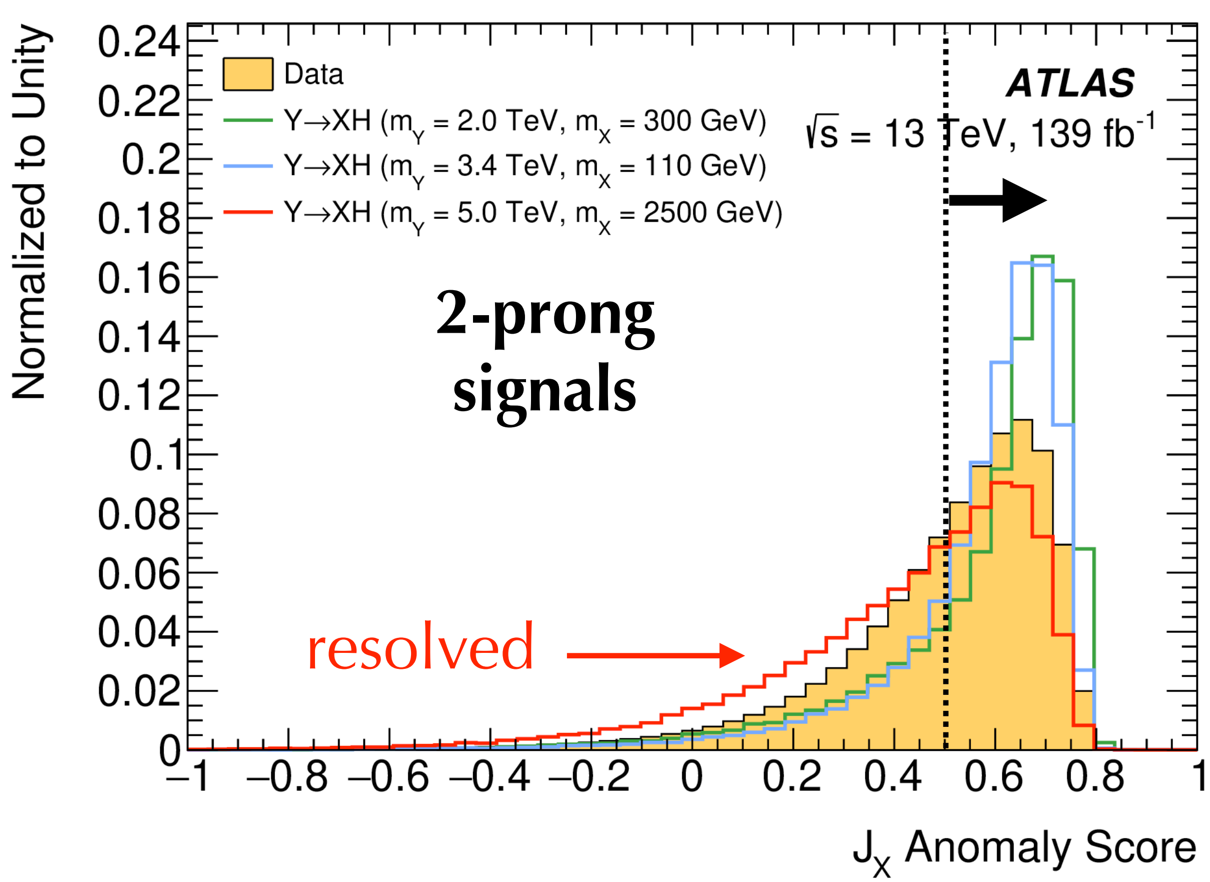
- two boosted jets [PRD 108 (2023) 052009]
  → *Now published!*
- lepton + jet(s) and photon + jet(s) [PRL 132 (2024) 081801]
  → *New at this conference!*

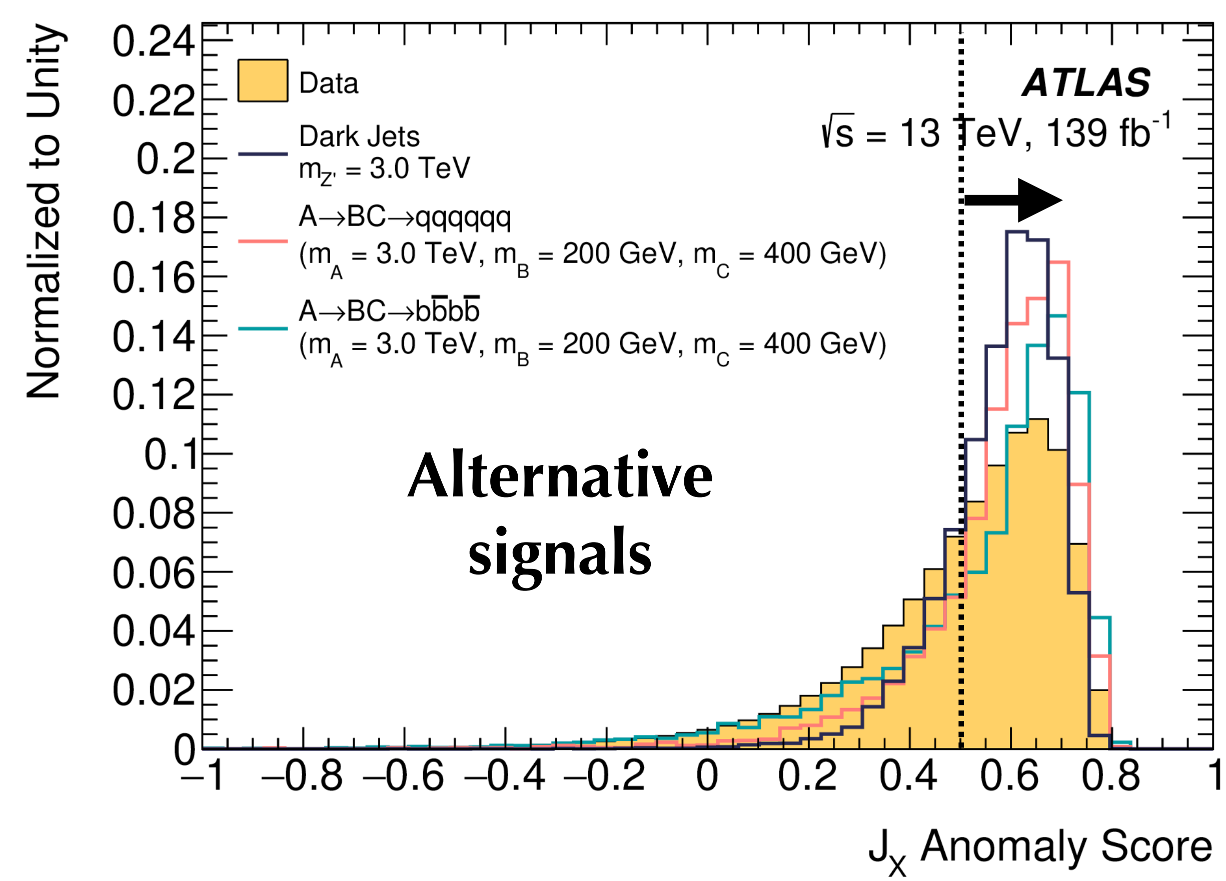
Increasing model dependence

Y→H+X search in ATLAS EXPERIMENT

- Idea recently applied to a search in ATLAS for a **generic heavy resonance Y decaying to a SM Higgs boson (bb decay) + a new generic particle X decaying hadronically**
- An autoencoder is trained on a sequence of up to **20 constituent four-vectors per jet** and conditioned on **four high-level 2/3-prong sensitive substructure observables**

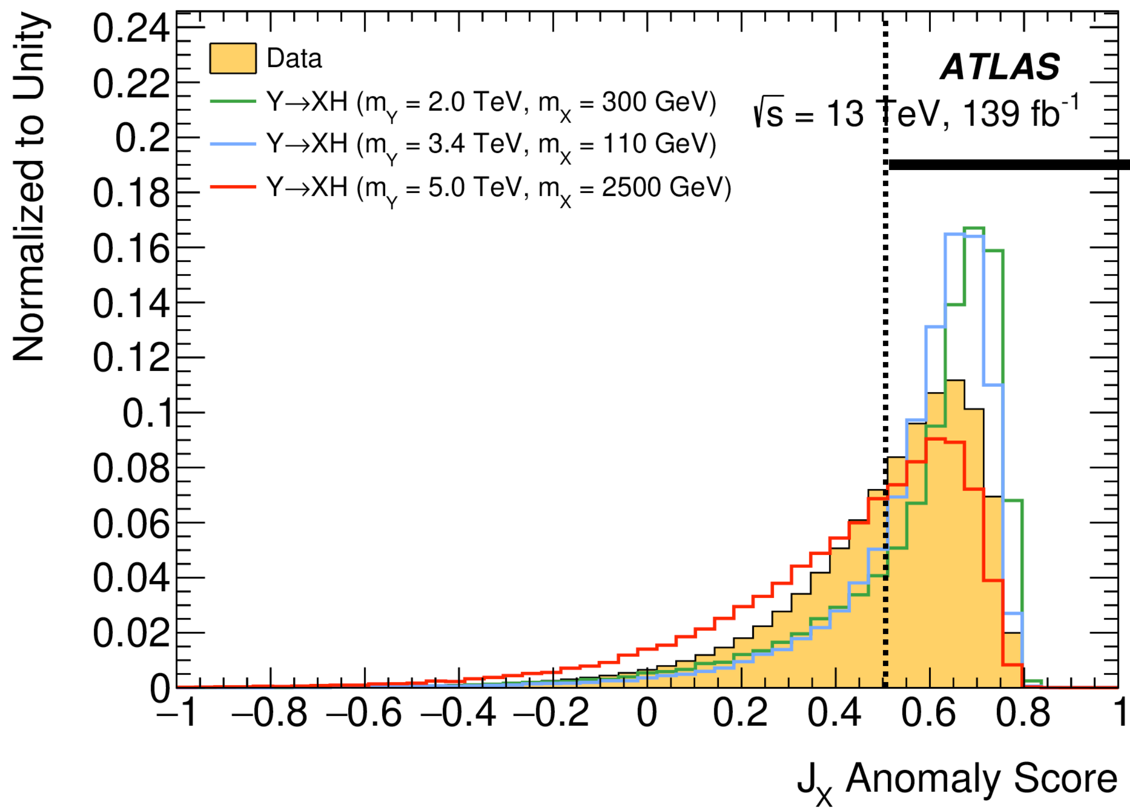






Phys. Rev. D 108 (2023) 052009

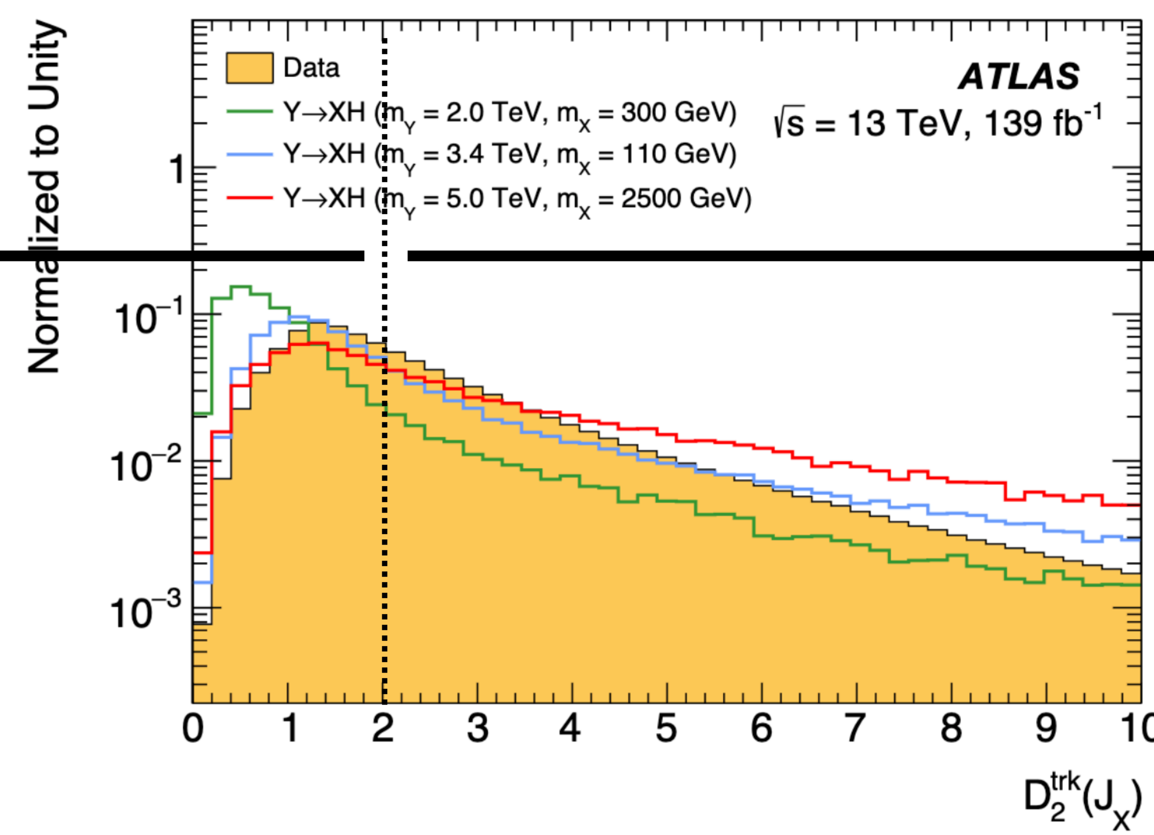
Y→H+X search in ATLAS EXPERIMENT



Category #1:
anomalous region

Two categories based on 2-prong high-level substructure observable

Category #2:
merged region

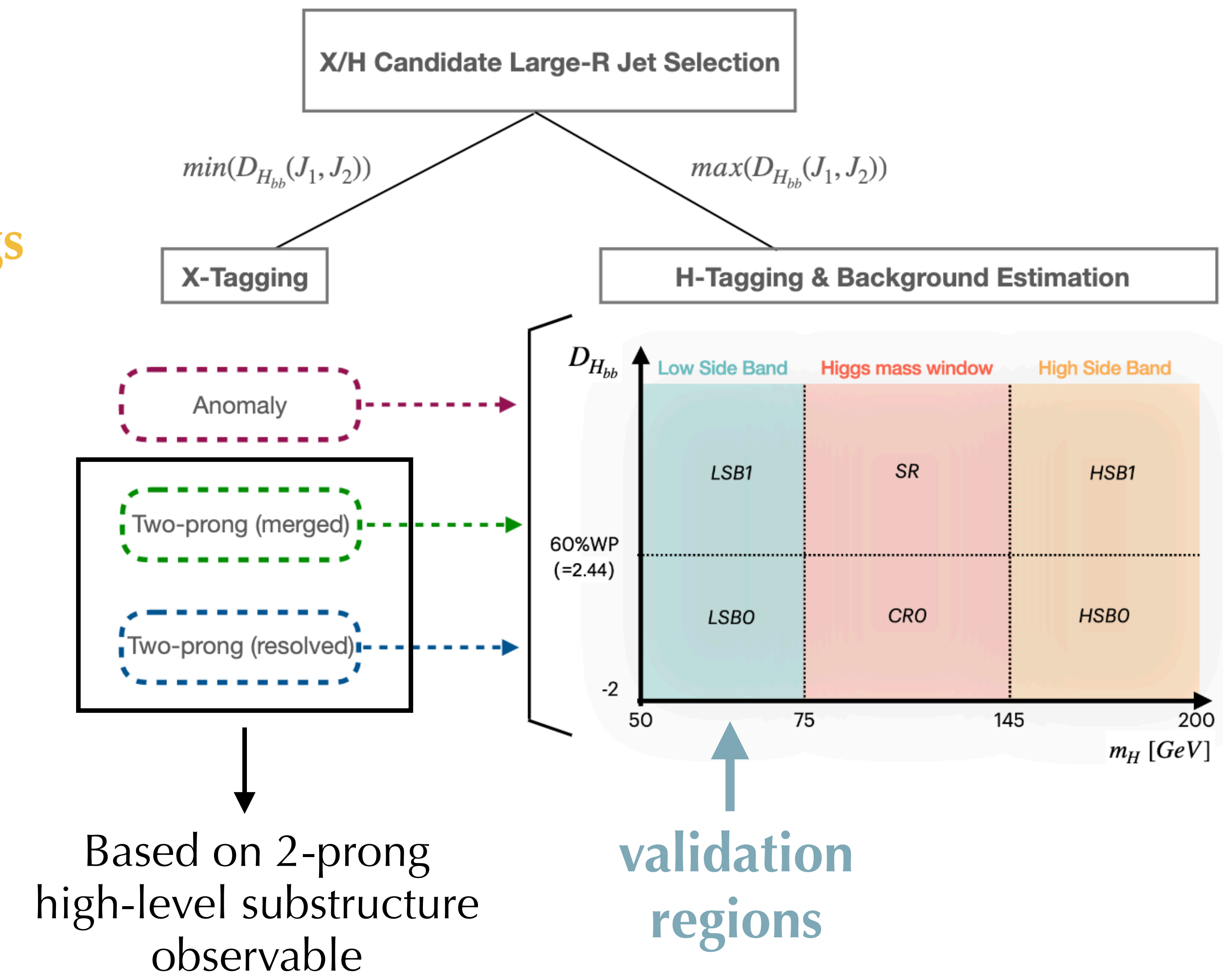


Category #3:
resolved region

Phys. Rev. D 108 (2023) 052009

Y→H+X search in ATLAS EXPERIMENT

- Fully data-driven background estimation
- Derived from data template in **high Higgs mass sideband** that fails H tagger score, reweighted to shape in **H-tagged region**

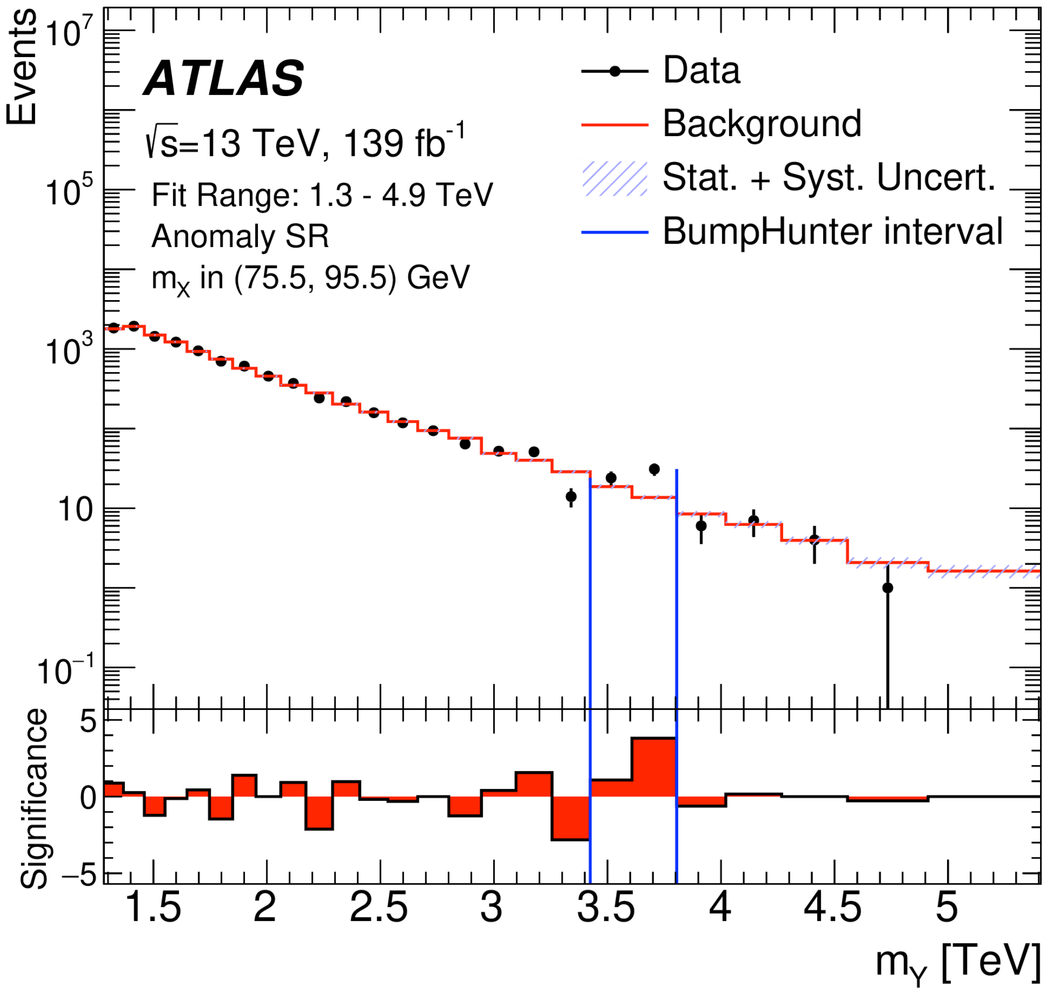


Phys. Rev. D 108 (2023) 052009

Y→H+X search in ATLAS EXPERIMENT

- Bump hunt performed by fitting m_{jj} across overlapping bins of anomalous jet mass

- Largest excess of **1.43σ (global)** in the m_X bin [75.5, 95.5] GeV and m_Y bin [3608, 3805] GeV

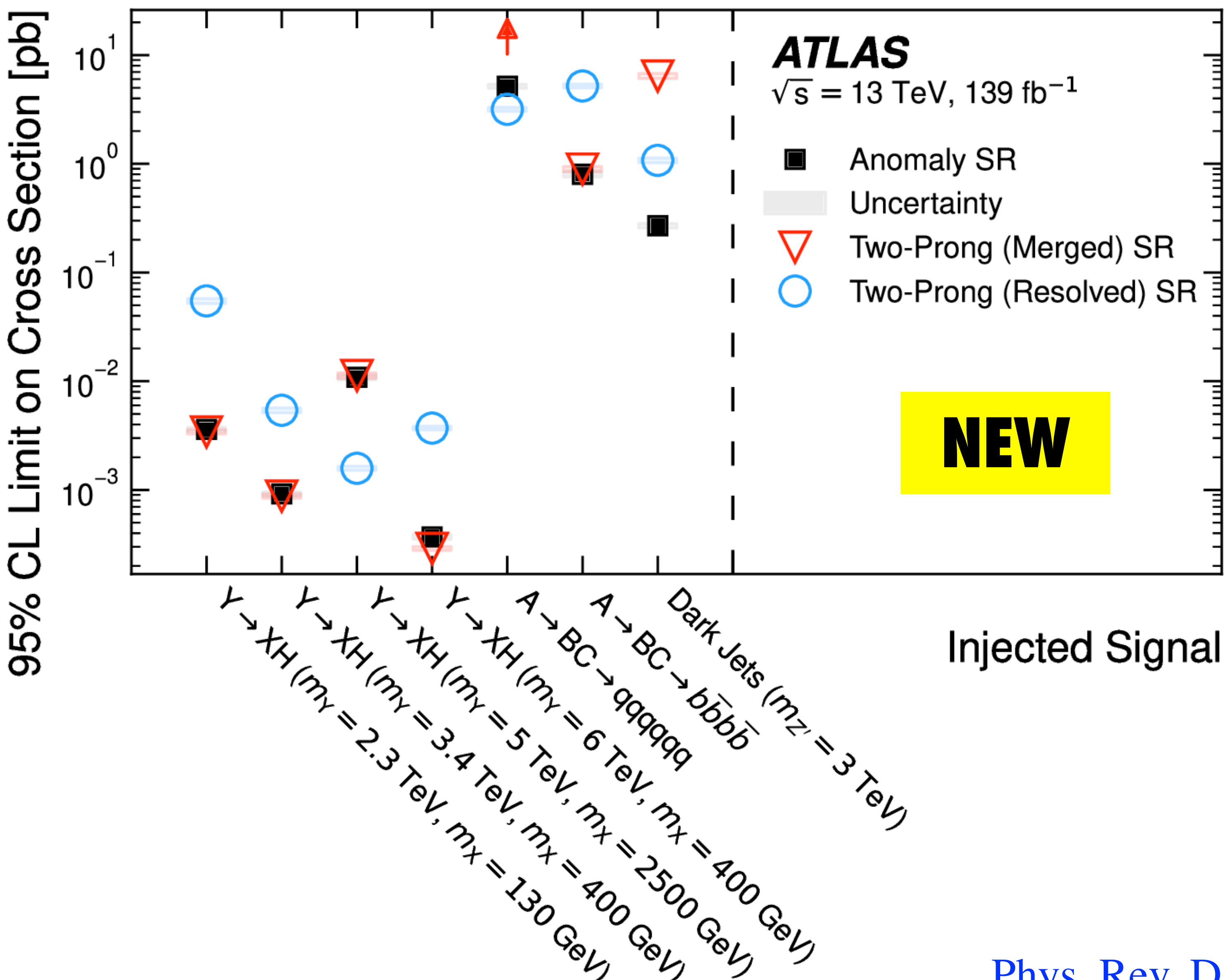


Phys. Rev. D 108 (2023) 052009

Y→H+X search in ATLAS EXPERIMENT

- 95% CL upper limits on the production cross section of several benchmark signals
  - inject signal into the data until the bump hunt *p*-value exceeds a significance of 2σ

→ Compare sensitivity of the three categories to the different signals:



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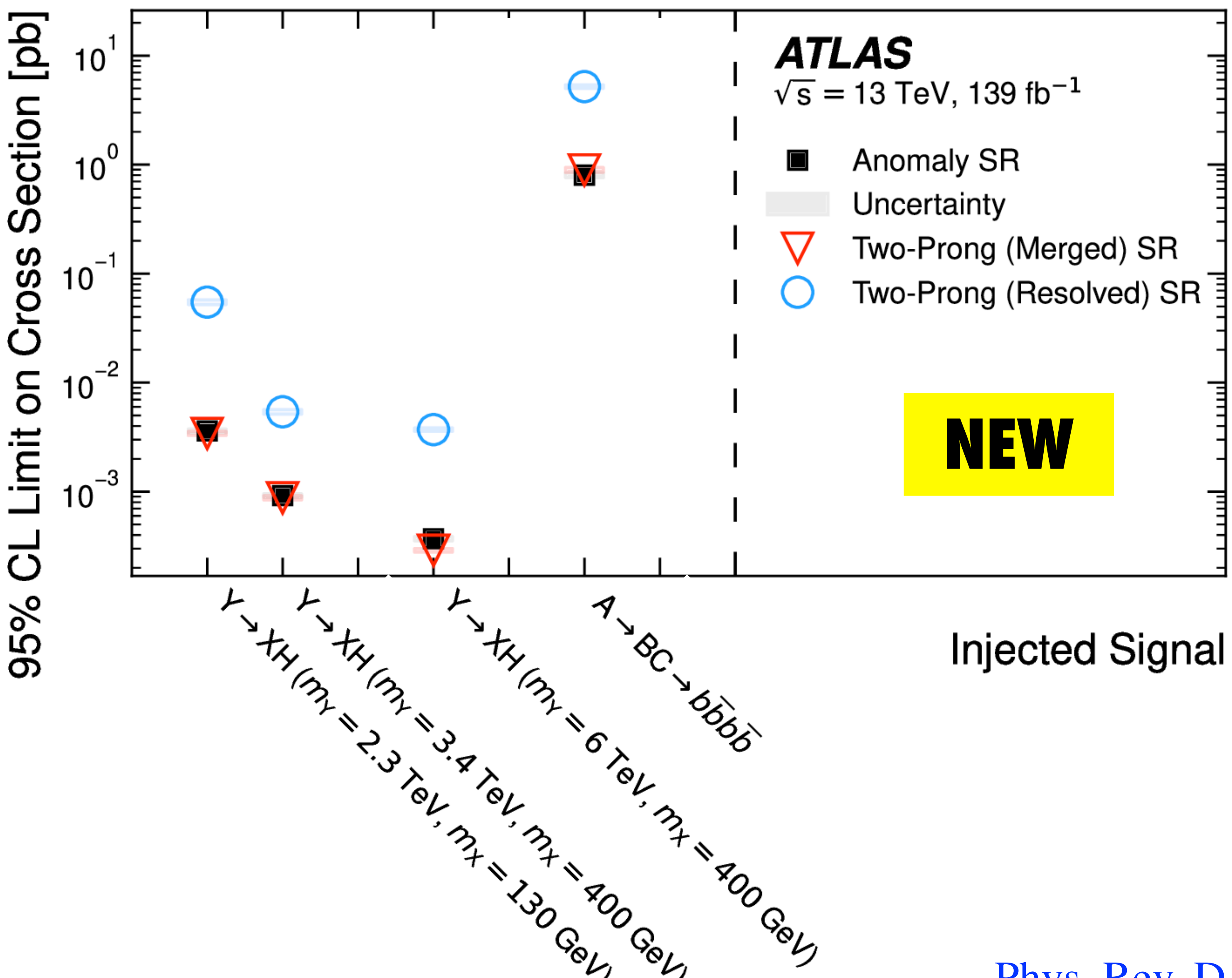

For 2-prong merged signals
→ **anomaly detection**
performs as **supervised search**

Phys. Rev. D 108 (2023) 052009

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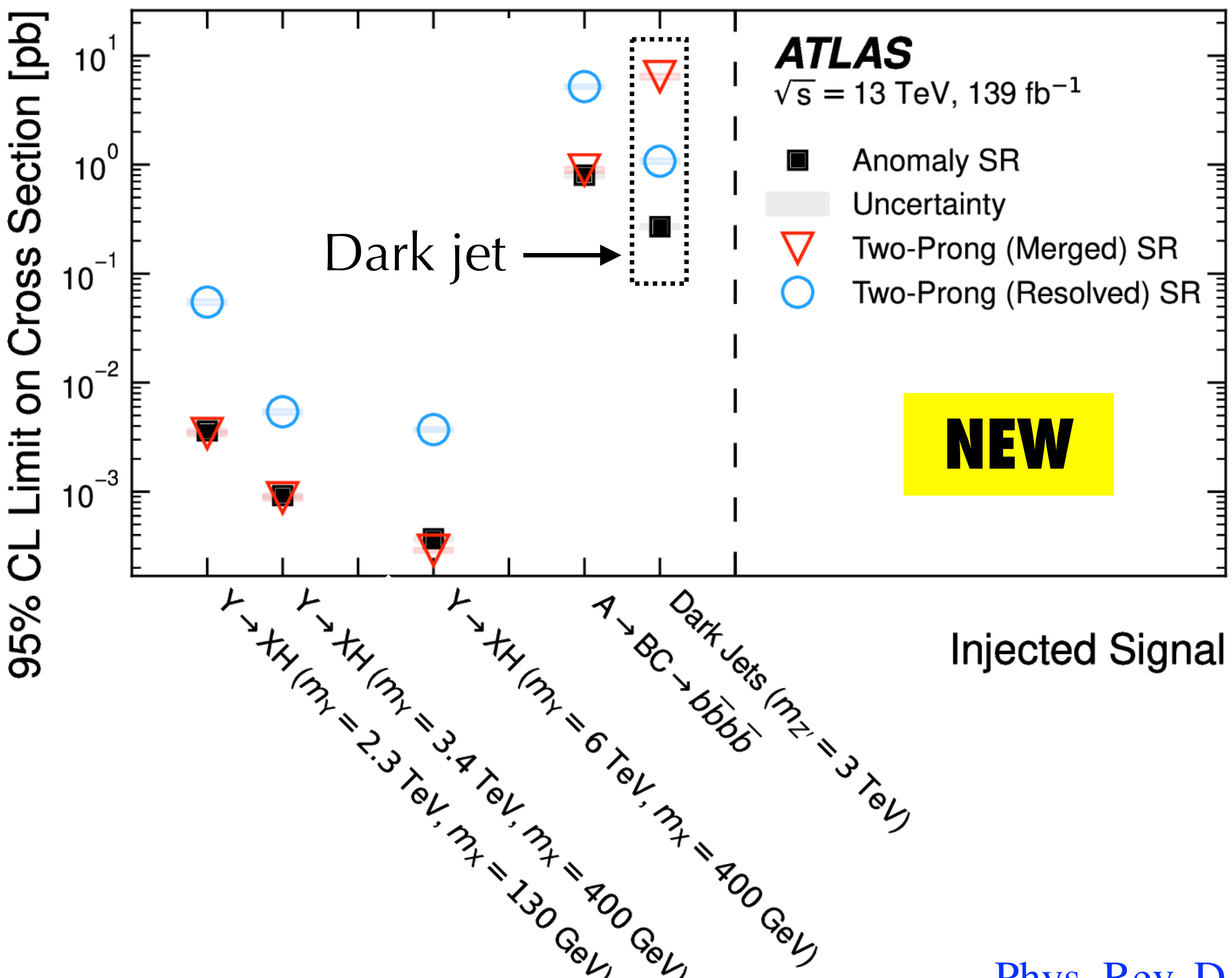

For 2-prong merged signals → **anomaly detection** performs as **supervised search**

On more exotic jets like Dark Jets **anomaly detection** performs better → *good generalization*

Phys. Rev. D 108 (2023) 052009

Go more general: beyond dijet signatures

- Reach other regions of phase space in a model-independent approach by **requiring one lepton or photon** → allow to search for anomalous events in final states with a variety of pairs of objects:
  - lepton + dijet of different flavour content (light and/or b-jet)
  - lepton (e,μ) + jet (or b-jet)
  - photon + jet (or b-jet)

NEW

ATLAS EXPERIMENT

Search for new phenomena in two-body invariant mass distributions using unsupervised machine learning for anomaly detection at $\sqrt{s}$ = 13 TeV with the ATLAS detector

The ATLAS Collaboration

Phys. Rev. Lett. 132 (2024) 081801

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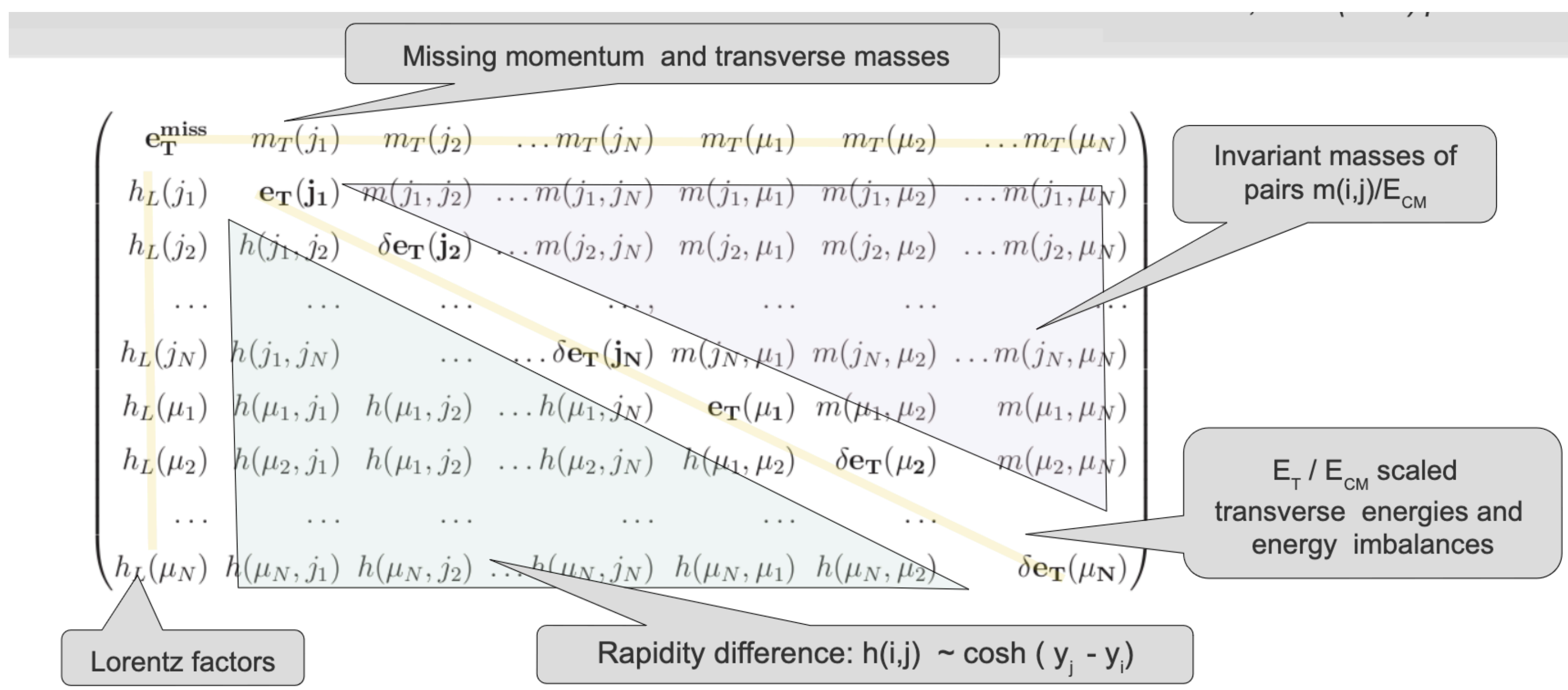
- Idea to train an **autoencoder on lepton/photon+jet triggered events to reconstruct high-level observables**



Original idea:
[NIM A 931 (2019) 92-99]

lepton/photon + jet/dijet in ATLAS EXPERIMENT

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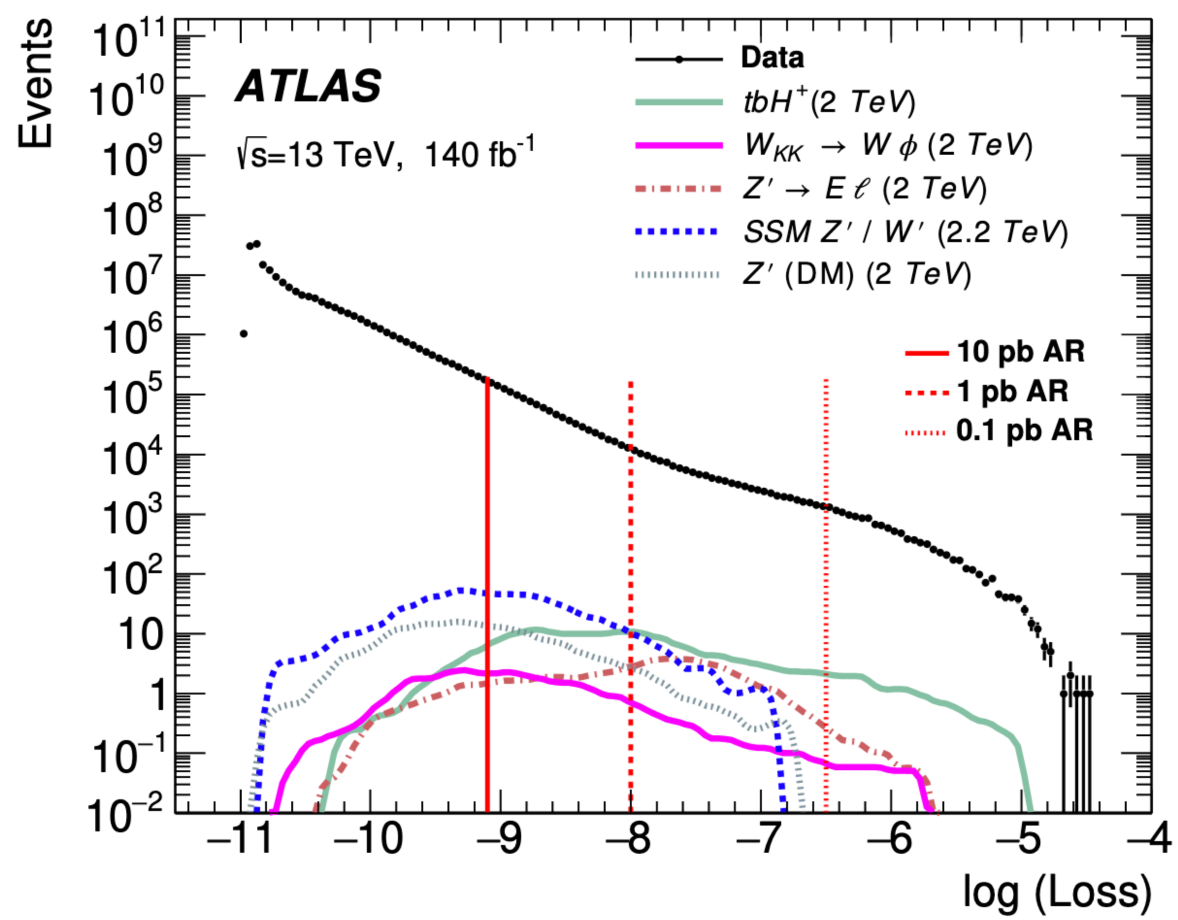
- Idea to train an **autoencoder on lepton/photon+jet triggered events to reconstruct high-level observables**
  → cut on anomaly score (e.g., reconstruction loss)
  → bump hunt on di-object invariant mass

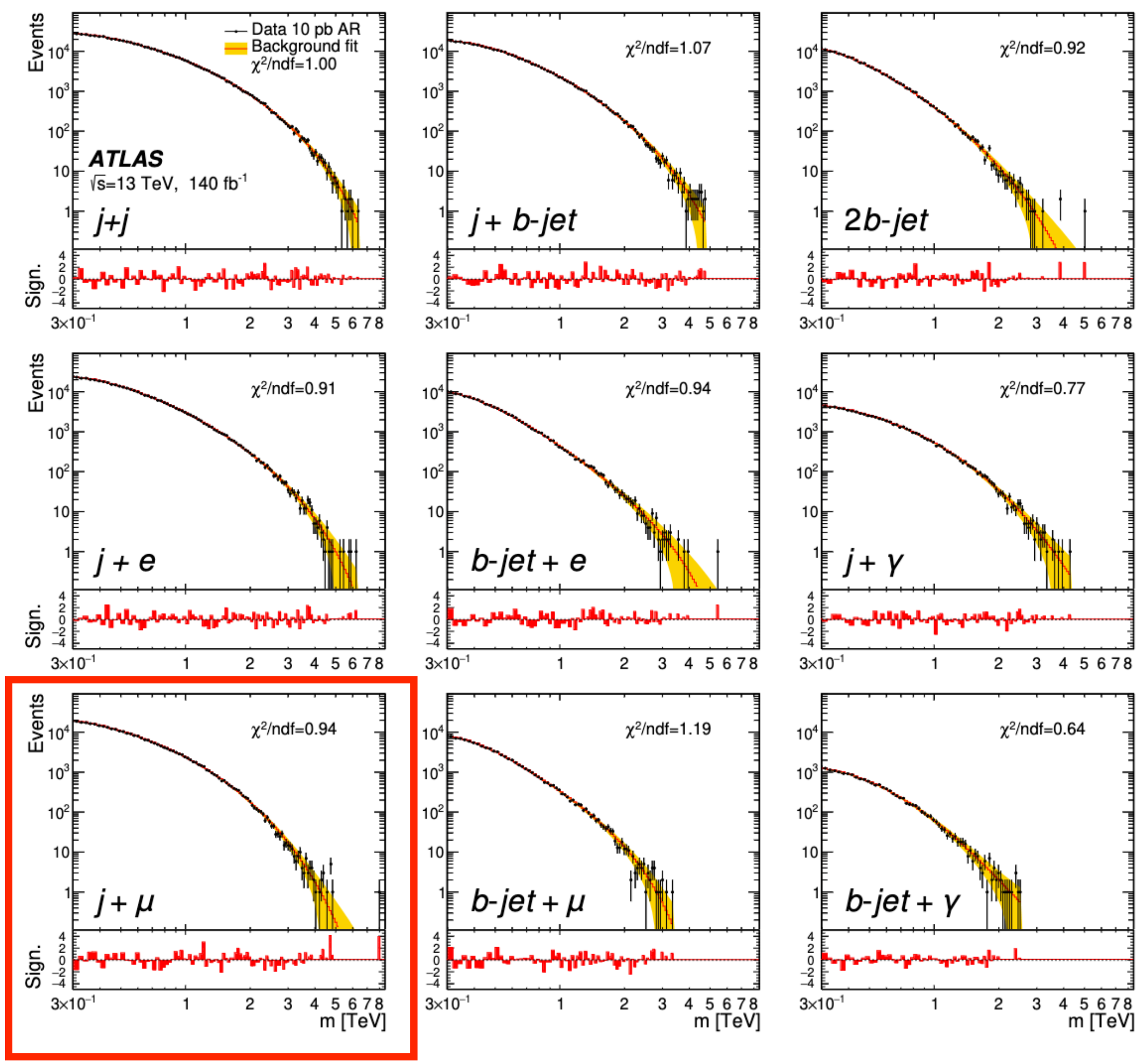


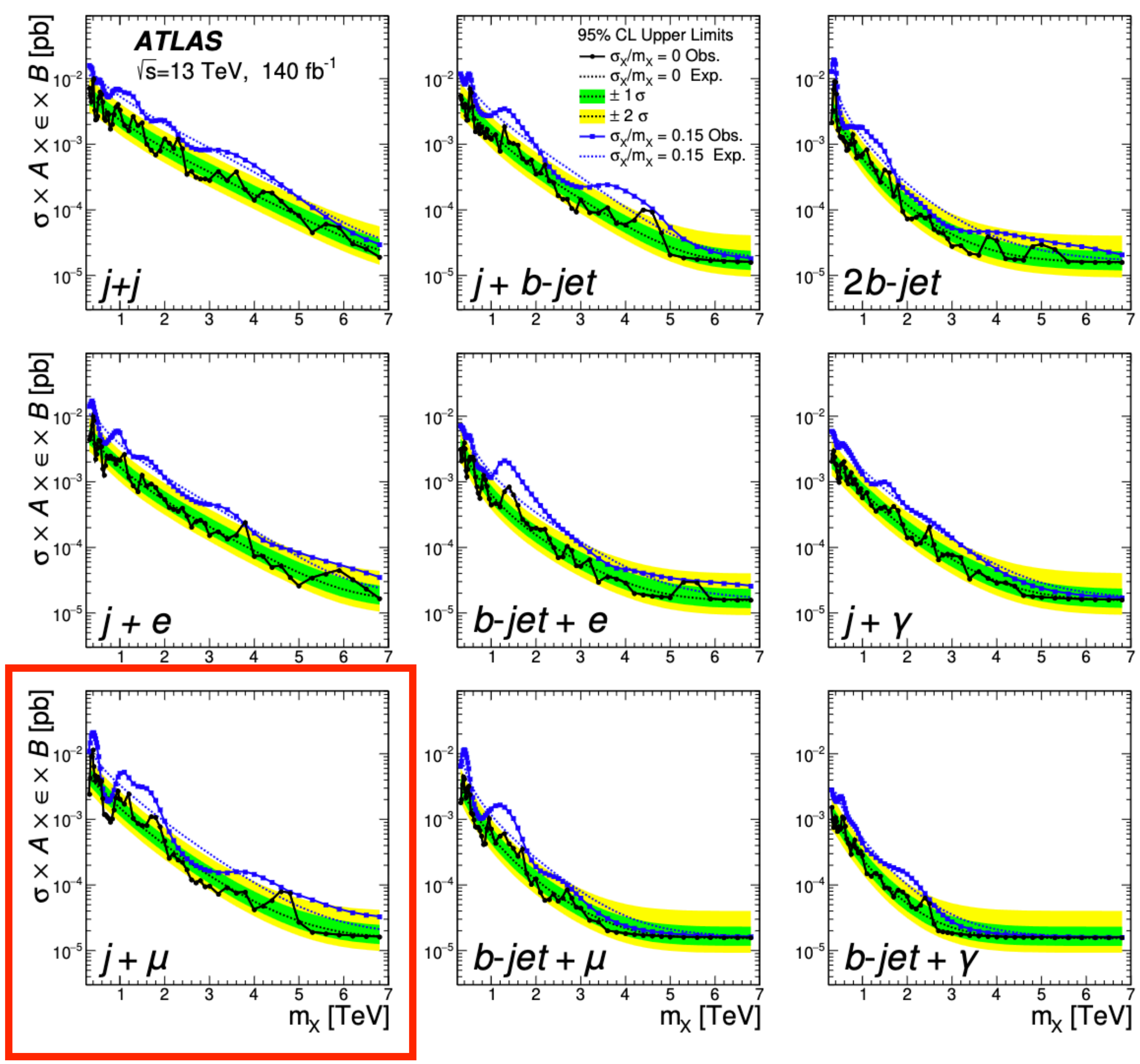
Phys. Rev. Lett. 132 (2024) 081801

lepton/photon + jet/dijet in ATLAS EXPERIMENT

NEW

- Highest significances of 2.8σ and 2.9σ found for $m_{j\mu}$ = 1.2 and 4.8 TeV
- Limits are set for a generic Gaussian signal hypotheses of different widths





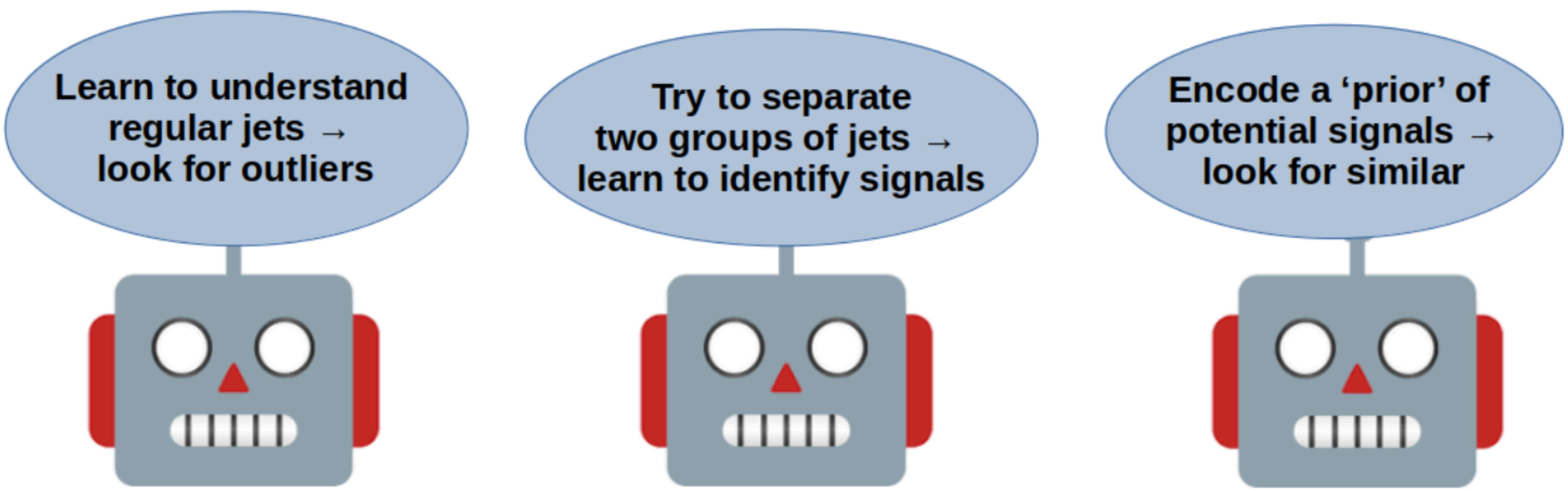
[Phys. Rev. Lett. 132 (2024) 081801]

New CMS search using all these approaches just released for this conference!

Model-agnostic search for dijet resonances with anomalous jet substructure in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS Collaboration

[CMS-PAS-EXO-22-026]



Autoenconders

Classification Without Labels
CATHODE
Tag N' Train

Quasi Anomalous Knowledge

Increasing model dependence

CMS approach: try them all !

NEW

[CMS-PAS-EXO-22-026](CMS-PAS-EXO-22-026)

Nice complementarity

Input features

VAE	CWoLa	TNT	CATHODE	QUAK
Constituents p_x, p_y, p_z	m_{SD} τ_{21} τ_{32} τ_{43} n_{const} leptonic energy fraction sub-jets B tag score	same as CWoLa	m_{SD}^{j1} $m_{SD}^{j1} - m_{SD}^{j2}$ τ_{41}^{j1} τ_{41}^{j2} --- + B tag score j1 **CATHODE-b**	$\rho = m_{SD}/p_T$ τ_{21} τ_{32} τ_{43} n_{const} $\sqrt{\tau_{21}} / \tau_1$ jet B tag score

→

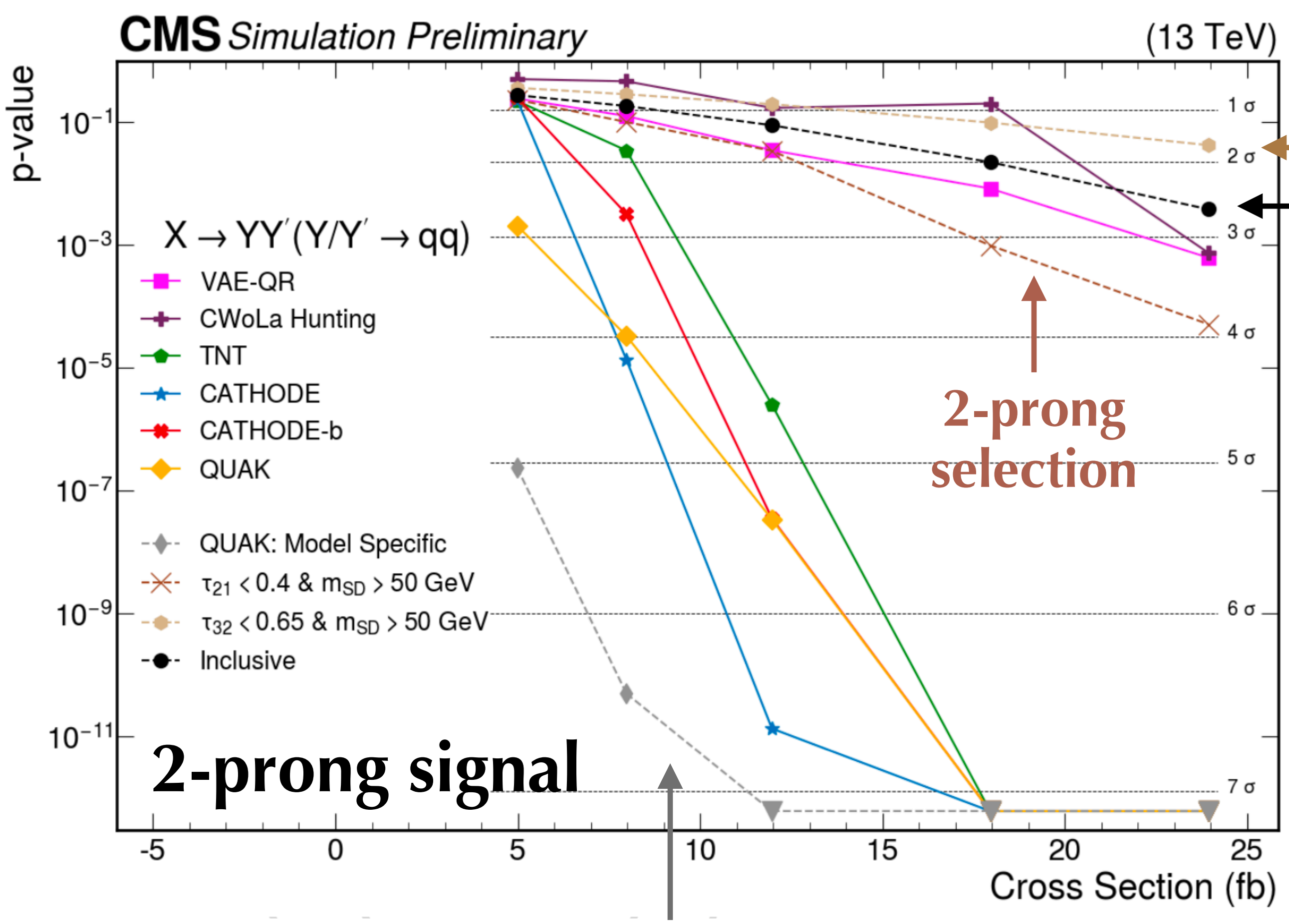
Increasing model dependence

CMS approach: try them all !

NEW

- Inject signal of varying cross section in QCD MC and calculate p-value
- Obtain comparison of sensitivity of different methods against
  - **inclusive search (i.e. no jets selection)**
  - **selection on jet 2-prong observable**
  - **selection on jet 3-prong observable**

MC only studies



3-prong selection

inclusive search

~ multivariate supervised search

All anomaly detection methods improve sensitivity wrt inclusive search!

The autoencoder (VAE) fully model-independent shows less improvement → a more expressive NN architecture and inputs expected to yield better performance

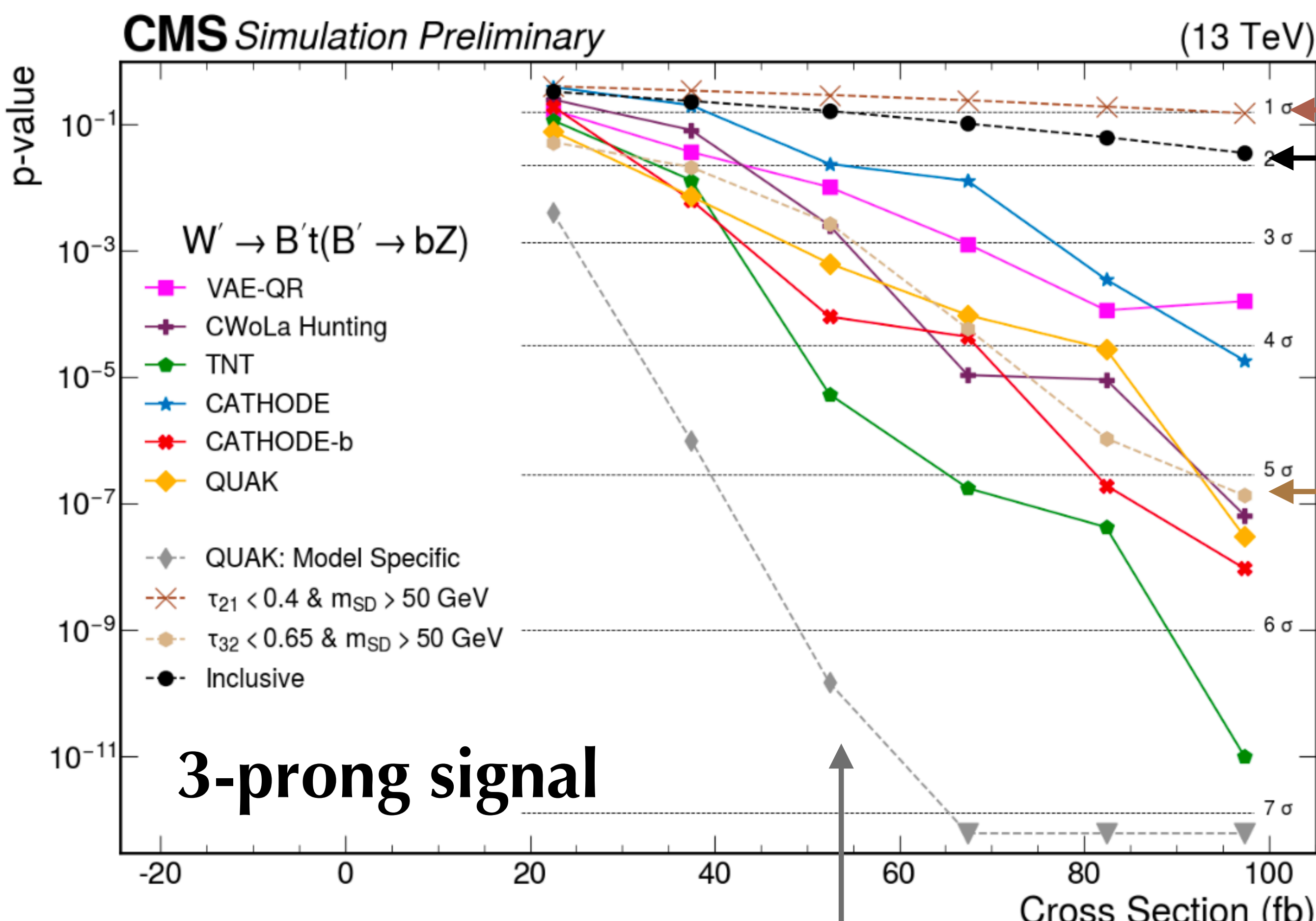
[CMS-PAS-EXO-22-026](CMS-PAS-EXO-22-026)

CMS approach: try them all !

NEW

- Similar results for a 3-prong signal with one b-jet → **good generalization**
- Relative performance of the anomaly detection methods vary between the two signals and no method found to be optimal for both → **good complementarity**

MC only studies



2-prong selection

inclusive search

3-prong selection

~ multivariate supervised search

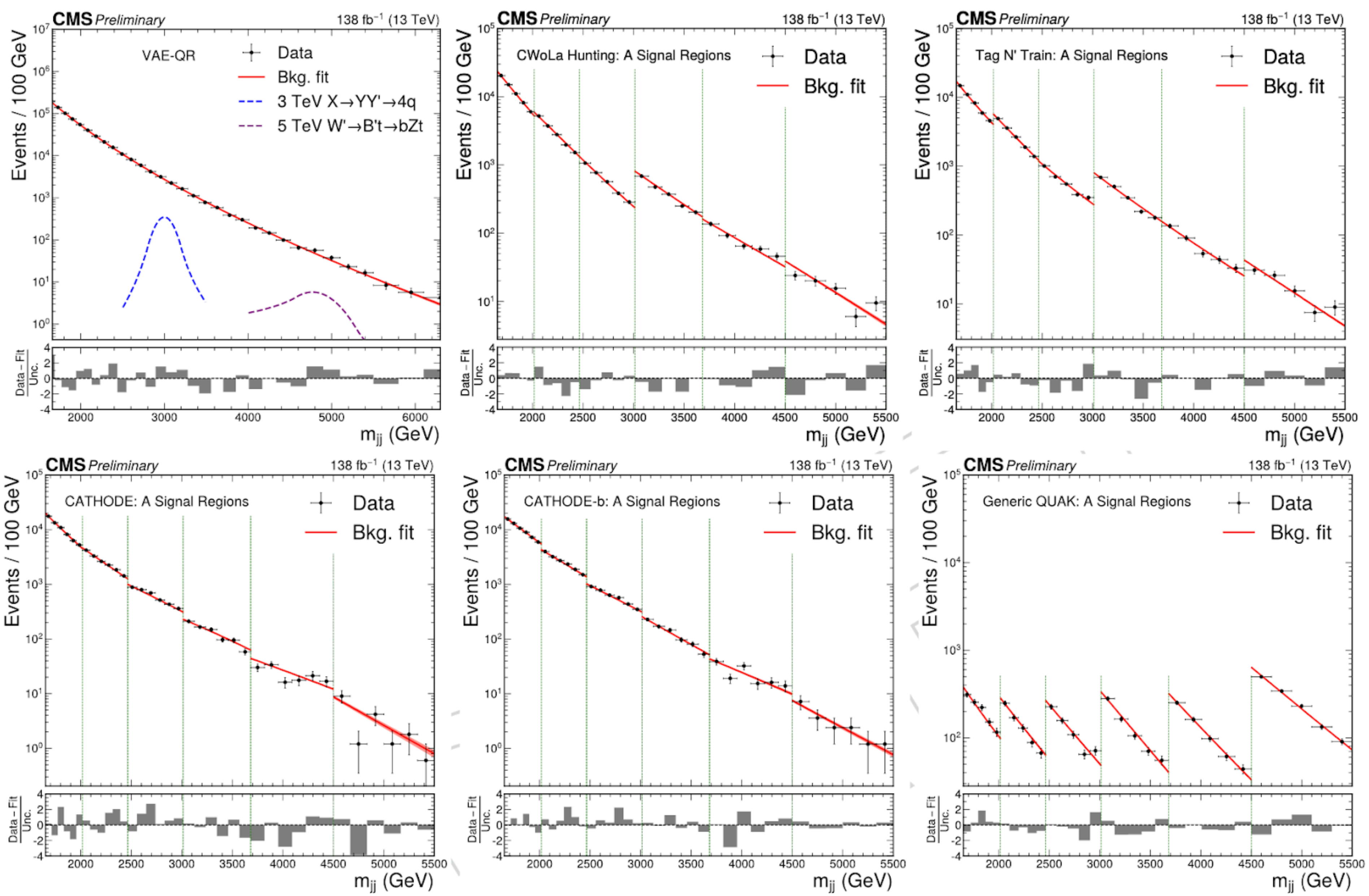
[CMS-PAS-EXO-22-026](CMS-PAS-EXO-22-026)

CMS approach: try them all !

NEW

CMS-PAS-EXO-22-026

- All methods perform bump hunt on dijet invariant mass spectrum after selection on anomaly score
- Discontinuity for all methods expect for the autoencoder due to multiple anomalous signal regions in m_{jj} depending on resonance mass assumption

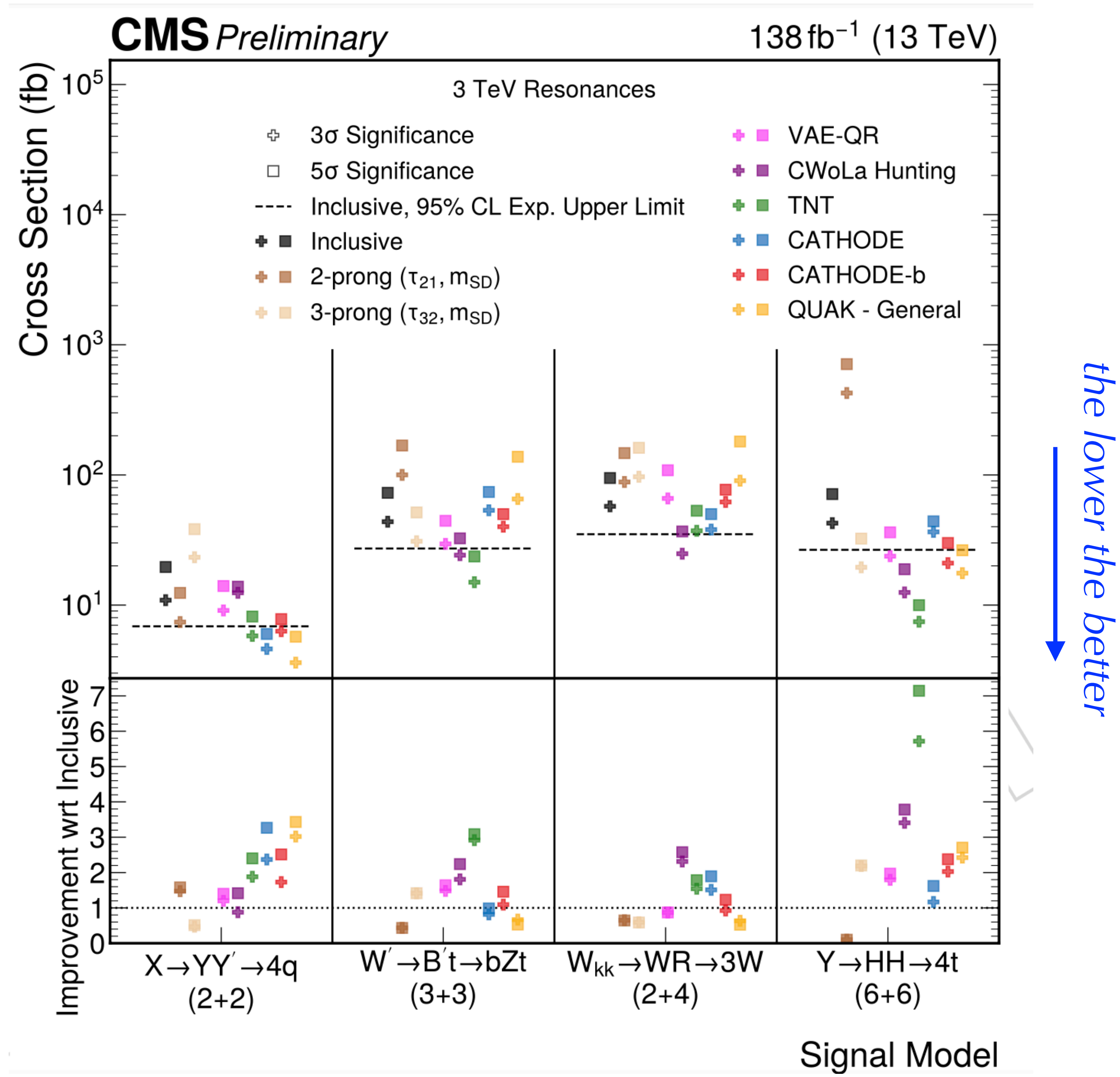


New metric: discovery sensitivity

[CMS-PAS-EXO-22-026](CMS-PAS-EXO-22-026)

NEW

- No excess observed → **inject signal to find which cross section would have lead to evidence (3σ) / discovery (5σ)**
- We probe many different signals with different combination of masses and substructure
- For every benchmark, at least one method could claim discovery where inclusive strategy can only set upper limits
- **All methods almost always better than inclusive / traditional search strategy!**

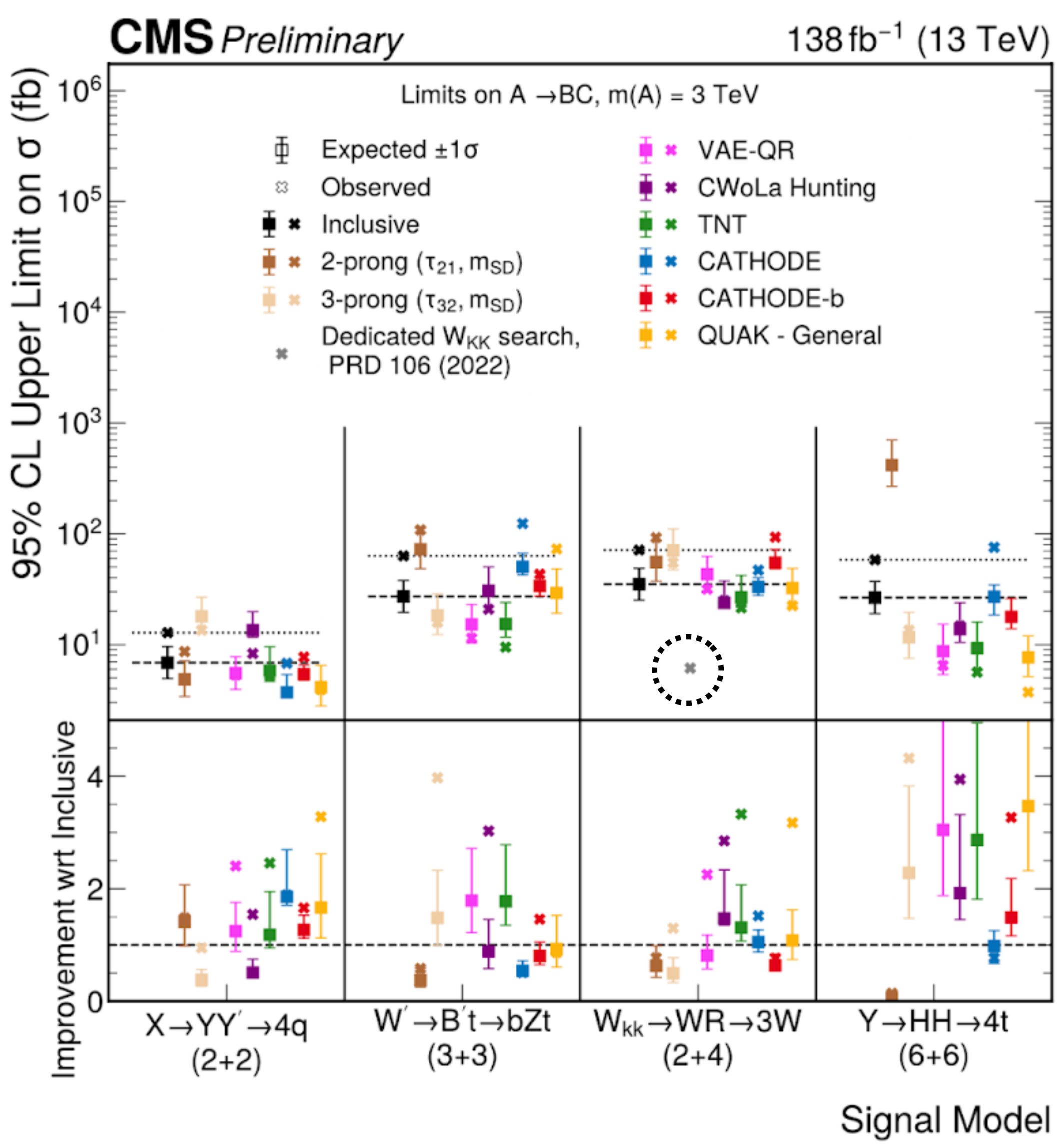


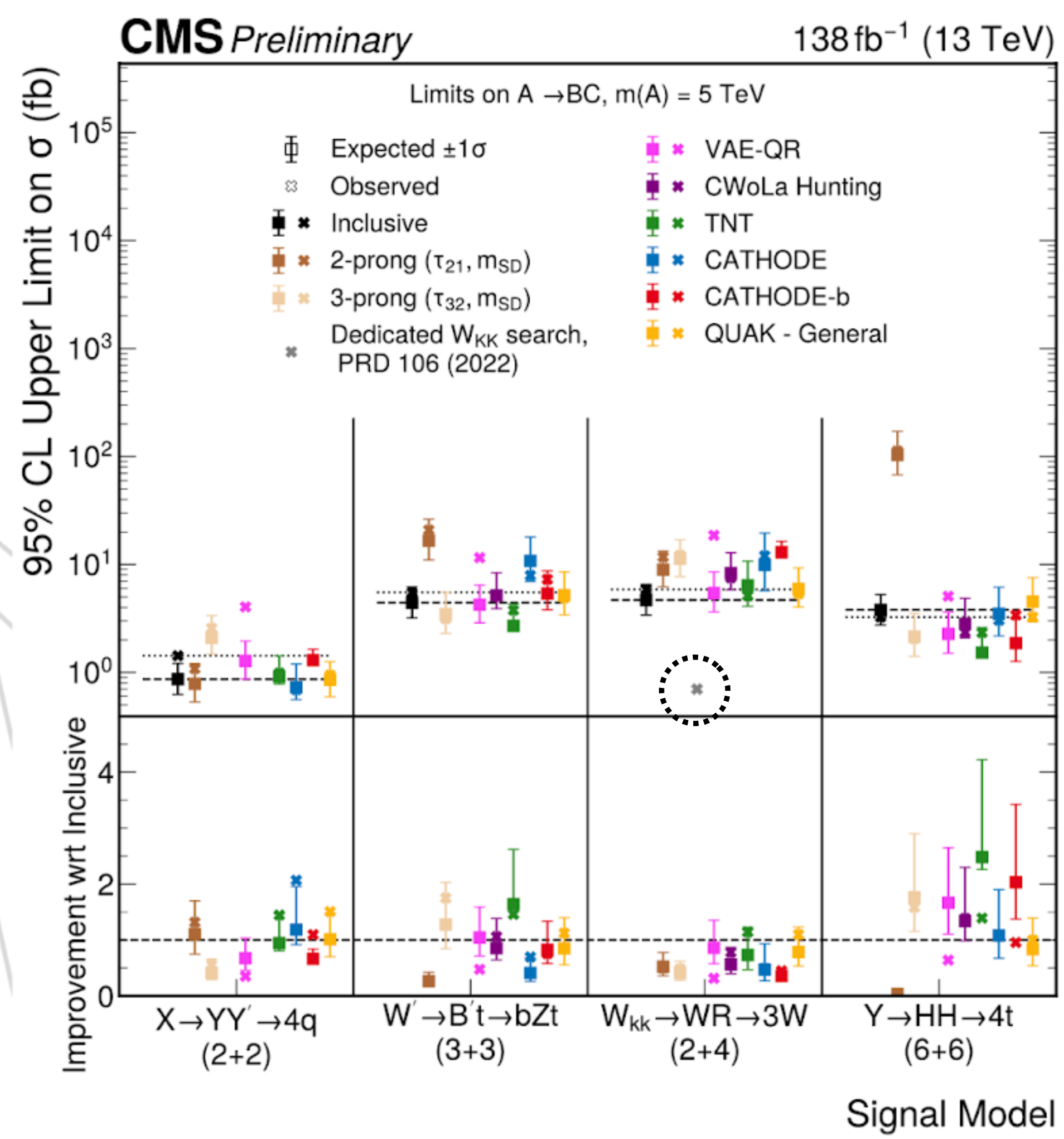
Usual metric: limits

CMS-PAS-EXO-22-026

NEW

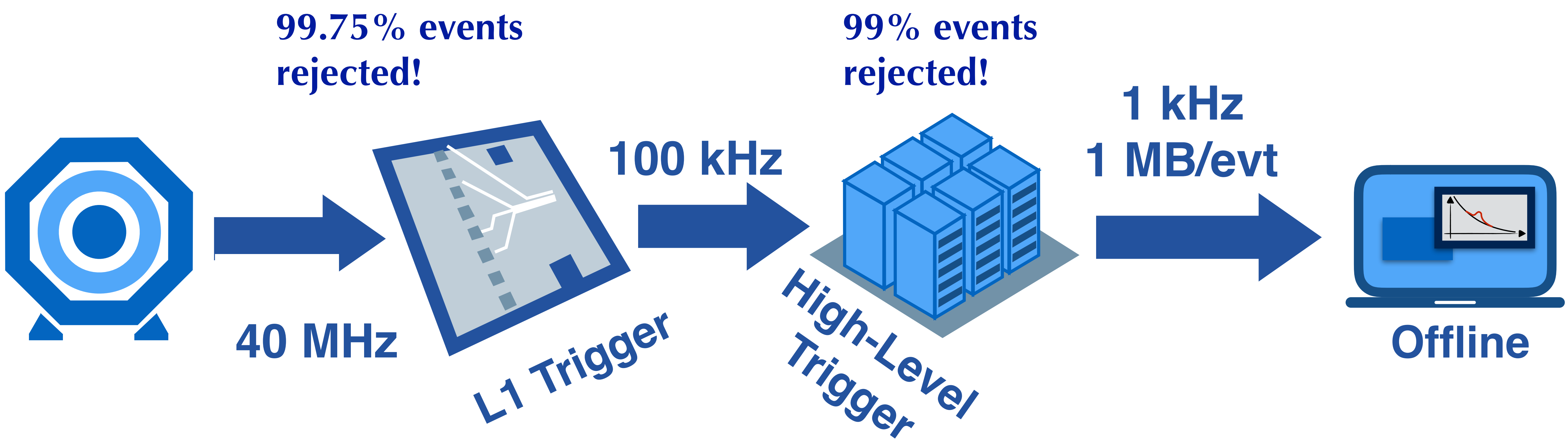
- Set 95% CL upper limits for all signal benchmarks
- Larger improvement over inclusive strategy at 3 TeV, running out of statistics at 5 TeV
- Dedicated W_{KK} search beats all anomaly detection methods (expected)





Data reduction @ LHC

O(Tb/s) data rates require multiple levels of filtering



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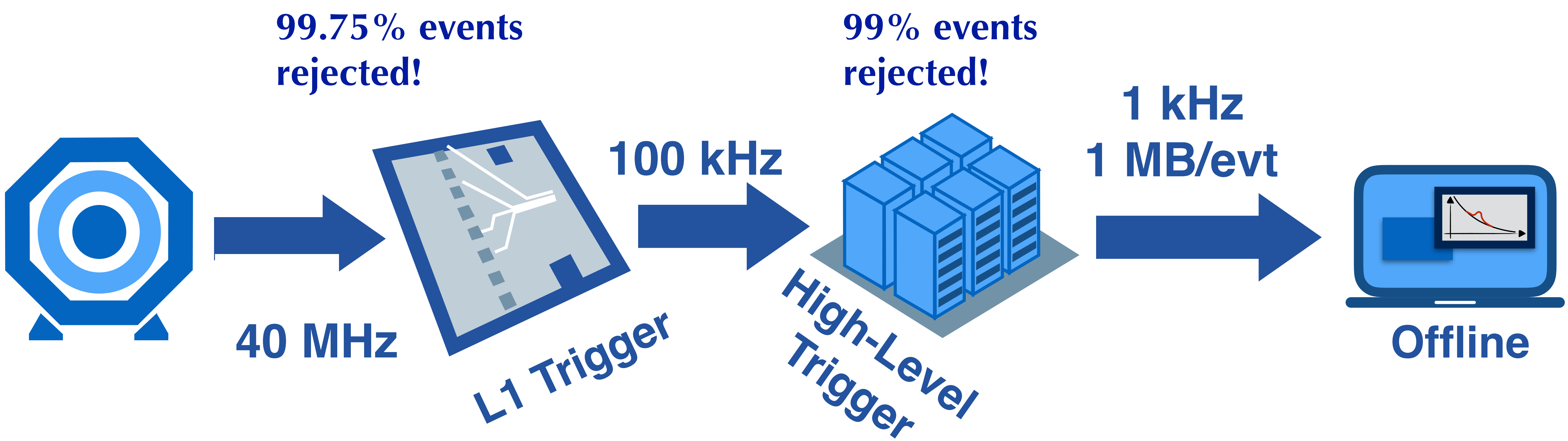
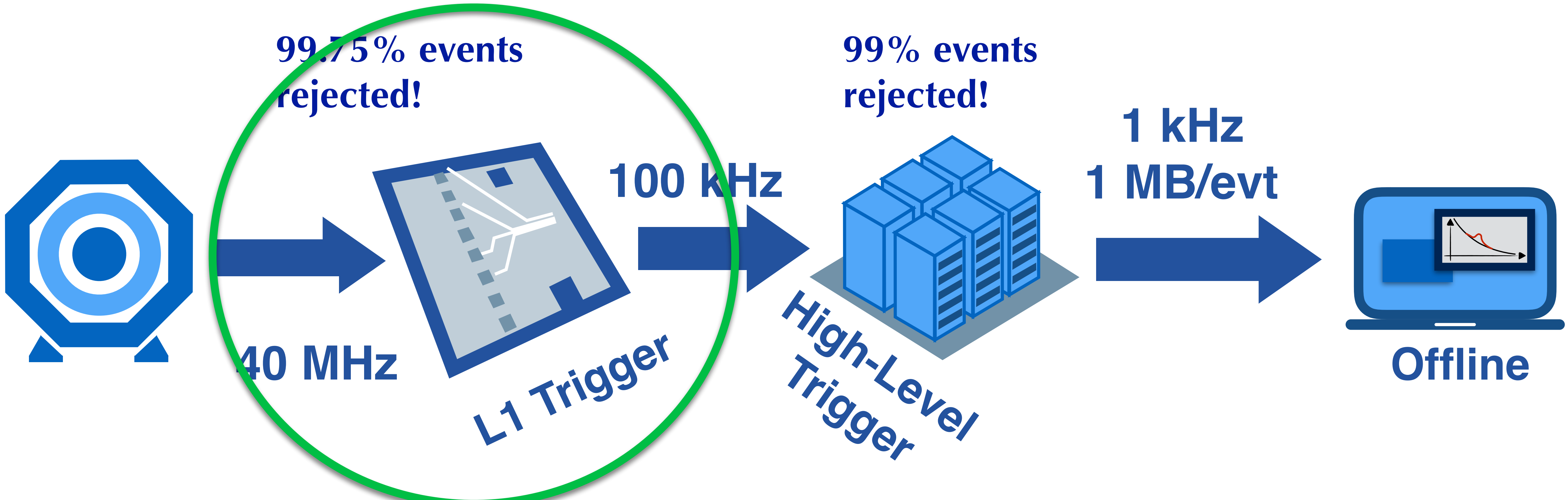


- **With 40M collisions/seconds and 1000 stored, we might just being writing the wrong events**
  - trigger algorithms quite model dependent
  - any other signature we did not think about could have easily be discarded

THE ANOMALY MIGHT BE DISCARDED BY THE TRIGGER



Correct the problem as early as possible in the data reduction workflow!

Bring anomaly detection to the trigger

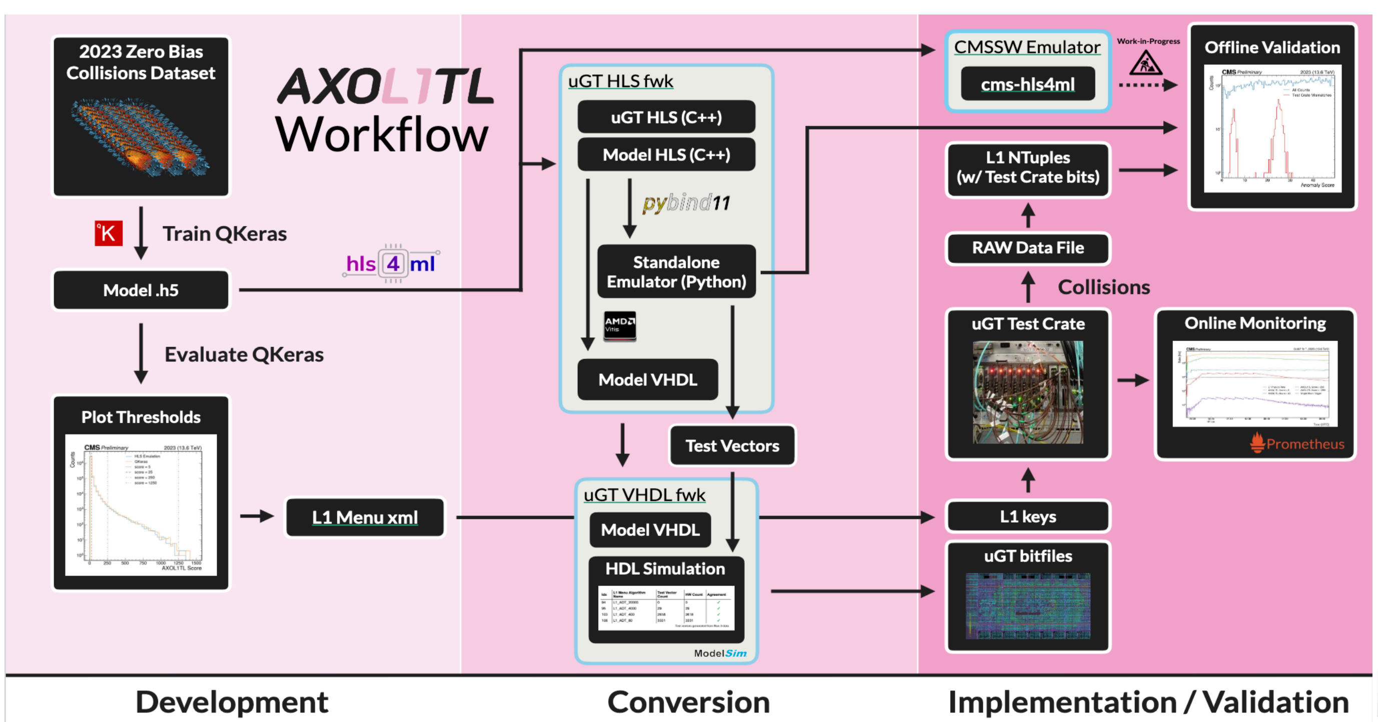
- **CMS has developed two anomaly detection autoencoders for the L1 Trigger with the hls4ml tool → sub-microsecond inference time on one FPGA**
  - based on global trigger inputs: 10 jets, 4 muons, 4 electrons, 1 MET
  - based on the ECAL+HCAL calorimeters image

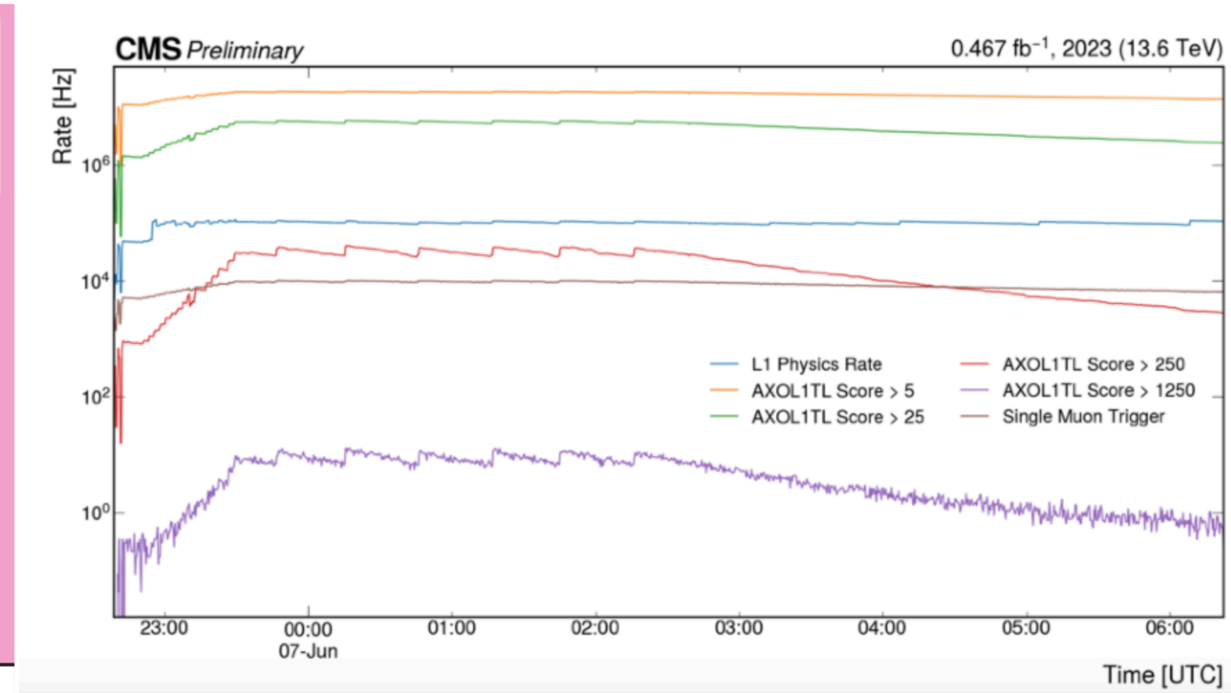
First time at colliders!

- **Firmware and rate stability tests** were performed last year on a hardware system replica able to monitor behaviour during collisions → great stability observed

- Next steps: **integrate in production firmware and establish central production workflow** for quasi-online retraining and deployment

CMS-DP-2023-086
CMS-DP-2023-079





Conclusions

- The search for new physics at the LHC through traditional analyses has **not yielded significant evidence for new physics**, suggesting the need for **novel analysis strategies** like anomaly detection

- Anomaly detection leverages **deep learning to learn directly from data**, eliminating the reliance on signal priors

- Various methods have been explored to enhance the detection of **dijet resonances**

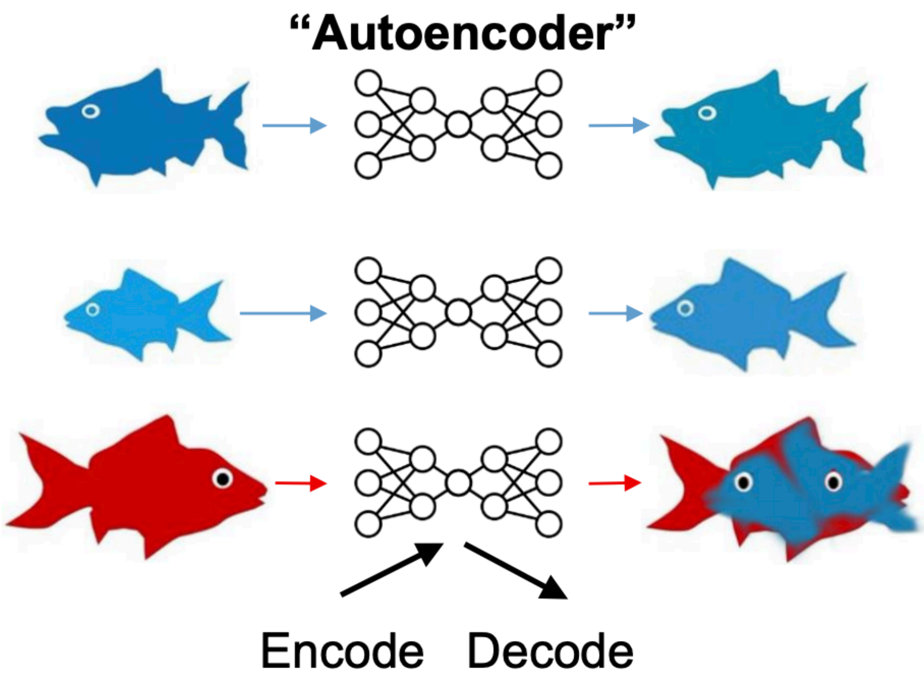
- Expanding the scope of anomaly detection **beyond dijet signatures** to include events with leptons or photons offers a broader reach in the search for new physics

- The CMS approach of **"trying them all"** highlights the importance of testing multiple anomaly detection methods

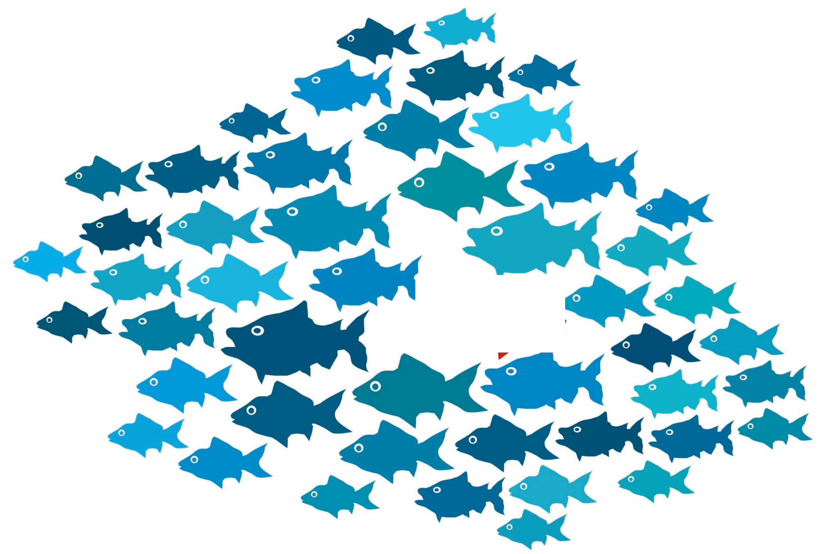
- The significant reduction of data at the LHC poses a challenge eemphasizing the **need for incorporating anomaly detection early at the trigger level**, to ensure potential anomalies are not missed

Backup

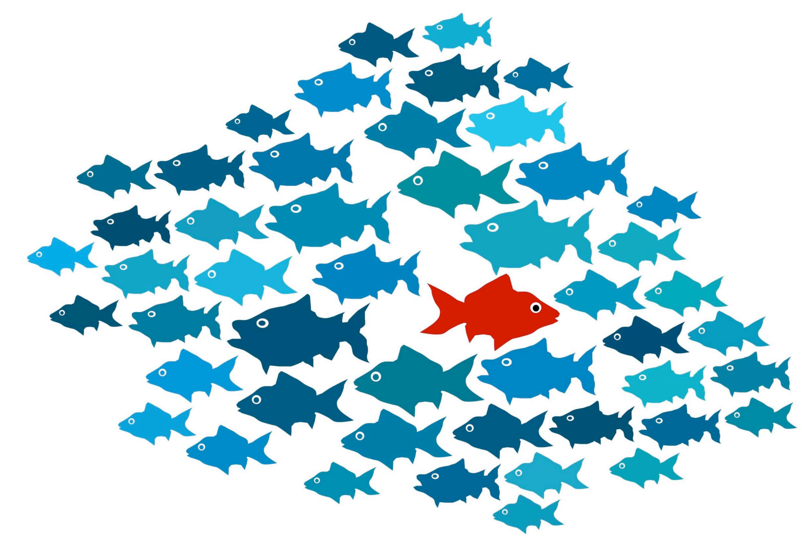
Autoencoders in a nutshell

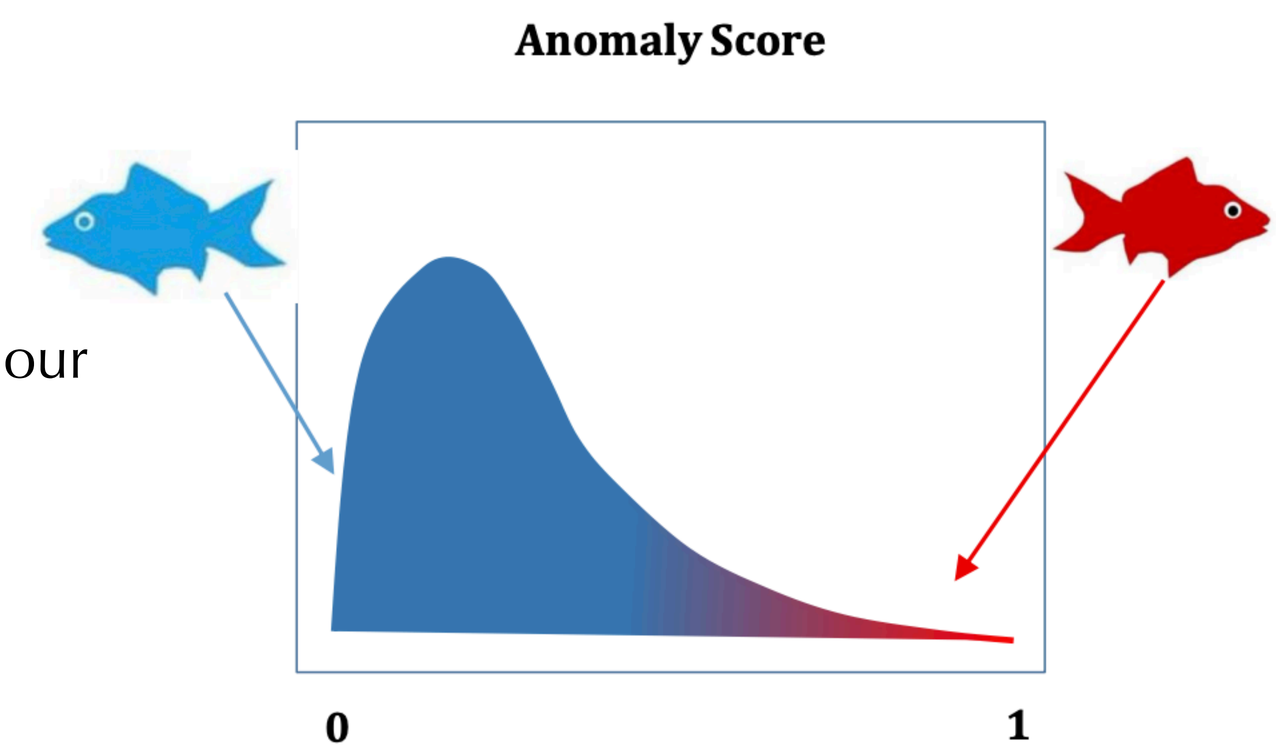


Training examples



Unknown examples

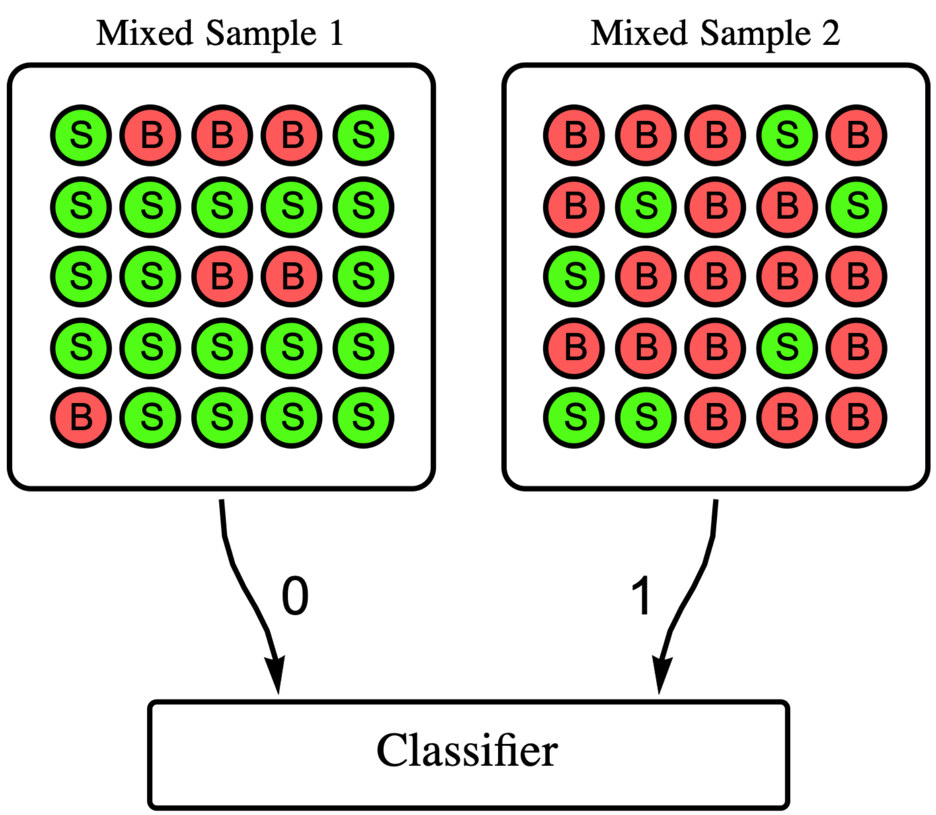




From J. Gonski

- Train on non-anomalous examples
  - model SM (QCD or others) as the normal behaviour
- Force information through a bottleneck and reconstruct input
  - focus on core features of normal examples
- **Fails at reconstructing exotic examples**

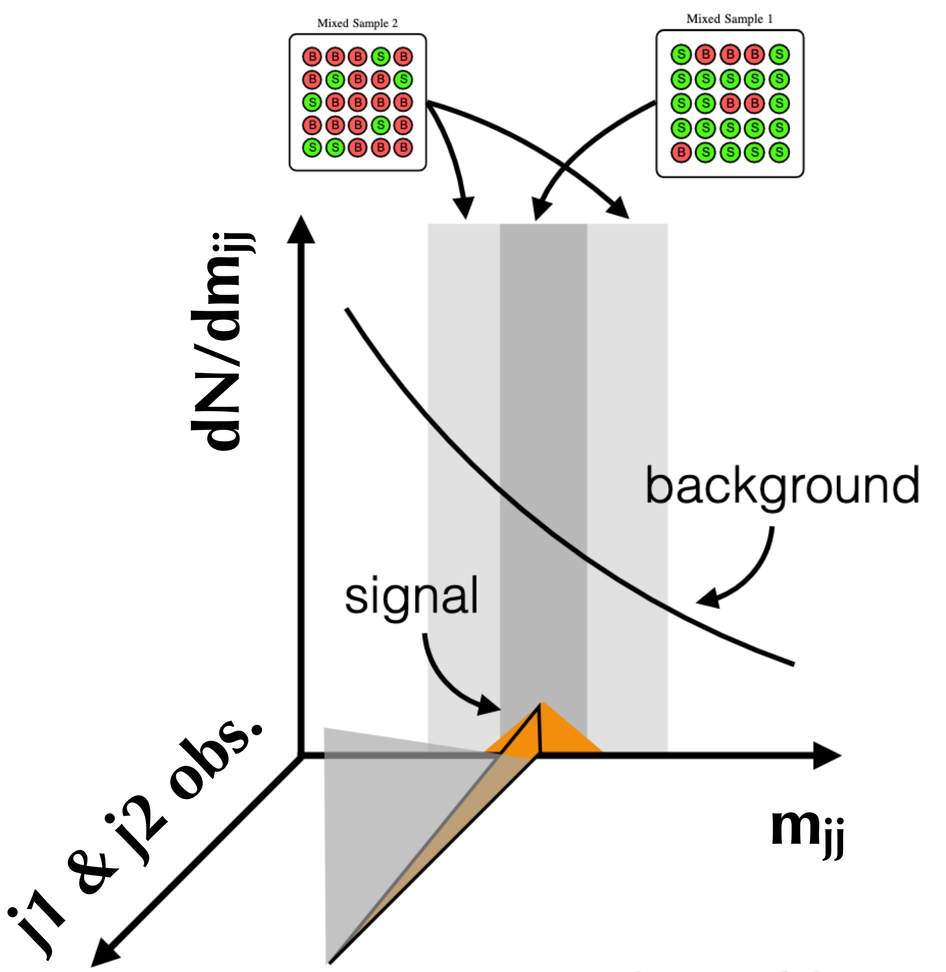
Weak supervision in a nutshell



- Two mixed samples of **signal** and **background** events **with different purities**
- **Train NN classifier on the two samples**
  - Learns to distinguish **signal** vs **background**
- Higher **signal** fraction → better classifier performance
- Model dependence comes from assumption of different purities

How to construct mixed samples

The Classification Without Labels (CWoLa) method

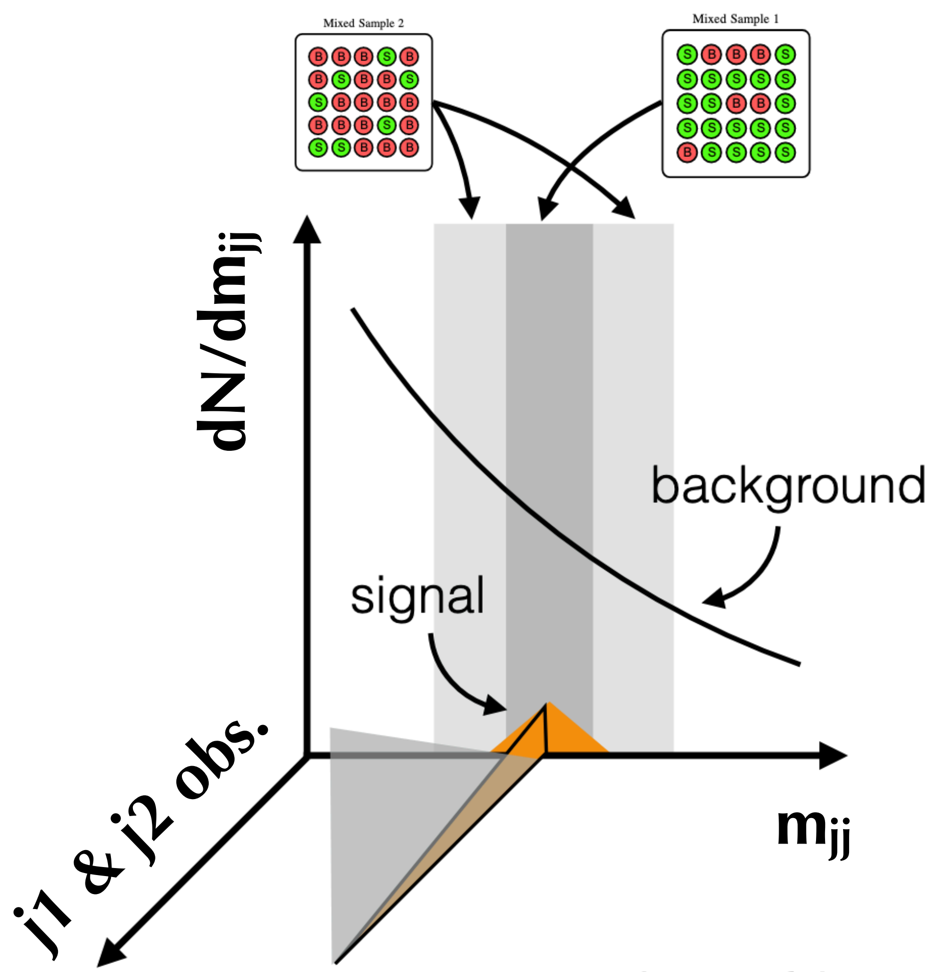


- **Assume** signal X is a narrow resonance with mass M_X → **choose** dijet mass (m_{jj}) windows based on M_X
  - **signal-rich sample** = events from m_{jj} window around M_X
  - **background-rich sample** = events from m_{jj} sidebands
- Train a NN classifier on the two jets observables from **signal-rich sample** vs. **background-rich sample**
- **Define event anomaly score*:** *max(score j_1, score j_2)*
- Many sliding m_{jj} windows defined to cover the full mass range

*CMS definition slightly different from original method paper: Phys. Rev. D 99, 014038

How to construct mixed samples

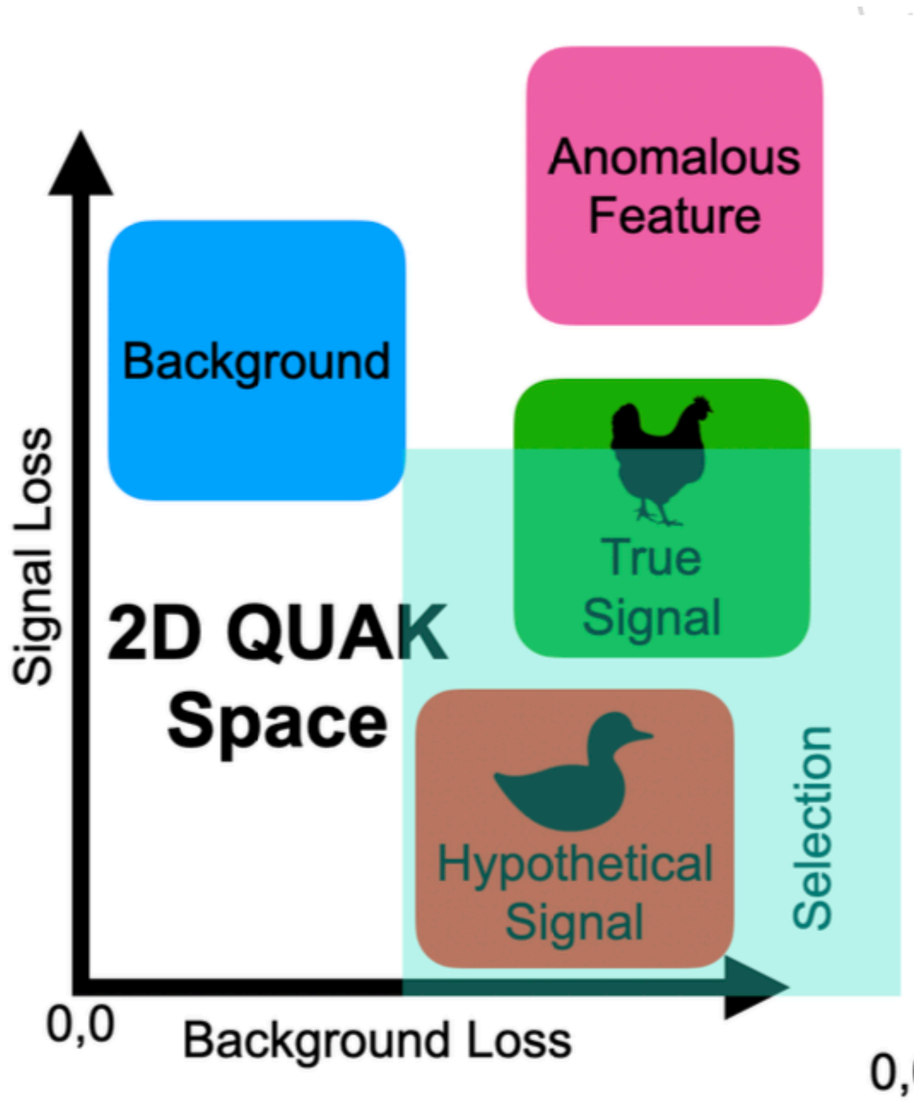
Tag N′ Train and CATHODE methods



- Other methods exist all assuming a narrow resonance:
  - **Tag N′ Train (TNT):** enrich purity of anomalies before training by using an autoencoder [1]
  - **CATHODE:** background in signal region obtained by sampling from sideband pdf estimated (normalizing flows) and interpolated in signal region [2]

[1] J. High Energ. Phys. 2021, 153 (2021)
[2] Phys. Rev. D 106, 055006 (2022)

Quasi Anomalous Knowledge



- **Hybrid** approach between model-independent and standard search
- Idea: **encode prior knowledge** of how a signal could look
- Train density estimator (normalizing flow) on mixture of **simulated signals**
- Train additional normalizing flow on **background simulation**
- Construct 2D space, select events with high background score and low signal score
  - new signal similar to encoded knowledge
- Can be made even **more signal specific by using only model to be probed for encoding**
  → aka supervised search

J. High Energ. Phys. 2021, 30 (2021)