



CMS new physics search highlights

— A lens on recent
experimental innovations

Congqiao Li (李聪乔) (*Peking University*)
on behalf of the CMS Collaboration

第十七届 TeV 工作组学术研讨会 · 南京
16 December, 2023

The CMS collaboration

3394

PHYSICISTS
(1228 STUDENTS)

1102

ENGINEERS

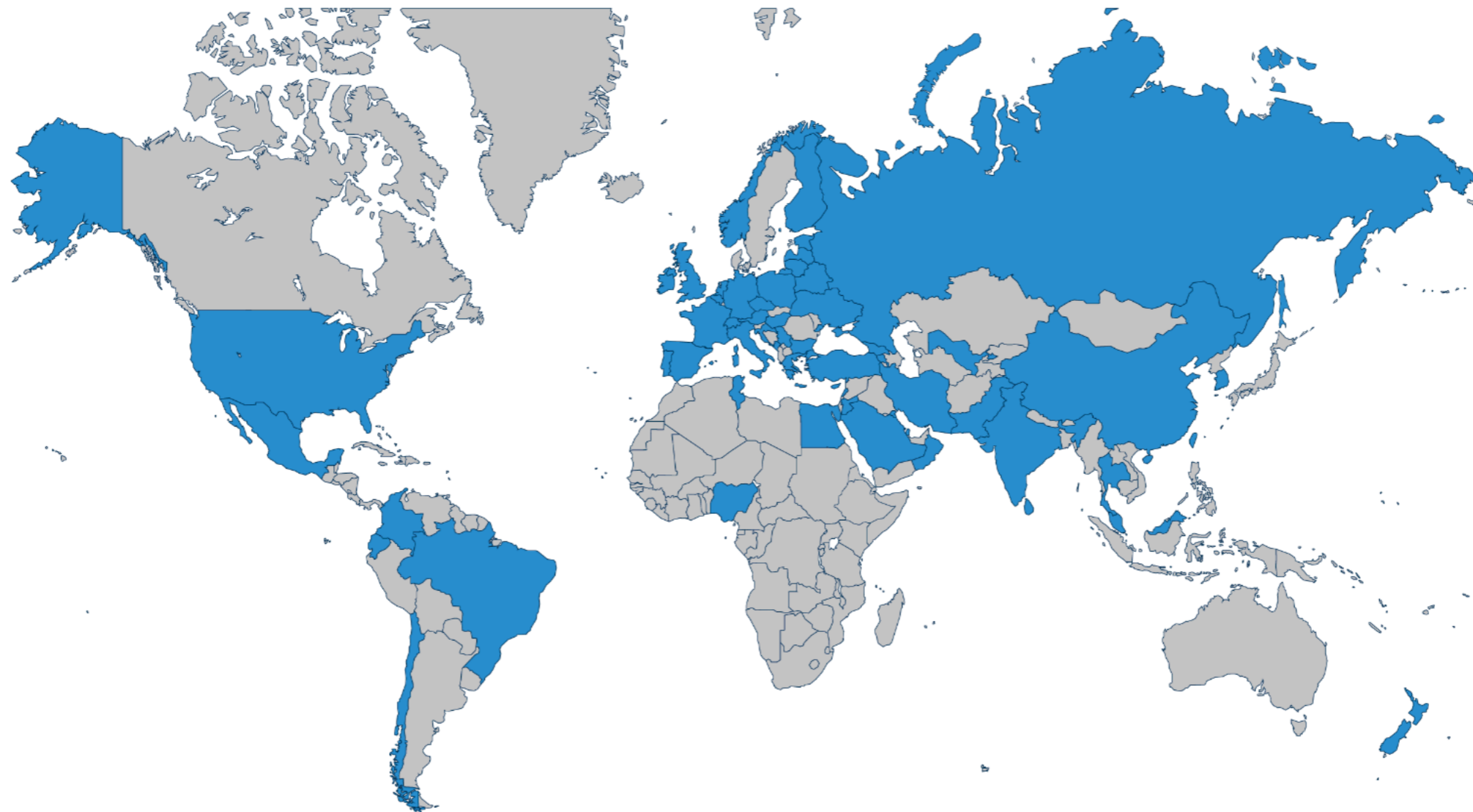
282

TECHNICIANS

247

INSTITUTES

57

COUNTRIES &
REGIONS*stat. from [link](#)*

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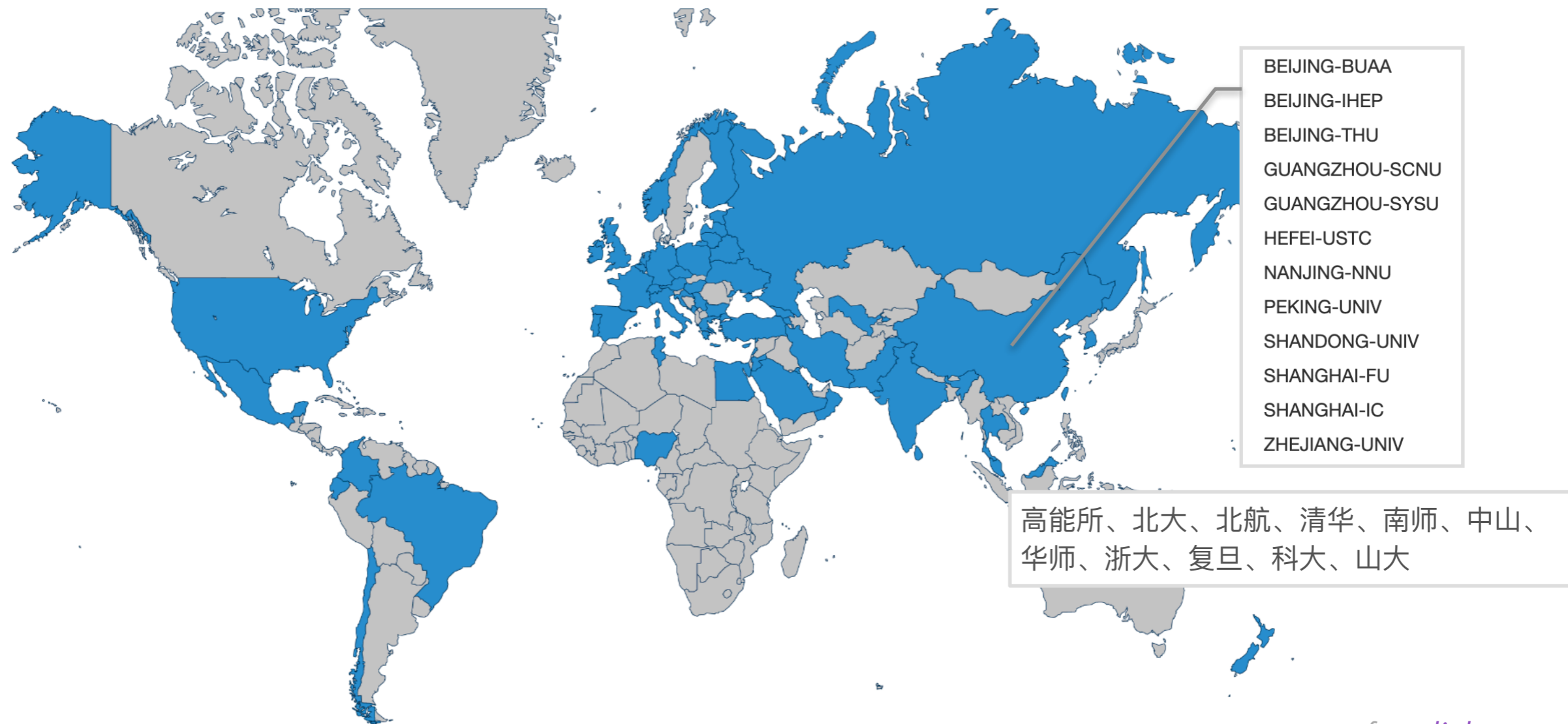
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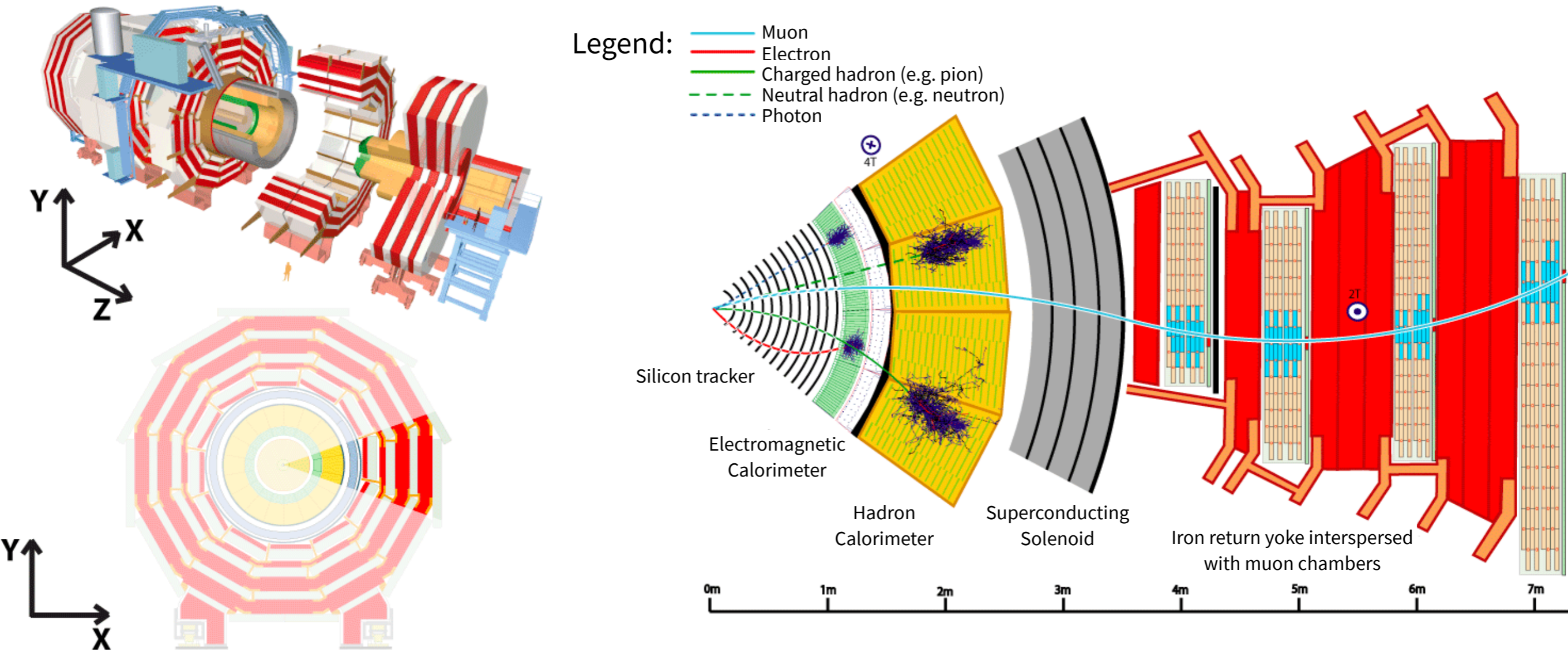
247

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The CMS detector



CMS publications

Show all

Total

Exotica

Standard Model

Supersymmetry

Higgs

Top

Heavy Ions

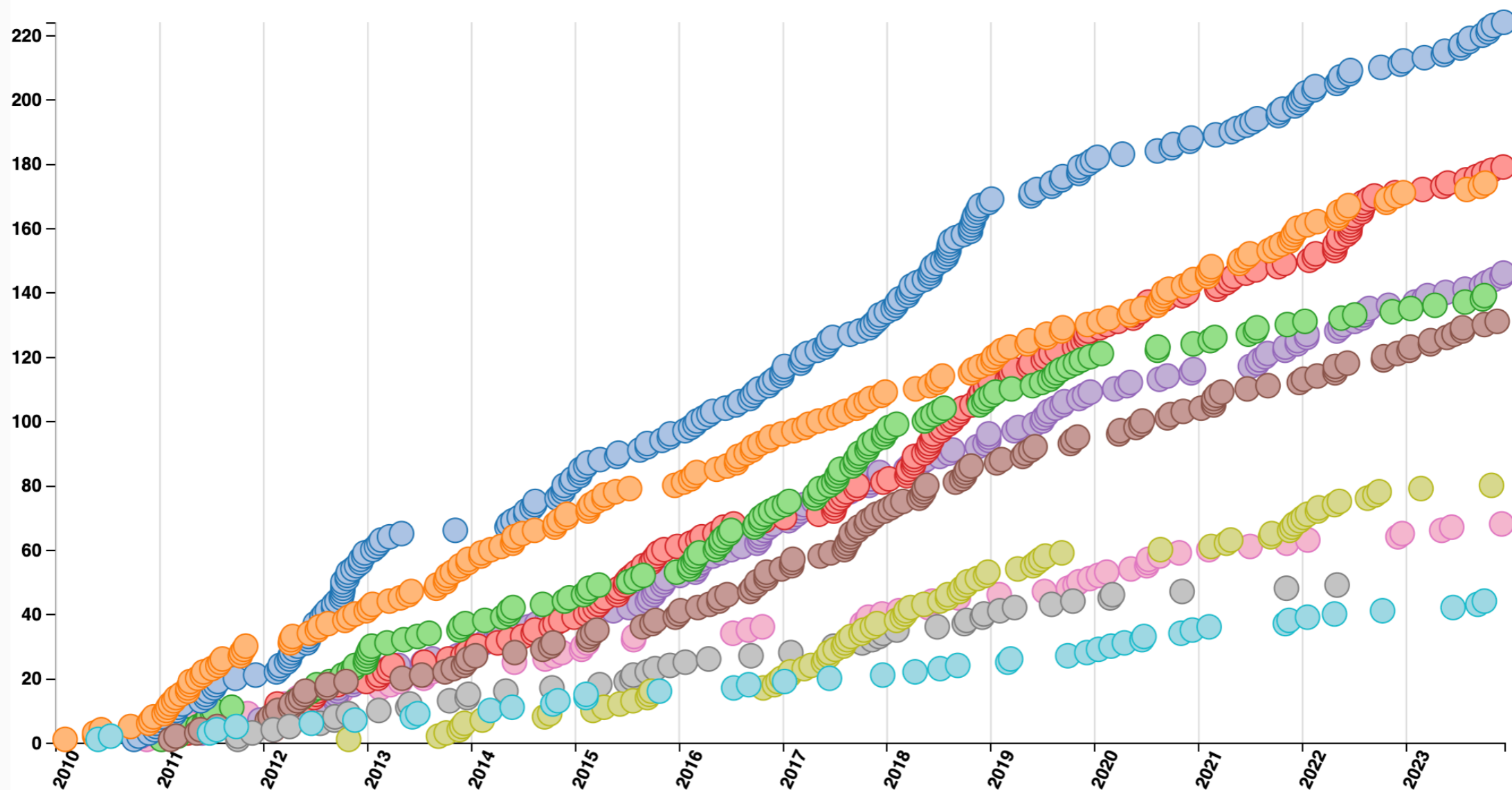
B and Quarkonia

Forward and Soft QCD

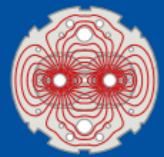
Beyond 2 Generations

Detector Performance

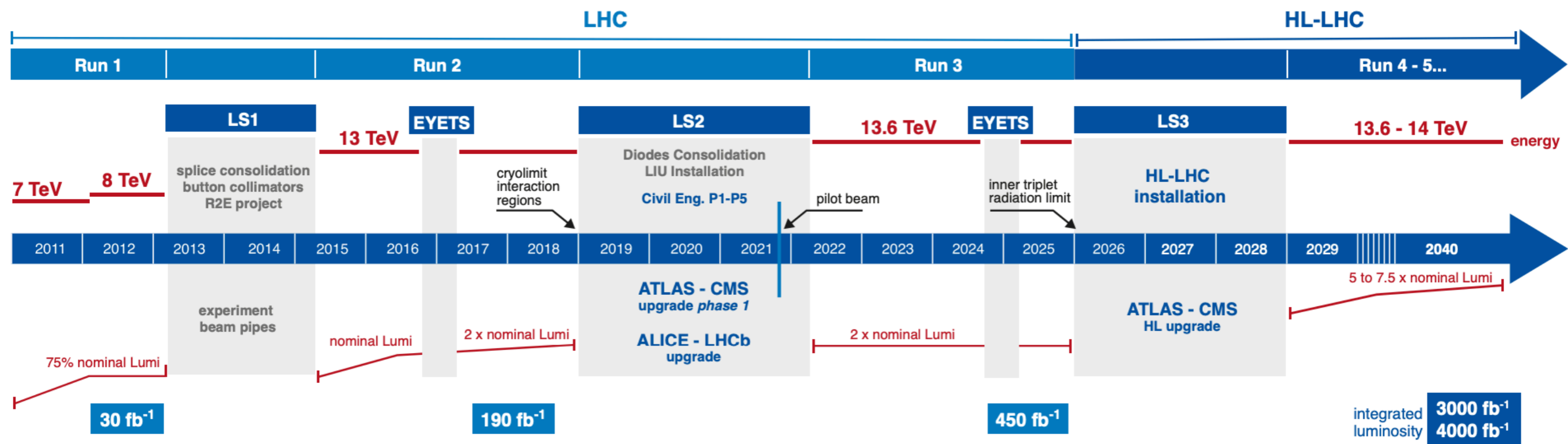
1234 collider data papers submitted as of 2023-12-13



LHC / HL-LHC schedule



LHC / HL-LHC Plan

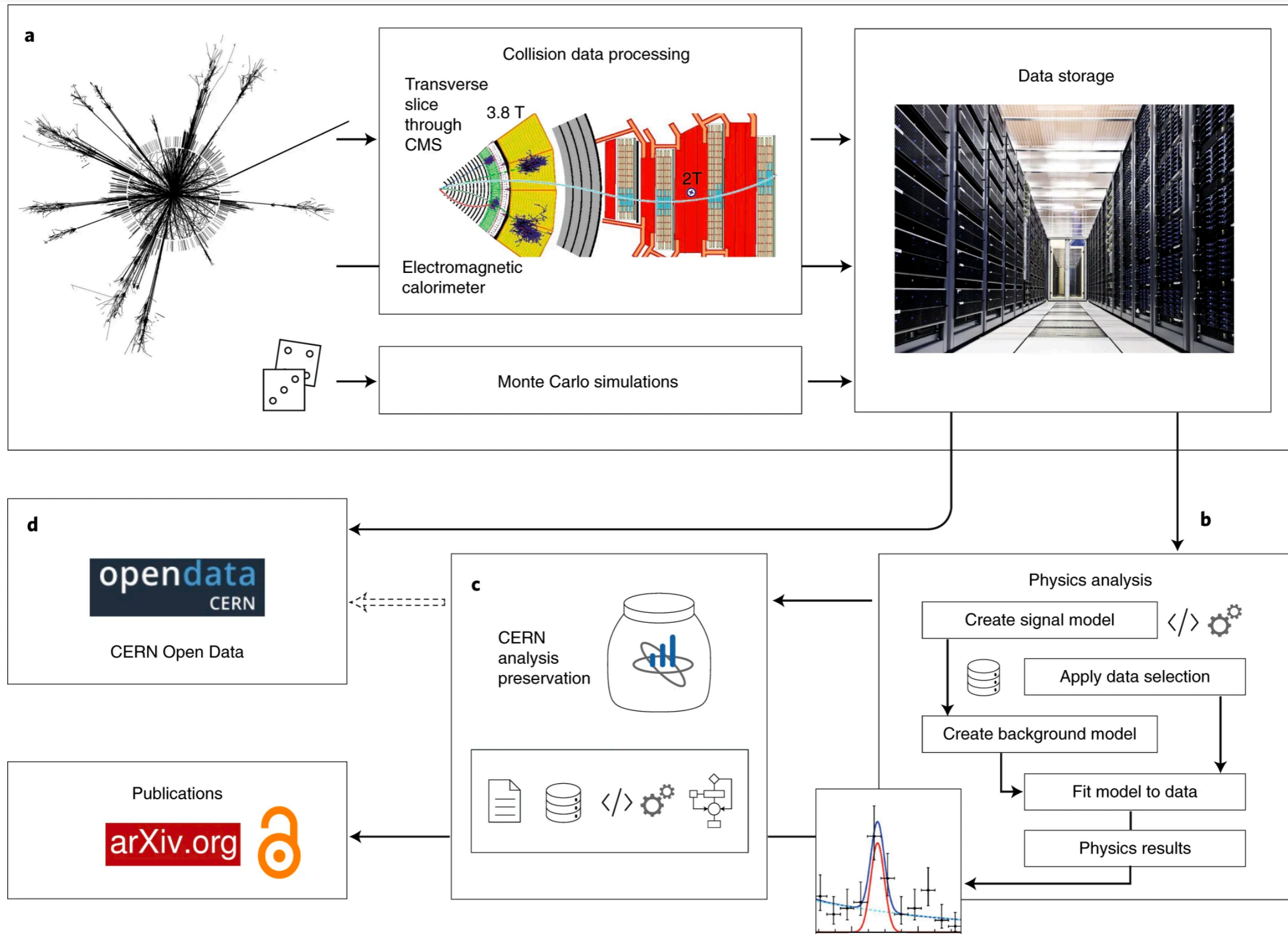


HL-LHC TECHNICAL EQUIPMENT:



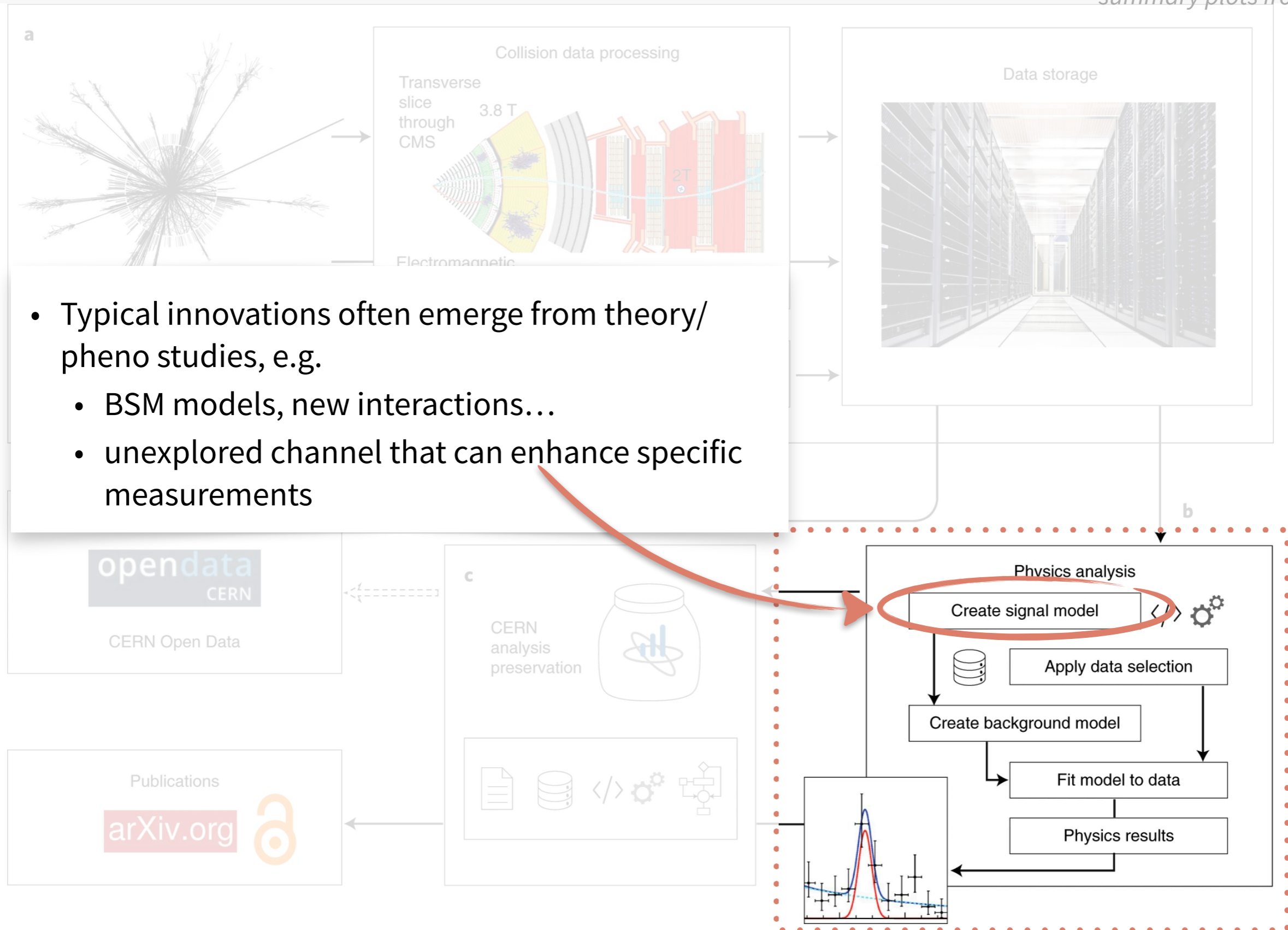
Typical CMS experiment workflow

borrow the figure from [link](#)



Typical CMS experiment workflow

summary plots from [link](#)

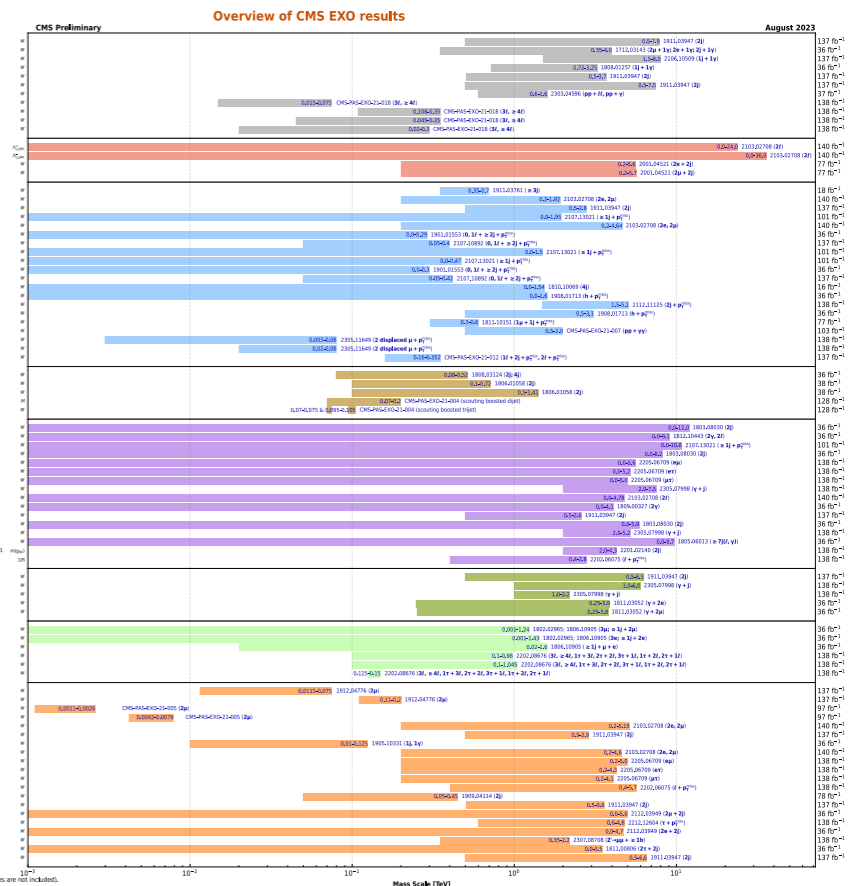


Typical CMS experiment workflow

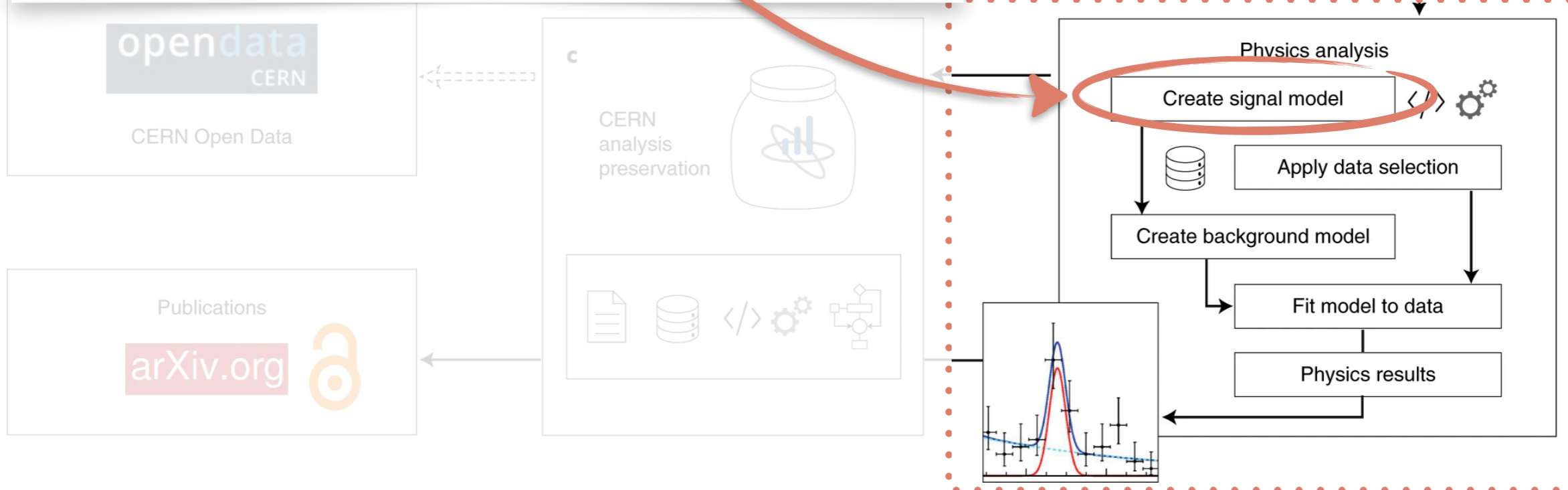
summary plots from [link](#)

Theory-oriented BSM searches:
pseudo-scalar particles (ALPs)
SUSY, LFV, LLPs, lepto-quarks, ...

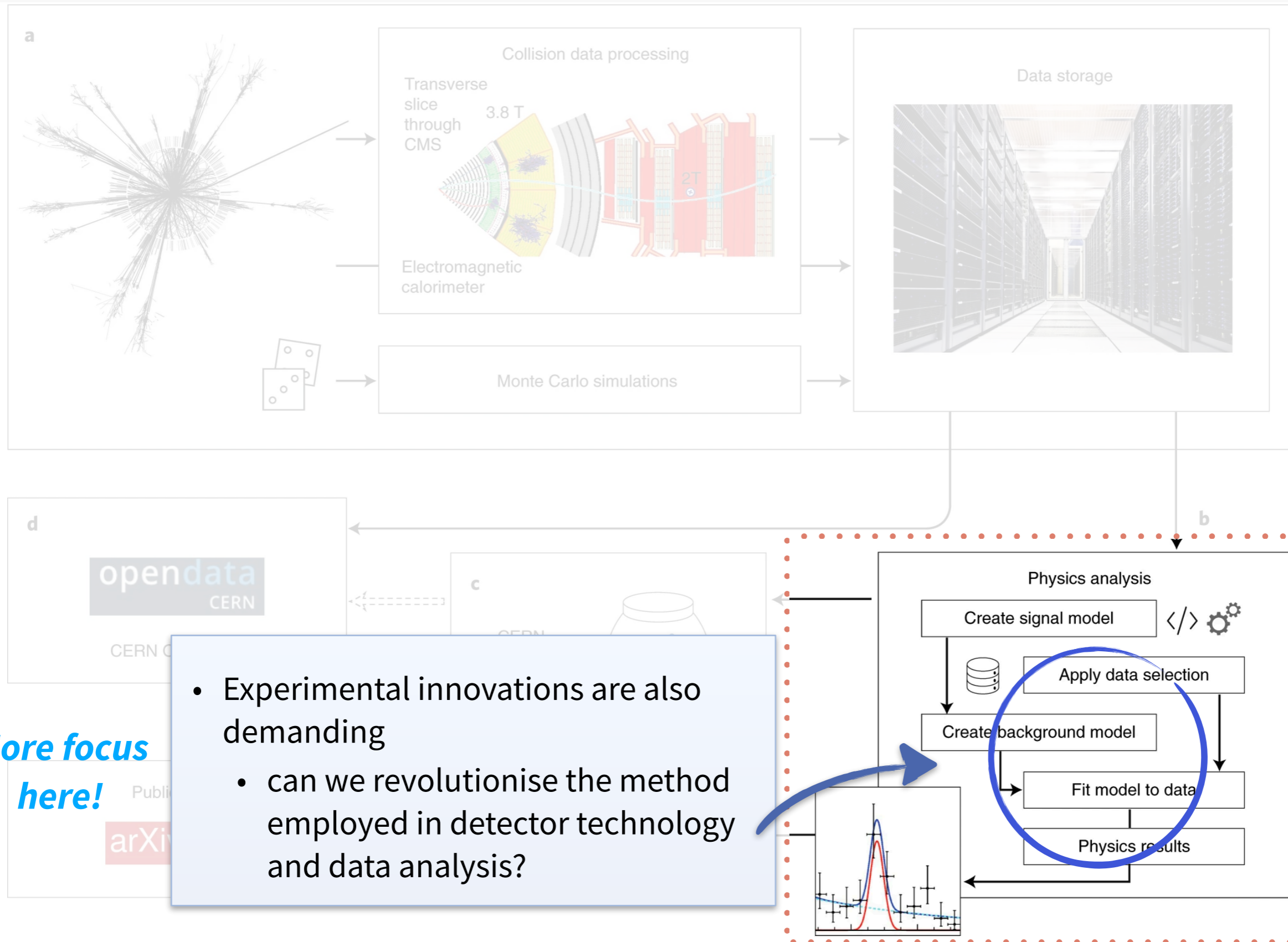
See selected CMS result overview →
But not our main focus today!



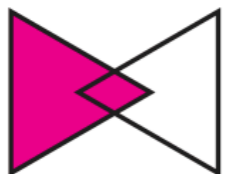
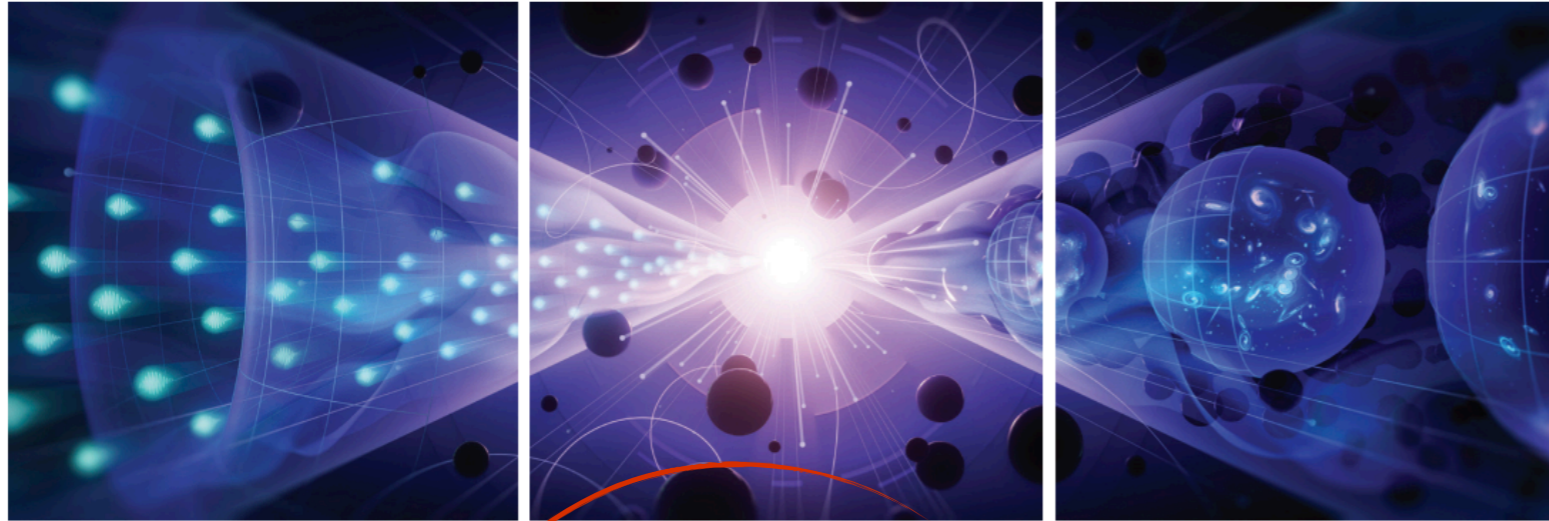
- Typical innovations often emerge from theory/pheno studies, e.g.
 - BSM models, new interactions...
 - unexplored channel that can enhance specific measurements



Highlight: experimental innovations



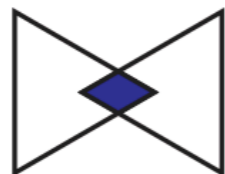
Highlight: experimental innovations



Decipher
the
Quantum
Realm

Elucidate the Mysteries
of Neutrinos

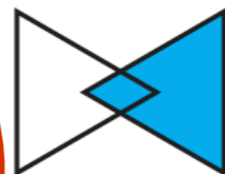
Reveal the Secrets of
the Higgs Boson



Explore
New
Paradigms
in Physics

Search for Direct Evidence
of New Particles

Pursue Quantum Imprints
of New Phenomena



Illuminate
the
Hidden
Universe

Determine the Nature
of Dark Matter

Understand What Drives
Cosmic Evolution

from 2023 P5 report

- theory-motivated search
- experimental data-driven search
- model-agnostic search

The most direct way of answering these questions is by discovering new fundamental particles. If these are very massive they can only be produced directly in high-energy colliders, as the higher the collider energy the higher the mass that can be produced. Another possibility is that these particles are produced at lower energy but very rarely, for example in decays of known particles such as the Higgs boson. This requires accelerators that produce very high numbers of particles, including neutrino experiments with their high intensity beams and massive detectors.

These complementary approaches provide access to an extensive theoretical parameter space that covers both higher mass scales and new physics that is weakly coupled to the Standard Model. Overall, these searches can be broadly categorized into those that are guided by specific theoretical ideas, searches driven by questions resulting from experimental data (e.g. dark matter), and searches that are model-agnostic and perform a general exploration of the unknown. Together, these approaches provide comprehensive coverage of the Beyond the Standard Model (BSM) landscape and have the potential to yield groundbreaking insights into the universe.

Focus of this talk

- In addition to sharing new CMS results, we want to highlight more on experimental innovations achieved these years
 - ❖ broadly driver by the rapid advancement in machine learning
- Cover two aspects
 - ❖ modern deep learning to process low-level data
 - ❖ model-agnostic resonance search
- Hope to share experimental insights with the broader HEP community

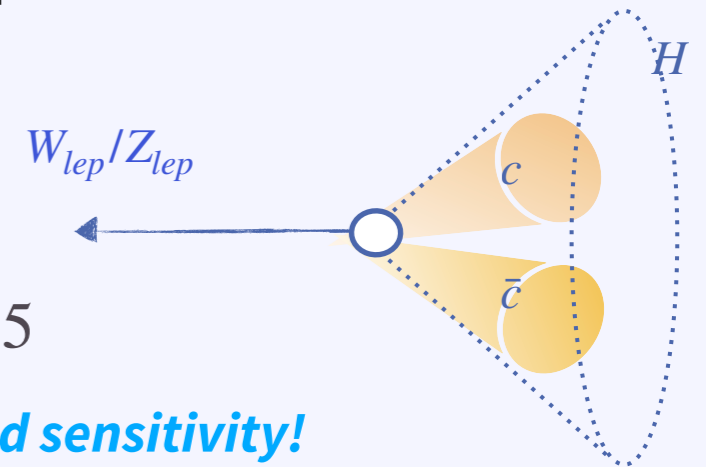


Modern deep learning for low-level input

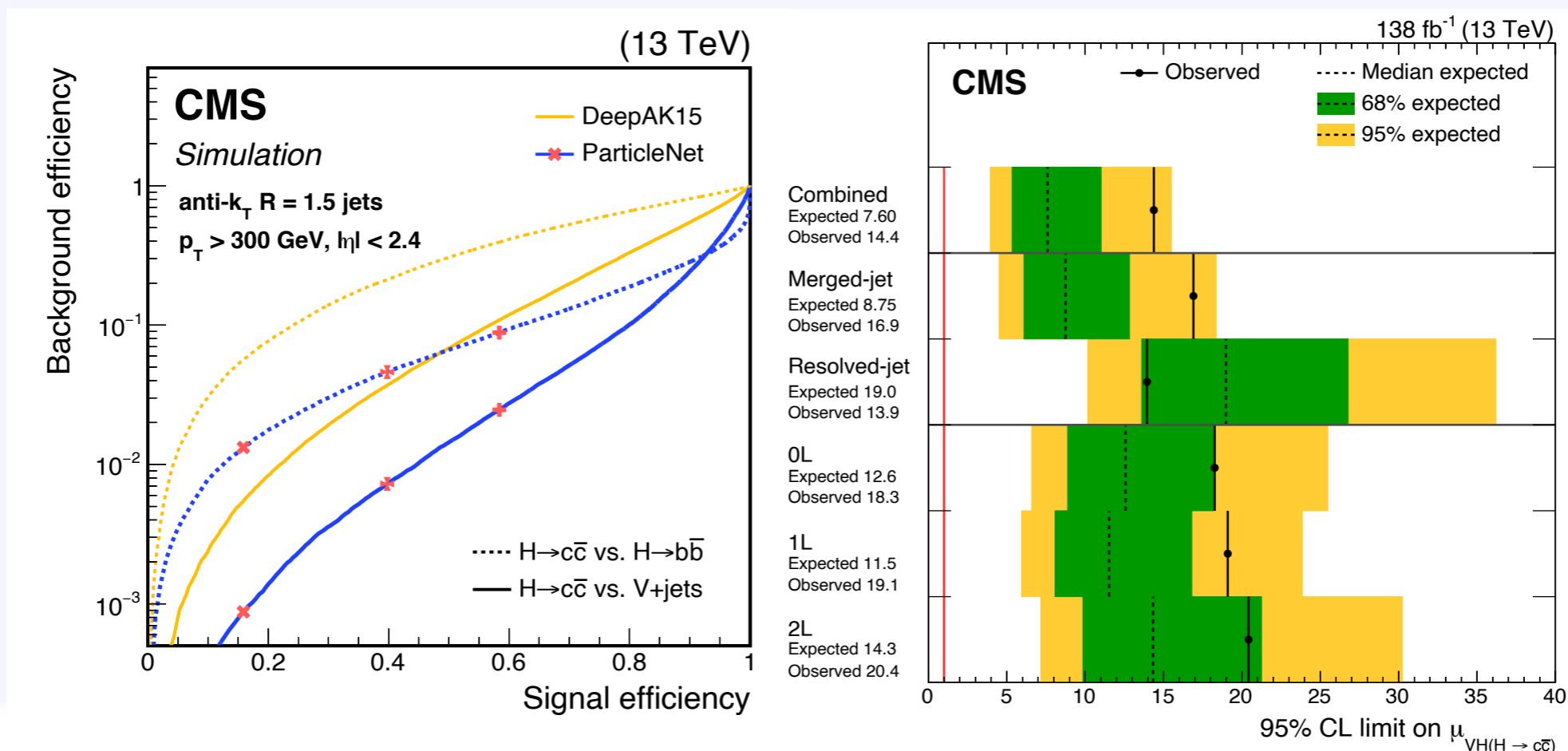
Recent CMS results in Higgs sector

PRL 131 (2023) 061801

- We start with two recent CMS results
- CMS measures κ_c via $VH(\rightarrow c\bar{c})$ production mode, including the merged-jet topology
 - ❖ in merged-jet topology: leveraging advanced jet neural network (ParticleNet) to identify $H\rightarrow c\bar{c}$ jets and reconstruct H mass
 - ❖ obtain the most stringent direct limit (95% C.L.) on κ_c : $1.1 < |\kappa_c| < 5.5$
 - ▶ ATLAS results: $|\kappa_c| < 8.5$ [EPJC 82 (2022) 717]



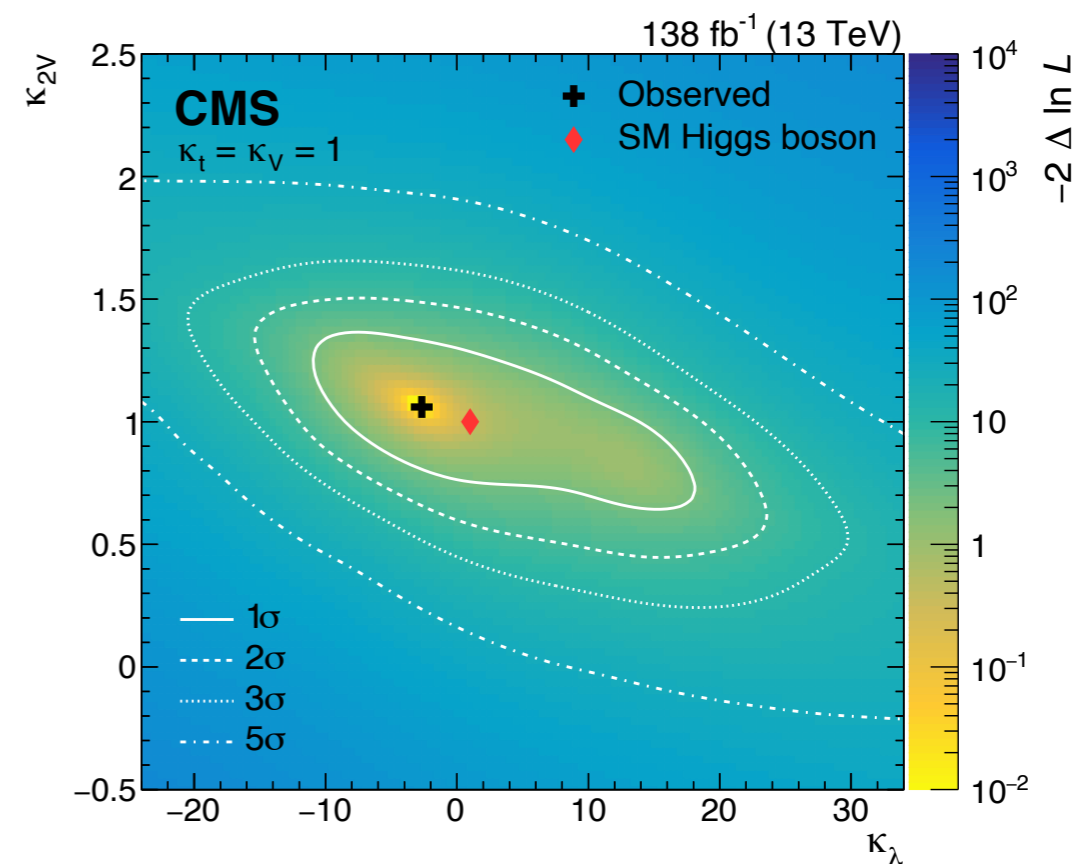
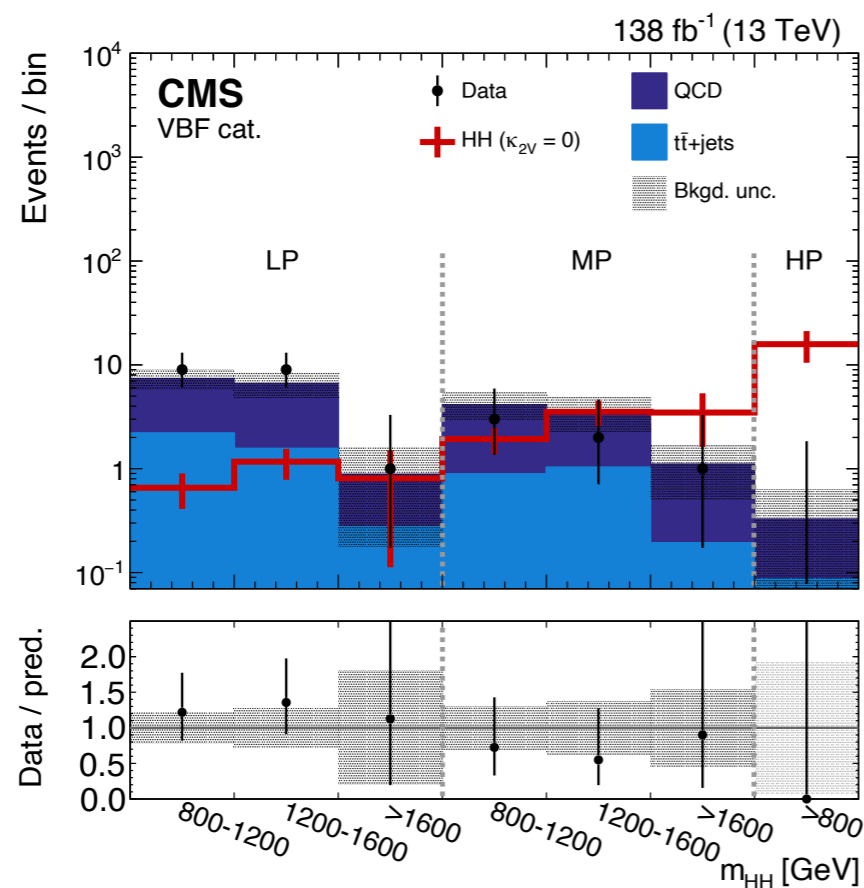
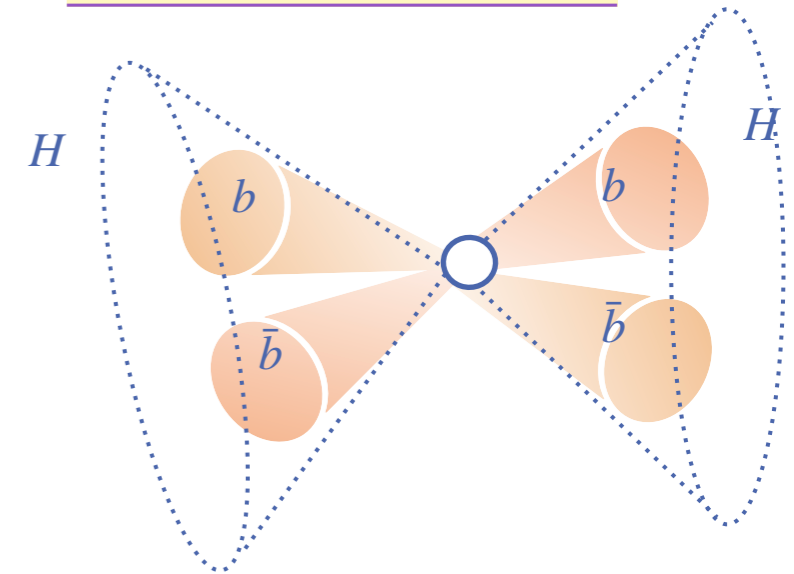
largely improved sensitivity!



Recent CMS results in Higgs sector

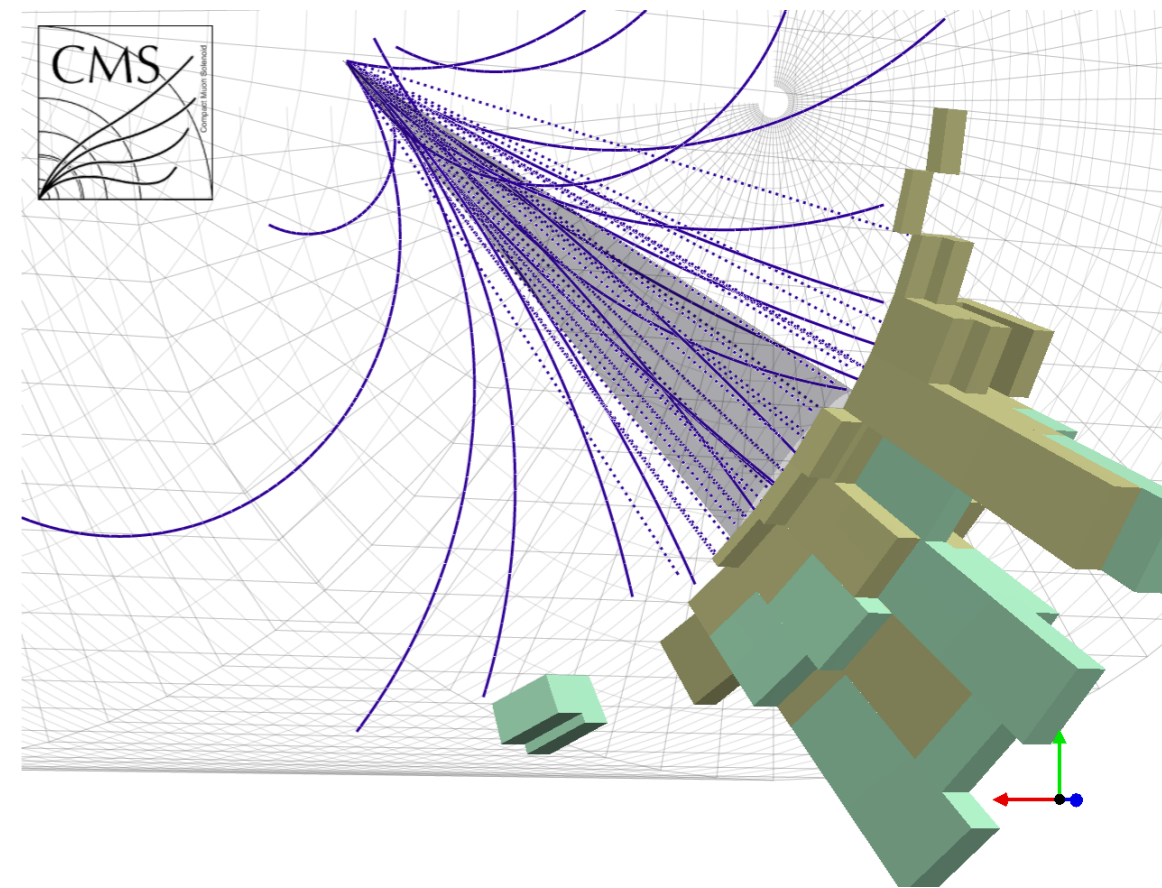
- Higgs self-coupling & quartic VHH coupling (κ_{2V}) measured via $HH \rightarrow 4b$ channel
- ❖ novel boosted-jet phase space explored by CMS
 - ❖ advanced NN (ParticleNet) for $H \rightarrow b\bar{b}$ jet identification and mass regression
 - ❖ **first time** excluding $\kappa_{2V} = 0$ (by 6.3σ)

[PRL 131 \(2023\) 041803](#)



Interpreting the improvement

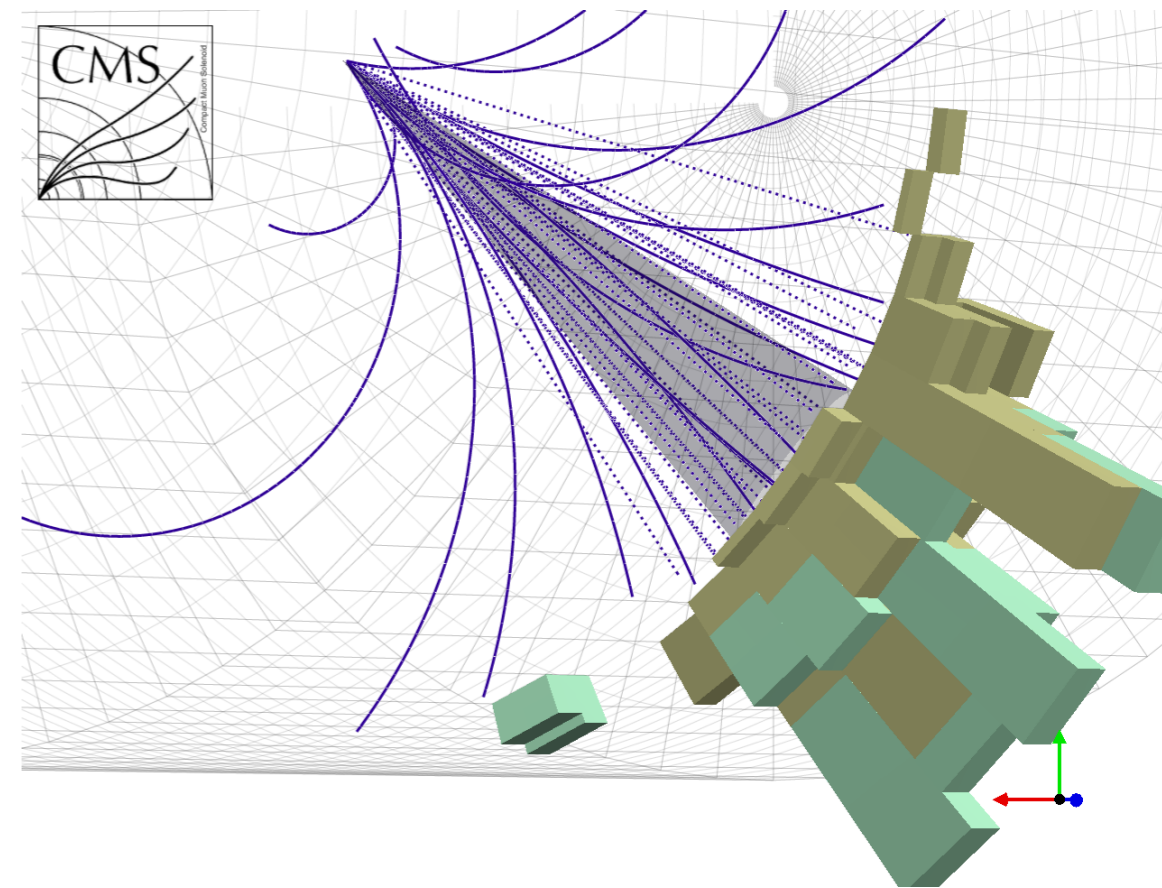
- Sophisticated networks have huge experimental potential when dealing with complex hadronic boosted-jet final states
- ❖ **sophisticated**: modern NN designs brought by the ML era (since ~2015)
- ❖ **complex**: a boosted jet contains $O(50-100)$ constituents



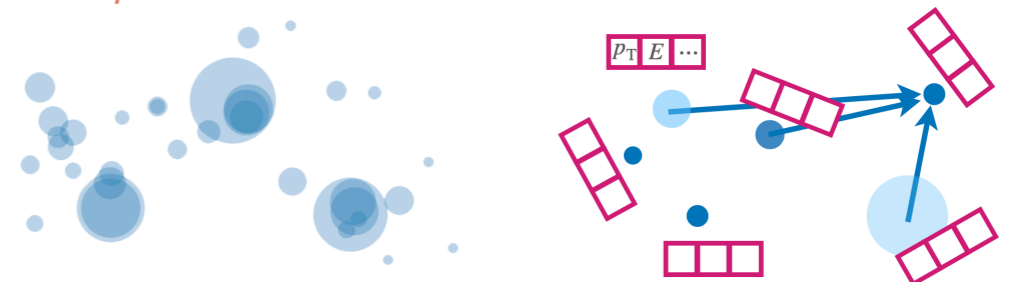
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 - ❖ **complex**: a boosted jet contains $O(50-100)$ constituents

- “ParticleNet” is a benchmark algorithm that leads the experimental advancement
 - ❖ sensitivity highly improved (~2-5 greater background rejection)
 - ❖ view a jet as a point cloud
 - ❖ allow message passing between neighbouring particles



point cloud representation



ParticleNet: Jet Tagging via Particle Clouds

Huilin Qu (UC, Santa Barbara), Loukas Gouskos (CERN)

Feb 22, 2019

[PRD 101 \(2020\) 056019](#)

↪ 250 citations

Philosophy of “event selection” and advanced NNs

- A theoretical upper bound exists to the “optimal event selection”
 - ❖ signal and bkg cannot be 100% distinguished: overlapping between signal and bkg phase space; ambiguity caused by detector resolution/reconstruction efficiency...
 - ❖ but an optimal selection exists, and it is defined on the signal and bkg likelihood ratio (although intractable due to its complexity)

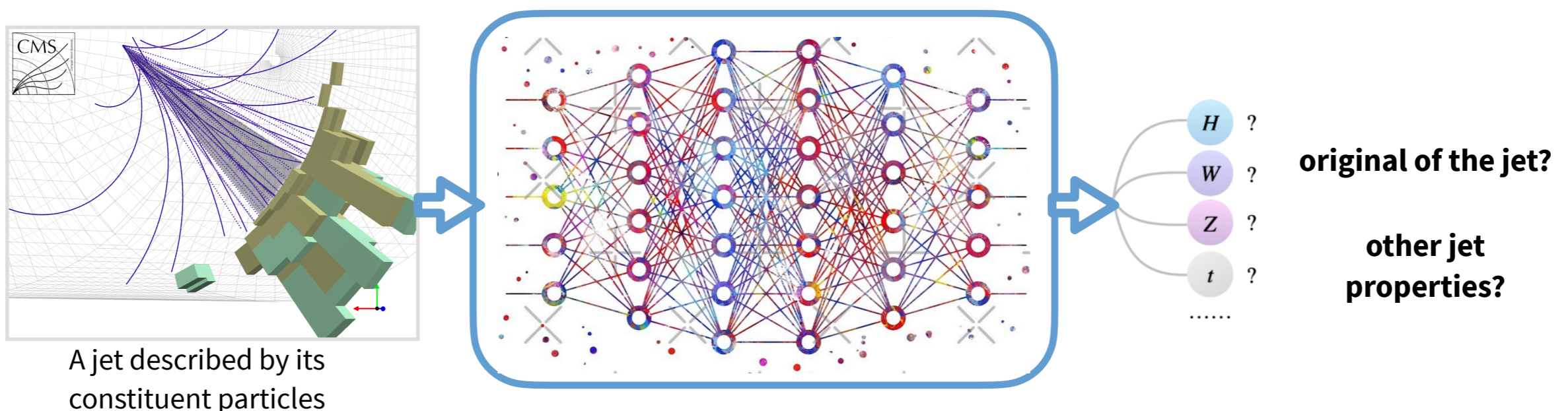
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- The big question for experimentalists: where is that limit, and how close are we now?
 - ❖ this is still an open question - current results imply that the data we collected at the LHC has not been fully explored (especially for hadronic final states)

Philosophy of “event selection” and advanced NNs

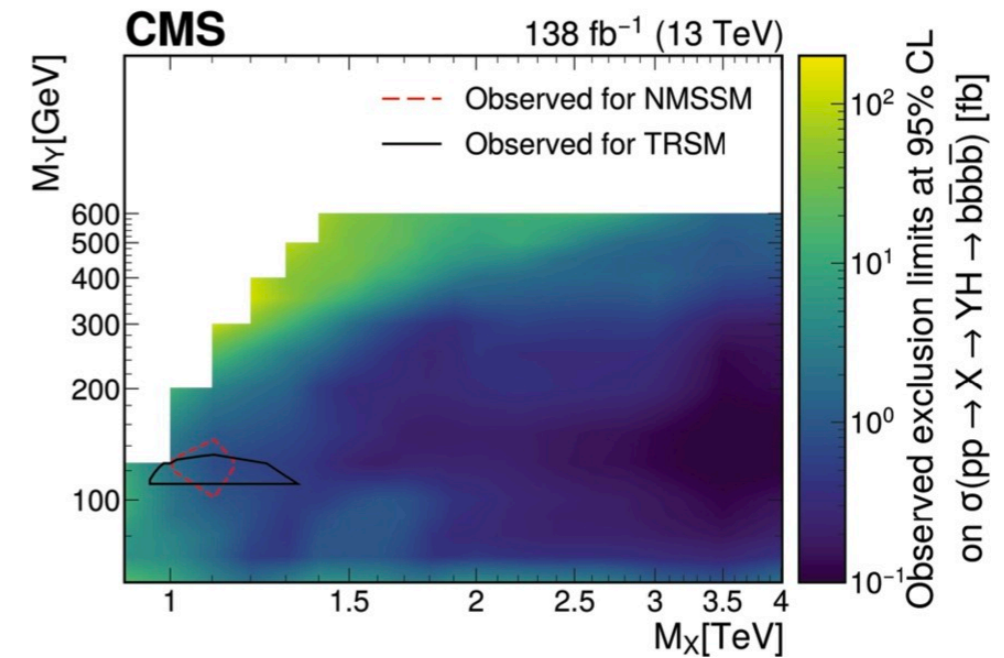
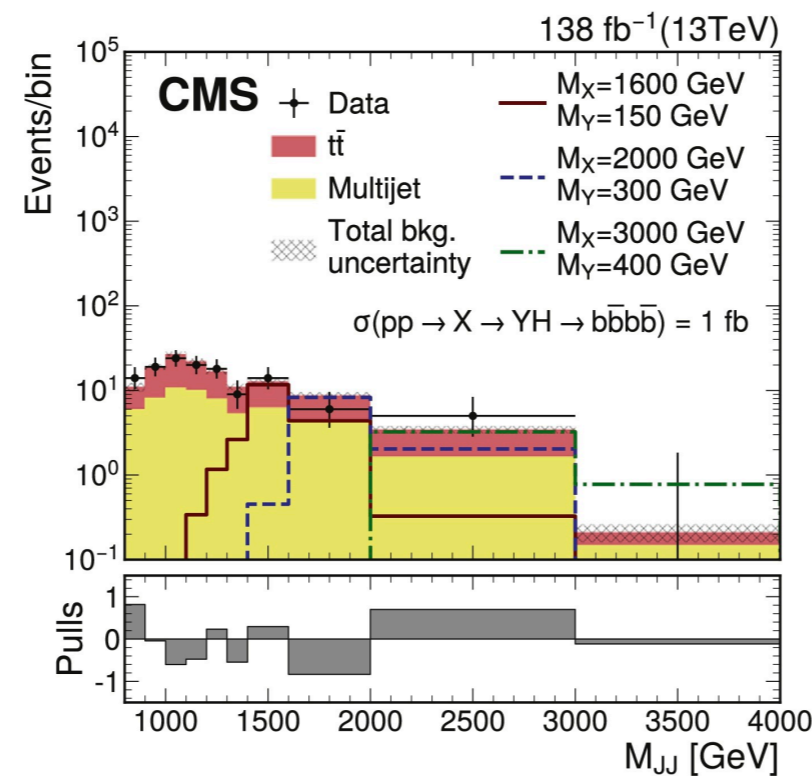
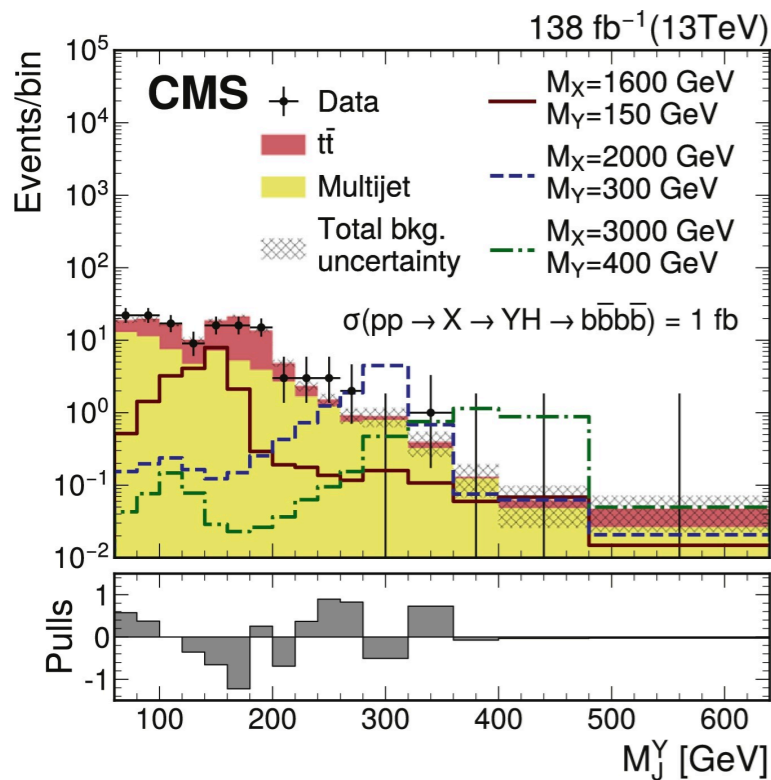
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- The big question for experimentalists: where is that limit, and how close are we now?
 - ❖ this is still an open question - current results imply that the data we collected at the LHC has not been fully explored (especially for hadronic final states)
- Advanced NN can serve as a powerful fitter to approach the theoretical limit
 - ❖ the training target of NN guarantees an optimum in classification/regression under present NN’s capability
 - ❖ better NN: better data representation (an ML+physics problem [[backup](#)])



Selected CMS BSM searches ($X \rightarrow YH \rightarrow b\bar{b}b\bar{b}$)

PLB 842 (2023) 137392

- Search for scalar particles in $X \rightarrow YH \rightarrow b\bar{b}b\bar{b}$ final states
- ❖ reconstruct H and Y in each in a large-R jet
- ❖ use advanced NN (ParticleNet) to select $H \rightarrow b\bar{b}$ and $Y \rightarrow b\bar{b}$ jets
- ❖ maximum likelihood fit on (m_{JJ}, m_J^Y) , model-independent constraint on the cross-section

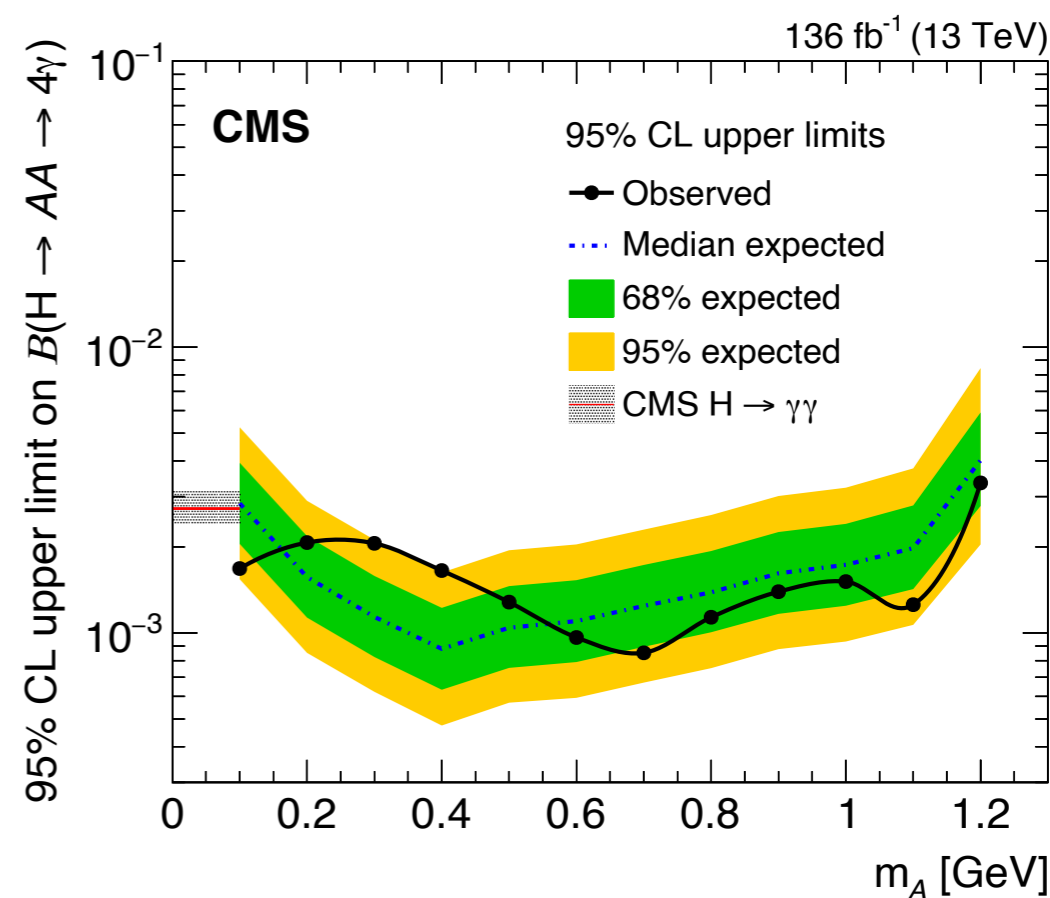
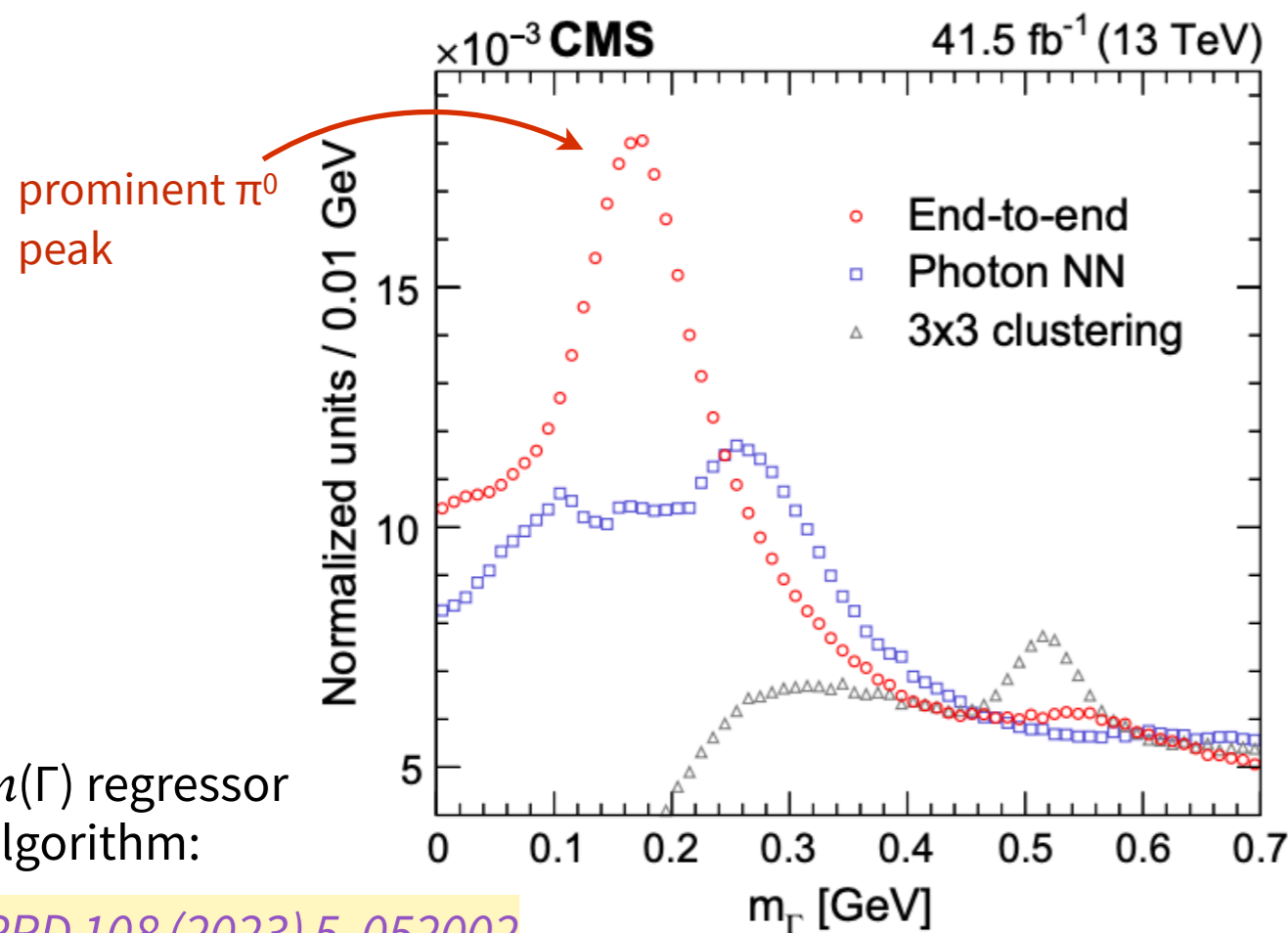
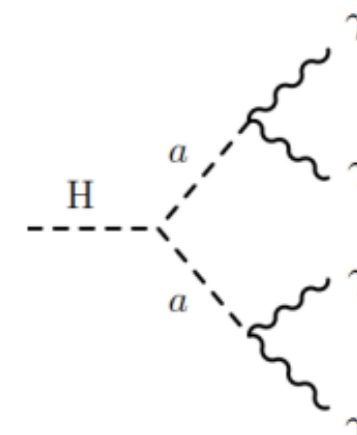


Selected CMS BSM searches ($H \rightarrow AA \rightarrow 4\gamma$)

[PRL 131 \(2023\) 101801](#)

→ Search for low mass (0.1–1.2 GeV) ALPs

- ❖ first direct search for Higgs exotic decay to ALPs with ALP to 2γ
- ❖ **merged** $\gamma\gamma$ reconstructed as a single photon-like object Γ ,
regress on $m(\Gamma)$ using low-level ECAL energy deposit as input
- ❖ set limit on $B(H \rightarrow AA \rightarrow 4\gamma)$



Modern model-agnostic searches

Modern model-agnostic searches

- Begin of journey in the modern (machine-learning-based) model-agnostic searching scheme at LHC

Anomaly Detection for Resonant New Physics with Machine Learning

Jack H. Collins (Maryland U. and Johns Hopkins U.), Kiel Howe (Fermilab), Benjamin Nachman (UC, Berkeley and LBL, Berkeley)

May 7, 2018

[PRL, 121 \(2018\) 24, 241803](#)

↻ 161 citations

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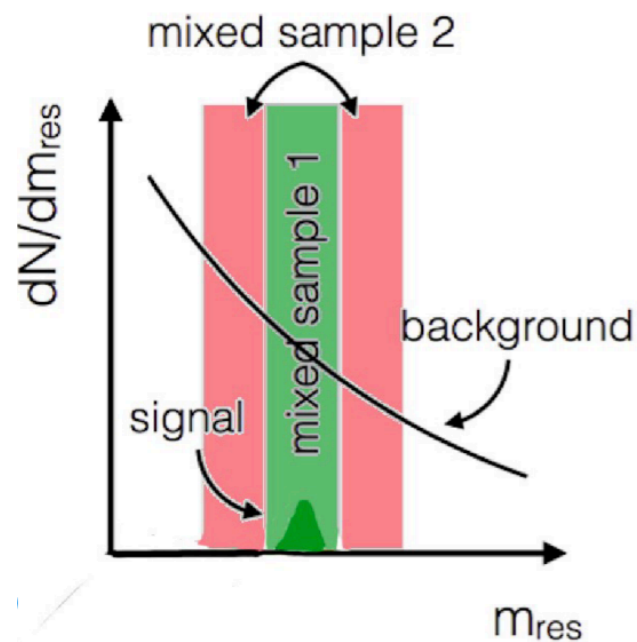
[PRL, 121 \(2018\) 24, 241803](#)

↻ 161 citations

- A “general method” for resonant search with minimal requirements
 - ❖ resonance localised in a mass window
 - ❖ can be reconstructed by two hadronic large- R jets
- General strategy:
 - ❖ scan on the mass spectrum → apply model-independent selection → purify the signal
- With no significant evidence of new physics found at LHC, a broader search strategy will be a meaningful

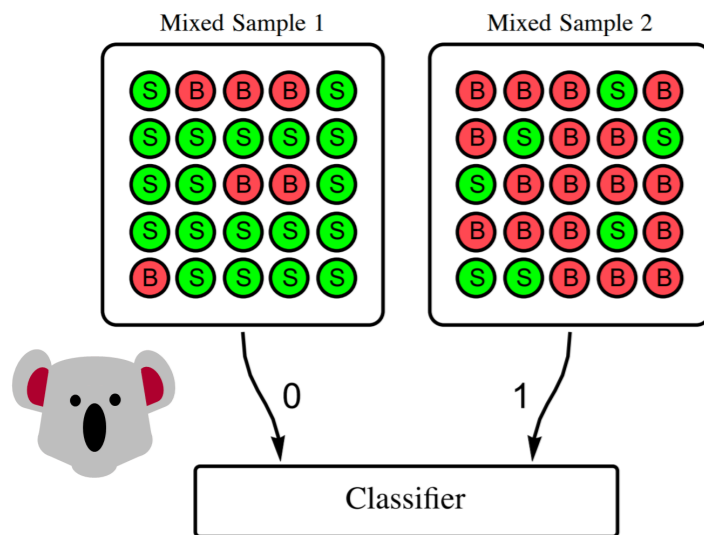
Weakly-supervised approach

JHEP 10 (2017) 174



→ Proposed “CWoLa (classification without labels) Hunting”

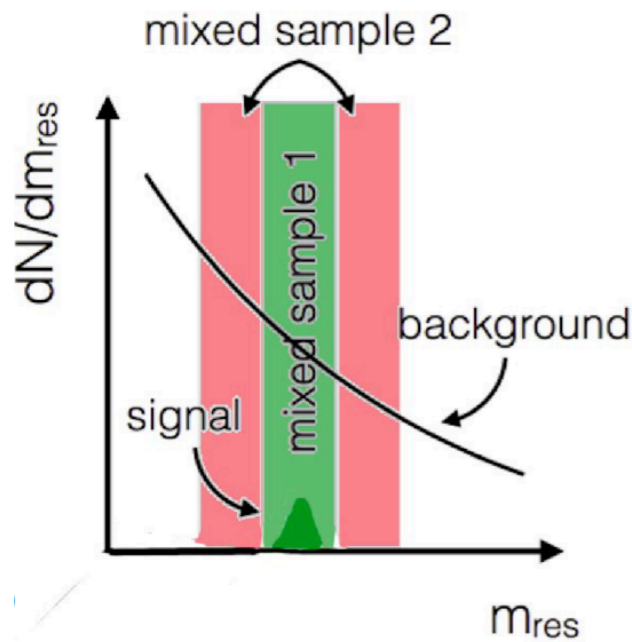
- ❖ allow to detect anomalies purely from data
- ❖ train a classifier for mass window vs mass sideband (mixed sample 1 vs 2)
- ❖ can prove that the effect is equivalent to training S vs B



Equivalent effect for training **S** vs **B**

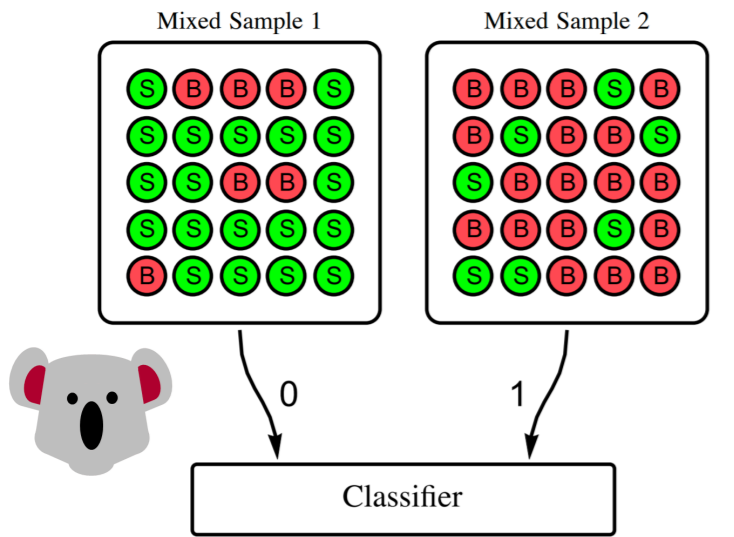
Weakly-supervised approach

[JHEP 10 \(2017\) 174](#)

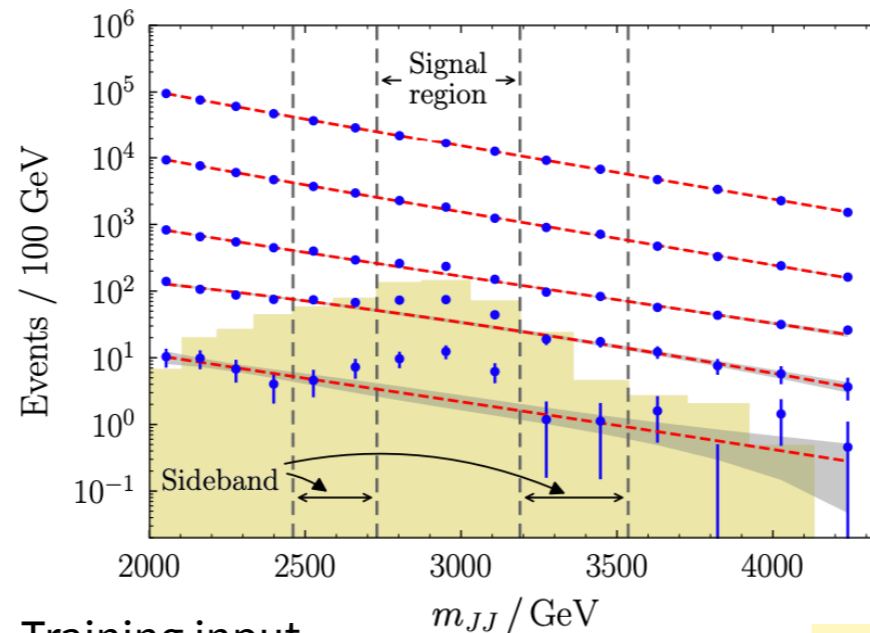


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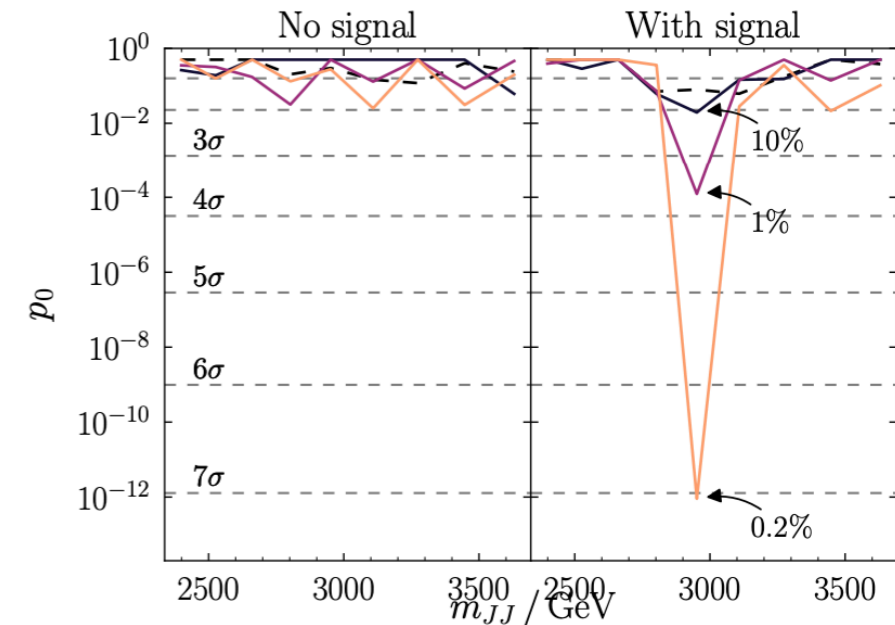


Equivalent effect for training **S** vs **B**



Training input

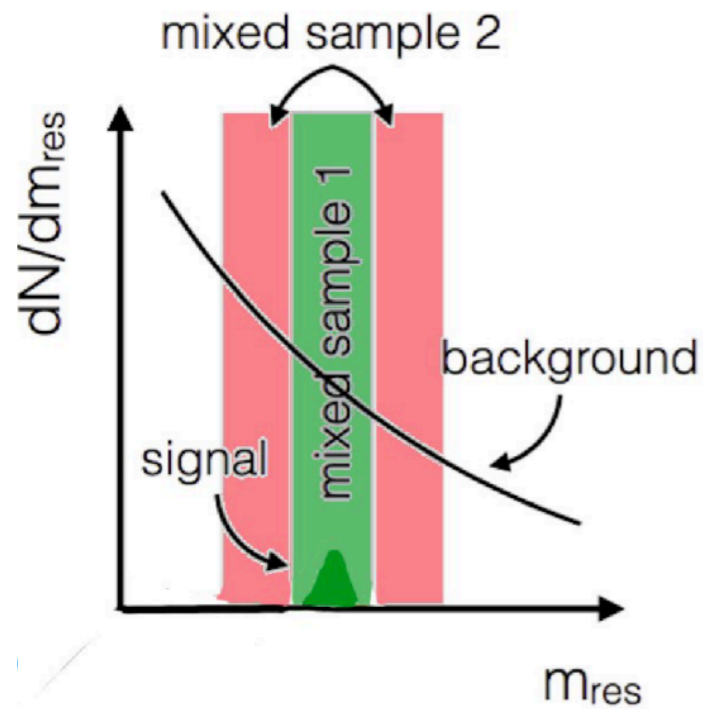
$$m_J, \sqrt{\tau_1^{(2)} / \tau_1^{(1)}}, \tau_{21}, \tau_{32}, \tau_{43}, n_{trk},$$



[PRL, 121 \(2018\) 24, 241803](#)

[PRD, 99 \(2019\) 1, 014038](#)

Improved methods

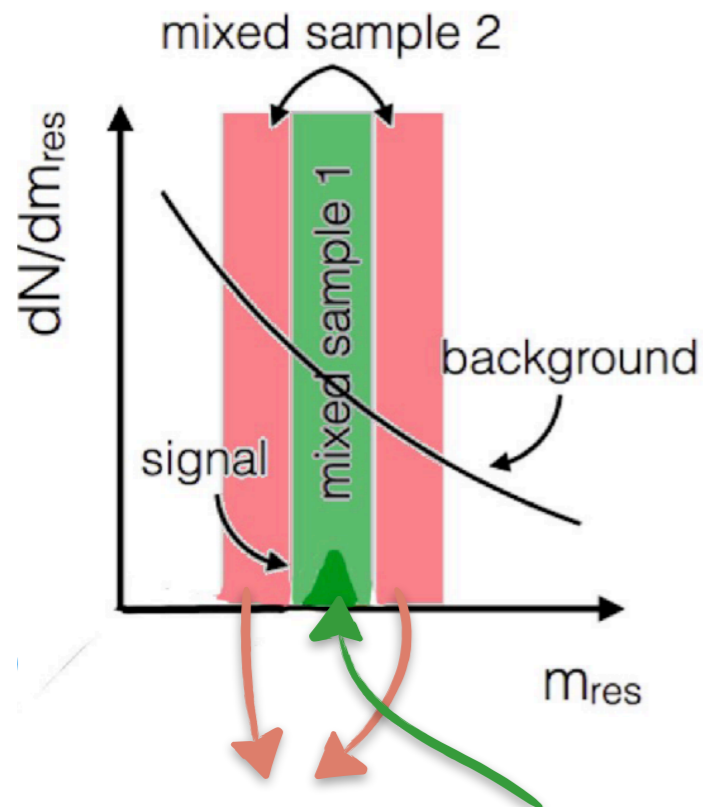


→ Improvement made to the weakly-supervised scheme

- ❖ **CWoLa**: train mixed sample 1 vs 2, i.e. taking sideband as the background

[PRD, 99 \(2019\) 1, 014038](#)

Improved methods



→ Improvement made to the weakly-supervised scheme

- ❖ **CWoLa**: train mixed sample 1 vs 2, i.e. taking sideband as the background
- ❖ **CATHODE** (Classifying Anomalies THrough Outer Density Estimation): interpolate background from the sideband

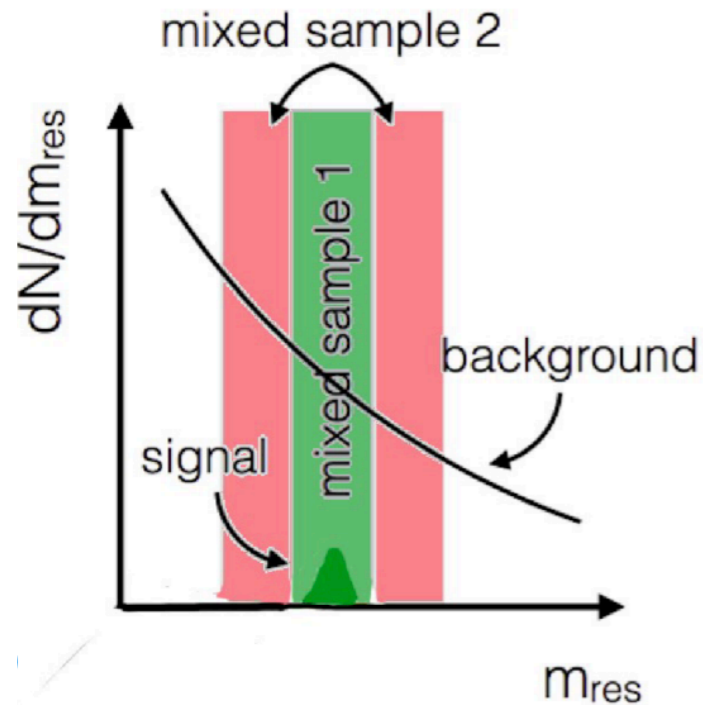
[PRD, 106 \(2022\) 5, 055006](#)

First, train an NN to generate input events conditioned on m_{res}

Then, generate events in the mass window → i.e. interpolate background from sideband

Finally, train a classifier over mixed sample 1 vs generated background

Improved methods

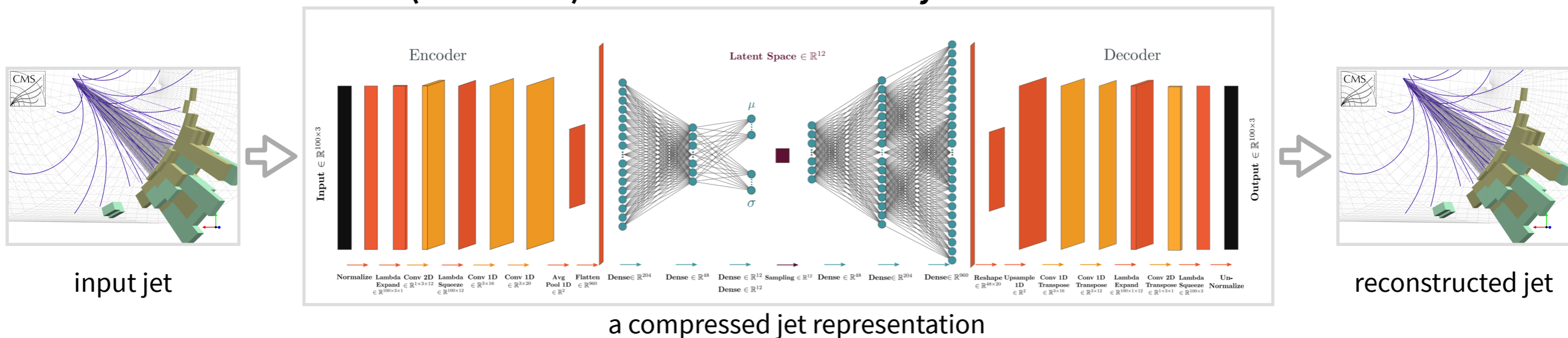


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- ❖ **CWoLa**: train mixed sample 1 vs 2, i.e. taking sideband as the background
- ❖ **CATHODE** (Classifying Anomalies THrough Outer Density Estimation): interpolate background from the sideband
- ❖ **Tag N' Train**: apply autoencoder preselection on each fatjet → target resonance from anomalous dijet

[JHEP 01 \(2021\) 153](#)

A view on (variational) autoencoder for anomaly detection



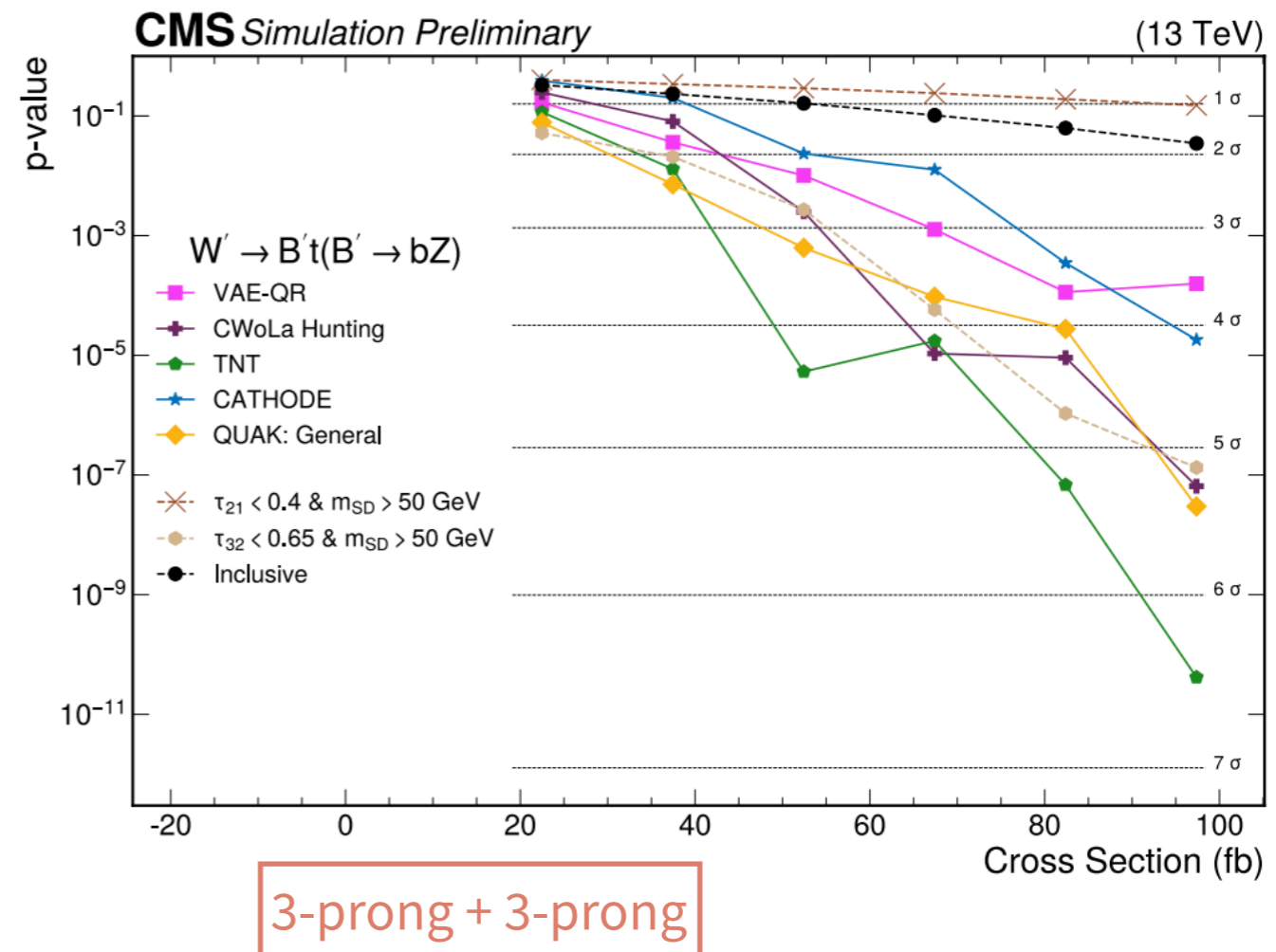
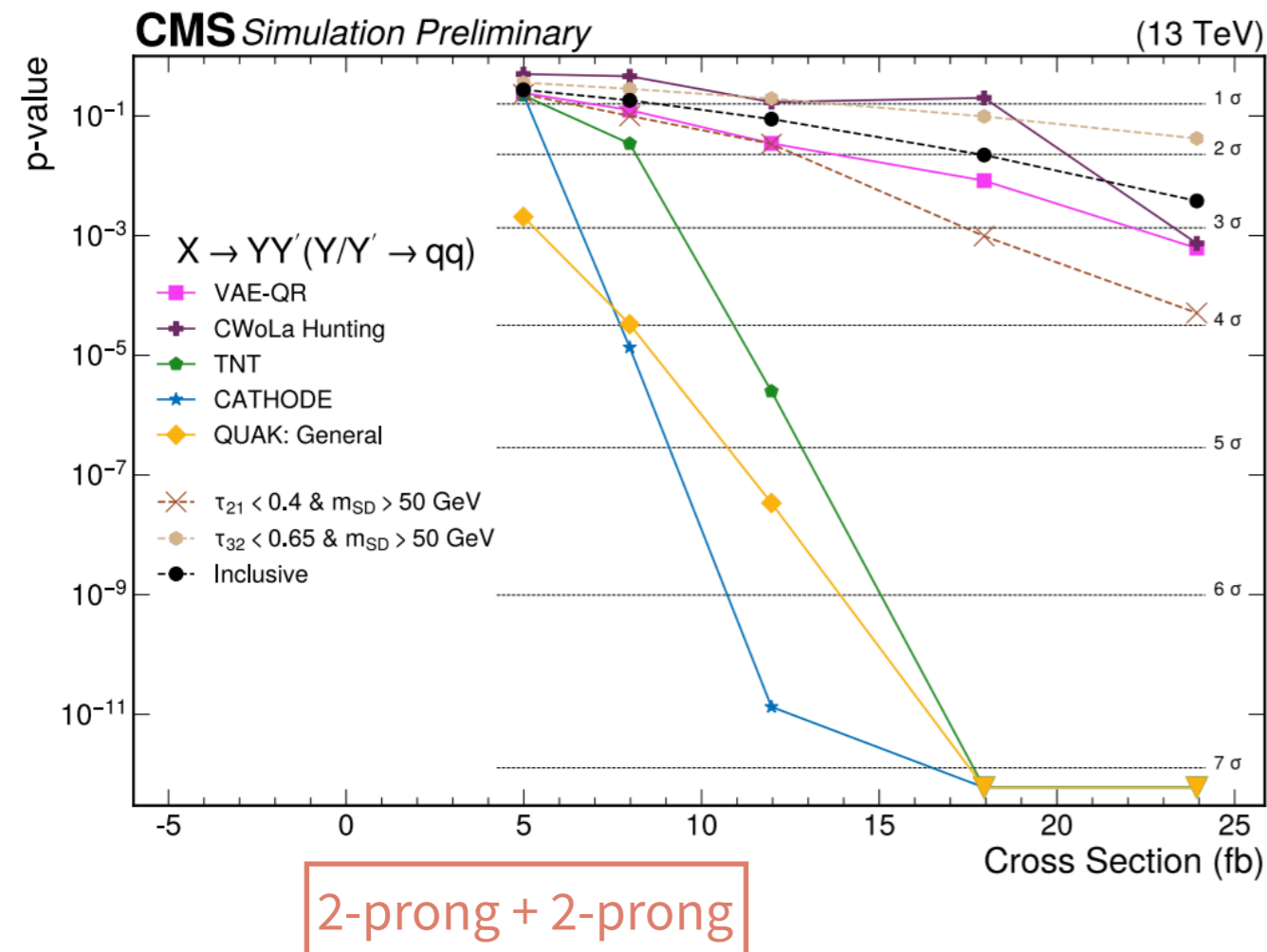
a compressed jet representation

Training on SM background jet

→ **anomalous jet will produce outlier latent scores** → make selection on the score

CMS model-agnostic resonant search

CMS-NOTE-2023-013

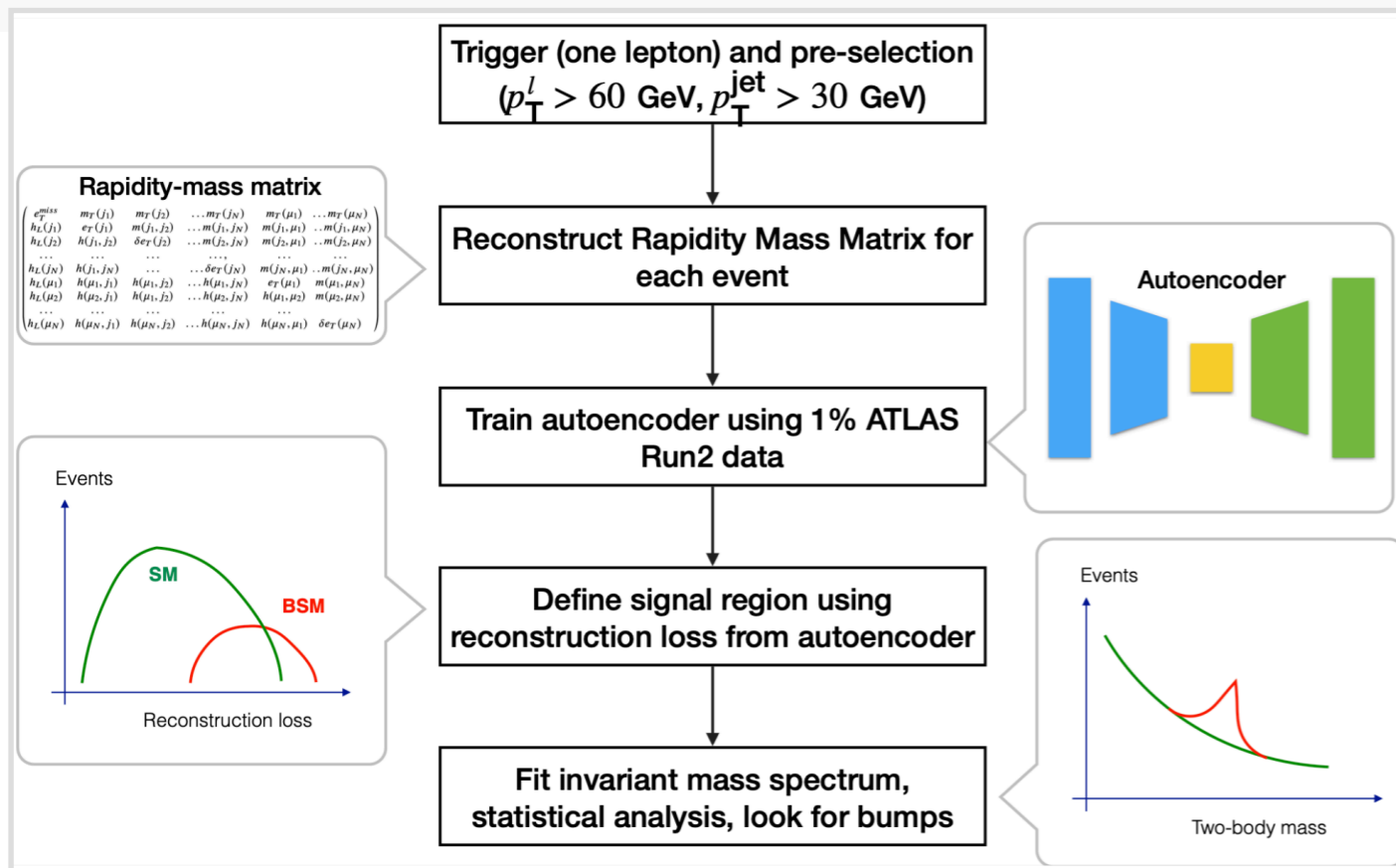


- CMS systematically test all model-agnostic approaches to search for resonance
- ❖ first performed on toy data (from simulation)
 - ❖ achieve comparable/better performance than conventional search using jet substructure selection (τ_{21} , τ_{32})

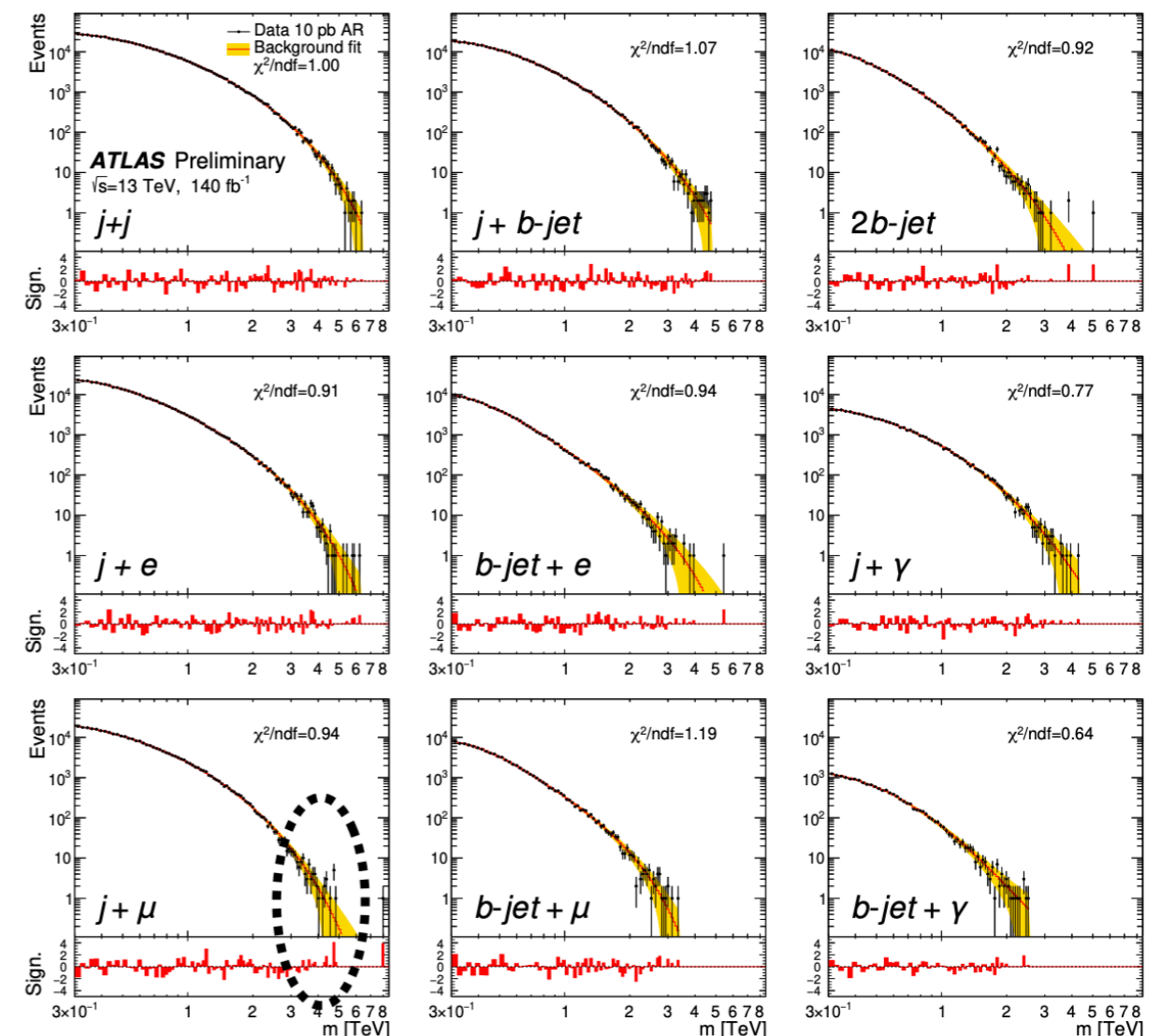
→ Intermediate release results - to perform on data

ATLAS's model-agnostic search

[arXiv:2307.01612](https://arxiv.org/abs/2307.01612)



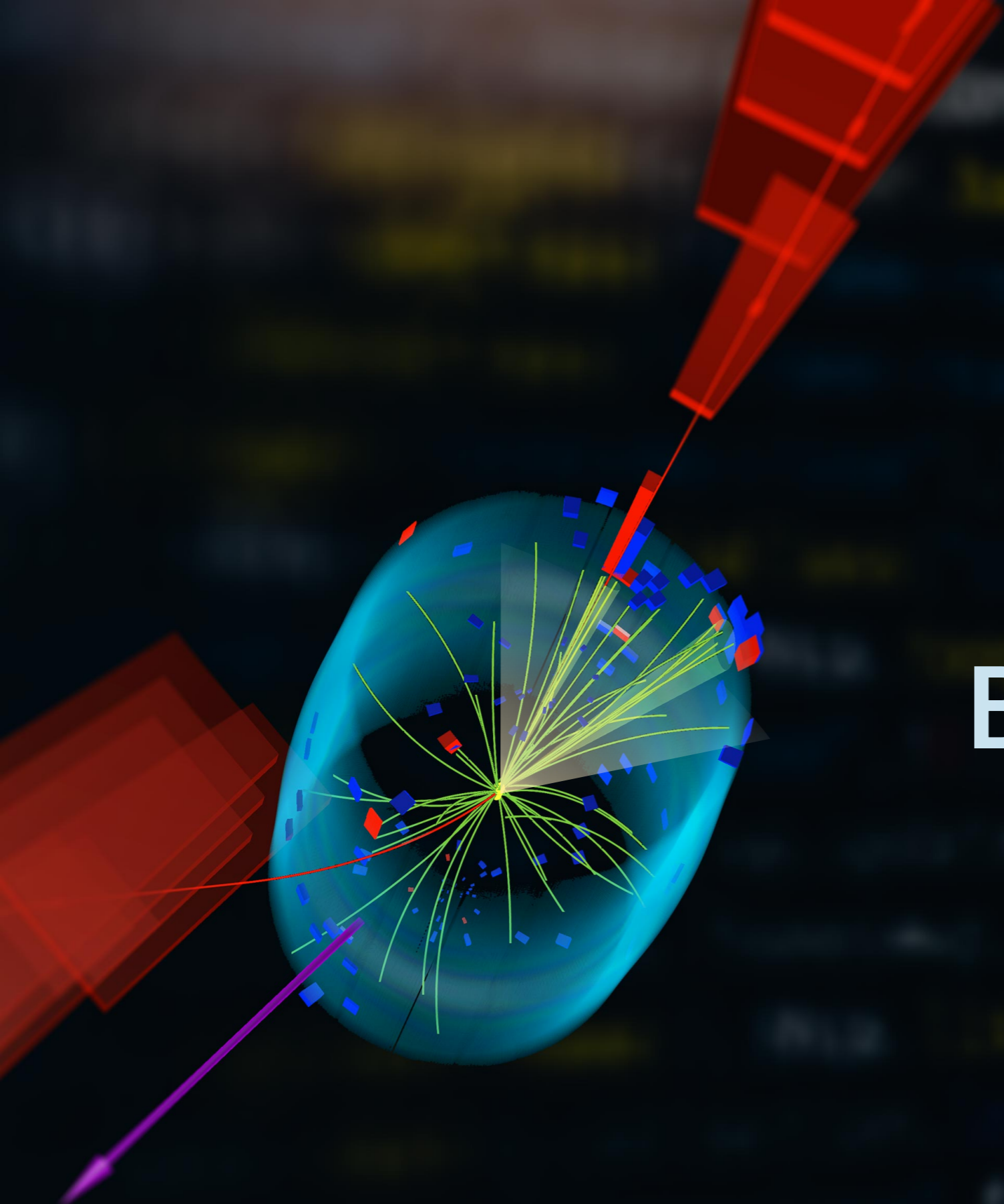
- ATLAS applies full-event-level anomaly detection
- Train “autoencoder” and select on the score
- Search in 9 invariant masses including di-jet, di-b-jet, with three anomaly regions



Conclusion

- We introduce the latest CMS results from an angle of experimental innovations
 - ❖ these aspects can be meaningful to a wide HEP community:
better use/analysis of the collected LHC data → accelerate our next HEP discovery!
- We share two innovations to showcase how they might **bring general impacts** to our physics programme
 - ❖ advent of advanced NNs to process low-level data → change the way we put selections/define observables, leading to substantial sensitivity improvements
 - ❖ advent of modern model-agnostic search → transform searching paradigm of BSM particles and still achieving optimal sensitivity
- Novel results including **Run 3 data** to bring more excitement
 - ❖ improvement foreseeable brought by more collected data + improved strategies
- Upgrade to HL-LHC is making good progress

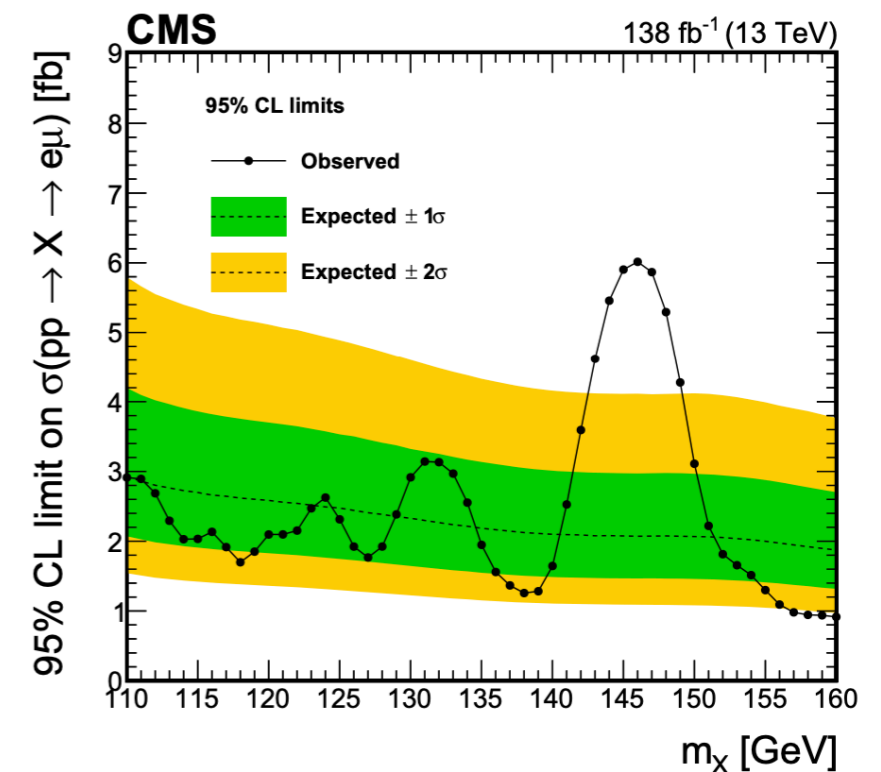
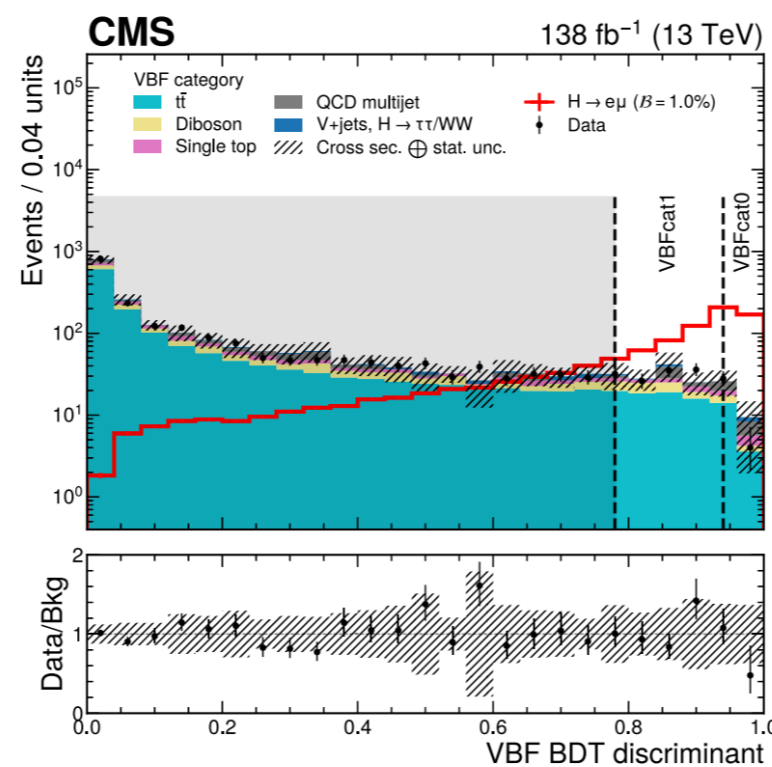
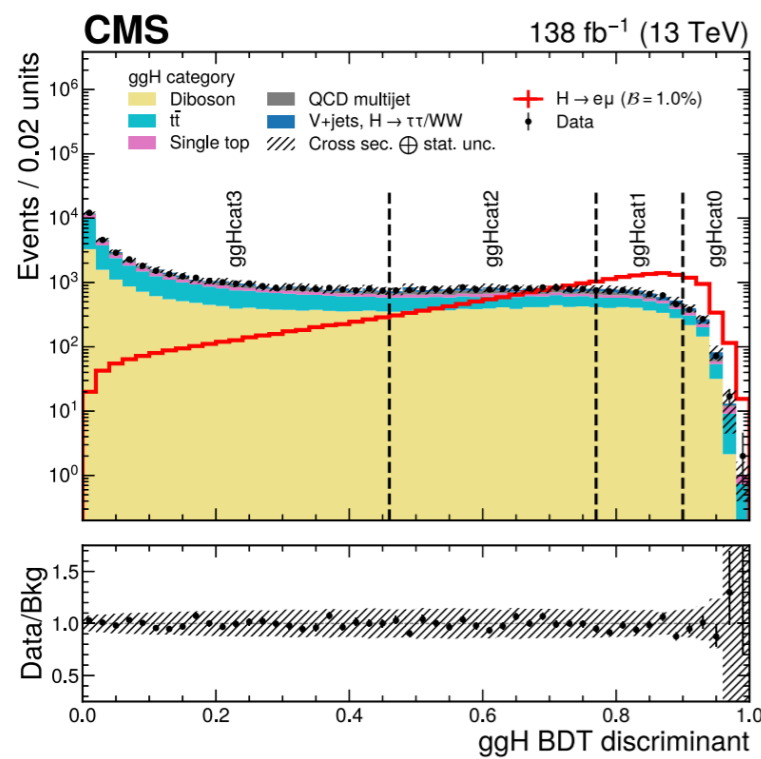
Backup



Lepton flavour violating

PRD, 108 (2023) 7, 072004

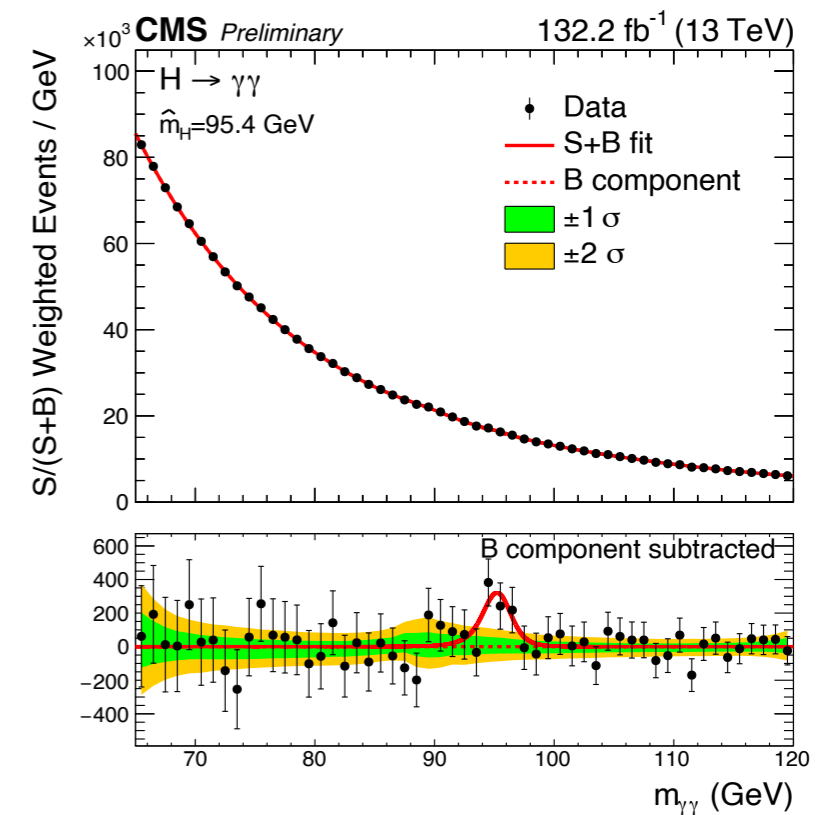
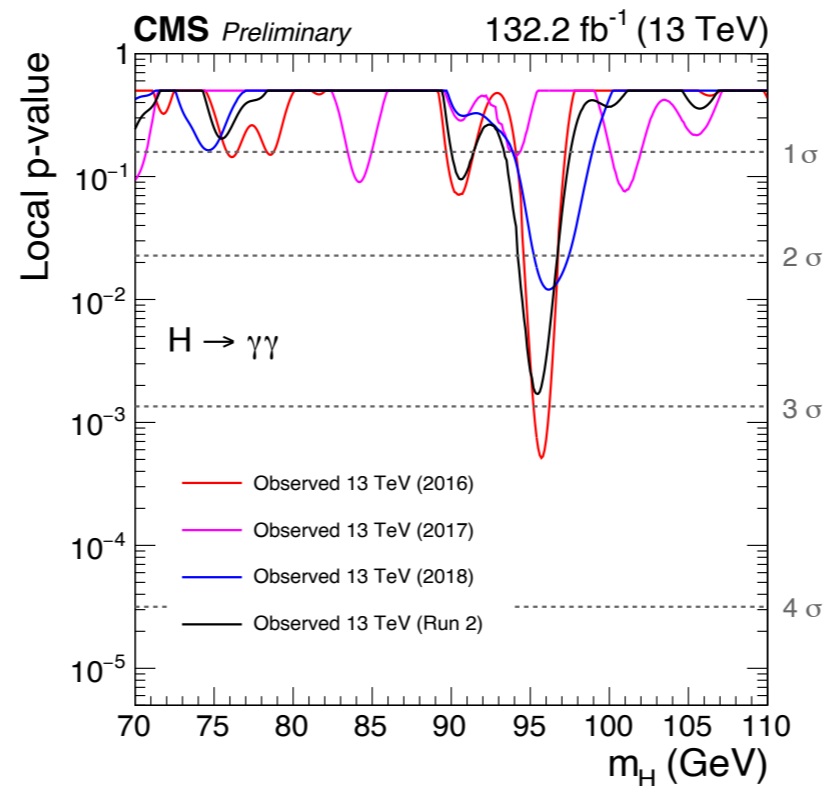
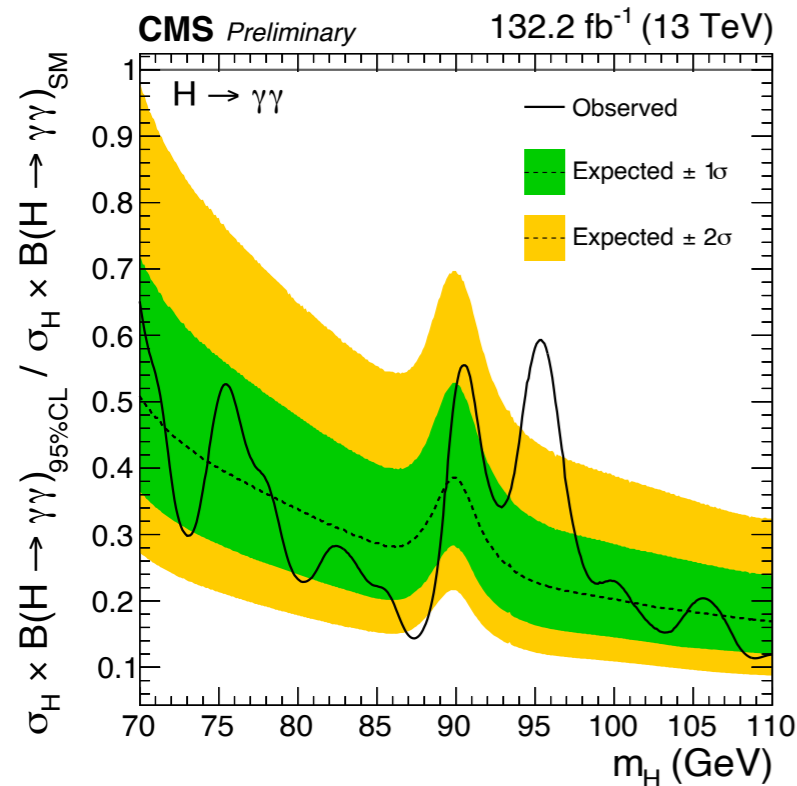
- Search LFV signature for $H \rightarrow e\mu$, also extending to $X \rightarrow e\mu$ (m_X : 100-160 GeV)
 - ❖ type III 2HDM predicts additional scalar bosons X , with LFV decays
- Fitting $m_{e\mu}$ distribution in signal regions (classified by BDT)
- Largest excess: 3.8σ (2.8σ) local (global) at 146 GeV



New resonance in $\gamma\gamma$ final state

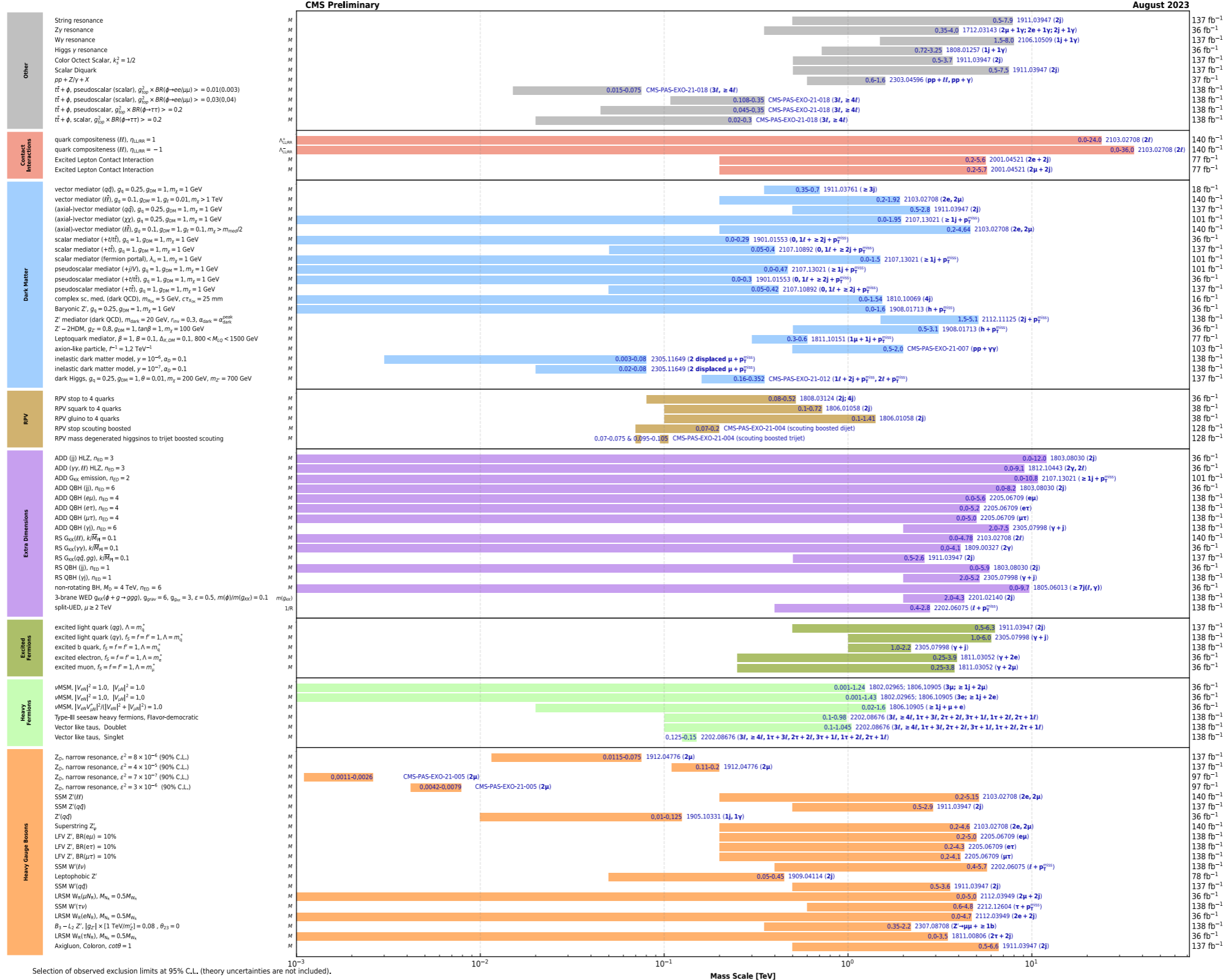
CMS-PAS-HIG-20-002

- Search for new resonance in the clean $\gamma\gamma$ final state
- Categories: 1 VBF + 3 classes defined by di-photon BDT
- Test statistic based on profile likelihood ratio constructed from the mass spectrum: 2.9σ local (1.3σ global) at 95.4 GeV



CMS exotic search results

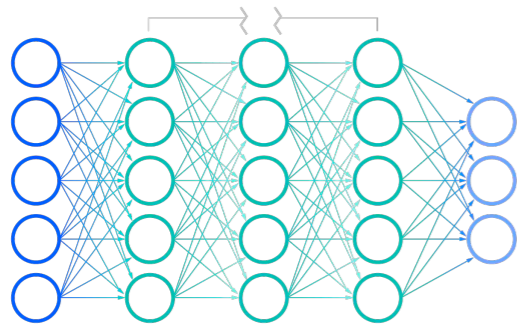
Overview of CMS EXO results



summary plots from [link](#)

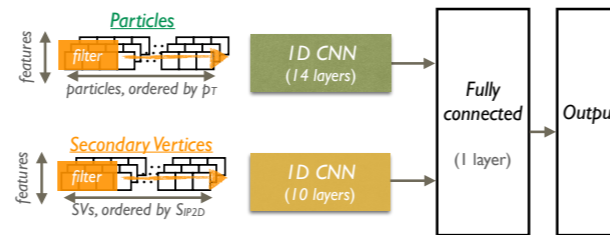
Evolution of jet NNs

feed-forward NN (high-level inputs) ... 1D/2D CNN, RNN (low-level inputs) ... graph NN (low-level inputs) ... ??



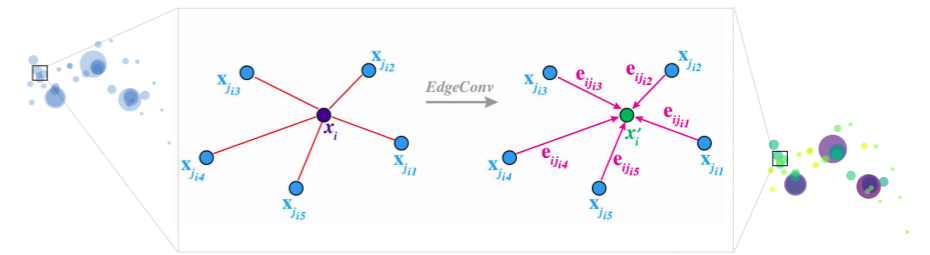
Shallow networks

- Using high-level features directly as input to a shallow network



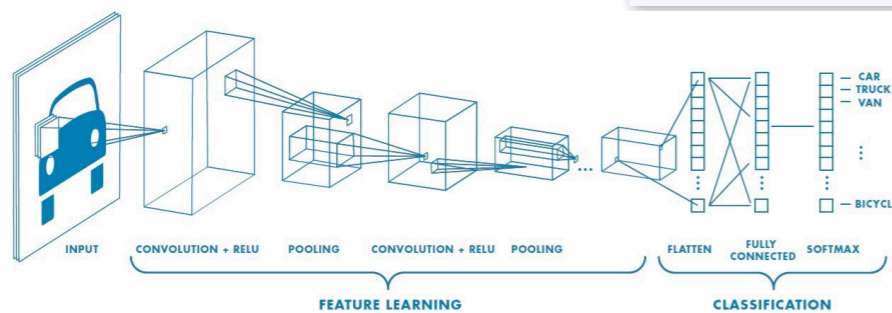
Deep NN with low-level inputs

- Using particle-level features
- Input data structure determines the type of networks
 - jet as a *image* (fixed-grid data structure)
 - jet as a *sequence* → 1D CNN or RNN

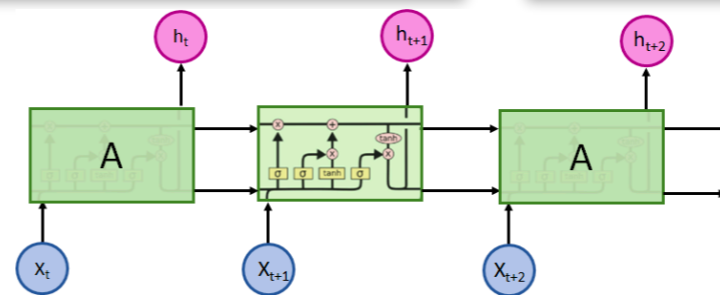


Graph structure

- Graph neural networks
 - treat a jet as a permutational-invariant set of particles (or, point cloud)
 - build “edges” between particles
- Transformer networks
 - modern architectural designs; like a full-connected graph



Typical CNN

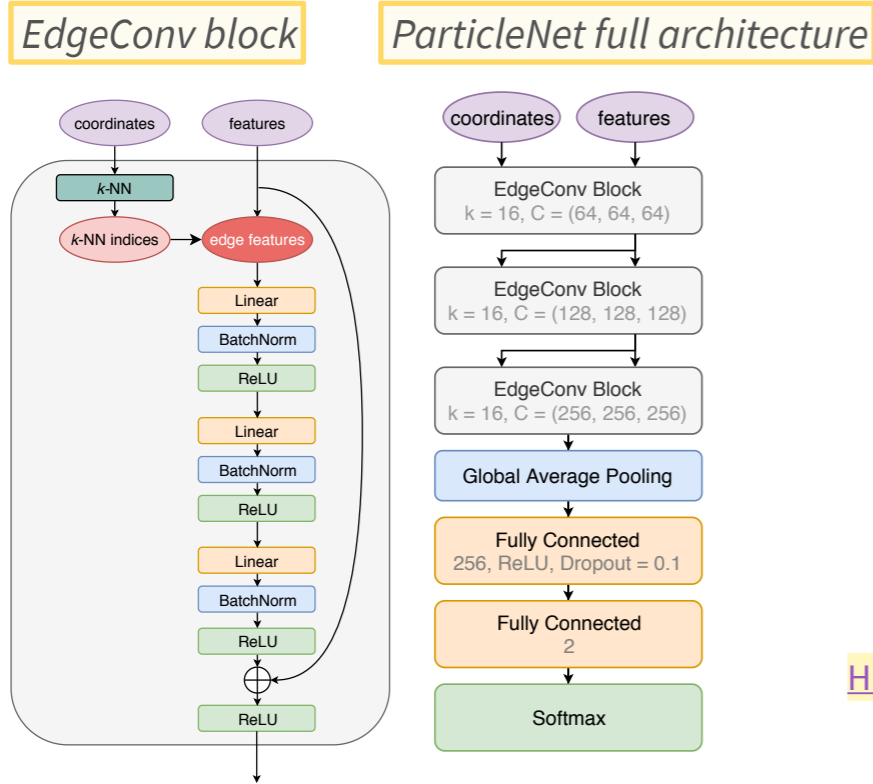


Typical RNN



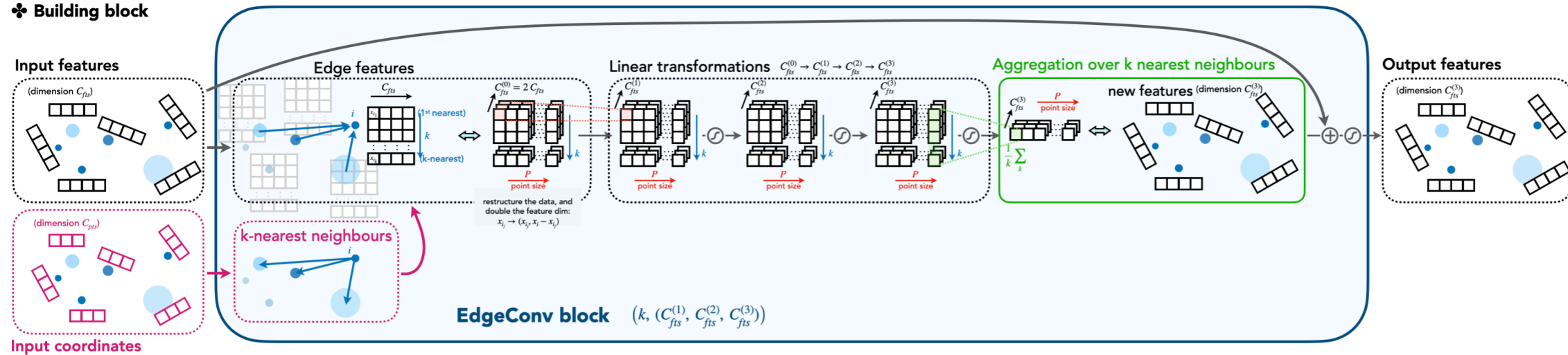
Typical graph

ParticleNet architecture

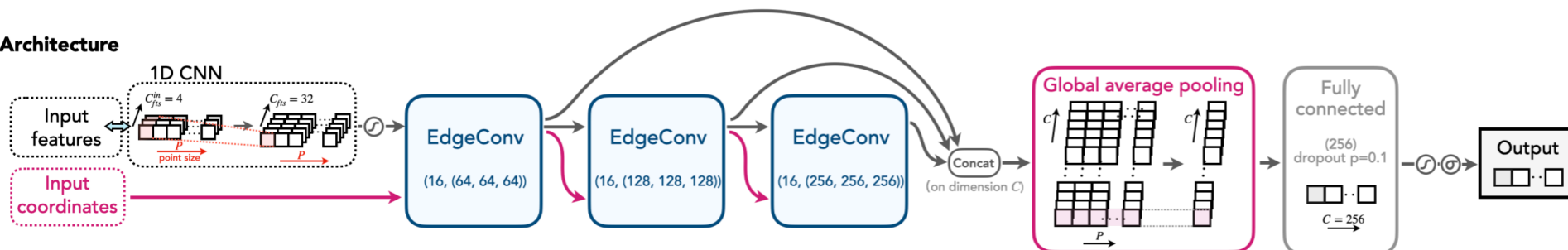


H. Qu, L. Gouskos, PRD 101, 056019 (2020)

Building block



Architecture



ParticleNet's full architecture

<https://cms-ml.github.io/documentation/inference/particlenet.html>