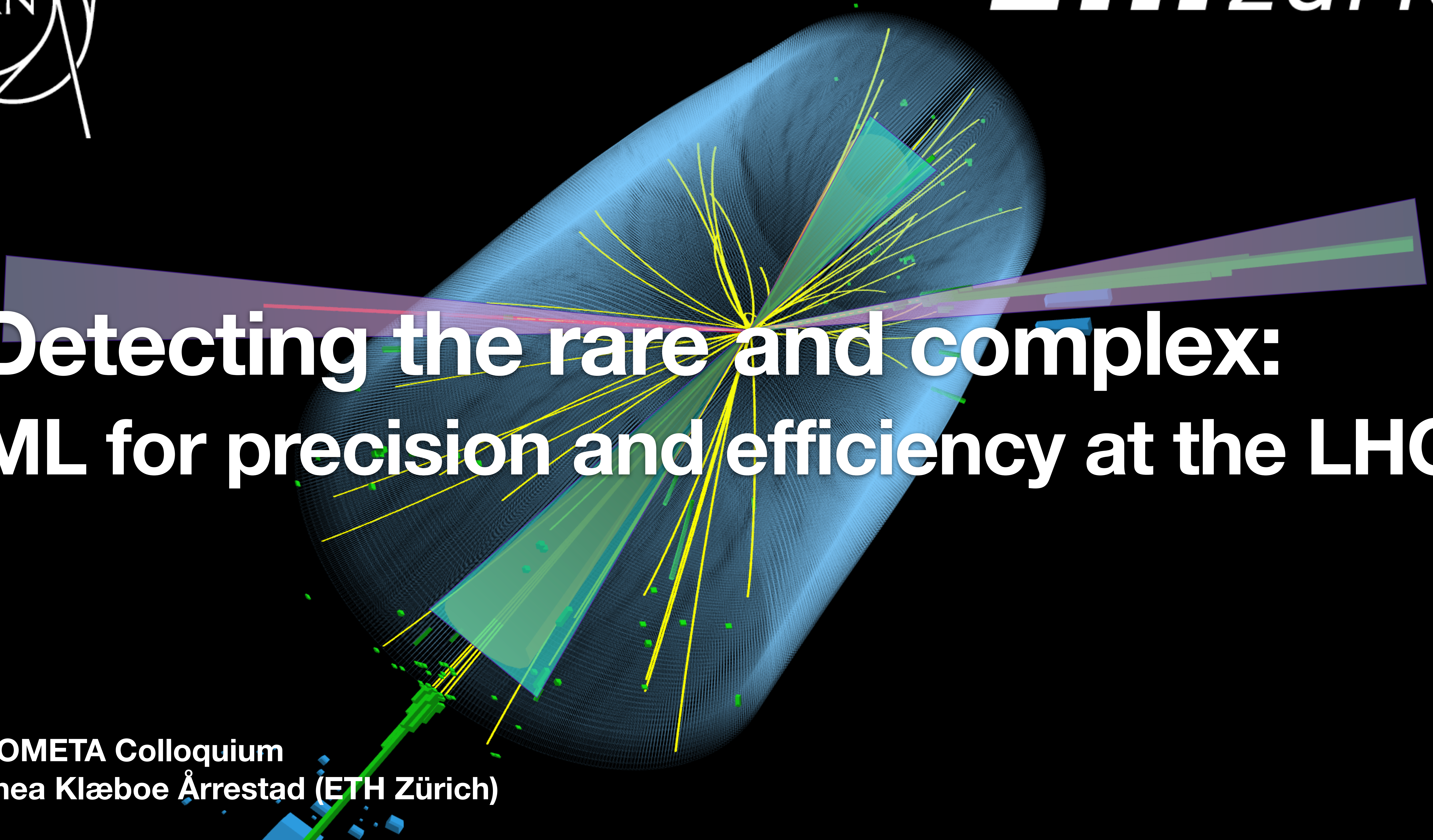
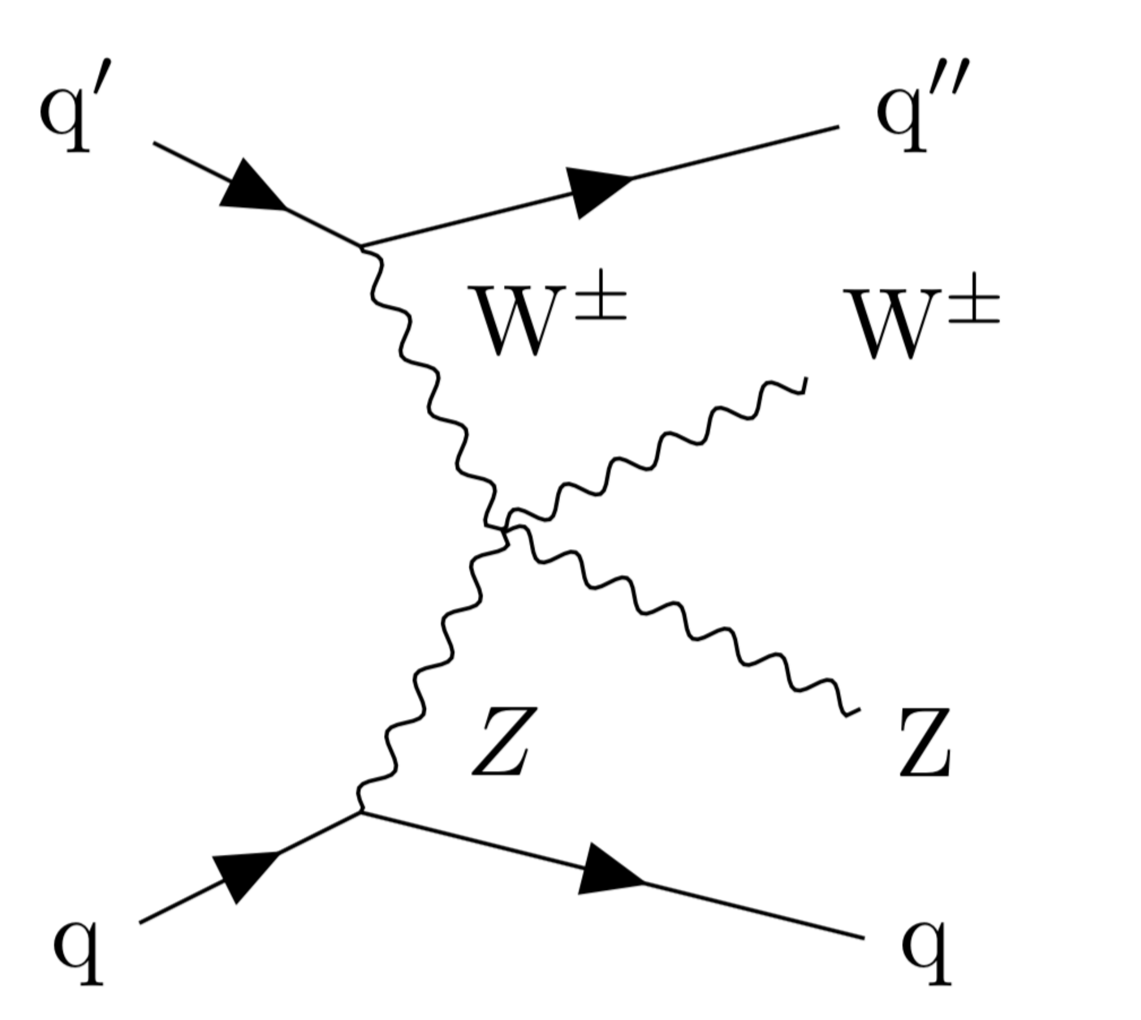
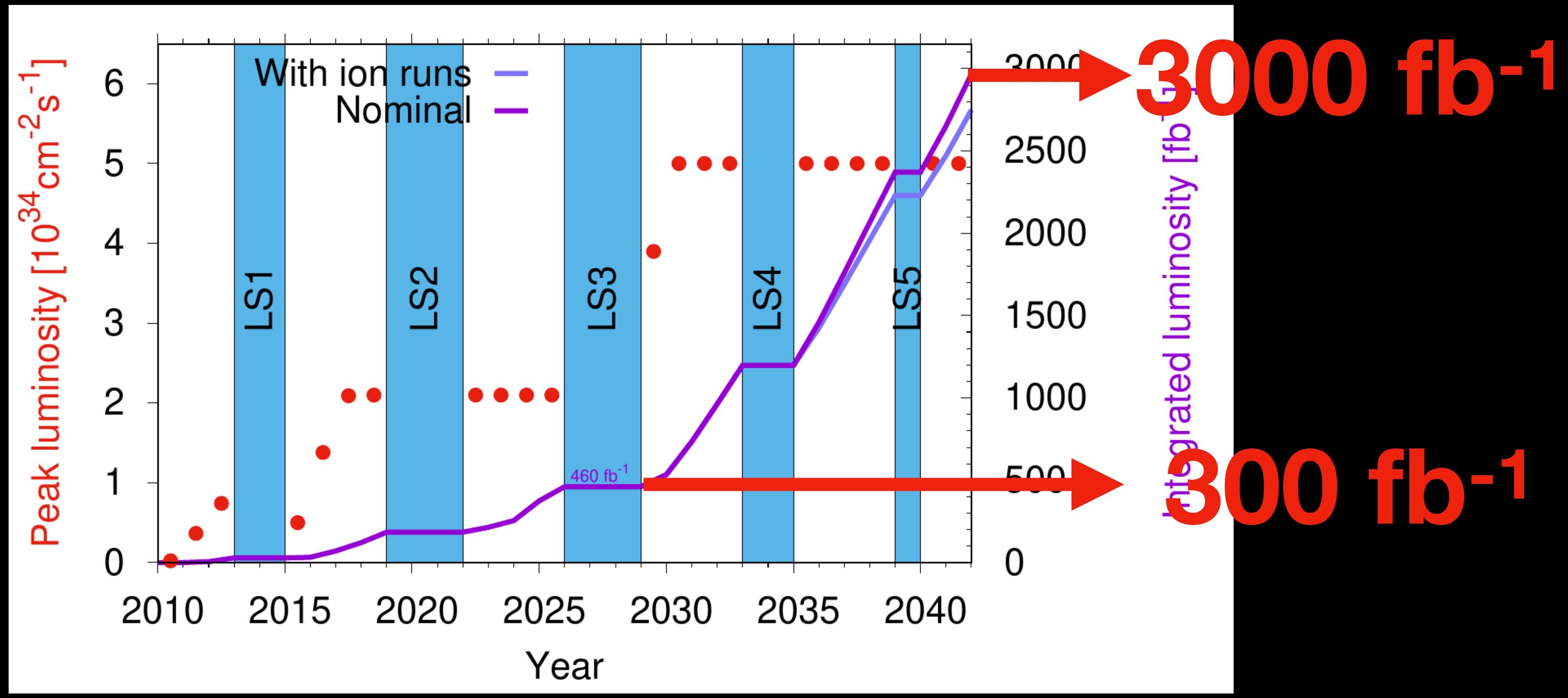


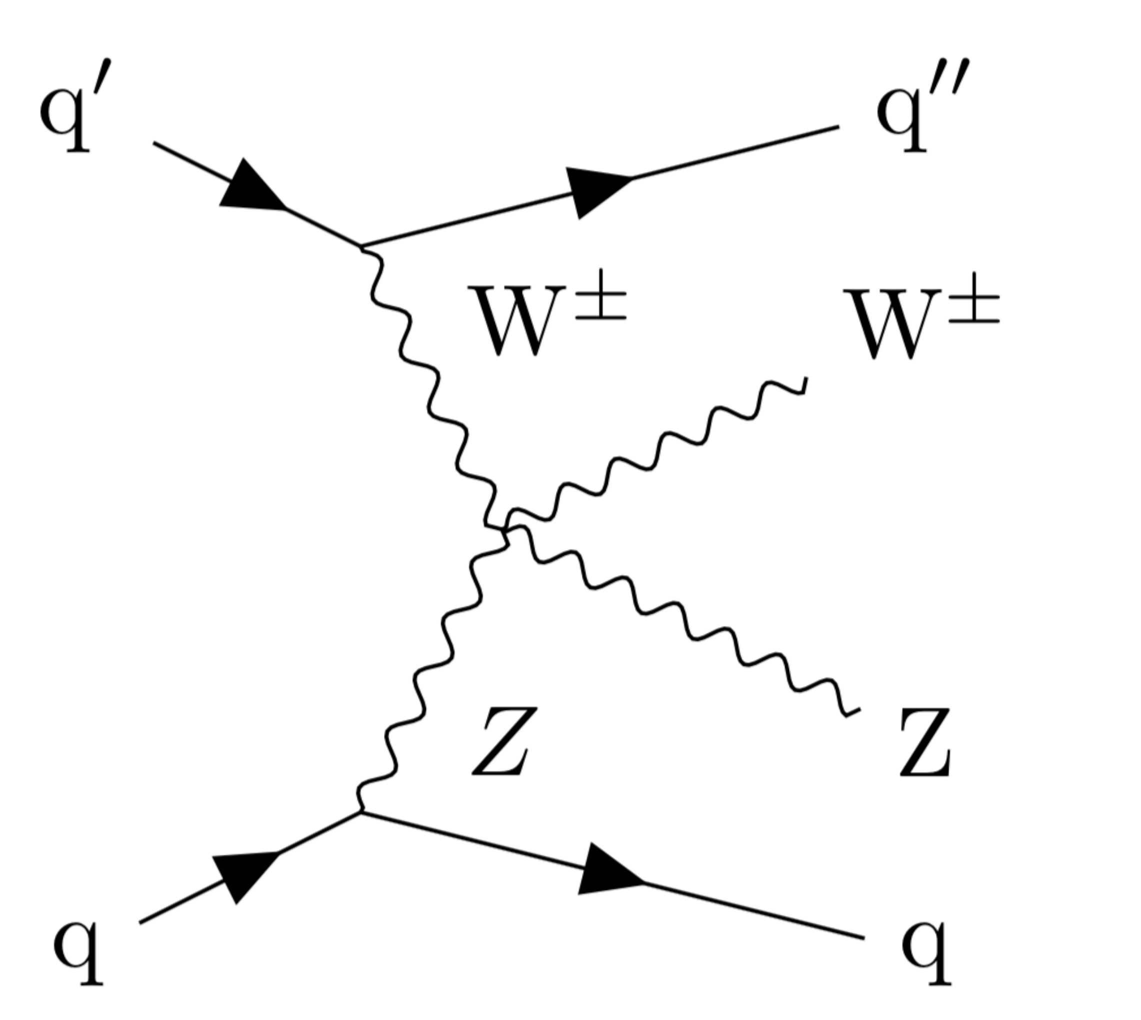
Detecting the rare and complex:
ML for precision and efficiency at the LHC

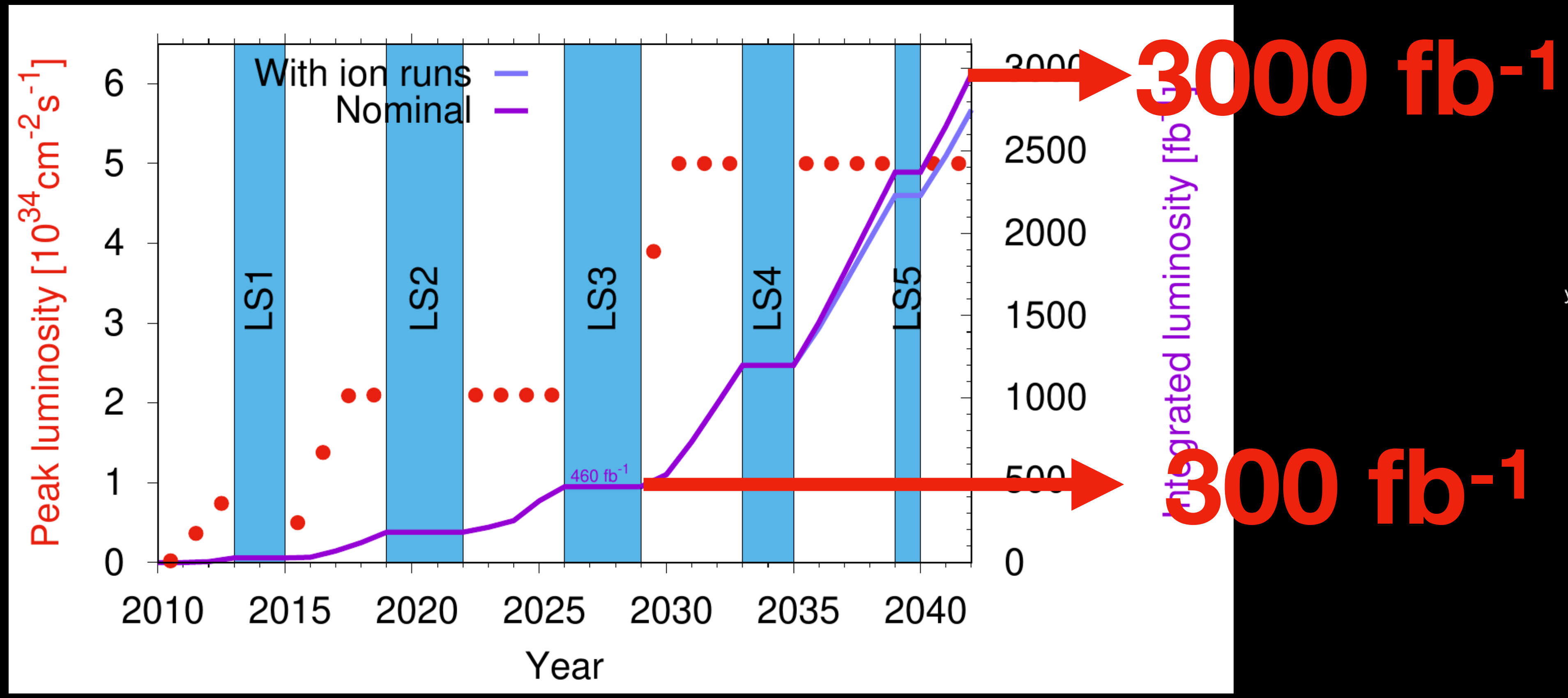
COMETA Colloquium
Thea Klæboe Årrestad (ETH Zürich)

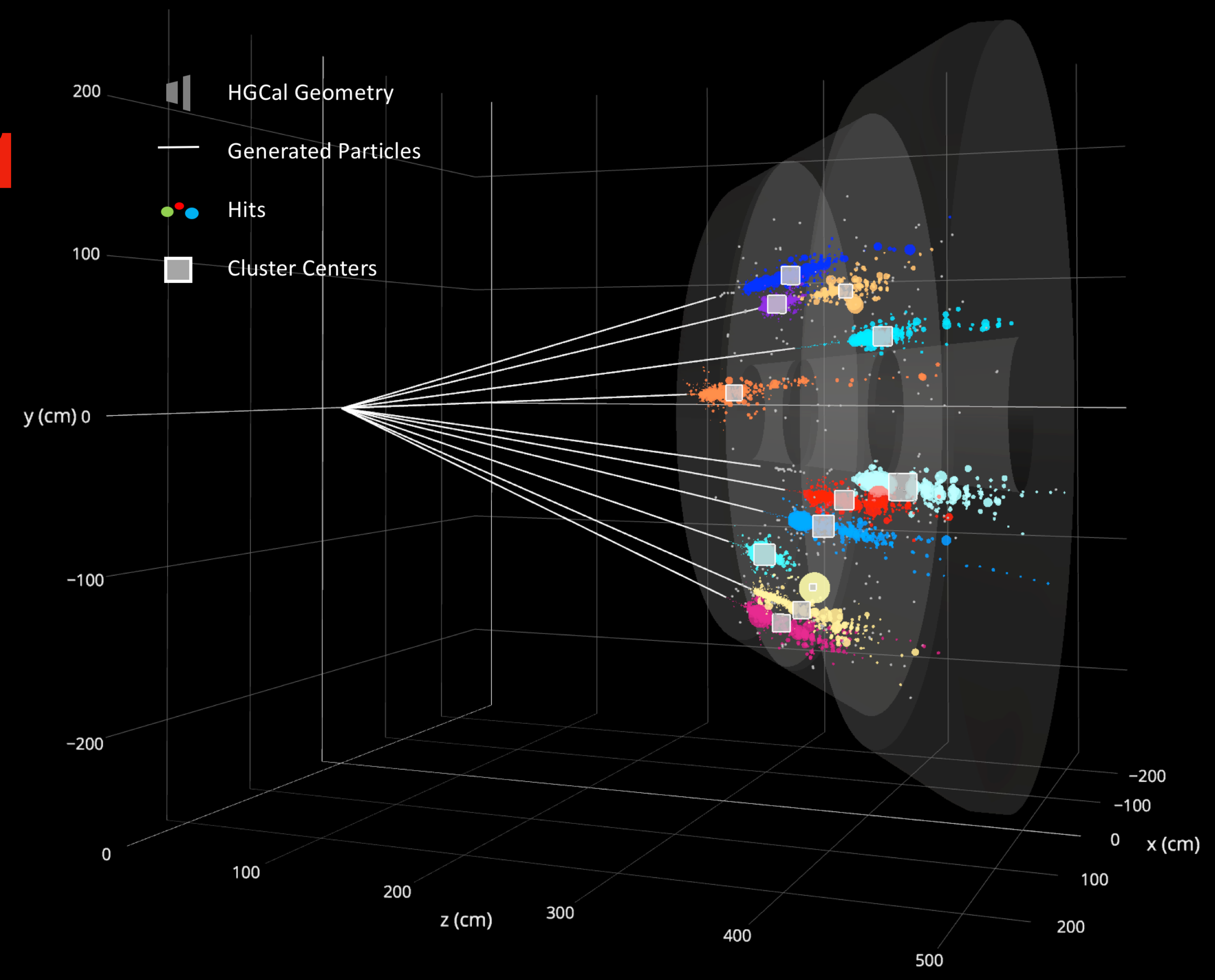




Luminosity: HL-LHC - 90% of final LHC dataset!

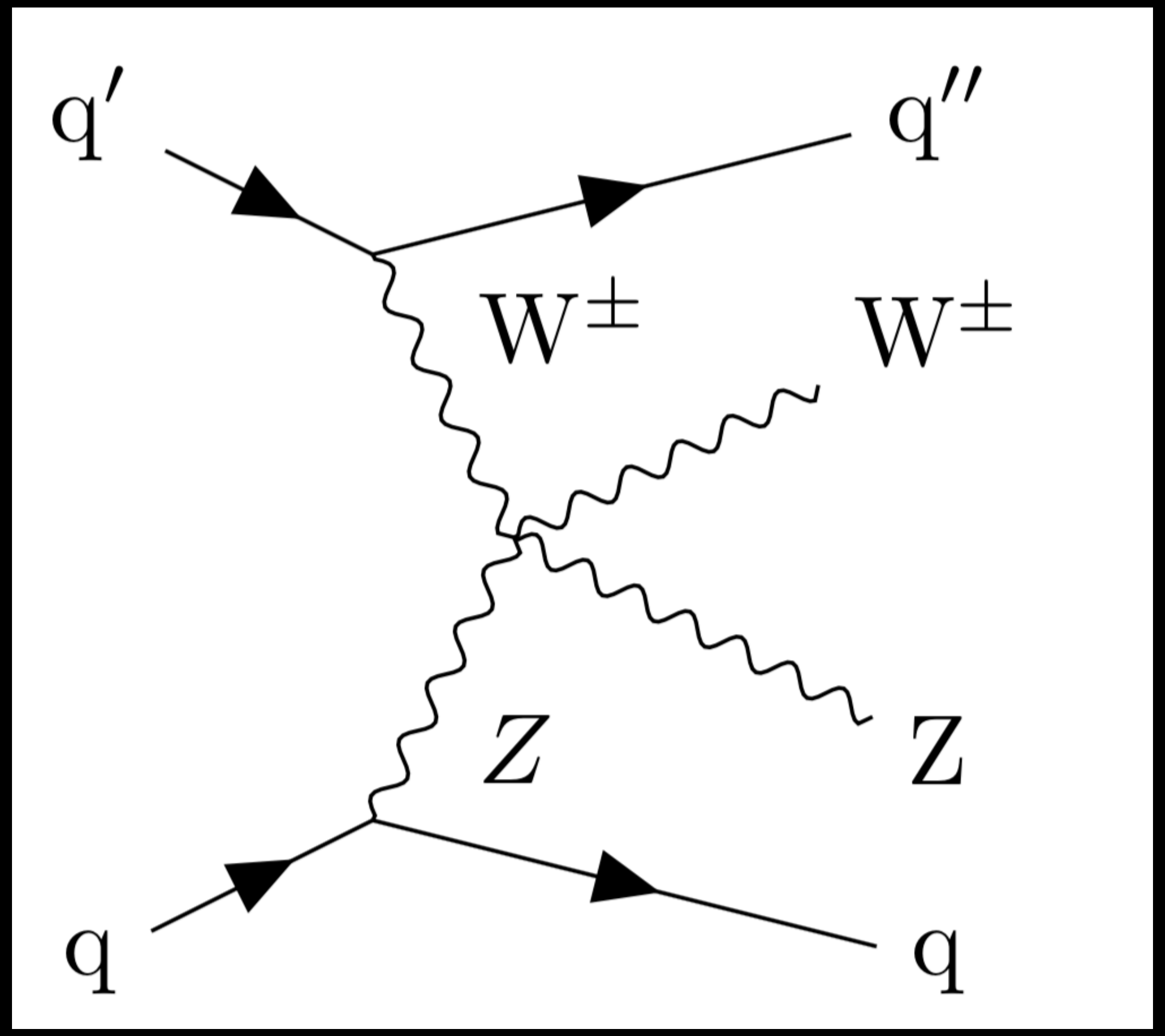


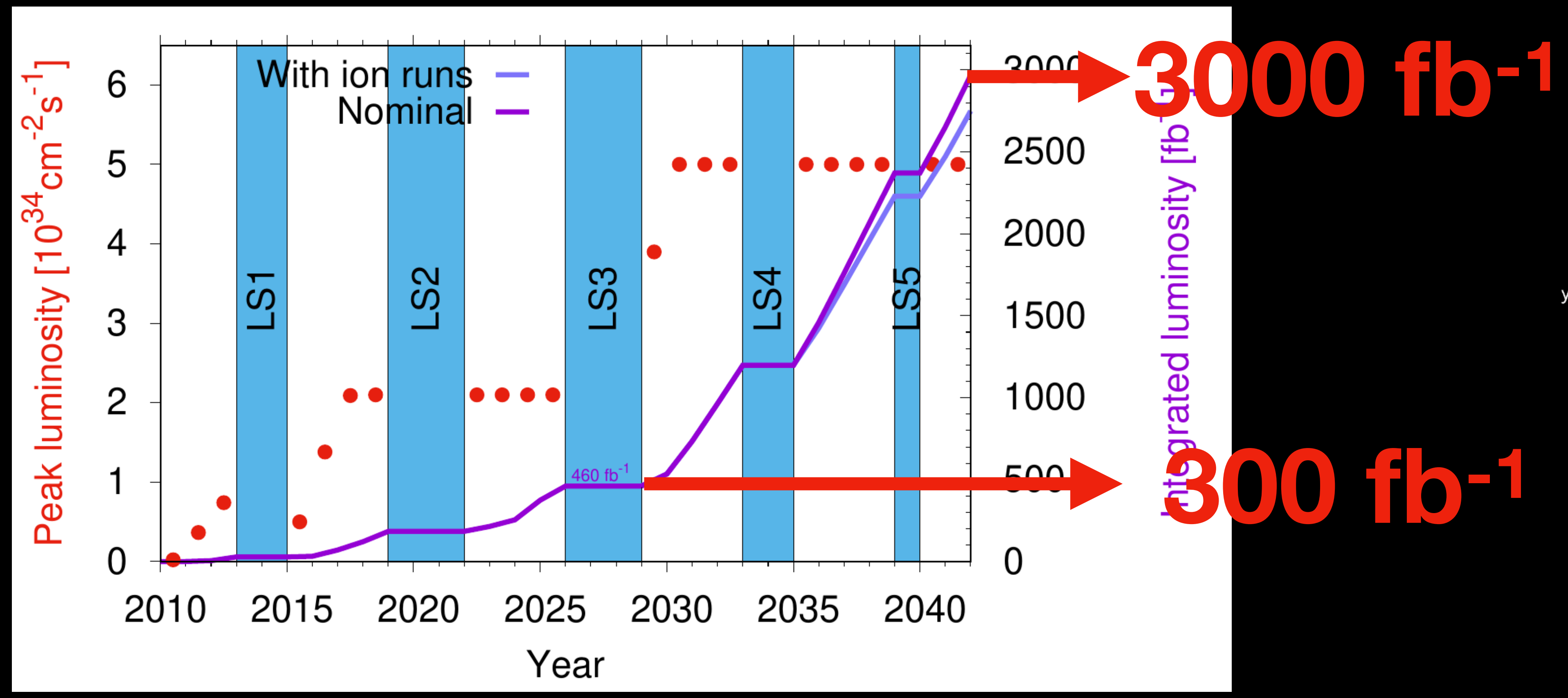


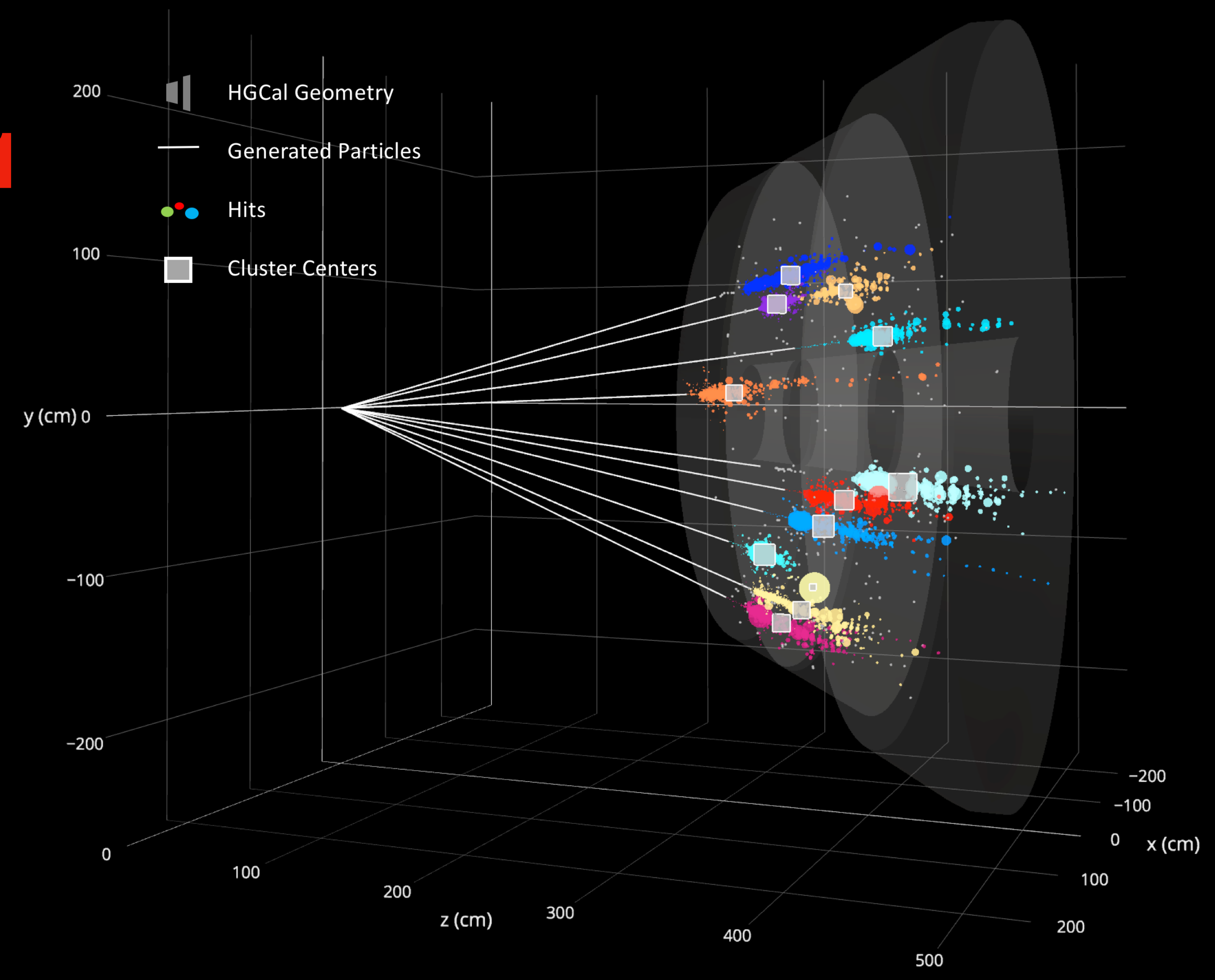


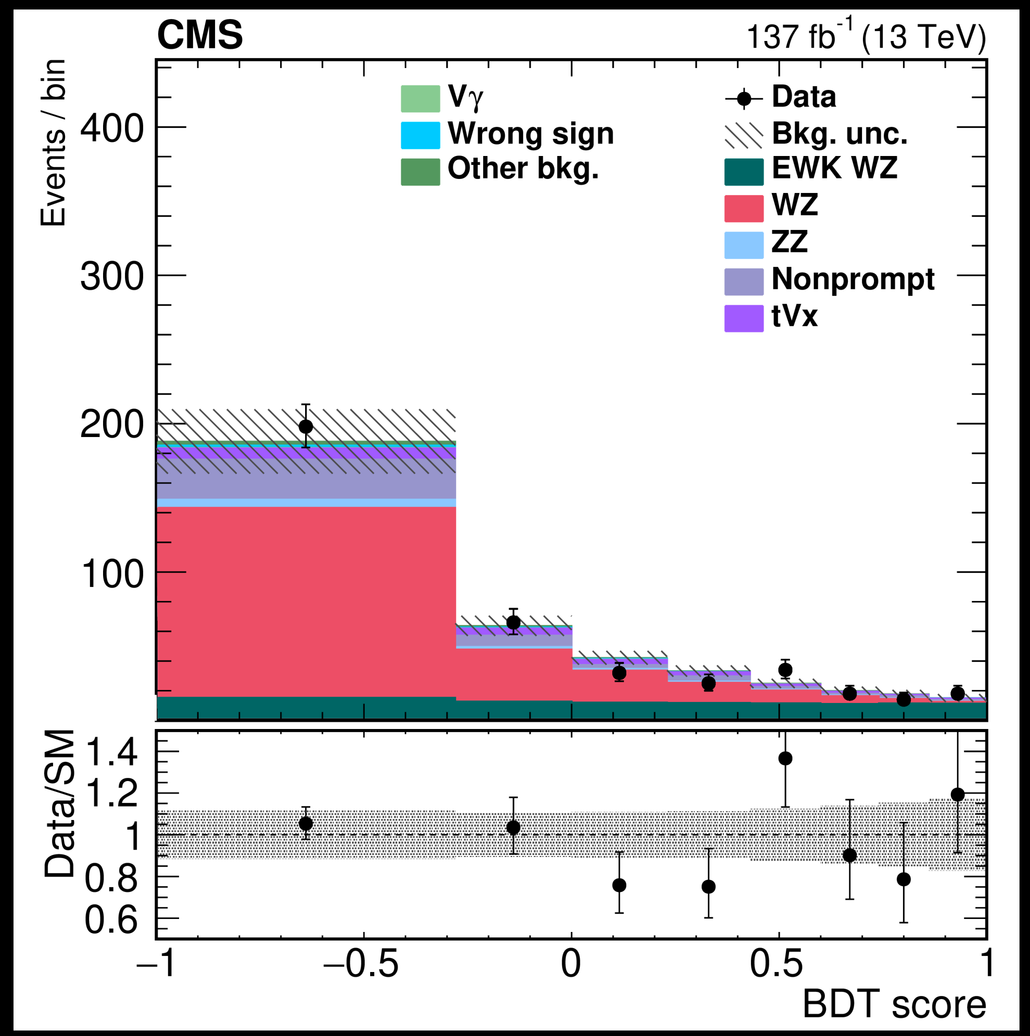
Luminosity: HL-LHC - 90% of final LHC dataset!

Detectors: Better data





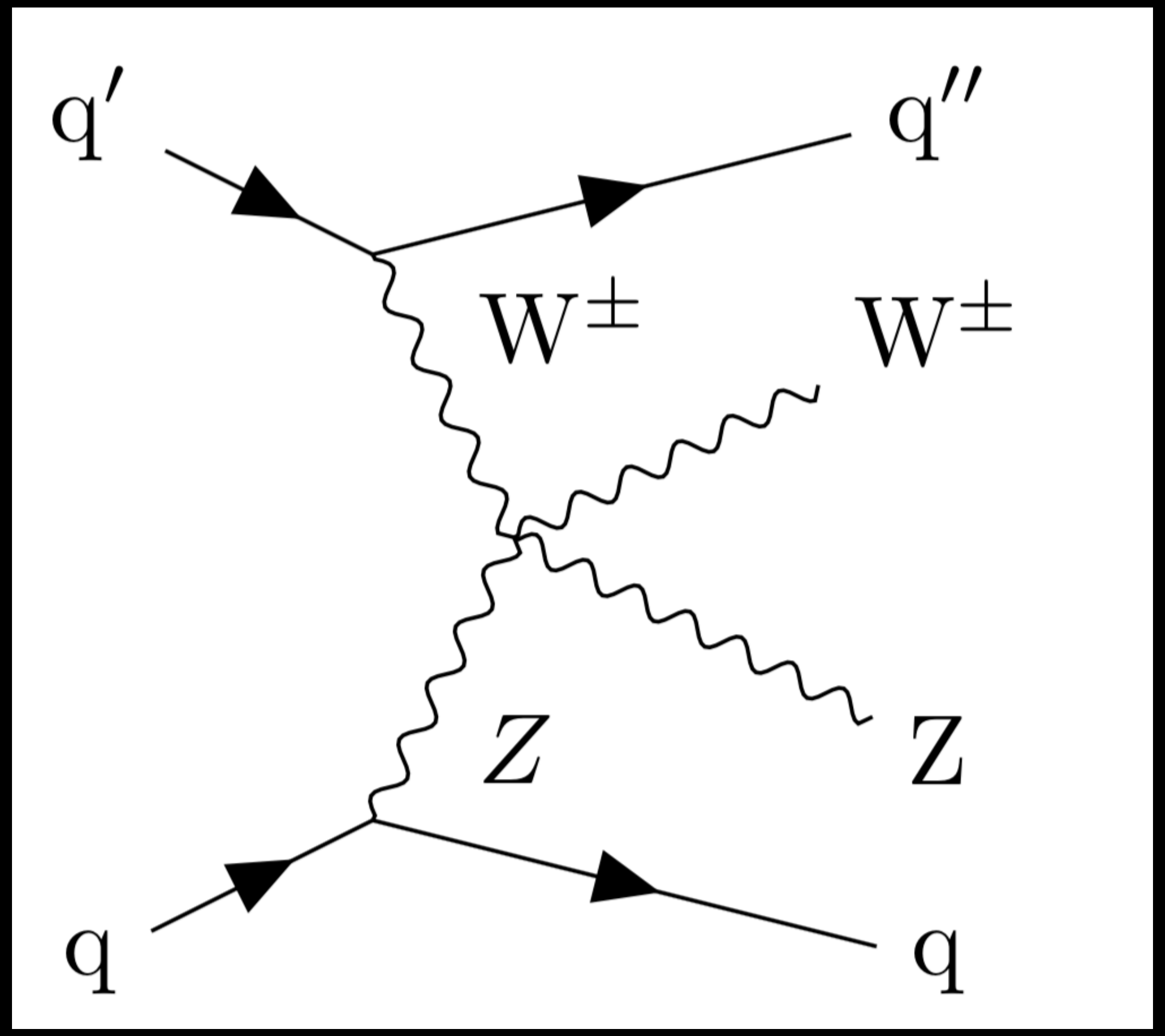


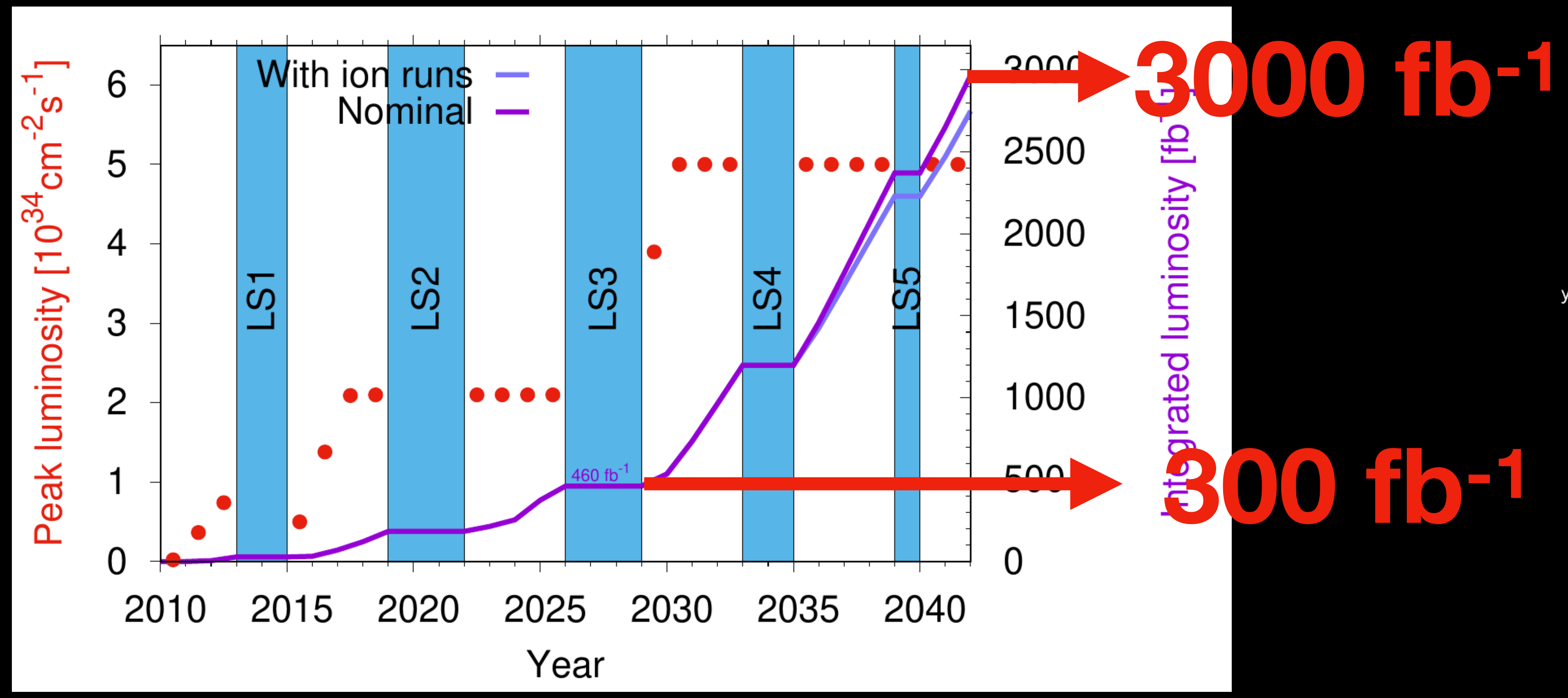


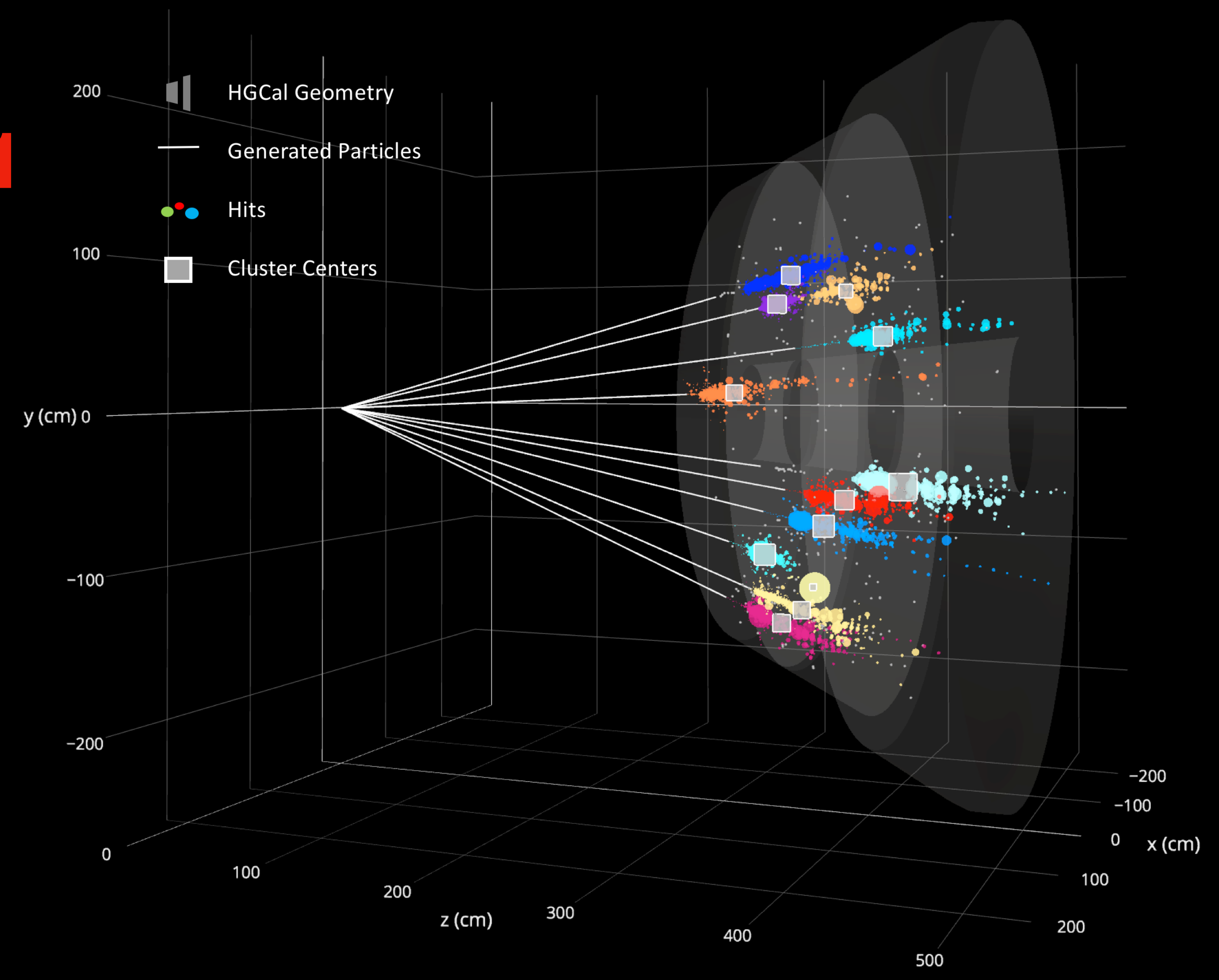
Luminosity: HL-LHC - 90% of final LHC dataset!

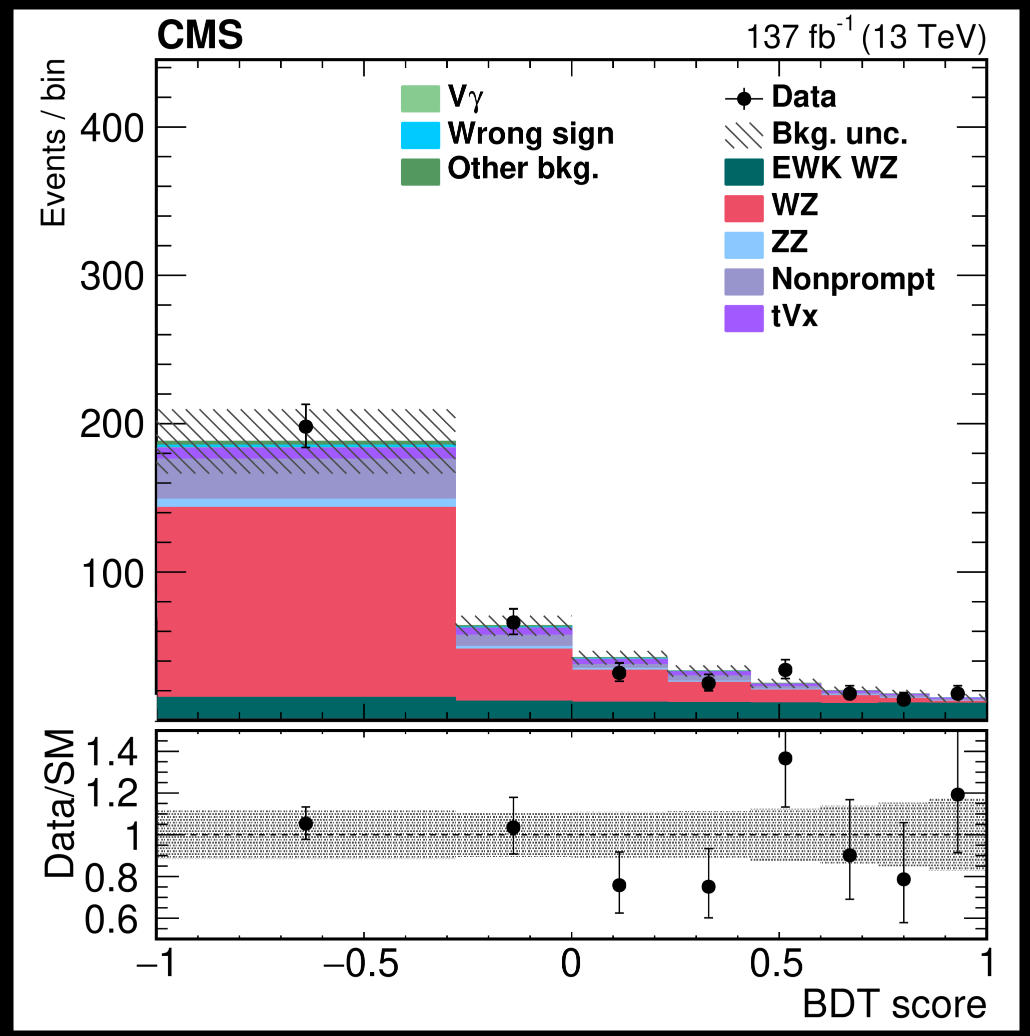
Detectors: Better data

Analyses: Squeeze the most out of data!





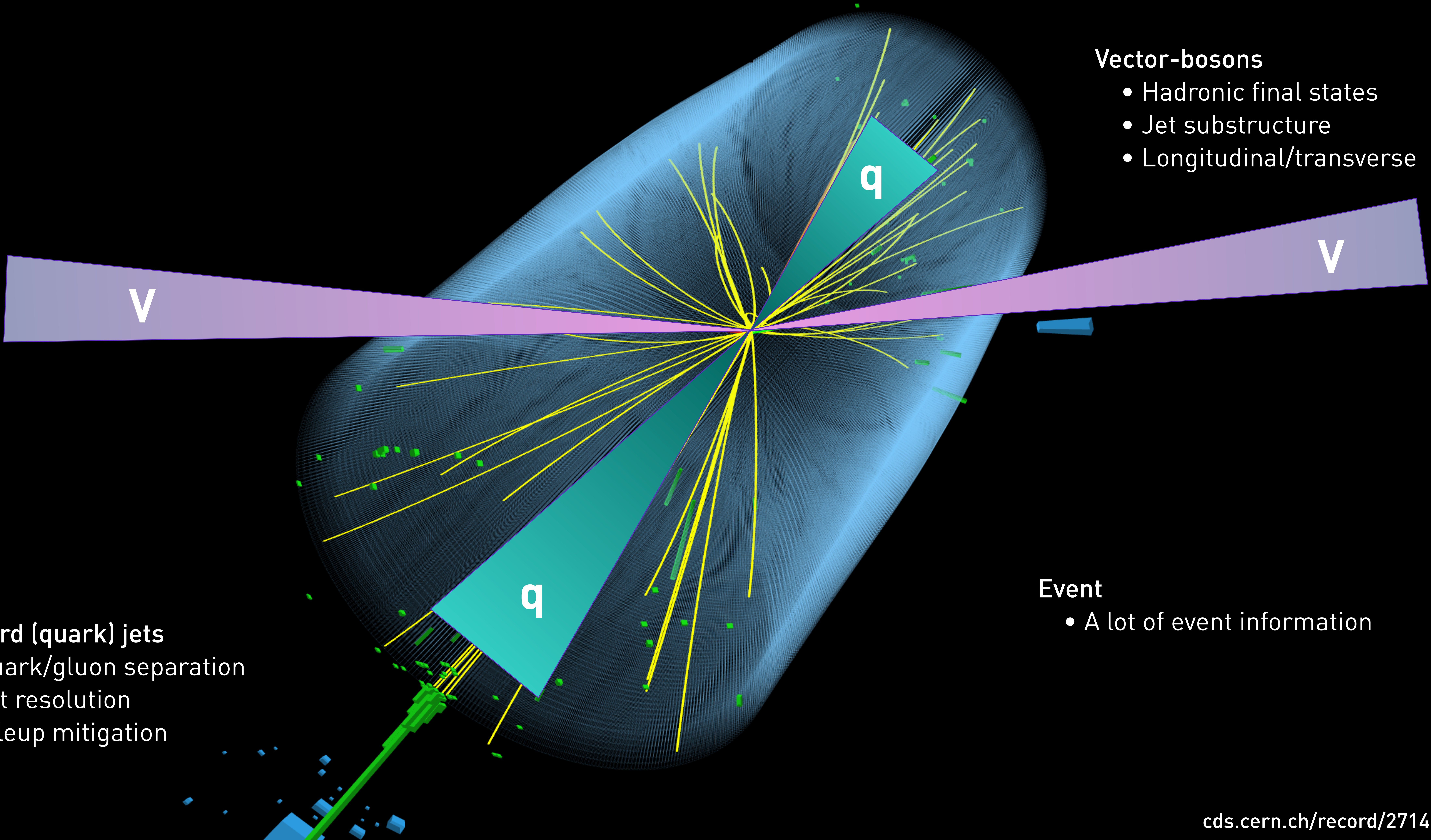




ML:
Manage data rates

ML:
Reconstruct complex patterns in complex detectors

ML:
Enhance S/√B



Vector-bosons
- Hadronic final states
- Jet substructure
- Longitudinal/transverse

Event
- A lot of event information

Forward (quark) jets
- Quark/gluon separation
- Jet resolution
- Pileup mitigation

cds.cern.ch/record/2714080

CERN 70 years!

La sixième session du Conseil fut organisée à Paris du 29 juin au
1er juillet 1953. C'est à cette occasion que la Convention établissant l'Organisation fut signée, sous réserve de ratification, par douze Etats membres.

The Sixth Session of the CERN Council took place in Paris on 29 June—1 July 1953. It was here that the Convention establishing the Organization was signed, subject to ratification, by twelve States.

Sep 29th 1954

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1er juillet 1953. C'est à cette occasion que la Convention établissant l'Organisation fut signée, sous réserve de ratification, par douze Etats membres.

For the German Federal Republic — Pour la République Fédérale d'Allemagne

subject to ratification

For the Kingdom of Belgium — Pour le Royaume de Belgique

sous réserve de ratification

For the Kingdom of Denmark — Pour le Royaume de Danemark

sous réserve de ratification

For the French Republic — Pour la République Française

sous réserve de ratification

For the Kingdom of Greece — Pour le Royaume de Grèce

sous reserve de ratification

For Italy — Pour l'Italie

sous reserve de ratification

For the Kingdom of Norway — Pour le Royaume de Norvège

Subject to ratification

For the Kingdom of the Netherlands — Pour le Royaume des Pays-Bas

Subject to ratification

For the United Kingdom of Great Britain and Northern Ireland — Pour le Royaume-Uni de la Grande-Bretagne et de l'Irlande du Nord

Subject to ratification.

For the Kingdom of Sweden — Pour le Royaume de Suède

Torsten Gustafson

Subject to ratification

For the Confederation of Switzerland — Pour la Confédération Suisse

sous réserve de ratification

For the Federal People's Republic of Yugoslavia — Pour la République Fédérative Populaire de Yougoslavie

Pavle Savić

sous réserve de ratification

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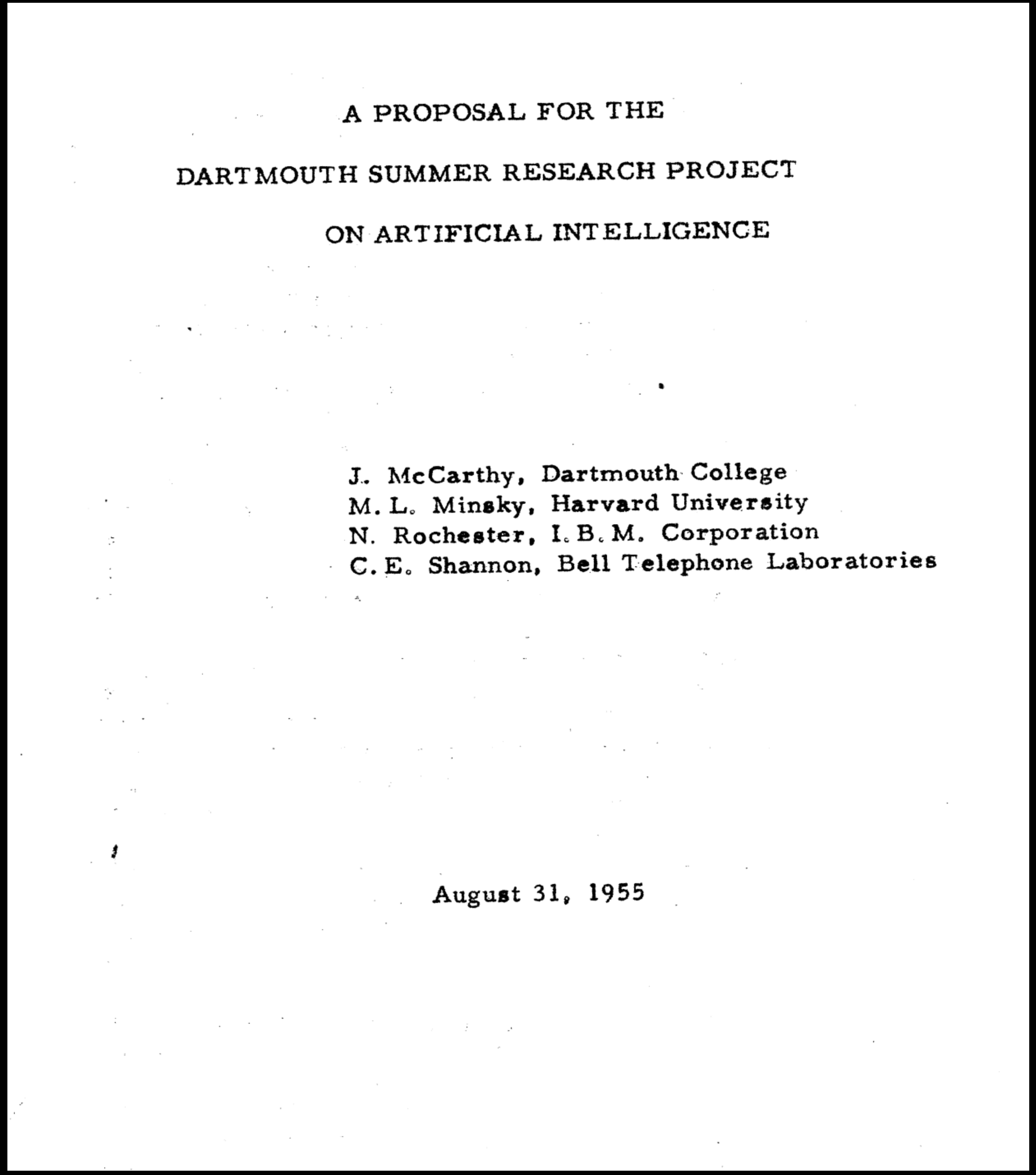
Sep 2nd 1955



A PROPOSAL FOR THE

DARTMOUTH SUMMER RESEARCH PROJECT

ON ARTIFICIAL INTELLIGENCE

J. McCarthy, Dartmouth College
M. L. Minsky, Harvard University
N. Rochester, I. B. M. Corporation
C. E. Shannon, Bell Telephone Laboratories

August 31, 1955

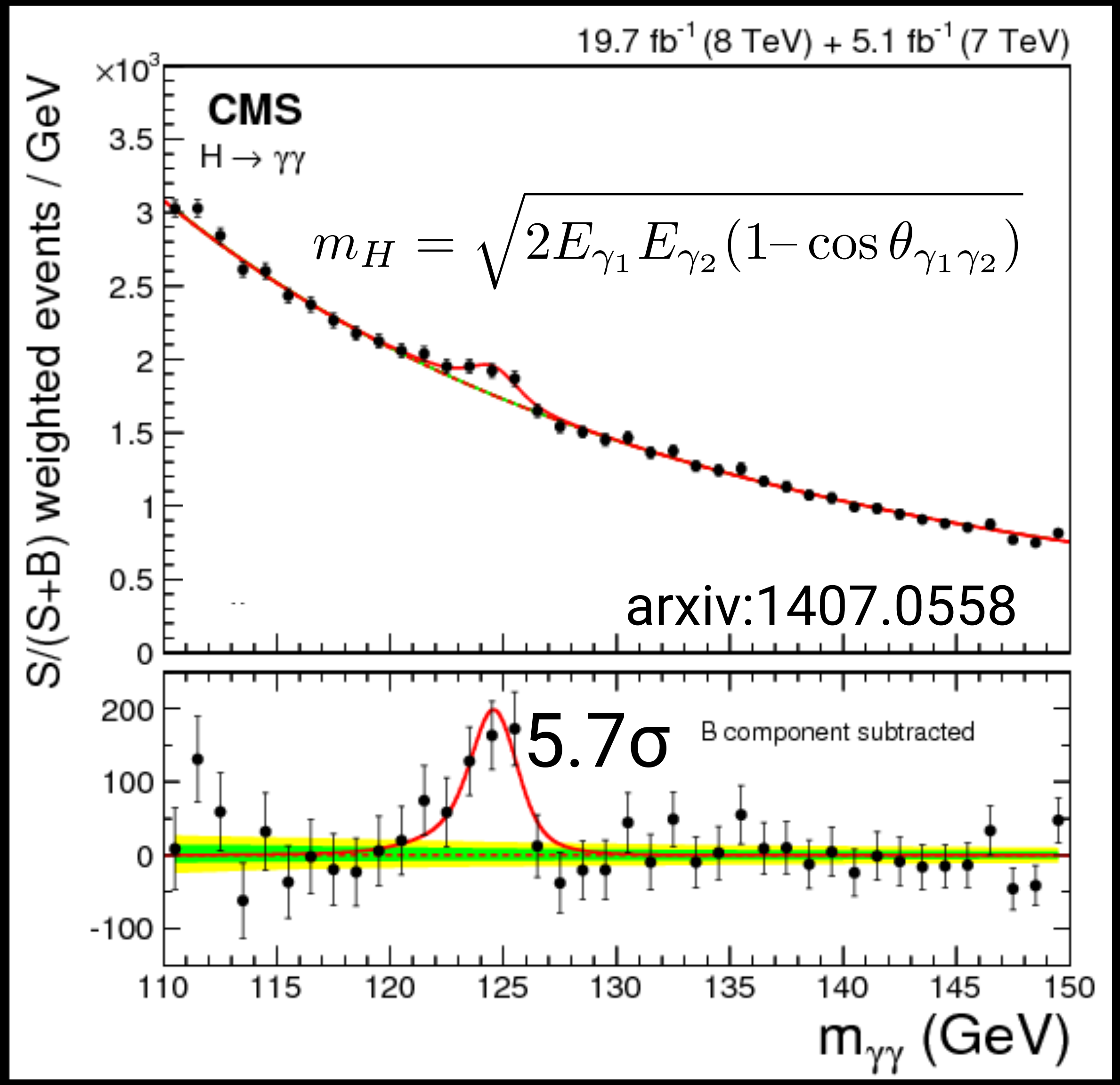
1957

1957

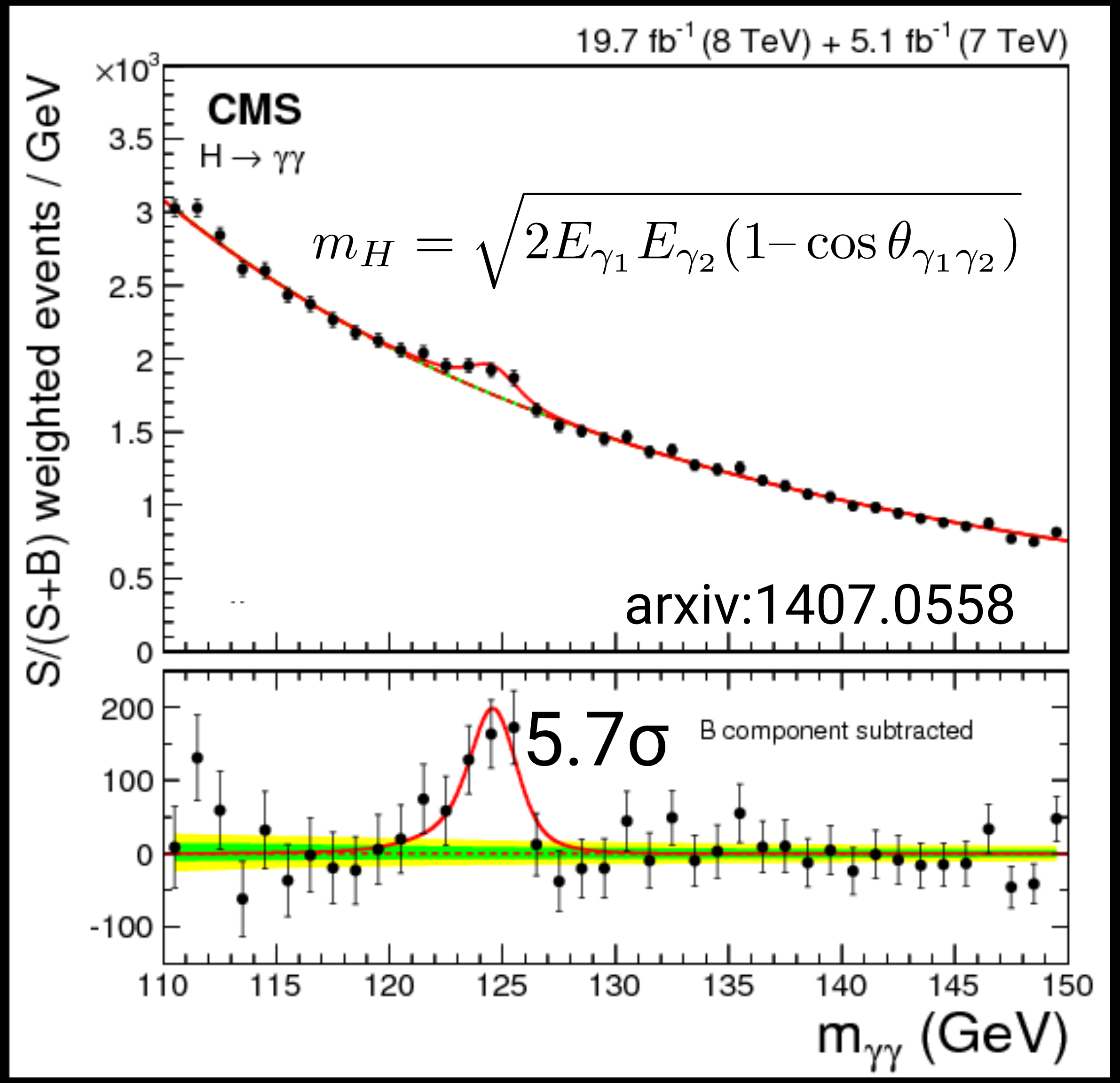
1958

a perceptron “may eventually be able to learn, make decisions, and translate languages.”

July 4th 2012



July 4th 2012



Sep 30th 2012

Large Scale Visual Recognition Challenge 2012 (ILSVRC2012

Held in conjunction with PASCAL Visua
Back to Main page

All results

- Task 1 (classification)
- Task 2 (localization)
- Task 3 (fine-grained classification)
- Team information and abstracts

Task 1

Team name	Filename	Error (5 guesses)	Description
SuperVision	test-preds-141-146.2009-131-137-145-146.2011-145f.	0.15315	Using extra training data from ImageNet Fall 2011 release
SuperVision	test-preds-131-137-145-135-145f.txt	0.16422	Using only supplied training data
ISI	pred_FVs_wLACs_weighted.txt	0.26172	Weighted sum of scores from each classifier with SIFT+FV, LBP+FV, GIST+FV, and
ISI			
ISI			
			each classifier with

SuperVision	Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton University of Toronto	Our model is a large, deep convolutional neural network trained on raw RGB pixel values. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three globally-connected layers with a final 1000-way softmax. It was trained on two NVIDIA GPUs for about a week. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of convolutional nets. To reduce overfitting in the globally-connected layers we employed hidden-unit "dropout", a recently-developed regularization method that proved to be very effective.

2024

The Nobel Prize in Physics 2024

Popular information

Ill. Niklas Elmehed © Nobel Prize Outreach

John J. Hopfield

Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach

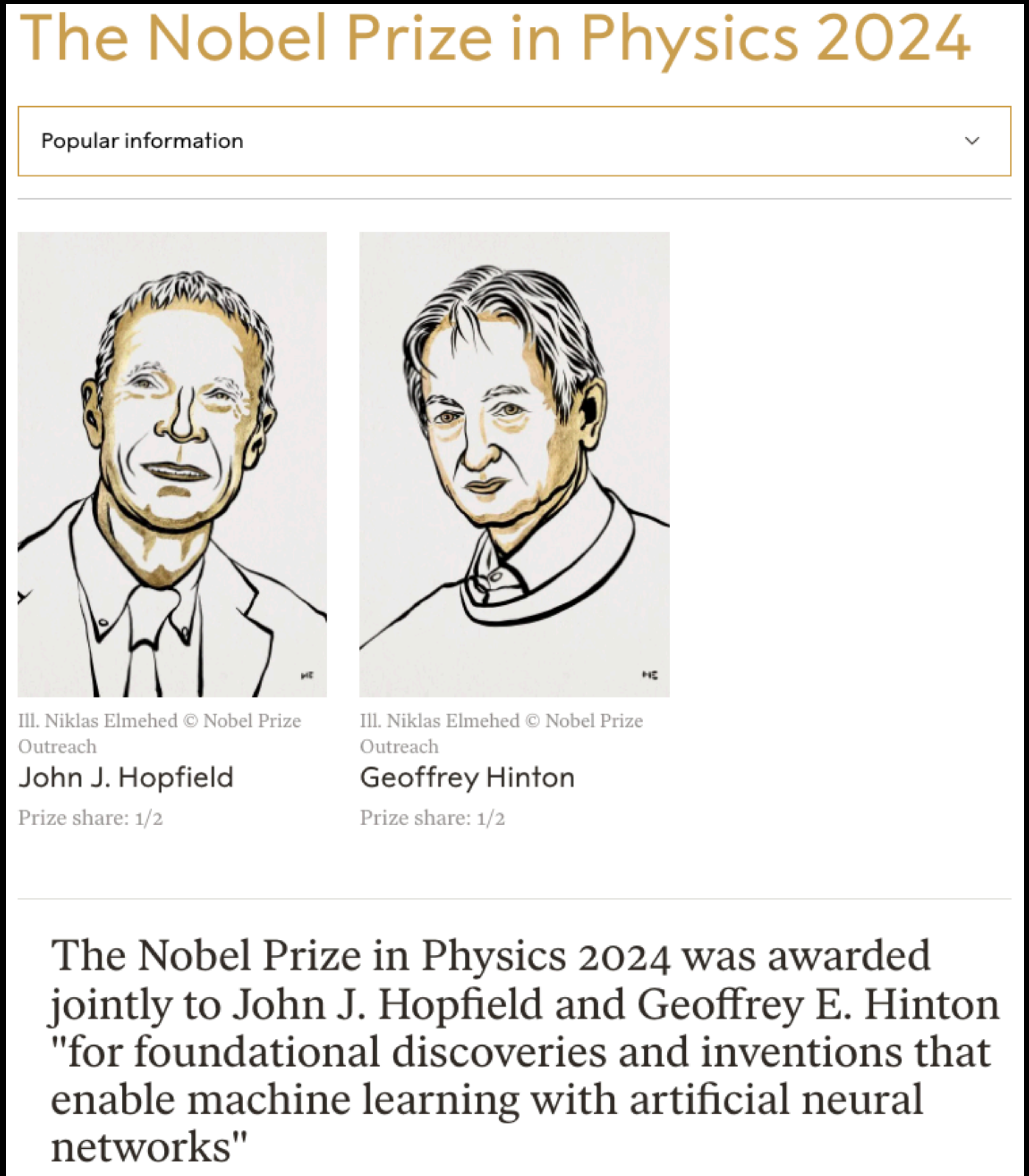
Geoffrey Hinton

Prize share: 1/2

The Nobel Prize in Physics 2024 was awarded jointly to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks"

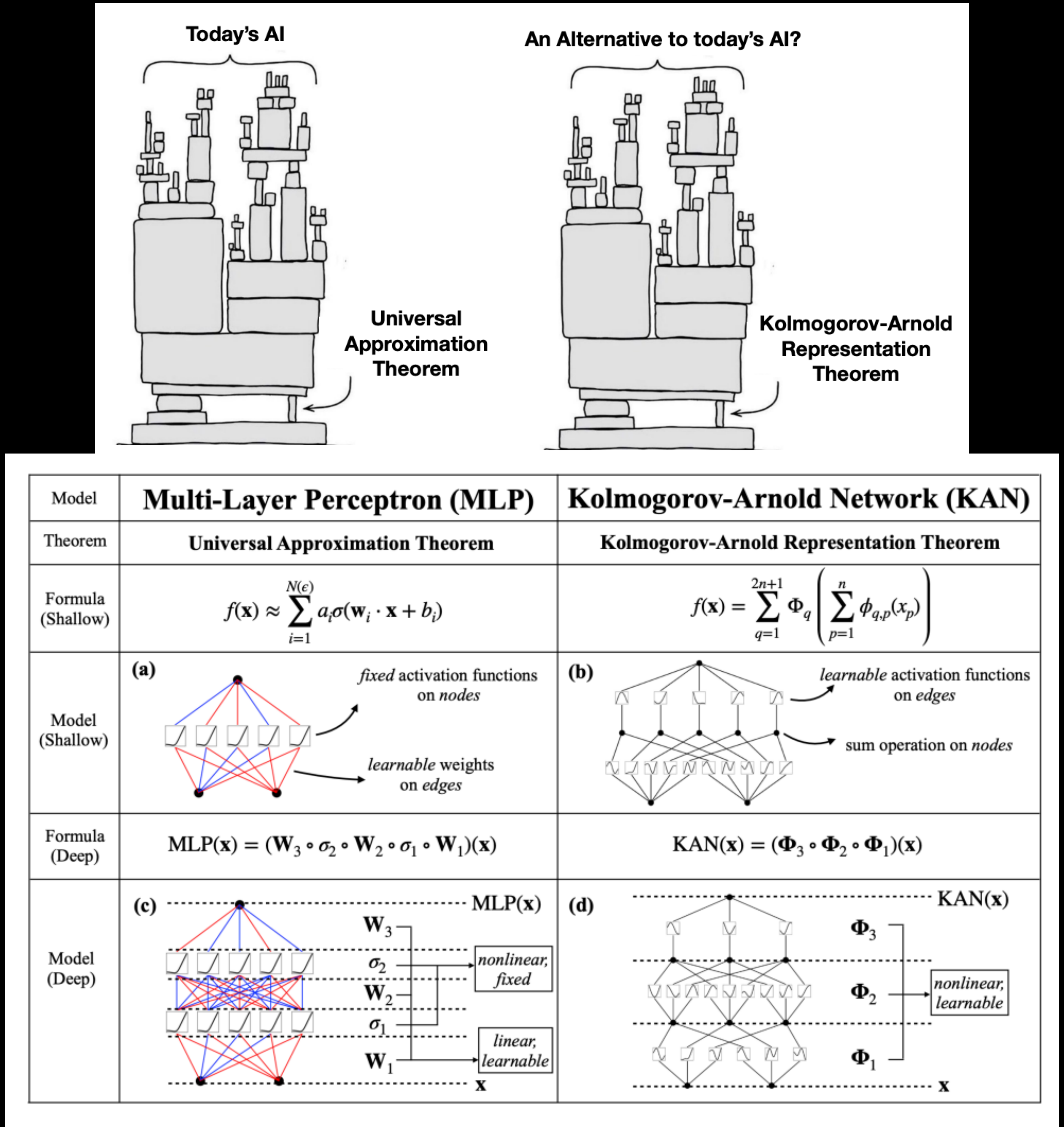
nobelprize.org/prizes/physics/2024

2024

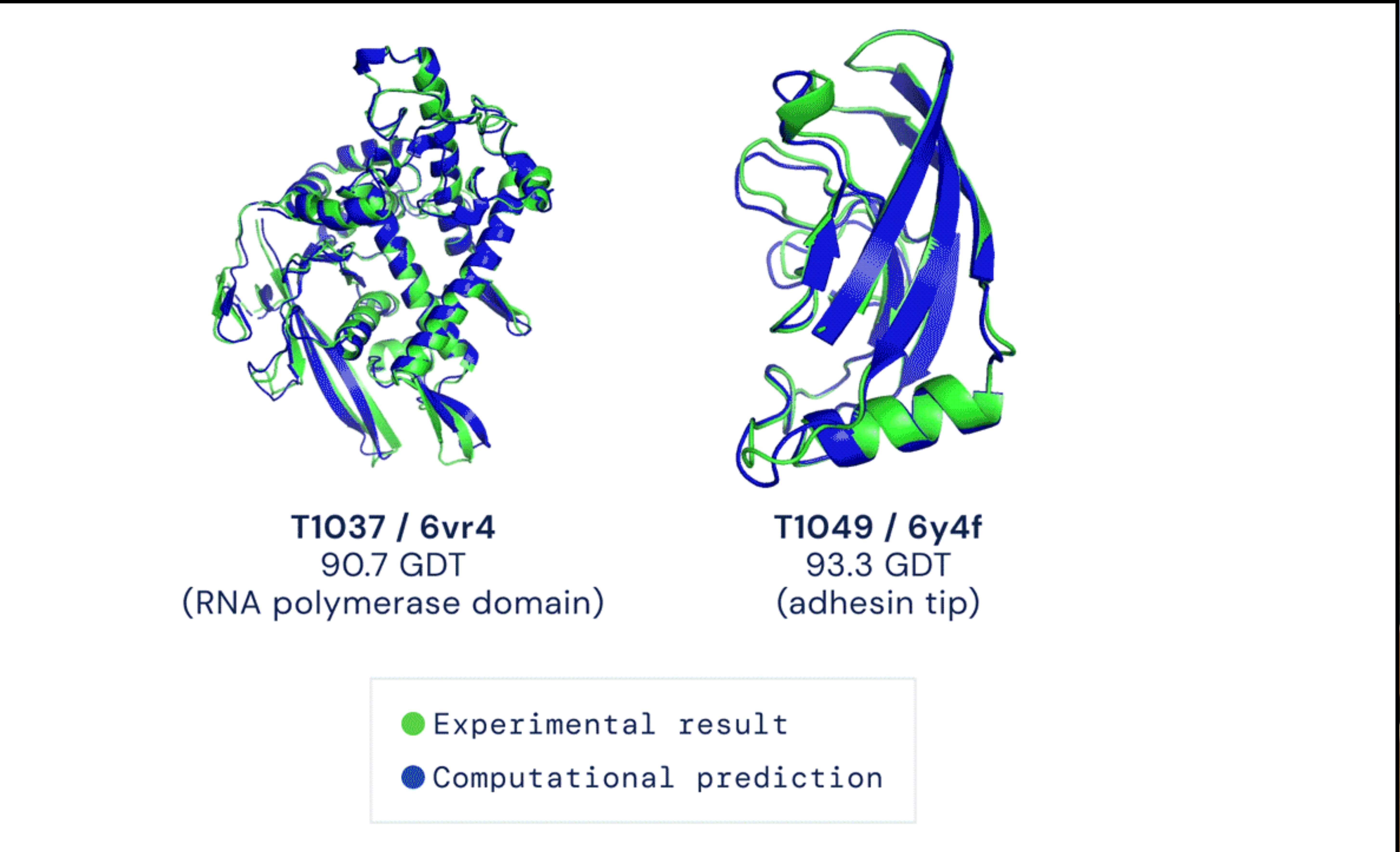


nobelprize.org/prizes/physics/2024

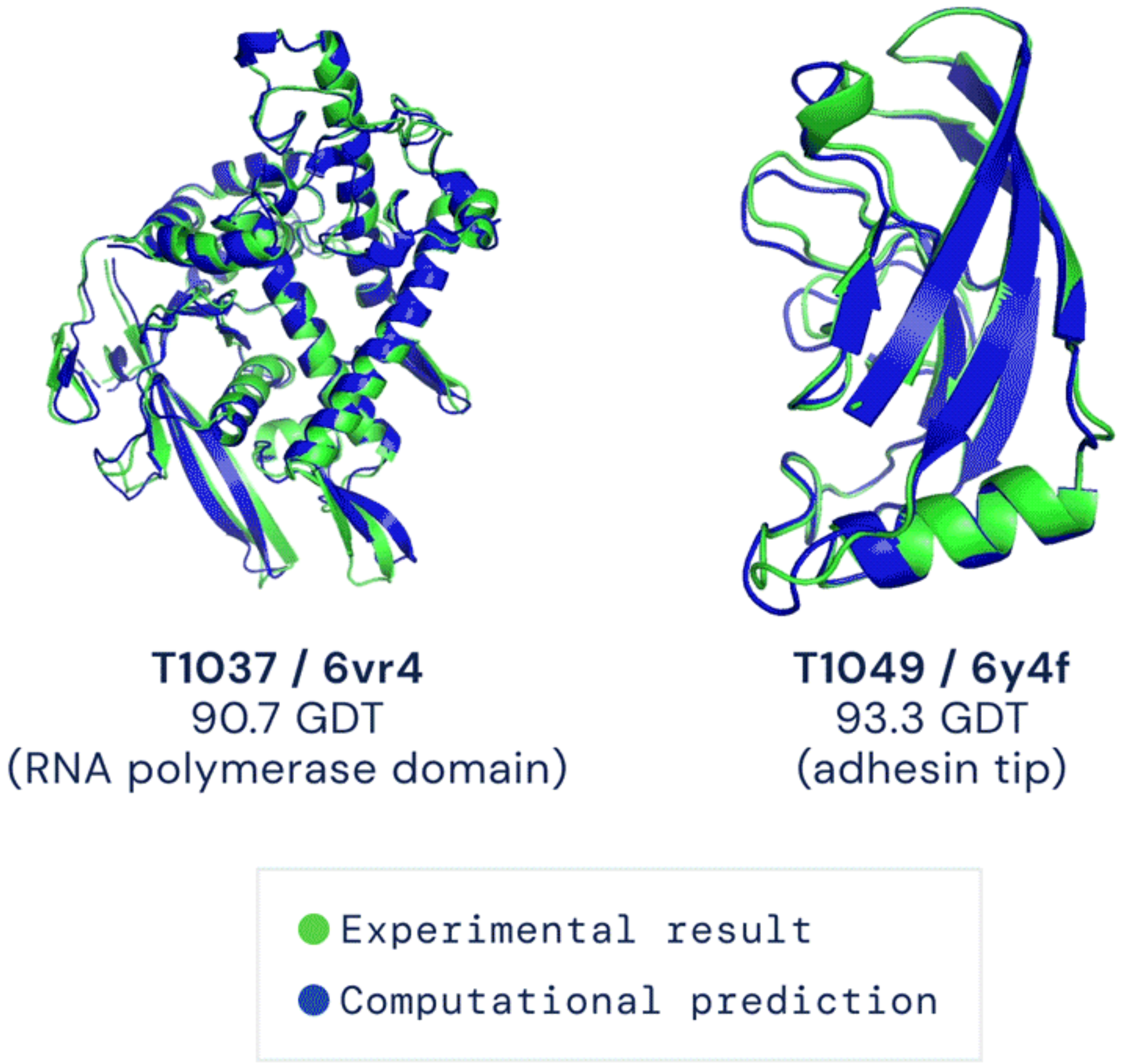
2024

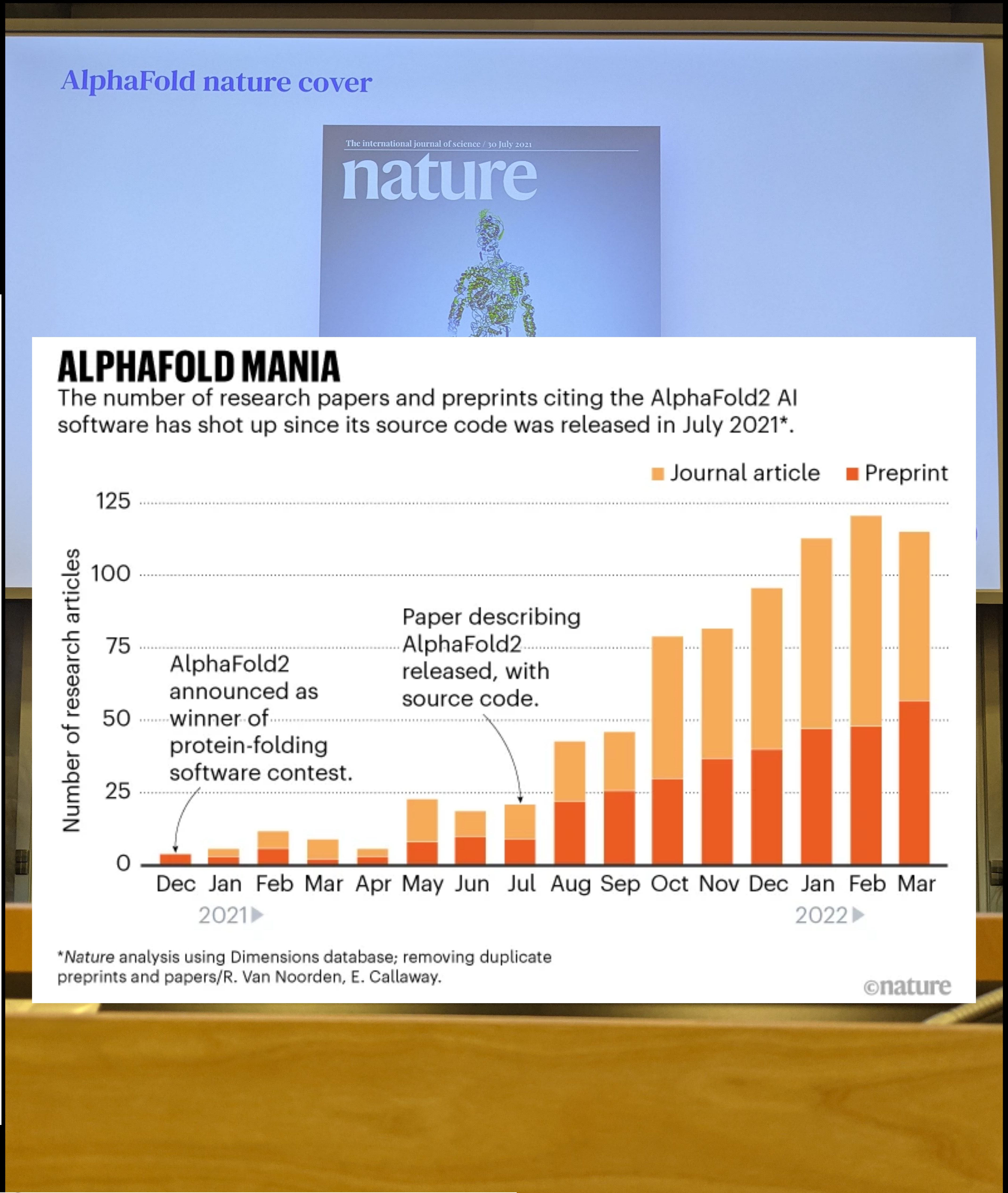


arxiv:2404.19756



sequence—the structure prediction component of the 'protein folding problem'[8]—has been an important open research problem for more than 50 years[9]. Despite recent





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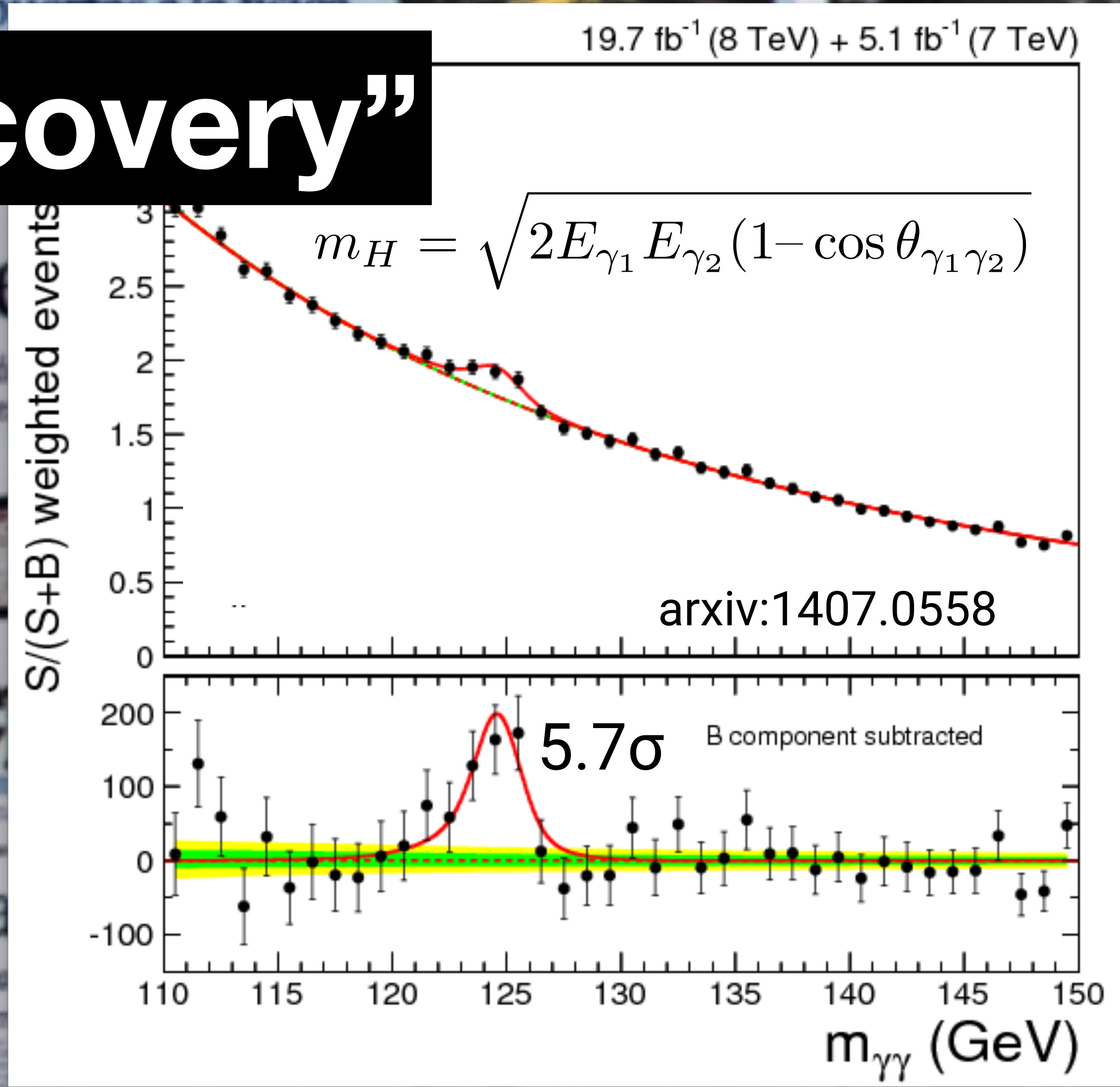
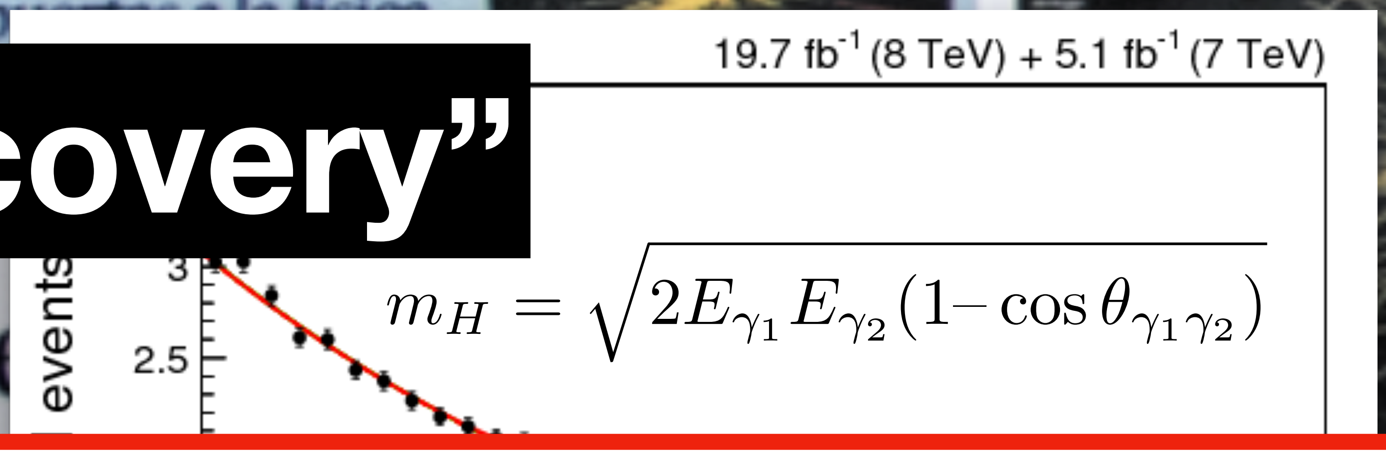
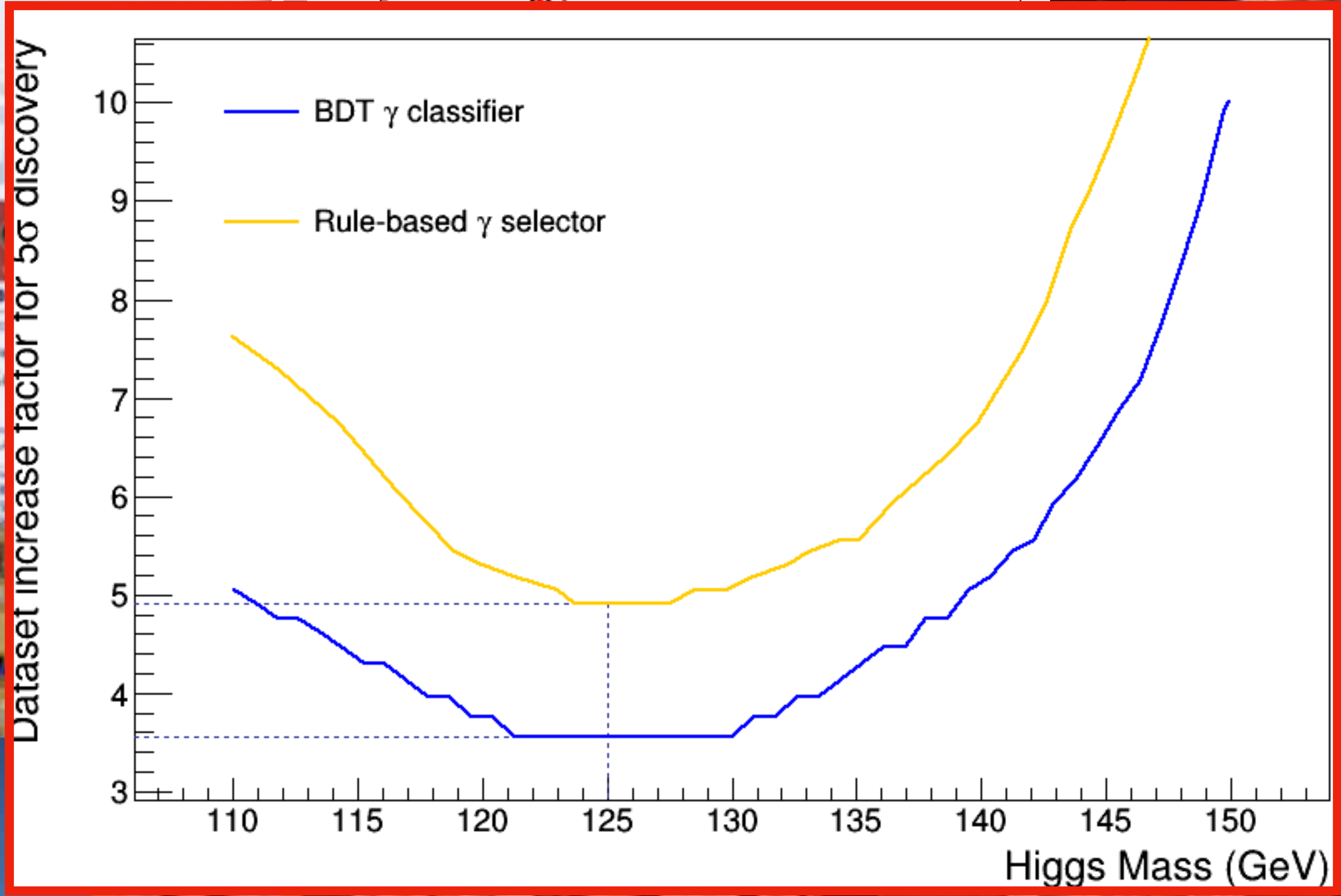
“ML for accelerated discovery”



CERN Summer student 2012

“ML for accelerated discovery”





CERN Summer student 2012

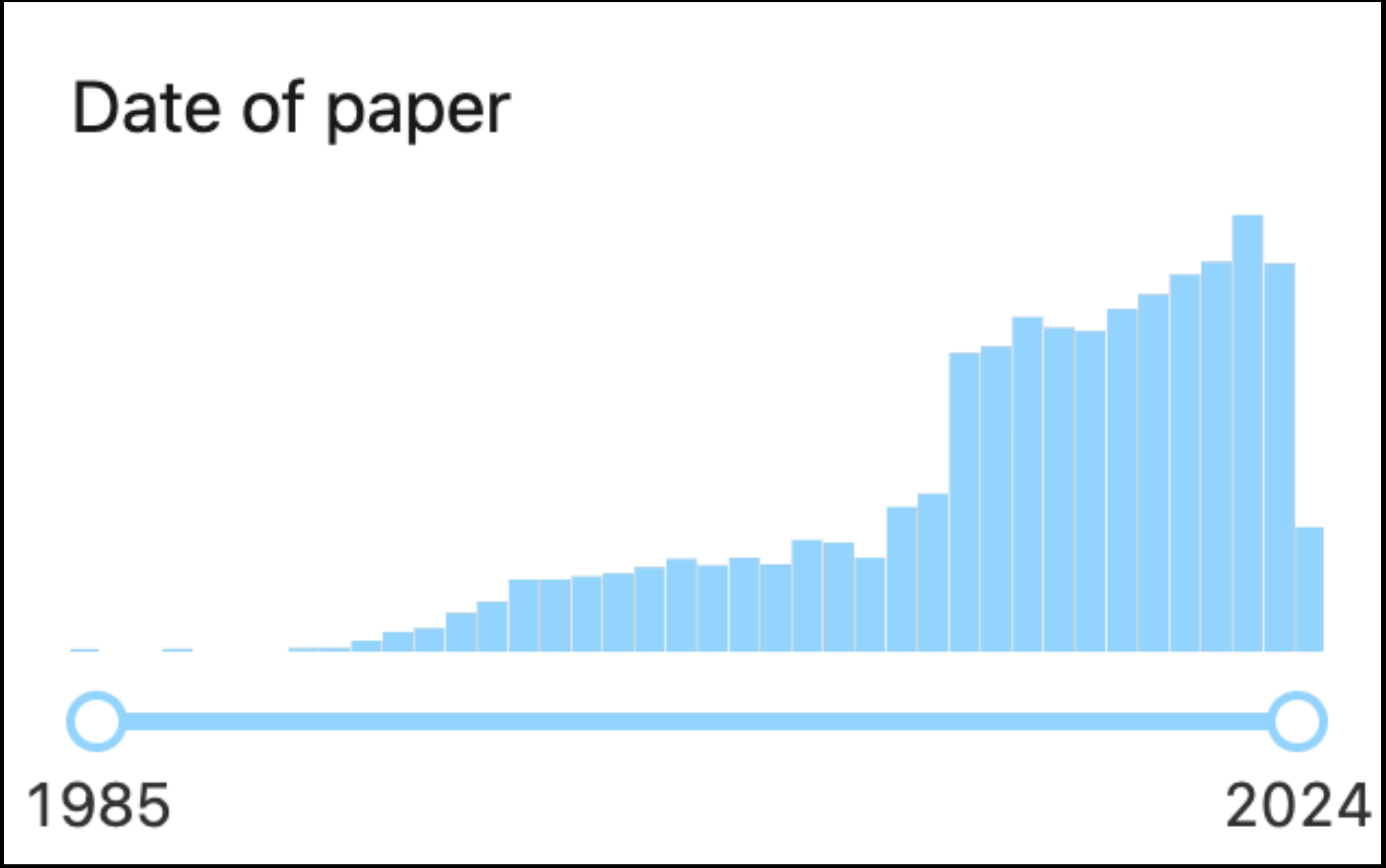
Nature Review

Analysis	Years of data collection	Sensitivity without machine learning	Sensitivity with machine learning	Ratio of P values	Additional data required
CMS[24] $H \to \gamma\gamma$	2011–2012	2.2σ, $P = 0.014$	2.7σ, $P = 0.0035$	4.0	51%
ATLAS[43] $H \to \tau^+\tau^-$	2011–2012	2.5σ, $P = 0.0062$	3.4σ, $P = 0.00034$	18	85%
ATLAS[99] $VH \to bb$	2011–2012	1.9σ, $P = 0.029$	2.5σ, $P = 0.0062$	4.7	73%
ATLAS[41] $VH \to bb$	2015–2016	2.8σ, $P = 0.0026$	3.0σ, $P = 0.00135$	1.9	15%
CMS[100] $VH \to bb$	2011–2012	1.4σ, $P = 0.081$	2.1σ, $P = 0.018$	4.5	125%

We were using ML for discovery very early on

CERN Summer student 2012

40 000 papers so far!



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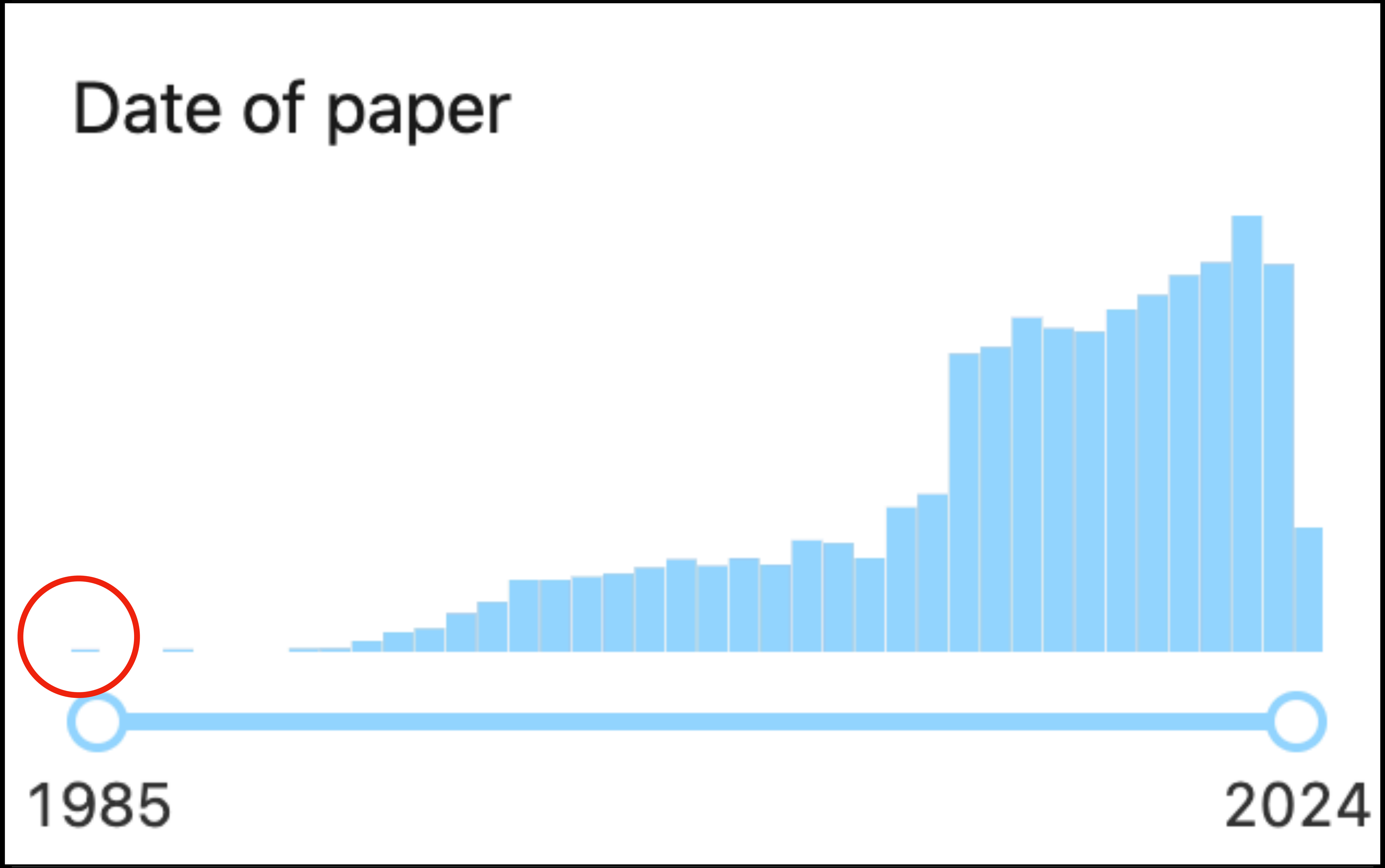

受入
85-1-167
高工研図書室

MPI-PAE/PTh 64/84
October 1984

An Evolutionary Procedure for Machine Learning

Leonard D. Mlodinow*

and

Ion O. Stamatescu**

Max-Planck-Institut für Physik und Astrophysik
- Werner-Heisenberg-Institut für Physik -
8000 Munich 40, West Germany

Abstract:

We discuss an evolutionary procedure for machine learning and present in detail an application of this procedure to the control of a robot TURTLE, which, beginning from a state of total ignorance, is able to develop the ability to circumnavigate a variety of obstacles. The procedure discussed is related to the strategy signature table method used in computer game playing.

NEURAL NETWORKS AND CELLULAR AUTOMATA IN EXPERIMENTAL HIGH ENERGY PHYSICS

B. DENBY

Laboratoire de l'Accélérateur Linéaire, Orsay, France

Received 20 September 1987; in revised form 28 December 1987

Within the past few years, two novel computing techniques, cellular automata and neural networks, have shown considerable promise in the solution of problems of a very high degree of complexity, such as turbulent fluid flow, image processing, and pattern recognition. Many of the problems faced in experimental high energy physics are also of this nature. Track reconstruction in wire chambers and cluster finding in cellular calorimeters, for instance, involve pattern recognition and high combinatorial complexity since many combinations of hits or cells must be considered in order to arrive at the final tracks or clusters. Here we examine in what way connective network methods can be applied to some of the problems of experimental high energy physics. It is found that such problems as track and cluster finding adapt naturally to these approaches. When large scale hard-wired connective networks become available, it will be possible to realize solutions to such problems in a fraction of the time required by traditional methods. For certain types of problems, faster solutions are already possible using model networks implemented on vector or other massively parallel machines. It should also be possible, using existing technology, to build simplified networks that will allow detailed reconstructed event information to be used in fast trigger decisions.

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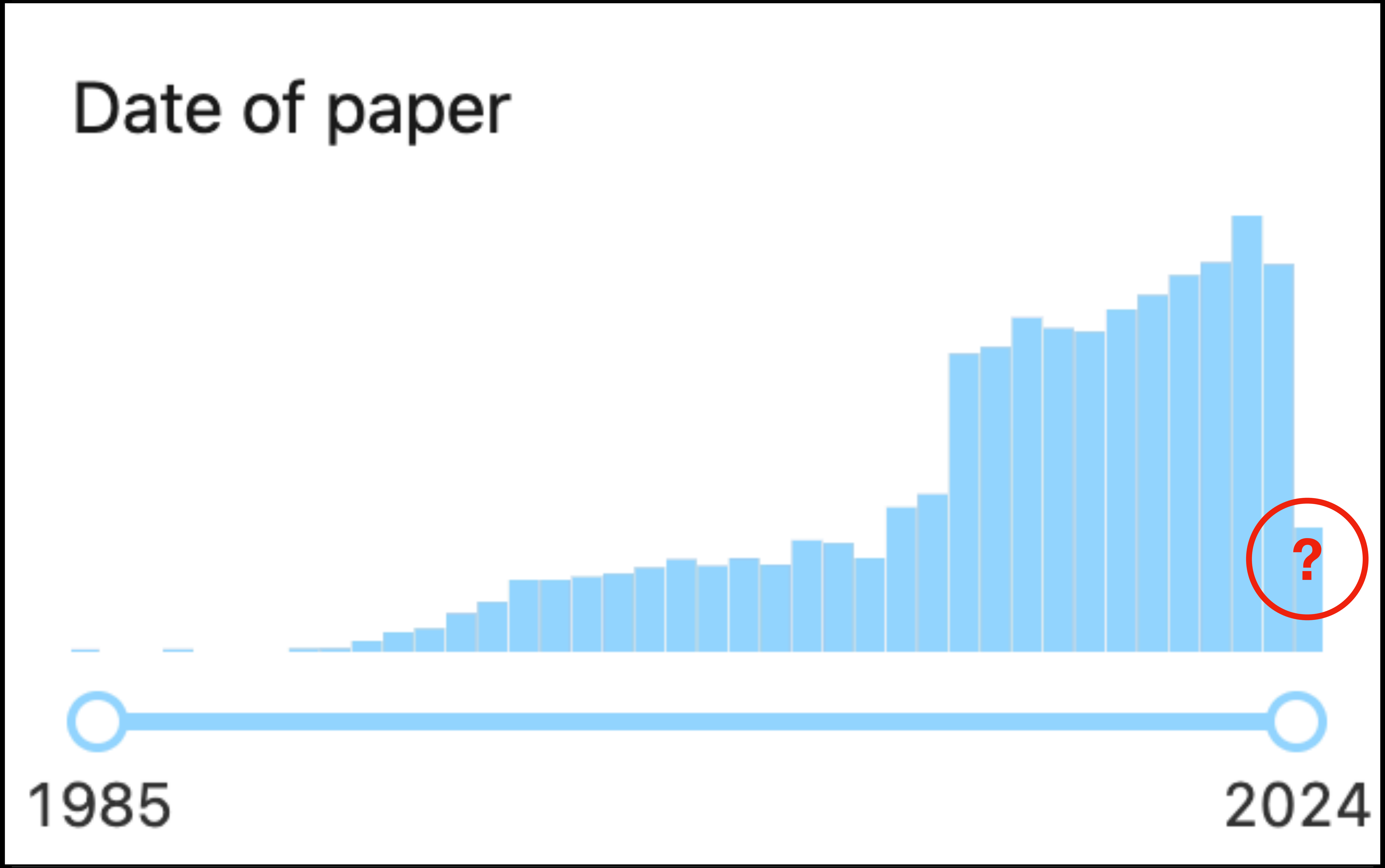
possible using model networks implemented on vector or other ma
existing technology, to build simplified networks that will allow d
trigger decisions.

What's in the article?

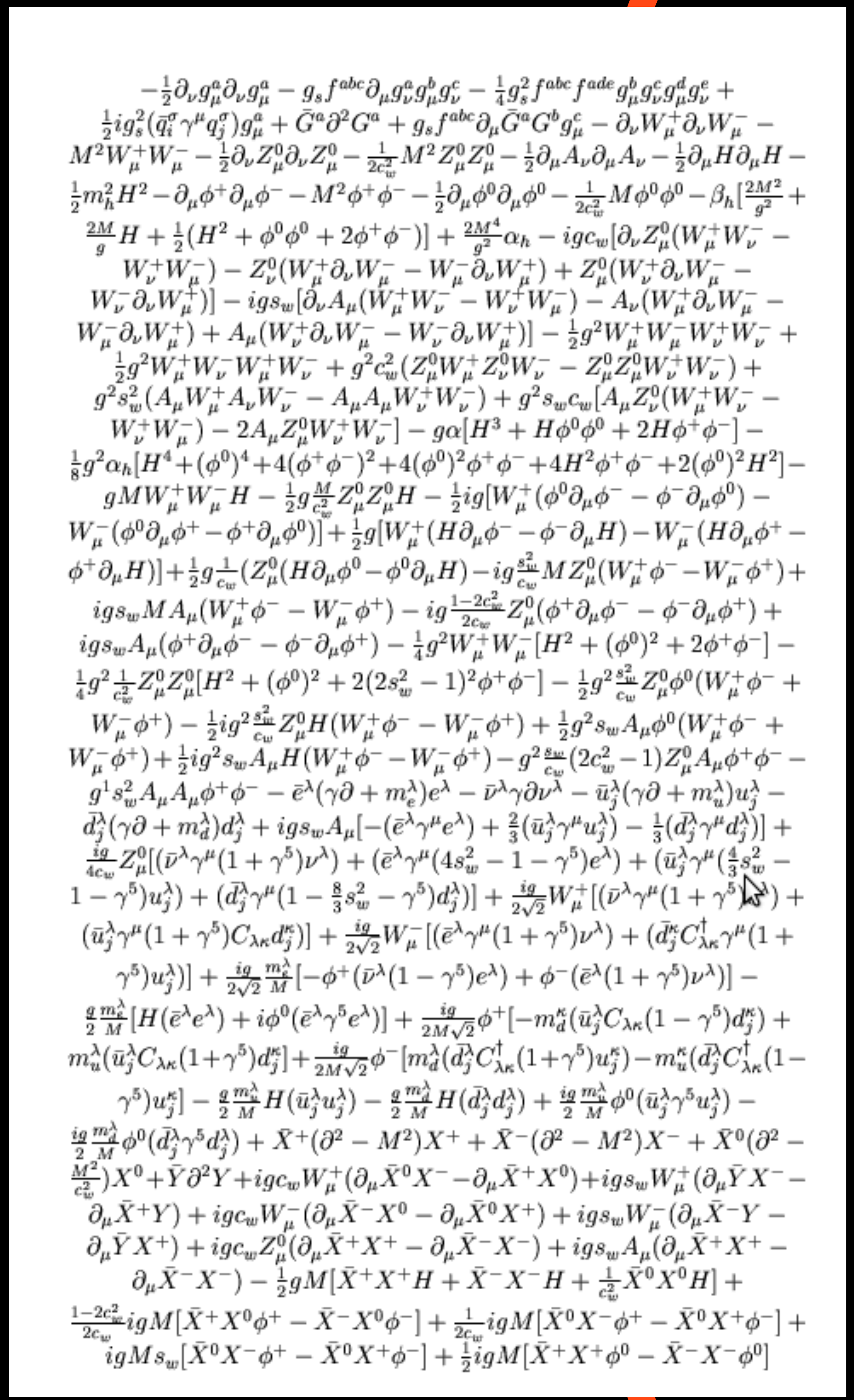
- Introduces **neural networks** to the HEP community for the first time
  - **Simple units** sum their inputs & apply an **activation function**
  - Outputs connect to other inputs via **weights**, and
  - **Perform a useful task** by mapping from inputs to outputs
- Proposes a recurrent neural network **algorithm** for **track finding** (*Denby-Peterson algorithm*)
- Highlights the **parallel nature** of calculating with neural networks and its interest for experimental **triggers**
- Also discusses **feed-forward neural networks** for **template matching**, and the possibility of using **learning**

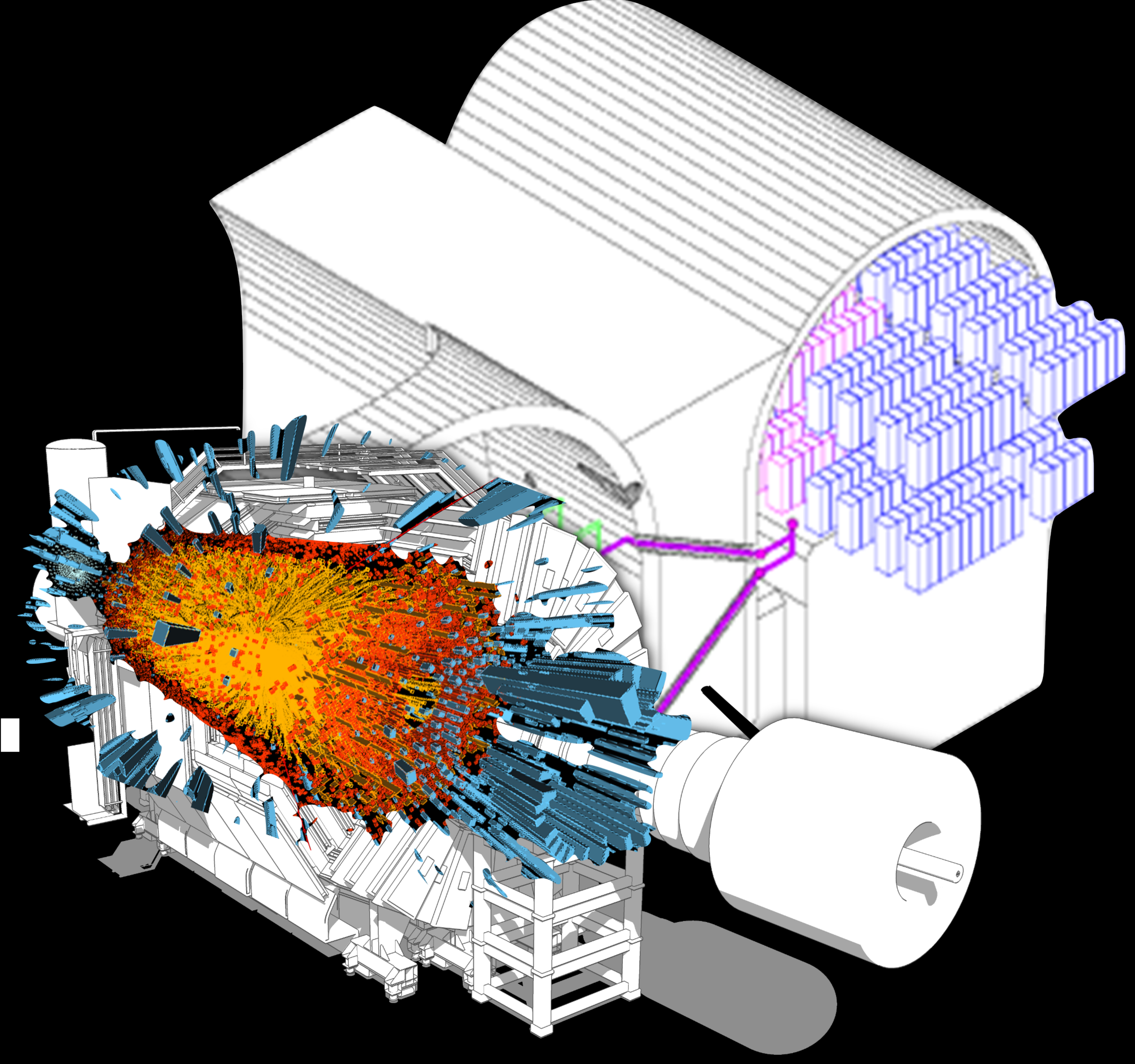
40 000 papers so far!



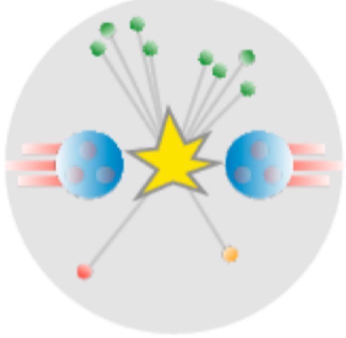
AI?

$$-\frac{1}{2}\partial_\nu g^a_\mu \partial_\nu g^a_\mu - g_s f^{abc}\partial_\mu g^a_\nu g^b_\mu g^c_\nu - \frac{1}{4}g_s^2 f^{abc} f^{ade} g^b_\mu g^c_\nu g^d_\mu g^e_\nu +$$
$$\frac{1}{2}ig_s^2(\bar{q}^\sigma_i \gamma^\mu q^\sigma_j)g^a_\mu + \bar{G}^a\partial^2 G^a + g_s f^{abc}\partial_\mu \bar{G}^a G^b g^c_\mu - \partial_\nu W^+_\mu \partial_\nu W^-_\mu -$$
$$M^2 W^+_\mu W^-_\mu - \frac{1}{2}\partial_\nu Z^0_\mu \partial_\nu Z^0_\mu - \frac{1}{2c_w^2}M^2 Z^0_\mu Z^0_\mu - \frac{1}{2}\partial_\mu A_\nu \partial_\mu A_\nu - \frac{1}{2}\partial_\mu H \partial_\mu H -$$
$$\frac{1}{2}m_h^2 H^2 - \partial_\mu \phi^+ \partial_\mu \phi^- - M^2\phi^+\phi^- - \frac{1}{2}\partial_\mu\phi^0\partial_\mu\phi^0 - \frac{1}{2c_w^2}M\phi^0\phi^0 - \beta_h[\frac{2M^2}{g^2} +$$
$$\frac{2M}{g}H + \frac{1}{2}(H^2 + \phi^0\phi^0 + 2\phi^+\phi^-)] + \frac{2M^4}{g^2}\alpha_h - igc_w[\partial_\nu Z^0_\mu(W^+_\mu W^-_\nu -$$
$$W^+_\nu W^-_\mu) - Z^0_\nu(W^+_\mu\partial_\nu W^-_\mu - W^-_\mu\partial_\nu W^+_\mu) + Z^0_\mu(W^+_\nu\partial_\nu W^-_\mu -$$
$$W^-_\nu\partial_\nu W^+_\mu)] - igs_w[\partial_\nu A_\mu(W^+_\mu W^-_\nu - W^+_\nu W^-_\mu) - A_\nu(W^+_\mu\partial_\nu W^-_\mu -$$
$$W^-_\mu\partial_\nu W^+_\mu) + A_\mu(W^+_\nu\partial_\nu W^-_\mu - W^-_\nu\partial_\nu W^+_\mu)] - \frac{1}{2}g^2 W^+_\mu W^-_\mu W^+_\nu W^-_\nu +$$
$$\frac{1}{2}g^2 W^+_\mu W^-_\nu W^+_\mu W^-_\nu + g^2 c_w^2(Z^0_\mu W^+_\mu Z^0_\nu W^-_\nu - Z^0_\mu Z^0_\mu W^+_\nu W^-_\nu) +$$
$$g^2 s_w^2(A_\mu W^+_\mu A_\nu W^-_\nu - A_\mu A_\mu W^+_\nu W^-_\nu) + g^2 s_w c_w[A_\mu Z^0_\nu(W^+_\mu W^-_\nu -$$
$$W^+_\nu W^-_\mu) - 2A_\mu Z^0_\mu W^+_\nu W^-_\nu] - g\alpha[H^3 + H\phi^0\phi^0 + 2H\phi^+\phi^-] -$$
$$\frac{1}{8}g^2\alpha_h[H^4 + (\phi^0)^4 + 4(\phi^+\phi^-)^2 + 4(\phi^0)^2\phi^+\phi^- + 4H^2\phi^+\phi^- + 2(\phi^0)^2H^2] -$$
$$gMW^+_\mu W^-_\mu H - \frac{1}{2}g\frac{M}{c_w^2}Z^0_\mu Z^0_\mu H - \frac{1}{2}ig[W^+_\mu(\phi^0\partial_\mu\phi^- - \phi^-\partial_\mu\phi^0) -$$
$$W^-_\mu(\phi^0\partial_\mu\phi^+ - \phi^+\partial_\mu\phi^0)] + \frac{1}{2}g[W^+_\mu(H\partial_\mu\phi^- - \phi^-\partial_\mu H) - W^-_\mu(H\partial_\mu\phi^+ -$$
$$\phi^+\partial_\mu H)] + \frac{1}{2}g\frac{1}{c_w}(Z^0_\mu(H\partial_\mu\phi^0 - \phi^0\partial_\mu H) - ig\frac{s_w^2}{c_w}MZ^0_\mu(W^+_\mu\phi^- - W^-_\mu\phi^+) +$$
$$igs_w MA_\mu(W^+_\mu\phi^- - W^-_\mu\phi^+) - ig\frac{1-2c_w^2}{2c_w}Z^0_\mu(\phi^+\partial_\mu\phi^- - \phi^-\partial_\mu\phi^+) +$$
$$igs_w A_\mu(\phi^+\partial_\mu\phi^- - \phi^-\partial_\mu\phi^+) - \frac{1}{4}g^2 W^+_\mu W^-_\mu[H^2 + (\phi^0)^2 + 2\phi^+\phi^-] -$$
$$\frac{1}{4}g^2\frac{1}{c_w^2}Z^0_\mu Z^0_\mu[H^2 + (\phi^0)^2 + 2(2s_w^2 - 1)^2\phi^+\phi^-] - \frac{1}{2}g^2\frac{s_w^2}{c_w}Z^0_\mu\phi^0(W^+_\mu\phi^- +$$
$$W^-_\mu\phi^+) - \frac{1}{2}ig^2\frac{s_w^2}{c_w}Z^0_\mu H(W^+_\mu\phi^- - W^-_\mu\phi^+) + \frac{1}{2}g^2 s_w A_\mu\phi^0(W^+_\mu\phi^- +$$
$$W^-_\mu\phi^+) + \frac{1}{2}ig^2 s_w A_\mu H(W^+_\mu\phi^- - W^-_\mu\phi^+) - g^2\frac{s_w}{c_w}(2c_w^2 - 1)Z^0_\mu A_\mu\phi^+\phi^- -$$
$$g^1 s_w^2 A_\mu A_\mu\phi^+\phi^- - \bar{e}^\lambda(\gamma\partial + m_e^\lambda)e^\lambda - \bar{\nu}^\lambda\gamma\partial\nu^\lambda - \bar{u}^\lambda_j(\gamma\partial + m_u^\lambda)u^\lambda_j -$$
$$\bar{d}^\lambda_j(\gamma\partial + m_d^\lambda)d^\lambda_j + igs_w A_\mu[-(\bar{e}^\lambda\gamma^\mu e^\lambda) + \frac{2}{3}(\bar{u}^\lambda_j\gamma^\mu u^\lambda_j) - \frac{1}{3}(\bar{d}^\lambda_j\gamma^\mu d^\lambda_j)] +$$
$$\frac{ig}{4c_w}Z^0_\mu[(\bar{\nu}^\lambda\gamma^\mu(1 + \gamma^5)\nu^\lambda) + (\bar{e}^\lambda\gamma^\mu(4s_w^2 - 1 - \gamma^5)e^\lambda) + (\bar{u}^\lambda_j\gamma^\mu(\frac{4}{3}s_w^2 -$$
$$1 - \gamma^5)u^\lambda_j) + (\bar{d}^\lambda_j\gamma^\mu(1 - \frac{8}{3}s_w^2 - \gamma^5)d^\lambda_j)] + \frac{ig}{2\sqrt{2}}W^+_\mu[(\bar{\nu}^\lambda\gamma^\mu(1 + \gamma^5)e^\lambda) +$$
$$(\bar{u}^\lambda_j\gamma^\mu(1 + \gamma^5)C_{\lambda\kappa}d^\kappa_j)] + \frac{ig}{2\sqrt{2}}W^-_\mu[(\bar{e}^\lambda\gamma^\mu(1 + \gamma^5)\nu^\lambda) + (\bar{d}^\kappa_j C^\dagger_{\lambda\kappa}\gamma^\mu(1 +$$
$$\gamma^5)u^\lambda_j)] + \frac{ig}{2\sqrt{2}}\frac{m_e^\lambda}{M}[-\phi^+(\bar{\nu}^\lambda(1 - \gamma^5)e^\lambda) + \phi^-(\bar{e}^\lambda(1 + \gamma^5)\nu^\lambda)] -$$
$$\frac{g}{2}\frac{m_e^\lambda}{M}[H(\bar{e}^\lambda e^\lambda) + i\phi^0(\bar{e}^\lambda\gamma^5 e^\lambda)] + \frac{ig}{2M\sqrt{2}}\phi^+[-m_d^\kappa(\bar{u}^\lambda_j C_{\lambda\kappa}(1 - \gamma^5)d^\kappa_j) +$$
$$m_u^\lambda(\bar{u}^\lambda_j C_{\lambda\kappa}(1 + \gamma^5)d^\kappa_j] + \frac{ig}{2M\sqrt{2}}\phi^-[m_d^\lambda(\bar{d}^\lambda_j C^\dagger_{\lambda\kappa}(1 + \gamma^5)u^\kappa_j) - m_u^\kappa(\bar{d}^\lambda_j C^\dagger_{\lambda\kappa}(1 -$$
$$\gamma^5)u^\kappa_j] - \frac{g}{2}\frac{m_u^\lambda}{M}H(\bar{u}^\lambda_j u^\lambda_j) - \frac{g}{2}\frac{m_d^\lambda}{M}H(\bar{d}^\lambda_j d^\lambda_j) + \frac{ig}{2}\frac{m_u^\lambda}{M}\phi^0(\bar{u}^\lambda_j\gamma^5 u^\lambda_j) -$$
$$\frac{ig}{2}\frac{m_d^\lambda}{M}\phi^0(\bar{d}^\lambda_j\gamma^5 d^\lambda_j) + \bar{X}^+(\partial^2 - M^2)X^+ + \bar{X}^-(\partial^2 - M^2)X^- + \bar{X}^0(\partial^2 -$$
$$\frac{M^2}{c_w^2})X^0 + \bar{Y}\partial^2 Y + igc_w W^+_\mu(\partial_\mu\bar{X}^0 X^- - \partial_\mu\bar{X}^+ X^0) + igs_w W^+_\mu(\partial_\mu\bar{Y}X^- -$$
$$\partial_\mu\bar{X}^+ Y) + igc_w W^-_\mu(\partial_\mu\bar{X}^- X^0 - \partial_\mu\bar{X}^0 X^+) + igs_w W^-_\mu(\partial_\mu\bar{X}^- Y -$$
$$\partial_\mu\bar{Y}X^+) + igc_w Z^0_\mu(\partial_\mu\bar{X}^+ X^+ - \partial_\mu\bar{X}^- X^-) + igs_w A_\mu(\partial_\mu\bar{X}^+ X^+ -$$
$$\partial_\mu\bar{X}^- X^-) - \frac{1}{2}gM[\bar{X}^+ X^+ H + \bar{X}^- X^- H + \frac{1}{c_w^2}\bar{X}^0 X^0 H] +$$
$$\frac{1-2c_w^2}{2c_w}igM[\bar{X}^+ X^0\phi^+ - \bar{X}^- X^0\phi^-] + \frac{1}{2c_w}igM[\bar{X}^0 X^-\phi^+ - \bar{X}^0 X^+\phi^-] +$$
$$igMs_w[\bar{X}^0 X^-\phi^+ - \bar{X}^0 X^+\phi^-] + \frac{1}{2}igM[\bar{X}^+ X^+\phi^0 - \bar{X}^- X^-\phi^0]$$





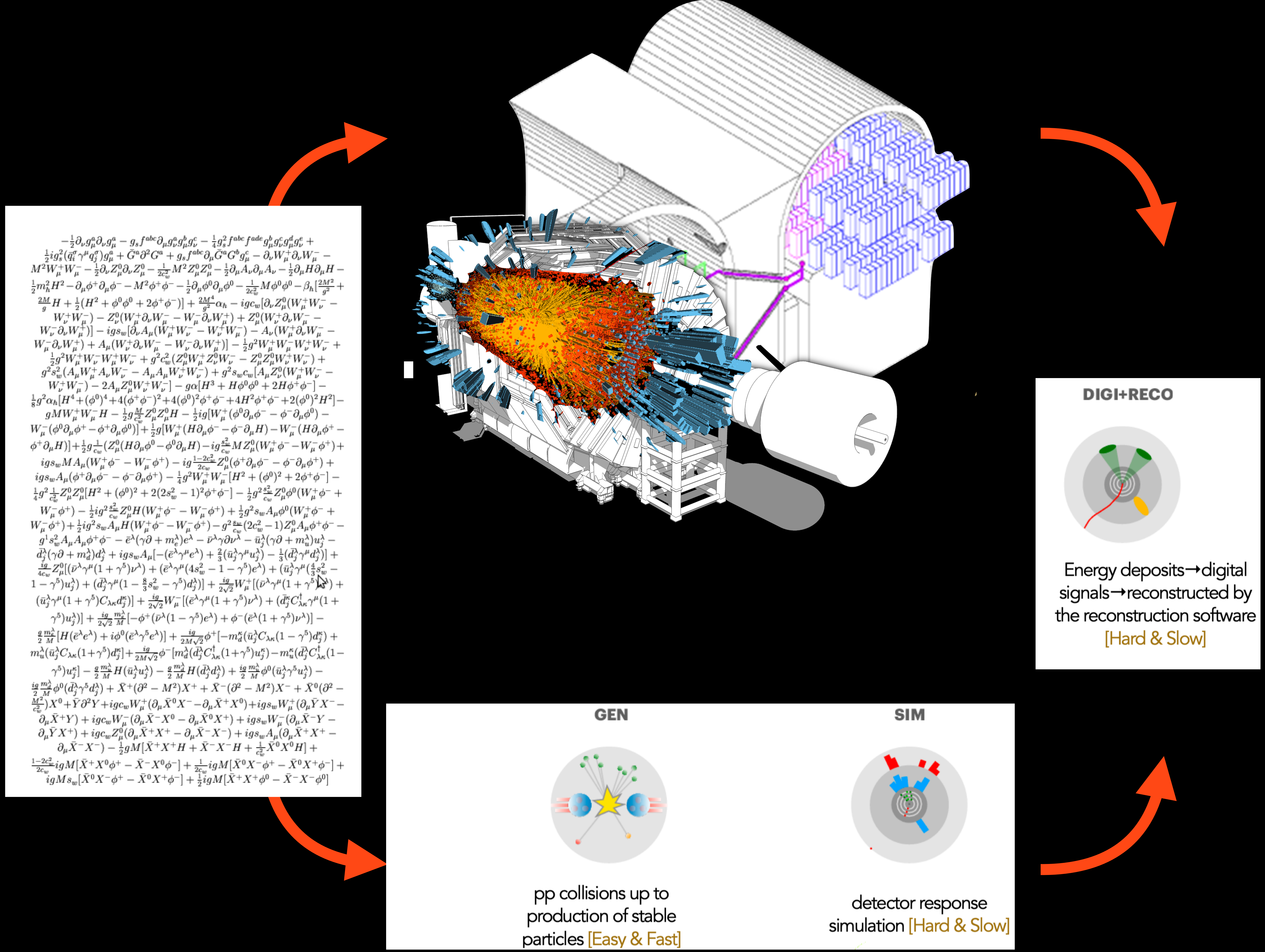
GEN



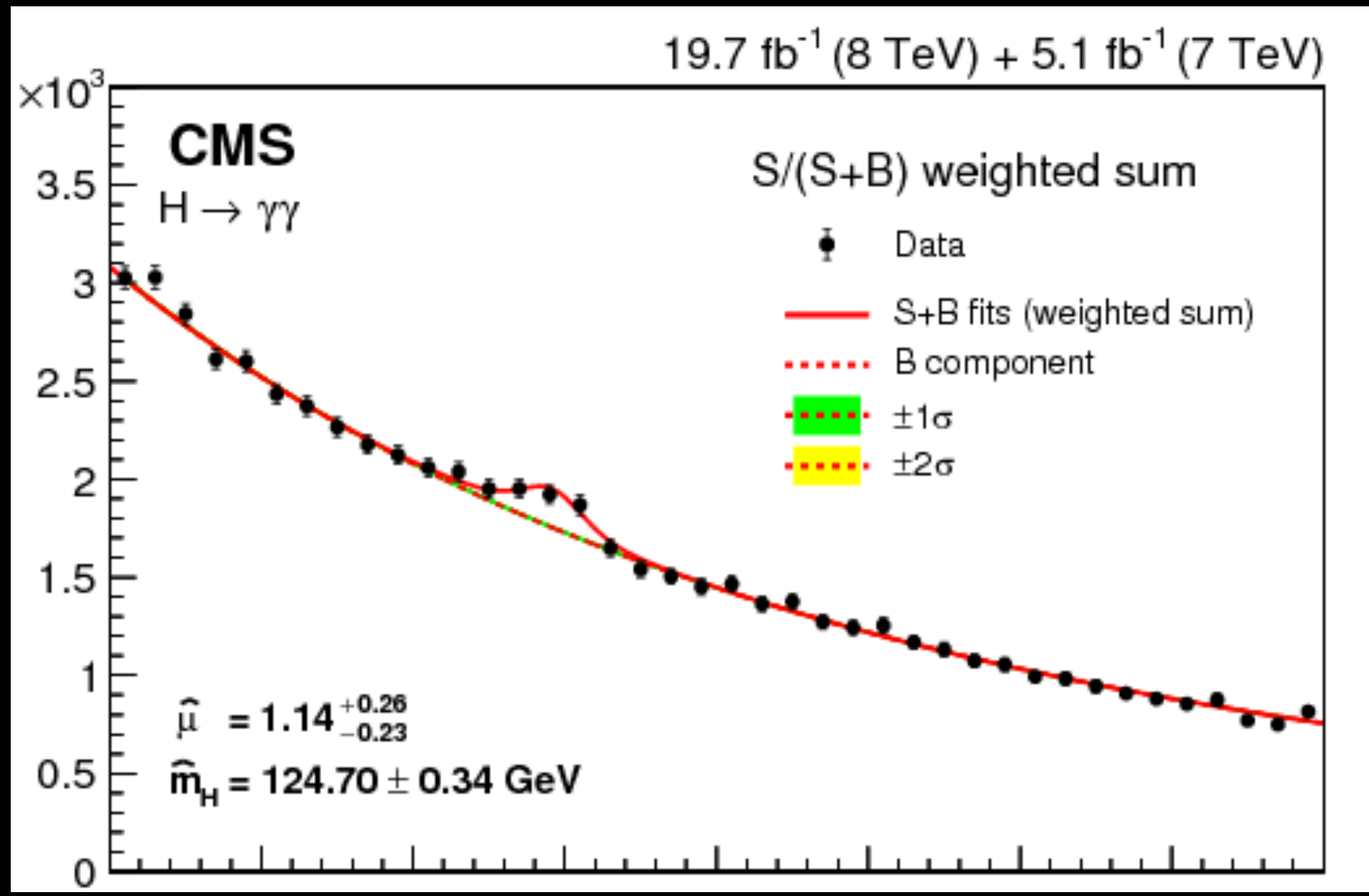
pp collisions up to production of stable particles [Easy & Fast]

SIM

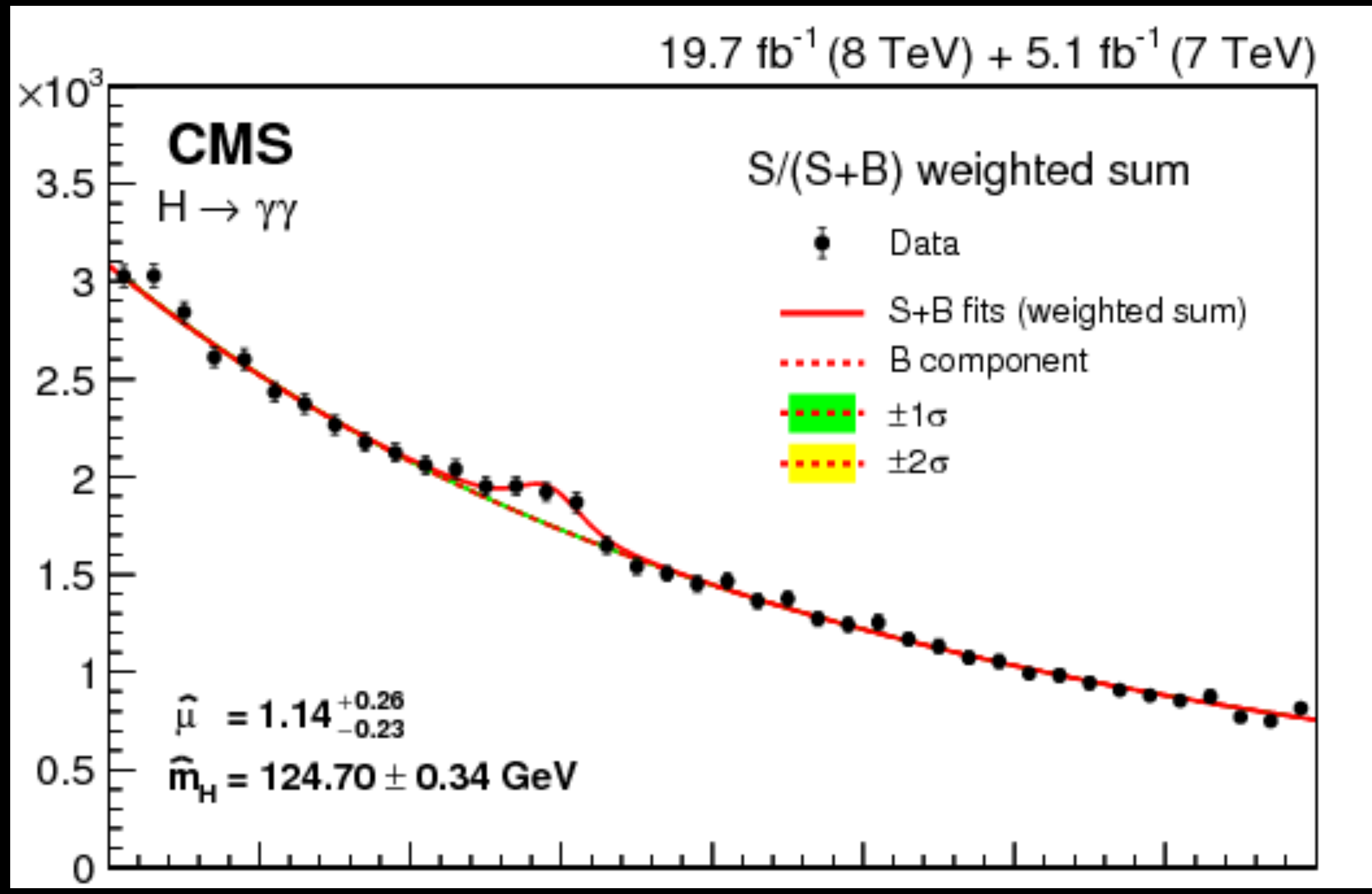
detector response simulation [Hard & Slow]


DIGI+RECO
Energy deposits→digital signals→reconstructed by the reconstruction software [Hard & Slow]
GEN
pp collisions up to production of stable particles [Easy & Fast]
SIM
detector response simulation [Hard & Slow]

DIGI+RECO
Energy deposits→digital signals→reconstructed by the reconstruction software [Hard & Slow]
19.7 fb-1 (8 TeV) + 5.1 fb-1 (7 TeV)
CMS
H → γγ
S/(S+B) weighted sum
Data
S+B fits (weighted sum)
B component
±1σ
±2σ
μ̂ = 1.14 +0.26 −0.23
m̂H = 124.70 ± 0.34 GeV
GEN
pp collisions up to production of stable particles [Easy & Fast]
SIM
detector response simulation [Hard & Slow]



19.7 fb-1 (8 TeV) + 5.1 fb-1 (7 TeV)
×10³
CMS
H → γγ
S/(S+B) weighted sum
Data
S+B fits (weighted sum)
B component
±1σ
±2σ
μ̂ = 1.14 +0.26 −0.23
m̂H = 124.70 ± 0.34 GeV
3.5
3
2.5
2
1.5
1
0.5
0


19.7 fb-1 (8 TeV) + 5.1 fb-1 (7 TeV)
×10³
CMS
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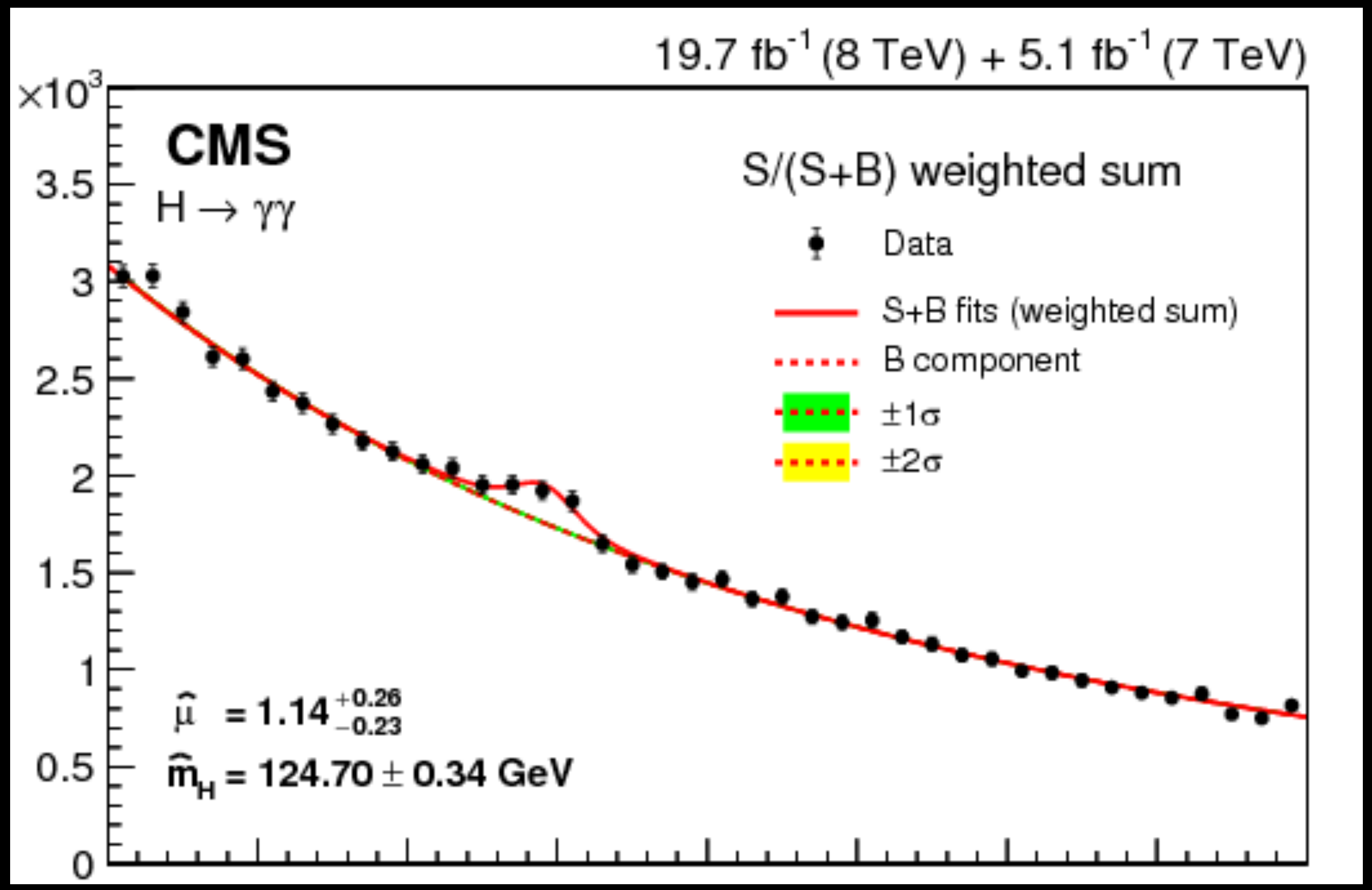
0


19.7 fb^{-1} (8 TeV) + 5.1 fb^{-1} (7 TeV)
CMS
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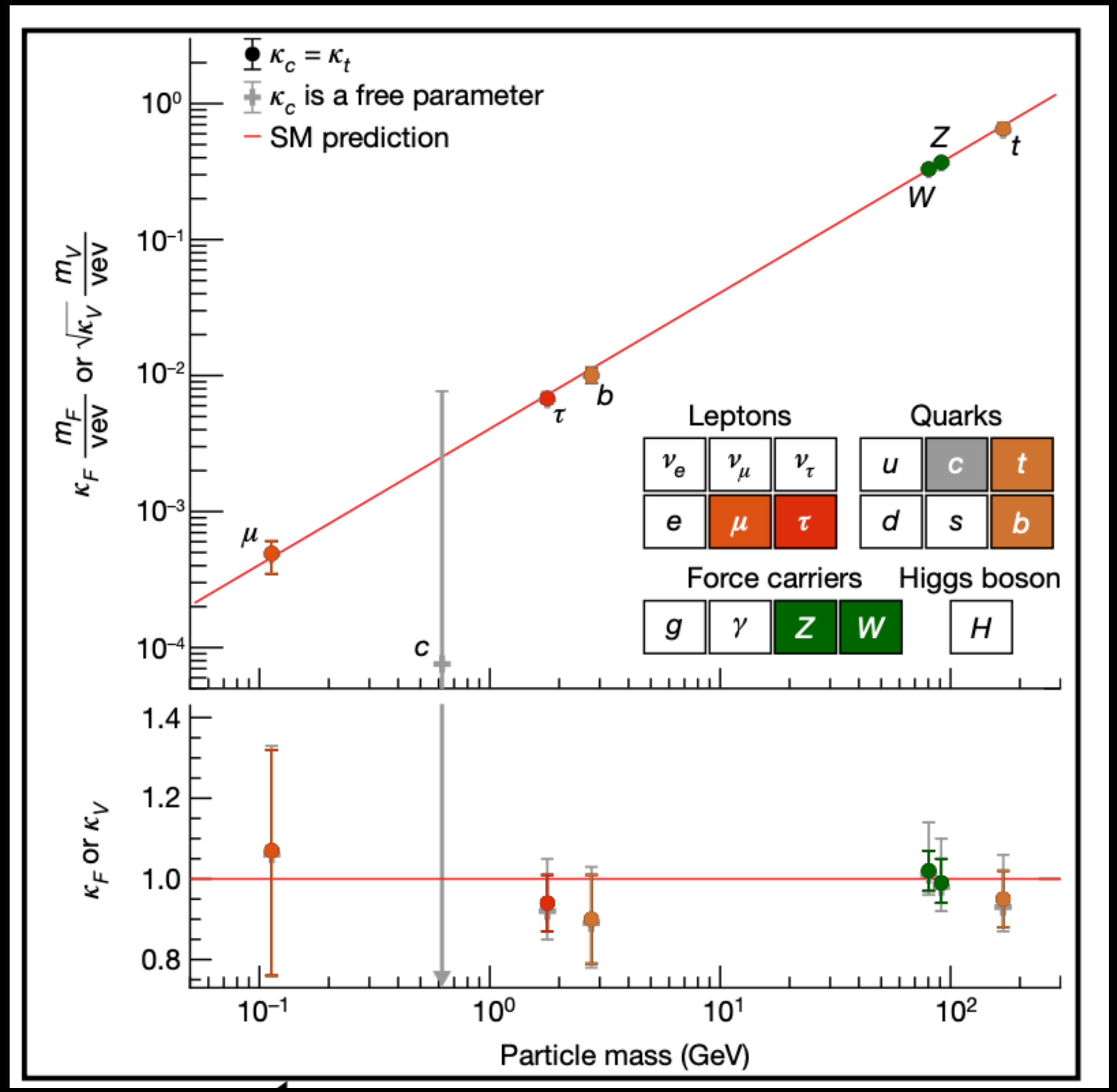
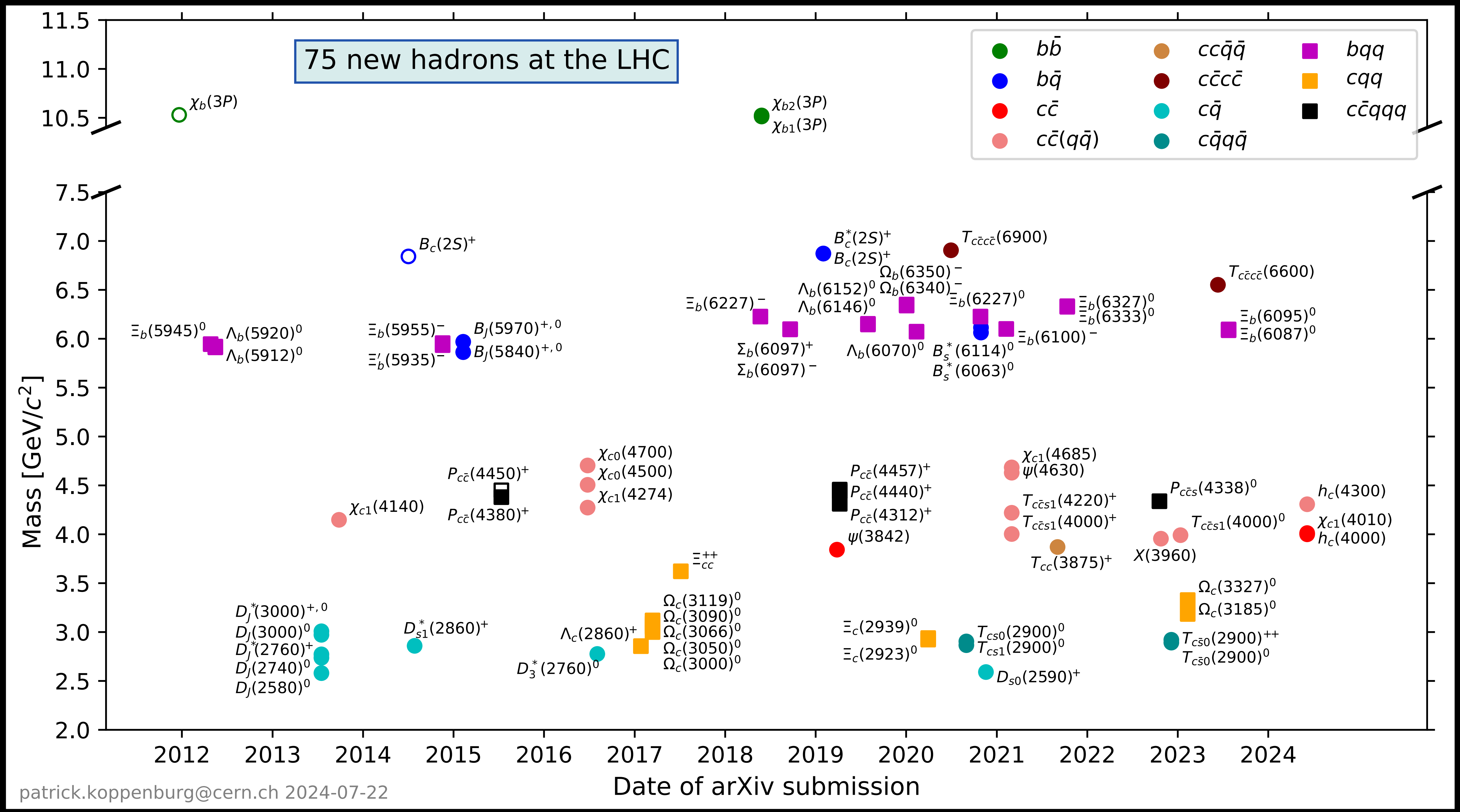
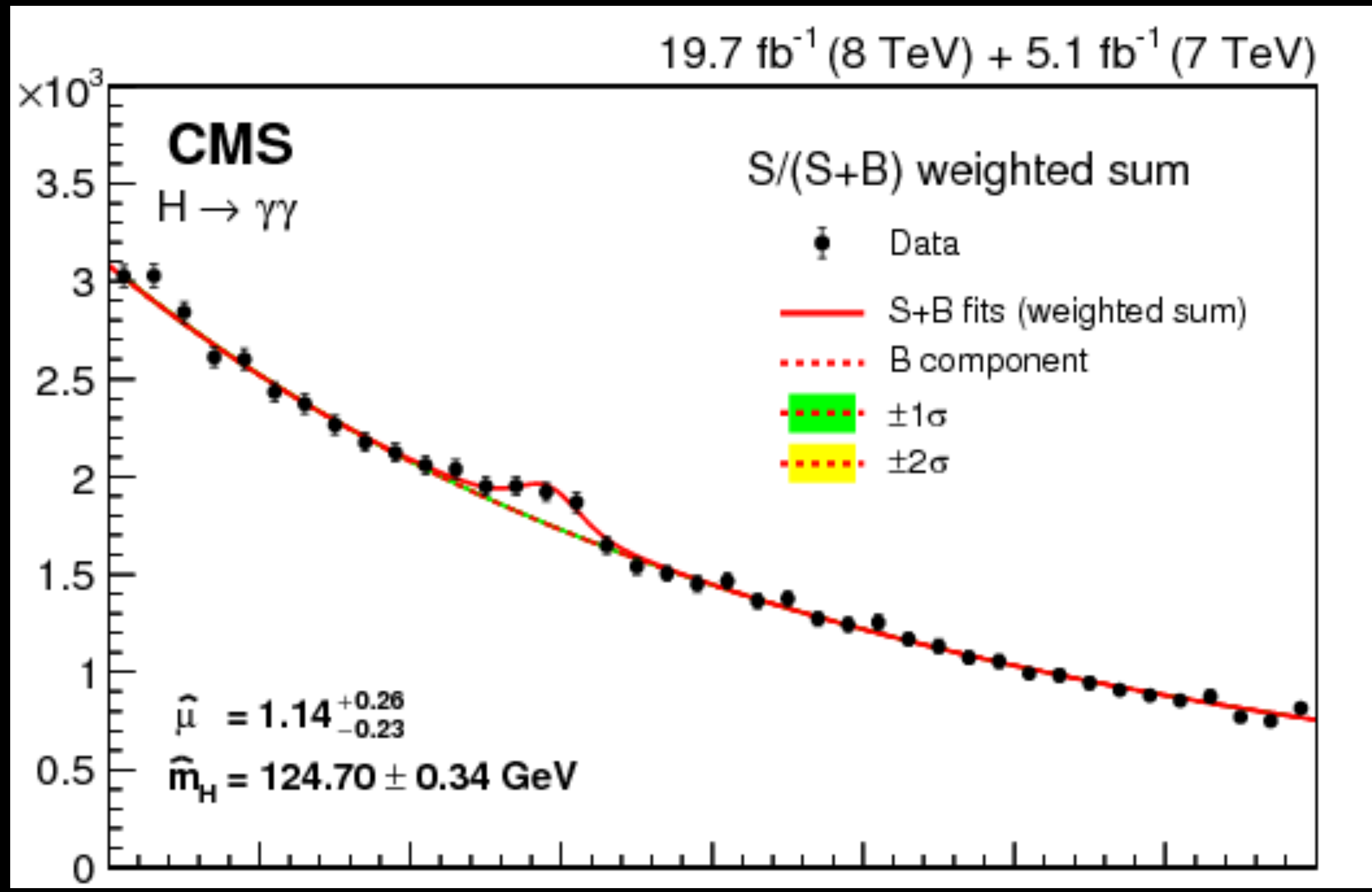
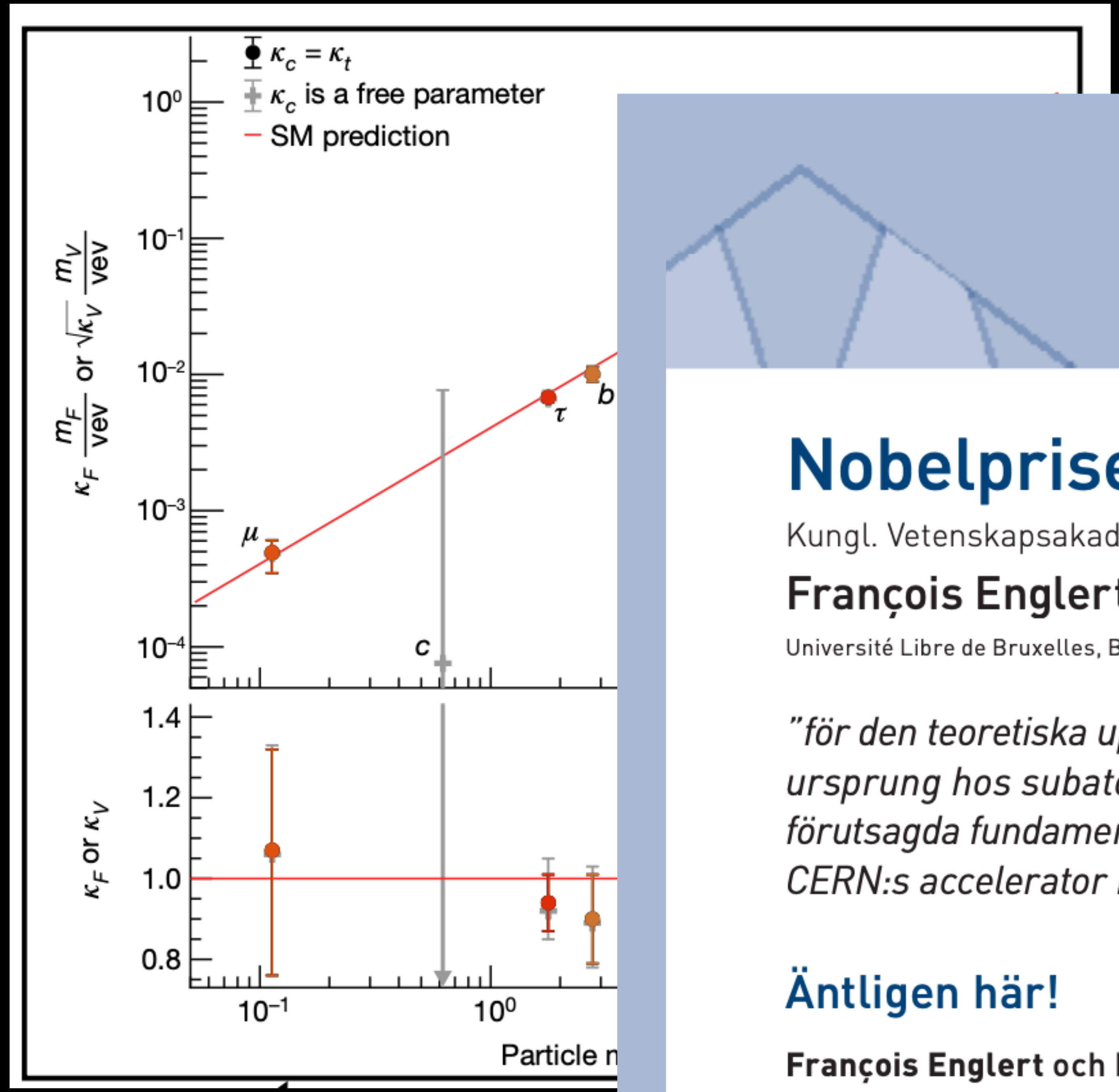
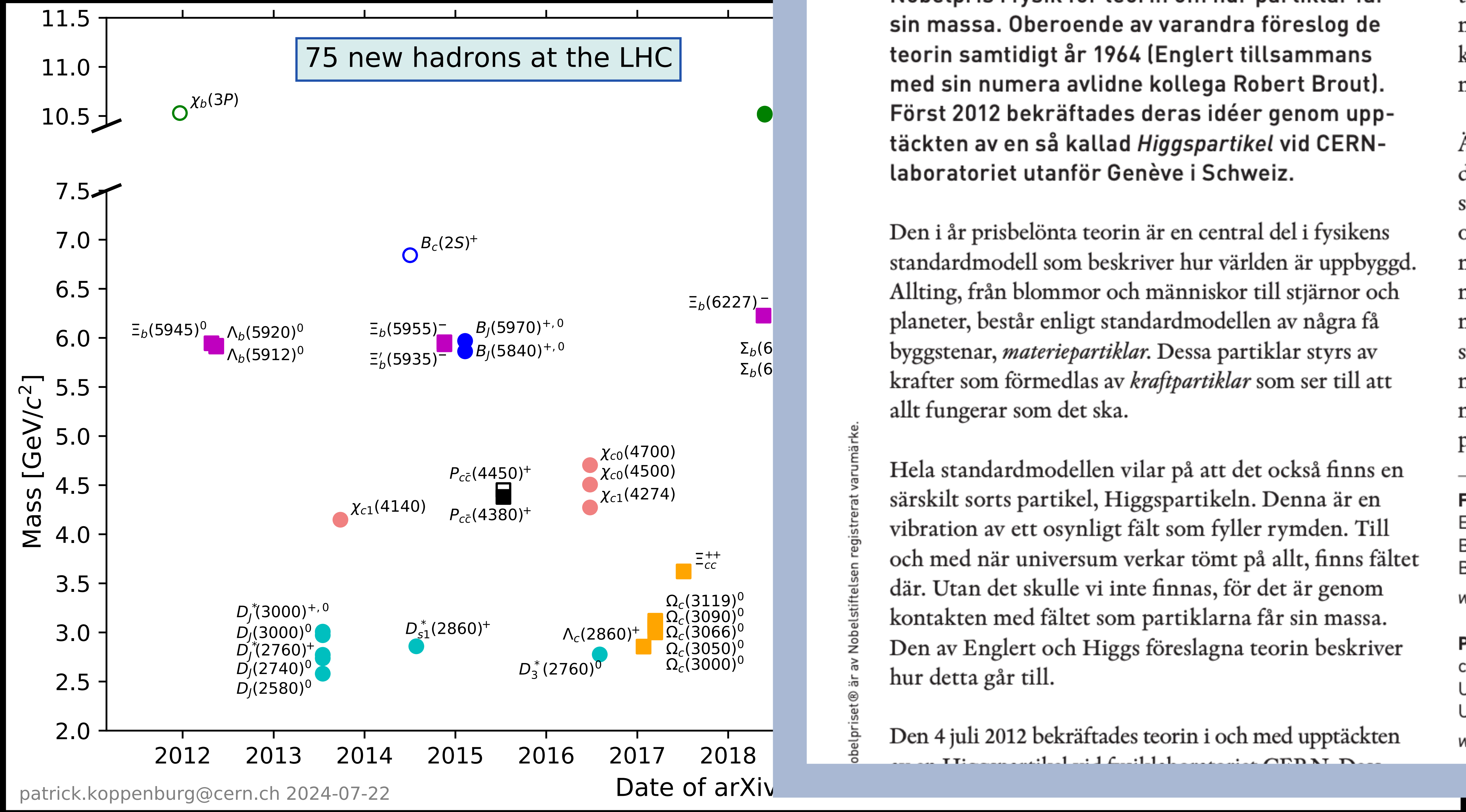
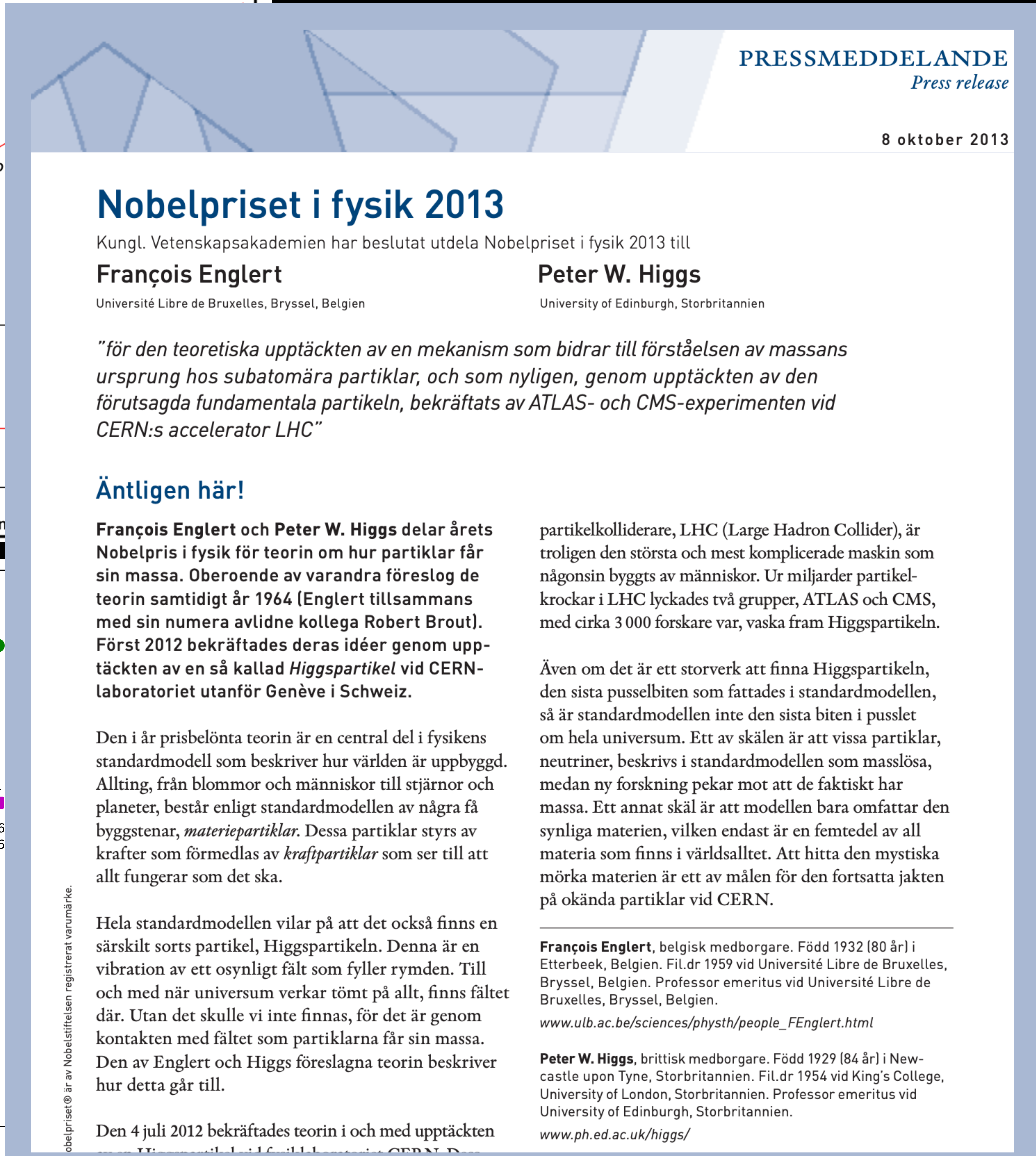

$\kappa_c = \kappa_t$
κ_c is a free parameter
SM prediction
$\kappa_F \frac{m_F}{vev}$ or $\sqrt{\kappa_V}\frac{m_V}{vev}$
Leptons
Quarks
Force carriers
Higgs boson
κ_F or κ_V
Particle mass (GeV)


75 new hadrons at the LHC
$b\bar{b}$
$b\bar{q}$
$c\bar{c}$
$c\bar{c}(q\bar{q})$
$cc\bar{q}\bar{q}$
$c\bar{c}c\bar{c}$
$c\bar{q}$
$c\bar{q}q\bar{q}$
bqq
cqq
$c\bar{c}qqq$
Mass [GeV/c^2]
Date of arXiv submission
patrick.koppenburg@cern.ch 2024-07-22









PRESSMEDDELANDE

Press release

8 oktober 2013

Nobelpriset i fysik 2013

Kungl. Vetenskapsakademien har beslutat utdela Nobelpriset i fysik 2013 till

François Englert
Université Libre de Bruxelles, Bryssel, Belgien

Peter W. Higgs
University of Edinburgh, Storbritannien

”för den teoretiska upptäckten av en mekanism som bidrar till förståelsen av massans ursprung hos subatomära partiklar, och som nyligen, genom upptäckten av den förutsagda fundamentala partikeln, bekräftats av ATLAS- och CMS-experimenten vid CERN:s accelerator LHC”

Äntligen här!

François Englert och Peter W. Higgs delar årets Nobelpris i fysik för teorin om hur partiklar får sin massa. Oberoende av varandra föreslog de teorin samtidigt år 1964 (Englert tillsammans med sin numera avlidne kollega Robert Brout). Först 2012 bekräftades deras idéer genom upptäckten av en så kallad *Higgspartikel* vid CERN-laboratoriet utanför Genève i Schweiz.

Den i år prisbelönta teorin är en central del i fysikens standardmodell som beskriver hur världen är uppbyggd. Allting, från blommor och människor till stjärnor och planeter, består enligt standardmodellen av några få byggstenar, *materiepartiklar*. Dessa partiklar styrs av krafter som förmedlas av *kraftpartiklar* som ser till att allt fungerar som det ska.

Hela standardmodellen vilar på att det också finns en särskilt sorts partikel, Higgspartikeln. Denna är en vibration av ett osynligt fält som fyller rymden. Till och med när universum verkar tömt på allt, finns fältet där. Utan det skulle vi inte finnas, för det är genom kontakten med fältet som partiklarna får sin massa. Den av Englert och Higgs föreslagna teorin beskriver hur detta går till.

Den 4 juli 2012 bekräftades teorin i och med upptäckten

partikelkolliderare, LHC (Large Hadron Collider), är troligen den största och mest komplicerade maskin som någonsin byggts av människor. Ur miljarder partikelkrockar i LHC lyckades två grupper, ATLAS och CMS, med cirka 3 000 forskare var, vaska fram Higgspartikeln.

Även om det är ett storverk att finna Higgspartikeln, den sista pusselbiten som fattades i standardmodellen, så är standardmodellen inte den sista biten i pusslet om hela universum. Ett av skälen är att vissa partiklar, neutriner, beskrivs i standardmodellen som masslösa, medan ny forskning pekar mot att de faktiskt har massa. Ett annat skäl är att modellen bara omfattar den synliga materien, vilken endast är en femtedel av all materia som finns i världsalltet. Att hitta den mystiska mörka materien är ett av målen för den fortsatta jakten på okända partiklar vid CERN.

François Englert, belgisk medborgare. Född 1932 (80 år) i Etterbeek, Belgien. Fil.dr 1959 vid Université Libre de Bruxelles, Bryssel, Belgien. Professor emeritus vid Université Libre de Bruxelles, Bryssel, Belgien.
www.ulb.ac.be/sciences/physth/people_FEnglert.html

Peter W. Higgs, brittisk medborgare. Född 1929 (84 år) i Newcastle upon Tyne, Storbritannien. Fil.dr 1954 vid King's College, University of London, Storbritannien. Professor emeritus vid University of Edinburgh, Storbritannien.
www.ph.ed.ac.uk/higgs/

Nobelpriset® är av Nobelstiftelsen registrerat varumärke.


AI?
$O(10)$
$O(10^3)$
10^{-18}m
10^{-15}m
10^{-6}m
GEN
pp collisions up to production of stable particles [Easy & Fast]
SIM
detector response simulation [Hard & Slow]
GEANT4
$O(10^{10})$
100m
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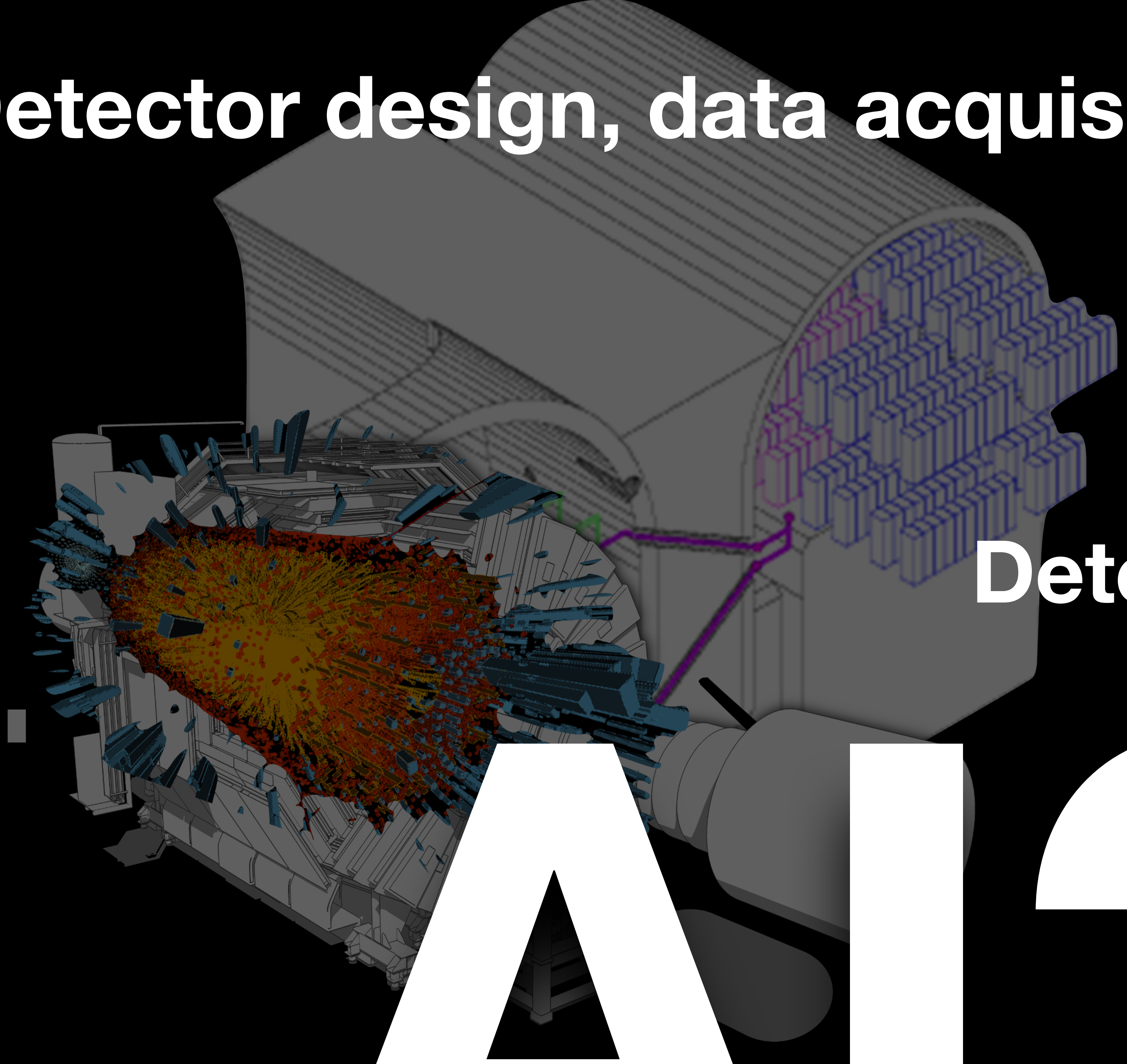
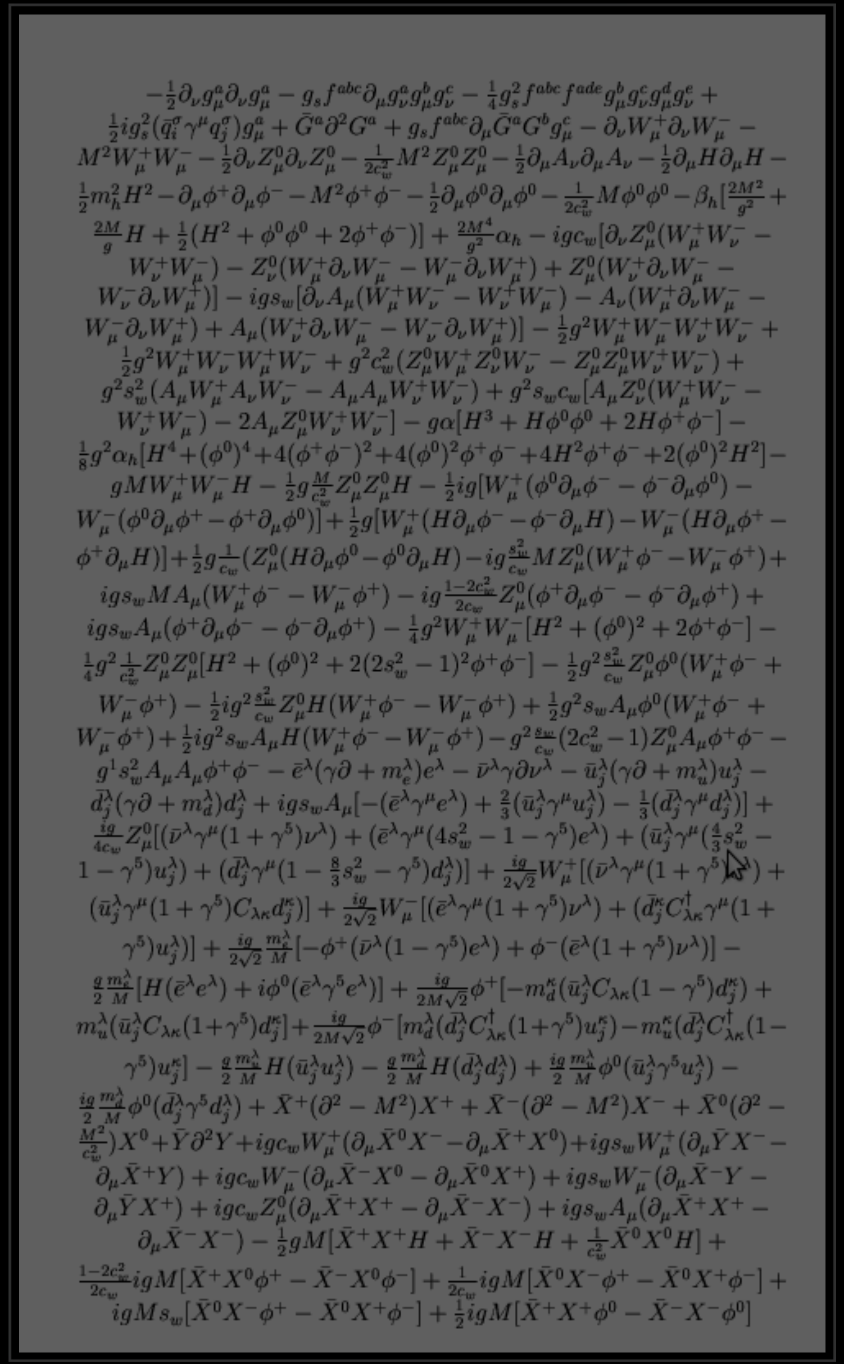
±1σ
±2σ
$\hat{\mu}$ = 1.14$^{+0.26}_{-0.23}$
$\hat{m}_H$ = 124.70 ± 0.34 GeV
×10^3

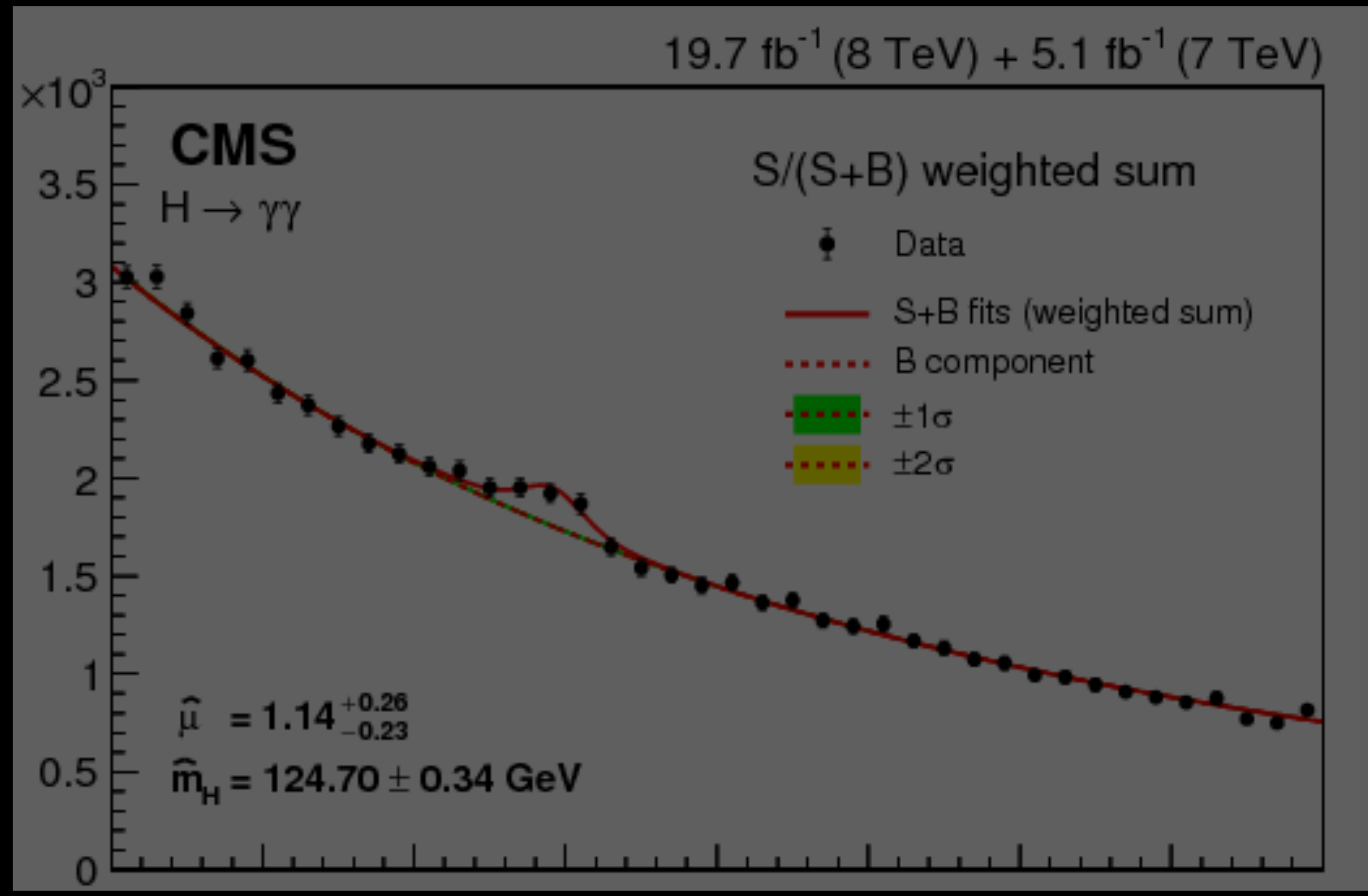
Detector design, data acquisition and triggering



Not in this talk

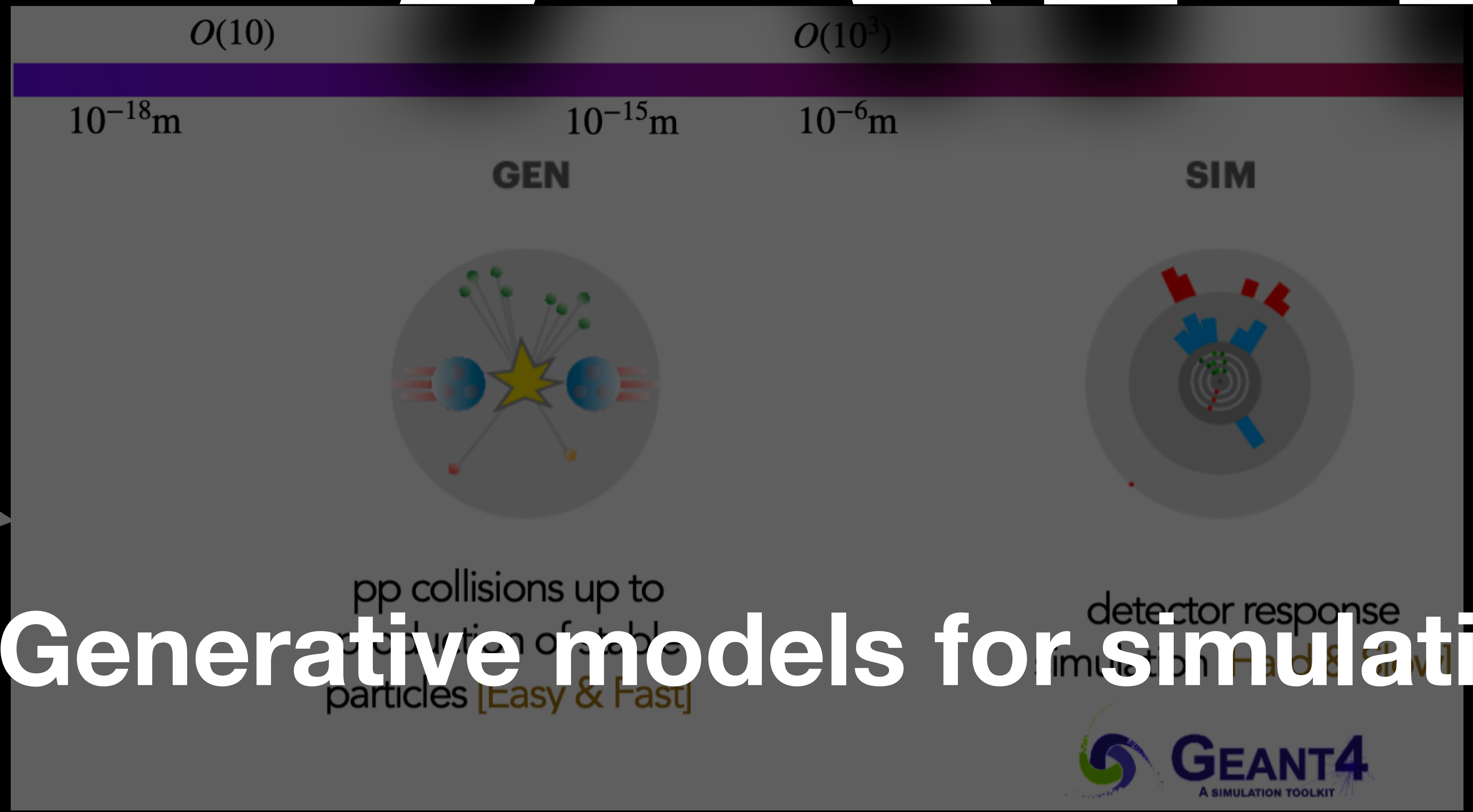


Detector reconstruction and tagging

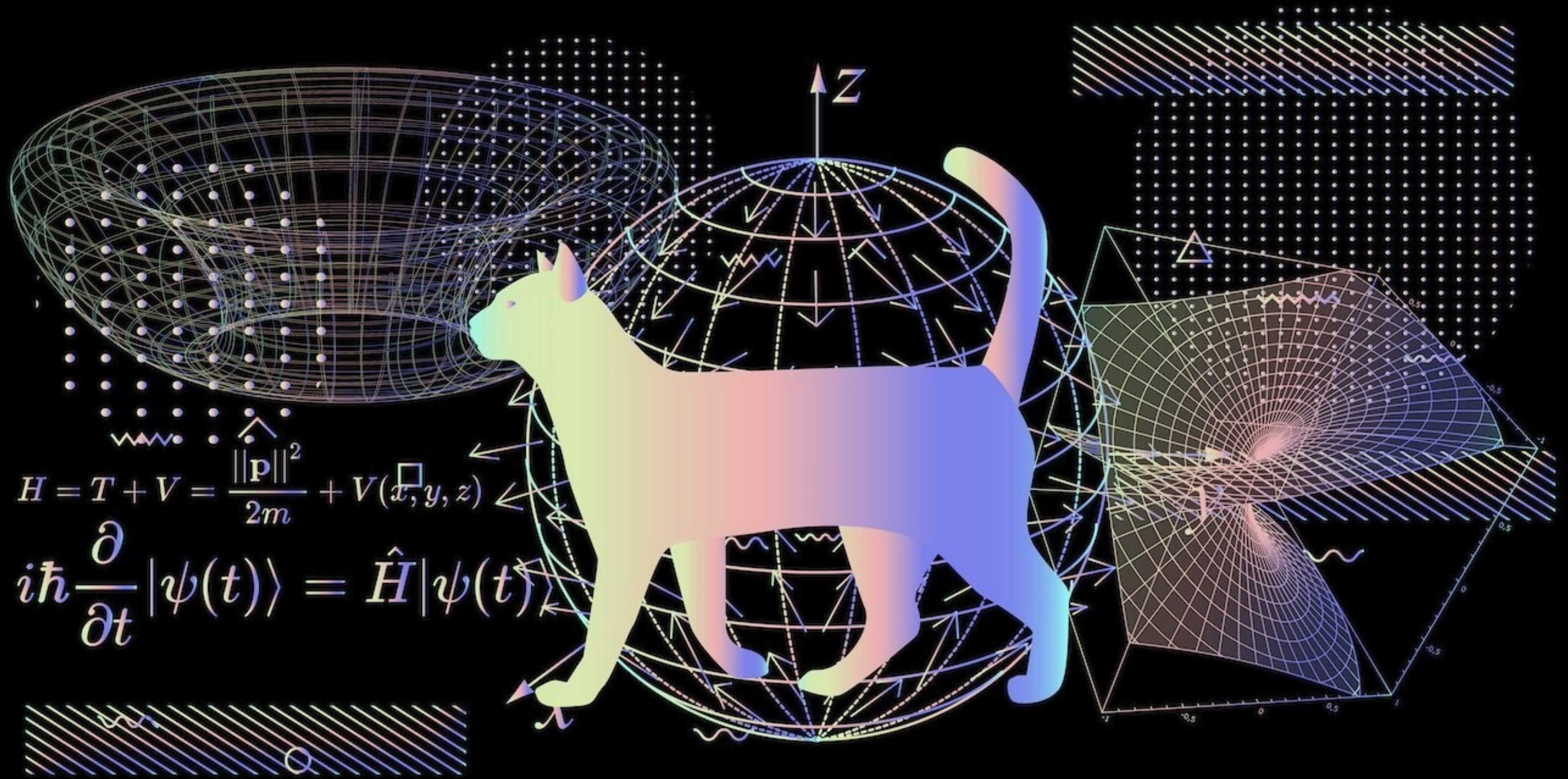


AI?

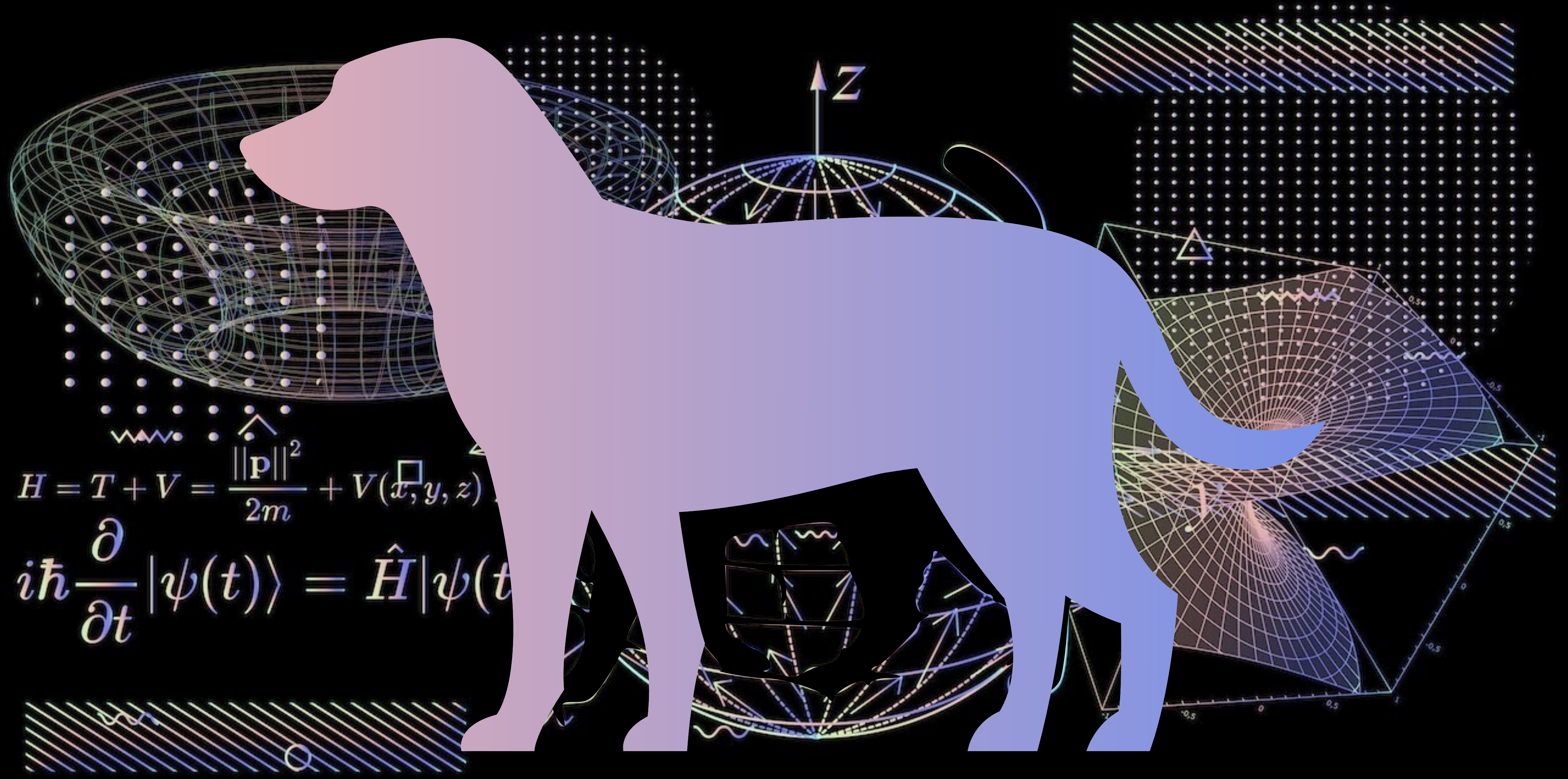
Data analysis



Generative models for simulation

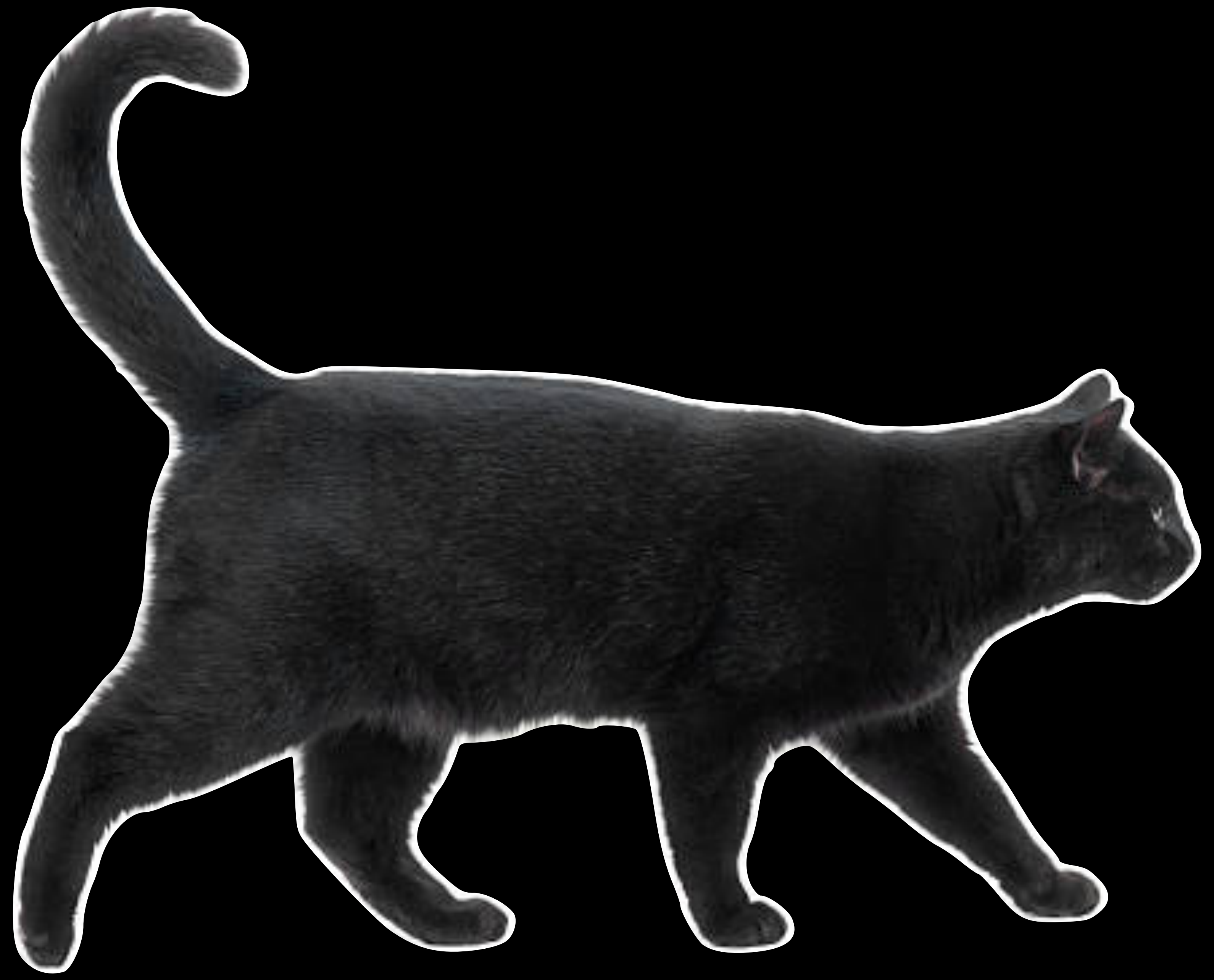


z
$H = T + V = \frac{\|\mathbf{p}\|^2}{2m} + V(x, y, z)$
$i\hbar \frac{\partial}{\partial t}|\psi(t)\rangle = \hat{H}|\psi(t)\rangle$



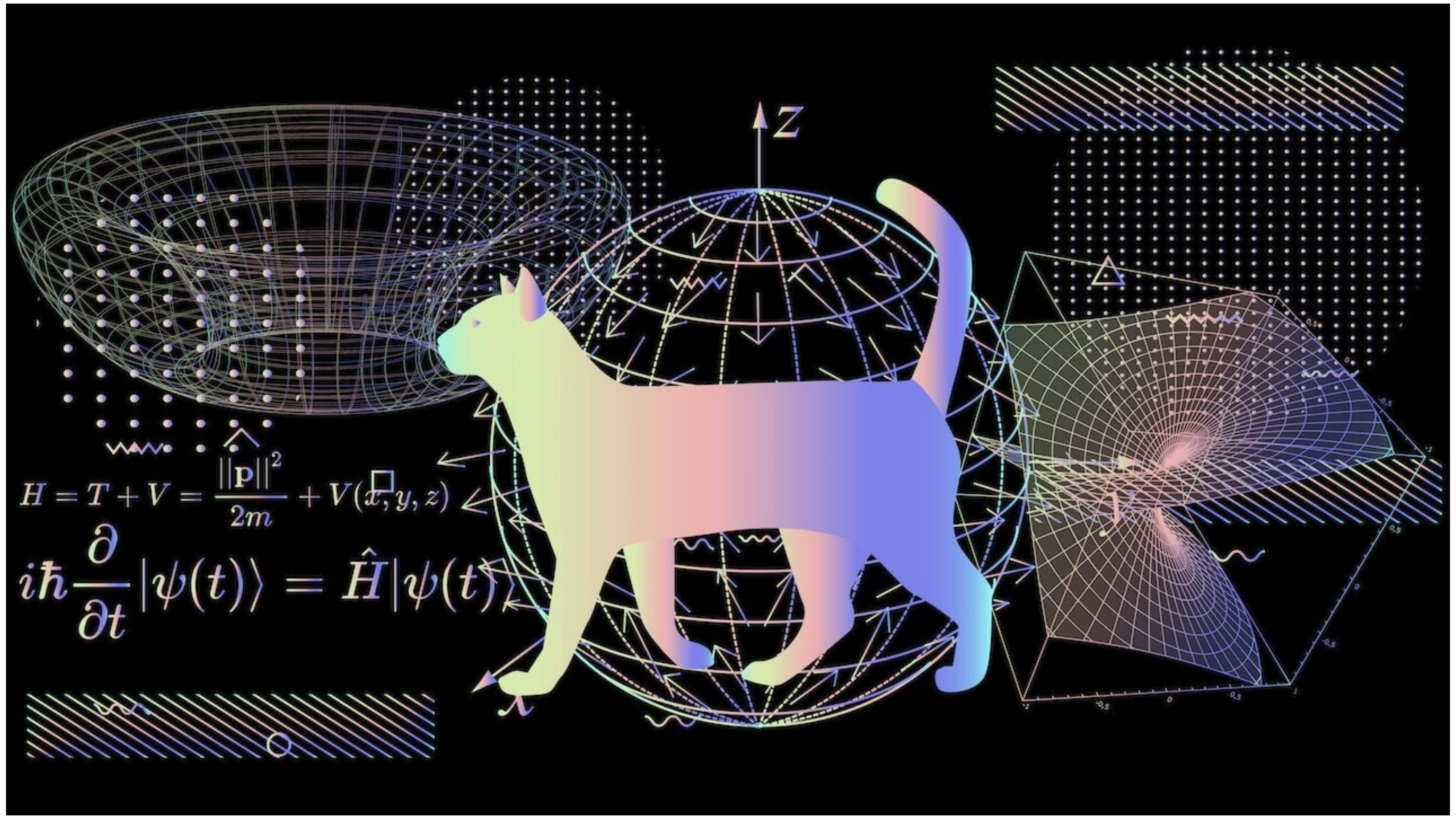
z
$H = T + V = \frac{\|\mathbf{p}\|^2}{2m} + V(x, y, z)$

!=



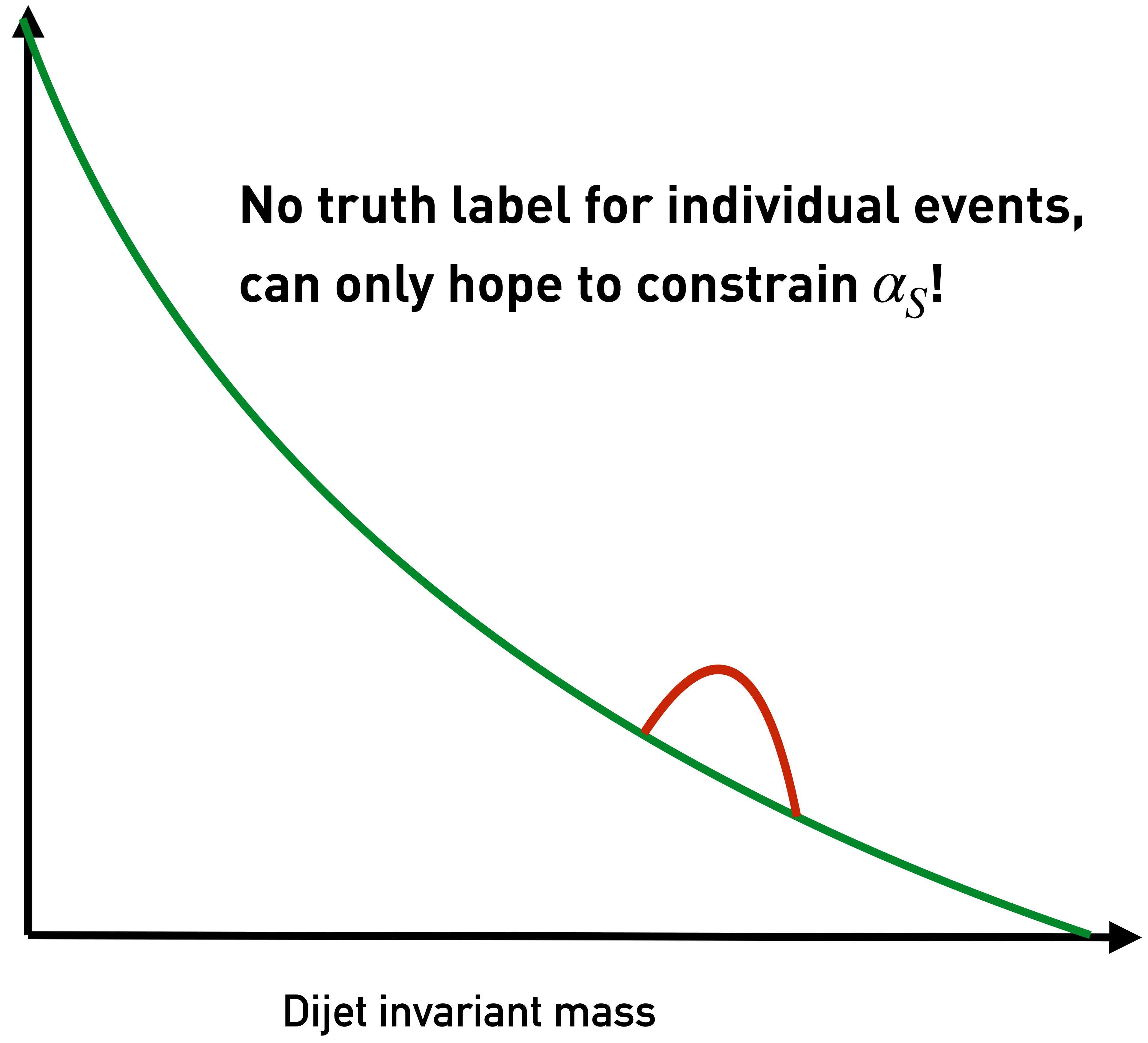
No labeled data!

$$dP^n_{data} = |M_S + M_B|^2 dp_1 dp_2 \ldots dp_n$$



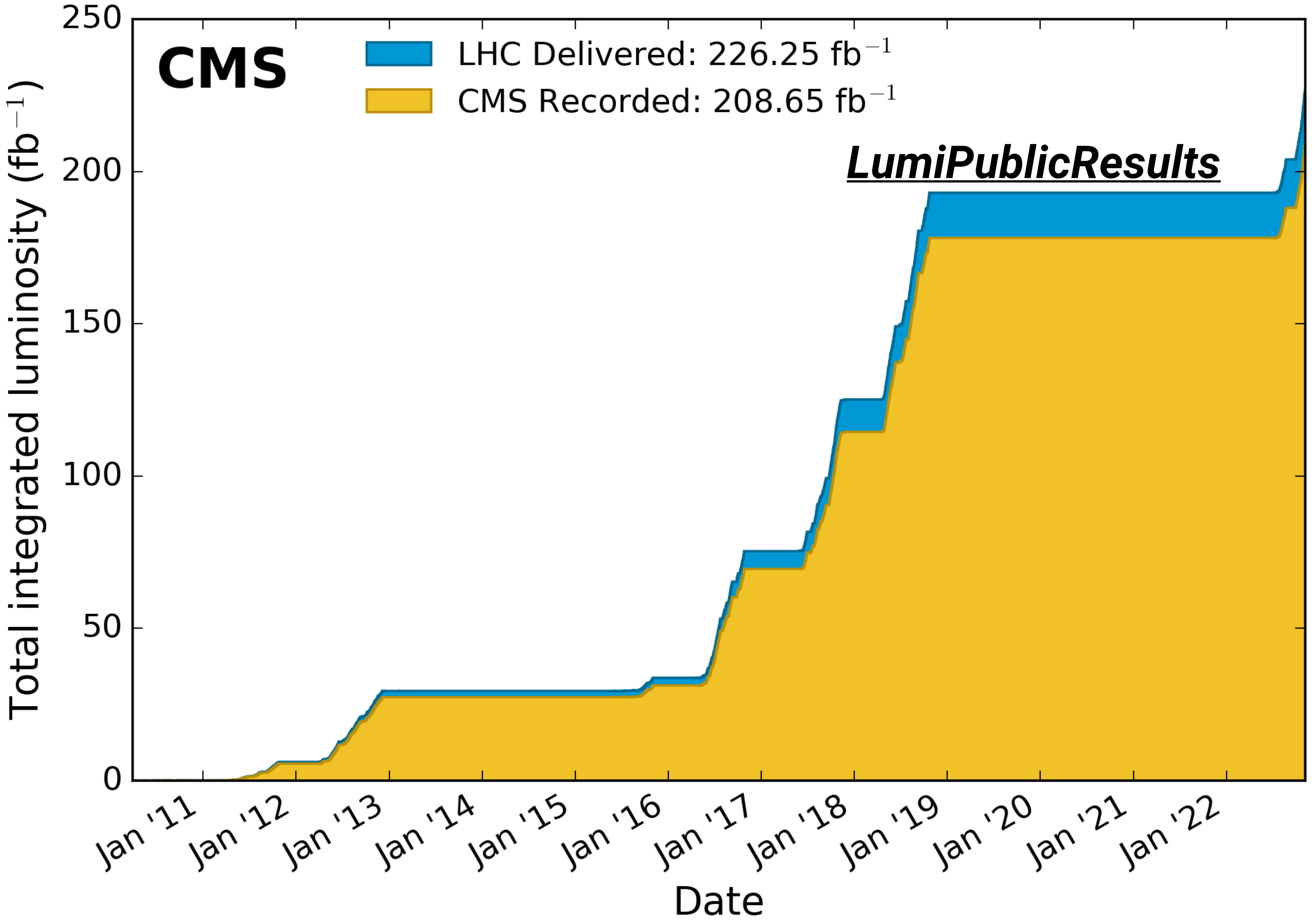
$$M_S M_B{}^* + M_B M_S{}^*$$

$$P_{data} = \alpha_S P_S + \alpha_B P_B$$



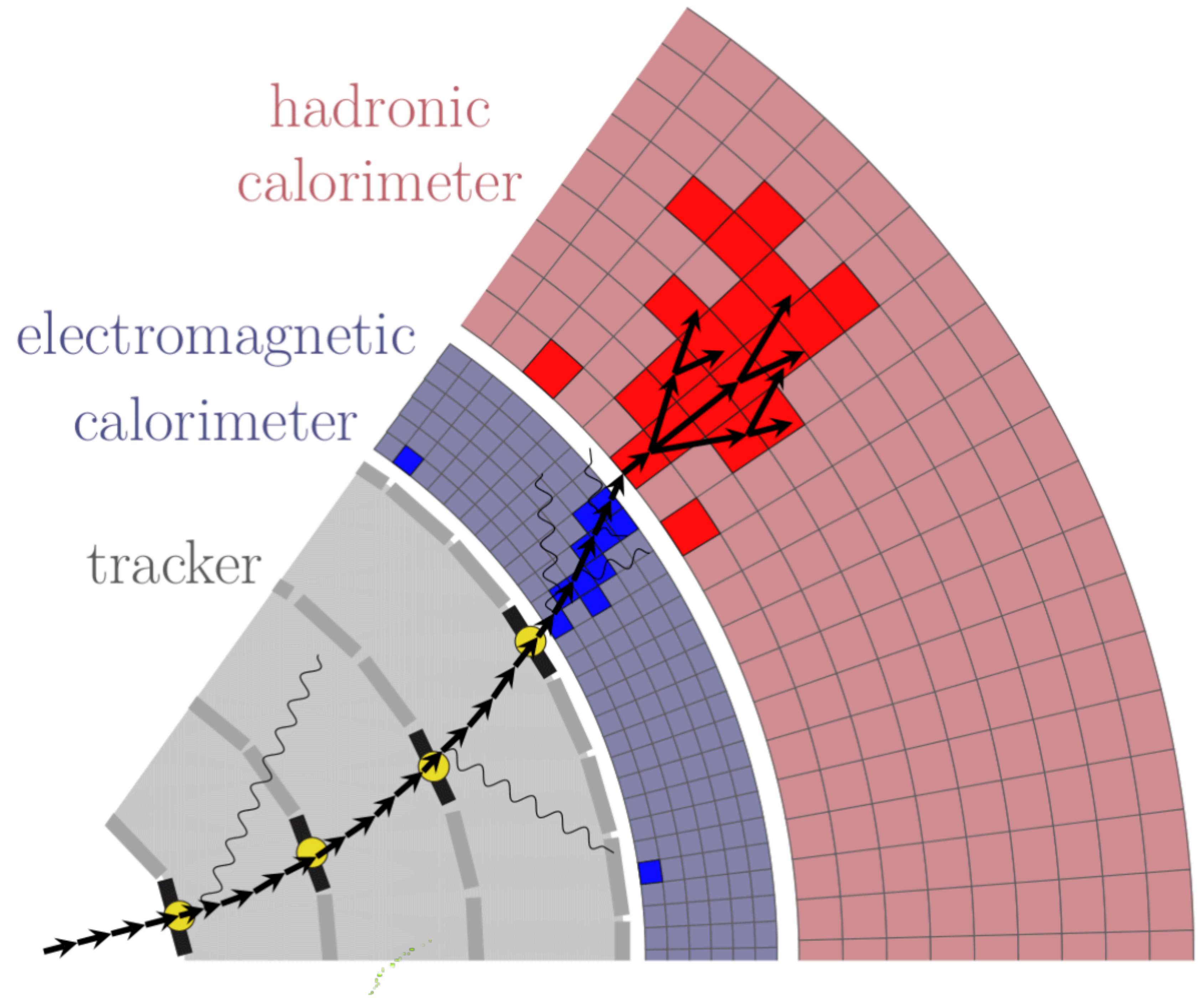
Monte Carlo simulation takes us over 20 orders of magnitude in length!

~40 quadrillion collisions recorded at LHC (1 fb^{-1} ~ 100 trillion collisions)

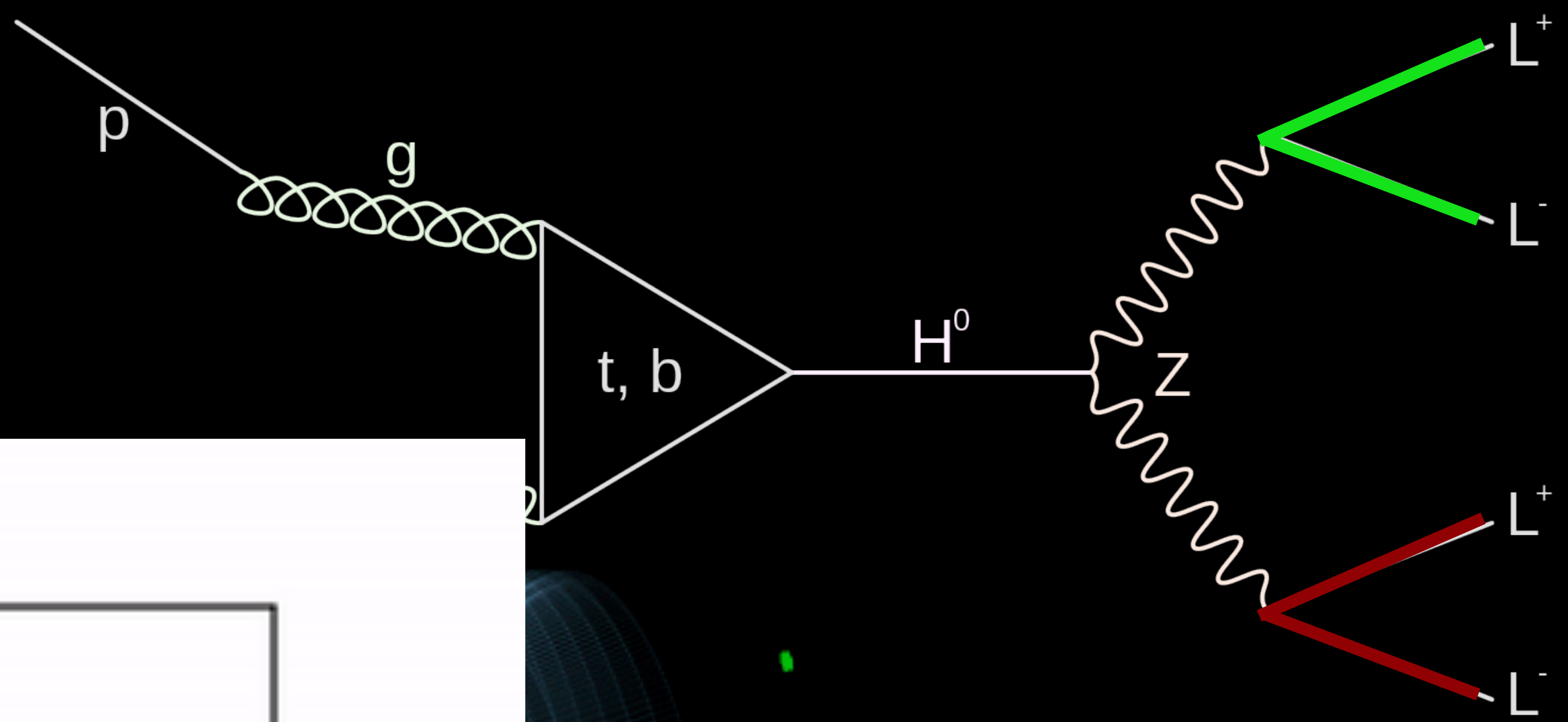


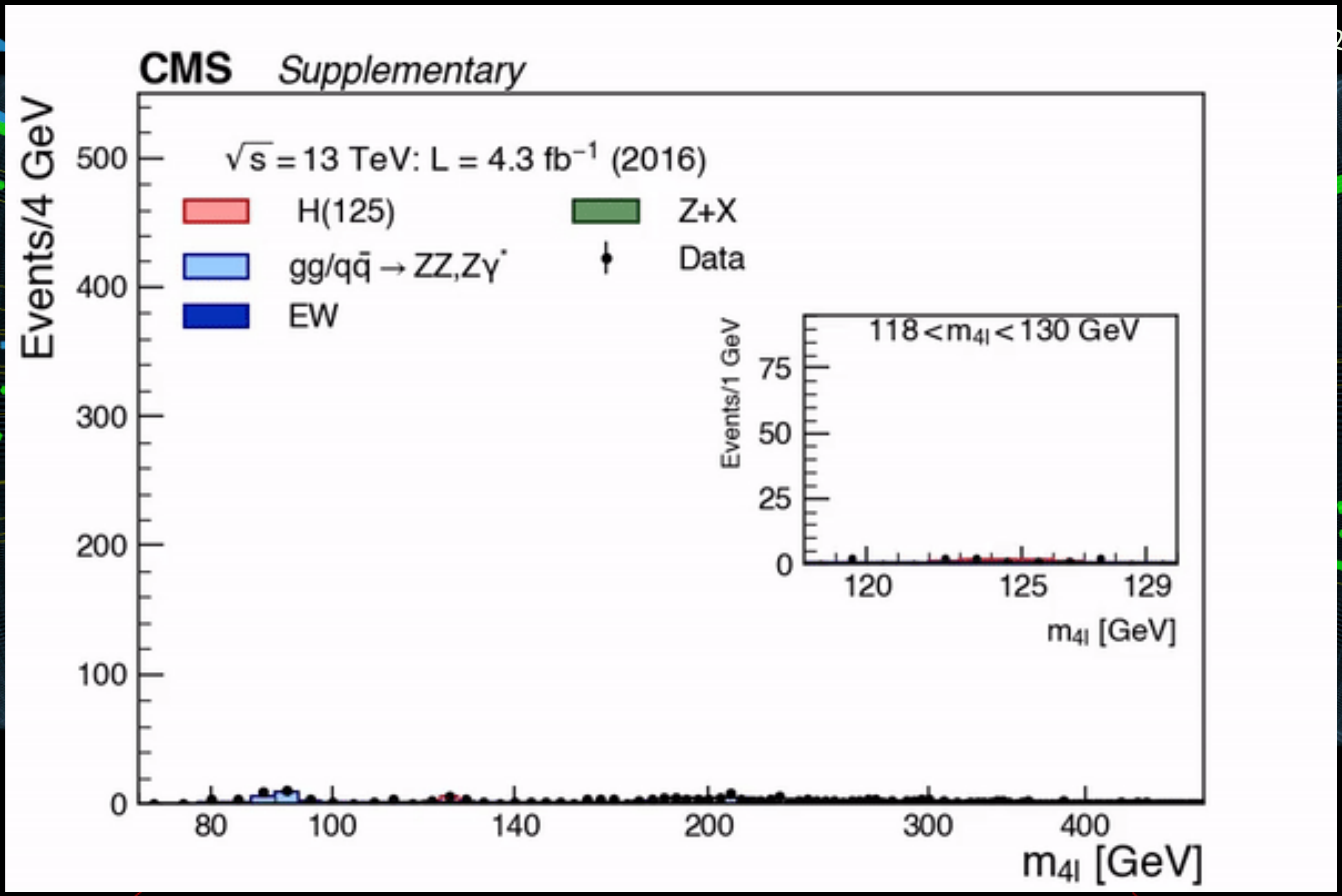
278 petabytes of data (Netflix 24/7 for more than 15,000 years)

O(1) trillion simulated events



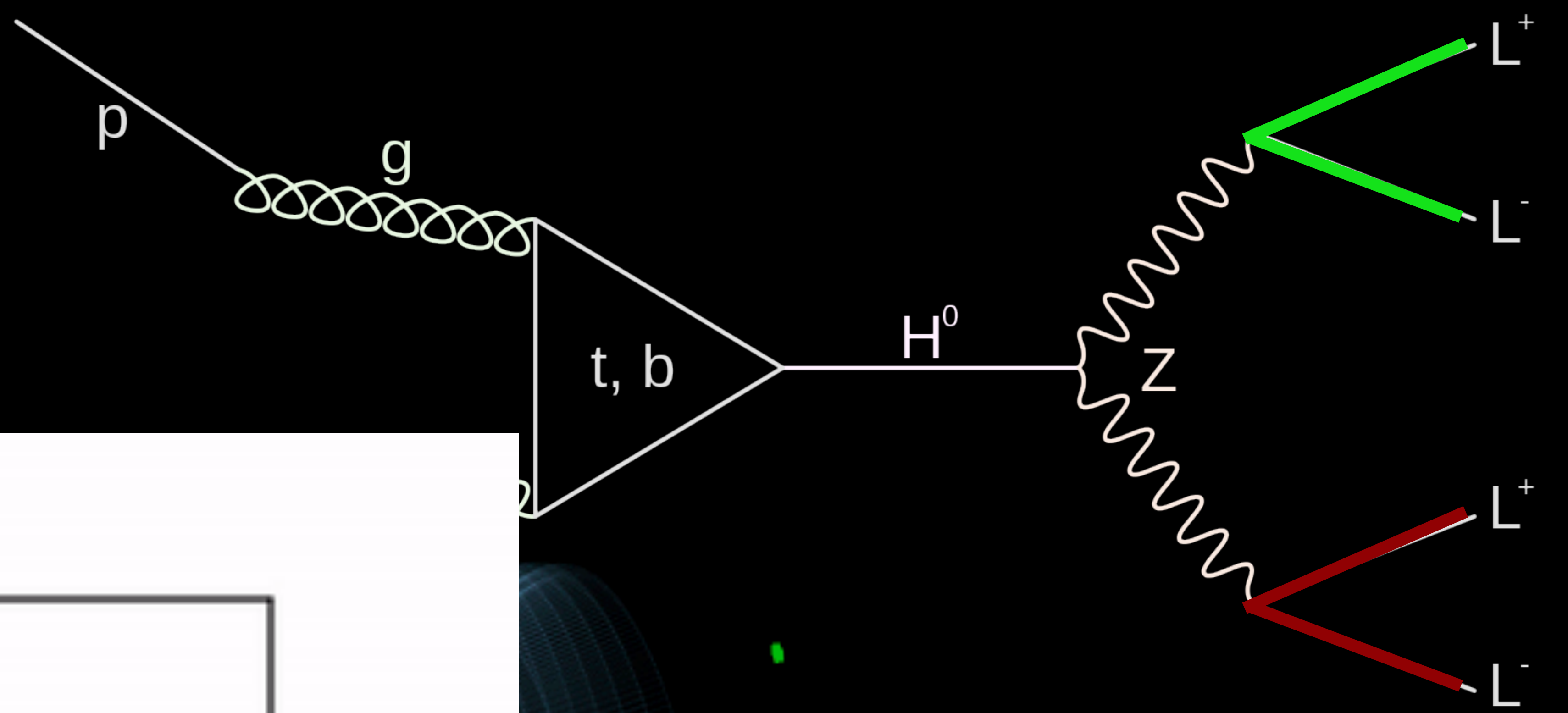
cmsexperiment.web.cern.ch

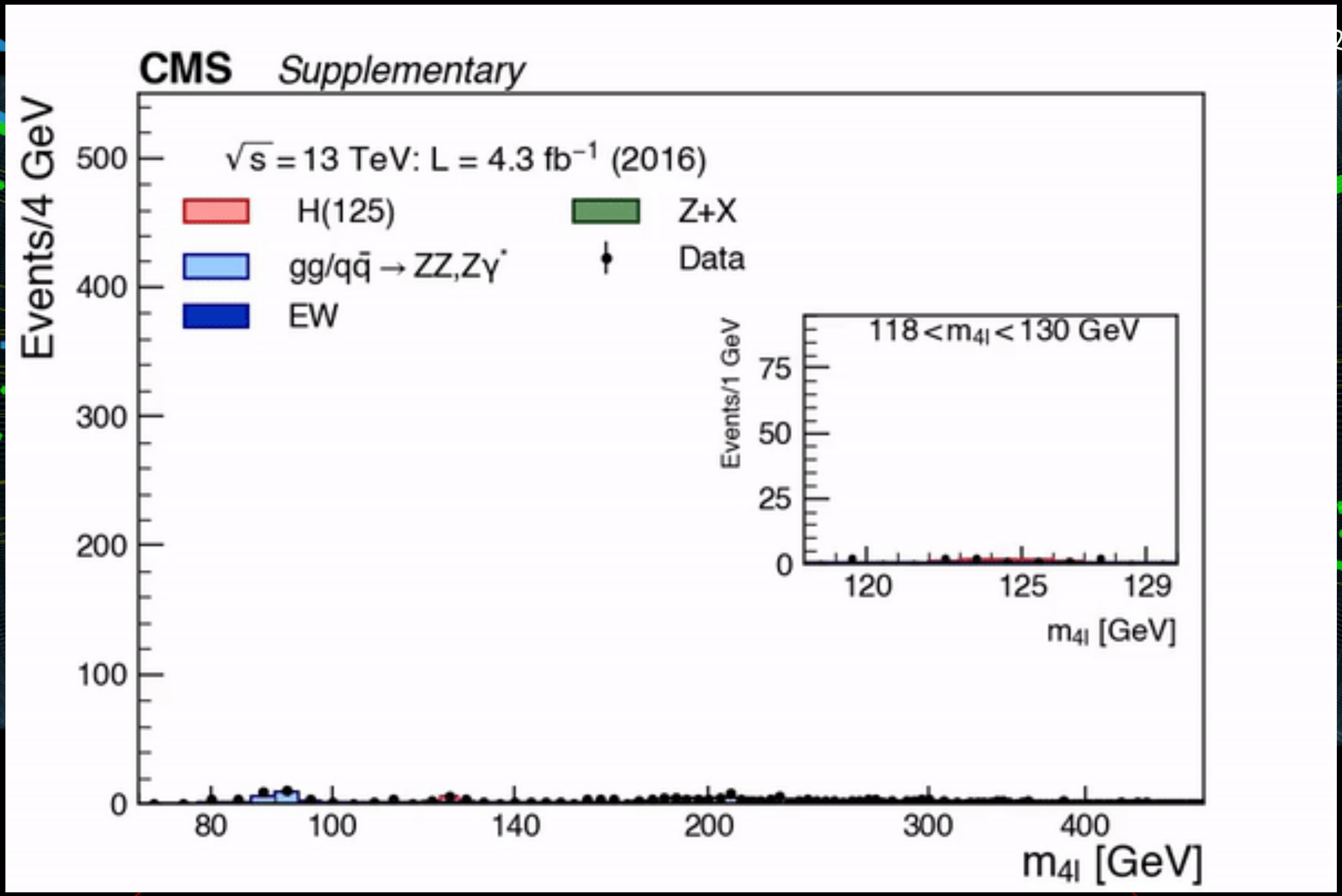




We had to collide billions of protons,
only around 10 signal events were needed to claim discovery!

cmsexperiment.web.cern.ch





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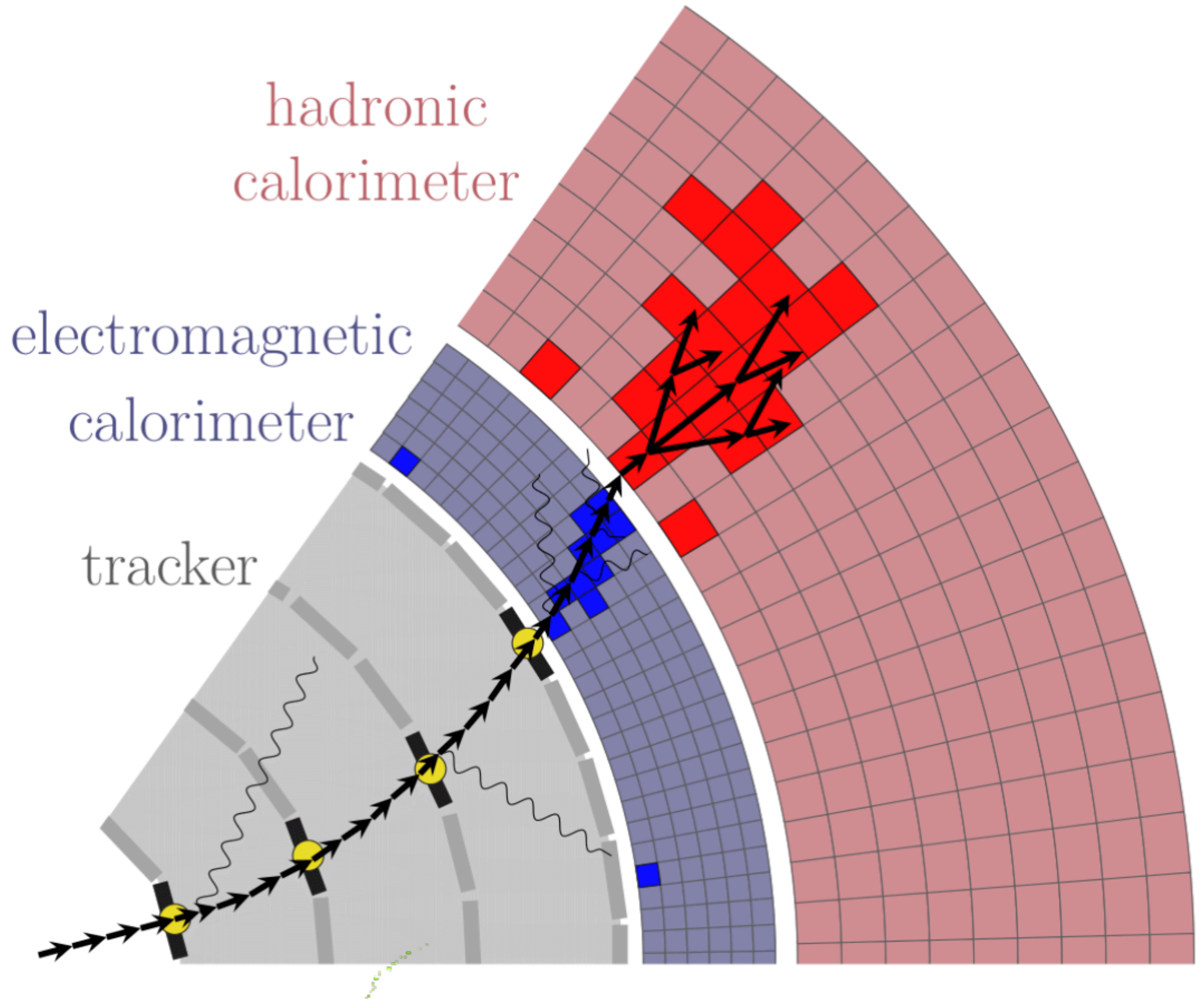
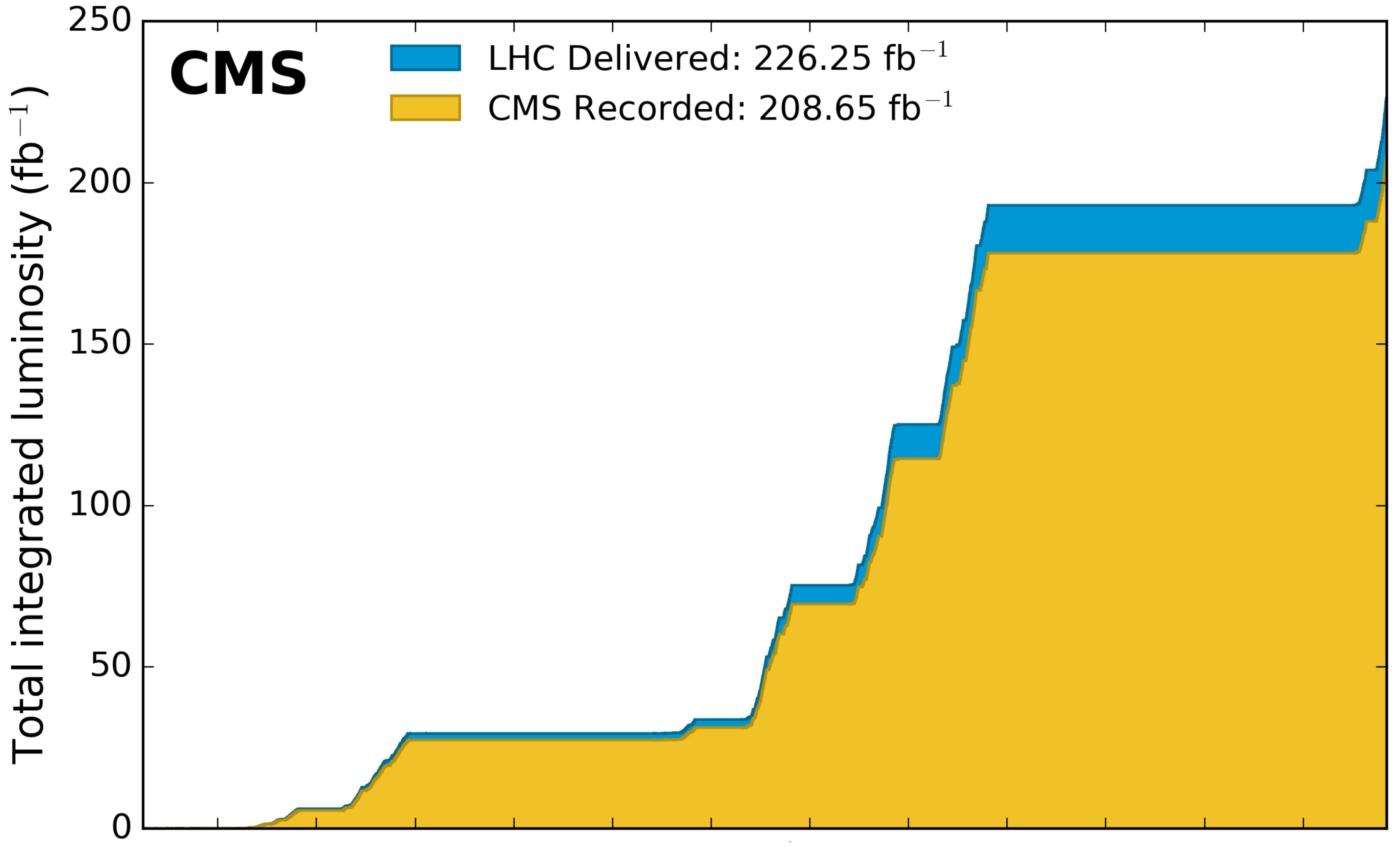
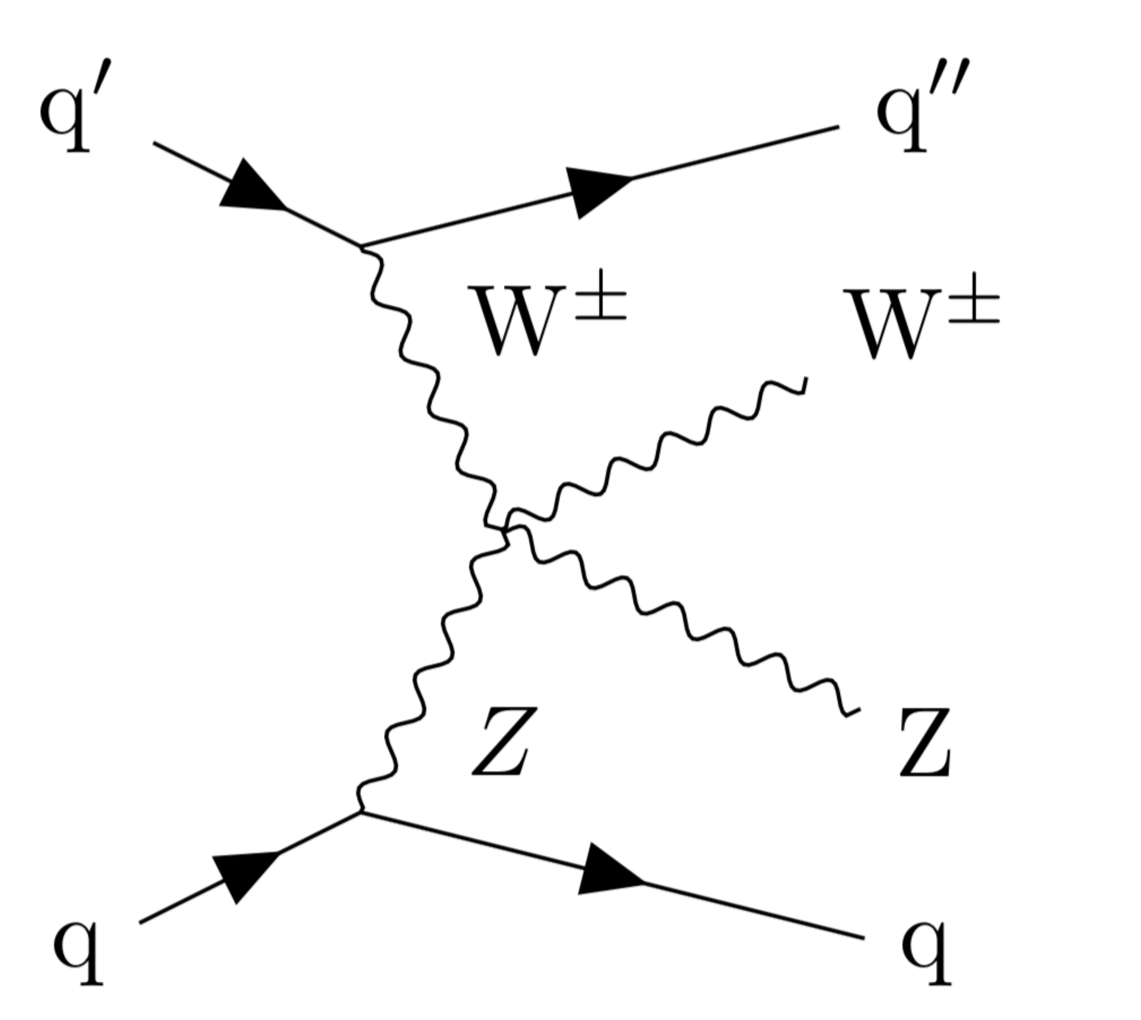


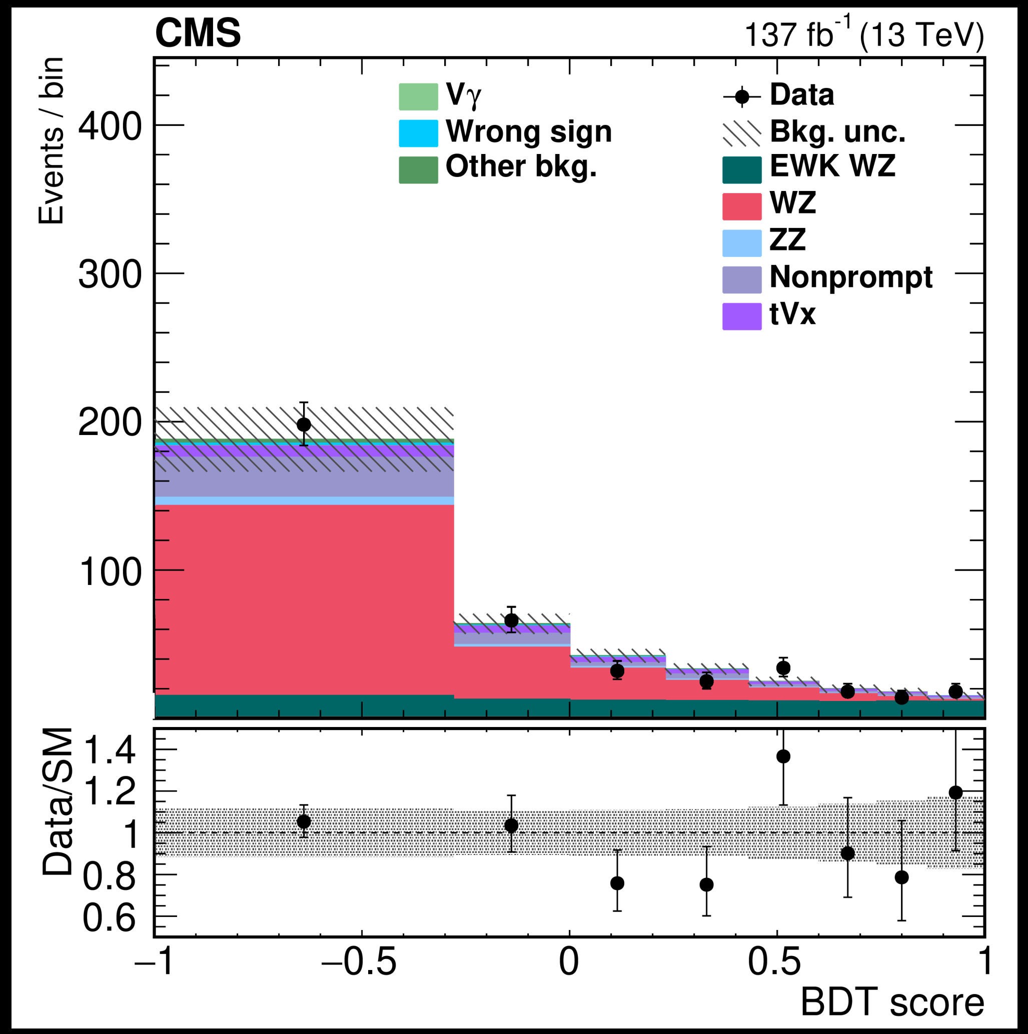


We have a lot of high quality simulated data that we want to use to train AI algorithms!

But we have even more unlabelled data we'd like to use!

Supervised versus unsupervised





ML:

Enhance S/√B


Detector reconstruction and tagging
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100m
IGI+RECO
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10^-15m
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GEN
SIM
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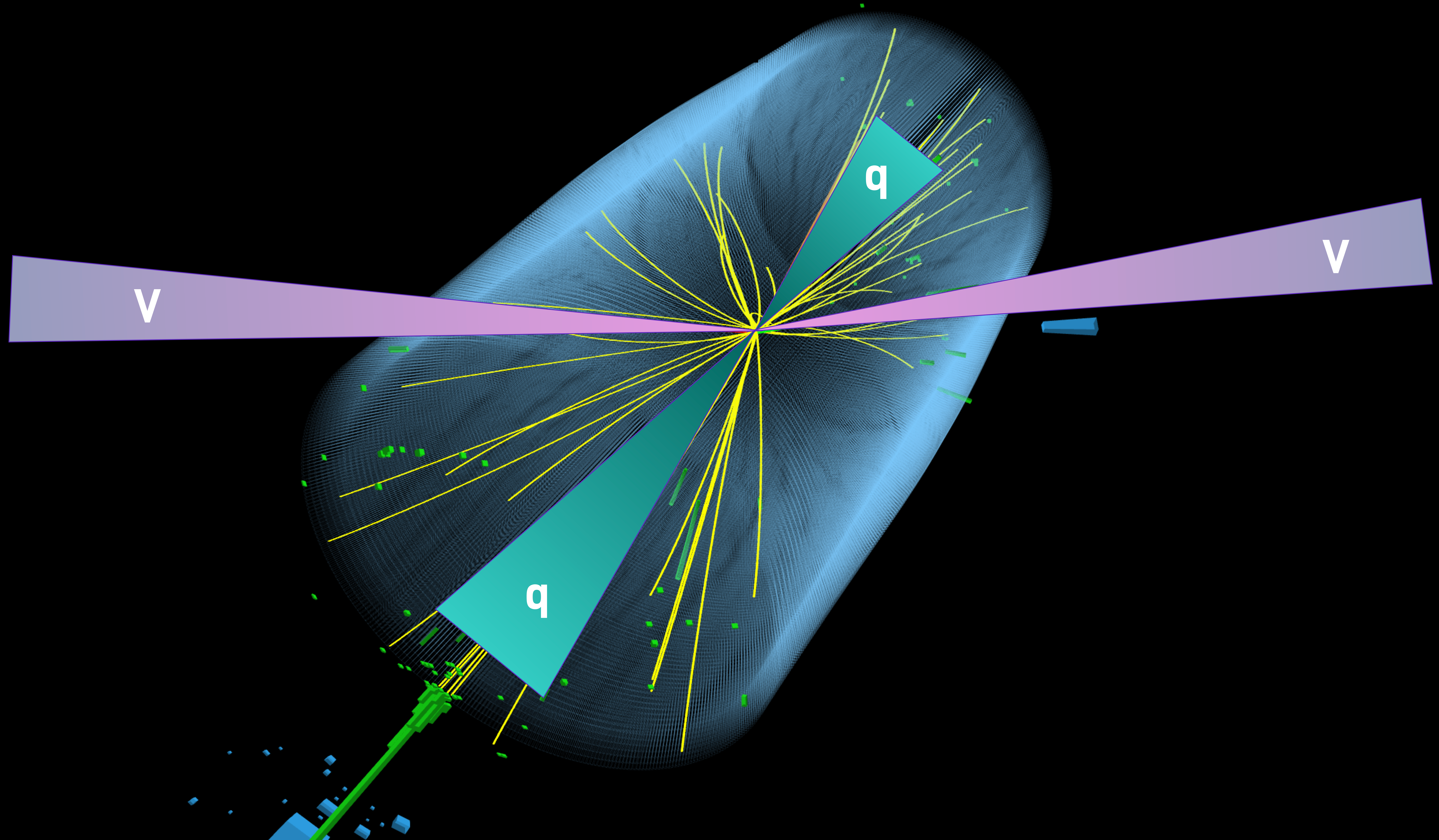
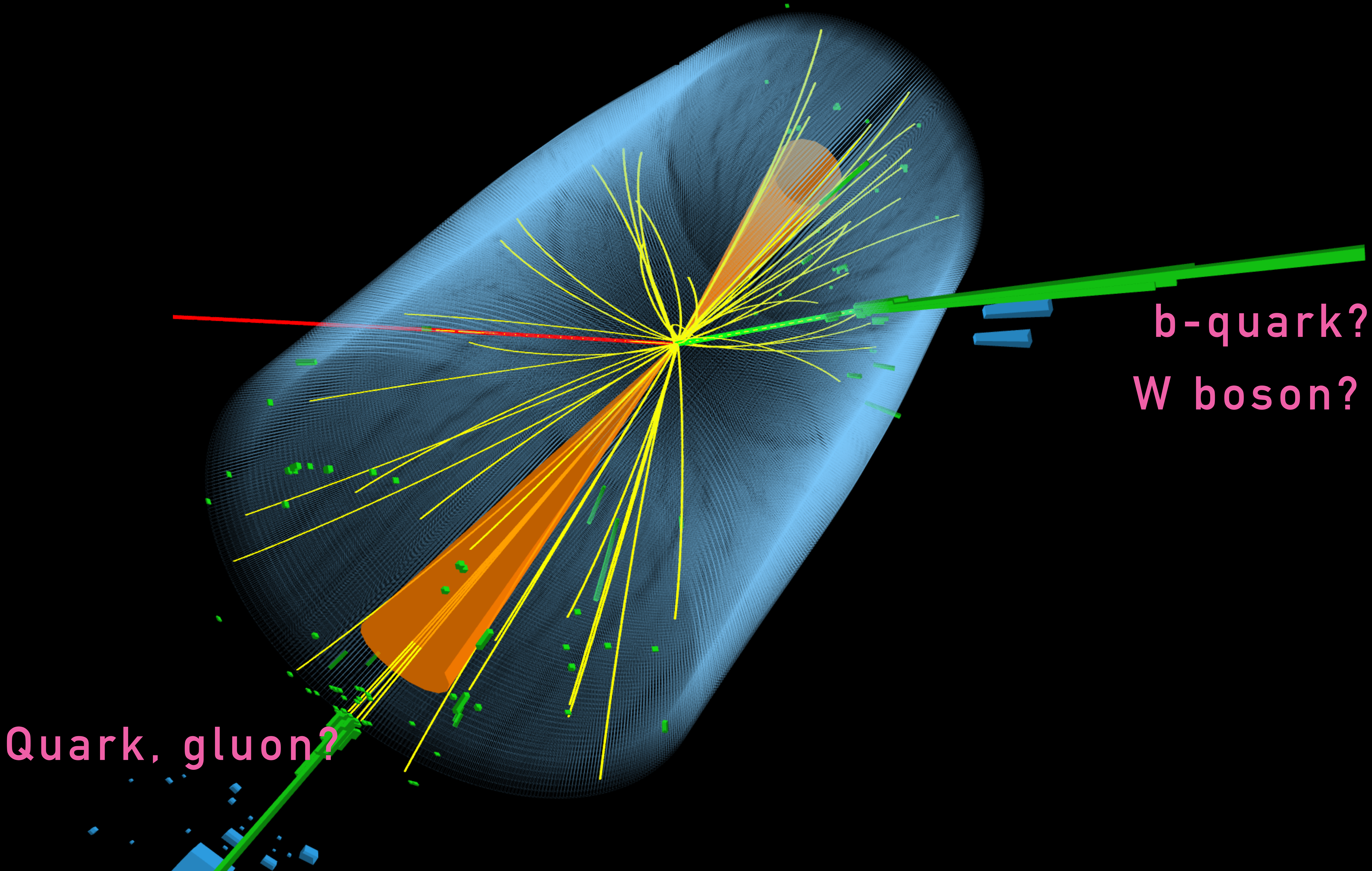
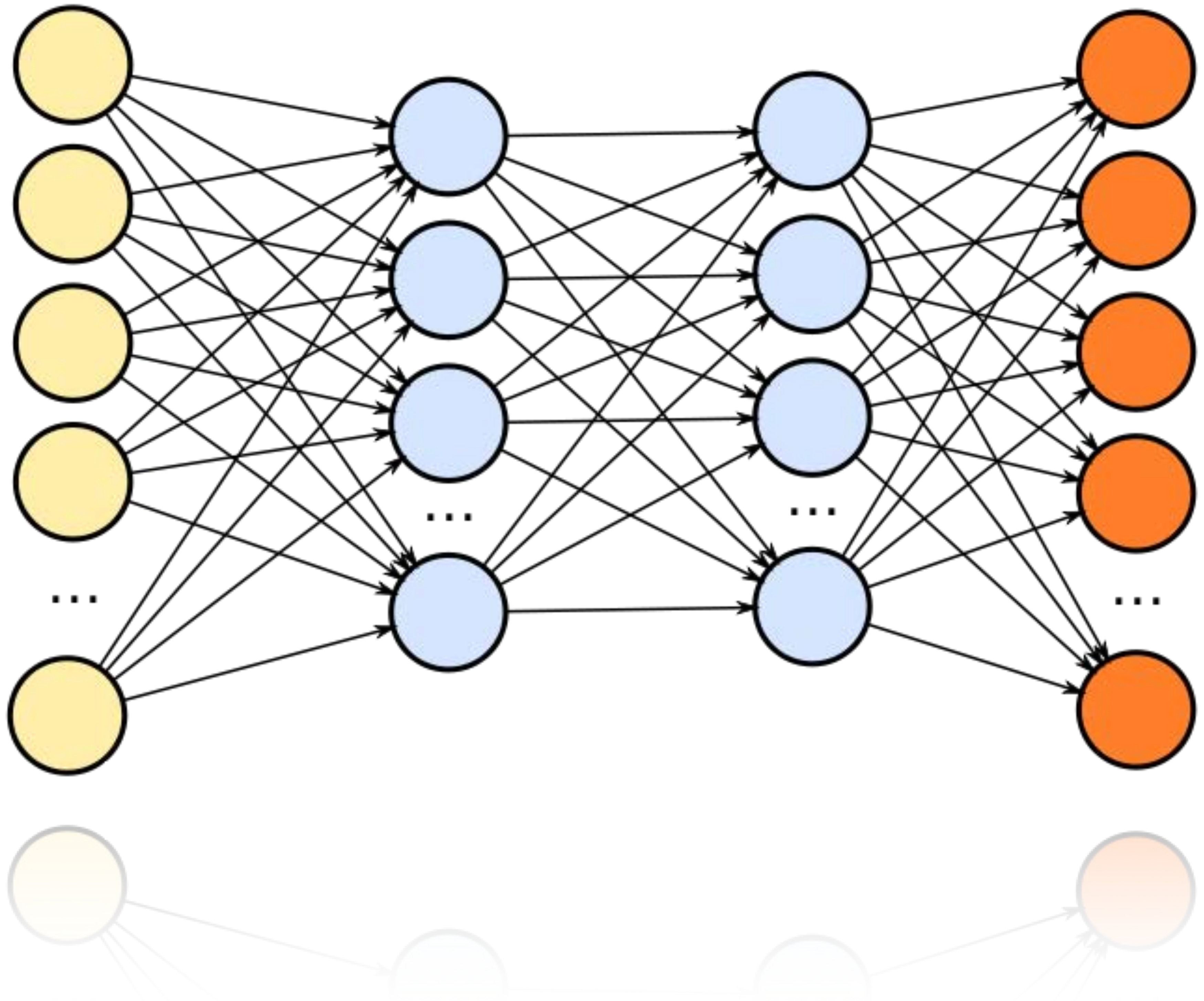

q
V
V
q

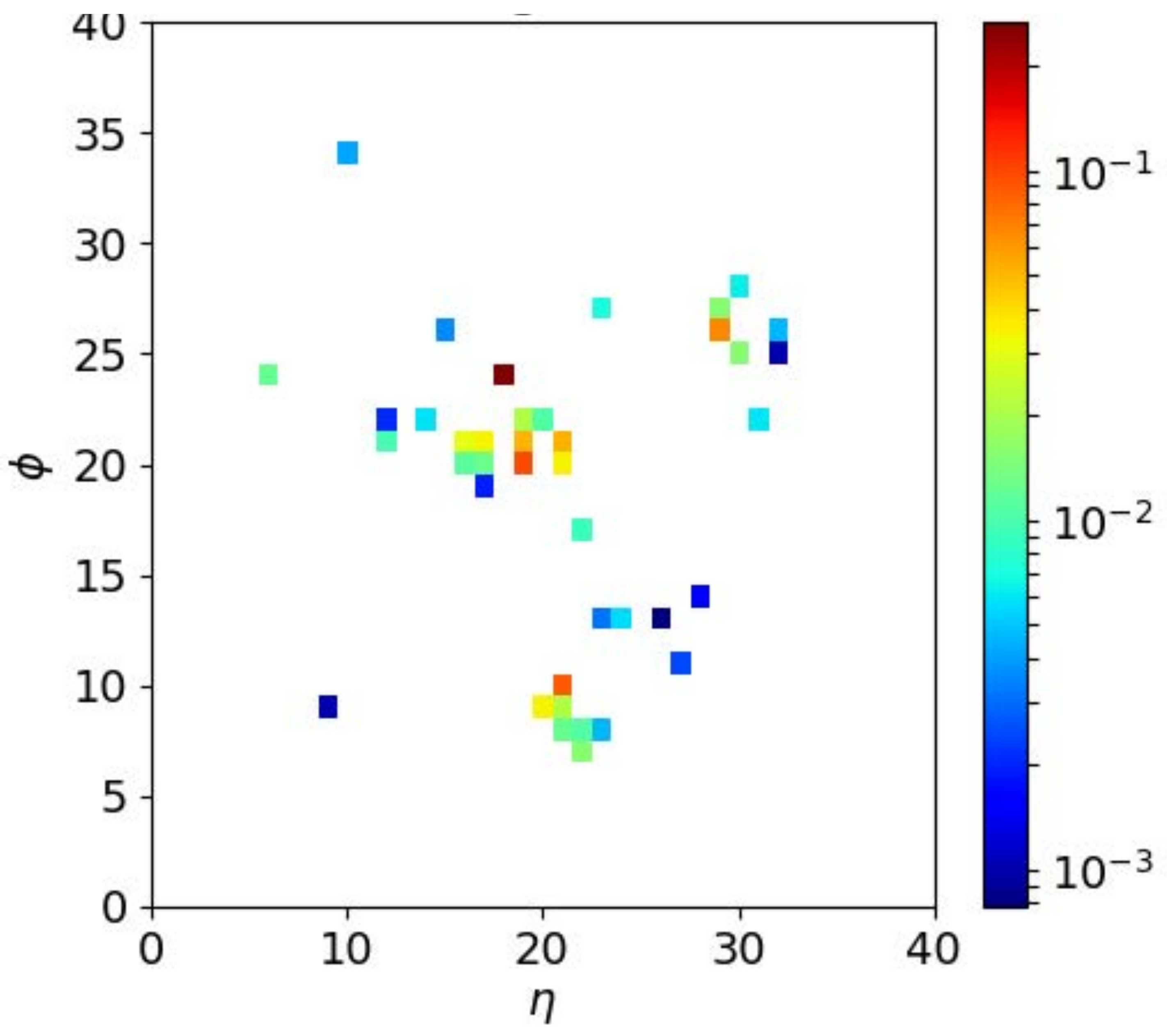

Data representation

Jet tagging - our MNIST!



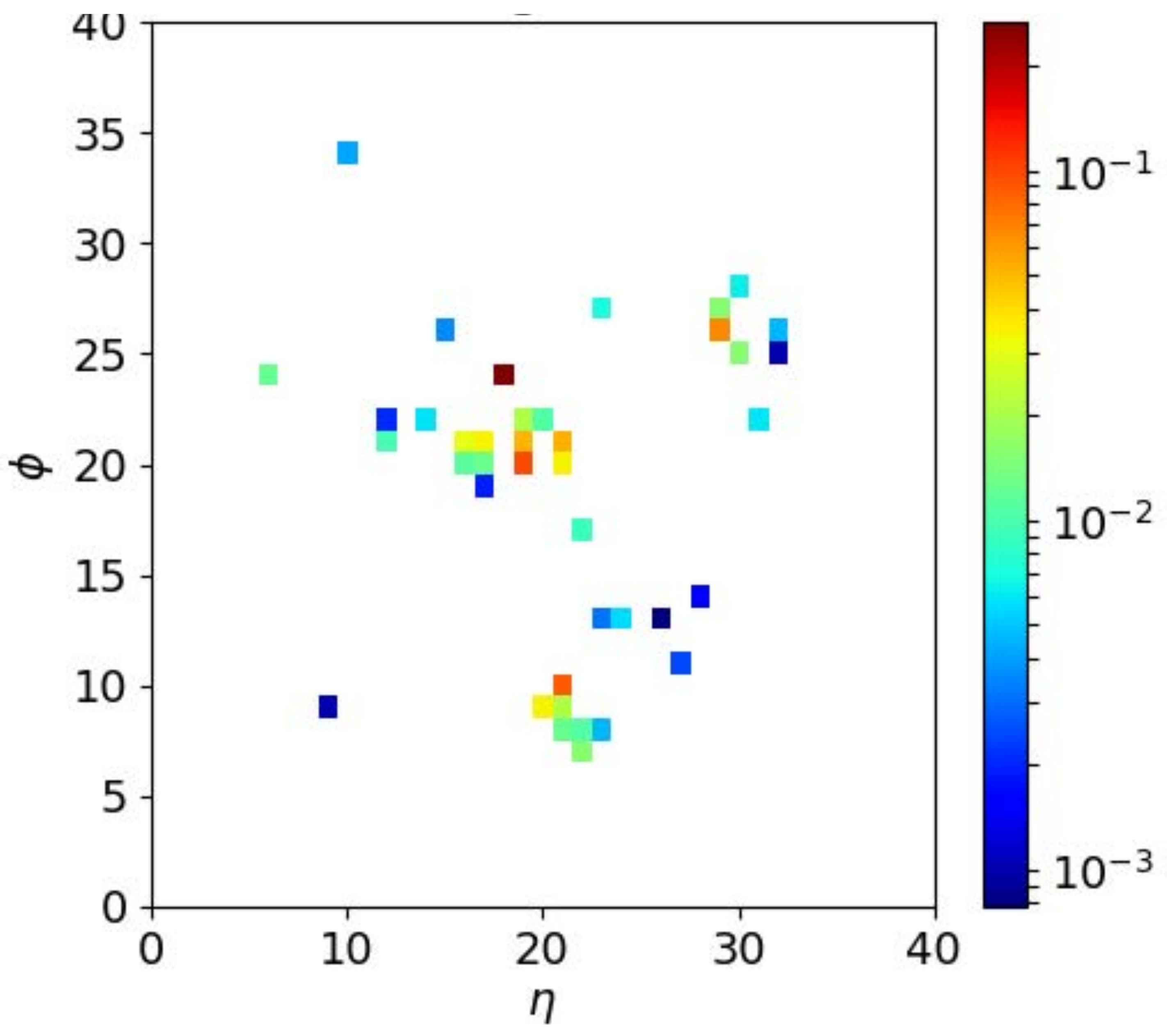


Image



arXiv:1511.05190

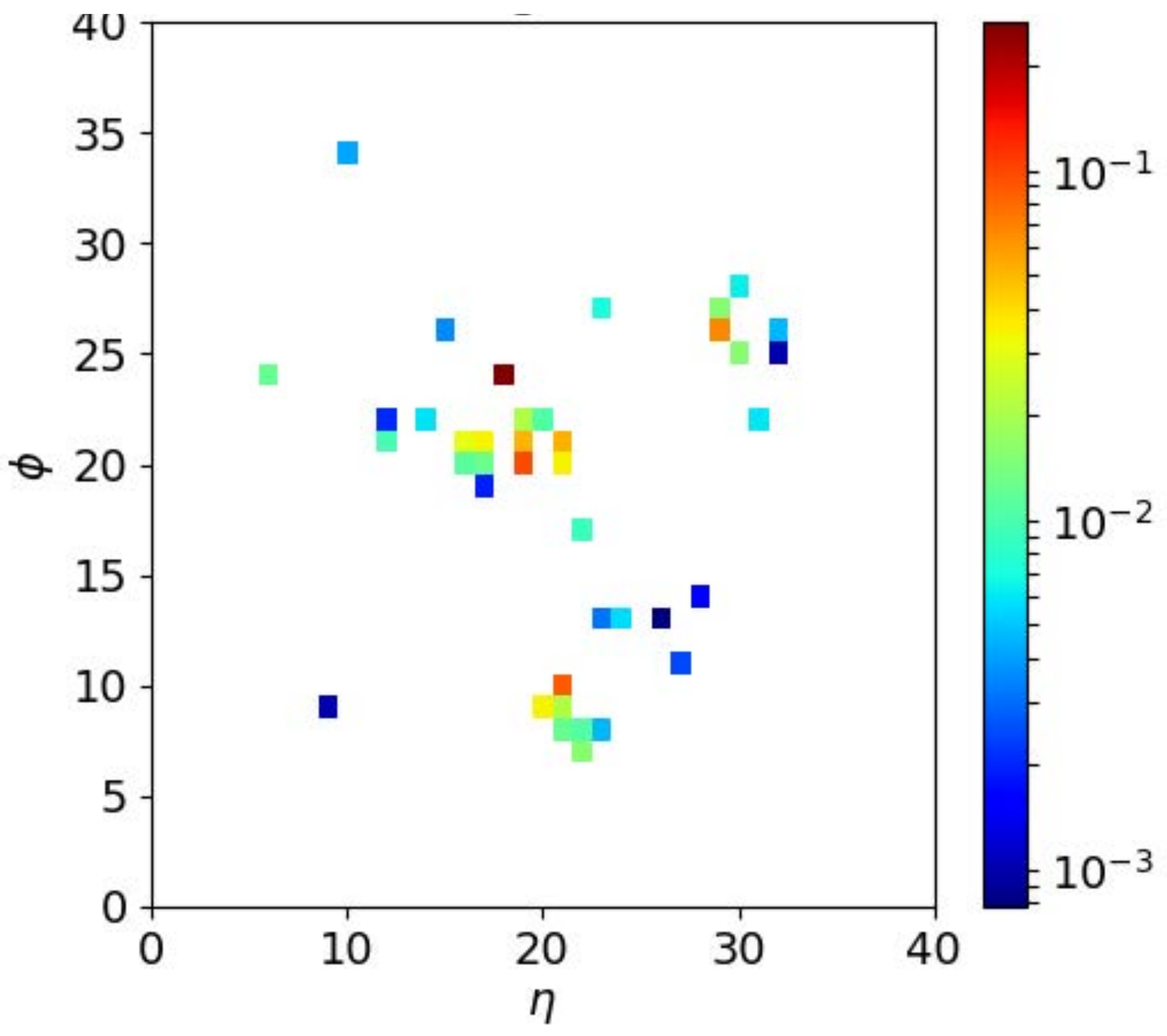
Image



arXiv:1511.05190

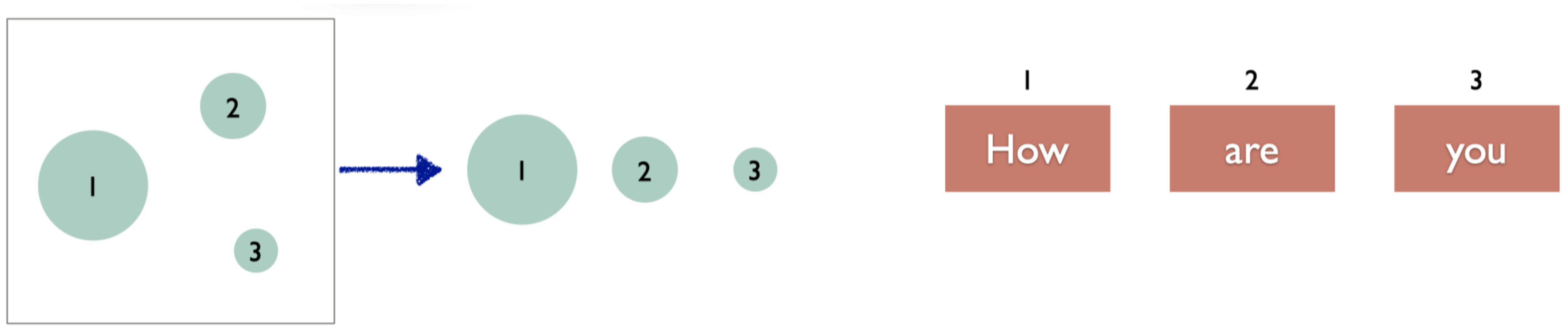
But… inhomogeneous geometry, high sparsity

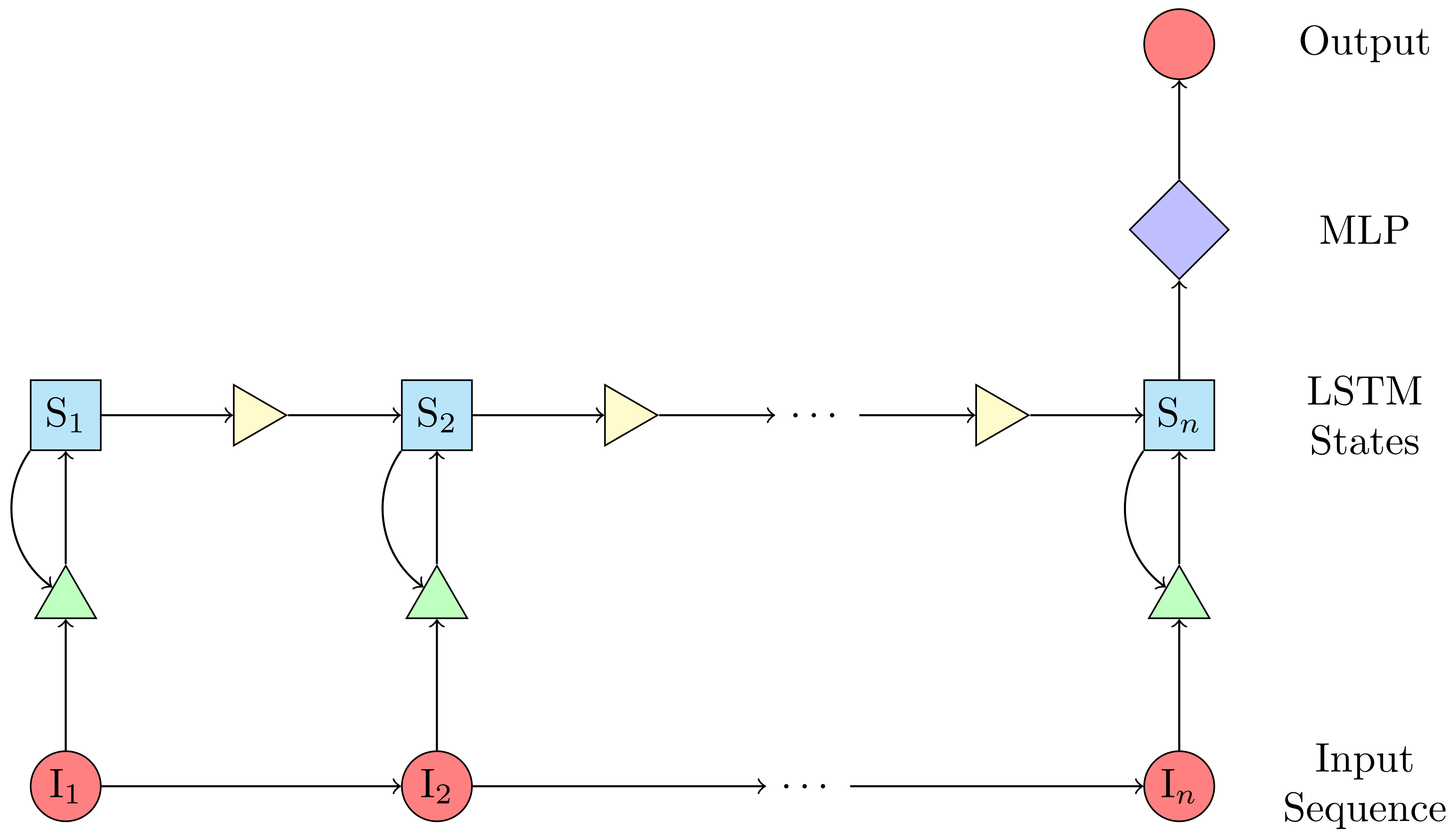
Image



arXiv:1511.05190

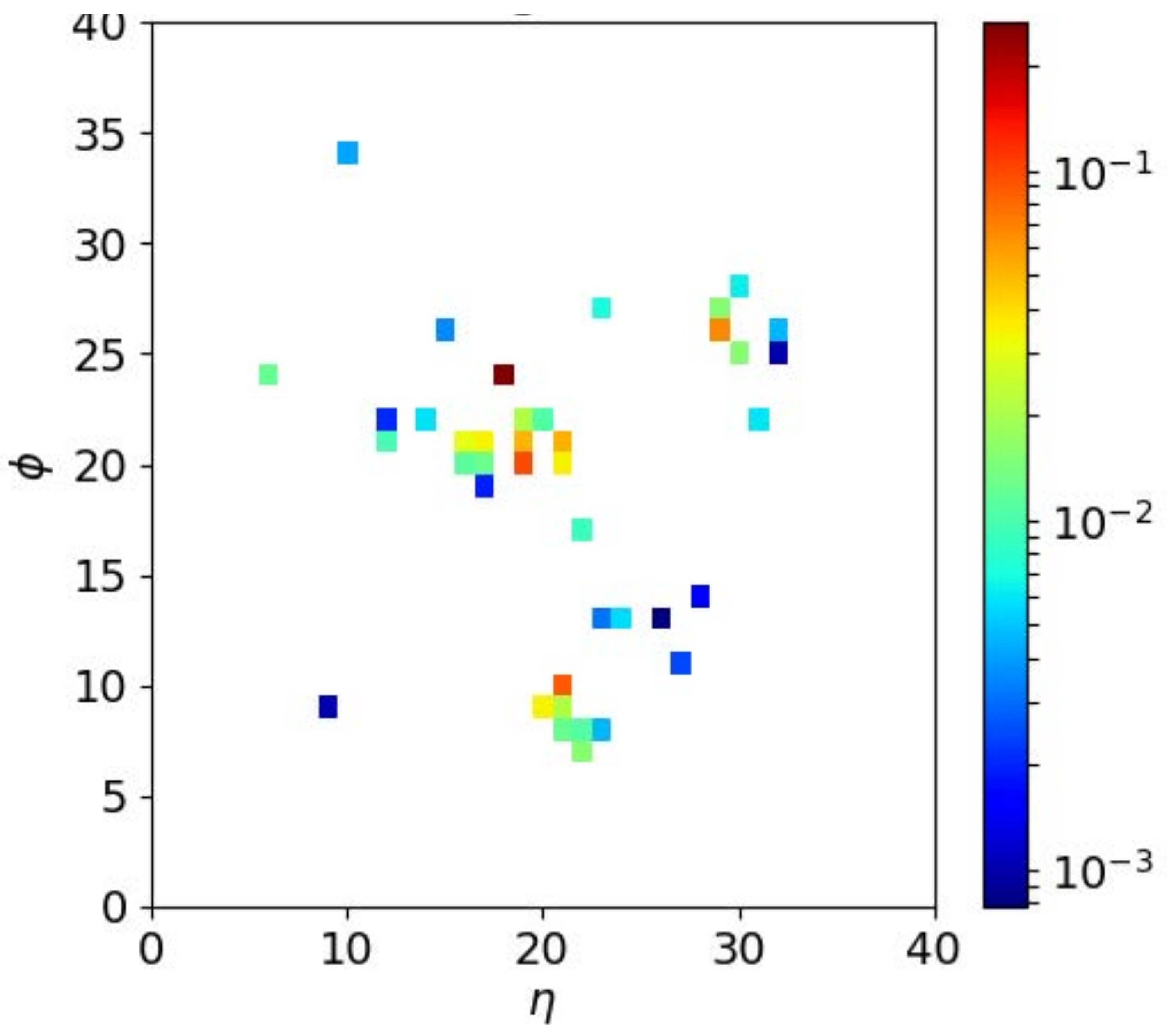
Sequence





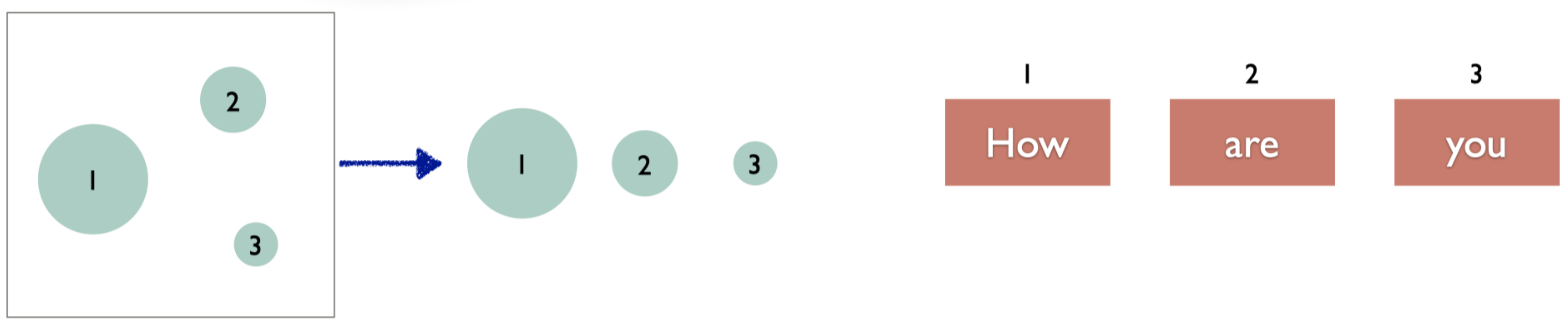
arXiv:1607.08633

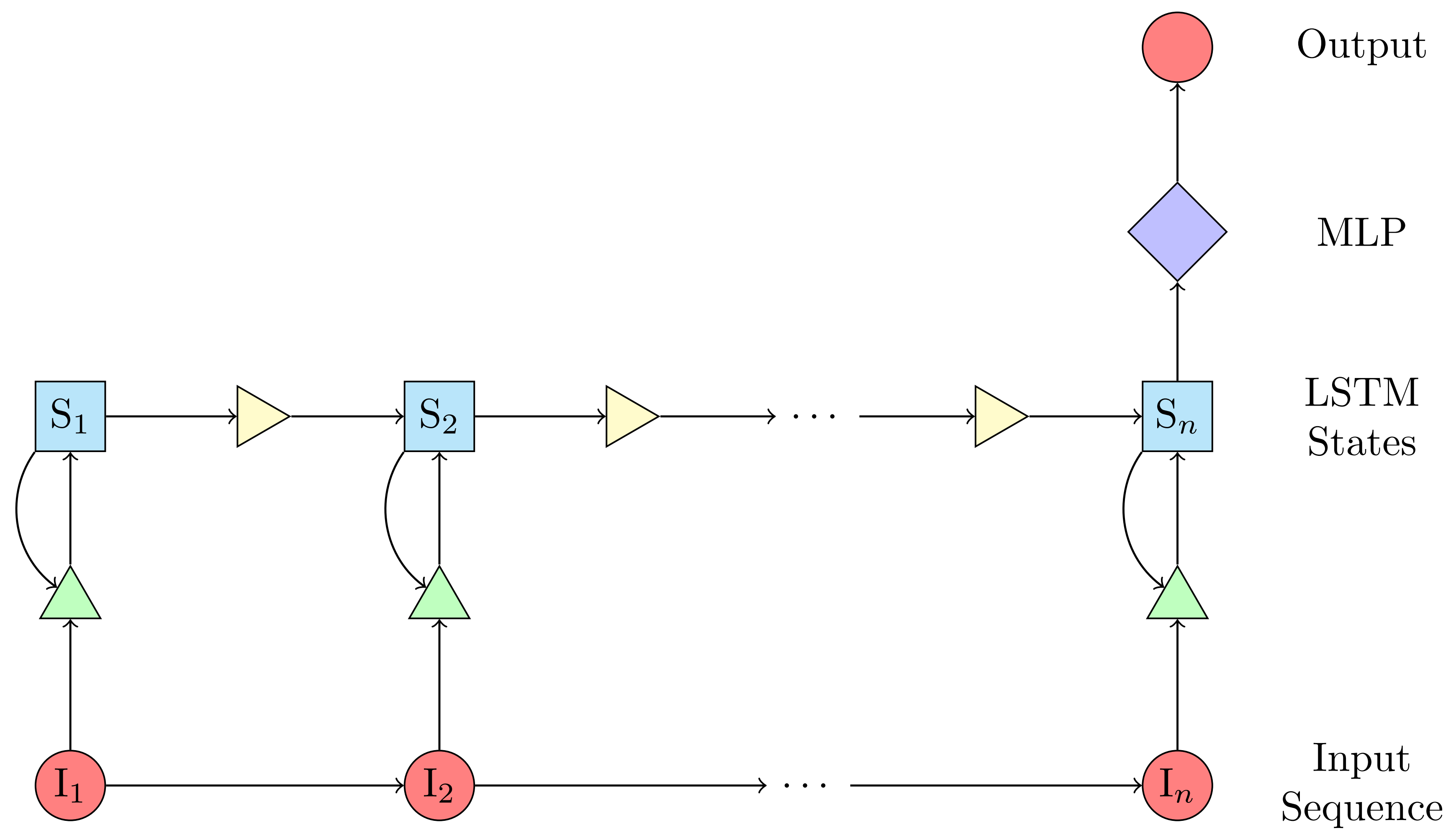
Image



arXiv:1511.05190

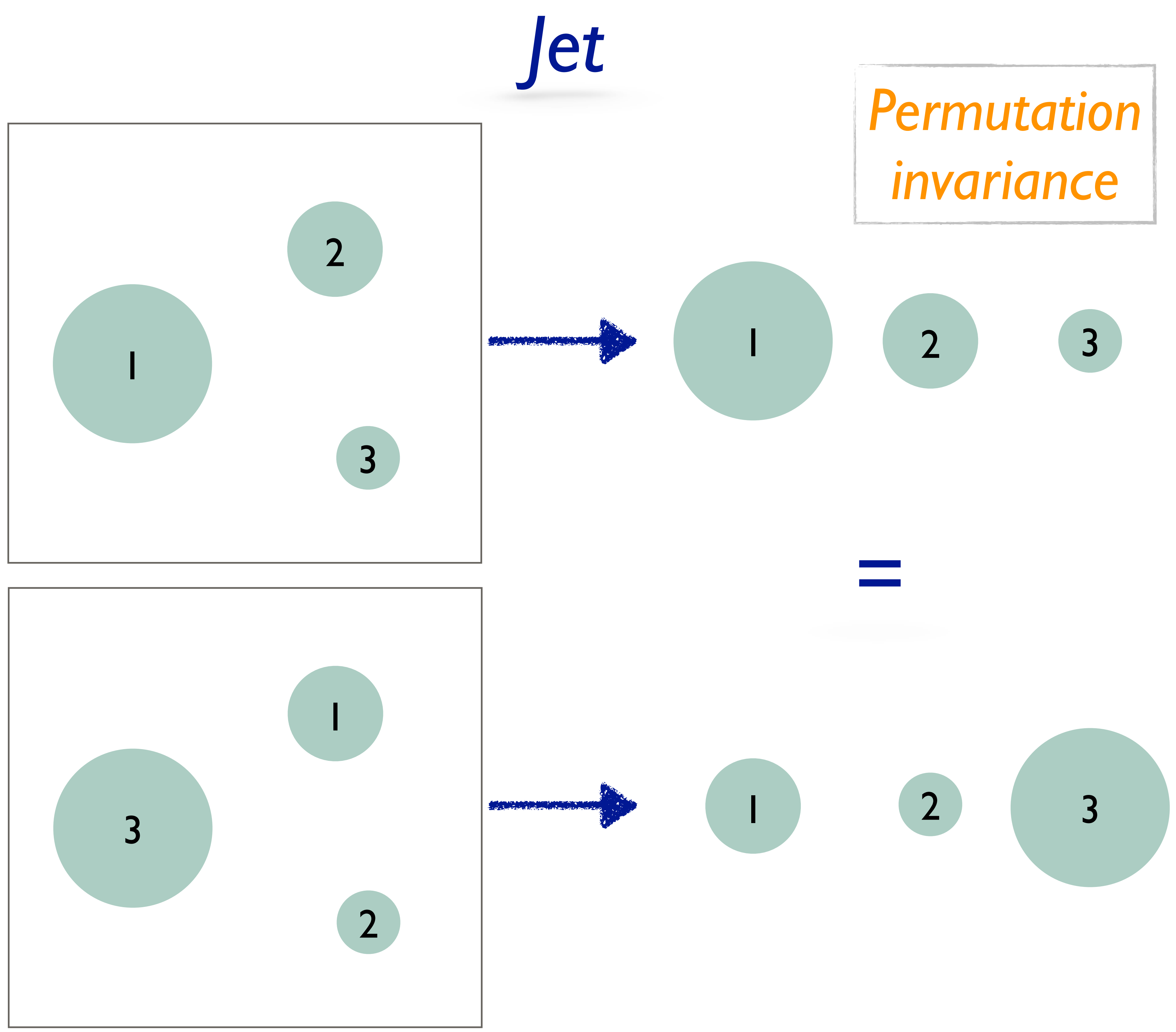
Sequence

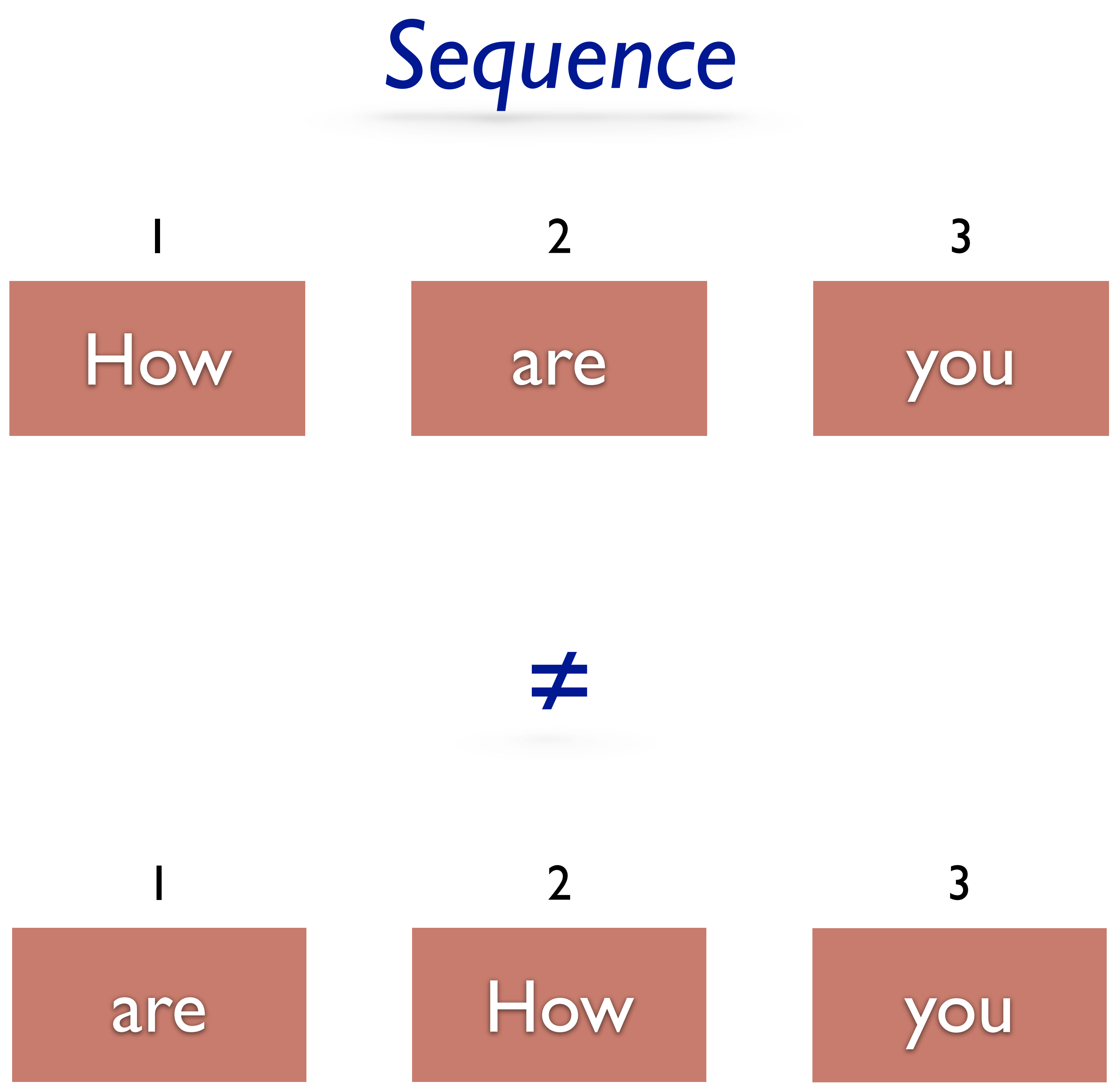




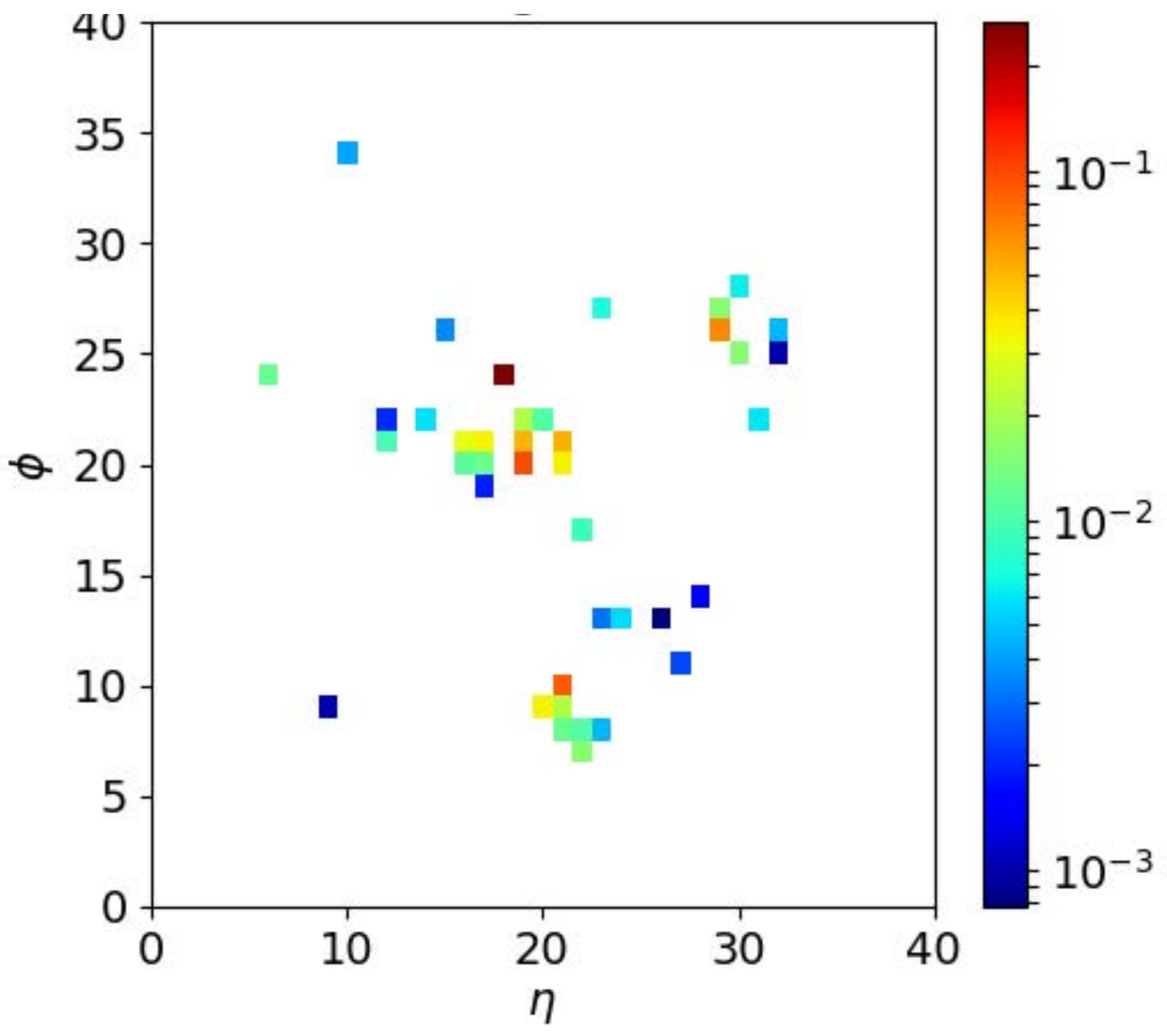
arXiv:1607.08633

But... permutation-invariance


Jet
Permutation invariance
1
2
3
=
3
1
2
1
2
3

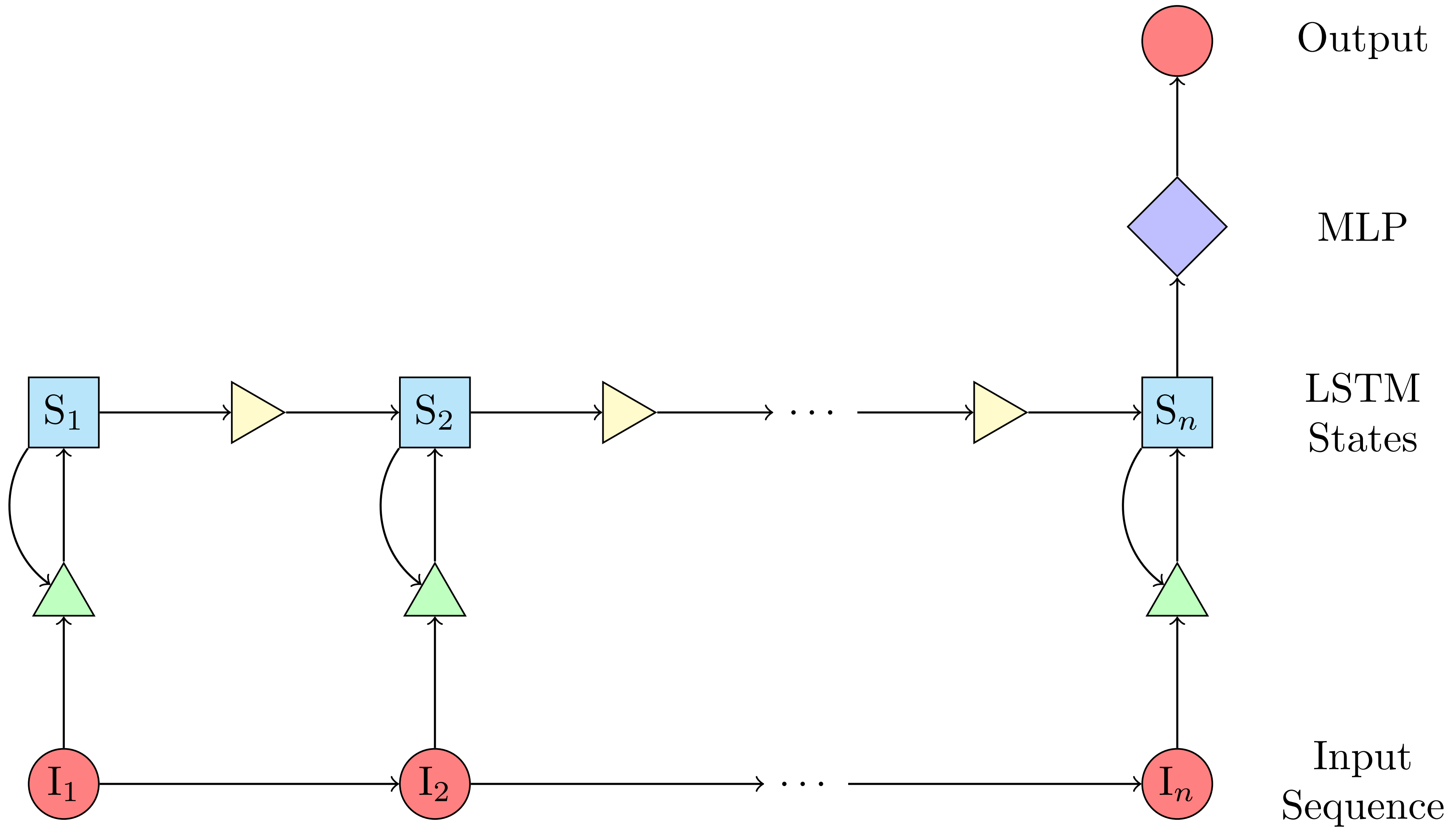

Sequence
1 2 3
How are you
≠
1 2 3
are How you

Image



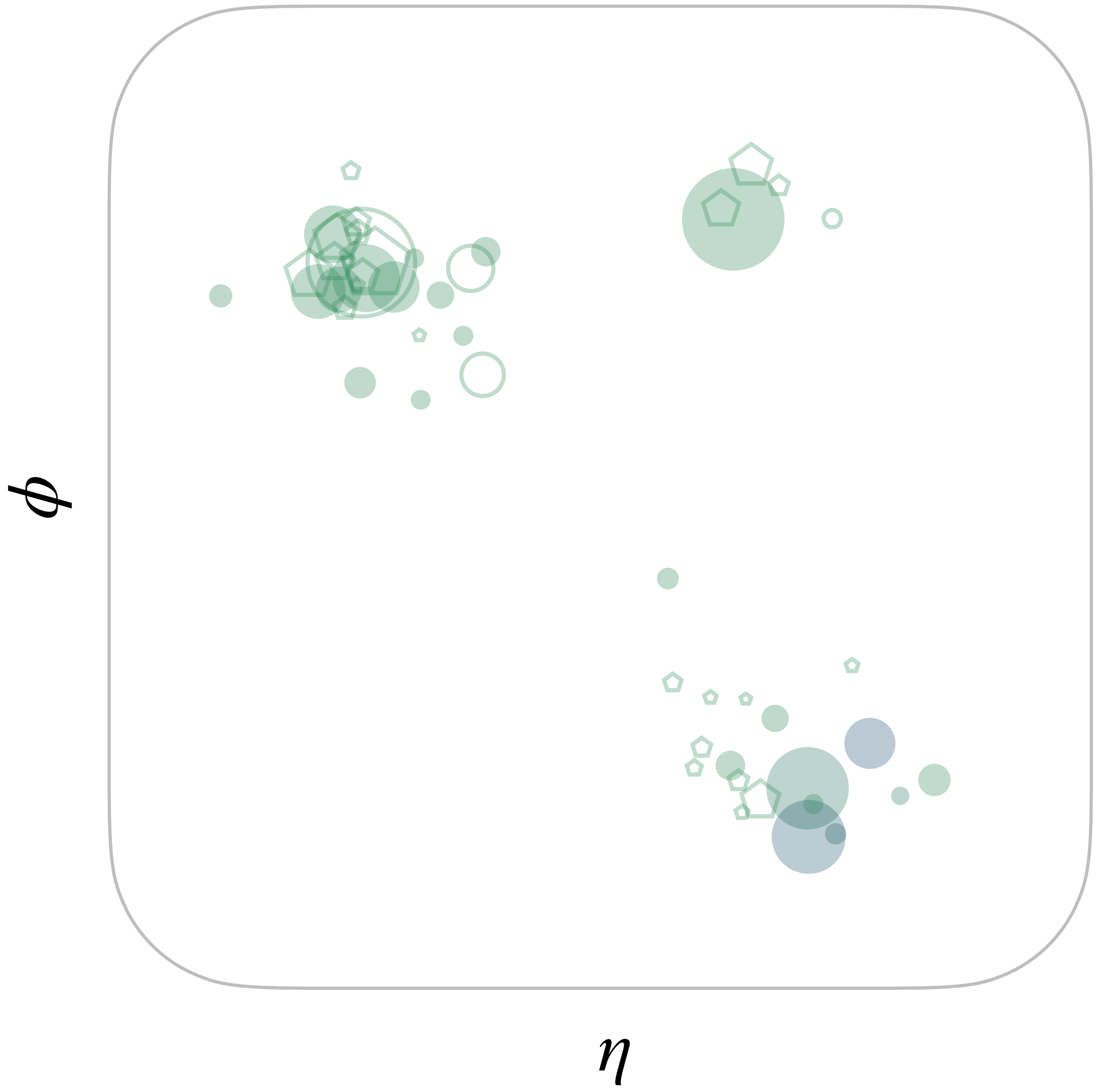
arXiv:1511.05190

Sequence

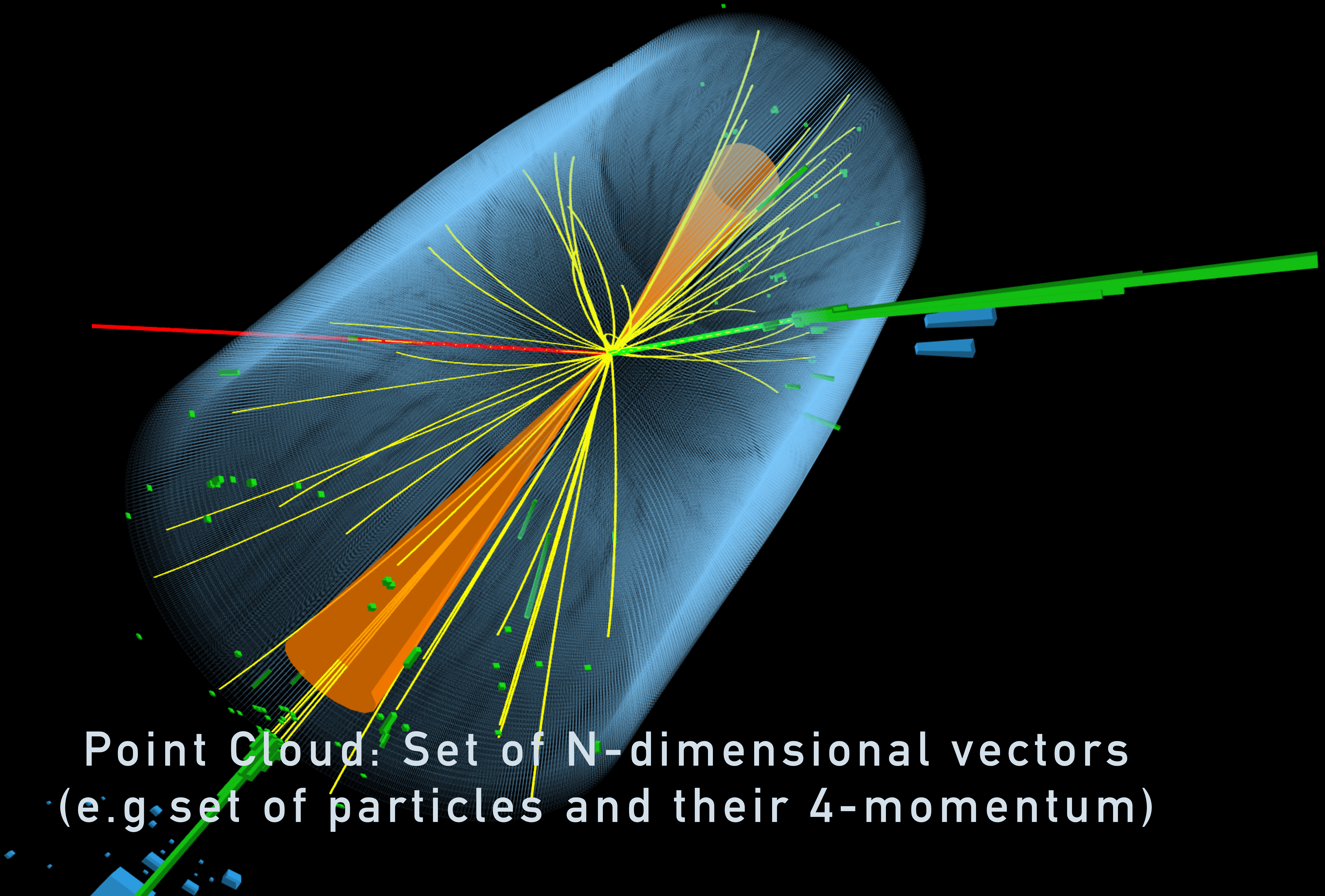


arXiv:1607.08633

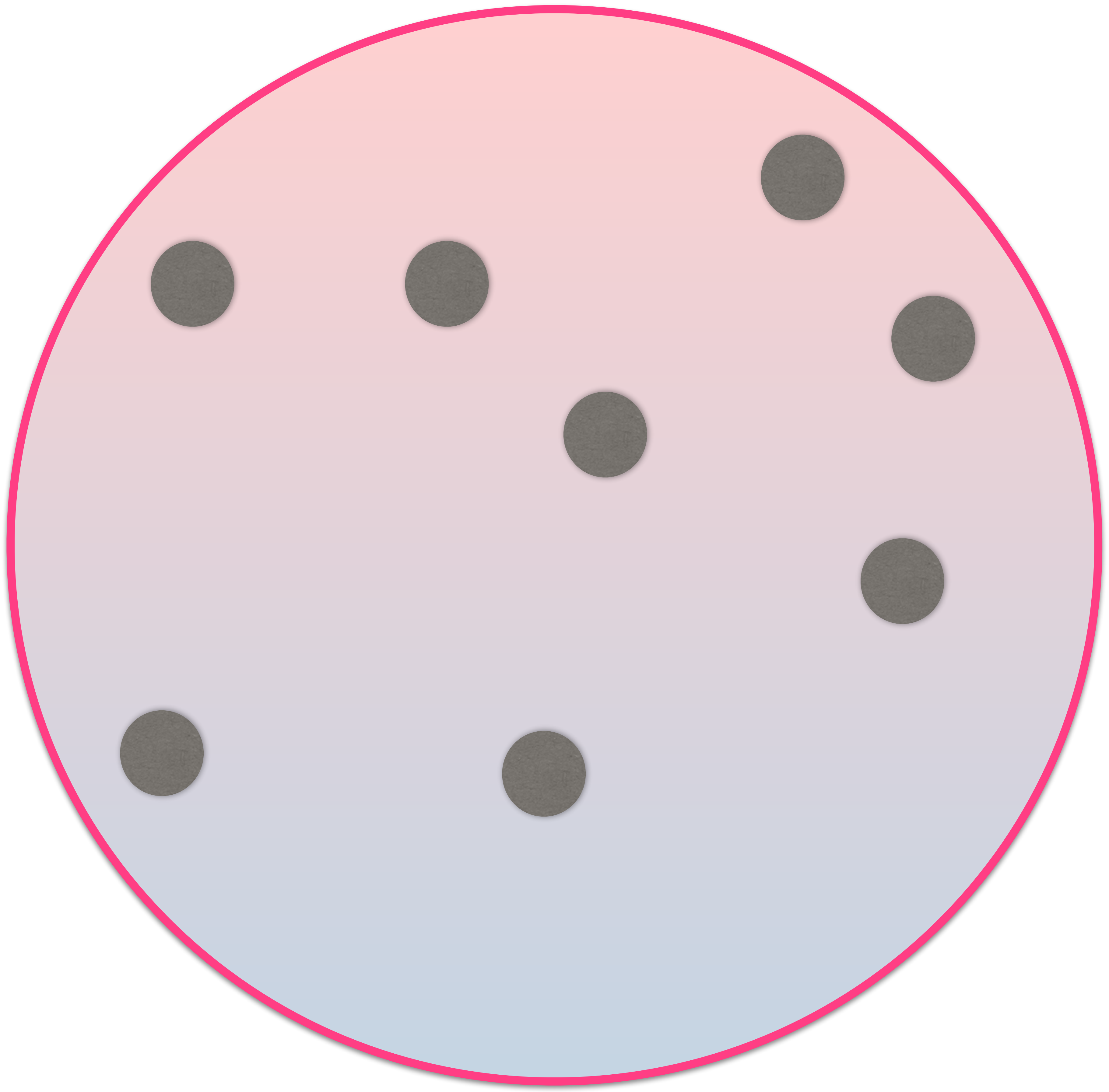
Point Cloud

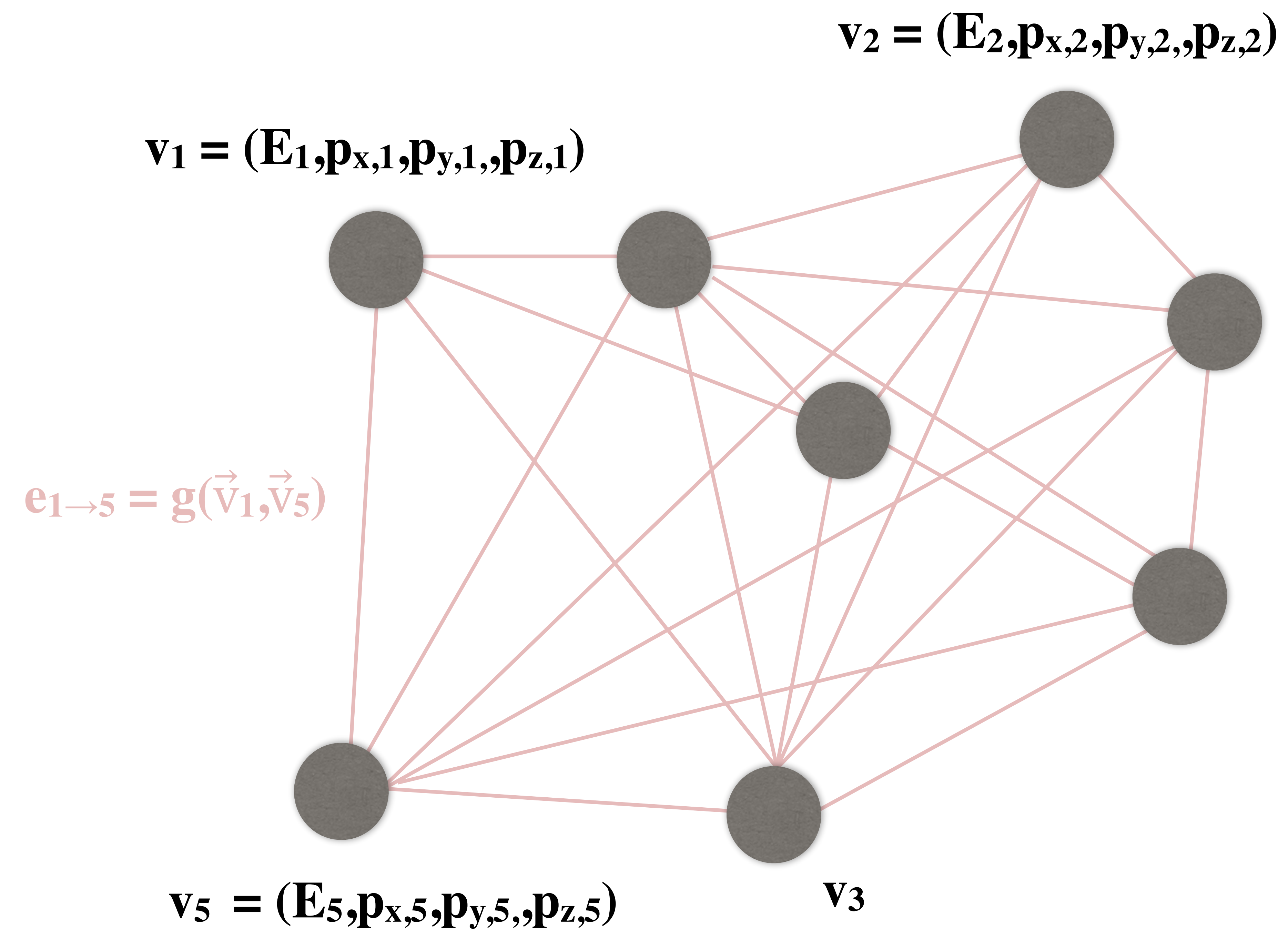


PRD:101.056019



Point Cloud: Set of N-dimensional vectors
(e.g set of particles and their 4-momentum)

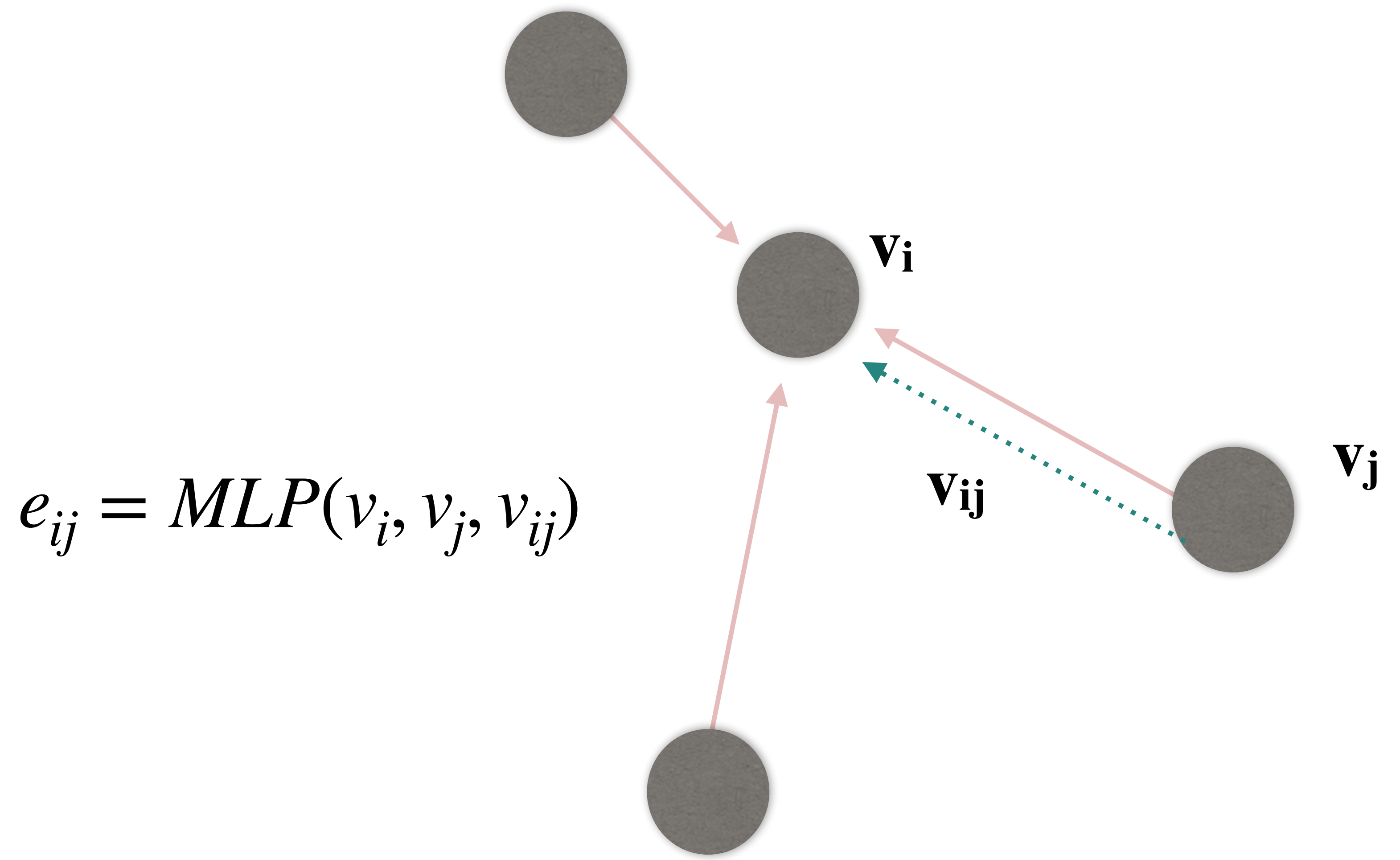


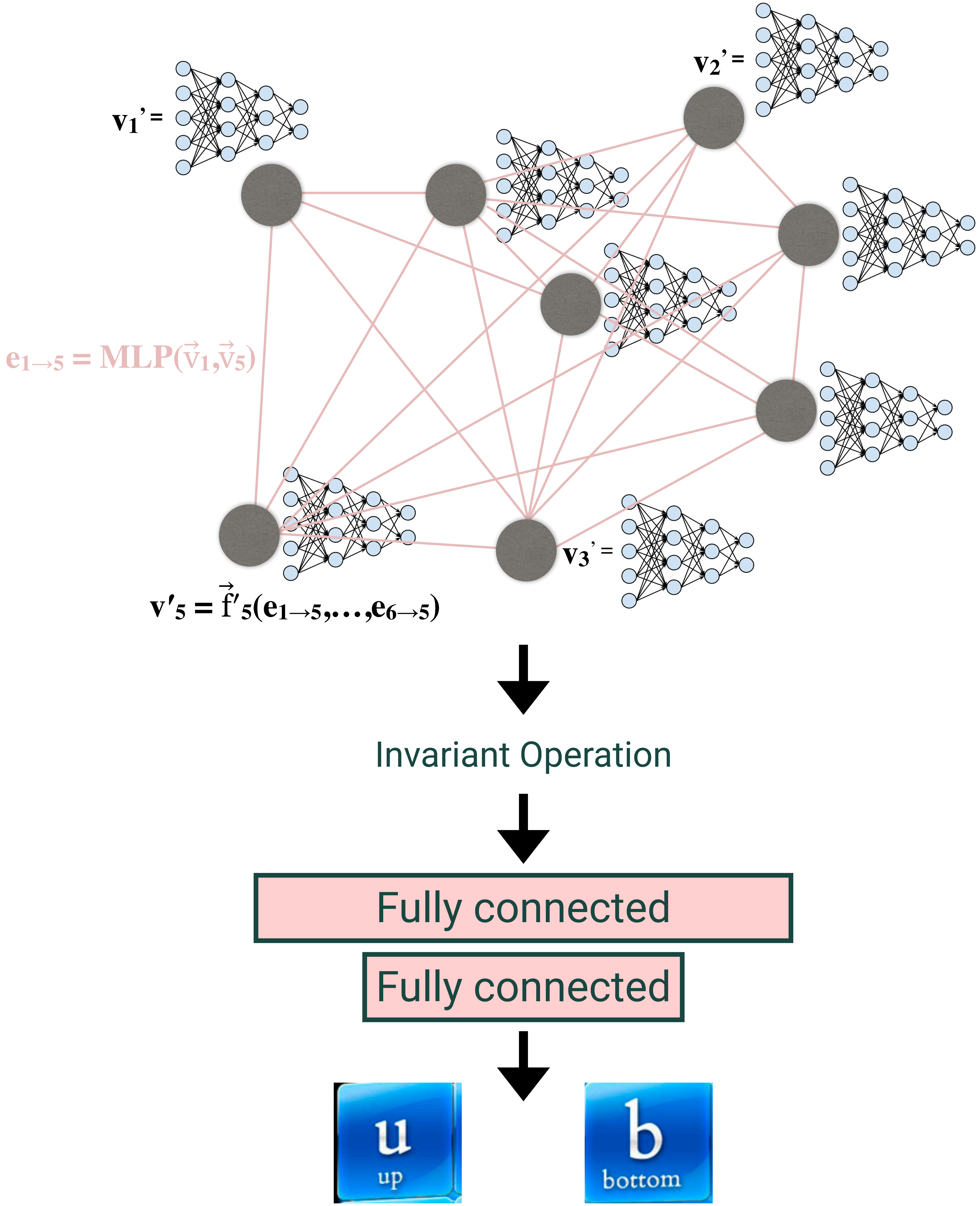


$v_2 = (E_2, p_{x,2}, p_{y,2}, p_{z,2})$
$v_1 = (E_1, p_{x,1}, p_{y,1}, p_{z,1})$
$e_{1\to5} = g(\vec{v}_1, \vec{v}_5)$
$v_5 = (E_5, p_{x,5}, p_{y,5}, p_{z,5})$
v_3

SOTA: Graph Neural Networks acting on point cloud data

- ParticleNet (GNN on point cloud)
  LundNet (GNN,Lund plane)
  ABCNet (GNN, attention)
  Point Cloud Transformers (transformer, attention)
  ParticleNeXt (GNN, attention, Lund)
  ParT (transformer, attention)

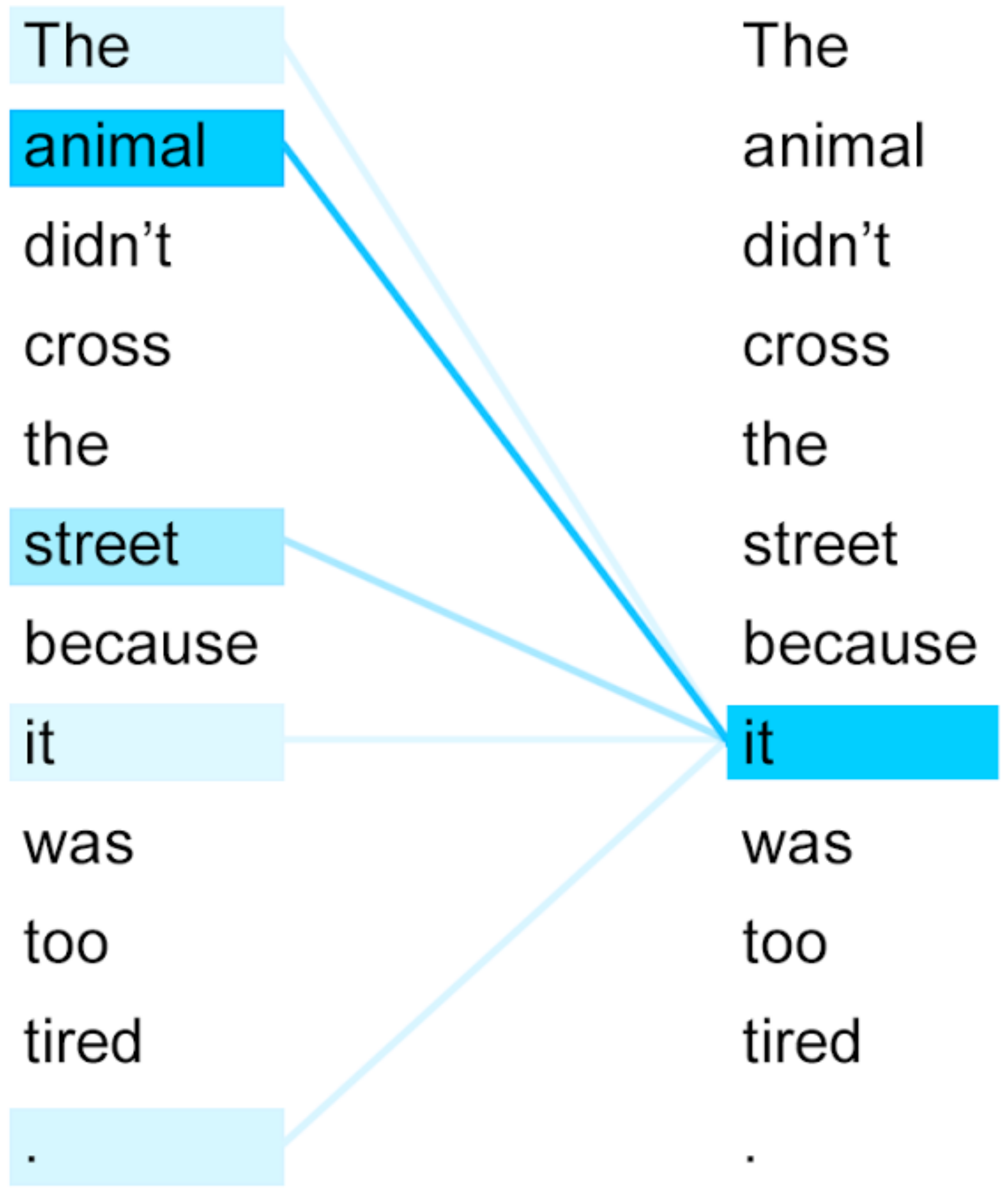


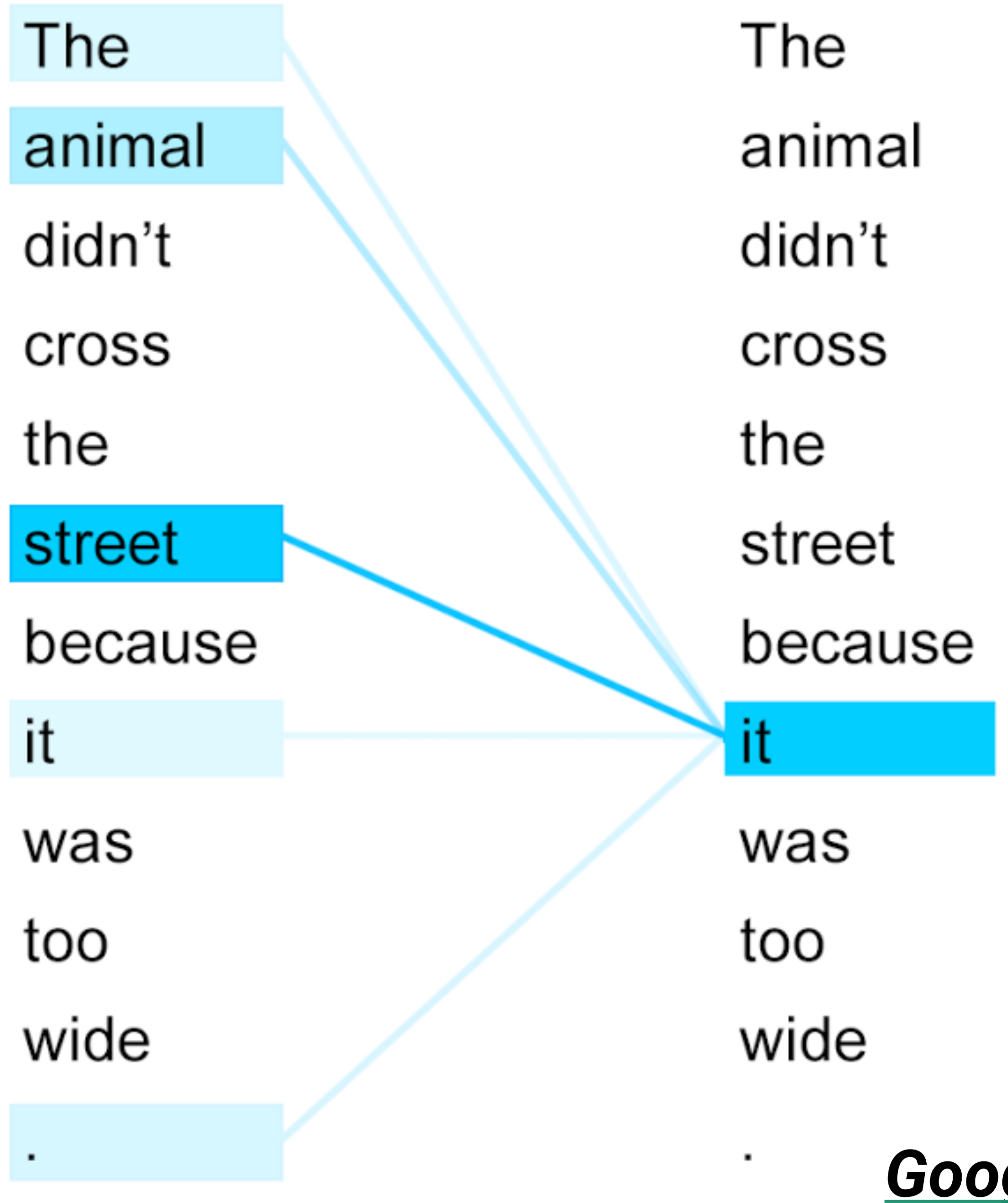


Transformers and (self-)attention

Adding (Self-)Attention

- Allows particles to interact with each other ("self") and find out which other particles they should pay more attention to ("attention")





Google AI blog

Transformers and (self-)attention

Adding (Self-)Attention

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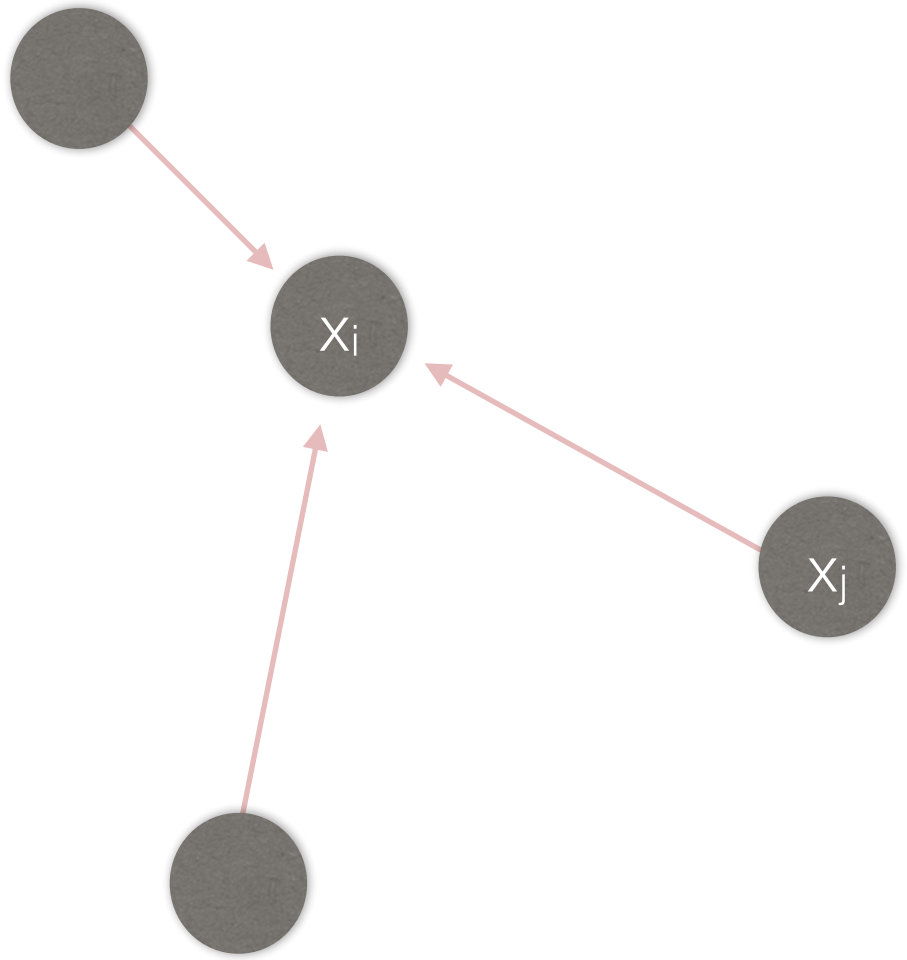


Weighted sum over all input vectors:

$$y_i = \sum_j w_{ij} x_j$$

Weight (how related inputs are):

$$w'_{ij} = x_i^{T} x_j$$

$x_j \rightarrow MLP(x_J)$
$x_i \rightarrow MLP(x_i)$

Map to [0,1]:

$$w_{ij} = \frac{\exp w'_{ij}}{\sum_j \exp w'_{ij}}$$

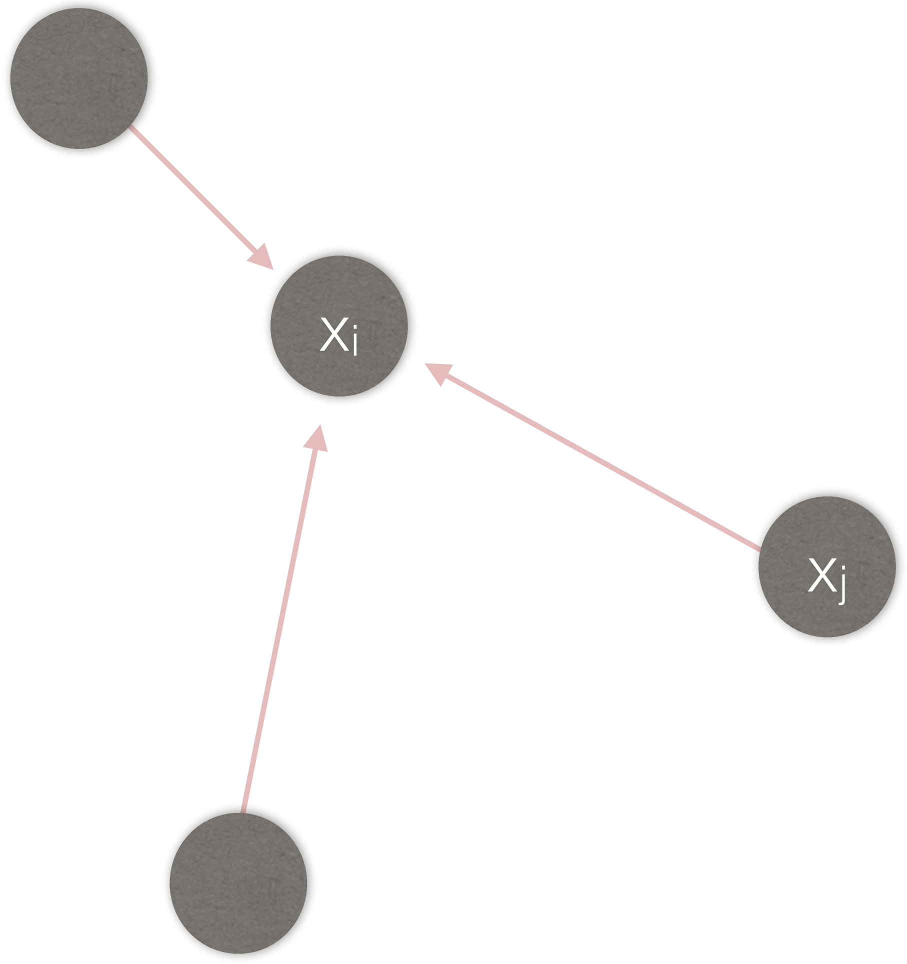
Transformers and (self-)attention

Adding (Self-)Attention

- Allows particles to interact with each other ("self") and find out which other particles they should pay more attention to ("attention")

Attention weights: weighted importance between each pair of particles

- Determine relationship between all particles of point cloud
- Several attention layers → different important features (multi-head attention)



Weighted sum over all input vectors:

$$\boldsymbol{y}_i = \sum_j w_{ij} \boldsymbol{x}_j$$

Weight (how related inputs are):

$$w'_{ij} = \boldsymbol{x}_i{}^{\mathsf{T}} \boldsymbol{x}_j$$

$x_j \rightarrow \mathrm{MLP}(x_J)$
$x_i \rightarrow \mathrm{MLP}(x_i)$

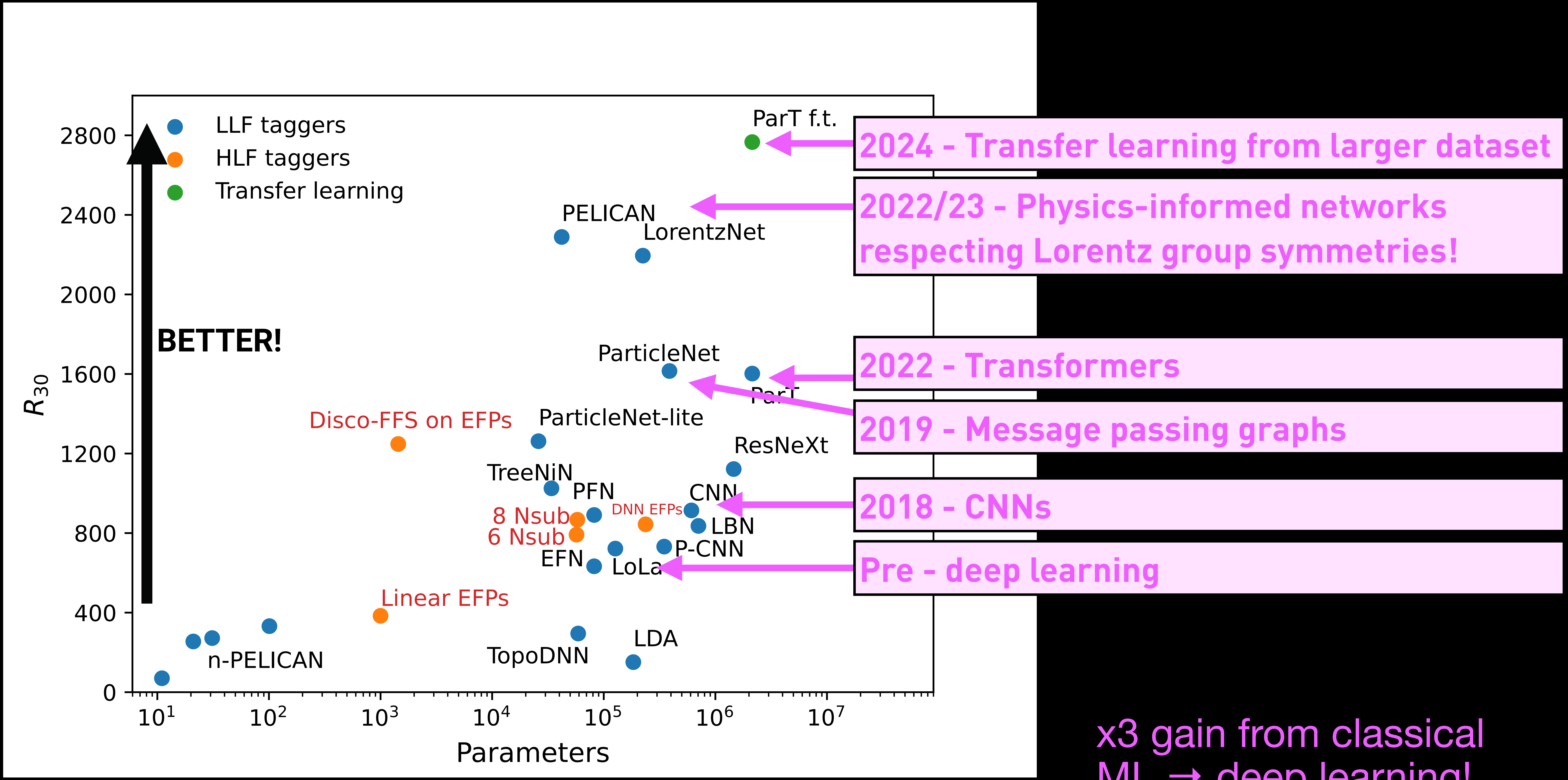
Map to [0,1]:

$$w_{ij} = \frac{\exp w'_{ij}}{\sum_j \exp w'_{ij}}$$

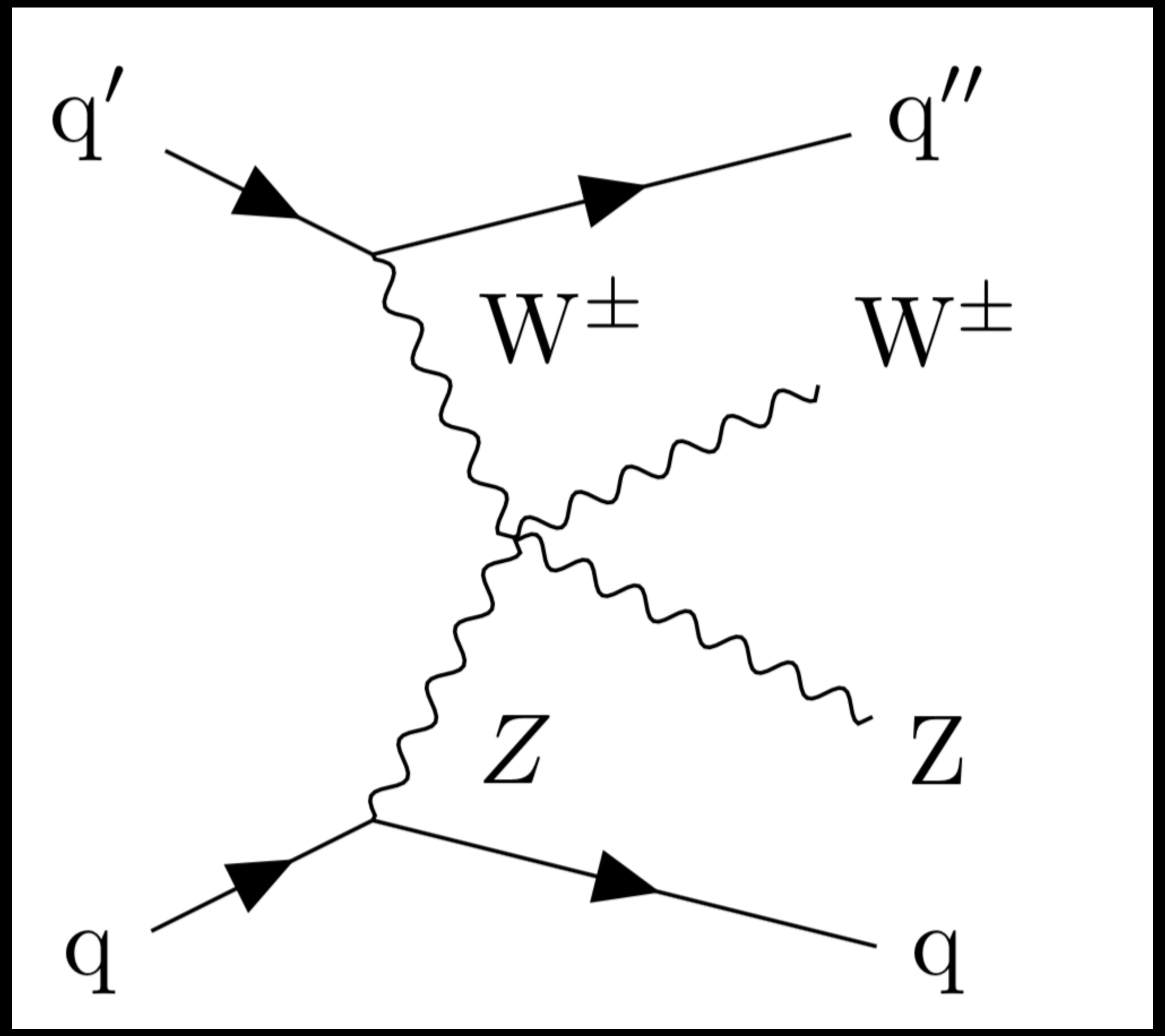
ABCNet:

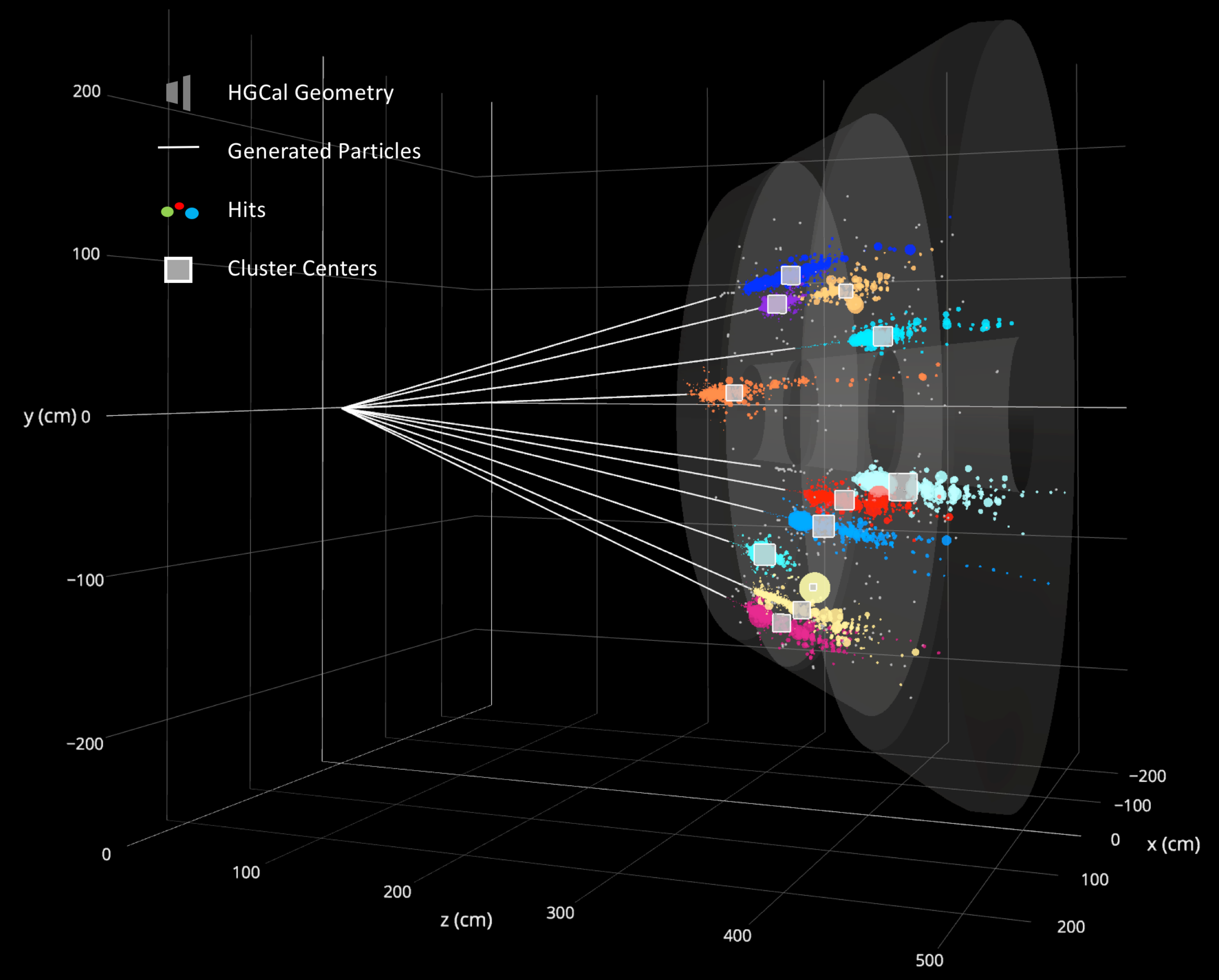
Pixel intensity = particle importance w.r.t most energetic particle in jet, from attention weights

Learned through attention!



x3 gain from classical ML → deep learning!



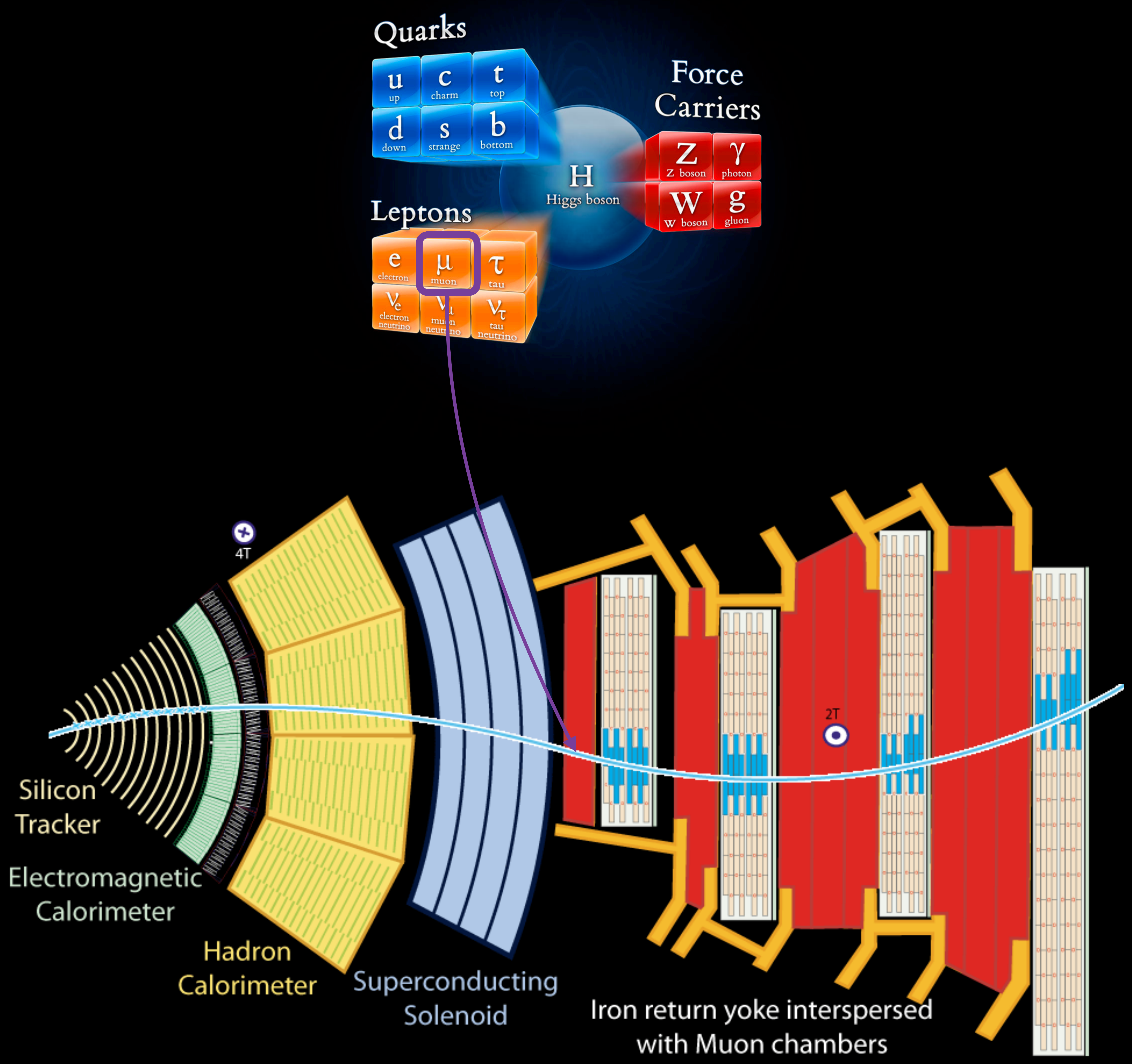


ML:

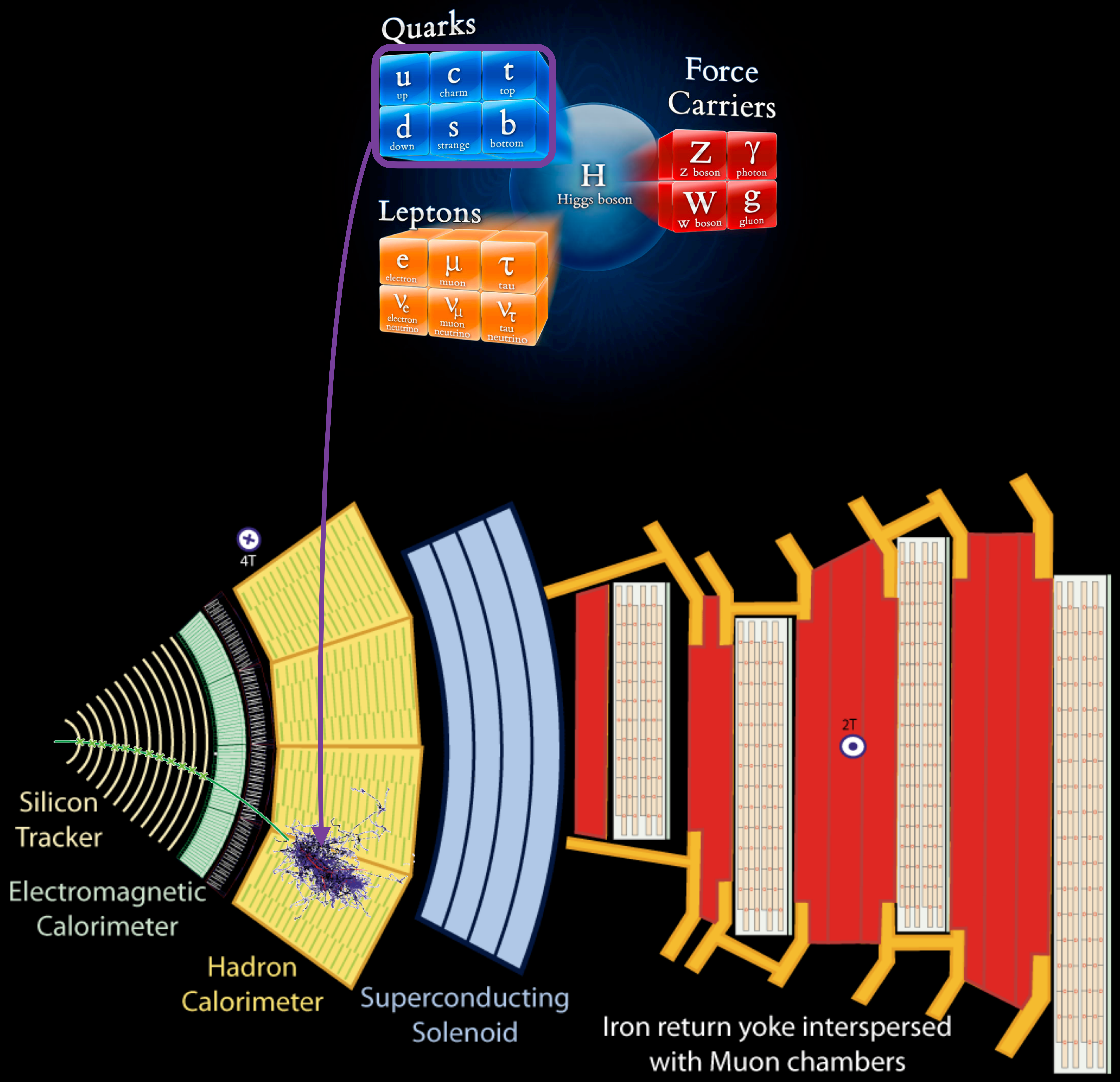
Reconstruct complex patterns in complex detectors

Detector reconstruction and tagging
AI?
O(10^10)
100m
DIGI+RECO
Energy deposits→digital signals→reconstructed by the reconstruction software [Hard & Slow]
19.7 fb^-1 (8 TeV) + 5.1 fb^-1 (7 TeV)
CMS
H → γγ
S/(S+B) weighted sum
Data
S+B fits (weighted sum)
B component
±1σ
±2σ
μ̂ = 1.14 +0.26 −0.23
m̂_H = 124.70 ± 0.34 GeV
O(10)
O(10^3)
10^-18m
10^-15m
10^-6m
GEN
SIM
pp collisions up to production of stable particles [Easy & Fast]
detector response simulation [Hard & Slow]
GEANT4

From billions of sensors to particles?

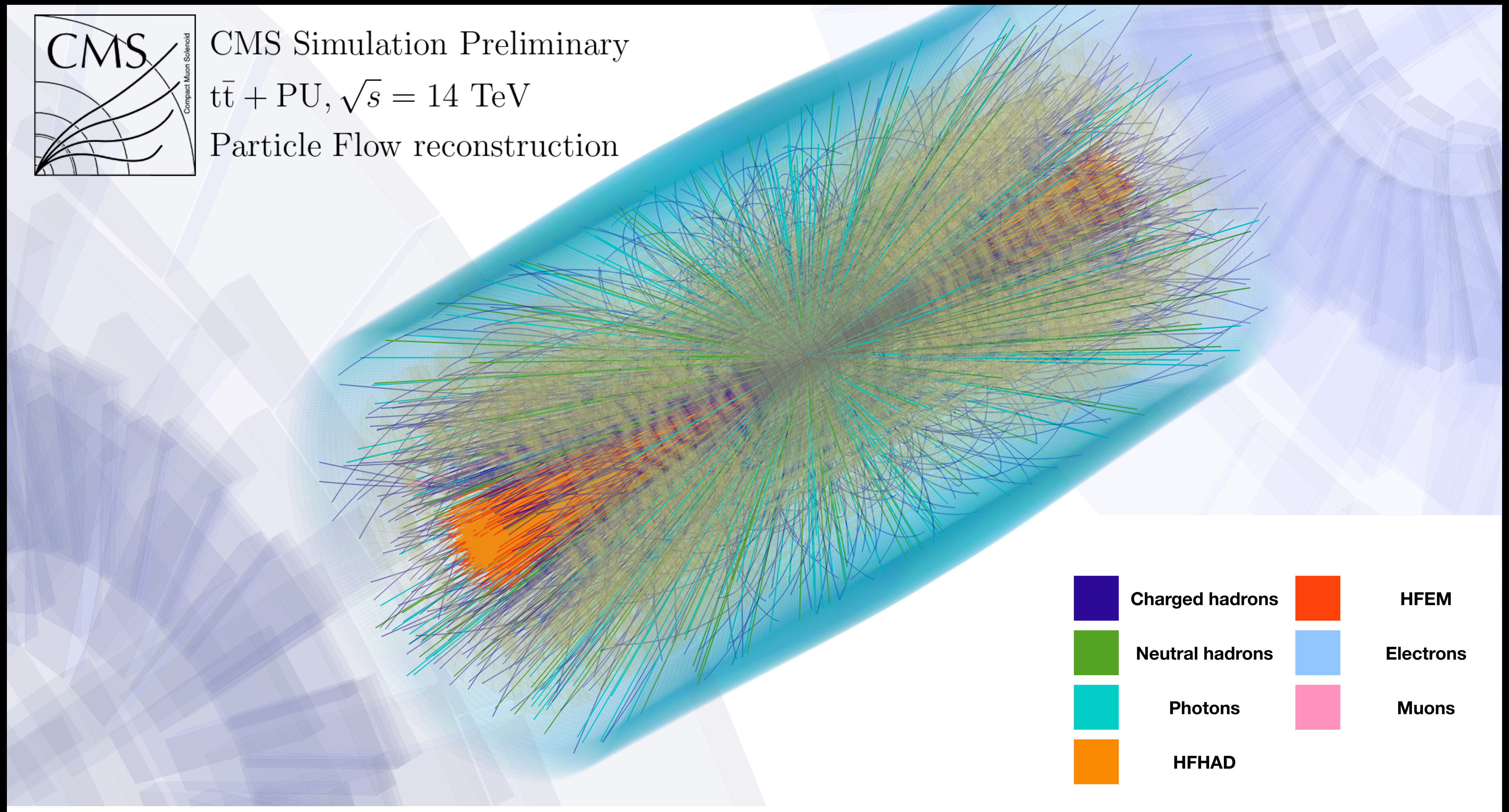


Quarks
u up
c charm
t top
d down
s strange
b bottom
Force Carriers
Z Z boson
γ photon
W W boson
g gluon
H Higgs boson
Leptons
e electron
μ muon
τ tau
νe electron neutrino
νμ muon neutrino
ντ tau neutrino
4T
2T
Silicon Tracker
Electromagnetic Calorimeter
Hadron Calorimeter
Superconducting Solenoid
Iron return yoke interspersed with Muon chambers

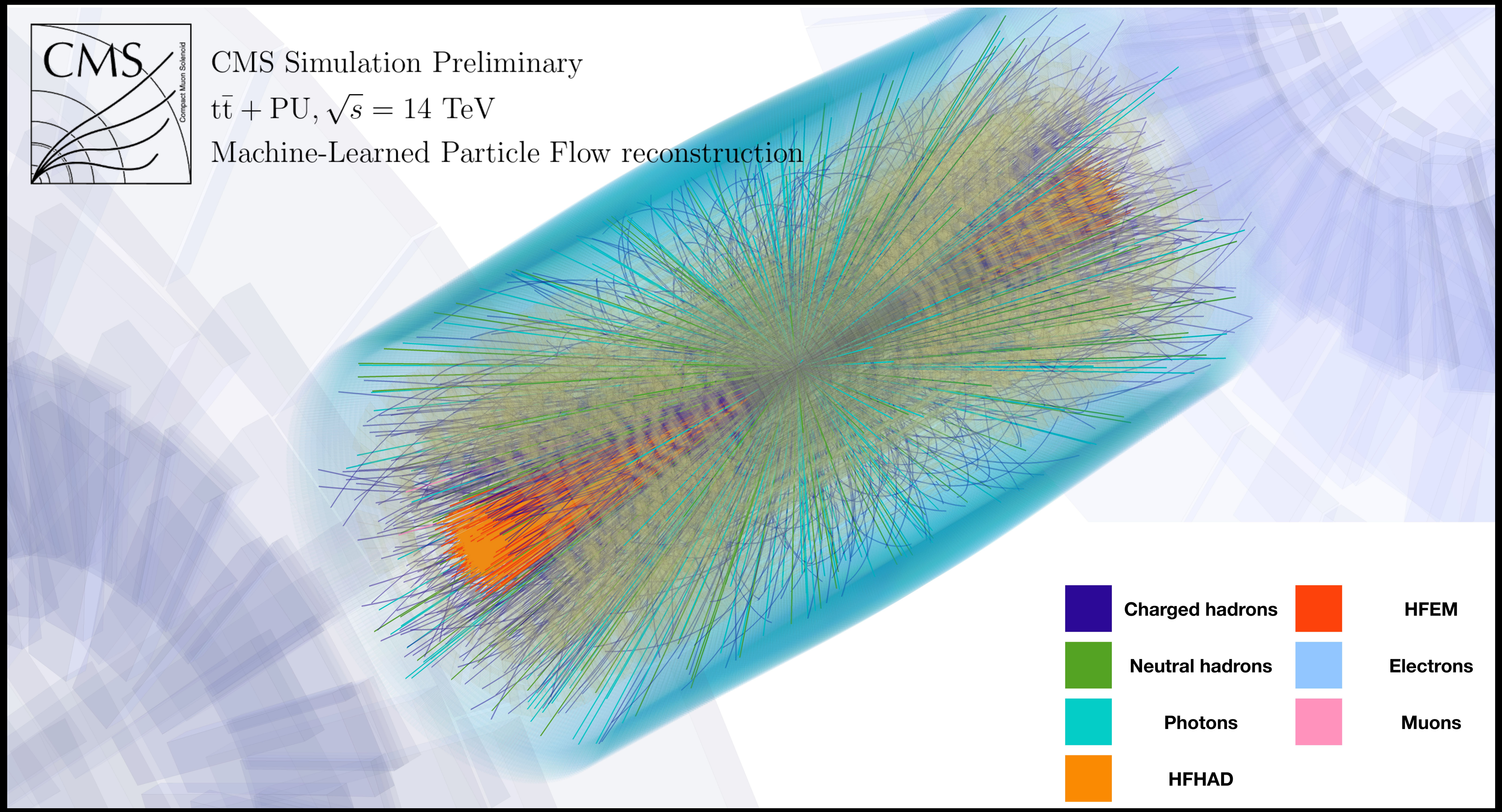

Quarks
u up
c charm
t top
d down
s strange
b bottom
Force Carriers
Z Z boson
γ photon
W W boson
g gluon
H Higgs boson
Leptons
e electron
μ muon
τ tau
νe electron neutrino
νμ muon neutrino
ντ tau neutrino
4T
2T
Silicon Tracker
Electromagnetic Calorimeter
Hadron Calorimeter
Superconducting Solenoid
Iron return yoke interspersed with Muon chambers

arxiv:2309.06782

Classical Particle Flow

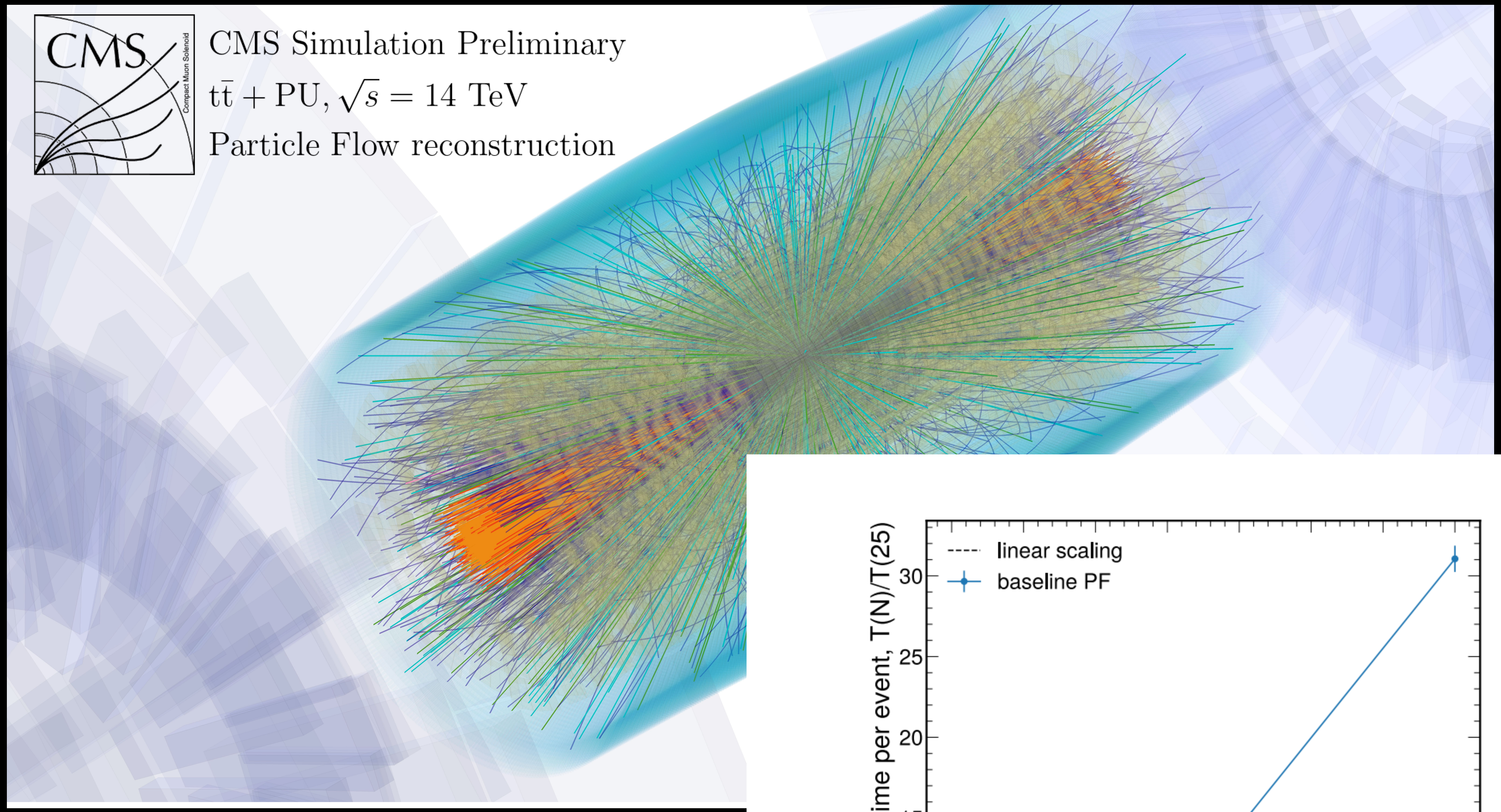


Graph Neural Network

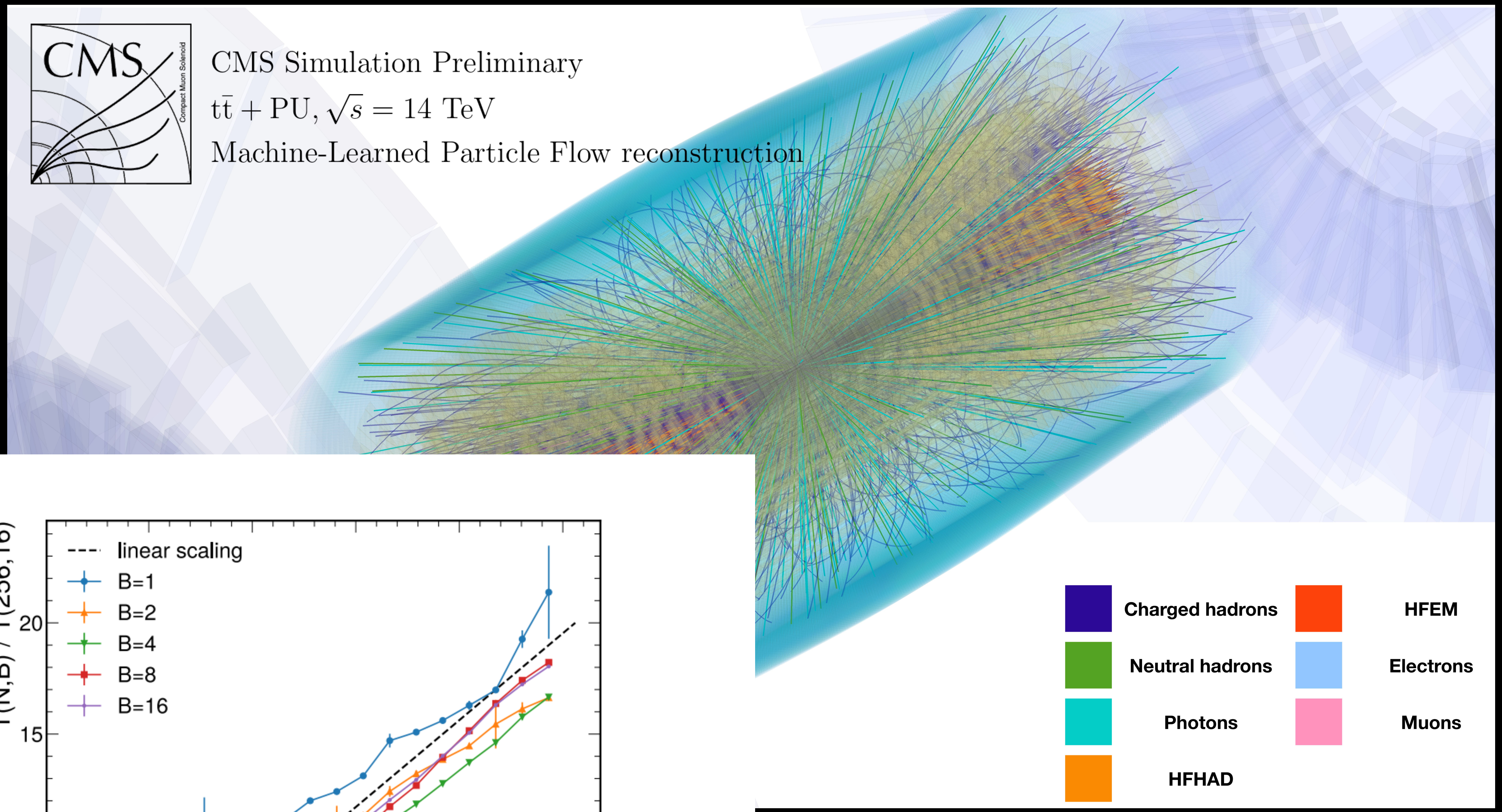


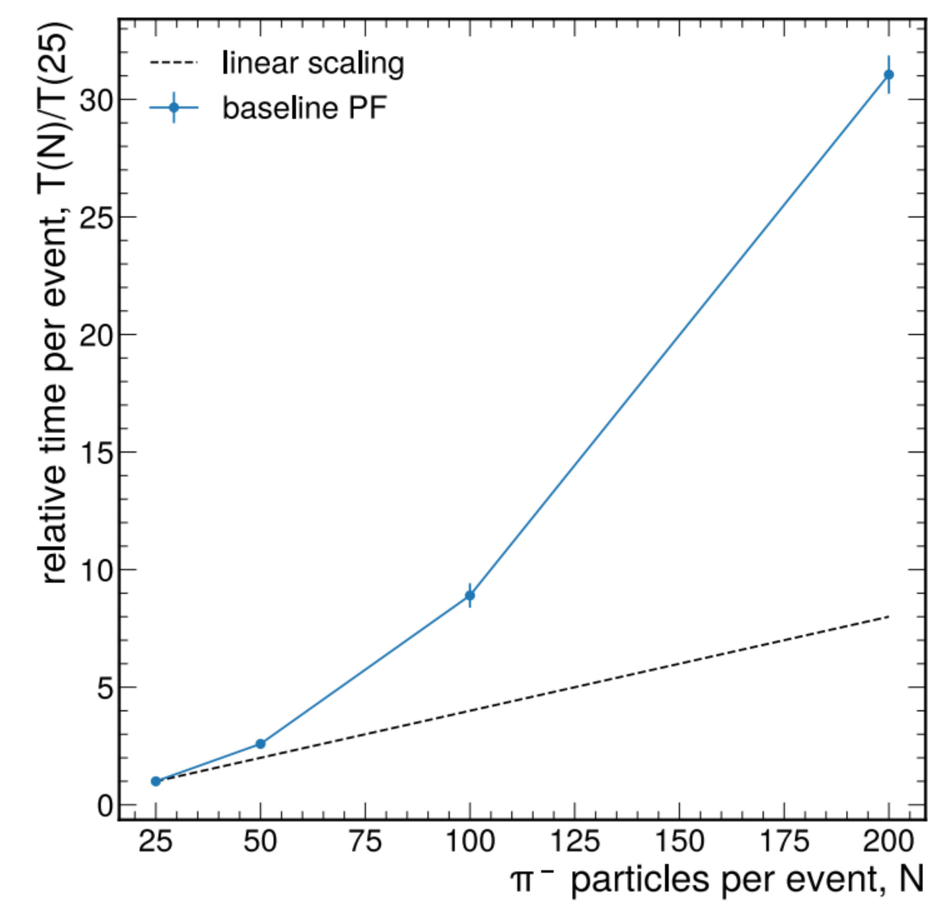
arxiv:2309.06782

Classical Particle Flow

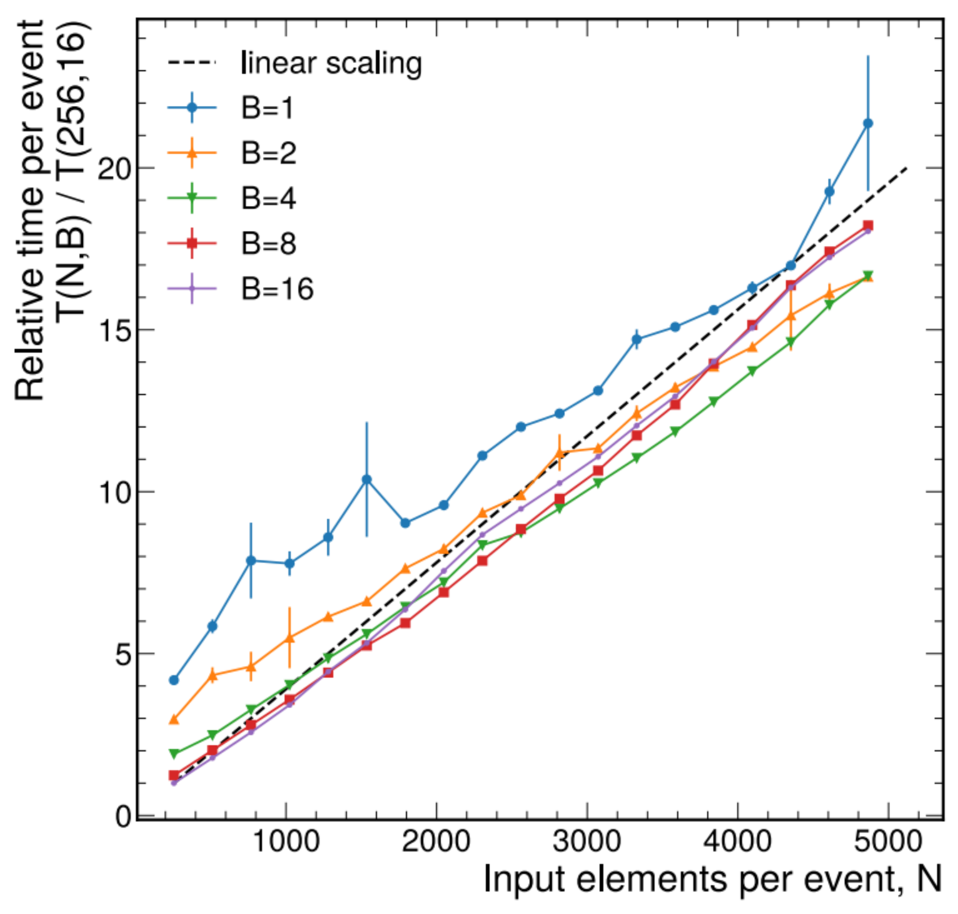


Graph Neural Network





PF baseline scales non-linearly with increasing input size

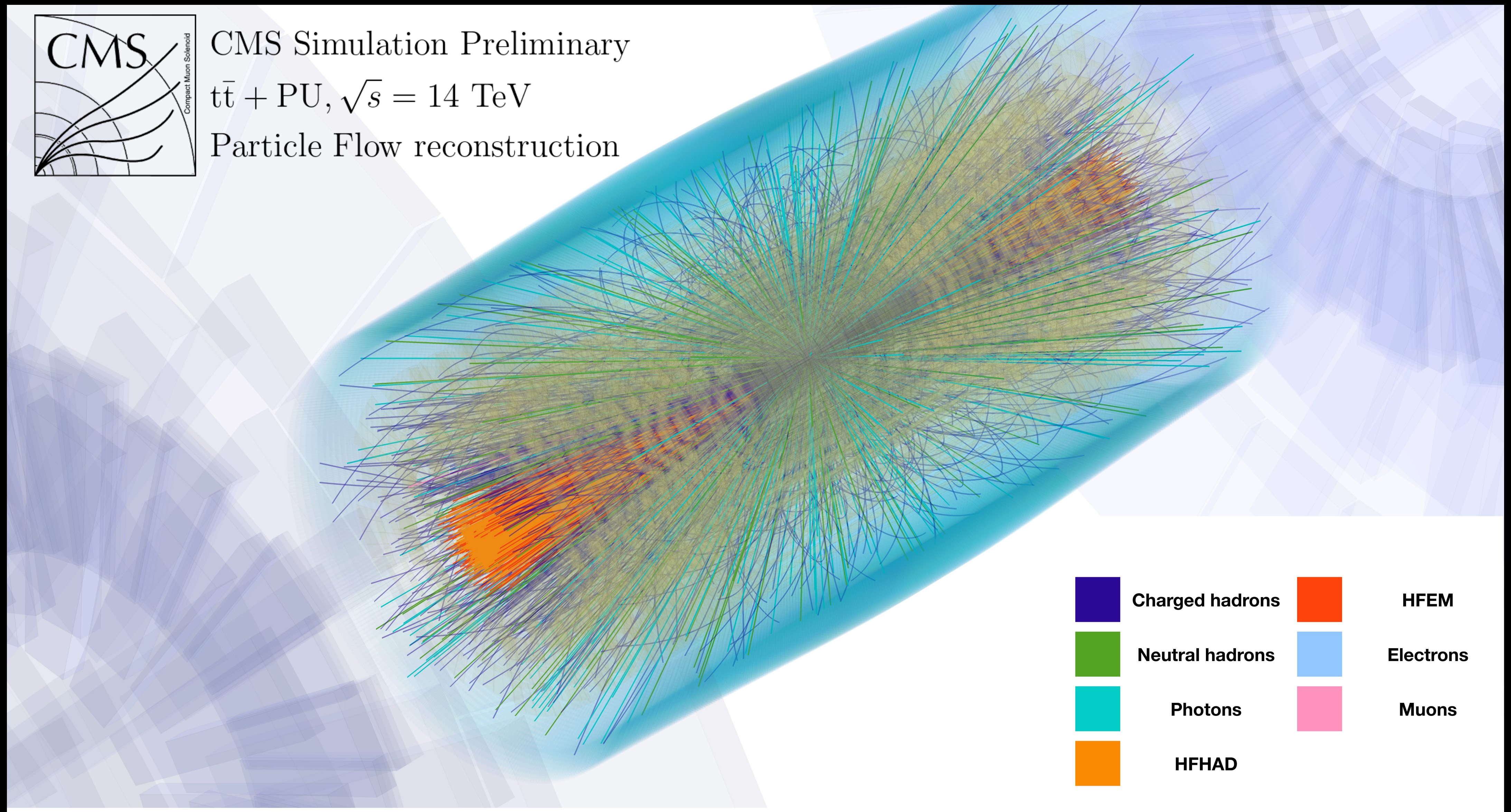


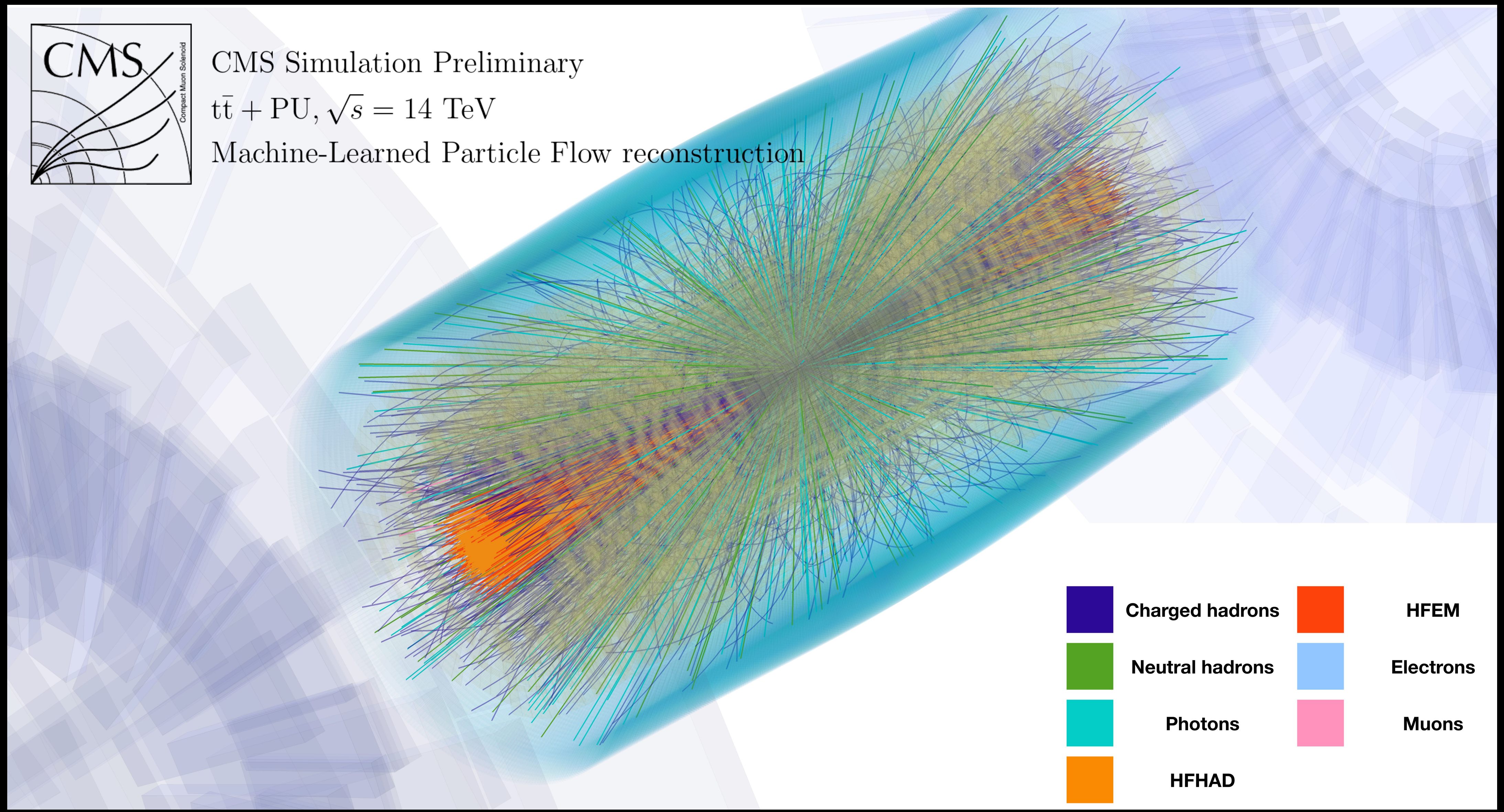
GNN-based model inference time scales approximately linearly with increasing input size

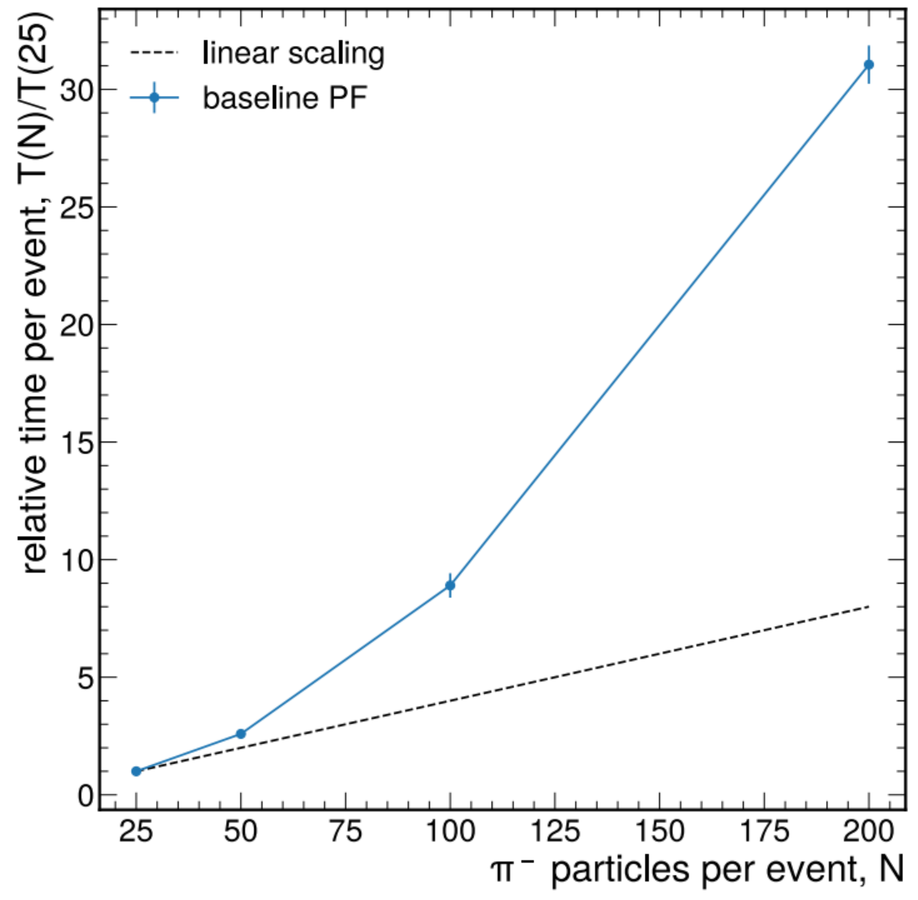
Classical Particle Flow

Graph Neural Network

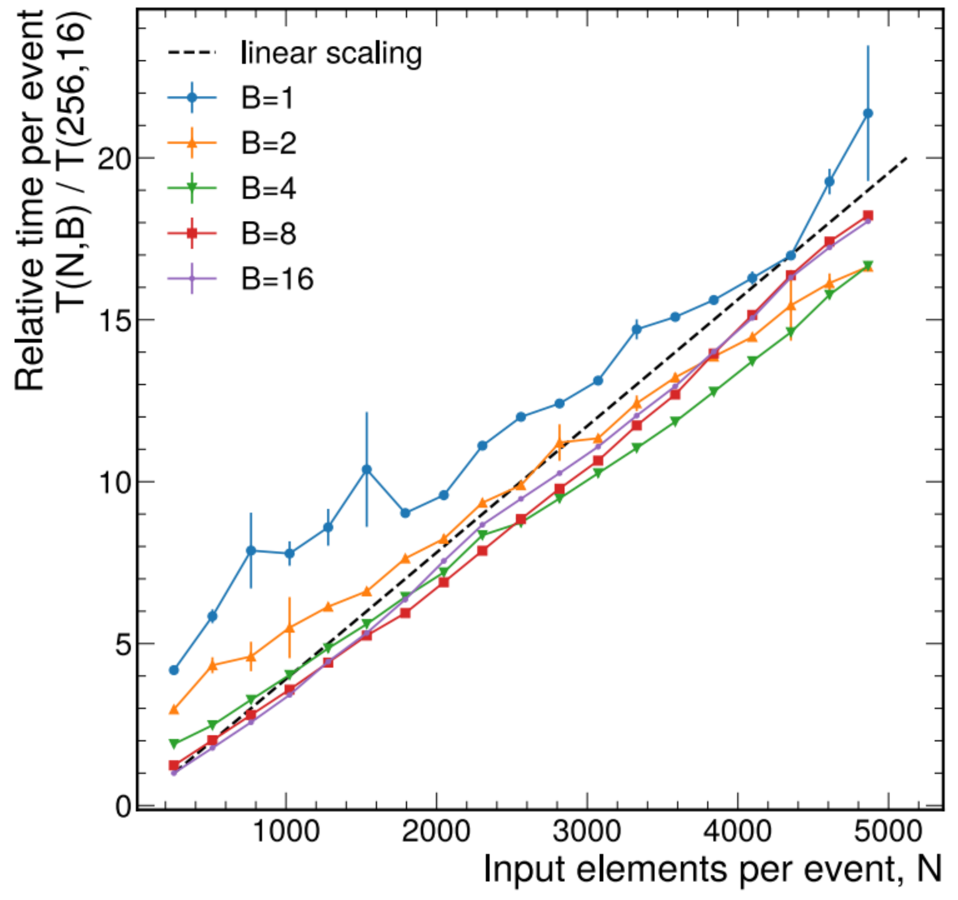
arxiv:2309.06782







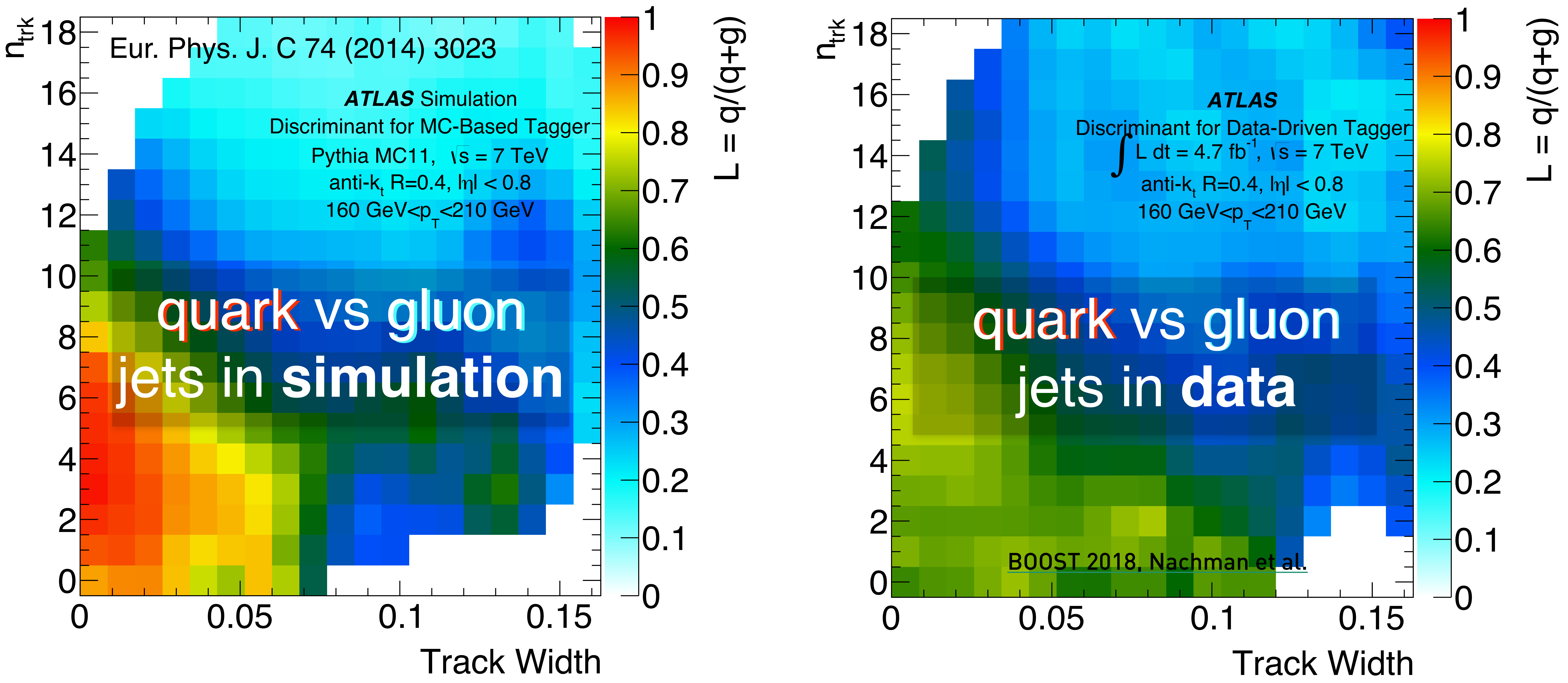
PF baseline scales non-linearly with increasing input size



GNN-based model inference time scales approximately linearly with increasing input size


AI?
Data analysis
O(10)
O(10^3)
10^-18m
10^-15m
10^-6m
GEN
SIM
pp collisions up to production of stable particles [Easy & Fast]
detector response simulation [Hard & Slow]
GEANT4
O(10^10)
100m
DIGI+RECO
Energy deposits→digital signals→reconstructed by the reconstruction software [Hard & Slow]
19.7 fb^-1 (8 TeV) + 5.1 fb^-1 (7 TeV)
CMS
H → γγ
S/(S+B) weighted sum
Data
S+B fits (weighted sum)
B component
±1σ
±2σ
μ̂ = 1.14 +0.26 −0.23
m̂H = 124.70 ± 0.34 GeV

Train on simulation, test on data



If data and simulation differ, this is sub-optimal!

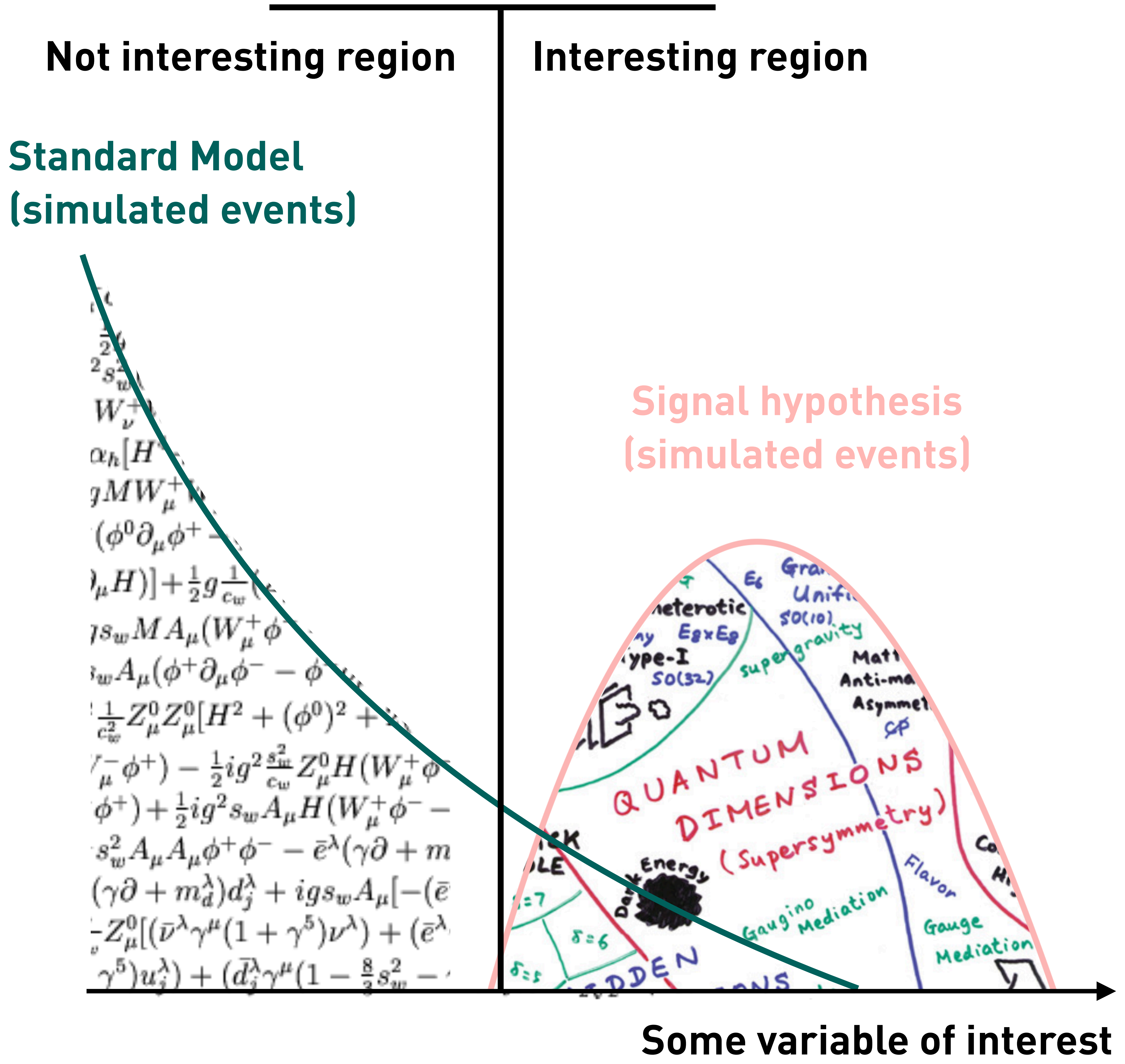
Bias in particle physics

Searches at LHC always start by

- assuming **Standard Model** and some **signal hypothesis**

This is fine when we know what “signal” is (like Higgs)

- **Tailor search** to a given theory
- Powerful, but **limited to model of choice**



Bias in particle physics

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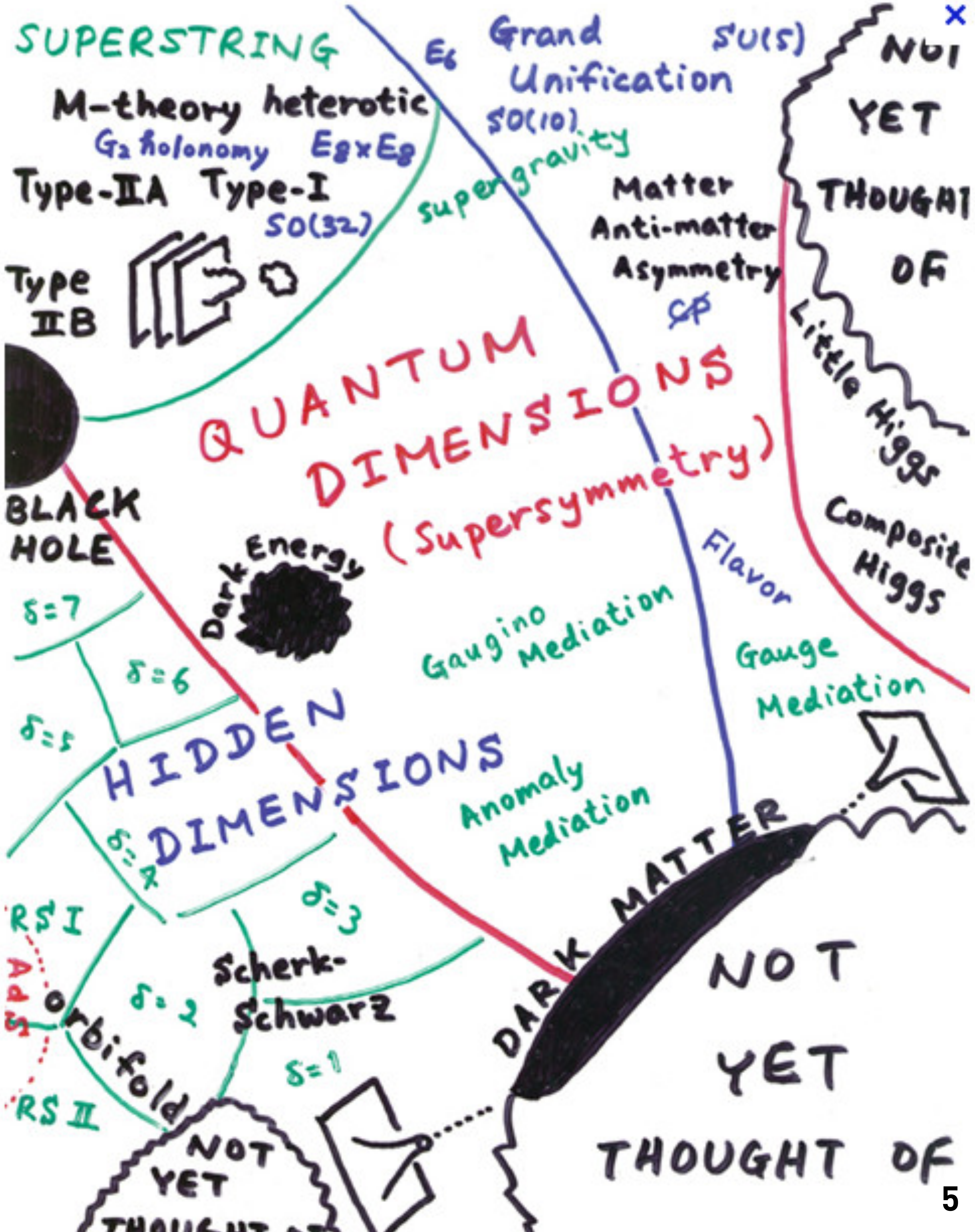
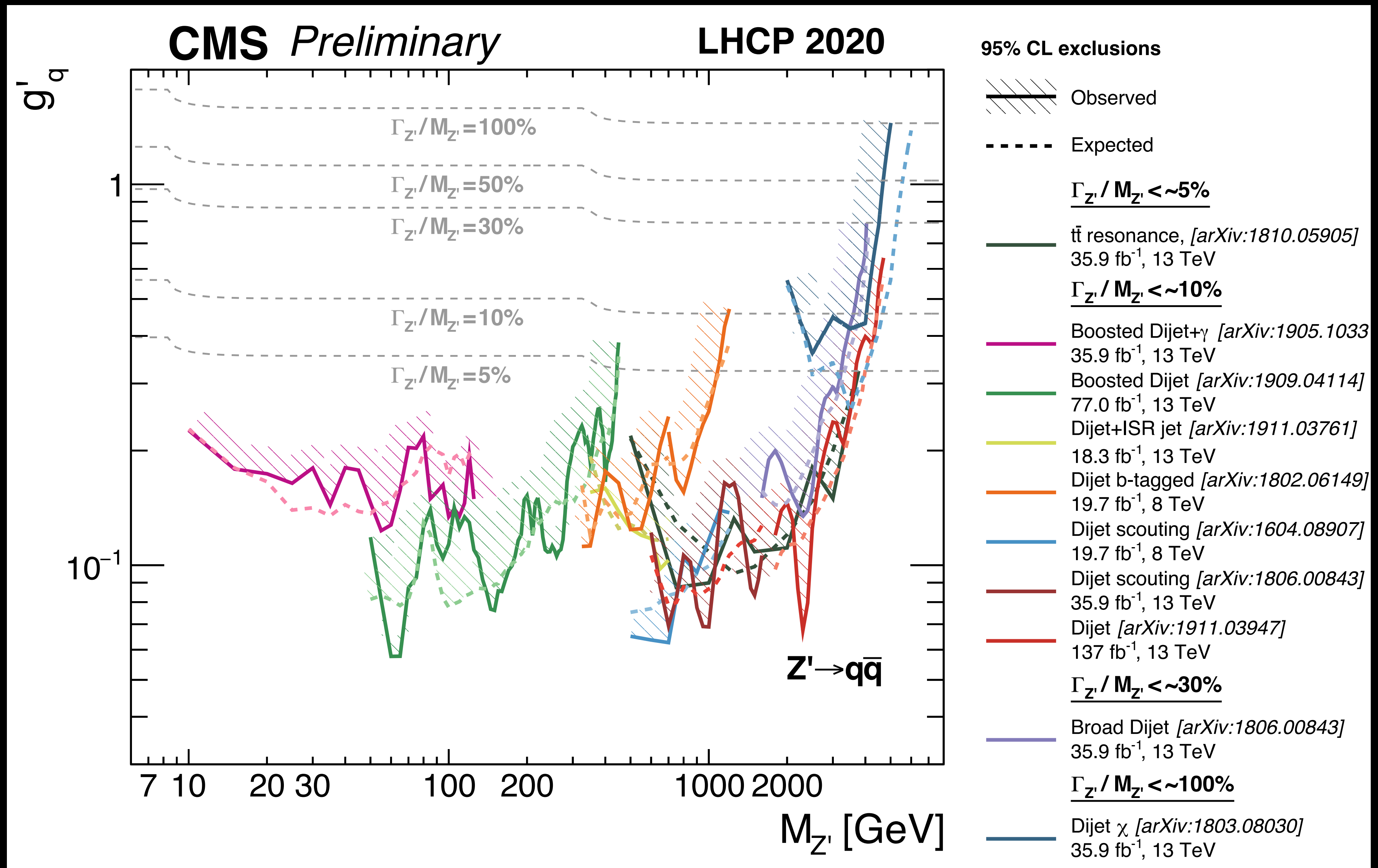
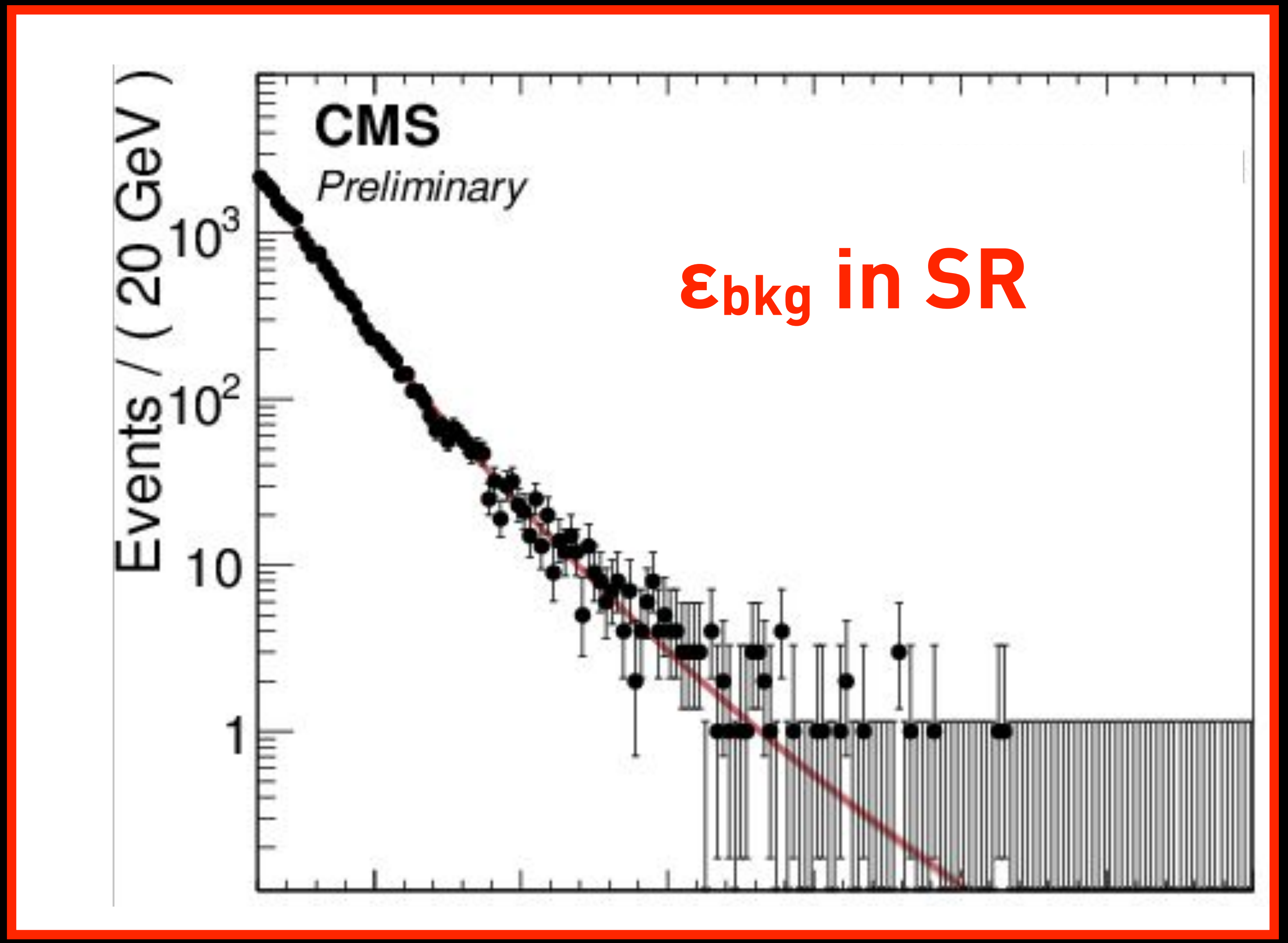
- Powerful, but **limited to model of choice**

- How do we know we are looking for the right thing in the enormous New Physics model landscape?



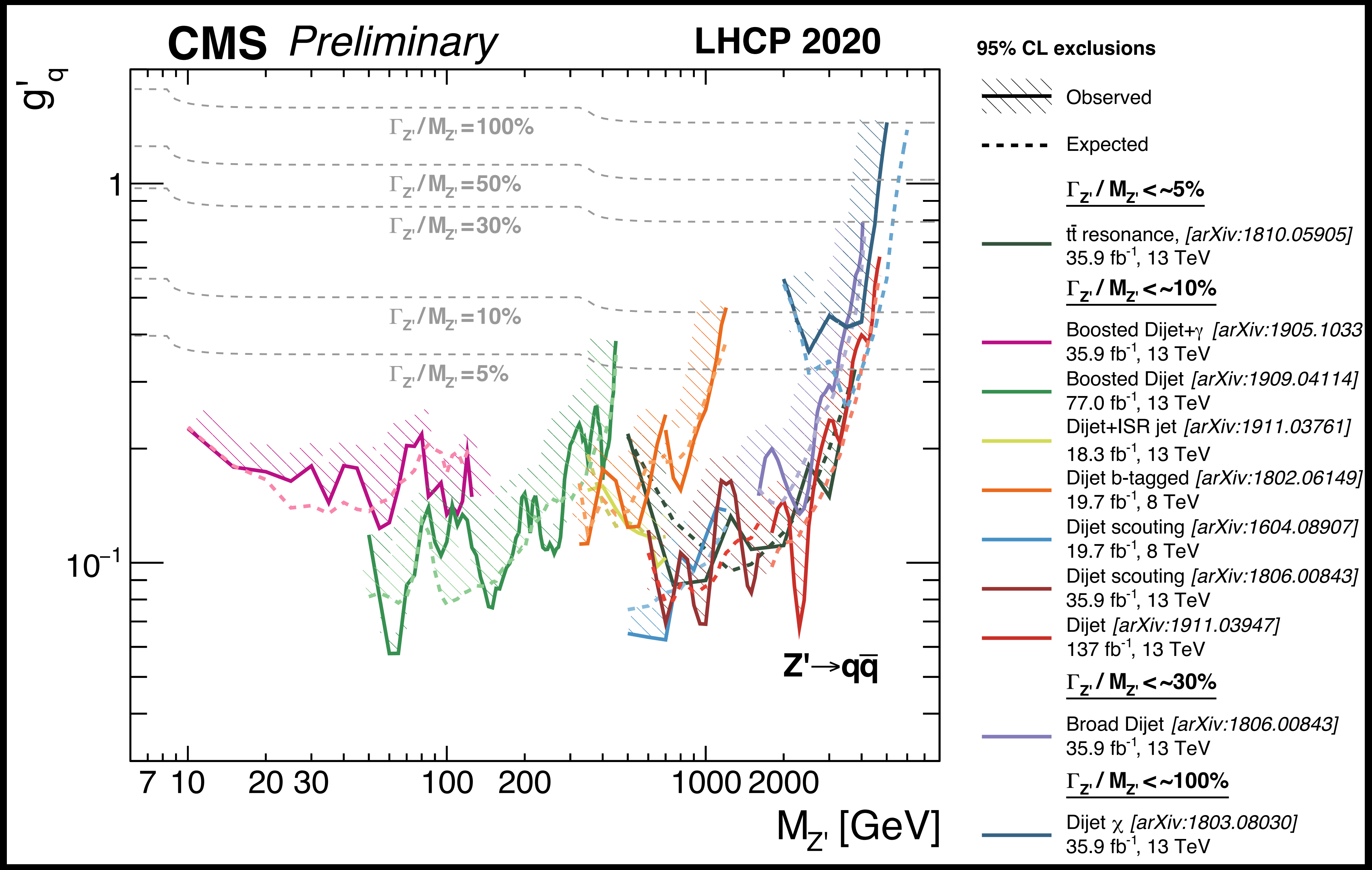
Anomaly detection for New Physics searches

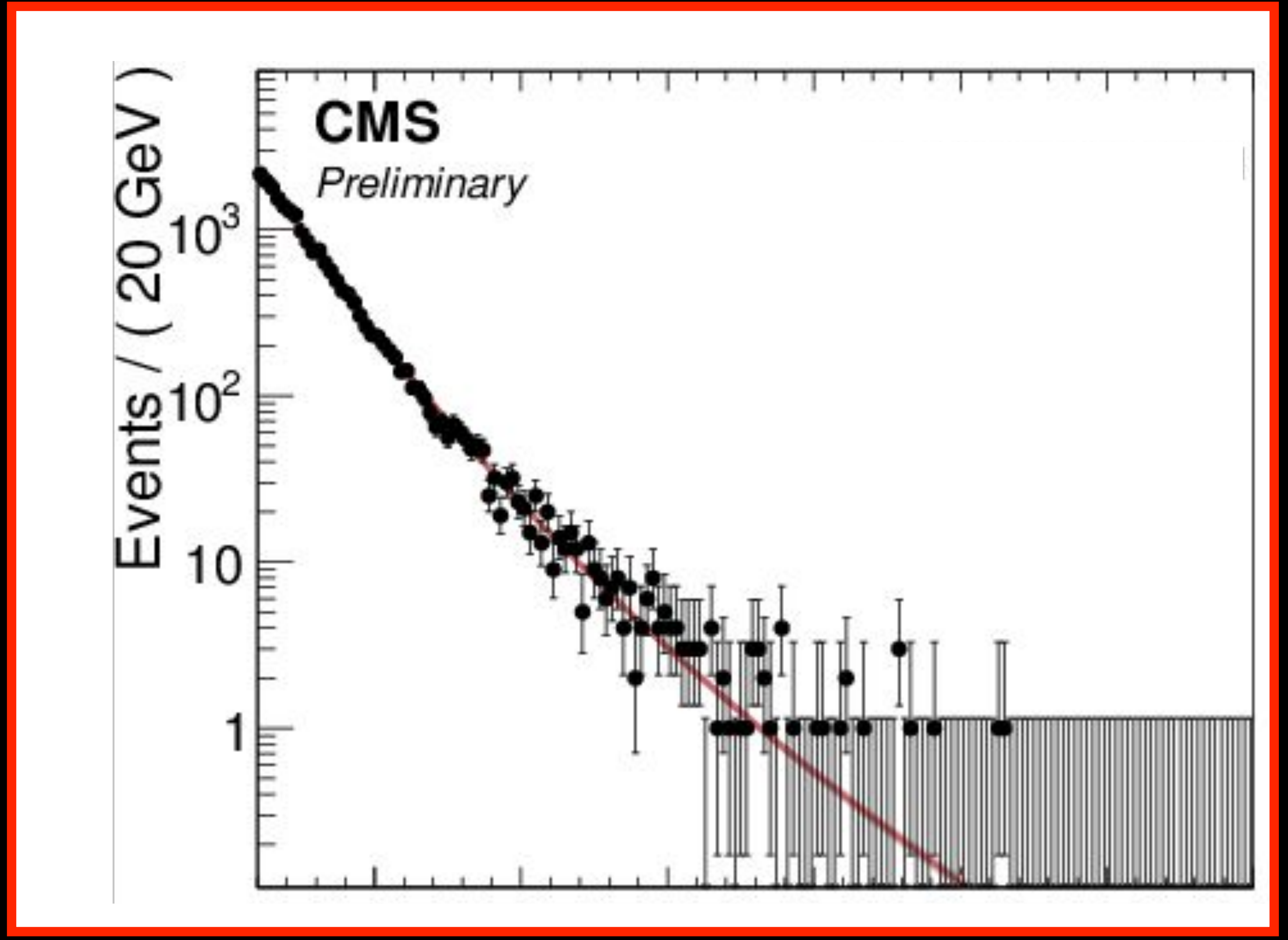




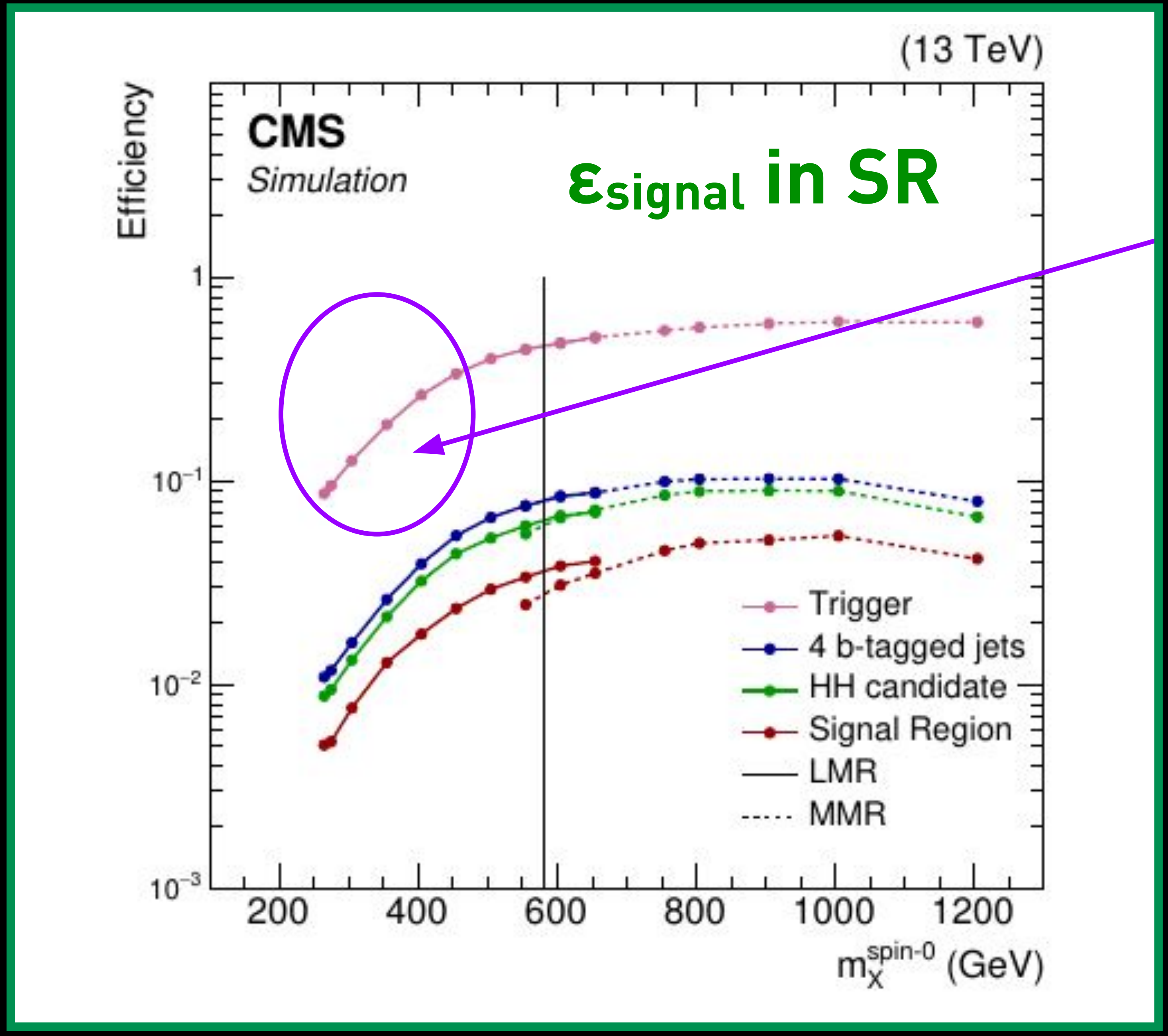
Can we reduce this

Anomaly detection for New Physics searches

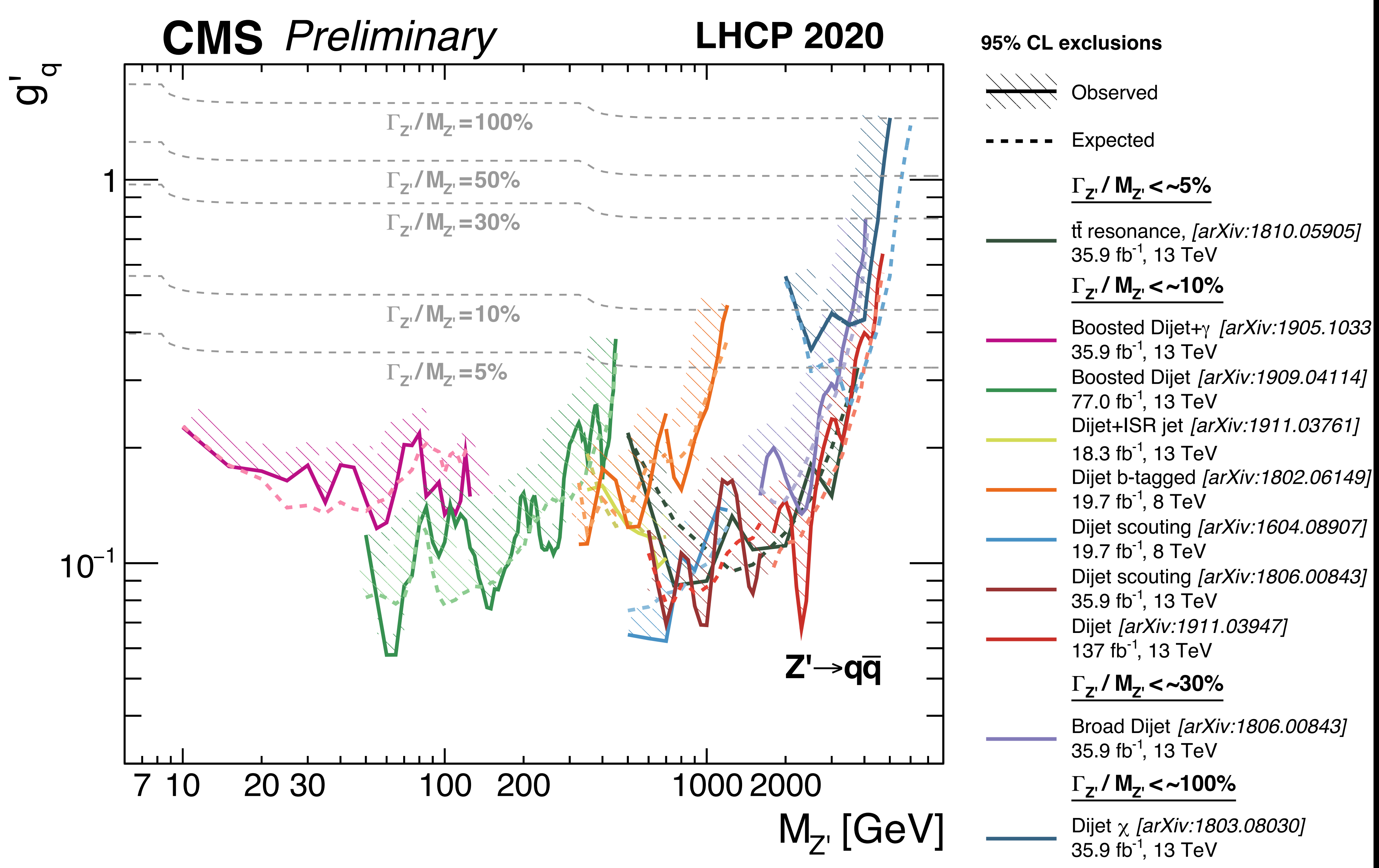


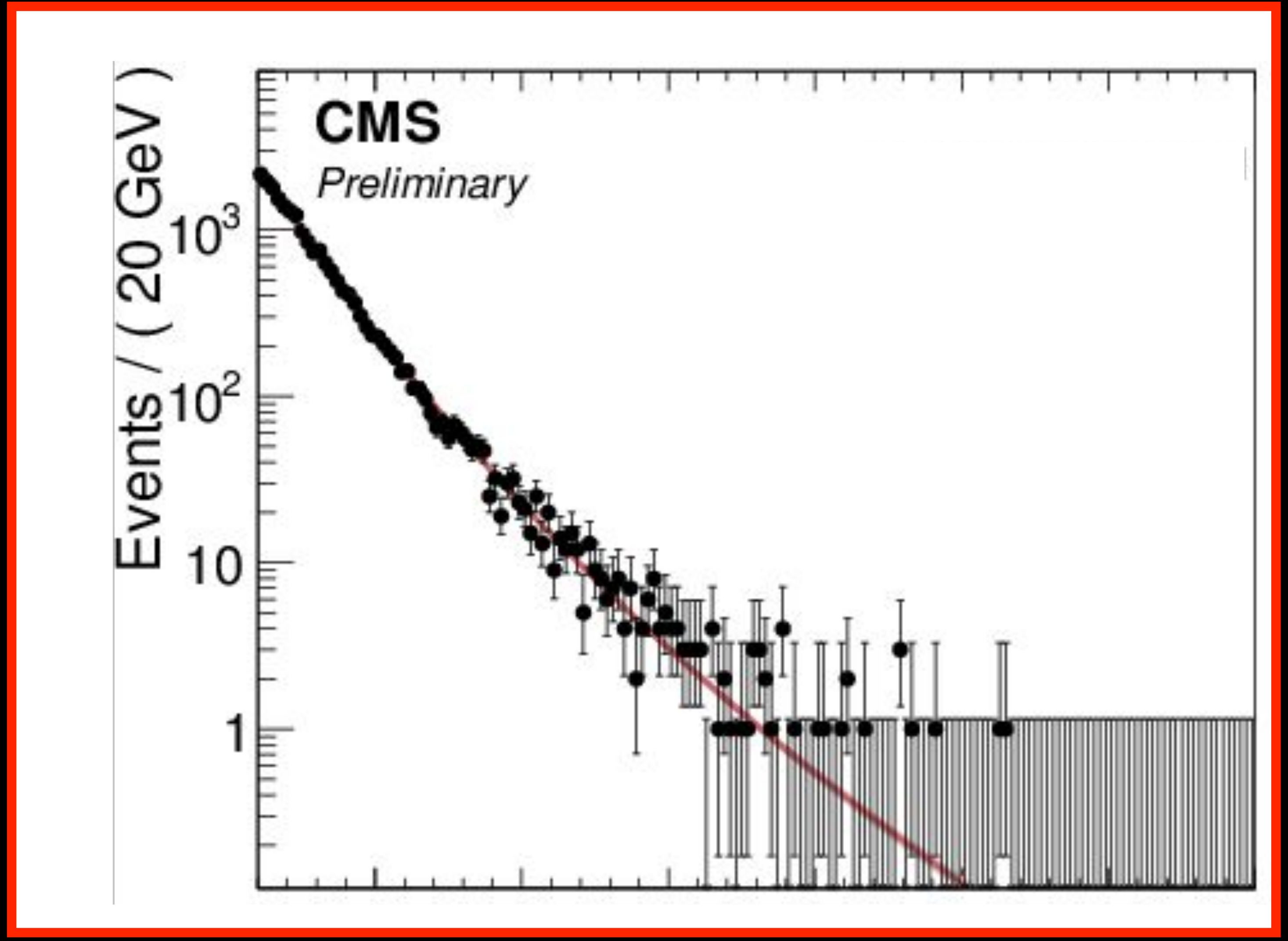


Can we reduce
this
and maximise
this

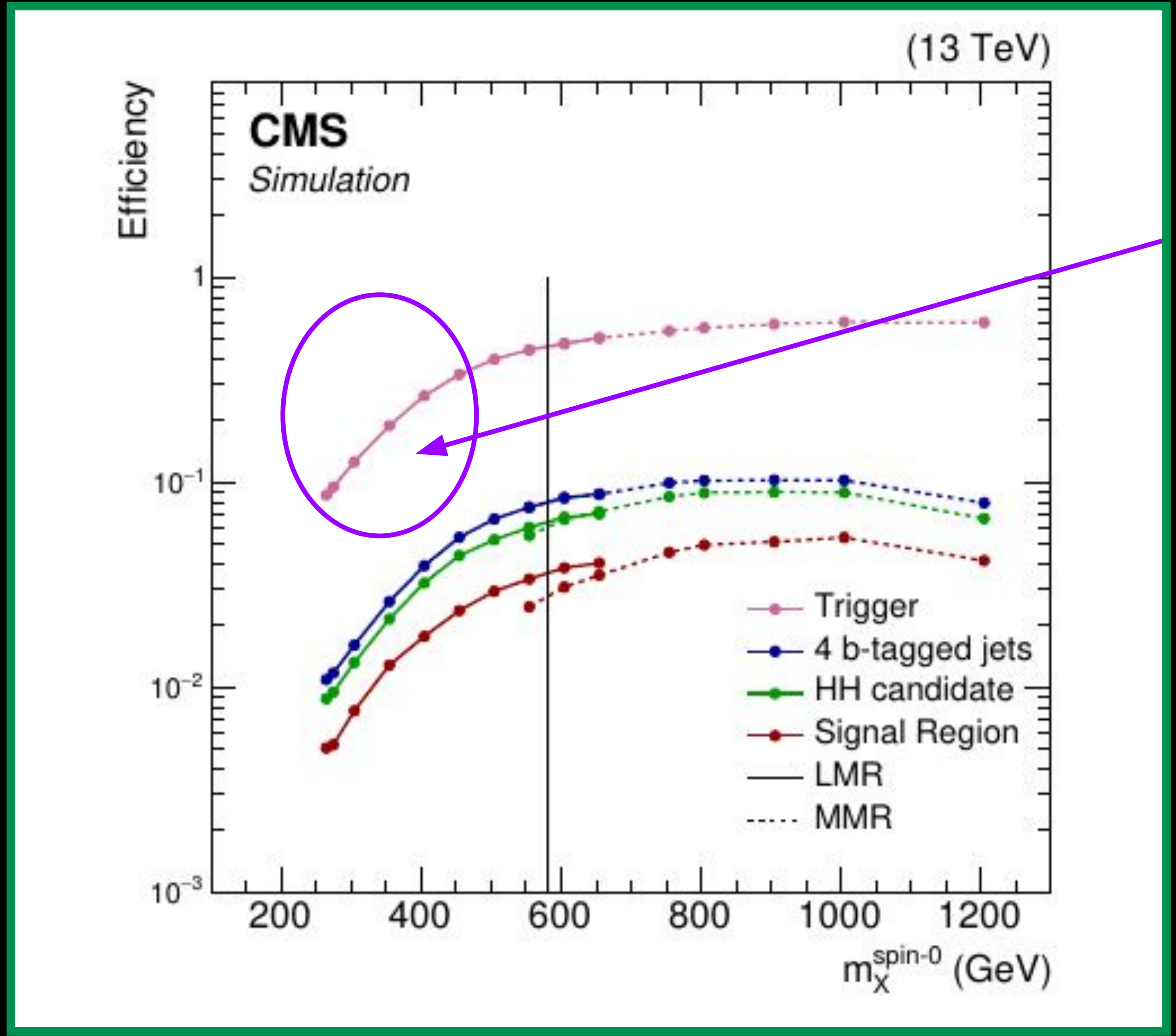


Anomaly detection for New Physics searches

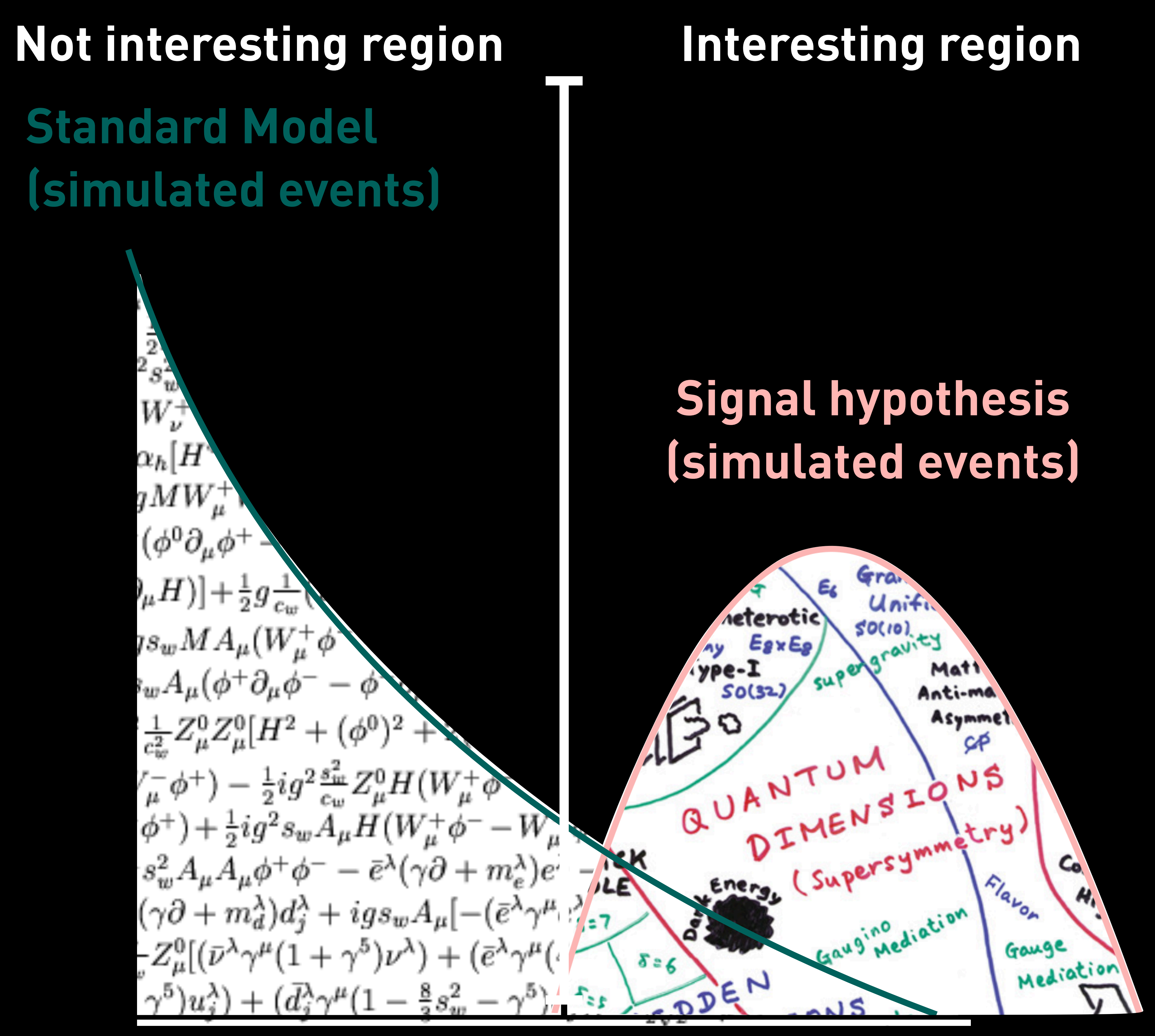




Can we reduce
this
and maximise
this
to probe hundreds of signal hypotheses all at once?
*(Maybe also some we didn't think of yet?)

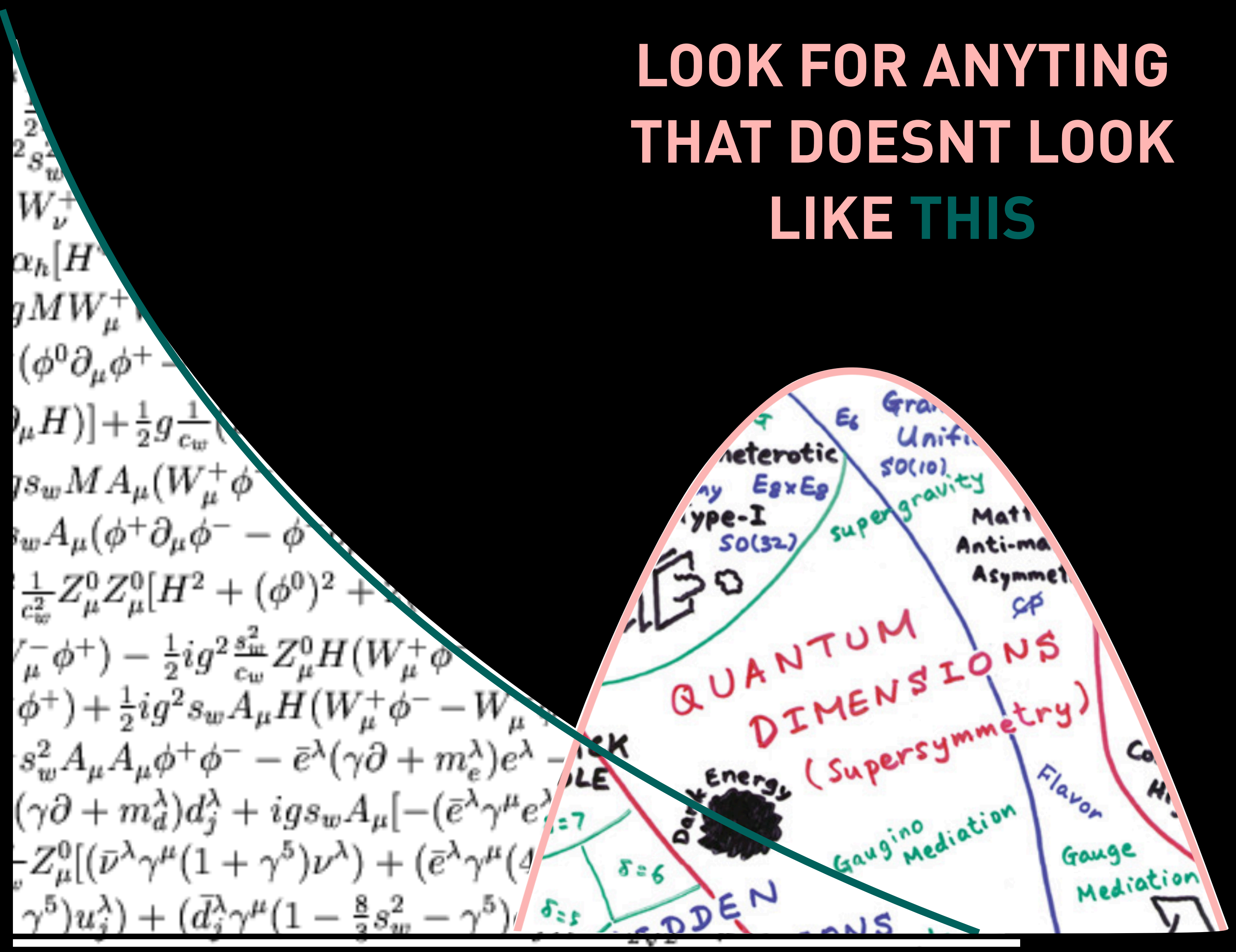


Anomaly detection for New Physics searches



Anomaly detection for New Physics searches

LEARN THIS FROM DATA

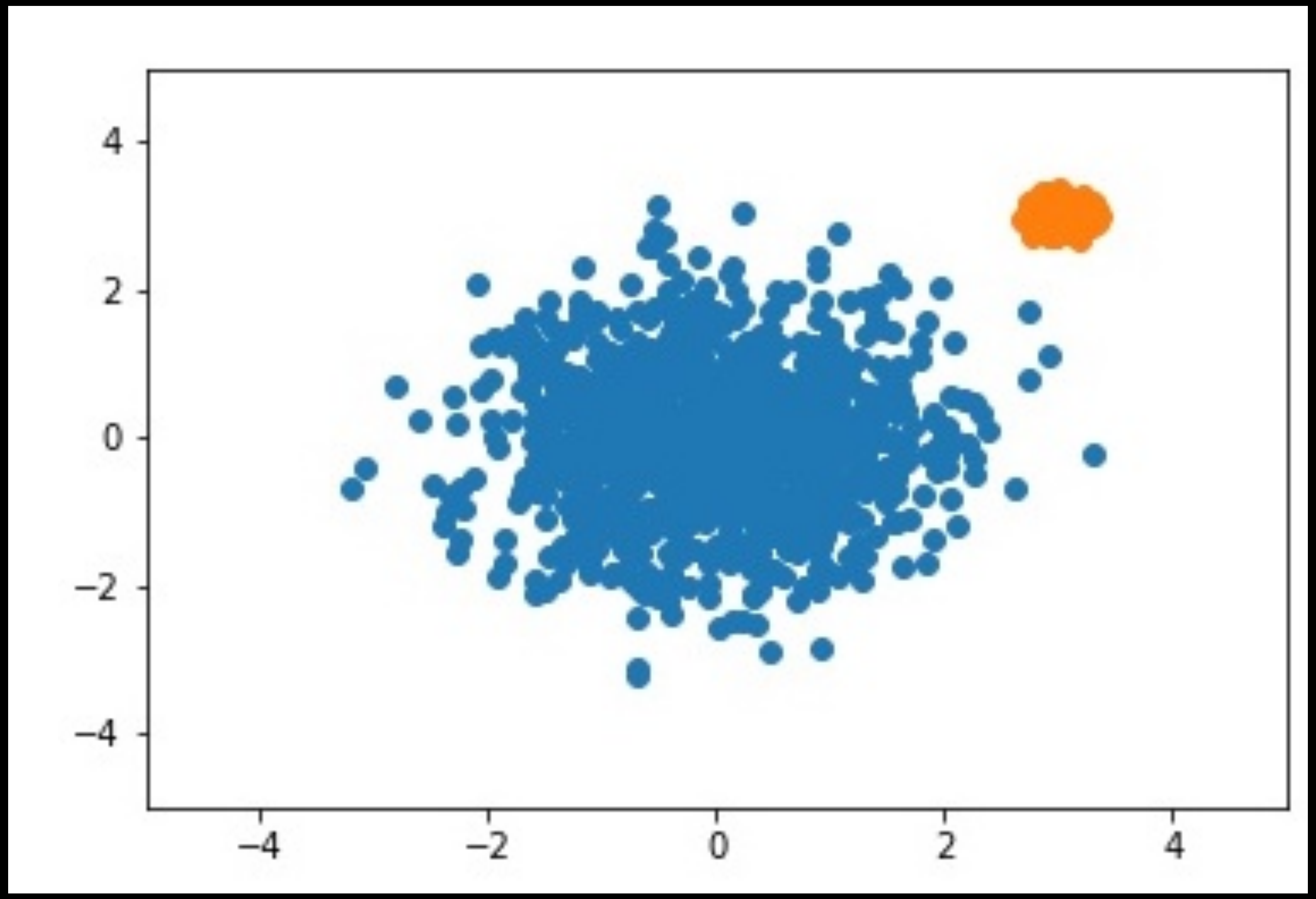


LOOK FOR ANYTING THAT DOESNT LOOK LIKE THIS

Types of anomaly detection

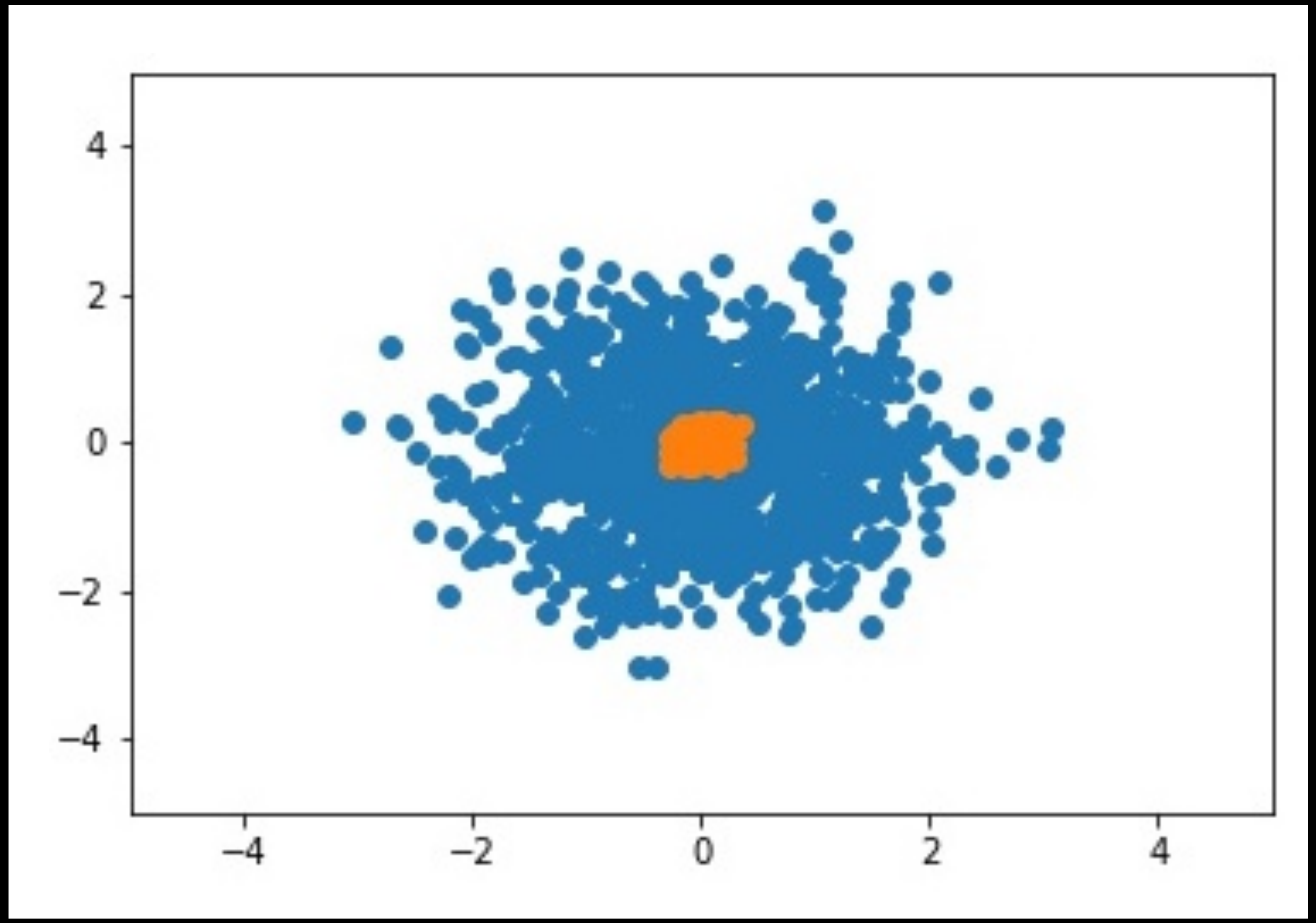
Outlier detection

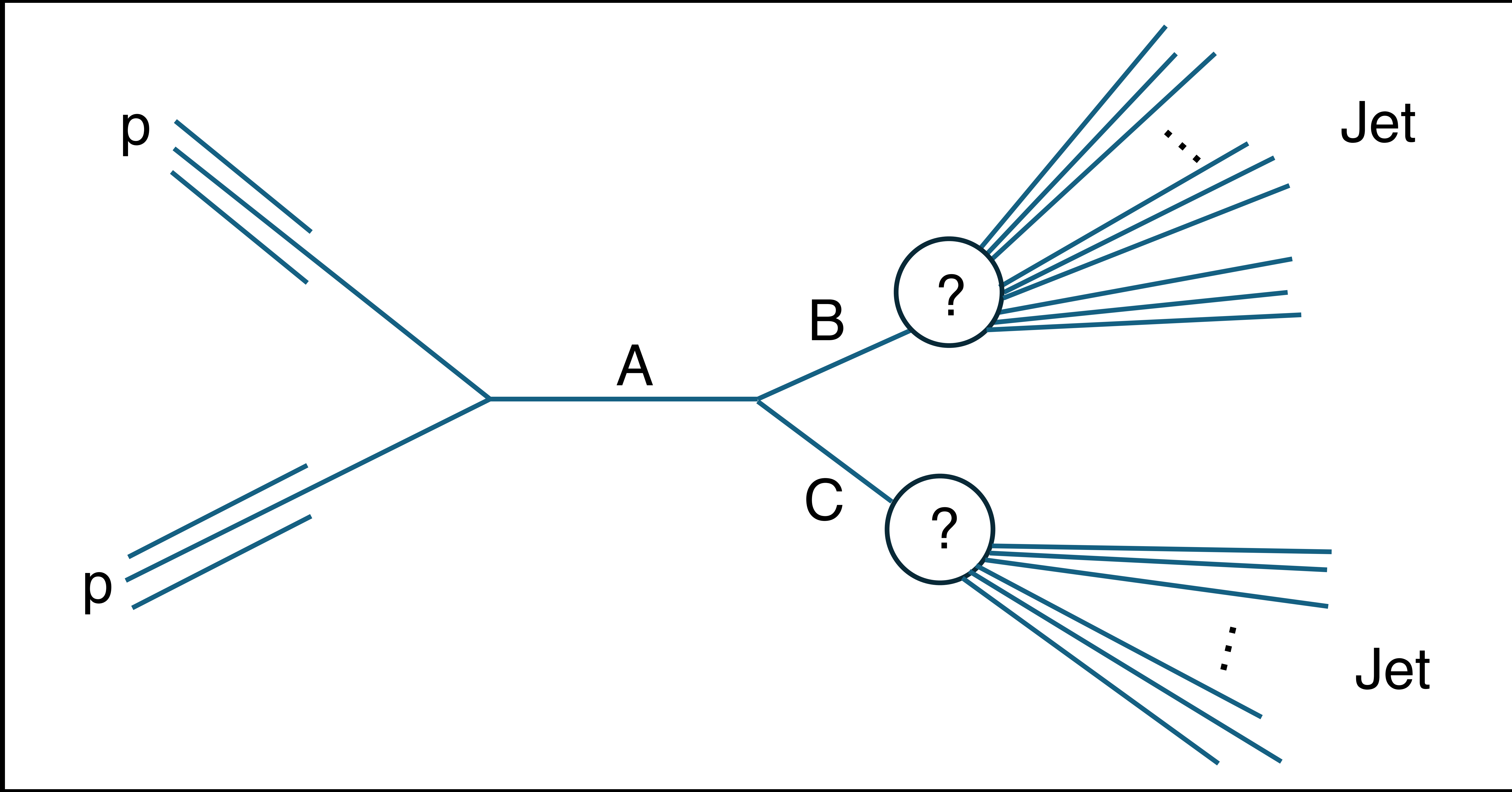
Find (non-resonant) out-of-distribution datapoints



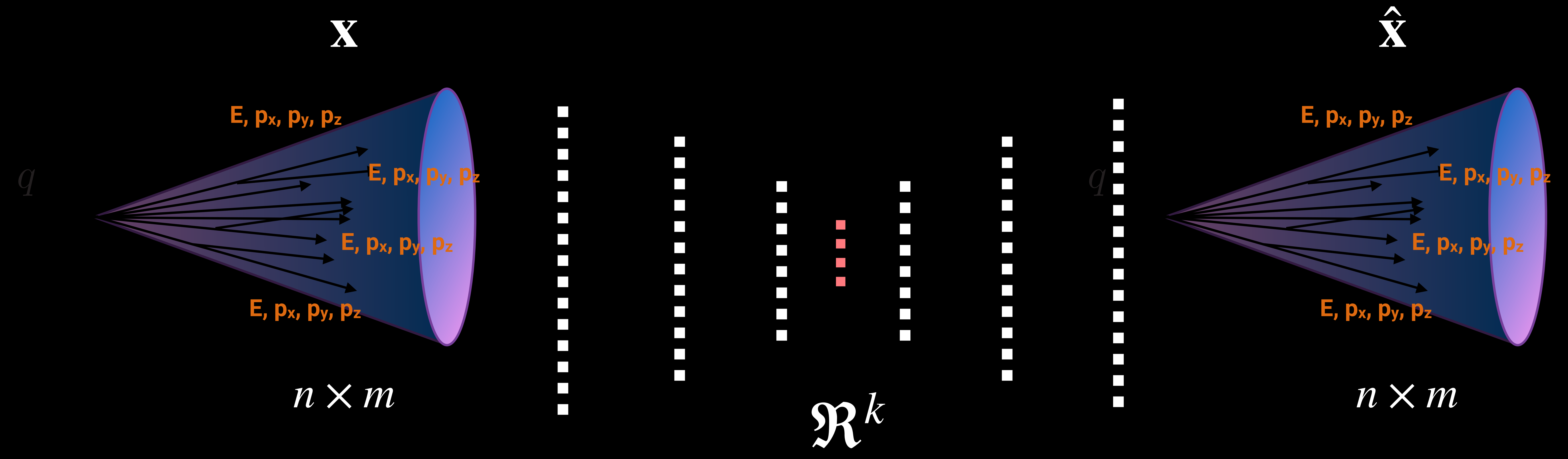
Detecting overdensities

Find (resonant) overdensities in distributions




p
p
A
B
C
?
?
Jet
Jet

Outlier detection

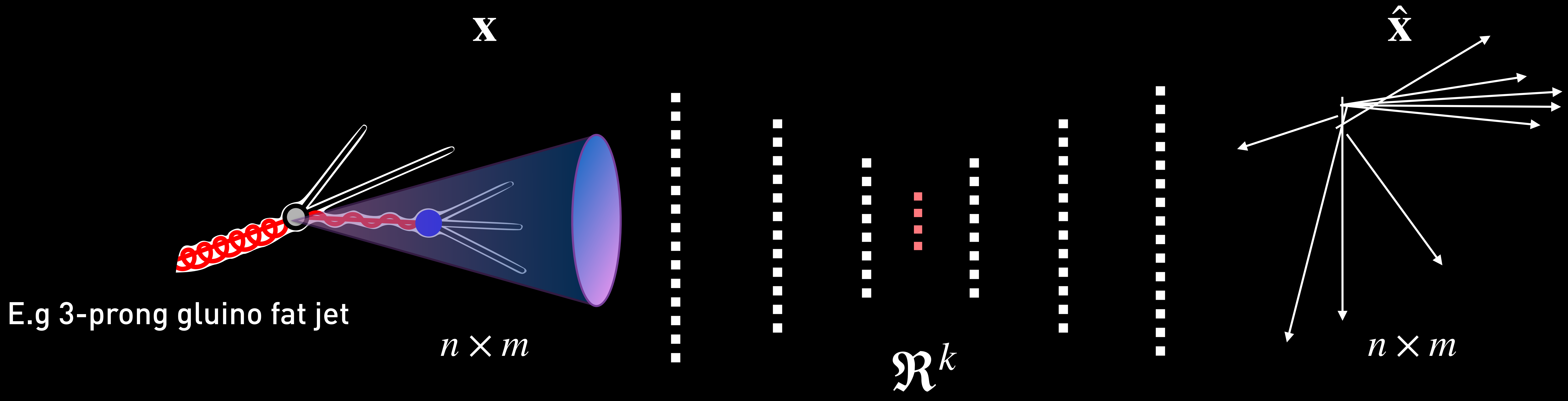


Compressed representation of x.

Latent space $\Re^k$, k < m×n

prevents memorisation of input, must learn

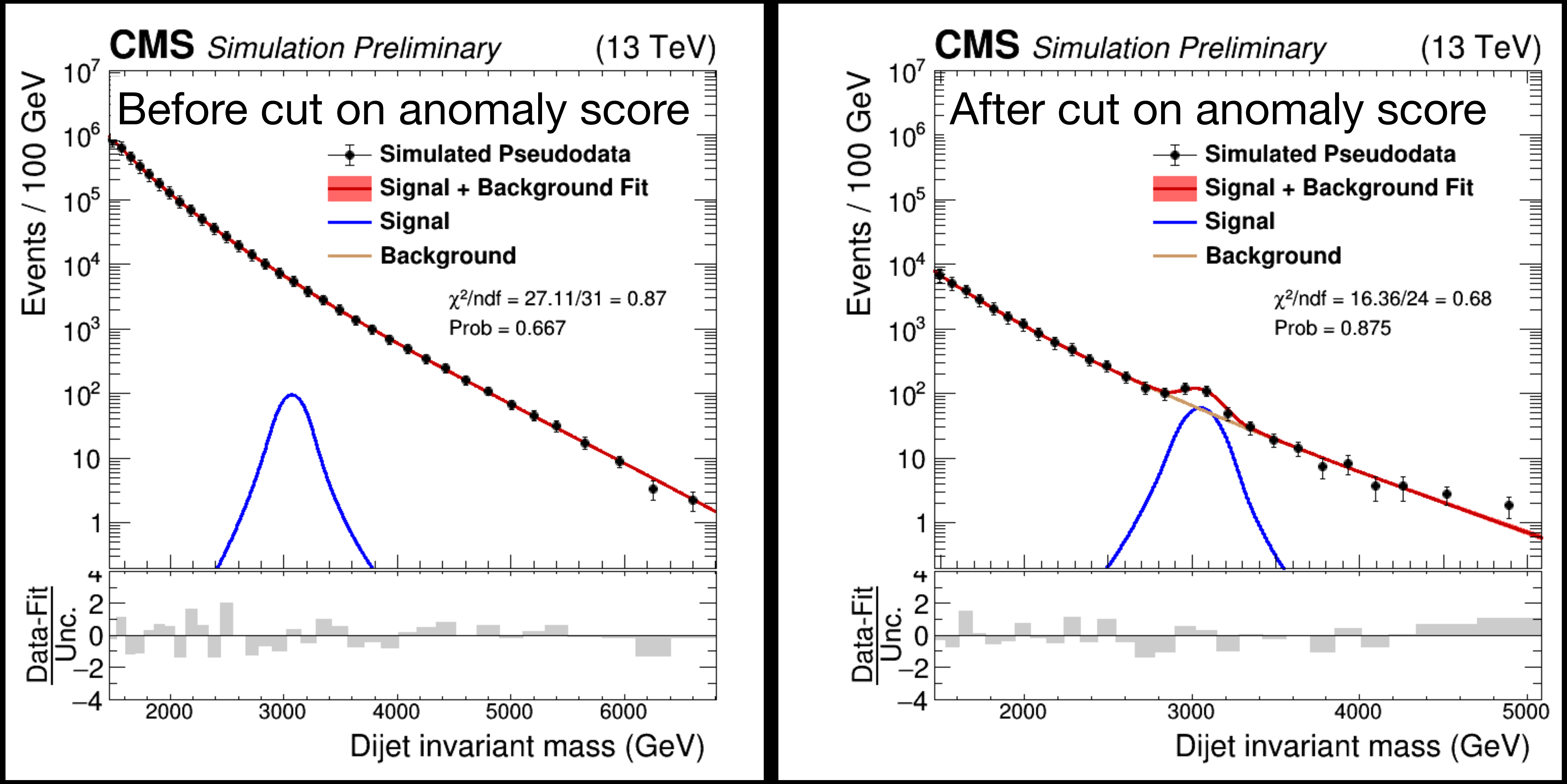
Outlier detection



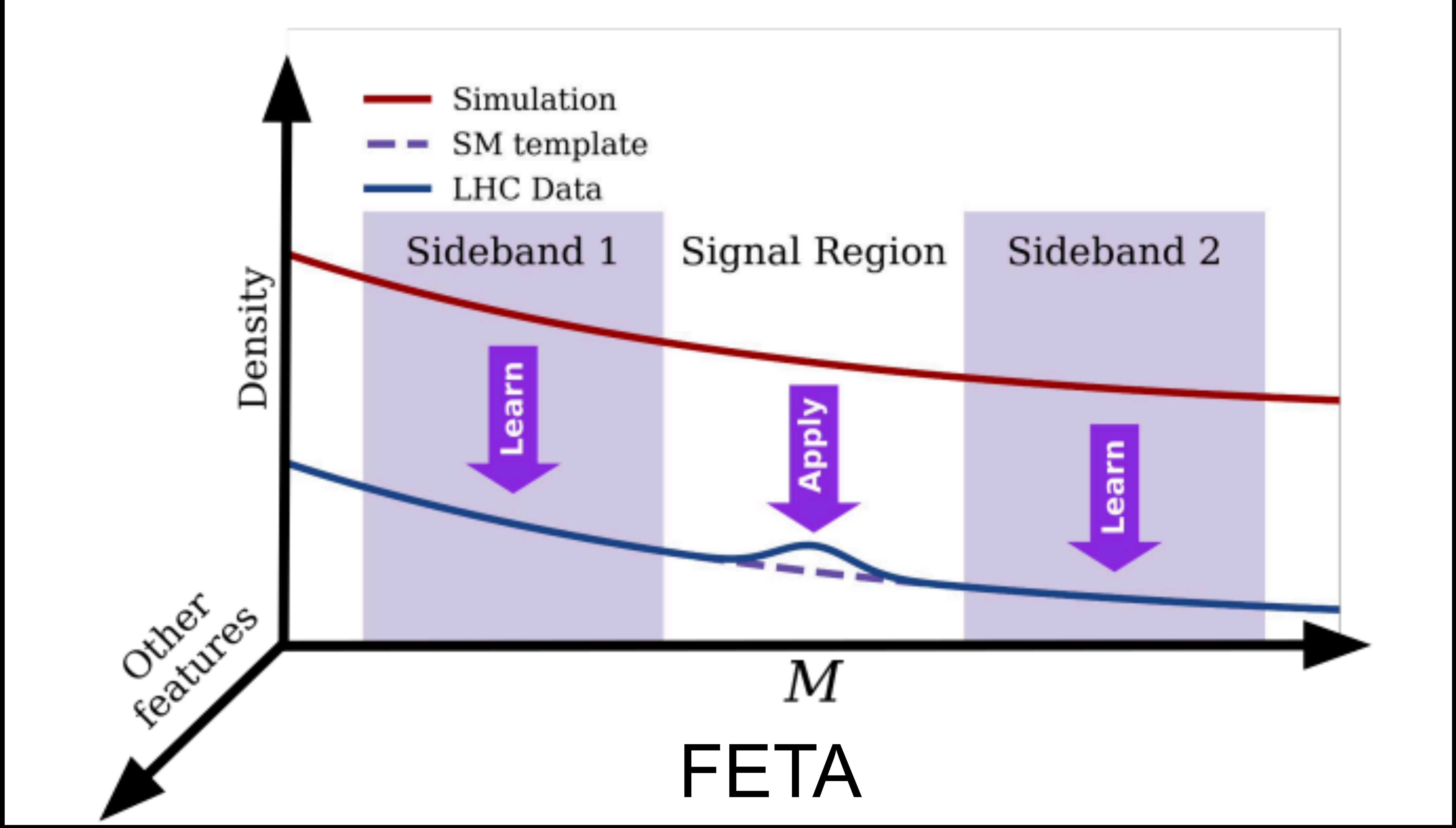
$\mathscr{L}(\mathbf{x}, \hat{\mathbf{x}})$ is Mean Squared Error$(\mathbf{x}, \hat{\mathbf{x}})$, "high error events" proxy for "degree of abnormality"

Outlier detection in analysis

E.g CASE

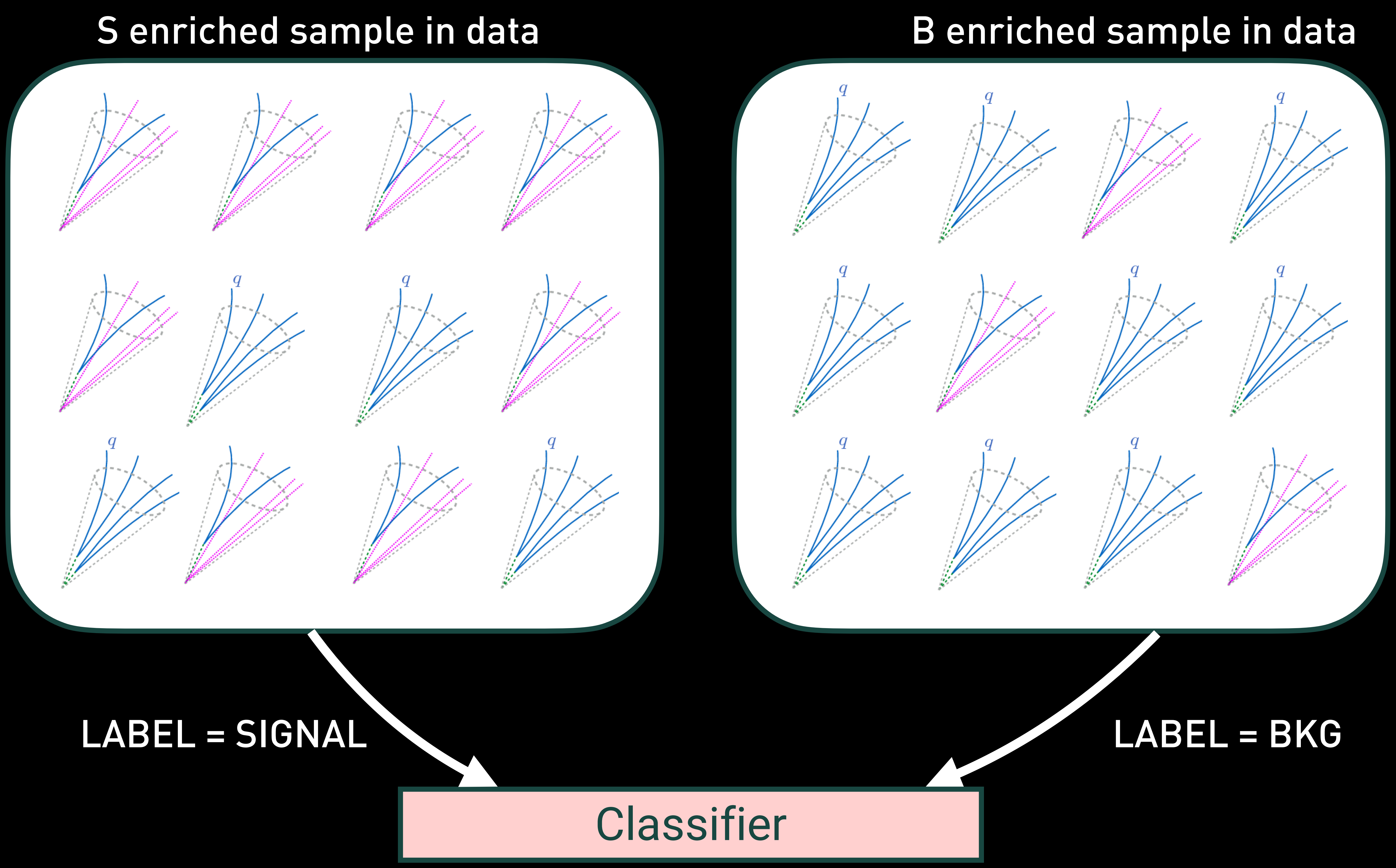


Finding overdensities

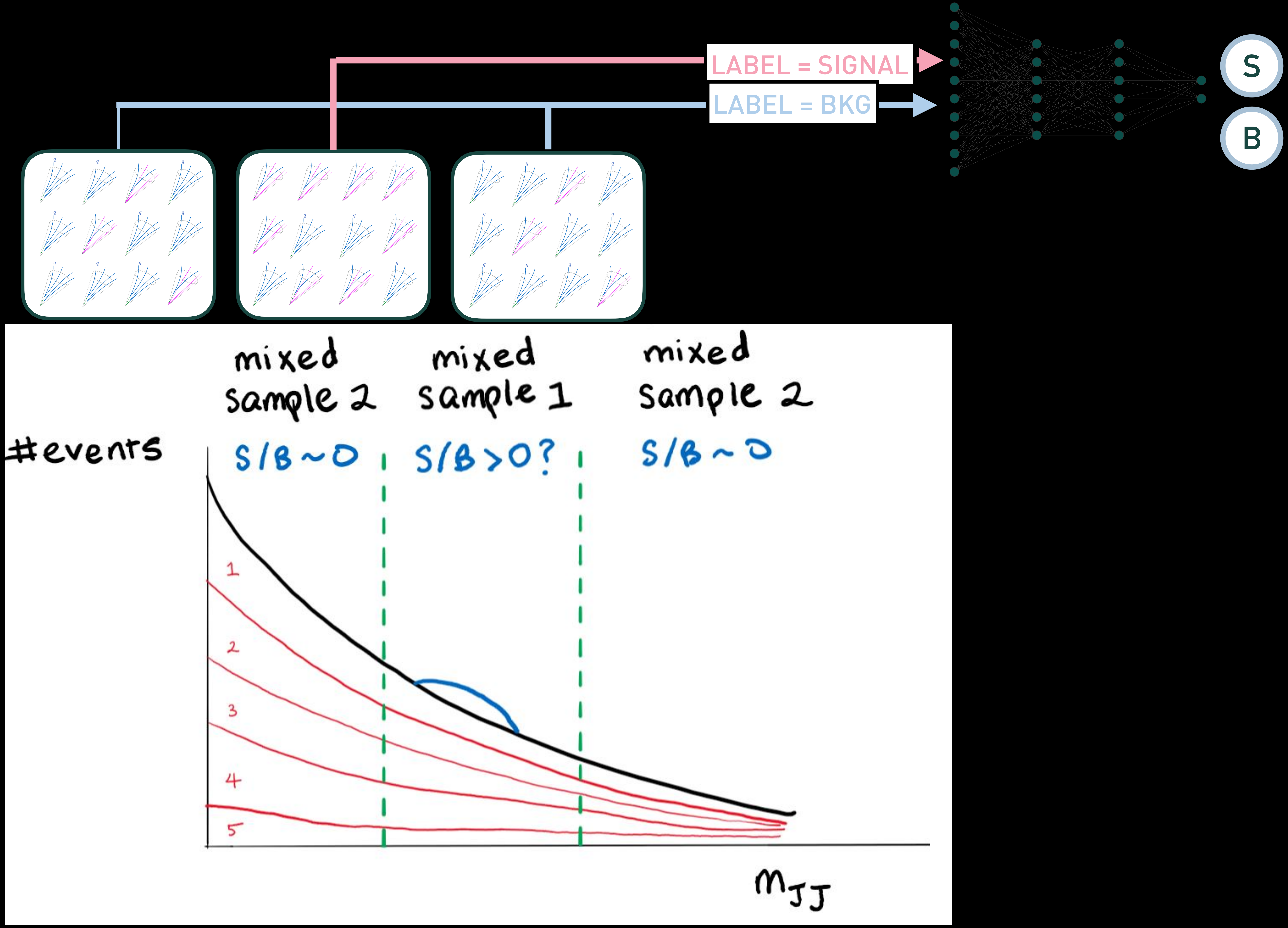


FETA

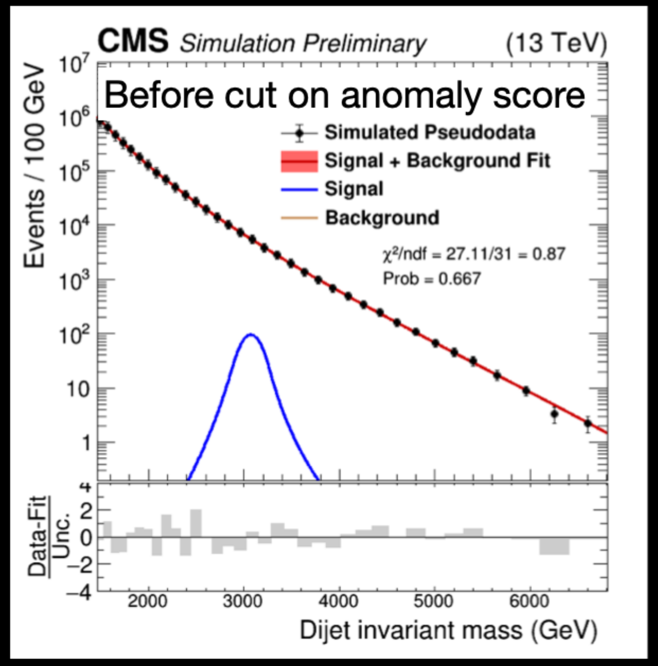
Finding overdensities - CWoLa bumphunt

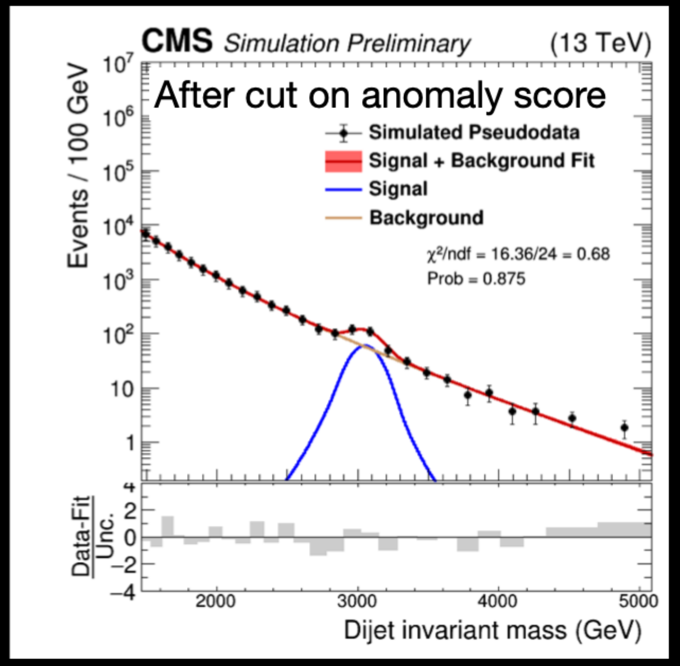


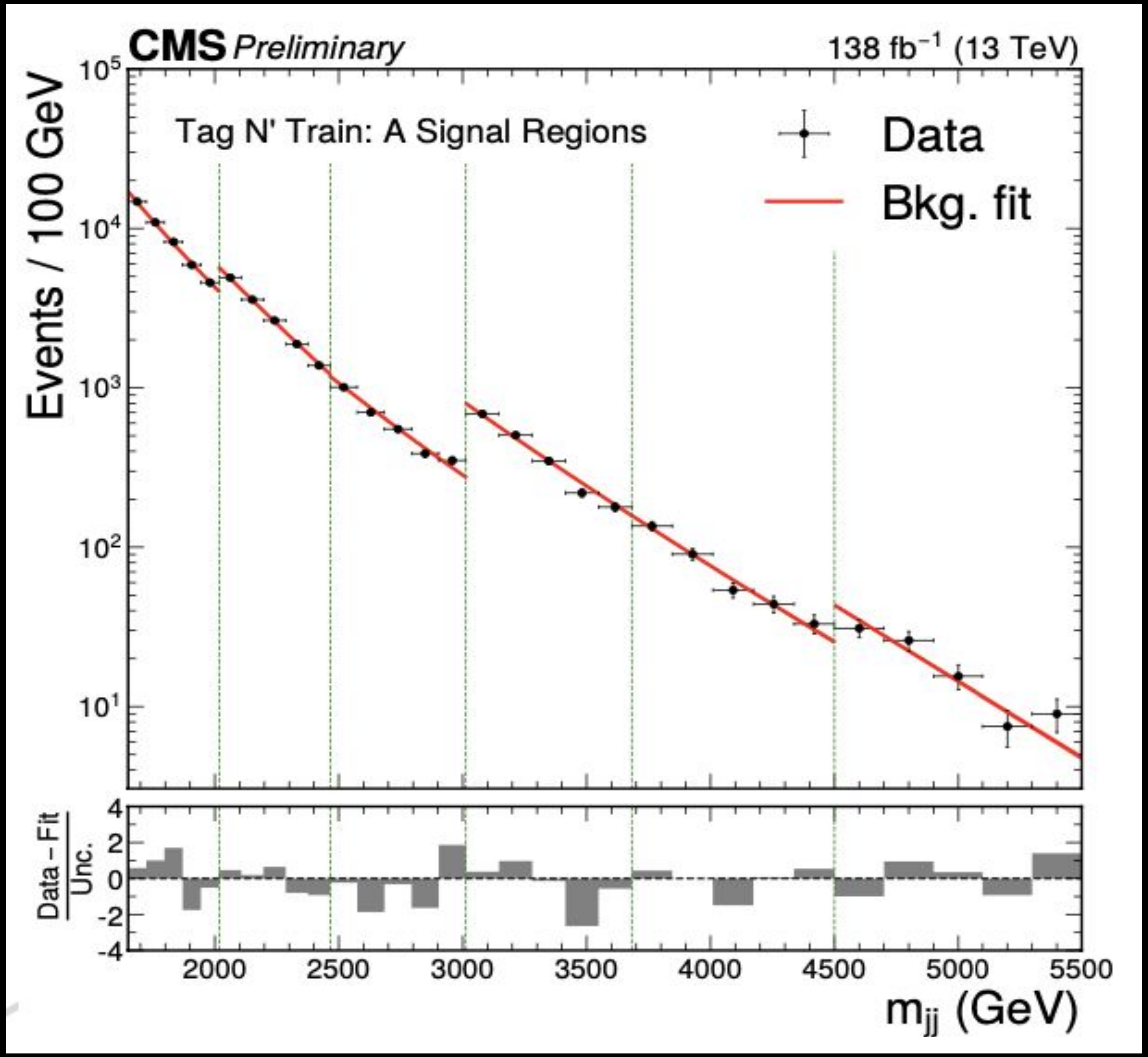
E.g CASE

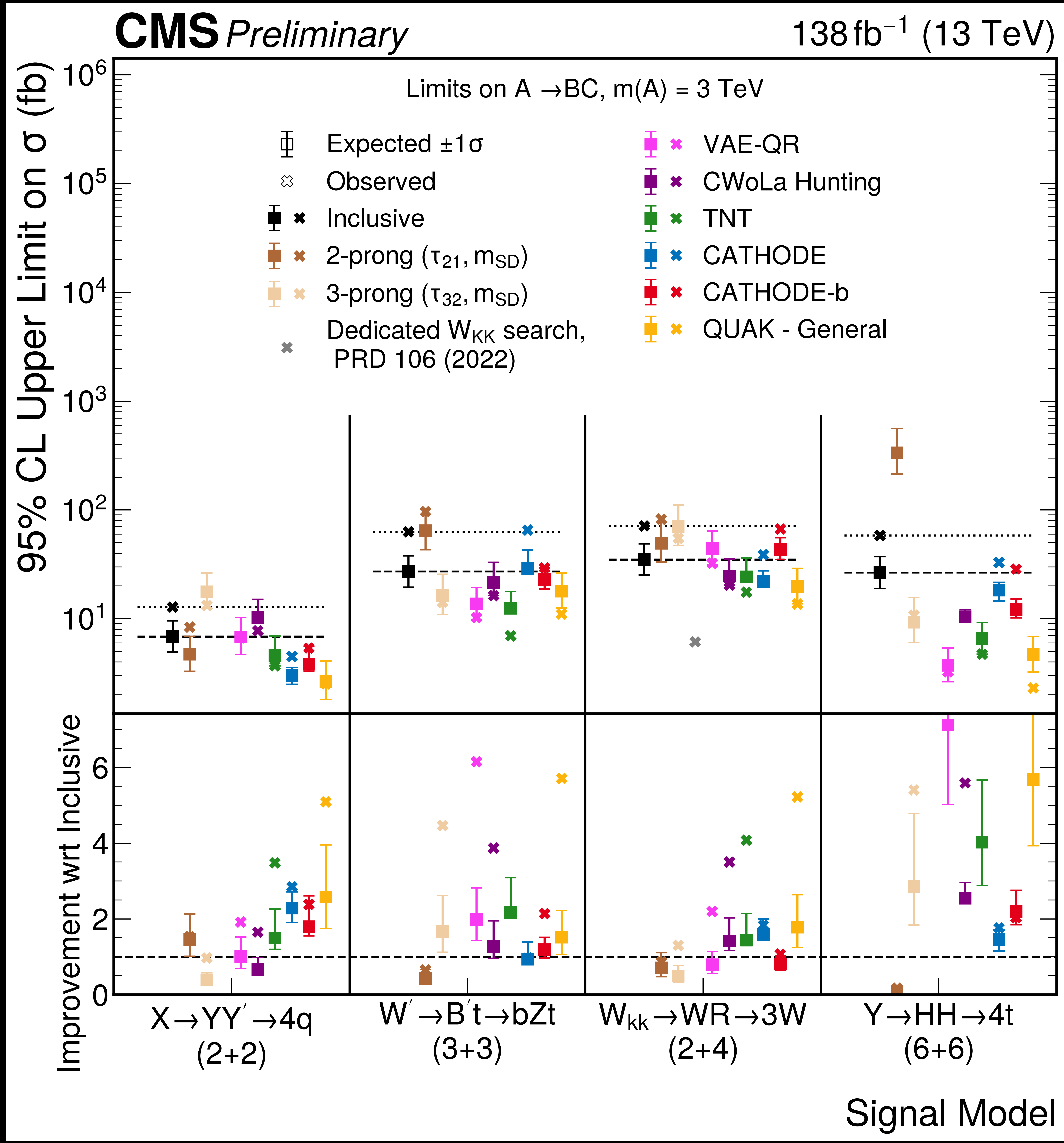

LABEL = SIGNAL
LABEL = BKG
S
B
mixed sample 2
mixed sample 1
mixed sample 2
#events
S/B ~ 0
S/B > 0?
S/B ~ 0
1
2
3
4
5
m_{JJ}

E.g CASE

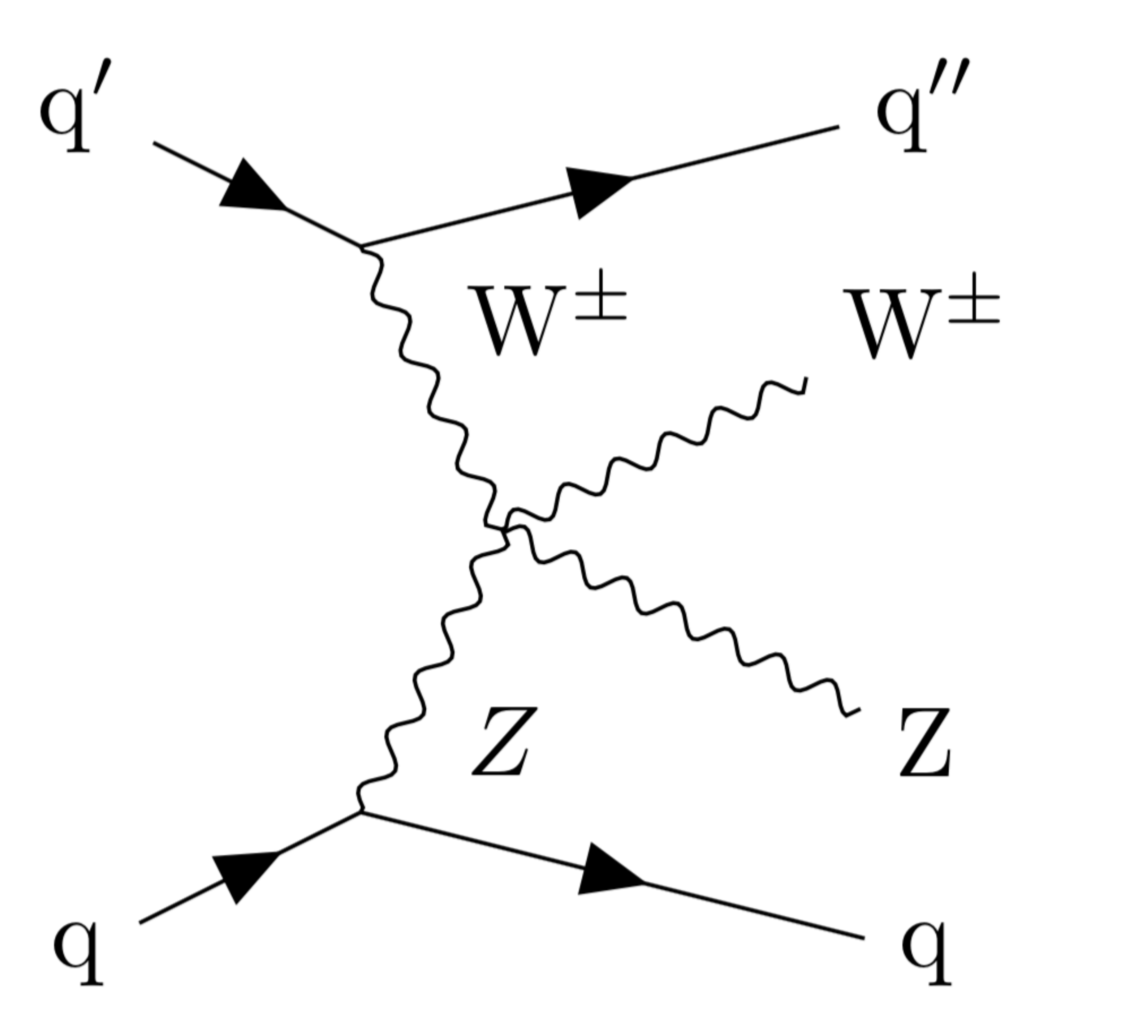

CMS Simulation Preliminary
(13 TeV)
Before cut on anomaly score
Simulated Pseudodata
Signal + Background Fit
Signal
Background
Events / 100 GeV
Dijet invariant mass (GeV)
Data-Fit / Unc.

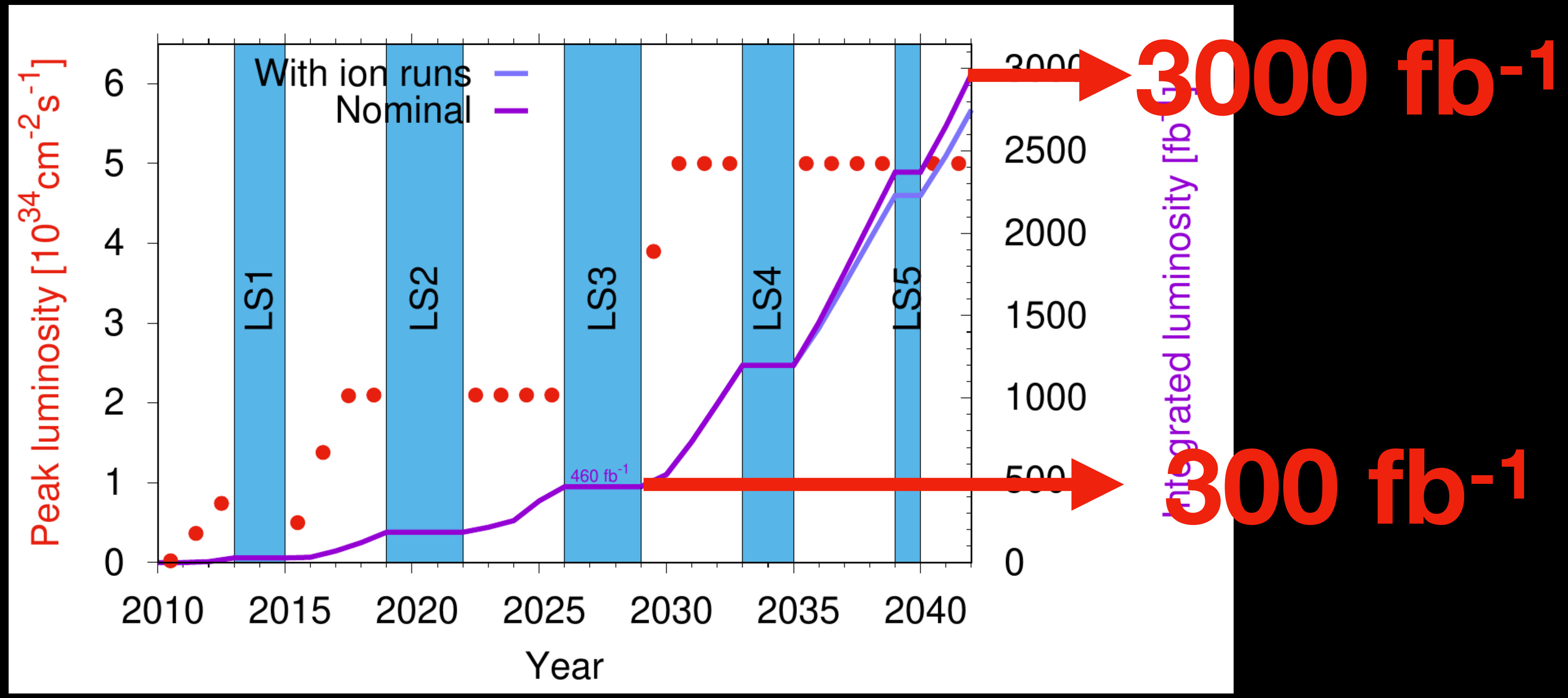

CMS Simulation Preliminary
(13 TeV)
After cut on anomaly score
Simulated Pseudodata
Signal + Background Fit
Signal
Background
Events / 100 GeV
Dijet invariant mass (GeV)
Data-Fit / Unc.


CMS Preliminary
138 fb^{-1} (13 TeV)
Tag N' Train: A Signal Regions
Data
Bkg. fit
Events / 100 GeV
Data – Fit / Unc.
m_{jj} (GeV)



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



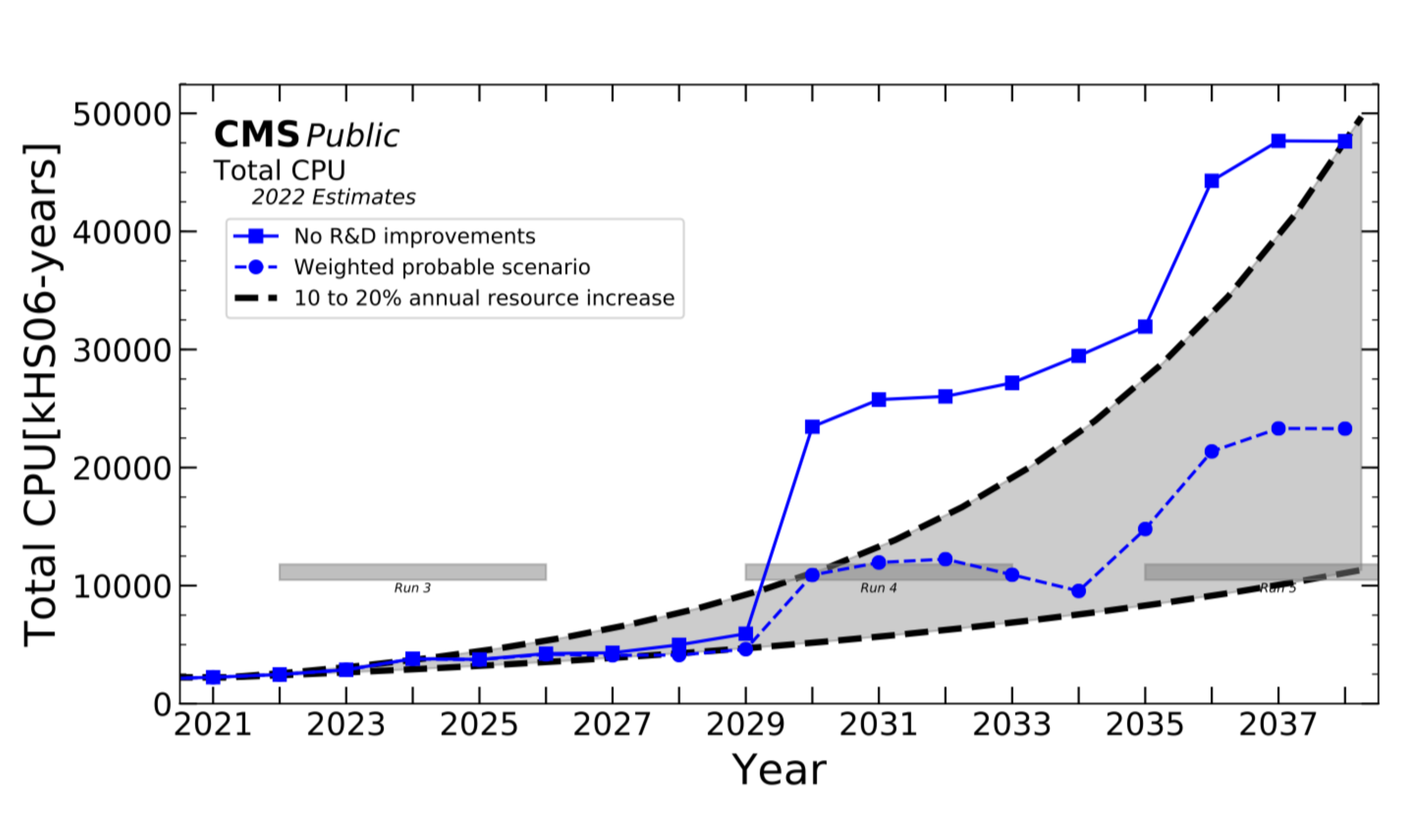


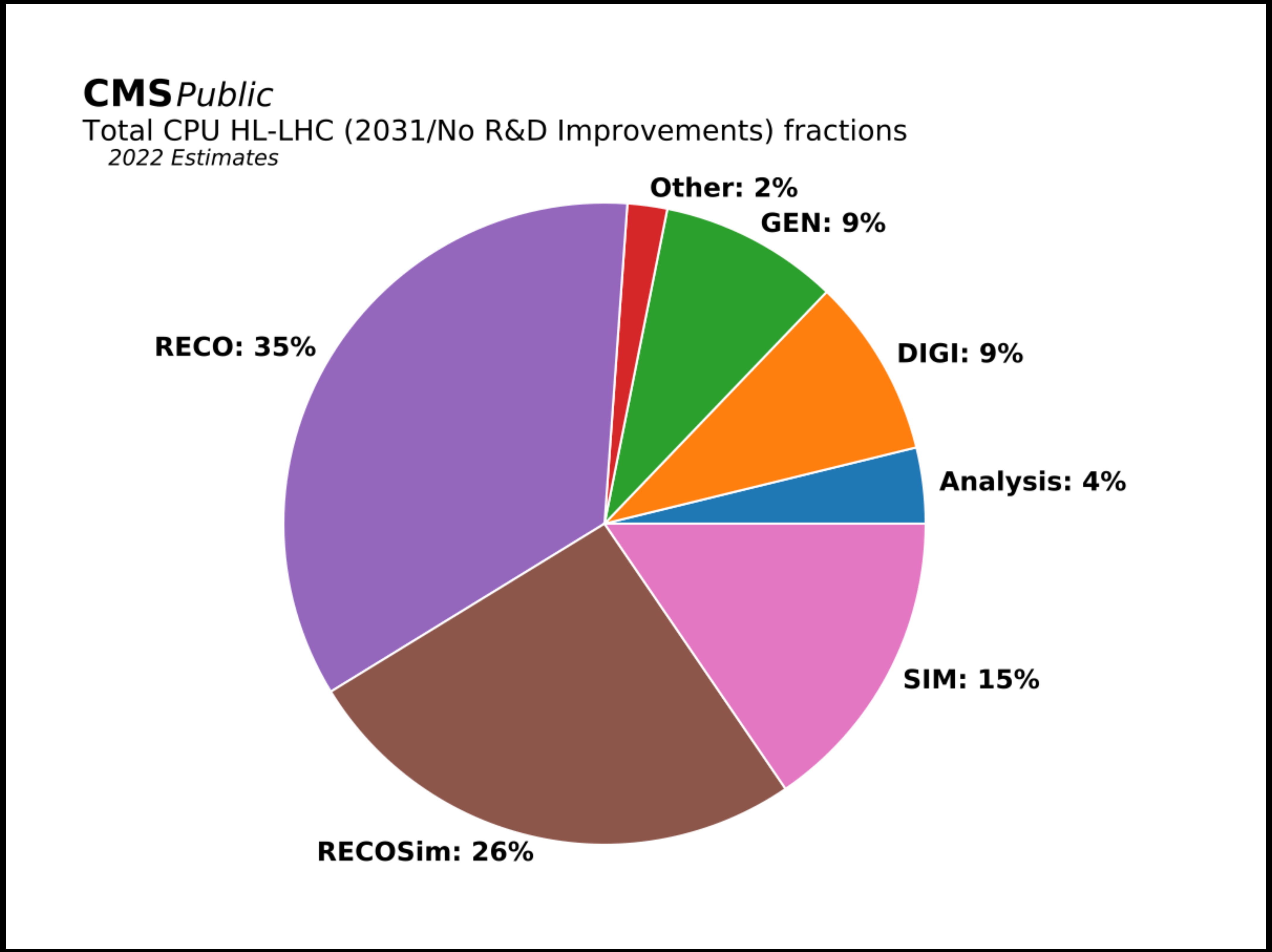
Luminosity: HL-LHC - 90% of final LHC dataset!

AI?

Generative models for simulation

60% of CPU used for simulation!

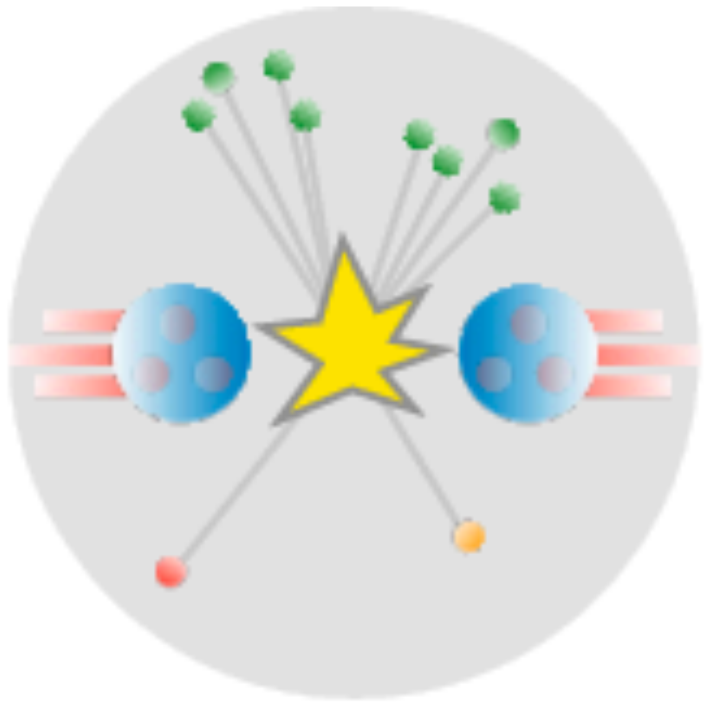




$O(10)$ $O(10^3)$ $O(10^{10})$

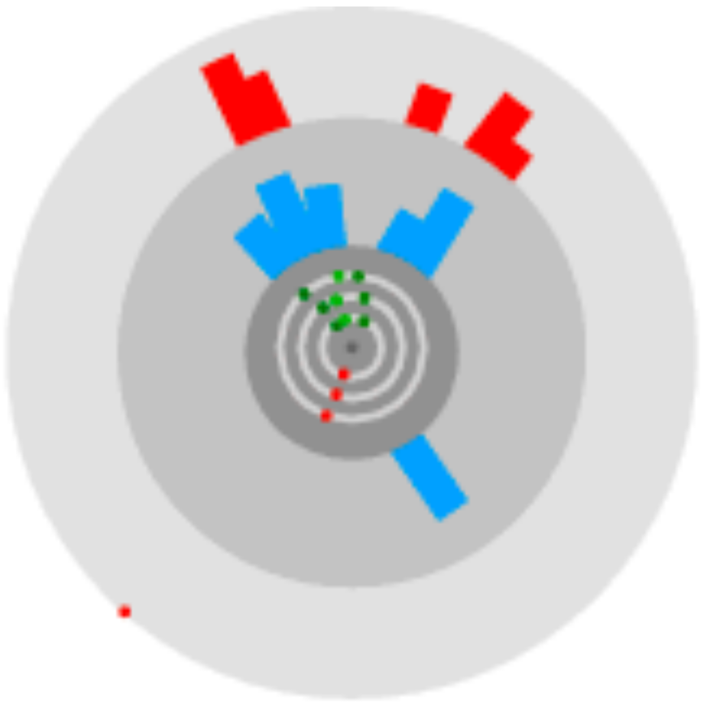
10^{-18}m 10^{-15}m 10^{-6}m 100m

GEN



pp collisions up to production of stable particles [Easy & Fast]

SIM



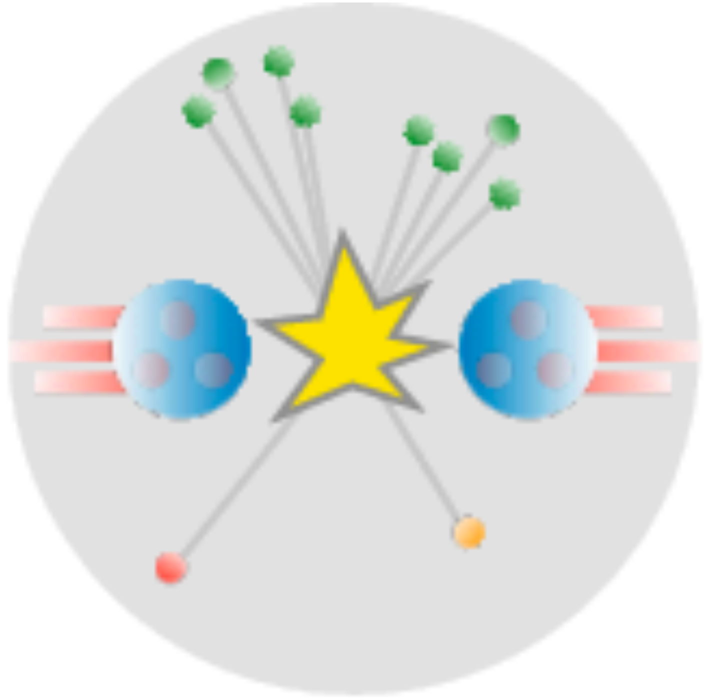
detector response simulation [Hard & Slow]

GEANT4
A SIMULATION TOOLKIT

DIGI+RECO

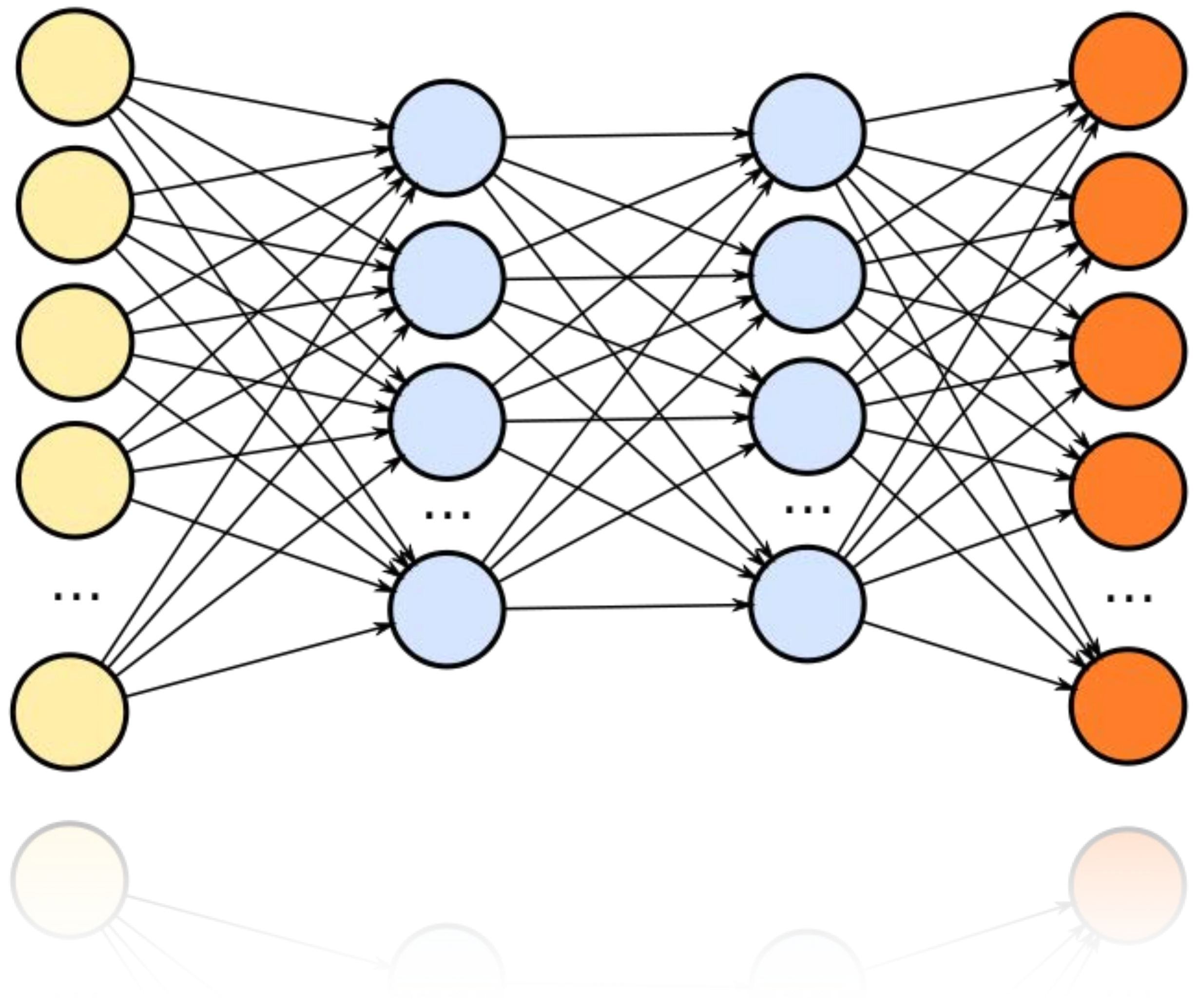
Energy deposits→digital signals→reconstructed by the reconstruction software [Hard & Slow]

GEN



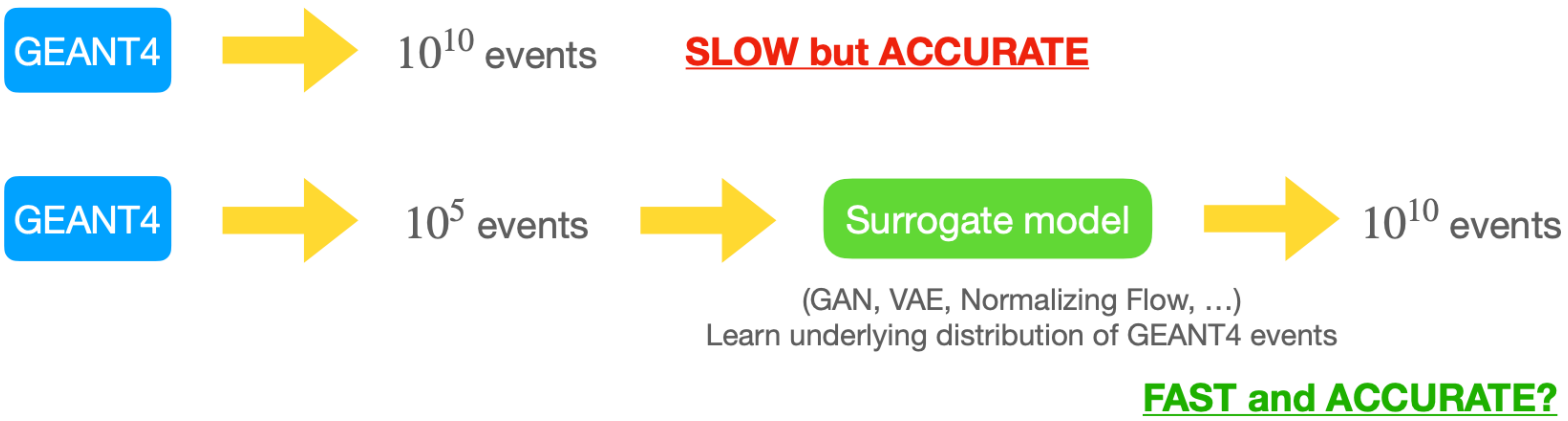
pp collisions up to production of stable particles [Easy & Fast]

SIM



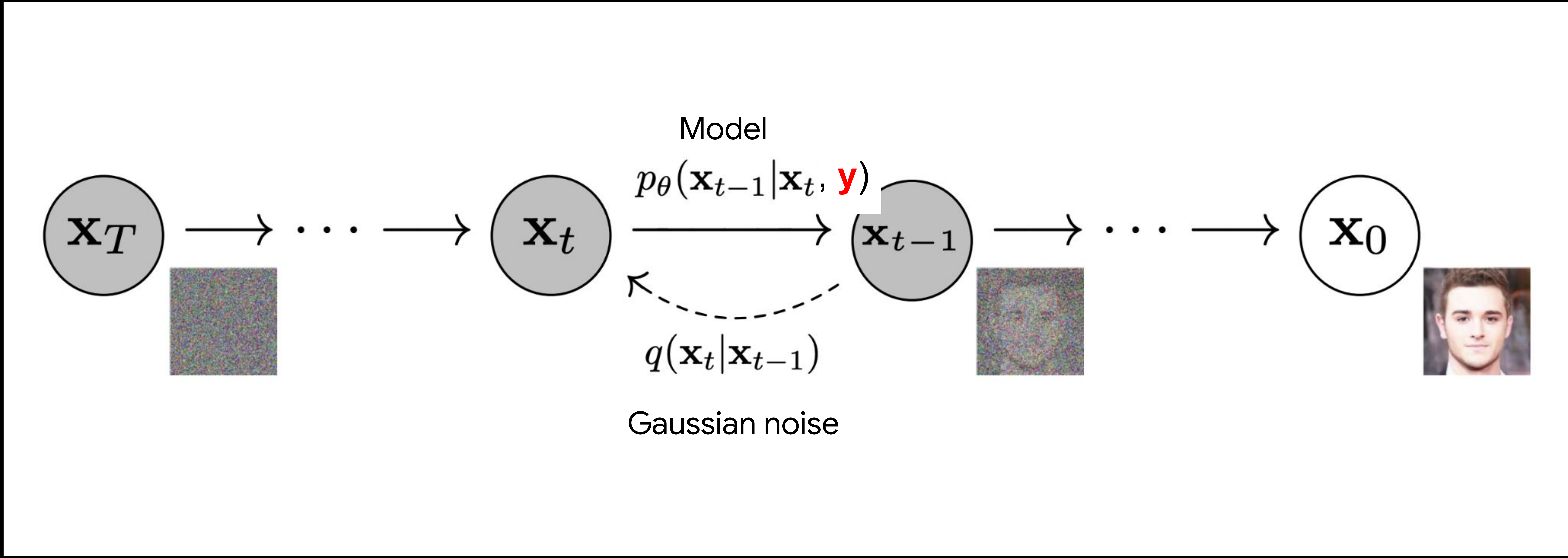
DIGI+RECO

Energy deposits→digital signals→reconstructed by the reconstruction software [Hard & Slow]



ML methods can provide fast and accurate “surrogate models” for GEANT4 etc

Diffusion models

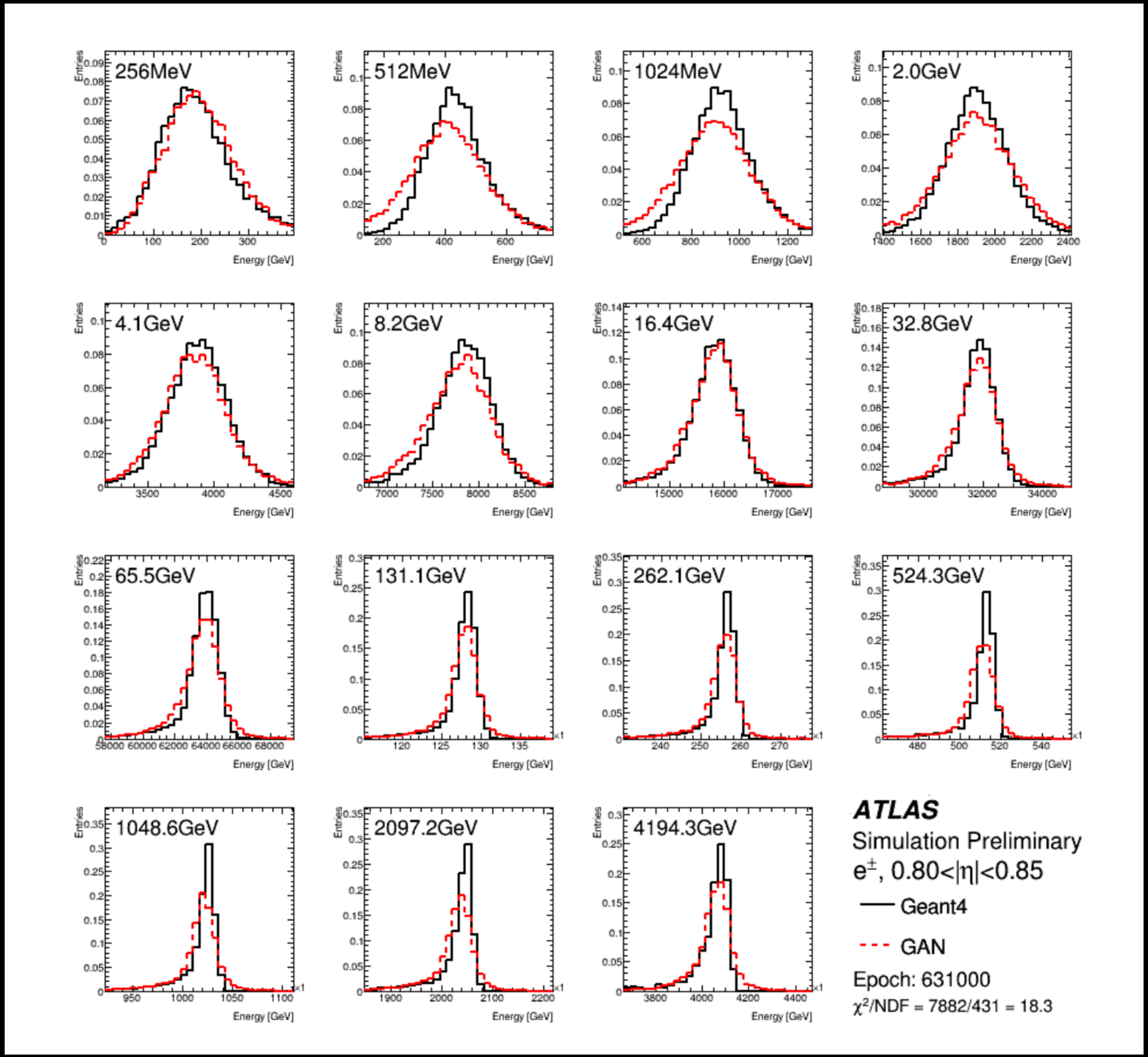


Learn systematic decay of information due to noise, then reverse process and recover the information back from the noise.

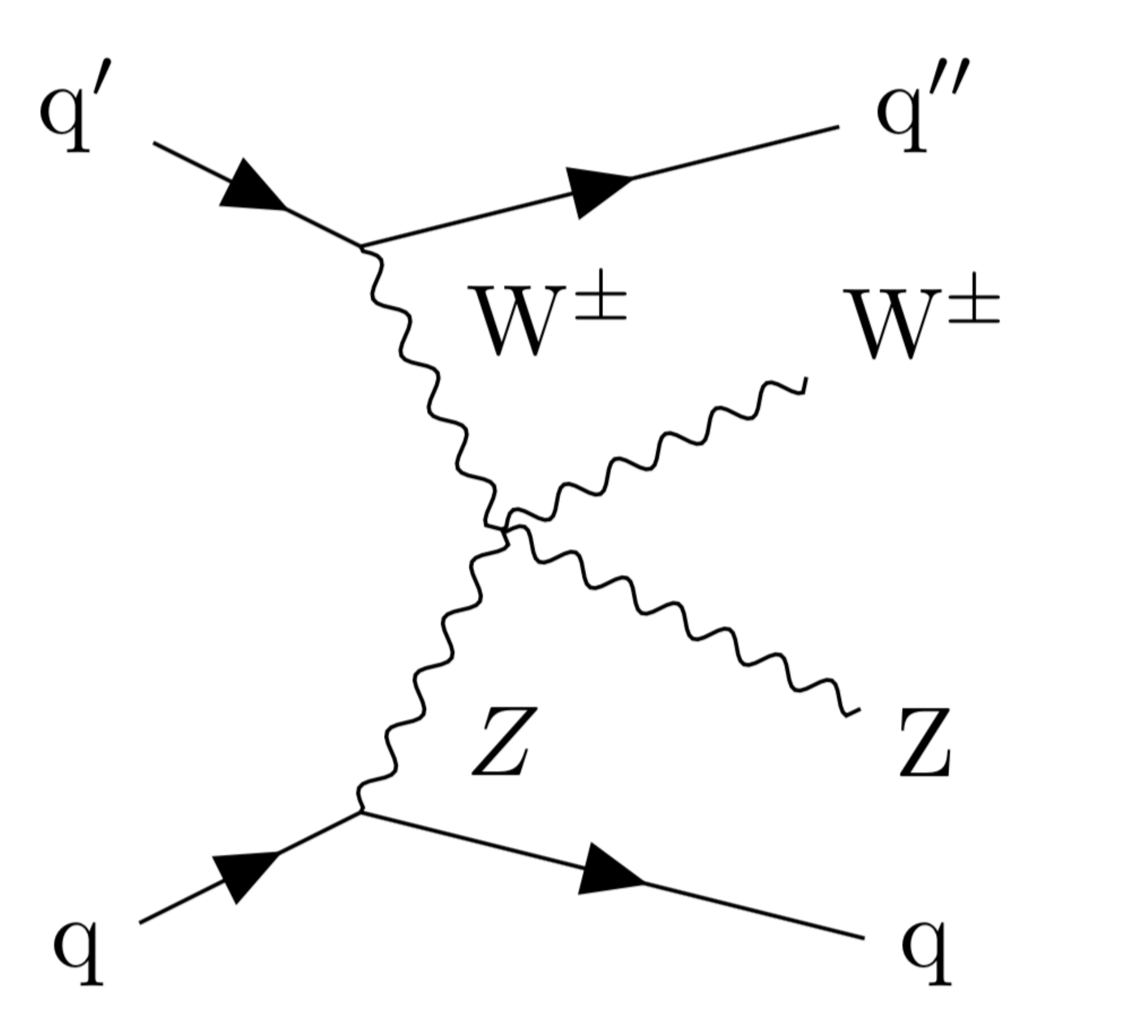
FastCaloGAN Being used in ATLAS!

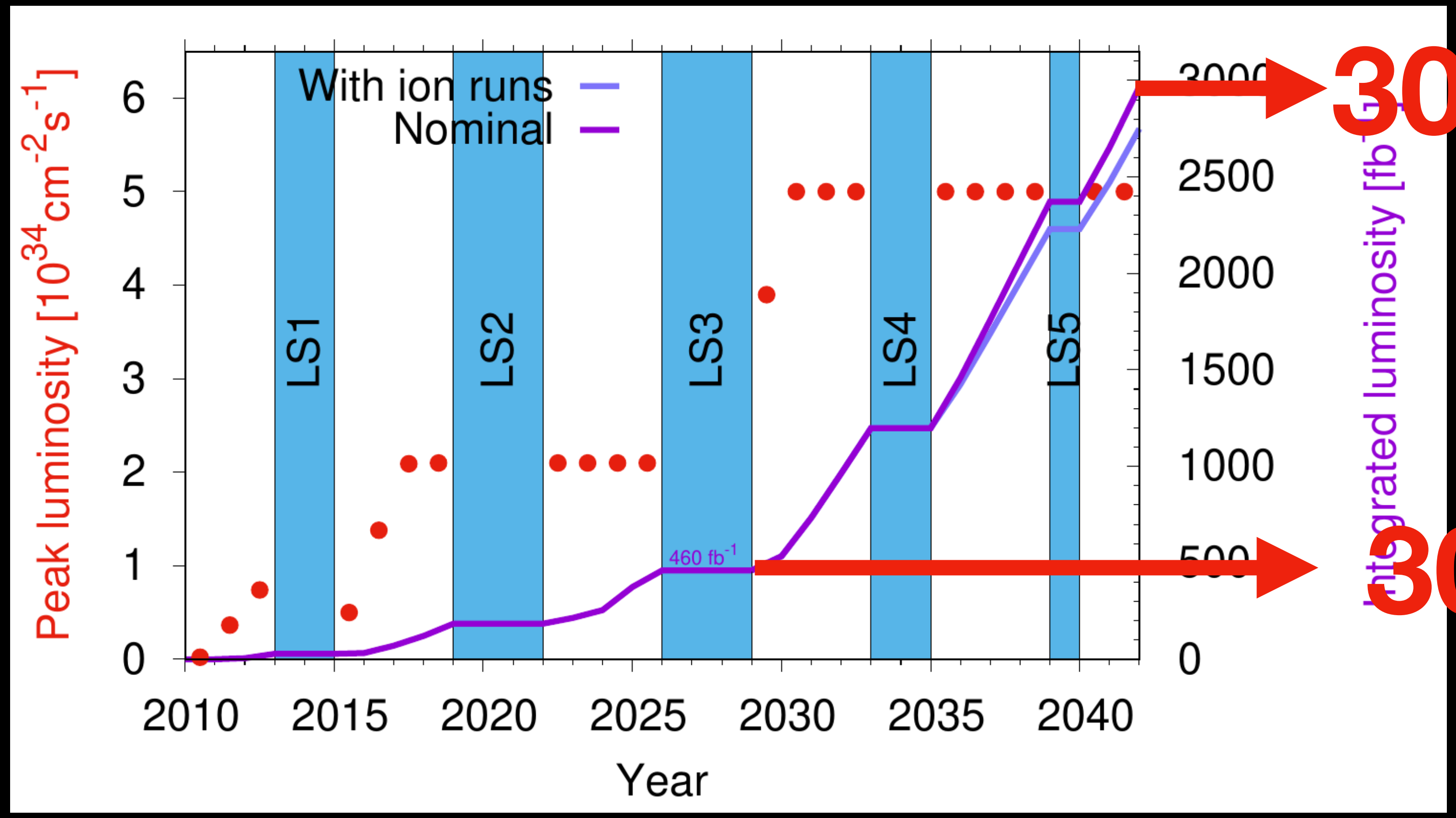
100 networks (slices in η)

O(500) voxels



ATL-SOFT-PUB-2020-006; ATLAS 2109.02551





3000 fb^{-1}

300 fb^{-1}

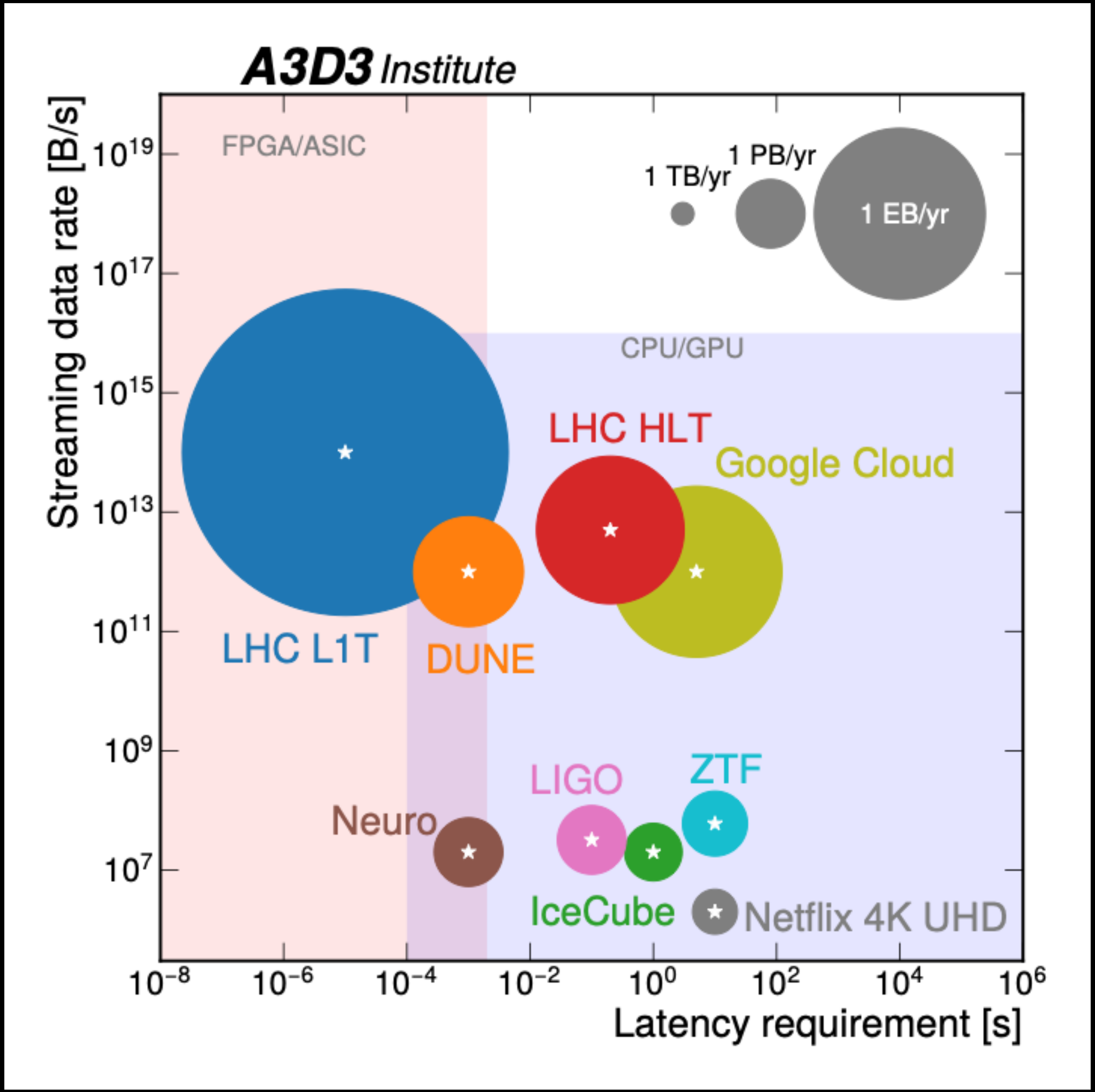
Luminosity: HL-LHC - 90% of final LHC dataset!

Detector design, data acquisition and triggering

1 billion collisions /s

~1 MB of data / collision

~1 PB of data / s


A3D3 Institute
Streaming data rate [B/s]
Latency requirement [s]
FPGA/ASIC
CPU/GPU
1 TB/yr
1 PB/yr
1 EB/yr
LHC L1T
DUNE
LHC HLT
Google Cloud
Neuro
LIGO
ZTF
IceCube
Netflix 4K UHD


Geneva
Geneva Lake
LHCb
ATLAS
ALICE
CMS
1 PB of data / second


Geneva
Geneva Lake
LHCb
CMS
LHC
Data temporarily stored
in detector electronics for 12(4) μs

Geneva
Geneva Lake
LHCb
CMS
5% internet traffic to L1
(63 Tb/s HL-LHC)
LHC


Geneva
Geneva Lake
LHCb
CMS
LHC
5% internet traffic to L1
(63 Tb/s HL-LHC)
L1 trigger:
~1000 AMD FPGAs
Decide which event to keep within ~12 μs latency
Discard >99% of collisions!


Geneva
Geneva Lake
LHCb
CMS
LHC
L1 bit:
Accept = 1
Reject = 0


Geneva
Geneva Lake
LHCb
ATLAS
ALICE
CMS
DATA
99.72% of events rejected!
110 kHz
LHC

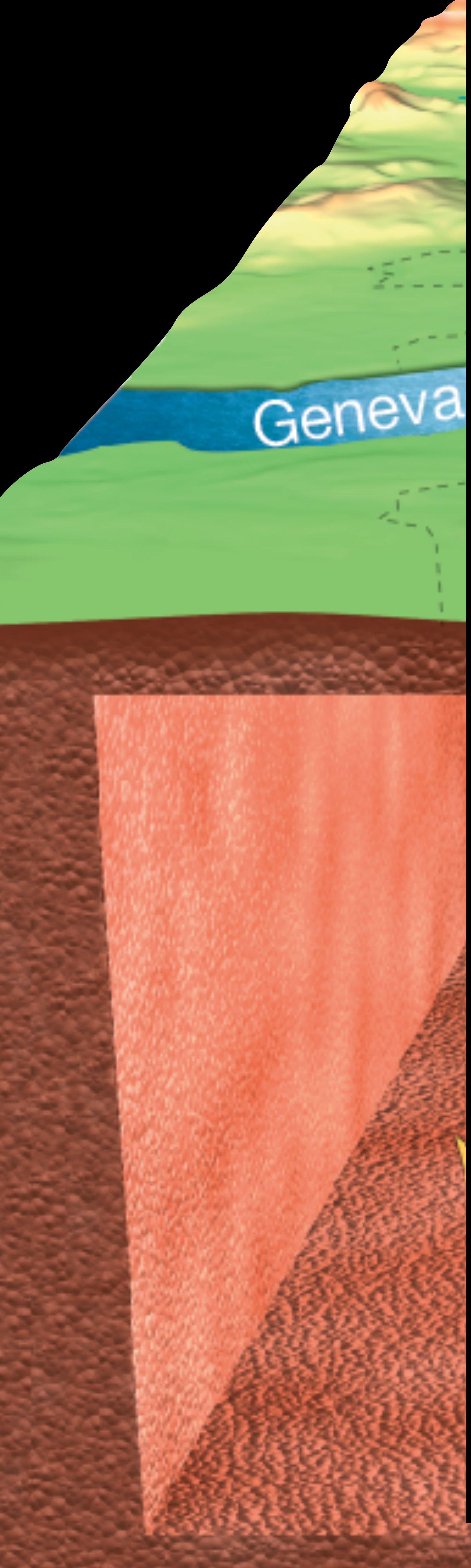

Geneva
Geneva Lake
LHCb
ATLAS
ALICE
CMS
DATA
99.72% of events rejected!
110 kHz
LHC

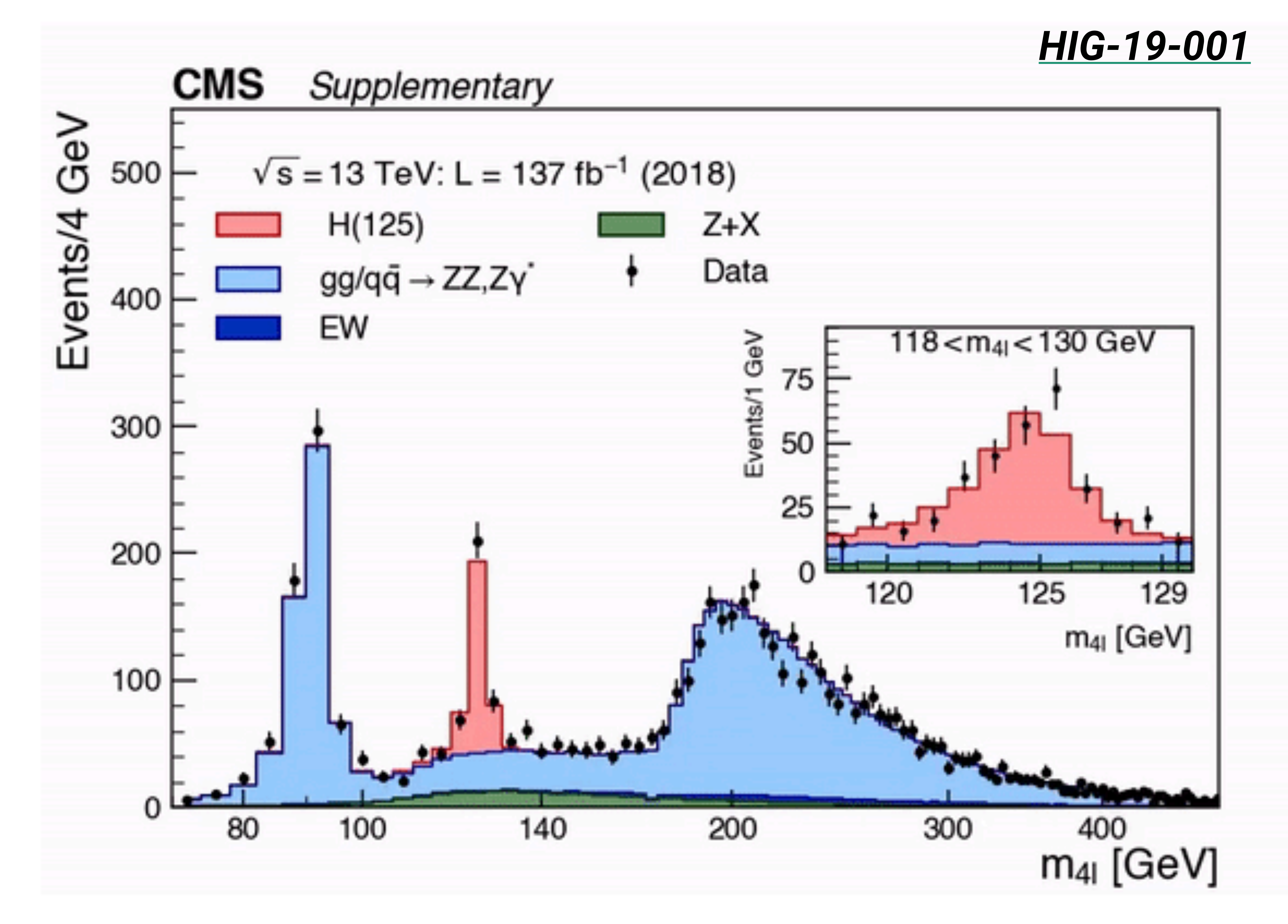

High Level Trigger:
25'600 CPUs / 400 GPUs
Latency: 3-400 ms
Reject further 99%!
eva
LHCb
ATLAS
ALICE
LHC

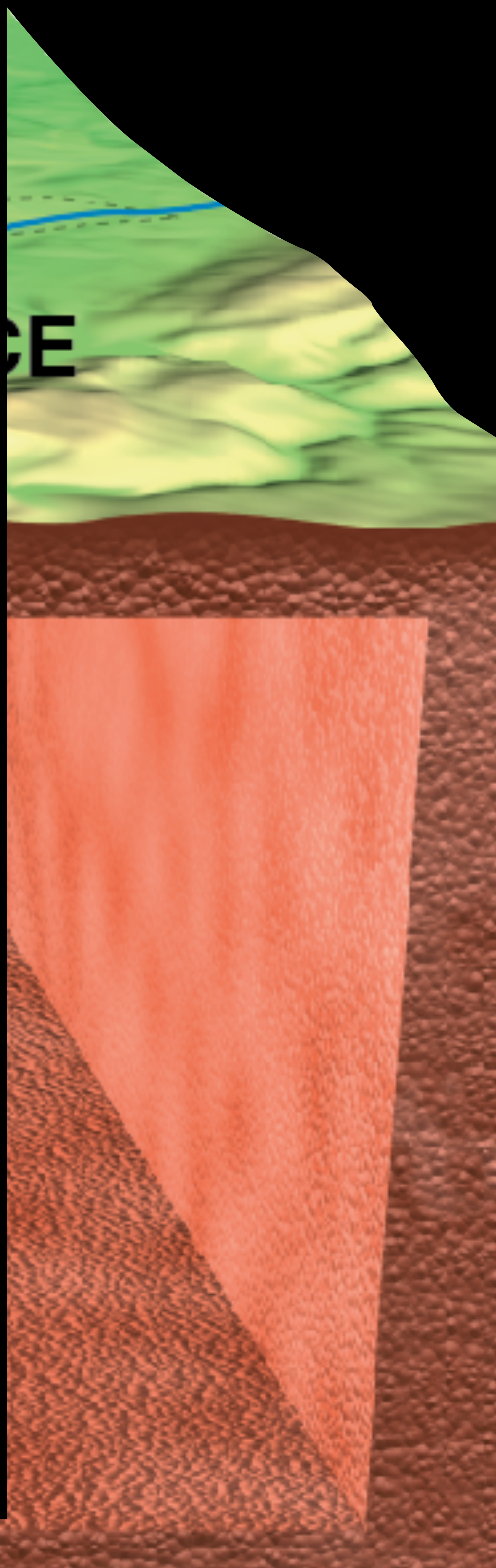

TIER 0: ∞
Geneva
High Level Trigger:
Latency O(100) ms
LHCb
ATLAS
CMS
DATA
99.9975% of events rejected!
1000 events/second
~5 GB/s
LHC


TIER 0: ∞
Geneva
High Level Trigger:
Latency O(100) ms
LHCb
ATLAS
CMS
DATA
99.9975% of events rejected!
1000 events/second
~5 GB/s
LHC


TIER 0: ∞
0.0025% of collision events remaining
Geneva
High Level Trigger:
Latency O(100) ms
LHCb
ATLAS
CMS
DATA
99.9975% of events rejected!
1000 events/second
~5 GB/s
LHC

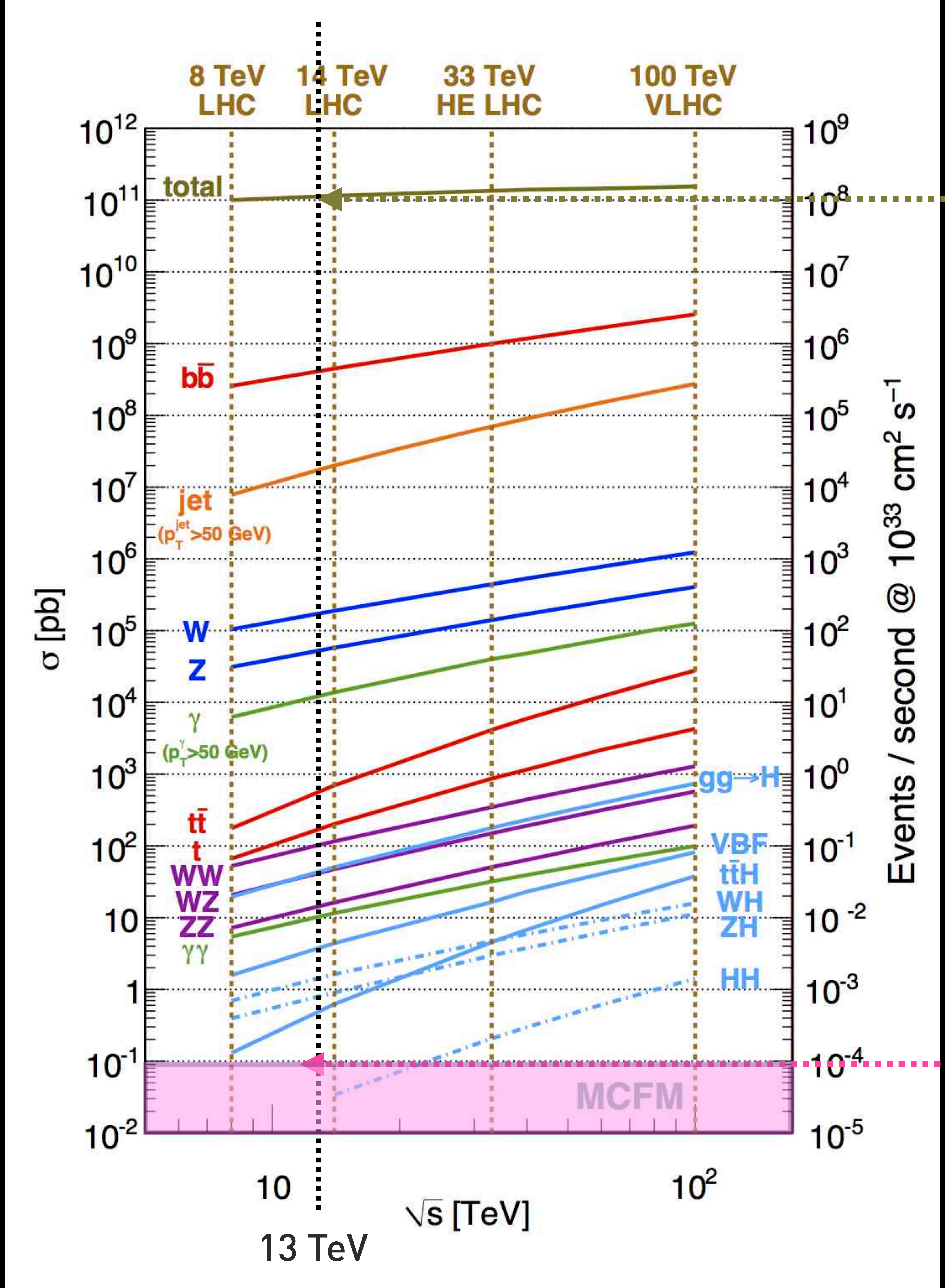






To make sure we select "the right" 0.0025%, algorithms must be

- Fast (get more data through)
- Accurate (select the right data)



"Probability" of producing "anything"

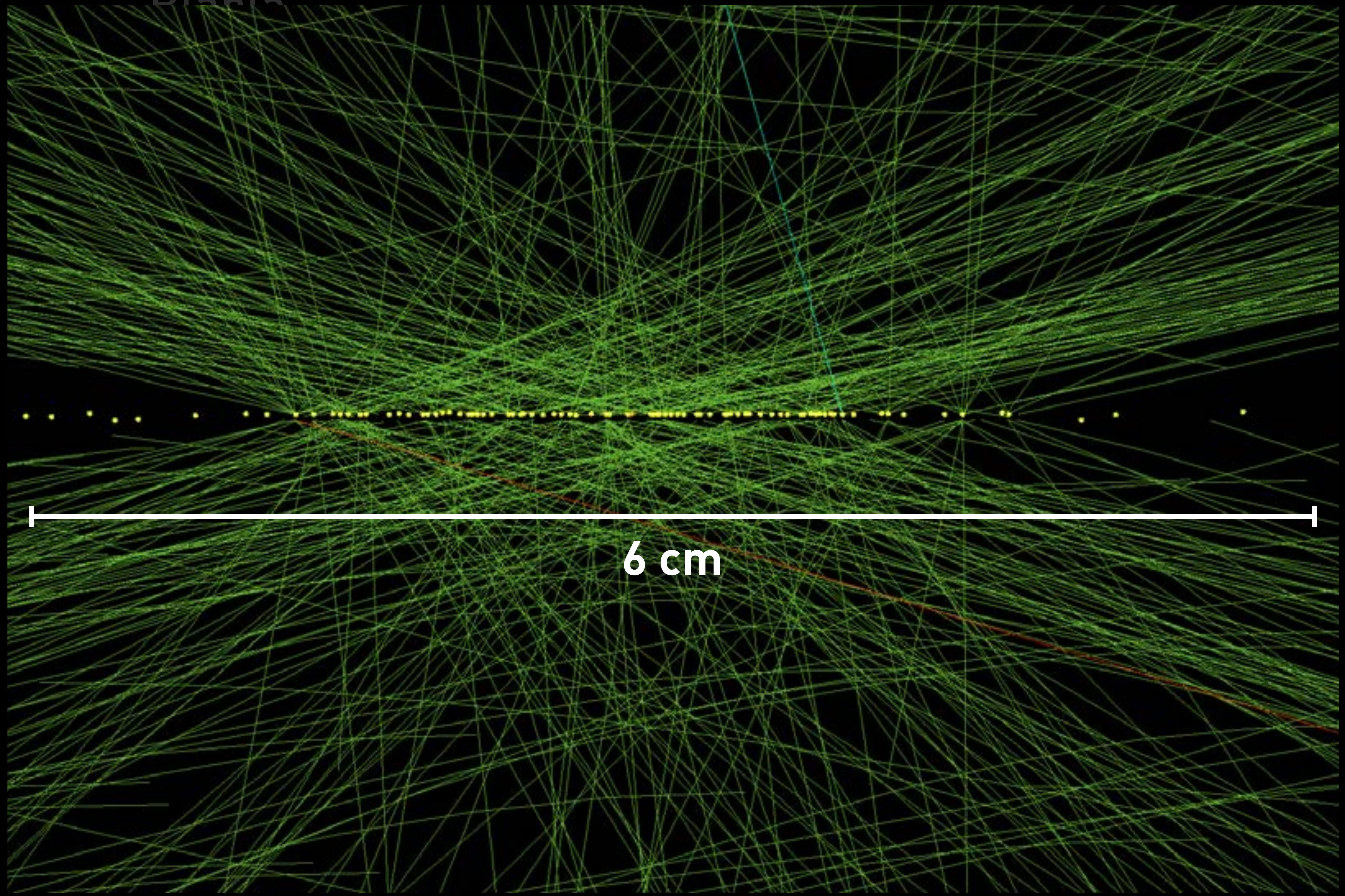
New Physics?

New Physics is produced less than 1 in a trillion (if at all)

Need more data!

LHC

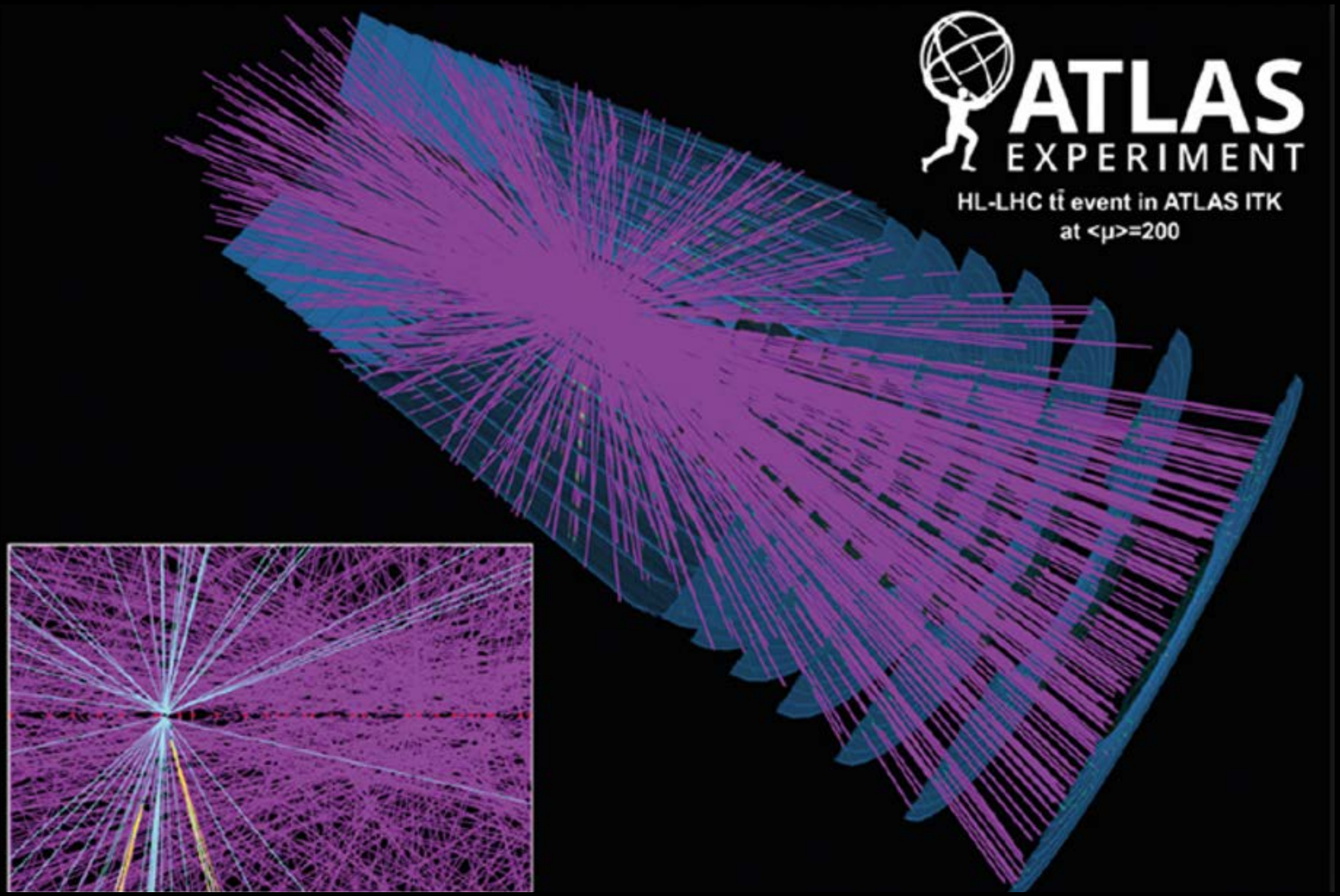
78 vertices
(average 60)



Run 3

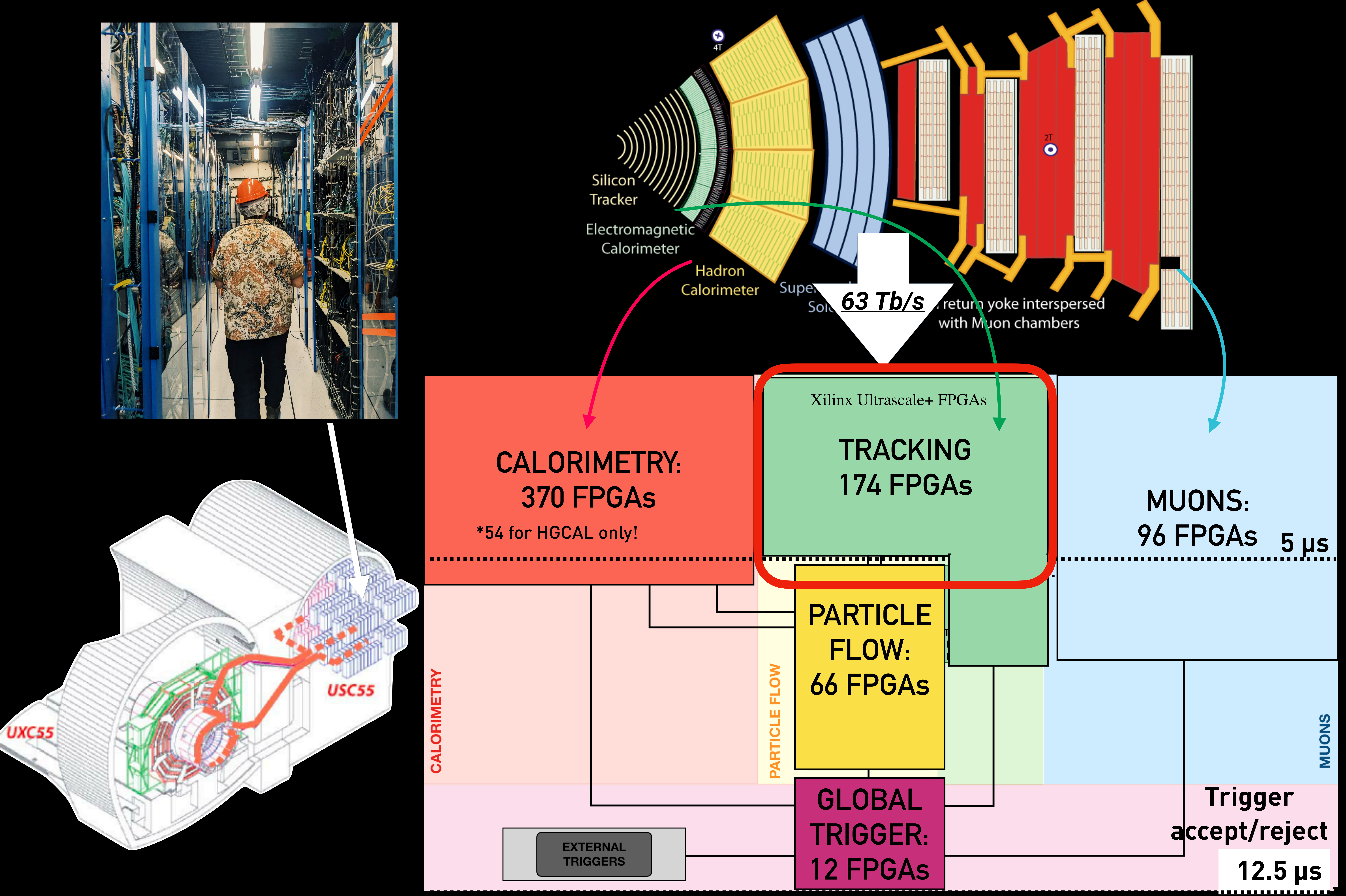
High Luminosity LHC

200 vertices
(average 140)

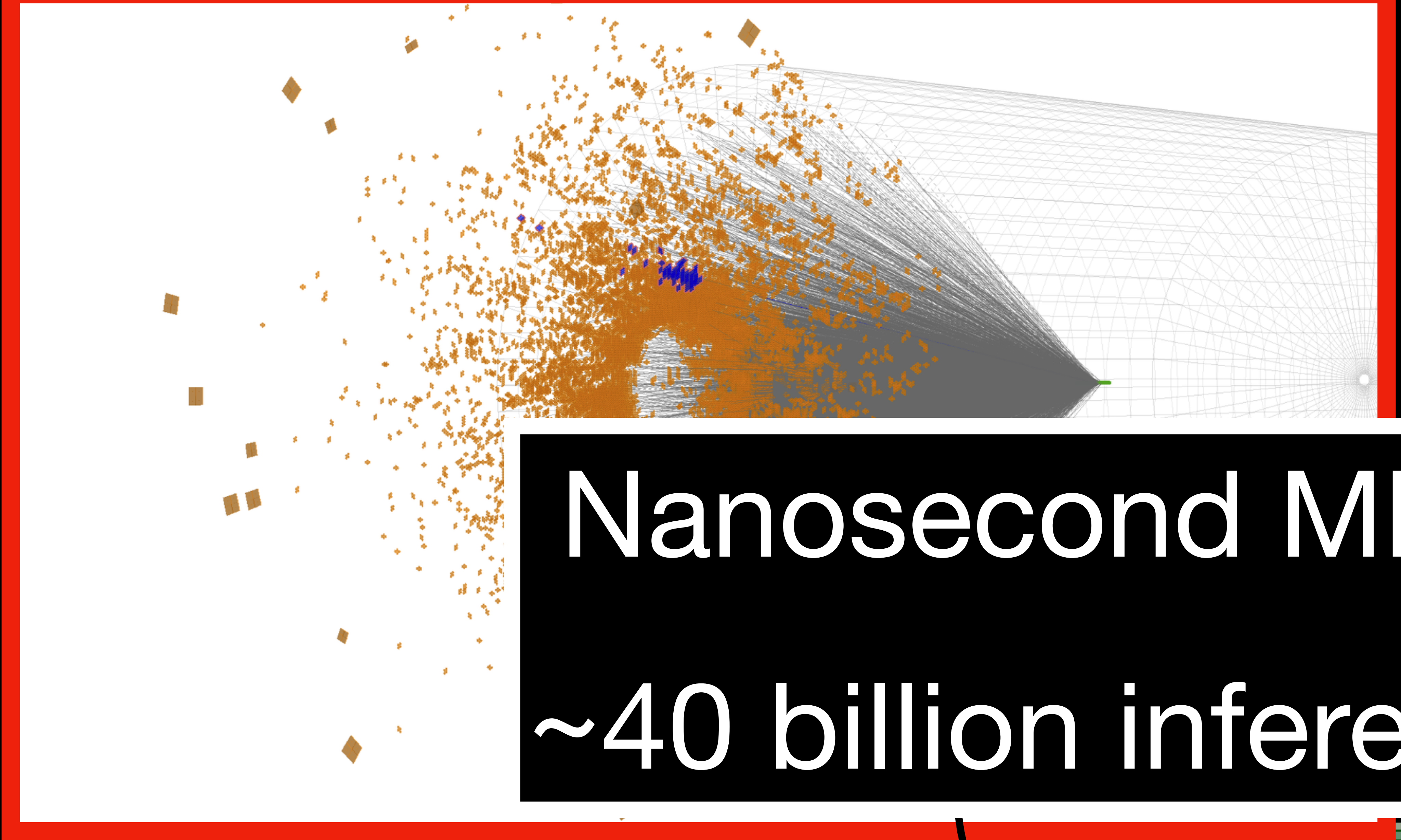


Run 4+5


Geneva
LHCb
ATLAS
ALICE
GPU inference
HLT trigger:
Latency O(100) ms
Fast inference on specialised hardware
ASIC inference
FPGA inference
Level-1 trigger:
Latency O(1) μs
Detector:
40 MHz
~Pb/s



4T
2T
Silicon Tracker
Electromagnetic Calorimeter
Hadron Calorimeter
63 Tb/s
with Muon chambers
Xilinx Ultrascale+ FPGAs
CALORIMETRY: 370 FPGAs
*54 for HGCAL only!
TRACKING 174 FPGAs
MUONS: 96 FPGAs
5 μs
PARTICLE FLOW: 66 FPGAs
GLOBAL TRIGGER: 12 FPGAs
EXTERNAL TRIGGERS
Trigger accept/reject
12.5 μs
CALORIMETRY
PARTICLE FLOW
MUONS
UXC55
USC55

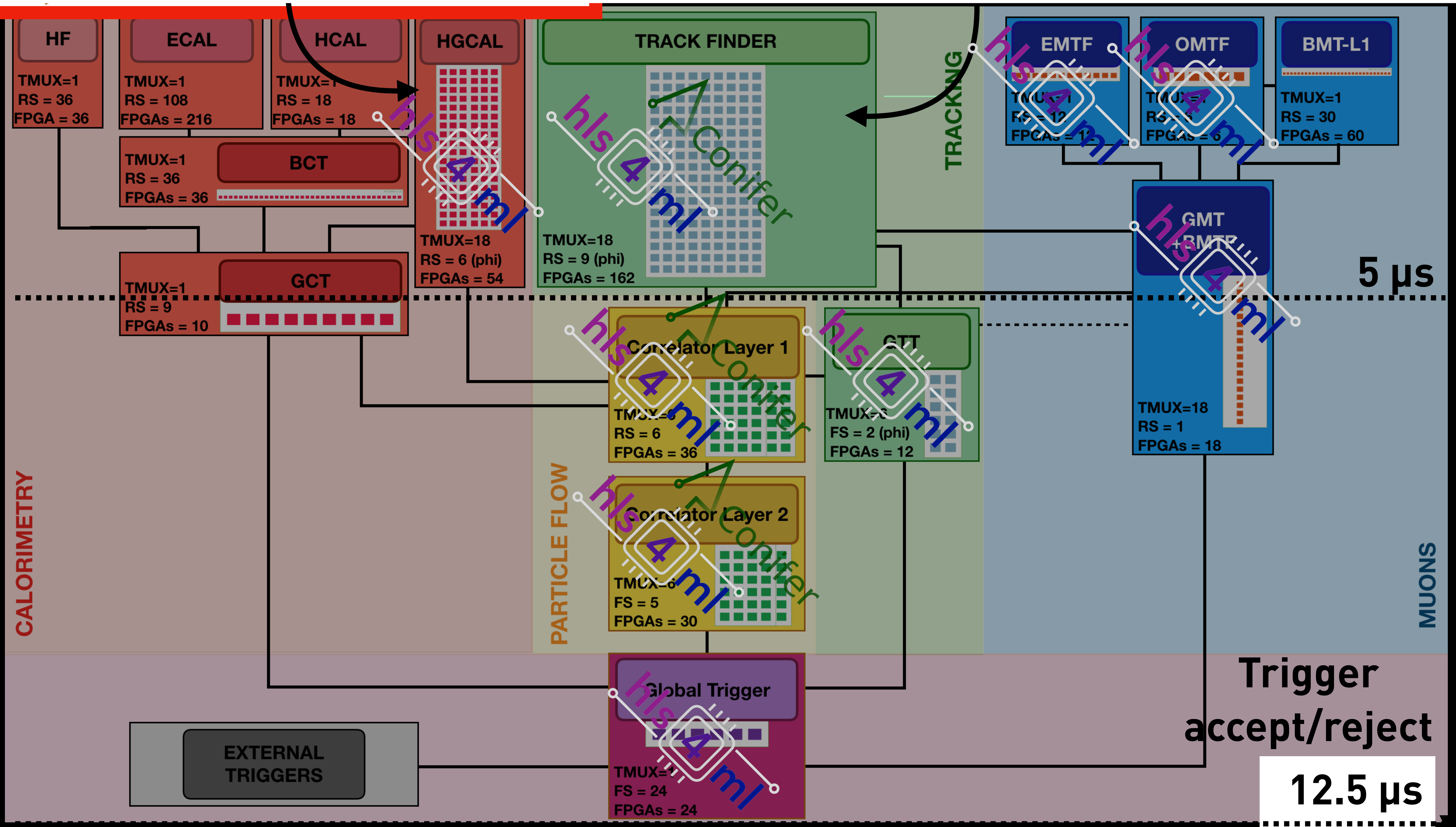


Nanosecond ML inference on FPGAs!

~40 billion inferences/s during HL-LHC

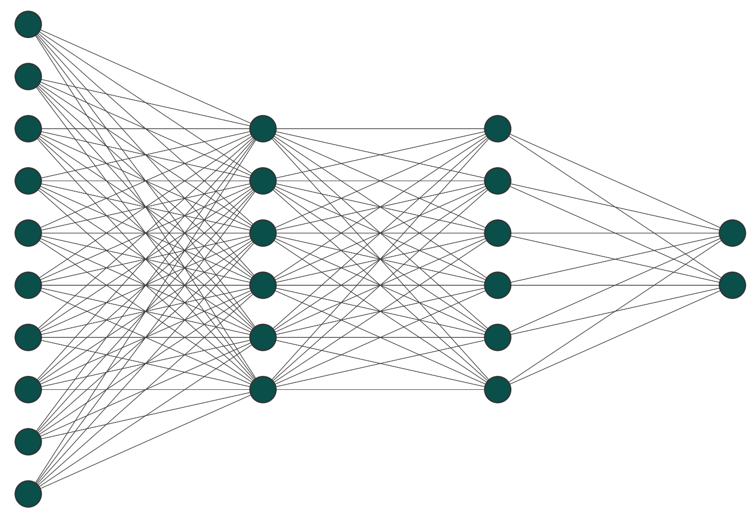
Conifer hls4ml

HEP developed libraries for fast ML on FPGAs



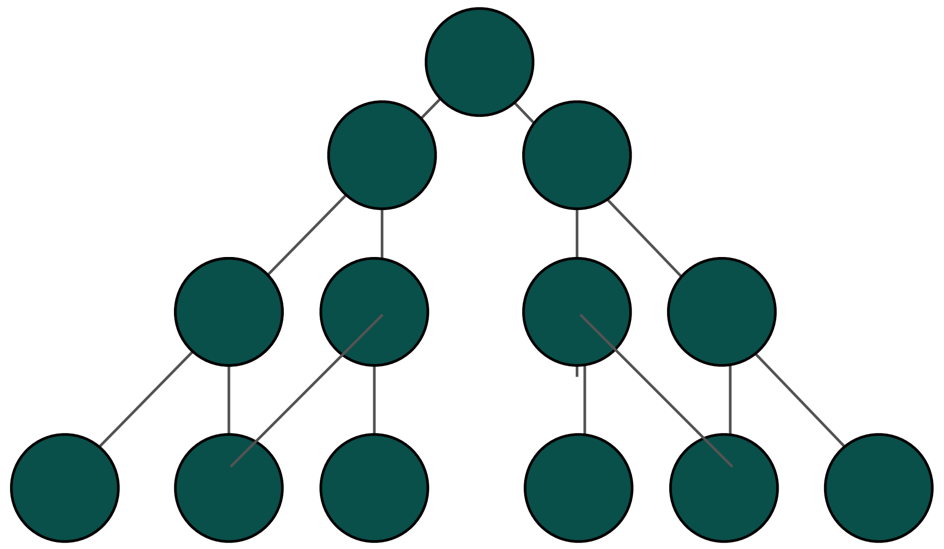
https://github.com/fastmachinelearning/hls4ml
https://fastmachinelearning.org/hls4ml/

KERAS / PyTorch / ONNX



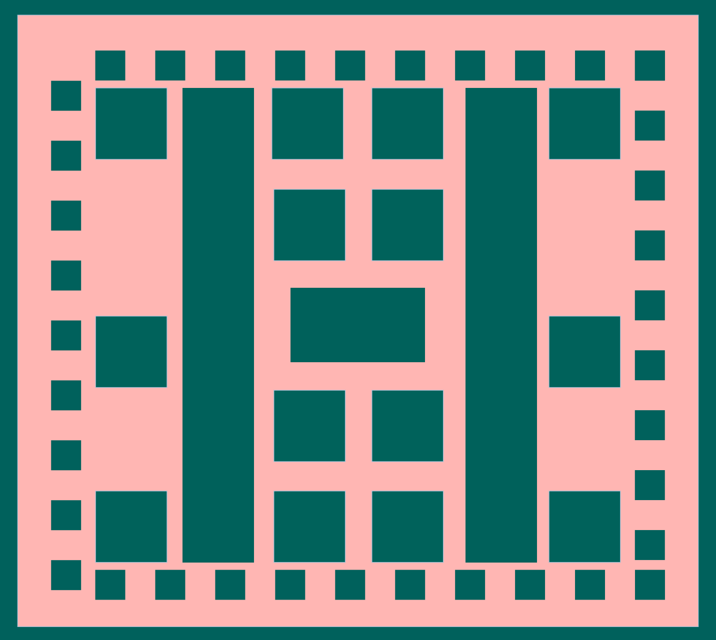
→ **hls4ml** →

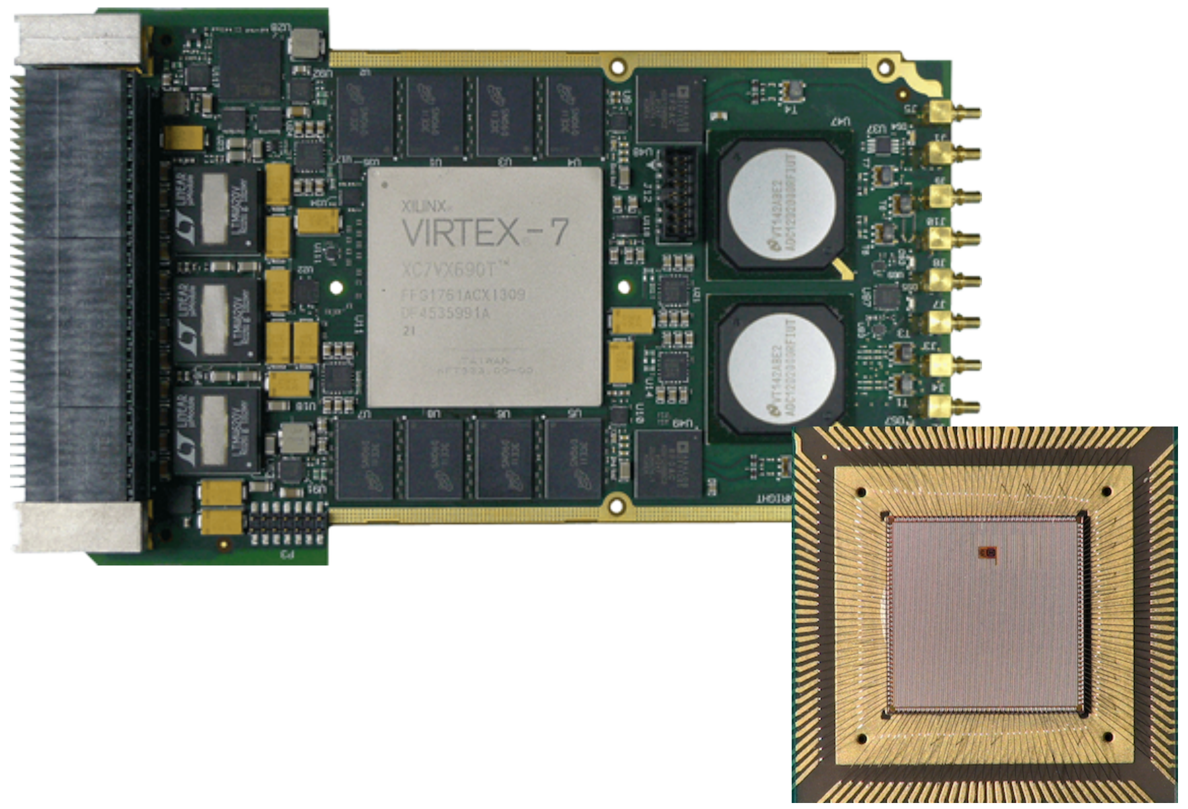
TensorFlow DF / scikit-learn / XGBoost



→ **Conifer** →

HLS project:
Vivado / Vitis / Intel Quartus / IntelOne API / Catapult



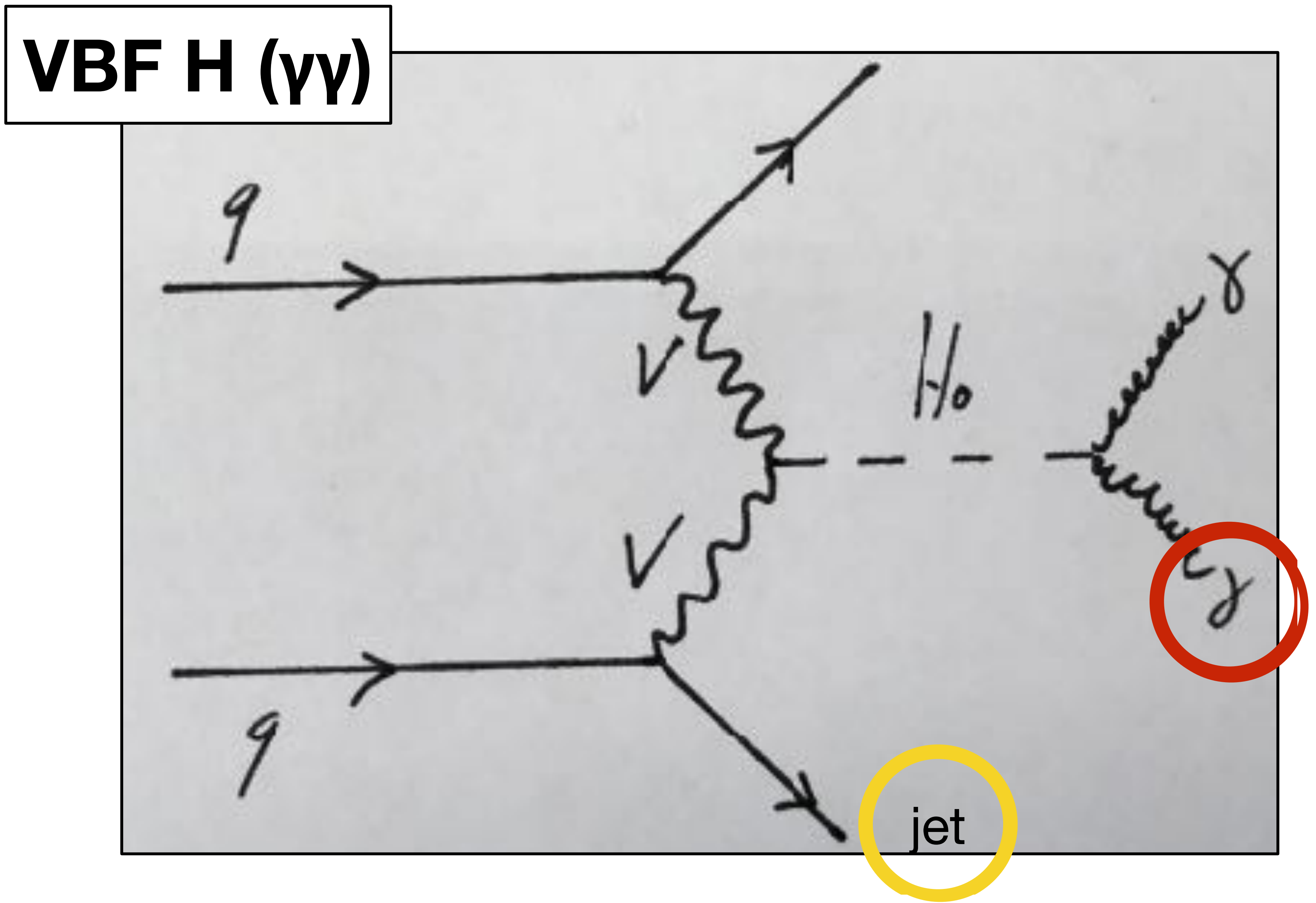



```
pip install hls4ml
pip install conifer
```

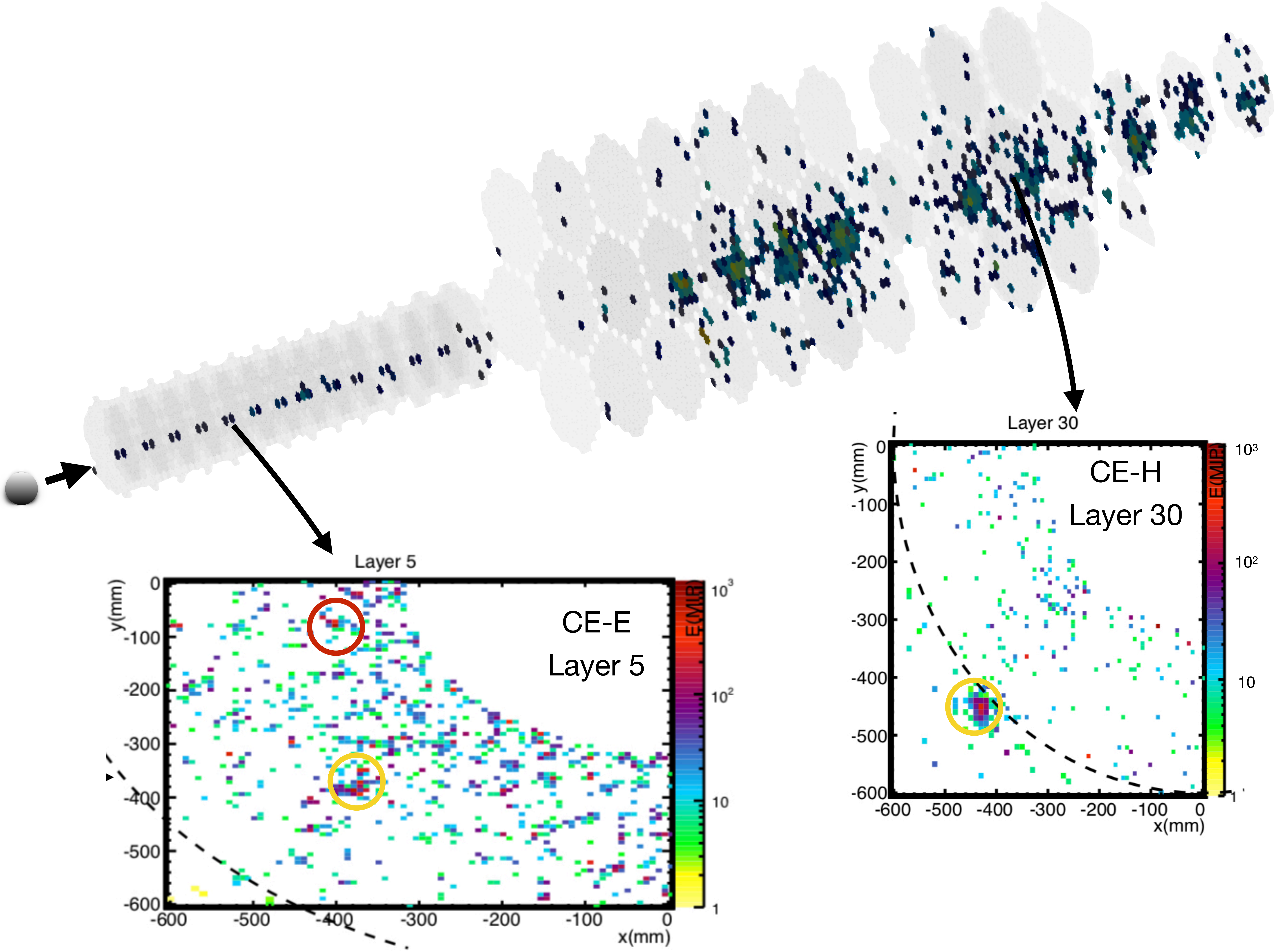

Geneva
Geneva Lake
LHCb
ATLAS
ALICE
CMS
TESLA
ASIC inference
Detector:
40 MHz
~Pb/s
LHC

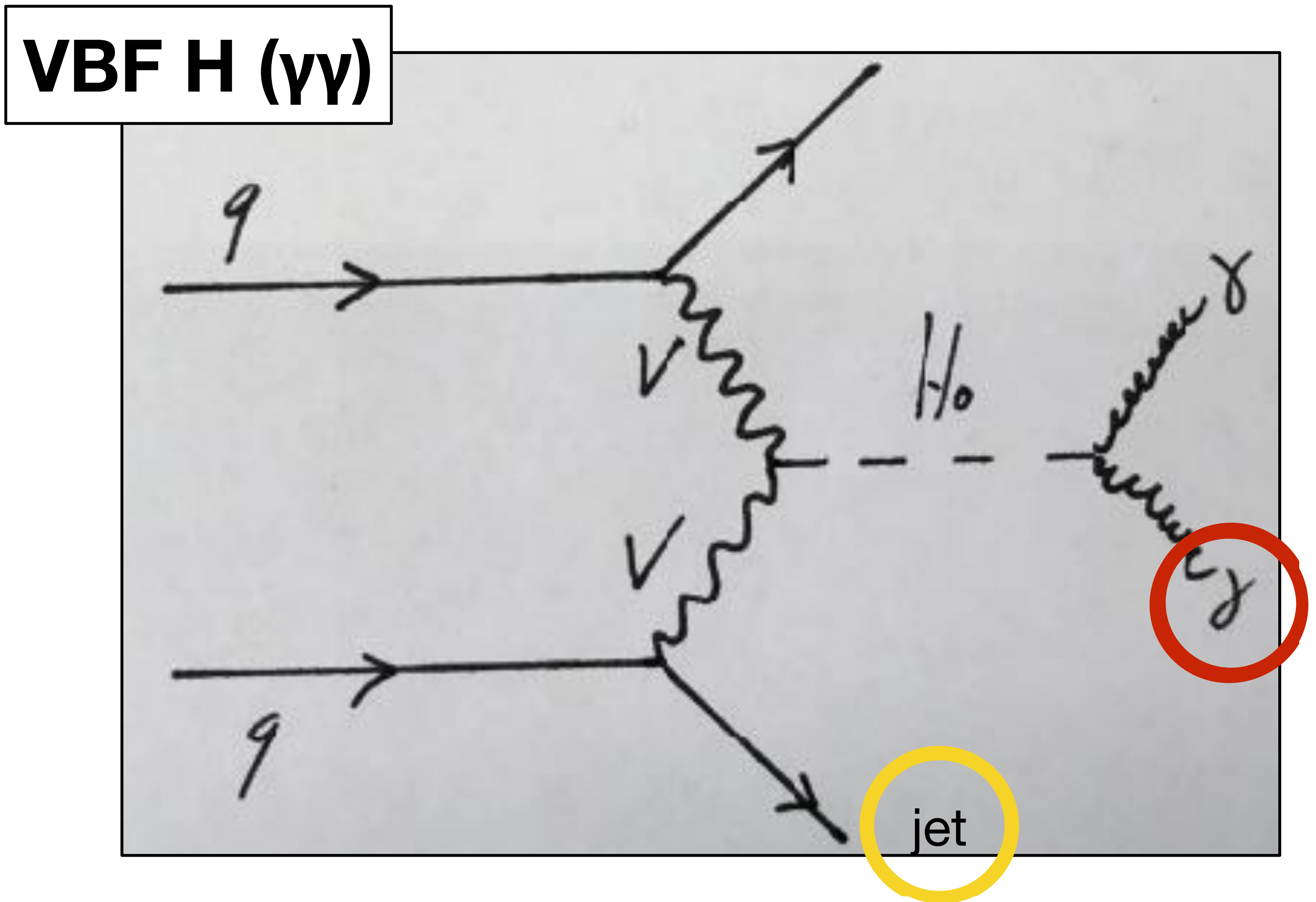
CMS High Granularity calorimeter

- 6.5 million readout channels, 50 layers



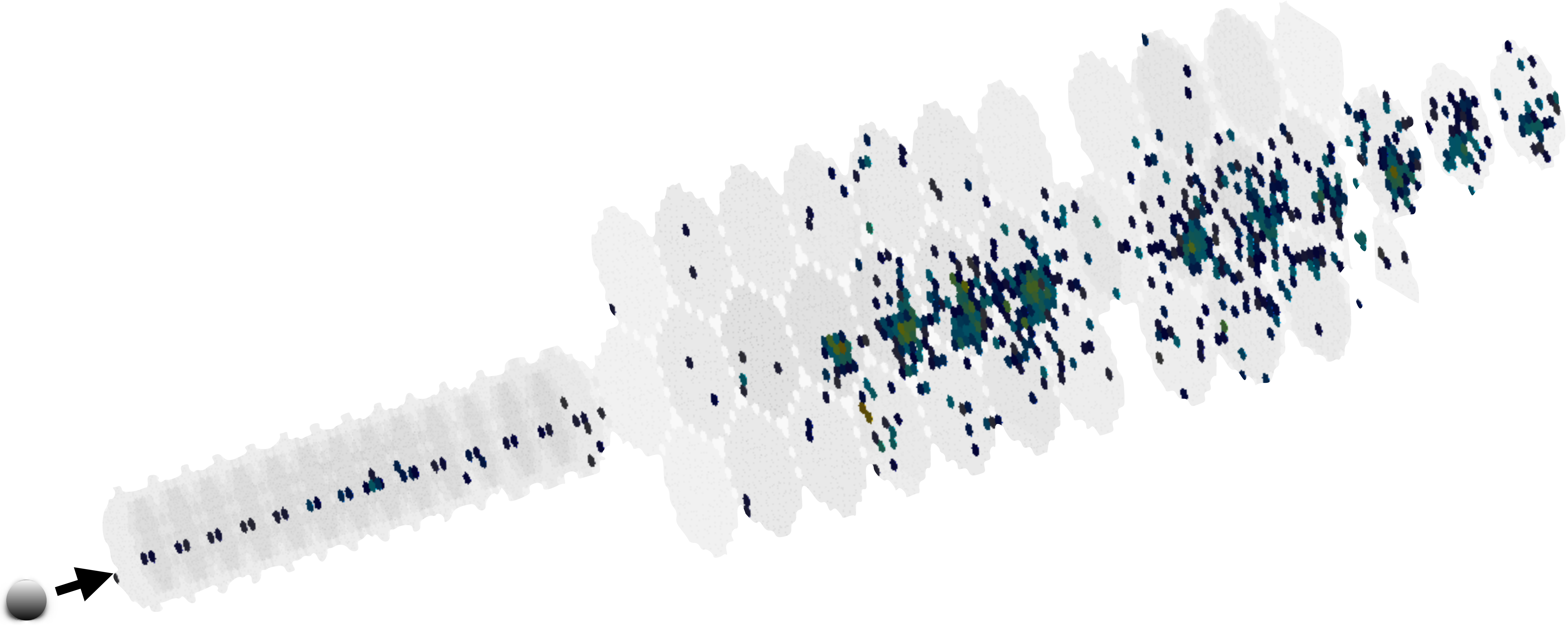
+

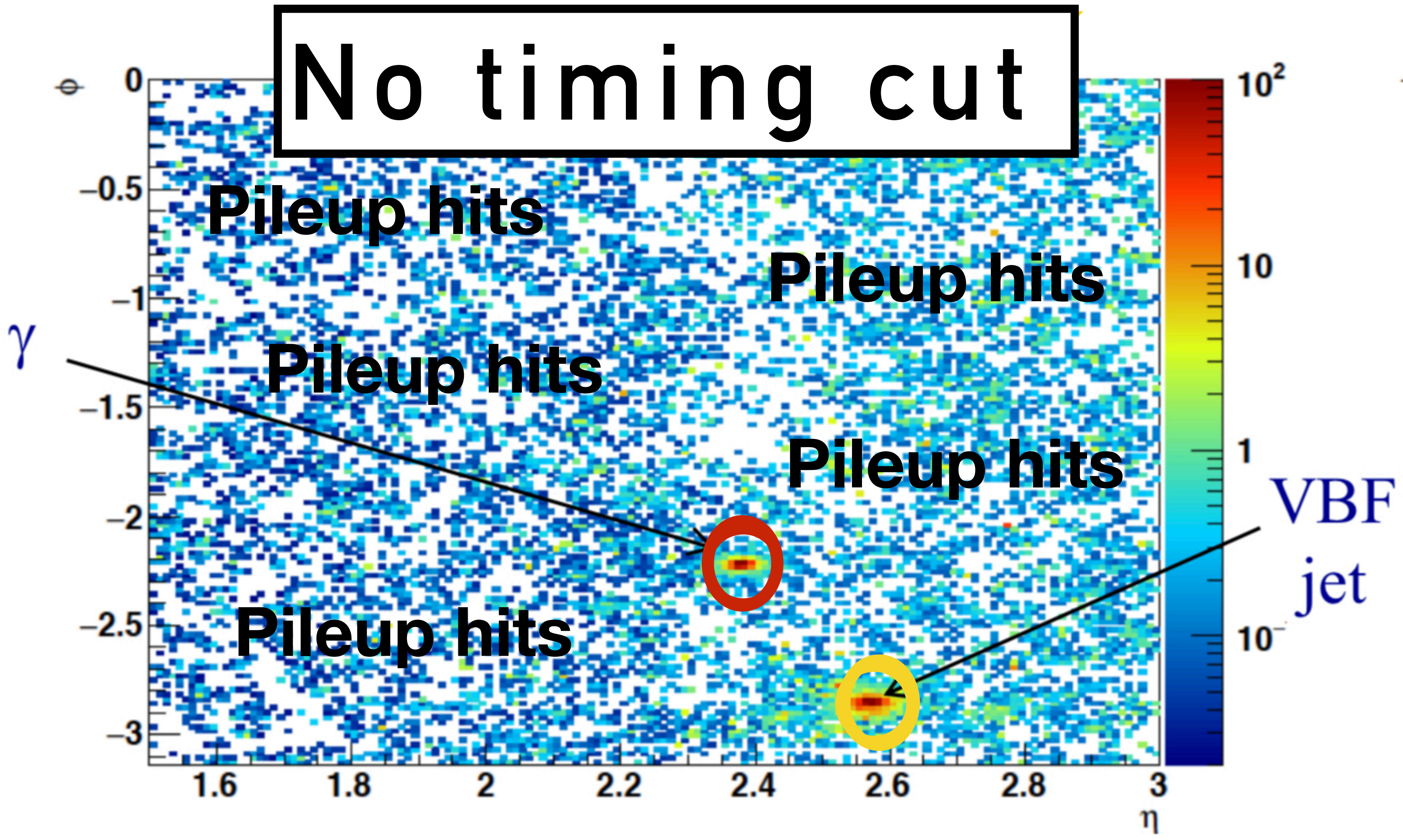


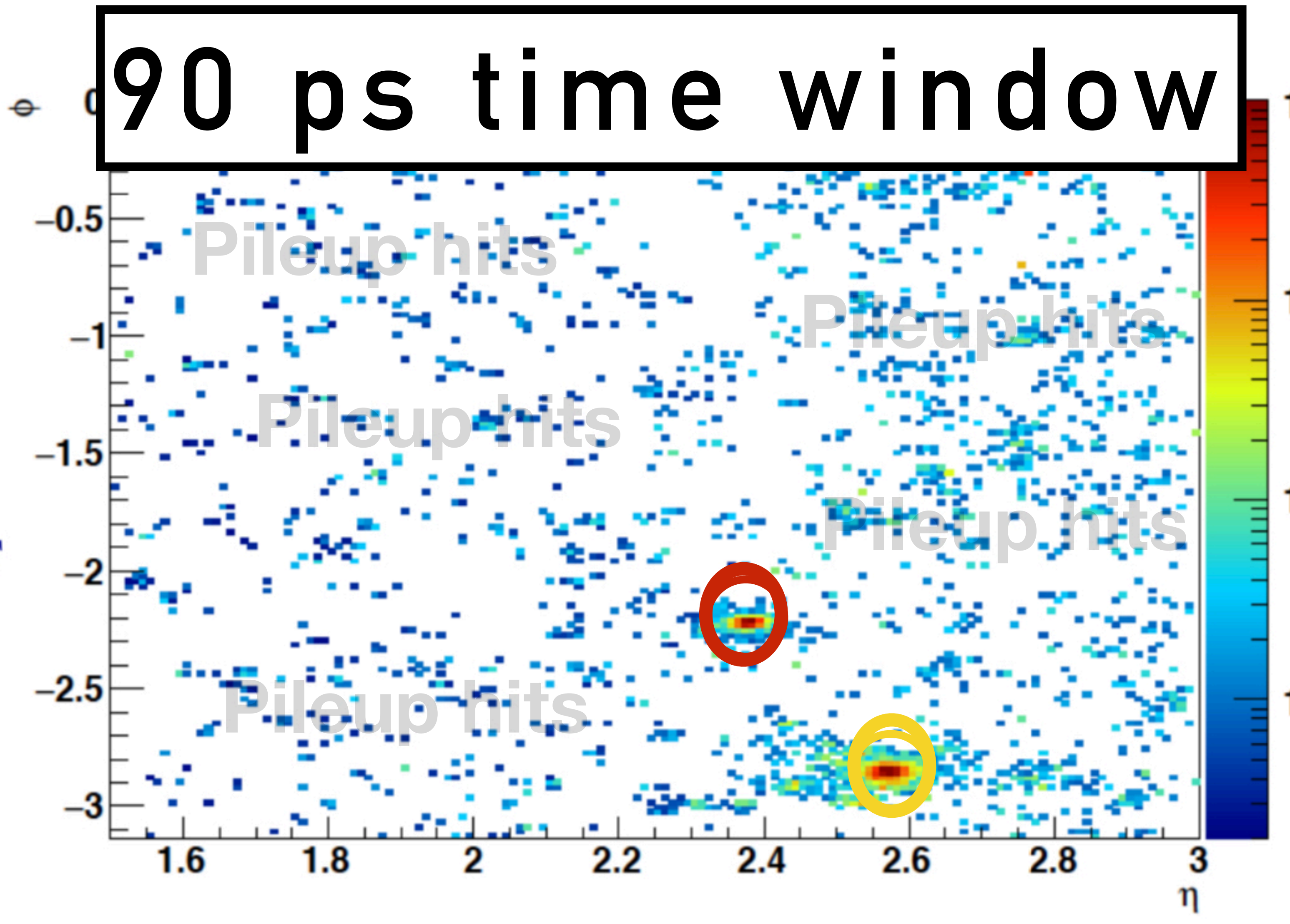

VBF H (γγ)
q
V
Ho
γ
V
q
jet

+

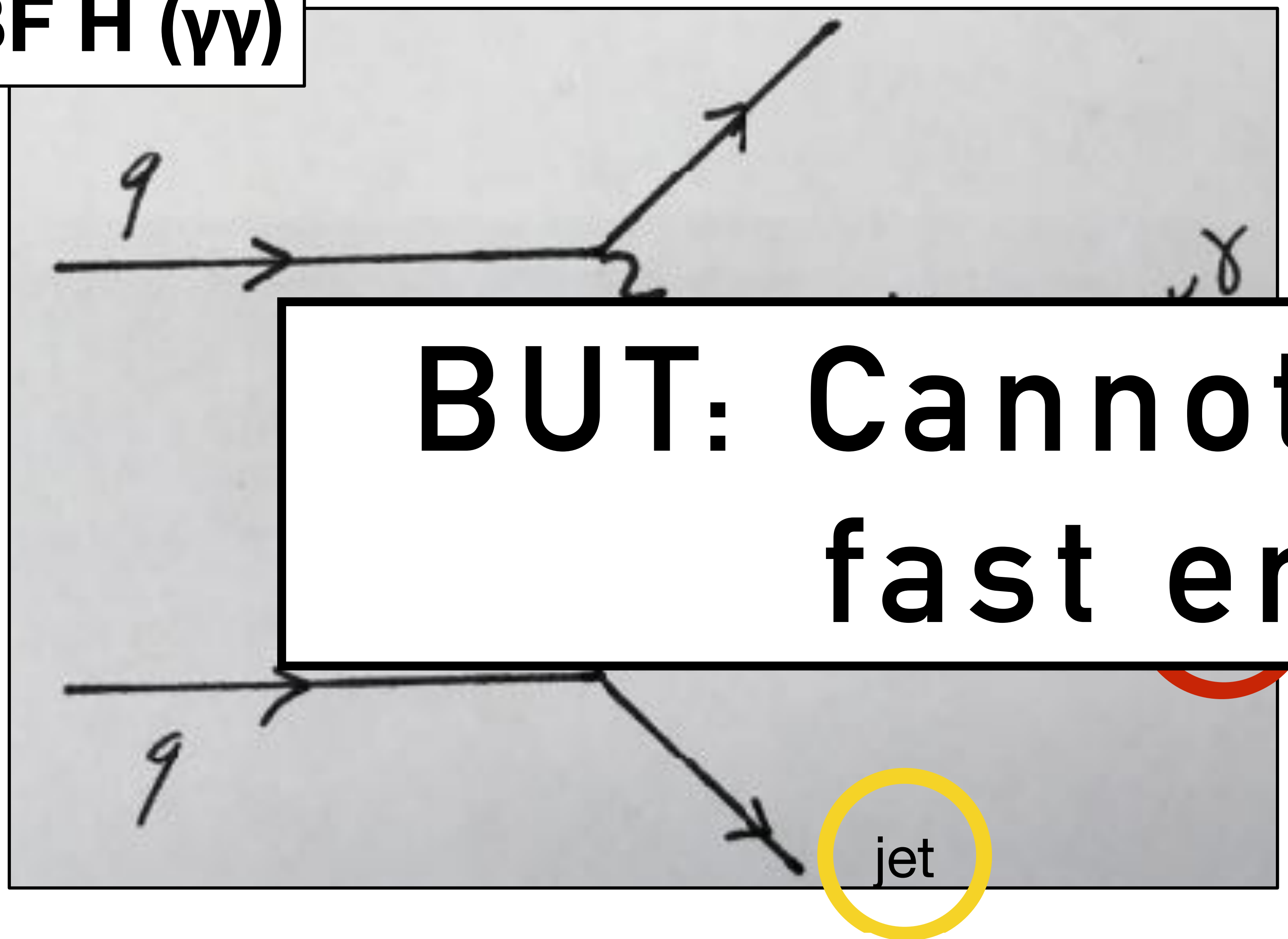

200 vertices

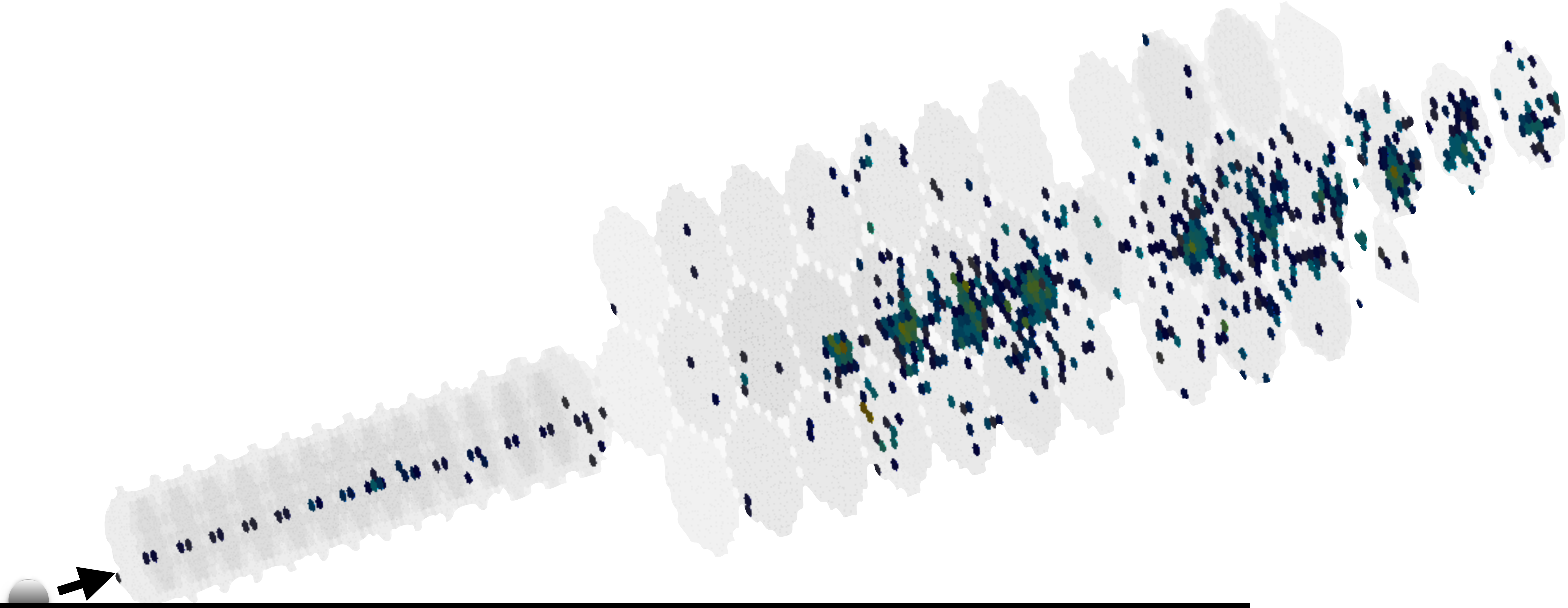



No timing cut
Pileup hits
Pileup hits
Pileup hits
Pileup hits
Pileup hits
γ
VBF jet
φ
η
1.6
1.8
2
2.2
2.4
2.6
2.8
3
0
−0.5
−1
−1.5
−2
−2.5
−3
10²
10
1


90 ps time window
φ
η
1.6
1.8
2
2.2
2.4
2.6
2.8
3
−0.5
−1
−1.5
−2
−2.5
−3

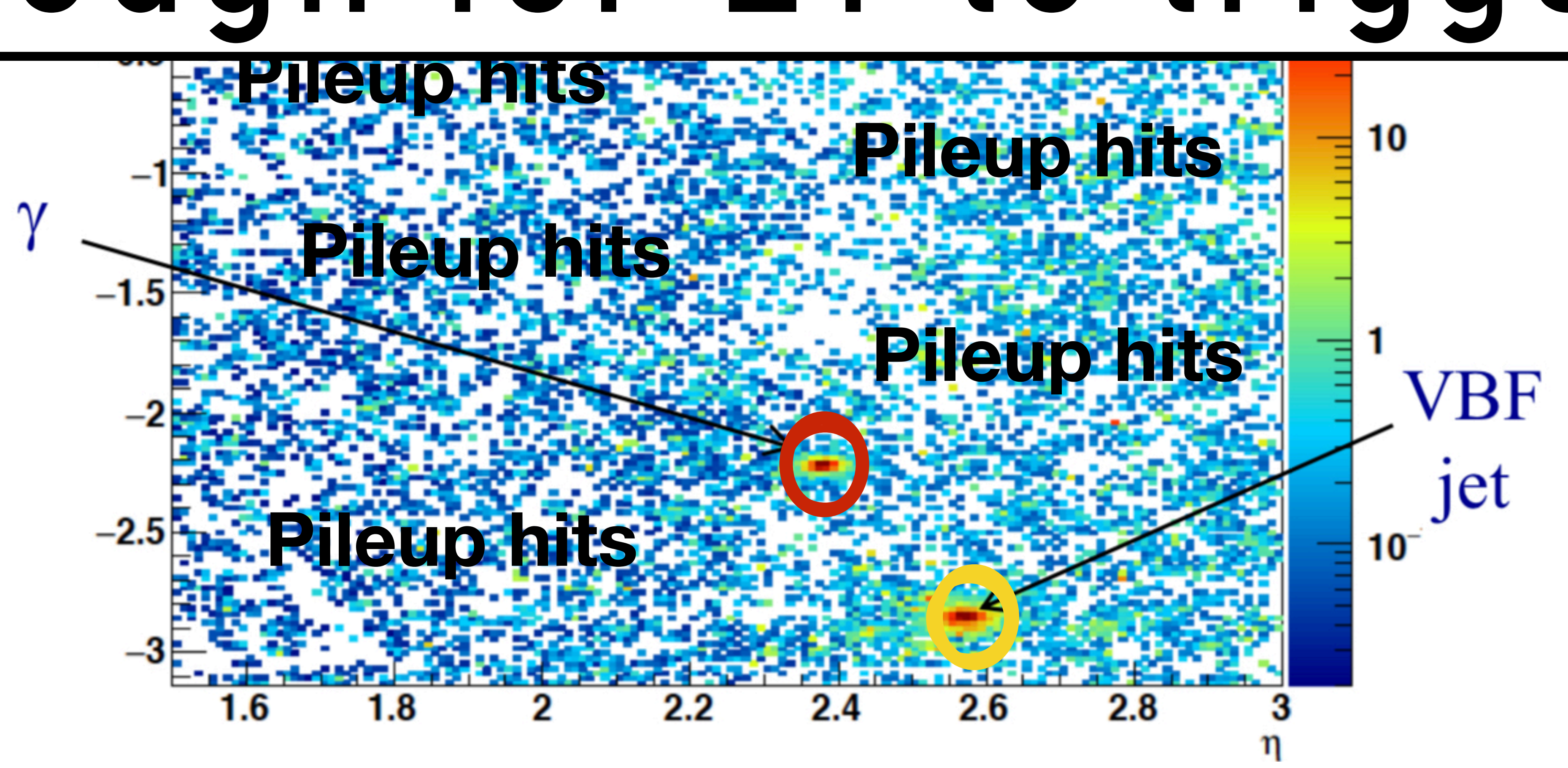
VBF H (γγ)



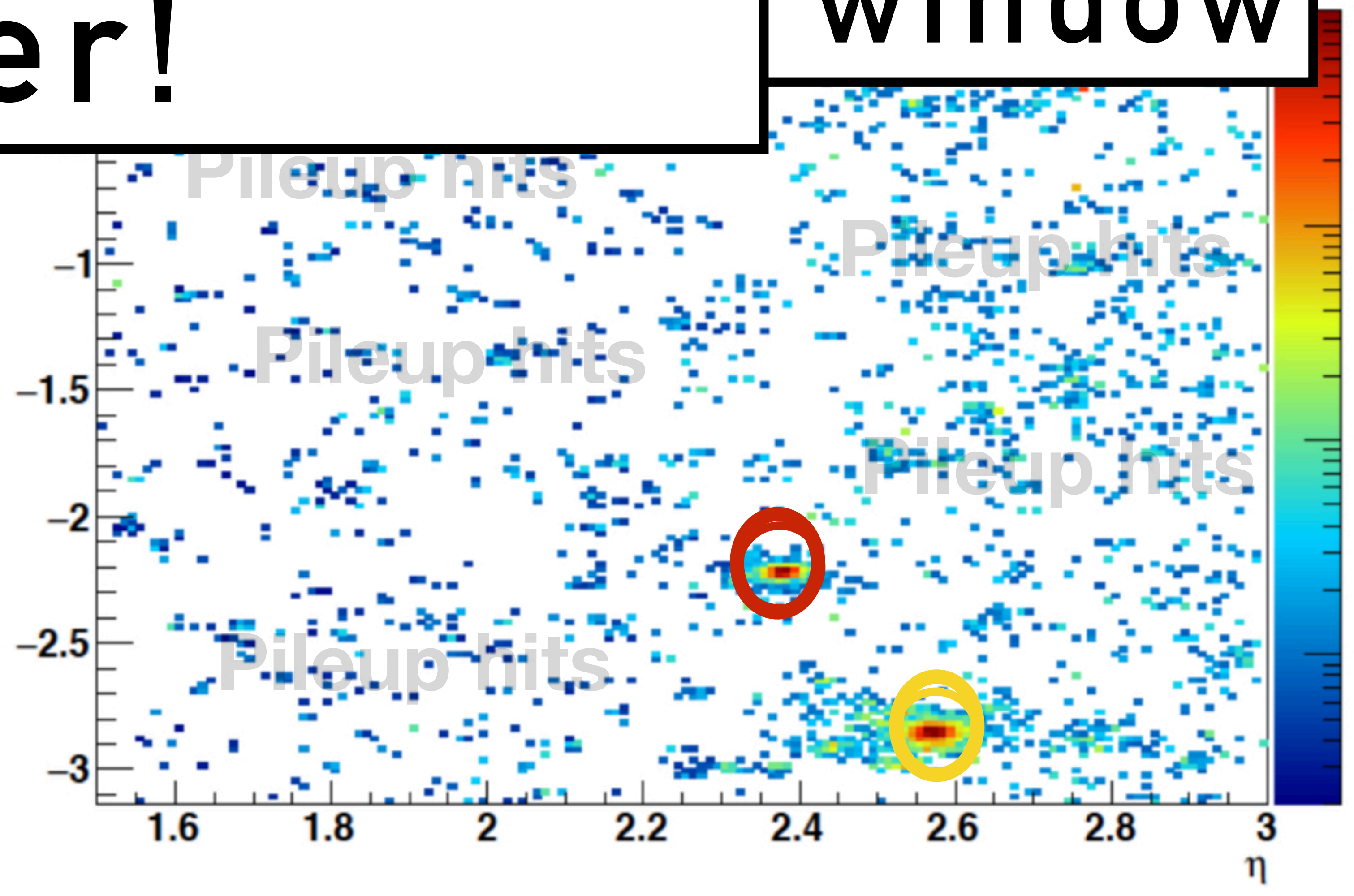


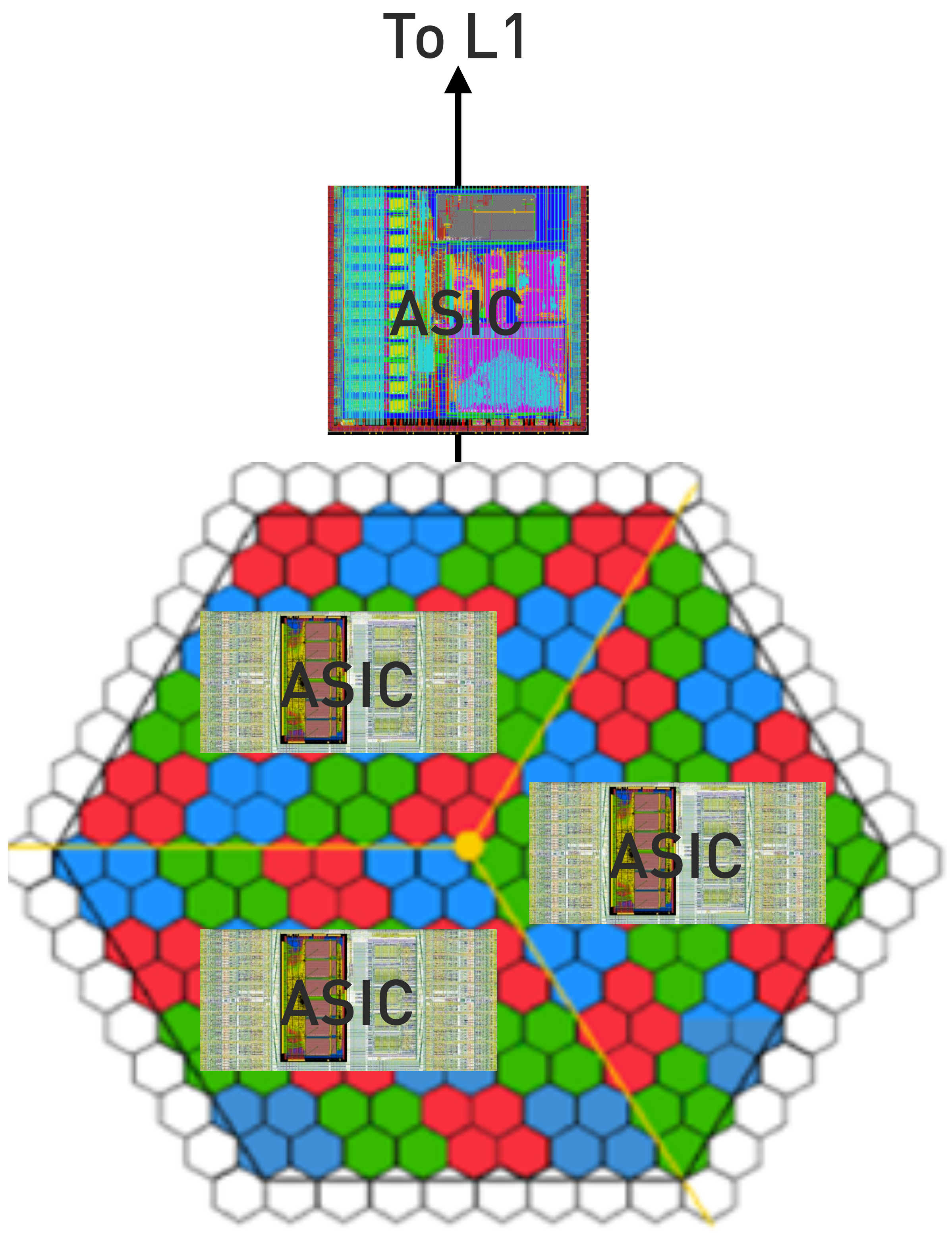
\+

BUT: Cannot read out all these channels fast enough for L1 to trigger!



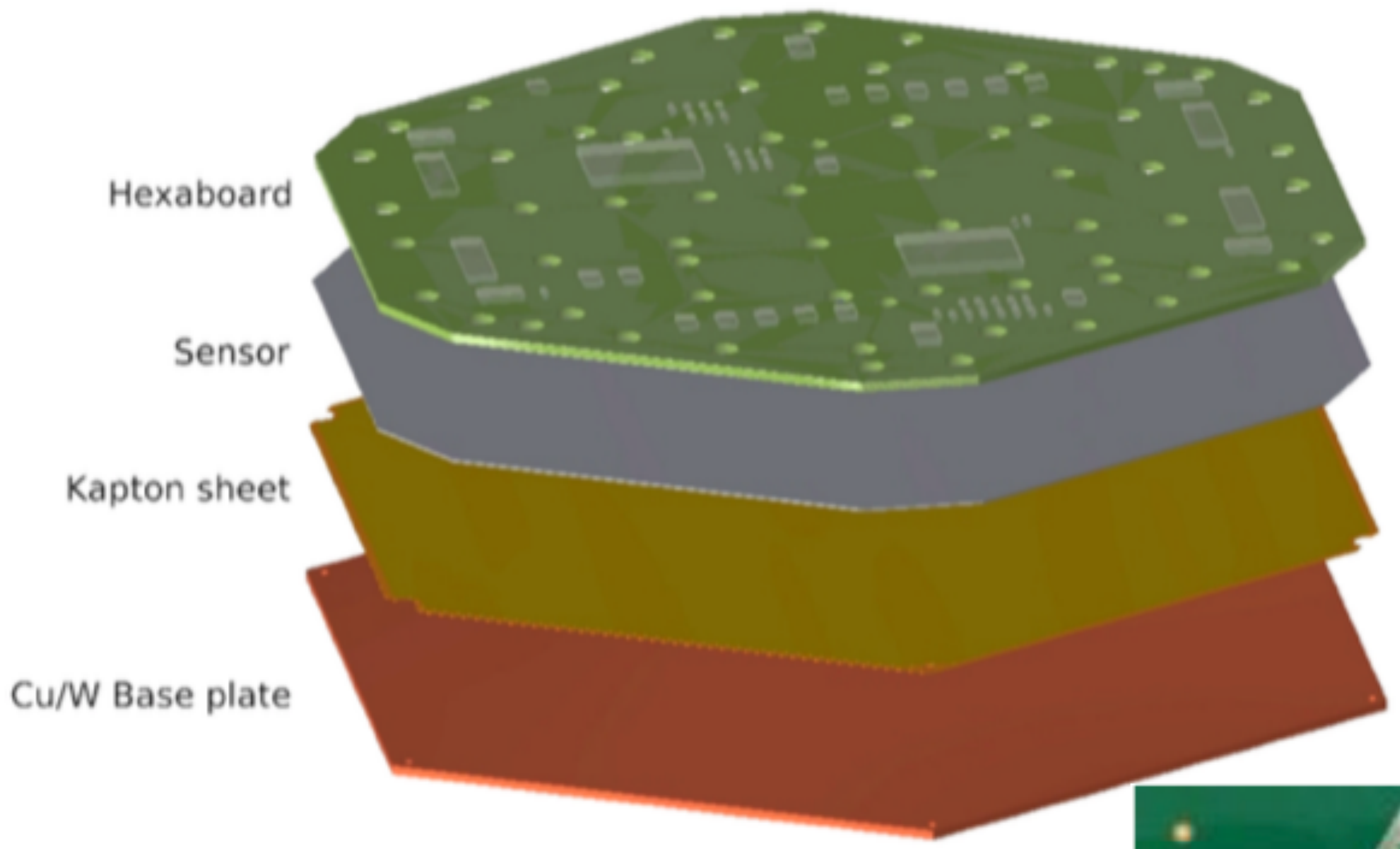
window

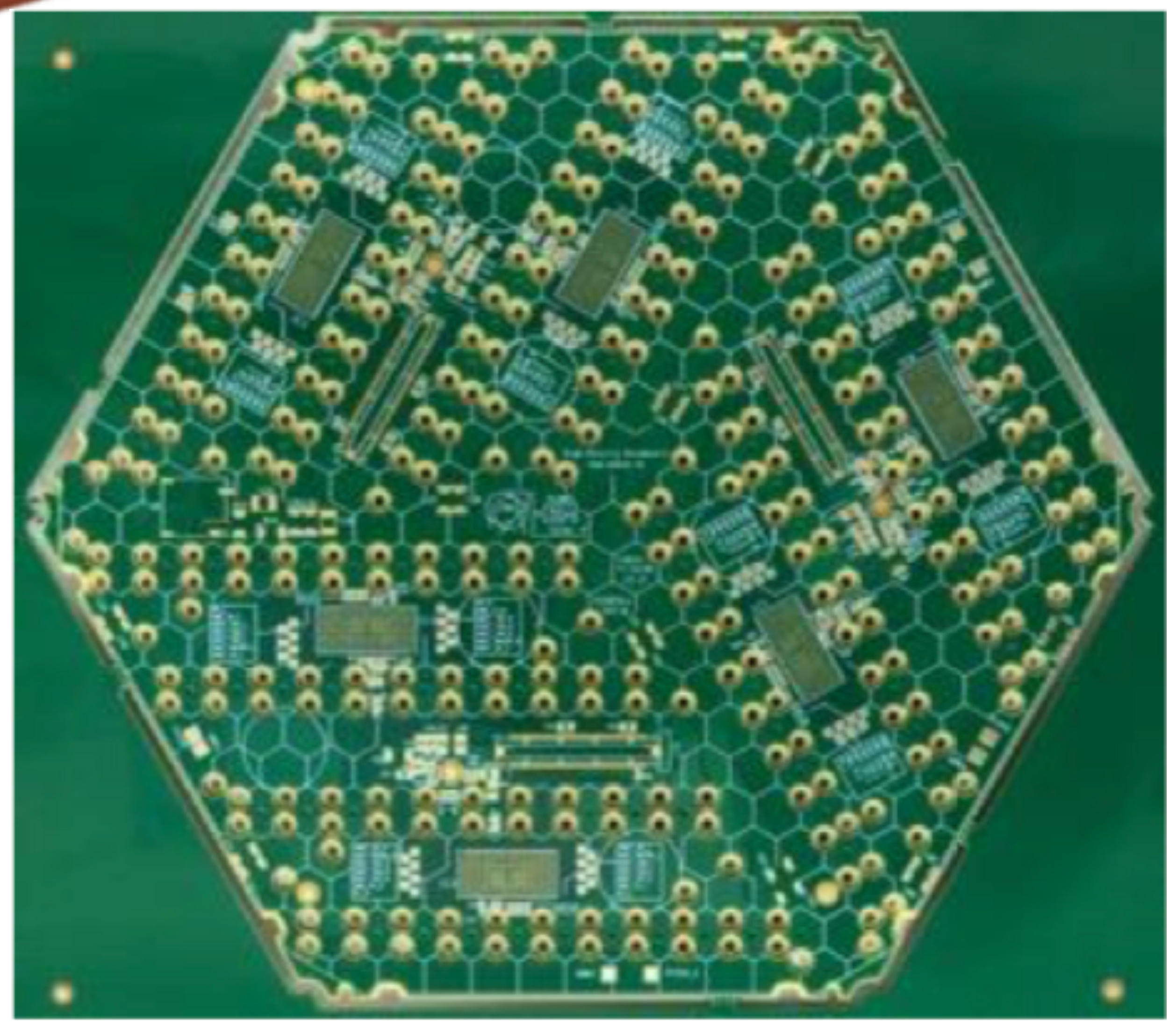


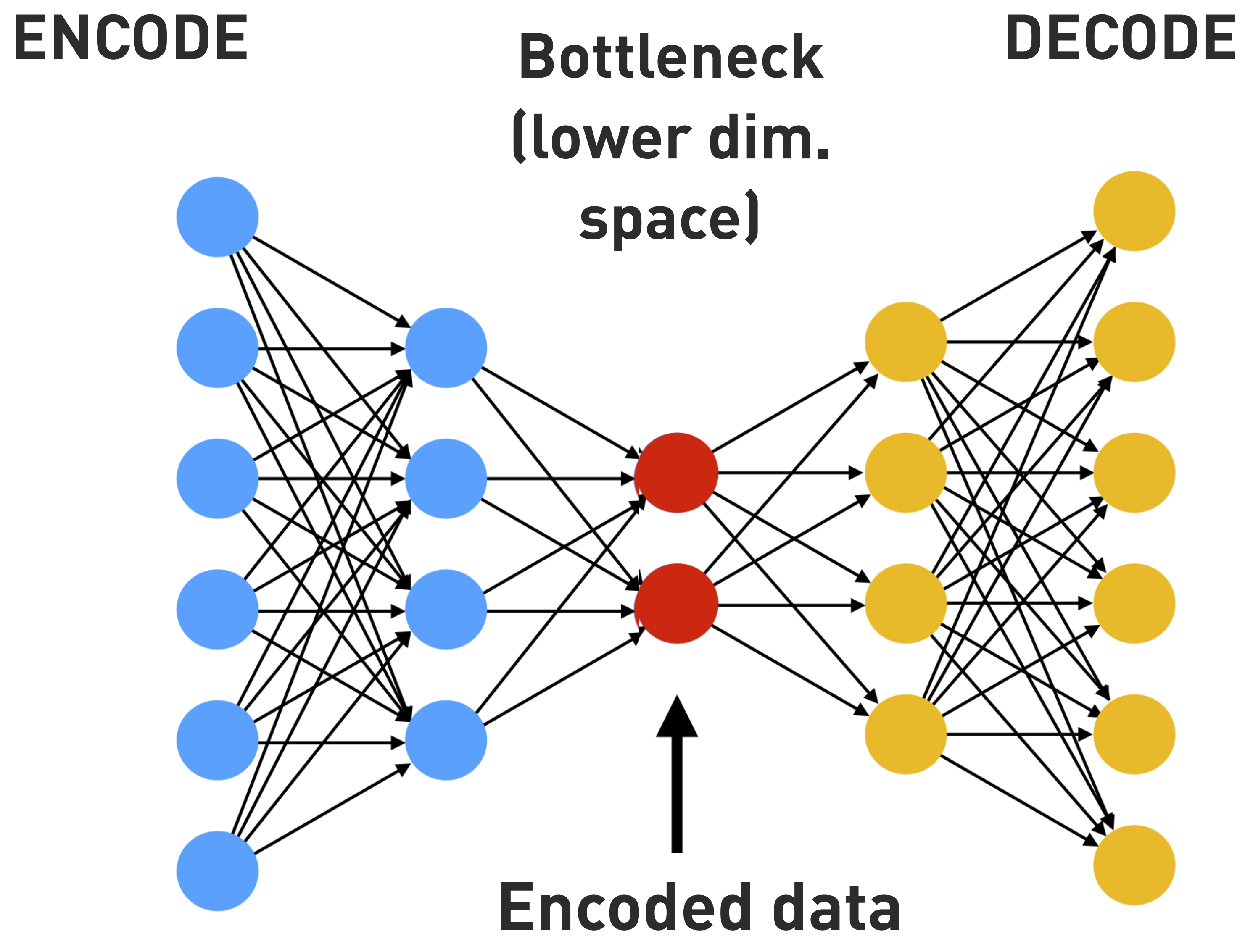


Compress data ON the detector

- ASICs reduce + transmit data
  - 40 MHz trigger data
  - 750 kHz DAQ data
- High radiation
- Cooled to -30 → low power (Max 500 mW total)
- 1.5 μs latency



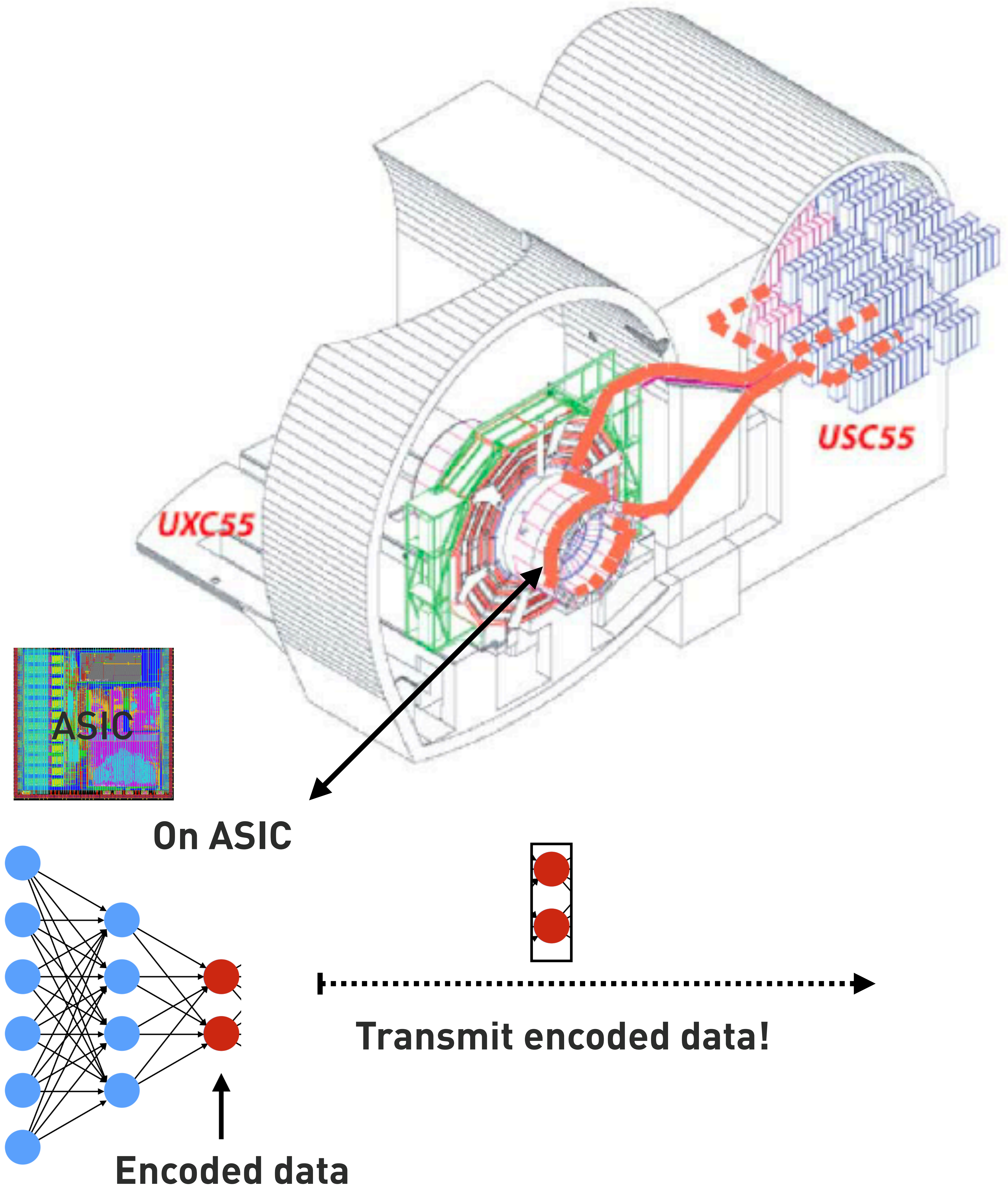




Variational Autoencoder

ECON-T, D. Noonan

AEs for compression also at LHCb!



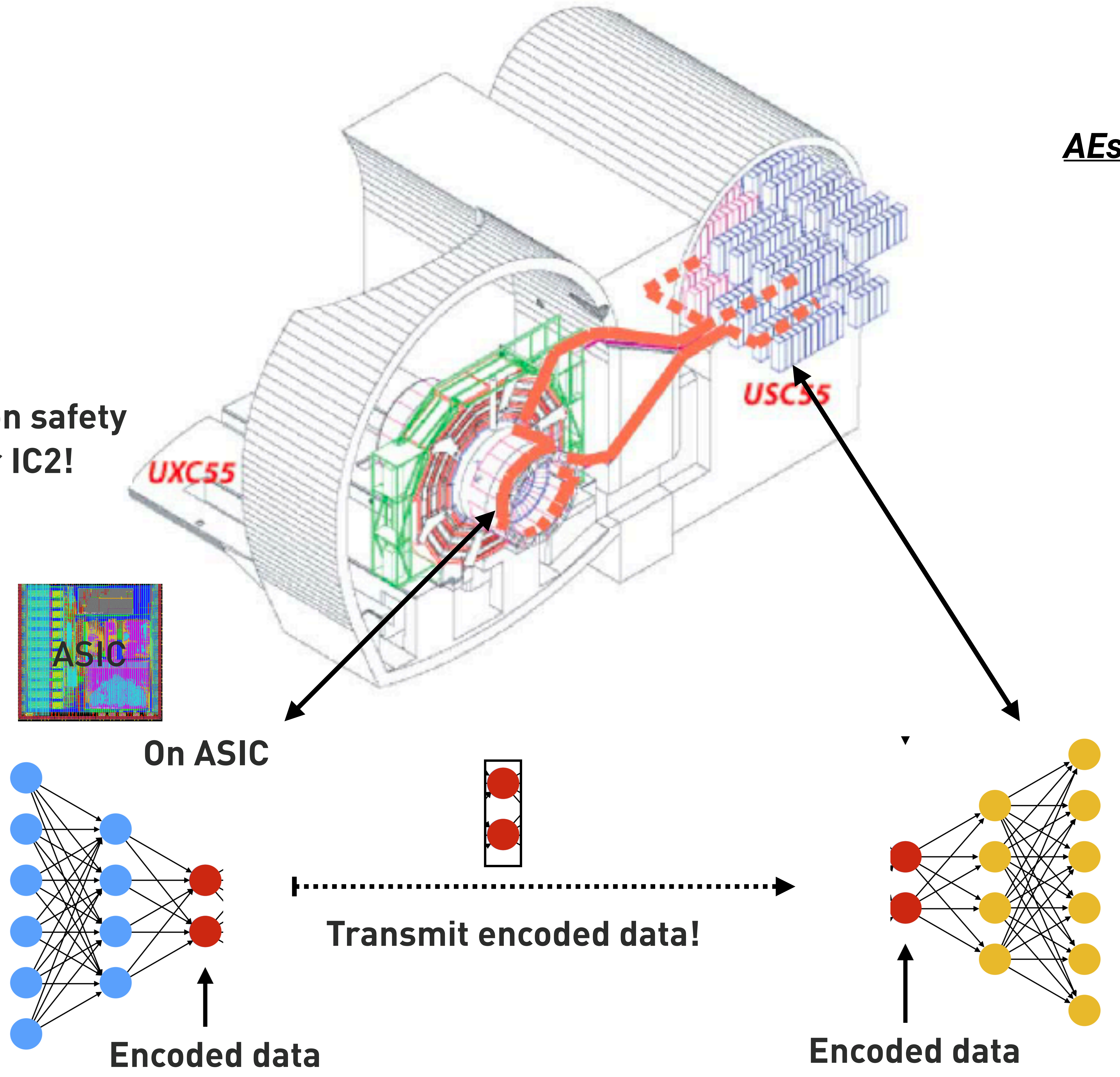
ECON-T, D. Noonan

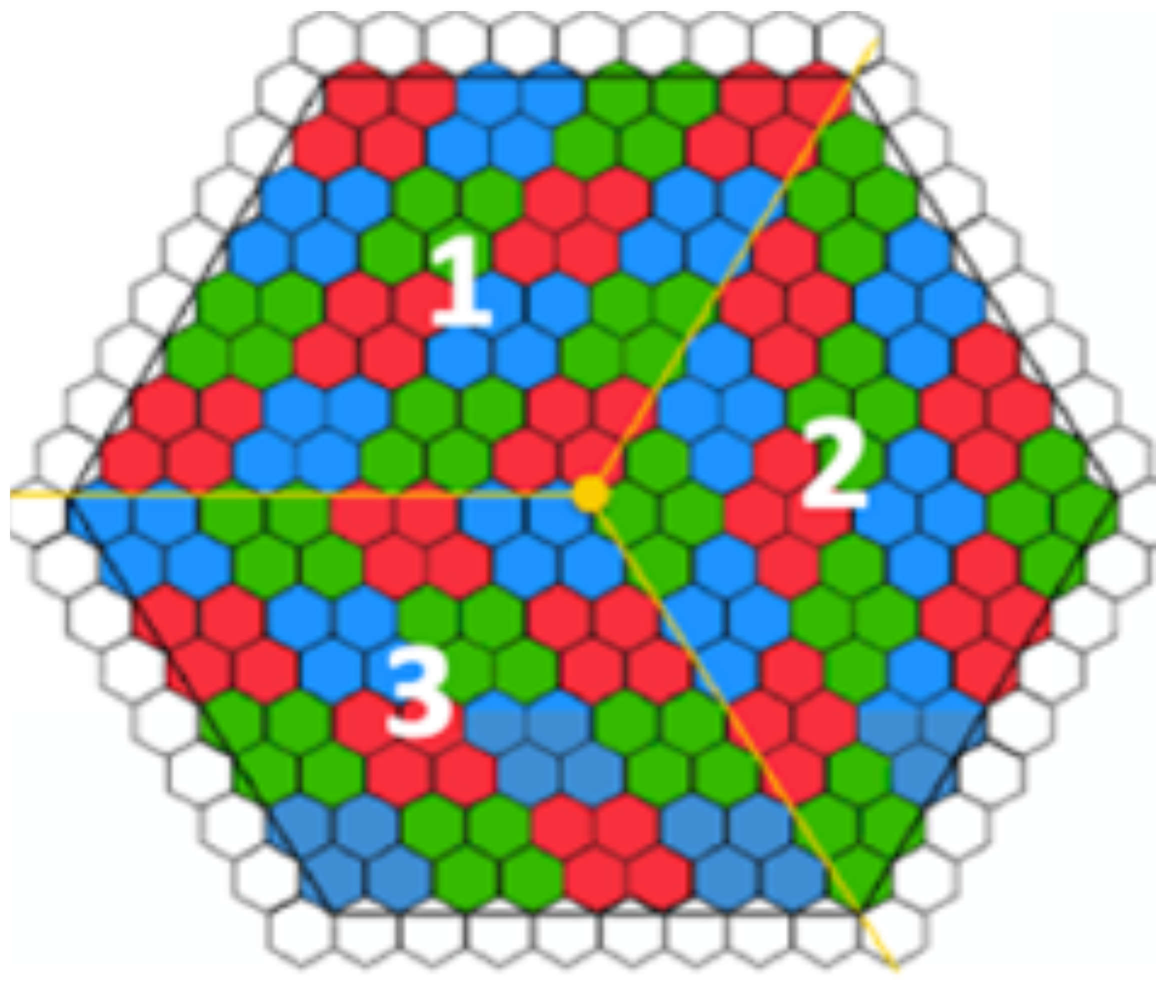
AEs for compression also at LHCb!

ECON-T, D. Noonan

AEs for compression also at LHCb!

- 75-100 mW
- Triplicated w/b for radiation safety
  Reprogrammable w/b over IC2!





ECON-T, D. Noonan

AEs for compression also at LHCb!

- 75-100 mW
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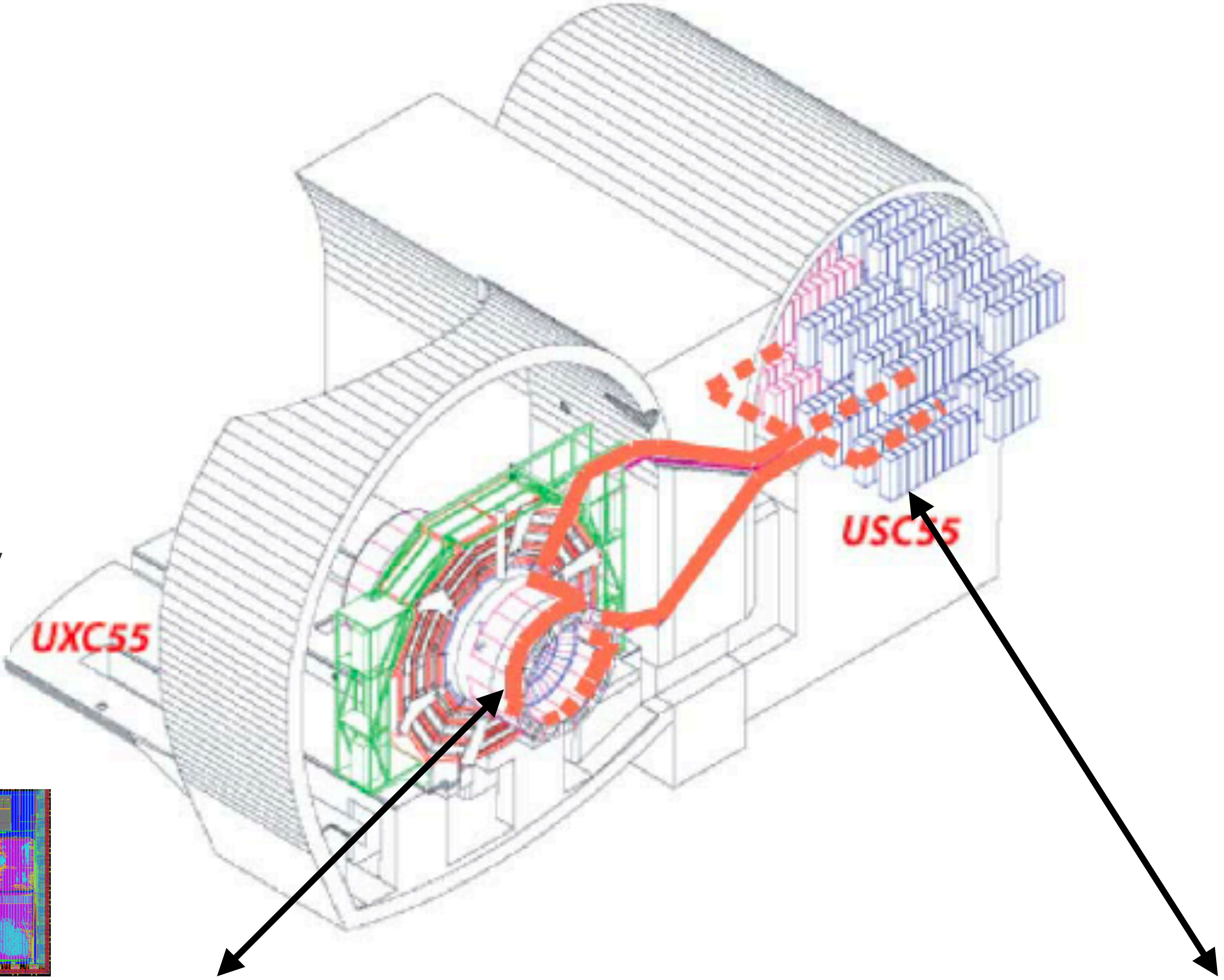
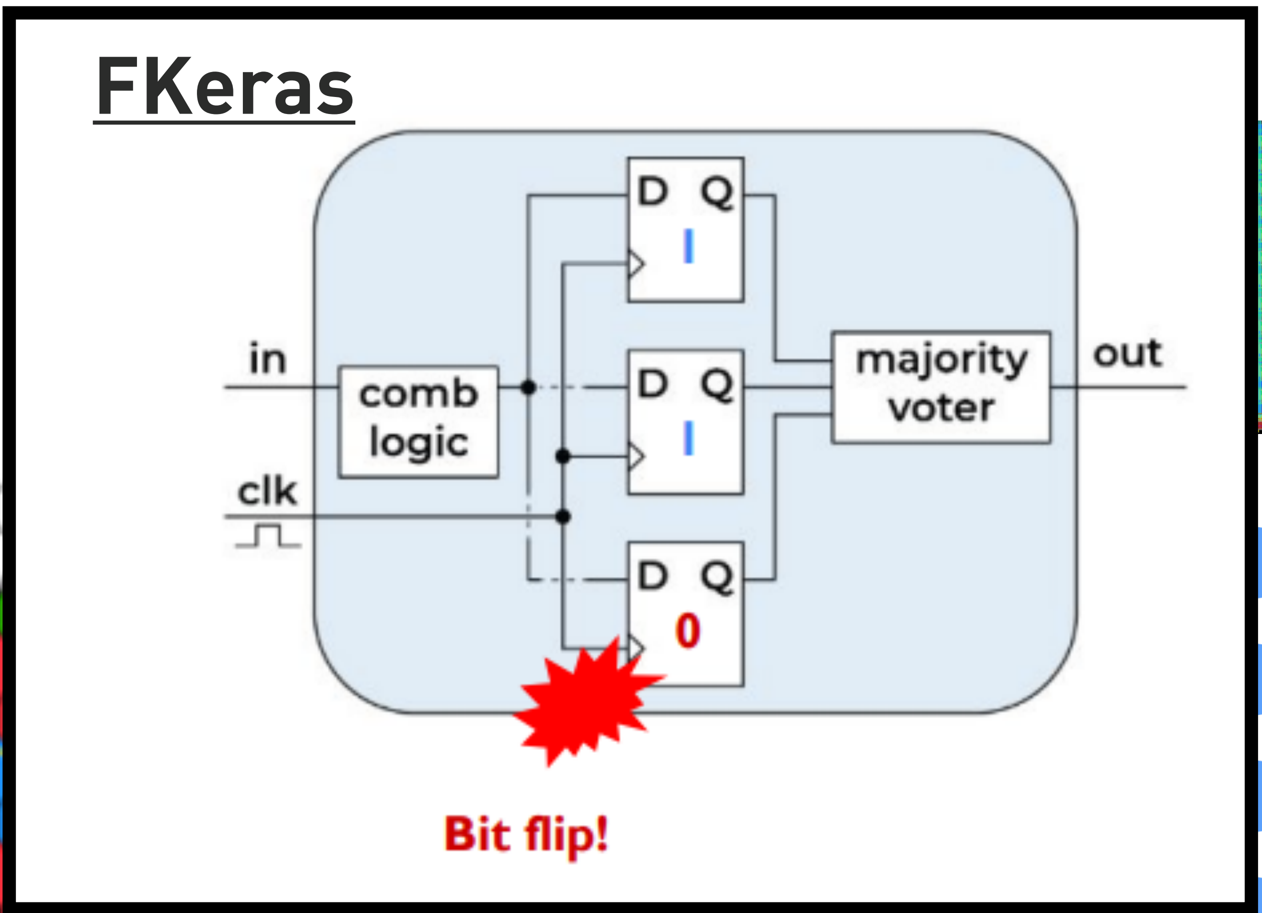
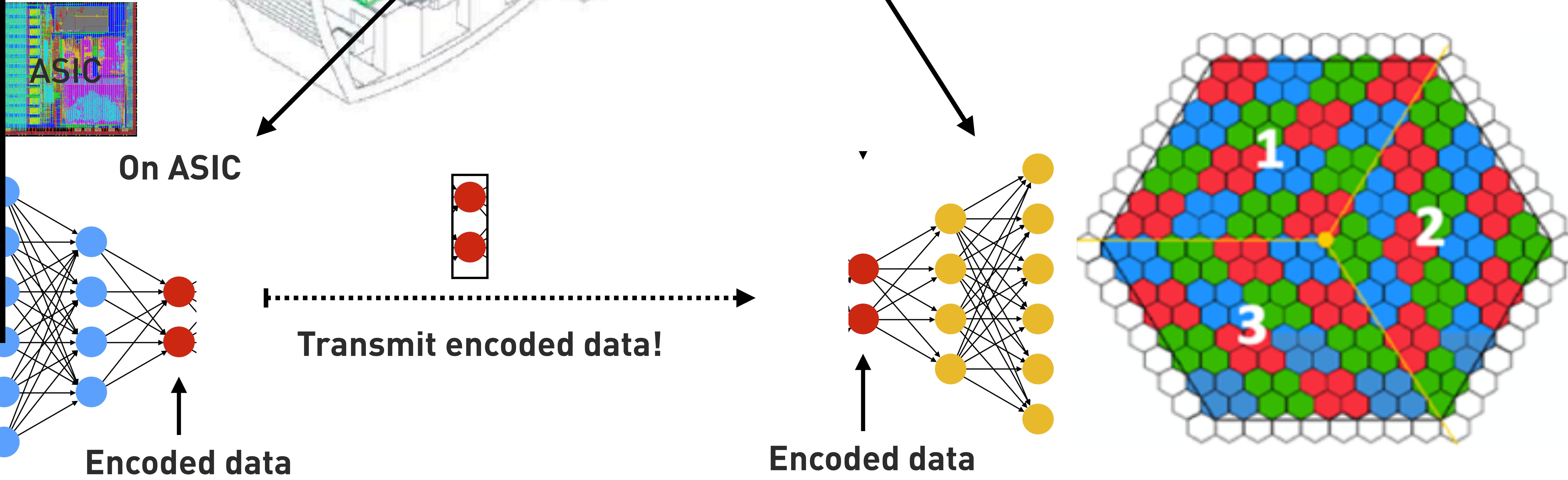
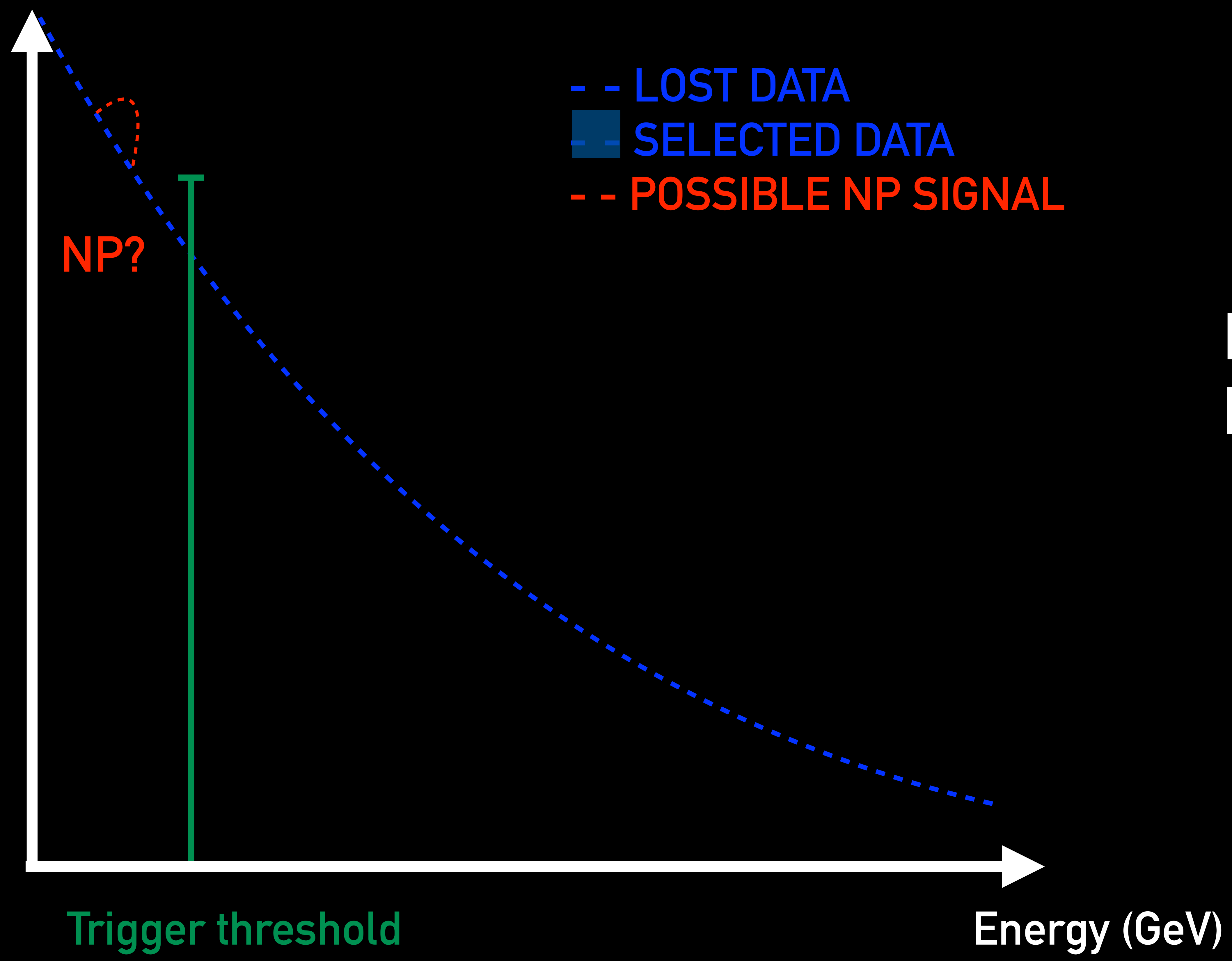






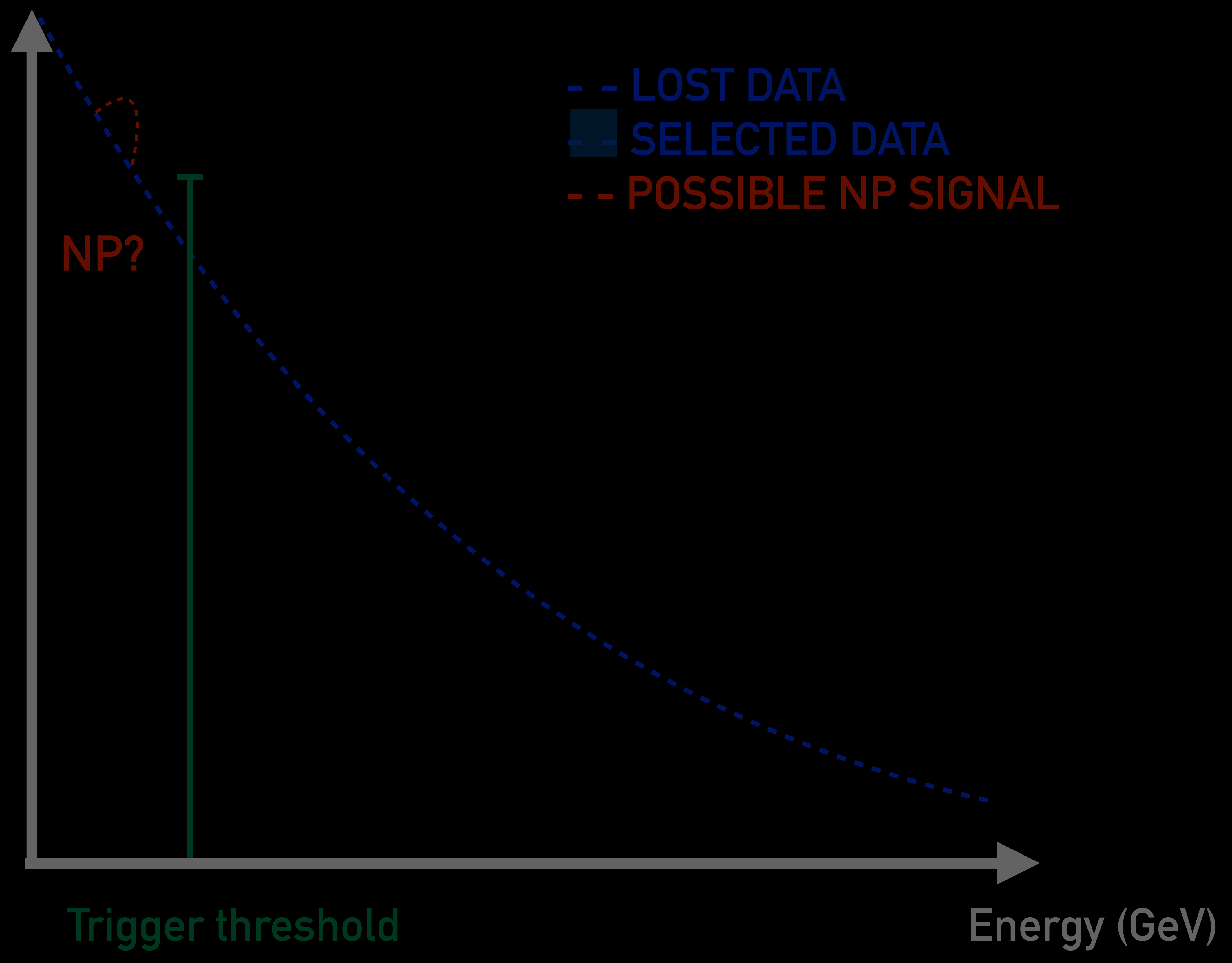
Geneva
Geneva Lake
LHCb
ATLAS
ALICE
CMS
TESLA
FPGA inference
Level-1 trigger:
Latency O(1) μs
LHC
VIRTEX-5

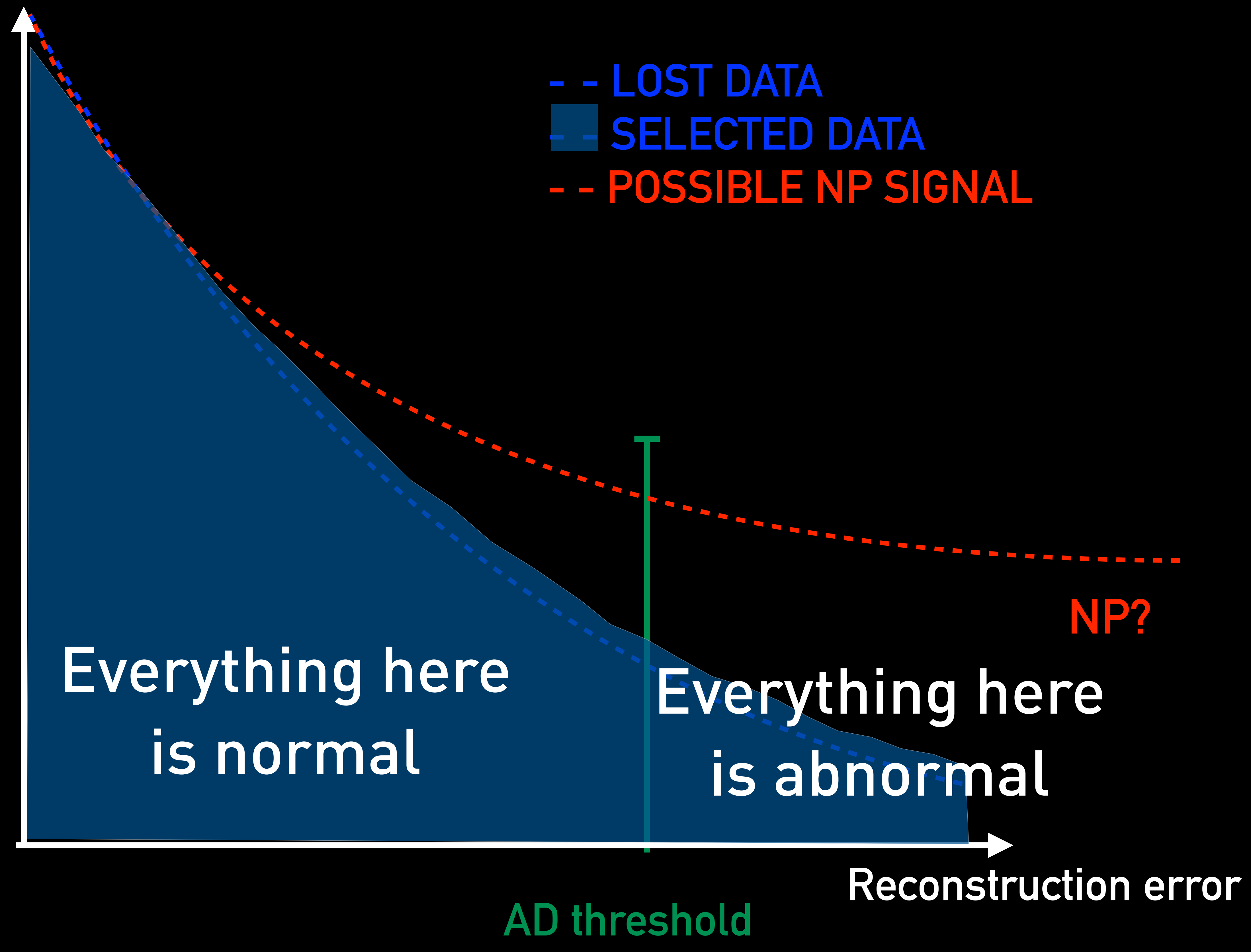
Anomaly Detection triggers



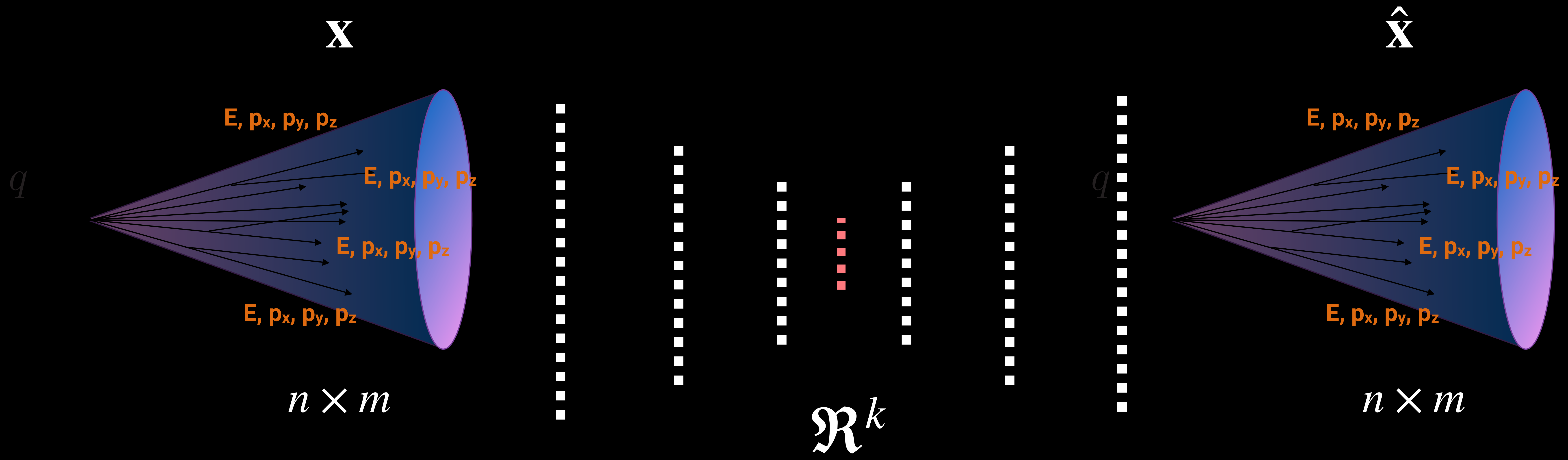
Level-1 rejects >99% of events!
Is there a smarter way to select?

Anomaly Detection triggers





Outlier detection

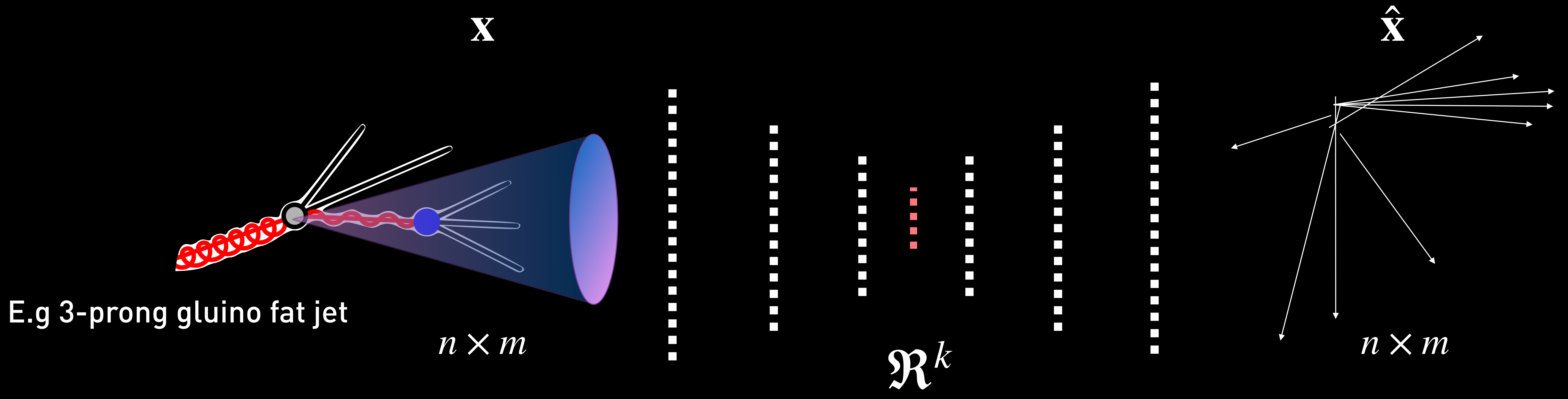


Compressed representation of x.

Latent space $\Re^k$, k < m×n

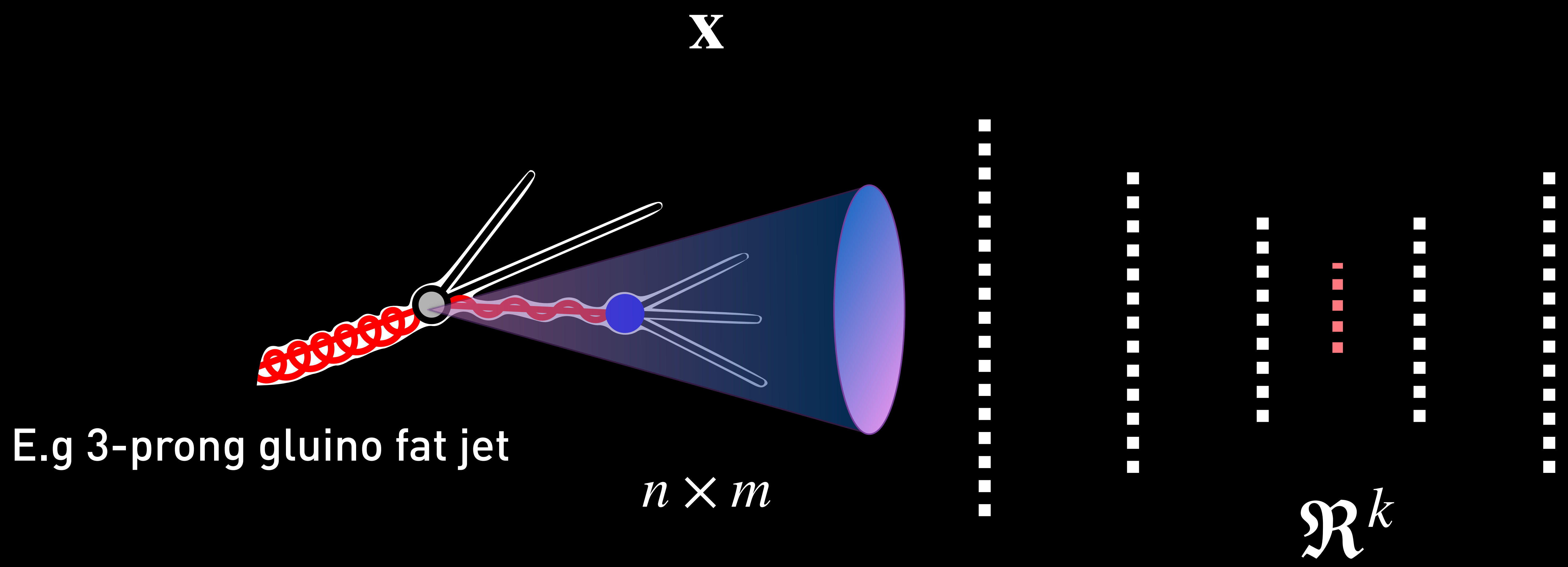
prevents memorisation of input, must learn

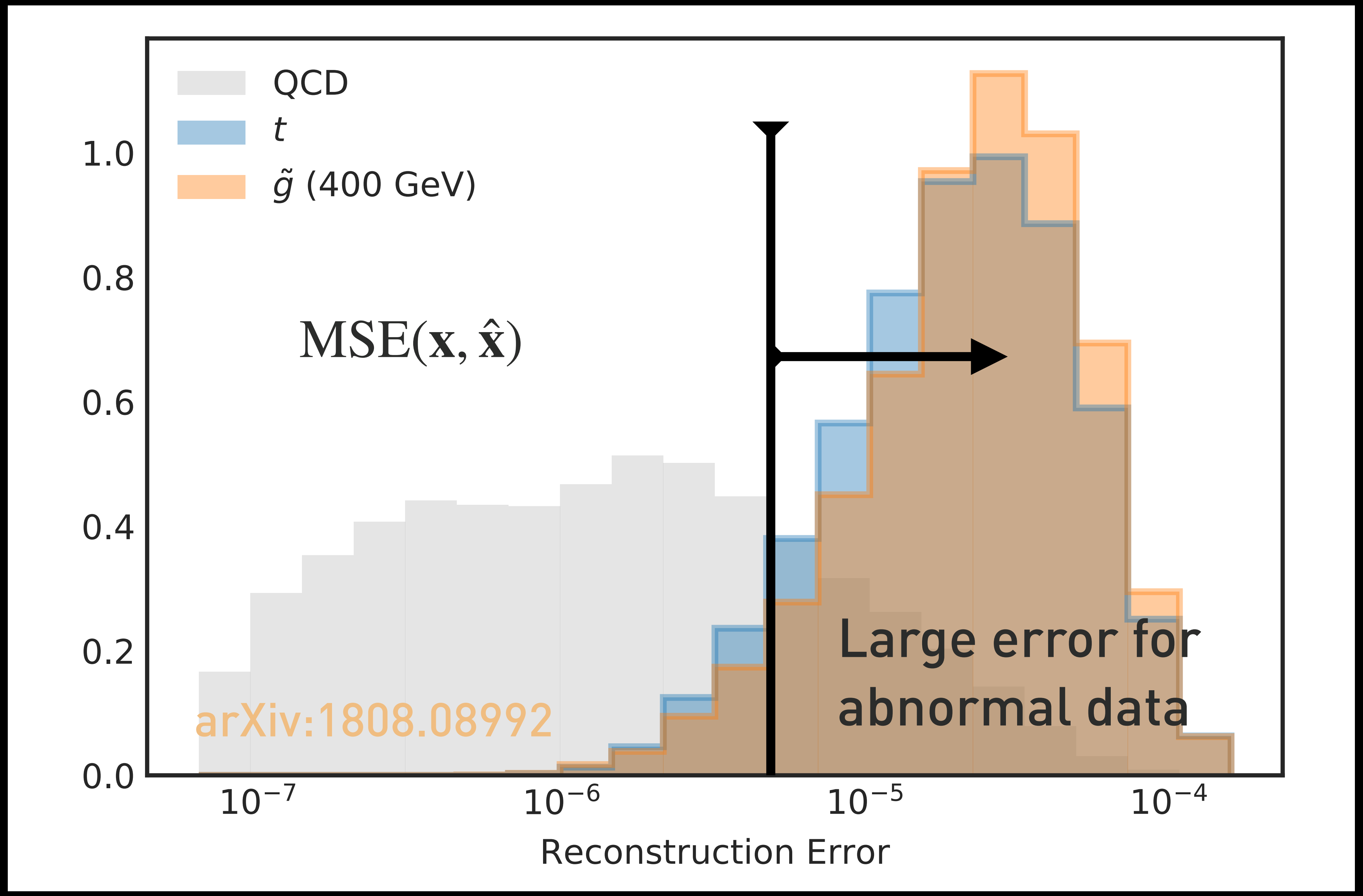
Outlier detection

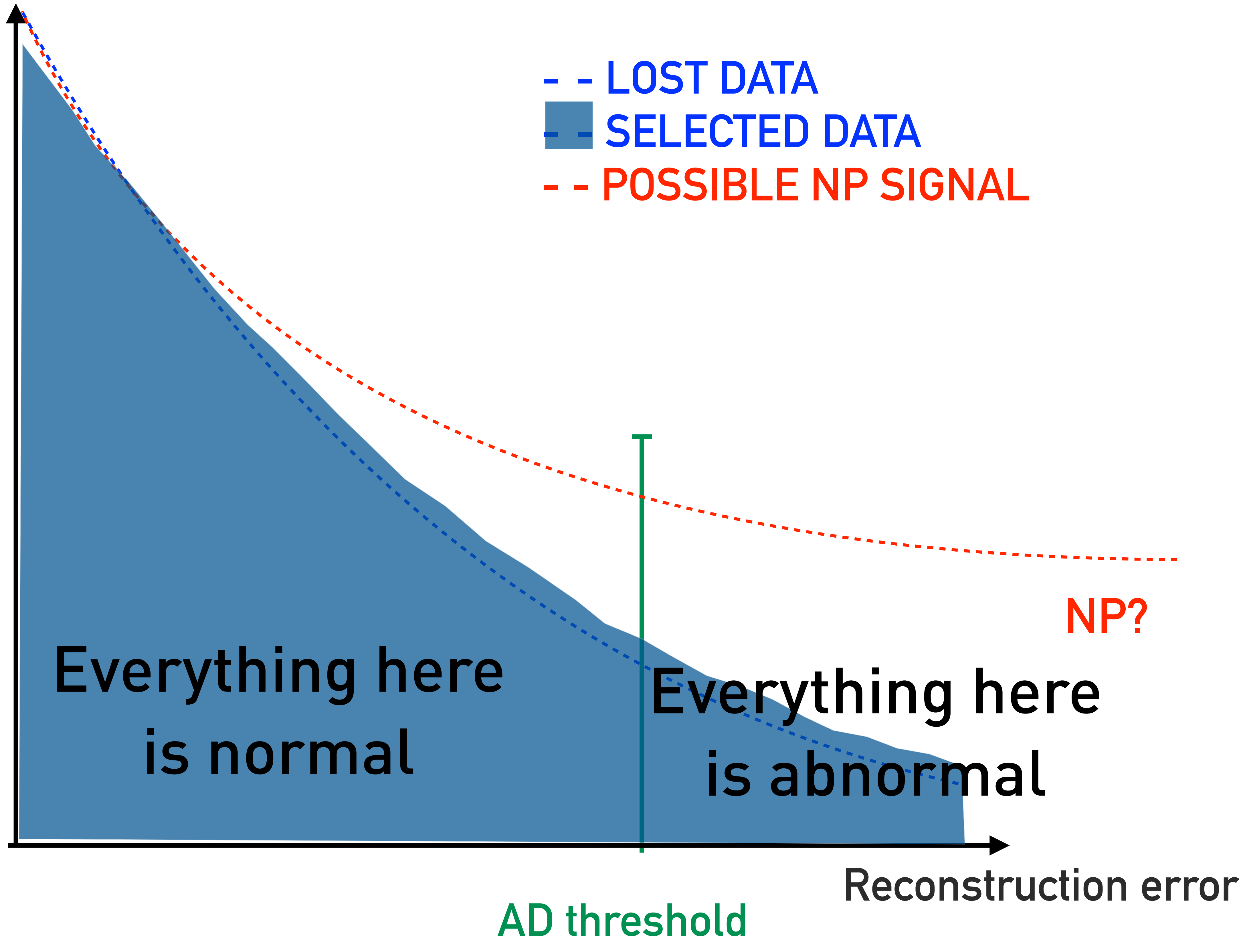


$\mathscr{L}(\mathbf{x}, \hat{\mathbf{x}})$ is Mean Squared Error$(\mathbf{x}, \hat{\mathbf{x}})$, “high error events” proxy for “degree of abnormality”

Outlier detection







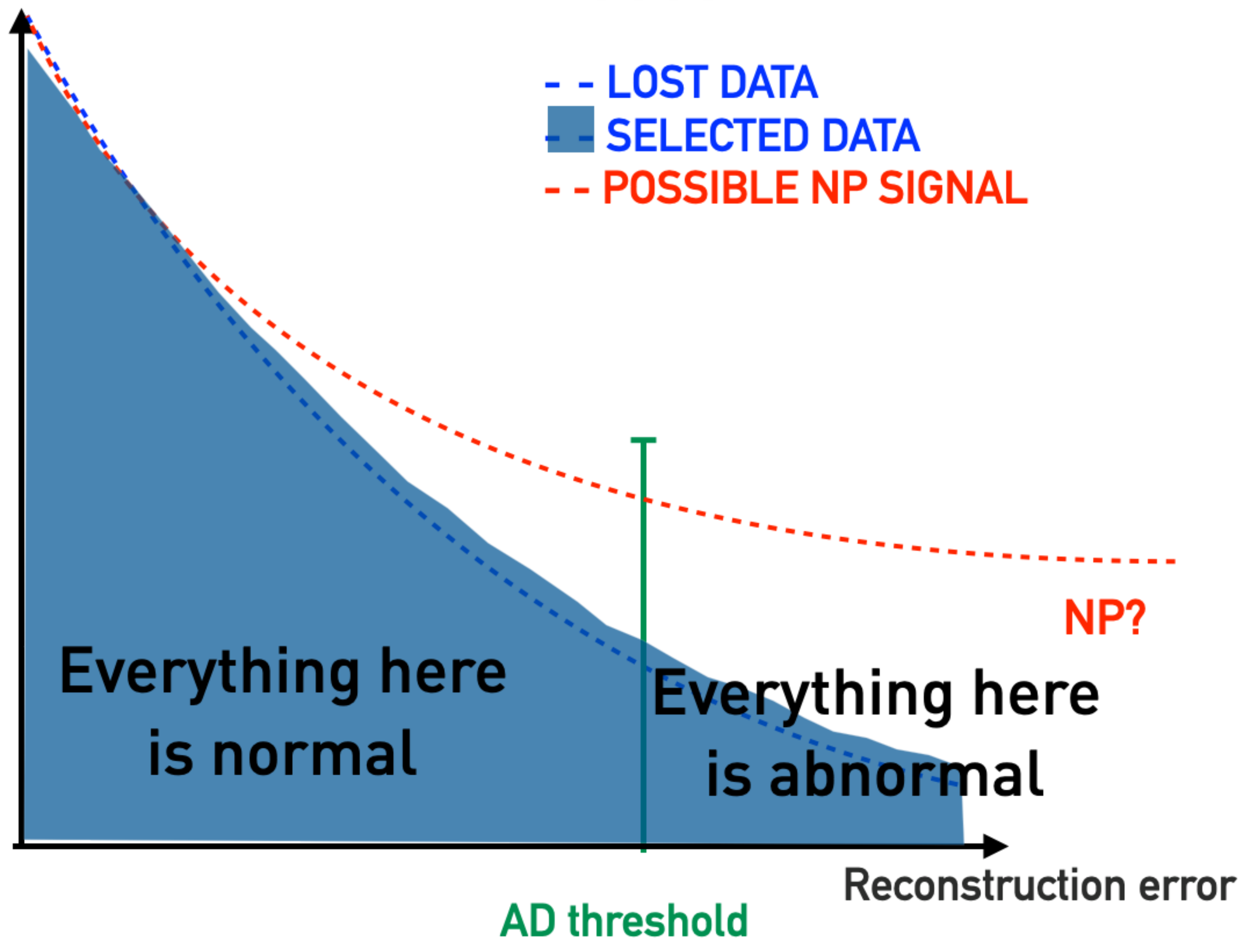
AXOL1TL

....in 50 nanoseconds! Currently recording 300 collisions per second in CMS!

First ML triggers in ATLAS and in CMS in 2024

DNN anomaly detection in 50 ns

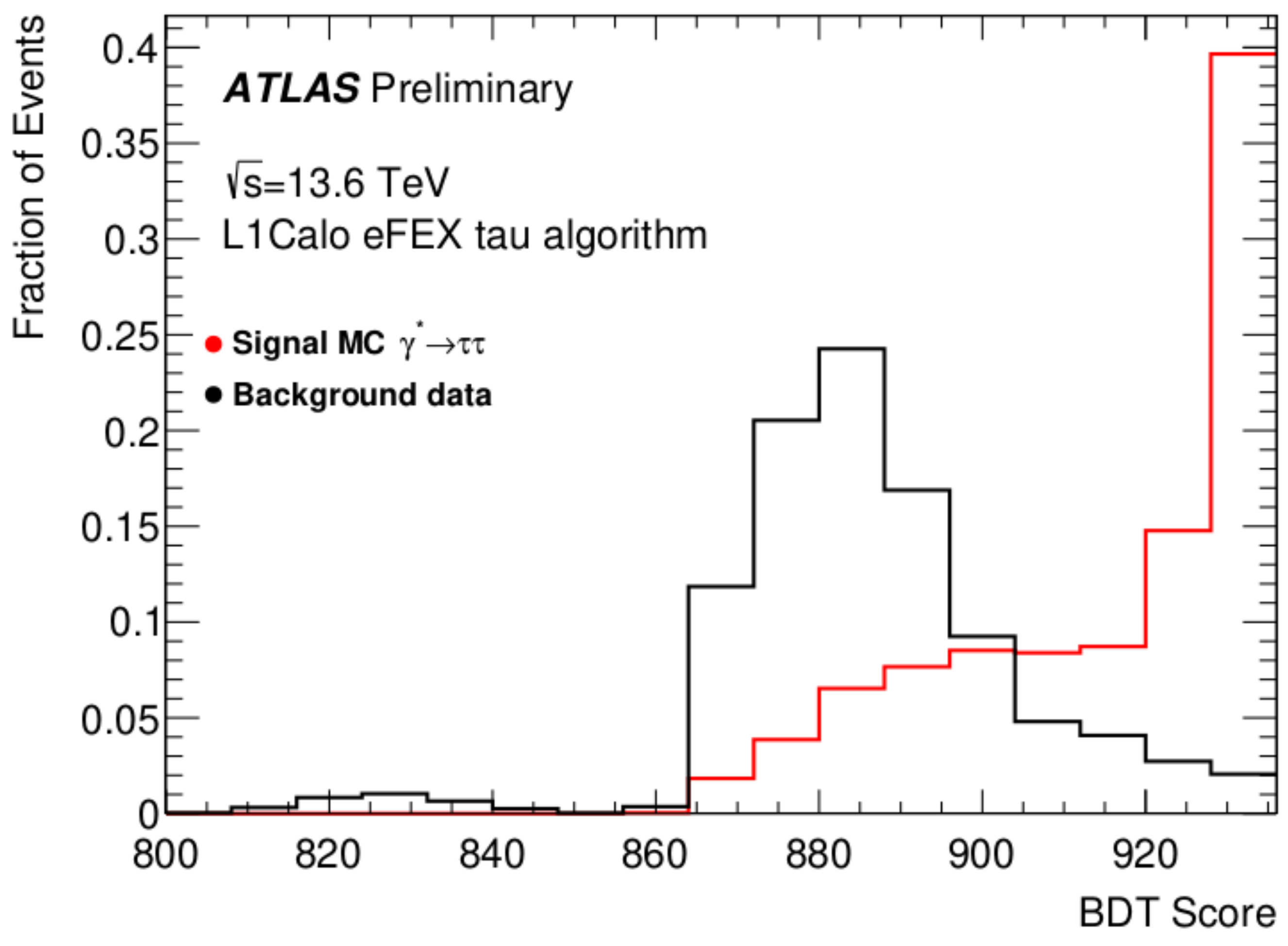
hls4ml



CMS DP2023_079

BDT selecting τ's <100 ns

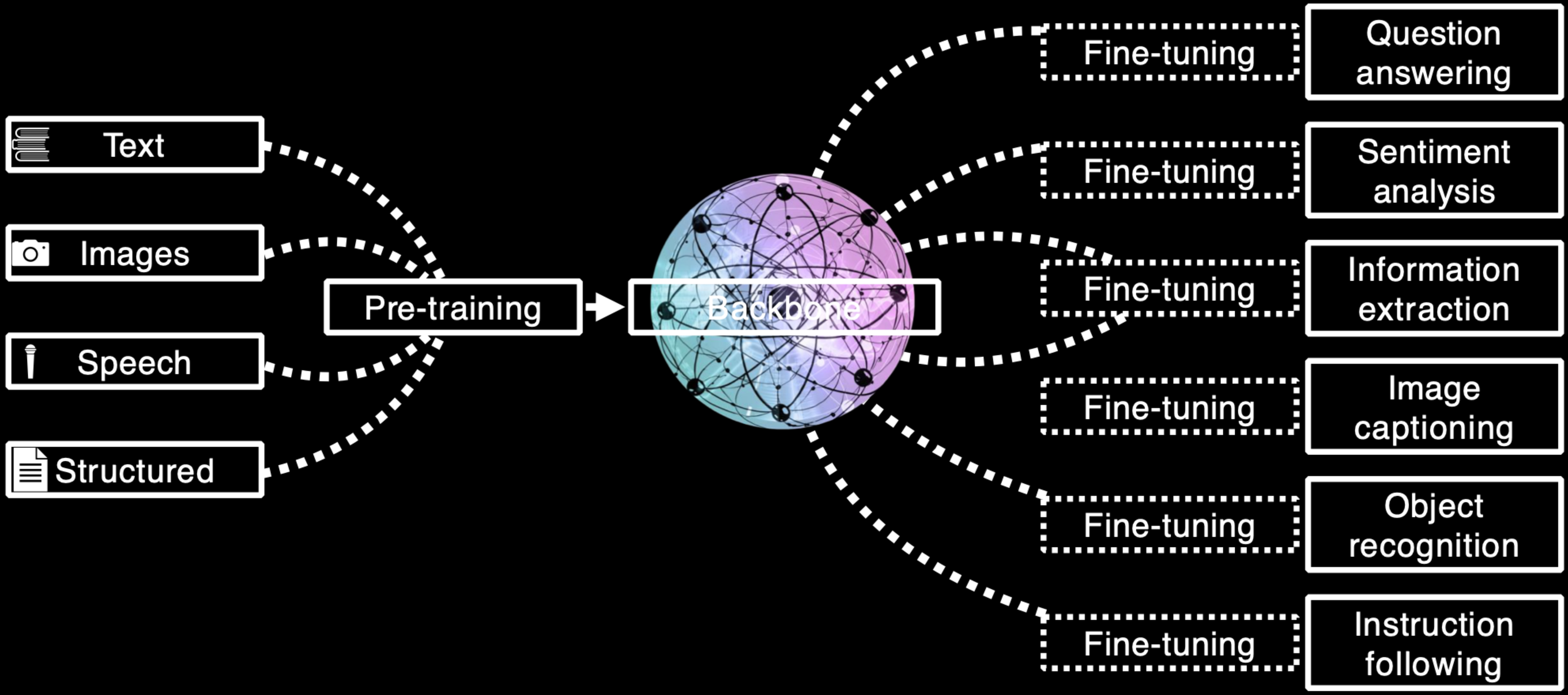
Conifer



L1CaloTriggerPublicResults

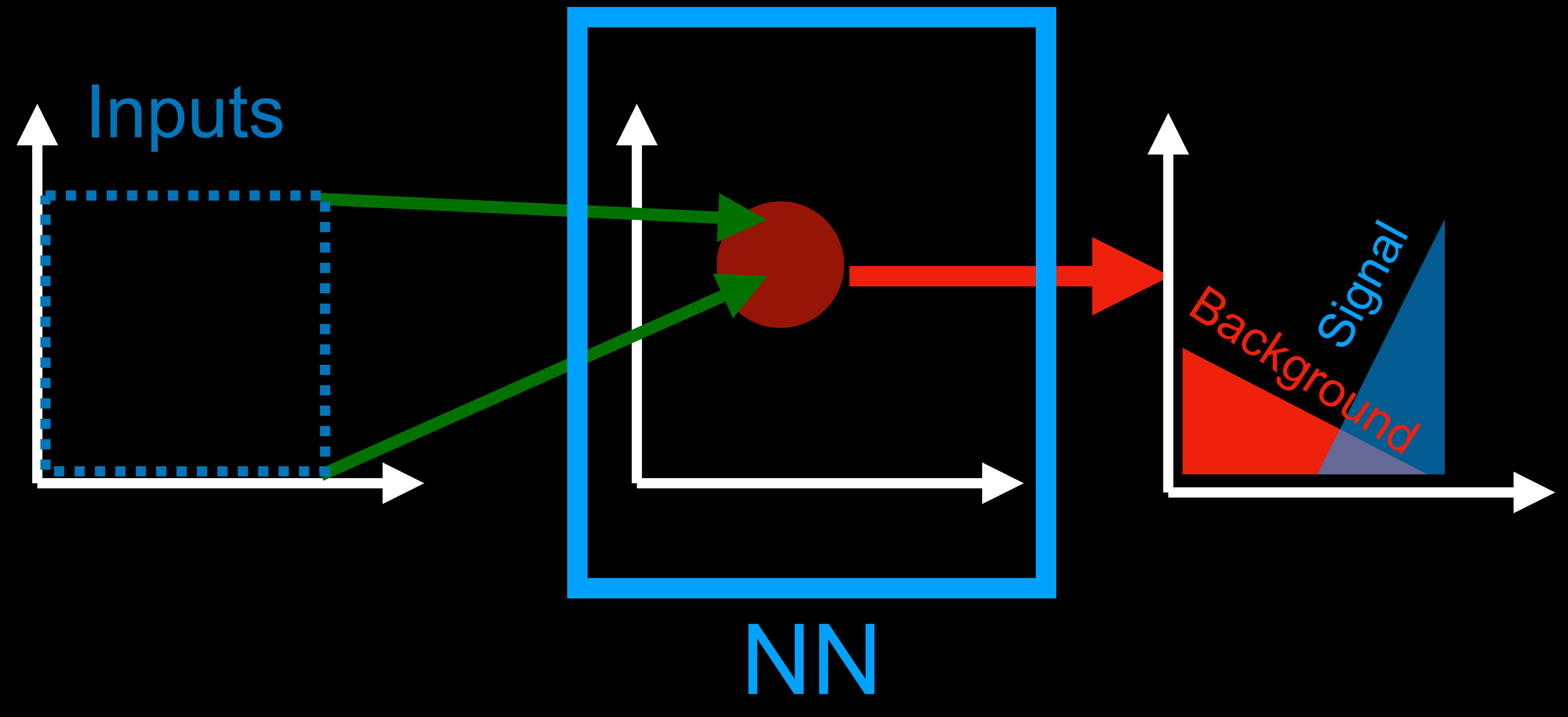
Foundation models

Foundation models


Text
Images
Speech
Structured
Pre-training
Backbone
Fine-tuning
Question answering
Fine-tuning
Sentiment analysis
Fine-tuning
Information extraction
Fine-tuning
Image captioning
Fine-tuning
Object recognition
Fine-tuning
Instruction following

Heterogeneous detector
Multi-modal input!
Pre-training
Backbone
Fine-tuning
Jet reconstruction
Fine-tuning
Electron reconstruction
Fine-tuning
Pile-up removal
Fine-tuning
Missing energy computation
Fine-tuning
Anomaly Detection
Fine-tuning
0/1?
(Generate simulation?)

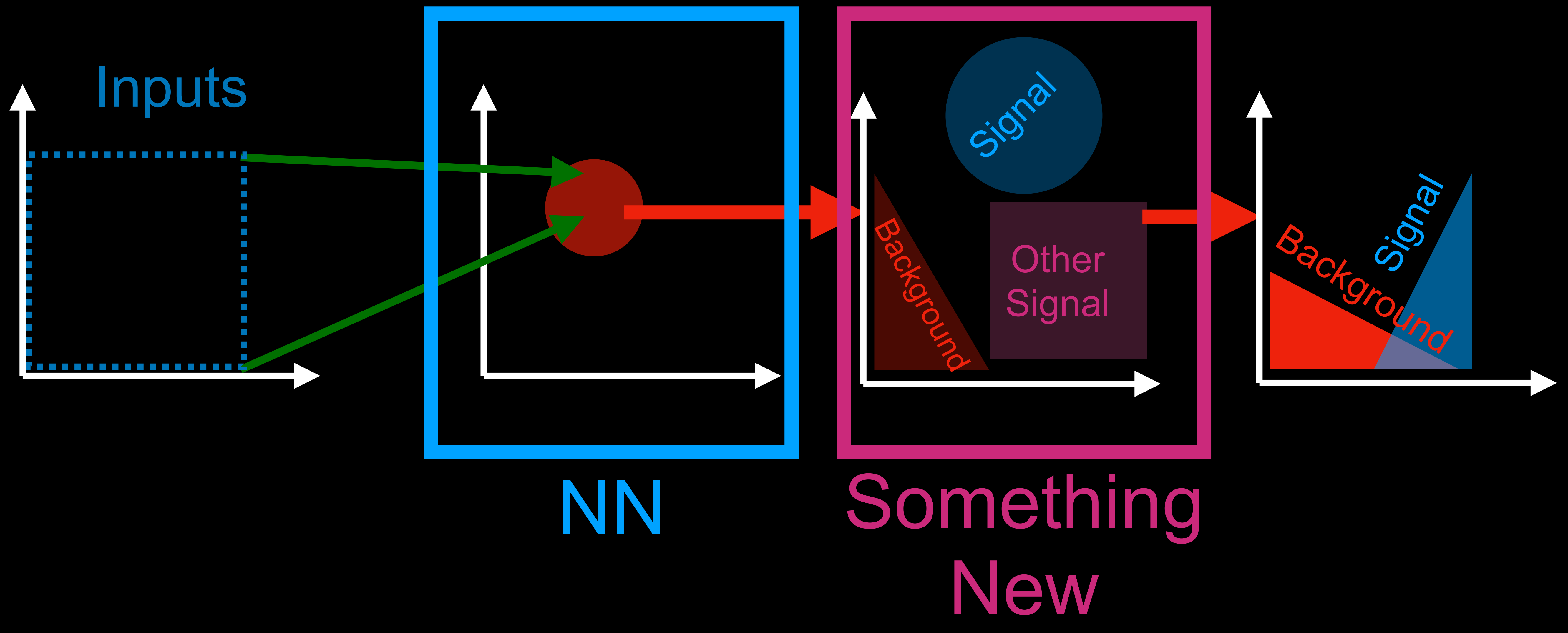
Too many models, too little learning?



$x = (x_1, x_2)$ $f(x; w^*)$ $\hat{y}$

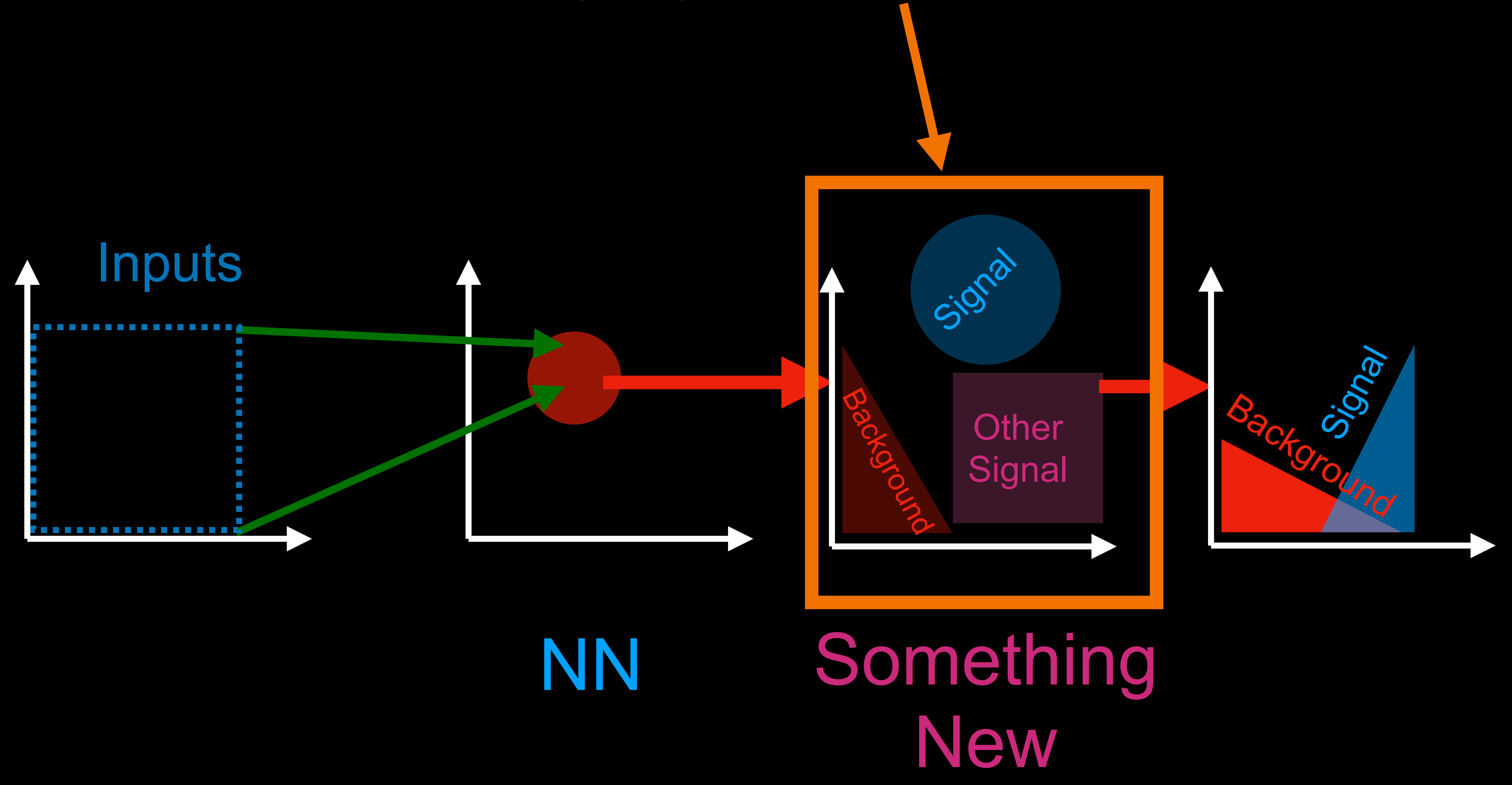
Discrimination

Instead of features like “says meow”, can we make new and better features?



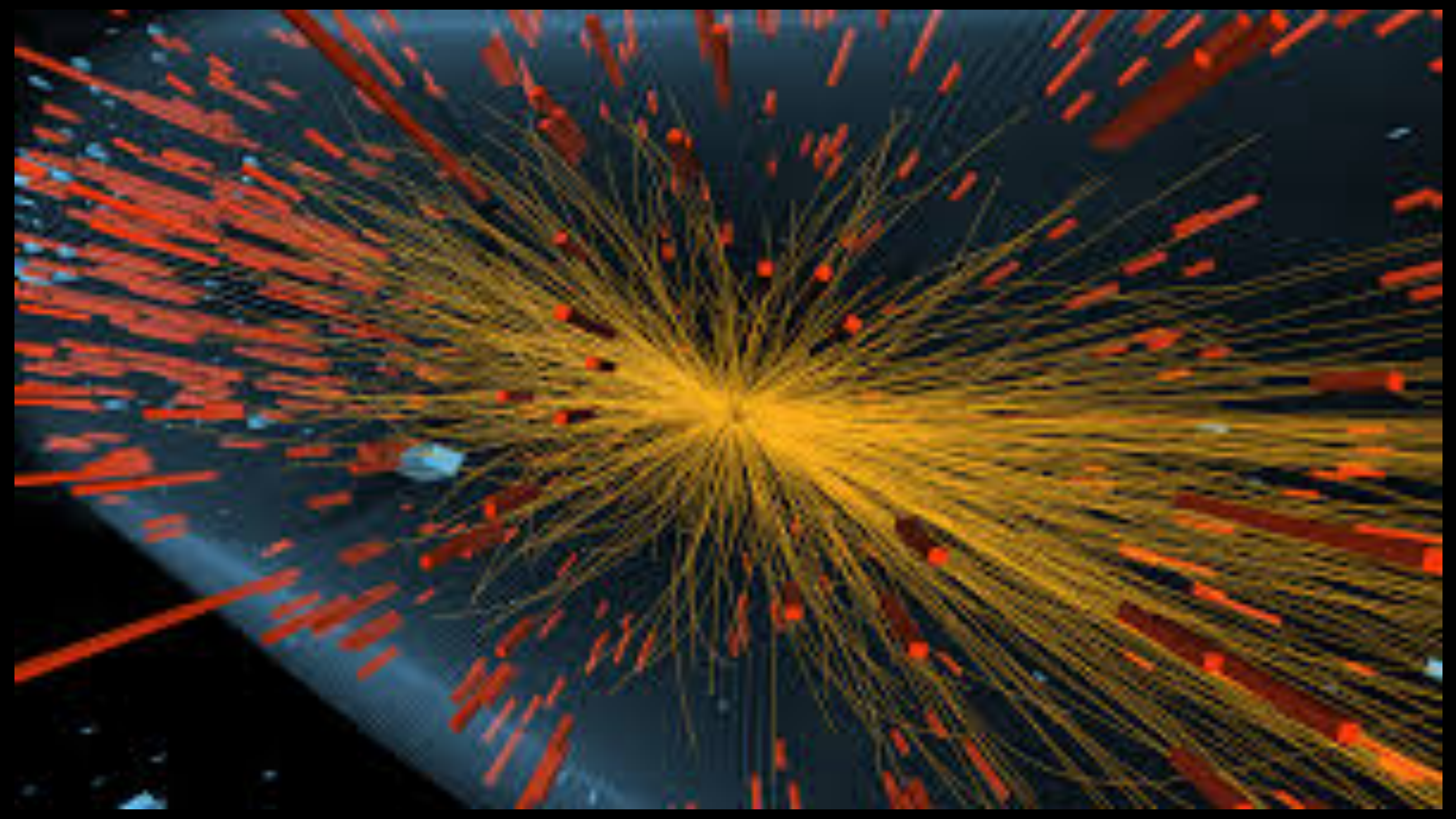
Metric Learning

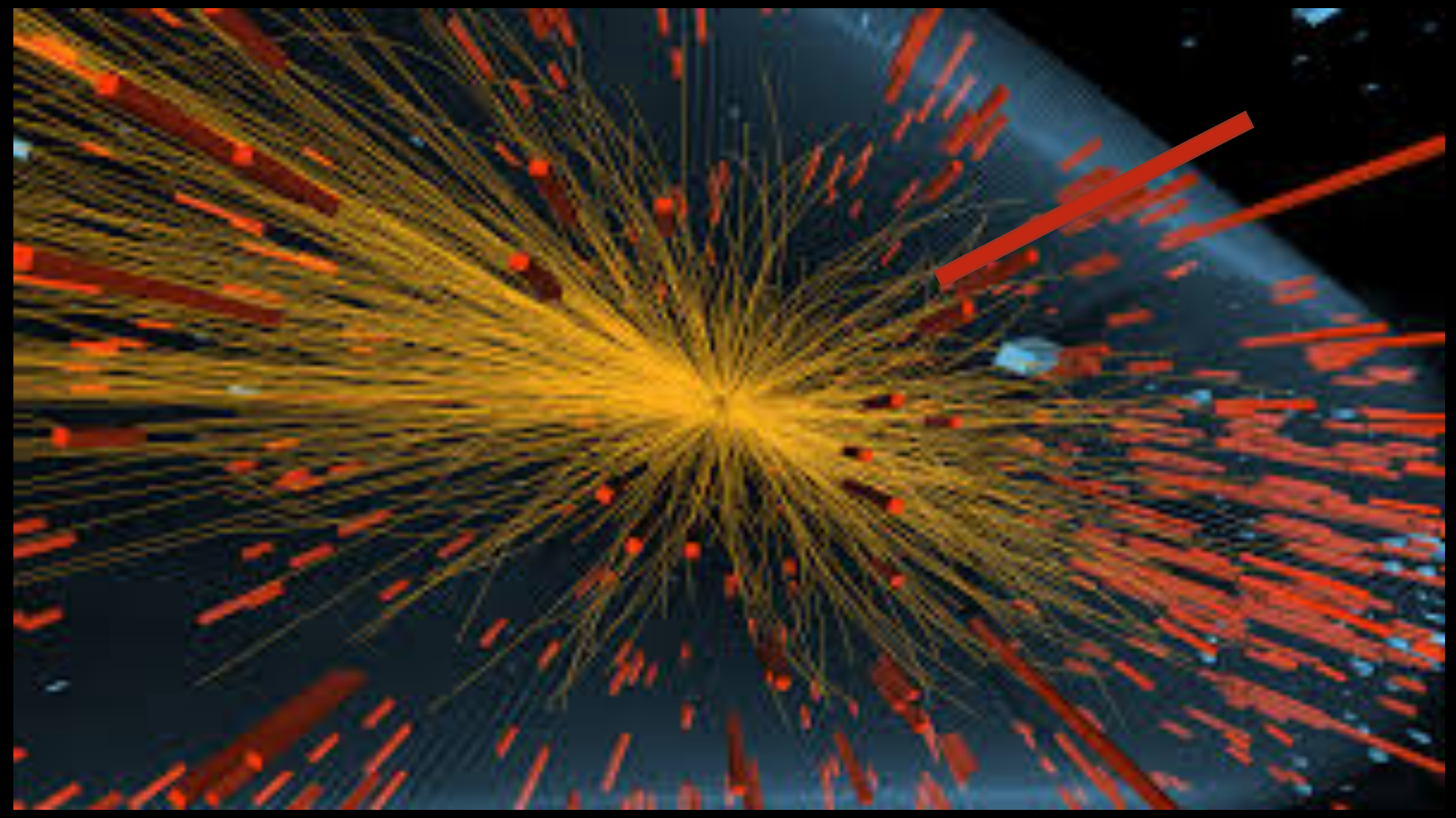
What if we really try to focus on this space



Neural embedding

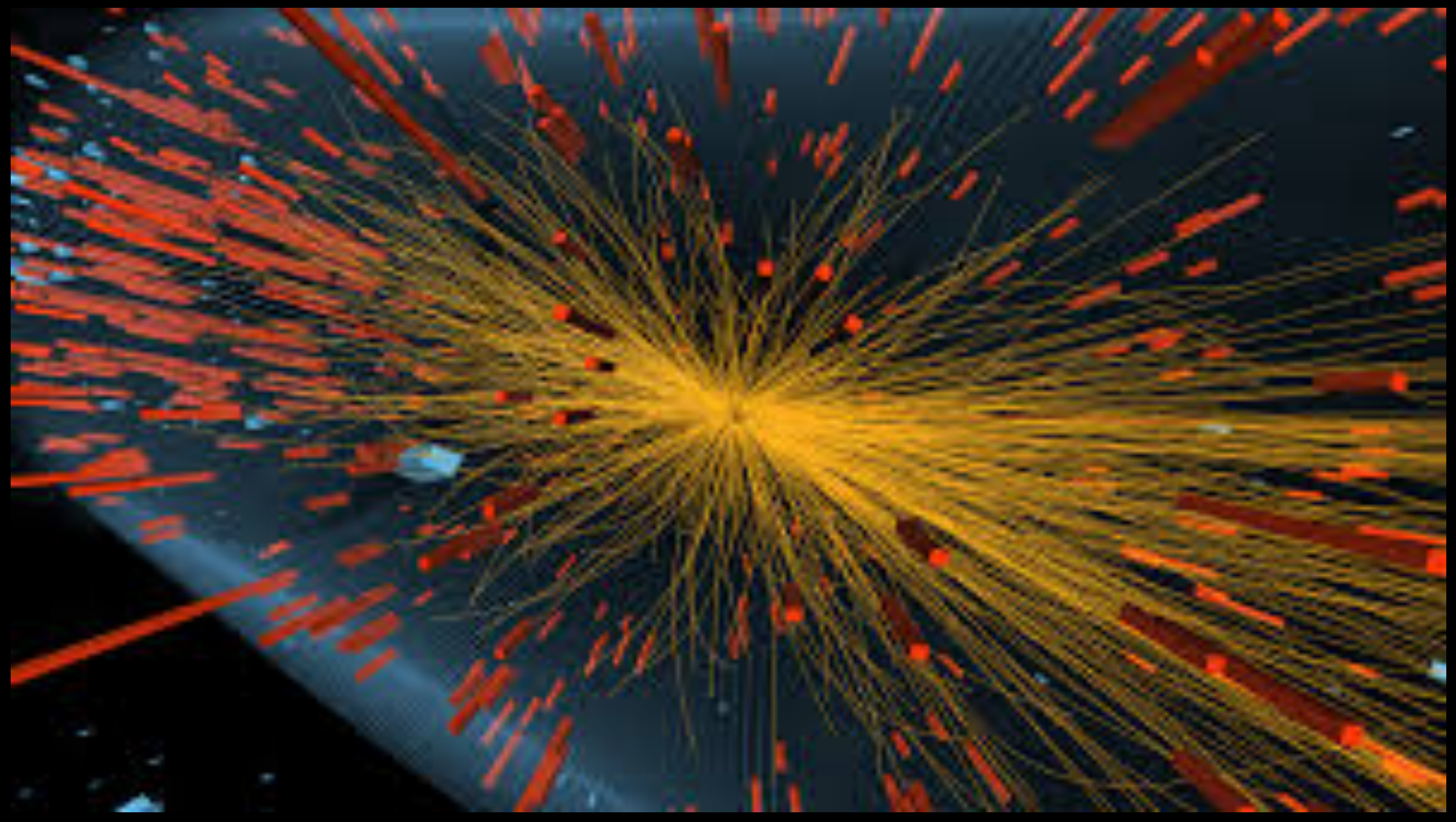
Learning the space

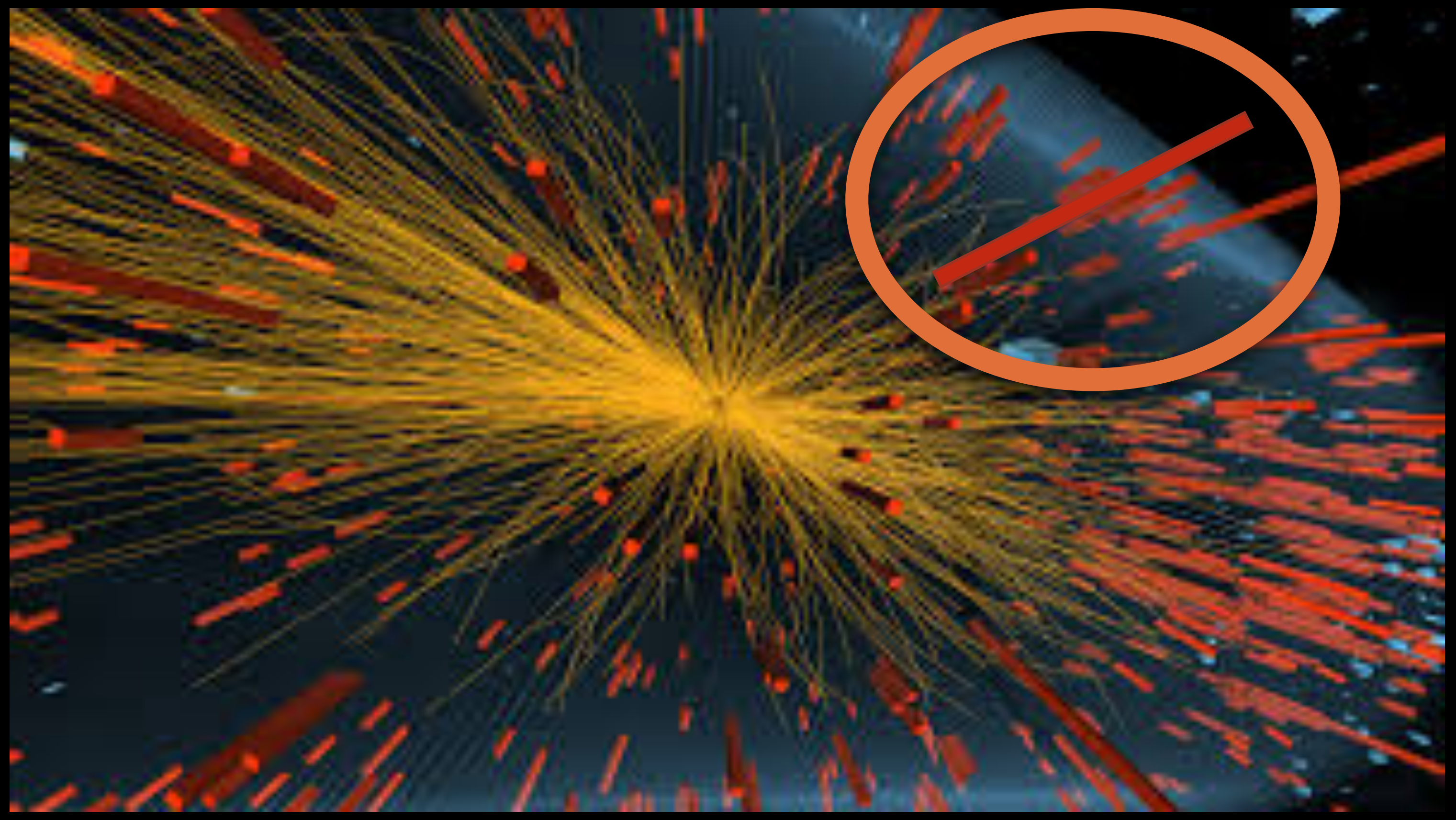




Learning the space

- By looking at data, we can learn a lot
  - Go over input piece by piece
  - Analyze every aspect
  - Compare every feature
- Find distinctive style of the input
  - can be done e.g by looking for a deviation

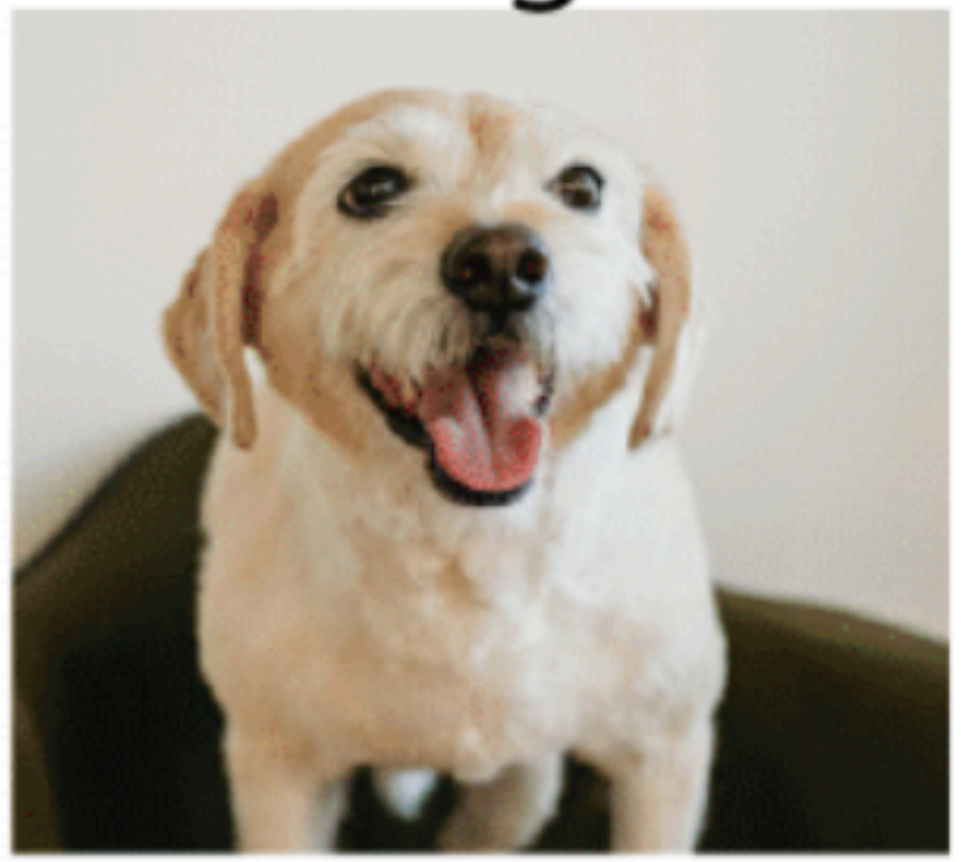


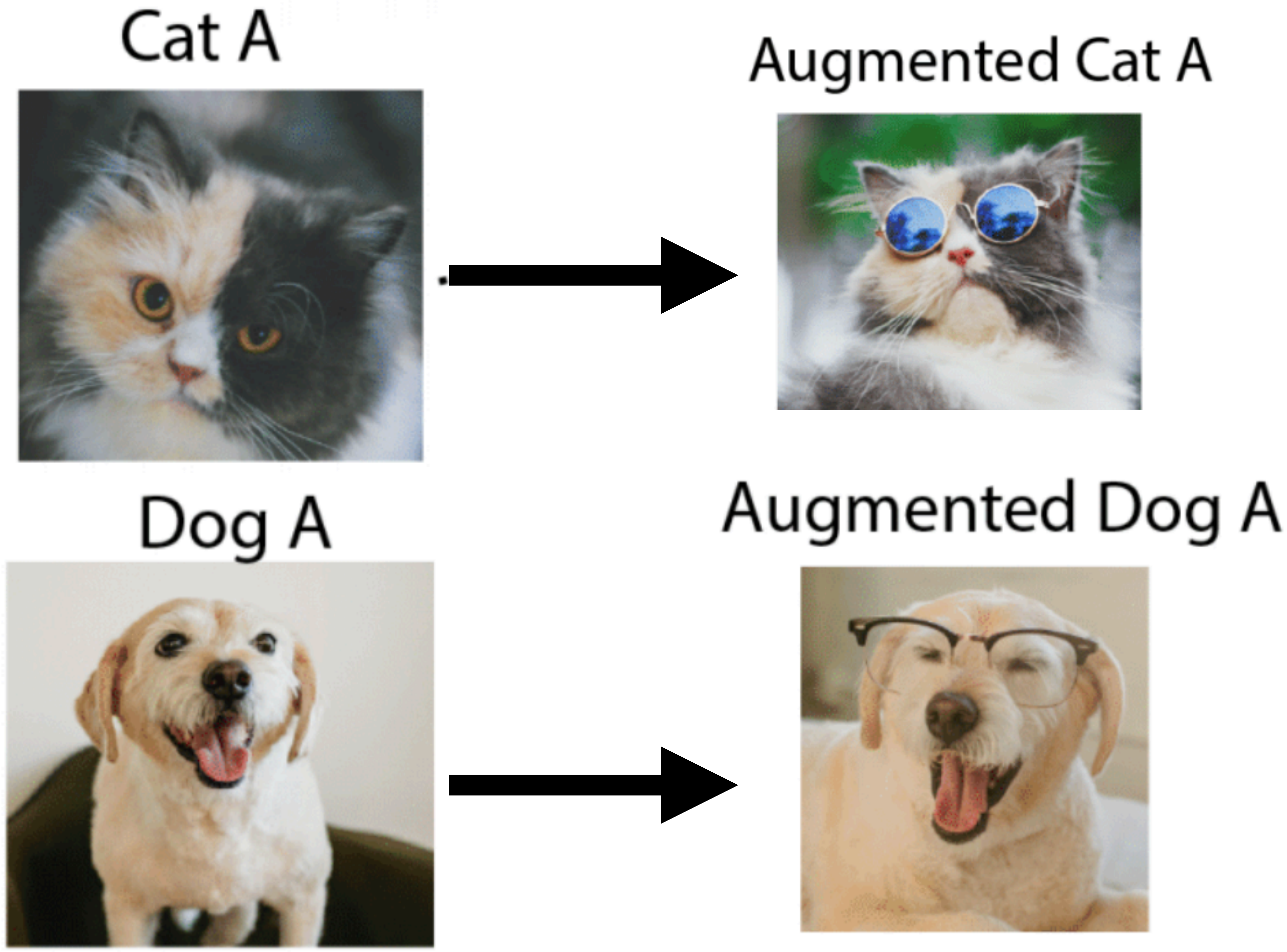


Contrastive learning (self-supervised)

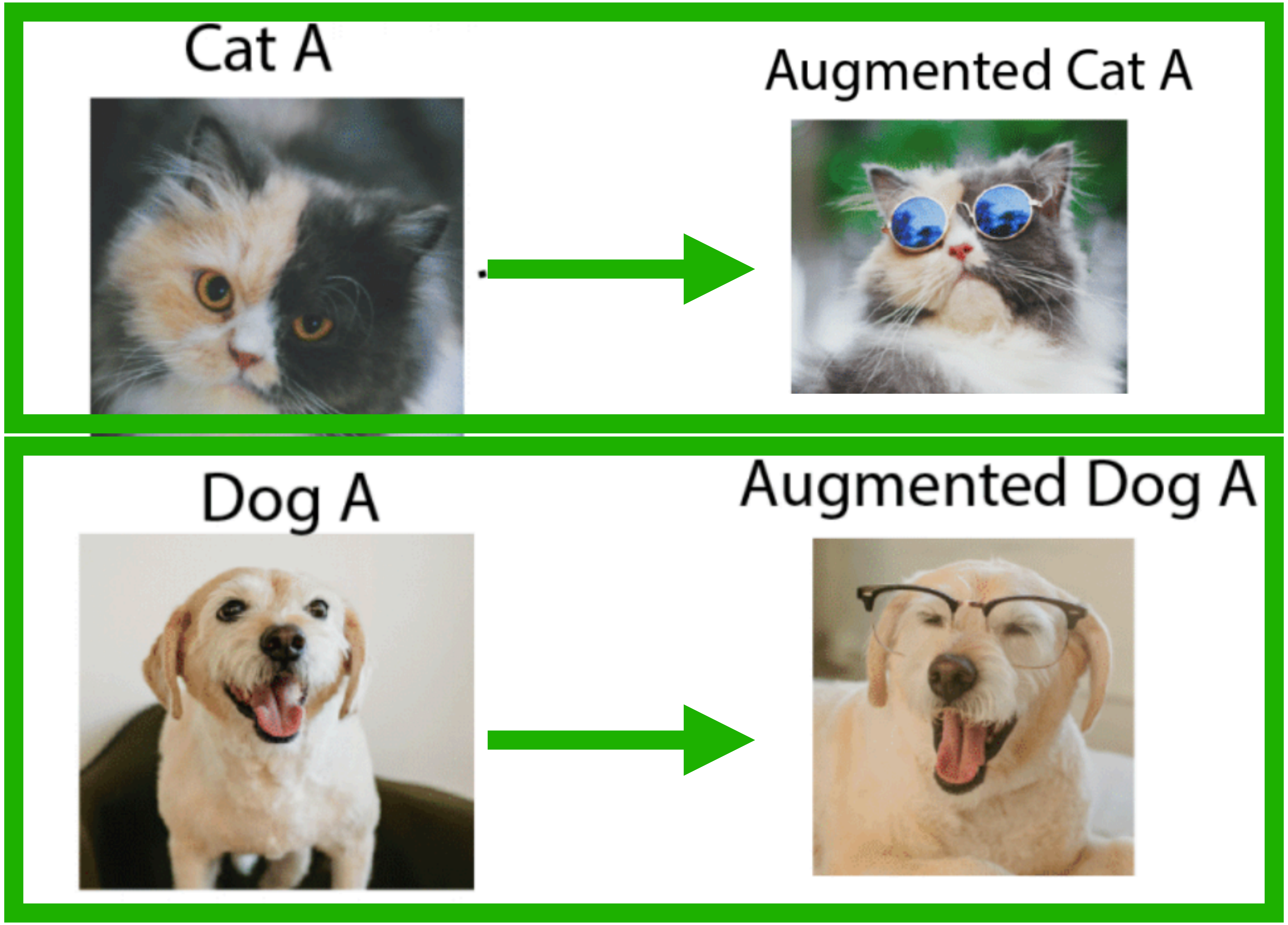
Cat A

Dog A

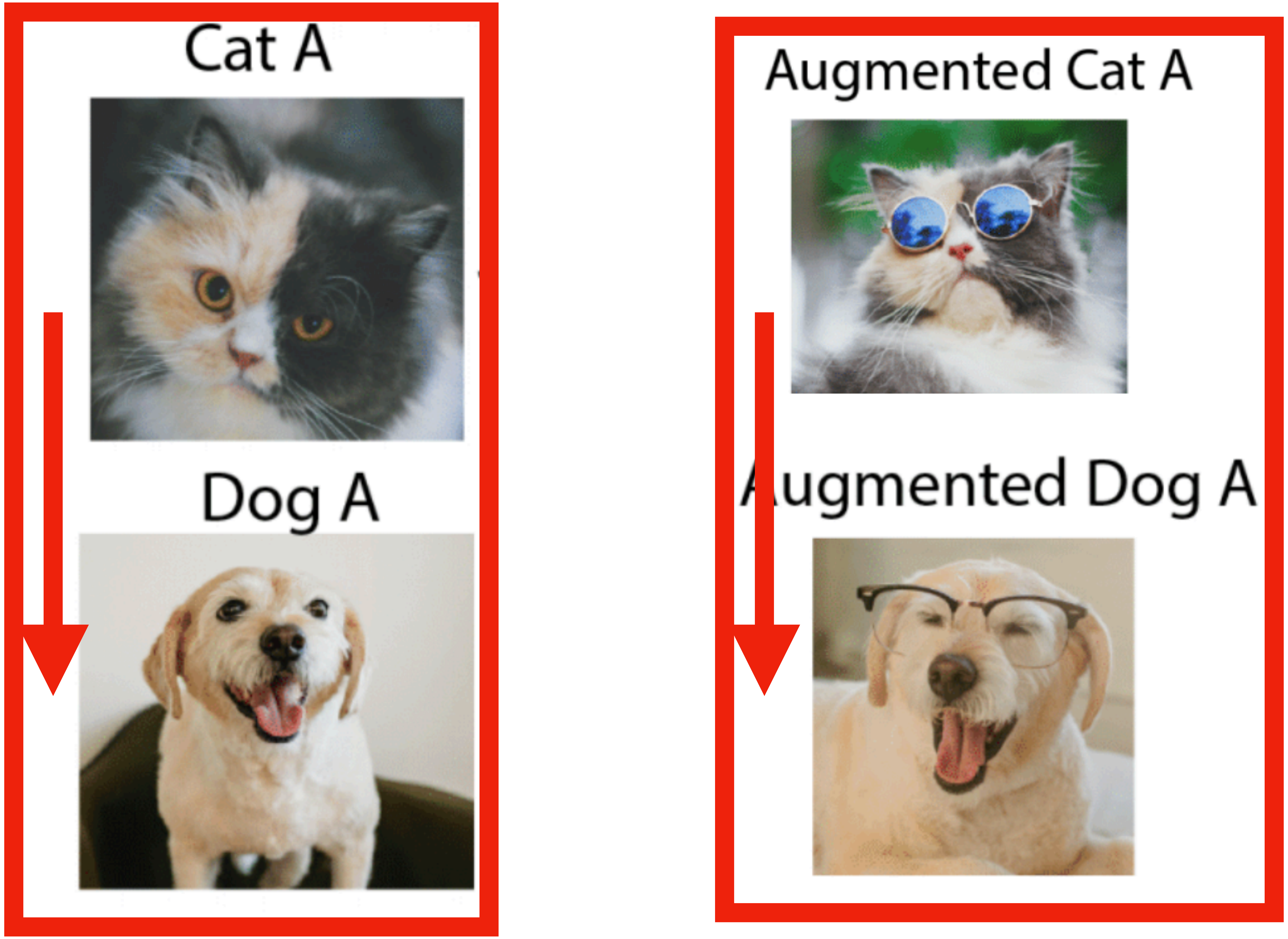



Cat A
Augmented Cat A
Dog A
Augmented Dog A

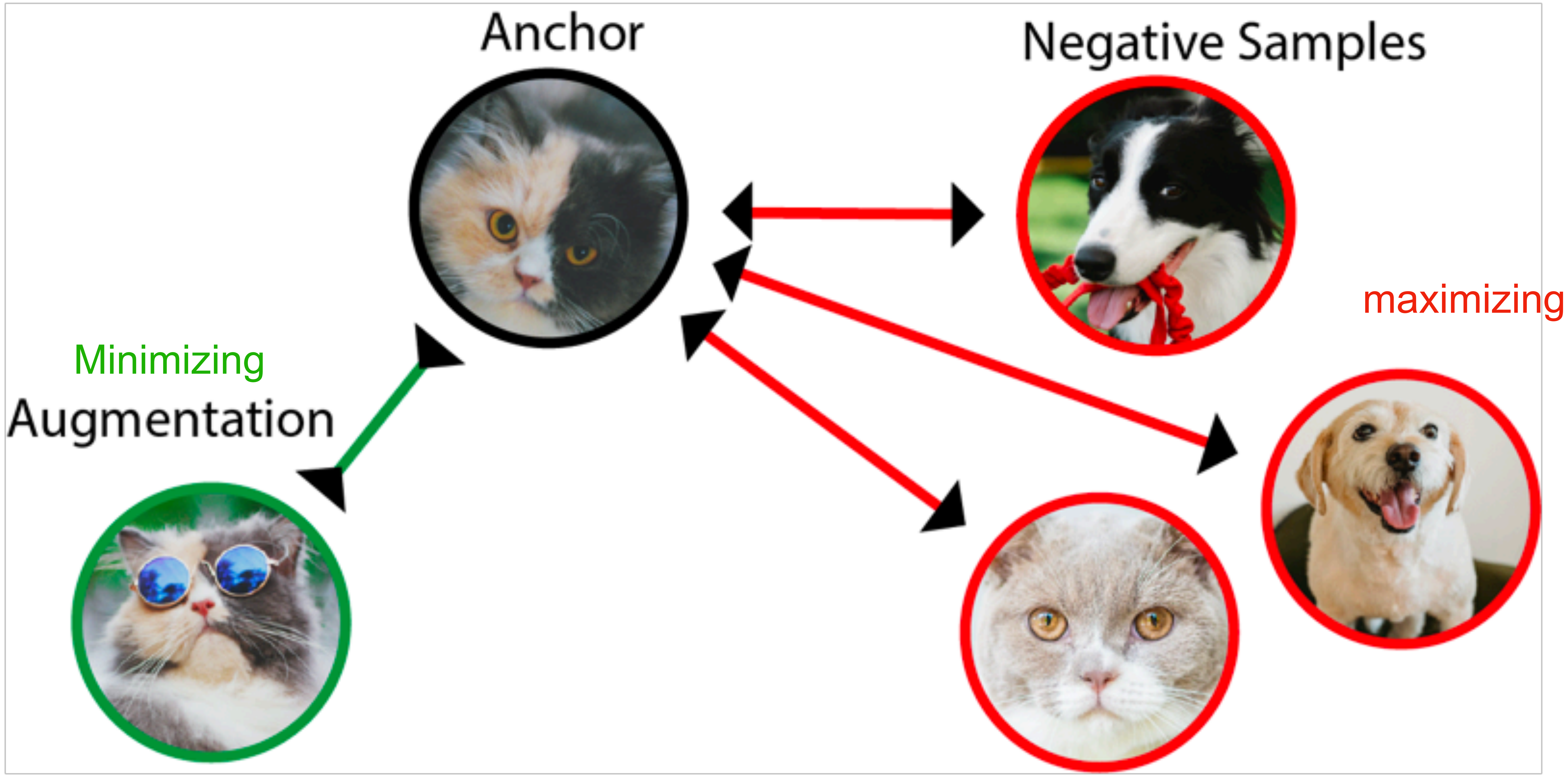
Minimize



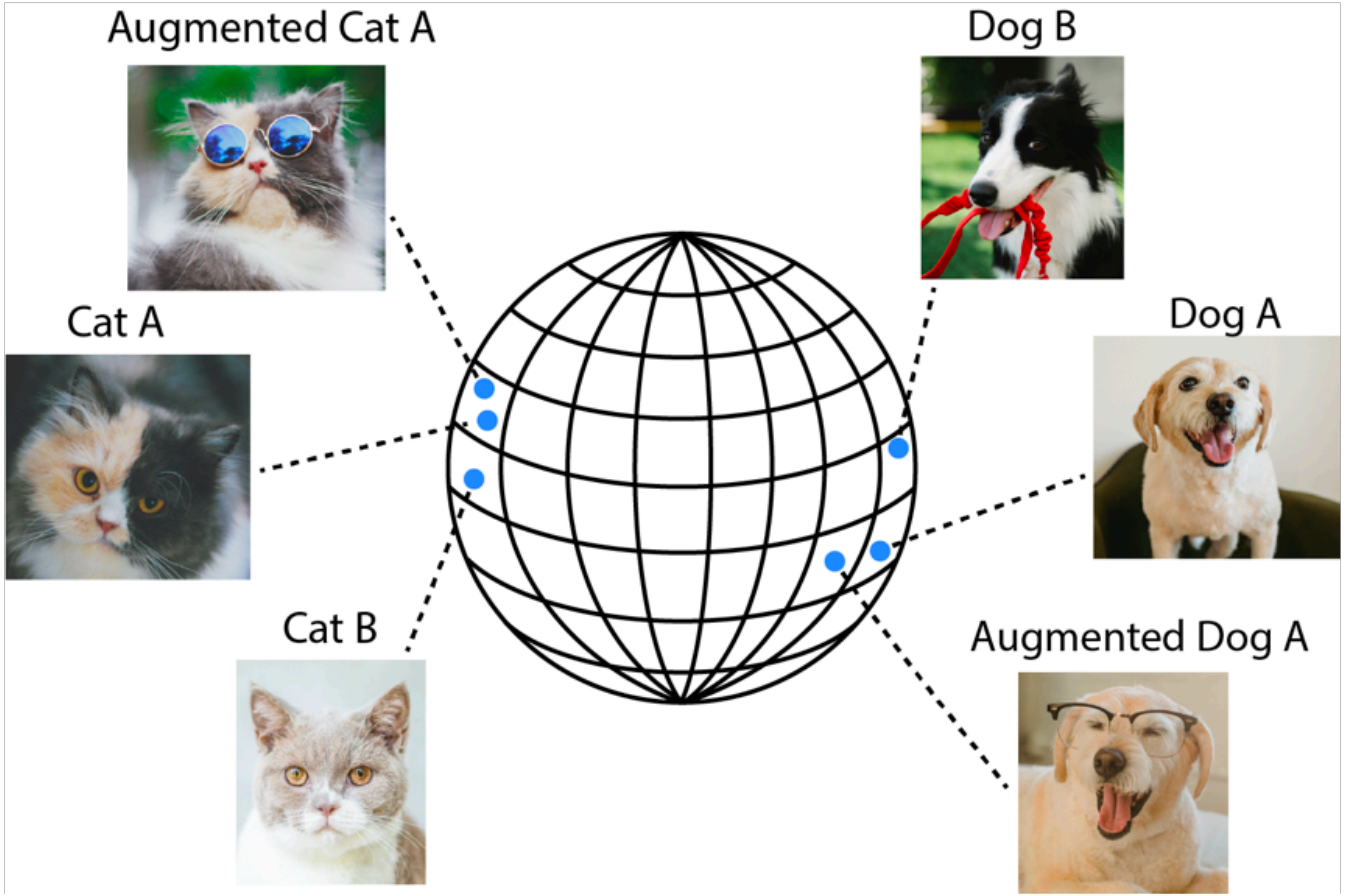
Maximize



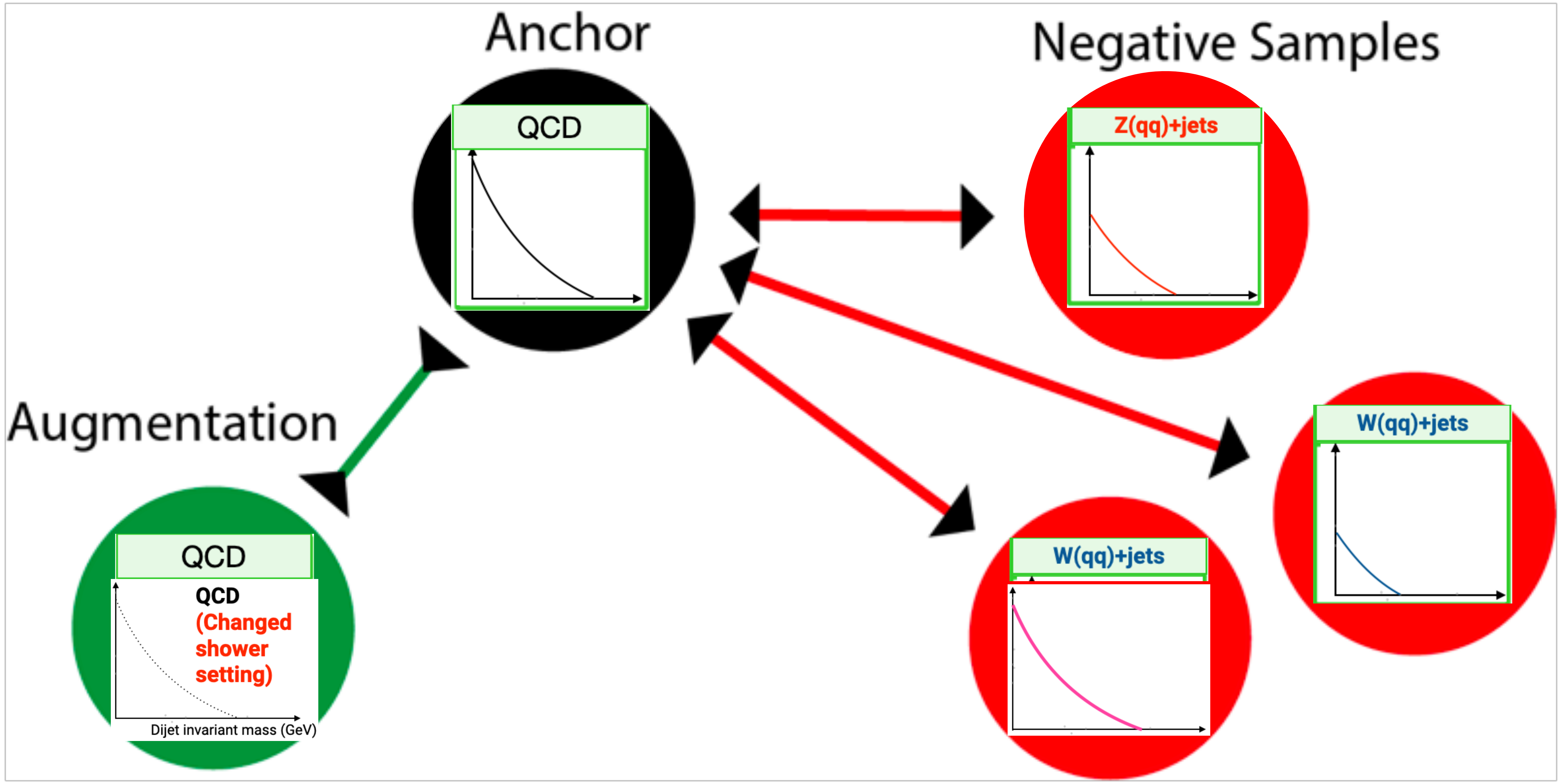
Contrastive learning (self-supervised)



- Minimizing and maximizing distances learns a space

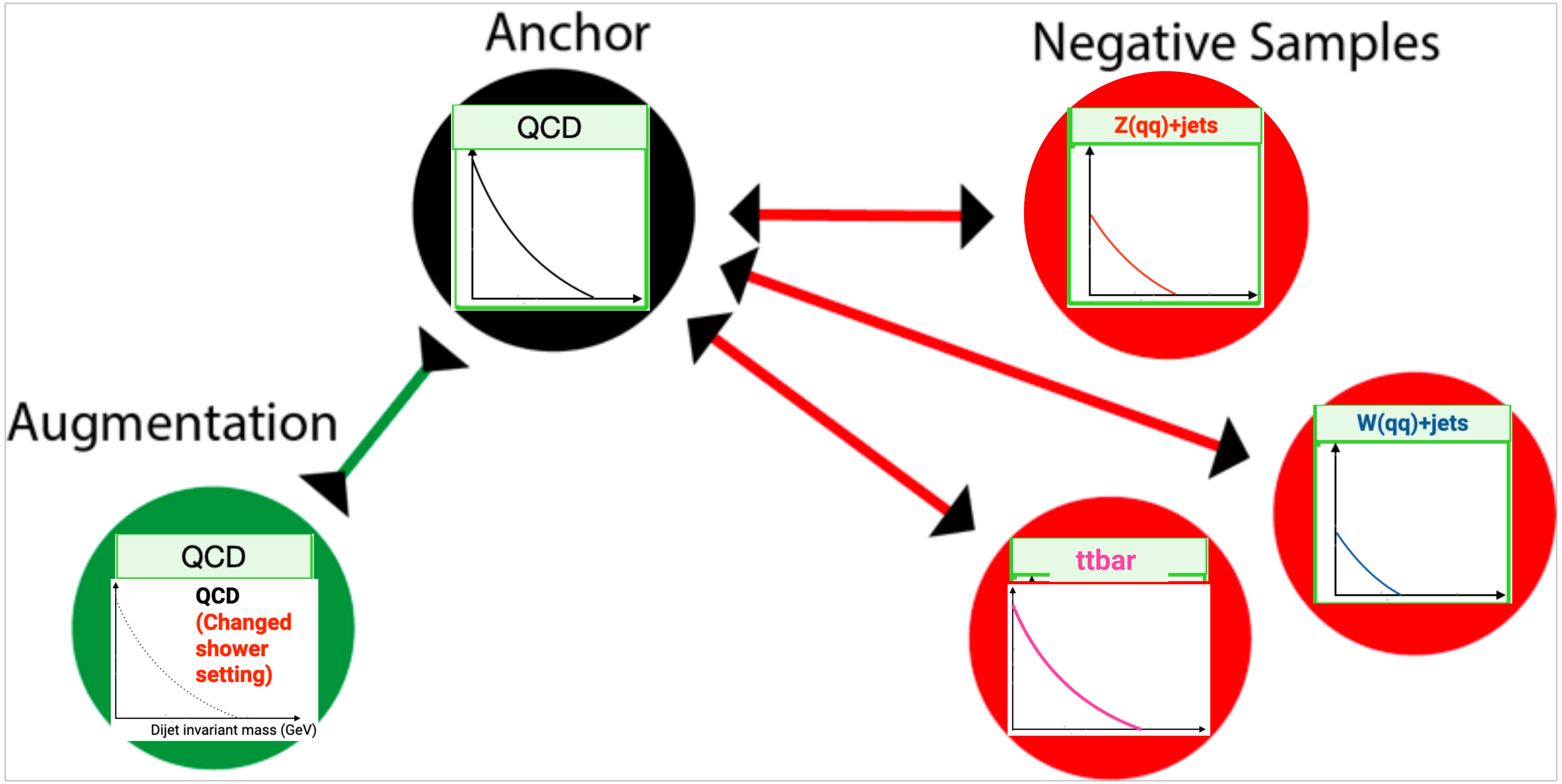

Augmented Cat A
Dog B
Cat A
Dog A
Cat B
Augmented Dog A

Physically motivated augmentations?

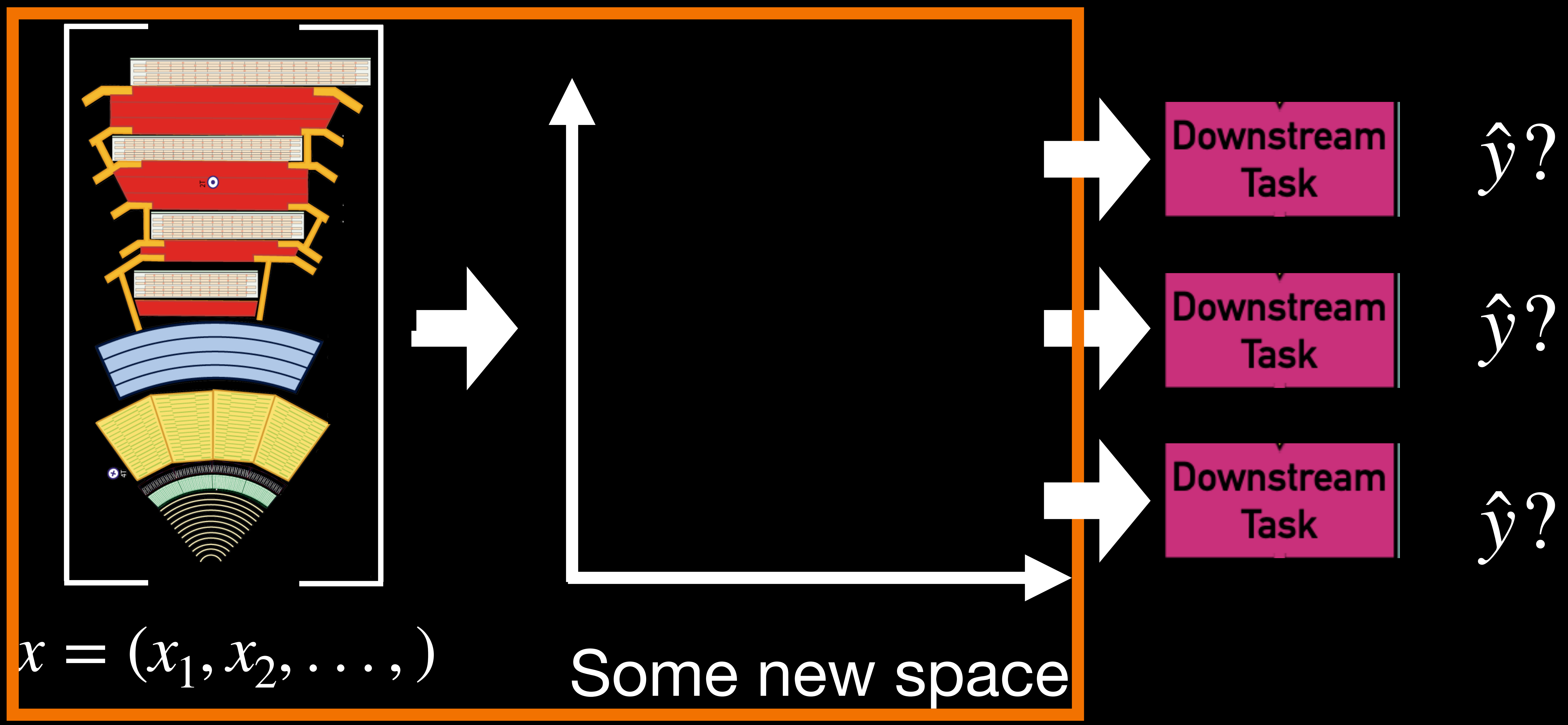


No class labels used in training! How do we augment detector data?

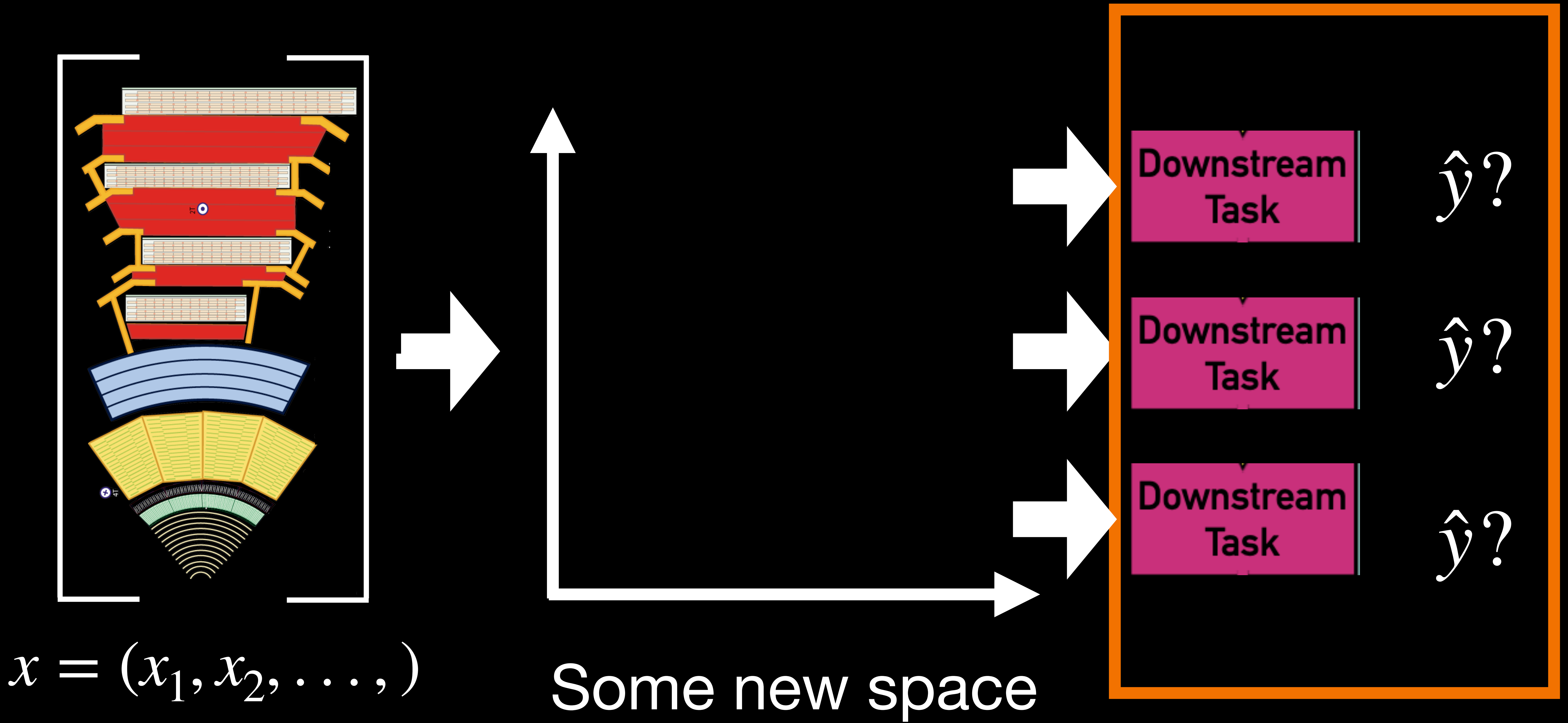
Physically motivated augmentations?



No class labels used in training! How do we augment detector data?

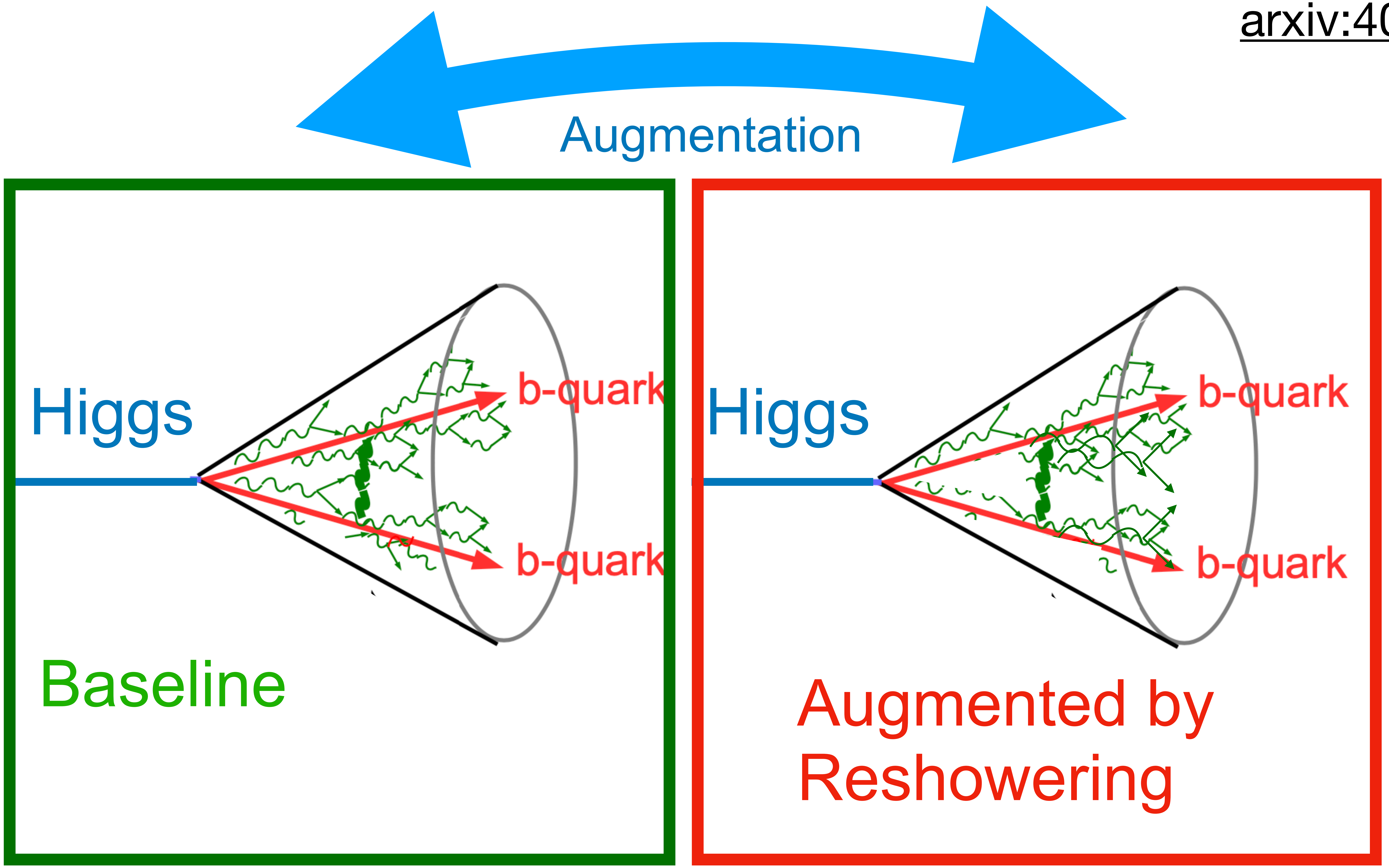


Training 1: Learn neural embedding
(on a lot of data, for a long time)
On simulation? On data?



Training 2: Fine tune for specific task
(fast, small dataset, simulation)

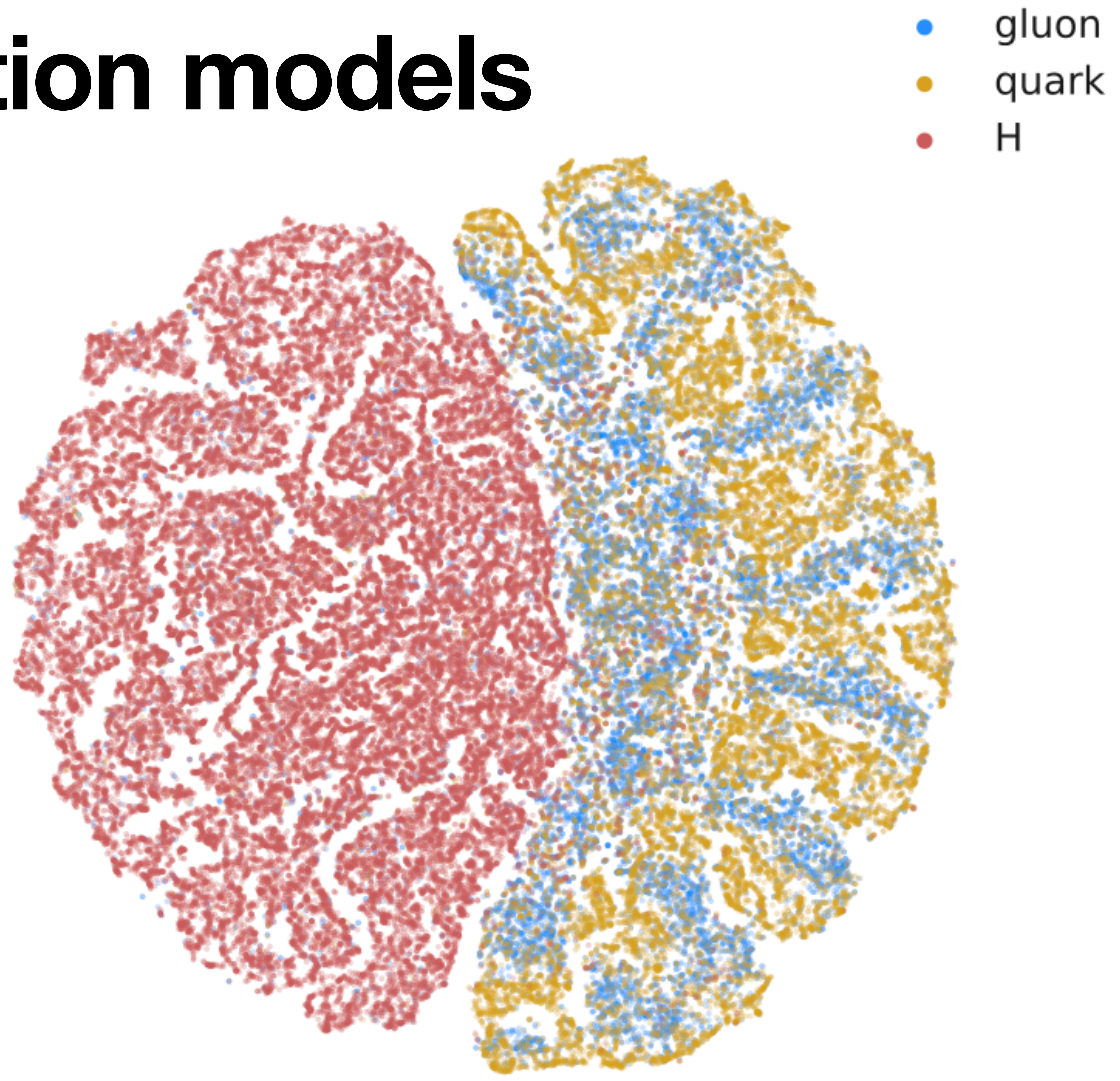
arxiv:403.07066



Embedded Space can use any NN to embed

arxiv:403.07066

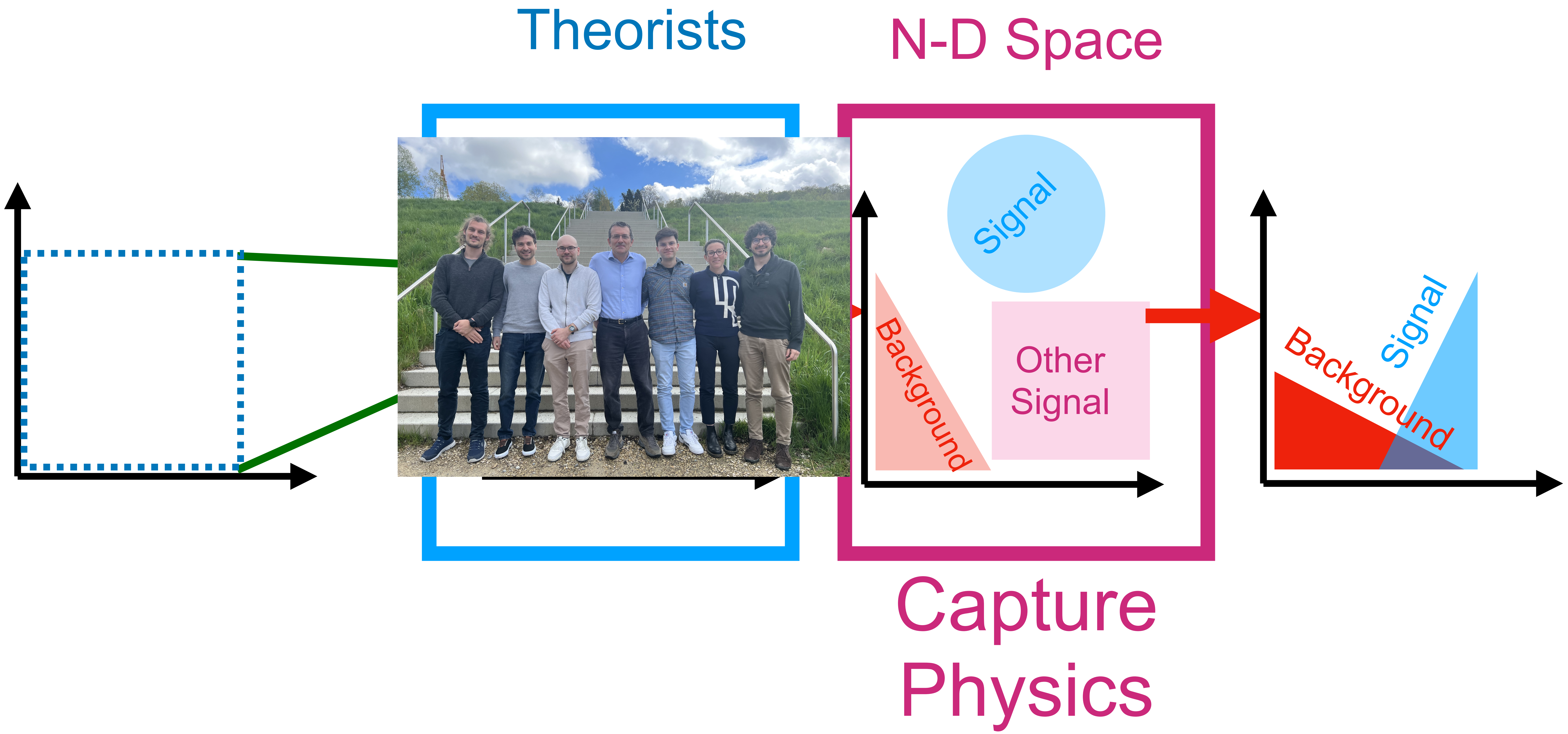
QM foundation models



→ embedding quantum mechanics into AI algorithm

From Phil Harris

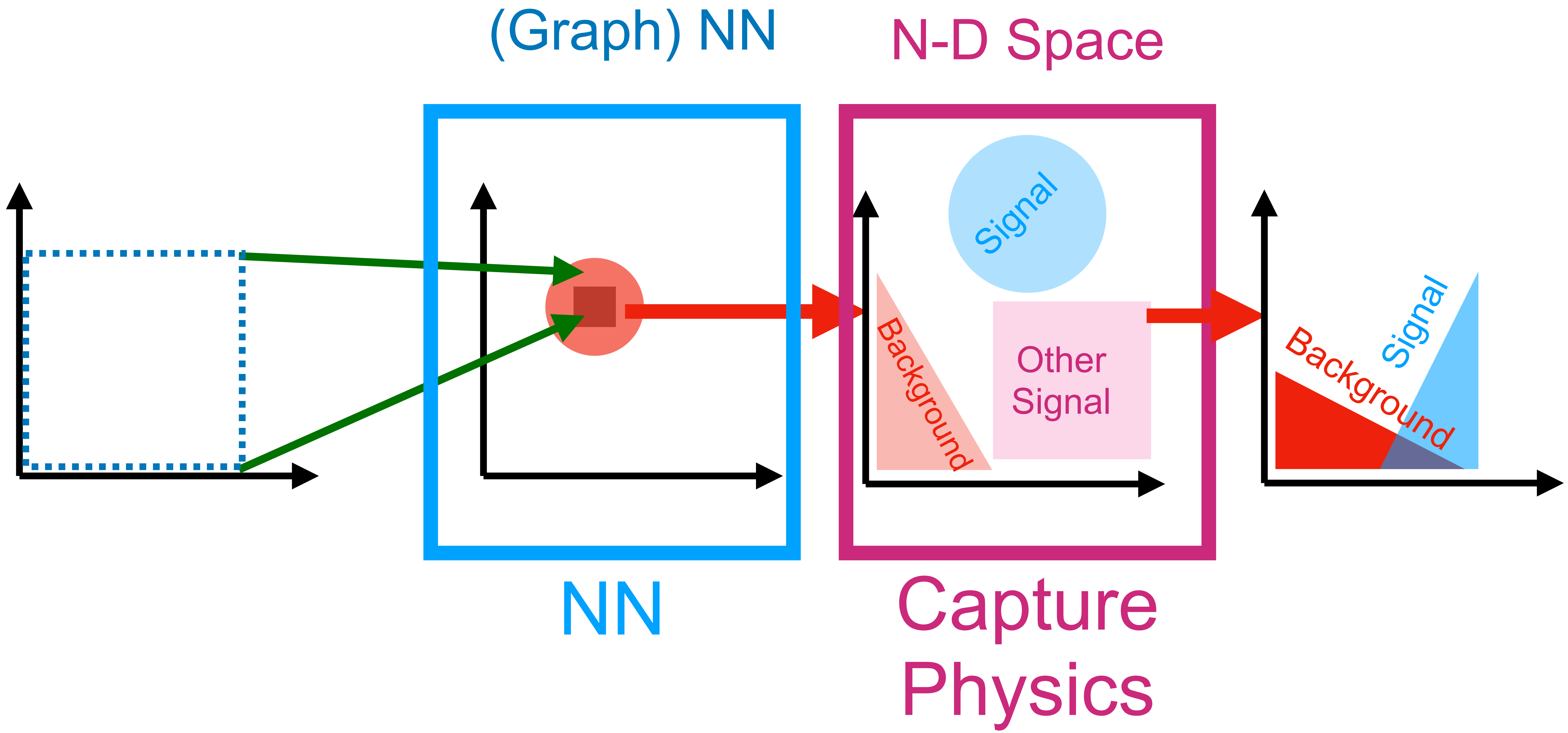
arxiv:403.07066



From Phil Harris

arxiv:403.07066

We can replace the QCD theorist with a NN
(And it works better)



Detector design, data acquisition and triggering
Detector reconstruction and tagging
AI!
Foundation models
Data analysis
Generative models for simulation
O(10^10)
100m
DIGI+RECO
Energy deposits→digital
signals→reconstructed by
reconstruction software
[Hard & Slow]
19.7 fb^-1 (8 TeV) + 5.1 fb^-1 (7 TeV)
CMS
H → γγ
S/(S+B) weighted sum
Data
S+B fits (weighted sum)
B component
±1σ
±2σ
μ̂ = 1.14 +0.26 −0.23
m̂_H = 124.70 ± 0.34 GeV
O(10)
O(10^3)
10^-18m
10^-15m
10^-6m
GEN
pp collisions up to
particles [Easy & Fast]
detector response
GEANT4