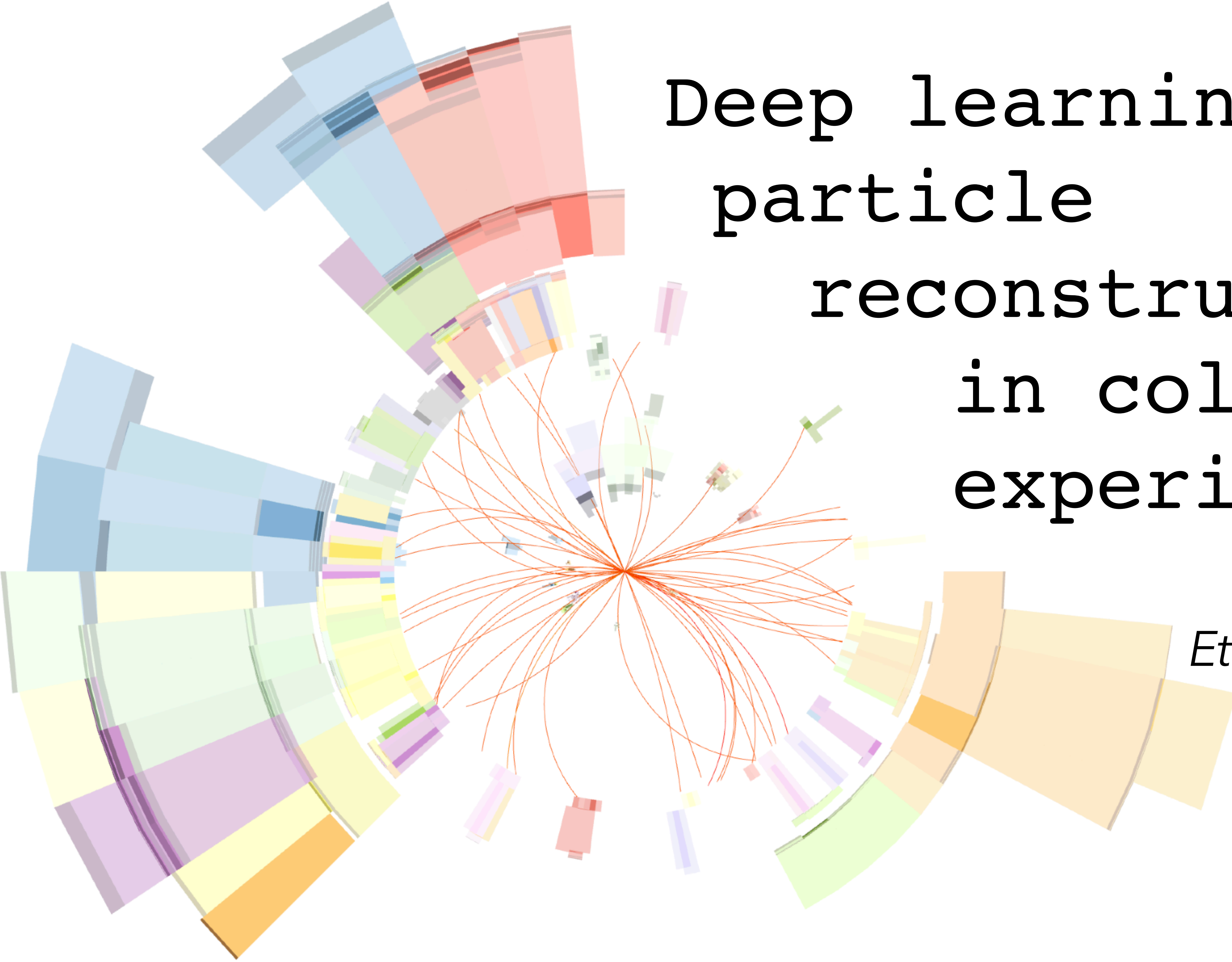


Deep learning for particle reconstruction in collider experiments

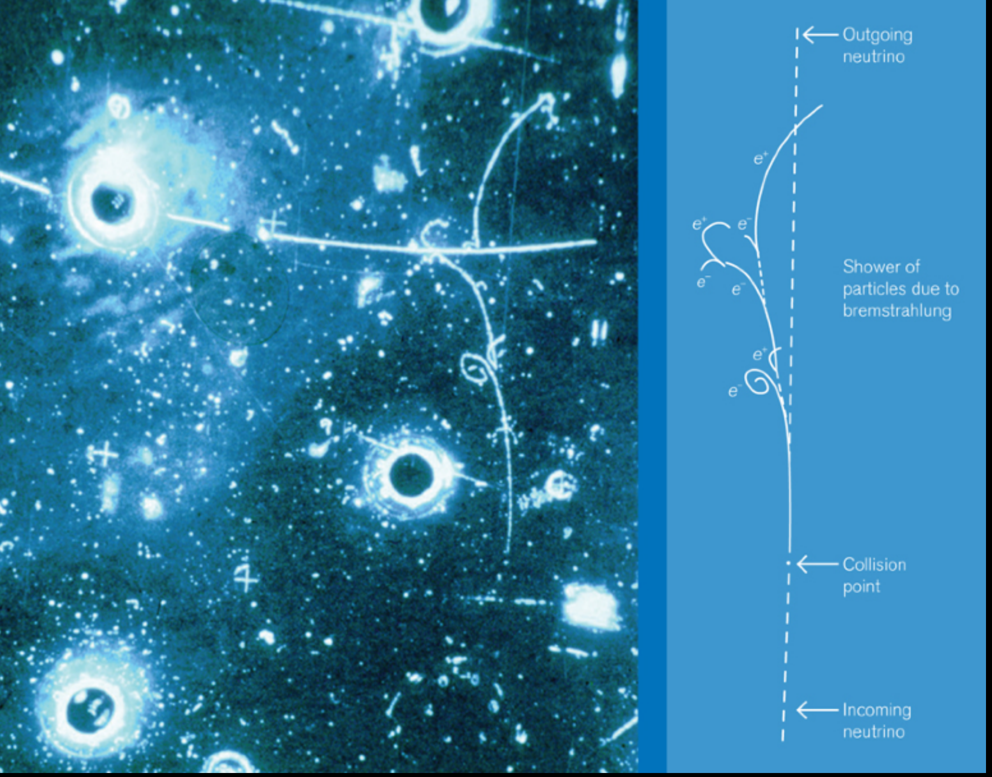
Etienne Dreyer

מכון ויצמן למדע
WEIZMANN INSTITUTE OF SCIENCE

17/12/2024, Genova

Digital Twins for Nuclear and Particle physics

A history of particle detectors



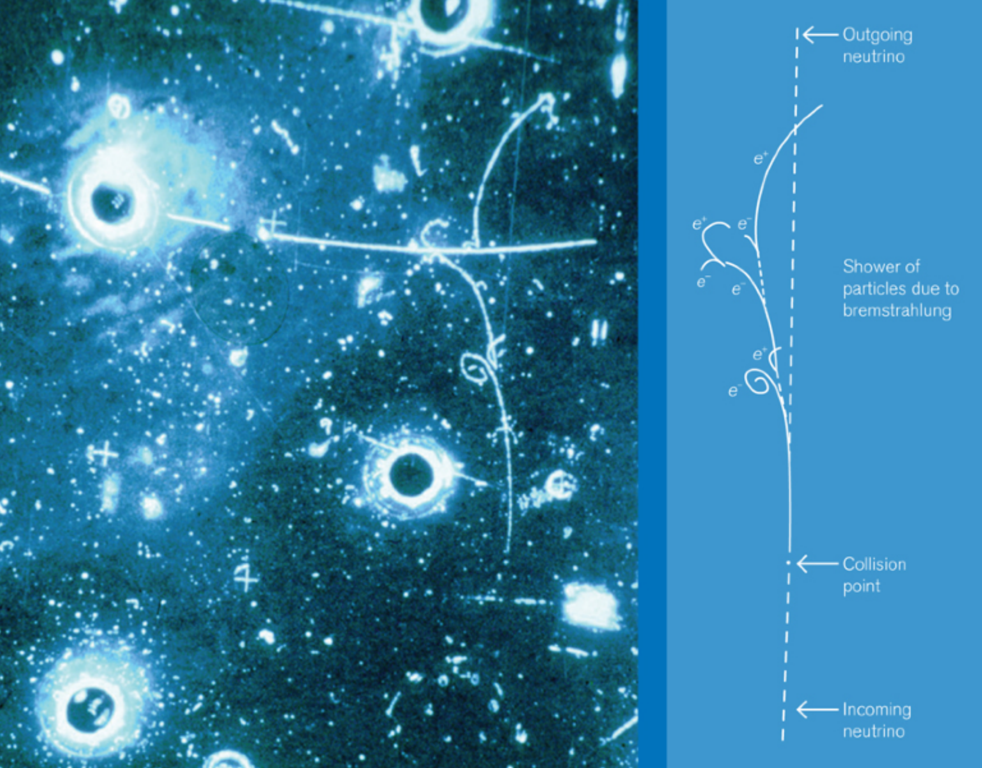
BEBC

1979

Weak neutral current

A history of particle detectors

A history of particle detectors



BEBC

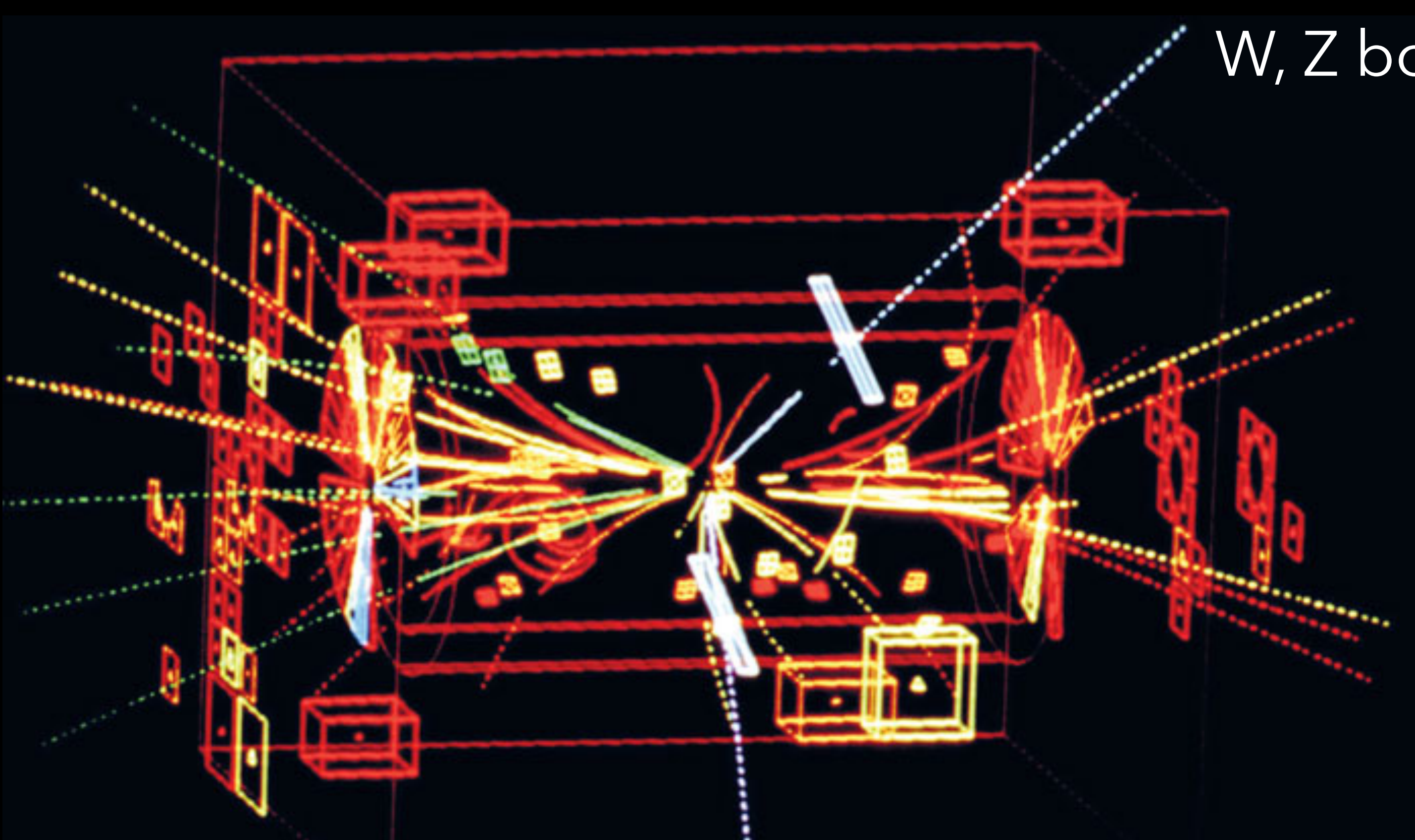
1979

Weak neutral current

UA1

1984

W, Z bosons



BEBC

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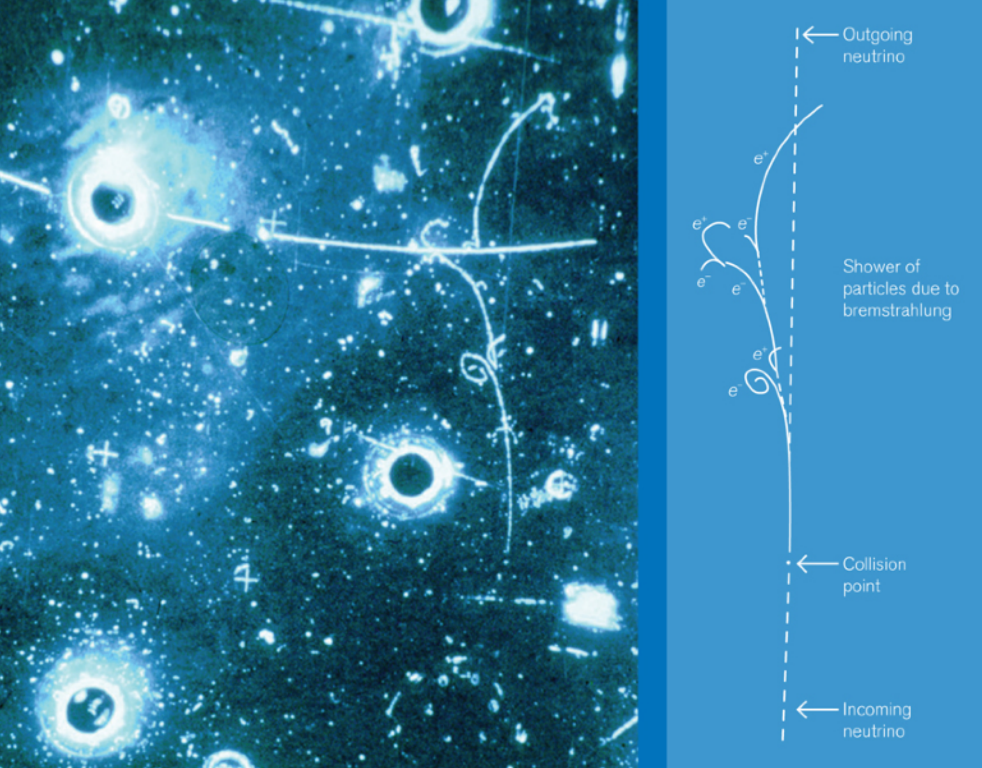
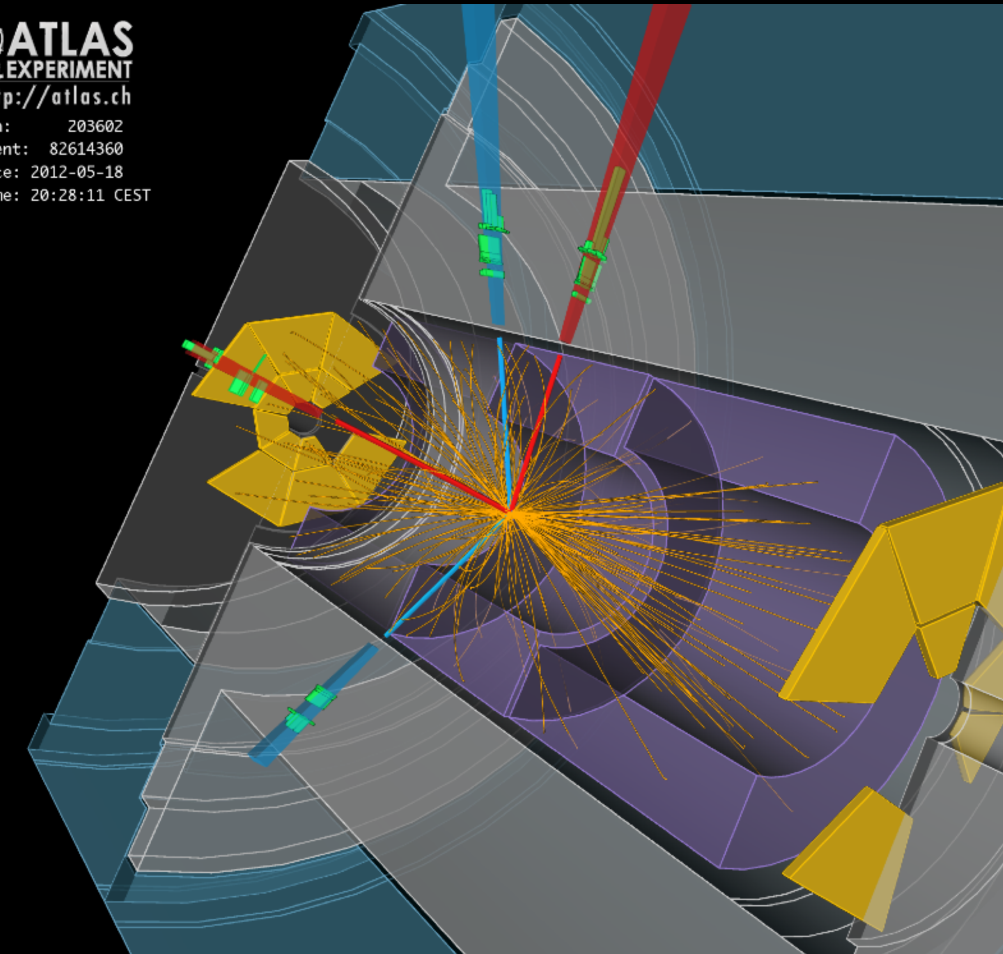
Weak neutral current





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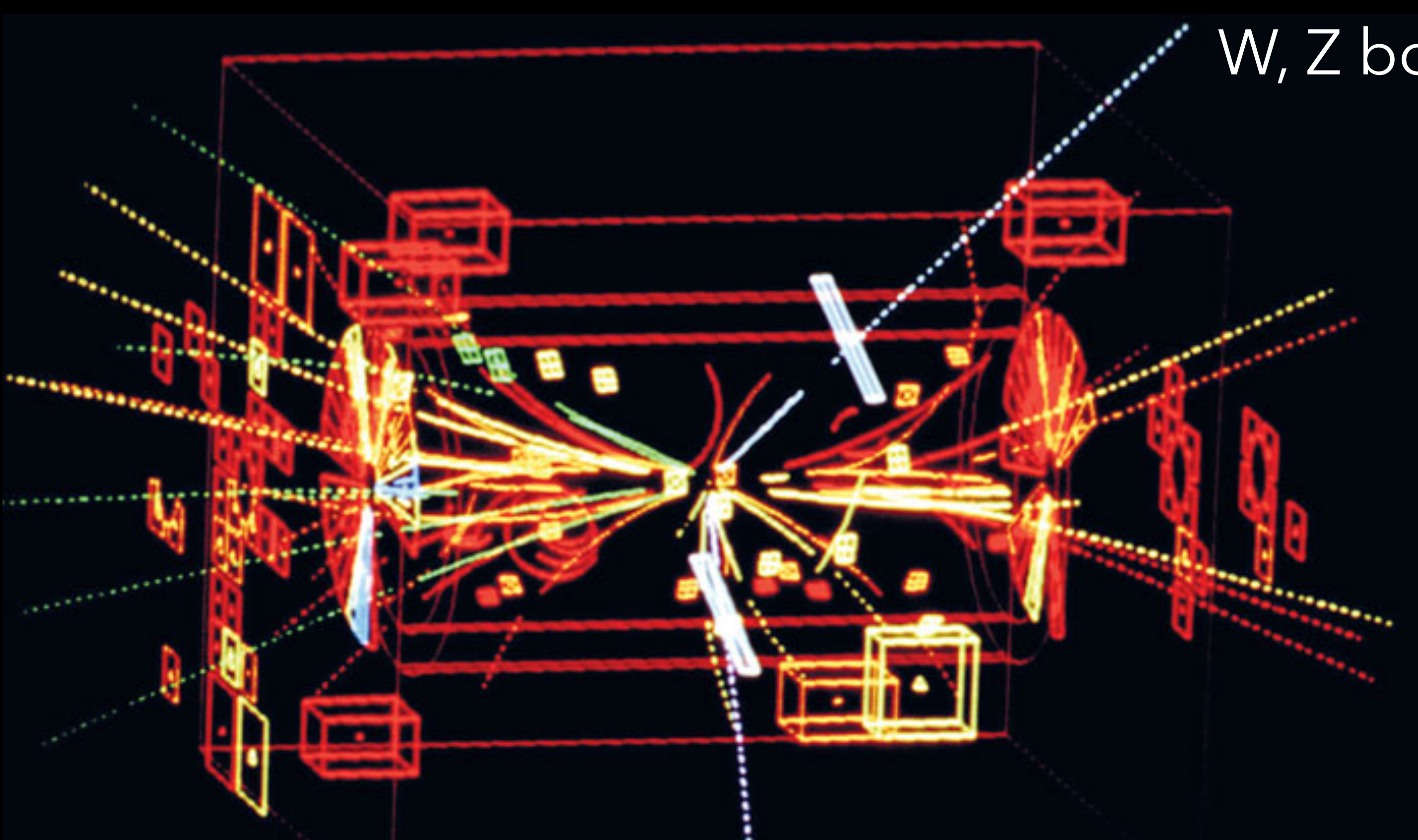
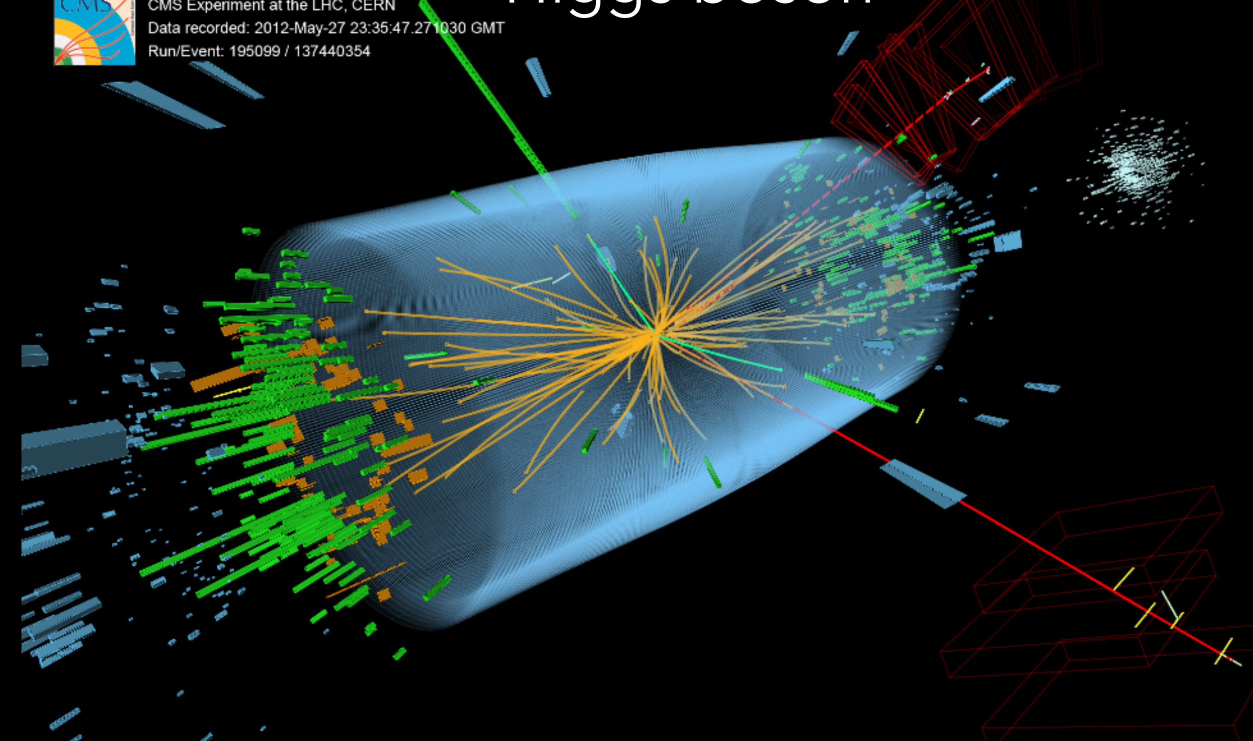


ATLAS & CMS

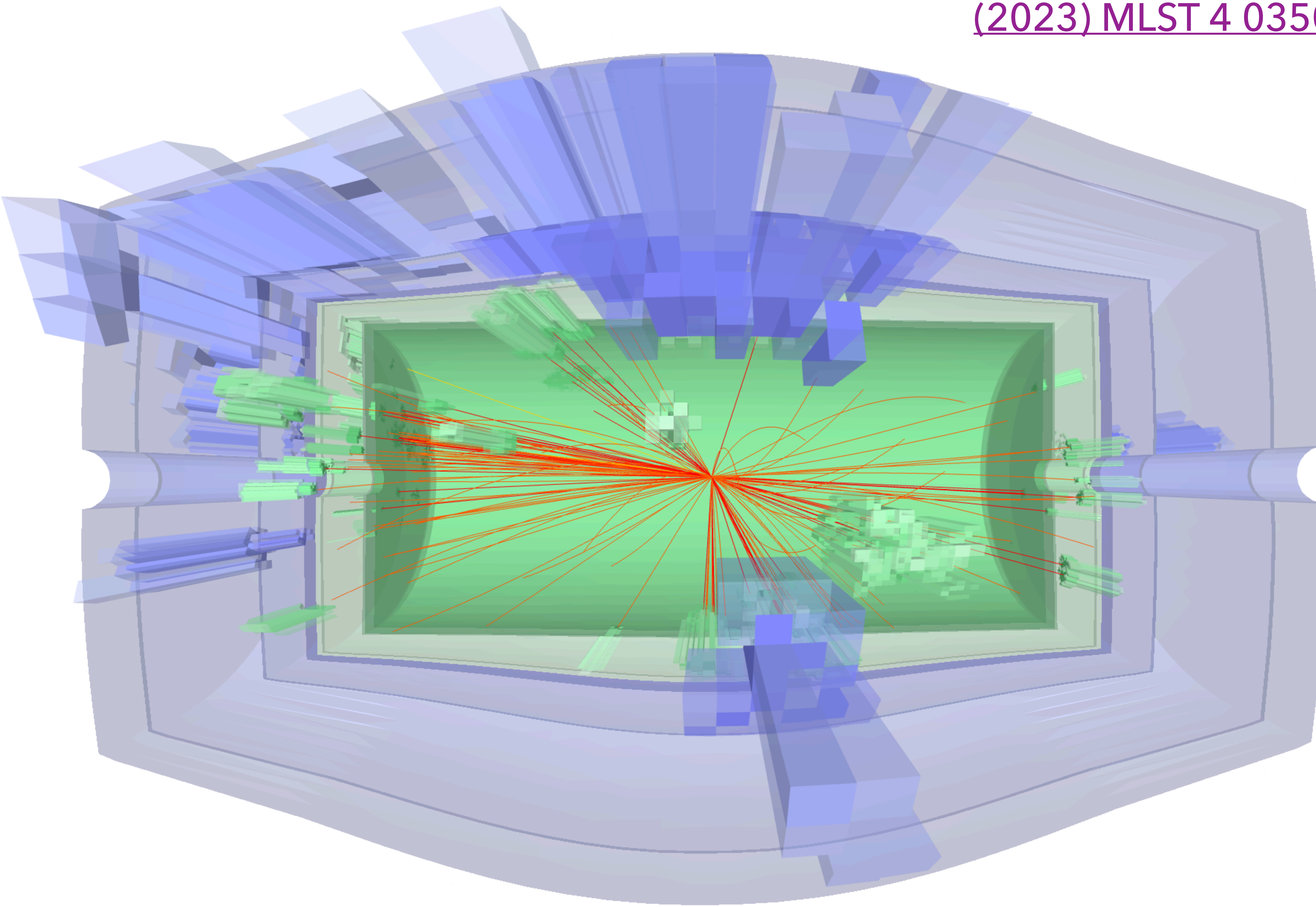
2013

Higgs boson



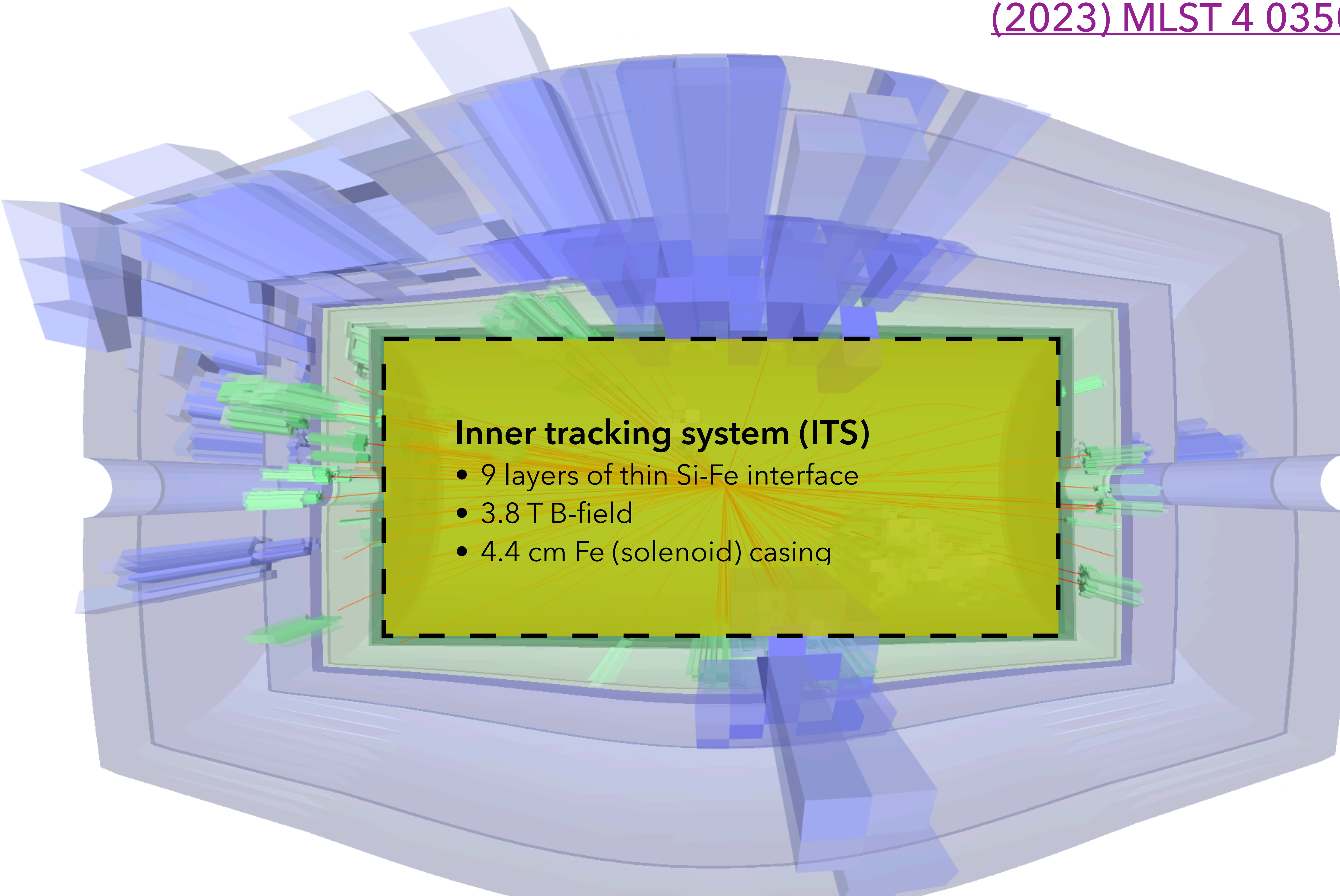
COCOA: Our "Digital Twin"

(2023) MLST 4 035042



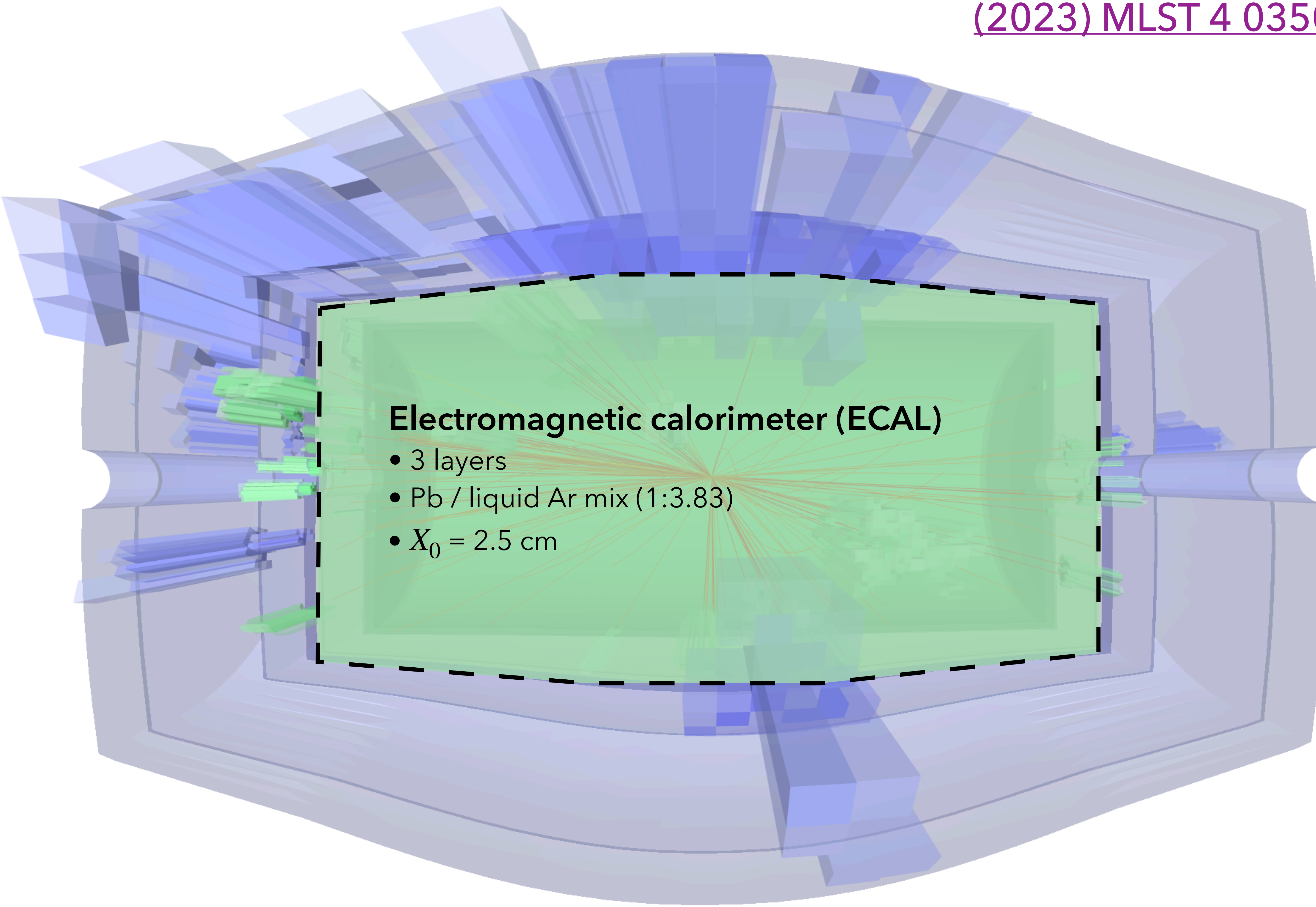
COCOA: Our "Digital Twin"

(2023) MLST 4 035042



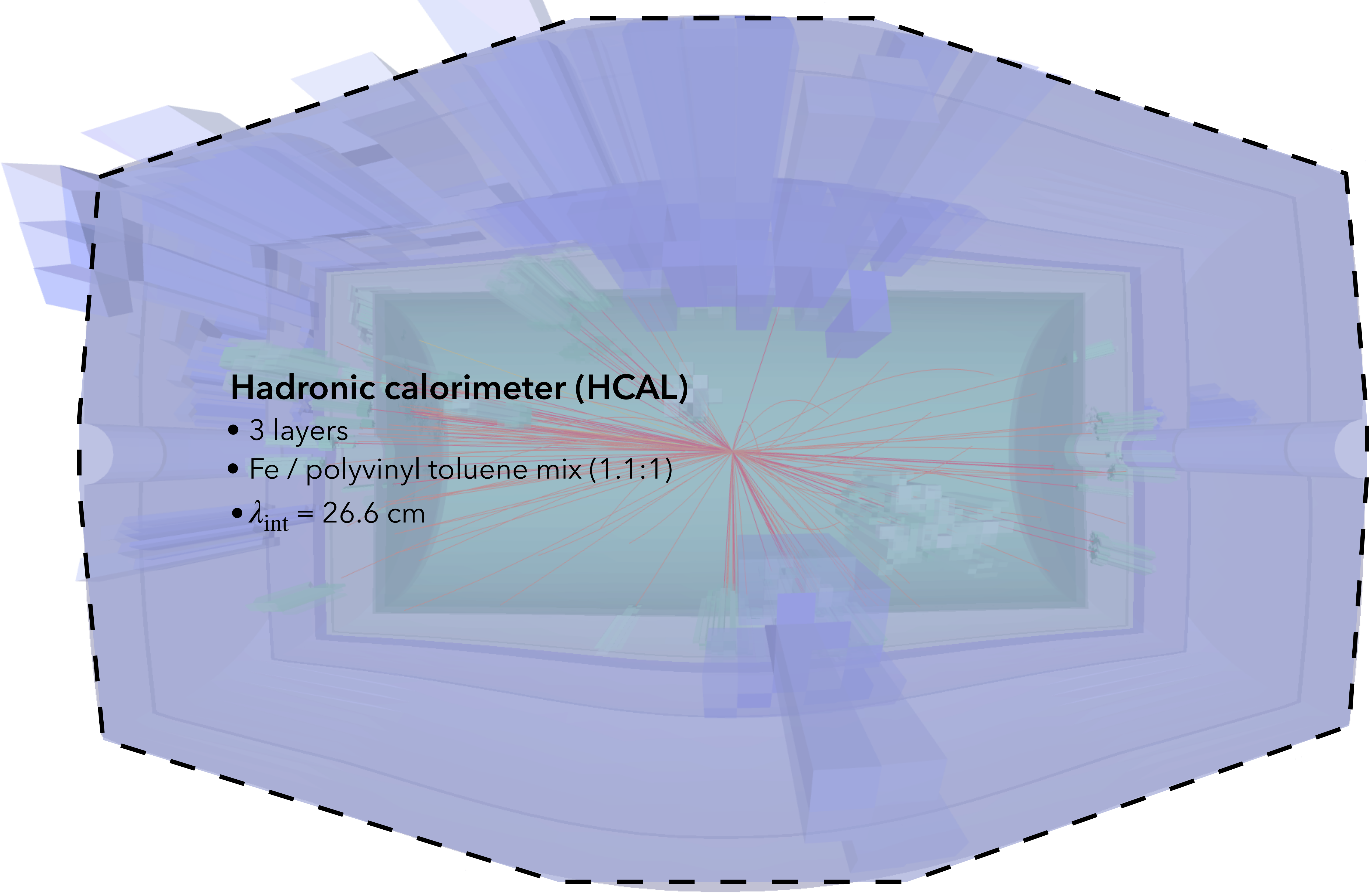
COCOA: Our "Digital Twin"

(2023) MLST 4 035042



COCOA: Our “Digital Twin”

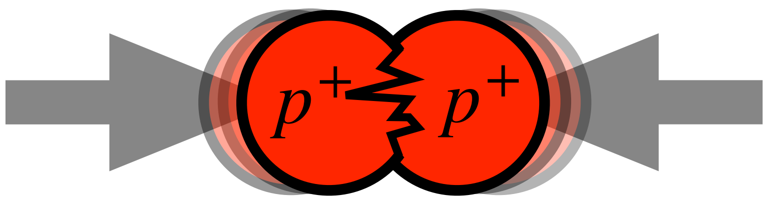
(2023) MLST 4 035042

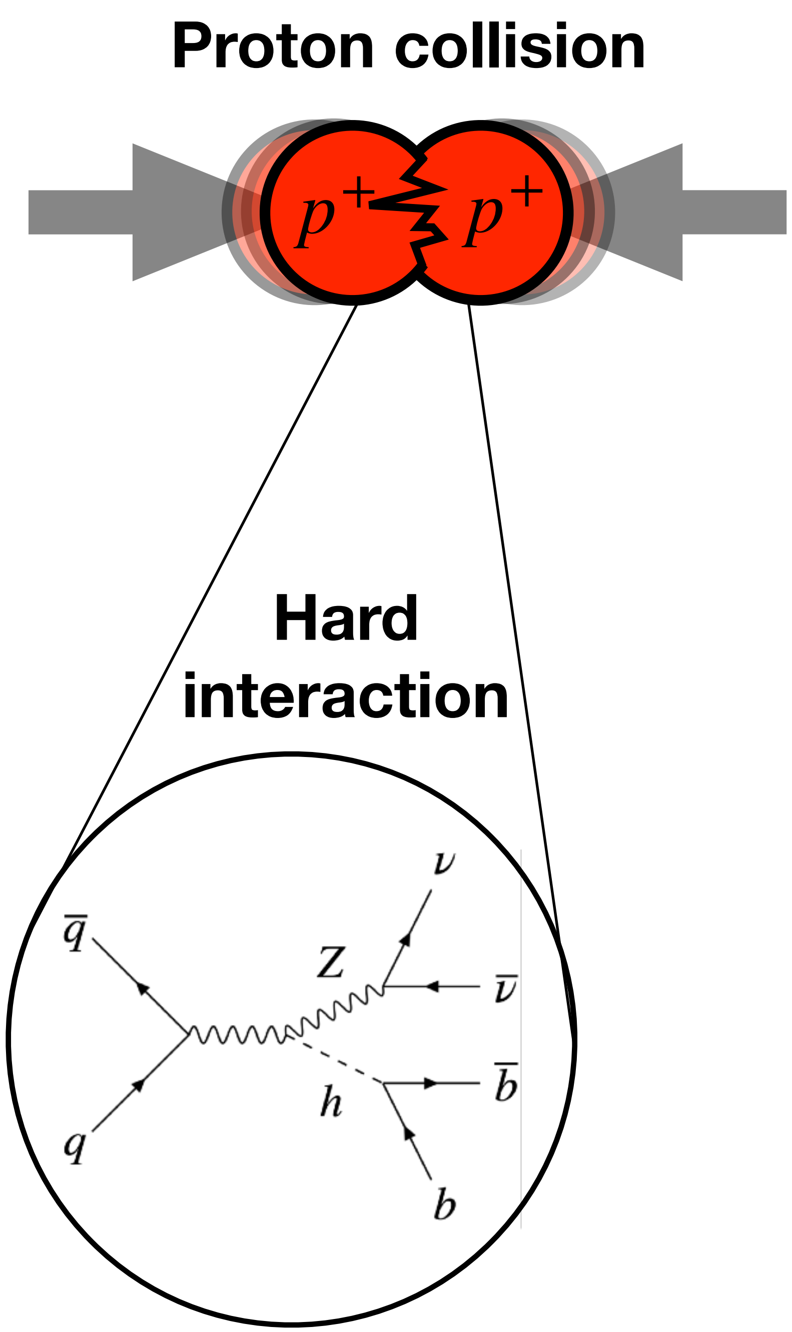


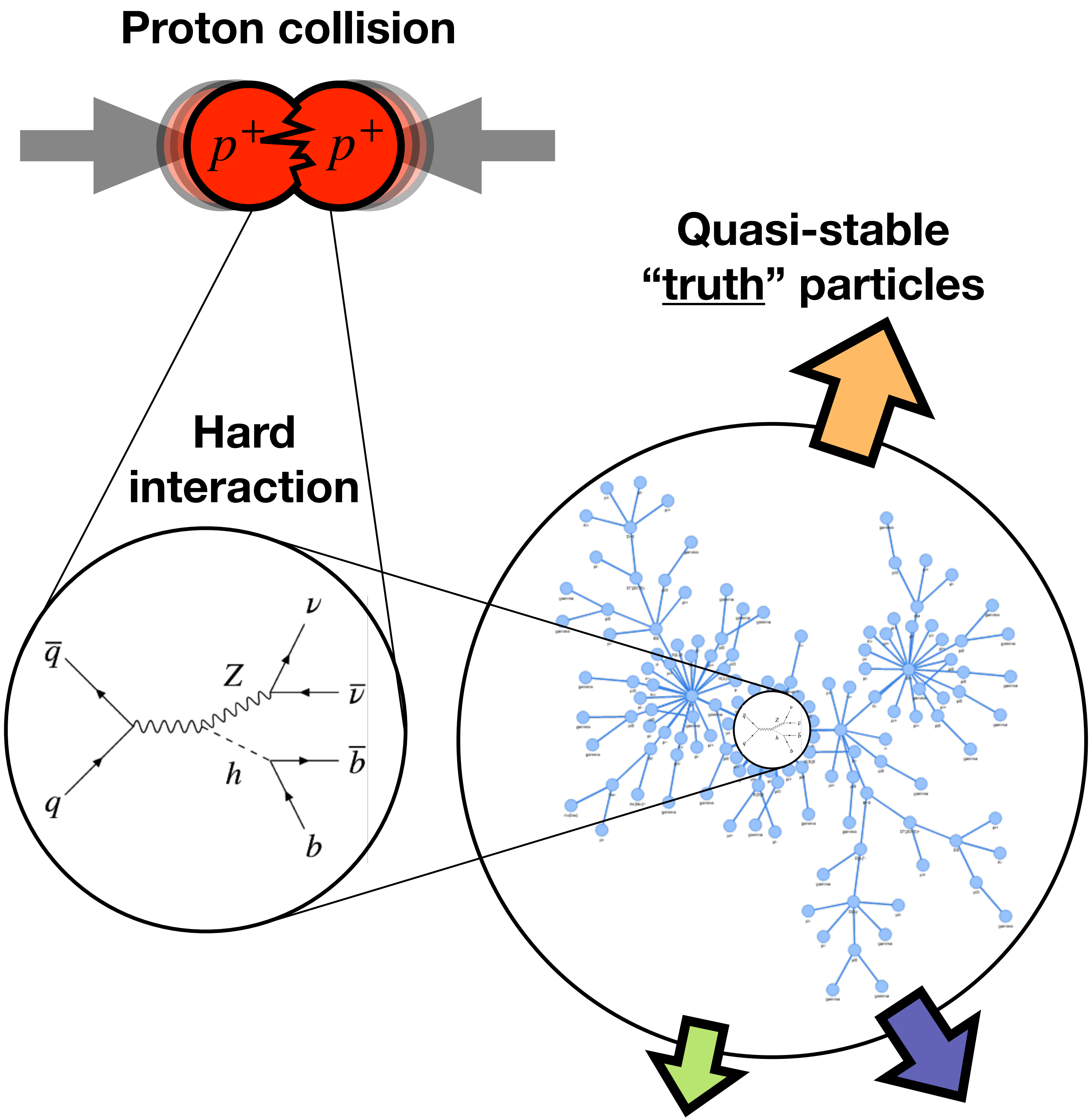
Hadronic calorimeter (HCAL)

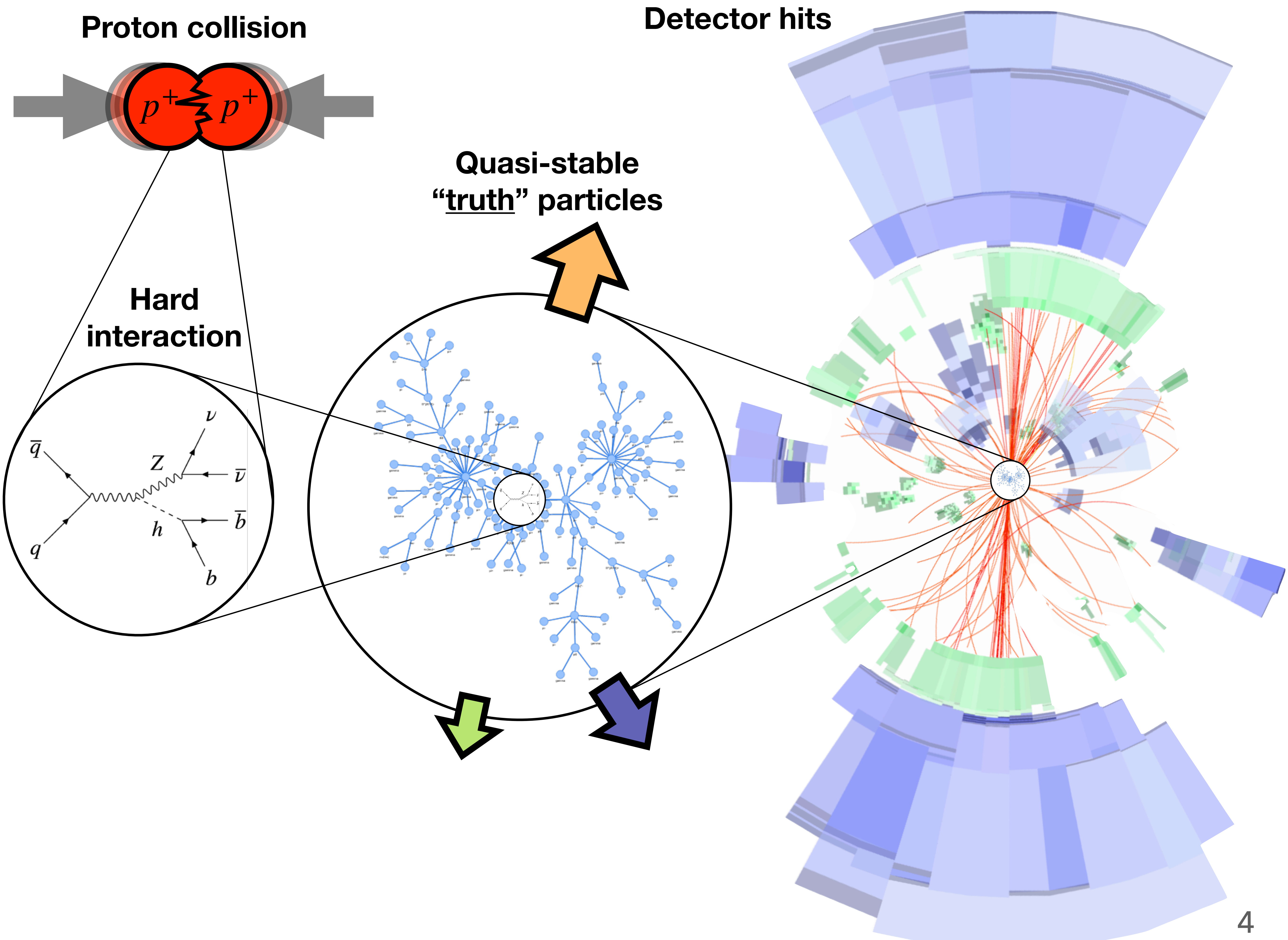
- 3 layers
- Fe / polyvinyl toluene mix (1.1:1)
- λ_{int} = 26.6 cm

Proton collision

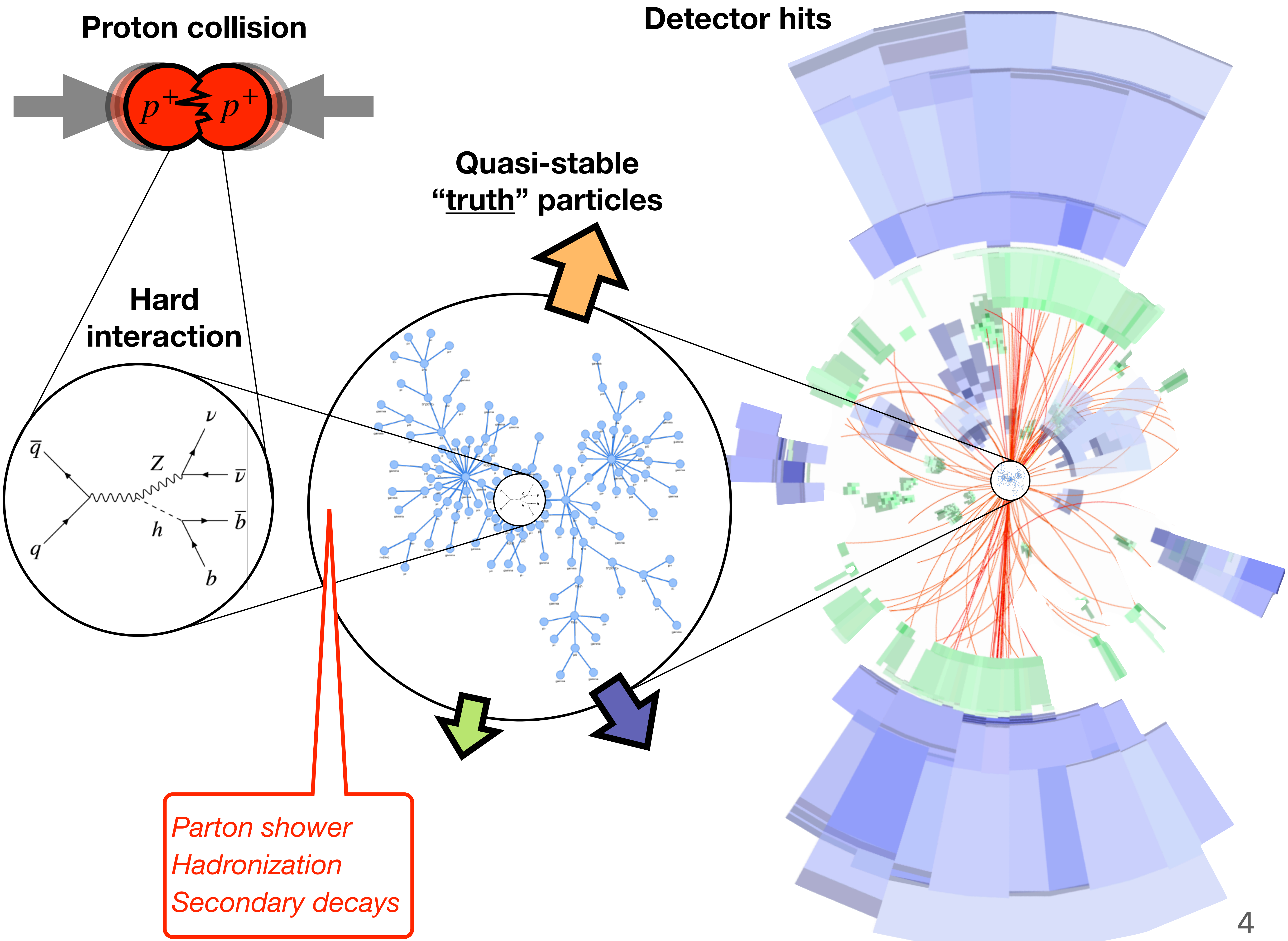



Proton collision
p^+
p^+
Hard
interaction
$\bar{q}$
q
Z
h
ν
$\bar{\nu}$
$\bar{b}$
b

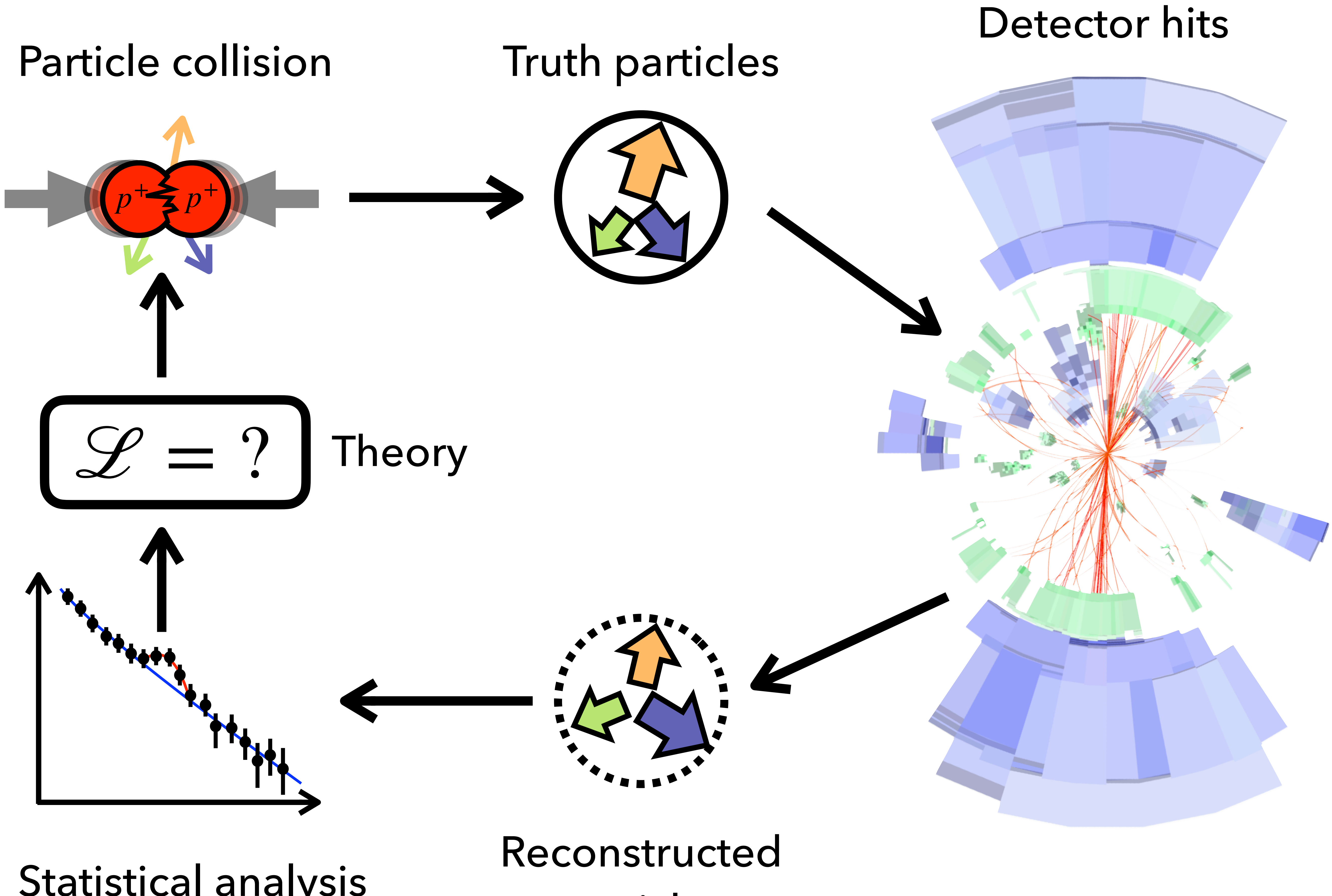

Proton collision
p^+
p^+
Quasi-stable
“truth” particles
Hard
interaction
$\overline{q}$
q
Z
h
ν
$\overline{\nu}$
$\overline{b}$
b



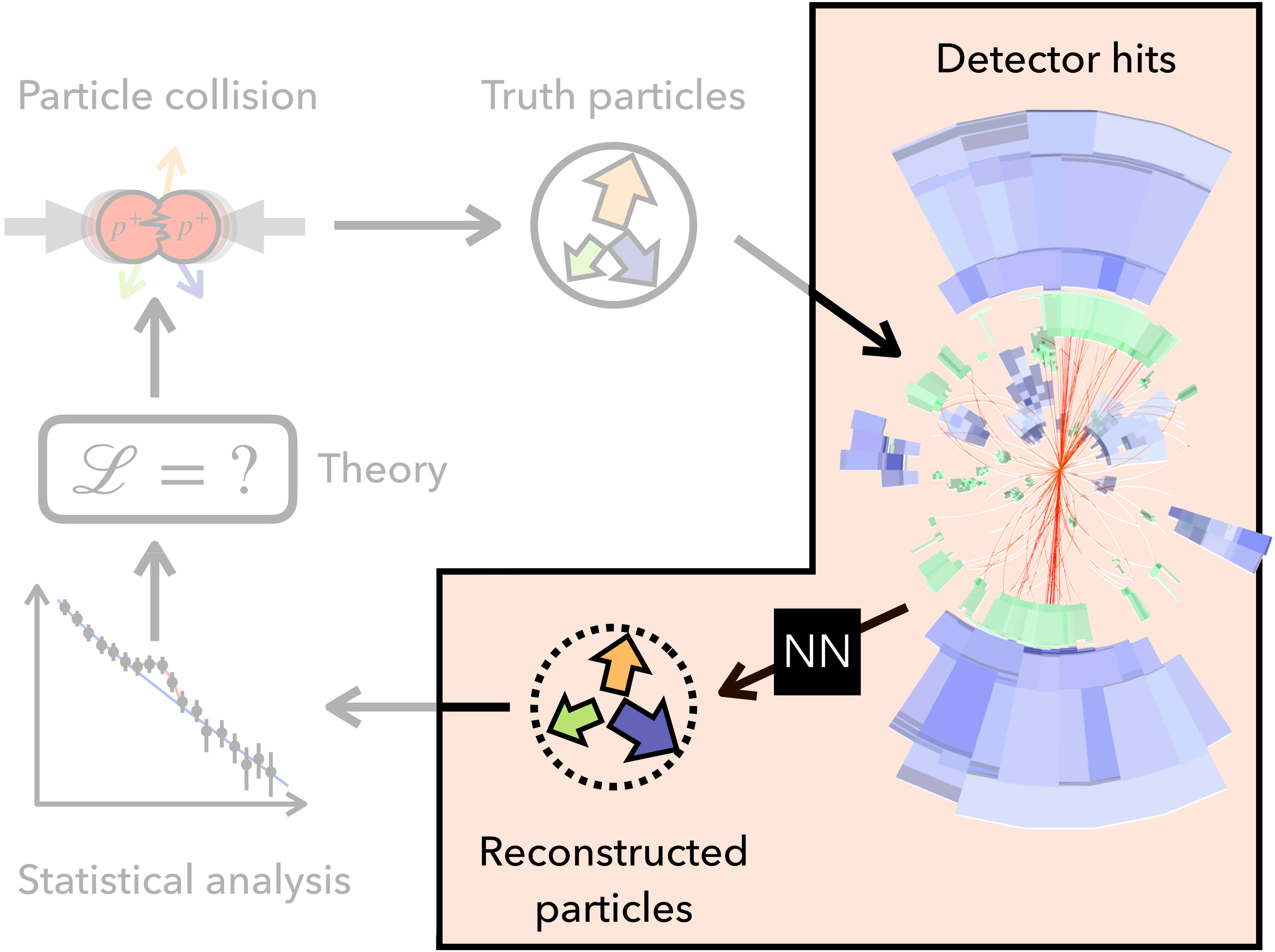
Proton collision
p^+
p^+
Detector hits
Quasi-stable
"truth" particles
Hard
interaction
$\bar{q}$
q
Z
h
ν
$\bar{\nu}$
$\bar{b}$
b



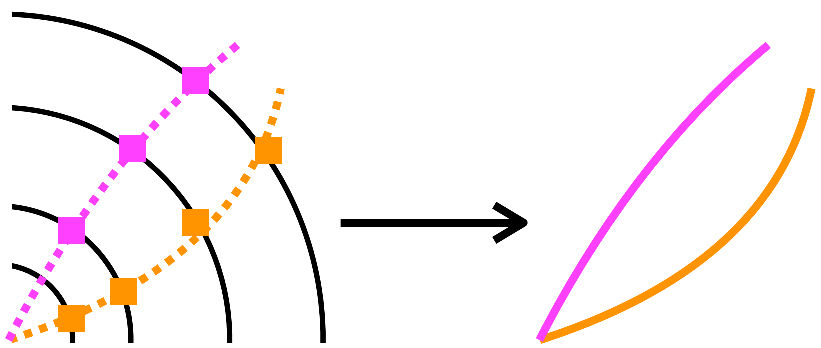
Proton collision
p^+ p^+
Detector hits
Quasi-stable
"truth" particles
Hard
interaction
$\bar{q}$ q Z h ν $\bar{\nu}$ $\bar{b}$ b
Parton shower
Hadronization
Secondary decays

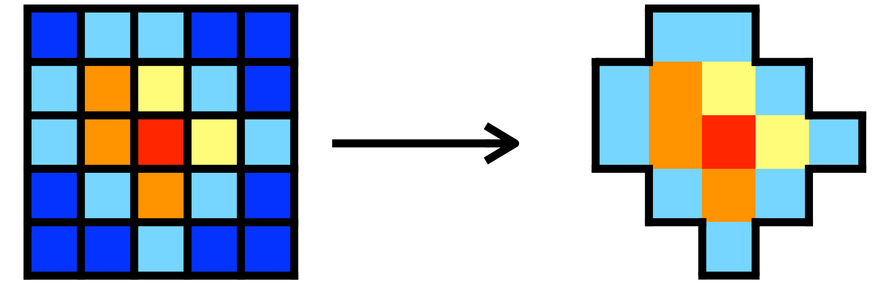


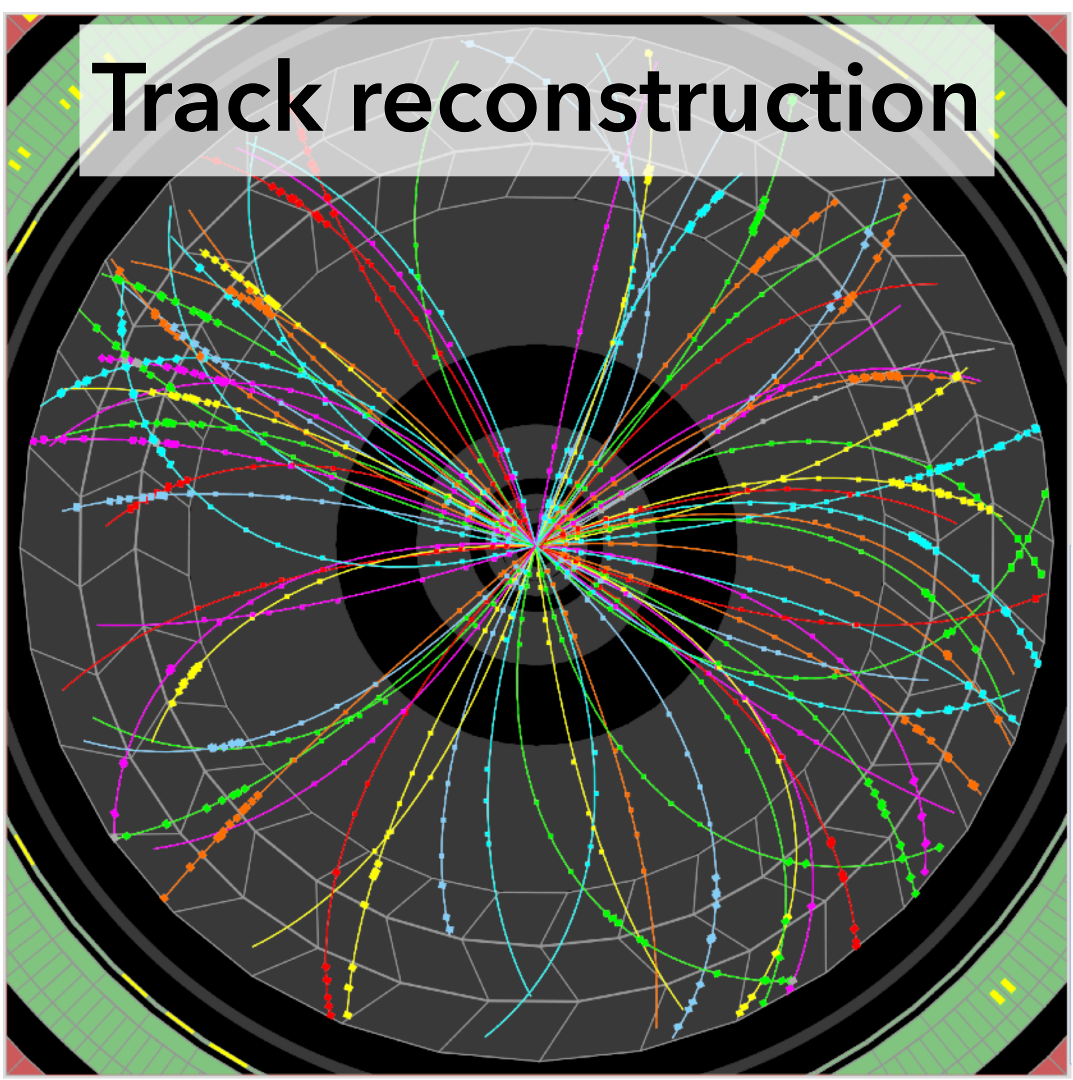
Particle collision
p^+
p^+
Truth particles
Detector hits
$\mathscr{L} = ?$
Theory
Statistical analysis
Reconstructed particles

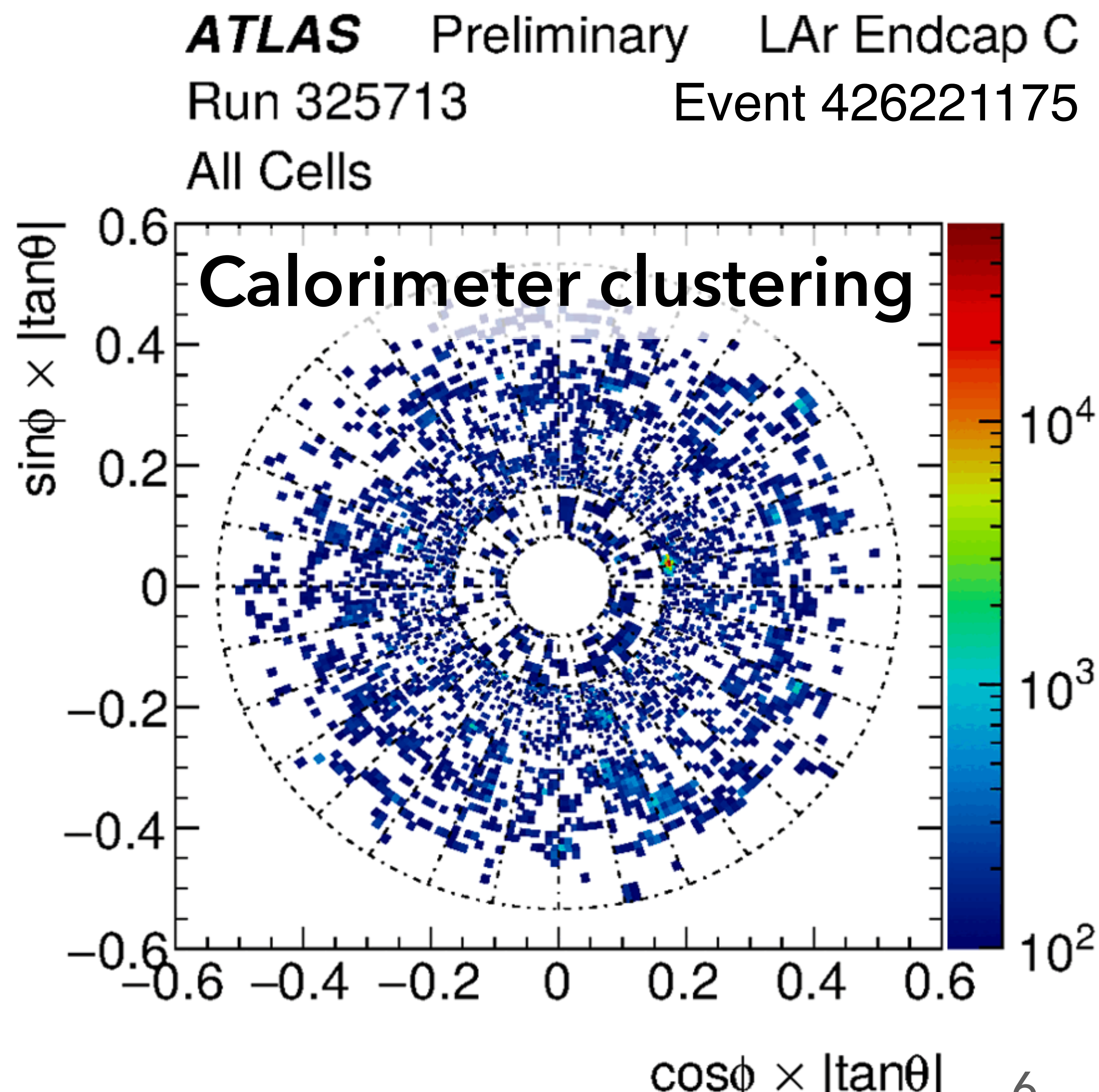

Particle collision
p^+ p^+
Truth particles
Detector hits
$\mathscr{L} = ?$
Theory
NN
Statistical analysis
Reconstructed particles

Dimensionality reduction



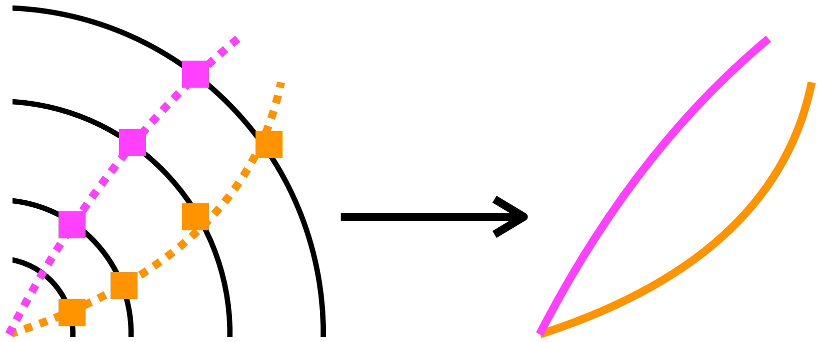


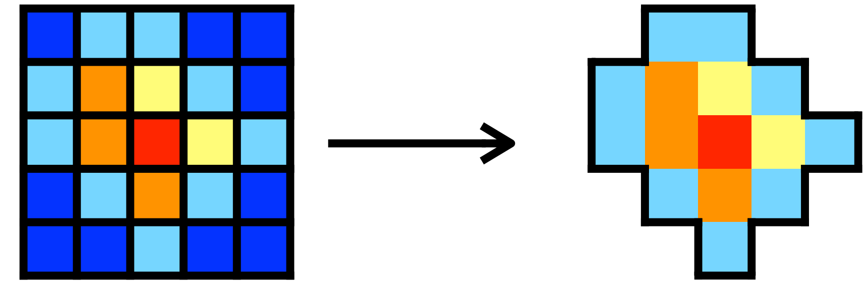


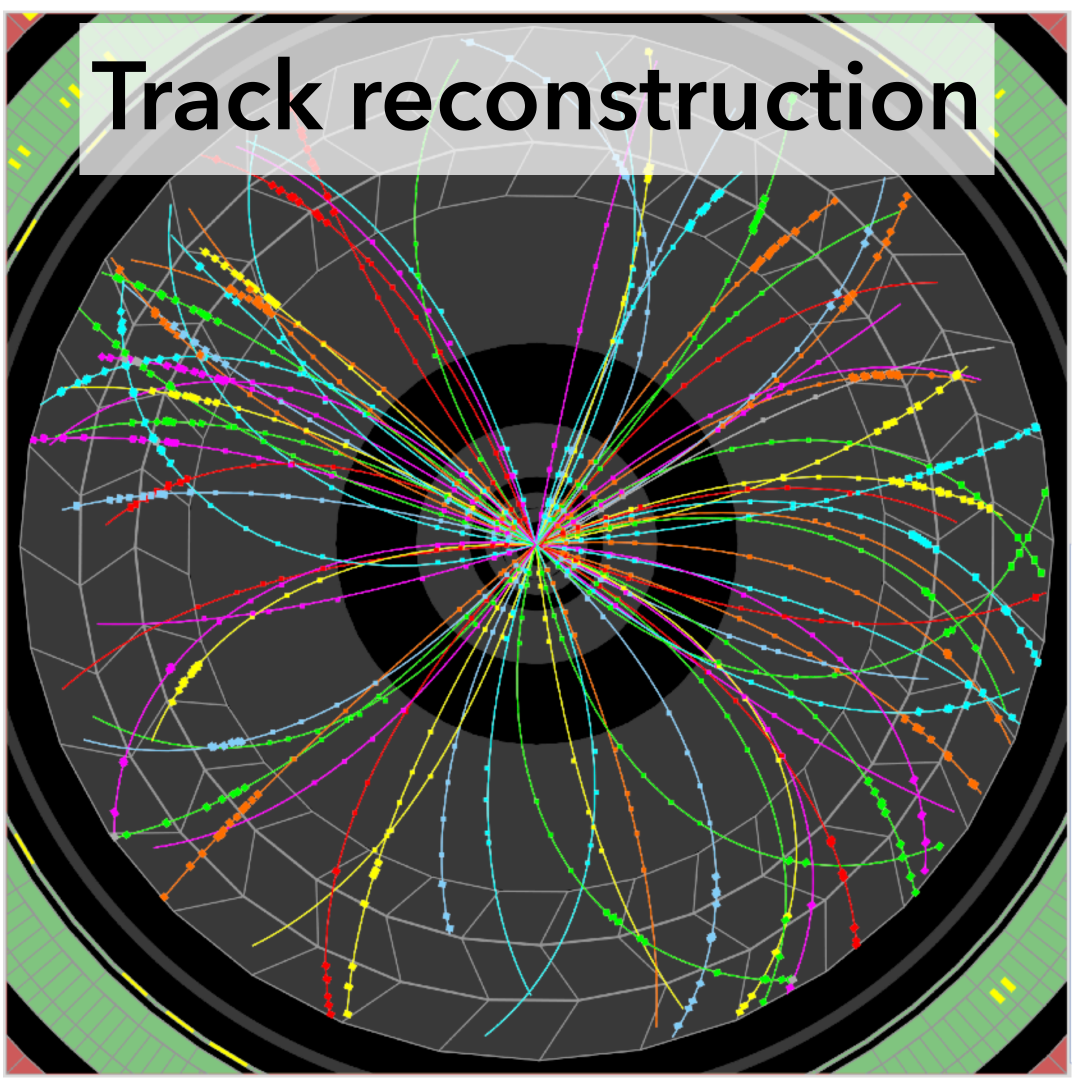


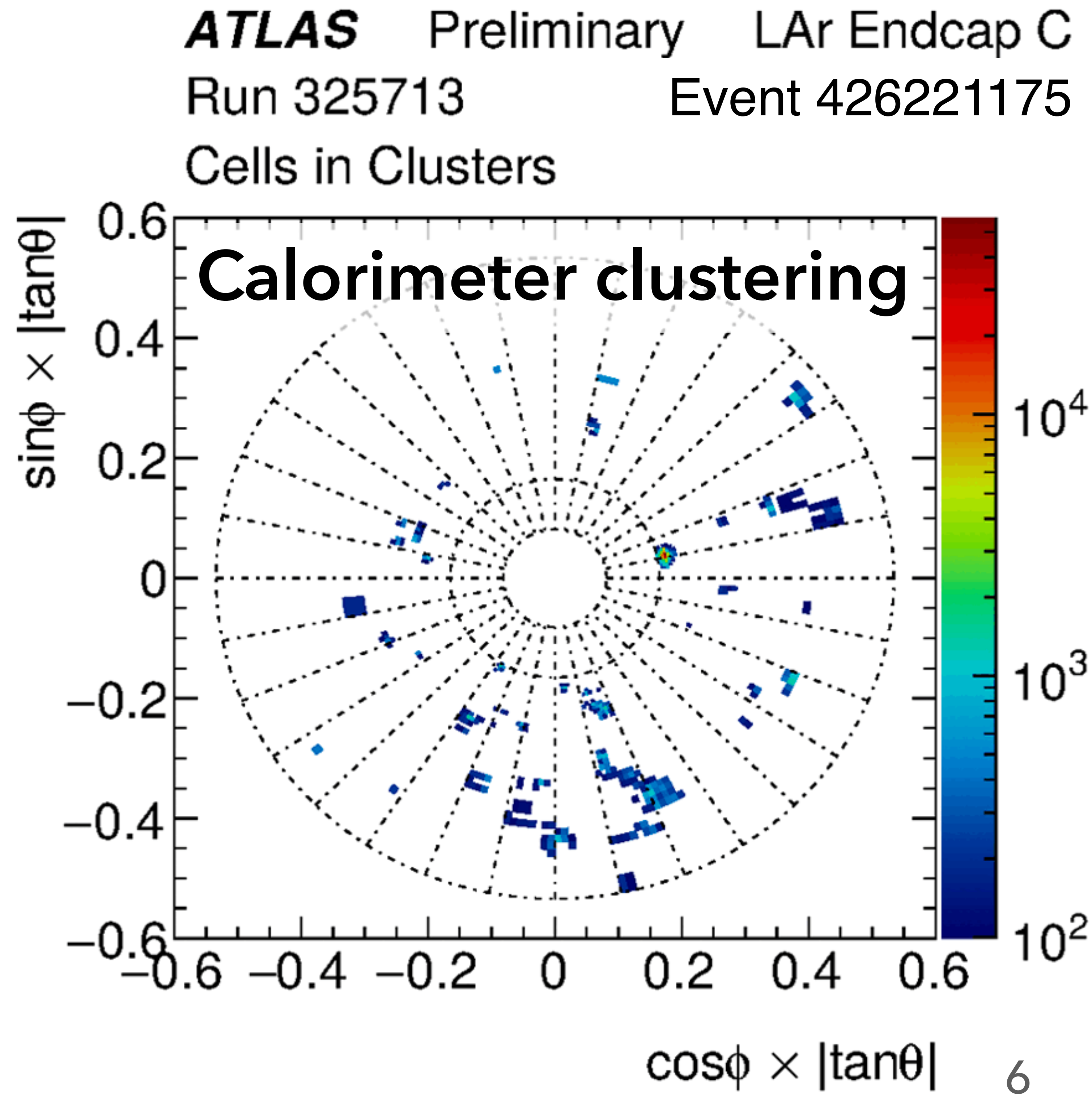
⇒ see talk by Tommaso R.

Dimensionality reduction









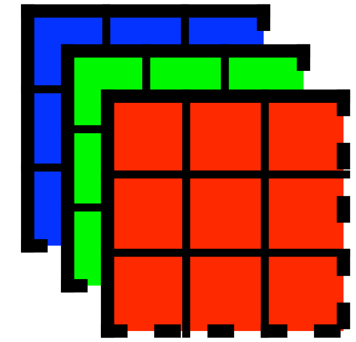
⇒ see talk by Tommaso R.

Classic object detection

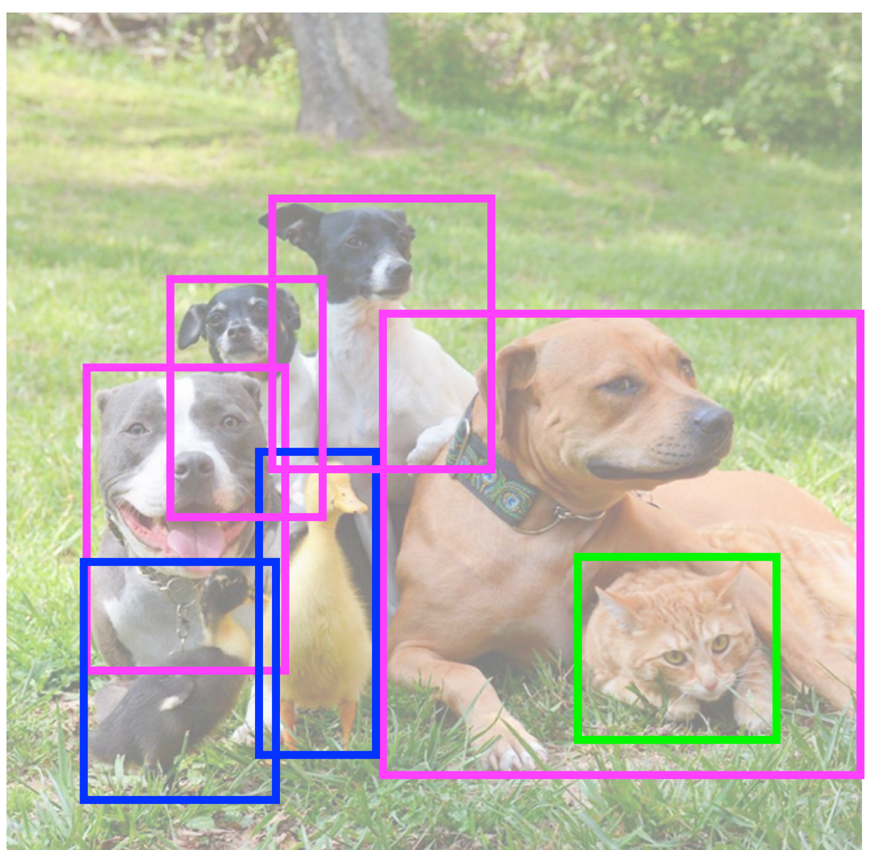
Credit: BoredPanda

Input

Features: `RGB value array`



Output



Cardinality

7

Class

person
dog
cat
duck
tree

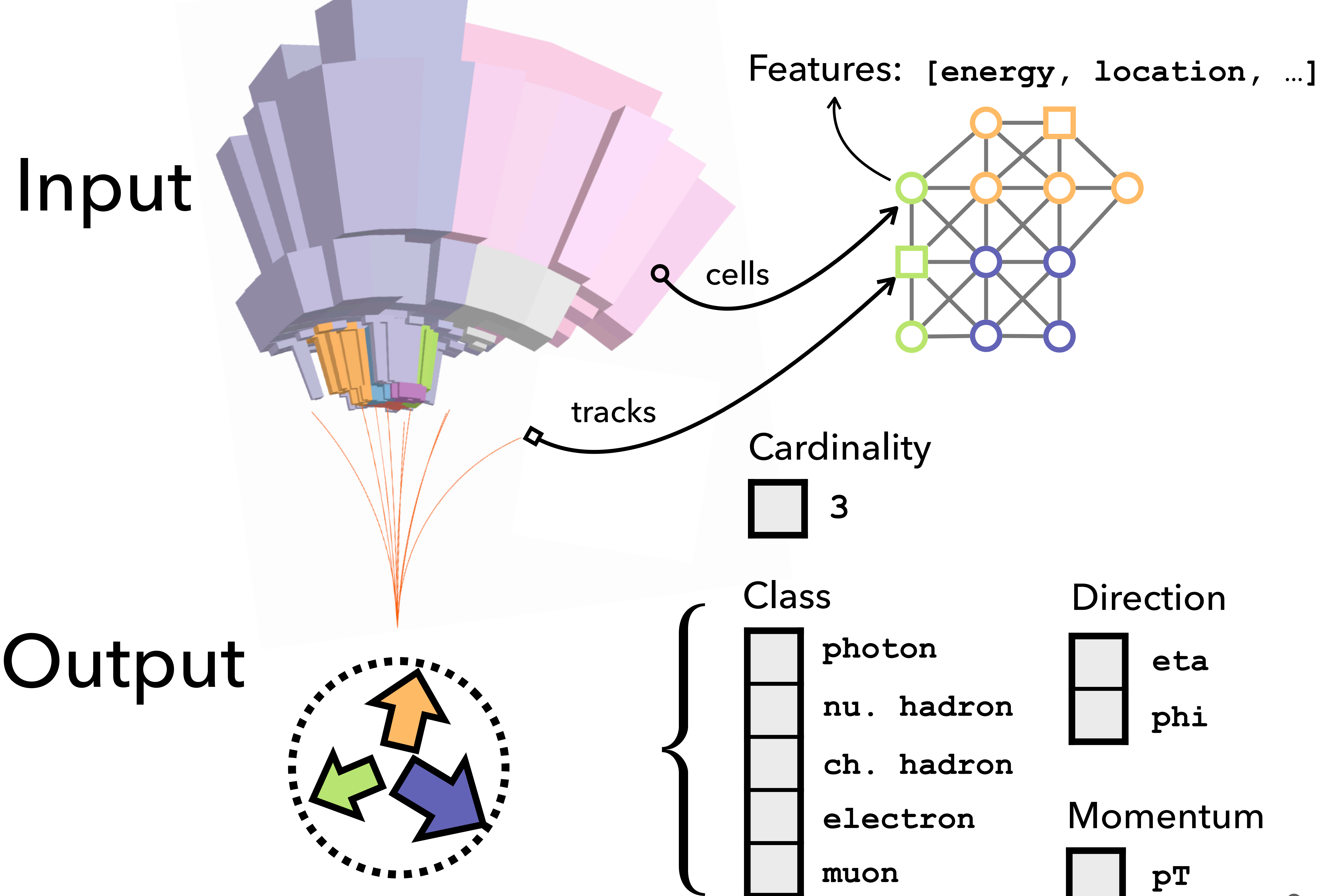
Position

x
Y

Size

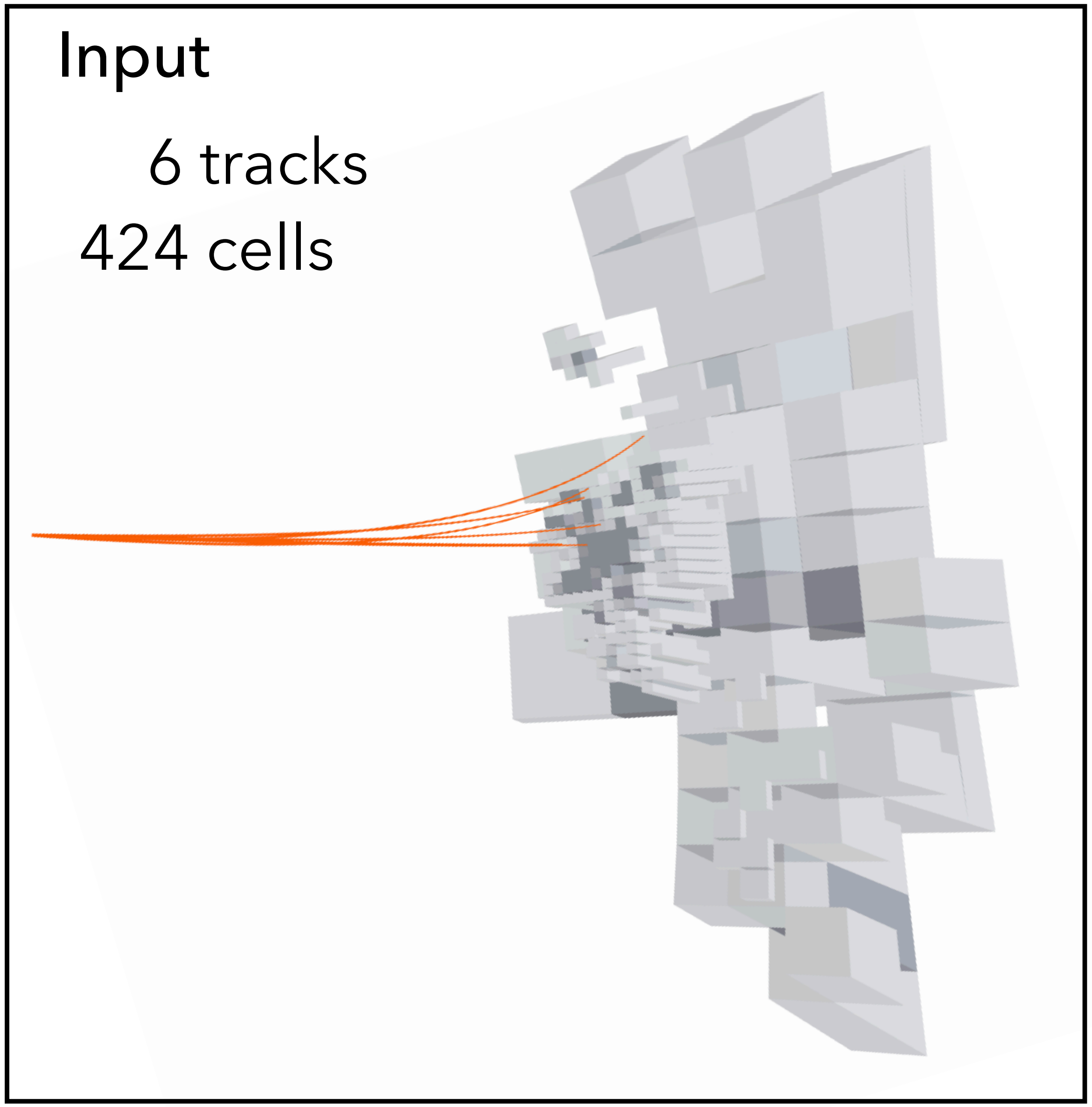
h
w

Particle reconstruction



Cardinality prediction

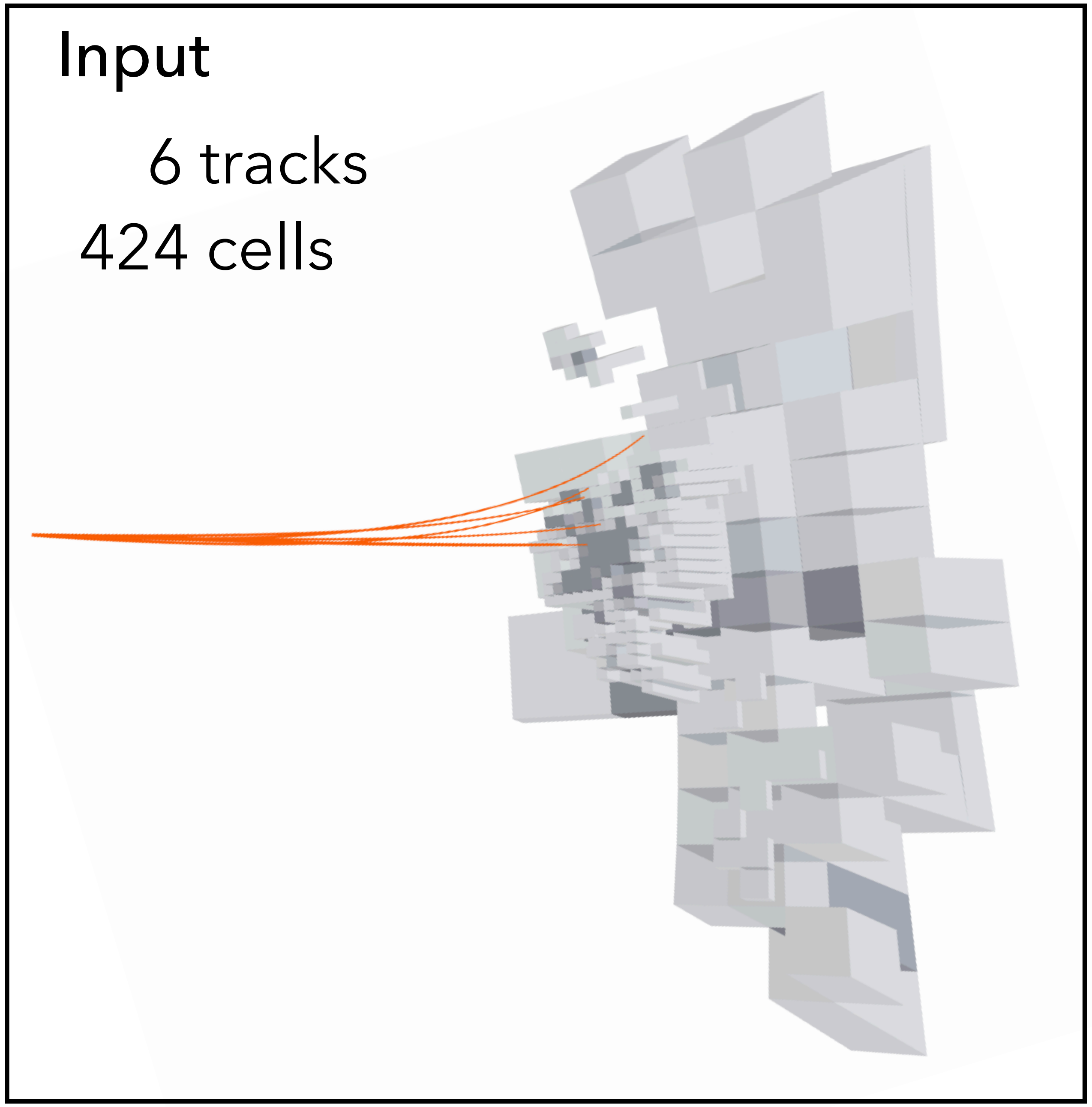
Ex: single jet of particles

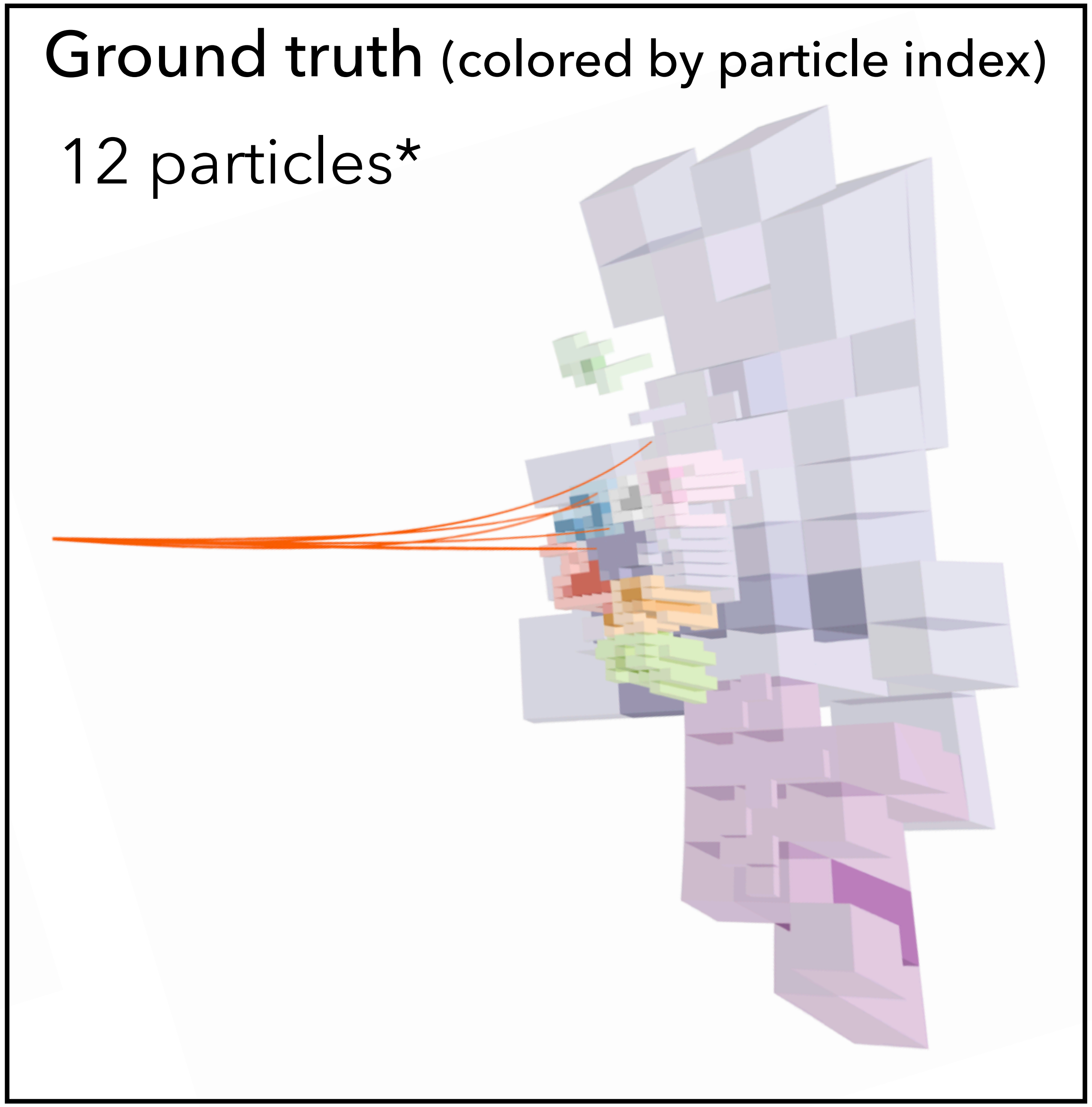


*Some particles are not dominant in any one of the cells (i.e. no dedicated color)

Cardinality prediction

Ex: single jet of particles

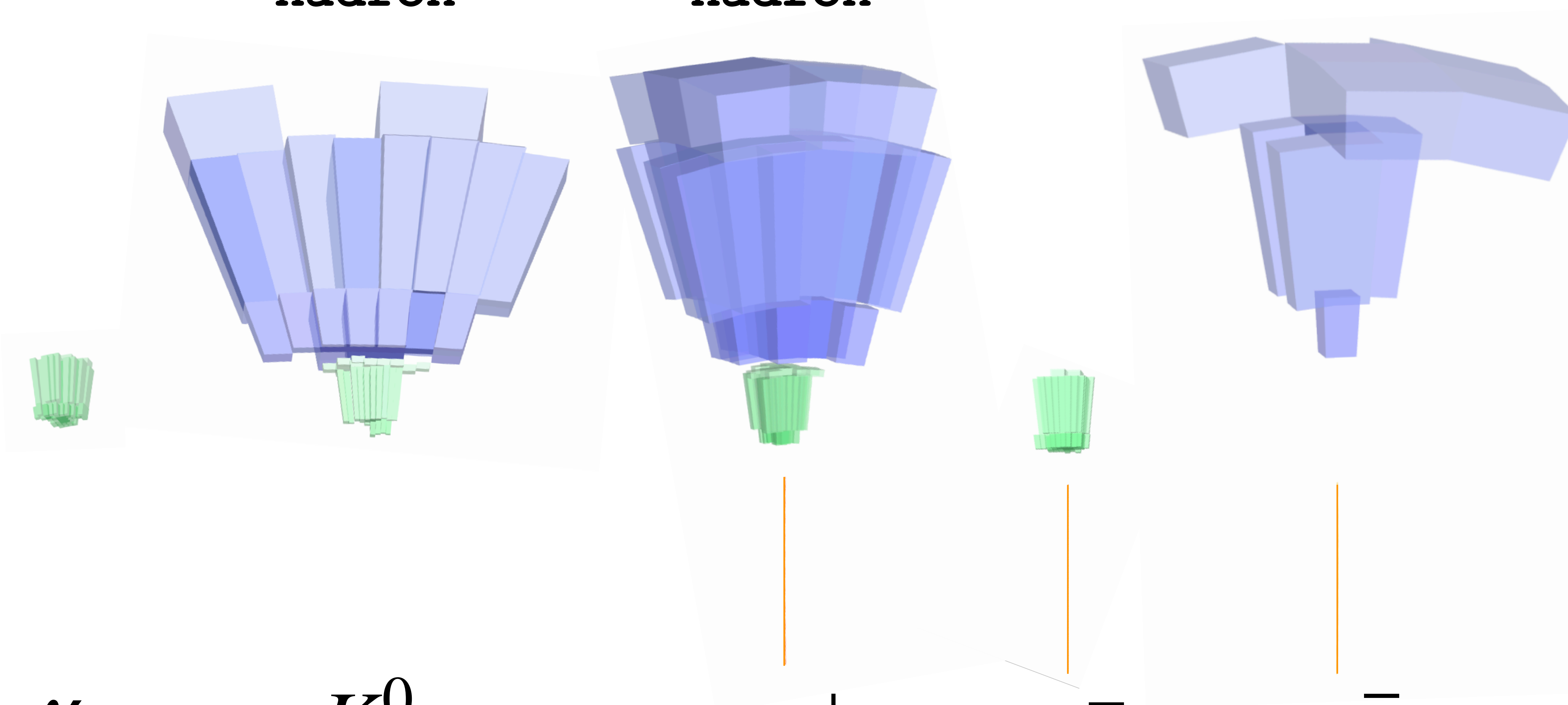




*Some particles are not dominant in any one of the cells (i.e. no dedicated color)

Particle classification

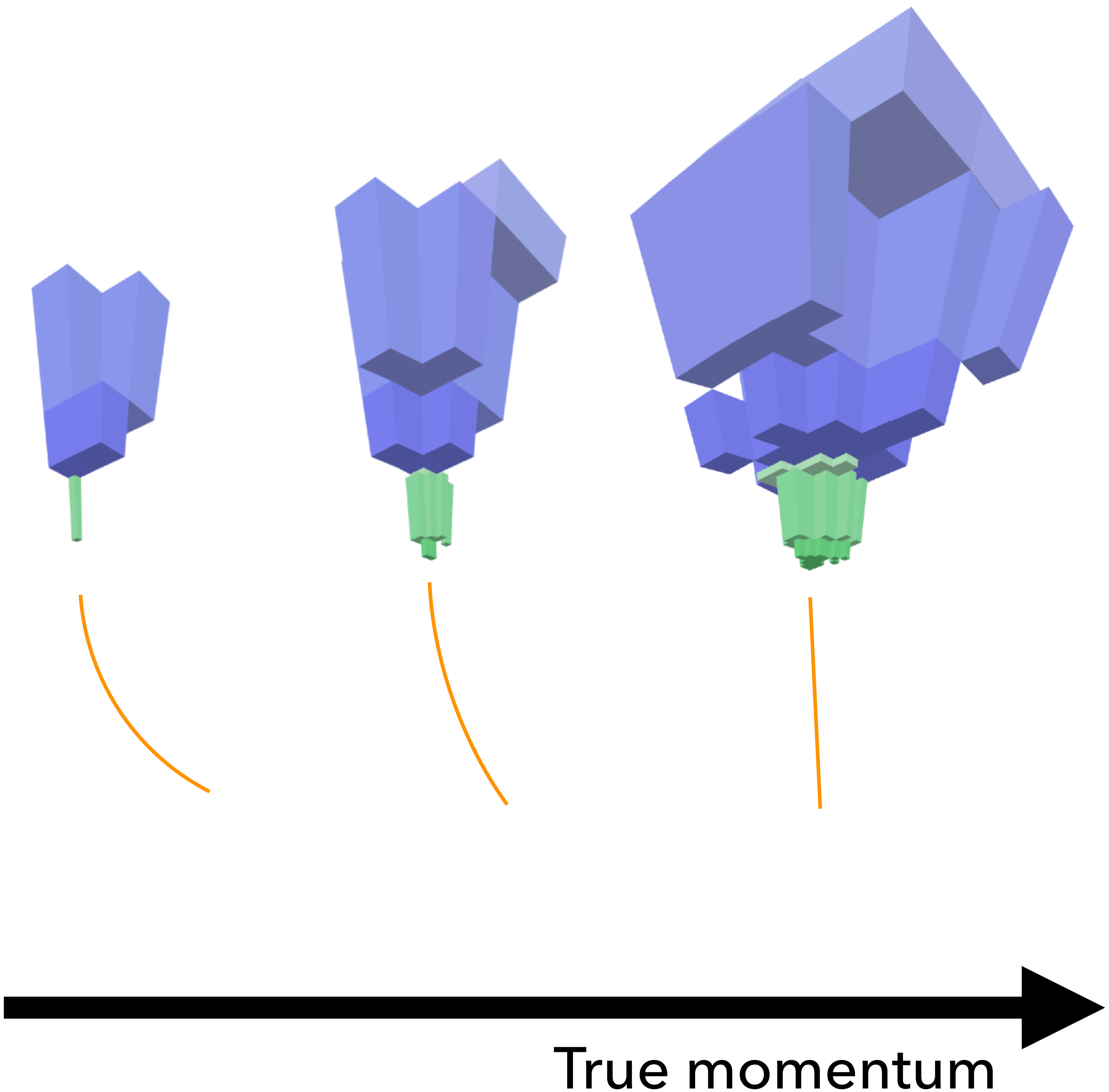
(0) photon | (1) neutral hadron | (2) charged hadron | (3) electron | (4) muon



γ | K_L^0 | π^+ | e^- | μ^-

All examples: $(E = 50\ \mathrm{GeV},\ \eta = 0)$

Particle momentum regression



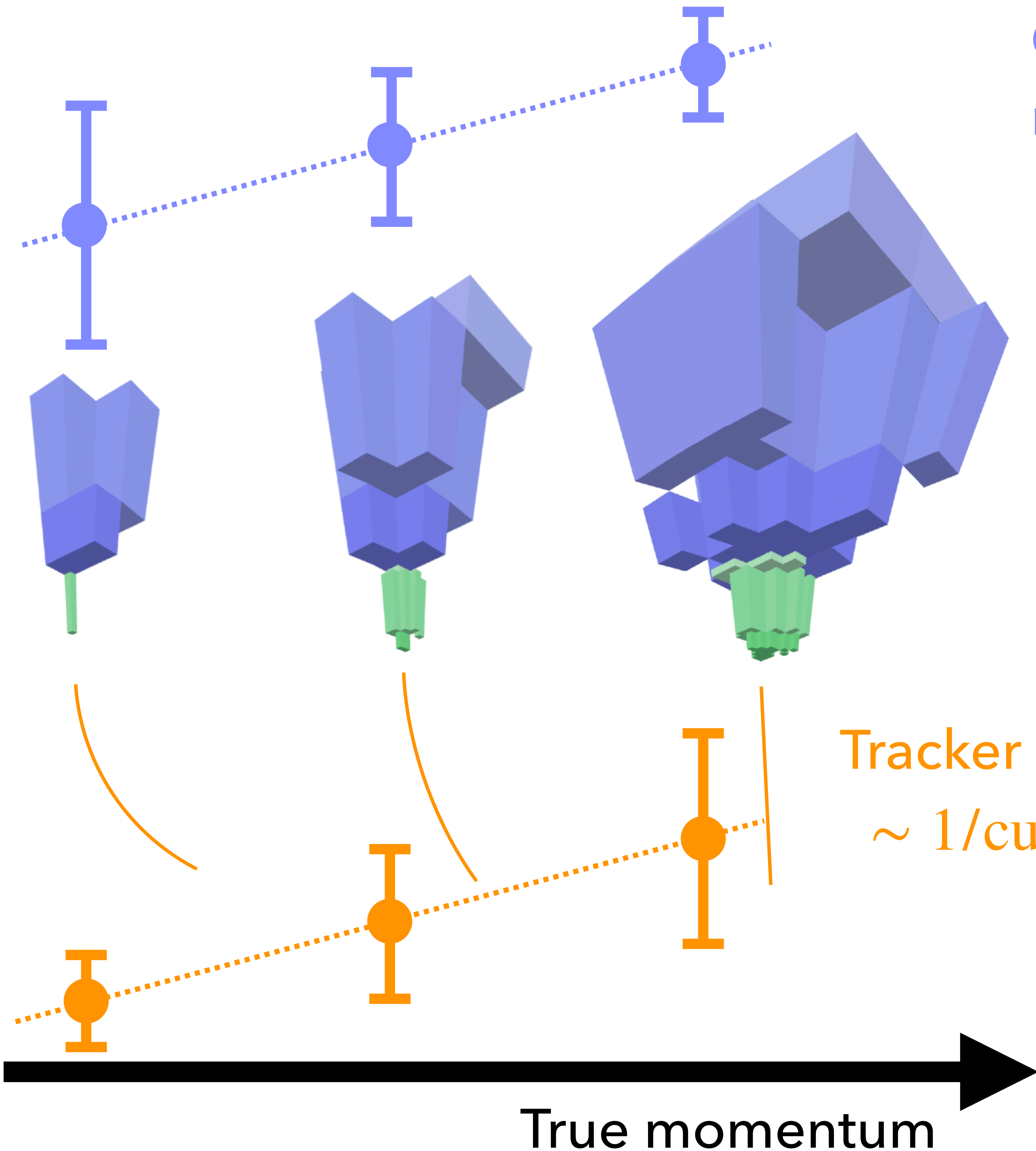
"Particle flow"

An algorithm that combines the information from both tracker and calorimeter to optimize the momentum prediction

Particle momentum regression

Calorimeter measurement

$$\sim \sum_{\text{cells}} E_i$$



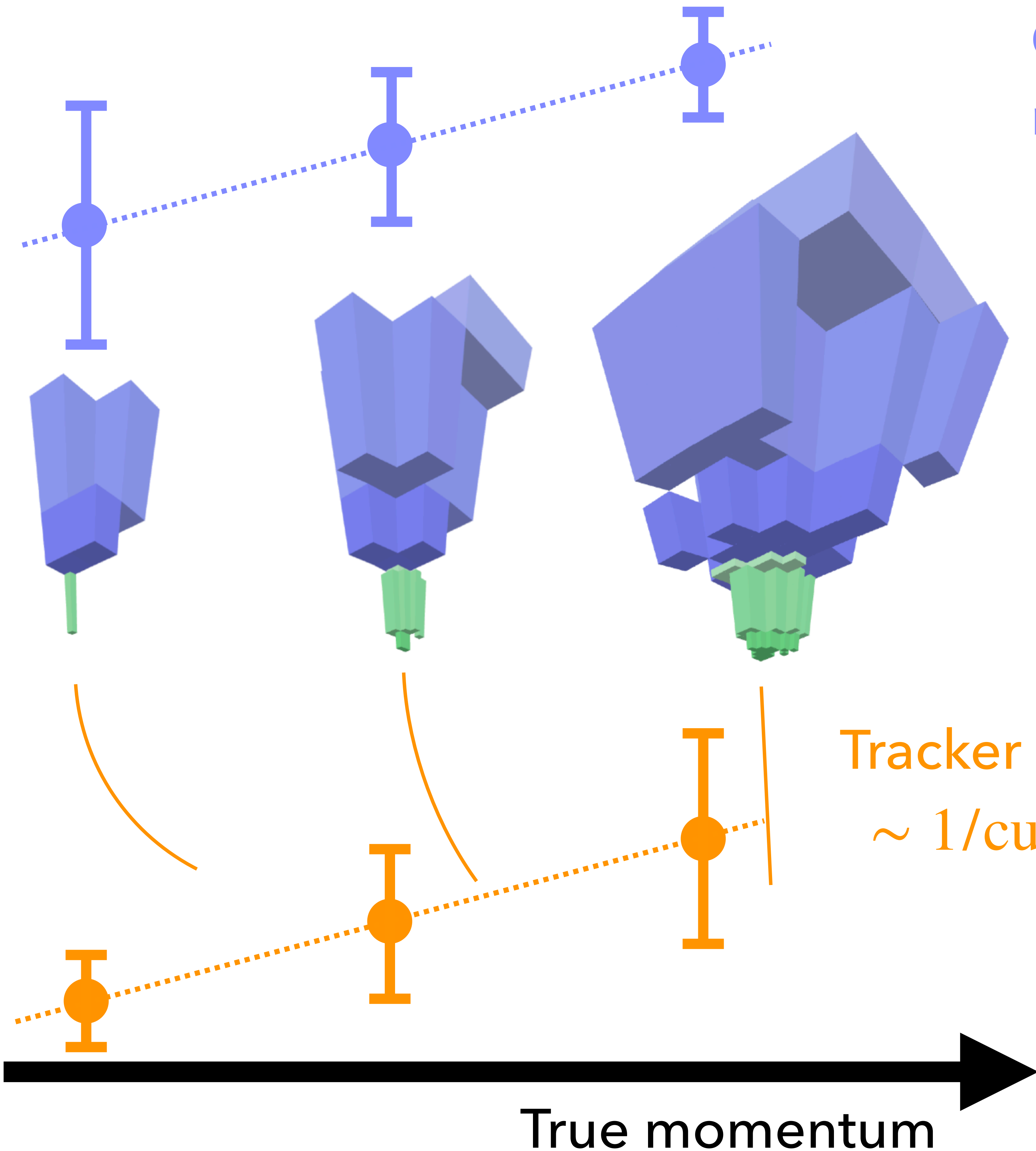
"Particle flow"

An algorithm that combines the information from both tracker and calorimeter to optimize the momentum prediction

Tracker measurement

$$\sim 1/\text{curvature}$$

Particle momentum regression



Calorimeter measurement

$\sim \sum_{\text{cells}} E_i$

Tracker measurement

$\sim$ 1/curvature

"Particle flow"

An algorithm that combines the information from both tracker and calorimeter to optimize the momentum prediction

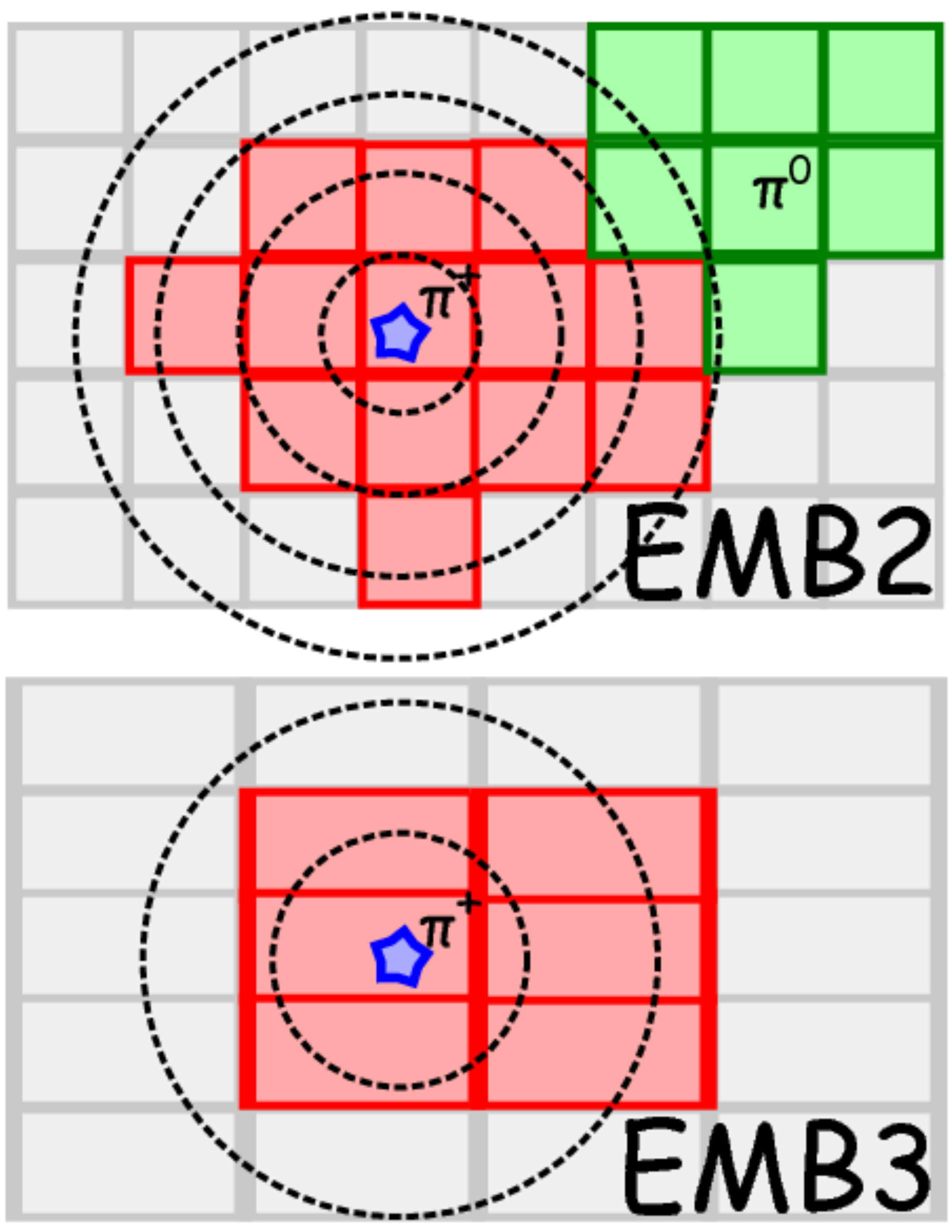
N.B. cannot naively "add" tracks!

ATLAS particle flow

We want to use tracks at low momentum (better resolution)…

… but we first need to remove their <u>expected</u> contribution

Subtract energy from cells
in rings around the track



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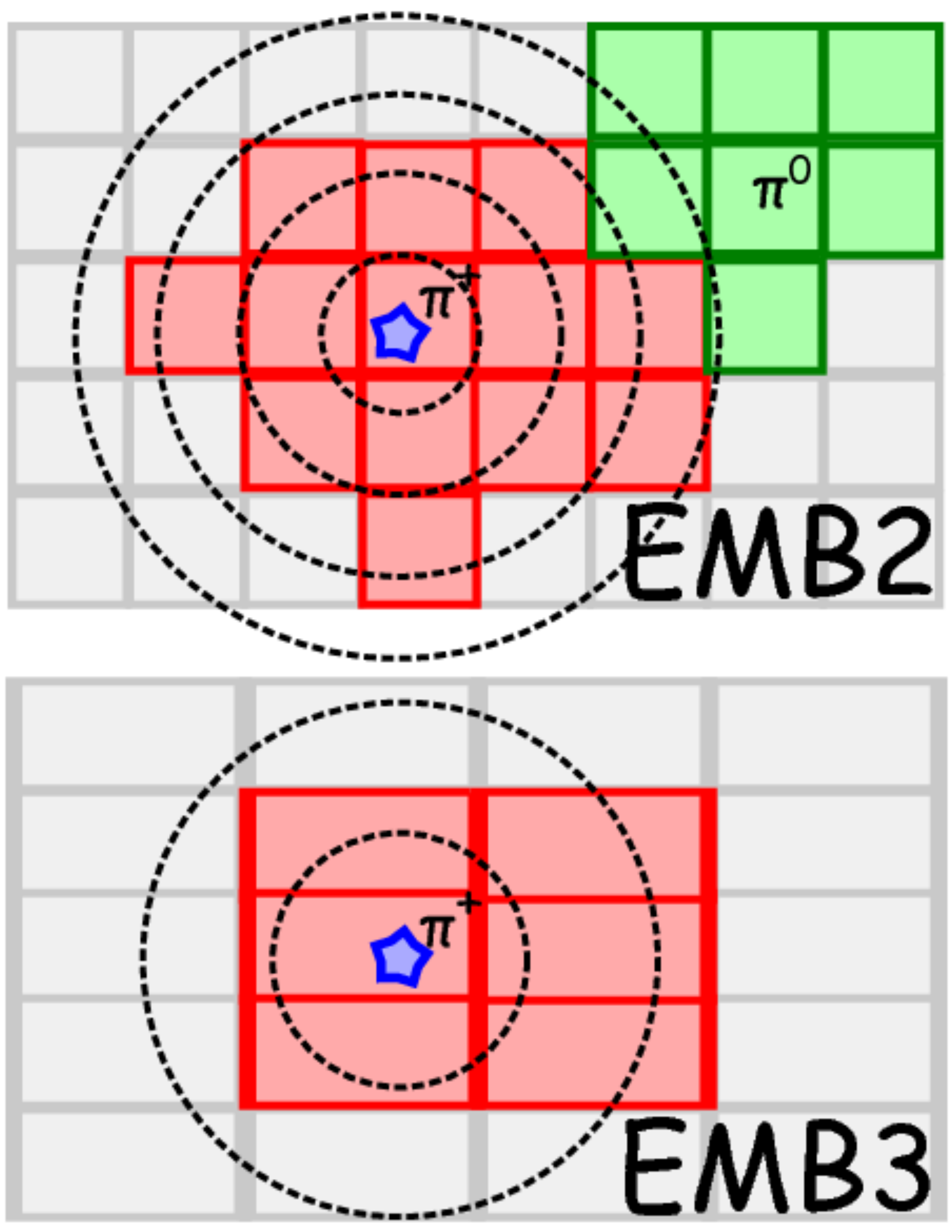

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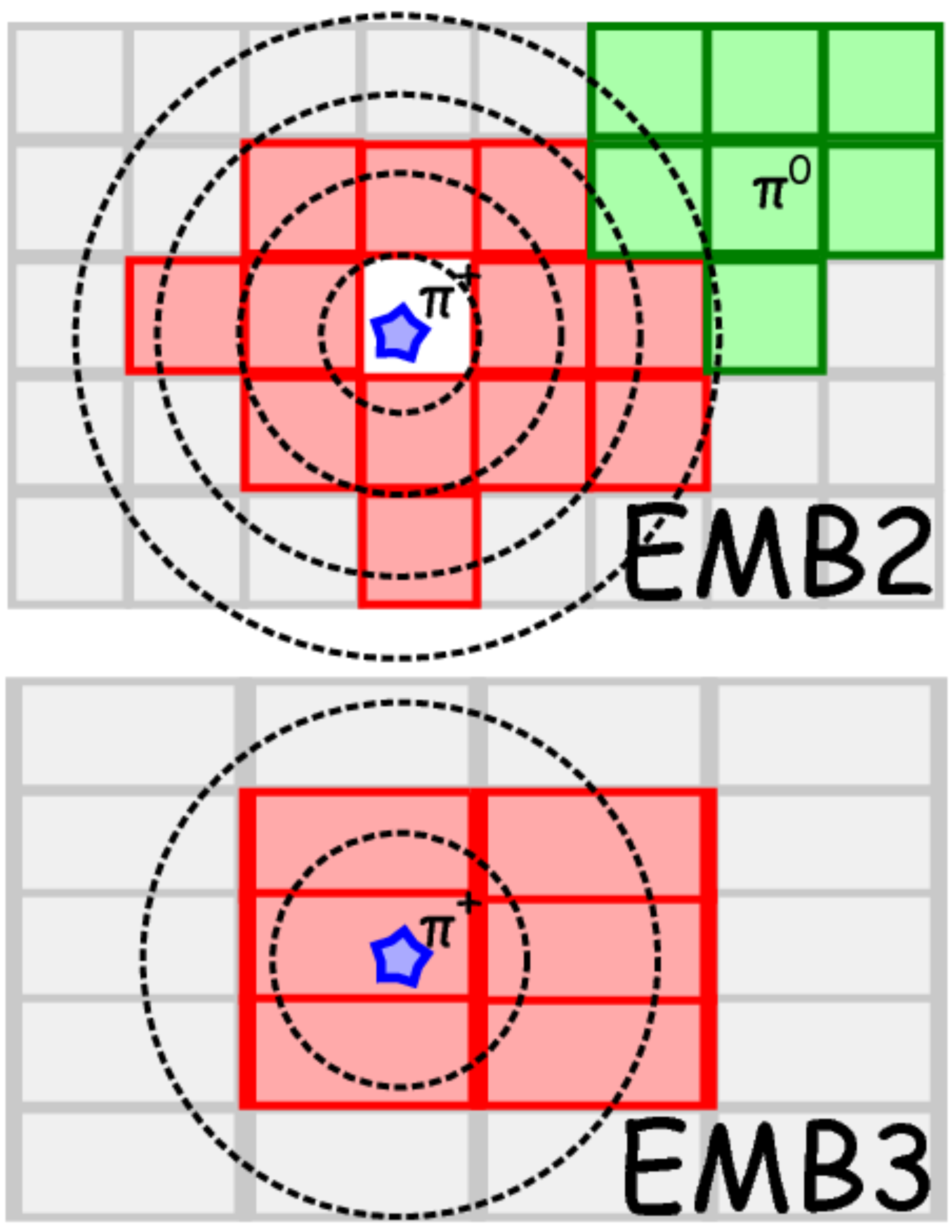

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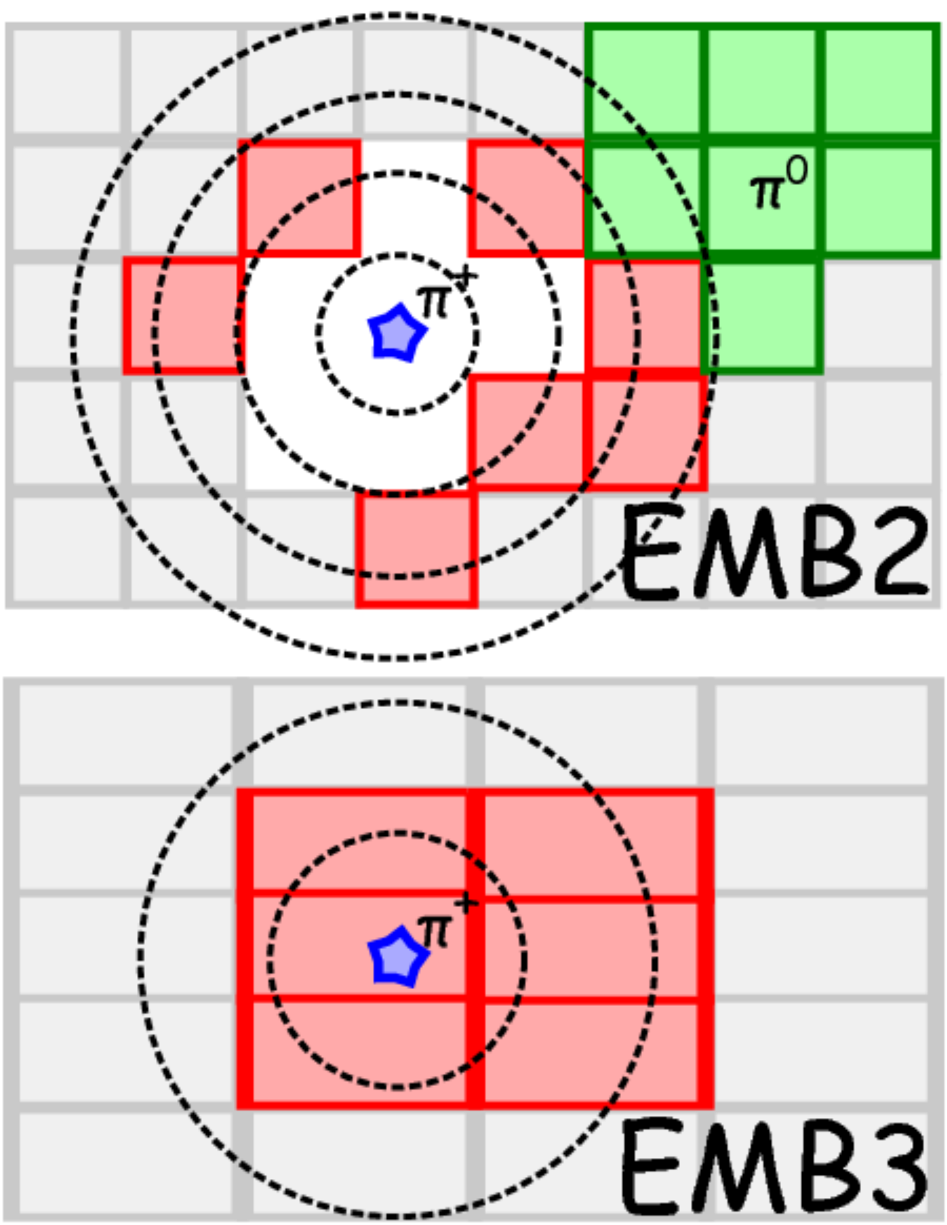

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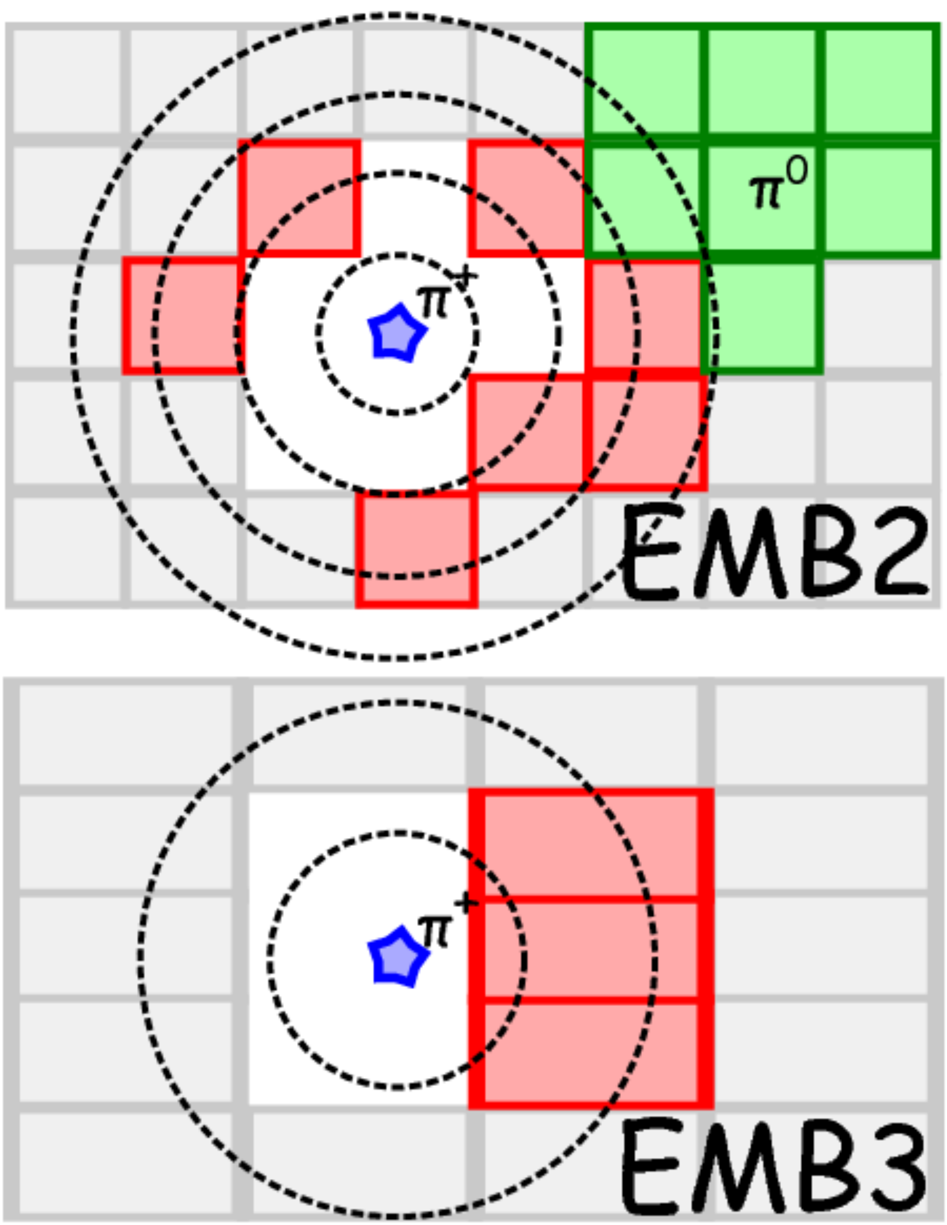

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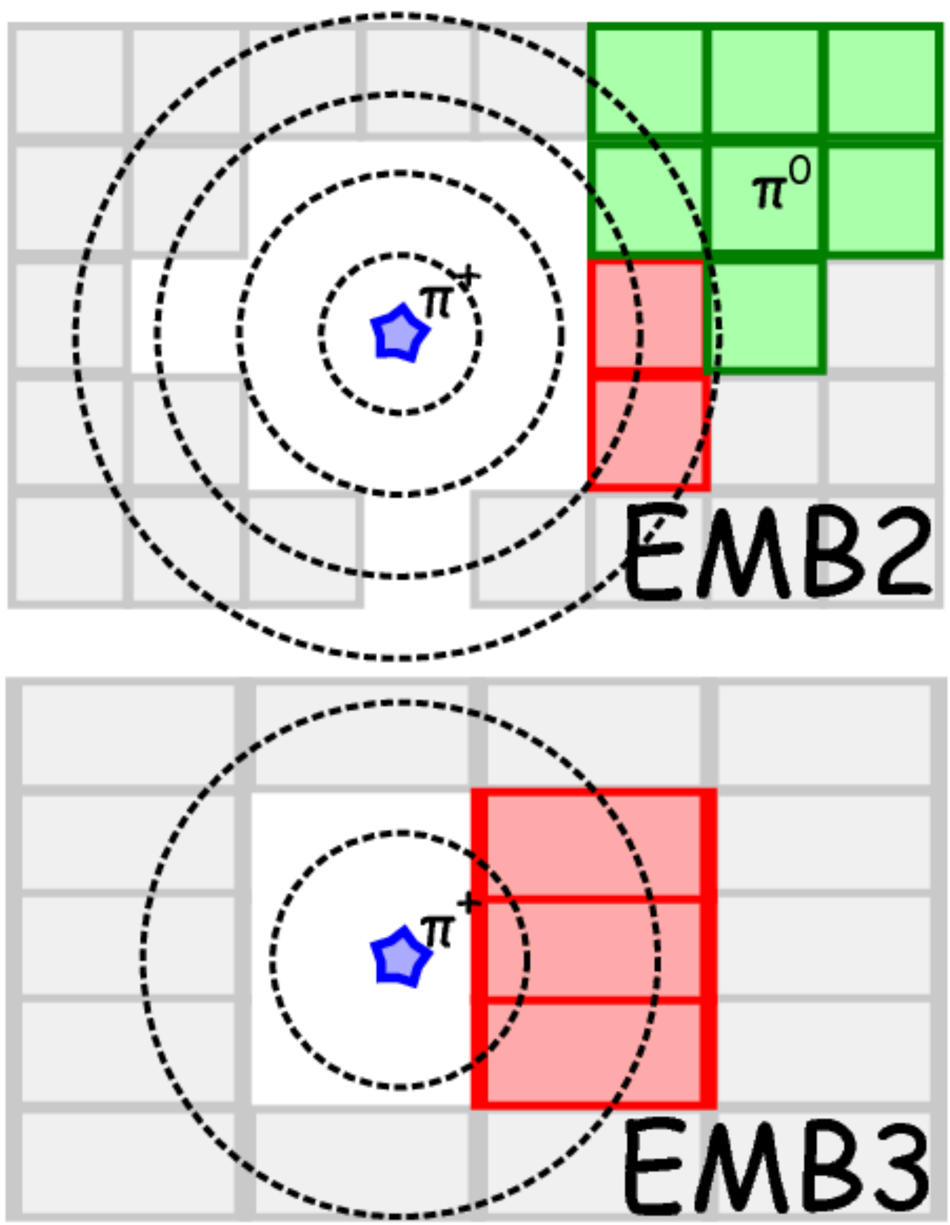

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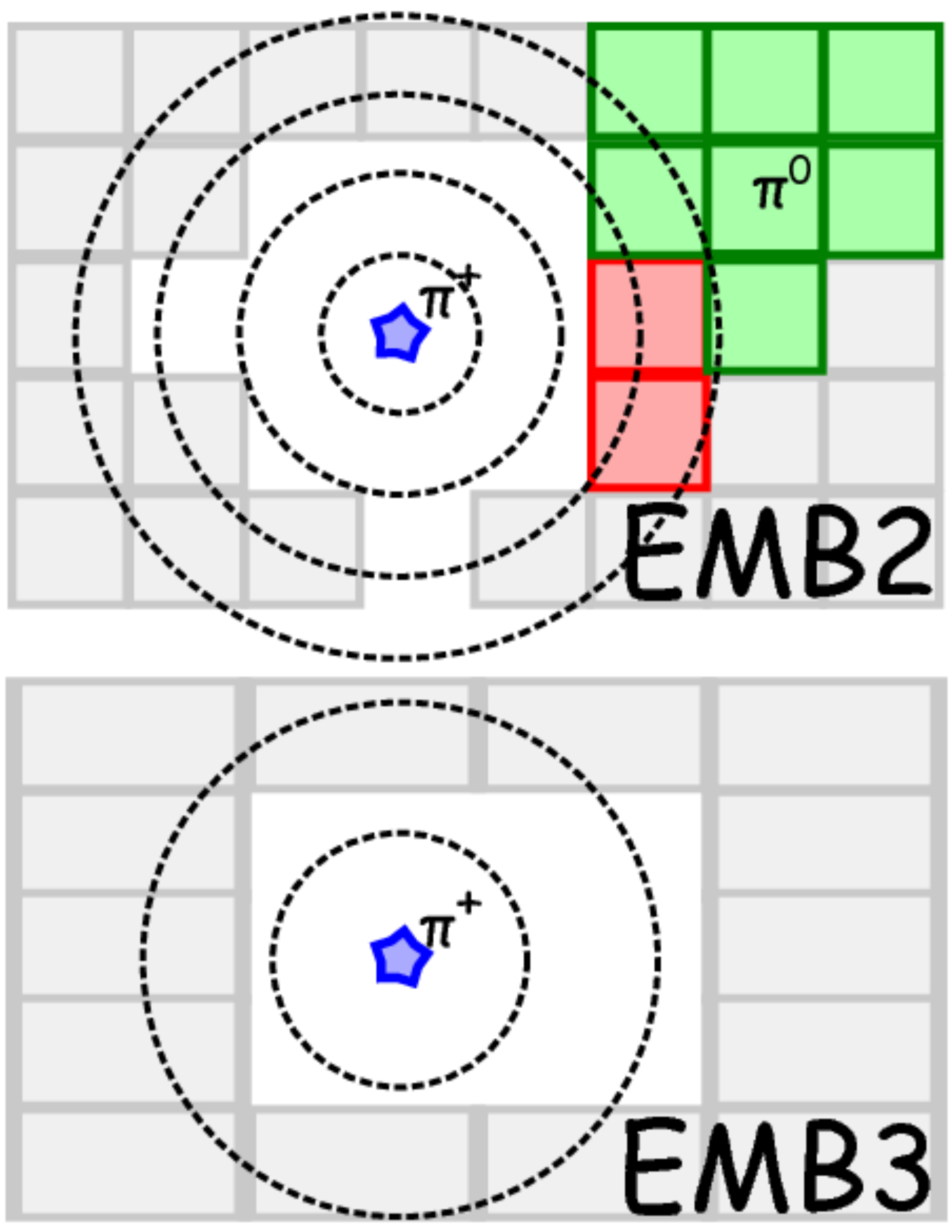

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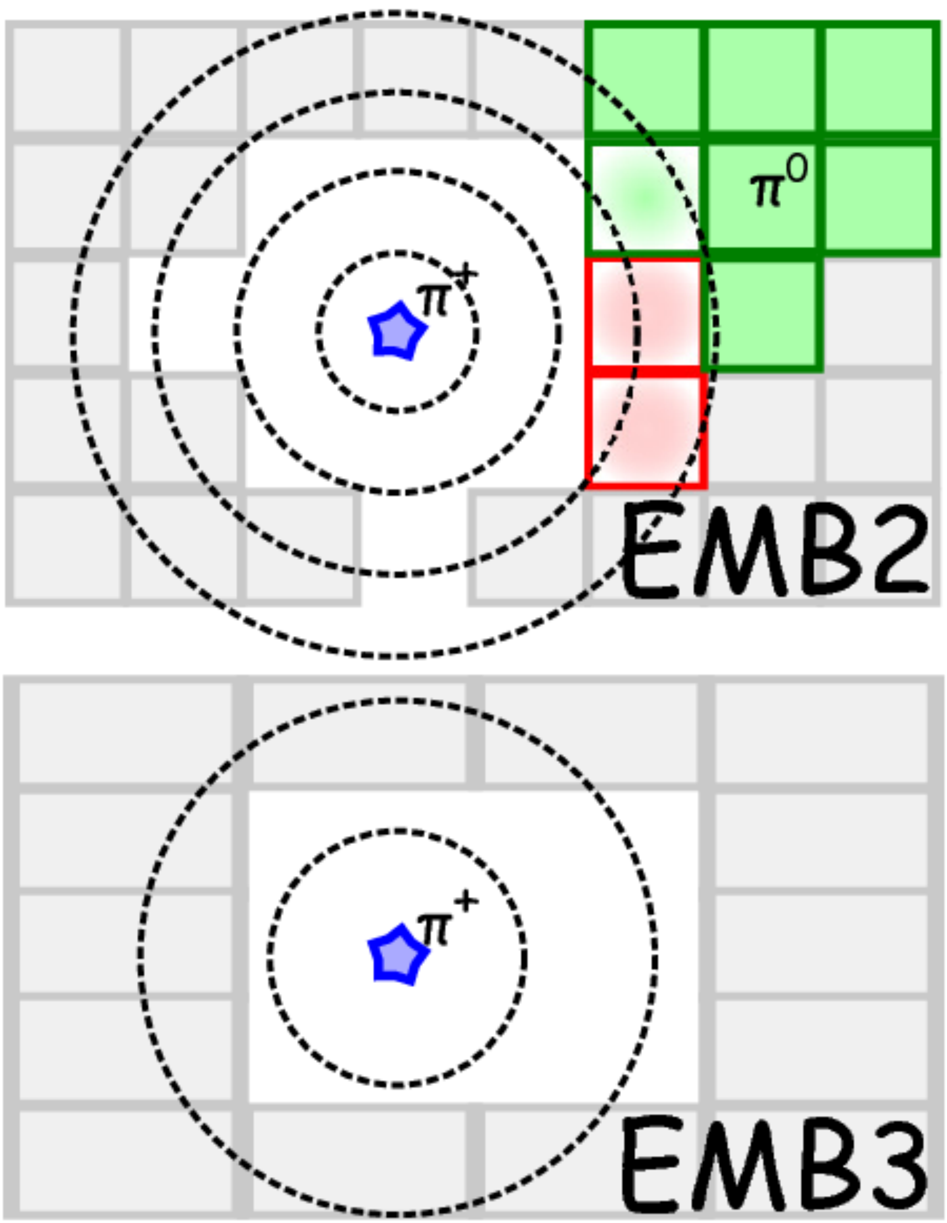

ATLAS particle flow

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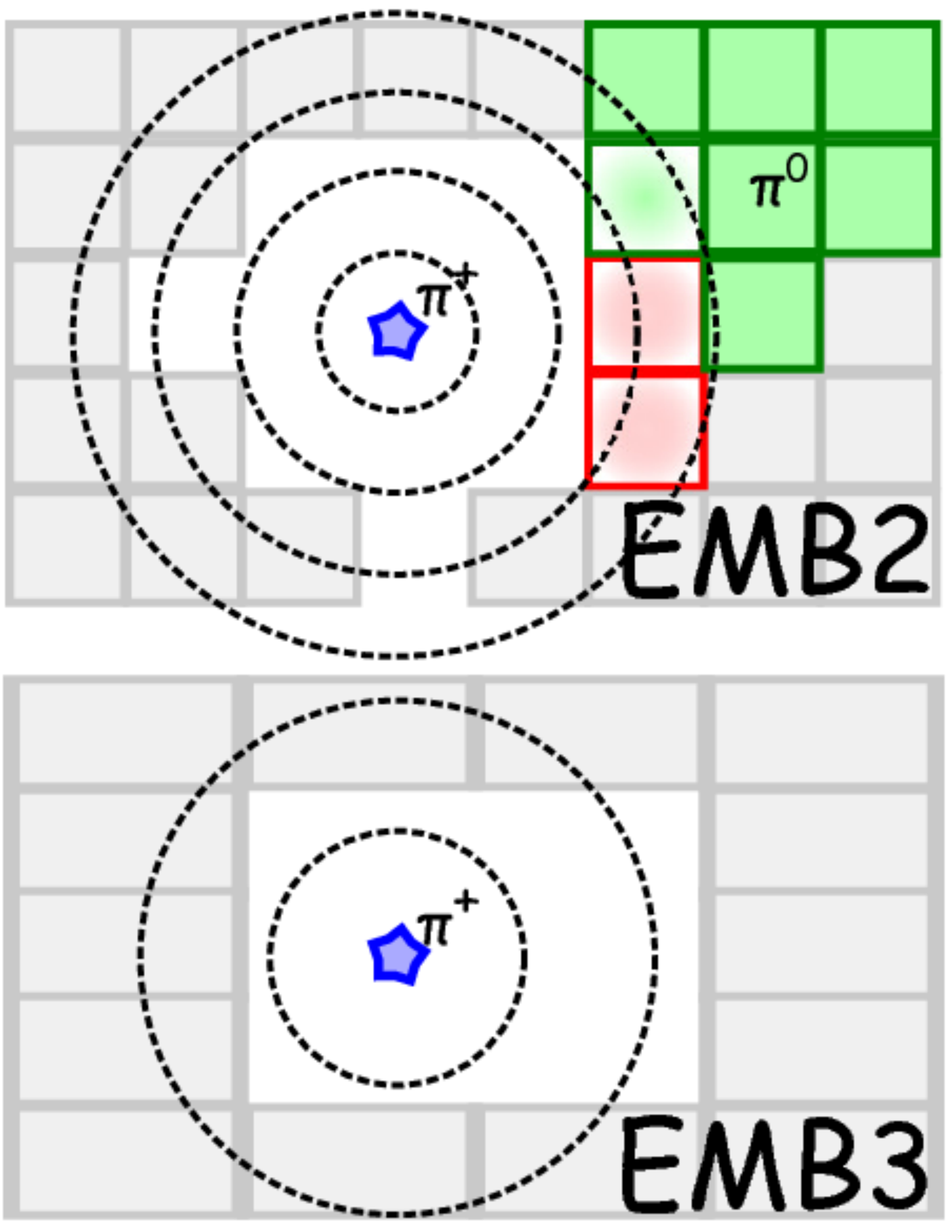
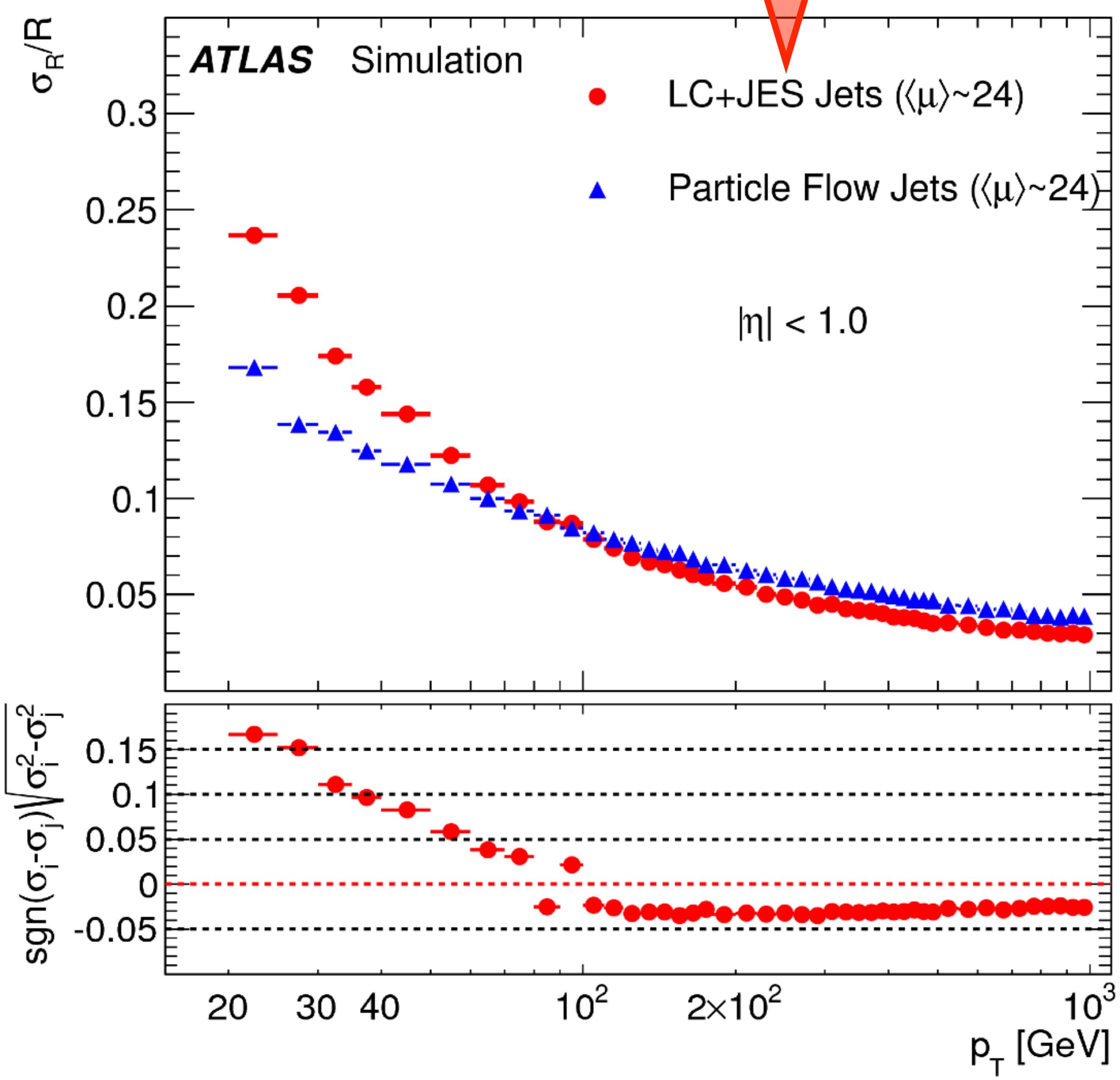
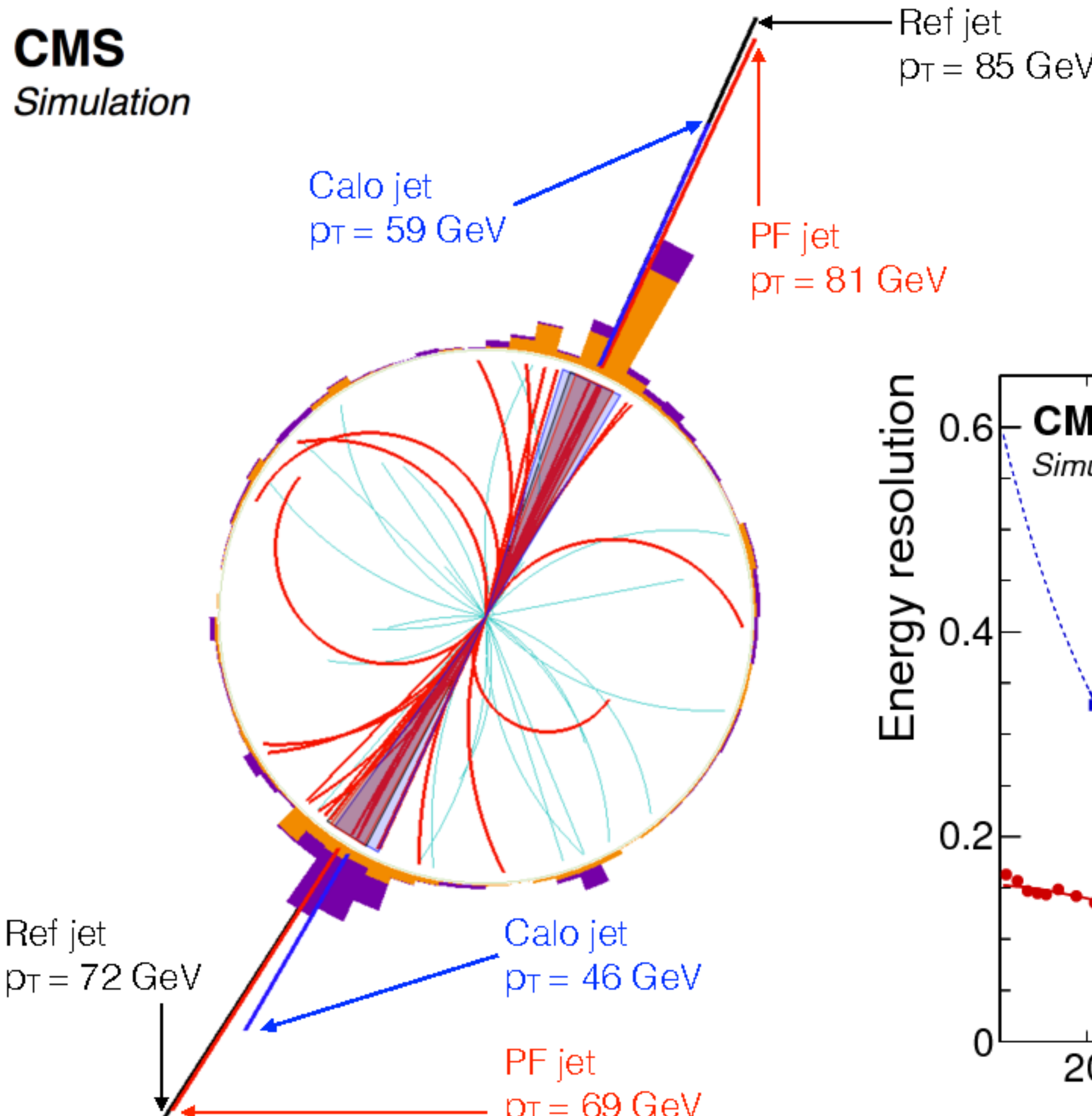


N.B. Comparing calibrated and uncalibrated jets



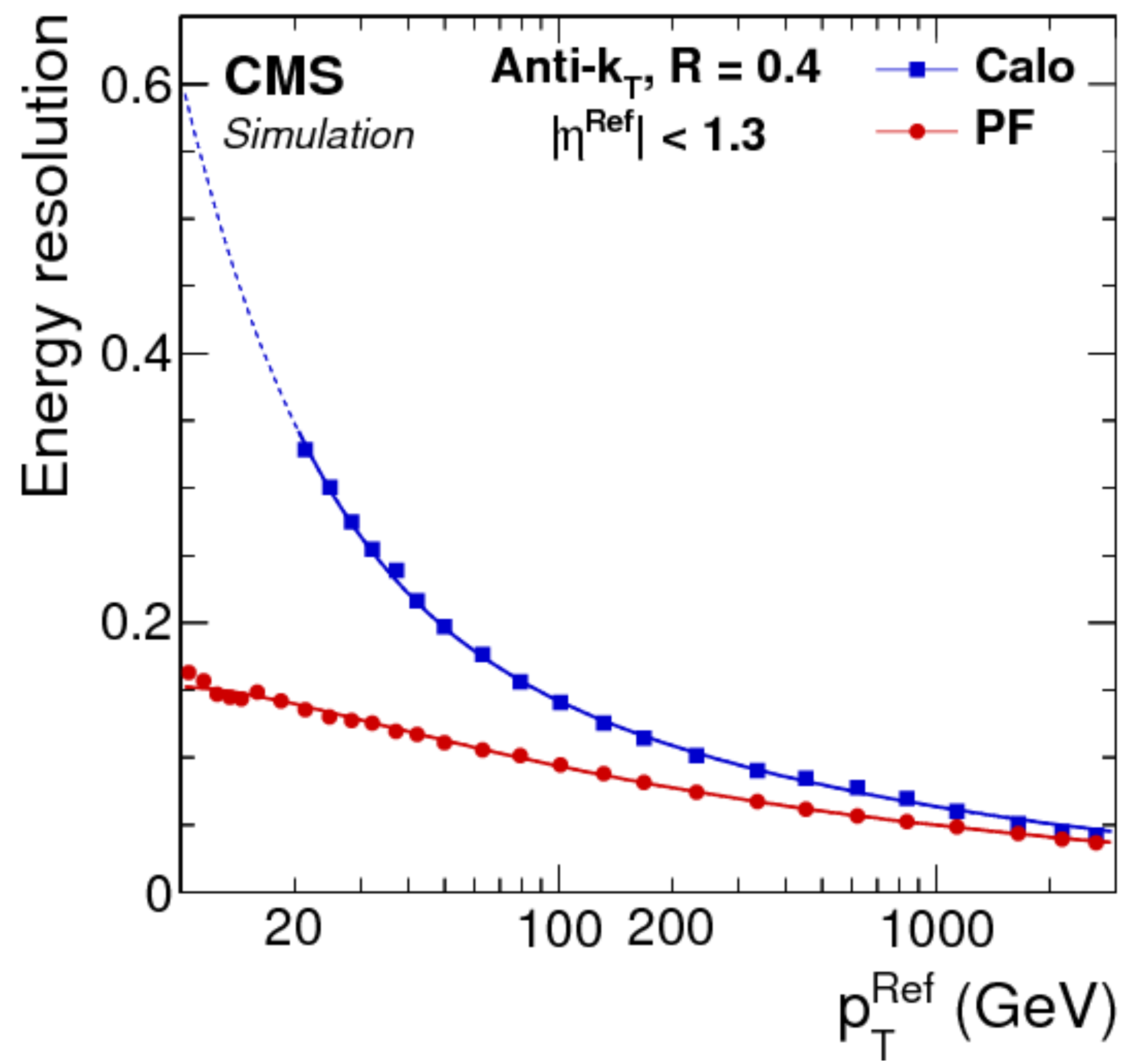
CMS particle flow



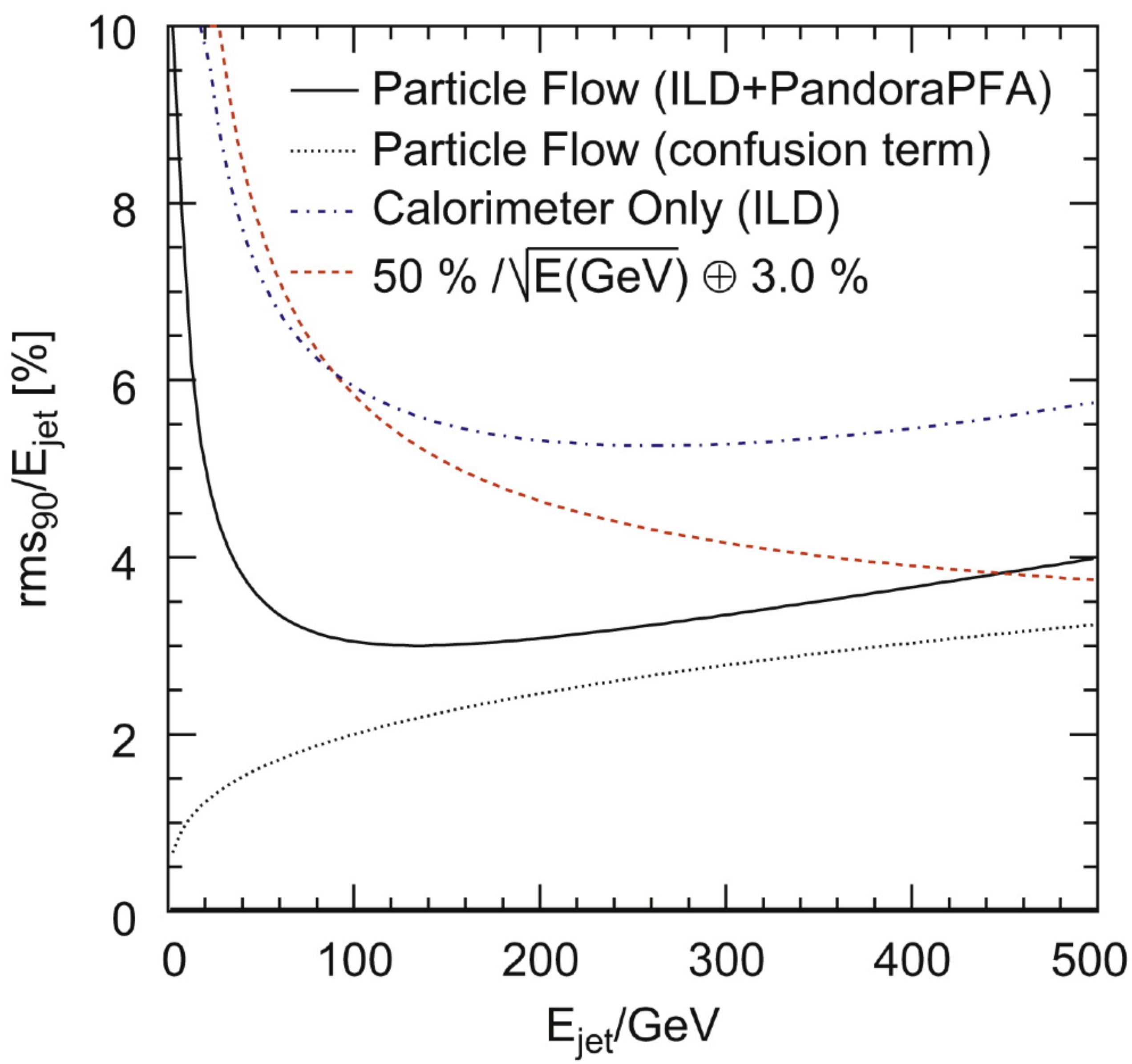
Calorimeter-only

vs.

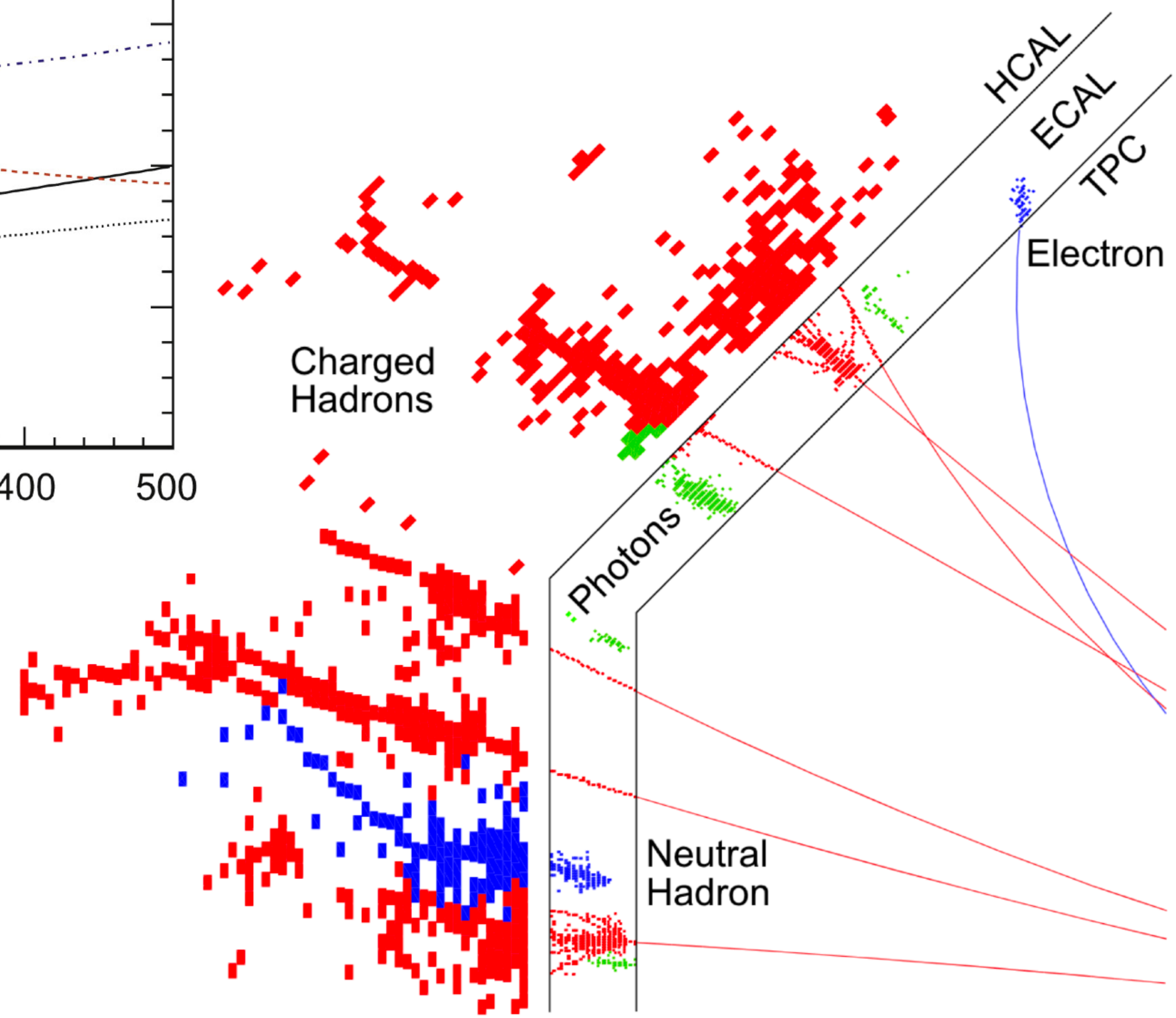
Particle flow



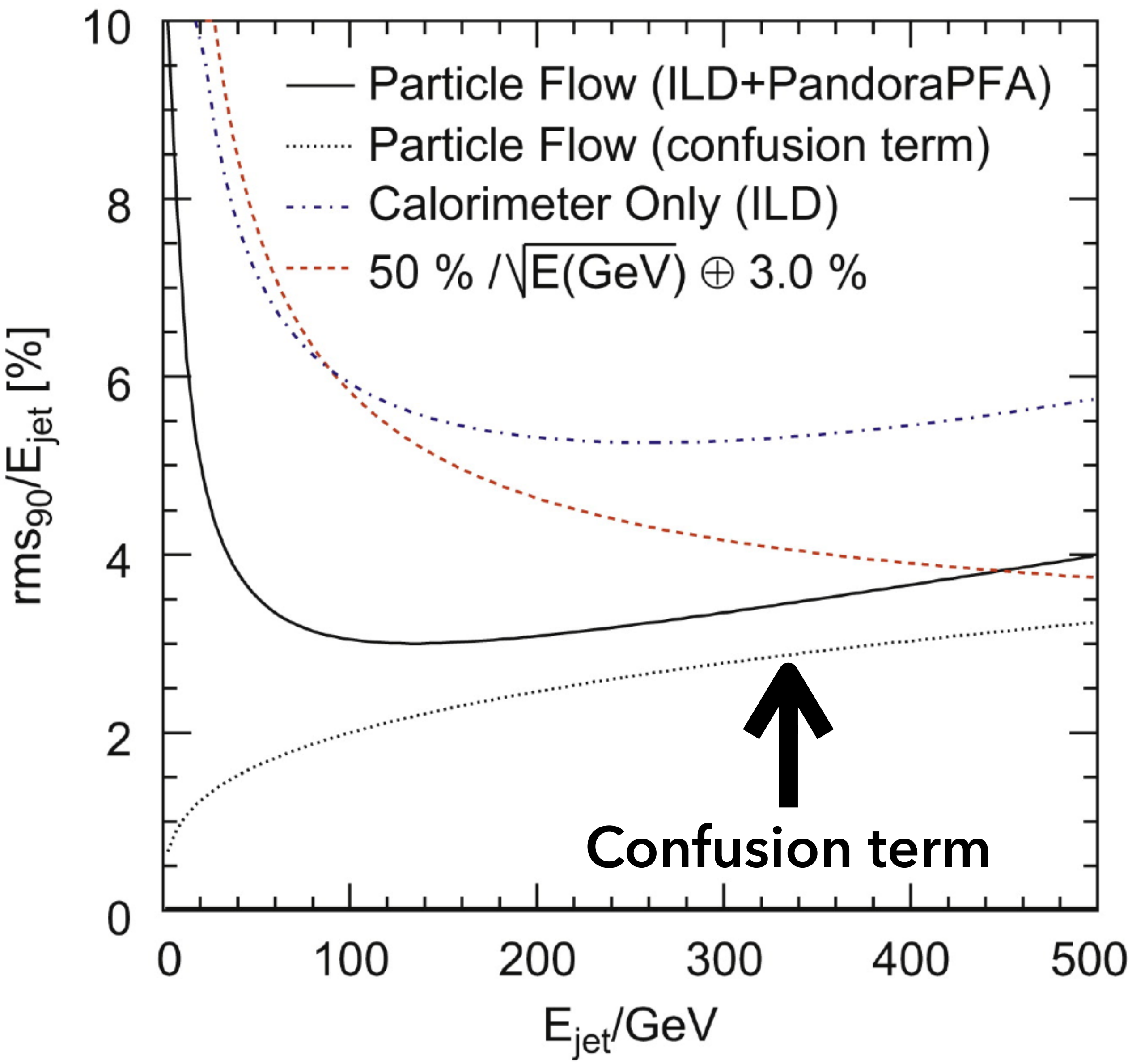
Pandora: particle flow for CLIC



- Multiple pattern recognition steps
- Highly-granular calorimeter
- Cleaner e^+e^- collision environment



Pandora: particle flow for CLIC



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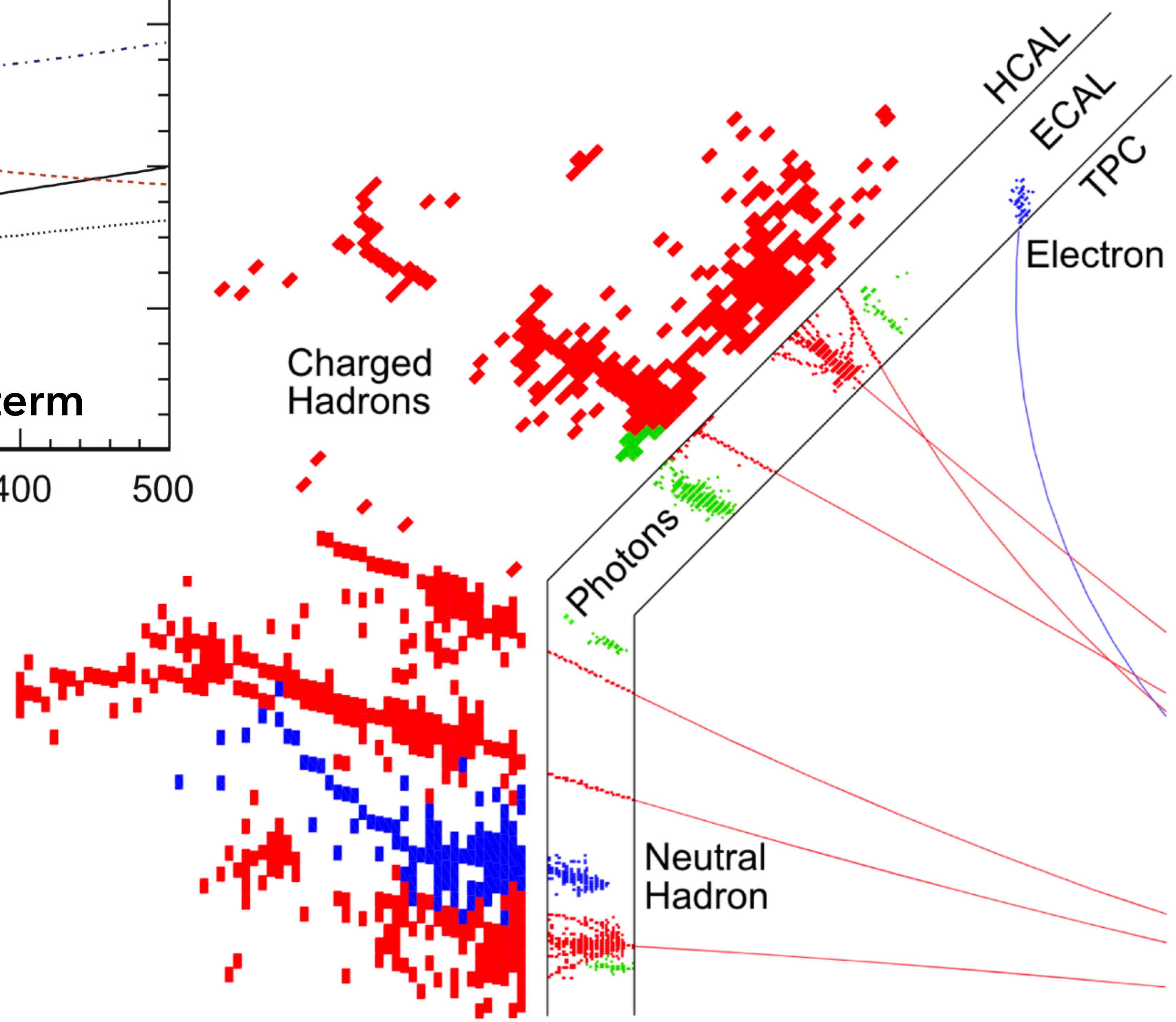
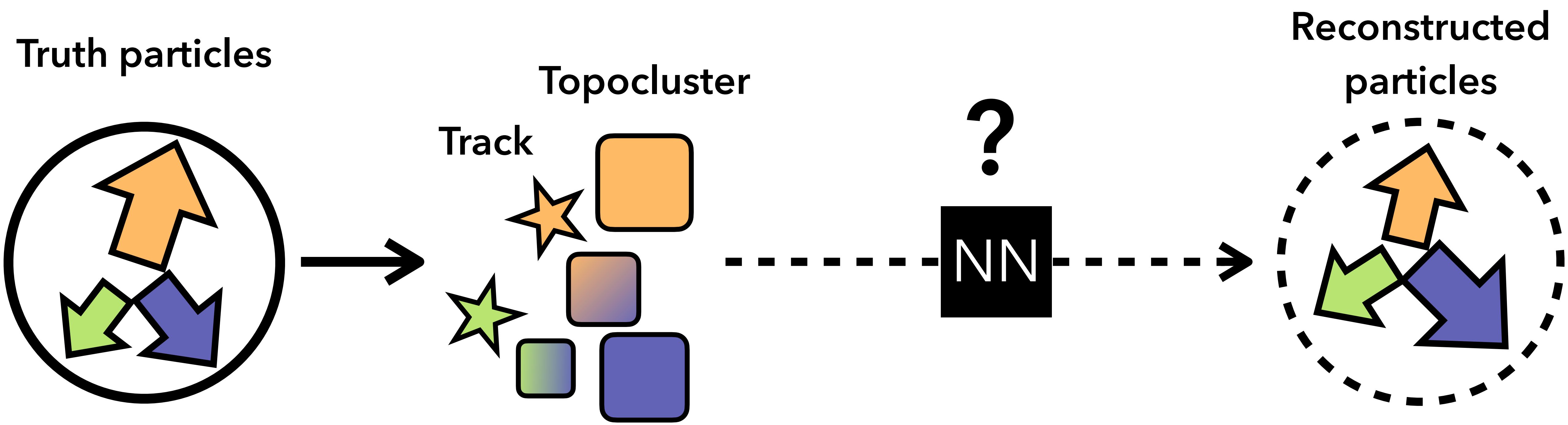
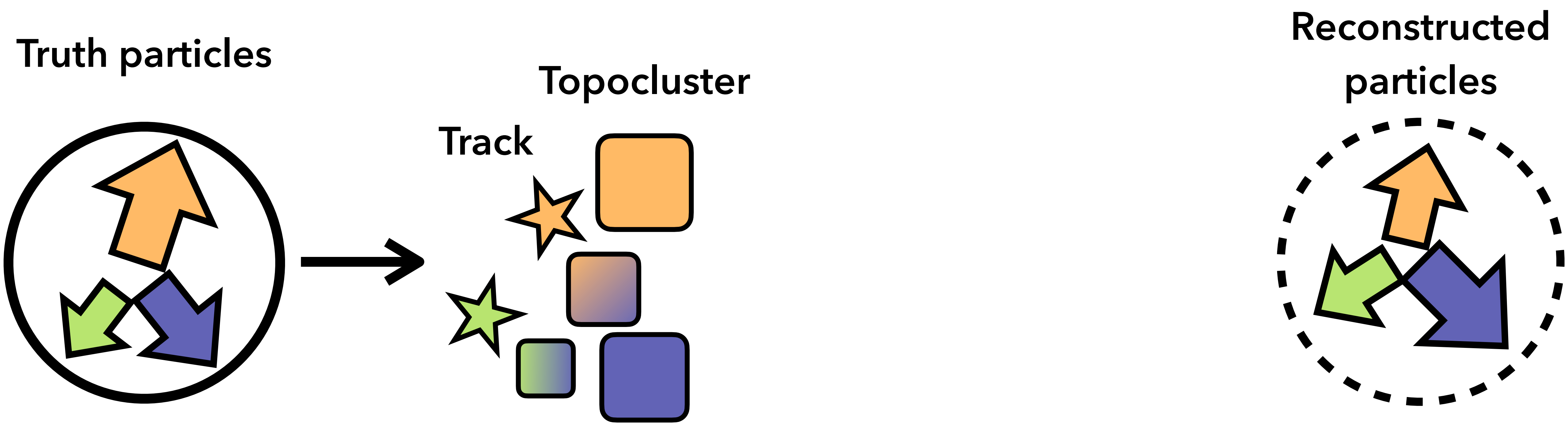


Set-to-set ML architecture



Benchmark: MLPF

arXiv:2101.08578 , arXiv:2309.06782



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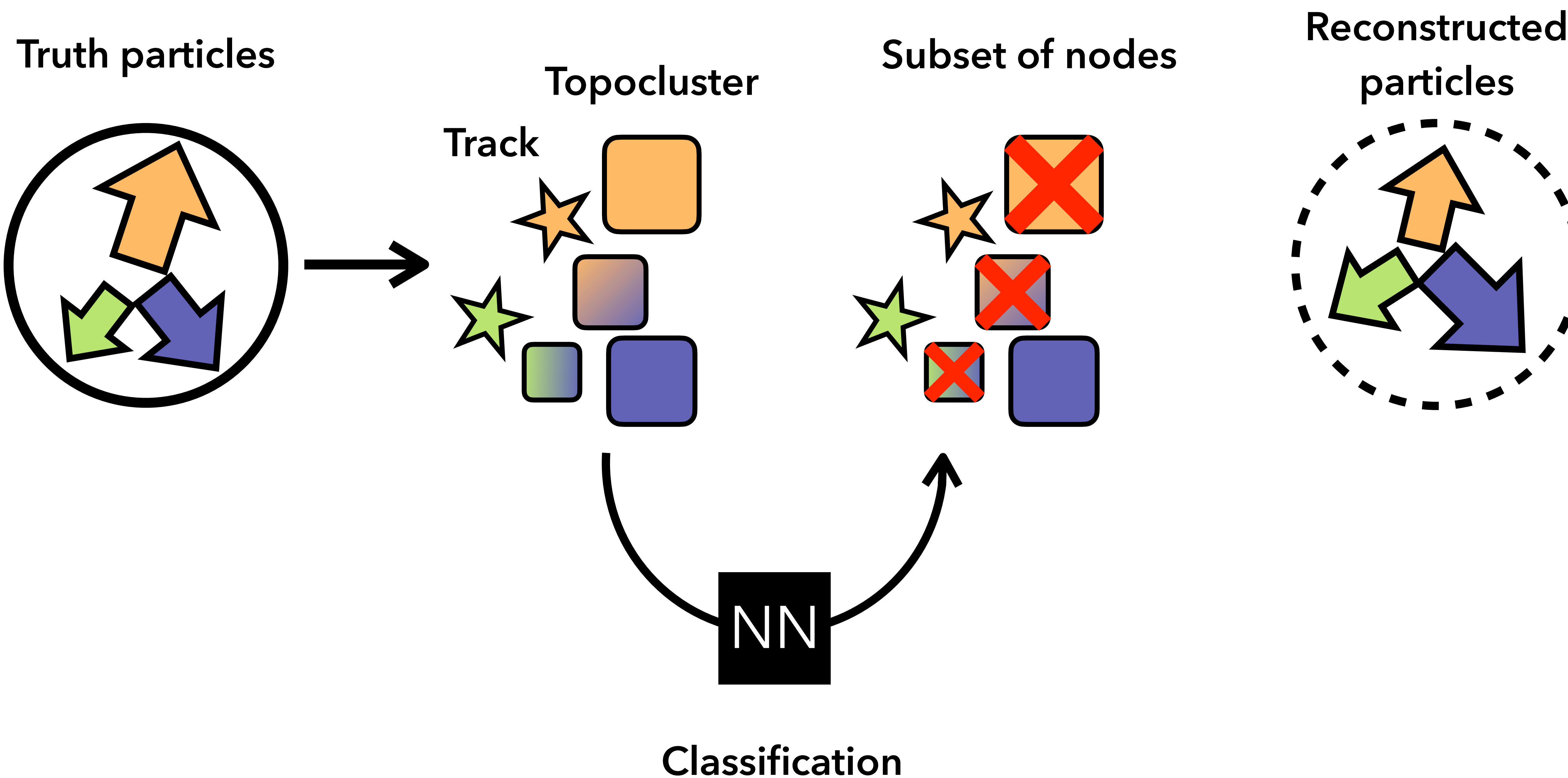

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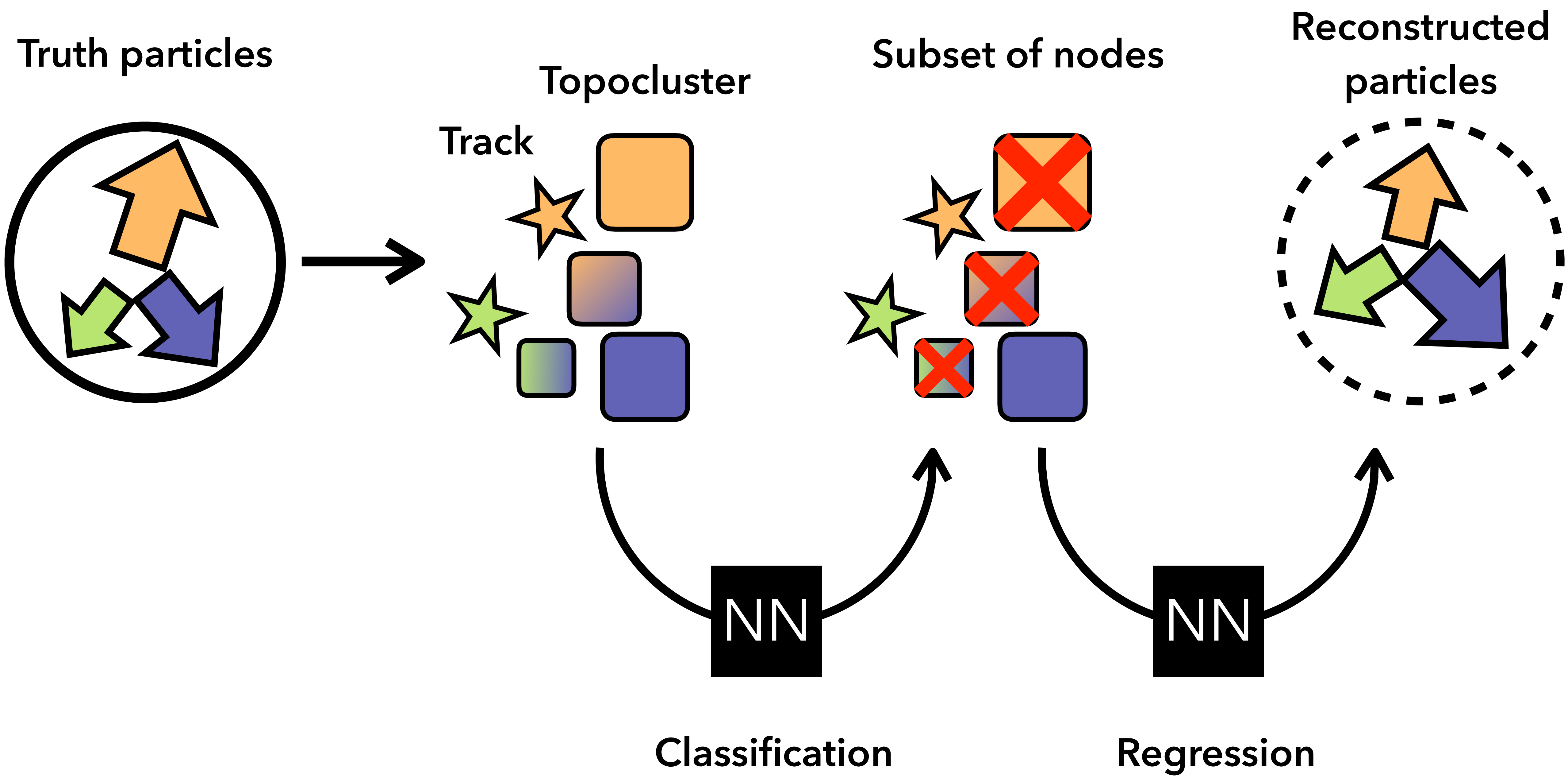
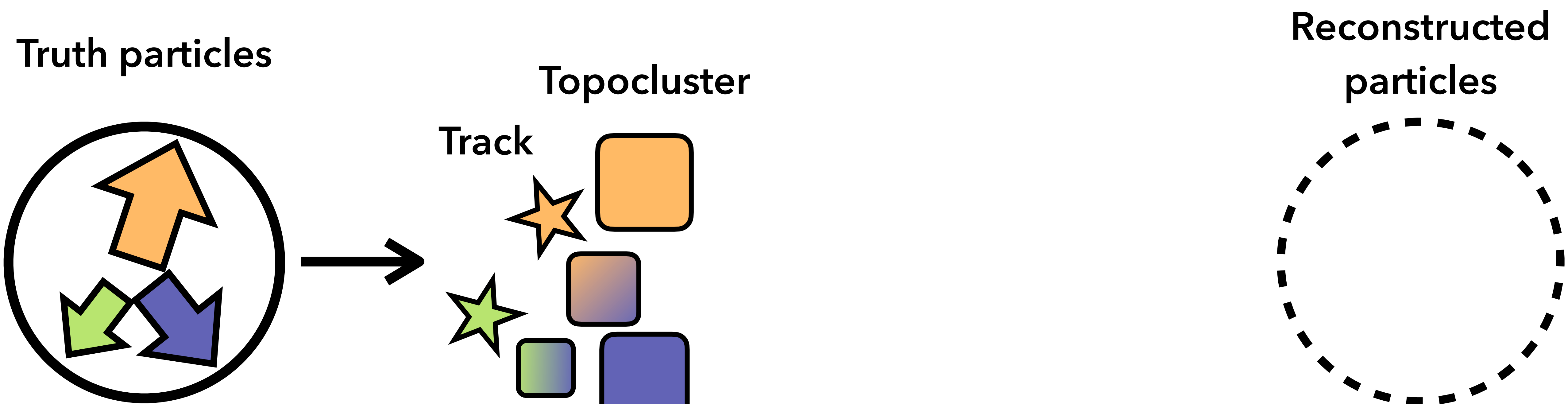


[**N.B.** ***in practice the tasks are simultaneous***]

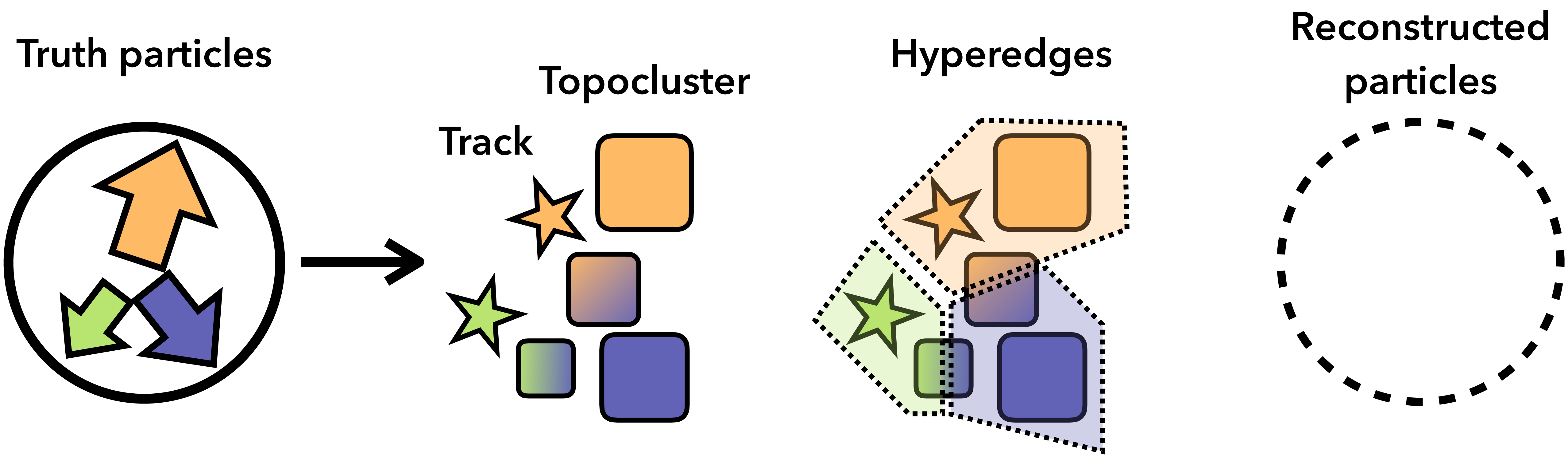
Ours: HGPflow

[arXiv:2212.01328](https://arxiv.org/abs/2212.01328) , [arXiv:2410.23236](https://arxiv.org/abs/2410.23236)



Ours: HGPflow

arXiv:2212.01328 , arXiv:2410.23236



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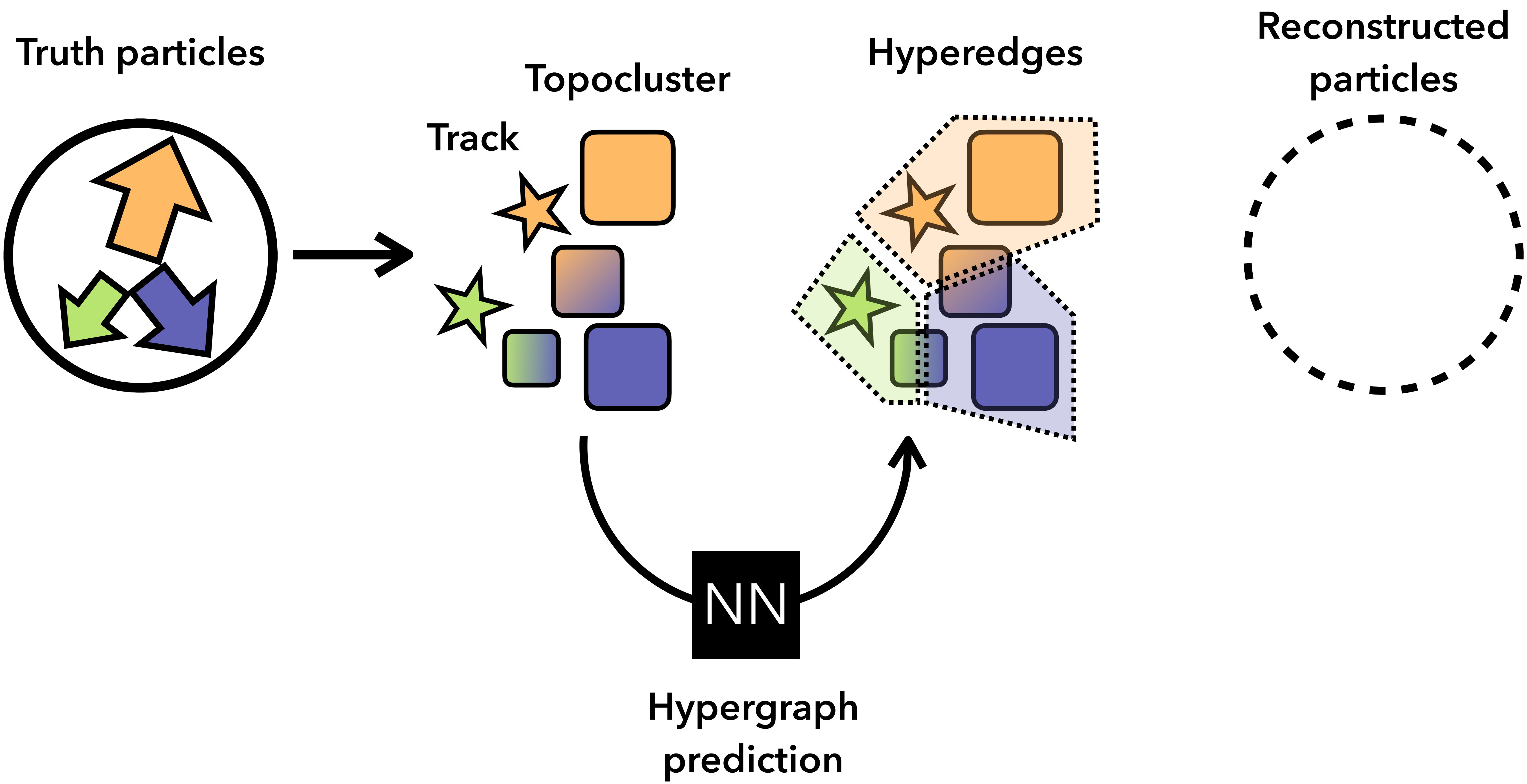
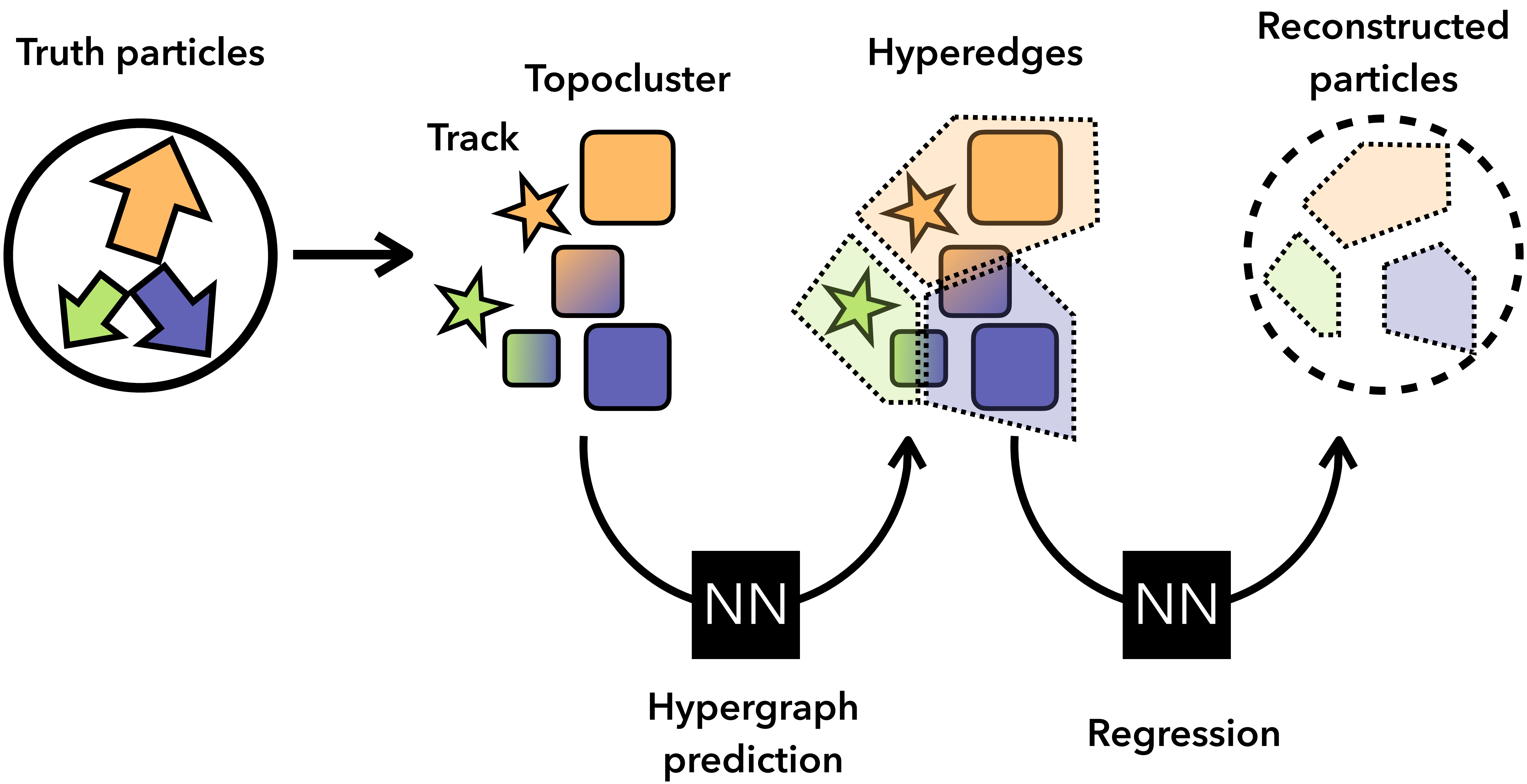
arXiv:2212.01328 , arXiv:2410.23236

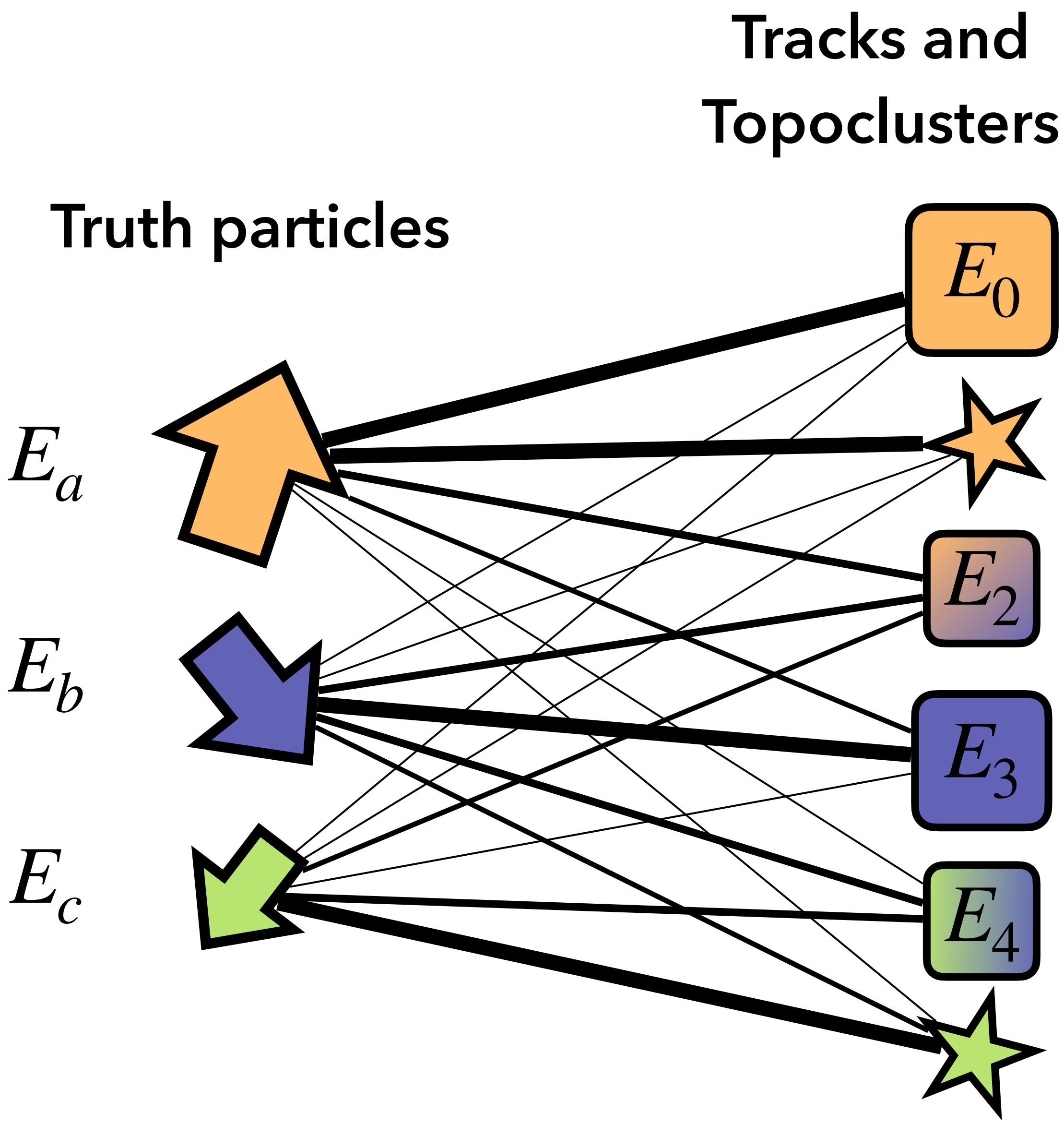


Ours: HGPflow

arXiv:2212.01328 , arXiv:2410.23236



How to predict a hypergraph?



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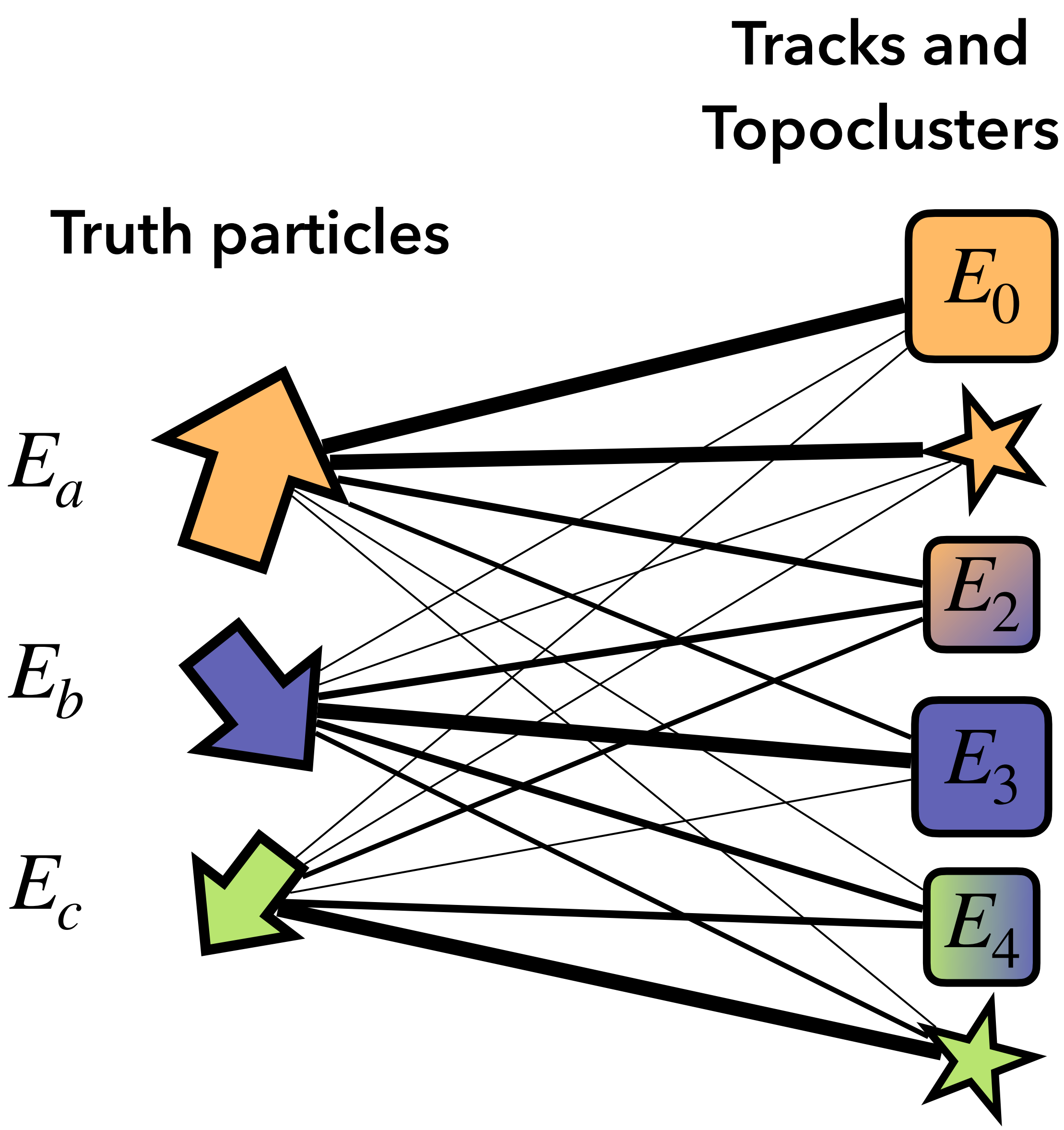
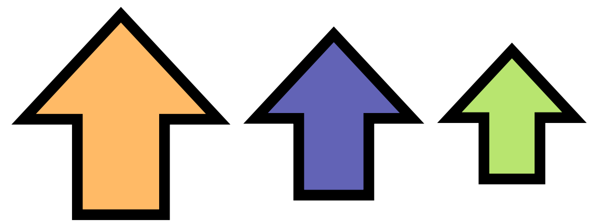


Incidence matrix

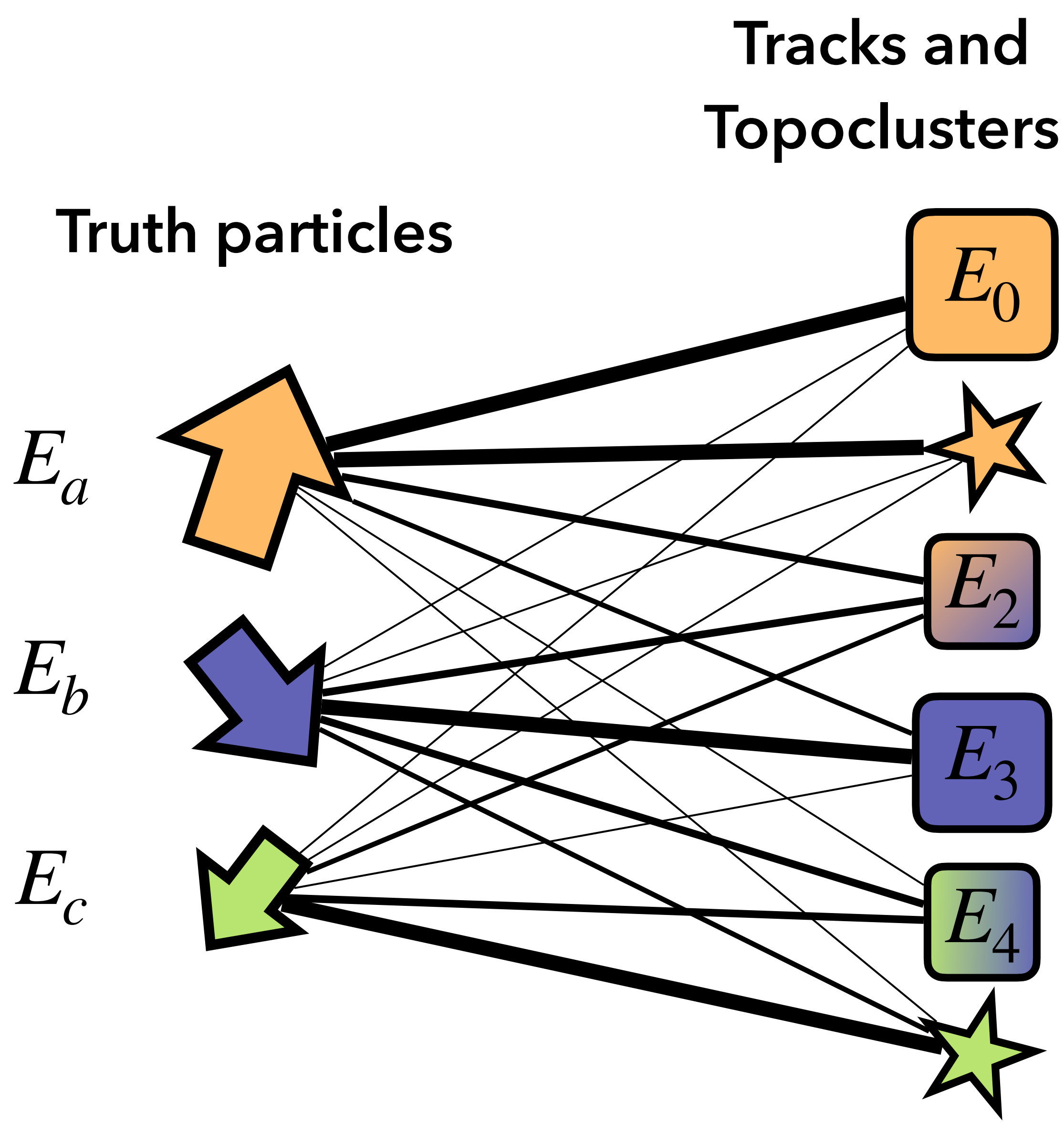


1.00		
1.00		
0.58	0.42	
0.15	0.85	
	0.25	0.75
		1.00

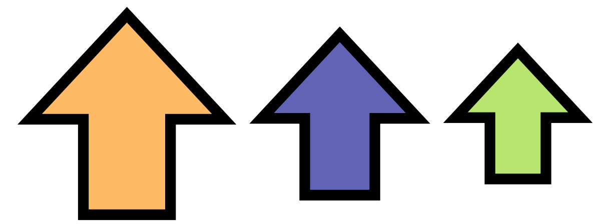
fraction of topocluster i's energy deposited by particle a

$$[I]_{ia} = \frac{E_{ia}}{E_i}$$

How to predict a hypergraph?



Incidence matrix



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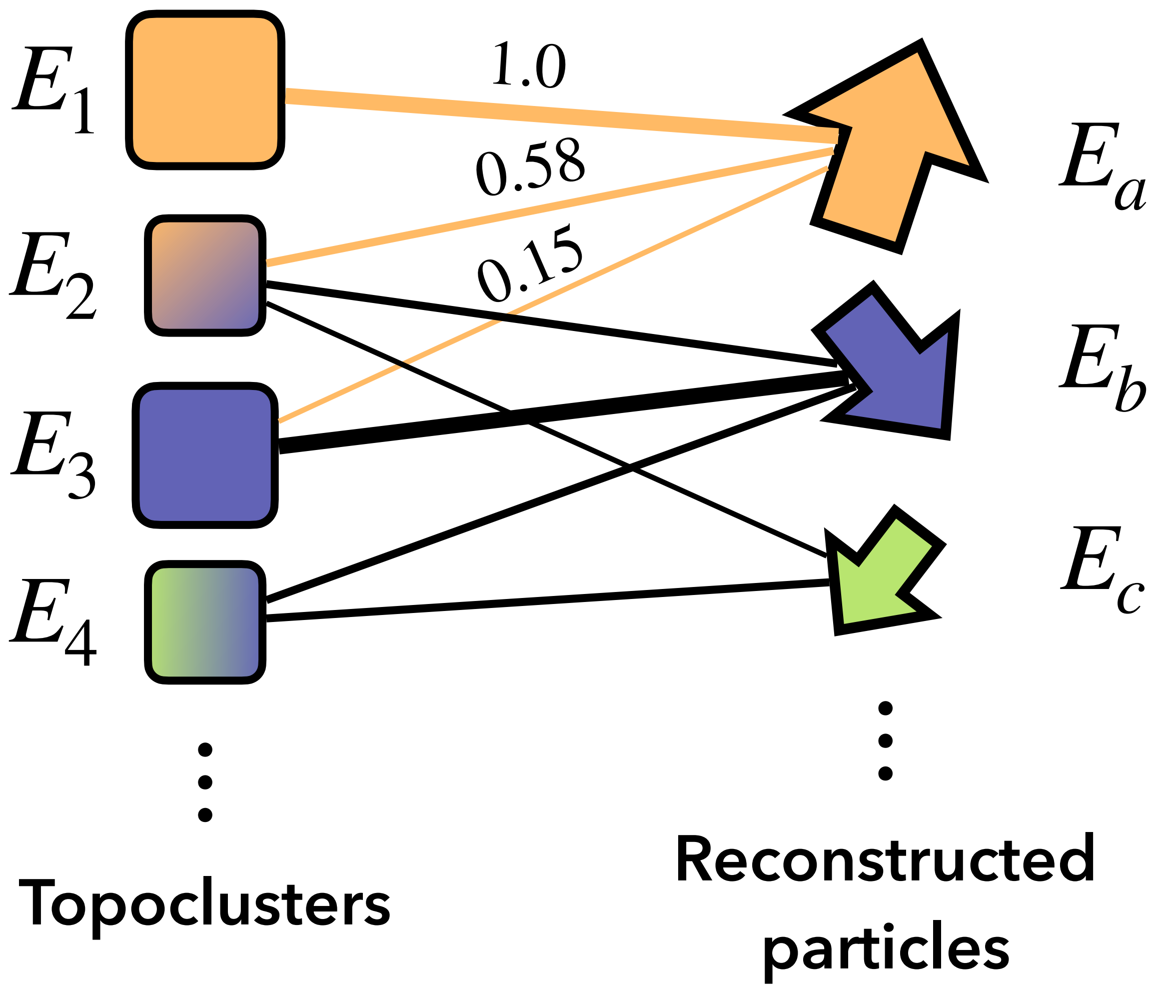
Training target

Perks of learning incidence matrix

Assuming we predicted the incidence matrix correctly…



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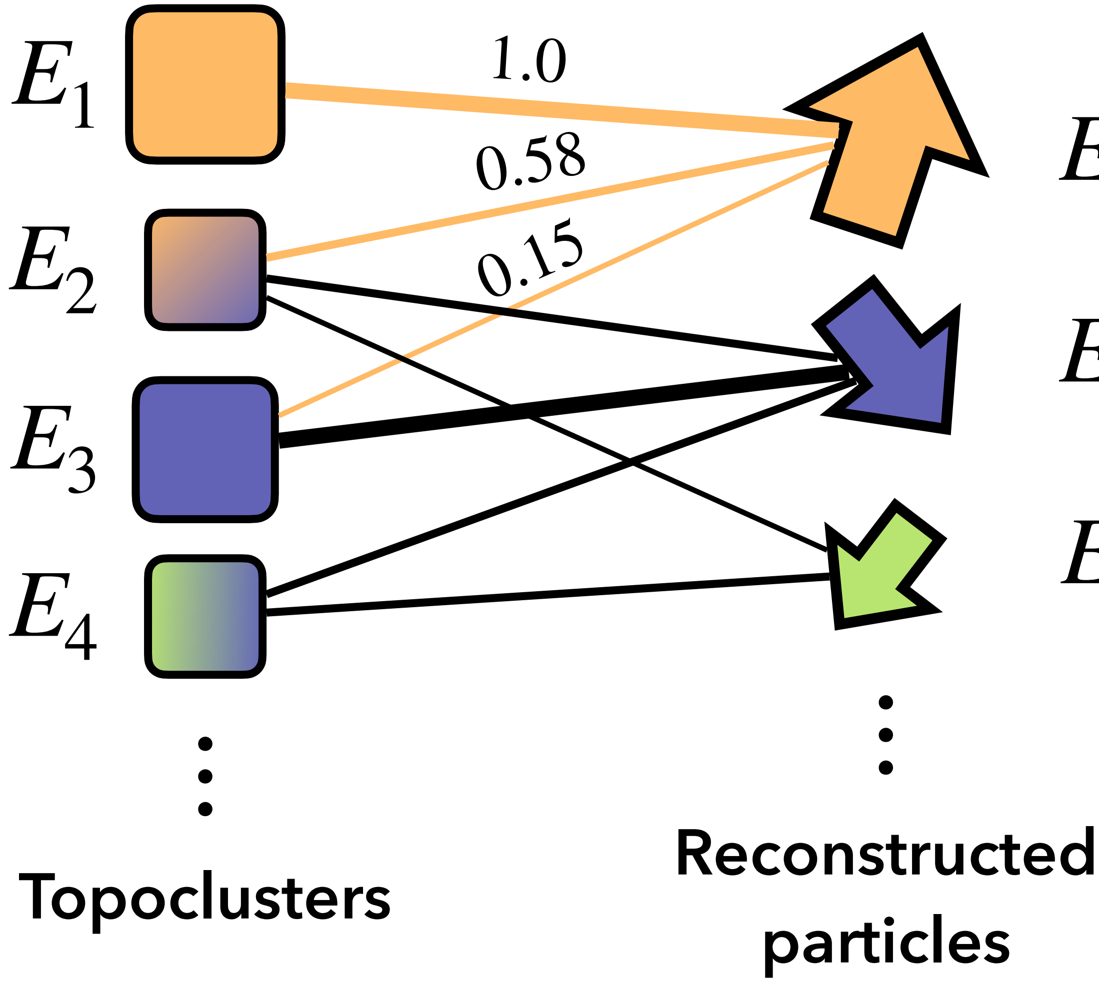

… then we can already estimate the properties of the particles:

$$E_a \simeq E_1 + (0.58 \cdot E_2) + (0.15 \cdot E_3)$$

E_b

E_c

Perks of learning incidence matrix

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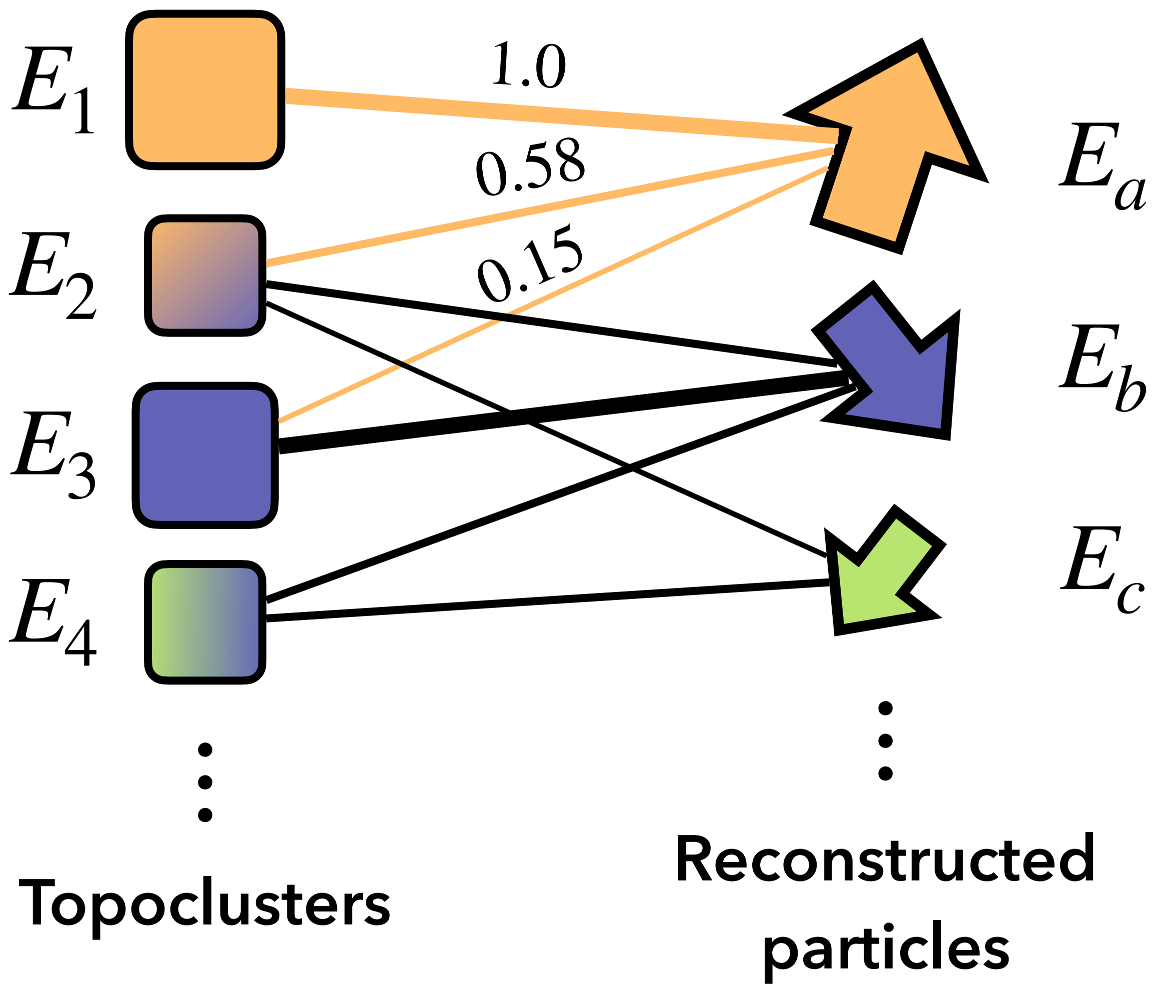
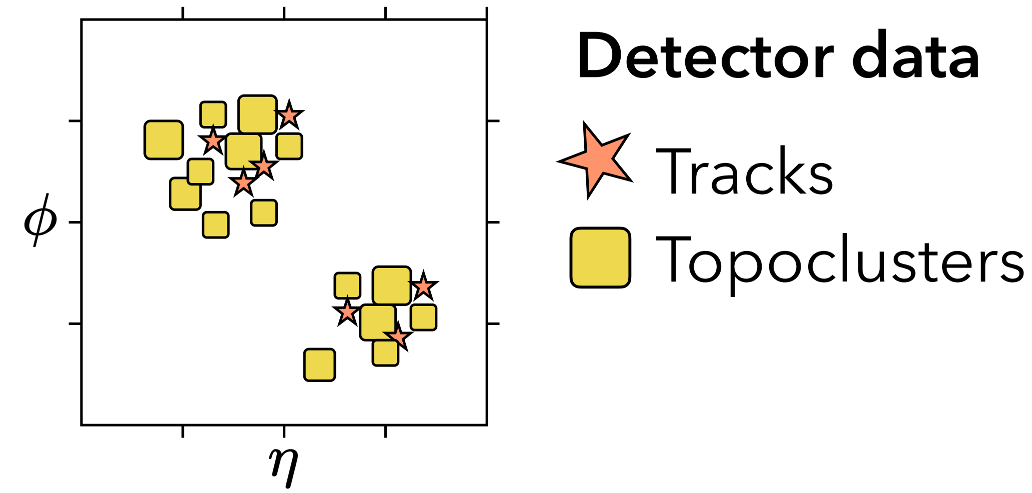
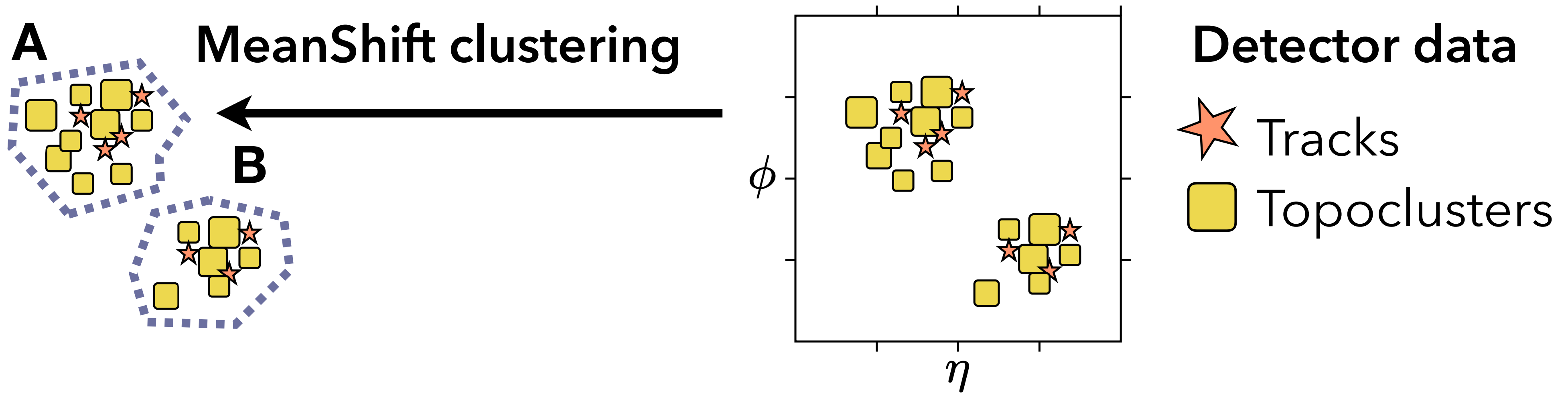


$$E_a \simeq E_1 + (0.58 \cdot E_2) + (0.15 \cdot E_3)$$

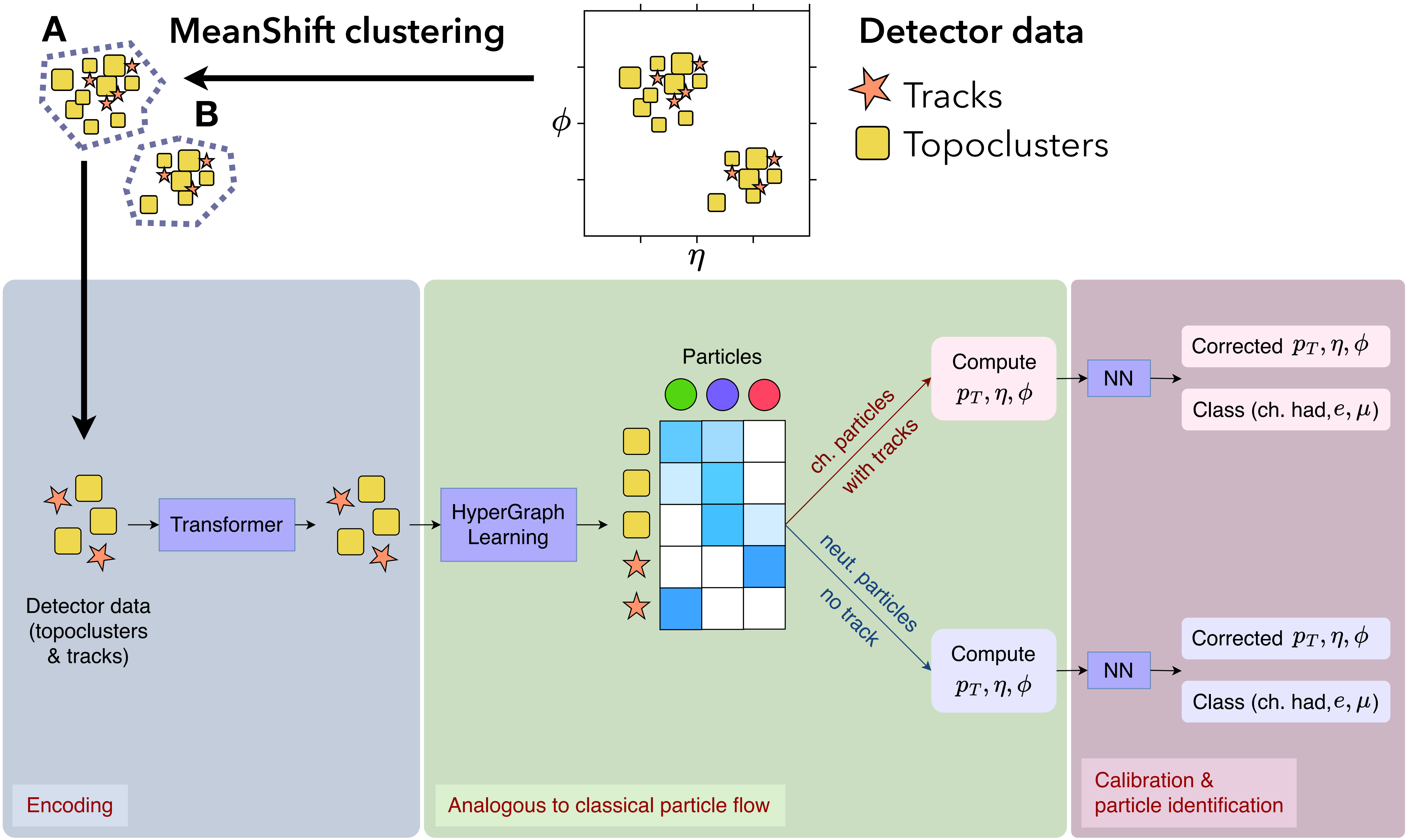
Learning the energy-based incidence matrix is an **inductive bias** that aids both prediction of particle properties and interpretability



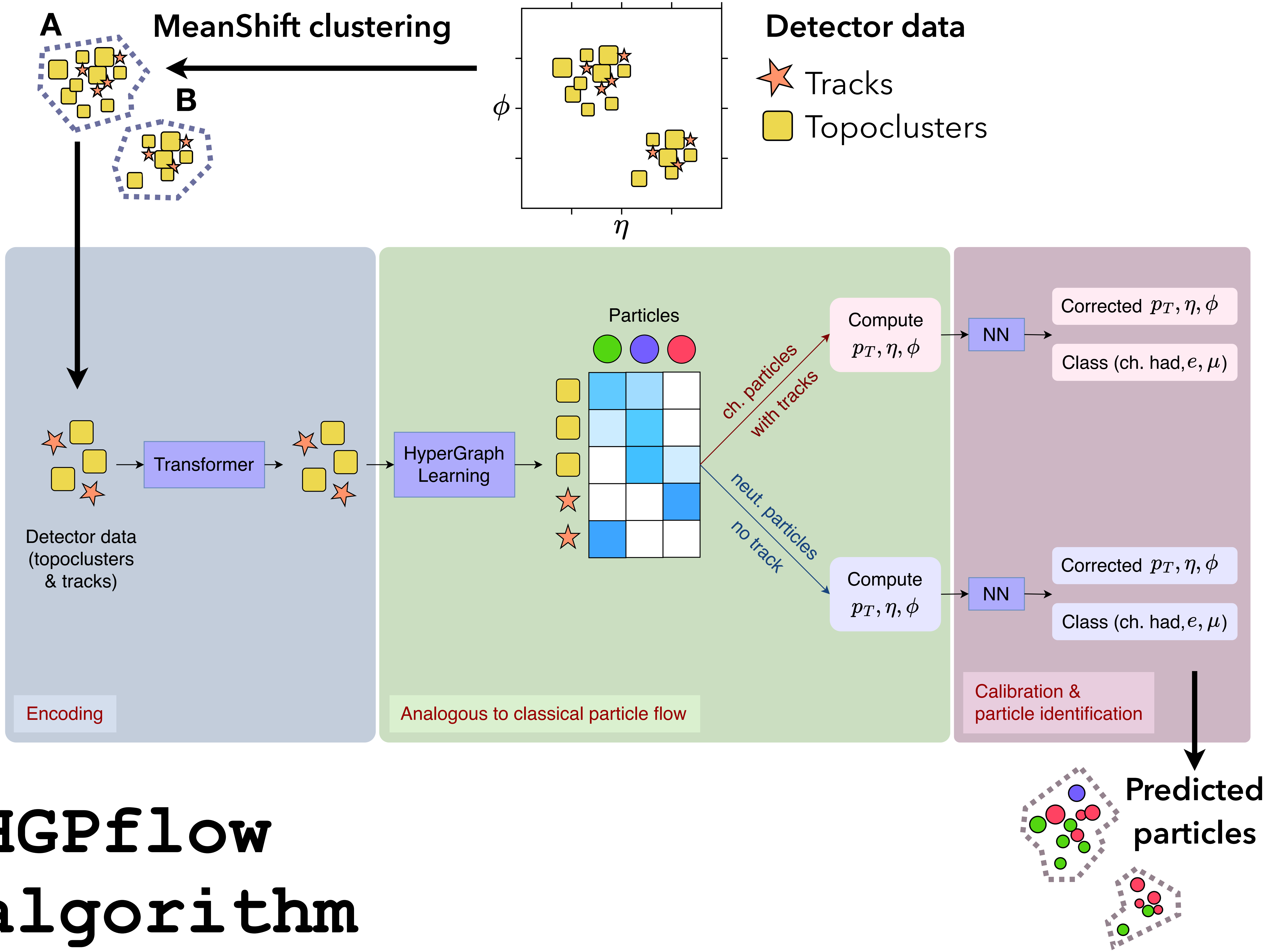
HGPflow algorithm



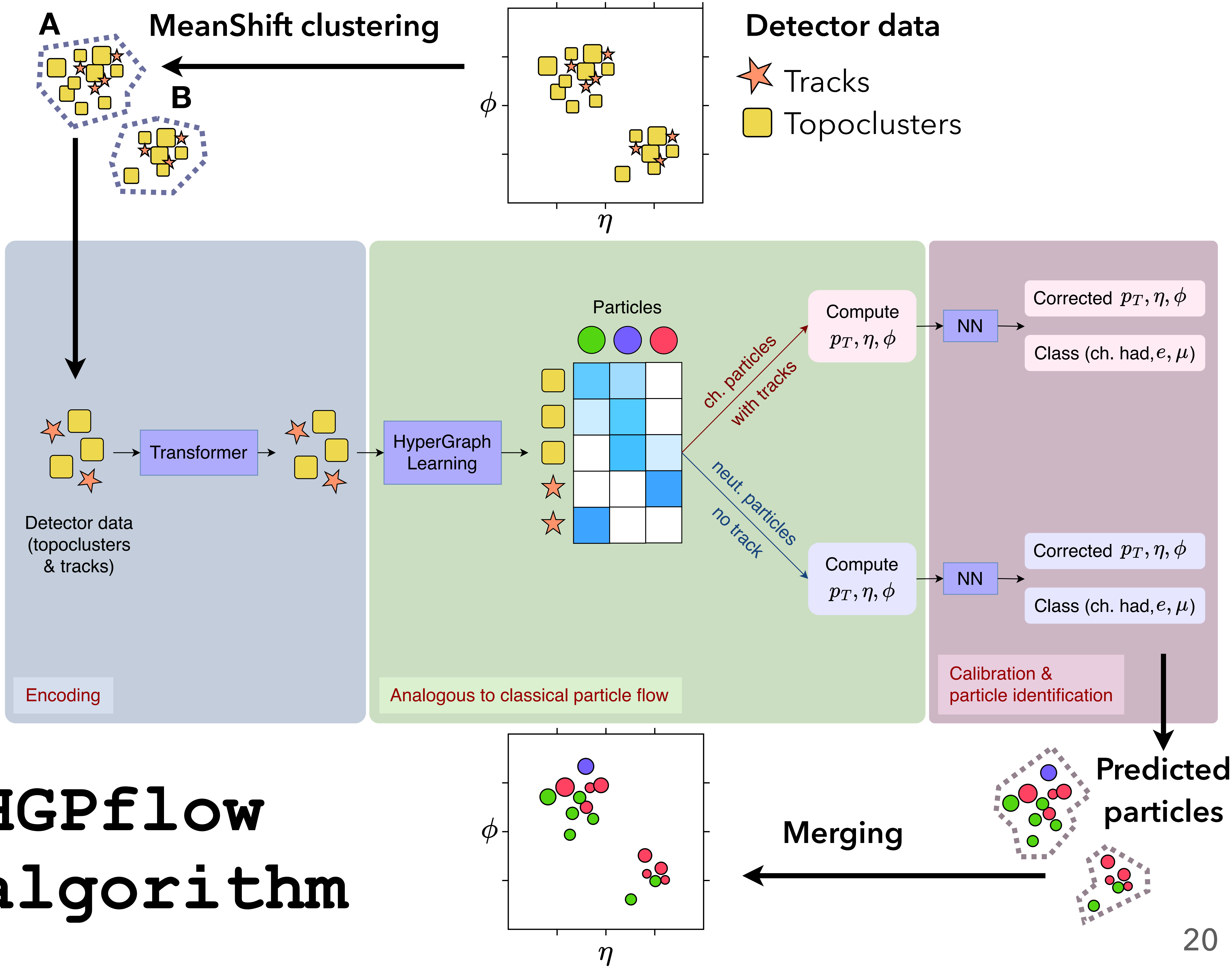
HGPflow algorithm



HGPflow algorithm



HGPflow algorithm



HGPflow algorithm

arXiv:2410.23236

arXiv > hep-ex > arXiv:2410.23236

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High Energy Physics – Experiment

[Submitted on 30 Oct 2024]

HGPflow: Extending Hypergraph Particle Flow to Collider Event Reconstruction

Nilotpal Kakati, Etienne Dreyer, Anna Ivina, Francesco Armando Di Bello, Lukas Heinrich, Marumi Kado, Eilam Gross

In high energy physics, the ability to reconstruct particles based on their detector signatures is essential for downstream data analyses. A particle reconstruction algorithm based on learning hypergraphs (HGPflow) has previously been explored in the context of single jets. In this paper, we expand the scope to full proton-proton and electron-positron collision events and study reconstruction quality using metrics at the particle, jet, and event levels. Rather than operating on the entire event in a single pass, we train HGPflow on smaller partitions to avoid potentially learning long-range correlations related to the physics process. We demonstrate that this approach is feasible and that on most metrics, HGPflow outperforms both traditional particle flow algorithms and a machine learning-based benchmark model.

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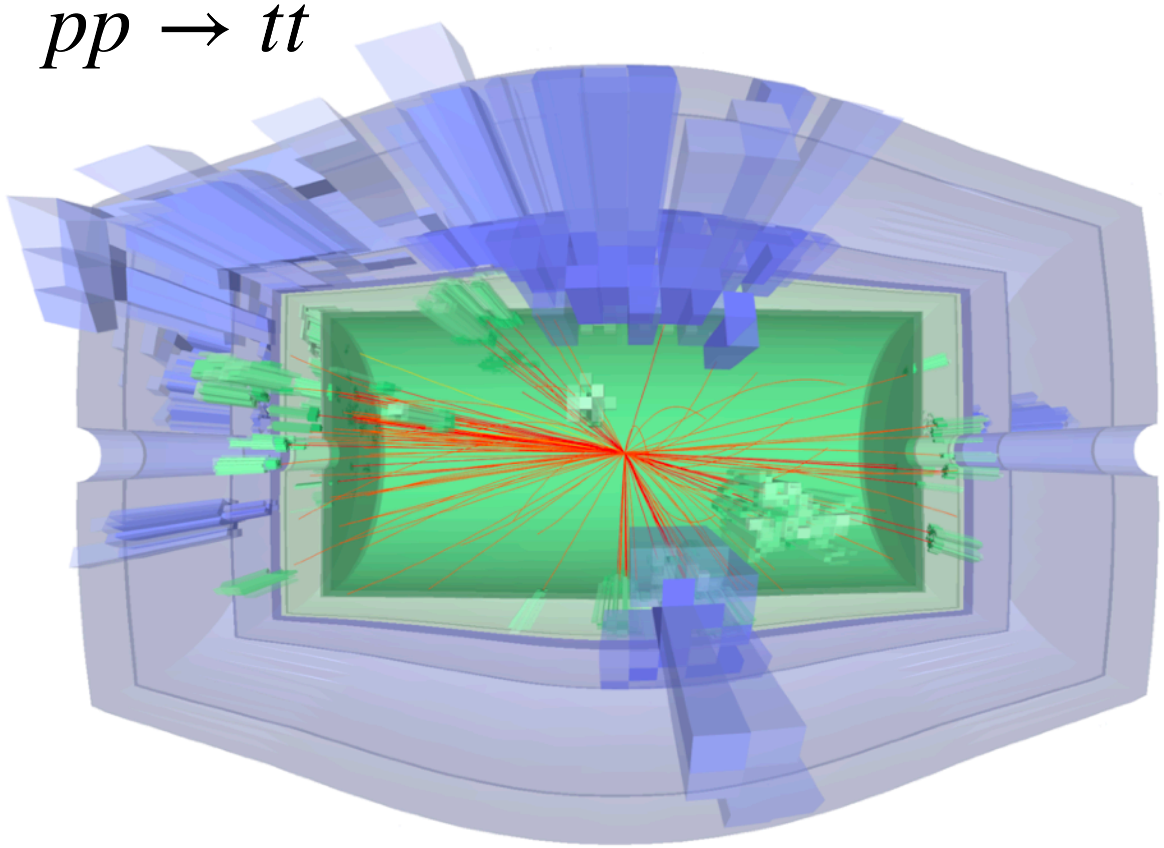
Datasets

COCOA (2023) MLST 4 035042

- Similar to ATLAS
- Relatively low granularity
- Comes with basic particle flow algorithm

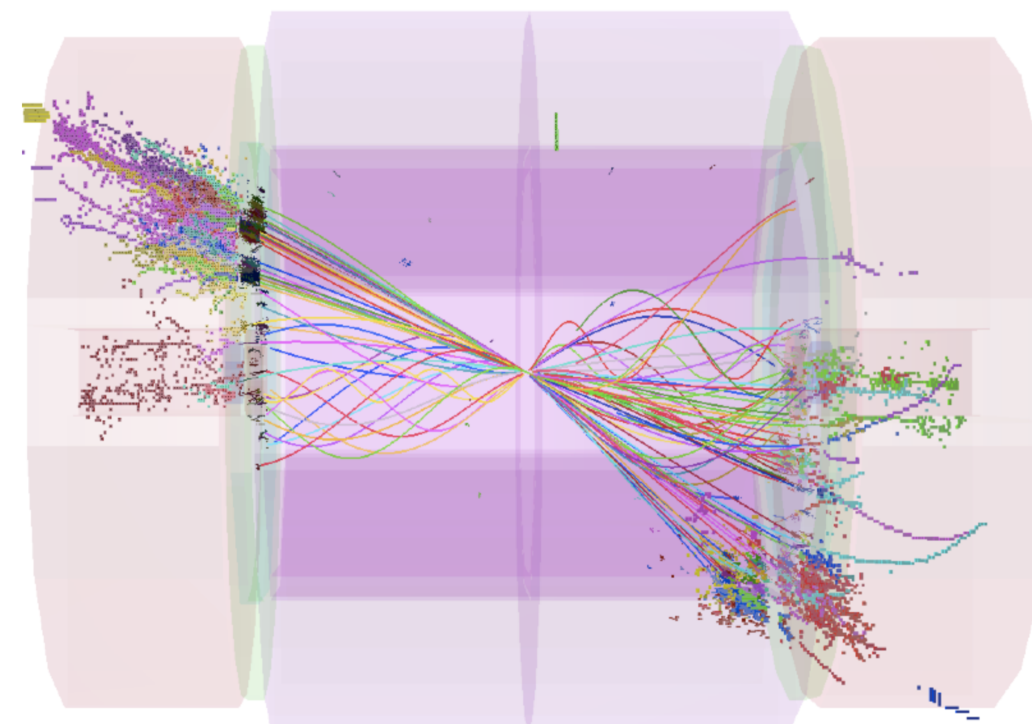
$pp \to t\bar{t}$



CLICdet arXiv:812.07337

- Publicly-available dataset: zenodo/8260741
- High granularity
- Sophisticated Pandora particle flow algo.

$e^+e^- \to t\bar{t}$

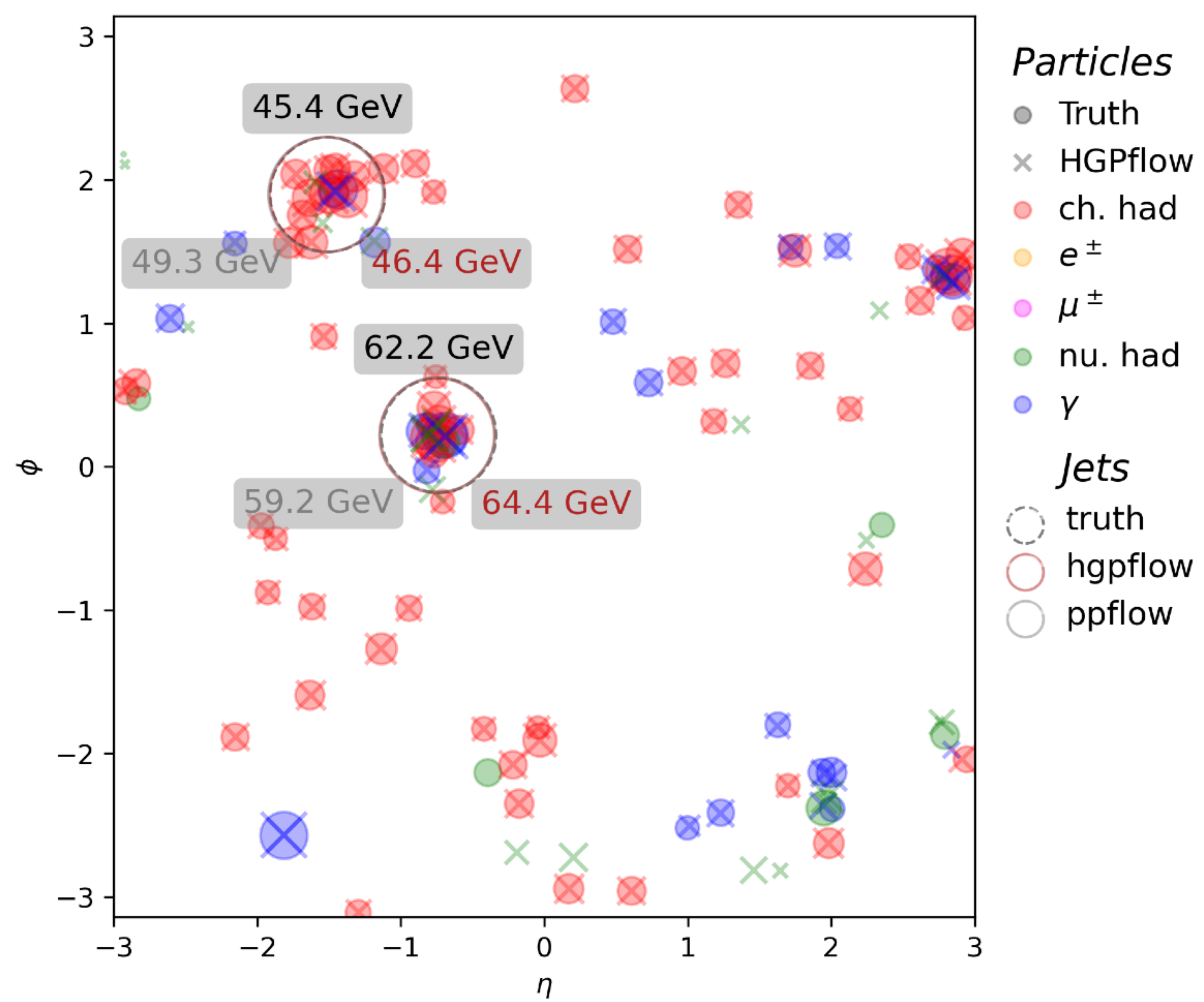


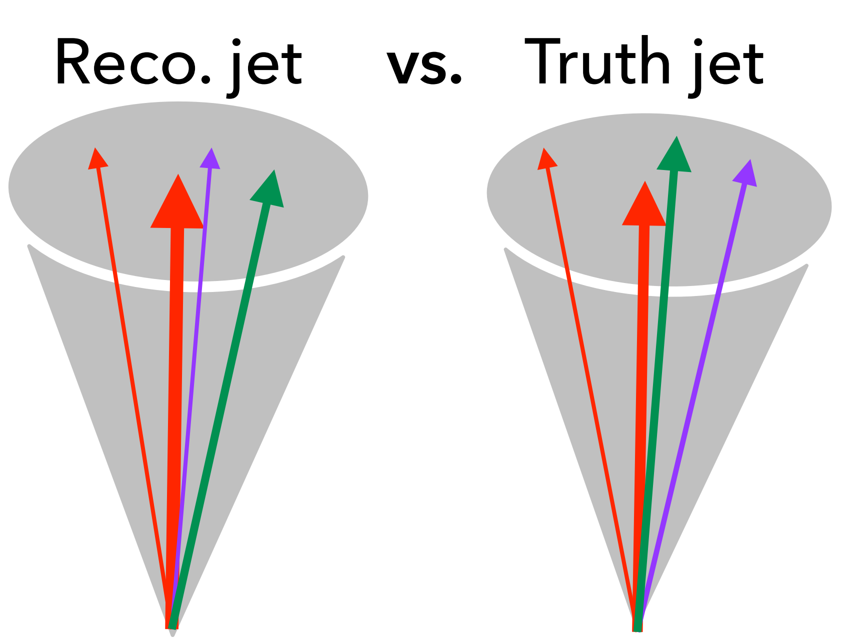
Source: arXiv:1208.1402

Detector	Process	Statistics train	Statistics val.	Statistics test
COCOA	$p^+p^+ \to q\bar{q}$	250k	10k	35k
	single π^+	–	–	30k / p_T bin
	$p^+p^+ \to t\bar{t}$	–	–	20k
	$p^+p^+ \to Z(\nu\bar{\nu})H(b\bar{b})$	–	–	10k
CLIC	$e^+e^- \to q\bar{q}$	1M	5k	20k

Performance: dijet events

Trained on 250k and tested on 35k





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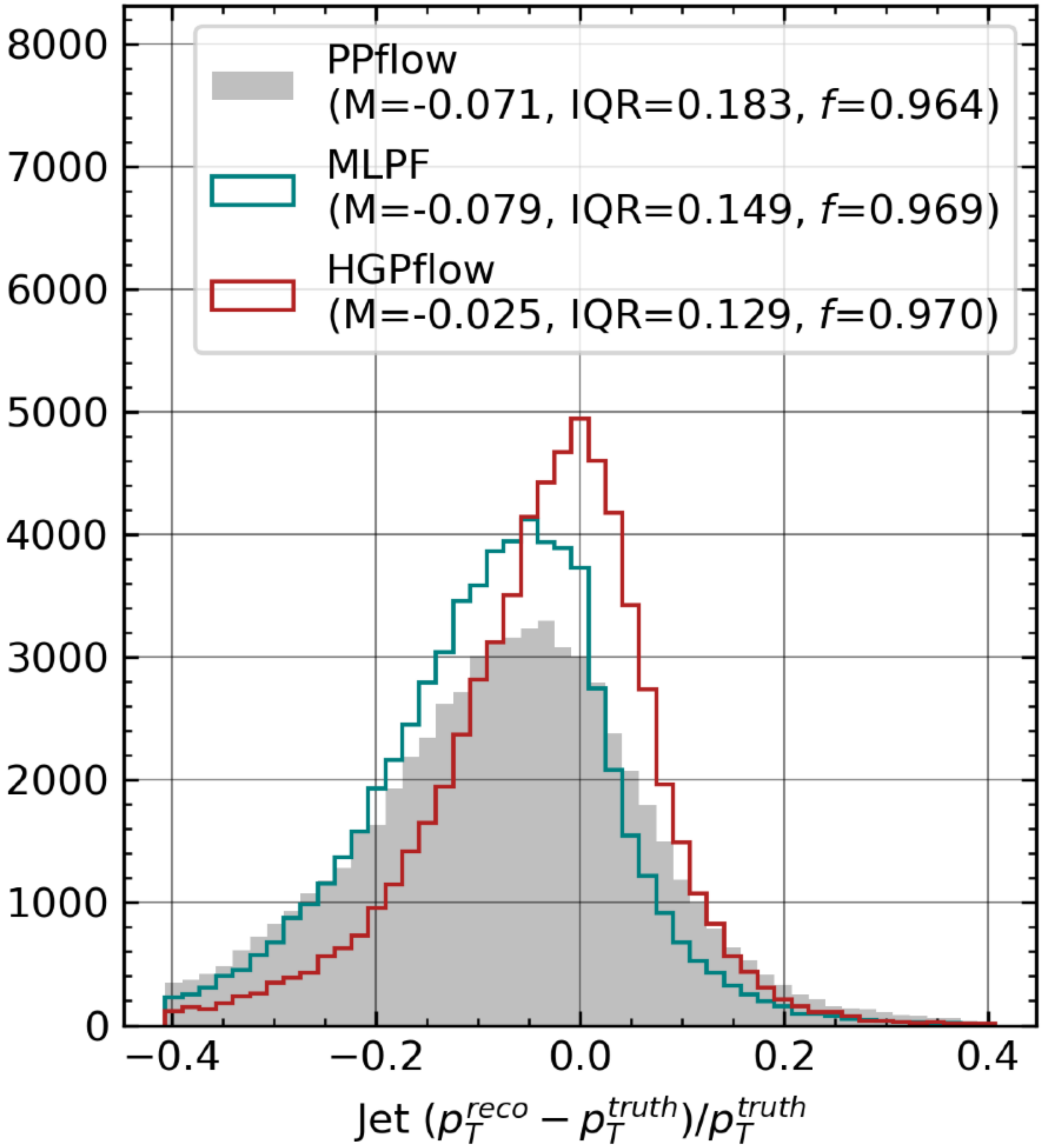
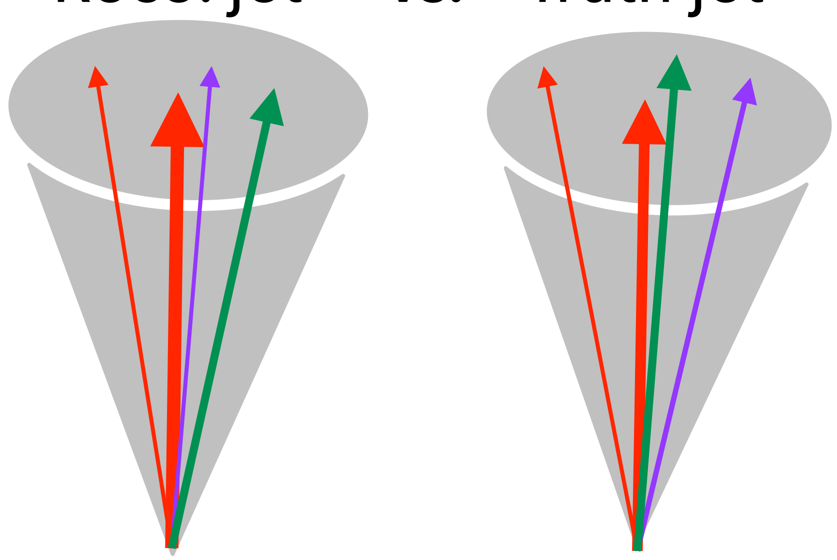
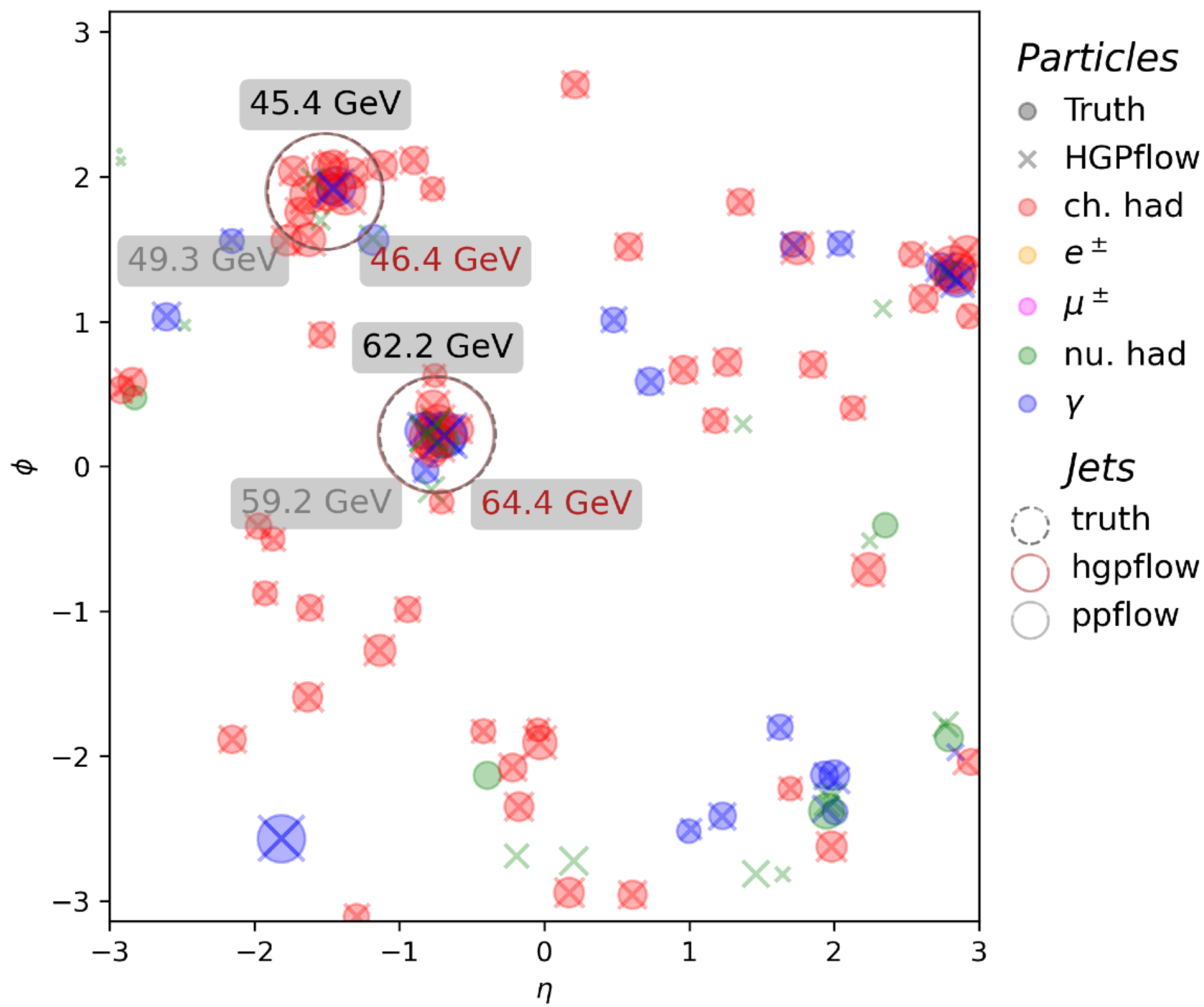
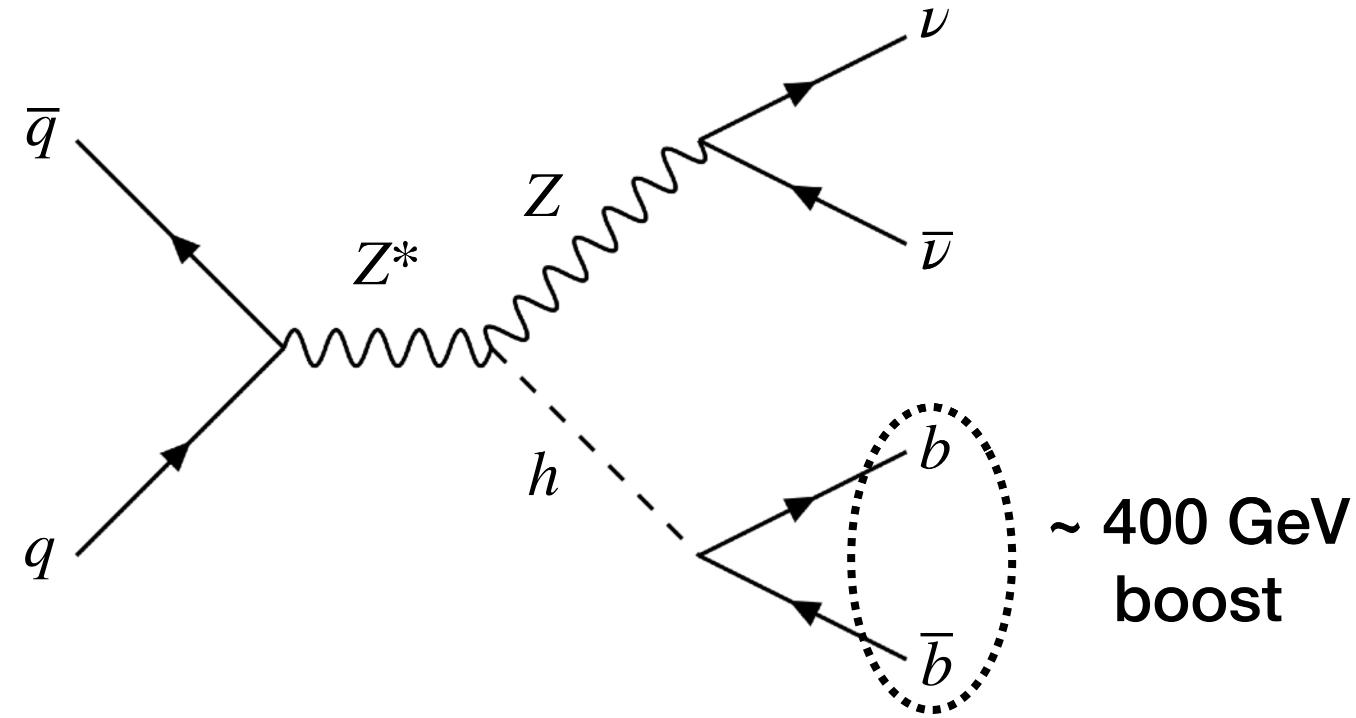


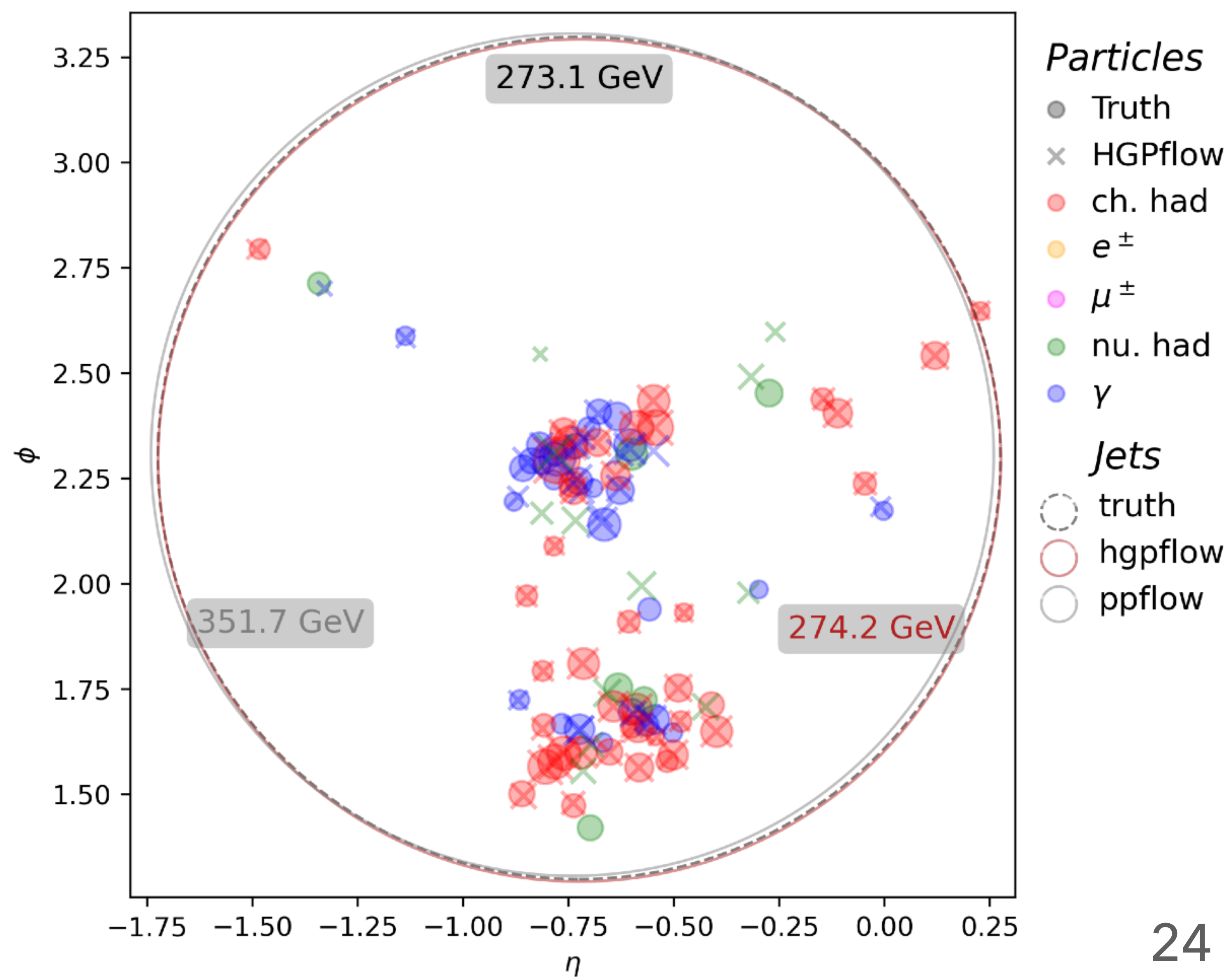




Performance: boosted Higgs

Not encountered during training!





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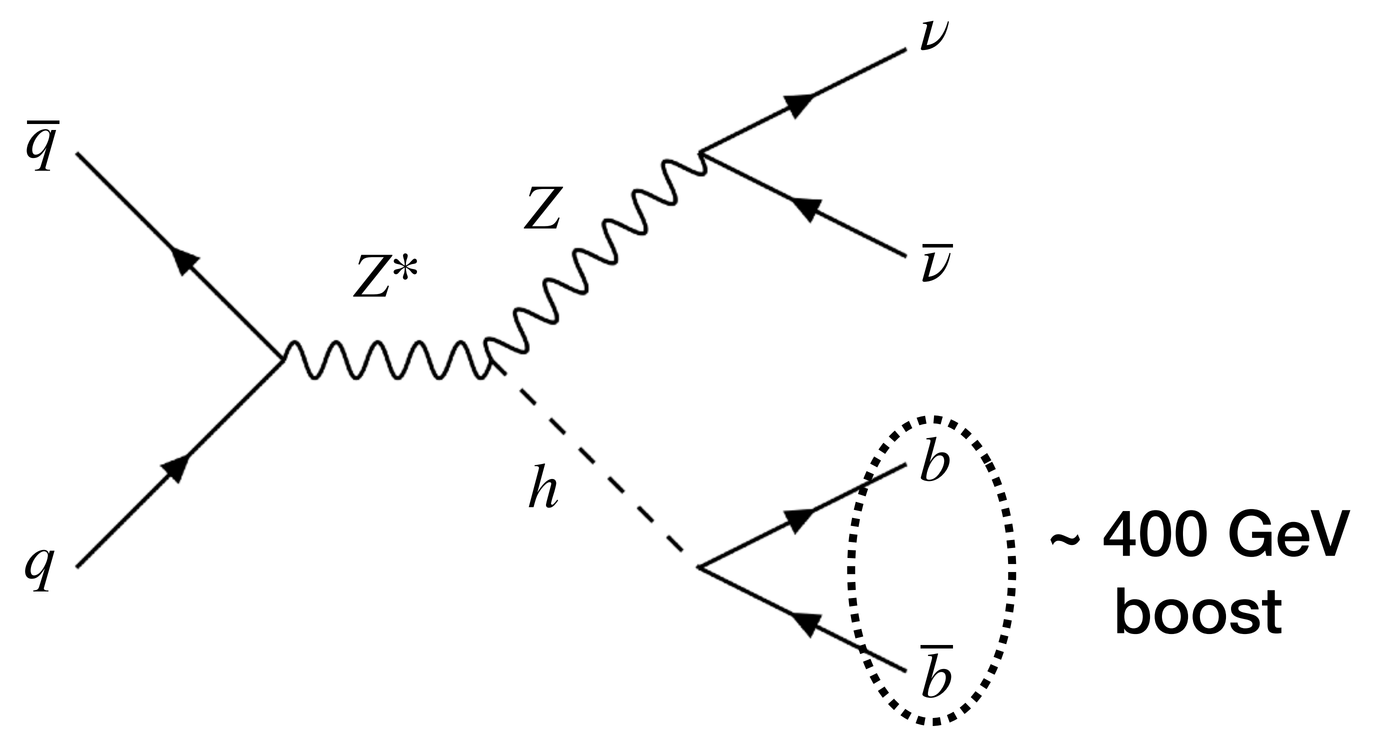

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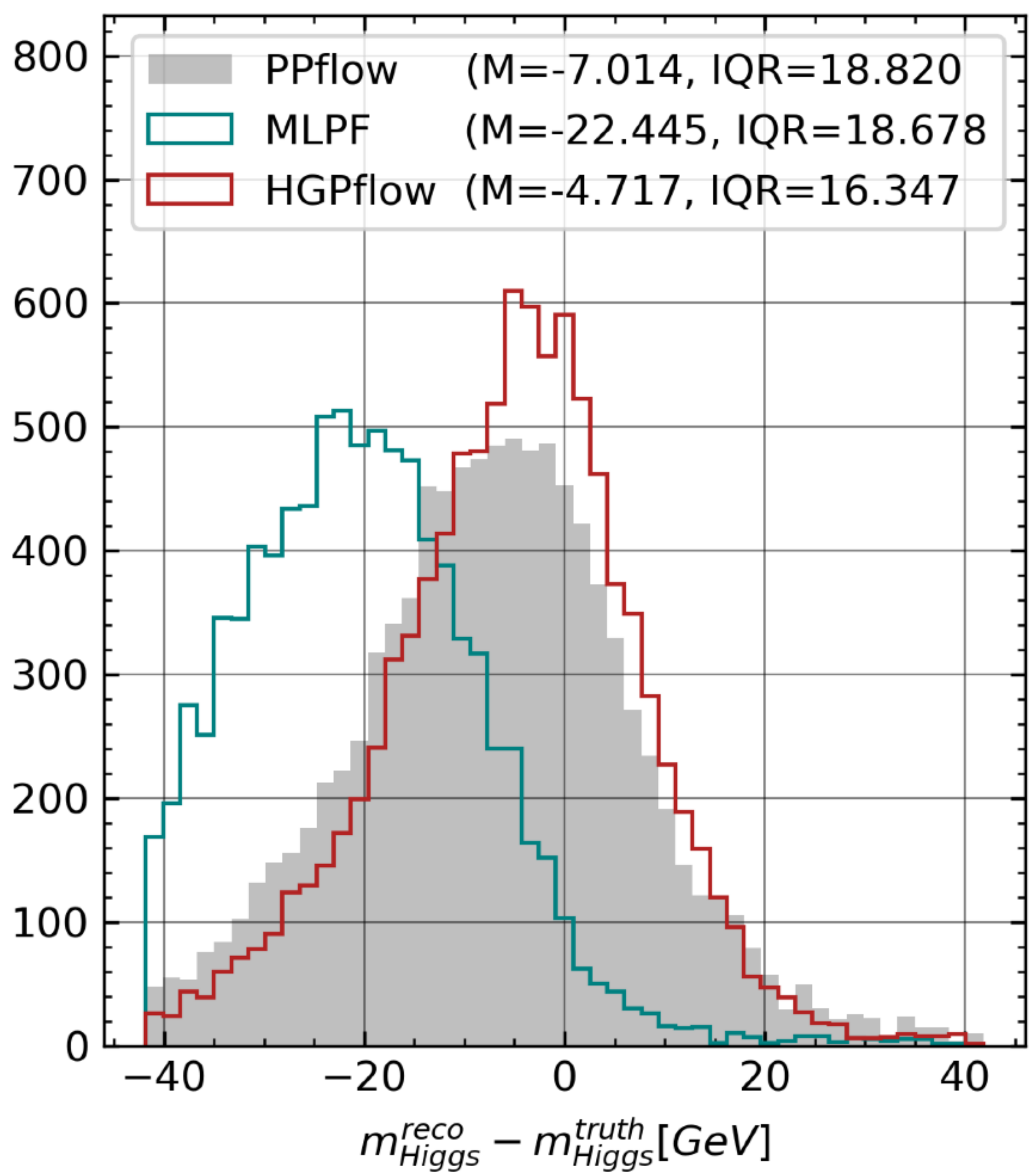
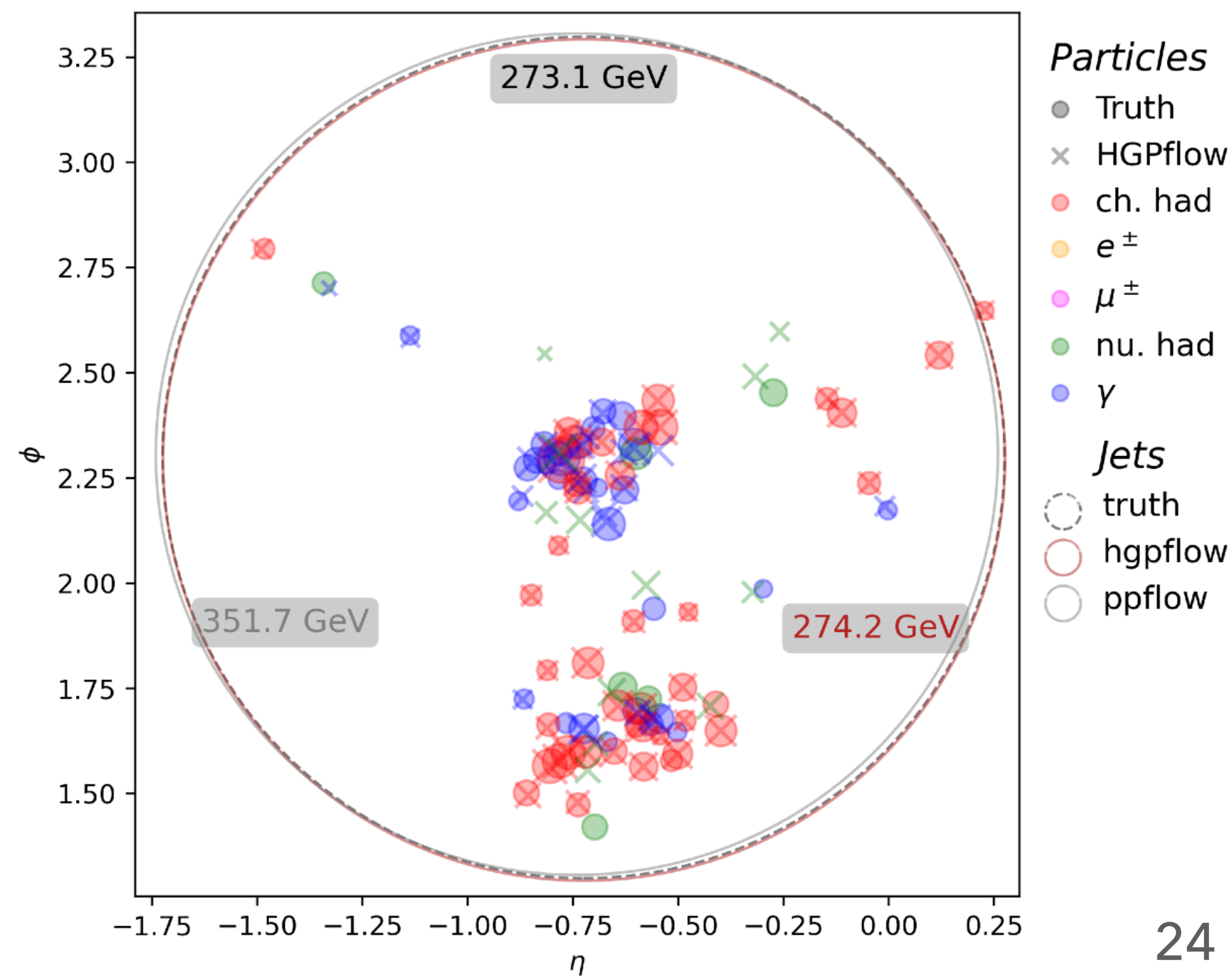
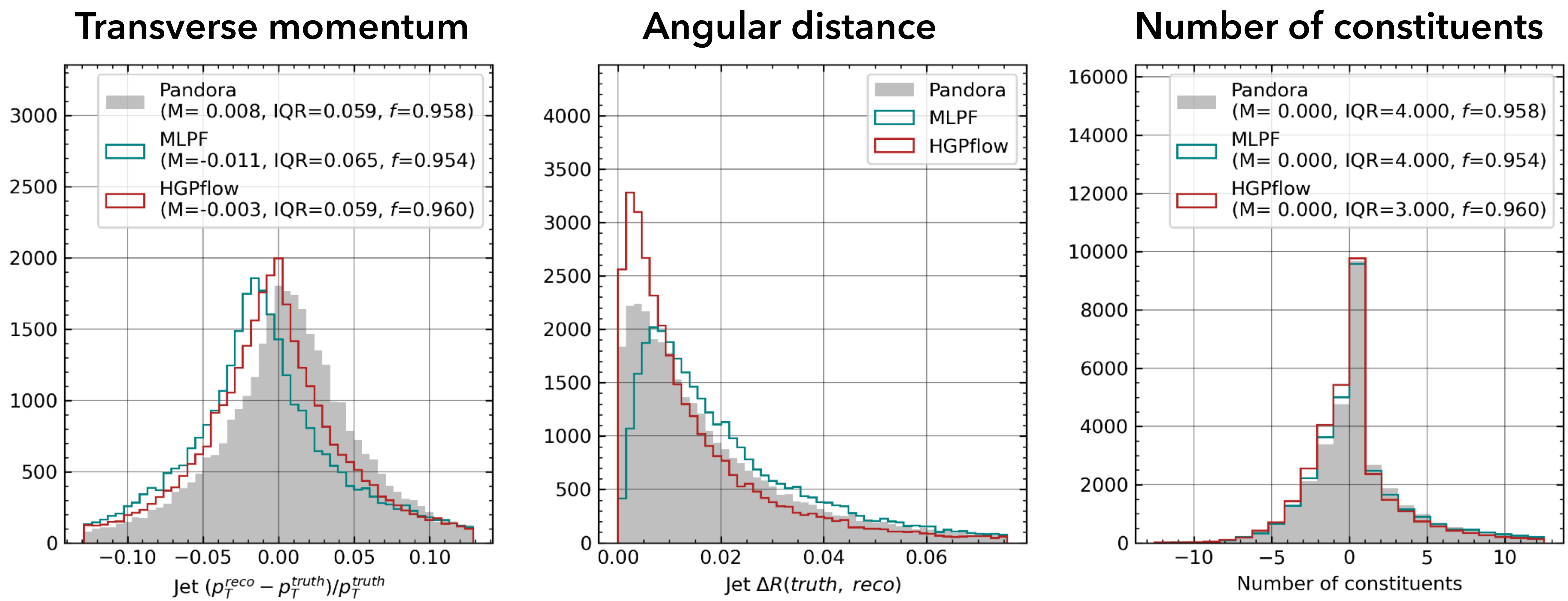




Performance on $e^+e^- \to q\bar{q}$ events

Trained on 1M and tested on 20k



HGPflow excels for high-granularity calorimeters too

- Slightly outperforms Pandora
- Promising for existing and future facilities

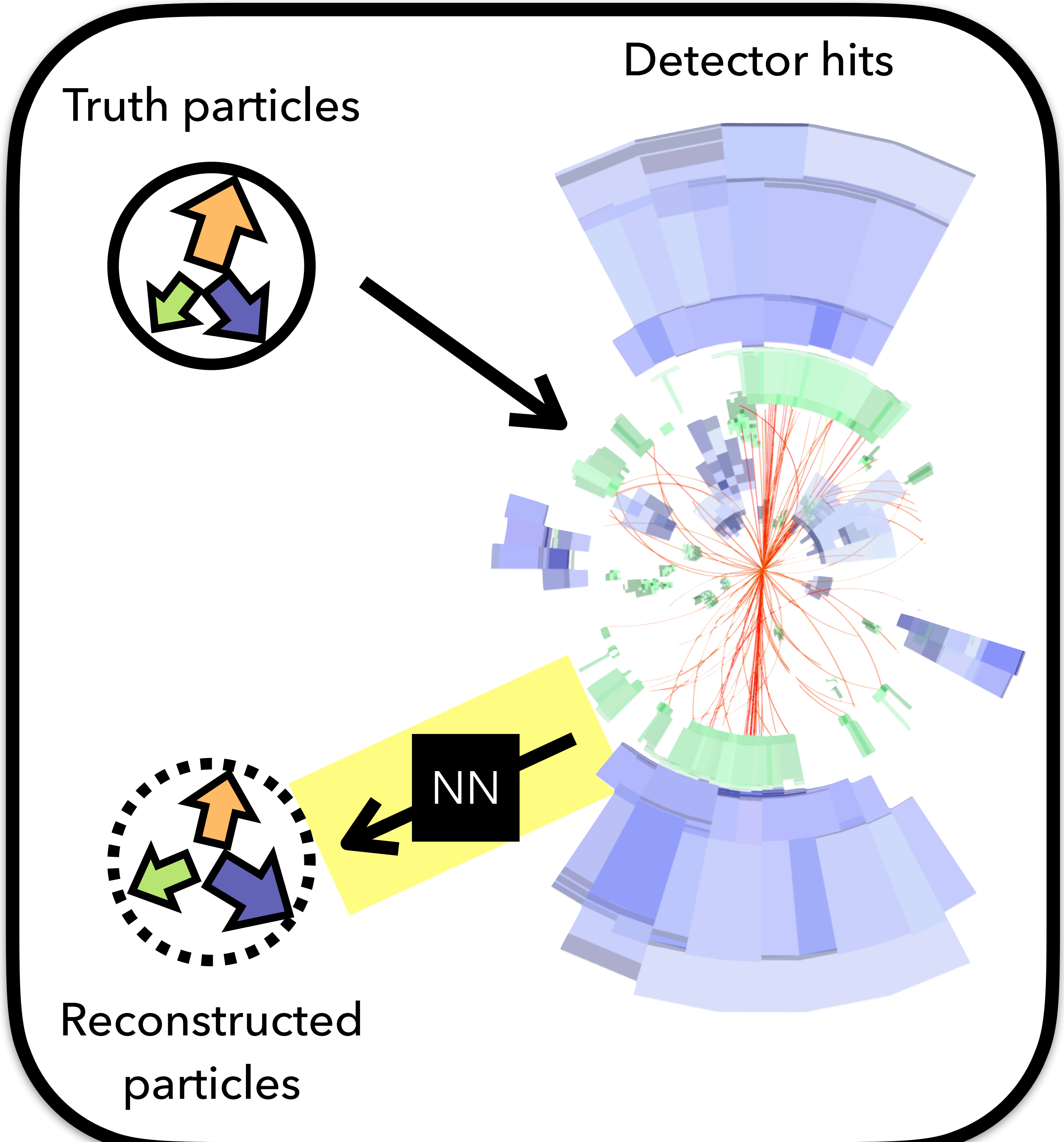
Summary

Particle reconstruction is foundational to experimental HEP

Deep learning is redefining what can be achieved

Hypergraph learning fits the problem well and is interpretable

Digital twin (i.e. GEANT4 simulation) required for training



Next step: implement at the LHC!