From detector hits to final state particles with Machine Learning

Nilotpal Kakati

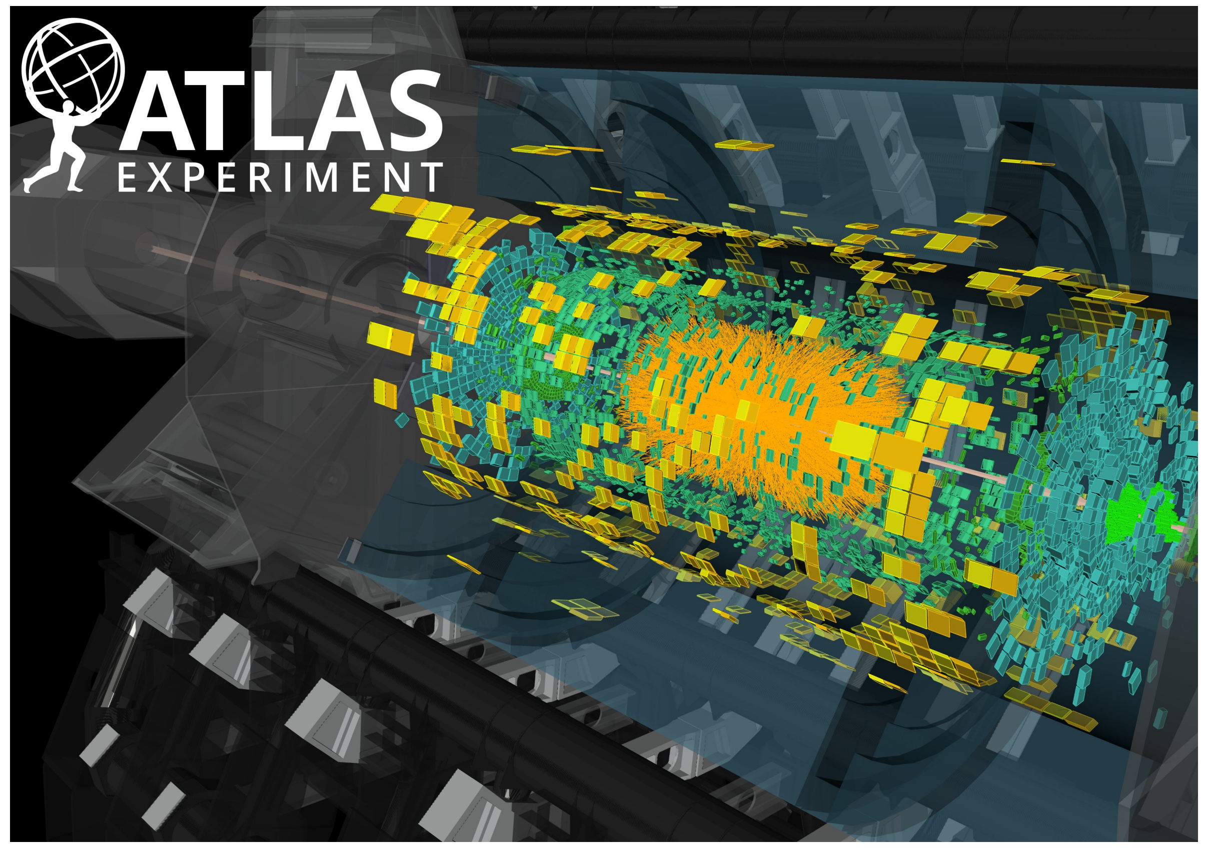
(nilotpal.kakati@weizmann.ac.il)

מכון ויצמן למדע
WEIZMANN INSTITUTE OF SCIENCE

University of Genova, 2022
17 November

Colliders: the answer (question) machine

- So what are these particles actually?
- What about the Higgs?
- Umm, tell me more…
- Is God real?



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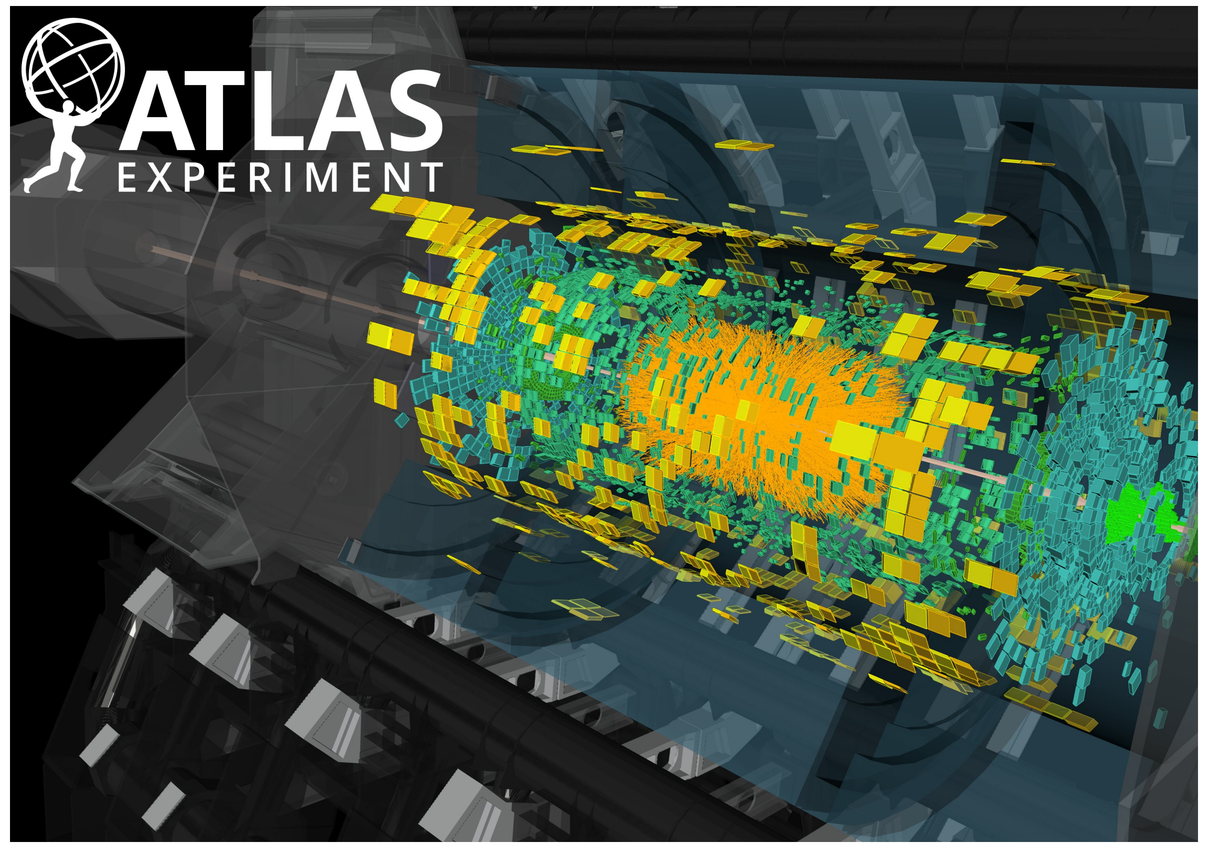

LHC actually does these collisions and we get data

How do we study them?

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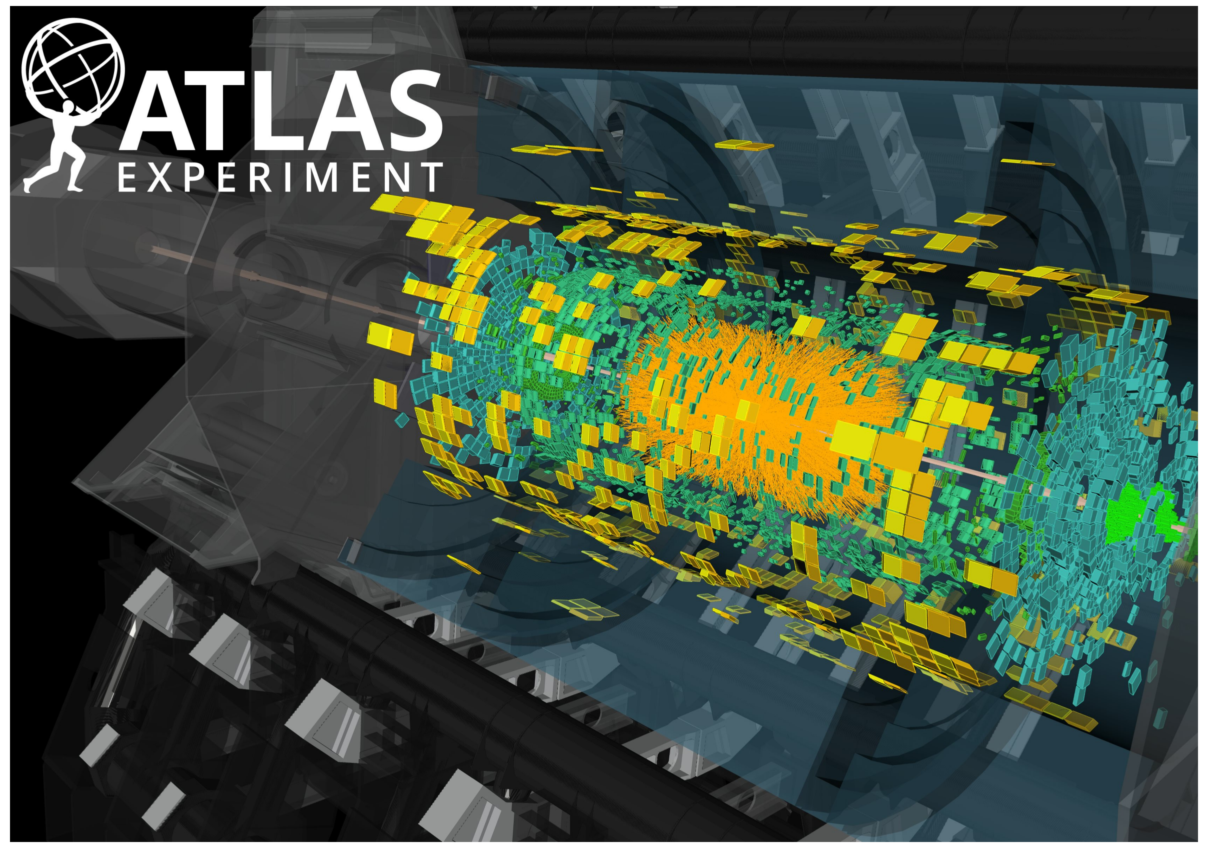

LHC actually does these collisions and we get data

- We compare our simulations with the data we get
- This tells us -
  - If what we think we know about physics is true!
  - If there is new "physics" to look for

How does it actually work though?

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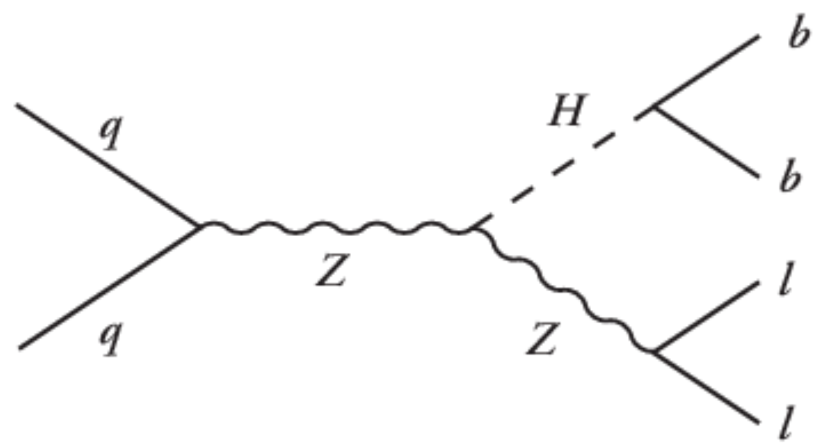

Collision

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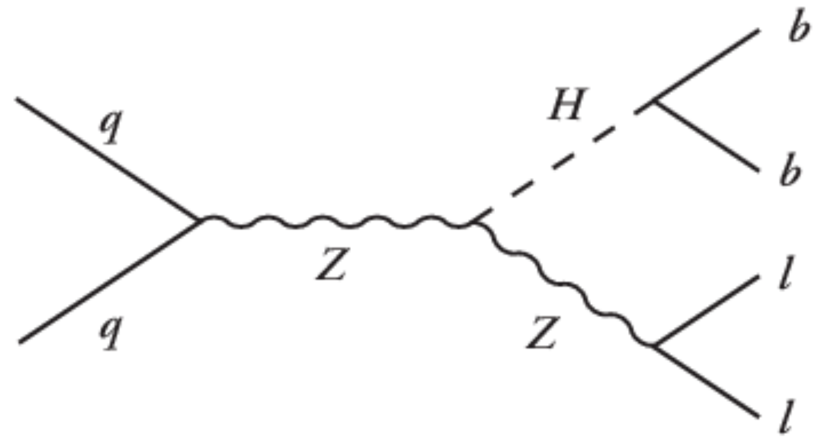

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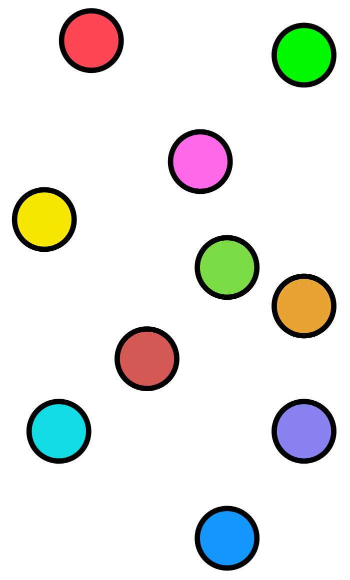

Truth Particles

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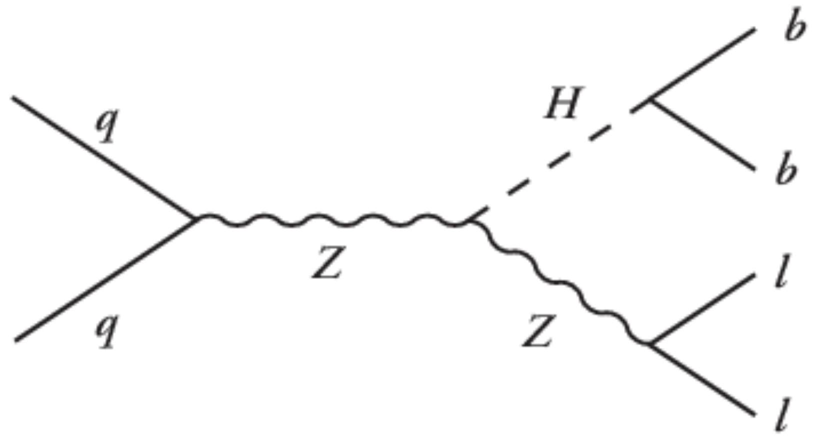

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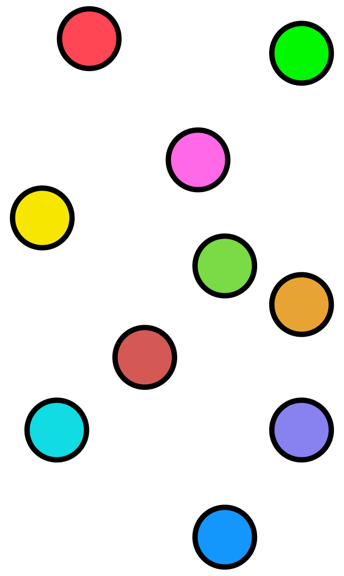

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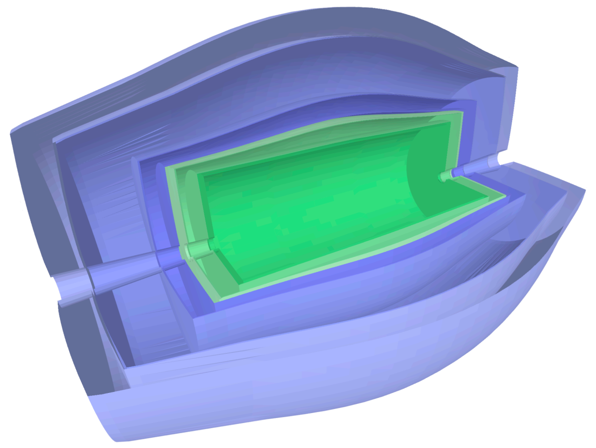

Detector

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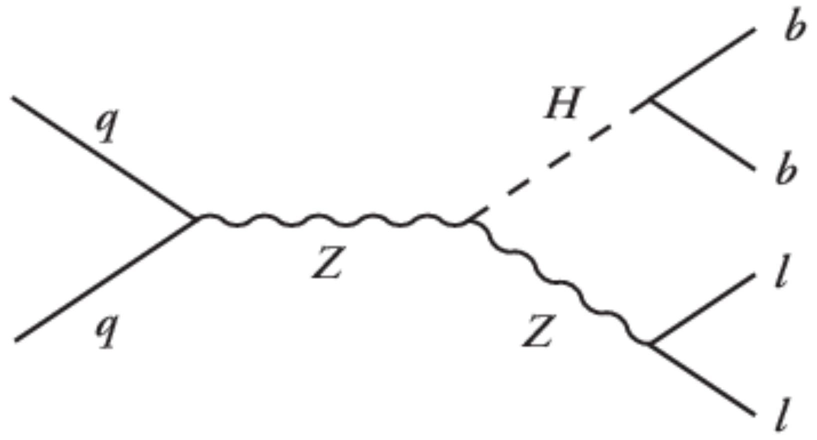

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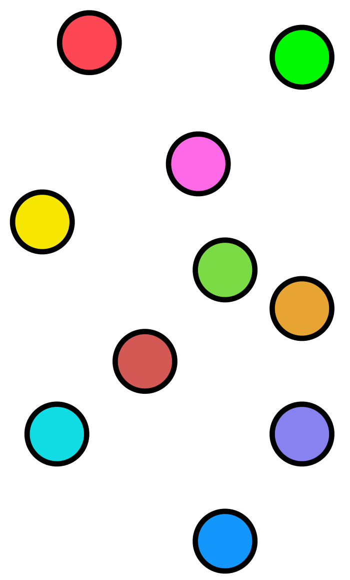

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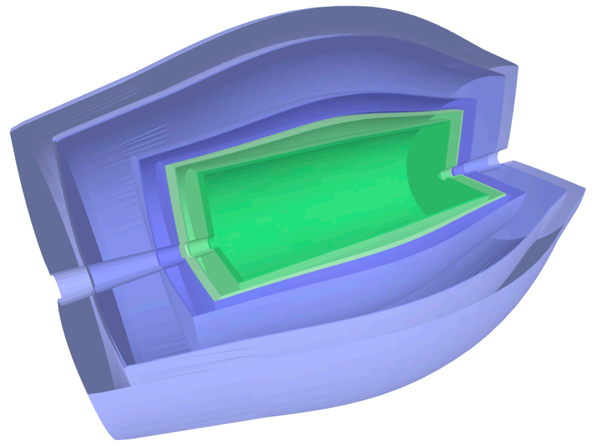

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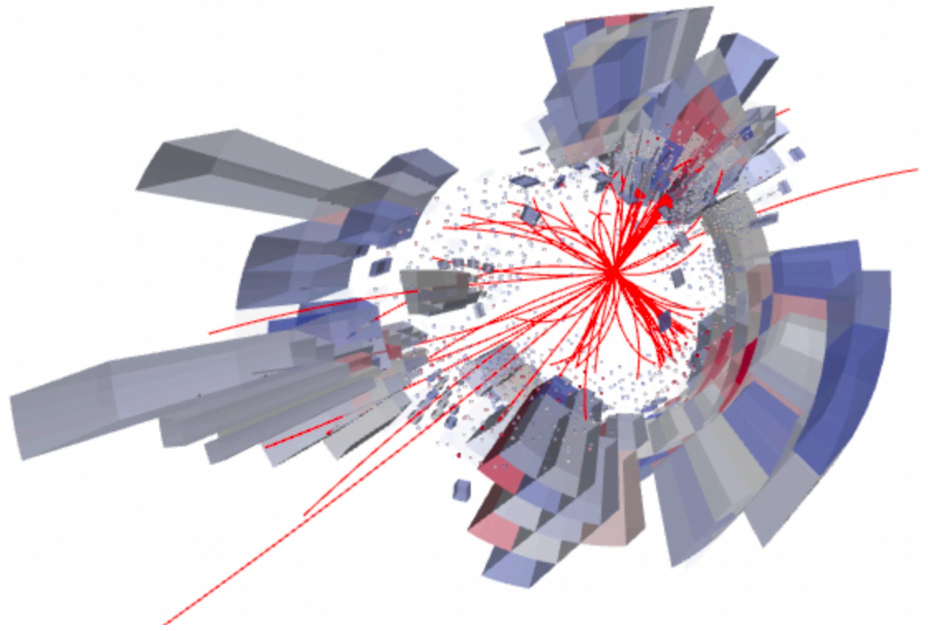

Detector hits

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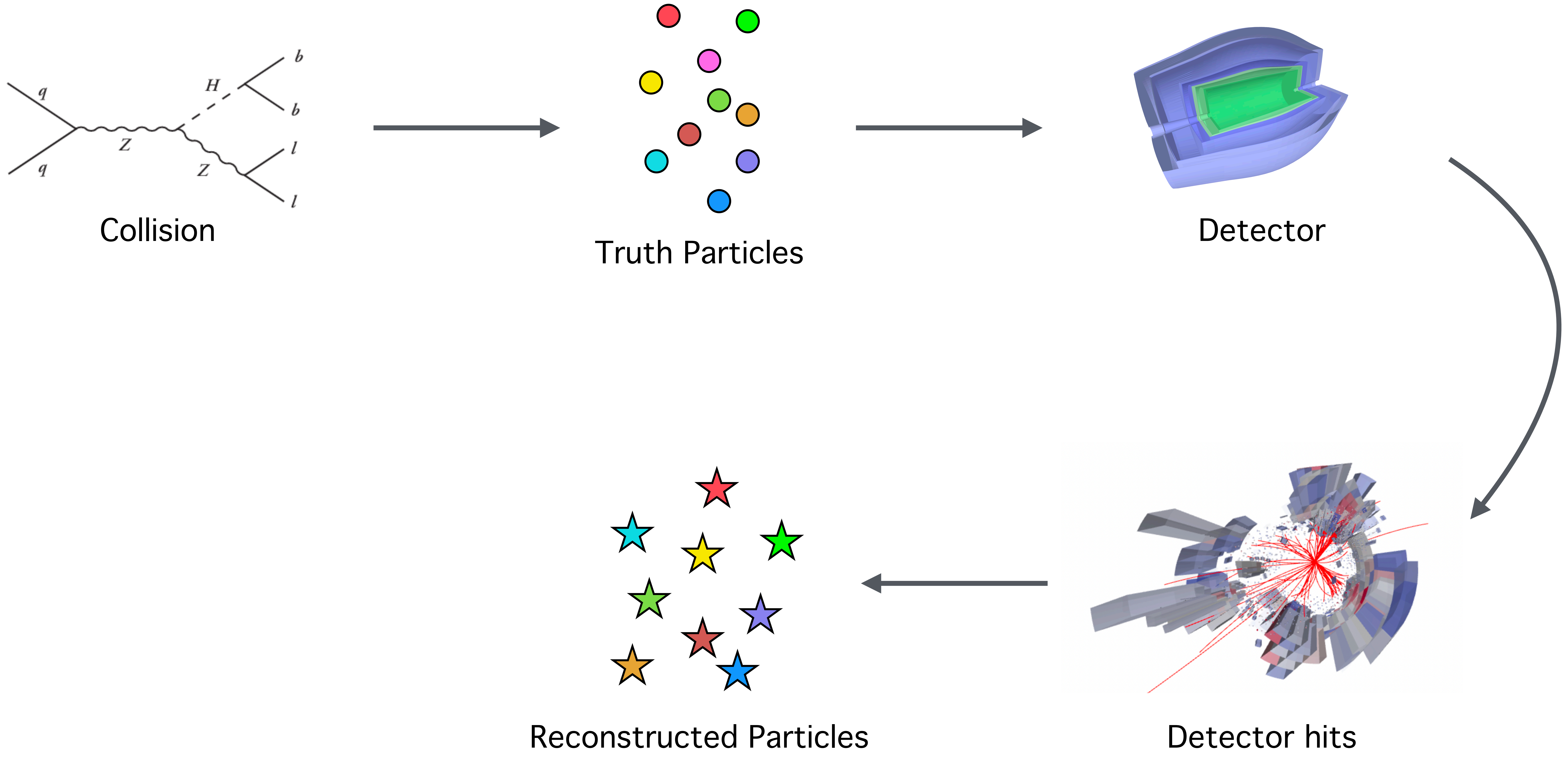

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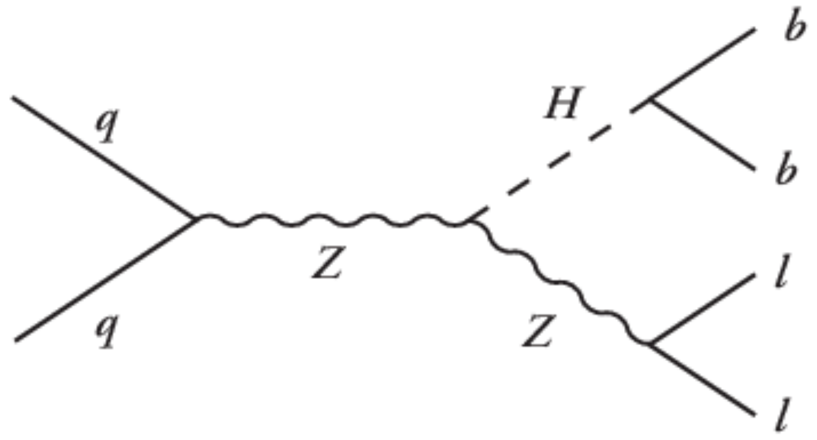

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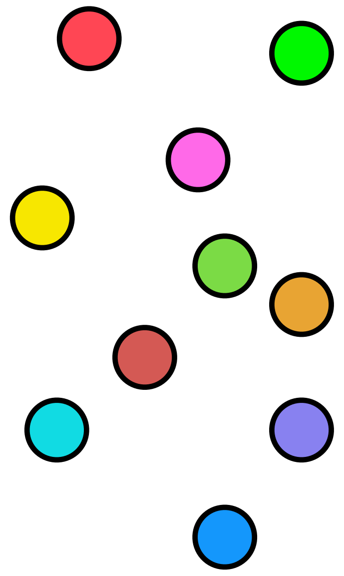

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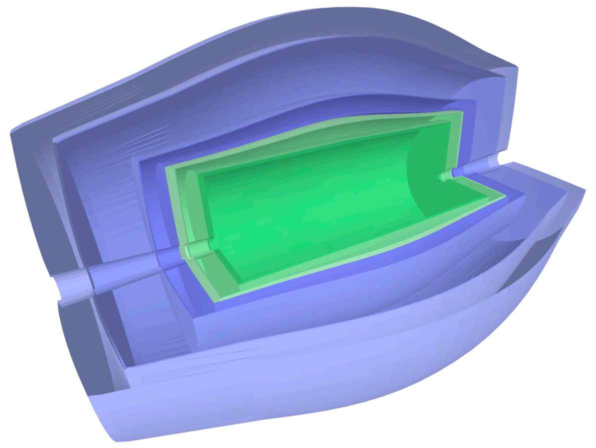

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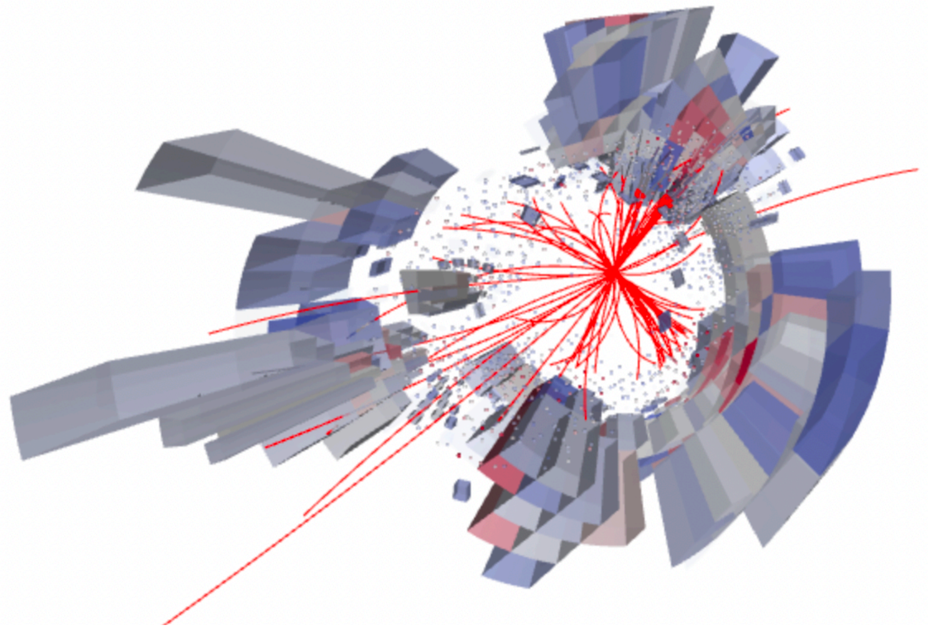

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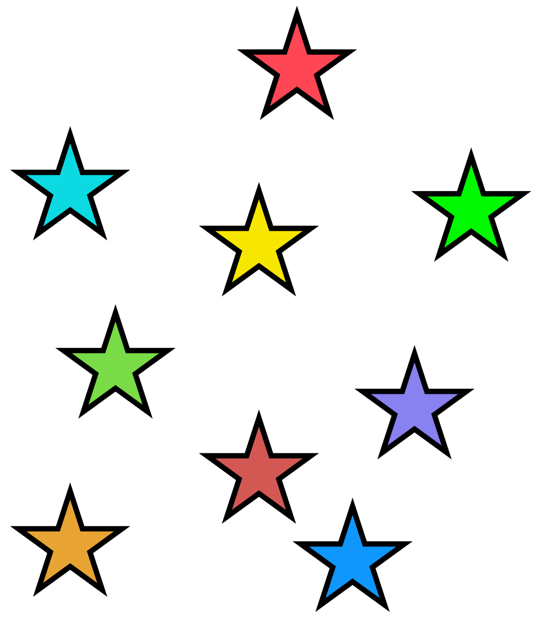
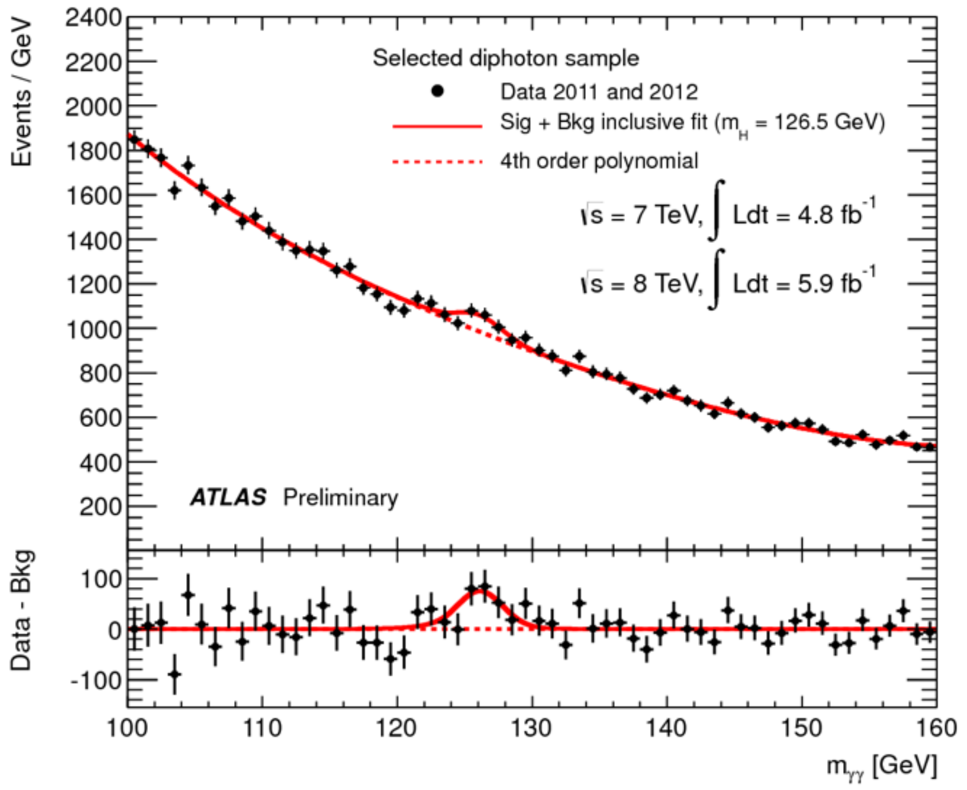


Reconstructed Particles



Analysis


SCD
Phoenix Menu
Detector
Labels
Event Data
Preset 1
Animate camera
event_num_0
30 FPS (0-61)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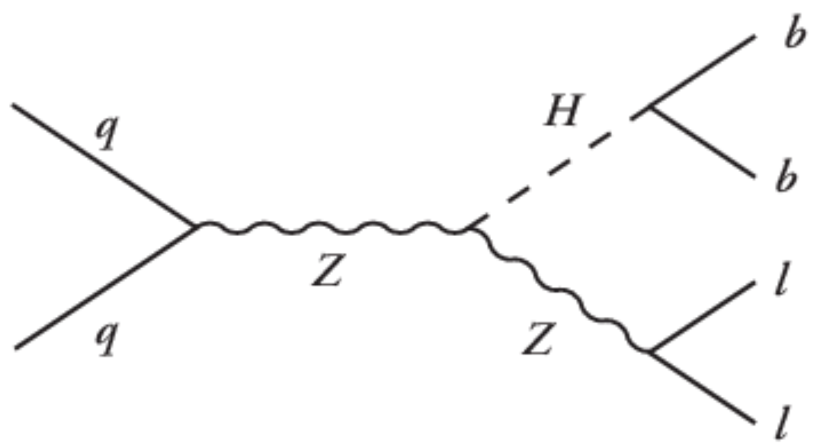

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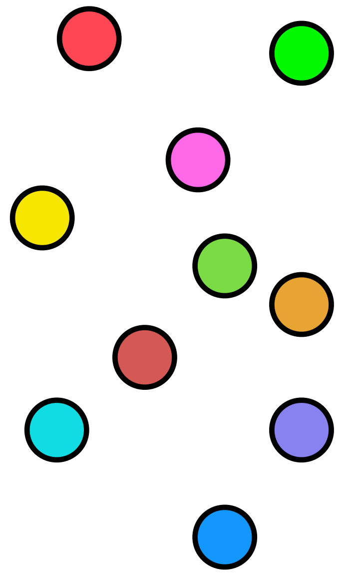

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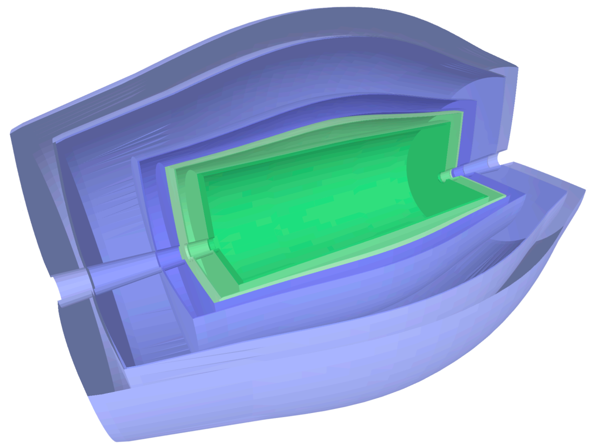

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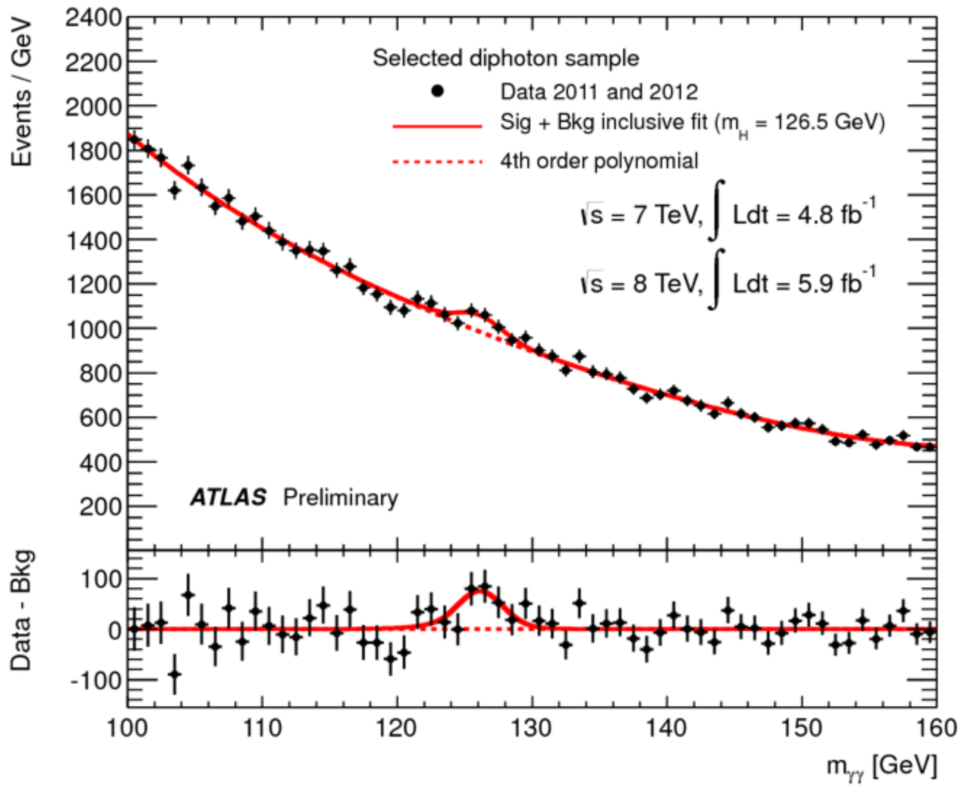
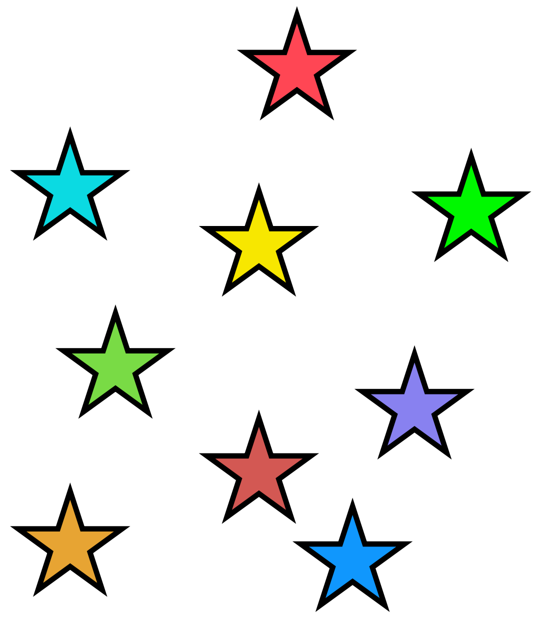


Analysis

Particle Flow



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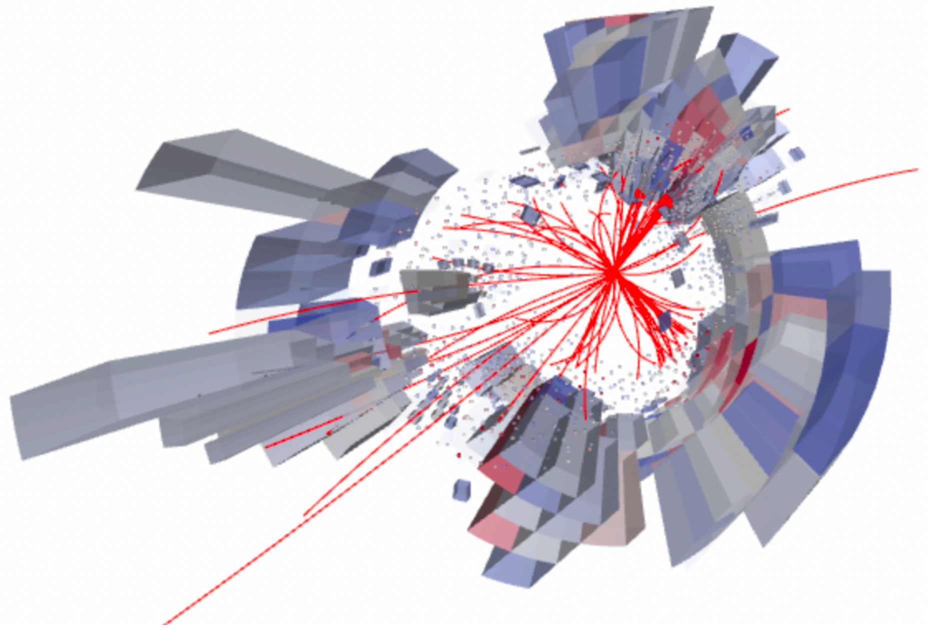


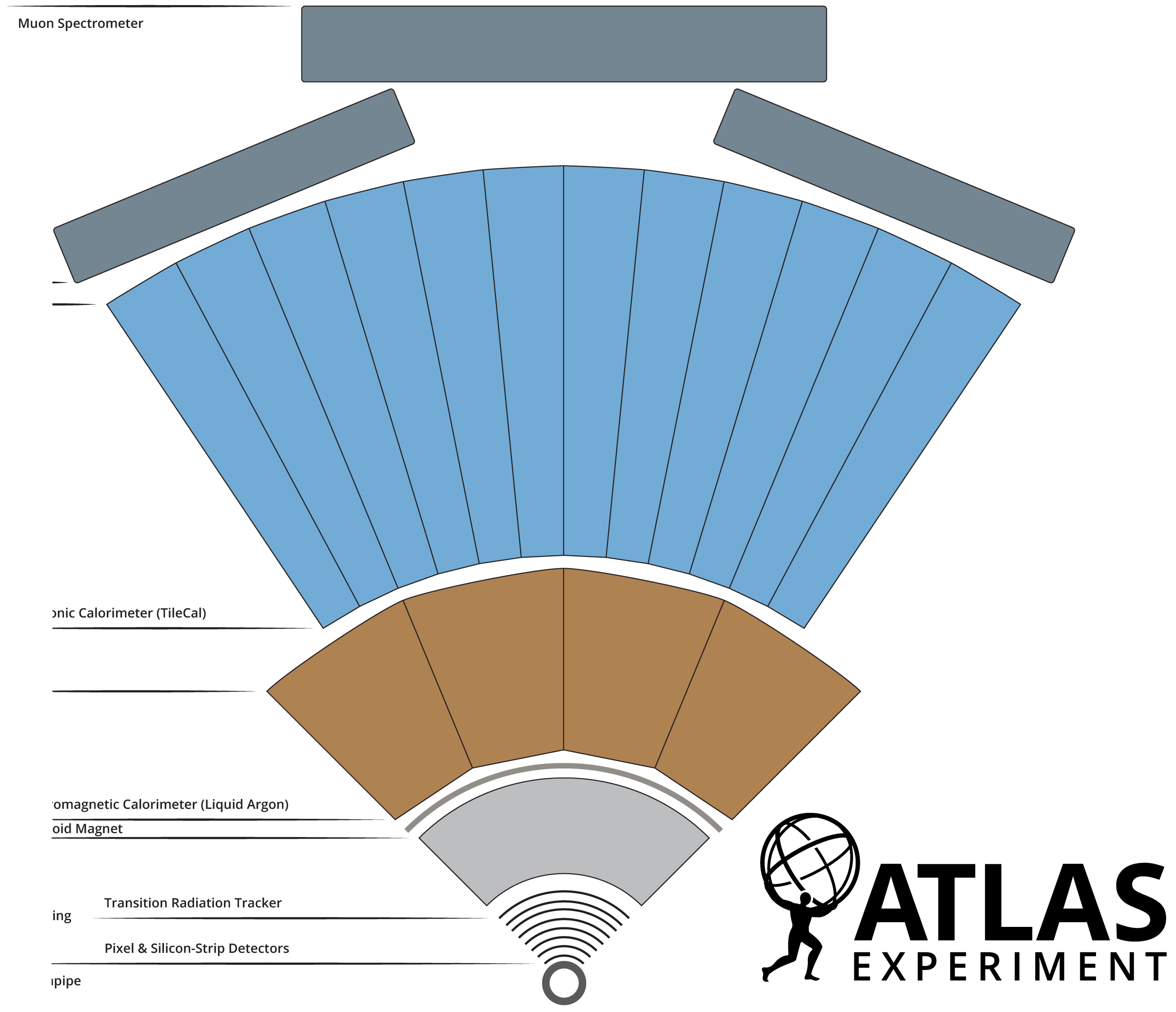
Detector hits

Particle Flow

- Two approaches for particle flow
- Parameterized particle flow:
  - Provide an optimal measurement
  - exploits the redundancy avoiding double counting
- Global particle flow:
  - Provide correct number of particles,
  - their kinematics, and their class
  - exploiting redundancy and avoiding double counting

Calorimeter
(Charged particles,
Neutral particles)

Tracker
(Charged particles)



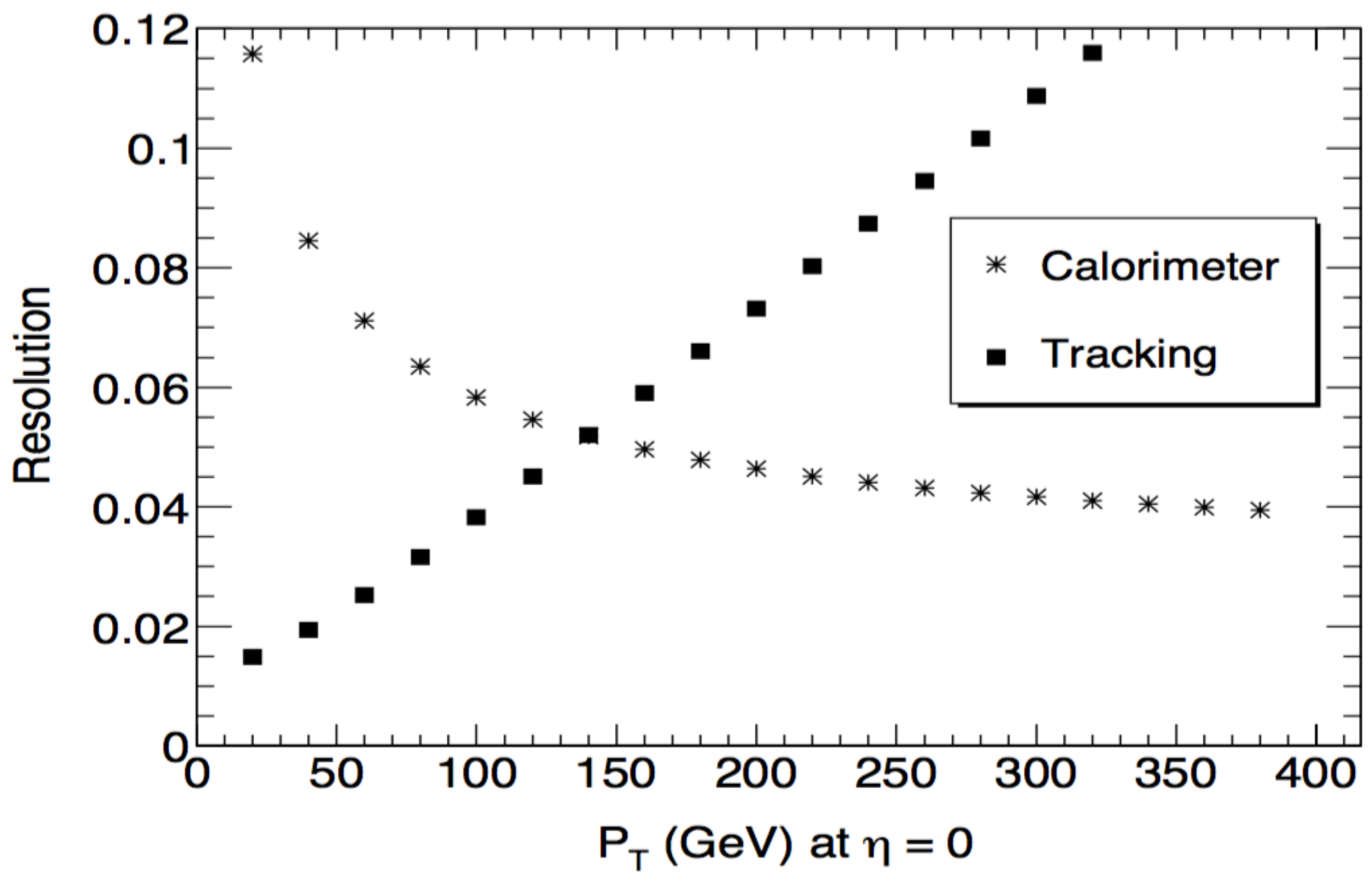


Figure 1: Resolution of Single Pions at $\eta = 0$ in Calorimeter and Charged Particle Tracking Detectors

Particle Flow with ML

Object condensation: one-stage grid-free multi-object reconstruction in physics detectors, graph, and image data

Jan Kieseler[1]
(jan.kieseler@cern.ch)

CERN, Experimental Physics Department, Geneva, Swi

the date of receipt and acceptance should be

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Multi-particle reconstruction in the High Granularity Calorimeter using object condensation and graph neural networks

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[1]CERN, EP/CMG
[2]Manchester Metropolitan University

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[1]Experimental Physics Department, CERN
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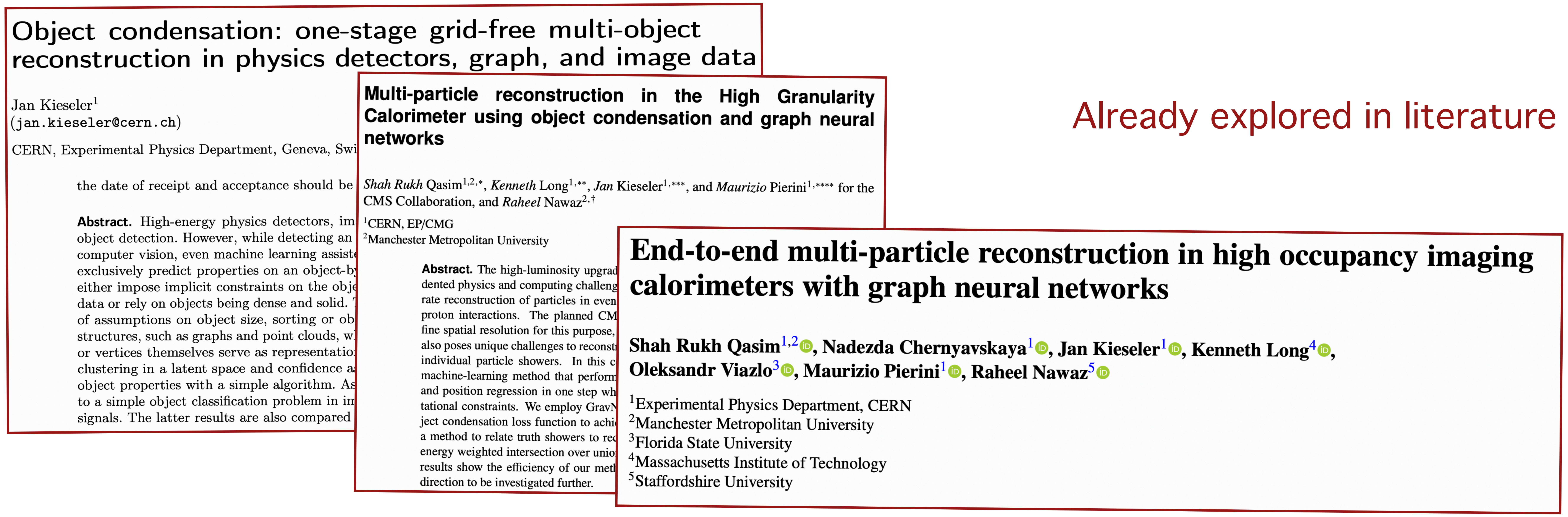
[5]Staffordshire University

Already explored in literature

Particle Flow with ML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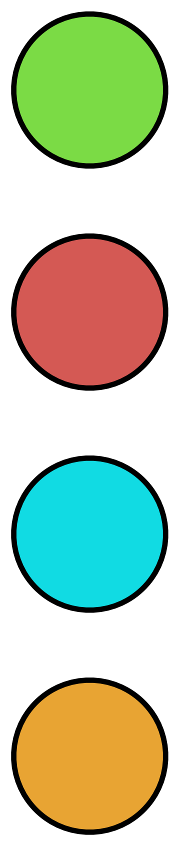
What's new?

- Focus on dense environments (inside jets)
- Adding the missing physics intuitions (energy conservations)

Particle Flow

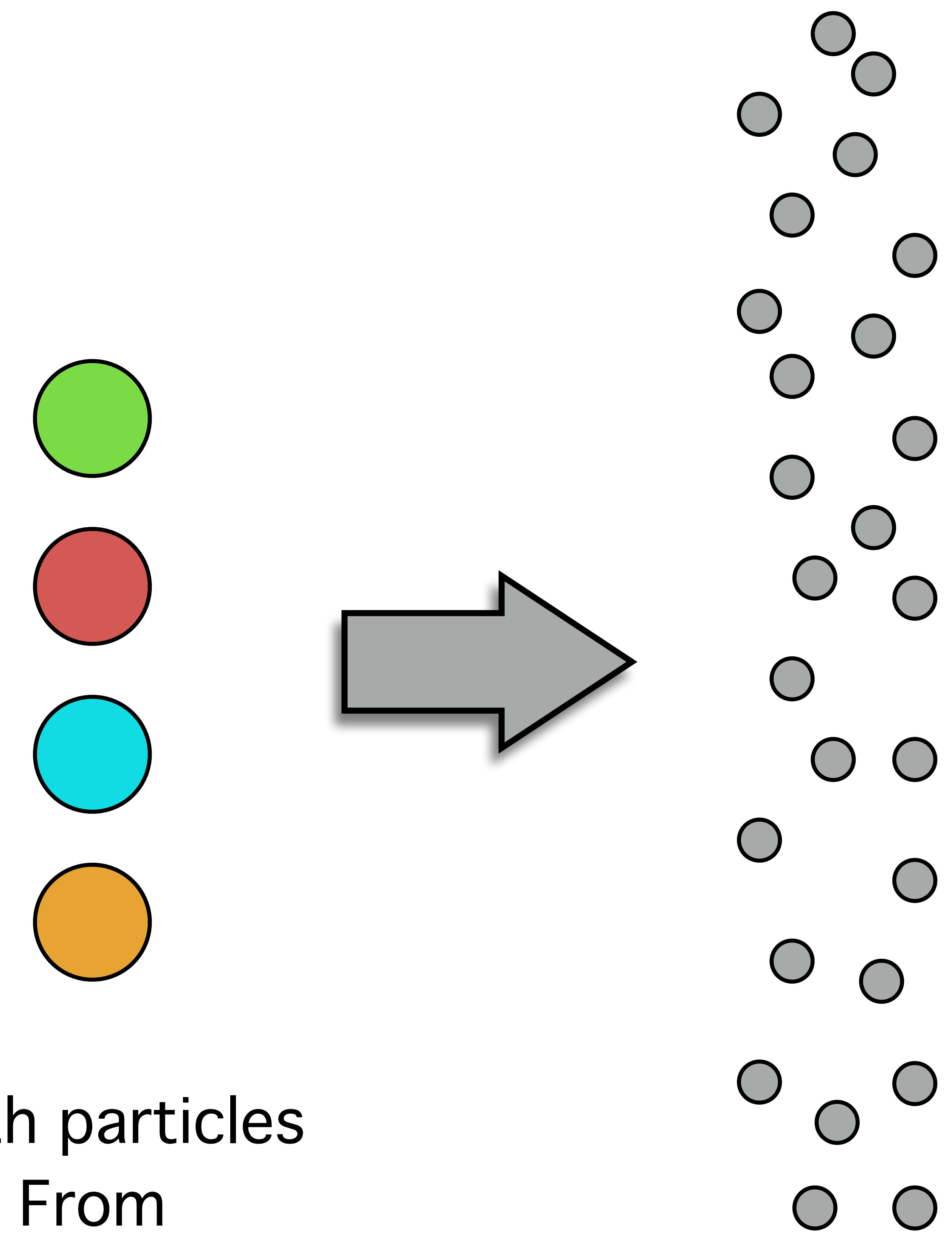
Particle Flow



Truth particles
From
Simulation/experiment

Particle Flow

(Messy environment inside jet)



Truth particles
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Simulation/experiment

Detector readout
(Tracks, cells)

Particle Flow

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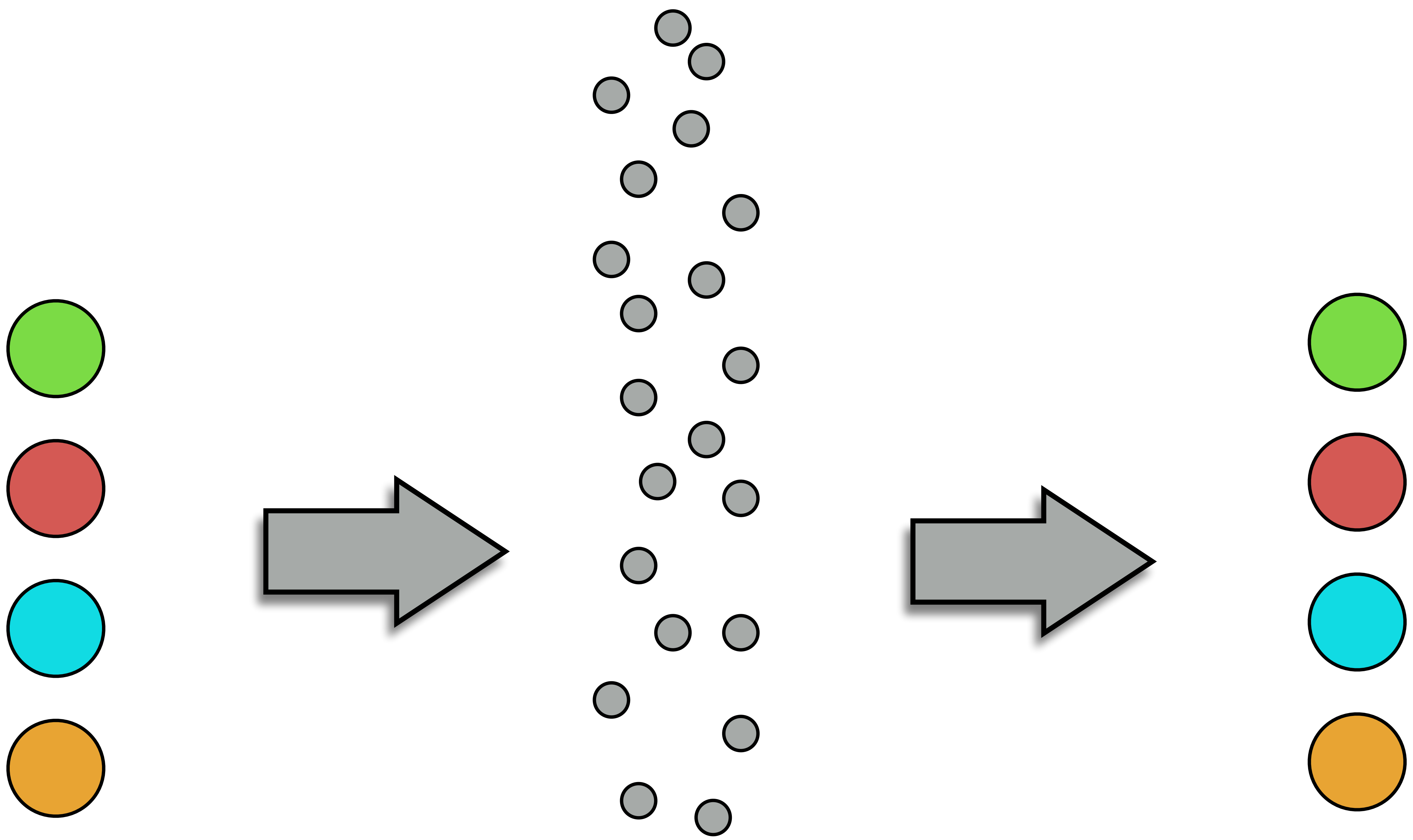

Hypergraph 101

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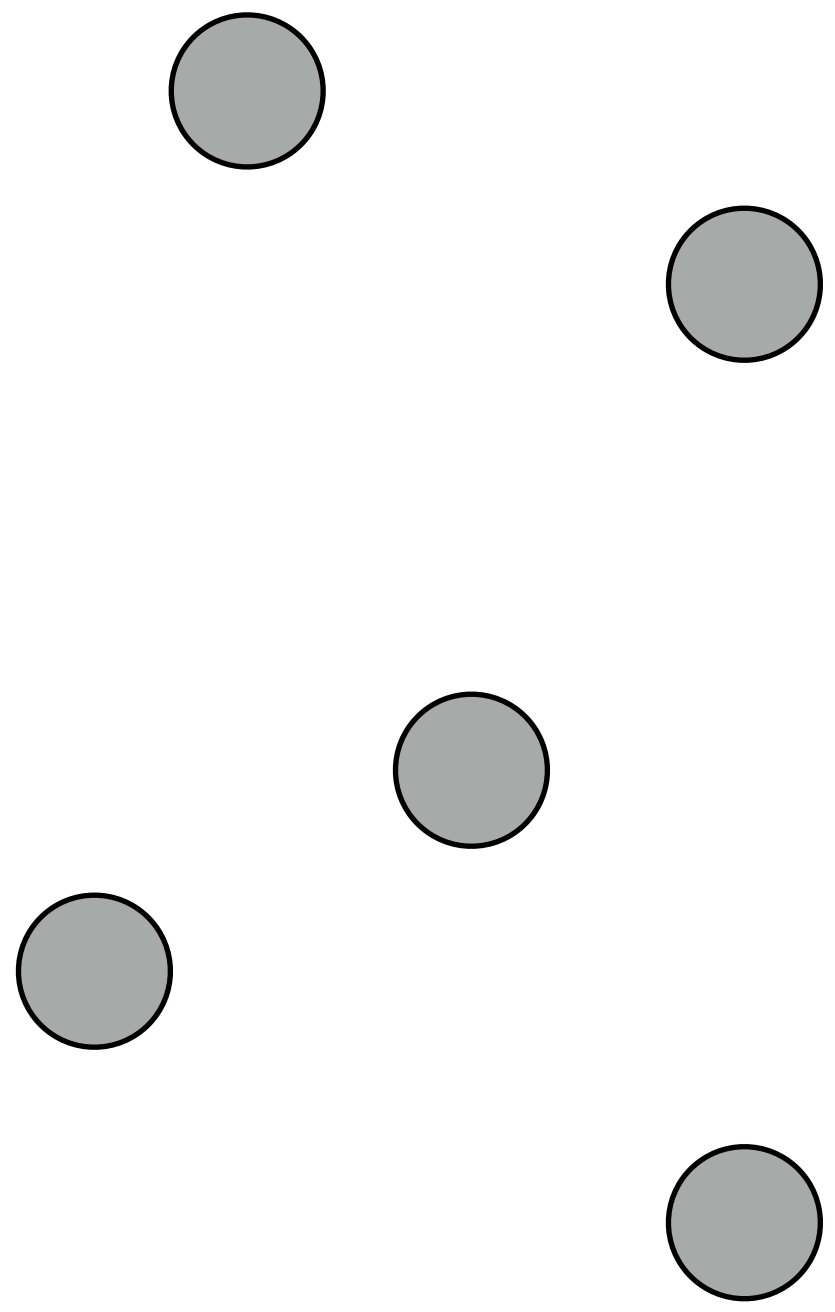

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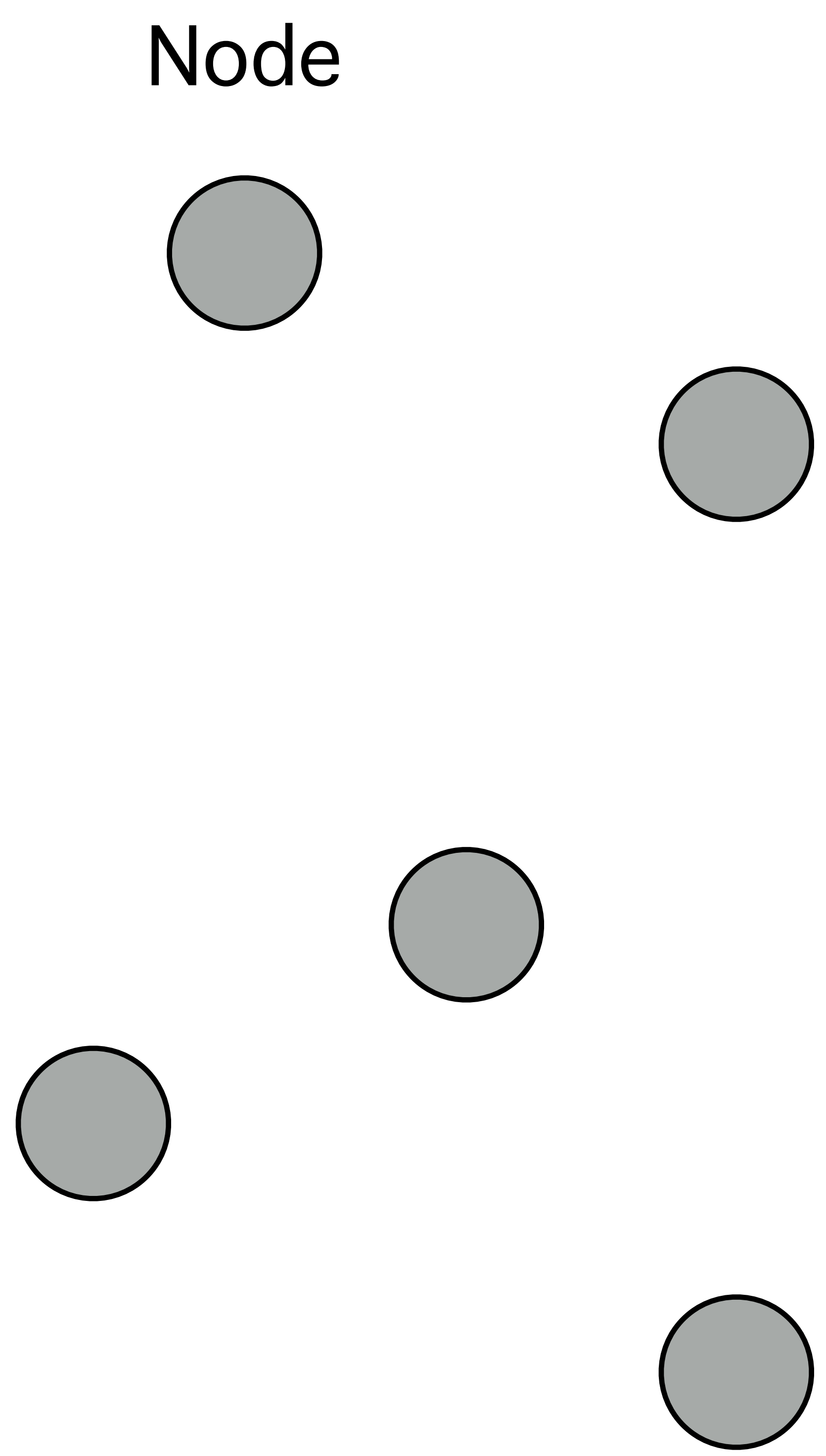

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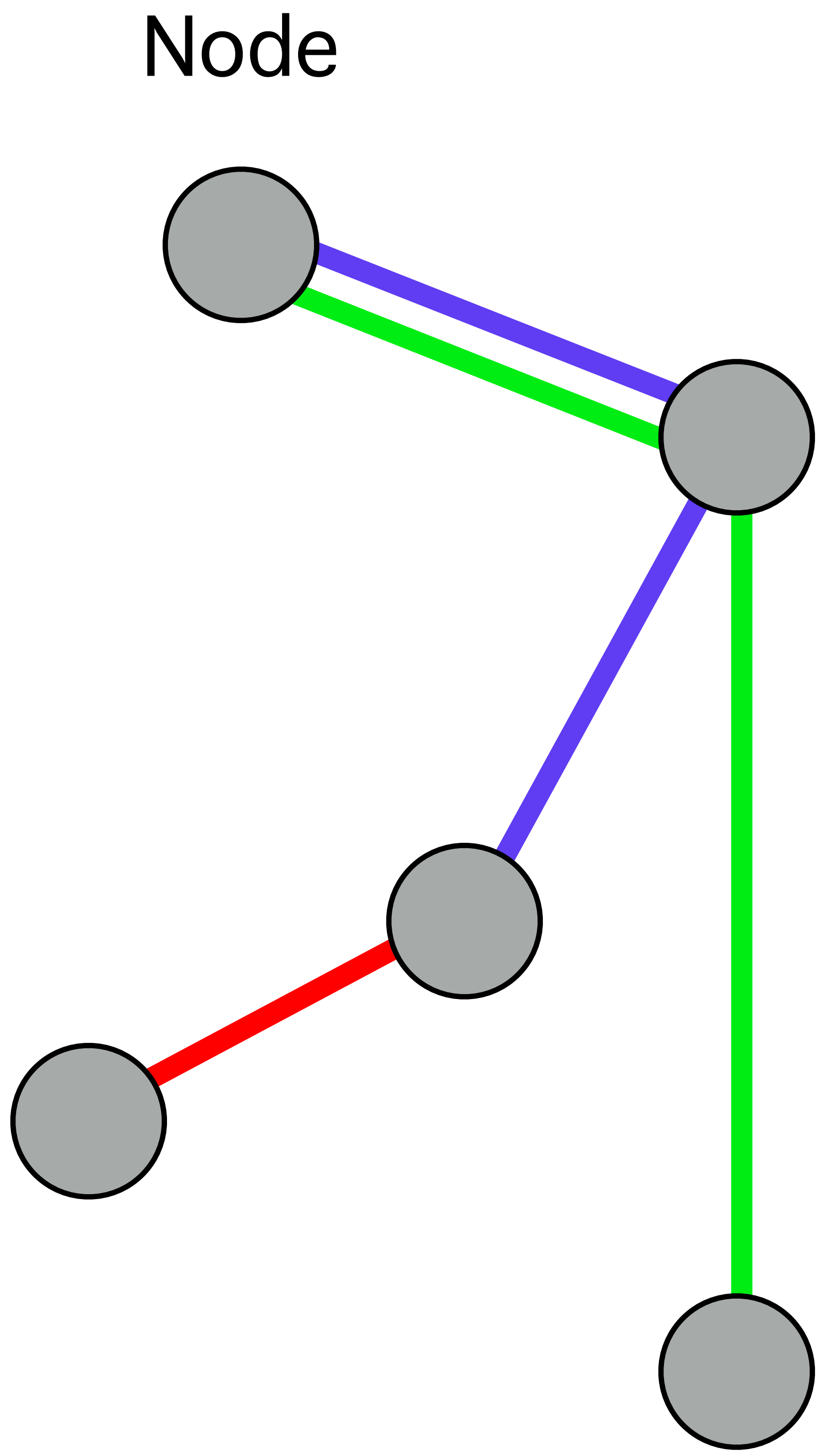

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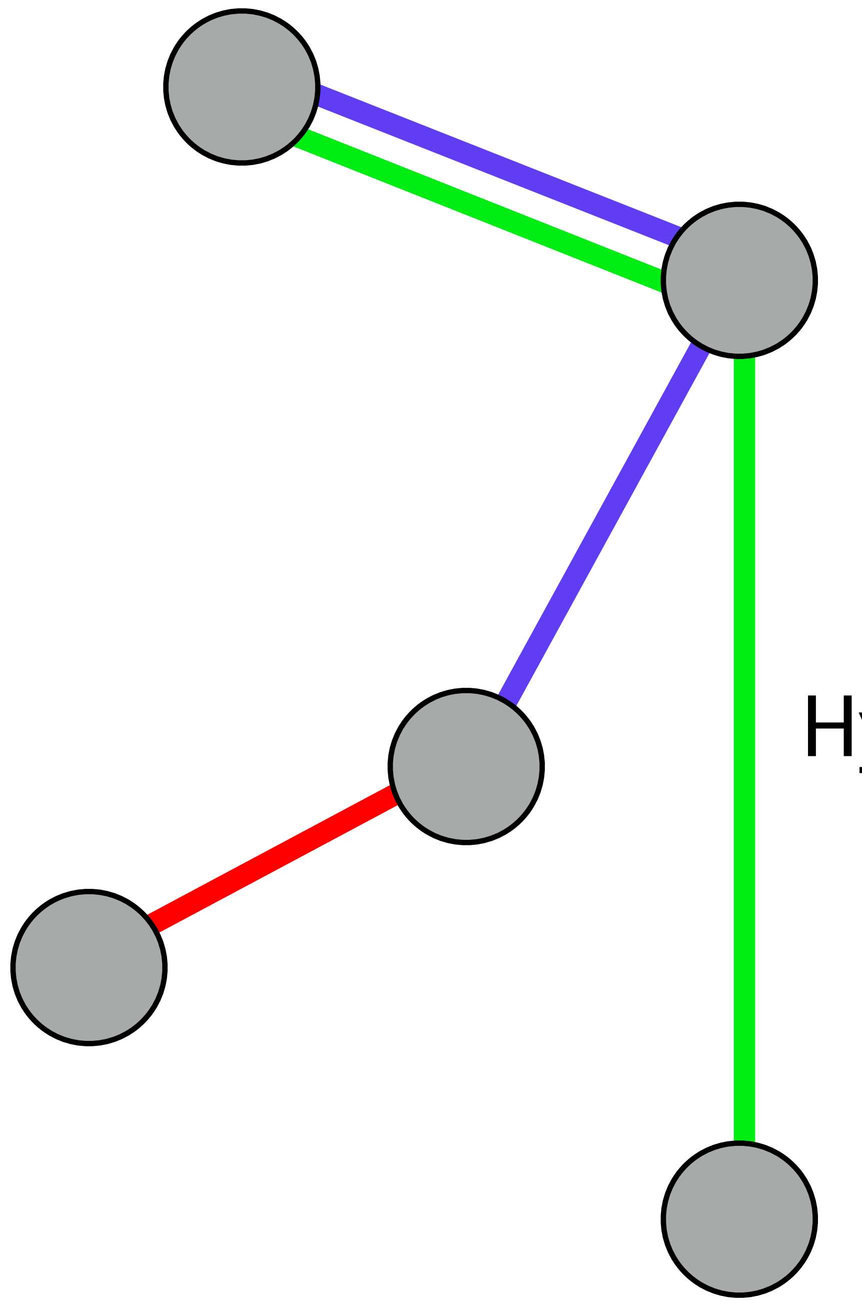

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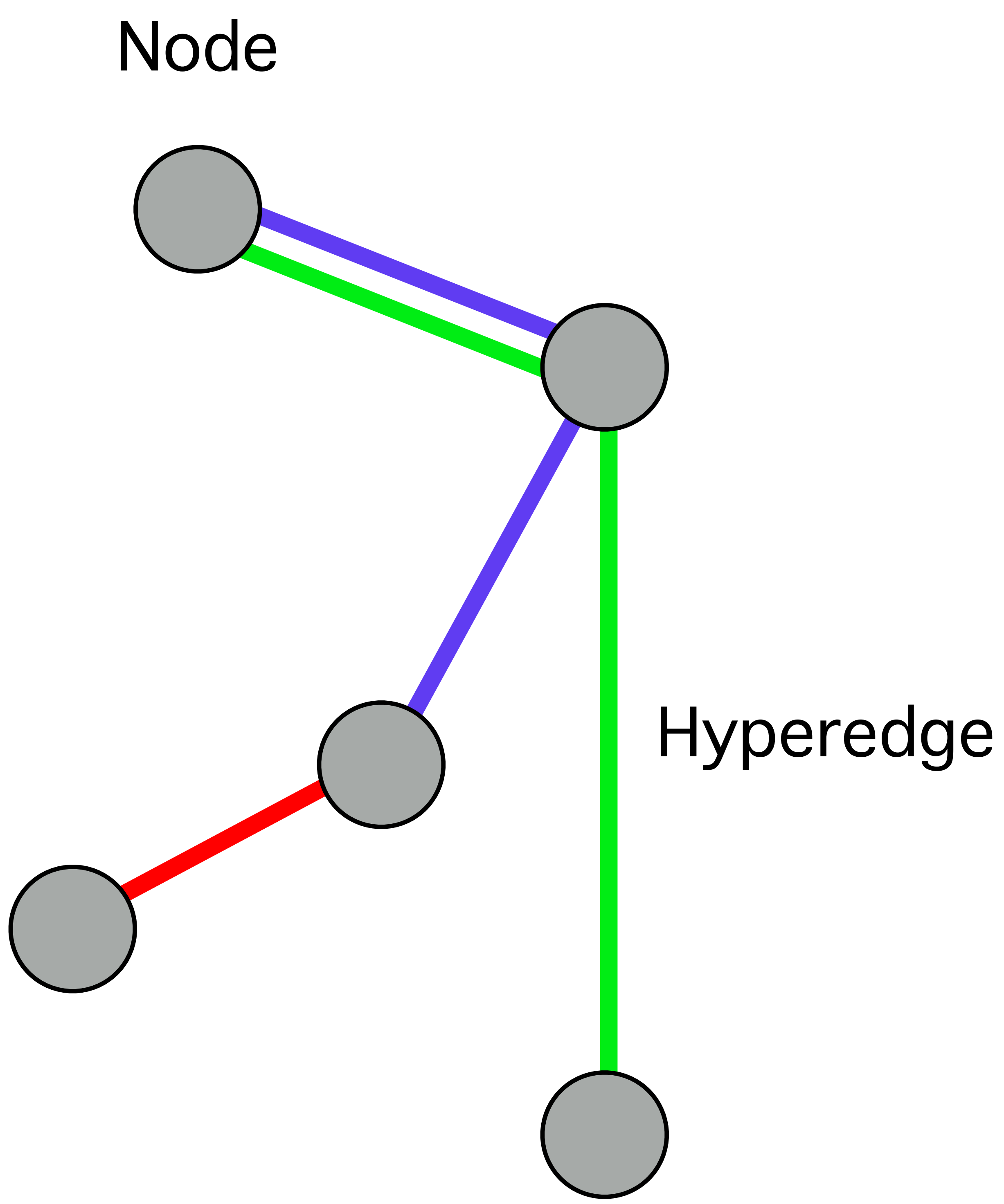

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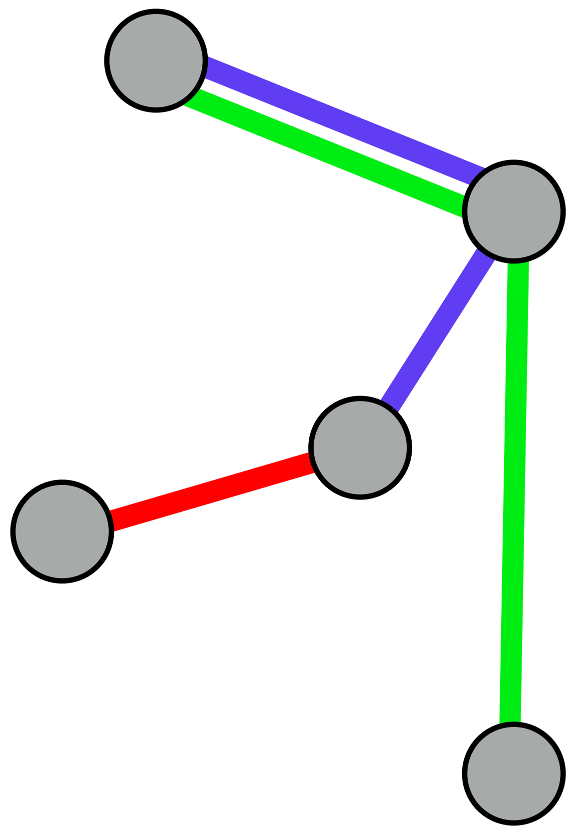
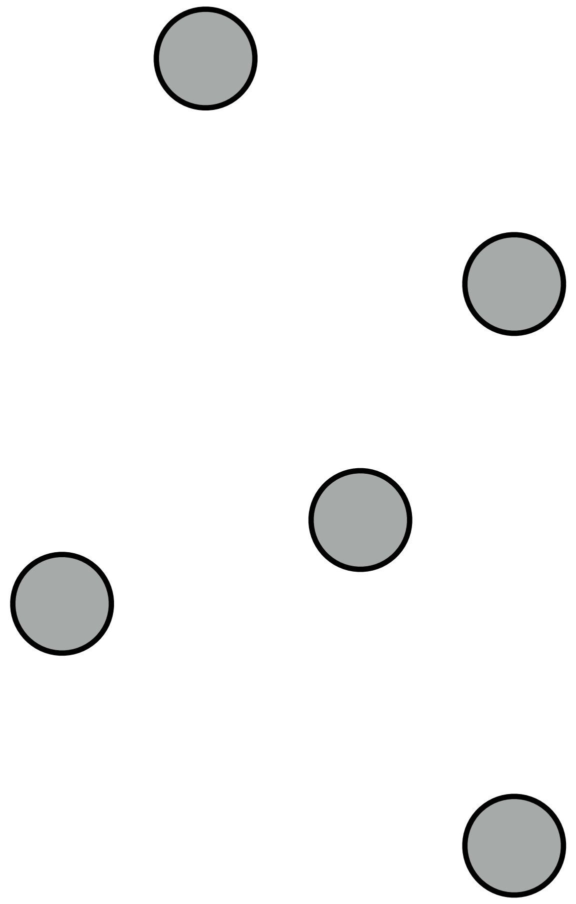


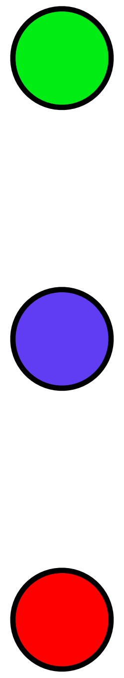
Hypergraph

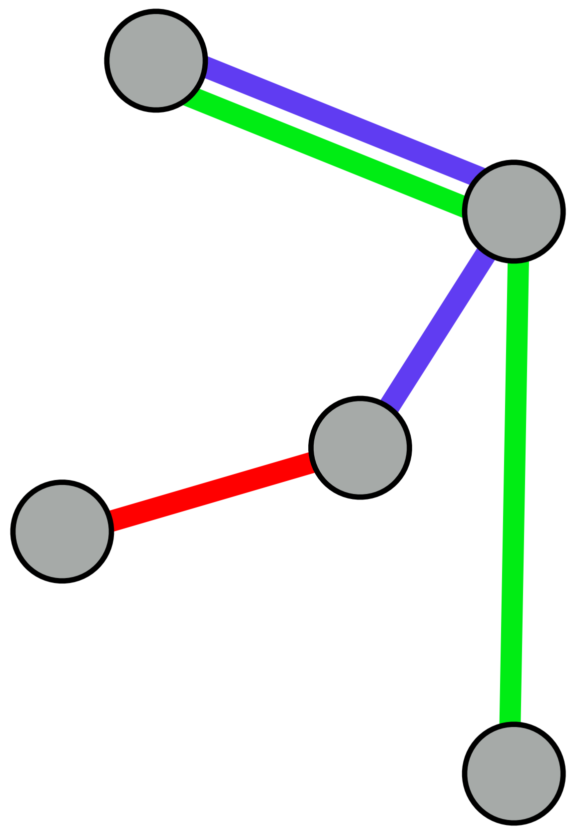
Hypergraph 101

Nodes



Hyperedges





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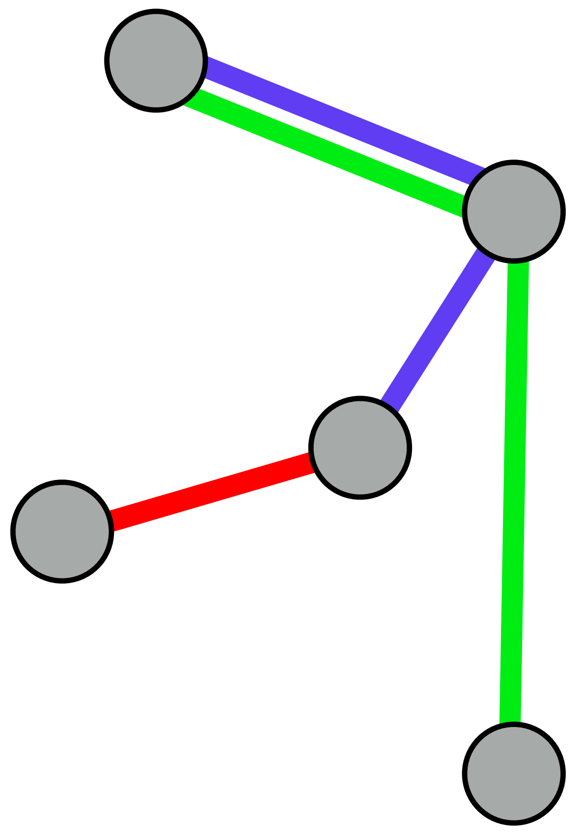

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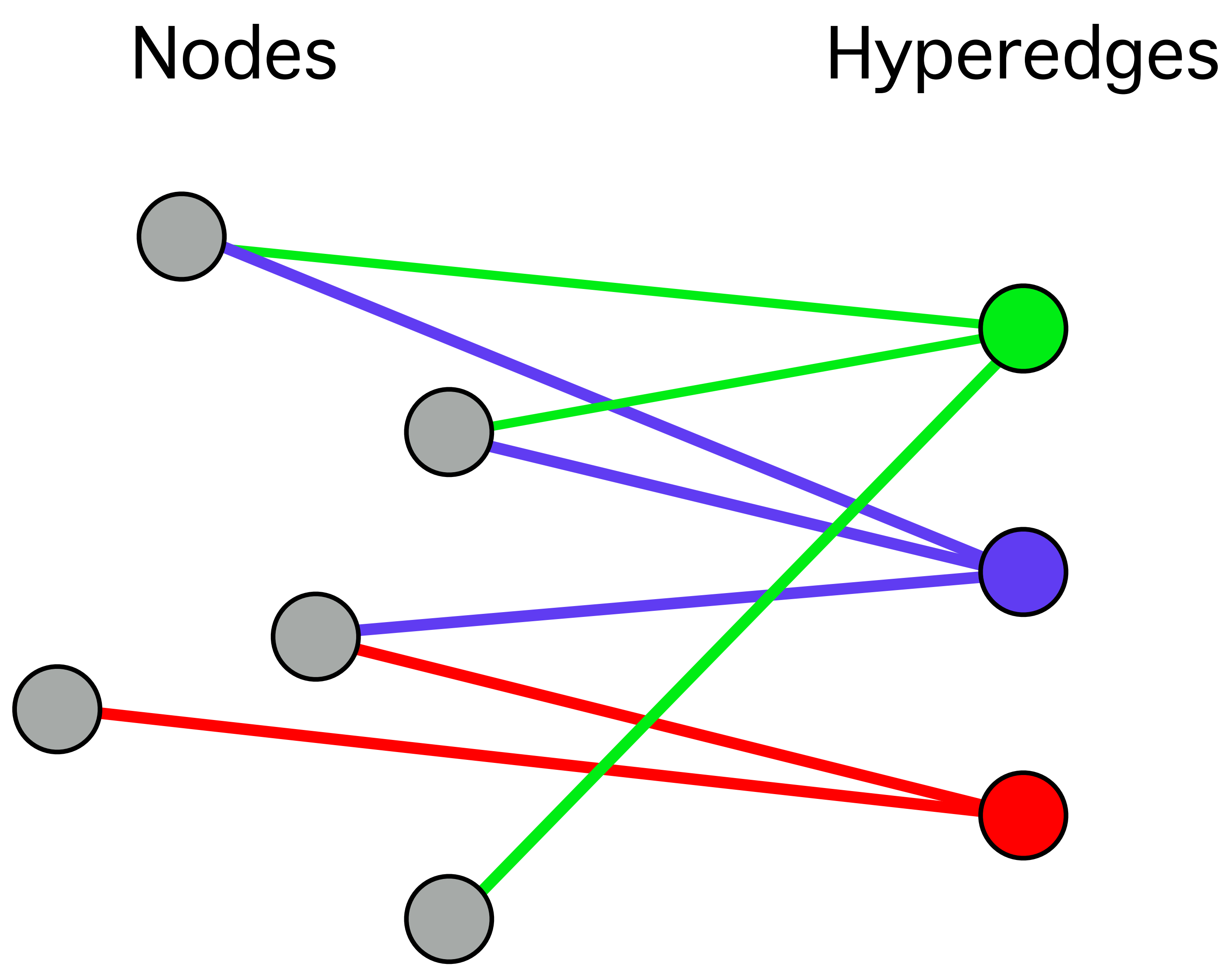
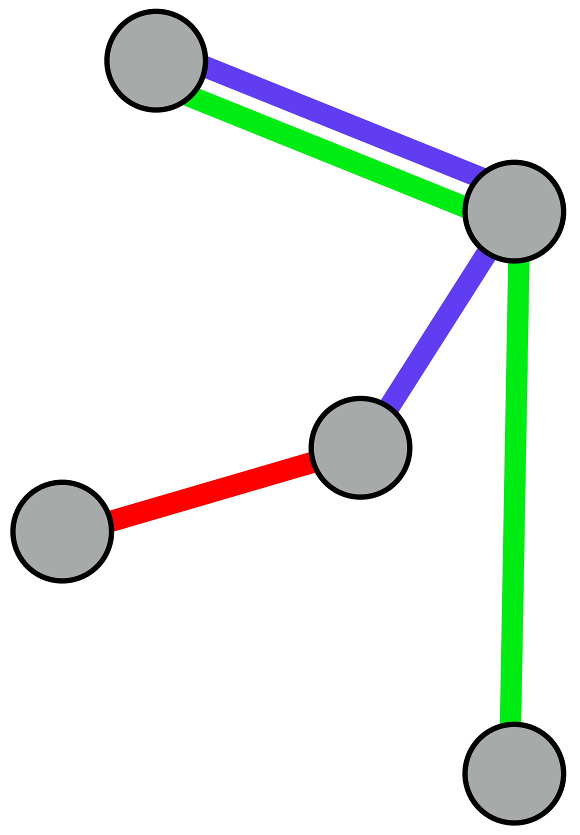


Bipartite graph

Hypergraph 101



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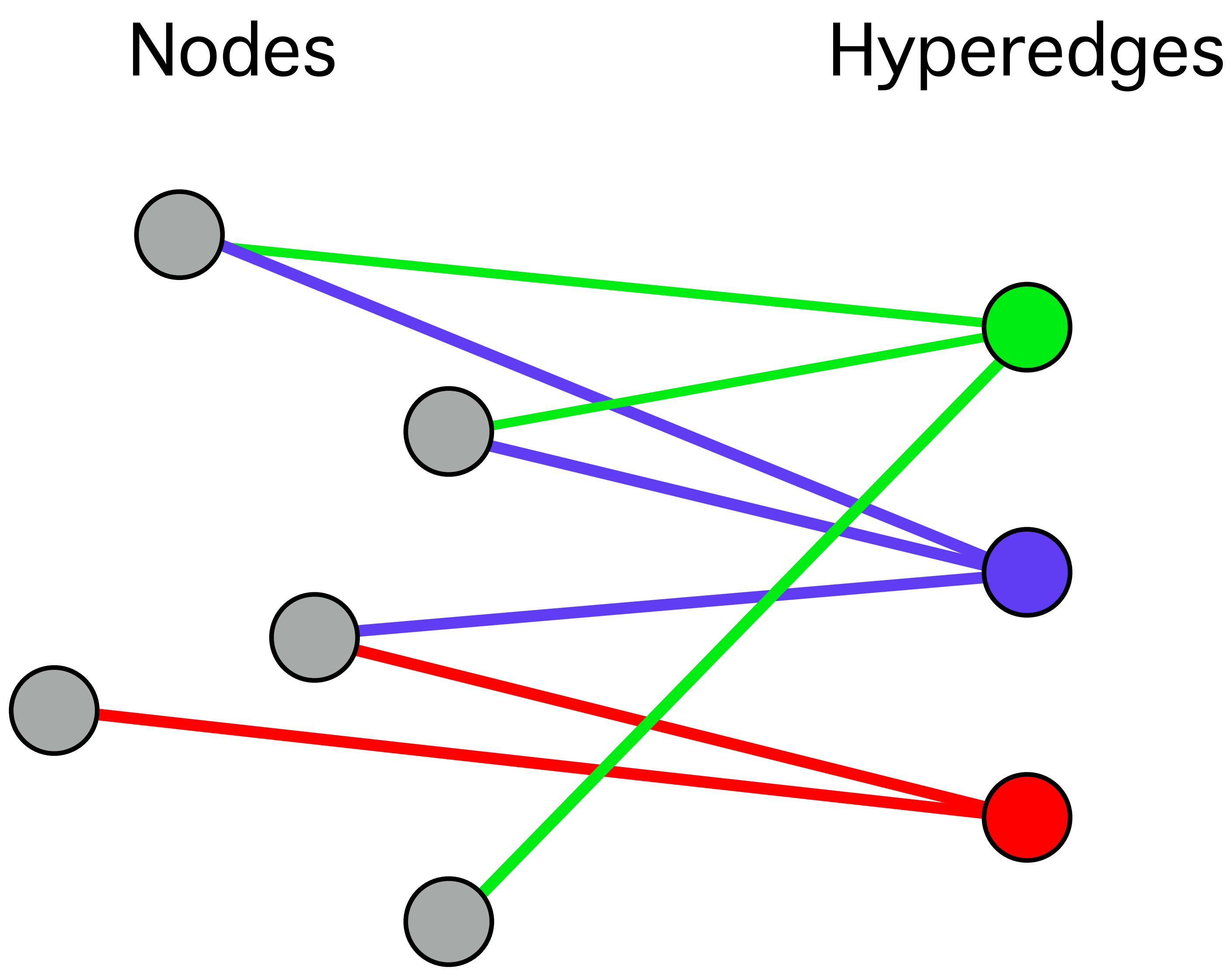

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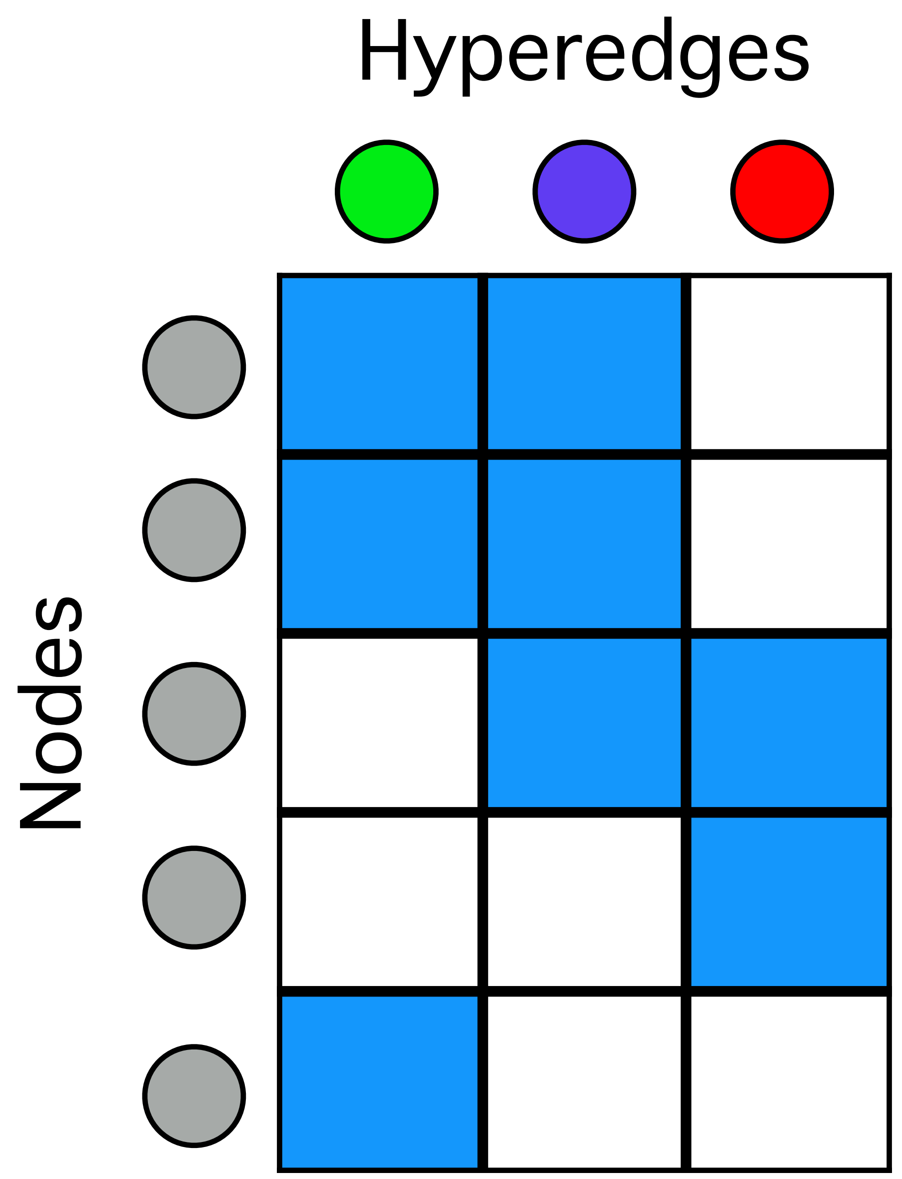

Incidence matrix

Why Hypergraphs?

Why Hypergraphs?

- Particle Flow = Learning a Hypergraph

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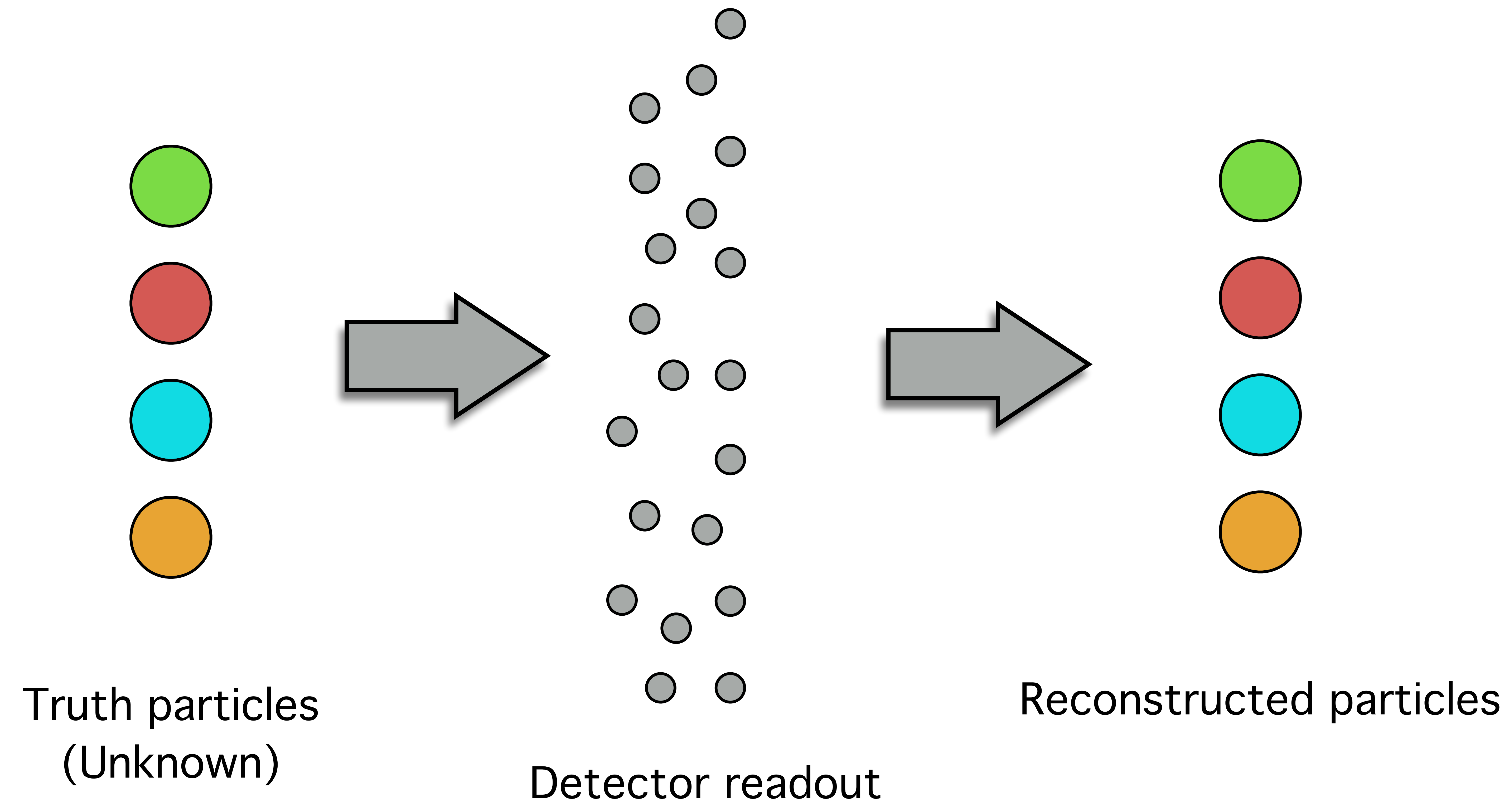

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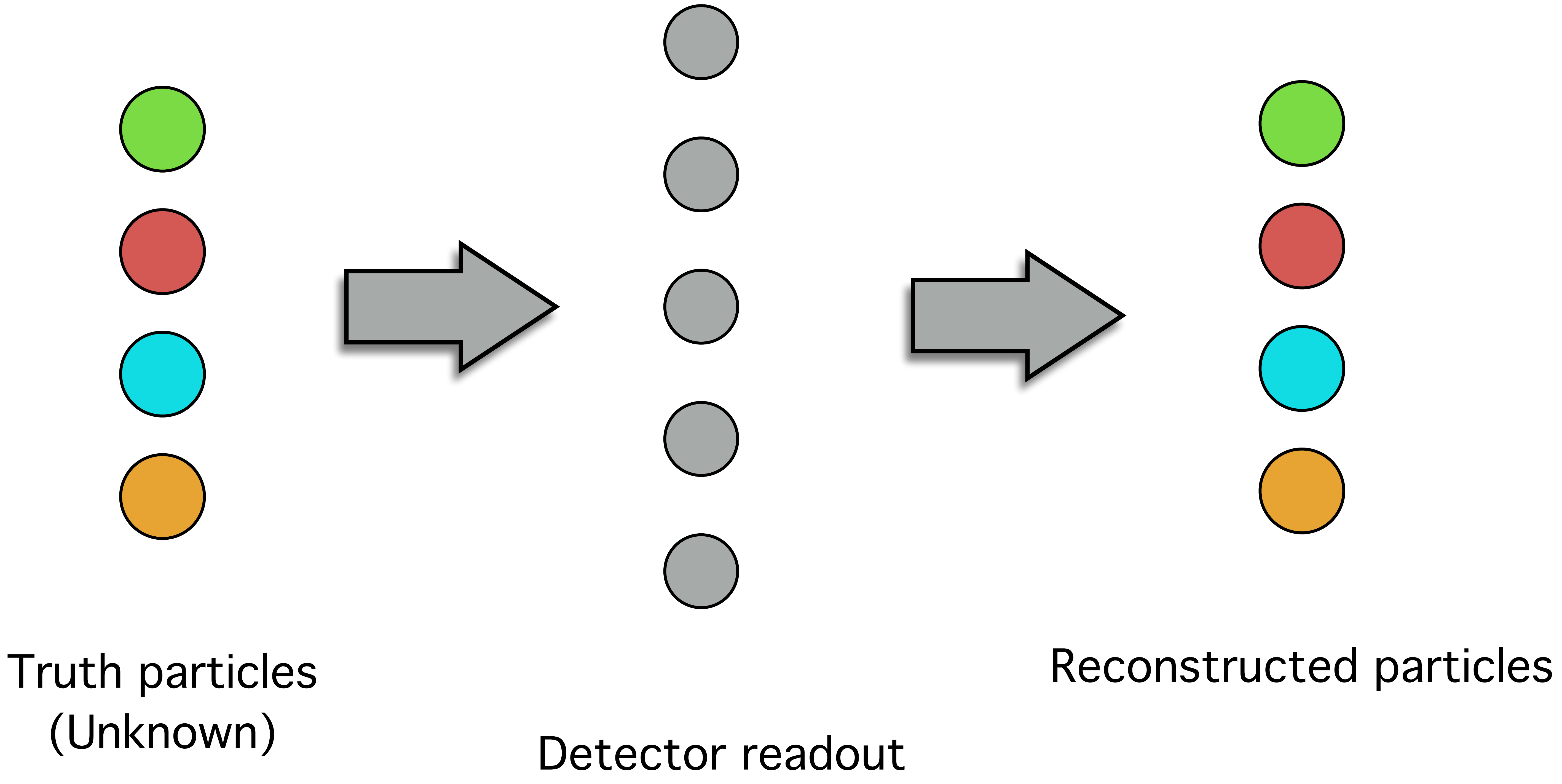

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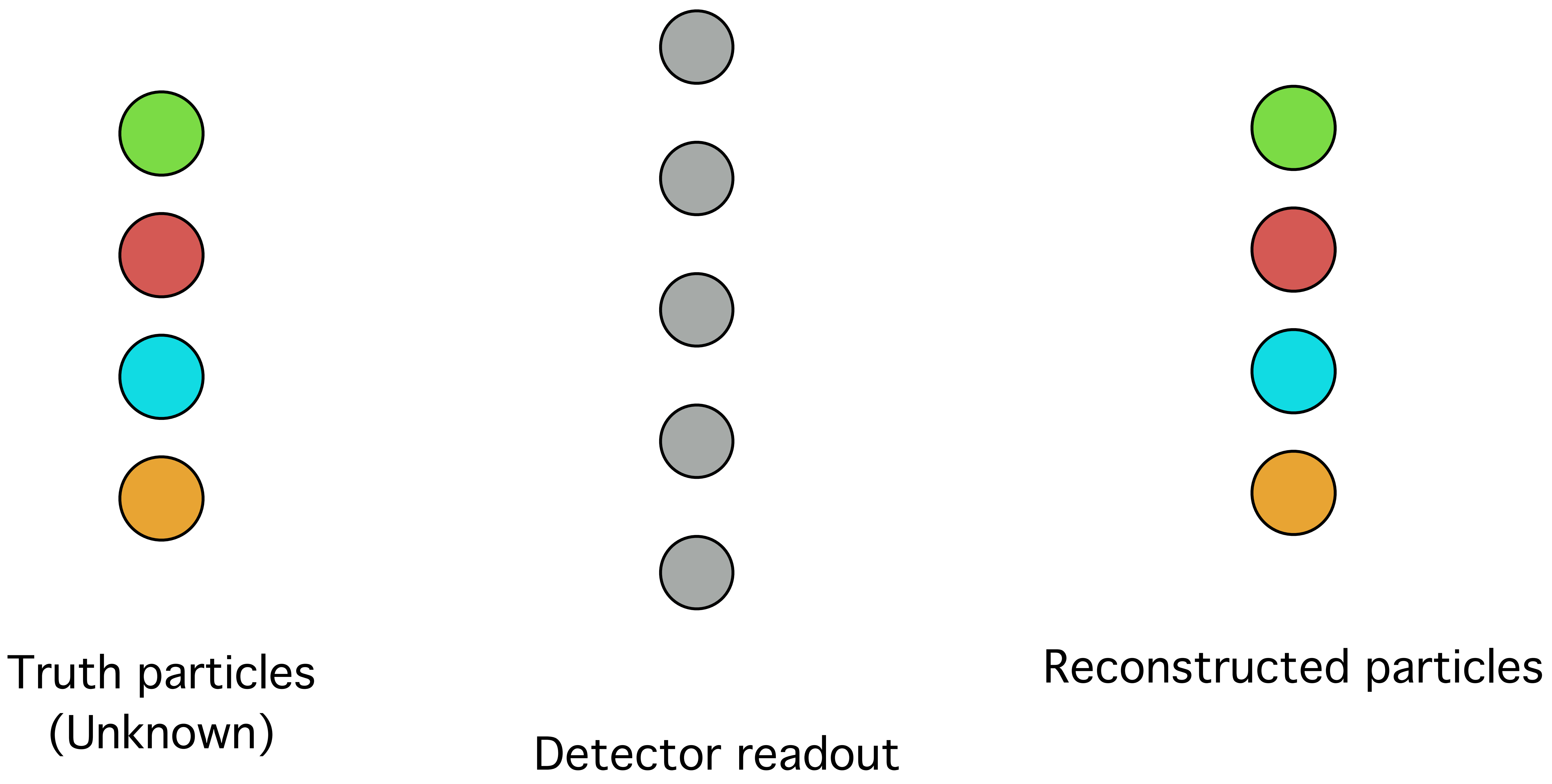

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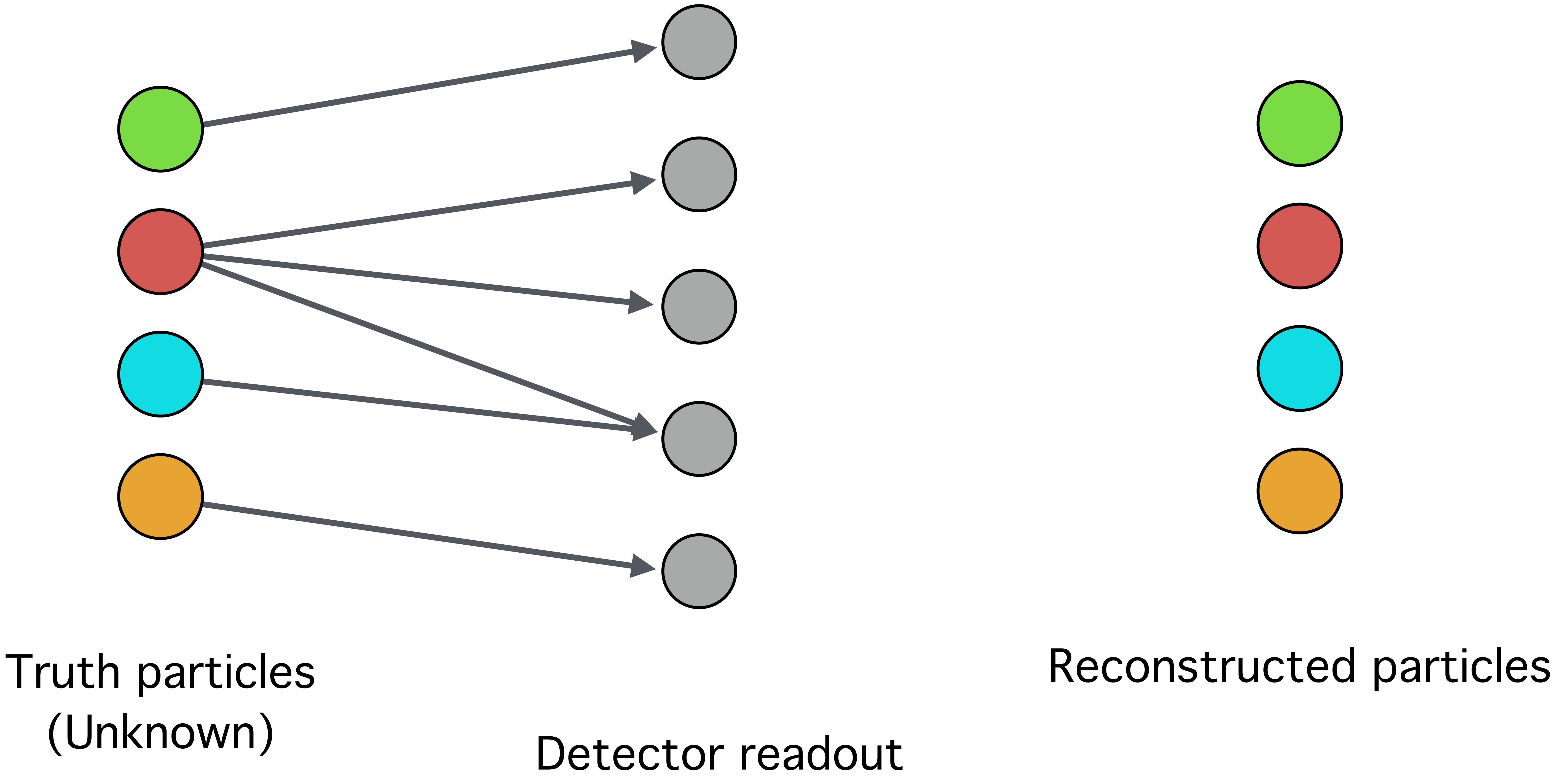

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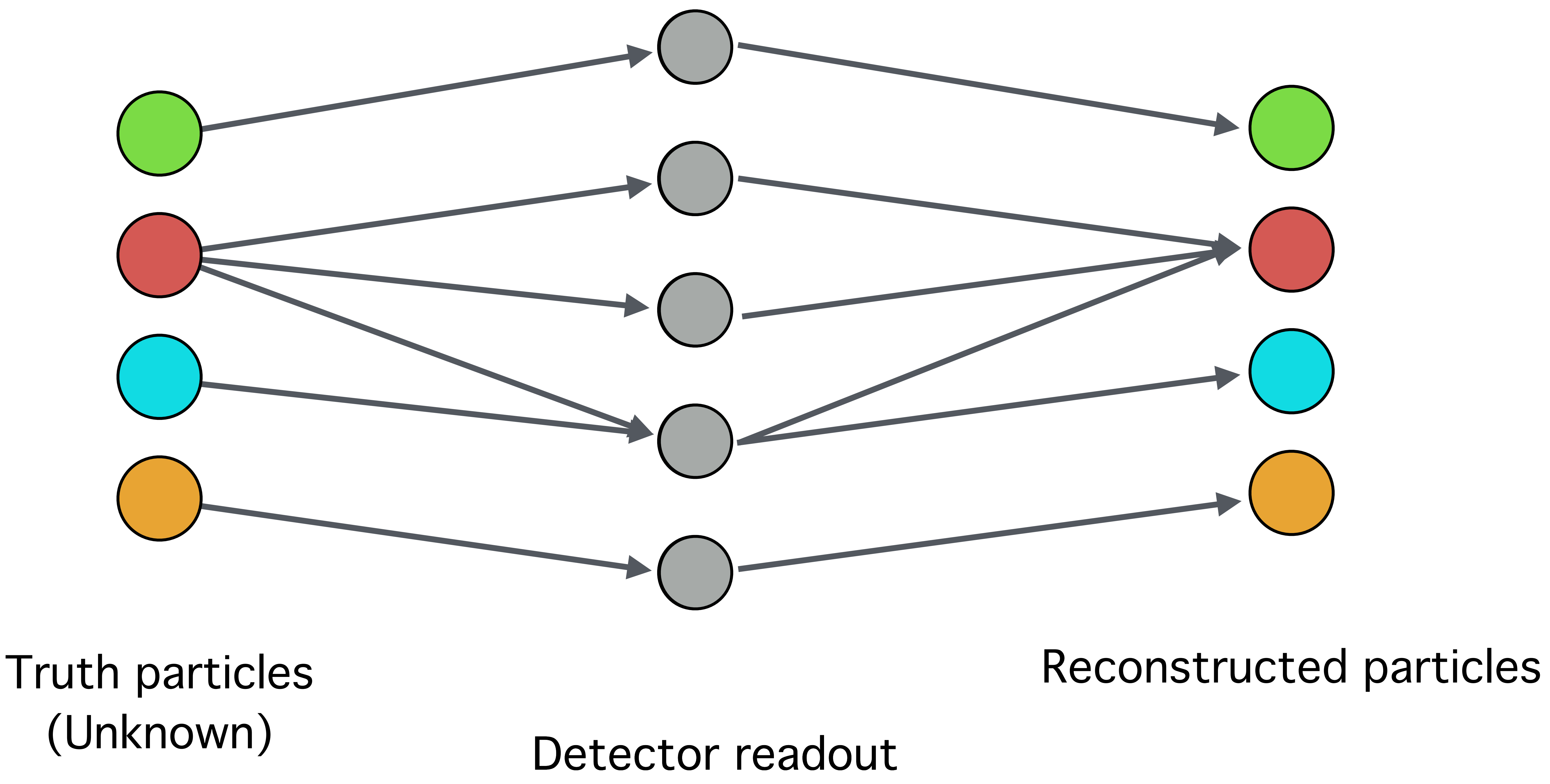

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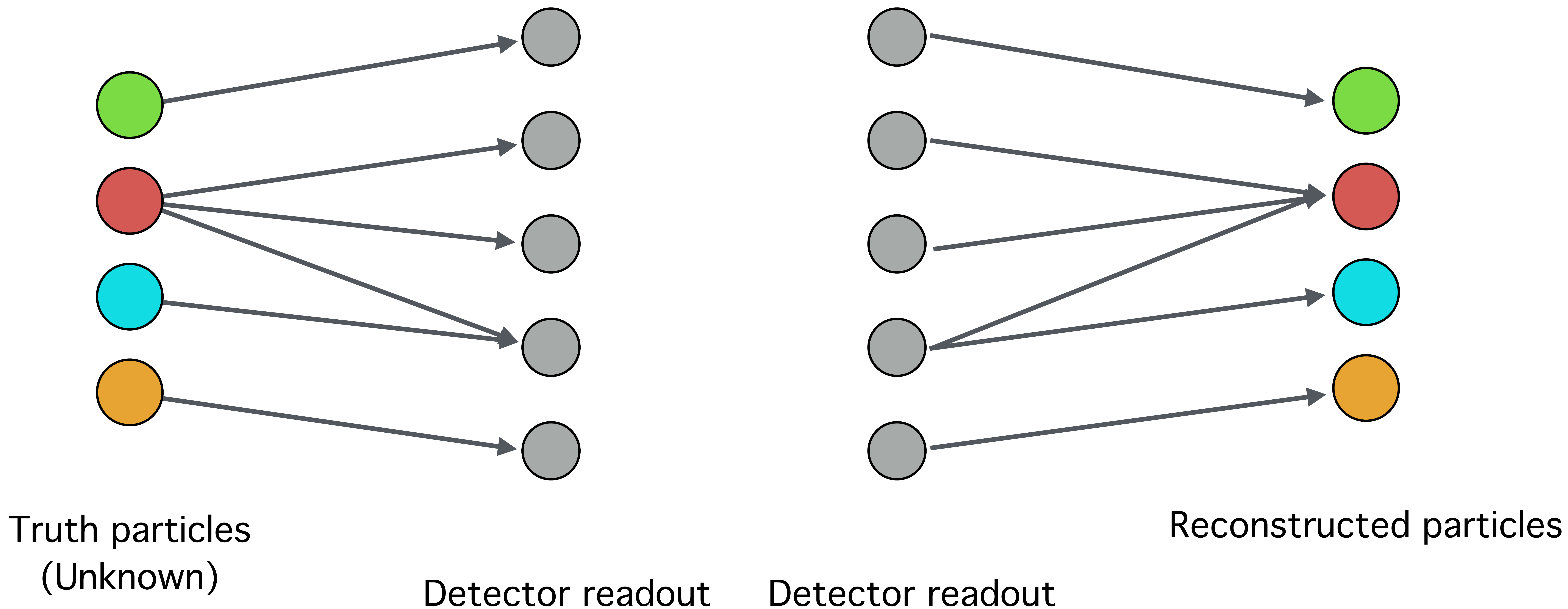

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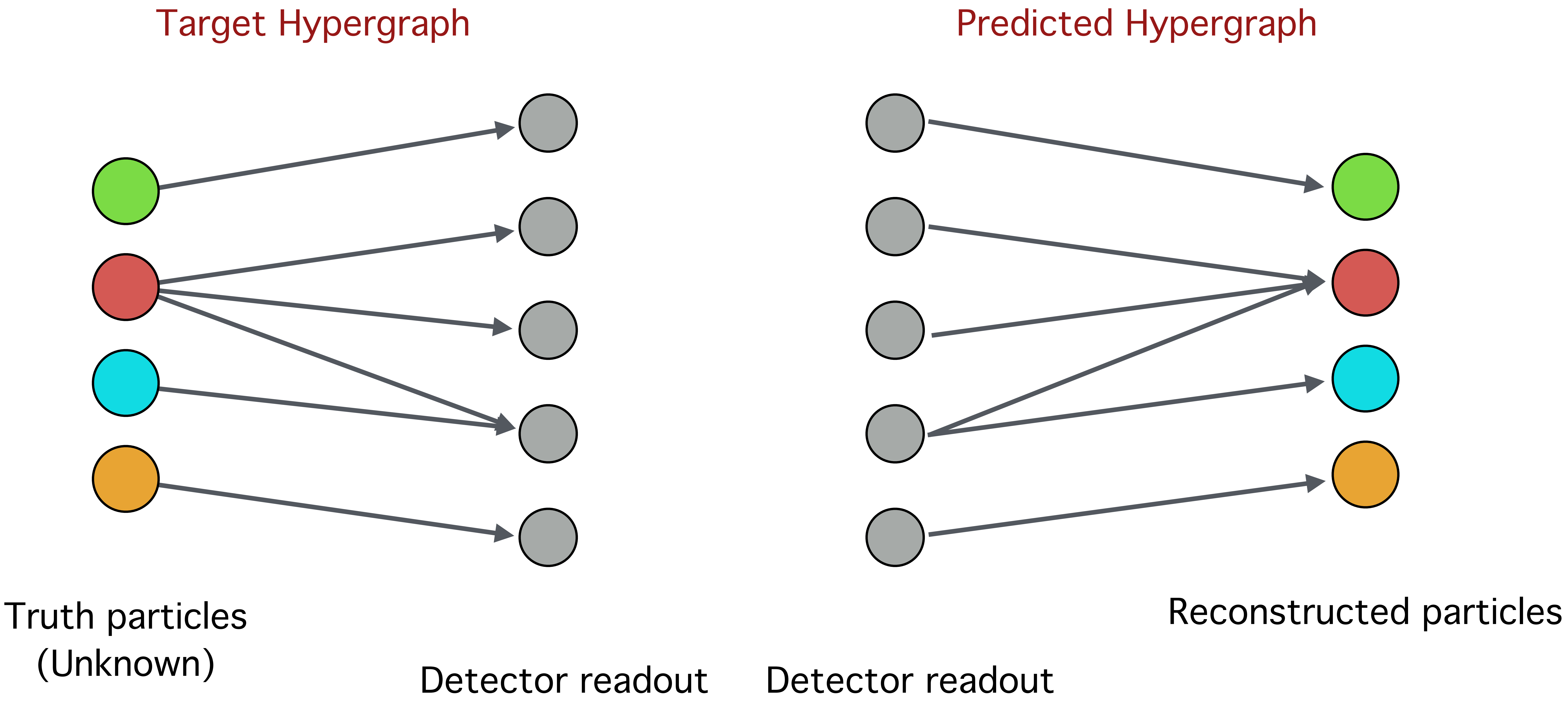

The plan

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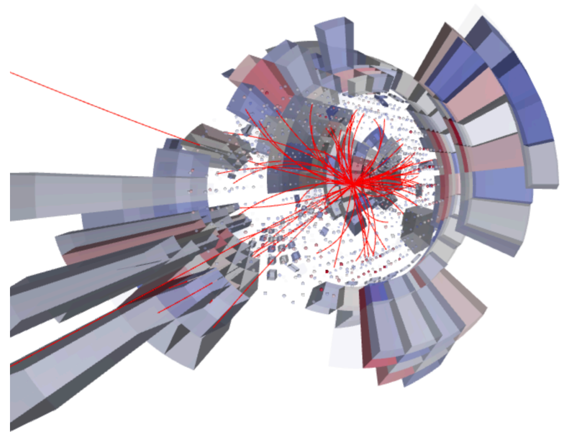
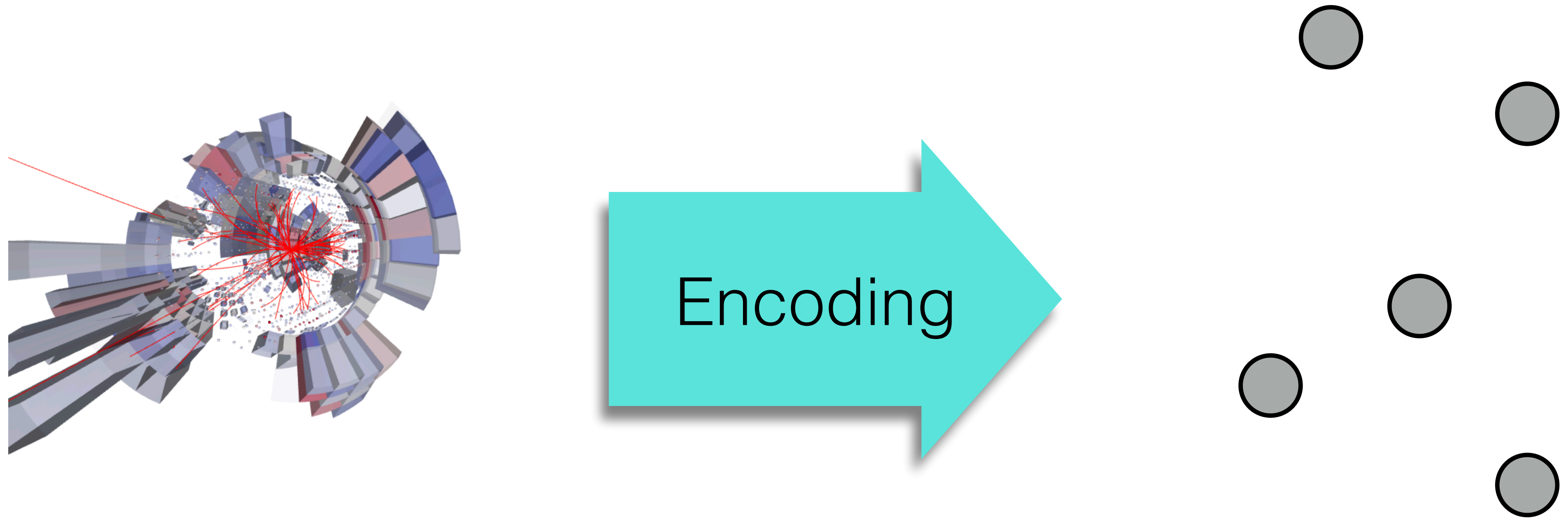


Detector data
(Tracks, cells)

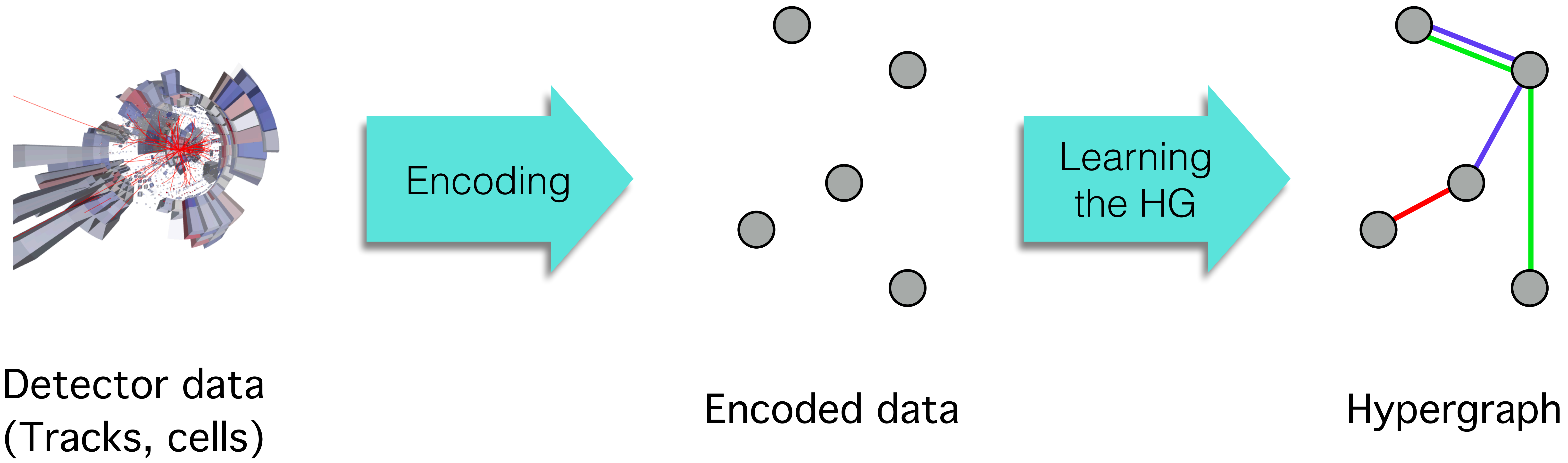
The plan



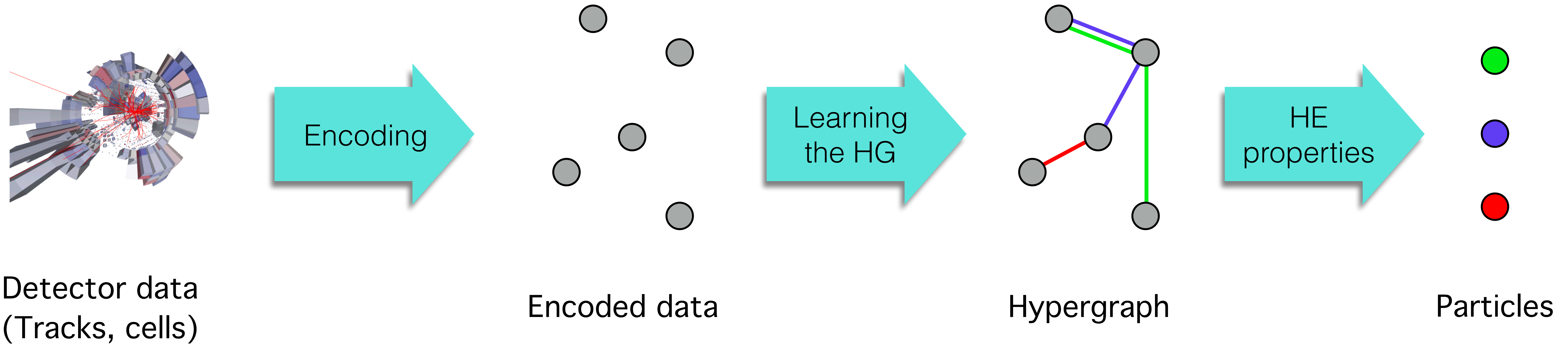
Detector data
(Tracks, cells)

Encoded data

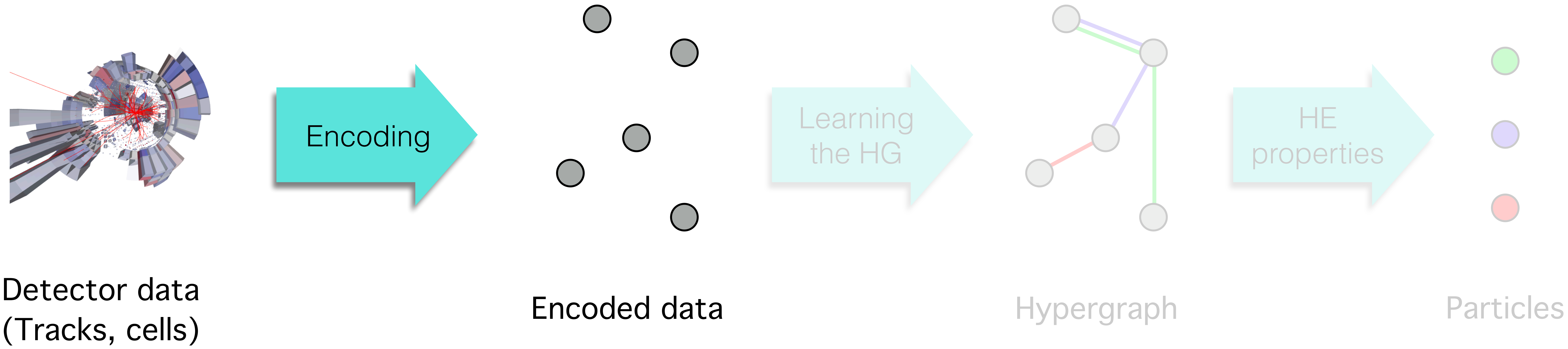
The plan


Encoding
Learning the HG
Detector data
(Tracks, cells)
Encoded data
Hypergraph

The plan


Encoding
Learning the HG
HE properties
Detector data (Tracks, cells)
Encoded data
Hypergraph
Particles

Step 1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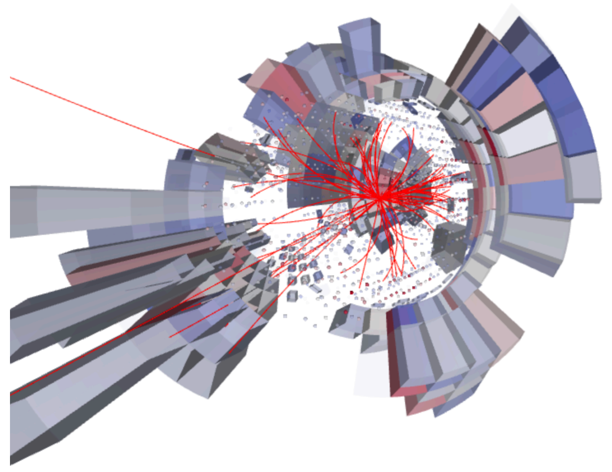
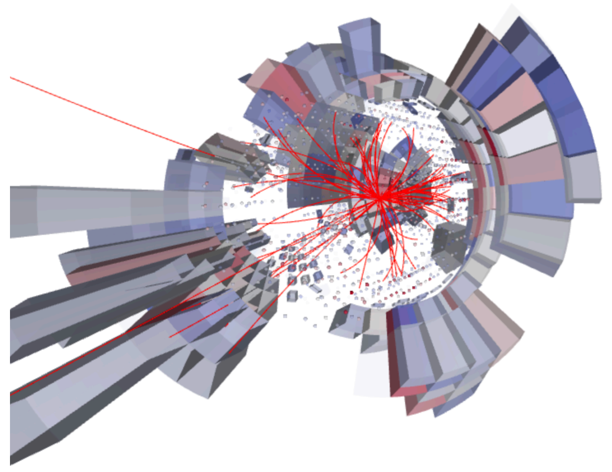


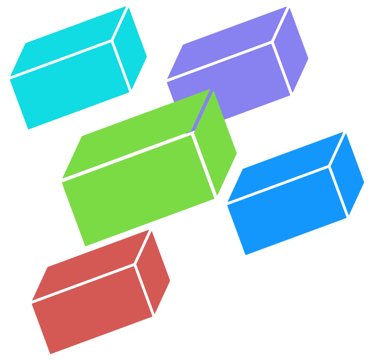
Detector readout

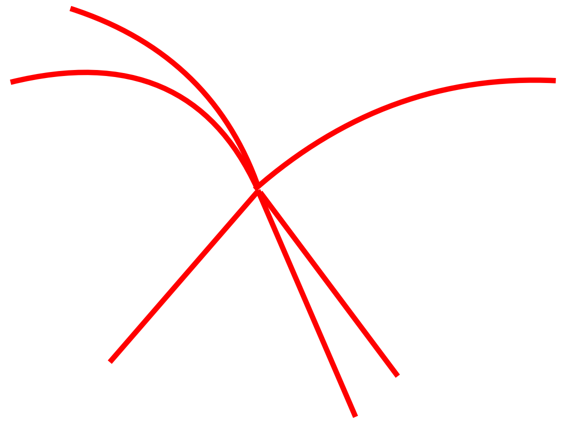
Encoding



Detector readout

=





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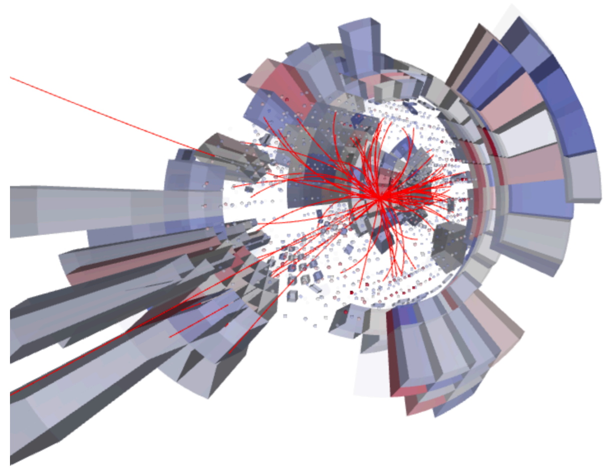

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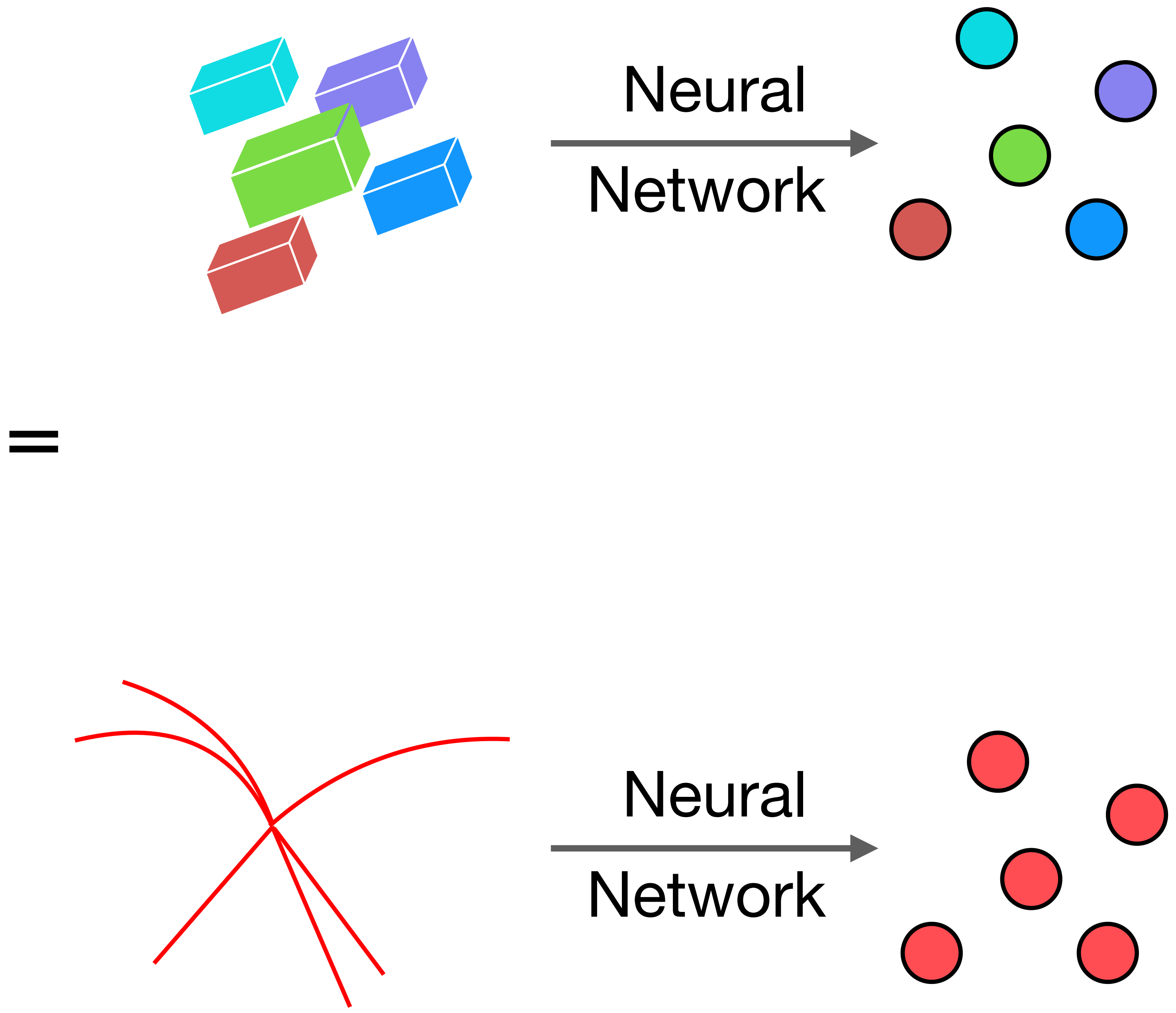

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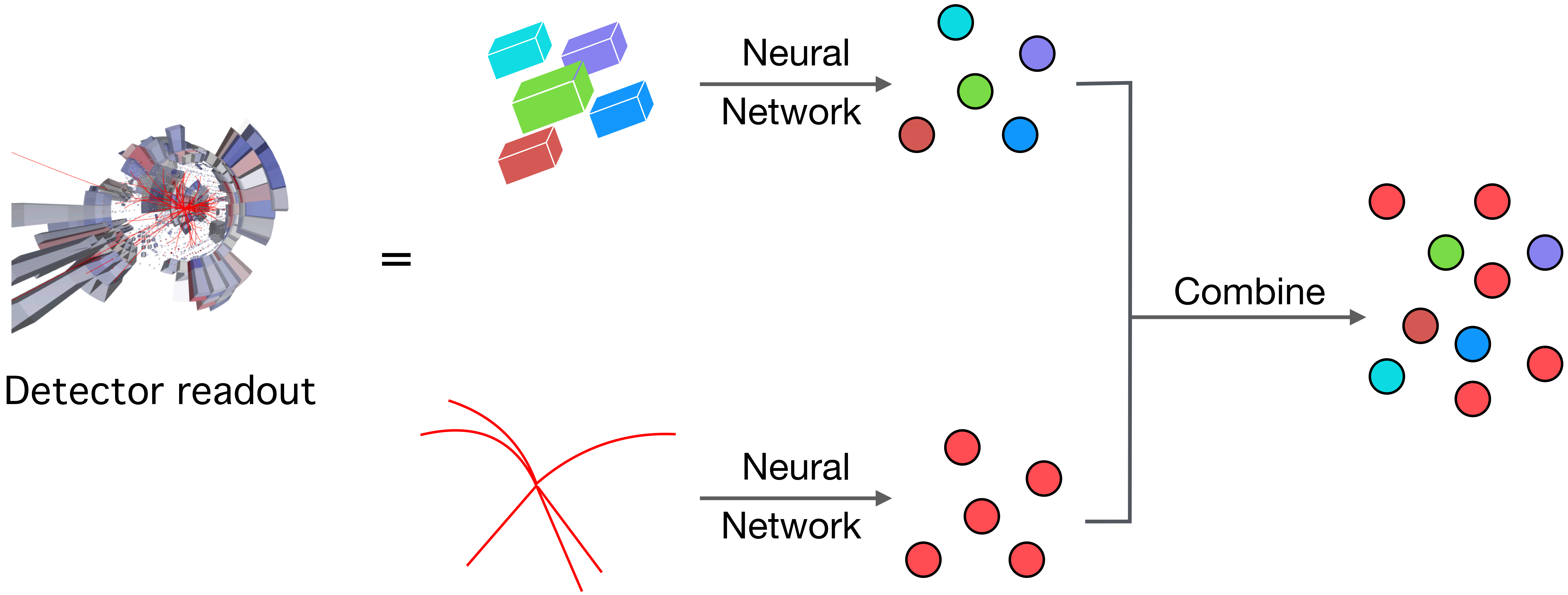

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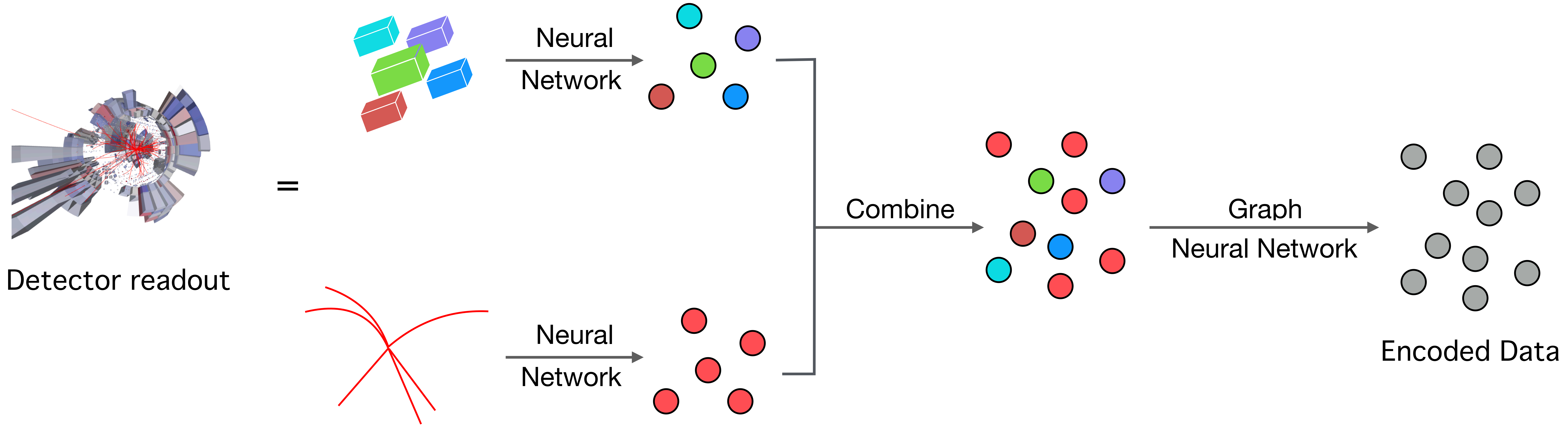
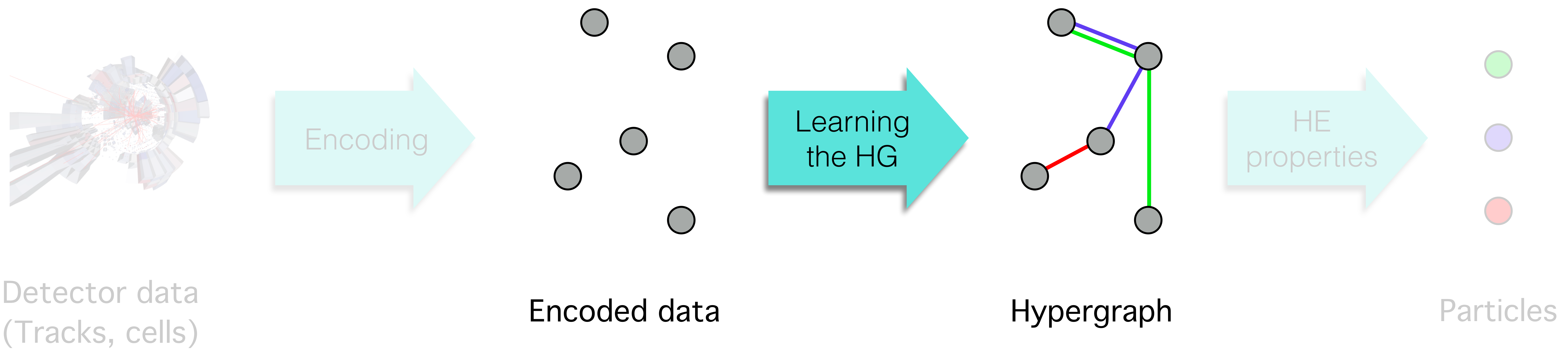


Detector readout
=
Neural
Network
Neural
Network
Combine
Graph
Neural Network
Encoded Data

Step 2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Learning the Hypergraph

Recurrently Predicting Hypergraphs

David W. Zhang
University of Amsterdam
w.d.zhang@uva.nl

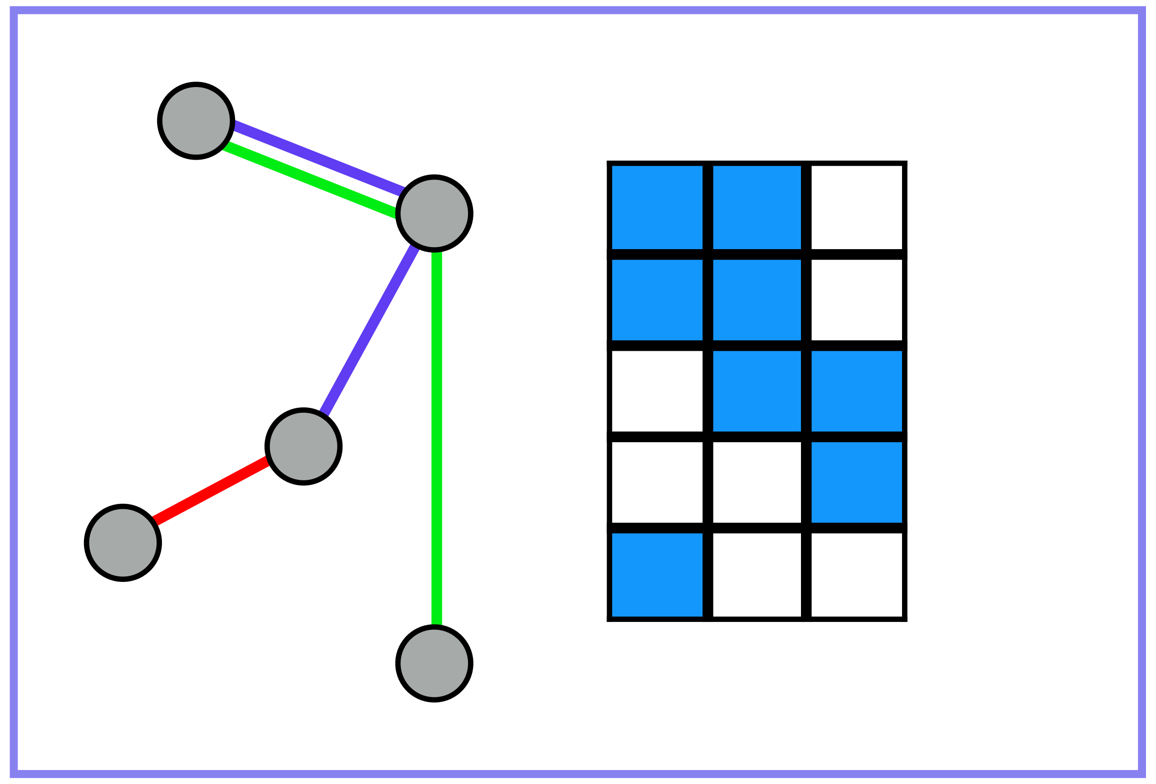
Gertjan J. Burghouts
TNO
gertjan.burghouts@tno.nl

Cees G. M. Snoek
University of Amsterdam
cgmsnoek@uva.nl

Aligns well with our Physics motivations

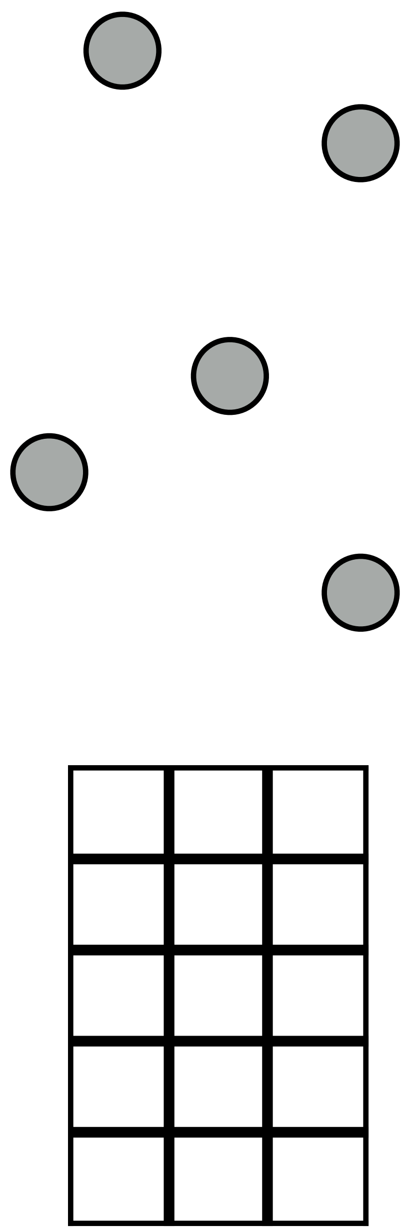
https://arxiv.org/pdf/2106.13919.pdf

Recurrently learning Hypergraph



Traget

G_0



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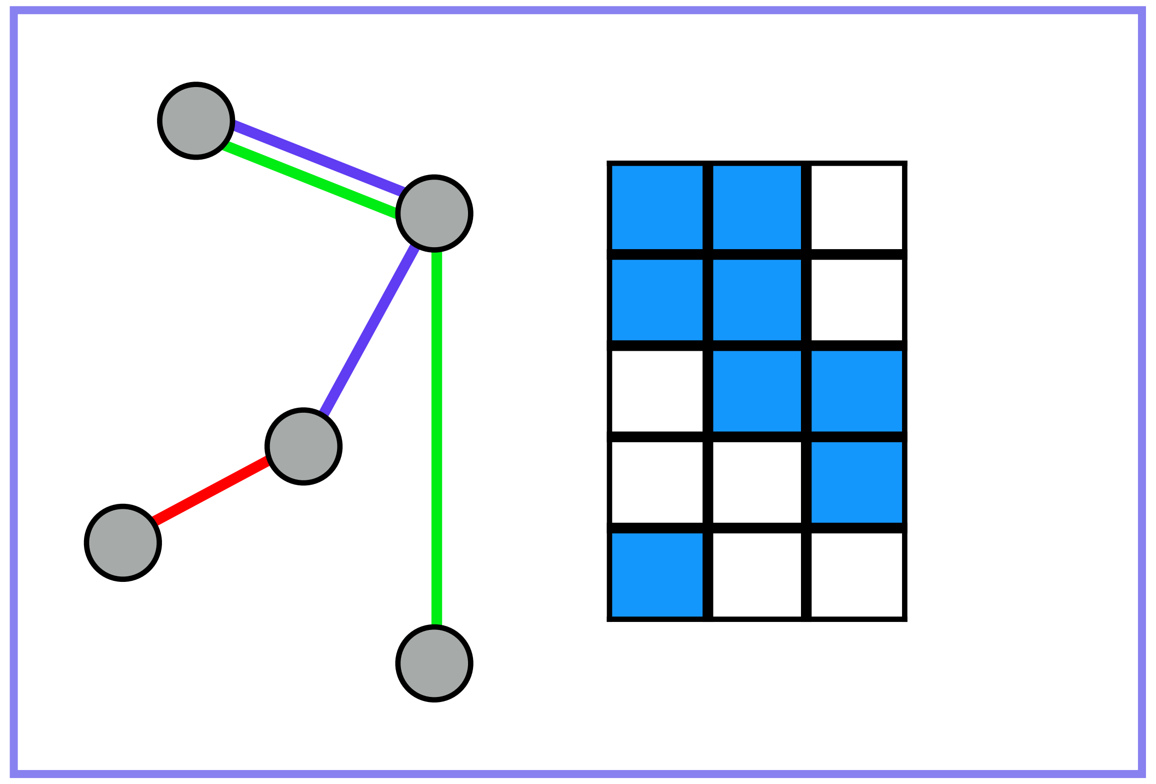

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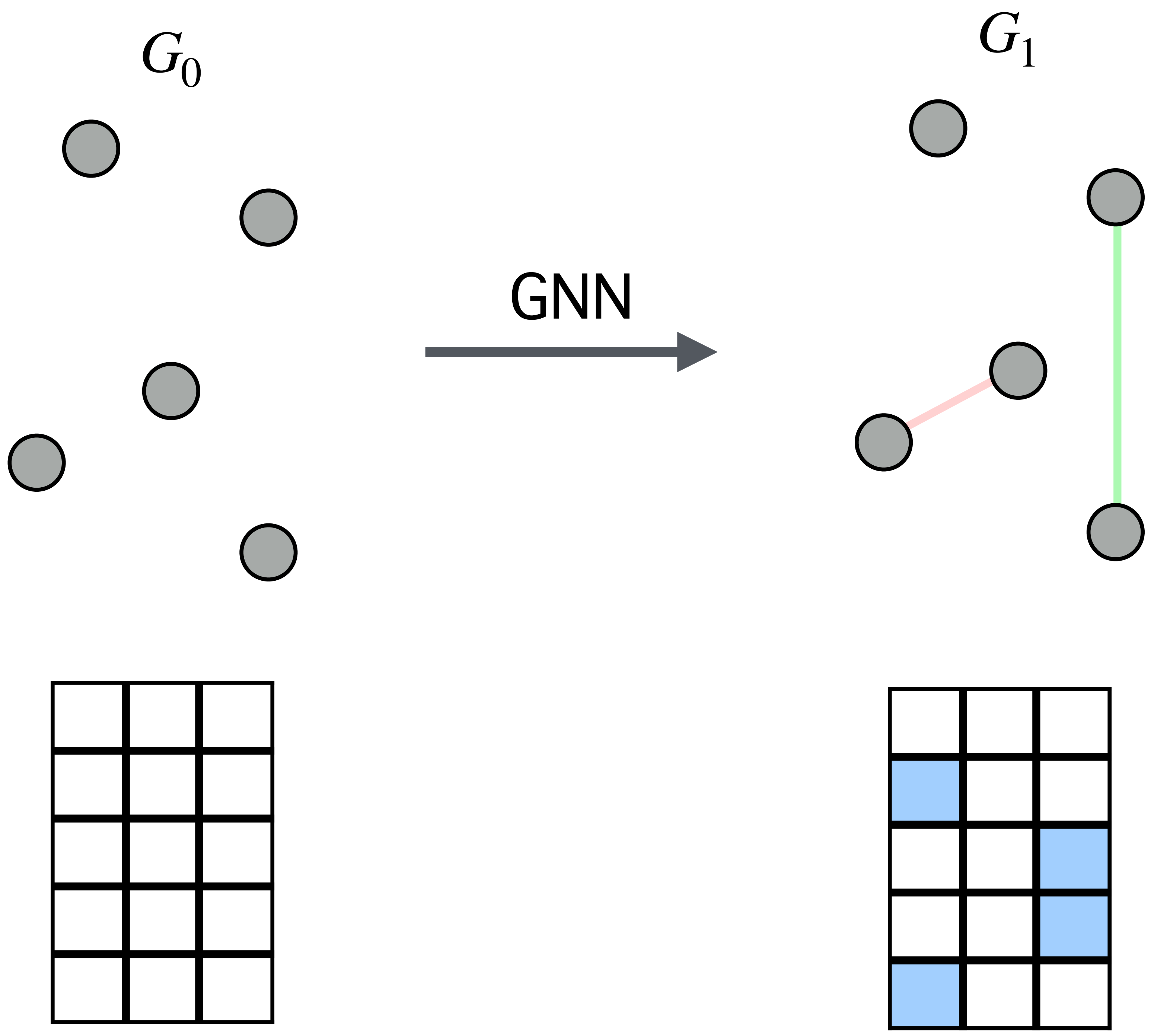

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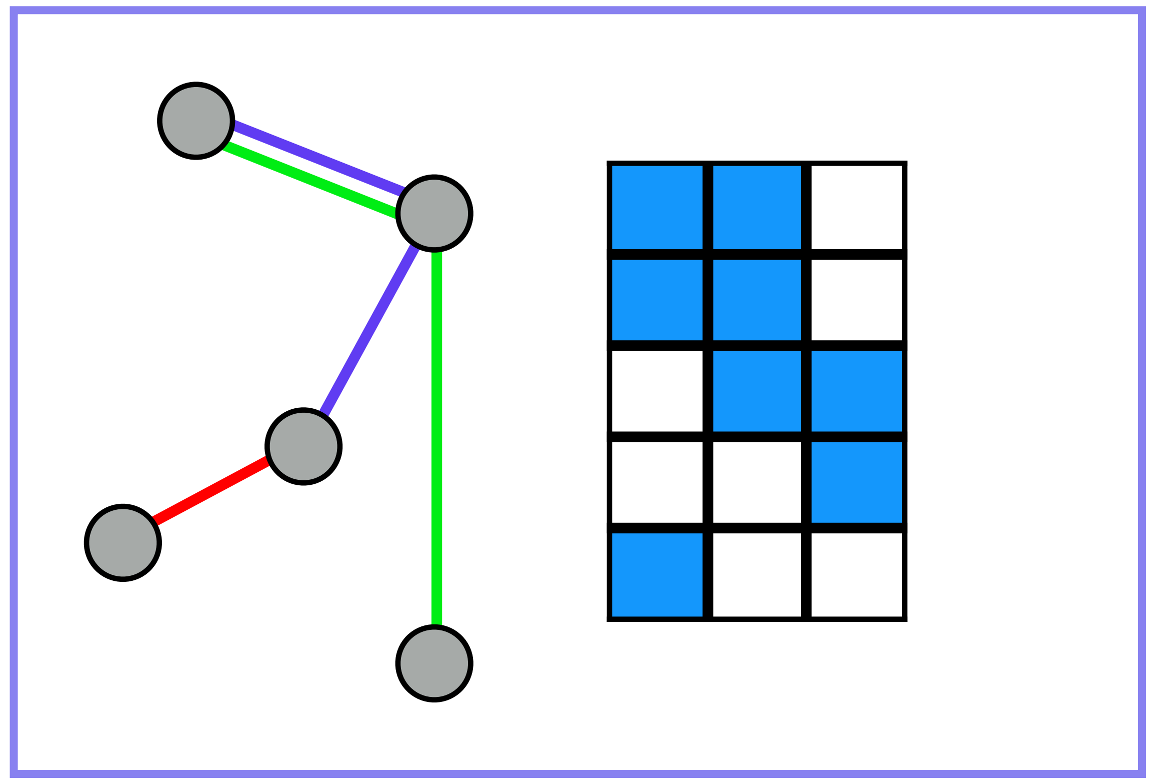

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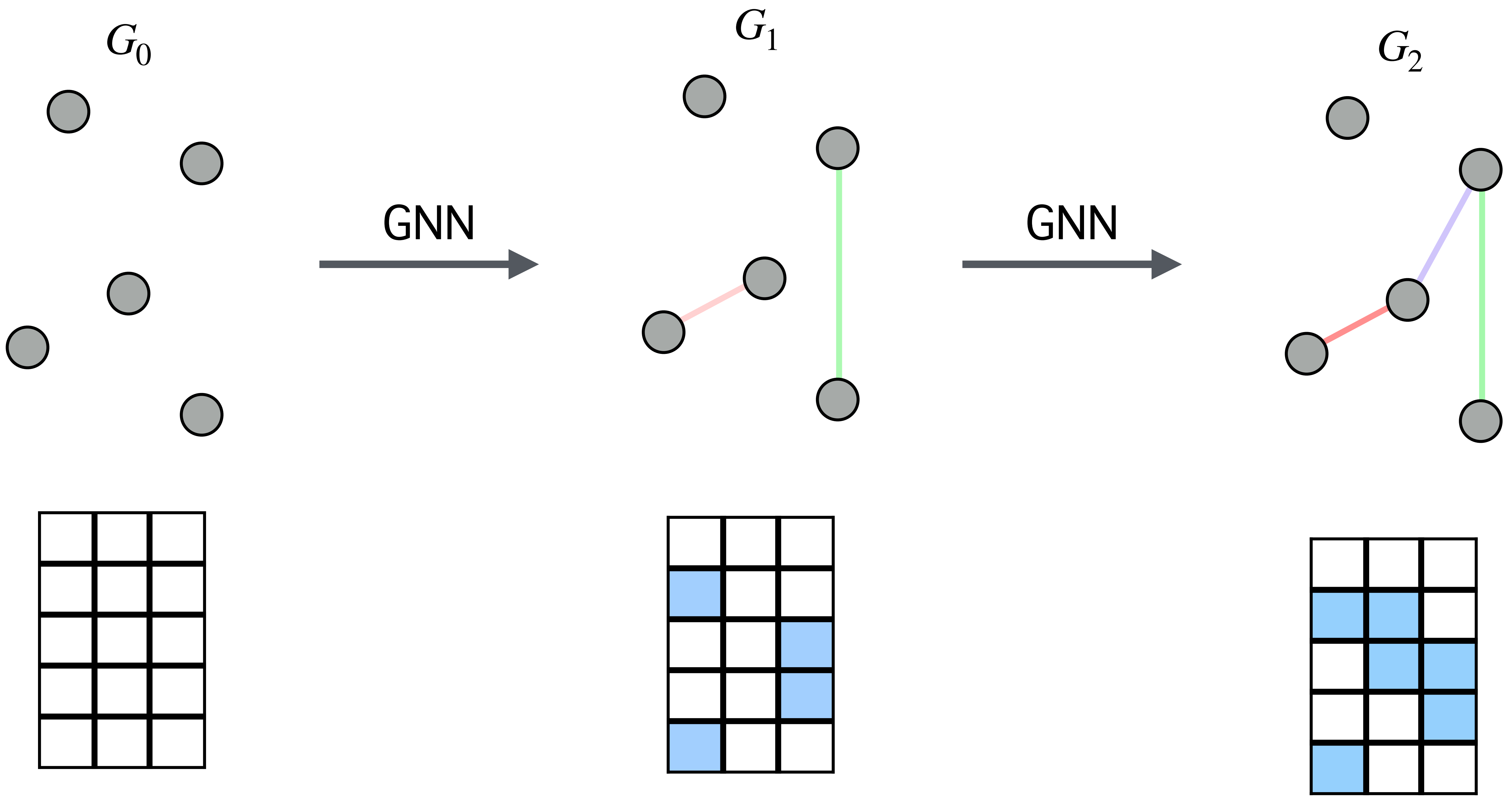

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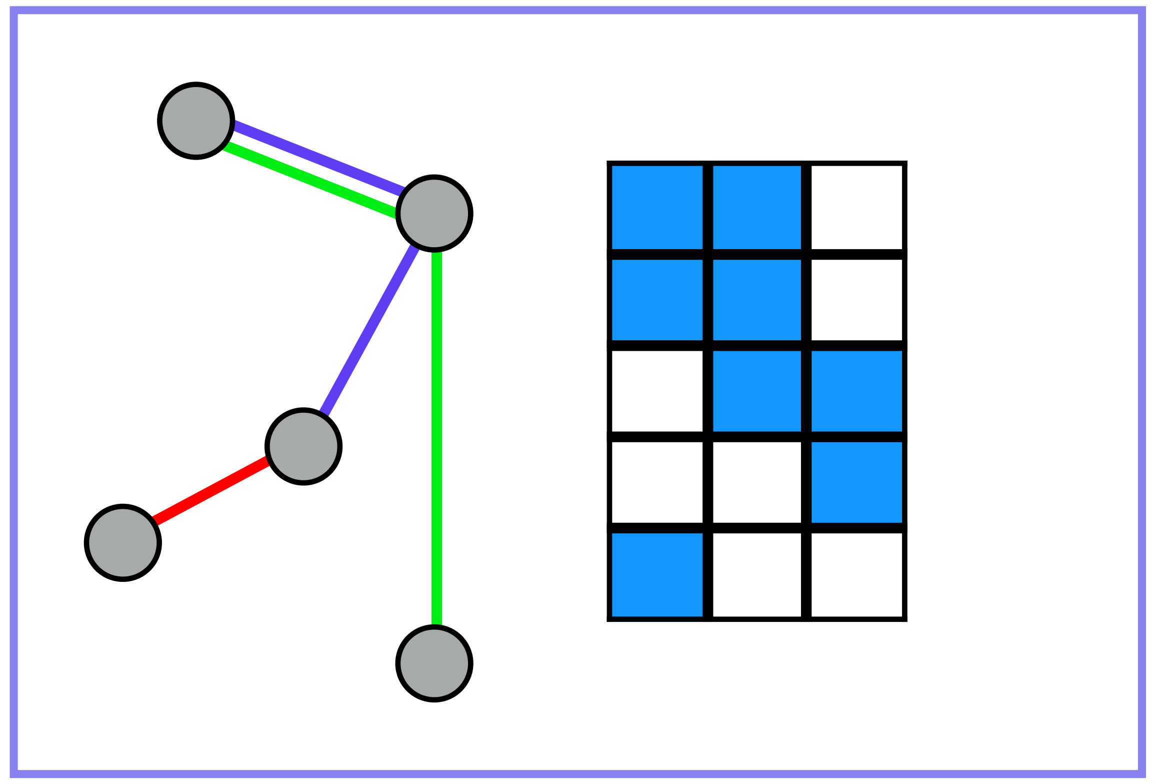

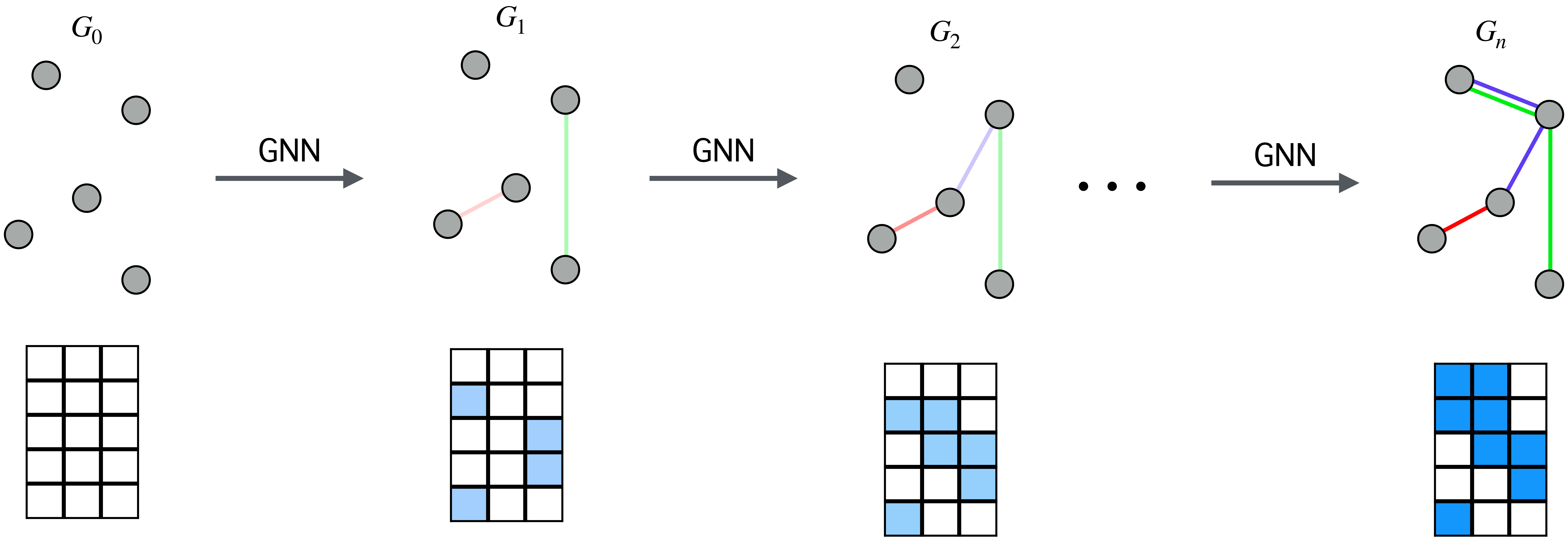

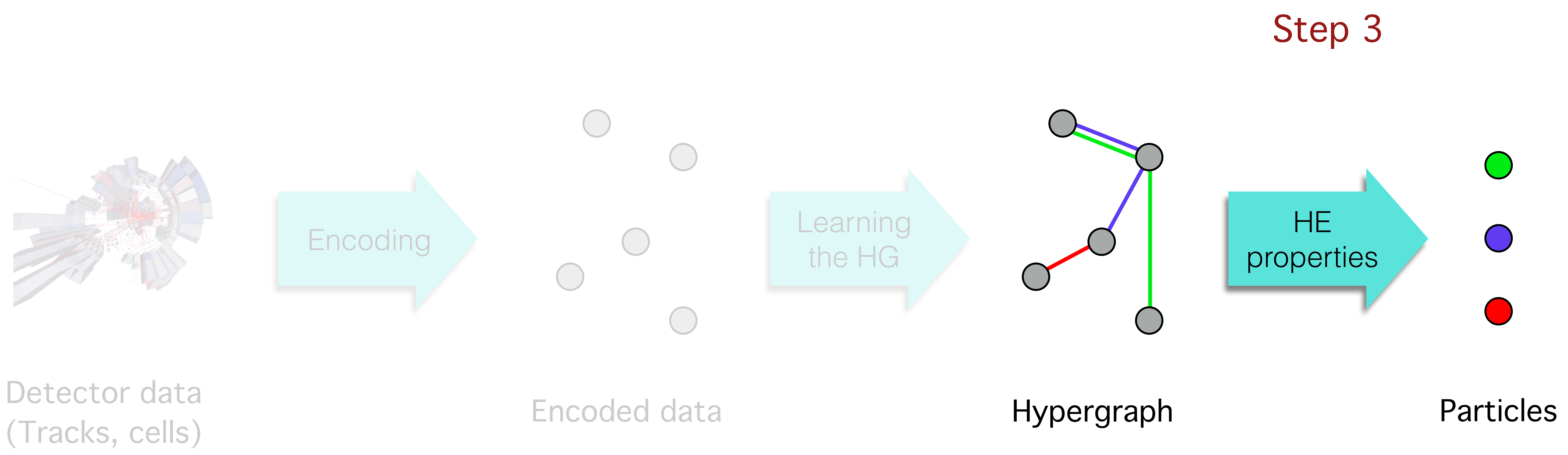
Step 3
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Hypergraph
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What about particle properties?

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- Learning the Hypergraph - most difficult task

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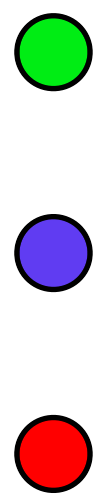

Learned Hyperedges

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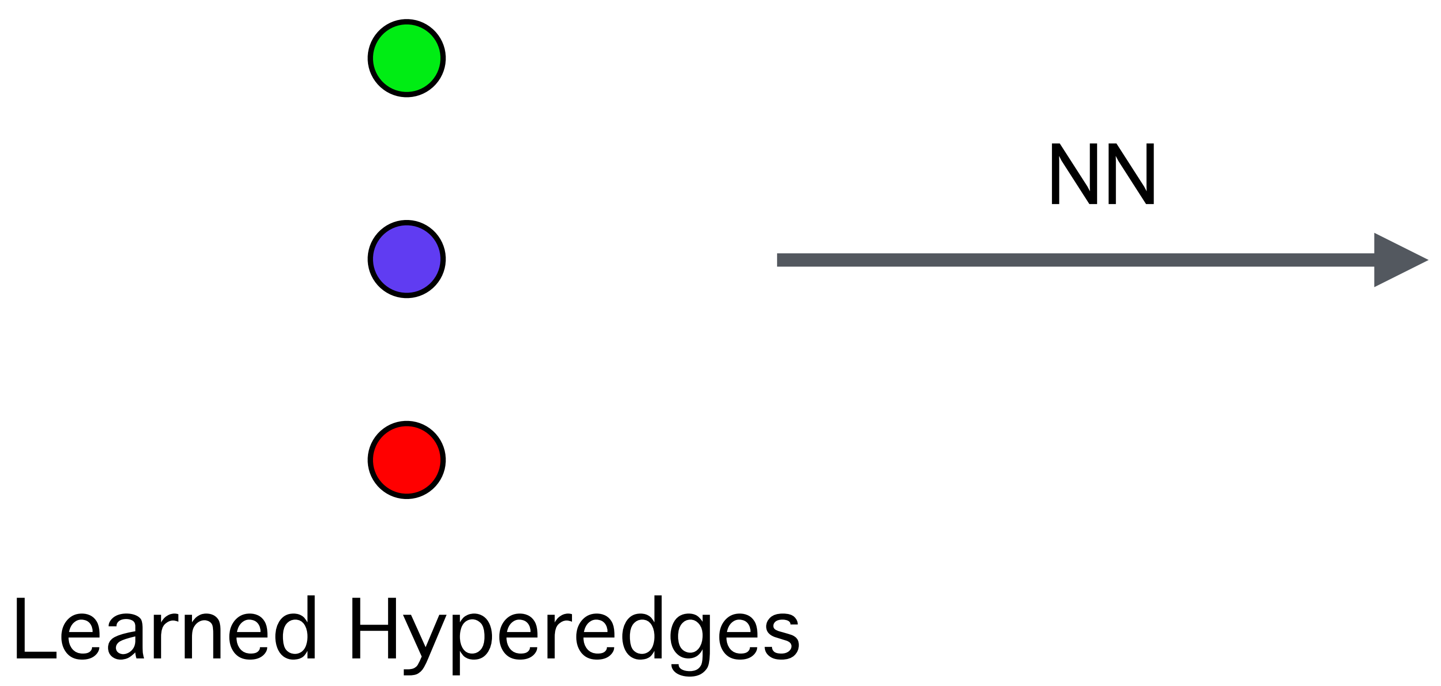

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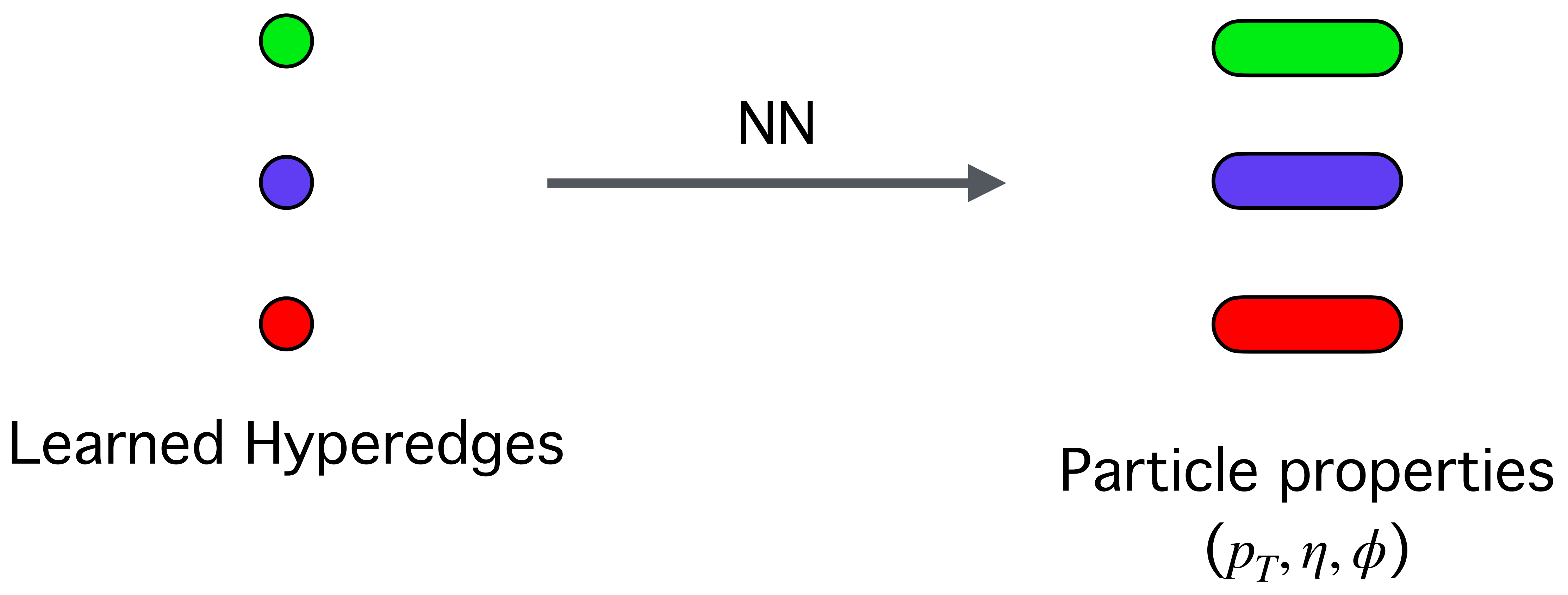

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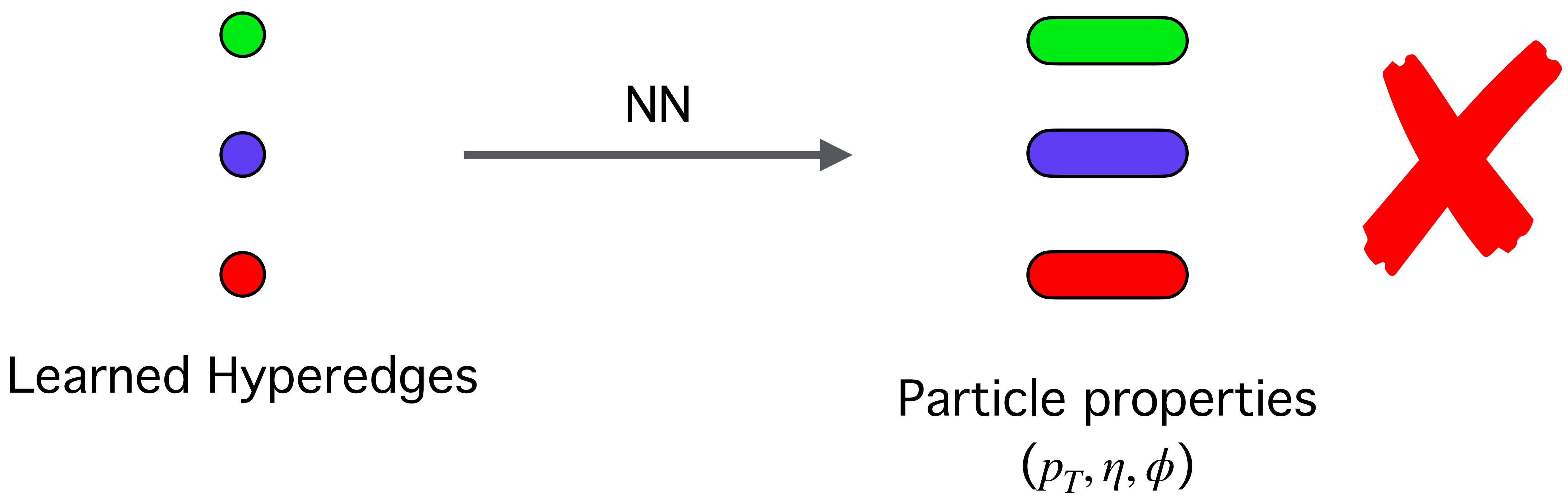

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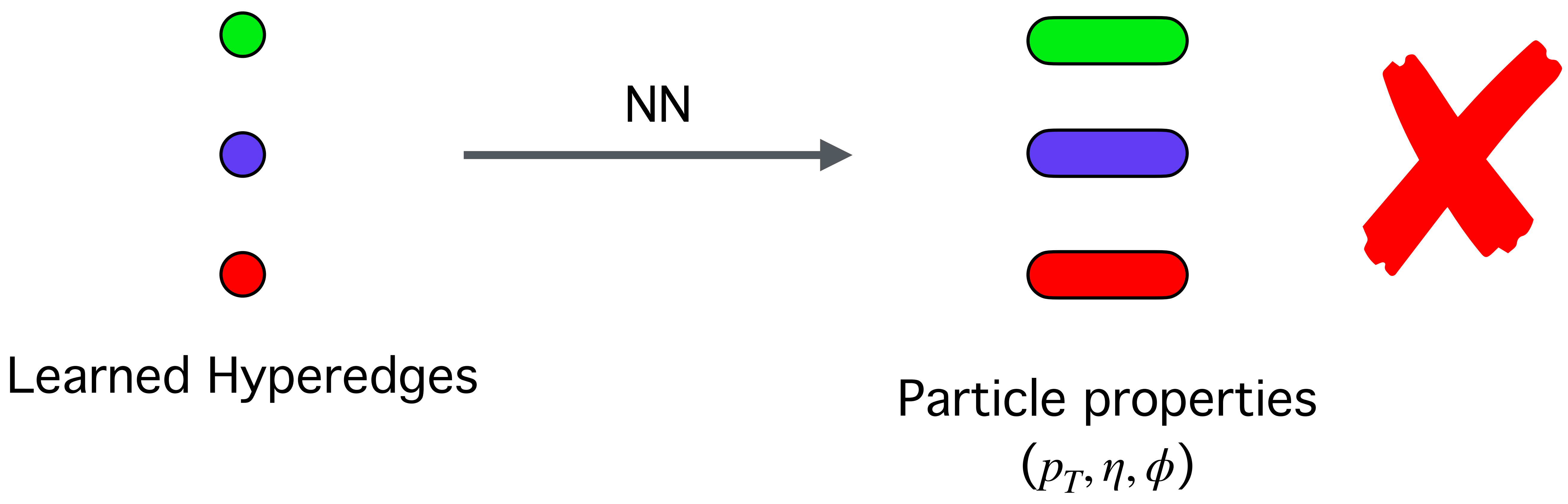

What now?

Let’s add some more physics…

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- We already know a lot about the system.

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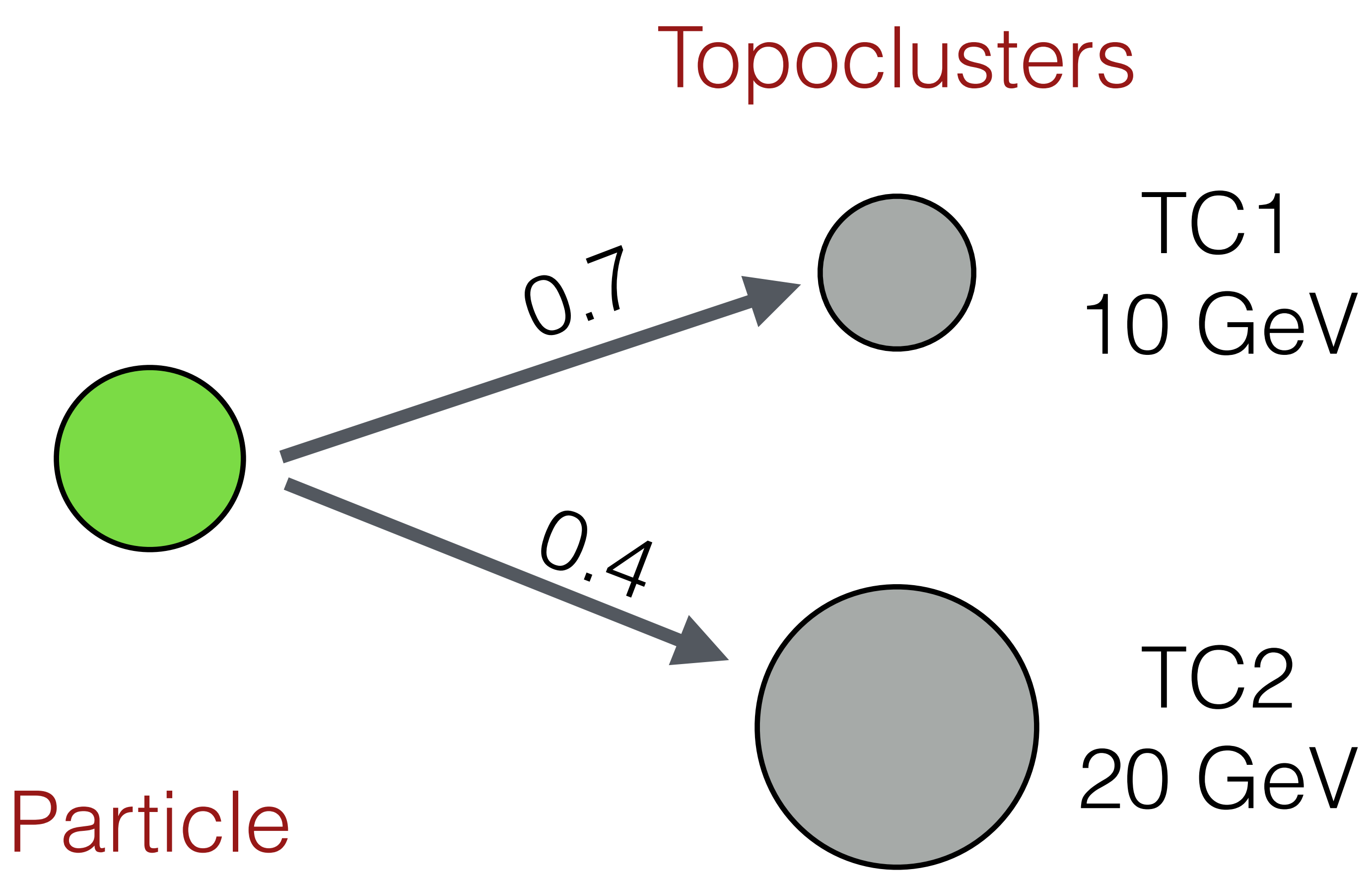
Let’s add some more physics…

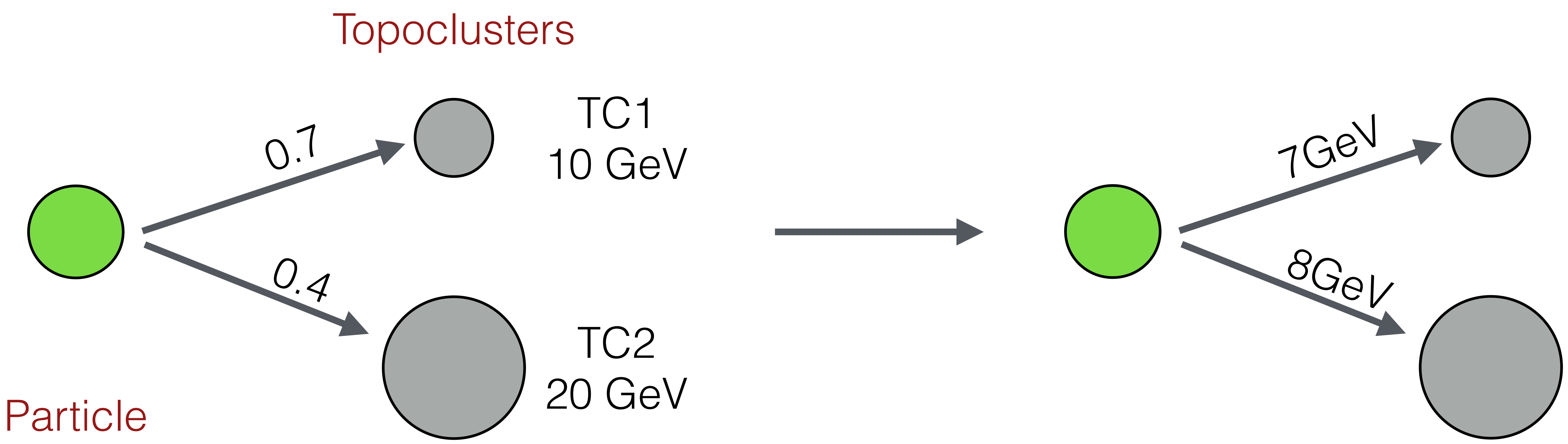
- We already know a lot about the system.
- Step 2 also tells us a lot about the particles that we want to produce
- Why not use that info!

Proxy properties

Proxy properties



Proxy properties



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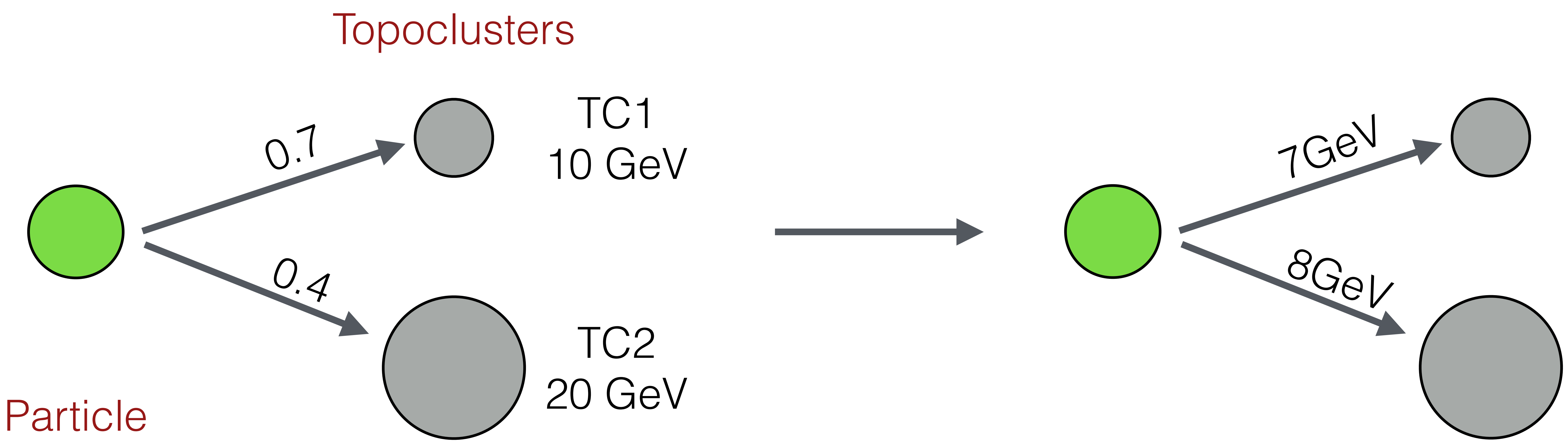

Proxy properties of

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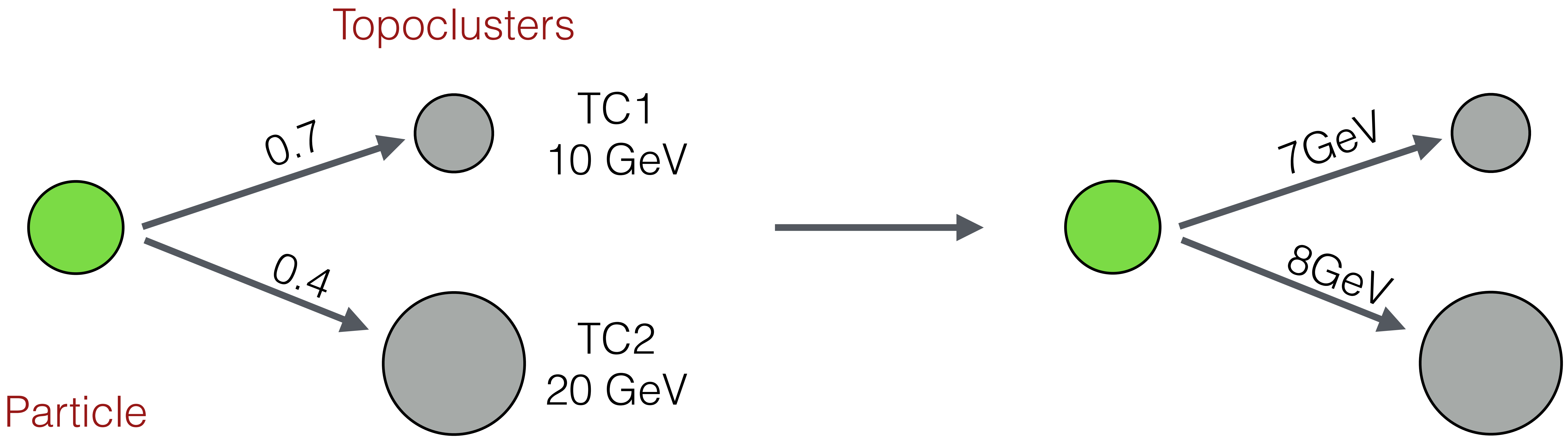
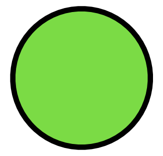
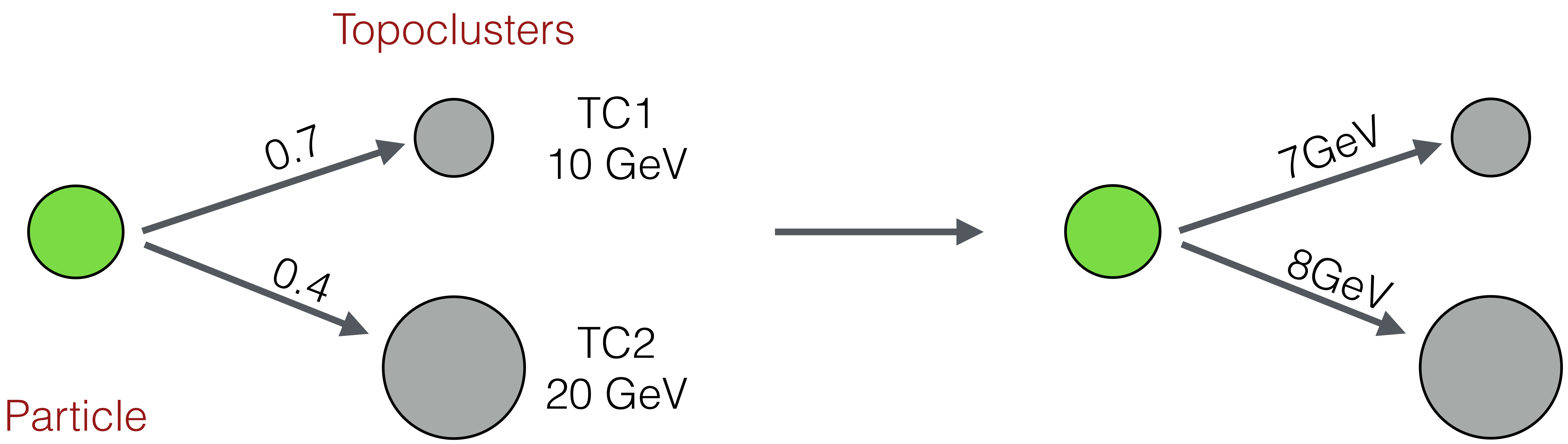
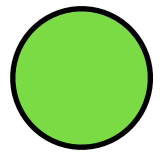


Proxy properties of 

- E = E1 + E2 = 15GeV

Proxy properties



Proxy properties of 

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- $\eta = \dfrac{7\eta_1 + 8\eta_2}{15}$

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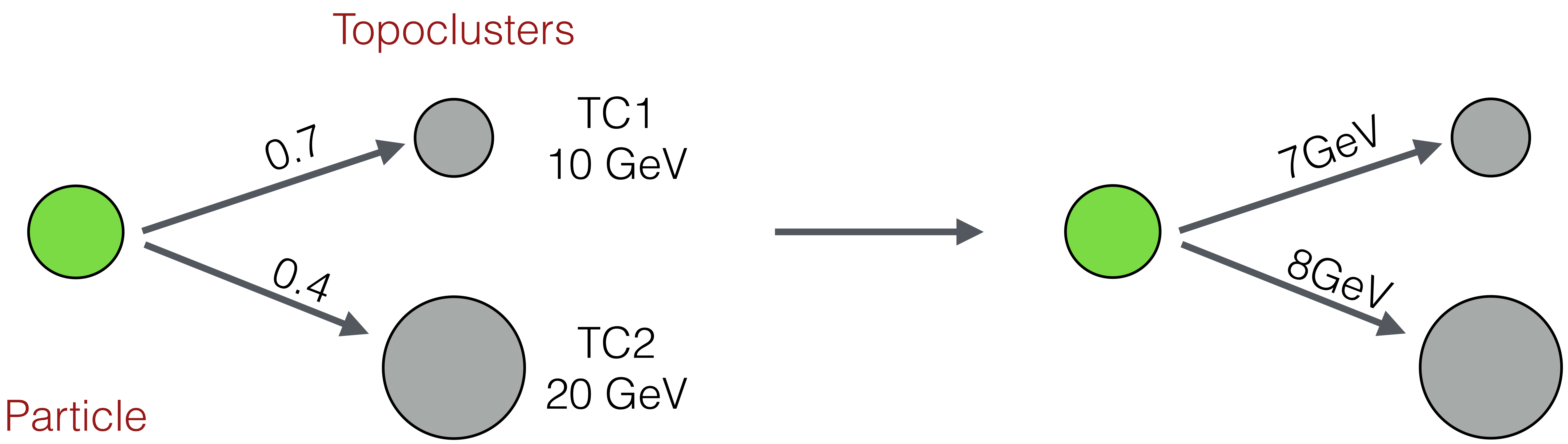
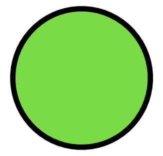


Proxy properties of 

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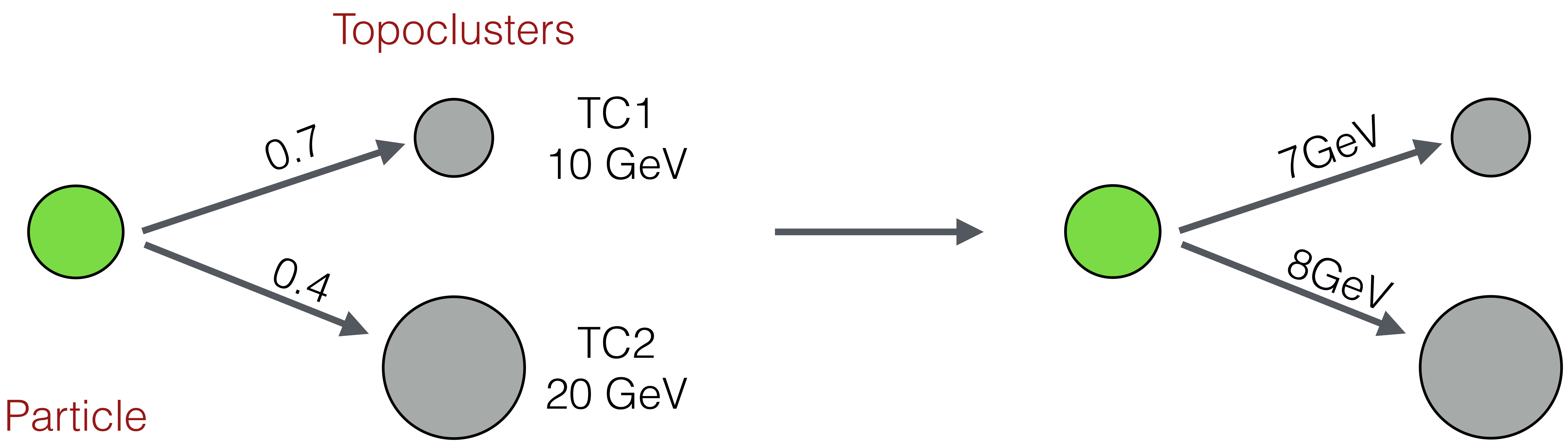
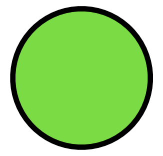


Proxy properties of 

- E = E1 + E2 = 15GeV
- $p_T = \dfrac{E}{cosh(\eta)}$
- $\eta = \dfrac{7\eta_1 + 8\eta_2}{15}$
- $\phi = \dfrac{7\phi_1 + 8\phi_2}{15}$

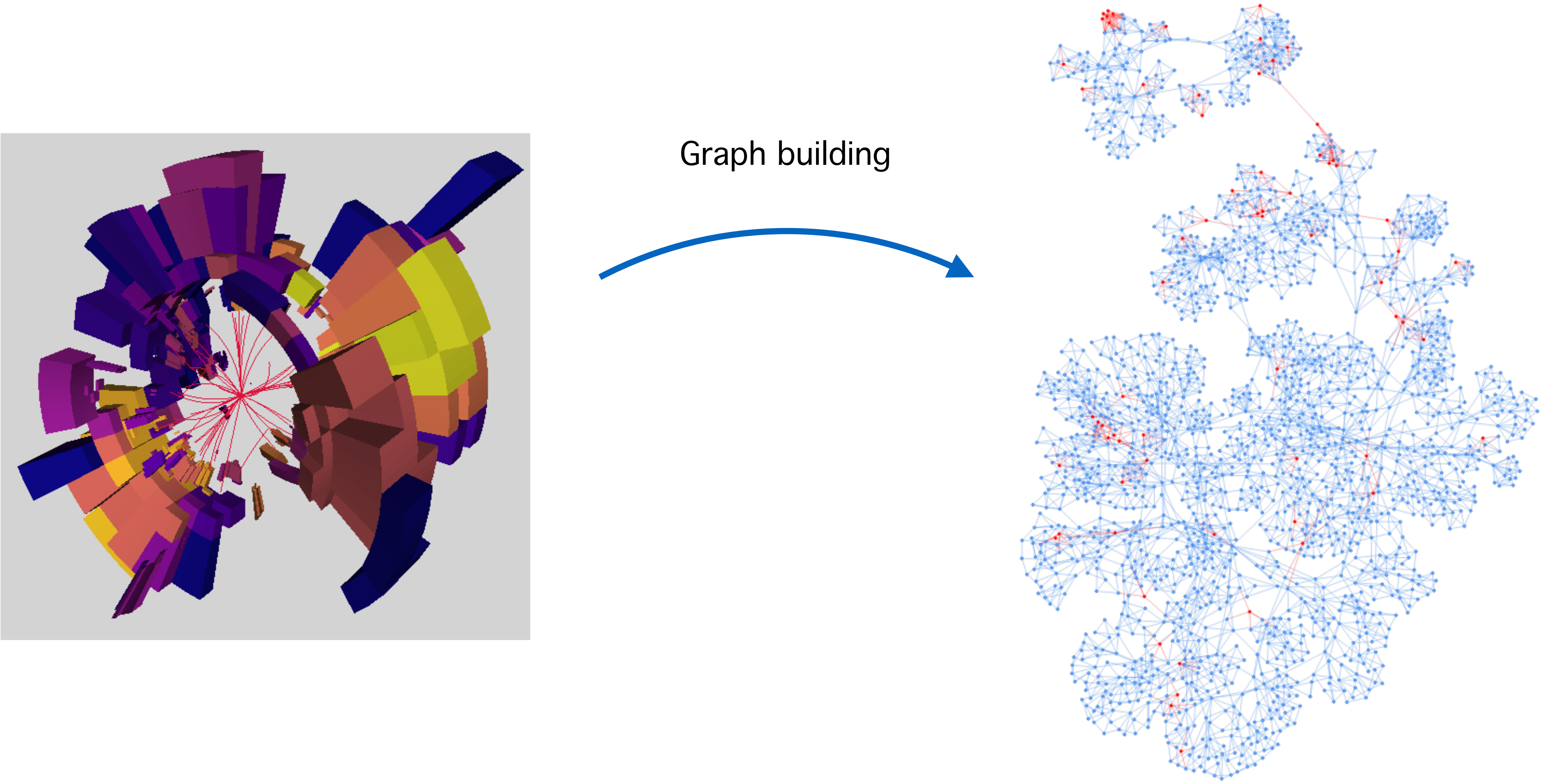
Additional network

Proxy properties $\xrightarrow{\text{Neural Network}}$ Predicted properties (p_T, η, ϕ, class)

(Tracks for charged particles
TC for neutral particles)

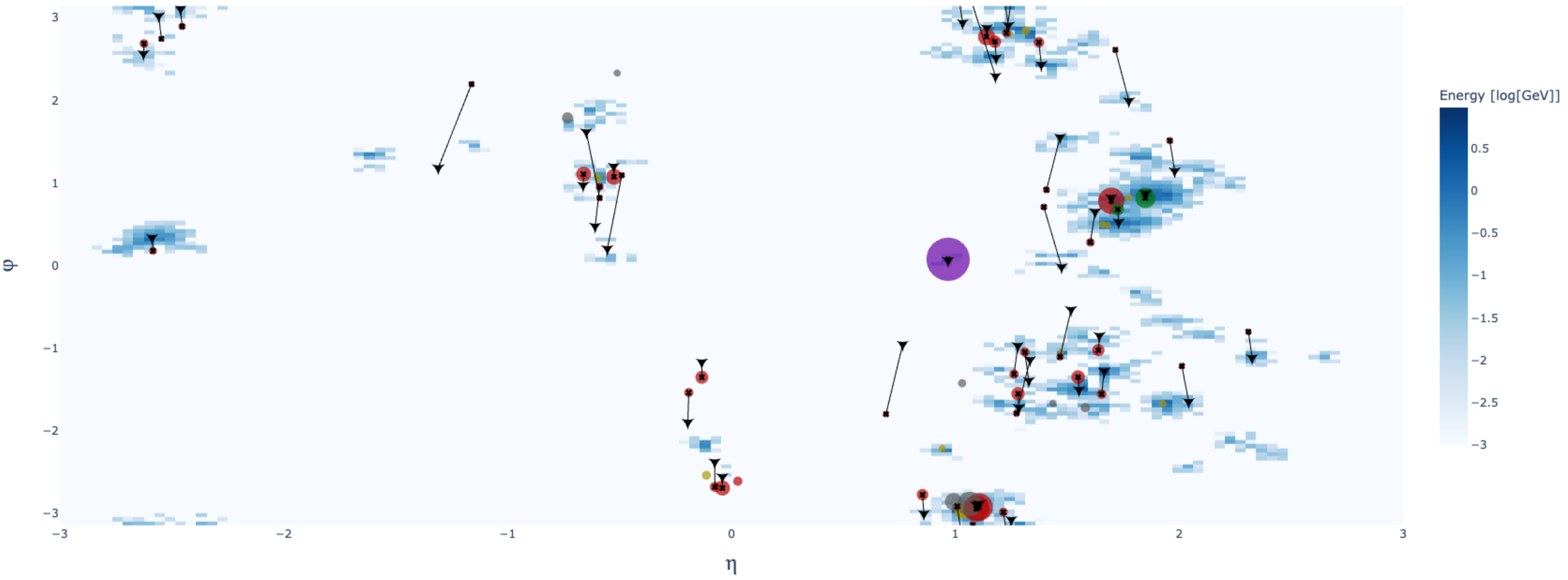
Dataset

- Single jet dataset
- Very dense environment
- No pileup



Dataset

ECAL1



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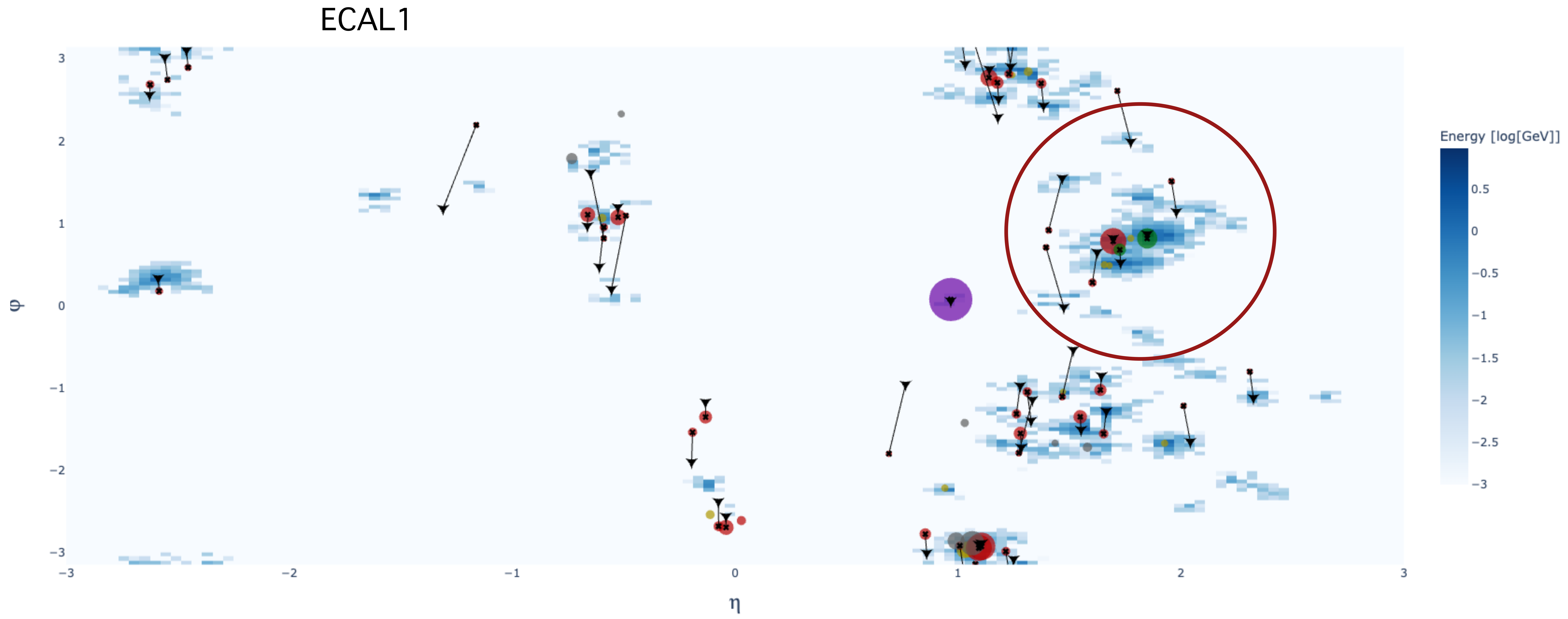
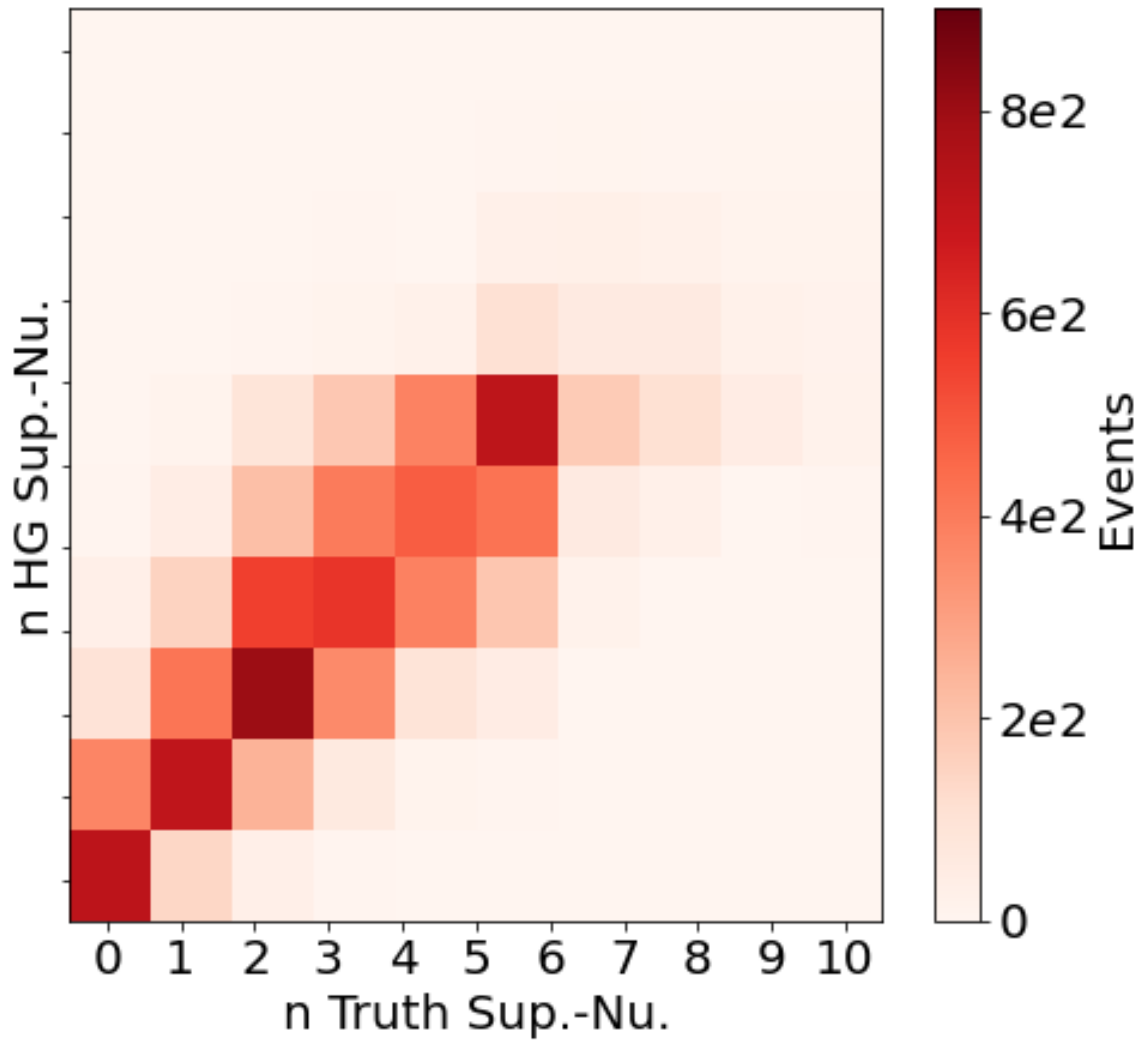


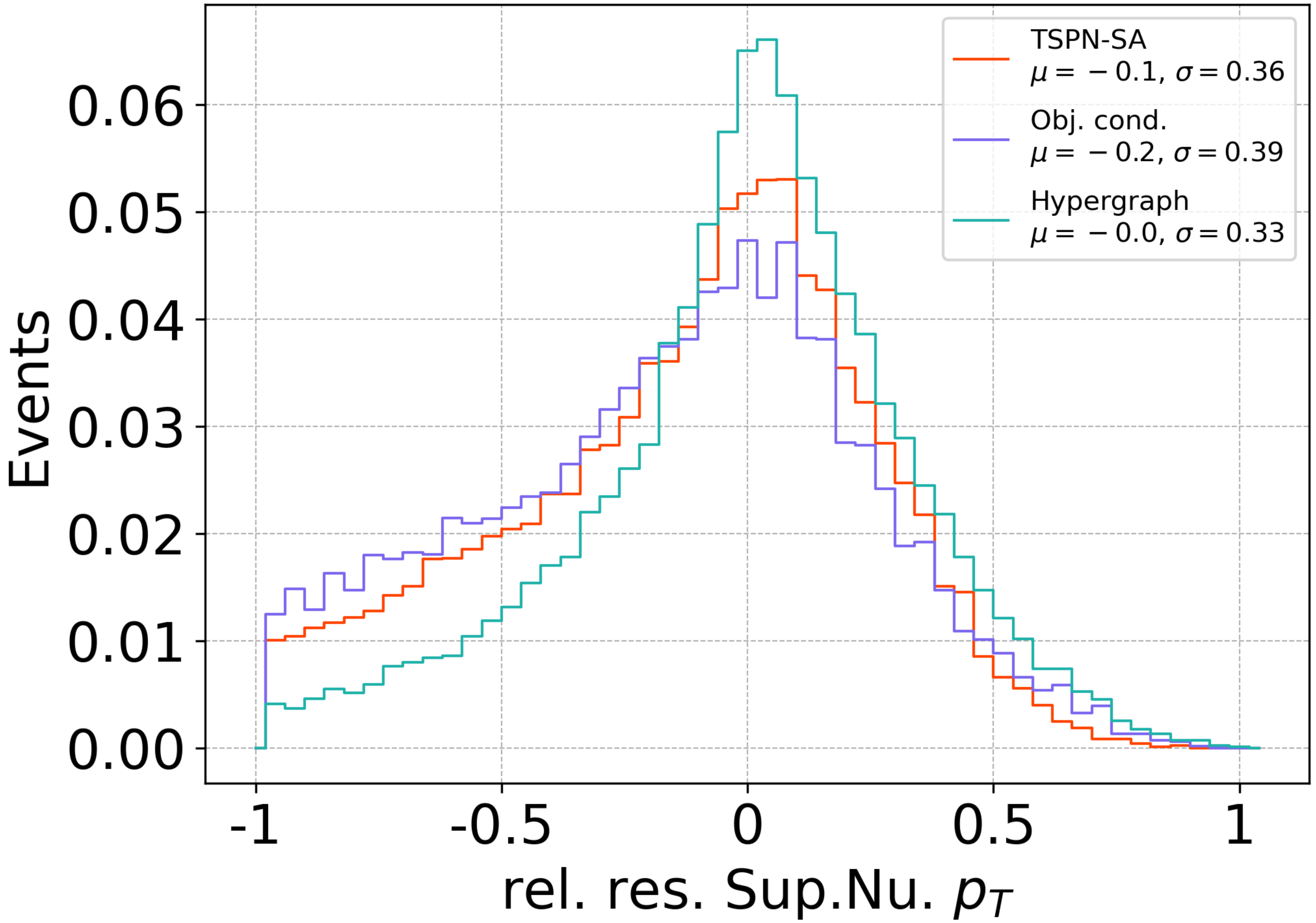
Cardinality

- For charged particles, tracks are proxy to particles
- Fairly diagonal result for neutral particles



Neutral particles

- HG can understand overlapping showers more precisely
- Helps in better reconstruction
- Obj cond. and TSPN-SA were two other models we were studying
- They lack the physics intuition we discussed

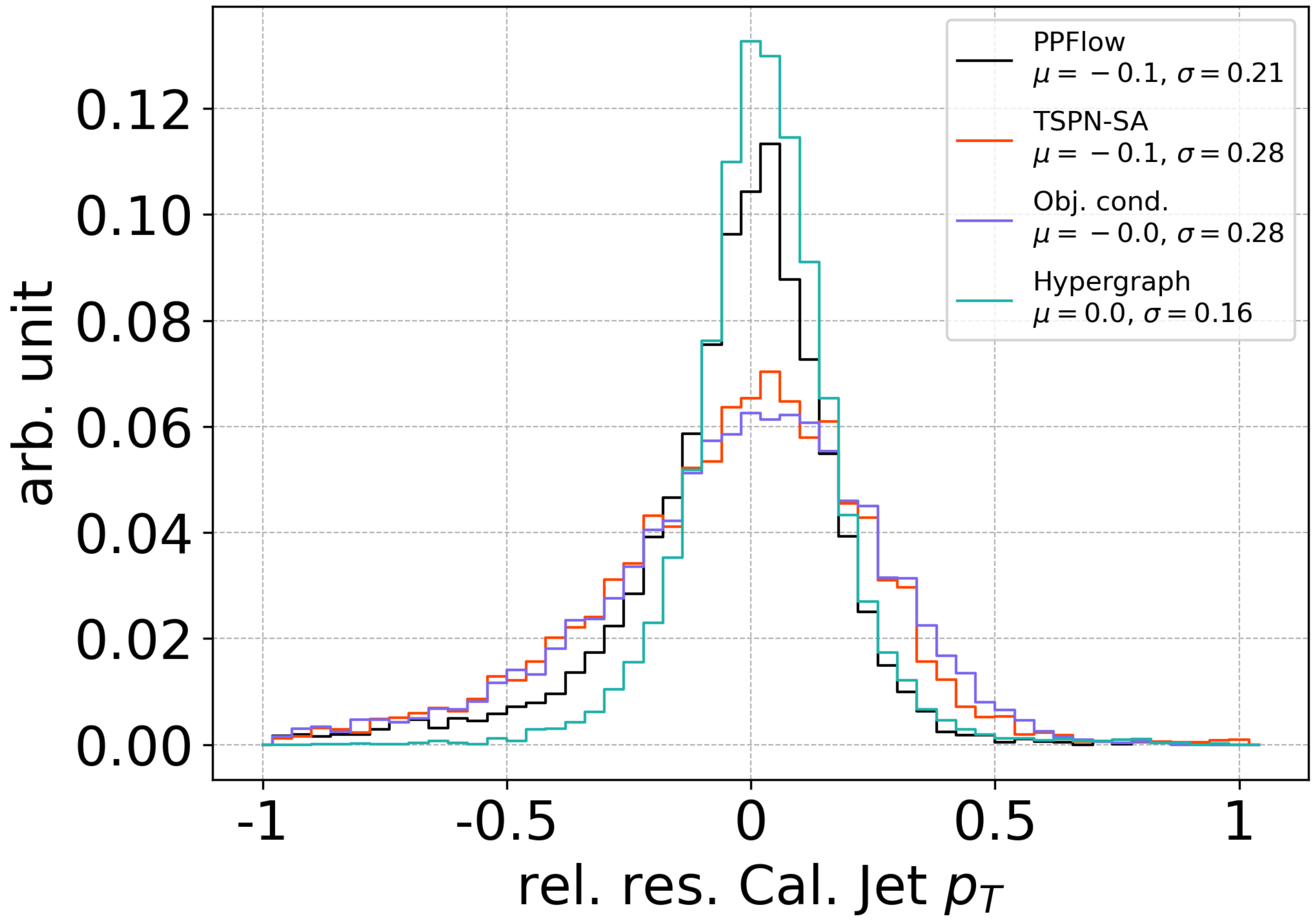


$$\frac{\text{Truth - predicted}}{\text{Truth}}$$

Jets

- Jets are the most important physical properties for the current analyses!
- Hypergraph improves the jet resolution
- (*PPflow is designed to have better jet resolution, can't predict individual particles*)

Improved Resolution!



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Interpretability

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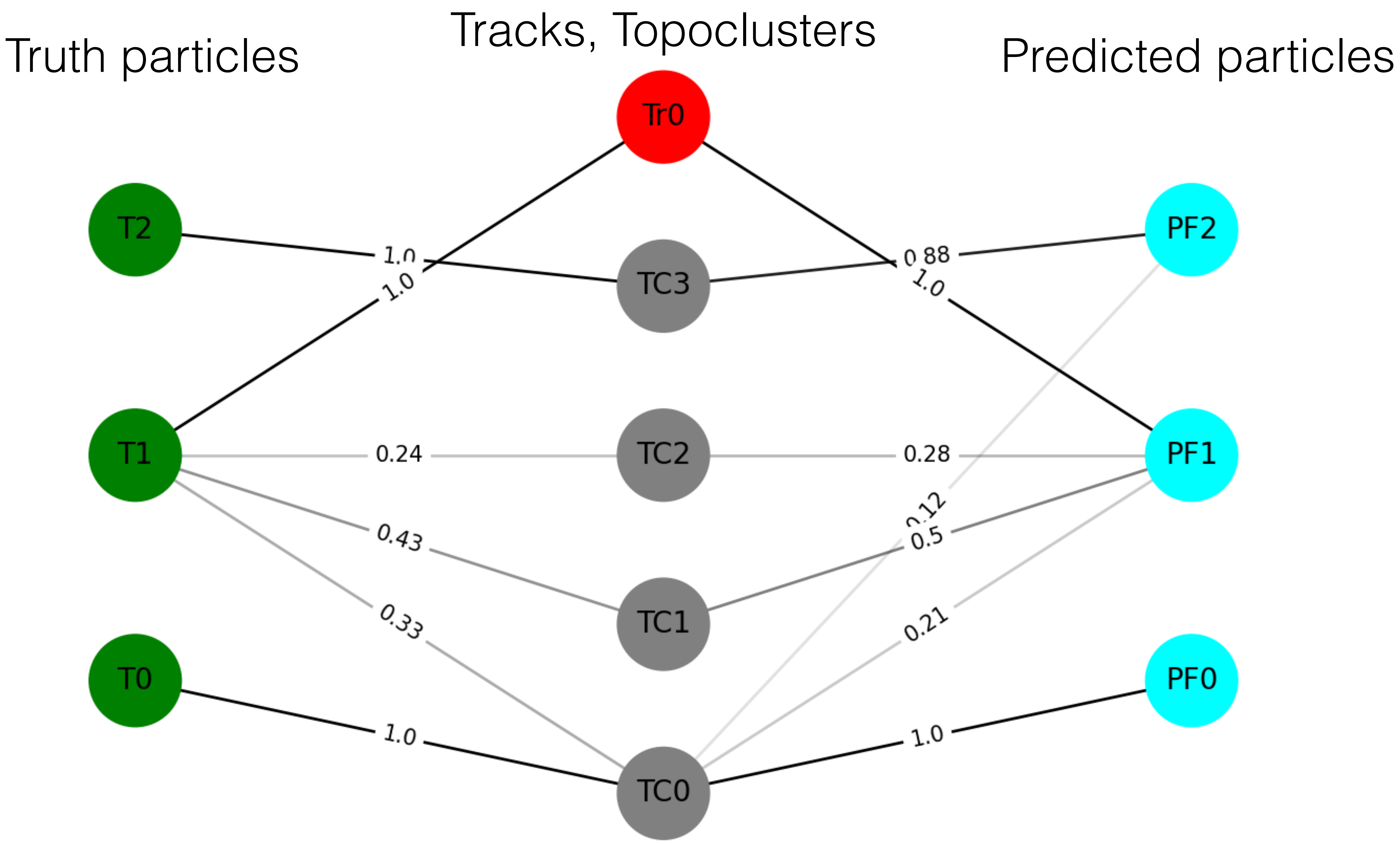

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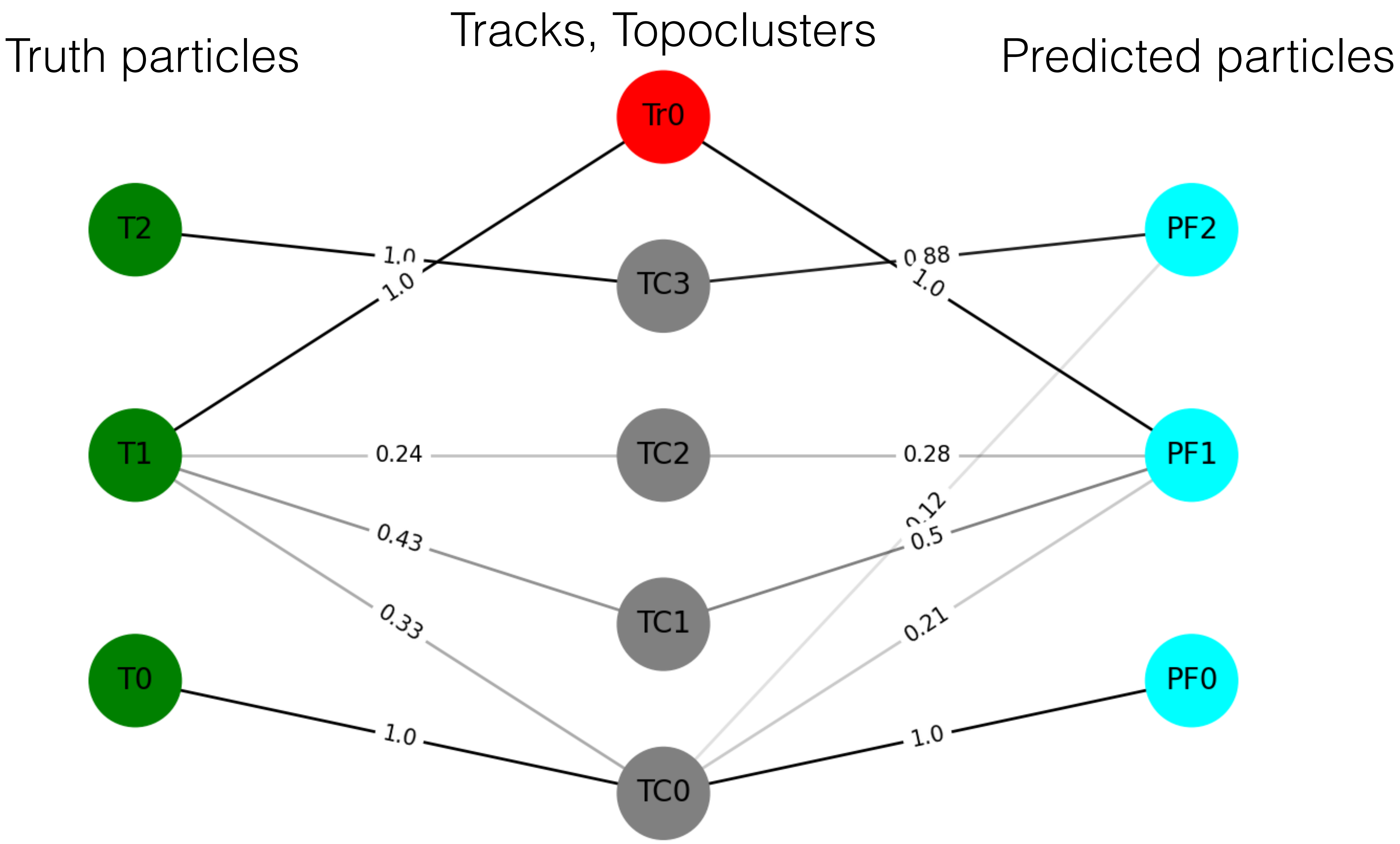

- Energy conservation is enforced in the prior

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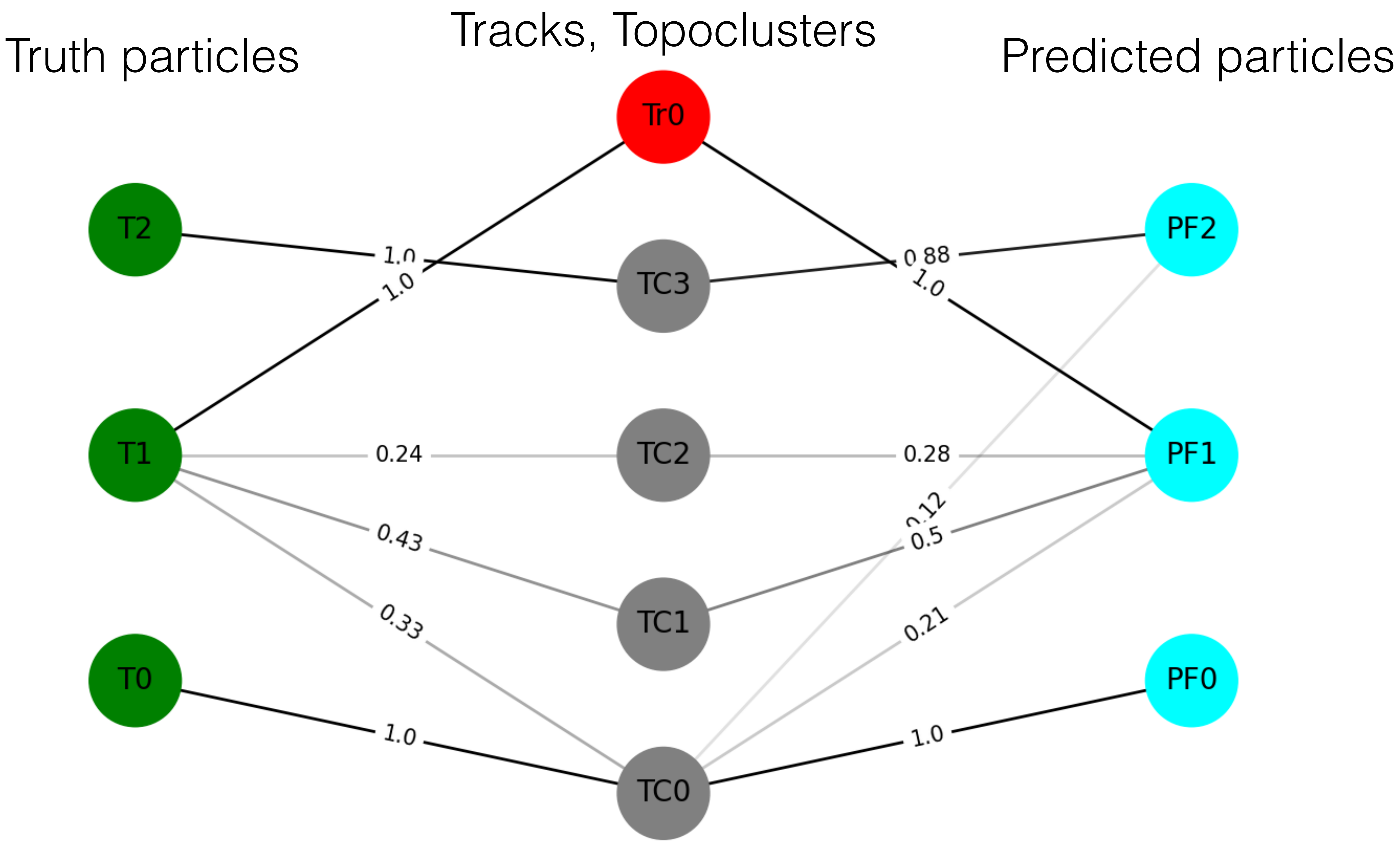

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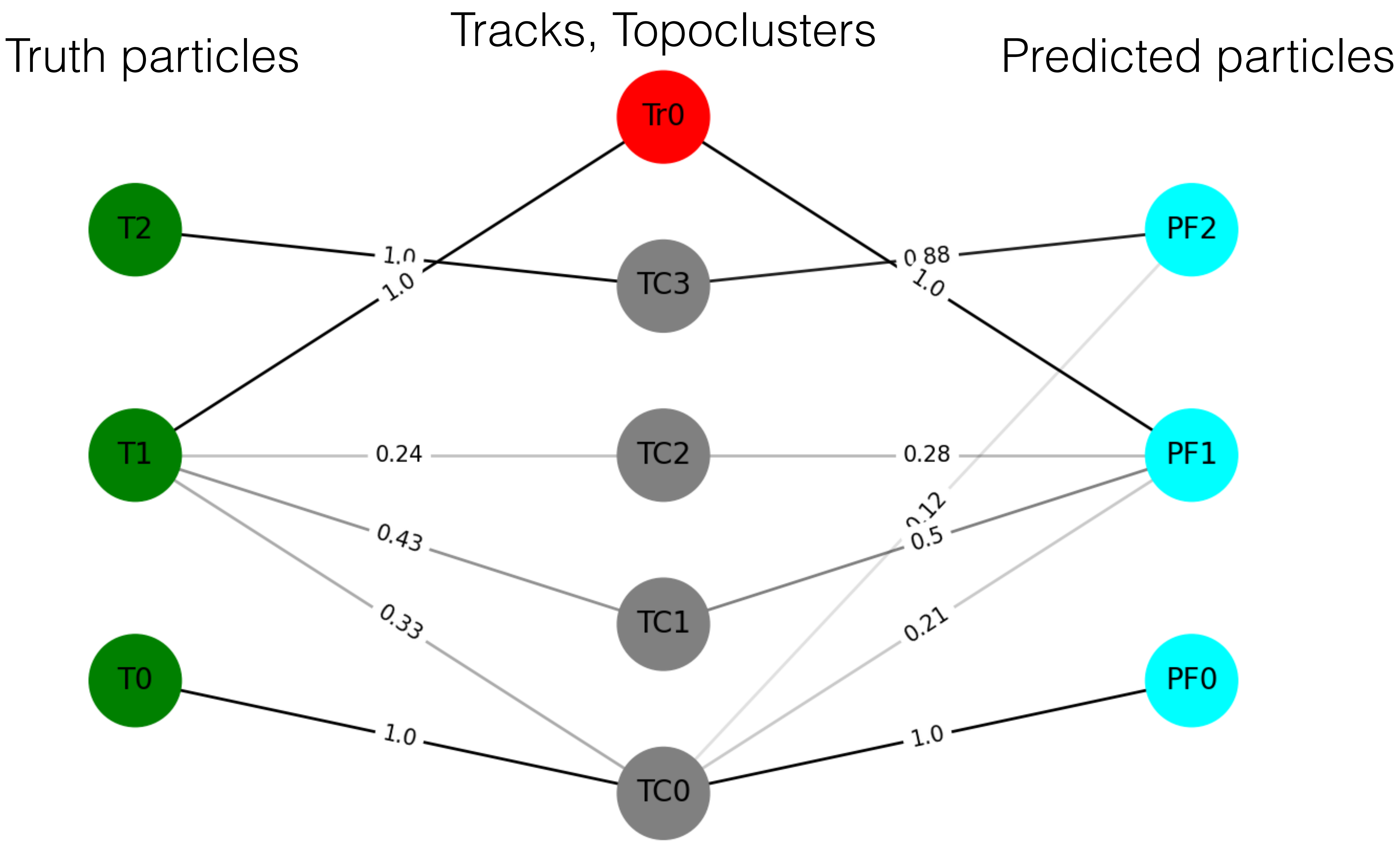

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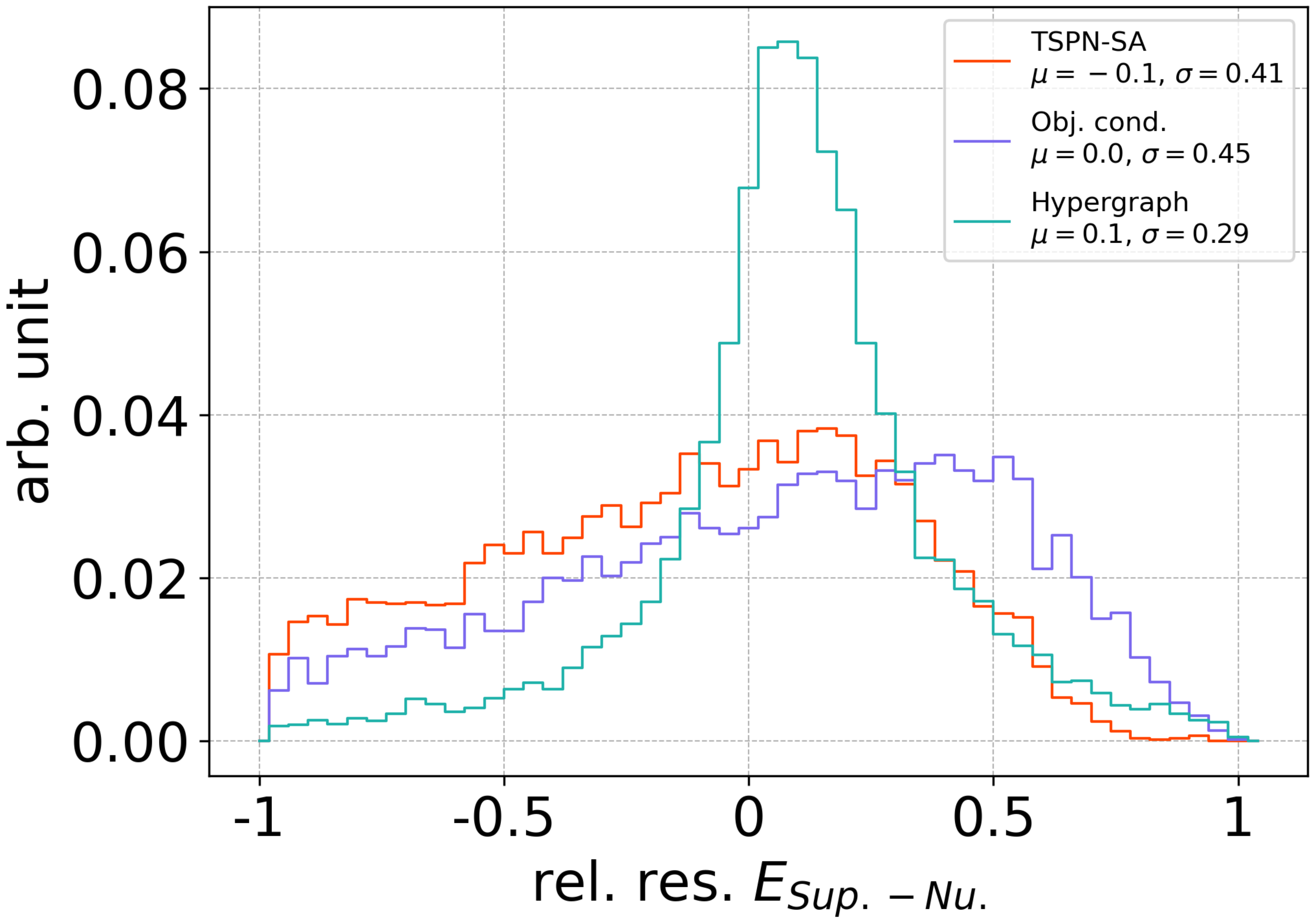

Interpretability - fakes and inefficiency

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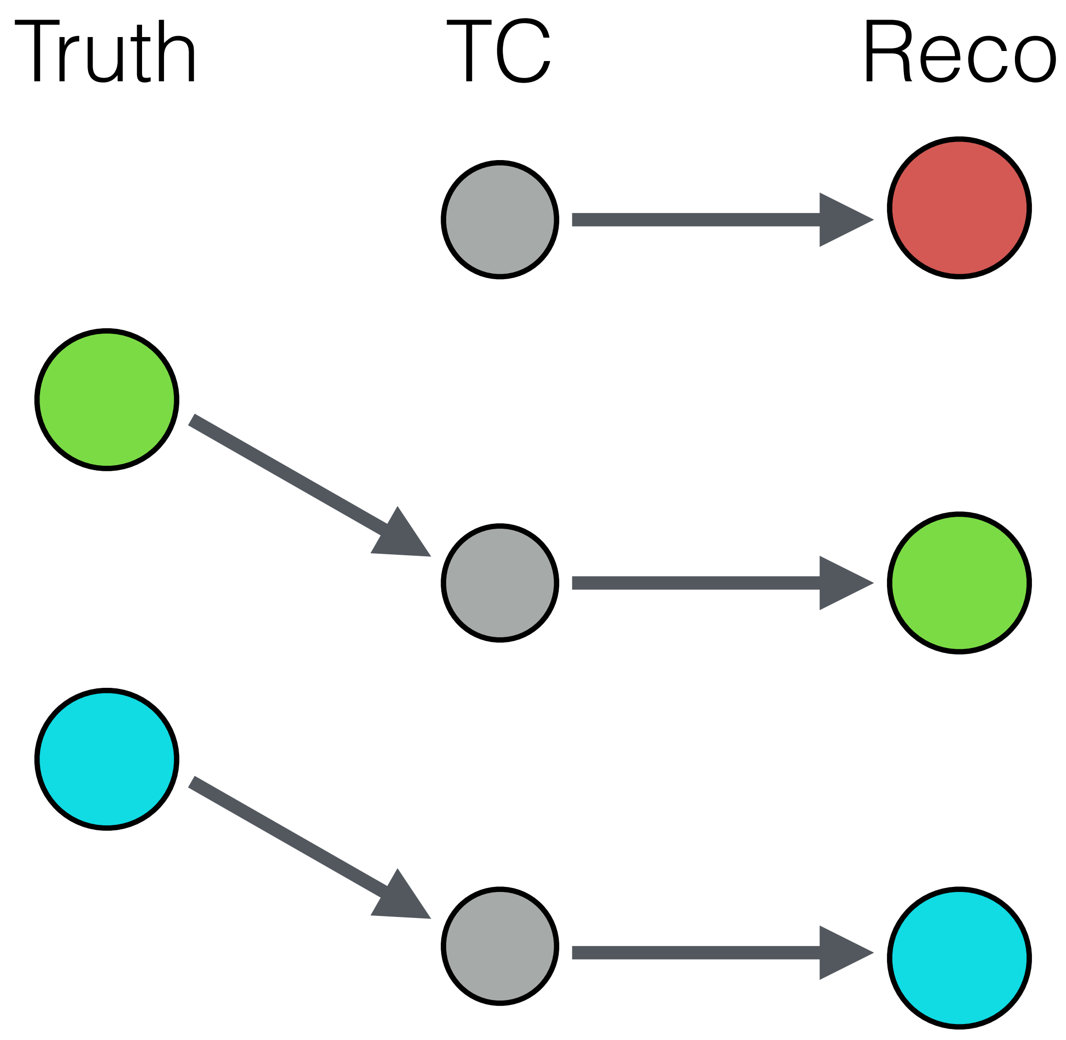
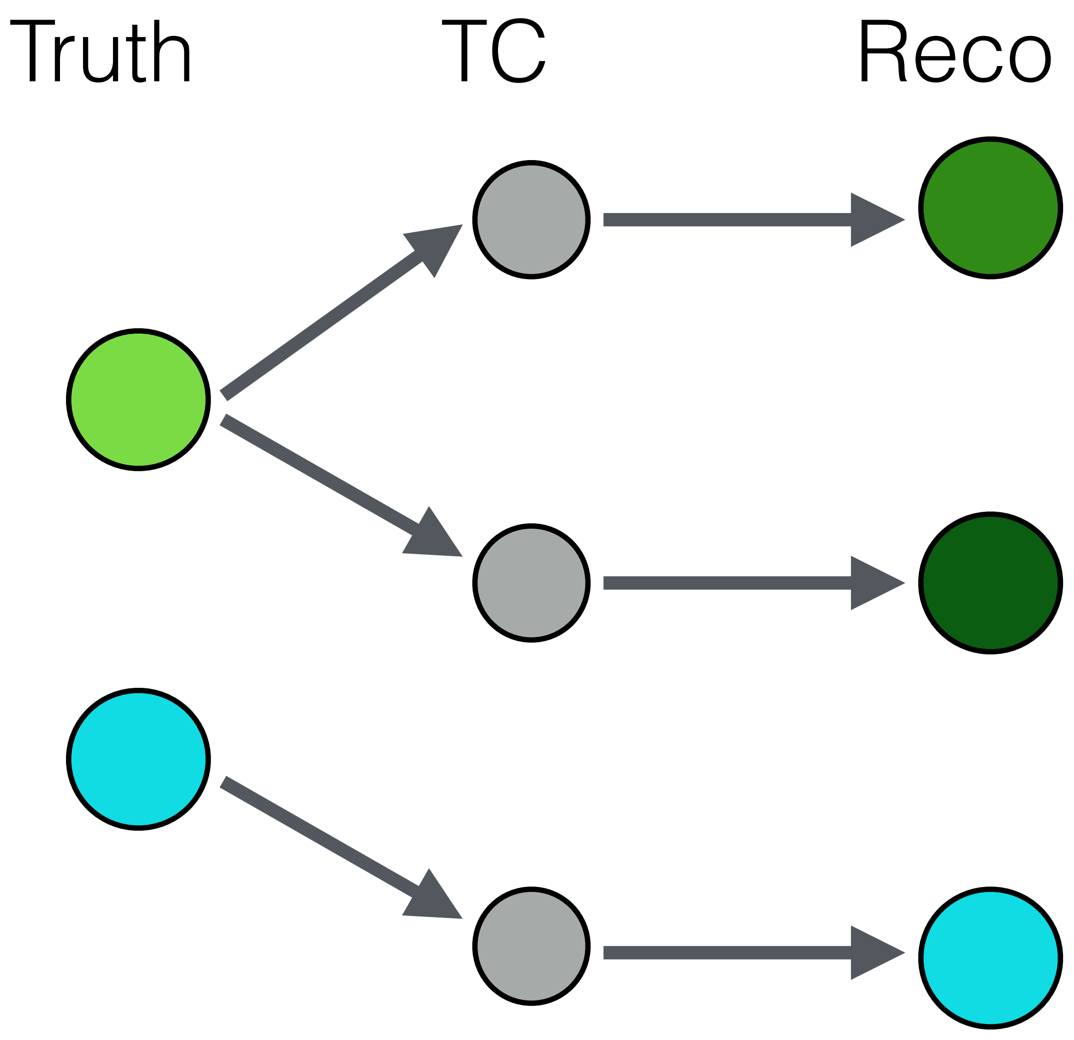


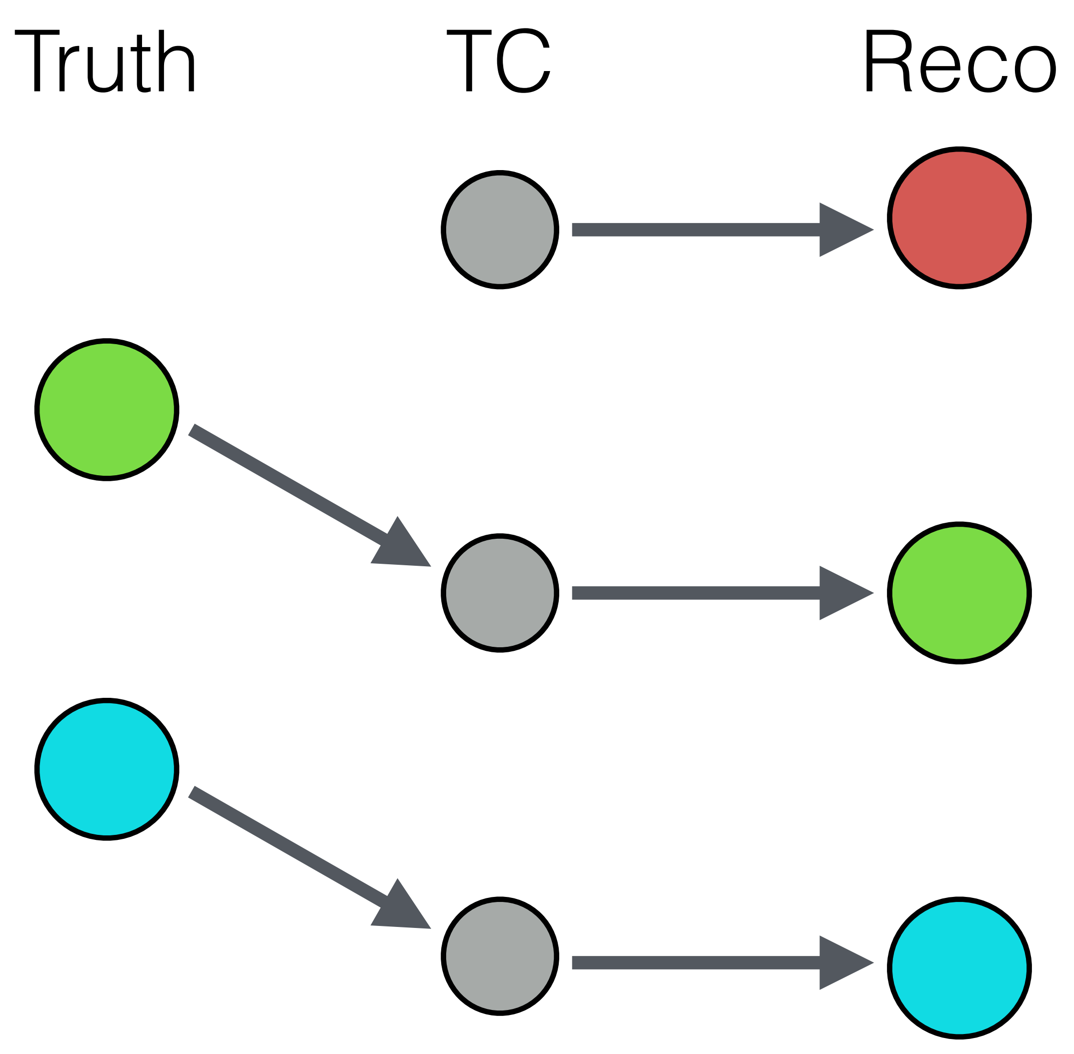
TC from pure noise



Multiple TC
(far away from each other)
from the same particle

Fakes

Interpretability - fakes and inefficiency



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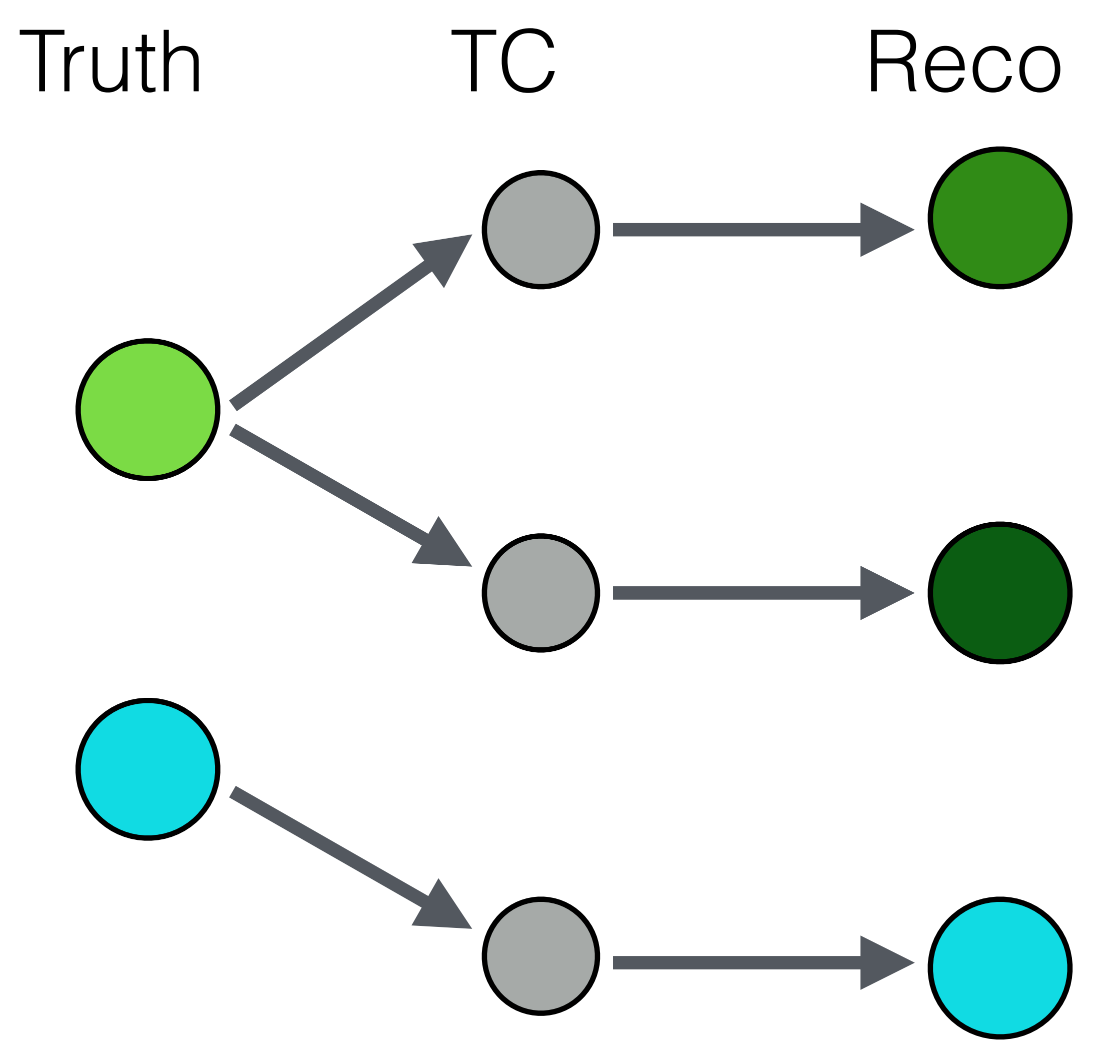

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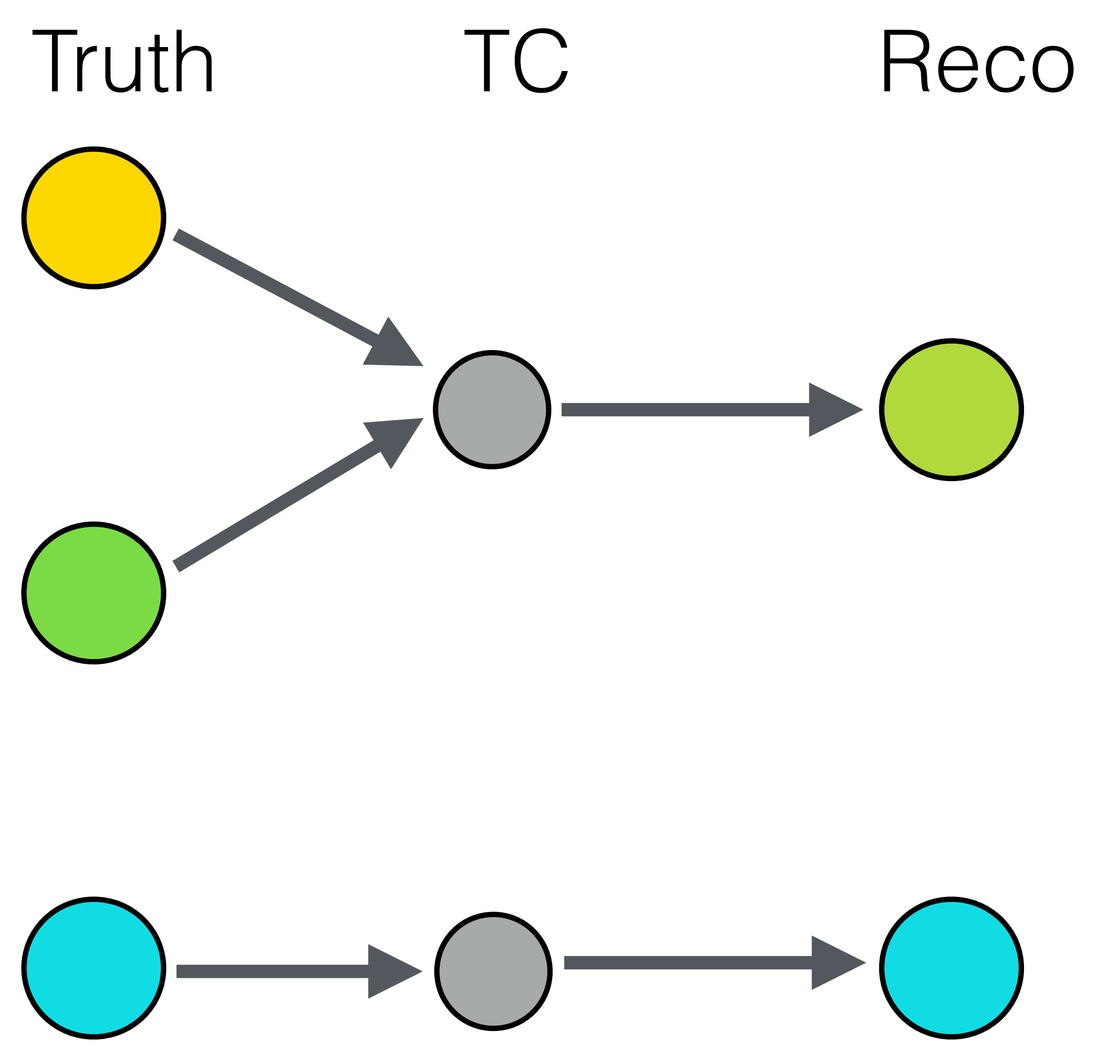


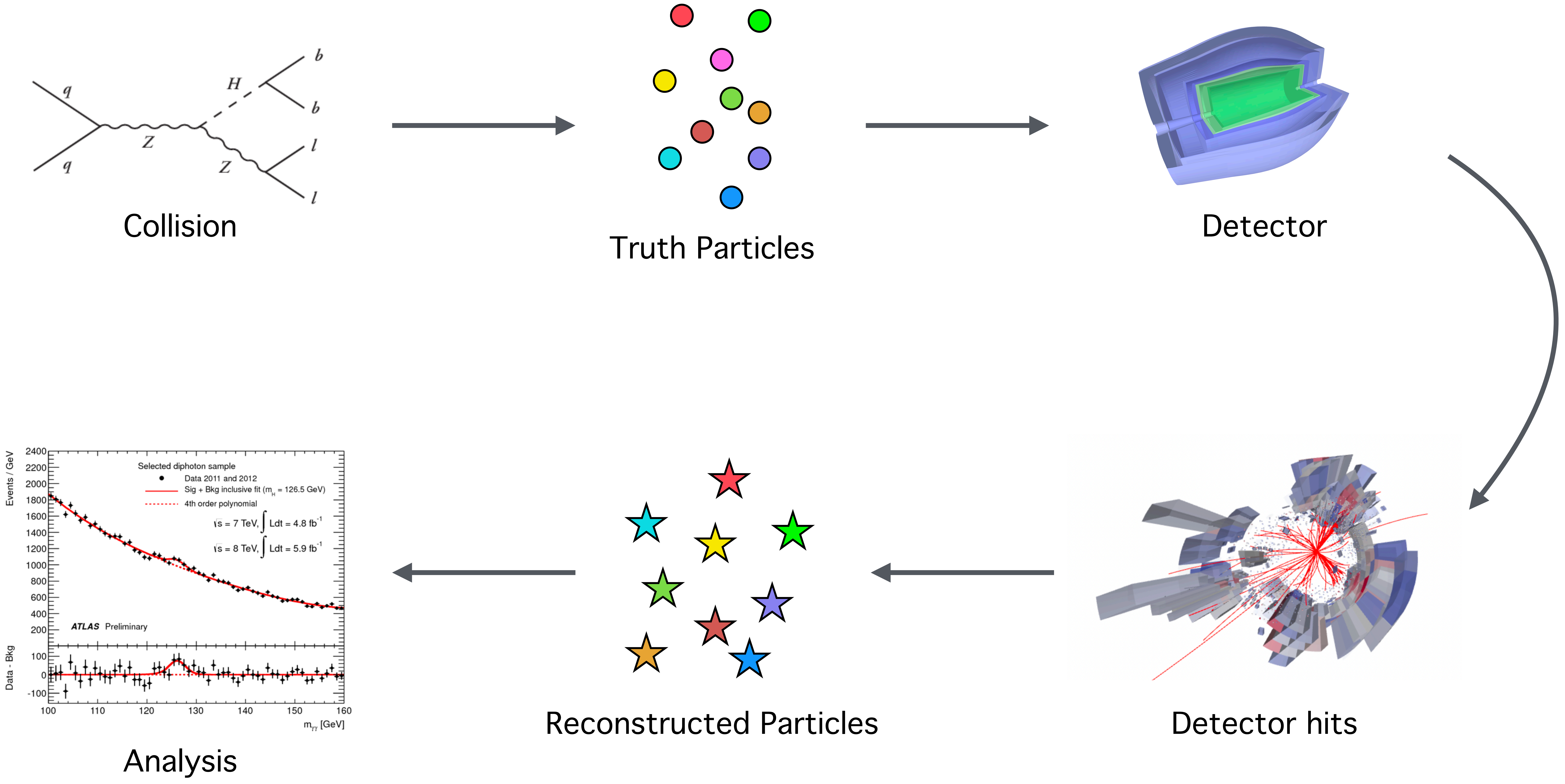
Inefficiency

What’s next?

- Paper on the way…
- There is still a lot to explore….
- Single jet → Full event
  - Train on full event (option 1)
  - Or make clusters from TC and tracks, and then run the current model in each cluster (option 2)
- Pileup?

New problem…

New problem: Time is expensive!



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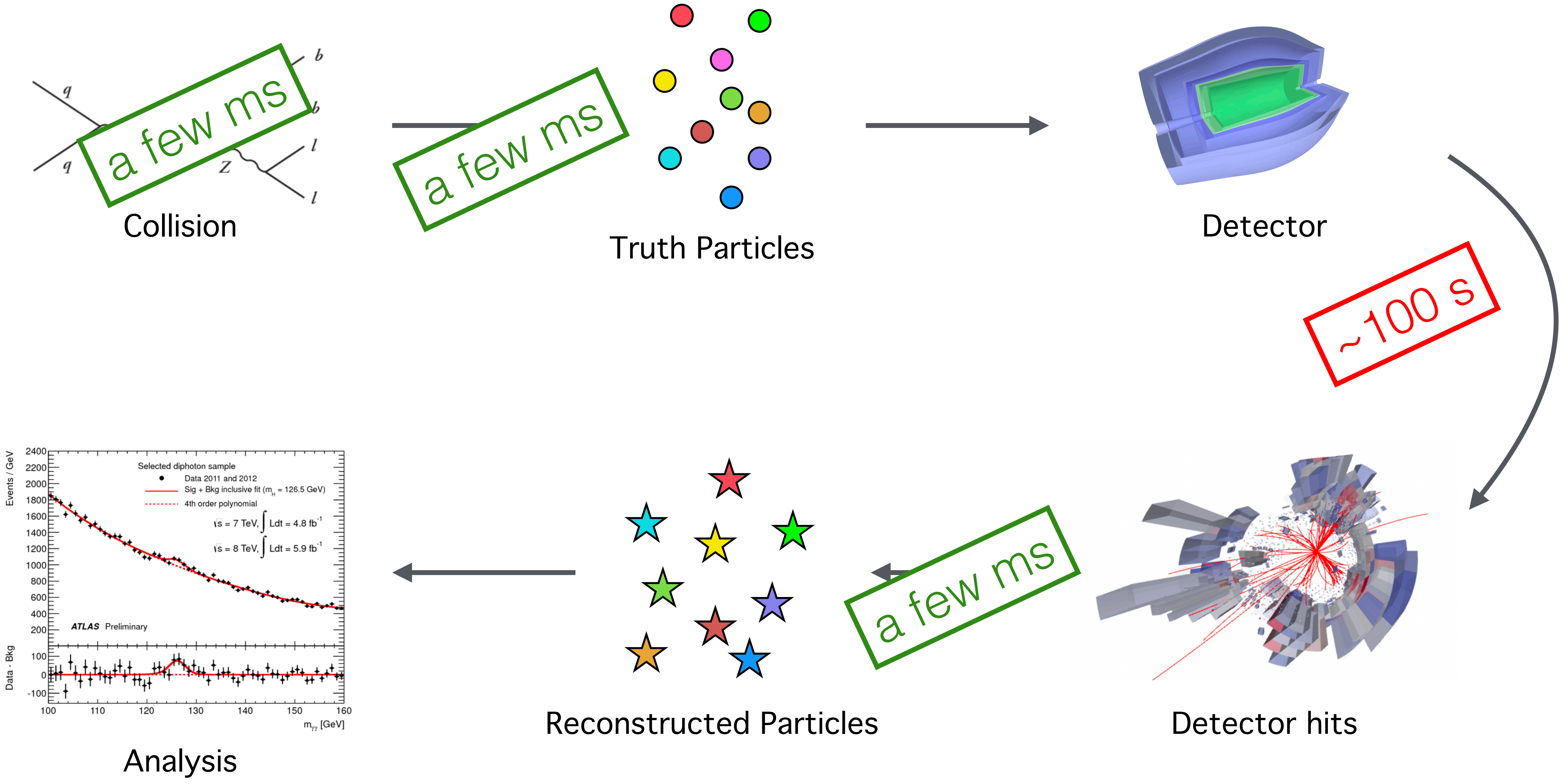

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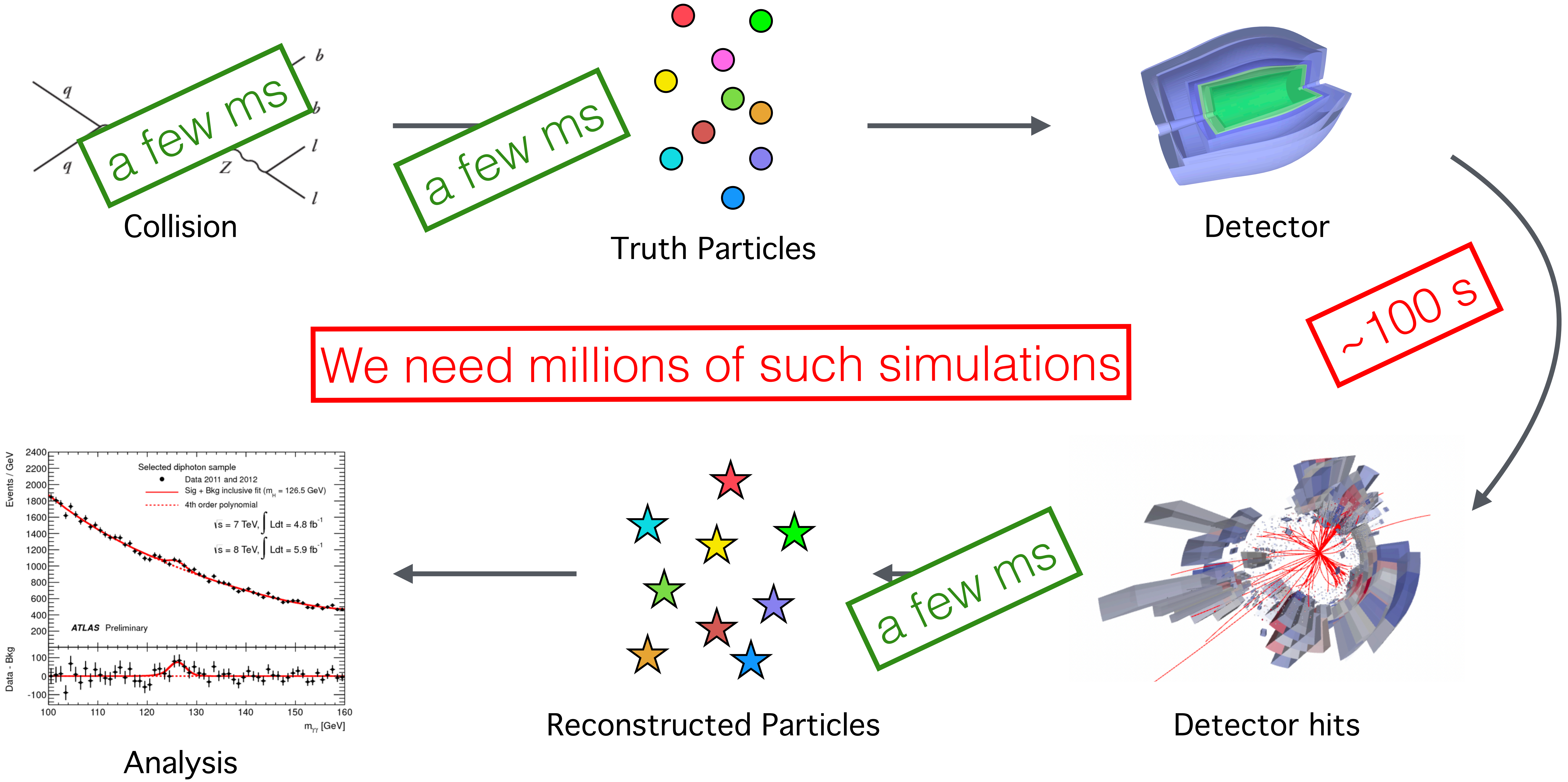
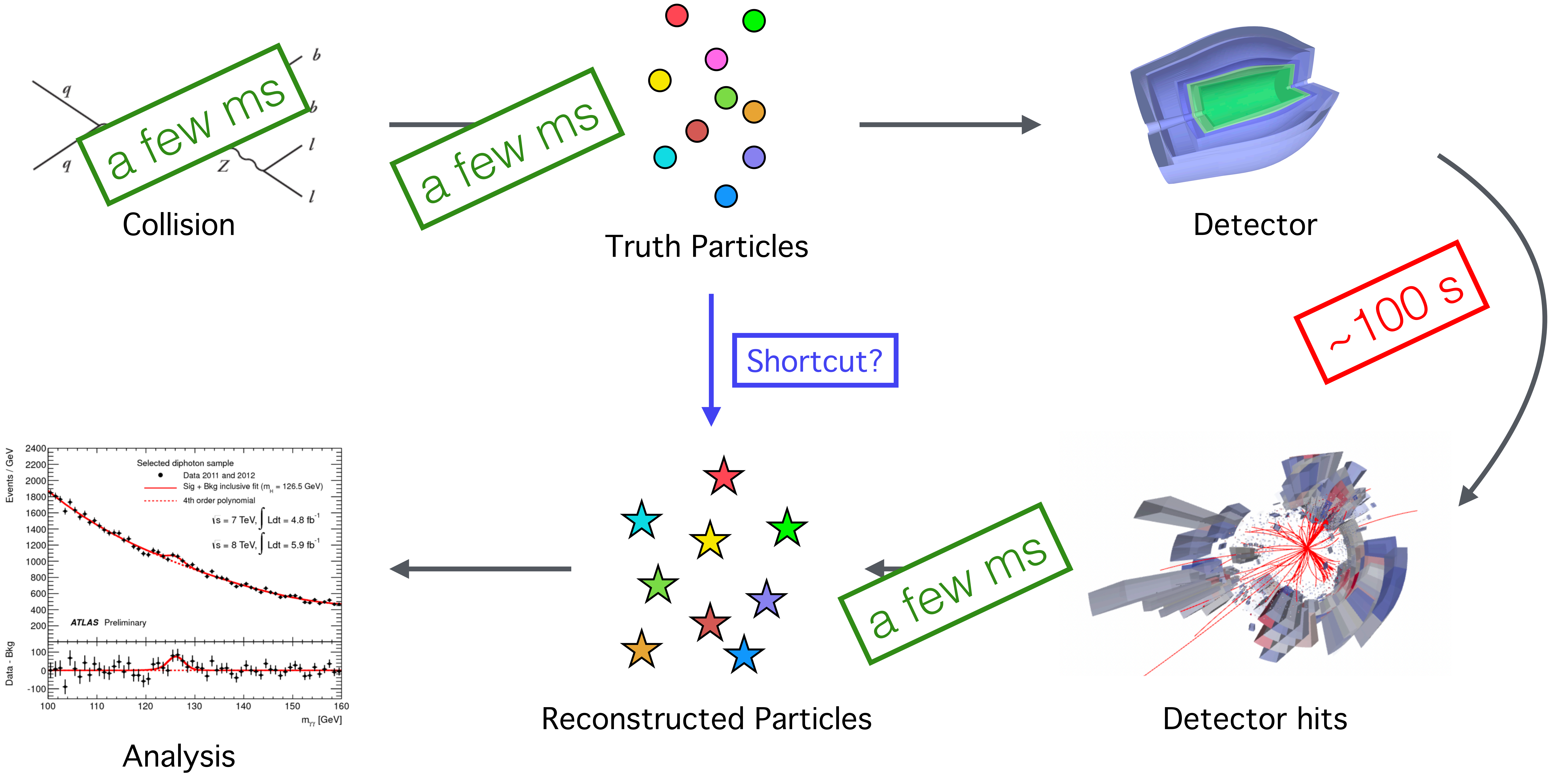
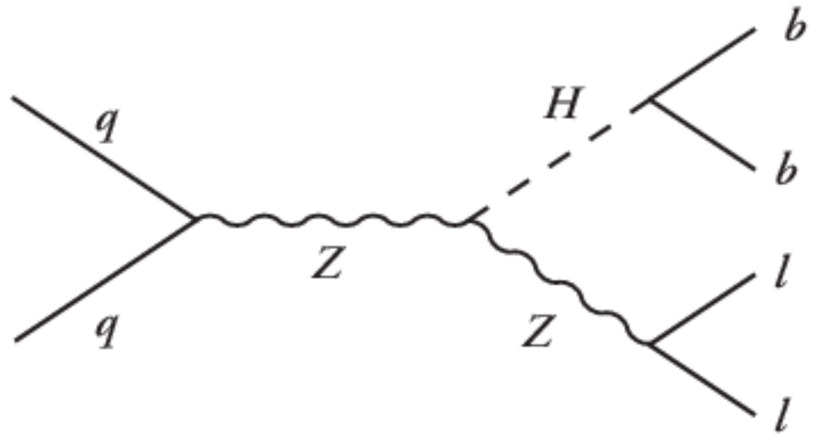


Shortcut?



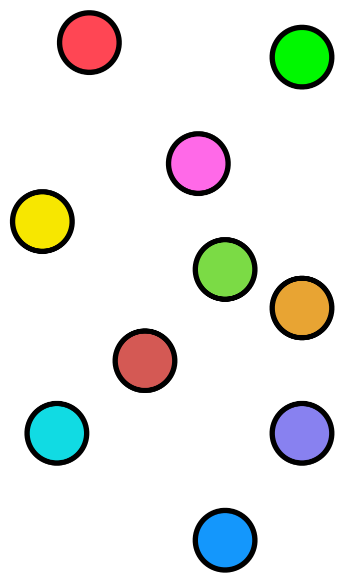
q
q
b
b
Z
l
l
a few ms
Collision
a few ms
Truth Particles
Detector
~100 s
Shortcut?
Detector hits
a few ms
Reconstructed Particles
Selected diphoton sample
Data 2011 and 2012
Sig + Bkg inclusive fit (m_H = 126.5 GeV)
4th order polynomial
$\sqrt{s}$ = 7 TeV, $\int$ Ldt = 4.8 fb^{-1}
$\sqrt{s}$ = 8 TeV, $\int$ Ldt = 5.9 fb^{-1}
ATLAS Preliminary
Events / GeV
Data - Bkg
$m_{\gamma\gamma}$ [GeV]
Analysis

Shortcut?

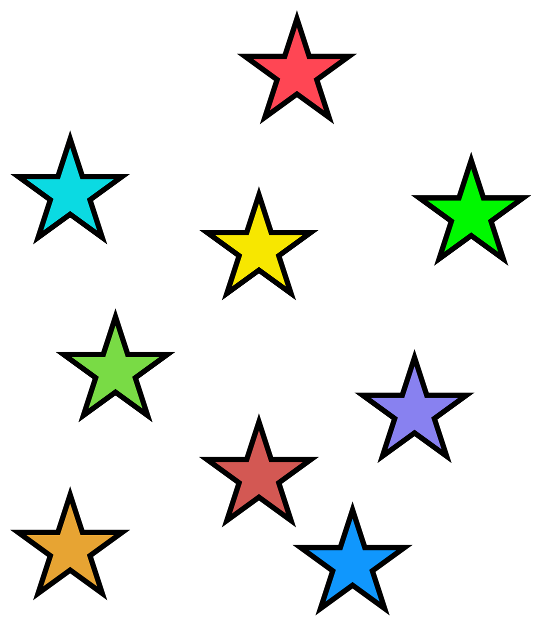


Collision

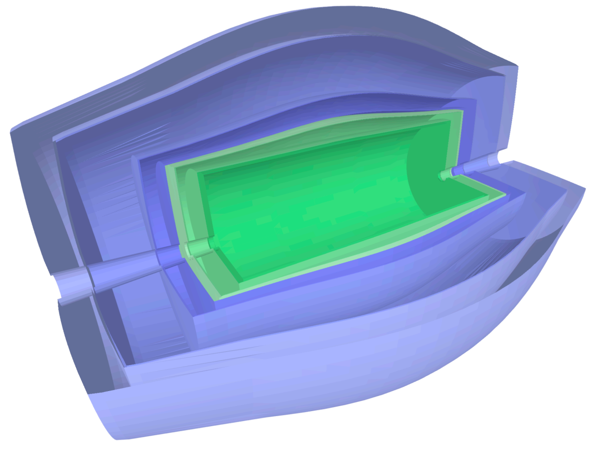
FastSim



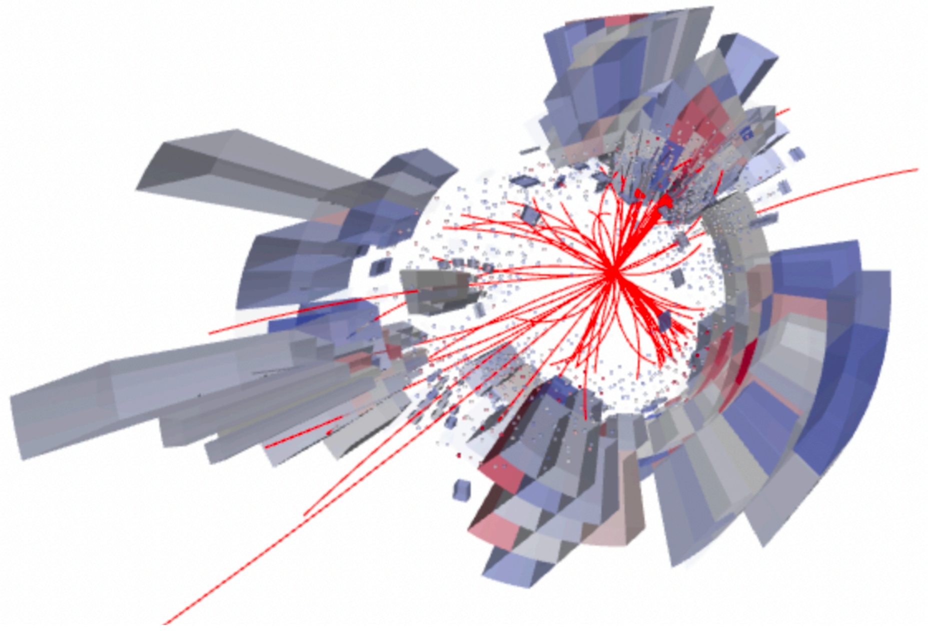
Truth Particles



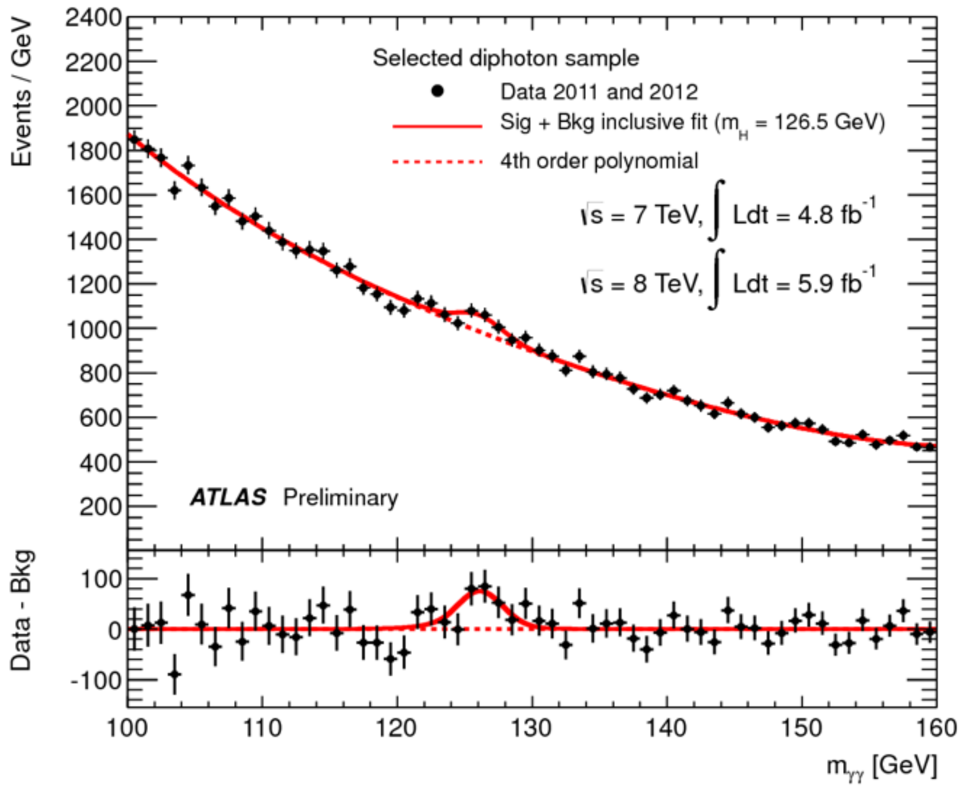
Reconstructed Particles



Detector

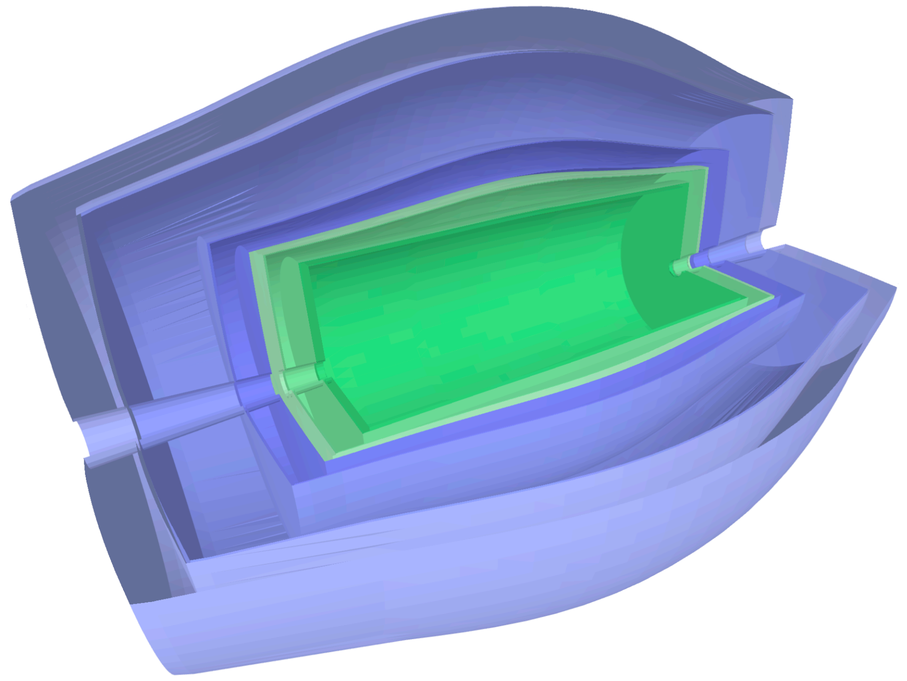


Detector hits



Analysis

But,...



Detectors are noisy and stochastic

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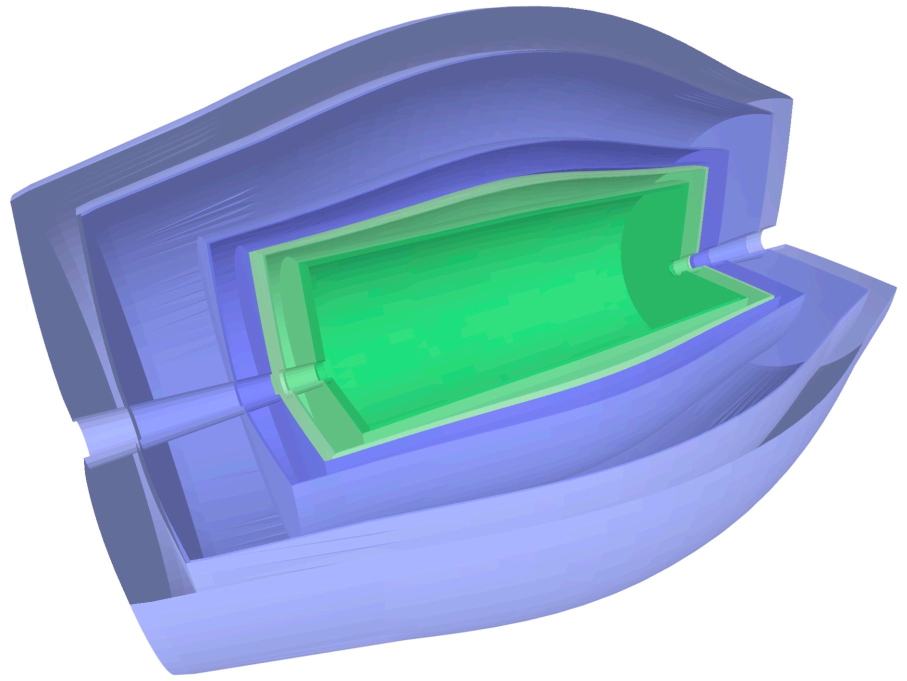

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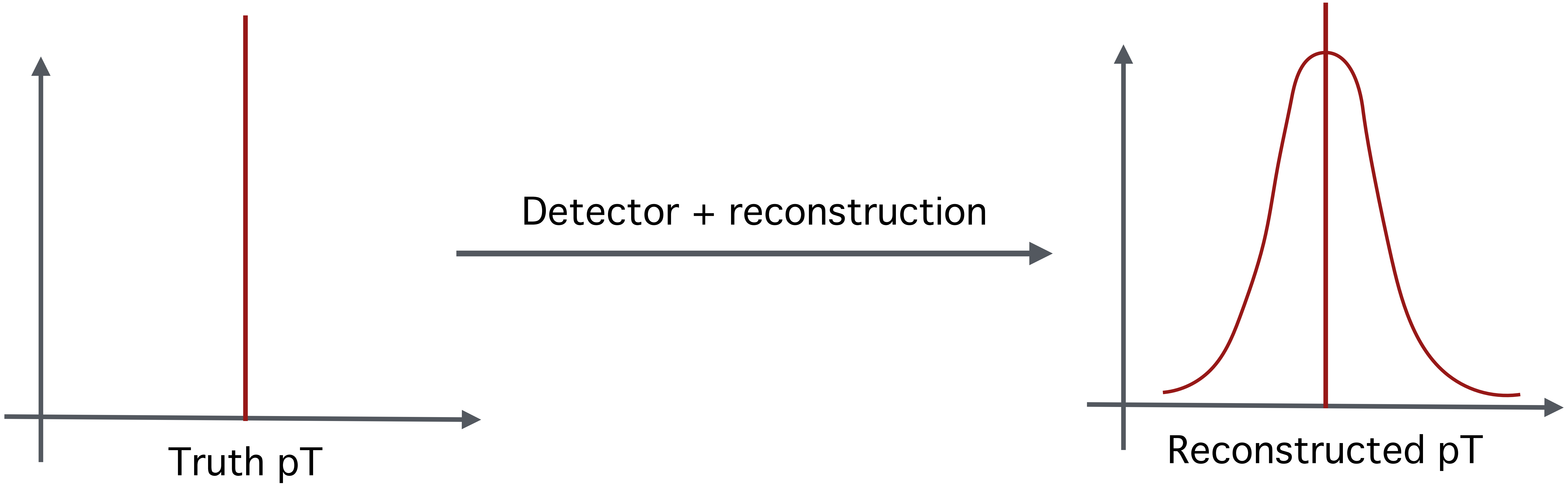

Solution? The replicas

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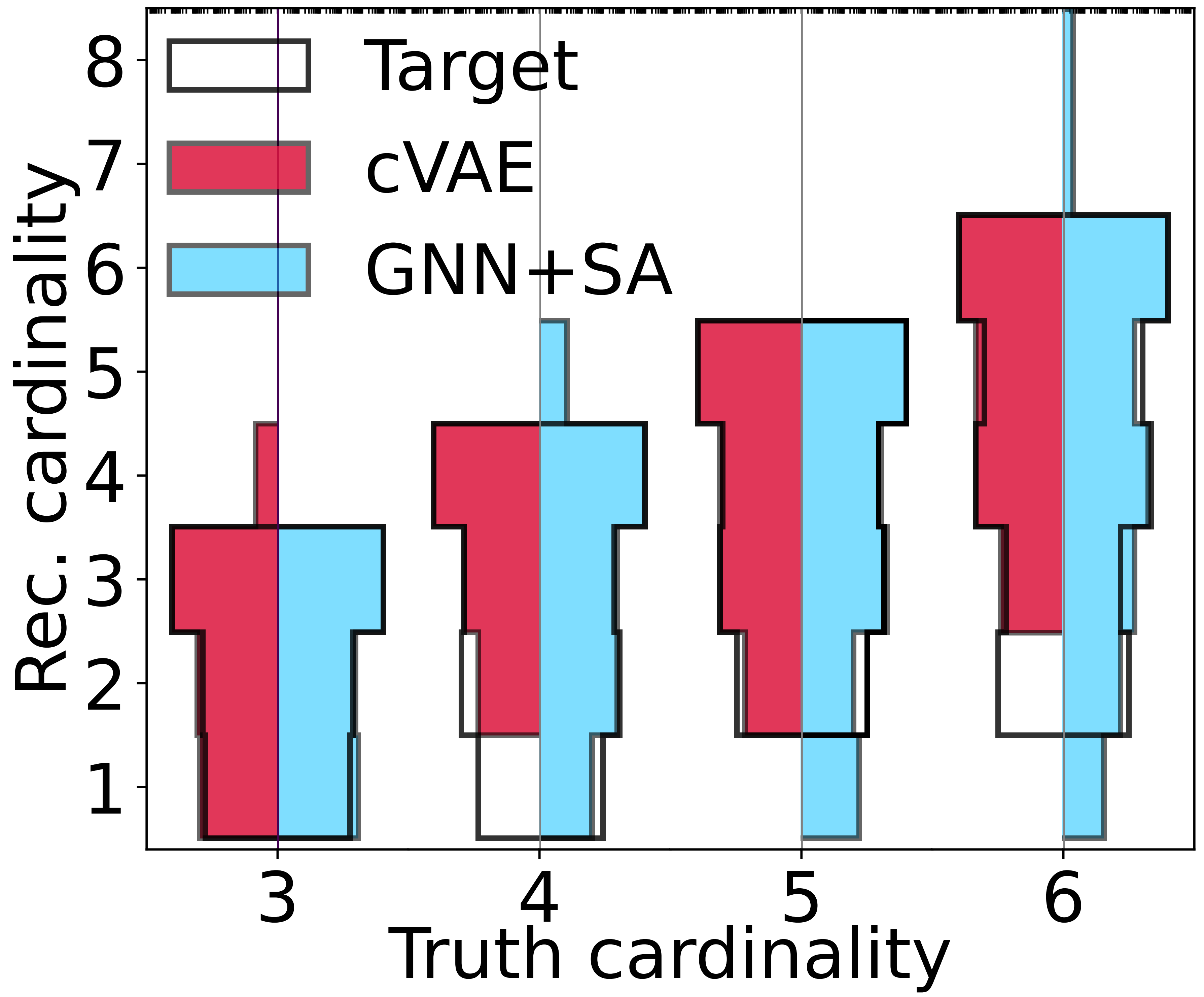
- Loss
  - Batch loss
  - Explicitly try to minimize the distribution

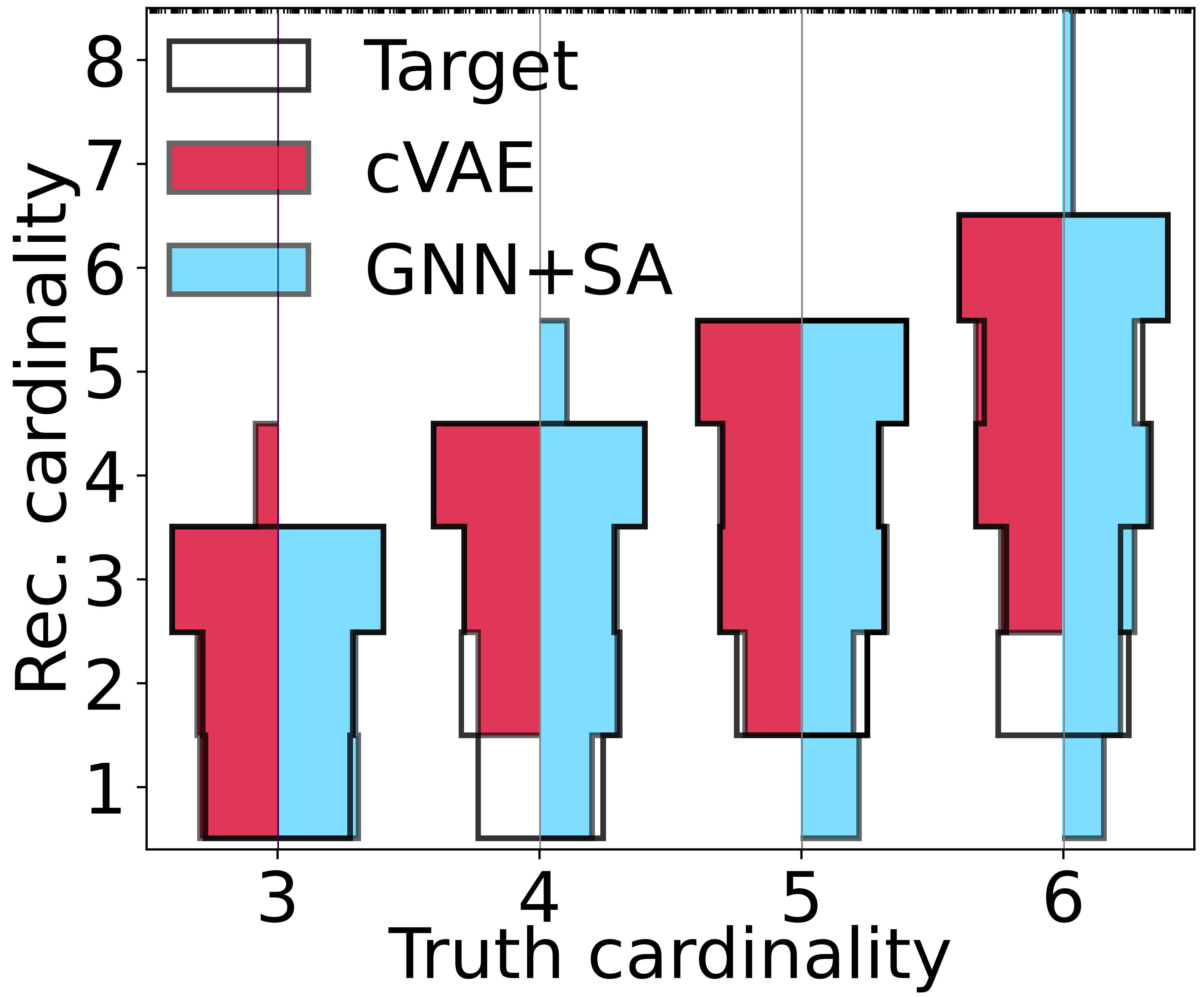
Dataset

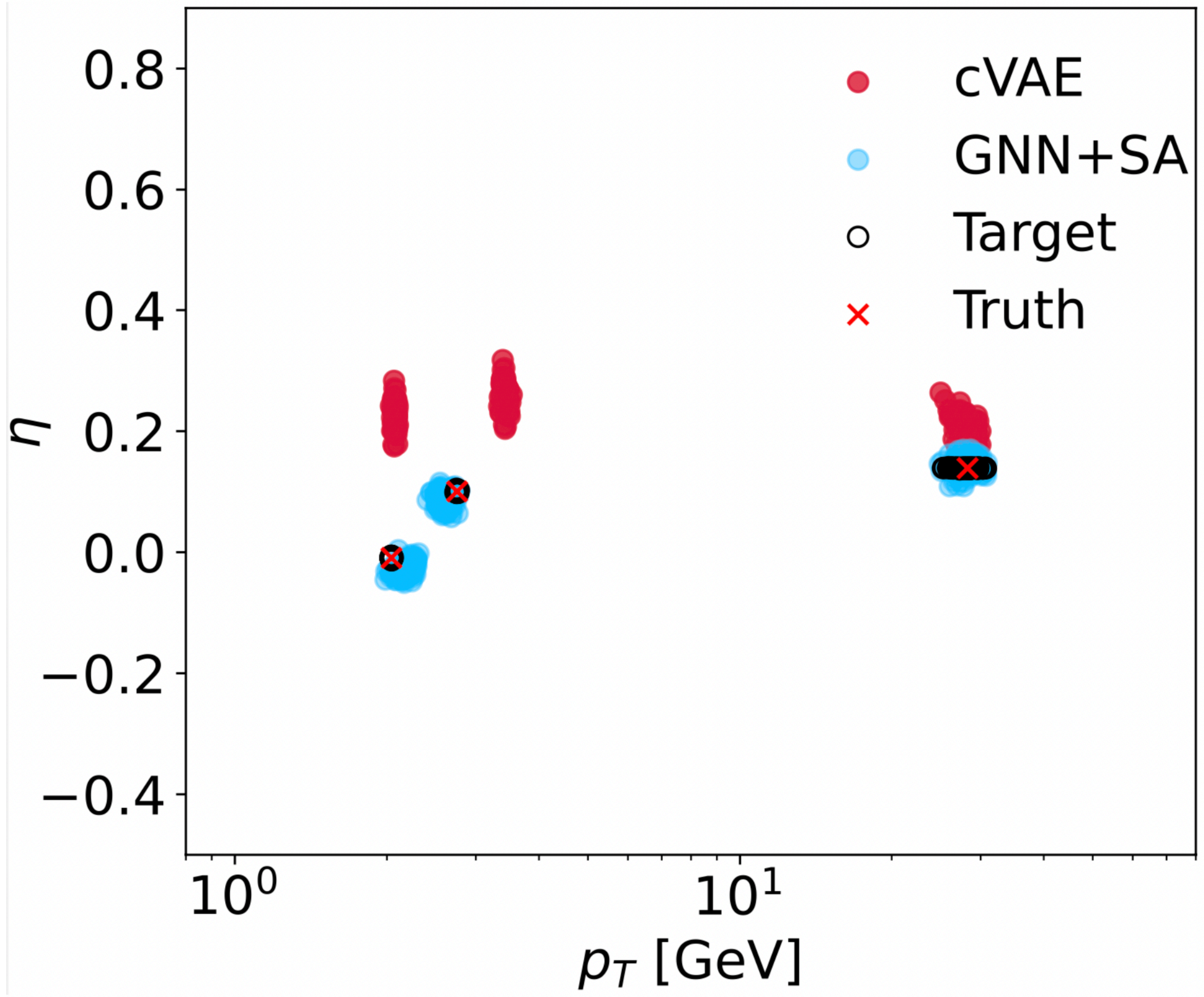
- Same as before
- But only with charged particles

Performance

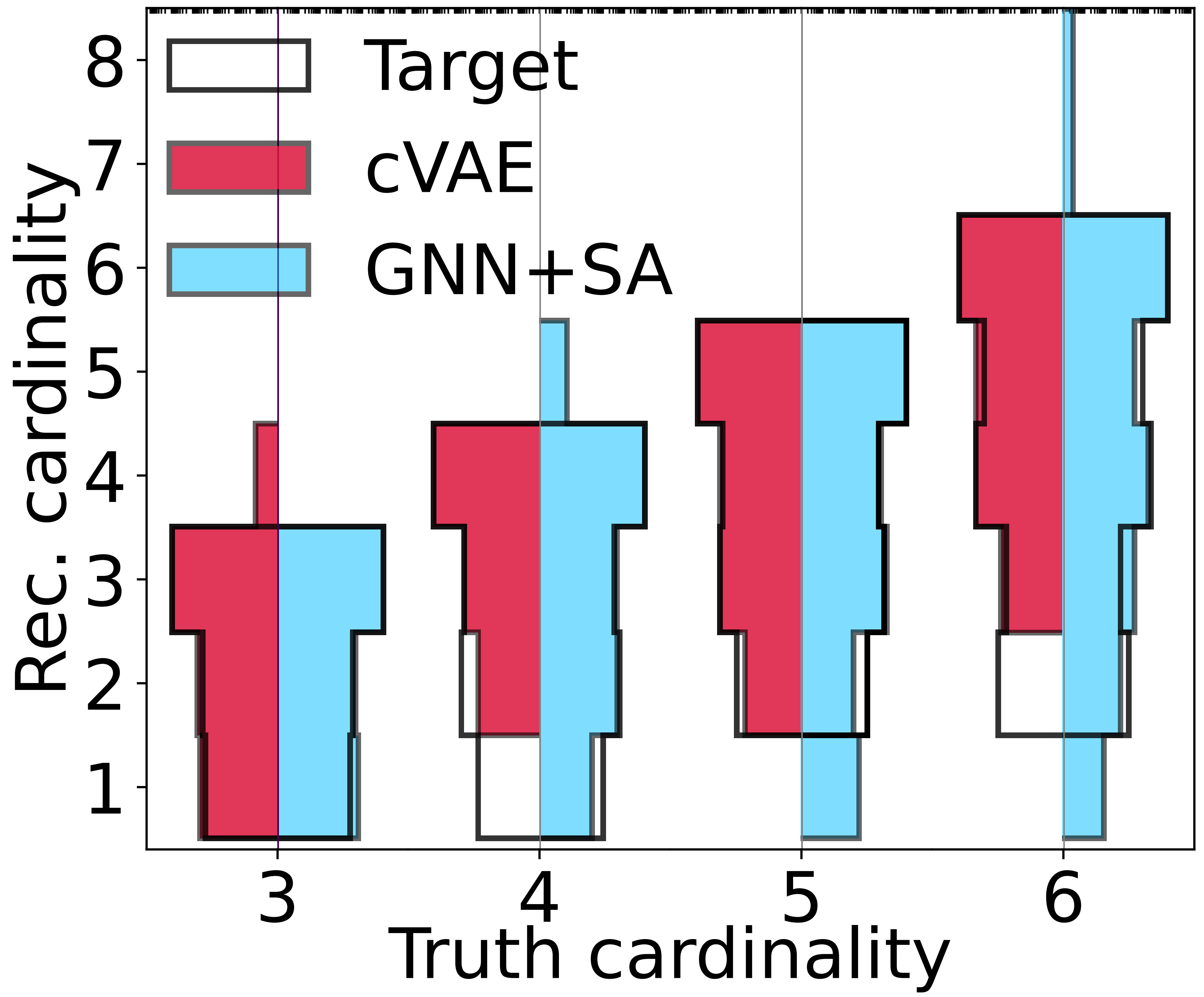


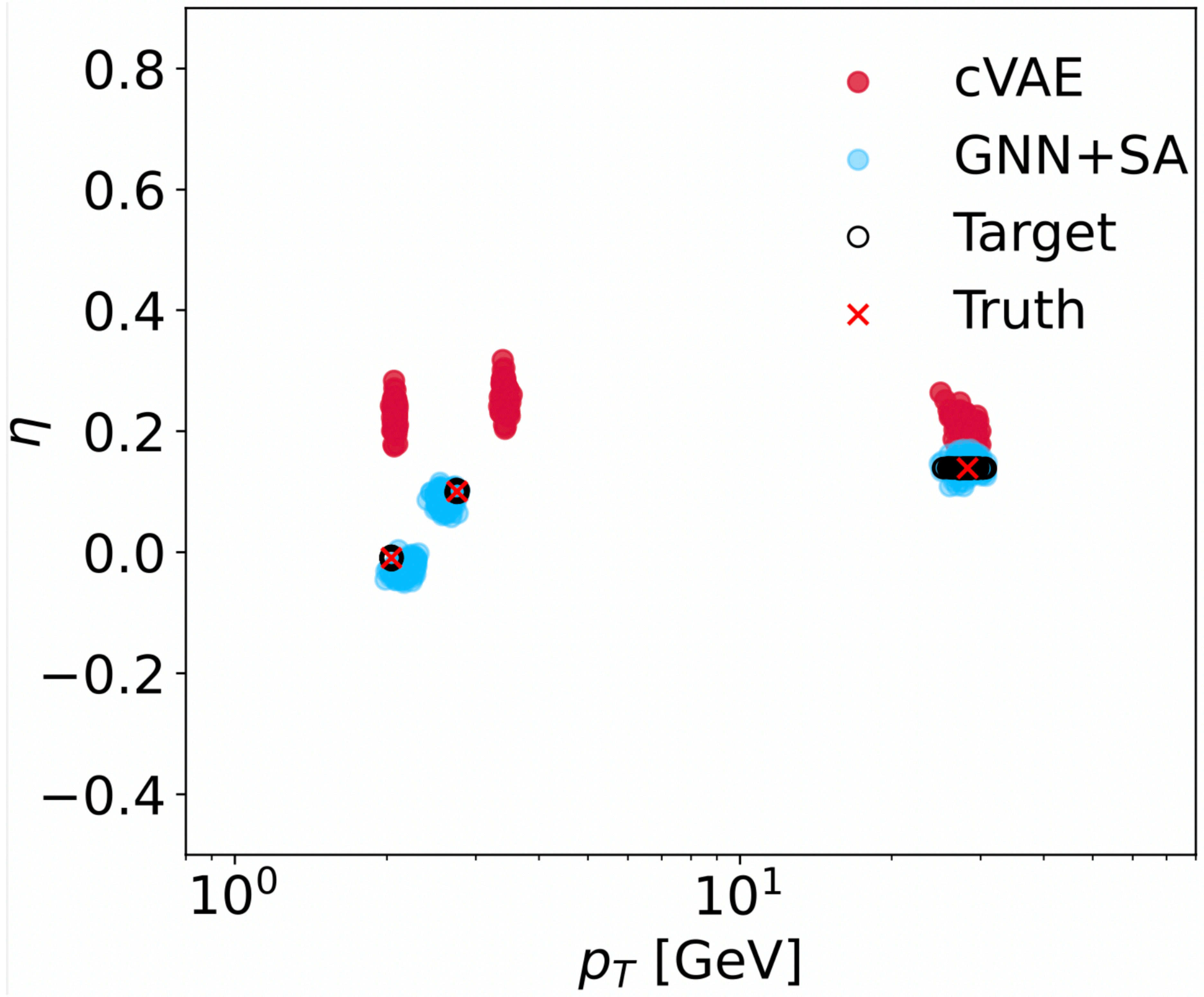
Performance





Performance





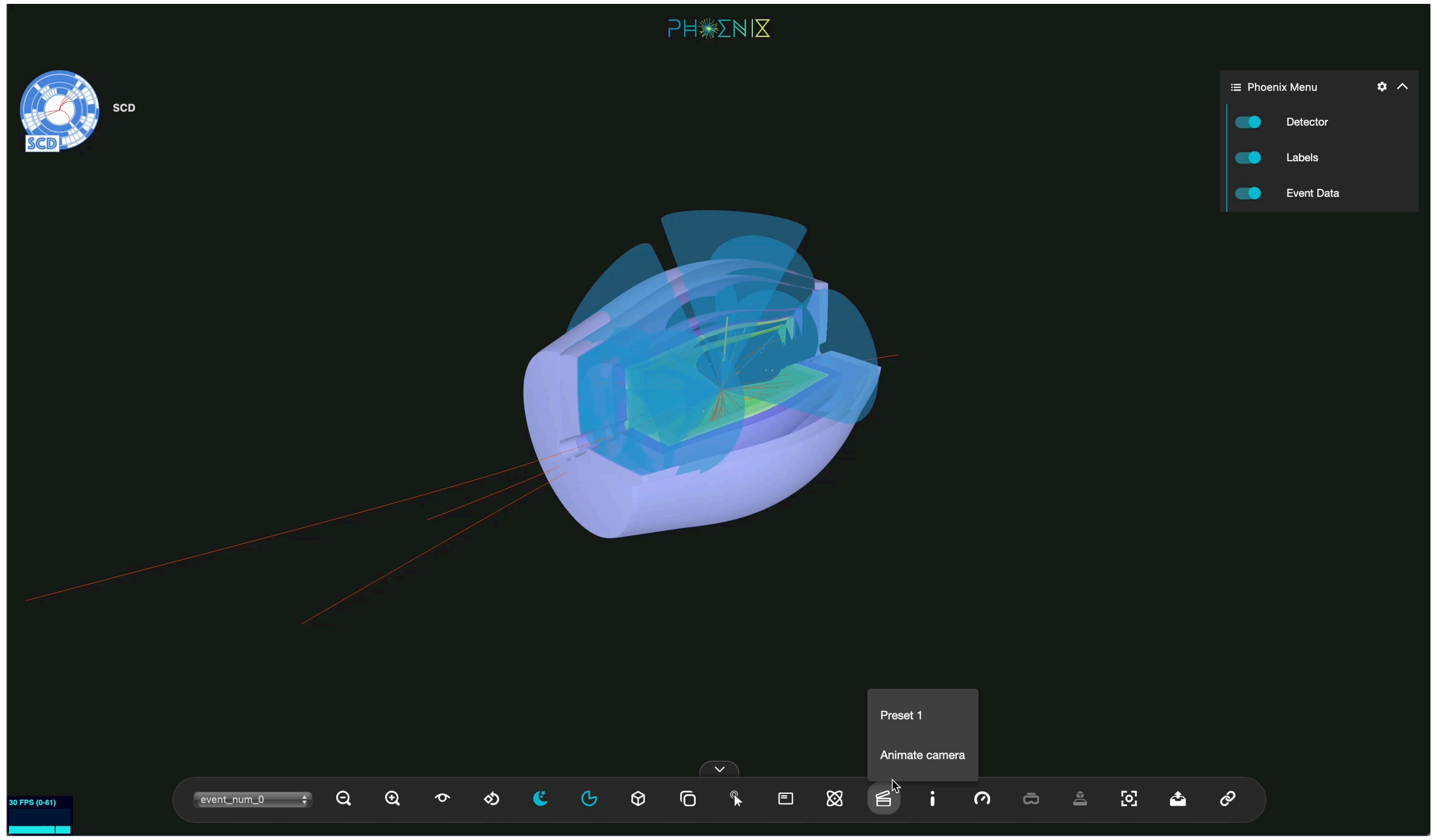
Still far from perfect, but it's a good start!

https://arxiv.org/pdf/2211.06406.pdf

The SCD

Simplified Cylindrical Detector (SCD)

- Open sourced, Geant4 based calorimeter simulation
- Fully configurable with json files (default setup mimics ATLAS)
- Current detector simulations are either
  - Very accurate but internal and proprietary (CMS, ATLAS)
  - Open but much simplified (Delphes)
- SCD can be a solution
- Expected to be public very soon. Stay tuned!



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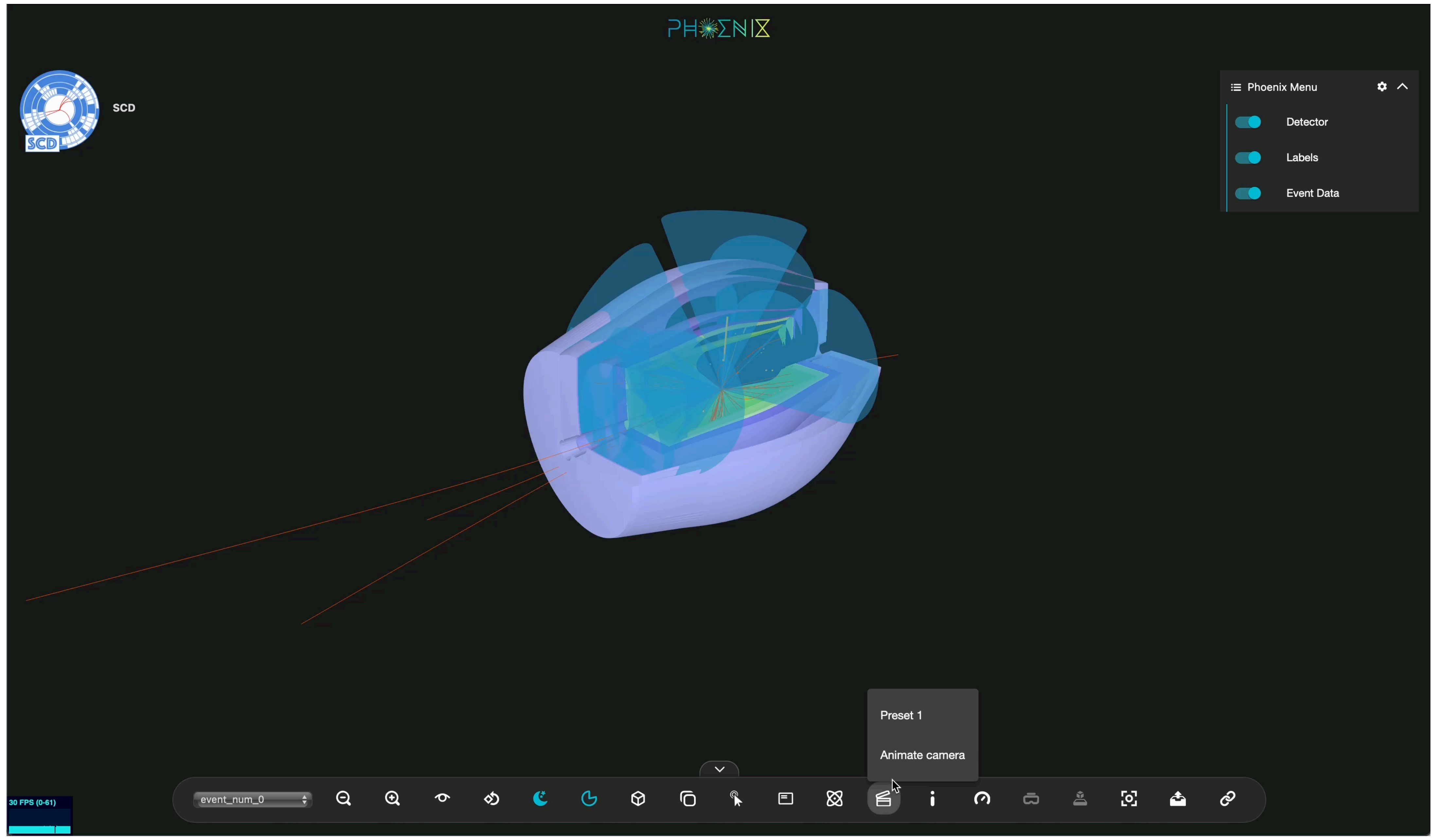

The faces behind all the work


Kyle Cranmer


Francesco A. Di Bello


Etienne Dreyer


Sanmay Ganguly


Anton C. Gorbulin


Eilam Gross


Lukas Heinrich


Anna Ivina


Marumi Kado


Nilotpal Kakati


Patrick Rieck


Lorenzo Santi


Jonathan Shlomi


Nathalie Soybelman


Matteo Tusoni

Big team
with a lot of people!

Thank you