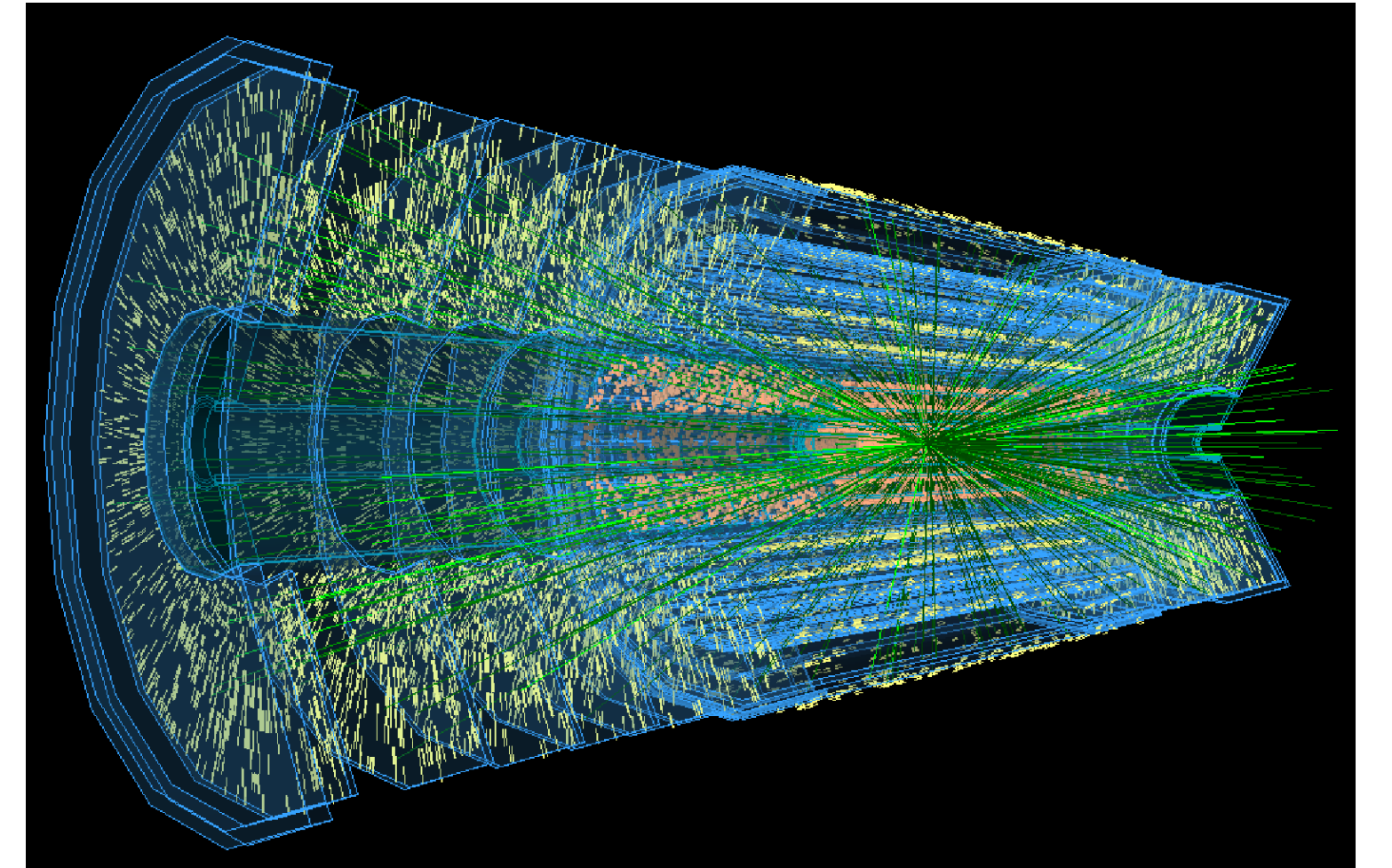


# Physics Performance of the ATLAS GNN4ITk Track Reconstruction Chain



Heberth Torres (L2I Toulouse)  
on behalf of the ATLAS Collaboration

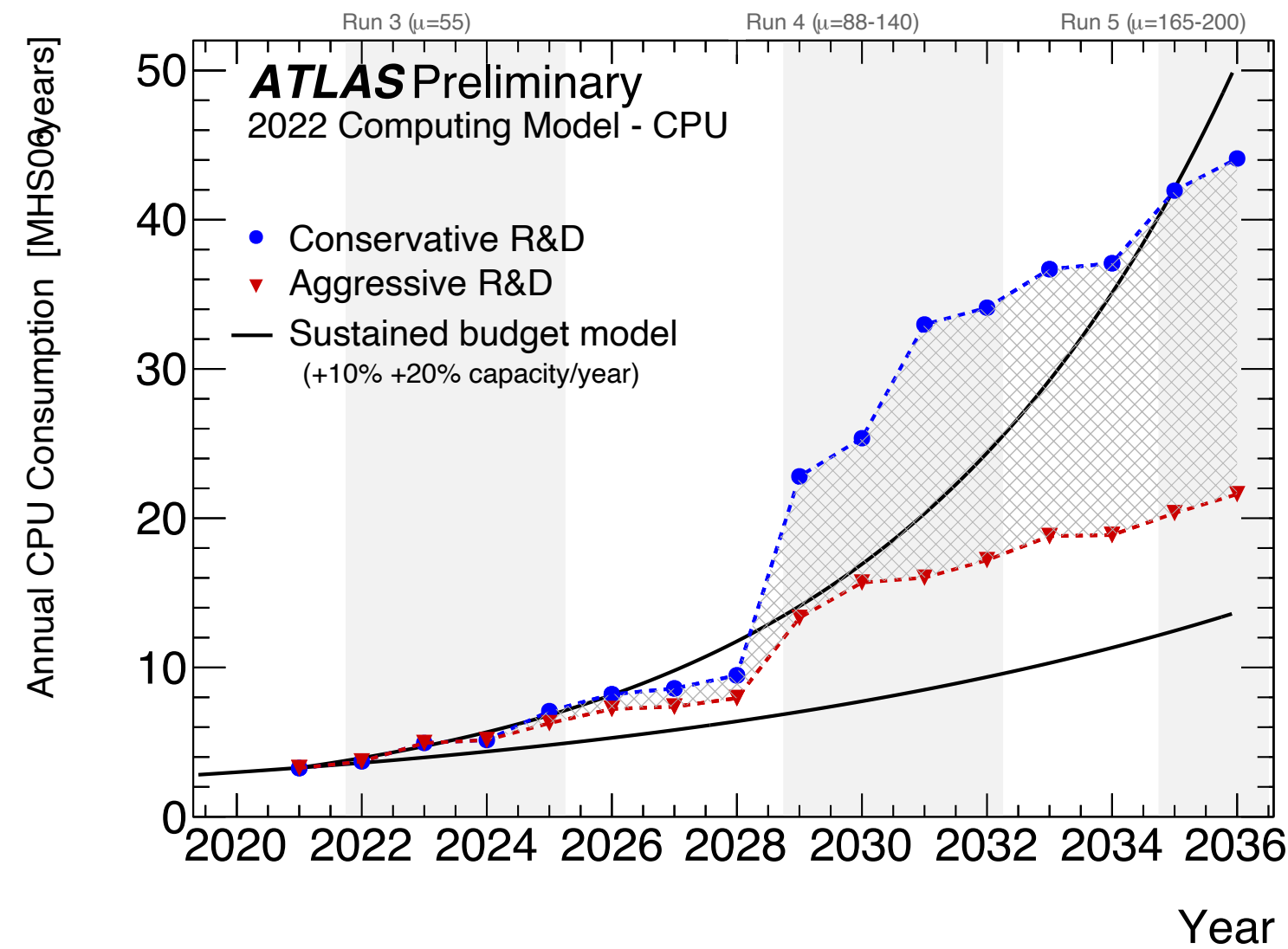
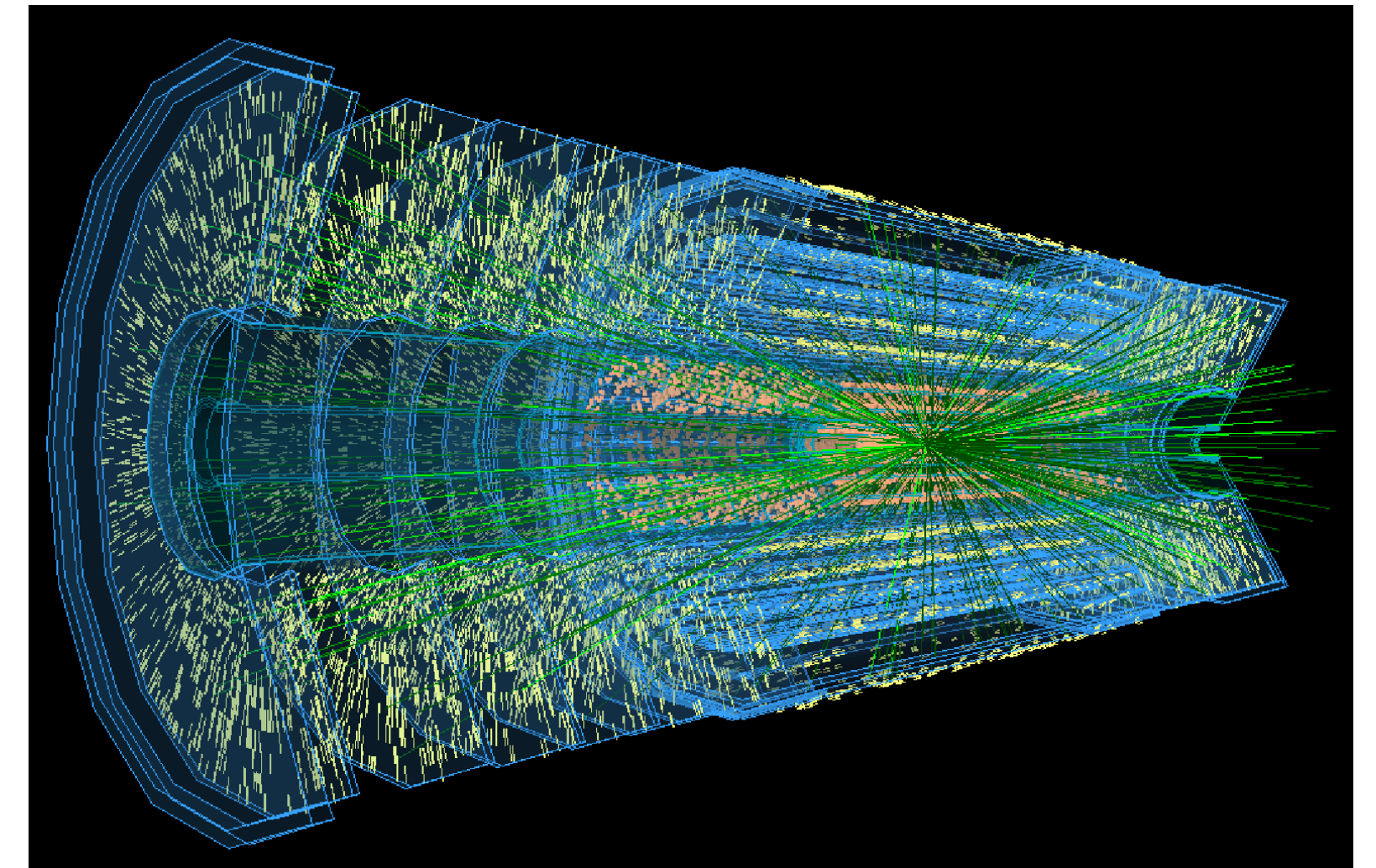
Connecting The Dots Workshop  
10/10/2023



# Introduction

## ATLAS GNN4ITk

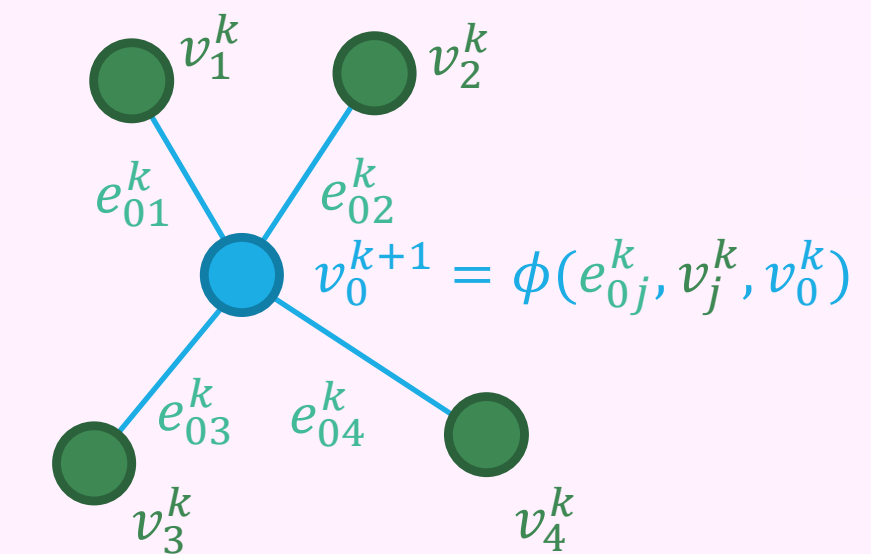
Future ATLAS Inner Tracker ITk  
for the High Luminosity LHC  
with extended coverage  $|\eta| < 4$   
expect  $10^5$  hits per event  
(200  $pp$  interaction pileup)



Projection of ATLAS compute usage shows the need for aggressive computing R&D

Graph Neural Networks GNN shown as promising solution for charged particle track reconstruction using GPUs (Exa.TrkX, L2IT, within ATLAS)

### Graph Neural Network



# Outline

- Description of the GNN4ITk tracking
- Physics performance
  - Efficiency
  - Track hit content
  - Resolution of track parameters

(ATLAS GNN4ITk plot references: May 2022, May 2023, **Oct. 2023**)

# Simulation data

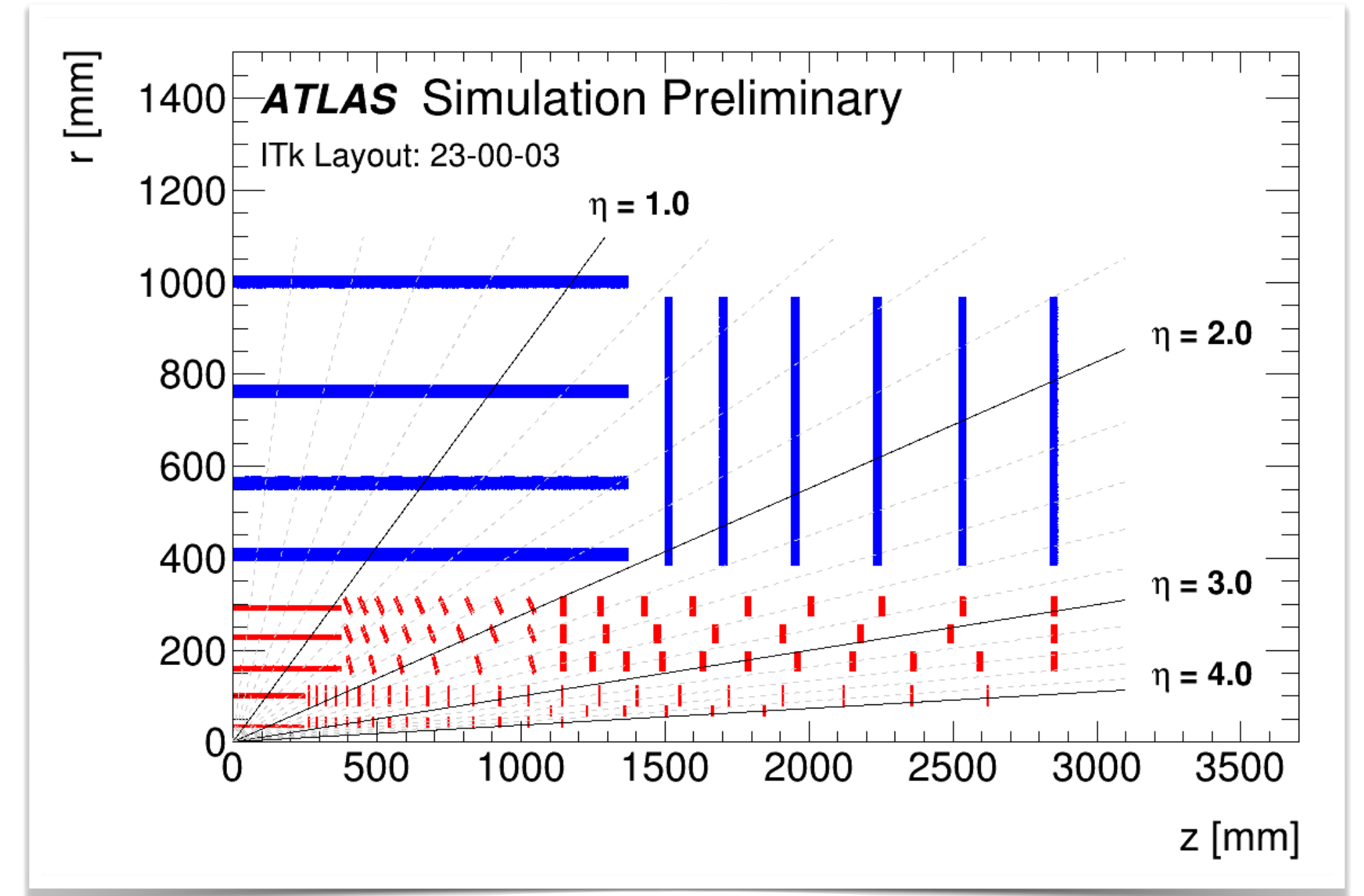
- Using ATLAS simulation event sample:

$pp$  collisions at  $\sqrt{s} = 14$  TeV,  $t\bar{t}$  process,  
 $\langle\mu\rangle = 200$   $pp$  interaction pileup

- For today's new physics performance plots: updated ITk layout 23-00-03  
(reduced radius of innermost pixel layer, and distribution of passive material with greater detail and accuracy)

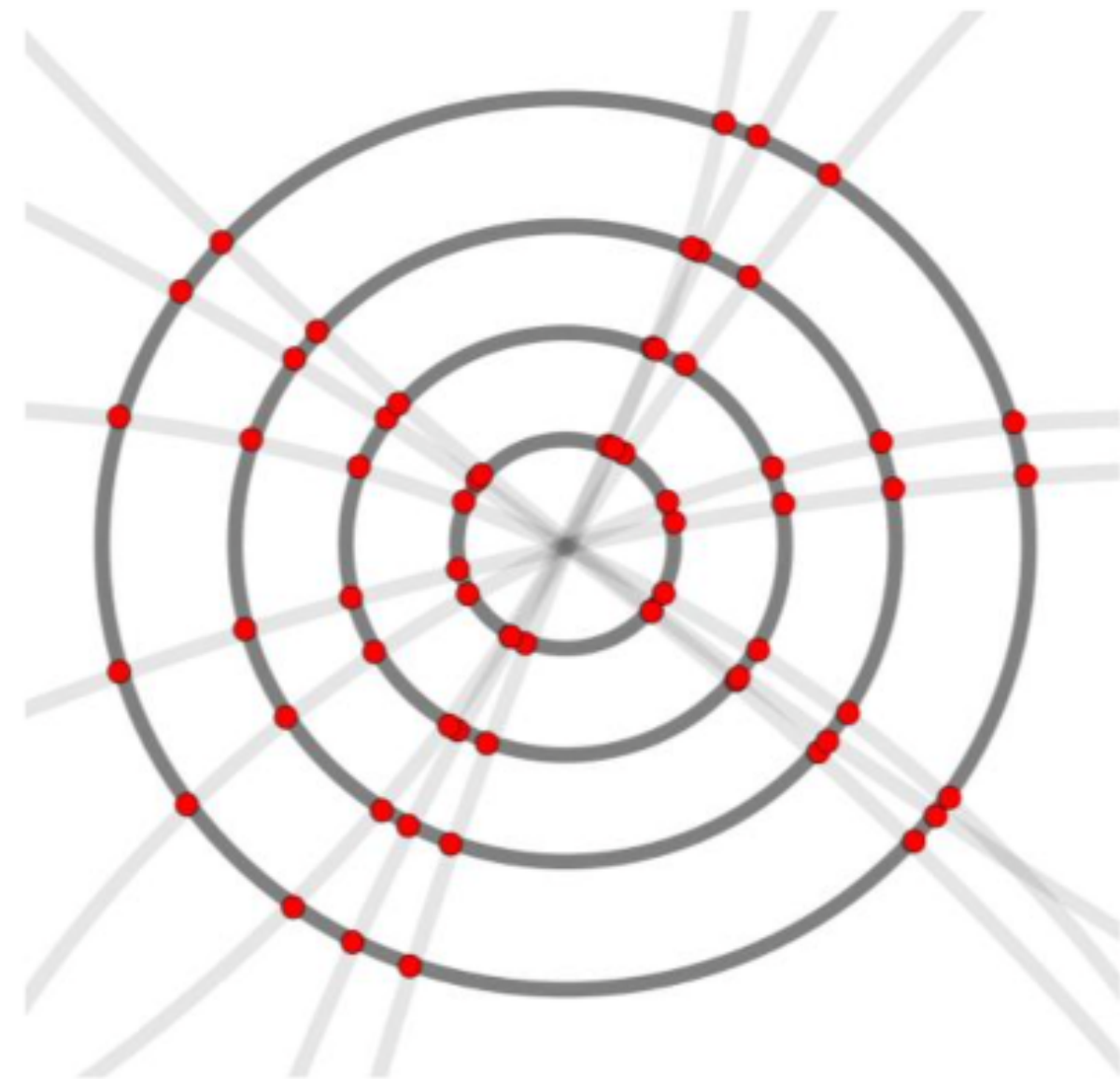
- Target particles:

- $p_T > 1$  GeV, with at least 3 hits or space points, no electron,
- **only primary particles** (including B hadron decays)  
(without "secondary" Geant4 particles from material interactions)



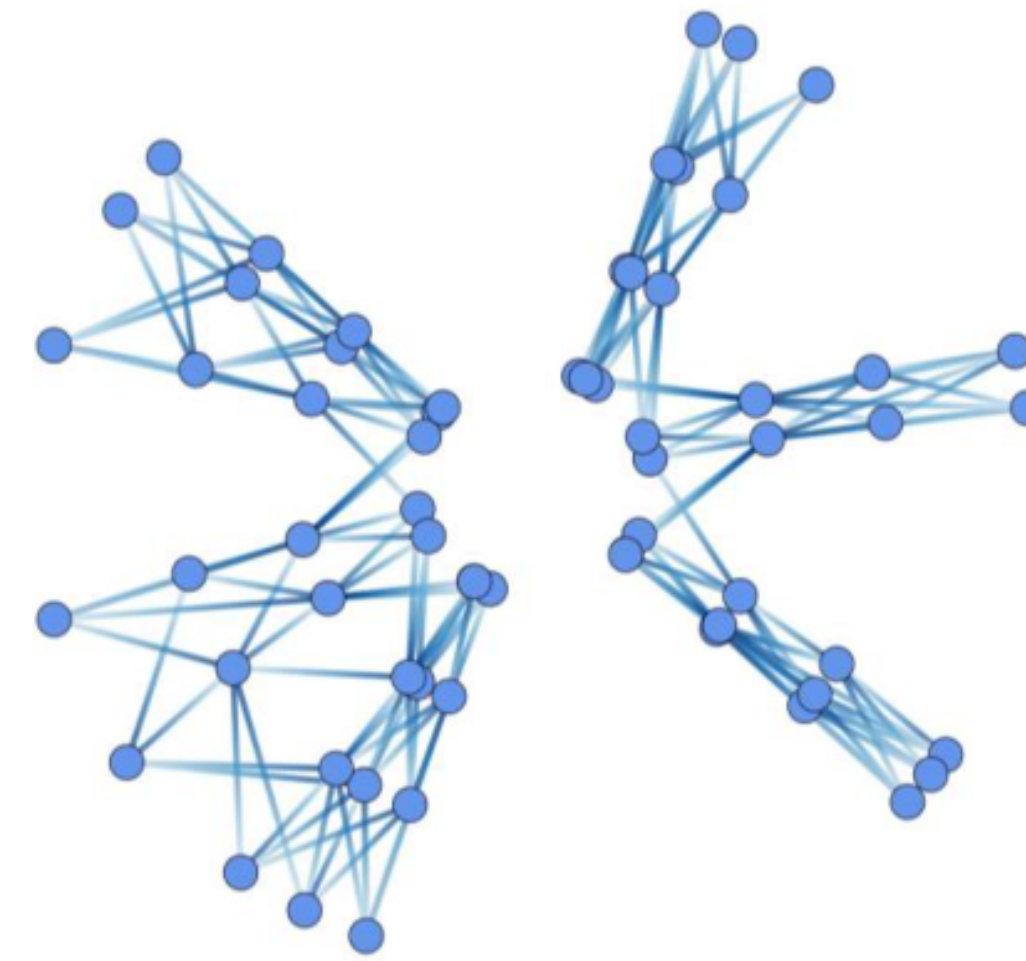
# ATLAS GNN4ITk

## Our graph definition



Hits

- Hit or space point in ITk

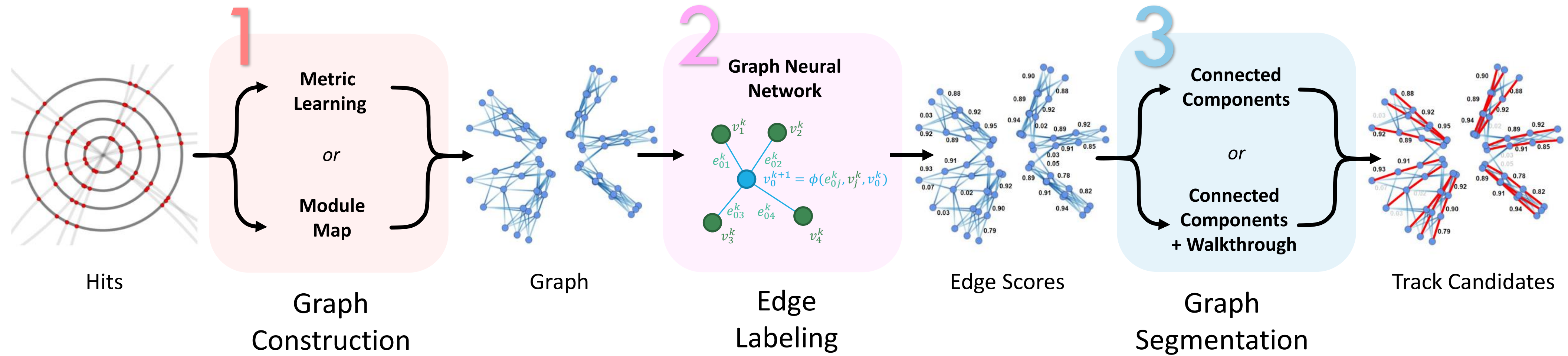


Graph

- **Graph:** Set of nodes and edges
- **Node:** Hit or space point
- **Edge:** Hypothesis: The two associated nodes represent two successive **hits of the same particle**

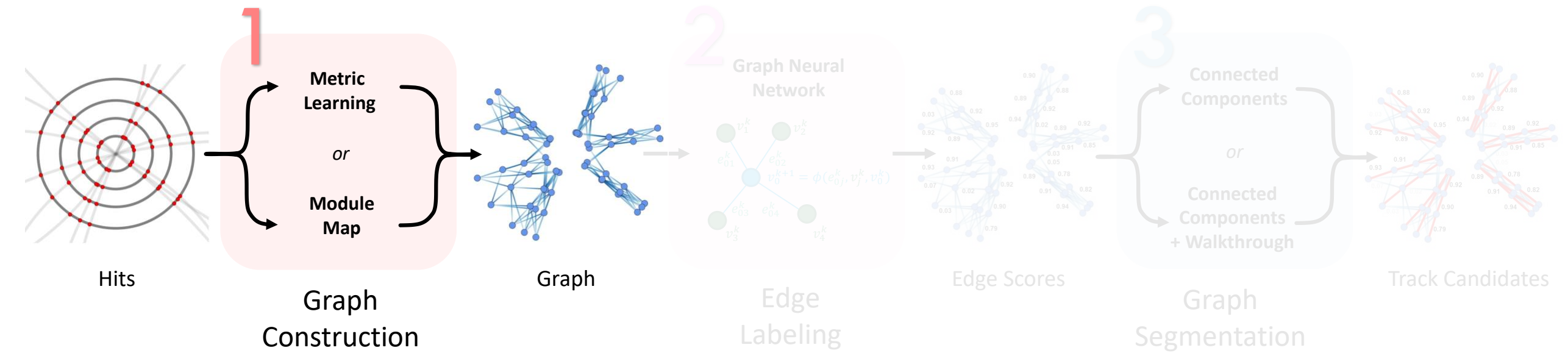
# ATLAS GNN4ITk

## Track Reconstruction Chain



# GNN4ITk

## Graph construction

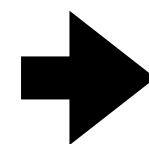
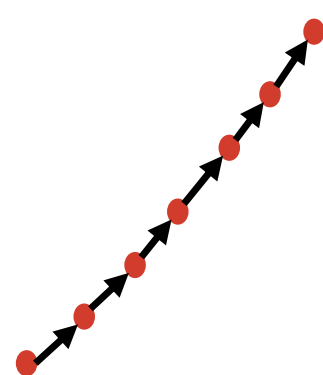


300k nodes fully interconnected yield  $10^{10}$  edges, too many!  
Two filtering alternative methods reduced edges to  $10^6$ :

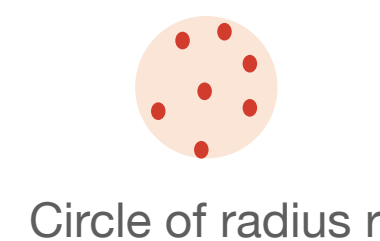
- Metric Learning

1. MLP is trained to embed nodes into a space, where common particle nodes are close

Physical space



Learned latent space



2. Additional filtering by another MLP

- Module Map

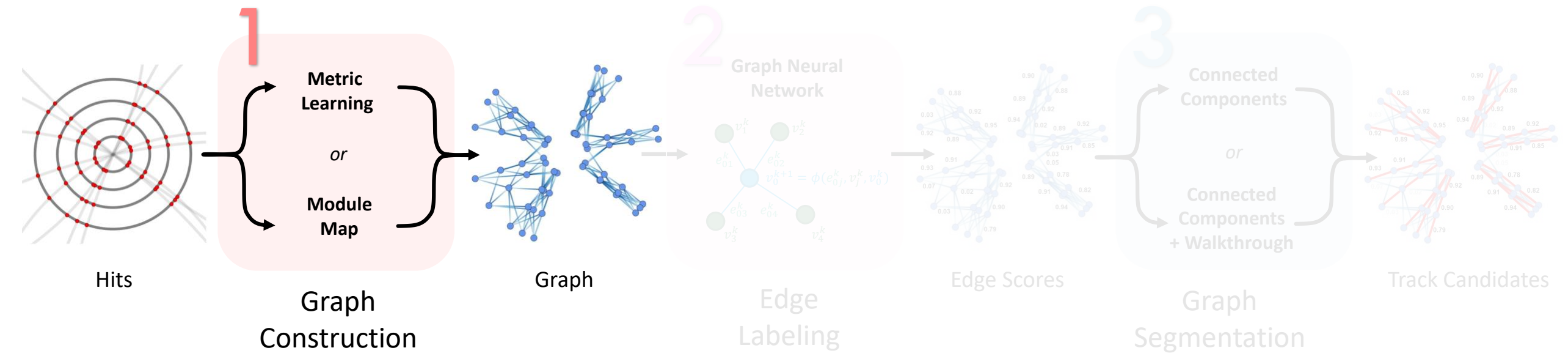
Module Map: Lookup table of 1M possible triple-module directional connections (table built with 90k simulation events)

1. Build edges based on the Module Map
2. Additional filtering with geometric cuts

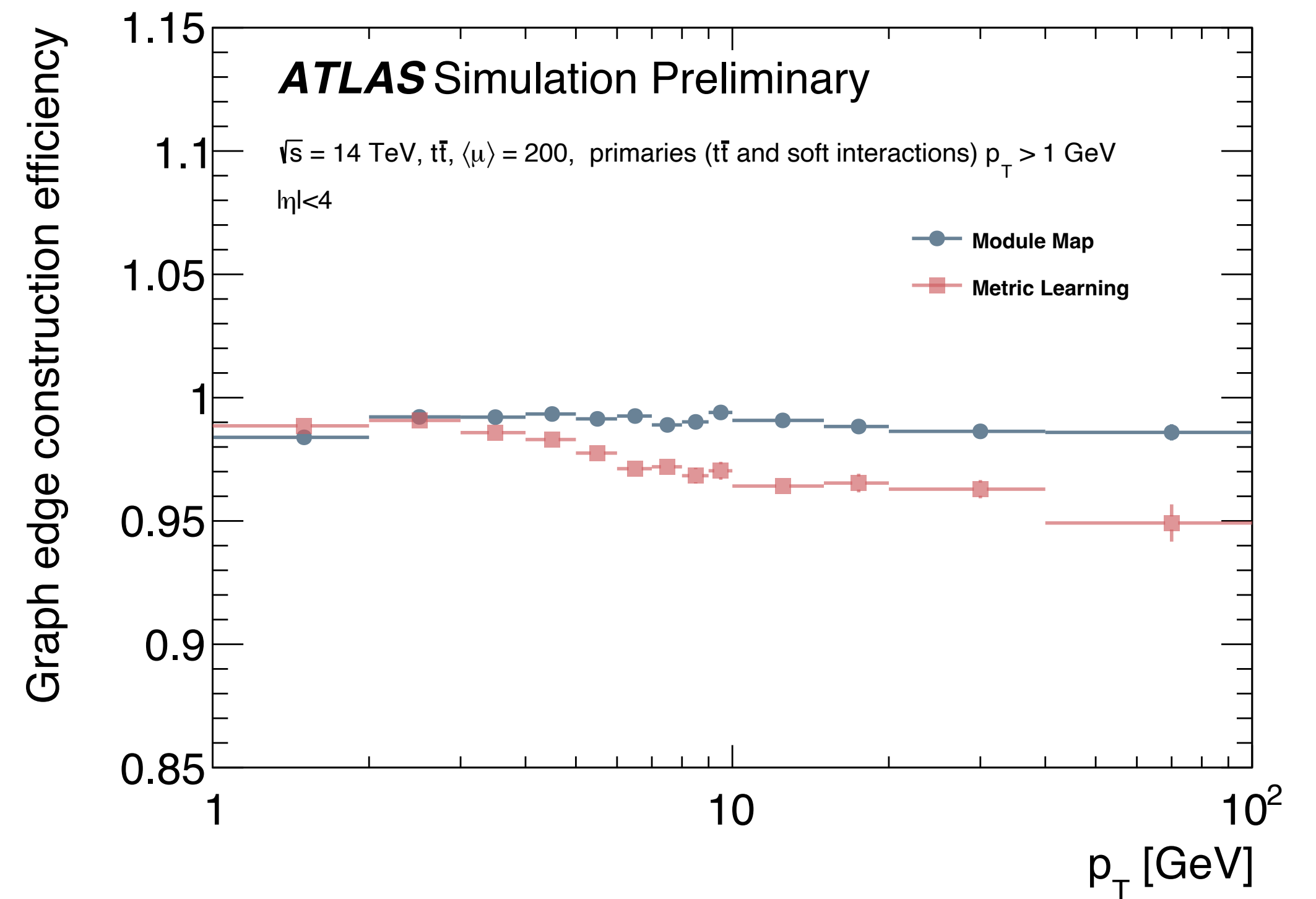
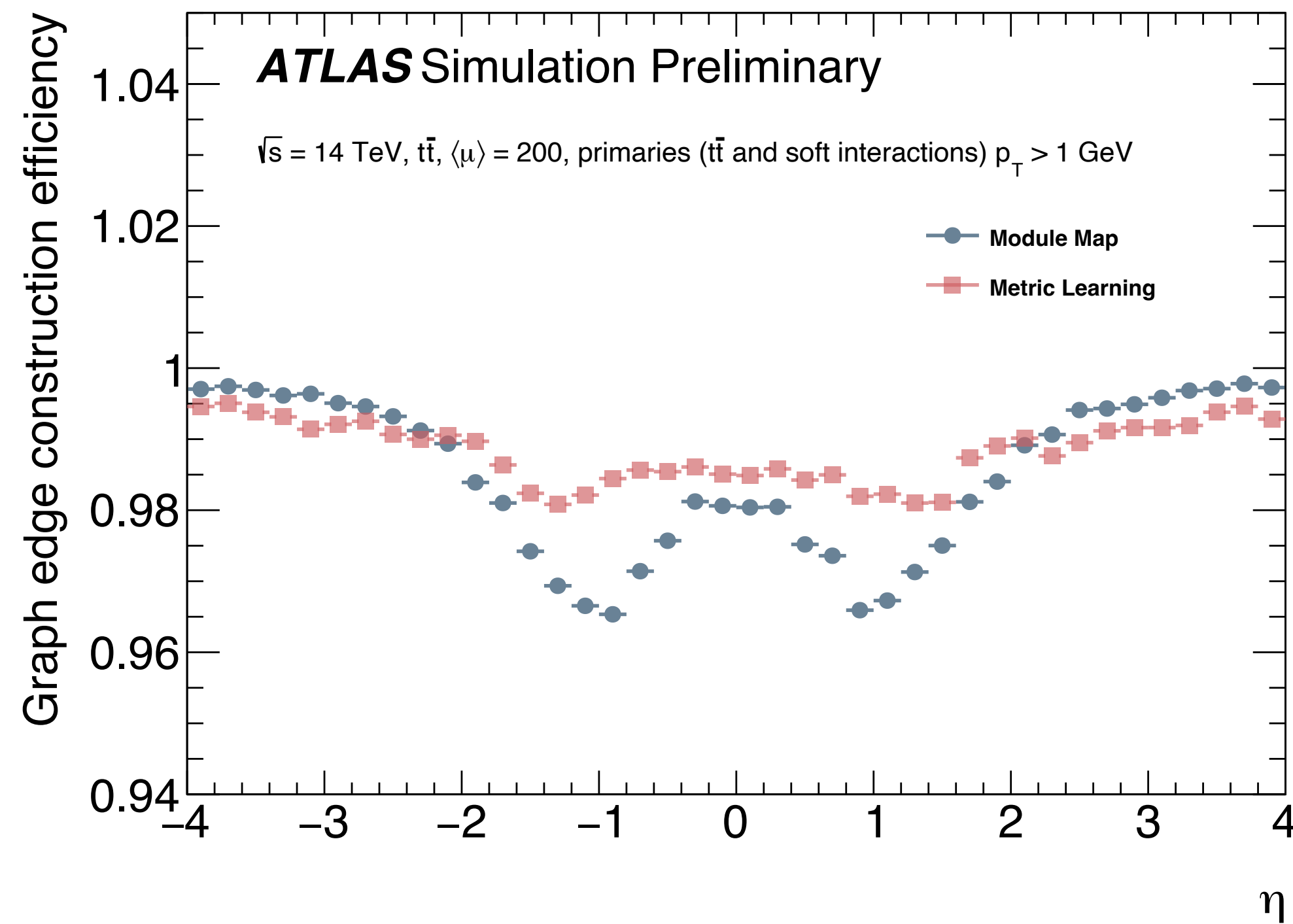
(For today's new physics performance plots: used Module Map)

# GNN4ITk

## Graph construction



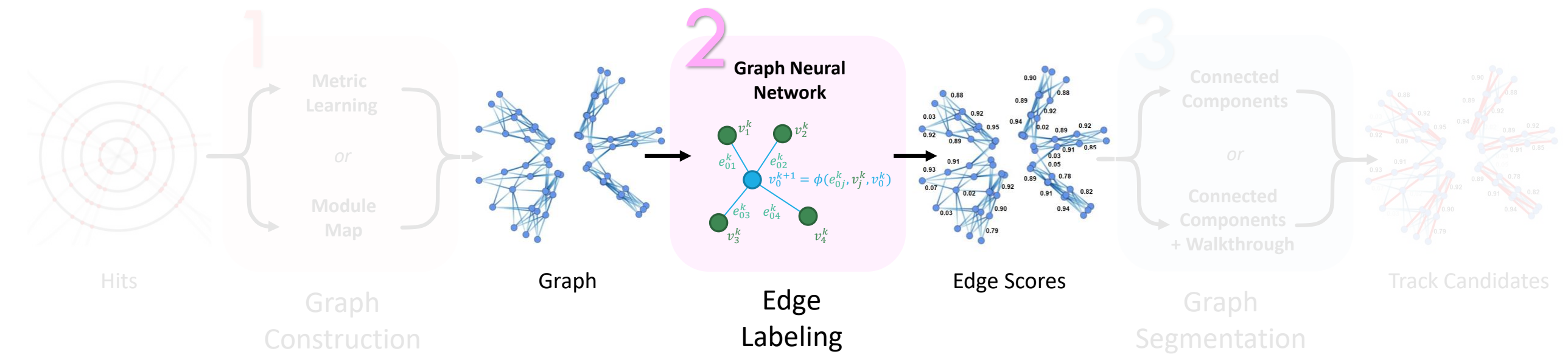
- Performance



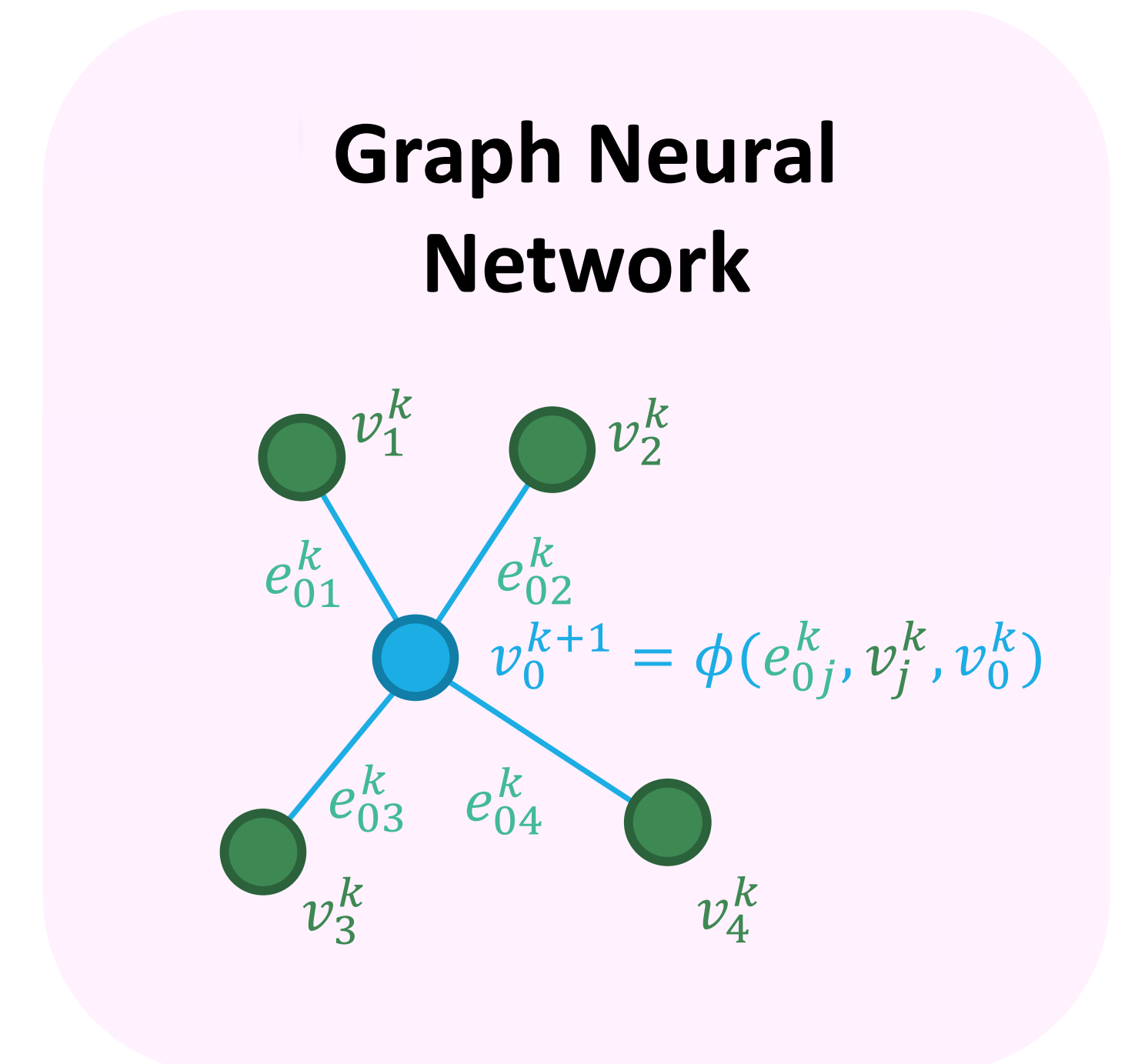


# GNN4ITk

## Edge labeling with GNN

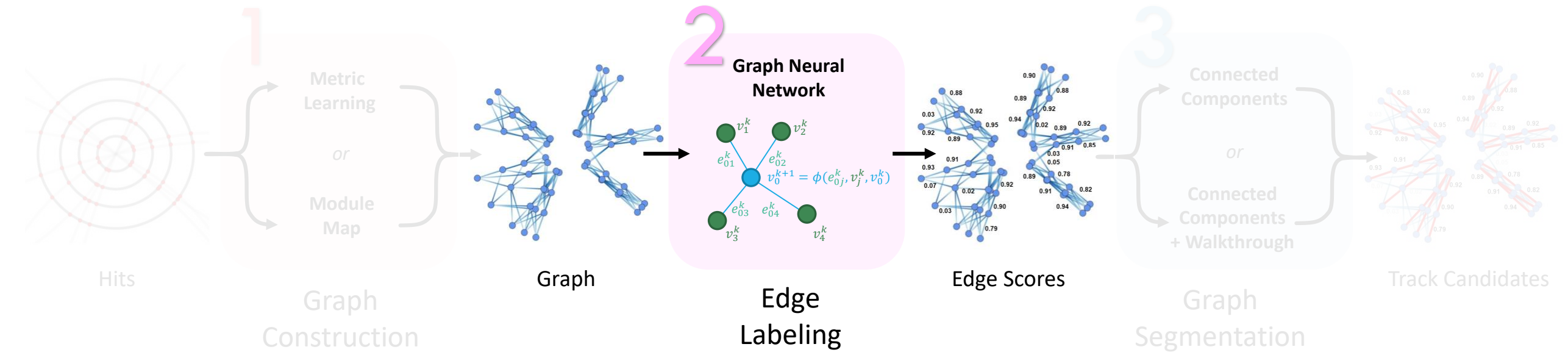


- Train Graph Neural Network to identify true edges based on geometric node and/or edge features
- It reduces number of edges:  $10^6 \rightarrow 10^4$



# GNN4ITk

## Edge labeling with GNN

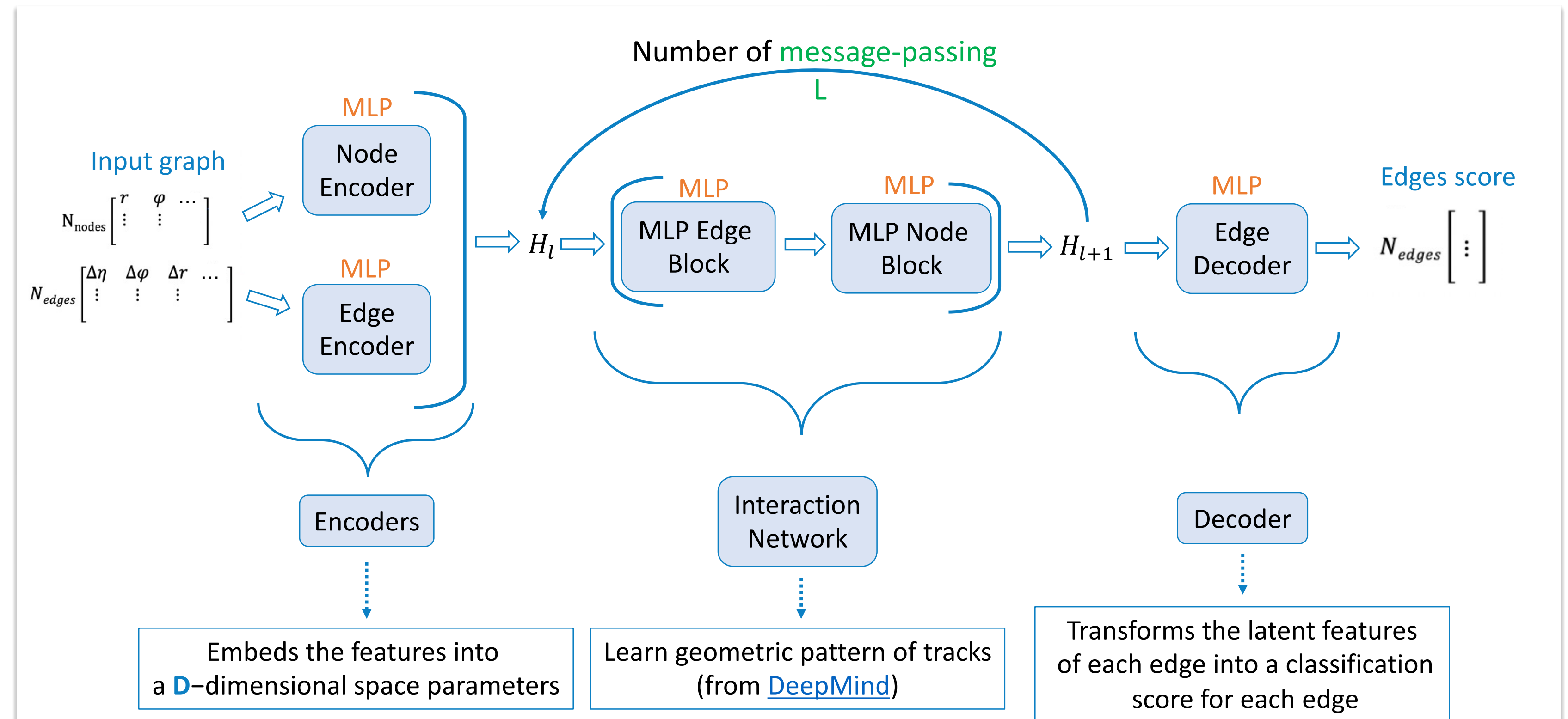


### GNN config:

- 2 layers per MLP
- 128D latent space
- 8 message-passing

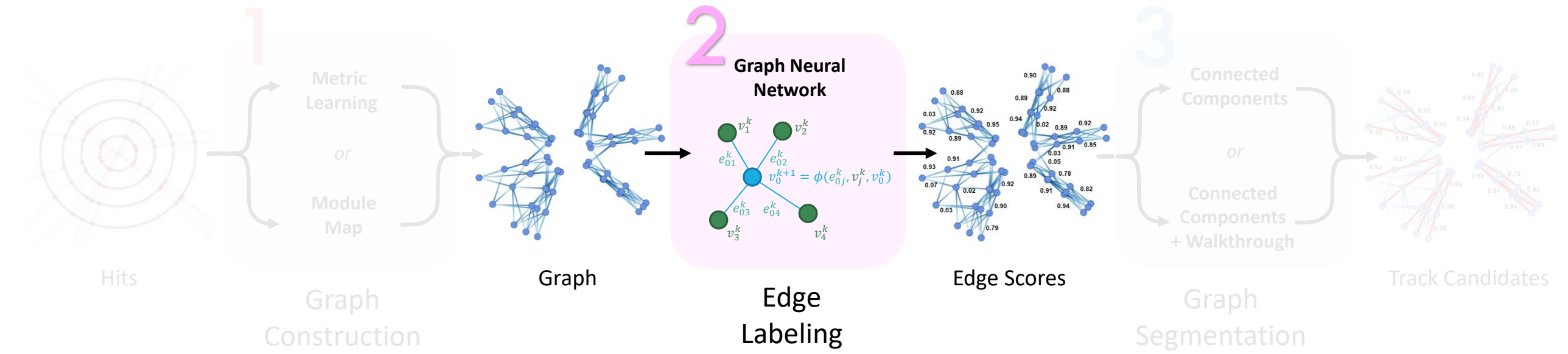
New w.r.t. CTD 2022:

- Non-recurrent interaction network
- Doing batch norm
- Heterogeneous data

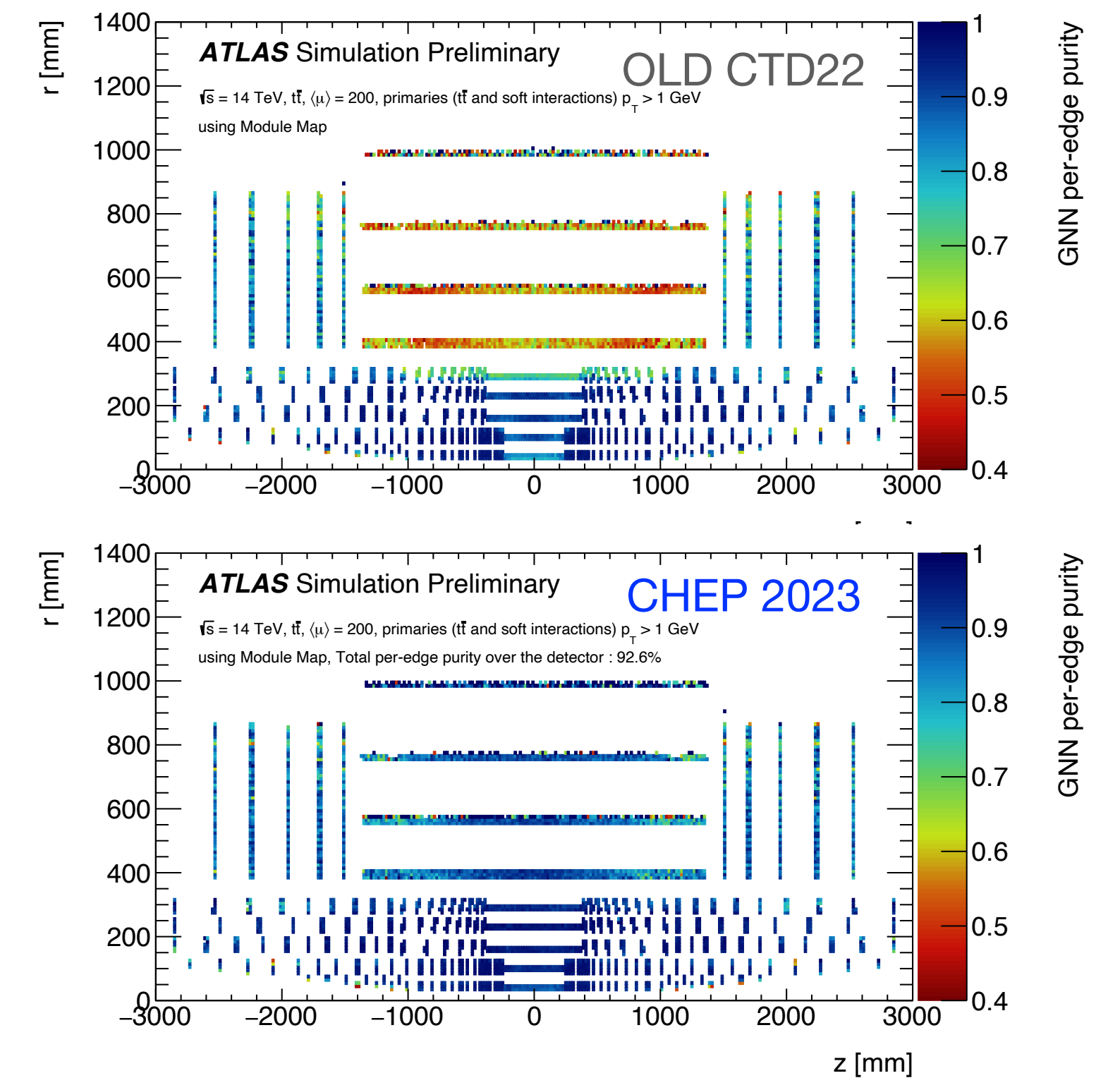
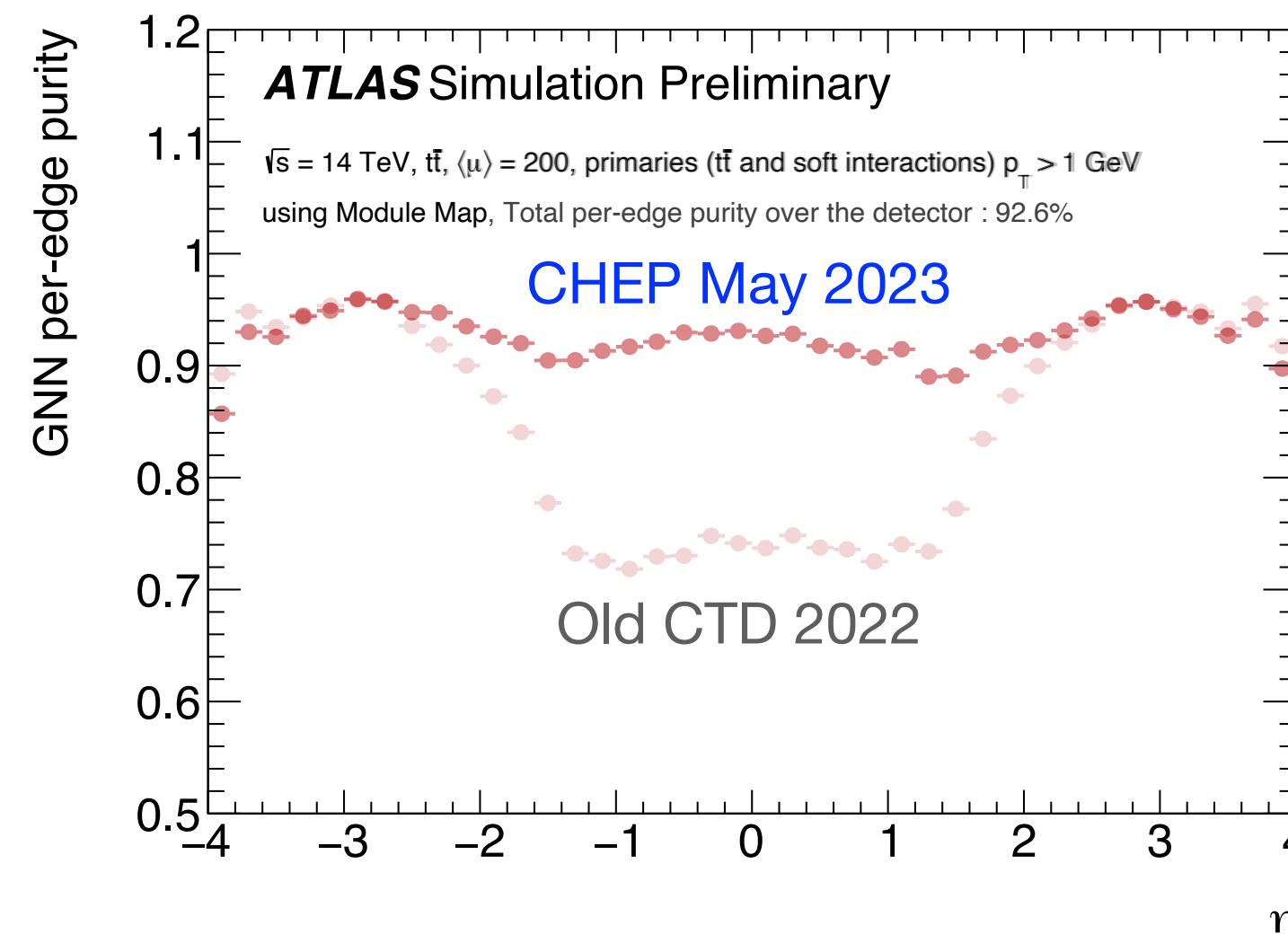
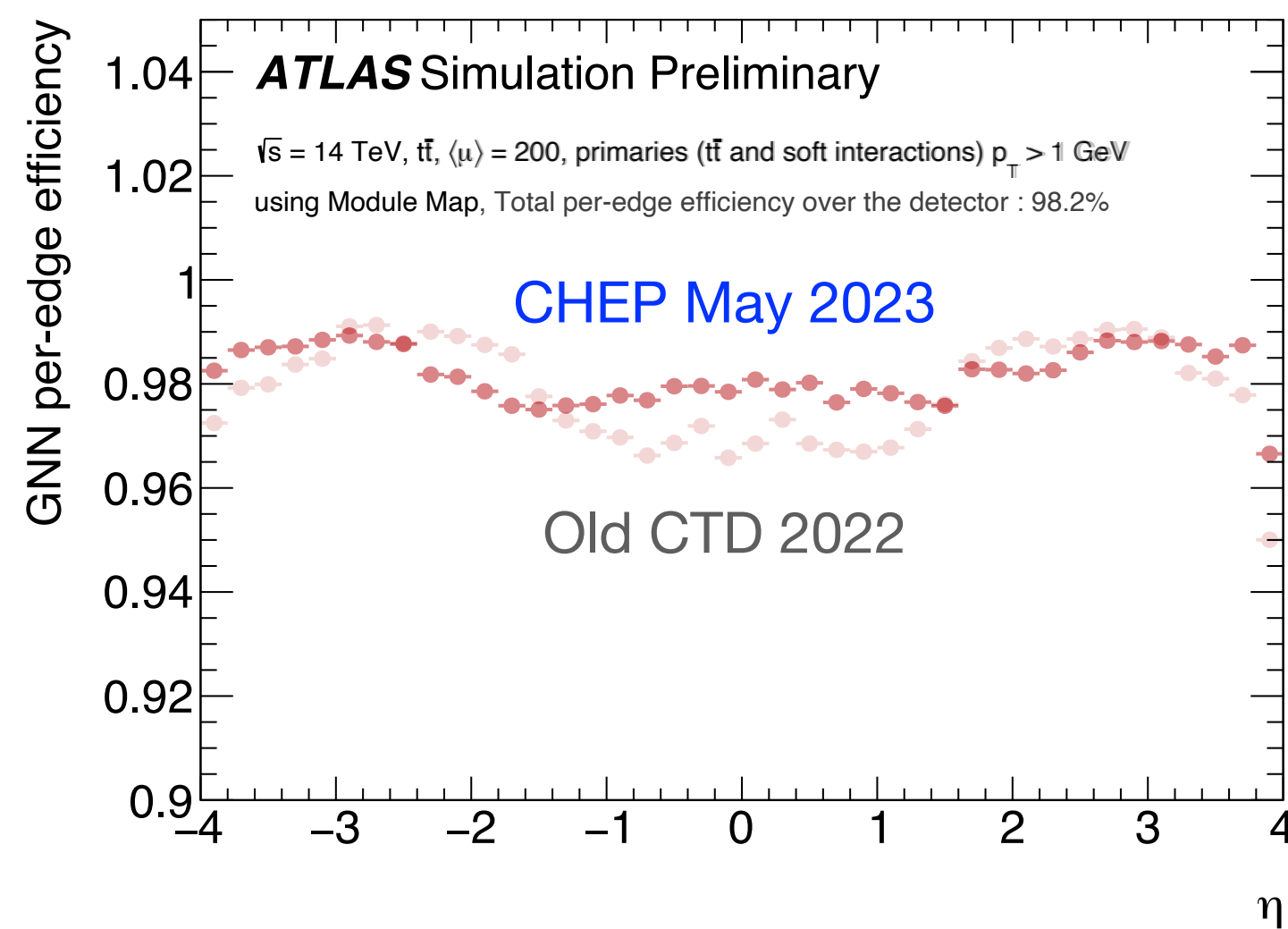


# GNN4ITk

## Edge labeling with GNN

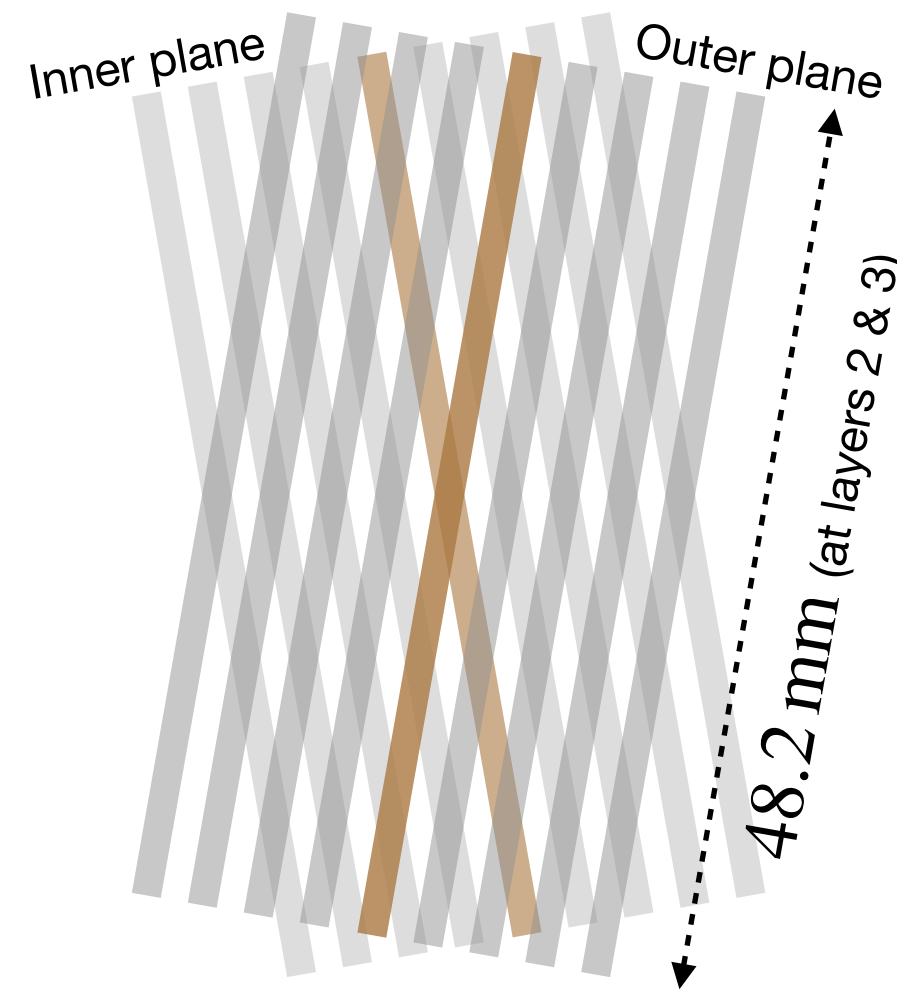


- Performance: Significant improvement compared to CTD22 (low spacial-resolution strip hits was affecting the GNN performance)



# GNN4ITk

## Edge labeling with GNN



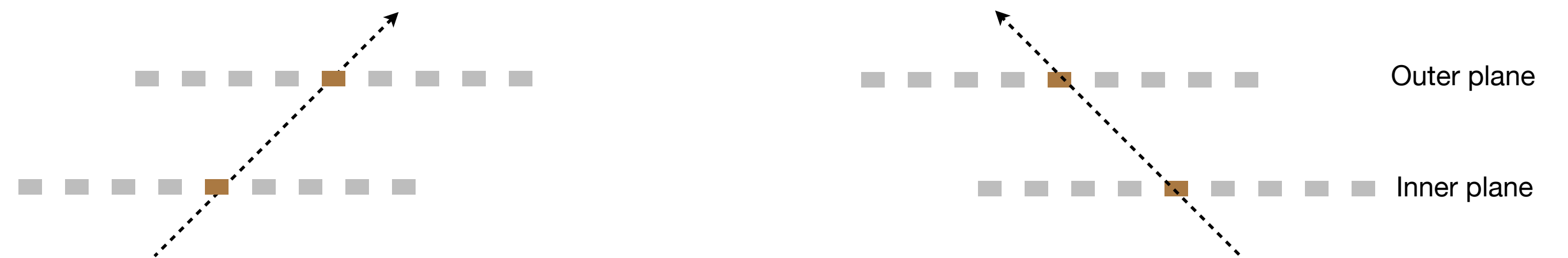
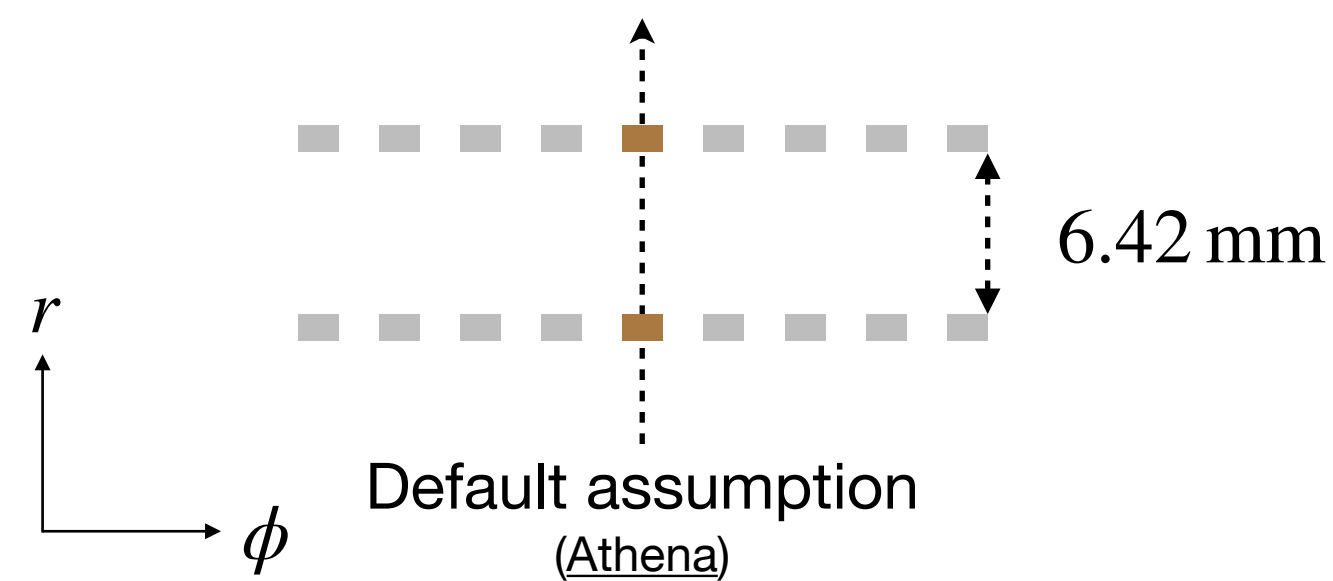
Double strip sensor planes in barrel module

Two strips fired by a particle in brown

Where did the particle hit the inner plane?

- Strip hits

Some possible options:



Default hits:  
 Poor  $\sigma_z \sim 1-3$  cm  
 (was limiting GNN performance)

- Problem addressed by passing info of the two individual strip clusters to the GNN; node features:

- Strip barrel:  $r_{hit}, \dots, r_{cl1}, \dots, r_{cl2}, \dots$

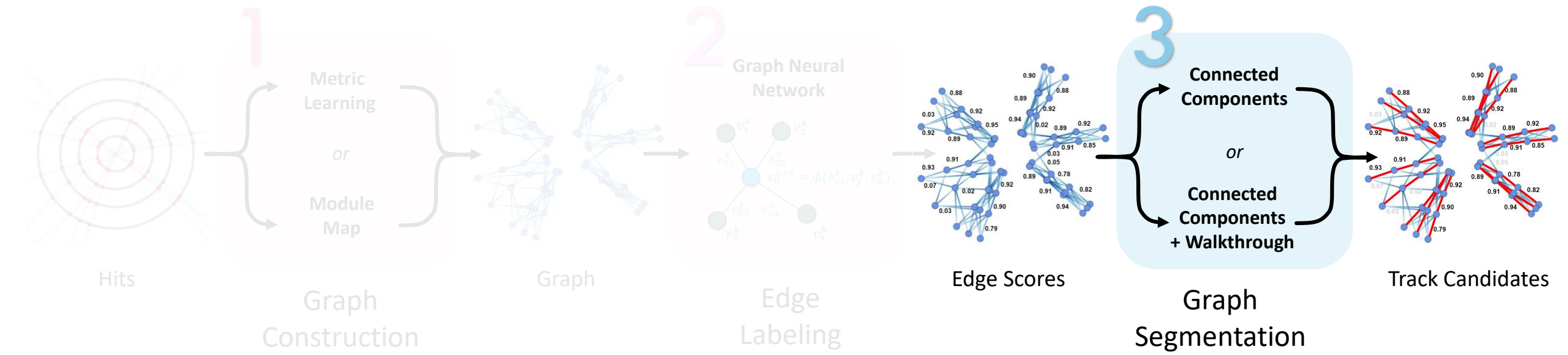
- Pixel:  $r_{hit}, \dots, r_{hit}, \dots, r_{hit}, \dots$

(Heterogeneous data format)

- Other alternatives under study: hand-engineered edge features based on hit pair info, & heterogeneous GNN model

# GNN4ITk

## Graph segmentation

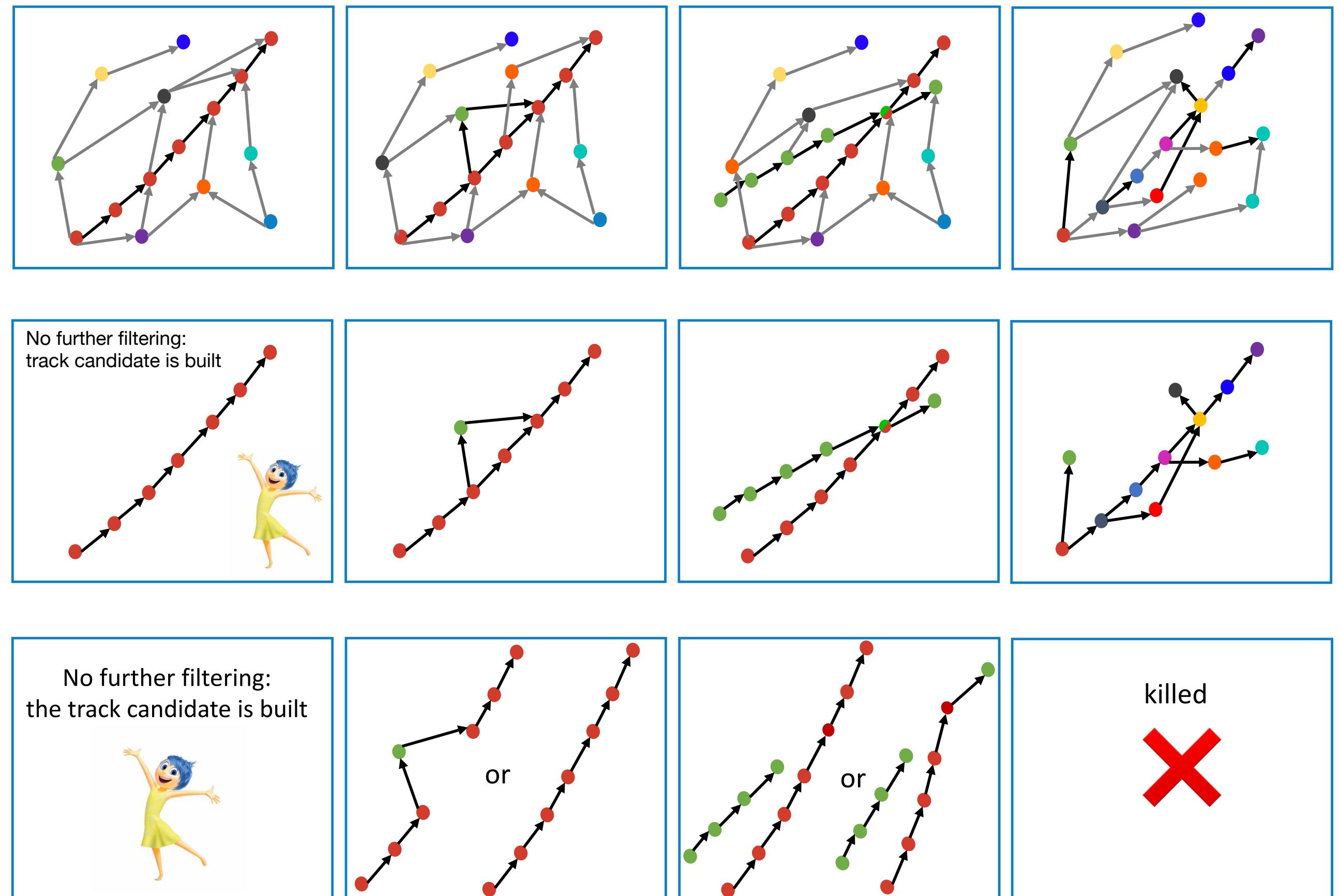


Legend:  
 Edge below threshold  
 Edge above threshold  
 Same color nodes = same particle nodes

Connected component algorithm,  
with loose edge score cut

The better GNN performance  
the more tracks are ready at this stage  
and the faster the reconstruction is

Walk-through algorithm,  
with tighter edge score cut

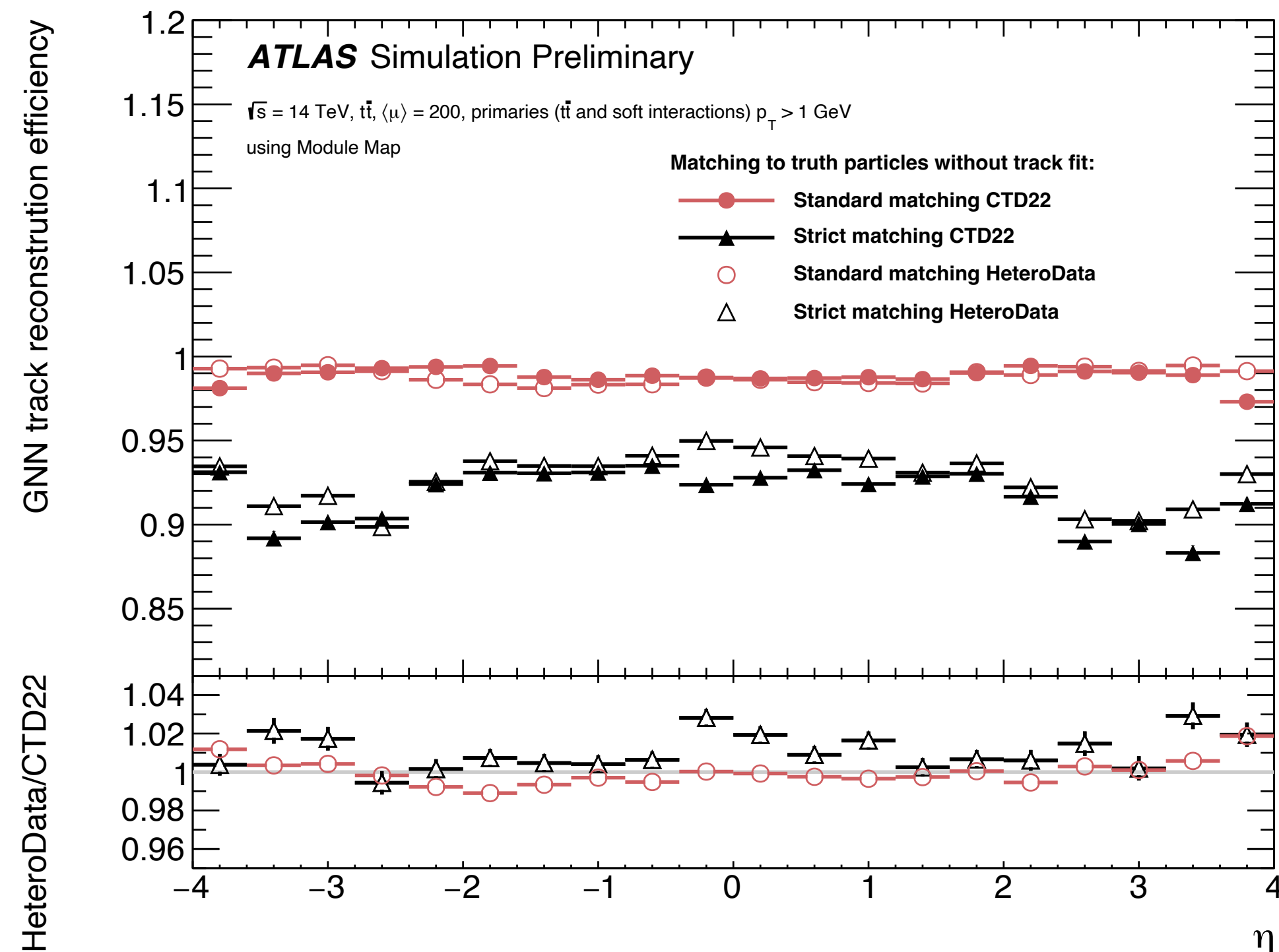


(Current graph segmentation mainly developed to complete the chain.  
Not yet optimized, e.g. could be combined with a Kalman Filter.)

Charline Rougier at CTD 2022

# Technical check

- Full chain performance: “Technical” tracking efficiency (defined based on our current target particles)



**Standard matching:**  
- Track has 50% hit purity

**Strict matching:**  
- Track includes 100% of the particle hits  
- Track has 100% hit purity

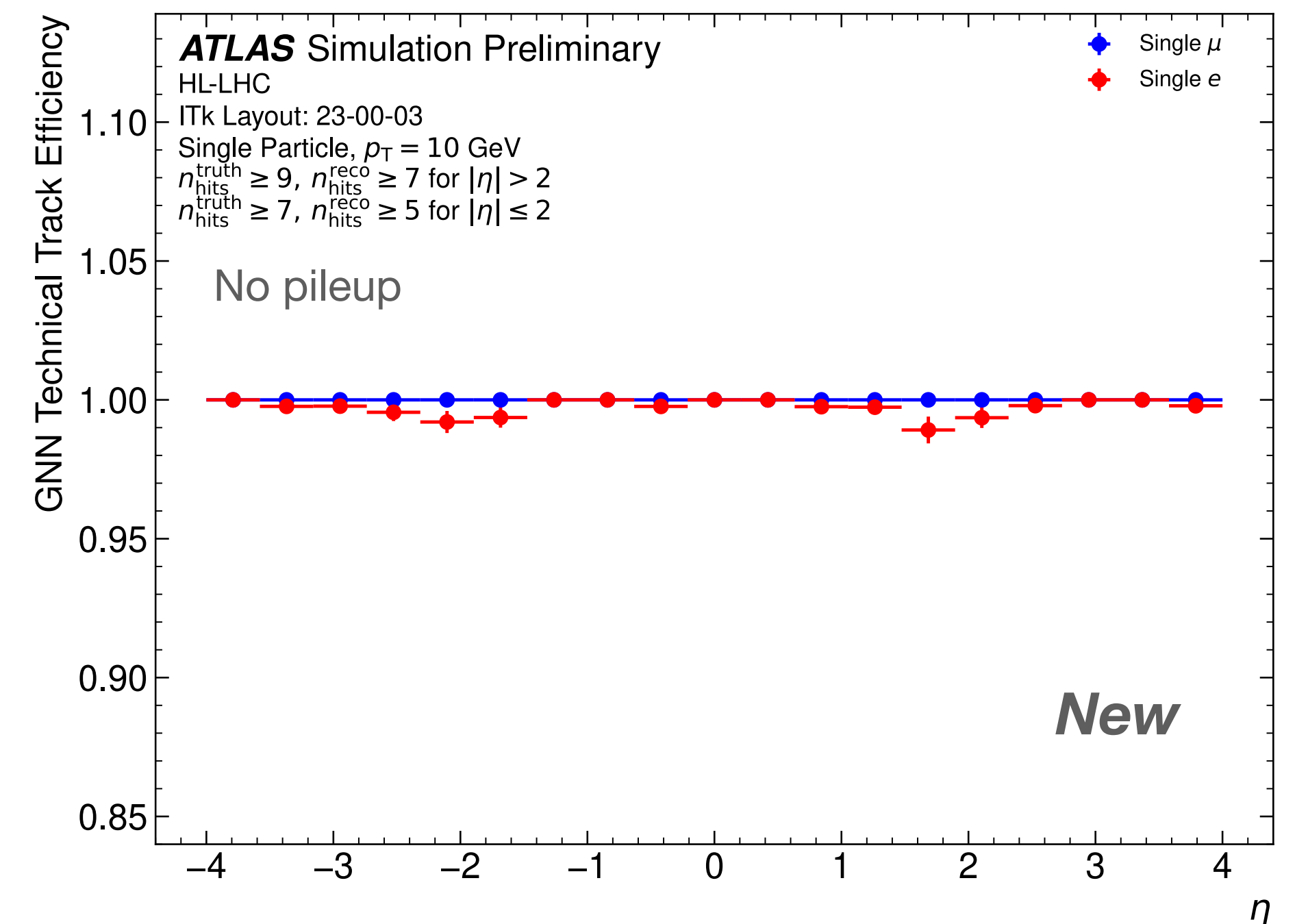
$O(10^{-3})$  fake tracks:  
Track candidates not matched to any particle

# Technical check

- Easy task: Single particle tracking

First time test for GNN4ITk

For the moment:  
Test done with Metric Learning graphs,  
with GNN model trained on  $t\bar{t}$  events artificially altered  
to contain only hits from particles with  $p_T > 1$  GeV

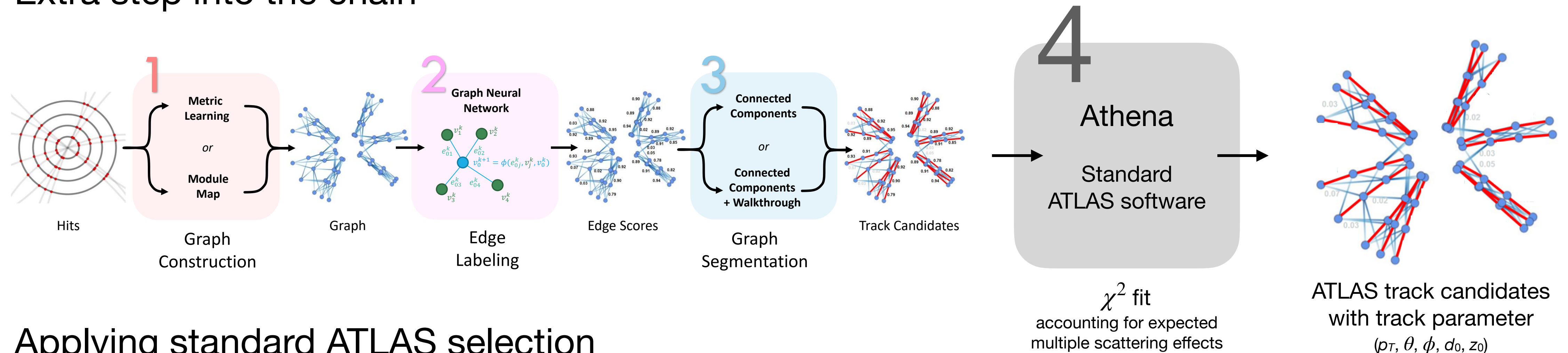


# Physics Performance of the **ATLAS GNN4ITk**



# Physics Performance of the ATLAS GNN4ITk and apples-to-apples comparison against ATLAS Combinatorial Kalman Filter

- Extra step into the chain



- Applying standard ATLAS selection

Requirements	Pseudorapidity interval		
	$ \eta  < 2.0$	$2.0 <  \eta  < 2.6$	$2.6 <  \eta  < 4.0$
pixel + strip hits	$\geq 9$	$\geq 8$	$\geq 7$
pixel hits	$\geq 1$	$\geq 1$	$\geq 1$
holes	$\leq 2$	$\leq 2$	$\leq 2$
$p_T$ [MeV]	$> 1000$		
$ d_0 $ [mm]	$\leq 2.0$	$\leq 2.0$	$\leq 10.0$
$ z_0 $ [cm]	$\leq 20.0$	$\leq 20.0$	$\leq 20.0$

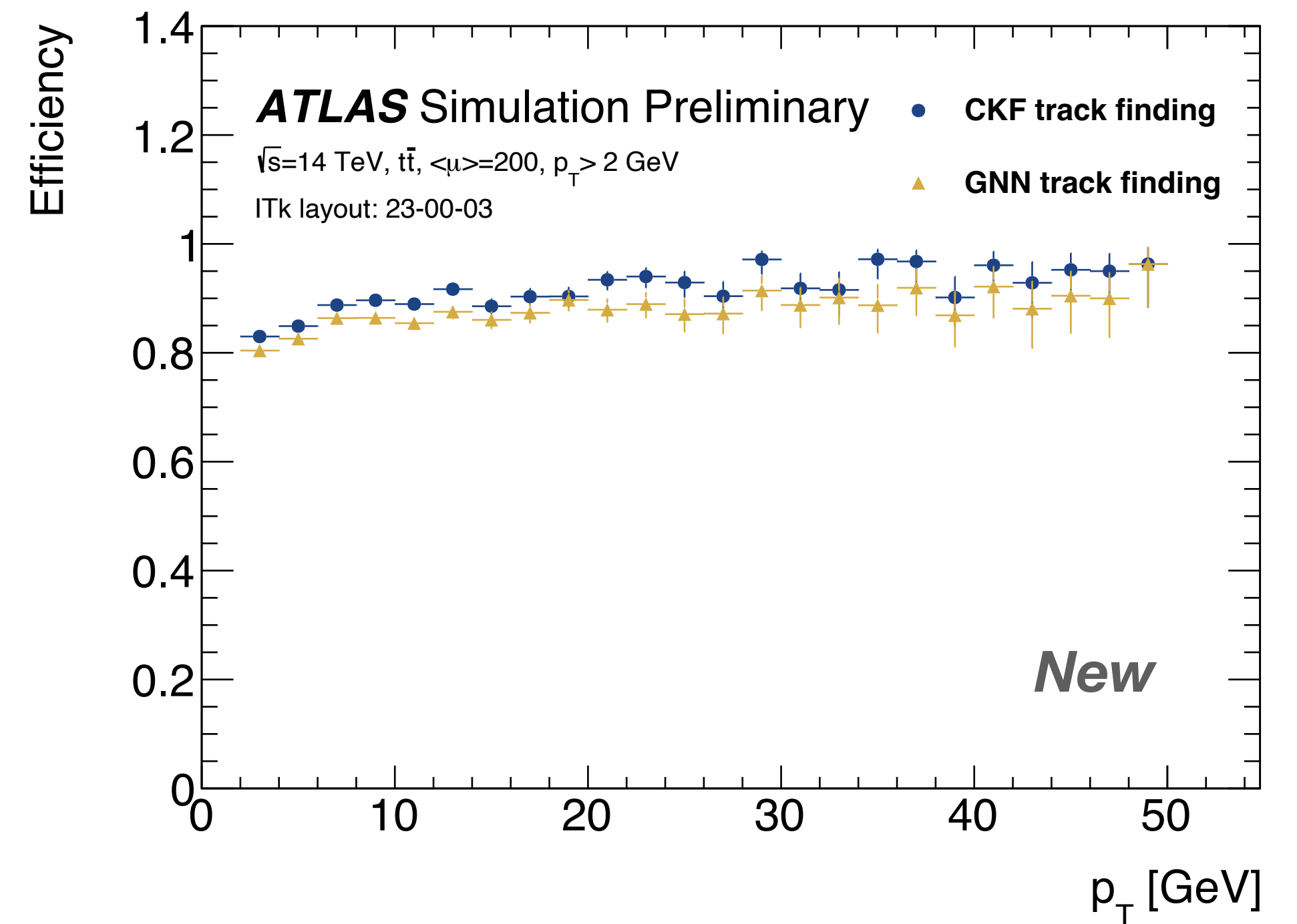
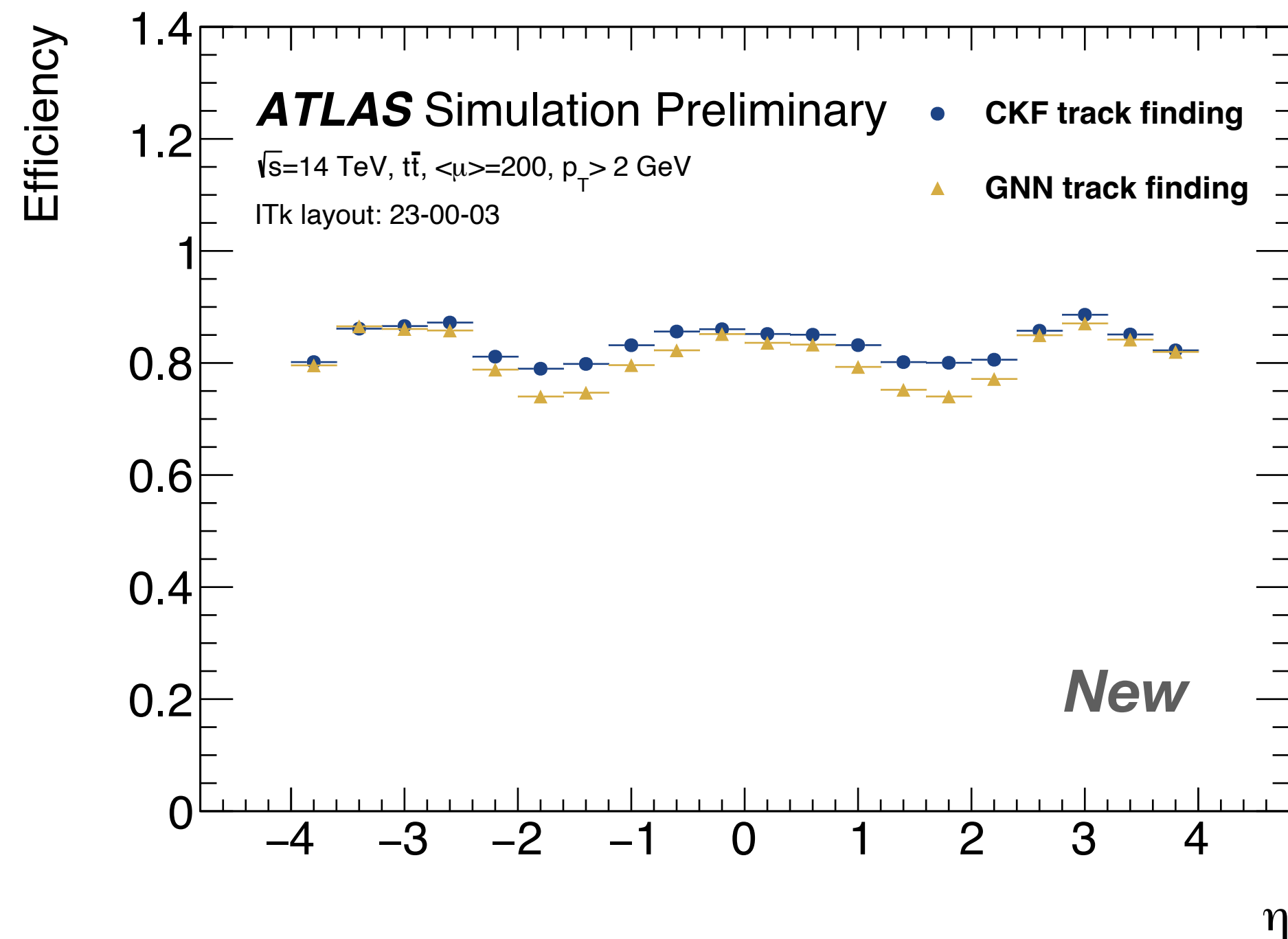
For GNN4ITk 3 cuts are looser:  
 pixel + strip hits  $\geq 8$ ,  
 $|d_0| < 20$  mm  
 $|z_0| < 25$  cm

ATL-PHYS-PUB-2021-024

# Tracking efficiency

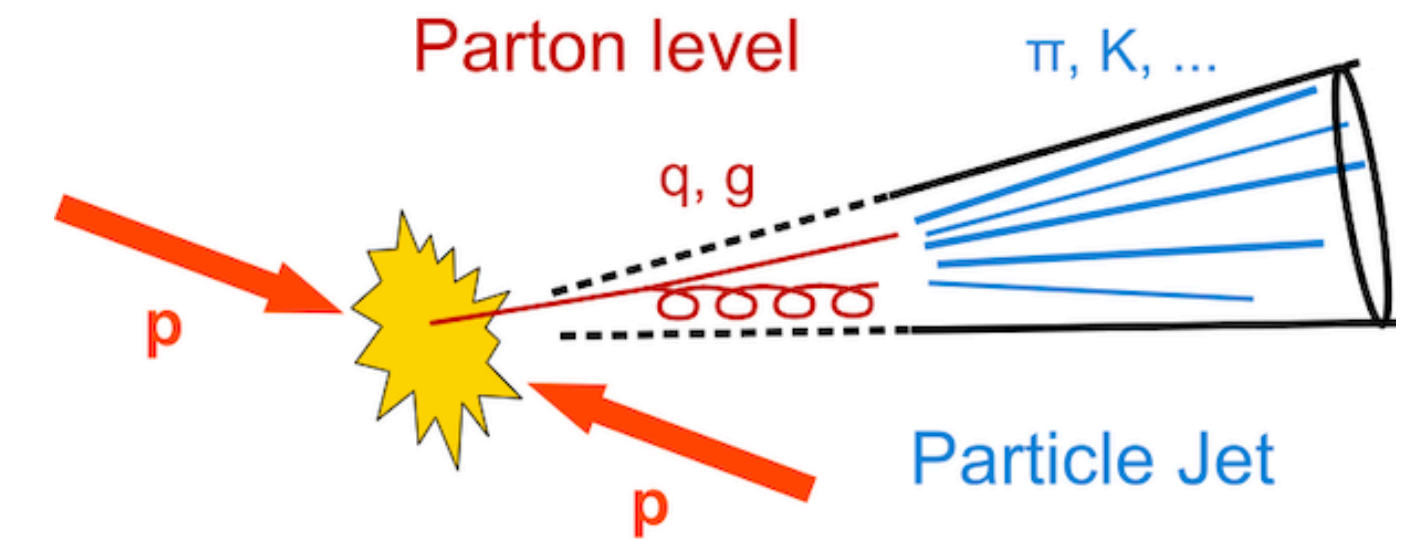
- Competitive “physics” efficiency (excluding electrons)

[O(10<sup>-3</sup>) fake tracks:  
Track candidates not matched to any particle]

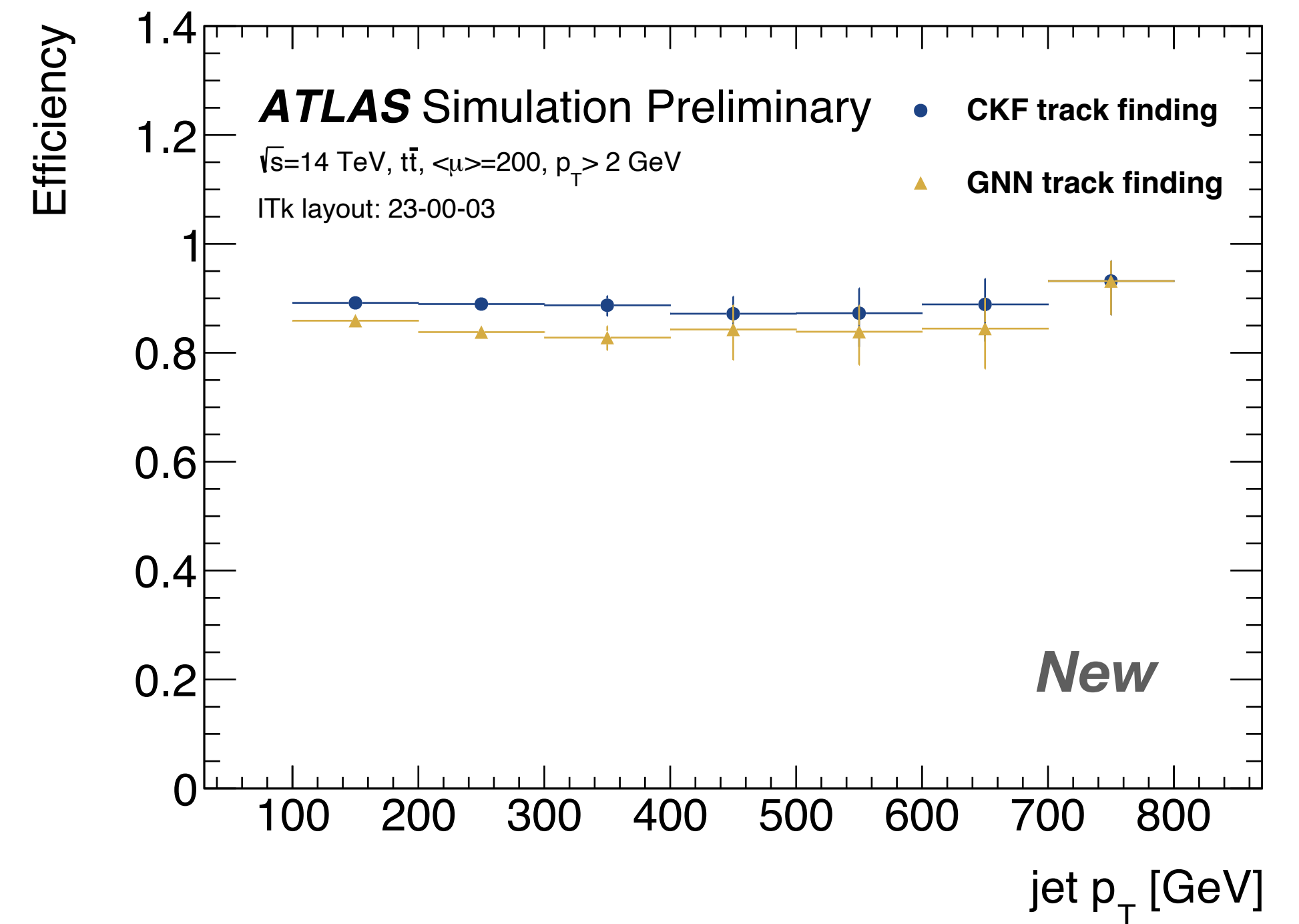
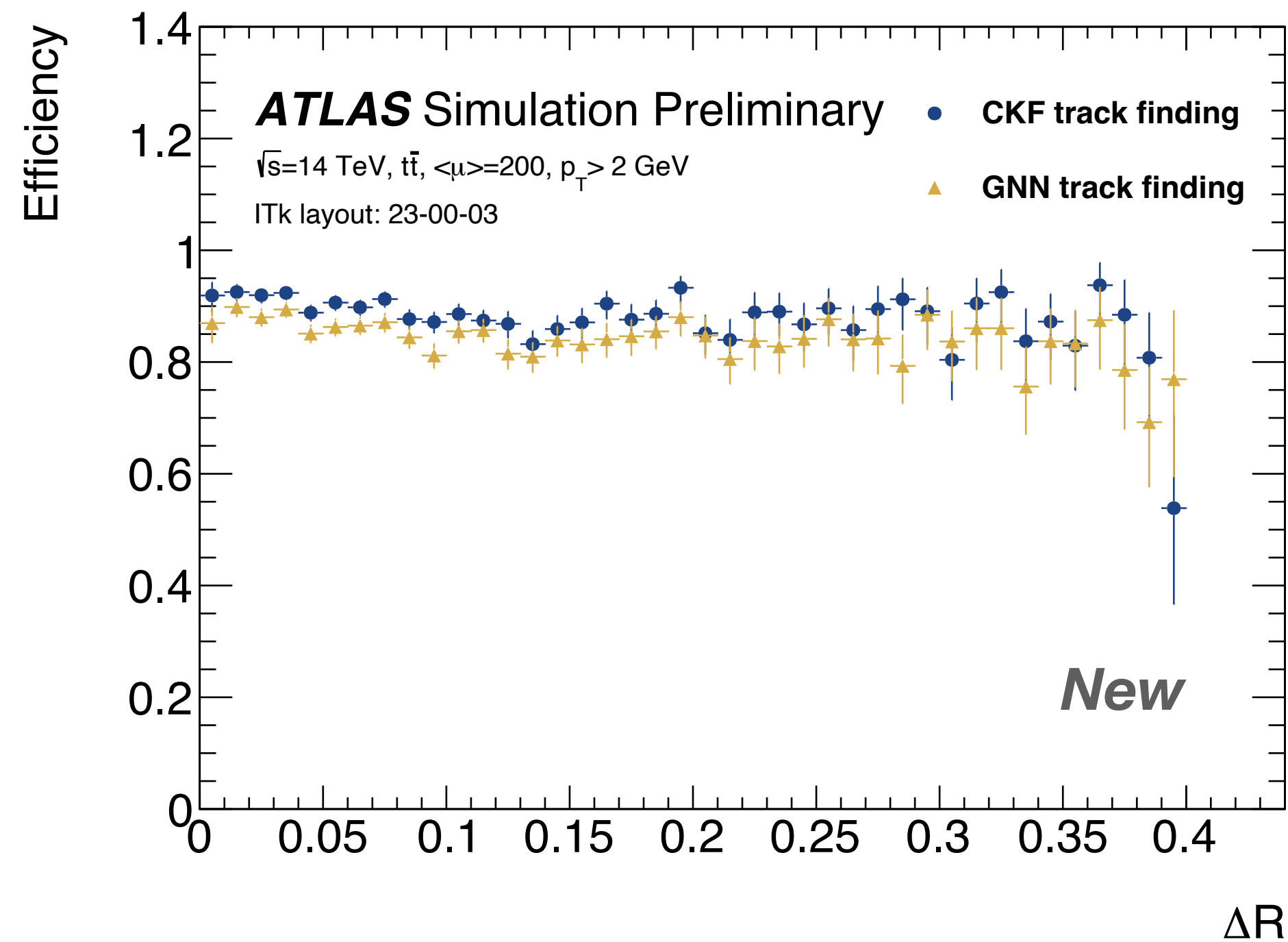


# Tracking efficiency

## Tracking inside jets



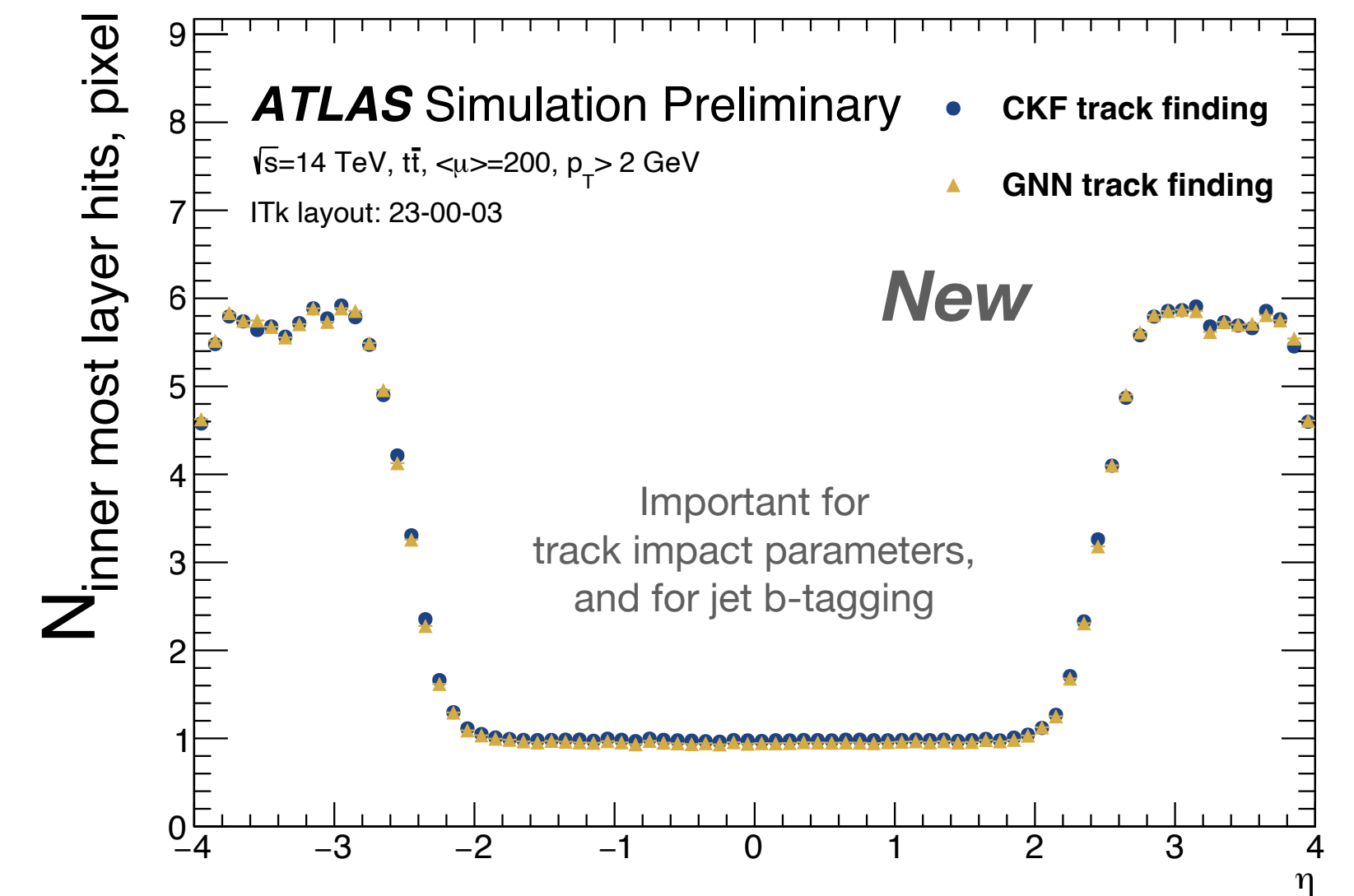
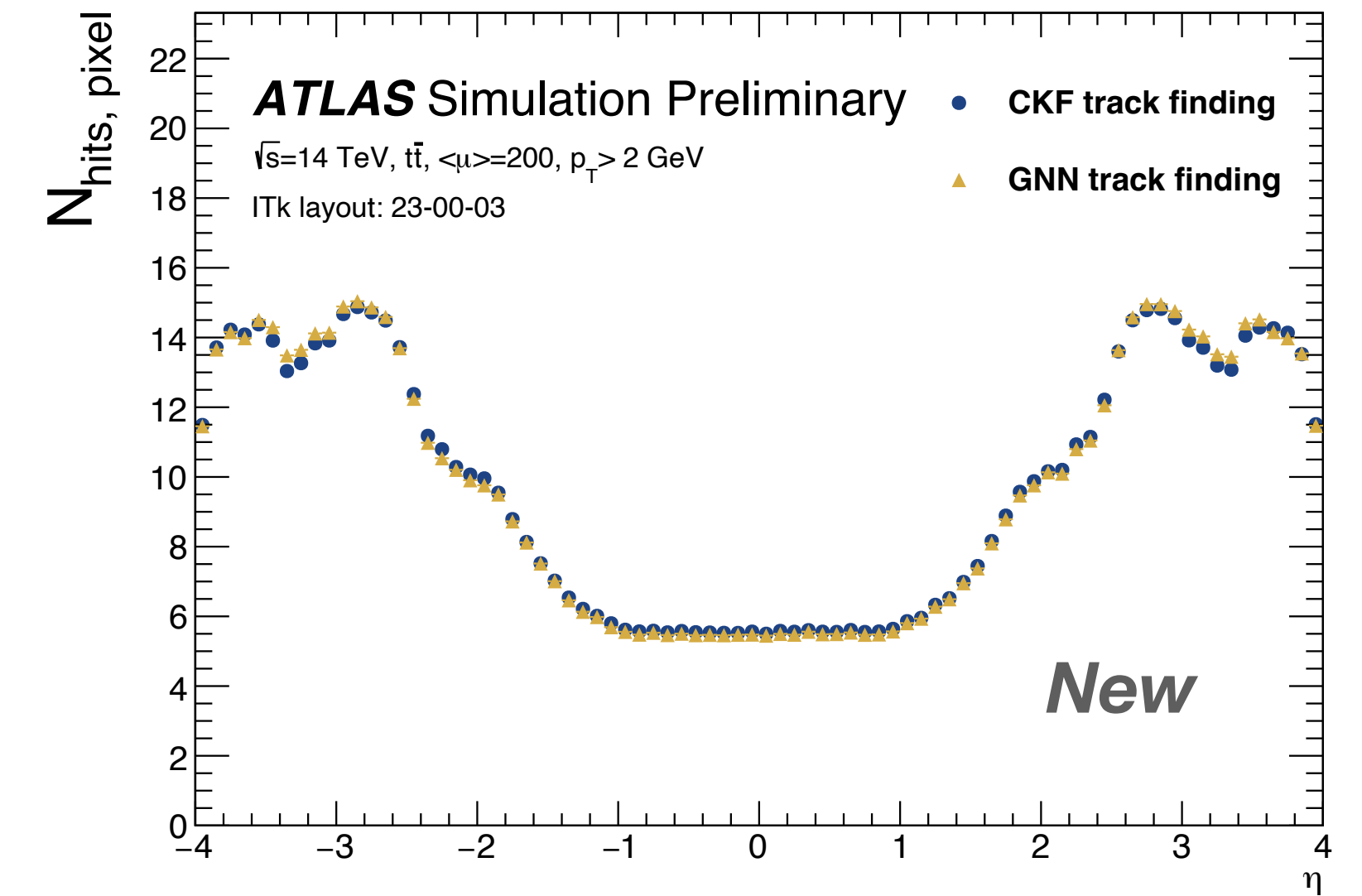
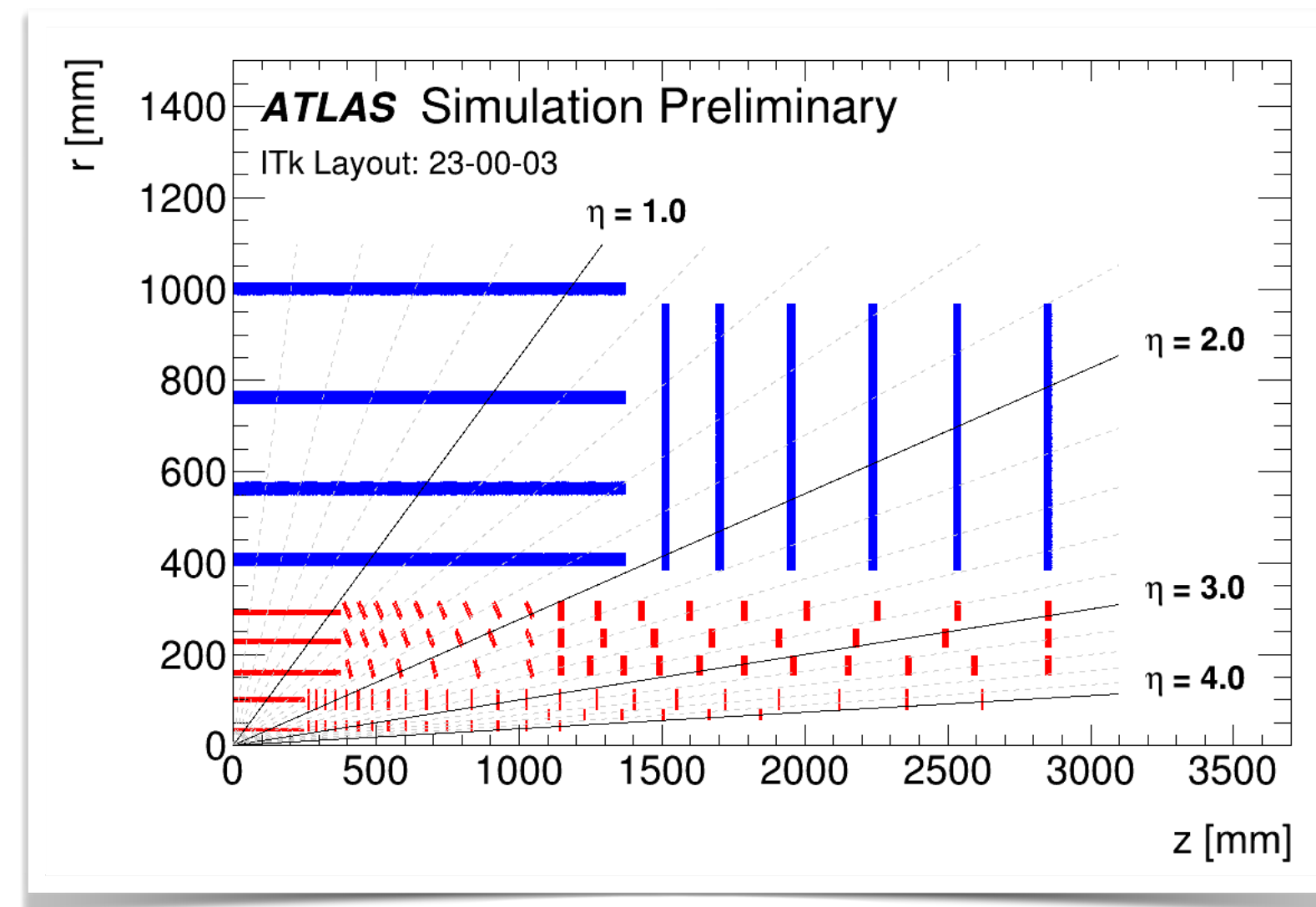
- Competitive “physics” efficiency even in dense environment (excluding electrons)



# Track hit content

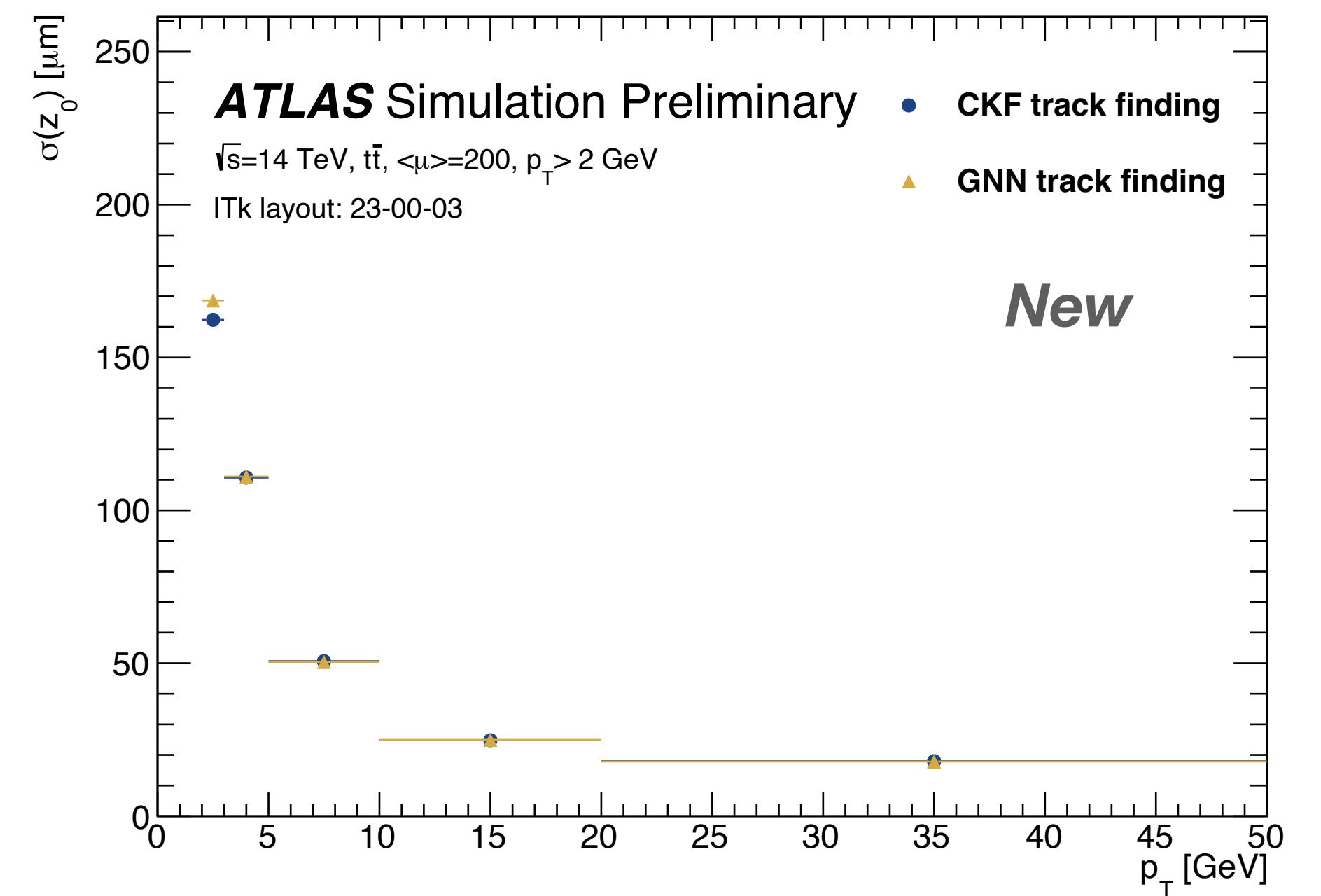
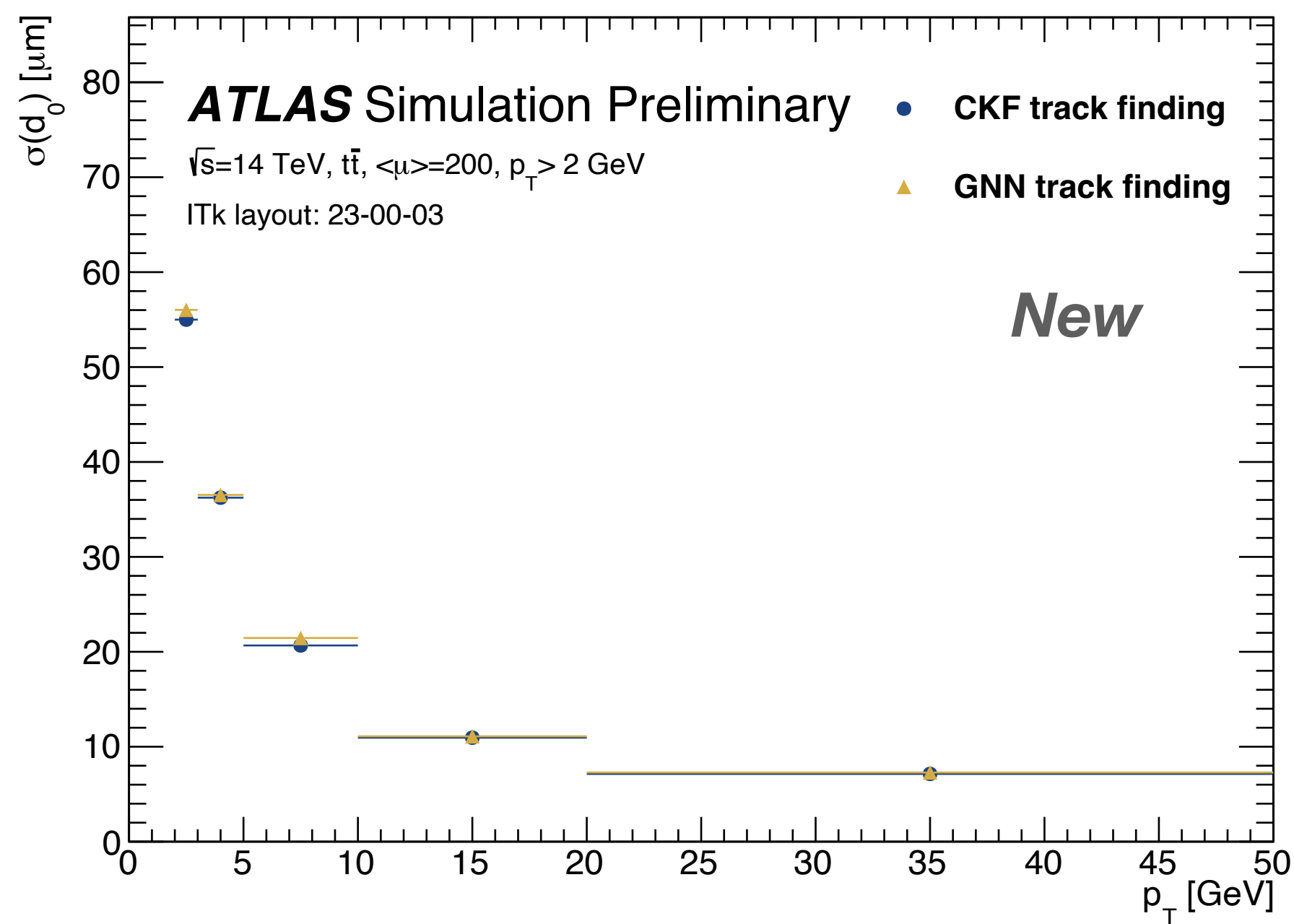
## Pixel hits

- Compatible with the detector, and with the CKF

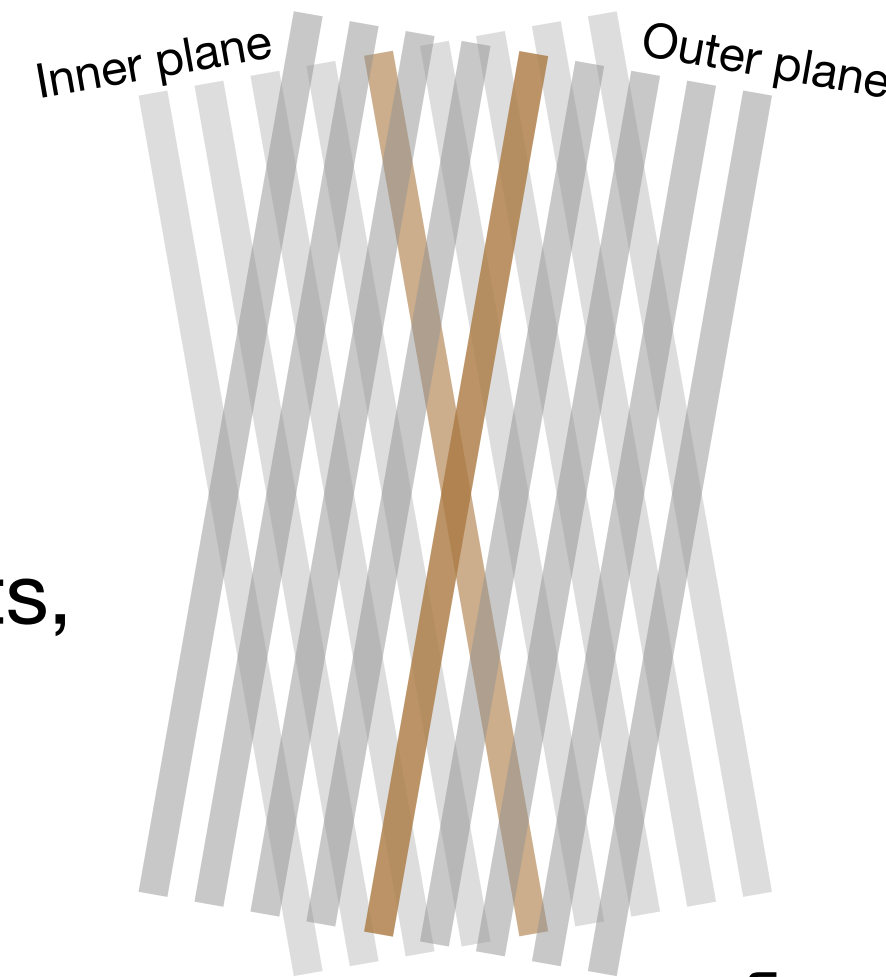


# Impact parameter resolution

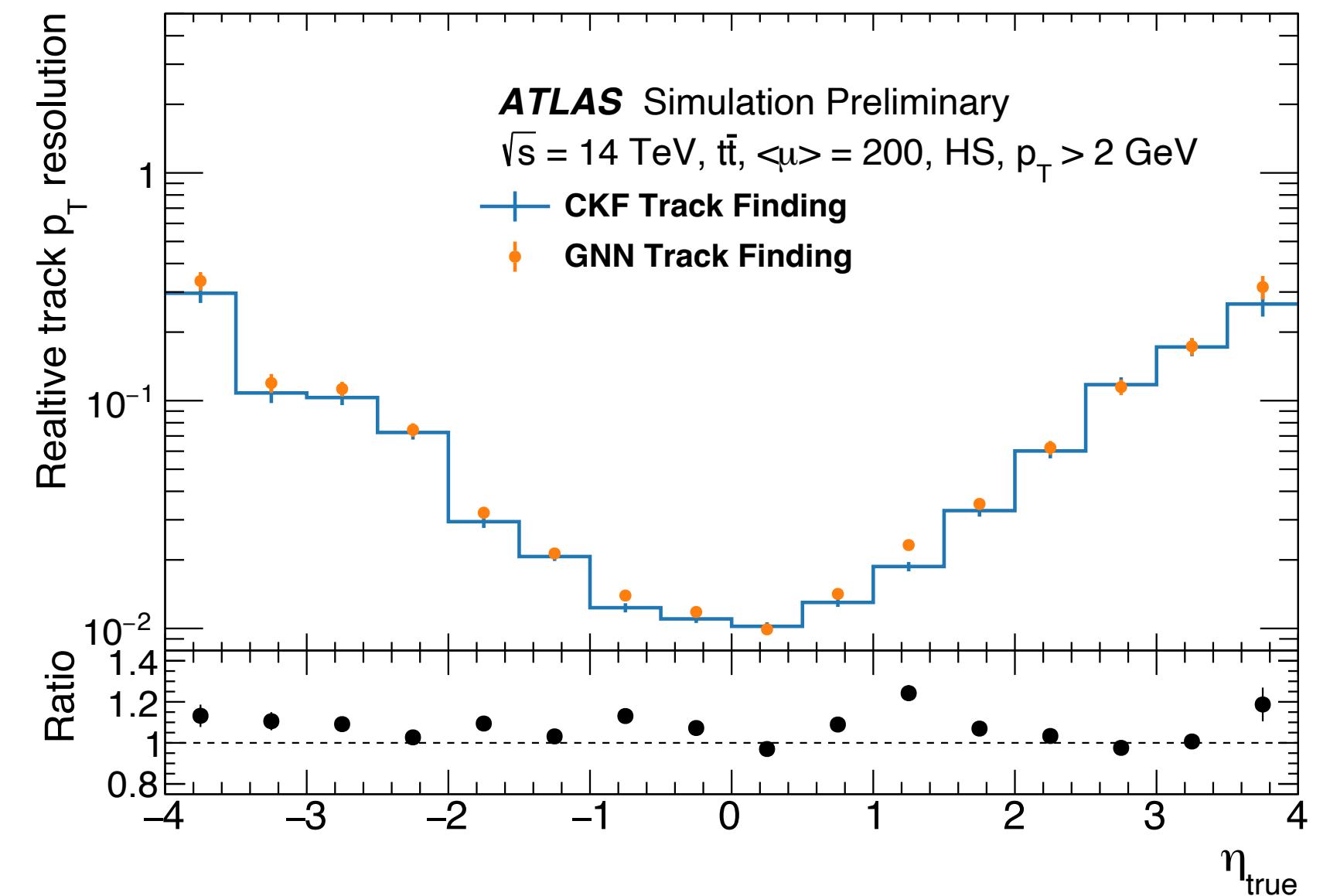
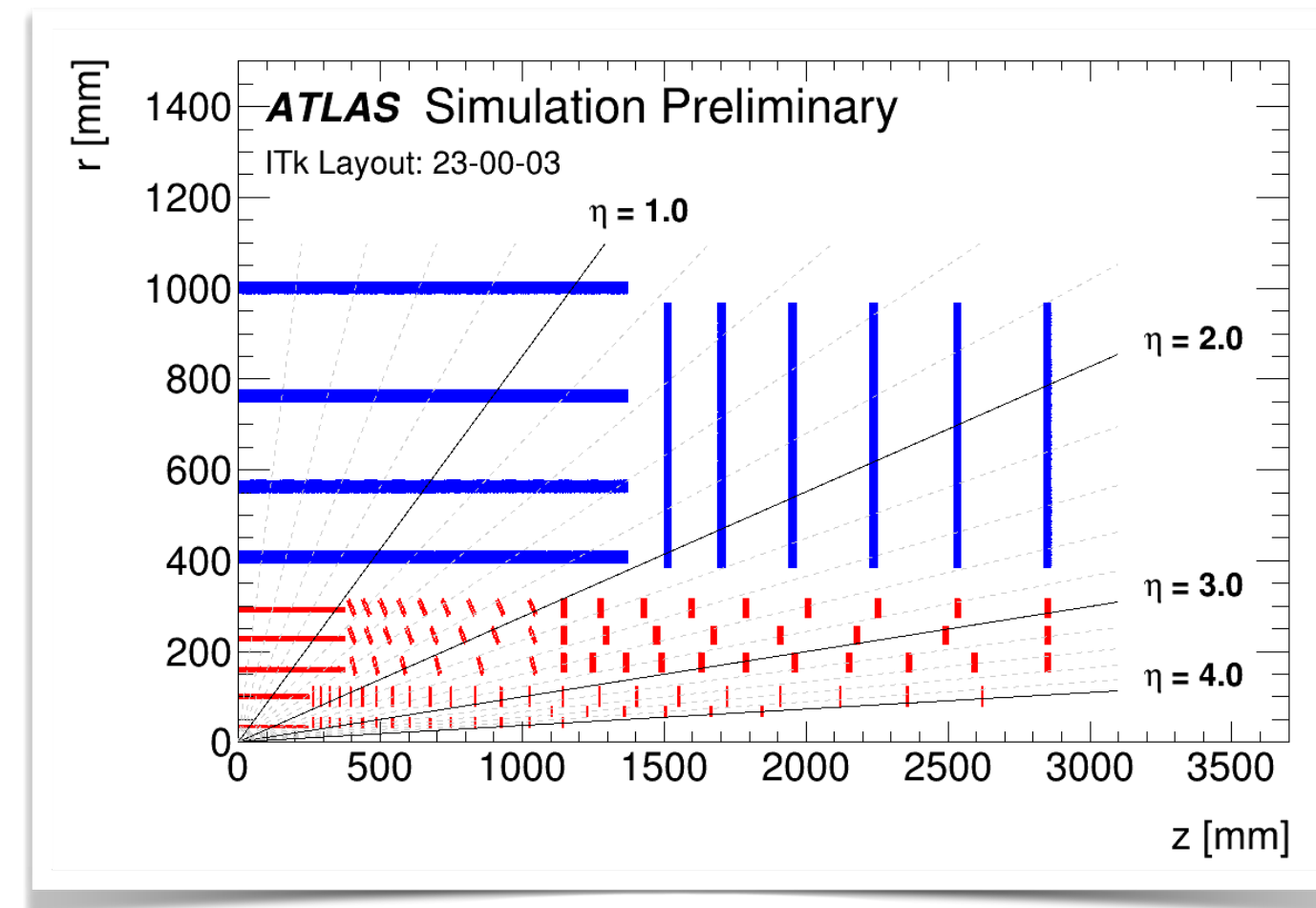
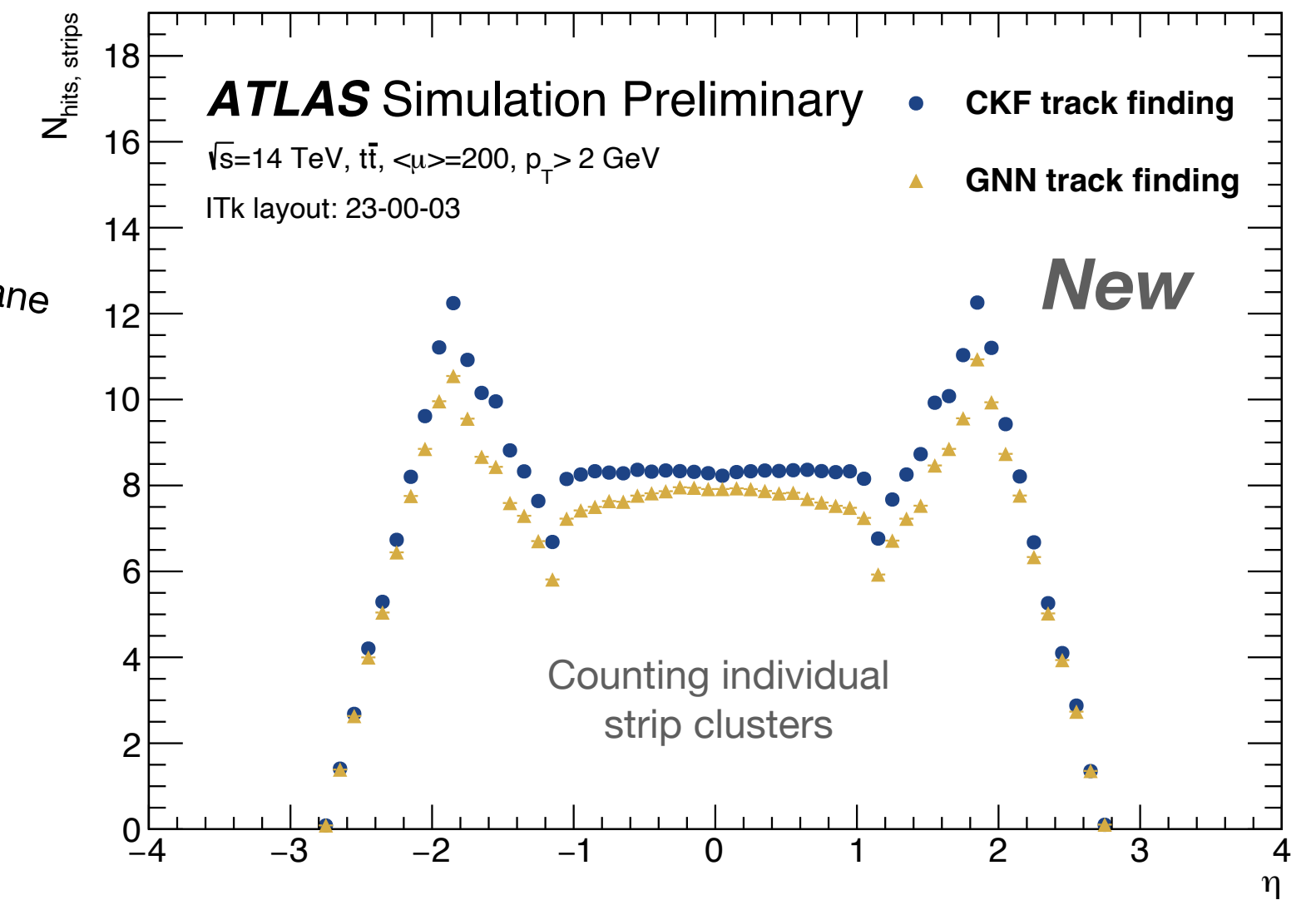
- Given the good pixel hit content, good impact parameter resolution



# Track strip-hit content and $p_T$ resolution



- Strip-hit content as expected  
GNN4ITk considers only “full” strip hits / space points, consisting of two strip clusters  
CKF considers also individual strip clusters
- Competitive  $p_T$  resolution, even with lower strip cluster counts



# Prospects

- Further optimization and acceleration of the full GNN4ITk chain
  - Acceleration of graph construction with GPU
  - Machine Learning model and heterogeneous GNN architectures
  - Study of corrections to strip-spacepoint positions
  - Investigate impact of missing strip-cluster singlets
- Continue physics performance studies  
(B-hadron decays tracks, electron tracks, etc.)
- Study robustness against detector effects  
(dead modules, mis-alignment, beam-spot variations)
- Integration of the GNN4ITk software into ACTS and the ATLAS Athena
- Already proven promising GNN inference speed with GPUs on TrackML dataset ([Exa.TrkX](#))

# Conclusion

First look at the physics performance of the GNN4ITk tracking chain  
(apples-to-apples comparison against the Combinatorial Kalman Filter).

- ✓ The GNN4ITk provides competitive tracking efficiency,
- ✓ even in challenging dense environment,
- ✓ and high quality track parameter resolution.

