

ATLAS ITk GNN Track Reconstruction Chain

Expected Tracking Performance

Alexis Vallier o.b.o. the ATLAS Collaboration — EPS-HEP 7 July 2025



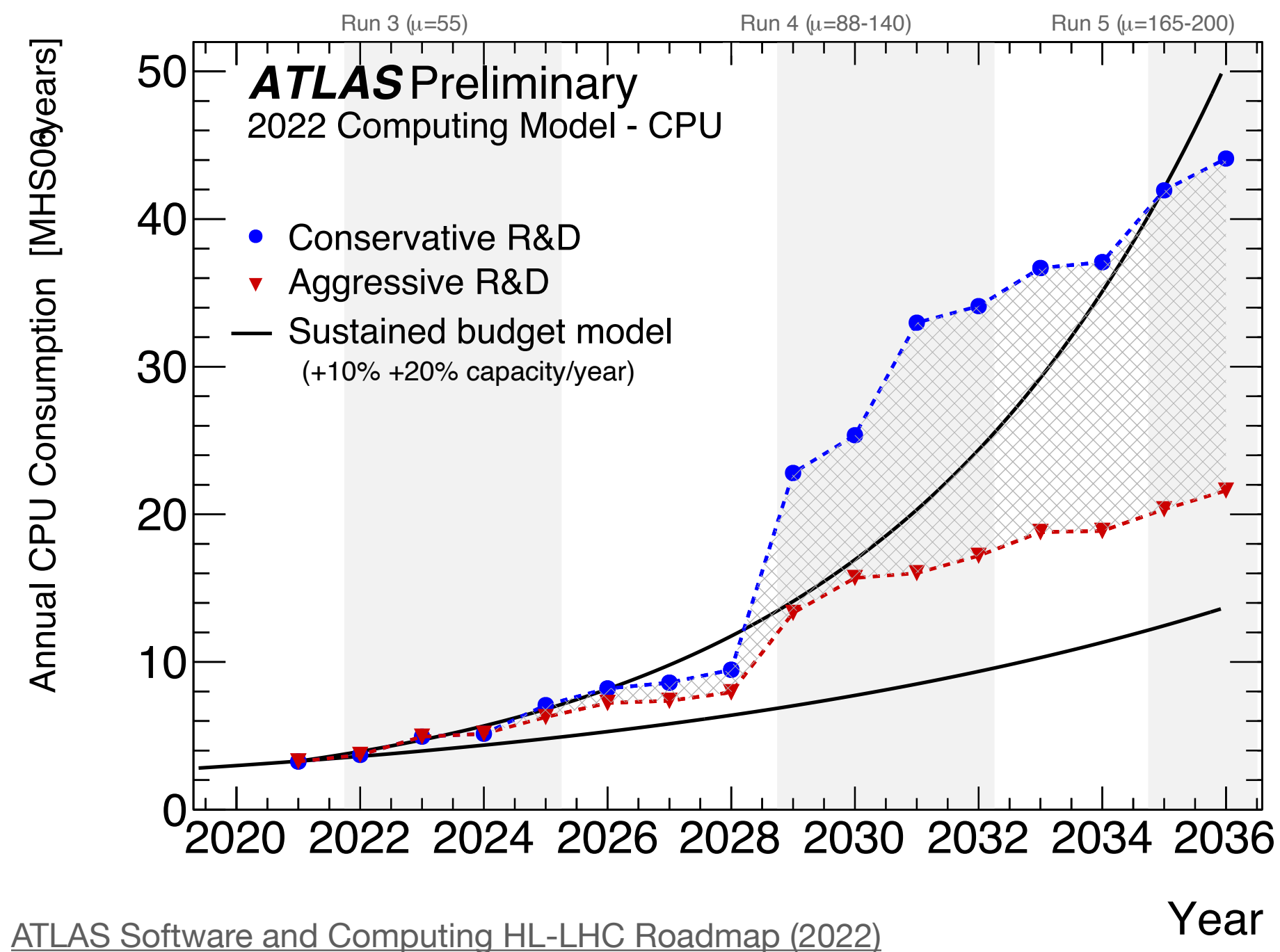
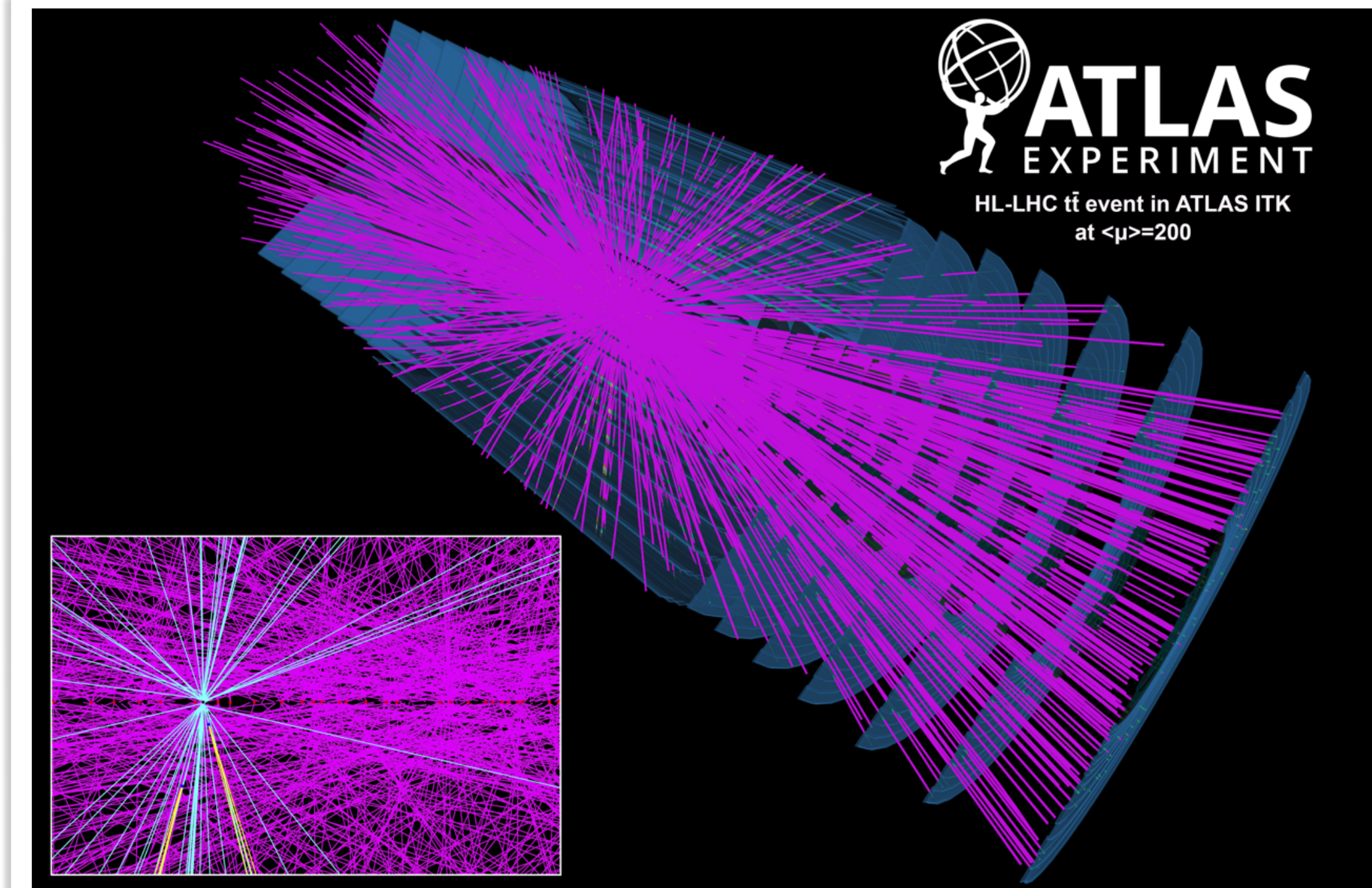
Track Reconstruction

In hadron collision @ High Luminosity

2030-2041 : High-Luminosity Phase of Large Hadron Collider (HL-LHC)

Detector occupancy pushed to extreme regime

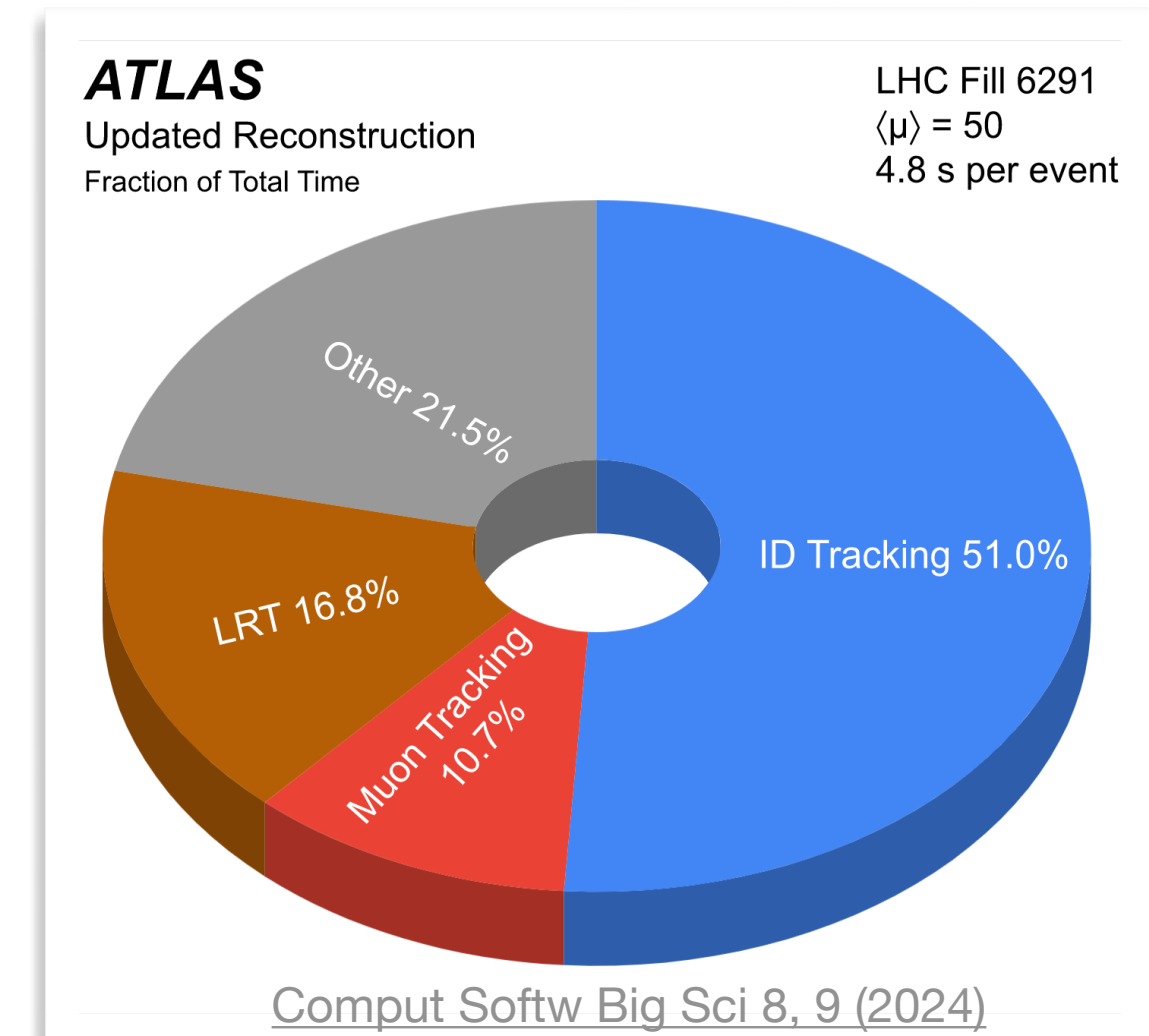
Very high number of simultaneous pp interactions : $\langle \mu \rangle = 200$



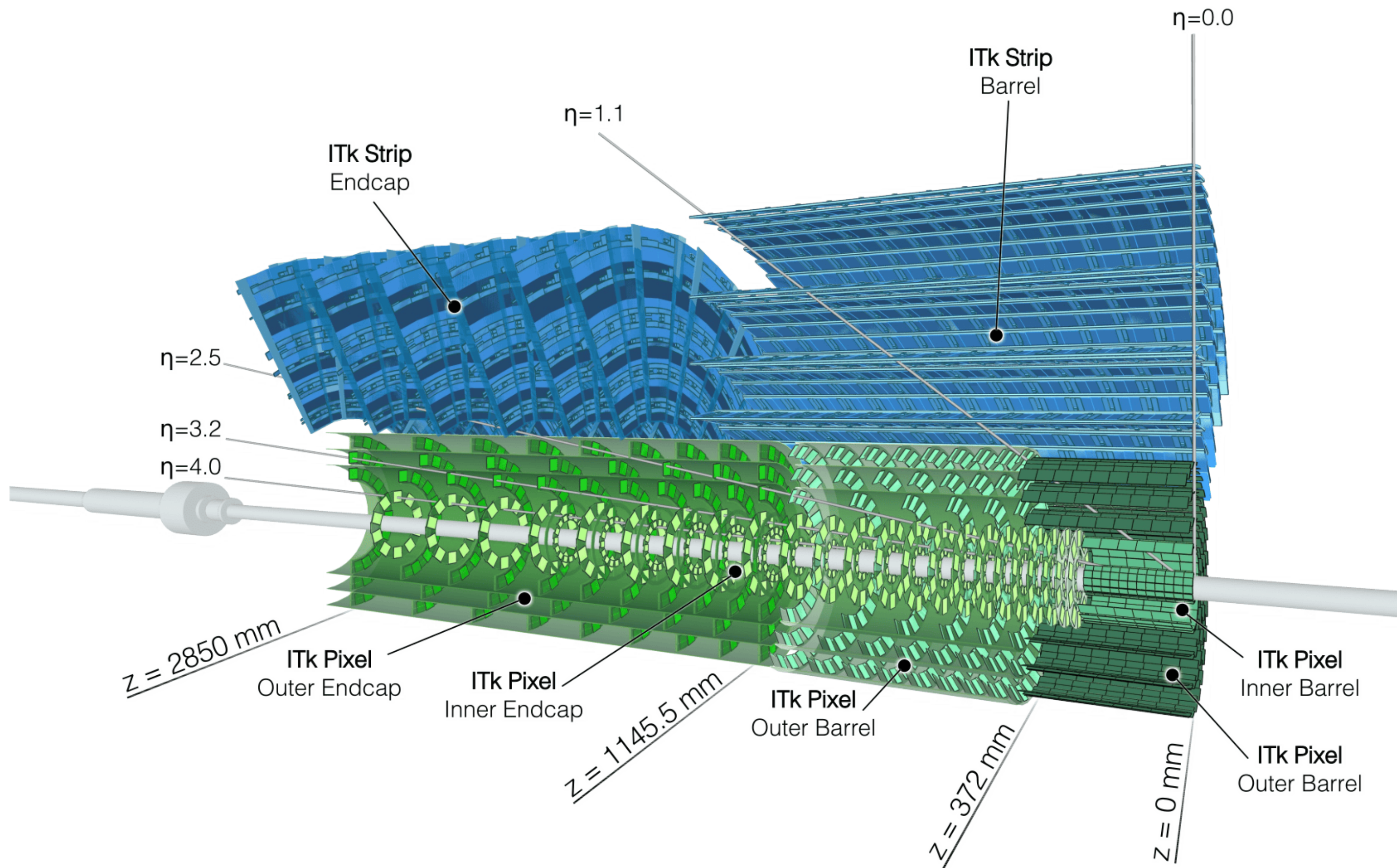
Need **aggressive Computing R&D** to process all the data recorded by ATLAS experiment

In event reconstruction **main part** is dedicated to charged particle **track reconstruction**

Must make faster tracking for HL-LHC

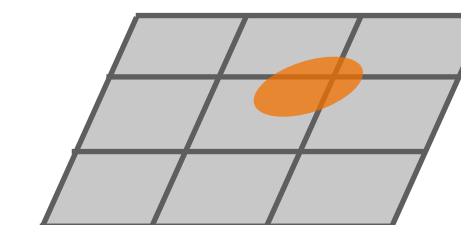


ATLAS ITk detector for HL-LHC



- Full silicon-based detector
 - pixel and strip
- Extended pseudorapidity coverage
 - up to $\eta = 4$
- Aims to reconstruct track of particles with $p_T > 1\text{ GeV}$
 - leave on average 9 hits in the detector

Pixel



Strip

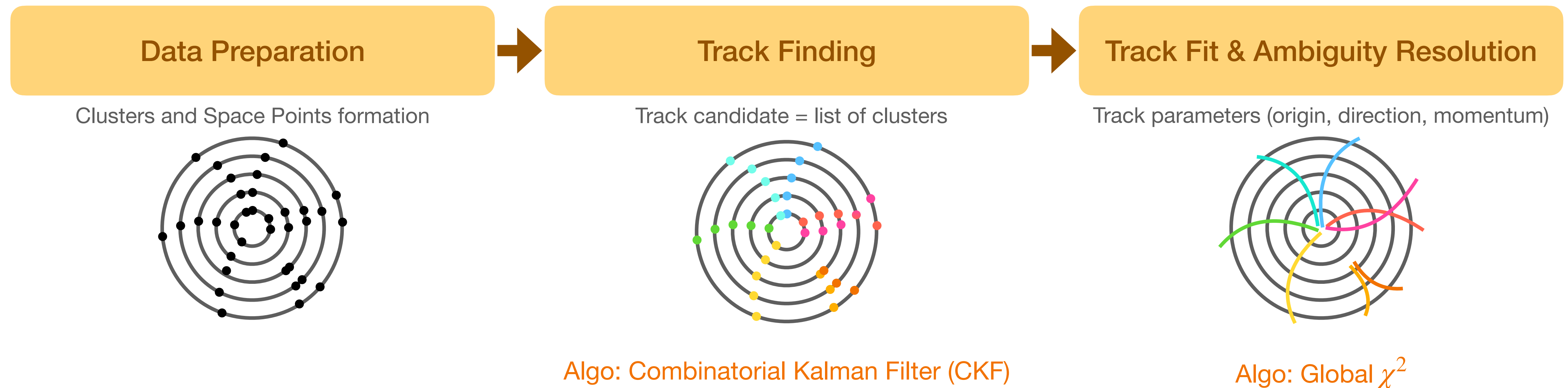


1 Cluster = 1 Space Point

2 Clusters = 1 Space Point

Track Reconstruction in ATLAS

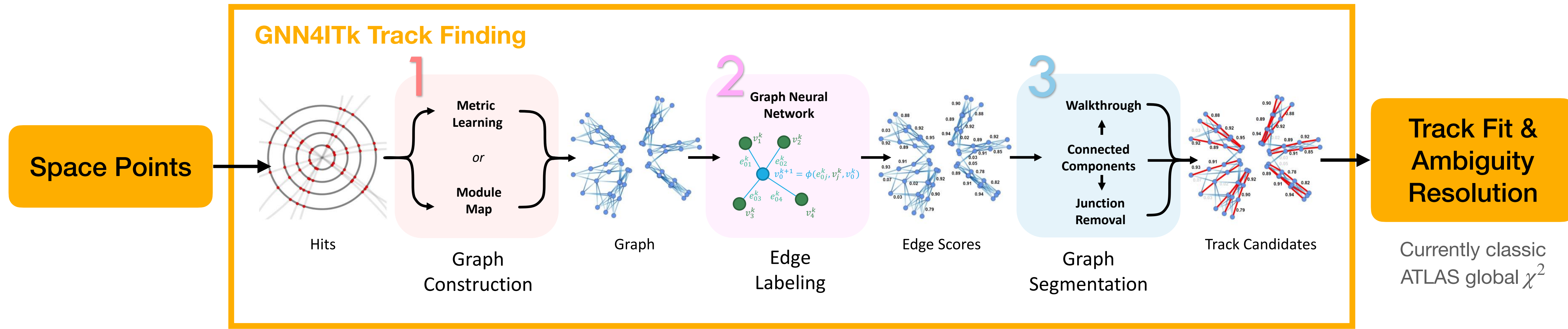
And Speed-up plans



- Projects for **faster track reconstruction** in ATLAS
 - Modern and **optimised CPU code** : use [ACTS](#) software in ATLAS framework (athena)
 - Port **classic algorithms to GPU** accelerator: [traccc](#)
 - Use modern Machine Learning algorithm on GPU accelerator: [GNN4ITk](#) [this talk]

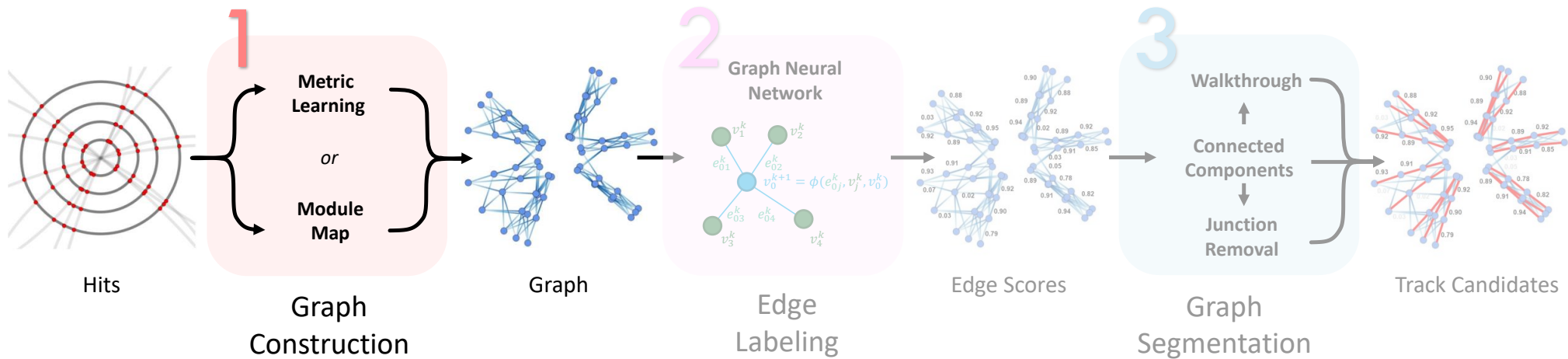
ATLAS GNN Track Reconstruction for Run 4

GNN4ITk project



- Replace CKF track finding with GNN inference on graph made from Space Points
- Python based R&D framework public: **acorn**
- Being put in production in ATLAS athena software and ACTS (including CUDA parts)

Graph Construction

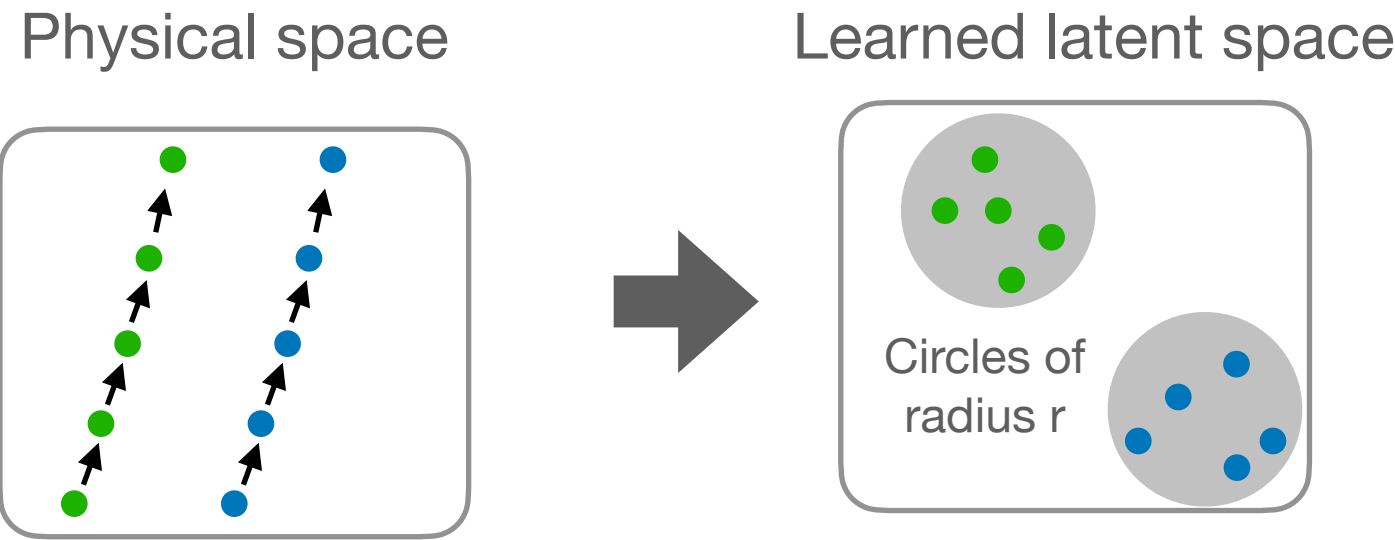


One event has **$O(300k)$ Space Points** : it would make **fully connected graphs of $O(10^{10})$ edges**, too large!

Need efficient methods to build **smaller & purer graphs**:

- Metric Learning**

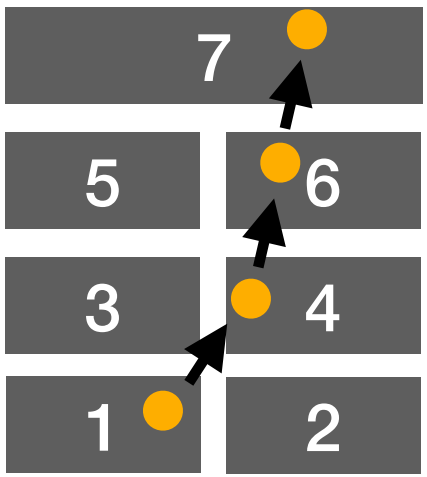
1. MLP is trained to embed nodes into latent space, where common particles hits are close
2. Additional filtering by GCN to reduce graph size



- Module Map**

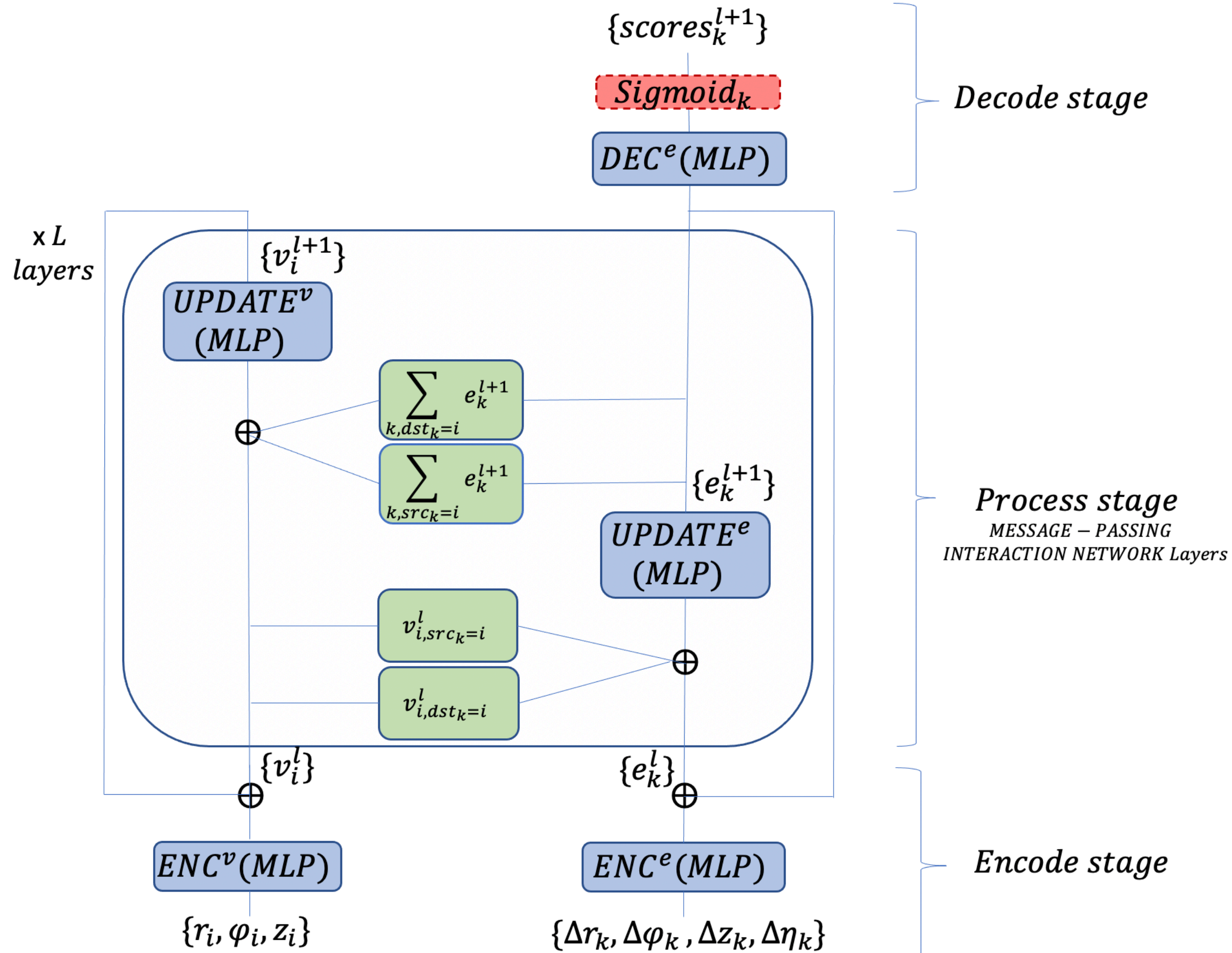
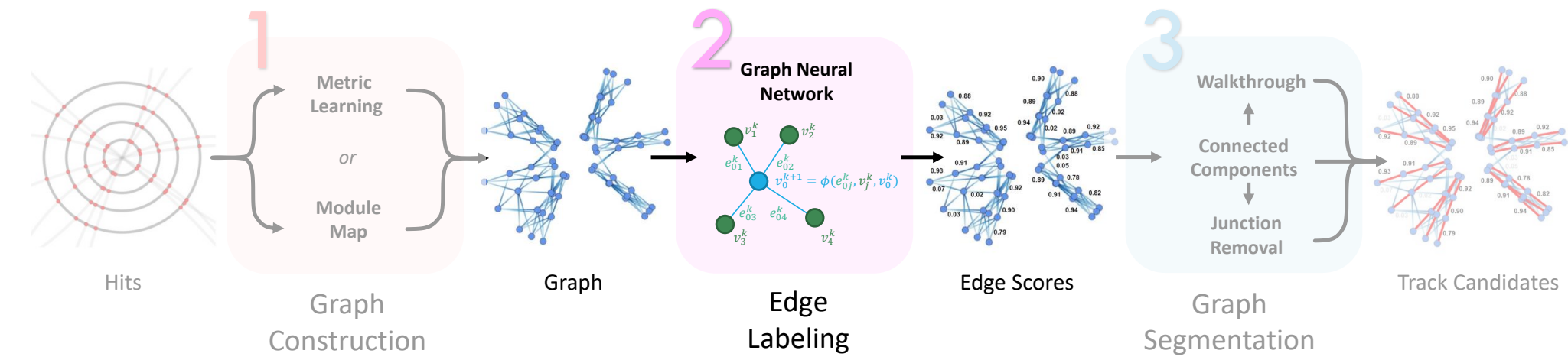
Lookup table of all possible module triplet connections, with [min,max,mean,rms] of geometric features ($\Delta\eta_{edge}$, Δr_{edge} , ...)

Computed from 90k $t\bar{t}$ simulated events



Allowed Triplets:
 $1 \rightarrow 4 \rightarrow 6$ with $x_{edge} \in [\text{mean} \pm n \times \text{rms}]$
 $4 \rightarrow 6 \rightarrow 7$ with $x_{edge} \in [\text{mean} \pm n \times \text{rms}]$
 (capped by min and max for each feature x)

GNN Model & Training

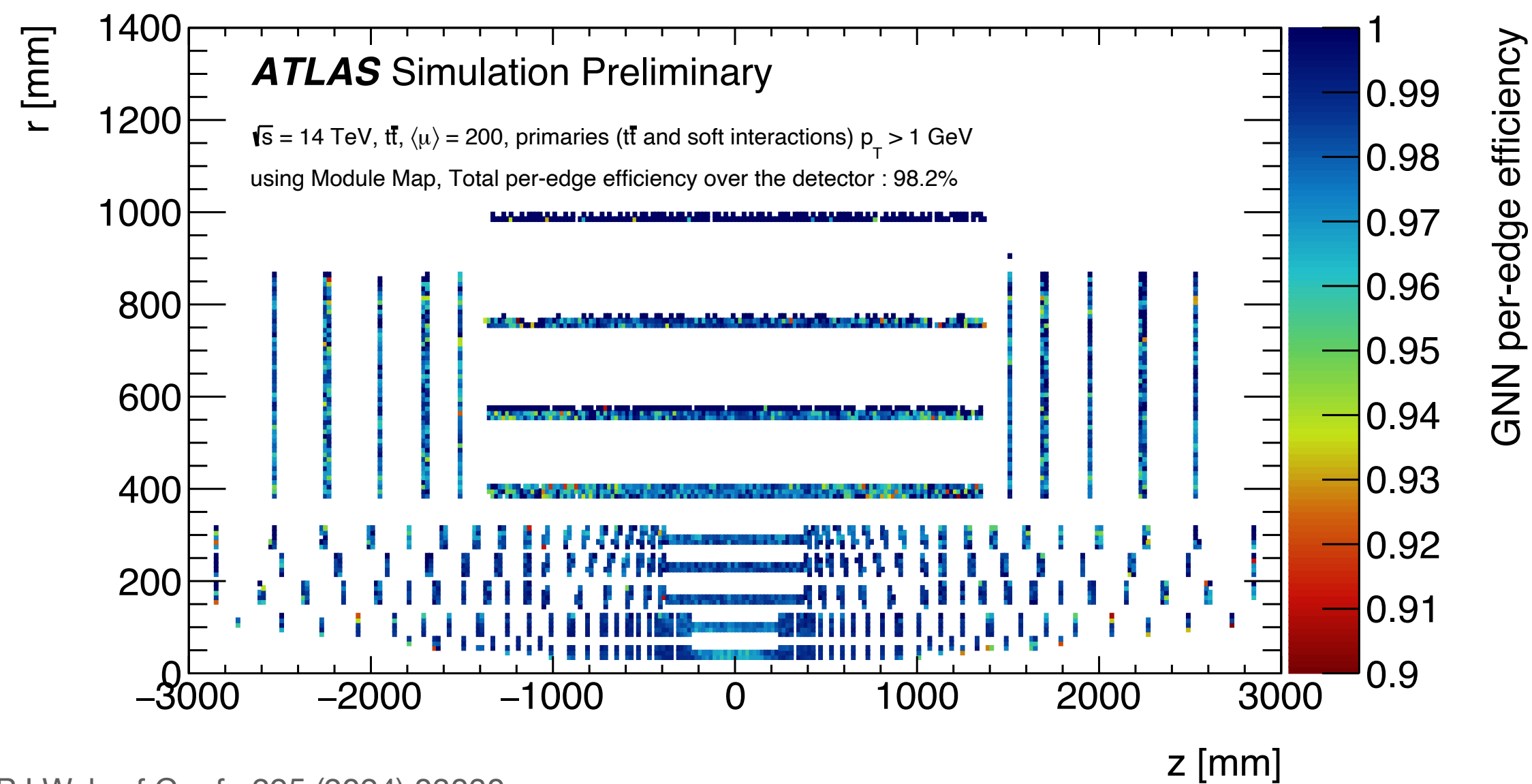


- GNN config:
 - 3 layers per MLP
 - 128D latent space
 - 8 message-passing
 - layer normalisation
 - Heterogeneous data (Pixel vs strips)
- Training sample: 10k $t\bar{t}$ at $\langle \mu \rangle = 200$
- Target particles:
 - $p_T > 1$ GeV, $R_{\text{production}} < 26$ cm
 - Primary particles with at least 3 space points
 - electrons are masked (at the moment)

GNN performance

edge-wise efficiency and purity

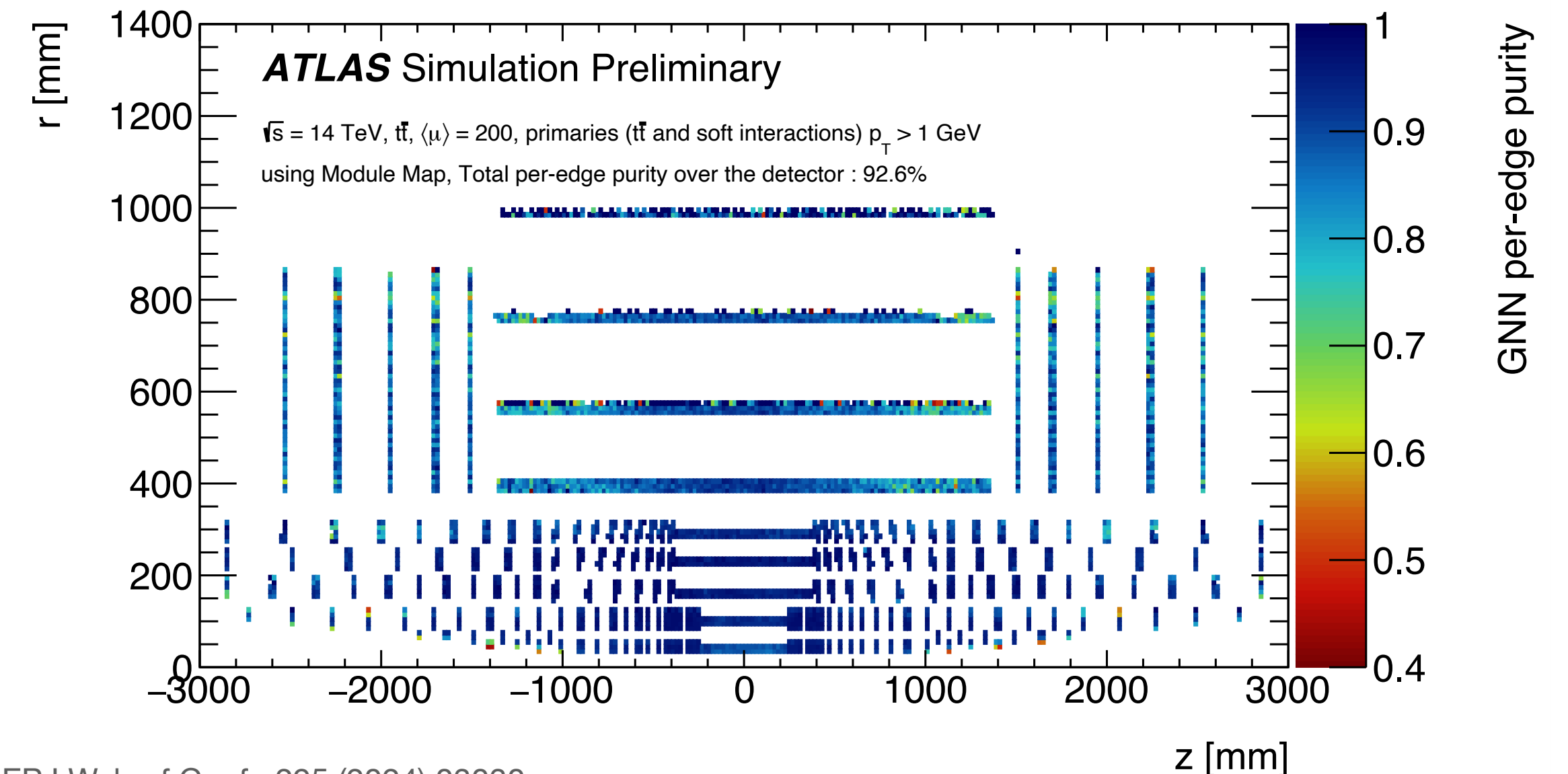
Edge efficiency for score > 0.5



EPJ Web of Conf., 295 (2024) 03030

$$\text{efficiency} = \frac{N_{\text{true edges}}(\text{score} > X)}{N_{\text{true edges}}}$$

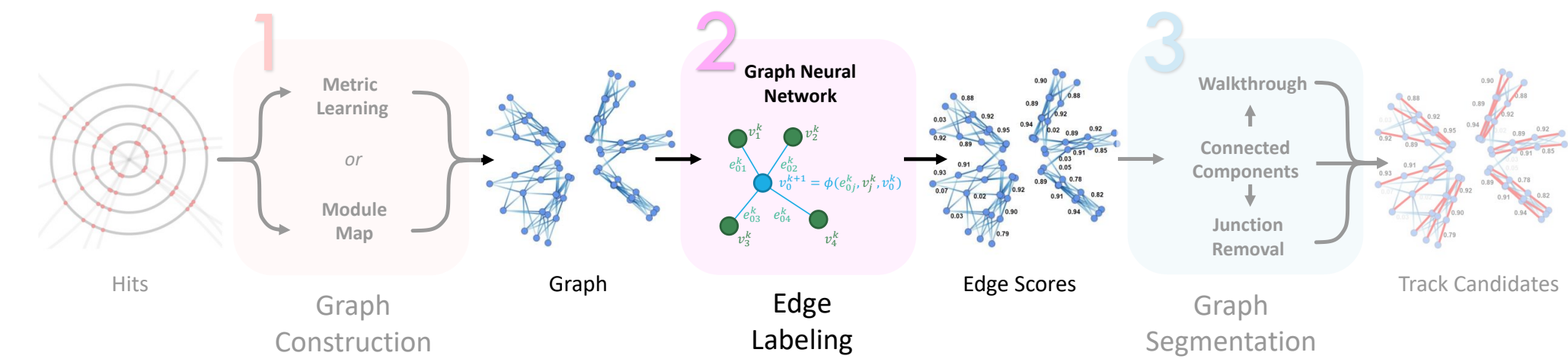
Edge purity for score > 0.5



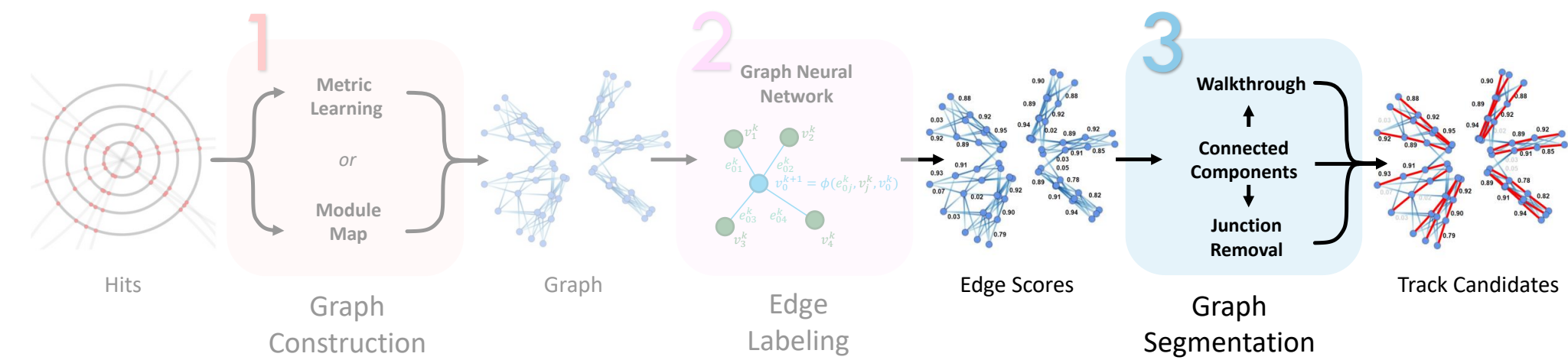
EPJ Web of Conf., 295 (2024) 03030

$$\text{purity} = \frac{N_{\text{true edges}}(\text{score} > X)}{N_{\text{true edges}}(\text{score} > X) + N_{\text{fake edges}}(\text{score} > X)}$$

- GNN is **able to identify edges** that connects hits from same particle
- Most **challenging regions**: luminous region **close to beamspot & strips**

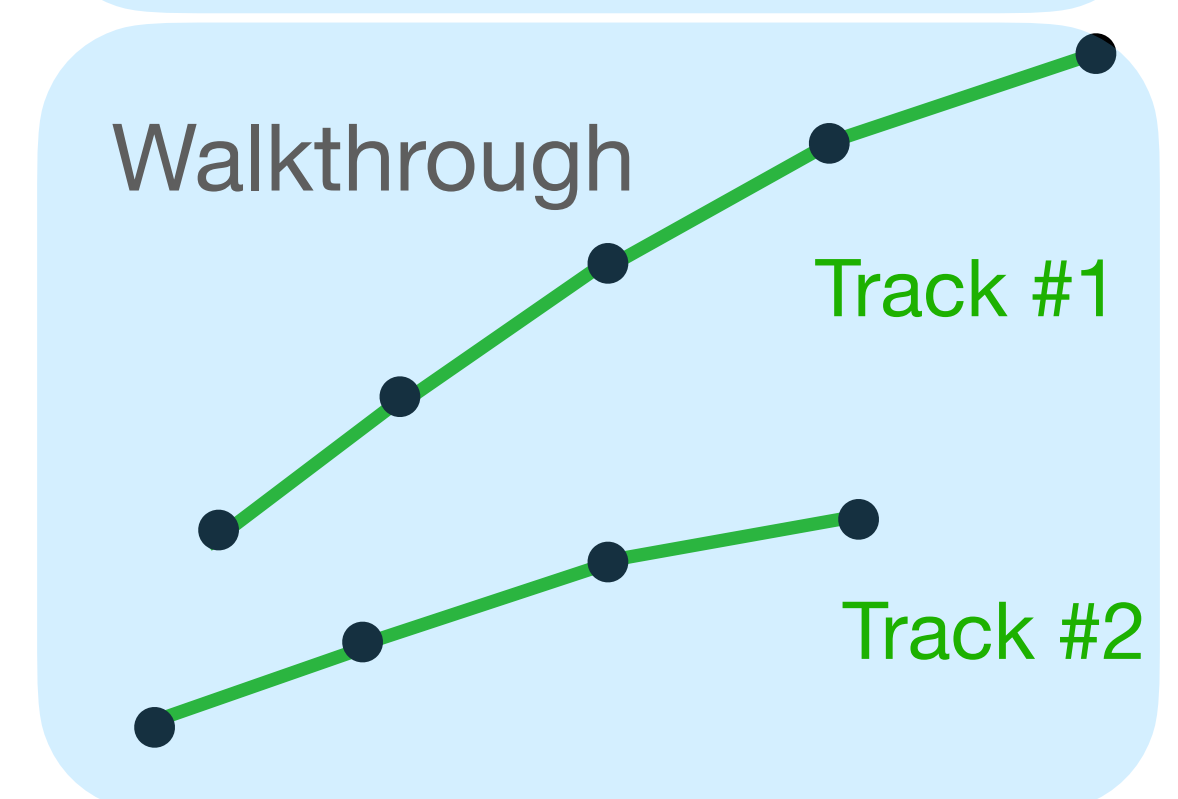
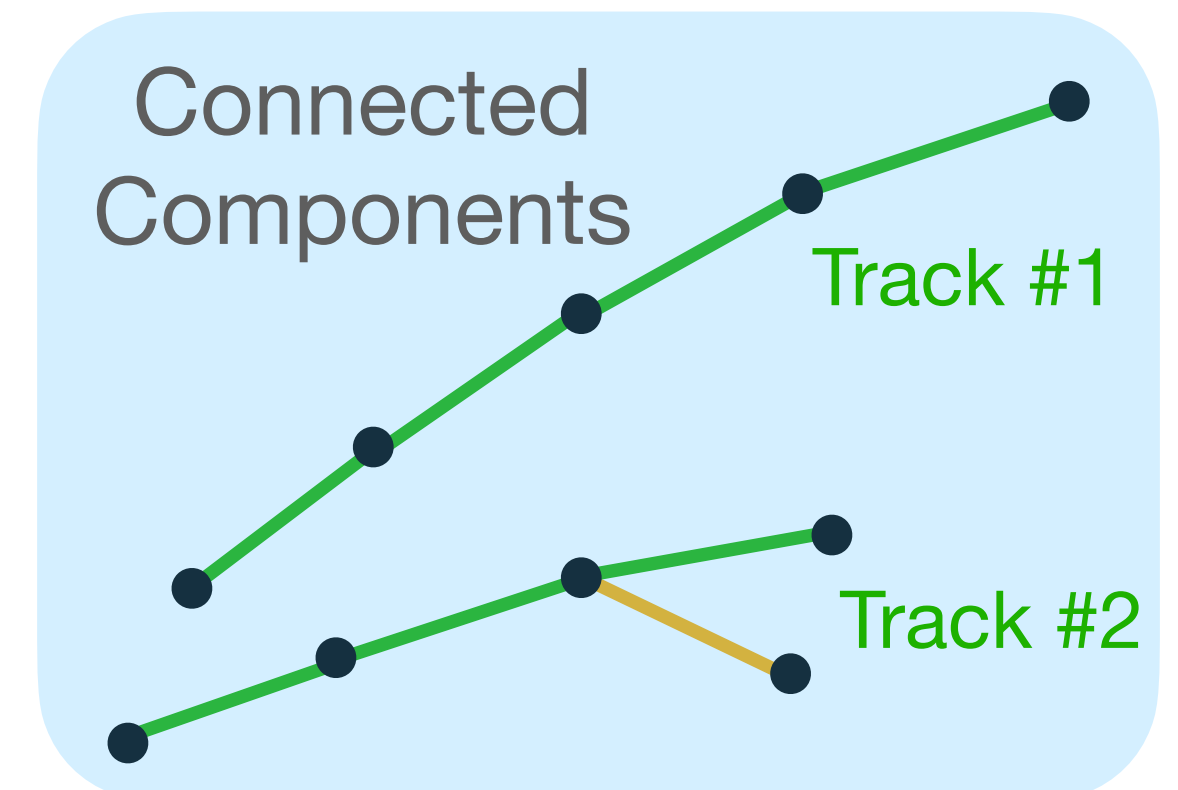
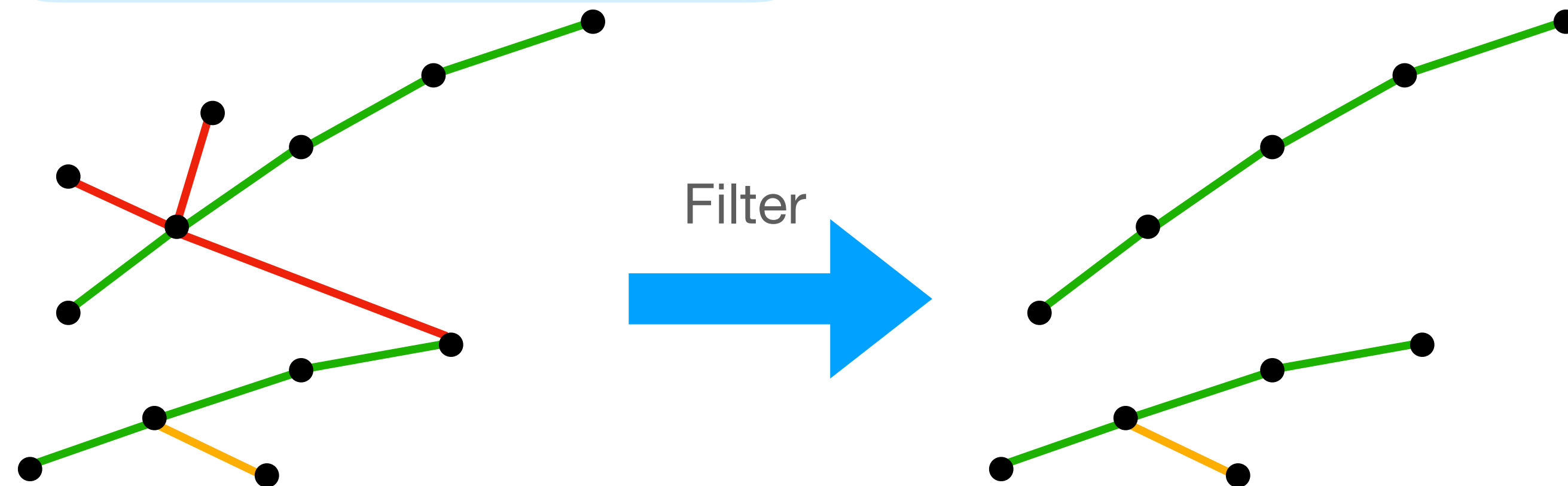


Graph segmentation aka Track candidates Building

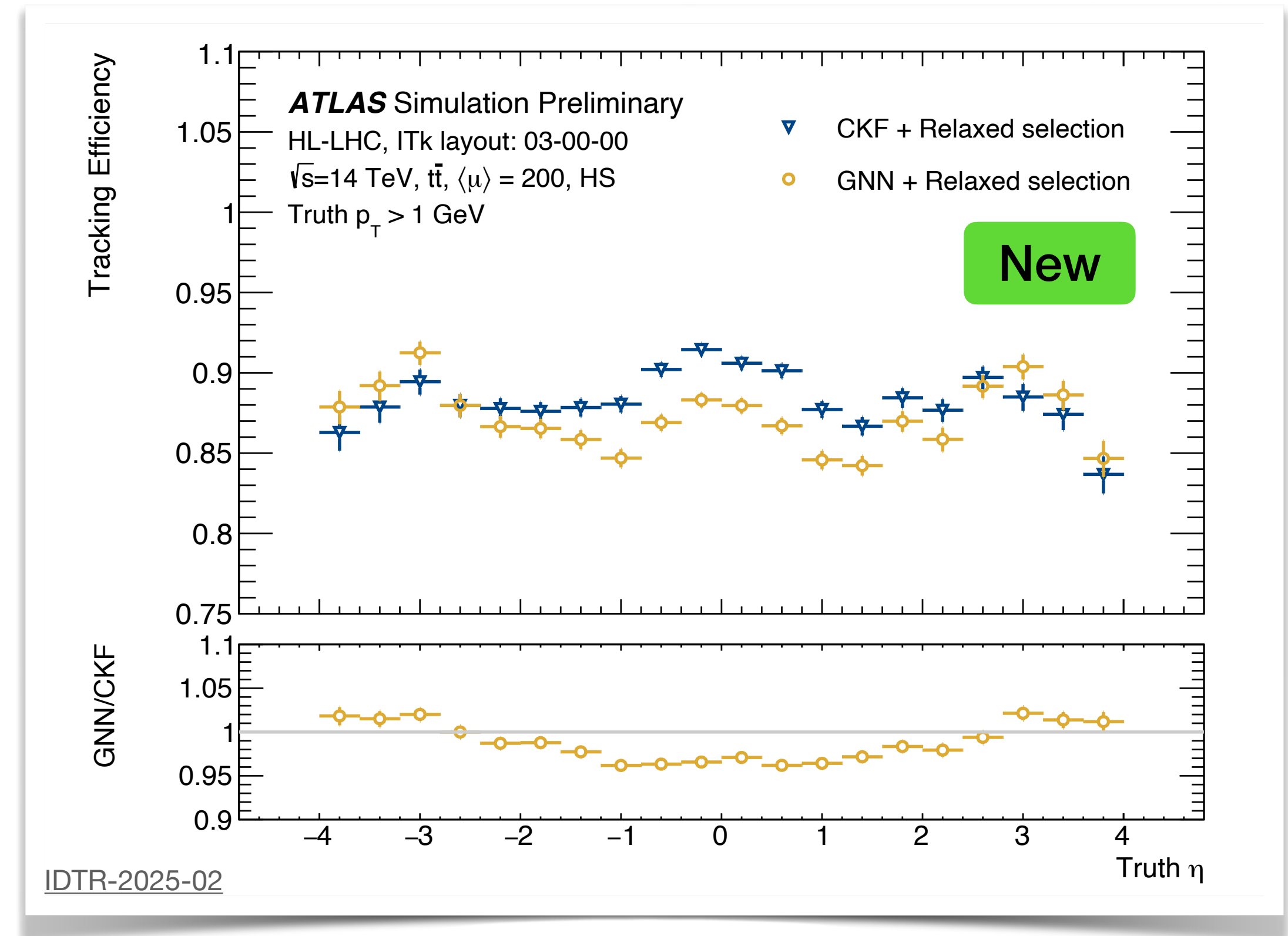
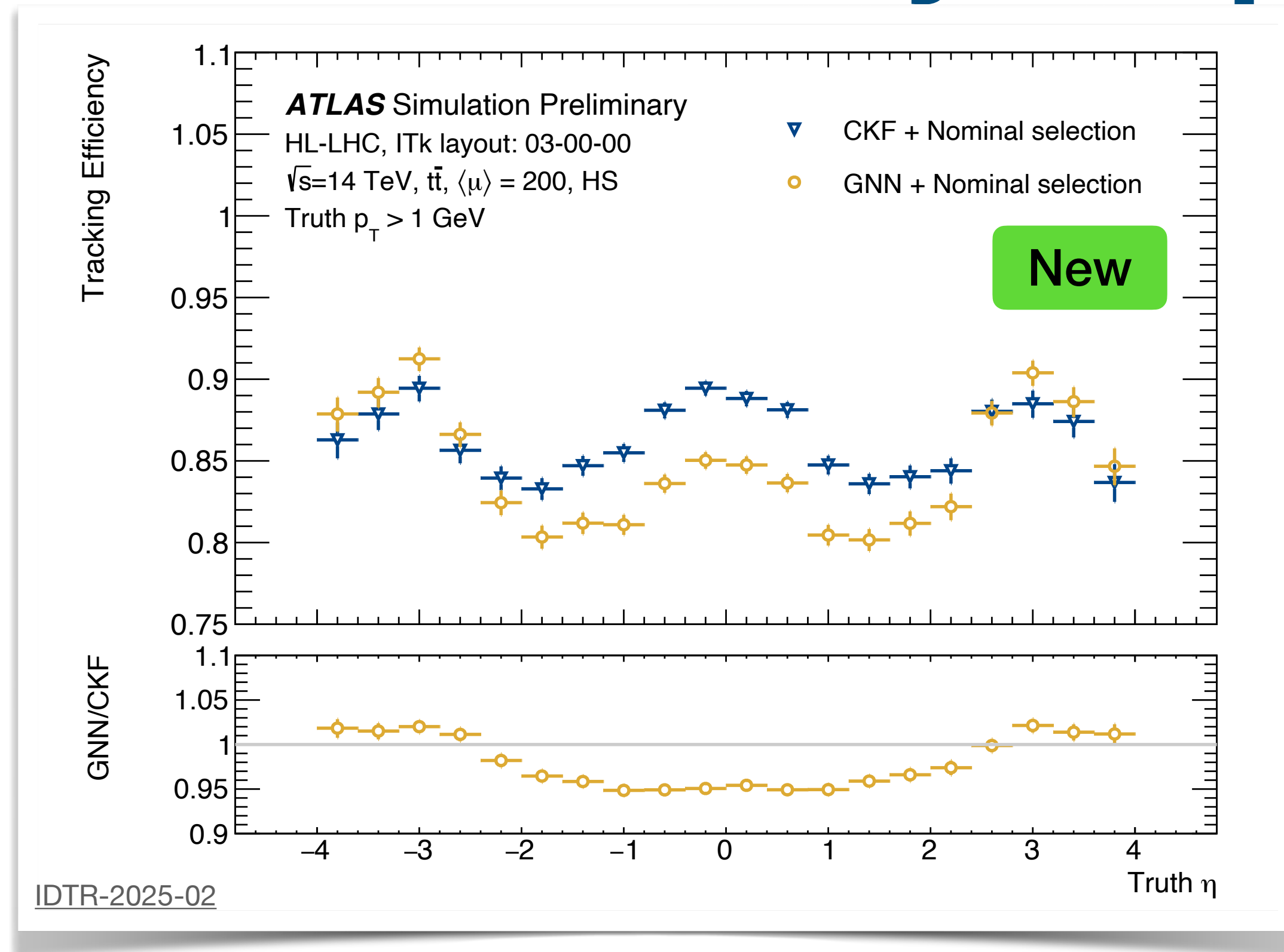


- Start from filtered graph (edge score cut)
 - Connected Component : one track candidate = 1 set of connected nodes
 - Walkthrough : walk through the graph, keep longest paths

— Above threshold
— Above threshold (lower score)
— Below threshold



Track efficiency vs η

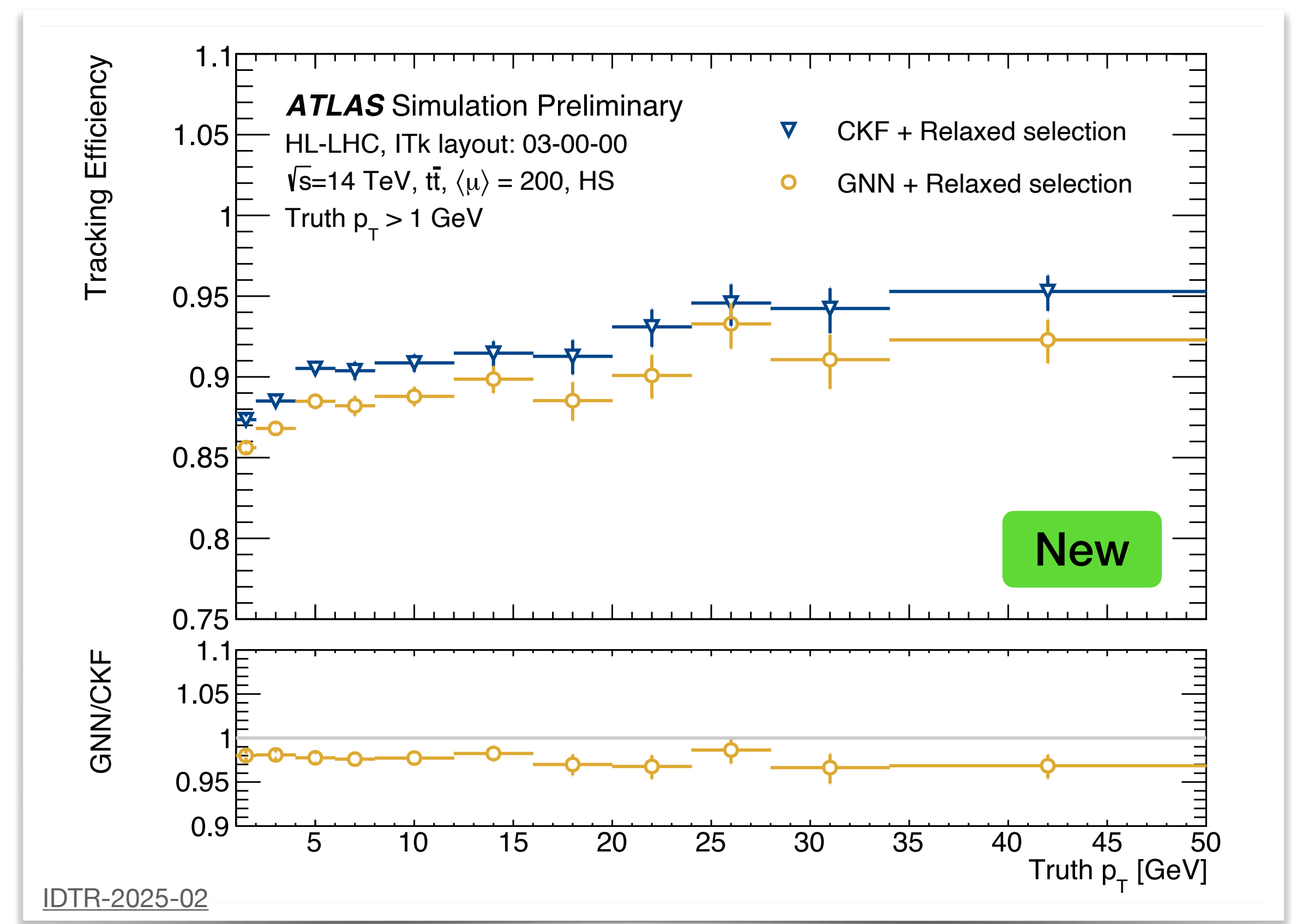
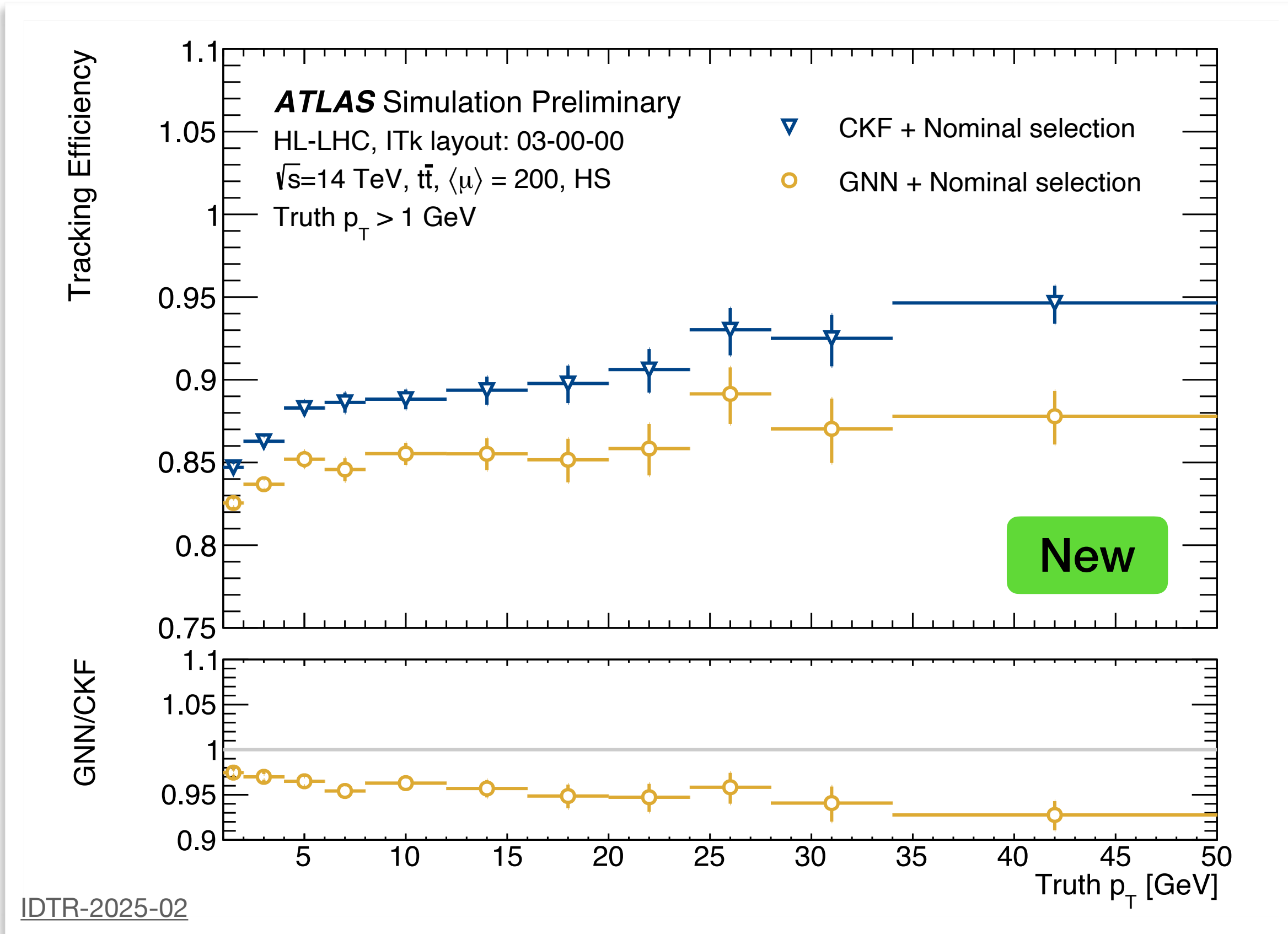


Nominal track selection defined for classic CKF reconstruction

GNN track finding based on Space Points not cluster: need to adapt selection due to Space Point formation inefficiencies → Relaxed selection (lower required number of clusters per track)

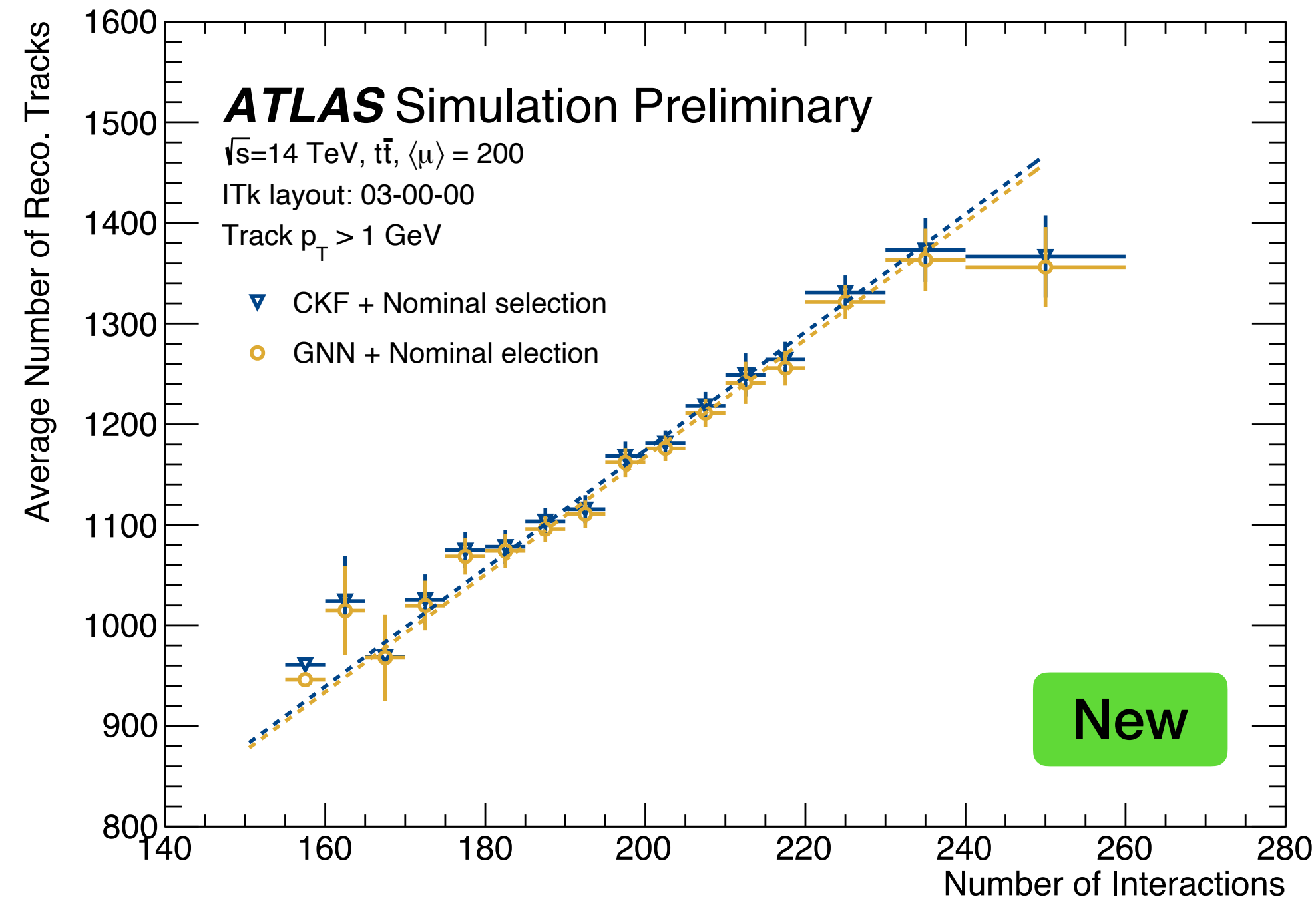
GNN tracking chain is able to reconstruct tracks with a good efficiency

Track efficiency vs p_T

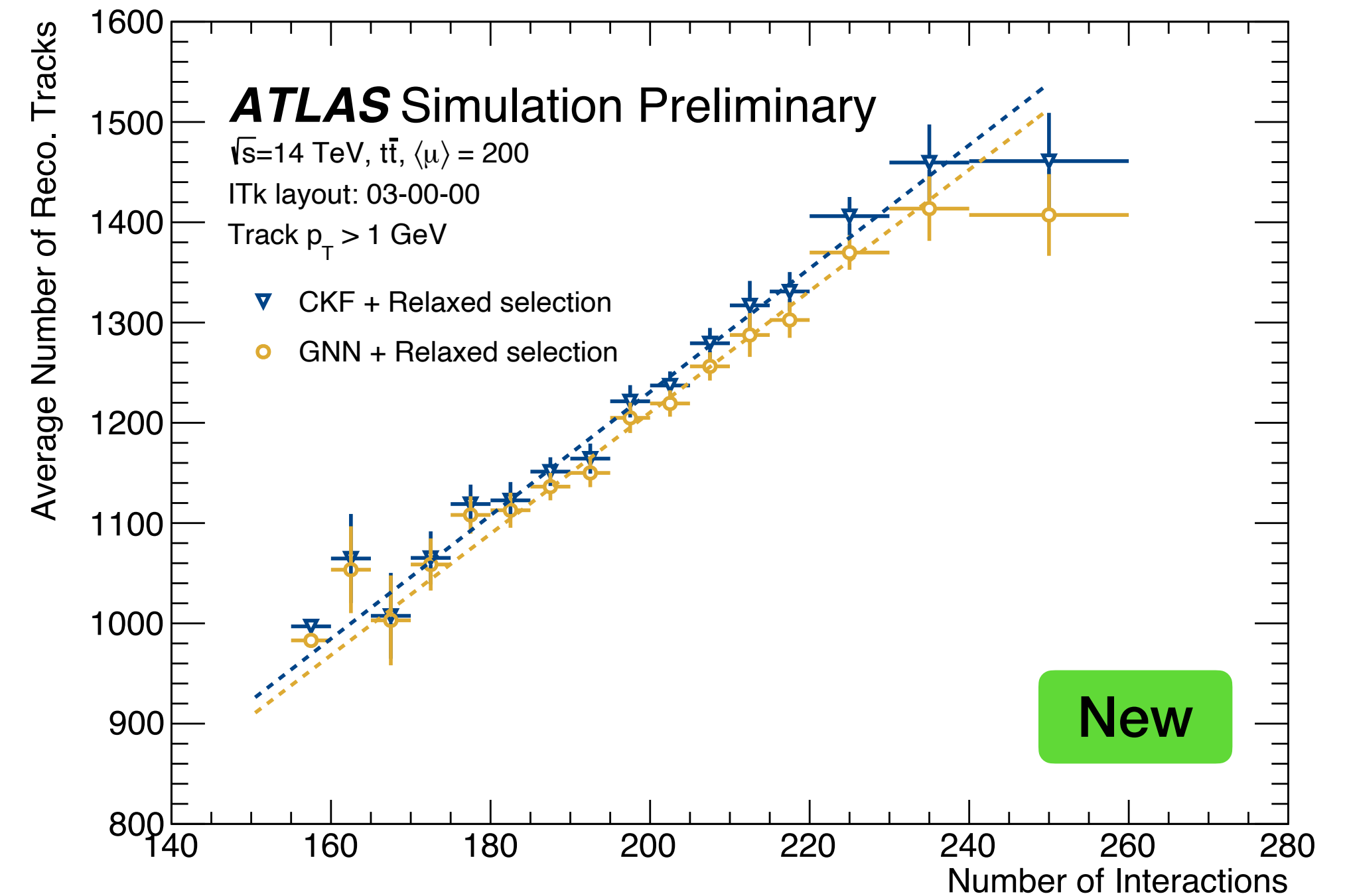


GNN tracking suffer a bit at high p_T because of reduced training statistics with $t\bar{t}$ sample
Should be mitigated in the future to use additional processes

Number of tracks vs μ



IDTR-2025-02

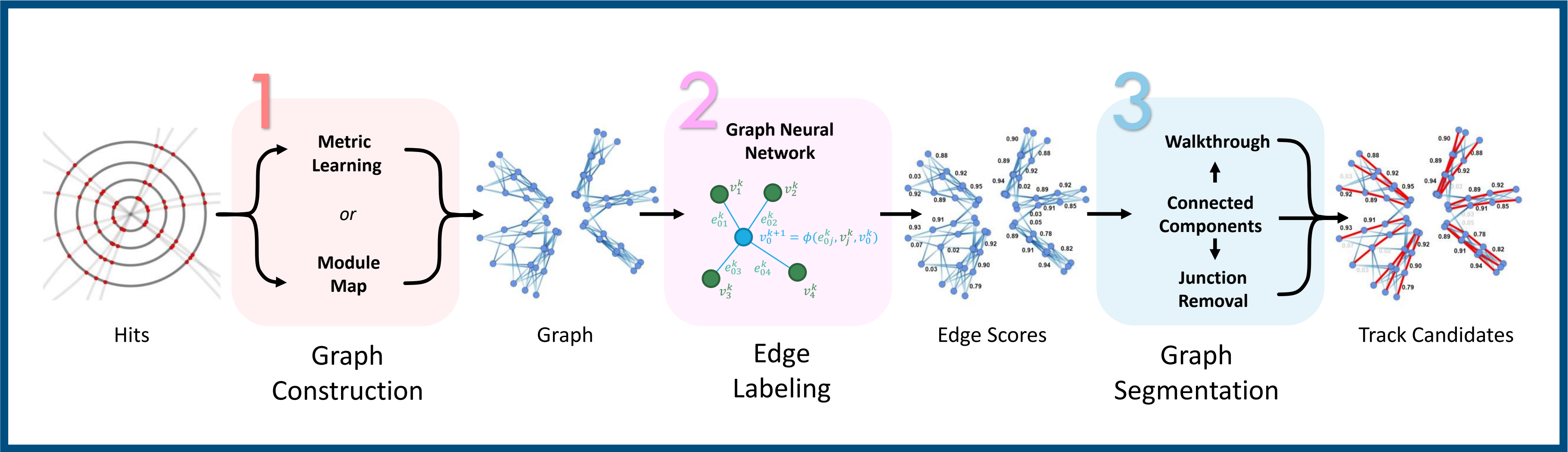


IDTR-2025-02

- Linear scaling : Fake and mis-reconstructed tracks are very low
- Even with relaxed cuts, fake rates for GNN does not significantly inflates

Compute Performance

Are we fast enough?



Module Map:	69 ms	+	323 ms	+	118 ms	=	510 ms
Metric Learning:	505 ms	+	108 ms	+	118 ms	=	731 ms

ATL-PHYS-PUB-2024-018

Several optimisation already made: graph building in CUDA, model compilation, automatic mixed precision

Already sub-second event processing

Even more are coming: model reduction & quantization, graph segmentation in CUDA...

Conclusion

& Outlook

We have designed a **GNN-based track finding algorithm** that is **competitive** with the standard **Combinatorial Kalman Filter** in terms of tracking performance

The **compute time is promising** to help processing HL-LHC data...

... and computing optimization have just started

The algorithm **is being integrated to the official ATLAS software**

Coming soon: **robustness studies** (non ideal detector) and **more detailed physics studies** (other processes than $t\bar{t}$, electrons, boosted jets, displaced vertices)

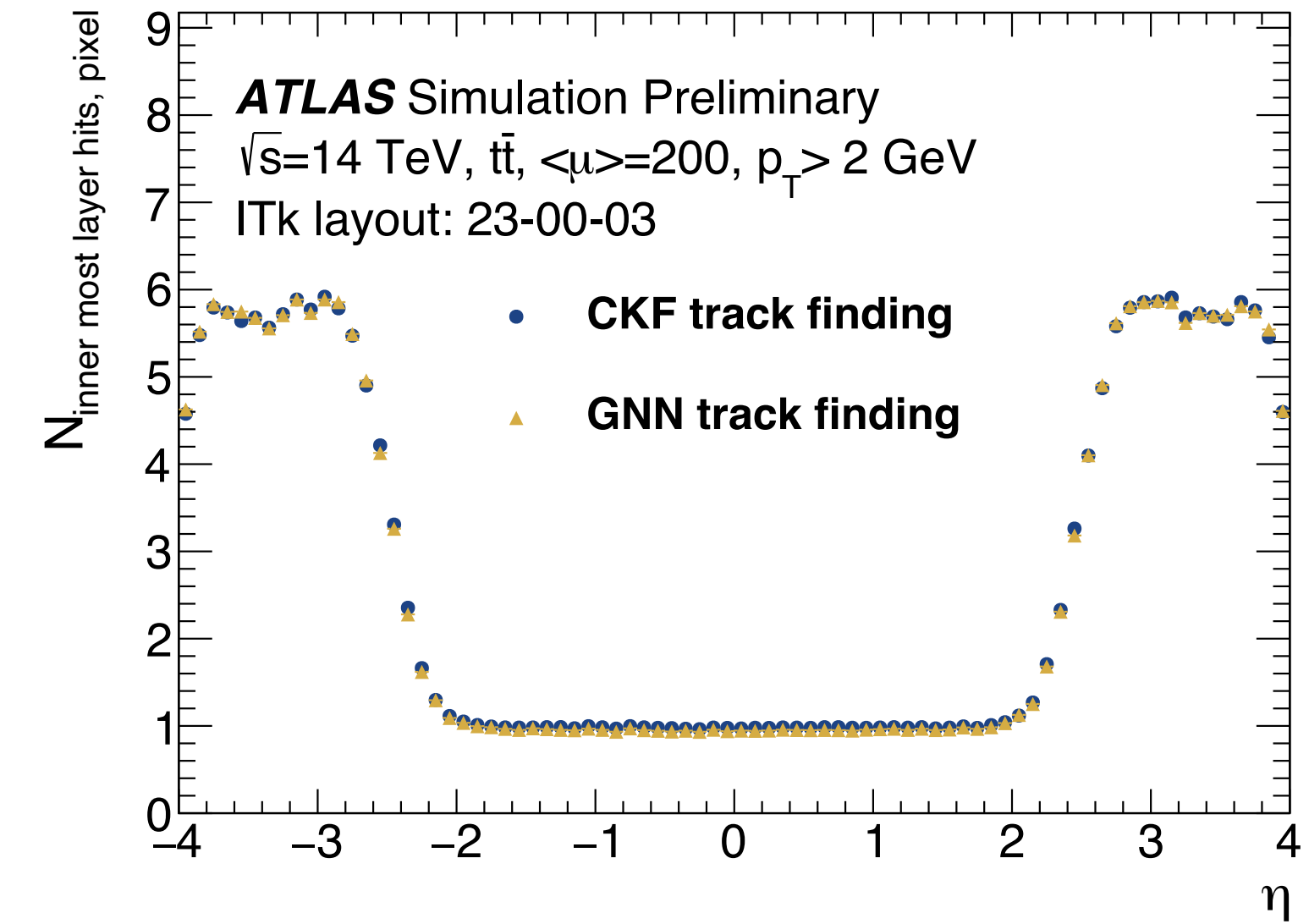
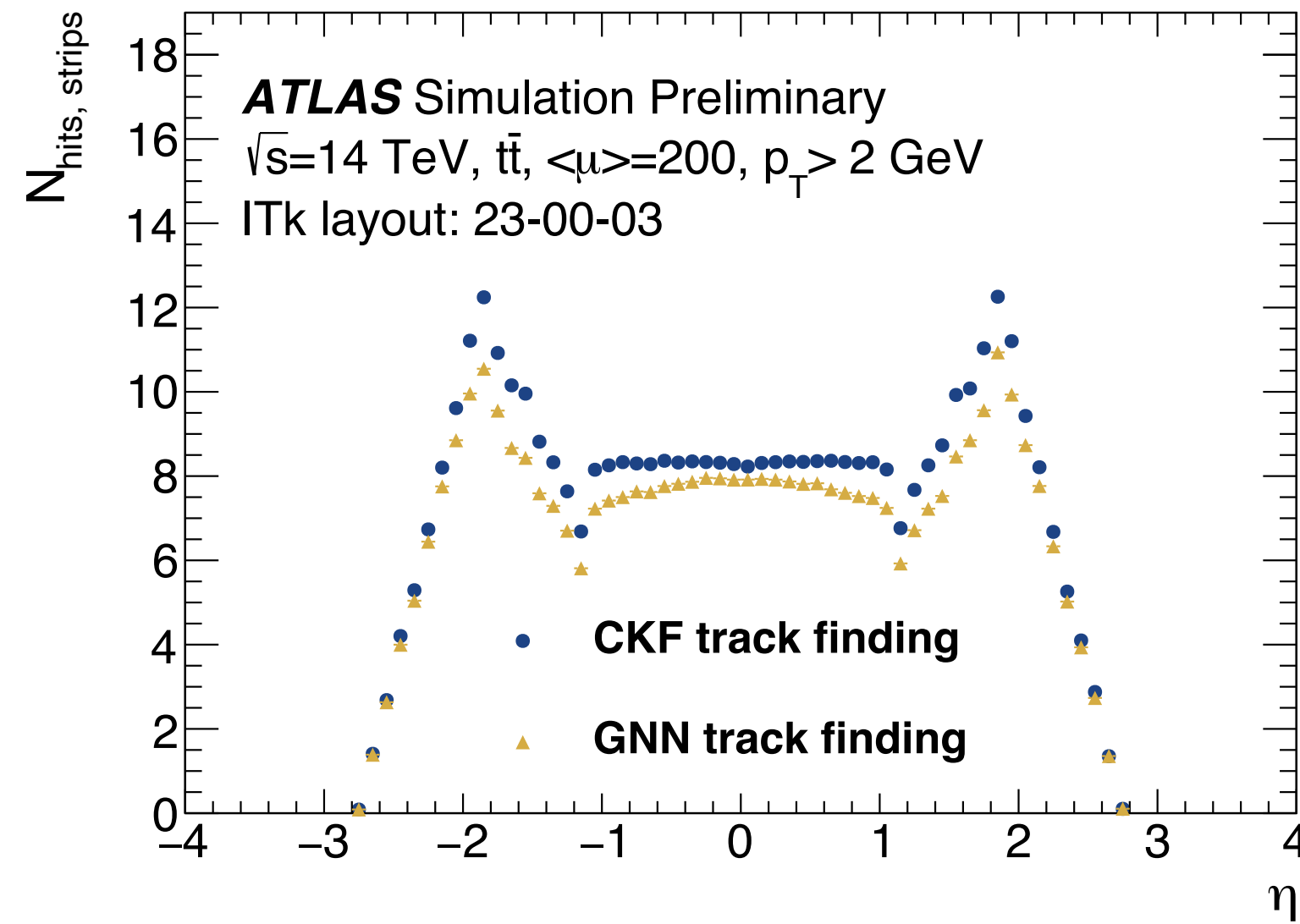
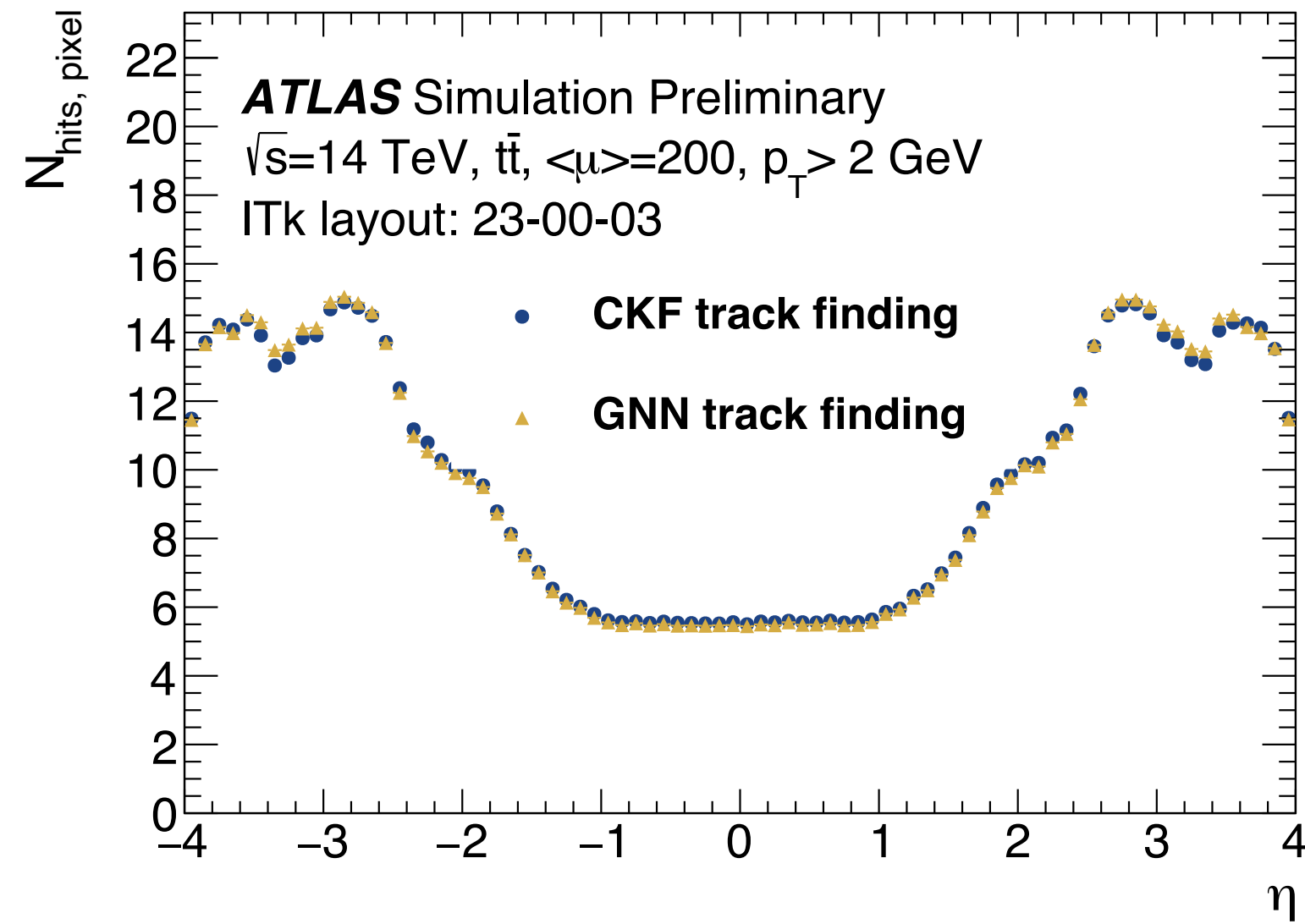
BACKUP

Track Selection

Nominal (Relaxed) Requirements	Pseudorapidity Interval		
	$ \eta \leq 2.0$	$2.0 < \eta \leq 2.6$	$2.6 < \eta \leq 4.0$
Pixel + Strip hits	≥ 9 (7)	≥ 8 (7)	≥ 7
Pixel hits	≥ 1	≥ 1	≥ 1
Holes	≤ 2 (4)	≤ 2 (4)	≤ 2
p_T [MeV]	> 900	> 400	> 400
$ d_0 $ [mm]	< 2.0	< 2.0	< 10.0
$ z_0 $ [cm]	< 20.0	< 20.0	< 20.0

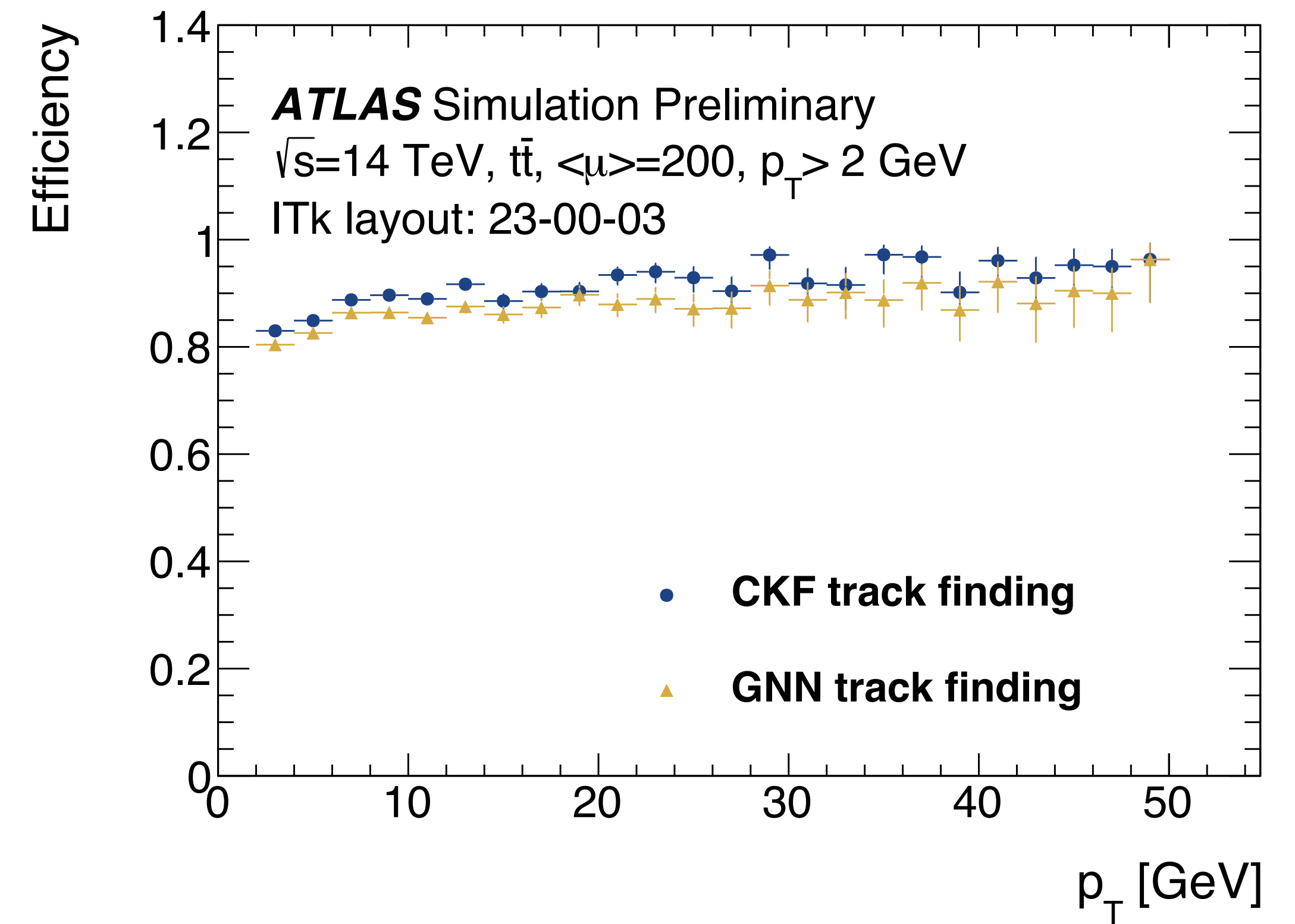
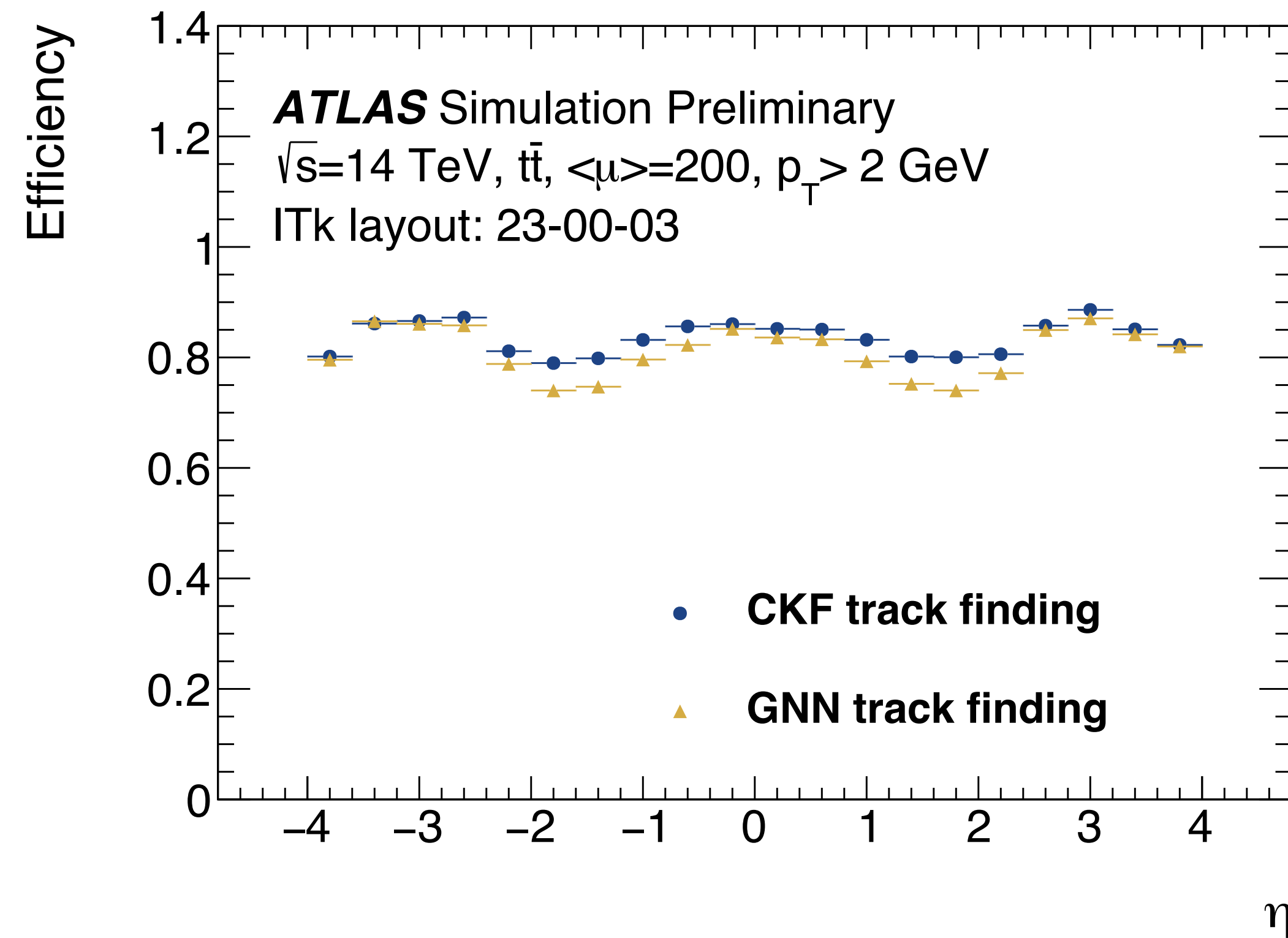
Previous results

hit content



Previous results

Efficiencies



Previous results

Jets

