Curvature-Aware Edge Filtering for Low-p_T Track Reconstruction at HL-LHC

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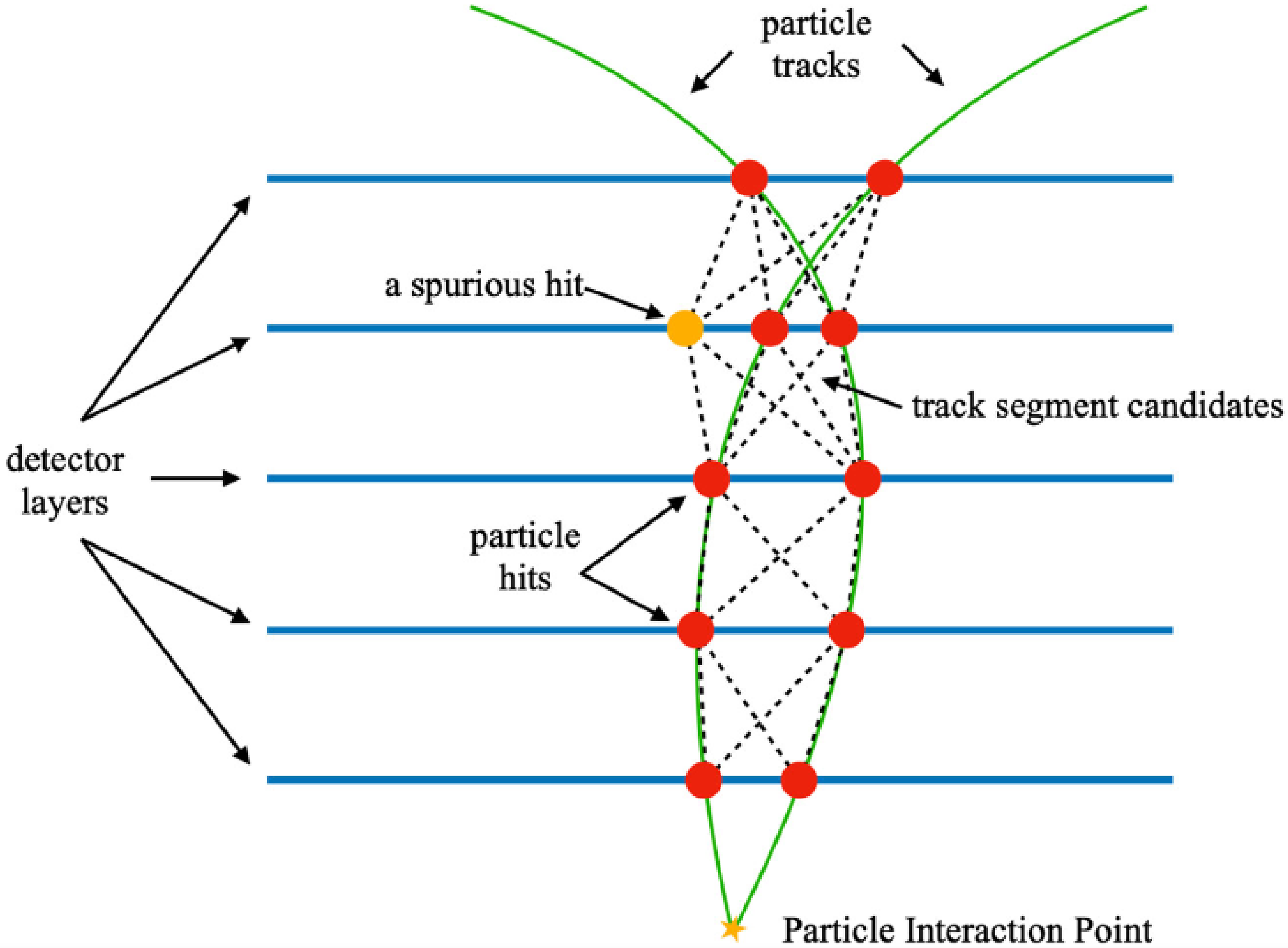
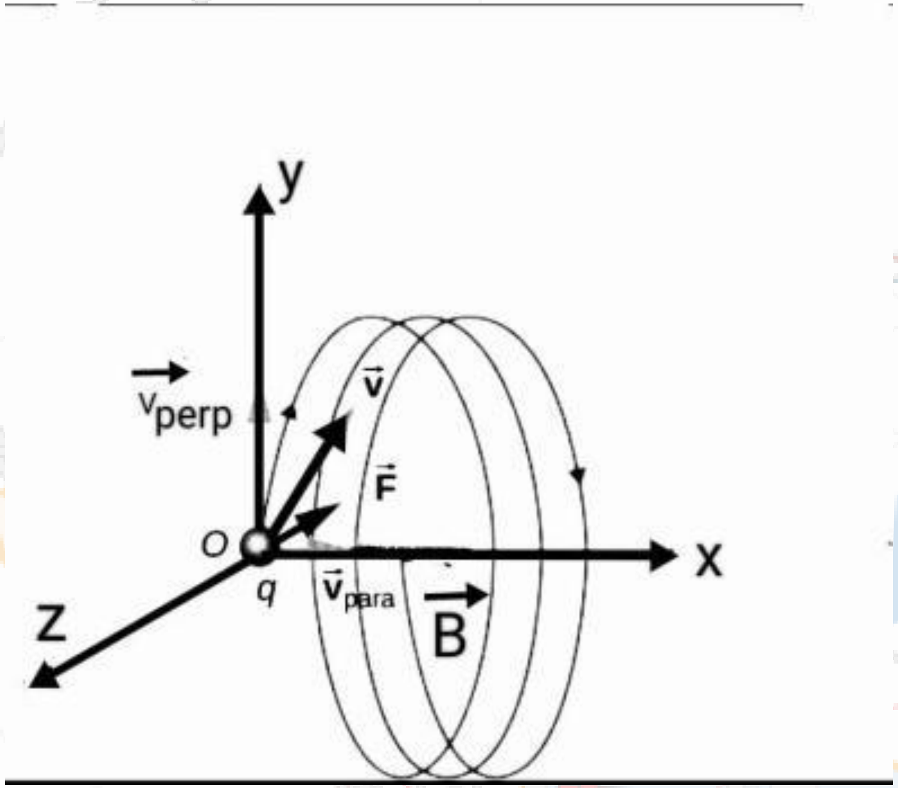
MLQC4FC

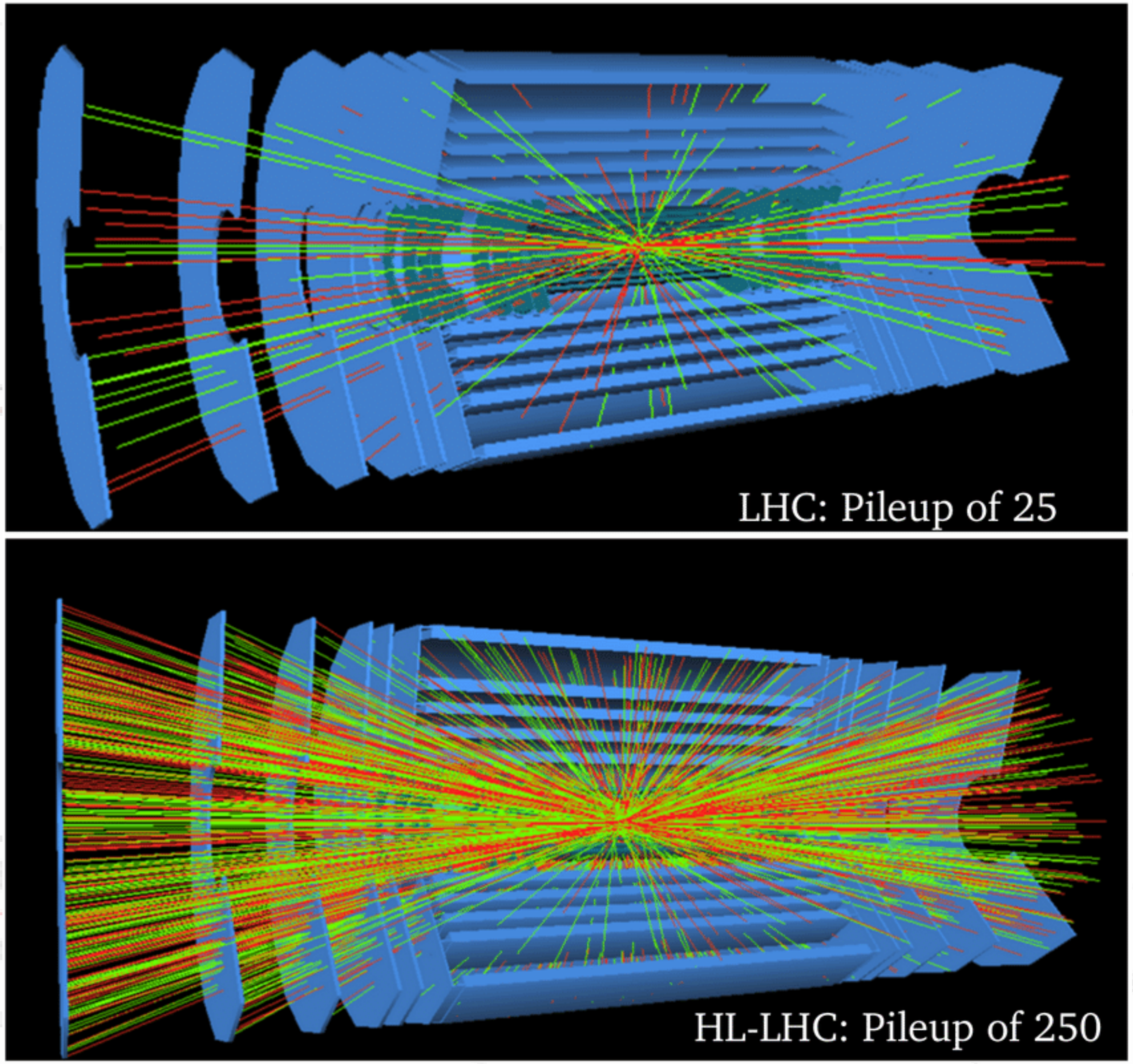
Track Reconstruction

Fig. 1 Drawing of particle track reconstruction problem. Particles interact near the origin of the coordinate system. Products of these interactions travel outwards from the origin. Charged particles bend in a direction depending on their electric charge. When these charged particles pass through the detectors, they create signals called as hits. Particle track reconstruction aims to connect hits belonging to the same particles

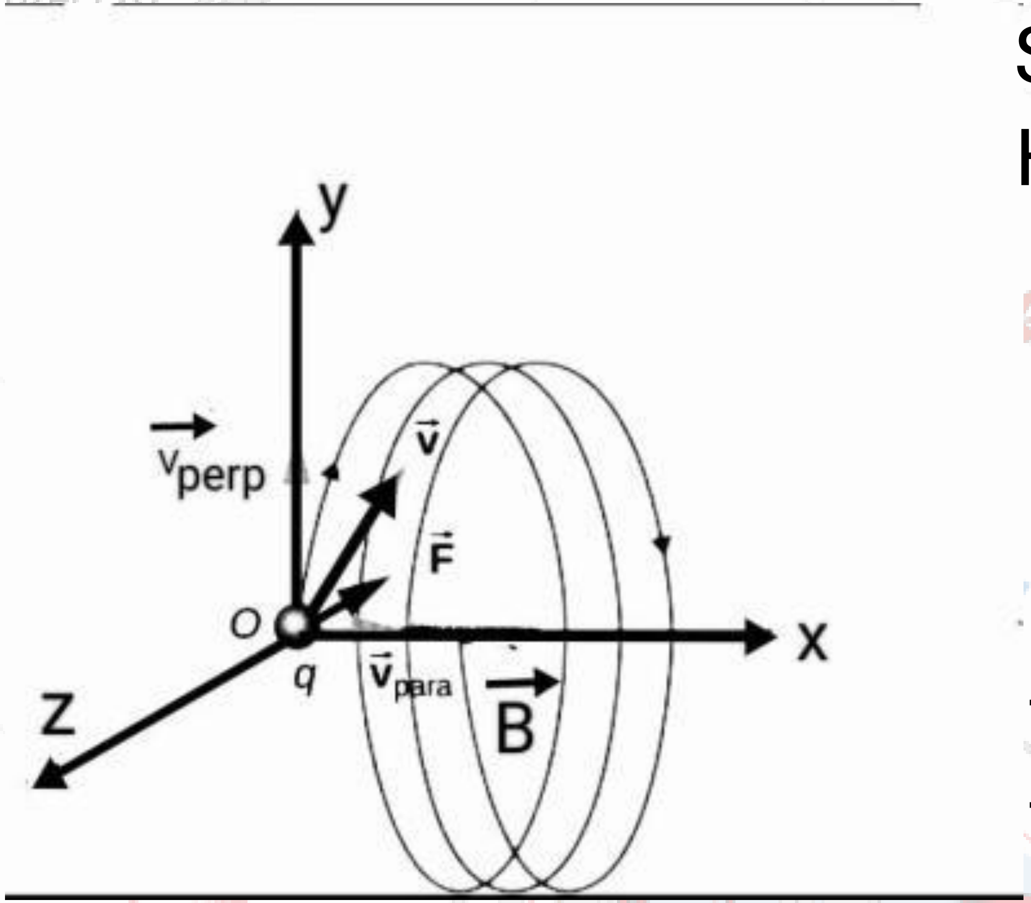


Problems with Track Reconstruction





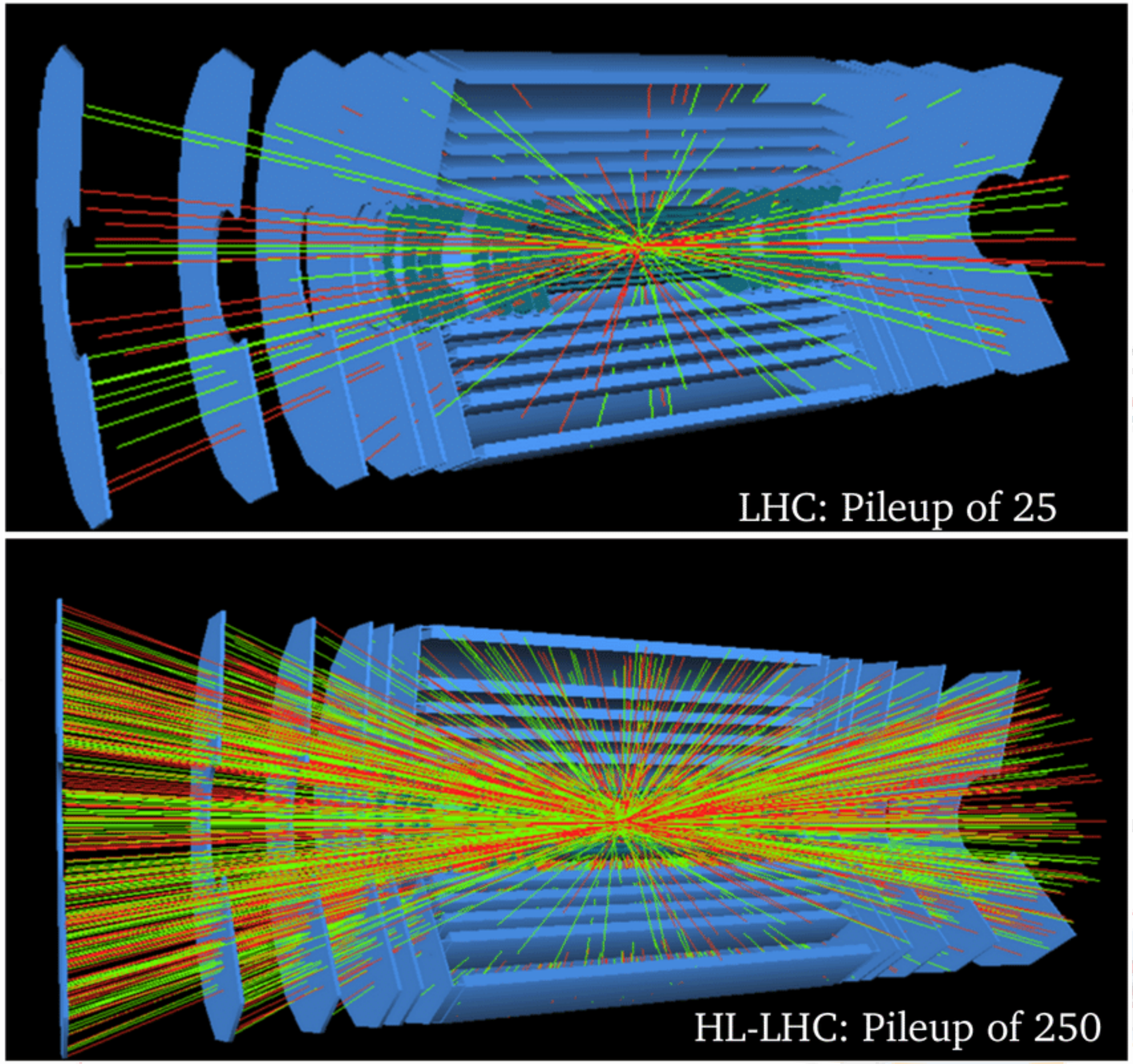
Problems with Track Reconstruction



Standard Model Tracks are strictly Helical in nature

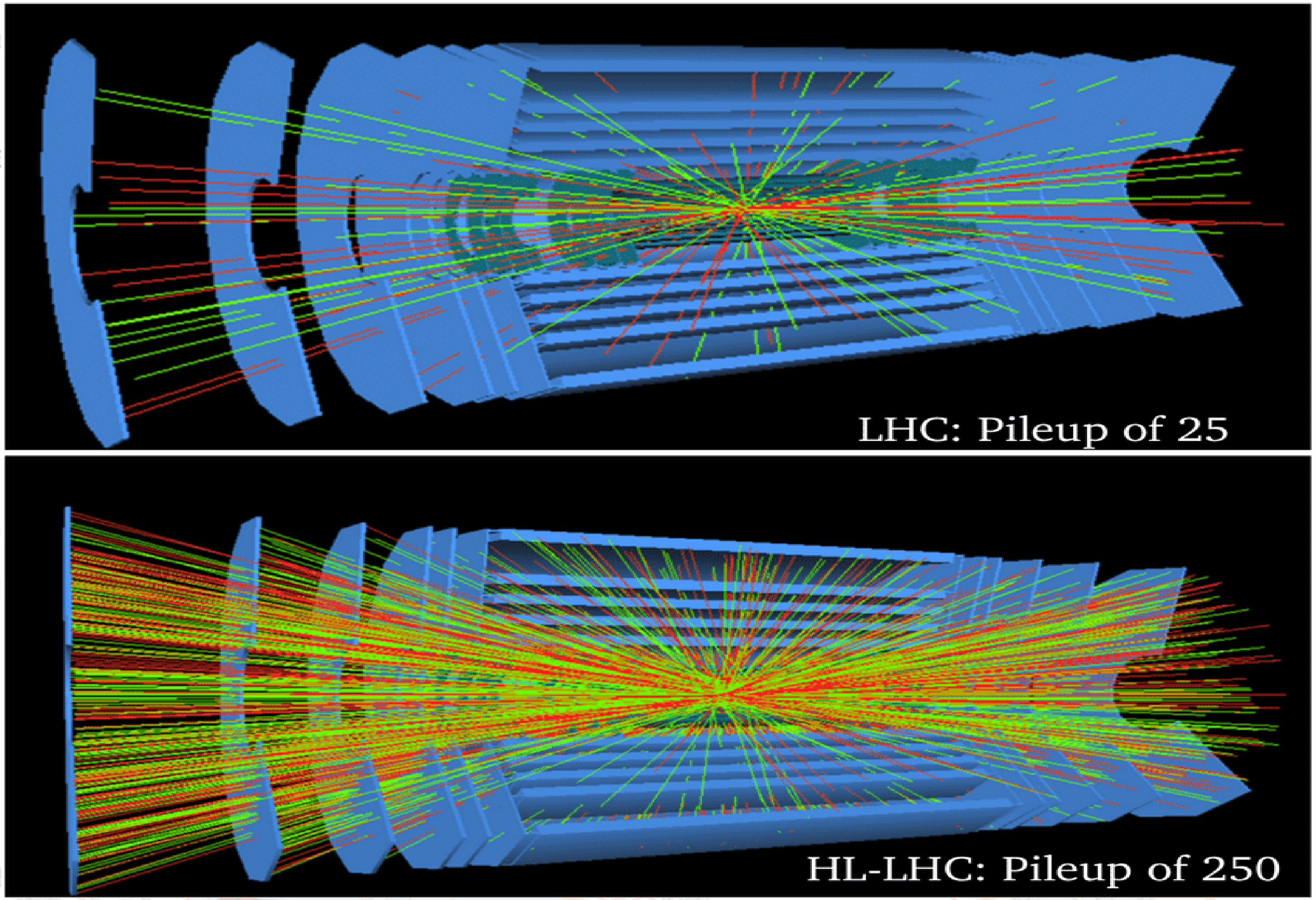
Local methods like The Kalman Filter cannot adapt to a fundamentally non-helical trajectory

Problems with Track Reconstruction



The Bottleneck: Hit-finding and track-fitting are coupled. Combinatorial background noise causes computing time to scale exponentially.

Problems with Track Reconstruction



CPU-heavy classical algorithms are **too slow and expensive** for real-time tracking under extreme HL-LHC conditions.

Enter graph-based approaches

about

TrkX

HEP advanced tracking algorithms at the exascale (Project Exa.TrkX)

summary Reconstructing the trajectories of thousands of charged particles from a collision event as they fly through a HEP detector is a combinatorially hard pattern recognition problem. Exa.TrkX, a DOE CompHEP project and a collaboration of data scientists and computational physicists from the ATLAS, CMS, and DUNE experiments, is developing Graph Neural Network models aimed at reconstructing millions of particle trajectories per second from Petabytes of raw data produced by the next generation of detectors at the Energy and Intensity Frontiers. Exa.TrkX is also exploring the scaling of distributed training of GNN models on DOE pre-exascale systems and the deployment of GNN models with microsecond latencies on FPGA-based real-time processing systems.

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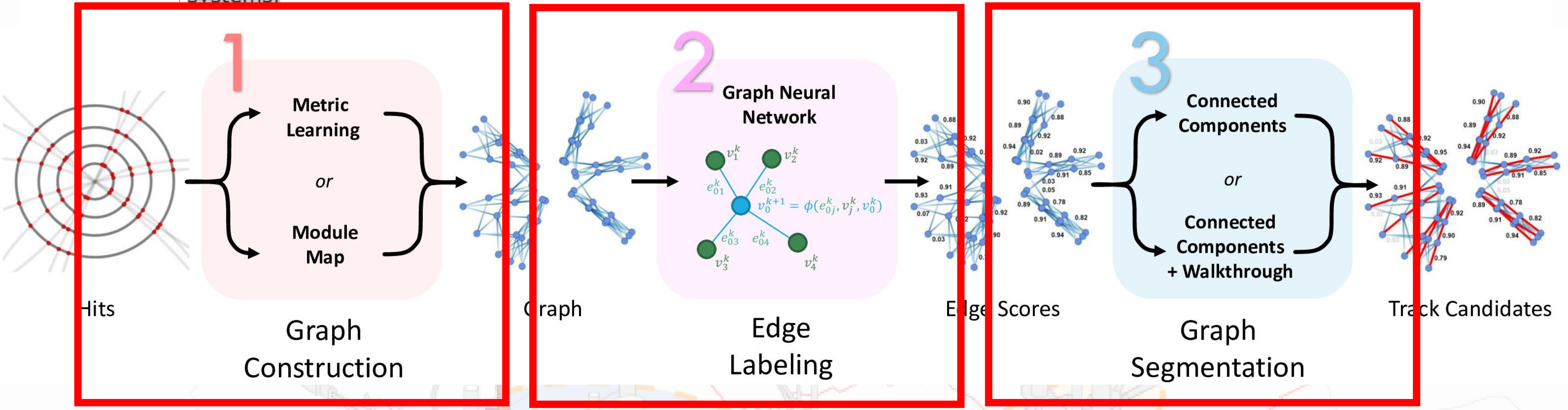
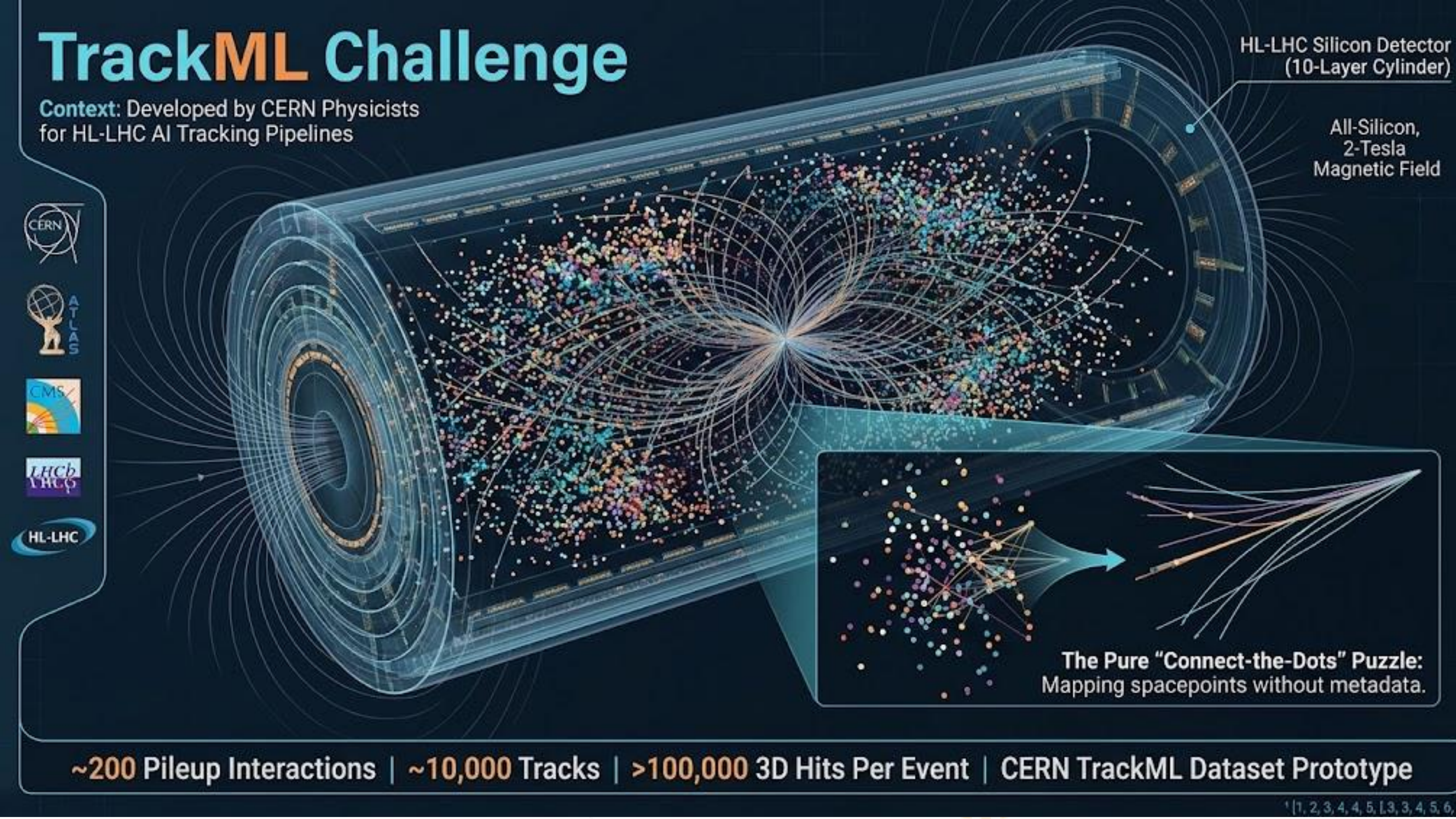


Hits are mapped to latent space and edges form between closed hits

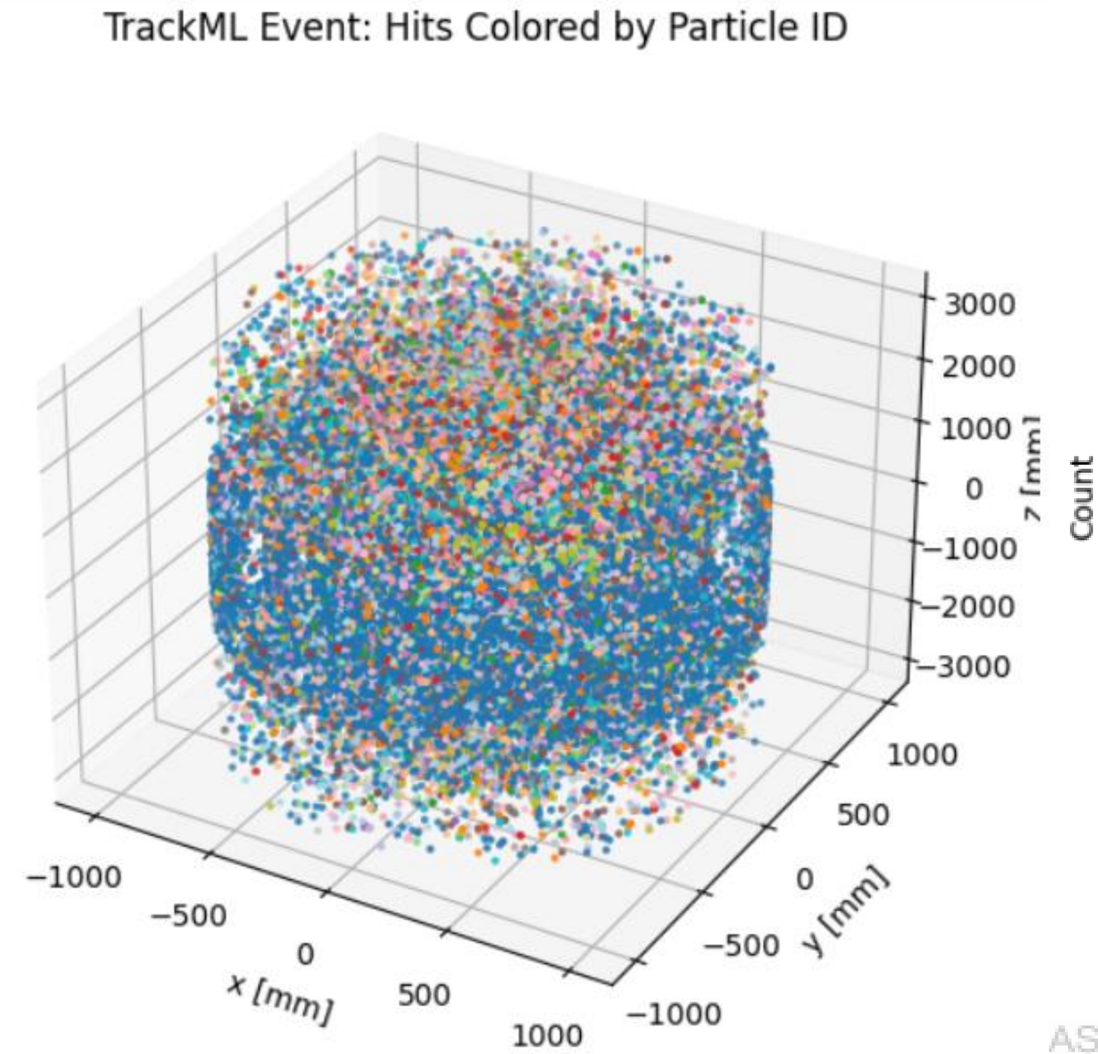
The GNN is trained to score edges

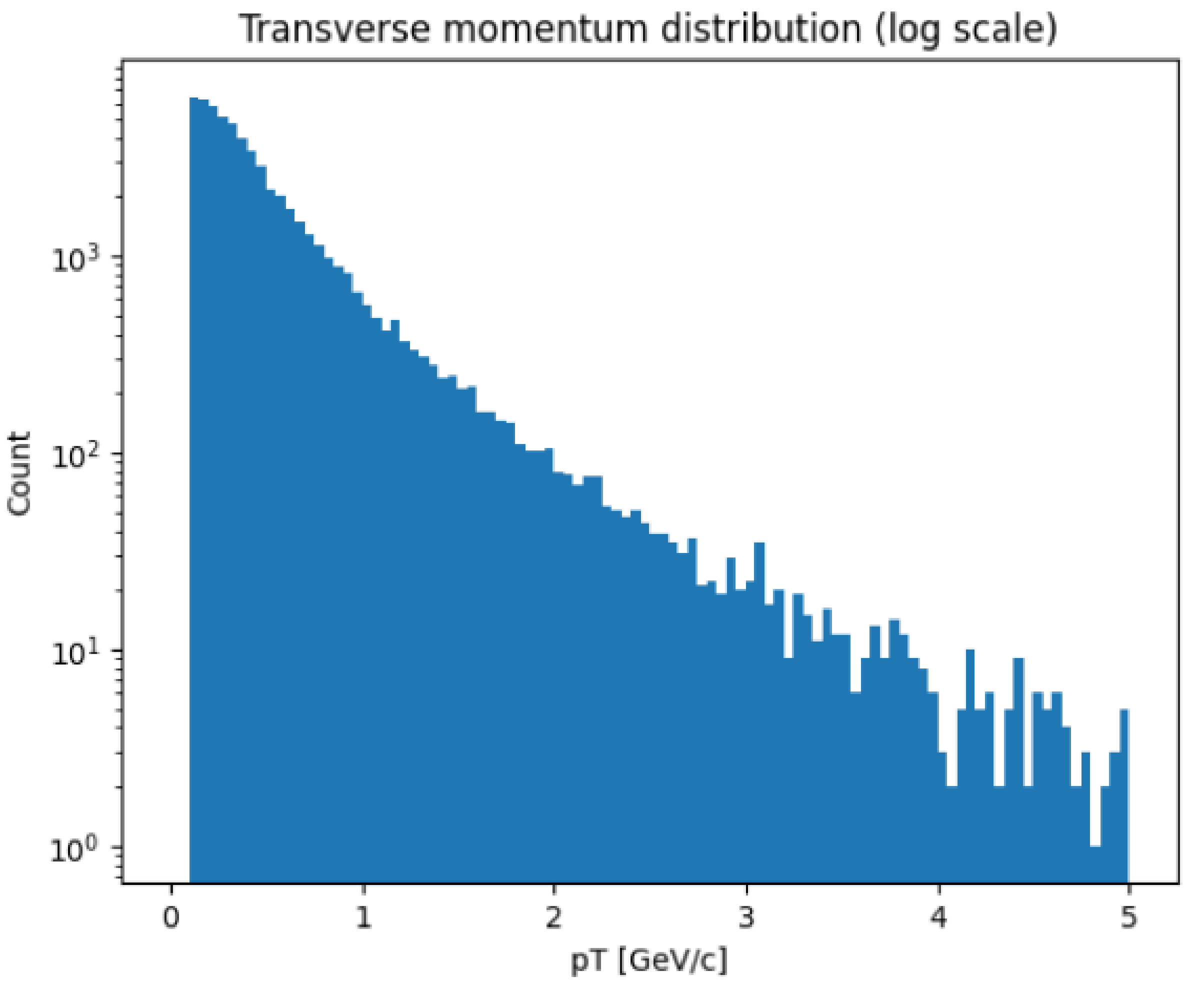
A graph segmentation algorithm creates track candidates by choosing what edges to keep



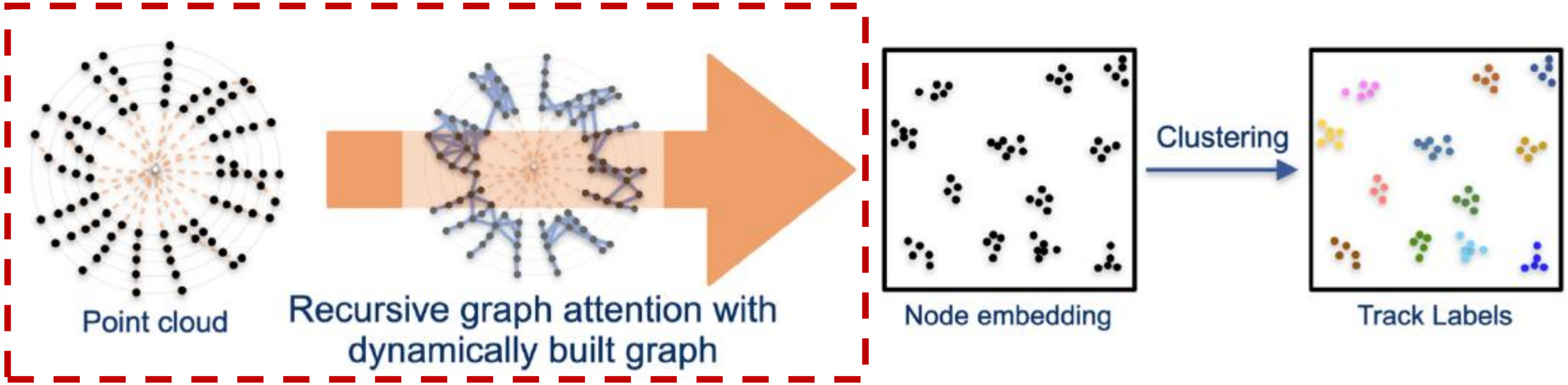
TrackML Challenge
Context: Developed by CERN Physicists
for HL-LHC AI Tracking Pipelines
HL-LHC Silicon Detector
(10-Layer Cylinder)
All-Silicon,
2-Tesla
Magnetic Field
CERN
ATLAS
CMS
LHCb
HL-LHC
The Pure "Connect-the-Dots" Puzzle:
Mapping spacepoints without metadata.
~200 Pileup Interactions | ~10,000 Tracks | >100,000 3D Hits Per Event | CERN TrackML Dataset Prototype

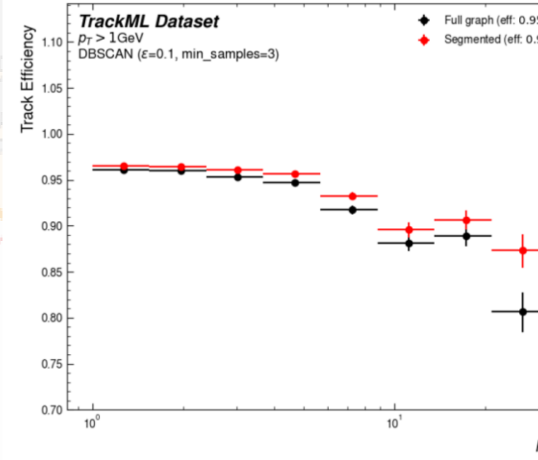
TrackML Challenge



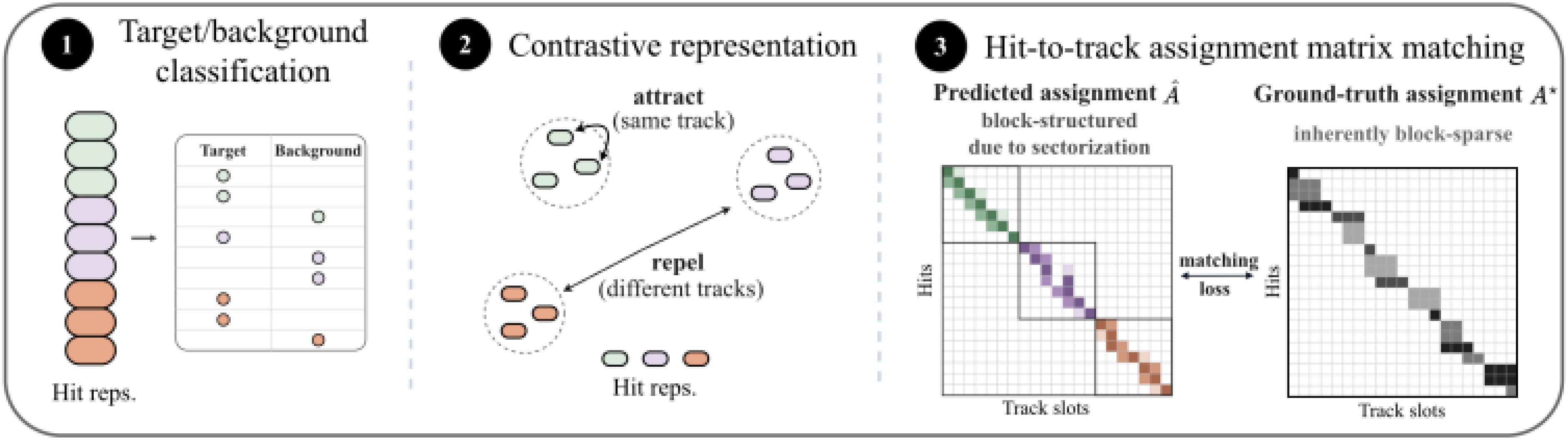


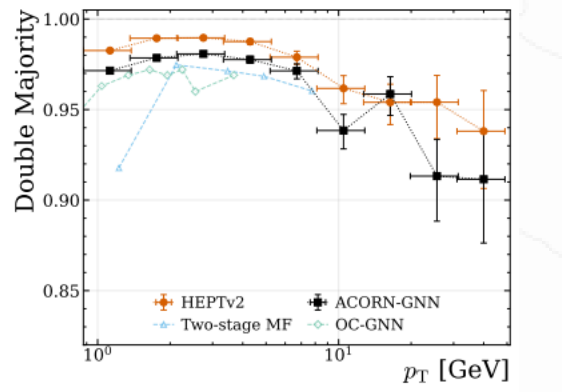
EGGNET: Evolving Graph-based Graph Attention Network ⟶ (arXiv: 2506.03415)





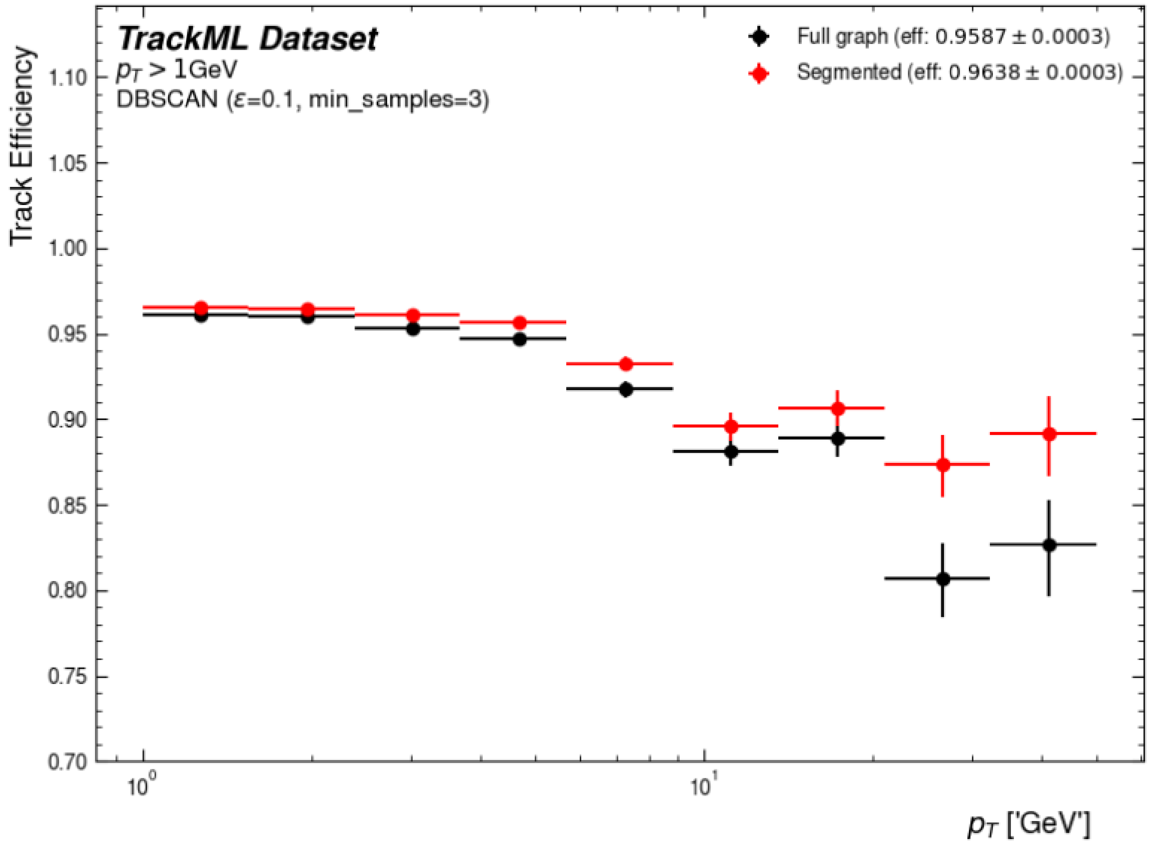
HEPTv2: End-to-End Efficient Point Transformer ⟶ (arXiv: 2606.20437)



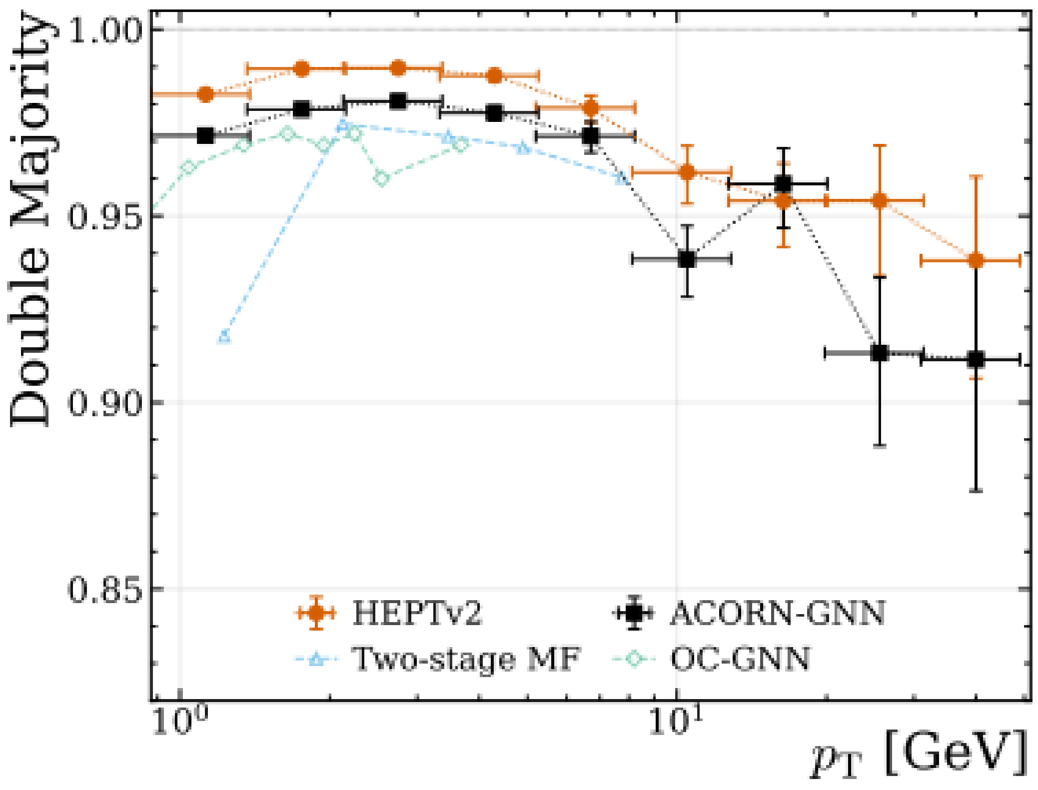


The Low P_T Limitation

EggNET



HEPTv2



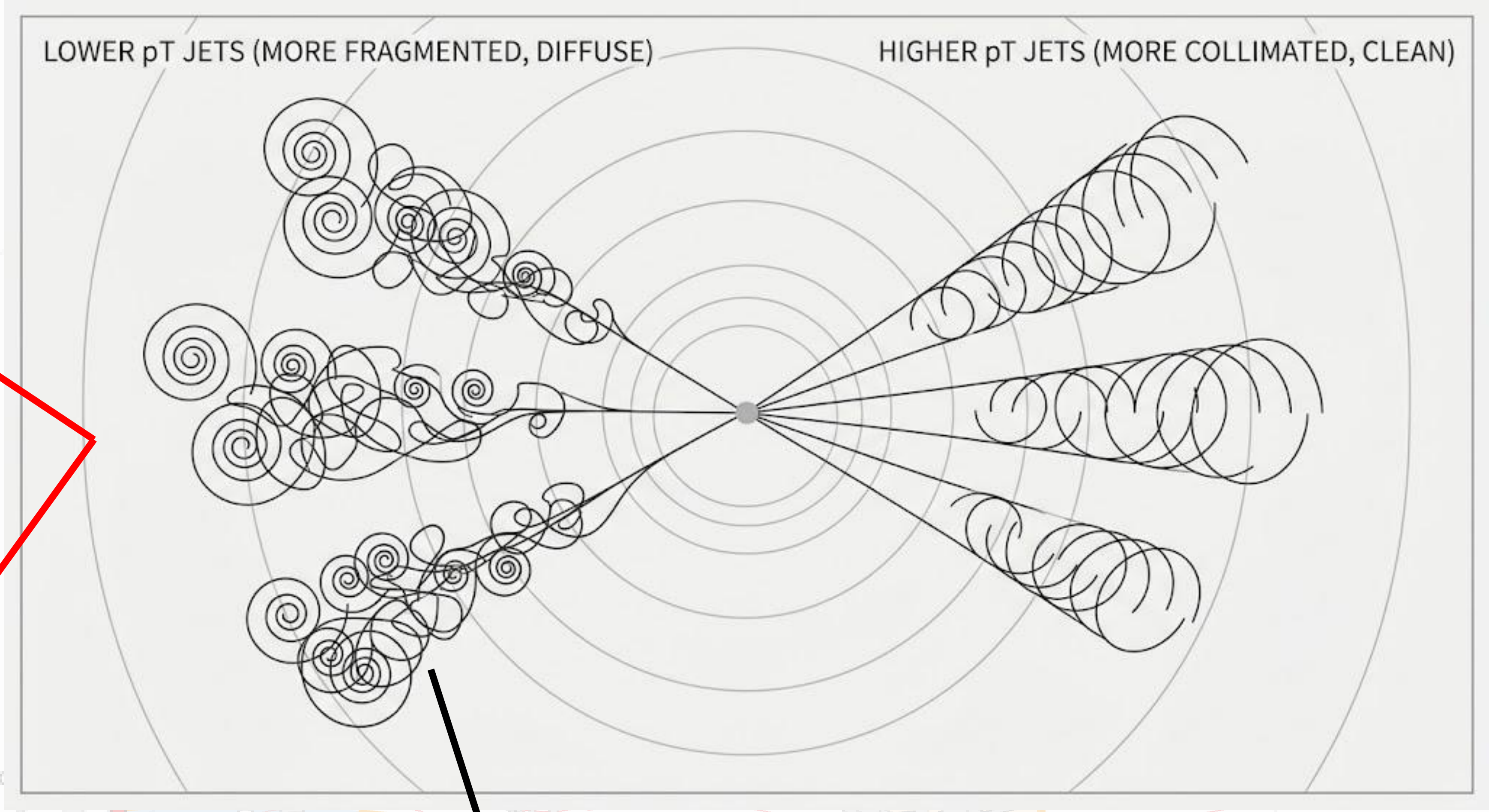
‡Results are taken from [32] and correspond to the slightly easier setting $\boxed{p_T > 1.0 \text{ GeV},}$ $|\eta| < 4$; all other methods use $\boxed{p_T > 0.9 \text{ GeV},}$ $|\eta| < 4$.

Could Low Pt Track reconstruction matter for HL-LHC?

1. Jet energy corrections & particle flow
(Soft Pions $P_T < 1\ GeV$)

Poor jet energy resolution

2. B-Physics
(Soft Pions in $B \rightarrow D^{*}\pi$)

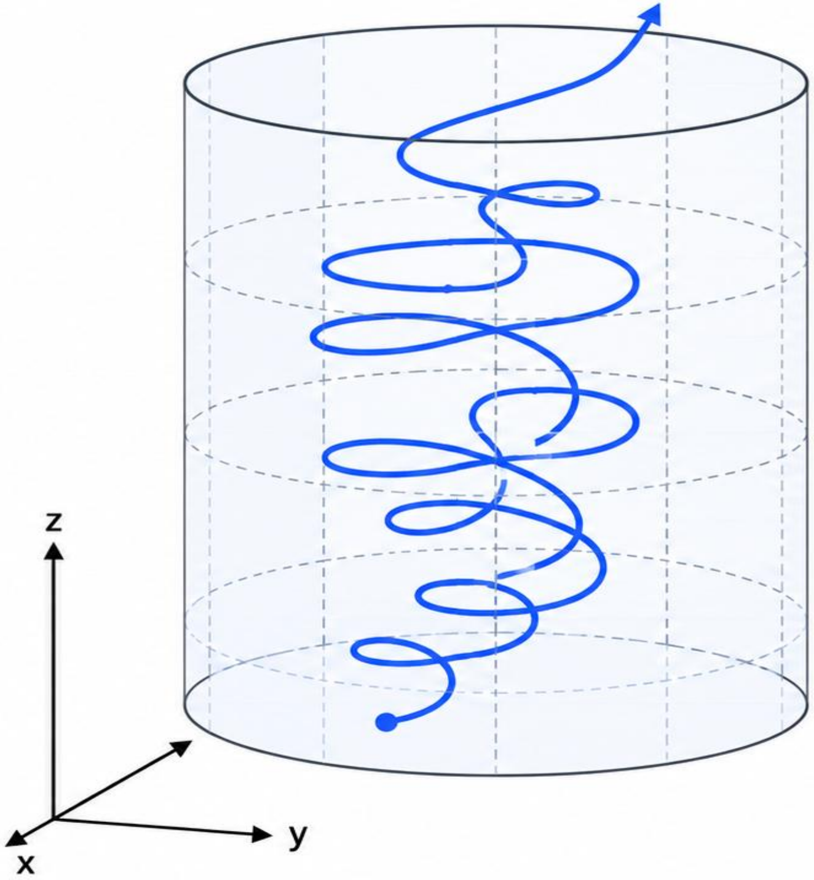


BSM Searches for SUEPs?
JHEP02(2023)034 → Set of long-lived and unconventional signatures

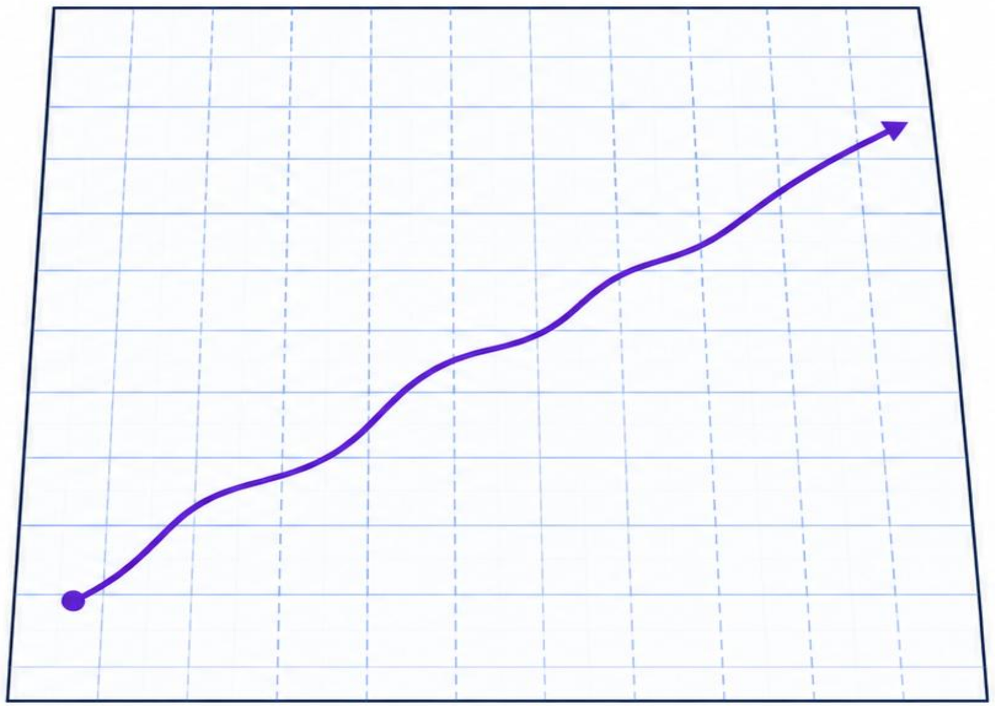
Learning on a Manifold

Drastically reduces required network capacity; filters noise instantly.

Cartesian Space (Euclidean)



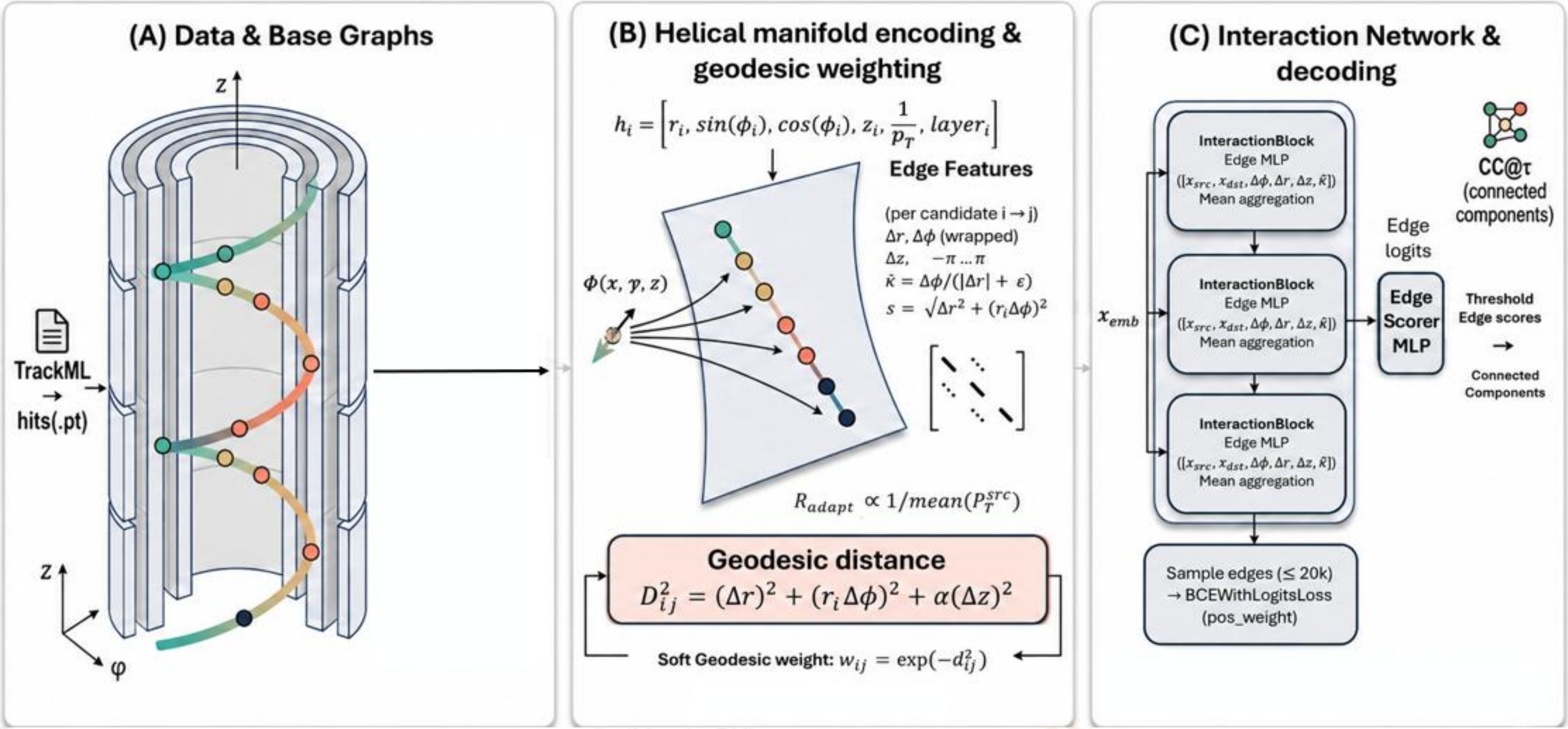
Helical Manifold Space

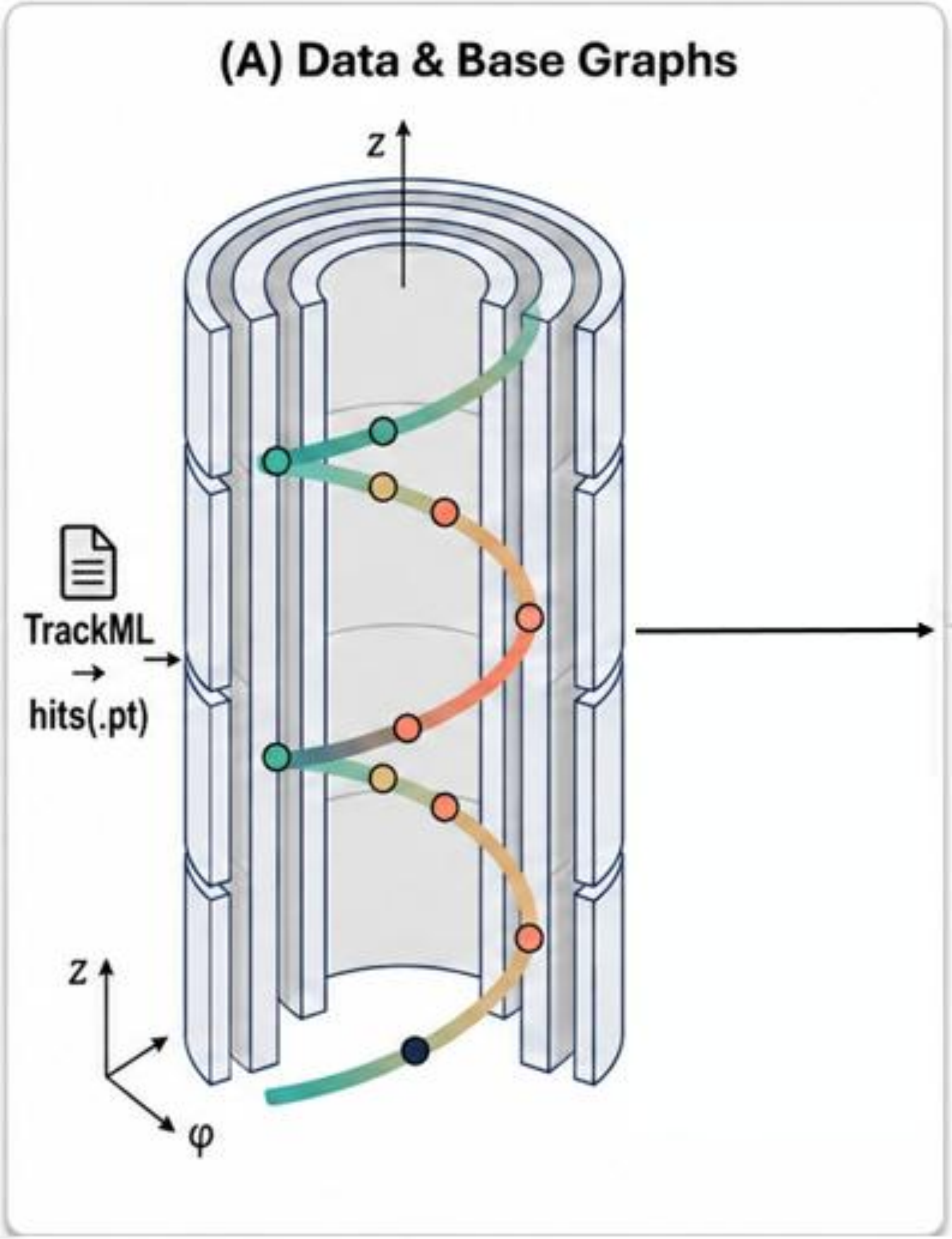


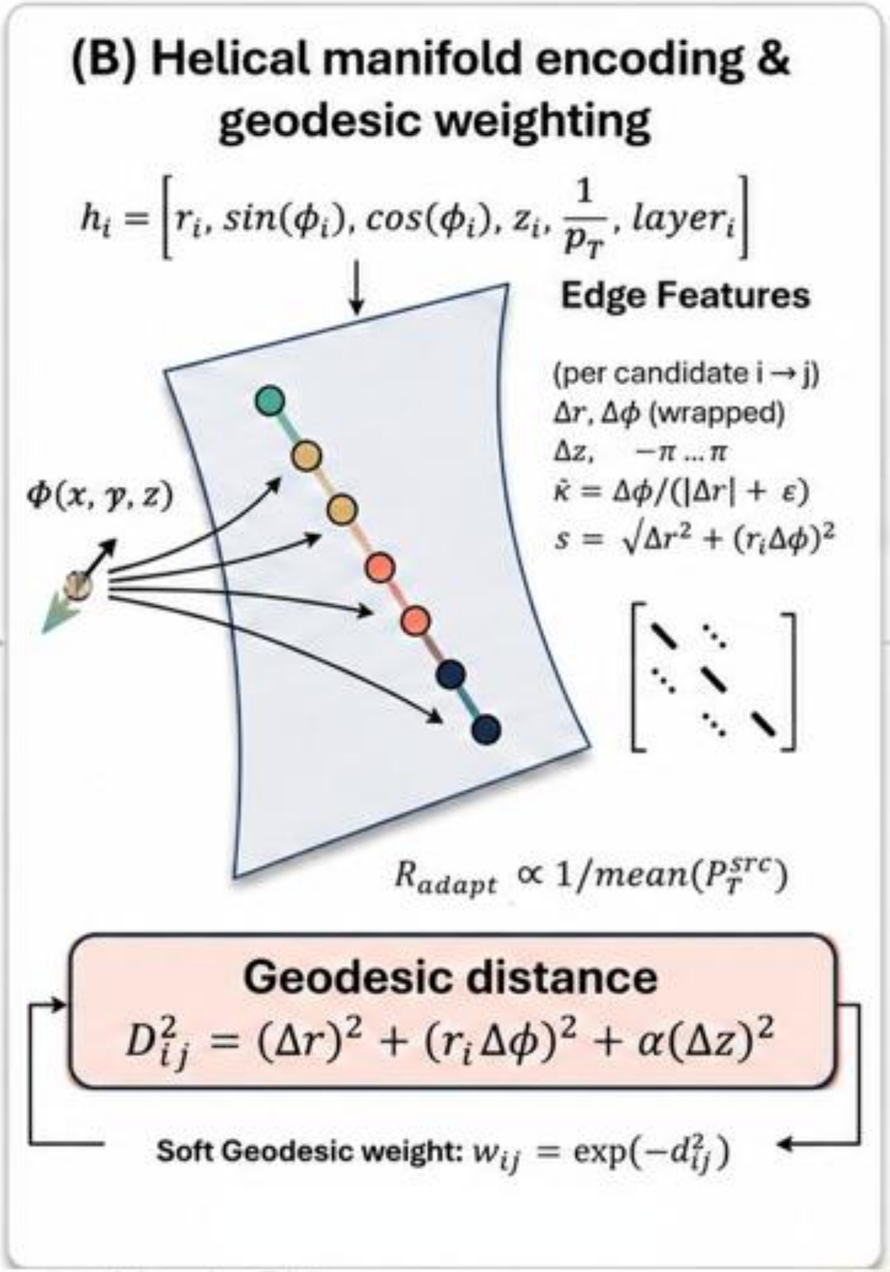
Complex 3D corkscrews confuse GNN hit-linking locally.

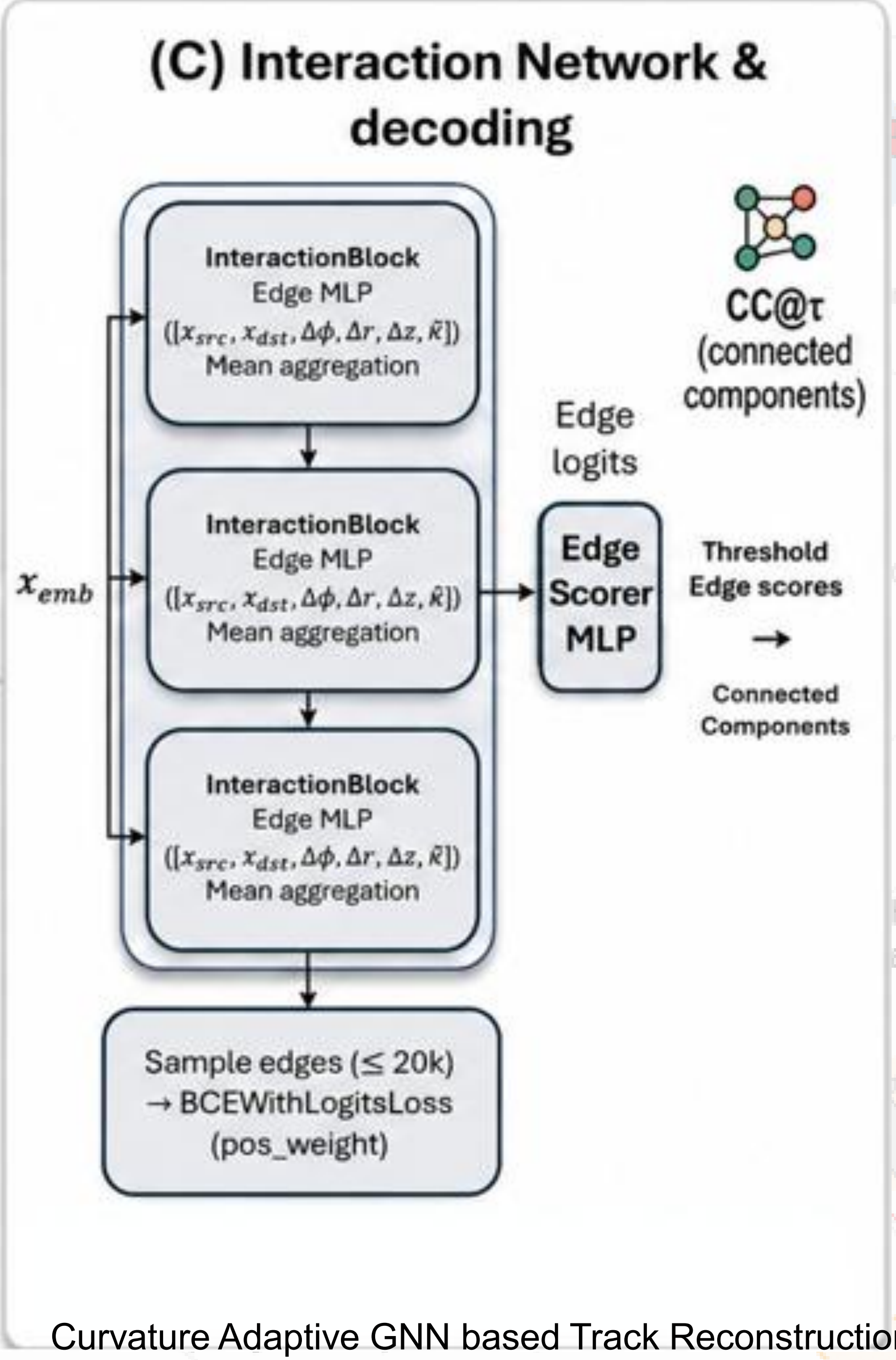
Non-helical tracks straighten into easily predictable drifts

Manifold Helical IN : Methodology



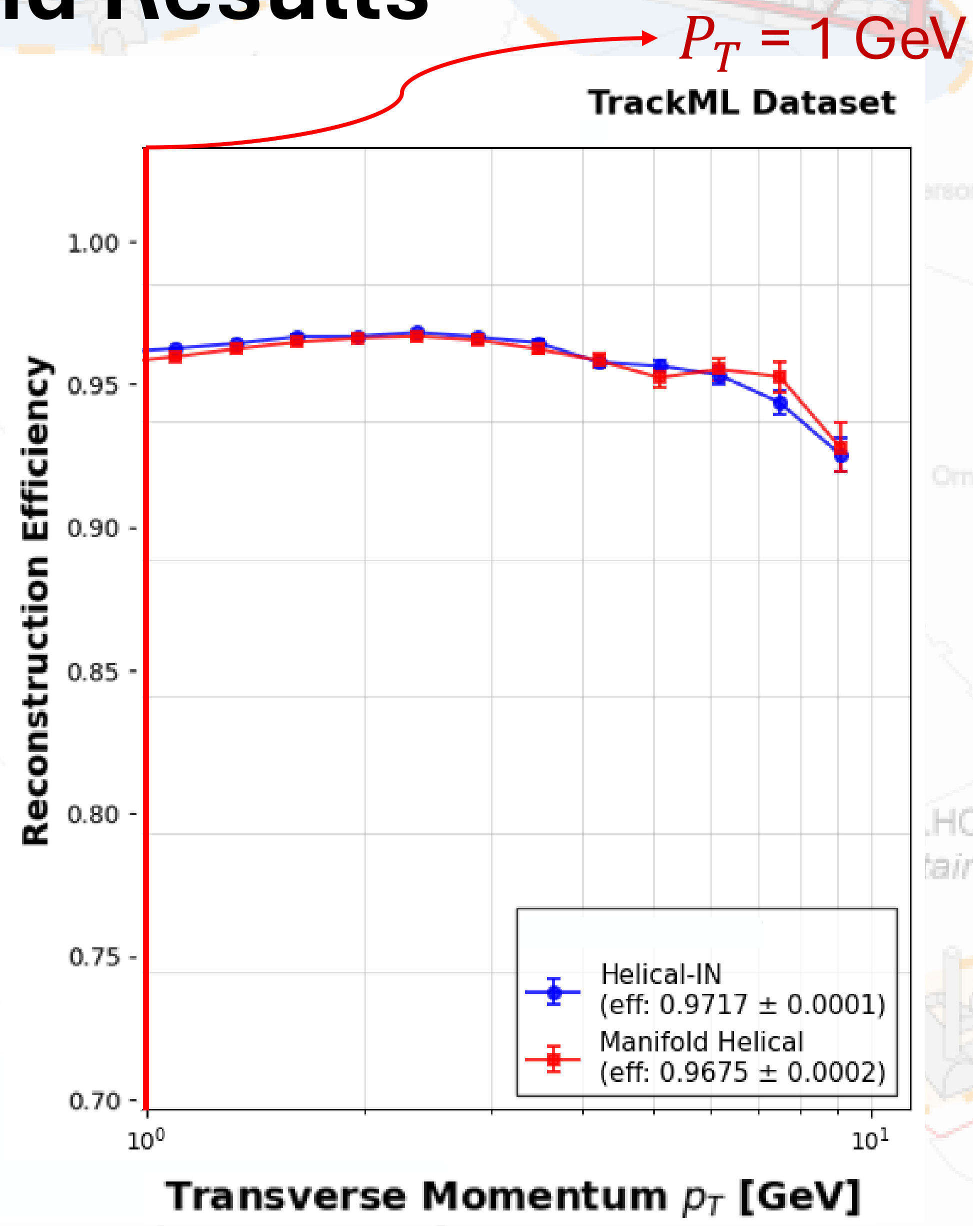

(A) Data & Base Graphs
z
TrackML
→
hits(.pt)
z
φ


(B) Helical manifold encoding & geodesic weighting
$h_i = \left[r_i, sin(\phi_i), cos(\phi_i), z_i, \frac{1}{p_T}, layer_i\right]$
Edge Features
(per candidate i → j)
$\Delta r, \Delta\phi$ (wrapped)
$\Delta z, \quad -\pi \dots \pi$
$\tilde{\kappa} = \Delta\phi/(|\Delta r| + \epsilon)$
$s = \sqrt{\Delta r^2 + (r_i\Delta\phi)^2}$
$\phi(x, y, z)$
$R_{adapt} \propto 1/mean(P_T^{src})$
Geodesic distance
$D_{ij}^2 = (\Delta r)^2 + (r_i\Delta\phi)^2 + \alpha(\Delta z)^2$
Soft Geodesic weight: $w_{ij} = \exp(-d_{ij}^2)$

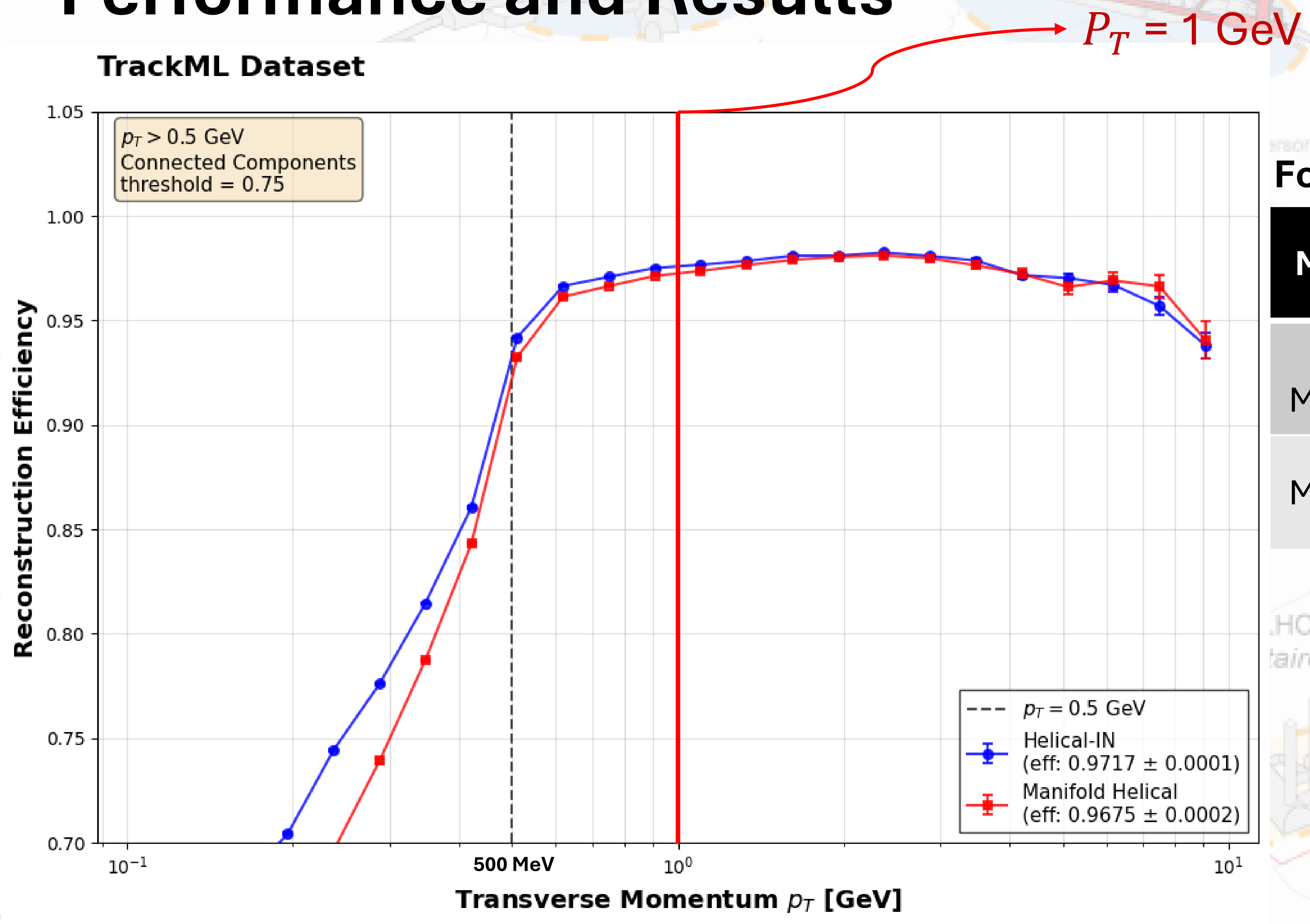


(C) Interaction Network & decoding
InteractionBlock
Edge MLP
$([x_{src}, x_{dst}, \Delta\phi, \Delta r, \Delta z, \tilde{\kappa}])$
Mean aggregation
InteractionBlock
Edge MLP
$([x_{src}, x_{dst}, \Delta\phi, \Delta r, \Delta z, \tilde{\kappa}])$
Mean aggregation
InteractionBlock
Edge MLP
$([x_{src}, x_{dst}, \Delta\phi, \Delta r, \Delta z, \tilde{\kappa}])$
Mean aggregation
x_{emb}
Edge logits
Edge Scorer MLP
CC@τ (connected components)
Threshold Edge scores
→
Connected Components
Sample edges (≤ 20k)
→ BCEWithLogitsLoss
(pos_weight)

Performance and Results



Performance and Results

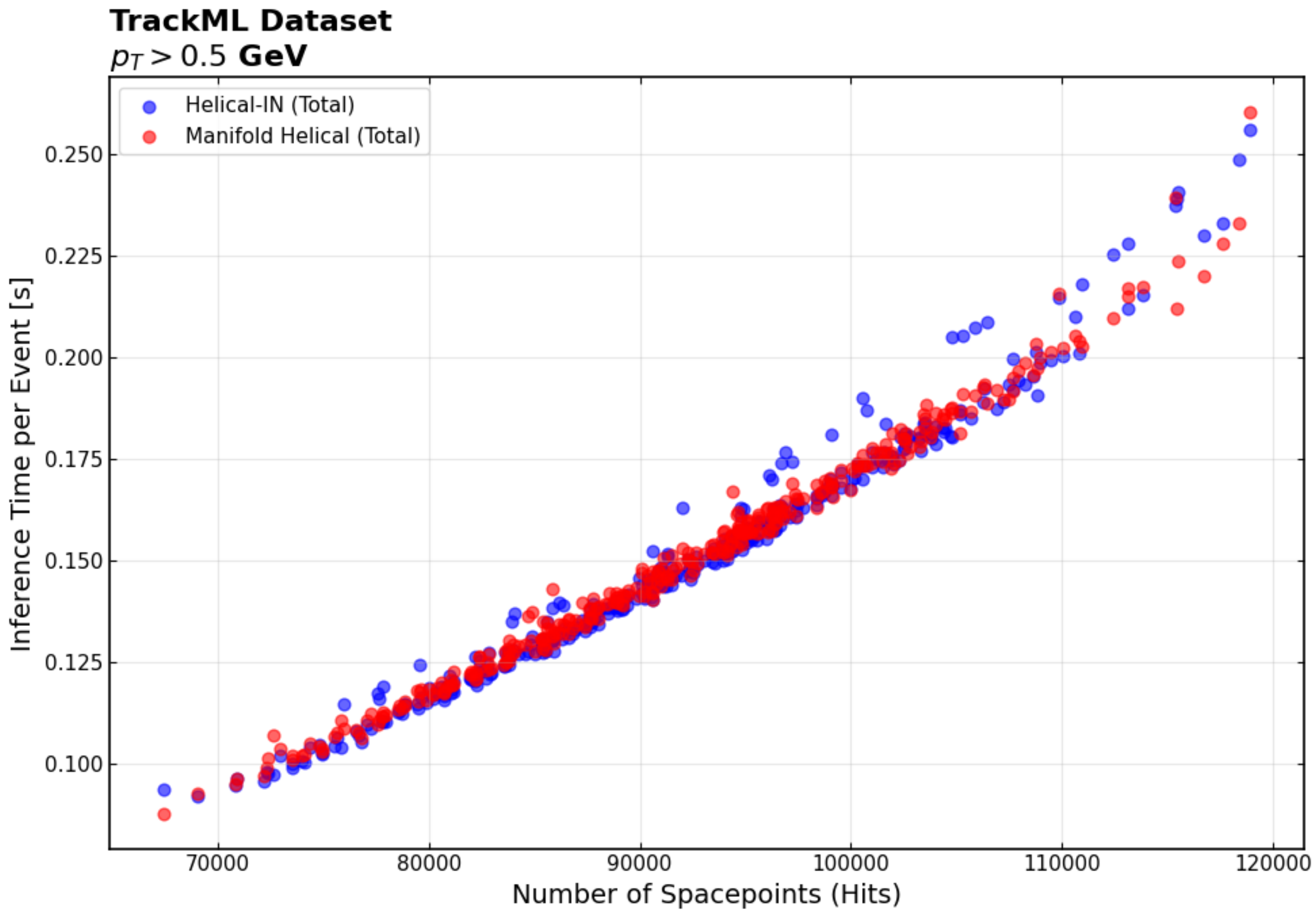


For all tracks of $P_T > 500\ MeV$

Method	Efficiency	Fake rate
No Manifold	0.9717	5.08%
Manifold	0.9675	0.37%

13x Reduction!

p_T Range (GeV)	Manifold Eff	Particles/Bin
0.10 – 0.12	0.0187 ± 0.0056	1,068
0.12 – 0.15	0.0338 ± 0.0068	1,480
0.15 – 0.18	0.6270 ± 0.0012	332,797
0.18 – 0.22	0.6428 ± 0.0010	494,708
0.22 – 0.26	0.6963 ± 0.0009	573,597
0.26 – 0.32	0.7392 ± 0.0008	631,618
0.32 – 0.38	0.7875 ± 0.0007	666,384
0.38 – 0.46	0.8431 ± 0.0006	658,874
0.46 – 0.56	0.9325 ± 0.0005	579,406
0.56 – 0.68	0.9614 ± 0.0004	510,029
0.68 – 0.83	0.9665 ± 0.0004	427,618
0.83 – 1.00	0.9713 ± 0.0004	332,865
1.00 – 1.21	0.9737 ± 0.0004	252,836
1.21 – 1.47	0.9765 ± 0.0005	187,968
1.47 – 1.78	0.9790 ± 0.0005	136,225
1.78 – 2.15	0.9805 ± 0.0006	92,115
2.15 – 2.61	0.9811 ± 0.0008	57,846
2.61 – 3.16	0.9798 ± 0.0010	34,463
3.16 – 3.83	0.9764 ± 0.0016	19,039
3.83 – 4.64	0.9723 ± 0.0023	10,481
4.64 – 5.62	0.9660 ± 0.0034	5,836
5.62 – 6.81	0.9691 ± 0.0041	3,394
6.81 – 8.25	0.9663 ± 0.0055	2,276
8.25 – 10.00	0.9406 ± 0.0088	1,598



Average Inference time on A100 GPU: 150 ms

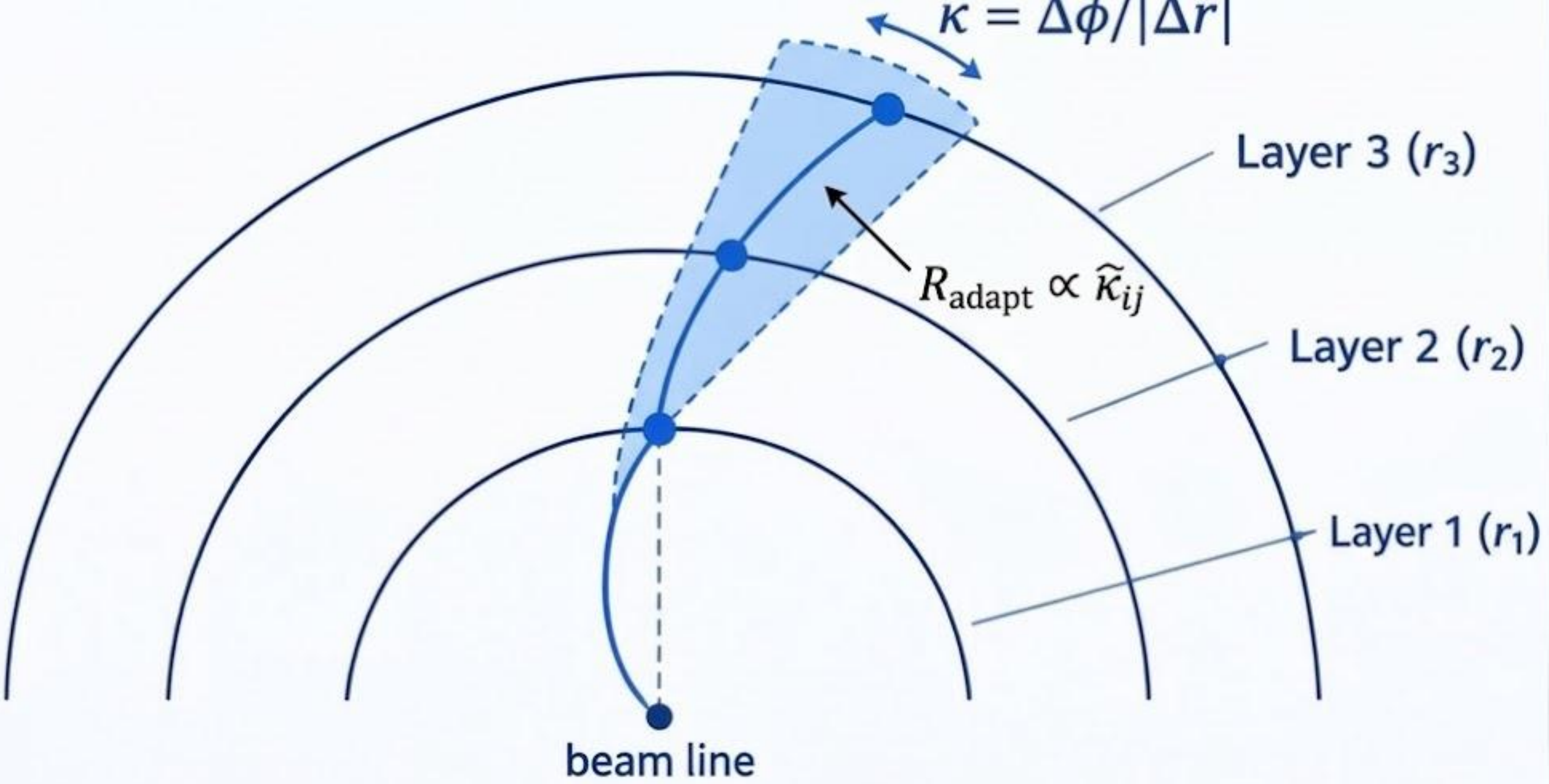
Bridging to Hardware: The truth P_T problem

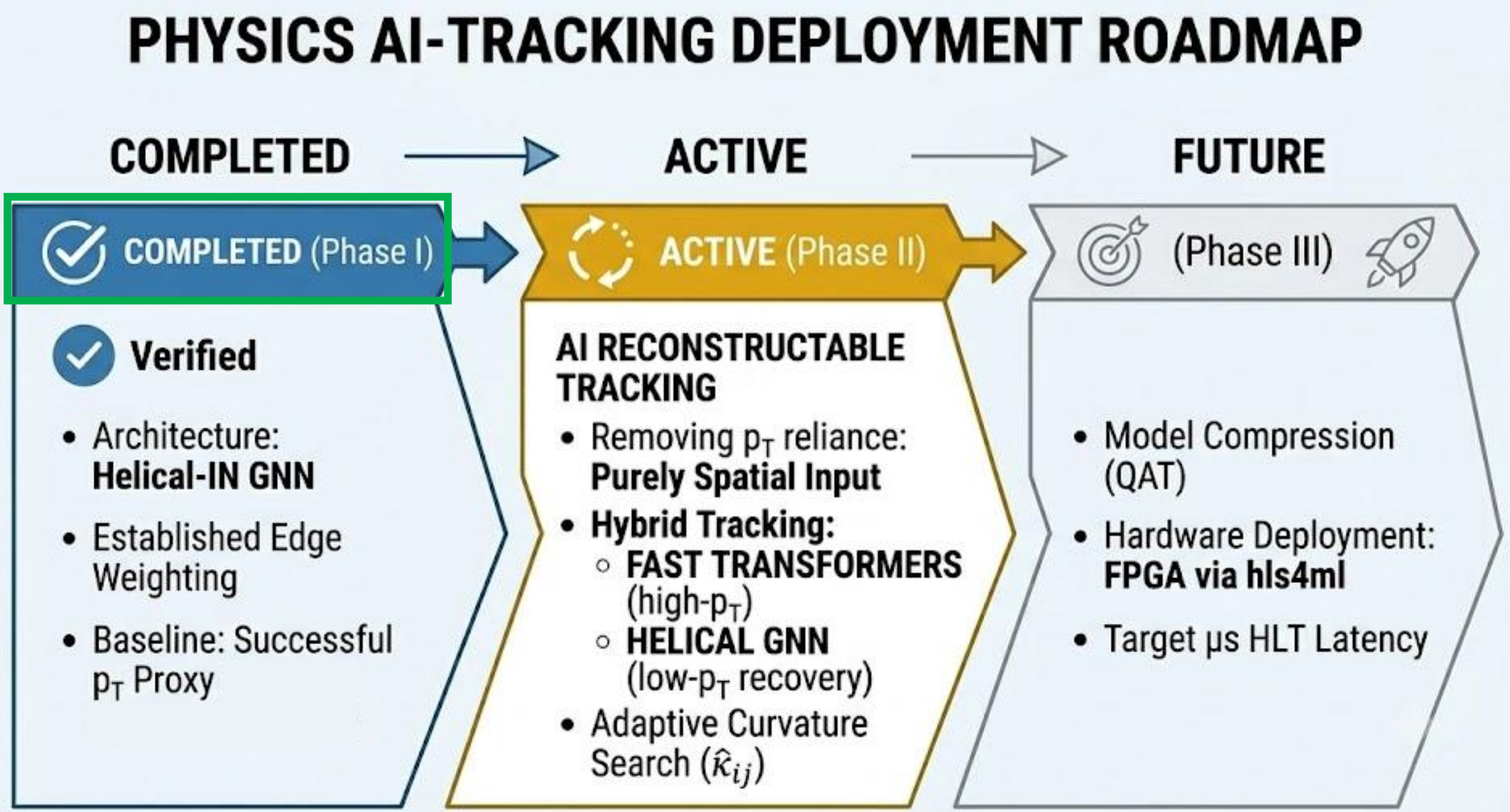
In a real detector, offline p_T is not available prior to reconstruction!

The Current Assumption: Manifold Helical-IN currently utilizes *truth-level* p_T as an idealized proxy to validate the manifold geometry proof of concept.

HOW DO WE FIX THIS?

Dynamic Curvature Estimation




PHYSICS AI-TRACKING DEPLOYMENT ROADMAP
COMPLETED
ACTIVE
FUTURE
COMPLETED (Phase I)
ACTIVE (Phase II)
(Phase III)
Verified
• Architecture: **Helical-IN GNN**
• Established Edge Weighting
• Baseline: Successful p_T Proxy
AI RECONSTRUCTABLE TRACKING
• Removing p_T reliance: **Purely Spatial Input**
• **Hybrid Tracking:**
○ **FAST TRANSFORMERS** (high-p_T)
○ **HELICAL GNN** (low-p_T recovery)
• Adaptive Curvature Search ($\hat{\kappa}_{ij}$)
• Model Compression (QAT)
• Hardware Deployment: **FPGA via hls4ml**
• Target μs HLT Latency

CONTACT ME

Thank You!

Questions?

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