Connecting The Dots 2022

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ATLAS ITk Track Reconstruction with a GNN-based Pipeline

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On behalf of the ATLAS collaboration

ATLAS EXPERIMENT

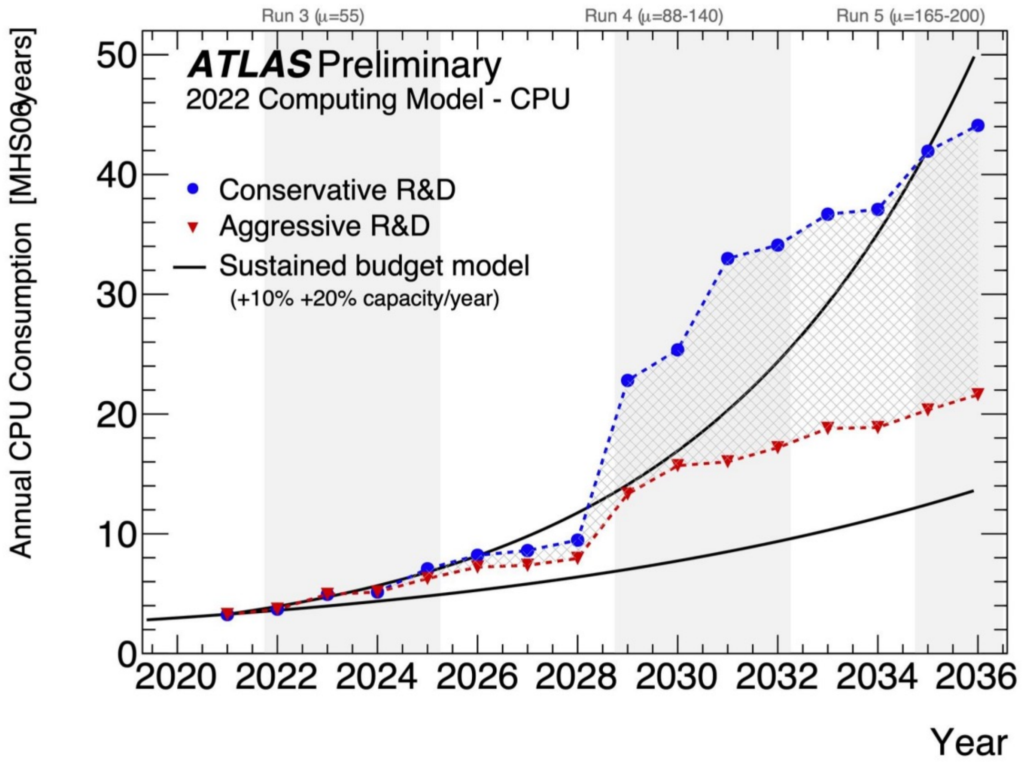
TrkX AND L2IT

LHC High Luminosity upgrades

- **The LHC upgrade: HL-LHC era**

➡ Physics run to start in 2029
➡ Increase in event complexity: ~ **200 proton-proton interactions μ per collision**
➡ Increase in data taking rate
➡ ATLAS detector upgrades: new **I**nner **T**rac**k**ing detector **ITk**

Brings unprecedented **challenges** for software and computing.

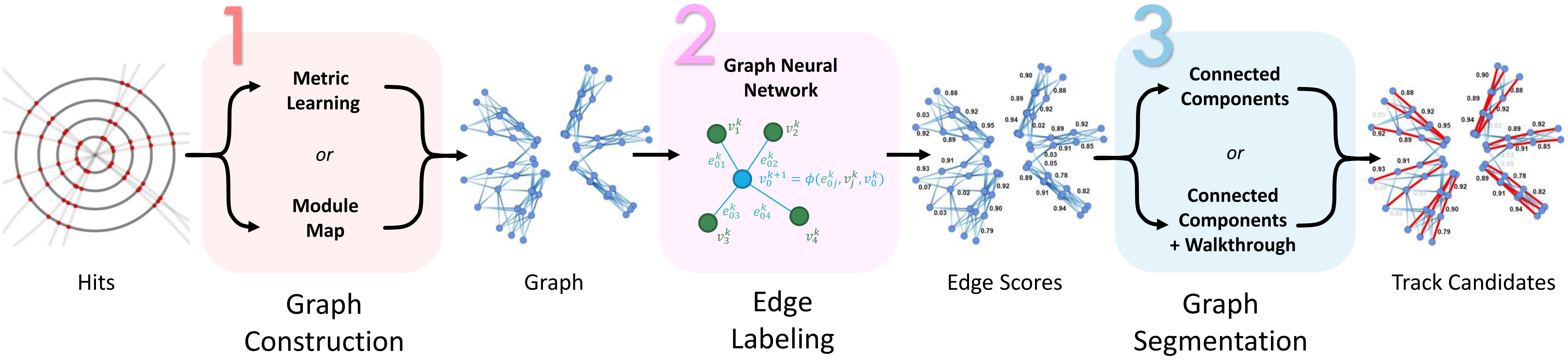


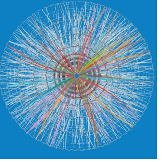
From *ATLAS HL-LHC Computing Conceptual Design Report*

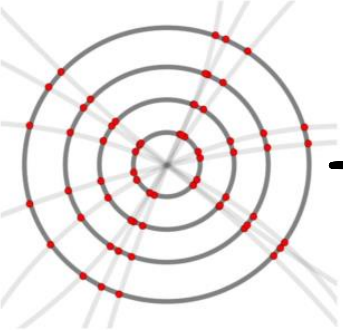
Machine learning applied to tracking

- **Track reconstruction = CPU-intensive stage**
  - ➡ ML techniques ? Raw data from collisions are **sparse** data

- **Graph Neural Networks (GNNs):** proof of principle by Exa.TrkX project
  - ➡ Method applied to TrackML data by L2IT and Exa.TrkX project







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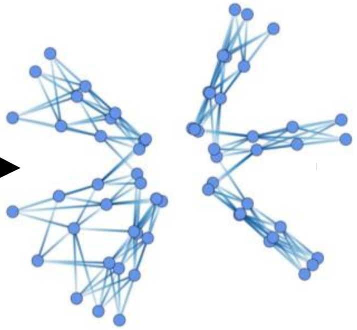
Metric Learning

or

Module Map



Hits

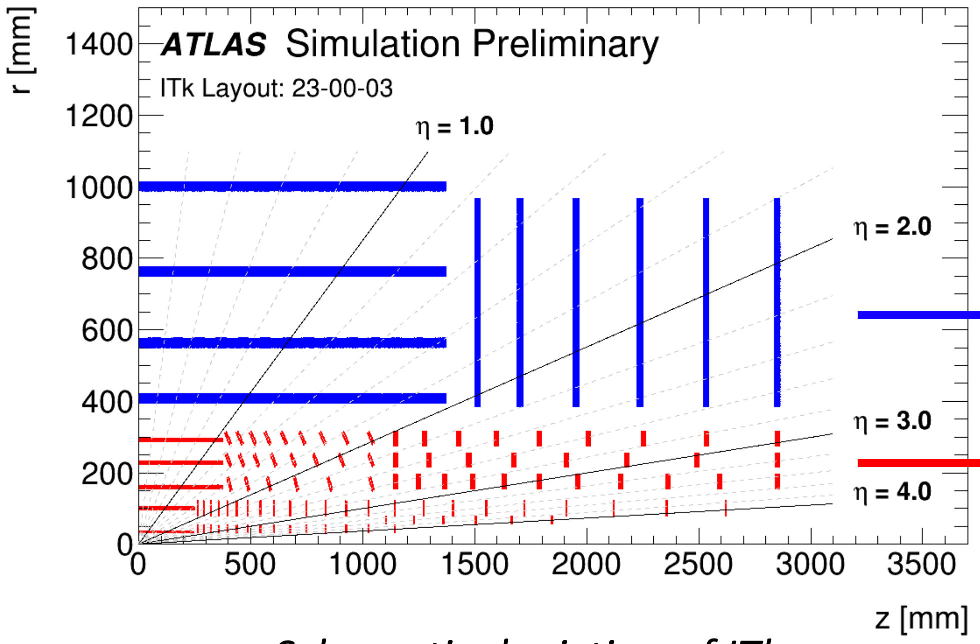
Graph

Graph Construction

Simulated sample

- **ATLAS simulated sample: $\mathbf{t\bar{t}}$ with $\boldsymbol{\langle\mu\rangle = 200}$ at $\boldsymbol{\sqrt{s} = 14\,TeV}$**
  - Define **target particles**:
    - $p_T > 1$ GeV
    - No secondaries
    - No electron
    - At least 3 space-points

Dominated by soft interactions



Schematic depiction of ITk

Strip subdetector: 1 space-point = 2 clusters

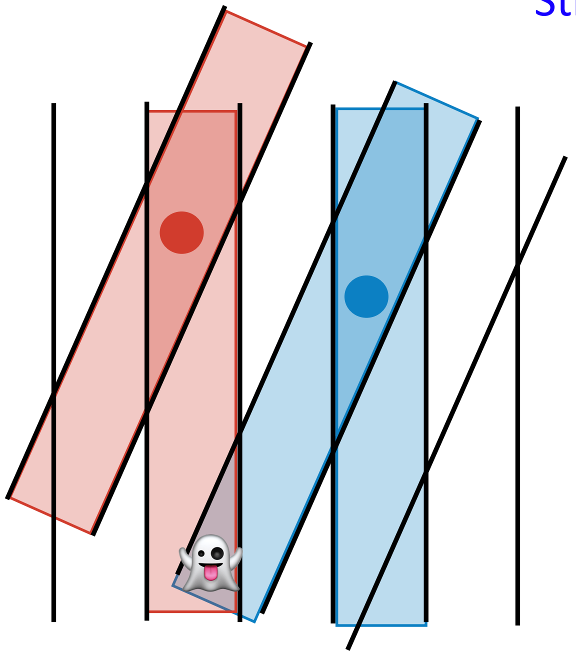
Pixel subdetector: 1 space-point = 1 cluster

Simulated sample

- **ATLAS simulated sample: $\mathbf{t\bar{t}}$ with $\langle \mu \rangle = 200$ at $\sqrt{s} = 14\ TeV$**
  - Define **target particles**:
    - $p_T > 1GeV$
    - No secondaries (barcode < 200000)
    - No electron
    - At least 3 space-points

Dominated by soft interactions

Strip subdetector: 1 space-point = 2 clusters



Space-points from a charged particle

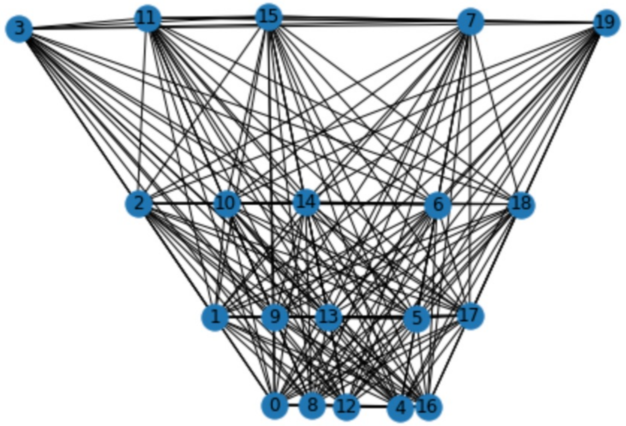
Ghost space-point: accidental combination of strip clusters

Graph representation of tracking data

Node = 1 space-point

Edge = connection between two nodes.

➡ Existence of edge = the 2 nodes could potentially represent 2 successive space-points on the same track.



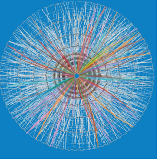
Example with 19 hits in the (z,r) plane

$\mathrm{O}(300\mathrm{k})$ space-points in an event => fully connected graph $O(10^{10})$ edges

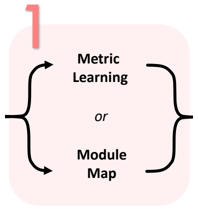
➡ Comprises unphysical connections

Key question of graph construction:

➡ **How de we choose the connections between nodes ?**



Graph creation: learning the connections



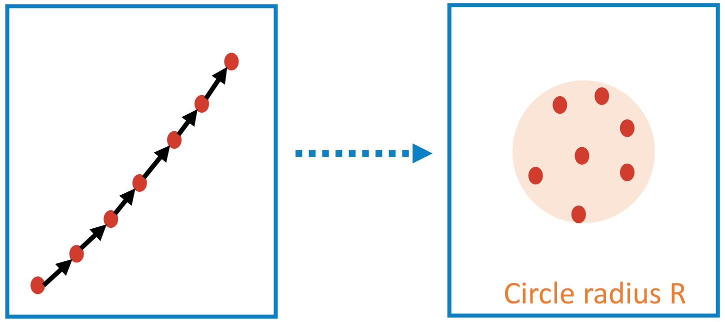
Graph Construction

Metric Learning

All possible pairs of nodes belonging to the same target particles are **learned** by a Multi-Layer Perceptron (MLP) to be embedded into a **space** where they are close.

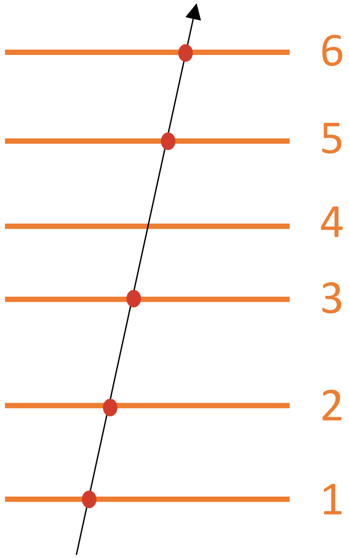
Euclidian space

N-dimensional space learned by the MLP



Module Map

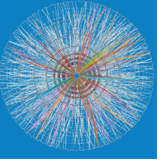
The path of a target particle is followed inside ITk to record all possible **connections** between silicon **modules**.



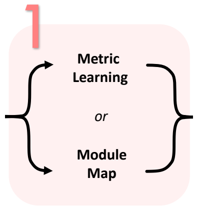
Connections record :

1 → 2 → 3
2 → 3 → 5
3 → 5 → 6

The Module Map is built using 90 000 events. It comprises **1 242 665** connections.



Graph creation: learning the connections



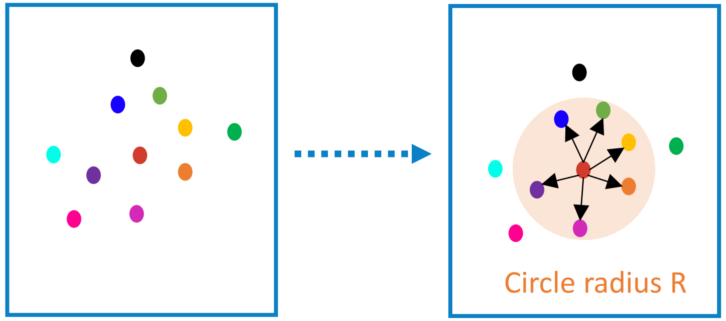
Graph Construction

Metric Learning

Given a source node, edges between this node and all nodes within a radius R from the source are created.

N-dimensional space learned by the MLP

Edges created



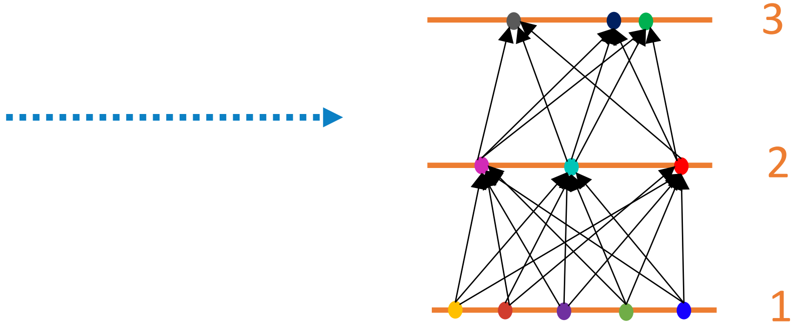
No particular meaning of direction.

Additional filtering is done using another MLP.

Module Map

Edges are created following the connections of the Module Map.

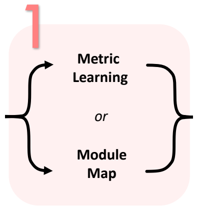
1 → 2 → 3
2 → 3 → 5
3 → 5 → 6



Direction "***inside-out***" are given to edges.

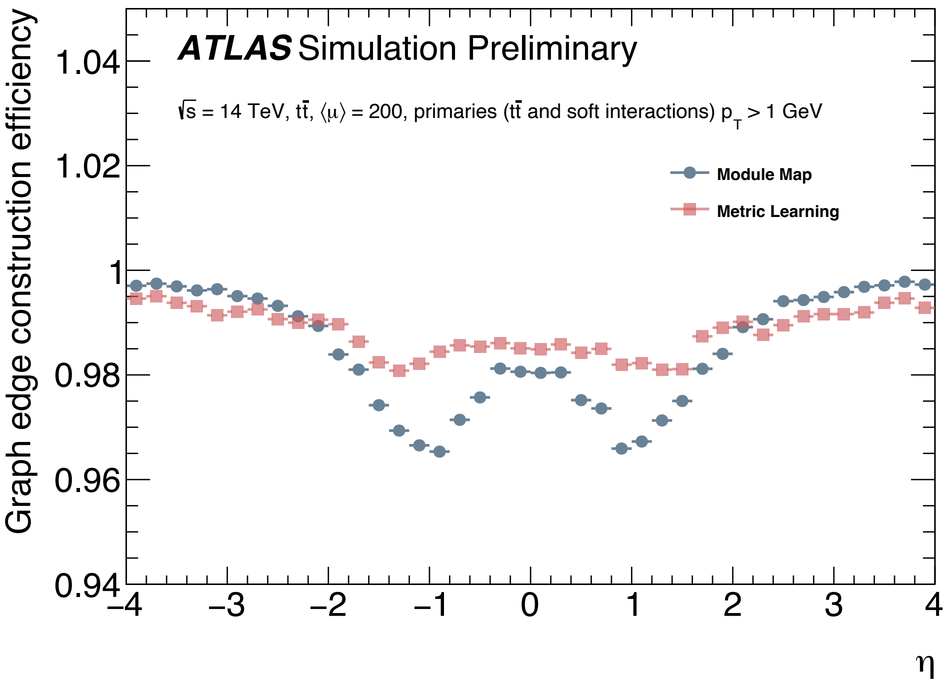
Additional filtering is done with geometric cuts.

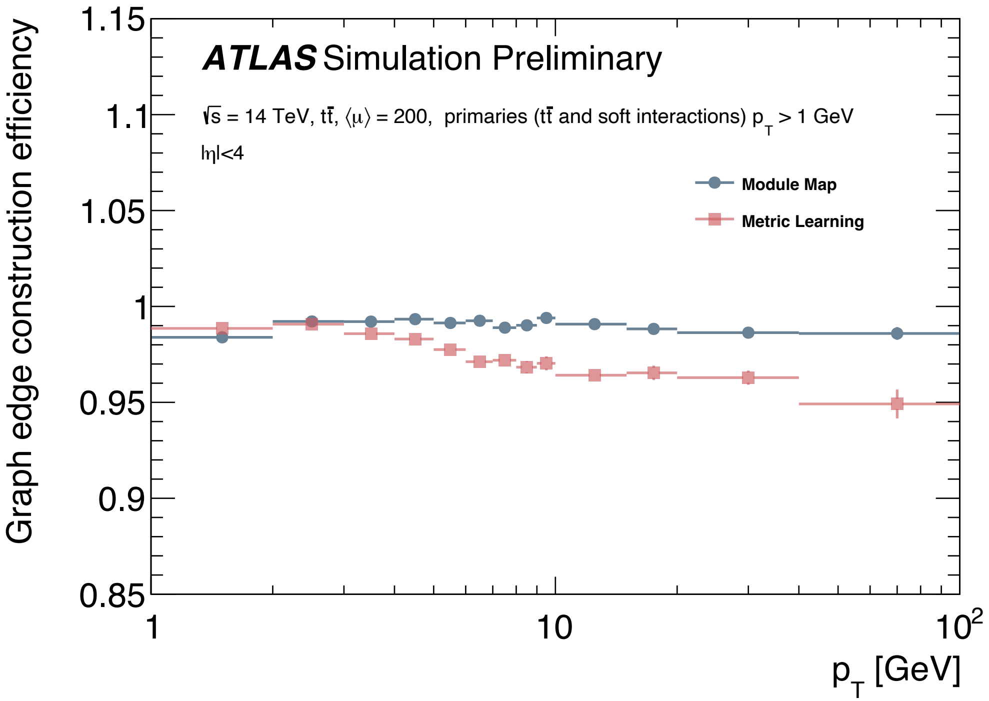
Graph edge construction efficiency

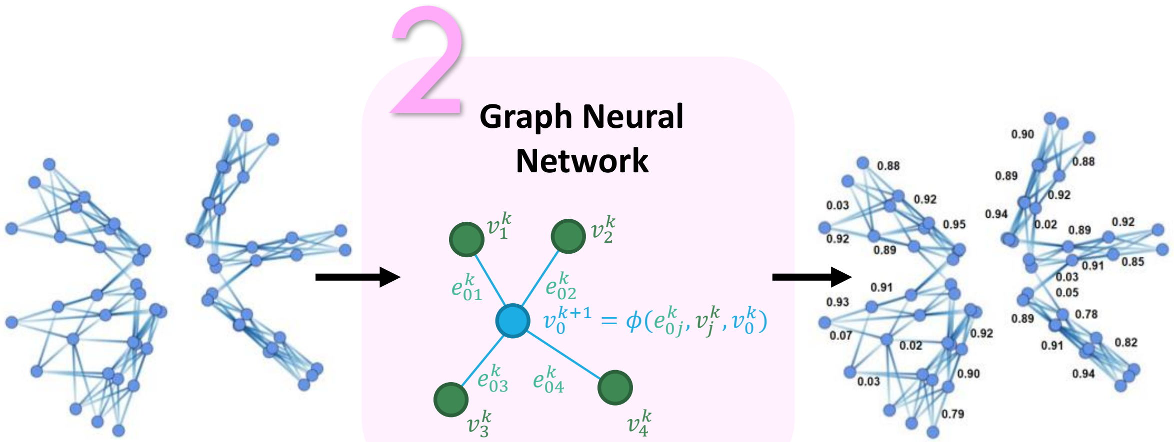


- **Graph edge construction efficiency**

High efficiency is a necessity: an edge lost during the graph construction can’t be retrieved later.



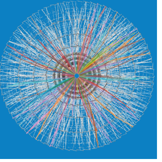




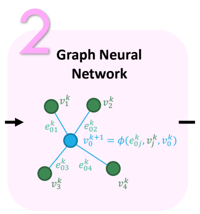
Graph

Edge Labeling

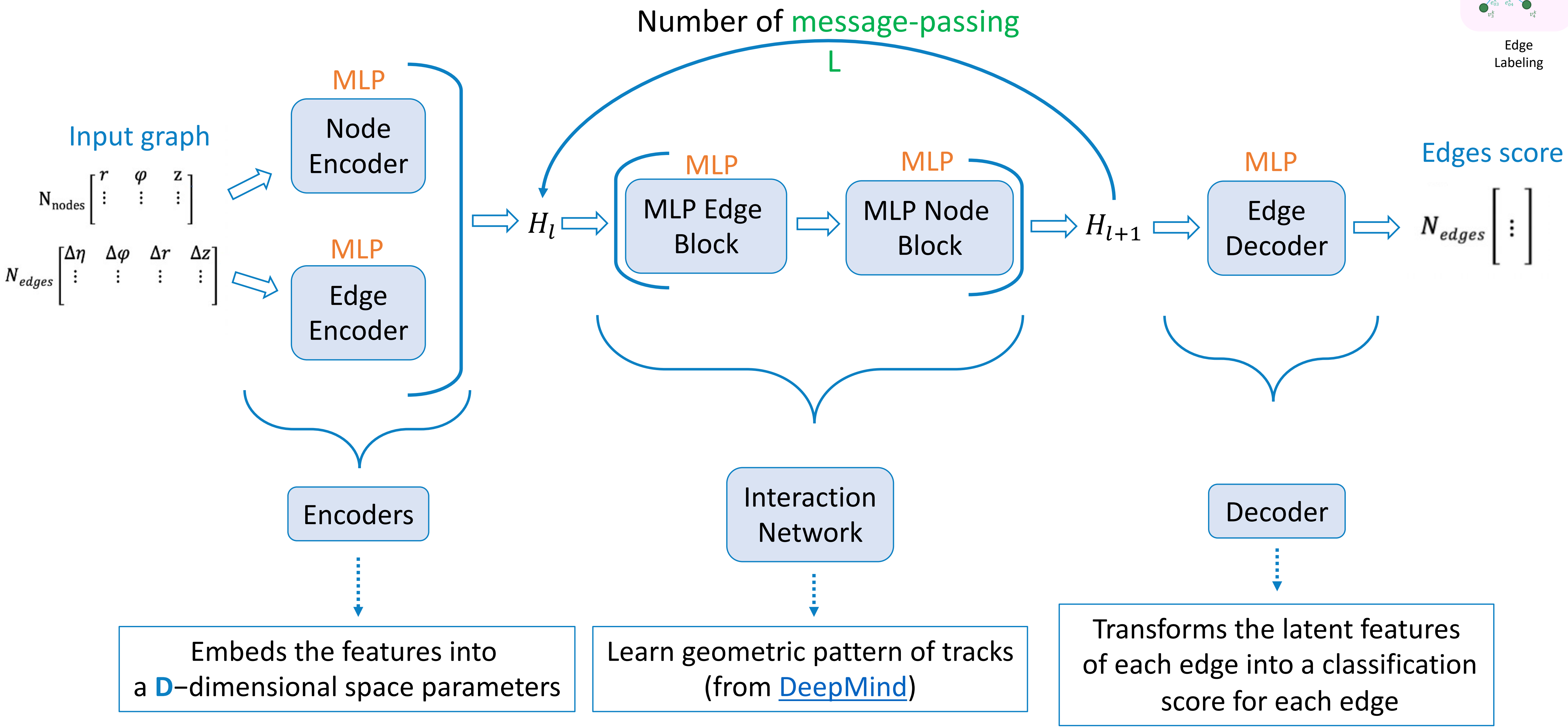
Edge Scores



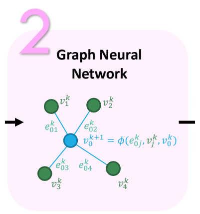
Graph Neural Network model



Edge Labeling



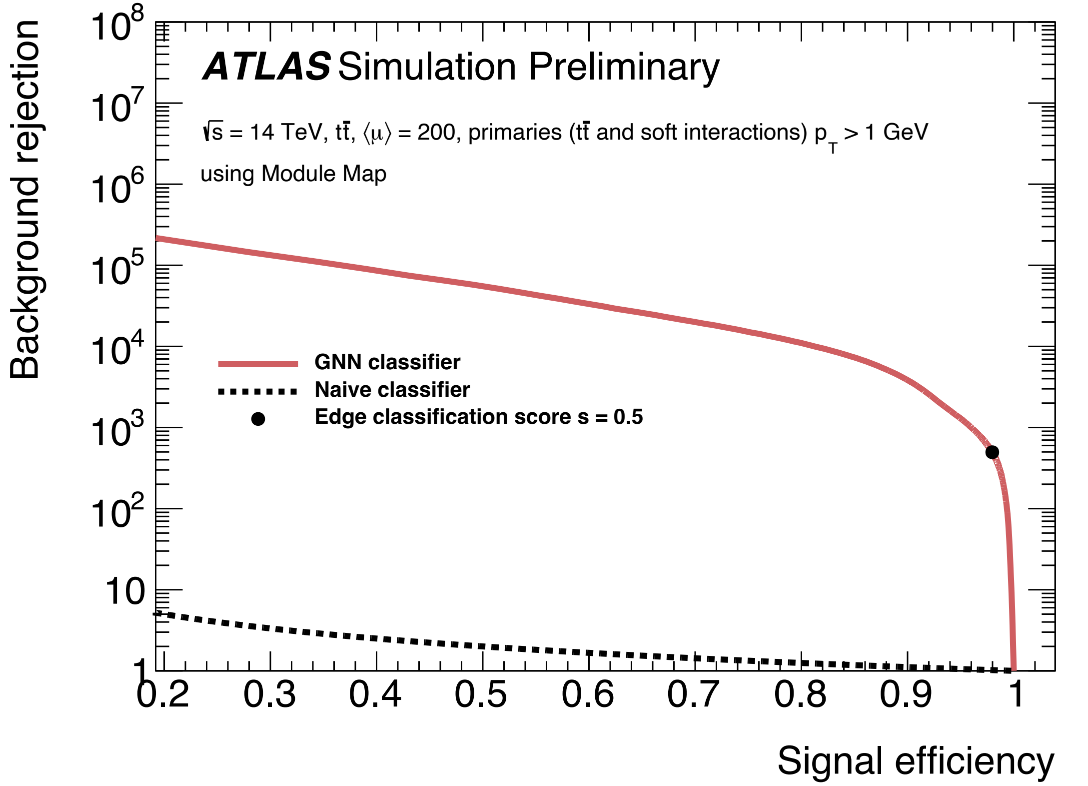
Training the GNN



Edge Labeling

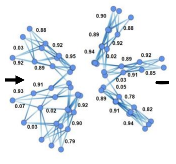
- **Configuration of the GNN architecture**
  - 2 layers in each MLPs
  - 128–dimensional space parameters
  - 8 message-passing

- **Training the GNN**
  - 400 graphs for training, 20 for validation
  - Amsgrad optimizer (Adam variant)
  - Binary Cross Entropy loss



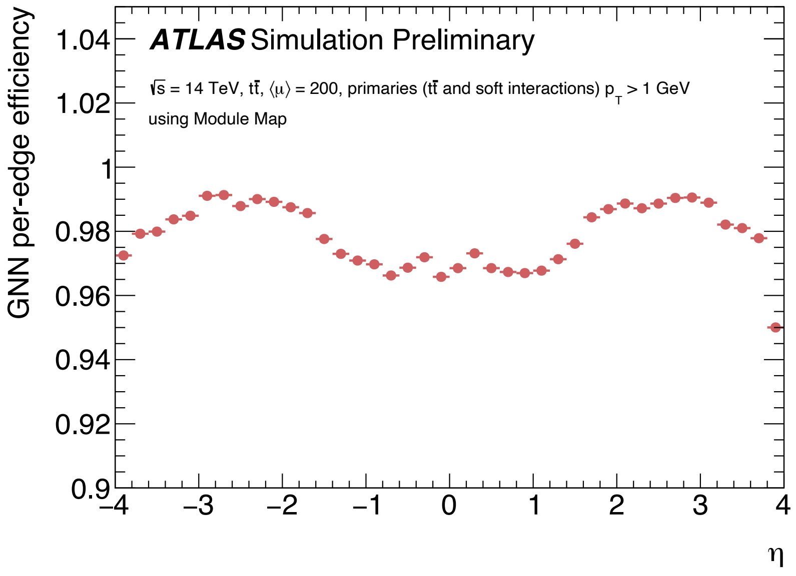
Cut at s = 0.5 on the edge classification score for illustration

GNN edge-performance

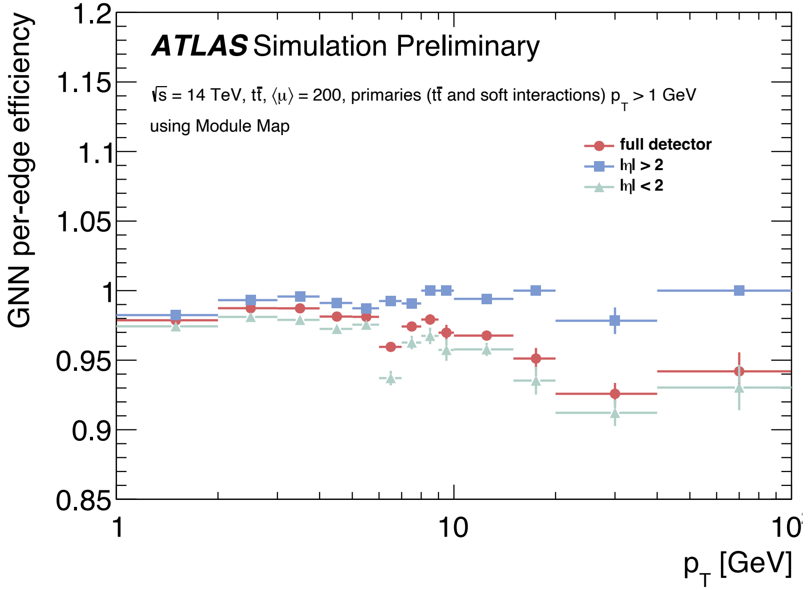


Cut at s = 0.5 on the edge classification score

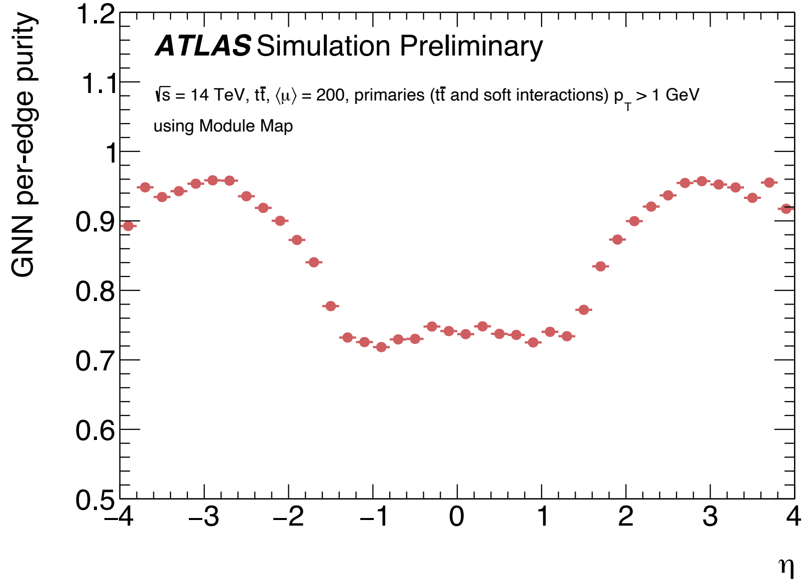
Efficiency vs. η



Efficiency vs. p_T

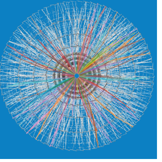


Purity vs. η

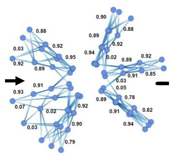


Efficiency and purity degradation in the central region.

➡**What is the source of this inefficiency ?**



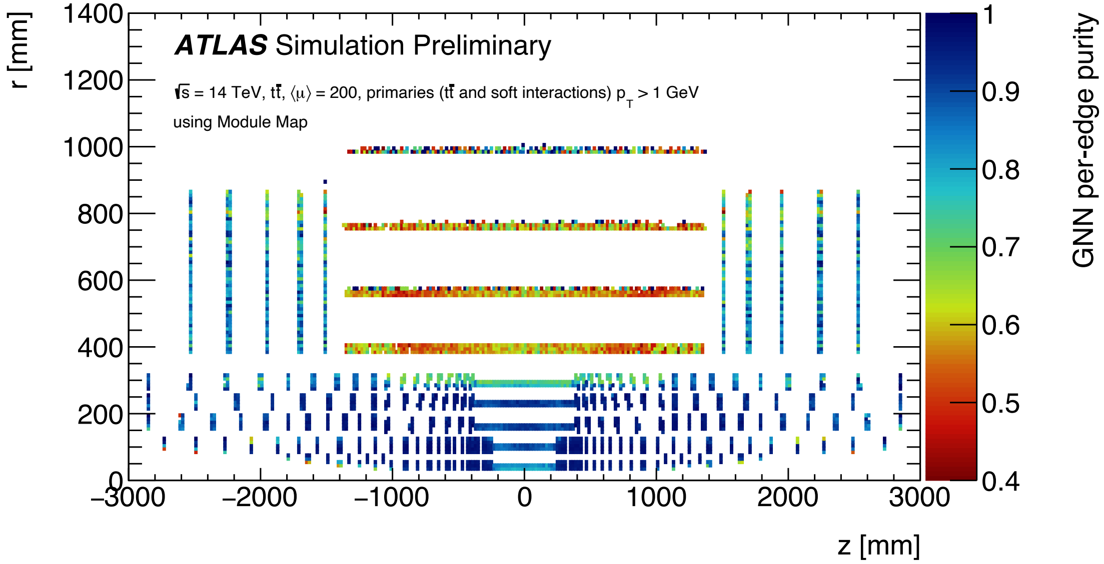
Investigation of the GNN edge-performance

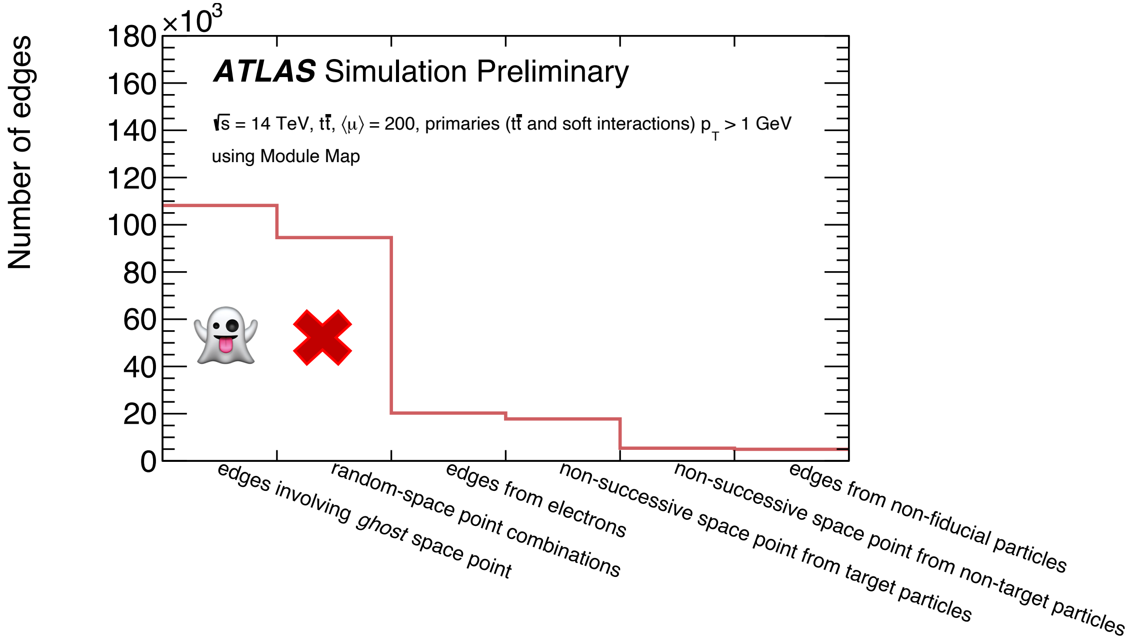


Edge Scores

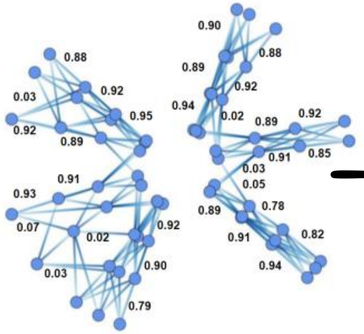
• Misclassification in the central region

Before building the tracks, the GNN classification must be good. We applied a cut at $s = 0.5$ on the GNN edge classification score.





The misclassification arises in the barrel of the strip detector: the lower spatial space-point resolution and the existence of ghost space points are the sources.



Edge Scores

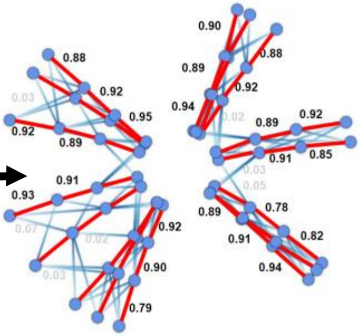
3

Connected Components

or

Connected Components + Walkthrough

Graph Segmentation



Track Candidates

Building track candidates

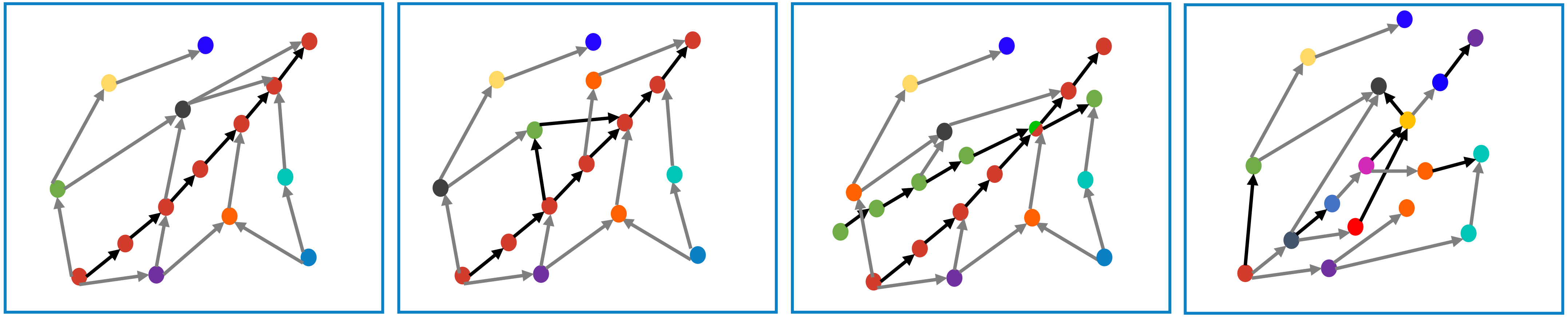
Legend

Edge below threshold

Edge above threshold

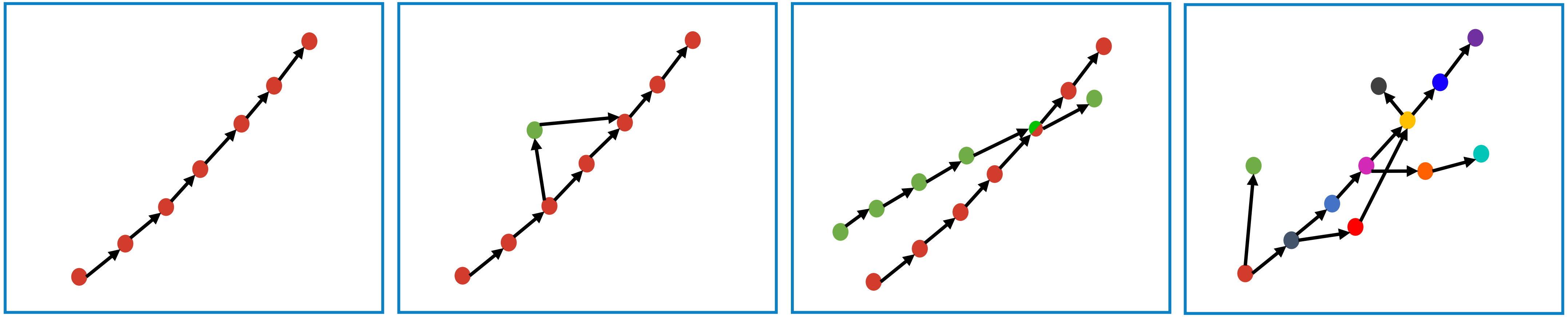
Nodes same color = Nodes same particles

Zoom on part of a graph



Low cut on the edge score classification: ~ 1.3M edges -> 30k edges

Connected component



Building track candidates

Legend

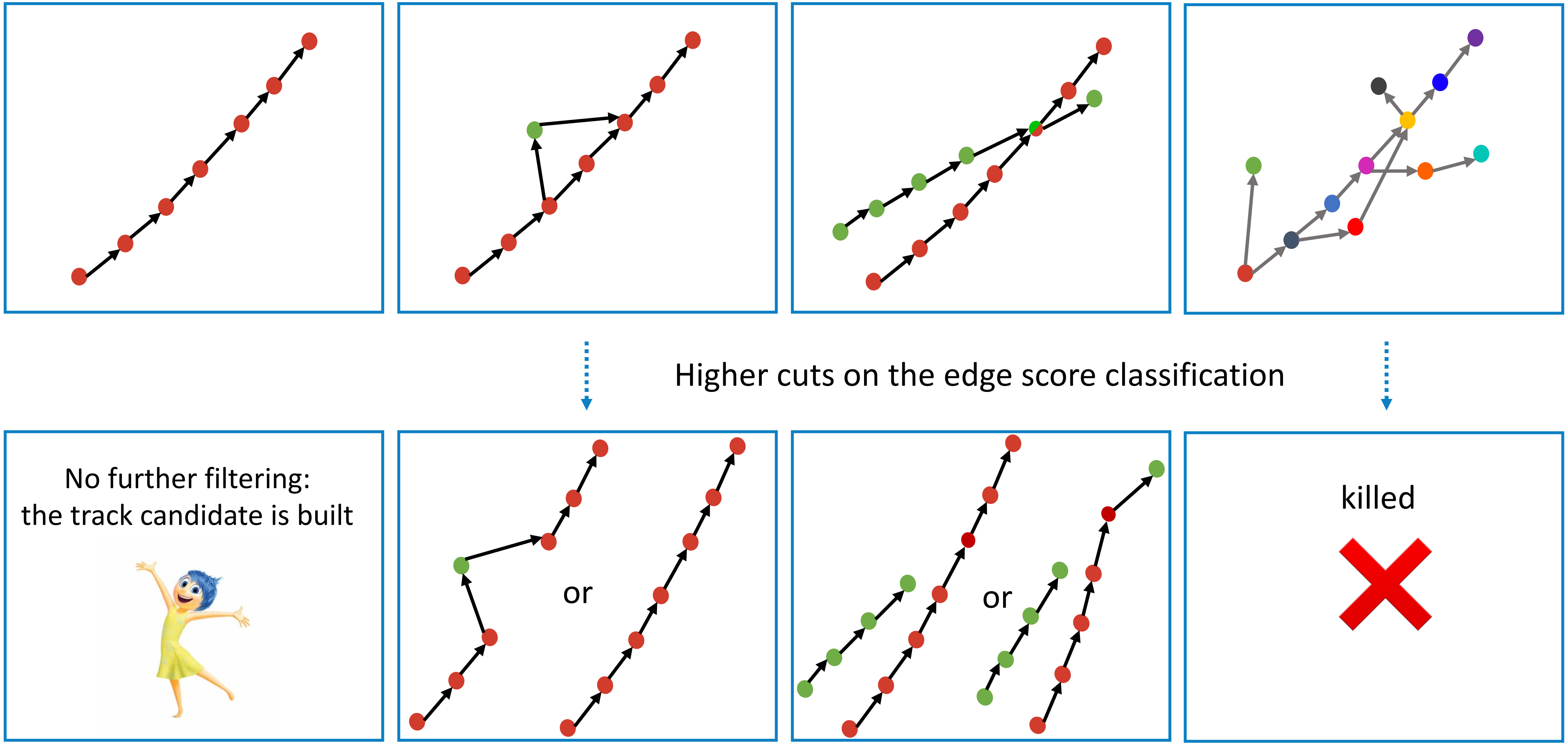
Edge below threshold

Edge above threshold

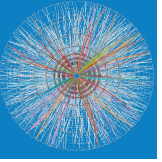
Nodes same color = Nodes same particles

Connected component

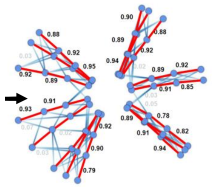
Walk-through algorithm



+ 2 possibilities



Track reconstruction matching criteria



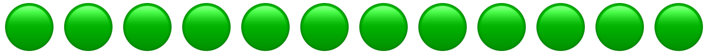
Track Candidates

- **Evaluation of the track candidates**

No track fit is applied.

- **Matching criteria**

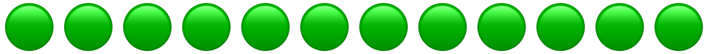
Particle



Track candidate

Standard matching

$$\mathrm{P}_{\mathrm{match}} > 0.5$$

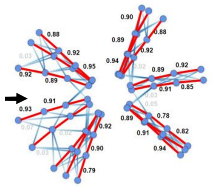


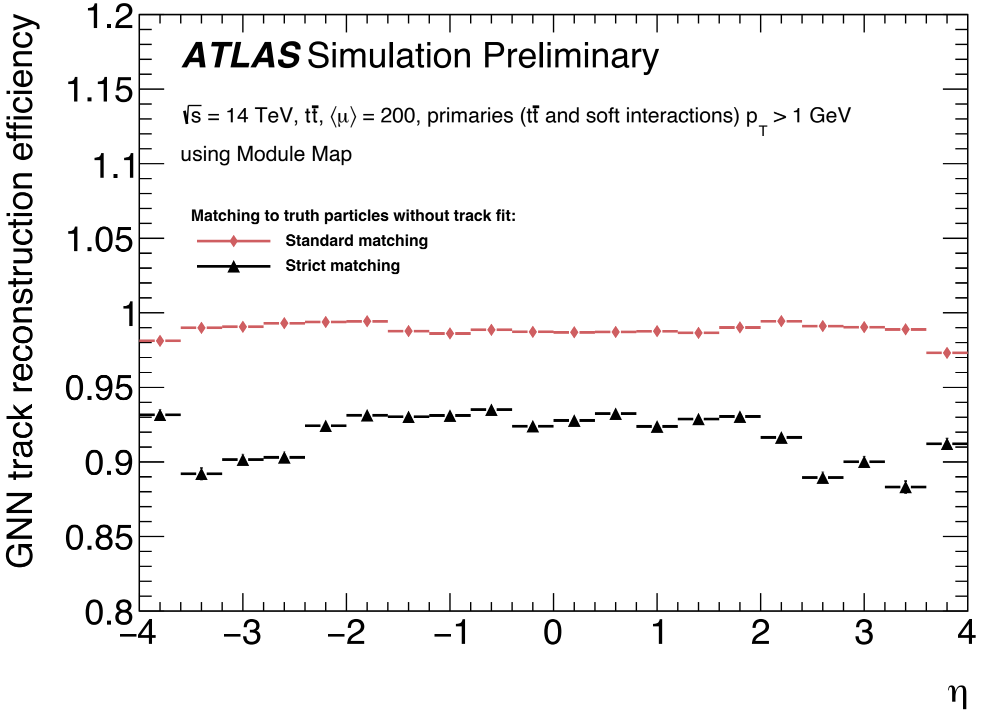
Strict Matching

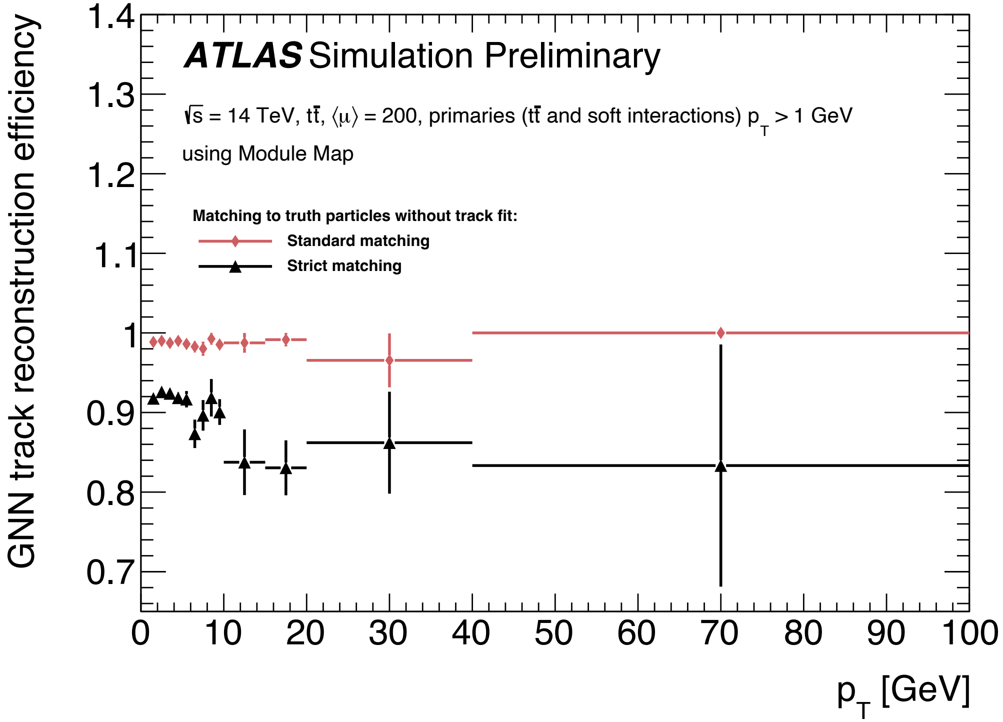
$$\mathrm{P}_{\mathrm{match}} = 1$$

Track purity = 1

GNN track reconstruction efficiency


Track Candidates





Track candidate not matched to any particle = fake track

➡ found to be $O(10^{-3})$

Conclusion and prospects

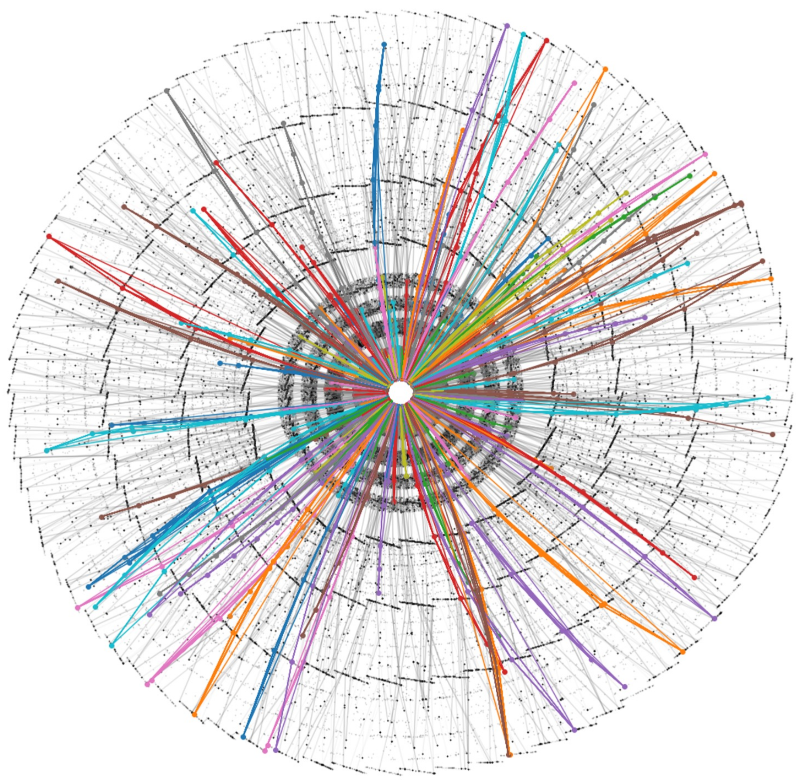
- **Conclusion**

First results using a GNN-based track reconstruction with ITk simulated data are promising and realistic.

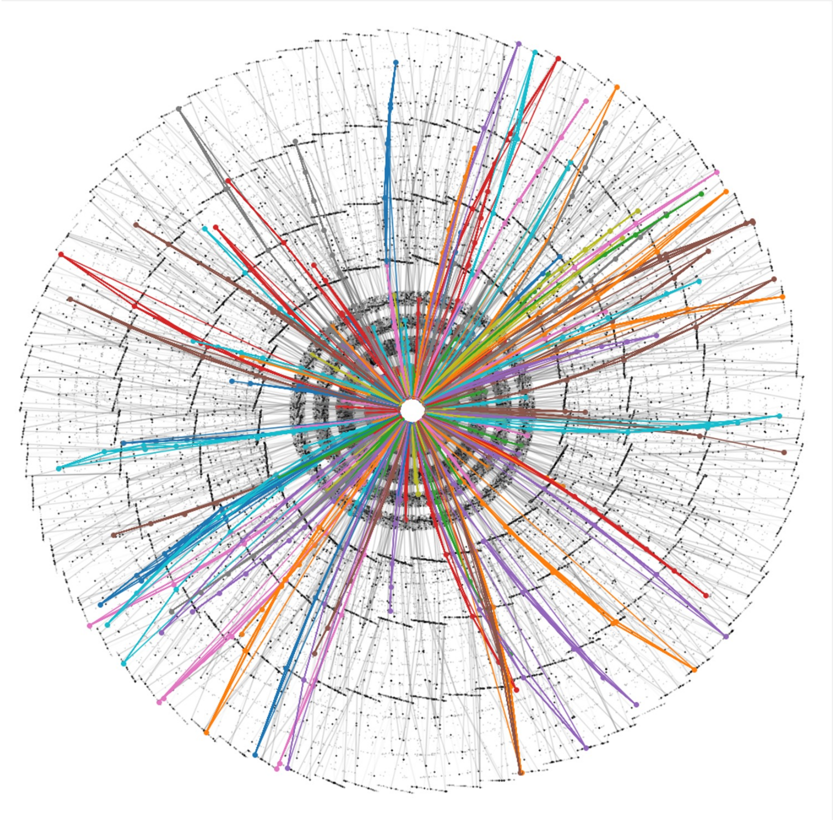
- **Prospects**

Several studies are ongoing:

- Finish integration to **A C**ommon **T**racking **S**oftware ACTS and Athena
- Comparison with the Kalman Filter
- New GNN architectures to fix the degradation of efficiency in the strips



Thanks for your attention ☺



BACK-UP

On the space-point spatial resolution